# Monitoring Streams – A New Class of Data Management Applications

Don Carney
Brown University
*dpc@cs.brown.edu*

Uğur Çetintemel
Brown University
*ugur@cs.brown.edu*

Mitch Cherniack
Brandeis University
*mfc@cs.brandeis.edu*

Christian Convey
Brown University
*cjc@cs.brown.edu*

Sangdon Lee
Brown University
*sdlee@cs.brown.edu*

Greg Seidman
Brown University
*gss@cs.brown.edu*

Michael Stonebraker
M.I.T.
*stonebraker@lcs.mit.edu*

Nesime Tatbul
Brown University
*tatbul@cs.brown.edu*

Stan Zdonik
Brown University
*sbz@cs.brown.edu*

## Abstract

This paper introduces monitoring applications, which we will show differ substantially from conventional business data processing. The fact that a software system must process and react to continual inputs from many sources (e.g., sensors) rather than from human operators requires one to rethink the fundamental architecture of a DBMS for this application area. In this paper, we present Aurora, a new DBMS that is currently under construction at Brandeis University, Brown University, and M.I.T. We describe the basic system architecture, a stream-oriented set of operators, optimization tactics, and support for real-time operation.

## 1 Introduction

Traditional DBMSs have been oriented toward business data processing, and consequently are designed to address the needs of these applications. First, they have assumed that the DBMS is a passive repository storing a large collection of data elements and that humans initiate queries and transactions on this repository. We call this a *Human-Active*, *DBMS-Passive* (*HADP*) model. Second, they have assumed that the current state of the data is the only thing that is important. Hence, current values of data elements are easy to obtain, while previous values can only be found torturously by decoding the DBMS log. The third assumption is that triggers and alerters are second-class citizens. These constructs have been added as an after thought to current systems, and none have an implementation that scales to a large number of triggers. Fourth, DBMSs assume that data elements are synchronized and that queries have exact answers. In many stream-oriented applications, data arrives asynchronously and answers must be computed with incomplete information. Lastly, DBMSs assume that applications require no real-time services.

There is a substantial class of applications where all five assumptions are problematic. Monitoring applications are applications that monitor continuous streams of data. This class of applications includes military applications that monitor readings from sensors worn by soldiers (e.g., blood pressure, heart rate, position), financial analysis applications that monitor streams of stock data reported from various stock exchanges, and tracking applications that monitor the locations of large numbers of objects for which they are responsible (e.g., audio-visual departments that must monitor the location of borrowed equipment). Because of the high volume of monitored data and the query requirements for these applications, monitoring applications would benefit from DBMS support. Existing DBMS systems, however, are ill suited for such applications since they target business applications.

First, monitoring applications get their data from external sources (e.g., sensors) rather than from humans issuing transactions. The role of the DBMS in this context is to alert humans when abnormal activity is detected. This is a *DBMS-Active*, *Human-Passive* (*DAHP*) model.

Second, monitoring applications require data management that extends over some history of values reported in a stream, and not just over the most recently reported values. Consider a monitoring application that tracks the location of items of interest, such as overhead transparency projectors and laptop computers, using electronic property stickers attached to the objects. Ceiling-mounted sensors inside a building and the GPS system in the open air generate large volumes of location data. If a reserved overhead projector is not in its proper location, then one might want to know the geographic position of the missing projector. In this case, the last value of the monitored object is required. However, an administrator might also want to know the duty cycle of the projector, thereby requiring access to the entire historical time series.

Third, most monitoring applications are trigger-oriented. If one is monitoring a chemical plant, then one wants to alert an operator if a sensor value gets too high or if another sensor value has recorded a value out of range more than twice in the last 24 hours. Every application could potentially monitor multiple streams of data, requesting alerts if complicated conditions are met. Thus, the scale of trigger processing required in this environment far exceeds that found in traditional DBMS applications.

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Fourth, stream data is often lost, stale, or intentionally omitted for processing reasons. An object being monitored may move out of range of a sensor system, thereby resulting in lost data. The most recent report on the location of the object becomes more and more inaccurate over time. Moreover, in managing data streams with high input rates, it might be necessary to shed load by dropping less important input data. All of this, by necessity, leads to approximate answers.

Lastly, many monitoring applications have real-time requirements. Applications that monitor mobile sensors (e.g., military applications monitoring soldier locations) often have a low tolerance for stale data, making these applications effectively real time. The added stress on a DBMS that must serve real-time applications makes it imperative that the DBMS employ intelligent resource management (e.g., scheduling) and graceful degradation strategies (e.g., load shedding) during periods of high load. We expect that applications will supply Quality of Service (QoS) specifications that will be used by the running system to make these dynamic resource allocation decisions.

Monitoring applications are very difficult to implement in traditional DBMSs. First, the basic computation model is wrong: DBMSs have a HADP model while monitoring applications often require a DAHP model. In addition, to store time-series information one has only two choices. First, he can encode the time series as current data in normal tables. In this case, assembling the historical time series is very expensive because the required data is spread over many tuples, thereby dramatically slowing performance. Alternately, he can encode time series information in binary large objects to achieve physical locality, at the expense of making queries to individual values in the time series very difficult. One system that tries to do something more intelligent with time series data is the Informix Universal Server, which implemented a time-series data type and associated methods that speed retrieval of values in a time series [2]; however, this system does not address the concerns raised above.

If a monitoring application had a very large number of triggers or alerters, then current DBMSs would fail because they do not scale past a few triggers per table. The only alternative is to encode triggers in some middleware application. Using this implementation, the system cannot reason about the triggers (e.g., optimization), because they are outside the DBMS. Moreover, performance is typically poor because middleware must poll for data values that triggers and alerters depend on.

Lastly, no DBMS that we are aware of has built-in facilities for approximate query answering. The same comment applies to real-time capabilities. Again, the user must build custom code into his application.

For these reasons, monitoring applications are difficult to implement using traditional DBMS technology. To do better, all the basic mechanisms in current DBMSs must be rethought. In this paper, we describe a prototype system, *Aurora*, which is designed to better support monitoring applications. We use Aurora to illustrate design issues that would arise in any system of this kind.

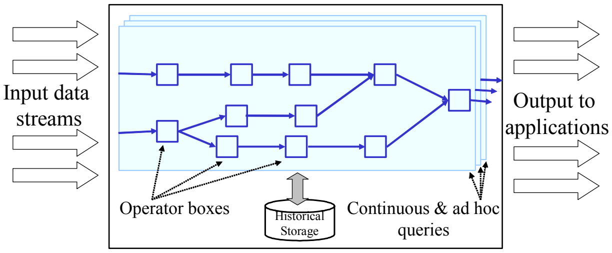


Figure 1: Aurora system model

Monitoring applications are applications for which streams of information, triggers, imprecise data, and real-time requirements are prevalent. We expect that there will be a large class of such applications. For example, we expect the class of monitoring applications for physical facilities (e.g., monitoring unusual events at nuclear power plants) to grow in response to growing needs for security. In addition, as GPS-style devices are attached to a broader and broader class of objects, monitoring applications will expand in scope. Currently such monitoring is expensive and is restricted to costly items like automobiles (e.g., Lojack technology). In the future, it will be available for most objects whose position is of interest.

In Section 2, we begin by describing the basic Aurora architecture and fundamental building blocks. In Section 3, we show why traditional query optimization fails in our environment, and present our alternate strategies for optimizing Aurora applications. Section 4 describes the run-time architecture and behavior of Aurora, concentrating on storage organization, scheduling, introspection, and load shedding. In Section 5, we discuss the myriad of related work that has preceded our effort. We describe the status of our prototype implementation in Section 6, and conclude in Section 7.

## 2 Aurora System Model

Aurora data is assumed to come from a variety of data sources such as computer programs that generate values at regular or irregular intervals or hardware *sensors*. We will use the term *data source* for either case. In addition, a data *stream* is the term we will use for the collection of data values that are presented by a data source. Each data source is assumed to have a unique source identifier and Aurora timestamps every incoming tuple to monitor the quality of service being provided.

The basic job of Aurora is to process incoming streams in the way defined by an *application administrator*. Aurora is fundamentally a data-flow system and uses the popular *boxes and arrows* paradigm found in most process flow and workflow systems. Hence, tuples flow through a loop-free, directed graph of processing operations (i.e., *boxes*). Ultimately, output streams are presented to *applications*, which must be programmed to deal with the asynchronous tuples in an output stream. Aurora can also maintain historical storage, primarily in order to support ad-hoc queries. Figure 1 illustrates the high-level system model.

## 2.1 Operators

Aurora contains built-in support for eight primitive operations for expressing its stream processing requirements. Included among these are *windowed* operators that operate on sets of consecutive tuples from a stream ("windows") at a time. Every windowed operator applies an input (user-defined) function to a window and then advances the window to capture a new set of tuples before repeating the processing cycle. *Slide* advances a window by "sliding" it downstream by some number of tuples. This operator could be used to perform rolling computations, as in a query that continuously determines the average value of IBM stock over the most recent three hours. *Tumble* resembles Slide except that consecutive windows have no tuples in common. Rather, Tumble effectively partitions a stream into disjoint windows. This is useful, for example, when calculating daily stock indexes, where every stock quote is used in exactly one index calculation. *Latch* resembles Tumble but can maintain internal state between window calculations. This is useful for "infinite window" calculations, such as one that maintains the maximum or average value of every stock, maintained over its lifetime. Finally, *Resample* produces a partially synthetic stream by interpolating tuples between actual tuples of an input stream.

Aside from Aurora's windowed operations are operators that act on a single tuple at a time. The *Filter* operator screens tuples in a stream for those that satisfy some input predicate. A special case of Filter is *Drop*, which drops random tuples at some rate specified as an operator input. *Map* applies an input function to every tuple in a stream. *GroupBy* partitions tuples across multiple streams into new streams whose tuples contain the same values over some input set of attributes. Finally, *Join* pairs tuples from input streams whose "distance" (e.g., difference in timestamps) falls within some given upper bound. For example, this distance might be set to 30 minutes if one wanted to pair stocks whose prices coincide within a half-hour of each other.

Other desirable idioms for stream processing can be expressed as compositions of Aurora's built-in primitives. For example, while Aurora has no built-in "CASE statement" operator, one can be simulated by first applying a Map operator to a stream (that assigns a value to a new attribute that is dependent on which case predicate is satisfied) and then using GroupBy to partition tuples according to values assigned to this attribute. Additionally, there is no explicit Split box; instead a query can connect the output of one box to the inputs of several others.

A full treatment of these operators is beyond the scope of this paper.

## 2.2 Query Model

Aurora supports continual queries (real-time processing), views, and ad-hoc queries all using substantially the same mechanisms. All three modes of operation use the same conceptual building blocks. Each mode processes flows based on *QoS specifications*—each output in Aurora is associated with two-dimensional QoS graphs that specify the utility of the output in terms of several performance and quality related attributes (see Section 4.1). The diagram in Figure 2 illustrates the processing modes supported by Aurora.

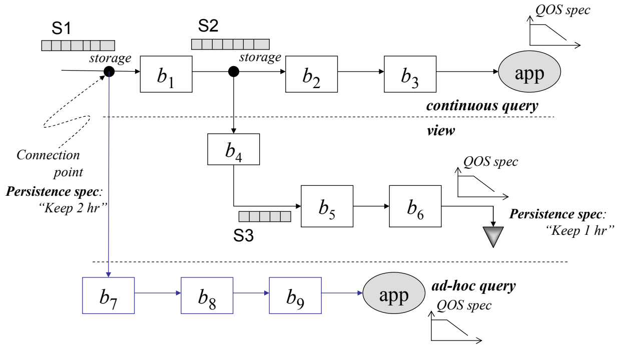


Figure 2: Aurora query model

The topmost path represents a *continuous query*. In isolation, data elements flow into boxes, are processed, and flow further downstream. In this scenario, there is no need to store any data elements once they are processed. Once an input has worked its way through all reachable paths, that data item is drained from the network. The QoS specification at the end of the path controls how resources are allocated to the processing elements along the path. One can also view an Aurora network (along with some of its applications) as a large collection of triggers. Each path from a sensor input to an output can be viewed as computing the *condition* part of a complex trigger. An output tuple is delivered to an application, which can take the appropriate action.

The dark circles on the input arcs to boxes $b_1$ and $b_2$ represent *connection points*. A connection point is an arc that will support dynamic modification to the network. New boxes can be added to or deleted from a connection point. When a new application connects to the network, it will often require access to the recent past. As such, a connection point has the potential for persistent storage (see Section 4.2). Persistent storage retains data items beyond their processing by a particular box. In other words, as items flow past a connection point, they are cached in a persistent store for some period of time. They are not drained from the network by applications. Instead, a persistence specification indicates exactly how long the items are kept. In the figure, the left-most connection point is specified to be available for *two hours*. This indicates that the beginning of time for newly connected applications will be two hours in the past.

The middle path in Figure 2 represents a *view*. In this case, a path is defined with no connected application. It is allowed to have a QoS specification as an indication of the importance of the view. Applications can connect to the end of this path whenever there is a need. Before this happens, the system can propagate some, all, or none of the values stored at the connection point in order to reduce latency for applications that connect later. Moreover, it can store these partial results at any point along a view path. This is analogous to a materialized or partially materialized view. View materialization is under the control of the scheduler.

The bottom path represents an *ad-hoc query*. An ad-hoc query can be attached to a connection point at any time. The semantics of an ad-hoc query is that the system will process data items and deliver answers from the earliest time $T$ (persistence specification) stored in the connection point until the query branch is explicitly disconnected. Thus, the semantics for an Aurora ad-hoc query is the same as a continuous query that starts executing at $t_{now} - T$ and continues until explicit termination.

### 2.3 Graphical User Interface

The Aurora user interface cannot be covered in detail because of space limitations. Here, we mention only a few salient features. To facilitate designing large networks, Aurora will support a hierarchical collection of groups of boxes. A designer can begin near the top of the hierarchy where only a few *superboxes* are visible on the screen. A *zoom* capability is provided to allow him to move into specific portions of the network, by replacing a group with its constituent boxes and groups. In this way, a browsing capability is provided for the Aurora diagram.

Boxes and groups have a tag, an argument list, a description of the functionality and ultimately a manual page. Users can *teleport* to specific places in an Aurora network by querying these attributes. Additionally, a user can place *bookmarks* in a network to allow him to return to places of interest.

These capabilities give an Aurora user a mechanism to query the Aurora diagram. The user interface also allows monitors for arcs in the network to facilitate debugging, as well as facilities for "single stepping" through a sequence of Aurora boxes. We plan a graphical performance monitor, as well as more sophisticated query capabilities.

## 3 Aurora Optimization

In traditional relational query optimization, one of the primary objectives is to minimize the number of iterations over large data sets. Stream-oriented operators that constitute the Aurora network, on the other hand, are designed to operate in a data flow mode in which data elements are processed as they appear on the input. Although the amount of computation required by an operator to process a new element is usually quite small, we expect to have a large number of boxes. Furthermore, high data rates add another dimension to the problem. Lastly, we expect many changes to be made to an Aurora network over time, and it seems unreasonable to take the network off line to perform a compile time optimization. We now present our strategies to optimize an Aurora network.

### 3.1 Dynamic Continuous Query Optimization

We begin execution of an unoptimized Aurora network; i.e., the one that the user constructed. During execution, we gather run time statistics, such as the average cost of box execution and box selectivity. Our goal is to perform run-time optimization of a network, without having to quiesce it. Hence, combining all the boxes into a massive query and then applying conventional query optimization is not a workable approach. Besides being NP-complete [23], it would require quiescing the whole network. Instead, the optimizer will select a portion of the network for optimization. Then, it will find all connection points that surround the subnetwork to be optimized. It will hold all input messages at upstream connection points and drain the subnetwork of messages through all downstream connection points. The optimizer will then apply the following local tactics to the identified subnetwork.

- *Inserting Projections.* It is unlikely that the application administrator will have inserted map operators to project out all unneeded attributes. Examination of an Aurora network allows us to insert or move such map operations to the earliest possible points in the network, thereby shrinking the size of the tuples that must be subsequently processed. Note that this kind of optimization requires that the system be provided with operator signatures that describe the attributes that are used and produced by the operators.
- *Combining Boxes.* As a next step, Aurora diagrams will be processed to combine boxes where possible. A pair-wise examination of the operators suggests that, in general, map and filter can be combined with almost all of the operators whereas windowed or binary operators cannot.

It is desirable to combine two boxes into a single box when this leads to some cost reduction. As an example, a map operator that only projects out attributes can be combined easily with any adjacent operator, thereby saving the box execution overhead for a very cheap operator. In addition, two filtering operations can be combined into a single, more complex filter that can be more efficiently executed than the two boxes it replaces. Not only is the overhead of a second box activation avoided, but also standard relational optimization on one-table predicates can be applied in the larger box. In general, combining boxes at least saves the box execution overhead and reduces the total number of boxes, leading to a simpler diagram.

- *Reordering Boxes.* Reordering the operations in a conventional relational DBMS to an equivalent but more efficient form is a common technique in query optimization. For example, filter operations can sometimes be pushed down the query tree through joins. In Aurora, we can apply the same technique when two operations commute.

To decide when to interchange two commutative operators, we make use of the following performance model. Each Aurora box, $b$, has a *cost*, $c(b)$, defined as the expected execution time for $b$ to process one input tuple. Additionally, each box has a *selectivity*, $s(b)$, which is the expected number of output tuples per input tuple. Consider two boxes, $b_i$ and $b_j$, with $b_j$ following $b_i$. In this case, for each input tuple for $b_i$, we can compute the amount of processing as $c(b_i) + c(b_j) \times s(b_i)$. Reversing the operators gives a like calculation. Hence, we can compute the condition used to decide whether the boxes should be switched as:

$$1 - s(b_j) / c(b_j) > 1 - s(b_i) / c(b_i)$$

It is straightforward to generalize the above calculation to deal with cases that involve fan-in or fan-out situations. Moreover, it is easy to see that we can obtain an optimal ordering by sorting all the boxes according to their corresponding ratios in decreasing order. We use this result in a heuristic algorithm that iteratively reorders boxes (to the extent allowed by their commutativity properties) until no more reorderings are possible.

When the optimizer has found all productive transformations using the above tactics, it constructs a new sub-network, binds it into the composite Aurora network that is running, and then instructs the scheduler to stop holding messages at the input connection points. Of course, outputs affected by the sub-network will see a *blip* in response time; however the remainder of the network can proceed unimpeded.

An Aurora network is broken naturally into a collection of *k* sub-networks by the connection points that are inserted by the application administrator. Each of these sub-networks can be optimized individually, because it is a violation of Aurora semantics to optimize across a connection point. The Aurora optimizer is expected to cycle periodically through all *k* sub-networks and run as a background task.

## 3.2 Ad-Hoc Query Optimization

One last issue that must be dealt with is ad-hoc query optimization. Recall that the semantics of an ad-hoc query is that it must run on all the historical information saved at the connection point(s) to which it is connected. Subsequently, it becomes a normal portion of an Aurora network, until it is discarded. Aurora processes ad-hoc queries in two steps by constructing two separate subnetworks. Each is attached to a connection point, so the optimizer can be run before the scheduler lets messages flow through the newly added subnetworks.

Aurora semantics require the historical subnetwork to be run first. Since historical information is organized as a B-tree, the Aurora optimizer begins at each connection point and examines the successor box(es). If the box is a filter, then Aurora examines the condition to see if it is compatible with the storage key associated with the connection point. If so, it switches the implementation of the filter box to perform an indexed lookup in the B-tree. Similarly, if the successor box is a join, then the Aurora optimizer costs performing a merge-sort or indexed lookup, chooses the cheapest one, and changes the join implementation appropriately. Other boxes cannot effectively use the indexed structure, so only these two need be considered. Moreover, once the initial box performs its work on the historical tuples, the index structure is lost, and all subsequent boxes will work in the normal way. Hence, the optimizer converts the historical subnetwork into an optimized one, which is then executed.

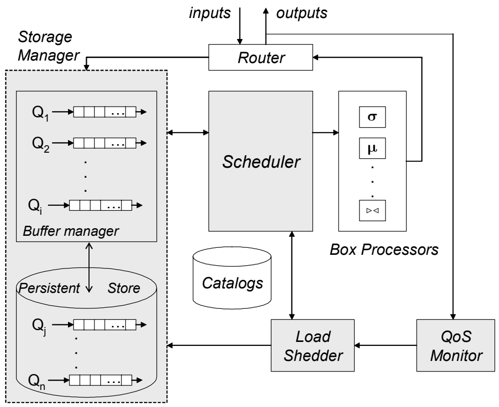


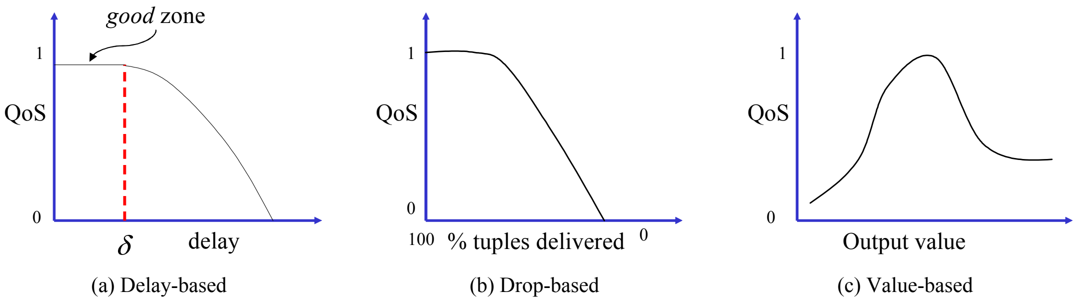
Figure 3: Aurora run-time architecture

When it is finished, the subnetwork used for continuing operation can be run to produce subsequent output. Since this is merely one of the sub-networks, it can be optimized in the normal way suggested above.

In summary, the initial boxes in an ad-hoc query can *pull* information from the B-tree associated with the corresponding connection point(s). When the historical operation is finished, Aurora switches the implementation to the standard *push-based* data structures, and continues processing in the conventional fashion.

# 4 Run-Time Operation

The basic purpose of Aurora run-time network is to process data flows through a potentially large workflow diagram. Figure 3 illustrates the basic Aurora architecture. Here, inputs from data sources and outputs from boxes are fed to the router, which forwards them either to external applications or to the storage manager to be placed on the proper queue. The storage manager is responsible for maintaining the box queues and managing the buffer. Conceptually, the scheduler picks a box for execution, ascertains what processing is required, and passes a pointer to the box description (together with a pointer to the box state) to the multi-threaded box processor. The box processor executes the appropriate operation and then forwards the output tuples to the router. The scheduler then ascertains the next processing step and the cycle repeats. The QoS monitor continually monitors system performance and activates the load shedder when it detects an overload situation and poor system performance. The load shedder then sheds load till the performance of the system reaches an acceptable level. The catalog in Figure 3 contains information regarding the network topology, inputs, outputs, QoS information, and relevant statistics (e.g., selectivity, average box processing costs), and is essentially used by all components.



(a) Delay-based

(b) Drop-based

(c) Value-based

Figure 4: QoS graph types

We now describe Aurora's primary run-time architecture in more detail, focusing primarily on the storage manager, scheduler, QoS monitor, and load shedder.

### 4.1 QoS Data Structures

Aurora attempts to maximize the perceived QoS for the outputs it produces. QoS, in general, is a multidimensional function of several attributes of an Aurora system. These include:

- *Response times*—output tuples should be produced in a timely fashion; as otherwise QoS will degrade as delays get longer;
- *Tuple drops*—if tuples are dropped to shed load, then the QoS of the affected outputs will deteriorate;
- *Values produced*—QoS clearly depends on whether important values are being produced or not.

Asking the application administrator to specify a multidimensional QoS function seems impractical. Instead, Aurora relies on a simpler tactic, which is much easier for humans to deal with: for each output stream, we expect the application administrator to give Aurora a two-dimensional QoS graph based on the processing delay of output tuples produced (as illustrated in Figure 4a). Here, the QoS of the output is maximized if delay is less than the threshold, $\delta$, in the graph. Beyond $\delta$, QoS degrades with additional delay.

Optionally, the application administrator can give Aurora two additional QoS graphs for all outputs in an Aurora system. The first, illustrated in Figure 4b, shows the percentage of tuples delivered. In this case, the application administrator indicates that high QoS is achieved when tuple delivery is near 100% and that QoS degrades as tuples are dropped. The second optional QoS graph for outputs is shown in Figure 4c. The possible values produced as outputs appear on the horizontal axis, and the QoS graph indicates the importance of each one. This value-based QoS graph captures the fact that some outputs are more important than others. For example, in a plant monitoring application, outputs near a critical region are much more important than ones well away from it. Again, if the application administrator has value-based QoS information, then Aurora will use it to shed load more intelligently than would occur otherwise.

Aurora makes several assumptions about the QoS graphs. First, it assumes that all QoS graphs are normalized, so that QoS for different outputs can be quantitatively compared. Second, Aurora assumes that the value chosen for $\delta$ is *feasible*, i.e., that a properly sized Aurora network will operate with all outputs in the *good* zone to the left of $\delta$ in steady state. This will require the delay introduced by the total computational cost along the longest path from a data source to this output not to exceed $\delta$. If the application administrator does not present Aurora with feasible QoS graphs, then the algorithms in the subsequent sections may not produce good results. Third, unless otherwise stated, Aurora assumes that all its QoS graphs are convex (the value-based graph illustrated in Figure 4c is an exception). This assumption is not only reasonable but also necessary for the applicability of *gradient walking* techniques used by Aurora for scheduling and load shedding.

Note that Aurora's notion of QoS is general and is not restricted to the types of graphs presented here. Aurora can work with other individual attributes (e.g., throughput) or composite attributes (e.g., a weighted, linear combination of throughput and latency) provided that they satisfy the basic assumptions discussed above. In the rest of this paper, however, we restrict our attention to the graph types presented here.

The last item of information required from the application administrator is *H*, the *headroom* for the system, defined as the percentage of the computing resources that can be used in steady state. The remainder is reserved for the expected ad-hoc queries, which are added dynamically.

### 4.2 Storage Management

The job of the Aurora Storage Manager (ASM) is to store all tuples required by an Aurora network. There are two kinds of requirements. First, ASM must manage storage for the tuples that are being passed through an Aurora network, and secondly, it must maintain extra tuple storage that may be required at connection points.

**Queue Management.** Each windowed operation requires a historical collection of tuples to be stored, equal to the size of the window. Moreover, if the network is currently saturated, then additional tuples may accumulate at various places in the network. As such, ASM must manage a collection of variable length queues of tuples. There is one queue at the output of each box, which is shared by all successor boxes. Each such successor box maintains two pointers into this queue. The *head* indicates the oldest tuple that this box has not processed. The *tail*, in contrast, indicates the oldest tuple that the box needs. The head and tail indicate box's current window, which slides

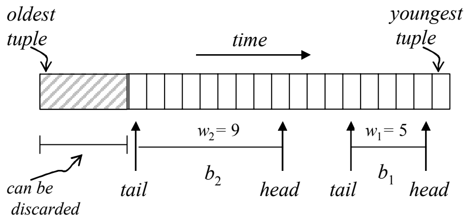


Figure 5: Queue organization

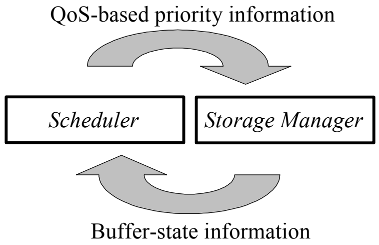


Figure 6: Scheduler-storage manager interaction

as new tuples are processed. ASM will keep track of these collections of pointers, and can normally discard tuples in a queue that are older than the oldest tail pointing into the queue. In summary, when a box produces a new tuple, it is added to the front of the queue. Eventually, all successor boxes process this tuple and it falls out of all of their windows and can be discarded. Figure 5 illustrates this model by depicting a two-way branch scenario where two boxes, $b_1$ and $b_2$, share the same queue (‘*w*’s refer to window sizes).

Normally, queues of this sort are stored as main memory data structures. However, ASM must be able to scale arbitrarily, and has chosen a different approach. Disk storage is divided into fixed length blocks, of a tunable size, *block_size*. We expect typical environment will use 128KB or larger blocks. Each queue is allocated one block, and queue management proceeds as above. As long as the queue does not overflow, the single block is used as a circular buffer. If an overflow occurs, ASM looks for a collection of two blocks (contiguous if possible), and expands the queue dynamically to 2 × *block_size*. Circular management continues in this larger space. Of course, queue underflow can be treated in an analogous manner.

At start up time, ASM is allocated a buffer pool for queue storage. It pages queue blocks into and out of main memory using a novel replacement policy. The scheduler and ASM share a tabular data structure that contains a row for each box in the network containing the current scheduling priority of the box and the percentage of its queue that is currently in main memory. The scheduler periodically adjusts the priority of each box, while the ASM does likewise for the main memory residency of the queue. This latter piece of information is used by the scheduler for guiding scheduling decisions (see Section 4.3). The data structure also contains a flag to indicate that a box is currently running. Figure 6 illustrates this interaction.

When space is needed for a disk block, ASM evicts the lowest priority main memory resident block. In addition, whenever, ASM discovers a block for a queue that does not correspond to a running block, it will attempt to “upgrade” the block by evicting it in favor of a block for the queue corresponding to a higher priority box. In this way, ASM is continually trying to keep all the required blocks in main memory that correspond to the top priority queues. ASM is also aware of the size of each queue and whether it is contiguous on disk. Using this information, it can schedule multi-block reads and writes and garner added efficiency. Of course, as blocks move through the system and conditions change, the scheduler will adjust the priority of boxes, and ASM will react by adjusting the buffer pool. Naturally, we must be careful to avoid the well-known *hysteresis* effect, whereby ASM and the scheduler start working at cross purposes, and performance degrades sharply.

**Connection Point Management.** As noted earlier, the Aurora application designer indicates a collection of connection points, to which collections of boxes can be subsequently connected. This satisfies the Aurora requirement to support ad-hoc queries. Associated with each connection point is a history requirement and an optional storage key. The history requirement indicates the amount of historical information that must be retained. Sometimes, the amount of retained history is less than the maximum window size of the successor boxes. In this case, no extra storage need be allocated. The usual case is that additional history is requested.

In this case, ASM will organize the historical tuples in a B-tree organized on the storage key. If one is not specified, then a B-tree will be built on the timestamp field in the tuple. When tuples fall off the end of a queue that is associated with a connection point, then ASM will gather up batches of such tuples and insert them into the corresponding B-tree. Periodically, it will make a pass through the B-tree and delete all the tuples, which are older than the history requirement. Obviously, it is more efficient to process insertions and deletions in batches, than one by one.

Since we expect B-tree blocks to be smaller than *block_size*, we anticipate splitting one or more of the buffer pool blocks into smaller pieces, and paging historical blocks into this space. The scheduler will simply add the boxes corresponding to ad-hoc queries to the data structure mentioned above, and give these new boxes a priority. ASM will react by prefetching index blocks, but not data blocks, for worthy indexed structures. In turn, it will retain index blocks, as long as there are not higher priority buffer requirements. No attempt will be made to retain data blocks in main memory.

## 4.3 Real-Time Scheduling

Scheduling in Aurora is a complex problem due to the need to simultaneously address several issues including large system scale, real-time performance requirements, and dependencies between box executions. Furthermore, tuple processing in Aurora spans many scheduling and execution steps (i.e., an input tuple typically needs to go through many boxes before potentially contributing to an output stream) and may involve multiple accesses to secondary storage. Basing scheduling decisions solely on QoS requirements, thereby failing to address end-to-end tuple processing costs, might lead to drastic performance degradation especially under resource constraints. To this end, Aurora not only aims to maximize overall QoS but also makes an explicit attempt to reduce overall tuple execution costs. We now describe how Aurora addresses these two issues.

**Train Scheduling.** In order to reduce overall processing costs, Aurora observes and exploits two basic *non-linearities* when processing tuples:

- *Inter-box non-linearity*: End-to-end tuple processing costs may drastically increase if buffer space is not sufficient and tuples need to be shuttled back and forth between memory and disk several times throughout their lifetime. One important goal of Aurora scheduling is, thus, to minimize tuple trashing. Another form of inter-box non-linearity occurs when passing tuples between box queues. If the scheduler can decide in advance that, say, box $b_2$ is going to be scheduled right after box $b_1$ (whose outputs feed $b_2$), then the storage manager can be bypassed (assuming there is sufficient buffer space) and its overhead avoided while transferring $b_1$'s outputs to $b_2$'s queue.
- *Intra-box non-linearity*: The cost of tuple processing may decrease as the number of tuples that are available for processing at a given box increases. This reduction in unit tuple processing costs may arise due to two reasons. First, the total number of box calls that need to be made to process a given number of tuples decreases, cutting down low-level overheads such as calls to the box code and context switch. Second, a box, depending on its semantics, may optimize its execution better with larger number of tuples available in its queue. For instance, a box can materialize intermediate results and reuse them in the case of windowed operations, or use merge-join instead of nested loops in the case of joins.

Aurora exploits the benefits of non-linearity in both inter-box and intra-box tuple processing primarily through *train scheduling*, a set of scheduling heuristics that attempt to (1) have boxes queue as many tuples as possible without processing—thereby generating long tuple trains; (2) process complete trains at once—thereby exploiting intra-box non-linearity; and (3) pass them to subsequent boxes without having to go to disk—thereby exploiting inter-box non-linearity. To summarize, train scheduling has two goals: its primary goal is to minimize the number of I/O operations performed per tuple. A secondary goal is to minimize the number of box calls made per tuple.

One important implication of train scheduling is that, unlike traditional blocking operators that wake up and process new input tuples as they arrive, Aurora scheduler tells each box when to execute and how many queued tuples to process. This somewhat complicates the implementation and increases the load of the scheduler, but is necessary for creating and processing tuple trains, which will significantly decrease overall execution costs.

**Priority Assignment.** The latency of each output tuple is the sum of the tuple's processing delay and its waiting delay. Unlike the processing delay, which is a function of input tuple rates and box costs, the waiting delay is primarily a function of scheduling. Aurora's goal is to assign priorities to outputs so as to achieve the per-output waiting delays that maximize the overall QoS.

The priority of an output is an indication of its urgency. Aurora currently considers two approaches for priority assignment. The first one, a *state-based* approach, assigns priorities to outputs based on their expected utility under the current system state, and then picks for execution, at each scheduling instance, the output with the highest utility. In this approach, the utility of an output can be determined by computing how much QoS will be *sacrificed* if the execution of the output is deferred. A second, *feedback-based* approach continuously observes the performance of the system and dynamically reassigns priorities to outputs, properly increasing the priorities of those that are not doing well and decreasing priorities of the applications that are already in their *good zones*.

**Putting It All Together.** Because of the large scale, highly dynamic nature of the system, and the granularity of scheduling, searching for optimal scheduling solutions is clearly infeasible. Aurora therefore uses heuristics to simultaneously address real-time requirements and cost reduction by first assigning priorities to select individual outputs and then exploring opportunities for constructing and processing tuple trains.

We now describe one such heuristic used by Aurora. Once an output is selected for execution, Aurora will find the first downstream box whose queue is in memory (note that for a box to be schedulable, its queue must at least contain its window's worth of tuples). Going upstream, Aurora will then consider other boxes, until either it considers a box whose queue is not in memory or it runs out of boxes. At this point, there is a sequence of boxes (i.e., a *superbox*) that can be scheduled one after another.

In order to execute a box, Aurora contacts the storage manager and asks that the queue of the box be pinned to the buffer throughout box's execution. It then passes the location of the input queue to the appropriate box processor code, specifies how many tuples the box should process, and assigns it to an available worker thread.

## 4.4 Introspection

Aurora employs static and run-time introspection techniques to predict and detect overload situations.

**Static Analysis.** The goal of static analysis is to determine if the hardware running the Aurora network is sized correctly. If insufficient computational resources are present to handle the steady state requirements of an Aurora network, then queue lengths will increase without bound and response times will become arbitrarily large.

As described before, each box $b$ in an Aurora network has an expected tuple processing cost, $c(b)$, and a selectivity, $s(b)$. If we also know the expected rate of tuple production $r(d)$ from each data source $d$, then we can use the following static analysis to ascertain if Aurora is sized correctly.

From each data source, we begin by examining the immediate downstream boxes: if box $b_i$ is directly downstream from data source $d_i$, then, for the system to be stable, the throughput of $b_i$ should be at least as large as the input data rate; i.e.,

$$1/c(b_i) \geq r(d_i)$$

We can then calculate the output data rate from $b_i$ as:

$$min(1/c(b_i), r(d_i)) \times s(b_i)$$

Proceeding iteratively, we can compute the output data rate and computational requirements for each box in an Aurora network. We can then calculate the minimum aggregate computational resources required per unit time, *min_cap*, for stable steady-state operation. Clearly, the Aurora system with a capacity $C$ cannot handle the expected steady state load if $C$ is smaller than *min_cap*. Furthermore, the response times will assuredly suffer under the expected load of ad-hoc queries if

$$C \times H < min\_cap$$

Clearly, this is an undesirable situation and can be corrected by redesigning applications to change their resource requirements, by supplying more resources to increase system capacity, or by load shedding.

**Dynamic Analysis.** Even if the system has sufficient resources to execute a given Aurora network under expected conditions, unpredictable, long-duration spikes in input rates may deteriorate performance to a level that renders the system useless. We now describe two run-time techniques to detect such cases.

Our technique for detecting an overload relies on the use of delay-based QoS information. Aurora timestamps all tuples from data sources as they arrive. Furthermore, all Aurora operators preserve the tuple timestamps as they produce output tuples (if an operator has multiple input tuples, then the earlier timestamp is preserved). When Aurora delivers an output tuple to an application, it checks the corresponding delay-based QoS graph (Figure 4a) for that output to ascertain that the delay is at an acceptable level (i.e., the output is in the *good* zone).

## 4.5 Load Shedding

When an overload is detected as a result of static or dynamic analysis, Aurora attempts to reduce the volume of Aurora tuple processing via *load shedding*. The naïve approach to load shedding involves dropping tuples at random points in the network in an entirely uncontrolled manner. This is similar to dropping overflow packets in packet-switching networks [27], and has two potential problems: (1) overall system utility might be degraded more than necessary; and (2) application semantics might be arbitrarily affected. In order to alleviate these problems, Aurora relies on QoS information to guide the load shedding process. We now describe two load-shedding techniques that differ in the way they exploit QoS.

**Load Shedding by Dropping Tuples.** The first approach addresses the former problem mentioned above: it attempts to minimize the degradation (or maximize the improvement) in the overall system QoS; i.e., the QoS values aggregated over all the outputs. This is accomplished by dropping tuples on network branches that terminate in *more tolerant* outputs.

If load shedding is triggered as a result of static analysis, then we cannot expect to use delay-based or value-based QoS information (without assuming the availability of a priori knowledge of the tuple delays or frequency distribution of values). On the other hand, if load shedding is triggered as a result of dynamic analysis, we can also use delay-based QoS graphs.

We use a greedy algorithm to perform load shedding. Let us initially describe the static load shedding algorithm driven by drop-based QoS graphs. We first identify the output with the *smallest* negative slope for the corresponding QoS graph. We move horizontally along this curve until there is another output whose QoS curve has a smaller negative slope at that point. This horizontal difference gives us an indication of the *output* tuples to drop (i.e., the selectivity of the drop box to be inserted) that would result in the minimum decrease in the overall QoS. We then move the corresponding drop box as far upstream as possible until we find a box that affects other outputs (i.e., a *split point*), and place the drop box at this point. Meanwhile, we can calculate the amount of recovered resources. If the system resources are still not sufficient, then we repeat the process.

For the run-time case, the algorithm is similar except that we can use delay-based QoS graphs to identify the problematic outputs, i.e., the ones that are beyond their delay thresholds, and we repeat the load shedding process until the latency goals are met.

In general, there are two subtleties in dynamic load shedding. First, drop boxes inserted by the load shedder should be among the ones that are given higher priority by the scheduler. Otherwise, load shedding will be ineffective in reducing the load of the system. Therefore, the load shedder simply does not consider the *inactive* (i.e., low priority) outputs, which are indicated by the scheduler. Secondly, the algorithm tries to move the drop boxes as close to the sources as possible to discard tuples before they redundantly consume any resources. On the other hand, if there is a box with a large existing queue, it makes sense to *temporarily* insert the drop box at that point rather than trying to move it upstream closer towards the data sources.

Presumably, the application is coded so that it can tolerate missing tuples from a data source caused by communication failures or other problems. Hence, load shedding simply artificially introduces additional missing tuples. Although the semantics of the application are somewhat different, the harm should not be too damaging.

**Semantic Load Shedding by Filtering Tuples.** The load shedding scheme described above effectively reduces the amount of Aurora processing by dropping *randomly selected* tuples at strategic points in the network. While this approach attempts to minimize the loss in overall system utility, it fails to control the impact of the dropped tuples on application semantics. Semantic load shedding addresses this limitation by using value-based QoS information, if available. Specifically, semantic load shedding drops tuples in a more controlled way; i.e., it drops less important tuples, rather than random ones, using filters.

If value-based QoS information is available, then Aurora can watch each output and build up a histogram containing the frequency with which value ranges have been observed. In addition, Aurora can calculate the expected utility of a range of outputs by multiplying the QoS values with the corresponding frequency values for every interval and then summing these values. To shed load, Aurora identifies the output with the *lowest utility interval*; converts this interval to a filter predicate; and then, as before, attempts to propagate the corresponding filter box as far upstream as possible to a split point. This strategy, which we refer to as *backward interval propagation*, admittedly has limited scope because it requires the application of the inverse function for each operator passed upstream (Aurora boxes do not necessarily have inverses). In an alternative strategy, *forward interval propagation*, Aurora starts from an output and goes upstream until it encounters a split point (or reaches the source). It then *estimates* a proper filter predicate and propagates it in downstream direction to see what results at the output. By trial-and-error, Aurora can converge on a desired filter predicate. Note that a combination of these two strategies can also be utilized. First, Aurora can apply backward propagation until a box, say *b*, whose operator's inverse is difficult to compute. Aurora can then apply forward propagation between the insertion location of the filter box and *b*. This algorithm can be applied iteratively until sufficient load is shed.

# 5 Related Work

A special case of Aurora processing is as a continuous query system. A system like Niagara [7] is concerned with combining multiple data sources in a wide area setting, while we are initially focusing on the construction of a general stream processor that can process very large numbers of streams.

Query indexing [3] is an important technique for enhancing the performance of large-scale filtering applications. In Aurora, this would correspond to a merge of some inputs followed by a fanout to a large number of filter boxes. Query indexing would be useful here, but it represents only one Aurora processing idiom.

As in Aurora, active databases [21, 22] are concerned with monitoring conditions. These conditions can be a result of any arbitrary update on the stored database state. In our setting, updates are append-only, thus requiring different processing strategies for detecting monitored conditions. Triggers evaluate conditions that are either true or false. Our framework is general enough to support queries over streams or the conversion of these queries into monitored conditions. There has also been extensive work on making active databases highly scalable (e.g., [11]). Similar to continuous query research, these efforts have focused on query indexing, while Aurora is constructing a more general system.

Adaptive query processing techniques (e.g., [4, 13, 26]) address efficient query execution in unpredictable and dynamic environments by revising the query execution plan as the characteristics of incoming data changes. Of particular relevance is the Eddies work [4]. Unlike traditional query processing where every tuple from a given data source gets processed in the same way, each tuple processed by an Eddy is dynamically routed to operator threads for partial processing, with the responsibility falling upon the tuple to carry with it its processing state. Recent work [17] extended Eddies to support the processing of queries over streams, mainly by permitting Eddies systems to process multiple queries simultaneously and for unbounded lengths of time. The Aurora architecture bears some similarity to that of Eddies in its division of a single query's processing into multiple threads of control (one per query operator). However, queries processed by Eddies are expected to be processed in their entirety; there is neither the notion of load shedding, nor QoS.

Previous work on stream data query processing architectures shares many of the goals and target application domains with Aurora. The Streams project [5] attempts to provide complete DBMS functionality along with support for continuous queries over streaming data. The Fjords architecture [16] combines querying of push-based sensor sources with pull-based traditional sources by embedding the pull/push semantics into queues between query operators. It is fundamentally different from Aurora in that operator scheduling is governed by a combination of schedulers specific to query threads and operator-queue interactions. Tribeca [25] is an extensible, stream-oriented data processor designed specifically for supporting network traffic analysis. While Tribeca incorporates some of the stream operators and compile-time optimizations Aurora supports, it does not address scheduling or load shedding issues, and does not have the concept of ad-hoc queries.

Work in sequence databases [24] defined sequence definition and manipulation languages over discrete data sequences. The Chronicle data model [14] defined a restricted view definition and manipulation language over append-only sequences. Aurora's algebra extends the capabilities of previous proposals by supporting a wider range of window processing (i.e., Tumble, Slide, Latch), classification (i.e., GroupBy), and interpolation (i.e., Resample) techniques.

Our work is also relevant to materialized views [10], which are essentially stored continuous queries that are re-executed (or incrementally updated) as their base data are modified. However, Aurora's notion of continuous queries differs from materialized views primarily in that Aurora updates are append-only, thus, making it much easier to incrementally materialize the view. Also, query results are streamed (rather than stored); and high stream data rates may require load shedding or other approximate query processing techniques that trade off efficiency for result accuracy.

Our work is likely to benefit from and contribute to the considerable research on temporal databases [20], main-memory databases [8], and real-time databases [15, 20]. These studies commonly assume an HADP model, whereas Aurora proposes a DAHP model that builds streams as fundamental Aurora objects. In a real-time database system, transactions are assigned timing constraints and the system attempts to ensure a degree of confidence in meeting these timing requirements. The Aurora notion of QoS extends the soft and hard deadlines used in real-time databases to general utility functions. Furthermore, real-time databases associate deadlines with individual transactions, whereas Aurora associates QoS curves with outputs from stream processing and, thus, has to support continuous timing requirements. Relevant research in workflow systems (e.g., [18]) primarily focused on organizing long-running interdependent activities but did not consider real-time processing issues.

There has been extensive research on scheduling tasks in real-time and multimedia systems and databases [19, 20]. The proposed approaches are commonly deadline driven; i.e., at each scheduling point, the task that has the earliest deadline or one that is expected to provide the highest QoS (e.g., throughput) is identified and scheduled. In Aurora, such an approach is not only impractical because of the sheer number of potentially schedulable tasks (i.e., tuples), but is also inefficient because of the implicit assumption that all tasks are memory-resident and are scheduled and executed in their entirety. To the best of our knowledge, however, our train scheduling approach is unique in its ability to reduce overall execution costs by exploiting intra- and inter-box non-linearities described here.

The work of [26] takes a scheduling-based approach to query processing; however, they do not address continuous queries, are primarily concerned with data rates that are too slow (we also consider rates that are too high), and they only address query plans that are trees with single outputs.

The congestion control problem in data networks [27] is relevant to Aurora and its load shedding mechanism. Load shedding in networks typically involves dropping individual packets randomly, based on timestamps, or using (application-specified) priority bits. Despite conceptual similarities, there are also some fundamental differences between network load shedding and Aurora load shedding. First, unlike network load shedding which is inherently distributed, Aurora is aware of the entire system state and can potentially make more intelligent shedding decisions. Second, Aurora uses QoS information provided by the external applications to trigger and guide load shedding. Third, Aurora's semantic load shedding approach not only attempts to minimize the degradation in overall system utility, but also quantifies the imprecision due to dropped tuples.

Aurora load shedding is also related to approximate query answering (e.g., [12]), data reduction, and summary techniques [6, 9], where result accuracy is traded for efficiency. By throwing away data, Aurora bases its computations on sampled data, effectively producing approximate answers using data sampling. The unique aspect of our approach is that our sampling is driven by QoS specifications.

## 6 Implementation Status

As of June 2002, we have a prototype Aurora implementation. The prototype has a Java-based GUI that allows construction and execution of Aurora networks. The interface is currently primitive, but will be extended over the next few months to support specification of QoS graphs, connection points, and zoom. The run-time system contains a primitive scheduler, a rudimentary storage manager, and code to execute most of the boxes. Aurora metadata is stored in a schema, which is stored in a Berkeley DB [1] database. Hence, Aurora is functionally complete, and multi-box networks can be constructed and run. However, there is currently no optimizer and load shedding. We expect to implement Aurora functionality in these areas over the course of the summer.

## 7 Conclusions and Future Work

Monitoring applications are those where streams of information, triggers, real-time requirements, and imprecise data are prevalent. Traditional DBMSs are based on the HADP model, and thus cannot provide adequate support for such applications. In this paper, we have described the architecture of Aurora, a DAHP system oriented towards monitoring applications. We argued that providing efficient support for these demanding applications not only require critically revisiting many existing aspects of database design and implementation, but also require developing novel proactive data storage and processing concepts and techniques.

In this paper, we first presented the basic Aurora architecture, along with the primitive building blocks for workflow processing. We followed with several heuristics for optimizing a large Aurora network. We then focused on run-time data storage and processing issues, discussing storage organization, real-time scheduling, introspection, and load shedding, and proposed novel solutions in all these areas.

We are currently implementing an Aurora prototype system, which we will use to investigate the practicality and efficiency of our proposed solutions. We are also investigating two important research directions. While the bulk of the discussion in this paper describes how Aurora works on a single computer, many stream-based applications demand support for distributed processing. To this end, we are working on a distributed architecture, Aurora*, which will enable operators to be pushed closer to the data sources, potentially yielding significantly improved scalability, energy use, and bandwidth efficiency. Aurora* will provide support for distribution by running a full Aurora system on each of a collection of communicating nodes. In particular, Aurora* will manage load by replicating boxes along a path and migrating a copy of this sub-network to another more lightly loaded node. A subset of the stream inputs to the replicated network would move along with the copy. We are also extending our basic data and processing model to cope with missing and imprecise data values, which are common in applications involving sensor-generated data streams.

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