

Access Methods for Markovian Streams

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Abstract—Model-based views have recently been proposed as an effective method for querying noisy sensor data. Commonly used models from the AI literature (*e.g.*, the hidden Markov model) expose to applications a stream of probabilistic and correlated state estimates computed from the sensor data. Many applications want to detect sophisticated patterns of states from these *Markovian streams*. Such queries are called *event queries*.

In this paper, we present a new storage manager, Caldera, for processing event queries over *stored* Markovian streams in the Lahar system. At the heart of Caldera is a set of access methods for Markovian streams that can improve event query performance by orders of magnitude compared to existing techniques, which must scan the entire stream. Our access methods use new adaptations of traditional B+ tree indexes, and a new index, called the *Markov-chain index*. They efficiently extract only the relevant timesteps from a stream, while retaining the stream’s Markovian properties. We have implemented our prototype system on BDB and demonstrate its effectiveness on both synthetic data and real data from a building-wide RFID deployment.

I. INTRODUCTION

Applications that make decisions based on sensor data are increasingly common, with sensor deployments now playing integral roles in supply chain automation [5], [39], environment monitoring [17], elder-care [25], [28], etc. Unfortunately, building applications on top of raw sensor data remains challenging because sensors produce inaccurate information, frequently fail, and can rarely collect data on an entire region of interest. As an example, consider a Radio Frequency Identification (RFID) tracking application [38] in which RFID readers are distributed throughout an environment. Ideally, when a tag (carried by a person or attached to an object) passes close to a reader, the reader detects and logs the tag’s presence: *e.g.*, Bob’s tag was sighted by reader A at time 7, reader B at time 8, etc. In practice, however, readers often fail to detect nearby tags [40], and cannot provide information about a tag’s position within the reader’s range. Applications are thus forced to deal with imprecise input streams.

The reduction of errors and gaps in sensor data streams is the focus of a large body of probabilistic modeling/inference techniques developed in the AI community [34]. While a limited number of these techniques can be applied in real time, the most effective (*Bayesian smoothing* [13]) can be applied only as a post-processing step, after the raw data stream is archived. Our goal is to support archive-based applications

that leverage this smoothed data in order to provide the most accurate possible answers to historical queries (*e.g.*, “Was Bob in his office yesterday?”, “Did Margot take her medication before breakfast every day last month?”, etc.).

The result of any smoothing technique is a *probabilistic stream* in which each timestep encodes not a single state, but a distribution over possible states. In the RFID tracking example, such a stream might indicate, for each timestep, the distribution over possible locations of a tag: *e.g.*, at time 7, Bob was in the hallway with probability 0.8 and in his office with probability 0.2. Additionally, states at consecutive timesteps can be correlated: *e.g.*, Bob’s location at time 8 is correlated with his location at time 7. We call these probabilistic, correlated streams *Markovian streams*. They are a materialized instance of a *model-based view* [10].

A natural class of queries on Markovian streams are *event queries* [1], [9], [33], [43], which find sophisticated patterns of states in streams. An example event query on an RFID stream is: “*When did Bob take a coffee break yesterday?*” where “coffee-break” is defined as Bob going from the coffee machine directly to the lounge.

Because of the probabilities and correlations present in a Markovian stream, archived event queries on these streams cannot be handled by any existing system. Indeed, stream processing engines that handle event queries [1], [9], [43] ignore probabilities. Probabilistic databases [3], [8], [20], [42], on the other hand, handle data uncertainty but do not support event queries and many do not handle correlations [3], [8], [42]. The only existing system able to manage Markovian streams is Lahar [33], which we originally developed to support *real-time* event queries. In order to preserve correlations, Lahar must currently process *every* timestep of the input stream. This full-data scan is grossly inefficient in archived settings.

In this paper, we present Caldera, a storage manager for Lahar that efficiently processes event queries on archived Markovian streams. Caldera’s challenge is to identify and process only the relevant portions of a Markovian stream in a manner that preserves cross-timestep correlations, but *without* scanning the entire stream history on disk. Caldera achieves this goal by using a battery of access methods that leverage pruning and precomputation strategies.

In Section II, we formally define Markovian streams and the event queries processed by Lahar+Caldera. An important contribution in this section is our division of these queries into two

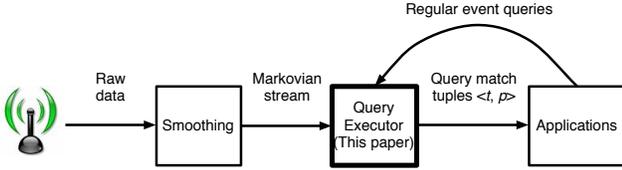


Fig. 1. The flow of data in Caldera. Raw sensor data is first smoothed into Markovian streams and archived on disk. Caldera processes application-specified Regular event queries on these archived Markovian streams and returns the result tuples $\langle t, p \rangle$ specifying the probability p that the query is satisfied at time t , for each timestep in the stream.

classes, which we call *fixed-length* and *variable-length* queries. We identify the challenges involved in processing each. Our algorithmic contributions are access methods optimized for each query class. Specifically, these contributions include:

- 1) An access method optimized for *fixed-length* queries, based upon a novel adaptation of standard indexing techniques (Section III-A).
- 2) A top-k optimization for *fixed-length* queries. This second access method exploits insights about the structure of Markovian event probabilities to adapt standard top-k pruning techniques to Markovian stream data, using standard B+ trees (Section III-B).
- 3) A novel index structure (the Markov chain index) and associated access method for *variable-length* queries, for which standard indexing is insufficient (Section III-C).
- 4) A discussion of practical issues relating to our three access methods, including predicate evaluation and a comparison of physical disk layouts (Section III-D).

In Section IV we demonstrate the efficiency of our four access methods on both real and synthetic data. We show on real data that Caldera’s access methods deliver speedups of up to two orders of magnitude over a naïve stream scan. We then use synthetic data to push beyond the limitations of our real dataset and confirm that our algorithms continue to provide similar speedups under a wider variety of stream conditions. Finally, we identify unique characteristics of location-based Markovian streams, and we discuss the impact of these characteristics upon access method performance, disk layout choice, and the quality of a heuristic-based, approximate access method.

II. PRELIMINARIES

In this section we give an overview of the queries and data processed by Lahar+Caldera (see Figure 1). We first sketch one of the many processes by which Markovian streams can be generated from sensor data. We then describe event queries over Markovian streams and outline the major challenges to processing them in an archived setting.

A. Hidden Markov Models and Markovian Streams

Consider again the example scenario in which RFID readers track Bob’s location as he moves throughout a building. Because RFID readers are placed at discrete locations and because of noise and interference, the raw RFID stream representing Bob’s location contains errors and gaps. Often, however, a system can use probabilistic *inference* to reduce errors and provide location estimates during times for which no sensor data is available.

Many of the methods for inferring these location estimates rely upon a simple and commonly-used graphical model called a *hidden Markov model* (HMM) [29]. The HMM is designed to infer a sequence of hidden state values (e.g. Bob’s locations) from a sequence of observations (e.g. RFID tag reads). The HMM incorporates both *physical constraints* (e.g. a person cannot go directly from office O1 to office O2, since this would involve walking through a wall; a tag is most likely no more than 5 feet from the RFID antenna detecting it, since antenna ranges are small) as well as *statistical likelihoods* (e.g. it is more likely that Bob will enter his own office, rather than his neighbor’s). The construction of this model is orthogonal to Caldera’s contribution, so we do not describe it here, but refer the reader instead to Rabiner’s excellent tutorial [29].

Standard probabilistic inference algorithms—including the one used in our experiments—can use these models to infer information missing from raw sensor streams. Fig. 2 illustrates the key idea behind a popular and intuitive class of these algorithms called *sample-based* inference techniques. The figure depicts a small RFID deployment in which readers A, B, and C are located in the corridors of a building. The figure shows two timesteps’ worth of *samples*, which are simply guesses about Bob’s location. The samples move through space at each timestep and congregate in areas consistent with sensor readings received by the system. Both the particle motion and the notion of sensor consistency are defined by the HMM parameters. To compute the marginal probability that Bob’s tag is in a particular location, e.g. H1, at a particular time, e.g. 7, the system simply counts the number of samples in H1 and divides by the total number of samples. In this example, 80% of Bob’s samples are in location H1.

In addition to marginal distributions, probabilistic smoothing algorithms also provide correlations *between* these distributions. Such correlations are called conditional probability tables, or CPTs. To demonstrate their importance, imagine that at two later timesteps, say 50 and 51, Bob is in either office O1 or O2, each with probability 0.5. Using correlations, the probability that Bob is in O1 at time 50 and O2 at time 51 is $0.5 * 0.0 = 0.0$. The second term in this product reflects the physical impossibility of moving directly between these two offices, and reduces the final trajectory probability appropriately to zero. Ignoring correlations, however, the probability that Bob moves from O1 to O2 is $0.5 * 0.5 = 0.25$! Bob’s sudden ability to walk through walls highlights the importance of the correlations in Markovian streams. Not surprisingly, maintaining these correlations is known to increase the *quality* of events [33]. We use the name *Markovian stream* for the correlated, temporal data produced by probabilistic smoothing on a raw input stream.

More precisely, a *Markovian stream* with value attributes A_1, \dots, A_k (where A_i has domain D_i for $i \in [1, k]$) is a pair (p_0, C) . Here p_0 is a distribution over $D_1 \times \dots \times D_k$, representing the initial probability distribution of the stream; C is a sequence of *conditional probability tables* (CPTs) $C(A_1, \dots, A_k, A'_1, \dots, A'_k, T, P)$. Each tuple in C uniquely describes the probability of a specific state transition from time t to $t + 1$. For example, a tuple $(a_1, \dots, a_k, a'_1, \dots, a'_k, t, p)$ in C indicates that p is the conditional probability that the state

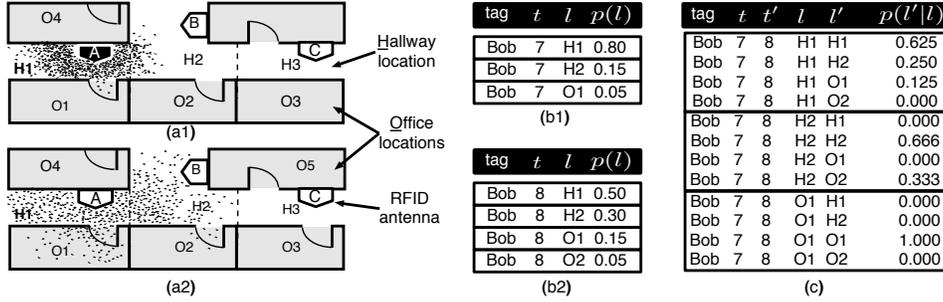


Fig. 2. (a) A sample-based distribution over Bob’s location at time 7 (a1) when antenna A detects Bob, and at the next time 8 (a2), when Bob is undetected. (b) The marginal distributions computed from the samples, for times 7 (b1) and 8 (b2) respectively. (c) The correlations between times 7 and 8.

of the stream is $(A_1 = a'_1, \dots, A_k = a'_k)$ at time $t + 1$, given that the state at time t was $(A_1 = a_1, \dots, A_k = a_k)$. The set of tuples sharing a value of $T = t$ together define the entire stream transition (CPT) between t and $t + 1$. For a full formal semantic, see Ré *et al.* [33].

For performance reasons, Caldera explicitly stores the marginal distributions over the stream state at each timestep, even though they are derivable from (p_0, C) . Figures 2(b) and 2(c) show the relational representation of a Markovian stream in which the single attribute A_1 represents Bob’s location. To further improve performance, zero-valued distribution entries (e.g. H3 at timesteps 7 and 8 in Figure 2) are not explicitly stored. Such values occur when inference is sample-based, or when very small distribution entries are pruned to zero.

B. Regular Queries on Markovian Streams

Streams lend themselves naturally to *event queries* [9], which ask questions about sequences of states. An example event query is, “When did Bob enter his office (300)?”. In this paper, we look at a subset of event queries called *Regular queries* [33]. These queries are analogous to regular expressions, or equivalently NFAs. An example Regular query is shown in Figure 3(a). This query is satisfied when Bob is first in a Hallway, and then in Office300 in the next timestep. Regular queries comprise only *linear* NFAs, which means that the directed automaton edges form a total order.

Regular query NFAs differ from standard NFAs in that they transition when *predicates* on the input stream are satisfied, instead of on static alphabet symbols. For example, the NFA in Fig. 3(a) transitions from the start state to state S_0 on input timesteps in which Bob’s location is a hallway (many locations might satisfy this predicate). If Bob’s location is not a hallway, then this transition is not possible and the automaton dies.

We define a *predicate* here as a Boolean function on stream attributes. For example, the Hallway predicate re-

turns true when the input location is a hallway. A *Regular query* comprises a list of such predicates organized in a way that respects the NFA’s linearity. Concretely, a Regular query is a concatenation of *links*, where each link is one of either 1) a single predicate (e.g. Hallway), or 2) a pair of predicates in which the first contains a Kleene star (e.g. $(\neg \text{CoffeeRoom}^*, \text{CoffeeRoom})$). In the latter case, we refer to the second predicate as the link’s primary predicate or simply ‘predicate’, since this is the predicate that transitions to the next query link. Because Regular query NFAs are linear, a list of links uniquely determines a query. Figures 3(a) and 3(b) show Regular query NFAs and their link expressions.

A technical contribution of this work is to divide the set of Regular queries into two classes for optimization: (1) *fixed-length queries*, whose NFA representations are loop-free, and (2) *variable-length queries*, whose NFAs contain loops. Figs 3(a) and 3(b) show example fixed- and variable-length queries, respectively. The class of fixed-length queries can be satisfied only by fixed-length stream intervals (i.e. an n -link query can be satisfied only by stream intervals of length n). In contrast, intervals satisfying variable-length queries may span an arbitrary number of timesteps. As we demonstrate in the following sections, this distinction allows for very different optimization of the queries in each class.

The output of a Regular query is a sequence of pairs $\langle t, p \rangle$, where p is the probability that the query is satisfied at timestep t . Figure 4 graphically illustrates the output of the Entered-Room query detected in a real RFID data stream. The query probability spikes when Bob enters his office ($t \approx 1100$), and shows a much lower series of peaks around a false positive ($t \approx 1600$). Applications can use simple thresholding to detect these event peaks (e.g. Bob is entering an office if $p > 0.3$).

C. Challenges for Archived Regular Query Processing

In our previous work we presented Lahar, a system that can efficiently process Regular queries on *streaming* data (i.e. in near-real time). Lahar requires as input an *entire* Markovian stream, making its use untenable in large-scale, archived scenarios where a large volume of data must be read from disk. Our current work focuses on Regular query processing in an *archived* setting, which poses the following challenges:

Our first challenge is that of *adapting classical techniques* (e.g. B+ tree indexing, merge joins, *etc.* [30], [44]) to the problem of processing large Markovian stream archives. This adaptation is non-trivial because only a subset of Regular

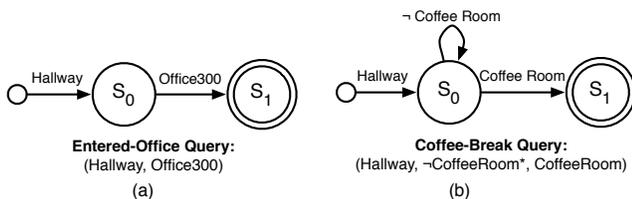


Fig. 3. Two two-link Regular event queries in NFA form and written syntax. (a) Entered-Room query asking when Bob is in the Hallway and then immediately in Office300. (b) Coffee-Break query asking when Bob is in the Coffee Room at any time after leaving the Hallway.

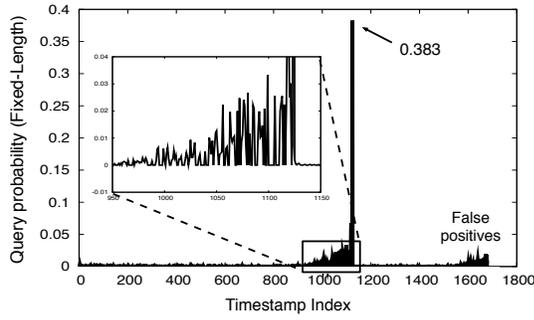


Fig. 4. Probability of the Entered-Room query on a real RFID data stream. Bob actually entered his office only once, around timestep 1100, but he walked past the office door again around timestep 1600.

queries can be processed using standard techniques. Thus the challenge is in identifying this class, and in mapping standard techniques onto the queries within it.

Our second challenge, *high-quality event retrieval*, arises from the abundance of low-quality events matching each query. The uncertainty in Markovian streams creates a large number of low-quality query matches for each high-quality peak in the query signal (see Figure 4). Top-k algorithms are a standard approach for dealing with such noise. The challenge in adapting top-k approaches to archived Markovian streams is that query match probabilities are a function of the data stream, but are not present directly in the stream data itself. As a result, effective top-k pruning conditions are non-obvious.

Our third challenge, *correlation retrieval*, arises from the correlations present in Markovian streams. Variable-length query matches can span intervals of arbitrary length, and the probabilities of these matches depend on correlations across the entire interval—computable only via a scan of all timesteps in the interval. The challenge in this case is to develop a data structure that makes effective use of precomputation to allow efficient lookup of the correlations between *any* two timesteps, without requiring excessive storage space.

III. ACCESS METHODS FOR MARKOVIAN STREAMS

Caldera’s query plans comprise three operators as illustrated in Figure 5(a). At the heart of each query plan is the Reg operator based on Lahar [33]. We represent Reg here as a stateful black box that is initialized with a Regular query Q . During execution of the query plan, Reg expects as input a series of Markovian stream timesteps, each labeled either as the beginning of a sequence (Reg.startSequence) or as a continuation (Reg.update). From each input, Reg produces a tuple $\langle t, p \rangle$ specifying the probability p that query Q is satisfied at the input timestep.

The Sort operator is a standard operator, for use in top-k queries. It sorts the $\langle t, p \rangle$ tuples produced by the Reg operator in order of decreasing probability. Finally, the Ex (extract) operator, which is the focus of this paper, extracts fragments of Markovian streams from disk using one of the access methods introduced shortly.

In this section, we present five physical implementations of the Ex operator. The first, Algorithm 1, is a naïve stream scan. In the absence of indexes this is the only possible approach.

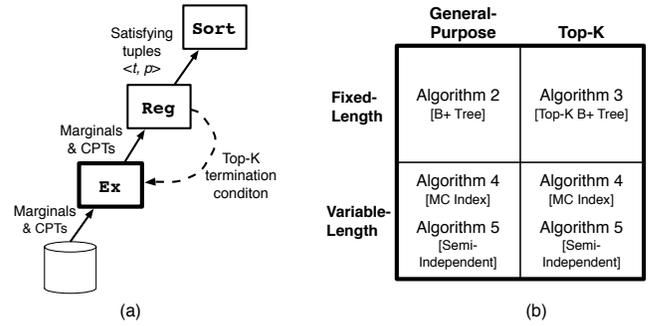


Fig. 5. (a) A Caldera query plan. (b) A breakdown of the space of Regular event queries and the Ex implementations we develop for each quadrant.

Algorithm 1 Naïve Scan Access Method

- $M[i]$: The i^{th} timestep in Markovian stream M .
- $M[i].t$: The timestamp of the i^{th} timestep in M .

Input: Regular query Q_R , Markovian stream M

Output: Probability that Q_R is satisfied at each timestep $t \in M$

- 1: Reg.startSequence($M[0].\text{marginal}$)
- 2: **for each** timestep i in M **do**
- 3: $\langle M[i].t, p \rangle = \text{Reg.update}(M[i].\text{cpt})$

This is the baseline against which we compare our optimized implementations.

Figure 5(b) outlines the space of Regular queries and the novel algorithms that we develop in this section. We first show how to leverage B+ tree indexes to efficiently answer fixed-length queries. We then show how to further leverage standard techniques to optimize top-k variants of these queries. For variable-length queries, we introduce a new type of index, called the Markov chain index (MC index) and an access method that uses this index to efficiently answer *any* Regular event queries.

For simplicity of presentation, we first introduce our algorithms under two simplifying assumptions: 1) we assume that all stream schemas contain only a single attribute A_1 ; 2) we assume that all predicates are of the form `attribute = constant` (e.g. predicates select single attribute values). In Section III-D we show how our algorithms generalize beyond these assumptions.

A. Fixed-Length Regular Queries

Fixed-length Regular queries can be processed using simple adaptations of standard indexing techniques (first challenge, Section II-C). In particular, we can leverage a standard B+ tree secondary index on a Markovian stream. The B+ tree uses search keys of the form: `(attribute, time)`. Here `attribute` is the stream attribute being indexed and `time` is the stream timestamp. For example, a query plan for the Entered-Office query in Figure 3(a) might leverage an index on `(location, time)`. We call this index BT_C (C for “chronological”, since this is the ordering of keys sharing the same attribute value). An example is shown in Figure 6.

Note that, because each timestep in a Markovian stream represents a distribution over states, each timestamp can appear multiple times in this index. For example, timestamp 7 in Figure 6 appears in three index keys, with locations H2,

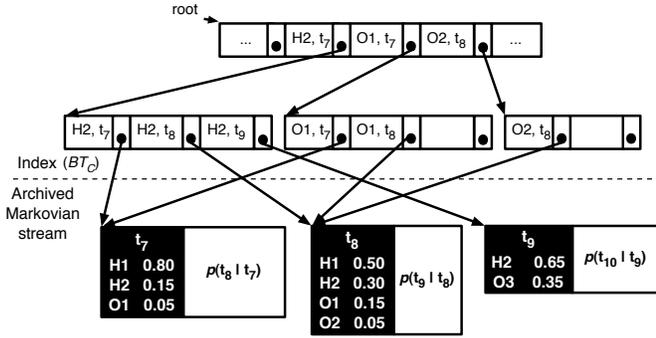


Fig. 6. Bottom: Three timesteps’ worth of the Markovian stream representing Bob’s location, also shown in Figure 2. Top: A portion of BT_C on this stream.

O1, and H1 (not shown). Importantly, the index includes only attribute/time pairs with a non-zero marginal probability, since zero-probability marginal entries are not explicitly stored in the stream.

Recall that a fixed-length query Q_F comprising n links can be satisfied only by stream intervals of length n . The goal of indexing in this case is to efficiently identify these intervals. For each predicate r in Q_F , an index such as BT_C can be used to retrieve the set of stream timesteps satisfying r . We define *satisfying timesteps* as the set of timesteps in which predicate r is satisfied with non-zero probability.

A standard equijoin between the sets of timesteps satisfying various query link predicates is useless for identifying relevant intervals. Instead, we require a temporally-aware join that identifies contiguous *sequences* of timesteps. We implement such a join using a separate index cursor on each predicate r . These cursors are advanced forward in parallel while maintaining the relative offsets required by the ordering of predicates in Q_F . We say that the cursors *intersect* when they together reference a sequence of n consecutive timesteps, in the appropriate query-specified ordering. Thus every *intersection* identifies a length- n stream interval that is a potential query match. This process is similar to the standard merge join, and shares the corresponding linear-time data complexity.

This access method, which we call the B+Tree approach, is shown in Algorithm 2. Lines 1-2 initialize cursors on the index entries satisfying the predicates of Q_F . In line 3 these cursors are advanced until they *intersect* on an interval I . Lines 4-6 process I through the Reg operator.

An example of the pruning done by the B+Tree approach can be seen on the stream segment pictured in Figure 6. On a two-link, fixed-length query comprising predicates $(H2, O2)$, the cursors on $H2$ and $O2$ first intersect on the interval (t_7, t_8) , which is passed to Reg. In contrast, the index entry $(H2, t_8)$ has no intersecting entry $(O2, t_9)$, so this interval is not retrieved from disk or passed through the Reg operator.

One convenient feature of our implementation of temporally-aware index joins is that it retrieves relevant intervals in chronological order. Overlapping intervals can thus be combined before invoking Reg. To see this, consider the fixed-length query $(O1, H2)$ on the data in Figure 6. The B+Tree algorithm will identify both (t_7, t_8) and (t_8, t_9) as requiring further processing. By instead passing the single, longer interval (t_7, t_9) , through Reg, it can avoid

Algorithm 2 Fixed-Length Query Access Method (General)

Note: For simplicity, merging of overlapping intervals is not shown.

Input: Fixed-length query Q_F comprising n links, Markovian stream M , B+ Tree index BT_C on the single attribute of M .

Output: Probability that Q_F is satisfied at each timestep $t \in M$

- 1: **for each** predicate r_j in Q_F **do**
- 2: Initialize cursor C_j on predicate r_j in BT_C
- 3: **for each** interval I in the *intersection* of (C_0, \dots, C_n) **do**
- 4: Reg.startSequence($I[0]$.marginal)
- 5: **for each** timestep i in I **do**
- 6: $\langle I[i].t, p \rangle = \text{Reg.update}(I[i].cpt)$

double-processing of timestep t_8 . Thus on the densest data sets, the B+Tree approach gracefully degenerates into a naïve stream scan, with additional overhead to handle the BT_C index cursors.

B. Top-K Optimization for Fixed-Length Regular Queries

The B+Tree algorithm efficiently computes the probability of every query match in a stream; however, recall from Section II-C (Figure 4) that many of these matches are of low quality and are thus uninteresting to applications. The challenge in this case is that of *high-quality event retrieval*, in which only the top k query matches, or only those matches with probabilities above a given fixed threshold, are returned.

The key observation for efficient optimization of these queries is the following: within a length- n interval, the marginal probability that the i^{th} link predicate is satisfied at the i^{th} timestep in the interval is an upper bound on the probability that the interval satisfies the query (*i.e.* that the query has a non-zero probability of being true at the last timestep in the interval). As an example, consider the fixed-length query $(H1, H2)$ on the interval (t_7, t_8) of Bob’s location stream in Figure 2(b). Both $p(H1 \text{ at } t_7) = 0.8$ and $p(H2 \text{ at } t_8) = 0.3$ are upper bounds on the probability that the interval (t_7, t_8) matches the query, which in this case is $0.8 * 0.25 = 0.2$. Intuitively, these marginal probabilities are upper bounds because a sequence of events cannot be *more* likely than any of its individual components.

This observation implies that we can adapt the well-known Threshold Algorithm (TA) and its variants [11], [26] to our problem. The basic idea is to process fixed-length stream intervals in decreasing order of marginal probability. For each interval, we use the maximum marginal probability among all query predicates to determine an upper bound on the probability that the interval will match the query; we then process each interval in order of decreasing upper bound.

More specifically, we introduce an additional secondary B+ tree index on the Markovian stream. We call this index the BT_P (p for “probability”) index. It uses search keys of the form $(\text{attribute}, \text{prob})$, where *attribute* is the stream attribute being indexed and *prob* is the marginal probability that the attribute value is true at the indexed timestep. Within the BT_P index, keys sharing an attribute value are ordered in *decreasing* order of marginal probability. As with the BT_C index, the BT_P index includes only keys with non-zero probability.

Algorithm 3 Fixed-Length Query Access Method (Top-K)

Input: Fixed-length query Q_F comprising n links, Markovian stream M , B+ Tree index BT_P on the single attribute of M , and k

Output: Top k timesteps at which Q_F is satisfied in M .

- 1: currTopK.initializeEmpty
- 2: **for each** predicate r_j in Q_F **do**
- 3: Initialize cursor C_j on predicate r_j in BT_P
- 4: **for each** timestep $M[t]$ w/ max prob. referenced by *any* C_j **do**
- 5: **if** $M[t].\text{marginal.prob}(r_j) \leq \text{currTopK.min}$ **then**
- 6: Terminate
- 7: $I = \{M[t - j], \dots, M[t - j + n]\}$
- 8: **if** $I[l].\text{marginal.prob}(r_j) > \text{currTopK.min}, \forall 0 \leq l < n$ **then**
- 9: Reg.startSequence($I[0].\text{marginal}$)
- 10: **for each** i in I **do**
- 11: $\langle I[i].t, p \rangle = \text{Reg.update}(I[i].\text{cpt})$
- 12: currTopK.evaluate(p)

Algorithm 3 outlines an access method (the top-k B+Tree approach) that leverages the BT_P index and the TA technique to efficiently process top-k queries. After initialization (lines 1-3), the algorithm scans in parallel all leaves of the B+ tree that match the different query predicates, returning the entry $M[t]$ with the highest remaining marginal probability (line 4). The algorithm terminates when the maximum marginal probability of all remaining index entries (e.g. the marginal probability of predicate r_j in timestep $M[t]$) is below the probability of all k of the current best query matches (lines 5-6). If this condition is not met, the marginal probability of *each* predicate in the interval I is examined (lines 7-8). If none of these is low enough to prune the interval, the interval is processed through the Reg operator (lines 9-12) and the resulting probability is incorporated into the top k matches if appropriate.

As mentioned above, the marginal probability of each predicate in a length- n interval is only an upper bound on the probability that the interval matches the query; the actual match probability may be much lower or even zero. In data where this is common, the top-k B+Tree algorithm has little opportunity for pruning, and the B+Tree implementation of Ex based on the BT_C index, followed by a sort on the output tuples, will often outperform the top-k B+Tree approach because of its ability to combine the processing of overlapping intervals. The top-k approach, by contrast, significantly outperforms the standard B+Tree approach on queries with clear peaks, such as that shown in Figure 3(b). We further explore the relationship between these two algorithms in our evaluation (Section IV).

C. Variable-Length Regular Queries

The fixed-length access methods in the previous section are inapplicable to variable-length queries, because variable-length queries can be satisfied by stream intervals of arbitrary length. A full stream scan can be avoided in this case using the following insight: while query match intervals may be arbitrarily long, generally only a small number of timesteps in each interval contain data *relevant* to the query (i.e., satisfy at least one query predicate with non-zero probability). Furthermore, the query NFA changes state only on these relevant inputs. In fact, the “irrelevant” intermediate timesteps require processing only because together they contain the correlation information relating each relevant timestep to the next. Thus we arrive at

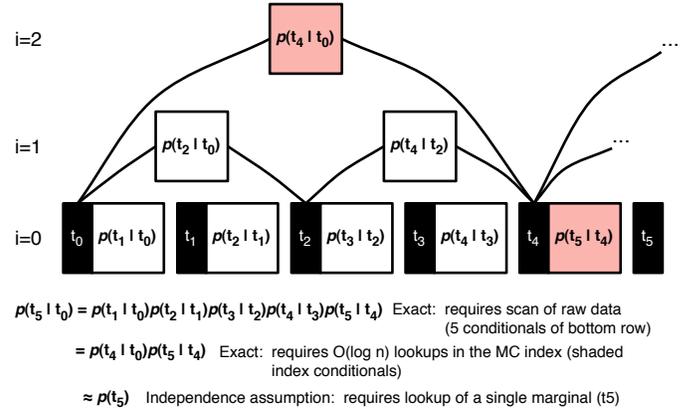


Fig. 7. Markov chain index for $\alpha = 2$. The bottom row ($i = 0$) is the raw data, abstracted here. The two index entries required to compute the CPT between timesteps t_0 and t_5 are shaded; without the index, a scan of the raw data would be required. The semi-independence assumption requires lookup only of the marginal at time t_5 , but computes an approximate result.

the final, *correlation retrieval* challenge: to develop an efficient (in both space and time) method for retrieving the correlations between distant stream timesteps.

We now introduce a novel Markov chain index (MC) that achieves this goal, along with an Ex implementation that leverages it.

1) *Markov Chain Index*: The Markov chain (MC) index is a tree-structured index that provides efficient lookup and/or computation of the CPT relating any two Markovian stream timesteps. The index stores a small set of precomputed CPTs organized in the tree structure shown in Figure 7. The lowest level of the tree ($i = 0$) is simply the set of all M CPTs in the raw, length- M Markovian stream. The density of additional levels of the tree is controlled by an integer parameter α . Each additional index level i contains a set of $M/(\alpha^i)$ entries, each of which relates a pair of timesteps separated by a distance of α^i . The total number of levels in the index is $\log_\alpha(M)$, and each index entry is the product of α entries of the index level below it. The example in Figure 7 is drawn for $\alpha = 2$; larger values of α decrease the storage requirements of the index.

CPTs not stored directly in the MC index can be computed as the product of existing entries, using the chain rule of probabilities: $p(t_j | t_i) = p(t_j | t_k)p(t_k | t_i)$. The upper bound on the number of CPTs that must be multiplied to compute a CPT spanning n timesteps is $2 \log_\alpha(n)$, since at most two entries from each applicable index level must participate. In comparison, without the index this number would be simply n . In Figure 7, the two shaded index entries represent those whose product is the CPT relating t_0 and t_5 .

2) *Variable-Length Algorithm*: The Markov chain index naturally yields a simple algorithm (Algorithm 4, which we call the MC index approach) for processing variable-length queries. In lines 2-3, a separate index cursor on BT_C is initialized on each query predicate. Line 4 advances these cursors forward in parallel, entering into the loop once for each timestep $M[t]$ satisfying *any* of the query predicates. Upon the first entrance into this loop, execution jumps to line 6. Upon subsequent iterations, line 8 uses the MC index to lookup/compute the CPT between the previous relevant

Algorithm 4 Variable-Length Query Access Method (MC Index)

Input: Variable-length query Q_V comprising n links, Markovian stream M , B+ Tree index BT_C on the single attribute of M , Markov chain index MC

Output: Probability that Q_V is satisfied at each timestep $t \in M$

```

1:  $t_{prev} = \emptyset$ ;
2: for each predicate  $r_j$  in  $Q_V$  do
3:   Initialize cursor  $C_j$  on predicate  $r_j$  in  $BT_C$ 
4: for each timestep  $M[t]$  referenced by any  $C_j$  do
5:   if  $t_{prev} == \emptyset$  then
6:     Reg.startSequence( $M[t]$ .marginal)
7:   else
8:      $cpt = MC.computeCPT(t_{prev}, t)$ 
9:      $\langle M[t].t, p \rangle = Reg.update(cpt)$ 
10:   $t_{prev} = t$ 

```

timestep (t_{prev}) and the current one (t). In line 9 this CPT is used to update the Reg operator. In this way the algorithm performs a single conceptual pass over the entire stream, but leverages the MC index to avoid retrieving large spans of irrelevant data from disk.

When a variable-length query contains loop predicates that are *not* negations of non-loop predicates (e.g. $(O1, H1*, O2)$), the MC index and algorithm as presented above appear insufficient. In this case, the large stream intervals requiring summarization are not those containing *irrelevant* data, but instead are those that continuously satisfy the query loop predicate ($H1$ in the example of the previous sentence). These conditionals are not present in the MC index as described above; however, they can be captured for a given predicate (e.g. $H1$) in a separate instance of the MC index whose entries are conditioned on satisfaction of the predicate. The details of the index construction and associated access method are extremely similar to those presented for the general case, and we omit them due to space limitations.

D. Practical Details

In this section we address several practical details which until this point have been abstracted away or simplified for the sake of presentation.

1) *Indexing Predicates:* Thus far we have assumed that all query predicates are expressed as trivial equality selections on a single stream attribute. However, Caldera can also support multi-attribute schemas and more sophisticated predicates. Caldera is designed to work with a star schema, analogously to data warehouses: the Markovian stream corresponds to the (multi-attribute) facts table, while separate dimension tables provide extra information about stream attributes. Consider as an example the RFID-derived Markovian stream with schema $(tagID, locationID, time, probability)$. Additional information about individual locationIDs could be stored in a dimension table called LocationType, with schema $(locationID, locationType)$ and tuples of the form $(\text{“Room300”}, \text{“CoffeeRoom”})$, $(\text{“HallwaySegment3”}, \text{“Hallway”})$, etc..

As in a data warehouse, Caldera supports join indexes between the stream relation M and one or more dimension

relations D . Conceptually, the join index extends the tuples in M with the attributes of D and indexes the resulting relation. In practice, we create the index directly on M without modifying it (e.g., the BT_C and BT_P indexes).

When the probability of a predicate P_i at a particular timestep t is required (e.g., to create the index entries of BT_P for time t), it is computed by summing the marginal probabilities of all tuples whose attribute values satisfy P_i at t ; this construction is valid because tuples with the same timestamp are disjoint. Conditional predicate probabilities are similarly combined via weighted averages.

In the case where a Markovian stream is defined over multiple attributes, it is possible that indexes exist on only a subset of these attributes. Our fixed-length access methods can simply use whatever indexes are available. Our variable-length access method, however, requires indexes on *all* attributes involved in any of the query predicates. If any of these indexes is unavailable, a naïve full data scan is the only processing option supported by Caldera.

Finally, with the exception of the top-k implementation, all access methods support both equality and range predicates.

2) *Physical Schema:* Markovian stream archives are most logically partitioned by stream, since Regular queries are each defined over a single stream (e.g. over Bob’s location or Sue’s location, but not both at the same time). Within a Markovian stream, we choose to order data chronologically since the Reg operator needs to process data in that order; however, several disk layouts fulfill this constraint.

Separated Layout: In this layout, the marginal and conditional sequences are each laid out chronologically, but in separate locations (e.g. separate files). This layout optimizes for situations where most accesses are made to one sequence or the other, but not to both. Indexes on this layout are constructed separately for each sequence.

Co-Clustered Layout: In this layout, the marginal and conditional sequences are interleaved such that the marginal and conditional tuples representing a single timestep are placed together on disk, immediately before the marginal/conditional tuples representing the chronologically-next timestep. This minimizes access cost for operations requiring access to both the marginal and conditional data for most timesteps. Indexes on this layout are constructed as shown in Figure 6.

While the optimal layout is workload-dependent, we find in Section IV that for common queries on an RFID-derived location stream, the separated layout yields faster performance.

3) *Variable-Length Algorithm (Approximate):* While our MC index algorithm provides applications with an elegant space/time tradeoff, we acknowledge that some disk-hungry or time-critical applications may not be satisfied by any point in this tradeoff space. For these applications we provide a final access method that is both more efficient than the semi-independent approach, and does not require use of the MC index; however, it returns only *approximate* results. We call this algorithm the semi-independent approach because it assumes independence between some—but not all—timesteps in a Markovian stream.

Algorithm 5 outlines the semi-independent approach which is similar to Algorithm 4 (we again assume a single-attribute

Algorithm 5 Approximate Variable-Length Access Method (Semi-Independent Algorithm)

Input: Variable-length query Q_V comprising n links, Markovian stream M , B+ Tree index BT_C on ALL attributes of Q_V

Output: Approximate probability that Q_V is satisfied at each timestep $t \in M$

```

1:  $t_{prev} = \emptyset$ ;
2: for each predicate  $r_j$  in  $Q_V$  do
3:   Initialize cursor  $C_j$  on predicate  $r_j$  in  $BT_C$ 
4: for each timestep  $M[t]$  referenced by any  $C_j$  do
5:   if  $t_{prev} == \emptyset$  then
6:      $Reg.startSequence(M[t].marginal)$ 
7:   else if  $t == t_{prev} + 1$  then
8:      $\langle M[t].t, p \rangle = Reg.update(M[t].cpt)$ 
9:   else if  $t > t_{prev} + 1$  then
10:     $\langle M[t].t, p \rangle = Reg.update(M[t].marginal)$ 
11:   $t_{prev} = t$ 

```

stream schema, for clarity). Where Algorithm 4 uses the *MC* index to retrieve correlations (lines 8-9), Algorithm 5 instead makes a choice: If the previous and current timesteps are adjacent, then it updates *Reg* using correlations (lines 7-8). If the two timesteps are not adjacent, then they are assumed independent and the correlations between them are ignored (lines 9-10). Updating the *Reg* operator with a marginal distribution instead of a CPT causes *Reg* to assume this independence.

We call this approach semi-independent instead of simply independent because it does *not* assume independence between adjacent timesteps. The CPTs relating adjacent timesteps can be read using a single disk access, equivalent in cost to the access of the marginal required to make the independence assumption. The costs of semi-independence and full independence are therefore the same, and we choose the algorithm that preserves as much correlation information as possible.

The semi-independence approach is only one sample from a large space of algorithms that trade probabilistic precision for speed. This tradeoff is particularly important for Markovian streams because the cost of preserving exact probabilities causes dramatic increases in both data storage and processing time requirements. We believe that approximate approaches will therefore play an important role in large-scale Markovian stream processing systems. We leave the development and analysis of such techniques to future work.

IV. EVALUATION

The following evaluations were performed on our Caldera prototype, implemented in Java and using Berkeley DB [27] as a data storage back-end. All experiments were conducted on a 2.00GHz Linux machine with 16GB of RAM.

We demonstrate on both synthetic and real data that standard B+ tree indexing techniques (the B+Tree [Algorithm 2] and top-k B+Tree [Algorithm 3] methods) provide orders of magnitude improvements in performance over a naïve stream scan on fixed-length queries, even while preserving the probabilistic, correlated relationships within Markovian streams. We further demonstrate that the novel Markov chain index provides the same magnitudes of speedup on variable-length queries. Finally we demonstrate that the approximate

semi-independent approach outperforms even the *MC* index approach, and we elaborate on its accuracy/efficiency tradeoff.

A. Setup

We evaluate Caldera on both synthetic and real Markovian streams, all from the RFID-based location tracking application used as our primary motivation throughout the paper.

1) *Synthetic RFID Data*: Each synthetic Markovian stream comprises 8 hours of data (30,000 timesteps). To maintain realistic properties, we constructed these streams by concatenating together various 30-second stream “snippets” generated from an RFID simulator reflecting the physical layout of our building and RFID deployment. In each snippet, a simulated person carrying an RFID tag walks down a short corridor, into a room where he stays for 15 seconds, and then back down the corridor. By altering the room labels in these snippets, we control the relevant properties of each stream with respect to our test queries.

2) *Real RFID Data*: Our real RFID dataset was collected using our building-wide RFID deployment. Eight volunteers carried 58 tags as they went through one-hour versions of typical daily routines (working in their offices, having meetings, taking coffee breaks, etc.). These routines visited locations across two floors, spanning an area of roughly 10,000 square feet discretized into 352 locations. The 17 antennas on each of the two floors were placed only in the corridors (offices, labs, etc. had no antennas inside them). We show performance on eight of these traces, selected for their length (8 minutes or more) and realistic reflection of location uncertainty (*i.e.*, some tags were never or almost never detected and we did not use the resulting traces).

We find that, on our real RFID dataset, the fraction of *relevant* timesteps (timesteps satisfying at least one query predicate with non-zero probability) exhibits bimodal behavior: either almost all or almost none of the timesteps in a stream are relevant to a specific query. We call this fraction of relevant timesteps *data density* and note that it is defined on a Markovian stream with respect to a specific query. Data density tends to be bimodal simply because the amount of time that a person spends in a given place tends to be bimodal. For example, the data density of queries involving a person’s office tend to be high (0.75 and up) since the majority of a person’s time is spent in his office. However, for queries about coffee rooms, other people’s offices, etc., the fraction of relevant timesteps is very small because the percentage of time a person spends near these places is low. Data density is an important parameter because it determines the relative performance of different access methods.

B. Access Methods for Fixed-Length Regular Queries

We evaluate the performance of the B+Tree algorithm (Algorithm 2) on a two-link Entered-Room query and compare the results to the naïve full stream scan. We perform this comparison using both the separated and co-clustered disk layouts in order to assess the benefits of each.

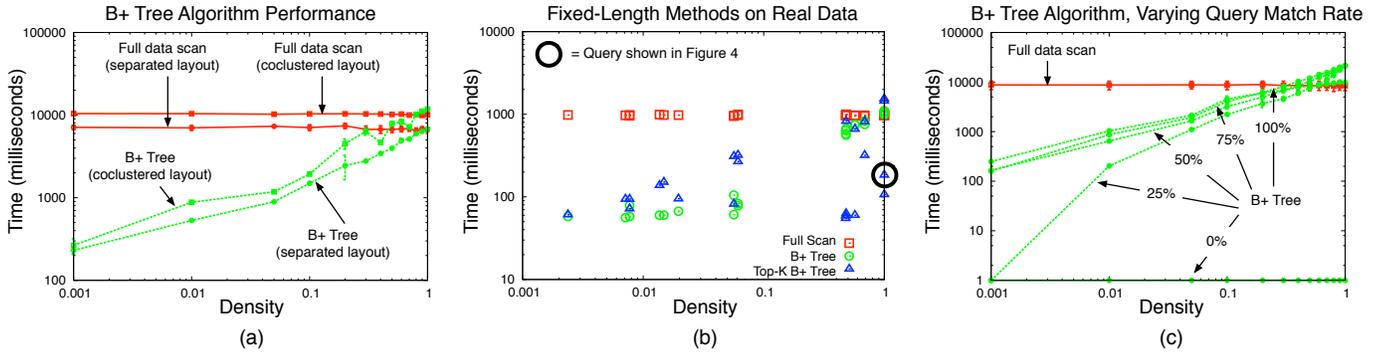


Fig. 8. Evaluation of access methods optimized for fixed-length queries. (a) Worst-case performance of the B+Tree algorithm using two disk layouts, on synthetic data. (b) Performance of fixed-length approaches on real-world data. (c) Performance of the B+Tree algorithm on increasingly-favorable datasets.

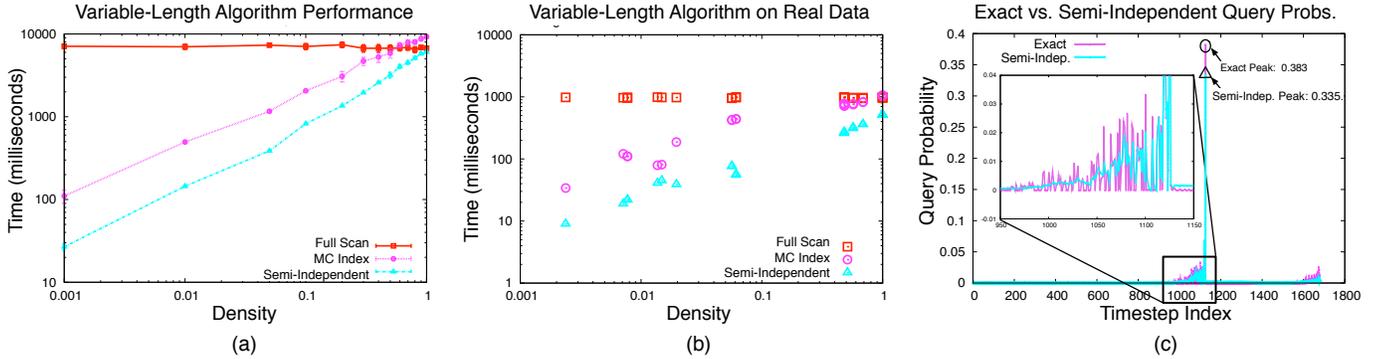


Fig. 9. Evaluation of access methods optimized for variable-length queries. (a) Performance of the three algorithms as the number of relevant timesteps varies. (b) Performance on a real-world stream. (c) Breakdown on a real-world query of the approximation error of the semi-independent approach.

1) *Performance Overview*: Figure 8(a) shows logscale performance numbers for both algorithms running on our synthetic data. As expected, when the data density is low, the B+Tree algorithm significantly outperforms a full stream scan—in this case, by 1-2 orders of magnitude. Conversely when most stream timesteps are relevant to the query, the B+Tree approach degenerates into a full data scan with additional overhead for the B+ tree lookups. We note that the B+Tree algorithm performance here is worst-case, because in this dataset, *every* relevant timestep (timesteps that satisfy at least one query predicate) participates in a valid query match. This property reduces the amount of pruning and increases the amount of disk I/O that the algorithm needs to do.

Figure 8(a) also demonstrates that both a full stream scan and the B+Tree algorithm perform more efficiently on streams archived using a separated disk layout. In the case of a full scan this is not surprising, since only CPTs (no marginals) are required. More interesting is the superior performance of the B+Tree approach on a separated layout. In theory, when data density is low, relevant stream intervals should be isolated and the B+Tree approach will process only n CPTs for every marginal (n is one less than the number of links in the query). A co-clustered layout will certainly outperform a separated layout in this case, since only a single disk I/O is required to access both marginal and CPT data. In real-world Markovian streams, however, and in our synthetic traces, intervals of relevant data are not isolated but instead overlap each other in long (e.g., 30 timesteps or more) stretches. This overlap increases the number of CPTs read from disk for each

marginal, and as this number increases, the separated layout dominates performance.

In order to show the best performance, we evaluate all algorithms throughout the remainder of this section using a separated disk layout. We note however that other types of Markovian streams may not exhibit the same locality of relevant timesteps, and for these streams the choice of optimal disk layout may be different.

2) *Real-World Query Performance (Fixed-Length)*: Figure 8(b) shows the performance of the three fixed-length query algorithms (Algorithms 1, 2, and 3) on a set of 22 different Entered-Room queries in one real, 28-minute stream. Each of the 22 queries corresponds to a different room, and is responsible for three plotted points (one for each algorithm). Not surprisingly, the plot confirms the results shown in Fig. 8(a): the speedup of the B+Tree approach over a naïve scan increases as density decreases, providing improvements of at least an order of magnitude when this density is low. The lack of data points in the x range $[0.1, 0.5]$ in Figure 8(b) reflects the bimodality of data density.

In the set of queries with low data density, the top- k B+Tree approach (Algorithm 3, plotted here for $k = 1$) performs poorly relative to the B+Tree algorithm. The sparse nature of the relevant data here provides the top- k B+Tree approach with little opportunity for additional pruning. Furthermore, the ability of the B+Tree algorithm to process overlapping intervals in a single pass often allows it to outperform the top- k B+Tree algorithm.

When the data density is high, however, the performance

of the top-k B+Tree algorithm is often—though not always—much better (here, by an order of magnitude) than that of either alternative. The key feature allowing efficient pruning and therefore fast performance is the existence of a small number of sharp peaks in the query signal. The query signal shown in Figure 3(b) exhibits such behavior, and indeed this query is responsible for the top-k B+Tree point highlighted in Fig. 8(b) at $x = 1.0$. While the existence of such a peak cannot be precisely determined ahead of query processing (indeed, to do so would be to answer the top-k query), a reasonable heuristic is to try and use the top-k B+Tree algorithm for queries expected to have a high data density.

3) *Broader Performance Trends*: Figure 8(c) shows a more detailed, synthetic-data evaluation of the behavior of the B+Tree approach on an Entered-Room query. Each curve plots the performance of the algorithm when a different, fixed fraction of relevant timesteps participate in query matches. The curve for a query match rate of 100% is precisely the curve from Figure 8(a).

For any single curve in Figure 8(c), decreasing the data density (x-axis) decreases the number of query match intervals that the B+Tree algorithm must fetch from disk and send through the Reg operator, which increases performance. For a given data density on the x-axis, a decrease in the number of query matches causes a proportional increase in performance. When the fraction of relevant timesteps is low (e.g. 0.01), the difference between a 100% and 25% query match rate results in an order of magnitude difference in processing time.

4) *Performance on Longer Queries*: We demonstrate the scalability of the B+Tree algorithm on queries comprising more than two links using the real data. Figure 10 shows the results. Each of the three major columns of this table contains performance data for a real-world stream on an Entered-Room query written using 2, 3, or 4 links (we do not expect real-world queries to require more than 4 links). The queries with 3 and 4 links require a tag’s presence at multiple specific hallway locations outside a room before the room is entered.

The Reg operator slows exponentially with each additional query link, as can be seen in the fourth row of Fig. 10. Because the B+Tree approach is able to avoid many Reg updates, the performance of the B+Tree approach relative to a full stream scan (row 6 vs. row 4) improves dramatically on longer queries. The performance of the top-k B+Tree algorithm shows similar trends, although the relative performance gain is slightly less pronounced than for the B+Tree approach.

The results in the figure show the performance of the B+Tree and top-k B+Tree algorithms when indexes serve to identify matching timesteps for all query predicates. In the case where some query predicates are not indexed, performance scales predominantly with the selectivity of the *intersection* of the available indexes, independent of the number of predicates indexed. A second-order effect reflects improved performance when the number of predicate indexes decreases, simply because the index overhead is reduced.

C. Access Methods for Variable-Length Queries

The performance of the MC index (Algorithm 4, $\alpha=2$) and semi-independent (Algorithm 5) approaches versus a

		Stream: James Q: Entered-Office # Subgoals in query:			Stream: Sally Q: Entered-Office # Subgoals in query:			Stream: Pat Q: Coffee-Room # Subgoals in query:		
		2	3	4	2	3	4	2	3	4
	Stream length (minutes)	7.7	7.7	7.7	7.6	7.6	7.6	28	28	28
	Stream length (timesteps)	462	462	462	458	458	458	1683	1683	1683
	# relevant timesteps	149	194	211	5	5	6	33	53	253
	Time: Full Scan (msec)	548	625	1206	554	613	1201	977	1124	3034
F I X E D	# query matches	26	26	11	2	1	1	3	1	1
	Time: B+ Tree (msec)	174	232	266	59	67	132	67	71	135
	Time: Top-K B+ Tree (msec)	56	75	214	67	98	165	95	366	1970
V A R	# query matches	145	188	188	2	1	1	3	21	21
	Time: MC Index (msec)	290	424	678	32	43	117	187	237	902
	Time: Semi-Indep. (msec)	114	156	379	9	12	22	39	68	398

Fig. 10. Statistics describing several streams from our real data set, and the speed of queries with varying lengths on these streams.

naïve stream scan, on synthetic data and the now-familiar Entered-Room query, are shown in Figure 9(a). Data density is again the dominant factor in the performance of both algorithms, which exhibit the same trends as the B+Tree approach. Figures 9(a) and 8(a) are directly comparable. The approximate, semi-independent approach is consistently faster than the precise MC index approach, by a factor of roughly 8.

1) *Real-World Query Performance (Variable-Length)*: The performance of the three variable-length query algorithms on real-world data is shown in Figure 9(b). As on the synthetic data in Figure 9(a), the MC index access method performance scales inversely with data density and outperforms the full data scan by more than an order of magnitude when density is low. The semi-independent approach continues to show performance improvements over the MC index algorithm measuring just under an order of magnitude.

The queries shown in Figure 9(b) are precisely the queries plotted in Figure 8(b), with Kleene closures added to make these queries variable-length. The data in these two plots is therefore directly comparable (note the fact that the naïve data scan reflects the same constant time in both figures). Algorithms 2 and 4 perform very similarly, yielding an interesting discussion about when one or the other might be preferable. The MC index approach is more general in that it can handle any kind of Regular query; however, it is applicable only when *all* stream attributes are indexed, and when the MC index is available.

2) *Accuracy vs. Efficiency*: The semi-independent approach is faster than MC index, but this performance gain comes at the cost of accuracy. The approximate, semi-independent algorithm makes no guarantees about the magnitude of the errors it may incur.

Many applications, however, can tolerate some imprecision. For such applications, the tradeoff between efficiency and accuracy depends on the types of approximation errors typically present in the Markovian streams of the application domain. An example of such errors on a real-world Markovian stream is shown in Figure 9(c). In this case, the approximate query probabilities track the magnitudes of the precise probabilities fairly well. The semi-independent algorithm correctly identifies the maximum-probability timestep (this is not guaranteed or even likely in some datasets), incurring a relative error of roughly 13%. Applications in many circumstances may be willing to use these approximate results in return for an order-

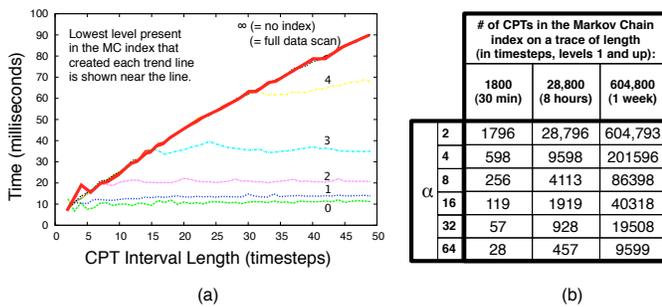


Fig. 11. (a) Time required to compute correlations across intervals of varying lengths using the Markov chain index. Each successive line plots performance when omitting an increasing number of lower index levels. (b) Storage requirements for the Markov chain index under varying α values.

of-magnitude speedup.

Anecdotally, we find the approximations in Figure 9(c) to be a fairly optimistic sampling of the output of the semi-independent algorithm. The semi-independent approach on other of our real-world Markovian streams failed to properly identify the maximum-probability timestep, giving errors with raw magnitudes up to 0.286.

D. Markov Chain Index

The purpose of the Markov chain index is to provide efficient access to (precomputed) correlations between distant Markovian stream timesteps. Figure 11 provides details of the index’s tradeoff between storage space and lookup speed.

Figure 11(a) shows the average time required to compute correlations between two timesteps separated by intervals of varying size. Because the placement of these intervals relative to stored index entries is important, reported results are the averages over all placements. Each higher curve in the graph represents performance when an additional index level is removed (this is a proxy for increasing α). Clearly, correlations across intervals *smaller* than the span of the lowest available level of the Markov chain index can be computed only with a full scan, which accounts for the upper-bound behavior of the leftmost, naïve scan curve. The spacing between the flat portions of each i curve demonstrates that each additional index level reduces CPT lookup time by half.

In terms of speed, then, MC indexes parameterized with lower values of α (roughly equivalent to the addition of increasingly low levels i in the above discussion) provide better performance by storing a greater number of precomputed conditionals. While this performance is gained at the cost of disk space, we note that the most efficient parameterization, using $\alpha = 2$, merely doubles the stream storage requirements. Certainly many applications in the archived, warehouse-like setting targeted by Caldera will find this an acceptable tradeoff; however, disk-starved applications can leverage the MC index within their resource limitations by increasing α . Storage requirements for various α on streams of varying lengths are shown in 11(b).

V. RELATED WORK

Management of large-scale archived RFID data sets has received significant attention, with much work focusing directly on the storage, processing, and analysis of raw,

noisy RFID data [14], [16], [24], [31], [39]. A complementary body of work addresses the cleanup of noisy RFID streams and presents methods for producing cleaned—but still deterministic—streams [19], [31], [39]. By contrast, Caldera preserves the uncertainty (probabilities and correlations) at the levels of both data and queries. In previous work, we proposed probabilistic RFID cleaning [21] and SQL-based event extraction [41] techniques. These approaches, however, ignore correlations, do not support Kleene Closures, and extract events by executing incremental SQL queries (our most recent related work, Lahar [33] is discussed below).

The problem of probabilistically inferring high-level information (e.g. location, activity) from low-level sensor data has a long history in the AI community. Temporal probabilistic models such as Hidden Markov Models [29] and Dynamic Bayesian Networks [23], [25] deal specifically with uncertain, temporal data. Particle filtering [2] (and associated smoothing algorithms [22], [7]) is a simple and popular way of performing inference in these models, and has also recently been used in the databases community to perform real-time inference inside a DBMS [20] and to infer the locations of RFID tags when both tag and antenna locations are unknown [37].

While inference in probabilistic models is highly developed in the AI community, work on answering relational and event-style queries on the output of these models is in its infancy. Deshpande *et al.*, propose treatment of these models within a DBMS as a model-based view [10] and explore answering selection and aggregation queries on these views [20]; Caldera in effect treats its stream archive as a materialization of such a view and explores event-based queries. The Data Furnace project [12] similarly proposes to perform model-based inference directly inside a DBMS; however to the best of our knowledge no technical results on this project have been published. Probabilistic databases like MystiQ [8] and Trio [3], [42] address a related problem space but cannot model the sequential, correlated data streams at the heart of Caldera.

Automaton-based processing of event queries on RFID or similar data streams has recently been explored in the Cayuga [9] and SASE [43] systems, but these systems assume a deterministic input stream. In Lahar [33], we adapted this style of processing to probabilistic input. Our current work on Caldera leverages Lahar’s stream processing algorithms.

Markovian streams are related to time series and time-evolving data, since they are temporal data sequences. Caldera’s workload (*i.e.*, event queries on probabilistic streams), however, differs significantly from the workload of time-series databases (*i.e.*, primarily similarity searching) and temporal databases (*i.e.*, selections of different object versions or objects valid within certain time intervals). Indexing techniques for time series [15] and temporal [35] data are thus orthogonal to Caldera’s techniques.

There has been recent work on top- k query processing of probabilistic relational systems [32], [36], [4]; however, none consider the problem of indexing *sequential* probabilistic data. Separately, there is work on probabilistic streams [18], [6], but this work does not consider access paths for the streams.

VI. CONCLUSION

In this paper we presented Caldera, a system for executing event queries over archived Markovian streams. In contrast to previous systems that must process the entire Markovian stream to answer an event query, Caldera selectively processes only relevant parts of the stream, thus achieving significant performance gains. At the same time, Caldera preserves result accuracy by retaining the Markovian properties of the stream while skipping data.

To achieve high performance, Caldera distinguishes different types of queries (fixed-length and variable-length). It then uses novel and efficient access methods specialized for each query type. For fixed-length queries, Caldera uses novel adaptations of standard B+ tree indexes. For variable-length queries, it leverages a new type of index, the MC index, to effectively summarize unimportant parts of a stream. Additionally, Caldera supports top-k queries that effectively filter out noise in query results and can also improve performance in the case of fixed-length queries. Using synthetic and real data, we demonstrated that Caldera offers performance that can be orders magnitude better than that of a full stream scan.

Overall, effective techniques for managing noisy sensor data are important for many applications today and we view this work as an important step in this direction.

ACKNOWLEDGEMENTS

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