Efficient Querying and Maintenance of Network Provenance at Internet-Scale

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ABSTRACT

Network accountability, forensic analysis, and failure diagnosis are becoming increasingly important for network management and security. Such capabilities often utilize *network provenance* – the ability to issue queries over network meta-data. For example, network provenance may be used to trace the path a message traverses on the network as well as to determine how message data were derived and which parties were involved in its derivation.

This paper presents the design and implementation of ExSPAN, a *generic and extensible* framework that achieves efficient network provenance in a distributed environment. We utilize the database notion of *data provenance* to "explain" the existence of *any* network state, providing a versatile mechanism for network provenance. To achieve such flexibility at Internet-scale, ExSPAN uses declarative networking in which network protocols can be modeled as continuous queries over distributed streams and specified concisely in a declarative query language. We extend existing data models for provenance developed in database literature to enable distribution at Internet-scale, and investigate numerous optimization techniques to maintain and query distributed network provenance efficiently. The ExSPAN prototype is developed using RapidNet, a declarative networking platform based on the emerging ns-3 toolkit. Experiments over a simulated network and an actual deployment in a testbed environment demonstrate that our system supports a wide range of distributed provenance computations efficiently, resulting in significant reductions in bandwidth costs compared to traditional approaches.

Categories and Subject Descriptors

C.2.4 [**Computer Systems Organization**]: Computer Communication Networks—*Distributed Systems*; E.1 [**Data Structures**]: Distributed Data Structures; H.2.1 [**Database Management**]: Logical Design—*Data Models*

General Terms

Design, Management, Performance

Keywords

Provenance, Distributed query processing, Declarative networking

1. INTRODUCTION

In database systems, data provenance [4] is a well-known concept, primarily used to answer questions concerning how query results are derived and which data sources they come from. A similar notion – *network provenance* [25] – is emerging in the networking domain. Network provenance describes the history and derivations of network state resulting from the execution of a distributed protocol. Typical network provenance use cases include discerning the origination of a message, the path that the message traversed on the network, and how communicated data were derived and which parties were involved in its derivation.

The capability to learn such information is essential to a diverse set of network management tasks such as performing network diagnostics, identifying malicious and misbehaving users, and enforcing trust management policies in distributed systems. Each goal has led to a series of application-specific proposals [21, 1, 11, 24, 9, 12] that focus on improving network support for accountability and providing efficient mechanisms to trace packets and information flows through the Internet.

This paper explores the *generic* data management challenges posed by the distribution, querying, and maintenance of network provenance at Internet-scale. Such scale has presented a unique challenge to provenance data management. Traditionally, provenance data are either stored in a centralized server or shared across only tens of nodes. In contrast, network applications in Internet domains usually involve thousands of nodes. Moreover, provenance computations are required to co-exist with existing network protocols. Bandwidth efficiency and minimal impact on convergence times are of significant importance.

As a step towards meeting these challenges, this paper proposes ExSPAN (*EXtenSible Provenance Aware Networked systems*), a platform that enables *generic* distributed systems to be specified, implemented, and analyzed with built-in distributed provenance support. ExSPAN provides a flexible framework for distributed querying of network meta-data. The type of network provenance ExSPAN provides can be customized along the dimensions of *granularity* (domains defined according to nodes, tuples, or networks), *distribution* (centralized or distributed), and *representation* (using derivation trees, binary decision diagrams [2], algebraic structures, etc.). We show that various distributed systems (in particular, diagnostics, network debugging, and distributed trust management) map naturally to network provenance.

This paper makes the following contributions:

Data model for network provenance. We define a distributed data model for storing network provenance. Our data model builds upon current work on representing provenance information as relational tables [10, 5], with extensions to supported distributed storage and querying. We propose two forms of distribution: a *value-based* approach in which all relevant information is piggy-backed onto communicated tuples, and a bandwidth-efficient *reference-based* approach that lazily creates provenance markers (or pointers) that can be resolved on demand via a distributed query.

Efficient provenance maintenance and querying. To maintain network provenance efficiently, we leverage the distributed query processing capabilities of *declarative networking* [17, 16, 15]. Declarative networking models network protocols as continuous queries over distributed streams. Declarative networking programs permit a variety of distributed network protocols to be specified concisely in a declarative query language. Given a declarative networking program, we demonstrate an automatic rewrite strategy that will augment the original program with additional queries for maintaining provenance information for the network protocol. Moreover, additional distributed queries can be formulated to derive various representations of network provenance, hence achieving a unifying framework for synthesizing and analyzing distributed systems. We further propose a variety of query optimization techniques aimed at reducing communication latency and bandwidth utilization.

ExSPAN prototype implementation and evaluation. We present the prototype of ExSPAN. Our implementation utilizes *RapidNet* [18], a declarative networking platform developed using the ns-3 network simulator [19]. Our experiments over simulated networks and an actual deployment on a testbed environment demonstrate that ExSPAN supports a wide range of distributed provenance computations efficiently, resulting in significant reduction in bandwidth utilization compared with centralized approaches.

The remainder of this paper is organized as follows. In Section 2, we present a background introduction to declarative networking. In Section 3, we then present a taxonomy of provenance along three axes and outline various use cases in distributed systems analysis. Based on the taxonomy, Section 4 presents the data model for distributed provenance, and declarative networking queries for maintaining provenance information in a distributed fashion. Section 5 demonstrates a similar use of declarative networking to query for various representations of network provenance. Section 6 presents various optimization techniques. Our evaluation results in simulation and on an actual testbed are presented in Section 7. We then conclude with related work (Section 8) and future work (Section 9).

2. BACKGROUND

Given ExSPAN's use of declarative networking, we briefly introduce declarative networking and the query language that will be used as a basis for enabling network provenance. The high level goal of *declarative networks* [17, 16, 15] is to build extensible network architectures that achieve a good balance of flexibility, performance, and safety. Declarative networks are specified using *Network Datalog* (*NDlog*), a distributed recursive query language used for querying network graphs. *NDlog* queries are executed using a distributed query processor to implement the network protocols and are continuously maintained as distributed views over existing network and host state. Declarative queries such as *NDlog* are a natural and compact way to implement a variety of routing protocols and overlay networks. For example, traditional routing protocols can be expressed in a few lines of code [17], and the Chord [23] distributed hash table in 47 lines of code [16]. When compiled and executed, these declarative networks perform efficiently relative to imperative implementations.

The techniques proposed in this paper can be generally realized using any sufficiently expressive distributed query processor. The advantage of using declarative networking is that several robust implementations exist that can be straightforwardly leveraged to develop ExSPAN. Moreover, since distributed protocols can themselves be expressed as declarative statements, declarative networking represents a natural means for unifying the synthesis and analysis of distributed protocols.

The declarative *NDlog* language used by ExSPAN is based on Datalog [20]. A Datalog program consists of a set of *rules*. Each rule has the form `p :- q1, q2, ..., qn.`, which can be read informally as "`q1` and `q2` and ... and `qn` imply `p`". Here, `p` is the *head* of the rule, and `q1`, `q2`,...,`qn` is a list of *literals* that constitutes the *body* of the rule. Literals are either *predicates* with *attributes* (which are bound to variables or constants by the query) or Boolean expressions that involve function symbols (including arithmetic) applied to attributes. Predicates in *NDlog* are typically relations, although in some cases they may represent functions. Commas are interpreted as logical conjunctions (*AND*). The names of predicates, function symbols, and constants begin with a lowercase letter, while variable names begin with an uppercase letter.

NDlog is a distributed variant of traditional Datalog, primarily designed for expressing distributed (recursive) computations. *NDlog* supports a *location specifier* in each predicate, expressed with the `@` symbol followed by an attribute. This attribute denotes the location of each corresponding tuple.

```
sp1 pathCost(@S,D,C) :- link(@S,D,C).
sp2 pathCost(@S,D,C1+C2) :- link(@Z,S,C1), bestPathCost(@Z,D,C2).
sp3 bestPathCost(@S,D,min<C>) :- pathCost(@S,D,C).
```

Figure 1: The MINCOST program in *NDlog*

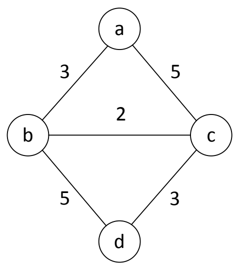
For example, consider the three-rule MINCOST program shown in Figure 1. MINCOST computes the best path cost between each pair of nodes in a network. Rules `sp1` and `sp2` specify the definition of the derived tuple `pathCost`. Rule `sp1` computes all one-hop path cost based on the base tuples from the `link` relation. Rule `sp2` expresses that "if there is a link from `S` to `Z` of cost `C1`, and the best path cost from `Z` to `D` is `C2`, then there is a path from `S` to `D` with cost `C1+C2`" (we assume links are symmetric, i.e. if there is a link from `S` to `D` with cost `C`, then a link from `D` to `S` with the same cost `C` also exists). Rule `sp3` aggregates all paths with the same pair of source and destination to compute the best path cost. By modifying this simple example, we can construct more complex routing protocols, such as the distance vector and path vector routing protocols.

When executed, MINCOST forms a distributed stream computation where streams of `link`, `pathCost`, and `bestPathCost` tuples are joined at different nodes to compute the best path costs. To maintain and derive tuples as the inputs to the rules are updated (e.g., `link` tuples are inserted), these queries are continuously executed. For more details on the incremental maintenance of declarative networking protocols, refer to references [13, 15].

```
f1 ePacket(@Next,Src,Dst,Payload) :- ePacket(@N,Src,Dst,Payload),
                                     bestHop(@N,Dst,Next).
```

Figure 2: The PACKETFORWARD program in *NDlog*

NDlog also supports *event predicates* (that is, tables for transient state). Events can trigger rule executions but are not materialized. By convention, event predicate names start with "e". The PACKETFORWARD program in Figure 2 illustrates how to use event predicates. Upon receiving an event `ePacket`, the next hop is found



link (@src, dest, cost)

src	dest	cost
a	b	3
a	c	5
b	a	3
b	c	2
b	d	5
c	a	5
c	b	2
c	d	3
d	b	5
d	c	3

Figure 3: Example network topology.

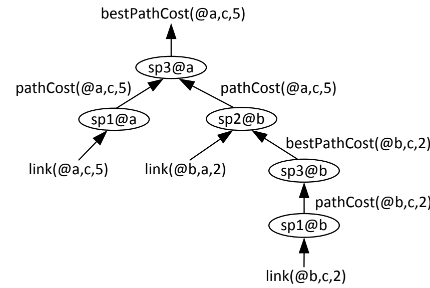


Figure 4: Provenance graph for `bestPathCost(@a,c,5)`.

by joining the `bestHop` table. The packet is then sent as another `ePacket` event to the next hop.

3. NETWORK PROVENANCE

ExSPAN is a generic and customizable framework that enables a variety of types of network provenance, which can be categorized along three orthogonal axes: (i) *granularity*, which reflects the detail level of the provenance maintained for derived tuples; (ii) *representation*, which defines how provenance is encoded internally; and (iii) *distribution*, which describes how provenance is distributed.

Granularity. ExSPAN provides three levels of granularity for provenance encoding. *Tuple-level* provenance maximizes provenance detail by encoding all intermediary tuples used in a given derivation. For instance, the ability to trace a tuple's construction makes tuple-level provenance a useful tool for debugging network protocols. As an example of tuple-level provenance, consider the network topology depicted in Figure 3 and the corresponding provenance graph for `bestPathCost(@a,c,5)` (computed using *MinCost*) shown in Figure 4. The tuple-level provenance for `bestPathCost(@a,c,5)` consists of all nodes and edges in the graph. In general, tuple-level provenance encodes the maximum amount of information, but incurs the largest communication overhead.

ExSPAN also supports *node-level* provenance in which provenance encodes only the nodes that are involved at each step of the derivation. For example, the node-level representation of `bestPathCost(@a,c,5)` is $\langle a, b \rightarrow a \rangle$, reflecting the nodes along the two derivation paths. Node-level provenance is a useful means to determine which elements of the network are responsible for a given tuple.

Finally, ExSPAN may store provenance at the *trust domain level*. Here, groups of nodes within a trusted domain share a domain identifier. Provenance encodes sufficient information only on the trust domains involved in each derivation. Trust domain level provenance enables, for example, access control policies based on *a priori* established trust relationships.

Representation. ExSPAN supports storing provenance internally using *graph representation*. A provenance graph reflects the relations between output tuples and the base tuples that contribute to them. Each internal node represents a database relational operator (e.g., union, join, selection and projection) tagged with its location, while each edge denotes a data flow among the operators.

Figure 4 shows the provenance graph for `bestPathCost(@a,c,5)`, derived and stored at node `a`. Each operator (denoted by an oval) is annotated with `ruleID@S`, indicating that rule `ruleID` is executed at node `S`. The edges in the graph show the intermediate computation results (i.e., `pathCost` and `bestPathCost` tuples).

Graph representation encodes tuple-level provenance information and is typically used to answer queries pertaining to fine-grained network state. For example, graph representation may be useful for debugging distributed systems [22, 14] and for accepting/rejecting network packets based on their traversed path.

Alternatively, provenance may be more compactly represented using *algebraic representation* [7, 3]. Algebraic representations encode provenance using the binary operations $+$ and $*$ (representing union and join, respectively). For instance, if α, β, and γ are the respective unique tuple IDs for `link(@a,c,5)`, `link(@b,a,2)` and `link(@b,c,2)`, then the provenance of `bestPathCost(@a,c,5)` in Figure 4 is encoded as $\alpha + \beta * \gamma$ (or `<a+a*b>` when using node-level provenance).

Algebraic representations can be further condensed [13] by encoding them as boolean expressions stored in *Binary Decision Diagrams* (BDDs) [2]. For example, `<a+a*b>` can be condensed to `<a>` since the trustworthiness of node `b` is inconsequential given `a`. As long as node `a` is trusted by the node that receives the `bestPathCost(@a,c,5)` tuple, the tuple will be accepted, regardless of whether node `b` is trusted. Enforcing trust policies based on such condensed forms of provenance is useful in network protocols (e.g., BGP) in which updates should only be accepted if they originate from trusted sources. Similarly, one can utilize the algebraic formulation to compute a trust value for each derivation.

Distribution. ExSPAN stores provenance in either a *centralized* or a *distributed* fashion. In *centralized provenance* [14], the entire provenance of a tuple is stored along with the tuple's content. In order to maintain complete centralized provenance, all provenance information is relayed to a centralized server. This approach presents a single bottleneck at the server, high aggregate bandwidth-utilization, and may not be feasible in a setting in which the distributed system being monitored spans administrative domains and/or large geographic locations.

Provenance may also be stored in a distributed fashion. In *value-based distributed provenance*, each derived tuple must include its entire provenance when transmitted between nodes. This paper introduces an alternative and more efficient means of storing distributed provenance which we call *reference-based* distributed provenance. In the reference-based variant, provenance information is dispersed among network nodes and lazily shipped. Here, only markers (pointers for subsequent traversal) are shipped with each tuple as the protocol executes, and the provenance information is fetched *on demand* via distributed queries. Rather than store complete provenance data at each tuple, tuples contain pointers that may be resolved recursively to reconstruct their derivations.

Reference-based distributed provenance imposes little communication overhead during query execution, but requires a (potentially expensive) distributed querying protocol to discern provenance information. Conversely, both centralized provenance and value-based provenance incur high communication costs when transmitting tuples (due to the provenance information contained in the

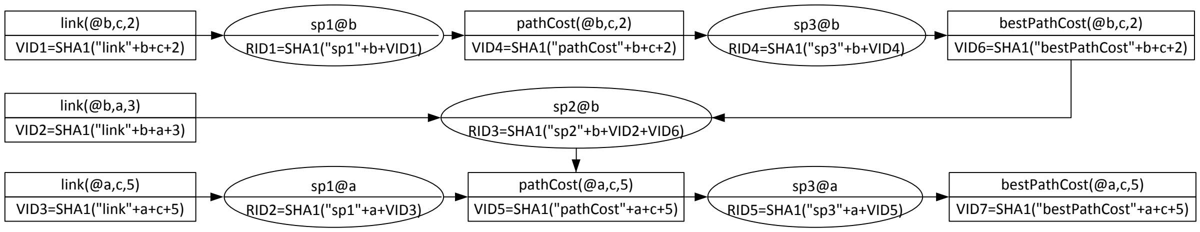


Figure 5: The provenance graph for the tuple `bestPathCost(@a,c,5)`. Ovals represent rule execution vertexes and rectangles denote tuple vertexes.

tuples and the propagation of provenance updates), but offer immediate provenance resolution.

Centralized provenance support may be straightforwardly achieved using traditional centralized database systems. Previous work [13] also shows value-based distributed provenance can be supported by modifying relational operators, such as `INSERT`, `DELETE` and `JOIN`, to include provenance information in the query evaluation towards a distributed fixpoint.

ExSPAN aims to support both centralized and distributed distribution. However, the focus of this paper is on enabling efficient network provenance using our reference-based approach.

4. MAINTAINING PROVENANCE

This section defines the data model used by ExSPAN to store and maintain network provenance in dynamic networks. The data model utilizes the graph-based representation introduced in Section 3 and applies to both centralized and distributed provenance. ExSPAN's graph-based data model is amenable to storage using a distributed relational database, and is sufficiently general to be used as a basis for generating other provenance representations.

4.1 Data Model

Given a tuple T, we model its provenance as an acyclic graph $G(V,E)$. By disallowing cycles in the graph, we simplify the process of issuing distributed queries (Section 5) at the expense of not permitting cyclical derivations. We note that such cycles are fairly rare in the usage scenarios we have encountered in networking applications, but supporting them is an interesting area of future work.

The vertex set V consists of *tuple vertices* and *rule execution vertices*. Each tuple vertex in the graph is either a base tuple or a computation result, and each rule execution vertex represents an instance of a rule execution given a set of input tuples. The edge set E consists of unidirectional edges that represent dataflows between tuples and rule execution vertices, where an edge from a tuple vertex t to a rule execution vertex o indicates t is taken as an input of o. Conversely, an edge from a rule execution vertex o to a tuple vertex t denotes that t is the evaluation result of o.

ExSPAN stores the graph representation of provenance in a relational table in a format similar to that used in existing work [6, 5] with the following modifications to enable efficient maintenance in a distributed setting: (We focus our discussion on reference-based distributed provenance, and adopt the declarative networking convention of having location predicates to denote tuples and their locations.)

To uniquely identify each vertex in a derivation graph, we assign a vertex ID (VID) to each vertex in the provenance graph, using cryptographic hash functions (e.g., SHA-1) to reduce the probability of collision.

For a tuple vertex, the VID is the hash of the tuple's contents (i.e., its location specifier, table name, and attribute values). For instance, the VID of a tuple vertex for `pathCost(@X,Y,C)` is VID $=$ $\mathtt{SHA1}(\text{“pathCost”} + X + Y + C)$, where $a+b$ denotes the concatenation of a and b.

For a rule execution vertex, its unique identifier (RID) is the concatenation of the location where the rule resides, the rule name, and the input tuple nodes. For example, when rule $r2$ at node X is executed with input tuples t_1 and t_2, its RID is $\mathtt{SHA1}(\text{“}r2\text{”} + X + t_1 + t_2)$.

Storage Model ExSPAN stores provenance information in the network using two tables – `prov` and `ruleExec` – that are distributed and partitioned across all nodes in the network.

The `prov` table maintains provenance information. Each entry in the relation represents a direct derivation of a tuple. Specifically, an entry in the `prov` relation is of the form `prov(@Loc,VID,RID,RLoc)`, with `VID` and `RID` as its keys, indicating that the tuple vertex `VID` located at node `Loc` is directly derivable from the rule execution vertex `RID` for a rule that resides at `RLoc`. This table is distributed across nodes, partitioned based on the location specifier `Loc`.

A separate table, `ruleExec(@RLoc,RID,R,VIDList)`, stores the actual meta-data of the rule execution. For a given `RID`, the table stores the actual rule identified by the label `R`, as well as the VIDs for all the input tuples used in the rule derivation. `RLoc` corresponds to the location where the rule resides.

4.1.1 Example Graph and Tables

Figure 5 shows the provenance graph for a derived tuple, `bestPathCost(@a,c,5)`, using the example network depicted in Figure 3. Ovals represent the rule execution vertices and rectangles depict tuple vertices. The graph encodes how tuples are derived during the execution of the MINCOST query. For instance, `bestpathCost(@a,c,5)` (bottom-right) is generated from rule `r3` at node `a` taking `pathCost(@a,c,5)` as the input. Note that the graph representation itself is distributed, where the location of each vertex is shown using the location specifier (`@`). To trace further, `pathCost(@a,c,5)` has two derivations: the locally derivable one-hop path $a \rightarrow c$ and the two-hop path $a \rightarrow b \rightarrow c$ that requires the distributed join (in rule `r2`) at node `b`.

Table 1 presents the `prov` table that corresponds to the provenance graph shown in Figure 5. For instance, the `prov` table contains two entries (the 2^{nd} and 3^{rd} lines) for `pathCost(@a,c,5)`, indicating that the tuple is derivable in two alternative ways: one that is directly derived from `link(@a,c,5)` and the other that is generated by joining `link(@b,a,3)` with `bestpathCost(@b,c,2)`. As a special case for base tuples (e.g., the `link` tuples), we assign *null* as the RID to differentiate from the tuples derived via rule evaluation.

4.1.2 Value- and Reference-Based Provenance

The previously described data model incurs very small communication overhead while maintaining reference-based distributed provenance. Only the 20-byte `Rloc` and `RID` attributes must be af-

Loc	VID	RID	RLoc	Derivation
a	VID3 = SHA1("*link*" + a + c + 5)	*null*	a	link(@a,c,5)
a	VID5 = SHA1("*pathCost*" + a + c + 5)	RID2	a	pathCost(@a,c,5)
a	VID5 = SHA1("*pathCost*" + a + c + 5)	RID3	b	pathCost(@a,c,5)
a	VID7 = SHA1("*bestPathCost*" + a + c + 5)	RID5	a	bestPathCost(@a,c,5)
b	VID1 = SHA1("*link*" + b + c + 2)	*null*	b	link(@b,c,2)
b	VID2 = SHA1("*link*" + b + a + 3)	*null*	b	link(@b,a,3)
b	VID4 = SHA1("*pathCost*" + b + c + 2)	RID1	b	pathCost(@b,c,2)
b	VID6 = SHA1("*bestPathCost*" + b + c + 2)	RID4	b	bestPathCost(@b,c,2)

Table 1: An example `prov` relation. The table is horizontally partitioned across all nodes, based on the location specifier `Loc`. The last column `Derivation` is not part of the table, but indicates the actual tuple derivation that corresponds to each `prov` entry.

RLoc	RID	R	VIDList	Derivation
a	RID2 = SHA1("*sp1*" + a + VID3)	*sp1*	(VID3)	pathCost(@a,c,5)
a	RID5 = SHA1("*sp3*" + a + VID5)	*sp3*	(VID5)	bestPathCost(@a,c,5)
b	RID1 = SHA1("*sp1*" + b + VID1)	*sp1*	(VID1)	pathCost(@b,c,2)
b	RID3 = SHA1("*sp2*" + b + VID2 + VID6)	*sp2*	(VID2, VID6)	pathCost(@a,c,5)
b	RID4 = SHA1("*sp3*" + b + VID4)	*sp3*	(VID4)	bestPathCost(@b,c,2)

Table 2: An example `ruleExec` relation that corresponds to the derivations shown in the `prov` table in Table 1. The last column `Derivation` indicates the actual derivation for the given rule execution instance.

fixed to tuples in order to reconstruct the provenance information via a distributed query.

To derive the derivation of a tuple encoded with reference-based provenance, the provenance graph is traversed in a distributed fashion. Given a derivation identified by `VID` (i.e., the hash of the tuples' contents), the corresponding `VIDList` can be retrieved by traversing the `RLoc` attribute value in the `prov` table and retrieving the contents corresponding to `RID` stored in the `ruleExec` table. The base tuples may then be retrieved by recursively traversing the entries in `VIDList`. Mechanisms for efficiently querying reference-based network provenance are described in more detail in Section 5.

In value-based distributed provenance, each transmitted tuple includes its entire provenance tree (that is, all the `prov` and `ruleExec` tuples that are relevant to its derivation). As we demonstrate in Section 7, the value-based provenance approach results in much higher communication overhead as compared to the reference-based approach. However, value-based distributed provenance is desirable for certain network management applications in which the decision to accept or reject an incoming message may depend on its (immediately available) provenance.

4.2 Distributed Provenance Maintenance

Given an *NDlog* program, incremental maintenance with provenance aims to achieve the following: Whenever a base tuple is inserted, rules incrementally recompute new derivations from existing *NDlog* rules. ExSPAN achieves incremental view maintenance through *delta rules* [13, 15], with additional bookkeeping to maintain multiple derivations of the same tuple. These delta rules are then processed in a pipelined fashion via the use of the *pipelined semi-naïve* algorithm (PSN) [15].

For a Datalog rule of the form: d :- d_1, d_2, ..., d_n, a delta rule is generated for each derived predicate, where the k^{th} *delta rule* is of the form:

$$\triangle d \text{ :- } d_1, .., d_{k-1}, \triangle d_k,\ d_{k+1}, .., d_n$$

where $\triangle d_k$ denotes a tuple $t_k \in d_k$ that is used as input to the rule for computing new d tuples. Each delta $\triangle d_k$ results in the creation of two delta rules, one for insertion and one for deletion. In PSN, tuples are processed one at a time in a pipelined fashion. Each node maintains a FIFO queue (ordered by arrival timestamp) of new input tuples. Each new tuple is dequeued and is used as input to its respective delta rule. The execution of a delta rule may generate new tuples which are either inserted into the local queue or sent to a remote node for further execution. Refer to references [13, 15] on details of PSN and handling of duplicate derivations.

As views are incrementally recomputed due to new insertions, each rule execution and new derivation results in the creation of new `prov` and `ruleExec` entries. Similarly, whenever a base tuple is deleted, all derivations resulted from *NDlog* rules that depend on the base tuple in the program are incrementally deleted, resulting in cascaded deletions of the respective `prov` and `ruleExec` entries in the provenance graphs of deleted tuples.

To perform the above incremental provenance maintenance (for both insertion and deletion), ExSPAN leverages the distributed query processing capabilities of its declarative networking engine. Given *any NDlog* program, additional *NDlog* provenance maintenance rules are *automatically* generated.

We present an example to demonstrate the intuition behind the generation of new provenance maintenance rules. The provenance maintenance rules for rule `sp2` in Figure 1 are automatically rewritten by ExSPAN as follows:

```
r20 ePathCostTemp(@RLoc,S,D,C,RID,R,List) :- link(@Z,S,C1),
      bestPathCost(@Z,D,C2), C=C1+C2, Z!=Y,
      RLoc=Z, R=``sp2'', PID1=f_sha1(``link''+Z+S+C1),
      PID2=f_sha1(``bestPathCost''+Z+D+C2),
      List=f_concat(PID1,PID2), RID=f_sha1(R+RLoc+List).

r21 ePathCost(@S,D,C,RID,RLoc) :-
      ePathCostTemp(@RLoc,S,D,C,RID,R,List).
r22 ruleExec(@RLoc,RID,R,List) :-
      ePathCostTemp(@RLoc,S,D,C,RID,R,List).

r23 pathCost(@S,D,C) :- ePathCost(@S,D,C,RID,RLoc).
r24 prov(@S,VID,RID,RLoc) :- ePathCost(@S,D,C,RID,RLoc),
      VID=f_sha1(``pathCost''+S+D+C).
```

Rules `r20` through `r24` re-implement the original rule `sp2` with additional rules for creating and maintaining provenance information. Rule r20 takes as input the original rule body predicates link and bestPathCost, and generates a new local event ePathCostTemp that contains the results of the derivation (attributes S, D, and C), as well as new attributes RLoc (rule location), R (rule label), RID (hash digest of rule), and List (VIDs of children vertices) necessary for the generation of the provenance information. The attributes stored in ePathCostTemp contain all the information necessary to instantiate the ruleExec entry locally (via rule r22) and create the prov entry at the remote node. This is achieved by a message event ePathCost that is sent from the node in which the rule is derived (RLoc) to node Z, the destination of the original derivation in rule sp2. Rule r23 receives the ePathCost event and generates the pathCost derivation. The prov entry is populated by rule r24.

Since rule r23 generates the original pathCost derivation in sp2, the above set of rules subsumes the original rule, adding additional information for provenance computation. Note that in addition to generating the correct derivation and provenance information (ruleExec and prov entries), the above program imposes only minimal additional communication overhead. The message event ePathCost contains only two additional attributes RID and RLoc. The bandwidth utilization is significantly lower compared with the value-based distributed approach, the latter of which requires shipping the entire provenance information with each tuple.

Finally, note that the above rewritten program integrates well with the use of cascading deletions used in PSN evaluation of declarative networking programs. Rule r20 compiles into a series of insertion and deletion delta rules that guarantees that whenever the input link and bestPathCost tuples are inserted/deleted, ePathCostTemp will trigger either an insert or delete delta rule appropriately, leading to the insertion/deletion of appropriate entries in the prov and ruleExec tables.

Reference [26] shows that the rewrite-based approach can be generalized to enable provenance maintenance for any *NDlog* program, where each rule is replaced by a set of new rules: the first rule generates an event containing all information required for creating the local ruleExec entry that corresponds to the meta-data of the rule execution; the generated event is then shipped to the target node to create the corresponding resulting tuple (e.g., pathCost in the above example) and the prov entry.

5. QUERYING PROVENANCE

The previous section presents the distributed provenance data model and introduces an algorithm for automatically rewriting *NDlog* programs to support provenance. In this section, we describe how ExSPAN allows users to query the provenance information via distributed queries.

Intuition: Before describing ExSPAN's provenance query mechanisms, we first present the intuition of provenance querying through an example. We consider the provenance graph shown in Figure 5 and a query for the full provenance of tuple bestPathCost(@a,c,5). The initial prov entry for this tuple (corresponding to the entry with VID=VID7 in Table 1) indicates that the tuple is derived from the execution of rule sp3 at node a. The query then retrieves the corresponding entry in the ruleExec table (in this case the entry for RID=RID5). The query subsequently traces back to the input tuple corresponding to VID5, i.e. pathCost(@a,c,5), by following the pointers maintained in VIDList. The process continues recursively by next retrieving the prov entries for VID5, followed by the corresponding ruleExec entries.

Since pathCost(@a,c,5) has two derivations (via sp1@a or sp2@b), two queries are initiated to further query the provenance along the two derivations. This results in cross-node communication, since sp2@b is located at a remote node. The recursive query stops at base tuples, e.g., link(@a,c,5), link(@b,c,2), and link(@b,a,3). Provenance information is returned through the reverse direction of the path traversed by the queries.

5.1 Distributed Recursive Query Formulation

Based on the above intuition, we next demonstrate the mechanisms by which ExSPAN formulates distributed queries to derive various representations from reference-based distributed provenance.

To derive provenance information, ExSPAN utilizes *NDlog* programs that express distributed recursive queries. These queries traverse provenance graphs (in the form the prov and ruleExec tables) in a distributed fashion, returning results to the querying node. ExSPAN's flexibility permits different granularities and representations of provenance (see Sec. 3). The programmer may select the type of network provenance by modifying the query specifications.

The following *NDlog* program demonstrates a generic distributed graph traversal operation on tables prov and ruleExec. The entire program is written in ten *NDlog* rules: two base rules (edb1 and c0) and two pairs of four rules for recursively querying the prov (idb1-idb4) and ruleExec (rv-rv4; not shown) tables. The rules are continuous, long-running queries that are initially installed at every ExSPAN node for handling distributed provenance queries.

```
// Base case
edb1 eProvResults(@Ret,QID,VID,Prov) :-
       eProvQuery(@X,QID,VID,Ret), prov(@X,VID,RID,RLoc),
       RID==NULL, Prov=f_pEDB(VID).

// Count number of children for each VID
c0 numChild(@X,VID,COUNT<*>) :- prov(@X,VID,RID,RLoc).

// Initializing Buffer
idb1 pResultTmp(@X,QID,Ret,VID,f_empty()) :-
       eProvQuery(@X,QID,VID,Ret), prov(@X,VID,RID,RLoc),
       RID!=NULL.

// Recursive case
idb2 eRuleQuery(@RLoc,RQID,RID,X) :-
       eProvQuery(@X,QID,VID,Ret), prov(@X,VID,RID,RLoc),
       RQID=f_sha1(QID+RID).

// Buffer sub-results
idb3 pResultTmp(@X,QID,Ret,VID,Buf) :-
       eRuleResults(@X,RQID,RID,Prov),
       pResultTmp(@X,QID,Ret,VID,Buf1),
       RQID=f_sha1(QID+RID), Buf=f_concat(Buf1,Prov).

// Calculate and return results
idb4 eProvResults(@Ret,QID,VID,Prov) :-
       pResultTmp(@X,QID,Ret,VID,Buf),
       numChild(@X,VID,C), C=f_size(Buf),
       Prov=f_pIDB(Buf,VID,X).
```

To customize provenance computations in the distributed graph traversal query, we introduce three user defined functions: f_pEDB, f_pIDB, and f_pRULE, which operate on the base tuples (f_pEDB), intermediate derivations (f_pIDB), and rule execution instance (f_pRULE). In Section 5.2, we describe these functions in greater detail, and via examples, show how they can be customized to return different provenance representations and granularities.

The initial provenance query is indicated by the event eProvQuery(@X,QID,VID,Ret), where node Ret issues a query to retrieve the provenance information of tuple VID stored at X. To uniquely identify the query, an additional attribute QID is added. Note that upon receiving this query, node X executes rules edb1, idb1, and idb2.

Rule edb1 is the base case and applies when the tuple VID is a base tuple (EDB), as indicated by the fact that it has no associated rule execution instance (that is, RID is null). In such cases, the provenance information is f_pEDB(VID) – the result of applying the user-defined function for EDBs to `VID`. For example, `f_pEDB` may simply return the tuple itself, indicating the base tuple is involved in the derivation.

Rule `idb1` initializes the `pResultTmp` table, which is later used to buffer intermediate query results. Rule `idb2` represents the recursive case in which the `prov` table is retrieved. Each entry with matching `VID` in the `prov` table indicates a rule execution instance that leads to the derivation of `VID`. These rule execution instances are additionally retrieved and buffered in `pResultTmp` table by issuing a remote query `eRuleQuery(@RLoc,RQID,RID,X)`. This requires sending a message to several matching `RLoc` nodes. The process continues recursively, where the nodes receiving the `eRuleQuery` message retrieve the matching `ruleExec` tuples, and recursively traverse children derivations until the base case is reached.

ExSPAN applies rule `idb3` when all children derivations have returned with the provenance information. The resulting provenance information is then combined in rule `idb4` using the `f_pIDB` function and the results are returned to the query node.

An additional four rules `rv1-rv4` (similar to `idb1-idb4`) perform a similar traversal of the `ruleExec` tables. We omit these rules due to space constraints. The intuition behind these rules is that the user recursively traverses `prov` and `ruleExec` tables across nodes until the entire provenance tree has been obtained. Since each rule execution takes several predicates as input, an additional user defined function `f_pRULE` enables the user to customize how the various inputs to the rule can be combined in the provenance tree.

5.2 Query Customization

Given the general querying framework present in Section 5.1, we now describe how users may customize provenance queries to meet various application requirements.

5.2.1 First Example: Provenance Polynomials

Our first customization example stores provenance information in the form of an algebraic expression called a *provenance semiring* [7]. Provenance can be encoded as an algebraic structure with two binary operations — addition and multiplication — indicated by "$+$" and "$\cdot$", where "$+$" indicates the combination of tuples with union and projection and "$\cdot$" denotes a natural join over tuples. The literals in the algebraic expression represent base tuples. By customizing the "$+$" and "$\cdot$" operators, various types of classic provenance annotation can be encoded. For example, $r_1(A+r_2(B\cdot C))$ indicates that rule r_2 applies JOIN on tuples B and C, and the result is then UNIONed with A in rule r_1.

To return provenance query results as polynomials, the three user-defined functions are implemented as follows:

`f_pEDB(VID)` takes as input the VID that uniquely identifies the base tuple. The function simply returns the base tuple itself or its primary keys (which can be retrieved by reading a systems table that maps VIDs to tuples).

`f_pIDB(Derivations,Loc)` takes as input `Derivations` that contain the polynomials (D_1,D_2,...,D_n) that represent all possible n ways to derive the tuple, and `Loc`, the location specifier of the tuple. The function iterates over all entries in `Derivations` and applies a "$+$" operation across them. The resulting provenance expression is annotated with the location as $(D_1+D_2+...+D_n)@Loc$.

`f_pRule(ChildPred,R,RLoc)` takes as input `ChildPred`, representing the polynomials of all n input tuples (P_1,P_2,...,P_n) that are used in the execution of rule `R` at location `Loc`. The function iterates over all entries in `ChildPred` and applies a "$\cdot$" operation across them. As above, the result is affixed with a rule label and location. The function returns the polynomial $\langle R@RLoc\rangle(P_1\cdot P_2\cdot...\cdot P_n)$.

5.2.2 Additional Examples

The second example returns the number of possible derivations of a given tuple. We define the three user-defined functions as follows: `f_pEDB(VID)` evaluates to 1, indicating each of the edb tuples has one derivation. For each intermediate derived tuple, the number of its derivations (i.e. `f_pIDB(Derivations,VID,Loc)`) can be calculated as the sum of the sub-results. For rule execution instances, `f_pRULE(ChildPred,R,Rloc)` is defined as the product of the sub-results.

ExSPAN's flexibility enables numerous other customizations. In reference [26], we describe additional examples which include calculating the set of nodes that participate in the derivation of a tuple, testing the derivability of a given tuple, and projecting the provenance graph according to imposed constraints. In all cases, the user need only modify the three user defined functions (`f_pEDB`, `f_pIDB` and `f_pRule`). The underlying *NDlog* program used for querying provenance is sufficiently general to support a diverse set of provenance applications.

ExSPAN's querying framework is directly applicable to various domains. For example, in distributed trust management, access requests may be granted or denied based on the nodes involved in formulating the request. Alternatively, a trust value may be assigned to each derivation based on a specific definition of trust. In the domain of recursive view maintenance, one may use the provenance to perform efficient incremental deletion [13] by performing the derivability tests.

6. QUERY OPTIMIZATIONS

In this section, we propose a number of optimization techniques aimed at reducing the bandwidth and latency overheads of our reference-based distributed querying algorithm.

6.1 Query Results Caching

In value-based distributed provenance, provenance information is communicated proactively in each tuple derivation, resulting in high-overhead. In contrast, reference-based distributed provenance takes a reactive (lazy) approach of generating reverse markers (via the `prov` and `ruleExec` tables) that can be recursively traversed on demand in response to a query.

Our first optimization technique attempts to achieve a "sweet-spot" between the proactive and reactive approaches via the use of *query results caching*. In cases in which queries are rare, reference-based distributed provenance aims to incur low communication overhead and minimally impact the convergence times of protocols. When queries are frequent, subsequent queries can leverage the results from prior queries.

Caching scheme Unlike traditional caching in a centralized database, the reference-based distributed provenance cache is distributed across several nodes in the network. Whenever a node `N` issues a distributed query to retrieve provenance information for a tuple `VID`, the resulting query results are not only cached at node `N`, they are also stored at intermediate nodes as the query results are returned along the reverse path.

Specifically, whenever rule `idb4` (or the equivalent rule for `ruleExec` traversal) is triggered, it indicates the completion of a query at an intermediate derivation. The query result will be maintained in events `eProvResults` or `eRuleResults`. Before `eProvResults` or `eRuleResults` is sent back to the query issuer, these results are cached in a `cache(@N,VID,Results)` table that stores (at node `N`) the provenance `Results` for `VID`. Further attributes can be added to distinguish results based on provenance representation. Note that subsequent queries need not be for the exact tuple (i.e., `VID`) in order to benefit from the cache: since the intermediate results are cached along the reverse path, any graph traversal query that reaches node `N` and requires a subgraph rooted at `VID` can use the cache results. The cached results are then sent back on the reverse path back to the node conducting the query without further traversal.

Cache invalidation Cached provenance query results become invalidated when a tuple is inserted or deleted. Upon receiving the update event for tuple updates, all the caches that depend on the tuple should be invalidated through an *invalidation propagation* procedure. This mechanism is similar to how distributed value-based provenance is maintained; however, rather than shipping the whole tuple (an expensive operation), the cache invalidation procedure requires only that an invalidation flag be sent.

After a cache is invalidated, future queries for the same tuple will have to perform distributed queries to compute the correct result and update the cache. However, since a tuple may have multiple derivations (some of which correspond to intact cache entries), the use of caching may still offer some performance benefits. To illustrate, consider the network depicted in Figure 5. Suppose the link between nodes `a` and `c` has failed. The `link` deletion will invalidate the cache for tuples `pathCost(a,c,5)`, `bestPathCost(a,c,5)` and the rule execution vertices along the path. However, if a query is issued for `bestPathCost(a,c,5)` after the link failure, when the traversal reaches the rule execution vertex `r2@b[link(@b,a), bestPath(@b,c)]`, the intact cached result will be directly returned, eliminating the need to further traverse the derivation graph.

6.2 Query Traversal Order

At each tuple vertex being traversed, the program shown in Section 5 simultaneously issues queries to all possible derivations. In essence, the distributed queries traverse the provenance graph using *Breadth First Order* (BFS). Intuitively, BFS must flood the queries throughout the whole provenance graph before any sub-results are obtained.

We explore another querying traversal order, *Depth First Order* (DFS), in which alternative derivations are explored in turns at each tuple vertex [26]. Instead of starting queries for each derivation simultaneously, DFS iterates through the list of alternative derivations. The exploration of the next derivation is started only after the results of the previous explorations have been received.

DFS may incur longer querying latencies than BFS since the former can stall before a sub-result is received. However, DFS provides the opportunity for bandwidth savings for *threshold-based* queries that check whether a tuple has more than T derivations or whether fewer than T' unique nodes participate in the derivation. DFS allows such threshold-based queries to terminate as soon as the threshold is reached, without incurring additional communication overhead. That is, DFS trades off query latency in favor of reduced communication overhead for threshold-based queries.

In addition to BFS and DFS, *random moonwalk* [24] traversal can be implemented by randomly selecting N alternative derivations to explore, where N is a pre-defined constant. This technique is particularly useful when the number of a tuple's derivations is significantly large. The random moonwalk pinpoints with high probability the pivotal tuple that contributes to a derivation. In the context of networking applications, such random moonwalks are useful for ascertaining the dominating sources of incoming traffic.

6.3 Condensed Provenance

Our third optimization technique applies a previously proposed compression scheme known as *absorption provenance* [13] to the algebraic representation of provenance (see Section 5.2.1). Absorption provenance aims to reduce the number of variables in an algebraic representation. For example, consider the algebraic expression $a \cdot (a+b)$. By applying *boolean absorption rules* [13], the expression is reduced to $a \cdot (a+b) = a + (a \cdot b) = a$. Note that savings in size comes at the expense of information loss. In our example, absorption provenance loses the fact that b is also involved in the derivation. However, such absorbed encodings can still retain sufficient information for derivability tests or enforcing security policies based on the trust of source origins (base tuples).

To implement absorption, we utilize BDDs [2] to encode provenance. BDDs provide a natural way to encode the algebraic representation of the provenance, and by default, apply absorption to save storage space. Since BDDs are frequently used in circuit synthesis and formal verification applications, highly optimized libraries provide abstract BDD types as well as Boolean operators that operate on them: pairs of BDDs can be ANDed or ORed; individual BDDs can be negated; and variables within BDDs can be set to true or false.

Note that the use of absorption provenance applies to both centralized provenance and value/reference-based distributed provenance. For example, in centralized and value-based provenance, the provenance information shipped for each tuple can be stored as BDDs. Similarly, for reference-based distributed provenance, query results can be returned in the form of BDD representations.

7. EVALUATION

In this section, we evaluate the ExSPAN network provenance system. The goals of our evaluation are twofold: (1) to measure the performance overhead incurred by value- and reference-based distributed network provenance; and (2) to study the effectiveness of optimizations at reducing communication cost.

Implementation and Experimental Setup ExSPAN is implemented as an add-on to ns-3 [19], an emerging discrete event-driven network simulator aimed to replace ns-2. ns-3 emulates all layers of the network stack, supporting configurable loss, packet queuing, and network topology models. ns-3 supports both a simulation mode, enabling the examination of ExSPAN's performance under various network topologies and conditions, as well as a deployment mode in which different hosts in a testbed environment execute the network provenance system. ExSPAN makes extensive utilization of RapidNet [18], a declarative networking platform that compiles *NDlog* programs into applications that are executed by the ns-3 runtime. ExSPAN uses the identical codebase for both simulation and deployment modes.

We generate transit-stub topologies for our simulation experiments using the GT-ITM topology generator [8]. The transit-stub topology consists of eight nodes per stub, three stubs per transit node, and four nodes per transit domain. We increase the number of nodes in the network by increasing the number of domains. Links between adjacent transit nodes experience a 50 ms latency and have a 1 Gbps bandwidth capacity; transit-stub connections have a 10 ms latency and a 100 Mbps capacity; the respective latency and bandwidth between stub nodes are 2 ms and 50 Mbps.

Our deployment experiments are executed within a local cluster of eight dual-core Intel 2.8GHz Pentium D hosts and 16 quad-core machines with Intel Xeon 2.33GHz CPUs. All machines run Linux 2.6 and are interconnected by high-speed Gigabit Ethernet. ExSPAN communicates messages between nodes via UDP packets. To increase the size of our network, we execute two instances of ExSPAN on each quad-core machine, enabling us to scale the experiments to 40 nodes. The deployment results described in Section 7.4 reflect the average of five executions of the experiment.

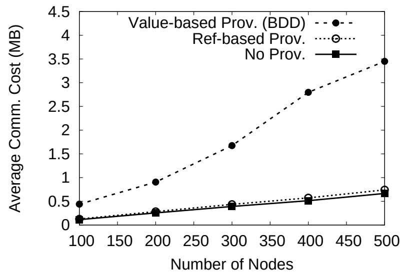


Figure 6: Average communication cost (MB) for MinCost.

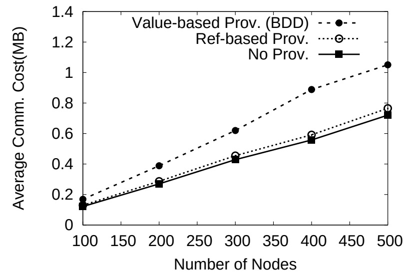


Figure 7: Average communication cost (MB) for PathVector.

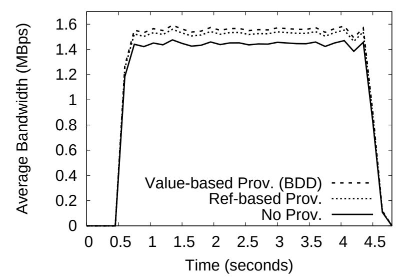


Figure 8: Average bandwidth cost (MBps) for PacketForward.

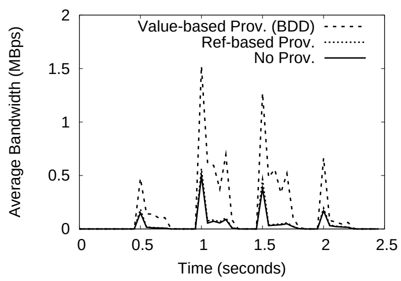


Figure 9: Average bandwidth cost (MBps) for MinCost when the network experiences a high level of churn.

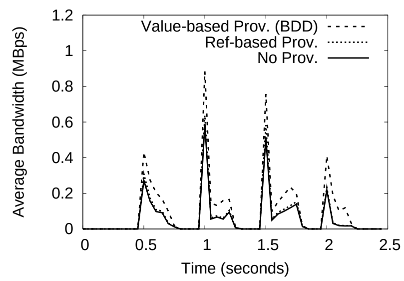


Figure 10: Average bandwidth cost (MBps) for PathVector when the network experiences a high level of churn.

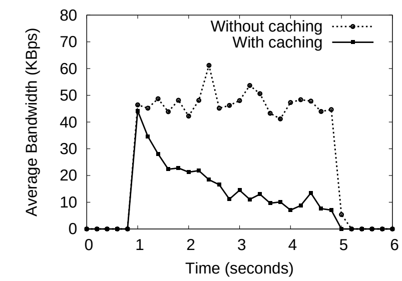


Figure 11: Average bandwidth cost (KBps) with and without caching.

Applications As workloads for our simulation and deployment experiments, we implement three *NDlog* applications: MinCost, introduced in Section 2, computes the costs of the best (least cost) paths between pairs of nodes. PathVector extends MinCost, enabling a node to discover the best path (transmitted as a vector of nodes) to a specified destination. Both MinCost and PathVector operate on the control plane, enabling nodes to discover routes to peers. In contrast, the PacketForward application operates on the data plane, relaying data packets using previously discovered paths.

For all experiments, each node is initialized with a `link` tuple for each of its neighbors. That is, nodes have *a priori* knowledge of their local links and use MinCost and PathVector to discover longer network paths. Link costs are fixed at 1, and hence MinCost and PathVector measure hopcount to the destination.

7.1 Communication Overhead

Network provenance incurs bandwidth overhead since additional information must be communicated. In the case of value-based provenance, each tuple carries its (potentially lengthy) derivation history. Reference-based provenance attempts to decrease this overhead by communicating pointers to provenance information rather directly conveying the information.

Figure 6 plots the communication cost (the number of transmitted bytes before reaching the fixpoint) averaged over all nodes, for various sized simulated networks when nodes execute the MinCost program. (For readability, the order of the labels in all figures in this section mirror the ordering of the plotted curves.)

Value-based provenance results in significant communication overhead. For example, in the 300-node network, even with the use of BDD representation, value-based provenance (line *"Value-based Prov. (BDD)"*) more than quadruples the query execution time as compared to executing MinCost without provenance (line *"No Prov."*). In contrast, reference-based provenance (line *"Ref-based Prov."*) incurs very little communication overhead, increasing the communication cost by just 0.04MB (11.3%) in the same 300-node network. The vast difference in bandwidth costs is due to MinCost's ability to produce multiple derivations for a given `bestPathCost` tuple (see, for example, Figure 4). All possible derivations must be communicated with each tuple when using value-based provenance. Our reference-based technique reduces the provenance information that must be transmitted since the same pointer may be shared between different derivations.

The average communication cost when running the PathVector program is shown in Figure 7. In contrast to MinCost, tuples have only one derivation (since PathVector returns a single best path), decreasing the amount of information that must be communicated using value-based provenance. However, due to space savings in communicating pointers rather than values, the reference-based technique imposes significantly less overhead (6% in the 300-node network) than the value-based technique (45% in the same network).

In addition to enabling provenance on the control plane, it may also be useful to provide provenance information on the data plane. As described above, the PacketForward program relays packets according to shortest-path "next hop" information stored at each node. Figure 8 shows the average bandwidth over time when forwarding packets in a 200-node network. Here, each node selects a peer at random and transmits 1024 byte tuples at the rate of 100 tuples per second. The overheads for PacketForward are roughly equivalent for value- and reference-based provenance. Sending packets with provenance incurs a small overhead, but is subsumed by the large payloads.

Due to the memory constraints of running large-scale ns-3 sim-

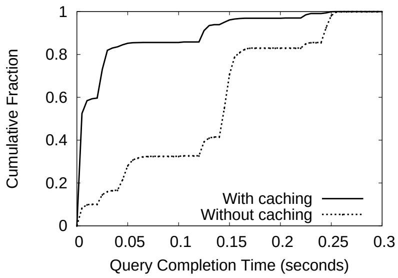


Figure 12: Cumulative distribution of query completion latencies with and without caching.

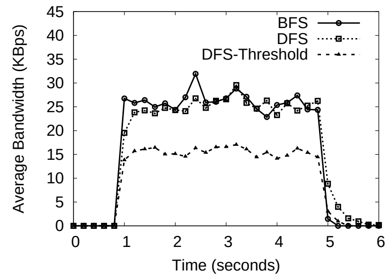


Figure 13: Average bandwidth cost (KBps) using different query traversal orders.

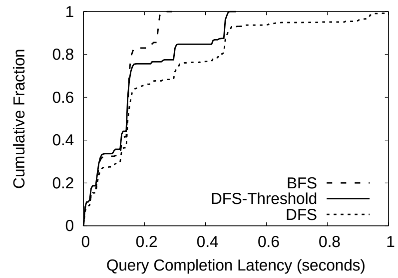


Figure 14: Cumulative fraction of query completion latencies using different query traversal orders.

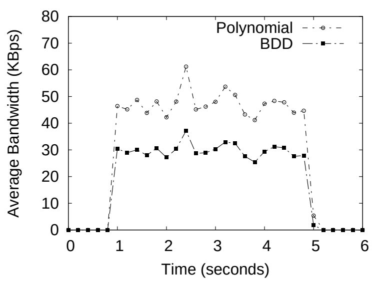


Figure 15: Average bandwidth (KBps) for querying POLYNOMIAL **and** BDD**.**

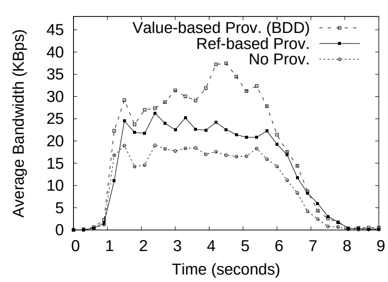


Figure 16: Average bandwidth cost for PATHVECTOR **in testbed deployment.**

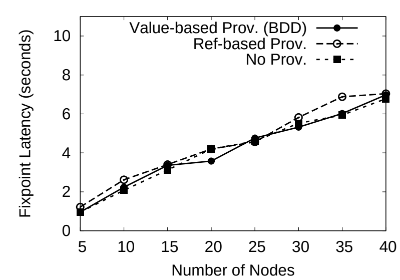


Figure 17: Fixpoint times for PATHVECTOR **in various sized testbed deployments.**

ulations on a single machine, we experimented with up to 500 nodes in our simulations. However, our results clearly demonstrate promising scalability trends for all protocols: the average communication costs of MINCOST and PATHVECTOR programs (without provenance) scale linearly with the number of nodes. This matches the expected scalability behavior for these two protocols. Moreover, with the addition of reference-based provenance, we note that the communication costs continues to scale linearly, hence maintaining the original scalability trends, demonstrating that reference-based provenance incurs minimal impact on the scalability of an existing protocol.

7.2 Incremental Maintenance

The experiments described above model a static topology in which nodes neither leave nor join the network and links never fail. Here, we evaluate ExSPAN's ability to mitigate a high level of node churn and link failure. We model churn by adding or deleting ten randomly selected stub-to-stub links in a 200-node simulated network (originally containing 315 stub-to-stub links) every 0.5 seconds, with addition or deletion occurring with equal probability.

Figures 9 and 10 show the respective average per-node bandwidth costs of running the MINCOST and PATHVECTOR protocols. In both instances, reference-based provenance does not incur significant bandwidth overhead (the lines for "No Prov." and "Ref-based Prov." closely overlap). For example, the maximum increase in bandwidth due to reference-based provenance (relative to conducting the query without provenance) is 0.07 and 0.05 Mbps for MINCOST and PATHVECTOR, respectively.

Value-based provenance consumes significantly greater bandwidth as complete provenance information must be affixed to each transmitted tuple. The respective increases in bandwidth for MINCOST and PATHVECTOR are 1.0 and 0.30 Mbps— 1329% and 500% greater than the equivalent overheads for reference-based provenance.

For both reference- and value-based provenance, a new fixpoint is reached within 0.5 seconds, indicating that ExSPAN is resistant to even high levels of churn regardless of the type of provenance.

7.3 Distributed Queries

Sections 7.1 and 7.2 evaluate the performance of provenance *maintenance* in ExSPAN. In this set of evaluations, we study the performance of *distributed querying* of provenance using the framework presented in Section 5. In addition, we validate the effectiveness of optimizations in reducing communication overhead during query. The experiments are performed using a 100-node simulated network which runs the MINCOST protocol. Our query measurements begin after the network has reached a fixpoint.

We utilize three queries in our evaluation: POLYNOMIAL, BDD, and #DERIVATION. POLYNOMIAL acquires the provenance of an arbitrary tuple in the form of provenance polynomials (see Section 5.2.1). BDD, as discussed in Section 6.3, encodes provenance in a more compact format. Using the customization described in Section 5.2.2, #DERIVATION computes the number of alternative derivations for a given tuple.

Caching Figure 11 plots the average per-node bandwidth over time when each node issues five POLYNOMIAL queries per second with each query targeted to a randomly selected `bestPathCost` tuple. Without caching, the average bandwidth utilization for each node is approximately 50 KBps. Each query therefore incurs an average bandwidth cost of 0.1KBps, an acceptable overhead for most current networks. (Of course, the precise cost of conducting POLYNOMIAL queries in other settings depends upon the provenance of the queried tuples.) The overhead imposed by POLYNOMIAL is due in part to its requirement that results must contain complete information regarding all possible tuple derivations.

As shown in Figure 11, POLYNOMIAL's overhead can be significantly reduced by enabling the caching optimization described in Section 6.1. Using caching, the average bandwidth utilization decreases to 20KBps after two seconds. The performance improvement is attributed to the fact that queries are more likely to benefit from the cached results of previous queries as time progresses.

Figure 12 presents the cumulative fraction of query completion times. Regardless of whether caching is used, results are returned in less than 0.3 seconds, highlighting that ExSPAN's provenance querying mechanisms are latency-wise efficient. The figure also shows the advantage of enabling caching: 80% of queries are returned within less than 50 ms if caching is enabled, a 67% improvement over query latency when caching is disabled.

Query Traversal Order To study the trade-offs between different query traversal orders, we conducted experiments in which nodes utilize the #DERIVATION query to determine whether a `bestPathCost` tuple has more than three alternative derivations (the average number of alternative derivations for `bestPathCost` is approximately three). The experiment is performed on three variants of the #DERIVATION query: (a) BFS, (b) DFS, and (c) DFS-THRESHOLD (DFS with threshold-based pruning). We use the same experimental setup as the caching experiment – that is, each node in the 100-node network issues five queries per second for randomly selected `bestPathCost` tuples.

Figure 13 shows the average bandwidth consumption for different query traversal orders. We observe that the bandwidth costs incurred by BFS and DFS are roughly equivalent (since both must traverse the entire provenance graph before a result is concluded). In contrast, DFS-THRESHOLD results in a 40% decrease in bandwidth consumption, due largely to its avoidance of a full traversal of provenance graphs for tuples with multiple derivations.

Figure 14 plots the cumulative distribution of query completion times for the query traversal strategies. Although the median latency is roughly equivalent for BFS and DFS, the latter experiences a long-tail distribution. For example, less than 80% of BFS queries complete within 0.16 seconds. In contrast, 80% of DFS queries require 0.45 seconds.

BFS's query completion is largely determined by the traversal depth in the provenance graph. Unlike BFS, DFS traverses alternative derivations in order, resulting in longer querying completion latencies. By terminating the query as soon as three derivations are explored, DFS-THRESHOLD avoids the long-tail distribution experienced by DFS. Using DFS-THRESHOLD, the query completion time for 80% of the queries decreases from 0.45 to 0.3 seconds.

Absorption Provenance We next compare the performance of the POLYNOMIAL and BDD queries. We use the same network configuration and query rates as were applied in previous experiment. Figure 15 shows the average bandwidth incurred by the POLYNOMIAL and BDD queries. POLYNOMIAL incurs 18KBps (57%) more bandwidth than BDD, due mainly to BDD's compact binary representation. As described in Section 6.3, BDD additionally decreases communication overhead by condensing provenance information using lossy compression (with information loss).

POLYNOMIAL and BDD have near-identical performance when defined in terms of query completion latency. The latency of a query is largely decided by its traversal depth. Since both query techniques follow *BFS* query traversal order and operate on the same topology, the distributions of query completion latencies across nodes is consistent across the two strategies.

7.4 Testbed Experiments

To empirically evaluate ExSPAN's computation and communication properties, we installed 40 instances of ExSPAN in a local cluster. Since nodes on the cluster are fully connected via a shared switch, we impose a less trivial virtual topology as follows: to ensure reachability, nodes are arranged in a ring structure. All links are bidirectional; that is, if there is a link between nodes *a* and *b*, then node *a* maintains a tuple `link(@a,b,1)` and node *b* has a tuple `link(@b,a,1)`. Each node in the network has links to its two neighbors (hence achieving the ring structure). Additionally, each node has a link to a random peer such that the maximum degree of all nodes is three (a link to each ring neighbor and a third to a random peer). All nodes execute the PATHVECTOR protocol.

As with the simulation experiments, our reference-based provenance technique significantly reduces the overhead of provenance compared to the value-based approach. When sending no provenance information, the average per-node bandwidth cost of executing PATHVECTOR is 1.24 KB before a fixpoint is reached. Reference-based provenance increases this cost by 29%, far less than the 204% increase caused by value-based provenance. This trend can be observed from Figure 16 which plots the average per-node bandwidth over time for the experiments. The relative overheads of reference- and value-based provenance mirror our earlier simulation results (see Section 7.1).

In addition to examining bandwidth costs, our deployment provides a mechanism to study the computational overhead of using the various provenance techniques. Figure 17 shows the fixpoint time for different network sizes. (As an invariant of network size, the degree of each node in the network is fixed at three.) As can be discerned from the Figure, neither provenance technique imposes any significant increase in fixpoint time.

The results of our deployment experiments therefore indicate that reference-based provenance achieves a substantial decrease in communication cost as compared to value-based techniques, while imposing little or no increase in fixpoint latency.

8. RELATED WORK

ExSPAN is related to a large body of work in the database literature on enabling provenance support in database systems. Of particular relevance to our work are recent attempts at storing provenance information in relational databases [10, 5]. The data and storage model in ExSPAN is also based on the relational model, but extends the basic model to enable distribution via the use of value-based and reference-based distributed provenance. In the space of distributed query processing, Liu *et al.* [13] explored a mechanism similar to the value-based provenance used by ExSPAN. Their approach stores BDD-based provenance information with each tuple for tracking derivability information.

In terms of application scenarios, our efforts in this paper are largely targeted at networking applications as surveyed by Zhou *et al.* [25]. Of closest relevance is the recent use of provenance in P2P data integration [10]. The operating environment however differs significantly. ExSPAN is targeted at Internet-scale deployments with relatively small network state per node, as opposed to only tens of databases storing large amounts of data. Hence, the techniques developed in ExSPAN focus on network-centric metrics such as reducing communication overhead, minimizing query latency, and avoiding negative impact on the convergence times of existing protocols. Rather than using a heavy-weight database system, ExSPAN leverages a declarative networking engine that provides networking and querying capabilities at Internet-scale, enabling it to be easily integrated into existing distributed systems.

While the focus of ExSPAN is on enabling provenance for large-scale distributed systems and networking protocols, in principle, the system is sufficiently general to enable other traditional use cases of provenance in P2P data integration. Exploring such use cases in ExSPAN via the use of declarative networking is an interesting avenue of future work.

9. CONCLUSION

This paper presents ExSPAN, a scalable framework for achieving network provenance in a distributed environment. ExSPAN utilizes declarative networking techniques and rewrite rules to efficiently affix provenance information to distributed network queries, enabling administrators to easily add accountability, trust management, and failure diagnostic capabilities to their networks.

To achieve provenance at Internet-scale, we introduce novel techniques for communicating network provenance. ExSPAN significantly reduces communication overhead by distributing provenance information among nodes. In contrast to existing approaches in which complete derivation trees must be attached to each communicated message, ExSPAN appends short provenance *pointers* to tuples to identify the nodes that maintain the relevant provenance information. Simulation and implementation results demonstrate that our reference-based provenance techniques impose substantially less communication overhead than existing approaches. For example, when providing provenance information for the path vector routing protocol, ExSPAN exhibits one ninth the communication overhead as incurred using traditional value-based distributed provenance techniques while achieving equivalent fixpoint latencies. Additionally, we present several optimization techniques for efficiently querying provenance information.

As future work, we are investigating mechanisms to protect the confidentiality and authenticity of provenance information. The ability to provide formal security guarantees for provenance data enables new classes of routing algorithms in which decisions can be based not only on the contents of messages, but also on the matter in which messages are created and transported. We are also exploring the integration of ExSPAN with legacy distributed systems. Here, the goal is to use ExSPAN to analyze the protocol behavior by capturing coarse-grained provenance information obtained by having these systems export their network state and incoming/outgoing messages to ExSPAN as tables.

10. ACKNOWLEDGMENTS

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