

Abstract of “Building Query Optimizers with Combinators” by Mitch Cherniack, Ph.D., Brown University, May 1999.

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This thesis addresses the correctness issue for query rewriting. We introduce a novel framework (COKO-KOLA) for expressing query rewrites that can be verified with an automated theorem prover. At its foundation lies KOLA: our *combinator-based* query algebra that permits expression of simple query rewrites (*rewrite rules*) without imperative code. While rewrite rules are easily verified, they lack the expressivity to capture many query rewrites used in practice. We address this issue in two ways:

- We introduce a language (COKO) to express complex query transformations using KOLA rule sets and an algorithm to control rule firing. COKO supports expression of query rewrites that are too *general* to be expressed with rewrite rules alone.
- We extend KOLA to permit expression of rewrite rules whose firing requires inferring *semantic conditions*. This extension permits expression of query rewrites that are too *specific* to be expressed with rewrite rules alone.

The recurring theme of this work is that all of the proposed techniques are made possible by a combinator-based representation of queries.

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Building Query Optimizers with Combinators

by
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This dissertation by Mitch Cherniack is accepted in its present form by the Department of Computer Science as satisfying the dissertation requirement for the degree of Doctor of Philosophy.

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Vita

Mitch Cherniack was born on August 18th, 1963 in Winnipeg, Canada. He completed secondary school in Denver, Colorado, and then attended McGill University in Montreal, Canada, where he received his Bachelor of Education degree (Elementary) in 1984, and a Diploma of Education degree (Secondary) in 1985. He taught in the far north of Canada for a time in 1984, and then taught high school Computer Science and Mathematics in Montreal from 1985–1989. He returned to school at Concordia University in Montreal in 1989, and subsequently earned a Diploma in Computer Science in 1990, and a Masters degree in Computer Science in 1992. He then joined the doctoral program at Brown University in the fall of 1992.

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Credits

Some of these chapters are adapted from our papers. Chapter 3 is based on our 1996 SIGMOD paper [22] and our 1995 DBPL paper [23]. Chapter 4 is based on our 1998 SIGMOD paper [20]. Chapter 5 is based on our 1998 VLDB paper [21]. Chapter 6 is based on a recent conference submission [19]. Chapter 7 forms the basis of a paper currently in preparation. All of these papers were written jointly with Stan Zdonik. As well, [23] was written jointly with Marian H. Nodine and [19] was written jointly with Ashok Malhotra.

Joon Suk Lee and Kee-Eung Kim were primarily responsible for the implementation of the compiler described in Chapter 4. Joon Suk Lee implemented the semantic extensions described in Chapter 5. Blossom Sumulong is building the prototype implementation described in Chapter 7.

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Chapter 1

Introduction

Query optimizers produce plans to retrieve data specified by queries. Optimizers are inherently difficult to build because for any given query, there can be a prohibitively large space of candidate evaluation plans to consider. Further, the difficulty of formulating estimates of plan costs makes the comparisons of plans within this space difficult. As a result, optimizers invariably forego searches for “best plans” and instead are considered effective if they usually produce good plans and rarely produce poor ones.

Query optimizers are perhaps the most complex and error-prone components of databases. In describing software testing methodology developed at Microsoft, Bill Gates reported that hundreds of randomly generated queries were processed incorrectly by Microsoft’s SQL Server [41]. The problem is not unique to Microsoft. Even research *literature* for query optimization has been susceptible to bugs, as in the notorious “COUNT bug” revealed of the optimization strategies proposed by Kim [63].

Software engineering has introduced formal methods for the development of correct software. This thesis applies software engineering methodology to the development of one error-prone component of query optimizers: the *query rewriter* [79].

1.1 Preliminaries

We begin by defining terms that appear throughout this thesis: *query optimization*, *query rewriting* and *rule-based query optimization and query rewriting*.

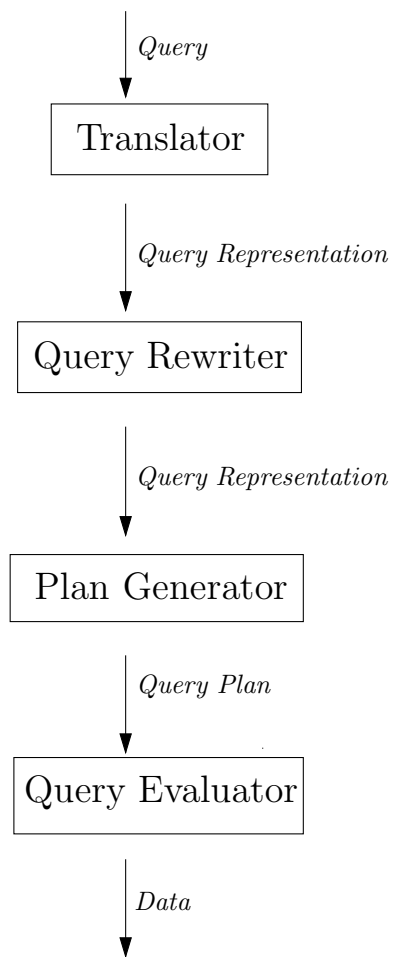


Figure 1.1: A Traditional Architecture for Query Processors

1.1.1 Query Optimization

Query optimizers typically follow an “assembly line” approach to processing queries, as illustrated in Figure 1.1:

1. *Translation* first maps a query posed in a standard query language such as SQL (for relational databases) or OQL [14] (for object-oriented databases), into an *internal representation* (or *algebra*) manipulated by the optimizer. Example internal representations include the Query Graph Model (or QGM) which is used in Starburst [79] and DB2, and Excess which is used in Exodus [13].
2. *Query Rewriting* uses heuristics to rewrite queries (more accurately, query representations) into equivalent queries that are more amenable to plan generation.¹
3. *Plan Generation* generates alternative execution plans that retrieve the data specified by the represented query, estimates the execution costs of each and then chooses the one it considers “best”.
4. *Plan Evaluation* can immediately follow plan generation (in the case of *ad hoc* queries) or can occur later if queries are compiled (as with *embedded* queries).

This architecture is by no means fixed. For example, Cascades [42] generates multiple queries during query rewriting, and generates plans for each before choosing one that is best.

1.1.2 Query Rewriting

Query rewriting has its roots in early relational databases such as System R [85] and Ingres [92] which supported *view merging*: the rewriting of a query over a view into a query over the data underlying the view. Kim [63] proposed *query unnesting* strategies that rewrite *nested queries* (queries containing other queries) into join queries, thereby giving plan generators more alternatives to consider. (Kim’s ideas were later refined by many, including Ganski and Wong [39], Dayal [29] and Muralikrishnan [75, 76].) What is common to these early proposals is that they were intended as ad hoc extensions of query optimizers.

Starburst [79] elevates these ad hoc extensions to a distinct phase of query optimization known as *query rewriting*. Rewrites applied during this phase include view merging and query unnesting, as well as other rewrites that accomplish one of the following objectives:

¹Some (e.g., [95]) call the heuristic preprocessing optimization stage *algebraic optimization*, because this stage involves manipulation of expressions of a query algebra. The term *query rewriting* was introduced by Starburst [79].

- *Normalization*: Queries sometimes get posed in ways that force optimizers to choose poor evaluation plans. For example, because query optimizers build plans incrementally (i.e., by composing plans for subqueries to build full execution plans), nested queries tend to get evaluated using nested loop algorithms. By rewriting nested queries to join queries, optimizers are able to consider alternative algorithms such as *sort-merge joins*, *hash joins* etc. Therefore, one goal of query rewriting is to normalize a query into a form that allows a query optimizer to consider a greater number of alternative plans.
- *Improvement*: Query rewriting might also apply heuristics that are likely to lead to better plans, regardless of the contents or physical representation of the collections being queried. An example of this is a rewrite of a query that performs duplicate elimination into a query that does not. This rewrite is valid when duplicate elimination is performed on a collection that is already free of duplicates (for example, a collection resulting from projecting on a *key* attribute of a relation). Duplicate elimination is costly, requiring an initial sort or grouping of the elements of a collection. Therefore, rewriting a query to avoid duplicate elimination is always worthwhile.

1.1.3 Rule-Based Query Optimizers and Query Rewriters

With the emergence of alternative data models in the 1980's (e.g., object-oriented) came the need for *extensible* query optimizers that could adjust to variations in data. Optimizers are extensible if they can be easily modified to account for new data models or data retrieval techniques. *Rule-based optimizers* (proposed concurrently by Freytag [38] and Graefe and DeWitt [13]) were the first optimizers introduced for this purpose.

Rule-based optimizers express the mapping of queries to plans (or queries to queries in the case of rule-based query rewriters) incrementally in terms of rules. Rules might be executed (*fired*) directly (as in Starburst, where rules are programmed in C), or used to *generate* an optimizer, as with Exodus/Volcano [13, 43] which express rules as rewrite rules supplemented with code. Rules make optimizers extensible because the behavior of the optimizer can be modified simply by modifying its rule set. Example rule-based systems aside from Starburst and Exodus/Volcano include Gral [6], Cascades [42] and Croque [50].

For query rewriters, rules offer a second potential benefit as formal specifications of query rewriting behavior, making it possible for query rewriters to be formally verified. This thesis shows how query rewrite rules can be expressed to enable their formal verification.

1.2 Issues in Query Rewriting

1.2.1 The Correctness Issue

As with other aspects of query optimization, query rewriting is complex and error-prone.

Definition 1.2.1 (Correctness) *A query rewriter is correct if rewriting always produces an semantically equivalent query (i.e., a query that is guaranteed to produce the same result over all database states as the original query).*

Many of Kim’s nested query rewrites were revealed to be incorrect by Kiessling [62]. Among the errors revealed was the “COUNT bug” which adversely affected unnesting rewrites of queries with aggregates (such as COUNT).² Developers of Starburst have pointed out that aside from nested queries, queries involving duplicates and NULL’s are also problematic for ensuring correctness [49]. The correctness problem is only getting worse with the emergence of *object databases* (i.e., *object-relational* and *object-oriented* databases). Object databases relax the flatness restrictions imposed by relational databases, and therefore allow queries to be nested to a far greater degree than was possible with relations. (For example, an OQL query can be nested in its SELECT clause and not just in its FROM and WHERE clauses.)

This thesis addresses the correctness issue for query rewriters. It is not enough to supplement rewrite strategies that appear in the literature with handwritten proofs. (Kim’s rewrites were accompanied by formal correctness proofs that had bugs like the rewrites they were intended to verify.) Our goal is to instead make query rewriters verifiable with an *automated theorem prover*. Theorem provers were developed within the artificial intelligence community to assist with the development and error-checking of logic proofs [51]. They have since been adopted by the software engineering community as a means of verifying software relative to their formal specifications [90]. Theorem provers have proven to be especially valuable in verifying complex software (such as concurrent systems [54]) and safety-critical systems [77]. Verification of query rewriting is another natural application of this technology.

Automated theorem provers vary greatly in their complexity. Many higher-order provers (such as Isabelle [78]) are powerful but hard to use. As such, they are tools for logicians rather than software engineers. As our goal is to influence the work of systems builders, we have chosen a simple first-order theorem prover (LP [46]) that is straightforward to learn and use. Automated theorem provers are also software, and as such are fallible. For this

²To this day, the “COUNT bug” has inspired numerous remedies. The most recent work we found to address the “COUNT bug” is Steenhagen’s 1994 work [91]. More comprehensive studies of query unnesting have since appeared, such as Fegaras’ 1998 work [32].

reason, absolute guarantees of software correctness are unrealistic. But correctness can be viewed as a relative measure of confidence rather than an absolute truth. Our inclination is to have more confidence in systems that have been verified with an established theorem prover than those that have not.

1.2.2 The Expressivity Issue

Query rewrites can be quite complex. Rewrites that unnest nested queries must be able to do so for any degree of nesting. Rewrites that eliminate the need for duplicate elimination must have *semantic* knowledge of the data being queried (e.g., knowledge about keys). The inherent complexity of many query rewrites is another reason that in practice, query rewrites get expressed with code.

As with correctness, object databases exacerbate the expressivity issue. Unnesting rewrites for object queries must account for more kinds of nesting (e.g., nesting in **SELECT** clauses, nesting resulting from methods or attributes returning collections) than do rewrites for relational queries. Object queries can also invoke user-defined methods that dominate the cost of query processing, and about which the optimizer knows nothing. Such methods make semantic reasoning more difficult and more crucial. In short, correctness gains in query rewriting cannot come at the expense of expressivity. This thesis attempts to balance these two concerns.

1.3 Contributions

1.3.1 Conceptual Contributions

This thesis addresses the correctness and expressivity issues for query rewriting. To address the former, it proposes a framework for the expression, verification and implementation of rule-based query rewriters. The foundation of this work is our query algebra, KOLA. KOLA is a *combinator-based* algebra (i.e., an algebra that does not use variables). Combinators make simple rewrites of KOLA queries expressible with rewrite rules whose correctness can be verified with the theorem prover, LP [46].

Not all query rewrites are simple. The other conceptual contributions of this work address the expressivity issue for query rewriters. First, we address the expression of *complex* query rewrites that are too **general** to be expressed as rewrite rules. To express rewrites such as these, we developed a language (COKO) that permits the association of multiple

KOLA rewrite rules with a *firing algorithm* that controls their firing. Expressivity is addressed without compromising correctness. As with KOLA rewrite rules, rewrites expressed in COKO are verifiable with LP.

Whereas COKO rewrites are too general to be expressed as rewrite rules, other rewrites are too **specific** to be expressed as rewrite rules. (That is, these rewrites depend on semantic, and not just syntactic properties of the queries they rewrite.) We have extended COKO and KOLA to permit the expression of such rewrites and the procedures that decide if semantic conditions hold. Again, this gain in expressivity does not compromise correctness; both semantic rewrites and condition checking are verifiable with LP.

1.3.2 Implementations

The conceptual contributions described above are complemented by the following more tangible contributions that serve as proofs of concept:

- a *formal specification* of KOLA using the Larch specification tool, LSL [46],
- *scripts* for the Larch theorem prover, LP [46] that verify several hundred query rewrites,
- a *translator* to translate set and bag queries from the object query language OQL [14] into KOLA,
- a *compiler* to translate COKO specifications (including those with semantic rewrites) into executable query rewriting components, and
- a *query rewriter* generated using the software and methodology presented in this thesis, for an object-oriented database presently under development at IBM.

1.3.3 High-Level Contributions

The high-level contribution of this work is the recognition of the impact of query representation on query optimizer design. The key to making query rewrites verifiable with a theorem prover is to express them *declaratively* (i.e., without supplemental code) as in the rewrite rules of term rewriting systems. In practice, query rewrites are not expressed declaratively and instead get expressed with code that performs the rewriting. This code is difficult to verify.

Query representations affect whether or not rewrites need to be expressed with code, and hence whether or not rewrites can be verified with a theorem prover. A query rewrite

will typically (1) identify one or more subexpressions in a given query (*subexpression identification*) and (2) formulate a new query expression by recomposing these subexpressions (*query formulation*). Both subexpression identification and query formulation are difficult to express declaratively over *variable-based* query representations (i.e., query representations that use variables to denote arbitrary elements of queried collections) such as QGM. The problem is that query subexpressions can include *free* variables, making their meaning dependent on context. Subexpression identification then requires code to examine the context of subexpressions to ensure that the correct ones are identified. Query formulation requires code to ensure that subexpressions that are used in new contexts have their meanings preserved. Combinator-based algebras, by eliminating variables, eliminate the need for this kind of code.

In short, the combinator-based representation of KOLA queries makes it possible to express simple, complex and semantic query rewrites in a manner facilitating their verification with a theorem prover. Further, combinator-based query algebras also make it possible to consider alternative query processing architectures that vary *when* query rewriting occurs. We are presently studying the potential benefits of *dynamic* query rewriting: query rewriting that occurs during a query’s evaluation. Dynamic query rewriting could potentially affect the processing of queries over collections whose contents and characteristics are not known until run-time, such as object queries (which might query embedded collections) or heterogeneous database queries (which might query collections known only to the local databases they oversee). Dynamic query rewriting also uses subexpression identification and query formulation, and therefore it too benefits from the combinator-based approach.

1.4 Outline

The thesis is structured as follows. In Chapter 2, we motivate the work presented in this thesis by describing an example object database schema, some example queries over this database and some query rewrites that would be useful to express. Chapter 3 describes KOLA; our combinator-based query algebra that makes it possible to use a theorem prover to verify rewrites. Chapter 4 describes COKO; our language for expressing complex query rewrites in terms of sets of KOLA rewrite rules. Chapter 5 describes extensions to COKO and KOLA that permit the expression of semantic rewrites. Chapter 6 assesses the practicality of the COKO-KOLA approach in light of experiences building a query rewriting component for an object-oriented database being developed at IBM. Chapter 7 describes ongoing work in dynamic query rewriting. Chapter 8 describes related work conclusions

and future work follow in Chapter 9.

Chapter 2

Motivation

In this chapter, a potential application of the thesis work is described. We have chosen an object database example to motivate this work, as the potential complexity of object queries illustrates the need for expressive query rewriting for which correctness can be assured.

The application is based on the Thomas web site [97], which describes the activities of the United States Congress. After describing how Thomas could be modeled with an object database, two example sets of queries are presented to illustrate correctness and expressivity challenges for query rewriting. The first set of queries (the “Conflict of Interests” queries) demonstrates the potential complexity of object query rewrites and why correctness is a concern. The second set of queries (the “NSF” queries) demonstrates the need for semantic rewrites, and motivates our ongoing work in dynamic query rewriting.

2.1 The Thomas Website

The United States Congress maintains the web site *Thomas* [97] to describe its daily activities. Thomas maintains information about each Congressional bill (both Senate resolutions and House resolutions) such as its name, topic and set of sponsors. Additionally, Thomas maintains information about every legislator (Senator and House Representative) such as his or her name, the region (state or Congressional district) he or she represents, his or her party affiliation, the city in which he or she was born, and the number of terms he or she has served. Every Congressional committee is represented with such information as its topic, chair and members. Thomas also includes links to related sites such as the United States Census Bureau [96], which maintains information about represented regions (states and Congressional districts) and cities. Regional information includes the name of the region, the set of major cities contained in the region, the largest city in the region and the

population of the region. Information about cities includes the name of the city, its mayor and its population. Information about mayors include their name, the city they represent, their party affiliation, the city in which they were born and the number of terms they have served.

Thomas is not a database but a file system with hyperlinks. As a result, querying of Thomas (as with most web sites) is restricted to navigational queries (i.e., following links) and keyword searches. There is no support for associative access to data, as in a query that identifies committees whose chairs have potential conflict of interests due to their membership in other subcommittees (Figure 2.1), or a query that identifies the cities that potentially had influence in the formulation of policies regarding research funding (Figure 2.4). To support queries such as this, Thomas would have to be provided with a database backbone.

2.2 An Object Database Schema for Thomas

An object database would be ideal for maintaining the data accessible from Thomas. Entities such as legislators, committees and bills are naturally modeled as objects. And because both object-oriented and object-relational databases support *complex data* (object attributes that name other objects or collections), a committee can have an attribute denoting its set of members, a bill can have an attribute denoting its set of sponsors, and a region can have an attribute denoting its set of major cities.

A schema for Thomas is shown in Table 2.1 and includes types: *Bill* (with subtypes *Senate_Resolution* and *House_Resolution*), *Legislator* (with subtypes *Senator* and *Representative*), *Mayor*, *Committee*, *Region* (with subtypes *State* and *District*) and *City*. The interface for these types is summarized below:

- Type *Bill* includes a **name**¹ attribute denoting the name of the bill, a **topic** attribute denoting the topic of the bill, and a **spons** attribute denoting the set of legislators who are the bill's sponsors. Subtypes *Senate_Resolution* and *House_Resolution* specialize their sets of sponsors to sets of Senators and House Representatives respectively.
- Type *Legislator* includes a **name** attribute denoting the name of the legislator, a **reps** attribute denoting the region of the country that the legislator represents, a

¹This proposal adopts the notational convention that all names of attributes are written in typewriter font (e.g., **name**).

Type	Supertype	Attributes	Collections
<i>Bill</i>		name <i>String</i> topic <i>String</i> spons { <i>Legislator</i> }	Bills*
<i>Senate_Resolution</i>	<i>Bill</i>	spons { <i>Senator</i> }	SenRes*
<i>House_Resolution</i>	<i>Bill</i>	spons { <i>Representative</i> }	HouseRes*
<i>Legislator</i>		name <i>String</i> reps <i>Region</i> pty <i>String</i> bornin <i>City</i> terms <i>Int</i>	
<i>Senator</i>	<i>Legislator</i>	reps <i>State</i>	Sens*
<i>Representative</i>	<i>Legislator</i>	reps <i>District</i>	HReps*
<i>Committee</i>		topic <i>String</i> chair <i>Legislator</i> mems { <i>Legislator</i> }	Coms, SComs
<i>Region</i>		name <i>String</i> cities { <i>City</i> } lgst_cit <i>City</i> popn <i>Integer</i>	
<i>State</i>	<i>Region</i>	–	Sts*
<i>District</i>	<i>Region</i>	–	Dists*
<i>City</i>		name <i>String</i> mayor <i>Mayor</i> popn <i>Integer</i>	Cits*
<i>Mayor</i>		name <i>String</i> city <i>City</i> pty <i>String</i> bornin <i>City</i> terms <i>Integer</i>	Mays*

Table 2.1: A Database Schema for Thomas

`pty` attribute denoting the name of the political party that the legislator is affiliated with, a `bornin` attribute denoting the city where the legislator was born, and a `terms` attribute denoting the number of terms that the legislator has served. Subtypes *Senator* and *Representative* specialize the type of object denoted by attribute `reps` to *State* and *District* respectively.

- Type *Committee* includes a `topic` attribute naming the topic being investigated by the committee, a `chair` attribute denoting the legislator who is chair of the committee, and a `mems` attribute denoting a set of legislators who are members of the committee.
- Type *Region* includes a `name` attribute denoting the name of the region, a `cities` attribute denoting the set of major cities located in the region, a `lgst_cit` attribute denoting the largest city contained in the region, and a `popn` attribute denoting the region’s population. Subtypes *State* and *District* do not specialize these attributes in any way.
- Like *Region*, *City* also has `name` and `popn` attributes. But unlike *Region*, *City* also has a `mayor` attribute denoting the mayor of the city.
- Type *Mayor* has the same attributes as *Legislator*, but with a `city` attribute (denoting the city represented by the mayor) instead of a `reps` attribute..

Collections of objects of each type are listed in the right most column of Table 2.1. Those with an asterisk denote the *extents* of the type (i.e., the collection of all objects of that type). For example, `Sens` is the extent of type *Senator*. The only collections that are not extents listed are `Coms` and `SComs`, that are collections of Congressional committees and subcommittees respectively. The union of these disjoint collections is the extent of type *Committee*.

2.3 The “Conflict of Interests” Queries (*COI*)

Figure 2.1 shows an OQL [14] query over the Thomas database (hereafter, this query will be referred to as COI_1 (*COI* is short for “Conflict of Interests”) that finds committees that are chaired by a member of a subcommittee chaired by someone from the same party. This query might be posed to identify those committees whose integrity could be called into question.²

²We deviate from OQL syntax in using “==” to denote an equality operator. We reserve “=” for reasoning about the meaning of query expressions throughout this thesis.


```

SELECT DISTINCT  $x$ 
FROM  $x$  IN Coms
WHERE EXISTS  $y$  IN (
  SELECT  $c$ 
  FROM  $c$  IN SComs
  WHERE  $x.chair.pty == c.chair.pty$ 
) : ( $x.chair$  IN  $y.mems$ )

```

Figure 2.1: COI_1 : Find all committees whose chairs belong to a subcommittee chaired by someone from the same party.

As in SQL, OQL queries have **SELECT**, **FROM** and **WHERE** clauses. The **FROM** clause of this query indicates that objects are drawn from the set of committees, **Coms**. The **WHERE** clause filters committees (x) by a complex predicate that determines whether a collection of committees returned by a subquery contains one (y) whose members ($y.mems$) include x 's chair ($x.chair$). The subquery is another **SELECT-FROM-WHERE** query that returns the subset of **SComs** whose chair belongs to the same party as x 's chair. The subset of committees in **Coms** that satisfy this predicate are returned free of duplicates (as directed by the “**DISTINCT**” qualifier in the **SELECT** clause).

2.3.1 Naive Evaluation of COI_1

A naive plan to evaluate COI_1 might perform the following steps:

1. For each x in **Coms**:
 - (a) Extract the values $x.chair$ and $x.chair.pty$
 - (b) Scan collection **SComs**. For each object c in **SComs**, extract the value $c.chair.pty$ and compare this value to $x.chair.pty$. If the values are the same, then add c to a temporary collection.
 - (c) For each object y in the collection generated in (b), extract the collection $y.mems$. Scan $y.mems$ comparing each object to $x.chair$.
 - (d) If $x.chair$ is found in $y.mems$ for some object y then add x to a temporary collection.
2. Remove duplicates from the temporary collection of legislators generated in 1d.

The naive evaluation plan is wasteful. First, it requires duplicates to be removed from a collection of committees that is guaranteed to be free of duplicates already. (A selection

```

SELECT DISTINCT x
FROM x IN Coms
WHERE EXISTS y IN ( SELECT c
                     FROM c IN SComs
                     WHERE x.chair.pty == c.chair.pty ) : (x.chair IN y.mems)

```

→

```

Temp = SELECT p, S: partition
        FROM c IN SComs
        GROUP BY p: c.chair.pty

```

```

SELECT DISTINCT x
FROM x IN Coms, t IN Temp
WHERE (x.chair.pty == t.p) AND (EXISTS y IN t.S : (x.chair IN y.mems))

```

Figure 2.2: Rewriting $COI_1 \rightarrow \overline{COI_1}$

of a set is a set.) Duplicate elimination is costly, requiring sorting or grouping of the collection. A more subtle problem with this plan is that it requires processing the collection `SComs` (Step 1b) more times than necessary. In particular, the collection of all subcommittees chaired by a Democrat (Republican) will be regenerated as the inner query result for each Democratic (Republican) chair of a committee in `Coms`. Below, a query rewrite to address this inefficiency is considered.

2.3.2 A Complex Query Rewrite for COI_1

Figure 2.2 shows how query COI_1 could be rewritten during query rewriting to an equivalent query for which plan generation is likely to be more effective. This figure shows the two queries, COI_1 and $\overline{COI_1}$ separated by the “rewrites to” symbol, “→”. Straightforward evaluation of $\overline{COI_1}$ would require first preprocessing the collection `SComs`, and producing a new collection, `Temp`. OQL’s “GROUP BY” operator partitions `SComs` on the equivalence of party affiliations of subcommittee chairs. The result of this partition (`Temp`) is a collection of pairs that associate a political party (p) with the set of subcommittees chaired by someone in that party (S), for each party affiliated with some subcommittee’s chair. (For each party p , the OQL keyword `partition` names the collection of subcommittees chaired by someone whose party is p .) `Temp` is then used as an input to a join with `Coms` to find those committees whose chair is a member of some subcommittee chaired by someone from the same party.

```

SELECT DISTINCT x
FROM x IN Coms
WHERE FOR ALL y IN ( SELECT c
                     FROM c IN SComs
                     WHERE x.chair.pty == c.chair.pty ) : (x.chair IN y.mems)

```

\nrightarrow

```

Temp = SELECT p, S: partition
        FROM c IN SComs
        GROUP BY p: c.chair.pty

```

```

SELECT DISTINCT x
FROM x IN Coms, t IN Temp
WHERE (x.chair.pty == t.p) AND (FOR ALL y IN t.S: (x.chair IN y.mems))

```

Figure 2.3: An Incorrect Query Rewrite

A better plan is likely to be generated for $\overline{COI_1}$ than for COI_1 for two reasons:

1. Plans for $\overline{COI_1}$ will generate the collection of subcommittees whose chairs are from the same party just once per party, rather than once per committee in **Coms** chaired by someone from that party.
2. Plans for $\overline{COI_1}$ will perform a join of **Coms** and **Temp** rather than scanning all of **SComs** for each object in **Coms**. The conversion to a join query is advantageous for two reasons. First, join queries offer more algorithmic choice (e.g., sort-merge join, hash join, nested-loop join etc.) than do nested queries, which tend to get evaluated using nested loops. Secondly, even if a nested loop algorithm is chosen for the join, **Temp** will likely have fewer objects than **SComs**, having one entry per political party rather than one entry per subcommittee.

2.3.3 Correctness

The unnesting query rewrite demonstrated in Figure 2.2 is useful, but under what circumstances is it correct? Clearly, it is correct if it is applied to queries that differ from COI_1 only in trivial ways such as the choice of attributes. But what about queries that differ in more substantial ways? For example, what about a query for which the existential quantifier `exists` is replaced by the universal quantifier, `for all` as shown in Figure 2.3?

```

SELECT STRUCT (
  bill:      r.name
  cities:    ( SELECT DISTINCT x.reps.lgst_cit
               FROM x IN r.spons ) )
FROM r IN HouseRes
WHERE r.topic == "NSF"

```

Figure 2.4: NSF_1 : Find all House resolutions relating to the NSF and associate them with the set of cities that are largest in districts that the bills’ sponsors represent

Such a subtle change results in an incorrect query rewrite. To see why, suppose there exists a committee in `Coms` chaired by Representative Bernie Sanders of Vermont, the sole independent in Congress, and suppose that Sanders is not the chair of any subcommittee in `SComs`. In this case, the initial query of Figure 2.3 will include the committee chaired by Sanders in the query result, but the rewritten (second) query of this figure will not. This is because no subcommittees are chaired by Sanders, and therefore independents are not represented in the preprocessed collection, `Temp`. Thus, Sanders will fail to satisfy the join predicate with all entries in `Temp` and will be excluded from the second query’s result.

This discrepancy in query results is very similar to that which was symptomatic of the “COUNT bug” of Kim [63]. In fact, the query rewrite demonstrated in Figure 2.3 generalizes the *Type JA* rewrite that contains the bug. The subtlety of this bug illustrates the difficulty of determining correctness conditions for query rewrites. This particular rewrite is correct if it is applied only to queries with predicates that are not true of empty collections. COI_1 is such a query because an existentially quantified predicate cannot be true of an empty collection. On the other hand, a universally quantified predicate is always true of an empty collection and therefore the effect of rewriting the initial query of Figure 2.3 is to produce a query with a different semantics.

2.4 The “NSF” Queries (NSF)

Figure 2.4 shows an OQL query (hereafter referred to as NSF_1) that associates every House resolution concerning the National Science Foundation (NSF) with the set of cities that are largest in the districts represented by the bill’s sponsors. This query finds the cities that potentially have the most influence on research funding policies. Unlike COI_1 , this query is nested in its `SELECT` clause and not its `WHERE` clause. Additionally, this query includes a

chain of attribute selections (a *path expression*),

`x.reps.lgst_cit`

that returns the largest city located in the district represented by legislator x . Path expressions can only be posed over object databases, as they require that all but the last attribute return a complex object.

2.4.1 Naive Evaluation of NSF_1

A naive plan for NSF_1 might perform the following steps:

For each r in `HouseRes`:

1. Extract the value $r.topic$. If this value is “NSF”, proceed to step 2.
2. Extract the collection attribute, $r.spons$. For each x in $r.spons$, extract the value

`x.reps.lgst_cit`.

3. Collect the extracted names of all cities identified in 2, and store in a new collection. Eliminate duplicates from this new collection.
4. Extract the value $r.name$. Add the tuple consisting of $r.name$ and the set resulting from the previous step to the result collection.

2.4.2 A Semantic Query Rewrite for NSF_1

The naive evaluation plan for the NSF_1 includes costly duplicate elimination (in Step 3) from collections of cities. Duplicate elimination from these collections is unnecessary because:

- a House resolution has a *set* of House Representatives as its sponsors,
- each House Representative represents a unique district (i.e., the `reps` attribute of type *Representative* is an *injective* function), and
- each district’s largest city is uniquely situated in that district (i.e., the `lgst_cit` attribute of type *Region* is an injective function.)³

³We make the simplifying assumption that every city is located in exactly one district. We can enforce this assumption by assigning a city to the district where the largest number of its residents reside.

```

SELECT STRUCT ( ( bill:    r.name,
                  cities: ( SELECT DISTINCT x.reps.lgst_cit
                             FROM x IN r.spons
                           ) ) )
FROM r IN HouseRes
WHERE r.topic == "NSF"

```

→

```

SELECT STRUCT ( ( bill:    r.name,
                  cities: ( SELECT x.reps.lgst_cit
                             FROM x IN r.spons
                           ) ) )
FROM r IN HouseRes
WHERE r.topic == "NSF"

```

Figure 2.5: Rewriting $NSF_1 \rightarrow \overline{NSF_1}$

Because each attribute in its chain is injective,

$$x.reps.lgst_cit$$

is also injective over type *Representative*. An injective function that is applied to all elements of a set generates another set. Therefore, the collection of largest cities situated in the represented districts is guaranteed to be free of duplicates, and duplicate elimination is unnecessary. Figure 2.5 shows the NSF query before and after the application of the *semantic rewrite* that exploits semantic knowledge about keys and duplicates to produce a query that avoids duplicate elimination.

This example motivates the need to express semantic rewrites. But note that injective path expressions can be of any length, as in

$$x.reps.lgst_cit.mayor$$

which finds the mayor of the largest city of the district represented by x , or even

$$x.reps.lgst_cit.mayor.city.lgst_cit$$

which returns the same result but in a more roundabout way. It is unrealistic to expect that any metadata file could list all injective path expressions, for there may be too many to list.⁴ Therefore, a query rewriting facility must provide some way for an optimizer to *infer* the semantic properties (such as injectivity) on which semantic rewrites are conditioned.

⁴Because the Thomas schema has mutually recursive references (e.g., a city has a mayor (`mayor`) and a mayor is born in a city (`bornin`)), the number of injective path expressions over this schema is infinite.

```

SELECT STRUCT (
  bill:    b.name,
  cities:  ( SELECT DISTINCT x.reps.lgst_cit
             FROM x IN b.spons
           )
)
FROM b IN Bills
WHERE b.topic == "NSF"

```

Figure 2.6: NSF_2 : Find all Bills (Senate and House resolutions) relating to the NSF and associate them with the set of cities that are largest in regions that the bills' sponsors represent

2.4.3 Dynamic Query Rewriting

Consider the second NSF query (NSF_2) shown in Figure 2.6. This query is similar to NSF_1 , but queries a collection (Bills) of House **and** Senate resolutions, and not just a collection of House resolutions.

As was stated previously, the application of the path expression,

$$x.reps.lgst_cit$$

over any set of House Representatives is guaranteed to return a set because **reps** is a key for type *House Representative* and **lgst_cit** is a key over type *Region*. However,

$$x.reps.lgst_cit$$

is **not** an injective function over type *Senator* because **reps** is not a key over type *Senator*. Rather, there are *two* Senators for every state represented by a Senator. Because Bills can include a Senate resolution b , $b.spons$ can be a set of Senators. Therefore, the query rewrite described in the previous section cannot be applied to this query.

On the other hand, query NSF_2 could be evaluated in the following way:

- For bills that are Senate resolutions, perform duplicate elimination on the collection of cities associated with the bill's sponsors.
- For bills that are House resolutions, do *not* perform duplicate elimination on the collection of cities associated with the bill's sponsors.

In other words, the semantic rewrite described in the previous section could be applied *dynamically* to rewrite subqueries applied to House resolutions and to leave alone subqueries applied to Senate resolutions. Because of its potential for avoiding duplicate elimination at least for some bills, this evaluation strategy offers potentially large savings in evaluation

cost. But this strategy requires the query rewriting to take place dynamically during a query’s evaluation and not just during its optimization. Examples such as this motivate our ongoing work on dynamic query rewriting.

2.5 Chapter Summary

The schema presented in this Chapter will serve as the schema underlying all example queries in this thesis. The two sets of queries presented in this Chapter motivate the work described in the thesis. The “Conflict of Interests” queries presented in Section 2.3 demonstrate the potential complexity of query rewrites and the subtlety of ensuring correctness. Query COI_1 is a nested query that can be transformed into a join query in the spirit of Kim’s unnesting rewrites [63]. Query COI_2 is syntactically very similar to COI_1 but for the choice of quantifier appearing in the `WHERE` clause. This subtle difference is enough to distinguish a query that can be rewritten into a join query (COI_1) from one that cannot (COI_2). Being able to pinpoint with confidence the exact conditions that make unnesting rewrites correct is one of the benefits that arises from the work presented in this thesis.

The “NSF” queries presented in Section 2.4 motivate our work on semantic rewrites, and our ongoing work studying dynamic query rewriting. Query NSF_1 shows an object query for which an appropriate query rewrite (that makes duplicate elimination unnecessary) depends upon the semantics of the underlying data (i.e., key information and knowledge about the lack of duplicates in collections). This example also motivates the need for query rewriters to infer the conditions that guard semantic rewrites. Query NSF_2 differs from NSF_1 in that the collection it queries can contain both Senate and House resolutions. For this query, the semantic rewrite that makes duplicate elimination unnecessary can only be applied when House resolutions are processed. Selective application of semantic query rewrites motivated our ongoing work on dynamic query rewriting which allows query rewrites to be performed in the midst of a query’s evaluation (e.g., as each bill is retrieved).

Chapter 3

KOLA: Correct Query Rewrites

This chapter motivates and describes KOLA, a novel *combinator-based* (variable-free) representation and query algebra. KOLA is intended to be a query representation for rule-based query rewriters, and thus is an alternative to query representations such as QGM [79], and query algebras such as Excess [13]. We chose to define a representation for a rule-based query rewriter because query rewrites expressed as rules offer the best opportunity for verification with a theorem prover. We chose to define a *new* representation because representations used in existing query optimizers, being variable-based, impede verification with a theorem prover.¹

3.1 The Need for a Combinator-Based Query Algebra

The firing of a query rewrite consists of two steps:

- *Step 1: Subexpression Identification*

During this initial step, the query rewrite identifies relevant subexpressions of the query on which it is fired. If some specified subexpression cannot be identified, the query is not rewritten. (This case is a *failed firing*.) The second step of the rewrite is performed only if all specified subexpressions are identified.

- *Step 2: Query Formulation*

During this step, a new query expression is formulated using the subexpressions identified in the previous step. This new query is returned as the result of the rewrite.

¹KOLA was developed in response to difficulties faced attempting to formulate declarative rules over the variable-based algebra, AQUA [70].

Different rule-based systems express subexpression identification and query formulation in different ways. Starburst [79] expresses both steps *algorithmically* with C code. Exodus and Volcano [13, 43] also use code, but as supplements to *rewrite rules*.

Rewrite rules consist of pairs of patterns and are *fired* using standard *pattern matching*. Firing first matches the pattern of the left-hand side of a rule (the *head* pattern) with the query on which the rule is fired. Patterns can include *pattern variables* that match arbitrary subexpressions. Therefore, successful matching creates a set of bindings (an *environment*) of subexpressions to pattern variables. Firing then proceeds to use this environment to substitute for pattern variables appearing in the pattern of the right-hand side of the rule (the *body* pattern). The resulting expression is returned as the result of firing.

The two steps of rule firing correspond to subexpression identification and query formulation. But unlike query rewrites that are expressed with code, query rewrites that are expressed with rewrite rules describe the effects of the rewrite without saying how the rewrite takes place. (The latter is instead described by the pattern matching algorithm.) Therefore, rewrite rules are *declarative* specifications of query rewrites. Declarative query rewrites are much easier to verify than query rewrites expressed with code because verification of the former simply requires proving the equivalence of the two expressions characterized by the head and body patterns of the rule. On the other hand, verification of query rewrites expressed with code requires reasoning about the state of the rewrite computation after each statement in the code is executed. Verification with a theorem prover is similarly far simpler when query rewrites are expressed with rewrite rules. This is because theorem provers are special-purpose term rewriting systems [51] that have natural application to proofs establishing that two expressions are equivalent.

3.1.1 Variables Considered Harmful

Exodus/Volcano and Starburst must express query rewrites with code because both systems use variable-based query representations. Variables make it difficult to express subexpression identification and query formulation with rewrite rules, as we show below.

Variables Complicate Subexpression Identification

Two queries represented in a variable-based representation can have syntactically identical parse trees and yet be semantically distinct and subject to different query rewrites. This is due to the nature of variables which typically are represented uniformly in a parse tree

```

SELECT DISTINCT x
FROM x IN Coms
WHERE EXISTS y IN ( SELECT c
                    FROM c IN SComs
                    WHERE x.chair.pty == c.chair.pty ) : y.chair IN y.mems

```

Figure 3.1: COI_2 : Find all committees whose chairs belong to a party that includes someone that both chairs and is a member of the same subcommittee.

representation regardless of the variable name. Pattern matching relies on syntactic distinctions recognized during subexpression identification to determine when rewrite rules can fire. Therefore, query rewrites over variable-based query representations must be at least partially expressed with code to make the distinctions that pattern matching cannot.

We illustrate this point with an example. Figure 3.1 shows an OQL query (COI_2) that is syntactically identical to query COI_1 of Figure 2.1. The only difference between these two queries is the variable that appears in the existentially quantified expression in the **WHERE** clause: for query COI_1 this variable is x ($x.chair IN y.mems$) and for query COI_2 this variable is y ($y.chair IN y.mems$).

Queries COI_1 and COI_2 differ only by this variable and therefore are syntactically identical. But these queries have very different semantics. Whereas COI_1 finds committees whose chairs belong to subcommittees chaired by someone from the same party, COI_2 finds committees whose chairs belong to parties that include members who are both chairs and members of the same subcommittees. COI_1 and COI_2 are also subject to different query rewrites. We showed in Section 2 that query COI_1 can be rewritten into the equivalent join query, $\overline{COI_1}$ (Figure 2.2). COI_2 can similarly be rewritten to $\overline{COI_2}$ as demonstrated by the first rewrite of Figure 3.2. But this query can be further rewritten into $\overline{\overline{COI_2}}$ as shown in the second query rewrite of Figure 3.2.² A rewrite rule for this query rewrite is shown in Figure 3.3. The rule separates two OQL patterns with the “rewrites to” symbol, $\overline{\overline{=}}$.³ These patterns include pattern variables:

$A_1, \dots, A_6, V_1, \dots, V_4, C_1, \dots, C_3,$ and Op_1 .

²The second rewrite returns a query that uses OQL’s **HAVING** clause to filter **Temp**. This clause excludes entries for parties with which some subcommittee chair is affiliated, but with which no subcommittee chair who is also a member of his subcommittee is affiliated. This rewrite is useful because the **mems** collection for a given subcommittee will be scanned once, rather than once for every committee in **Coms** whose chair is from the same party.

³ $\overline{\overline{=}}$ should not be confused with \rightarrow , which separates two queries rather than two patterns.

$\overline{COI_2}$ matches the head pattern of this rule by making the following bindings of subexpressions to pattern variables:

$A_1 = p$	$V_1 = c$	$C_1 = \text{Coms}$
$A_2 = S$	$V_2 = x$	$C_2 = \text{SComs}$
$A_3 = \text{chair.pty}$	$V_3 = t$	$C_3 = \text{Temp}$
$A_4 = \text{chair.pty}$	$V_4 = y$	$Op_1 = \text{IN}$
$A_5 = \text{chair}$		
$A_6 = \text{mems}$		

Substituting for the pattern variables appearing in the body pattern of the rule leaves $\overline{\overline{COI_2}}$.

The rule of Figure 3.3 appropriately expresses the transformation in such a way that $\overline{COI_2}$ will be rewritten and $\overline{COI_1}$ will not be. This discrimination is guaranteed by the use of the same pattern variable (V_4) in both operands of the operator (Op_1) that appears in the **WHERE** clause. But this discrimination comes at a cost of making this predicate pattern overly specific. This rule should transform queries whose quantified predicate includes no variables other than y (i.e., the variable bound by the quantifier). For example, queries that substitute any of the following expressions for

`y.chair IN y.mems`

should be rewritten according to this rule, but will not be given its expression in Figure 3.3:

- `y.chair == "Newt Gingrich",`
- `"Newt Gingrich" IN y.mems`
- `y.chair.pty == "GOP".`

The condition that an expression contain only one particular free variable cannot be expressed with a head pattern alone. Instead a head pattern would have to match all expressions, and supplemental code would have to analyze matched expressions to see if variables other than y occur free. Code supplements to rules could be defined perhaps by the writers of rules, or could be provided by way of a library available to rule designers. Regardless, the actions of code supplements (such as checking for the existence of free variables) are meta-level actions and as such complicate verification, making it necessary to use complicated (higher-order) theorem prover tools for which performance and ease-of-use become issues. This example illustrates the need for code to perform subexpression identification for rules expressed over variable-based query representations.

```

SELECT DISTINCT  $x$ 
FROM  $x$  IN Coms
WHERE EXISTS  $y$  IN ( SELECT  $c$ 
                     FROM  $c$  IN SComs
                     WHERE  $x$ .chair.pty ==  $c$ .chair.pty ) :  $y$ .chair IN  $y$ .mems

```

(COI_2)

→

```

Temp = SELECT p, S : partition
        FROM  $c$  IN SComs
        GROUP BY p :  $c$ .chair.pty

```

```

SELECT DISTINCT  $x$ 
FROM  $x$  IN Coms,  $t$  IN Temp
WHERE ( $x$ .chair.pty ==  $t$ .p) AND (EXISTS  $y$  IN  $t$ .S : ( $y$ .chair IN  $y$ .mems))

```

$\overline{(COI_2)}$

→

```

Temp = SELECT p, S : partition
        FROM  $c$  IN SComs
        GROUP BY p :  $c$ .chair.pty
        HAVING EXISTS  $y$  IN partition : ( $y$ .chair IN  $y$ .mems)

```

```

SELECT DISTINCT  $x$ 
FROM  $x$  IN Coms,  $t$  IN Temp
WHERE  $x$ .chair.pty ==  $t$ .p

```

$\overline{\overline{(COI_2)}}$

Figure 3.2: Transforming $COI_2 \rightarrow \overline{COI_2} \rightarrow \overline{\overline{COI_2}}$

```

C1 = SELECT A1, A2 : partition
      FROM V1 IN C2
      GROUP BY A1 : V1.A3

SELECT DISTINCT V2.A7
FROM V2 IN C1, V3 IN C3
WHERE (V2.A4 == V3.A1) AND (EXISTS V4 IN V3.A2 : (V4.A5 Op1 V4.A6))

⇒
≡

C1 = SELECT A1, A2 : partition
      FROM V1 IN C2
      GROUP BY A1 : V1.A3
      HAVING EXISTS V4 IN partition : (V4.A5 Op1 V4.A6)

SELECT DISTINCT V2.A7
FROM V2 IN C1, V3 IN C3
WHERE V2.A4 == V3.A1

```

Figure 3.3: A Rewrite Rule Justifying $\overline{COI_2} \rightarrow \overline{\overline{COI_2}}$

To summarize, queries COI_1 and COI_2 are syntactically similar but semantically distinct. Further, these two queries are subject to different query rewrites. Query rewrites perform subexpression identification in part to determine if rewriting can occur. As pattern matching can only make syntactic distinctions between expressions, code must be used by any non-trivial query rewrite that rewrites $\overline{COI_2}$ to $\overline{\overline{COI_2}}$ to ensure that $\overline{COI_1}$ is not affected.

Variables Complicate Query Formulation

In formulating new queries, query rewrites can reuse subexpressions identified in the original query. But if these subexpressions include free variables, the meanings of these subexpressions may change as a result of their use in a different context. Code is required under these circumstances to massage subexpressions to ensure that their semantics are preserved.

We illustrate this again with an example. Figure 3.4a shows an equivalent query to COI_1 (COI_{1*}) and its rewrite into COI_1 . This rewrite uses a quantified predicate expression,

$$x.chair.pty == y.chair.pty$$

```

SELECT DISTINCT x
FROM x IN Coms
WHERE EXISTS y IN SComs : ((x.chair IN y.mems) AND (x.chair.pty == y.chair.pty))

```

$$(COI_{1*})$$

$$\rightarrow$$

```

SELECT DISTINCT x
FROM x IN Coms
WHERE EXISTS y IN (
  SELECT c
  FROM c IN SComs
  WHERE x.chair.pty == c.chair.pty
) : x.chair IN y.mems

```

$$(COI_1)$$

$$(a)$$

```

SELECT DISTINCT V1
FROM V1 IN C1
WHERE EXISTS V2 IN C2 : (E1 AND (V3.A1 Op1 V2.A2))

```

$$\Rightarrow$$

```

SELECT DISTINCT V1
FROM V1 IN C1
WHERE EXISTS V2 IN (
  SELECT V4
  FROM V4 IN C2
  WHERE V3.A1 Op1 V4.A2
) : E1

```

$$(b)$$

Figure 3.4: $COI_{1*} \rightarrow COI_1$ (a) and a Rule to Justify It (b)

as a filter condition for a new (inner) subquery:

```
SELECT c
FROM c IN SComs
WHERE x.chair.pty == c.chair.pty.
```

This rewrite is useful as it enables COI_{1*} to be subsequently rewritten into $\overline{COI_1}$.

Figure 3.4b shows a rewrite rule expressing this rewrite. Again, this rewrite rule is overly specific. Any predicate expression can be moved out of a quantifier and into an inner query; predicate expressions need not be of the form,

$$V_3.A_1 \text{ Op}_1 V_2.A_2$$

as stipulated by the rule of Figure 3.4b. But if any predicate that is moved includes occurrences of the quantified variable V_2 (y), then all occurrences of this variables must be renamed. In this case, y is renamed to c , changing the expression

$$x.chair.pty == y.chair.pty$$

to

$$x.chair.pty == c.chair.pty.$$

Thus, code is necessary to rename variables appearing in subexpressions used to formulate new queries, and more generally, to substitute any expressions (not just variables) for variables appearing in other expressions.

3.1.2 The Need for a Combinator-Based Query Algebra: Summary

Query rewrites perform two steps in rewriting a query: (1) subexpression identification, and (2) query formulation. For query rewrites to be expressed as rewrite rules, a query representation must ensure that subexpressions of the query:

1. can be identified on the basis of their structure (syntax), and
2. have context-independent semantics so that they can be reused without modification when new queries are formulated.

Variable-based query representations fail to satisfy both criteria. Therefore, query rewrites expressed over variable-based representations must be fully or partially expressed with code that analyzes or manipulates the variables appearing in subexpressions. Combinator-based representations eliminate variables, and in so doing, eliminate the need for this supplementary code. In the next section, we illustrate this by revisiting the examples presented in this section in the context of our combinator-based query algebra, KOLA.

3.2 KOLA

Variable-based query representations impede the formulation of query rewrites with rewrite rules. Therefore, we designed the query algebra, KOLA, which is variable-free (*combinator-based*).⁴ More accurately, KOLA is an algebra of functions and predicates, of which query operators are simply those that apply to or return collections.

KOLA functions and predicates are expressed using combinator *primitives* whose semantics are predefined, and combinator *formers* (second-order functions) that produce complex functions and predicates from simpler ones. Because combinators have no variables, KOLA avoids the problems that variables introduce. The semantics of a KOLA expression is tied to its structure and **not** to the context in which it appears. Therefore KOLA rewrite rules need no code to assist with subexpression identification or query formulation.

It should be noted that KOLA is a language for optimizers and not users, and KOLA queries are far more difficult to read than OQL queries. As best as possible, we will assist the reader in decomposing KOLA queries referring to the definitions that appear in the coming sections. The reader is advised to trace reductions of KOLA queries as we do in the next section, until becoming comfortable with the notation and combinator style.

3.2.1 An OQL Query Expressed in KOLA

KOLA is a language for expressing functions and predicates invocable on objects. Invocation is explicit, with “ $f ! x$ ” denoting the invocation of function f on object x (returning an object of any type) and “ $p ? x$ ” denoting the invocation of predicate p on object x (returning a *Bool*). The KOLA style of querying is illustrated with a simple query shown in Figure 3.5. Figure 3.5a shows an OQL query that finds all subcommittees in *SComs* chaired by Republicans. Figure 3.5b shows its KOLA equivalent.

The KOLA query of Figure 3.5b includes:

- the primitive identity function, **id**, which maps every object to itself,
- the complex predicate,

$$C_p (\mathbf{eq}, \text{“GOP”}) \oplus (\mathbf{pty} \circ \mathbf{chair})$$

which is true of a committee if its chair is Republican, and

⁴KOLA resembles AQUA but for its combinator foundation and some other language differences described in our 1995 DBPL paper [23]. Thus, the name KOLA was coined from the acronym, [K]ind [O]f [L]ike [A]QUA.

```

SELECT c
FROM c IN SComs
WHERE c.chair.pty == "GOP"

```

(a)

```

iterate (Cp (eq, "GOP") ⊕ (pty ∘ chair), id) ! SComs

```

(b)

Figure 3.5: A Simple OQL Query (a) and its KOLA Equivalent (b): *Name All Subcommittees Chaired by Republicans*

- the complex query function,

```

iterate (Cp (eq, "GOP") ⊕ (pty ∘ chair), id)

```

which filters a bags of committees for those whose chair is Republican.

We can break these query components down even further as follows.

- `pty` and `chair` are primitive functions named for attributes of the Thomas schema (Table 2.1). For any legislator l ,

$$\text{pty} ! l = l.\text{pty}$$

and for any committee c ,

$$\text{chair} ! c = c.\text{chair}.$$

Therefore, the semantics of attribute-based primitives such as these depend on the values of the corresponding attributes for objects populating the database.

- `eq` is a primitive equality predicate invoked on *pairs* (denoted by $[_, _]$) of objects of the same type. The definition of `eq` is depends on each type's definition of equality (`==`).
- `_ ∘ _` is a function composition *former* that builds a new function that invokes two other functions in succession. That is, given functions f and g the function $f \circ g$ has an operational semantics defined in terms of invocation on an object x :

$$(f \circ g) ! x = f ! (g ! x).$$

For example, given a committee x , the semantics of $(\text{pty} \circ \text{chair}) ! x$ is revealed by the reduction below:

$$\begin{aligned} (\text{pty} \circ \text{chair}) ! x &= \text{pty} ! (\text{chair} ! x) \\ &= \text{pty} ! (x.\text{chair}) \\ &= x.\text{chair}.\text{pty} \end{aligned}$$

- \mathbf{C}_p ($_$, $_$) is a currying predicate *former* that builds a unary predicate from a binary predicate by binding the first argument. The semantics of this predicate can be expressed in terms of any binary predicate p and objects x and y by the equation,

$$\mathbf{C}_p (p, x) ? y = p ? [x, y].$$

For example, given some string, x , $(\mathbf{C}_p (\mathbf{eq}, \text{"GOP"}) ? x)$ has semantics revealed by the reduction below:

$$\begin{aligned} \mathbf{C}_p (\mathbf{eq}, \text{"GOP"}) ? x &= \mathbf{eq} ? [\text{"GOP"}, x] \\ &= \text{"GOP"} == x \\ &= x == \text{"GOP"} \end{aligned}$$

- $_ \oplus _$ is a combination predicate former that builds a predicate from another predicate and function. Much like function composition, $_ \oplus _$ first applies the function to its argument and then tests the predicate on the result. That is, given predicate p and function f , the predicate $(p \oplus f)$ has semantics expressible in terms of invocation on an object x :

$$(p \oplus f) ? x = p ? (f ! x).$$

For example, when invoked on a committee, x ,

$$\mathbf{C}_p (\mathbf{eq}, \text{"GOP"}) \oplus (\text{pty} \circ \text{chair})$$

has semantics revealed by the reduction below:

$$\begin{aligned} (\mathbf{C}_p (\mathbf{eq}, \text{"GOP"}) \oplus (\text{pty} \circ \text{chair})) ? x \\ &= \mathbf{C}_p (\mathbf{eq}, \text{"GOP"}) ? ((\text{pty} \circ \text{chair}) ! x) \\ &= \mathbf{C}_p (\mathbf{eq}, \text{"GOP"}) ? (x.\text{chair}.\text{pty}) \\ &= x.\text{chair}.\text{pty} == \text{"GOP"} \end{aligned}$$

- **iterate** ($_$, $_$) is a querying function former that builds a function on bags given a predicate and a function as inputs. Given any predicate p , function f and bag A , we have

$$\mathbf{iterate} (p, f) ! A = \{(f ! x)^i \mid x^i \in A, p ? x\},$$

such that the expression on the right hand side describes a bag (delimited by “{” and “}”) that contains the result of invoking f on all objects in A that satisfy p . The expression, $x^i \in A$ indicates that there are i copies of x in A and that $i > 0$.⁵ Therefore, the number of elements, x that are in A determines the number of elements, $f ! x$ that are inserted into the result.

Given these definitions, we can reduce the query expression,

$$\mathbf{iterate} (\mathbf{C}_p (\mathbf{eq}, \text{“GOP”}) \oplus (\mathbf{pty} \circ \mathbf{chair}), \mathbf{id}) ! \mathbf{SComs}$$

as follows:

$$\begin{aligned} & \mathbf{iterate} (\mathbf{C}_p (\mathbf{eq}, \text{“GOP”}) \oplus (\mathbf{pty} \circ \mathbf{chair}), \mathbf{id}) ! \mathbf{SComs} \\ &= \{(\mathbf{id} ! x)^i \mid x^i \in \mathbf{SComs}, (\mathbf{C}_p (\mathbf{eq}, \text{“GOP”}) \oplus (\mathbf{pty} \circ \mathbf{chair})) ? x\} \\ & \quad \text{(By the definition of } \mathbf{iterate} \text{)} \\ &= \{x^i \mid x^i \in \mathbf{SComs}, (\mathbf{C}_p (\mathbf{eq}, \text{“GOP”}) \oplus (\mathbf{pty} \circ \mathbf{chair})) ? x\} \\ & \quad \text{(By the definition of } \mathbf{id} \text{)} \\ &= \{x^i \mid x^i \in \mathbf{SComs}, x.\mathbf{chair}.\mathbf{pty} == \text{“GOP”}\} \\ & \quad \text{(By the definitions of } \mathbf{C}_p, \mathbf{eq}, \oplus, \circ, \mathbf{pty} \text{ and } \mathbf{chair}.\text{)} \end{aligned}$$

Thus, this query returns those committees in \mathbf{SComs} whose chair is Republican.

3.2.2 The KOLA Data Model

The KOLA data model assumes a universe of objects, each associated with a type that defines its interface. A type’s interface can include operators that *construct* the object, or *observe* or *mutate* its state. A type which includes operators that can mutate an object’s

⁵To keep our notation similar to set comprehension notation, we write $x \notin A$ when there are no copies of x in A rather than $x^0 \in A$.

state is called a *mutable type* and its objects are *mutable objects*. Conversely, a type or object upon which no mutating operations are defined is *immutable*.

Immutable objects have immutable state, and hence their state reveals their identity. That is, the integer object 3 has an identity that is inseparable from its value (i.e., all instances of objects representing the value 3 are equal). On the other hand, mutable objects should not be compared on the basis of their mutable states as this makes their identities ephemeral and provokes unintuitive behaviors in any collections that contain them [23]. Rather, mutable objects are assumed to be implemented with immutable, unique *object identifiers* (*OID*'s) that are used by the run-time system to decide if two objects are equal. In short, KOLA supports both mutable and immutable objects, but mutable objects are assumed to be compared for equality on the basis of their immutable object identifiers while immutable objects are compared on the basis of keys.

An informal description of the object types supported by the KOLA data model follows. Appendix A includes a formal specification of the data model expressed in Larch [46].

- *Base Types*

The base types supported in KOLA are the immutable types *Bool* (booleans), *Int* (integers), *Char* (characters), *Float* (floats) and *String* (strings). A standard interface for these types is assumed. Constants of these types have the usual form. As well, NULL is assumed to be a constant belonging to all types.

- *Class Types*

KOLA permits queries over collections of objects that are instances of class types. It is assumed that a class definition defines an interface to which queries have access. In particular, we assume that queries can invoke the observer operators of objects but not their mutators or constructors, as queries are assumed to be free of side-effects.⁶ Finally, it is assumed that observers are unary (*attributes*).

- *Pair Types*

A pair type is any type of the form

$$(t_1 \times t_2)$$

⁶This is one way that KOLA is less expressive than OQL, as OQL queries can return collections of new mutable objects. This confuses the issue of optimizer correctness which must then be based on similarity rather than equality of results. We discuss this issue at length elsewhere [18], but have yet to modify KOLA in light of our analysis.

such that t_1 and t_2 are types. Given object x of type t_1 ($x : t_1$) and y of type t_2 ($y : t_2$), $[x, y]$ is a pair object of type $(t_1 \times t_2)$ ($[x, y] : (t_1 \times t_2)$). (For example, the type of $[3, Joe]$ is $(Int \times Person)$ assuming that 3 is of type Int and Joe is of type $Person$.) Pairs are used to express relationships between objects of potentially differing types.

- *Collection (Bag and Set) Types*

For any type t , $\{\!\{t\}\!\}$ denotes the type of *bags* whose elements are all of type t . Formally, a bag $A : \{\!\{t\}\!\}$ is a function, $t \rightarrow \mathcal{Z}$ such that for any object $x : t$, $A(x)$ is the number of occurrences of x in A . It is easier to formalize bags and bag operators when bags are defined in terms of their characteristic functions rather than as collections containing elements. But sometimes it is more intuitive to use comprehension notation (as used, for example, in Fegaras and Maier’s work [33]) to reason about the “contents” of a bag. Therefore, this proposal uses the following shorthand notation:

- for any bag $A : \{\!\{t\}\!\}$ and expression $e : t$,

$$e \in A$$

is shorthand for $A(e) > 0$ and

$$e^i \in A$$

(for $i > 0$) is shorthand for $A(e) = i$.

- for any $x_1, \dots, x_n : t$, and positive integers i_1, \dots, i_n ,

$$\{\!\{(x_1)^{i_1}, \dots, (x_n)^{i_n}\}\!\}$$

denotes a bag $B : \{\!\{t\}\!\}$ containing elements x_1, \dots, x_n whose count of any element, y ($B(y)$) is

$$\sum_{1 \leq j \leq n, y == x_j} i_j.$$

For example, $\{\!\{(3)^1, (-3)^2, (2)^2, (-3)^1\}\!\}$ denotes the bag B such that:

$$\begin{aligned} B(-3) &= 3, \\ B(2) &= 2, \\ B(3) &= 1, \end{aligned}$$

and for any i not equal to $-3, 2$ or 3 , $B(i) = 0$. As a further shorthand, we write

$$\{\!\{x_1, \dots, x_n\}\!\}$$

when the element “counts” are implicitly 1. That is,

$$\{\{x_1, \dots, x_n\} = \{\{(x_1)^1, \dots, (x_n)^1\}$$

- for any bag, $A : \{\{t\}$, variable $x : t$, and expressions, $f(x) : u$, $g(x) : Int$ and $p(x) : Bool$,

$$\{\{f(x)^{g(i)} \mid x^i \in A, p(x)\}$$

denotes a bag $B : \{\{u\}$ containing elements $f(x)$ (for each $x \in A$) whose count of any element $y : u$ ($B(y)$) is:

$$\sum_{x^i \in A, y = f(x), p(x)} g(i)$$

For example, if $A = \{\{3, -3, 2, -3\}$. Then

$$\{\{(x * x)^i \mid x^i \in A\}$$

denotes the bag, B such that

$$\begin{aligned} B(4) &= 1, \\ B(9) &= 3, \end{aligned}$$

and for any e not equal to 4 or 9, $B(e) = 0$.

More generally, for bags $A_1 : \{\{t_1\} \dots A_n : \{\{t_n\}$, variables $x_1 : t_1, \dots x_n : t_n$, positive integers i_1, \dots, i_n and $g(i_1, \dots, i_n)$, and expressions $f(x_1, \dots, x_n) : u$, $p(x_1, \dots, x_n) : Bool$, and $y : u$:

$$\{\{f(x_1, \dots, x_n)^{g(i_1, \dots, i_n)} \mid (x_1)^{i_1} \in A_1, \dots, (x_n)^{i_n} \in A_n, p(x_1, \dots, x_n)\}$$

denotes $B : \{\{u\}$ such that for all $y : u$:

$$B(y) = \sum_{(x_1)^{i_1} \in A_1, \dots, (x_n)^{i_n} \in A_n, y = f(x_1, \dots, x_n), p(x_1, \dots, x_n)} g(i_1, \dots, i_n)$$

As an example, suppose that A is defined as above and $A' = \{\{5, 11, 5, 6\}$, then

$$\{\{(x + y)^{ij} \mid x^i \in A, y^j \in A'\}$$

denotes the bag, B such that

$$\begin{aligned} B(2) &= 4, \\ B(3) &= 2, \\ B(7) &= 2, \\ B(8) &= 5, \\ B(9) &= 1, \\ B(13) &= 1, \\ B(14) &= 1, \end{aligned}$$

and for any i not equal to 2, 3, 7, 8, 9, 13 or 14, $B(i) = 0$.

A set is a special kind of bag whose element counts are either 0 or 1. That is, A is a set of elements of t if it is a bag of t 's and for all x of type t , $A(x) = 1$ or $A(x) = 0$. We use set comprehension notation in discussing sets. That is, for any $x : t$, $p(x) : Bool$ and $f(x) : u$

$$\{f(x) \mid x \in A, p(x)\}$$

is equivalent to

$$\{(f(x))^1 \mid x \in A, p(x)\}$$

For simplicity, we assume a namespace of identifiers that refer exclusively to stored collections. All named bags and sets (e.g., `Coms`, `SComs`, `Lgs` etc.) are assumed to be mutable. However, all bags and sets constructed by KOLA operators are assumed to be immutable (as in OQL). For queries, the mutable vs. immutable distinction only makes a difference when deciding if two bags (sets) are equal. Two mutable bags (sets) are equal if they are the same object (i.e., they have the same object identifier). Two immutable bags (sets) are equal if they have the same members (modulo equality definitions for the type of objects they contain). An immutable bag (set) is never equal to a mutable bag (set). Thus, a query rewrite that rewrites the OQL query,

```
SELECT x
FROM x IN Coms
```

to “`Coms`” is incorrect, as this rewrites a query returning an immutable collection into one that returns a mutable collection.

3.2.3 KOLA Primitives and Formers

The operators of KOLA are listed in Tables 3.1 (primitives), 3.2 (formers) and 3.3 (query formers). Each primitive or former is named in the left columns of these tables, and given

an operational semantics in the right columns of these tables. These tables are intended to provide a brief summary of KOLA, and therefore express KOLA’s semantics somewhat informally. A formal semantics of KOLA expressed in Larch [46] is presented in Appendix A.

Table 3.1: KOLA’s Primitives

KOLA’s primitives functions and predicates are listed in Table 3.1. The operational semantics of these primitives are defined by showing the result of invoking these primitives on arbitrary objects (x , y and z), integers or floats (i and j), bags (A and B) and bags containing bags (X).

Primitive functions include the *identity function* (**id**) defined over all types, and *projection functions* (π_1 and π_2) and *shifting functions* (**shl** and **shr**) defined over pairs. Integer and float primitives include an absolute value function (**abs**) and basic arithmetic operations (**add**, **sub**, **mul**, and **div**). The remainder function, **mod** is also a primitive defined on pairs of integers only. String functions include an *indexing* function on ($string \times integer$) pairs to isolate a character in the string (**at**) and a string *concatenation* function on pairs of strings (**concat**). Bag primitives include a *singleton* constructor (**single**), an *element extraction* function (**elt**), a *duplicate removal* function (**set**), a nested bag *flattening* function (**flat**), bag *union* (**uni**), *intersection* (**int**) and *difference* (**dif**) operators over pairs of bags, an insertion function (**ins**), and aggregate operators **max**, **min**, **cnt**, **sum** and **avg**. KOLA’s aggregate operators are defined with the same semantics as their corresponding SQL/OQL aggregates as defined in [28]. Therefore, some of these aggregates (e.g., **MAX**) return NULL when invoked on empty collections.

Basic predicate primitives include *equality* (**eq**) and *inequality* (**neq**) predicates on pairs of objects of the same type. String, float and integer predicate primitives include the *ordering relations* (**lt**, **leq**, **gt** and **geq**) on pairs of integers and pairs of strings. Not listed but assumed are schema-dependent functions and predicates based on unary methods or attributes of objects such as **pty** and **chair**. The semantics of such primitives are determined by the population of the underlying database.

Table 3.2: KOLA’s Basic Formers

KOLA’s basic function and predicate formers are listed in Table 3.2. The operational semantics of functions and predicates formed with these formers are given in terms of arbitrary functions (f and g), predicates (p and q), objects (x and y) and bools (b).

Description	Semantics
<i>Basic Function Primitives</i>	
<i>identity</i>	id ! $x = x$
<i>projection (1)</i>	π_1 ! $[x, y] = x$
<i>projection (2)</i>	π_2 ! $[x, y] = y$
<i>shift left</i>	shl ! $[x, [y, z]] = [[x, y], z]$
<i>shift right</i>	shr ! $[[x, y], z] = [x, [y, z]]$
<i>Int and Float Function Primitives (i, j integers or floats)</i>	
<i>absolute value</i>	abs ! $i = i $
<i>addition</i>	add ! $[i, j] = i + j$
<i>subtraction</i>	sub ! $[i, j] = i - j$
<i>multiplication</i>	mul ! $[i, j] = i * j$
<i>division</i>	div ! $[i, j] = i / j$
<i>modulus</i>	mod ! $[i, j] = i \text{ mod } j$ (for integers i and j only)
<i>String Function Primitives (s, t strings (arrays of chars))</i>	
<i>string indexing</i>	at ! $[s, i] = s[i]$
<i>string concatenation</i>	concat ! $[s, t] = s t$
<i>Bag Function Primitives (A, B bags, X a bag of bags)</i>	
<i>singleton</i>	single ! $x = \{x\}$
<i>element extraction</i>	elt ! $\{x\} = x$
<i>duplicate removal</i>	set ! $A = \{x \mid x \in A\}$
<i>bag flattening</i>	flat ! $X = \{x^{ij} \mid x^i \in A, A^j \in X\}$
<i>bag union</i>	uni ! $[A, B] = \{x^{(i+j)} \mid x^i \in A, x^j \in B\}$
<i>bag intersection</i>	int ! $[A, B] = \{x^{\min(i,j)} \mid x^i \in A, x^j \in B\}$
<i>bag difference</i>	dif ! $[A, B] = \{x^{(i-j)} \mid x^i \in A, x^j \in B, i > j\}$
<i>insertion</i>	ins ! $[x, A] = \text{uni} ! [\{x\}, A]$
<i>Aggregate Primitives (A a bag of integers or floats, u, v integers or floats)</i>	
<i>maximum</i>	max ! $A = v \text{ s.t. } (v^i \in A \wedge \forall u(u^j \in A \Rightarrow v \geq u))$
<i>minimum</i>	min ! $A = v \text{ s.t. } (v^i \in A \wedge \forall u(u^j \in A \Rightarrow v \leq u))$
<i>count</i>	cnt ! $A = \sum_{v^i \in A} (i)$
<i>sum</i>	sum ! $A = \sum_{v^i \in A} (vi)$
<i>average</i>	avg ! $A = (\text{sum} ! A) / (\text{cnt} ! A)$
<i>Basic Predicate Primitives (x and y of type T)</i>	
<i>equality</i>	eq ? $[x, y] = x == y$
<i>inequality</i>	neq ? $[x, y] = x \neq y$
<i>String, Float and Int Predicate Primitives (x and y strings or integers)</i>	
<i>less than</i>	lt ? $[x, y] = x < y$
<i>less than or equal</i>	leq ? $[x, y] = x \leq y$
<i>greater than</i>	gt ? $[x, y] = x > y$
<i>greater than or equal</i>	geq ? $[x, y] = x \geq y$

Table 3.1: KOLA Primitives

Description	Semantics
<i>Basic Function Formers</i>	
<i>composition</i>	$(f \circ g) ! x = f ! (g ! x)$
<i>pairing</i>	$\langle f, g \rangle ! x = [f ! x, g ! x]$
<i>products</i>	$(f \times g) ! [x, y] = [f ! x, g ! y]$
<i>constant function</i>	$K_f (x) ! y = x$
<i>curried function</i>	$C_f (f, x) ! y = f ! [x, y]$
<i>conditional function</i>	$\mathbf{con} (p, f, g) ! x = \begin{cases} f ! x, & \text{if } p ? x \\ g ! x, & \text{else} \end{cases}$
<i>Basic Predicate Formers</i>	
<i>combination</i>	$(p \oplus f) ? x = p ? (f ! x)$
<i>conjunction</i>	$(p \& q) ? x = (p ? x) \wedge (q ? x)$
<i>disjunction</i>	$(p q) ? x = (p ? x) \vee (q ? x)$
<i>negation</i>	$\sim (p) ? x = \neg (p ? x)$
<i>inverse</i>	$p^{-1} ? [x, y] = p ? [y, x]$
<i>products</i>	$(p \times q) ? [x, y] = (p ? x) \wedge (q ? y)$
<i>constant predicate</i>	$K_p (b) ? x = b$
<i>curried predicate</i>	$C_p (p, x) ? y = p ? [x, y]$

Table 3.2: Basic KOLA Formers

Function formers include the function *composition* former (\circ), the function *pairing* former ($\langle \rangle$) that produces functions that construct pairs, the *pairwise product* function former (\times) that applies separate functions to separate members of a pair to produce another pair, the *constant function* former (K_f) that builds a function that always returns the same result, the *currying* function former (C_f) that fixes one argument of a binary (pair) function to produce a unary function and a *conditional* function former (\mathbf{con}) that applies one of two functions to its arguments depending on whether a given predicate holds.

KOLA's predicate formers include the predicate/function *combination* former (\oplus) that acts much like function composition but producing a predicate, the logic-inspired *conjunction*, *disjunction* and *negation* predicate formers ($\&$, $|$ and \sim), the predicate *inverse* former ($^{-1}$) that flips its pair argument before applying a given predicate, a *pairwise* predicate former (\times) that applies distinct predicates to each element of a pair, a *constant predicate* former (K_p) that always returns *true* or always returns *false*, and a *currying* predicate former (C_p) that fixes one of the arguments of a binary predicate to produce a unary predicate.

Description	Semantics
<i>Query Function Formers</i>	
<i>iteration</i>	iterate $(p, f) ! A = \{(f ! x)^i \mid x^i \in A, p ? x\}$
<i>iteration₂</i>	iter $(p, f) ! [x, B] = \{(f ! [x, y])^j \mid y^j \in B, p ? [x, y]\}$
<i>unnest</i>	unnest $(f, g) ! A = \{(f ! [x, y])^{ij} \mid x^i \in A, y^j \in (g ! x)\}$
<i>join</i>	join $(p, f) ! [A, B] =$ $\{(f ! [x, y])^{ij} \mid x^i \in A, y^j \in B, p ? [x, y]\}$
<i>left semijoin</i>	lsjoin $(p, f) ! [A, B] = \{(f ! x)^i \mid x^i \in A, p ? [x, B]\}$
<i>right semijoin</i>	rsjoin $(p, f) ! [A, B] = \{(f ! y)^j \mid y^j \in B, p ? [y, A]\}$
<i>nested join</i>	njoin $(p, f, g) ! [A, B] =$ $\{[x, g ! \{(f ! y)^j \mid y^j \in B, p ? [x, y]\}] \mid x \in A\}$
<i>Query Predicate Formers</i>	
\exists	exists $(p) ? A = \exists x (x \in A \wedge p ? x)$
\forall	forall $(p) ? A = \forall x (x \in A \Rightarrow p ? x)$
\exists_2	ex $(p) ? [x, B] = \exists y (y \in B \wedge p ? [x, y])$
\forall_2	fa $(p) ? [x, B] = \forall y (y \in B \Rightarrow p ? [x, y])$

Table 3.3: KOLA Query Formers

Table 3.3: KOLA's Query Formers

A *query former* is simply a former that constructs a function or predicate on bags. KOLA's query formers are listed in Table 3.3. As with tables 3.2, p and q denote predicates, f , g and h denote functions, and x and y denote function and predicate arguments. As well, A and B denote bags, X denotes a bag of bags and i and j are integers denoting element counts.

KOLA's Function Formers: KOLA's function query formers include the following:

- **iterate** (p, f) forms a function on bags, A that behaves much like SQL/OQL's SELECT-FROM-WHERE in that it invokes a function (f) on every element of A that satisfies a predicate (p).
- **iter** (p, f) forms a function on object, bag pairs, $[x, B]$ that behaves much like **iterate** but absorbs the constant x into binary predicate p and binary function f .
- **unnest** (f, g) forms a function on bags A that returns a bag of elements, $f ! [x, y]$ for each x drawn from A and each y drawn from $(g ! x)$.

- **join** (p, f) forms a function on pairs of bags, $[A, B]$ that applies f to every pair of elements, $[x, y]$ such that x is in A , y is in B and the pair $[x, y]$ satisfies p .
- **lsjoin** (p, f) (short for *left semijoin*) forms a function on pairs of bags, $[A, B]$ that applies f to every element of A , x for which $[x, B]$ satisfies p .
- **rsjoin** (p, f) (short for *right semijoin*) forms a function on pairs of bags, $[A, B]$ that applies f to every element of B , y for which $[y, A]$ satisfies p .
- **njoin** (p, f, g) (short for *nested join*) forms a function on pairs of bags, $[A, B]$ that returns a set of pairs, $[x, S_x]$ for each $x \in A$. For a given x , S_x is the result of invoking g on the collection of $(f ! y)$'s such that $y \in B$ and $[x, y]$ satisfies p . For example, the SQL query,

```
SELECT T.c1, agg (T.c2)
FROM T
GROUP BY T.c1
```

would be translated into the KOLA query,

$$\mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times \mathbf{c}_1), \mathbf{c}_2, \overline{\mathbf{agg}}) ! [\mathbf{iterate} (K_p (\mathbf{true}), \mathbf{c}_1) ! T, T]$$

such that $\overline{\mathbf{agg}}$ is the KOLA equivalent of SQL aggregate, \mathbf{agg} (e.g., $\overline{\mathbf{COUNT}} = \mathbf{cnt}$, $\overline{\mathbf{SUM}} = \mathbf{sum}$).

Nested joins formed by **njoin** can also express groupings resulting from joins and outerjoins. For example, the SQL join query,

```
SELECT T1.c1, agg (T2.c2)
FROM T1, T2
WHERE T1.c3 == T2.c3
GROUP BY T1.c1
```

is equivalent to the KOLA query,

$$\mathbf{njoin} (\mathbf{eq} \oplus (\pi_1 \times (\mathbf{c}_1 \circ \pi_1)), \pi_2, \overline{\mathbf{agg}}) ! [\mathbf{iterate} (K_p (\mathbf{true}), \mathbf{c}_1 \circ \pi_1) ! A, A]$$

such that

$$A = \mathbf{join} (\mathbf{eq} \oplus (\mathbf{c}_3 \times \mathbf{c}_3), \mathbf{id} \times \mathbf{c}_2) ! [T_1, T_2].$$

The SQL outerjoin query,

```
SELECT T1.c1, agg (T.c2)
FROM T1 LEFT JOIN T2 ON T1.c1 == T2.c1
GROUP BY T1.c1
```

is expressed in similar fashion to **GROUP BY** queries:

njoin (**eq** \oplus (**id** \times c₁), c₂, $\overline{\text{agg}}$) ! [**iterate** (K_p (**true**), c₁) ! T₁, T₂].

Note that if for some element of $t_1 \in T_1$ there are no elements $t_2 \in T_2$ such that

$$t_1.c_1 == t_2.c_2,$$

then $t_1.c_1$ will be paired with ($\overline{\text{agg}}$! \emptyset) in the result. If **agg** is an aggregate that returns NULL when applied to an empty collection (such as **MAX**), then ($\overline{\text{agg}}$! \emptyset) is also NULL and $t_1.c_1$ is paired with NULL in the result.

The OQL query below partitions a bag on the basis of predicates p_1, \dots, p_n .

```
SELECT *
FROM t IN T
GROUP BY label1 : p1, ..., labeln : pn.
```

The result of this query is a set of tuples consisting of $n + 1$ fields. The first n fields contain the truth values for the n predicates for a given partition of elements of T that agree on these values. The $(n + 1)^{th}$ field contains the associated partition of T . The KOLA version of this query uses functions of the form,

$$f_i = \mathbf{con} (\overline{p_i}, K_f (1), K_f (0)),$$

that when invoked on some object, x , return a 1 or 0 depending on whether predicate $\overline{p_i}$ (the KOLA translation of p_i) is satisfied by x . The partition of T is then based on equivalence of the bitstring formed by applying functions f_i for each $1 \leq i \leq n$. That is, given

$$f = \langle f_1, \langle f_2, \dots \langle f_{n-1}, f_n \rangle \dots \rangle \rangle,$$

the KOLA equivalent to the OQL query above is:

njoin (**eq** \oplus (**id** \times f), **id**, **id**) ! [**iterate** (K_p (**true**), f) ! T, T].

KOLA’s Predicate Formers: KOLA’s query predicate formers include the following.

- Formers **exists** (p) and **forall** (p) form existential and universal quantifier predicates on bags A that return *true* if some (all) elements of A satisfy p .
- Formers **ex** and **fa** are to **exists** and **forall** as **iter** is to **iterate**. Like functions formed with **iter**, **ex** (p) and **fa** (p) are invoked on pairs of the form $[x, B]$, such that x is absorbed into the predicate, p . The result of invocation depends on whether any (**ex**) or all (**fa**) elements y in B are such that $(p \ ? \ [x, y])$ holds.

3.3 Using a Theorem Prover to Verify KOLA Rewrites

3.3.1 A Formal Specification of KOLA Using LSL

Appendix A contains a formal specification of the KOLA data model and algebra. The specification is expressed in the Larch algebraic specification language, LSL. LSL permits the definition of *traits*, which roughly correspond to *abstract data types* [72]. LSL includes a library of basic traits such as `Int`, `Bool`, `FloatingPoint` and `String`, which are assumed by the KOLA specification.

KOLA bags (`bag [T]`) are defined by two traits: `BagBasics` (which defines bag constructors, `{}` and `insert` and unary operators on bags) and `Bag` which defines binary bag operators (such as union and intersection) These traits introduce the bag *constructors*,

$$\begin{aligned}
 \text{empty bag:} \quad \{ \} &: && \rightarrow \text{bag [T]}, \\
 \text{singleton bag:} \quad \{ _ \} &: && \text{T} \rightarrow \text{bag [T]}, \text{ and} \\
 \text{bag insertion:} \quad \text{insert} &: && \text{T, bag [T]} \rightarrow \text{bag [T]},
 \end{aligned}$$

as well as operators,

$$\begin{aligned}
 \text{membership:} \quad _ \in _ &: && \text{T, bag [T]} \rightarrow \text{Bool}, \\
 \text{element difference:} \quad _ - _ &: && \text{bag [T], T} \rightarrow \text{bag [T]}, \\
 \text{bag union:} \quad _ \cup _ &: && \text{bag [T], bag [T]} \rightarrow \text{bag [T]}, \\
 \text{bag intersection:} \quad _ \cap _ &: && \text{bag [T], bag [T]} \rightarrow \text{bag [T]}, \text{ and} \\
 \text{bag difference:} \quad _ - _ &: && \text{bag [T], bag [T]} \rightarrow \text{bag [T]}.
 \end{aligned}$$

The axioms for these operators assume universally quantified variables A and B of type `bag [T]` and x and y of type T . Membership is defined by the axioms:

$$\begin{aligned}
 x \in \{ \} &= \text{false}, \text{ and} \\
 x \in \text{insert} (y, A) &= (x == y) \vee (x \in A).^7
 \end{aligned}$$

Element difference is defined by axioms:

$$\begin{aligned} & \{\} - x = \{\}, \text{ and} \\ \neg (x == y) & \Rightarrow (\text{insert } (x, A) - y == \text{insert } (x, A - y)). \end{aligned}$$

Bag union, intersection and difference are defined by axioms:

$$\begin{aligned} (1) \quad & \{\} \cup B = B, \\ (2) \quad & \text{insert } (x, A) \cup B = \text{insert } (x, A \cup B), \\ (3) \quad & \{\} \cap B = \{\}, \\ (4) \quad & x \in B \Rightarrow (\text{insert } (x, A) \cap B == \text{insert } (x, A \cap (B - x))), \\ (5) \quad & \neg (x \in B) \Rightarrow (\text{insert } (x, A) \cap B == A \cap B) \\ (6) \quad & \{\} - B = \{\}, \\ (7) \quad & x \in B \Rightarrow (\text{insert } (x, A) - B == A - (B - x)), \text{ and} \\ (8) \quad & \neg (x \in B) \Rightarrow (\text{insert } (x, A) - B == \text{insert } (x, A - B)). \end{aligned}$$

These axioms are typical of algebraic specifications, in that they define each operator over each constructor. Note that the use of the element difference operator “ $-$ ” in axioms (4) and (7) distinguishes the definition of bags from sets. The corresponding axioms for sets would be:

$$\begin{aligned} (4b) \quad & x \in B \Rightarrow (\text{insert } (x, A) \cap B == \text{insert } (x, A \cap B)), \text{ and} \\ (7b) \quad & x \in B \Rightarrow (\text{insert } (x, A) - B == A - B). \end{aligned}$$

Note also that the axiom defining the singleton bag, $\{x\}$, establishes it as shorthand for $\text{insert } (x, \{\})$. Therefore, this constructor does not need to be accounted for in these axioms.

All function primitives and formers “inherit” the generic **Function** specification, which introduces invocation ($_ ! _ : \text{fun } [T, U], T \rightarrow U$) (for domain type T and range type U), and function equality ($_ == _ : \text{fun } [T, U], \text{fun } [T, U] \rightarrow \text{Bool}$), which is defined universally for functions f and g ($\text{fun } [T, U]$) by the axiom,

$$f == g = \forall x:T (f ! x == g ! x).$$

Similarly, predicate primitives and formers “inherit” the generic **Predicate** specification, which introduces invocation ($_ ? _ : \text{pred } [T], T \rightarrow \text{Bool}$) (for domain type T), and predicate equality ($_ == _ : \text{pred } [T], \text{pred } [T] \rightarrow \text{Bool}$) which is defined universally for predicates p and q ($\text{pred } [T]$) by the axiom,

$$p == q = \forall x:T (p ? x == q ? x).$$

The axioms defining all KOLA predicate and function primitives and formers are given in Appendix A. Axioms defining basic primitives and formers (i.e., defining functions and predicates on arguments that are not collections) resemble the equations shown in Tables 3.1 and 3.2. Query primitives and formers are defined inductively over bag constructors `{}` and `insert`, as in the axioms for

$$\text{iterate} : \text{pred } [T], \text{ fun } [T,U] \rightarrow \text{fun } [\text{bag } [T], \text{bag } [U]]$$

shown below:

$$\begin{aligned} & \text{iterate } (p, f) ! \{ \} = \{ \}, \\ p ? x \Rightarrow & \\ & (\text{iterate } (p, f) ! \text{insert } (x, A) == \text{insert } (f ! x, \text{iterate } (p, f) ! A)), \text{ and} \\ \neg (p ? x) \Rightarrow & (\text{iterate } (p, f) ! \text{insert } (x, A) == \text{iterate } (p, f) ! A). \end{aligned}$$

3.3.2 Proving KOLA Rewrite Rules Using LP

Theorem provers are term rewriters that apply rewrite rules to simplify terms. The LP theorem prover interprets notation that resembles the notation of logic proofs as operations to the term rewriting system. LP then gives the following operational interpretations to these elements of logical proofs:

- the operational interpretation of a conjecture, goal or subgoal is a term,
- the operational interpretation of an axiom is a rewrite rule, and
- the operational interpretation of a proof is a rewrite of a term (conjecture) to the built-in term `true`.⁸

To illustrate the operation of LP, we demonstrate a proof of the KOLA rewrite rule that pushes projections and selections past unions::

$$\text{iterate } (p, f) ! (A \cup B) \xrightarrow{=} (\text{iterate } (p, f) ! A) \cup (\text{iterate } (p, f) ! B).$$

⁸Larch uses a number of built-in rewrite rules to supplement those that are generated from formal specifications. For example, Larch has a rewrite rule that rewrites any term of the form

$$e == e$$

for some expression `e` into the term `true`. Therefore, rewrites of conjectures into the term `true` are possible even when `true` does not appear as a term in a formal specification, as in the specification of KOLA.

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
prove
  iterate (p, f) ! (A \U B) =
    (iterate (p, f) ! A) \U (iterate (p, f) ! B)
  ..

  resume by induction on A                                     % Step 1

    % Base Case: Trivial
    % Trivial Case

  resume by induction on B                                     % Step 2

    % Base Case: Trivial
    % Trivial Case

  resume by cases p ? u1                                     % Step 3

    % Case 1
    resume by cases pc ? u                                   % Step 4a

    % Case 2
    resume by cases pc ? u                                   % Step 4b

qed
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

Figure 3.6: An Example LP Proof Script

As with OQL rules, KOLA rules are expressed with patterns (KOLA queries supplemented with pattern variables) separated by “ \Rightarrow ”. Verification of this rule requires proving the LP conjecture

$$\text{iterate } (p, f) ! (A \setminus U B) = (\text{iterate } (p, f) ! A) \setminus U (\text{iterate } (p, f) ! B)$$

Verification of this conjecture proceeds according to the the *proof script* shown in Figure 3.6⁹. To facilitate the tracing of this script, we have numbered the steps that appear in the script in comments (delimited by %) to the right of each executable statement. Below we trace the logic behind the proof, and the mechanics of the theorem prover as it processes each step’s instruction.

⁹We use ASCII notation in presenting inputs to LP (e.g., $\setminus U$ is used instead of \cup , p is used instead of p etc.) to emphasize their executable flavor.

1. $\{\} \setminus U B \rightarrow B$
2. $\text{insert}(x, A) \setminus U B \rightarrow \text{insert}(x, A \setminus U B)$
3. $\text{iterate}(p, f) ! \{\} \rightarrow \{\}$
4. $(p ? x) ::$
 $\quad \text{iterate}(p, f) ! \text{insert}(x, A) \rightarrow \text{insert}(f ! x, \text{iterate}(p, f) ! A)$
5. $\sim(p ? x) ::$
 $\quad \text{iterate}(p, f) ! \text{insert}(x, A) \rightarrow \text{iterate}(p, f) ! A$

Figure 3.7: Some LP Rewrite Rules Generated from Specification Axioms

The proof begins with the generation of a bank of rewrite rules from the axioms defining the operators appearing in the proof. For this proof, these axioms generate a bank of rewrite rules that include those shown in Figure 3.7. As with KOLA’s rewrite rules, LP’s rewrite rules consist of pairs of patterns (separated by “ \rightarrow ” rather than \equiv to distinguish them from KOLA rules). As well, LP’s rules can be *conditional* — an idea inspiring extensions to KOLA presented in Chapter 5. Rules 4 and 5 can fire only if the conditions, $(p ? x)$ and $\sim(p ? x)$ are respectively satisfied.

Step 1: The proof begins by induction on the collection **A**. The theorem prover interprets this instruction by first creating the basis subgoal,

$$\begin{aligned} &\text{iterate}(p, f) ! (\{\} \setminus U B) == \\ &(\text{iterate}(p, f) ! \{\}) \setminus U (\text{iterate}(p, f) ! B). \end{aligned}$$

This subgoal trivially reduces to **true** (i.e., is proven) by LP rewrite rules 1 and 3 of Figure 3.7.

Successful proof of the basis subgoal initiates the addition of a new rewrite rule (corresponding to the induction hypothesis) and the attempted proof of a second subgoal (corresponding to the induction subgoal). For this proof, the induction hypothesis is the rewrite rule,

$$\begin{aligned} &\text{iterate}(p, f) ! (Ac \setminus U B) \rightarrow \\ &(\text{iterate}(p, f) ! Ac) \setminus U (\text{iterate}(p, f) ! B) \end{aligned}$$

and the induction subgoal is,

$$\begin{aligned} &\text{iterate}(p, f) ! (\text{insert}(u, Ac) \setminus U B) == \\ &(\text{iterate}(p, f) ! \text{insert}(u, Ac)) \setminus U (\text{iterate}(p, f) ! B) \end{aligned}$$

Step 2: Induction is again initiated, this time on the collection B in order to prove the induction subgoal remaining after step 1. The basis subgoal,

$$\begin{aligned} & \text{iterate } (p, f) ! (\text{insert } (u, Ac) \setminus U \{\}) == \\ & (\text{iterate } (p, f) ! \text{insert } (u, Ac)) \setminus U (\text{iterate } (p, f) ! \{\}) \end{aligned}$$

again reduces to `true` by rewrite rules 1 and 3 of Figure 3.7. Again, a rewrite rule corresponding to an induction hypothesis is added:

$$\begin{aligned} & \text{iterate } (p, f) ! \text{insert } (u, Ac \setminus U Bc) == \\ & (\text{iterate } (p, f) ! \text{insert } (u, Ac)) \setminus U (\text{iterate } (p, f) ! Bc) \end{aligned}$$

and a new induction subgoal is generated:

$$\begin{aligned} & \text{iterate } (p, f) ! \text{insert } (u, Ac \setminus U \text{insert } (u1, Bc)) == \\ & (\text{iterate } (p, f) ! \text{insert } (u, Ac)) \setminus U (\text{iterate } (p, f) ! \text{insert } (u1, Bc)) \end{aligned}$$

Step 3: The rest of the proof proceeds by cases. A proof by cases requires proving the current subgoal assuming each case in turn. The assumption of a case is captured operationally by adding the rewrite rule, $p \rightarrow \text{true}$ (such that p is the term corresponding to the case) to the bank of rewrite rules available to the rest of the proof. Step 3 first adds the rewrite rule,

$$p ? u1 \rightarrow \text{true}$$

to the bank of rewrite rules.

Step 4a: A second case is assumed, adding

$$p ? u \rightarrow \text{true}$$

to the bank of rewrite rules. This rule, taken with the rule generated in step 3 and rule 4 of Figure 3.7 is sufficient to prove the induction subgoal. Then the converse case is considered, with

$$p ? u \rightarrow \text{false}$$

added to the bank of rewrite rules in place of the previously added rule. Again, the induction subgoal is proved using this rule, the rule added in step 3 and rule 5 of Figure 3.7.

Step 4b: Having proven the conjecture assuming the case, $p \text{ ? } u1$ (Step 3), the converse case is assumed and

$p \text{ ? } u1 \text{ --> false}$

is added to the bank of rewrite rules replacing the rule added in Step 3. As in Step 4a, a second case adds

$p \text{ ? } u \text{ --> true}$

and

$p \text{ ? } u \text{ --> false}$

successively to the bank of rewrite rules. The induction subgoal is proven in both cases with the rewrite rules generated from the case assumptions, and rules 4 and 5 of Figure 3.7. \square

Proofs such as that for the rewrite rule shown above have been completed for well over 300 KOLA rules. LP proof scripts that execute the operational versions of some of these proofs are available electronically from the addresses listed in Appendix B.

3.4 Revisiting the “Conflict of Interests” Queries

In this section, we revisit the “Conflict of Interests” queries presented earlier in this chapter and in Chapter 2. In Section 3.4.1, we show how each OQL query, COI_1 (Figure 2.1), COI_{1*} (Figure 3.4), $\overline{COI_1}$ (Figure 2.2), and COI_2 , $\overline{COI_2}$ and $\overline{\overline{COI_2}}$ (Figure 3.2), would get expressed in KOLA. Then in Section 3.4.2, we show how the same set of rules and sequence of rule applications rewrites KOLA translations of COI_1 , COI_2 , and COI_{1*} into their final forms. The point of this section is to show that these rewrites, when expressed over KOLA query representations, can be expressed without code.

3.4.1 KOLA Translations of the COI Queries

Figure 3.8 shows KOLA translations of the Conflicts of Interests queries of Chapter 2 and Section 3.1.1. Queries 1–3 in this figure are translations of COI_1 , COI_{1*} and $\overline{COI_1}$ from Figures 2.1, 3.4a and 2.2 respectively. Queries 4–6 are translations of queries COI_2 , $\overline{COI_2}$, and $\overline{\overline{COI_2}}$ from Figure 3.2. As before, we begin this section begins by tracing the reductions of these queries to show that they are valid translations of their OQL equivalents.

Queries 1, 2 and 3 of Figure 3.8 are the KOLA translations of OQL queries COI_1 , COI_{1*} and $\overline{COI_1}$ (from Figures 2.1, 3.4a and 2.2) respectively. Therefore, each of these

1. **set ! (iterate (ex (\bar{p}) \oplus $\langle \text{id}, \bar{f} \rangle$), **id**) ! Coms)**
 COI_1^K : A KOLA Translation of COI_1 (Figure 2.1)
2. **set ! (iterate (ex ($\bar{p} \ \& \ \bar{q}$) \oplus $\langle \text{id}, K_f \ (\text{SComs}) \rangle$), **id**) ! Coms)**
 COI_{1*}^K : A KOLA Translation of COI_{1*} (Figure 3.4a)
3. **set ! (join ($\bar{r} \ \& \ (\text{ex } (\bar{p}) \ \oplus \ (\text{id} \times \pi_2))$), π_1) ! [Coms, Temp $_K$])**
 $\overline{COI_1^K}$: A KOLA Translation of $\overline{COI_1}$ (Figure 2.2)
4. **set ! (iterate (ex (\bar{p}_2) \oplus $\langle \text{id}, \bar{f} \rangle$), **id**) ! Coms)**
 COI_2^K : A KOLA Translation of COI_2 (Figure 3.2)
5. **set ! (join ($\bar{r} \ \& \ (\text{ex } (\bar{p}_2) \ \oplus \ (\text{id} \times \pi_2))$), π_1) ! [Coms, Temp $_K$])**
 $\overline{COI_2^K}$: A KOLA Translation of $\overline{COI_2}$ (Figure 3.2)
6. **set ! (join (\bar{r}, π_1) ! [Coms, iterate (\bar{p}_3, id) ! Temp $_K$])**
 $\overline{\overline{COI_2^K}}$: A KOLA Translation of $\overline{\overline{COI_2}}$ (Figure 3.2)

such that

$$\begin{aligned}
 \bar{p} &\equiv \text{ex } (\text{eq}) \oplus \langle \text{chair} \circ \pi_1, \text{mems} \circ \pi_2 \rangle \\
 \bar{p}_2 &\equiv \text{ex } (\text{eq}) \oplus \langle \text{chair} \circ \pi_2, \text{mems} \circ \pi_2 \rangle \\
 \bar{p}_3 &\equiv \text{exists } (\text{ex } (\text{eq}) \oplus \langle \text{chair}, \text{mems} \rangle) \oplus \pi_2 \\
 \\
 \bar{q} &\equiv \text{eq} \oplus ((\text{pty} \circ \text{chair}) \times (\text{pty} \circ \text{chair})) \\
 \bar{r} &\equiv \text{eq} \oplus ((\text{pty} \circ \text{chair}) \times \pi_1) \\
 \bar{f} &\equiv \text{iter } (\bar{q}, \pi_2) \circ \langle \text{id}, K_f \ (\text{SComs}) \rangle \\
 \\
 \text{Temp}_K &\equiv \text{njoin } (\text{eq} \oplus (\text{id} \times (\text{pty} \circ \text{chair})), \text{id}, \text{id}) ! \\
 &\quad [\text{iterate } (K_f \ (\text{true}), \text{pty} \circ \text{chair}) ! \text{SComs}, \text{SComs}]
 \end{aligned}$$

Figure 3.8: KOLA Translations of the Conflict of Interests Queries

queries returns a set consisting of committees whose chairs are members of a subcommittee whose chair is from the same party. Queries 4, 5 and 6 of Figure 3.8 translate OQL queries COI_2 , $\overline{COI_2}$ and $\overline{\overline{COI_2}}$ from Figure 3.2. Therefore, each of these queries returns a set of committees whose chairs who belong to a party that includes someone who both chairs and is a member of the same subcommittee. All of these queries remove duplicates from intermediate subquery results generated with **iterate** or **join**.

These queries are fairly complex, and are easiest to understand when decomposed. Therefore, we begin by examining some of the common subexpressions that appear in these queries.

1. The predicate \overline{p} ,

$$\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair} \circ \pi_1, \mathbf{mems} \circ \pi_2 \rangle$$

appears in queries 1, 2 and 3, and is a predicate on committee, subcommittee pairs, $[x, y]$. The expression, $\overline{p} ? [x, y]$ reduces as follows:

$$\begin{aligned} & (\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair} \circ \pi_1, \mathbf{mems} \circ \pi_2 \rangle) ? [x, y] \\ &= \mathbf{ex}(\mathbf{eq}) ? (\langle \mathbf{chair} \circ \pi_1, \mathbf{mems} \circ \pi_2 \rangle ! [x, y]) \\ &= \mathbf{ex}(\mathbf{eq}) ? [(\mathbf{chair} \circ \pi_1) ! [x, y], (\mathbf{mems} \circ \pi_2) ! [x, y]] \\ &= \mathbf{ex}(\mathbf{eq}) ? [(\mathbf{chair} \circ \pi_1) ! [x, y], \mathbf{mems} ! (\pi_2 ! [x, y])] \\ &= \mathbf{ex}(\mathbf{eq}) ? [\mathbf{chair} ! x, \mathbf{mems} ! y] \\ &= \mathbf{ex}(\mathbf{eq}) ? [x.\mathbf{chair}, y.\mathbf{mems}] \\ &= \exists z : \mathit{Legislator}(z \in y.\mathbf{mems} \wedge \mathbf{eq} ? [x.\mathbf{chair}, z]) \\ &= \exists z : \mathit{Legislator}(z \in y.\mathbf{mems} \wedge x.\mathbf{chair} == z) \\ &= x.\mathbf{chair} \in y.\mathbf{mems} \end{aligned}$$

Therefore, $\overline{p} ? [x, y]$ is equivalent to the OQL boolean expression,

$$x.\mathbf{chair} \text{ IN } y.\mathbf{mems}.$$

2. The predicate $\overline{\overline{p_2}}$,

$$\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair} \circ \pi_2, \mathbf{mems} \circ \pi_2 \rangle$$

appears in queries 4 and 5, and is similar to \overline{p} in that it too is a predicate on committee, subcommittee pairs, $[x, y]$. However, $\overline{\overline{p_2}}$ ignores x as shown in the reduction below.

$$(\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair} \circ \pi_2, \mathbf{mems} \circ \pi_2 \rangle) ? [x, y]$$

$$\begin{aligned}
&= \mathbf{ex}(\mathbf{eq}) ? (\langle \mathbf{chair} \circ \pi_2, \mathbf{mems} \circ \pi_2 \rangle ! [x, y]) \\
&= \mathbf{ex}(\mathbf{eq}) ? [(\mathbf{chair} \circ \pi_2) ! [x, y], (\mathbf{mems} \circ \pi_2) ! [x, y]] \\
&= \mathbf{ex}(\mathbf{eq}) ? [(\mathbf{chair} \circ \pi_2) ! [x, y], \mathbf{mems} ! (\pi_2 ! [x, y])] \\
&= \mathbf{ex}(\mathbf{eq}) ? [\mathbf{chair} ! y, \mathbf{mems} ! y] \\
&= \mathbf{ex}(\mathbf{eq}) ? [y.\mathbf{chair}, y.\mathbf{mems}] \\
&= \exists z : \mathit{Legislator}(z \in y.\mathbf{mems} \wedge \mathbf{eq} ? [y.\mathbf{chair}, z]) \\
&= \exists z : \mathit{Legislator}(z \in y.\mathbf{mems} \wedge y.\mathbf{chair} == z) \\
&= y.\mathbf{chair} \in y.\mathbf{mems}
\end{aligned}$$

Therefore, $\overline{p_2} ? [x, y]$ is equivalent to the OQL boolean expression,

$$y.\mathbf{chair} \text{ IN } y.\mathbf{mems}.$$

3. The predicate $\overline{p_3}$,

$$\mathbf{exists}(\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair}, \mathbf{mems} \rangle) \oplus \pi_2$$

appears in query 6, and is a predicate on pairs, $[p, S]$, such that p is the name of a party and S is a set of subcommittees. Reducing $\overline{p_3} ? [p, S]$, we get:

$$\begin{aligned}
&(\mathbf{exists}(\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair}, \mathbf{mems} \rangle) \oplus \pi_2) ? [p, S] \\
&= \mathbf{exists}(\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair}, \mathbf{mems} \rangle) ? (\pi_2 ! [p, S]) \\
&= \mathbf{exists}(\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair}, \mathbf{mems} \rangle) ? S \\
&= \exists y (y \in S \wedge (\mathbf{ex}(\mathbf{eq}) \oplus \langle \mathbf{chair}, \mathbf{mems} \rangle) ? y) \\
&= \exists y (y \in S \wedge \mathbf{ex}(\mathbf{eq}) ? (\langle \mathbf{chair}, \mathbf{mems} \rangle ! y)) \\
&= \exists y (y \in S \wedge \mathbf{ex}(\mathbf{eq}) ? [y.\mathbf{chair}, y.\mathbf{mems}]) \\
&= \exists y (y \in S \wedge \exists z (z \in y.\mathbf{mems} \wedge \mathbf{eq} ? [y.\mathbf{chair}, z])) \\
&= \exists y (y \in S \wedge \exists z (z \in y.\mathbf{mems} \wedge y.\mathbf{chair} == z)) \\
&= \exists y (y \in S \wedge (y.\mathbf{chair} \in y.\mathbf{mems})).
\end{aligned}$$

Thus, $\overline{p_3} ? [p, S]$, is equivalent to the OQL boolean expression,

$$\mathbf{EXISTS} y \text{ IN } S : (y.\mathbf{chair} \text{ IN } y.\mathbf{mems}).$$

4. The predicate \overline{q} ,

$$\mathbf{eq} \oplus ((\mathbf{pty} \circ \mathbf{chair}) \times (\mathbf{pty} \circ \mathbf{chair}))$$

appears in every query in Figure 3.8, and is a predicate on committee, subcommittee pairs, $[x, y]$. Reducing $\bar{q} ? [x, y]$, we get:

$$\begin{aligned}
& (\mathbf{eq} \oplus ((\mathbf{pty} \circ \mathbf{chair}) \times (\mathbf{pty} \circ \mathbf{chair}))) ? [x, y] \\
&= \mathbf{eq} ? [(\mathbf{pty} \circ \mathbf{chair}) ! x, (\mathbf{pty} \circ \mathbf{chair}) ! y] \\
&= \mathbf{eq} ? [\mathbf{pty} ! (\mathbf{chair} ! x), \mathbf{pty} ! (\mathbf{chair} ! y)] \\
&= \mathbf{eq} ? [\mathbf{pty} ! (x.\mathbf{chair}), \mathbf{pty} ! (y.\mathbf{chair})] \\
&= \mathbf{eq} ? [x.\mathbf{chair}.\mathbf{pty}, y.\mathbf{chair}.\mathbf{pty}] \\
&= x.\mathbf{chair}.\mathbf{pty} == y.\mathbf{chair}.\mathbf{pty}
\end{aligned}$$

Thus, $\bar{q} ? [x, y]$, is equivalent to the OQL boolean expression,

$$x.\mathbf{chair}.\mathbf{pty} == y.\mathbf{chair}.\mathbf{pty}.$$

5. The predicate \bar{r} ,

$$\mathbf{eq} \oplus ((\mathbf{pty} \circ \mathbf{chair}) \times \pi_1)$$

of queries 3, 5 and 6 is similar to \bar{q} , but is a predicate on *nested* pairs, $[x, [p, S]]$ such that x is a committee in **Coms**, p is the name of a political party and S is a bag of subcommittees. Reducing $\bar{r} ? [x, [p, S]]$, we get:

$$\begin{aligned}
& (\mathbf{eq} \oplus ((\mathbf{pty} \circ \mathbf{chair}) \times \pi_1)) ? [x, [p, S]] \\
&= \mathbf{eq} ? (((\mathbf{pty} \circ \mathbf{chair}) \times \pi_1) ! [x, [p, S]]) \\
&= \mathbf{eq} ? [(\mathbf{pty} \circ \mathbf{chair}) ! x, \pi_1 ! [p, S]] \\
&= \mathbf{eq} ? [\mathbf{pty} ! (x.\mathbf{chair}), p] \\
&= \mathbf{eq} ? [x.\mathbf{chair}.\mathbf{pty}, p] \\
&= x.\mathbf{chair}.\mathbf{pty} == p
\end{aligned}$$

Thus, $\bar{r} ? [x, [p, S]]$, is equivalent to the OQL boolean expression,

$$x.\mathbf{chair}.\mathbf{pty} == p.$$

6. The function \bar{f} ,

$$\mathbf{iter} (\bar{q}, \pi_2) \circ \langle \mathbf{id}, K_f (\mathbf{SComs}) \rangle$$

appears in queries 1 and 4, and is a function on committees, x . Reducing $\bar{f} ! x$, we get:

$$(\mathbf{iter} (\bar{q}, \pi_2) \circ \langle \mathbf{id}, K_f (\mathbf{SComs}) \rangle) ! x$$

$$\begin{aligned}
&= \mathbf{iter} (\bar{q}, \pi_2) ! (\langle \mathbf{id}, K_f (\text{SComs}) \rangle ! x) \\
&= \mathbf{iter} (\bar{q}, \pi_2) ! [\mathbf{id} ! x, K_f (\text{SComs}) ! x] \\
&= \mathbf{iter} (\bar{q}, \pi_2) ! [x, \text{SComs}] \\
&= \{(\pi_2 ! [x, c])^j \mid c^j \in \text{SComs}, \bar{q} ? [x, c]\} \\
&= \{c^j \mid c^j \in \text{SComs}, \bar{q} ? [x, c]\} \\
&= \{c^j \mid c^j \in \text{SComs}, x.\text{chair.pty} == c.\text{chair.pty}\}
\end{aligned}$$

Thus, $\bar{f} ! x$ is equivalent to the OQL query expression,

```

SELECT c
FROM c IN SComs
WHERE x.chair.pty == c.chair.pty.

```

7. Temp_K is a subquery of queries 3, 5 and 6. Temp_K uses **iterate** and **njoin** to generate the KOLA equivalent of subquery Temp of Figure 2.2. This is illustrated by the derivation below:

$$\begin{aligned}
&\mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times (\text{pty} \circ \text{chair})), \mathbf{id}, \mathbf{id}) ! \\
&\quad [\mathbf{iterate} (K_p (\text{true}), \text{pty} \circ \text{chair}) ! \text{SComs}, \text{SComs}] \\
&= \mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times (\text{pty} \circ \text{chair})), \mathbf{id}, \mathbf{id}) ! \\
&\quad [\{((\text{pty} \circ \text{chair}) ! c)^i \mid c^i \in \text{SComs}, K_p (\text{true}) ? c\}, \text{SComs}] \\
&= \mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times (\text{pty} \circ \text{chair})), \mathbf{id}, \mathbf{id}) ! \\
&\quad [\{(\text{pty} ! (\text{chair} ! c))^i \mid c^i \in \text{SComs}, K_p (\text{true}) ? c\}, \text{SComs}] \\
&= \mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times (\text{pty} \circ \text{chair})), \mathbf{id}, \mathbf{id}) ! \\
&\quad [\{(\text{pty} ! (c.\text{chair}))^i \mid c^i \in \text{SComs}\}, \text{SComs}] \\
&= \mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times (\text{pty} \circ \text{chair})), \mathbf{id}, \mathbf{id}) ! \\
&\quad [\{(c.\text{chair.pty})^i \mid c^i \in \text{SComs}\}, \text{SComs}] \\
&= \{[c.\text{chair.pty}, S_c] \mid c.\text{chair.pty} \in \{(c.\text{chair.pty})^i \mid c^i \in \text{SComs}\}\} \text{ s.t.} \\
&\quad S_c = \mathbf{id} ! \{(\mathbf{id} ! s)^j \mid s^j \in \text{SComs}, (\mathbf{eq} \oplus (\mathbf{id} \times \text{pty} \circ \text{chair})) ? [p, s]\}
\end{aligned}$$

$$\begin{aligned}
&= \{s^j \mid s^j \in \text{SComs}, (\text{eq} \oplus (\text{id} \times (\text{pty} \circ \text{chair}))) ? [p, s]\} \\
&= \{s^j \mid s^j \in \text{SComs}, \text{eq} ? ((\text{id} \times (\text{pty} \circ \text{chair})) ! [p, s])\} \\
&= \{s^j \mid s^j \in \text{SComs}, \text{eq} ? [\text{id} ! p, (\text{pty} \circ \text{chair}) ! s]\} \\
&= \{s^j \mid s^j \in \text{SComs}, \text{eq} ? [\text{id} ! p, \text{pty} ! (\text{chair} ! s)]\} \\
&= \{s^j \mid s^j \in \text{SComs}, \text{eq} ? [p, s.\text{chair}.\text{pty}]\} \\
&= \{s^j \mid s^j \in \text{SComs}, p == s.\text{chair}.\text{pty}\} \\
&= \{[c.\text{chair}.\text{pty}, S_c] \mid c^i \in \text{SComs}\} \\
&\quad s.t. S_c = \{s^j \mid s^j \in \text{SComs}, c.\text{chair}.\text{pty} == s.\text{chair}.\text{pty}\}
\end{aligned}$$

Therefore, this subquery returns a set of pairs, $[p, S]$, such that p is the name of a party affiliated with some subcommittee's chair and S is the bag of all subcommittees chaired by someone from that party. In other words, Temp_K is equivalent to the OQL query,

```

SELECT p, S : partition
FROM c IN SComs
GROUP BY p : c.chair.pty

```

Using the subexpressions above, a description of each of the queries of Figure 3.8 follows.

COI_1^K (1):

Predicates \bar{p} , \bar{q} and \bar{f} are all subexpressions of COI_1^K 's subpredicate, $(\text{ex}(\bar{p}) \oplus \langle \text{id}, \bar{f} \rangle)$, which when invoked on a committee $x \in \text{Coms}$ is equivalent to the OQL expression,

$$\text{EXISTS } y \text{ IN } \left(\begin{array}{l} \text{SELECT } c \\ \text{FROM } c \text{ IN SComs} \\ \text{WHERE } x.\text{chair}.\text{pty} == c.\text{chair}.\text{pty} \end{array} \right) : (x.\text{chair} \text{ IN } y.\text{mems}).$$

as is demonstrated by the derivation below:

$$\begin{aligned}
(\text{ex}(\bar{p}) \oplus \langle \text{id}, \bar{f} \rangle) ? x &= \text{ex}(\bar{p}) ? (\langle \text{id}, \bar{f} \rangle ! x) \\
&= \text{ex}(\bar{p}) ? [x, \bar{f} ! x] \\
&= \text{ex}(\bar{p}) ? [x, S_x] \\
&\quad s.t. S_x = \{c^j \mid c^j \in \text{SComs}, x.\text{chair}.\text{pty} == c.\text{chair}.\text{pty}\} \\
&= \exists y (y \in S_x \wedge \bar{p} ? [x, y]) \\
&= \exists y (y \in S_x \wedge x.\text{chair} \in y.\text{mems})
\end{aligned}$$

Therefore, the **iterate** subquery generates the collection derived below,

$$\begin{aligned}
& \mathbf{iterate} \ (\mathbf{ex} \ (\bar{\mathbf{p}}) \oplus \langle \mathbf{id}, \bar{\mathbf{f}} \rangle, \ \mathbf{id}) \ ! \ \mathbf{Coms} \\
& = \ \{ \langle \mathbf{id} \ ! \ x \rangle^i \mid x^i \in \mathbf{Coms}, \ (\mathbf{ex} \ (\bar{\mathbf{p}}) \oplus \langle \mathbf{id}, \bar{\mathbf{f}} \rangle) \ ? \ x \} \\
& = \ \{ x^i \mid x^i \in \mathbf{Coms}, \ (\mathbf{ex} \ (\bar{\mathbf{p}}) \oplus \langle \mathbf{id}, \bar{\mathbf{f}} \rangle) \ ? \ x \} \\
& = \ \{ x^i \mid x^i \in \mathbf{Coms}, \ \exists y \ (y \in S_x \ \wedge \ x.\mathbf{chair} \in y.\mathbf{mems}) \}
\end{aligned}$$

Removing duplicates from this result leaves,

$$\{ x \mid x \in \mathbf{Coms}, \ \exists y \ (y \in S_x \ \wedge \ x.\mathbf{chair} \in y.\mathbf{mems}) \}$$

which is the same result returned by the OQL query, COI_1 .

COI_{1*}^K (2):

COI_{1*}^K is similar to COI_1^K in that it performs duplicate elimination on the result of an **iterate** subquery, and contains the same subpredicates, $\bar{\mathbf{p}}$ and $\bar{\mathbf{q}}$. But this query differs from COI_1^K in that it does not generate an intermediate collection (S_x) for each $x \in \mathbf{Coms}$. Instead, the existential predicate ($\mathbf{ex} \ (\bar{\mathbf{p}} \ \& \ \bar{\mathbf{q}})$) searches \mathbf{SComs} for some subcommittee y that with x satisfies both $\bar{\mathbf{p}}$ and $\bar{\mathbf{q}}$. Therefore, when invoked on a committee $x \in \mathbf{Coms}$, this predicate is equivalent to the OQL expression,

$$\mathbf{EXISTS} \ y \ \mathbf{IN} \ \mathbf{SComs} : ((x.\mathbf{chair} \ \mathbf{IN} \ y.\mathbf{mems}) \ \mathbf{AND} \ (x.\mathbf{chair.pty} == y.\mathbf{chair.pty})),$$

as shown by the derivation below:

$$\begin{aligned}
& (\mathbf{ex} \ (\bar{\mathbf{p}} \ \& \ \bar{\mathbf{q}}) \oplus \langle \mathbf{id}, \mathbf{K}_f \ (\mathbf{SComs}) \rangle) \ ? \ x \\
& = \ \mathbf{ex} \ (\bar{\mathbf{p}} \ \& \ \bar{\mathbf{q}}) \ ? \ (\langle \mathbf{id}, \mathbf{K}_f \ (\mathbf{SComs}) \rangle \ ! \ x) \\
& = \ \mathbf{ex} \ (\bar{\mathbf{p}} \ \& \ \bar{\mathbf{q}}) \ ? \ [\mathbf{id} \ ! \ x, \ \mathbf{K}_f \ (\mathbf{SComs}) \ ! \ x] \\
& = \ \mathbf{ex} \ (\bar{\mathbf{p}} \ \& \ \bar{\mathbf{q}}) \ ? \ [x, \ \mathbf{SComs}] \\
& = \ \exists y \ (y \in \mathbf{SComs} \ \wedge \ (\bar{\mathbf{p}} \ \& \ \bar{\mathbf{q}}) \ ? \ [x, \ y]) \\
& = \ \exists y \ (y \in \mathbf{SComs} \ \wedge \ \bar{\mathbf{p}} \ ? \ [x, \ y] \ \wedge \ \bar{\mathbf{q}} \ ? \ [x, \ y]) \\
& = \ \exists y \ (y \in \mathbf{SComs} \ \wedge \ x.\mathbf{chair} \in y.\mathbf{mems} \ \wedge \ x.\mathbf{chair.pty} == y.\mathbf{chair.pty})
\end{aligned}$$

Thus, the **iterate** subquery of COI_{1*}^K returns:

$$\mathbf{iterate} \ (\mathbf{ex} \ (\bar{\mathbf{p}} \ \& \ \bar{\mathbf{q}}) \oplus \langle \mathbf{id}, \mathbf{K}_f \ (\mathbf{SComs}) \rangle, \ \mathbf{id}) \ ! \ \mathbf{Coms}$$

$$\begin{aligned}
&= \{\langle \mathbf{id} ! x \mid x^i \in \mathbf{Coms}, (\mathbf{ex} (\bar{p} \ \& \ \bar{q}) \oplus \langle \mathbf{id}, K_f (\mathbf{SComs}) \rangle) ? x \rangle\} \\
&= \{\langle x^i \mid x^i \in \mathbf{Coms}, (\mathbf{ex} (\bar{p} \ \& \ \bar{q}) \oplus \langle \mathbf{id}, K_f (\mathbf{SComs}) \rangle) ? x \rangle\} \\
&= \{\langle x^i \mid x^i \in \mathbf{Coms} \\
&\quad \exists y (y \in \mathbf{SComs} \wedge x.\mathbf{chair} \in y.\mathbf{mems} \wedge x.\mathbf{chair.pty} == y.\mathbf{chair.pty}) \rangle\}.
\end{aligned}$$

Removing duplicates from this result leaves,

$$\{x \mid x \in \mathbf{Coms}, \exists y (y \in \mathbf{SComs} \wedge x.\mathbf{chair} \in y.\mathbf{mems} \wedge x.\mathbf{chair.pty} == y.\mathbf{chair.pty})\},$$

which is also the result of the OQL query, COI_{1*} .

$\overline{COI_1^K}$ (3):

$\overline{COI_1^K}$ computes the same result as COI_1^K and COI_{1*}^K , but using **join** in its subquery rather than **iterate**. The join is of \mathbf{Coms} and \mathbf{Temp}_K , and uses predicates \bar{r} and $(\mathbf{ex} (\bar{p}) \oplus (\mathbf{id} \times \pi_2))$. The latter complex predicate is a predicate on nested pairs

$$[x, [p, S]]$$

(such that $x \in \mathbf{Coms}$ and $[p, S] \in \mathbf{Temp}_K$) that is equivalent to the OQL boolean expression,

$$\mathbf{EXISTS} \ y \ \mathbf{IN} \ S : (x.\mathbf{chair} \ \mathbf{IN} \ y.\mathbf{mems})$$

as illustrated by the derivation below:

$$\begin{aligned}
(\mathbf{ex} (\bar{p}) \oplus (\mathbf{id} \times \pi_2)) ? [x, [p, S]] &= \mathbf{ex} (\bar{p}) ? ((\mathbf{id} \times \pi_2) ! [x, [p, S]]) \\
&= \mathbf{ex} (\bar{p}) ? [\mathbf{id} ! x, \pi_2 ! [p, S]] \\
&= \mathbf{ex} (\bar{p}) ? [x, S] \\
&= \exists y (y \in S \wedge \bar{p} ? [x, y]) \\
&= \exists y (y \in S \wedge x.\mathbf{chair} \in y.\mathbf{mems})
\end{aligned}$$

Therefore, the result of the join is a collection of committees whose chairs are members of a subcommittee chaired by someone from the same party, as illustrated by the derivation:

$$\begin{aligned}
&\mathbf{join} (\bar{r} \ \& \ (\mathbf{ex} (\bar{p}) \oplus (\mathbf{id} \times \pi_2)), \pi_1) ! [\mathbf{Coms}, \mathbf{Temp}_K] \\
&= \{(\pi_1 ! [x, [p, S]])^{ij} \mid \\
&\quad x^i \in \mathbf{Coms}, [p, S]^j \in \mathbf{Temp}_K, (\bar{r} \ \& \ (\mathbf{ex} (\bar{p}) \oplus (\mathbf{id} \times \pi_2))) ? [x, [p, S]]\} \\
&= \{x^{ij} \mid x^i \in \mathbf{Coms}, [p, S]^j \in \mathbf{Temp}_K, (\bar{r} \ \& \ (\mathbf{ex} (\bar{p}) \oplus (\mathbf{id} \times \pi_2))) ? [x, [p, S]]\}
\end{aligned}$$

$$\begin{aligned}
&= \{x^i \mid x^i \in \text{Coms}, [p, S] \in \text{Temp}_K, (\bar{r} \& (\mathbf{ex}(\bar{p}) \oplus (\mathbf{id} \times \pi_2))) ? [x, [p, S]]\} \\
&= \{x^i \mid x^i \in \text{Coms}, [p, S] \in \text{Temp}_K, \\
&\quad \bar{r} ? [x, [p, S]], (\mathbf{ex}(\bar{p}) \oplus (\mathbf{id} \times \pi_2)) ? [x, [p, S]]\}
\end{aligned}$$

After duplicate elimination, this becomes,

$$\{x \mid x \in \text{Coms}, [p, S] \in \text{Temp}_K, \bar{r} ? [x, [p, S]], (\mathbf{ex}(\bar{p}) \oplus (\mathbf{id} \times \pi_2)) ? [x, [p, S]]\}.$$

Because $\bar{r} ? [x, [p, S]]$ is true if

$$x.\text{chair.pty} == p$$

and $(\mathbf{ex}(\bar{p}) \oplus (\mathbf{id} \times \pi_2)) ? [x, [p, S]]$ is true if

$$\exists y (y \in S \wedge x.\text{chair} \in y.\text{mems}),$$

this expression reduces to

$$\{x \mid x \in \text{Coms}, [p, S] \in \text{Temp}_K, x.\text{chair.pty} == p, \exists y (y \in S \wedge x.\text{chair} \in y.\text{mems})\}$$

which is also what is returned by the OQL query, $\overline{COI_1}$.

COI₂^K (4):

Query COI_2^K (4) is almost identical to query COI_1^K (1) but using the predicate \bar{p}_2 rather than \bar{p} . Given a committee $x \in \text{Coms}$, $((\mathbf{ex}(\bar{p}_2) \oplus \langle \mathbf{id}, \bar{f} \rangle) ? x)$ is equivalent to the OQL expression,

$$\text{EXISTS } y \text{ IN } \left(\begin{array}{l} \text{SELECT } c \\ \text{FROM } c \text{ IN } \text{SComs} \\ \text{WHERE } x.\text{chair.pty} == c.\text{chair.pty} \end{array} \right) : y.\text{chair} \text{ IN } y.\text{mems}$$

as is revealed by the derivation below:

$$\begin{aligned}
&(\mathbf{ex}(\bar{p}_2) \oplus \langle \mathbf{id}, \bar{f} \rangle) ? x \\
&= \mathbf{ex}(\bar{p}_2) ? [\mathbf{id} ! x, \bar{f} ! x] \\
&= \mathbf{ex}(\bar{p}_2) ? [x, S_x] \\
&\quad \text{such that } S_x = \{c^i \mid c^i \in \text{SComs}, x.\text{chair.pty} == c.\text{chair.pty}\} \\
&= \exists y (y \in S_x \wedge \bar{p}_2 ? [x, y]) \\
&= \exists y (y \in S_x \wedge y.\text{chair} \in y.\text{mems})
\end{aligned}$$

Therefore, the **iterate** subquery of this query generates the collection,

$$\{\{x^i \mid x^i \in \mathbf{Coms}, \exists y (y \in S_x \wedge y.\mathbf{chair} \in y.\mathbf{mems})\}\}.$$

Removing duplicates from this result leaves,

$$\{x \mid x \in \mathbf{Coms}, \exists y (y \in S_x \wedge y.\mathbf{chair} \in y.\mathbf{mems})\},$$

which is the same result returned by the OQL query, COI_2 .

$\overline{COI_2^K}$ (5):

Query $\overline{COI_2^K}$ (5) is almost identical to query $\overline{COI_1^K}$ (3) but for its use of $\overline{p_2}$ rather than \overline{p} . The join predicate for this query consists of \overline{r} and $(\mathbf{ex}(\overline{p_2}) \oplus (\mathbf{id} \times \pi_2))$. The latter predicate on nested pairs $[x, [p, S]]$ (such that x is in \mathbf{Coms} and $[p, S]$ is in \mathbf{Temp}_K) is equivalent to the OQL expression

$$\mathbf{EXISTS} \ y \ \mathbf{IN} \ S : (y.\mathbf{chair} \ \mathbf{IN} \ y.\mathbf{mems}),$$

as is revealed by the derivation below:

$$\begin{aligned} (\mathbf{ex}(\overline{p_2}) \oplus (\mathbf{id} \times \pi_2)) ? [x, [p, S]] &= \mathbf{ex}(\overline{p_2}) ? ((\mathbf{id} \times \pi_2) ! [x, [p, S]]) \\ &= \mathbf{ex}(\overline{p_2}) ? [\mathbf{id} ! x, \pi_2 ! [p, S]] \\ &= \mathbf{ex}(\overline{p_2}) ? [x, S] \\ &= \exists y (y \in S \wedge \overline{p_2} ? [x, y]) \\ &= \exists y (y \in S \wedge y.\mathbf{chair} \in y.\mathbf{mems}). \end{aligned}$$

Therefore, the result of the join is a collection of committees whose chairs belong to a party which also includes someone who both chairs and is a member of some subcommittee:

$$\begin{aligned} &\mathbf{join}(\overline{r} \ \& \ (\mathbf{ex}(\overline{p_2}) \oplus (\mathbf{id} \times \pi_2)), \pi_1) ! [\mathbf{Coms}, \mathbf{Temp}_K] \\ &= \{\{x^{ij} \mid x^i \in \mathbf{Coms}, [p, S]^j \in \mathbf{Temp}_K, (\overline{r} \ \& \ (\mathbf{ex}(\overline{p_2}) \oplus (\mathbf{id} \times \pi_2))) ? [x, [p, S]]\}\} \\ &= \{\{x^i \mid x^i \in \mathbf{Coms}, [p, S] \in \mathbf{Temp}_K, (\overline{r} \ \& \ (\mathbf{ex}(\overline{p_2}) \oplus (\mathbf{id} \times \pi_2))) ? [x, [p, S]]\}\} \\ &= \{x^i \mid x^i \in \mathbf{Coms}, [p, S] \in \mathbf{Temp}_K, \\ &\quad \overline{r} ? [x, [p, S]], (\mathbf{ex}(\overline{p_2}) \oplus (\mathbf{id} \times \pi_2)) ? [x, [p, S]]\} \end{aligned}$$

After duplicate elimination, this becomes,

$$\{x \mid x \in \mathbf{Coms}, [p, S] \in \mathbf{Temp}_K, \overline{r} ? [x, [p, S]], (\mathbf{ex}(\overline{p_2}) \oplus (\mathbf{id} \times \pi_2)) ? [x, [p, S]]\}.$$

Because $\bar{r} ? [x, [p, S]]$ is true if

$$x.\text{chair.pty} == p$$

and $(\mathbf{ex} (\bar{p}_2) \oplus (\mathbf{id} \times \pi_2)) ? [x, [p, S]]$ is true if

$$\exists y (y \in S \wedge y.\text{chair} \in y.\text{mems}),$$

this expression reduces to

$$\{x \mid x \in \text{Coms}, [p, S] \in \text{Temp}_K, x.\text{chair.pty} == p, \exists y (y \in S \wedge y.\text{chair} \in y.\text{mems})\},$$

which is what is also returned by the OQL query, COI_2 .

$\overline{\overline{COI_2^K}}$ (6):

Query $\overline{\overline{COI_2^K}}$ (6) generates Temp_K as a subquery result as in $\overline{\overline{COI_2^K}}$, but then filters this result before proceeding with the join. The filtering subquery uses the predicate \bar{p}_3 which is a predicate on pairs from Temp_K $[p, S]$ that is equivalent to the OQL boolean expression,

$$\text{EXISTS } y \text{ IN } S : (y.\text{chair} \text{ IN } y.\text{mems})$$

as illustrated by the derivation below:

$$\begin{aligned} & (\mathbf{exists} (\mathbf{ex} (\mathbf{eq}) \oplus \langle \text{chair}, \text{mems} \rangle) \oplus \pi_2) ? [p, S] \\ &= \mathbf{exists} (\mathbf{ex} (\mathbf{eq}) \oplus \langle \text{chair}, \text{mems} \rangle) ? (\pi_2 ! [p, S]) \\ &= \mathbf{exists} (\mathbf{ex} (\mathbf{eq}) \oplus \langle \text{chair}, \text{mems} \rangle) ? S \\ &= \exists y (y \in S \wedge (\mathbf{ex} (\mathbf{eq}) \oplus \langle \text{chair}, \text{mems} \rangle) ? y) \\ &= \exists y (y \in S \wedge \mathbf{ex} (\mathbf{eq}) ? (\langle \text{chair}, \text{mems} \rangle ! y)) \\ &= \exists y (y \in S \wedge \mathbf{ex} (\mathbf{eq}) ? [y.\text{chair}, y.\text{mems}]) \\ &= \exists y (y \in S \wedge \exists z (z \in y.\text{mems} \wedge \mathbf{eq} ? [y.\text{chair}, z])) \\ &= \exists y (y \in S \wedge \exists z (z \in y.\text{mems} \wedge y.\text{chair} == z)) \\ &= \exists y (y \in S \wedge (y.\text{chair} \in y.\text{mems})). \end{aligned}$$

Therefore, the result of filtering Temp_K is the set of party, subcommittee collection pairs $([p, S])$ such that for some subcommittee in $c \in S$, c 's chair is also a member of c . The intermediate result returned as a result of **join** is therefore:

$$\mathbf{join} (\bar{r}, \pi_1) ! [\text{Coms}, \text{iterate} (\bar{p}_3, \mathbf{id}) ! \text{Temp}_K]$$

$$\begin{aligned}
&= \mathbf{join} (\bar{\tau}, \pi_1) ! [\mathbf{Coms}, \{(\mathbf{id} ! [p, S])^j \mid [p, S]^j \in \mathbf{Temp}_K, \bar{p}_3 ? [p, S]\}] \\
&= \mathbf{join} (\bar{\tau}, \pi_1) ! [\mathbf{Coms}, \{[p, S] \mid [p, S] \in \mathbf{Temp}_K, \bar{p}_3 ? [p, S]\}] \\
&= \{(\pi_1 ! [x, [p, S]])^i \mid x^i \in \mathbf{Coms}, [p, S] \in \mathbf{Temp}_K, \bar{p}_3 ? [p, S], \bar{\tau} ? [x, [p, S]]\} \\
&= \{x^i \mid x^i \in \mathbf{Coms}, [p, S] \in \mathbf{Temp}_K, \bar{p}_3 ? [p, S], \bar{\tau} ? [x, [p, S]]\}.
\end{aligned}$$

Because $\bar{\tau} ? [x, [p, S]]$ is true if

$$x.\mathbf{chair.pty} == p$$

and $\bar{p}_3 ? [p, S]$ is true if

$$\exists y (y \in S \wedge (y.\mathbf{chair} \in y.\mathbf{mems})),$$

this expression reduces to,

$$\{x^i \mid x^i \in \mathbf{Coms}, [p, S] \in \mathbf{Temp}_K, \exists y (y \in S \wedge (y.\mathbf{chair} \in y.\mathbf{mems})), x.\mathbf{chair.pty} == p\},$$

which is also what is returned by the OQL query, $\overline{\overline{COI_2}}$.

3.4.2 A Rule Set for Rewriting the COI Queries

Figure 3.9 shows a set of KOLA rewrite rules that can be fired in the same sequence to rewrite:

- $COI_1^K \rightarrow COI_{1*}^K \rightarrow \overline{COI_1^K}$, and
- $COI_2^K \rightarrow \overline{COI_2^K} \rightarrow \overline{\overline{COI_2^K}}$.

(The KOLA transformation chain is slightly different than that presented for the OQL versions of these queries in that COI_1^K is transformed into COI_{1*}^K rather than vice-versa.)

The sequence used for these rules is:

$$1, 2, 3, 4, 5, 6, 5^{-1}, 7, 5, 8, 9$$

such that 5^{-1} indicates that rule 5 is fired in right-to-left fashion. For the purposes of discussion, this sequence can be broken down into four subsequences.¹⁰ To show the effects of firing these rules, we illustrate by tracing the rewrite of query COI_2^K (Query 4 of Figure 3.8) first into query $\overline{COI_2^K}$ (5) and then into $\overline{\overline{COI_2^K}}$ (6). The steps of this query rewrite are shown in Figure 3.10 and summarized below.

¹⁰These rewrites could instead be expressed with four rules (one for each subsequence), but these four rules would be very complex and would make the specification of the rewrite harder to understand and verify. Such complex rules also hide the fact that the simpler rules have general applicability (rules 4, 5 and 7 being the most obvious in this example). Thus, it was decided to keep rules as simple as possible and to group rules into complex rewrites using COKO, as will be discussed in Section 4.

$$\begin{aligned}
(1) \quad & \mathbf{ex} (p) \oplus \langle \mathbf{id}, \mathbf{iter} (q, \pi_2) \circ \langle \mathbf{id}, K_f (B) \rangle \rangle \stackrel{\Rightarrow}{=} \mathbf{ex} (q \& p) \oplus \langle \mathbf{id}, K_f (B) \rangle \\
(2) \quad & \mathbf{set} ! (\mathbf{iterate} (\mathbf{ex} (p) \oplus \langle \mathbf{id}, K_f (B) \rangle), f) ! A \stackrel{\equiv}{=} \mathbf{set} ! (\mathbf{join} (p, f \circ \pi_1) ! [A, B]) \\
(3) \quad & \mathbf{set} ! (\mathbf{join} (q \& p, h \circ \pi_1) ! [A, B]) \stackrel{\equiv}{=} \\
& \mathbf{set} ! (\mathbf{join} (r \& (\mathbf{ex} (p) \oplus \langle \mathbf{id} \times \pi_2 \rangle), h \circ \pi_1) ! [A, T]) \\
& \text{such that} \\
& q = \mathbf{eq} \oplus (f \times g) \\
& r = \mathbf{eq} \oplus (f \times \pi_1) \\
& T = \mathbf{njoin} (\mathbf{eq} \oplus \langle \mathbf{id} \times g \rangle, \mathbf{id}, \mathbf{id}) ! [\mathbf{iterate} (K_p (\mathbf{true}), g) ! B, B] \\
(4) \quad & \langle f \circ h, g \circ h \rangle \stackrel{\Rightarrow}{=} \langle f, g \rangle \circ h \\
(5) \quad & p \oplus (f \circ g) \stackrel{\equiv}{=} (p \oplus f) \oplus g \\
(6) \quad & \mathbf{ex} (p \oplus \pi_2) \stackrel{\equiv}{=} \mathbf{exists} (p) \oplus \pi_2 \\
(7) \quad & \pi_2 \circ (f \times g) \stackrel{\equiv}{=} g \circ \pi_2 \\
(8) \quad & \mathbf{join} (p \& (q \oplus \pi_2), f) ! [A, B] \stackrel{\equiv}{=} \mathbf{join} (p, f) ! [A, \mathbf{iterate} (q, \mathbf{id}) ! B] \\
(9) \quad & \mathbf{id} \circ f \stackrel{\equiv}{=} f
\end{aligned}$$

Figure 3.9: Rewrite Rules For the Query Rewrites of the ‘‘Conflict of Interests’’ Queries

Firing Rule 1: Rule 1 pulls a predicate (q) out of an inner query ($\mathbf{iter} (q, \pi_2)$) and into the existential quantifier, \mathbf{ex} . Matching rule 1 with COI_2^K binds pattern variables p and q to KOLA predicates $\overline{p_2}$ and \overline{q} . Rewriting then absorbs the predicate \overline{q} in $\mathbf{iter} (\overline{q}, \pi_2)$ into the existentially quantified predicate, resulting in $\mathbf{ex} (\overline{q} \& \overline{p_2})$. In short, the result of firing this rule on COI_2^K is a KOLA query equivalent to the OQL query,

```

SELECT DISTINCT x.chair
FROM x IN Coms
WHERE EXISTS y IN SComs : ((y.chair ∈ y.mems) AND (x.chair.pty == y.chair.pty)).

```

Firing Rules 2 and 3: Rules 2 and 3 together transform the query resulting from the previous step into $\overline{COI_2^K}$. Rule 2 fires on queries matching the head pattern

$$\mathbf{set} ! (\mathbf{iterate} (\mathbf{ex} (p) \oplus \langle \mathbf{id}, K_f (B) \rangle), f) ! A).$$

This pattern characterizes nested OQL and SQL queries whose **WHERE** clause contains a correlated membership or existence predicate (p). Once fired, Rule 2 transforms such queries into the form,

$$\mathbf{set} ! (\mathbf{join} (p, f \circ \pi_1) ! [A, B]),$$

$$\begin{aligned}
& \text{set ! (iterate (ex } \overline{p_2} \oplus \langle \text{id}, \overline{f} \rangle, \text{id}) ! \text{Coms})} \\
& \quad \overline{p_2} \equiv \text{ex (eq)} \oplus \langle \text{chair} \circ \pi_2, \text{mems} \circ \pi_2 \rangle \\
& \quad \overline{q} \equiv \text{eq} \oplus ((\text{pty} \circ \text{chair}) \times (\text{pty} \circ \text{chair})) \\
& \quad \overline{f} \equiv \text{iter } (\overline{q}, \pi_2) \circ \langle \text{id}, K_f \text{ (SComs)} \rangle \\
\end{aligned}$$

$$\begin{aligned}
& \xrightarrow{1} \text{set ! (iterate (ex } (\overline{q} \ \& \ \overline{p_2}) \oplus \langle \text{id}, K_f \text{ (SComs)} \rangle, \text{id}) ! \text{Coms})} \\
& \xrightarrow{2} \text{set ! (join } (\overline{q} \ \& \ \overline{p_2}, \text{id} \circ \pi_1) ! [\text{Coms}, \text{SComs}])} \\
& \xrightarrow{3} \text{set ! (join } (\overline{q} \ \& \ \overline{p_2}, \text{id} \circ \pi_1) ! [\text{Coms}, \text{Temp}_K])} \\
& \quad \text{Temp}_K \equiv \text{njoin (eq} \oplus (\text{id} \times (\text{pty} \circ \text{chair})), \text{id}, \text{id}) ! \\
& \quad \quad \quad [\text{iterate } (K_p \text{ (true)}, \text{pty} \circ \text{chair}) ! \text{SComs}, \text{SComs}] \\
& \quad \overline{p_2} \equiv \text{ex (ex (eq)} \oplus \langle \text{chair} \circ \pi_2, \text{mems} \circ \pi_2 \rangle) \oplus (\text{id} \times \pi_2) \\
& \quad \overline{q} \equiv \text{eq} \oplus ((\text{pty} \circ \text{chair}) \times \pi_1) \\
& \quad (a) \text{ The first transformation of } COI_2^K \text{ to } \overline{COI_2^K} \\
\end{aligned}$$

$$\begin{aligned}
& \xrightarrow{4} \text{set ! (join } (\overline{q} \ \& \ \overline{p_2}, \text{id} \circ \pi_1) ! [\text{Coms}, \text{Temp}_K])} \\
& \quad \overline{p_2} \equiv \text{ex (ex (eq)} \oplus (\langle \text{chair}, \text{mems} \rangle \circ \pi_2)) \oplus (\text{id} \times \pi_2) \\
& \xrightarrow{5} \text{set ! (join } (\overline{q} \ \& \ \overline{p_2}, \text{id} \circ \pi_1) ! [\text{Coms}, \text{Temp}_K])} \\
& \quad \overline{p_2} \equiv \text{ex (ex (eq)} \oplus \langle \text{chair}, \text{mems} \rangle \oplus \pi_2) \oplus (\text{id} \times \pi_2) \\
& \xrightarrow{6,5^{-1}} \text{set ! (join } (\overline{q} \ \& \ \overline{p_2}, \text{id} \circ \pi_1) ! [\text{Coms}, \text{Temp}_K])} \\
& \quad \overline{p_2} \equiv \text{exists (ex (eq)} \oplus \langle \text{chair}, \text{mems} \rangle) \oplus (\pi_2 \circ (\text{id} \times \pi_2)) \\
& \xrightarrow{7,5} \text{set ! (join } (\overline{q} \ \& \ \overline{p_2}, \text{id} \circ \pi_1) ! [\text{Coms}, \text{Temp}_K])} \\
& \quad \overline{p_2} \equiv \text{exists (ex (eq)} \oplus \langle \text{chair}, \text{mems} \rangle) \oplus \pi_2 \oplus \pi_2 \\
& \xrightarrow{8} \text{set ! (join } (\overline{q}, \text{id} \circ \pi_1) ! [\text{Coms}, \text{iterate } (\overline{p_3}, \text{id}) ! \text{Temp}_K])} \\
& \quad \text{Temp}_K \equiv \text{njoin (eq} \oplus (\text{id} \times (\text{pty} \circ \text{chair})), \text{id}, \text{id}) ! \\
& \quad \quad \quad [\text{iterate } (K_p \text{ (true)}, \text{pty} \circ \text{chair}) ! \text{SComs}, \text{SComs}] \\
& \quad \overline{p_3} \equiv \text{exists (ex (eq)} \oplus \langle \text{chair}, \text{mems} \rangle) \oplus \pi_2 \\
& \quad \overline{q} \equiv \text{eq} \oplus ((\text{pty} \circ \text{chair}) \times \pi_1) \\
& \xrightarrow{9} \text{set ! (join } (\overline{q}, \pi_1) ! [\text{Coms}, \text{iterate } (\overline{p_3}, \text{id}) ! \text{Temp}_K])} \\
& \quad (b) \text{ The second transformation of } \overline{COI_2^K} \text{ to } \overline{\overline{COI_2^K}} \\
\end{aligned}$$

Figure 3.10: Transforming $COI_2^K \rightarrow \overline{COI_2^K} \rightarrow \overline{\overline{COI_2^K}}$

thus eliminating the nesting by eliminating the existential predicate former, **ex**, and replacing it with a join. Thus, this rule generalizes the Type N and Type J query transformations of Kim [63].

Rule 3 is the most complex rule in this rule set. It fires on queries matching the head pattern,

$$\mathbf{set} \ ! \ (\mathbf{join} \ (q \ \& \ p, \ h \ \circ \ \pi_1) \ ! \ [A, \ B])$$

such that $q = \mathbf{eq} \oplus (f \times g)$. Queries matching this pattern return

$$\{h \ ! \ a \mid a \in A, b \in B, f \ ! \ a == g \ ! \ b, p \ ? \ [a, b]\}$$

as their result. What is noteworthy is that an element, $(h \ ! \ a)$ only figures into the result if there exists some $b \in B$ such that $f \ ! \ a == g \ ! \ b$ and $p \ ? \ [a, b]$. The idea behind rule 3 is to group elements of B by their values for $(g \ ! \ b)$ so that the comparison,

$$f \ ! \ a == g \ ! \ b$$

need not be made for each $b \in B$ but instead for each unique value of $(g \ ! \ b)$. This grouping is expressed with the body pattern subexpression,

$$T = \mathbf{njoin} \ (\mathbf{eq} \oplus (\mathbf{id} \times g), \ \mathbf{id}, \ \mathbf{id}) \ ! \ [\mathbf{iterate} \ (\mathbb{K}_p \ (\mathbf{true}), \ g) \ ! \ B, \ B]$$

that returns the grouped result,

$$\{[g \ ! \ b, \ S_b] \mid b \in B\}$$

such that

$$S_b = \{(b_2)^i \mid (b_2)^i \in B, g \ ! \ b == g \ ! \ b_2\}.$$

That is, this subquery produces a set of pairs, $[g \ ! \ b, S_b]$ such that S_b is the subcollection of B whose elements have the same value for g as b .

The entire body pattern of rule 3 is:

$$\mathbf{set} \ ! \ (\mathbf{join} \ (r \ \& \ (\mathbf{ex} \ (p) \ \oplus \ (\mathbf{id} \times \pi_2)), \ h \ \circ \ \pi_1) \ ! \ [A, \ T])$$

such that $r = \mathbf{eq} \oplus (f \times \pi_1)$. Queries rewritten to this form perform a join of A and T , and for each pair $[a, [g \ ! \ b, S_b]]$ such that $a \in A$ and $[g \ ! \ b, S_b] \in T$: determines if:

- $f \ ! \ a == g \ ! \ b$, and
- $\exists b_2 \in S_b (p \ ? \ [a, b_2])$.

Finally, duplicates are removed from the result of this join. The result of firing these two rules on COI_2^K is $\overline{COI_2^K}$.

Firing Rules 4, 5, 6, 5⁻¹, 7 and 5: These rules are fired on the predicate $\overline{p_2}$ of $\overline{COI_2^K}$. The effect is to normalize the predicate to make it of the form, $p \oplus \pi_2$ for some predicate p . This sequence prepares it for the *predicate pushdown* rule, 8b.

When applied to $\overline{COI_2^K}$, rule 4 factors the function π_2 from the pair function,

$$\langle \mathbf{chair} \circ \pi_2, \mathbf{mems} \circ \pi_2 \rangle,$$

leaving

$$\langle \mathbf{chair}, \mathbf{mems} \rangle \circ \pi_2.$$

Rules 5, 6, 5⁻¹, 7 and 5 again continue to factor π_2 from p_2 , leaving a predicate, $p_2 \oplus \pi_2$ such that

$$p_2 = \mathbf{exists} (\mathbf{ex} (\mathbf{eq}) \oplus \langle \mathbf{chair}, \mathbf{mems} \rangle) \oplus \pi_2.$$

On the other hand, rule 4 fails to fire on $\overline{COI_1^K}$'s corresponding subfunction,

$$\langle \mathbf{chair} \circ \pi_1, \mathbf{mems} \circ \pi_2 \rangle.$$

The other rules that continue to factor π_2 out of \overline{p} (6 and 7) fail to fire also.

Firing Rule 8: This rule identifies the join predicate (\overline{p}) that is a predicate on the second argument to the join, and pushes this predicate onto a selection over this second argument. Thus, the firing of this rule after the normalizing steps of the previous subsequence of rules transforms $\overline{COI_2^K}$ into $\overline{\overline{COI_2^K}}$. This rule has no effect on $\overline{COI_1^K}$ because this query was not normalized by the previous set of rule firings,

Firing Rule 9: Finally, rule 9 simplifies the data function of the **join**, rewriting $\mathbf{id} \circ \pi_1$ to π_1 .

3.5 Discussion

3.5.1 The Expressive Power of KOLA

There are downsides to using KOLA as a query representation, but a lack of expressive power for denoting queries is not one of them. Combinators can appear to lack expressivity to those who first use them, but the right set of combinators can have rich expressive power. For example, Schönfinkel [82] established that three combinators (**S**, **K** and **I**) were all that were required as an alphabet for a free algebra over which one could translate all of the lambda calculus. (It even was shown later that **I** was unnecessary.) Within the context of

querying, the rich expressivity of KOLA has been established via the design, correctness proof and implementation of a translator from a set and bag based subset of OQL to KOLA. This translator is described in Chapter 6.

3.5.2 Addressing the Downsides of KOLA

KOLA Query Representations Are Large

KOLA query representations tend to be larger than their variable-based counterparts (as measured in parse tree nodes). The size increase is up to a factor of m where m is a measure of how nested the query is.¹¹ Intuitively, combinator representations are bigger because functions can require expression with several parse tree nodes, whereas variable references (which they replace) always require just one node. Deeply nested queries can be especially problematic because variables that are used long after they are declared will be replaced by functions that are long compositions of projection functions (π_1 and π_2) that probe the nested pair data structures that replace the variable's implicitly constructed environment.

The representation size issue has been a major concern to the functional programming community's effort to use combinators internally to represent functional programs within a compiler. One solution applied to this problem is to add combinators to the representation language at the expense of redundancy. Also, a solution has been proposed that has special-purpose combinators (*supercombinators*) generated on-the-fly [52].

The supercombinator approach has little practical benefit for querying given that query rewriting relies on the existence of a *fixed* set of query operators. But queries tend to be smaller than programs, and thus such drastic solutions may not be required. We could get around the problem of having large representations for deeply nested queries by adding special purpose environment accessing combinators (e.g., π_3, π_4, \dots) to make the increase in representation size effectively linear in the size of the original query. But as yet, we haven't come across queries that have produced representations that were too large for our system.

The potential modification of KOLA brings up another philosophical issue, which is that this thesis does not argue for KOLA as the ideal query algebra, but rather for the benefits of (any) well-designed combinator-based query algebra. KOLA has been and continues to be plastic – operators are added, removed and modified regularly as new insights are gleaned into the optimization process. Thus, the potential addition of combinators (such as π_3) will

¹¹More precisely, m is the maximum number of variables that ever appear in an environment at one time while evaluating the variable-based query.

not compromise our position. We fully expect KOLA to live and grow.

KOLA Requires More Rules than Variable-Based Representations

The other downside to KOLA specifically, and combinator-based query algebras in general, is the apparent need for multiple rules to express desired transformations. In some ways, this problem is self-induced. KOLA rules are purposely kept as small as possible to make them more likely to be reused and understood. But optimizers that are left on their own to choose a sequence in which to apply multiple rules to perform a single complex transformation are greatly handicapped when there is an explosion in the number of rules to consider.

As we saw in Section 3.4.2, a fixed sequence of rule applications (perhaps with some rules applied conditionally) can express a complex transformation for a large class of queries. This makes a specific sequence of rule firings resemble a theorem prover script that guides normalization of one expression into another to establish that the two expressions are equivalent. This similarity reveals a serendipitous detail of this thesis work. Theorem prover verifiability inspired KOLA, but actually working with a theorem prover and seeing how it operated motivated COKO, our language for “programming” KOLA rule firing scripts. COKO is discussed in the next section.

3.6 Chapter Summary

In order to use a theorem prover to verify query rewrites, rewrites must be expressed *declaratively*, as in rewrite rules of term rewriting systems. In practice however, query rewrites get expressed with code, or with rewrite rules supplemented with code.

Query rewrites perform two tasks: (1) subexpression identification identifies relevant subexpressions of a query, and (2) query formulation constructs new query expressions from the identified subexpressions. These two steps are captured within standard pattern matching by actions that use head and body patterns of a rule respectively. But pattern matching is insufficient for expressing query rewrites when the underlying query representation is *variable-based*. The problem is that an expression can contain free variables, which make its semantics dependent on the context in which it appears. Context-dependent semantics makes subexpression identification require context analysis, and query formulation require massaging of subexpressions to ensure that their semantics are preserved when used in a new query. Neither of these actions can be expressed with rule patterns, and therefore in practice, they get expressed with code.

As variables are the problem, our solution was to remove the variables. We have introduced the combinator-based query algebra, KOLA, which expresses functions and predicates as primitives or as the result of instantiating formers with other functions and predicates. This approach made it possible to express query rewrites that had been problematic to express over variable-based representations, in a purely declarative fashion.

Chapter 4

COKO: Complex Query Rewrites

Our KOLA work only partially explains the reason why, in practice, query rewrites get expressed with code. Rewrite rules are inherently “small” in their operation. They are well-suited for expressing simple rewrites, such as ones that change the order of arguments to a join or push selections past joins. But some query rewrites are too complex to be expressed with rewrite rules, regardless of the underlying query representation. For example, a rewrite to convert Boolean expressions to *conjunctive normal form* (CNF) cannot be expressed with a rewrite rule because patterns are too constraining to capture its generality. (All boolean expressions can be transformed into CNF.) Instead, this rewrite is more appropriately described algorithmically. In this chapter, we introduce a language, COKO,¹) for specifying complex query rewrites such as CNF, in a manner that permits verification with a theorem prover.

A COKO specification of a query rewrite (a *transformation*) consists of two parts:

1. a set of KOLA rewrite rules, and
2. a *firing algorithm* that specifies how the KOLA rewrite rules are to be fired.

Code is confined to firing algorithms that specify the order in which KOLA rewrite rules are fired, the query subexpressions on which rules are fired and the conditions that must be satisfied for firing to occur. Code is **not** used to rewrite queries. Instead, rewriting occurs only by firing KOLA rewrite rules. Therefore, a COKO transformation is correct if each of the KOLA rewrite rules it fires is correct. We showed in Chapter 3 that a theorem prover can verify KOLA rewrite rules. By implication, a theorem prover can verify COKO transformations also.

¹COKO is an acronym for [C]ontrol [O]f [K]OLA [O]ptimizations.

This work generalizes and extends KOLA. COKO transformations behave like rewrite rules in that they can be *fired* and can succeed or fail as a result. Therefore, the set of “rules” maintained by a rule-based optimizer could include KOLA rules to express simple query rewrites, and COKO transformations to express complex query rewrites. COKO transformations are also built from KOLA rules. By grouping sets of KOLA rewrite rules into COKO transformations, one can control the number of derivations produced by a rule-based optimizer. Further, the modular approach of expressing complex transformations in terms of simpler rewrite rules simplifies reasoning about the meanings of rewrites, just as expressing complex KOLA queries in terms of simpler functions simplified reasoning about the meanings of queries.

We begin this chapter in Section 4.1 by describing why COKO is necessary, and why general purpose programming languages such as C do not satisfy our goal of expressing complex query rewrites in a manner permitting verification with a theorem prover. We then introduce COKO in Section 4.2 with three example transformations that convert KOLA predicates into CNF. These examples also show how firing algorithms can determine the performance of query rewriting.² We discuss COKO’s language of firing algorithms fully in Section 4.3. Then in Sections 4.4, 4.5, and 4.6 we demonstrate the expressive power of COKO by showing how we were able to specify a number of complex, yet useful query rewrites. These rewrites include a normalization (SNF) to identify subpredicates of a binary predicate that are effectively unary (Section 4.4), and some common rewrites such as *predicate-pushdown* (Section 4.5.1), *join-reordering* (Section 4.5.2) and the *magic-sets* rewrites of Mumick et al. [74] (Section 4.6).

4.1 Why COKO?

A complex query rewrite such as CNF cannot be expressed with a rewrite rule. Such rewrites are best described algorithmically. But why invent a new language for expressing these query rewrites? Why not use a general purpose programming language (such as C) to express rewrites as in Starburst?

What COKO provides that general purpose programming languages do not is *disciplined* query rewriting. COKO transformations are expressed algorithmically, but modifications of queries can only occur as a result of firing rewrite rules. This restriction ensures that COKO transformations are correct if the KOLA rewrite rules they fire are correct. Given

²Note that the performance of query rewriting differs from the performance of queries *produced* as the result of rewriting.

the results of Chapter 3, COKO transformations can therefore be verified with a theorem prover.

On the other hand, languages like C do not impose this discipline. Query rewrites expressed in C might use assignment statements both to modify a query and to change the position of a cursor within the query representation (e.g., as the representation is traversed). This dual use of assignment statements makes it difficult to identify which parts of the rewrite code make changes to a query representation, and therefore which parts require verification. Also, assignment statements are much finer-grained modification primitives than are rule firings. The changes made to a query by one rule may have to be expressed with several assignment statements, each but the last leaving the query in an inconsistent state. Thus, verification is also complicated by the need to consider the flow of control of the rewrite code to determine if consistent states are revisited once left.

All of this is not to say that correct query rewrites cannot be written in C. Of course they can, but incorrect query rewrites can be written in C also and discerning between them is difficult. Writers of COKO transformations have a far easier task as they are using a language that permits easy identification of proof obligations (i.e., rules), and can use a theorem prover to help with the task of proving the rules correct.

4.2 Example 1: CNF

In this section, we introduce COKO by presenting COKO transformations that rewrite KOLA predicates into CNF. These transformations demonstrate the potential performance benefits possible from customizing firing algorithms.

We first describe what CNF means for KOLA predicates, and show three COKO transformations that rewrite predicates to CNF. The first two transformations are *exhaustive* in that they simply fire some set of KOLA rules on a query until rule firing no longer has any effect. The last transformation uses a more efficient rewrite algorithm than the exhaustive algorithms, thereby demonstrating that COKO firing algorithms can do more than just group rules.

4.2.1 CNF for KOLA Predicates

A boolean subexpression of an OQL or SQL query is in *CNF* if it is a conjunct (AND) of disjuncts (OR) of (possibly negated (NOT)) *literals* (i.e., expressions lacking conjuncts, disjuncts and negations). A query rewrite to convert predicates into CNF is a typical

preprocessing step in the course of rewriting. For example, this rewrite might be fired before selection predicates are reordered.

A KOLA predicate p is in CNF if for any argument x , $p ? x$ reduces by the definitions of Tables 3.1, 3.2, and 3.3 to a boolean expression that is in CNF. Put another way, p is in CNF if it is a conjunction (&) of disjunctions (|) of (possibly negated (\sim)) literals (i.e., predicates lacking subpredicates of forms, $(q \ \& \ r)$, $(q \ | \ r)$ or $(\sim (q))$).

Figures 4.1a and 4.1b shows example KOLA predicates over the Thomas schema of Table 2.1. Both queries contain subpredicates (literals) over pairs of committees ($[x, y]$)

- P_k : which when invoked on a pair, $[x, y]$ is equivalent to the OQL expression,

$$x.chair.pty == y.chair.pty,$$

- Q_k : which when invoked on a pair, $[x, y]$ is equivalent to the OQL expression,

$$x.chair.terms > y.chair.terms,$$

- R_k : which when invoked on a pair, $[x, y]$ is equivalent to the OQL expression,

$$x.topic == \text{“NSF”}, \text{ and}$$

- S_k : which when invoked on a pair, $[x, y]$ is equivalent to the OQL expression,

$$(x.chair.terms + \text{SUM} \left(\begin{array}{l} \text{SELECT } y.terms \\ \text{FROM } y \text{ IN } x.mems \end{array} \right)) > 100$$

The query of Figure 4.1b is equivalent to that of Figure 4.1a, but is in CNF.

4.2.2 An Exhaustive Firing Algorithm

Figure 4.2 shows two COKO transformations that convert KOLA predicates lacking negations (i.e., subpredicates of the form, $\sim (p)$) into CNF. A COKO transformation begins with the keyword, TRANSFORMATION, followed by the name of the transformation. The rest of the transformation consists of two parts:

- a rule section (introduced by the keyword, USES) that lists the KOLA rewrite rules and other COKO transformations fired by the transformation, and
- a firing algorithm (delimited by keywords BEGIN and END).

$$\begin{array}{ll}
(P_k \ \& \ Q_k \ \& \ R_k) \mid S_k & (P_k \mid S_k) \ \& \ (Q_k \mid S_k) \ \& \ (R_k \mid S_k) \\
\text{(a)} & \text{(b)} \\
\end{array}$$

such that

$$\begin{array}{l}
P_k = \mathbf{eq} \oplus \langle f \circ \pi_1, f \circ \pi_2 \rangle, \\
Q_k = \mathbf{gt} \oplus \langle g \circ \pi_1, g \circ \pi_2 \rangle, \\
R_k = \mathbf{eq} \oplus \langle \mathbf{topic} \circ \pi_1, K_f \text{ ("NSF")} \rangle, \\
S_k = \mathbf{gt} \oplus \langle \mathbf{add} \circ \langle g \circ \pi_1, \mathbf{sum} \circ h \circ \mathbf{mems} \circ \pi_1 \rangle, K_f \text{ (100)} \rangle \\
\\
f = \mathbf{pty} \circ \mathbf{chair} \\
g = \mathbf{terms} \circ \mathbf{chair} \\
h = \mathbf{iterate} (K_p \text{ (true)}, \mathbf{terms})
\end{array}$$

Figure 4.1: A KOLA Predicate Before (a) and After (b) its Transformable into CNF

TRANSFORMATION CNF-BU	TRANSFORMATION CNF-TD
USES	USES
d1: $(p \ \& \ q) \mid r \xrightarrow{\equiv} (p \mid r) \ \& \ (q \mid r)$	d1: $(p \ \& \ q) \mid r \xrightarrow{\equiv} (p \mid r) \ \& \ (q \mid r)$
d2: $r \mid (p \ \& \ q) \xrightarrow{\equiv} (p \mid r) \ \& \ (q \mid r)$	d2: $r \mid (p \ \& \ q) \xrightarrow{\equiv} (p \mid r) \ \& \ (q \mid r)$
BEGIN	BEGIN
BU {d1 d2} \rightarrow CNF-BU	TD {d1 d2} \rightarrow CNF-TD
END	END
(a)	(b)

Figure 4.2: Exhaustive CNF Transformations Expressed in COKO

A COKO transformation can be fired on any KOLA parse tree (example KOLA parse trees are shown in Figure 4.3), and may transform this tree as a result. In describing the transformations of Figure 4.4, we will assume that they have been fired on the parse tree for some KOLA predicate p . Hereafter, we will use p to name the KOLA predicate and its parse tree and rely on context to differentiate between the two.

CNF-BU

CNF-BU uses two KOLA rewrite rules that distribute disjunctions over conjunctions:

$$\begin{array}{l}
d1: (p \ \& \ q) \mid r \xrightarrow{\equiv} (p \mid r) \ \& \ (q \mid r) \\
d2: r \mid (p \ \& \ q) \xrightarrow{\equiv} (p \mid r) \ \& \ (q \mid r)
\end{array}$$

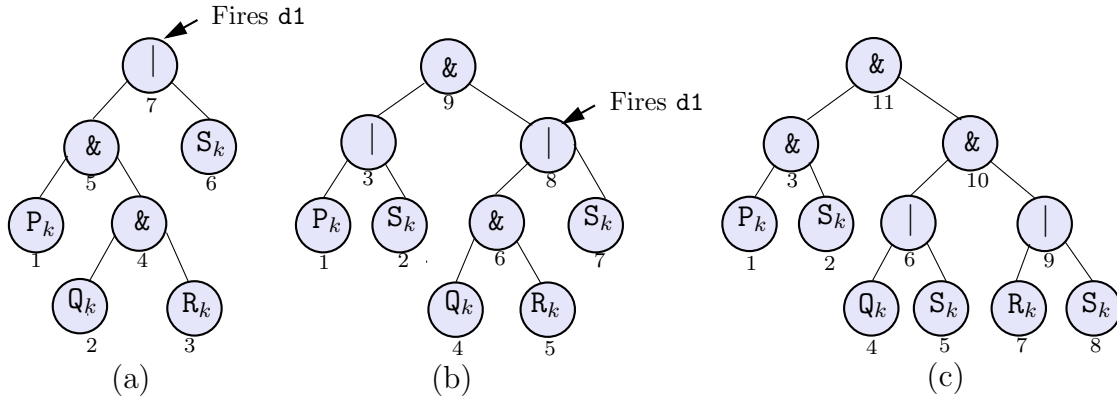


Figure 4.3: Illustrating CNF-BU on the KOLA Predicate of Figure 4.1a

In relation to a KOLA parse tree, the effect of either rule is to “push down” a disjunction ($|$) past a conjunction ($\&$). Fired exhaustively on an unnegated predicate, these rules “push down” all disjuncts past all conjuncts, thereby leaving the predicate in CNF.

The firing algorithm for CNF-BU consists of the single complex COKO statement,

$$\text{BU } \{d1 \ || \ d2\} \rightarrow \text{CNF-BU.}$$

This statement can be broken down as follows:

- $d1$ and $d2$ are rule firing statements. That is, by referencing these rules in the firing algorithm (and provided each was defined in the rule section), these rules get fired. Each rule succeeds in firing if, as a result of pattern matching, its head pattern matches with the KOLA predicate on which it is fired.
- $\text{BU } \{d1 \ || \ d2\}$ instructs the transformation to perform a *bottom-up* (or more accurately, a preorder) traversal of predicate p , executing the statement,

$$\{d1 \ || \ d2\}$$

on each visited subtree, s . The effect of executing this statement on s is to first fire $d1$ on s . If $d1$ succeeds in firing, then the statement is finished executing. If $d1$ fails to fire, then $d2$ is fired on s . This statement succeeds if either $d1$ or $d2$ successfully fires, and fails if both rules fail. The full statement

$$\text{BU } \{d1 \ || \ d2\}$$

succeeds if the statement,

$$\{d1 \ || \ d2\}$$

succeeds when executed on any subtree. Therefore, the effect of this statement as a whole is to perform a bottom-up pass of p , firing $d1$ and $d2$ on each visited subtree and succeeding if one of these rules successfully fires once.

- $BU \{d1 \parallel d2\} \rightarrow CNF\text{-}BU$ executes the statement,

$$BU \{d1 \parallel d2\},$$

and if it succeeds, fires $CNF\text{-}BU$ recursively. Therefore, the effect of this statement (and the transformation as a whole) is to perform successive bottom-up passes of p , firing rules $d1$ and $d2$, and continuing with new passes until a pass of p is completed where no rules have successfully fired. Put another way, this transformation fires rules $d1$ and $d2$ *exhaustively* in bottom-up fashion.

Figure 4.3 illustrates the effect of firing $CNF\text{-}BU$ on the KOLA predicate of Figure 4.1a. Figure 4.3a shows the parse tree representation of this predicate before it is transformed. The bottom-up pass visits the subtrees rooted at shaded nodes of the initial tree in the order indicated beneath each. Attempts to fire $d1$ and $d2$ on each proper subtree fail. But $d1$ successfully fires on the root, resulting in the predicate tree of Figure 4.3b. Because $d1$ successfully fired, another bottom-up pass is initiated on the tree resulting from firing (Figure 4.3b). Rule $d1$ fires successfully on the 8th subtree visited during this pass, resulting in the parse tree of Figure 4.3c. A final pass is performed over this parse tree where no rules successfully fire. Therefore, the tree of Figure 4.3c is returned as the final result of the transformation.

CNF-TD

Transformation $CNF\text{-}TD$ (Figure 4.2b) is also an exhaustive algorithm for CNF. Unlike $CNF\text{-}BU$, $CNF\text{-}TD$ fires rules in *top-down* (i.e., inorder) fashion during each pass, as indicated by the COKO operator TD . For CNF, the order in which subtrees are visited makes no difference to the final result. Rules $d1$ and $d2$ form a *confluent set* — the same result is returned no matter what order these rules are fired and no matter in what order parse trees are visited, provided that these rules are fired exhaustively.

Though the order in which subtrees are visited during rule firing has no effect on the predicate that results, order *does* affect the performance of the query rewrite itself. Table 4.1 shows a performance comparison of $CNF\text{-}TD$ and $CNF\text{-}BU$. The transformations were compiled with our COKO compiler (described in Section 4.3.3) into C++ code which in turn was compiled on Sparcstation 10's using the Sun C++ compiler. For each height class, both

Height	Elapsed		CPU	
	CNF-TD	CNF-BU	CNF-TD	CNF-BU
4	0.17	0.17	0.07	0.07
5	0.42	0.48	0.23	0.26
6	1.19	2.05	1.07	1.68
7	3.24	4.18	3.05	3.98
8	7.71	12.95	6.69	11.63

Table 4.1: Average Times (in seconds) for CNF-TD and CNF-BU

transformations were run on the same 25 randomly generated queries. Both the elapsed time (the total time taken by the system to perform the rewrite) and the CPU time (the time for which the CPU is busy) were measured, and the times for all 25 queries were averaged.

For CNF, top-down exhaustive firing has better performance overall than bottom-up exhaustive firing. The performance discrepancy is due to the rules involved in these transformations. Consider that the result of firing either rule successfully is a conjunction of the form, $(p \mid r) \& (q \mid r)$. If additional rule firings are required, it would be because p (Case 1), q (Case 2) or r (Case 3) are of the form $p_1 \& p_2$, or because (Case 4) the entire predicate is a subpredicate, p_1 of some disjunctive predicate, $p_1 \mid p_2$. Each of the four cases is equally likely given that our randomized query generating algorithm decides that a node is a conjunct or disjunct with equal probability. But top-down passes of the query tree will “catch” cases 1, 2 or 3 on the same pass that resulted in the initial firing because p , q and r will be subtrees of the newly formed predicate. On the other hand, a bottom-up pass will only “catch” case 4 on the same pass as the initial firing, and will require an additional pass to “catch” cases 1, 2 and 3. Therefore, a bottom-up transformation is more likely to require an additional pass to deal with the repercussions of a successful rule firing. This example illustrates how even subtle differences in firing algorithms such as traversal order can result in differences in performance. As we show below, the performance differences become marked when exhaustive firing algorithms can be avoided altogether.

4.2.3 A Non-Exhaustive Firing Algorithm for CNF

Figure 4.4 shows an alternative COKO transformation (CNF) that rewrites KOLA predicates into CNF using a firing algorithm that is more efficient than the exhaustive algorithms of CNF-BU and CNF-TD. When CNF is fired on a predicate p , the statement

BU CNFAux

	TRANSFORMATION CNFAux
TRANSFORMATION CNF	USES
USES	d1: $(p \ \& \ q) \mid r \ \equiv \ (p \mid r) \ \& \ (q \mid r)$
CNFAux	d2: $r \mid (p \ \& \ q) \ \equiv \ (p \mid r) \ \& \ (q \mid r)$
BEGIN	BEGIN
BU CNFAux	{d1 d2} \rightarrow
END	{GIVEN p' & q' DO {CNFAux (p'); CNFAux (q')}}}
	END
(a)	(b)

Figure 4.4: An Efficient CNF Transformation

performs a bottom-up pass of p , firing the auxiliary transformation, **CNFAux** on every subtree of p . The effect of firing **CNFAux** on a subtree s is described below:

1. As in **CNF-BU** and **CNF-TD**, {d1 || d2} fires d1 on s , and then fires d2 on s if d1 fails.
2. Successful firing of either d1 or d2 results in the execution of the statement,

$$\{\text{GIVEN } p' \ \& \ q' \ \text{DO } \{\text{CNFAux}(p'); \text{CNFAux}(q')\}\}$$

on the predicate resulting from firing. This predicate will have the form,

$$(p \mid r) \ \& \ (q \mid r).$$

The pattern, $(p' \ \& \ q')$ that follows the keyword **GIVEN** is matched with this predicate (i.e., p' gets bound to $(p \mid r)$ and q' gets bound to $(q \mid r)$) and **CNFAux** is fired recursively on the subtrees bound to p' and q' respectively.

In short, **CNF** performs a bottom-up (BU) pass of p , firing the auxiliary transformation, **CNFAux**, on each visited subtree. **CNFAux** fires rewrite rules d1 and d2 and if either succeeds, initiates top-down passes on the conjunct subtrees that result from rule firing (by recursively firing **CNFAux**). Each top-down pass proceeds until a subtree is visited on which both d1 and d2 fail to fire.

The effect of this transformation on the KOLA predicate of Figure 4.1a are illustrated in Figure 4.5. Figure 4.5a shows the parse tree representation of this predicate before it is transformed. The bottom-up pass visits the shaded nodes of the initial tree in the order indicated beneath each. The firing of **CNFAux** fires d1 and d2. **CNFAux** fails to fire both rules (and therefore fails to fire) on every visited subtree except the root which is visited

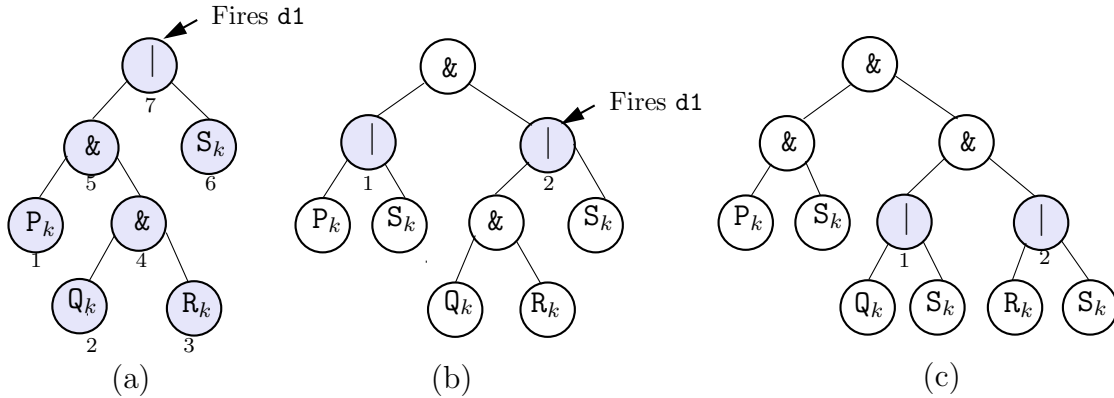


Figure 4.5: Illustrating the CNF Firing Algorithm on the KOLA Predicate of Figure 4.1a

Height	Elapsed		CPU	
	CNF-TD	CNF	CNF-TD	CNF
4	0.17	0.15	0.07	0.05
5	0.42	0.20	0.23	0.10
6	1.19	0.35	1.07	0.24
7	3.24	0.59	3.05	0.48
8	7.71	1.35	6.69	1.17

Table 4.2: Average Times (in seconds) for CNF-TD and CNF

last (node 7). Firing d_1 on the root results in the predicate tree of Figure 4.5b. Because d_1 successfully fired, CNF_{Aux} is fired recursively on the two disjuncts produced from firing (the subtrees rooted by the shaded nodes of Figure 4.5b). Firing d_1 and d_2 on the first of these subtrees fails, and therefore terminates the top-down pass of this subtree. But d_1 fires successfully on the second subtree, producing the predicate tree of Figure 4.5c. Again, successful firing initiates recursive firings of CNF_{Aux} on the subtrees rooted by the shaded nodes of Figure 4.5c. d_1 and d_2 fail to fire on both subtrees, and the tree of Figure 4.5c is returned.

Table 4.2 shows a performance comparison of the more efficient of the two exhaustive CNF transformations (CNF-TD) and CNF. CNF was run on the same 25 randomly generated queries as was used for the comparisons of Table 4.1. As before, both the elapsed time (the total time taken by the system to perform the transformation) and the CPU time (the time for which the CPU is busy) were measured, and the times for all 25 queries were averaged.

CNF exhibits far better performance than either of the exhaustive transformations. (For predicates of height 8, performance was improved by a factor of 6.) Intuitively, this is

because CNF is discriminating in how it fires rules:

- Successful firing of either **d1** and **d2** requires both exhaustive transformations to perform additional passes over the entire query tree. On the other hand, successful firing of either rule requires CNF to perform passes over only selected parts of the query tree.
- The exhaustive transformations require a complete pass of failed rule firings in order to terminate. This pass is not required by transformation CNF.

The savings in rule firings is illustrated by considering how all three transformations transform the KOLA predicate,

$$(P_k \ \& \ Q_k \ \& \ R_k) \mid S_k.$$

CNF performs one complete and two partial passes over this predicate’s representation, firing rules 20 times with two firings succeeding. On the other hand, CNF-TD performs two complete passes over this predicate’s representation, firing rules 42 times with two succeeding. CNF-TD performs three complete passes over this predicate’s representation, firing rules 52 times with two succeeding.³

Exhibited Features of COKO Firing Algorithms

CNF exhibits the fine-grained control of rule and transformation firing supported by COKO firing algorithms. It is this control that makes it possible to express efficient query rewrites. COKO supports four forms of rule-firing control:

- *Explicit Firing*: Rewrite rules used within a transformation are named (e.g., **d1** and **d2**) and explicitly fired by the firing algorithm.
- *Traversal Control*: Both bottom-up (in CNF) and top-down (in CNFAux) passes can be performed in the course of rewriting predicates into CNF.
- *Selective firing*: CNFAux is fired recursively on the two disjuncts that result from successful firings of either **d1** or **d2**. CNFAux is not fired on the conjunct resulting from these firings because both **d1** and **d2** can only succeed on trees rooted by “|”.

³For simplicity, we count each rule’s firing on a literal (such as P_k) as one firing. In fact, each literal is a subtree with multiple nodes. Therefore, visiting a literal results in more than one firing. These uncounted firings are the same for each algorithm. However, CNF will visit literals less frequently than the exhaustive transformations, and therefore will exhibit even better performance in comparison.

- *Conditional firing*: Some firings are conditioned on the success or failure of previous firings. E.g., CNFAux fires d2 only if d1 fails; CNFAux is only fired recursively if one of the rules d1 or d2 succeeds.

Correctness of CNF

Theorem 4.2.1 (Correctness) *CNF is correct.*

Proof: All query modification performed by CNF occurs as result of firing CNFAux, which in turn occurs as result of firing rules d1 and d2. Therefore, CNF is correct if both rewrite rules are correct. Rules d1 and d2 are proved correct by execution of the theorem prover scripts of Appendix B.1 using LP [46]. \square

Proof that CNF transforms all KOLA predicates into CNF follows below.

Lemma 4.2.1 *Let p be a KOLA predicate tree lacking negations, and whose child subtrees are in CNF. Then CNFAux (p) is in CNF.*

Proof: (By induction on the height, $h(p)$ of the highest $\&$ -node in p .) For the base case ($h(p) = 0$) p must contain no $\&$ -nodes and therefore is in CNF and is returned untouched by CNFAux. For the inductive case, either p is already in CNF and is returned untouched, or p is not in CNF and is a disjunction, $Q \mid R$ such that Q and R are in CNF and at least one of Q or R is a conjunction ($x_0 \& x_1$). For the case where exactly one of Q and R is a conjunction, assume without loss of generality that Q is a conjunction. Then, $h(Q)$ is larger than both $h(x_0)$ and $h(x_1)$ because both x_0 and x_1 are children of a $\&$ -node. Further, because R is in CNF it has no $\&$ -nodes and therefore $h(p) = h(Q)$. Firing d1 on $(Q \mid R)$ returns $(S \& T)$ such that $S = (x_0 \mid R)$ and $T = (x_1 \mid R)$, and CNFAux is subsequently fired on S and T . But $h(S) = h(x_0)$ and $h(T) = h(x_1)$ and therefore by induction, these firings result in trees that are in CNF. Therefore, the tree returned by CNFAux (p) is in CNF.

For the case where both Q ($x_0 \& x_1$) and R ($y_0 \& y_1$) are conjunctions, $h(p)$ is larger than $h(x_0)$, $h(x_1)$, $h(y_0)$ and $h(y_1)$ as all of the latter subtrees are children of $\&$ -nodes. Firing CNFAux on p fires d1 once, and d2 on each of the resulting disjuncts, leaving

$$(S_1 \& S_2) \& (T_1 \& T_2)$$

such that $S_1 = (x_0 \mid y_0)$, $S_2 = (x_1 \mid y_0)$, $T_1 = (x_0 \mid y_1)$ and $T_2 = (x_1 \mid y_1)$. CNFAux is fired on each of S_1 , S_2 , T_1 and T_2 and by induction, each of these firings return a predicate in CNF. Therefore, CNFAux (p) is in CNF. \square

```

TRANSFORMATION CNF-NEG
USES
  CNF,
  involution:  $\sim (\sim (p)) \equiv p$ ,
  deMorgan1:  $\sim (p \ \& \ q) \equiv \sim (p) \ | \ \sim (q)$ ,
  deMorgan2:  $\sim (p \ | \ q) \equiv \sim (p) \ \& \ \sim (q)$ 
BEGIN
  TD {involution || deMorgan1 || deMorgan2};
  BU {involution};
  CNF
END

```

Figure 4.6: The Full CNF Transformation Expressed in COKO

Theorem 4.2.2 *Let p be any KOLA predicate lacking negations. Then $\text{CNF}(p)$ is in CNF.*

Proof: Note that $\text{CNF}(p)$ fires CNFAux on every subtree visited during a bottom-up traversal of p . By **Lemma 4.2.1**, each firing leaves a subtree in CNF, and therefore p is left in CNF. \square

Accounting for Negations

Figure 4.6 contains a COKO transformation that transforms all KOLA predicates into CNF, including those with negations. Besides using CNF , this transformation includes three other rules:

- `involution` eliminates double negations,
- `deMorgan1` pushes down a negation past a conjunction, and
- `deMorgan2` pushes down a negation past a disjunction.

The firing algorithm for the full CNF transformation executes two statements on the argument tree, p before firing CNF . These statements effectively push negations to the bottom of p 's query tree while ensuring that consecutive negations are eliminated. The first statement performs a top-down pass of p firing the `involution` and `deMorgan` rules on each subtree visited during the traversal. `Involution` is then performed in a bottom-up pass of the resulting tree. This second pass is necessary because the first pass may construct doubly negated predicates. For example, a predicate of the form,

$$\sim (\sim (p) \ \& \ q)$$

will be transformed after the first pass to

$$\sim (\sim (p)) \mid \sim (q)$$

which must be transformed by a second pass firing the involution rule to

$$p \mid \sim (q).$$

Once all negations have been pushed to the bottom of the query (i.e., below all conjuncts and disjuncts), the resulting predicate can then be transformed into CNF using transformation **CNF**.

We have introduced COKO with a simple yet practical example. The normalization of predicates into CNF is a typical preprocessing rewrite for useful rewrites such as one that reorders selection predicates. We showed a COKO transformation (**CNF**) that performs this rewrite for predicates lacking negations and a complete COKO transformation (**CNF-NEG**) that removes this restriction and fires **CNF** as if it were a subroutine. Because its rules are confluent, **CNF** can also be implemented with exhaustive firing algorithms as in **CNF-BU** and **CNF-TD**. But exhaustive firing is an inefficient means of performing this transformation. Therefore, this example demonstrates the potential performance benefits from using customized firing algorithms to express complex query rewrites.

4.3 The Language of COKO Firing Algorithms

The semantics of statements that appear in COKO transformation firing algorithms have two parts:

- their *operation* (what they do when executed), and
- their *success value* (what they return as a result of execution).

Success values are truth values that indicate if a statement succeeds when executed. For example, fired rules return success values of *true* if their head patterns match the expressions on which they are fired. In general, success values are intended to indicate whether or not a statement accomplishes what it is intended to do. Note that a success value of false does **not**, in general, mean that a statement has failed to modify the expression on which it was executed.

4.3.1 The COKO Language

Below we present COKO's statements, categorizing them by the kinds of firing control they provide. Each is presented with its *operation* and *success value* semantics. For the purposes of discussion, we assume that statements are contained in some transformation that has been fired on some KOLA query tree, p .

Explicit Firing

Rules and transformations declared in the **USES** section of a transformation can be fired as if they were procedures invoked in a programming language such as C. Rules and transformations can be fired on subtrees of p named by pattern variables (see Section 4.3.1) or can be fired on p directly, in which case no argument needs to be named. As well, rules that use the same pattern variables in their heads and their bodies can be fired *inversely*. For example, **d1** of Figure 4.4 could be fired inversely (**d1 INV**) to factor a common subexpression (\mathbf{r}) from a conjunction of disjuncts. Rule (and inverse rule) firings return *true* as their success values if they successfully fire. Transformation firings succeed if the complex statements that are their main bodies succeed (see Section 4.3.1).

Traversal Control

Query trees can be traversed in bottom-up (postorder) or top-down (preorder) fashion. For any statement S ,

BU S

performs a bottom-up pass of p executing S on every subtree. Analogously, **TD** S executes S on every subtree during a top-down pass of p . Both traversal statements return a success value of *true* if S succeeds when fired on some subtree visited during the traversal. Also,

REPEAT S

fires S repeatedly on p until S no longer succeeds, and returns a success value of *true* if S succeeds at least once. Thus far, we have found **BU**, **TD** and **REPEAT** to be sufficient for expressing the kinds of traversal control we have needed to express for our firing algorithms. Our COKO compiler could be easily extended however, should we determine the need for another form of traversal control at a later point.

Selective Firing

Rules and transformations need not be fired on all of p and can instead be fired on selected subtrees of p . These subtrees are identified by matching patterns to query trees using COKO's **GIVEN** statement.

GIVEN patterns are like rule patterns, but can also include “don't care” variables (“ $_$ ”),⁴ which act like pattern variables, but whose bindings are ignored. The COKO matching statement, **GIVEN**, identifies these patterns with variables, producing environments for use in subsequent statements. A **GIVEN** statement has the form,

$$\mathbf{GIVEN} \text{ } eqn_1, \dots, eqn_n \mathbf{DO} \text{ } S.$$

such that S is any COKO statement, and each “equation”, eqn_i is of the form,

$$\langle \text{variable}_i \rangle = \langle \text{pattern}_i \rangle$$

(or just $pattern_i$, if this pattern is to be matched with all of p). The processing of eqn_i results in an attempted match of $pattern_i$ with the tree previously bound to $variable_i$. Successful matching adds the variables appearing in $pattern_i$ (and the subtrees that they matched) to an environment that is then visible to equations appearing after eqn_i and S . The success value for the entire **GIVEN** statement is *true* if all n equations successfully match.

Unlike most programming languages, the environment visible inside statement S can shrink dynamically. Dynamically varying environments are necessary because environment entries label parts of a tree that can become obsolete as a result of a rule or transformation firing. To illustrate, suppose that the **GIVEN** statement,

$$\mathbf{GIVEN} \text{ } \mathbf{f} ! _ , \mathbf{f} = \mathbf{g} \circ _ , \mathbf{g} = \langle \mathbf{h}, \pi_2 \rangle \mathbf{DO} \{ \mathbf{transform-1}(\mathbf{g}); \mathbf{transform-2}(\mathbf{h}) \}$$

were executed on the query,

$$(\langle \pi_1, \pi_2 \rangle \circ \pi_1) ! [[\mathbf{x}, \mathbf{y}], \mathbf{z}].$$

The result of matching the three equations is to create an environment consisting of the labels \mathbf{f} , \mathbf{g} and \mathbf{h} matched with the subtrees shown in Figure 4.7a.

Suppose that **transform-1** is a transformation or rule that replaces \mathbf{g} with a completely new tree. For example, **transform-1** could be the rule,

$$\langle \pi_1, \pi_2 \rangle \xrightarrow{\quad} \mathbf{id}.$$

⁴The COKO compiler recognizes four different “don't care” variables denoting predicates ($_P$), functions ($_F$), objects ($_O$) and Booleans ($_B$) respectively. To simplify the presentation, we will use only a single “don't care” variable ($_$) for the examples presented in this thesis.

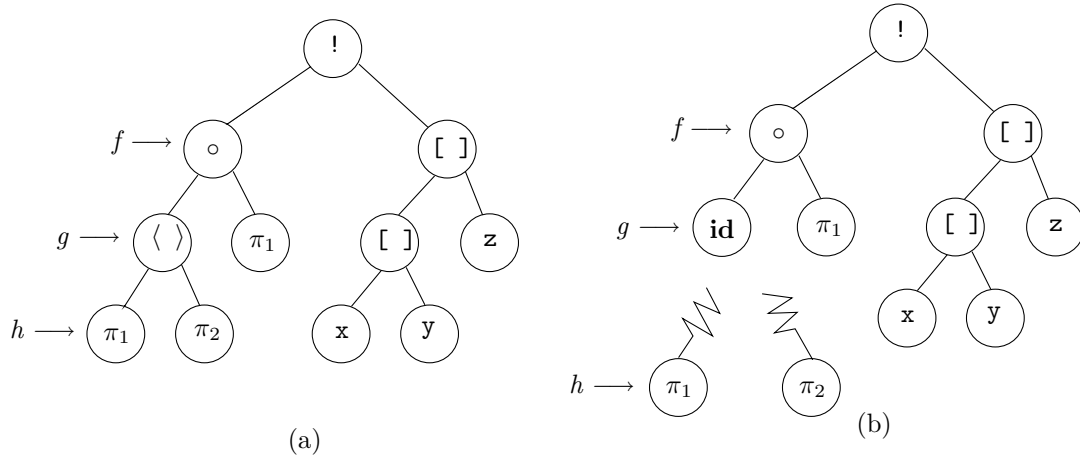


Figure 4.7: The Effects of a GIVEN Statement on Environments

Then the result of this firing would invalidate all variable bindings to trees that were proper subtrees of g (i.e., h), as these would no longer point to valid subtrees. Thus, the result of this firing would be to change the environment seen by the statement that follows to remove invalidated variable bindings, to the transformed environment of Figure 4.7b that no longer includes an entry for h .

The COKO compiler performs a dependency analysis of variables declared in matching equations, and indicates at compile time if a variable is used after it is invalidated. Thus, it would flag the firing of `transform-2` (h) in this example as an error. In general, the invalidation of a variable, v occurs following execution of some statement S provided that S is a statement that modifies a query (i.e., a firing of a rule or another transformation), and S is executed on some variable w such that v names a subtree of the tree named by w .

Conditional Firing

One can condition the execution of a COKO statement, S' on the result of a previous statement, S in three ways:

- $S \rightarrow S'$ executes S and then executes S' if S succeeds. This statement succeeds if S succeeds.
- $S \parallel S'$ executes S and then executes S' if S fails. This statement succeeds if S or S' succeed.
- $S ; S'$ executes S and then executes S' . This statement succeeds if either S or S' succeed.

The complex statement connector, “ \rightarrow ” is right-associative, and “|” and “;” are left-associative. One can override default associativities using braces ($\{\}$).

4.3.2 TRUE, FALSE and SKIP

TRUE, FALSE and SKIP allow one to circumvent the default success values associated with COKO statements. For any statement, S ,

TRUE S

executes S and returns a success value of *true*, regardless of the success value of S . (Similarly, FALSE S returns a success value of *false*.)

The statement SKIP performs no action at all and returns a success value of *true*. This statement is useful if one wants to define a transformation that returns a success value of *true* only if it rewrites expressions to a particular form. For example, consider a transformation whose purpose is to rewrite KOLA functions into constant functions (i.e., of the form, $K_f(x)$ for some x). It might be desirable to return a success value of *true* only if functions that result from the transformation are of this form. However, the firing algorithm for this transformation may be a complex statement, S that does not always return the proper success value. In this case, one can achieve the desired effect by replacing the firing algorithm with

FALSE S ;
GIVEN $K_f(x)$ DO SKIP

The effect of this firing algorithm is to first execute S . Then, if a constant function is produced by S , the subsequent GIVEN statement succeeds and a success value of *true* is returned (because the “;”-separated statement succeeds if either of the separated statements succeeds, and because the GIVEN statement succeeds if the pattern, $K_f(x)$ successfully matches the expression resulting from executing S). If a constant function is not generated by S , the GIVEN statement fails and so too does the transformation as a whole.

4.3.3 The COKO Compiler

We have implemented a compiler for COKO ([68]) that generates C++ classes from COKO transformations. Objects of these generated classes manipulate KOLA trees according to the firing algorithm of the compiled COKO transformation. The compiler has an object-oriented design. Every COKO statement is implemented with its own C++ class. Each of these classes is a subclass of the virtual class, **Statement**, and is obligated to define a

method `exec` that takes an environment of variable-to-KOLA tree bindings as input and produces a transformed version of this environment as output. These environments include entries for the trees on which each statement is executed.

The compilation of a COKO transformation generates a new subclass of `Statement`, complete with an implementation of an `exec` method. The `exec` method definition for a compiled transformation simply constructs a tree of COKO `Statement` objects corresponding to the parse structure of the COKO code, and then invokes `exec` on the root. By compiling COKO transformations into `Statements`, COKO’s language of firing algorithms is made extensible even at the level of its implementation.

4.4 Example 2: “Separated Normal Form” (SNF)

In this section we describe a novel normalization and show its expression in COKO. The normalization is of binary predicates, (in KOLA, predicates on pairs) and involves isolating those subpredicates that act as unary predicates on just one argument. This normalization is a useful preprocessing step when unary predicates need to be moved to other parts of the query as in predicate-pushdown, join-reordering and magic-sets rewrites. Because this normalization “separates” unary and binary subpredicates, we characterize the predicates that result as being in “*Separated Normal Form*” or SNF.

The point of this example is to show that COKO transformations are expressive enough to to be used in place of rules in existing rule-based systems. We make this point in several ways:

- The SNF normalization is more complex than CNF, even firing CNF as part of its firing algorithm. Therefore, COKO is expressive enough to capture complex normalizations.
- SNF is itself fired in the firing algorithms of many transformations that are not normalizations. These include predicate-pushdown (Section 4.5.1), join-reordering (Section 4.5.2) and Magic-Sets rewrites (Section 4.6). These examples show that COKO can express a wide variety of complex rewrites in modular fashion.
- SNF is not usually thought of as a normalization, and as far as we know has not been expressed before with declarative rewrite rules. Thus, COKO can express rewrites that are usually expressed only with code.

4.4.1 Definitions

Intuitively, a KOLA binary predicate, op on pairs $[x, y]$ is in SNF if it is of the form,

$$p \ \& \ q \ \& \ r$$

such that p is a unary predicate on x , q is a unary predicate on y and r is the minimal subpredicate of op that is a predicate on both x and y . In this section, we present a COKO transformation (SNF) that converts unnested SQL predicates into SNF. More formal definitions follow.

Qualifications

A *qualification predicate* is defined by Ramakrishnan [80] as:

... a Boolean combination (i.e., an expression using the logical connectives AND, OR and NOT) of *conditions* of the form *expression* **cmp** *expression*, where **cmp** is one of the comparison operators $\{<, <=, =, <>, >=, >\}$, [and an] *expression* is a *column* name, a *constant* or an arithmetic or string expression.

Essentially, qualifications are the predicates of unnested SQL queries.

KOLA qualification predicates are translations of SQL qualification predicates. They are defined formally in terms of *basic functions* (the KOLA equivalents of *expressions*) and *basic predicates* (the KOLA equivalents of *conditions*).

Definition 4.4.1 (Basic Functions) *A basic function is a KOLA function of one of the forms below:*

- $\text{att} \circ \pi_1$ such that **att** is a primitive attribute (e.g., a column name),
- $\text{att} \circ \pi_2$ such that **att** is a primitive attribute,
- $K_f(c)$ such that c is a constant, or
- $op \circ \langle f, g \rangle$ such that f and g are basic functions and op is a binary primitive function (e.g., **add**).

Definition 4.4.2 (Basic Predicate) *A basic predicate is a predicate of the form,*

$$p \oplus \langle f, g \rangle$$

*such that p is a binary primitive (**eq**, **lt**, **gt**, **leq**, **geq** or **neq**), and f and g are basic functions.*

Definition 4.4.3 (Qualifications) A KOLA qualification predicate is a predicate consisting of conjunctions ($\&$), disjunctions ($|$) and negations (\sim) of basic predicates.

SNF

We begin by defining functions and predicates that are *inherently binary*. Intuitively, inherently binary functions and predicates cannot be simplified in any way that makes them unary.

Definition 4.4.4 (Inherently Binary Functions) A KOLA function \bar{f} is inherently binary if it is of either of the forms:

- $op \circ \langle f \circ \pi_1, g \circ \pi_2 \rangle$,
- $op \circ \langle f \circ \pi_2, g \circ \pi_1 \rangle$, or
- $op \circ \langle f, g \rangle$ such that f or g is inherently binary.

Definition 4.4.5 (Inherently Binary Predicates) A KOLA predicate \bar{p} is inherently binary if it is of the form,

$$p \oplus f$$

such that f is an inherently binary function, or of the form.

$$p | q$$

such that

- p or q is inherently binary, or
- one of p or q is of the form $(r_1 \oplus \pi_1)$ and the other is of the form $(r_2 \oplus \pi_2)$.

Definition 4.4.6 (SNF) A KOLA predicate p is in SNF if it is of the form,

$$(\rho \oplus \pi_1) \& (\sigma \oplus \pi_2) \& \tau$$

such that τ is a conjunction,

$$\tau_1 \& \dots \& \tau_m$$

of inherently binary and constant (\mathbb{K}_p (b)) predicates.

$$\begin{aligned}
& (\rho \oplus \pi_1) \ \& \ (\sigma \oplus \pi_2) \ \& \ \tau \ \text{such that} \\
\rho &= (\mathbf{R2}_k \mid \mathbf{S2}_k) \\
\sigma &= \mathbf{K}_p(\mathbf{true}) \\
\tau &= ((\mathbf{P}_k \mid (\mathbf{S2}_k \oplus \pi_1)) \ \& \ (\mathbf{Q}_k \mid (\mathbf{S2}_k \oplus \pi_1))) \\
\mathbf{P}_k &= \mathbf{eq} \oplus \langle f \circ \pi_1, f \circ \pi_2 \rangle, \\
\mathbf{Q}_k &= \mathbf{gt} \oplus \langle g \circ \pi_1, g \circ \pi_2 \rangle, \\
\mathbf{R2}_k &= \mathbf{eq} \oplus (\langle \mathbf{id}, \mathbf{K}_f(\text{"NSF"}) \rangle \circ \mathbf{topic}) \\
\mathbf{S2}_k &= \mathbf{gt} \oplus (\langle \mathbf{id}, \mathbf{K}_f(100) \rangle \circ (\mathbf{add} \circ \langle g, \mathbf{sum} \circ h \circ \mathbf{mems} \rangle)) \\
f &= \mathbf{pty} \circ \mathbf{chair} \\
g &= \mathbf{terms} \circ \mathbf{chair} \\
h &= \mathbf{iterate}(\mathbf{K}_p(\mathbf{true}), \mathbf{terms})
\end{aligned}$$

Figure 4.8: The SQL/KOLA Predicates of Figure 4.1 in SNF

Given any pair argument $[x, y]$, $(\rho_k \oplus \pi_1) ? [x, y] = \rho_k ? x$ and therefore ρ_k denotes a predicate that requires only the first of its arguments. Similarly, σ_k denotes a predicate requiring the second argument. The restriction that τ consist of inherently binary predicates ensures that a predicate in SNF has “moved” as many non-constant subpredicates into ρ and σ as possible. Figure 4.8 shows the SNF equivalent of the KOLA predicates of Figure 4.1. Note that for this predicate, τ is a conjunction of inherently binary predicates,

$$\mathbf{P}_k \mid (\mathbf{S2}_k \oplus \pi_1)$$

(which is inherently binary because \mathbf{P}_k is inherently binary), and

$$\mathbf{Q}_k \mid (\mathbf{S2}_k \oplus \pi_1)$$

(which is inherently binary because \mathbf{Q}_k is inherently binary).

4.4.2 A COKO Transformation for SNF

A COKO transformation that rewrites qualification predicates into SNF is shown in Figure 4.9 and its auxiliary transformations are shown in Figure 4.10. The latter figure contains three COKO transformations: `SimpLits`, `LBConj` and `OrderConjs`.

Tracing the Execution

The firing algorithm for transformation SNF of Figure 4.9 consists of the seven steps described below. We demonstrate these steps by showing how this transformation rewrites

```

TRANSFORMATION SNF
USES
  SimpLits, CNF, LBConj, OrderConjs,
init:  p  $\equiv$  (Kp (true)  $\oplus$   $\pi_1$ ) & (Kp (true)  $\oplus$   $\pi_2$ ) & Kp (true) & p,
pull1: (p  $\oplus$  f) | (q  $\oplus$  f)  $\equiv$  (p | q)  $\oplus$  f,
pull2: (p  $\oplus$  f) | Kp (b)  $\equiv$  (p | Kp (b))  $\oplus$  f,
pull3: Kp (b) | (q  $\oplus$  f)  $\equiv$  (Kp (b) | q)  $\oplus$  f,
pull4: Kp (b1) | Kp (b2)  $\equiv$  Kp (b1 OR b2),
simp:  Kp (true) & p  $\equiv$  p
BEGIN
  SimpLits; -- (1)
  CNF; -- (2)
  init; -- (3)
  BU {pull1 || pull2 || pull3 || pull4}; -- (4)
  LBConj; -- (5)
  OrderConjs; -- (6)
  GIVEN (p  $\oplus$   $\pi_1$ ) & (q  $\oplus$   $\pi_2$ ) & r DO {simp (p); simp (q); simp (r)} -- (7)
END

```

Figure 4.9: The SNF Normalization Expressed in COKO

qualification predicate p of Figure 4.1a:

$$\begin{aligned}
P_k &= \mathbf{eq} \oplus \langle f \circ \pi_1, f \circ \pi_2 \rangle, \\
Q_k &= \mathbf{gt} \oplus \langle g \circ \pi_1, g \circ \pi_2 \rangle, \\
R_k &= \mathbf{eq} \oplus \langle \mathbf{topic} \circ \pi_1, K_f (\text{"NSF"}) \rangle, \\
S_k &= \mathbf{gt} \oplus \langle \mathbf{add} \circ \langle g \circ \pi_1, \mathbf{sum} \circ h \circ \mathbf{mems} \circ \pi_1 \rangle, K_f (100) \rangle \\
\\
f &= \mathbf{pty} \circ \mathbf{chair} \\
g &= \mathbf{terms} \circ \mathbf{chair} \\
h &= \mathbf{iterate} (K_p (\mathbf{true}), \mathbf{terms})
\end{aligned}$$

into the predicate of Figure 4.8. Figures 4.11 and 4.12 show the parse tree for this predicate at various stages during the execution of the transformation. The original predicate tree is shown in Figure 4.11a.

Step 1: The first step of SNF fires the transformation **SimpLits** (Simplify Literals) shown in Figure 4.10. The effect of firing **SimpLits** is to reduce subpredicates of the form $(p \oplus f)$ to the forms $(p \oplus \pi_1)$ or $(p \oplus \pi_2)$ if such a reduction is possible. More precisely, **SimpLits**

TRANSFORMATION SimpLits

USES

$$\begin{aligned} \text{sft} &: f \circ (g \circ h) && \xrightarrow{\equiv} (f \circ g) \circ h \\ \text{s11} &: \langle K_f(x), K_f(y) \rangle && \xrightarrow{\equiv} K_f([x, y]), \\ \text{s12} &: f \circ K_f(x) && \xrightarrow{\equiv} K_f(f ! x), \\ \text{s13} &: \langle f, K_f(x) \rangle && \xrightarrow{\equiv} \langle \text{id}, K_f(x) \rangle \circ f, \\ \text{s14} &: \langle K_f(x), f \rangle && \xrightarrow{\equiv} \langle K_f(x), \text{id} \rangle \circ f, \\ \text{s15} &: \langle f \circ h, g \circ h \rangle && \xrightarrow{\equiv} \langle f, g \rangle \circ h, \\ \text{s16} &: p \oplus (f \circ g) && \xrightarrow{\equiv} p \oplus f \oplus g, \\ \text{s17} &: p \oplus K_f(x) && \xrightarrow{\equiv} K_p(p ? x) \end{aligned}$$

BEGIN

$$\text{BU } \{\text{s11} \parallel \text{s12} \parallel \{\{\text{s13} \parallel \text{s14}\} \rightarrow \text{REPEAT sft}\} \parallel \text{s15} \parallel \text{s16} \parallel \text{s17} \parallel \text{REPEAT sft}\}$$

END

TRANSFORMATION LBConj

USES

$$\text{sftp} : p \& (q \& r) \longrightarrow (p \& q) \& r$$

BEGIN

$$\text{BU } \{\text{sftp} \rightarrow \{\text{GIVEN } p \& _ \text{ DO LBConj } (p)\}\}$$

END

TRANSFORMATION OrderConjs

USES

$$\begin{aligned} \text{oc1} &: (p \oplus \pi_1) \& (q \oplus \pi_2) \& r \& (s \oplus \pi_1) && \xrightarrow{\equiv} ((p \& s) \oplus \pi_1) \& (q \oplus \pi_2) \& r, \\ \text{oc2} &: (p \oplus \pi_1) \& (q \oplus \pi_2) \& r \& (s \oplus \pi_2) && \xrightarrow{\equiv} (p \oplus \pi_1) \& ((q \& s) \oplus \pi_2) \& r, \\ \text{oc3} &: (p \oplus \pi_1) \& (q \oplus \pi_2) \& r \& s && \xrightarrow{\equiv} (p \oplus \pi_1) \& (q \oplus \pi_2) \& (r \& s) \end{aligned}$$

BEGIN

$$\text{BU } \{\text{oc1} \parallel \text{oc2} \parallel \text{oc3}\}$$

END

Figure 4.10: Auxiliary Transformations Used by SNF

transforms any basic predicate lacking subfunctions of the form $(f \circ \pi_1)$ to either of the forms $(p \oplus \pi_2)$ or $K_p(x)$ (and similarly for predicates lacking $(f \circ \pi_2)$ as a subfunction).

`SimpLits` performs a single bottom-up pass of the input predicate, firing rules

`s11, ..., s17`

on each visited subtree. Rules `s11, ..., s15` only fire successfully on function subtrees while `s16` and `s17` only fire successfully on predicate subtrees. Because the pass is bottom-up, a basic predicate is visited only after its subfunctions are visited.

`SimpLits` rewrites R_k (to $R2_k$) and S_k (to $S2_k$) but has no effect on P_k or Q_k . In rewriting R_k , `SimpLits` first fires rule `s13` on its subfunction,

$\langle \text{topic} \circ \pi_1, K_f(\text{"NSF"}) \rangle$

generating

$\langle \text{id}, K_f(\text{"NSF"}) \rangle \circ (\text{topic} \circ \pi_1)$.

The successful firing of `s13` triggers the firing of `sft` leaving

$(\langle \text{id}, K_f(\text{"NSF"}) \rangle \circ \text{topic}) \circ \pi_1$.

Finally, rule `s16` fires on the entire predicate leaving $(R2_k \oplus \pi_1)$.

When fired on S_k , `SimpLits` first fires `s15` on its subfunction

$\langle g \circ \pi_1, \text{sum} \circ h \circ \text{mems} \circ \pi_1 \rangle$

leaving

$\langle g, \text{sum} \circ h \circ \text{mems} \rangle \circ \pi_1$.

Then, `s13`, `sft` and `s16` fire, resulting in $(S2_k \oplus \pi_1)$. Therefore, the result of firing `SimpLits` on p is

$$p_1 = (P_k \ \& \ Q_k \ \& \ (R2_k \oplus \pi_1)) \mid (S2_k \oplus \pi_1)$$

as illustrated in Figure 4.11b.

Step 2: Next, transformation `CNF` of Figure 4.4 is fired. Applied to p_1 , this firing results in

$$p_2 = (P_k \mid (S2_k \oplus \pi_1)) \ \& \ (Q_k \mid (S2_k \oplus \pi_1)) \ \& \ ((R2_k \oplus \pi_1) \mid (S2_k \oplus \pi_1))$$

as illustrated in Figure 4.11c.

Step 3: Rule `init` is fired, appending trivial conjuncts to the current predicate. The purpose of this step is to ensure the satisfaction of an invariant for **Step 4** which performs a bottom-up pass on the resulting predicate. This invariant establishes that every subtree visited during this bottom-up pass is of the form,

$$(\rho \oplus \pi_1) \& (\sigma \oplus \pi_2) \& \tau$$

such that τ is a conjunction of subpredicates to be “appended” to either ρ , σ or neither. Fired on p_2 , this step results in

$$p_3 = (K_p(\text{true}) \oplus \pi_1) \& (K_p(\text{true}) \oplus \pi_2) \& K_p(\text{true}) \& p_2$$

as illustrated in Figure 4.11d.

Step 4: This step executes the COKO statement,

$$\text{BU } \{\text{pull11} \parallel \text{pull12} \parallel \text{pull13} \parallel \text{pull14}\}.$$

The effect of firing these rules in bottom-up fashion is to “pull” common functions out of disjuncts. For example, the result of executing `pull11` on p_3 ’s subpredicate,

$$(\mathbf{R2}_k \oplus \pi_1) \mid (\mathbf{S2}_k \oplus \pi_1)$$

is $(\mathbf{R2}_k \mid \mathbf{S2}_k) \oplus \pi_1$. Therefore, this step converts disjuncts to the forms $(p \oplus \pi_1)$ or $(p \oplus \pi_2)$ where possible. Applied to p_3 , this statement results in

$$p_4 = ((K_p(\text{true}) \oplus \pi_1) \& (K_p(\text{true}) \oplus \pi_2) \& K_p(\text{true})) \& \\ ((\mathbf{P}_k \mid (\mathbf{S2}_k \oplus \pi_1)) \& (\mathbf{Q}_k \mid (\mathbf{S2}_k \oplus \pi_1)) \& ((\mathbf{R2}_k \mid \mathbf{S2}_k) \oplus \pi_1)$$

as illustrated in Figure 4.11e.

Step 5: This step executes the COKO transformation, `LBComp`. This transformation rewrites a predicate that is in CNF,

$$p_1 \& p_2 \& \dots \& p_n$$

(with conjunctions associated in any way), into a predicate of the form,

$$(\dots(p_1 \& p_2) \& \dots \& p_n)$$

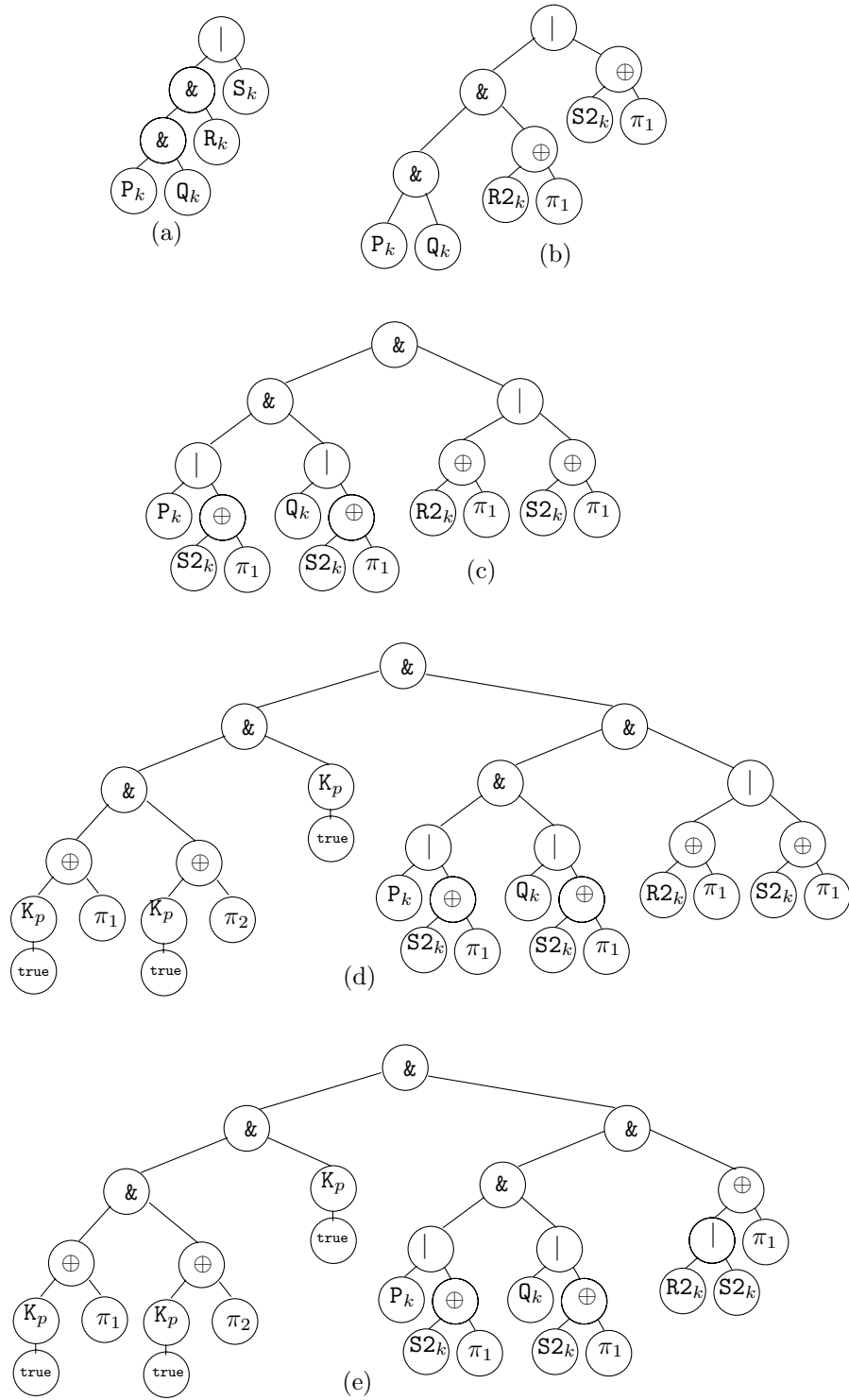


Figure 4.11: Tracing the effects of SNF on the Predicate p of Fig 4.1a (Part 1)

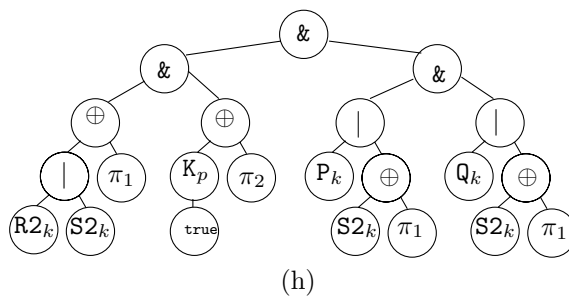
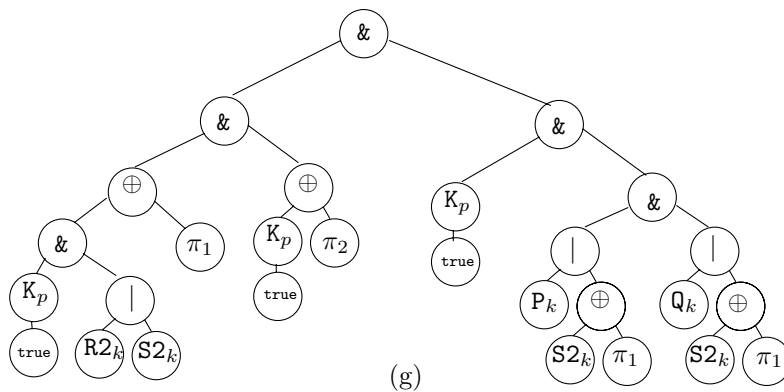
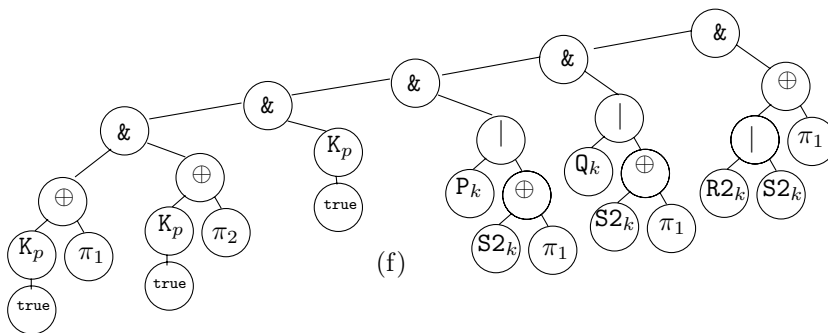


Figure 4.12: Tracing the effects of SNF on the Predicate p of Fig 4.1a (Part 2)

that is “left-bushy” with respect to its parse tree. (Left-bushy conjunctions are defined more formally in the next section.) This step prepares the predicate for the following step that orders conjuncts. When applied to p_4 , `LBConj` returns the left-bushy conjunction,

$$p_5 = ((((((K_p(\text{true}) \oplus \pi_1) \& (K_p(\text{true}) \oplus \pi_2)) \& K_p(\text{true})) \& (P_k \mid (S2_k \oplus \pi_1))) \& (Q_k \mid (S2_k \oplus \pi_1))) \& ((R2_k \mid S2_k) \oplus \pi_1))$$

as illustrated in Figure 4.12f.

Step 6: This step fires the transformation `OrderConjs` shown in Figure 4.10. This transformation performs a bottom-up pass, firing rules `oc1`, `oc2` and `oc3` on subtrees of the form,

$$(p \oplus \pi_1) \& (q \oplus \pi_2) \& r \& S$$

for predicates p , q , r and S . Because of step **3**, the first subtree visited with this form has p , q and r equal to $K_p(\text{true})$, and S equal to a conjunct from the original predicate. The structure of S determines which rule gets fired:

- if S is of the form $(s \oplus \pi_1)$, then s is merged with p by rule `oc1` to form $((p \& s) \oplus \pi_1)$.
- if S is of the form $(s \oplus \pi_2)$, then s is merged with q by rule `oc2` to form $((q \& s) \oplus \pi_2)$.
- if S is of any other form, then it is combined with r by rule `oc3` to form $(r \& s)$.

The effect of this step on p_5 is to transform it to

$$p_6 = ((K_p(\text{true}) \& \rho_k) \oplus \pi_1) \& (\sigma_k \oplus \pi_2) \& (K_p(\text{true}) \& \tau_k)$$

(as illustrated in Figure 4.12g) such that ρ_k , σ_k and τ_k are as defined in Figure 4.8.

Step 7: Finally, this step fires rule `simp` to get rid of the $K_p(\text{true})$ predicates that were added in **Step 3**. (Note that σ_k of p_6 above is not affected by this step.) The effect of this step on p_6 is to produce the final KOLA predicate of Figure 4.8 that is illustrated in Figure 4.12h.

Correctness of SNF

Theorem 4.4.1 (Correctness) *SNF is correct.*

Proof: All query modification performed by SNF occurs as result of firing rules `init`, `pull1`, `...`, `pull14`, and `simp` of transformation SNF; `sft`, `s11`, `...` `s17`, of transformation `SimplLits`;

sftp of transformation LBComp; d1, d2, involution, deMorgan1 and deMorgan2 of CNF; and oc1, oc2, and oc3 of OrderConjs. Therefore, SNF is correct if these rules are correct. CNF's rules are proven correct by execution of the LP [46] theorem prover scripts of Appendix B.1. All other rules are proven correct by execution of the LP [46] theorem prover scripts of Appendix B.2. \square

Proof that SNF succeeds in transforming KOLA qualification predicates into SNF is shown by the lemmas and theorem below.

Lemma 4.4.1 (The Effect of SimpLits on Basic Functions) *Let f be any basic function. Then `SimpLits` (f) will be a function of any of the forms shown below:*

- $\bar{f} \circ \pi_1$ (type 1),
- $\bar{f} \circ \pi_2$ (type 2),
- $K_f(x)$ (type 3), or
- \bar{f} such that \bar{f} is an inherently binary function (type 4).

Proof: (by induction on the height of f). For the base case, assume that f has height, $h \leq 2$. Then f must be either:

1. `att` \circ π_1 ,
2. `att` \circ π_2 , or
3. $K_f(x)$.

In any of these cases, no rules in `SimpLits` are fired and the functions are returned as is. The returned functions are types 1, 2 and 3 respectively.

For the inductive case, f has height = $k > 2$, and therefore must be of the form,

$$op \circ \langle f_1, f_2 \rangle$$

for some function op and basic functions f_1 and f_2 . Because `SimpLits` works bottom-up, induction applies to f_1 and f_2 and therefore, by the time the root of f is visited, f_1 and f_2 will have been rewritten to one of types 1, 2, 3 or 4. We summarize all possible combinations for f_1 and f_2 below:

Case 1 — f_1 and f_2 are type 3: Assume that $f_1 = K_f(x)$ and $f_2 = K_f(y)$. In this case, rule **s11** fires on $\langle f_1, f_2 \rangle$ leaving $K_f([x, y])$. Subsequently, rule **s12** fires on $(op \circ K_f([x, y]))$ leaving

$$K_f(op ! \langle x, y \rangle)$$

which is also type 3.

Case 2 — f_1 and f_2 are both type 1 or type 2: Let n be the type of f_1 and f_2 . Assume that $f_1 = f'_1 \circ h$ and $f_2 = f'_2 \circ h$ such that $h = \pi_1$ or $h = \pi_2$. In this case, rule **s15** fires on $\langle f'_1 \circ h, f'_2 \circ h \rangle$ leaving $(\langle f'_1, f'_2 \rangle \circ h)$. Subsequently, rule **sft** fires on $(op \circ (\langle f'_1, f'_2 \rangle \circ h))$, leaving,

$$(op \circ \langle f'_1, f'_2 \rangle) \circ h$$

which is type n .

Case 3 — One of f_1 and f_2 is type 3, and the other is type n (for $n \neq 3$): Suppose first that f_1 is type 3 and $f_2 = f'_2 \circ h$ is type n . Then, rule **s14** fires on $\langle f_1, f_2 \rangle$ leaving

$$\langle g_1, g_2 \rangle \circ (f'_2 \circ h)$$

for some functions g_1 and g_2 . **Sft** subsequently fires on this function leaving

$$(\langle g_1, g_2 \rangle \circ f'_2) \circ h.$$

Sft fires again on

$$op \circ (\langle g_1, g_2 \rangle \circ f'_2) \circ h$$

leaving

$$(op \circ (\langle g_1, g_2 \rangle \circ f'_2)) \circ h$$

which is type n .

A symmetric argument (such that **s13** is fired instead of **s14**) handles the case where f_2 is type 3.

Case 4 – One of f_1 and f_2 is type 4, or one is type 1 and the other is type 2: If one of f_1 or f_2 is type 4, then no rules fire and $\langle f_1, f_2 \rangle$ is inherently binary. No rules fire on $(op \circ \langle f_1, f_2 \rangle)$, and **SimpLits** returns this type 4 function.

If one of f_1 or f_2 is type 1 and the other is type 2, then no rules fire and again $\langle f_1, f_2 \rangle$ is inherently binary. No rules fire on $(op \circ \langle f_1, f_2 \rangle)$, and **SimpLits** returns this type 4 function. \square

Lemma 4.4.2 (The Effect of `SimpLits` on Pairs of Basic Functions) *Let f_1 and f_2 be any basic functions. Then `SimpLits` ($\langle f_1, f_2 \rangle$) will be a function of one of the forms shown below:*

- $\bar{f} \circ \pi_1$ (type 1),
- $\bar{f} \circ \pi_2$ (type 2),
- $K_f(x)$ (type 3), or
- \bar{f} such that \bar{f} is an inherently binary function (type 4).

Proof: Because `SimpLits` works bottom-up, f_1 and f_2 will be visited before $\langle f_1, f_2 \rangle$. By **Lemma 4.4.1**, when $\langle f_1, f_2 \rangle$ is visited, both f_1 and f_2 will be of one of the following forms:

- $\bar{f} \circ \pi_1$ (type 1),
- $\bar{f} \circ \pi_2$ (type 2),
- $K_f(x)$ (type 3), or
- \bar{f} such that \bar{f} is an inherently binary function (type 4).

The proof then proceeds by cases as before.

Case 1 — f_1 and f_2 are both type 3: Assume that $f = K_f(x)$ and $g = K_f(y)$. In this case, rule `s11` fires on $\langle f, g \rangle$ leaving

$$K_f([x, y])$$

which is type 3.

Case 2 — f_1 and f_2 are both type 1 or type 2: Let n be the type of f_1 and f_2 . Assume that $f_1 = f'_1 \circ h$ and $f_2 = f'_2 \circ h$ such that $h = \pi_1$ or $h = \pi_2$. In this case, rule `s15` fires on $\langle f'_1 \circ h, f'_2 \circ h \rangle$ leaving

$$\langle f'_1, f'_2 \rangle \circ h,$$

which is type n .

Case 3 — One of f_1 and f_2 is type 3, and the other is type n (for $n \neq 3$): Suppose first that f_1 is type 3 and $f_2 = f'_2 \circ h$ is type n . Then, rule **s14** fires on $\langle f_1, f_2 \rangle$ leaving

$$\langle g_1, g_2 \rangle \circ (f'_2 \circ h)$$

for some functions g_1 and g_2 . **Sft** subsequently fires on this function leaving

$$(\langle g_1, g_2 \rangle \circ f'_2) \circ h$$

which is type n . A symmetric argument (such that **s13** is fired instead of **s14**) handles the case where f_2 is type 3.

Case 4 – One of f_1 and f_2 is type 4, or one is type 1 and the other is type 2: If one of f_1 or f_2 is type 4, then no rules fire and $\langle f_1, f_2 \rangle$ is inherently binary (type 4). If one of f_1 or f_2 is type 1 and the other is type 2, then no rules fire and again $\langle f_1, f_2 \rangle$ is inherently binary (type 4). \square

Lemma 4.4.3 (The Effect of **SimpLits on Basic Predicates)** *Let $p = q \oplus f$ be any basic predicate. Then **SimpLits** (p) will be a predicate of one of the following forms:*

- $\bar{p} \oplus \pi_1$ (type 1),
- $\bar{p} \oplus \pi_2$ (type 2),
- K_p (b) (type 3), or
- \bar{p} such that \bar{p} is an inherently binary predicate (type 4).

Proof: Observe that the bottom-up pass of **SimpLits** ensures that f is visited before p . Function f is of the form, $\langle f_1, f_2 \rangle$ such that f_1 and f_2 are basic functions. By **Lemma 4.4.2**, once p is visited during the bottom-up pass of **SimpLits**, it is of one of the forms below:

1. $\bar{p} \oplus (\bar{f} \circ \pi_1)$
2. $\bar{p} \oplus (\bar{f} \circ \pi_2)$,
3. $\bar{p} \oplus K_f$ (x), or
4. $\bar{p} \oplus \bar{f}$ such that \bar{f} is inherently binary.

In the first two cases, rule **s16** fires, leaving either

$$\begin{aligned} &(\bar{p} \oplus \bar{f}) \oplus \pi_1 \quad (\text{type 1}), \text{ or} \\ &(\bar{p} \oplus \bar{f}) \oplus \pi_2 \quad (\text{type 2}). \end{aligned}$$

In the third case, rule **s17** fires leaving

$$K_p (\bar{p} ? x) \quad (\text{type 3}).$$

And in the fourth case, no rule fires leaving the inherently binary predicate,

$$\bar{p} \oplus \bar{f} \quad (\text{type 4}) \quad \square.$$

Lemma 4.4.4 (The Effect of **SimpLits on Qualification Predicates)** *Let p be a qualification predicate. Then **SimpLits** (p) will consist of conjunctions, disjunctions and negations of predicates of one of the forms listed below:*

- $\bar{p} \oplus \pi_1$,
- $\bar{p} \oplus \pi_2$,
- $K_p (b)$, or
- \bar{p} such that \bar{p} is an inherently binary predicate.

Proof: Because **SimpLits** works bottom-up, all basic predicates are visited before those of the form $(p \ \& \ q)$, $(p \ | \ q)$ or $(\sim (p))$. **SimpLits** has no effects on predicates of these latter forms. Therefore, by **Lemma 4.4.3** **SimpLits** leaves a predicate consisting of conjuncts, disjuncts or negations of predicates of the forms above. \square

Definition 4.4.7 (Left-Bushy Conjunctions) *A left-bushy conjunction is any KOLA predicate that can be constructed according to the following rules:*

- literals and disjuncts containing no subpredicates of the form $(r_1 \ \& \ r_2)$ are left-bushy conjunctions,
- $p \ \& \ q$ is a left-bushy conjunction if p is a left-bushy conjunction and q is a literal or disjunct containing no subpredicates of the form $(r_1 \ \& \ r_2)$.

Next, we show that **LBComp** rewrites predicates in CNF into left-bushy conjunctions.

Lemma 4.4.5 (The Effect of **LBConj on Predicates in CNF (Part 1))** *Let p and q be left-bushy conjunctions. Then, **LBConj** ($p \ \& \ q$) is a left-bushy conjunction.*

Proof: The proof is by induction on the number, n , of conjunctions in q . For the base case, $n = 0$, $(p \ \& \ q)$ is already left-bushy and **LBConj** does nothing. In the inductive case, $q = q_1 \ \& \ q_2$. By the definition of left-bushy conjunctions, q_1 is a left-bushy conjunction and q_2 is a literal or disjunct containing no subpredicates that are conjunctions. In this case, rule **sftp** fires leaving,

$$(p \ \& \ q_1) \ \& \ q_2.$$

LBConj is subsequently fired on $(p \ \& \ q_1)$ leaving, by induction, a left-bushy conjunction, p_2 . Therefore, the predicate

$$p_2 \ \& \ q_2$$

is also a left-bushy conjunction. \square

Lemma 4.4.6 (The Effect of LBConj on Predicates in CNF (Part 2)) *Let p be a predicate in CNF. Then, **LBConj** (p) is left-bushy conjunction.*

Proof: Because **LBConj** works bottom up, it visits p and q before it visits $(p \ \& \ q)$. A simple inductive argument using **Lemma 4.4.5** establishes **LBConj** to return a left-bushy conjunction when fired on p . \square

Theorem 4.4.2 (SNF) *Given any KOLA qualification predicate p , **SNF** (p) is a predicate in SNF.*

Proof: The proof consists of seven parts, proving invariants that hold after the execution of each step 1-7.

Invariant 1 : After firing **SimpLits**, p consists of conjunctions, disjunctions and negations of predicates of one of the forms listed below:

- $\bar{p} \oplus \pi_1$ (type 1),
- $\bar{p} \oplus \pi_2$ (type 2),
- $K_p(b)$ (type 3),
- \bar{p} such that \bar{p} is an inherently binary predicate (type 4).

This invariant was shown to result from firing **SimpLits** by **Lemma 4.4.4**.

Invariant 2: After firing CNF, p is of the form,

$$p_0 \ \& \ \dots \ \& \ p_n$$

with each p_i a disjunction of possibly negated literals of one of the four types listed in **Invariant 1**. This invariant was shown to result from firing CNF in Section 4.2.3.

Invariant 3: After firing `init`, p is of the form,

$$(K_p(\text{true}) \oplus \pi_1) \ \& \ (K_p(\text{true}) \oplus \pi_2) \ \& \ (K_p(\text{true})) \ \& \ p_1 \ \& \ \dots \ \& \ p_n$$

with each p_i disjunction of possibly negated literals of one of the four types listed in **Invariant 1**.

Invariant 4: After executing BU `{pull1 || pull2 || pull3 || pull4}`, p is of the form,

$$(K_p(\text{true}) \oplus \pi_1) \ \& \ (K_p(\text{true}) \oplus \pi_2) \ \& \ (K_p(\text{true})) \ \& \ q_1 \ \& \ \dots \ \& \ q_n$$

such that each q_i is of any of the forms shown below:

- $\bar{p} \oplus \pi_1$ (type 1),
- $\bar{p} \oplus \pi_2$ (type 2),
- $K_p(b)$ (type 3), or
- \bar{p} such that \bar{p} is an inherently binary predicate (type 4).

Note that none of the rewrite rules, `pull1`, `...`, `pull4`, affect the conjuncts at the top of the tree, or the negations at the bottom. Rather, only disjuncts are affected. The proof then is by induction on the height h of a disjunct (such that literals are viewed as having height 0). For the base case, $h = 0$ and no rules fire. In this case, we are left with a literal of types 1, 2, 3 or 4 (as listed in **Invariant 1**).

The induction proof considers the disjunct, $p_1 \mid p_2$ such that p_1 and p_2 are (by induction) of types 1, 2, 3 or 4. The proof proceeds by cases:

- *Case 1* — p_1 and p_2 are both type 1 or type 2: Let n be the type of p_1 or p_2 . In this case, rule `pull1` fires and we are left with a type n predicate.
- *Case 2* — p_1 and p_2 are both type 3: In this case, `pull4` fires and we are left with a type 3 predicate.
- *Case 3* — One of p_1 or p_2 is type 4, or one is type 1 and the other is type 2: In this case, no rule fires and we are left with a type 4 predicate.

Invariant 5: After firing `LBConj`, p is a left-bushy conjunction (as proven by **Lemma 4.4.6**).

Invariant 6: After firing `OrderConjs`, p will be of the form

$$(\rho \oplus \pi_1) \& (\sigma \oplus \pi_2) \& \tau$$

such that τ is a conjunction of m ($m \geq 0$) inherently binary or constant predicates (i.e., p will be in SNF). Again, the proof of the invariant is by structural induction. exploiting the bottom-up nature of `OrderConjs`. In the base case, `OrderConjs` is fired on

$$(\text{K}_p(\text{true}) \oplus \pi_1) \& (\text{K}_p(\text{true}) \oplus \pi_2) \& \text{K}_p(\text{true}),$$

doing nothing and leaving a predicate that is trivially in SNF.

Because p is a left-bushy conjunction, in the inductive case `OrderConjs` is fired on a predicate of the form,

$$(((\rho \oplus \pi_1) \& (\sigma \oplus \pi_2)) \& \tau) \& p_1$$

such that p_1 is of one of the types listed in **Invariant 4**. If p_1 is type 1, then it is merged with ρ by rule `oc1` to form $(\rho \& p_1) \oplus \pi_1$, leaving,

$$((\rho \& p_1) \oplus \pi_1) \& (\sigma \oplus \pi_2) \& \tau$$

which is in SNF. If p_1 is type 2, then it is merged with σ by rule `oc2` to form $(\sigma \& p_1) \oplus \pi_2$, leaving,

$$(\rho \oplus \pi_1) \& ((\sigma \& p_1) \oplus \pi_2) \& \tau$$

which is in SNF. Finally, if p_1 is type 3 or 4, then it is merged with τ by rule `oc3` to form $(\tau \& p_1)$, leaving,

$$(\rho \oplus \pi_1) \& (\sigma \oplus \pi_2) \& (\tau \& p_1)$$

which is in SNF.

Invariant 7: After completion of the final step of the firing algorithm, we are left with a predicate in SNF,

$$(\rho \oplus \pi_1) \& (\sigma \oplus \pi_2) \& \tau$$

such that neither ρ , σ nor τ is of the for,

$$\text{K}_p(\text{true}) \& p.$$

Satisfaction of this invariant follows trivially by examination of the rewrite rule, `simp`.

4.5 Example Applications of SNF

4.5.1 Example 3: Predicate-Pushdown

Figure 4.13 shows a COKO transformation that pushes predicates past joins. The key rule of this transformation is **push**, which identifies subpredicates (\mathbf{p} and \mathbf{q}) of join predicates that apply only to one argument, and pushes these subpredicates out of the join and onto the join inputs. This heuristic is useful as it will usually result in a join of smaller collections.

Rule **push** will not fire successfully on every join query, for the predicate used in the join may not be in a form that makes “pushable” subpredicates recognizable. For example, if this rule were fired on the query,

$$\mathbf{join} (p, \pi_1) ! [\mathbf{Coms}, \mathbf{SComs}]$$

such that \mathbf{Coms} and \mathbf{SComs} are collections of committees and subcommittees respectively as presented in Table 2.1, and p is the predicate of Figure 4.1a, it fails because this predicate does not match the pattern,

$$(\mathbf{p} \oplus \pi_1) \& (\mathbf{q} \oplus \pi_2) \& \mathbf{r}.$$

Therefore before this rule is fired, the predicate argument to **join** is normalized into SNF so that “pushable” subpredicates can be identified. In the case of the predicate of Figure 4.1a, normalization into SNF results in the query,

$$\mathbf{join} ((\rho \oplus \pi_1) \& (\sigma \oplus \pi_2) \& \tau, \pi_1) ! [\mathbf{Coms}, \mathbf{SComs}]$$

such that ρ , σ and τ are as defined in Figure 4.8. Once in this form, firing **push** results in

$$\mathbf{join} (\tau, \pi_1) ! [\mathbf{iterate} (\rho, \mathbf{id}) ! \mathbf{Coms}, \mathbf{iterate} (\sigma, \mathbf{id}) ! \mathbf{SComs}].$$

In this case, σ is $K_p(\mathbf{true})$. Therefore, the subsequent firing of rule, **simplify** results in the query,

$$\mathbf{join} (\tau, \pi_1) ! [\mathbf{iterate} (\rho, \mathbf{id}) ! \mathbf{Coms}, \mathbf{SComs}].$$

4.5.2 Example 4: Join-Reordering

Figure 4.14 shows a COKO transformation that might be fired to change the order in which multiple joins are evaluated. Transformation **Join-Associate** reassociates a composition of join queries. That is, a query of the form,

$$\mathbf{join} (\dots, \dots) ! [\mathbf{join} (\dots, \dots) ! [A, B], C]$$

```

TRANSFORMATION Pushdown
USES
  SNF,
  push:      join ((p  $\oplus$   $\pi_1$ ) & (q  $\oplus$   $\pi_2$ ) & r, f) ! [A, B]  $\xrightarrow{=}$ 
              join (r, f) ! [iterate (p, id) ! A, iterate (q, id) ! B],
  simplify:  iterate ( $K_p$  (true), id) ! A  $\xrightarrow{=}$  A
BEGIN
  GIVEN join (p, —) ! — DO SNF (p);
  push;
  GIVEN — ! [A, B] DO {simplify (A); simplify (B)}
END

```

Figure 4.13: Pushdown: A COKO Transformation to Push Predicates Past Joins

gets rewritten to

$$\mathbf{join} (\dots, \dots) ! [A, \mathbf{join} (\dots, \dots) ! [B, C]].$$

Join-Associate first normalizes join predicates into SNF. The innermost join predicate (**q**) gets normalized by SNF into,

$$(\mathbf{p}_2 \oplus \pi_1) \& (\mathbf{q}_2 \oplus \pi_2) \& \mathbf{r}_2.$$

The outermost join predicate (**p**) gets normalized by SNF into the form,

$$(\mathbf{p}_1 \oplus \pi_1) \& (\mathbf{q}_1 \oplus \pi_2) \& \mathbf{r}_1.$$

The innermost join predicate applies to pairs, $[a, b]$ (for $a \in A$ and $b \in B$). Therefore, \mathbf{p}_2 applies to a , \mathbf{q}_2 applies to b , and \mathbf{r}_2 applies to $[a, b]$. The outermost join predicate applies to pairs, $[\mathbf{f}_2 ! [a, b], c]$ (for $\mathbf{f}_2 ! [a, b]$ in the result of the innermost join, and $c \in C$). Therefore, \mathbf{p}_1 applies to $\mathbf{f}_2 ! [a, b]$, \mathbf{q}_2 applies to c , and \mathbf{r}_3 applies to $\mathbf{f}_2 ! [[a, b], c]$.

Firing **shift** on this normalized query results in a new query for which the innermost join predicate and function are applied to pairs, $[b, c]$ and and the outermost join predicate and function are applied to pairs, $[a, [b, c]]$. Therefore, the rewrite rule places:

- $(\mathbf{q}_2 \oplus \pi_1)$ in the innermost predicate because $(\mathbf{q}_2 \oplus \pi_1) ? [b, c] = \mathbf{q}_2 ? b$.
- $(\mathbf{q}_1 \oplus \pi_2)$ in the innermost predicate because $(\mathbf{q}_1 \oplus \pi_2) ? [b, c] = \mathbf{q}_1 ? c$.
- $(\mathbf{p}_2 \oplus \pi_1)$ in the outermost predicate because $(\mathbf{p}_2 \oplus \pi_1) ? [a, [b, c]] = \mathbf{p}_2 ? a$.
- $(\mathbf{r}_2 \oplus (\mathbf{id} \times \pi_1))$ in the outermost predicate because

$$(\mathbf{r}_2 \oplus (\mathbf{id} \times \pi_1)) ? [a, [b, c]] = \mathbf{r}_2 ? [a, b].$$

TRANSFORMATION Join-Associate

USES

shift: **join** $((p_1 \oplus \pi_1) \& (q_1 \oplus \pi_2) \& r_1, f_1) !$
 $[\mathbf{join} ((p_2 \oplus \pi_1) \& (q_2 \oplus \pi_2) \& r_2, f_2) ! [A, B], C] \xrightarrow{=}$
join $((p_1 \oplus f_1) \& (r_1 \oplus h_1) \& (p_2 \oplus f_2) \& (r_2 \oplus h_2), f_1 \circ h_1) !$
 $[A, \mathbf{join} ((q_1 \oplus g_1) \& (q_2 \oplus g_2), \mathbf{id}) ! [B, C]]$

SNF

BEGIN

GIVEN **join** $(p, _)$! **[join** $(q, _)$! $[_, _], _]$ DO {SNF (p) ; SNF (q) ; shift}

END

such that

$$\begin{aligned} f_1 &= f_2 \circ (\mathbf{id} \times \pi_1) \\ g_1 &= \pi_2 \\ h_1 &= \langle f_2 \circ (\mathbf{id} \times \pi_1), \pi_2 \circ \pi_2 \rangle \\ f_2 &= \pi_1 \\ g_2 &= \pi_1 \\ h_2 &= \mathbf{id} \times \pi_1 \end{aligned}$$

Figure 4.14: Join-Associate: A COKO Transformation to Reassociate a Join

- $(p_1 \oplus (f_2 \oplus (\mathbf{id} \times \pi_1)))$ in the outermost predicate because

$$(p_1 \oplus (f_2 \oplus (\mathbf{id} \times \pi_1))) ? [a, [b, c]] = p_1 ? (f_2 ! [a, b]),$$

and

- $(r_1 \oplus \langle f_2 \circ (\mathbf{id} \times \pi_1), \pi_2 \circ \pi_2 \rangle)$ in the outermost predicate because

$$(r_1 \oplus \langle f_2 \circ (\mathbf{id} \times \pi_1), \pi_2 \circ \pi_2 \rangle) ? [a, [b, c]] = r_1 ? [f_2 ! [a, b], c].$$

While the predicates that result from this rewrite are quite complex, in most cases they can be simplified afterwards. For example, any subpredicates for which p_1, q_1, \dots, r_2 is K_p (**true**) can be made to drop away as a result of simplification.

4.6 Example 5: Magic-Sets

The idea behind the Magic-Sets transformation for relational queries introduced by Mumick et al [74] is to restrict the inputs to a join by filtering those elements that cannot possibly satisfy the join predicate. Therefore, this transformation is very much in the spirit of predicate-pushdown, but passing filter predicates “sideways” from one join input to another,


```

SELECT c
FROM c IN Coms, t in Temp
WHERE P(c,t) AND Q(c,t) AND R(c)

Temp (chair, avgTerms) =
  SELECT z.chair, AVG (SELECT m.terms FROM x IN partition, m IN x.mems)
  FROM z IN Coms
  GROUP BY z.chair

P(c,t) = c.chair == t.chair
Q(c,t) = c.chair.terms > t.avgTerms
R(c) = c.chair.pty == "Dem"

```

a. Before (OQL)

```

join (Pk & Qk & Rk, π1) ! [Coms, TempK]

TempK =
  njoin (eq ⊕ (id × chair), mems, avg ∘ flat) !
  [iterate (Kp (true), chair) ! Coms, Coms]

Pk = eq ⊕ ⟨chair ∘ π1, π1 ∘ π2⟩
Qk = gt ⊕ ⟨terms ∘ chair ∘ π1, π2 ∘ π2⟩
Rk = eq ⊕ ⟨pty ∘ chair ∘ π1, Kf ("Dem")⟩

```

b. Before (KOLA)

Figure 4.15: OQL (a) and KOLA (b) queries to *find all committees whose chair is a Democrat and has served more than the average number of terms of the members of his/her chaired committees.*

rather than down from the join predicate. As with predicate-pushdown and join-reordering, the magic-sets rewrite requires first normalizing the join predicate into SNF so that the predicate that can be passed sideways can be identified.

4.6.1 An Example Magic-Sets Rewrite

Expressed in OQL

To illustrate, consider the OQL query of Figure 4.15a. This query returns the committees in `Coms` that are chaired by someone who is a Democrat and who has served more terms than

```

SELECT c
FROM c IN MComs, t IN MTemp
WHERE P(c, t) AND Q(c, t)

MComs =
  SELECT m3
  FROM m3 IN MComs
  WHERE R(m3)

CSet (chair) =
  SELECT DISTINCT m2.chair
  FROM m2 IN MComs

MTemp (chair, avgTerms) =
  SELECT z.chair, AVG (SELECT m.terms FROM x IN partition, m IN x.mems)
  FROM z IN Coms, y IN CSet
  WHERE z.chair == y.chair
  GROUP BY z.chair

P(c, t) = c.chair == t.chair
Q(c, t) = c.chair.terms > t.avgTerms
R(m3) = m3.chair.pty == "Dem"

```

c. After (OQL)

```

join (P'_k & Q'_k, π1) ! [MComsk, MTempk]

MComsk = iterate (R'_k, id) ! Coms

CSetk = set ! (iterate (Kp (true), chair) ! MComsk)

MTempk = njoin (eq ⊕ (id × chair), mems, avg ∘ flat) ! [CSetk, Coms]

P'_k = eq ⊕ (chair × id) ⊕ (id × π1)
Q'_k = gt ⊕ ((terms ∘ chair) × π2) ⊕ (id × π2)
R'_k = eq ⊕ ((id, Kf ("Dem")) ∘ pty ∘ chair)

```

d. After (KOLA)

Figure 4.16: The queries of Figure 4.15 after rewriting by Magic-Sets

is average for the members of the committees he or she chairs. The query result is generated from a join of `Coms` and the view, `Temp`. `Temp` groups each committee chair, `c.chair` with the result of the OQL expression,

```
AVG (SELECT m.terms FROM x IN partition, m IN x.mems)
```

that averages the number of terms served by members of committees chaired by `c.chair` (`partition` names the collection of all member sets for committees chaired by a given legislator). The join of `Coms` and `Temp` then uses join predicates P , Q and R on pairs from `Coms` (`c`) and `Temp` (`t`) such that

- P holds if `c` is chaired by the chair represented by `t`,
- Q holds if `c`'s chair has served more terms than the number of terms associated with `t`, and
- R holds if `c` is chaired by a Democrat.

Each entry in `Temp` can be expensive to calculate, as each requires averaging values extracted from a collection of collections. The Magic-Sets query rewrite addresses this expense by observing that entries need not be computed for every committee chair. In particular, only committees whose chairs are Democrats can possibly contribute to the query result. Therefore, the Magic-Sets rewrite passes the predicate on `Coms` that requires committee chairs to be Democrats (R) sideways to `Temp`. Rewriting produces the query shown in Figure 4.16c, which includes three view definitions:

- `MComs` is the subcollection of `Coms` chaired by Democrats.
- `CSet` is the set of committee chairs who are Democrats.
- `MTemp` is the subcollection of `Temp` consisting of entries only for those committee chairs who are represented in `CSet`.

Unlike `Temp` of Figure 4.15a, `MTemp` does not compute average numbers of terms for every chair of a committee in `Coms`. Instead, only those chairs who are represented in `CSet` are represented in the result. `CSet` is the set of all committee chairs who are Democrats. Therefore, the equijoin of `Coms` and `CSet` prior to grouping ensures that aggregation is performed only for committee chairs that are Democrats.

The main query then is a join of `MComs` and `MTemp` using join predicates P and Q . Unlike the original form of the query, this form of the query requires additional projection and

duplicate elimination to generate **CSet** and an additional join to compute **MTemp**. However, in many cases this additional cost is more than offset by the savings in not having to compute average terms for committee chairs who are not Democrats.

Expressed in KOLA

Figures 4.15b and 4.16d show the KOLA equivalents of the OQL queries of Figures 4.15a and 4.16c respectively. The main query of Figure 4.15b performs a join of **Coms** and **Temp_K** (the KOLA equivalent of **Temp**). The join predicate is the conjunction,

$$P_k \ \& \ Q_k \ \& \ R_k$$

such that P_k is the KOLA equivalent to P and so on. The join function returns the first element (the committee) of each pair, $[c, t]$ ($c \in \mathbf{Coms}$ and $t \in \mathbf{Temp}_K$) satisfying the join predicate.

Temp_K is the KOLA equivalent of **Temp**, but for the naming of fields in the result. It uses **njoin** to associate chairs of committees in **Coms**,

$$(\mathbf{iterate} \ (\mathbf{K}_p \ (\mathbf{true}), \ \mathbf{chair}) \ ! \ \mathbf{Coms})$$

with the sets of committees they chair. (For any committee chair l and committee c ,

$$(\mathbf{eq} \oplus \ \langle \pi_1, \ \mathbf{chair} \circ \pi_2 \rangle) \ ? \ [l, \ c]$$

holds if c is chaired by l .) For each committee c chaired by l , the set of c 's members ($c.\mathbf{mems}$) are added to an intermediate collection of legislator collections associated with l . Then, the function, $\mathbf{avg} \circ \mathbf{flat}$ is applied to the result, first flattening this collection into a single collection of legislators, and then averaging the number of terms they have served.

As with the OQL query of Figure 4.16c, the KOLA query of Figure 4.16d performs a join of two new collections, **MComs_k** and **MTemp_k**. The join predicate for this join is a conjunction of predicates P'_k and Q'_k that are equivalent but transformed versions of predicates P_k and Q_k of Figure 4.15b. Like **MComs**, **MComs_k** filters **Coms** for those committees that satisfy R'_k (which is equivalent to R_k , but rewritten into a unary predicate). Like **MTemp**, **MTemp_k** groups committees only if the committees are chaired by someone represented in **CSet_k** (**CSet**). And like **CSet**, **CSet_k** determines the set of committee chairs for committees in **MComs_k** (**MComs**).

```

TRANSFORMATION Magic
USES
  SNF2, Pushdown, SimplifyJoins,
magic:  join (q ⊕ (id × π1) & r, f) ! [A1, njoin (p, g, h) ! [A2, B]] ≡→
        join (q ⊕ (id × π1) & r, f) !
          [A1, njoin (p, g, h) !
            [set ! (join (q, π2) ! [A1, A2]), B]],

sftp:   (p & q) & r ≡→ p & (q & r)
BEGIN
  Pushdown;                                     -- Step 1
  GIVEN join (p, --) ! -- DO {SNF2 (p); sftp (p)} -- Step 2
  magic                                       -- Step 3
  GIVEN _ ! [_, A], A = _ ! [B, _] DO {SimplifyJoin (B)} -- Step 4
END

```

Figure 4.17: The Magic-Sets Rewrite Expressed in COKO

4.6.2 Expressing Magic-Sets in COKO

A COKO Magic-Sets transformation that converts the KOLA query of Figure 4.15b to that of Figure 4.16d is shown in Figure 4.17. The key rewrite rule of this transformation is **magic**, which assumes that a predicate argument to a join query has first been normalized into the form

$$(q \oplus (\text{id} \times \pi_1)) \& r.$$

This normal form isolates the subpredicate, q , which relates elements of $A1$ and $A2$, as is evident by tracing the evaluation of this predicate on any pair, $[a_1, [a_2, S]]$ such that $a_1 \in A1$, and $[a_2, S]$ belongs to the result of the **njoin** subquery:

$$\begin{aligned} (q \oplus (\text{id} \times \pi_1)) ? [a_1, [a_2, S]] &= q ? [\text{id} ! a_1, \pi_1 ! [a_2, S]] \\ &= q ? [a_1, a_2]. \end{aligned}$$

Rule **magic** then rewrites the query so that q is used to “filter” elements of $A2$ so that only those that relate to some element of $A1$ will be involved in the grouping and aggregate computation performed by **njoin**. This filtering is expressed in the body pattern of **magic** with the subexpression,

$$\text{join } (q, \pi_2) ! [A1, A2]$$

which performs a right semi-join of $A1$ and $A2$ with respect to q . The elements of B that are collected from this query are then freed of duplicates via a subsequent invocation of **set**.

Note that the semantics of **njoin** show that duplicate elimination on the result of the semi-join is strictly not necessary (**njoin** ignores duplicates in the first collection argument). The reason that rule **magic** introduces this unnecessary operator is to prepare this expression for simplification by transformation **SimplifyJoin** whose rewrite rules are listed in Figure 4.3. Rule (8) of Figure 4.3 rewrites this semijoin into an intersection. But semijoins can only be rewritten into intersections when the result of the semijoin is returned as a set. Therefore, the operator **set** is introduced into the semijoin expression as an “indicator” that duplicates in the result can be ignored.

Below we describe the steps performed by this transformation, demonstrating their effects on the KOLA query of Figure 4.15b, and showing how they result in a rewrite of this query to that shown in Figure 4.16d. In practice, translation into KOLA performs view merging, and therefore the query of Figure 4.15b would be presented to the COKO Magic transformation as Q_0 :

```

join ( $P_k$  &  $Q_k$  &  $R_k$ ,  $\pi_1$ ) !
  [Coms, njoin (eq  $\oplus$  (id  $\times$  chair), mems, avg  $\circ$  flat) !
    [iterate ( $K_p$  (true), chair) ! Coms, Coms]]

```

such that

$$\begin{aligned}
 P_k &= \mathbf{eq} \oplus \langle \mathbf{chair} \circ \pi_1, \pi_1 \circ \pi_2 \rangle \\
 Q_k &= \mathbf{gt} \oplus \langle \mathbf{terms} \circ \mathbf{chair} \circ \pi_1, \pi_2 \circ \pi_2 \rangle, \text{ and} \\
 R_k &= \mathbf{eq} \oplus \langle \mathbf{pty} \circ \mathbf{chair} \circ \pi_1, K_f (\text{“Dem”}) \rangle
 \end{aligned}$$

Steps 1 and 2:

The purpose of the first two steps of the transformation is to isolate that part of the join predicate,

$$P_k \& Q_k \& R_k$$

that is of the form

$$(\mathbf{q} \oplus (\mathbf{id} \times \pi_1)) \& \mathbf{r}$$

to prepare it for firing by **magic**.

1. In Step 1, transformation **pushdown** (Section 4.5.1) is fired. **Pushdown** fires **SNF** on the join predicate to convert it to the form,

$$(\rho \oplus \pi_1) \& (\sigma \oplus \pi_2) \& \tau.$$

Then, ρ and σ are pushed out of the join. Applied to Q_0 , this step leaves Q_1 :

$$\begin{aligned} & \mathbf{join} (P_k \ \& \ Q_k, \ \pi_1) \ ! \\ & \quad [\mathbf{MComs}_k, \ \mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times \mathbf{chair}), \ \mathbf{mems}, \ \mathbf{avg} \circ \mathbf{flat}) \ ! \\ & \quad \quad [\mathbf{iterate} (K_p (\mathbf{true}), \ \mathbf{chair}) \ ! \ \mathbf{Coms}, \ \mathbf{Coms}]] \end{aligned}$$

such that

$$\begin{aligned} \mathbf{MComs}_k &= \mathbf{iterate} (R'_k, \ \mathbf{id}) \ ! \ \mathbf{Coms}, \ \text{and} \\ R'_k &= \mathbf{eq} \oplus (\langle \mathbf{id}, \ K_f (\text{“Dem”}) \rangle \circ \mathbf{pty} \circ \mathbf{chair}). \end{aligned}$$

2. The second step normalizes τ by an SNF-like normalization. Transformation **SNF2** is similar to **SNF**, but rewrites τ into the form,

$$(\alpha \oplus (\mathbf{id} \times \pi_1)) \ \& \ (\beta \oplus (\mathbf{id} \times \pi_2)) \ \& \ \gamma.$$

After these steps, the predicate is easily put into the desired form by setting $\mathbf{q} = \alpha$ and $\mathbf{r} = ((\beta \oplus (\mathbf{id} \times \pi_2)) \ \& \ \gamma)$. This step prepares the predicate for a subsequent firing of rule **magic**.

SNF2 is identical to **SNF** (Figure 4.9) but for the following exceptions:

1. Rather than firing **SimpLits** in Step 1, **SNF2** fires the transformation **SimpLits2** of Figure 4.18.
2. Rather than firing rule **init** in Step 4, **SNF2** fires the rule,

$$\mathbf{p} \xrightarrow{\Rightarrow} (K_p (\mathbf{true}) \oplus (\mathbf{id} \times \pi_1)) \ \& \ (K_p (\mathbf{true}) \oplus (\mathbf{id} \times \pi_2)) \ \& \ K_p (\mathbf{true}) \ \& \ \mathbf{p}.$$

3. Rather than firing **OrderConjs** in Step 6, **SNF2** fires the transformation **OrderConjs2** which fires the rules,

$$\begin{aligned} \mathbf{oc21} : \ (\mathbf{p} \oplus (\mathbf{id} \times \pi_1)) \ \& \ \mathbf{q} \ \& \ \mathbf{r} \ \& \ (\mathbf{s} \oplus (\mathbf{id} \times \pi_1)) & \xrightarrow{\Rightarrow} \ (\mathbf{p} \mid \mathbf{s}) \oplus (\mathbf{id} \times \pi_1) \ \& \ \mathbf{q} \ \& \ \mathbf{r}, \\ \mathbf{oc22} : \ \mathbf{p} \ \& \ (\mathbf{q} \oplus (\mathbf{id} \times \pi_2)) \ \& \ \mathbf{r} \ \& \ (\mathbf{s} \oplus (\mathbf{id} \times \pi_2)) & \xrightarrow{\Rightarrow} \ \mathbf{p} \ \& \ ((\mathbf{q} \mid \mathbf{s}) \oplus \pi_2) \ \& \ \mathbf{r}, \\ \mathbf{oc23} : \ \mathbf{p} \ \& \ \mathbf{q} \ \& \ \mathbf{r} \ \& \ \mathbf{s} & \xrightarrow{\Rightarrow} \ \mathbf{p} \ \& \ \mathbf{q} \ \& \ (\mathbf{r} \ \& \ \mathbf{s}) \end{aligned}$$

instead of rules **oc1**, **oc2** and **oc3** of Figure 4.10.

SimpLits2 adds transformation **Pr2Times** and rules **s18** – **s113** to the rules fired by **SimpLits**. **Pr2Times** converts functions to products ($f \times g$) where possible. Together with the rules of **SimpLits**, rules **s18** – **s113** ensure that predicates on pairs $[a, [b, S]]$ of the form,

$$p = q \oplus \langle f, g \rangle$$

such that f and g are basic functions, are transformed into one of the forms shown below:

TRANSFORMATION `SimpLits2`

USES

`Pr2Times,`

<code>sft : f ◦ (g ◦ h)</code>	<code>⇒</code>	<code>(f ◦ g) ◦ h</code>
<code>s11 : ⟨K_f (x), K_f (y)⟩</code>	<code>⇒</code>	<code>K_f ([x, y]),</code>
<code>s12 : f ◦ K_f (x)</code>	<code>⇒</code>	<code>K_f (f ! x),</code>
<code>s13 : ⟨f, K_f (x)⟩</code>	<code>⇒</code>	<code>⟨id, K_f (x)⟩ ◦ f,</code>
<code>s14 : ⟨K_f (x), f⟩</code>	<code>⇒</code>	<code>⟨K_f (x), id⟩ ◦ f,</code>
<code>s15 : ⟨f ◦ h, g ◦ h⟩</code>	<code>⇒</code>	<code>⟨f, g⟩ ◦ h,</code>
<code>s16 : p ⊕ (f ◦ g)</code>	<code>⇒</code>	<code>p ⊕ f ⊕ g,</code>
<code>s17 : p ⊕ K_f (x)</code>	<code>⇒</code>	<code>K_p (p ? x),</code>
<code>s18 : ⟨f ◦ π₁, g ◦ (id × h)⟩</code>	<code>⇒</code>	<code>⟨f ◦ π₁, g⟩ ◦ (id × h),</code>
<code>s19 : ⟨f ◦ (id × h), g ◦ π₁⟩</code>	<code>⇒</code>	<code>⟨f, g ◦ π₁⟩ ◦ (id × h),</code>
<code>s110 : ⟨f ◦ (h ◦ π₂), g ◦ (id × h)⟩</code>	<code>⇒</code>	<code>⟨f ◦ π₂, g⟩ ◦ (id × h),</code>
<code>s111 : ⟨f ◦ (id × h), g ◦ (h ◦ π₂)⟩</code>	<code>⇒</code>	<code>⟨f, g ◦ π₂⟩ ◦ (id × h),</code>
<code>s112 : ⟨f ◦ (g ◦ π₂), g ◦ π₂⟩</code>	<code>⇒</code>	<code>⟨f ◦ g, h⟩ ◦ π₂,</code>
<code>s113 : ⟨f ◦ π₂, h ◦ (h ◦ π₂)⟩</code>	<code>⇒</code>	<code>⟨f, h ◦ g⟩ ◦ π₂,</code>

BEGIN

```
BU {Pr2Times || s11 || s12 || {{s13 || s14} → REPEAT sft} || s15 || s16 || s17 ||
    s18 || s19 || s110 || s111 || s112 || s113 || REPEAT sft}
```

END

TRANSFORMATION `Pr2Times`

USES

<code>co1 : ⟨f ◦ π₁, g ◦ (h ◦ π₂)⟩</code>	<code>⇒</code>	<code>(f × g) ◦ (id × h),</code>
<code>co2 : ⟨f ◦ (h ◦ π₂), g ◦ π₁⟩</code>	<code>⇒</code>	<code>⟨π₂, π₁⟩ ◦ (f × g) ◦ (id × h),</code>
<code>co3 : ⟨f ◦ (π₁ ◦ π₂), g ◦ (π₂ ◦ π₂)⟩</code>	<code>⇒</code>	<code>(f × g) ◦ π₂,</code>
<code>co4 : ⟨f ◦ (π₂ ◦ π₂), g ◦ (π₁ ◦ π₂)⟩</code>	<code>⇒</code>	<code>⟨π₂, π₁⟩ ◦ (f × g) ◦ π₂,</code>
<code>co5 : ⟨f ◦ π₁, g ◦ π₂⟩</code>	<code>⇒</code>	<code>(f × id) ◦ (id × g),</code>
<code>co6 : ⟨f ◦ π₂, g ◦ π₁⟩</code>	<code>⇒</code>	<code>⟨π₂, π₁⟩ ◦ (f × id) ◦ (id × g),</code>
<code>co7 : ⟨π₁, π₂⟩</code>	<code>⇒</code>	<code>id,</code>
<code>co8 : f ◦ id</code>	<code>⇒</code>	<code>f,</code>
<code>co9 : id ◦ f</code>	<code>⇒</code>	<code>f</code>

BEGIN

```
BU {co1 || co2 || co3 || co4 || co5 || co6 || co7 || co8 || co9}
```

END

Figure 4.18: Transformation `SimpLits2` and its Auxiliary Transformation `Pr2Times`

- $K_p(b)$ (if q ignores its inputs),
- $\bar{p} \oplus \pi_1$ (if q only requires a),
- $\bar{p} \oplus \pi_2$ (if q only requires b and S),
- $\bar{p} \oplus (\mathbf{id} \times \pi_1)$ (if q only requires a and b),
- $\bar{p} \oplus (\mathbf{id} \times \pi_2)$ (if q only requires a and S).

When fired on P_k , rule `co5` transforms the function,

$$\langle \mathbf{chair} \circ \pi_1, \pi_1 \circ \pi_2 \rangle$$

into

$$(\mathbf{chair} \times \mathbf{id}) \circ (\mathbf{id} \times \pi_1).$$

Then, rule `pr1` fires leaving the predicate

$$\mathbf{eq} \oplus (\mathbf{chair} \times \mathbf{id}) \oplus (\mathbf{id} \times \pi_1).$$

When fired on Q_k , rule `co5` transforms the function,

$$\langle \mathbf{terms} \circ \mathbf{chair} \circ \pi_1, \pi_2 \circ \pi_2 \rangle$$

into

$$((\mathbf{terms} \circ \mathbf{chair}) \times \mathbf{id}) \circ (\mathbf{id} \times \pi_2).$$

Then, rule `pr1` fires leaving the predicate

$$\mathbf{gt} \oplus ((\mathbf{terms} \circ \mathbf{chair}) \times \mathbf{id}) \oplus (\mathbf{id} \times \pi_2).$$

All subsequent steps in `SimpLits2` are as in `SimpLits`. Therefore, the the result of firing `SimpLits2` on Q_1 is the query, Q_2 :

```

join (( $\alpha \oplus (\mathbf{id} \times \pi_1)$ ) & (( $\beta \oplus (\mathbf{id} \times \pi_2)$ ) &  $\gamma$ ),  $\pi_1$ ) !
  [MComsk, njoin ( $\mathbf{eq} \oplus (\mathbf{id} \times \mathbf{chair})$ , mems,  $\mathbf{avg} \circ \mathbf{flat}$ ) !
    [iterate ( $K_p(\mathbf{true})$ , chair) ! Coms, Coms]]

```

such that

$$\begin{aligned} \alpha &= \mathbf{eq} \oplus (\mathbf{chair} \times \mathbf{id}), \text{ and} \\ \beta &= \mathbf{gt} \oplus ((\mathbf{terms} \circ \mathbf{chair}) \times \mathbf{id}), \text{ and} \\ \gamma &= K_p(\mathbf{true}). \end{aligned}$$

After SNF2 is fired, rule **sftp** is fired to reassociate the three conjunct join subpredicates,

$$((\alpha \oplus (\mathbf{id} \times \pi_1)) \& (\beta \oplus (\mathbf{id} \times \pi_2))) \& \gamma$$

into

$$(\alpha \oplus (\mathbf{id} \times \pi_1)) \& ((\beta \oplus (\mathbf{id} \times \pi_2)) \& \gamma).$$

This firing prepares the predicate for the firing of rule **magic** in the next step. The result of firing **sftp** on Q_2 is Q_3 :

$$\begin{aligned} & \mathbf{join} ((\mathbf{q} \oplus (\mathbf{id} \times \pi_1)) \& \mathbf{r}, \pi_1) ! \\ & [\mathbf{MComs}_k, \mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times \mathbf{chair}), \mathbf{mems}, \mathbf{avg} \circ \mathbf{flat}) ! \\ & \quad [\mathbf{iterate} (K_p (\mathbf{true}), \mathbf{chair}) ! \mathbf{Coms}, \mathbf{Coms}]] \end{aligned}$$

such that

$$\begin{aligned} \mathbf{q} &= \mathbf{eq} \oplus (\mathbf{chair} \times \mathbf{id}), \text{ and} \\ \mathbf{r} &= ((\mathbf{gt} \oplus ((\mathbf{terms} \circ \mathbf{chair}) \times \mathbf{id})) \oplus (\mathbf{id} \times \pi_2)) \& K_p (\mathbf{true}). \end{aligned}$$

Step 3:

Next, rewrite rule **magic** is fired. This rule introduces the left join argument (A1) into the right-hand side of the join. Firing **magic** makes it possible to restrict the input (A2) to **njoin** to elements that are related by \mathbf{q} to A1. Fired on Q_3 , **magic** leaves Q_4 :

$$\begin{aligned} & \mathbf{join} ((\mathbf{q} \oplus (\mathbf{id} \times \pi_1)) \& \mathbf{r}, \pi_1) ! \\ & [\mathbf{MComs}_k, \mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times \mathbf{chair}), \mathbf{mems}, \mathbf{avg} \circ \mathbf{flat}) ! [\mathbf{CSet}'_k, \mathbf{Coms}]] \end{aligned}$$

or equivalently,

$$\begin{aligned} & \mathbf{join} (P'_k \& Q'_k, \pi_1) ! \\ & [\mathbf{MComs}_k, \mathbf{njoin} (\mathbf{eq} \oplus (\mathbf{id} \times \mathbf{chair}), \mathbf{mems}, \mathbf{avg} \circ \mathbf{flat}) ! [\mathbf{CSet}'_k, \mathbf{Coms}]] \end{aligned}$$

such that

$$\begin{aligned} \mathbf{CSet}'_k &= \mathbf{set} ! (\mathbf{join} (\mathbf{eq} \oplus (\mathbf{chair} \times \mathbf{id}), \pi_2) ! \\ & \quad [\mathbf{MComs}_k, \mathbf{iterate} (K_p (\mathbf{true}), \mathbf{chair}) ! \mathbf{Coms}]), \end{aligned}$$

$$\begin{aligned} \mathbf{MComs}_k &= \mathbf{iterate} (R'_k, \mathbf{id}) ! \mathbf{Coms}, \\ P'_k &= \mathbf{eq} \oplus (\mathbf{chair} \times \mathbf{id}) \oplus (\mathbf{id} \times \pi_1), \text{ and} \\ Q'_k &= \mathbf{gt} \oplus ((\mathbf{terms} \circ \mathbf{chair}) \times \pi_2) \oplus (\mathbf{id} \times \pi_2) \end{aligned}$$

1.	$(\mathbf{id} \times \mathbf{id})$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	\mathbf{id}
2.	$\mathbf{p} \oplus \mathbf{id}$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	\mathbf{p}
3.	$K_p(\mathbf{true}) \oplus \mathbf{f}$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$K_p(\mathbf{true})$
4.	$\mathbf{p} \& K_p(\mathbf{true})$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	\mathbf{p}
5a.	$\mathbf{f} \circ \mathbf{id}$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	\mathbf{f}
5b.	$\mathbf{id} \circ \mathbf{f}$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	\mathbf{f}
6.	$(\mathbf{f} \times \mathbf{g}) \circ (\mathbf{h} \times \mathbf{j})$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$(\mathbf{f} \circ \mathbf{h}) \times (\mathbf{g} \circ \mathbf{j})$
7.	$\mathbf{p} \oplus \mathbf{f} \oplus \mathbf{g}$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$\mathbf{p} \oplus (\mathbf{f} \circ \mathbf{g})$
8.	$\mathbf{set} ! (\mathbf{join}(\mathbf{eq}, \pi_2) ! [\mathbf{A}, \mathbf{B}])$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$\mathbf{set} ! (\mathbf{A} \cap \mathbf{B})$
9.	$\mathbf{join}(\mathbf{p} \oplus (\mathbf{f} \times \mathbf{g}), \pi_2) ! [\mathbf{A}, \mathbf{B}]$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$\mathbf{join}(\mathbf{p} \oplus (\mathbf{id} \times \mathbf{g}), \pi_2) ! [\mathbf{iterate}(K_p(\mathbf{true}), \mathbf{f}) ! \mathbf{A}, \mathbf{B}]$
10.	$\mathbf{iterate}(\mathbf{p}, \mathbf{f}) ! (\mathbf{iterate}(\mathbf{q}, \mathbf{g}) ! \mathbf{A})$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$\mathbf{iterate}(\mathbf{q} \& (\mathbf{p} \oplus \mathbf{g}), \mathbf{f} \circ \mathbf{g}) ! \mathbf{A}$
11.	$(\mathbf{iterate}(\mathbf{p}, \mathbf{f}) ! \mathbf{A}) \cap (\mathbf{iterate}(K_p(\mathbf{true}), \mathbf{f}) ! \mathbf{A})$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$\mathbf{iterate}(\mathbf{p}, \mathbf{f}) ! \mathbf{A}$
12.	$\mathbf{njoin}(\mathbf{p}, \mathbf{f}, \mathbf{g}) ! [\mathbf{set} ! \mathbf{A}, \mathbf{B}]$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$\mathbf{njoin}(\mathbf{p}, \mathbf{f}, \mathbf{g}) ! [\mathbf{A}, \mathbf{B}]$
13.	$\mathbf{iterate}(\mathbf{p}, \mathbf{f}) ! \mathbf{A}$	$\begin{array}{l} \Rightarrow \\ \equiv \end{array}$	$\mathbf{iterate}(K_p(\mathbf{true}), \mathbf{f}) ! (\mathbf{iterate}(\mathbf{p}, \mathbf{id}) ! \mathbf{A})$

Table 4.3: Rewrite Rules Used In SimplifyJoin

Step 4:

Step 4 fires transformation `SimplifyJoin` on the semijoin expression resulting from the previous step. `SimplifyJoin` uses the rules of Table 4.3 to rewrite \mathbf{CSet}'_k into \mathbf{CSet}_k (of Figure 4.16d) as we show below:

- The first rule fired is rule 9, which rewrites \mathbf{CSet}'_k ,

$$\mathbf{set} ! (\mathbf{join}(\mathbf{eq} \oplus (\mathbf{chair} \times \mathbf{id}), \pi_2) ! [\mathbf{MComs}_k, \mathbf{iterate}(K_p(\mathbf{true}), \mathbf{chair}) ! \mathbf{Coms}])$$

to

$$\mathbf{set} ! (\mathbf{join}(\mathbf{eq} \oplus (\mathbf{id} \times \mathbf{id}), \pi_2) ! [\mathbf{iterate}(K_p(\mathbf{true}), \mathbf{chair}) ! \mathbf{MComs}_k, \mathbf{iterate}(K_p(\mathbf{true}), \mathbf{chair}) ! \mathbf{Coms}]).$$

- Firing rules 1 and 2 simplifies the join predicate, leaving

$$\mathbf{set} ! (\mathbf{join}(\mathbf{eq}, \pi_2) ! [\mathbf{iterate}(K_p(\mathbf{true}), \mathbf{chair}) ! \mathbf{MComs}_k, \mathbf{iterate}(K_p(\mathbf{true}), \mathbf{chair}) ! \mathbf{Coms}]).$$

- Expanding for MComs_k and firing rules 10, 3, 4 and 5a, leaves

$$\begin{aligned} & \text{set !} \\ & (\text{join (eq, } \pi_2) \text{ !} \\ & \quad [\text{iterate (} R'_k, \text{ chair) ! Coms, iterate (} K_p (\text{true}), \text{ chair) ! Coms}]). \end{aligned}$$

- Next, rule 8 fires, converting the right semijoin to an intersection. Firing rule 8 leaves:

$$\text{set ! } ((\text{iterate (} R'_k, \text{ chair) ! Coms}) \cap (\text{iterate (} K_p (\text{true}), \text{ chair) ! Coms)).$$

- This expression in turn reduces by firing rule 11 to:

$$\text{set ! (iterate (} R'_k, \text{ chair) ! Coms),$$

which then gets split up by firing rule 13 to:

$$\begin{aligned} & \text{set ! (iterate (} K_p (\text{true}), \text{ chair) ! (iterate (} R'_k, \text{ id) ! Coms))} \\ & = \text{set ! (iterate (} K_p (\text{true}), \text{ chair) ! MComs}_k) \\ & = \text{CSet}_k. \end{aligned}$$

Therefore, after `SimplifyJoin` has finished firing, we are left with the query of Figure 4.16d:

$$\text{join (} P'_k \& Q'_k, \pi_1) \text{ ! [MComs}_k, \text{MTemp}_K]$$

such that MTemp_K is:

$$\text{njoin (eq } \oplus (\text{id} \times \text{chair}), \text{ mems, avg } \circ \text{flat) ! [CSet}_k, \text{Coms]}.$$

4.7 Discussion

4.7.1 The Expressivity of COKO

COKO is still evolving. Our goal is to reach a point with it where we are able to express all of the useful query rewrites that can be expressed with a programming language without compromising the separation of rewrite rules from firing algorithms. To this end, our design process alternates between modifying the language and using it to express complex query rewrites. In this chapter, we have presented some of the rewrites that we have generated with COKO, including `CNF` (exhaustive and non-exhaustive versions), `SNF`, `Pushdown`, `Join-Associate` and `Magic`.

Though COKO is evolving, it is not immature. We believe that COKO already provides most of the useful idioms required to express query rewriting. By combining COKO statements in varying ways, we are able to express such common firing algorithms as

- BU $\{r_1 \parallel \dots \parallel r_n\}$:
fire every rule r_1, \dots, r_n successively on every subtree,
- BU $r_1; \dots; BU r_n$:
fire every rule r_1, \dots, r_n on every successive subtree,
- BU $\{\{\text{REPEAT } r_1\}; \dots; \{\text{REPEAT } r_n\}\}$:
fire every rule r_1, \dots, r_n repeatedly on every successive subtree,
- $S \rightarrow S' \parallel S''$:
execute S and then S' if S succeeds and S'' if S fails, and
- $S \rightarrow$ recursive fire:
execute S exhaustively.

As before, attempts to express transformations drive the design of the language. Provided that we are able to maintain the separation of rewrite rules from firing algorithms, we are prepared to let COKO evolve into a steady and usable state.

4.7.2 The Need for Normalization

The CNF and SNF query rewrites are normalizations: query rewrites that convert expressions into syntactically characterizable (i.e., normal) forms. Normalizations epitomize the kinds of complex query rewrites that cannot be expressed as rewrite rules and that typically get expressed with code.

Normalization gets little attention in the optimizer literature. And yet, normalization can be more complex, expensive and error-prone than the optimizations they precede. (Consider that Kim's erroneous rewrites are normalizations whose normal forms are join queries.) In the context of object-oriented and object-relational databases, normalization assumes even greater importance. Firstly, nested object queries are far more prevalent and can be more deeply nested than relational queries making their normalization more difficult and more urgent. Secondly, because many object databases are built as extensions of existing systems (e.g., object-relational extensions of relational systems), normalization

affords the opportunity to rewrite complex (e.g., object) queries into a series of simpler (e.g., relational) queries that can be posed of the original query engine. (We will see an example of this object \rightarrow relation translation in Chapter 6.)

We have shown with two examples (CNF and SNF) that COKO is capable of expressing complex normalizations that typically get expressed only with code. For both normalizations, we were able to show not only *correctness*, but also prove that the firing algorithms for these transformations did as they were intended. Neither of these results is straightforward when the normalizations are expressed with code, even when the normalizations themselves have more straightforward expression with code.⁵ Therefore, the correctness results arising from the COKO-KOLA approach come at a complexity cost for expressing certain rewrites. In designing future versions of COKO, our goal will be to make firing algorithms simpler to formulate, in order to lower this cost.

4.8 Chapter Summary

In this chapter, we introduced a language (COKO) for defining *transformations*: complex query rewrites for rule-based optimizers. COKO transformations generalize rewrite rules. Like rules, they can be fired and can succeed or fail as a result. But because they are expressed algorithmically, they are able to express many rewrites (such as normalizations) that rewrite rules cannot.

A COKO transformation consists of a set of rewrite rules and a firing algorithm specifying how they are fired. The separation of rewriting (expressed with rewrite rules) and firing control (expressed with firing algorithms) makes it possible to express complex and efficient rewrites that can still (because rewrite rules are over KOLA queries) be verified with a theorem prover.

COKO transformations can be made efficient and expressive. The language for firing algorithms includes the kinds of operators that are most useful for describing rewrites. These include explicit rule firing, traversal control, selective firing and conditional firing. We demonstrated the efficiency benefits of firing algorithms with an example COKO transformation that converts predicates to CNF. We demonstrated the expressivity of COKO with numerous examples that typically do not get expressed with declarative rewrite rules. These examples included a complex normalization (SNF) and three complex rewrites that

⁵SNF for example, is straightforward to express with code that 1) converts a binary predicate to CNF, and 2) traces the origins of all attributes appearing in each conjunct to see which conjuncts involve attributes only from the first input, second input or both.

depend on it (predicate-pushdown, join-reordering and Magic-Sets rewrites).

COKO extends and generalizes KOLA. Whereas KOLA used a modular approach to build queries from functions, COKO uses a modular approach to build complex query rewrites from rewrite rules. This modular approach facilitates the verification of query rewriters.

Chapter 5

Semantic Query Rewrites

Rewrite rules are inherently simple and as such, are not expressive enough to specify many query rewrites. In the previous chapter, we considered how to express complex query rewrites that are too *general* to express with rewrite rules. The CNF rewrite for example, cannot be expressed as a rewrite rule because no pair of patterns is both general enough to match all Boolean expressions and specific enough to express their CNF equivalents. To address this issue, we introduced the language COKO. COKO transformations express complex query rewrites using sets of KOLA rewrite rules accompanied by firing algorithms.

In this chapter, we consider the complementary issue of expressing query rewrites that are too *specific* for rewrite rules. To illustrate, consider a query rewrite that transforms a query that performs duplicate elimination into one that does not. The correctness of this rewrite depends on duplicate elimination being redundant, as it is when performed on the result of a subquery that projects on a key. A rewrite rule expressing this rewrite for SQL queries is shown below.

$$\begin{array}{ccc} \text{SELECT DISTINCT } x.f & & \text{SELECT } x.f \\ \text{FROM } x \text{ IN } A & \Rightarrow & \text{FROM } x \text{ IN } A \\ \text{WHERE } p & & \text{WHERE } p \end{array}$$

This rule must be qualified by additional restrictions that ensure that attributes matching f are keys and collections matching A are sets. Any query that matches the head pattern of this rule but does not satisfy these additional conditions could have its semantics (specifically, its element counts) changed as a result of rewriting. Semantic conditions such as those identifying f as a key and A as a set cannot be expressed with patterns. Therefore, query rewrites whose correctness depends on semantic conditions such as these cannot be expressed solely with rewrite rules.

As with complex query rewrites, existing rule-based systems address this expressivity issue by replacing or supplementing rewrite rules with code. Whereas complex query rewrites use code to manipulate matched expressions in ways that cannot be expressed with patterns, semantic query rewrites use code to test semantic conditions of expressions that successfully unify. For example, the SQL transformation above that eliminates duplicate removal would be expressed in Starburst [79] with C code that examined annotations of the underlying query representation (QGM) to decide if a matched attribute was a key and if a matched collection was a set.

This chapter proposes an alternative approach for expressing semantic query rewrites that is consistent with our goal of making query rewriters verifiable with a theorem prover. As with COKO, this work builds upon the KOLA work introduced in Chapter 3. We add two new kinds of rules to the COKO-KOLA framework:

- *Conditional rewrite rules*, and
- *Inference rules*.

Conditional rewrite rules resemble (unconditional) rewrite rules, except that when they are fired, the match of the rule’s head pattern to a query expression is followed by analysis to see if certain conditions hold of identified subexpressions. Inference rules tell the optimizer how to decide if these conditions hold.

The contributions of the work presented in this chapter are:

1. *Verifiable Semantic Query Rewrites*: In keeping with our goal outlined in Chapter 1, all query rewrites specifiable with inference and conditional rewrite rules are verifiable with a theorem prover.
2. *Use of Inference Rules to Infer Query Semantics*: This work is unique in its use of inference rules to specify semantic conditions. This technique separates the rules that depend on semantic conditions (conditional rewrite rules) from the decision-making process that decides if these semantic conditions hold. Our approach is distinct from that of existing rule-based systems that embed decision-making code within the rule that may or may not fire as a result.

The use of inference rules to specify semantic conditions makes optimizers extensible in ways that standard rule-based optimizers are not. By modifying a set of rewrite rules used by an optimizer, one can change *how* a query gets rewritten. On the other hand, by

modifying a set of inference rules used by an optimizer, one can change *when* rewrite rules predicated on inferred conditions get fired.

The rest of this chapter proceeds as follows. In Section 5.1, we motivate this work by presenting queries over the Thomas database, and showing how the semantics of their data functions (in this case, their injectivity) can be inferred and exploited for rewriting. In this section, we also show how the conditional rewrite rules and inference rules that specify these semantic rewrites would be expressed within COKO-KOLA. Section 5.2 presents a second example of a semantic condition (*predicate strength*) that can be used as a condition for many useful semantic rewrites. Section 5.3 describes how our COKO compiler was modified to account for inference and conditional rewrite rules. Section 5.4 discusses issues that arose in the design and implementation of this compiler extension, and a chapter summary follows in Section 5.5.

The semantic query rewrites presented in this chapter are not new. The injectivity-based rewrites of Section 5.1 have been discussed in numerous texts (e.g., Ullman’s introductory text on databases [95]). The predicate strength rewrites of Section 5.2 are similar to the predicate “move-around” rewrites introduced by Levy, et al. [71]. Our work is unique in its declarative expression of these rewrites that makes them verifiable with a theorem prover. Further, the use of inference rules to define these conditions makes rule-based query rewriters extensible in ways that have not been proposed before.

5.1 Example 1: Injectivity

Figures 5.1a and 5.1b show two simple OQL queries over the Thomas database. The “Major Cities” query (Figure 5.1a) queries a set of House Representatives (**HReps**) applying the *path expression*, `x.reps.lgst_cit`, to each. The result of this query is the collection of cities that are the largest of those located in the districts represented by House Representatives in **HReps**, with duplicate cities removed.¹ The “Mayors” query (Figure 5.1b) also queries a set of House Representatives. For each Representative, this query returns the mayors of major cities located in the district that the Representative represents (this time, with duplicate mayor collections removed from the result).

The “Major Cities” query and the “Mayors” query can be evaluated in similar ways: by first retrieving House Representatives in **HReps**, applying a data function to each to generate

¹As we mentioned in Chapter 2, we make the simplifying assumption that cities are located in only one Congressional district. While this may not be the case in practice, we can enforce this assumption by assigning every city to that district where a majority of its inhabitants reside.

<pre>SELECT DISTINCT <i>x</i>.reps.lgst_cit FROM <i>x</i> IN HReps</pre>	<pre>SELECT DISTINCT (SELECT <i>d</i>.mayor FROM <i>d</i> IN <i>x</i>.reps.cities) FROM <i>x</i> IN HReps</pre>
(a)	(b)
↓	↓
<pre>SELECT <i>x</i>.reps.lgst_cit FROM <i>x</i> IN HReps</pre>	<pre>SELECT (SELECT <i>d</i>.mayor FROM <i>d</i> IN <i>x</i>.reps.cities) FROM <i>x</i> IN HReps</pre>

Figure 5.1: The “Major Cities” (a) and “Mayors” (b) Queries Before and After Rewriting

an intermediate collection, and then eliminating duplicates. For the “Major Cities” query, duplicates are cities with the same OID. For the “Mayors” query, duplicates are collections with the same members.

Duplicate elimination is expensive, requiring an initial sort or hash of the contents of a collection. But for both the “Major Cities” query and the “Mayors” query, duplicate elimination is unnecessary. Because of the *semantics* of their data functions, both queries generate intermediate collections that already are free of duplicates. No Congressional district is represented by more than one House Representative, and no city is found in more than one district.² Therefore, the “Major Cities” query inserts a distinct city into its intermediate result for each distinct House Representative. As `HReps` has no duplicates, neither will this collection of cities. Similarly, every district has a unique collection of major cities and every city has a unique mayor. Therefore, the collections of mayors generated as an intermediate result of the “Mayors” query will not require duplicate elimination.

Rewritten versions of these queries that do not perform duplicate elimination are shown below the original queries. The query rewrite resulting in these queries is similar to the relational query rewrite presented at the onset of this chapter. However, this rewrite is more general in that it can be applied to queries that cannot be expressed as relational queries (such as object queries with path expressions or subqueries as data functions). For the object version of this rewrite to be correct, a query’s data function need not be a key attribute but any *injective* function (of which keys comprise a special case). And whereas

²Again, according to our simplifying assumption.

$$\begin{array}{c}
\mathbf{set} \ ! \ (\mathbf{iterate} \ (K_p \ (\mathbf{true}), \ f) \ ! \ \mathbf{HReps}) \\
\text{s.t.: } f = \mathbf{lgst_cit} \circ \mathbf{reps} \\
\downarrow \\
\mathbf{iterate} \ (K_p \ (\mathbf{true}), \ f) \ ! \ \mathbf{HReps} \\
\text{s.t.: } f = \mathbf{lgst_cit} \circ \mathbf{reps}
\end{array}$$

KOLA Equivalentents of the “Major Cities” Query (Before and After Rewriting)

$$\begin{array}{c}
\mathbf{set} \ ! \ (\mathbf{iterate} \ (K_p \ (\mathbf{true}), \ f) \ ! \ \mathbf{HReps}) \\
\text{s.t.: } f = \mathbf{iterate} \ (K_p \ (\mathbf{true}), \ \mathbf{mayor}) \circ \mathbf{cities} \circ \mathbf{reps} \\
\downarrow \\
\mathbf{iterate} \ (K_p \ (\mathbf{true}), \ f) \ ! \ \mathbf{HReps} \\
\text{s.t.: } f = \mathbf{iterate} \ (K_p \ (\mathbf{true}), \ \mathbf{mayor}) \circ \mathbf{cities} \circ \mathbf{reps}
\end{array}$$

KOLA Equivalentents of the “Mayors” Query (Before and After Rewriting)

Figure 5.2: KOLA Translations of Figures 5.1a and 5.1b

a relational query rewriter need only consult metadata files (e.g., the database schema) to determine whether a query’s data function is a key, this approach is inadequate for deciding the injectivity of functions that might appear in object queries. The number of injective path expressions alone might be very large and even infinite. (Aside from $x.\mathbf{reps.lgst_cit}$, other injective path expressions on House Representatives are $x.\mathbf{name}$, $x.\mathbf{reps}$, $x.\mathbf{reps.cities}$, $x.\mathbf{reps.lgst_cit.mayor}$ and so on.) Thus, it is unlikely that metadata files can be scaled to keep track of all injective data functions, and inference is required instead.

Figure 5.2 shows KOLA equivalentents of the “Major Cities” query and “Mayors” query both before and after the application of a semantic query rewrite to remove duplicate elimination (**set**). The KOLA translations of the data functions (f) for these two queries are:

- $\mathbf{lgst_cit} \circ \mathbf{reps}$, equivalent to the “Major Cities” query path expression,

$$x.\mathbf{reps.lgst_cit},$$

and

- **iterate** (K_p (`true`), `mayor`) \circ `cities` \circ `reps`, equivalent to the “Mayors” query sub-query,

```
SELECT d.mayor
FROM d IN x.reps.cities.
```

5.1.1 Expressing Semantic Query Rewrites in COKO-KOLA

To express semantic rewrites in COKO, we introduce two new kinds of *declarative* rules to the language:

- **Conditional Rewrite Rules** resemble (unconditional) rewrite rules, but can include semantic conditions on the subexpressions of matched query expressions. These conditions can, for example, indicate that a given KOLA function must be injective or that a given KOLA collection must be a set. Like unconditional rules, conditional rewrite rules can be fired within COKO transformations.
- **Inference Rules** specify how semantic conditions can be inferred of KOLA functions, predicates, objects and collections. A *property* is a set of rules that can be used to infer the same condition. We have modified our COKO compiler to compile properties into code that gets executed during rule firing.

Conditional Rewrite Rules in COKO

Conditional rewrite rules have the form,

$$C :: L \rightrightarrows R$$

such that L and R are patterns of KOLA expressions (i.e., such that $L \rightrightarrows R$ is an unconditional rewrite rule), and C is a set of semantic conditions that must hold of various subexpressions of query expressions that unify with L . Figure 5.3 shows two example conditional rewrite rules that eliminate redundant duplicate elimination. `Inj1` can be fired on either the “Major Cities” query or the “Mayors” query. (`Inj2` will be discussed in Section 5.1.3.) The head pattern of this rule matches queries that remove duplicates (with `set`) from the results of `iterate` queries. The rule’s body pattern shows the same query as the rule’s head pattern, but with the invocation of `set` removed. The conditions of the rule state that the rule is correct provided that function `f` is injective and collection `A` is a set. Therefore, conditional rewrite rules specify query rewrites that should only be fired if certain conditions hold.

$$\begin{aligned}
\text{inj1: } & \text{is_inj}(f), \text{is_set}(A) \quad :: \\
& \text{set ! (iterate}(p, f) ! A) \xrightarrow{\equiv} \text{iterate}(p, f) ! A \\
\text{inj2: } & \text{is_inj}(f), \text{is_set}(g ! _) \quad :: \\
& \text{set} \circ \text{iterate}(p, f) \circ g \xrightarrow{\equiv} \text{iterate}(p, f) \circ g
\end{aligned}$$

Figure 5.3: Conditional Rewrite Rules to Eliminate Redundant Duplicate Elimination

Inference Rules (Properties) in COKO

To perform a query rewrite that removes redundant duplicate elimination, a rewriter must determine that a query’s data function is injective and that a collection is a set. Like most semantic properties of functions, injectivity is undecidable in general. Determination of whether or not a given collection is a set could be made at runtime, but this requires processing (sorting the collection and scanning for duplicates) that the conditional rewrite rules of Figure 5.3 are intended to avoid. Therefore, it is not realistic to assume that a complete reasoning system for user-defined properties is possible or even desirable. But with guidance, a rewriter can infer that properties such as injectivity hold in some cases. Incomplete inference is preferable to not performing inference at all for at least in these cases, rewriting might improve the evaluation of the query. Therefore, we care about soundness and not about completeness in inferring semantic properties.

Guidance comes from two sources:

- *metadata* provided by the user that declares object types, integrity (including key) constraints, etc., and
- *inference rules* defined by the optimizer developer.

For example, a user might state that a particular attribute of a type is a key.³ As well, a user might identify the *types* of objects that are globally named, thus identifying some named collections as sets and others as bags. The depth and accuracy of the information supplied by the user determines the quality and correctness of rewriting.

³In the relational world, a key is typically thought of as a property of a collection (i.e., a relation) rather than a property of a type. However, relations are often used to represent the extent of a type and in this case the association of key with type is natural. Further, equality definitions for types must be defined in terms of keys for sets of objects of that type to be well-behaved. (See our DBPL ’95 paper [23] for the argument as to why this is so.) Therefore, keys can be thought of as properties of types and not just collections.

The inference rules supplied to the optimizer enable inference of conditions that are not explicitly stated. For example, a user might identify `lgst_cit` and `reps` as being key attributes for sets of Congressional districts and House Representatives respectively, but is unlikely to identify longer path expressions (such as `x.reps.lgst_cit`) as keys given that there can be too many path expressions to anticipate and consider. But an inference rule can be used to infer that a path expression is injective given that each of the attributes in its path is a key. Or, it can be used to infer that a tuple construction is injective if any of its fields is derived from a key.

A rewriter constructed using the COKO compiler could infer that some functions are injective according to the *inference rules* defined in the *property* definitions of Figure 5.4a. Inference rules have the form,

$$body \implies head$$

(or just *head* which states a *fact* that is unconditionally true). The *head* of an inference rule names a condition (e.g., `is_inj (f)`) to infer. A condition is an uninterpreted logical relation whose arguments can be either KOLA expressions or pattern variables (such as `f`) that implicitly are universally quantified. The *body* of an inference rule is a logical sentence (i.e., consisting of conjunctions (\wedge), disjunctions (\vee) and negations (\neg) of terms), whose terms are conditions that must be satisfied to infer the head condition. To illustrate, the rules of Figure 5.4a should be interpreted as follows:

1. the identity (`id`) function is injective,
2. a KOLA function is injective if it is a key (`is_key` is a built-in property generated from metadata specific to a database schema),
3. KOLA function `f o g` is injective if both `f` and `g` are injective,
4. KOLA function `<f, g>` is injective if either `f` or `g` is injective, and
5. KOLA query function `iterate (Kp (true), f)` is injective if `f` is injective.

Figure 5.4b shows a COKO property definition to help decide if collections are sets. The rules contained in this property state that:

1. the result of invoking the function, `set`, on any collection is a set (as with COKO's GIVEN statement, a “don't care” expression (`_`) in a pattern denotes a variable whose binding is irrelevant),
2. a collection `A` is a set if its declared type is a set,

```

PROPERTY Injective
BEGIN
  is_inj (id). (1)
  is_key (f)  $\implies$  is_inj (f) (2)
  is_inj (f)  $\wedge$  is_inj (g)  $\implies$  is_inj (f  $\circ$  g) (3)
  is_inj (f)  $\vee$  is_inj (g)  $\implies$  is_inj ( $\langle$ f, g $\rangle$ ). (4)
  is_inj (f)  $\implies$  is_inj (iterate ( $K_p$  (true), f)) (5)
END

```

(a)

```

PROPERTY Is_Set
BEGIN
  is_set (set ! _). (1)
  is_type (A, set (_))  $\implies$  is_set (A). (2)
  is_type (m, _, set(_))  $\implies$  is_set (m ! _). (3)
  is_set (A)  $\wedge$  is_set (B)  $\implies$  is_set (A  $\times$  B). (4)
  is_set (A)  $\vee$  is_set (B)  $\implies$  is_set (A  $\cap$  B). (5)
  is_set (A)  $\implies$  is_set (A - B). (6)
END

```

(b)

Figure 5.4: Properties Defining Inference Rules for Injective Functions (a) and Sets (b)

3. a method `m` whose range type is a set returns a set when invoked,
4. the Cartesian product of two sets is a set,
5. the intersection of any two collections, of which one is a set, is a set, and
6. taking the difference of any collection from a set returns a set.

Provided that a query rewriter can discern from metadata that `reps` and `lgst_cit` are keys and that `HReps` is a set of House Representatives, Rules 2, 3 and 5 of Figure 5.4a, and Rule 2 of Figure 5.4b are sufficient to decide that the “Major Cities” query and “Mayors” query can be safely rewritten.

5.1.2 Correctness

Semantic query rewrites expressed in COKO can be verified with LP. Correctness proofs require that all conditions that appear in a conditional rewrite rule be given a formal

iterate (C_p (**eq**, “NSF”) \oplus **topic**, f) ! **HouseRes**
 s.t. $f = \langle \text{name}, \text{set} \circ \text{iterate} (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) \circ \text{spons} \rangle$

Figure 5.5: NSF_{1k} : The “NSF” Query of Figure 2.4 expressed in KOLA

specification. For example, **is_inj** would be defined in Larch with the axiom:

$$\forall f : \text{fun } [T, U]$$

$$\text{is_inj} (f) = \forall x, y : T ((f ! x) == (f ! y)) \Rightarrow (x == y)$$

Condition **is_set** is defined by the axiom:

$$\forall A : \text{bag } [T] (\text{is_set} (A) == \forall x : T \neg(x \in (A - x))).$$

Once formally specified, the inference rules that infer these conditions and the conditional rewrite rules that use them are straightforward to verify. A conditional rewrite rule,

$$C :: L \vec{=} R$$

is correct if C implies that $L = R$:

$$C \Rightarrow (L == R).$$

An inference rule, $B \Rightarrow H$ is correct if the conditions in the body of the rule (B) imply the condition in the head of the rule (i.e., if $B \Rightarrow H$). The inference rules and conditional rewrite rules presented in this section were verified with the LP theorem prover scripts of Appendix B.5.

5.1.3 Revisiting the “NSF” Query of Chapter 2

Figure 5.5 shows the KOLA equivalent of the “NSF” query of Figure 2.4. It might be remembered that this query associates the name of every House resolution concerning the NSF with the set of universities that are largest in the regions represented by one of the resolution’s sponsors.

As with the “Major Cities” and “Mayors” queries, the duplicate elimination performed in the data function of this query is unnecessary. That is, the subfunction,

$$\text{set} \circ \text{iterate} (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) \circ \text{spons}$$

can be rewritten to

$$\text{iterate} (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) \circ \text{spons}.$$

This rewrite requires the inference rules of Figure 5.4 along with the conditional rewrite rule, `inj2` of Figure 5.3. In particular, because `reps` is a key for any set of House Representatives, and `lgst_cit` is a key for any set of Congressional districts, by inference rule (3) of Figure 5.4a,

$$\text{lgst_cit} \circ \text{reps}$$

is an injective function. Also, the schema of Table 2.1 indicates that when applied to a House resolution, `spons` returns a set of House Representatives. Therefore, the conditions guarding `inj2` are satisfied by this query.

Rule `inj2` resembles `inj1`, but is defined on compositions rather than invocations of functions. That is, `inj2` rewrites a composition of functions, $(\text{set} \circ f)$ to f unlike `inj1`, which rewrites an invocation of functions $(\text{set} ! (f ! x))$ to $(f ! x)$. The need for two rules reflects the fact that query expressions can denote collections or data functions (in the case of nested queries). `Inj1` gets fired on query expressions denoting collections, as in the “Major Cities” and “Mayors” queries. `Inj2` gets fired on query expressions denoting functions, as in the “NSF” query.⁴

5.1.4 More Uses for Injectivity

Another conditional rewrite rule conditioned on the injectivity of a function is shown below:

$$\begin{aligned} \text{is_inj}(\mathbf{f}) :: \\ \text{iterate}(\mathbf{p}, \mathbf{f}) ! (\mathbf{A} \cap \mathbf{B}) \equiv (\text{iterate}(\mathbf{p}, \mathbf{f}) ! \mathbf{A}) \cap (\text{iterate}(\mathbf{p}, \mathbf{f}) ! \mathbf{B}). \end{aligned}$$

Intersection is typically implemented with joins. Thus, this rule effectively pushes selections (`p`) and projections (`f`) past joins. Function `f` must be injective for the rewrite to be correct, for if it is not, then the query that results from firing this rule might return more answers than the original query. (For example, if `f` is the noninjective squaring function, `A` contains 3 but not -3, and `B` contains -3 but not 3, then the query resulting from firing this rule may include 9 in its result whereas the original query will not.)

If `HReps2` is another collection of House Representatives, then this rule could be used with the inference rules described earlier to rewrite a query that returns the largest cities of all districts represented by House Representatives in both `HReps` and `HReps2` who have served at least 5 terms,

$$\text{iterate}(\mathbf{C}_p(\text{lt}, 5) \oplus \text{terms}, \text{lgst_cit} \circ \text{reps}) ! (\text{HReps} \cap \text{HReps}_2)$$

⁴If translation into KOLA translates **all** expressions into functions, then only rule `inj2` is necessary. In fact, our OQL \rightarrow KOLA translator translates all KOLA expressions into functions or predicates as we show in Chapter 6.

into the equivalent query,

$$\begin{aligned} & (\text{iterate } (C_p \text{ (lt, 5)} \oplus \text{terms, lgst_cit} \circ \text{reps}) ! \text{HReps}) \\ & \quad \cap \\ & (\text{iterate } (C_p \text{ (lt, 5)} \oplus \text{terms, lgst_cit} \circ \text{reps}) ! \text{HReps}_2). \end{aligned}$$

The initial query first takes a potentially expensive intersection of collections of House Representatives before filtering the result for those who have served more than 5 terms. The transformed version of this query filters the collections of House Representatives for their senior members before performing the intersection of the presumably smaller collections that result.

5.2 Example 2: Predicate Strength

In this section, we show another example of a condition (this time concerning predicates rather than functions) whose inference enables a number of useful query rewrites. *Predicate strength* is unlike injectivity in that it holds of two predicates rather than of individual functions. A predicate p is “stronger” than a predicate q ($\text{is_stronger}(p, q)$) if p always implies q . Predicate strength is specified in Larch with the following axiom:

$$\begin{aligned} & \forall p, q : \text{pred } [T] \\ & \text{is_stronger}(p, q) = (\forall x : T (p ? x \Rightarrow q ? x)). \end{aligned}$$

As with the injectivity examples, the query rewrites presented in this section are not new — many are implemented in commercial database systems and some were proposed in the context of relations by Levy, et al. in [71]. What is new is their expression with declarative rules that simplifies their verification and extension.

5.2.1 Some Rewrite Rules Conditioned on Predicate Strength

Predicate strength is used as a condition for two kinds of rewrite rules:

- If p is stronger than q and a query requires that both p and q be invoked on some object, x , then the query can be rewritten to one that only invokes p . This rewrite is advantageous in certain circumstances because it saves the cost of invoking q .
- If p is stronger than q and a query requires that p be invoked on some object, x , then the query can be rewritten to one that invokes both p and q . This rewrite is advantageous in cases where q is much cheaper to invoke than p , and therefore invoking q before invoking p limits the objects on which p must be invoked.

```

str1: is_stronger (p, q) :: (p & q)  $\overset{\rightarrow}{\equiv}$  p
str2: is_stronger (p, q) :: p  $\overset{\rightarrow}{\equiv}$  (p & q)
str3: is_stronger (p, q) :: forall (q) ? (iterate (p, id) ! _)  $\overset{\rightarrow}{\equiv}$  true
str4: is_stronger (p, q) :: exists (q) ? (iterate (p, id) ! A)  $\overset{\rightarrow}{\equiv}$  exists (p) ? A
str5: is_stronger (p, q) :: forall (q) ? (join (p, id) ! [_, _])  $\overset{\rightarrow}{\equiv}$  true

```

Figure 5.6: Rewrite Rules Conditioned on Predicate Strength

```

PROPERTY is_stronger
USES is_inj
BEGIN
is_stronger (p, p). (1)
is_stronger ((eq ⊕ (f × g)) & (p ⊕ f ⊕ π1), p ⊕ g ⊕ π2). (2)
is_stronger ((eq ⊕ (f × g)) & (p ⊕ g ⊕ π2), p ⊕ f ⊕ π1). (3)
is_stronger (eq ⊕ (f × f), eq ⊕ ((g ∘ f) × (g ∘ f))). (4)
is_stronger (p, q) ∧ is_stronger (p', q')  $\implies$  is_stronger (p & p', q & q'). (5)
is_stronger (p, r) ∨ is_stronger (q, r)  $\implies$  is_stronger (p & q, r). (6)
is_inj (f)  $\implies$  is_stronger (eq ⊕ (f × f), eq ⊕ (g × g)). (7)
END

```

Figure 5.7: A COKO Property for Predicate Strength

Figure 5.6 shows rewrite rules conditioned on predicate strength. Rule **str1** says that if p is stronger than q , then the conjunction of p and q can be rewritten to p . Rule **str2** is the *inverse* of rule (1). Rules **str3**, **str4** and **str5** state that quantification with a weaker predicate over the result of filtering a collection with a stronger predicate can be simplified to avoid traversing the collection at all (Rules **str3** and **str5**) or to quantify over an unfiltered collection (Rule **str4**).

5.2.2 A COKO Property for Predicate Strength

Figure 5.7 shows a COKO property with inference rules for inferring predicate strength. Rule (1) states that any predicate is stronger than itself. Rule (2) states that if

$$f ! x == g ! y,$$

and predicate p is known to be true of $(f ! x)$, then p must also be true of $(g ! y)$. Rule (3) similarly infers that p is true of $(f ! x)$ if p is true of $(g ! y)$ and $(f ! x == g ! y)$. Rule (4) states that equality of partial path expressions implies equality on full path expressions. That is:

$$\begin{aligned} x.a_1 \dots a_i = y.a_1 \dots a_i &\implies \\ x.a_1 \dots a_i \dots a_n = y.a_1 \dots a_i \dots a_n. \end{aligned}$$

Rules (5) and (6) show how predicate strength can be inferred of predicate conjuncts. Rule (7) uses the injectivity property described earlier to say that equality of keys implies equality of all other attributes.

5.2.3 Example Uses of Predicate Strength

Below we show some example OQL queries whose KOLA equivalents can be rewritten using the conditional rewrite rules of Figure 5.6 and the the inference rules of Figure 5.7.

Example 1: The OQL predicate expression below applies a universally quantified predicate to the result of a subquery. The subquery performs a join of Senator collections, `Sens` and `Sens2` returning a collection of Senator pairs representing the same state. `FOR ALL` returns true if the largest cities of the states represented by each pair of Senators is the same.

$$\text{FOR ALL } y \text{ IN } \left(\begin{array}{l} \text{SELECT STRUCT (one : s1, two : s2)} \\ \text{FROM s1 IN Sens, s2 IN Sens}_2 \\ \text{WHERE s1.reps == s2.reps} \end{array} \right) :$$

$$y.one.reps.lgst_cit == y.two.reps.lgst_cit.$$

Because all pairs of Senators resulting from the subquery represent the same state, the largest cities of the states represented by the pairs of Senators will also be the same. Therefore, this complex expression can be transformed into the constant, `true`.

Expressed over KOLA, this query rewrite transforms the predicate invocation,

$$\begin{aligned} &\mathbf{fa} \left(\mathbf{eq} \oplus \left((\mathbf{lgst_cit} \circ \mathbf{reps}) \times (\mathbf{lgst_cit} \circ \mathbf{reps}) \right) \right) ? \\ &\left(\mathbf{join} \left(\mathbf{eq} \oplus (\mathbf{reps} \times \mathbf{reps}), \mathbf{id} \right) ! [\mathbf{Sens}, \mathbf{Sens}_2] \right) \end{aligned}$$

to the constant `true`. This rewrite is captured by the conditional rewrite rule, `str5` of Figure 5.6 and uses inference rule (3) of Figure 5.7.

Example 2: Whereas the previous example used predicate strength to avoid invoking predicates unnecessarily, the following examples *add* predicates to queries to make them more efficient to evaluate. These examples evoke the spirit of “predicate move-around” rewrites [71].

The OQL query below joins House Representatives from collections `HReps` and `HReps2` who have served the same number of terms such that the House Representative from `HReps` has served more than 5 terms. As this query stands, it likely would be evaluated by first filtering House Representatives in `HReps` to include only those who have served more than 5 terms, and then joining this result with `HReps2`.

```
SELECT *
FROM h1 IN HReps, h2 IN HReps2
WHERE (h1.terms > 5) AND (h1.terms == h2.terms)
```

A better form of this query introduces a new predicate (`h2.terms > 5`) on House Representatives in `HReps2`:

```
SELECT *
FROM h1 IN HReps, h2 IN HReps2
WHERE (h1.terms > 5) AND (h1.terms == h2.terms) AND (h2.terms > 5)
```

The addition of this predicate does not change the semantics of the query, as any House Representatives from `HReps2` that appear in the original query result will have served more than 5 terms because they will have served the same number of terms as some House Representative in `HReps` who has served more than 5 terms. Put another way, this query rewrite is correct because the predicate,

$$(h1.terms > 5) \text{ AND } (h1.terms == h2.terms)$$

is stronger than the predicate, `h2.terms > 5`. This rewrite is advantageous as it makes it likely that *both* `HReps` and `HReps2` will be filtered for their senior House Representatives, before being submitted as inputs to the join.

The KOLA equivalents of these two queries are shown below. The first query would be expressed in KOLA as,

$$\text{join } (\rho, \text{id}) ! [\text{HReps}, \text{HReps}_k]$$

such that ρ is:

$$(\text{eq} \oplus (\text{terms} \times \text{terms})) \& (\mathbf{C}_p (\text{lt}, 5) \oplus \text{terms} \oplus \pi_1).$$

The second query is

$$\mathbf{join} (\rho \ \& \ \tau, \mathbf{id}) ! [\mathbf{HReps}, \mathbf{HReps}_2]$$

such that τ is:

$$\mathbf{C}_p (\mathbf{lt}, 5) \oplus \mathbf{terms} \oplus \pi_2.$$

The transformation of ρ to $\rho \ \& \ \tau$ is justified by rewrite rule **str2** of Figure 5.6 with p set to ρ and q set to τ . That p is stronger than q is justified by inference rule (2) of Figure 5.7 (setting p to $\mathbf{C}_p (\mathbf{lt}, 5)$ and f and g to **terms**).

Example 3: Predicate strength rules can be used to generate *new* predicates and not just to duplicate existing ones as the following example shows. The query below pairs House Representatives in **HReps** who represent Congressional districts whose largest cities have more than 100 000 people, with mayors in **Mays** who are the mayors of those cities:

```
SELECT *
FROM h IN HReps, m IN Mays
WHERE (h.reps.lgst_cit.popn > 100K) AND (h.reps.lgst_cit == m.city)
```

The KOLA equivalent to this query is, $\mathbf{join} ((\rho \oplus \gamma \oplus \pi_1) \ \& \ \tau, \mathbf{id}) ! [\mathbf{HReps}, \mathbf{Mays}]$ such that

$$\begin{aligned} \rho &= \mathbf{C}_p (\mathbf{lt}, 100K) \oplus \mathbf{popn}, \\ \gamma &= \mathbf{lgst_cit} \circ \mathbf{reps}, \text{ and} \\ \tau &= \mathbf{eq} \oplus (\gamma \times \mathbf{city}). \end{aligned}$$

Rule (2) of Figure 5.7 can be used to generate a **new** predicate that can filter the mayors that participate in the join. Specifically, by setting f to γ , g to **city** and p to ρ , the new predicate,

$$\mathbf{C}_p (\mathbf{lt}, 100K) \oplus \mathbf{popn} \oplus \mathbf{city} \oplus \pi_2$$

can be determined to be weaker than

$$(\rho \oplus \gamma \oplus \pi_1) \ \& \ \tau.$$

Thus, applying rewrite rule (2) of Figure 5.6 leaves a query that would be expressed in OQL as:

```
SELECT *
FROM h IN HReps, m IN Mays
WHERE (h.reps.lgst_cit.popn > 100K) AND
      (h.reps.lgst_cit == m.city) AND
      (m.city.popn > 100K)
```

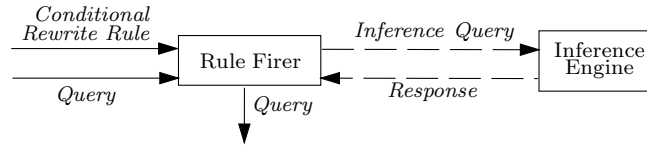


Figure 5.8: A Conditional Rewrite Rule Firer

such that $m.\text{city.popn} > 100K$ is a *new* predicate and not just a copy of a predicate that appeared elsewhere in the original query. If the number of mayors who serve cities with populations over 100 000 is small, or if mayors are indexed on the populations of their cities, then this rewrite is likely to make the query more efficient to evaluate.

5.3 Implementation

In this section, we show how both conditional rewrite rules and properties (inference rules) are processed in our implementation.

5.3.1 Implementation Overview

A key component of a rule-based query rewriter is a *rule firer*, which accepts representations of a query and a rule as inputs and produces a new query representation (resulting from firing the rule) as a result. We implemented the ideas presented in this chapter by extending the operation of the traditional pattern-matching-based rule firer. The modified rule firer, illustrated in Figure 5.8, extends the traditional rule firer in two ways:

- *Inference*: The modified rule firer can consult an *inference engine* to infer conditions relevant to the firing of conditional rewrite rules. The rule firer can issue *inference queries* such as:
 - *is the function, $\text{lgst_cit} \circ \text{reps}$ injective?*, or
 - *can any predicate be generated that is weaker than:*

$$(\mathbf{C}_p (\mathbf{lt}, 5) \oplus \mathbf{terms} \oplus \pi_1) \ \& \ (\mathbf{eq} \oplus (\mathbf{terms} \times \mathbf{terms}))?$$

The inference engine answers queries with a simple yes or no (as in the first inference query above) or with KOLA expressions that satisfy the inference query (as in the second inference query above).

- *Conditional Rule Firing*: The modified rule firer accepts conditional rewrite rules (as well as unconditional rules) as inputs. When such rules are fired, inference queries are posed to the inference engine and the answers interpreted.

Section 5.3.2 presents the inference engine component of our optimizer. Section 5.3.3 describes the operation of our rule firer in the presence of conditional functions.

5.3.2 Performing Inference

Our inference engine is the Sicstus Prolog interpreter [83]. Using a Prolog interpreter as an inference engine makes our implementation a prototype rather than one of commercial quality. We envision replacing the Prolog interpreter with specialized matching routines that operate directly on KOLA queries as future work.

The interpreter’s inputs are Prolog programs that are:

- built-in facts and rules describing aspects of the data model that are invariant (e.g., rules for inferring subtyping, type information for KOLA operators, etc.),
- facts and rules generated from inference rules, and
- facts generated from metadata information specific to a given database instance, such as types contained in the schema, signatures of attributes, types of persistent data, and attributes that are keys.

Presently, metadata based rules are generated manually. However, Prolog facts and rules are generated automatically by compiling COKO properties.

COKO inference rules are either of the form “ $B \implies H$ ” or simply “ H ”, such that H names a condition to infer and B is a logical sentence of conditions. Compilation of the latter generates the Prolog fact, “ \overline{H} ” (described below). Compilation of the former generates the Prolog rule, “ $\overline{H} :- \overline{B}.$ ” such that \overline{B} is the Prolog translation of the logic sentence, B .

Conditions generally have the form,

$$\text{ident } (k_1, \dots, k_n)$$

such that each k_i is a KOLA pattern. These terms are translated into Prolog terms,

$$\text{ident } (\overline{k_1}, \dots, \overline{k_n})$$

such that the translation, $\overline{k_i}$ of KOLA pattern k_i :

- prepends KOLA’s pattern variables with an uppercase “V” (Prolog requires all variables to begin with a capital letter),
- translates all built-in primitive functions and predicates (e.g., **id**) into corresponding Prolog constants (e.g., **id**),
- translates all user-defined primitive functions and predicates (e.g., **reps**) into Prolog terms that associate a function with its domain and range (e.g., **fun (kreps, kRepresentative, kDistrict)**),
- translates all KOLA object names (e.g., **HReps**) into Prolog terms prepended with a lower-case ‘o’ (e.g., **oHReps**), and
- translates KOLA’s formers into prefix notation. For example, the function pattern, $f \circ g$ is translated into the string “**compose (Vf, Vg)**” while invocation ($f ! A$) is translated into the string “**invoke (Vf, VA)**”.

Translation of logical expressions into Prolog expressions translates conditions as described above, and maps:

- *conjunctive expressions* “ $p_1 \wedge p_2$ ” to “ $\overline{p_1}, \overline{p_2}$ ”,
- *disjunctive expressions* “ $p_1 \vee p_2$ ” to “ $\overline{p_1}; \overline{p_2}$ ”,
- *negation expressions* “**not** (p_1)” to “**not** ($\overline{p_1}$)”,
- *equations* “ $p_1 = p_2$ ” to “ $\overline{p_1} = \overline{p_2}$ ”, and
- *arithmetic comparisons* “ $p_1 < p_2$ ” to “ $\overline{p_1} < \overline{p_2}$ ”, etc.

To illustrate translation into Prolog, the result of compiling property **is_inj** of Figure 5.4a is the set of Prolog rules and facts shown below:

```

is_inj (id).
is_inj (times).
is_inj (Vf)                : - is_key (Vf).
is_inj (compose (Vf, Vg)) : - is_inj (Vf), is_inj (Vg).
is_inj (sum (Vf, Vg))     : - is_inj (Vf); is_inj (Vg).
is_inj (iterate (const (true), Vf)) : - is_inj (Vf).

```

Any conditional rule will consult the Prolog rules and facts compiled from the properties named in the **USES** clause of the containing transformation. As well, two more Prolog files

are consulted automatically. The first of these is a collection of facts and rules automatically generated from database metadata (for now this file is generated manually). These include typing information for all global names and all attributes and methods, and semantic information (such as key constraints) specific to the database. The second file consulted is a set of built-in rules that provide information that is invariant across database populations. These built-in rules include typing rules regarding KOLA's primitives and formers.

5.3.3 Integrating Inference and Rule Firing

Below we illustrate the steps that are performed when a conditional rewrite rule is fired on a query. We demonstrate these steps by tracing the firing of rule `inj1` of Figure 5.3 on the KOLA version of the “Major Cities” query (Figure 5.2: 1a).

1. The head pattern of the rule above is matched with the “Major Cities” query generating an *environment* of bindings for pattern variables: `p` (bound to `Kp (true)`), `f` (bound to `lgst_cit ◦ reps`) and `A` (bound to `HReps`).
2. A Prolog query is generated. First, Prolog subqueries of the form, $V_i = T_i$ are generated for each variable, V_i appearing in the head pattern (`p`, `f` and `A`). For a given variable V_i , T_i is the Prolog translation of the subexpression bound to V_i . In the case of the “Major Cities” query, the generated subqueries are:

```
Vp = const (true),
Vf = compose (fun (klgst_cit, kDistrict, kCity),
              fun (kreps, kRepresentative, kDistrict)), and
VA = oHReps.
```

These Prolog subqueries are then added to a Prolog subquery generated by translating the conditions of the conditional rewrite rule. The Prolog query generated from firing the conditional rewrite rule on the “Major Cities” query is

```
?- Vp = const (true),
   VA = oHReps,
   Vf = compose (fun (klgst_cit, kDistrict, kCity),
                 fun (kreps, kRepresentative, kDistrict)),
   pis_inj (Vf), pis_set (VA).
```

3. The generated Prolog query is issued to the Prolog interpreter with the built-in rules described earlier, and the relevant Prolog facts and rules generated from inference

rules and metadata. In the case of the “Major Cities” query, the relevant Prolog rules would be those resulting from the compilation of the inference rules of Figure 5.4a and 5.4b, and the metadata facts:

```
pis_key (fun(klgst_cit, kDistrict, kCity)),
pis_key (fun(kreps, kRepresentative, kDistrict)), and
pis_type (oHReps, set(oRepresentative)).
```

4. The Prolog query is posed of the Prolog interpreter and the results interpreted. If the results include new variable bindings to KOLA expressions expressed as Prolog terms, these terms are translated back into KOLA expressions and added to the environment of (variable, subexpression) bindings generated in Step (1). For the “Major Cities” query, the Prolog interpreter uses the translations of inference rules (2) and (3) (Figure 5.4a) and (2) (Figure 5.4b) to reduce the inference query generated in step (2) to the simpler queries,

```
pis_key (fun(klgst_cit, kDistrict, kCity)),
pis_key (fun(kreps, kRepresentative, kDistrict)) and
pis_type (oHReps, set(_)).
```

These simpler queries all are satisfied by facts generated from metadata.

5. The environment generated in steps (1) and (4) is used to instantiate the pattern variables appearing in the body pattern of the conditional rewrite rule. The instantiated pattern is then returned as the output of rule firing. In the case of the “Major Cities” query, the returned query is: **iterate** (K_p (true), $lgst_cit \circ reps$) ! HReps.

5.4 Discussion

5.4.1 Benefits to this Approach

The examples presented in this chapter demonstrate our approach to *expressing* semantic query rewrites. The query rewrite presented at the chapter’s onset that eliminates redundant duplicate elimination is used in many commercial relational database systems. It is also presented as one of the Starburst query rewrites in [79]. In Starburst, this rewrite is used as a normalization step before view merging. Subqueries that perform duplicate elimination make view merging impossible because duplicate semantics are lost as a result of the merge. Starburst uses this rewrite in order to recognize subqueries that can be transformed into equivalent queries that perform no duplicate elimination so that view merging

can take place. The rewrites of Section 5.2 that use predicate strength have also been considered elsewhere. Those that remove quantification from complex predicates (Example 1 of Section 5.2) are standard techniques that one can find in many textbooks. Those that introduce new predicates (Examples 2 and 3 of Section 5.2) are similar to the “predicate move-around” techniques for transforming relational queries [71].

What is unique in our work is the use of declarative conditional rewrite rules and inference rules to express these complex transformations. With our approach we can verify all of the rules presented in these sections with a theorem prover. (See Appendix B.5 for LP theorem prover scripts for these rules.) Verification of conditional rewrite rules establishes that query semantics are preserved when these rules are fired on queries satisfying the rules’ semantic preconditions. Verification of inference rules establishes that semantic conditions are inferred only when appropriate (soundness).

The other contribution of this approach concerns extensibility. Starburst and “predicate move-around” rewrites use the ideas discussed in Sections 5.1 and 5.2 in the context of relational databases. To simulate their results, we do not need all of the inference rules of Figure 5.4a that infer injectivity, nor do we need all of the inference rules of Figure 5.7 that infer predicate strength. For example, to capture the duplicate elimination query rewrite presented in Starburst for relational queries, we only need inference rules that establish an attribute to be injective if it is a key (Figure 5.4a, Rule (2)) and if it is a pair (equivalently, a relational tuple) containing a key (Figure 5.4a, Rule (4)). Rule (3) of Figure 5.4a is not needed as there is no notion of a composed data function in the relational data model. But if the relational version of this rewrite were expressed in our framework, it would be straightforward to *extend* this rewrite (to work for example, in an object database setting) simply by adding a verified inference rule such as Rule (3) of Figure 5.4a. Note that the addition of this one inference rule makes the rewrite rules conditioned on injectivity fired in a greater variety of contexts (e.g., when queries include path expressions with keys, or tuples with fields containing path expressions with keys etc.). By similar reasoning, not all of the predicate strength inference rules of Figure 5.7 are required to express the “predicate move-around” rewrites when confined to relations (e.g., Rule (4) of Figure 5.7 is unnecessary because of its use of function composition). Again, rules such as this one can be added to simply extend a relational optimizer to work robustly in an object setting.

5.4.2 The Advantage of KOLA

We argued in Chapter 3 that the combinator flavor of KOLA makes declarative rewrite rules easy to express. The meaning of a KOLA subexpression is context-independent. Therefore, code supplements are not required to identify subexpressions, nor are code supplements required to formulate new queries that reuse identified subexpressions in new contexts.

The advantage of combinators extends to the formulation of conditional rewrite rules and inference rules. Conditional rewrite rules must identify subexpressions upon which to express conditions. Inference rules also must identify subexpressions because conditions tend to be inferred from conditions held of subexpressions (e.g., the injectivity of complex functions can be inferred from the injectivity of their subfunctions). Again, variables in a query representation complicate the identification of these subexpressions.

Consider as an example, the data functions appearing in the “Major Cities” query and the “Mayors” query. The KOLA forms of these functions are:

$$\text{lgst_cit} \circ \text{reps}, \text{ and}$$

$$\text{iterate} (K_p (\text{true}), \text{mayor}) \circ \text{cities} \circ \text{reps}.$$

These two functions are both injective by similar reasoning: they are compositions of other functions that are injective. Inferring injectivity of the OQL forms of these data functions,

$x.\text{reps.lgst_cit}$, and

```
SELECT DISTINCT d.mayor
FROM d IN x.reps.cities
```

is more complicated. The identification of both of these data functions as being compositions of other functions requires machinery beyond what can be expressed with rewrite rules. Specifically, determining exactly what are the subfunctions of these functions requires reversing the process of substituting expressions for variables by factoring the complex expressions denoting the functions into two expressions for which the substitution of one for a variable in the other reproduces the original expression. For the path expression, $x.\text{reps.lgst_cit}$, these subfunctions are $x.\text{reps}$ and $x.\text{lgst_cit}$ (as substituting the first of these expressions for x in the second expression reproduces the original path expression). For the subquery, the subfunctions are, $x.\text{reps.cities}$ and

```
SELECT DISTINCT d.mayor
FROM d IN x
```

as again, substituting the first expression for x in the second expression results in the original expression. The decomposition required to identify subfunctions is inexpressible with declarative rewrite rules and instead requires calls to supplemental code.

5.5 Chapter Summary

This chapter presents our approach to extending the expressive power of rewrite rules without compromising the ease with which they can be verified. The techniques proposed here target the expression of query rewrites that are too specific to be captured with rewrite rules. The correctness of these rewrites depends on the semantics, and not just the syntax of the queries on which they fire.

This work builds upon the foundation laid with KOLA. We introduced *conditional rewrite rules*; rewrite rules whose firing depends on the satisfaction of semantic conditions of matched expressions. We then introduced *inference rules* that tell query rewriters how to decide if these semantic conditions hold. In the spirit of KOLA, both conditional rewrite rules and inference rules are expressed declaratively and are verifiable with LP.

This work contributes to the extensibility and verifiability of query rewriters. With respect to verification, the declarative flavor of both forms of rules makes them amenable to verification with a theorem prover. This approach is in stark contrast to the code-based rules of existing rule-based systems such as Starburst [79] and Cascades [42], which express conditions and condition-checking with code. With respect to extensibility, the separation of a condition's inference rules from the rewrite rules that depend on them, achieves a different form of extensibility than was provided by rewrite rules alone. Whereas rewrite rules make optimizers extensible by making it simple to change the potential actions taken by an optimizer, inference rules make optimizers extensible by making it simple to change the contexts in which these rules get fired.

Chapter 6

Experiences With COKO-KOLA

The goal of the work presented in this chapter was to determine the feasibility of the COKO-KOLA approach in an industrial setting. The COKO-KOLA approach clearly offers large gains in the formal methods aspects of query optimizer development; it is the first rule-based optimizer framework whose inputs can be verified with a theorem prover. But do these gains come at some practical cost? Can fully functional query optimizers be built within this framework or are we limited to toy examples with trivial functionality? Just how expressive is COKO for expressing the kinds of query rewrites that get used in real optimizers?

To address these questions, we teamed up with researchers from the IBM Thomas J. Watson Research Center and the IBM AS/400 Divisions to build a query rewriting component for a query optimizer for an object-oriented database. The IBM San Francisco project implements an Object-Oriented database using the relational database, DB2. Our contribution to this project was to use COKO-KOLA build a query rewriter that translates object queries on this object-oriented database (expressed in an experimental subset of OQL, informally called Query Lite) into equivalent SQL queries over the underlying DB2 relations. This project thereby provided a workbench with which we could consider the following issues concerning the practicality of the COKO-KOLA approach:

- *Integration:* How easy is it to use query rewriters generated from COKO transformations with existing query processors? That is, can we use COKO-KOLA to generate components that improve upon the behavior of an optimizer (either by making it work over a larger set of queries or by making it produce “better” plans), without having to make changes to optimizer code?
- *Ease-Of-Use:* How straightforward is it to express useful query rewrites? For the

Query Lite project, how many COKO transformations, KOLA rewrite rules and lines of firing algorithm code would be required to express the object \rightarrow relational query mapping?

This chapter begins in Section 6.1 with background on the San Francisco project and Query Lite. Sections 6.2 and 6.4 describe additions to the COKO-KOLA implementation required to complete this project, including translators to translate:

- Query Lite queries (and more generally, OQL’s set-and-bag queries) into KOLA (Section 6.2), and
- KOLA queries into SQL (Section 6.4).

Section 6.3 describes the COKO transformations developed for the San Francisco project. These include a normalization transformation described in Section 6.3.2, whose purpose is to normalize KOLA queries resulting from translation (from Query Lite or OQL) into a form that makes query rewriting straightforward, and a transformation (presented in Section 6.3.3) to rewrite these normalized queries into a form that can be translated into SQL. Section 6.5 considers the feasibility issues in light of these transformations. Section 6.6 summarizes the chapter.

6.1 Background

The San Francisco project uses relational technology to implement an object-oriented database. Specifically, the database implementation for this project uses DB2 as its relational backbone.

6.1.1 San Francisco Object Model

The object model for San Francisco is similar to the ODMG object model outlined in [14], and therefore similar also to the KOLA data model described in Section 3.2.2. Specifically, objects have unique immutable identifiers (OID’s), and are classifiable by their types. An object type defines a set of public *methods* that can be invoked on collections of objects of that type in a query. These methods can have any arity, are invoked using message passing syntax, and can return values of basic types (e.g., integers), OID’s for other objects, or references to collections. These methods can either be *attribute-based* (meaning they simply return a value associated with the object, as with *instance variables*) or *derived*, in which case the returned value is computed rather than retrieved.

Objects themselves can be contained in any number of object collections and will at least be included in the automatically maintained collection of instances of objects of the same type (the type’s *extent*).

6.1.2 Relational Implementation of the Object Model

The relational implementation of objects is straightforward, and similar to schemes described elsewhere (e.g., [60]). Firstly, any collection of objects of a particular type (including a type extent) is represented by a relation. The structure of this relation is derived from the interface of the associated object type in the following way:

- A column (which for simplicity we will name `OID`) is dedicated to denote each object’s unique identifier. Such identifiers are typically strings.
- Columns are reserved for each attribute-based method (except those that are collection-valued.) Attribute-based methods that return values of some basic type (e.g., integers) are represented by columns with values of that type. Attribute-based methods that return other objects are represented by columns whose values are strings denoting object identifiers.

To illustrate the object \rightarrow relational mapping, a relational implementation of a portion of the object schema illustrated in Figure 2.1 is described. Object collections `Sens` and `Sts` would be implemented with the relations `Sens` and `Sts` shown below with their respective structures:

`Sens`: (`OID`: `String`, `name`: `String`, `reps`: `String`, `pty`: `String`, `terms`: `Int`)
`Sts`: (`OID`: `String`, `name`: `String`, `lu`: `String`)

An object population that included Senator objects `s1` and `s2` representing Rhode Island (“`R.I.`”), and named “`Jack Reed`” and “`John Chafee`” respectively would result in the following entries in these relations:

Sens				
OID	name	reps	pty	terms
“s1”	“Jack Reed”	“r1”	“Dem”	1
“s2”	“John Chafee”	“r1”	“GOP”	5

Sts		
OID	name	lu
“r1”	“R.I.”	“University of R.I.”

Objects with attribute-based methods returning collections are treated as a special case in the relational implementation. Specifically, these methods are represented with their own relations that associate OID's with the values or OID's of objects contained in the collection. For example, the collection `SRs` of Senate resolution objects (as defined in Figure 2.1) would be implemented with the relations shown below:

```
SRs : (OID : String, topic : String)
SRs--spons : (OID1 : String, OID2 : String).
```

Relation `SRs` stores Senate resolution object identifiers with the values of their non-collection attribute-based method, `topic`. Relation `SRs-spons` stores Senate resolution object identifiers with the OID's of objects contained in the collection returned by attribute-based method, `spons`. For example, if `sr1` is a Senate resolution object whose topic is “NSF funding”, and that is sponsored by the Senators, `s1` and `s2`, then relations `SRs` and `SRs-spons` would include the following entries:

SRs		SRs-spons	
OID	topic	OID1	OID2
“sr1”	“NSF Funding”	“sr1”	“s1”
		“sr1”	“s2”

6.1.3 Querying

A query processor for San Francisco is under development. Early releases will support a limited subset of OQL called Query Lite. Query Lite restricts queries to those of the form,

```
SELECT x
FROM x IN A
[WHERE BoolExp]
[ORDER BY OrderExp]
```

such that `[...]` denotes an optional component, `BoolExp` denotes a boolean expression consisting of conjunctions, disjunctions and negations of simple comparison expressions, and `OrderExp` is either the name of an externally defined comparison function or a list of unary methods defined on the objects in `A`. Like OQL, Query Lite queries can contain invocations of methods with multiple arguments and path expressions (although only in their `WHERE` clause). But Query Lite supports neither join queries nor embedded collections. A full grammar for Query Lite is shown in Table 6.1.

6.1.4 Our Contribution

Our contribution was to build a query rewriter (using COKO-KOLA) that transforms Query Lite queries with path expressions, into equivalent SQL queries over the underlying relational implementation.¹ For example, the Query Lite query,

```
SELECT x
FROM x IN Sens
WHERE x.reps.name == "R.I."
```

gets rewritten by our rewriter into the SQL query,

```
SELECT x
FROM x IN Sens, y IN Sts
WHERE x.reps == y.OID AND y.name == "R.I."
```

(assuming the scheme for representing object collections as relations described in the previous section). This effort required that we (1) translate Query Lite queries with path expressions into KOLA, (2) rewrite the KOLA path expression queries into KOLA join queries, and (3) translate the KOLA join queries into SQL.² The components required for each of these tasks are illustrated in Figure 6.1. Sections 6.2, 6.3 and 6.4 present the designs and implementations of these components.

6.2 Translating Query Lite Queries into KOLA

The simplicity of Query Lite makes a Query Lite \rightarrow KOLA translator straightforward to design. However, as the eventual goal of the San Francisco project is to support querying in OQL, a sophisticated approach to translation is required. In this section, we describe the reasoning behind our approach to translation, which accounts for an eventual migration to OQL.

¹Because KOLA does not yet have support for lists, we only address Query Lite queries that do not contain an `ORDER BY` clause.

²A fourth step to provide an object view over the relational data returned by the SQL queries is not considered here.

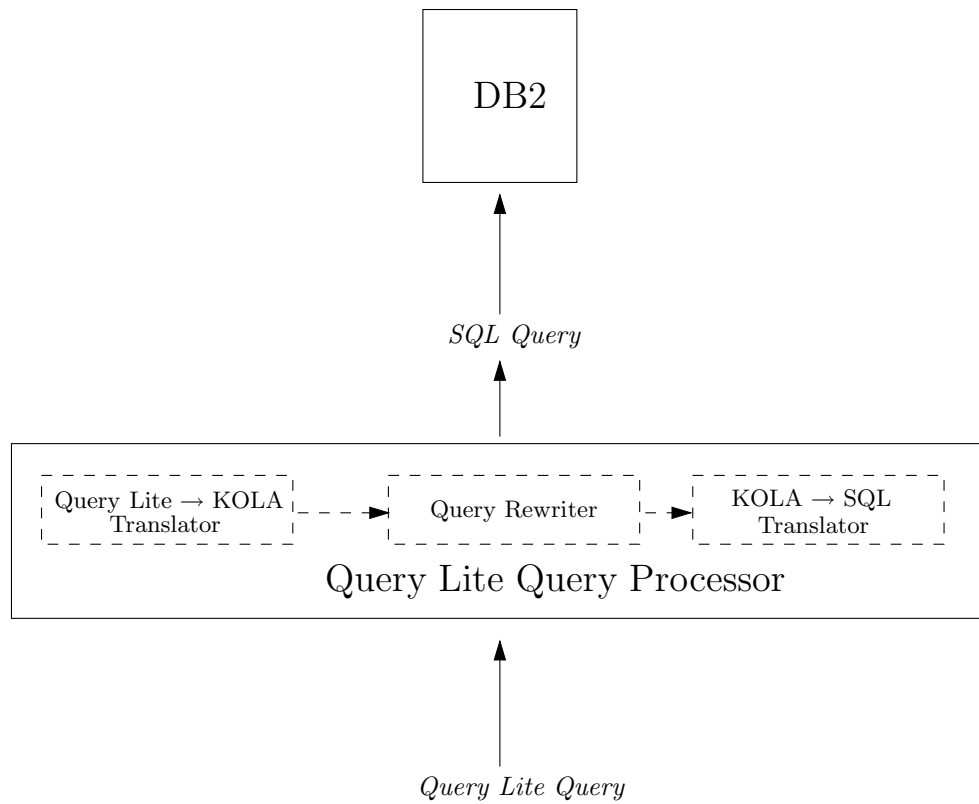


Figure 6.1: An Architecture for the Query Lite Query Rewriter

		<i>Constants, Variables and Path Expressions</i>
<i>Exp</i>	:	<i>c</i> (<i>c</i> a non-Bool constant/global name)
		IDENT (<i>an identifier denoting the name of a variable</i>)
		<i>Exp</i> . IDENT
		<i>Exp</i> . IDENT (<i>Exp</i> , <i>Exp</i> , ... , <i>Exp</i>)
		<i>Arithmetic Expressions</i>
		- (<i>Exp</i>)
		ABS (<i>Exp</i>)
		<i>Exp</i> + <i>Exp</i>
		<i>Exp</i> - <i>Exp</i>
		<i>Exp</i> * <i>Exp</i>
		<i>Exp</i> / <i>Exp</i>
		<i>Exp</i> MOD <i>Exp</i>
		<i>Query Expressions</i>
<i>Query</i>	:	SELECT <i>x</i> (<i>Any variable name can be substituted for x</i>)
		FROM <i>x</i> IN IDENT
		[WHERE <i>BoolExp</i>]
		[ORDER BY <i>OrdExp</i>]
		<i>Boolean Expressions</i>
<i>BoolExp</i>	:	TRUE
		FALSE
		<i>Exp</i> IS NULL
		<i>Exp</i> IS NOT NULL
		<i>Exp</i> == <i>Exp</i>
		<i>Exp</i> != <i>Exp</i>
		<i>Exp</i> < <i>Exp</i>
		<i>Exp</i> > <i>Exp</i>
		<i>Exp</i> <= <i>Exp</i>
		<i>Exp</i> >= <i>Exp</i>
		NOT (<i>BoolExp</i>)
		<i>BoolExp</i> AND <i>BoolExp</i>
		<i>BoolExp</i> OR <i>BoolExp</i>
		<i>Ordering Expressions</i>
<i>OrderExp</i>	:	IDENT . IDENT , ... , IDENT . IDENT <i>Direction</i>
		IDENT <i>Direction</i>
<i>Direction</i>	:	ASC DESC

Table 6.1: The Syntax of Query Lite

6.2.1 Translation Strategies

Translation from Query Lite into KOLA is straightforward. Given a Query Lite query e ,

```
SELECT  $x$ 
FROM  $x$  IN  $A$ 
WHERE  $p(x)$ ,
```

KOLA equivalent of e ($\mathbf{T} \llbracket e \rrbracket$) is

```
iterate ( $\mathbf{T} \llbracket p \rrbracket$ ,  $\mathbf{id}$ ) !  $A$ .
```

This simplistic approach says that translation generates a KOLA query of the form,

$$f ! x,$$

such that x (the *data component* of the KOLA query) is generated from the expression in the query's FROM clause, and f (the *function component* of the KOLA query) is generated from the expressions in the query's SELECT and WHERE clauses.

We decided against this translation strategy because it does not generalize well to OQL, the language that eventually will be used as the query language for San Francisco. Specifically, determining which parts of a query correspond to the data and function components of the KOLA translation becomes blurred in the presence of nested queries and embedded collections. Consider for example, the OQL query of Figure 6.2a, which finds all committees with Republican members. This query invokes the method `mems` to return the embedded collection of members of any given committee. The simplistic assumption that what appears in a query's FROM clause is automatically the data component of a query is violated here, as a collection of committee members can only be determined by applying a function (`mems`) to a given committee. Therefore, the simplistic translation strategy that works for Query Lite queries does not work for queries such as this.

An Alternative Strategy: The 1st Collection in a FROM Clause is Data

Consider the following alternative translation strategy: rather than designating all expressions appearing a query's FROM clause as data components, instead designate only the *first* collection named in the FROM clause as a data component. Therefore, translation of the query of Figure 6.2a would designate `Coms` as the only data component of the query, and produce a KOLA query on `Coms`:

```
(iterate (eq  $\oplus$   $\langle$ pty  $\circ$   $\pi_2$ ,  $K_f$  ("GOP")),  $\pi_1$ )  $\circ$  unnest ( $\mathbf{id}$ ,  $\mathbf{mems}$ ) !  $\mathbf{Coms}$ .
```

```

SELECT DISTINCT x
FROM x IN Coms, y IN x.mems
WHERE y.ptty == "GOP"

```

a. A Query with a Path Expression (*x.mems*) in its FROM Clause

```

SELECT ( SELECT y
         FROM y IN x.mems
         WHERE y.terms > 5 )
FROM x IN Coms
WHERE x.topic == "NSF"

```

b. A Nested Query

Figure 6.2: OQL Queries that make Translation into KOLA Difficult

This query first pairs every committee with each of its members (**unnest**), and then determines which (committee, member) pairs satisfy the condition that member is a Republican (**iterate**).

Once queries can be nested, this strategy also fails. Consider the nested query of Figure 6.2*b* which finds the senior members of committees in *Coms* that study the NSF. The subquery

```

SELECT y
FROM y IN x.mems
WHERE y.terms > 5

```

has the path expression, *x.mems* in its FROM clause. This expression is not a data component and instead must be mapped to a function, even though it is the first expression in the FROM clause. Therefore, this translation strategy must treat *outer* queries (queries that include subqueries, which must get translated to function invocations) differently from *inner* queries (queries that are subexpressions of outer queries, which must get translated into functions).

Our Strategy: Everything Generates a Function

The solution we take is to designate *all* parts of the query as function components. This approach to translation simplifies the design of the translator greatly as it removes the need to analyze each subexpression to see if it constitutes data or function. However, the consequence of this design decision is that translation returns KOLA expressions that are not intuitive. This problem is addressed after translation by a normalization (defined in COKO) to rewrite translated queries into more intuitive forms.


```

SELECT x
FROM x IN Sens
WHERE x.terms > 5

```

a. *A Query Lite Query*

```

(iterate (gt ⊕ ⟨terms ∘ π2, Kf (5)⟩, π2) ∘
  unnest (id, Kf (Sens)) ∘
  single) ! NULL

```

b. *Translation Into KOLA*

```

iterate (gt ⊕ ⟨id, Kf (5)⟩ ⊕ terms, id) ! Sens

```

c. *After Normalization*

Figure 6.3: A Query Lite Query (a), its Translation (b) and its Normalization (c)

Figures 6.3a and 6.3b show a simple Query Lite query (that finds all Senators who have served more than 5 terms) and the result of translating this query according to this strategy. Note that translation produces a function that gets invoked on `NULL`. `NULL` is an arbitrary argument to this function; in fact the function would return the same result no matter what was its argument (i.e., the function generated by the translator is a *constant function*). This translation strategy makes the result of translation counterintuitive, as the query that is produced does not get invoked on one or more collections, but on a constant that does not even figure in the final result.

The result of translation shown in 6.3b is not as intuitive a translation as the equivalent KOLA query shown in Figure 6.3c, which simply filters Senators in `Sens` who have served more than 5 terms. However, the KOLA expression of Figures 6.3b has the same semantics as the initial Query Lite query, as is demonstrated by the reduction below:

```

(iterate (gt ⊕ ⟨terms ∘ π2, Kf (5)⟩, π2) ∘
  unnest (id, Kf (Sens)) ∘ single) ! NULL

1→ iterate (gt ⊕ ⟨terms ∘ π2, Kf (5)⟩, π2) !
    (unnest (id, Kf (Sens)) ! (single ! NULL))

2→ iterate (gt ⊕ ⟨terms ∘ π2, Kf (5)⟩, π2) ! (unnest (id, Kf (Sens)) ! {NULL})

3→ iterate (gt ⊕ ⟨terms ∘ π2, Kf (5)⟩, π2) !
    ({(id ! [x, s])ij | xi ∈ {NULL}, sj ∈ (Kf (Sens) ! x)})

4→ iterate (gt ⊕ ⟨terms ∘ π2, Kf (5)⟩, π2) ! ({[x, s]ij | xi ∈ {NULL}, sj ∈ Sens})

```

$$\begin{aligned}
&\xrightarrow{5} \mathbf{iterate} (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) ! (\{ [\mathbf{NULL}, s]^j \mid s^j \in \mathbf{Sens} \}) \\
&\xrightarrow{6} \{ (\pi_2 ! [\mathbf{NULL}, s])^j \mid s^j \in \mathbf{Sens}, (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f (5) \rangle) ? [\mathbf{NULL}, s] \} \\
&\xrightarrow{7} \{ (\pi_2 ! [\mathbf{NULL}, s])^j \mid s^j \in \mathbf{Sens}, \mathbf{gt} ? (\langle \mathbf{terms} \circ \pi_2, K_f (5) \rangle ! [\mathbf{NULL}, s]) \} \\
&\xrightarrow{8} \{ s^j \mid s^j \in \mathbf{Sens}, \mathbf{gt} ? [(\mathbf{terms} \circ \pi_2) ! [\mathbf{NULL}, s], K_f (5) ! [\mathbf{NULL}, s]] \} \\
&\xrightarrow{9} \{ s^j \mid s^j \in \mathbf{Sens}, \mathbf{gt} ? [\mathbf{terms} ! (\pi_2 ! [\mathbf{NULL}, s]), K_f (5) ! [\mathbf{NULL}, s]] \} \\
&\xrightarrow{10} \{ s^j \mid s^j \in \mathbf{Sens}, \mathbf{gt} ? [\mathbf{terms} ! s, K_f (5) ! [\mathbf{NULL}, s]] \} \\
&\xrightarrow{11} \{ s^j \mid s^j \in \mathbf{Sens}, \mathbf{gt} ? [s.\mathbf{terms}, K_f (5)] \} \\
&\xrightarrow{12} \{ s^j \mid s^j \in \mathbf{Sens}, s.\mathbf{terms} > 5 \}
\end{aligned}$$

Step 1 of this reduction follows from the definition of \circ . Step 2 follows from the definition of **single**. Step 3 follows from the definition of **unnest**. Step 4 follows from the definitions of **id** and K_f . Step 5 follows from the fact that x^i is being drawn from a singleton set. Step 6 follows from the definition of **iterate**. Step 7 follows from the definition of \oplus . Step 8 follows from the definition of $\langle \rangle$. Step 9 follows from the definition of \circ . Step 10 follows from the definition of π_2 . Step 11 follows from the definition of function attribute primitives and K_f . Step 12 follows from the definition of **gt**.

Our approach to translation is similar to how Query Lite or OQL queries would be given a denotational semantics. Because arbitrary Query Lite and OQL expressions can have occurrences of free variables (e.g., x in “ $x > 5$ ”), the semantics of such expressions is dependent on an *environment* that defines what is referred to by the free variables appearing within the expression. More precisely, an *environment* is a list of (variable, value) pairs

$$((v_1, d_1), (v_2, d_2), \dots, (v_n, d_n))$$

providing the bindings of all free variables, v_1, \dots, v_n appearing in a given expression. (If an environment ρ gives bindings to every free variable in an expression, e , we say that e is *well-formed* with regard to ρ .) The denotational semantics of a Query Lite or OQL expression, e is a function (**Eval** $\llbracket e \rrbracket$) that maps all environments for which it is well-formed to values. For example,

$$\mathbf{Eval} \llbracket x > 5 \rrbracket \rho$$

is *true* if $\rho = ((x, 6))$ but *false* if $\rho = ((x, 4))$. Queries that do not appear as subexpressions of other queries will have no free variables, and therefore are well-formed with regard to the empty environment, $()$. The denotational semantics of these expressions are constant functions.

The idea behind this translation strategy is to map every expression e to the KOLA function $\mathbf{T} \llbracket e \rrbracket$ whose operational semantics coincides with e 's denotational semantics. More precisely, if e is well-formed with respect to some environment,

$$\rho = ((v_1, d_1), (v_2, d_2), \dots, (v_n, d_n)),$$

then $\mathbf{T} \llbracket e \rrbracket$ is a KOLA function satisfying the constraint that

$$\mathbf{T} \llbracket e \rrbracket ! (\bar{\rho}) = \mathbf{Eval} \llbracket e \rrbracket \rho$$

such that $\bar{\rho}$ is the KOLA nested pair representation of environment ρ ,

$$[\dots [d_1, d_2], \dots d_n].^3$$

Queries that are well-formed with regard to the empty environment get mapped to constant KOLA functions. The choice of `NULL` as an argument to these functions can be thought of as reflecting how KOLA represents the empty environment (i.e., $\bar{() = \text{NULL}}$).

6.2.2 T: The Query Lite \rightarrow KOLA Translation Function Described

We have defined a translator from a set-and-bag-based subset of OQL to KOLA. This subset of OQL is a superset of Query Lite. The part of the translator that processes Query Lite queries is described here. (The full OQL translator is described and proven correct in [17].⁴)

The translation of a Query Lite query q , is

$$\mathbf{T} \llbracket q \rrbracket ! \text{NULL}$$

such that $\mathbf{T} \llbracket q \rrbracket$ is as defined in Table 6.2. Below we examine this translation function, defined over all Query Lite queries and expressions.

Translating Constants

All non-Bool constants (e.g., `-3`, `5.322`, `"Hello World"`, `NULL`, ...) are translated into constant functions ($K_f(-3)$, $K_f(5.32)$, $K_f(\text{"Hello World"})$, $K_f(\text{NULL})$, ...). (Bool constants are translated into constant predicates $K_p(\text{TRUE})$ and $K_p(\text{FALSE})$.)

³A boolean expression b would similarly be mapped to KOLA predicate, $\mathbf{T} \llbracket b \rrbracket$ such that

$$\mathbf{T} \llbracket b \rrbracket ? (\bar{\rho}) = \mathbf{Eval} \llbracket b \rrbracket \rho.$$

⁴In fact, an older translator that translates a *set-based* (as opposed to a set-and-bag based) subset of OQL is presented and proven correct in a technical report [17]. The correctness proof (by structural induction) is nonetheless highly suggestive of what the correctness proof for this version of the translator will involve. The updated correctness proof is future work.

Constants, Variables and Path Expressions

$$\begin{aligned}
\mathbf{T} \llbracket c \rrbracket &= K_f (c) \quad (c \text{ a non-Bool constant/global name}) \\
\mathbf{T} \llbracket V_0 \rrbracket &= \pi_2 \\
\mathbf{T} \llbracket V_i \rrbracket &= \mathbf{T} \llbracket V_{i-1} \rrbracket \circ \pi_1 \quad (\text{for } i > 0) \\
\mathbf{T} \llbracket Exp . IDENT \rrbracket &= IDENT \circ \mathbf{T} \llbracket Exp \rrbracket \\
\mathbf{T} \llbracket Exp . IDENT (Exp_1, Exp_2, \dots, Exp_n) \rrbracket &= \\
&IDENT \circ \langle \mathbf{T} \llbracket Exp \rrbracket, \langle \dots \langle \mathbf{T} \llbracket Exp_1 \rrbracket, \mathbf{T} \llbracket Exp_2 \rrbracket \rangle, \dots \rangle, \mathbf{T} \llbracket Exp_n \rrbracket \rangle
\end{aligned}$$

Arithmetic Expressions

$$\begin{aligned}
\mathbf{T} \llbracket -(Exp) \rrbracket &= C_f (\text{mul}, -1) \circ \mathbf{T} \llbracket Exp \rrbracket \\
\mathbf{T} \llbracket ABS (Exp) \rrbracket &= \text{abs} \circ \mathbf{T} \llbracket Exp \rrbracket \\
\mathbf{T} \llbracket Exp_0 + Exp_1 \rrbracket &= \text{add} \circ \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 - Exp_1 \rrbracket &= \text{sub} \circ \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 * Exp_1 \rrbracket &= \text{mul} \circ \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 / Exp_1 \rrbracket &= \text{div} \circ \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 \text{ MOD } Exp_1 \rrbracket &= \text{mod} \circ \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle
\end{aligned}$$

Query Expressions

$$\mathbf{T} \left[\begin{array}{l} \text{SELECT } x \\ \text{FROM } x \text{ IN IDENT} \\ \text{WHERE } BoolExp \end{array} \right] = \begin{array}{l} \text{iterate} (\mathbf{T} \llbracket BoolExp \rrbracket, \pi_2) \circ \\ \text{unnest} (\text{id}, K_f (\text{IDENT})) \circ \\ \text{single} \end{array}$$

Boolean Expressions

$$\begin{aligned}
\mathbf{T} \llbracket TRUE \rrbracket &= K_p (\text{TRUE}) \\
\mathbf{T} \llbracket FALSE \rrbracket &= K_p (\text{FALSE}) \\
\mathbf{T} \llbracket Exp \text{ IS NULL} \rrbracket &= \text{isnull} \oplus \mathbf{T} \llbracket Exp \rrbracket \\
\mathbf{T} \llbracket Exp \text{ IS NOT NULL} \rrbracket &= \text{isnotnull} \oplus \mathbf{T} \llbracket Exp \rrbracket \\
\mathbf{T} \llbracket Exp_0 == Exp_1 \rrbracket &= \text{eq} \oplus \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 != Exp_1 \rrbracket &= \text{neq} \oplus \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 < Exp_1 \rrbracket &= \text{lt} \oplus \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 > Exp_1 \rrbracket &= \text{gt} \oplus \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 <= Exp_1 \rrbracket &= \text{leq} \oplus \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket Exp_0 >= Exp_1 \rrbracket &= \text{geq} \oplus \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle \\
\mathbf{T} \llbracket NOT (BoolExp) \rrbracket &= \sim (\mathbf{T} \llbracket BoolExp \rrbracket) \\
\mathbf{T} \llbracket BoolExp_0 \text{ AND } BoolExp_1 \rrbracket &= \mathbf{T} \llbracket BoolExp_0 \rrbracket \& \mathbf{T} \llbracket BoolExp_1 \rrbracket \\
\mathbf{T} \llbracket BoolExp_0 \text{ OR } BoolExp_1 \rrbracket &= \mathbf{T} \llbracket BoolExp_0 \rrbracket \mid \mathbf{T} \llbracket BoolExp_1 \rrbracket
\end{aligned}$$

Table 6.2: \mathbf{T} : The Query Lite \rightarrow KOLA Translation Function

Translating Variables

The translation of variables is perhaps the most complex aspect of translation. Conceptually, variable translation works from a preprocessed version of the query in which all variable references are replaced by deBruijn variables [30]. A deBruijn variable is a variable *index* (V_i for $i \geq 0$) that indicates the position of a variable reference relative to its declaration. (Higher values of i indicate a greater “distance” between reference and declaration. V_0 always refers to the most “recently” declared variable.)

The preprocessing step that converts variable references into deBruijn variables must first associate every referenced variable with its declaration. Variable declarations typically occur in a query’s **FROM** clause, as in “ x **IN** **COLL**”, which declares variable x to range over the elements of collection **COLL**. In OQL, variable declarations can also occur in a query’s **WHERE** clause if it contains a *quantifier expression*, as in

$$\text{EXISTS } x \text{ IN COLL: } p(x)$$

which also declares variable x to range over the elements of collection **COLL**.

The algorithm followed during this preprocessing step visits each subexpression of a given query expression’s **FROM**, **SELECT** and **WHERE** clauses in turn. Each subexpression is associated with a *scope list* which is a list of variables that can be referenced by the subexpression.⁵ Scope lists of subexpressions are propagated and amended during each step of the expression traversal. That is, the visit of a subexpression will accept the scope list associated with a previously visited subexpression (its *incoming* scope list). If the subexpression declares a new variable, this variable is appended to the incoming scope list to produce a scope list for subexpressions still to be visited (its *outgoing* scope list).

The algorithm is described below with respect to the generic OQL query of Figure 6.4.⁶ In this figure, E_s , E_w , and E_i, \dots, E_m ($0 \leq i \leq m$) are OQL subexpressions that potentially include free occurrences of variables. For this example, it is assumed that this query has

$$(x_0, \dots, x_{i-1})$$

as its incoming scope list. (If the query is not a subexpression of another query, then its incoming scope list is (). That is, $i = 0$.)

The subexpressions of this query are visited and processed as follows:

⁵The variables in a subexpression’s scope list are those that must be bound by any environment for which that subexpression is well-formed.

⁶The algorithm is described in terms of an OQL query rather than a Query Lite query because every Query Lite query declares exactly one variable, making preprocessing trivial.

```

SELECT  $E_s$ 
FROM  $x_i$  IN  $E_i, \dots, x_m$  IN  $E_m$ 
WHERE  $E_w$ 

```

Figure 6.4: A Prototypical OQL Query

1. for each FROM subexpression: E_k ($i \leq k \leq m$):
 - E_k 's incoming scope list is (x_0, \dots, x_{k-1}) .
 - conversion into deBruijn notation replaces each x_j appearing in E_k with V_{k-j-1} .
 - E_k 's outgoing scope list is (x_0, \dots, x_k) . (That is, x_k is appended to the incoming scope list.)
2. for SELECT subexpression, E_s and WHERE subexpression E_w :
 - E_s 's and E_w 's incoming scope lists are both (x_0, \dots, x_m) .
 - conversion into deBruijn notation replaces each x_j in E_s or E_w with V_{m-j} .

To illustrate the algorithm, we trace its effects on the OQL query of Figure 6.2b that is nested in its SELECT clause. Assume that the outer query does not appear as a subexpression of another query (i.e., the outer query is defined with respect to the empty environment, $()$). The algorithm visits subexpressions of this query in the following order:

1. “ x IN K_f (Coms)”:
 - 1's *Incoming Scope List*: $()$
 - 1's *Outgoing Scope List*: (x)

Expression 1's outgoing scope list is the result of appending its declared variable x to its incoming scope list, $()$.
2. “SELECT y FROM y IN x .mems WHERE y .terms > 5”:
 - 2's *Incoming Scope List*: (x)
 - (a) “ y IN x .mems” (in inner query's FROM clause):
 - 2a's *Incoming Scope List*: (x)
 - 2a's *deBruijn Conversion*: variable reference x is replaced by V_0
 - 2a's *Outgoing Scope List*: (x, y)

```

SELECT ( SELECT V0
        FROM y IN V0.mems
        WHERE V0.terms > 5 )
FROM x IN Coms
WHERE V0.topic == "NSF"

```

Figure 6.5: The Query of Figure 6.2b After deBruijn Conversion

Expression 2a’s outgoing scope list is the result of appending its declared variable y to its incoming scope list, (x) .

(b) “SELECT y ” (*in inner query*):

2b’s Incoming Scope List: (x, y)

2b’s deBruijn Conversion: variable reference y is replaced by V_0

Variable y was the most “recently” declared variable in the incoming scope list and hence its reference is replaced by V_0 . Had this reference instead been to x , it would have been replaced by V_1 .

(c) “WHERE y .terms > 5” (*in inner query*):

2c’s Incoming Scope List: (x, y)

2c’s deBruijn Conversion: variable reference y is replaced by V_0

After preprocessing of this query is completed, we are left with the query of Figure 6.5. Note that the relative referencing of deBruijn notation means that the same deBruijn index can refer to multiple variables within a single query. In the query of Figure 6.5, deBruijn variable V_0 refers to a committee in `Coms` in the `WHERE` clause of the outer query and the `FROM` clause of the inner query, but refers to a committee member in the `SELECT` and `WHERE` clauses of the inner query.

The translation of a deBruijn variable (V_i) into KOLA is defined as follows:

- $\mathbf{T} \llbracket V_0 \rrbracket = \pi_2$, and
- $\mathbf{T} \llbracket V_i \rrbracket$ (for $i > 0$) = $\mathbf{T} \llbracket V_{i-1} \rrbracket \circ \pi_1$

The result of translation then, is a function that can be invoked on the KOLA representation ($\bar{\rho}$) of the environment (ρ) associated with the translated variable. When invoked on this representation, the value bound to the variable in the environment is returned. For example, suppose that variable reference x is associated with the incoming scope list,

(w, x, y, z)

and is therefore well-formed with regard to environment ρ :

$$((w, 3), (x, 5), (y, -7.3), (z, \text{“Hello”})).$$

The translation of x into KOLA first generates the deBruijn variable, V_2 and then produces the KOLA function, $\pi_2 \circ \pi_1 \circ \pi_1$. When invoked on the KOLA pair, $\bar{\rho}$:

$$[[[3, 5], -7.3], \text{“Hello”}],$$

this function returns 5; the value that had been associated with x in ρ .

Translating Path Expressions:

The translation of a unary method invocation,

$$Exp . m$$

is

$$m \circ \mathbf{T} \llbracket Exp \rrbracket.$$

The translation of an n -ary method invocation,

$$Exp . m (Exp_0, Exp_1, \dots, Exp_{n-1})$$

is

$$m \circ \langle \mathbf{T} \llbracket Exp \rrbracket, \langle \dots \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle, \dots \rangle, \mathbf{T} \llbracket Exp_{n-1} \rrbracket \rangle.$$

Assuming that $Exp . m$ and $Exp . m (Exp_0, Exp_1, \dots, Exp_{n-1})$ are well-formed with regard to some environment, ρ , the results of invoking their KOLA translations on $\bar{\rho}$ are:

$$m ! (\mathbf{T} \llbracket Exp \rrbracket ! \bar{\rho})$$

and

$$m ! [\mathbf{T} \llbracket Exp \rrbracket ! \bar{\rho}, [\dots [\mathbf{T} \llbracket Exp_1 \rrbracket ! \bar{\rho}, \mathbf{T} \llbracket Exp_2 \rrbracket ! \bar{\rho}], \dots, \mathbf{T} \llbracket Exp_n \rrbracket ! \bar{\rho}]]$$

respectively. Because m is a method, these expressions reduce to

$$(\mathbf{T} \llbracket Exp \rrbracket ! \bar{\rho}) . m$$

and

$$(\mathbf{T} \llbracket Exp \rrbracket ! \bar{\rho}) . m (\mathbf{T} \llbracket Exp_1 \rrbracket ! \bar{\rho}, \mathbf{T} \llbracket Exp_2 \rrbracket ! \bar{\rho}, \dots, \mathbf{T} \llbracket Exp_n \rrbracket ! \bar{\rho})$$

respectively, the KOLA equivalents of the original method invocations.

Translating Arithmetic Expressions:

Every arithmetic operator (e.g., ‘+’) has a corresponding KOLA primitive (e.g., **add**). The translation of any arithmetic subexpression,

$$Exp_0 \text{ ArithOp } Exp_1,$$

is the KOLA function,

$$\overline{\text{ArithOp}} \circ \langle \mathbf{T} \llbracket Exp_0 \rrbracket, \mathbf{T} \llbracket Exp_1 \rrbracket \rangle$$

such that $\overline{\text{ArithOp}}$ is the KOLA primitive corresponding to *ArithOp*.

Translating Query Expressions:

For any OQL or Query Lite query, *q*:

$$\begin{aligned} & \mathbf{T} \left[\begin{array}{l} \text{SELECT } E_s \\ \text{FROM } x_0 \text{ IN } E_0, \dots, x_n \text{ IN } E_n \\ \text{WHERE } E_w \end{array} \right] \\ & \qquad \qquad \qquad = \\ & \mathbf{iterate} (\mathbf{T} \llbracket E'_w \rrbracket, \mathbf{T} \llbracket E'_s \rrbracket) \circ \\ & \quad \mathbf{unnest} (\mathbf{id}, \mathbf{T} \llbracket E'_n \rrbracket) \circ \dots \circ \mathbf{unnest} (\mathbf{id}, \mathbf{T} \llbracket E'_0 \rrbracket) \circ \\ & \quad \mathbf{single} \end{aligned}$$

such that each E'_i (for $i \in \{0, \dots, n, s, w\}$) is equivalent to E_i but for the replacement of all variable references with their deBruijn equivalents. The translation of a Query Lite query (for which $n = 0$) follows from the more general translation of OQL queries shown here.

That the translation of query expressions preserves semantics is demonstrated below. Suppose that *q* (above) is well-formed with regard to some environment, ρ . Then $\mathbf{T} \llbracket q \rrbracket ! (\bar{\rho})$ reduces as follows:

1. Function **single** is invoked to create the singleton bag, $\{\{\bar{\rho}\}\}$.
2. Successive invocations of **unnest** (**id**, E'_0), ..., **unnest** (**id**, $\mathbf{T} \llbracket E'_n \rrbracket$) generate the collection,

$$\begin{aligned} & \{[\dots [[\bar{\rho}, e_0], e_1], \dots e_n] \mid \\ & \quad e_0 \in (\mathbf{T} \llbracket E'_0 \rrbracket ! (\bar{\rho})), \\ & \quad e_1 \in (\mathbf{T} \llbracket E'_1 \rrbracket ! ([\bar{\rho}, e_0])), \\ & \quad \dots, \\ & \quad e_n \in (\mathbf{T} \llbracket E'_n \rrbracket ! ([\dots [[\bar{\rho}, e_0], e_1], \dots, e_{n-1}]))\}. \end{aligned}$$

The result above is a bag of KOLA pairs,

$$[\dots [[\bar{\rho}, e_0], e_1], \dots e_n]$$

such that e_i ($0 \leq i \leq n$) is an element of the collection denoted by E_i with regard to ρ supplemented with pairs,

$$((x_0, e_0), \dots, (x_{i-1}, e_{i-1})).$$

Put another way, this result is an $(n + 1)$ -way cartesian product of the collections denoted by E_0, \dots, E_n with regard to the environments derived from ρ , and from elements of preceding collections.

3. Query **iterate** ($\mathbf{T} \llbracket E'_w \rrbracket$, $\mathbf{T} \llbracket E'_s \rrbracket$) is invoked on the result of 2, thereby applying the expression in the original query's **SELECT** clause ($\mathbf{T} \llbracket E'_s \rrbracket$) to every tuple produced in 2 that satisfies the query's **WHERE** clause ($\mathbf{T} \llbracket E'_w \rrbracket$).

Translating Boolean Expressions:

The translation of Boolean expressions is straightforward, resembling the translation of non-Boolean expressions but with combination (\oplus) replacing composition (\circ).

6.2.3 Sample Traces of Translation

In this section, we trace the application of the translation function on two queries: the Query Lite query of Figure 6.3 and the OQL query of Figure 6.2b. The result of translating the Query Lite query is shown in Figure 6.3b. The result of translating the OQL query and also that of Figure 6.2a are shown in Figure 6.6.

Tracing the Translation of the Query Lite Query of Figure 6.3

The translation of the Query Lite query of Figure 6.3 first converts all variable references to deBruijn variables, producing the query,

```
SELECT V0
FROM x IN Sens
WHERE V0.terms > 5.
```

Translation then proceeds as follows:

```
 $\mathbf{T} \llbracket \text{SELECT } V_0 \text{ FROM } x \text{ IN Sens WHERE } V_0.\text{terms} > 5 \rrbracket$ 
```

$$\begin{aligned}
a: & \quad (\mathbf{set} \circ \mathbf{iterate} (\mathbf{eq} \oplus \langle \mathbf{pty} \circ \pi_2, K_f (\text{"GOP"}) \rangle), \pi_2 \circ \pi_1) \circ \\
& \quad \mathbf{unnest} (\mathbf{id}, \mathbf{mems} \circ \pi_2) \circ \mathbf{unnest} (\mathbf{id}, K_f (\mathbf{Coms})) \circ \mathbf{single} \text{ ! NULL} \\
b: & \quad (\mathbf{iterate} (\mathbf{eq} \oplus \langle \mathbf{topic} \circ \pi_2, K_f (\text{"NSF"}) \rangle), f) \circ \\
& \quad \mathbf{unnest} (\mathbf{id}, K_f (\mathbf{Coms})) \circ \mathbf{single} \text{ ! NULL} \\
\text{such that } f = & \quad (\mathbf{iterate} (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f (5) \rangle), \pi_2) \circ \\
& \quad \mathbf{unnest} (\mathbf{id}, \mathbf{mems} \circ \pi_2) \circ \mathbf{single}
\end{aligned}$$

Figure 6.6: Results of Translating the OQL queries of Figure 6.2

$$\begin{aligned}
& = \mathbf{iterate} (\mathbf{T} \llbracket V_0.\mathbf{terms} > 5 \rrbracket, \mathbf{T} \llbracket V_0 \rrbracket) \circ \mathbf{unnest} (\mathbf{id}, \mathbf{T} \llbracket \mathbf{Sens} \rrbracket) \circ \mathbf{single} \\
& = \mathbf{iterate} (\mathbf{T} \llbracket V_0.\mathbf{terms} > 5 \rrbracket, \pi_2) \circ \mathbf{unnest} (\mathbf{id}, K_f (\mathbf{Sens})) \circ \mathbf{single} \\
& = \mathbf{iterate} (\mathbf{gt} \oplus \langle \mathbf{T} \llbracket V_0.\mathbf{terms} \rrbracket, \mathbf{T} \llbracket 5 \rrbracket \rangle, \pi_2) \circ \mathbf{unnest} (\mathbf{id}, K_f (\mathbf{Sens})) \circ \mathbf{single} \\
& = \mathbf{iterate} (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \mathbf{T} \llbracket V_0 \rrbracket, K_f (5) \rangle, \pi_2) \circ \mathbf{unnest} (\mathbf{id}, K_f (\mathbf{Sens})) \circ \mathbf{single} \\
& = \mathbf{iterate} (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) \circ \mathbf{unnest} (\mathbf{id}, K_f (\mathbf{Sens})) \circ \mathbf{single}
\end{aligned}$$

Tracing the Translation of the OQL Query of Figure 6.2b

The translation of the OQL query of Figure 6.2b first converts all variable references to deBruijn variables, producing the query of Figure 6.5. Translation then proceeds as follows:

$$\begin{aligned}
& \mathbf{T} \left[\left[\begin{array}{l} \mathbf{SELECT} \left(\begin{array}{l} \mathbf{SELECT} V_0 \\ \mathbf{FROM} y \text{ IN } V_0.\mathbf{mems} \\ \mathbf{WHERE} V_0.\mathbf{terms} > 5 \end{array} \right) \\ \mathbf{FROM} x \text{ IN } \mathbf{Coms} \\ \mathbf{WHERE} V_0.\mathbf{topic} == \text{"NSF"} \end{array} \right] \right] \\
& = \mathbf{iterate} (\mathbf{T} \llbracket V_0.\mathbf{topic} == \text{"NSF"} \rrbracket, f) \circ \\
& \quad \mathbf{unnest} (\mathbf{id}, \mathbf{T} \llbracket \mathbf{Coms} \rrbracket) \circ \mathbf{single} \\
& \text{s.t. } f = \mathbf{T} \left[\left[\begin{array}{l} \mathbf{SELECT} V_0 \\ \mathbf{FROM} y \text{ IN } V_0.\mathbf{mems} \\ \mathbf{WHERE} V_0.\mathbf{terms} > 5 \end{array} \right] \right]
\end{aligned}$$

$$\begin{aligned}
&= \text{iterate } (\mathbf{T} \llbracket V_0.\text{topic} == \text{"NSF"} \rrbracket, f) \circ \\
&\quad \text{unnest } (\text{id}, \mathbf{T} \llbracket \text{Coms} \rrbracket) \circ \text{single} \\
s.t. \ f &= \text{iterate } (\mathbf{T} \llbracket V_0.\text{terms} > 5 \rrbracket, \mathbf{T} \llbracket V_0 \rrbracket) \circ \\
&\quad \text{unnest } (\text{id}, \mathbf{T} \llbracket V_0.\text{mems} \rrbracket) \circ \text{single} \\
&= \text{iterate } (\text{eq} \oplus \langle \mathbf{T} \llbracket V_0.\text{topic} \rrbracket, \mathbf{T} \llbracket \text{"NSF"} \rrbracket \rangle, f) \circ \\
&\quad \text{unnest } (\text{id}, \mathbf{T} \llbracket \text{Coms} \rrbracket) \circ \text{single} \\
s.t. \ f &= \text{iterate } (\text{gt} \oplus \langle \mathbf{T} \llbracket V_0.\text{terms} \rrbracket, \mathbf{T} \llbracket 5 \rrbracket \rangle, \mathbf{T} \llbracket V_0 \rrbracket) \circ \\
&\quad \text{unnest } (\text{id}, \mathbf{T} \llbracket V_0.\text{mems} \rrbracket) \circ \text{single} \\
&= \text{iterate } (\text{eq} \oplus \langle \mathbf{T} \llbracket V_0.\text{topic} \rrbracket, K_f (\text{"NSF"}) \rangle, f) \circ \\
&\quad \text{unnest } (\text{id}, K_f (\text{Coms})) \circ \text{single} \\
s.t. \ f &= \text{iterate } (\text{gt} \oplus \langle \mathbf{T} \llbracket V_0.\text{terms} \rrbracket, K_f (5) \rangle, \mathbf{T} \llbracket V_0 \rrbracket) \circ \\
&\quad \text{unnest } (\text{id}, \mathbf{T} \llbracket V_0.\text{mems} \rrbracket) \circ \text{single} \\
&= \text{iterate } (\text{eq} \oplus \langle \text{topic} \circ \mathbf{T} \llbracket V_0 \rrbracket, K_f (\text{"NSF"}) \rangle, f) \circ \\
&\quad \text{unnest } (\text{id}, K_f (\text{Coms})) \circ \text{single} \\
s.t. \ f &= \text{iterate } (\text{gt} \oplus \langle \text{terms} \circ \mathbf{T} \llbracket V_0 \rrbracket, K_f (5) \rangle, \mathbf{T} \llbracket V_0 \rrbracket) \circ \\
&\quad \text{unnest } (\text{id}, \text{mems} \circ \mathbf{T} \llbracket V_0 \rrbracket) \circ \text{single} \\
&= \text{iterate } (\text{eq} \oplus \langle \text{topic} \circ \pi_2, K_f (\text{"NSF"}) \rangle, f) \circ \\
&\quad \text{unnest } (\text{id}, K_f (\text{Coms})) \circ \text{single} \\
s.t. \ f &= \text{iterate } (\text{gt} \oplus \langle \text{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) \circ \\
&\quad \text{unnest } (\text{id}, \text{mems} \circ \pi_2) \circ \text{single}
\end{aligned}$$

The bravehearted can now follow the reduction of this function when invoked on NULL, to confirm that translation has preserved query semantics.

$$\begin{aligned}
& (\text{iterate } (\text{eq} \oplus \langle \text{topic} \circ \pi_2, K_f (\text{"NSF"}) \rangle), f) \circ \\
& \quad \text{unnest } (\text{id}, K_f (\text{Coms})) \circ \text{single} \text{ ! NULL} \\
s.t. \ f = & \quad \text{iterate } (\text{gt} \oplus \langle \text{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) \circ \\
& \quad \text{unnest } (\text{id}, \text{mems} \circ \pi_2) \circ \text{single} \\
= & \quad \text{iterate } (\text{eq} \oplus \langle \text{topic} \circ \pi_2, K_f (\text{"NSF"}) \rangle, f) \text{ !} \\
& \quad (\text{unnest } (\text{id}, K_f (\text{Coms})) \text{ ! } (\text{single} \text{ ! NULL})) \\
s.t. \ f = & \quad \text{iterate } (\text{gt} \oplus \langle \text{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) \circ \\
& \quad \text{unnest } (\text{id}, \text{mems} \circ \pi_2) \circ \text{single} \\
= & \quad \text{iterate } (\text{eq} \oplus \langle \text{topic} \circ \pi_2, K_f (\text{"NSF"}) \rangle, f) \text{ !} \\
& \quad (\text{unnest } (\text{id}, K_f (\text{Coms})) \text{ ! } \{\text{NULL}\}) \\
s.t. \ f = & \quad \text{iterate } (\text{gt} \oplus \langle \text{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) \circ \\
& \quad \text{unnest } (\text{id}, \text{mems} \circ \pi_2) \circ \text{single} \\
= & \quad \text{iterate } (\text{eq} \oplus \langle \text{topic} \circ \pi_2, K_f (\text{"NSF"}) \rangle, f) \text{ ! } \{([\text{NULL}, c])^i \mid c^i \in \text{Coms}\} \\
s.t. \ f = & \quad \text{iterate } (\text{gt} \oplus \langle \text{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) \circ \\
& \quad \text{unnest } (\text{id}, \text{mems} \circ \pi_2) \circ \text{single} \\
= & \quad \{(f \text{ ! } [\text{NULL}, c])^i \mid c^i \in \text{Coms}, (\text{eq} \oplus \langle \text{topic} \circ \pi_2, K_f (\text{"NSF"}) \rangle) ? [\text{NULL}, c]\} \\
s.t. \ f = & \quad \text{iterate } (\text{gt} \oplus \langle \text{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) \circ \\
& \quad \text{unnest } (\text{id}, \text{mems} \circ \pi_2) \circ \text{single} \\
= & \quad \{(f \text{ ! } [\text{NULL}, c])^i \mid c^i \in \text{Coms}, \text{eq} ? [c.\text{topic}, \text{"NSF"}]\} \\
s.t. \ f = & \quad \text{iterate } (\text{gt} \oplus \langle \text{terms} \circ \pi_2, K_f (5) \rangle, \pi_2) \circ \\
& \quad \text{unnest } (\text{id}, \text{mems} \circ \pi_2) \circ \text{single}
\end{aligned}$$

The invocation of f on $[\text{NULL}, c]$ then reduces as follows:

$$\begin{aligned}
f ! [\text{NULL}, c] &= (\text{iterate } (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f(5) \rangle, \pi_2) \circ \\
&\quad \mathbf{unnest} (\mathbf{id}, \mathbf{mems} \circ \pi_2) \circ \mathbf{single}) ! [\text{NULL}, c] \\
&= \text{iterate } (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f(5) \rangle, \pi_2) ! \\
&\quad (\mathbf{unnest} (\mathbf{id}, \mathbf{mems} \circ \pi_2) ! (\mathbf{single} ! [\text{NULL}, c])) \\
&= \text{iterate } (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f(5) \rangle, \pi_2) ! \\
&\quad (\mathbf{unnest} (\mathbf{id}, \mathbf{mems} \circ \pi_2) ! \{[\text{NULL}, c]\}) \\
&= \text{iterate } (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f(5) \rangle, \pi_2) ! \\
&\quad \{([\text{NULL}, c], m)^j \mid m^j \in ((\mathbf{mems} \circ \pi_2) ! [\text{NULL}, c])\} \\
&= \text{iterate } (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f(5) \rangle, \pi_2) ! \\
&\quad \{([\text{NULL}, c], m)^j \mid m^j \in c.\mathbf{mems}\} \\
&= \{(\pi_2 ! [[\text{NULL}, c], m])^j \mid \\
&\quad m^j \in c.\mathbf{mems}, (\mathbf{gt} \oplus \langle \mathbf{terms} \circ \pi_2, K_f(5) \rangle) ? [[\text{NULL}, c], m]\} \\
&= \{m^j \mid m^j \in c.\mathbf{mems}, m.\mathbf{terms} > 5\}
\end{aligned}$$

The result of this reduction then is

$$\{\{m^j \mid m^j \in c.\mathbf{mems}, m.\mathbf{terms} > 5\}^i \mid c^i \in \mathbf{Coms}, c.\mathbf{topic} == \text{“NSF”}\}$$

which is a nested bag of committee members for committees whose topic concerns the NSF (i.e., the result specified by the original OQL query).

6.2.4 Translator Implementation

The translator described above was implemented with the Ox compiler generator tool [8]. Ox is an attribute-grammar [3] based compiler tool in the spirit of Lex and Yacc [55]. Lex is a tool for generating lexical scanners and Yacc is a tool for generating parsers. Lex specifications designate a set of *tokens* (or *terminal symbols*) and associate regular expressions with each. The generated scanner maps text to tokens according to these specifications. Yacc specifications are context-free grammars consisting of *non-terminals* and tokens. The generated parser finds parse trees for strings according to the grammar specification, and can also invoke semantic actions based on the parse.

Ox generalizes the operation of Yacc in the same manner that attribute grammars generalize context-free grammars. Ox specifications are Lex and Yacc specifications that

are augmented with definitions of attributes that are either *synthesized* (passed up the parse tree) or *inherited* (passed down the parse tree). Ox then uses these specifications to generate a program that constructs and decorates attributed parse trees. Ox facilitates the generation of compilers by making it possible to succinctly specify actions for those aspects of compiler generation for which Yacc falls short, such as type checking, code generation and so on.

To use Ox for the OQL/Query Lite \rightarrow KOLA translator, we used a grammar augmented with attributes denoting:

- *functions and predicates*: As described earlier, our translator returns a function or predicate as the result of translating every expression. The function or predicate for any given expression is constructed from the functions and predicates of its subexpressions, as the translation function **T** of Table 6.2 illustrates. Therefore, **func** and **pred** are *synthesized* attributes of all expression non-terminals.
- *incoming and outgoing scope lists*: Scope lists are propagated from subexpression to subexpression; one subexpression's outgoing scope list becomes the next visited subexpression's incoming scope list. Therefore, **ins1** is an *inherited* attribute denoting the incoming scope list of all expressions, and **outs1** is a *synthesized* attribute denoting the outgoing scope list.

6.3 Query Rewriting

This section presents COKO transformations that rewrite KOLA translations of Query Lite queries into a form that can be translated into SQL. Section 6.3.1 presents a library of general purpose COKO transformations used by these transformations. Section 6.3.2 presents a specialized COKO transformation that normalizes KOLA queries resulting from translation into a more intuitive form.⁷ Section 6.3.3 presents a specialized COKO transformation that rewrites the resulting normalized KOLA queries into equivalent KOLA queries that can be translated into SQL.

6.3.1 A Library of General-Purpose COKO Transformations

Many of the transformations defined for the Query Lite rewrites serve a more general-purpose as *normalization* or *simplification* transformations. Whereas normalizations rewrite

⁷These normalizations are strictly unnecessary, but make it easier to implement rewrites proposed in the literature in terms of the more intuitive expressions of queries.

```

TRANSFORMATION LBComp
USES
  sft:  f ◦ (g ◦ h)  → (f ◦ g) ◦ h
BEGIN
  BU {sft →
      {GIVEN f ◦ _F DO LBComp (f);
       LBComp}
     }
END

```

Figure 6.7: Transformation LBComp

expressions into structurally characterizable forms, simplifications make expressions “smaller” by removing redundancies or trivial subexpressions. In this section, we describe the library of general-purpose transformations defined for this task.

Normalizations

Left-Bushy Compositions LBComp (shown in Figure 6.7) is a normalization transformation that gets fired on KOLA functions. If the function is of the form,

$$f_0 \circ f_1 \circ \dots \circ f_n$$

(with compositions associated in any way), this transformation returns the equivalent function in “left-bushy” form:

$$(\dots(f_0 \circ f_1) \circ \dots \circ f_n).$$

The transformation of Figure 6.7 is similar to transformation LBComp from Figure 4.10 (Chapter 4). The firing algorithms and rewrite rules for these transformations are identical, but for the use LBComp’s use of a composition former where LBConj has a conjunction former, and LBComp’s use of function variables where LBConj has predicate variables.

Left-Bushy Joins Transformation LBJoin (Figure 6.8) gets applied to KOLA **join** queries that have subqueries that are also **joins**. The effect of this transformation is to rewrite a query with multiple applications of KOLA’s **join** operator into left-bushy form. For example, the bushy join,

$$\mathbf{join} (p, f) ! [\mathbf{join} (q, g) ! [A_1, A_2], \mathbf{join} (r, h) ! [B_1, B_2]]$$

gets transformed into the left-bushy join,

$$\mathbf{join} (p', f') ! [\mathbf{join} (K_p (\mathbf{true}), \mathbf{id}) ! [\mathbf{join} (K_p (\mathbf{true}), \mathbf{id}) ! [A_1, A_2], B_1], B_2]$$

such that p' is derived from p , q and r , f' is derived from f , g and h , and **join** (K_p (**true**), **id**) is the KOLA equivalent of the Cartesian product operator.

LBJoin is defined in terms of auxiliary transformations **LBJAux** (shown in Figure 6.8), **LBJAux2** (shown in Figure 6.9) and **PullFP** (also shown in Figure 6.9). Its firing algorithm does the following:

1. *Step 1:* The auxiliary transformation, **PullFP**, “pulls up” all data functions and predicates from **join** subqueries into the outermost **join**. The effect of this step is to return a new **join** query that has the same structure as the initial query, but with all but the outermost **join** replaced with Cartesian products.
2. *Step 2:* In this step, the large data predicate and data function now contained in the outermost **join** (i.e., p and f in **join** (p , f)) are simplified by calls to COKO transformations **SimpPred** and **SimpFunc** respectively. (These simplification transformations are presented in the next section.)
3. *Step 3:* This step performs all the necessary reassociations of joins to make the expression left-bushy. Transformation **LBJAux** (shown in Figure 6.8) invokes **LBJAux2** in bottom-up fashion. **LBJAux2** reassociates individual **join** by firing rule **sft**, which rewrites a right associated **join** to a left associated **join** by combining (composing) the data function (data predicate) instantiating the outermost join with **shr** (shift right).
4. *Step 4:* This step repeats the action of *Step 2* to simplify the data function and data predicate in the outermost **join** operator.

Simplifications

Function Simplification Figure 6.10 shows the COKO transformation **SimpFunc** and its auxiliary transformations. These transformations simplify functions built from the KOLA primitives, **id**, π_1 , π_2 , **shr** and **shl**, and the KOLA formers, \circ , $\langle \rangle$ and K_f . **SimpFunc** first normalizes functions so that all composition chains (i.e., functions of the form $f_0 \circ \dots \circ f_n$) contained as subfunctions are made left-bushy (via a call to **LBComp**). Next, auxiliary transformation **SFAux** is invoked. This transformation applies the simplifying identities of transformations **BSAux1** and **BSAux2** in a bottom-up fashion. If none of the rules in these latter transformations fires on a given subquery, rules **sft** and **dis** are successively fired to see if reassociation of compositions or distribution of compositions over function pairs ($\langle \rangle$)

```

TRANSFORMATION LBJoin
-- Convert n-ary join to left-bushy join
USES
  cu: iterate (Kf (true), id) ! A → A,
  SimpPred,
  SimpFunc,
  PullFP,
  LBJAux
BEGIN
  -- Step 1: Pull Up Data Predicates and Data Functions
  PullFP;

  -- Step 2: Simplify Top-Most Predicate and Data Function
  {GIVEN iterate (p, f) ! A DO {SimpPred (p); SimpFunc (f); cu}} ||
  {GIVEN join (p, f) ! _0 DO {SimpPred (p); SimpFunc (f)}};

  -- Step 3: Reorder
  LBJAux;

  -- Step 4: Simplify
  {GIVEN iterate (p, f) ! A DO {SimpPred (p); SimpFunc (f); cu}} ||
  {GIVEN join (p, f) ! _0 DO {SimpPred (p); SimpFunc (f)}}
END

TRANSFORMATION LBJAux
-- Helps to Convert n-ary join to left-bushy join
USES
  LBJAux2
BEGIN
  BU {GIVEN join (_P, _F) ! _0 DO LBJAux2}
END

```

Figure 6.8: Transformations LBJoin and LBJAux

```

TRANSFORMATION LBJAux2
-- Helps to Convert n-ary join to left-bushy join
USES
pull1: join (p, f) ! [join (q, g) ! [A1, A2], B] →
      join ((q ⊕ π1) & (p ⊕ ⟨g ∘ π1, π2⟩), f ∘ ⟨g ∘ π1, π2⟩) !
      [join (Kf (true), id) ! [A1, A2], B],
pull2: join (p, f) ! [A, join (q, g) ! [B1, B2]] →
      join ((q ⊕ π2) & (p ⊕ ⟨π1, g ∘ π2⟩), f ∘ ⟨π1, g ∘ π2⟩) !
      [A, join (Kf (true), id) ! [B1, B2]],
sft: join (p, f) ! [A, join (Kf (true), id) ! [B1, B2]] →
      join (p ⊕ shr, f ∘ shr) ! [join (Kf (true), id) ! [A, B1], B2],
SimpFunc,
SimpPred
BEGIN
  pull1 ||
  {pull2 → sft → {GIVEN join (p, f) ! [A, _0] DO LBJAux2 (A)}}
END

```

```

TRANSFORMATION PullFP
-- Pull all data functions and data predicates into top-most
-- iterate or join
USES
ru1: iterate (p, f) ! (iterate (q, g) ! A) →
      iterate (q & (p ⊕ g), f ∘ g) ! A,
ru2: iterate (p, f) ! (join (q, g) ! [A, B]) →
      join (q & (p ⊕ g), f ∘ g) ! [A, B],
ru3: join (p, f) ! [iterate (q, g) ! A, B] →
      join ((q ⊕ π1) & (p ⊕ ⟨g ∘ π1, π2⟩), f ∘ ⟨g ∘ π1, π2⟩) ! [A, B],
ru4: join (p, f) ! [A, iterate (q, g) ! B] →
      join ((q ⊕ π2) & (p ⊕ ⟨π1, g ∘ π2⟩), f ∘ ⟨π1, g ∘ π2⟩) ! [A, B],
ru5: join (p, f) ! [join (q, g) ! [A1, A2], B] →
      join ((q ⊕ π1) & (p ⊕ ⟨g ∘ π1, π2⟩), f ∘ ⟨g ∘ π1, π2⟩) !
      [join (Kf (true), id) ! [A1, A2], B],
ru6: join (p, f) ! [A, join (q, g) ! [B1, B2]] →
      join ((q ⊕ π2) & (p ⊕ ⟨π1, g ∘ π2⟩), f ∘ ⟨π1, g ∘ π2⟩) !
      [A, join (Kf (true), id) ! [B1, B2]]
BEGIN
  BU {GIVEN _F ! _0 DO {ru1 || ru2 || {{ru3 || ru5}; {ru4 || ru6}}}}
END

```

Figure 6.9: Transformations LBJAux2 and PullFP Auxiliary Transformations

```

TRANSFORMATION SimpFunc
USES
  SFAux,
  LBComp
BEGIN
  TD LBComp;
  SFAux;
  TD LBComp
END

TRANSFORMATION SFAux
USES
  SFAux1,
  SFAux2,
  sft:  $(f \circ g) \circ h \longrightarrow f \circ (g \circ h)$ ,
  dis:  $\langle f, g \rangle \circ h \longrightarrow \langle f \circ h, g \circ h \rangle$ ,
  LBComp
BEGIN
  BU {SFAux1 ||
      SFAux2 ||
      sft  $\rightarrow$  {SFAux; sft INV} ||
      dis  $\rightarrow$  {SFAux; dis INV} ||
      dis INV  $\rightarrow$ 
        {GIVEN  $f \circ \_F$  DO
          {SFAux (f);
           REPEAT {SFAux1 || SFAux2}}
        }
    }
END

TRANSFORMATION BSAux1
USES
  ru1:  $\mathbf{shl} \circ \mathbf{shr} \longrightarrow \mathbf{id}$ ,
  ru2:  $\mathbf{shr} \circ \mathbf{shl} \longrightarrow \mathbf{id}$ ,
  ru3:  $\pi_1 \circ \mathbf{shr} \longrightarrow \pi_1 \circ \pi_1$ ,
  ru4:  $\pi_2 \circ \mathbf{shl} \longrightarrow \pi_2 \circ \pi_2$ ,
  ru5:  $f \circ \mathbf{id} \longrightarrow f$ ,
  ru6:  $\mathbf{id} \circ f \longrightarrow f$ ,
  ru7:  $\langle \pi_1, \pi_2 \rangle \longrightarrow \mathbf{id}$ ,
  ru8:  $\langle \pi_1, \pi_1 \rangle \longrightarrow \langle \mathbf{id}, \mathbf{id} \rangle \circ \pi_1$ ,
  ru9:  $\pi_1 \circ \mathbf{shl} \longrightarrow \langle \pi_1, \pi_1 \circ \pi_2 \rangle$ ,
  ru10:  $\pi_2 \circ \mathbf{shr} \longrightarrow \langle \pi_2 \circ \pi_1, \pi_2 \rangle$ 
BEGIN
  ru1 || ru2 || ru3 || ru4 || ru5 ||
  ru6 || ru7 || ru8 || ru9 || ru10
END

TRANSFORMATION BSAux2
USES
  ru9:  $\langle \pi_2, \pi_2 \rangle \longrightarrow \langle \mathbf{id}, \mathbf{id} \rangle \circ \pi_2$ ,
  ru10:  $\langle K_f(x), K_f(y) \rangle \longrightarrow K_f([x, y])$ ,
  ru11:  $K_f(x) \circ f \longrightarrow K_f(x)$ ,
  ru12:  $\pi_1 \circ \langle f, g \rangle \longrightarrow f$ ,
  ru13:  $\pi_2 \circ \langle f, g \rangle \longrightarrow g$ ,
  ru14:  $\langle K_f(x), f \rangle \longrightarrow \langle K_f(x), \mathbf{id} \rangle \circ f$ ,
  ru15:  $\langle f, K_f(x) \rangle \longrightarrow \langle \mathbf{id}, K_f(x) \rangle \circ f$ ,
  LBComp
BEGIN
  ru9 || ru10 || ru11 || ru12 || ru13 ||
  GIVEN  $\langle K_f(x), \mathbf{id} \rangle$  DO SKIP ||
  GIVEN  $\langle \mathbf{id}, K_f(x) \rangle$  DO SKIP ||
  {ru14 || ru15}  $\rightarrow$  BU {LBComp}
END

```

Figure 6.10: Transformation SimpFunc and Its Auxiliary Transformations

makes it possible for these rules to be fired. The second attempt to fire the rules of BSAux1 and BSAux2 is triggered by a recursive firing of transformation SFAux.

Predicate Simplification Transformation SimpPred of Figure 6.11 simplifies predicates in a manner similar to how SimpFunc simplifies functions. Predicates simplified are those

formed from predicate formers, $\&$, $|$, \sim , \oplus and K_p . `SimpPred` visits a predicate's subpredicates and subfunctions in bottom-up fashion (as achieved via recursive calls at the beginning of the firing algorithm.) Then, auxiliary transformation `SimpDisj` is called on disjunct subpredicates ($p | q$), `SimpConj` is called on conjunct subpredicates ($p \& q$), `SimpNeg` is called on negation subpredicates ($\sim (p)$), and `SimpOpls` is called on combination subpredicates ($p \oplus f$) (after a call of `REPEAT sft` first moves as much of the function out of the predicate p as possible). Each of these specialized transformations attempts to fire rules to simplify predicates that are specific to the kind of predicate for which they are named. As with `SimpFunc`, failure to fire any of the rules in the specialized auxiliary transformations makes `SimpPred` attempt to reassociate predicate combinations.

Common Path Expression Elimination Transformation `PullComFunc` is shown in Figure 6.13 along with its auxiliary transformation, `PCFAux`. `PullComFunc` rewrites predicates of the form,

$$(p_1 \oplus f_1) \& \dots \& (p_n \oplus f_n)$$

by grouping common functions, f_i leaving a predicate of the form,

$$(p'_1 \oplus f_1) \& \dots \& (p'_m \oplus f_m)$$

such that $m \leq n$ and no two functions, f_i and f_j ($i \neq j$) are the same. **Step 1** of the firing algorithm for `PullComFunc` first normalizes input conjunction predicates into left-bushy form (via a call to `LBConj`). Then in **Step 2**, auxiliary transformation `PCFAux` is called on every conjunction subpredicate in bottom-up fashion.

To illustrate the effects of `PCFAux`, Figure 6.12 shows the parse tree for the i th conjunction subpredicate visited. The call of `PCFAux` on this subtree is intended to merge subpredicate p_{i+1} with a subpredicate below it, p_j provided that $f_{i+1} = f_j$. Merging is accomplished by comparing f_{i+1} with each of the functions f_i, f_{i-1}, \dots in turn, until one or none is found that is the same as f_{i+1} . (Note that the invariant for this algorithm establishes that because `PCFAux` is called in bottom-up fashion on successive subtrees, that each of the functions f_1, \dots, f_i is distinct). `PCFAux` handles each of the possible cases for function comparisons as described below:

- *Case 1:* $i = 1, f_2 = f_1$

This case is handled by the successful firing of rule `fac1` leaving

$$(p_i \& p_{i+1}) \oplus f_i.$$

```

TRANSFORMATION SimpPred
USES
  sft: (p ⊕ f) ⊕ g → p ⊕ (f ∘ g),
  SimpFunc,
  SimpConj,
  SimpDisj,
  SimpOpls,
  SimpNeg
BEGIN
  GIVEN p & q DO {SimpPred (p); SimpPred (q); SimpConj} ||
  GIVEN p | q DO {SimpPred (p); SimpPred (q); SimpDisj} ||
  GIVEN ~ (p) DO {SimpPred (p); SimpNeg} ||
  {REPEAT sft;
   GIVEN p ⊕ f DO {SimpPred (p); SimpFunc (f); SimpOpls}
   REPEAT {sft INV}}
END

TRANSFORMATION SimpDisj
USES
  d1: p | Kp (true) → Kp (true),
  d2: Kp (true) | p → Kp (true),
  d3: p | Kp (false) → p,
  d4: Kp (false) | p → p,
  d5: p | p → p,
  d6: p | ~ (p) → Kp (true),
  d7: ~ (p) | p → Kp (true)
BEGIN
  d1 || d2 || d3 || d4 ||
  d5 || d6 || d7
END

TRANSFORMATION SimpConj
USES
  c1: p & Kp (true) → p,
  c2: Kp (true) & p → p,
  c3: p & Kp (false) → Kp (false),
  c4: Kp (false) & p → Kp (false),
  c5: p & p → p,
  c6: p & ~ (p) → Kp (false),
  c7: ~ (p) & p → Kp (false)
BEGIN
  c1 || c2 || c3 || c4 ||
  c5 || c6 || c7
END

TRANSFORMATION SimpOpls
USES
  opls1: p ⊕ id → p,
  opls2: Kp (b) ⊕ f → Kp (b)
BEGIN
  opls1 || opls2
END

TRANSFORMATION SimpNeg
USES
  neg1: ~ (Kp (false)) → Kp (true),
  neg2: ~ (Kp (true)) → Kp (false)
BEGIN
  neg1 || neg2
END

```

Figure 6.11: Transformation SimpPred and Its Auxiliary Transformations

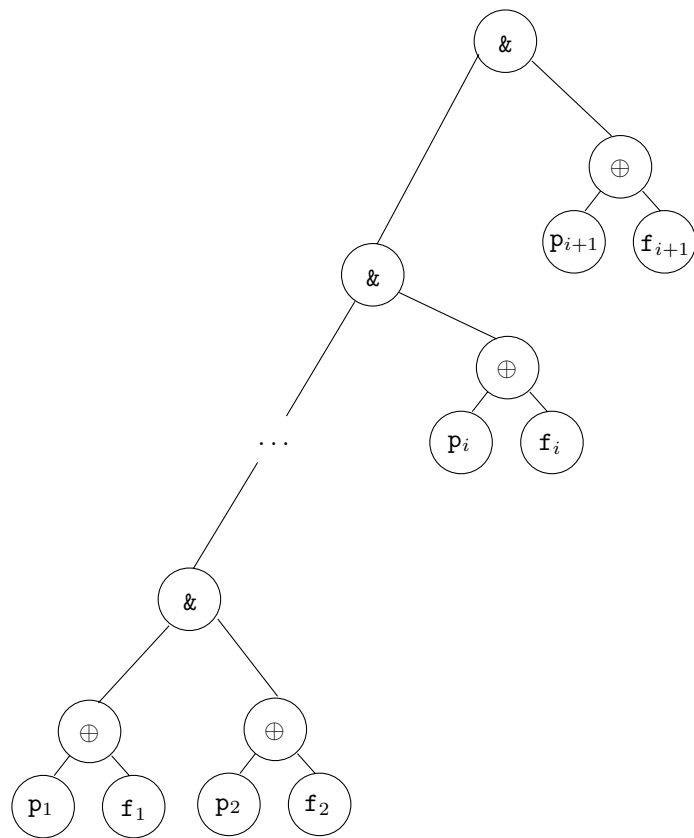


Figure 6.12: An Input KOLA Parse Tree to PCFAux

- *Case 2: $i > 1, f_{i+1} = f_i$*

This case is handled by the successful firing of rule **fac2**, which will rewrite the current predicate into the form,

$$\bar{p} \ \& \ ((p_i \ \& \ p_{i+1}) \oplus f_i)$$

such that \bar{p} is

$$(p_1 \oplus f_1) \ \& \ \dots \ \& \ (p_{i-1} \oplus f_{i-1}).$$

- *Case 3: $i = 1, f_2 \neq f_1$*

In this case, none of the rules successfully fires and the predicate is not rewritten.

- *Case 4: $i > 1, f_{i+1} \neq f_i$*

In this case, f_{i+1} must be compared to the functions “below” $f_i: f_{i-1}, \dots, f_1$. These comparisons are accomplished by firing rule **swtch** which switches the order of subpredicates, $(p_{i+1} \oplus f_{i+1})$ and $(p_i \oplus f_i)$, and then calling **PCFAux** recursively on the left bushy conjunct subpredicate that now has $(p_{i+1} \oplus f_{i+1})$ as its right-most branch.

Analysis

Table 6.3 summarizes the contents of the COKO transformations presented in this Section. The table has 5 columns:

- the *name* of the transformation,
- the *figure* in which the transformation appears,
- the *number of KOLA rewrite rules* fired by the transformation,
- the *number of the above rules* that have been *verified* thus far with LP, and
- the *number of lines* of (firing algorithm) code that the transformation contains.

Admittedly, the number of lines of code is largely dependent on programming style; what may be a single line of code for some, may be broken up into many lines of code for others. The style used for the transformations in this chapter attempts to achieve readability and clear presentation. For that reason, our line count is likely generous. Further, we count all lines in a firing algorithm including white space, comments, and even the lines with the reserved words **BEGIN** and **END**.

The library then, is quite small (roughly 100 lines of code) and dominated by rules (over 50) in all. All of the rewrite rules used for the transformations in the library have been verified with the theorem prover, LP [46].


```

TRANSFORMATION PullComFunc
-- given a conjunctive predicate, rewrites it to the form
-- ((p11 & ... & p1n) OPLUS f1) & ... ((pm1 & ... & pmn) OPLUS fm)
-- by factoring common functions from separate conjuncts
USES
  sft:   $p \oplus (f \circ g) \longrightarrow p \oplus f \oplus g,$ 
  PCFAux,
  LBConj
BEGIN
  -- Step 1: Next make Conjunct Left Bushy
  LBConj;

  -- Step 2: Then Pull Up Common Subfunctions
  BU {GIVEN _P & _P DO PCFAux}
END

TRANSFORMATION PCFAux
-- Helper transformation for PullComFunc, rewriting
-- conjunctive predicates to the form
-- ((p11 & ... & p1n)  $\oplus$  f1) & ... ((pm1 & ... & pmn)  $\oplus$  fm)
-- by factoring common functions from separate conjuncts
USES
  fac1:   $(p \oplus f) \& (q \oplus f) \longrightarrow (p \& q) \oplus f,$ 
  fac2:   $(p \& (q \oplus f)) \& (r \oplus f) \longrightarrow p \& ((q \& r) \oplus f),$ 
  swtch:   $(p \& q) \& r \longrightarrow (p \& r) \& q$ 
BEGIN
  -- Either merge the two leaf conjuncts or switch them
  -- and try with the next two
  {fac1  $\rightarrow$  GIVEN  $p \oplus \_F$  DO PCFAux (p) ||
  fac2  $\rightarrow$  GIVEN  $\_P \& (p \oplus \_F)$  DO PCFAux (p) ||
  swtch  $\rightarrow$  GIVEN  $p \& \_P$  DO PCFAux (p)
  }
END

```

Figure 6.13: Transformation PullComFunc and Its Auxiliary Transformation

<i>Transformation</i>	<i>Figure</i>	<i>No. Rules</i>	<i>No. Verified Rules</i>	<i>No. Lines in Firing Algorithm</i>
LBComp	6.7	1	1	6
LBJoin	6.8	1	1	15
LBJAux	6.8	0	0	3
LBJAux2	6.9	3	3	4
PullFP	6.9	6	6	3
SimpFunc	6.10	0	0	5
SFAux	6.10	2	2	11
BSAux1	6.10	10	10	4
BSAux2	6.10	7	7	6
SimpPred	6.11	1	1	9
SimpDisj	6.11	7	7	4
SimpConj	6.11	7	7	4
SimpOpls	6.11	2	2	3
SimpNeg	6.11	2	2	3
PullComFunc	6.13	1	1	7
PCFAux	6.13	3	3	8
<i>Total</i>	–	53	53	95

Table 6.3: Analysis of the General-Purpose COKO Transformations

6.3.2 Normalizing the Results of Translation

Translation of Query Lite and OQL queries, q generate KOLA functions, $\mathbf{T} \llbracket q \rrbracket$, of the form,

$$\mathbf{iterate} (p, f) \circ \mathbf{unnest} (\mathbf{id}, f_n) \circ \dots \circ \mathbf{unnest} (\mathbf{id}, f_0) \circ \mathbf{single}.$$

This function gets applied to KOLA representations of environments for which the original query is well-formed. For example, if q is well-formed with regard to ρ , then $\mathbf{T} \llbracket q \rrbracket ! \bar{\rho}$ reduces to:

$$\begin{aligned} \{ & f ! [\dots [\bar{\rho}, e_0], \dots e_n] \mid \\ & e_0 \in (f_0 ! (\bar{\rho})), \\ & e_1 \in (f_1 ! ([\bar{\rho}, e_0])), \\ & \dots, \\ & e_n \in (f_n ! ([\dots [\bar{\rho}, e_0], \dots e_{n-1}])), \\ & p ? [\dots [\bar{\rho}, e_0], \dots, e_n] \}. \end{aligned}$$

```

set !
(iterate (eq  $\oplus$  id, "GOP")  $\oplus$  pty  $\oplus$   $\pi_2$ ,  $\pi_1$ ) !
(unnest (id, mems) ! Coms)

```

Figure 6.14: The KOLA Query of Figure 6.6a After Normalization

When $\rho = ()$ ($\bar{\rho} = \text{NULL}$), this expression is:

$$\{f ! [\dots [\text{NULL}, e_0], \dots e_n] \mid$$

$$e_0 \in (f_0 ! (\text{NULL})),$$

$$e_1 \in (f_1 ! ([\text{NULL}, e_0])),$$

$$\dots,$$

$$e_n \in (f_n ! ([\dots [\text{NULL}, e_0], \dots e_{n-1}])),$$

$$p ? [\dots [\text{NULL}, e_0], \dots, e_n]\}.$$

The purpose of the COKO transformation presented in this section is to rewrite the translations that are invoked on NULL into a more intuitive form. More formally, this transformation rewrites KOLA expressions of the form,

$$(\mathbf{iterate} (p, f) \circ$$

$$\mathbf{unnest} (\mathbf{id}, f_n) \circ \dots \circ \mathbf{unnest} (\mathbf{id}, f_1) \circ \mathbf{single}) ! \text{NULL}$$

into the equivalent KOLA expression,

$$\mathbf{iterate} (p', f') !$$

$$(\mathbf{unnest} (\mathbf{id}, f'_m) ! (\dots ! (\mathbf{unnest} (\mathbf{id}, f'_1) ! A) \dots))$$

such that:

- $0 \leq m < n$ (i.e., at least one and as many as all **unnest** functions are removed), and
- A is either the name of a collection, or a query expression that invokes **iterate** or **join** on one or more named collections.

For example, this normalization converts the Query Lite translation of Figure 6.3b into the KOLA expression of Figure 6.3c. The latter expression is much simpler, and unlike the former expression, performs no operations with NULL. This normalization also converts the KOLA expression of Figure 6.6a to the more intuitive expressions shown in Figure 6.14a. The normalized queries differ from the unnormalized queries in that they invoke functions on collections that figure into the result (i.e., **Coms** in Figure 6.14a) rather than invoking functions on NULL.

```

TRANSFORMATION NormTrans
-- get rid of NULL appearing in translated query
USES
nonull:  $K_f(x) ! y \longrightarrow x$ ,
comp:  $(f \circ g) ! x \longrightarrow f ! (g ! x)$ ,
un2j:  $\text{unnest}(f, K_f(B)) ! A \longrightarrow \text{join}(K_f(\text{true}), f) ! [A, B]$ ,

collij:  $\text{iterate}(p, f) ! (\text{join}(q, g) ! [A, B]) \longrightarrow$ 
 $\text{join}(q \& (p \oplus g), f \circ g) ! [A, B]$ ,

colljj:  $\text{join}(p, f) ! [\text{join}(q, g) ! [A1, A2], B] \longrightarrow$ 
 $\text{join}((q \oplus \pi_1) \& (p \oplus \langle g \oplus \pi_1, \pi_2 \rangle), f \circ \langle g \circ \pi_1, \pi_2 \rangle) !$ 
 $[\text{join}(K_p(\text{true}), \text{id}) ! [A1, A2], B]$ ,

FactorK, SimpFunc, SimpPred, OrdUnnests, LBComp
BEGIN
-- Step 1: First get rid of NULL's
GIVEN f ! _0 DO {FactorK (f); nonull}

-- Step 2: Next, normalize to ensure result is of form
-- (f1 ! (f2 ! ... (fn ! x) ...))

GIVEN f ! _0 DO LBComp (f);
REPEAT comp;

-- Step 3: Reorder Unnests so Joins on Constant
-- Expressions are Evaluated 1st

OrdUnnests;

-- Step 4: Convert unnests over constant collections to joins
BU {un2j};

-- Step 5: Collapse composed iterates and joins
BU {{collij || colljj} →
GIVEN join (p, f) ! _0 DO {SimpPred (p); SimpFunc (f)}}
END

```

Figure 6.15: Transformation NormTrans

```

TRANSFORMATION OrdUnnests
USES
  comm:  unnest (f, Kf (B)) ! (unnest (g, h) ! A) →
        unnest (f ∘ ⟨⟨π1 ∘ π1, π2⟩, π2 ∘ π1⟩, h ∘ π1) !
        (unnest (id, Kf (B)) ! A,
SimpFunc
BEGIN
  BU {GIVEN F ∘ unnest (F, Kf (_)) DO SKIP ||
      comm → {GIVEN unnest (f, g) ! _ DO {SimpFunc (f); SimpFunc (g)};
            GIVEN F ! x DO OrdUnnests (x)
      }
}
END

```

Figure 6.16: Transformation OrdUnnests

Transformation NormTrans

Transformation NormTrans (Figure 6.15) is the “main” COKO transformation that removes NULL from the result of translation. If the original query has more than one collection expression in its FROM clause, this transformation also reorders the FROM clause expressions so that all named collections appear before all path expressions. For example, the OQL query,

```

SELECT x
FROM x IN Coms, y IN x.mems, z IN Sens

```

gets rewritten to

```

SELECT x
FROM x IN Coms, z IN Sens, y IN x.mems

```

so that the path expression *x.mems* appears after the named collection *Sens*. (In terms of KOLA, the resulting expression will have all **unnest** functions appearing before all **join** functions.)

The firing algorithm for NormTrans has 5 steps, described below in terms of their effects on the translation of the OQL join query of Figure 6.17a shown in Figure 6.17b: $q_0 =$

$$\begin{aligned}
 & (\text{iterate} (\text{eq} \oplus \langle \text{pty} \circ \text{chair} \circ \pi_2 \circ \pi_1, \text{pty} \circ \text{chair} \circ \pi_2 \rangle, \pi_2 \circ \pi_1) \circ \\
 & \text{unnest} (\text{id}, K_f (\text{SComs})) \circ \text{unnest} (\text{id}, K_f (\text{Coms})) \circ \text{single}) ! \text{NULL}.
 \end{aligned}$$

Step 1: In the first step, transformation FactorK and rule nonull combine to remove NULL from the query produced by translation. In general, when called on a KOLA expression of

```

SELECT x
FROM x IN Coms, y IN SComs
WHERE x.chair.pty == y.chair.pty

```

(a)

```

(iterate (eq  $\oplus$  ⟨pty  $\circ$  chair  $\circ$   $\pi_2$   $\circ$   $\pi_1$ , pty  $\circ$  chair  $\circ$   $\pi_2$ ⟩,  $\pi_2$   $\circ$   $\pi_1$ )  $\circ$ 
unnest (id,  $K_f$  (SComs)))  $\circ$  unnest (id,  $K_f$  (Coms))  $\circ$  single) ! NULL

```

(b)

Figure 6.17: An OQL Join Query (a) and Its Translation into KOLA (b)

the form,

```

(iterate (p, f)  $\circ$ 
unnest (id,  $f_n$ )  $\circ$  ...  $\circ$  unnest (id,  $f_0$ )  $\circ$  single) ! NULL,

```

FactorK returns an expression, $K_f (A) ! \text{NULL}$ such that A is of the form,

```

(iterate (p', f')  $\circ$ 
unnest (id,  $f_n$ )  $\circ$  ...  $\circ$  unnest (id,  $f_0$ )) ! B

```

and B is either a named collection or an expression $\text{iterate } (p, f) ! B'$, such that B' is a named collection. Put simply, **FactorK** rewrites the KOLA expression produced by translation into an invocation of a constant function on **NULL**: $K_f (A) ! \text{NULL}$. Rule **nonnull** then rewrites this expression to A . To illustrate, **FactorK** transforms the query q_0 above to $q_1 = K_f (A) ! \text{NULL}$ such that A is:

```

(iterate (eq  $\oplus$  ⟨pty  $\circ$  chair  $\circ$   $\pi_1$ , pty  $\circ$  chair  $\circ$   $\pi_2$ ⟩,  $\pi_1$ )  $\circ$ 
unnest (id,  $K_f$  (SComs))) ! Coms

```

Nonnull then rewrites this expression to A . The firing algorithm for **FactorK** is described later in this chapter.

Step 2: Steps 2 and 3 prepare the query expression resulting from Step 1 for application of rule **un2j** which rewrites **unnest** functions to **joins**. Step 2 first removes compositions from the query A resulting from step 1, replacing them with function invocations. Replacing compositions with invocations is accomplished by making the query function left-bushy by calling **LBComp**, and then repeatedly firing rule **comp**. In general, this step returns a KOLA query of the form

```

iterate (p', f') !
(unnest (id,  $f_n$ ) ! (... ! (unnest (id,  $f_0$ ) ! B) ...)).

```

To illustrate this step, its effect on query q_1 resulting from Step 1 is q_2 :

$$\begin{aligned} & \mathbf{iterate} (\mathbf{eq} \oplus \langle \mathbf{pty} \circ \mathbf{chair} \circ \pi_1, \mathbf{pty} \circ \mathbf{chair} \circ \pi_2 \rangle, \pi_1) ! \\ & (\mathbf{unnest} (\mathbf{id}, K_f (\mathbf{SComs})) ! \mathbf{Coms}). \end{aligned}$$

Step 3: Step 3 reorders the **unnest** functions appearing in the result of Step 2, so that those instantiated with constant functions,

$$\mathbf{unnest} (\mathbf{id}, K_f (A))$$

are pushed past those that are not. This reordering is accomplished by transformation **OrdUnnests** (Figure 6.16) which traverses a KOLA expression in bottom-up fashion. If during this traversal, two **unnest** functions appear in the wrong order, they are commuted (by firing rule **comm**) and the **unnest** function with the constant function is then pushed further down with a recursive call to the transformation (much like a bubble sort). In general, this step rewrites queries produced by Step 2 into the form,

$$\begin{aligned} & \mathbf{iterate} (p', f') ! \\ & (\mathbf{unnest} (\mathbf{id}, g_m) ! (\dots (\mathbf{unnest} (\mathbf{id}, g_0) ! \\ & (\mathbf{unnest} (\mathbf{id}, K_f (A_k)) ! (\dots (\mathbf{unnest} (\mathbf{id}, K_f (A_0)) ! B) \dots))) \dots)) \end{aligned}$$

such that no function g_i is a constant function. This step has no effect on query q_2 above, which already satisfies the invariant.

Step 4: Step 4 converts all **unnest** functions that are instantiated with constant functions into **joins**. Note that for any collections A and B ,

$$\begin{aligned} \mathbf{unnest} (\mathbf{id}, K_f (B)) ! A &= \{(\mathbf{id} ! [a, b])^{ij} \mid a^i \in A, b^j \in (K_f (B) ! a)\} \\ &= \{([a, b])^{ij} \mid a^i \in A, b^j \in B\} \\ &= \mathbf{join} (K_p (\mathbf{true}), \mathbf{id}) ! [A, B]. \end{aligned}$$

This identity (expressed by rule **un2j**) gets fired in bottom-up fashion to rewrite queries of the form,

$$\begin{aligned} & \mathbf{iterate} (p', f') ! \\ & (\mathbf{unnest} (\mathbf{id}, g_m) ! (\dots (\mathbf{unnest} (\mathbf{id}, g_0) ! \\ & (\mathbf{unnest} (\mathbf{id}, K_f (A_k)) ! (\dots (\mathbf{unnest} (\mathbf{id}, K_f (A_0)) ! B) \dots))) \dots)) \end{aligned}$$

to

$$\begin{aligned} & \mathbf{iterate} (p', f') ! \\ & (\mathbf{unnest} (\mathbf{id}, g_m) ! (\dots (\mathbf{unnest} (\mathbf{id}, g_1) ! \\ & (\mathbf{join} (K_p (\mathbf{true}), \mathbf{id}) ! [\dots \mathbf{join} (K_p (\mathbf{true}), \mathbf{id}) ! [B, A_1], \dots, A_k] \dots)] \dots)), \end{aligned}$$

if $k > 0$, and

$$\begin{aligned} & \mathbf{iterate} (p', f') ! \\ & (\mathbf{unnest} (\mathbf{id}, g_m) ! (\dots (\mathbf{unnest} (\mathbf{id}, g_1) ! A_1) \dots)) \end{aligned}$$

(such that A_1 is not a **join**) if $k = 0$. Applied to query q_2 , this step leaves q_4 :

$$\begin{aligned} & \mathbf{iterate} (\mathbf{eq} \oplus \langle \mathbf{pty} \circ \mathbf{chair} \circ \pi_1, \mathbf{pty} \circ \mathbf{chair} \circ \pi_2 \rangle, \pi_1) ! \\ & (\mathbf{join} (K_p (\mathbf{true}), \mathbf{id}) ! [\mathbf{Coms}, \mathbf{SComs}]). \end{aligned}$$

Step 5: In the final step, rules *collii* and *collij* are fired in bottom-up fashion to “collapse” successive **joins** and **iterates**. If there are no **unnest** functions resulting from Step 4 (i.e., if there are no path expressions in the FROM clause of the original OQL or Query Lite query), this step will result in a query of the form,

$$\begin{aligned} & \mathbf{join} (p', f') ! \\ & [\dots \mathbf{join} (K_p (\mathbf{true}), \mathbf{id}) ! [B, A_1], \dots, A_k]. \end{aligned}$$

Applied to q_4 , this step results in the query,

$$\mathbf{join} (\mathbf{eq} \oplus \langle \mathbf{pty} \circ \mathbf{chair} \circ \pi_1, \mathbf{pty} \circ \mathbf{chair} \circ \pi_2 \rangle, \pi_1) ! [\mathbf{Coms}, \mathbf{SComs}].$$

Transformation FactorK

Transformation **FactorK** is called to rewrite query functions resulting from translation into the form

$$K_f (A)$$

for some collection A . The listing of the transformation’s firing algorithm is not shown but is described instead below.

An OQL or Query Lite query q that is well-formed with regard to the empty environment gets translated into a KOLA expression of the form, $\mathbf{T} \llbracket q \rrbracket ! \mathbf{NULL}$, such that $\mathbf{T} \llbracket q \rrbracket$ is:

$$\begin{aligned} & (\mathbf{iterate} (p, f) \circ \\ & \mathbf{unnest} (\mathbf{id}, f_n) \circ \dots \circ \mathbf{unnest} (\mathbf{id}, f_0) \circ \mathbf{single}). \end{aligned}$$

The reduction of $\mathbf{T} \llbracket q \rrbracket ! \mathbf{NULL}$ leaves:

$$\begin{aligned} & \{f ! [\dots [\mathbf{NULL}, e_0], \dots e_n] \mid \\ & e_0 \in (f_0 ! (\mathbf{NULL})), \\ & e_1 \in (f_1 ! ([\mathbf{NULL}, e_0])), \\ & \dots, \\ & e_n \in (f_n ! ([\dots [\mathbf{NULL}, e_0], \dots e_{n-1}])), \\ & p ? [\dots [\mathbf{NULL}, e_0], \dots, e_n]\}. \end{aligned}$$

$$\begin{aligned}
(1) \quad & f \xrightarrow{\equiv} (f \circ \mathbf{shl}) \circ \mathbf{shr} \\
(2) \quad & f \circ \pi_2 \circ \mathbf{shl} \xrightarrow{\equiv} f \circ \pi_2 \circ \pi_2 \\
(3) \quad & f \circ \pi_1 \circ \pi_1 \circ \mathbf{shl} \xrightarrow{\equiv} f \circ \pi_1 \\
(4) \quad & f \circ \pi_2 \circ \pi_1 \circ \mathbf{shl} \xrightarrow{\equiv} f \circ \pi_1 \circ \pi_2
\end{aligned}$$

Figure 6.18: Rewrite Rules in PullP2SHRF

Because $\mathbf{T} \llbracket q \rrbracket$ is a constant function, functions f_0, \dots, f_n , do not depend on `NULL`. Rather,

- f_0 can be rewritten to a constant function that returns a collection (i.e., $K_f(A_0)$ for some collection A_0),
- f_1 can be rewritten to a function on e_0 (i.e., $f'_1 \circ \pi_2$ for some collection f'_1),
- f_2 can be rewritten to a function on e_0 and e_1 (i.e., $f'_2 \circ \pi_2 \circ \mathbf{shr}$ for some collection f'_2),
- ...
- f_n can be rewritten to a function on e_0, e_1, \dots, e_n (i.e.,

$$f'_n \circ \pi_2 \circ \underbrace{\mathbf{shr} \circ \dots \circ \mathbf{shr}}_{n-1}$$

for some function f'_n).

Similarly, function f can be rewritten to a function on e_0, e_1, \dots, e_n (i.e., (i.e.,

$$f' \circ \pi_2 \circ \underbrace{\mathbf{shr} \circ \dots \circ \mathbf{shr}}_n$$

for some function f') and predicate p can be rewritten to a predicate on e_0, e_1, \dots, e_n (i.e.,

$$p' \oplus (\pi_2 \circ \underbrace{\mathbf{shr} \circ \dots \circ \mathbf{shr}}_n)$$

for some predicate p').

The first step performed by transformation `FactorK` is to normalize all data functions f_0, f_1, \dots, f_n and f and the data predicate p in the manner just described. This step uses the rewrite rules listed in Figure 6.18. For each `unnest` function, `unnest (id, f_i)`, these rules are fired $i - 1$ times on f_i . (They are fired n times on f and p of `iterate (p, f)`.) First, rule (1) is fired on f_i leaving

$$f_i \circ \mathbf{shl} \circ \mathbf{shr}.$$

$$\begin{aligned}
& (\text{iterate } (\overline{p}, \overline{f}) \circ \\
& \quad \text{unnest } (\text{id}, \overline{f_n}) \circ \text{unnest } (\text{id}, \overline{f_{n-1}}) \circ \dots \circ \text{unnest } (\text{id}, \overline{f_1}) \circ \text{unnest } (\text{id}, \overline{f_0}) \circ \\
& \quad \text{single}) ! \text{ NULL} \\
& \qquad \qquad \qquad \text{such that} \\
& \overline{p} = p' \oplus (\pi_2 \circ \mathbf{shr}^n) \\
& \overline{f} = f' \circ \pi_2 \circ \mathbf{shr}^n \\
& \overline{f_i} = f'_i \circ \pi_2 \circ \mathbf{shr}^{i-1} \quad (\text{for } i > 0), \text{ and} \\
& \overline{f_0} = K_f(A)
\end{aligned}$$

Figure 6.19: Translated OQL Queries Following Rewriting of their Data Functions

Then, rules (2) and (3) and (4) are successively fired on

$$f_i \circ \mathbf{shl}.$$

After $i - 1$ applications of these rules, we are left with a function of the form

$$f_i'' \circ g \circ \underbrace{\mathbf{shr} \circ \dots \circ \mathbf{shr}}_{i-1}.$$

Note that f_i is a function that gets invoked on arguments of the form,

$$[\dots [\text{NULL}, e_0], \dots e_{i-1}].$$

The invocation of

$$f_i'' \circ g \circ \underbrace{\mathbf{shr} \circ \dots \circ \mathbf{shr}}_{i-1}.$$

on this argument reduces to

$$f_i'' ! (g ! [\text{NULL}, [e_0, \dots [e_{i-2}, e_{i-1}] \dots]]).$$

As f_i ignores NULL, g must be π_2 . Therefore, the effect of this step is to leave a query expression of the form shown in Figure 6.19.

The rest of this transformation proceeds in five steps and uses the rules of Figure 6.20. In this figure and in the text, we use the notation “ δ_i ” to denote a KOLA function defined for $i \geq 0$ as follows:

$$\begin{aligned}
\delta_0 &= \mathbf{shr} \\
\delta_i &= \langle \pi_1, \delta_{i-1} \circ \pi_2 \rangle, \quad \text{for } i > 0
\end{aligned}$$

Substituting for δ in rules (10) and (11) of Figure 6.20 reveals these rules to be strictly unnecessary: rule (11) follows from rule (7), and rule (12) follows from rule (9) (fired n

- $$\begin{aligned}
(1) \quad & \mathbf{iterate} (\mathbf{p} \oplus (\mathbf{f} \circ \mathbf{h}), \mathbf{g} \circ \mathbf{h}) \circ \mathbf{unnest} (\mathbf{h1}, \mathbf{h2}) \xrightarrow{\equiv} \\
& \mathbf{iterate} (\mathbf{p} \oplus \mathbf{f}, \mathbf{g}) \circ \mathbf{unnest} (\mathbf{h} \circ \mathbf{h1}, \mathbf{h2}) \\
(2) \quad & \mathbf{unnest} (\mathbf{f} \circ \mathbf{shr} \circ \mathbf{shr}, \mathbf{g} \circ \mathbf{shr}) \circ \mathbf{unnest} (\mathbf{h1}, \mathbf{h2}) \xrightarrow{\equiv} \\
& \mathbf{unnest} (\mathbf{f} \circ \delta_1 \circ \mathbf{shr}, \mathbf{g}) \circ \mathbf{unnest} (\mathbf{shr} \circ \mathbf{h1}, \mathbf{h2}) \\
(3) \quad & \mathbf{unnest} (\mathbf{f} \circ \pi_2 \circ \mathbf{shr}, \mathbf{g} \circ \pi_2) \circ \mathbf{unnest} (\mathbf{h1}, \mathbf{h2}) \xrightarrow{\equiv} \\
& \mathbf{unnest} (\mathbf{f}, \mathbf{g}) \circ \mathbf{unnest} (\pi_2 \circ \mathbf{h1}, \mathbf{h2}) \\
(4) \quad & \mathbf{unnest} (\pi_2 \circ \mathbf{shr}, \mathbf{f} \circ \pi_2) \circ \mathbf{unnest} (\mathbf{id}, \mathbf{K}_f (\mathbf{A})) \circ \mathbf{single} \xrightarrow{\equiv} \\
& \mathbf{K}_f (\mathbf{unnest} (\mathbf{id}, \mathbf{f}) ! \mathbf{A}) \\
(5) \quad & \mathbf{f} \circ \mathbf{K}_f (\mathbf{x}) \xrightarrow{\equiv} \mathbf{K}_f (\mathbf{f} ! \mathbf{x}) \qquad (6) \quad \mathbf{f} \xrightarrow{\equiv} \mathbf{f} \circ \mathbf{shl} \circ \mathbf{shr} \\
(7) \quad & \pi_2 \circ \langle \mathbf{f}, \mathbf{g} \rangle \xrightarrow{\equiv} \mathbf{g} \qquad (8) \quad \mathbf{f} \circ \mathbf{id} \xrightarrow{\equiv} \mathbf{f} \\
(9) \quad & \mathbf{shr} \circ \langle \pi_1, \mathbf{f} \circ \pi_2 \rangle \circ \mathbf{shl} \xrightarrow{\equiv} \langle \pi_1, \langle \pi_1, \mathbf{f} \circ \pi_2 \rangle \circ \pi_2 \rangle \\
(10) \quad & \pi_2 \circ \delta_i \xrightarrow{\equiv} \delta_{i-1} \circ \pi_2 \qquad (11) \quad \mathbf{shr}^i \circ \delta_1 \circ \mathbf{shl}^i \xrightarrow{\equiv} \delta_{i+1}
\end{aligned}$$

Figure 6.20: Rewrite Rules in FactorK and FKAux

times). In fact the COKO implementations of these transformations cannot express rules (10) and (11) (and instead would fire rules (7) and (10) as many times as necessary) because the matching of these rules to queries would require counting. (Note however that we can fire rule (2) once we substitute $\langle \pi_1, \mathbf{shr} \circ \pi_2 \rangle$ for δ_1 .) We include these “macro rules” here to simplify the description of this transformation.

The normalization firing algorithm proceeds by visiting each subfunction of the form, $f \circ g$ of the query shown in Figure 6.19. Therefore, the first subfunction visited is

$$\mathbf{iterate} (p, f) \circ \mathbf{unnest} (\mathbf{id}, f_n),$$

the second is

$$\mathbf{unnest} (\mathbf{id}, f_n) \circ \mathbf{unnest} (\mathbf{id}, f_{n-1})$$

(modulo the normalizations of p , f and f_n and the changes made to $\mathbf{unnest} (\mathbf{id}, f_n)$ after visiting the first subfunction) and so on. These visits are described below.

Step 1: Substituting for p and f , the first visited subfunction is

$$\mathbf{iterate} (p' \oplus (\pi_2 \circ \mathbf{shr}^n), f' \circ \pi_2 \circ \mathbf{shr}^n) \circ \mathbf{unnest} (\mathbf{id}, \overline{f_n}).$$

Rule (1) of Figure 6.20 fires on this function $n + 1$ times, and rule (9) fires once, leaving a query of the form,

$$\begin{aligned} & (\mathbf{iterate} (p', f') \circ \\ & \quad \mathbf{unnest} (\pi_2 \circ \mathbf{shr}^n, \overline{f_n}) \circ \mathbf{unnest} (\mathbf{id}, \overline{f_{n-1}}) \circ \dots \circ \mathbf{unnest} (\mathbf{id}, \overline{f_1}) \circ \mathbf{unnest} (\mathbf{id}, \overline{f_0}) \circ \\ & \quad \mathbf{single}) ! \text{ NULL} \end{aligned}$$

such that p' , f' and $\overline{f_i}$ are as defined in Figure 6.19.

Step 2: In this step, each pair of adjacent **unnest** subfunctions in the composition chain,

$$\mathbf{unnest} (\pi_2 \circ \mathbf{shr}^n, \overline{f_n}) \circ \mathbf{unnest} (\mathbf{id}, \overline{f_{n-1}}) \circ \dots \circ \mathbf{unnest} (\mathbf{id}, \overline{f_0})$$

is visited in turn. The purpose of this is to “push” the data function “ $\pi_2 \circ \mathbf{shr}^n$ ” from the left-most **unnest** function into the **unnest** functions to its right. Each “push” loses one of the “**shr**” subfunctions, and so the effect of this step is to rewrite the above composition chain into

$$\begin{aligned} & \mathbf{unnest} (g_n, \overline{f_n}) \circ \\ & \quad \mathbf{unnest} (g_{n-1}, \overline{f_{n-1}}) \circ \\ & \quad \dots \circ \\ & \quad \mathbf{unnest} (g_2, \overline{f_2}) \circ \\ & \quad \mathbf{unnest} (\pi_2 \circ \mathbf{shr}, \overline{f_1}) \circ \\ & \quad \mathbf{unnest} (\mathbf{id}, \overline{f_0}) \end{aligned}$$

for some functions g_2, \dots, g_n .

Substituting for $\overline{f_i}$, the visit of the $(n - i + 1)^{th}$ pair of **unnest** functions,

$$\mathbf{unnest} (\pi_2 \circ \mathbf{shr}^i, f'_i \circ \pi_2 \circ \mathbf{shr}^{i-1}) \circ \mathbf{unnest} (\mathbf{id}, f_{i-1})$$

pushes the data function “ $\pi_2 \circ \mathbf{shr}^{i-1}$ ” out of the left **unnest** function and into the right. This is captured by the “macro rule”,

$$\begin{aligned} & \mathbf{unnest} (\pi_2 \circ \mathbf{shr}^i, \mathbf{f} \circ \pi_2 \circ \mathbf{shr}^{i-1}) \circ \mathbf{unnest} (\mathbf{id}, \mathbf{g} \circ \pi_2 \circ \mathbf{shr}^{i-2}) \rightrightarrows \\ & \quad \mathbf{unnest} (F, \mathbf{f}) \circ \mathbf{unnest} (\pi_2 \circ \mathbf{shr}^{i-1}, \mathbf{g} \circ \pi_2 \circ \mathbf{shr}^{i-2}) \end{aligned}$$

for some function F . Again, this rule is not expressible in COKO and instead we specify a COKO transformation that achieves the same result with the KOLA rules of Figure 6.20. In visiting the $(n - i + 1)^{th}$ pair of **unnest** functions (for $i \geq 2$),

$$\mathbf{unnest} (\pi_2 \circ \mathbf{shr}^i, f'_i \circ \pi_2 \circ \mathbf{shr}^{i-1}) \circ \mathbf{unnest} (\mathbf{id}, f_{i-1}),$$

this transformation first fires rule (2) and rule (8), leaving:

$$\mathbf{unnest} (\pi_2 \circ \mathbf{shr}^{i-2} \circ \delta_1 \circ \mathbf{shr}, f'_i \circ \pi_2 \circ \mathbf{shr}^{i-2}) \circ \mathbf{unnest} (\mathbf{shr}, f_{i-1}).$$

Next, rule (6) fires $i - 2$ times, leaving:

$$\mathbf{unnest} (\pi_2 \circ \gamma \circ \mathbf{shr}^{i-1}, f'_i \circ \pi_2 \circ \mathbf{shr}^{i-2}) \circ \mathbf{unnest} (\mathbf{shr}, f_{i-1}).$$

such that

$$\gamma = \mathbf{shr}^{i-2} \circ \delta_1 \circ \mathbf{shl}^{i-2}.$$

The firing of “macro rule” (11) (equivalently, $(i - 2)$ firings of rule (9)) on γ leaves:

$$\mathbf{unnest} (\pi_2 \circ \delta_{i-1} \circ \mathbf{shr}^{i-1}, f'_i \circ \pi_2 \circ \mathbf{shr}^{i-2}) \circ \mathbf{unnest} (\mathbf{shr}, f_{i-1}).$$

Then, the firing of “macro rule” (10) (equivalently, rule (7)) leaves:

$$\mathbf{unnest} (\delta_{i-2} \circ \pi_2 \circ \mathbf{shr}^{i-1}, f'_i \circ \pi_2 \circ \mathbf{shr}^{i-2}) \circ \mathbf{unnest} (\mathbf{shr}, f_{i-1}).$$

This pass is repeated for every occurrence of “**shr**” that needs to be passed from right to left. In this case, $(i - 1)$ passes are completed in all, leaving

$$\mathbf{unnest} (\delta_{i-2} \circ \dots \circ \delta_0 \circ \pi_2 \circ \mathbf{shr}, f'_i \circ \pi_2) \circ \mathbf{unnest} (\mathbf{shr}^{i-1}, f_{i-1}).$$

Subsequently, rule (3) fires, leaving:

$$\mathbf{unnest} (\delta_{i-2} \circ \dots \circ \delta_0, f'_i) \circ \mathbf{unnest} (\pi_2 \circ \mathbf{shr}^{i-1}, f_{i-1})$$

and, substituting for $\overline{f_{i-1}}$ the next adjacent pair of **unnest** functions,

$$\mathbf{unnest} (\pi_2 \circ \mathbf{shr}^{i-1}, f'_i \circ \pi_2 \circ \mathbf{shr}^{i-2}) \circ \mathbf{unnest} (\mathbf{id}, f_{i-2})$$

is visited. In all, $n - 1$ visits are made of adjacent **unnest** functions, leaving a query of the form,

$$\begin{aligned} &(\mathbf{iterate} (p', f') \circ \\ &\mathbf{unnest} (\delta_{n-2} \circ \dots \circ \delta_0, f'_n) \circ \mathbf{unnest} (\delta_{n-3} \circ \dots \circ \delta_0, f'_{n-1}) \circ \\ &\dots \circ \\ &\mathbf{unnest} (\delta_0, f'_2) \\ &\mathbf{unnest} (\pi_2 \circ \mathbf{shr}, f'_1 \circ \pi_2) \circ \mathbf{unnest} (\mathbf{id}, K_f (A)) \circ \mathbf{single}) ! \text{NULL}. \end{aligned}$$

<i>Transformation</i>	<i>Figure</i>	<i>No. Rules</i>	<i>No. Verified Rules</i>	<i>No. Lines in Firing Algorithm</i>
NormTrans	6.15	4	3	14
OrdUnnests	6.16	1	0	7
FactorK	6.20	13	9	15
<i>Total</i>	–	18	12	36

Table 6.4: Analysis of the COKO Normalization Transformations

Steps 3, 4 and 5: In the next step,

$$\mathbf{unnest} (\pi_2 \circ \mathbf{shr}, f'_1 \circ \pi_2) \circ \mathbf{unnest} (\mathbf{id}, K_f (A)) \circ \mathbf{single}$$

is rewritten by rule (4) leaving

$$\begin{aligned} & (\mathbf{iterate} (p', f') \circ \\ & \mathbf{unnest} (\delta_{n-2} \circ \dots \circ \delta_0, f'_n) \circ \mathbf{unnest} (\delta_{n-3} \circ \dots \circ \delta_0, f'_{n-1}) \circ \\ & \dots \circ \\ & \mathbf{unnest} (\delta_0, f'_2) \circ K_f (\mathbf{unnest} (\mathbf{id}, f'_1) ! A)) ! \mathbf{NULL}. \end{aligned}$$

Then, rule (5) is fired in bottom-up fashion, leaving

$$\begin{aligned} & K_f (\mathbf{iterate} (p', f') ! \\ & (\mathbf{unnest} (\delta_{n-2} \circ \dots \circ \delta_0, f'_n) ! (\mathbf{unnest} (\delta_{n-3} \circ \dots \circ \delta_0, f'_{n-1}) ! \dots ! \\ & (\mathbf{unnest} (\delta_0, f'_2) ! (\mathbf{unnest} (\mathbf{id}, f'_1) ! A)))))) ! \mathbf{NULL}. \end{aligned}$$

Thus, the original query expression has been rewritten to the form $K_f (A) ! \mathbf{NULL}$ for some collection A .

Analysis

Table 6.4 summarizes the transformations required to perform the normalization of translated KOLA queries. As before, the normalization is expressed with little code (fewer than 40 lines of firing algorithm code) and mostly in terms of rewrite rules.

Transformation `NormTrans` has been tested with over 100 Query Lite and OQL queries of varying complexity, including the Query Lite query of Figure 6.3 and the OQL queries of Figures 6.6a and 6.17b.⁸

⁸As yet this transformation does not work over queries nested in their `SELECT` clauses such as that of Figures 6.6b.

```

SELECT s
FROM s IN Sens
WHERE s.reps.lgst_cit.popn > 1M

```

a. Query Lite Query 1

```

iterate (gt  $\oplus$   $\langle$ id,  $K_f$  (10) $\rangle$   $\oplus$  popn  $\oplus$  lgst_cit  $\oplus$  reps, id) ! Sens

```

b. Its Normalization

```

join (((( $p_1$  &  $p_2$ )  $\oplus$   $\pi_2$ ) &  $p_3$ )  $\oplus$  shr,  $\pi_1 \circ \pi_1$ ) !
[join ( $K_p$  (true), id) ! [Sens, Sts], Cits]
  such that
 $p_1$  = gt  $\oplus$   $\langle$ id,  $K_f$  (1M) $\rangle$   $\oplus$  popn  $\oplus$   $\pi_2$ 
 $p_2$  = eq  $\oplus$   $\langle$ lgst_cit  $\circ$   $\pi_1$ , OID  $\circ$   $\pi_2$  $\rangle$ 
 $p_3$  = eq  $\oplus$   $\langle$ reps  $\circ$   $\pi_1$ , OID  $\circ$   $\pi_2$  $\rangle$ 

```

c. Its Rewrite by PEWhere

```

SELECT s
FROM s IN Sens, r IN Sts, c IN Cits
WHERE (c.popn > 1M) AND (r.lgst_cit == c.OID) AND (s.reps == r.OID)

```

d. Its Translation Into SQL

Figure 6.21: Query 1 (a), Normalization (b), Rewrite by PEWhere (c) In SQL (d)

```

SELECT s
FROM s IN Sens
WHERE (s.reps.lgst_cit.popn > 1M) AND
      (s.terms > 5) AND
      (s.reps.lgst_cit.mayor.bornin.popn > 1M)

```

a. Query Lite Query 2

```

iterate ((gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ lgst_cit ⊕ reps) &
        (gt ⊕ ⟨id, Kf (5)⟩ ⊕ terms) &
        (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ bornin ⊕ mayor ⊕ lgst_cit ⊕ reps), id) !
Sens

```

b. Its Normalization

```

join ((((((((((p1 & p2) ⊕ π2) & p3 & p4) ⊕ π2) & p5) ⊕ π2) &
        ((p6 & p7) ⊕ ⟨π1, (π1 ∘ π2)⟩)) ⊕
        ⟨π1, ⟨π1 ∘ π1, shr ∘ ⟨π2 ∘ π1, π2⟩⟩ ∘ π2) ⊕ shr) ⊕
        ⟨⟨π1 ∘ π1 ∘ π1, shr ∘ ⟨⟨π2 ∘ π1, π2⟩ ∘ π1, π2⟩⟩ ∘ π1, π2⟩),
        π1 ∘ ⟨π1 ∘ π1 ∘ π1, shr ∘ ⟨⟨π2 ∘ π1, π2⟩ ∘ π1, π2⟩⟩ ∘ π1) !
[join (Kp (true), id) !
 [join (Kp (true), id) !
  [join (Kp (true), id) ! [Sens, Sts], Cits], Mays], Cits]
      such that
p1 = gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ π2
p2 = eq ⊕ ⟨bornin ∘ π1, OID ∘ π2⟩
p3 = eq ⊕ ⟨mayor ∘ π1, OID ∘ π1 ∘ π2⟩
p4 = gt ⊕ ⟨id, Kf (1M)⟩ ∘ popn ⊕ π1
p5 = eq ⊕ ⟨lgst_cit ∘ π1, OID ∘ π1 ∘ π2⟩
p6 = gt ⊕ ⟨id, Kf (5)⟩ ⊕ terms ⊕ π1
p7 = eq ⊕ ⟨reps ∘ π1, OID ∘ π2⟩

```

c. Its Rewrite by PEWhere

```

SELECT s
FROM s IN Sens, r IN Sts, c IN Cits, m IN Mays, x IN Cits
WHERE (x.popn > 1M) AND (m.bornin == x.OID) AND
      (c.mayor == m.OID) AND (c.popn > 1M) AND
      (r.lgst_cit == c.OID) AND (s.terms > 5) AND (s.reps == r.OID)

```

d. Its Translation Into SQL

Figure 6.22: Query 2 (a), Normalization (b), Rewrite by PEWhere (c) In SQL (d)


```

SELECT s
FROM s IN Sens
WHERE s.bornin.mayor.terms < 4 AND
      s.pty.name == "GOP" AND
      s.reps.lgst_cit.mayor.bornin.popn > 1M AND
      NOT (s.bornin.popn > 1M) AND
      s.reps.popn > 10M AND
      s.reps.lgst_cit.mayor.terms < 3 AND
      s.terms > 5 AND
      s.bornin.mayor.pty == "Dem" AND
      NOT (s.reps.lgst_cit.name == "Providence")

```

a. Query Lite Query 3

```

iterate ((lt ⊕ ⟨id, Kf (40)⟩ ⊕ terms ⊕ mayor ⊕ bornin) &
        (eq ⊕ ⟨id, Kf (GOP)⟩ ⊕ name ⊕ pty) &
        (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ bornin ⊕ mayor ⊕ lgst_cit ⊕ reps) &
        (~ (gt) ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ bornin) &
        (gt ⊕ ⟨id, Kf (10M)⟩ ⊕ popn ⊕ reps) &
        (lt ⊕ ⟨id, Kf (30)⟩ ⊕ terms ⊕ mayor ⊕ lgst_cit ⊕ reps) &
        (gt ⊕ ⟨id, Kf (50)⟩ ⊕ terms) &
        (eq ⊕ ⟨id, Kf ("Dem")⟩ ⊕ pty ⊕ mayor ⊕ bornin) &
        (~ (eq) ⊕ ⟨id, Kf ("Providence")⟩ ⊕ name ⊕ lgst_cit ⊕ reps), id) !
Sens

```

b. Its Normalization

Figure 6.23: Query 3 (a), Normalization (b), ...

```

join (((((((((p1 & p2) ⊕ π2) & (p3 & p4)) ⊕ π2) &
  (((((((((((p5 & p6 & p7) ⊕ π2) & ((p8 & p9) ⊕ ⟨π1, π1 ∘ π2⟩)) ⊕ π2) &
  ((p10 & p11) ⊕ ⟨π1, π1 ∘ π2⟩)) ⊕ π2) &
  ((p12 & p13) ⊕ ⟨π1, π1 ∘ π2⟩)) & p14) ⊕ π1) & p15) ⊕
  ⟨π1, π1 ∘ π2⟩)) ⊕ shr) ⊕ ⟨⟨π1 ∘ π1 ∘ π1 ∘ π1, ⟨π2 ∘ π1 ∘ π1 ∘ π1, shr
  ∘ ⟨π2 ∘ π1, π2⟩ ∘ π1), π2⟩⟩ ∘ π1, π2) ∘ π1, π2),
  π1 ∘ π1 ∘ ⟨⟨π1 ∘ π1 ∘ π1 ∘ π1, ⟨π2 ∘ π1 ∘
  π1 ∘ π1, shr ∘ ⟨π2 ∘ π1, π2⟩ ∘ π1, π2⟩⟩ ∘ π1, π2) ∘ π1) !
  [join (Kp (true), id) !
  [join (Kp (true), id) !
  [join (Kp (true), id) !
  [join (Kp (true), id) !
  [join (Kp (true), id) ! [Sens, Sts], Cits], Mays], Cits], Cits], Mays]
    such that
    p1 = eq ⊕ ⟨OID, Kf (“Dem”)⟩ ⊕ pty
    p2 = lt ⊕ ⟨OID, Kf (40)⟩ ⊕ terms
    p3 = ~ (gt) ⊕ ⟨OID, Kf (1)⟩ ∘ popn ⊕ π1
    p4 = eq ⊕ ⟨mayor ∘ π1, OID ∘ π2⟩
    p5 = gt ⊕ ⟨OID, Kf (1)⟩ ∘ popn ⊕ π2
    p6 = lt ⊕ ⟨OID, Kf (30)⟩ ∘ terms ⊕ π1
    p7 = eq ⊕ ⟨bornin ∘ π1, OID ∘ π2⟩
    p8 = ~ (eq) ⊕ ⟨OID, Kf (“Providence”)⟩ ∘ name ⊕ π1
    p9 = eq ⊕ ⟨mayor ∘ π1, OID ∘ π2⟩
    p10 = gt ⊕ ⟨OID, Kf (1)⟩ ∘ popn ⊕ π1
    p11 = eq ⊕ ⟨lgst_cit ∘ π1, OID ∘ π2⟩
    p12 = eq ⊕ ⟨OID, Kf (“GOP”)⟩ ∘ pty ⊕ π1
    p13 = eq ⊕ ⟨reps ∘ π1, OID ∘ π2⟩
    p14 = gt ⊕ ⟨OID, Kf (50)⟩ ∘ terms ⊕ π1
    p15 = eq ⊕ ⟨bornin ∘ π1 ∘ π1, OID ∘ π2⟩

```

c. Its Rewrite by PEWhere

```

SELECT s
FROM s IN Sens, r IN Sts, c IN Cits, m IN Mays, x IN Cits, y IN Cits, z IN Mays
WHERE (z.pty == “Dem”) AND (z.terms < 4) AND (NOT (y.popn > 1M)) AND
  (y.mayor == z.OID) AND (x.popn > 1M) AND (m.terms < 3) AND
  (m.bornin == x.OID) AND (NOT (c.name == “Providence”)) AND
  (c.mayor == m.OID) AND (r.popn > 1M) AND (r.lgst_cit == c.OID) AND
  (s.pty == “GOP”) AND (s.reps == r.OID) AND
  (s.terms > 5) AND (s.bornin == y.OID)

```

d. Its Translation Into SQL

Figure 6.24: Query 3 (cont.) . . . , Rewrite by PEWhere (c) In SQL (d)

6.3.3 Transforming Path Expressions to Joins

This section describes a COKO transformation (**PEWhere**) that rewrites Query Lite queries with path expressions in their **WHERE** clause into SQL join queries. Specifically, Query Lite queries that are translated and then normalized with the transformations described in Section 6.3.2 are those affected by **PEWhere** and its auxiliary transformation, **PEWAux**.

Unlike those of the previous section, the COKO transformations described in this section are few (2 in all) and short, requiring 3 rewrite rules, 2 inference rules and fewer than 20 lines of firing algorithm code in all. In addition, the transformations presented here demonstrate a novel application of the semantic query rewrite facility described in Chapter 5. The semantic property concerns foreign keys.

Path Expression Elimination Overview

Consider Query Lite Query 1 of Figure 6.21a that finds all Senators in **Sens** who represent states whose largest cities have a population of over 1 million people. This query includes the path expression,

`s.reps.lgst_cit.popn`

in its **WHERE** clause to find the population of the largest city in the state represented by Senator *s*. Specifically, for any Senator *s*:

- `s.reps` returns the object denoting the state that *s* represents,
- `s.reps.lgst_cit` returns the object denoting the largest city of the state that *s* represents, and
- `s.reps.lgst_cit.popn` returns the integer denoting the population of the largest city of the state that *s* represents.

The relational implementation of San Francisco described in Section 6.1 uses relations to implement each type extent, with the **OID** columns as keys. For the object schema of Figure 2.1,

- **Sens** is a relation representing the extent of objects of type *Senator*,
- **Sts** is a relation representing objects of type *Region* that are states, and
- **Cits** is a relation representing objects of type *City*.

As a result, for path expression $s.reps.lgst_cit.popn$, method `reps` is a *foreign key* for `Sts`, and `lgst_cit` is a foreign key for `Cits`. This information makes it possible to rewrite the Query Lite query of Figure 6.21 into the SQL join query,

```
SELECT s
FROM s IN Sens, r IN Sts, c IN Cits
WHERE (c.popn > 1M) AND (r.lgst_cit == c.OID) AND (s.reps == r.OID)
```

The COKO transformations described in this section perform the rewrite above. These transformations exploit semantic knowledge of foreign keys (metadata information that is assumed to be available to the optimizer), to decide when methods in a path expression can be translated into relational joins. More precisely, these transformations rewrite Query Lite queries of the form,

```
SELECT x
FROM x IN A
WHERE Comp1 AND ... AND Compm
```

such that each $Comp_i$ is a simple comparison predicate involving a path expression such as,

$$x.m_0 \dots m_n \text{ op } k$$

or

$$\text{NOT } (x.m_0 \dots m_n \text{ op } k).$$

As well, these transformations have the following characteristics:

- comparisons can appear in the opposite order, as in,

$$k \text{ op } x.m_0 \dots m_n,$$

- `WHERE` clauses can also contain disjunctions provided that the disjunctions disappear when the `WHERE` clauses is converted into CNF,
- *sharing* of path expressions is recognized.

To illustrate sharing, consider Query Lite Query 2 of Figure 6.22a, which finds senators who have served more than 5 terms, and who represent a state whose largest city: (1) has more than 1 million people, and (2) has a mayor who was born in a city with more than 1 million people. This query contains two path expressions that contain the common subexpression,

$$s.reps.lgst_cit.$$

The transformations presented here rewrite this query into the SQL query,

```
SELECT s
FROM s IN Sens, r IN Sts, c IN Cits, m IN Mays, x IN Cits
WHERE (x.popn > 1M) AND (m.bornin == x.OID) AND
      (c.mayor == m.OID) AND (c.popn > 1M) AND
      (r.lgst_cit == c.OID) AND (s.terms > 5) AND (s.reps == r.OID)
```

rather than to the more naive translation,

```
SELECT s
FROM s IN Sens, r IN Sts, c IN Cits, m IN Mays, x IN Cits, r2 IN Sts, c2 IN Cits
WHERE (x.popn > 1M) AND (m.bornin == x.OID) AND
      (c.mayor == m.OID) AND (c.popn > 1M) AND
      (r.lgst_cit == c.OID) AND (s.terms > 5) AND (s.reps == r.OID) AND
      (r2.lgst_cit == c2.OID) AND (c2.mayor == m.OID) AND (s.reps == r2.OID)
```

which is a 7-way join rather than a 5-way join, redundantly joining collections `Sts` and `Cits` twice (once for each occurrence of the common subexpression).

The transformations described here not only recognize common subexpressions in path expressions, but do so for:

- any number of path expressions in a `WHERE` clause,
- any degree of sharing amongst path expressions, and
- any number of path expressions sharing a given subexpression (even when path expressions with shared subexpressions are not adjacent).

An example application of this transformation is shown in Figures 6.23a. Figure 6.23a and 6.23b show the original Query Lite query and the result of its translation and normalization. Figure 6.24c show the result of rewriting this query by `PEwhere`. Figure 6.24d shows this same query after its translation into SQL.

Query 3 includes path expressions with varying degrees of sharing, such as:

- `s.bornin.mayor.terms < 4`, which shares:
 - `s.bornin` with: `NOT (s.bornin.popn > 1M)`, and
 - `s.bornin.mayor` with: `s.bornin.mayor.pty == "Dem"`, and
- `s.reps.lgst_cit.mayor.bornin.popn > 1M`, which shares:

- *s.reps* with: *s.reps.popn* > 1M,
- *s.reps.lgst_cit* with: NOT (*s.reps.lgst_cit.name* == “Providence”), and
- *s.reps.lgst_cit.mayor* with: *s.reps.lgst_cit.mayor.terms* < 3.

The result of rewriting shown in Figure 6.24 exploits this sharing and joins as few collections as possible.

Transformation PEWhere and Its Auxiliary Transformation

Translation of Query Lite queries generates KOLA expressions of the form,

$$(\text{iterate } (p, \text{id}) \circ \text{unnest } (\text{id}, K_f (A)) \circ \text{single}) ! \text{NULL}.$$

After normalization using the transformations of Section 6.3.2, these queries are of the form,

$$\text{iterate } (q, \text{id}) ! A.$$

If Query Lite queries have WHERE clauses as characterized in the previous section (i.e., conjunctions of simple comparisons), then the predicate *p* in the query produced by translation is of the form,

$$p_0 \ \& \ \dots \ \& \ p_m$$

such that each *p_i* is of the form

$$op \oplus \langle m_{i_n} \circ \dots \circ m_0 \circ g_i, K_f (k) \rangle$$

or

$$\sim (op \oplus \langle m_{i_n} \circ \dots \circ m_0 \circ g_i, K_f (k) \rangle),$$

op is a KOLA comparison primitive (such as **eq**), each *m_j* is a method primitive and *k* is a constant. For these same queries, normalization results in predicates *p'* of the form,

$$op \oplus \langle \text{id}, K_f (k) \rangle \oplus m_{i_n} \circ \dots \circ m_0 \circ g_i$$

or

$$\sim (op) \oplus \langle \text{id}, K_f (k) \rangle \oplus m_{i_n} \oplus \dots \oplus m_0 \oplus g_i$$

(as illustrated by the normalized translations of Query Lite Queries: 1 (Figure 6.21b), 2 (Figure 6.22b), and 3 (Figure 6.23b)).

PEWhere (Figure 6.25) gets invoked after translation and normalization, and therefore affects queries of the form,

$$\text{iterate } (p'_1 \ \& \ \dots \ \& \ p'_m, \text{id}) ! A$$

```

TRANSFORMATION PEWhere
  -- Transforms QL queries with where predicates of the form,
  -- x.a1()...an() op k, or k op x.a1()...an()
  -- into join queries using scoping rules for attributes
  USES
    LBJoin,
    PEWAux,
    PullComFunc,
    SimpFunc,
    SimpPred
  BEGIN
    -- Step 1: Find common subfunctions of conjuncts and factor out
    GIVEN iterate (p, _F) ! _O DO PullComFunc (p);

    -- Step 2: Call PEWAux
    PEWAux;

    -- Step 3: Recombine iterate's and joins into left-bushy join tree
    LBJoin
  END

TRANSFORMATION PEWAux
  USES
    pe2j: scope (B, f, A) ::
      iterate (p  $\oplus$  f, id) ! A  $\longrightarrow$ 
        join (eq  $\oplus$  <f  $\circ$   $\pi_1$ , OID  $\circ$   $\pi_2$ >,  $\pi_1$ ) ! [A, iterate (p, id) ! B],
    splcon: iterate (p & q, id) ! A  $\longrightarrow$  iterate (p, id) ! (iterate (q, id) ! A),
    SimpPred
  INFERS
    Scope
  BEGIN
    splcon  $\rightarrow$  GIVEN _F ! x DO {PEWAux (x); PEWAux};
    pe2j  $\rightarrow$  GIVEN join (p, _F) ! [_O, B] DO PEWAux (B)
  END

```

Figure 6.25: Transformation PEWhere and its Auxiliary Transformation

such as those of Figures 6.21, 6.22 and 6.23. PEWhere operates in 3 steps, which are demonstrated in terms of their effect on the query of Figure 6.22b: the result of translating and normalizing the Query Lite Query 2 of Figure 6.22a.

Step 1: In the first step of this transformation, PullComFunc (Section 6.3.1) rewrites conjunction predicates,

$$p_1 \& \dots \& q_n$$

into the form,

$$(q_1 \oplus f_1) \& \dots \& (q_m \oplus f_m)$$

such that $m \leq n$ and no two functions f_i and f_j ($i \neq j$) are the same. This step extracts the common subexpressions from distinct path expressions.

Applied to Query 2:

When applied to the query of Figure 6.22b, this step results in the expression, Q :

$$\mathbf{iterate} (((q_{1a} \& q_{1b}) \oplus \mathbf{lgst_cit} \oplus \mathbf{reps}) \& q_2, \mathbf{id}) ! \mathbf{Sens}$$

such that

$$\begin{aligned} q_{1a} &= \mathbf{gt} \oplus \langle \mathbf{id}, K_f(1M) \rangle \oplus \mathbf{popn}, \\ q_{1b} &= \mathbf{gt} \oplus \langle \mathbf{id}, K_f(1M) \rangle \oplus \mathbf{popn} \oplus \mathbf{bornin} \oplus \mathbf{mayor} \text{ and} \\ q_2 &= \mathbf{gt} \oplus \langle \mathbf{id}, K_f(5) \rangle \oplus \mathbf{terms}. \end{aligned}$$

Step 2: The second step of this transformation invokes auxiliary transformation, PEWAux on the expression resulting from 1. PEWAux has two key rules. The first is rule `splcon`, which splits an `iterate` function instantiated with a conjunction predicate into two. When applied to queries of the form,

$$\mathbf{iterate} (q_1 \& \dots \& q_m, \mathbf{id}) ! A$$

such as those resulting from Step 1 of PEWhere's firing algorithm, this rule returns

$$\mathbf{iterate} (q_1, \mathbf{id}) ! (\mathbf{iterate} (q_2 \& \dots \& q_m, \mathbf{id}) ! A).$$

The effect of the recursive calls to PEWAux that follow the successful firing of `splcon` is to invoke PEWAux successively on subqueries:

- `iterate (qm, id) ! A`,


```

scope (Sts, reps, Sens).
scope (Cits, reps, Mays).
scope (Cits, bornin, Sens).
scope (Cits, bornin, Mays).

scope (Cits, lgst_cit, Rgs).
scope (Cits, lgst_cit, Sts).

scope (Mays, mayor, Cits).

```

Figure 6.26: Scope Facts Assumed Known for these Examples

- **iterate** (q_{m-1} , **id**) ! (**iterate** (q_m , **id**) ! A),
- **iterate** (q_{m-2} , **id**) ! (**iterate** (q_{m-1} , **id**) ! (**iterate** (q_m , **id**) ! A)), etc.

The second rule, `pej2`, is a conditional rewrite rule that depends on the condition, `scope (B, f, A)`. This condition holds of collections A and B and function f if f is a function on elements of A and is also a foreign key of B . Figure 6.26 shows the scope facts that are assumed to hold (and to be part of the schema accessible by our optimizer) for the examples in this chapter.

Figure 6.27 shows a property definition for `Scope` that lists three inference rules for inferring this property. The first of these rules,

$$\text{scope (B, f, A)} \implies \text{scope (B, f, iterate (p, id) ! A)}$$

says that if f is a foreign key for B that is defined on A , then it is also a foreign key for B that is defined on any selection on A . The second and third rules,

$$\begin{aligned} \text{scope (B, f, A)} &\implies \text{scope (B, f, join (p, \pi_1) ! [A, _0])}. \\ \text{scope (B, f, A)} &\implies \text{scope (B, f, join (p, \pi_2) ! [_0, A])}. \end{aligned}$$

say that if f is a foreign key for B that is defined on A , then it is a foreign key for B that is defined on (left and right) semi-joins on A .

Provided that `scope` is inferred to be true for collection B , function f and collection A , the query,

$$\text{iterate (p} \oplus f, \text{id) ! A}$$

can be rewritten to a join of A and the subcollection of B satisfying p :

$$\text{join (eq} \oplus \langle f \circ \pi_1, \text{OID} \circ \pi_2 \rangle, \pi_1) ! [A, \text{iterate (p, id) ! B}].$$

```

PROPERTY Scope
BEGIN
  scope (B, f, A)  $\implies$  scope (B, f, iterate (p, id) ! A).
  scope (B, f, A)  $\implies$  scope (B, f, join (p,  $\pi_1$ ) ! [A, _0]).
  scope (B, f, A)  $\implies$  scope (B, f, join (p,  $\pi_2$ ) ! [_0, A]).
END

```

Figure 6.27: Property **Scope** and Sample Metadata Information Regarding **Scope**

This query screens B for those elements satisfying p , and then joins the result with A to return those elements of A whose values for f are represented on the subcollection of B . In terms of Query Lite queries, the left-hand side of the rule denotes queries of the form,

```

SELECT x
FROM x IN A
WHERE p (f (x)).

```

In terms of SQL queries, the right-hand side of the rule denotes queries of the form,

```

SELECT x
FROM x IN A, y IN B
WHERE f (x) == y AND p (y).

```

Each time **pe2j** is successfully fired, it returns a query of the form,

```

join (eq  $\oplus$   $\langle f \circ \pi_1, \text{OID} \circ \pi_2 \rangle, \pi_1$ ) ! [A, iterate (p, id) ! B],

```

and **PEWAux** is called recursively on the second argument to the join,

```

iterate (p, id) ! B.

```

This recursive call ensures that all methods appearing in a path expression contribute to the rewrite into a join query.

Applied to Query 2:

1. First, **sp1con** successfully fires and triggers a recursive call of **PEWAux** on

```

iterate (q2, id) ! Sens.

```

Rule `pe2j` does not successfully fire on this expression (because there is no collection B such that

$$\text{scope } (B, \text{terms}, \text{Sens})$$

holds.) Therefore, a second recursive call to `PEWAux` is made on

$$\text{iterate } ((q_{1a} \ \& \ q_{1b}) \oplus \text{lgst_cit} \oplus \text{reps}, \text{id}) ! (\text{iterate } (q_2, \text{id}) ! \text{Sens}).$$

2. The call of `PEWAux` on this query fails to fire `splcon`, but succeeds in firing `pe2j`. The first inference rule for `Scope` in Figure 6.27 together with the fact,

$$\text{scope } (\text{Sts}, \text{reps}, \text{Sens}),$$

makes it possible to infer,

$$\text{scope } (\text{Sts}, \text{reps}, \text{iterate } (q_2, \text{id}) ! \text{Sens}),$$

and therefore `pej2` successfully fires. This results in the query,

$$\begin{aligned} &\text{join } (\text{eq} \oplus \langle \text{reps} \circ \pi_1, \text{OID} \circ \pi_2 \rangle, \pi_1) ! \\ &[\text{iterate } (q_2, \text{id}) ! \text{Sens}, \text{iterate } ((q_{1a} \ \& \ q_{1b}) \oplus \text{lgst_cit}, \text{id}) ! \text{Sts}]. \end{aligned}$$

3. The successful firing of rule `pe2j` triggers another recursive call of `PEWAux`, this time on

$$\text{iterate } ((q_{1a} \ \& \ q_{1b}) \oplus \text{lgst_cit}, \text{id}) ! \text{Sts}.$$

Again, `pe2j` successfully fires on this subquery because of the fact,

$$\text{scope } (\text{Cits}, \text{lgst_cit}, \text{Sts}).$$

This leaves the subexpression,

$$\begin{aligned} &\text{join } (\text{eq} \oplus \langle \text{lgst_cit} \circ \pi_1, \text{OID} \circ \pi_2 \rangle, \pi_1) ! \\ &[\text{Sts}, \text{iterate } (q_{1a} \ \& \ q_{1b}, \text{id}) ! \text{Cits}]. \end{aligned}$$

4. Next, `PEWAux` is recursively called on

$$\text{iterate } (q_{1a} \ \& \ q_{1b}, \text{id}) ! \text{Cits},$$

or equivalently,

$$\begin{aligned} &\text{iterate } ((\text{gt} \oplus \langle \text{id}, K_f(1M) \rangle) \oplus \text{popn}) \ \& \\ &(\text{gt} \oplus \langle \text{id}, K_f(1M) \rangle) \oplus \text{popn} \oplus \text{bornin} \oplus \text{mayor}, \text{id}) ! \text{Cits}. \end{aligned}$$

First `splcon` is fired leaving,

```
iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn, id) !
(iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ bornin ⊕ mayor, id) ! Cits).
```

Then `PEWAux` is fired on

```
iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ bornin ⊕ mayor, id) ! Cits.
```

The fact

```
scope (Mays, mayor, Cits),
```

leads to a successful firing of `pej2`, leaving

```
join (eq ⊕ ⟨mayor ∘ π1, OID ∘ π2⟩, π1) !
[Cits, iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ bornin, id) ! Mays].
```

5. Next, `PEWAux` is again called recursively on

```
iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn ⊕ bornin, id) ! Mays.
```

The fact `scope (Cits, bornin, Mays)` leads `pej2` to fire, leaving,

```
join (eq ⊕ ⟨bornin ∘ π1, OID ∘ π2⟩, π1) !
[Mays, iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn, id) ! Cits].
```

The subsequent recursive call of `PEWAux` on

```
iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn, id) ! Cits
```

fails (as there is no collection B such that `scope (B, popn, Cits)` and the recursion terminates at all levels. Finally, the transformation call is finished leaving the query,

```
join (eq ⊕ ⟨reps ∘ π1, OID ∘ π2⟩, π1) ! [iterate (q2, id) ! Sens, B]
```

such that B is:

```
join (eq ⊕ ⟨lgst_cit ∘ π1, OID ∘ π2⟩, π1) !
[Sts, iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn, id) !
  join (eq ⊕ ⟨mayor ∘ π1, OID ∘ π2⟩, π1) !
    [Cits, join (eq ⊕ ⟨bornin ∘ π1, OID ∘ π2⟩, π1) !
      [Mays, iterate (gt ⊕ ⟨id, Kf (1M)⟩ ⊕ popn, id) ! Cits]]]].
```

<i>Transformation</i>	<i>Figure</i>	<i>No. Rules</i>	<i>No. Verified Rules</i>	<i>No. Lines in Firing Algorithm</i>
PEWhere	6.25	1	1	15
PEWAux	6.25	2	1	4
Scope	6.27	2	2	
<i>Total</i>	–	5	4	19

Table 6.5: Analysis of the Query Lite \rightarrow SQL Transformations

Step 3: The final step of this transformation converts the query resulting from step 2 into a left-bushy join. This step is strictly not required, but simplifies the task of converting the resulting query into SQL as we show in Section 6.4. Applied to the query above, this step returns the query of Figure 6.22c. Expressed in SQL, this query is:

```
SELECT s
FROM s IN Sens, r IN Sts, c IN Cits, m IN Mays, x IN Cits
WHERE (x.popn > 1M) AND (m.bornin == x.OID) AND
      (c.mayor == m.OID) AND (c.popn > 1M) AND
      (r.lgst_cit == c.OID) AND (s.terms > 5) AND (s.reps == r.OID)
```

Analysis

Table 6.5 summarizes the transformations and property presented in this section. Note that this complex rewrite is expressed with 3 rewrite rules, 2 inference rules and fewer than 20 lines of firing algorithm code.

6.4 Translating KOLA into SQL

Transformation PEWhere leaves Query Lite queries in the form

```
join (p1 & ... & pn, f) !
  [join (Kp (true), id) !
   join (Kp (true), id) !
   [... [join (Kp (true), id) ! [A1, A2], ...], Am-2], Am-1], Am]
```

or in the form **iterate** (p , f) ! A . The sublanguage of KOLA that consists of such expressions only includes primitives: **id**, π_1 , π_2 , **shr**, **shl**, **OID**, **m** (**m** a method), **abs**, **add**, **sub**, **mul**, **div**, **mod**, **eq**, **neq**, **lt**, **gt**, **leq**, **geq**; and formers: $\langle \rangle$, \circ , K_f , C_f , **iterate**, **join**, \oplus , $\&$,

Basic Function Primitives

$$\begin{aligned}
\mathbf{T}^{-1} \llbracket \mathbf{id} ! x \rrbracket &= \mathbf{T}^{-1} \llbracket x \rrbracket \\
\mathbf{T}^{-1} \llbracket \pi_1 ! [x, y] \rrbracket &= \mathbf{T}^{-1} \llbracket x \rrbracket \\
\mathbf{T}^{-1} \llbracket \pi_2 ! [x, y] \rrbracket &= \mathbf{T}^{-1} \llbracket y \rrbracket \\
\mathbf{T}^{-1} \llbracket \mathbf{m} ! x \rrbracket &= \mathbf{T}^{-1} \llbracket x \rrbracket .\mathbf{m} \quad (\text{for } \mathbf{m} \text{ a unary method}) \\
\mathbf{T}^{-1} \llbracket \mathbf{m} ! [x, [\dots [y_1, y_2], \dots, y_n]] \rrbracket &= \mathbf{T}^{-1} \llbracket x \rrbracket .\mathbf{m} (\mathbf{T}^{-1} \llbracket y_1 \rrbracket, \dots, \mathbf{T}^{-1} \llbracket y_n \rrbracket) \\
&\quad (\text{for } \mathbf{m} \text{ an } n\text{-ary method})
\end{aligned}$$

Int and Float Function Primitives (i, j integers or floats)

$$\begin{aligned}
\mathbf{T}^{-1} \llbracket \mathbf{abs} ! i \rrbracket &= \mathbf{abs} (\mathbf{T}^{-1} \llbracket i \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{add} ! [i, j] \rrbracket &= (\mathbf{T}^{-1} \llbracket i \rrbracket) + (\mathbf{T}^{-1} \llbracket j \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{sub} ! [i, j] \rrbracket &= (\mathbf{T}^{-1} \llbracket i \rrbracket) - (\mathbf{T}^{-1} \llbracket j \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{mul} ! [i, j] \rrbracket &= (\mathbf{T}^{-1} \llbracket i \rrbracket) * (\mathbf{T}^{-1} \llbracket j \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{div} ! [i, j] \rrbracket &= (\mathbf{T}^{-1} \llbracket i \rrbracket) / (\mathbf{T}^{-1} \llbracket j \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{mod} ! [i, j] \rrbracket &= (\mathbf{T}^{-1} \llbracket i \rrbracket) \text{ MOD } (\mathbf{T}^{-1} \llbracket j \rrbracket)
\end{aligned}$$

Basic Predicate Primitives (x and y of type T)

$$\begin{aligned}
\mathbf{T}^{-1} \llbracket \mathbf{eq} ? [x, y] \rrbracket &= (\mathbf{T}^{-1} \llbracket x \rrbracket) == (\mathbf{T}^{-1} \llbracket y \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{neq} ? [x, y] \rrbracket &= (\mathbf{T}^{-1} \llbracket x \rrbracket) != (\mathbf{T}^{-1} \llbracket y \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{isnull} ? x \rrbracket &= (\mathbf{T}^{-1} \llbracket x \rrbracket) \text{ IS NULL} \\
\mathbf{T}^{-1} \llbracket \mathbf{isnotnull} ? x \rrbracket &= (\mathbf{T}^{-1} \llbracket x \rrbracket) \text{ IS NOT NULL}
\end{aligned}$$

String and Int Predicate Primitives (x and y strings or integers)

$$\begin{aligned}
\mathbf{T}^{-1} \llbracket \mathbf{lt} ? [x, y] \rrbracket &= (\mathbf{T}^{-1} \llbracket x \rrbracket) < (\mathbf{T}^{-1} \llbracket y \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{gt} ? [x, y] \rrbracket &= (\mathbf{T}^{-1} \llbracket x \rrbracket) > (\mathbf{T}^{-1} \llbracket y \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{leq} ? [x, y] \rrbracket &= (\mathbf{T}^{-1} \llbracket x \rrbracket) <= (\mathbf{T}^{-1} \llbracket y \rrbracket) \\
\mathbf{T}^{-1} \llbracket \mathbf{geq} ? [x, y] \rrbracket &= (\mathbf{T}^{-1} \llbracket x \rrbracket) >= (\mathbf{T}^{-1} \llbracket y \rrbracket)
\end{aligned}$$

Table 6.6: \mathbf{T}^{-1} : Applied to KOLA Primitives

\sim , K_p , and C_p . Further, all queries in this sublanguage are assumed to be **iterate** queries, binary **join** queries, or left-bushy n -ary join queries.

A translation function, \mathbf{T}^{-1} to translate KOLA expressions over this subset of KOLA into SQL is defined in Tables 6.6 and 6.7. Note that Table 6.7 includes two translation definitions for **join**. The first of these is for translating n -ary joins ($n > 2$) only. The second of these is for translating binary joins only.

The following example illustrates this translation function. As shown in Section 6.3.3, when invoked on Query Lite query 1 of Figure 6.21b, transformation **PEwhere** returns the query of Figure 6.21c. This query gets translated into SQL as follows:

$$\mathbf{T}^{-1} \left[\left[\begin{array}{l} \mathbf{join} \left(((p_1 \ \& \ p_2) \oplus \pi_2) \ \& \ p_3 \right) \oplus \mathbf{shr}, \pi_1 \circ \pi_1 \right) ! \\ \left[\mathbf{join} \left(K_p \left(\mathbf{true} \right), \mathbf{id} \right) ! \left[\mathbf{Sens}, \mathbf{Sts} \right], \mathbf{Cits} \right] \end{array} \right] \right]$$

such that

$$\begin{aligned} p_1 &= \mathbf{gt} \oplus \langle \mathbf{id}, K_f(1M) \rangle \oplus \mathbf{popn} \oplus \pi_2 \\ p_2 &= \mathbf{eq} \oplus \langle \mathbf{lgst_cit} \circ \pi_1, \mathbf{OID} \circ \pi_2 \rangle \\ p_3 &= \mathbf{eq} \oplus \langle \mathbf{reps} \circ \pi_1, \mathbf{OID} \circ \pi_1 \circ \pi_2 \rangle \end{aligned}$$

$$\begin{aligned} & \mathbf{SELECT} \left((\pi_1 \circ \pi_1) ! \left[[s, r], c \right] \right) \\ = & \mathbf{FROM} \ s \ \mathbf{IN} \ \mathbf{Sens}, \ r \ \mathbf{IN} \ \mathbf{Sts}, \ c \ \mathbf{IN} \ \mathbf{Cits} \\ & \mathbf{WHERE} \left((((((p_1 \ \& \ p_2) \oplus \pi_2) \ \& \ p_3) \oplus \mathbf{shr}) ? \left[[s, r], c \right] \right). \end{aligned}$$

Reducing the predicates in this expression leaves,

```
SELECT s
FROM s IN Sens, r IN Sts, c IN Cits
WHERE (((((p1 & p2) ⊕ π2) & p3) ⊕ shr) ? [[s, r], c])
```

```
SELECT s
= FROM s IN Sens, r IN Sts, c IN Cits
WHERE (((p1 & p2) ⊕ π2) & p3) ? [s, [r, c]]
```

```
SELECT s
= FROM s IN Sens, r IN Sts, c IN Cits
WHERE (((p1 & p2) ⊕ π2) ? [s, [r, c]]) AND (p3 ? [s, [r, c]])
```

```
SELECT s
= FROM s IN Sens, r IN Sts, c IN Cits
WHERE ((p1 & p2) ? [r, c]) AND (p3 ? [s, [r, c]])
```

```
SELECT s
= FROM s IN Sens, r IN Sts, c IN Cits
WHERE (p1 ? [r, c]) AND (p2 ? [r, c]) AND (p3 ? [s, [r, c]])
```

Reducing each subpredicate in turn, we get:

$$\begin{aligned}
 p_1 ? [r, c] &= (\mathbf{gt} \oplus \langle \mathbf{id}, K_f(1M) \rangle \oplus \mathbf{popn} \oplus \pi_2) ? [r, c] \\
 &= (\mathbf{gt} \oplus \langle \mathbf{id}, K_f(1M) \rangle \oplus \mathbf{popn}) ? c \\
 &= (\mathbf{gt} \oplus \langle \mathbf{id}, K_f(1M) \rangle) ? (c.\mathbf{popn}) \\
 &= \mathbf{gt} ? [c.\mathbf{popn}, 1M] \\
 &= c.\mathbf{popn} > 1M,
 \end{aligned}$$

$$\begin{aligned}
 p_2 ? [r, c] &= (\mathbf{eq} \oplus \langle \mathbf{lgst_cit} \circ \pi_1, \mathbf{OID} \circ \pi_2 \rangle) ? [r, c] \\
 &= \mathbf{eq} ? [(\mathbf{lgst_cit} \circ \pi_1) ! [r, c], (\mathbf{OID} \circ \pi_2) ! [r, c]] \\
 &= \mathbf{eq} ? [r.\mathbf{lgst_cit}, c.\mathbf{OID}] \\
 &= r.\mathbf{lgst_cit} == c.\mathbf{OID}, \text{ and}
 \end{aligned}$$

$$\begin{aligned}
p_3 ? [s, [r, c]] &= (\mathbf{eq} \oplus \langle \mathbf{reps} \circ \pi_1, \mathbf{OID} \circ \pi_1 \circ \pi_2 \rangle) ? [s, [r, c]] \\
&= \mathbf{eq} ? [(\mathbf{reps} \circ \pi_1) ! [s, [r, c]], (\mathbf{OID} \circ \pi_1 \circ \pi_2) ! [s, [r, c]]] \\
&= \mathbf{eq} ? [s.\mathbf{reps}, r.\mathbf{OID}] \\
&= s.\mathbf{reps} == r.\mathbf{OID}.
\end{aligned}$$

Reduction leaves the SQL query,

```

SELECT s
FROM s IN Sens, r IN Sts, c IN Cits
WHERE (c.popn > 1M) AND (r.lgst_cit == c.OID) AND (s.reps == r.OID)

```

Other examples of translation are shown for the results of rewriting (with transformation PEWhere) Query Lite queries 1 (Figure 6.21d is the SQL translation of Figure 6.21c), 2 (Figure 6.22d is the SQL translation of Figure 6.22c), and 3 (Figure 6.24d is the SQL translation of Figure 6.24c).

6.5 Discussion

In this section, we reflect upon our experiences using COKO and KOLA to determine how well this framework met our integration and ease-of-use goals described at the chapter's onset.

6.5.1 Integration Capabilities of COKO-KOLA

COKO-KOLA is a generator of query rewriting components designed to accept queries as inputs and generate inputs for cost-based optimizers. But how easy is it to integrate these query rewriters within real query processing environments?

The integration of the COKO-KOLA framework within the San Francisco project required the development of two translators. The first (described in Section 6.2) translates Query Lite queries (and more generally, all set and bag-based OQL queries) into KOLA. The second (described in Section 6.4) translates a subset of KOLA queries into SQL. Of these translators, the first was by far the easiest to design and implement. This translator has a similar flavor to the many combinator translations of the lambda calculus (e.g., [27]). The availability of sophisticated compiler generator tools such as Ox [8] made this part of the project straightforward.

On the other hand, translation from KOLA to SQL was more tricky. The problem here was specifying *exactly* the sublanguage of KOLA that *could* be translated into SQL.

Basic Function Formers

$$\begin{aligned}
\mathbf{T}^{-1} \llbracket (f \circ g) ! x \rrbracket &= \mathbf{T}^{-1} \llbracket f ! (g ! x) \rrbracket \\
\mathbf{T}^{-1} \llbracket \langle f, g \rangle ! x \rrbracket &= [\mathbf{T}^{-1} \llbracket f ! x \rrbracket, \mathbf{T}^{-1} \llbracket g ! x \rrbracket] \\
\mathbf{T}^{-1} \llbracket K_f (x) ! y \rrbracket &= \mathbf{T}^{-1} \llbracket x \rrbracket \\
\mathbf{T}^{-1} \llbracket C_f (f, x) ! y \rrbracket &= \mathbf{T}^{-1} \llbracket f ! [x, y] \rrbracket
\end{aligned}$$

Basic Predicate Formers

$$\begin{aligned}
\mathbf{T}^{-1} \llbracket (p \oplus f) ? x \rrbracket &= \mathbf{T}^{-1} \llbracket p ? (f ! x) \rrbracket \\
\mathbf{T}^{-1} \llbracket (p \& q) ? x \rrbracket &= (\mathbf{T}^{-1} \llbracket p ? x \rrbracket) \text{ AND } (\mathbf{T}^{-1} \llbracket q ? x \rrbracket) \\
\mathbf{T}^{-1} \llbracket \sim (p) ? x \rrbracket &= \text{NOT } (\mathbf{T}^{-1} \llbracket p ? x \rrbracket) \\
\mathbf{T}^{-1} \llbracket K_p (b) ? x \rrbracket &= \mathbf{T}^{-1} \llbracket b \rrbracket \\
\mathbf{T}^{-1} \llbracket C_p (p, x) ? y \rrbracket &= \mathbf{T}^{-1} \llbracket p ? [x, y] \rrbracket
\end{aligned}$$

Query Function Formers

$$\begin{aligned}
\mathbf{T}^{-1} \llbracket \text{iterate } (p, f) ! A \rrbracket &= \begin{array}{l} \text{SELECT } (\mathbf{T}^{-1} \llbracket f ! x \rrbracket) \\ \text{FROM } x \text{ IN } A \\ \text{WHERE } (\mathbf{T}^{-1} \llbracket p ? x \rrbracket) \end{array} \\
\mathbf{T}^{-1} \left[\begin{array}{l} \text{join } (p, f) ! \\ \llbracket \text{join } (K_p (\text{true}), \text{id}) ! \\ \dots \\ \text{join } (K_p (\text{true}), \text{id}) ! \\ [A_1, A_2], \dots, A_n \rrbracket \end{array} \right] &= \begin{array}{l} \text{SELECT } (\mathbf{T}^{-1} \llbracket f ! [\dots [x_1, x_2], \dots], x_n \rrbracket) \\ \text{FROM } x_1 \text{ IN } A_1, \dots, x_n \text{ IN } A_n \\ \text{WHERE } (\mathbf{T}^{-1} \llbracket p ? [\dots [x_1, x_2], \dots], x_n \rrbracket) \end{array} \\
\mathbf{T}^{-1} \llbracket \text{join } (p, f) ! [A_1, A_2] \rrbracket &= \begin{array}{l} \text{SELECT } (\mathbf{T}^{-1} \llbracket f ! [x_1, x_2] \rrbracket) \\ \text{FROM } x_1 \text{ IN } A_1, x_2 \text{ IN } A_2 \\ \text{WHERE } (\mathbf{T}^{-1} \llbracket p ? [x_1, x_2] \rrbracket) \end{array}
\end{aligned}$$

Table 6.7: \mathbf{T}^{-1} : Applied to KOLA Formers

Some restrictions are easy. For example, **flat** can never be translated into SQL because the input to this function (a nested collection) is forbidden by the flatness restrictions of the relational model. Other restrictions are harder to specify. For example, queries of the form, **iterate** (p, f) ! A , can be translated into KOLA, but only in certain cases. For example,

- f cannot be another **iterate** or **join** query,
- f can be a composition of some functions (e.g., **add** \circ \langle terms, K_f (1) \rangle) but not others (e.g., **lgst_cit** \circ **reps**) that translate into path expressions.

Our approach to this issue is unsatisfying in the long term. In defining our KOLA \rightarrow SQL translation function, \mathbf{T}^{-1} , we assumed that inputs were generated from the pipeline of (1) the Query Lite \rightarrow KOLA translator, (2) the **NormTrans** query rewrite, and (3) the **PEwhere** rewrite. In fact, \mathbf{T}^{-1} is not defined for all of KOLA, and worse, would translate some queries that were not produced by the pipeline into queries not recognized by SQL.

The long term solution of this problem will be to somehow characterize useful sublanguages of KOLA (depending on the underlying object \rightarrow relational data model mapping) that can be translated into SQL. We consider this challenge to be extremely important. Query rewriting is likely to become the primary technique for reusing query processing software with new kinds of queries. San Francisco provides one example of this, extending the capabilities of the DB2 query processor to handle object-oriented queries. But we foresee other applications to object database products that want to provide query support for OQL or SQL3 while using existing optimizer technology, and heterogeneous databases that might want to rewrite queries expressed over an entire federation of databases into separate queries specific to the individual databases included within the federation. We believe KOLA to be an ideal intermediate representation for these efforts, both because of its expressive power and because KOLA rewrites are verifiable with a theorem prover. But this will require far more precision in specifying sublanguages of KOLA that will serve as targets for query rewriting (e.g., the sublanguage of KOLA that can be translated into SQL).

In short, the integration of the COKO-KOLA framework within existing query processing systems requires translation to and from KOLA. Translation to KOLA is not a problem; already KOLA is expressive enough to express queries in the most complex of query languages such as OQL, and can be readily extended when it falls short in this regard (e.g., as it does presently with respect to lists and arrays). However, translation *from* KOLA will often be to a language with less expressive power than KOLA (such as SQL). Understanding exactly what are interesting sublanguages of KOLA that can be translated (and therefore is the target for query rewriting) represents a challenging component of future work.

6.5.2 Ease-Of-Use of COKO-KOLA

For the San Francisco project, we used COKO-KOLA to generate:

1. a library of general-purpose normalization and simplification transformations (presented in Section 6.3.1),
2. a normalization to make the KOLA queries resulting from translation from OQL or Query Lite more intuitive (presented in Section 6.3.2), and
3. a transformation to rewrite Query Lite queries with path expressions in their **WHERE** clauses to SQL join queries (presented in Section 6.3.3).

Of these generated rewrites, the third by far was the easiest to write. This transformation rewrites queries with any number of path expressions, of any length, and with any degree of sharing. Yet, the transformation itself required fewer than 20 lines of firing algorithm code. The ease with which this transformation was written is encouraging, as it is exactly these kinds of transformations that are most likely to be developed for optimizers.

On the other hand, by far the most difficult transformation to write was the translation normalization transformation, **NormTrans**, and all of its auxiliary transformations. This transformation required over 50 rewrite rules, roughly 100 lines of firing algorithm code. Further, this work is not yet complete. This transformation presently does not normalize queries that are nested in their **SELECT** clauses (i.e., **iterate** or **join** queries with **iterate** or **join** queries as their data functions). While we believe that this part of the normalization will not be difficult to add (it will likely require merging the functionality of transformations **SimpFunc** and **FactorK**), the task has clearly proved to be non-trivial.

Of course, it should be remembered that this normalization need only be written once and users of the COKO-KOLA framework would most likely get **NormTrans** from a library of rewrites at their disposal, rather than programming it themselves. But on the other hand, our experience writing this transformation was revealing in certain deficiencies of COKO as a programming language and development environment. It is these revelations that will motivate improvements in future versions of the language and compiler. Amongst our observations are the following:

COKO's Control Language This exercise provided quite a bit of experience with COKO's language for firing algorithms, and revealed certain parts of the language that could be improved. One aspect of the language that requires some additional thought is the association of success values with statements in the language. For some statements (e.g.,

rule firings and complex statements), success values are quite natural. COKO provides for concise expression of algorithms such as that which exhaustively applies a set of rules:

$$\text{BU } \{\text{ru1} \parallel \dots \parallel \text{run}\} \rightarrow \text{recursive call},$$

or which conditionally executes a statement (S_2) if another statement (S_1) succeeds and a different statement (S_3) if it fails:

$$S_1 \rightarrow S_2 \parallel S_3.$$

But for other statements, the success values associated with the statements sometimes ran counter to the desired flow of control. The most obvious example of this concerns the **GIVEN** statement. **GIVEN** statements have the form,

$$\text{GIVEN } eqn_1, \dots, eqn_n \text{ DO } S.$$

and return a success value of *true* if all equations, eqn_i succeed in unifying and *false* otherwise. While this success result is desirable sometimes, at other times the desired result is to return *true* if all equations succeed in unifying **and** statement S succeeds. To address this problem, we could change the default success value for **GIVEN** statements to return *true* if both equations and follow-up statement succeed. Then, one could simulate the old behavior of **GIVEN** (i.e., return *true* if all equations succeed regardless of the success value of the follow-up statement) by writing:

$$\text{GIVEN } eqn_1, \dots, eqn_n \text{ DO } \{\text{TRUE } S\}.$$

The other part of the firing algorithm language that deserves reconsideration are the success values associated with “;”-separated statements. Presently, a complex statement,

$$S_1; \dots; S_n$$

succeeds if any statement, S_i succeeds. Often though, what one desires is for this statement to succeed if one of a particular subset of statements succeeds. The only way to express this presently is to preface those statements that should not figure into the determination of the success value with **FALSE**, as in:

$$\text{FALSE } \{S_1\}; \dots; \text{FALSE } \{S_n\}$$

such that all statements S_i would be replaced by **FALSE** $\{S_i\}$ except for those whose success should influence the success of the entire complex statement. Ideally however, we would

like to avoid the use of `TRUE` and `FALSE` statements, as their sole purpose is to circumvent the default success values of statements. Eliminating these statements may require us to rethink the entire notion of success values completely, perhaps restricting success values to rule and transformation invocations and adding `if-then-else` statements to the firing algorithm language to express desired control.

Parameterized (or Template) COKO Transformations In Section 6.3.1, we described a COKO transformation (`LBComp`) that has an identical firing algorithm and rewrite rules to transformation `LBConj` of Figure 4.10, but for the substitution of one former symbol (`o`) for another (`&`) and one set of variables (function variables) for another (predicate variables). This example suggests another way that COKO could be improved, by allowing the definition of parameterized transformations (e.g., `LB`) such that different instantiations would generate different COKO transformations (e.g., `LB (&, p, q, r)` could generate `LBConj` while `LB (o, f, g, h)` could generate `LBComp`).

Pattern Matching Associative Formers One of the most time-consuming programming tasks is to account for the various ways that associative functions and predicates (e.g., $(f \circ g \circ h)$ or $(p \ \& \ q \ \& \ r)$) can be associated. Presently, we address this problem by normalizing functions and predicates in advance so that a certain association can be assumed (e.g., `LBComp` and `LBConj` make compositions and conjunctions left-associative (or “left-bushy”). But determining the associative structure guaranteed of transformation results (when such guarantees are possible) is difficult, and frequently we find ourselves normalizing perhaps unnecessarily, to ensure that functions and predicates are structured in a particular way.

In the long term, we believe that a better approach to this problem will be to adapt our matching algorithm to account for associative function and predicate formers. That is, under this scheme the pattern,

$$f \circ g \circ h$$

would match either possible association of compositions,

$$f \circ (g \circ h) \text{ or } (f \circ g) \circ h.$$

This approach is taken by theorem provers such as LP [46].

Speed of Generated Code The query rewrites that are generated from COKO transformations sometimes have poor performance. For example, while transformation `PEWhere`

performs well on “small queries” such as those of Figures 6.21a and Figures 6.22a, it is noticeably slower with larger queries such as that of Figure 6.23a, requiring upwards of 3 minutes to perform the desired rewrite on a 200Mz Sparcstation 10.

We need to examine our compiler implementation to find the performance bottleneck, but there are many areas that could be contributing factors. Among them:

- As described in Chapter 4, our COKO compiler was designed for simplicity rather than performance. The code it produces generates a parse tree for the compiled transformations, and then invokes a method (`exec`) on its root (triggering subsequent calls to `exec` in descendants of the tree). This approach was simple and made it easy to extend the language with new statements (as we did by adding `TRUE`, `FALSE` and `SKIP` statements, and as is done with the definition of every new COKO transformation). However, the resulting code frequently has inadequate performance. For example, the COKO statement,

$$S_1; \dots; S_n$$

gets compiled into code that builds a binary parse tree of minimum height n , as each “;” appears as a node in the tree with the two statements it separates as its immediate children. This design results in a great deal of information passing (e.g., environments of pattern variables must be passed between parse tree nodes) and thereby puts a strain on performance. Further, the generated parse trees can be so large that the C++ compiler cannot generate the code that builds them. We have often been forced to “break up” COKO transformations into separate subparts in order to get around this deficiency.

- In Chapter 4, we showed an example of the kinds of efficiency one can get by having fine control of rule firing. Transformation `CNF` exhibited far better performance with a sophisticated and selective firing algorithm, then it did when implemented as an algorithm that exhaustively applies deMorgan rules.

Unfortunately, we have not yet developed a methodology for developing efficient firing algorithms such as that for `CNF`. Many of the algorithms used for the rewrites presented in this chapter are naive in their application of rewrite rules. For example, transformation `PCFAux`, an auxiliary transformation to `PullComFunc` that collapses subpredicates with common subfunctions (see Section 6.3.1), uses an algorithm analagous to a bubble-sort algorithm in order to compare subfunctions appearing in a predicate. Part of the problem lies with the inherent limitations of the rule-based

approach which demands that algorithms be composed from local operations (individual rule firings). But at the very least, the performance of firing algorithms used in our library of common normalizations and simplifications should be improved, given how often these transformations are likely to be used. But we look forward to future study of a methodology for writing firing algorithms that minimizes failed rule firings, achieving for all transformations what we were able to achieve for CNF.

- As described in Chapter 5, our implementation of semantic query rewrites invokes a Prolog interpreter during rewriting to issue a semantic query. As in the case of PEWAux, semantic queries can be posed numerous times during the course of rewriting. (For example, in rewriting the relatively simple query of Figure 6.22a, the conditional rewrite rule, `pe2j` was fired 9 times (succeeding 4 times).) Each call to the Prolog interpreter incurs a tremendous amount of overhead from loading and initializing the interpreter, and converting to and from Prolog representations of KOLA expressions. We believe that performance of generated rewrites will improve greatly once our Prolog-based implementation of semantic query rewrites is replaced by specialized pattern matching routines for KOLA trees.

In short, the message from our experience is that the COKO-KOLA framework potentially has much to offer in the development of “real-world” query rewriters given its formal foundation. But for this potential to be realized, its implementation must grow beyond its present prototype status. We were especially encouraged by the concise and elegant manner with which we were able to express the path expression-to-join query rewrite described in Section 6.3.3. This rewrite exploited all facets of the COKO-KOLA framework, including the semantic rewrite facility in order to infer knowledge of foreign keys, and recursive firing algorithms to ensure the handling of an unbounded number of path expressions of unbounded length and unbounded degree of subexpression sharing. But while our implementation is adequate as a proof of concept, it still is only a research prototype.

6.6 Chapter Summary

In this chapter, we have described our experiences using the COKO-KOLA framework presented in the preceding three chapters. Our challenge was to use COKO-KOLA to develop a query rewriting facility for an experimental language for the IBM San Francisco project. The query rewriter developed would translate object-oriented queries expressed in a simple object-oriented query language, into equivalent SQL queries over the underlying

relational implementation of the object-oriented database.

This project allowed us to determine the ease with which generated rewrites could be integrated within existing query processor environments, and with which “real” query rewrites could be expressed. To support integration, we built translators to translate Query Lite and OQL queries into KOLA, and to translate KOLA queries into SQL. This work revealed a challenging future direction in specifying sublanguages of KOLA equivalent in expressive power to other known languages (e.g., SQL), but also showed our framework to be easily integrated into existing query processor settings. To assess ease of use, we analyzed the size and effort required to build COKO transformations that were general purpose normalization and simplification routines, normalizations specific to the result of translation, and Query Lite \rightarrow SQL rewrites. Surprisingly, the library of normalizations (especially the normalization of translated queries) proved most difficult to build. But the experience revealed to us deficiencies in the COKO language and compiler implementation that must be addressed in future versions. Most encouraging to us was the ease with which we were able to write the transformation that did the “actual work” of the query rewrite. Transformations PEWhere and PEWAux required few rules and few lines of firing algorithm code to express a powerful and useful query rewrite.

Chapter 7

Dynamic Query Rewriting

In Chapters 3, 4 and 5, we proposed a framework for the expression of query rewrites. In Chapter 3, we presented KOLA: a combinator-based query algebra and representation that supports the expression of simple query rewrites with declarative rules. In Chapter 4, we introduced COKO: a language for expressing complex rewrites in terms of sets of KOLA rules and firing algorithms. And in Chapter 5, we introduced extensions to COKO and KOLA that made it possible to express rewrites whose correctness depended on semantic properties of queries and data. All of the rewrites presented in these chapters are verifiable with a theorem prover. This is due to the combinator flavor of KOLA that makes it possible to express subexpression identification and query formulation without code.

In this chapter, we consider another benefit arising from KOLA. This work concerns *when* query rewrites get fired rather than *how* they get expressed. An intelligent decision about how to rewrite or evaluate a query requires knowing the representations and contents of the collections involved (e.g., whether or not collections are indexed, sorted, or contain duplicates). Dynamic query rewriting (query rewriting that takes place during the query's evaluation) incorporates this philosophy in settings where this information is not known until data is accessed (i.e., until run-time). Such settings include:

- *object databases* that permit queries on anonymous, embedded collections whose contents and representations might only become apparent at run-time,
- *network databases* (e.g., web databases) that permit queries on collections whose availability can vary every time the query is executed, and
- *heterogeneous databases* that permit queries on collections maintained by local databases with data models and storage techniques known only to them.

Dynamic query rewriting requires that a query evaluator identify subexpressions of the processed query, and formulate new queries to ship to the query rewriter for further processing. Because KOLA simplifies the expression of these tasks, it is an ideal underlying query representation.

The work described in this chapter is ongoing and focuses on the application of dynamic query rewriting to object databases. We have designed a dynamic query rewriter for the ObjectStore object-oriented database [67], and an implementation of this design is in development.¹ We present this design using the “NSF” query (NSF_2 of Figure 2.6) as a running example. After presenting the design of the dynamic query rewriter for ObjectStore in Section 7.1, we trace the evaluation and rewriting of this query in Section 7.2. Finally, we consider some performance issues that have yet to be addressed and again look at the role of KOLA in the design of the query rewriter in Section 7.3, before summarizing the chapter in Section 7.4.

7.1 A Dynamic Query Rewriter for ObjectStore

The potential heterogeneity of collections in an object database makes it sometimes appropriate for evaluation strategies to vary from object to object. In Chapter 2, we introduced the query NSF_2 (Figure 2.6) that pairs every bill concerning the NSF with the largest cities in the regions represented by the bill’s sponsors. The collection of bills queried (`Bills`) can contain both House and Senate resolutions whose sponsors are sets of House Representatives and Senators respectively. The path expression, `x.reps.lgst_cit`, that finds the largest city in the region represented by legislator x , is an injective function over objects of type *Representative*, but not over objects of type *Senator*. Therefore, a semantic query rewrite to eliminate redundant duplicate elimination (as described in Section 5.1) must be applied selectively to affect the processing of House resolutions but not the processing of Senate resolutions. Dynamic query rewriting is query rewriting that occurs during a query’s evaluation (i.e., at run-time). Selective processing of NSF_2 can be achieved by firing the duplicate elimination query rewrite dynamically as bills are retrieved and their origins (House or Senate) identified.

We have designed a dynamic query rewriter and query evaluator for ObjectStore [67], and the implementation and evaluation of this design is ongoing work. This design deviates from the traditional query processor architecture presented in Chapter 1 (Figure 1.1). The

¹ObjectStore already performs a limited form of dynamic query optimization involving run-time exploitation of indexes, but does nothing by way of dynamic query rewriting.

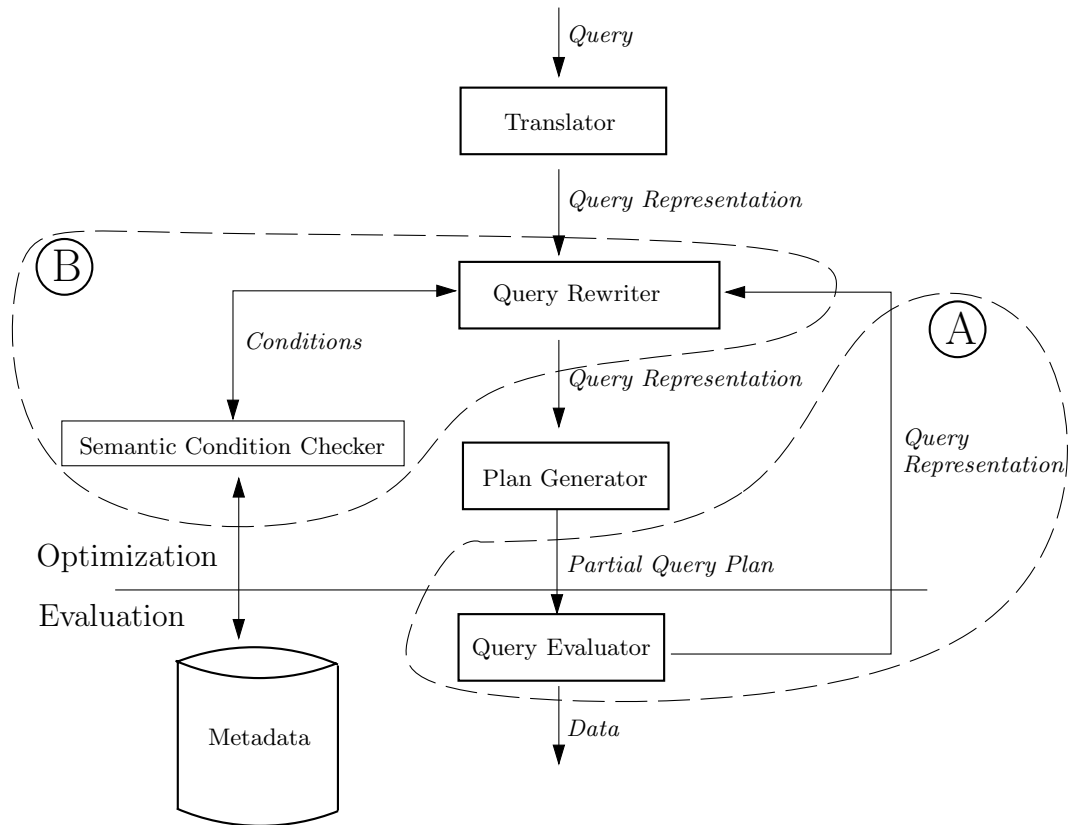


Figure 7.1: An Alternative Architecture for Object Database Query Processors

new architecture (illustrated in Figure 7.1) introduces a *feedback loop* between evaluation and rewriting (labeled A in Figure 7.1), as well as incorporating the semantic rewrite components described in Chapter 5 (B). The input to the evaluator is not a complete plan, but a *partial plan* with “holes” left for those parts of the plan that will be generated dynamically.

To implement this architecture, our design includes two components:

- a *plan language* that permits expression of partial plans, and
- a *query evaluator* with hooks back to the optimizer.

After describing these two components, we demonstrate their intended behavior with respect to the processing of query NSF_2 .

7.1.1 Making ObjectStore Objects Queryable

The present design of our dynamic query rewriter processes queries over ObjectStore. Our eventual goal is for this design to be usable with other databases also. Therefore, a design

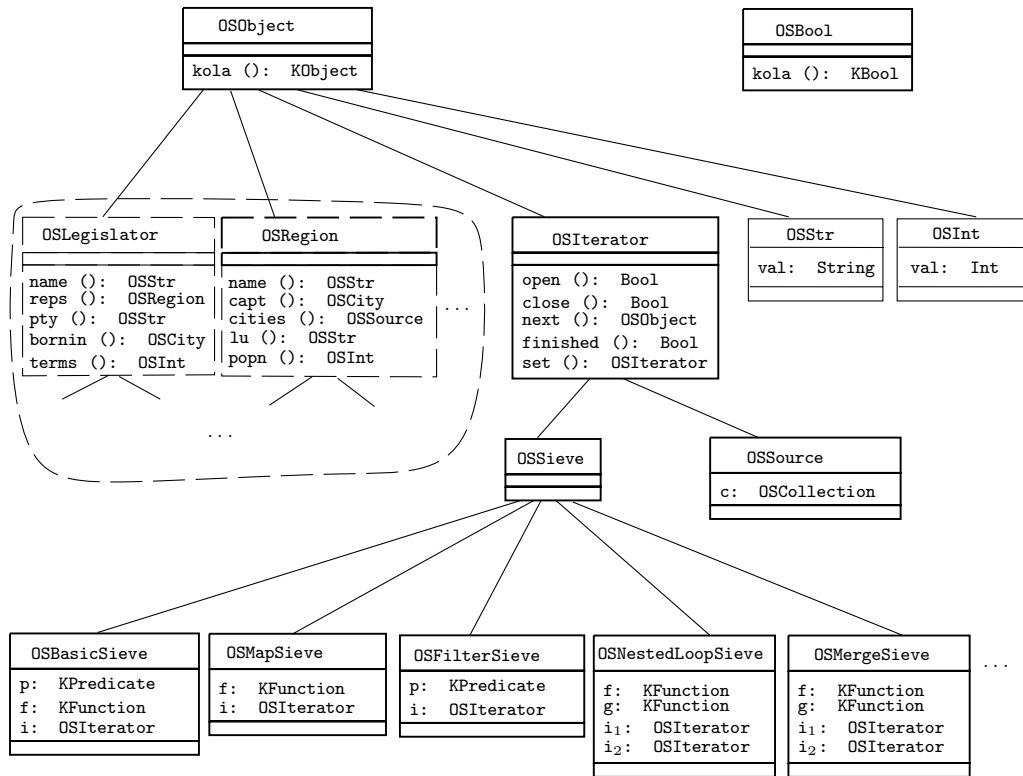


Figure 7.2: The ObjectStore Queryable Class Hierarchy

goal was to maintain a loose coupling between the rewriter and ObjectStore.

Loose coupling is achieved by maintaining separate class hierarchies for ObjectStore objects (which can be stored in an ObjectStore database) and KOLA objects (which can appear in queries). Because of this design, ObjectStore's implementation requires no modification to account for KOLA querying, and our design need not be restricted to processing ObjectStore objects. The cost of this decision is redundancy in the two class hierarchies, and the need to translate between the two representations during a query's evaluation. Because of the latter issue, a non-prototype design of the dynamic query rewriter would likely integrate the two object representations.

The only requirement we introduce of queryable ObjectStore objects is that they belong to a subclass of a class we provide (`OSObject`). All attributes of these classes should also have types that are subclasses of `OSObject` (or `OSBool` if they are boolean-valued attributes). This ensures that all classes of objects maintained in the database will have a KOLA translation function inherited from `OSObject` and `OSBool` (`kola`), even though designers of such classes may not be aware of this. Other queryable ObjectStore object

classes are provided as part of our design (e.g., basic classes such as strings (`OSStr`) and integers (`OSInt`)) as is illustrated in the ObjectStore class hierarchy presented in Figure 7.2.

Figure 7.2 includes two of the classes defined for the Thomas database of Section 2 — `OSLegislator` (*Legislator*) and `OSRegion` (*Region*). Subtypes could be defined to inherit from these classes (e.g., *State* could be defined as a subtype of *Region* in this way). This figure also includes a subhierarchy of *iterators* rooted at `OSIterator`. While instances of these classes are data (returned as the results of collection generating queries), the classes themselves comprise the plan language for KOLA. This design is described below.

7.1.2 Iterators

The result of a query can be very large. If a query returns a collection, this collection might contain many objects (i.e., the result might have a large *cardinality*). As well, each object in the result might include other collections and other complex objects as attributes (i.e., the result might have a large *arity* also). Thus, it would be inappropriate for a query processor to return a query result “all at once” and instead a more lazy approach is called for.

Like many query processors (e.g., Exodus [13]) KOLA’s plan language merges query results with the plans to retrieve them. An *iterator* is a *view* for a given collection with a specialized interface that provides access to the collection one element at a time. Queries that construct collections in fact return iterators. Thus, iterators serve as both data and plan.

Our design defines several kinds of iterators (all subclasses of `OSIterator`) that can be returned as the result of a query. There is at least one iterator per KOLA query former or primitive, although not all are shown in Figure 7.2. Designed in an object-oriented style, each iterator is obligated to provide implementations of the following methods:

- **open**: which opens all files required by the iterator to retrieve elements, and which initializes any data structures required for processing,
- **next**: which returns the next element of the collection maintained by the iterator,
- **finished**: which returns *true* if there are no more elements to return,
- **close**: which closes all files and data structures opened or created by the iterator, and
- **set**: which constructs a new stored collection (and accompanying iterator) with duplicates removed.²

²`Set` builds a new stored collection, because our assumption is that duplicate elimination is necessary

Thus, if one views a plan language as a collection of algorithms, the method implementations for the collection of iterators comprise the KOLA plan language.

Iterators can range over collections stored on disk (*access methods*), or collections generated on the fly (*query operators*). Our design introduces the class `OSSource` to act as the supertype of all access method iterators, and `OSSieve` to act as the supertype of all query operator iterators. Examples of the latter include `OSBasicSieve`, `OSMapSieve` and `OSFilterSieve`. Objects of class `OSBasicSieve` act as a view with respect to some KOLA predicate p and function f over the result of some other iterator, i . Calling `next` on an `OSBasicSieve` results in repeated calls of `next` on i until some element is returned that satisfies p (or until the entire collection has been processed at which point an “End-Of-Collection” token is returned). Function f is then applied to this element and the result is returned. On the other hand, an `OSMapSieve` acts as a view solely with respect to a KOLA function f over the result of some other iterator, i . Calling `next` on an `OSMapSieve` results in a single call of `next` on i , with f applied to the result and returned. Finally, an `OSFilterSieve` acts as a view with respect to a KOLA predicate p over the result of some other iterator, i . As with an `OSBasicSieve`, calling `next` on an `OSFilterSieve` repeatedly calls `next` on i until some element is returned that satisfies p . Unlike an `OSBasicSieve`, this element is then returned as is. Our simple plan generator generates an `OSBasicSieve` for queries of the form,

$$\text{iterate } (p, f) ! A,$$

an `OSMapSieve` for queries of the form,

$$\text{iterate } (K_p (\text{true}), f) ! A,$$

and an `OSFilterSieve` for queries of the form,

$$\text{iterate } (p, \text{id}) ! A.$$

Other iterators are defined for other KOLA query formers. For example, there are two *join* iterators, each of which references a KOLA predicate, p , a KOLA function, f and two input iterators, i_1 and i_2 . Class `OSNestedLoopSieve` does no preprocessing in its `open` method, and a call to `next` iterates through i_2 looking for an element that together with the last read element of i_1 , satisfies p . (If none is found, the `next` element of i_1 is retrieved and the process repeats itself.) Thus, this iterator performs a *nested loop* join. The `open`

if `set` is executed. Queries for which duplicate elimination is recognized as unnecessary get rewritten into plans that do not execute `set`.

method of `OSMergeSieve` sorts i_1 and i_2 , creating two temporary `OSSource` iterators for the results of the sorts. A call to `next` then scans these sorted collections in parallel, thus performing a *sort-merge* join.

The two most important features of these iterators are that they are *extensible* and that they support the *partial specification* of plans. The object-oriented design of iterators (i.e., all iterator implementations inherit from `OSIterator`) makes it straightforward to *extend* the plan language by adding additional iterators. For example, an iterator that uses an index to filter objects contained in a collection could be added as a subclass of `OSSieve`. Objects of this class could then be returned by `iterate` queries when indexes are available on the data predicate. Our present design includes a simplistic plan generator that associates most KOLA query formers with only a single iterator. But because additional subclasses of `OSIterator` such as the ones above can be simply added, plan generation can be made more sophisticated without disrupting the other components of the optimizer.

Iterators also support the partial specification of plans. All query operator iterators (i.e., objects belonging to subclasses of `OSSieve`) specify one or more iterators from which data elements are drawn, and an operation to perform on these data elements. Data operations are not specified with plans but with KOLA functions and predicates. In this way, an iterator only partially specifies a plan. To complete the specification, each data element retrieved can be packaged with the associated KOLA predicate or function and resubmitted as a new query to the query rewriter. That is, KOLA functions and predicates serve as specifications for the missing components of a plan, describing what the missing plan must produce without committing to an algorithm. Partial specifications of plans make dynamic query rewriting possible, marking the parts of a plan for which details must be supplied at run-time.

7.1.3 Combining Rewriting With Evaluation

Translation of OQL queries results in KOLA parse trees. The nodes of KOLA's parse trees are instances of classes whose hierarchy is shown in part in Figure 7.3. The mappings of KOLA functions, predicates, objects and bools to their associated classes within this hierarchy are shown in Table 7.1. All function (predicate) classes are subclasses of `KFunction` (`KPredicate`), obligating them to provide implementations for virtually defined methods `invoke` and `exec`. As will be described in some detail below, `invoke` performs partial evaluation and query rewriting, and `exec` performs full evaluation and plan generation for the function (predicate) denoted by the `KFunction` (`KPredicate`) parse tree. All object (bool)

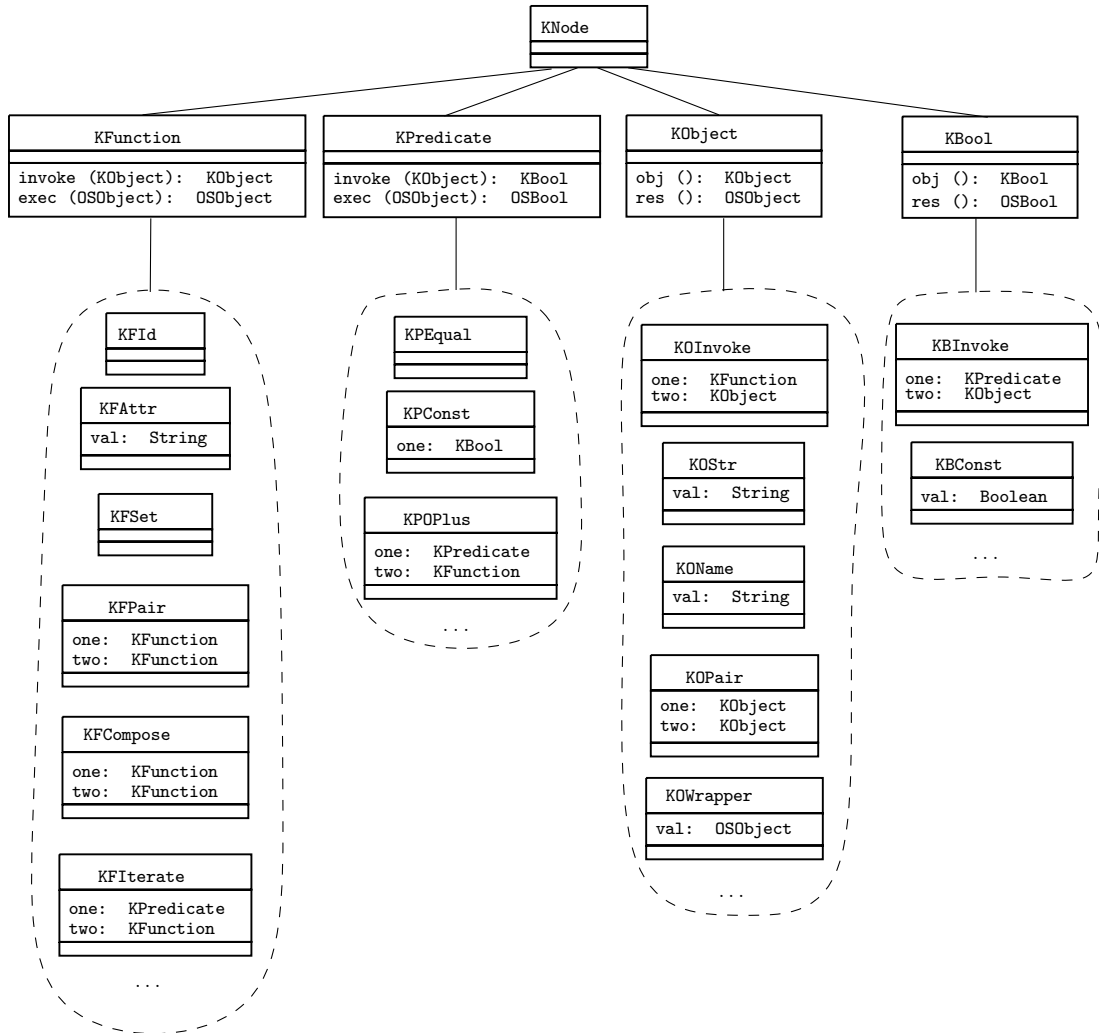


Figure 7.3: The KOLA Representation Class Hierarchy

KOLA Operator (q)	Node Class	Comment
Subclasses of KFunction		
id	KFID	–
set	KFSet	–
$\langle f, g \rangle$	KFPair	one is f , two is g
$f \circ g$	KFCompose	one is f , two is g
iterate (p, f)	KFIterate	one is p , two is f
<i>any attribute</i>	KFAttr	val is the name of the attribute
Subclasses of KPredicate		
eq	KPEqual	–
$K_p(b)$	KPConst	one is b
$p \oplus f$	KPOPlus	one is p , two is f
Subclasses of KObject		
$f ! x$	KOInvoke	one is f , two is x
$[x, y]$	KOPair	one is x , two is y
<i>any string constant</i>	KOStr	val is the string constant
<i>any ObjectStore object</i>	KOWrapper	val is the ObjectStore object
<i>any object name</i>	KOName	val is the object name
Subclasses of KBool		
$p ? x$	KBInvoke	one is p , two is x
<i>true or false</i>	KBConst	val is the truth value

Table 7.1: Mappings of KOLA Operators to their Parse Tree Representations

classes are subclasses of `KObject` (`KBool`), obligating them to provide implementations for virtually defined methods `obj` and `res`: methods that call `invoke` and `exec` respectively.

In describing how a query is processed, we will refer to KOLA expressions and their parse trees interchangeably and rely on context to differentiate between the two. For example, the expression,

$$(\text{set} ! A) \rightarrow \text{obj} ()$$

denotes a call of method `obj` on the parse tree representation of `(set ! A)`. In other words, method `obj` defined in class `KOInvoke` (written `KOInvoke::obj`) gets invoked on the associated KOLA tree. As much as possible in this discussion, we will supplement such expressions with descriptions that point out which methods defined in which classes get invoked.

Partial Evaluation and Query Rewriting

True to object-oriented style, evaluation routines are distributed across the KOLA tree representations they affect. Whereas evaluation (and plan generation) occur as a result of calls to `exec` (for function and predicate nodes) and `res` (for object and bool nodes), query

rewriting (and partial evaluation) occur as a result of calls to `invoke` (for function and predicate nodes) and `obj` (for object and bool nodes).

The processing of a KOLA query, q occurs as a result of the chain of calls,

$$q \rightarrow \text{obj } () \rightarrow \text{res } ()$$

which invokes method `obj` on the parse tree representation of q , and method `res` on the parse tree resulting from the invocation of `obj`. The call of `obj` performs query rewriting and partial evaluation on q . (The call of `res` returns an iterator, as discussed in the next section.) For queries of the form $(f ! x)$ that apply functions or predicates to objects, the call

$$(f ! x) \rightarrow \text{obj } ()$$

executes `KOInvoke::obj`, resulting in the subsequent call of,

$$f \rightarrow \text{invoke } (x \rightarrow \text{obj } ()).$$

Thus, `invoke` and `obj` are related functions that initiate query rewriting and partial evaluation.

`Invoke` is defined differently for different functions and predicates. Basic function formers perform evaluation of the query up to the point where disk access is required or methods are invoked. Thus, the call,

$$\mathbf{id} \rightarrow \text{invoke } (x)$$

`(KFID::invoke)` completely evaluates the expression, $(\mathbf{id} ! x)$, returning (the parse tree representation of) x . In this case `invoke` fully evaluates the the function invocation $(\mathbf{id} ! x)$. On the other hand, for any attribute `att`,

$$\text{att} \rightarrow \text{invoke } (x)$$

`(KFAttr::invoke)` returns

$$\text{att} ! x$$

(i.e., a KOLA parse tree rooted by a `KOInvoke` object), performing no evaluation at all. In general, `invoke` partially evaluates a query, as in

$$\langle \mathbf{id}, \text{att} \rangle \rightarrow \text{invoke } (x)$$

that returns the partially evaluated `KOPair`,

$$[x, \text{att} ! x].$$

When invoked on query functions or predicates, `invoke` initiates query rewriting. Every KOLA function and predicate node can be associated with its own rewriter generated from a COKO definition. Thus, `KOFSet` (`set`) might be associated with a transformation that invokes rules `de1` and `de2` of Figure 5.3, and `KFIterate` (`iterate`) might be associated with a COKO transformation that performs normalization with respect to `iterate` queries. Most likely, only nodes representing query formers will be associated with rewriters. If the parse tree representation of some function f is instantiated with a COKO transformation object, t , then

$$f \rightarrow \text{invoke } (x)$$

generates a call to t 's `exec` method (see Section 4.3.3) with the parse tree representation of $(f ! x)$ as its argument. The rewriter then returns the representation for an equivalent expression that has been normalized in some way. Definitions of `obj` for some subclasses of `KObject` and `KBool`, and `invoke` for some subclasses of `KFunction` and `KPredicate` are presented in the tables of Table 7.2.

Evaluation and Plan Generation

Just as `obj` and `invoke` initiate query rewriting and partial evaluation, `res` and `exec` initiate plan generation and complete evaluation. And analogously to `obj` and `invoke`, `res` and `exec` are related in that the call,

$$(f ! x) \rightarrow \text{res } ()$$

for some KOLA function f and KOLA object x generates the call,

$$f \rightarrow \text{exec } (x \rightarrow \text{res } ()).$$

As with `invoke`, `exec` is defined differently for different KOLA functions and predicates. For KOLA query functions and predicates, `exec` returns an iterator over the collection that the query denotes. For attributes, `exec` performs attribute extraction. For KOLA's arithmetic functions (`add`, `mul`, etc.) `exec` performs the arithmetic.

Our simplistic plan generator performs no data analysis in deciding upon an iterator to return as the result of evaluating a query. Most formers generate a single iterator. (The former, `iterate` is an exception as it can generate an `OSBasicSieve`, `OSMapSieve` or `OSFilterSieve`.)³

³A more sophisticated plan generator would generate multiple iterators and choose a best amongst them based on some cost model that estimates the cost of retrieving elements from each.

KOLA Class	obj ()
KObject	
KOInvoke	one \rightarrow invoke (two \rightarrow obj ())
KOStr	self
KOName	self
KOWrapper	self
KOPair	KOPair (one \rightarrow obj (), two \rightarrow obj ())
KBool	
KBInvoke	one \rightarrow invoke (two \rightarrow obj ())
KBConst	self

KOLA Class	invoke (k: KObject)
KFunction	
KFID	k
KFMethod	KOInvoke (self, k)
KFCompose	KOInvoke (one, KOInvoke (two, k))
KFPair	KOPair (KOInvoke (one, k), KOInvoke (two, k))
KFSet	<i>Calls optimizer on KOInvoke (self, k)</i>
KFIterate	<i>Calls optimizer on KOInvoke (self, k)</i>
KPredicate	
KPEqual	KBInvoke (equal, k)
KPConst	one
KPCurry	one \rightarrow invoke (OPair (two, k))
KPOPlus	one \rightarrow invoke (two \rightarrow invoke (k))

Table 7.2: Results of Partially Evaluating and Rewriting KOLA Queries

KOLA Class	res ()
KObject	
KOInvoke	one \rightarrow exec (two \rightarrow res ())
KOStr	OSStr (val)
KOName	<i>Performs lookup of val in database. Returns object stored, if not a collection. Returns an OSSource, if a collection.</i>
KOWrapper	val
KOPair	STRUCT (one: one \rightarrow res (), two: two \rightarrow res ())
KBool	
KBInvoke	one \rightarrow exec (two \rightarrow res ())
KBConst	val

KOLA Class	exec (o: OSObject)
KFunction	
KFID	<i>Never called</i>
KFMethod	<i>Calls method on o</i>
KFCompose	<i>Never called</i>
KFPair	<i>Never called</i>
KFSet	(o \rightarrow res ()) \rightarrow set ()
KFIterate	$\left\{ \begin{array}{ll} \text{OSMapSieve (two, o),} & \text{if one = } K_p \text{ (true)} \\ \text{OSFilterSieve (one, o),} & \text{if two = id} \\ \text{OSBasicSieve (one, two, o),} & \text{otherwise} \end{array} \right.$
KPredicate	
KPEqual	o.one == o.two
KPConst	<i>Never called</i>
KPCurry	<i>Never called</i>
KPOPlus	<i>Never called</i>

Table 7.3: Results of Evaluating KOLA Queries

The definitions of `res` for some subclasses of `KObject` and `KBool`, and `exec` for some subclasses of `KFunction` and `KPredicate` are presented in the tables of Table 7.3. Note that for some function and predicate representation nodes (e.g., `KFID`, `KFCompose`), `exec` will never be called as calling `invoke` beforehand will transform query representations using these nodes into representations that don't.

$$\begin{aligned}
 NSF_k &= \text{iterate } (p, f) ! \text{ Bills} \quad \text{such that} \\
 p &= \mathbf{C}_p (\mathbf{eq}, \text{“NSF”}) \oplus \text{topic}, \\
 f &= \langle \text{name}, \text{set} \circ \text{iterate } (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) \circ \text{spons} \rangle
 \end{aligned}$$

Figure 7.4: NSF_{2k} : The KOLA Translation of Query NSF_2 of Figure 2.6

7.2 Putting It All Together: The NSF Query

We illustrate our design by tracing the processing of the KOLA version of NSF_2 (NSF_{2k}) shown in Figure 7.4. Figure 7.5 illustrates the parse tree representation of this query over which query evaluation takes place via successive calls of `obj` and `res`.

7.2.1 Initial Rewriting and Evaluation

For query NSF_{2k} , there is little query rewriting or partial evaluation that can be performed until data is touched. Calling `obj` on the parse tree representation of this query returns the parse tree untouched. A subsequent call of `res` returns an `OSBasicSieve` with

- the parse tree representation of $(\mathbf{C}_p (\mathbf{eq}, \text{“NSF”}) \oplus \text{topic})$ as its predicate, p ,
- the parse tree representation of

$$\langle \text{name}, \text{set} \circ \text{iterate } (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) \circ \text{spons} \rangle$$

as its function, f , and

- The iterator object for `Bills` (i.e., an `OSSource` object) as its inner iterator, i .

This result is illustrated in Figure 7.6. In this figure and in others that include both KOLA and `ObjectStore` objects, the two are differentiated by their shape: KOLA objects are drawn with circles while `ObjectStore` objects are drawn with rectangles.

7.2.2 Dynamic Query Rewriting: Extracting Elements from the Result

The only query rewriting performed on NSF_{2k} occurs when objects are retrieved from the query’s iterator result. That is, rewriting occurs dynamically as a result of a call of `next` on the `OSBasicSieve` of Figure 7.6. A call of `next` on this iterator in turn calls `next` on the `OSSource` iterator for `Bills`. With each bill b returned by this call, a new KOLA expression is formulated using the predicate (p) associated with the `OSBasicSieve`.

The formulated expression packages p with a predicate invocation node (`KBInvoke`) and the KOLA translation of b (`KOWrapper (b)`) to construct the parse tree representation of $(p ? \llbracket b \rrbracket)$ (such that $\llbracket b \rrbracket$ denotes the KOLA wrapper object referencing b). This is illustrated in Figure 7.7 (A). Figure 7.7 (B) shows the result of calling `obj` on this tree. Figure 7.7 (C) shows the result of calling `res` on the KOLA pair that is an argument to the predicate, `eq`. (Evaluation then proceeds by comparing the `one` and `two` fields of the `struct` in (C).)

A trace of the calls of `obj` and `res` that lead to each result illustrated in Figure 7.7 is presented below. Each step in the trace shows the “current” representation and the method that was invoked most recently to generate it.

$$\begin{aligned}
& ((C_p (\mathbf{eq}, \text{“NSF”}) \oplus \mathbf{topic}) ? \llbracket b \rrbracket) \rightarrow \mathbf{obj} () \\
= & (C_p (\mathbf{eq}, \text{“NSF”}) \oplus \mathbf{topic}) \rightarrow \mathbf{invoke} (\llbracket b \rrbracket \rightarrow \mathbf{obj} ()) \quad (\text{by } \mathbf{KBInvoke} :: \mathbf{obj}) \\
= & (C_p (\mathbf{eq}, \text{“NSF”}) \oplus \mathbf{topic}) \rightarrow \mathbf{invoke} (\llbracket b \rrbracket) \quad (\text{by } \mathbf{KOWrapper} :: \mathbf{obj}) \\
= & C_p (\mathbf{eq}, \text{“NSF”}) \rightarrow \mathbf{invoke} (\mathbf{topic} \rightarrow \mathbf{invoke} (\llbracket b \rrbracket)) \quad (\text{by } \mathbf{KPOPlus} :: \mathbf{invoke}) \\
= & C_p (\mathbf{eq}, \text{“NSF”}) \rightarrow \mathbf{invoke} (\mathbf{topic} ! \llbracket b \rrbracket) \quad (\text{by } \mathbf{KFAttr} :: \mathbf{invoke}) \\
= & \mathbf{eq} \rightarrow \mathbf{invoke} ([\text{“NSF”}, \mathbf{topic} ! \llbracket b \rrbracket]) \quad (\text{by } \mathbf{KPCurry} :: \mathbf{invoke}) \\
= & \mathbf{eq} ? [\text{“NSF”}, \mathbf{topic} ! \llbracket b \rrbracket] \quad (\text{by } \mathbf{KPEqual} :: \mathbf{invoke})
\end{aligned}$$

Suppose that b is a House resolution. Calling `res` on

$$\mathbf{eq} ? [\text{“NSF”}, \mathbf{topic} ! \llbracket b \rrbracket]$$

leads to the comparison of the fields of the ObjectStore `STRUCT` of Figure 7.7 (C) as illustrated below.


```

(eq ? ["NSF", topic ! [[b]]] → res ())

= eq → exec (["NSF", (topic ! [[b]])] → res ())      (by KBIInvoke :: res)

= eq → exec (STRUCT (one: "NSF" → res (), two: (topic ! [[b]]) → res ()))
                                                    (by KOPair :: res)

= eq → exec (STRUCT (one: "NSF", two: (topic ! [[b]]) → res ()))
                                                    (by KOString :: res)

= eq → exec (STRUCT (one: "NSF", two: topic → exec ([[b]] → res ())))
                                                    (by KOInvoke :: res)

= eq → exec (STRUCT (one: "NSF", two: topic → exec (b)))
                                                    (by KOWrapper :: res)

= eq → exec (STRUCT (one: "NSF", two: b.topic))      (by KFAttr :: exec)

= "NSF" == b.topic                                  (by KPEqual :: exec)

```

Suppose that $b.topic == \text{"NSF"}$. Then this expression evaluates to *true* and b is packaged with f to construct the query tree of Figure 7.8 (A), $(\langle \text{name, set} \circ h \circ \text{spons} \rangle ! [[b]])$, such that

$$h = \text{iterate} (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}).$$

Calling `obj` on this tree results in the query tree of Figure 7.8 (B) as is shown in the

execution trace below.

$$\begin{aligned}
& \langle (\text{name}, \text{set} \circ h \circ \text{spons}) ! \llbracket b \rrbracket \rangle \rightarrow \text{obj} () \\
= & \langle \text{name}, \text{set} \circ h \circ \text{spons} \rangle \rightarrow \text{invoke} (\llbracket b \rrbracket \rightarrow \text{obj} ()) && (\text{by } \text{K0Invoke} :: \text{obj}) \\
= & \langle \text{name}, \text{set} \circ h \circ \text{spons} \rangle \rightarrow \text{invoke} (\llbracket b \rrbracket) && (\text{by } \text{KOWrapper} :: \text{obj}) \\
= & [\text{name} \rightarrow \text{invoke} (\llbracket b \rrbracket), (\text{set} \circ h \circ \text{spons}) \rightarrow \text{invoke} (\llbracket b \rrbracket)] && (\text{by } \text{KFPair} :: \text{invoke}) \\
= & [\text{name} ! \llbracket b \rrbracket, (\text{set} \circ h \circ \text{spons}) \rightarrow \text{invoke} (\llbracket b \rrbracket)] && (\text{by } \text{KFAttr} :: \text{invoke}) \\
= & [\text{name} ! \llbracket b \rrbracket, (\text{set} \circ h) \rightarrow \text{invoke} (\text{spons} \rightarrow \text{invoke} (\llbracket b \rrbracket))] && (\text{by } \text{KFCompose} :: \text{invoke}) \\
= & [\text{name} ! \llbracket b \rrbracket, (\text{set} \circ h) \rightarrow \text{invoke} (\text{spons} ! \llbracket b \rrbracket)] && (\text{by } \text{KFAttr} :: \text{invoke}) \\
= & [\text{name} ! \llbracket b \rrbracket, \text{set} \rightarrow \text{invoke} (h \rightarrow \text{invoke} (\text{spons} ! \llbracket b \rrbracket))] && (\text{by } \text{KFCompose} :: \text{invoke})
\end{aligned}$$

The next step of this reduction executes `FIterate :: invoke` which fires a COKO transformation to rewrite the query,

$$\text{iterate} (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) ! (\text{spons} ! \llbracket b \rrbracket).$$

Suppose that this rewriter has no effect on this query. Then the next step of the execution trace is:

$$[\text{name} ! \llbracket b \rrbracket, \text{set} \rightarrow \text{invoke} (\text{iterate} (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) ! (\text{spons} ! \llbracket b \rrbracket))].$$

At this point, the COKO transformation associated with `set` is fired to rewrite the query,

$$\text{set} ! (\text{iterate} (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) ! (\text{spons} ! \llbracket b \rrbracket)).$$

If the COKO transformation is one that eliminates redundant duplicate elimination (firing the rules of Figure 5.3), then the reduction continues as shown below:

1. Firing rule `de1` of Figure 5.3 matches the pattern, `set ! (iterate (p, f) ! A)` with

the above query producing the variable bindings:

```
p = Kp (true)
f = lgst_cit ◦ reps, and
A = spons ! [[b]]
```

2. A Prolog query is issued to the Prolog interpreter to determine the truth values of conditions:

```
is_inj (lgst_cit ◦ reps)
```

and

```
is_set (spons ! [[b]]).
```

The latter condition is satisfied by inference rule (2) of Figure 5.4b in combination with schema information establishing the type of `spons` to return a set of House Representatives. The former condition is satisfied by inference rules (2) and (3) of Figure 5.4a in combination with metadata information identifying `lgst_cit` as a key for sets of regions, and `reps` as a key for sets of House Representatives.⁴

3. The success of the Prolog query leads to the firing of the conditional rewrite rule, `del`, leading to a rewrite of the query that performs duplicate elimination to one that does not:

```
iterate (Kp (true), lgst_cit ◦ reps) ! (spons ! [[b]]).
```

Thus, the call of `next` on the `OSBasicSieve` of Figure 7.6 has led to a dynamic call of the query rewriter to perform the semantic rewrite that eliminates redundant duplicate elimination. The execution trace then concludes, producing the representation,

```
[name ! [[b]], h ! (spons ! [[b]])]
```

such that

```
h = iterate (Kp (true), lgst_cit ◦ reps).
```

⁴Our implementation resolves overloading (e.g., of attribute `reps`) by translating all references to functions appearing in a schema, metadata files or queries to Prolog terms of the form,

```
fun (name, D, R)
```

such that `name` is the name of the function, `D` is the domain type of the function, and `R` is the range type of the function. Therefore, `fun (kreps, kHouse_Representative, kRegion)` would be identified as a key and `fun (kreps, kSenator, kRegion)` would not be. A similar representation strategy is applied to predicates.

A call of `res` on this representation produces the result shown in Figure 7.8 (C) as is illustrated by the execution trace below:

```

[name ! [[b]], h] → res ()

= STRUCT (one: (name ! [[b]]) → res (), two: h ! (spons ! [[b]]) → res ())
                                               (by KOPair :: res)

= STRUCT (one: name → exec ([[b]] → res ()), two: (h ! (spons ! [[b]])) → res ())
                                               (by KOInvoke :: res)

= STRUCT (one: name → exec (b), two: (h ! (spons ! [[b]])) → res ())
                                               (by KOWrapper :: res)

= STRUCT (one: b.name, two: (h ! (spons ! [[b]])) → res ()) (by KFAttr :: exec)

= STRUCT (one: b.name, two: g → exec ((spons ! [[b]]) → res ()))
                                               (by KOInvoke :: res)

= STRUCT (one: b.name, two: g → exec (spons → exec ([[b]] → res ())))
                                               (by KOInvoke :: res)

= STRUCT (one: b.name, two: g → exec (spons → exec (b))) (by KOWrapper :: res).

```

Because the bill attribute `spons` returns a set, the result of the invocation,

$$\text{spons} \rightarrow \text{exec } (b)$$

is an `OSSource` iterator (which will be expressed through the remainder of the trace as “`OSSource (b.spons)`”). Therefore, the next expression in the execution trace becomes,

$$\text{STRUCT } (\text{one: } b.\text{name}, \text{two: } g \rightarrow \text{exec } (\text{OSSource } (b.\text{spons}))).$$

Substituting for `g`, the expression labeled by `two` is:

$$\text{iterate } (K_p (\text{true}), \text{lgst_cit} \circ \text{reps}) \rightarrow \text{exec } (\text{OSSource } (b.\text{spons})).$$

Because the predicate argument to `iterate` is `Kp (true)`, the call of `KFIterate::exec` generates an `OSMapSieve` object, which will be written in the remainder of the trace as

“OSMapSieve (lgst_cit ◦ reps, OSSource (b.spons))”. Therefore, the next expression in the execution trace becomes,

```
STRUCT (one: b.name, two: OSMapSieve (lgst_cit ◦ reps, OSSource (b.spons))).
```

The last step of the trace inserts the field names of the `struct` (`bill` and `schools`) that appeared in the original OQL query and that are retained by translation into KOLA:

```
STRUCT (bill: b.name,
        schools: OSMapSieve (lgst_cit ◦ reps, OSSource (b.spons))).
```

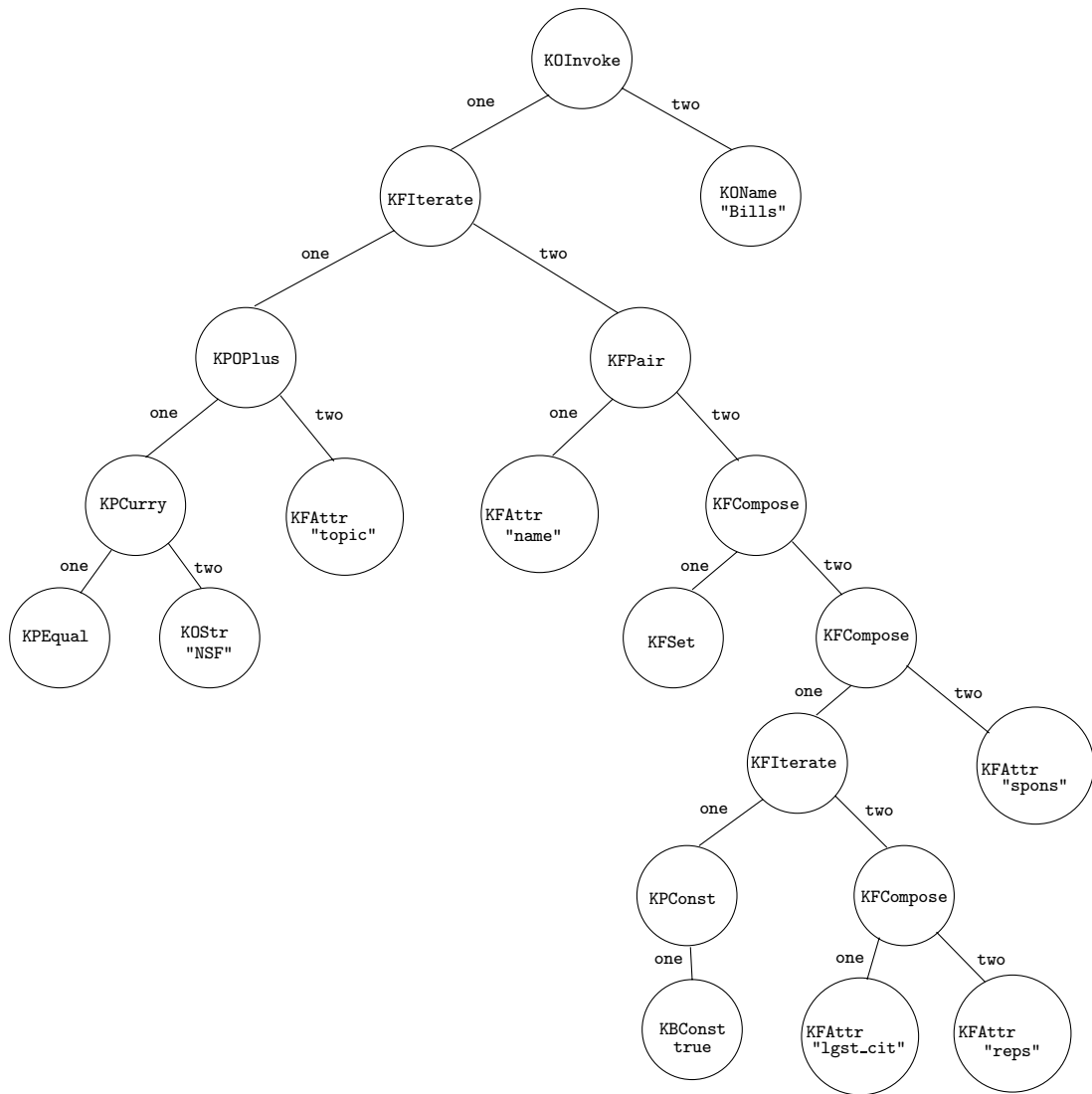
7.2.3 Extracting Results from the Nested Query

The result of calling `next` on the `OSBasicSieve` of Figure 7.6 itself generates a record (`STRUCT`) whose second value (`schools`) is another query operator. As elements from this inner query result can also be extracted via calls to `next`, this makes it possible for the query rewriter to be called deeply within evaluation. In this case, the function argument of the `OSMapSieve` is simple enough that the rewriter is not called. A call of `next` on the `OSMapSieve` initiates a call of `next` on the `OSSource` iterator over `b.spons`. The result of this latter call (either a Senator or a House Representative, `l`) results in the formulation of the expression,

$$(\text{lgst_cit} \circ \text{reps}) ! \llbracket l \rrbracket$$

whose parse tree representation is illustrated in Figure 7.9 (A). A call of `obj` on this tree generates the KOLA tree of Figure 7.9 (B) as shown below:

$$\begin{aligned} & ((\text{lgst_cit} \circ \text{reps}) ! \llbracket l \rrbracket) \rightarrow \text{obj} () \\ = & (\text{lgst_cit} \circ \text{reps}) \rightarrow \text{invoke} (\llbracket l \rrbracket \rightarrow \text{obj} ()) \quad (\text{by } \text{KOInvoke} :: \text{obj}) \\ = & (\text{lgst_cit} \circ \text{reps}) \rightarrow \text{invoke} (\llbracket l \rrbracket) \quad (\text{by } \text{KOWrapper} :: \text{obj}) \\ = & \text{lgst_cit} \rightarrow \text{invoke} (\text{reps} \rightarrow \text{invoke} (\llbracket l \rrbracket)) \quad (\text{by } \text{KFCompose} :: \text{invoke}) \\ = & \text{lgst_cit} \rightarrow \text{invoke} (\text{reps} ! \llbracket l \rrbracket) \quad (\text{by } \text{KFAttr} :: \text{invoke}) \\ = & \text{lgst_cit} ! (\text{reps} ! \llbracket l \rrbracket) \quad (\text{by } \text{KFAttr} :: \text{invoke}). \end{aligned}$$

Figure 7.5: The Parse Tree Representation of NSF_{2k}

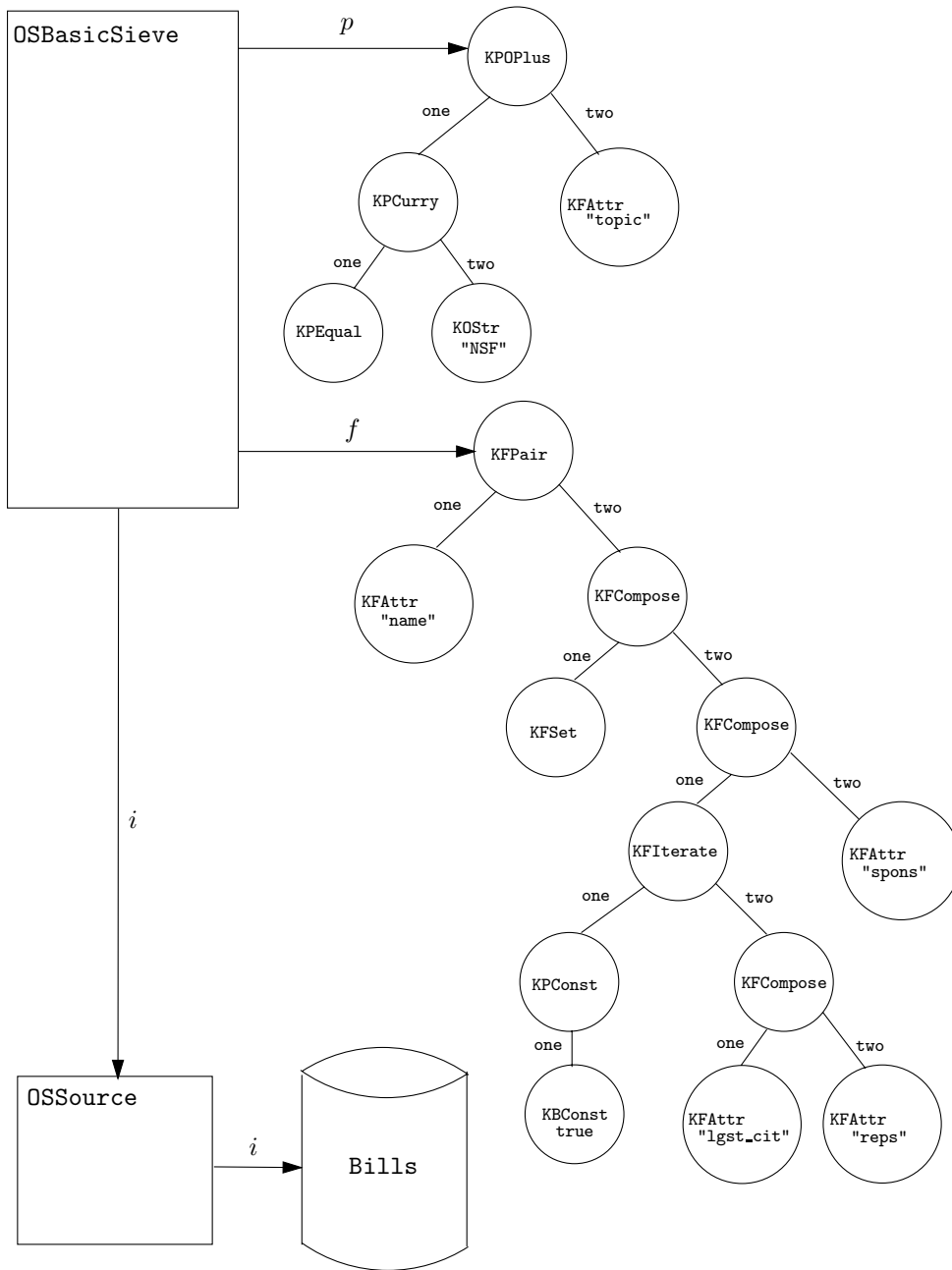


Figure 7.6: The result of calling `obj` and `res` on the "NSF Query"

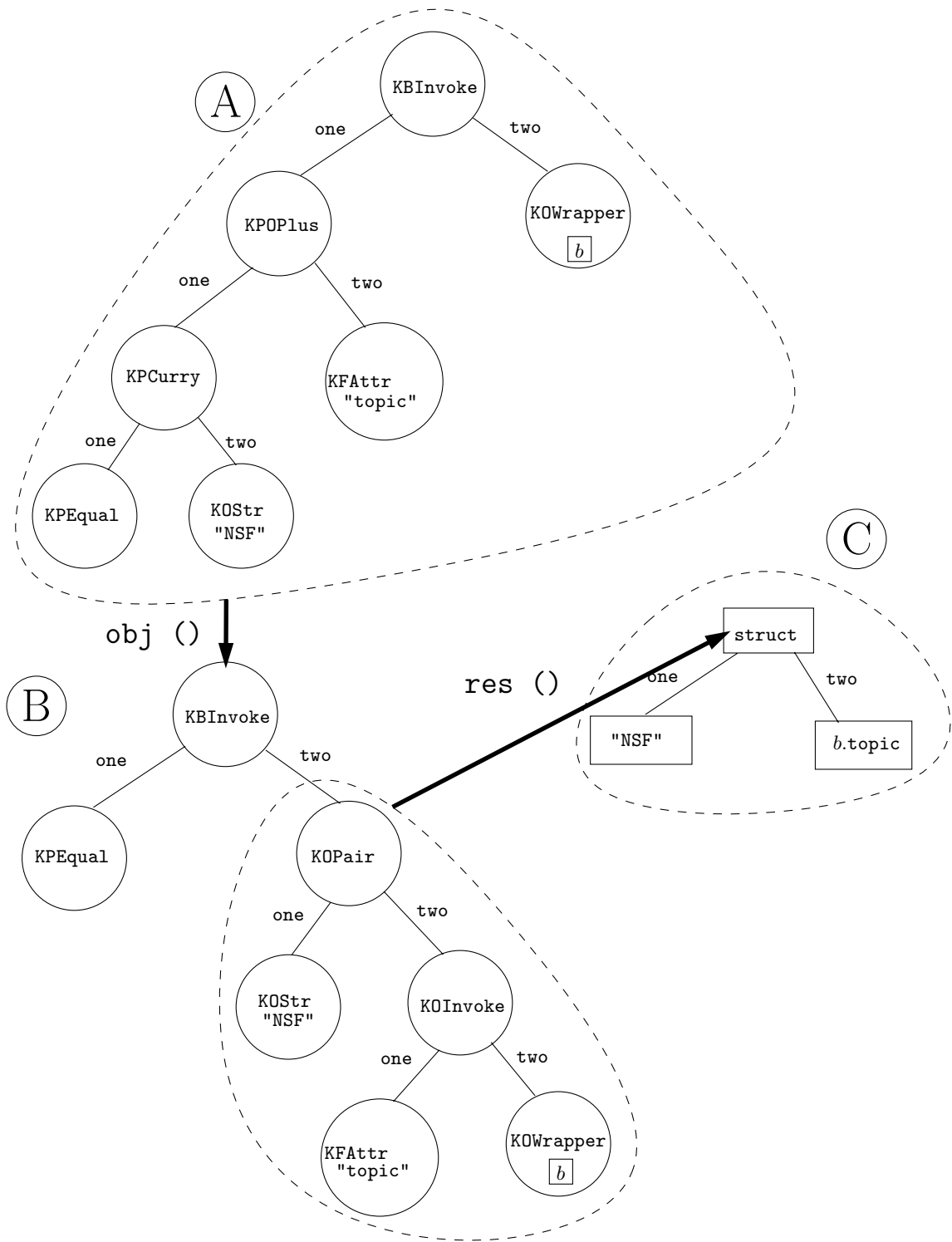


Figure 7.7: Calling query NSF_{2k} 's predicate on a bill, b

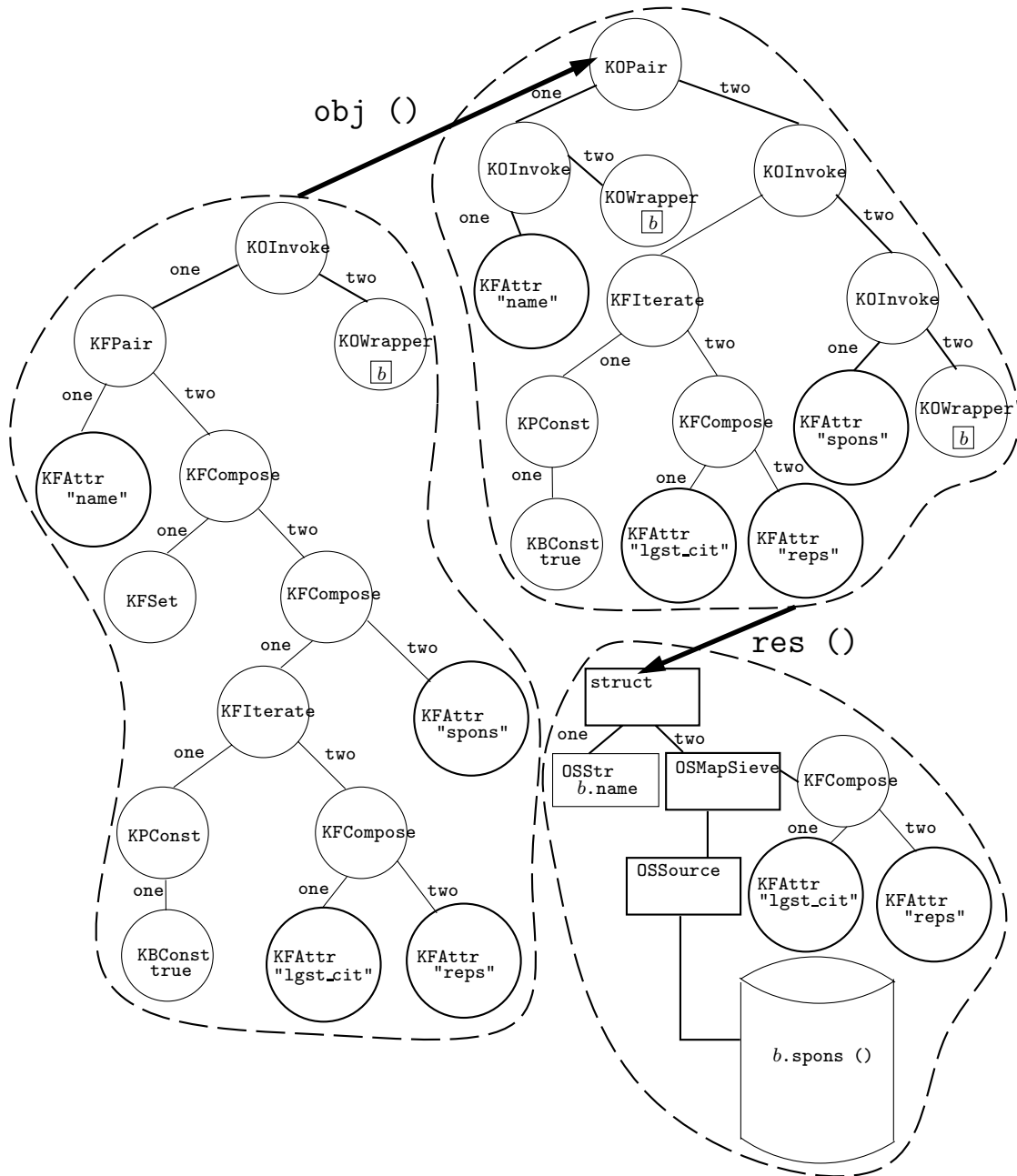


Figure 7.8: Calling NSF_{2f} 's data function on a House resolution, b

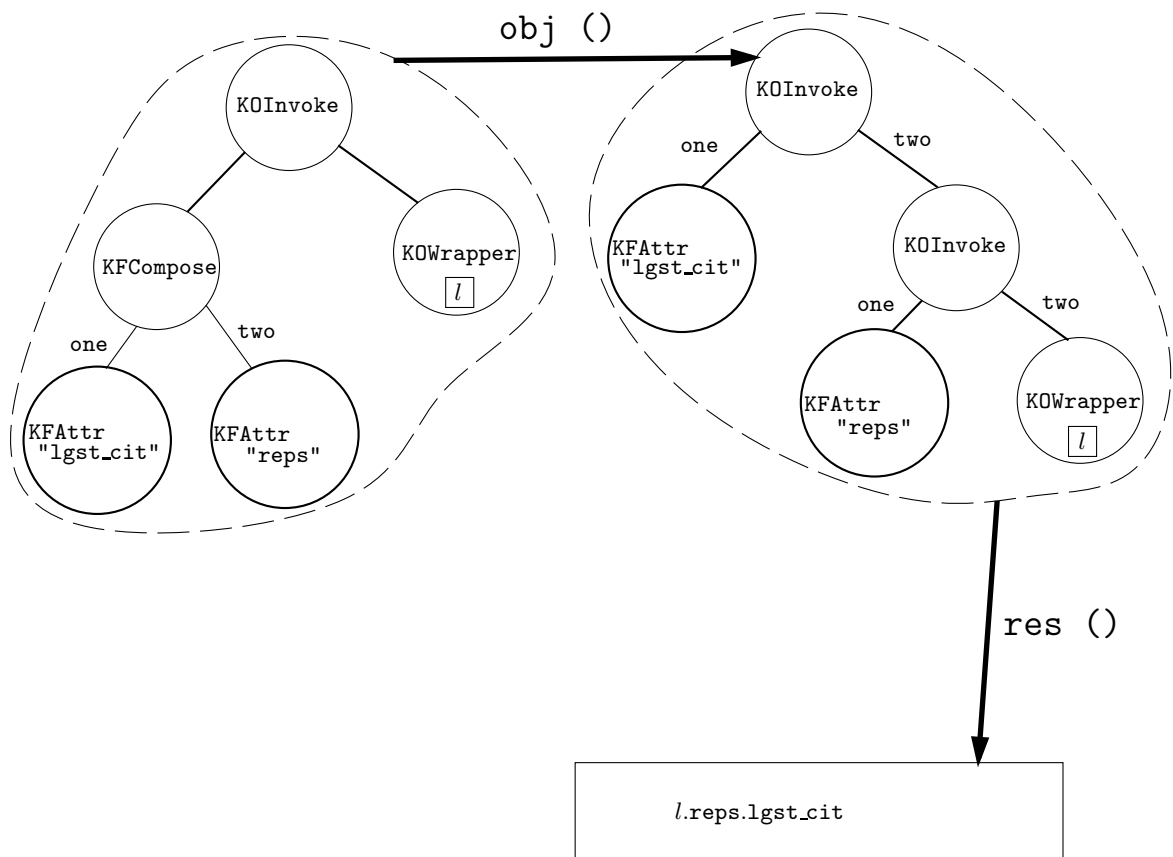


Figure 7.9: Calling NSF_{2k} 's inner query function on a House Representative, l

Calling `res` on this KOLA tree generates path expression

$$l.\text{reps}.\text{lgst_cit}$$

as demonstrated below:

$$\begin{aligned}
 & (\text{lgst_cit} ! (\text{reps} ! \llbracket l \rrbracket)) \rightarrow \text{res} () \\
 = & \text{lgst_cit} \rightarrow \text{exec} ((\text{reps} ! \llbracket l \rrbracket) \rightarrow \text{res} ()) && (\text{by } \text{KOInvoke} :: \text{res}) \\
 = & \text{lgst_cit} \rightarrow \text{exec} (\text{reps} \rightarrow \text{exec} (\llbracket l \rrbracket \rightarrow \text{res} ())) && (\text{by } \text{KOInvoke} :: \text{res}) \\
 = & \text{lgst_cit} \rightarrow \text{exec} (\text{reps} \rightarrow \text{exec} (l)) && (\text{by } \text{KOWrapper} :: \text{res}) \\
 = & \text{lgst_cit} \rightarrow \text{exec} (l.\text{reps}) && (\text{by } \text{KFAttr} :: \text{exec}) \\
 = & l.\text{reps}.\text{lgst_cit} && (\text{by } \text{KFAttr} :: \text{exec})
 \end{aligned}$$

7.3 Discussion

7.3.1 Cost Considerations

This chapter describes ongoing work and therefore inspires more questions than answers. Dynamic query rewriting offers potentially enormous benefits for query evaluation given that the wisdom or validity of some rewrites may depend on factors that cannot be determined until run-time. In this chapter, we showed an example query (NSF_{2k}) for which dynamic query rewriting was beneficial. In processing this query, duplicate elimination was avoided in many circumstances where it would have been required otherwise. If duplicate elimination can be avoided multiple times in processing a query and avoided for large collections, enormous savings in evaluation cost are likely.

On the other hand, dynamic query rewriting adds overhead to the cost of evaluating a query. This cost arises because of the need to generate subplans during query evaluation. For ad hoc querying (for which optimization and evaluation occur consecutively), this is not an issue. But for queries that are compiled, an obvious question is whether or not the costs of dynamic optimization outweigh its potential benefits.

Once our implementation is complete, this question will need to be addressed. But there are reasons for optimism. First, dynamic query rewriting need not invoke the large

and expensive query rewrite routines that are likely to be invoked statically. Our present design permits distinct COKO transformations to be associated with each KOLA query operator. These rewriters could be quite simple, and perform only those rewrites that offer large cost savings that justify the cost of dynamic rewriting. The rewrite to avoid redundant duplicate elimination is one such example. The cost of the semantic reasoning needed to decide whether duplicate elimination can be avoided is modest, but the potential cost savings from avoiding duplicate elimination (especially for large collections) can be enormous.

A second reason for optimism is that it may be possible to streamline the rewriting that does occur dynamically. For example, *memoization* of the results of semantic queries could greatly improve performance. Consider the example we presented in this chapter. For this example, there are only two possibilities considered during semantic rewriting. Either a bill is a House resolution for which duplicate elimination is avoidable, or it is a Senate resolution for which duplicate elimination is required. Given the present design, the processing of each bill results in one of two semantic queries being generated:

1. Is A a set given that it consists of sponsors of a House resolution, and is

$$\text{lgst_cit} \circ \text{reps}$$

injective given that it is a function over House Representatives?, or

2. Is A a set given that it consists of sponsors of a Senate resolution, and is

$$\text{lgst_cit} \circ \text{reps}$$

injective given that it is a function over Senators?

If the answers to these questions can be memoized when they are first answered, then evaluation of semantic queries becomes trivial for all but the bills processed initially. In fact, the use of a Prolog interpreter makes the implementation of memoization trivial. Prolog facts (such as one that directly states that $\text{lgst_cit} \circ \text{reps}$ is injective if reps ranges over House Representatives) can be *asserted* as they are inferred.

The issues discussed in the Chapter 5 also are material here. Once our COKO compiler generates more efficient code, and our semantic rewriter reasons directly over KOLA trees instead of their Prolog interpretations, we believe that all rewrites (whether fired statically or dynamically) will become more efficient.

Finally, dynamic query rewriting might be circumvented in some cases by allowing for conditional plans (as in the Volcano dynamic optimization work of Graefe and Cole [25]).

Rather than deferring rewriting decisions until run-time, a conditional plan would statically list multiple cases and associate plans to perform for each. Conditional plans could be useful when the cases that will be considered dynamic query rewriter can be anticipated statically, and when these cases are unlikely to change. We believe that dynamic query rewriting should not be replaced by conditional plans in all cases because it can be hard to anticipate all cases statically. For example, in this chapter we have shown that the subtype to which an object belongs can be relevant to the choice of query evaluation strategy. New subtypes are easily defined for object-oriented databases. Therefore, a conditional plan that is unaware of changes to the schema can become obsolete.

7.3.2 The Advantage of KOLA

In previous chapters, we showed how KOLA's combinator style facilitates the expression of declarative rules. Term rewriting and semantic inference are similar in that both must perform subexpression identification and query formulation. Expressed over KOLA queries, neither of these tasks require supplemental code.

In this chapter, we have shown that subexpression identification and query formulation have uses beyond the expression of a query rewrites. Dynamic query rewriting is query rewriting that occurs during a query's evaluation. Typically, dynamic query rewriting requires a query evaluator to identify subexpressions of the query it is processing, and to formulate new queries to dynamically submit to a query rewriter. We have shown that the expression of these two tasks is simplified with the use of KOLA as the underlying query representation. Therefore, dynamic query rewriting provides another example of how KOLA benefits the development of query optimizers.

7.4 Chapter Summary

This chapter has described ongoing work in dynamic query rewriting. Query rewriting is most effective when a rewriter has knowledge about the representations and contents of the collections involved. Dynamic query rewriting is useful when this information is unavailable until data is accessed, as in object-oriented databases, network databases and heterogeneous databases.

We have confined our discussion in this chapter to potential benefits and design approaches for dynamic query rewriting over object-oriented databases. We showed an object-oriented query (NSF_{2k}) that could be evaluated efficiently with dynamic query rewriting.

Specifically, dynamic query rewriting makes it possible to evaluate this query without having to perform duplicate elimination as many times as would be required otherwise. We described the design of a dynamic query rewriter for ObjectStore for which an implementation is under development. While the work in this area is incomplete, the ideas demonstrate an exciting direction for query processing enabled by a combinator representation of queries.

Chapter 8

Related Work

In this chapter, we consider work related to the work presented in this thesis. The chapter is divided into four sections that correspond to Chapters 3 (KOLA), 4 (COKO), 5 (Semantic Query Rewriting) and 7 (Dynamic Query Rewriting) respectively.

8.1 KOLA

KOLA is both a query algebra and an internal data structure for query optimizers. The association of data structure with algebra is deliberate, and reflects our goal of simplifying both the operation and verification of query rewriting.

The best known query algebra is the relational algebra of Codd [24]. While used to describe logical query rewrites in many database texts (e.g., [66], [80]), the relational algebra is not usually used as a *data structure* within query optimizer implementations.¹ The Starburst query rewriter [79] for example, uses the Query Graph Model (QGM) as its internal representation. QGM query representations resemble instances of the entity-relationship data model. The entities (vertices) for this model are collections such as stored tables or queries. Edges reveal relationships between collections that indicate that one is an input to the other (the other being a query), or that a correlated predicate compares elements from each.

Starburst query rewrite rules are written in C. In [79], it is argued that it is necessary to code rules in this way because QGM is a C data structure. We dispute this conclusion — rules could be expressed more declaratively and a compiler could generate C code

¹Although Microsoft's SQL Server does use a variation of the relational algebra in this way.

from these more abstract specifications. (For example, KOLA’s data structures are implemented in C++ and COKO transformations and KOLA rewrite rules are compiled into C++ code.) Instead, we believe that code is necessary to specify Starburst rules because the close association between QGM and SQL makes QGM a variable-based representation.

8.1.1 KOLA and Query Algebras

KOLA joins the numerous object query algebras that have been proposed over the years, including AQUA [70], EQUAL [87], EXTRA [99], OFL [40], GOM [61], Revelation [98], LERA [35], ADL [91], and the unnamed algebra of Beeri and Kornatzky [7]. Despite the lack of a standard, there is an encouraging overlap in the operators found in all of these algebras. These operators include:

- *generalizations of relational operators* (e.g., (1) a *mapping* operator generalizing relational projection by mapping a function over all members of a collection, (2) a *selection* operator generalizing relational selection by selecting elements of a collection satisfying a given predicate, and (3) a *join* operator generalizing relational joins by relating elements drawn from multiple collections),
- *aggregation operators* (such as the `fold` operator of AQUA [70] and Revelation [98]) that give algebras expressive equivalence with standard query languages with operators such as `SUM` and `COUNT`, and
- *conversion operators* to convert back and forth between flat and non-flat collections (including a *grouping* or *nesting* operator to convert a flat collection to a non-flat collection, and a *flattening* or *unnesting* operator to flatten a non-flat collection).

KOLA defines operators in each of the above categories. Mapping and selection are captured by KOLA’s `iterate` and `iter` formers. Joins are expressed by a number of query primitives and formers, including `join`, `lsjoin`, `rsjoin` and `int`. Grouping is captured by `njoin`. Collection flattening is captured by `unnest` and `flat`. Thus, KOLA is equivalent in spirit to other object query algebras. The uniqueness of KOLA is in form — KOLA is a combinator-based representation specifically designed to simplify the operation and the verification of the query rewriter.

The KOLA Heritage – The AQUA Family of Query Algebras: The direct ancestors of KOLA are AQUA [70], EQUAL [87], EXTRA [99] and Revelation [98]. AQUA [70] was the immediate predecessor to KOLA. (KOLA was defined in response to difficulties

defining a formal specification for AQUA and expressing rewrite rules over AQUA queries.) AQUA was designed by the inventors of EQUAL [87], EXCESS [99] and Revelation [98] who attempted to integrate and reconcile the approaches taken with their predecessor algebras.

AQUA defines a very general set of query operators, each of which can be instantiated with any data function or data predicate. For example, AQUA's join operator can be instantiated with a tuple concatenation function to express a relational join, or with a function that uses a query operator to express a join over an object-oriented database. This approach to query operators influenced the design of KOLA's query formers.

Aside from its combinator style, KOLA's primary distinction from AQUA concerns how it integrates data and query functions and how it constrains the definition of equality predicates. In AQUA, data functions are defined as *lambda expressions* whereas query functions are not. In KOLA, all functions are defined uniformly. This approach simplifies query formulation which need not massage query functions to make them data functions or vice-versa. This is especially important in an object query algebra where the pervasiveness of nesting means that query functions are often used as data functions.

AQUA allows arbitrary equivalence relations to act as equality predicates. Query operators whose semantics depend on equality definitions (such as set and bag union) are defined with equality predicate parameters so that the semantics of these operators can be configured according to their intended use. KOLA demands that equality definitions be *confluences* (as in CLU [72]): predicates that determine two objects to be equal only if they are indistinguishable. For mutable object types, equality predicates must compare immutable object identifiers. For immutable object types, equality predicates must be keys. KOLA has a more rigid policy with respect to equality predicates because substituting arbitrary equivalence relations for equality predicates can result in unintuitive query results. For example, a query that is instantiated with a non-confluent equality predicate can be issued twice over the same data and return two collections with distinct cardinalities (making these collections unequal by any reasonable interpretation of equality). As well, equality definitions that determine two distinct objects to be equal (perhaps because at the time of comparison, their states were identical) can result in a collection whose cardinality can change as a result of mutating one of its elements. These issues are discussed at length in our DBPL '95 paper [23].

OFL: Like KOLA, OFL [40] is inspired by functional programming languages [34]. OFL is an algebra intended to simplify the generation of graph representations of queries. The strategy taken to evaluate the query varies according to how this graph representation is

traversed.

OFL is an alternative intermediate representation to parse structures of standard object algebras. These algebras, it is argued, unnecessarily constrain the choice of execution algorithms. For example, the algebraic representation of path expressions demands evaluation by an inefficient object-at-a-time navigation. On the other hand, the graph-based representation espoused by this work enables the same query to be mapped to a plan that evaluates the query using joins. This then is an alternative approach to solving the normalization problem addressed by query rewriting. The usual example used to motivate query rewriting involves nested queries that force optimizers to choose nested loop evaluation strategies. Rewriting transforms nested queries into equivalent join queries that offer optimizers more algorithmic choice. In Chapter 6, we showed how query rewriting could also normalize queries with path expressions to ensure the consideration of evaluation plans involving joins.

The OFL language consists of both functional and imperative constructs (such as a sequencing operator). The imperative flavor makes OFL more of a plan language than an algebra, as algebraic equivalences are hard to establish and verify when expressions are described by the algorithms that generate them. But we find the alternative to query rewriting proposed by this work intriguing. In short, this approach generates multiple evaluation alternatives by fixing, rather than rewriting, a query's representation and instead varying traversal orders over it. Therefore OFL has some commonality with COKO which is also concerned about the order in which a given query representation is visited, though in the context of rewriting rather than evaluation.

LERA, GOM and ADL: Object query algebras LERA [35, 36], ADL [91] and GOM [61] are generalizations of the relational algebra. All of these algebras support tuple operators such as tuple concatenation (used in joins, unnests and nests). The KOLA data model includes pairs rather than tuples because the fixed number of fields in a pair simplifies its formal specification. Translation of OQL queries into KOLA maps tuples (**structs**) into (nested) pairs with tuple references replaced by compositions of projections that make appropriate extractions. (Our translator implementation keeps track of field names so that KOLA pair results can be translated back into tuples before they are stored.)

Like KOLA, LERA avoids direct references to variables within queries. But rather than using a combinator notation, LERA uses a numbering scheme to replace a variable reference with an index indicating the collection over which the variable ranges. Therefore, LERA's scheme is similar to the deBruijn [30] scheme (see Chapter 6), but is static. That

is, collections appearing in a query are numbered from left to right rather than according to their relative positions within environments. The purpose of this notation is to avoid ambiguity (e.g., if the same collection appears twice in a join). With respect to rewrite rules, this approach still suffers from the same problems that make rewrite rules over query expressions require code. In particular, subexpression identification over such expressions requires code because a variable's index does not indicate whether or not it is free. As well, query formulation requires code because a variable index may have to be adjusted if rewriting results in changes to the collections that appear in a query's FROM clause (e.g., as in a nested query \rightarrow join query normalization).

GOM [61] and ADL [91] contain semijoin and nested join operators that inspired equivalent operators in KOLA. Specifically, KOLA's **njoin** former was inspired by ADL's **njoin** and GOM's **djoin** operators. ADL also defines semijoin and antijoin operators that are semantically equivalent to instantiations of KOLA's left semi-join former. (The function,

$$\mathbf{lsjoin} (\mathbf{ex} (p), \mathbf{id})$$

is equivalent to ADL's semijoin operator with respect to predicate p , and

$$\mathbf{lsjoin} (\mathbf{fa} (\sim (p)), \mathbf{id})$$

is equivalent to ADL's antijoin operator with respect to predicate p .) GOM defines a left outer join operator that performs a union on the result of these two functions, but applying different functions (f and g) to the results of the semijoin and antijoin. Left outer-joins are also expressible in KOLA. For any pair of collections A and B , the left outer-join of A with respect to B is:

$$\mathbf{uni} ! [\mathbf{lsjoin} (\mathbf{ex} (p), f) ! [A, B], \mathbf{lsjoin} (\mathbf{fa} (\sim (p)), g) ! [A, B]].$$

8.1.2 KOLA and Combinators

KOLA's combinator style was inspired by Backus' functional language, FP. Like FP, KOLA was initially intended to be a user-level language. But we abandoned this approach when it became clear that combinators make languages difficult for users to use.

The use of combinators as internal representations of functional programs originated with Turner's seminal work [93]. Ever since, combinators have been used within strict functional language compilers (e.g., Miranda [94]) as internal representations of lambda expressions. The use of combinators in this way makes evaluation by graph reduction more efficient, as lambda expressions with free variables force unnecessary copying of potentially

large function bodies [34]. Approaches to combinator translations can be classified according to whether the combinator set is *fixed* or *variable*. *Fixed* combinator sets consist of a finite set of combinators that are used as the target for all lambda expression translations. The best known of the fixed sets of combinators is the **SKI** combinator set introduced by Schönfinkel [82]. It has been shown that this small set is sufficient to translate all of the lambda calculus (in fact **I** is superfluous), but the size of the resulting code is too large to be of practical use [57]. Variations of the **SKI** combinator sets add additional, redundant combinators (e.g. **B** and **Y**) to reduce the size of the translated code. Curien [27] proposed a set of combinators inspired by Category Theory, which he used to provide an alternative semantics for the lambda calculus. Of all of the combinator translations we found described in the literature, KOLA most closely resembles Curien’s combinator set, but adjusted to account for sets and bags rather than lists, and avoiding the overly powerful combinators (**App** and Λ) that are expressive but difficult to optimize prior to their application to arguments.

Lambda lifting [56] and supercombinators [52] are translation techniques that use variable sets of combinators. These techniques construct new combinators during each translation. The goal of this technique is to keep the number of combinators in the result small (the combinators generated tend to be fairly complicated). Thus, the goal of removing free variables from lambda expressions is achieved without an explosion in the size of the resulting code.

Despite the wide-spread use of supercombinators in functional language compilers, we settled on a fixed set of combinators for KOLA for the following reasons:

- query optimization (which relies on a set of known rewrite rules) must reference a known (i.e., fixed) set of operators, and
- query optimization can tolerate query representations that are larger (within reason) than queries because queries tend to be small compared with functional programs.

KOLA is not the first combinator query algebra or query language. ADAPLAN [31] was proposed as a combinator-style query language, but combinators are difficult for users to master and ill-suited as query languages. FQL [12], NRL [10] and the unnamed algebra of Beeri and Kornatzky [7] are combinator-based query algebras. FQL was an early effort and limited to relational databases. The algebra of Beeri and Kornatzky and NRL are mathematical formalisms rather than optimizer data structures. That is, the purpose of both of these algebras is to simplify the correctness of rules expressing query rewrites. Both algebras are *minimal* in that they include no redundant operators. A minimal algebra

simplifies proof obligations, but is less effective as an optimizer data structure. Redundant operators (such as join operators) are necessary in optimizer implementations because they are highly suggestive of the kinds of algorithms that a plan generator should consider. This redundancy is exactly what query rewriting normalizations exploit — rewriting queries into alternative forms that use operators to suggest alternative evaluation strategies.

8.1.3 KOLA and Query Calculi

A query calculus differs from a query algebra in that it specifies a query in a more declarative way (i.e., by describing the result of the query rather than the sequence of operators that generate it). The declarative flavor of query expressions can make it easier for a plan generator to generate multiple execution plans, and therefore calculus-based query representations have advantages over query algebras for which plan generation is more constrained. Put another way, the translation of queries into a declarative calculus is another way to achieve the normalization goal of query rewriting. But the declarative nature of query calculi makes it difficult to express heuristics that are easily expressed over a query algebra. For example, it is not clear how one would express a rewrite that reorders filter predicates over queries with a calculus-based representation.

As was the case for algebras, a standard for object query calculi has yet to emerge. But perhaps the most common calculus for object queries stems from the monoid homomorphism work of Tannen et al [9]. That work describes *structural recursion*: a simple and highly expressive formalism for specifying both queries and data types, but requiring that functional inputs to homomorphisms satisfy certain undecidable algebraic properties (commutativity, associativity and idempotence). Later work from this group [10] proposed specific instantiations of these homomorphisms that were known to satisfy these properties (e.g., instantiations with set union), but at the expense of expressivity. Further, while ensuring a clean mathematics the idempotence restriction makes it difficult to express certain query operations such as aggregations. For example, SQL’s SUM operator cannot be simulated with a homomorphism instantiated with addition ($+$), because $+$ is not idempotent.

The Monoid Comprehension calculus of Fegaras and Maier [33] is defined in terms of monoid homomorphisms, but restricts the homomorphisms that can be expressed. In this way, the problem of deciding algebraic properties of functions is avoided, as are other problems inherent in the structural recursion model such as whether or not a given monoid homomorphism instantiation can be evaluated in polynomial time. (All queries expressed in the Monoid Comprehension calculus can be evaluated in polynomial time.) We consider

the Monoid Comprehension calculus to be complementary to object query algebras such as KOLA, much as the relational calculus is complementary to the relational algebra. However, unlike the relational calculus and algebra, the Monoid Comprehension calculus is not able to express certain operators found in most object algebras. For example, operators based on OQL's bag intersection and bag difference operators cannot be expressed as homomorphisms and are therefore inexpressible in the Monoid Comprehension calculus.

8.2 COKO

In Chapter 4, we introduced a language (COKO) for expressing complex query rewrites. Other rule-based systems express complex query rewrites in one of two ways:

- as individual rewrite rules (usually supplemented with code), or
- as groups of rules.

8.2.1 Systems that Express Complex Query Rewrites With Single Rules

Most rule-based systems express complex query rewrites with individual rules. However, the rules of these systems are not declarative rewrite rules that get fired by pattern matching. Some systems (e.g., Exodus/Volcano [13, 43], EDS [36] and OGL [84]) allow rewrite rules to be supplemented with code. Other systems (e.g., Starburst [79], and Opt++ [58]) allow rules to be expressed completely in code, thus avoiding pattern matching altogether. Still other systems (e.g., OGL [84] and Gral [6]) employ a variation of pattern matching to make its effects more drastic. One rule-based optimizer generator (Cascades [42]) does all of these things.

Starburst: Starburst [79] fires *production rules* (as in expert systems such as [11]) during query rewriting. These rules consist of two code routines (loosely corresponding to the head and body patterns of a rewrite rule) that are both written in C. Because they are written in C, Starburst's query rewrite rules can express a wide variety of transformations including view merging, nested query unnesting (both discussed in [79]) and magic sets transformations ([74, 86]). However, Starburst rules are difficult to understand and verify, requiring a detailed understanding of the underlying graph-based query representation (QGM).

Opt++ and Epoq: Opt++ [58] is not a rule-based system *per se*, but does permit the modular expression of query rewrites. Opt++ is a C++-based framework for the

development of optimizers. This framework includes a family of classes from which optimizer developers can inherit. One of these classes (`Tree2Tree`) defines objects that transform tree representations of queries. Query rewrite rules would be implemented as instances of subclasses of `Tree2Tree`. Thus, rules in this system would be code-based. Epoq [73] also defines a framework for building optimizers. The modules for this framework (*regions*) are special purpose optimizers that may or may not be rule-based. Epoq is intended to be flexible enough to support any conception of rule including those defined with code.

Exodus/Volcano/Cascades: Exodus [13] and its successors, Volcano [43] and Cascades [42] use rules that resemble rewrite rules, but that can have code supplements. Cascades goes so far as to allow rewrite rules to be replaced by code altogether (such rules are called “function rules”²). Cascades also uses a variation on pattern matching. (Cascade rules fire on sets of query expressions and returns sets of modified query expressions as a result.) Complex rewrites not expressible in this way would have to be expressed with function rules.

EDS and OGL: Like the Exodus family of optimizer generators, EDS [36] and OGL [84] permit code supplements to rules. EDS rules can have the form,

$$\textit{if } \langle \textit{term}_0 \rangle \textit{ under } \langle \textit{constraint} \rangle \textit{ then execute } \langle \textit{method list} \rangle \textit{ rewrite } \langle \textit{term}_1 \rangle$$

such that \textit{term}_0 is a head pattern, \textit{term}_1 is a tail pattern, and $\langle \textit{constraint} \rangle$ and $\langle \textit{method list} \rangle$ contain calls to supplemental code written in C or C++. OGL rewrite rules can include *condition code* (code supplements to head patterns) and can use meta-patterns to circumvent standard pattern matching (e.g., “*V” is a *multivariable* that “matches” multiple terms at once). While multivariables make some rules more general (an example shown in [84] demonstrates how a pattern with a multivariable could be reused to reassociate a conjunction expression with any number of conjuncts), other rules that require separating the terms that collectively matched the multivariable become inexpressible. In general, the use of rewrite rules makes the rules of all of these systems simpler to understand and verify than those that are expressed completely with code. However, the code supplements to these rules which enhance their expressive power offset their gains in verifiability.

Gral: Of the rule-based systems we looked at, Gral [6] comes closest to ours in its effort to make rules declarative by avoiding code. Gral also expands the expressive power of a

²In fact, a Cascades paper [42] cites a query rewrite analogous to SNF of Chapter 4 as an example rewrite that would be encoded as a function rule.

rewrite rule, but not by adding code supplements as in Exodus of EDS. Instead, Gral uses a variation of pattern matching to recognize rules that have multiple tail patterns. Each tail pattern of a rule is associated with a declarative condition on the queried data. A query that matches a head pattern and satisfies some set of conditions is then rewritten according to the associated tail pattern.

The conditions associated with tail patterns analyze the data that is queried such as its representation, the existence of indices, cardinality etc. Therefore, Gral rules have expressive power above and beyond traditional rewrite rules because they incorporate semantic reasoning into the decision as to whether or not to fire a rule. But a Gral rule resembles a conditional rewrite rule in KOLA rather than a COKO transformation. While useful for expressing semantic rewrites, such rules cannot express the traversal strategies and controlled rule firing that a complex query rewrite requires. Instead, such rewrites must be expressed using the Gral meta-rule language as discussed below.

8.2.2 Systems that Express Complex Query Rewrites With Rule Groups

Many systems (e.g., Starburst [79], Gral [6], EDS [36], GOM [61] and OGL [84]) provide some form of meta-control language for rules that includes rule grouping and sometimes sequencing. Rule groups can be associated with *search strategies* that indicate how the rules in a group should be fired.

It is tempting to view COKO as a meta-rule language in this style, and to compare COKO transformations with rule groups and firing algorithms with search strategies and sequencing control. But this analogy is misleading. Firstly, the “rules” that are grouped by these systems are more analogous to COKO transformations than KOLA rules. Secondly, the purpose of rule grouping in these systems is to control the search for a “best” (according to some cost model) alternative to a given query expression. Typically, rules in a rule group will be fired on a query (or set of queries) exhaustively,³ with each successful firing generating a new candidate query expression. The set of all candidate query expressions is then pruned for those that are considered to be efficient to evaluate. This approach reflects a *competitive* use for rule grouping – group all rules that contribute to some cost-based objective and let the best sequence of rule firings reveal itself through attrition.

Given the competitive model, an exhaustive approach to firing is guaranteed to find an optimal expression relative to some cost-model. Therefore, all of these systems allow rule

³Exhaustive firing of rule groups resembles exhaustive firing of individual rules — every rule in the rule group is fired on every subexpression on the query repeatedly until rule firing no longer has any effect.

firing to be exhaustive, though many also provide other competitive strategies that are more efficient than exhaustive searches. For example, EDS allows a parameter to be set that limits the number of rule firing passes made of a query. Other systems provide pruning strategies so that only some alternatives are generated (e.g, OGL provide search strategies such as branch-and-bound and simulated annealing). Other systems permit rules (Starburst, GOM and Exodus) or algebraic operators (Gral) to be ranked to help the optimizer decide which rule to fire next thereby reducing the likelihood that poor alternatives are generated.

The purpose of rule grouping in COKO is not to generate alternatives but to modularize the expression of a complex query rewrite. Rules are fired *cooperatively* rather than *competitively*, and according to a firing algorithm tailored to a specific set of rules, rather than to a search strategy that is defined independently. There is no search involved. Rewriting is blind to the data and is concerned with the syntax of the result rather than its expected cost. Therefore, firing algorithms operate differently from search strategies. Of the search strategies listed above, the *exhaustive* strategy can work as a firing algorithm, but only in restricted cases (rewrite rules must form a confluent set) and usually sacrificing performance in the process (as with CNF). Firing algorithms needn't be generic nor exhaustive and instead can be customized to specific, fixed sets of rules. By avoiding exhaustive firing in these cases, rewriting is made more efficient.

In short, rule grouping can be either competitive and cooperative. Competitive rule grouping is supported by many existing rule-based systems, and is complementary to COKO which simply provides a means of specifying the rules that are to be grouped. Cooperative rule grouping is unique to COKO and is a technique for defining complex query rewrites that are efficient to fire and verifiable with a theorem prover.

8.2.3 Theorem Provers

Whereas KOLA was designed to enable query rewrites to be verified with LP, COKO was inspired by the use of LP itself. As we showed in Chapter 3, LP proofs are accompanied by *proof scripts* that tell the theorem prover how to complete the proof.⁴ Proof scripts resemble handwritten proofs, except that proof methods are interpreted operationally to make the proof executable.

In many ways, a COKO transformation resembles a theorem prover proof script. Both query rewrite and proof rely on the existence of some set of simpler rewrite rules (derived

⁴Scripts with similar purposes are found in other theorem provers. For example, tacticals in Isabelle [78] are analogous to LP proof scripts.

from specification axioms in the case of proofs). In some cases, exhaustive firing of these rewrite rules would complete the rewrite or proof. But in other cases, this could lead to nonterminating derivations and in most cases, the rewrite and proof could be performed more efficiently. Both proof script and COKO transformation control when rewrite rules get fired to ensure efficient rewriting and ensure termination.

That having been said, there are of course many differences between LP and COKO. LP includes instructions that correspond to proof techniques such as induction, contradiction and proof by cases. COKO “proofs” are far more straightforward, requiring only the rewriting of terms through successive rule firings. There is no need to rewrite the same term to the same result multiple times with different sets of rewrite rules as is done when an LP proof proceeds by cases or induction. There is no need find inconsistencies in an augmented set of rewrite rules as is done when an LP proof proceeds by contradiction. But COKO provides fine-grained control of rule firing not provided with LP by controlling the order and the subtrees on which rules are fired. This form of firing control ensures that a COKO rewrite is efficient compared to a theorem prover, which would be far too slow to be a query rewriter.

8.3 Semantic Query Rewriting

Related work in semantic query rewriting and semantic query optimization⁵ either describes specific semantic optimization *strategies*, or describes *frameworks* within which strategies can be expressed.

8.3.1 Semantic Optimization Strategies

Most semantic optimization strategies exploit knowledge of integrity constraints. Integrity constraints are assertions that get evaluated during database updates to guard against data corruption. Because integrity constraints guard updates, they are constraints on data values and are expressed primarily by describing data dependencies. For example, a *domain* constraint ensures that specified columns have no values in common. *Referential integrity* constraints ensure that values appearing in one column of a relation also appear as values in a column of another relation. *Functional dependency* constraints ensure that tuples that share values for some columns share values for other columns also.

⁵The latter term is more commonly used in the literature.

The very early semantic optimization papers [48, 64, 15] propose rewrites that exploit knowledge about integrity constraints to generate alternative expressions of relational queries. Hammer and Zdonik [48] use inclusion dependencies to substitute smaller collections for larger ones as inputs to queries (*domain refinement*). Many systems (such as Starburst) use key dependencies to determine when duplicate elimination is unnecessary (as described in Chapter 5). Predicate Move-Around [71] exploits knowledge of functional dependencies to generate new filtering predicates for collections used as inputs to joins. Order optimization [89] exploits functional dependencies to determine when sorting can be performed early during evaluation or avoided altogether.

Semantic optimization strategies for object databases [1, 45, 16] exploit not only the semantics of data (i.e., integrity constraints), but the semantics of the functions that appear in queries as well. Aberer and Fischer [1] correctly point out that object query optimizers require semantic capabilities to avoid (when possible) invoking expensive methods that can dominate the cost of query processing. They suggest a number of ways that method semantics can be expressed (e.g., by declaring that one chain of method calls equals another) and used by rewrites over the queries that invoke them. The work of Chaudhuri and Shim [16] and Grant et al. [45] also permit equivalent method expressions to be declared. The latter work also supports the expression of more *algebraic* descriptions of functions (e.g., that a function is monotonic). Beeri and Kornatzky [7] also define rewrites over object queries that depend on algebraic conditions (such as the idempotence of a function). KOLA's semantic capabilities permit expression of integrity constraints as well as function equivalences and algebraic properties of functions. KOLA's uniqueness is in expressing these properties in a manner that allows them to be inferred, and permitting the inference of properties to be easily extended and verified.

8.3.2 Semantic Optimization Frameworks

As discussed in Chapter 5, the contribution of our work is not in presenting new semantic query optimization strategies but in introducing a framework for their expression that ensures verifiability with a theorem prover. Optimization frameworks that incorporate semantic query optimization strategies can be divided into three categories:

- *Category 1*: systems that support operator-specific rewrites,
- *Category 2*: systems that support conditional rewrites, and
- *Category 3*: systems that support both conditional rewrites and semantic inference.

As we move from the first to the third category, systems get more succinct in describing semantic rewrites and hence more scalable. To illustrate, a category (1) system might permit the expression of a rule such as

$$\text{clip}(\text{blur}(i)) \equiv \text{blur}(\text{clip}(i))$$

which says that the result of clipping a blurred image is the same as the result of blurring a clipped image. (The latter is likely more efficient to perform given that blurring tends to be an expensive operation, and clipping results in a smaller image to blur.) For other functions that commute (e.g., an image inversion function (`invert`) and `clip`), a similar rule would have to be defined:

$$\text{clip}(\text{invert}(i)) \equiv \text{invert}(\text{clip}(i)).$$

A category (2) system would permit the expression of the more general rule,

$$\text{commutes}(f, g) :: f(g(i)) \equiv g(f(i)),$$

which establishes that any functions f and g can be reordered provided that they commute, and then permit metadata to identify pairs of commuting functions (e.g., `commute(clip, blur)` and `commute(clip, invert)`). Category (2) systems provide a more succinct way to express a semantic rewrite because one rule can be defined to account for all commuting functions, rather than one rule per pair of commuting functions as would be required in a Category (1) system. This difference becomes even more pronounced if other rules are defined that are also conditioned on the commutativity of pairs of functions. These rules can use the same set of metadata facts used by the previous rule.

A category (3) system would allow the commutativity of pairs of functions to be inferred. For example, a category (3) system might infer that a function f commutes with a composition of functions, $(g \circ h)$ if f commutes with each of g and h . Category (3) systems would allow a rewriter to infer that image clipping commutes with a function that first blurs an image and then inverts it given that `clip` commutes with each of `blur` and `invert`. A category (3) system is more succinct than a category (2) system at expressing semantic rewrites, as a category (2) system would have to list all functions that commute (including `clip` and `(blur \circ invert)`). Below we consider related work in semantic query optimization frameworks, classifying each in terms of these categories.

Category (1)

Chaudhuri and Shim's work [16] involves optimizations of SQL queries that contain foreign functions. They incorporate rewrite rules over foreign functions to express equivalent expressions. Each equivalence must be captured in a separate rule. These rules are always valid, therefore they perform no inference nor conditional rewrites and fall under category (1).

The work on E-ADT's in the Predator Database System [88] also falls under category (1). One of the goals of this work is to localize semantic optimizations to optimization components that are responsible only for queries involving the associated abstract data types. The rule facility defined for Predator demands that rules be operator-specific. But in fairness, the primary contribution of Predator is architectural. There is no reason that a category (3) semantic rewriting system could not be incorporated into their framework. Schema-specific properties (e.g., establishing that `reps` is a key) could be localized to E-ADT's, and inference rules could be maintained globally.

Category (2)

Beeri and Kornatsky [7] present several rewrite rules that are conditioned on function properties. For example, several of their rules are conditioned on the idempotence of a function. However, they do not define a mechanism to define how properties such as idempotence are inferred. Therefore the semantic rewriting proposed in this work falls under category (2).

More recent work in the context of object models has looked at semantic rewriting in the presence of methods. Aberer and Fischer [1] consider semantic rewrites that depend on method equivalences, and predicate implications derived from method semantics. Method equivalences are conditioned on the domain of free variables appearing within the expressions, and are used to rewrite query expressions according to a fixed set of rules. For example, an equivalence can establish that two functions, $f(x)$ and $g(x)$ are equivalent for all x in some collection C . The system uses this equivalence to infer that mapping f over C is equivalent to mapping g over C .

The work of Aberer and Fischer falls short of other category (2) systems because the rewrites that can depend on semantic conditions are limited to those provided by the system. Equivalence relationships are only used to rewrite queries involving mapping and selection. Predicate implication (which resembles predicate strength) is used in a rule that rewrites selections (presumably with expensive predicates) to natural joins of collections filtered with the cheaper predicates. No other rewrites that exploit these conditions can be added, and

no other conditions can be defined.

Category (3)

Grant et al [45] propose a framework for semantic query optimization (SQO) by which object queries expressed in query languages such as OQL get translated into Datalog for semantic processing. Semantic information about the underlying object schema (e.g., subtyping information and methods) get expressed as Datalog rules that infer new integrity constraints to attach to these queries. Various checks are then made of the resulting predicates (e.g., to see if the new predicates introduce inconsistencies thereby eliminating the need to evaluate the query) before the Datalog queries are then translated back into the language in which they were posed.

This work falls under category (3) because of the use of inference to generate new integrity constraints. But the inference performed by SQO is less general in its application than that performed by COKO. SQO performs inference to generate predicates that get attached to queries. COKO properties can infer *any* condition that guards the firing of a rewrite rule, and not just predicate strength. Moreover, inferred conditions can guard the firing of *any* conditional rewrite rule, and not just a rule that adds weaker predicates to existing predicates. Effectively, this rule is the only conditional rule invoked by SQO. Its KOLA equivalent is captured by rewrite rule `str2` of Figure 5.6.

SQO improves upon our work in its use of a more powerful inference technique (partial subsumption) to generate new predicates. We are interested in studying this inference technique to see if it could be used to strengthen our inference capabilities and thereby make our semantic rewriting component a better approximation of a complete system.

In summary, related work in semantic query optimization describes strategies and/or frameworks for expressing semantic query rewrites. Semantic optimizations for relational queries primarily use integrity (i.e., data) constraints. Semantic optimizations for object databases reason about the semantics of functions also. This is appropriate given that functions appearing in object queries are not limited to trivial extractions of values from columns, and can dominate the cost of evaluating the query.

Frameworks for semantic query optimization can be classified into three categories that are successively more succinct in expressing classes of query rewrites. Systems in category (1) permit the expression of operator-specific rewrites. Systems in category (2) permit the expression of more general conditional rewrites. Systems in category (3) permit the expression of conditional rewrites and techniques for inferring the conditions that are not explicitly

stated. Our work is unique in how it captures data and function-based semantic rewrites within a category (3) framework in a manner supporting extensibility and verification with a theorem prover.

8.4 Dynamic Query Rewriting

In this section, we describe work related to our dynamic query rewriting work that is ongoing and presented in Chapter 7. Because our work is ongoing, we do not yet have experimental results to justify or refute our intuitions. Therefore, the comparisons made to other work in the area are confined primarily to approach rather than to a relative analysis of performance.

The dynamic query optimization strategies that have been proposed in the literature have exclusively concerned plan generation. Dynamic plan generation defers the generation of complete execution plans until cost-related factors can be observed at run-time. Such factors can include availability of resources [53], run-time values for host variables in embedded queries [25], or selectivity estimations [5].

The systems discussed here differ primarily by when alternative plans are generated. The first category of systems (described in Section 8.4.1) use dynamic plan *selection* rather than dynamic plan *generation*. That is, what these approaches have in common is that compile-time optimization produces a fixed set of alternative plans from which a choice is made at run-time. Work falling in this category includes the dynamic optimization work for Volcano of Graefe and Cole [25], parametric query optimization [53] and the dynamic optimization performed by Oracle RDB [5]. The second category of systems (described in Section 8.4.2) perform *adaptive* query optimization. These systems generate complete execution plans at compile-time but permit all or portions of these plans to be replaced during query evaluation. Proposals in this category include the query scrambling work out of the University of Maryland [4] and the mid-query reoptimization work for Paradise of Kabra and DeWitt [59]. Dynamic query rewriting more closely resembles systems in the latter category, but generating partial plans rather than complete plans at compile-time.

Dynamic query rewriting is closely related to partial evaluation [26], as it reduces compile-time query optimization to partial plan generation. We consider this relationship more fully in Section 8.4.3.

8.4.1 Dynamic Plan Selection

We classify systems that choose plans dynamically from a fixed set of alternatives generated at compile-time as dynamic plan *selection* strategies. The work of Graefe and Ward [44] and later, Graefe and Cole [25] for Volcano was among the first dynamic plan selection strategies proposed. This work proposes a plan language that includes a *choose-plan* operator that makes it possible to express *conditional plans*. All subplans appearing below a *choose-plan* operator are alternative plans that compute the same result. The execution of this operator performs a cost analysis at run-time to determine which of these alternative plans should be executed.

Graefe and Cole rule out dynamic invocations of the query optimizer, arguing that the overhead involved would offset the performance gains from dynamically generated plans. This is undoubtedly true in certain cases, but ignores certain factors that make dynamic calls to an optimizer (and rewriter) of potential benefit:

- It assumes that a call to a dynamic query optimizer is a call to the same query optimizer that performed compile-time optimization. In fact, there is no reason not to define more streamlined optimizers and rewriters specifically defined to perform optimizations that are quick and most likely to have cost benefit (such as query rewrites). This is the approach taken in Oracle RDB [5] (which has separate optimizer components for their query compiler and query executor)

The Volcano solution can be viewed as dynamically invoking an optimizer that is as streamlined as an optimizer can be, deciding between a fixed set of plans according to a fixed set of metrics. We believe that the optimizers that are invoked dynamically could fall anywhere on a complexity scale, depending on the costs of the optimizations they perform and the potential benefits that they offer to the query being evaluated.

- The more sophisticated the reasoning performed by a conditional Volcano plan (i.e., the more *choose-plan* operators that appear in the conditional plan) the larger the generated plan will be. Large plans can end up using resources (e.g., buffer space) that would otherwise be used in evaluating the query. Less sophisticated reasoning will produce smaller plans but are less likely to be effective in general. No study is made in [25] of the sizes of conditional plans and the impact of plan size on evaluation performance.

In short, this work was pioneering in suggesting how to implement a limited form of dynamic query optimization. But the results presented here can be generalized in two ways:

1. The complexity of the optimizer invoked dynamically can vary and not be just one that chooses between a fixed set of plans on the basis of a fixed set of cost factors.
2. Dynamically invoked optimizers need not be cost-based plan generators/selectors but could be heuristic-based query rewriters that perform semantic inference. In fact, query rewrites typically involve far simpler reasoning than do plan generators and can have far greater impact on performance. This makes them ideal as candidate dynamic optimizations where the cost : benefits ratio is of utmost concern.

Oracle RDB [5] justifies the dynamic optimization it performs by noting that the reliability of compile-time cost (specifically, selectivity) estimation degenerates quickly in the presence of complex predicates (e.g. p AND q). The problem is that the commonly held assumption of predicate independence (i.e., the assumption that the *correlation* between p and q has value 0) is overly simplistic — in fact correlation between predicates can fall anywhere between -1 (meaning that for all x , $p(x) \Rightarrow \neg q(x)$) and 1 (meaning that for all x , $p(x) \Rightarrow q(x)$). When correlation factors are assumed to be non-zero, selectivity estimation of complex predicates such as “ p AND q ” fall in a (Zipfean) distribution that is relatively constant independent of the individual selectivities of p and q . Therefore, cost estimation provides little guidance to the plan generator which is likely to generate the same plan independently of selectivities associated with specific predicates appearing in the query.

The Oracle RDB optimization strategy chooses multiple plans that are ideal assuming different selectivity scenarios. Evaluation then runs all of these plans in parallel for a short period of time. Zipfean selectivity distributions make it likely that one of these plans will produce a complete result quickly. Dynamic optimization chooses which of these multiple plans to continue in the unlikely event that all plans fail to return a complete result in the small window of time they were given to run.

This solution does not eliminate the need to make better compile-time cost estimations, as these would eliminate the need to perform dynamic optimization and parallel plan execution in some cases (thereby reducing the evaluation overhead of the queries involved). We are interested in determining if knowledge of underlying semantics might help in compile-time cost estimations. For example, predicate strength inferences could potentially be generalized to infer other correlation factors between predicates (predicate strength infers only correlation factors of -1 or 1). Defining inference rules to infer correlation factors in some cases would not be of use in our semantic rewrite scheme where semantic conditions determine the validity of a rewrite. However, it is possible that inferences such as these could be attached to query representations that are passed down to plan generation.

The goal of parametric query optimization [53] is to generate a plan-producing function as a result of optimizing a query. This function accepts a vector describing run-time parameters (e.g., available buffers) and produces a plan customized to those conditions. Compile-time optimization divides the k -dimensional space of run-time parameters (k is the length of the vector) into partitions that share the same optimal plan. Run-time optimization finds the partition in which an input vector resides to determine the plan to execute.

This work complements the work of Graefe and Cole [25] by demonstrating a technique for deciding where *choose-plan* operators go in a conditional plan and how to generate the plans from which a dynamic choice is made. As with [25], this work describes dynamic plan *selection* rather than dynamic plan *generation* and says nothing about query rewriting.

8.4.2 Adaptive Query Optimization

Adaptive query optimization is distinct from dynamic plan selection in that it involves generating and comparing alternative plans dynamically, and not just selecting from a fixed set of plans generated at compile-time. Query scrambling [4] is one example of adaptive query optimization. The context for this work is widely distributed databases (e.g., web databases). Dynamic optimization is triggered in this setting by the unavailability of queried data sources. Specifically concerned with the orderings of multiple joins, query scrambling dynamically alters a chosen join ordering when processing delays occur due to unavailable data. This affects the plan generated at compile-time (the “join tree”) in two phases:

- *Phase 1:* During this phase, scrambling alters the traversal of the join tree (say from a preorder traversal) so that intermediate results from other parts of the tree can be generated.
- *Phase 2:* This phase makes changes to the join tree by reordering joins, so that intermediate results can be generated from available data sources.

Kabra and DeWitt also propose a technique for reoptimizing queries during evaluation [59]. Unlike query scrambling for which dynamic reoptimization is triggered by data unavailability, reoptimization in this setting is triggered by recognition of errors in compile-time cost estimates. An execution plan is generated at compile-time that is annotated with the cost estimates used to generate the plan. Inserted at select positions in the plan are instances of a plan operator that triggers statistical analysis (e.g., cardinality measures). The execution of this plan then performs the indicated statistical analysis when these operators are executed on the basis of data that has been processed. The costs measured at

this time are then compared to the statically estimated costs that annotate the tree. Then, depending on factors such as the cost of the query, the error in static cost estimations and so on, reoptimization may be initiated.

Both adaptive query optimization schemes described here differ from dynamic query rewriting in that both involve the *reoptimization* of queries. That is, both of these approaches generate complete plans at compile-time and then dynamically replace these plans as run-time circumstances warrant. On the other hand, dynamic query rewriting generates only partial plans at compile-time, leaving the holes in these plans to fill at run-time. Thus, the goal of dynamic query rewriting is not to reoptimize but to delay optimization. This approach is appropriate in the context of rewriting, which applies heuristics that are independent of physical properties of the environment and underlying database. That is, dynamic query rewriting is triggered, not by the recognition of cost factors that make certain evaluation strategies *inappropriate*, but by semantic properties of objects and functions that make certain rewrites *invalid*.

In short, dynamic query optimization resembles dynamic query rewriting in that it involves making decisions affecting evaluation strategies at run-time. But dynamic query optimization involves making cost-based decisions about evaluation plans at run-time, whereas dynamic query rewriting involves heuristically rewriting query representations depending on their validity established by identifying properties of objects recognized at run-time. Rather than being competitive, in fact the two techniques are complementary — dynamic query rewriting necessarily would precede dynamic query optimization.

8.4.3 Partial Evaluation

Partial evaluation is a technique for generating a program by specializing another with respect to some of its inputs [26]. Essentially, the technique requires decoupling the control flow of a program from its inputs. This can be done by *unfolding*, which replaces references to expressions with the code that computes them (as in *inlining*) or by *specializing*, which generates a program that has performed portions of the overall computation given knowledge of certain inputs. Typically, specialization uses *symbolic computation* to partially evaluate the expression computed by the more general program.

Partial evaluation techniques have been used in many areas of computer science including compiler generation [55, 8] and pattern matching [65]. Recently, compiler technology has adopted partial evaluation techniques to provide run-time code generation [69]. Dynamic query optimization and dynamic query rewriting similarly incorporate partial evaluation

into code generation for queries.

Dynamic query rewriting and optimization necessitates that certain decisions about plan generation be deferred until run-time. This transforms the static query rewriter and optimizer into system components that produce partial results. If one looks at a generated execution plan as a result of evaluation, then the partial plans generated by static optimizers in this context are produced as a result of partial evaluation.⁶

On the other hand, dynamic query rewriting is in many ways the dual of partial evaluation. The purpose of partial evaluation is to move certain steps of a run-time computation (evaluation) into compile-time to achieve speed-up. But the purpose of dynamic query rewriting is to move certain steps of a compile-time computation (query optimization) into run-time to achieve greater flexibility. Note the essential difference here: query rewriting is made no more efficient as a result of dynamic rewriting. The goal instead is for query rewriting to be more flexible and therefore for the *generated plans* to be more efficient.

⁶Of the approaches described in this section, adaptive query optimization least resembles partial evaluation because static optimization produces a complete plan (and not a partial plan) that can get replaced dynamically.

Chapter 9

Conclusions and Future Work

Query optimizers are perhaps the most complex and error-prone components of databases. The query rewriter is especially difficult to design and implement correctly. A query rewriter is correct if it preserves the semantics of the queries it transforms. Errors in query rewriting have been identified in both in research [63] and practice [41]. To this day, query rewriting techniques are often published with handwaving correctness proofs or worse, without proofs at all. This approach to correctness undermines confidence in the query processors that incorporate these techniques.

This thesis addresses the correctness issue for query rewriting. Our goal was to build query rewriters that could be verified with an automated theorem prover. Theorem provers have been adopted by the software engineering community as tools for reasoning about formal specifications and verifying implementations relative to those specifications. Commonly used for complex and safety-critical systems, query rewriting is yet another natural application of this technology.

The key contribution of this thesis is to define methodologies and tools for meeting this correctness goal. We have introduced COKO-KOLA: a novel framework for the specification and generation of query rewrite rules for rule-based query rewriters. Query rewrite rules generated within this framework are verifiable with the theorem prover LP. The foundation of this work is KOLA, a combinator-based (i.e., variable-free) algebra and internal query representation. Combinators are unintuitive to read and hence ill-suited as query languages. However, combinators are ideal query representations for rule-based query rewriters because combinator representations make it straightforward to declaratively (i.e., without code) specify *subexpression identification* and *query formulation*. Subexpression identification distinguishes the relevant subexpressions of queries that are being rewritten. Successful

identification of these subexpressions indicates that rewriting should proceed and defines a bank of subexpressions that can be used during query formulation. Query formulation uses identified subexpressions to construct new query expressions that are returned as the result of rewriting.

Combinator representations make it possible to express subexpression identification and query formulation with declarative rewrite rules that get fired according to standard pattern matching. This is because combinator expressions, being variable free, contain no occurrences of free variables which can make syntactically identical expressions have distinct semantics. Code supplements to rules are required when underlying representations are variable-based. Supplements used for subexpression identification analyze the context of identified subexpressions containing free variables. Supplements used for query formulation massage identified subexpressions to ensure that their semantics are preserved when used in new contexts. These code supplements are unnecessary when variables are removed from the underlying query representation.

KOLA is a fully expressive object query algebra over sets and bags. It contains similar operators as other object algebras, but differs from these algebras in its combinator foundation and its uniform treatment of query and data functions. Because KOLA rewrite rules are expressible without code supplements, they can be verified with an automated theorem prover. We have verified several hundred KOLA rewrite rules with the theorem prover LP [46]. The motivation for KOLA, its semantics and several examples of its use in expressing queries and rewrite rules were presented in Chapter 3.

Rewrite rules are inherently simple. On the other hand, query rewrites can be complex. Therefore, KOLA is insufficient for expressing many of the query rewrites that get used in practice. In Chapters 4 and 5 we proposed techniques for expressing query rewrites that are too general and too specific respectively, to be expressed as rewrite rules. Query rewrites that are too general for rewrite rules include such complex normalizations as CNF — a rewrite to convert query predicates into conjunctive normal form. CNF cannot be expressed as a single rewrite rule because no pair of patterns is both general enough to capture all expressions that can be rewritten into CNF (i.e., all Boolean expressions) and specific enough to express their CNF equivalents. Put another way, any rewrite rule that expresses a predicate and its CNF equivalent will not be general enough to successfully fire on all predicates. To express complex and general rewrites such as this, we introduced the language COKO in Chapter 4.

COKO transformations specify and generate complex query rewrites. Transformations are both extensions and generalizations of KOLA rules. Transformations generalize KOLA

rules because they can be fired and succeed or fail as a result. Transformations extend KOLA rules because they supplement sets of KOLA rewrite rules with a firing algorithm that controls the manner in which they are fired. COKO's firing algorithm language supports explicit control of rule firing, traversal control over query representation trees, conditional rule firing, and selective firing over subtrees. COKO makes it possible to express efficient query rewrites as we demonstrated in Chapter 4 with CNF. But while firing algorithms control when and where rules get fired, only rewrite rule firings can modify query representations. Therefore, COKO transformations are correct if the KOLA rewrite rules they fire are correct, and by implication, COKO transformations can be verified with a theorem prover. The motivation for COKO, the semantics of its firing algorithm language, and several applications of COKO that rewrite query expressions into CNF or SNF, push predicates, reorder joins and apply magic sets techniques were presented in Chapter 4.

In Chapter 5, we addressed an expressivity issue that is complementary to that addressed by COKO. This issue concerns query rewrites that are too specific to be expressed as rewrite rules. The validity of such rewrites depends on the semantics and not just the syntax of the queries on which they are fired. To express such rewrites, we added *conditional rewrite rules* and *inference rules* to COKO-KOLA. Conditional rewrite rules get fired like (unconditional) rewrite rules, except that identified subexpressions must also satisfy declaratively expressed conditions. These conditions are specified with *properties*: collections of declarative inference rules that our compiler compiles into code that gets executed during rule firing. Both conditional rewrite rules and inference rules are expressed without code and hence are verifiable with a theorem prover. The motivation and implementation of semantic extensions to COKO-KOLA were presented with examples of their use in Chapter 5.

An example application of the COKO-KOLA framework was presented in Chapter 6. In this chapter, we described and assessed our experience building a query rewriting component for the San Francisco project of IBM. We learned from this experience that the COKO-KOLA framework, while in need of refinement and an industrial strength implementation, makes it possible to express “real” query rewrites succinctly and with confidence.

What is common to KOLA, COKO and the semantic extensions to COKO-KOLA is the need to identify subexpressions and formulate new queries. KOLA's conditional and unconditional rewrite rules identify subexpressions and formulate new queries when they successfully fire. COKO transformations must frequently identify subexpressions of queries on which to fire rules (using the **GIVEN** statement). Inference rules identify subexpressions of query expressions so that properties of these expressions can be inferred of the expressions that contain them. We showed in Chapter 3 that combinators simplify the expression

of these tasks and make them verifiable with a theorem prover. Therefore, the high-level contribution of this work is the recognition of the impact of query representations in general and combinator-based representations in particular on the design, implementation and verification of a query optimizer. When built with combinators, query rewriters can be verified with a theorem prover, thereby achieving the goal we set out at the onset to address the inherent difficulty in building query rewriters correctly.

In Chapter 7, we identified another potential benefit of combinator-based query representations. Whereas previous chapters considered how combinators simplify *how* rewrites get expressed, in this chapter we showed how combinators could be used to change *when* they get fired. Dynamic query rewriting proposes that some query rewriting take place *during* the evaluation of a query. Dynamic query rewriting would be beneficial in settings where the information that justifies the firing of a rewrite rules is unavailable until queried data is retrieved. Such settings include object databases, whose queries may be invoked on anonymous embedded collections; network databases, whose queries may join collections whose availability may be unknown until runtime; and heterogeneous databases whose queries may reference collections that are represented with data structures known only to the local databases they oversee. Dynamic query rewriting requires identifying relevant subqueries and formulating new queries by packaging these subqueries with accessed data. Therefore, dynamic query rewriting also benefits from combinator-based query representations.

9.1 Future Directions

Unlike the work presented in previous chapters, dynamic query rewriting is work in progress. Therefore, future directions for this thesis work are primarily concentrated in this area. A design for a dynamic query rewriter and query evaluator for ObjectStore [67] is complete and an implementation is ongoing. Once complete, it will be necessary to run a performance study to determine when (and if) the benefits of dynamic query rewriting outweigh its costs. We plan to construct and populate the Thomas database described in Chapter 2 according to the guidelines described in Section 7.1.1. Thereafter, a testbed of OQL queries will be formulated to query this database. A variety of query rewriters will be generated using the COKO compiler, varying in the degree and kinds of semantic and dynamic query rewriting that each performs. That is, the COKO routines compared will include ones that:

- fire no rewrites,
- fire rewrites, but neither semantic nor dynamic rewrites,

- fire semantic but not dynamic rewrites, and
- fire both semantic and dynamic rewrites.

It should be straightforward to come up with examples (such as the “NSF” Query) for which semantic and dynamic rewriting will prove useful. But the cost of performing dynamic rewriting must be weighed relative to the improved performance of query evaluation. Much of the cost of query processing is incurred when elements are retrieved from the iterators returned as the results of queries. Therefore, these comparisons should include ones that measure the time to retrieve all elements contained in a collection returned by the query.

Our study of dynamic query rewriting has been confined thus far to object databases. We are also interested in the potential benefits of dynamic query rewriting in other settings such as network databases and heterogeneous databases. With respect to the former, we are interested in exploring the potential benefits of this technique to queries posed over dissemination-based data delivery systems [2, 37]. Efficient evaluation of queries posed in these settings will require knowledge of how data has been scheduled for delivery. As schedules are sometimes formulated online and subject to modification, this may require query strategies to be reformulated on-the-fly. We believe this to be a promising application for dynamic query rewriting strategies which provide the processing flexibility required to do this. Heterogeneous database queries typically get posed in higher-order query languages such as SchemaLog [47] that permit queries to be posed over collections of relations. As these relations can vary in representation, sort order, duplicate status and so on, dynamic query rewriting could well prove beneficial here also.

Future directions for KOLA, COKO and semantic extensions to COKO and KOLA will involve refining their designs and implementations. Eventually, we would like KOLA to be an algebra with the same expressivity as OQL and adjust the translator to translate all of OQL to KOLA. This work will require extending the formal specification of KOLA to include lists, arrays and mutable objects. The impact of mutable objects on KOLA and query rewriting correctness was described in a white paper resulting from our joint discussions with the Thor group of MIT [18].

Once an $OQL \rightarrow KOLA$ translator is complete, we will need to prove its correctness. We proved the correctness of an early version of this translator (see [17]) that translated a set-based subset of OQL into KOLA. This result required a denotational semantics for this subset of OQL and an operational semantics for KOLA in terms of OQL (i.e., each KOLA construct was associated with its OQL equivalent). We then used structural induction to prove that the denotational semantics of any OQL expression e that is well-formed with

respect to some environment ρ ($\mathbf{Eval} \llbracket e \rrbracket \rho$) is equivalent to the denotational semantics of the OQL expression resulting from first translating of e into a KOLA function that is invoked on the nested pair equivalent of ρ , and then translating this expression back into OQL ($\mathbf{Eval} \llbracket \mathbf{T} \llbracket e \rrbracket ! \bar{\rho} \rrbracket ()$). The final translator will be verified in the same way.

Future work for COKO will involve refinements to the firing algorithm language, a new design and implementation for the COKO compiler and the development of a debugging facility. Refinements to the firing algorithm language will be motivated by the experiences of users of the language. (Some refinements based on our experiences were proposed in Chapter 6.) We intend to rethink our decision to associate success values with all statements in the language and determine if a more traditional control language might make COKO simpler to use.

The existing COKO compiler was designed for simplicity rather than efficiency. The compiler produces code that generates a parse tree corresponding to the COKO transformation's firing algorithm, and then invokes a recursive method (`exec`) on the root of this tree. This design made it straightforward to modify COKO and therefore was an appropriate design for a prototype. However, generated COKO parse trees can be large and unwieldy and therefore, an alternative design is required for industrial use.

Finally, the programming of firing algorithms is not an easy task. Part of the problem is due to deficiencies in the firing algorithm language. For example, in the discussion section of Chapter 6, we noted the difficulties introduced by associative KOLA formers such as function composition. The problem is that a given KOLA rewrite rule might fail to fire due to the manner in which a composition is associated. While addressing these deficiencies in the language design should make programming somewhat easier, in the long term we envision the development of a debugging environment to support transformation development. Such a debugger could provide standard debugging tools such as breakpoints and stepping through the execution of statements. Ideally, it also will permit the actions of a COKO transformation to be visualized in terms of a graphical representation of a KOLA tree.

Future work for semantic extensions to COKO-KOLA also will involve revisiting the implementation. The current implementation invokes a Prolog interpreter to answer semantic queries. This design has a performance overhead from invoking a foreign interpreter (the rest of the rule firing engine was programmed in C++), and from translating KOLA parse trees to and from Prolog. We intend to replace this design with one that performs reasoning over KOLA trees directly, perhaps replacing the inference algorithm (currently unification-based [81]) with more powerful inference techniques such as those described in

the work of Grant et al [45].

9.2 Conclusions

This thesis has addressed the correctness problem for query rewriters. We have defined a framework for generating query rewriters that can be verified with a theorem prover. We have identified the impact of query representations on query optimizer design, showing with several examples how combinator-based query representations simplify the expression of query rewrites. We introduced a novel query algebra (KOLA), a novel language for expressing complex query rewrites (COKO) and novel semantic extensions to the query rewriting process. As well, we have constructed several proofs of concept that include a formal specification of KOLA, several hundred proof scripts verifying KOLA rewrite rules and COKO transformations, a translator mapping OQL queries into their KOLA equivalents, a compiler to map COKO transformations into executable query rewrites, and an example query rewriter for a real database system. In addressing the correctness problem, we have contributed methodology and tools that impose a discipline on the design and implementation of query rewriters. In adhering to this discipline, the “COUNT bug” and its kin should become relics of the past.

Appendix A

A Larch Specification of KOLA

A.1 Functions and Predicates

%%%

Function (T, U): trait

% Class of Invokable Functions.

introduces

% Invocation Operator.

% -----

-- ! --: fun [T, U], T → U

asserts

$\forall f, g: \text{fun } [T, U], x: T$

% When are two functions equal?

% -----

$f = g \Leftrightarrow \forall x ((f ! x) = (g ! x))$

%%%

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Predicate (T): trait
```

```
% Class of Invokable Predicates.
```

```
introduces
```

```
% Invocation Operator
```

```
% -----
```

```
__ ? __: pred [T], T → Bool
```

```
asserts
```

```
∀ p, q: pred [T], x: T
```

```
% When are two predicates equal?
```

```
% -----
```

```
% p is rewritable to q if they are evaluate to the same result
```

```
% for all objects
```

```
p = q ⇔ ∀ x (p ? x ⇔ q ? x)
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

A.2 Objects

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
BagBasics (T): trait
```

```
% The trait of Generic KOLA bags (i.e., not mutable or immutable).
```

```
includes
```

InsertGenerated (\emptyset for empty, T for E, bag [T] for C)

introduces

$\emptyset: \rightarrow \text{bag [T]}$
 $\text{insert}: T, \text{bag [T]} \rightarrow \text{bag [T]}$

$\{_ \}: T \rightarrow \text{bag [T]}$
 $_ \in _ : T, \text{bag [T]} \rightarrow \text{Bool}$
 $_ - _ : \text{bag [T]}, T \rightarrow \text{bag [T]}$

asserts

$\forall A, B: \text{bag [T]}, x, y: T$

$\sim(\text{insert } (x, A) = \emptyset)$
 $\text{insert } (x, \text{insert } (y, A)) == \text{insert } (y, \text{insert } (x, A))$

$x \in \emptyset == \text{false}$
 $x \in \text{insert } (y, A) == (x = y) \vee x \in A$

$\{x\} == \text{insert } (x, \emptyset)$

$\emptyset - x == \emptyset$
 $\sim (x = y) \Rightarrow \text{insert } (x, A) - y = \text{insert } (x, A - y)$

implies

$\forall A, B: \text{bag [T]}, x, y: T$

$\sim (x \in A) \Rightarrow (A - x) = A$
 $x \in (A - y) \Rightarrow x \in A$
 $A = \text{insert } (x, B) \Rightarrow (A - x) = B$
 $((x \in A) \wedge ((A - x) = B)) \Rightarrow A = \text{insert } (x, B)$

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Bag (T): trait
```

```
  includes
```

```
    BagBasics (T)
```

```
  introduces
```

```
    -- ∪ --: bag [T], bag [T] → bag [T]
```

```
    -- ∩ --: bag [T], bag [T] → bag [T]
```

```
    -- - --: bag [T], bag [T] → bag [T]
```

```
  asserts
```

```
    ∀ x, y: T, A, B: bag [T]
```

```
    ∅ ∪ B == B
```

```
    insert (x, A) ∪ B == insert (x, A ∪ B)
```

```
    ∅ ∩ B == ∅
```

```
    (x ∈ B) ⇒ insert (x, A) ∩ B = insert (x, A ∩ (B - x))
```

```
    ~ (x ∈ B) ⇒ insert (x, A) ∩ B = (A ∩ B)
```

```
    ∅ - A == ∅
```

```
    (x ∈ B) ⇒ insert (x, A) - B = A - (B - x)
```

```
    ~ (x ∈ B) ⇒ insert (x, A) - B = insert (x, A - B)
```

```
% All Bags are empty or of form, insert (e, B)
```

```
% -----
```

$$(A = \emptyset) \vee \exists x \exists B (A = \text{insert } (x, B))$$

$$(x \in A) \Rightarrow \exists B (A = \text{insert } (x, B))$$

implies

$$\forall x, y: T, A, B: \text{bag } [T]$$

$$A \cup \emptyset == A$$

$$A \cup \text{insert } (y, B) == \text{insert } (y, A \cup B)$$

$$A \cap \emptyset == \emptyset$$

$$(y \in A) \Rightarrow (A \cap \text{insert } (y, B) = \text{insert } (y, (A - y) \cap B))$$

$$\sim (y \in A) \Rightarrow (A \cap \text{insert } (y, B) = (A \cap B))$$

$$A - \emptyset == A$$

$$(y \in A) \Rightarrow (A - \text{insert } (y, B) = (A - y) - B)$$

$$\sim (y \in A) \Rightarrow (A - \text{insert } (y, B) = A - B)$$

$$x \in (A \cup B) == (x \in A) \vee (x \in B)$$

$$x \in (A \cap B) == (x \in A) \wedge (x \in B)$$

$$x \in (A - B) == (x \in A) \wedge \sim(x \in B)$$

%%%

%%%

Pairs (T1, T2): trait

% Trait specifying pairs of objects.

introduces

% The Pairing Constructor

A.3 Primitives (Table 3.1)

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Id (T): trait
```

```
% Trait of the Polymorphic, Invokable Identity Function, id
```

```
includes
```

```
    Function (T, T)
```

```
introduces
```

```
    id :  $\rightarrow$  fun [T, T]
```

```
asserts
```

```
     $\forall$  x: T
```

```
    % Semantics of id
```

```
    % -----
```

```
    id ! x == x
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Projection (T1, T2): trait
```

```
% Trait of the Polymorphic, Invokable Projection Functions,  $\pi_1$  and  $\pi_2$ 
```

```
%
```

```

% a. properties of these functions
% b. semantics of these functions

assumes

    Pairs (T1, T2)

includes

    Function (pair [T1, T2], T1),
    Function (pair [T1, T2], T2)

introduces

     $\pi_1$ :  $\rightarrow$  fun [pair [T1, T2], T1]
     $\pi_2$ :  $\rightarrow$  fun [pair [T1, T2], T2]

asserts

     $\forall$  x: T1, y: T2

    % Semantics of  $\pi_1$ ,  $\pi_2$ 
    % -----
     $\pi_1$  ! [x, y] == x
     $\pi_2$  ! [x, y] == y

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Shifts (T, U, V): trait

% Trait of the Polymorphic, Left and Right Pair Shifting
% Functions shl and shr

```

assumes

```
Pairs (T, U),
Pairs (U, V),
Pairs (pair[T, U], V),
Pairs (T, pair[U, V])
```

includes

```
Function (pair [pair [T, U], V], pair [T, pair [U, V]]),
Function (pair [T, pair [U, V]], pair [pair [T, U], V])
```

introduces

```
shl : → fun [pair [T, pair [U, V]], pair [pair [T, U], V]]
shr : → fun [pair [pair [T, U], V], pair [T, pair [U, V]]]
```

asserts

```
∀ t: T, u: U, v: V
```

```
% Semantics of shl, shr
```

```
% -----
```

```
shl ! [t, [u, v]] == [[t, u], v]
```

```
shr ! [[t, u], v] == [t, [u, v]]
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
IntegerPrimitives: trait
```

```
% Trait of primitive functions and predicates on Integers
```

```
assumes
```

```
    Integer,
    Pairs (Int, Int)
```

```
includes
```

```
    Function (Int, Int),
    Function (pair [Int, Int], Int),
    Predicate (pair [Int, Int])
```

```
introduces
```

```
% Unary Functions
```

```
% -----
```

```
abs: → fun [Int, Int]
```

```
% Binary Functions
```

```
% -----
```

```
add: → fun [pair [Int, Int], Int]
```

```
sub: → fun [pair [Int, Int], Int]
```

```
mul: → fun [pair [Int, Int], Int]
```

```
div: → fun [pair [Int, Int], Int]
```

```
mod: → fun [pair [Int, Int], Int]
```

```
% Binary Predicates
```

```
% -----
```

```
lt: → pred [pair [Int, Int]]
```

```
leq: → pred [pair [Int, Int]]
```

```
gt: → pred [pair [Int, Int]]
```

```
geq: → pred [pair [Int, Int]]
```

```
asserts
```

```

    ∀ i, j: Int

% Semantics of Integer Function Primitives
% -----
abs ! i == abs (i)

add ! [i, j] == i + j
sub ! [i, j] == i - j
mul ! [i, j] == i * j
div ! [i, j] == div (i, j)
mod ! [i, j] == mod (i, j)

% Semantics of Integer Predicate Primitives
% -----
lt ? [i, j] == i < j
leq ? [i, j] == i <= j
gt ? [i, j] == i > j
geq ? [i, j] == i >= j

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

FloatPrimitives: trait

% Trait of primitive functions and predicates on Floats

assumes

    FloatingPoint (Float for F),
    Pairs (Float, Float)

includes

```

```

Function (Float, Float),
Function (pair [Float, Float], Float),
Predicate (pair [Float, Float])

```

introduces

```

% Unary Functions
% -----
abs: → fun [Float, Float]

% Binary Functions
% -----
add: → fun [pair [Float, Float], Float]
sub: → fun [pair [Float, Float], Float]
mul: → fun [pair [Float, Float], Float]
div: → fun [pair [Float, Float], Float]

% Binary Predicates
% -----
lt:  → pred [pair [Float, Float]]
leq: → pred [pair [Float, Float]]
gt:  → pred [pair [Float, Float]]
geq: → pred [pair [Float, Float]]

```

asserts

```

∀ f1, f2: Float

% Semantics of Float Function Primitives
% -----
abs ! f1 == abs (f1)

add ! [f1, f2] == f1 + f2
sub ! [f1, f2] == f1 - f2

```

```

mul ! [f1, f2] == f1 * f2
div ! [f1, f2] == f1 / f2

% Semantics of Float Predicate Primitives
% -----
lt ? [f1, f2]  == f1 < f2
leq ? [f1, f2] == f1 <= f2
gt ? [f1, f2]  == f1 > f2
geq ? [f1, f2] == f1 >= f2

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

StringPrimitives: trait

% Trait of primitive functions on Strings

assumes

    Integer,
    String (Char, Str),
    Pairs (Str, Str),
    Pairs (Str, Int)

includes

    Function (pair [Str, Int], Char),
    Function (pair [Str, Str], Str),
    Function (pair [Str, Int], Str)

introduces

    at: → fun [pair [Str, Int], Char]

```



```

concat: → fun [pair [Str, Str], Str]

length: Str → Int

asserts

  ∀ i: Int, s, s': Str

% Semantics of String Primitives
% -----
length (empty) == 0
~ (s = empty) ⇒ (length (s) = 1 + (length (tail (s))))

at ! [s, i] == s [i]
(i < length (s)) ⇒
(at ! [concat ! [s, s'], i] = at ! [s, i])

(i >= length (s)) ⇒
(at ! [concat ! [s, s'], i] = at ! [s', i - length (s)])

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
BagPrimitives (T): trait

% Trait of primitive functions on Bags

assumes

  Bag (T),
  Bag (U),
  Pairs (T, T),
  Pairs (bag [T], bag [T]),

```

```

Pairs (bag [T], bag [U]),
Pairs (T, bag [U]),
Pairs (T, U),
Bag (bag [T])

```

includes

```

Function (bag [T], T),
Function (T, bag [T]),
Function (bag [T], bag [T]),
Function (bag [bag [T]], bag [T]),
Function (pair [T, bag [U]], bag [pair [T, U]]),
Function (pair [bag [T], bag [U]], bag [pair [T, U]]),
Function (pair [bag [T], bag [T]], bag [T])

```

introduces

```

% Unary Functions
% -----
single: → fun [T, bag [T]]
elt: → fun [bag [T], T]
set: → fun [bag [T], bag [T]]
flat: → fun [bag [bag [T]], bag [T]]

% Binary Functions
% -----
uni: → fun [pair [bag [T], bag [T]], bag [T]]
int: → fun [pair [bag [T], bag [T]], bag [T]]
dif: → fun [pair [bag [T], bag [T]], bag [T]]
ins: → fun [pair [T, bag [T]], bag [T]]

```

asserts

$\forall x, y: T, A, B: \text{bag } [T], X: \text{bag } [\text{bag } [T]], U: \text{bag } [U], u, v: U$

% Semantics of Unary Function Primitives

% -----

single ! $x = \{x\}$

elt ! $\{x\} = x$

ins ! $[x, A] = \text{insert } (x, A)$

set ! $\emptyset == \emptyset$

set ! $\text{insert } (x, A) ==$

if $(x \in A)$ then **set** ! A else $\text{insert } (x, \text{set} ! A)$

flat ! $\emptyset == \emptyset$

flat ! $\text{insert } (A, X) == A \cup (\text{flat} ! X)$

% Semantics of Binary Function Primitives

% -----

uni ! $[A, B] == A \cup B$

int ! $[A, B] == A \cap B$

dif ! $[A, B] == A - B$

implies

$\forall x, y: T, A, B: \text{bag } [T], X: \text{bag } [\text{bag } [T]],$

$U: \text{bag } [U], u, v: U, e: T, z: \text{pair } [T, U]$

$(\text{set} ! A) = (\text{set} ! B) == \forall x:T (x \in A \Leftrightarrow x \in B)$

$e \in (\text{set} ! A) == e \in A$

$e \in (\text{flat} ! X) == \exists A (A \in X \wedge e \in A)$

$e \in (A \cup B) == (e \in A) \vee (e \in B)$

$e \in (A \cap B) == (e \in A) \wedge (e \in B)$

$e \in (A - B) == (e \in A) \wedge \sim (e \in B)$

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Avg: trait
```

```
% Trait of the primitive, avg, which averages the
% elements in a bag. Bag elements must be integers
% or floats.
```

```
assumes
```

```
    Integer,
    FloatingPoint (Float for F),
    Bag (Int),
    Bag (Float),
    Count (Int),
    Count (Float),
    Sum (Int),
    Sum (Float)
```

```
includes
```

```
    Function (bag [Int], Float),
    Function (bag [Float], Float)
```

```
introduces
```

```
    avg : → fun[bag [Int], Float]
    avg : → fun[bag [Float], Float]
```

```
asserts
```

```
    ∀ A: bag [Int], B: bag [Float]
```

```

% Semantics of avg
% -----
~(A =  $\emptyset$ )  $\Rightarrow$ 
    (avg ! A = (float ((sum ! A) / 1) / float ((count ! A) / 1)))
~(B =  $\emptyset$ )  $\Rightarrow$ 
    (avg ! B = ((sum ! B) / float ((count ! B) / 1)))

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Count (T): trait

% Trait of the primitive, cnt, which counts the
% number of elements in a bag

assumes

    Bag (T),
    Integer

includes

    Function (bag [T], Int)

introduces

    cnt :  $\rightarrow$  fun [bag [T], Int]

asserts

     $\forall$  x: T, A: bag [T]

```

```

% Semantics of count
% -----
cnt !  $\emptyset$  == 0
cnt ! insert (x, A) == 1 + (cnt ! A)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Max (T): trait

% Trait of the primitive, max finds the largest
% element in a bag

assumes

    Bag (T),
    TotalOrder (T) % T is ok as long as it has a max and min

includes

    Function (bag [T], T)

introduces

    max :  $\rightarrow$  fun[bag [T], T]

asserts

     $\forall$  x: T, A: bag [T]

% Semantics of max

```

```

% -----
max ! {x} == x
max ! insert (x, A) == if (x > (max ! A)) then x else (max ! A)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Min (T): trait

% Trait of the primitive, min finds the smallest
% element in a bag

assumes

    Bag (T),
    TotalOrder (T)    % T is ok as long as it has a max and min

includes

    Function (bag [T], T)

introduces

    min : → fun[bag [T], T]

asserts

    ∀ x: T, A: bag [T]

% Semantics of min
% -----
min ! {x} == x

```

```

    min ! insert (x, A) == if (x < (min ! A)) then x else (min ! A)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Sum (U): trait

% Trait of the primitive, sum, which sums the
% elements in a bag

assumes

    Bag (U),
    AbelianGroup (U for T, + for o, 0 for unit)
    % U is ok as long as it has a commutative, associative +
    % with identity, 0

includes

    Function (bag [U], U)

introduces

    sum : → fun[bag [U], U]

asserts

    ∀ x: U, A: bag [U]

% Semantics of sum
% -----
sum ! ⊙ == 0

```


A.4 Basic Formers (Table 3.2)

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Composition (T, X, U): trait
```

```
% Trait of the Polymorphic, Composition Function former, -- o --
```

```
assumes
```

```
    Function (T, X), % for g
```

```
    Function (X, U) % for f
```

```
includes
```

```
    Function (T, U) % for f o g
```

```
introduces
```

```
    -- o -- : fun [X, U], fun [T, X] → fun [T, U]
```

```
asserts
```

```
    ∀ x: T, f: fun [X, U], g: fun [T, X]
```

```
    % Semantics of o
```

```
    % -----
```

```
    (f o g) ! x == f ! (g ! x)
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Pairing (T, U1, U2): trait
```

```
% Trait of the Polymorphic, Pairing Function former, <_, _>
```

```
assumes
```

```
    Function (T, U2), % for g
    Function (T, U1)  % for f
```

```
includes
```

```
    Pairs (U1, U2),
    Function (T, pair [U1, U2]) % for f + g
```

```
introduces
```

```
    ⟨ __, _ ⟩: fun [T, U1], fun [T, U2] → fun [T, pair [U1, U2]]
```

```
asserts
```

```
    ∀ x: T, f: fun [T, U1], g: fun [T, U2]
```

```
    % Semantics of < >
```

```
    % -----
```

```
    ⟨ f, g ⟩ ! x == [f ! x, g ! x]
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
ProductsF (T1, U1, T2, U2): trait
```

```
% Trait of the Polymorphic, Product Function former, __ x __
```

```
assumes
```

```
    Function (T2, U2), % for g
    Function (T1, U1)  % for f
```

```
includes
```

```
  Pairs (T1, T2),
  Pairs (U1, U2),
  Function (pair [T1, T2], pair [U1, U2]) % for f x g
```

```
introduces
```

```
  _ × _ : fun [T1, U1], fun [T2, U2] →
          fun [pair [T1, T2], pair [U1, U2]]
```

```
asserts
```

```
  ∀ x: T1, y: T2, f: fun [T1, U1], g: fun [T2, U2]
```

```
  % Semantics of ×
```

```
  % -----
```

```
  (f × g) ! [x, y] == [f ! x, g ! y]
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
ConstantF (T, U): trait
```

```
% Trait of Constant function former  $K_f$  (—)
```

```
includes
```

```
  Function (T, U) % for  $K_f$  (e)
```

```
introduces
```

```
   $K_f$  : U → fun [T, U]
```

```

asserts

     $\forall y: U, x: T$ 

    % Semantics of  $K_f$ 
    % -----
     $K_f(y) \neq x == y$ 

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

CurryingF (T1, T2, U): trait

% Trait of Curried function,  $C_f$  ( $\_$ ,  $\_$ )

assumes

    Pairs (T1, T2),           % for domain of f
    Function (pair [T1, T2], U)

includes

    Function (T2, U)         % for  $C_f$  (f, e)

introduces

     $C_f : \text{fun [pair [T1, T2], U], T1} \rightarrow \text{fun [T2, U]}$ 

asserts

     $\forall f: \text{fun [pair [T1, T2], U], x: T1, y: T2}$ 

    % Semantics of C

```



```

Combination (T, U): trait

% Trait of the Polymorphic, Combining Predicate former,  $\_ \oplus \_$ 

assumes

    Function (T, U),
    Predicate (U)

includes

    Predicate (T)

introduces

     $\_ \oplus \_ : \text{pred [U]}, \text{fun [T, U]} \rightarrow \text{pred [T]}$ 

asserts

     $\forall x: T, f: \text{fun [T, U]}, p: \text{pred [U]}$ 

    % Semantics of  $\oplus$ 
    % -----
     $(p \oplus f) ? x == p ? (f ! x)$ 

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Conjunction (T): trait

% Trait of the Polymorphic, Conjunction Predicate former,  $\_ \& \_$ 

assumes

```

Predicate (T)

introduces

$-- \& -- : \text{pred } [T], \text{pred } [T] \rightarrow \text{pred } [T]$

asserts

$\forall x: T, p, q: \text{pred } [T]$

% Semantics of &

% -----

$(p \& q) ? x == (p ? x \wedge q ? x)$

%%%

%%%

Disjunction (D): trait

% Trait of the Polymorphic, Disjunction Predicate former, $-- | --$

%

assumes

Predicate (D)

introduces

$-- | -- : \text{pred } [D], \text{pred } [D] \rightarrow \text{pred } [D]$

asserts

$\forall e: D, p, q: \text{pred } [D]$


```

% Trait of Inverse Predicate Former  $p^{-1}$ 

assumes

    Pairs (T1, T2),
    Predicate (pair [T1, T2])

includes

    Pairs (T2, T1),
    Predicate (pair [T2, T1])

introduces

     $_{-}^{-1} : \text{pred } [\text{pair}[T1, T2]] \rightarrow \text{pred } [\text{pair } [T2, T1]]$ 

asserts

     $\forall x: T1, y: T2, p: \text{pred } [\text{pair } [T1, T2]]$ 

    % Semantics of  $^{-1}$ 
    % -----
     $(p^{-1}) ? [y, x] == p ? [x, y]$ 

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
ProductsP (DL, DR): trait

% Trait of the Polymorphic, Predicate Product former,  $_{-} \times _{-}$ 

assumes

```

```

    Predicate (DL),
    Predicate (DR),
    Pairs (DL, DR)

includes

    Predicate (pair [DL, DR])

introduces

    -- × -- : pred [DL], pred [DR] → pred [pair [DL, DR]]

asserts

    ∀ e: DL, e': DR, p: pred [DL], q: pred [DR]

    % Semantics of p × q
    % -----
    (p × q) ? [e, e'] == p ? e ∧ q ? e'

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

ConstantP (T): trait

% Trait of Constant Predicate  $K_p$  (--)

includes

    Predicate (T) % for  $K_p$  (b)

introduces

     $K_p$  : Bool → pred [T]

```

```

asserts

     $\forall x: T, b: \text{Bool}$ 

    % Semantics of  $K_p$ 
    % -----
     $K_p(b) ? x == b$ 

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

CurryingP (T1, T2): trait

% Trait of Curried predicate,  $C_p$  (__, _)

assumes

    Pairs (T1, T2),      % for domain of p
    Predicate (pair [T1, T2])

includes

    Predicate (T2)      % for  $C_p$  (p, x)

introduces

     $C_p : \text{pred [pair [T1, T2]], } T1 \rightarrow \text{pred [T2]}$ 

asserts

     $\forall p: \text{pred [pair [T1, T2]], } x: T1, y: T2$ 

    % Semantics of  $C_p$ 

```

```
% -----
  Cp (p, x) ? y == Cp ? [x, y]
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

A.5 Query Formers (Table 3.3)

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Iterate (T, U): trait
```

```
% Former that emulates SELECT--FROM--WHERE. General Unary
% Iterator
```

```
assumes
```

```
  Function (T, U),
  Predicate (T),
  Bag (T)
```

```
includes
```

```
  Bag (U),
  Function (bag [T], bag [U])
```

```
introduces
```

```
  iterate: pred [T], fun [T, U] → fun [bag [T], bag [U]]
```

```
asserts
```

```
  ∀ p: pred [T], f: fun [T, U], A: bag [T], x: T
```

```
% Semantics of iterate
% -----
```

```

iterate (p, f) !  $\emptyset$  ==  $\emptyset$ 
(p ? x)  $\Rightarrow$ 
    iterate (p, f) ! insert (x, A) = insert (f ! x, iterate (p, f) ! A)
 $\sim$  (p ? x)  $\Rightarrow$ 
    iterate (p, f) ! insert (x, A) = iterate (p, f) ! A

```

implies

```

 $\forall$  p: pred [T], f: fun [T, U], A: bag [T], x: T, e: U
e  $\in$  (iterate (p, f) ! A) ==  $\exists$  x (x  $\in$  A  $\wedge$  (p ? x)  $\wedge$  e = (f ! x))

```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

```

```

Iter (T, U): trait

```

```

% Binary Iterator.

```

assumes

```

Pairs (T, U),
Pairs (T, bag [U]),
Bag (T),
Pairs (bag [T], U),
Function (pair [T, U], V),
Predicate (pair [T, U])

```

includes

```

Bag (V),
Function (pair [T, bag [U]], bag [V]),
CurryingP (T, U),
CurryingF (T, U, V),
Iterate (U, V)

```

introduces

$$\text{iter: pred [pair [T, U]], fun [pair [T, U], V] \rightarrow}$$

$$\text{fun [pair [T, bag [U]], bag [V]]}$$

asserts

$$\forall p: \text{pred [pair [T, U]], f: fun [pair [T, U], V], A: bag [U], x: T}$$

% Semantics of Iter

% -----

$$\text{iter (p, f) ! [x, A] == iterate (C}_p \text{ (p, x), C}_f \text{ (f, x)) ! A}$$

implies

$$\forall p: \text{pred [pair [T, U]], f: fun [pair [T, U], V],}$$

$$\text{A: bag [U], x: T, e: V, u: U}$$

$$e \in (\text{iter (p, f) ! [x, A]}) ==$$

$$\exists u (u \in A \wedge (p ? [x, u]) \wedge e = (f ! [x, u]))$$

%%%

%%%

Unnest (T, U, V): trait

% Trait of the unnesting former, **unnest**, which pairs
 % T elements (t) with each member of some bag that is
 % generated by invoking a function on t.

assumes

Bag (T),

```

    Bag (U),
    Pairs (T, U),
    Function (pair [T, U], V),
    Function (T, bag [U])

includes

    Bag (V),
    Function (bag [T], bag [V]),

    ConstantP (U),
    CurryingF (T, U, V),
    Iterate (U, V)

introduces

    unnest: fun [pair [T, U], V], fun [T, bag [U]] →
              fun [bag [T], bag [V]]

asserts

    ∀ f: fun [pair [T, U], V], g: fun [T, bag [U]], x: T, A: bag [T]

    % Semantics of unnest
    % -----
    unnest (f, g) ! ∅ == ∅
    unnest (f, g) ! insert (x, A) ==
      (iterate (Kp (true), Cf (f, x)) ! (g ! x)) ∪ (unnest (f, g) ! A)

implies

    ∀ f: fun [pair [T, U], V],
      g: fun [T, bag [U]], x: T, y: U, A: bag [T], e: V

```



```
e ∈ (unnest (f, g) ! A) ==
  (∃ x ∃ y (x ∈ A ∧ (e = f ! [x, y]) ∧ y ∈ (g ! x)))
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%
```

```
Join (T1, T2, U): trait
```

```
% General Binary Iterator
```

```
assumes
```

```
  Pairs (T1, T2),
  Function (pair [T1, T2], U),
  Predicate (pair [T1, T2]),
  Bag (T1),
  Bag (T2),
  Pairs (bag [T1], bag [T2])
```

```
includes
```

```
  Bag (U),
  Function (pair [bag [T1], bag [T2]], bag [U]),
  CurryingP (T1, T2),
  CurryingF (T1, T2, U),
  Iterate (T2, U),
  InverseP (T1, T2),
  Pairs (T2, T1),
  Projection (T2, T1),
  CurryingP (T2, T1),
  CurryingF (T2, T1, U),
  Pairing (pair [T2, T1], T1, T2),
  Composition (pair [T2, T1], pair [T1, T2], U),
```



```

LSJoin (T1, T2, U): trait

% Left semi-join

assumes

    Bag (T1),
    Bag (T2),
    Pairs (bag [T1], bag [T2]),
    Pairs (T1, bag [T2]),
    Predicate (pair [T1, bag [T2]]),
    Function (T1, U)

includes

    Bag (U),
    Function (pair [bag [T1], bag [T2]], bag [U])

introduces

    lsjoin: pred [pair [T1, bag [T2]]], fun[T1, U] →
            fun [pair [bag [T1], bag [T2]], bag [U]]

asserts

    ∀ p: pred [pair [T1, bag [T2]]],
      f: fun[T1, U], A: bag [T1], B: bag [T2], x: T1

% Semantics of lsjoin
% -----
lsjoin (p, f) ! [⊙, B] == ⊙
lsjoin (p, f) ! [insert (x, A), B] ==
  (if p ? [x, B] then
    insert (f ! x, lsjoin (p, f) ! [A, B]) else
    lsjoin (p, f) ! [A, B])

```

```

implies

  ∀ p: pred [pair [T1, bag [T2]]], f: fun[T1, U],
    A: bag [T1], B: bag [T2], e: U, x: T1

    e ∈ (lsjoin (p, f) ! [A, B]) == ∃ x (x ∈ A ∧ p ? [x, B] ∧ e = (f ! x))

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

RSJoin (T1, T2, U): trait

% Right semi-join

assumes

  Bag (T1),
  Bag (T2),
  Pairs (bag [T1], bag [T2]),
  Pairs (T2, bag [T1]),
  Predicate (pair [T2, bag [T1]]),
  Function (T2, U)

includes

  Bag (U),
  Function (pair [bag [T1], bag [T2]], bag [U])

introduces

  rjoin: pred [pair [T2, bag [T1]]], fun[T2, U] →
    fun [pair [bag [T1], bag [T2]], bag [U]]

```

```

asserts

  ∀ p: pred [pair [T2, bag [T1]]],
    f: fun[T2, U], A: bag [T1], B: bag [T2], y: T2

% Semantics of rjoin
% -----
rjoin (p, f) ! [A, ∅] == ∅
rjoin (p, f) ! [A, insert (y, B)] ==
  (if p ? [y, A] then
    insert (f ! y, rjoin (p, f) ! [A, B]) else
    rjoin (p, f) ! [A, B])

implies

  ∀ p: pred [pair [T2, bag [T1]]], f: fun[T2, U],
    A: bag [T1], B: bag [T2], e: U, y: T2

  e ∈ (rjoin (p, f) ! [A, B]) == ∃ y (y ∈ B ∧ p ? [y, A] ∧ e = (f ! y))

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

NJoin (T1, T2, U, V): trait

% Trait of the nested-join former, njoin, which is applied
% to a pair of bags (of T1 and T2 elements respectively)
% and returns a bag of [T1, V] pairs such that
% the first member is some element, t of the first bag
% input, and the second member is the result of applying
% a function (g: bag [U] → V) to the bag resulting
% from applying another function (f: T2 → U) to elements
% in the second bag input that are related by a predicate
% (p: [T1, T2] → Bool) to t

```

assumes

```

Bag (T1),
Bag (T2),
Bag (U),
Function (T2, U),
Function (bag [U], V),
Predicate (pair [T1, T2]),
Pairs (T1, T2),
Pairs (bag [T1], bag [T2])

```

includes

```

Pairs (T1, V),
Bag (pair [T1, V]),
Function (pair [bag [T1], bag [T2]], bag [pair [T1, V]]),
CurryingP (T1, T2),
Iterate (T2, U)

```

introduces

```

njoin: pred [pair [T1, T2]] , fun [T2, U], fun [bag [U], V] →
      fun [pair [bag [T1], bag [T2]], bag [pair [T1, V]]]

```

asserts

```

∀ A:bag[T1], B:bag[T2], p: pred [pair [T1, T2]],
   f: fun[T2, U], g: fun [bag [U], V], x: T1

```

% Semantics of **njoin**

% -----

```

njoin (p, f, g) ! [∅, B] == ∅

```

```

(x ∈ A) ⇒

```

```

(njoin (p, f, g) ! [insert (x, A), B] = njoin (p, f, g) ! [A, B])
~(x ∈ A) ⇒
(njoin (p, f, g) ! [insert (x, A), B] =
  insert ([x, g ! (iterate (Cf (p, x), f) ! B)],
    njoin (p, f, g) ! [A, B]))

```

implies

```

∀ A:bag[T1], B:bag[T2], p: pred [pair [T1, T2]], f: fun[T2, U],
  g: fun [bag [U], V], x: T1, Bs: bag [U], e: pair [T1, V]

```

```

e ∈ (njoin (p, f, g) ! [A, B]) ==
∃ x ∃ Bs (x ∈ A ∧ Bs = (iterate (Cp (p, x), f) ! B) ∧ e = [x, g ! Bs])

```

%%%

%%%

Ex (T1, T2): trait

% Trait of the general binary quantifier former, ex which forms
 % binary quantifier formers on pairs.

assumes

```

Bag (T2),
Pairs (T1, T2),
Predicate (pair [T1, T2])

```

includes

```

Pairs (T1, bag [T2]),
Predicate (pair [T1, bag [T2]])

```

introduces

$ex : \text{pred } [\text{pair } [T1, T2]] \rightarrow \text{pred } [\text{pair } [T1, \text{bag } [T2]]]$

asserts

$\forall y: T2, x: T1, p: \text{pred } [\text{pair } [T1, T2]], A: \text{bag } [T2]$

% Semantics of ex

% -----

$ex (p) ? [x, A] == \exists y (y \in A \wedge p ? [x, y])$

%%%

%%%

Fa (T1, T2): trait

% Trait of the general binary quantifier former, fa which forms
% binary quantifier formers on pairs.

assumes

Bag (T2),
Pairs (T1, T2),
Predicate (pair [T1, T2])

includes

Pairs (T1, bag [T2]),
Predicate (pair [T1, bag [T2]])

introduces


```

    fa : pred [pair [T1, T2]] → pred [pair [T1, bag [T2]]]

asserts

    ∀ y: T2, x: T1, p: pred [pair [T1, T2]], A: bag [T2]

% Semantics of ex
% -----
    fa (p) ? [x, A] == ∀ y (y ∈ A ⇒ p ? [x, y])

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

Exists (T): trait

% Trait of the general quantifier iterator former, exists
% form quantifier style predicates on bags of T.

assumes

    Bag (T),
    Predicate (T)

includes

    Predicate (bag [T])

introduces

    exists : pred [T] → pred [bag [T]]

asserts

```

```

    ∀ p: pred [T], A: bag [T], x: T

% Semantics of exists
% -----
exists (p) ? A == ∃ x (x ∈ A ∧ p ? x)

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%%

ForAll (T): trait

% Trait of the general quantifier iterator former, forall
% form quantifier style predicates on bags of T.

assumes

    Bag (T),
    Predicate (T)

includes

    Predicate (bag [T])

introduces

    forall : pred [T] → pred [bag [T]]

asserts

    ∀ p: pred [T], A: bag [T], x: T

% Semantics of exists

```


Appendix B

LP Proof Scripts

B.1 Proof Scripts for CNF

Available from <ftp://wilma.cs.brown.edu/u/mfc/cnf-scripts.lp>.

B.2 Proof Scripts for SNF

Available from <ftp://wilma.cs.brown.edu/u/mfc/snf-scripts.lp>.

B.3 Proof Scripts for Predicate Pushdown

Available from <ftp://wilma.cs.brown.edu/u/mfc/pushdown-scripts.lp>.

B.4 Proof Scripts for Magic Sets

Available from <ftp://wilma.cs.brown.edu/u/mfc/magic-scripts.lp>.

B.5 Proof Scripts for Rules of Chapter 5

Available from <ftp://wilma.cs.brown.edu/u/mfc/vldb-scripts.lp>.

B.6 Proof Scripts for Rules of Chapter 6

Available from <ftp://wilma.cs.brown.edu/u/mfc/exp-scripts.lp>.

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