Storing Semistructured Data with STORED

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Abstract

Systems for managing and querying semistructured-data sources often store data in proprietary object repositories or in a tagged-text format. We describe a technique that can use relational database management systems to store and manage semistructured data. Our technique relies on a mapping between the semistructured data model and the relational data model, expressed in a query language called STORED. When a semistrcutured data instance is given, a STORED mapping can be generated automatically using data-mining techniques. We are interested in applying STORED to XML data, which is an instance of semistructured data. We show how a document-type-descriptor (DTD), when present, can be exploited to further improve performance.

1 Introduction

Semistructured data is becoming ubiquitous. The emergence of XML, which is a data format for semistructured data, will increase the availability of semistructured data. Such data is best defined as a graph-based, self-describing object instance model. Data consists of a collection of objects; each object is either atomic (e.g., integer, string, image, audio, video), or complex (i.e., a set of (attribute, object) pairs). Since attribute names are stored with the data, the data is self-describing.

Existing systems for managing and querying semistructured data sources store the schema with the data. Lorel [17] and Tsimmis [16] store their data as graphs; the schema is stored as attributes labeling the graph's edges. Strudel [6] stores the data externally as structured text, and internally as a graph. XML often is stored in proprietary object repositories or in text files, in which tags encode the schema. Storing the schema with the data provides the flexibility required by semistructured data. In data integration, for example, data from new sources can be loaded immediately, regardless of its structure, and changes to the structure of old sources can be handled seamlessly. This flexibility, however, incurs a *space cost*, because the schema is replicated at each data item, and a *time cost*, because of the additional processing of the replicated schema. A more fundamental disadvantage however, is that we cannot use a commercial RDBMS for managing the semistructured data.

We describe a technique for using an RDBMS to store, query and manage semistructured data. Semistructured data can always be stored as a ternary relation, since the data is an edge-labeled graph, but this is no better than storing the schema with the data. Instead, our technique relies on an aggressive mapping from the semistructured data model to the relational model. The mapping is expressed in STORED (Semistructured TO Relational Data), a declarative query language. A relational schema is chosen, then the STORED mapping translates the semistructured data instance into that schema. The mapping is always lossless: parts of the semistructured data that do not fit the schema are stored in an "overflow" graph.

We expect this technique to be used (1) to store and manage efficiently existing semistructured data sources, and (2) to convert relational sources into a semistructured format, such as XML.

In the first application, the semistructured-data instance exists, e.g., it might be a large XML file. The main issue is generating the relational schema and the STORED mapping automatically from patterns discovered in the data instance. Subsequently, queries and updates over the semistructured view are automatically rewritten into queries and updates over the relational store. If some query mix is known in advance, it may be used during the generation phase. As the data or the query mix changes, the performance of the relational storage may degrade, and a new mapping should be generated (and the relational data reorganized). In the second application, a relational data source is exported in a semistructured view, e.g., in an XML view. In this case, the STORED mapping is defined by the application writer. This application is easier than the first, because the mapping need not be generated automatically. We expect this application will become more important as information providers export data in XML.

Given a semistructured data instance, we have to gen-

*Part of this work was done while the author visited AT&T Labs.

erate a “good” relational schema and STORED mapping to that schema. The meaning of “good” depends on the application, but usually includes minimizing disk space, reducing data fragmentation, and satisfying constraints of the RDBMS (e.g., maximum number of attributes per relation). When a query mix on the semistructured data is known, a “good” relational storage reduces the weighted cost of those queries. Hence, this can be modeled as a cost optimization problem. Unlike other optimization problems (of query plans [20] or data warehouse design [18]), our input is the data instance, not a set of queries[1]. This problem is NP-hard in the size of the data. For that reason, we did not pursue the cost bases approach, but instead developed a heuristic algorithm. Wang and Li [21] have described a data-mining algorithm for semistructured data, and we adapt their algorithm to our problem. The result of the data-mining phase is used to produce a reasonable relational schema and STORED mapping.

Given the relational mapping of the STORED query, the system automatically generates the overflow mapping necessary to ensure that any semistructured instance is stored losslessly. This part of the STORED mapping specifies which objects or object parts are stored in the overflow graph. The mapping must be lossless for *any* data instance, because we support updates, which are propagated to the relational store or the overflow graph. These overflow mappings can be unnecessarily conservative; for XML data, we show that a DTD can be used to simplify the overflow mappings.

Given the complete STORED mapping, our system accepts queries and updates over the semistructured source and rewrites them into queries and updates on the relational source. Rewriting of relational or datalog queries is a well-understood problem [11, 14]. Since STORED is a new query language with novel features, we revisit query rewriting. We show that arbitrary queries on semistructured data, with regular expressions and tree-like patterns, can be rewritten in terms of STORED mappings. Updates are important as well. We show that insertions in the semistructured data can be automatically rewritten as insertions into the relational and overflow stores.

This paper makes the following contributions:

- STORED, a declarative language for specifying *storage mappings* from the semistructured-data model to the relational model plus overflow graphs.

- A schema-generation algorithm, which constructs a relational schema and STORED mappings for a semistructured data instance and, possibly, a query mix.

- An algorithm for automatic generation of STORED overflow mappings for a given relational mapping, which can exploit a DTD.

- A query- and an update-rewriting algorithm.

[1]We may also consider as input a query mix, but that size is negligible compared to the data.

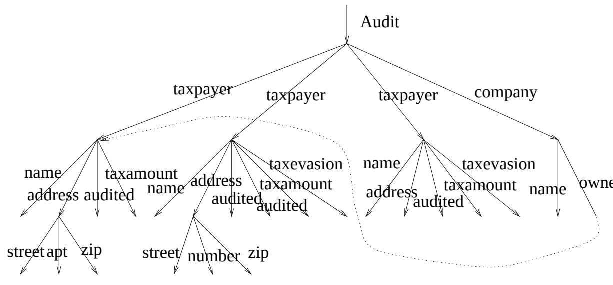

Figure 1: An instance of semistructured data. Values and object identifiers are omitted.

```
Audit: &o1
  {taxpayer: &o24
     {name : &o41 "Gluschko",
      address : &o34 {street : &105 "Tyuratam",
                      appartment : &o623 "2C"
                      zip : &121 "07099"}
      audited : &o46 "10/12/63",
      taxamount : &o47 12332},
   taxpayer : &o21
     {name : &o132 "Kosberg",
      address : &o25 {street : &427 "Tyuratam",
                      number : &928 206,
                      zip : &121 "92443"}
      audited : &o46 "11/1/68",
      audited : &o46 "10/12/77",
      taxamount : &o283 0,
      taxevasion : &o632 "likely"}
   taxpayer : &o20
     {name : &o132 "Korolev",
      address : &o253 "Baikonur, Russia",
      audited : &o46 "10/12/86",
      taxamount : &o283 0,
      taxevasion : &o632 "likely"}
   company : &o26
      {name : &o623 "Rocket Propulsion Inc.",
       owner : &o24}
  }
```

Figure 2: Textual representation of data

Example Mapping. Our semistructured model is an ordered version of the OEM model [16]. Data consists of a collection of objects, in which each object is either *complex* or *atomic*. A complex object is an ordered set of `(attribute, object)` pairs, and an atomic object is an atomic value of type `int`, `string`, `video`, etc. Hence, data is a *graph*, with edges labeled by attributes and some leaves labeled with atomic values. Data is exchanged in a text representation: the data graph in Fig. 1 is represented textually in Fig. 2. The order of an object's attributes is the only difference from the OEM model, and we use the order only when storing the data. Any order will do; it can be the order in the text representation or obtained in some other way.

The text representation specifies the data in a tree-like format. To specify arbitrary graphs, we write references to object identifiers, e.g., the value of the `Audit.company.owner` attribute in Fig. 2 is the object `&o24`. In this paper, we consider the data to be a tree. Object identifiers in the text representation are optional. If no object identifier is specified, an object is assigned a unique identifier automatically. These assumptions are consistent with XML.

Taxpayer1

oid	name	street	no	apt	zip	audit1	audit2	taxamount	taxevasion
o24	Gluschko	Tyuratam		2C	07099	10/12/63		12332	
o21	Kosberg	Tyuratam	206		92443	11/1/68	10/12/77	0	likely

Taxpayer2

oid	name	address	audited	taxamount	taxevasion
o20	Korolev	Baikonur	10/12/86	0	likely

Company

name	owner
Rocket Propulsion Inc.	o24

Figure 3: Relational storage

The following is an example of the kind of mapping to a relational schema on which we base our technique. One choice of a relational schema and its corresponding instance is in Fig. 3. We separate objects by their "types": `taxpayers` and `companies` are stored separately. We separate `taxpayers` with a complex `address` from those with a string-valued `address`. Even after this decomposition, objects are not uniform: there are many nulls. Table `taxpayer1` has two attributes `audit1` and `audit2` to accommodate objects with two occurrences of the `audit` attribute. Most object identifiers from the semistructured data are omitted. The actual "mapping" is not explicitly defined, but implied by the choice of attribute and table names. For instance, the path `Audit.taxpayer.name` is mapped to both `name` in `Taxpayer1` and `name` in `Taxpayer2`, and the path `Audit.taxpayer.audited` is mapped to `audit1` and `audit2` in `Taxpayer1`, and to `audit` in `Taxpayer2`. Data like that in Fig. 3 can be managed by any RDBMS. Unlike semistructured data, the schema is not stored with the data. Of course, this choice is not unique or necessarily the best. For example, we could store all `taxpayers` in one relation, and split their `addresses`, depending on their structure. Some updates to the semistructured data instance cannot be accommodated by the chosen relational storage. For example, we cannot add a new taxpayer with a `phone` attribute. Instead, we store that data in an *overflow* graph. Any semistructured data repository can store the overflow graph. Efficiency is not crucial, because the overflow graph should be small. System issues arise from the integration of a relational storage with a semistructured overflow, but they are not addressed in this paper.

In Sec. 2, we introduce the STORED language, and in Sec. 3, we describe an algorithm for automatically generating the relational STORED mappings from a data instance. Sec. 4 shows how to generate automatically the overflow mappings. Sec. 5 describes query and update rewriting algorithms, and Sec. 6 reports some experimental results.

2 STORED

We describe STORED (Semistructured TO Relational Data). A *relational schema* is a collection of relation names $R_1, \ldots, R_m$ with arities $n_1, \ldots, n_m$. An *overflow schema* is a collection of graph names, $G_1, \ldots, G_k$. Conceptually, each graph G_i contains a unary relation $G_i.roots(X)$ and a ternary one $G_i.edges(X, L, Y)$ (X, Y object identifiers, L attribute name). A *mixed schema* contains a relational schema and an overflow schema. A STORED mapping translates semistructured data into instances of some mixed schema. STORED is more restrictive than other query languages for semistructured data: it doesn't have joins or regular-path expressions. This ensures losslessness: it must be possible to reconstruct *any* semistructued data instance from its transformation over the mixed schema.

Simple Storage Queries. A STORED mapping consists of one or more `FROM WHERE STORE` queries. The `FROM` clause is a single pattern that binds several variables. The `STORE` clause states how values bound to variables are stored. In this example, nested `addr` objects are flattened into the 4-ary relation `Taxpr1`:

```
M1 = FROM Audit.taxpayer : $X
     { name : $N,
       addr : {street : $S, zip :q $Z}}
    STORE Taxpr1($X, $N, $S, $Z)
```

Each `FROM` clause defines a unique *key* variable; by default, it is the first variable in the pattern, e.g., `$X` above. Each binding of the key variable that matches the pattern causes one tuple to be stored by the `STORE` clause. Patterns are sequences of attribute constants. All variables in the `FROM` clause must be used in the `STORE` clause, but intermediate variables may be removed from the pattern, i.e., it's not necessary to write `$A` in `addr:$A {street:$S, zip:$Z}`.

We can also store optional attributes:

```
M2 = FROM Audit.taxpayer : $X
      { name : $N, addr : { street $S, zip $Z },
        OPT { audited : $A, taxamount : $T }}
    STORE Taxpr2($X, $N, $S, $Z, $A, $T)
```

Here `name, addr.street` and `addr.zip` are required attributes, therefore the first four columns of `Taxpr2` are always non-null, but `audited` and `taxamount` are optional. When one of them is missing, the last two attributes in `Taxpr2` are `null`. we can check for `audited` and `taxamount` independently:

```
M3 = FROM Audit.taxpayer : $X
     { name : $N, addr : {street $S, zip $Z}
       OPT{audited : $A},
       OPT{taxamount : $T}}
    STORE Taxpr3($X, $N, $S, $Z, $A, $T)
```

Each STORED pattern has a required subpattern and an arbitrary number of `OPT` subpatterns; the latter can be nested (i.e., each `OPT` subpattern has its required subpattern and other `OPT` subpatterns). The matching succeeds at an object `x` if the required subpattern matches that object; a successful matching binds the required variables. The `OPT` subpatterns are tentatively matched too, starting from their required subpatterns.

A STORED mapping may contain several queries. This example shows how to cluster `taxpayers` into two relations, using combinations of their attributes:

```
M4a = FROM Audit.taxpayer : $X
      { name : $N, addr : $P,
        OPT{audited : $A}, OPT{taxamount : $T}}
      WHERE typeOf($P, "string")
      STORE Taxpr4a($X, $N, $P, $A, $T)
M4b = FROM Audit.taxpayer : $X
      { name : $N,
        addr :  { street $S,
                  OPT{city $C, OPT{zip $Z}}}
        OPT{audited : $A}, OPT{taxamount : $T}}
   STORE Taxpr4b($X, $N, $S, $Ap, $C, $Z, $A, $T)
```

Taxpayers with an `addr` attribute of type `string` are stored in `Taxpr4a` and the others in `Taxpr4b`. In the latter case, `street` must be present, but `city` is optional. When `city` is present, then `zip` is optional[2]. Each `STORE` clause must refer to a distinct relation (`Taxpr4a` and `Taxpr4b` in the example), to simplify reconstructing the semistructured data.

In this example, only one of M4a or M4b will succeed for a given object, because the conditions on `addr` are mutually exclusive. In general, several queries may succeed, and a single object may be stored in multiple relations. This replication can be desirable when rewriting queries, because it permits the system to choose the target relation that best matches the query, but it incurs a higher cost in disk space.

Multiple Attributes. One characteristic of semistructured data is that objects may have multiple occurrences of the same attribute; for example, a person may have two `phone` attributes and several `subordinate` attributes. We distinguish two classes of multiply occurring attributes. A *small-set* attribute usually has low cardinality and most often is one; e.g., most people have one `phone`, but some may have two. A *collection* attribute denotes a collection of objects, usually with high cardinality; e.g., bosses usually can have many `subordinates`. For small-set attributes, we may increase the number of columns in a relation to accommodate all occurrences, whereas for collection attributes, we may store the attributes in a nested or separate relation. We show how to express both classes in STORED.

Below, the `audited` attribute occasionally occurs twice:

```
M7 = FROM Audit.taxpayer : $X
     { name : $N, audited : $A1, OPT{ audited : $A2 }}
     STORE Taxpr7($N, $A1, $A2)
```

`M7` stores objects with at least one `audited` attribute; the value of `$A2` may be `null`. In a declarative semantics, when some object has two `audited` attributes with values `u, v`, then both `u,v` and `v,u` are valid bindings for `$A1, $A2`. However, in our context, it suffices to store a single permutation in `Taxpr7`. Here, we use the order in the data model. Conceptually, STORED queries are rewritten such that each occurrence of an attribute name `a` is uniquely indexed as `a[1], a[2], a[3], ...`:

```
M8 = FROM Audit.taxpayer : $X
     { name[1] : $N, audited[1] : $A1,
       OPT{ audited[2] : $A2 }}
     STORE Taxpr8(N, A1, A2)
```

[2]To be precise: a `zip` without a `city` is not stored, while a `city` without a `zip` *is* stored.

Only attributes below the key variable are enumerated: `Audit` and `taxpayer` are not. For each data object `x`, we enumerate all its attributes; e.g., its `audited` attributes become `audited[1], audited[2]`, etc. This guarantees the matching between the pattern and the data is unique.

Collection attributes can be stored in nested relations or as separate relations, if nested relations are not supported. In this example, we assume that each `irscenter` has a collection attribute `hearing`:

```
M11a = FROM Audit.irscenter : $X
       {  centername : $N, centeraddress : $A}
       STORE IrsCenter($X, $N, $A)
M11b = FROM Audit.irscenter:$X.hearing:$Y
       { hearingdate : $D, taxpayername : $TN,
         auditorname  : $AN, decision : $Z}
       KEY $Y
       STORE Hearings($Y, $X, $D, $IN, $AN, $Z)
```

This stores a many-to-one mapping from `Hearings` to `IrsCenter`. `M11b`'s key variable is `$Y`, which is not the first variable, so it must be declared explicitly. STORED requires that the key variable be outside any `{...}` subpattern: e.g. `$TN` cannot be declared to be the key variable in `M11b`.

Label Variables. Some instances of semistructured data store data as attributes. For example a person's name could be an attribute name, like in:

```
Data: {john: {phone:5551234,fax:5551235},
       joe:  {phone:5552345,fax:5552346}, ... }
```

STORED supports *label variables* which are stored in relations as values. Label variables must occur before the key variable, for example:

```
FROM Data.$L: $X {phone:$P, fax:$F}
STORE R($X, $L, $P, $F)
```

Overflow Queries. So far we have described relational queries, whose target are the relations of the mixed schema. Next, we describe overflow queries, targeting the overflow graphs. For example, consider the relational query below:

```
M13a = FROM Audit.taxpayer : $X
       { name : $N, OPT{ address : {street $S, city $C}}}
       STORE R($X,$N,$S,$C)
```

We could complement it with the following two overflow queries, storing other attributes besides `name`, `address.street`, and `address.city`:

```
M13b = FROM Audit.taxpayer : $X
       { name : $N, OPT{address : $A},
         $L : _}
       OVERFLOW G1($L)
M13c = FROM Audit.taxpayer : $X
       { name : $N,
         address : {street $S, city $C, $K : _}}
       OVERFLOW G2($K)
```

Syntactically, overflow queries resemble relational ones, except that they must have one attribute variable that occurs last in the pattern, which is "stored" in the overflow graph by the `OVERFLOW` statement. We illustrate the semantics on `M13b`. Assume that `$X` is bound to some object identifier `x`. After matching `name` and possibly `address`, `$L` is bound successively to all other attributes. For each binding of `$L` to some attribute name `l` with value `y`: (1) `x` is stored in `G.roots`, (2) the edge `(x,l,y)` is stored in `G.edges`, and (3) the subtree rooted at `y` is stored in `G.edges`. Note that if some object `$X` has several `name` or `address` attributes, the first one is stored in `R`, and all others are stored in `G1`. Similarly, `M13c` stores in `G2` all subobjects of `address`, except the first occurrence of `street` and `city`. An object can be reconstructed from `R, G1, G2`.

As a convenience, the value of the key variable is always stored in `G.roots`, even if it is not the actual root of the subgraph being stored. For example the following are stored by `M13c`: `G2.roots($X)` and `G2.edges($X, $K, _)` (where _ is the actual value of the `$K` attribute).

Overflow queries cannot have nested patterns other than those containing the attribute variable.

In addition to storing relations in a relational repository, the overflow graphs are stored in a semistructured data object repository. Integrating the relational and overflow systems is necessary to preserve the flexibility of the original semistructured data. The performance requirements for the overflow system, however, are less demanding than for a stand-alone object repository, because the relational system handles most of the data.

3 Generating Storage Mappings

We now describe how to generate automatically the relational STORED mapping `M` given a semistructured data instance `D` (the overflow mapping is deferred to Sec. 4). Several competing goals determine M's effectiveness. First, we want to limit the number of tables. Although many RDBMs do not limit the number of tables, storing each object in a separate table is undesirable. Second, we want to bound the disk space. Although the size of the data instance `D` is fixed, its relational storage may be arbitrarily large, because an object may be stored in more than one relation. A related goal is minimizing the number of nulls. Some RDBMS store nulls efficiently, e.g., a null entry in a record requires only a byte, and nulls at the end of the record take no space. Nonetheless, we do not want to generate wide, sparse tables, since even one byte per null entry becomes expensive. A related restriction is that some RDBMS impose an upper limit on the number of attributes per table[3]. Depending on the application, other goals may include reducing object splits and their redundant storage in multiple relations, or, on the contrary, increasing object redundancy to improve query evaluation.

These goals are best modeled as a cost-optimization problem. Given a data instance `D`, generate a STORED mapping `M` that minimizes a *storage-cost function* `c(M)`, the cost of storing `M(D)`. The generator must also accommodate hard constraints, e.g., the limit of attributes per table. A query mix, $\bar{\mathtt{Q}} = \{\mathtt{Q}_1, \ldots, \mathtt{Q}_k\}$, can also be considered. For a given STORED mapping `M`, each query $\mathtt{Q}_i$ can be rewritten as a relational query,

[3]Oracle 8.0.4 imposes a limit of 1000.

Parameter Name	Meaning
K	Max tables
A	Max attributes per table
S	Max disk space
C	Collection size threshold
Supp	Min Support

Table 1: Storage-generation parameters

$\mathtt{Q}_i^{\mathtt{M}}$, on `M(D)` (Sec. 5). Given a weight $\mathtt{f}_i$ for each query $\mathtt{Q}_i$, and a query cost function $\mathtt{d}(\mathtt{Q}_i^{\mathtt{M}})$ that denotes the cost of evaluating $\mathtt{Q}_i^{\mathtt{M}}$ on the relational data, a second goal is to minimize the *query-cost* function, $d(M) = \sum_{i=1,k} f_i d(Q_i^M)$. The optimization problem can now be applied to the *combined cost* $\mathtt{c(M)} + \mathtt{d(M)}$.

Unfortunately, the storage-cost cost optimization problem is NP-hard in the size of the input data (by reduction from the *rectilinear picture compression* problem [8]).

Theorem 3.1 *The problem of computing an optimal storage mapping* `M` *is NP-hard in the size of the semistructured data* `D`*.*

This is a daunting complexity. Typically, query optimization problems are NP-complete in the size of a *query*, but here the problem is NP-hard in the size of the *data*. Search algorithms like dynamic programming are unlikely to work, so we consider heuristics, starting from frequent patterns in the data discovered by data mining. Wang and Li [21] describe a data-mining algorithm for semistructured data. We review it briefly and refer to it as *WL's algorithm*.

WL's Data-Mining Algorithm. WL's data model is a large collection of semistructured objects, i.e., a graph with many roots. WL's algorithms searches for *tree patterns*, which are trees consisting of attribute constants and the symbol `"?"`, which means *any* attribute. Attributes are indexed in WL, to allow for multiple attribute occurrences. An example of a WL pattern in our notation is:

```
{name[1], phone[1], phone[2],
 address[1]: {street[1], city[1], zip[1]}}
```

The support of this pattern is the number of root objects that contain at least `name`, two `phones`, and an `address`, with the latter containing at least `street, city, zip`. Given a particular semistructured instance and a minimum support, WL's algorithm has two steps. First, it finds all paths with high support: the set of such paths is called F_1. The second step is an adaptation of the standard apriory algorithm [2] in which items are replaced by paths, and itemsets by tree patterns (in WL's setting each ordered set of k paths uniquely corresponds to a pattern tree with k leaves). The algorithm generates successively the sets $F_2, F_3, \ldots, F_k, \ldots$, where each F_k consists of sets of k paths, whose associated pattern trees have high support.

Storage-Generation Algorithm. Our storage generation algorithm has five parameters, listed in Table 1. It generates a relational storage with at most K tables, each having at most A attributes, and with total disk space at most S. We assume fixed-length records. C distinguishes between "small sets" and "collections". An attribute with less than C occurrences is a small set, and the algorithm attempts to produce one column for each member of the set. Attributes with C or more occurrences are represented by nested relations. Finally, Supp is the minimum support, a parameter for the data-mining algorithm, chosen and tuned by the database administrator.

We define a type of pattern, called *storage patterns*, that are different from WL's patterns. A storage pattern has the form F:B, where F is the prefix and B the body. The prefix is a word $\mathtt{l}_1.\mathtt{l}_2\ldots\mathtt{l}_k$, where the labels $\mathtt{l}_1,\ldots,\mathtt{l}_k$ are either a (an attribute name) or - (a wildcard similar to WL's "?"). The last label, $\mathtt{l}_k$, must be an attribute name. The body B has the form $\{\mathtt{l}_1:\mathtt{B}_1,\ldots,\mathtt{l}_p:\mathtt{B}_p\}$, where $\mathtt{B}_1,\ldots,\mathtt{B}_p$ are other bodies, and each label is an indexed attribute a[i] (denoting i occurrences of attribute a) or a[*] (denoting a nested collection). An example of a pattern is:

```
Audit.taxpayer:{name[1], phone[2],
                address[*]:{street[1], city[1]}}
```

Intuitively, this pattern is contained in all taxpayer objects with at least a name, two phones, and C addresses, the latter with streets and cities. Note that phone[1] is missing: only the highest index occurs in the pattern. The relationship between these patterns and STORED mappings is formalized below.

Given a pattern P = F:B and a semistructured data instance D, the *pattern support* of P is defined as follows. Let $\mathtt{o}_1,\ldots,\mathtt{o}_n$ be all objects in D reachable from the root by a path matching the prefix F. The support is defined to be the number of objects $\mathtt{o}_i$ which *contain* the body B. Containment is defined as follows. First, replace every occurrence of a label a[*] in B with a[C]. Assuming $\mathtt{B}=\{\mathtt{l}_1:\mathtt{B}_1,\ldots,\mathtt{l}_p:\mathtt{B}_p\}$, an object o contains B iff for each label $\mathtt{l}_j$ of the form a[i] the object has at least i outgoing edges labeled a, to objects $\mathtt{o}_1,\ldots,\mathtt{o}_i$ and each $\mathtt{o}_i$ contains the pattern $\mathtt{B}_j$.

Queries on semistructured data have one or more data patterns, which specify paths to match in the input data (example queries are in Sec. 5). Our algorithm converts each query pattern into a data tree and extends the data-mining algorithms to these new data items. Any other conditions in the queries (other than patterns) are ignored. Given the weight f of some query Q, each of its patterns is converted into f occurrences of the corresponding data tree. Since queries may contain regular-path expressions, our data trees may have edges labeled with regular-path expressions: the definition of containment above is extended in an obvious way to the case when $\mathtt{o}_i$ contains regular-path expressions.

Given a query mix $\mathtt{Q}_1,\ldots,\mathtt{Q}_k$ with weights $\mathtt{f}_1,\ldots,\mathtt{f}_k$, we define the *query support* of a storage pattern P to be the sum of all $\mathtt{f}_i$ for which P is contained in $\mathtt{Q}_i$. The *mixed support* of P is the sum of the data support and the query support.

```
ALGORITHM: Automatic Storage Generation
INPUT:     K, A, S, C, Supp,  and query mix Q
OUTPUT:    Set of relational STORED mappings

METHOD:
   Step 1: Find all minimal prefixes
                with data support >= Supp

   Step 2: - Run the WL data mining algorithm
              with the changes in the text.

           - Let K' = number of maximally
               contained  patterns found

   Step 3: Select K0 (<= K) patterns out of the K'


   Step 4: For each of the K0 patterns, select
            the set of ''required'' attributes

   Step 5: For each of the K0 patterns with
           required attributes, generate one or
           more STORED relational queries.
```

Figure 4: Automatic Storage Generation Algorithm

We explain each step of the algorithm, which appears in Fig. 4.

Step 1: Compute minimal path prefixes. First, we generate all prefixes $\mathtt{l}_1.\mathtt{l}_2\ldots\mathtt{l}_k$ with support $\geq$ Supp. This requires a single pass through the data, during which we construct a trie structure in memory that encodes all prefixes in the data. Each trie node uniquely corresponds to a prefix, and has only those outgoing attributes a that were discovered in the data, plus - (the wildcard). We start with the empty trie and extend it as we traverse the data. Each trie node stores the support for that prefix. Once a trie node reaches minimal support Supp, we delete the tree underneath, and do not further expand that node.

Each prefix with high support identifies the collection of objects in the semistructured-data instance D that become the root objects for the data-mining algorithm in Step 2.

Step 2: Data mining. We use WL's data mining algorithm with the following changes. First, we compute both the data support and the combined support (data plus query support). The algorithm is guided by the combined support, i.e., patterns are grown as long as their combined support is large. Second, we keep backpointers to subpatterns with high data support; this information is used in Step 3. Recall that WL's algorithm generates a new set P of k paths in F_k by combining two sets of $k-1$ paths in F_{k-1}. We store one backpointer in P to whichever of its parent pattern has higher data support. This means some non-maximal patterns in F_{k-1} cannot be deleted at the end of phase k, which increases memory usage. The increase, however, is not prohibitive, e.g., there will be k additional sets retained for each set in F_k. Finally, we terminate the algorithm either when the combined support decreases below Supp or when k reaches A.

Step 3: Select K0 patterns. From Step 2, we have K' maximally contained patterns, each with support $\geq$ Supp. Recall that WL's algorithm also retains F_1, the set of highly supported paths. Now we use a greedy algorithm to select a subset of no more than K of the K' patterns that best cover the paths in F_1. We sort F_1 by the data support and start by picking any pattern $\mathtt{P}_1$ that covers (i.e., contains) paths in F_1 with highest support. In general, we pick pattern $\mathtt{P}_k$ such as to (a) minimize the maximum overlap with $\mathtt{P}_1, \ldots, \mathtt{P}_{k-1}$, and (b) in case of ties, cover the paths with highest support in F_1 which is still uncovered. We stop when we cover all paths in F_1 or when k reaches K (the maximum number of relations allowed).

Step 4: Select required attributes. For each of the KO patterns P selected in Step 3, we have a chain of backpointers to strictly smaller subpatterns, $\mathtt{P} = \mathtt{R}^1, \mathtt{R}^2, \ldots, \mathtt{R}^n$, with increasing data support (with $\mathtt{R}^n$ in F_1). In Step 4, we choose some i for each pattern so that the subpattern $\mathtt{R}^i$ becomes the required part of P. We attempt to choose a small i, i.e., a pattern with the fewest attributes, because such a pattern will match more semistructured objects in the mapping associated to P.

Choosing a small i, however, will increase the number of nulls and the overlap with the set of objects stored in different relations, and therefore increase the total disk space. For a given i, the disk space requirement for P can be computed from the data supports. In Step 4, we initialize the i counter for each pattern to 1 and increment them in a round-robin fashion, until we are within the limit for the allowed disk space S. In addition, we stop incrementing the i's before two patterns end up containing each other's required part: we allow one to contain the required part of the other, but then we will stop reducing its required part.

Step 5: Generate STORED queries. Each storage pattern P, with its required subpattern R, is converted into one or more STORED queries. This is pretty straightforward. For example, for the following pattern/subpattern:

```
P = Audit.taxpayer:{name[1], phone[2],
          address[*]:{street[1], city[1]}}
R = Audit.taxpayer:{name[1], phone[1]}
```

we associate the following STORED queries:

```
M1 = FROM Audit.taxpayer:$X
     { name:$N, phone:$P1,
       OPT { phone:$P2 }}
     STORE R1($X, $N, $P1, $P2)
M2 = FROM  Audit.taxpayer:$X.address:$Y
     { street $S, city $C}
     KEY $Y
     STORE R2($X, $Y, $S, $C)
```

A collection attribute like address[*] results either in a nested relation (if the RDBMS supports it), or in a separate relation: in the example we assumed the latter, hence the separate relation R2.

4 Generating Overflow Mappings

In Sec. 3, we showed how to generate automatically the relational mapping from a data instance. Next we show how to construct the accompanying overflow mapping, which ensures that the storage is lossless.

When nothing is known about the semistructured data overflow queries are always needed and tend to be complex. In practice, we found that specifying overflow queries is much simpler given information about the data's *structure*. Such information is sometimes available, for instance, the structure of XML data is specified by a DTD. Hence we discuss overflow mappings in the context of semistructured data schemas.

Consider the schema:

```
S1 = SCHEMA {Audit :
        {(taxpayer: {name: String,
                     address: String,
                     (address: String)?,
                     (taxreturn: S2)*}
           )*}}
S2 = SCHEMA {year: String, amount: String,
             (extension:String)?}
```

It specifies that the data has arbitrarily many taxpayers, each with one name, one or two addresses, and arbitrarily many taxreturns. The latter are of "type" S2, meaning that they have a year, an amount, and zero or one extensions. Multiple types can be defined and recursion is permitted. As this example illustrates, schemas may contain regular expressions, with the usual operators (alternation " | ", Kleene star "*", zero-or-one "?", concatenation ","), like in DTD's. However, unlike DTDs, these regular expressions are unordered [9].

Schemas may also contain attribute variables, and simple inequalities may be imposed on these variables. For example:

```
S3 = SCHEMA {Audit:  {(taxpayer:
     { name: String, address:
        { street: String, zip: int, ($K: Any)*},
       ($L: Any)*} )*}}
     WHERE $K <> zip, $L not in {name, address}
Any = SCHEMA {($P: Any)*}
```

Here taxpayers can have exactly one name and address, and any number of additional attributes different from name, address. Note that Any is a schema for *any* semistructured data. This is of particular interest for us: when nothing is known about the data, we assume that the schema is Any.

Schemas like those presented here lead quickly to high complexity [3], although much of their power is not needed in practice. For instance, they allow us to define useless types like S4 = SCHEMA {name:String, (office:String,office:String)*}, which specifies that a person has an even number of offices. We consider here restricted schemas. A *restricted schema* is a schema in which every regular expression is a concatenation of expressions of the form (a:T), or (a:T)?, or (a:T)*. The schemas S1, S2, S3, Any, defined above, are restricted schemas, but S4 is not. Every schema S can be converted into a restricted schema $\mathtt{S}_r$ by performing the following transformations repeatedly (here p, p',... denote pairs (a:S), (a':S'), ...):

```
(p | p') -> p?, p'?      (p,p')*  -> p*,p'*
(p,p') ? -> p?, p'?      (p*)*    ->   p*
(p*) ?   -> p*           (p?)*    -> p*
(p?) ?   -> p?
```

```
ALGORITHM Automatic Overflow Generation
INPUT        Relational mapping M, schema S
OUTPUT       Overflow mapping O

METHOD
    Step 1: for each attribute a in S
                construct set of databases $D_a$
    Step 2: for each $D \in D_a$
                compute M on D
                if a is not stored by M
                then generate overflow mapping
```

Figure 5: Generation of overflow mappings

In the remainder of this section, we use an abbreviated notation for restricted schemas, indicating the attributes' ranges. For example, schema `S1` is denoted:

```
S1=Audit[1] : { taxpayer[0,*] :
    {name[1], address[1,2],
     taxreturn[0,*]:{year[1], amount[1], extension[0,1]}}}
```

Each range is `[i,j]`, with `i` a number and `j` a number or `*`. When `i=j`, the range is abbreviated by `[i]`.

We describe next the algorithm for overflow generation, for a given relational STORED mapping `M`, and a restricted schema `S`. For presentation purposes we assume `S` is non-recursive, has no variables, and each attribute occurs at most once in `S`. Thus `S` is equivalent to a tree, with each attribute `a` occurring exactly once, labeled with a range denoted `range(a)`. We will relax these assumptions later.

We start by indexing all attribute names in `M`, as in Sec. 2. For each attribute name `a` in `M`, define `high(a)` to be its maximum index: when `a` is not indexed (occurs before the key variable), then `high(a) = 0`. We illustrate our algorithm on the following STORED mapping:

```
M = FROM Audit.taxpayer: $X
    { name[1]:$N, address[1]:$A,
      OPT taxreturn[1]:
        year[1]: $Y, amount[1]: $A, extension[1]: $E}
    STORE R($X, $N, $A, $Y, $A, $E)

M’ = FROM Audit.taxpayer:$X.taxreturn:$Z
            { year[1]: $Y, amount[1]: $A}
     KEY $Y
     STORE Q($X, $Z, $Y, $A)
```

We have:

```
high(Audit)=0, high(taxpayer)=0, high(name)=1,
high(address)=1, high(taxreturn)=1, high(year)=1,
high(amount)=1, high(extension)=1
```

The algorithm is shown in Fig. 5 and is illustrated in Fig. 6 on the schema `S1` and the relational STORED queries `M, M'`. Step 1 constructs a set D_a of canonical databases, for each attribute `a` in `S`. Intuitively these databases "challenge" `M` to prove that it can store the attribute `a`. D_a is obtained by recursively traversing the tree associated to `S`, and creating for each attribute `b` several copies, labeled `b[1], b[2], ..., b[k]`, and possibly `b[*]`, as follows. Let `range(b) = [i,j]`:

- When `b` $\neq$ `a` and `b` is not an ancestor of `a` in `S`, then we create `i` copies `b[1], b[2], ..., b[i]`.

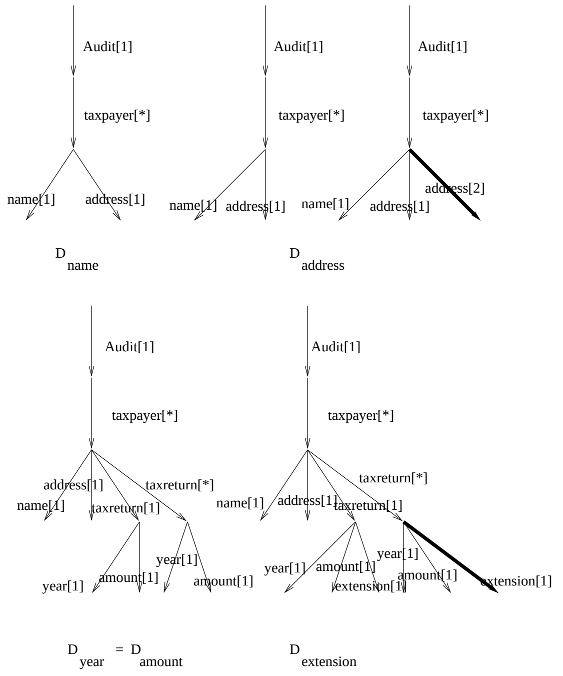

Figure 6: Canonical Databases for Schema `S1`

- When `b = a`, or `b` is an ancestor of `a` in `S`, then we choose a certain `k` and create copies labeled `b[1], b[2], ..., b[k]`. Each value of `k` results in a different database in D_a. Let `high(b) = m`. When `j=*` then `k` is choosen to be each of `i, i+1, ..., m, *`. When `j` is a number, then `k` is choosen to be each of `i, i+1, ..., min(j, m+1)`.

Fig. 6 depicts the construction of D_a for most attributes `a` (the other attributes, `Audit`, `taxpayer`, `taxreturn`, are similar).

In Step 2, the algorithm evaluates `M` on each canonical database $D \in D_a$, and checks whether `M` stores the value of every `a` attribute: if not, then an overflow query is generated. In Fig. 6, this happens in two cases: `address[2]` in $D_{address}$ and `extension[1]` in $D_{extension}$ (both edges are emboldened). The corresponding overflow queries are generated from `D` in an obvious fashion. In our example the two queries are:

```
O1 = FROM Audit.taxpayer:$X
     { name:$N, address:$A, $L:_}
     WHERE $L = address
     OVERFLOW G1($L)

O2 = FROM Audit.taxpayer:$X
     { name:$N, address:$A, taxreturn:$T,
       taxreturn: { year:$Y, amount:$A, $L:_ }}
     WHERE $L = extension
     OVERFLOW G2($L)
```

We address now the restrictions in our algorithm. First, recursive types in `S` are handled by unfolding. Although, in general, this results in an infinite tree, only a finite portion needs to be considered, because the queries in `M` are non-recursive (have no regular-path expressions). Second, label variables `$L` in `S` will occur as constants in the canonical databases. Conceptually, `$L` can be one of the attribute constants occurring in the

```
ALGORITHM Query rewriting
INPUT     Stored mapping M, user query Q
OUTPUT    Set of rewritten queries Q1, ..., Qk
          over the mixed schema

METHOD
Step 1 (preprocessing)
        From M, construct inversion rules I
        From I, construct canonical data instance D

Step 2 Compute Q on D, ignoring the WHERE conditions

Step 3 For each answer, compute all minimal covers
       of the answer with inversion rules

Step 4 For each cover generate a query Qi
       by adding WHERE conditions from Q, from
       gluing the inversion rules, and from I
```

Figure 7: Rewriting algorithm

query and schema, or anything else, and the algorithm takes this into account when evaluating `M`. Finally, repeated attributes in the schema are handled by replacing them with the concatenation of all attributes above them.

5 Query and Update Rewriting

Given a STORED mapping, the system accepts queries and updates over the semistructured data and *rewrites* them into queries and updates over the relational store, and the overflow graphs. This section describes the rewriting algorithm. We start first with query rewriting, then address update rewriting.

The algorithm appears in Fig. 7. We explain it below and illustrate it on the STORED mapping `M`:

```
Ma  = FROM Audit.taxpayer: $X
      { name[1] : {firstname[1] : $FN,
                   lastname[1] : $LN},
        addr[1] : {street[1] : $S,
                   city[1] : $C},
        OPT{taxamount[1] : $T}}
      STORE Taxpayer($X, $FN, $LN, $S, $C, $T)
Mb  = FROM Audit.taxpayer: $X
      { addr[1] : {street[1] : $S,
                   city[1] : $C, $L : _}}
      OVERFLOW G1($L)
Mc  = FROM Audit.taxpayer: $X
      { name[1] : $N,
        OPT{taxamount[1] : $T},
        $L : _}
      OVERFLOW G2($L)
```

Our example query `Q` returns the names of taxpayers whose `taxamount` is less than `10%` of their income on some W4 form and whose `address` contains `"Philadelphia"`:

```
Q = SELECT $N
    FROM Audit.taxpayer:$X
    { name : $N, taxamount:$T,
      w4form.income:$I, address.*:$A}
    WHERE $T < 0.1 * $I, $A = "Philadelphia"
```

Note that the query returns a set of `name` oids, each with `firstname` and `lastname`.

The queries we consider have patterns with regular expressions (in the `FROM` clause), and arbitrary conditions in the `WHERE` clause (i.e., joins are allowed).

```
Ia0 = FROM Taxpayer($X, $FN, $LN, $S, $C, $T)
      CONSTRUCT Audit : S_Audit()
       {taxpayer: S_taxpayer($X)
          { name : S_name_1($X)
               {firstname : S_firstname_1($X), $FN,
                lastname : S_lastname_1($X) $LN},
            addr : S_addr_1($X)
               {street : S_street_1($X) $S,
                city :  S_city_1($X) $C}}}

Ia1 = FROM Taxpayer($X, $FN, $LN, $S, $C, $T)
      WHERE $T != null
      CONSTRUCT Audit : S_Audit()
        {taxpayer: S_taxpayer($X)
             { taxamount : S_taxamount_1($X) $T}}

Ib  = FROM  G1.roots($X), G1.edges($X,$L,$Y)
      CONSTRUCT Audit : S_Audit()
        {taxpayer: S_taxpayer($X)
           {addr : S_addr_1($X) {$L : $Y}}}

Ic  = FROM G2.roots($X), G2.edges($X, $K, $Z)
      WHERE $K != taxamount
      CONSTRUCT Audit : S_Audit()
         {taxpayer: S_taxpayer($X) {$K : $Z}}
```

Figure 8: Inversion rules for query `M`.

These are common features of all query languages for semistructured data [17, 4, 7, 6].

Step 1 is a preprocessing step and starts by constructing *inversion rules* for the queries in `M`. This step is an adaptation from [14], where inversion rules were first used in query rewriting. In our context, the rules are generated internally by the system and are not intended for the user. We describe them in a concrete syntax for presentation purposes only. Each rule consists of a `FROM`, `WHERE`, and `CONSTRUCT` clause. The first two are as before; the `CONSTRUCT` clause contains a tree constructor, in which node oids are generated by Skolem Functions which, in turn, correspond to attribute names (including indexes). For our example, the inversion rules are shown in Fig. 8, and the Skolem functions are `S_Audit`, `S_taxpayer`, `S_name_1`, etc. For each relational query in `M`, one inversion rule is created for the required subpattern, and one inversion rule for each `OPT` subpattern. For each overflow query, a single inversion rule is created for its required subpattern (and `OPT` subpatterns are ignored). Thus, `Ia0` and `Ia1` are created for `Ma`, and `Ib` and `Ic` are created from `Mb` and `Mc` respectively. As in [14], inversion rules have the property that they reconstruct the entire semistructured data.

Step 1 continues by constructing a single canonical data instance `D` from the inversion rules. This is achived by "fusing" all symbolic objects in the `CONSTRUCT` clauses of all inversion rules (Fig. 9). Its nodes are labeled with Skolem function names or overflow graph names, and edges are either unlabeled (when the target is an overflow graph) or labeled with an attribute name. In addition, edges are annotated with the name of the inversion rule (e.g. `[Ia0]`, `[Ia1]`, `[Ib]`, `[Ic]`).

Steps 2 and 3 do the actual rewriting (this is related to *query decomposition and algebraic optimization* [15] for the Mediator Specification Language, MSL). Step 2 is a simple computation of the query on `D`, during which the conditions in the `WHERE` clause are not checked, and

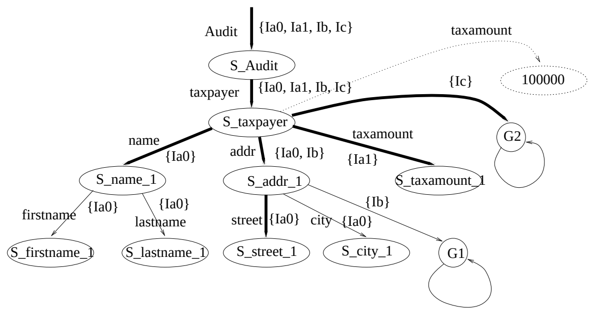

Figure 9: Canonical data instance D. The dotted edge is an extension, used for updates.

unlabeled edges in D may match any attribute in the query. For our example, the result of the evaluation is:

$X	$N	$T	$I	$A
S_taxpayer	S_name_1	S_taxamount_1	G2	S_street_1
S_taxpayer	S_name_1	S_taxamount_1	G2	S_city_1
S_taxpayer	S_name_1	S_taxamount_1	G2	G1
S_taxpayer	S_name_1	G2	G2	S_street_1
S_taxpayer	S_name_1	G2	G2	S_city_1
S_taxpayer	S_name_1	G2	G2	G1
S_taxpayer	G2	S_taxamount_1	G2	S_street_1
S_taxpayer	G2	S_taxamount_1	G2	S_city_1
S_taxpayer	G2	S_taxamount_1	G2	G1
S_taxpayer	G2	G2	G2	S_street_1
S_taxpayer	G2	G2	G2	S_city_1
S_taxpayer	G2	G2	G2	G1

Step 3 considers each row in the answer relation, and finds all minimal covers of the corresponding subgraph of D by the inversion rules. Consider the first row above, the edges of the corresponding subgraph of D are highlighted in Fig. 9, and the unique minimal cover is { Ia0, Ia1, Ic}

Finally, for each minimal cover, Step 4 constructs a query over the mixed schema. The query is essentially obtained by joining all inversion rules in the cover (which results in new WHERE conditions), and adding conditions from the original query Q. For our example, the resulting query is:

```
SELECT S_name($X)
  { firstname : S_firstname($X) $FN,  // reconstruct
    lastname : S_lastname($X) $LN }   // name
FROM Taxpayer($X, $FN, $LN, $S, $C, $T),  // Ia0, Ia1
     G2.roots($X'), $X'.w4form.income $I' // Ic
WHERE $T != null,  // from Ia1
      $X = $X'     // glue Ia1 with Ic at S_taxpayer
      $T < 0.1 * $I, $S = "Philadelphia"  // from Q
```

This query checks "Philadelphia" in the street position: another query would check for it in the city position. The query reconstructs the name using Skolem functions. Its FROM clause contains mixed relational goals (like Taxpayer(...)) with semistructured data patterns on the overflow graphs. The WHERE clause may have join conditions, like $X = $X'.

Updates. We consider a strict subset of the Lorel's [1] update statements:

```
UPDATE <object-selector> += <object-expression>
UPDATE <object-selector> := <value-expression>
```

In both statements <object-selector> is a query whose result must be a single object identifier o, and <object-expression> is a constant expression denoting a complex-value object o' (syntax like in Fig. 2). The first statement adds all (attribute, value) pairs of o' to o (to the end of the order). The second statement replaces the value of the atomic object o with <value-expression>. We describe the rewriting of the first update statement; the second is easier and handled similarly.

Update rewriting has two steps. First, <object-selector> is evaluated on the canonical database D. We illustrate with the STORED mapping M above and the following update:

```
UPDATE (SELECT $X
        FROM Audit.taxpayer:$X { name.lastname:$N }
        WHERE $N = "Smith") +=  {taxamount: "100000"}
```

Referring to Fig. 9, there are two results in Step 1: ($X = S_taxpayer, $N = S_lastname), and ($X = S_taxpayer, $N = G2). We illustrate in the sequel with the first result only.

In the second step, for each row in the result, we extend D with <object-expression>: this is the dotted edge in Fig. 9. Now we execute every STORED query in M on the extended object, but only consider results that use at least some edge of the extension (the "dotted" edges). For each such result, we generate one update instruction on the mixed schema. We illustrate using queries Ma and Mc. One of the bindings of Ma's variables is:

```
$X = S_taxpayer, $FN = S_firstname,
$LN = S_lasname_1, $S = S_street_1, $C = S.city_1
```

This corresponds to the following update:

```
UPDATE Taxpayer($X, $FN, $LN, $S, $C, $T)
SET    $T := 100000
WHERE  $LN="Smith"
```

When evaluating Mc, the order of the two taxamount attributes in Fig. 9 matters. There are two bindings for Mc: we consider the one that binds $L to the new taxamount, which meand taxamount[1] (in Mc) must have been bound to the first edge. This translates into the update:

```
UPDATE G2.roots($X), G2.edges($X,taxamount,100000)
WHERE Taxpayer($X, $FN, $LN, $S, $C, $T),
      $LN="Smith", $T != null
```

6 Preliminary Experiments

We ran some preliminary experiments with our automatic STORED generation algorithm. Our data set is DBLP, the popular database bibliography Web site[4], a collection of XML-like files. It does not have an explicit structure. Each XML file corresponds to one publication: a proceedings paper, a journal article, a book, a PhD thesis, etc. The directory structure captures alot of information. For example, the top level contains books, conf, journals, ms, persons, and phd directories. Under conf, there is one subdirectory

[4]http://www.informatik.uni-trier.de/~ley/db/about/instr.html

```
FROM Bib.inproceedings $X
{ author: $A1, OPT{author: $A2, OPT{author: $A3}},
  OPT{title: $T}, OPT{pages: $PP}, OPT{year: $Y},
  OPT{booktitle: $B}, OPT{url: $U}}
STORE R1($A1, $A2, $A3, $T, $PP, $Y, $B, $U)


FROM Bib.article $X
{ author :$A,
  OPT{title: $T}, OPT{pages: $PP}, OPT{year: $Y},
  OPT{volume: $V}, OPT{journal: $J}, OPT{number: $N},
  OPT{url: $U}}
STORE R2($A, $T, $PP, $Y, $V, $J, $N, $U)

FROM Bib.article $X
{ author: $A1, author: $A2, OPT{author: $A3},
  OPT{pages: $PP}, OPT{year: $Y}, OPT{volume: $V},
  OPT{number: $N}}}
STORE R3($A1, $A2, $A3, $PP, $Y, $V, $N)
```

Figure 10: STORED query for A=8

for each conference (255 in total), etc. The directory information, however, can be fully recovered from the publications themselves. A typical entry is:

```
<inproceedings key="Abiteboul97">
<author>Serge Abiteboul</author>,
<title>Querying Semi-Structured Data.</title>,
<pages>1-18</pages>,
<year>1997</year>,
<booktitle>ICDT</booktitle>,
<url>db/conf/icdt/icdt97.html#Abiteboul97</url>
</inproceedings>
```

The publication data is irregular: some entries have multiple author's, optional url's, or many citation attributes; a few have unfamiliar attributes. Most attributes have scalar values, but some have structure. There are about 92,000 publications that, when represented as a semistructured data, have 861,000 edges. The total disk space is 95M.

We decided to ignore the directory structure and moved all files in one directory. We chose a minimum support of 8500, which is 8.6%. Only articles and inproceedings had minimum support (books are only 307, phd thesis 67). In a separate experiment (not reported for lack of space), we also considered a query mix, in which one query with high weight referred to books. In that experiment, books did have minimum support, and the system generated a relation for storing book objects. We found no collection attributes; citation was a good candidate, but it did not have high enough support. We also found no nested attributes with high enough support.

Fig. 10 contains an example of one generated STORED mapping with A=8. There were only 8 attributes of high support for inproceedings, and all 8 in combination still had high support: hence a single STORED query maps inproceedings. There were more than 8 attributes of high support for article, therefore these objects are split into two relations: R2, tries to cover most objects, by requiring only the author attribute, while R3, requires two authors, giving it the best chance to store objects *not* stored in R2.

We ran two sets of experiments: one that varied the maximum number of attributes per relation, A, and one that varied total disk space allocated to the relations, S. The results are shown in Table 2.

A	3	4	5	6	7	8	9
Queries	9	9	5	4	4	3	3
Coverage (%)	91	94	94	90	92	90	90
Space (M)	1.19	1.59	1.15	1	1	0.9	1.2
Nulls (k)	23	116	112	123	91	106	201

S	0.5M	0.78M	0.93M	1.0M
Nulls	2.5k	40k	106k	106k
Coverage	59%	77%	90%	90%

Table 2: Effect of varying maximum number of attributes per relation and maximum disk space.

We varied A from 3 to 9 (since there were 10 attributes of high support). We assessed the quality by the algorithm by measuring the *number of queries*, the *data coverage*, and the number of nulls. *Queries* is the total number of relational STORED queries generated (hence, relations). *Coverage* is the percentage of the $861k$ edges that are stored in the relations. *Space* is the estimated disk space required by the relational storage (assuming fixed-length records). *Nulls* represent the amount of space occupied by nulls.

The first table shows that data fragmentation directly depends on the maximum relation arity. When A is small, objects need to be split across many relations (then, joined at query time). On the other hand, space is better utilized for small A's, because the number of null entries is smaller. The coverage (total number of edges stored in the relational part) is consistent, at approximately 90%. The actual overflow graphs would be larger than 10% of the data, because some overlap would exist between the overflow graphs and the relational store.

The second set of results show a clear degradation of the coverage when disk space for the relations is limited. When S is small, the algorithm generates more required attributes (Sec. 3): this decrease the number of nulls and to improve utilization of the relations, but covers fewer objects.

In summary, under reasonable assumptions, the generated STORED queries can cover a large percentage of the data, and they do this by exploiting the regularities found in the DBPL data instance.

7 Related Work and Discussion

Data clustering is the problem of grouping a large number of points in R^d into sets (clusters), where the distances between any two points in the same cluster is small. BIRCH [22] produces good clusters in just a few passes over a large data set. We found the storage-generation problem hard to model as a data clustering problem, because objects with widely different structures may be well stored together. Nestorov, Abiteboul, and Motwani [13] describe a clustering-based algorithm which, when given a semistructured data, extracts a schema for that data.

Theodoratos and Sellis [18] describe a warehouse-configuration algorithm that when given a relational database instance and a set of queries, generates an optimal set of views that best support the query set. This is related to the storage-generation problem, where we search for relational views over semistructured data. In our problem, however, the input is a data instance instead of a query set, and our "views" must be lossless.

Tsatalos et al. [19] pioneered the idea of achieving physical data independence by means of relational views. STORED follows a similar philosophy in achieving independence from the underlying relational storage.

Linguistically, STORED is closely related to query languages for semistructured data, such as Lorel [17, 1], UnQL [4], MSL [15], and StruQL [7, 6], all of which provide path expressions for matching attribute paths in semistructured data. Due to its unique requirements, STORED is strictly weaker than these languages.

Object-oriented databases [5] can store SGML and XML documents without explicitly storing their schema, but they require a DTD to derive an object-oriented schema. This can be an effective storage mechanism for XML data when the DTD is known, but in some applications, a DTD may not exist. Also, the technique can increase data fragmentation, because new classes and objects must be created to convert a DTD into a class hierarchy [10, 12]. Our technique is complementary: it does not require a DTD, and it uses a RDBMS instead of an ODBMS.

Wang and Li [21] extended data-mining techniques to semistructured data. Their algorithm finds "interesting patterns", i.e., subtrees with high support. Data mining is a good foundation for the STORED generation algorithm, although we must search for more complex patterns and attempt to cover most of the data. If applied directly, Wang and Li's patterns would generate a simple relational storage that covers only a small fragment of the data.

Storing semistructured data in relations is an ambitious goal, because the two models are apparently incompatible. Our hypothesis is that many semistructured data sources have a regular structure, with few outliers: this structure should be exploited when storing the data. Our preliminary experiments using the DBLP bibliography database support this hypothesis: in particular, DBLP data *is* quite regular, even if some outliers escape normal classification.

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