Querying RDF Data Using A Multigraph-based Approach

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ABSTRACT

RDF is a standard for the conceptual description of knowledge, and SPARQL is the query language conceived to query RDF data. The RDF data is cherished and exploited by various domains such as life sciences, Semantic Web, social network, etc. Further, its integration at Web-scale compels RDF management engines to deal with complex queries in terms of both size and structure. In this paper, we propose AMbER (Attributed Multigraph Based Engine for RDF querying), a novel RDF query engine specifically designed to optimize the computation of complex queries. AMbER leverages subgraph matching techniques and extends them to tackle the SPARQL query problem. First of all RDF data is represented as a multigraph, and then novel indexing structures are established to efficiently access the information from the multigraph. Finally a SPARQL query is represented as a multigraph, and the SPARQL querying problem is reduced to the subgraph homomorphism problem. AMbER exploits structural properties of the query multigraph as well as the proposed indexers, in order to tackle the problem of subgraph homomorphism. The performance of AMbER, in comparison with state-of-the-art systems, has been extensively evaluated over several RDF benchmarks. The advantages of employing AMbER for complex SPARQL queries have been experimentally validated.

1. INTRODUCTION

In the recent years, structured knowledge represented in the form of RDF data has been increasingly adopted to improve the robustness and the performances of a wide range of applications with various purposes. Popular examples are provided by Google, that exploits the so called knowledge graph to enhance its search results with semantic information gathered from a wide variety of sources, or by Facebook, that implements the so called entity graph to empower its search engine and provide further information extracted, for instance by Wikipedia. Another example is supplied by recent question-answering systems [4, 15] that automatically translate natural language questions in SPARQL queries and successively retrieve answers considering the available information in the different Linked Open Data sources. In all these examples, complex queries (in terms of size and structure) are generated to ensure the retrieval of all the required information. Thus, as the use of large knowledge bases, that are commonly stored as RDF triplets, is becoming a common way to ameliorate a wide range of applications, efficient querying of RDF data sources using SPARQL is becoming crucial for modern information retrieval systems.

All these different scenarios pose new challenges to the RDF query engines for two vital reasons: firstly, the automatically generated queries cannot be bounded in their structural complexity and size (e.g., the DBPEDIA SPARQL Benchmark [12] contains some queries having more than 50 triplets [1]); secondly, the queries generated by retrieval systems (or by any other applications) need to be efficiently answered in a reasonable amount of time. Modern RDF data management, such as x-RDF-3X [7], Virtuoso [13], and Virtuoso [7], are designed to address the scalability of SPARQL queries but they still have problems to answer big and structurally complex SPARQL queries [2]. Our experiments with state-of-the-art systems demonstrate that they fail to efficiently manage such kind of queries (Table 1).

<table>
<thead>
<tr>
<th>Systems</th>
<th>AMbER</th>
<th>gStore</th>
<th>Virtuoso</th>
<th>x-RDF-3X</th>
</tr>
</thead>
<tbody>
<tr>
<td>Time (sec)</td>
<td>1.56</td>
<td>11.96</td>
<td>20.45</td>
<td>&gt;60</td>
</tr>
</tbody>
</table>

Table 1: Average Time (seconds) for a sample of 200 complex queries on DBPEDIA. Each query has 50 triplets.

In order to tackle these issues, in this paper, we introduce AMbER (Attributed Multigraph Based Engine for RDF querying), which is a graph-based RDF engine that involves two steps: an offline stage where RDF data is transformed into multigraph and indexed, and an online step where an efficient approach to answer SPARQL query is proposed. First of all RDF data is represented as a multigraph where subjects/objects constitute vertices and multiple edges (predicates) can appear between the same pair of vertices. Then, new indexing structures are conceived to efficiently access RDF multigraph information. Finally, by representing the SPARQL queries also as multigraphs, the query answering...
2. BACKGROUND AND PRELIMINARIES

In this section we provide basic definitions on the interplay between RDF and its multigraph representation. Later, we explain how the task of answering SPARQL queries can be reduced to multigraph homomorphism problem.

2.1 RDF Data

As per the W3C standards \(^2\), RDF data is represented as a set of triples \(<s, p, o>\), as shown in Figure 1a, where each triple \(<s, p, o>\) consists of three components: a subject, a predicate and an object. Further, each component of the RDF triple can be of any two forms; an IRI (Internationalized Resource Identifier) or a literal. For brevity, an IRI is usually written along with a prefix (e.g., \(<http://dbpedia.org/resource/isPartOf>\)).

\(^1\)http://www.w3.org/TR/sparql11-overview/
\(^2\)http://www.w3.org/TR/2014/RE0-rdf11-concepts-20140225/

Figure 1: (a) RDF data in n-triple format; (b) graph representation (c) attributed multigraph \(G\)

task can be reduced to the problem of subgraph homomorphism. To deal with this problem, AMnER employs an efficient approach that exploits structural properties of the multigraph query as well as the indices previously built on the multigraph structure. Experimental evaluation over popular RDF benchmarks show the quality in terms of time performances and robustness of our proposal.

In this paper, we focus only on the SELECT/WHERE clause of the SPARQL language that contains the most important operation of any RDF query engines. It is out of the scope of this work to consider operators like FILTER, UNION and GROUP BY or manage RDF update. Such operations can be addressed in future as extensions of the current work.

The paper is organized as follows. Section 2 introduces the basic notions about RDF and SPARQL language. In Section 3 AMnER is presented. Section 4 describes the indexing strategy while Section 5 presents the query processing. Related works are discussed in Section 6. Section 7 provides the experimental evaluation. Section 8 concludes.
To summarise, an RDF tripleset is transformed into a data multigraph \( G \) (Figure 1c), which is formally defined as follows.

**Definition 1. Directed, Vertex Attributed Multigraph.**

A directed, vertex attributed multigraph \( G \) is defined as a 4-tuple \((V, E, \mathcal{L}, \mathcal{V})\) where \( V \) is a set of vertices, \( E \subseteq V \times V \) is a set of directed edges with \((v, v') \neq (v', v)\), \( \mathcal{L} \) is a labelling function that assigns a subset of vertex attributes \( A \) to the set of vertices \( V \), and \( \mathcal{V} \) is a labelling function that assigns a subset of edge-types \( T \) to the edge set \( E \).

In any valid SPARQL query (as in Figure 2a), every triplet has at least one unknown variable ?X, whose bindings are to be found in the RDF data. In the current work, we address the SPARQL queries with ‘SELECT/WHERE’ option, where the predicate is always instantiated as an IRI (Figure 2a). The SELECT clause identifies the variables to appear in the query results while the WHERE clause provides triple patterns to match against the RDF data.

### 2.2 SPARQL Query

A SPARQL query usually contains a set of triple patterns, much like RDF triples, except that any of the subject, predicate and object may be a variable, whose bindings are to be found in the RDF data. It should now be easy to observe that a SPARQL query can be represented in the form of a graph as in Figure 2b, which in turn is transformed into a query multigraph \( \mathcal{Q} \) as in Figure 2c.

In the query multigraph representation, each unknown variable ?X is mapped to a vertex \( u \), that forms the vertex set \( U \) component of the query multigraph \( \mathcal{Q} \) (e.g., ?X\(_0\) is mapped to \( u_0 \)). Since a predicate is always instantiated as an IRI, we use the edge-type dictionary in Table 2b, to map the predicate to an edge-type identifier \( t \in T \) (e.g., ‘isMarriedTo’ is mapped as \( t_2 \)). When an object \( o \) is a literal, we use the attribute dictionary (Table 2c), to find the attribute identifier \( a\) for the predicate-object tuple \((p, o)\) (e.g., \( \{a_0\} \) forms the attribute for \( v_{x0} \)). Further, when a subject or an object is an IRI, which is not a variable, we use the vertex dictionary (2a), to map it to an IRI-vertex \( u'\) (e.g., ‘x:United_States’ is mapped to \( u'_{x6} \)) and maintain a set of IRI vertices \( R \). Since this vertex is not a variable and a real vertex of the query, we portray it differently by a shaded squared shaped vertex. When a query vertex \( u \) does not have any vertex attributes associated with it (e.g., \( u_0, u_1, u_2, u_3, u_6 \)), a null attribute \( \{ \} \) is assigned to it. On the other hand, an IRI-vertex \( u''\) \( \in R \) does not have any attributes. Thus, a SPARQL query is transformed into a query multigraph \( \mathcal{Q} \).

In this work, we always use the notation \( V \) for the set of vertices of \( G \), and \( U \) for the set of vertices of \( \mathcal{Q} \). Consequently, a data vertex \( v \in V \), and a query vertex \( u \in U \). Also, an incoming edge to a vertex is positive (default), and an outgoing edge from a vertex is labelled negative (‘\(-\)’).

### 2.3 SPARQL Querying by Adopting Multigraph Homomorphism

As we recall, the problem of SPARQL querying is addressed by finding the solutions to the unknown variables \( ?X \), that can be bound with the RDF data entities, so that the relations (predicates) provided in the SPARQL query are respected. In this work, to harness the transformed data multigraph \( G \) and the query multigraph \( \mathcal{Q} \), we reduce the problem of SPARQL querying to a sub-multigraph homomorphism problem. The RDF data is transformed into data multigraph \( G \) and the SPARQL query is transformed into query multigraph \( \mathcal{Q} \). Let us now recall that finding SPARQL answers in the RDF data is equivalent to finding all the sub-multigraphs of \( G \) in \( \mathcal{Q} \) that are homomorphic. Thus, let us now formally introduce homomorphism for a vertex attributed, directed multigraph.

**Definition 2. Sub-multigraph Homomorphism.**

Given a query multigraph \( \mathcal{Q} = (U, E^\mathcal{Q}, L^\mathcal{Q}, \mathcal{V}^\mathcal{Q}) \) and a data multigraph \( G = (V, E, \mathcal{L}, \mathcal{V}) \), the sub-multigraph homomorphism from \( G \) to \( \mathcal{Q} \) is a surjective function \( \psi : U \rightarrow V \) such that:

1. \( \forall u \in U, L^\mathcal{Q}(u) \subseteq L^\mathcal{Q}(\psi(u)) \).
2. \( \forall (u_m, u_n) \in E^\mathcal{Q}, \exists \psi(u_m), \psi(u_n) \in E, \text{ where } (u_m, u_n) \text{ is a directed edge, and } L^\mathcal{Q}(u_m, u_n) \subseteq L_E(\psi(u_m), \psi(u_n)). \)

Thus, by finding all the sub-multigraphs in \( G \) that are homomorphic to \( \mathcal{Q} \), we enumerate all possible homomorphic embeddings of \( \mathcal{Q} \) in \( G \). These embeddings contain the solution for each of the query vertex that is an unknown variable.

Thus, by using the inverse mapping function \( M^{-1}_\mathcal{Q}(u) \) (introduced already), we find the bindings for the SPARQL
query. The decision problem of subgraph homomorphism is NP-complete. This standard subgraph homomorphism problem can be seen as a particular case of sub-multipigraph homomorphism, where both the labelling functions \( L_E \) and \( L_K \) always return the same subset of edge-types for all the edges in both \( G \) and \( G' \). Thus the problem of sub-multipigraph homomorphism is at least as hard as subgraph homomorphism. Further, the subgraph isomorphism problem is a generic scenario of subgraph isomorphism where, the injectivity constraints are slackened [11].

### 3. AMBER: A SPARQL QUERYING ENGINE

We now present an overview of our proposal - AMbER (Attributed Multigraph Based Engine for RDF querying). AMbER contains two different stages: (i) an offline stage during which, RDF data is transformed into multigraph \( G \) and then a set of index structures \( I \), the homomorphic matches of \( Q \) in \( G \) are obtained. Given a multigraph representation \( Q \) of a SPARQL query, AMbER decomposes the query vertices \( U \) into a set of core vertices \( U_c \) and satellite vertices \( U_s \). Intuitively, a vertex \( u \in U \) is a core vertex, if the degree of the vertex is more than one; on the other hand, a vertex \( u \) with degree one is a satellite vertex. For example, in Figure 2c, \( U_c = \{ u_1, u_3, u_5 \} \) and \( U_s = \{ u_0, u_2, u_4, u_6 \} \). Once decomposed, we run the sub-multipigraph matching procedure on the query structure spanned only by the core vertices. However, during the procedure, we also process the satellite vertices (if available) that are connected to a core vertex that is being processed. For example, while processing the core vertex \( u_1 \), we also process the set of satellite vertices \( \{ u_0, u_2, u_4 \} \) connected to it; whereas, the core vertex \( u_5 \) has no satellite vertices to be processed. In this way, as the matching proceeds, the entire structure of the query multigraph \( Q \) is processed to find the homomorphic embeddings in \( G \). The set of indexing structures \( I \) are extensively used during the process of sub-multipigraph matching. The homomorphic embeddings are finally translated back to the RDF entities using the inverse mapping function \( M_v^{-1} \) as discussed in Section 2.

### 4. INDEX CONSTRUCTION

Given a data multigraph \( G \), we build the following three different indices: (i) an inverted list \( A \) for storing the set of data vertex for each attribute in \( a_i \in A \) (ii) a trie index structure \( S \) to store features of all the data vertices \( V \) (iii) a set of trie index structures \( N \) to store the neighbourhood information of each data vertex \( v \in V \). For brevity of representation, we ensemble all the three index structures into \( I := \{ A, S, N \} \).

During the query matching procedure (the online step), we access these indexing structures to obtain the candidate solutions for a query vertex \( u \). Formally, for a query vertex \( u \), the candidate solutions are a set of data vertices \( C_u = \{ v \mid v \in V \} \) obtained by accessing \( A \) or \( S \) or \( N \), denoted as \( C_u^A, C_u^S \) and \( C_u^N \) respectively.

#### 4.1 Attribute Index

The set of vertex attributes is given by \( A = \{ a_0, \ldots, a_n \} \) (Section 2), where a data vertex \( v \in V \) might have a subset of \( A \) assigned to it. We now build the vertex attribute index \( A \) by creating an inverted list where a particular attribute \( a_i \) has the list of all the data vertices in which it appears.

Given a query vertex \( u \) with a set of vertex attributes \( u.A \subseteq A \), for each attribute \( a_i \in u.A \), we access the index structure \( A \) to fetch a set of data vertices that have \( a_i \). Then we find a common set of data vertices that have the entire sub-set \( u.A \). For example, considering the query vertex \( u_5 \) (Fig. 2c), it has an attribute set \( \{ a_1, a_2 \} \). The candidate solutions for \( u_5 \) are obtained by finding all the common data vertices, in \( A \), between \( a_1 \) and \( a_2 \).

#### 4.2 Vertex Signature Index

The index \( S \) captures the edge type information from the data vertices. For a lucid understanding of this indexing schema we formally introduce the notion of vertex signature that is defined for a vertex \( v \in V \), which encapsulates the edge information associated with it.

**Definition 3. Vertex signature.** For a vertex \( v \in V \), the vertex signature \( \sigma_v \) is a multiset containing all the directed multi-edges that are incident on \( v \), where a multi-edge between \( v \) and a neighbouring vertex \( v' \) is represented by a set that corresponds to the edge types. Formally, \( \sigma_v = \bigcup_{v' \in N(v)} \mathcal{E}_{G}(v,v') \) where \( N(v) \) is the set of neighbourhood vertices of \( v \), and \( \bigcup \) is the union operator for multiset.
Table 3: Vertex signatures and the corresponding synopses for the vertices in the data multigraph (Figure 1c)

The index $S$ is constructed by tailoring the information supplied by the vertex signature of each vertex in $G$. To extract some interesting features, let us observe the vertex signature $\sigma_u$ as supplied in Table 3. To begin with, we can represent the vertex signature $\sigma_u$ separately for the incoming and outgoing multi-edges as $\sigma_{u+} = \{(t_1), \{t_2\}, \{t_0\}, \{t_3\}\}$ and $\sigma_{u-} = \{-t_0\} \{-t_2\}$ respectively. Now we observe that $\sigma_{u+}$ has four distinct multi-edges and $\sigma_{u-}$ has two distinct multi-edges. Now, lets think that we want find candidate solutions for a query vertex $u$. The data vertex $v_2$ can be a match for $u$ only if the signature of $u$ has at most four incoming ($+$) edges and at most two outgoing ('-') edges; else $v_2$ can not be a match for $u$. Thus, more such features (e.g., maximum cardinality of a set in the vertex signature) can be proposed to filter out irrelevant candidate vertices. Thus, for each vertex $v$, we propose to extract a set of features by exploiting the corresponding vertex signature. These features constitute a *synopses*, which is a surrogate representation that approximately captures the vertex signature information.

The synopsis of a vertex $v$ contains a set of features $F$, whose values are computed from the vertex signature $\sigma_v$. In this background, we propose four distinct features: $f_1$ - the maximum cardinality of a set in the vertex signature; $f_2$ - the number of unique dimensions in the vertex signature; $f_3$ - the minimum index value of the edge type; $f_4$ - the maximum index value of the edge type. For $f_1$ and $f_4$, the index values of edge type are nothing but the position of the sequenced alphabet. These four basic features are replicated separately for outgoing (negative) and incoming (positive) edges, as seen in Table 3. Thus for the vertex $v_2$, we obtain $f_1^+ = 2$, $f_2^+ = 4$, $f_3^+ = -1$ and $f_4^+ = 7$ for the incoming edge set and $f_1^- = 1$, $f_2^- = 2$, $f_3^- = 0$ and $f_4^- = 2$ for the outgoing edge set. Synopses for the entire vertex set $V$ for the data multigraph $G$ are depicted in Table 3.

Once the synopses are computed for all data vertices, an R-tree is constructed to store all the synopses. This R-tree constitutes the vertex signature index $S$. A synopsis with $|F|$ fields forms a leaf in the R-tree.

When a set of possible candidate solutions are to be obtained for a query vertex $u$, we create a vertex signature $\sigma_u$ in order to compute the synopsis, and then obtain the possible solutions from the R-tree structure.

The general idea of using an R-tree is as follows. A synopsis $F$ of a data vertex spans an axes-parallel rectangle in an $|F|$-dimensional space, where the maximum coordinates of the rectangle are the values of the synopses fields $(f_1, \ldots, f_{|F|})$, and the minimum co-ordinates are the origin of the rectangle (filled with zero values). For example, a data vertex represented by a synopsis with two features $F(v) = [2, 3]$ spans a rectangle in a 2-dimensional space in the interval range $[[0, 2], [0, 3]]$. Now, if we consider synopses of two query vertices, $F(u_1) = [1, 3]$ and $F(u_2) = [1, 4]$, we observe that the rectangle spanned by $F(u_1)$ is wholly contained in the rectangle spanned by $F(v)$ but $F(u_2)$ is not wholly contained in $F(v)$. Thus, $u_1$ is a candidate match while $u_2$ is not.

**Lemma 1.** *Querying the vertex signature index $S$ constructed with synopses, guarantees to output at least the entire set of candidate solutions.*

**Proof.** Consider the field $f_1^+$ in the synopses that represents the maximum cardinality of the neighbourhood signature. Let $\sigma_u$ be the signature of the query vertex $u$ and let $\{\sigma_{v_1}, \ldots, \sigma_{v_n}\}$ be the set of signatures on the data vertices. By using $f_1$ we need to show that $C_u^{\sigma_0}$ has at least all the valid candidate matches. Since we are looking for a superset of query vertex signature, and we are checking the condition $f_1^+(u) \leq f_1^+(v_i)$, where $v_i \in V$, a vertex $v_i$ is pruned if it does not match the inequality criterion since, it can never be an eligible candidate. This analogy can be extended to the entire synopses, since it can be applied disjunctively.

Formally, the candidates solutions for a vertex $u$ can be written as $C_u^{\sigma_0} = \{v | v \in \{v_1, \ldots, v_n\} \land f_1^+(u) \leq f_1^+(v)\}$, where the constraints are met for all the $|F|$-dimensions. Since we apply the same inequality constraint to all the fields, we negate the fields that refer to the minimal index value of the edge type ($f_3^+$ and $f_3^-$) so that the rectangular containment problem still holds good. Further to respect the rectangular containment, we populate the synopses fields with 0 values, in case, the signature does not have either positive or negative fields in it, as seen for $v_1$, $v_3$, $v_4$, $v_5$ and $v_7$.

For example, if we want to compute the possible candidates for a query vertex $u_0$ in Figure 2c, whose signature is $\sigma_{u_0} = \{-t_3\}$, we compute the synopsis which is $[0 0 0 0 1 1 5 5]$. Now we look for all those vertices that subsume this synopsis in the R-tree, whose elements are depicted in Table 3, which gives us the candidate solutions $C_{u_0}^{\sigma_0} = \{v_1, v_7\}$, thus pruning the rest of the vertices.

The $S$ index helps to prune the vertices that do not respect the edge type constraints. This is crucial since this pruning is performed for the initial query vertex, and hence many candidates are cast away, thereby avoiding unnecessary recursion during the matching procedure. For example,

<table>
<thead>
<tr>
<th>Data vertex $v$</th>
<th>Signature</th>
<th>Synopses $f_1^+, f_2^+, f_3^+, f_4^+$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$v_0$</td>
<td>${-t_6}, {t_7}$</td>
<td>$1 \leq f_1^+ = 1$</td>
</tr>
<tr>
<td>$v_1$</td>
<td>${-t_8}, {-t_7}, {-t_8}, {-t_4}, {-t_3}$</td>
<td>$0 \leq f_1^+ = 0$</td>
</tr>
<tr>
<td>$v_2$</td>
<td>${t_0}, {t_4}, {-t_2}, {t_8}, {t_6}, {t_4, t_3}$</td>
<td>$2 \leq f_1^+ = 2$</td>
</tr>
<tr>
<td>$v_3$</td>
<td>${t_0}, {t_3}, {-t_1}$</td>
<td>$1 \leq f_1^+ = 1$</td>
</tr>
<tr>
<td>$v_4$</td>
<td>${t_2}$</td>
<td>$1 \leq f_1^+ = 1$</td>
</tr>
<tr>
<td>$v_5$</td>
<td>${t_3}, {t_4}$</td>
<td>$1 \leq f_1^+ = 1$</td>
</tr>
<tr>
<td>$v_6$</td>
<td>${t_4}, {t_3}$</td>
<td>$1 \leq f_1^+ = 1$</td>
</tr>
<tr>
<td>$v_7$</td>
<td>${-t_6}, {-t_3}, {-t_5}$</td>
<td>$0 \leq f_1^+ = 0$</td>
</tr>
<tr>
<td>$v_8$</td>
<td>${t_0}$</td>
<td>$1 \leq f_1^+ = 1$</td>
</tr>
</tbody>
</table>
4.3 Vertex Neighbourhood Index

The vertex neighbourhood index $N$ captures the topological structure of the data multigraph $G$. The index $N$ comprises of 1-neighbourhood trees built for each data vertex $v \in V$. Since $G$ is a directed multigraph, and each vertex $v \in V$ can have both the incoming and outgoing edges, we construct two separate index structures $N^+$ and $N^-$ for incoming and outgoing edges respectively, that constitute the structure $N$.

To understand the index structure, let us consider the data vertex $v_2$ from Figure 1c, shown separately in Figure 3a. For this vertex $v_2$, we collect all the neighbourhood information (vertices and multi-edges), and represent this information by a tree structure, built separately for incoming ('+') and outgoing ('-') edges. Thus, the tree representation of a vertex $v$ contains the neighbourhood vertices and the corresponding multi-edges, as shown in Figure 3b, where the vertices of the tree structure are represented by the edge types.

![Figure 3: Building Neighbourhood Index for data vertex $v_2$](image)

In order to construct an efficient tree structure, we take inspiration from [14] to propose the structure - Ordered Trie with Inverted List (OTIL). To construct the OTIL index as shown in Figure 3b, we insert each ordered multi-edge that is incident on $v$ at the root of the trie. Consider a data vertex $v_i$, with a set of $n$ neighbourhood vertices $N(v_i)$. Now, for every pair of incoming edge $(v_i, N^+(v_i))$, where $j \in \{1, \ldots, n\}$, there exists a multi-edge $\{t_i, \ldots, t_j\}$, which is inserted into the OTIL structure $N^+$. Similarly, for every pair of outgoing edge $(N^-(v_i), v_i)$, there exists a multi-edge $\{t_i, \ldots, t_n\}$, which is inserted into the OTIL structure $N^-$ maintaining two OTIL structures that constitute $N$. Each multi-edge is ordered (w.r.t. increasing edge type indexes), before inserting into the respective OTIL structure, and the order is universally maintained for all data vertices. Further, for every edge type $t_i$, we maintain a list that contains all the neighbourhood vertices $N^+(v_i)/N^-(v_i)$, that have the edge type $t_i$ incident on them.

To understand the utility of $N$, let us consider an illustrative example. Considering the query multigraph $Q$ in Figure 2c, let as assume that we want to find the matches for the query vertices $u_1$ and $u_0$ in order. Thus, for the initial vertex $u_1$, let us say, we have found the set of candidate solutions which is $\{v_2\}$. Now, to find the candidate solutions for the next query vertex $u_0$, it is important to maintain the structure spanned by the query vertices, and this is where the indexing structure $N$ is accessed. Thus to retain the structure of the query multigraph (in this case, the structure between $u_1$ and $u_0$), we have to find the data vertices that are in the neighbourhood of already matched vertex $v_2$ (a match for vertex $u_1$), that has the same structure (edge types) between $u_1$ and $u_0$ in the query graph. Thus to fetch all the data vertices that have the edge type $t_5$, which is directed towards $v_2$ and hence '-' edge, we access the neighbourhood index trie $N^+$ for vertex $v_2$, as shown in Figure 3. This gives us a set of candidate solutions $C_{v_0} = \{v_1, v_2\}$. It is easy to observe that, by maintaining two separate index structures $N^+$ and $N^-$, for both incoming and outgoing edges, we can reduce the time to fetch the candidate solutions.

Thus, in a generic scenario, given an already matched data vertex $v$, the edge direction '+' or '-', and the set of edge types $T' \subseteq T$, the index $N$ will find a set of neighbourhood data vertices $\{v' | (v', v) \in E \land T' \subseteq L_E(v, v') \}$ if the edge direction is '+' (incoming), while $N$ returns $\{v' | (v, v') \in E \land T' \subseteq L_E(v, v') \}$ if the edge direction is '-' (outgoing).

5. QUERY MATCHING PROCEDURE

In order to follow the working of the proposed query matching procedure, we formalize the notion of core and satellite vertices. Given a query graph $Q$, we decompose the set of query vertices $U$ into a set of core vertices $U_c$ and a set of satellite vertices $U_s$. Formally, when the degree of the query graph $\Delta(Q) > 1$, $U_c = \{u | u \in U \land deg(u) > 1\}$; however, when $\Delta(Q) = 1$, i.e. when the query graph is either a vertex or a multiedge, we choose one query vertex at random as a core vertex, and hence $|U_c| = 1$. The remaining vertices are classified as satellite vertices, whose degree is always 1. Formally, $U_s = \{U \setminus U_c\}$, where for every $u \in U_s$, $deg(u) = 1$. The decomposition for the query multigraph $Q$ is depicted in Figure 4, where the satellite vertices are separated (vertices under the shaded region in Fig. 4a), in order to obtain the query graph that is spanned only by the core vertices (Fig. 4b).

![Figure 4: Decomposing the query multigraph into core and satellite vertices](image)

The proposed AMinER-Algorithm (Algorithm 3) performs recursive sub-multigraph matching procedure only on the query structure spanned by $U_c$ as seen in Figure 4b. Since the entire set of satellite vertices $U_s$ is connected to the query structure spanned by the core vertices, AMinER-Algorithm processes the satellite vertices while performing sub-multigraph matching on the set of core vertices. Thus during the recursion, if the current core vertex has satellite vertices connected to it, the algorithm retrieves directly a list of possible matching for such satellite vertices and it includes them in
the current partial solution. Each time the algorithm executes a recursion branch with a solution, the solution not only contains a data vertex match $v_i$ for each query vertex belonging to $U_v$, but also a set of matched data vertices $V_s$ for each query vertex belonging to $U_r$. Each time a solution is found, we can generate not only one, but a set of embeddings through the Cartesian product of the matched elements in the solution.

Since finding SPARQL solutions is equivalent to finding homomorphic embeddings of the query multigraph, the homomorphic matching allows different query vertices to be matched with the same data vertices. Recall that there is no injectivity constraint in sub-multigraph homomorphism as opposed to sub-multigraph isomorphism. Thus during the recursive matching procedure, we do not have to check if the potential data vertex has already been matched with previously matched query vertices. This is an advantage when we are processing satellite vertices: we can find matches for each satellite vertex independently without the necessity to check for a repeated data vertex.

Before getting into the details of the AMBER-ALgo, we first explain how a set of candidate solutions is obtained when there is information associated only with the vertices. Then we explain how a set of candidate solutions is obtained when we encounter the satellite vertices.

### 5.1 Vertex Level Processing

To understand the generic query processing, it is necessary to understand the matching process at vertex level. Whenever a query vertex $u \in U_v$ is being processed, we need to check if $u$ has a set of attributes $A$ associated with it or any IRIs are connected to it (recall Section 2.2).

**Algorithm 1: ProcessVertex**

```plaintext
if u.A \neq \emptyset then
    CandAtt = QUERYATTINDEX(A, u.A)
else if u.R \neq \emptyset then
    CandAtt = \{ QUERYNEIGHINDEX(N, u.R(u, u'iri), u'iri) \}
else
    return CandAtt
```

To process an arbitrary query vertex, we propose a procedure **ProcessVertex**, depicted in Algorithm 1. This algorithm is invoked only when a vertex $u$ has at least, either a set of vertex attributes or any IRIs connected with it. The **ProcessVertex** procedure returns a set of data vertices **CandAtt**, which are matchable with $u$; in case **CandAtt** is empty, then the query vertex $u$ has no matches in $V$.

As seen in Lines 1-2, when a query vertex $u_s$ with a set of vertex attributes, i.e., $u.A \neq \emptyset$, we obtain the candidate solutions $C_{u_s}^\emptyset$ by invoking **QUERYATTINDEX** procedure, that fetches the index $A$ as explained in Section 4.1. For example, the query vertex $u_2$ with vertex attributes $\{a_1, a_2\}$, can only be matched with the data vertex $v_3$; thus $C_{u_2}^\emptyset = \{v_3\}$.

When a query vertex $u$ has IRIs associated with it, i.e., $u.R \neq \emptyset$ (Lines 3-4), we find the candidate solutions $C_{u_s}^\emptyset$ by invoking the **QUERYNEIGHINDEX** procedure. As we recall from Section 2.2, a vertex $u$ is connected to an IRIs $u'R(u, u'iri)$ through a multi-edge $L_{u'}^R(u, u'iri)$. An IRIs vertex $u'R(u, u'iri)$ always has only one data vertex $v_i$ that can match. Thus, the candidate solutions $C_{u_s}^\emptyset$ are obtained by invoking the **QUERYNEIGHINDEX** procedure, that fetches all the neighbours of $v$ that respect the multi-edge $L_{u'}^R(u, u'iri)$. The procedure is invoked until all the IRIs vertices $u.R$ are processed (Line 4). Considering the example in Figure 2c, $u_3$ is connected to an IRIs-vertex $v_5^\emptyset$, which has a unique data vertex match $v_5$, through the multi-edge $\{-t_3\}$. Using the neighbourhood index $N$, we look for the neighbourhood vertices of $v_5$, that have the multi-edge $\{-t_3\}$, which gives us the candidate solutions $C_{v_5}^\emptyset = \{v_1\}$.

Finally in Line 5, the merge operator $\cap$ returns a set of common candidates **CandAtt** only if $u.A \neq \emptyset$ and $u.R \neq \emptyset$. Otherwise, $C_{u_s}$ or $C_{u_s}^\emptyset$ are returned as **CandAtt**.

### 5.2 Processing Satellite Vertices

In this section, we provide insights on processing a set of satellite vertices $U_{sat} \subseteq U_r$ that are connected to a core vertex $u_1 \in U_v$. This scenario results in a structure that appears frequently in SPARQL queries called star structure [8, 10].

A typical star structure depicted in Figure 5, has a core vertex $u_1 = u_1$, and a set of satellite vertices $U_{sat} = \{u_0, u_2, u_4\}$ connected to the core vertex. For each candidate solution of the core vertex $u_1$, we process $u_0, u_2, u_4$ independently of each other, since there is no structural connectivity (edges) among them, although they are only structurally connected to the core vertex $u_1$.

**Lemma 2.** For a given star structure in a query graph, each satellite vertex can be independently processed if a candidate solution is provided for the core vertex $u_1$.

**Proof.** Consider a core vertex $u_1$ that is connected to a set of satellite vertices $U_{sat} = \{u_0, \ldots, u_s\}$, through a set of edge-types $T' = \{t_0, \ldots, t_s\}$. Let us assume $v_i$ is a candidate solution for the core vertex $u_1$, and we want to find candidate solutions for $u_i \in U_{sat}$ and $u_j \in U_{sat}$, where $i \neq j$. Now, the candidate solutions for $u_i$ and $u_j$ can be obtained by fetching the neighbourhoods of already matched vertex $v_i$ that respect the edge-type $t_i \in T'$ and $t_j \in T'$ respectively. Since two satellite vertices $u_i$ and $u_j$ are never connected to each other, the candidate solutions of $u_i$ are independent of that of $u_j$. This analogy applies to all the satellite vertices.

Given a core vertex $u_1$, we initially find a set of candidate solutions $Cand_{u_1}$ by using the index $S$. Then, for each candidate solution $v_i \in Cand_{u_1}$, the set of solutions for all the satellite vertices $U_{sat}$ that are connected to $u_i$ are returned by the **MATCHSATVERTICES** procedure, described in Algorithm 2. The set of solution tuple $M_{sat}$ defined in Line 1, stores the candidate solutions for the entire set of satellite vertices $U_{sat}$. Formally, $M_{sat} = \{\{u_0, V_0\}\}_{\forall u_0 \in M_{sat}}$, where $u_0 \in U_{sat}$ and $V_0$ is a set of candidate solutions for $u_0$. In order to obtain candidate solutions for $u_2$, we query the

![Figure 5: A star structure in the query multigraph Q](image-url)
neighbourhood index \( N \) (Line 3); the \textsc{queryNeighbourIndex} function obtains all the neighbourhood vertices of already matched \( v_c \), that also considers the multi-edge in the query multigraph \( U^D_{sat}(u, u_c) \). As every query vertex \( u_s \in U_{sat} \) is processed, the solution set \( M_{sat} \) that contains candidate solutions grows until all the satellite vertices have been processed (Lines 2-8).

In Line 4, the set of candidate solutions \( \text{Cand}_{u_s} \) are refined by invoking Algorithm 1 (\textsc{vertexProcessing}). After the refinement, if there are finite candidate solutions, we update the solution \( M_{sat} \); else, we terminate the procedure as there can be no matches for a given matched vertex \( v_c \). The \textsc{matchSatVertices} procedure performs two tasks: firstly, it checks if the candidate vertex \( v_c \in \text{Cand}_{u_s} \) is a valid matchable vertex and secondly, it obtains the solutions for all the satellite vertices.

5.3 Arbitrary Query Processing

Algorithm 3 shows the generic procedure we develop to process arbitrary queries.

Recall that for an arbitrary query \( Q \), we define two different types of vertexes: a set of core vertexes \( U \), and a set of satellite vertexes \( U_{sat} \). The \textsc{queryDecompose} procedure in Line 1 of Algorithm 3, performs this decomposition by splitting the query vertices \( U \) into \( U_c \) and \( U_s \), as observed in Figure 4.

To process arbitrary query multigraphs, we perform recursive sub-multigraph matching procedure on the set of core vertexes \( U_c \subseteq U \); during the recursion, satellite vertexes connected to a specific core vertex \( u \) are processed too. Since the recursion is performed on the set of core vertexes, we propose a few heuristics for ordering the query vertexes.

Ordering of the query vertexes forms one of the vital steps for subgraph matching algorithms [11]. In any subgraph matching algorithm, the embeddings of a query subgraph are obtained by exploring the solution space spanned by the data graph. But since the solution space itself can grow exponentially in size, we are compelled to use intelligent strategies to traverse the solution space. In order to achieve this, we propose a heuristic procedure \textsc{vertexOrdering} (Line 2, Algorithm 3) that employs two ranking functions.

The first ranking function \( r_1 \) relies on the number of satellite vertices connected to the core vertex, and the query vertexes are ordered with the decreasing rank value. Formally, \( r_1(u) = |U_{sat}| \), where \( U_{sat} = \{ u | u \in U_c \land (u, u_c) \in E(Q) \} \). A vertex with more satellite vertexes connected to it, is rich in structure and hence it would probably yield fewer candidate solutions to be processed under recursion. Thus, in Figure 4, \( u_1 \) is chosen as an initial vertex. The second ranking function \( r_2 \) relies on the number of incident edges on a query vertex. Formally, \( r_2(u) = \sum_{j=1}^{n} |\sigma(u)| \), where \( u \) has \( m \) multiedges and \( |\sigma(u)| \) captures the number of edge types in the \( j \)th multiedge. Again, \( U_{sat} \) contains the ordered vertexes with the decreasing rank value \( r_2 \). Further, when there are no satellite vertexes in the query \( Q \), this ranking function gets the priority. Despite the usage of any ranking function, the query vertices in \( U_{ord}^{ord} \), when accessed in sequence, should be structurally connected to the previous set of vertexes. If two vertexes tie up with the same rank, the rank with lesser priority determines which vertex wins. Thus, for the example in Figure 4, the set of ordered core vertexes is \( U_{ord} = \{ u_1, u_3, u_5 \} \).

Algorithm 2: \textsc{matchSatVertices}(\( A, N, Q, U_{sat}, v_c \))

1. \( \text{SET:} M_{sat} = \emptyset \) where \( M_{sat} = \{ (u_s, V_s) \} \)
2. \( \text{FOR all} u_s \in U_{sat} \) \text{DO}
3. \( \text{Cand}_{u_s} = \text{queryNeighbourIndex}(N, U^D_{sat}(u_s, u_s), v_c) \)
4. \( \text{Cand}_{u_s} = \text{Cand}_{u_s} \land \text{processVertex}(u_s, Q, A, N) \)
5. \( \text{IF} \text{Cand}_{u_s} \neq \emptyset \) \text{THEN}
6. \( \text{M}_{sat} = \text{M}_{sat} \cup (u_s, \text{Cand}_{u_s}) \) /* Satellite solutions */
7. \( \text{ELSE} \)
8. \( \text{return} \text{M}_{sat} := 0 \) /* No solutions possible */
9. \( \text{return} \text{M}_{sat} \) /* Matches for satellite vertexes */

Algorithm 3: \textsc{amner-algo} (\( I, Q \))

1. \( \text{queryDecompose: Split} U \text{into} U_c \text{and} U_s \)
2. \( U_{ord} = \text{vertexOrdering}(Q, U_c) \)
3. \( u_{init} = u | u \in U_{ord} \)
4. \( \text{CandInit} = \text{querySyNIndex}(u_{init}, S) \)
5. \( \text{CandInit} = \text{CandInit} \land \text{processVertex}(u_{init}, Q, A, N) \)
6. \( \text{fetch}: U_{ord}^{ord} = \{ u | u \in U_c \land (u_{init}, u) \in E(Q) \} \)
7. \( \text{Set}: \text{Emb} = \emptyset \)
8. \( \text{FOR} v_c \in \text{CandInit} \) \text{DO}
9. \( \text{SET:} M = \emptyset, M_c = \emptyset, M_s = \emptyset \)
10. \( \text{IF} U^{ord} \neq \emptyset \) \text{THEN}
11. \( \text{M}_{sat} = \text{matchSatVertices}(A, N, Q, U^{ord}_{init}, v_{init}) \)
12. \( \text{IF} \text{M}_{sat} \neq \emptyset \) \text{THEN}
13. \( \text{FOR} (u_s, V_s) \in \text{M}_{sat} \) \text{DO}
14. \( \text{UPDATE:} M_c = M_c \cup (u_s, V_c) \)
15. \( \text{UPDATE:} M_s = M_s \cup (u_{init}, V_s) \)
16. \( \text{Emb} = \text{Emb} \cup \text{homomorphicMatch}(M, I, Q, U^{ord}) \)
17. \( \text{ELSE} \)
18. \( \text{UPDATE:} M_c = M_c \cup (u_{init}, V_c) \)
19. \( \text{Emb} = \text{Emb} \cup \text{homomorphicMatch}(M, I, Q, U^{ord}) \)
20. \( \text{return} \text{Emb} /\!* \text{homomorphic embeddings of query multigraph} /\!* \)
we perform recursion to obtain homomorphic embeddings (lines 8-19). Before getting into recursion, for each initial match \( v_{nxt} \in CandInit \), if it has satellite vertices connected to it, we invoke the MATCHSATVERTICES procedure (Lines 10-11). This step not only finds solution matches for satellite vertices, if there are, but also checks if \( v_{nxt} \) is a valid candidate vertex. If the returned solution set \( M_{sat} \) is empty, then \( v_{nxt} \) is not a valid candidate and hence we continue with the next \( v_{nxt} \in CandInit \); else, we update the set of solution pairs \( M_{sat} \) for satellite vertices and the solution pair \( M_{sat} \) for the core vertex (Lines 12-15) and invoke HOMOMORPHICMATCH procedure (Lines 17). On the other hand, if there are no satellite vertices connected to \( v_{nxt} \), we update the core vertex solution set \( M_{sat} \) and invoke HOMOMORPHICMATCH procedure (Lines 18-19).

### Algorithm 4: HOMOMORPHICMATCH\((M, I, Q, U_{ord})\)

```plaintext
1  if \(|M| = |U|\) then
2    return GenEmb(M)
3 Emb = ∅
4  Fetch: \( u_{ord} = w \in U_{ord} \)
5  \( N_u = \{u, v \in M \mid \not\exists (u, v) \in E(M)\} \)
6  \( N_u = \{v \in M \mid (u, v) \in E(M)\} \), where \( u, v \in N_q \)
7  \( CandInit = \{\{u, v\} \mid QueryNeighIndex(N, \lambda \lambda, (u, v))\} \)
8  \( CandInit = \{\{u, v\} \mid ProcessVertex(u, Q, A, N)\} \)
9  for each \( u_{ord} \in CandInit \) do
10     Fetch: \( U_{ord} = \{w \in U \mid v_{nxt}, u \in E(Q)\} \)
11    if \( U_{ord} \neq \emptyset \) then
12       \( M_{ord} = MATCHSATVERTICES(A, N, Q, U_{ord}, v_{nxt}) \)
13    if \( M_{ord} \neq \emptyset \) then
14        for every \( [u', V'] \in M_{ord} \) do
15          Update: \( M = M \cup [u', V'] \)
16    \( Emb = Emb \cup HomomorphicMatch(M, I, Q, U_{ord}) \)
18  else
19        Update: \( M = M \cup (u_{nxt}, v_{nxt}) \)
20    return Emb = Emb \cup HomomorphicMatch(M, I, Q, U_{ord})
```

In the HOMOMORPHICMATCH procedure (Algorithm 4), we fetch the next query vertex from the set of ordered core vertices \( U_{ord} \) (Line 4). Then we collect the neighbourhood vertices of already matched core query vertices and the corresponding matched data vertices (Lines 5-6). As we recall, the set \( M_{sat} \) maintains the solution pair \( m_s = (u_c, v_c) \) of each matched core query vertex. The set \( N_q \) collects the already matched core vertices \( u_c \in M_{sat} \) that are also in the neighbourhood of \( u_{nxt} \), whose matches have to be found. Further, \( N_q \) contains the corresponding matched query vertices \( v_c \in M_{sat} \). As the recursion proceeds, we find those matchable data vertices of \( u_{nxt} \) that are in the neighbourhood of all the matched vertices \( v \in N_q \), so that the query structure is maintained. In Line 7, for each \( u \in N_q \) and the corresponding \( v \in N_q \), we query the neighbourhood index \( V \), to obtain the candidate solutions \( Cand_{nxt} \), that are in the neighbourhood of already matched data vertex \( v \) and have the multidegree \( L_K^{(n)}(u, u_{nxt}) \), obtained from the query multigraph \( Q \). Finally (line 7), the set of candidates solutions that are common for every \( u \in N_q \) are retained in \( Cand_{nxt} \).

Further, the candidate solutions are refined with the help of ProcessVertex procedure (Line 8). Now, for each of the valid candidate solution \( v_{nxt} \in Cand_{nxt} \), we recursively call the HOMOMORPHICMATCH procedure. When the next query vertex \( u_{nxt} \) has no satellite vertices attached to it, we update the core vertex solution set \( M_{sat} \) and call the recursion procedure (Lines 19-20). But when \( u_{nxt} \) has satellite vertices attached to it, we obtain the candidate matches for all the satellite vertices by invoking the MATCHSATVERTICES procedure (Lines 11-12); if there are matches, we update both the satellite vertex solution \( M_{sat} \) and the core vertex solution \( M_{sat} \) and invoke the recursion procedure (Line 17).

Once all the query vertices have been matched for the current recursion step, the solution set \( M \) contains the solutions for both core and satellite vertices. Thus when all the query vertices have been matched, we invoke the GenEmb function (Line 2) which returns the set of embeddings, that are updated in \( Emb \). The GenEmb function treats the solution vertex \( v_c \) of each core vertex as a singleton and performs Cartesian product among all the core vertex singletons and satellite vertex sets. Formally, \( Emb_{part} = \{v^{(1)}_c \times \ldots \times \{v^{(i)}_c\} \times V \times \ldots \times V^{(d)}\} \). Thus, the partial set of embeddings \( Emb_{part} \) is added to the final result \( Emb \).

### 6. RELATED WORK

The proliferation of semantic web technologies has influenced the popularity of RDF as a standard to represent and share knowledge bases. In order to efficiently answer SPARQL queries, many stores and APIs inspired by relational models were proposed \([7, 3, 13, 5]\). x-RDF-3X \([13]\), inspired by modern RDBMS, represent RDF triples as a big three-attribute table. The RDF query processing is boosted using an exhaustive indexing schema coupled with statistics over the data. Also Virtuoso \([7]\) heavily exploits RDBMS mechanism in order to answer SPARQL queries. Virtuoso is a column-store based systems that employs sorts multi-column column-wise compressed projections. Also these systems build table indexing using standard B-trees. Jena \([5]\) supplies API for manipulating RDF graphs. Jena exploits multiplex-property tables that permit multiple views of graphs and vertices which can be used simultaneously.

Recently, the database community has started to investigate RDF stores based on graph data management techniques \([6, 16, 11]\). The work in \([6]\) addresses the problem of supporting property graphs as RDF, since majority of the graph databases are based on property graph model. The authors introduce a property graph to RDF transformation scheme and propose three models to address the challenge of representing the key/value properties of property graph edges in RDF. gStore \([16]\) applies graph pattern matching techniques using filter-and-refinement strategy to answer SPARQL queries. It employs an indexing schema, named VS*-tree, to concisely represent the RDF graph. Once the index is built, it is used to find promising subgraphs that match the query. Finally, exact subgraphs are enumerated in the refinement step. Turbo_Hom++ \([11]\) is an adaptation of a state of the art subgraph isomorphism algorithm (TurboISO\([9]\)) to the problem of SPARQL queries. Exploiting the standard graph isomorphism problem, the authors relax the injectivity constraint to handle the graph homomorphism, which is the RDF pattern matching semantics.

Unlike our approach, Turbo_Hom++ does not index the RDF graph, while gStore concisely represents RDF data through VS*-tree. Another difference between AMiNER and the other graph stores is that our approach explicitly manages the multigraph induced by the SPARQL queries while no clear discussion is supplied for the other tools.
7. EXPERIMENTAL ANALYSIS

In this section, we perform extensive experiments on the three RDF benchmarks. We evaluate the time performance and the robustness of AMnER w.r.t. state-of-the-art competitors by varying the size, and the structure of the SPARQL queries. Experiments are carried out on a 64-bit Intel Core i7-4900MQ @ 2.80GHz, with 32GB memory, running Linux OS - Ubuntu 14.04 LTS. AMnER is implemented in C++.

7.1 Experimental Setup

We compare AMnER with the four standard RDF engines: Virtuoso-7.1 [7], x-RDF-3X [13], Apache Jena [5] and gStore [16]. For all the competitors we employ the source code available on the web site or obtained by the authors. Another recent work TurboHom++ [11] has been excluded since it is not publicly available.

For the experimental analysis we use three RDF datasets - DBPEDIA, YAGO and LUBM. DBPEDIA constitutes the most important knowledge base for the Semantic Web community. Most of the data available in this dataset comes from the Wikipedia Infobox. YAGO is a real world dataset built from factual information coming from Wikipedia and WordNet semantic network. LUBM provides a standard RDF benchmark to test the overall behaviour of engines. Using the data generator we create LUBM100 where the number represents the scaling factor.

<table>
<thead>
<tr>
<th>Dataset</th>
<th># Triples</th>
<th># Vertices</th>
<th># Edges</th>
<th># Edge types</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBPEDIA</td>
<td>33,071,359</td>
<td>4,983,349</td>
<td>14,992,982</td>
<td>676</td>
</tr>
<tr>
<td>YAGO</td>
<td>35,543,536</td>
<td>3,160,832</td>
<td>10,683,425</td>
<td>44</td>
</tr>
<tr>
<td>LUBM100</td>
<td>13,824,437</td>
<td>2,179,780</td>
<td>8,952,366</td>
<td>13</td>
</tr>
</tbody>
</table>

Table 4: Benchmark Statistics

The data characteristics are summarized in Table 4. We can observe that the benchmarks have different characteristics in terms of number of vertices, number of edges, and number of distinct predicates. For instance, DBPEDIA has more diversity in terms of predicates (~700) while LUBM100 contains only 13 different predicates.

The time required to build the multigraph database as well as to construct the indexes are reported in Table 5. We can note that the database building time and the corresponding size are proportional to the number of triples. Regarding the indexing structures, we can underline that both building time and size are proportional to the number of edges. For instance, DBPEDIA has the biggest number of edges (~15M) and, consequently, AMnER employs more time and space to build and store its data structure.

<table>
<thead>
<tr>
<th>Dataset</th>
<th>Building Time</th>
<th>Size</th>
<th>Index X Building Time</th>
<th>Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>DBPEDIA</td>
<td>307</td>
<td>1300</td>
<td>45.18</td>
<td>1573</td>
</tr>
<tr>
<td>YAGO</td>
<td>379</td>
<td>2400</td>
<td>29.1</td>
<td>1322</td>
</tr>
<tr>
<td>LUBM100</td>
<td>67</td>
<td>497</td>
<td>18.4</td>
<td>1057</td>
</tr>
</tbody>
</table>

Table 5: Offline stage: Database and Index Construction time (in seconds) and memory usage (in Mbytes)

7.2 Workload Generation

In order to test the scalability and the robustness of the different RDF engines, we generate the query workloads considering a similar setting as in [8, 1, 9]. We generate the query workload from the respective RDF datasets, which are available as RDF tripleset. In specific, we generate two types of query sets: a star-shaped and a complex-shaped query set; further, both query sets are generated for varying sizes (say k) ranging from 10 to 50 triples, in steps of 10.

To generate star-shaped or complex-shaped queries of size $k$, we pick an initial-entity at random from the RDF data. Now to generate star queries, we check if the initial-entity is present in at least $k$ triples in the entire benchmark, to verify if the initial-entity has $k$ neighbours. If so, we choose those $k$ triples at random; thus the initial entity forms the central vertex of the star structure and the rest of the entities form the remaining star structure, connected by the respective predicates. To generate complex-shaped queries of size $k$, we navigate in the neighbourhood of the initial-entity through the predicate links until we reach size $k$. In both query types, we inject some object literals as well as constant IRIs; rest of the IRIs (subjects or objects) are treated as variables. However, this strategy could choose some very unselective queries [8]. In order to address this issue, we set a maximum time constraint of 60 seconds for each query. If the query is not answered in time, it is not considered for the final average (similar procedure is usually employed for graph query matching [9] and RDF workload evaluation [1]). We report the average query time and, also, the percentage of unanswered queries (considering the given time constraint) to study the robustness of the approaches.

7.3 Comparison with RDF Engines

In this section we report and discuss the results obtained by the different RDF engines. For each combination of query type and benchmark we report two plots by varying the query size: the average time and the corresponding percentage of unanswered queries for the given time constraint. We remind that the average time per approach is computed only on the set of queries that were answered.

The experimental results for DBPEDIA are depicted in Figure 6 and Figure 7. The time performance (averaged over 200 queries) for Star-Shaped queries (Fig. 6a), affirm that AMnER clearly outperforms all the competitors. Further the robustness of each approach, evaluated in terms of percentage of unanswered queries within the stipulated time, is shown in Figure 6b. For the given time constraint, x-RDF-3X and Jena are unable to output results for size 20 and 30 onwards respectively. Although Virtuoso and gStore output results until query size 50, their time performance is still poor. However, as the query size increases, the percentage of unanswered queries for both Virtuoso and gStore keeps on increasing from ~0% to 65% and ~45% to 95% respectively. On the other hand AMnER answers >98% of the queries, even for queries of size 50, establishing its robustness.

Analyzing the results for Complex-Shaped queries (Fig. 7), we underline that AMnER still outperforms all the competitors for all sizes. In Figure 7a, we observe that x-RDF-3X and Jena are the slowest engines; Virtuoso and gStore perform better than them but nowhere close to AMnER. We further observe that x-RDF-3X and Jena are the least robust as they don’t output results for size 30 onwards (Fig. 7b);
on the other hand AMbER is the most robust engine as it answers >85% of the queries even for size 50. The percentage of unanswered queries for Virtuoso and gStore increase from 0% to ~80% and 25% to ~70% respectively, as we increase the size from 10 to 50.

The results for YAGO are reported in Figure 8 and Figure 9. For the Star-Shaped queries (Fig. 8), we observe that AMbER outperforms all the other competitors for any size. Further, the time performance of AMbER is 2-3 orders of magnitude better than its nearest competitor Virtuoso. Similar to the YAGO experiments, x-RDF-3X, Jena are not able to manage queries from size 20 onwards; the same trend is observed for gStore too. Further, Virtuoso always loses its robustness as the query size increases. On the other hand, AMbER answers queries for all sizes.

To summarise, we observe that Virtuoso is enough robust for Complex-Shaped smaller queries (10-20), but fails for bigger (>20) queries. x-RDF-3X fails for queries with size bigger than 10. Jena has reasonable behavior until size 20, but fails to deliver from size 30 onwards. gStore has a reasonable behavior for size 10, but its robustness deteriorates from size 20 onwards. To summarize, AMbER clearly outperforms, in terms of time and robustness, the state-of-the-art RDF engines on the evaluated benchmarks and query configuration. Our proposal also scales up better than all the competitors as the size of the queries increases.

8. CONCLUSION

In this paper, a multigraph based engine AMbER has...
been proposed in order to answer complex SPARQL queries over RDF data. The multigraph representation has bestowed us with two advantages: on one hand, it enables us to construct efficient indexing structures, that ameliorate the time performance of AMbER; on the other hand, the graph representation itself motivates us to exploit the valuable work done until now in the graph data management field. Thus, AMbER meticulously exploits the indexing structures to address the problem of sub-multigraph homomorphism, which in turn yields the solutions for SPARQL queries. The proposed engine AMbER has been extensively tested on three well established RDF benchmarks. As a result, AMbER stands out w.r.t. the state-of-the-art RDF management systems considering both the robustness regarding the percentage of answered queries and the time performance. As a future work, we plan to extend AMbER by incorporating other SPARQL operations and, successively, study and develop a parallel processing version of our proposal to scale up over huge RDF data.

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10. REFERENCES