Plan-based Complex Event Detection across Distributed Sources [*]

Mert Akdere
Brown University
makdere@cs.brown.edu

Uğur Çetintemel
Brown University
ugur@cs.brown.edu

Nesime Tatbul
ETH Zurich
tatbul@inf.ethz.ch

ABSTRACT

Complex Event Detection (CED) is emerging as a key capability for many monitoring applications such as intrusion detection, sensor-based activity & phenomena tracking, and network monitoring. Existing CED solutions commonly assume centralized availability and processing of all relevant events, and thus incur significant overhead in distributed settings. In this paper, we present and evaluate communication efficient techniques that can efficiently perform CED across distributed event sources.

Our techniques are *plan-based*: we generate multi-step event acquisition and processing plans that leverage temporal relationships among events and event occurrence statistics to minimize event transmission costs, while meeting application-specific latency expectations. We present an optimal but exponential-time dynamic programming algorithm and two polynomial-time heuristic algorithms, as well as their extensions for detecting multiple complex events with common sub-expressions. We characterize the behavior and performance of our solutions via extensive experimentation on synthetic and real-world data sets using our prototype implementation.

1. INTRODUCTION

In this paper, we study the problem of complex event detection (CED) in a monitoring environment that consists of potentially a large number of distributed event sources (e.g., hardware sensors or software receptors). CED is becoming a fundamental capability in many domains including network and infrastructure security (e.g., denial of service attacks and intrusion detection [22]) and phenomenon and activity tracking (e.g., fire detection, storm detection, tracking suspicious behavior [23]). More often than not, such sophisticated (or "complex") events "happen" over a period of time and region. Thus, CED often requires consolidating over time many "simple" events generated by distributed sources.

Existing CED approaches, such as those employed by stream processing systems [17, 18], triggers [1], and active databases [8], are based on a centralized, push-based event acquisition and processing model. Sources generate simple events, which are continually pushed to a processing site where the registered complex events are evaluated as continuous queries, triggers, or rules. This model is neither efficient, as it requires communicating all base events to the processing site, nor necessary, as only a small fraction of all base events eventually make up complex events.

This paper presents a new plan-based approach for communication-efficient CED across distributed sources. Given a complex event, we generate a cost-based multi-step detection plan on the basis of the temporal constraints among constituent events and event frequency statistics. Each step in the plan involves acquisition and processing of a subset of the events with the basic goal of postponing the monitoring of high frequency events to later steps in the plan. As such, processing the higher frequency events conditional upon the occurrence of lower frequency ones eliminates the need to communicate the former in many cases, thus has the potential to reduce the transmission costs in exchange for increased event detection latency.

Our algorithms are parameterized to limit event detection latencies by constraining the number of steps in a CED plan. There are two uses for this flexibility: First, the local storage available at each source dictates how long events can be stored locally and would thus be available for retrospective acquisition. Thus, we can limit the duration of our plans to respect *event life-times* at sources. Second, while timely detection of events is critical in general, some applications are more delay-tolerant than others (e.g., human-in-the-loop applications), allowing us to generate more efficient plans.

To implement this approach, we first present a dynamic programming algorithm that is optimal but runs in exponential time. We then present two polynomial-time heuristic algorithms. In both cases, we discuss a practical but effective approximation scheme that limits the number of candidate plans considered to further trade off plan quality and cost. An integral part of planning is cost estimation, which requires effective modeling of event behavior. We show how commonly used distributions and histograms can be used to model events with independent and identical distributions and then discuss how to extend our models to support temporal dependencies such as burstiness. We also study CED in the presence of multiple complex events and describe extensions that leverage shared sub-expressions for improved performance. We built a prototype that implements our algorithms; we use our implementation to quantify the behavior and benefits of our algorithms and extensions on a variety of workloads, using synthetic and real-world data (obtained from PlanetLab).

The rest of the paper is structured as follows. An overview of our event detection framework is provided in Section 2. Our plan-based approach to CED with plan generation and execution algorithms is described in Section 3. In Section 4, we discuss the details of our cost and latency models. Section 5 extends plan optimization to shared subevents and event constraints. We present our experimental results in Section 6, cover the related work in Section 7, and conclude with future directions in Section 8.

[*]This work has been supported by the National Science Foundation under Grant No. IIS-0448284 and CNS-0721703.

PVLDB '08, August 23-28, 2008, Auckland, New Zealand
Copyright 2008 VLDB Endowment, ACM 978-1-60558-305-1/08/08

2. BASIC FRAMEWORK

Events are defined as activities of interest in a system [10]. Detection of a person in a room, the firing of a cpu timer, and a Denial of Service (DoS) attack in a network are example events from various application domains. All events signify certain activities, however their complexities can be significantly different. For instance, the firing of a timer is instantaneous and simple to detect, whereas the detection of a DoS attack is an involved process that requires computation over many simpler events. Correspondingly, events are categorized as *primitive* (base) and *complex* (compound), basically forming an event hierarchy in which complex events are generated by composing primitive or other complex events using a set of event composition operators (Section 2.2).

Each event has an associated time-interval that indicates its occurrence period. For primitive events, this interval is a single point (i.e., identical start and end points) at which the event occurs. For complex events, the assigned intervals contain the time intervals of *all* subevents. This *interval-based semantics* better capture the underlying event structure and avoid some well-known correctness problems that arise with point-based semantics [9].

2.1 Primitive Events

Each event type (primitive and complex) has a schema that extends the base schema consisting of the following required attributes:

- **node_id** is the identifier of the node that generated the event.
- **event_id** is an identifier assigned to each event instance. It can be made unique for every event instance or set to a function of event attributes for *similar* event instances to get the same id. For example, in an RFID-enabled library application a book might be detected by multiple RFID receivers at the same time. Such readings can be discarded if they are assigned the same event identifier.
- **start_time** and **end_time** represent the time interval of the event and are assigned by the system based on the event operator semantics explained in the next subsection. These time values come from an ordered domain.

Primitive event declarations specify the details of the transformation from raw source data into primitive events. The syntax is:

primitive `name`
on `source_list`
schema `attribute_list`

Each primitive event is assigned a unique name using `name`. The set of sources used in a primitive event is listed in the `source_list`. The schema component expresses the names and domains of the attributes of the primitive event type and automatically inherits the attributes in the base schema.

An example primitive event, expressing the detection of a person, is shown below together with the declaration of a *person_detector* source (e.g., a face detection module running on a smart camera).

source person_detector
schema int id, double loc_x, double loc_y

primitive person_detected
on person_detector as PD, node
schema event_id **as** hash_f(person_detected, node.id, node.time, PD.id),
loc **as** [PD.loc_x, PD.loc_y],
person_id **as** PD.id

We use the pseudo-source `node` that enables access to context information such as the location of the source and the current value of node clock. We use a hash function, `hash_f`, to generate unique ids for event instances. Similar to its use in SQL, **as** describes how an attribute is derived from others.

2.2 Event Composition

Complex events are specified on simpler events using the syntax:

complex `name`
on `source_list`
schema `attribute_list`
event `event_expression`
where `constraint_list`

A unique name is given to each complex event type using the `name` attribute. Subevents of a complex event type, which can be other complex or primitive events, are listed in `source_list`. As in primitive events, the source list may contain the `node` pseudo-source as well. The `attribute_list` contains the attributes of a complex event type that together form a super set of the base schema and describes the way they are assigned values. In other words, the schema specifies the transformation from subevents to complex events.

We use a standard set of event composition operators for easy specification of complex event expressions in the `event` clause. Our event operators, `and`, `or` and `seq`, are all *n-ary* operators extended with *time window* arguments. The time window, w, of an event operator specifies the maximum time duration between the occurrence of any two subevents of a complex event instance. Hence, all the subevents are to occur within w time units. In addition, we allow non-existence constraints to be expressed on the subevents inside `and` and `seq` operators using the negation operator `!`. Negation cannot be used inside an `or` operator or on its own as negated events only make sense when used together with non-negated events.

Formal semantics of our operators are provided below. We denote subevents with $e_1, e_2, \ldots, e_n$ and the start and end times of the output complex event with t_1 and t_2.

- **and**$(e_1, e_2, \ldots, e_n; w)$ outputs a complex event with $t_1 = min_i$ $(e_i.start\_time)$, $t_2 = max_i(e_i.end\_time)$ if $max_{i,j}$ $(e_i.end\_time - e_j.end\_time) <= w$. Note that the subevents can happen in any order.
- **seq**$(e_1, e_2, \ldots, e_n; w)$ outputs a complex event with $t_1 = e_1.start\_time$, $t_2 = e_n.end\_time$ if (i) $\forall i$ in $1, \ldots, n-1$ we have $e_i.end\_time < e_{i+1}.start\_time$ and (ii) $e_n.end\_time - e_1.end\_time \leq w$. Hence, `seq` is a restricted form of `and` where events need to occur in order without overlapping.
- **or**$(e_1, e_2, \ldots, e_n)$ outputs a complex event when a subevent occurs. t_1 and t_2 are set to start and end times of the subevent. Note that this operator does not require a window argument.
- **negation** (i) For `and(`$e_1, e_2, .., !e_i, .., e_n; w$`)`, we need $\nexists\, e_i$: max_j $(e_j.end\_time) - w \leq e_i.end\_time \leq min_j$ $(e_j.end\_time) + w$ where j ranges over the indices of the non-negated subevents.

  (ii) For `seq(`$e_1, e_2, .., !e_i, .., e_n; w$`)`, if $i \notin \{1, n\}$, we need to have $\nexists\, e_i : e_p.end\_time \leq e_i.end\_time \leq e_q.start\_time$ where e_p and e_q are the previous and next non-negated subevents for e_i. If $i = 1$ (i.e. negated start [7]), we need to have $\nexists\, e_i : e_n.end\_time - w \leq e_i.end\_time \leq e_2.start\_time$. And finally if $i = n$ (i.e. negated end) we need $\nexists\, e_i : e_{n-1}.end\_time \leq e_i.end\_time \leq e_1.end\_time + w$. At least one of the subevents in a complex event should be left non-negated.

In most applications, users will be interested in complex events that impose additional constraints on their subevents. For instance, users may be interested in events occurring in nearby locations. Our system allows the expression of such spatial constraints in the `where` clause of the event specifications. Moreover, parameterized attribute-based constraints between events and value-based comparison constraints can be specified in the where clause as well. We illustrate the use of the constraints through the following "running person" complex event.

```
complex running_person
     on person_detected as PD1,person_detected as PD2, node
 schema event_id as hash_f(running_person, node.id,
                           node.time, person_id),
        loc as PD2.loc,
        person_id as PD1.person_id
  event seq(PD1,PD2;3)
  where PD1.person_id = PD2.person_id
        and distance(PD1.loc, PD2.loc) ≥ 12
```

2.3 Event Detection Graphs

Our event detection model is based on *event detection graphs* [8]. For each event expression, we construct an event detection tree. These trees are then merged to form the event detection graph. Common events in different event trees, which we refer to as shared events, are merged to form nodes with multiple parents. Nodes in an event detection graph are either operator nodes or primitive event nodes. The non-leaf nodes, operator nodes which execute the event language operators on their inputs, are the operator nodes. The inputs to operator nodes are either complex or primitive events. and their outputs are complex The leaf nodes in the graph are primitive event nodes. A primitive event node exists for each primitive event type and stores references to the instances of that primitive event type.

2.4 System Architecture

The main components in our system are the event *sources* and the *base* node (Figure 1). Sources generate events; e.g., routers and firewalls in a network monitoring application and a temperature sensor in a disaster monitoring application are examples. Sources have local storage that allows them to log events of interest temporarily. These logs can be queried and events be acquired when necessary. In practice, some event sources may not have any local storage or be autonomous and outside our control (e.g., RSS sources on the web). In such cases, we rely on *proxy* nodes that provide these capabilities on their behalf. Thus, we use the term *source* when referring to either the original event source or its proxy.

The base station is responsible for generating and executing CED plans. Plan execution involves coordination with event sources as events are transmitted upon demand from the base. Consequently, our system combines the pull and push paradigms of data collection to avoid the disadvantages of a purely push-based system. The CED plans we generate strive to reduce the network traffic towards the base station by carefully choosing which sources will transmit what events.

3. PLANNING FOR EFFICIENT CED

3.1 Event Detection Plans: Overview

A common approach to event detection would be to continuously transmit all the events to the base where they would be processed as soon as possible. This push-based approach is typical of continuous query processing systems (e.g., [17, 18, 19]). From an efficiency point of view, this approach leads to a hot-spot at the base and significant resource consumption at sources for event transmission. From a semantic point of view, many applications do not require access to all "raw" events but only a small fraction of the relevant ones. *Our goal is to avoid continuous global acquisition of data without missing any complex events of interest, as specified by the users.*

To achieve this goal, we use *event detection plans* to guide the event acquisition decisions. Event detection plans specify multi-step event acquisition strategies that reduce network transmission costs. The simplest plan, which corresponds to the push-based approach, consists of a single step in which all subevents are simultaneously monitored (referred to as the *naive plan* in the sequel). More complex plans have up to *n* steps, where *n* is the number of subevents, each involving the monitoring of a subset of events. The number of plans for a complex event defined using `and` or `seq` operators over *n* primitive subevents is exponential in *n* as given by the recursive relation $T(n) = \sum_{i=1}^{n} \binom{n}{i} T(n-i)$, where we define $T(0)$ to be 1.

To demonstrate the basic idea behind the event detection plans, consider a simple complex event `and`$(e_1, e_2; w)$. The transmission cost when using the naive plan for monitoring this event would be the total cost for transmitting every instance of e_1 and e_2. On the other hand, a two-step plan, where we continuously monitor e_1 and acquire the instances of e_2 (which are within w of an instance of e_1) through pull requests when necessary, could cost less. However, observe that the two-step plan would incur higher detection latency than the naive plan, which offers the minimum possible latency. Studying this tradeoff between cost and latency is an important focus of our work: we aim to find low-cost event detection plans that meet event-specific latency expectations.

We use a *cost-latency model* based on event occurrence probabilities to calculate the expected costs and latencies of candidate event detection plans. We define the *expected cost of a plan* as the expected number of events the plan asks nodes to send to the base per time unit. We expect transmission costs to be the bottleneck for many networked systems, especially for sensor networks with thin, wireless pipes. Even with Internet-based systems, bandwidth problems arise, especially around the base, with increasing event generation rates. Additionally, we define the *latency of a plan* for a complex event as the time between the occurrence of the event and its detection by the system executing the plan. We assume that there is an estimated latency to access each event source and that detection latencies are dominated by network latencies, thus ignoring the event processing costs at the base station. However, since we strive to decrease the number of events sent to base, our approach should reduce *both* network and processing costs. Note that we abstractly define both metrics to avoid overspecializing our results to particular system configurations and protocol implementations.

As briefly mentioned earlier, event latency constraints may originate from two different sources. First, we may have user specified, explicit latency deadlines based on application requirements. Second, latency deadlines can arise from limited data logging capabilities: an event source may be able to store events only for a limited time before it runs out of space and has to delete data. Therefore, a plan that assumes the availability of events for longer periods is not going to be useful. In practice, we can consider both cases and use the most strict latency target for a complex event.

Let's summarize some key assumptions we make in the rest of the paper. First, we assume event sources are time-synchronized, as otherwise there might be false/missed event detections. Second, we bound the maximum network latency for events and use timeout mechanisms for event detection. Finally, event delivery is assumed to be reliable.

We represent our plans with extended finite state machines (FSMs). Consider the complex event `and`$(e_1, e_2, e_3;\ w)$ where e_1, e_2, e_3 are primitive events and *w* is the window size. There are T(3) = 13 different detection plans for this complex event. State machines of the plans for this complex event have at most $n = 3$ states (except the final state) representing the monitoring order specified by the plan, in each of which a subset of primitive events is monitored. One state machine of each size is given in Figure 2. For instance, the 3-step monitoring plan: "First, continuously monitor e_1, then on e_1 lookup e_2, and finally on e_1 and e_2 lookup e_3", is illustrated in Figure 2(c), where the notation $e_1 \rightarrow e_2 \rightarrow e_3$ is used to denote this plan.

The FSMs we use for representing plans are *nondeterministic*, since they can have multiple active states at a time. Every active state corresponds to a partial detection of the complex event. For example, in state S_{e_1} of the plan given in Figure 2(c), there can be active in-

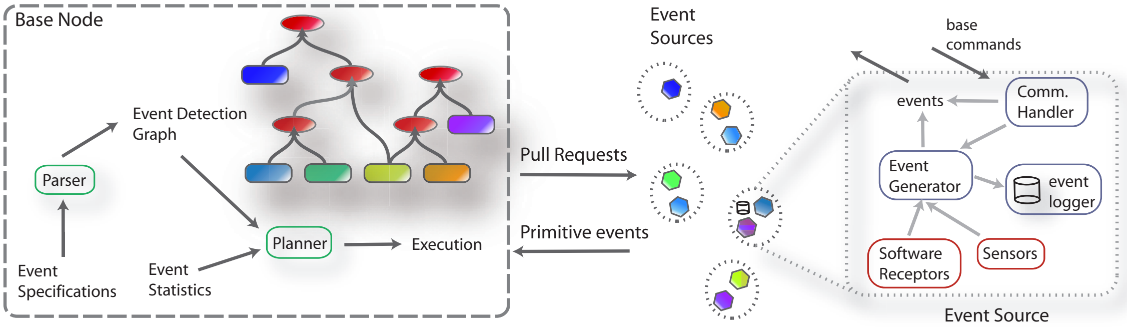
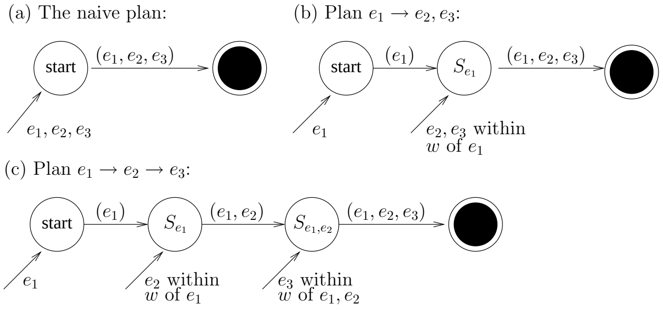


Figure 1: Complex event detection framework: The base node plans and coordinates the event detection using low network cost event detection plans formed by utilizing event statistics. The event detection model is an event detection graph generated from the given event specifications. Information sources feed the system with primitive events and can operate both in pull and push based modes.

stances of e_1 waiting for instances of e_2. When an instance of e_2 is detected, in addition to the transition to next state, a self-transition will also occur so that an instance of e_1 can match multiple instances of e_2 (self-transitions are not shown in the figure). Unlike the initial state that is always active, intermediate states are active only as long as the windowing constraints among event instances are met.


(a) The naive plan:

(b) Plan $e_1 \rightarrow e_2, e_3$:

(c) Plan $e_1 \rightarrow e_2 \rightarrow e_3$:

Figure 2: Event detection plans represented as finite state machines

3.2 Plan Generation

We now describe how event detection plans are generated with the goal of optimizing the overall monitoring cost while respecting latency constraints. First, we consider the problem of plan generation for a complex event defined by a single operator. We provide two algorithms for this problem: a dynamic programming solution and a heuristic method (in sections 3.2.1 and 3.2.2, respectively). Then, in section 3.2.3, we generalize our approach to more complicated events by describing a hierarchical plan generation method that uses as building blocks the candidate plans generated for simpler events. The dynamic programming algorithm can find optimal plans and achieve the minimum global cost for a given latency. However, it has exponential time complexity and is thus only applicable to small problem instances. The heuristic algorithm, on the other hand, runs in polynomial time and, while it cannot guarantee optimality, it produces near optimal results for the cases we studied (Section 6).

3.2.1 The dynamic programming approach

The input to the dynamic programming (DP) plan generation algorithm is a complex event C defined over the subevents S and a set of plans for monitoring each subevent. For the primitive subevents, the only possible monitoring plan is the single step plan, whereas for the complex subevents there can be multiple monitoring plans. Given these inputs, the DP algorithm produces a set of *pareto optimal* plans for monitoring the complex event C. These plans will then be used in the hierarchical plan generation process to produce plans for higher-level events (Section 3.2.3).

A plan is *pareto optimal* if and only if no other plan can be used to reduce cost or latency without increasing the other metric.

Definition 1. A plan p_1 with cost c_1 and latency l_1 is *pareto optimal* if and only if $\nexists\, p_2$ with cost c_2 and latency l_2 such that $(c_1 > c_2$ and $l_1 \geq l_2)$ or $(l_1 > l_2$ and $c_1 \geq c_2)$.

The DP solution to plan generation is based on the following *pareto optimal substructure property*: Let $t_i \subseteq S$ be the set of subevents monitored in the i^{th} step of a pareto optimal plan p for monitoring C. Define p_i to be the subplan of p, consisting of its first i steps used for monitoring the subevents $\cup_{j=1}^{i} t_j$. Then the subplan p_{i+1} is simply the plan p_i followed by a single step in which the subevents t_{i+1} are monitored. The pareto optimal substructure property can then be stated as: if p_{i+1} is pareto optimal then p_i must be pareto optimal. We prove the pareto optimal substructure property below with the assumption that "reasonable" cost and latency models are being used (that is both cost and latency values are monotonously increasing with increasing subevents).

PROOF : PARETO OPTIMAL SUBSTRUCTURE. Let the cost of p_i be c_i and its latency be l_i. Assume that p_i is not pareto optimal. Then by definition $\exists p_i'$ with cost c_i' and latency l_i' such that $(c_i > c_i'$ and $l_i \geq l_i')$ or $(l_i > l_i'$ and $c_i \geq c_i')$. However, then p_i' could be used to form a p_{i+1}' such that $(c_{i+1} > c_{i+1}'$ and $l_{i+1} \geq l_{i+1}')$ or $(l_{i+1} > l_{i+1}'$ and $c_{i+1} \geq c_{i+1}')$ which would contradict the pareto optimality of p_{i+1}. □

This property implies that, if p, the plan used for monitoring the complex event C, is a pareto optimal plan, then p_i for all i, must be pareto optimal as well. Our dynamic programming solution leveraging this observation is shown in Algorithm 1 for the special case where all the subevents are primitive. Generalization of this algorithm to the case with complex subevents (not shown here due to space constraints) basically requires repeating the lines between 6 and 15 for all possible plan configurations of monitoring events in set s in a single step. After execution, all pareto optimal plans for the complex event C will be in $poplans[S]$, where $poplans$ is the pareto optimal plans table. This table has exactly $2^{|S|}$ entries, one for each subset of S. Every entry stores a list of pareto optimal plans for monitoring the corresponding subset of events. Moreover, the addition of a plan to an entry $poplans[s]$ may render another plan in $poplans[s]$ non-pareto optimal. Hence, when adding a pareto optimal plan to the list (line 12), we remove the non-pareto optimal ones.

At iteration i of the plength for loop, we are generating plans of length (number of steps) i, whose first $i-1$ steps consist of the events in set $j \subseteq t$ and last step consists of the events in set s. Therefore, in the i^{th} iteration of the plength for loop, we only need to consider the sets s and j that satisfy:

$$|t| + 1 \geq i \Rightarrow |t| \geq i - 1 \quad (1)$$

$$\Rightarrow |t| = |S| - |s| \geq i - 1 \Rightarrow |s| \leq |S| - i + 1 \quad (2)$$

$$|j| \geq i - 1 \quad (3)$$

Algorithm 1 Dynamic programming solution to plan generation

```
Input: S = $\{e_1, e_2, \ldots, e_N\}$
for plength $= 1$ to $|S|$ do
  for all s $\in 2^S \setminus \emptyset$ do
    p = new plan
    t = S $\setminus$ s
    if plength ! $= 1$ then
      for all j $\in 2^t \setminus \emptyset$ do
        for all plan $p_j$ in poplans[$j$] do
          p.steps = $p_j$.steps
          p.steps.add(new step(s))
          if p is pareto optimal for poplans[$s \cup j$] then
            poplans[$s \cup j$].add(p)
    else
      p.steps.add(new step(s))
      poplans[s].add(p)
```

Otherwise, at iteration i, we would redundantly generate the plans with length less than i. However, for simplicity we do not include those constraints in the pseudocode shown in Algorithm 1 as they do not change the correctness of the algorithm.

Finally, the analysis of the algorithm (for the case of primitive subevents) reveals that its complexity is $O(|S|2^{2|S|}k)$, where the constant k is the maximum number of pareto optimal plans a table entry can store. When the number of pareto optimal plans is larger than the value of k: (i) non-pareto optimal plans may be produced by the algorithm, which also means we might not achieve global optimum and; (ii) we need to use a strategy to choose k plans from the set of all pareto optimal plans. To make this selection, we explored a variety of strategies such as naive random selection, and selection ranked by cost, latency or their combinations. We discuss these alternatives and experimentally compare them in Section 6.

3.2.2 Heuristic techniques

Even for moderately small instances of complex events, enumeration of the plan space for plan generation is not a viable option due to its exponential size. As discussed earlier, the dynamic programming solution requires exponential time as well. To address this tractability issue, we have come up with a strategy that combines the following two heuristics, which together generate a representative subset of all plans with distinct cost and latency characteristics:

- Forward Stepwise Plan Generation: This heuristic starts with the minimum latency plan, a single-step plan with the minimum latency plan selected for each complex subevent, and repeatedly modifies it to generate lower cost plans until the latency constraint is exceeded or no more modifications are possible. At each iteration, the current plan is transformed into a lower cost plan either by moving a subevent detection to a later state or replacing the plan of a complex subevent with a cheaper plan.

- Backward Stepwise Plan Generation: This heuristic starts by finding the minimum cost plan, i.e., an n-step plan with the minimum cost plan selected for each complex subevent, where n is the number of subevents. This plan can be found in a greedy way when all subevents are primitive, otherwise a nonexact greedy solution which orders the subevents in increasing $cost \times occurrence\ frequency$ order can be used. At each iteration, the plan is repeatedly transformed into a lower latency plan either by moving a subevent to an earlier step or changing the plan of a complex subevent with a lower latency plan, until no more alterations are possible.

Thus, the first heuristic starts with a single-state FSM and grows it (i.e., adds new states) in successive iterations, whereas the second one shrinks the initially n-state FSM (i.e., reduces the number of states). Moreover, both heuristics are greedy as they choose the move with the highest cost-latency gain at each iteration and both finish in a finite number of iterations since the algorithm halts as soon as it cannot find a move that results in a better plan. Thus, the first heuristic aims to generate low-latency plans with reasonable costs, and the latter strives to generate low-cost plans meeting latency requirements complementing the other heuristic.

As a final step, the plans produced by both heuristics are merged into a feasible plan set, one that meets latency requirements. During the merge, only the plans which are pareto optimal within the set of generated plans are kept. As is the case with the dynamic programming algorithm, only a limited number of these plans will be considered by each operator node for use in the hierarchical plan generation algorithm. The selection of this limited subset is performed as discussed in the previous subsection.

3.2.3 Hierarchical plan composition

Plan generation for a multi-level complex event proceeds in a hierarchical manner in which the plans for the higher level events are built using the plans of the lower level events. The process follows a depth-first traversal on the event detection graph, running a plan generation algorithm at each node visited. Observe that using only the minimum latency or the minimum cost plan of each node does not guarantee globally optimal solutions, as the global optimum might include high-cost, low-latency plans for some component events and low-cost, high-latency plans for the others. Hence, each node creates a set of plans with a variety of latency and cost characteristics. The plans produced at a node are propagated to the parent node, which uses them in creating its own plans.

The DP algorithm produces exclusively pareto optimal plans, which are essential since *non-pareto optimal plans lead to suboptimal global solutions* (the proof, which is not shown here, follows a similar approach with the pareto optimal substructure property proof in section 3.2.1). Moreover, if the number of pareto optimal plans submitted to parent nodes is not limited, then using the DP algorithm for each complex event node we can find the global optimum selection of plans (i.e., plans with minimum total cost subject to the given latency constraints). Yet, as mentioned before, the size of this pareto optimal subset is limited by a parameter trading computation with the explored plan space size. On the other hand, the set of plans produced by the heuristic solution does not necessarily contain the pareto optimal plans within the plan space. As a result, even when the number of plans submitted to parent nodes is not limited, the heuristic algorithm still does not guarantee optimal solutions. The plan generation process continues up to the root of the graph, which then selects the minimum cost plan meeting its latency requirements. This selection at the root also fixes the plans to be used at each node in the graph.

3.3 Plan Execution

Once plan selection is complete, the set of primitive events which are to be monitored continuously according to the chosen plans are identified and activated. When a primitive event arrives at the base station, it is directed to the corresponding primitive event node. The primitive event node stores the event and then forwards a pointer of the event to its active parents. An active parent is one which according to its plan is interested in the received primitive event (i.e. the state of the parent node plan which contains the child primitive event is active). Observe that there will be at least one active parent node for each received primitive event, namely the one that activated the monitoring of the primitive event.

Complex event detection proceeds similarly in the higher level nodes. Each node acts according to its plan upon receiving events either by activating subevents or by detecting a complex event and passing it along to its parents. Activating a subevent includes expressing a time interval in which the activator node is interested in the detection of the subevent. This time interval could be in the past, in which case previously detected events are to be requested from event sources, or in the immediate future in which case the event detectors should start monitoring for event occurrences.

A related issue that has been discussed mainly in the active database literature [5, 9] is *event instance consumption*. An event consumption policy specifies the effects of detecting an event on the instances of that event type's subevents. Options range from highly-restrictive consumption policies, such as those that allow each event instance to be part of only a single complex event instance, to non-restrictive policies that allow event instances to be shared arbitrarily by any number of complex events. Because the consumption policy affects the set of detected events, it affects the monitoring cost as well. Our results in this paper are based on the non-restrictive policy — using more restrictive policies will further reduce the monitoring cost.

Observe that, independent of the consumption policy being used, the events which are guaranteed not to generate any further complex events due to window constraints can always be consumed to save space. Hence, both the base and the monitoring nodes need only store the event instances for a limited amount of time as specified by the window constraints.

4. COST-LATENCY MODELS

The cost model uses event occurrence probabilities to derive expected costs for event detection plans. Our cost model is not strictly tied to any particular probability distribution. In this section, we provide the general cost model, and also derive the cost estimations for two commonly-used probability models: *Poisson* and *Bernoulli* distributions. Moreover, nonparametric models can be easily plugged-in as well, e.g., histograms can be used to directly calculate the probability values in the general cost model if the event types do not fit well to common parametric distributions. Model selection techniques, such as Bayesian model comparison [13], can be utilized to select a probability model out of a predefined set of models for each event type. We first assume independent event occurrences and later relax this assumption and discuss how to capture dependencies between events.

For latency estimation, we associate each event type with a latency value that represents the maximum latency its instances can have. Here, we consider identical latencies for all primitive event types for simplicity. However, different latency values can be handled by the system as well.

Poisson distributions are widely used for modeling discrete occurrences of events such as receipt of a web request, and arrival of a network packet. A Poisson distribution is characterized by a single parameter λ that expresses the average number of events occurring in a given time interval. In our case, we define λ to be the occurrence rate for an event type in a single time unit. In addition, our initial assumption that events have independent occurrences means that the event occurrences follows a Poisson process with rate λ. When modeling an event type e with the Bernoulli distribution, e has independent occurrences with probability p_e at every time step, provided that the occurrence rate is less than 1.

As described before, an event detection plan consists of a set of states each of which corresponds to the monitoring of a set of events. The cost of a plan is the sum of the costs of its states weighted by state reachability probabilities. The cost of a state depends on the cost of the events monitored in that state. The reachability probability of a state is defined to be the probability of detecting the partial complex event that activates that state. For instance, in Figure 2c, the event that activates state S_{e_1} is e_1. State reachability probabilities are derived using interarrival distributions of events. When using a Poisson process with parameter λ to model event occurrences, the interarrival time of the event is exponentially distributed with the same parameter. Hence, the probability of waiting time for the first occurrence of an event to be greater than *t* is given by $e^{-\lambda t}$. On the other hand, the interarrival times have geometric distribution for the Bernoulli case. The reachability probability for initial state is 1 since it is always active and the probability for final state is not required for cost estimation. Below, we consider the monitoring cost and latency of a simple complex event as an example.

Example: We define the event *and*$(e_1, e_2, e_3; w)$ where e_1, e_2 and e_3 are primitive events with Δt latency and use Poisson processes with rates λ_{e_1}, λ_{e_2} and λ_{e_3} to model their occurrences. First, we consider the naive plan in which all subevents are monitored at all times. Its cost is simply the sum of the rates of the subevents: $\sum_{i=1}^{3} \lambda_{e_i}$, whereas its latency is the maximum latency among the subevents: Δt. The cost derivation for the three step plan $e_1 \to e_2 \to e_3$ (Figure 2c) is more complex. Using the interarrival distributions for the reachability probabilities the cost of the three step plan is given by:

$$\text{cost for } e_1 \to e_2 \to e_3 = \lambda_{e_1} + (1 - e^{-\lambda_{e_1}})2w\lambda_{e_2} +$$
$$((1 - e^{-\lambda_{e_1}})(1 - e^{-w\lambda_{e_2}}) + (1 - e^{-\lambda_{e_2}})(1 - e^{-w\lambda_{e_1}}))2w\lambda_{e_3}$$

The plan has $3\Delta t$ latency since this is the maximum latency it exhibits (for instance, when the events occur in the order e_3, e_2, e_1 or e_2, e_3, e_1). For simplicity, we do not include the latencies for the pull requests in this paper. However, observe that the pull requests do not necessarily increase the latency of event detection as they may be requests for monitoring future events or their latencies may be suppressed by other events. In the cost equation above and the rest of the paper, we omit the cost terms originating from events occurring in the same time step, assuming that we have a sufficiently fine-grained time model. We do not model the cost reduction due to possible overlaps in monitoring intervals of multiple pull requests, although in practice each event is pulled at most once.

4.1 Operator-specific Models

Below we discuss cost-latency estimation for each operator first for the case where all subevents are primitive and are represented by the same distribution, and then for the more general case with complex subevents. Allowing different probability models for subevents requires using the corresponding model for each subevent in calculating the probability terms, complicating primarily the treatment of the sequence operator, as sums of random variables can no longer be calculated in closed forms.

And Operator. Given the complex event *and*$(e_1, e_2, \ldots, e_n; w)$, a detection plan with $m + 1$ states S_1 through S_m, and the final state S_{m+1}, we show the cost derivation both for Poisson and Bernoulli distributions below. For event e_j we represent the Poisson process parameter with λ_{e_j} and the Bernoulli parameter with p_{e_j}.

The general cost term for and with n operands is given by $\sum_{i=1}^{m} P_{S_i} \times cost_{S_i}$ where P_{S_i} is the state reachability probability for state S_i and $cost_{S_i}$ represents the cost of monitoring subevents of state S_i for a period of length $2W$. In the case that all subevents are primitive $cost_{S_i} = \sum_{e_j \in S_i} 2W\lambda_{e_j}$ when Poisson processes are used and $cost_{S_i} = \sum_{e_j \in S_i} 2Wp_{e_j}$ for Bernoulli distributions.

P_{S_i}, the reachability probability for S_i, is equal to the occurrence probability of the partial complex event that causes the transition to state S_i. For this partial complex event to occur in the "current" time step, all its constituent events need to occur within the last W time units with the last one occurring in the current time step (otherwise the event would have occurred before). Then, P_{S_i} is 1 when *i* is 1 and for $m \geq i > 1$ is given for Poisson processes (i) and Bernoulli distributions (ii) by:

$$\text{(i)} \quad \sum_{e_j \in \bigcup_{k=1}^{i-1} S_k} (1 - e^{-\lambda_{e_j}}) \prod_{\substack{e_t \neq e_j \\ e_t \in \bigcup_{k=1}^{i-1} S_k}} (1 - e^{-\lambda_{e_t} W})$$

$$\text{(ii)} \quad \sum_{e_j \in \bigcup_{k=1}^{i-1} S_k} p_{e_j} \prod_{\substack{e_t \neq e_j \\ e_t \in \bigcup_{k=1}^{i-1} S_k}} (1 - (1 - p_{e_t})^W)$$

Under the identical latency assumption, the latency of a plan for *and* operator is defined by the number of the states in the plan (except the final state). Hence, the latency of a plan for the event *and(*$e_1, e_2, \ldots, e_n$*)* can range from Δt to $n\Delta t$.

Sequence Operator. We can consider the same set of plans for seq as well. However, sequence has the additional constraint that events have to occur in a specific order and must not overlap. Therefore, the time interval to monitor a subevent depends on the occurrence times of other subevents.

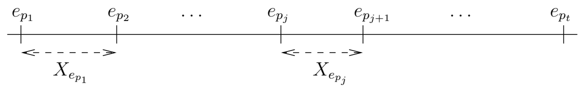


Figure 3: subevents for $seq(e_{p_1}, e_{p_2}, \ldots, e_{p_t}; w)$

The expected cost of monitoring the complex event $seq(e_1, e_2, \ldots, e_n; w)$ using a plan with $m + 1$ states has the same form $\sum_{i=1}^{m} P_{S_i} \times cost_{S_i}$. Let $seq(e_{p_1}, e_{p_2}, \ldots, e_{p_t}; w)$ with $t \leq n$ and $p_1 < p_2 < \ldots < p_t$ be the partial complex event consisting of the events before state S_i, i.e. $\cup_{k=1}^{i-1} S_k = \{e_{p_1}, e_{p_2}, \ldots, e_{p_t}\}$. Then

1. P_{S_i} is equal to the occurrence probability of $seq(e_{p_1}, e_{p_2}, \ldots, e_{p_t}; w)$ at a time point. For this complex event to occur subevents has to be detected in sequence as in Figure 3 within W time units. We define the random variable $X_{e_{p_j}}$ to be the time between $e_{p_{j+1}}$ and the occurrence of e_{p_j} before $e_{p_{j+1}}$ (see Figure 3). Then, $X_{e_{p_j}}$ is exponentially distributed with $\lambda_{e_{p_j}}$ if we are using Poisson processes, or has geometric distribution with $p_{e_{p_j}}$ when using Bernoulli distributions.

   For the Poisson case, we have $P_{S_i} =$ (1-$e^{-\lambda_{e_{p_t}}}$) (1-R(W)) where R(W) = P($\sum_{j=1}^{t-1} X_{e_{p_j}} \geq$ W). Closed form expressions for $R(W)$ are available [15]. For the Bernoulli case, $P_{S_i} = p_{e_{p_t}}(1 - R(W))$ where $R(W)$ is defined on a sum of geometric random variables. In this case, there is no parametric distribution for $R(W)$ unless the geometric random variables are identical. Hence, it has to be numerically calculated.

2. Any event e_{i_k} of state S_i should either occur (i) between e_{p_j} and $e_{p_{j+1}}$ for some j or (ii) before e_{p_1} or after e_{p_t} depending on the sequence order. In case *i*, we need to monitor e_{i_k} between e_{p_j} and $e_{p_{j+1}}$ for $X_{e_{p_j}}$ time units (see Figure 3). For case *ii* we need to monitor the event for $W - \sum_{j=1}^{t-1} X_{e_{p_j}}$ time units. In the cost estimation, we use the expectation values E[$X_{e_{p_j}} \mid \sum_{k=1}^{t-1} X_{e_{p_k}} \leq W$] and $W -$ E[$\sum_{k=1}^{t-1} X_{e_{p_k}} \mid \sum_{k=1}^{t-1} X_{e_{p_k}} \leq W$] for estimating $L_{e_{i_k}}$, the monitoring interval. Then $cost_{S_i}$ is $\sum_{e_{i_k} \in S_i} L_{e_{i_k}} \lambda_{e_{i_k}}$ with Poisson processes and $\sum_{e_{i_k} \in S_i} L_{e_{i_k}} p_{e_{i_k}}$ with Bernoulli distributions.

The latency for sequence depends only on the latency of the events which are in the same state with the last event (e_n) or are in later states if we ignore the unlikely cases where the latency of the events in earlier states are so high that the last event might occur before they are received. If the sequence event is being monitored with an m-step plan where the j^{th} step contains e_n, then its latency is $(m - j + 1)\Delta t$. This latency difference between and and seq exists because unlike seq, with and any of the subevents can be the last event that causes the occurrence. This discontinuity in latency introduced by the last event in sequence seems to create an exception for the DP algorithm as the pareto optimal substructure property depends on non-decreasing latency values for the plans formed from smaller subplans. However, in such cases, the pareto optimal plans will include only the minimum cost subplans for monitoring the events in earlier states than e_n, and because one of the minimum cost subplans will always be pareto optimal, DP will still find the optimal.

Negation Operator. In our system, negation can be used on the subevents of *and* and *seq* operators. The plans we consider for such complex events (in addition to the naive plan) resemble a filtering approach. First, we detect the partial complex event consisting of non-negated subevents only. When that complex event is detected, we monitor the negated subevents. The detection plans for the complex event defined by non-negated events is then the same with the plans for *and* and *seq* operators. The same set of plans can be considered for negated events as well. However, we now have to look for the absence of an event instead of its presence. The cost estimations for *and* and *seq* operators can be applied here by changing the occurrence probabilities with nonoccurrence probabilities. Finally, to generate plans for events involving the negation operator, both plan generation algorithms (Section 3.2) have been modified such that at any point during their execution the set of generated plans is restricted to the subset of plans that match the described criteria.

Or Operator. As discussed before, or generates a complex event for every event instance it receives. Hence, the only detection plan for *or* operator is the *naive* plan. The cost of the naive plan is the sum of the costs of the subevents and its latency is the highest latency among the subevents.

Generalization to Complex Subevents: Given a plan for a complex event E, we are given a specific plan to use in monitoring each subevent and an order for monitoring them. For the complex subevents of E, which generally provide multiple monitoring plans, this means that a particular plan among the available plans is being considered. Also as the occurrence probability of a subevent is independent of the plan it is being monitored with, the only difference between distinct plans is the latency and cost values.

For seq, the presented cost model is still valid in the presence of complex subevents. For and, minor changes are required for dealing with complex subevents. The *and* operator requires only the end points of complex subevents to be in the window interval. Therefore, the complex subevents could have start times before the window interval and, as such, some of their subevents could originate outside the window interval. As a result, the monitoring of the subevents of the complex subevents extend beyond the window interval. In such cases, we calculate an estimated monitoring interval based on the window values of event E and its corresponding complex subevent. As negation operator has a single operand and is directly applied on *and* and *seq* operators, no changes are required for it. Finally, the or operator requires the same modifications with *and* operator.

4.2 Addressing Event Dependencies

The cost model presented in Section 4.1 makes the independent and identical distribution (i.i.d.) assumption for the instances of an event type. This assumption simplifies the cost model and reduces the required computation for the plan costs. However, for certain types of events the i.i.d. assumption may be restrictive. A very general subclass of such event types is the event types involving sequential patterns across time. As an example, consider the *bursty behavior* of the corrupted bits in network transmissions. While a general solution that models event dependencies is outside the scope of this paper, we take the first step towards a practical solution.

To illustrate the effects of this sequential behavior on the cost model and plan selection we provide the following example scenario, which we verified experimentally. Consider the complex event $and(e_1, e_2; w)$ where e_1 and e_2 are primitive events with e_1 exhibiting bursty behavior. Also assume that e_1 has a lower occurrence rate than e_2. When the cost model makes the i.i.d. assumption and the occurrence rates of e_1 and e_2 are high enough, it decides to use the naive plan as no multi-step plan seems to provide lower cost. However, when we use a Markov model (as described below) for modeling the bursty behavior of e_1, the cost model finds out that the 2-step plan $e_1 \rightarrow e_2$ has much less cost since most of the instances of e_1 occur in close proximity and therefore require monitoring of e_2 at overlapping time intervals.

One of the most commonly used and simplest approaches to modeling dependencies between events is the Markov models. We discuss an m^{th} order discrete-time Markov chain in which occurrence of an event in a time step depends only on the last m steps. This is generally a nonrestrictive assumption as recent event instances are likely to be more revealing and not all the previous event instances are relevant. We build this model on the Bernoulli cost model.

Denoting the occurrence of the event type e_1 at time t as a binary random variable e_1^t, we have $P(e_1^t|e_1^1, e_1^2, .., e_1^{t-1}) = P(e_1^t|e_1^{t-m}, .., e_1^{t-1})$. Such an m^{th} order Markov chain can be represented as a first order Markov chain by defining a new variable y as the last m values of e_1 so that the chain follows the well-known Markov property. Then, we can define the Markov chain by its transition matrix, P, mapping all possible values of the last m time steps to possible next states. The stationary distribution of the chain, $\bar{\pi}$, can be found by solving $\bar{\pi}P = \bar{\pi}$. In this case, modifying the cost model to use the Markov chain requires one to use $\bar{\pi}$ as the occurrence probability of the event at a time step and utilize the transition matrix for calculating the state reachability probabilities.

5. OPTIMIZATION EXTENSIONS

5.1 Leveraging Shared Subevents

The hierarchical nature of complex event specification may introduce common subevents across complex events. For example, in a network monitoring application we could have the *syn* event indicating the arrival of a TCP *syn* packet. Various complex events could then be specified using the *syn* event, such as syn-flood (sending syn packets without matching acks to create half-open connections for overwhelming the receiver), a successfull TCP session, and another event detecting port scans where the attacker looks for open ports.

The overall goal of plan generation is to find the set of plans for which the total cost of monitoring all the complex events in the system is minimized. The plan generation algorithms presented in Section 3.2 do not take the common subevents into account as they are executed independently for each event operator in a bottom-up manner. As such, while the resulting plans minimize the monitoring cost of each complex event separately, they do not necessarily minimize the total monitoring cost when shared events exist. Here, we modify our algorithm to account for the reduction in cost due to sharing and to exploit common subevents to further reduce cost when possible.

To estimate the cost reduction due to sharing, we need to find out the expected amount of sharing on a common subevent. However, the degree of sharing depends on the plans selected by the parents of the shared node, as the monitoring of the shared event is regulated by those plans. Since the hierarchical plan generation algorithm (Section 3.2.3) proceeds in a bottom-up fashion, we cannot identify the amount of sharing unless the algorithm completes and the plans for all nodes are selected. To address these issues, we modify the plan generation algorithm such that it starts with the independently selected plans and then iteratively generates new plans with increased sharing and reduced cost. The modified algorithm is given in Algorithm 2 for the case of a single shared event.

After the independent plan generation is complete (line 3), each node will have selected its plan, but the computed plan costs will be incorrect as sharing has not yet been considered. To fix the plan costs, first for each parent of the shared node, we calculate the probability that it monitors the shared event in a given time unit (lines 5-7). We have already computed this information during the initial plan generation as the plan costs involve the terms: *probability of monitoring the shared node* × *occurrence rate of the shared event*. We can obtain these values with little additional bookkeeping during plan generation. Next, using the probability values, we adjust the cost of each plan to only include the estimated shared cost for the common subevent (lines 8-10). We assume the parents of the shared node function independently and fix the cost for the cases where the shared event is monitored by multiple parents simultaneously.

Algorithm 2 Plan generation with a shared event

```
1.  s = shared event, A = s.parents
2.  P = $0^{|A|}$ // zero vector of length $|A|$
3.  plans = generatePlans() // execute hierarchical plan generation
4.                           // from Section 3.2.3
5.  for all  a ∈ A do
6.     q = plan for $a$ in plans
7.     P[a] = cost of s in q / occurrence rate of s
8.  for all ancestors $a$ of s do
9.     q = plan for $a$ in plans
10.    q.cost -= cost of s in q − shared cost of s under P with q
11. isLocalMinimum = false, P′ = $0^{|A|}$
12. while !isLocalMinimum do
13.    newplans = generatePlans(A,P)
14.    for all  a ∈ A do
15.       q = plan for $a$ in newplans
16.       $P'[a]$ = cost of s in q / occurrence rate of s
17.    for all ancestors $a$ of s do
18.       q = plan for $a$ in newplans
19.       q.cost -= cost of s in q - shared cost of s under P′ with q
20.    if newplans.cost > plans.cost || newplans == plans then
21.       isLocalMinimum = true
22.    else
23.       plans = newplans, P = P′
```

Then, we proceed to the plan generation loop during which at each iteration new plans are generated for the nodes starting from the parents of the shared node. However, in this execution of the plan generation algorithm (line 13), for each operator node, the algorithm computes the reduction in plan costs due to sharing by using the previous shared node monitoring probabilities, P, and updating the shared node monitoring probability with each plan it considers. Hence, the ancestors of the shared node may now change their plans to reduce cost. Moreover, the new plans generated in each iteration are guaranteed to increase the amount of sharing if they have lower cost than the previous plans. This is because the plan costs can only be reduced by monitoring the shared node in earlier states. The algorithm iterates till a plan set with a local minimum total cost is reached. We consider it future work to study techniques such as simulated annealing and tabu search [14] for convergence to global minimum cost plans. The algorithm can be extended to multiple shared nodes (excluding the cases where cycles exist in the event detection graph), by keeping a separate monitoring probability vector for each shared node s, and at each iteration updating the plans of each node in the system using the shared node probabilities from all its shared descendant nodes.

5.2 Leveraging Constraints

We now briefly describe how spatial and attribute-based constraints affect the occurrence probabilities of events and discuss additional optimizations in the presence of these constraints. A comprehensive evaluation of these techniques is outside the scope of this paper.

First, we consider **spatial constraints** that we define in terms of regional units. The space is divided into regions such that events in a given region are assumed to occur independently from the events in other regions. The division of space into such independent regions is typical for some applications. For instance, in a security application we could consider the rooms (or floors) of a building as independent regions. In addition, it is also easy for users to specify spatial constraints (by combining smaller regions) once regional units are provided. An alternative would be to treat the spatial domain as a continuous ordered domain of real-world (or virtual) coordinates and then perform region-coordinate mappings. This latter approach would allow us to use math expressions and perform optimizations using spatial-windowing constraints, similar to what we described for temporal constraints.

The effects of region-based spatial constraints on event occurrence probabilities can then be incorporated in our framework with minor changes. First, we modify our model to maintain event occurrence statistics per each independent region and event type. Then, when a spatial constraint on a complex event is given, we only need to combine the information from the corresponding regions to derive the associated event occurrence probability. For example, if we have Poisson processes with parameters λ_1 and λ_2 for two regions, then the Poisson process associated with the combined region has the parameter $\lambda_1 + \lambda_2$. Hence, by combining the Poisson processes we can easily construct the Poisson process for any arbitrary combination of independent regions. If the regions are not independent, we need to derive the corresponding joint distributions. An interesting optimization would be to use different plans for monitoring different spatial regions if doing so reduces the overall cost.

Attribute-based constraints on the subevents of a complex event can be used to reduce the transmission costs as well. Value-based attribute constraints can be pushed down to event sources avoiding the transmission of unqualified events. Similarly, parameterized attribute constraints between events can also be pushed down whenever one of the events is monitored earlier than the other. Constraint selectivities, which are essential to make decisions in this case, can be obtained from histograms for deriving the event occurrence probabilities.

6. EXPERIMENTAL EVALUATION

6.1 Methodology

We implemented a prototype complex event detection system together with all our algorithms in Java. In our experiments, we used both synthetic and real-world data sets. For synthetic data sets, we used the *Zipfian* distribution (with default skew = 0.255) to generate event occurrence frequencies, which are then plugged into the exponential distribution to generate event arrival times. Correspondingly, we used the Poisson-based cost model in the experiments. The real data set we used is a collection of Planetlab network traffic logs obtained from Planetflow [20]. Specific hardware configurations used in the experimentation are not relevant as our evaluation metrics do not depend on the run-time environment (except in one study, which we describe later).

The actual number of messages or "bytes" sent in a distributed system is highly dependent on the underlying network topology and communication protocols. To cleanly separate the impact of our algorithms from those of the underlying configuration choices, we use high-level, abstract performance metrics. We do, however, also provide a mapping from the abstract to the actual metrics for a representative real-world experiment.

As such, our primary evaluation metric is the "transmission factor", which represents the ratio of the number of primitive events received at the base to the total number of primitive events generated by the sources. This metric quantifies the extent of event suppression our plan-based techniques can achieve over the standard push-based approach used by existing event detection systems. We also present the "minimum transmission factor", the ratio of the number of primitive events that participate in the complex events that actually occurred to the total number generated. This metric represents the *theoretical best* that can be achieved and thus serves as a tight lower bound on transmission costs. All the experiments involving synthetic data sets are repeated till results statistically converged with approximately 1.2% average and 5% maximum variance.

6.2 Single-Operator Analysis

We first analyze in-depth the base case where our complex events consist of individual operators.

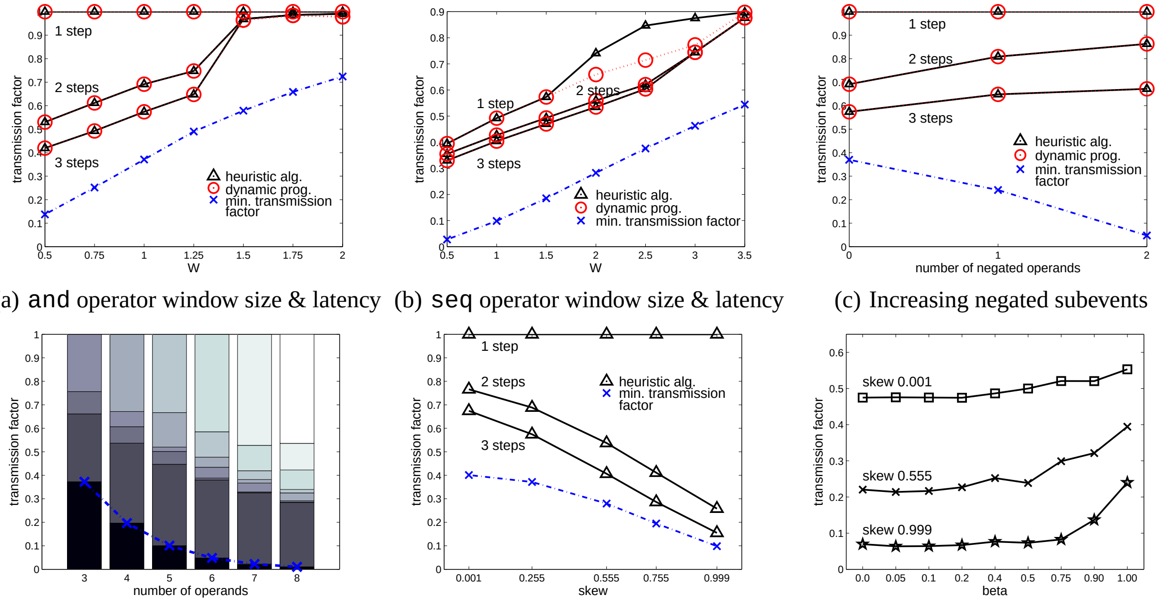
Window size and detection latency: We defined the complex events $\texttt{and}(e_1, e_2, e_3; w)$ and $\texttt{seq}(e_1, e_2, e_3; w)$, where e_1, e_2 and e_3 are primitive events. We ran both the dynamic programming (DP) and heuristic-based algorithms for different window sizes (w) and plan lengths (as an indication of execution plan latency). The results are shown in Figures 4(a) and 4(b).

Our results reveal that, as the number of steps in the plan increases, the event detection cost generally decreases. In the case of the `and` operator, both the heuristic method and the DP algorithm find the optimal solution, as we are considering a trivial complex event. However, in the case of the `seq` operator, there is some difference between the two algorithms for the 1-step case (i.e. the minimum latency case). Recall that due to the ordering constraint, the `seq` operator does not need to monitor the later events of the sequence unless the earlier events occur. Therefore, it can reduce the cost using multi-step plans even under hard latency requirements. However, this asymmetry introduced by the `seq` operator is also the reason why our heuristic algorithm fails to produce the optimal solution. Finally, the event detection costs tend to increase with increasing window sizes since larger windows increase the probability of event occurrence. If the window is sufficiently large, the system would expect the complex event to occur roughly for each instance of a primitive event type in which case the system will monitor all the events continuously and relaxing the latency target will not reduce the cost.

Effects of negation: We performed an experiment with the event $\texttt{and}(e_1, e_2, e_3; w = 1)$ in which we varied the number of negated subevents. We observe that the cost increases with more negated subevents, although fewer complex events are detected (Figure 4(c)). This is mainly because (1) all the transmitted non-negated subevents have to be discarded when a negated subevent that prevents them from forming a complex event is detected, and (2) as described in Section 4, the monitoring of the negated and non-negated events are not interleaved: the negated sub-events are monitored only after the non-negated subevents. Results are similar for uniformly distributed event frequencies (yet the cost seems to be more independent of the number of negated subevents in the uniform case). For highly-skewed event frequencies, the results depend on the particular frequency distribution. For instance, if the frequency of the negated event (or one of the negated events) is very high, then the complex event almost never occurs, but the monitoring cost is also low since other events have low frequencies. Finally, `seq` operator also performs similarly.

Increasing the operator fanout: We now analyze the relation between the cost and the fanout (number of subevents) using an `and` operator with a fixed window size of 1. To eliminate the effects of frequency skew, we used uniform distribution for event frequencies. Results from running the heuristic algorithm (DP results are similar) are shown in Figure 4(d), in which the lowest dark portion of each bar shows the minimal transmission factor and the cost values for increasingly strict deadlines are stacked on top of each other. We see that (i) increasing the fanout tends to decrease the number of detected complex events and (ii) larger fanout implies we have a wider latency spectrum, thus a larger plan space and more flexibility to reduce cost.

Effects of frequency skew: In this experiment, we define the complex event $\texttt{and}(e_1, e_2, e_3; w = 1)$ and vary the parameter of the Zipfian distribution with which event frequencies are generated. The total number of primitive events for different event frequency values are kept constant. Figure 4(e) shows that a higher number of complex events is detected with low-skew streams and the cost is thus higher. Furthermore, our algorithms can effectively capitalize on high-skew cases where there is significant difference between event occurrence frequencies by postponing the monitoring of high-frequency events



(a) and operator window size & latency (b) seq operator window size & latency (c) Increasing negated subevents

(d) Increasing operands (fanout) (e) Increasing frequency skew (f) Tolerance to estimation errors

Figure 4: Operator wise experiments

as much as the latency constraints allow.

Tolerance to statistical estimation errors: We now analyze the effects of parameter estimation accuracy on system performance using $and(e_1, e_2, \dots, e_5; w = 1)$, where $e_1, e_2, \dots, e_5$ are primitive events. We use the Zipfian distribution to create the "true" occurrence rates $\lambda^T = [\lambda^T_{e_1}, \lambda^T_{e_2}, \dots, \lambda^T_{e_5}]$ of events. We then define λ^β with $\lambda^\beta_{e_i} = \lambda^T_{e_i} \pm \beta\lambda^T_{e_i}$ for $1 \leq i \leq 5$ as an estimator of λ^T with error β (the $\pm$ indicates that the error is either added or subtracted based on a random decision for each event). The results are in figure 4(f).

For highly skewed occurrence rates, the estimation error has a larger impact on the cost as the occurrence rates are far apart in such cases. For very low skew values, error does not affect the cost much since most of the events are "exchangeable", i.e., selected plans are independent of the monitoring order of the events as switching an event with another does not change the cost much. We did a similar experiment using events with many operators instead of a single one. The relative results and averages were similar, however, the variance was higher (approximately 10%), meaning for some complex event instances the cost could be highly affected by the estimation error.

6.3 Effects of Event Complexity

Increasing event complexity: For this experiment, we generated complex event specifications using all the operator types and varied the number of operators in an expression from 1 to 7. Each operator was given 2 or 3 subevents with equal probability and a window of size 2.5. In figure 5(a), we provide the average event detection costs for the complex events that have approximately the same number of occurrences (as shown by the minimum transmission factor curve) for low, medium and high latency values (latencies depend on the number of operators in a complex event, and represent the variety of the latency spectrum). We can see that the cost does not depend on the number of operators in the expression but instead depends on the occurrence frequency of the complex event.

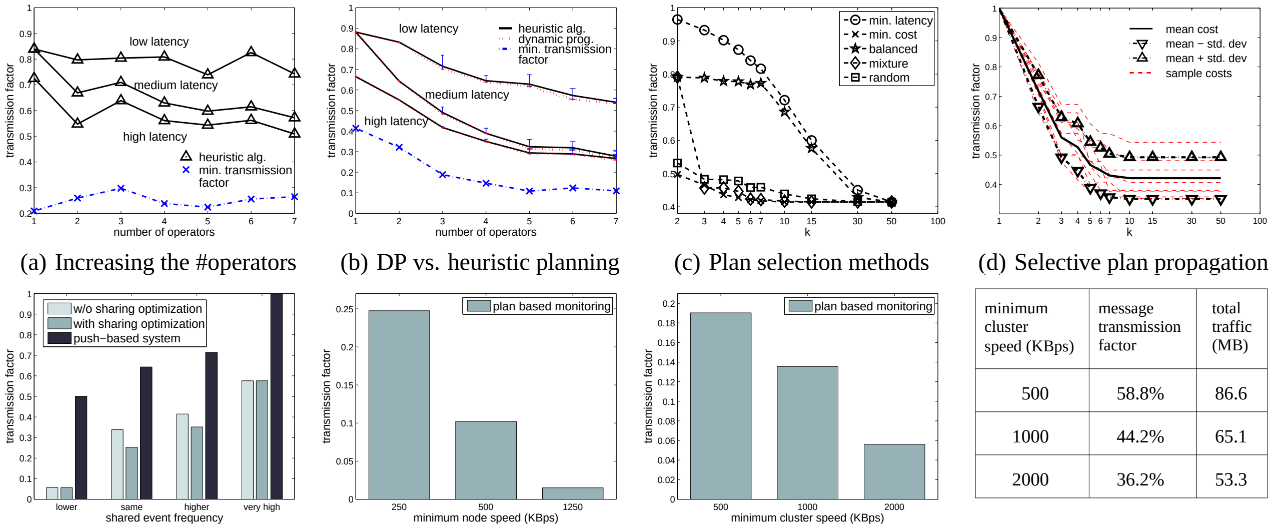
Dynamic programming vs. heuristic plan generation: Using the same settings with the previous experiment, we compare the average event detection costs of heuristic and DP plan generation algorithms (figure 5(b)). The results show that the heuristic method performs, on average, very close to the dynamic programming method. The error bars indicate the standard deviation of the difference between the two cost values.

Selective hierarchical plan propagation: In this experiment, we analyze the effects of the parameter k, which limits the number of plans propagated by operator nodes to their parents during hierarchical plan generation (see section 3.2.1). We defined complex events using exclusively and operators, each with a fixed window size of 2.5, and together forming a complete binary tree of height 4. We consider the following strategies for picking k plans from the set of all plans produced by an operator:

- **random selection**: randomly select k plans from all plans.
- **minimum latency**: pick the k plans with minimum latency.
- **minimum cost**: pick the k plans with minimum cost.
- **balance cost and latency**: represent each plan in the $\Re^2$ (cost, latency) space, then pick the k plans with minimum length projections to the $cost = latency$ line.
- **mixture**: pick $k/3$ plans using the minimum latency strategy, $k/3$ using the minimum cost strategy and the other $k/3$ plans using the balanced strategy.

The average cost of event detection for each strategy with different k values are given in figure 5(c) in which DP is used. Greater values of k generally means reduced cost since increasing the value of k helps us get closer to the optimal solution. The mixture and the minimum cost strategies perform similarly and approach the optimal plan even for low values of k. However, the minimum cost strategy does not guarantee finding a feasible plan for each complex event since it does not take the plan latency into account during plan generation. On the other hand, the mixture strategy will find the feasible plans if they exist since it always considers the minimum latency plans.

We repeated the same experiment with the heuristic plan generation method using the mixture strategy (figure 5(d)). Results are similar to the DP case; however, the heuristic algorithm, unlike the DP algorithm, does not produce the set of all pareto optimal plans. Moreover, the size of the plan space explored by the heuristic algorithm depends on the number of moves it can make without reaching a point where no more moves are available. Therefore, even when the value of k is unlimited, the heuristic method does not guarantee optimal solutions, which is not the case with the DP approach.



(a) Increasing the #operators (b) DP vs. heuristic planning (c) Plan selection methods (d) Selective plan propagation

minimum cluster speed (KBps)	message transmission factor	total traffic (MB)
500	58.8%	86.6
1000	44.2%	65.1
2000	36.2%	53.3

(e) Leveraging sharing (f) Load spike event (g) Suspicious activity event (h) Network traffic mapping

Figure 5: Event complexity, shared optimization, plan generation and PlanetLab experiments

6.4 Effects of Event Sharing

To quantify the potential benefits of leveraging shared subevents across multiple complex events, we generated two complex events with a common subevent tree and compared the performance with and without shared optimization. Each complex event has 3 and operators, one of which is shared. There is a total of 6 primitive events, 2 of which are common to both complex events. In the experiment, we varied the frequency of the complex event that corresponds to the shared subtree. In Figure 5(e), we see that when the frequency of the shared part is low, leveraging sharing does not lead to a noteworthy improvement since the shared part is chosen to be monitored earlier in both cases anyway. When the frequency of the shared part is the same with or slightly higher than the non-shared parts, the latter are monitored earlier without sharing optimization. In this case, shared optimization reduces the cost by monitoring the shared part first. Finally, when the shared part has very high frequency, non-shared parts are monitored first in both cases.

6.5 Experiments with the PlanetLab Data Set

The PlanetLab data set we used consists of 5 hours of network logs (1pm-6pm on 6/10/2007) for 49 PlanetLab nodes [20]. The logs provide aggregated information on network connections between PlanetLab nodes and other nodes on the Internet. For each connection, indicated by source and destination IP/port pairs, the information includes the start and end times, the amount of generated traffic and the network protocol used. We experimented with a variety of complex events commonly used in network monitoring applications. Here, we present the results for two representative complex events.

Capturing load spikes: We define a PlanetLab node as (i) *idle* if its average network bandwidth consumption (incoming and outgoing) within the last minute is less than 125KBps and as (ii) *active* if the average speed is greater than a threshold T. The *spike* event monitors for the following overall network load change: the event that more than half of all nodes are idle, followed by the event that more than half is active within a specified time interval. Thus, the complex event is defined as seq*(count(idle) > %50 of all nodes, count(active) > %50 of all nodes; w=30min)*. Note here that the *count* operator is evaluated in an entirely push-based manner and thus does not affect plan generation or execution. The results are provided in Figure 5(f) for T = 250, 500, and 1250 KBps. We see substantial savings that range from 75% to 97%. For this complex event, our system chooses to monitor the active nodes first, and upon detection of the event that more than half of the nodes are active it queries the event sources for the event that most nodes were idle in the past 30 minutes.

Active-diverse clusters: Here, we use a complex event (Figure 6) inspired by Snort rules [22]. The basic idea is to identify a cluster of machines that exhibit high traffic activity (active) through a large number of connections (diverse) within a time window.

We define a cluster to be a set of machines from the same $/8$ IP class. A *diverse cluster* is defined as a cluster with more than C=500 connections to PlanetLab nodes within the last minute (multiple connections from the same IP address are counted distinctly). To specify this complex event we first define a *locally diverse cluster* event which monitors the event that a PlanetLab node has more than $\frac{C}{N=49}$ connections with a cluster. The diverse cluster complex event is specified as *sum(conns)*$>$ C *group by cluster*. Then, it is and'ed with the locally diverse cluster event which acts as a prerequisite for the diverse cluster event and helps reduce monitoring cost. Next, using the diverse cluster event, we define the *unexpected diverse cluster* event as the diverse cluster event preceded by no occurrences of the event that the same cluster has more than C/2 connections within the last 5 minutes. Moreover, we define the active cluster event, similar to the diverse cluster event, but thresholding on the network traffic instead of the connections. Finally, we define the top level complex event as the and of the active cluster and unexpected diverse cluster events.

Figure 5(g) shows the event transmission factors for three cluster speed threshold values. In all cases, we observe significant savings that increase with increasing thresholds. The primary reason for this behavior is that the active cluster complex event and its subevents become less likely to happen as we increase the threshold, thereby yielding increasingly more savings for our plan-based approach. In figure 5(h), we provide the actual network costs by assuming a fully-connected TCP mesh with a fixed packet size of 1500 bytes, the maximum possible for a TCP packet. The cost for our system is still much lower than the cost of a push-based system despite the existence of the pull requests. Moreover, the results overestimate the cost of our system as event messages and pull requests are much smaller than the fixed packet size. Finally, we note that a more sophisticated implementation can use more efficient pull-request distribution techniques (e.g., an overlay tree) to significantly reduce these extra pull costs.

7. RELATED WORK

In continuous query processing systems such as TinyDB [2] for wireless sensor networks, and Borealis [17] for stream processing

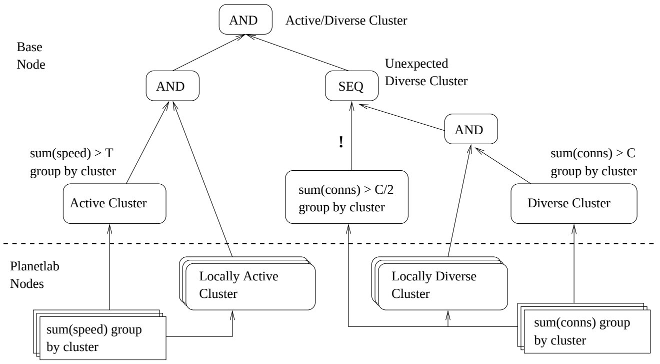


Figure 6: Active/Diverse cluster event specification

applications queries are expected to constantly produce results. Push based data transfer, either to a fixed node or to an arbitrary location in a decentralized structure, is characteristic of such continuous query processing systems. On the other hand, event detection systems are expected to be silent as long as no events of interest occur. The aim in event systems is not continuous processing of the data, but is the detection of events of interest.

In the active database community, ECA (event-condition-action) rules have been studied for building triggers [8]. Triggers offer the event detection functionality through which database applications can subscribe to in-database events, e.g. the insertion of a tuple. However, most in-database events are simple whereas more complex events could be defined in the environments we consider. Many active database systems such as Samos [4], Ode Active Database [5], and Sentinel [6] have been produced as the results of the studies in the active database area. Most systems provide their own event languages. These languages form the base of the event operators in our system.

In the join ordering problem, query optimizers try to find ordering of relations for which intermediate result sizes are minimized [21]. Most query optimizers only consider the orders corresponding to left-deep binary trees mainly for two reasons: (1) Available join algorithms such as nested-loop joins tend to work well with left-deep trees, and (2) Number of possible left-deep trees is large but not as large as number of all trees. Our problem of constructing minimum cost monitoring plans is different from the join ordering problem for the following reasons. First, we are not limited to binary trees since multiple event types can be monitored in parallel. Second, our cost metric is the expected number of events sent to base. Finally, we have an additional latency constraint further limiting the solution space.

In high performance complex event processing [7], optimization methods for efficient event processing are described. There the aim is to reduce processing cost at the base station where all the data is assumed to be available. While our system also helps reduce the processing cost, our main goal is to minimize the network traffic. As such, our work can be considered orthogonal to that work and the integration of both approaches is possible.

Event processing has also been considered in event middleware systems which are extensions to the publish/subscribe systems. In Hermes [3], a complex event detection module has been implemented and an event language based on regular expressions is described. Decentralized event detection is also discussed. However, plan-based event detection is not considered. In [16], authors describe model based approximate querying techniques for sensor networks. Similar to our work, plan based approaches to data collection has been considered for network efficiency. Authors also discuss confidence based results and consider dependencies between sensor readings.

Previous literature on multi-query optimization focuses on efficient execution of a given set of queries by exploiting common subexpressions. Studies include efficient detection of sharing opportunities across queries [12], and search algorithms for finding efficient query execution plans that materialize the common intermediate results for reuse [11]. Our shared optimization extensions build on similar techniques while the goal is to improve communication efficiency.

8. CONCLUSIONS AND FUTURE WORK

CED is a critical capability for emerging monitoring applications. While earlier work mainly focused on optimizing processing requirements, our effort is towards optimizing communication needs using a plan-based approach when distributed sources are involved. To our knowledge, we are the first to explore cost-based planning for CED.

Our results, based on both artificial and real-world data, show that communication requirements can be substantially reduced by using plans that exploit temporal constraints among events and statistical event models. Specifically, the big benefits came from a novel multi-step planning technique that enabled "just-enough" monitoring of events. We believe some of the techniques we introduced can be applied to CED on even centralized disk-based systems (i.e., to avoid pulling all primitive events from the disk)

CED is a rich research area with many open problems. Our immediate work will explore probabilistic plans for sensor-based applications and augmenting manual event specifications with learning.

9. REFERENCES

[1] Eric N. Hanson, et al. Scalable Trigger Processing. ICDE 1999.
[2] S. Madden, M. J. Franklin, J. M. Hellerstein, and W. Hong. Tinydb. TODS 2005.
[3] Peter R. Pietzuch. "Hermes: A Scalable Event-Based Middleware". Ph.D. Thesis, University of Cambridge, 2004.
[4] S. Gatziu and K. R. Dittrich. Detecting composite events in active database systems using petri nets. In Proc. 4. Intl. Workshop on Research Issues in Data Engineering, 1994.
[5] S. Chakravarthy, et al. Composite Events for Active Databases: Semantics, Contexts and Detection, VLDB 1994.
[6] S. Chakravarthy and D. Mishra. Snoop: An Expressive Event Specification Language for Active Databases. Data and Knowledge Engineering, 14(10):1–26, 1994.
[7] Eugene Wu, et al. High-Performance Complex Event Processing over Streams. SIGMOD 2006
[8] N. Paton and O. Diaz, 'Active Database Systems', ACM Comp. Surveys, Vol. 31, No. 1, 1999.
[9] Zimmer, D. and Unland, R. On the Semantics of Complex Events in Active Database Management Systems. ICDE'99.
[10] The Power of Events. David Luckham, May 2002.
[11] Sellis, T. K. Multiple-query optimization. TODS Mar. 1988.
[12] Zhou, J., et al. Efficient exploitation of similar subexpressions for query processing. SIGMOD'07.
[13] Pattern Recognition and Machine Learning. Bishop, Christopher M. 2006, ISBN: 978-0-387-31073-2.
[14] Combinatorial optimization: algorithms and complexity. Christos H. Papadimitriou, Kenneth Steiglitz. 1998.
[15] S. V. Amaria and R. B. Misra, Closed-form expressions for distribution of sum of exponential random variables, IEEE Trans. Reliability, vol. 46, no. 4, pp. 519-522, Dec. 1997.
[16] Amol Deshpande, et al. Model-based approximate querying in sensor networks. VLDB J. 14(4): 417-443 (2005)
[17] Daniel Abadi, et al. The Design of the Borealis Stream Processing Engine. CIDR'05.
[18] S. Chandrasekaran, et al. TelegraphCQ: Continuous Dataflow Processing. In ACM SIGMOD Conference, June 2003.
[19] R. Motwani, et al. Query Processing, Approximation, and Resource Management in a Data Stream Management System. In CIDR Conference, January 2003.
[20] http://planetflow.planet-lab.org
[21] Selinger, P. G., et al. 1979. Access path selection in a relational database management system. SIGMOD '79.
[22] SNORT Network Intrusion Detection. http://www.snort.org
[23] S. Li, et al. Event Detection Services Using Data Service Middleware in Distributed Sensor Networks. IPSN 2003.