AFilter: Adaptable XML Filtering with Prefix-Caching and Suffix-Clustering

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ABSTRACT
XML message filtering problem involves searching for instances of a given, potentially large, set of patterns in a continuous stream of XML messages. Since the messages arrive continuously, it is essential that the filtering rate matches the data arrival rate. Therefore, the given set of filter patterns needs to be indexed appropriately to enable real-time processing of the streaming XML data. In this paper, we propose AFilter, an adaptable, and thus scalable, path expression filtering approach. AFilter has a base memory requirement linear in filter expression and data size. Furthermore, when additional memory is available, AFilter can exploit prefix commonalities in the set of filter expressions using a loosely-coupled prefix caching mechanism as opposed to tightly-coupled active state representation of alternative approaches. Unlike existing systems, AFilter can also exploit suffix-commonalities across filter expressions, while simultaneously leveraging the prefix-commonalities through the cache. Finally, AFilter uses a triggering mechanism to prevent excessive consumption of resources by delaying processing until a trigger condition is observed. Experiment results show that AFilter provides significantly better scalability and runtime performance when compared to state of the art filtering systems.

1. INTRODUCTION
XML message filtering systems are used for sifting through real-time messages to support publish/subscribe [11, 25, 26], real-time business data mining, accounting, and reporting for enterprises. A filtering system continuously evaluates a given set of registered filter predicates on real-time message streams to identify the relevant data for higher-level processing. Thus, XML filtering problem is concerned with finding instances of a given, potentially large, set of patterns in a continuous stream of data trees (XML messages). Specifically, if \{x_1, x_2, \ldots\} denotes a stream of XML messages, where \(x_i\) is \(i^{\text{th}}\) XML message in the stream, and \(\{q_1, \ldots, q_m\}\) is a set of filter predicates (described in an XML query language, such as XPath or XQuery [1]) then an XML filtering system identifies (in real-time) \(\langle x_i, q_j, PT_{ij} \rangle\) triplets, such that the message \(x_i\) satisfies the filter query \(q_j\). The set \(PT_{ij}\) includes each instantiation of the query (referred to as path-tuples in [14]).

1.1 Existing Approaches and Challenges
Obviously, the XML filtering problem is related to, but different from, the more traditional stored XML data retrieval problem, where given a stored collection of XML data objects and a query, the system needs to identify those data instances which satisfy the given query. XML query processing approaches concentrate on finding effective mechanisms for matching query strings to indexed data strings [9] or indexing data paths and data elements to efficiently check structural relationships. In contrast, in XML filtering, instead of the data (which is transitional), the collection of filter patterns themselves need to be indexed.

Automata-based Schemes. The state of the art in XML filtering include, finite state automaton (FSA)-based schemes, YFilter [4, 13] XScan [18], and XQR2 [15]. In these, each data node causes a state transition in the underlying finite state automata representation of the filters. The active states of the machine usually correspond to the prefix matches identified in the data. In general, for deep and recursive XML data, the number of active states can be exponentially large [7, 8, 13, 16]. In fact [16] shows that for a linear filter, an eager deterministic FA has \(O(n_{m, predicates} \times \text{query depth} \times \text{alphabet size})\) active states. When there are multiple path expressions, [16] shows that an eager DFA may result in \(O(2^{n_{m, predicates}})\) active states. Furthermore, most of the states may never lead to results. [16] showed that using a lazy (as opposed to eager) scheme may reduce the number of active states to \(O(\text{query depth}^{\sigma \cdot \text{selecivity} \cdot \text{k}})\). YFilter uses a nondeterministic FA for reducing the number of automata states. However, since during runtime each NFA state can be visited (and inserted into runtime storage) multiple times, as stated in [13], deep documents could theoretically cause an exponential blow-up in the number of active, run-time states.

Push Down Approaches. XPush [17], instead, translates the collection of filter statements into a single deterministic pushdown automaton. The eager Xpush machine still needs exponential number of states. However, [17] also proposes a lazy implementation, which delays the discovery of the states and avoids redundant state enumeration, to bring the memory requirement down to \((\frac{1+\sigma}{1+\sigma+1})^n\), where \(n\) is the number of filter queries, \(\sigma\) is the selectivity of the predicates, and \(k\) is the number of predicates per query. SPLEX [23] uses a network of transducers to evaluate regular path expressions with XPath-like qualifiers. For representing the transducer stack, SPLEX needs memory quadratic in stream depth. Like SPLEX, XSQ [24] uses a push-down transducer based approach for XPath filtering, where stacks keep track of matching begin and end tags and buffers store potential results to compute predicates.

Alternative Memory Organizations. PathM [12] uses a stack representation (where one stack is associated to each query no-
de) of data to obtain a memory requirement bound by the size of the query times the document depth. TurboXPath [19] avoids the translation of the query into a finite state machine and requires memory only linear in query size. [7] also deviates from automata and transducers to achieve \(O(\text{query size} \times \text{degree of recursion} \times \log(\text{data depth}))\) space and \(O(\text{query size} \times \text{data size} \times \text{degree of recursion} \times \text{data})\) time per registered query. X Trie [10] represents path expressions as strings and indexes them into a trie structure, which leverage prefix commonalities in filters. The trie is used for detecting the occurrence of matching substrings as the input document is parsed. FiST [21] also represents queries as sequences; however, unlike X T ries, these sequences represent each filter query wholistically and, thus, each query pattern is filtered independently without leveraging any prefix sharing. In fact, most schemes can not exploit both prefix and suffix commonalities. Yet, as experiments in Section 8 show, the best results are obtained when both prefix and suffix sharing are exploited simultaneously.

1.2 Contributions of this Paper
We first note that the execution time of any filtering scheme is lower bounded by the result enumeration step: since a given data path can result in exponential (in depth) number of matches, major savings in execution time can only come from effective prefix and suffix sharing across filters. However, sharing can be costly: if all matching prefixes are enumerated and stored naively as automata states, this may require extensive storage and time [7, 13, 16].

We note that a new and adaptive design, which can leverage different, hitherto conflicting, approaches simultaneously can help with both storage and execution time challenges. Such a mechanism should

- leverage both prefix and suffix commonalities across filter statements for reducing overall filtering time,
- avoid unnecessarily eager result/state enumerations (such as NFAs enumeration of active states), and
- decouple memory management task from result enumeration to ensure correct results even when memory is tight.

With these in mind, we introduce AFilter (Section 2), which encompasses the following advantages:

**Simultaneous Prefix and Suffix Sharing:** The proposed approach benefits from prefix commonalities across path expressions, while simultaneously leveraging suffix commonalities to reduce the cost of exploration of the potential matches.

**Delayed State/Result Enumeration:** As opposed to the rather wasteful active state enumeration mechanisms of finite-state-machine based approaches, AFilter uses a lazy mechanism to discover relevant matches only when an interesting trigger condition occurs. In the proposed scheme, the trigger conditions are associated with the leaves (last name tests) of query patterns to benefit from the generally more stringent data selectivities at the leaves.

**Decoupling of Prefix-Caching (Efficiency) from Result Enumeration (Correctness):** AFilter can function correctly with a runtime representation linear in filter and message depth. Query and data representations are discussed in Sections 3 and 4, respectively. Furthermore, AFilter can also leverage an on-demand prefix-caching mechanism (PRCache, Section 5), which can exploit additional memory to reduce filtering time, even if filter steps are clustered under common filter suffixes (Sections 6, 7).

Although the eventual goal of AFilter is to provide filtering for a large class of XQuery [1] statements, in this paper we focus on path expressions of type, \(P(//.+).\) Such path expressions are composed of query steps, each consisting of an axis (parent/child "+" or ancestor/descendant "/") test between data elements and a label test (including the "*" wildcard). In this respect, our approach is analogous to that of YFilter [4, 13], though we differ significantly in approach and provide significantly better performance, as evidenced in Section 8. The effective use of such path expressions in more complex scenarios, which could include predicates, twig queries of form \(P(//.+).\) [21], other types of axes [6], and more complete XQuery statements, have been discussed elsewhere [13, 14, 18, 20]. Therefore, within the context of these existing path expression based frameworks, in this paper, we only focus on the efficient and scalable filtering of the \(P(//.+).\) statements.

2. AFILTER: PATH EXPRESSION FILTERING THROUGH PREFIX-CACHING AND SUFFIX CLUSTERING
AFilter is composed of three components (Figure 1): A linear size data structure, called PatternView, to index registered pattern expressions; a runtime data structure called StackBranch, (linear in the depth of the message tree) to represent the current data branch; and PR Cache, which stores prefix sub-matches for re-use.

2.1 “PatternView” to Index Filter Patterns
PatternView is a collection of linear size data structures that represent the query patterns that are registered in the system:

- **AxisView:** AxisView is a directed graph capturing the query steps registered in the system. Each node in the graph corresponds to a label and each edge corresponds to a set of axis tests. Each edge is annotated with a set of axis assertions that needs to be verified to identify matches.

- **PRLabel-tree:** PRLabel-tree is an (optional) “trie” data structure which clusters path expressions based on the commonalities in their prefixes. This is used for enabling prefix-based sharing of subresults across path expressions.

- **SFLabel-tree:** SFLabel-tree is an (optional) “trie” data structure which clusters path expressions based on their overlapping suffixes. It is used for clustering the evaluation of the assertions on the AxisView edges.

PatternView is incrementally maintainable. To complement the linear space PatternView data structure for registered filter expressions, we also use a compact stack-based representation (StackBranch ) of the data being processed.

2.2 “StackBranch” for Encoding Data
StackBranch is a linear size data structure which represents the current root-to-element path being considered. StackBranch uses one stack per AxisView node. As the streaming data is consumed, the stacks are populated with stack objects. Pointers associated with these stack objects maintain the ancestor/descendant and
3. PATTERNVIEW: A COMPACT REPRESENTATION OF FILTER EXPRESSIONS

PatternView is a linear space data structure for representing registered filter expressions.

3.1 AxisView: Axis-clustered Representation of Filters

A filter expression, of type \( P^i/j^j//s^s \), is a sequence of steps where each step has a navigation axis (parent-child or descendant) and a label (name test) predicate. The AxisView data structure captures and clusters axes of all filter expressions registered in the system in the form of a directed graph (Figure 2(a)).

Let \( Q = \{q_1, \ldots, q_m\} \) be a set of filter expressions. Let \( \Sigma = \{\alpha_0, \alpha_1, \ldots, \alpha_k\} \), where \( \alpha_0 = “q$root” \), be the label alphabet composed of the element names in the filter expressions in \( Q \). Let also \( \Sigma' = \Sigma \cup \{\alpha_\$\} \) be the alphabet extended with the wildcard symbol, \( \alpha_\$ = “/” \). The corresponding AxisView, \( AV(Q) = (V, E, AN) \), structure is a labeled directed graph:

- For each \( \alpha_0 \in \Sigma', V \) contains a node \( n_0 \).
- If there is an axis, “\( \alpha_i / \alpha_i \)” or “\( \alpha_i / \alpha_i \)” in filter predicates in \( Q \), then \( E \) contains an edge \( e_\alpha = (l, k) \) from \( n_l \) to \( n_k \).
- Each edge, \( e_\alpha \), has an associated annotation, \( AN(e_\alpha) \); each annotation contains a set of assertions that, if verified, can be used to identify a filter result.

Let “\( \alpha_i / \alpha_i \)” or “\( \alpha_i / \alpha_i \)” be the \( s^s \) axis in a filter pattern, \( q_j \). Furthermore, let \( e_\alpha = (l, k) \) be the edge from \( n_l \) to \( n_k \).

Then, the set of annotations associated with \( e_\alpha \) contains an assertion \( assert_h \in \text{AN}(e_\alpha) \), such that

- if the axis is of the form “\( \alpha_i / \alpha_i \)” then
  * if \( \alpha_i \) is the last label test in the filter pattern, \( q_j \), then \( assert_h \) is “\( (q_j, s)^n \)” else \( assert_h \) is “\( (q_j, s)^n \)”
- if the axis is of the form “\( \alpha_i / \alpha_i \)” then
  * if \( \alpha_i \) is the last label test in \( q_j \), then \( assert_h \) is “\( (q_j, s)^n \)” else \( assert_h \) is “\( (q_j, s)^n \)”.

The two symbols, \( \uparrow \) and \( \uparrow \), in the assertions denote the trigger conditions (through parent/child and ancestor.descendant axes respectively).

**Example 1 (AxisView Example).** Consider the following four filter expressions:

- \( q_1 = “/d//a//b//b” \)
- \( q_2 = “/a//b//a//b” \)
- \( q_3 = “/a//b//c//” \)
- \( q_4 = “/a//c” \)

Figure 2(a) illustrates the corresponding AxisView data structure.

Note that, unlike state machine-based schemes (such as YFilter [13]), AxisView is not an NFA traversed in a forward manner to generate partial matches. Instead, AxisView acts as a blueprint for the construction of the run-time data structure, StackBranch, which is traversed in the reverse direction and only when a trigger condition is observed. In fact, if no trigger conditions are observed in the XML data stream, it is possible that no traversal will occur.

3.2 Space Complexity of the AxisView Data Structure

If the size of \( Q \) is \( \text{size}(Q) \), the size of \( AV(Q) \) is also \( \text{size}(Q) \); in other words, the AxisView data structure is linear in the size of filter statements. Furthermore, AxisView is incrementally maintainable. Details are omitted as both results are straightforward.

3.3 PRL-label-tree and SFL-label-tree

Query path expressions can also overlap in terms of their prefixes and suffixes. Most existing schemes rely on either prefix or suffix commonalities, but not both. AFilter, on the other hand, leverages both types of overlaps through (optional) linear trie-based data structures, PRL-label-tree and SFL-label-tree.

**Example 2 (PRL-label-tree and SFL-label-tree).** Reconsider the expressions in Example 1. Figure 2 depicts the prefix and suffix labels computed using PRL-label- and SFL-label-trees.
The use of PRL-label-tree for enabling prefix-based sharing of subresults across path expressions is discussed in detail Section 5. The use of SFLabel-tree for pruning unpromising trigger conditions is discussed in Section 6.

Note that, as long as the prefix and suffix labels are chosen such that they enable efficient discovery of parent/child and ancestor/descendant relationships in PRL-label-tree and SFLabel-tree, the actual data structures do not need to be maintained in the memory. Candidate labeling schemes for the PRL-label-tree and SFLabel-tree include the positional encoding or the extended Dewey [22].

4. STACKBRANCH FOR COMPACT DATA ENCODING

As its name implies, StackBranch uses a stack representation of the active XML data branch. In the literature, due to their compact representation of the XML data paths, stacks have been used to implement structural join operators on stored data. The relevant work includes TwigStack/PathStack [9] and and StackTree-Desc/Anc [3]. More recently, stack-based schemes are also being considered for XML filtering schemes, such as XSQ [24], PathM [12], and XPush [17]. StackBranch leverages the AxisView graph discussed in the previous section to construct a highly compact representation of the runtime state of the data, suitable for both prefix- and suffix-clustered operations.

StackBranch, $S_B(Q) = \{S_\alpha | \alpha \in \Sigma \}$, of $Q$ is a set of stacks corresponding to the nodes of the AxisView, $AV(Q) = (V, E, A, N)$. StackBranch contains one stack for each node in the AxisView; i.e., only one stack for each symbol in the label alphabet. Stacks are also included for the root ($q,r,o,x,t$) and the "*" wildcard.

At any given point in time, StackBranch represents the data path from the root of the current document to the last seen element. Thus, as the streaming data is consumed (in a document-order manner), these stacks are populated appropriately with stack objects.

4.1 XML Message Stream

We use the conventional well-formed XML message model, where each message in the stream is an ordered tree of elements. The beginning of each element is marked with a start tag and its end is marked with an end tag; all the descendant elements start and end between these two tags. If $x$ is an XML message, then $x[i]$ denotes the $i$th element seen during the document-order (pre-order) traversal of $x$. The label, $\alpha_i = tag(x[i]) \in \Sigma$ denotes the label of this element and $depth(x[i])$ is its depth in the message. An XML stream is, then, a sequence $\{x_1, x_2, \ldots\}$ of XML messages.

4.2 Maintaining StackBranch

The runtime state of StackBranch is affected when a start tag of an XML element is encountered or when an end tag is seen.

Each time a start tag is observed in the data stream, a new stack object is created and is pushed into the stack corresponding to the element label. Each stack object contains the index of the element, its depth in the message, and as many pointers as the out-degree of the corresponding node in the AxisView data structure. Each pointer corresponds to an edge in the AxisView and points to the topmost object in the stack corresponding to the destination of the edge. If any of the queries also contain the "*" wildcard symbol, then for each new stack object inserted into its own stack, a corresponding stack object is created and inserted into the special $S_j$ stack. The push algorithm is depicted in Figure 3.

**Example 3** (Start Tag Observed in Data).

Figure 4(a) shows the stacks of an empty StackBranch corresponding to the AxisView in Example 1 and Figure 2.

Figure 4(b) shows the state of StackBranch after the stream $<a><d><a><b>$ is observed. Figure 4(c), shows the StackBranch after the next tag, $<$, is observed in the stream.

There is one stack per label symbol (independent of the number of filter statements). When $<$ is observed in the data, a new stack object $e_1$ is created and is inserted into the $S_j$ stack. This new stack object has two outgoing pointers, corresponding to the edges $e_5$ and $e_7$ in the AxisView (Figure 2). These pointers point to the topmost objects of the destination stacks.
Figure 5: The pop step is executed each time a close tag is seen

Then, a new stack object, c1, (again corresponding to \(<\)) is created and pushed into the S0 stack. This object has a pointer, corresponding to edge e1, pointing to the topmost object in S1.

Note that, stack S1.root always contains a single object. The special stack for \("^{*}\) \textit{is} on the other hand, contains one stack object for every element observed on the current root-to-node branch.

As soon as the end tag of an element is seen, the corresponding stack object can be popped and eliminated (along with its pointers) from the data structure. The pop algorithm is shown in Figure 5.

Example 4 (End Tag Observed in Data). If after seeing the data stream \(<a>d</a>b</c> c\textgreater, we encounter the end tag \(</c>\), then, StackBranch reverts back to its state in Figure 4(b) from its state in Figure 4(c).

4.2.1 Total Time Complexity of the Push and Pop

Each push operation has to create a new stack object and set all of its pointers to the topmost objects in the destination stacks. Therefore, given an XML message, x, and a set of filter expressions, Q, the worst case total cost of the push operations is $O(\text{size}(x) \times \max_{j} \text{max-fanout}(AV(Q)))$. Since the maximum number of outgoing edges in a StackBranch node is $|\Sigma_e|$ (i.e., $\max_{j} \text{max-fanout}(AV(Q)) \leq |\Sigma_e|$), the complexity of push is $O(\text{size}(x))$. The total cost of the pop operation is simply $O(\text{size}(x))$.

4.2.2 Space Complexity of StackBranch

The size of the StackBranch depends on how many stack objects are stored at a given point in time and the number of pointers associated with these objects:

- **Number of objects**: The total number of objects in the StackBranch at any point in time is $2d + 1$ where, $d$ is the depth of the last seen start tag. The factor of 2 comes from the fact that objects may need to be created for the $S_j$ stack along with their own stacks.

- **Number of pointers**: For each object in the StackBranch, the maximum number of outgoing pointers is limited with the out-degree of the corresponding node in the AxisView. Again, the maximum number of outgoing edges is limited with the size of the label alphabet $\Sigma_e$. Therefore, the worst case number of pointers in StackBranch is bounded by $2d|\Sigma_e|$ i.e. it is independent of the number of queries.

In other words, since StackBranch associates only one stack per label symbol (as opposed to one stack for each filter query step) the memory requirement is linear in the message depth. In contrast, for instance, the memory requirement of PathM [12] is bound by the size of the query times the document depth.

4.3 TriggerCheck: Identifying Candidate Assertions

As mentioned in the introduction, as opposed to the finite automata based systems which traverse the state automata as they consume the input stream, AxisView and StackBranch structures are not traversed until a trigger condition is observed. To benefit from the generally more stringent selectivities in the leaves of XML data, we use the leaves of filter predicates as triggers. Thus, we consider the trigger assertions (\(\uparrow\) or \(\uparrow\uparrow\)) associated with the AxisView edges corresponding to the pointers of the StackBranch objects. In particular, if the edge associated with a newly created pointer has a trigger assertion associated with it, then we know that the new stack object corresponds to the last node of at least one filter expression registered in the system. This is a trigger condition.

Example 5 (Checking Trigger Conditions). In Figure 6, the stack object $b_1$ corresponding to the \(<\) open tag is pushed into the stack $S_0$. The AxisView edge $e_a$, corresponding to the outgoing pointer, has a total of four assertions: $(q_1, 2)\uparrow\uparrow$, $(q_2, 3)\uparrow\uparrow$, $(q_2, 1)\uparrow\uparrow$, and $(q_3, 1)\uparrow\uparrow$. Two of these, $(q_1, 2)\uparrow\uparrow$ for filter $q_1 = /a/b/|/a/b$ and $(q_2, 3)\uparrow\uparrow$ for $q_2 = /a/b/|/a/b$, are trigger assertions.

Note also that, although the path expression $q_3 = /a/b/|/a/b$ has two bs, only the last (leaf) label test is triggered.

Once trigger assertions are identified, the system needs to verify whether these assertions correspond to any actual matches or not. In some cases, it is easy to deduce that trigger assertions are not promising. For instance, for a filter expression to have a match, there must be at least one pointer between all the relevant stacks. Also, the number of label tests in the filter query should be less than or equal to the depth of data. If these conditions do not hold, there can not be any matches. These pruning conditions can be implemented efficiently and can be useful, especially if the leaves have less stringent selectivities than earlier label tests in a given filter query. If an assertion is not pruned, then the StackBranch pointers have to be followed (or traversed) to identify whether there are actual matching path expressions.

Figure 7 shows the trigger phase operations. The processing of all non-pruned candidate assertions is performed by traversing the pointers outgoing from the triggering stack object (Step 3b). The traversal operation (discussed in Section 4.4) will return the subresults for all validated candidate assertions. These validated assertions will then be expanded by mapping with the matching subresults (Step 3c) and will be returned as results.

4.3.1 Time Complexity of the TriggerCheck Phase

Given an XML document, x, and a set of path expressions, Q, if we consider the extreme case where all insertions result in candidate assertions for all edges in the AxisView, then in the worst-case, there will be $O(\text{size}(x) \times \text{size}(Q))$ TriggerCheck conditions which need to be traversed for verification.

4.4 Pointer Traversal for Enumerating Matches

In this paper, we consider the general filtering problem, where the system returns all matching elements along the matched filter expressions (referred to a path-tuples in [14]). Note that not

\textsuperscript{2}This is not a strong requirement; more traditional XPath semantics, where only the element matching the last label test is returned, is a straightforward subset of the algorithms presented here.
Figure 7: The TriggerCheck step is executed each time a new stack object is created.

all candidate assertions triggered in the TriggerCheck step correspond to an actual match. Some triggered assertions, on the other hand, may correspond to multiple matches. Therefore, triggered assertions need to be verified and the corresponding matches must be identified. This process involves traversal of the pointers embedded in the StackBranch structure from the stack object, where a trigger condition is identified, back to the root object, q_oo0.

EXAMPLE 6 (TRACING STACKBRANCH). Figure 6 shows the two candidate assertions triggered due to the <b> tag seen in the data. Since the pointer associated with the corresponding stack object, b_1, points to the object a_0 in stack S_0, verification of this trigger will require the system to traverse the corresponding pointer towards the stack object a_2. Note that the pointer is traversed only once (in a grouped manner) for both candidates, (q_1, 2)_{m_1} and (q_2, 3)_{m_1}, asserted by the trigger.

The stack object a_0, on the other hand, has two outgoing pointers, one pointing to stack S_8 and the other to S_oo0. These pointers are associated with AxisView edges, e_8 and e_9, respectively; therefore whether these pointers will be traversed or not depends on whether the local assertions associated with these two edges are compatible with the two candidate assertions, (q_1, 2)_{m_1} and (q_2, 3)_{m_1}. We say that a candidate assertion assert_1 = (q_1, s_1) is compatible with a local assertion assert_2 = (q_2, s_2) if q_1 = q_2 and s_1 = s_2 + 1.

Figure 8 illustrates the traversal process:
(a) First the pointer associated with edge e_8, from a_2 to q_oo0, is considered (Figure 8(a)). In this case, the only common filter query between the sets of candidate and local assertions is q_2. However, the required steps of the trigger assertion and the local assertion (2 and 0 respectively) do not match; naturally, a query step 2 can only be preceded by a query step 1. Therefore, this pointer does not lead into further traversals.
(b) When the outgoing pointer associated with edge e_9, from a_2 to d_1, is considered (Figure 8(b)), however, we find that there is a common query, q_1, which has matching assertions (steps 1 and 2, respectively). Therefore, there is a possible match and the outgoing pointers associated with d_1 should be further traversed.

(c) In the next step (Figure 8(c)), the outgoing edge, e_1, from d_1 is considered. In this case, the candidate (q_1, 1)_{m_1} matches the local assertion (q_1, 0). Therefore, the pointer can be traversed to its destination, q_oo0. Since the root is reached, this identifies a match for filter expression, q_1. The match consists of stack objects, d_1, a_2, and b_1.

d) Since the stack based representation guarantees that any stack object under a_2 in the stack S_1 will also be an ancestor of b_1 and since the candidate assertion being checked for e_9 is an ancestor/descendent axis, we need to look further down the stack to see if there are any further potential matches.

In this example, the S_1 stack contains the stack object a_1 under a_2; therefore, a_1 needs to be considered. In this case, a_1 only has one single outgoing pointer, corresponding to the edge e_2; however, as before, the local filter conditions of e_2 do not match the incoming candidates. Hence, this object can not lead into further matches.

The traverse logic underlying this example is shown in Figure 9.

4.4.1 Time Complexity of the Traverse Operations
Since the number of candidate and local assertions to match against each other can be fairly large, a hash-join based scheme (which, for each incoming candidate assertion (q, s), searches for the hash of (q, s - 1) in the set of local assertions corresponding to a given pointer) is used for identifying the matches at Steps 7c and 7(e)/( of the algorithm in Figure 9; therefore, the cost of the matching of incoming and local assertions is linear in the number of assertions.

Some traversed candidate assertions result in matches, while others fail to return any (sub)results. Thus, the total cost of the traverse operations involves both. In the worst case (when the selectivities are less stringent at the leaves) the failing assertions will be recognized only when the traversal is already close to the query root object, q_oo0. Thus, the worst case complexities of both of these terms are similar. For a triggered candidate assertion, the number of traversals on StackBranch is bounded by max(query_depth)_{m_1} + data_depth. Note that max_stack_depth ≤ data_depth.

Since for lazy automata-based approaches [16], enumerating and storing each new state would cost time, there is a close correspondence between their time and space complexities. Note that, the above worst case time for AFilter is similar to the state enumeration complexity, O(query_depth + data_depth + 2 * level), achieved by [16] using lazy DFA. [16] shows that this is significantly lower in complexity than the (theoretical) worst case of eager solutions.

In the case of AFilter, however, the above worst case complexity arises only when the basic, memoryless algorithm is used; i.e., when AFilter does not remember earlier traversals. Although this can be an advantage in low-memory installations, where the AFilter algorithm can work even when other algorithms may fail due to lack of sufficient memory, when there is extra memory, the filtering cost can be significantly reduced if positive (success) or negative (failure) results could be cached and reused.

5. PRCACHE: PREFIX-CACHING SUPPORT FOR ELIMINATING REDUNDANT POINTER TRAVERSALS
Let us reconsider Steps 7(d) and 7(e)/( of the traverse algorithm in Figure 9. In these steps, for a given set (cand[EF]_{m_1}) of candidate assertions, the corresponding pointer, ptr_{m_1}, is (recursively) traversed to verify the assertions and collect possible submatches.
As we stated earlier, for a given candidate assertion, traversal of a pointer can either be successful, i.e., can lead into one or more (sub)matches, or may fail to provide any results.

Note that if the same stack object is visited more than once during the filtering of an XML document (for example due to similar trigger conditions observed in the data), then it is possible that traversals originating from this object will repeatedly try to validate the same candidate assertions. This is wasteful: since stacks grow from root to the leaves in a monotonic fashion, it is straightforward to see that for a given stack object, repeated evaluations of the same candidate assertion will always lead to the same result.

Therefore, to avoid repeated traversals of the pointers in StackBranch for the same assertions, PRCache caches the success or failure of the candidate assertions associated with each traversed pointer (along with the results obtained during the first ever traversal of this pointer). This enables future traversals involving the same assertions to be resolved through an efficient table lookup.

### 5.1 Prefix-Caching for a Single Filter

Repeated traversals of the same step of the same filter expression is especially common in (a) tree structured data, where a shared portion of the data needs to be considered for multiple XML data branches or (b) in recursive data with repeated element names which can trigger the same filter multiple times.

Given a pointer, ptr, and an assertion, assert, associated with this pointer, PRCache caches the traverseresult, returned in Steps 7(di) and 7(c)viA of the Traverse algorithm (in Figure 9) for the (assert, ptr) pair. Thus, next time the same assertion needs to be validated through the same pointer, the algorithm simply returns the corresponding matches from the PRCache; in other words, each prefix of each query is discovered only once.

This loosely-coupled memory structure enables AFilter to scale to the available memory space: unlike the existing mechanisms, if the cache storage space is limited, AFilter can completely eliminate the use of PRCache or use cache replacement policies (such as LRU) to keep an upperbound on the number of cached prefixes, maximizing the utilization of the cache.

A second and (in terms of memory) cheaper caching alternative is to cache only the failed verifications (i.e., assertions with empty matches in traverseresult). In this approach, since the positive results are not cached, the same sub-matches may be identified multiple times. However, it eliminates repeated failtraverses and since positive results are not cached, it has a significantly lower (linear in the number of query steps) cache storage demand.

### 5.2 Sharing Caches across Filter Expressions

A cached result for an assertion assert1 = \(q1 = (s1)\), can be used for another assertion assert2 = \(q2 = (s2)\), if we can ensure that assert1 and assert2 have identical intermediate results. In other words, prefix-commonalities across filter statements can be exploited for improving the utilization of the PRCache entries.

AFilter exploits prefix-commonalities through PRLABEL-tree (trie) data structure which labels common prefixes across path expressions. The entries in PRCache are then hashed in such a way that query steps sharing the same prefix also share cached results.

### Example 7 (Prefix Sharing).
Consider
- \(q1 = a/b/c\)
- \(q2 = a/b/d\)
- \(q3 = e/a/b/d\)

Figure 10(a) depicts the prefix clustering of individual query steps. Any assertions clustered under the same prefix ID in this figure can be cached under the same cache index. In this example, pairs, \(q1 = (q2, 0)\) and \(q1 = (q3, 1)\), of assertions can be cached under the same prefixes, \(pre_1\) and \(pre_2\), respectively.

### 6. SHARING WITH SUFFIX-COMPRESSED AXISVIEW

Prefix caching is useful in eliminating redundant traversals of the StackBranch pointers. However, even when such redundant traversals are eliminated, the cost of the Step7c of the traversal algorithm (Figure 9), where candidate assertions are matched against the local assertions associated with the outgoing pointers, can be high.

As discussed in Section 4.4, StackBranch implements this through a hash-join; thus, the cost of the operation is linear in the number of candidate assertions to be matched. Naturally, reducing the number of candidate assertions would also reduce the time spent at the Step7c of Traversal. Since traversals are from the leaves toward the root, clustering assertions in terms of shared suffixes would reduce the number of candidate assertions to consider.

### Example 8 (Suffix Sharing). Let us consider
- \(q1 = a/b\)
- \(q2 = a/b/a/b\)
- \(q3 = a/c/a/b\)

which all share a common suffix \(/a/b/). The corresponding SFLABEL-tree structure (shown in Figure 13(a)) captures this suffix overlap.

Note that the original AxisView data structure, shown in Figure 13(b), does not capture the suffix commonality \(/a/b/ across
7. PREFIX-BASED CACHING WITH SUFFIX-COMPRESSION

A label in a suffix-compressed AxisView clusters suffixes of the filter patterns, whereas PRCache caches intermediary results based on the common prefixes of the filters. As shown in Figure 11, there may be many to many relationships between prefix and suffix labels. Unfortunately, suffixes and prefixes are not always compatible and suffix-based clustering can prevent prefix-based caching.

Figure 11: Many-to-many rel. between suffix-and-prefix labels

Figure 12: Although the two assertions, \((q_a, s_a)\) and \((q_b, s_b)\), share the same prefix, two different suffix label pairs, \(suf_f\) and \(suf_j\), place these two assertions into separate clusters. Thus, if in AxisView, assertions are clustered under suffixes, then these two assertions can not benefit from each others’ prefix caches.
assertion, assertions clustered under the suffix label, su_f3, is unfolded; the corresponding pointer will be traversed in an unclustered manner (while the unaffected pointers continue to be traversed in a suffix-compressed manner with suffix labels, su_f2 and su_f6).

 opportunities. In particular, some of the prefix commonalities in filter statements will be hidden by suffix labels (Figure 12). This naturally reduces the utilization rate of the cache.

**Example 9 (Suffix vs. Prefix Sharing).** Let us reconsider the following three filter statements, first considered in Example 7 and Figure 10:

- $q_1 = |/a|/b|/c$.
- $q_2 = |/a|/b|/d$, and
- $q_3 = |/c|/a|/b|/d$.

It is easy to see that the prefixes ($|/a|/b$) of filter statements $q_1$ and $q_2$ overlap, whereas the suffixes ($|/a|/b|/d$) of $q_2$ and $q_3$ are also identical. The corresponding PRLabel-tree and SFLabel-tree data structures are shown in Figures 10(a) and 10(b), respectively.

This leads to a conflict: for prefix sharing, $(q_2, 1)$ needs to be able to access the cached results of $(q_1, 1)$; on the other hand, to benefit from suffix clustering, $(q_2, 1)$ needs to be clustered with $(q_3, 2)$, under the suffix label, su_f2.

Thus, benefiting from prefix caching, while also exploiting suffix clustering, requires unfolding (or unclustering) of suffix-based clusters as needed. There are two unfolding alternatives, early and late unfolding, both of which we discuss below.

### 7.1 Early Unfolding of Suffix Clusters

During the backward traversal of the StackBranch, the early unfolding mechanism un-clusters a suffix-label as soon as the system determines that one of the candidate assertions contained in a suffix-based cluster can be delivered from the cache. Let us assume that, during the pointer traversal step, we identify that a candidate assertion, $(q_j, s_j)$, clustered under the suffix label, su_fj, can benefit from a result already in PRCache. In early unfolding, the suffix label, su_fj, will be immediately unfolded and all the candidate assertions clustered under su_fj will be further verified individually.

**Figure 13: Suffix support for reduced filtering**

$q_1 = |/a|/b$, $q_2 = |/a|/b|/a|/b$, and $q_3 = |/c|/a|/b|/b$.

**Figure 14: Early unfolding of suffix clusters: since can5 can be served from the cache, the corresponding cluster with the suffix label, su_f4, is unfolded; the corresponding pointer will be traversed in an unclustered manner (while the unaffected pointers continue to be traversed in a suffix-compressed manner with suffix labels, su_f2 and su_f6).**

**Figure 15: Late unfolding of suffix clusters, with candidate assertion removal and branch pruning**

**Example 10 (Early Unfolding).** Figure 14 illustrates this process with an example. If prefix caching is not used, the incoming suffix-label su_f1 will result in traversals of suffix labels, su_f2, su_f3, and su_f4, on three outgoing pointers.

Let us assume that, the suffix label su_f4, clusters two candidate assertions, can_5 and can_6, and the assertion can_5 can be served from the cache. In this case, to benefit from the cached results, the early unfolding mechanism would stop traversing the pointer corresponding to su_f4 in the suffix domain. Instead, it would traverse the pointer for the individual non-cached assertion (can_5 in this example). The pointers that can not benefit from the cache will continue to be traversed in a suffix clustered manner (su_f2 and su_f6).

While PRLabel-tree and SFLabel-tree data structures are constructed, prefix IDs are associated with the suffix labels (Figure 11). When an assertion with a given prefix ID, prej, is cached in PRCache, an unfold[su_fj] bit for each suffix label, su_fj ∈ su_fj.cache[prej], is set (Figure 11(b)). If a suffix label with a set unfold bit needs to be traversed, that suffix label will be immediately unclustered and the individual assertions will be traversed independently.

### 7.2 Late Unfolding of Suffix Clusters

Unfolding has an associated cost in terms of the lost assertion clustering opportunities. Especially in cases where (a) suffix clusters are large, but (b) the prefix cache hit rate is low (i.e., when only a few candidate assertions per suffix cluster can actually be served from the prefix cache), early unfolding can cause unnecessary performance degradations. In such cases, it may be more advantageous to delay the unfolding of suffix-clusters.

**Example 11 (Late Unfolding).** Consider Figure 15, where the suffix label su_f2 contains a candidate assertion, can_4, which can be served from the cache early in the traversal process.

In this case, early unfolding would require unfolding of all the assertions clustered under the label su_f2. However, if su_f2 is unfolded at this stage, none of the subsequent steps can be performed in the suffix clustered domain.

---

**Figure 13: Suffix support for reduced filtering**

$q_1 = |/a|/b$, $q_2 = |/a|/b|/a|/b$, and $q_3 = |/c|/a|/b|/b$.

**Figure 14: Early unfolding of suffix clusters: since can5 can be served from the cache, the corresponding cluster with the suffix label, su_f4, is unfolded; the corresponding pointer will be traversed in an unclustered manner (while the unaffected pointers continue to be traversed in a suffix-compressed manner with suffix labels, su_f2 and su_f6).**

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Let us assume that, the suffix label su_f4, clusters two candidate assertions, can_5 and can_6, and the assertion can_5 can be served from the cache. In this case, to benefit from the cached results, the early unfolding mechanism would stop traversing the pointer corresponding to su_f4 in the suffix domain. Instead, it would traverse the pointer for the individual non-cached assertion (can_5 in this example). The pointers that can not benefit from the cache will continue to be traversed in a suffix clustered manner (su_f2 and su_f6).

While PRLabel-tree and SFLabel-tree data structures are constructed, prefix IDs are associated with the suffix labels (Figure 11). When an assertion with a given prefix ID, prej, is cached in PRCache, an unfold[su_fj] bit for each suffix label, su_fj ∈ su_fj.cache[prej], is set (Figure 11(b)). If a suffix label with a set unfold bit needs to be traversed, that suffix label will be immediately unclustered and the individual assertions will be traversed independently.

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In this case, early unfolding would require unfolding of all the assertions clustered under the label su_f2. However, if su_f2 is unfolded at this stage, none of the subsequent steps can be performed in the suffix clustered domain.
In contrast, late unfolding refrains from immediately un-clustering the set of candidate assertions under $su_f_2$. While $can_4$ is served locally from the cache, the edge corresponding to the suffix-based label $su_f_2$ continues to be traversed using the suffix label, instead of being traversed as individual assertions.

The challenge with such a delayed (or late) unfolding mechanism, however, is to ensure that cluster domain traversal does not cause redundant work for the already cached result. In the above example, since $can_4$ will eventually be served from the cache, this assertion should be removed from further consideration to prevent redundant work: in other words, the semantics of the suffix-label, $su_f_2$, needs to be modified to exclude $can_4$ (illustrated with a cross on $can_4$ in Figure 15). Thus, when an assertion with a given prefix ID, $pre_j$, is cached in PRCache, a $remove[ su_f_j ][ pre_j ]$ bit is set for each suffix label, $su_f_j \in suffixes[ pre_j ]$ (Figure 11(b) illustrates $suffixes[ pre_j ]$).

7.2.1 Pruning Redundant Prefix x Cache Accesses

If an assertion can be served from the cache, its prefixes do not need to be served from their own caches. Therefore, if an assertion is marked for removal from its suffix cluster, its prefixes should also be removed from their corresponding suffix-labels.

Example 12 (Pruning Cache Accesses). This is illustrated in Figure 15: let us assume that candidate assertions $can_7$, $can_12$, $can_26$, and $can_49$ are all prefixes of the candidate assertion $can_4$, which is removed from consideration. The cache will not be accessed for such non-maximal prefixes.

In AFilter, when a suffix label, $su_f_j$, is traversed, each $pre_j$ such that $remove[ su_f_j ][ pre_j ]$ is being set, is also inserted into a prune set. This is achieved by setting a $prunecache[ pre_j ]$ bit. Note that, if $pre_2$ is a prefix of $pre_3$, then $remove[ su_f_2 ][ pre_2 ] \rightarrow remove[ su_f_3 ][ pre_3 ]$, and 

$$prunecache[ pre_2 ] \rightarrow prunecache[ pre_3 ].$$

This is used for pruning non-maximal prefixes of removed prefix labels from further consideration.

7.2.2 Pruning Redundant Traversals

Under late unfolding, if all candidates clustered under a suffix label are removed (i.e., can be served from the cache), the corresponding pointer does not need to be further traversed.

Example 13 (Pruning Traversals). In Figure 15, $su_f_2$ clusters only two candidate assertions, $can_26$ and $can_12$, both of which have been marked for removal from consideration. Therefore, the corresponding pointer does not need to be further traversed.

Pruning condition for suffix, $su_f_2$, is checked by considering whether $pre_2 \in prefixes[ su_f_2 ]$; the removal bit $remove[ su_f_2 ][ pre_2 ]$ is set or not (Figure 11(a) illustrates $prefixes[ su_f_2 ]$).

The performance of late unfolding depends on how easy it is to look into the clusters for checking (a) if any of the clustered assertions can be served from the cache, (b) if any of such assertions are in the removal list, or (c) if each candidate clustered under a suffix label is a prefix of another one which has already been removed.

We note that the cost of checking if any of the clustered assertions can be served from the cache is the same as the early unfolding scheme would have to pay to use the PRCache. On the other hand, as described above, sharing of the removal bits between prefixes requires the propagation of the removed prefixes along the traversal path using the $prunecache[ pre_f_j ][ P ]$ bits. As evidenced in the next section, despite this overhead, late unfolding provides the best of both prefix caching and suffix-clustering approaches, and thus significantly outperforms all alternatives.

<table>
<thead>
<tr>
<th>Acronym</th>
<th>Filtering approach</th>
</tr>
</thead>
<tbody>
<tr>
<td>YF</td>
<td>YFilter</td>
</tr>
<tr>
<td>AF-nx-suf</td>
<td>AFilter, no cache, no suffix compression</td>
</tr>
<tr>
<td>AF-pre-suf</td>
<td>Suffix compressed AFilter, no cache</td>
</tr>
<tr>
<td>AF-pre-suf-only</td>
<td>AFilter, prefix caching only, no suffix compression</td>
</tr>
<tr>
<td>AF-pre-suf-early</td>
<td>Suffix compressed AFilter, prefix caching, early unfolding</td>
</tr>
<tr>
<td>AF-pre-suf-late</td>
<td>Suffix compressed AFilter, prefix caching, late unfolding</td>
</tr>
</tbody>
</table>

**Table 1: Notation used for various filtering deployments**

**Table 2: Experiment parameters (unless specified otherwise)**

8. EXPERIMENTAL EVALUATION

In the previous sections, we discussed the various components of the AFilter algorithm for efficient and adaptive filtering of path expressions. In this section, we provide an extensive evaluation of AFilter through comparisons of the various properties of AFilter with those of a state-of-the-art XML filtering algorithm, YFilter [13]. We chose YFilter for comparison, as both AFilter and YFilter primarily perform filtering of path expressions. Unlike AFilter, however, YFilter relies on a finite state automata based approach and requires maintenance of all active states in the memory. Furthermore, YFilter exploits only prefix commonalities between filter statements, while AFilter can exploit both. Therefore, YFilter provides opportunities for a one-to-one comparison of various novel approaches underlying AFilter. Table 1 provides an overview of different filtering setups, with various AFilter components turned on and off, compared against YFilter.

We have implemented AFilter in Java (JDK 1.5). For comparison purposes, we used the YFilter implementation available at [2]. All experiments were conducted on a 1.7GHZ Pentium 4 machine with 1GB RAM. For the experiments reported in this section, unless stated otherwise, we generated XML data using the NITF DTD available through the YFilter test suites [2] and the ToXgene data generator [5]. The filter queries were generated using YFilter’s query generator. Table 2 lists the various parameters and parameter value ranges we used for generating the data and filter queries we are reporting in this section. We also experimented with different parameters (such as $query/data depth, message size, and skewness$); results were consistent with the sample we are reporting.

8.1 Time vs. Number of Filter Expressions

Figure 16 shows the effect of the number of expressions on the time required for filtering a given set of filter expressions. For this experiment, we varied the number of filter expressions from 10K to 100K and we observed the filtering performance of different schemes. AFilter’s performance varies depending on the scheme chosen. As expected the low memory AxisView-only (no-caching, no-suffix clustering) scheme takes more time than the others, including YFilter. Path-caching-only AFilter gives comparable results to YFilter, especially for smaller filter sets. On the other hand, when both suffix and path caching are used, the performance of AFilter becomes significantly better than YFilter, requiring only less than 15-30% of YFilter’s performance for large filter sets.

8.2 Comparison of Compression Approaches

Figure 17 compares the three suffix-compressed approaches to AFilter: suffix-compressed AxisView with no prefix caching (AF-nx-suf), suffix-compressed AxisView with prefix caching and early unfolding (AF-pre-suf-early), and suffix-compressed AxisView...
with prefix caching and late unfolding (AF-pre-suf-late). As expected, when the number of filter statements are large, the loss in the suffix clustering opportunities due to early unfolding renders the AF-pre-suf-early scheme worse among the three. On the other hand, caching with late-unfolding (AF-pre-suf-late) brings together the desirable properties of both prefix caching and suffix-clustering, and performs significantly better than all other alternatives.

8.3 Time vs. Probability of Wildcards

Figure 18 shows the effects of different types and probabilities of wildcards on the various filtering schemes. As can be seen in this figure, both "*" and "//" affect the performance of YFilter. In contrast, the suffix-compressed AFilter schemes are less affected by the increase in the number of wildcards in the queries. One exception is the early-unfolding approach which is affected by the increase in the "*" wildcards; however, as expected, the suffix-compressed AFilter with prefix caching and late unfolding is minimally affected by the increase and outperforms all other alternatives.

8.4 Cache size vs. Time

Figure 19 shows that AFilter does indeed benefit from larger cache space, when available. As expected increasing the cache size improves AFilter’s performance. Naturally, beyond some point, having more cache space does not help.

8.5 Number of Filters vs. Index Space

Figure 20(a) compares the amount of base memory requirement (i.e., AxisView) against the memory requirement of YFilter. As illustrated here, the base version of AFilter can run with lower available index memory than YFilter. Note that, for this dataset (since the number of unique labels are large and the depth of the data is relatively smaller), the index memory requirement significantly dominated the runtime memory requirement for both YFilter and StackBranch (Figure 20(b)).

8.6 Results for a Different Data Set

In order to verify that the above results hold across different data characteristics, we also experimented with a different DTD. For these experiments, we used the book DTD available at [1]. This DTD has a higher recursion rate and a smaller number of unique labels. In order to see the performance of different schemes in light- and heavy-usage usage of wildcards, we experimented with different wildcard ("*" and "//") occurrence probabilities and different filter set sizes. Note that the numbers of distinct path expressions (of a given depth) generated under these scenarios are smaller since there are fewer unique labels.

Figure 21 shows the results of YFilter against the suffix-compressed AFilter schemes (as shown before, without suffix clustering the runtime of AFilter is worse than YFilter). Suffix-clustering improves the performance. Once again, suffix-clustering with prefix-caching and late-unfolding outperforms other alternatives and consistently requires less than 50% of YFilter.

9. CONCLUSIONS

In this paper, we introduced, AFilter, for filtering path expressions. In addition to the overview in Section 1.1, here we provide a short summary of how AFilter compares with the earlier work.

Automata-based schemes, such as YFilter, consume input symbols and traverse a state space. Active states have to be identified and maintained in an internal storage before the next symbol is considered. The number of active states that have to be maintained in memory for the automata-based schemes can be exponentially large [7, 13, 16]. In contrast, AFilter operates in two stages:

(a) As each symbol is consumed, AFilter constructs an interme-
The stack-based linear data storage mechanism is analogous to the data indexing schemes used in TwigStack/PathStack [9] and mobile simultaneously various sharing opportunities: common steps (AxisView), and common suffixes (SFLabel-tree). Tries are fundamental data structures, used in many works (including YFilter [13] and XTries [10]) where prefix sharing is needed. Unlike most schemes (such as XTries) which use tries for matching path-segments, AFilter uses the PLabel-tree/ SLabel-tree to generate prefix and suffix labels that are used to annotate AxisView edges. Thus, both prefix- and suffix-sharing can be exploited simultaneously leading to significantly higher savings than is achieved by relying only one alternative (Section 8).

The experiment results in Section 8 showed that AFilter brings together the desirable properties of effective memory utilization, trigger-based result enumeration, and prefix-caching/suffix-clustering to enable scalable and high performance path expression filtering. In fact, the best results are obtained when both prefix and suffix clustering are exploited simultaneously.

10. REFERENCES