G-SPARQL: A Hybrid Engine for Querying Large Attributed Graphs

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ABSTRACT

Graphs are widely used for modeling complicated data such as social networks, bibliographical networks and knowledge bases. The growing sizes of graph databases motivate the crucial need for developing powerful and scalable graph-based query engines. We propose a SPARQL-like language, G-SPARQL, for querying attributed graphs. The language enables the expression of different types of graph queries that are of large interest in the databases that are modeled as large graph such as: pattern matching, reachability and shortest path queries. Each query can combine both of structural predicates and value-based predicates (on the attributes of the graph nodes/edges). We describe an algebraic compilation mechanism for our proposed query language which is extended from the relational algebra and based on the basic construct of building SPARQL queries, the Triple Pattern. We describe an efficient hybrid Memory/Disk representation of large attributed graphs where only the topology of the graph is maintained in memory while the data of the graph are stored in a relational database. The execution engine of our proposed query language splits parts of the query plan to be pushed inside the relational database (using SQL) while the execution of other parts of the query plan are processed using memory-based algorithms, as necessary. Experimental results on real and synthetic datasets demonstrate the efficiency and the scalability of our approach and show that our approach outperforms native graph databases by several factors.

1. INTRODUCTION

Graphs are popular data structures which are used to model structural relationship between objects. Recently, graph query processing has attracted a lot attention from the database research community due to the increasing popularity of graph databases in various application domains. In general, existing research on graph databases and graph query processing can be classified into two main categories. The *first* category represents graph databases which consists of a large number of small graphs (usually called *Transactional Graph Database*) such as bioinformatic applications [24], cheminformatics applications [27] and repositories of business process models [38]. In this category, there are two types of queries that are commonly studied in the literature:

a) *Subgraph query* which aims to find all the graphs in the database such that a given query graph is a subgraph of them [47, 48].
b) *Supergraph query* that aims to find all the graphs in the database that are subgraphs of the given query graph [10, 49].

The *second* category of graph databases are usually represented as one (or a very small number) of large graphs such as social networks [7], bibliographical networks [45] and knowledge bases [42]. In this category, there are three common types of queries:

a) *Pattern match query* that tries to find the existence(s) of a pattern graph (e.g. path, star, subgraph) in the large graph [51, 52].
b) *Reachability query* that verifies if there exists a path between any two vertices in the large graph [12, 26].
c) *Shortest path query* which represents a variant version of the reachability query as it returns the shortest path distance (in terms of number of edges) between any two vertices in the large graph (if the two vertices are connected) [11, 46].

In this paper, we focus on query processing in the *second* category of graph databases. In many real applications of this category, both the graph topological structure in addition to the properties of the vertices and edges are important. For example, in a social network, a vertex can be described with a property that represents the *age* of a person while the topological structure could represent different types of relationships (directed edges) with a group of people. Each of these relations can be described by a *start date* property. Each vertex is associated with a basic descriptive attribute that represents its *label* while each edge has a *label* that describes the type of relationship between the connected vertices. The problem studied in this paper is to query a graph associated with attributes (called as *attributed graph*) based on both structural and attribute conditions. Unfortunately, this problem did not catch much attention in the literature and there is no solid foundation for building query engines that can support a combination of different types of queries over large graphs. Formally, an *attributed graph* is denoted as $(V, E, L_v, L_e, F_v, F_e, \Lambda_v, \Lambda_e)$ where V is the set of vertices; $E \subseteq V \times V$ is the set of edges joining two distinct vertices; L_v is the set of vertex labels; L_e is the set

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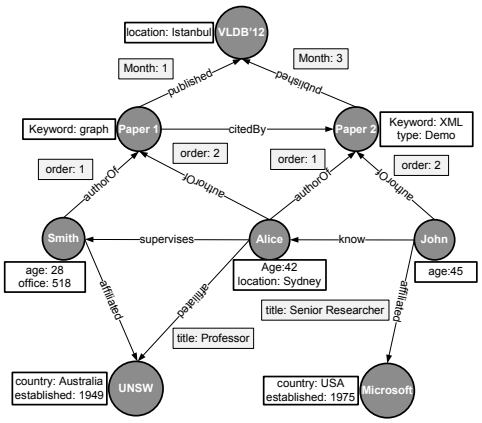


Figure 1: An example attributed graph.

of edge labels; F_V is a function $V \rightarrow L_v$ that assigns labels to vertices and F_e is a function $E \rightarrow L_e$ that assigns labels to edges; $\Lambda_v = \{a_1, a_2, ..., a_m\}$ is a set of m attributes that can be associated with any vertex in V. Each vertex $v \in V$ can be described with an attribute vector $[a_1(v), ..., a_m(v)]$ where $a_j(v)$ is the attribute value of vertex v on attribute a_j. $\Lambda_e = \{b_1, b_2, ..., b_n\}$ is a set of n attributes that can be associated with any edge in E. Each edge $e \in E$ can be described with an attribute vector $[b_1(e), ..., b_n(e)]$ where $b_k(e)$ is the attribute value of edge e on attribute b_k.

Figure 1 shows a snippet of an example large graph where a vertex represents an entity instance (e.g. *author*, *paper*, *conferences*) and an edge represents a structural relationship (e.g. *co-author*, *affiliated*, *published*). In addition, there are attributes (e.g. *age*, *keyword*, *location*) that describe the different graph vertices while other attributes (e.g. *order*, *title*, *month*) describe the graph edges. In practice, a user may need to pose a query on the large graph that can involve more than one of the common graph query types. Examples of these queries are:

1) Find the names of two authors, `X` and `Y`, where `X` and `Y` are connected by a path (sequence of edges) of any length (number of edges), the author `X` is affiliated at `UNSW`, the author `Y` is affiliated at `Microsoft` and each of the authors has published a paper in `VLDB'12`. *This query involves pattern matching and reachability expressions.*
2) Find the names of two authors, `X` and `Y`, where `X` and `Y` are connected by a path of any length, the author `X` is affiliated at `UNSW`, the author `Y` is affiliated at `Microsoft`, each of the authors has published a paper in `VLDB'12` as a `first` author and each of the authors has an `age` which is more than or equal 35. *This query involves pattern matching expression with conditions on the attributes of graph nodes and edges in addition to reachability expression.*
3) Find the names of two authors, `X` and `Y`, and the connecting path(s) between them where `X` and `Y` are connected by a path with a length which is less than or equals 3 edges, the author `X` is affiliated at `UNSW`, the author `Y` is affiliated at `Microsoft` and each of the authors has published a paper in `VLDB'12` as a `first` author. *This query involves pattern matching and reachability expressions where the reachability expression is constrained by a path filtering condition and returns the information of the connecting paths(s) in the query output.*
4) Find the names and the ages of two authors, `X` and `Y`, and the shortest path between them where the author `X` is affiliated at `UNSW`, the author `Y` is affiliated at `Microsoft` and each of the authors has published a paper at `VLDB'12`. *This query involves pattern matching and shortest path expressions.*
5) Find the titles of two papers, `P1` and `P2`, and the path between them where each edge in the path represent the `cited by` relationship and the maximum path length is three edges where the affiliation of the `first` author of `P1` is affiliated at `UNSW` and the affiliation of the `first` author of `P2` is `Microsoft`. *This query involves a pattern matching expression with condition on the attributes of graph edges in addition to a constrained reachability expression.*

1.1 Limitations of Existing Approaches

The emerging wave of new graph-based applications in different domains have triggered the calls for new systems for managing large graphs. Several techniques have been proposed in the literature for querying large graphs. However, in practice, the existing techniques turn to be inadequate in many cases due to the following deficiencies.

- The existing techniques follow the approach of building an index for storing information about the main features of the graph database. The structure and content of this index is usually optimized for accelerating the evaluation of *one* of the common types of the graph queries but usually they can not be used for accelerating the evaluation of other types of queries. For example, different subgraph query processing techniques exploit different types of graph features for building their indices (e.g. path [51], tree [48], subgraph [47]) while proposed techniques for handling reachability queries use different indexing mechanisms such as the 2-hop cover [12] and 3-hop cover [26]. In practice, answering user requests that can involve more than one of the common graph query types would require maintaining different type of indices which would be very expensive in terms of memory consumption. In addition, it imposes significant overheads for both constructing these indices (in offline pre-processing phase) and maintaining them in case of supporting updates on the underlying graph database. Moreover, given the increasing sizes of the graph database, the efficiency of such indexing techniques will break down after a certain limit is reached.
- The existing graph querying methods (of both categories of graph databases) that have been presented in the literature mainly focus on querying the topological structure of the graphs [47, 48, 51] and very few of them have considered the use of attributed graphs [39, 43]. While methods for querying the topological structure are more required for applications of transactional graph database, it is more common that the querying requirements for the applications of large graph databases (e.g. social networks or bibliographical networks) would involve querying the graph data (attributes of nodes/edges) in addition to the graph topology. In practice, answering queries that involve predicates on the attributes of the graphs (vertices or edges) in addition to the topological structure is more challenging as it requires extra memory consumption for

building indices over the graph attributes in addition to the structural indices in order to accelerate the query evaluation process. Furthermore, it makes the query evaluation and optimization process more complex (e.g. evaluation order and join order).

- The existing techniques assume that the whole graph (or at least their constructed indices) can always live *entirely* in the main memory. This assumption hinders the scalability of the proposed techniques due to their huge memory consumption. Very few approaches have assumed the use of persistent disk to store the graph databases (or portion of it) during the query evaluation process [32, 36, 44].
- The Resource Description Framework (RDF) represents a special kind of the considered attributed graphs. SPARQL is the official W3C standard query language for RDF graphs [35]. Several graph query processing techniques were proposed for large RDF graphs [6, 31, 53]. However, these approaches can not be directly reused for general attributed graphs due to the differences in the data model and the specifications of the query requirements. For example, in the RDF data model, graph edges can not be described by attributes. In addition, graph edges are used to represent both of the attribute/literal value pairs of the nodes and the structural relationship with other nodes in the graph with no differentiation. Such uniform treatment for the graph data and graph structure information dramatically increase the size of graph topology. Moreover, the initial specifications of SPARQL [35] did not provide any facility for expressing *path queries* or *reachability* expressions. The recent specifications of the SPARQL 1.1 query language[1] has addressed this limitation in a limited manner. However, no systems have, yet, been proposed to support these features. In addition, some query types that are of common interest in the general domain of large graph such as *shortest path* queries might not be of direct interest in the scope of RDF/SPARQL domain and is thus, so far, not been considered.
- Recently, some native graph database systems have been introduced (e.g. Neo4j[2], HypergraphDB[3]). These systems are mainly designed to provide efficient graph traversal functions[4]. However, these systems lack the support of *declarative* query interfaces and do not apply any query optimization strategies. In particular, they are language-specific and have their own APIs and low-level interfaces. Therefore, the efficiency of execution for any graph query is *programmer-dependent*. Thus, it can turn to be quite inefficient in many cases especially when the programmer has no or little knowledge about the characteristics of the underlying graph. Pregel system [29] has been introduced by Google as a large scale graph processing platform. However, Pregel is designed to work as a batch system for running graph analytical operations and it does not support online query processing.

[1]http://www.w3.org/TR/sparql11-query/
[2]http://neo4j.org/
[3]http://www.kobrix.com/hgdb.jsp
[4]A traversal refers to visiting the graph vertices sequentially by following the graph edges in some algorithmic fashion (e.g. depth-first or breadth-first)

1.2 Our Approach and Contributions

We present an approach for *interactive* querying of large attributed graphs which aims to address the above mentioned deficiencies. In particular, we rely on a hybrid main memory/disk-based relational representation of the graph database and devising efficient algebraic-based query processing mechanisms for different types of graph queries. In our approach, the incoming queries are compiled into algebraic plans where parts of the query plans are pushed down and executed inside the relational database layer while the rest of the query plan is processed using memory-based algorithms. In principle, the main reason behind our decision for relying on a relational database at the physical storage layer is to leverage the decades' worth of research in the database systems community. Some optimizations developed during this period include the careful layout of data on disk, indexing, sorting, buffer management and query optimization. By combining the memory representation of the graph topology and memory-based graph algorithms with the storage layer of the RDBMS, we are able to gain the best features of both worlds. Our goal is to optimize the performance of query processing while minimizing the memory consumption and achieving the scalability goals. In particular, our main contributions can be summarized as follows:

- We propose a SPARQL-like language, called *G-SPARQL*, for querying attributed graphs. The language enables combining the expression of different types of graph queries into one request. We show that the language is sufficiently expressive to describe different types of interesting queries (Section 2).
- We present an efficient hybrid Memory/Disk representation of large attributed graphs where only the *topology* of the graph is maintained in memory while *data* of the graph is stored and processed using relational database (Section 3).
- We describe an execution mechanism for our proposed query language where the incoming query is first compiled into an intermediate algebraic plan. Then, a split query evaluation mechanism is applied where the execution of parts of the query plan is pushed inside the relational database (using SQL) while the execution of other parts of the query plan is processed using memory-based algorithms, as necessary, for optimizing the query performance (Section 4).
- We conduct extensive experiments with real and synthetic data to evaluate our approach (Section 5).

We review the related work on querying graph databases in Section 6 before we conclude the paper in Section 7.

2. QUERY LANGUAGE AND SUPPORTED QUERY TYPES

To represent queries, a language is needed. Therefore, a number of graph query languages, with corresponding graph models, have been proposed in the literature [4]. For example, PQL [28] is a special-purpose language which is designed for querying pathways in biological networks. GraphQL [23] was developed as a general language for querying both large sets of small graphs as well as small sets of large graphs . It is designed for querying graph patterns based on graph structure in addition to the node and edge attributes. The language considers graphs as the basic unit of abstraction where the output of each expression is restricted to take the

form of a graph structure. However, GraphQL lacks the ability to express queries about arbitrary path structures in the graph. Therefore, some important types of queries for large graphs such as reachability queries and shortest path queries can not be expressed using GraphQL. Facebook has introduced the Facebook Query Language (FQL)[5] that provides the users with a way to query their own data that can be accessed through API functions. The language uses a SQL-style interface and offers a rather primitive and restricted set of queries in order to achieve good performance. For example, the clauses are of the form `select-from-where` with a single from table and join operations are not supported in the language.

The SPARQL query language is the official W3C standard for querying and extracting information from RDF graphs [35]. It represents the counterpart to *select-project-join* queries in the relational model. It is based on a powerful *graph matching* facility that allows the binding of variables to components in the input RDF graph. In principle, the RDF data model represents a special kind of the general model of attributed graph which represents our main focus in this paper. In particular, the main differences between the two kind of models (RDF and attributed graph) can be specified as follows:

- In the RDF data model, graph edges are used for representing the structural relationships (graph topology) between the graph entities (connecting two vertices) in addition to representing the *graph data* by connecting the graph entities to the information of their attribute values (connecting a vertex with a literal value). Such uniform treatment leads to a significant increase in the size of the graph topology as the graph data is considered as a part of the topology and not as a separate part. The situation is different in the attributed graph model where the graph data (attributes of graph nodes/edges) are represented differently from the structural information of the graph.
- In attributed graphs, edges are treated as first class citizens where any edge (similar to any vertex) can be described by an arbitrary set of attributes. However, that is not the case in the RDF data model where there is no support for edges to be described by any attribute information (only vertices).

In general, a good query language should have powerful expressiveness so as to satisfy the users' query requirements. In addition, it should be as clear and concise as possible in syntax expressions. Therefore, we introduce *G-SPARQL* as a SPARQL-like query language that employs the basic graph matching facilities of the SPARQL language. However, the language introduces new constructs that handle the above mentioned differences in the data model in addition to compensating the lack of some querying requirements that are not supported by the standard specification of the SPARQL language. In particular, our language aims to fulfill the following set of large graph querying requirements:

- The language supports querying structural graph patterns where filtering conditions can be specified on the attributes of the graph vertices and/or edges which are participating in the defined patterns as well.
- The language supports various forms for querying graph paths (sequence of edges) of possibly unknown lengths that connect the graph vertices. In particular, the language enables the expression of reachability queries and shortest path queries between the graph vertices where filtering conditions can be applied on the queried path patterns (e.g. constraints on the path length).

[5]http://developers.facebook.com/docs/reference/fql/

```
        <Query> =  SELECT <VarList>
                   WHERE{ <Triple>+
                   [FILTER (<Predicate>)]*
                   [FILTERPATH (<PathPredicate>)]* }
      <VarList> =  {?var | <PathVar>}
      <PathVar> =  ??var | ?*var
       <Triple> =  <Term> (<Term> | <Edge> | <Path> ) <Term>
         <Term> =  literal | ?var
         <Edge> =  literal | literal+ | @literal | ?var(literal)
         <Path> =  <PathVar> | <PathVar>(literal)
    <Predicate> =  BooleanFunction
<PathPredicate> =  Length(<PathVar>, Predicate) |
                   AtLeastNode(<PathVar>, number, Predicate) |
                   AtMostNode(<PathVar>, number, Predicate) |
                   ALLNodes(<PathVar>, Predicate) |
                   AtLeastEdge(<PathVar>, number, Predicate) |
                   AtMostEdge(<PathVar>, number, Predicate) |
                   AllEdges(<PathVar>, Predicate)
```

Figure 2: *G-SPARQL* grammar

Figure 2 shows the grammar of the *G-SPARQL* language whereas non-terminal `Query`, defining a *G-SPARQL* query, is the start symbol of this grammar. More details about the syntax and semantics of the *G-SPARQL* language are discussed in the following subsections.

2.1 Querying Attributes of Nodes and Edges

The standard specifications of the SPARQL query language supports defining query graph patterns and expressing various restrictions on the entities and the relationships which are participating in defining these patterns. In particular, each SPARQL query defines a graph pattern P that is matched against an RDF graph G where each variable in the query graph pattern P is replaced by matching elements of G such that the resulting graphs are contained in G (pattern matching). The basic construct of building these graph patterns is the so-called a *Triple Pattern* [33]. A Triple Pattern represents an RDF triple `(subject, predicate, object)` where *subject* represents an entity (vertex) in the graph and *predicate* represents a relationship (edge) to an *object* in the graph. This object in the triple pattern can represent another entity (vertex) in the graph or a *literal* value. Each part of this triple pattern can represent either a constant value or a variable `(?var)`. Hence, a set of triple patterns concatenated by `AND (.)` represents the query graph pattern. The following example shows a simple SPARQL query that finds all persons who are affiliated at UNSW and are at least of 30 years old.

```
SELECT ?X
WHERE {?X affiliatedAt UNSW.   ?X age ?age.
       FILTER (?age >= 30)}
```

In our context, we need to differentiate between the representation of two types of query predicates.

a) *Structural predicates*: specify conditions on the structural *relationship* between graph vertices (the *object* part of the query triple pattern represent a graph vertex).

b) *Value-based predicates*: specify conditions on the values of the *attributes* in the graph (the *object* part of the query triple pattern represent a literal value).

Therefore, the *G-SPARQL* syntax uses the symbol (@) at the *predicate* part of the query triple patterns that represent value-based predicates and differentiate them from the standard structural predicates. To illustrate, let us consider the following example of two query triple patterns:

```
T1 --> ?Alice affiliatedBy UNSW
T2 --> ?Alice @affiliatedBy "UNSW"
```

where $T1$ represents a structural predicate that specifies the condition of having the graph vertices represented by the variable `?Alice` connected by an edge that represents the `affiliatedBy` relationship to a vertex with the label `UNSW` while $T2$ represents a value-based predicate that specifies the condition of having the vertices represented by the variable `?Alice` described by an `affiliatedBy` attribute that stores the literal value of `UNSW`.

Unlike the RDF data model, the model of attributed graphs enables describing each graph edge with an arbitrary set of attributes. Therefore, our query language enables representing two types of *value-based* predicates. *Vertex predicates* which enables specifying conditions on the attributes of the graph vertices. *Edge Predicates* which enables specifying conditions on the attributes of graph edges. In particular, we rely on the standard query triple pattern to represent both types of predicates. However, we use the round brackets `()` for the *subject* part of the query triple pattern to differentiate edge predicates. In these predicates, the subject parts refers to graph edges and not for graph vertices. To illustrate, let us consider the following example of query triple patterns:

```
T3 --> ?Alice ?E(affiliatedBy) UNSW
T4 --> ?E @Role "Professor"
T5 --> ?Alice @officeNumber 518
```

where $T3$ represents a structural predicate that specifies the condition that the vertices represented by the variable `?Alice` is connected to a vertex with the label `UNSW` with an `affiliatedBy` relationship. $T4$ represents an *edge predicate* that determines that the *Role* attribute of the `affiliatedBy` relationship (where the edge representing the relationship is bound to the variable E) should store the value $Professor$. $T5$ represents a *vertex predicate* that specifies the condition that *Alice* is described by an `officeNumber` attribute that stores the value 518.

2.2 Querying Path Patterns

One of the main requirements in querying large graphs is the ability to express matching queries based on path patterns. This querying feature is quite important especially when the information about the graph topology or the exact connection patterns between the queried graph vertices are unknown. For example, reachability query is an important type of queries in large graphs that aims to check if there exists a path (of any unknown length) between any two vertices in the large graph. Similarly, the shortest path query aims to determine the shortest connection (number of sequenced edges) between any two vertices in the graph. The initial specifications of the SPARQL query language [35] lack the constructs that support expressing such type of queries. Therefore, several extensions to the SPARQL query language have been proposed to address some of these requirements such as: *SPARQ2L* [5] and *PSPARQL* [3]. The most recent specifications of SPARQL 1.1 have tried to address some of these limitations, however, in a limited manner. In particular, SPARQL 1.1 supports the ability to match arbitrary length paths where the end of the path pattern can be represented as an RDF value or a variable. However, variables can not be used as a part of the path itself, only the ends. For such type of expressions, the query answer includes all matches of that path expression and binds the subject or object variable as specified. To illustrate, let us consider the following examples of query triple patterns:

```
T6 --> ?Alice knows+ ?X
T7 --> ?Alice knows+ John
```

where $T6$ assigns to the variable `X` all vertices that can be reached from the vertices that are represented by the variable `?Alice` through the relationship `knows`. The symbol (`+`) indicates that the path can be of any length where each edge in the path needs to represent the relationship `knows`. $T7$ represents a structural predicate that describes a reachability test which verifies if the vertices represented by the variable `?Alice` are connected to a vertex with label `John` by any path (sequence of edges) where each edge in that path represents the relationship `knows`. The predicate filters out the vertices which are bound to the variable `?Alice` and do not satisfy the condition.

G-SPARQL supports this extension for expressing path patterns and, similar to *SPARQ2L* [5] and *PSPARQL* [3], allows path variables in the predicate position of a triple pattern (`subject, path variable, object`). In particular, *G-SPARQL* supports the following options of binding path variables in the path patterns.

```
T8 --> subject ??P object
T9 --> subject ?*P object
T10 --> subject ??P(predicate) object
T11 --> subject ?*P(predicate) object
```

where $T8$ binds the path variable P to the connecting paths between the two vertices of the `subject` and `object`. The symbol (`??`) indicates that the matching paths between the `subject` and `object` can be of any arbitrary length. In $T9$, the symbol (`?*`) indicates that the variable P will be matched with the *shortest* path between the two vertices of `subject` and `object`. $T10$ ensures that each edge in the matching paths represents the specified relationship `predicate`. Similarly, $T11$ ensures that each edge in the matched shortest path represents the relationship `predicate`.

In general, any two graph vertices can be connected with multiple paths. Therefore, *G-SPARQL* enables expressing filtering conditions that can specify *boolean* predicates on the nodes and the edges of the matching paths which are bound to the path variable. In particular, *G-SPARQL* supports the following filtering conditions over the matched paths.

- `Length(PV, P)`: This filtering condition verifies that the length (number of edges) of each matching path which is bound to the variable `PV` satisfies the predicate `P` and filters out those paths which do not satisfy the predicate `P`. For example, the following path filtering condition `FilterPath (Length(??X, < 4))` ensures that the length of each path which is assigned to the path variable (`X`) is less than 4 edges.
- `AtLeastNode(PV, N, P)`: Verifies if at least `N` number of nodes on each path which is bound to the variable `PV` satisfies the predicate `P` and filters out those paths which do not satisfy the predicate `P`. This predicate can be a structural predicate or value-based predicate. Let us consider the following examples of these predicates.
  - `AtLeastNode(??X, 2, livesIn Sydney)` ensures

that at least 2 nodes of each path, which is bound to the variable X, are satisfying the structural predicate of being connected through the livesIn relationship to a vertex with the label Sydney.
  - AtLeastNode(??X, 1, @affiliated UNSW) ensures that at least 1 node of each path, which is bound to the variable X, satisfies the value-based predicate of having a value of the affiliated attribute equals to UNSW.
- AtMostNode(PV, N, P): Ensures that at most N number of nodes on each path which is bound to the variable PV satisfies the structure/value-based predicate P.
- AllNodes(PV, P): Ensures that every node of each path which is bound to the variable PV satisfies the structure/ value-based predicate P.
- AtLeastEdge(PV, N, P): Ensures that at least N number of edges on each path which is bound to the variable PV satisfies the value-based predicate P (structural predicates can not be represented for graph edges).
- AtMostEdge(PV, N, P): Ensures that at most N number of edges on each path which is bound to the variable PV satisfies the value-based predicate P.
- AllEdges(PV, P): Ensures that at every edge of each path which is bound to the variable PV satisfies the value-based predicate P.

3. HYBRID REPRESENTATION OF LARGE ATTRIBUTED GRAPHS

Due to the lack of scalable graph indexing mechanisms and cost-effective graph query optimizers, it becomes very challenging to search and analyze any reasonably large networks. Therefore, there is a crucial need and strong motivation to take advantage of well-studied relational database indexing and query optimization techniques to address the problems of querying large graphs. In general, relational databases have been considered as the main choice for most traditional data-intensive storage and retrieval applications for decades. In practice, relational database systems are generally very efficient for queries that requires extensive use of physical indexing (e.g. B-tree) and sophisticated query optimization techniques (e.g. selectivity estimation and join ordering). For example, by applying predicates, relational indices can limit the data that must be accessed to only those rows that satisfy those predicates. In addition, query evaluations can be achieved using index-only access and save the necessity to access the data pages by providing all the columns needed for the query evaluation. However, relational databases turn to be inefficient for answering the queries that would require looping or recursive access to large numbers of records by executing multiple expensive join operations which may yield to very large intermediate results. Hence, executing traversal operations over relationally stored graphs can be time-inefficient due to the large number of potential joins in addition to the expensive disk access cost to retrieve the target vertices. As such, it is much more efficient to rely on algorithms that execute on main memory data structures to answer graph queries that requires heavy traversal operations on the graph topology. Therefore, in our graph representation, we rely on a hybrid mechanism where the entire graph information (topology + data) are stored in relational database while only the topology information of the graph needs to be loaded onto the main memory for accelerating the query evaluation process when necessary.

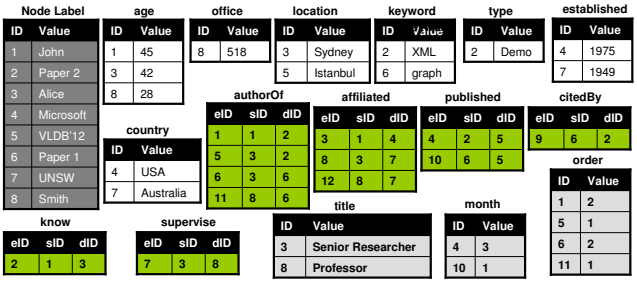


Figure 3: Relational Representation of Attributed Graph of Figure 1.

In our approach, we physically store the attributed graph in a relational database. In general, it is a virtue of the relational database model that its canonical physical representation, tables of tuples, is simple and thus efficient to implement. Therefore, several approaches have been proposed for storing XML [18] and RDF [37] databases using relational databases. However, none of these approaches can be directly reused for storing attributed graphs due to the differences in the data model and the specifications of the query requirements. Therefore, we adopted an approach for storing attributed graphs in relational database using a fully decomposed storage model (DSM) [1, 13]. In particular, we start by assigning identifiers (IDs) for each vertex and edge in the graph. Then, the attributed graph is mapped into $M+N$ two-column tables and P three-column tables where M is the number of *unique* attributes of the graph vertices, N is the number of *unique* attributes of the graph edges and P is the number of *unique* relationships that exist between the graph vertices. The first column (ID) for each of the $(M+N)$ two-column attribute tables stores the identifiers of those vertices/edges that are described by the associated attribute while the second column ($Value$) stores the literal values for those attributes. Obviously, the vertices/edges which are not described by a particular attribute will simply not have a representative record in the associated table for that attribute. Multi-valued attributes will be represented with multiple rows (with the same ID value) in the table for that attribute.

Each table is sorted with a clustered index on the ID column in order to enable a fast execution for merge joins where multiple attributes of the same vertex/edge need to be retrieved. In addition, a *partitioned B-tree index* $(Value, ID)$ is created for each table in order to allow efficient execution for value-based predicates on the attributes of the graphs by reducing the access costs of the secondary storage to retrieve those nodes/edges that satisfy the condition of a predicate to a minimum [19]. The P three-column tables capture the graph *topology* information. In particular, each of these tables groups the information of all graph edges that represent a particular relationship where each edge is described by three pieces of information: the edge identifier (eID), the identifier of the source vertex of the edge (sID) in addition to the identifier of the destination vertex (dID). Figure 3 illustrates an example of our relational representation for the attributed graph of Figure 1.

A main advantage of the DSM-based mapping for the attributed graph is that it is agnostic to the graph schema.

Therefore, it can be straightforwardly applied to any attributed graph with any schema. In addition, during the query processing, the disk access costs can be significantly reduced because only the records of the tables of those attributes/relationships which are involved in a query will be processed. On the other hand, some queries may need to query/access several attributes for the same entity (vertex or edge). In this case, a number of attribute tables which is equal to the number of the attributes that are involved in the query have to be joined in order to re-group the fragmented information of the graph entities over multiple tables. However, this challenge can be tackled by relying on inexpensive merge joins which make use of the sorting of the tables in their ID columns and their clustered indices. In practice, it is not very common that the posed queries would involve a *very large* number of attributes/relationships.

In our hybrid graph representation, we rely on a native pointer-based data structure for representing the graph topology information in the main memory. In particular, this memory-based representation of the graph topology encodes the information of the P (*Relationship*) tables that store the *structural* information of the graph edges. In principle, this information represents the mandatory knowledge for executing the index-free and memory-based algorithms that involve heavy traversal operations on the graph topology or that of recursive nature such as performing the Dijkstra's algorithm to obtain the shortest path between any two vertices or performing a breath-first search (BFS) to answer reachability queries [14]. Therefore, our hybrid representation achieves a clear reduction in the main memory consumption as it avoids loading the attributes of the graph vertices/edges and their data values ($M + N$ attribute tables) into the main memory. In addition, it avoids building extra main memory indices for the graph attributes which might be required for accelerating the query evaluation process of the query predicates and pushes these tasks to the underlying relational storage. Such reduction in the main memory consumption provides better scalability opportunities for handling larger graphs for a given fixed size of the available main memory.

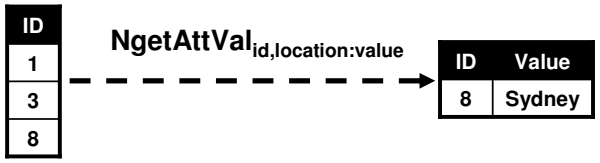
4. ALGEBRAIC COMPILATION AND SPLIT OF QUERY EVALUATION

A crucial strength of any graph query language is that it can be efficiently implemented. In general, one of the key effective query optimization techniques for any query language is the availability of a powerful algebraic compilation and rewriting framework of logical query plans. For example, relational algebra has been a crucial foundation for relational database systems and has played a large role in enabling their success. In XML query processing, some approaches have relied on a form of tree algebra where trees are the basic unit and the operators work on collections of trees [25] while some other approaches have relied on a relational algebraic mechanism for compiling XML queries [22]. GraphQL [23] compiles its graph queries using a form of graph algebra where graphs are the basic unit of information and each operator takes one or more collections of graphs as input and generates a collection of graphs as output.

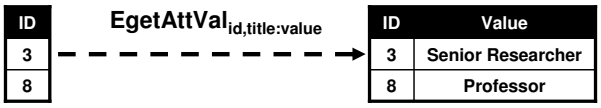
Several approaches have been proposed for compiling SPARQL queries into relational algebraic plans [9, 15, 16], as an abstract intermediate language for representing the queries. We follow the same approach of [15, 22] where we rely on a dialect of *tuple algebra* for compiling *G-SPARQL* queries. Hence, we can leverage the well-established relational query planning and optimization techniques in several venues before further translating our query plans (or parts of them) into SQL queries. In particular, our algebra considers *tuples* as the basic unit of information. Each algebraic operator manipulates collections of tuples. However, our logical algebra extends the set of traditional relational algebraic operators (e.g. selection, projection, cartesian product, join) with a set of logical operators that are capable of expressing complex *G-SPARQL* operations that can not be matched with the semantics of the traditional relational operators. The descriptions of these algebraic operators are listed in Table 1.

As we previously described, query triple patterns represent the main constructs of building *G-SPARQL* queries where each variable in the query triple pattern is replaced by matching elements from the queried graph. Evaluating a *G-SPARQL* query yields to a set of variable bindings (a mapping from variable names to values). Shared variable names are represented as join equality predicates in the query plan. The semantics of each of our defined operators is identical to exactly one possible query triple pattern in *G-SPARQL*. Descriptions of the *G-SPARQL* algebraic operators (Table 1) are given as follows:

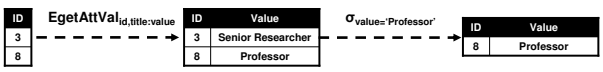
- The `NgetAttVal` is a unary operator which is used for retrieving the values of a specific attribute for a set of graph nodes. The operator receives a set of tuples where the column (id) of the input relation identifies the graph nodes and the name of the attribute to be accessed ($attName$). The schema of the output tuples extends the schema of the input tuples with the ($value$) column that represent the values of the accessed attribute. Based on the attributed graph of Figure 1 and its relational representation in Figure 3, Figure 4(a) illustrates an example for the behavior of the `NgetAttVal` operator where it retrieves the values of the `location` attribute for an input relation with the (id) of three graph vertices (`"John"`,`"Alice"`,`"Smith"`). The output relation includes only one record (for the vertex `"Alice"`) that has the `location` attribute with the value `"Sydney"`. The other two vertices are filtered out because they do not have values for the indicated `location` attribute. Similarly, the `EgetAttVal` operator retrieves the values of a specific attribute for a set of graph edges. Figure 4(b) illustrates an example for the behavior of the `EgetAttVal` operator where it retrieves the values of the `title` attribute for an input relation with the (id) of two graph edges. The schema of the output relation extends the schema of the input relation with an attribute that stores the value of the accessed attribute. The traditional relational `Selection` operator (σ_p) is used for representing value-based predicates over the values of the attributes of graph nodes or edges. It selects only those tuples of an input relation for which a value-based predicated (p) over a specific column holds. Hence, it represents the right match for reflecting the expressivity of the SPARQL `FILTER` expressions. Figure 4(c) illustrates an extension of the example of Figure 4(b) where the input edges are filtered based on a predicate (`title = "Professor"`) for the retrieved values of the `title`



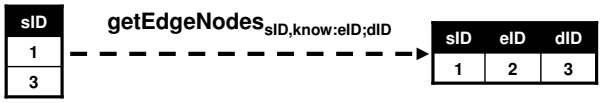
(a) The `NgetAttVal` operator



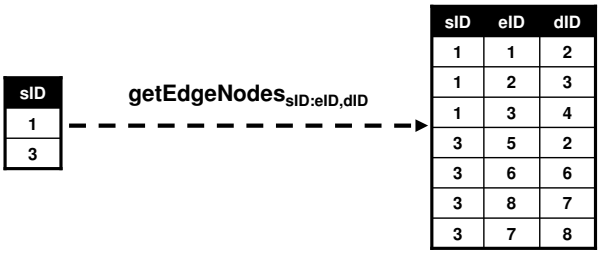
(b) The `EgetAttVal` operator



(c) The `Filter` operator

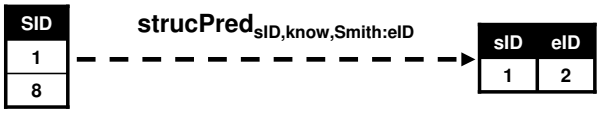


(d) The `getEdgeNodes` operator (specified relationship)

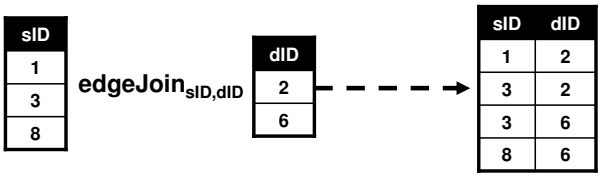


(e) The `getEdgeNodes` operator (all relationships)

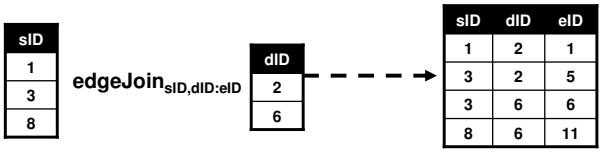
(f) The `strucPred` operator



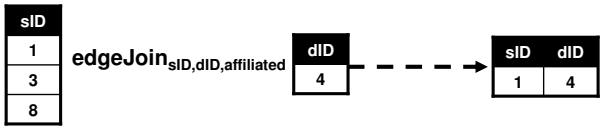
(g) The `strucPred` operator (with projection)



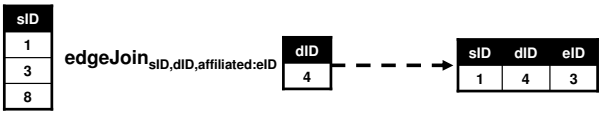
(h) The `edgeJoin` operator



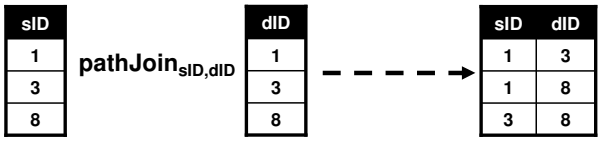
(i) The `edgeJoin` operator (with projection)



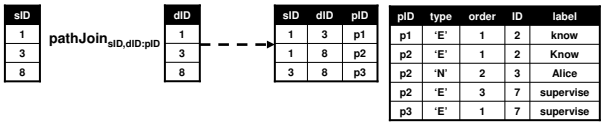
(j) The `edgeJoin` operator (specified relationship)



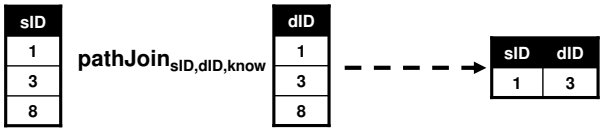
(k) The `edgeJoin` operator (specified relationship with projection)



(l) The `pathJoin` operator

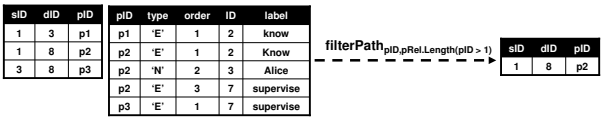


(m) The `pathJoin` operator (with projection)



(n) The `pathJoin` operator (specified relationship)

(o) The `pathJoin` operator (specified relationship with projection)



(p) The `filterPath` operator

Figure 4: Example behavior of *G-SPARQL* algebraic operators.

Operator	Description	Relational
$\texttt{NgetAttVal}_{id,(attName):value}$	Retrieves the values of a specific attribute for a set of nodes	Yes
$\texttt{EgetAttVal}_{id,(attName):value}$	Retrieves the values of a specific attribute for a set of edges	Yes
$\texttt{getEdgeNodes}_{sID,(eLabel):eID,dID}$	Retrieves the set of adjacent nodes, optionally through a specific relation (edge label), for a set of graph nodes	Yes
$\texttt{strucPred}_{sID,(eLabel),(dNLabel):[eID]}$	Filters a set of nodes based on their connection to other nodes through a specific edge relation and optionally return the ID of the connecting edges.	Yes
$\texttt{edgeJoin}_{sID,dID,[(eLabel)]:[eID]}$	Checks if a pair of nodes is connected with an edge, optionally of a specified relationship, filters out the not connected pairs and optionally returns the ID of the connecting edges.	Yes
$\texttt{pathJoin}_{sID,dID,[(eLabel)]:[pID,pRel]}$	Checks if a pair of nodes is connected by a sequence of edges of any length, optionally with a specified relationship, filters out the not connected pairs and optionally returns the information of the connecting paths.	No
$\texttt{sPathJoin}_{sID,dID,[(eLabel)]:pID,pRel}$	Checks if a pair of nodes is connected by a sequence of edges of any length, optionally with a specified relationship, filters out the not connected pairs and returns the information of the *shortest* connecting path.	No
$\texttt{filterPath}_{pID,pRel,(cond)}$	Filters out the paths which do not fulfill a specified filtering condition	No

Table 1: *G-SPARQL* Algebraic Operators

attribute.

- The `getEdgeNodes` is a unary operator which is used for retrieving a set of adjacent nodes that are connected through a specified relation. The operator receives a set of tuples where the column (id) of the input relation identifies the graph nodes and the specified relation for accessing the adjacent nodes ($eLabel$). The schema of the output tuples extends the schema of the input tuples with the two columns that represent the identifiers of the connecting edge (eID) of the specified relation and the adjacent node (dID). The operator filters out the tuples where the nodes identified by the column (id) do not have adjacent nodes connected with the specified relation. Figure 4(d) illustrates an example of the `getEdgeNodes` operator where it retrieves the adjacent nodes through the relationship `know` of an input relation with the (id) of two graph vertices (`"John","Alice"`). The output relation filters out the `"Alice"` vertex as it is not connected to any other node through the `know` relationship. Figure 4(e) illustrates an example of the `getEdgeNodes` operator where it retrieves *all* the adjacent nodes for an input relation with the (id) of two graph vertices (`"John","Alice"`).
- The `strucPred` is another unary operator which is used for filtering a set of nodes based on a specified structural predicate. It receives a set of tuples where the column (sID) of the input relation identifies the graph nodes and a structural predicate which is described by the label of the connecting relation ($eLabel$) and the label for the adjacent node that should be accessed through this relation ($dNLabel$). Figure 4(f) illustrates an example of the `strucPred` operator where it applies a structural predicate which filters out the graph vertices that are not connected to an adjacent vertex with the label `Smith` through the `know` relationship. Figure 4(g) illustrates another example of the `strucPred` operator which projects the information of the connecting edges that represent the structural predicate. In this example, the schema of the output relation is extended with an additional column that stores the ID of the connecting edges (eID).
- The `edgeJoin` is a binary join operator which receives two relations (S and D) where the two columns (sID) and (dID) identify the graph nodes of S and D, respectively. The operator checks for each pair of nodes whether it is connected with any graph edge, filters out the not connected pairs and returns the tuples of the connected pairs as a result. The output of the operator is a single relation where the schema of the output tuples concatenates the columns of (S and D). Figure 4(h) illustrates an example of the `edgeJoin` operator where it receives two sets of graph vertices - (`"John"`,`"Alice"`,`"Smith"`) and (`"Microsoft"`)- and returns pairs of graph vertices that are connected through any relationship. The operator can receive an optional parameter which imposes a condition on the connecting edge between each pair of nodes to be representing a specified relationship label ($eLabel$). Figure 4(j) illustrates another example of the `edgeJoin` operator where it receives two sets of graph vertices - the same as Figure 4(h) - and returns pairs of graph vertices that are connected through an `affiliated` relationship. Moreover, the `edgeJoin` operator can optionally project the information of the connecting edge(s) where it extends the schema of the output relation by an additional column (eID) that represents the identifiers of the connecting edges between each pair of nodes in the output tuples according to the specified input parameters. Figures 4(i) and 4(k) illustrate another examples of the behavior of the `edgeJoin` operator which are similar to the examples shown in Figures 4(h) and 4(j), respectively, with only one difference that the output relations include the (ID) of the connecting edges between the output pair of vertices.
- The `pathJoin` operator is another binary join operator which receives two relations (S and D) where the two columns (sID) and (dID) identify the graph nodes of S and D, respectively. The operator checks for each pair of nodes whether it is connected by a sequence of edges (of any length), filters out the not connected pairs and returns the tuples of the connected pairs as a result. Figure 4(l) illustrates an example of the `pathJoin` operator where it receives two sets of graph vertices - (`"John"`,`"Alice"`,`"Smith"`) and (`"John"`,`"Alice"`,`"Smith"`)- and returns pairs of graph vertices that are connected through a sequence of relationships of any length. The operator can receive an optional parameter which imposes a condition on the edges of each connecting path between each pair of nodes to be representing a specified relationship label ($eLabel$). Figure 4(n) illustrates an example of the `pathJoin` operator where it receives two sets of graph vertices - the same as Figure 4(n) - and returns pairs of graph vertices that are connected through a sequence

of any length of `know` relationships. Moreover, the `pathJoin` operator can optionally project the information of the connecting path(s) as follows:

- It extends the schema of the input relation by an additional column (pID) that represents an assigned identifier for each connecting edge between each pair of nodes. It should be noted that each pair of nodes can be connected with multiple paths. Therefore, each input pair of nodes can have multiple representing tuples that describes the information of the bound paths.
- It returns another output relation ($pRel$) which describes the information of the resulting paths where each path is described by a sequence of tuples that represent the nodes and edges constituting the path in an orderly manner. In particular, the tuples are described by the following fields: (pID) represents the path identifier, ($type$) represents if the tuple describes a node (then it has a value $'N'$) or an edge (value $'E'$), ($order$) represents the order of the node/edge that participates in the path (the order of each path always start with an edge ordered as 1 followed by a node ordered as 2 and then it alternates till the last constituting edge of the path), (ID) represents the identifier of the node/edge in addition to its ($Label$) information. The value of a path variable in the query output is represented by a serialization of the ($Label$) information of its associated tuples in this relation according to their ascending ($order$).

Figures 4(m) and 4(o) illustrate another examples of the behavior of the `pathJoin` operator which are similar to the example of Figures 4(l) and 4(n), respectively, with the difference that they project the information of the resulting connecting paths. The `sPathJoin` operator work in the same way of the `pathJoin` operator with only one difference is that it returns a *single* path that represent the *shortest* connection between each pair of nodes (if exist a connection).

- The `filterPath` is a binary operator which receives two relations (R and $pRel$) where the column (pID) of the relation (R) represents the path identifiers that have their associated description information represented by the relation ($pRel$). The operator returns the relation (R) where the tuples which have paths (pID) with information ($pRel$) that do not fulfill the condition ($cond$) are filtered out. The ($cond$) parameter represents one of the path filtering conditions which we previously described in Section 2.2. Figure 4(p) illustrates an example of the `filterPath` operator which filters a set of paths based on a *length* condition (number of edges) which returns the paths with lengths greater than 1 and filters out the rest.

As indicated in Table 1, not all of our algebraic operators can be represented by the standard relational algebraic operators. Based on our relational representation of the attributed graphs, Figure 5 depicts the relational representations for those operators that can be compiled into a pattern of standard relational algebraic operators. For example, the `NgetAttVal` operator is mapped to a join operation between the column ($nodeID$) of the input relation (R) and the (ID) column of the relation that represents the specified node attribute ($attName$). The operator extends the schema of the input tuples ($R.*$) with the ($value$) column for the relation of the specified attribute ($attName$). Since the semantic of the operators `getEdgeNodes` and `edgeJoin` can be not restricted by a specified relationship ($eLabel$), compiling these operators using the standard relational operators requires joining the input relation(s) with each of the *relation* tables, separately, and then union all the results. To simplify, we have created a materialized view (`allEdges`) that represents such union of all *relation* tables. Figure 6 depicts the inference rules for the SQL translation templates of the algebraic operators. A sample interpretation of the inference rule TRANS-1 that represents the translation of the `NgetAttVal` operator is: Given the information that the relation (R) represents the SQL evaluation of the triple pattern t, the translation of the ($\texttt{NgetAttVal}_{nodeID,(attName):value}$) operator is defined using the following SQL code:

```
SELECT R.*, attName.Value FROM R, attName
WHERE R.nodeID = attName.ID;
```

In general, the design of our compilation procedure and our logical operators are independent of any specific disk or memory representation of the attributed graph. In addition, they are independent of the underlying query evaluation engine. Therefore, in a first compilation step, we decide for each query triple pattern a mapping onto algebraic operators. Figures 7 and 8 illustrate the inference rules for mapping the *G-SPARQL* query triple patterns into our algebraic operators. A sample interpretation of the inference rule OPMAP-1 is that it maps a query triple pattern `(?var, @attName, ?var2)` of query q into the algebraic operator ($\texttt{NgetAttVal}_{ID,(attName):value}$) where the variable `?var2` is bound to the column `value` (`Col(?var2)` $\equiv$ `value`) of the output relation from applying the `NgetAttVal` operator *given that* the mapping of the variable `?var` (`Map(?var)`) is bound to the column `ID` as a part of the input relation `R`. In these rules, `Triple(q)` refers to the set of triple patterns of a query `q`, `PathFilter(q)` refers to the set of path filters of a query `q` and `allEdges` (Rule OPMAP-8) refers to the materialized that represents a union of all relation tables. Figure 10 illustrates an example algebraic compilation for the following query:

```
SELECT ?L1 ?L2
WHERE {?X @label ?L1.     ?Y @label ?L2.
       ?X @age  ?age1.    ?Y @age  ?age2.
       ?X affiliated UNSW. ?X livesIn Sydney.
       ?Y ?E(affiliated) Microsoft.
       ?E @title "Researcher".
       ?X ??P  ?Y.
       FILTER(?age1 >= 40). FILTER(?age2 >= 40)}
```

During this compilation step, a set of query rewriting rules is applied in order to optimize the execution time of the query evaluation. Examples of these rewriting rules which are specific to our introduced constructs are represented in Figure 9. A sample interpretation of the inference rule REWRITE-1 is that it rewrites a triple pattern `(subject, ?*var, object)` of query q (`Triple(q)`) into the triple pattern `(subject, ??var, object)` given that the path variable (`?*var`) is not part of the output variable list of the query q (`outVarList(q)`). In addition, this compilation steps reorders the query triple patterns according to their *restrictiveness* (the more restrictive pattern has higher precedence) in order to optimize the join computations based on

$\texttt{NgetAttVal}_{nodeID,(attName):value} \Rightarrow \pi_{R.*,attName.value}(R \bowtie_{R.nodeID=attName.ID} attName)$
$\texttt{EgetAttVal}_{edgeID,(attName):value} \Rightarrow \pi_{R.*,attName.value}(R \bowtie_{R.edgeID=attName.ID} attName)$
$\texttt{getEdgeNodes}_{sID,(eLabel):eID,dID} \Rightarrow \pi_{R.*,eLabel.eID,eLabel.dID}(R \bowtie_{R.sID=eLabel.sID} eLabel)$
$\texttt{getEdgeNodes}_{sID:eID,dID} \Rightarrow \pi_{R.*,allEdges.eID,allEdges.dID}(R \bowtie_{R.sID=allEdges.sID} allEdges)$
$\texttt{strucPred}_{sID,(eL),(dNL)} \Rightarrow \sigma_{nodeLabel.Value=dNL}((R \bowtie_{R.sID=eL.SID} eL) \bowtie_{eL.dID=nodeLabel.ID} nodeLabel)$
$\texttt{strucPred}_{sID,(eL),(dNL):eID} \Rightarrow \pi_{R.*,eL.eID}(\sigma_{nodeLabel.Value=dNL}((R \bowtie_{R.sID=eL.SID} eL) \bowtie_{eL.dID=nodeLabel.ID} nodeLabel))$
$\texttt{edgeJoin}_{R.sID,S.dID} \Rightarrow \pi_{R.*,S.*}((R \bowtie_{R.sID=allEdges.SID} allEdges) \bowtie_{allEdges.dID=S.dID} S)$
$\texttt{edgeJoin}_{R.sID,S.dID:eID} \Rightarrow \pi_{R.*,S.*,allEdges.eID}((R \bowtie_{R.sID=allEdges.SID} allEdges) \bowtie_{allEdges.dID=S.dID} S)$
$\texttt{edgeJoin}_{R.sID,S.dID,(eLabel)} \Rightarrow \pi_{R.*,S.*}((R \bowtie_{R.sID=eLabel.SID} eLabel) \bowtie_{eLabel.dID=S.dID} S)$
$\texttt{edgeJoin}_{R.sID,S.dID,(eLabel):eID} \Rightarrow \pi_{R.*,S.*,eLabel.eID}((R \bowtie_{R.sID=eLabel.SID} eLabel) \bowtie_{eLabel.dID=S.dID} S)$

Figure 5: Relational Representation of *G-SPARQL* Algebraic Operators

the following rules. Let `tp1`, `tp2` $\in$ `Triple(q)` be two triple patterns of *G-SPARQL* query `q`.

- `tp1` is defined as less restrictive than `tp2` (`tp1` $\gg$ `tp2`) if `tp1` contains more number of path variables (`??` or `?*`) than `tp2`.
- `tp1` is defined as more restrictive than `tp2` (`tp1` $\ll$ `tp2`) if `tp1` contains less number of variables than `tp2`.
- `tp1` is defined as more restrictive than `tp2` (`tp1` $\ll$ `tp2`) if `tp1` contains the same number of variables than `tp2` and the number of filter expressions over the variables of `tp1` is more than the number of filter expressions over the variables of `tp2`.

The second compilation step is specific to our hybrid memory/disk representation of attributed graphs where we start by mapping the operators of the plan to their relational representation, when applicable (Figure 5), then we start optimizing the algebraic plans using a set of rules. These rules includes the traditional rules for relational algebraic optimization (e.g. pushing the selection operators down the plan) [17, 34] in addition to some rules that are specific to the context of our algebraic plans. In particular, the main strategy of our rules is to push the non-standard algebraic operators (with memory-based processing) above all the standard relational operators (that can be pushed inside the relational engine) in order to delay their execution (which is the most expensive due to its recursive nature) to be performed after executing all data access and *filtering* operations that are represented by the standard relational operators.

At the execution level, the basic strategy of our query processing mechanism is to push those parts of query processing that can be performed independently into the underlying RDBMS by issuing SQL statements [21]. In particular, our execution split mechanism makes use of the following two main heuristics:

- Relational databases are very efficient for executing queries that represent structural predicates or value-based predicates on the graph attributes (vertices or edges) due to its well-established powerful indexing mechanisms and its sophisticated query optimizers. In addition, relational databases are very efficient on finding the most efficient physical execution plan including considering different possible variants such as different join implementations and different join orderings.
- Relational databases are inefficient for executing queries with operators of a recursive nature (e.g. path patterns). Main memory algorithms are much faster for evaluating such types of operators which require heavy traversal operations over the graph topology.

As shown in Figure 10, our algebraic plans come in a DAG shape. Therefore, we perform the translation of these plans into SQL queries by traversing the algebraic plan in a

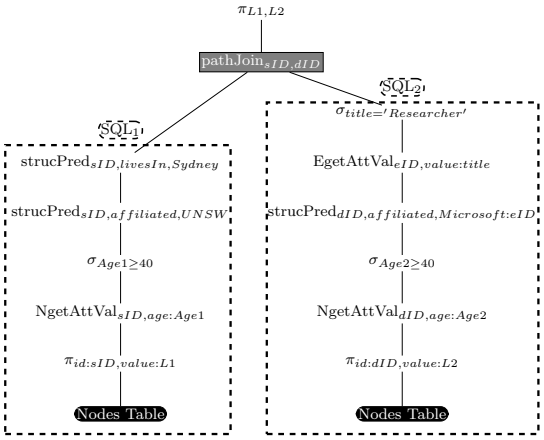


Figure 10: An example DAG plan for G-SPARQL.

bottom-up fashion (starting from the leaves and then climb the different paths back to the root) using a set of defined pattern-based translation rules [20]. This climbing process for each path stops if it hits one of the operators that does not have a standard relational representation for its semantics or if it reaches the root. Each generated SQL query is tempting to simply then rely on the underlying relational backends for the physical optimization and processing. For example, in Figure 10, all operators can be translated into standard relational operators except of the `pathJoin` operator (filled with gray color). In this example, as indicated by dashed rectangles in the figure, two SQL queries are generated (SQL_1 and SQL_2) where the results of these queries (Figure 11) are then passed for further memory-based processing using the `pathJoin` operator and the following operators in the plan.

The main implementation of our query evaluation engine relies on index-free main memory algorithms for evaluating reachability and shortest path operators [14]. However, our algebraic compilation approach remains agnostic to the physical execution of its logical operator and can make use of any available indexing information for accelerating the query evaluation process of the different types of queries taking into consideration the trade-off of building and maintaining their indices in addition to their main memory consumption. For example, we rely on BFS to implement the evaluation of reachability. However, we can make use of any indexing information (such as the 2-hop cover or the 3-hop cover) to accelerate the physical execution of the logical operator. Similarly, we rely on the Dijkstra algorithm to implement the shortest path operator. However, other indexings method can be utilized as well.

$$\frac{SQL(t) : R}{\left(\begin{array}{l}\texttt{SQL(NgetAttVal}_{nodeID,(attName):value}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, attName.Value FROM R, attName WHERE R.nodeID = attName.ID;}\end{array}\right)} \text{(TRANS-1)}$$

$$\frac{SQL(t) : R}{\left(\begin{array}{l}\texttt{SQL(EgetAttVal}_{edgeID,(attName):value}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, attName.Value FROM R, attName WHERE R.edgeID = attName.ID;}\end{array}\right)} \text{(TRANS-2)}$$

$$\frac{SQL(t) : R}{\left(\begin{array}{l}\texttt{SQL(getEdgeNodes}_{sID,(eLabel):eID,dID}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, eLabel.eID, eLabel.dID FROM R, eLabel} \\ \texttt{WHERE R.edgeID = eLabel.SID;}\end{array}\right)} \text{(TRANS-3)}$$

$$\frac{SQL(t) : R}{\left(\begin{array}{l}\texttt{SQL(getEdgeNodes}_{sID:eID,dID}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, allEdges.eID, allEdges.dID FROM R, allEdges} \\ \texttt{WHERE R.edgeID = allEdges.SID;}\end{array}\right)} \text{(TRANS-4)}$$

$$\frac{SQL(t) : R}{\left(\begin{array}{l}\texttt{SQL(strucPred}_{sID,(eLabel),(dNLabel)}\texttt{)} \Rightarrow \\ \texttt{SELECT R.* FROM R, eLabel, NodeLabel} \\ \texttt{WHERE R.sID = eLabel.sID AND eLabel.dID = dNLabel.ID} \\ \texttt{AND NodeLabel.Value = 'dNLabel';}\end{array}\right)} \text{(TRANS-5)}$$

$$\frac{SQL(t) : R}{\left(\begin{array}{l}\texttt{SQL(strucPred}_{sID,(eLabel),(dNLabel):eID}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, eLabel.eID FROM R, eLabel, NodeLabel} \\ \texttt{WHERE R.sID = eLabel.sID AND eLabel.dID = dNLabel.ID} \\ \texttt{AND NodeLabel.Value = 'dNLabel';}\end{array}\right)} \text{(TRANS-6)}$$

$$\frac{SQL(t_1) : R \qquad SQL(t_2) : S}{\left(\begin{array}{l}\texttt{SQL(edgeJoin}_{R.sID,S.dID}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, S.* FROM R, S, allEdges} \\ \texttt{WHERE R.sID = allEdges.sID AND allEdges.dID = S.dID;}\end{array}\right)} \text{(TRANS-7)}$$

$$\frac{SQL(t_1) : R \qquad SQL(t_2) : S}{\left(\begin{array}{l}\texttt{SQL(edgeJoin}_{R.sID,S.dID:eID}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, S.*, eLabel.eID FROM R, S, allEdges} \\ \texttt{WHERE R.sID = allEdges.sID AND allEdges.dID = S.dID;}\end{array}\right)} \text{(TRANS-8)}$$

$$\frac{SQL(t_1) : R \qquad SQL(t_2) : S}{\left(\begin{array}{l}\texttt{SQL(edgeRJoin}_{R.sID,S.dID,(eLabel)}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, S.* FROM R, S, eLabel} \\ \texttt{WHERE R.sID = eLabel.sID AND eLabel.dID = S.dID;}\end{array}\right)} \text{(TRANS-9)}$$

$$\frac{SQL(t_1) : R \qquad SQL(t_2) : S}{\left(\begin{array}{l}\texttt{SQL(edgeRJoin}_{R.sID,S.dID,(eLabel):eID}\texttt{)} \Rightarrow \\ \texttt{SELECT R.*, S.*, eLabel.eID FROM R, S, eLabel} \\ \texttt{WHERE R.sID = eLabel.sID AND eLabel.dID = S.dID;}\end{array}\right)} \text{(TRANS-10)}$$

Figure 6: SQL Translations of Algebraic Operators.

$$\frac{\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{ID}}{\texttt{(?var, @attName, ?var2)} \Rightarrow \begin{array}{l} \texttt{NgetAttVal}_{ID,(attName):value}\texttt{(R)} \\ \texttt{Col(?var2)} \equiv \texttt{value} \end{array}} \text{ (OpMap-1)}$$

$$\frac{\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{ID}}{\texttt{(?var, @attName, 'attValue')} \Rightarrow \pi_{ID}(\sigma_{value='attValue'}(\texttt{NgetAttVal}_{ID,(attName):value}\texttt{(R)}))} \text{ (OpMap-2)}$$

$$\frac{\begin{array}{c}\texttt{(subject, ?E(predicate), object)} \in \texttt{Triple(q)} \\ \texttt{Map(?E)} \in \texttt{R} \quad \texttt{Col(?E)} \equiv \texttt{ID}\end{array}}{\texttt{(?E, @attName, ?var)} \Rightarrow \begin{array}{l} \texttt{EgetAttVal}_{ID,(attName):value}\texttt{(R)} \\ \texttt{Col(?var)} \equiv \texttt{value} \end{array}} \text{ (OpMap-3)}$$

$$\frac{\begin{array}{c}\texttt{(subject, ?E(predicate), object)} \in \texttt{Triple(q)} \\ \texttt{Map(?E)} \in \texttt{R} \quad \texttt{Col(?E)} \equiv \texttt{ID}\end{array}}{\texttt{(?E, @attName, 'attValue')} \Rightarrow \pi_{ID}(\sigma_{value='attValue'}(\texttt{EgetAttVal}_{ID,(attName):value}\texttt{(R)}))} \text{ (OpMap-4)}$$

$$\frac{\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID}}{\texttt{(?var, eLabel, dNLabel)} \Rightarrow \texttt{strucPred}_{sID,(eLabel),(dNLabel)}\texttt{(R)}} \text{ (OpMap-5)}$$

$$\frac{\begin{array}{c}\texttt{(?E, predicate, object)} \in \texttt{Triple(q)} \\ \texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID}\end{array}}{\texttt{(?var, ?E(eLabel), dNLabel)} \Rightarrow \begin{array}{l} \texttt{strucPred}_{sID,(eLabel),(dNLabel):eID}\texttt{(R)} \\ \texttt{Col(?E)} \equiv \texttt{eID} \end{array}} \text{ (OpMap-6)}$$

$$\frac{\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID}}{\texttt{(?var, eLabel, ?var2)} \Rightarrow \begin{array}{l} \texttt{getEdgeNodes}_{sID,(eLabel):eID,dID}\texttt{(R)} \\ \texttt{Col(eLabel.eID)} \equiv \texttt{eID} \quad \texttt{Col(?var2)} \equiv \texttt{dID} \end{array}} \text{ (OpMap-7)}$$

$$\frac{\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID}}{\texttt{(?var, eLabel, ?var2)} \Rightarrow \begin{array}{l} \texttt{getEdgeNodes}_{sID,:eID,dID}\texttt{(R)} \\ \texttt{Col(allEdges.eID)} \equiv \texttt{eID} \quad \texttt{Col(?var2)} \equiv \texttt{dID} \end{array}} \text{ (OpMap-8)}$$

$$\frac{\begin{array}{c}\texttt{(?E, predicate, object)} \in \texttt{Triple(q)} \\ \texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID}\end{array}}{\texttt{(?var, ?E(eLabel), ?var2)} \Rightarrow \begin{array}{l} \texttt{(R) edgeJoin}_{sID,dID,(eLabel):eID}\texttt{ (S)} \\ \texttt{Col(?E)} \equiv \texttt{eID} \end{array}} \text{ (OpMap-9)}$$

$$\frac{\begin{array}{c}\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID}\end{array}}{\texttt{(?var, eLabel, ?var2)} \Rightarrow \texttt{(R) edgeJoin}_{sID,dID,(eLabel)}\texttt{ (S)}} \text{ (OpMap-10)}$$

$$\frac{\begin{array}{c}\texttt{(?E, predicate, object)} \in \texttt{Triple(q)} \\ \texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID}\end{array}}{\texttt{(?var, ?E, ?var2)} \Rightarrow \begin{array}{l} \texttt{(R) edgeJoin}_{sID,dID:eID}\texttt{ (S)} \\ \texttt{Col(?E)} \equiv \texttt{eID} \end{array}} \text{ (OpMap-11)}$$

$$\frac{\begin{array}{c}\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID}\end{array}}{\texttt{(?var, ?E, ?var2)} \Rightarrow \texttt{(R) edgeJoin}_{sID,dID}\texttt{ (S)}} \text{ (OpMap-12)}$$

$$\frac{\begin{array}{c}\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID} \\ \texttt{FilterPath(??P)} \in \texttt{PathFilter(q)}\end{array}}{\texttt{(?var, ??P, ?var2)} \Rightarrow \begin{array}{l} \texttt{(R) pathJoin}_{sID,dID:pID,pRel}\texttt{ (S)} \\ \texttt{Col(??P)} \equiv \texttt{pID} \\ \texttt{Schema(pRel) = (pID, type, order, ID, Label)} \end{array}} \text{ (OpMap-13)}$$

Figure 7: G-SPARQL Operator Mapping Rules (1).

$$\frac{\begin{array}{l}\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID} \\ \texttt{FilterPath(??P)} \in \texttt{PathFilter(q)}\end{array}}{\begin{array}{l}\texttt{(?var, ??P(eLabel), ?var2)} \Rightarrow \quad \texttt{(R) pathJoin}_{sID,dID,(eLabel):pID,pRel}\ \texttt{(S)} \\ \qquad\qquad\qquad\qquad\quad \texttt{Col(??P)} \equiv \texttt{pID} \\ \qquad\qquad\qquad\qquad\quad \texttt{Schema(pRel) = (pID, type, order, ID, Label)}\end{array}} \text{ (OpMap-14)}$$

$$\frac{\begin{array}{l}\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID}\end{array}}{\texttt{(?var, ??P, ?var2)} \Rightarrow \quad \texttt{(R) pathJoin}_{sID,dID}\ \texttt{(S)}} \text{ (OpMap-15)}$$

$$\frac{\begin{array}{l}\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID}\end{array}}{\texttt{(?var, ??P(eLabel), ?var2)} \Rightarrow \quad \texttt{(R) pathJoin}_{sID,dID,(eLabel)}\ \texttt{(S)}} \text{ (OpMap-16)}$$

$$\frac{\begin{array}{l}\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID} \\ \texttt{FilterPath(?*P)} \in \texttt{PathFilter(q)}\end{array}}{\begin{array}{l}\texttt{(?var, ?*P, ?var2)} \Rightarrow \quad \texttt{(R) sPathJoin}_{sID,dID:pID,pRel}\ \texttt{(S)} \\ \qquad\qquad\qquad\qquad\quad \texttt{Col(?*P)} \equiv \texttt{pID} \\ \qquad\qquad\qquad\qquad\quad \texttt{Schema(pRel) = (pID, type, order, ID, Label)}\end{array}} \text{ (OpMap-17)}$$

$$\frac{\begin{array}{l}\texttt{Map(?var)} \in \texttt{R} \quad \texttt{Col(?var)} \equiv \texttt{sID} \\ \texttt{Map(?var2)} \in \texttt{S} \quad \texttt{Col(?var2)} \equiv \texttt{dID} \\ \texttt{FilterPath(?*P)} \in \texttt{PathFilter(q)}\end{array}}{\begin{array}{l}\texttt{(?var, ?*P(eLabel), ?var2)} \Rightarrow \quad \texttt{(R) sPathJoin}_{sID,dID,(eLabel):pID,pRel}\ \texttt{(S)} \\ \qquad\qquad\qquad\qquad\quad \texttt{Col(?*P)} \equiv \texttt{pID} \\ \qquad\qquad\qquad\qquad\quad \texttt{Schema(pRel) = (pID, type, order, ID, Label)}\end{array}} \text{ (OpMap-18)}$$

Figure 8: G-SPARQL Operator Mapping Rules (2).

$$\frac{\begin{array}{c}\texttt{(subject, ?*var, object)} \in \texttt{Triple(q)} \\ \texttt{?*var} \ni \texttt{outVarList(q)}\end{array}}{\texttt{(subject, ?*var, object)} \Rightarrow \texttt{(subject, ??var, object)}} \text{ (Rewrite-1)}$$

$$\frac{\begin{array}{c}\texttt{(subject, ?*var(Predicate), object)} \in \texttt{Triple(q)} \\ \texttt{?*var} \ni \texttt{outVarList(q)}\end{array}}{\texttt{(subject, ?*var(Predicate), object)} \Rightarrow \texttt{(subject, ??var(Predicate), object)}} \text{ (Rewrite-2)}$$

$$\frac{\begin{array}{c}\texttt{(subject, ?var(Predicate), object)} \in \texttt{Triple(q)} \\ \texttt{?var} \ni \texttt{outVarList(q)} \\ \texttt{(?var, @literal, literal)} \ni \texttt{Triple(q)} \\ \texttt{(?var, @literal, ?var2)} \ni \texttt{Triple(q)}\end{array}}{\texttt{(subject, ?var(Predicate), object)} \Rightarrow \texttt{(subject, Predicate, object)}} \text{ (Rewrite-3)}$$

$$\frac{\begin{array}{c}\texttt{(subject, ?*var, object)} \in \texttt{Triple(q)} \\ \texttt{(Length(?*var, =1))} \in \texttt{PathPredicate(q)}\end{array}}{\texttt{(subject, ?*var, object)} \Rightarrow \texttt{(subject, ?var, object)}} \text{ (Rewrite-4)}$$

$$\frac{\begin{array}{c}\texttt{(subject, ?*var(Predicate), object)} \in \texttt{Triple(q)} \\ \texttt{(Length(?*var, =1))} \in \texttt{PathPredicate(q)}\end{array}}{\texttt{(subject, ?*var(Predicate), object)} \Rightarrow \texttt{(subject, ?var(Predicate), object)}} \text{ (Rewrite-5)}$$

$$\frac{\begin{array}{c}\texttt{(subject, ??var, object)} \in \texttt{Triple(q)} \\ \texttt{(Length(??var, =1))} \in \texttt{PathPredicate(q)}\end{array}}{\texttt{(subject, ??var, object)} \Rightarrow \texttt{(subject, ?var, object)}} \text{ (Rewrite-6)}$$

$$\frac{\begin{array}{c}\texttt{(subject, ??var(Predicate), object)} \in \texttt{Triple(q)} \\ \texttt{(Length(??var, =1))} \in \texttt{PathPredicate(q)}\end{array}}{\texttt{(subject, ??var(Predicate), object)} \Rightarrow \texttt{(subject, ?var(Predicate), object)}} \text{ (Rewrite-7)}$$

Figure 9: G-*SPARQL* Query Rewriting Rules.

```
SQL1: SELECT N1.ID as sID, N1.Value as L1
FROM NodeLabel as N1, age, affiliated, livesIn,
NodeLabel as N2, NodeLabel as N3
WHERE N1.ID = age.ID AND N1.ID = affiliated.sID AND
affiliated.dID = N2.ID AND N2.value ="UNSW" AND N1.ID
= livesIn.sID AND livesIn.dID = N3.ID and N3.Value =
"Sydney" AND age.Value >= 40;

SQL2: SELECT N1.ID as dID, N1.Value as L2
FROM NodeLabel as N1, age, title, affiliated, NodeLabel
as N2
WHERE N1.ID = age.ID AND N1.ID = affiliated.sID AND
affiliated.dID = N2.ID AND N2.value ="Microsoft" AND
affiliated.eID= title.ID AND title.Value = "Researcher"
AND age.Value >= 40;
```

Figure 11: SQL Translations of an example DAG plan shown in Figure 10.

	Vertices	Edges	Attribute Values	Topology Information
Small	126,137	297,960	610,302	9%
Medium	242,074	761,558	1,687,465	11%
Large	825,433	3,680,156	7,336,899	12%

Table 2: Characteristics of real datasets

5. PERFORMANCE EVALUATION

We implemented a native pointer-based memory representation of the graph topology in addition to the Dijkstra and BFS algorithms (with slightly different variants that can represent each of our non-relational algebraic operators (Table 1)) using C++. We used IBM DB2 RDBMS for storage, indexing and performing all SQL queries. In order to measure the relative effectiveness of our query split execution mechanism, we compared the performance results of our approach with the performance of the native graph database system, Neo4j (version 1.5 GA). Neo4j is an open source project which is recognized as one of the foremost graph database systems. According to the Neo4j website, "*Neo4j is a disk-based, native storage manager completely optimized for storing graph structures for maximum performance and scalability*". It has an API that is easy to use and provides powerful traversal framework that can implement all queries which can be expressed by *G-SPARQL*. Neo4j uses Apache Lucene for indexing the graph attributes. We conducted our experiments on a PC with 3.2 GHz Intel Xeon processors, 8 GB of main memory storage and 500 GB of SCSI secondary storage.

5.1 Results on Real Dataset

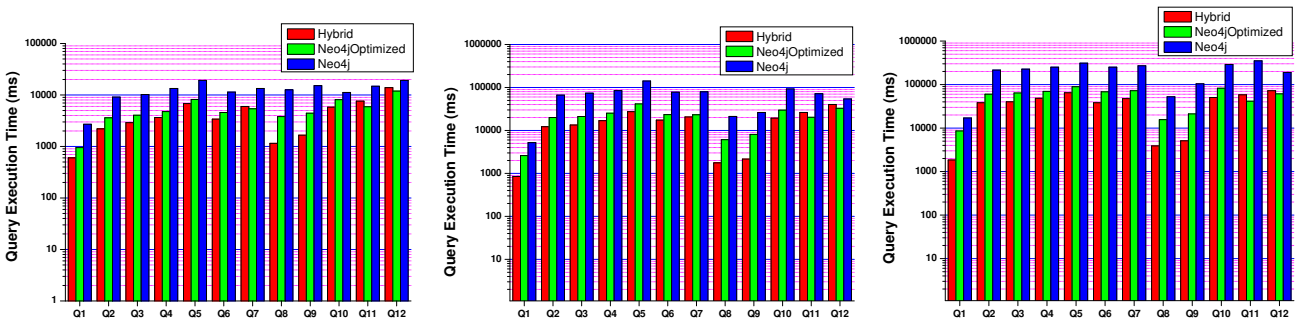
Dataset: We used the ACM digital library dataset (which includes the information of all ACM publications till September 2011) to construct the attributed graph. The graph vertices represent 8 different types of entities (*author*, *article*, *series*, *conference*, *proceedings*, *journal*, *issue* and *publisher*). The original data describes 12 different types of relationships between the graph entities (e.g. *authorOf*, *editorOf*, *publishedBy*, *citedBy*, *partOfIsuue*, *partOfProceedings*). In addition, we have created the *co-author* relationships (edges) between any two *author* nodes which are sharing the authorship of at least one paper. Each created edge is described by a *noPapers* attribute that represents the number of joint papers between the connected authors. The original dataset has a total of 76 unique attributes, of which 62 attributes are describing the graph vertices and 14 attributes are describing the graph edges. In addition, for each author, we created a *prolific* attribute where authors with more than 25 papers are labeled as highly prolific. In addition, for each *citedBy* edge, we created a *source* attribute which is labeled as an external citation if there is an empty intersection between the author lists of the two connected papers. In our experiments, we used three different sizes of graph subsets (small, medium and large) in order to test the scalability of our approach. The *small* subset represents all journal and magazine publications, the *medium* subset adds the newsletter and transaction publications while the *large* subset adds the conference proceedings. Table 2 lists the characteristics of the three sets. On average, the graph topology information that needs to be loaded onto the main memory represents 10% of the whole graph information (topology + values of attributes of graph nodes and edges) while the remaining 90% resides in the underlying relational database.

Query Workload: Our query workload consists of 12 query templates (Figure 12) where we used random literal values to generate different query instances. The queries are designed to cover the different types of the triple patterns that are supported by *G-SPARQL*. The algebraic plans of the query templates are described in the Appendix section of this article. As we previously described, the efficiency of execution for any graph query using Neo4j is programmer-dependent and each query template can have different ways of implementations using Neo4j APIs. The execution times of these implementations can dramatically vary. In our experiments, for each query template, we created two associated Neo4j implementations. The first implementation is an optimized version that considers a pre-known knowledge about the result size of each query step (triple pattern) while the second version is a non-optimized one that does not consider this knowledge. Each query template is instantiated 20 times where the data values are generated randomly. Each instance is executed 5 times and execution times were collected. All times are in milliseconds. In order to to ensure that any caching or system process activity would not affect the collected results, the longest and shortest times for each query instance were dropped and the remaining three times were averaged.

Query Evaluation Times: The average query evaluation times for the 20 instances of each of the 12 query templates are shown in Figure 13 for the small (Figure 14(a)), medium (Figure 14(b)) and large (Figure 14(c)) sized experimental graphs. As has been well recognized in conventional query processing, a good query plan is a crucial factor in improving the query performance by orders of magnitude. The results of the experiments show that our approach is on average 3 times faster than the Neo4j non-optimized implementations of the query workload on the small subset of the experimental graph, 4 times faster on the medium subset of the experimental graph and 5 times faster on the large subset of the experimental graph. In particular, our approach outperforms the Neo4j non-optimized implementations in each of the defined query templates. In native graph database systems, such as Neo4j, users are required to implement their graph queries using the available system APIs. The implementation process, in fact, defines a specific query plan. Therefore, when users have sufficient knowledge about the characteristics of the underlying graph and query optimization rules they can define very efficient query plans. The results of the experiments show that the average

Q1	**Pattern Matching** *Find the names of two authors who are highly prolific, affiliated at "affiliation 1" and "affiliation 2" respectively, and jointly co-authored more than two papers.* `SELECT ?Name1 ?Name2 WHERE {?X @name ?Name1. ?Y @name ?Name2. ?X @prolific "High". ?Y @prolific "High". ?X @affilation "%affiliation1%". ?Y @affilation "%affiliation2%". ?X ?E(co-author) ?Y. ?E @noPapers ?NO. FILTER (?NO >= 2).}`
Q2	**Pattern Matching + Reachability** *Find the names of two authors who are highly prolific, affiliated at "affiliation 1" and "affiliation 2" respectively, and are connected by a path of any length where all edges of the path represent the co-author relationship.* `SELECT ?Name1 ?Name2 WHERE {?X @name ?Name1. ?Y @name ?Name2. ?X @prolific "High". ?Y @prolific "High". ?X @affilation "%affiliation1%". ?Y @affilation "%affiliation2%". ?X co-author+ ?Y.}`
Q3	**Pattern Matching + Reachability (With Projection)** *Find the names of two authors and the connecting path between them where the two authors are highly prolific, affiliated at "affiliation 1" and "affiliation 2" respectively. The connecting path can be of any length where all edges of the path represent the co-author relationship.* `SELECT ?Name1 ?Name2 ??P WHERE {?X @name ?Name1. ?Y @name ?Name2. ?X @prolific "High". ?Y @prolific "High". ?X @affilation "%affiliation1%". ?Y @affilation "%affiliation2%". ?X ??P(co-author+) ?Y.}`
Q4	**Pattern Matching + Shortest Path (With Projection)** *Find the names of two authors and the shortest connecting path between them where the two authors are highly prolific, affiliated at "affiliation 1" and "affiliation 2 "respectively. The connecting path can be of any length where all edges of the path represent the co-author relationship.* `SELECT ?Name1 ?Name2 ?*P WHERE {X @name ?Name1. Y @name ?Name2. ?X @prolific "High". ?Y @prolific "High". X @affilation "%affiliation1%". Y @affilation "%affiliation2%". ?X ?*P(co-author+) ?Y.}`
Q5	**Pattern Matching + Reachability (With Projection)** *Find the names of two authors and the connecting path between them where the authors are highly prolific, affiliated at "affiliation 1" and "affiliation 2" respectively. The connecting path can be of any length where each edge can represent any relationship.* `SELECT ?Name1 ?Name2 ??P WHERE {X @name ?Name1. Y @name ?Name2. ?X @prolific "High". ?Y @prolific "High". X @affilation "%affiliation1%". Y @affilation "%affiliation2%". ?X ??P ?Y.}`
Q6	**Pattern Matching + Reachability (With Projection) + Path Filtering** *Find the names of two authors and the connecting path between them where the authors are highly prolific, affiliated at "affiliation 1" and "affiliation 2" respectively. The connecting path length can not be of more than 3 edges where each edge of the path represent the co-author relationship.* `SELECT ?Name1 ?Name2 ??P WHERE {?X @name ?Name1. ?Y @name ?Name2. ?X @prolific "High". ?Y @prolific "High". ?X @affilation "%affiliation1%". ?Y @affilation "%affiliation2%". ?X ??P(co-author+) ?Y. FilterPath(Length(??P, <= 3)).}`
Q7	**Pattern Matching + Reachability (With Projection) + Path Filtering** *Find the names of two authors and the path between them where the authors are highly prolific, affiliated at "affiliation 1" and "affiliation 2" respectively. The connecting path length can not be of more than 3 edges where each edge of the path represent the co-author relationship.* `SELECT ?Name1 ?Name2 ??P WHERE {?X @name ?Name1. ?Y @name ?Name2. ?X @prolific "High". ?Y @prolific "High". ?X @affilation "%affiliation1%". ?Y @affilation "%affiliation2%". ?X ??P(co-author+) ?Y. FilterPath(AllNodes(??P, @prolific "High")).}`
Q8	**Pattern Matching** *Find the name of an author, the title of a paper, the year of an issue where the author is the first author of the paper and is highly prolific, the paper has a keyword "keyword" and is part of a journal issue which has a code equals to "code".* `SELECT ?Name ?Title ?Year WHERE {?X @name ?Name. ?X @prolific "High". ?X ?E(authorOf) ?Paper. ?E @seqNo 1. ?Paper @title ?Title. ?Paper @keyword "%keyword%". ?Paper partOf ?Issue. ?Issue @year ?Year. ?Issue issueOf ?Journal. ?Journal @code "%code%".}`
Q9	**Pattern Matching** *Find the title of a paper (P) and the name of three highly prolific authors (AU1, AU2, AU3) where the paper (P) is cited by three papers (P1, P2, P3) such that: P1 is authored by AU1, P2 is authored by AU2 and P3 is authored by AU3.* `SELECT ?Title ?Name1 ?Name2 ?Name3 WHERE {?P @title Title. ?P @keyword "%keyword%". ?P citedBy ?P1. ?P citedBy ?P2. ?P citedBy ?P3. Au1 authorOf ?P1. ?Au2 authorOf ?P2. ?Au3 authorOf ?P3. ?AU1 @prolific "High". ?AU2 @prolific "High". ?AU3 @prolific "High". ?Au1 @name ?Name1. ?Au2 @name ?Name2. ?Au3 @name ?Name3.}`
Q10	**Pattern Matching + Reachability + Path Filtering** *Find the titles of two papers, Paper1 and Paper2, where both of the papers are described by the keyword "keyword", Paper1 is authored by "name" and Paper1 is connected to Paper2 with a path of length which is less than or equal 2 edges where each edge represents the citedBy relationship.* `SELECT ?T1 ?T2 WHERE {?X @name ="%name%". ?X authorOf ?Paper1. ?Paper1 @Title ?T1. ?Paper2 @Title ?T2. ?Paper1 @Keyword "%keyword%". ?Paper2 @Keyword "%keyword%". ?Paper1 ??P(citedBy+) ?Paper2. FilterPath(Length(??P, <= 2)).}`
Q11	**Pattern Matching + Reachability + Path Filtering** *Find the titles of two papers, Paper1 and Paper2, where both of the paper are described by the keyword "keyword", Paper1 is authored by "name" and Paper1 is connected to Paper2 with a path of length which is less than or equal 4 edges where each edge represents the citedBy relationship of an external source of citation.* `SELECT ?T1 ?T2 WHERE {?X @name ="%name%". ?X authorOf ?Paper1. ?Paper1 @Title ?T1. ?Paper2 @Title ?T2. ?Paper1 @Keyword "%keyword%". ?Paper2 @Keyword "%keyword%". ?Paper1 ??P(citedBy+) ?Paper2. FilterPath(Length(??P, <= 4)). FilterPath(AllEdges(??P, @source "External")).}`
Q12	**Pattern Matching + Reachability + Path Filtering** *Find the name of an author who is connected to two authors with names "name1" and "name2" where the connecting path with each of two authors is of length which is less than or equal two edges that are representing the co-author relationship. In addition, all the co-author edges of the connecting path with the author "name1" are described by a "@noPapers" attribute with a value which is greater than 2.* `SELECT ?Name WHERE {?X @name ?Name. ?Y @name "%name1%". ?Z @name "%name2%". ?X ??E1(co-author+) ?Y. ?X ??E2(co-author+) ?Z. FilterPath(Length(??E1, <= 2)). FilterPath(Length(??E2, <= 2)). FilterPath(AllEdges(??E1, @noPapers >2)).}`

Figure 12: Query templates of our experimental workload.



(a) Small Graph Size (b) Medium Graph Size (c) Large Graph Size

Figure 13: Average query evaluation times of real datasets

query evaluation times of our approach is %17 faster than the Neo4j optimized implementations on the small subset of the experimental graph, 22% faster on the medium subset and 28% faster on the large experimental graph. The Neo4j optimized implementations outperforms our approach in 2 of the 12 query templates (`Q11` and `Q12`) while our approach performs better in the rest of the queries. In general, the well-known maturity of the indexing and built-in optimization techniques of physical query evaluation (e.g. join algorithms) provided by the underlying RDBMs play the main role of outperforming Neo4j optimized implementations. For example, the performance of relational partitioned B-tree indices outperforms the performance of the indexing service of Neo4j that uses Lucene[6] which is more optimized for full-text indexing rather than traditional data retrieval queries.

To better understand the reasons for the differences in performance between our approach and optimized Neo4j implementations, we look at the performance differences for each query. `Q1`, `Q8` and `Q9` are pattern matching queries where, in our approach, the whole of their executions can be pushed inside the underlying RDBMS. In particular, `Q1` seeks for a pattern of two vertices (`authors`) which are connected by a `co-author` relationship. The query involves 5 value-based predicates where each of the two queried vertices are filtered based on the 2 value-based predicates on the `affiliation` and `prolific` attributes and the connecting edges are filtered based on a value-based predicate on their `noPapers` attribute. `Q8` specifies a *path pattern* that consists of 4 vertices (`author`, `paper`, `issue`, `Journal`) that are connected by 3 relationships (`authorOf`, `partOf`, `issueOf`) respectively. The query involves 4 value-based predicates on the `prolific` attribute of the `author` vertex, the `keyword` attribute of the `paper` vertex, the `code` attribute of the `journal` vertex and the `seqNo` attribute of the `authorOf` relationship. `Q9` represents a *star pattern* that seeks for `paper` vertices which are filtered based on a specific `keyword` and cited by 3 `papers` where each `paper` has an `author` which is `prolific`. Relational engine has shown to be more efficient than Neo4j as a native graph engine in performing such pattern matching queries that purely relies on the efficiency of the underlying physical execution properties of the engine, mainly physical indices and join algorithms, and do not involve any recursive operations. The scalability feature of the relational database engine is also shown by the increasing percentage of improvement for these queries over Neo4j with the increasing size of the underlying graph size. For example, for `Q8`, the relational execution is 3.3 times faster than the optimized Neo4j execution for the small subset of the experimental graph graph while it is 4.2 times faster on the large subset of the experimental graph.

`Q2`, `Q3`, `Q4`, `Q5`, `Q6` and `Q7` are queries that involve recursive join operations between two filtered set of vertices. In particular, all of these queries are seeking for two sets of authors where each set is filtered based on the `prolific` and `affiliation` attributes. `Q2` verifies for each pair of vertices (one from each filtered set) whether they are connected by a sequence of edges of any length where all edges of the connecting path represent the `co-author` relationship. Assuming the numbers of vertices in the first and second sets are equal to M and N respectively, then the number of verification operations (represented by the `pathJoin` operator) equals $M * N$. `Q3` is similar to `Q2` but it returns additional information about the connecting paths between each pair of vertices ($\texttt{pathJoin}_{sID,dID,co-author:eID}$). That is why `Q3` is slightly more expensive than `Q2`. `Q4` is again similar to `Q3`. However, it only returns the information of the *shortest path* between each pair of vertices ($\texttt{sPathJoin}_{sID,dID,co-author:eID}$). Evaluating the *shortest path* over the graph topology is also slightly more expensive than the general reachability verification (`Q2` and `Q3`). `Q5` represents a more expensive variant of `Q2` that generalizes the reachability verification test for each pair of vertices so that they can be connected by a sequence of edges of any length where each edge in the connecting path can represent any relationship ($\texttt{pathJoin}_{sID,dID:eID}$). Obviously, allowing the edges of the resulting connecting paths to be representing any relationship increases the number of visited and verified paths and consequently the number of traversing operations over the graph topology. `Q6` and `Q7` extend `Q3` by adding filtering conditions on the connecting paths between each pair of vertices (the `filterPath` operator). In particular, `Q6` filters out the paths with more than 3 edges. `Q7` verifies that the `author` vertices for each of the resulting paths between each pair of vertices are highly `prolific`. Our hybrid approach outperforms the optimized Neo4j implementations for all of these queries by splitting the execution of the query plans between the underlying relational engine and the available topology information in the main memory. In particular, it leverages the efficiency of the relational engine for retrieving each set of vertices, utilizes memory-based topology information for fast execution of the

[6]http://lucene.apache.org/

required traversal operations and avoids loading/accessing unnecessary information that are not involved in evaluated queries.

In our approach, the execution of the path filtering condition of `Q7` is an expensive operation as it can be only applied in a post-processing step after determining all the connecting paths between each pair of vertices. This post-processing step needs to issue an SQL statement that retrieves the values of the `prolific` attributes for all nodes of the connecting paths as they are not available in the topology information which are loaded onto the main memory and then filters out all paths that contains any node that does not satisfy the filtering condition over the retrieved attribute values. This SQL statement can be depicted as follows:

```
SELECT Value FROM prolific WHERE id IN
([list of node identifiers that are members of the
connecting paths]);.
```

On the contrary, the cost of the post-processing execution of the path filtering condition of `Q6` (based on path length) is rather cheap as it does not need to retrieve any data from the underlying database during the memory-based processing.

`Q10` and `Q11` are another two queries that involve recursive join operations between two filtered set of vertices. In particular, `Q10` is seeking for two sets of papers where both sets are filtered based on the same value-based predicate on the `keyword` attribute and one of the sets is further filtered to only those papers that are authored by a specific author. `Q10` verifies for each pair of vertices whether they are connected by a path with a length that is less than or equal to 4 edges where all edges represent the `citedBy` relationship. `Q11` extends `Q10` by further filtering the connecting paths to only those paths where all of their edges are described as `external` on their `source` attribute. While our approach is faster on evaluating `Q10`, Neo4j is faster for evaluating `Q11`. The main reason behind this is the expensive cost of retrieving the `external` attribute of the edges of the connecting paths for further filtering them. Optimized Neo4j implementation outperforms our approach in `Q12` as well where the query seeks for all authors that are connected to two authors, `X` and `Y`, where the length of the connecting `co-author` paths between the target authors and both of `X` and `Y` do not exceed two edges and all edges of the connecting paths to `X` are described by `noPapers` greater than 2.

In general, one of the main limitations of our approach is the inefficiency of evaluating path filtering predicates over a set of paths resulting from evaluating path operators (e.g. `pathJoin`, `sPathJoin`). The main reason behind this is that we load onto the main memory only the graph topology information (the attributes of the graph nodes/edges are not loaded and only available in the underlying relational database). Therefore, the evaluation of these predicates require late retrieval of the required values for the attributes (using SQL statement of the form (`SELECT ... IN ...`)) of the *set* of nodes/edges over which the predicate condition need to be applied. In practice, the efficiency of this retrieval operation is affected by the size of this intermediate set. The retrieval of these attribute values using the SQL statement (`SELECT ... IN ...`) can not make effective use of the existing database indices. On the other side, Neo4j loads the whole traversed nodes/edges information (attributes) onto the memory during the execution of the graph traversal operations and thus the execution of the path filtering information is much more efficient by paying of a higher memory consumption. One approach to overcome this limitation in our approach is to load onto the main memory, the frequently used attributes in path filtering conditions in addition to the graph topology. For example, for our query workload by loading the edge attributes `source` and `noPapers`, the performance of our approach for queries `Q11` and `Q12` is improved by an average of %31 and thus we can outperform the Neo4j optimized implementation. Obviously, there is a trade-off between the main memory consumption and the performance that can be gained on evaluating the path filtering conditions by loading more attributes of the graph nodes/edges. In addition, effective determination of which attributes should be loaded onto the memory would require pre-known knowledge about the characteristics of the query workloads. On the contrary, evaluating filtering condition on the path length can be achieved very efficiently as the path length information is computed during the traversal operations for evaluating the path operators and does not require any data retrieval from the underlying database.

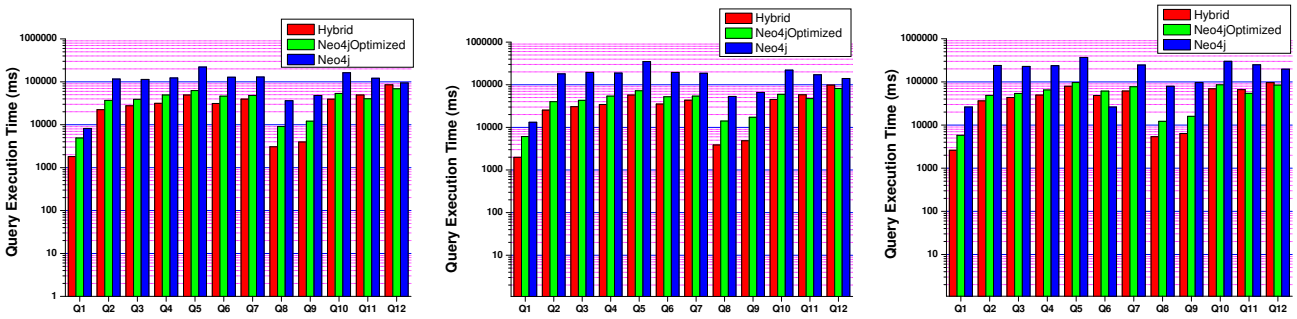
	Vertices	Edges	Att. Values	Topology Info.
Synthetic1 ($V500kE5AR50T150$)	**500K**	**2,5M**	**15M**	**21%**
Synthetic2 ($V500kE10A3R50T150$)	**500K**	**5M**	**17,5M**	**29%**
Synthetic3 ($V1000kE5A5R75T250$)	**1M**	**5M**	**30M**	**23%**

Table 3: Characteristics of synthetic graph datasets

5.2 More Results on Synthetic Datasets

We have also evaluated our approach and Neo4j implementations using synthetic graphs. A set of synthetic graph datasets is generated by our implemented data generator following the same idea of the *R-MAT* generator [8]. The generator allows the user to specify the number of vertices (V), the average number of outgoing edges for each vertex (E), the average number of attributes for each graph node or edge (A), the total number of distinct relationships (R) and the the total number of distinct attributes (T) of graph nodes and edges. We use the notation $VvEeAaRrTt$ to represent the generation parameter of each dataset. Table 3 illustrates the characteristics of synthetic graph datasets that are used in our experiments.

The query workload of the synthetic graph datasets has been generated using the 12 query templates (Figure 12) of the real dataset where we used random assignment of the queried graph attributes and edges in addition to random literal values to generate the different query instances. Similar to the experiments of the real datasets, each query template is instantiated 20 times and each instance is executed 5 times. The average query evaluation times for the 20 instances of each of the 12 query templates over the synthetic graph datasets are shown in Figure 14. The results of the experiments show the scalability of our approach with regards to the increasing sizes of either the topology information or the data information of the graph database. For example, the generation parameters of the dataset `Synthetic2` are equal to the generation parameters of the dataset `Synthetic1` with only one difference that the value of the average number of outgoing edges for each ver-



(a) Synthetic1 (b) Synthetic2 (c) Synthetic3

Figure 14: Average query evaluation times of synthetic datasets

tex (E) of `Synthetic2` is double the value of the same parameter in `Synthetic1`. Such increase in the value of (E) leads to an increase in the cost of all operators that involve traversal operations over the graph topology (e.g. `pathJoin` and `sPathJoin`) especially for the queries that do not restrict the traversal operation with a specified relationship (e.g. `Q5`). The average percentage of increase (between `Synthetic2` and `Synthetic1`) in the execution times for evaluating the queries in our approach (16%) is less than the average percentage of cost increase for Neo4j implementations (19% for optimized implementations and 32% for non-optimized implementations) due to leveraging the advantage of our approach in holding the whole graph topology information in the main memory. The percentages of increase in the execution times for evaluating the queries between `Synthetic2` and `Synthetic1` for the different approaches are computed using the following formula:

$$\frac{Time(Synthetic2) - Time(Synthetic1)}{Time(Synthetic1)}$$

On the other side, the total number of vertices, edges and attribute values of `Synthetic3` dataset is twice the total number of vertices, edges and attribute values of `Synthetic1` dataset respectively. However, the average percentage of increase (between `Synthetic3` and `Synthetic1`) in the execution times for evaluating the queries in our approach is 31%. In principle, while the evaluation costs of the parts of the query plans that can be pushed inside the relational database can make use of its well-known scalability in optimizing the performance of processing large datasets (by relying on its built-in indexing and query optimization techniques), the evaluation costs for the parts of the query plans which are executed by main memory operators increases linearly with the size of the processing datasets. For example, in `Q2`, `Q3`, `Q4`, `Q5`, `Q6` and `Q7`, increasing the size of the graph database leads to an increase in the size of the input relations of the main memory operator `pathJoin` and consequently increases the number of join operations and the number of graph traversal operations. the average percentage of cost increase (between `Synthetic3` and `Synthetic1`) in evaluating the queries using the optimized and non-optimized Neo4j implementations are 38% and 44% respectively.

6. RELATED WORK

The field of graph data management has attracted a lot of attention from the database research community in recent years because of the emerging wave of new applications in different domains. Several graph querying techniques have been proposed in the literature for handling different types of graph queries over large graphs such as: pattern matching query [51, 52], reachability query [12, 26] and *shortest path query* [11, 46]. SPath [51] and GADDI [50] are presented as subgraph search techniques over large graphs. These methods rely on constructing some indices to prune the search space of each vertex to reduce the whole search space. For example, SPath [51] constructs an index by neighborhood signature which utilizes the shortest paths within the k-neighborhood subgraph of each vertex. GADDI [50] index is based on neighboring discriminating substructure (NDS) distances which needs to count the number of some small discriminating substructures. Some other techniques have been proposed for handling graph reachability queries [12, 26]. These techniques are mainly designed to efficiently check whether there exist any path connections (sequence of edges) from a vertex u to another vertex v in a large directed graph. For example, Cohen et al. [12] labels a graph based on the so-called *2-hop* covers. In this method, each hop is a pair (h, v) where h is a path in G and v is one of the endpoints of h. Hence, if there are some paths from u to v, there must exist $(h1, u)$ and $(h2, v)$ and one of the paths between v and u would be the concatenation of $h1$ and $h2$. The *3-hop* indexing scheme [26] uses chain structures in combination with hops to minimize the number of structures that must be indexed. Thus, it does not need to compute the entire transitive closure. Instead, it only needs to compute and record a number of so-called *contour* vertex pairs which can be much smaller than the size of the transitive closure. The *TEDI* indexing structure [46] has been proposed for answering shortest path queries. TEDI is based on a tree decomposition methodology where the graph is decomposed into a tree in which each node represents a bag that contains more than one vertex from the graph. Based on this index, a bottom-up operation is executed to find the shortest path between any two vertices in the graph.

In general, these techniques are mainly focusing on querying the topological structures of the underlying databases and usually ignore the attributes of vertices and edges in the querying process. Each of these techniques assumes a specific organization of its indexing structure which is mainly designed and optimized for supporting a specific target type of graph queries without any consideration for the requirement of the other types of graph queries. In addition, these techniques are very expensive in their memory consumption so that they cannot scale to support very large

graphs. Moreover, they rely on a very expensive offline preprocessing step for building their indexing structures. Usually, the maintenance of these indices is very expensive especially in the case of dynamic graph databases. However, our approach can effectively utilize the information of any of these indices (if available) to accelerate the physical evaluation of our logical operator.

Several graph query processing techniques were proposed on large RDF graphs [1, 6, 31, 53]. In general, most of these techniques have been *mainly focusing* on supporting the graph matching mechanism of the SPARQL query language. For example, the *RDF-3X* query engine [31] stores the whole RDF graph in a three-column table (subject, predicate, object) and tries to overcome the expensive cost of self-joins by building indices over all 6 permutations of the three dimensions that constitute an RDF triple. The query optimizer relies upon its cost model in finding the lowest-cost execution plan and mostly focuses on join order and the generation of execution plans [30]. *SW-Store* [1] is an RDF storage system which uses a fully decomposed storage model (DSM) [13] where the RDF triples table is rewritten into n two- column tables where n is the number of unique properties in the RDF dataset. The implementation of *SW-Store* relies on a column-oriented DBMS, C-store [41], to store tables as collections of columns rather than as collections of rows. In standard row-oriented databases (e.g., Oracle, DB2, SQLServer, Postgres, etc.) entire tuples are stored consecutively. Abadi et al. [1] reported that storing RDF data in column-store database is better than that of row-store database while Sidirourgos et al. [40] have shown that the gain of performance in column-store database depends on the number of predicates in the RDF dataset. *DOGMA* [6] is a disk-based graph index for RDF databases. It represents a generalization of the well known binary-tree indexing structure where each node occupies a disk page and is labeled by a graph that captures its two children. Therefore, if a node N has two children, N_1 and N_2, then the graph labeling node N would be a k-merge of the graphs labeling its children. The gStore index [53] stores an RDF graph as a disk-based adjacency list table where each vertex in the RDF graph is assigned a bitstring as its vertex signature according to its adjacent edge labels and neighbor vertex labels. Hence, an RDF graph is converted into a data signature graph. During query processing, the input query is encoded in the same way and a matching process is applied. In general, RDF graphs represent a special kind of attributed graphs that are considered in our approach. Therefore, our graph representation and algebraic-based querying methods are more general and can be easily adopted to answer queries on large RDF graphs.

The idea of splitting the execution of database queries between two different environments has been previously employed in the HadoopDB system [2] which has been designed as a query engine with a hybrid architecture for processing data warehousing queries and analytical workloads using the MapReduce framework and relational database.

7. CONCLUSIONS

We presented *G-SPARQL*, a novel language for querying attributed graphs. The language has a number of appealing features. It supports querying structural graph patterns where filtering conditions can be specified on the attributes of the graph vertices/edges. In addition, it supports various forms for querying and conditionally filtering path patterns. We presented an efficient hybrid Memory/Disk representation of large attributed graphs where only the topology of the graph is maintained in memory while the data of the graph are stored in a relational database. We developed an algebraic compilation mechanism for our supported queries based on an extended form of the standard relational algebra and a split of execution mechanism for the generated query plans. Experimental studies on real and synthetic graphs validated the efficiency and scalability of our approach. As a future work, we are planning to extend our approach to support the recently introduced SPARQL 1.1 features such as nested queries and aggregate queries.

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Appendix

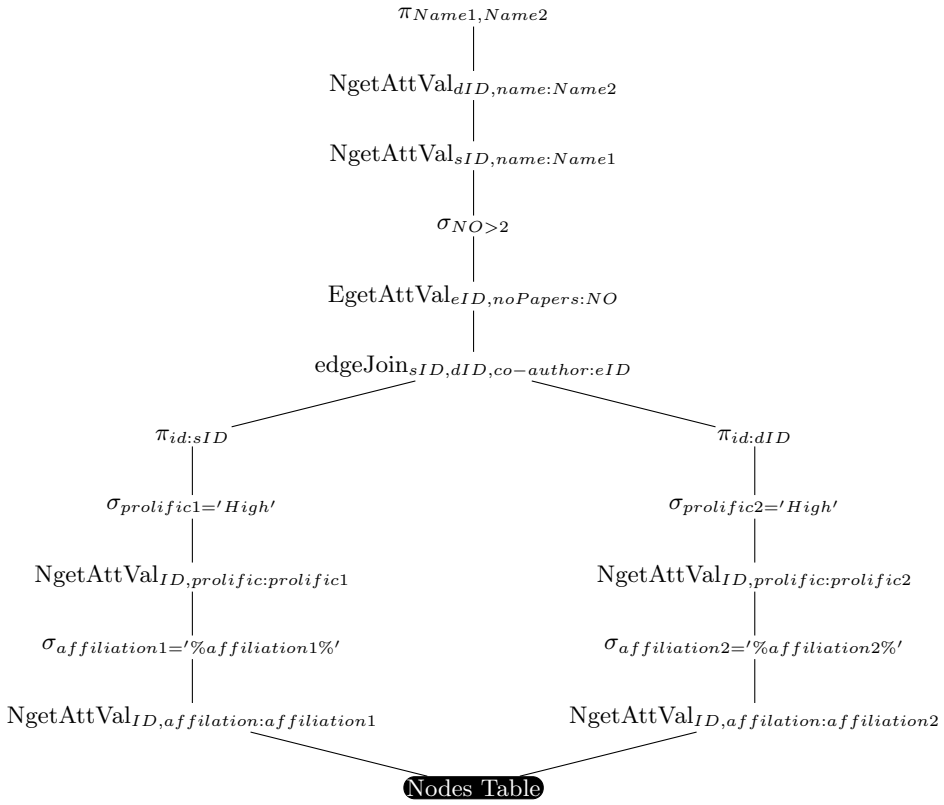

Figure 15: Algebraic Plan of Q1.

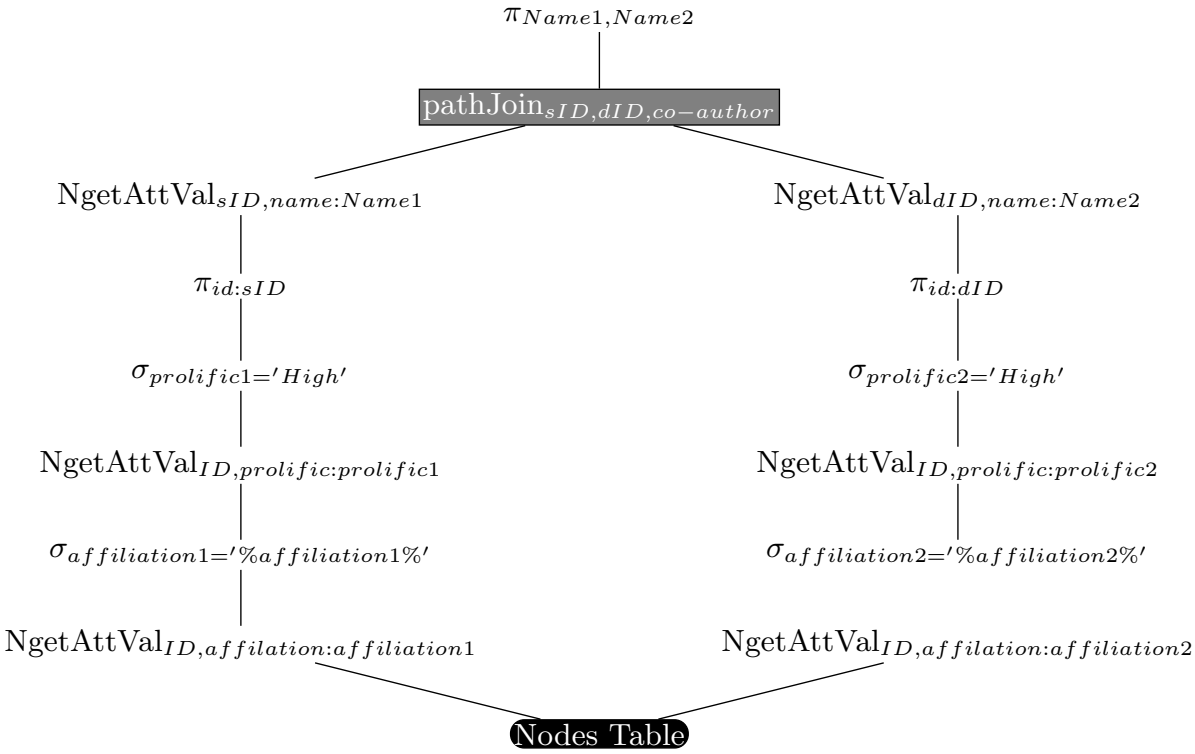

Figure 16: Algebraic Plan of Q2.

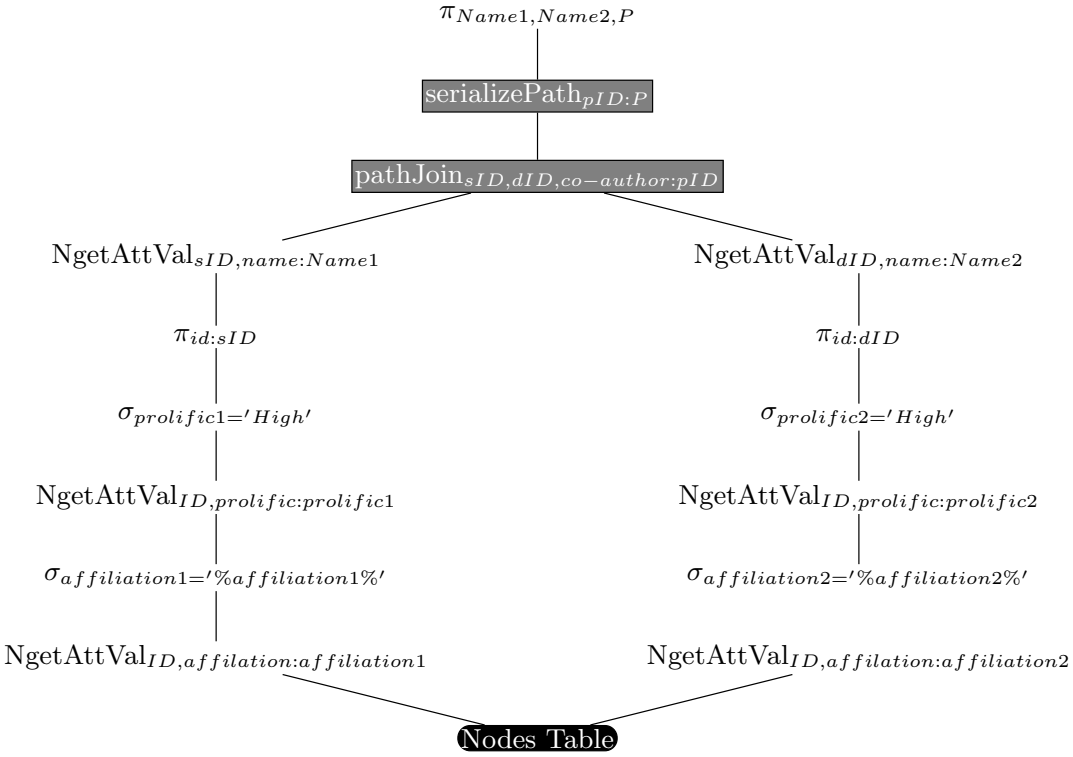

Figure 17: Algebraic Plan of Q3.

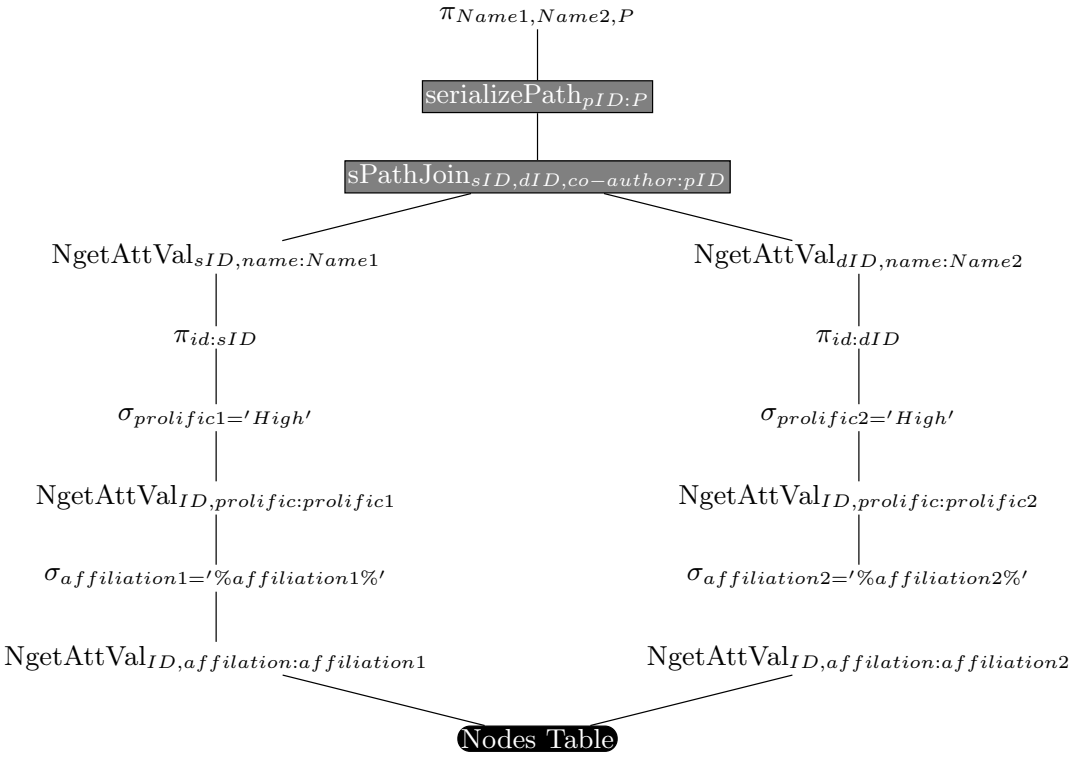

Figure 18: Algebraic Plan of Q4.

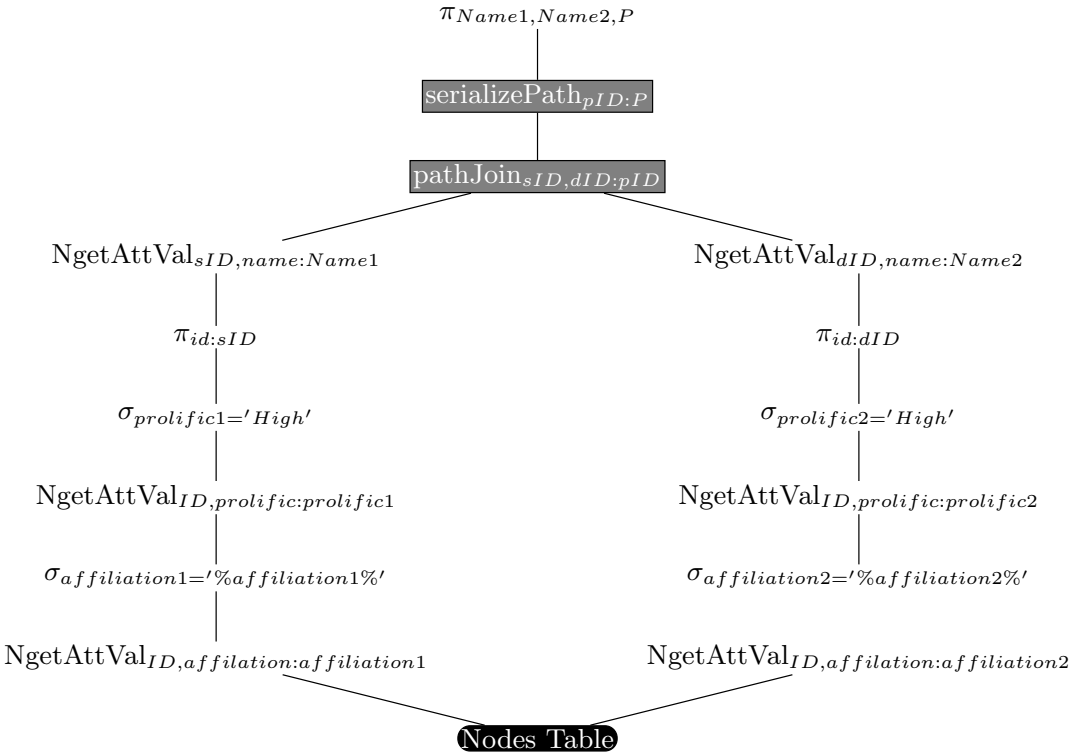

Figure 19: Algebraic Plan of Q5.

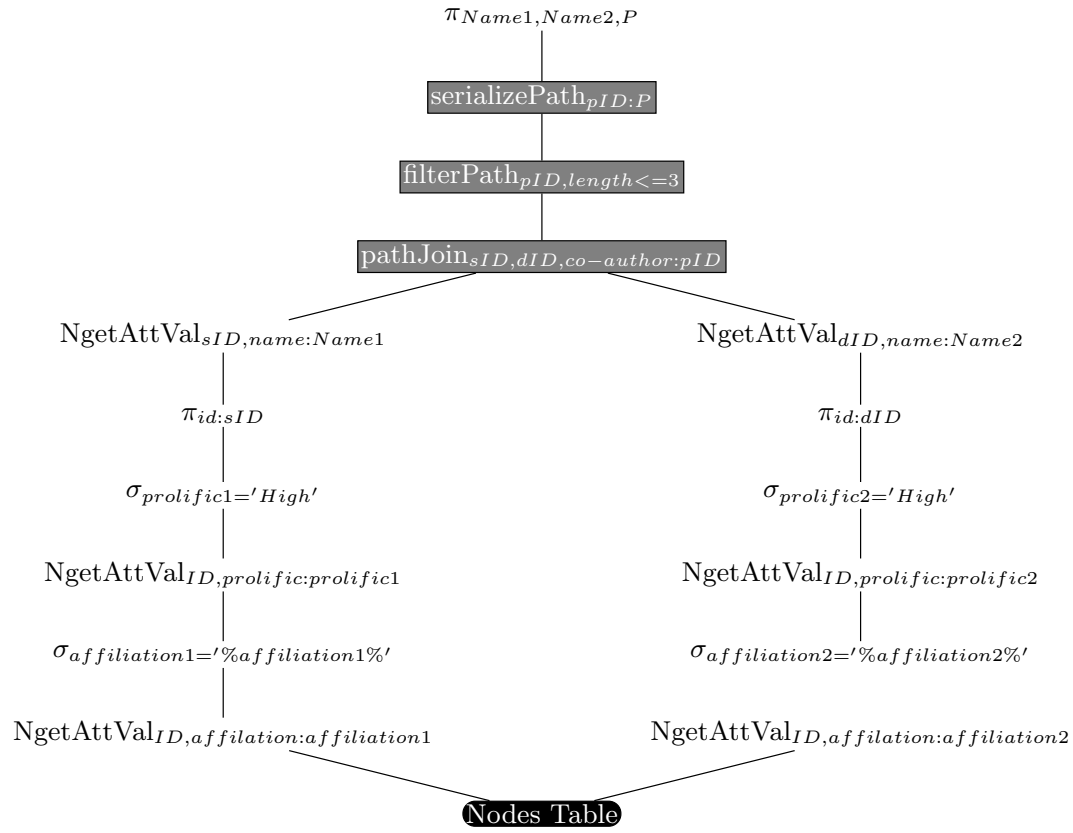

Figure 20: Algebraic Plan of Q6.

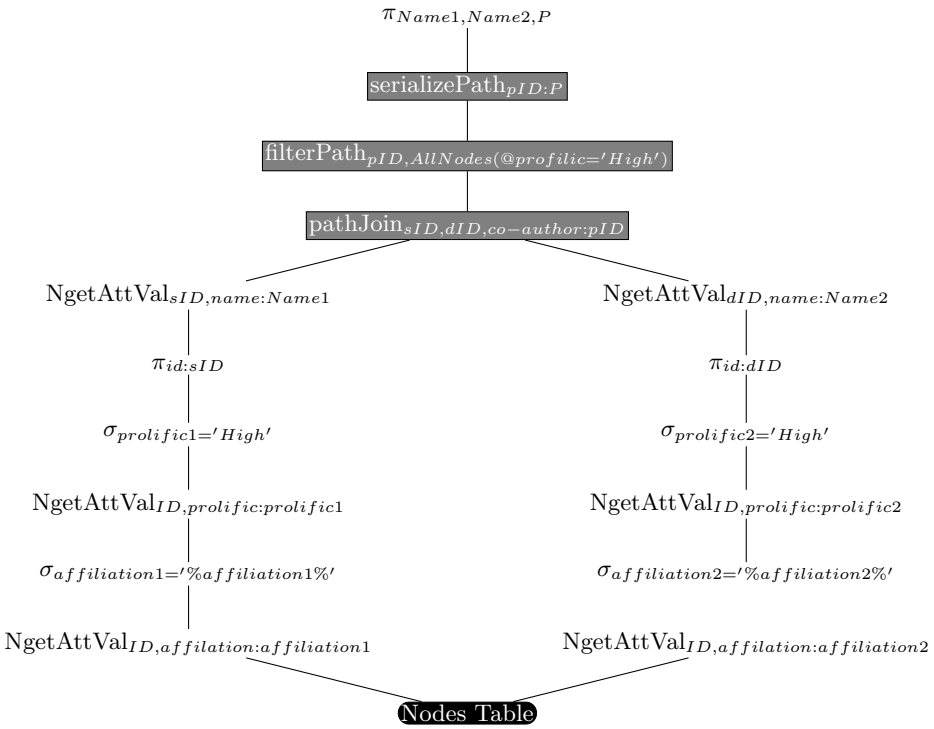

Figure 21: Algebraic Plan of Q7.

Figure 22: Algebraic Plan of Q8.

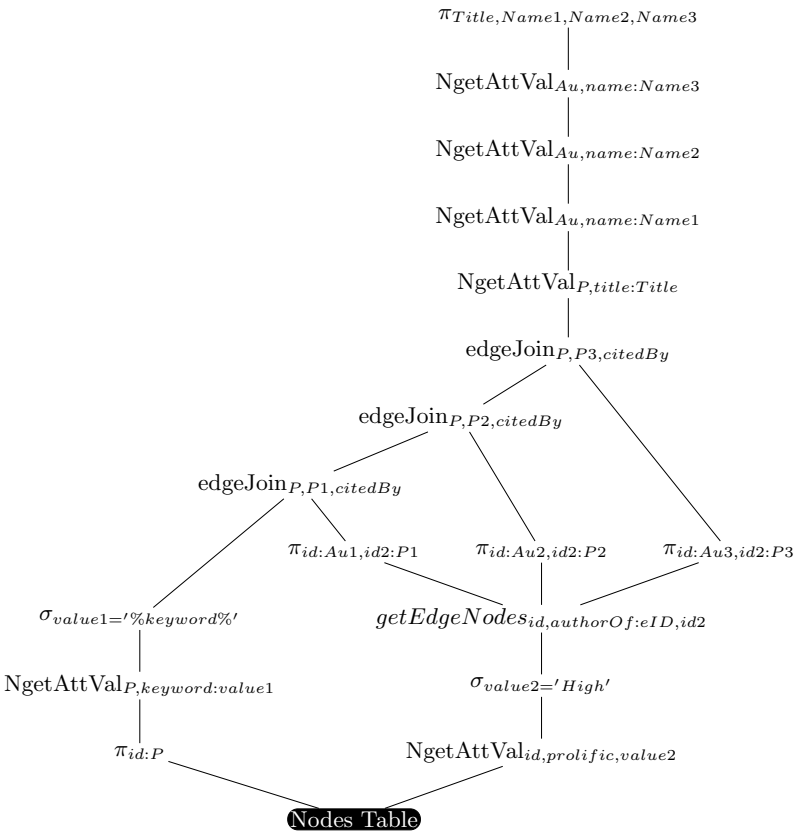

Figure 23: Algebraic Plan of Q9.

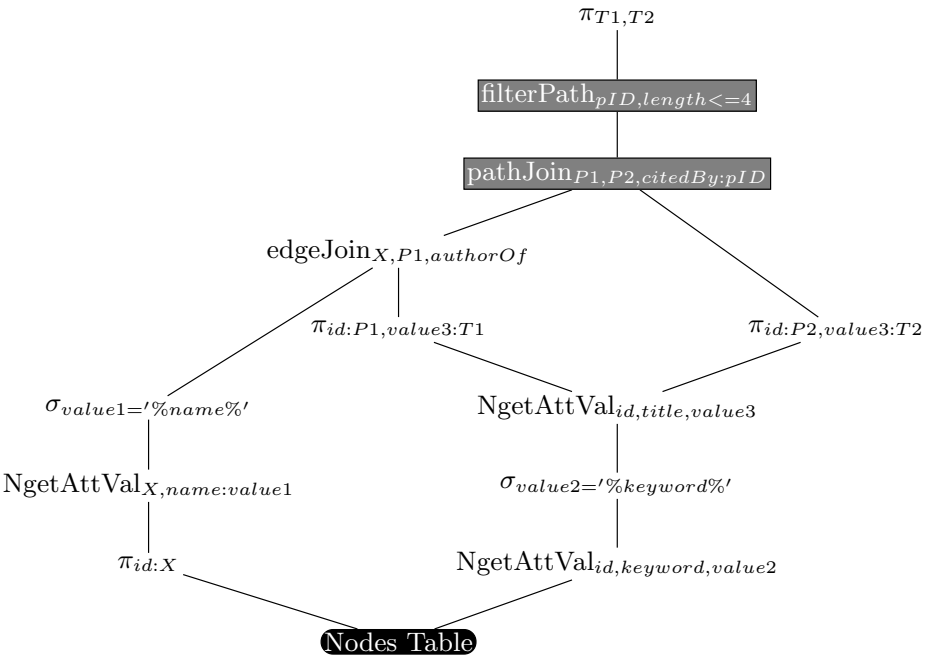

Figure 24: Algebraic Plan of Q10.

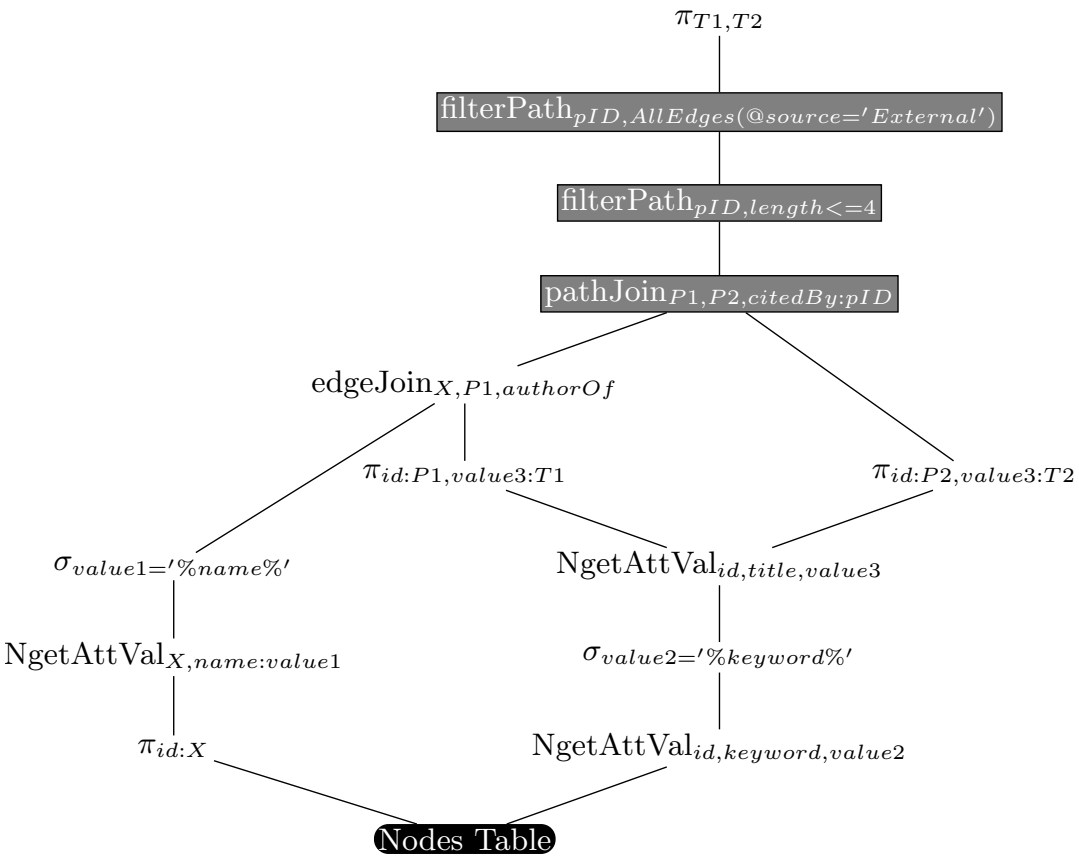

Figure 25: Algebraic Plan of Q11.

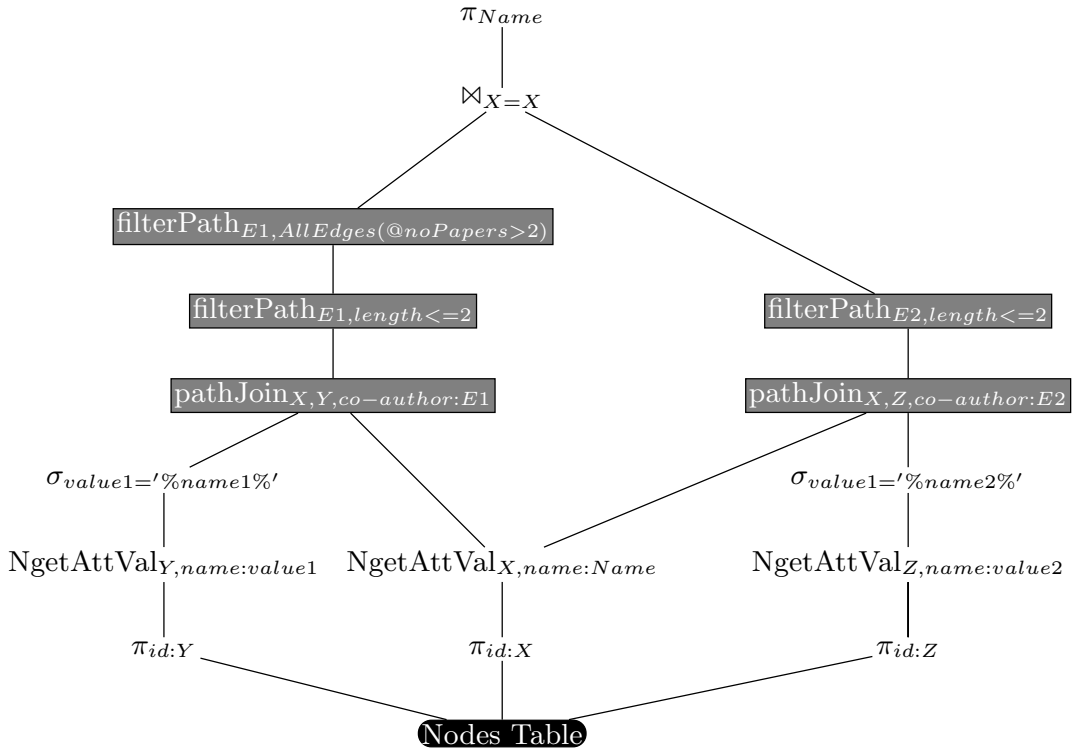

Figure 26: Algebraic Plan of Q12.