

Epistemic categorization for analysis of customer complaints

Boris Galitsky

School of Computer Science and Information Systems
Birkbeck College, University of London
Malet Street, London WC1E 7HX, UK
galitsky@dcs.bbk.ac.uk

Anca Pascu

Université de Bretagne Occidentale
Campus Victor Segalen 20, rue Duquesne
B.P. 814 29285 BREST Cedex France
Anca.Pascu@univ-brest.fr

Abstract

We introduce the particular functionality of the Complaint Engine suite, the integrated complaint management component for mediating consumer disputes. We formulate the problem of epistemic categorization: whether a given complaint submitted by an upset customer is an adequate representation of company's product, service and attitude towards customers. To do that, a sequence of communicative actions and argumentation patterns in the course of complaint resolution (as described by a complainant) is analyzed. Instead of natural language processing of textual complaints we use two interactive forms: the first one, to specify communicative actions and argumentative links between their parameters, and the second one, to specify the argumentative relations between the major claims. We briefly outline the reasoning components involved in processing the above data to extract information which would then be expected to be truthful. We then perform the comparative evaluation of the involved reasoning units.

Introduction

In the last few decades, the task of resolving customer complaints is becoming more and more important. When a number of businesses of a various natures do not meet their expectations, customers tend to complain, addressing their requests to customer services of the respective companies. Even though there is no established infrastructure that reduces company reputation because a high number of complains, companies spend substantial resources to retain customers. It is a general understanding that if a business does not attempt to handle customer complaints properly, they may get out of control and damage the smooth business conduct, from a

start-up to a mature stage of the development of this business.

As to the customer side, on average, there is one situation per months per person when there is a feeling of dissatisfaction with a service or a product. Frequently, filing a complaint is stressful for a customer, as well as for a company officer whose wrongdoing is claimed in a complaint. Our experience with customer complaints (addressed to consumer advocacy establishments) shows that a serious complaint is submitted when a customer is dissatisfied with both product/service itself action with customer support. A typical complaint includes both description of a product failure and the process of failed interactions with customer support.

Building a software infrastructure for *automatic or decision support-based processing of complaints* can streamline the complaint resolution procedure and reduce the emotional load of participating parties. We have developed a set of software tools that assist both parties: a disappointed customer in filing a sound well-articulated complaint remaining in a positive mood, and a company representative in handling it in a more efficient, fair and unbiased manner (Galitsky & Tumarkina 2004, Galitsky et al 2005). For the companies, these tools aid in finding the compromise between customer satisfactions and saving company's resources to compensate for problematic products.

In this paper we focus on such task of the *ComplaintEngine* as how to decide whether a given complaint can be trusted, without taking into account domain-specific knowledge (which is not feasible). To do that, a sequence of communicative actions and argumentation patterns (Chesñevar et al 2000) in the course of complaint resolution as described by a complainant is analyzed. Consistent communication discourse and sound argumentation constitute an evidence for trusted information that can then be used to propose a complaint resolution strategy and for other company

purposes. Trusted information extracted from a complaint is important not only for its resolution, but also for the improvement of the product/service and/or the customer support policy. Conversely, description of an implausible sequence of communicative actions, and providing inconsistent claims suggest that a complaint might not be caused by a faulty product, and the information provided should not be trusted (Galitsky & Tumarkina 2004, Galitsky 2006).

A number of models for argumentation-based negotiation have been proposed for the environment when the goals of parties and interaction protocols are available. Most of negotiation protocols are designed for automated agents; a typical example of such a domain is auction agents. In case of complaints we deal with human agents instead of automated ones, information about complainant is distorted, and there is a lack of information about opponents. Neither company policies on handling complaints nor details of possible product failure are available. Nevertheless, a decision on how a given complaint should be handled is sought in such uncertain conditions.

One of the goals of understanding a complaint is assessing whether it should be trusted and informative or not. In the uncertainty of factual knowledge about the product failure one can judge on whether a complaint can be trusted given its adequate logical structure, particularly the sequence of communicative actions and argumentation. *ComplaintEngine* takes advantage of the possibility to access whether a complaint is informative, using epistemic data *only*. In this paper we discover that following the logical structure of how negotiations are represented in a scenario (represented as a text or in a structured way), it is possible to judge about consistency of this scenario (Galitsky et al 2005).

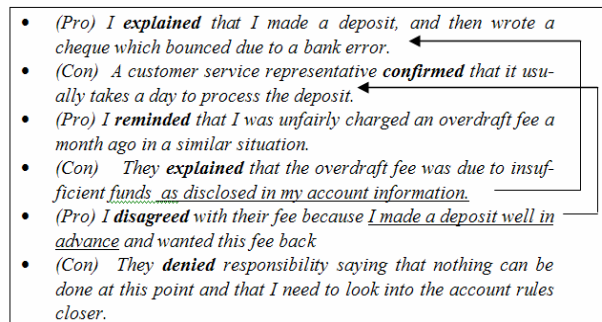
We suggest the methodology of complaint processing that combines various forms of reasoning, machine learning and efficient human-computer interaction. To overcome the bottleneck of natural language processing, we offer to advanced users to input their complaints via interactive forms which encourage a customer to formulate a conflict in a form comprehensible by a computer. Instead of natural language processing of textual complaints we use two interactive forms: the first one, to specify communicative actions and argumentative links between their parameters, and the second one, to specify the argumentative relations between the major claims. In the sections to follow, we introduce the functionality of *ComplaintEngine* to detect whether a complaint is informative, briefly outline the reasoning components, and perform their comparative evaluation.

Specifying communicative actions in the complaint scenario

Let us consider the text given below representing a complaint scenario in which a client is presenting a complaint against a company because he was charged

with an overdraft fee which he considers to be unfair (Figure 1). We denote both parties in this complaint scenario as *Pro* and *Con* (proponent and opponent), to make clear the dialectical setting. In this text mental actions are shown in **bold**. Some expressions appear underline, indicating that they are defeating earlier statements (of an opponents by a proponent).

Fig. 1: A scenario which includes communicative actions of a



proponent and an opponent with defeat relation on their arguments (arrows).

The user interface to specify a complaint scenario (Interactive Encounter Form) is shown at Figure 2. Communicative actions (Bach & Harnish 1979) are selected from the list of twenty or more, depending on the industry sector of a complaint. The parameters of communicative actions are specified as text in the Interactive Form; however they are not present in the formal graph-based scenario representation. Defeat relations between the parameters (subjects) of communicative actions are specified in paired check boxes (shown by bold arrows). A complainant enumerates his/her communicative actions on the left side, and of his/her opponents on the right side of the form.

A complainant has a choice to use the above form or to input complaint as a text so that the linguistic processor processes the complaint automatically and fills the form for her. Using the form encourages complainants to enforce a logical structure on a complaint and to provide a sound argumentation for the dialog. After a complaint is partially or fully specified, the user evaluates its consistency.

A similar form to Figure 2 is used for a complainant to file a complaint, and for a company to store complaints, analyze them, determine whether it is informative/uninformative, explain how the decision has been made, and finally to advise on a strategy for complaint resolution. *ComplaintEngine* provides the explanation of its decision, highlighting the cases which are similar to a given one, and those which are different from it. Moreover, *ComplaintEngine* indicates the communicative actions (steps) that are common to the given one and other informative/uninformative complaints to further back up its decision. The interactive form is available at

dcs.bbk.ac.uk/~galitsky/CLAIMS/ComplaintEngineSuite.zip.

you explain that my cheque I wrote after I made a deposit bounced

input your complaint

Your problem in one sentence (or choose from the list)

Your initial request
 Your problem in one sentence (or choose from the list)
 essence of request: inadequate deposit
 you explain that my cheque I wrote after I made a deposit bounced

Your second request/iteration
 essence of request: you revised that I unfairly charged an overdraft fee a month ago in a
 also, you disregard that their fee and wanted it deposited back to my acc
 and you none that

Your third request/iteration
 essence of request: you none that
 also, you none that
 and you none that

Complaint status: **unjustified**

| | | | | |
|---------------------------------|---------------------------------------|---|--|--|
| Add Complaint Features to KB | Run complaint validity accessor | Initialise complaint validity accessor | Show steps, important for decision Clear highlighted features | Show other cases which led to decision Clear highlighted cases |
|---------------------------------|---------------------------------------|---|--|--|

Fig.2: The screen-shot of the Interactive Encounter Form. Above: communicative action of a proponent (list box) with its subject (input text area) shown enlarged.

Assessing the truthfulness of complainant's claims

Above we have considered how argumentation links between the statements which are being communicated are the subjects of communicative actions. Argumentation links were used together with communicative actions to express a *similarity* between complaints. In this section we verify the truthfulness of each complainant's claim via a special form which assists in structuring a complaint. Use of The Interactive Argumentation Form enforces a user to explicitly indicate all causal and argumentation links between statements which are included in a complaint. The form can be used by a complainant to input an original complaint or by a company representative to process a complaint received as a text or over the phone.

The form includes eight input areas where a complainant presents a component-based description of a problem (Figure 3). At the beginning, the subject of the dispute is specified: an operation (or a sequence of

operations) which are believed by a complainant to be performed by a company in a different manner that was expected <Where company got confused>. Then the essence of the problem is described, what exactly turned out to be wrong. In the section <Company wrongdoing> the complainant the way the company performed its duties which caused the current complaint. The customer's perception of the damage is inputted in section <How it harmed me>. In the fourth section <Why I think this was wrong> the customer backs up his belief concerning the above two sections, <Where company got confused> and <Company wrongdoing>.

Usually, customer dissatisfaction event is followed by negotiation procedure, which is represented by two sections, <What company accepted> and <How company explained>. The acceptance section includes the circumstances which are confirmed by the company (in the complainant's opinion) to lead to the event of the customer's dissatisfaction. The latter section includes the customer's interpretation of how these issues are commented on by the company, the belief of its representative on what lead to the event of the customer's dissatisfaction and the consequences. <Unclear> section includes the issues which remain misunderstood and/or unexplained by the company, in particular, problems with providing relevant information to customers.

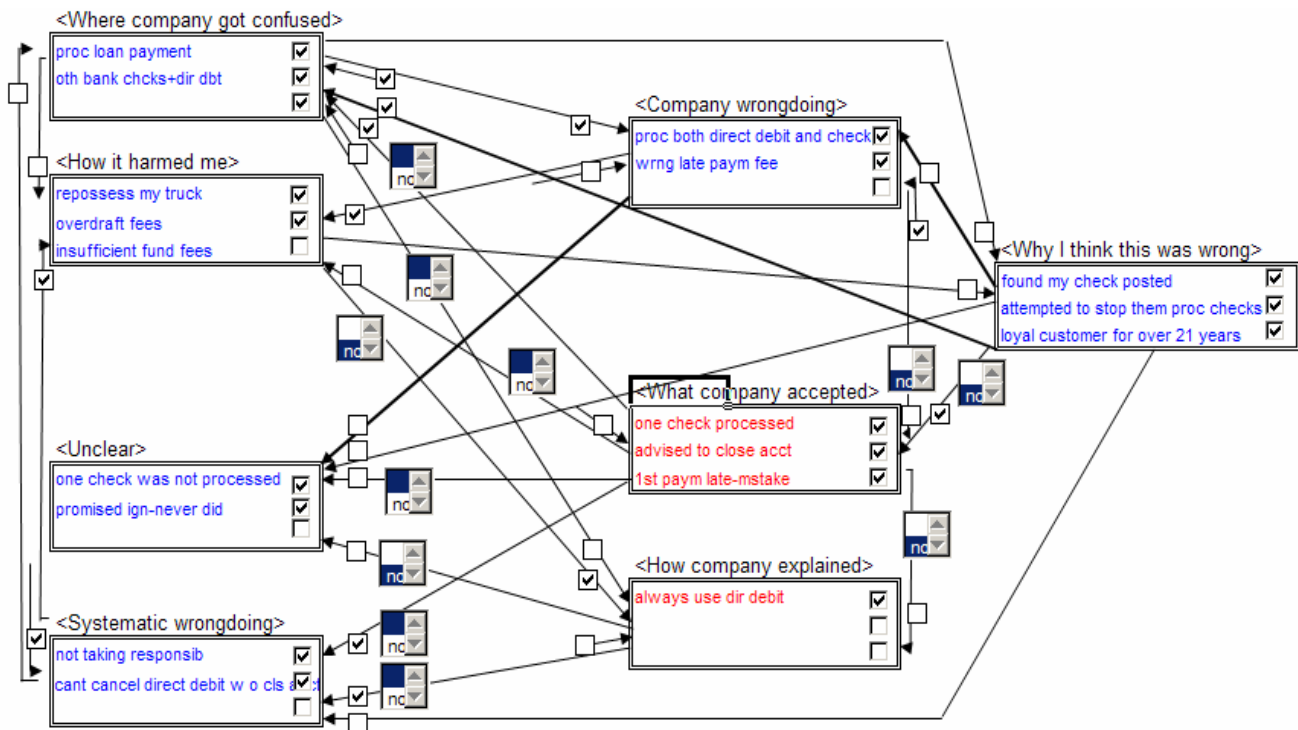


Fig. 3 The Interactive Argumentation Form.

Finally, <Systematic wrongdoing> section includes customers' conclusion about the overall business operation in similar situations, how in customer's opinion her experience can serve as a basis to judge on treatment of other customers in similar situations.

Each section includes one or more sentences which provide relevant information, mentioning background information and/or backing up claims in this or other sections from the standpoint of the customer. Each statement which participates in (at least one) argumentation link is marked by a 3D check box **debit and check**

All possible causal and argumentation links are shown as arrows. Arrows denote the links between the sentences in the respective sections; some arrows go one way and other both ways (only the ending portion is shown in this case). If the user does not find an arrow between two sections for a pair of inputted sentences, it means that either or both of these sentences belong to a wrong section: the data needs to be modified to obey the pre-defined structure. End of each arrow is assigned by a check-box to specify the respective link is active for a given complaint. Bold arrows denote most important links

The list box **nc** is used to specify for a particular link (going either way) whether it is supporting or defeating. To specify supporting and defeating links for a number of statements for each section, multiple instances

of these forms may be required for a given complaint.

The role of the Interactive Argumentation Form is a visual representation of argumentation, as well as its intuitive preliminary analysis. Since even for a typical complaint manual consideration of all argumentation links is rather hard, automated analysis of inter-connections between the complaint components is desired. We use the defeasible logic programming (García and Simari 2004) approach to verify whether the complainant's claims are valid (cannot be defeated given the available data).

Enumeration of reasoning components

In this section we briefly enumerate the reasoning components for processing data obtained via the forms introduced in the above sections (Table 1). Their detailed descriptions are available at the specified URLs.

We use labeled directed acyclic graphs with arcs for describing interaction of two parties in a conflict. A learning model needs to be focused on a specific graph representation for these conflicts. The learning strategies used here are based on ideas similar to that of Nearest Neighbors, and concept-based learning (Ganter & Kuznetsov 2001) or JSM-method (Finn 1991) which we develop as a logic program. JSM-based learning is used to assure avoidance of false positives in as much degree as possible. Moreover, JSM based learning delivers the most cautious approach to classification of a human behavior and attitude to comply with ethical and legal norms. This is important for deployment in such area as customer relation management (Galitsky 2006).

| Component name | Component role | Sample encoded knowledge for the component |
|--|---|--|
| Behavior simulation: reasoning about mental states and actions NL_MAMS | To provide a simulation environment for agents' choice of future mental actions, given the current mental state of interacting agents. The unit includes the library of behaviors available for agents. It yields the consecutive mental states given the initial one, simulating the decision-making process of agents in mental (not physical) space | <i>forgive(Cust, CS, WrongAdvice):- advice(CS, Cust, WrongAdvice), believe(Cust, know(CS, not (howToFix(Happen):- WrongAdvice))), explain(CS, Cust, believe(CS, (howToFix(Happen):- WrongAdvice))), trust(Cust, CS).</i> http://www.dcs.bbk.ac.uk/~galitsky/NL_mams |
| Classical clauses Defeasible rules | To define entities, to specify links between them which always hold | <i>followAdviceNoResult :- ask(Cust, CS, what(Happen)), suggest(CS, Cust, satisfaction(Cust) :- howToFix(Happen)), do(Cust, howToFix(Happen)), not satisfaction(Cust). justified_complaint -< lieCS, consistent_discourse. ~ justified_complaint-< consistent_discourse, ~ loss(Cust).</i> http://www.dcs.bbk.ac.uk/~galitsky/DeLP/ |
| | To specify when some entities may support serve as arguments for a given entity | |
| Reasoning about action: plan building rules so that the assistant agent can advise on future actions | To specify what the future (physical) action of an agents will be, given the pre-conditions of possible actions and their effects, taking into account the current development (of interaction between agents). This component predicts the opponent actions given the explicitly coded pre-conditions and effect axioms (similar to GOLOG, Levesque at al 1997); | <i>poss(do(Cust, fixProd(WayToFix)) :- suggest(CS, Cust, Satisfaction :- howToFix(Happen)), lost_trust(Cust, CustServ).</i> <i>holds(disinformed, do(E, S)):- E = explainWronglyCS.</i> http://www.dcs.bbk.ac.uk/~galitsky/JaSMine/GOLOG/ |
| Machine learning: matching the cases Jasmine | To predict the future interaction of involved agents and to determine their parameters given the previously accumulated cases (represented as sequences of communicative actions). Matching a current formalized complaint with the dataset of complaints with assigned status. | <i>ask(Cust, P1), explain(CS, P1), disagree(Cust,P1). confirm(Cust, P1), agree(CS,P2), suggest(CS, P2), accept(Cust, P2), request(Cust, P2), promise(CS, P2), remind(Cust, P2), ask(Cust, P2).</i> Note two subjects of communicative actions: P1 and P2. http://www.dcs.bbk.ac.uk/~galitsky/JaSMine/ |

Table 1: Reasoning components of the *ComplaintEngine*. All components are implemented as logic programs available at URLs specified in the text. The right column contains the examples of rules for domain-independent complaint-specific ontology. We use the Prolog variables Cust and CS for “customer” and “customer service” respectively.

Evaluation

ComplaintEngine has been evaluated in such domains as education, financial, medical services in both artificial and real-world environments (Galitsky & Tumarkina 2004, Galitsky et al 2005). In this section we present the results of estimating complaint validity in the particular machine learning setting, using the domain of banking complaints. We formed the training dataset randomly selecting half of the available complaints for each bank. The other half of complaints for each bank was used for evaluation of accuracy. The complaints we used were downloaded from the public website PlanetFeedback.com during 3 months starting from March 2004. Each complaint was manually inputted in both forms and assigned a status by experts of the *ComplaintEngine* development team. We used the data for fourteen banks,

20 complaints for training and 20 complaints for evaluation. For simplicity, we consider the same penalty for false positives and false negatives.

The first set of evaluation results is obtained applying the *simulation of consecutive mental states* NL_MAMS to the ones explicitly mentioned in complaint scenarios. If it is possible to derive consecutive mental states and communicative actions, and they are consistent with the ones explicitly mentioned in the complaint, then it is considered *informative*, and *uninformative* otherwise. No adjustment to the training dataset was conducted except the refinement of the library of available behaviors. The second set of evaluation result is obtained when we attempted to recognize whether a complaint is informative, performing the procedure of prediction of a consecutive actions (**reasoning about actions** component). In terms of the setting of action prediction, a complaint is considered informative if most of actions appear to be predictable. Conversely, if a complaint turns

out to be atypical or random and prediction of action fails most of times, the complaint is considered uninformative. Using the training dataset, we select the threshold proportion of predictable actions to achieve the highest accuracy for relating to the class of informative or uninformative.

Both first and second sets of evaluation results is based on extraction from text described elsewhere (Galitsky 2006). Note that the prediction mechanism for the second set uses reasoning about actions (communicative and physical (e.g. financial or litigation transaction), and for the first set it uses simulation of *only mental* states and actions.

The third, fourth, and fifth evaluation results are based on the *machine learning* setting using *Jasmine*. The evaluation settings in these three cases take into account communicative actions only, argumentation patterns only, and both for kinds of data respectively to match a given scenario with ones from the evaluation dataset. The data is obtained from the Interactive Encounter Form (Figure 2).

The sixth set is based on the attempt to defeat complainant's claims using his or her own way to express links between the specified facts, applying DeLP. If complainants' claims can be defeated, there is a good reason not to trust the whole story (Figure 3), and if it is impossible to defeat any claim, then the complaint is considered informative in this evaluation set. Obviously, there is no adjustment for the training dataset for the sixth set.

The seventh, integrated evaluation set includes the above reasoning components. Evaluation is performed based on the rule that if there are two reasoning components which vote for uninformative class, then such class is assigned by the integrated system. This kind of rule proved useful in the selected training dataset to compensate for the inaccuracy of the individual reasoning components: they rather tend to consider a complaint informative when it is not the case.

Hence we observe that machine learning provides the best stand-alone accuracy, when both communicative actions and argumentation links are taken into account. Furthermore, the component which attempts to defeat complainants' claims is the best augmentation of the machine learning components (not shown in Table 2). At the same time the roles of NL_MAMS component in a stand-alone mode is the lowest (20%), followed by reasoning about action component (36%); in both these components too many uninformative complaints are missed.

Looking at the machine learning component, one observes that argumentation improves the classification accuracy for this dataset by about 22%, and the stand-alone argumentation analysis delivers less than 50% classification accuracy. We believe that the relation between the above percentages is an important outcome compared with these percentages as such being domain-dependent. It is also worth mentioning that these

recognition settings assume relating a scenario to a class and providing a background for the decisions.

| Bank | # of complaints | Correctness of decisions, % | | | | | | | |
|---------|-----------------|-----------------------------|---------------|----------------------------------|-------------------|--------------------|-------------------|---------------------------------|-------------------|
| | | Training/eval. | Using NL_MAMS | Using pre-conditions and effects | machine learning | | | Argumentative links between cla | Integrated system |
| | | | | | Communic. actions | Argumentation patt | Communic. actions | | |
| | | | | | | | | | |
| Bank 1 | 20/20 | 15 | 35 | 45 | 35 | 65 | 35 | 75 | |
| Bank 2 | 20/20 | 20 | 40 | 75 | 45 | 70 | 35 | 85 | |
| Bank 3 | 20/20 | 30 | 35 | 60 | 35 | 75 | 40 | 80 | |
| Bank 4 | 20/20 | 25 | 30 | 70 | 45 | 80 | 45 | 85 | |
| Bank 5 | 20/20 | 20 | 45 | 65 | 40 | 70 | 35 | 80 | |
| Bank 6 | 20/20 | 15 | 25 | 60 | 35 | 75 | 30 | 75 | |
| Bank 7 | 20/20 | 20 | 35 | 65 | 45 | 85 | 40 | 75 | |
| Bank 8 | 20/20 | 15 | 40 | 60 | 50 | 75 | 45 | 75 | |
| Bank 9 | 20/20 | 25 | 35 | 60 | 45 | 65 | 40 | 75 | |
| Bank 10 | 20/20 | 20 | 35 | 65 | 55 | 75 | 45 | 80 | |
| Bank 11 | 20/20 | 15 | 45 | 70 | 40 | 75 | 40 | 75 | |
| Bank 12 | 20/20 | 20 | 40 | 50 | 40 | 65 | 30 | 85 | |
| Bank 13 | 20/20 | 25 | 35 | 65 | 45 | 75 | 35 | 80 | |
| Bank 14 | 20/20 | 20 | 30 | 55 | 40 | 70 | 45 | 85 | |
| Average | | 20.4 | 36.1 | 61.8 | 42.5 | 72.9 | 38.6 | 79.3 | |

Table 2: Evaluation results for the hybrid system.

References

- Chesñevar, C., Maguitman, A. & Loui, R. 2000. Logical Models of Argument. *ACM Computing Surveys* 32(4) 337-383.
- Finn, V.K. 1991. Plausible Reasoning in Systems of JSM-type, *Itogi Nauki i Techniki, Seriya Iformatika*, 15, 54-101, [in Russian] (1991).
- García, A., Simari, G. 2004. Defeasible Logic Programming: an argumentative approach. *Theory and Practice of Logic Programming* 4(1), 95-138.
- Bach, K. and Harnish, R.M. 1979. *Linguistic Communication and Speech Acts*, Cambridge, Mass. MIT Press.
- Galitsky, B., Kuznetsov, S. and Samokhin, M. 2005. Analyzing Conflicts with Concept-Based Learning. *Intl. Conf on Concept Structures*.
- Galitsky, B. and Tumarkina, I. 2004. Justification of Customer Complaints using Emotional States and Mental Actions. *FLAIRS Miami, FL*.
- Galitsky, B. 2006. Merging deductive and inductive reasoning for processing textual descriptions of inter-human conflicts. *Journal of Intelligent Information Systems* (to appear).
- Ganter, B. and Kuznetsov, S. 2001. Pattern Structures and Their Projections, *Proc. 9th Int. Conf. on Conceptual Structures, ICCS'01*, G. Stumme and H. Delugach, Eds., *Lecture Notes in Artificial Intelligence*, vol. 2120 129-142.