# Automaton In or Out: Run-time Plan Optimization for XML Stream Processing

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## ABSTRACT

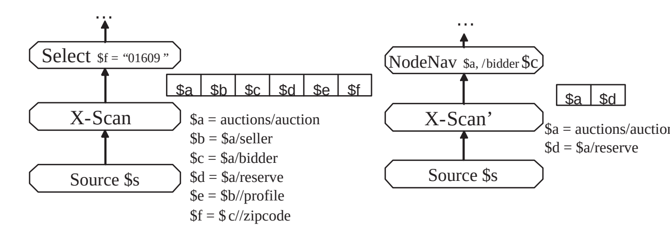
Many systems such as Tukwila and YFilter combine automaton and algebra techniques to process queries over tokenized XML streams. Typically in this architecture, an automaton is first used to locate all query patterns in the input stream and compose the matched tokens into XML element nodes. These XML nodes are then passed to the tuple-based algebraic operators for further filtering or restructuring. This common processing style is however not always optimal. At times it is more efficient to retrieve only a subset of the patterns in the automaton while retrieving the rest of the patterns on the XML element nodes. In this paper, we use a cost-based solution to explore this novel optimization opportunity. We design three plan optimization algorithms, namely, *MinExhaust*, *GreedyBasic* and *FastPrune*. We also study how to migrate from a currently running plan to a new plan in a safe and efficient manner. Our experimentations have shown that the *GreedyBasic* or *FastPrune* algorithm can quickly find a plan that is close to optimal in most scenarios. Also we illustrate that the overhead in our approach for run-time statistics collection and plan migration are very lightweight.

## 1. INTRODUCTION

State-of-the-art XML stream engines commonly combine automaton and algebra for query processing [9, 10, 19]. Let us use the XQuery in Figure 1 (a) as an example. This query asks to pair certain *seller* and *bidder* elements located within the same *auction* parent element. Figure 1 (b) depicts the Tukwila plan [19] for this query. The query processing consists of two stages: automaton processing and algebraic processing. In the first stage, all patterns in the query such as $\$a = auctions/auction$ and $\$b = \$a/seller$ are retrieved by the X-scan operator which is an abstraction of an automaton. If certain patterns need to be further filtered or returned, the automaton extracts the tokens matching the patterns from the stream and composes them into the tree structured XML element nodes. For example, in Figure 1 (b), X-scan composes *auction* and *seller* element nodes and binds them to variables $\$a$ and $\$b$ respectively in the output tuples. In the second stage, these generated tuples are further manipulated by tuple-based algebraic operators, for example, by $Select_{\$f=\text{“01609”}}$ operator.

```
for $a in stream(“open_auctions”)/auctions/auction[reserve ]
    $b in $a/seller, $c in $a/bidder
where $b//profile contains “frequent” and $c//zipcode = “01609”
return
  <auction> {$b, $c} </auction>
```

(a) Example Query




(b) Tukwila Query Plan: Retrieving All Patterns in Automaton

(c) Alternative Plan: Retrieving Part of Patterns in Automaton

**Figure 1: Alternative Tukwila Plans**

Retrieving all patterns in the automaton requires only one single pass of read over the input. It has thus been assumed by the current literature [9, 10, 19] to be the most effective manner for pattern retrieval. We have demonstrated analytically and experimentally this commonly made assumption is not necessarily true [16, 17]. In the plan in Figure 1 (b), patterns are retrieved independently. For example, whether $\$a/reserve$ occurs in a binding of $\$a$ does not affect whether $\$a/seller$ will be retrieved, and vice versa. Now consider a variation of the Tukwila plan as shown in Figure 1 (c). This plan retrieves only *auctions/auction* and $\$a/reserve$ in X-Scan'. In the output tuples of X-Scan', the bindings of $\$a$ contain only those *auction* elements that have *reserve* child elements. These tuples are further manipulated to locate the remaining patterns. For example, $NodeNav_{\$a,/bidder}\$c$ navigates into the bindings of $\$a$, i.e., the *auction* element nodes, to locate */bidder*.

The latter plan essentially “serializes” the retrieval of $\$a/reserve$ and the other patterns including $\$a/seller$, $\$a/bidder$, $\$b//profile$ and $\$c//zipcode$. If only a small number of *auction* elements has *reserve* child elements, very few output tuples are generated by X-Scan'. This plan then saves the pattern retrieval of $\$a/seller$, $\$a/bidder$, $\$b//profile$ and $\$c//zipcode$ compared to the former plan. These savings can be significant because retrieving patterns $\$b//profile$ and $\$c//zipcode$ which contain the recursion navigation step "//" can be rather expensive [11].

In our previous work [16, 17], we have proposed an algebra to support plans that can retrieve patterns both in and out of the automaton. In this paper, we now address the *automaton-in-or-out* optimization problem, that is, deciding which patterns should be retrieved in the automaton versus out of the automaton. The major challenges tackled by our work are as follows.

First, we define a cost model for the plans that support pattern retrieval both in and out of the automaton. Although costing of tuple-based XML operators has been studied [1,21], there is little research on costing token-based pattern retrieval. The novelty of our cost model lies in the costing of automaton computations.

Second, we develop several plan search algorithms catering to different scenarios. When $n$, the number of patterns in the query, is small, our *MinExhaust* algorithm guarantees to find the optimal plan in O($2^n$) time. Given its high complexity, we design a second algorithm called *GreedyBasic* which finds a plan in $O(n^2)$ time. A third algorithm called *FastPrune* expedites *GreedyBasic* by pruning sub-optimal plans during the plan search, thus still generating the same plans as *GreedyBasic*.

Third, since the statistics of the stream source are often unavailable before the stream arrives, and worse yet they may continue to change over time [3], we have to perform the optimization at run-time. We study how to collect the statistics as the plan is running. We also study how to migrate the currently running plan to a better plan. In particular, we design an efficient, incremental migration strategy that avoids recreating the automaton for the new plan. We also define a migration time window in which the migration can be safely undertaken.

Our experiments illustrate that the optimization techniques reduce the processing time significantly in many cases. The experiments also demonstrate that the run-time statistics collection and plan migration have a very low overhead.

## 2. XML STREAM QUERY PLANS

We now briefly review the XML stream processing model that combines automaton and algebra. We use the Raindrop [15–17] XML stream processor for illustration purposes. The automaton used in Raindrop is similar to those in Tukwila [19] and YFilter [9]. In fact, it serves as the core of many other automaton-style XML stream engines [11,12,22]. Hence the techniques discussed in this paper are not limited to Raindrop engine. Any stream engine using the automaton and algebra processing model [9,10,19] can apply these techniques.

Table 1 describes the Raindrop operators used in this paper. Figure 2 depicts a *Raindrop* plan for the query in Figure 1 (a). The highlighted subplan retrieves $\$b$ = *$a/seller* and $\$e$ = *$b//profile*. $TokenNav_{\$a,/seller}\$b$ locates all the to-

| *Operator* | *Description* |
|---|---|
| Source$_{sourceName}\$s$ | Bind data source to column $\$s$ |
| TokenNav$_{\$v1,path}\$v2$ | $\$v1$ represents a sequence of tokens that corresponds to an element. TokenNav$_{\$v1,path}\$v2$ locates the tokens of elements that are accessible via $path$ from $\$v1$. |
| Extract$_{\$v1}\$v2$ | Take token inputs from $TokenNav_{\$v1,path}\$v2$, compose these tokens into XML nodes and bind them to $\$v2$. |
| NodeNav$_{\$v1,path}\$v2$ | $\$v1$ represents an element node. NodeNav$_{\$v1,path}\$v2$ locates the element nodes that are accessible via $path$ from $\$v1$ and binds these nodes to $\$v2$ |
| StructuralJoin$_{\$b}$ | Joins input tuples whose column $\$b$ contains the same element. |
| Tagger$_{pattern}\$v$ | Tagger an input tuple according to $pattern$. |

**Table 1: Semantics of Raindrop Operators**

kens that are part of the *seller* elements. $Extract_{\$a}\$b$ then composes these tokens into XML element nodes. Similarly, $TokenNav_{\$b,//profile}\$e$ and $Extract_{\$b}\$e$ locate and compose *profile* element nodes. $StructuralJoin_{\$a}$ finally joins each *seller* element node with its descendant *profile* element nodes.

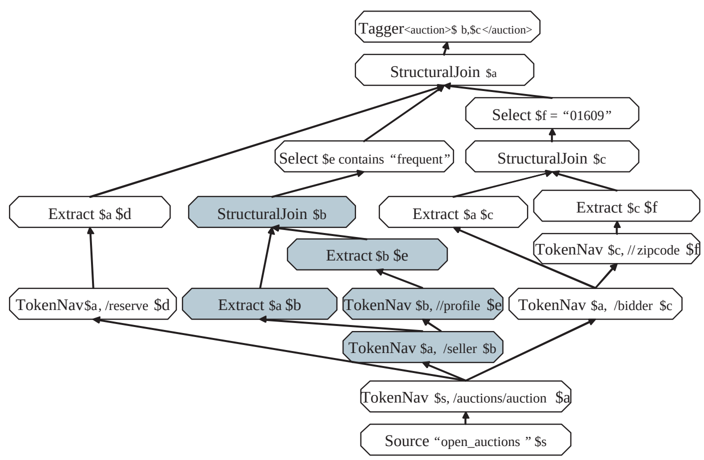



**Figure 2: Plan for Query in Figure 1 (a)**

Top of Figure 3 shows the automaton which implements the $TokenNav$ and $Extract$ operators in the Raindrop plan. A stack is used to store the history of state transitions. Bottom of Figure 3 depicts the snapshot of the stack after each token (annotated under the stack) in an example stream is processed. Initially, the stack contains only the start state $q0$ (see the first stack). As we need to define the cost for pattern retrieval in the automaton, we now describe how the automaton functions.

1. When an incoming token is a start tag:

(a) If the stack top is not empty, the automaton checks whether the states at the stack top can be transitioned. For example, when <*auctions*> is encountered, the automaton transitions $q_0$ to $q_1$ and pushes $q_1$ onto the stack (see the $2^{nd}$ stack). If no states are transitioned to, the automaton

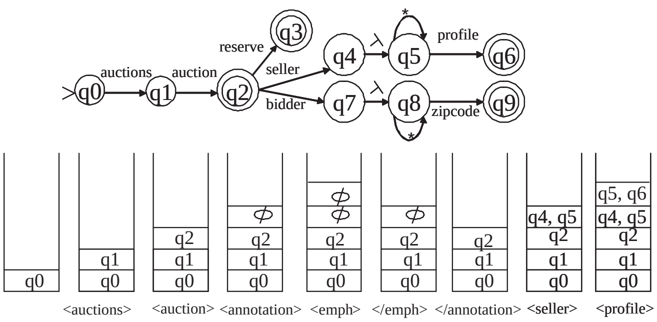



**Figure 3: Snapshots of Automaton Stack**

pushes an empty set (denoted as $\emptyset$) onto the stack. For example, before <*annotation*> is encountered, stack top contains a $q_2$ (see the $3^{rd}$ stack). No transition with label "annotation" starts from $q_2$. Therefore, a $\emptyset$ is pushed onto the stack after <*annotation*> is processed (see the $4^{th}$ stack).

(b) If the stack top is empty ($\emptyset$), the automaton directly pushes another empty set onto the stack without any transition lookup (see the $5^{th}$ stack after we see <*emph*>).

2. When an incoming token is a PCDATA token: the automaton makes no change to the stack.

3. When an incoming token is an end tag: the automaton pops off the states at the stack top (see the $6^{th}$ stack after we see </*emph*>).

$TokenNav$ and $Extract$ consume tokens and are called *automaton-inside*. The other operators such as $NodeNav$ and $Tagger$ consume tuples containing XML element nodes and are called *automaton-outside*. Tree-like element nodes can be accessed in a non-sequential manner, and hence are advantageous over XML tokens, which can be accessed only in a sequential manner. For example, in a tree structure, from an entry node, we can access its second child node without having to access all descendants of the first child node. It is therefore more efficient to locate patterns in such tree structures than over those only sequentially accessible tokens. Therefore once an element node has been formed, it will not be converted back to tokens again. That is to say, the output of automaton-outside operators will not be consumed by automaton-inside operators.

# 3. AUTOMATON PULL-OUT OR PUSH-IN REWRITE

We now present the rewrite rules that move pattern retrieval into or out of the automaton. In the plan in Figure 4 (a), $\$v2 = \$v1/p1$ is retrieved in the automaton. The pull-out rule eliminates $TokenNav_{\$v1,p1}\$v2$ and $Extract_{\$v1}\$v2$ and introduces $NodeNav_{\$v1,p1}\$v2$ (see the rewritten plan in Figure 4 (b)). If $Extract_{\$v0}\$v1$ operator, which forms the XML nodes bound to $\$v1$ so that $NodeNav_{\$v1,p1}\$v2$ can navigate into, had not existed in Figure 4 (a), it would be introduced into the rewritten plan. We can also rewrite the plan in Figure 4 (b) back to the plan in Figure 4 (a) by pushing $\$v2 = \$v1/p1$ into the automaton. We refer to the pull-out or push-in of a pattern retrieval as **mode change** of the corresponding $TokenNav$ or $NodeNav$ operator respectively.

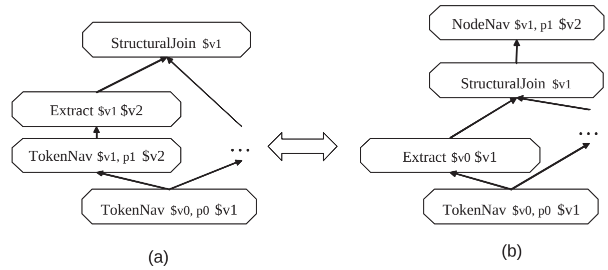



**Figure 4: Automaton Pull-out/Push-in**

Let us consider a more complicated case. Suppose we want to change the mode of $TokenNav_{\$a,/seller}\$b$ in Figure 2 where $\$b$ is further navigated into by $TokenNav_{\$b,//profile}\$e$. We say $\$b = \$a/seller$ is the **ancestor pattern** of $\$e = \$b//profile$; or $\$e = \$b//profile$ is the **descendant pattern** of $\$b = \$a/seller$. Changing $TokenNav_{\$a,/seller}\$b$ to $NodeNav_{\$a,/seller}\$b$ makes $/seller$ to be retrieved in XML element nodes bound to $\$a$. Since $\$b$ is located within $\$a$, bindings of $\$b$ must also be XML nodes. This dictates $\$e = \$b//profile$ being retrieved in XML nodes. Therefore, the mode of $TokenNav_{\$b,//profile}\$e$ has to be changed as well. An $Extract_{\$s}\$a$ operator is introduced so that $NodeNav_{\$a,/seller}\$b$ can be performed. Figure 5 shows the rewritten plan with the new operators highlighted.

On the other hand, in Figure 5, if we push in $\$b//profile$, bindings of $\$b$ must be tokens. Since $\$b$ is located within $\$a$ ($\$b = \$a/seller$), bindings of $\$a$ must be tokens as well. As a result, the mode of $NodeNav_{\$a,/seller}\$b$ has to be changed. This leads to the property below.

**Property 1 Secondary effect of mode change:** If we change the mode of $TokenNav_{\$v1,path}\$v2$ (resp. $NodeNav_{\$v1,path}\$v2$), then we must also change the mode of any $TokenNav$ that retrieves *path*'s descendant pattern (resp. any $NodeNav$ that retrieves *path*'s ancestor pattern).

When considering the mode change of a $TokenNav$ operator, if we were to put the newly generated $NodeNav$ operator in a suboptimal position out of the automaton, we may be biased towards disallowing this mode change. We thus adopt the commonly used commute rewrite rules to optimize the tuple-based portion of the query plan. These commute rules are traditional and omitted here, but can be found in [14]. Other rewrite rules for optimizing the tuple-based portion of the plan can be equally plugged into our optimization algorithms.

# 4. COSTING STREAM QUERY PLANS

We now define a cost model for comparing plans with different amount of pattern retrievals in the automaton. Since the stream can be infinite, we define the cost on a finite input unit instead of the entire input. In Raindrop, we refer to the elements retrieved by the bottommost $TokenNav$ operator as the **bottom input elements**. We define the cost of an operator as the average time of processing the data that

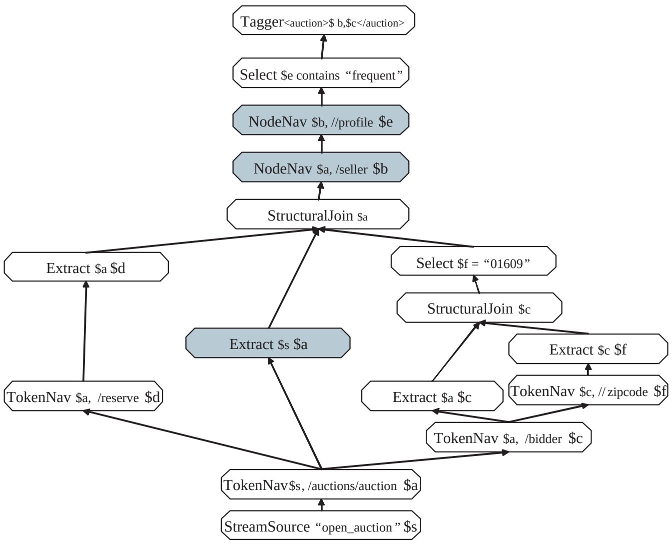



**Figure 5: Rewritten Plan After Mode Change of $TokenNav_{\$a,/seller}\$b$ in Figure 2**

originate from one bottom input element. For example, the cost of the plan in Figure 5 is the average processing time of one *auction* element[1].

***Costing TokenNav Operators.*** When costing a $TokenNav$ operator, we need to be careful with "amortized" computations. For example, in Figure 3, the rightmost stack contains $q5$ and $q6$ at the top. An incoming $</profile>$ will lead to a stack backtrack. However we cannot solely assign this backtrack cost to $TokenNav_{\$b,//profile}\$e$. Suppose the query does not ask for $\$b//profile$. After a $<profile>$ is processed, the stack top would contain an empty set. Next, when a $</profile>$ arrives, the backtrack is still needed to restore the stack to the status before the matching $<profile>$ has been encountered.

To avoid repeatedly counting the amortized computations, we compare the costs of automata $A_{with}$ and $A_{without}$. $A_{with}$ encodes $\$v1/p1$ and all the ancestor patterns of $\$v1/p1$. $A_{without}$ encodes only the ancestor patterns of $\$v1/p1$. The cost difference between $A_{with}$ and $A_{without}$ is then the cost of retrieving $\$v1/p1$. Using the notations in Table 2, Equation 1 captures the cost of $TokenNav$ operators in an automaton $A$.

EQUATION 1. *Cost*($TokenNav$ *operators in automaton* $A$)

= *state transition cost for processing start tags* (1)

+ *stack backtrack cost for processing end tags* (2)

$= \sum_{q \in Q(A)} n_{active}(q)\ C_{nonEmp}$ (3.a)

[1]When the query has $n$ input streams and $n > 1$, the cost of a plan can be easily extended to be the average time of processing $n$ elements each of which is a bottom input element from a different input stream.

| Notation | Explanation |
|---|---|
| $Q(A)$ | states in an automaton $A$ |
| $C_{nonEmp}$ | cost of processing a start token when stack top is not empty |
| $C_{emp}$ | cost of processing a start token when stack top is empty |
| $C_{backtrack}$ | cost of popping off states at the stack top |
| $C_{extract}(q)$ | cost of extracting elements, whose start tags activates state $q$, in a bottom input element |
| $n_{active}(q)$ | the number of times that stack top contains a state $q$ in a bottom input element. |
| $n_{start}$, $n_{end}$ | number of start or end tags in a bottom input element. |

**Table 2: Notations for Costing Automaton**

$+ [n_{start} - \Sigma_{q \in Q(A)} n_{active}(q)]\ C_{emp}$ (3.b)

$+\ n_{end}\ C_{backtrack}$ (4)

$= \sum_{q \in Q(A)} n_{active}(q)\ (C_{nonEmp} - C_{emp}) + n_{start}(C_{emp} + C_{backTrack})$

In Equation 1, Expression (1) is expanded into Expressions (3.a) and (3.b). $\sum_{q \in Q(A)} n_{active}(q)$ is equal to the number of start tokens that are processed with a non-empty stack top. Expression (3.a) then denotes the cost of processing start tags with a non-empty stack top.

The number of start tags that are processed with an empty stack top is equal to ($n_{start}$ − number of start tags that are processed with an non-empty stack top), i.e., ($n_{start} - \Sigma_{q \in Q(A)} n_{active}(q)$). Expression (3.b) then denotes the cost of processing start tags with an empty stack top.

The cost of processing an end tag is equal to the cost of popping out the states at the stack top, namely, $C_{backtrack}$. Since there are $n_{end}$ end tags in a bottom input element, Expression (4) denotes the cost of processing end tags.

Let us use $A_{p1}$ to denote the sub-automaton that encodes $\$v1/p1$ only. We then have Equation 2.

EQUATION 2. *Cost*($TokenNav_{\$v1,p1}\$v2$)

= *Cost*($TokenNav$ *operators in* $A_{with}$) − *Cost*($TokenNav$ *operators in* $A_{without}$)

$= \sum_{q \in Q(A_{with}) - Q(A_{without})} n_{active}(q)\ (C_{nonEmp} - C_{emp})$

$= \sum_{q \in Q(A_{p1})} n_{active}(q)\ (C_{nonEmp} - C_{emp})$

***Costing Extract Operators.*** For an $Extract_{\$v1}\$v2$, suppose the start token of a binding of $\$v2$ activates state $q$. $n_{active}(q)$ is then the number of elements bound to $\$v2$ in one bottom input element. Therefore, the cost of $Extract_{\$v1}\$v2$ operator is $n_{active}(q)C_{extract}(q)$.

***Costing NodeNav Operators.*** We implement $NodeNav_{\$v1,p}\$v2$ as a width-first tree traverse. Suppose $p = p_1/p_2/.../p_n$ where $p_i$ ($1 \leq i \leq n$) is either a navigation step or a descendant axis "//". We first traverse all the children of the entry node $\$v1$ and find those whose tag names match $p_1$. From these matched nodes, we again traverse their children to match $p_2$ and so on. We use $n_{p_i}$, $w_{p_i}$ and $C_{visit}$ to denote the number of nodes matching $p_1/.../p_i$, the number of children of these matched nodes and the time for visiting one node. The time $NodeNav_{\$v1,p}\$v2$ spends on processing one input tuple is then $\sum_{i=1}^{n} n_{p_{i-1}} w_{p_{i-1}} C_{visit}$.

*Costing of Other Automaton-outside Operators.* The full list of cost models can be found in [14]. Some automaton-outside operators such as *Select*, when appearing in one plan, must appear in all other alternative plans because we do not provide any rewrite rule to eliminate a *Select* operator. For these operators, we can always observe the actual time it spends on processing one input tuple in the current running plan. There is no need to provide an equation to estimate such single unit processing cost.

# 5. RUN-TIME STATISTICS COLLECTION

Currently we use a simple statistics collection model. To optimize a query, we run an initial plan of this query on the incoming stream while at the same time collecting the statistics needed for this particular query. For example, we attach counters to the states in the automaton. Each time when a start tag arrives, the counter of each state at the top of the stack is incremented by 1. This way we can get $n_{active}(q)$, which is needed for costing the automaton (see Table 2), for each state $q$. The statistics collection is rather straightforward so that we omit the discussion here.

# 6. MINEXHAUST: FINDING OPTIMAL PLAN

In this section, we first present a baseline search algorithm that guarantees to find an optimal plan. We then examine search redundancies in the baseline algorithm, i.e., same plans may be explored multiple times. Eliminating these redundancies gives us the *MinExhaust* algorithm.

## 6.1 Baseline Exhaustive Algorithm

Suppose an initial plan, denoted as $G$ in Figure 6, has $n$ patterns $p_1$, $p_2$, ..., $p_n$. For each pattern retrieval operator, we change its mode and get a new plan, denoted as $G_1$, $G_2$ and so on. Cycles on the new plans denote that we optimize the tuple-based portion of the new plans. Currently in Raindrop, we use the commuting optimization techniques in [18]. Any other optimization on tuple-based plans can be also plugged in here. We then treat the new plans as initial plans and repeat the above process. For example, from $G_1$, we change the mode of the operator retrieving $p_2$ (resp. $p_3$, ..., $p_n$) and get a new plan $G_{12}$ (resp. $G_{12}$, ..., $G_{1n}$). Note that we do not change the mode of the operator that retrieves $p_1$ in $G_1$ because that would generate a same plan as $G$. We continue the process until no new plans are generated. This process explores all possible plans and thus guarantees to find the optimal plan.

## 6.2 Eliminating Redundancy

In Figure 6, there is a path from the plan we start with, G, to any other plan, G'. We can encode the process to obtain G' from G in a sequence of patterns. We use $[p_{i1}, p_{i2}, ..., p_{in}]$, called a **rewrite sequence**, to denote that we

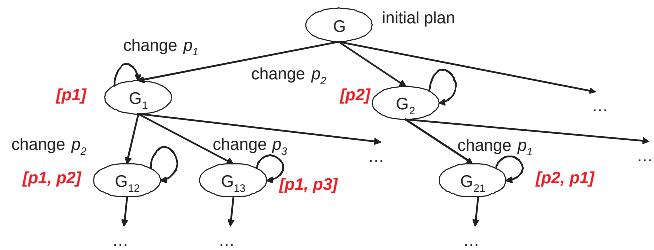



**Figure 6: Baseline Exhaustive Search**

change the mode of the operator retrieving $p_{i1}$ first, then change the mode of the operator retrieving $p_{i2}$ and so on. Two rewrite sequences are **redundant** to each other if they generate the same plans. We now present two lemmas about redundancy of rewrite sequences. Below, we use $navOp$ to generally represent a pattern retrieval operator, i.e., either a $TokenNav$ or a $NodeNav$. Also, recall the definition of ancestor and descendant patterns in Section 3.

LEMMA 1. ***Redundancy due to Pattern Dependency:*** *Suppose $p_1$ is the ancestor or descendant pattern of* p2 *(we say $p_1$ and $p_2$ have dependencies). Given a rewrite sequence $S$ containing both $p_1$ and $p_2$, there always exists another rewrite sequence that contains no patterns with dependency and yet produces the same plan.*

EXAMPLE 1. *In Figure 7 (a), $\$b$ = $\$a/seller$ and $\$g$ = $\$b//phone$ have a dependency. We apply a rewrite sequence [$\$a/seller$, $\$b//phone$] on this plan. We first pull out $\$b$ = $\$a/seller$. Due to the secondary effect (see Property 1 in Section 3), $\$e$ = $\$b//profile$ is also pulled out. Figure 7 (b) shows the plan after this rewrite. Next, we push in $\$g$ = $\$b//phone$. Due to the secondary effect, $\$b$ = $\$a/seller$ is pushed back into the automaton which undoes part of the first rewrite. We get a final plan in Figure 7 (c).*

*We can also derive the final plan by pulling out $\$b//profile$ and pushing in $\$b//phone$ in Figure 7 (a). The corresponding rewrite sequence is [$\$b//profile$, $\$b//phone$] in which the two patterns have no dependency. The first rewrite sequence is redundant.*

LEMMA 2. ***Redundancy due to Order Insensitivity:*** *If a rewrite sequence $S$ does not contain patterns that have dependencies with one another, then $S$ generates the same plan as any other rewrite sequence that contains the same set of operators in $S$ but in a different order.*

EXAMPLE 2. *In Figure 7 (a), we can either apply the rewrite sequence [$\$b//profile$, $\$b//phone$] or [$\$b//phone$, $\$b//profile$] to derive the plan in Figure 7 (c).*

Proofs for both lemmas can be found in [14]. Based on the above two lemmas, we design an *MinExhaust* algorithm that eliminates the generation of any redundant plan in the

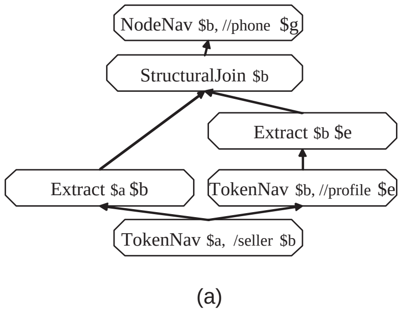



**Figure 7: (a) Initial Plan; (b) Pull out $\$a/seller$ in (a); (c) Push in $\$b//phone$ in (b)**

baseline exhaustive search. According to the *redundancy due to order insensitivity* lemma, this algorithm enumerates the combinations (instead of permutations) of $n$ patterns. Changing the modes of all operators in one such combination leads to one alternative plan. Also, according to the *redundancy due to pattern dependency* lemma, we exclude any combinations that include two patterns with dependencies. Each remaining combination now leads to one *unique* alternative plan. It can be easily seen that for a query with $n$ patterns, *MinExhaust* explores up to $2^n$ alternative plans.

# 7. FAST SEARCH WITH PRUNING

We now present the $GreedyBasic$ and $FastPrune$ algorithms whose complexity is more practical for large queries than $MinOptimal$. Given an initial plan with $n$ patterns, $GreedyBasic$ changes the mode of each pattern retrieval operator and gets a new plan respectively, denoted as $G_1$, ..., $G_n$. Among the new plans, if the best plan is better than the initial plan, it is picked as the current plan. Suppose $G_1$ is picked after the first iteration. In the second iteration, $GreedyBasic$ explores changing the modes of operators that retrieve $p_2$, ..., $p_n$ in $G_1$ respectively. This time we get a new current plan. The iterations continue until no new plan is found to be better than the current plan.

We can further improve $GreedyBasic$ by applying a pruning technique of sub-optimal plans. Below we use *NavOp* for convenience to denote a pattern retrieval operator, be it either *TokenNav* or *NodeNav*. Let us use $CostCut(NavOp, G)$ to denote (cost of the plan after mode change of $NavOp$ − cost of plan $G$). Suppose for a $NavOp$ we can estimate a constant $c$ such that $CostCut(NavOp, G) > c > 0$ for any plan $G$. For any plan $G$, the mode change of $NavOp$ increases the cost. We can then safely exclude the mode change of $NavOp$ during the plan search.

We now consider the case where $NavOp$ is a $TokenNav_{\$v1,p1}\$v2$ with $\$v1 = \$v0/p0$. Let us use $G$ and $G'$ to denote the plan before and after the mode change of $TokenNav_{\$v1,p1}\$v2$ respectively. Equation 3 denotes the cost cut by pulling out $\$v1/p1$.

EQUATION 3. $CostCut(TokenNav_{\$v1,p1}\$v2, G)$

$= Cost(G') - Cost(G)$

$= \textit{automaton cost in } G' - \textit{automaton cost in } G$ (1)

$+ \textit{non-automaton cost in } G' - \textit{non-automaton cost in } G$ (2)

$= Cost(Extract_{\$v0}\$v1) \; * isIntroduced$ (3.a)

$- Cost(TokenNav_{\$v1,p1}\$v2)$ (3.b)

$+ Cost(NodeNav_{\$v1,p1}\$v2)$ (4.a)

$+$ (*cost of automaton-outside operators except* $NodeNav_{\$v1,p1}\$v2$ *in* $G'$ − *cost of automaton-outside operators in* $G$) (4.b)

In Equation 3, (1) is expanded into (3.a) and (3.b). An $Extract_{\$v0}\$v1$ operator may be introduced during the rewrite (see Figure 4 in Section 3). $isIntroduced$ in (3.a) is a boolean indicating whether an $Extract_{\$v0}\$v1$ is introduced or not.

(2) is expanded into Expressions (4.a) and (4.b). For (4.a), $Cost(NodeNav_{\$v1,p1}\$v2)$ can vary in different plans depending on the position of $NodeNav_{\$v1,p1}\$v2$ in the plan. We can easily compute this minimal cost of $NodeNav_{\$v1,p1}\$v2$ by applying the commute rules to pull up $NodeNav_{\$v1,p1}\$v2$. This way $NodeNav_{\$v1,p1}\$v2$ consumes the least input and thus costs the least. We denote this minimal cost as $min(Cost(NodeNav_{\$v1,p1}\$v2))$. We then have Exp. (4.a) $> min(Cost(NodeNav_{\$v1,p1}\$v2))$.

Exp. (4.b) is guaranteed to be no less than 0 if no *Select* or $NodeNav$ operators in $G$ select on or navigate into $\$v2$. The optimal ordering of the automaton-outside operators is determined by their rankings [18]. The ranking function of an operator is defined on two factors, the operator's selectivity and its processing time on one input tuple. Therefore, the optimal ordering of automaton-outside operators in $G'$ remains the same as in $G$. However, some operators executed before the automaton-outside operators in $G$ can now be executed after them. For example, in Figure 7 (c), $NodeNav_{\$b,//profile}\$e$ is executed after $TokenNav_{\$b,//phone}\$g$. In contrast, in Figure 7 (c), $NodeNav_{\$b,//profile}\$e$ is executed before $NodeNav_{\$b,//phone}\$g$. The cost of an automaton-outside operator in $G'$ is always no less than that in $G$. In summary, we have Exp. (4.b) $\geq 0$.

In summary, $CostCut(TokenNav_{\$v1,p1}\$v2, G) \geq$

$min(Cost(NodeNav_{\$v1,p1}\$v2)) - Cost(TokenNav_{\$v1,p1})\$v2$. This leads to the following lemma.

Lemma 3. ***Pruning by Bounding Cost Cut.*** Given a $NavOp = TokenNav_{\$v1,p1}\$v2$ where $\$v2$ is not further selected on nor navigated into, if $min(Cost(NodeNav_{\$v1,p1}\$v2)) - Cost(TokenNav_{\$v1,p1})\$v2 \geq 0$, mode change on $NavOp$ always leads to a worse plan.

We apply the pruning strategy on $GreedyBasic$, now called $FastPrune$. The correctness of this pruning strategy does not depend on the search strategy, i.e., it could be applied to any other algorithms including $MinOptimal$.

# 8. RUN-TIME OPTIMIZATION

*Run-time Statistics Collection..* To optimize a query, we run an initial plan of this query on the incoming stream while at the same time collecting the statistics. For example, we attach counters to the states in the automaton. Each time when a start tag arrives, the counter of each state at the stack top is incremented by 1. This way we can get $n_{active}(q)$ for each stats $q$, which is needed for costing the automaton ($n_{active}(q)$ is the number of times that stack top contains a state $q$, see Table 2). The statistics collection is rather straightforward so that we omit the discussion here.

*Run-time Plan Migration..* At the run time, the optimizer is invoked periodically. If a new plan is found, the current running plan is migrated to the new plan. We now describe how to efficiently and safely perform the plan migration.

The optimization algorithms above generate algebraic plans, but not the automata which are indispensable for plan execution. We can save the cost of reconstructing a new automaton from scratch by reusing the current automaton. For this purpose, our optimization algorithm returns not only a new plan but also a set of pattern retrieval operators in the current plan whose modes have been changed. If a pattern $\$v1/p$ has been pulled out, we remove the states that encode path $p$ in the current automaton. If a pattern $\$v1/p$ has been pushed in, we add states that encode $p$ to the current automaton.

Even when we have a new plan and a new automaton ready, we cannot just start the migration at a random time. This may corrupt the running system. Suppose we are running the plan in Figure 2. Figure 3 shows the stack content as tokens are processed. Assume we now pause this running plan in the middle of processing a *seller* element, say, when processing $<profile>$ (see last stack). We then start to migrate to the new plan in Figure 5 which results from the pull-out of $\$a/seller$. Now all states after $q_4$ in the automaton in Figure 2 are removed. For the next incoming start tag, the transition entry of the state at the stack top, i.e., $q_5$ and $q_6$, would be looked up. However neither $q_5$ nor $q_6$ is in the automaton. The processing then corrupts.

To avoid such corruption, we define a **migration window**. The migration can start whenever the execution is *not* in the middle of processing a bottom input element. In the above example, the migration can only start whenever the execution is not in the middle of processing an *auction*. For example, the migration can start right after a $</auction>$ is processed.

# 9. EXPERIMENTAL EVALUATION

We run experiments on two Pentium III 800 Mhz machines with 512MB memory each. One machine sends XML token streams via sockets to the second machine which then processes the received data. We compare the plan search time and the quality of the plan found by *MinExhaust*, *GreedyBasic* and *FastPrune* algorithms. We test queries conforming to the three pattern trees shown in Figure 8, similar to previous work on XQuery optimization [4, 13, 25]. In our pattern tree, a node represents an XML element. The top node in the pattern tree represents the bottom input element. The label $p$ on the edge from a parent node $u$ to a child node $v$ indicates that a path $p$ exists within the element represented by $u$. The bottom input elements that contain all the specified patterns are returned as the query results.

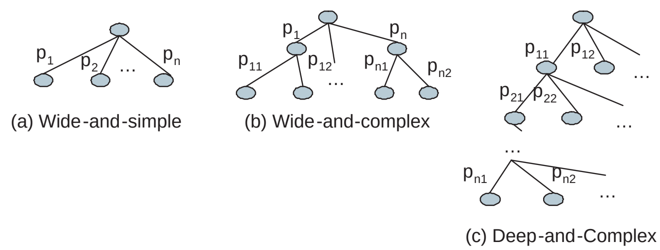



**Figure 8: Pattern Trees**

## 9.1 Wide-and-Simple Pattern Trees

**Query Sets:** We design three queries that conform to the wide-and-simple pattern tree in Figure 8 (a). These three queries differ in the number of patterns in the query, i.e., the value of $n$ in Figure 8 (a) is 5, 10 and 20 respectively.

**Data Sets:** We use the XMark DTD [2] which describes auction data. We add more child elements to the *auction* root element in XMark DTD so that we are able to issue queries that contain up to 20 patterns. We use ToXGene [7] to generate two streams each of which has a size around 52M. In stream 1 (stream 2 resp.), for any of the three queries, 4/5 of the patterns have a selectivity of 10% (90% resp.) while 1/5 of the patterns have a selectivity of 90% (10% resp.). These two streams are used to test the algorithms in the extreme cases. In stream 1, most pattern retrieval operators have a low selectivity and are favored to be retrieved in the automaton. Therefore, in stream 1, the initial plan which retrieves all patterns in the automaton is close to the optimal plan. In contrast, in stream 2, most pattern retrieval operators have a high selectivity so that they are more favorable to be pulled out from the automaton in the initial plan. We expect that more changes need to be made to the initial plan to get the optimal plan in this case.

For each stream, we run an initial plan that retrieves all patterns in the automaton, collect statistics from the stream and apply the search algorithm to get a new plan. We then

| stream | n | MinExhaust | | | | GreedyBasic | | | | FastPrune | | | | Initial Plan Exec. Time |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | # of plans | Opt. Time | Plan Exec. Time | Effectiveness | # of plans | Opt. Time | Plan Exec. Time | Effectiveness | # of plans | Opt. Time | Plan Exec. Time | Effectiveness | |
| 1 | 5 | 32 | 592 | 1543 | 117% | 9 | 232 | 1543 | 96% | 1 | 64 | 1543 | 88% | 1821 |
| | 10 | 1024 | 15921 | 5439 | 336% | 27 | 475 | 5439 | 94% | 3 | 106 | 5439 | 87% | 6349 |
| | 20 | $\infty$ | $\infty$ | N/A | N/A | 144 | 2271 | 9402 | 92% | 10 | 242 | 9402 | 77% | 12468 |
| 2 | 5 | 32 | 508 | 3987 | 84% | 15 | 381 | 3987 | 79% | 10 | 142 | 3987 | 77% | 5340 |
| | 10 | 1024 | 14982 | 9283 | 166% | 54 | 823 | 9283 | 69% | 36 | 294 | 9283 | 65% | 14611 |
| | 20 | $\infty$ | $\infty$ | N/A | N/A | 204 | 3126 | 22271 | 68% | 136 | 1053 | 22271 | 63% | 36841 |

**Table 3: *MinExhaust*, *GreedyBasic* and *FastPrune* on Wide-and-Simple Queries (all time in ms.)**

run the new plan on the same stream again and measure its execution time. Table 3 reports the result. The column "effectiveness" of a search algorithm is defined as (time spent on finding a plan + time spent on executing the plan found )/(time spent on executing the initial plan). The smaller the number is (i.e., spent less time on finding a plan that runs faster), the more effective the search algorithm is.

The number of plans explored by *MinExhaust* is fixed given a query. When $n = 10$, the optimization time already far exceeds the execution time on both XML streams 1 and 2. When $n = 20$, *MinExhaust* is impractical so that we do not report it. In contrast, the number of plans explored by *GreedyBasic* varies with different streams because *GreedyBasic* terminates whenever no single mode change in the current plan yields a better plan. Although *GreedyBasic* explores much less plans than *MinExhaust*, it still succeeds to find optimal plans on both streams.

$FastPrune$ can prune the pull-out of a pattern that has no descendant patterns. In the wide and simple queries, $p_1$, $p_2$, ..., and $p_n$ all have no descendant patterns. The technique of "pruning by bounding cost cut" is tried on all of them. It excludes the pull-out of those $TokenNav$ with selectivity of 10%. The optimization time is improved most significantly in the third experiment (see row 3), since the initial plan has more $TokenNav$ operators that have a selectivity of 10% than any of the other five initial plans.

## 9.2 Wide-and-Complex Pattern Trees

We generate XML streams conforming to the DTD describing Ebay's auction data [24]. We design a query as shown in Figure 9 with $\$b$, $\$c$, $\$d$ and $\$e$ having 2, 2, 12 and 5 filters respectively. This query conforms to the wide-and-complex pattern tree in Figure 8 (b). We test on a set of data streams with different data characteristics as shown in Table 4. The purpose is to generate a "random" data set.

for $\$a$ in */listing*
let $\$b$ :=$\$a/seller\_info[seller\_rating > 4][seller\_name$ contains "SF"];
$\$c$ := $\$a$/*bid_history*[...]...[...];
$\$d$ := $\$a/auction\_info$[...]...[...];
$\$e$ := $\$a/item\_info$[...]...[...]
where $\$b$ and $\$c$ and $\$d$ and $\$e$
return $\$a$

**Figure 9: Wide-and-Complex Query on Ebay Data**

Table 5 reports the result. *MinExhaust* is impractical for such a query that contains 25 patterns. Thus it is not reported here. *GreedyBasic* explores a limited number of alternative plans yet in all cases it finds a plan that cuts the initial execution time by 15% to 56%. *FastPrune* cuts down the number of plans explored most significantly in the third experiment (see row 3). This is because the search in the third experiment goes through most iterations. In each iteration, we avoid exploring the pull-out of certain patterns. So accumulatively, we save most plan explorations.

| Stream | Selectivity of $\$b$ | Selectivity of $\$c$ | Selectivity of $\$d$ | Selectivity of $\$e$ |
|---|---|---|---|---|
| 1 | 10% | 50% | 70% | 90% |
| 2 | 90% | 10% | 50% | 70% |
| 3 | 70% | 90% | 10% | 50% |
| 4 | 50% | 70% | 90% | 10% |

**Table 4: Random Data Sets Conforming to Ebay's DTD: Each Stream around Size 55M**

| | GreedyBasic | | | FastPrune | | | Initial Plan Exec. Time |
|---|---|---|---|---|---|---|---|
| | # of plans | Opt. Time | Plan Exec. Time | # of plans | Opt. Time | Plan Exec. Time | |
| 1 | 57 | 852 | 23088 | 52 | 779 | 23088 | 30072 |
| 2 | 59 | 825 | 22209 | 50 | 776 | 22209 | 38690 |
| 3 | 76 | 1118 | 21924 | 28 | 615 | 21924 | 25828 |
| 4 | 37 | 545 | 18590 | 19 | 423 | 18590 | 42301 |

**Table 5: *GreedyBasic* and *FastPrune* for Query in Figure 9 on XML Streams in Table 4**

## 9.3 Deep-and-Complex Pattern Trees

It is interesting to observe that for queries conforming to the deep-and-complex pattern tree in Figure 8 (d), $GreedyBasic$ terminates very quickly. According to *redundancy due to pattern dependency* lemma in Section 6, two operators that have a pattern dependency cannot both undergo mode changes. Suppose from a current plan, the mode change on $p_{i2}$ ($1 < i < n$) in Figure 8 is chosen, then the mode changes on its ancestor and descendant patterns, including $p_{11}$, $p_{21}$, ..., $p_{(i-1)1}$, need no longer be considered. Suppose the mode change on $p_{i1}$ is chosen. Then even more mode changes are disqualified for consideration, including mode changes on patterns $p_{11}$, $p_{21}$, ..., and $p_{n1}$.

Table 6 reports the result. Since *GreedyBasic* already explores a very small number of alternative plans, *FastPrune* brings fairly small gains and thus is not reported. Even for the queries involving a large number of patterns, *GreedyBasic*

| $n$ | MinExhaust | | | GreedyBasic | | | Initial Plan Exec. Time |
|---|---|---|---|---|---|---|---|
| | # of plans explored | Opt. Time | Plan Exec. Time | # of plans explored | Opt. Time | Plan Exec. Time | |
| 3 | 147 | 2296 | 7356 | 10 | 205 | 8059 | 9122 |
| 4 | 595 | 8674 | 10086 | 14 | 364 | 11202 | 13569 |
| 5 | 2387 | 38500 | 12176 | 17 | 487 | 12176 | 17045 |
| 6 | 9555 | 180078 | 13408 | 20 | 647 | 14280 | 20055 |

**Table 6: *MinExhaust* and *GreedyBasic* for Deep-and-Complex Queries on a 51M XML Stream**

terminates quickly. For example, for the last row in Table 6, when $n = 6$, there are 18 patterns in total in the tree. $MinExhaust$ explores 9555 alternatives while $GreedyBasic$ only explores 20 alternatives.

## 9.4 Overhead of Statistics Collection and Plan Migration

With plan search time already studied above, we now study the overhead of statistics collection and plan migration in the run-time optimization.

**Query Sets:** We design two queries conforming to the pattern tree in Figure 8 (b). The two queries differ in the number of patterns in the query ($n$ in Figure 8 (b) is 5 and 10 respectively). We therefore can compare the overhead of two plans that collect different amount of statistics.

**Data Sets:** We also design two streams. For a query running on XML stream 1, the optimal plan is only slightly different from the initial plan. In contrast, the optimal plan of the same query on XML stream 2 is significantly different from the initial plan. We therefore can compare the overhead of a simple plan migration with a more complicated plan migration process.

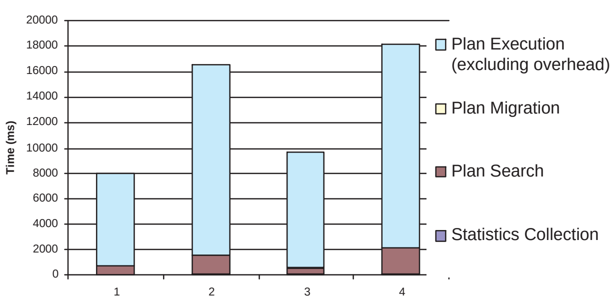



**Figure 10: Cost Ingredients of Run-time Optimization (statistics collection time/migration time too small to be recognizable)**

Given the above two queries and two streams, we explore four experiment settings. In Figure 10, for each experiment setting, we illustrate the four cost ingredients of query processing with run-time optimization, i.e., (1) plan execution time of initial plan + plan execution time of optimized plan, (2) plan search time by $GreedyBasic$, (3) time for statistics collection and (4) time for plan migration. The costs of the latter three correspond to the overhead of the run-time optimization. In all four experiments, the plan search time dominates the overhead. The time of statistics collection ranges from 10ms - 20ms while that of plan migration ranges from 0ms - 40ms in the four experiments.

## 10. RELATED WORK

Cost-based optimization has been actively studied for static XML processing [1, 21, 25]. Lorel [21] proposes a cost model for various XML indices. Lorel uses a greedy search algorithm to choose among path navigation alternatives via different indices. Halverson and Burger etc [1] propose two pattern retrieval methods on stored XML data, i.e., tree navigation and structural-join based pattern matching. Both methods can be used as different implementations of the $NodeNav$ operator in Raindrop algebra. What they study can be seen as breaking a $NodeNav_{\$v1,p}\$v2$ operator into several $NodeNav$ operators retrieving smaller pieces of $p$ and choosing the implementation method for each $NodeNav$ (of course their techniques are more suitable in a static database since indices are required). Since a path expression is usually not very long, the search space is not large. They therefore use a dynamic programming approach to search for the best plan. Timber [25], another static XML processor, proposes a dynamic programming algorithm with pruning techniques to choose an optimal order for structural joins.

In the XML stream query field, there are three major approaches. One approach is to use automata or automaton-like SAX event handlers to process the whole query [5, 6, 20, 22]. In this approach, there is no traditional algebraic query plan. Non-pattern-retrieval functionalities such as filtering or restructuring are also encoded in the automata. The input, output, and intermediate data in the processor are all tokens. No XML nodes would ever be formed. The second approach is to use algebra only. The BEA/XQRL streaming XQuery processor [8] models the query as an *expression tree* where an expression can be seen as an operator in an algebraic query plan. Both the input or output of expressions are tokens. The third approach is then to combine automaton and algebra [9, 10, 15, 19]. The processors using the third approach can take advantage of our automaton-in-or-out optimization techniques.

There have been work on run-time optimization in relational streams [3, 23, 26]. In one of the representative paradigms, namely, *Eddy* [3], no fixed query plans are ever constructed. Instead, each tuple, driven by the processing cost or selectivity of the operators and tuple arrival rate, can go through operators in a flexible order. The query plan is reformulated on a tuple-by-tuple basis. Eddy's plan reformulation focuses on changing the order of operators. It is not clear how to apply this technique to choose among plans that have a different set of operators as in the automaton-in-or-out optimization.

## 11. CONCLUSION

We have identified a unique optimization opportunity for XML stream processing. The previous literature on XML stream processing considers only query plans where all pattern retrieval is pushed into the automaton. We however find that for different queries and data characteristics, different automaton pushdown strategies are needed for generating optimal plans.

To explore this optimization opportunity, we use a cost-based approach. We design three plan optimization algorithms. *MinExhaust* enumerates all possible plans while avoiding repeated exploration of the same search space. Given a query with $n$ patterns, it guarantees to find an optimal plan in $O(2^n)$ time. In contrast, *GreedyBasic* uses heuristics to quickly find a plan in $O(n^2)$ time. *FastPrune* further prunes the sub-optimal plans in the search by bounding the cost change from one plan to another plan. Our experimental study illustrates that the plans found by *GreedyBasic* or *FastPrune* algorithm are often close to the optimal plan found by *MinExhaust*.

In order to optimize at run-time, we design an incremental and thus efficient plan migration strategy. The migration window we define ensures that the migration can safely undertake without generating wrong result. Our experiments illustrate that our run-time statistics collection and plan migration strategies are very lightweight.

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