Duplicate-Aware Federated Query Processing over the Data Web

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ABSTRACT

Categories and Subject Descriptors

H.2.4 [**Database Management**]: Systems—*Distributed databases*

General Terms

Algorithms, Experimentation, Theory

Keywords

Federated queries, SPARQL, deduplication

1. INTRODUCTION (AN+MS)

Over the last years, the Linked Data Web has developed into a large compendium of interlinked data sets from diverse domains. One of the central principles underlying the architecture of these data sets is the reuse of URIs and vocabularies as well as the linking of knowledge bases. One of the results of this architectural choice is that certain queries can only be answered by retrieving information from several knowledge bases. This type of querying, called *federated querying*, is of central importance for manifold applications such as question answering, knowledge retrieval and data integration. In addition to the information necessary to answering queries being distributed, certain pieces of information (i.e., triples) can be found in several knowledge bases. For example, the name of movie directors can be found both in DBpedia and LinkedMDB. Similarly, the authors of papers can be found in both the ACM and DBLP libraries. We call triples that can be found in several knowledge bases across the Web of Data *duplicates*.

While the importance of federated queries over the Web of Data has been stressed in previous work, the impact of duplicates has not received much attention. Yet (as we will show in the remainder of this paper), a duplicate-aware approach to query processing can lead to more time-efficient and effective algorithms for federated queries. In this paper, we address this drawback by presenting a duplicate-aware approach for query processing based on min-wise independent permutation (MIPS) vectors. Our approach is able to predict the amount of new information contained in a knowledge base with a higher accuracy than the state of the art, leading to a better performance with respect to source ranking and result set size optimization. In the rest of this paper, we aim to show experimentally that our approach outperforms the state-of-the-art by running it against ?? methods on ?? queries. We begin by giving a brief overview of the state of the art in federated query processing. In addition, we argue for the use of MIPS for the approximation of result size sets. Thereafter, we present our duplicate-aware federated query processing approach. After an overview of the datasets used in this paper, we present experimental results which corroborate the superior efficiency of our approach. We conclude the paper with a discussion of our findings and an overview of future work.

2. RELATED WORK (MS)

2.1 Federated SPARQL queries

The research work on federated query processing over the Data Web can be categorized into two main directions:

- Service description/index-assisted approaches, which make use of the dataset summaries that have been collected in a pre-processing stage. These approaches lead to a more efficient query federation. However, the index needs to be constantly updated to ensure up-to-date results. Also, the index size should not be large to ensure that it does not increase the overall query processing time.

- Index-free approaches, in which the query federation is performed without using any stored data summaries. This approach is less efficient however; the query response time is faster than index assisted approach.

Both of the above approaches can further be divided into two categories (a) Query federation with complete result retrieval (b) Query federation with partial (sufficient) record retrieval. In our case, we are focusing on index-assisted, sufficient record retrieval.

Heiner et. al [1] describes how to extend the Sesame RDF repository to support distributed SeRQL queries over multiple Sesame RDF repositories. They use a special index structure to determine the relevant sources for a query. Quilitz and Leser [2] uses the theoretical knowledge of [1] to develop the first federated query engine (named DARQ) for

remote RDF data sources. DARQ uses service descriptions for relevant data source selection. A service description describes the capabilities of a SPARQL endpoint. They used query rewriting mechanism based on [8] and a cost-based optimization algorithm to reduce the query processing time with the minimum bandwidth usage. DARQ is compatible with any SPARQL endpoint that implements the SPARQL standard. Their experimental results show that the optimization algorithm can greatly reduce the query processing time.

Andreas et al. [3] proposed a solution similar to DARQ using a mediator approach. All the SPARQL endpoints need to register first with the mediator using HTTP POST requests with an RDF document attached. The mediator continuously monitors the SPAQL endpoints for any dataset changes and updates the service descriptions automatically. Unlike DARQ, the service descriptions remain up-to-date all time.

Olaf et al. [4] present a new approach for federated query processing over the Web of Data. Their approach discovers data that might be relevant for answering a query during the query execution itself. The discovery of relevant data is accomplished by traversing RDF links. They used an iterator-based pipeline and a URI prefetching approach for efficient query execution. Both DARQ and [3] are not able to discover relevant data sources by the query itself.

The previous techniques cannot answer all types of queries due to index or service description limitations. Umbrich et al. [5], [6] proposed a Qtree-based index structure which summarizes the content of data source for query execution over the Web of Data. They concluded that this approach is able to handle more expressive queries and return more complete results than previous approaches. Schwarte et al. [7] proposed an index-free query federation for the Web of Data. Their approach gives a reasonably fast data retrieval as compared to all the previous techniques. However, since they do not keep any statistics, it works only for limited data sources.

Li and Heflin [15] build a tree structure which supports the integration of data from multiple heterogeneous sources. The tree is built in a bottom-up fashion; each triple pattern is rewritten according to the annotations on its corresponding datasets. Kaoudi et al. [16] propose a technique that runs on Atlas, a P2P system for processing RDF distributed data that are stored in hash tables. The purpose of this technique is to minimize the query execution time and the bandwidth consumed; this is done by reducing the cardinality of intermediate results. A dynamic programming algorithm was implemented that relies on message exchange among sources

The Tukwila integration system [17] executes queries through several autonomous and heterogeneous sources. Tukwila decomposes original queries into a number of sub-queries on each source, and uses adaptive techniques to hide delays. Ludwig and Tran [18] propose a mixed query engine; sources are selected using aggregated indexes that keep information about triple patterns and join cardinalities for available sources; these statistics are updated on-the-fly. The execution ends when all relevant sources have been processed or a stop condition given by the user is reached; additionally, the Symmetric Hash Join is implemented to incrementally produce answers; recently, this approach was extended to also process Linked Data locally stored [19].

Maribel et al. [21] presented ANAPSID, an adaptive query engine for SPARQL endpoints that adapts query execution schedulers to data availability and run-time conditions. ANAPSID provides physical SPARQL operators that detect when a source becomes blocked or data traffic is bursty, and opportunistically, the operators produce results as quickly as data arrives from the sources.

Avalanche [24] produces the first k results, and sources are interrogated to obtain statistics which are used to decompose queries into sub-queries that are executed based on their selectivity; sub-queries results are sent to the next most selective source until all sub-queries are executed; execution ends when a certain stop condition is reached. Also, heuristics-based techniques are proposed to minimize query intermediate results [25].

Other noteable contributions LIMES [26], SILK [27], EAGLE [28] provides time-efficient approaches for Link Discovery using various distance measure techniques. LIMES framework utilize the mathematical characteristics of metric spaces to compute similarity estimates between instances. It makes use of the triangle inequality to partition the metric space into different portions. Each of these portions of the space is then represented by an exemplar [33] that allows to compute an accurate distance approximation between different instances. SILK implements a multi-dimensional blocking approach for link discovery. The Levenshtein distance [34] is used for approximate for similarity estimation between different instances. EAGLE presents a novel active learning approach to learning link specications based on genetic programming. EAGLE generates highly accurate link specications while reducing the annotation burden for the user.

None of the above techniques used statistical information stored in the index or service description for pre-processing dataset overlap estimation. In the initial stage, like DARQ engine, we use service descriptions for query federation. In addition, we store MIPs vector statistics for each of the indexed data source. Query federator makes use of this special statistic information to estimate the possible overlap between the results of different sub-queries.

2.2 Filters

The overlap between two datasets can be estimated using min-wise independent permutations [9], bloom filters [10], or compressed bloom filters [11]. Bender et al. [12] also proposed a technique for predicting the query-specific mutual overlap between peers. However, MIPs have proved to be the more accurate overlap estimation with small bandwidth consumption [9].

3. NOTATION

In this section, we present the core of the notation that will be used throughout this paper. We denote data sources with S and the total number of data sources with n. The set of all possible result sets is denoted R while the set of all possible SPARQL queries is labeled with Q. A data source ranking function $rank : S \times Q \rightarrow \{1 \dots n\}$ is a function that assigns a ranking to each data source given a particular query $q \in Q$. Note that for any source ranking function $rank$, we assume that $\forall S, S' \forall q \in Q : S \neq S' \iff rank(S, q) \neq rank(S', q)$. A result set estimation function $est : S \times Q \rightarrow \mathbb{N}$ aims at approximating the size of the result set that will be returned by a given query. Note that this function plays a crucial role

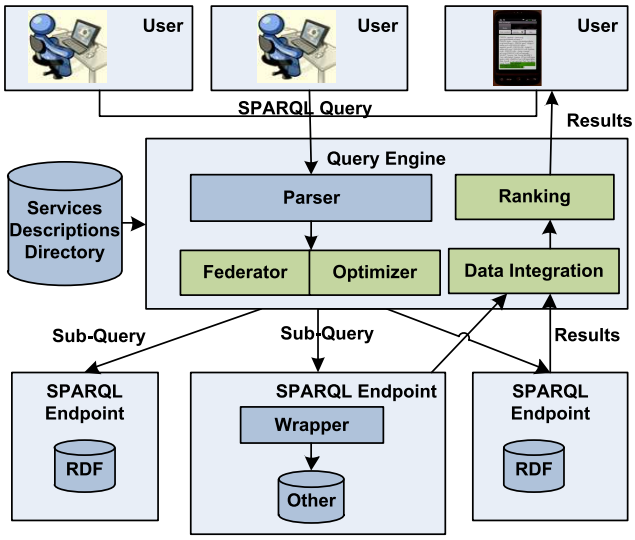
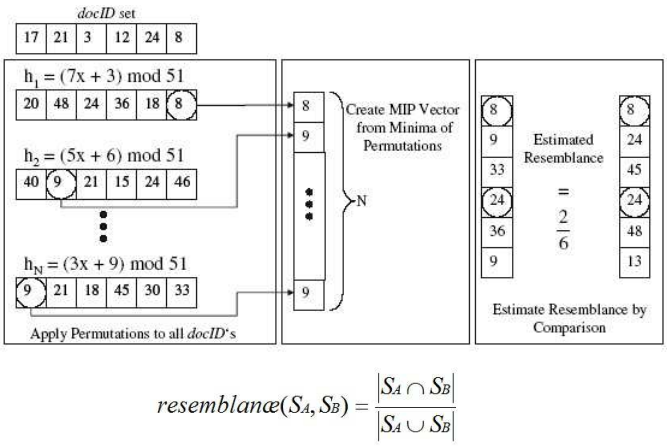


Figure 1: Federated SPARQL query processing architecture



$$resemblance(S_A, S_B) = \frac{|S_A \cap S_B|}{|S_A \cup S_B|}$$

Figure 2: Min-Wise independent permutations (image taken from [13] with permission)

in the processing of federated queries as it is most commonly used to decide upon the ranking of data sources for a given query. The aim of a federated query system such as the one described in this work is thus to optimize its estimation function *est* so as to ensure a ranking of the source close to the optimal ranking.

4. APPROACH (MS)

4.1 Overview

Overall, our approach works as follows: The user begins by issuing a SPARQL query using any input form. The query is then forwarded to the query engine. Upon receiving, it is parsed to get all triples. The parser rewrites the original query the original query in an execution-optimized form. The federator then makes use of the services descriptions directory/index to decompose single query into multiple sub-queries. The query optimizer takes all sub-queries to generate an optimize execution plan. At last, all the optimized sub-queries are forwarded to the relevant SPARQL endpoints. The results of each sub-query execution are integrated and finally sent back to the user. This architecture for distributed query processing is shown in figure 1.

While this architecture is the same for all federated query systems, the federator and optimizer of our system differ significantly from those of other approaches as they make use of the MIPs statistical information to generate a precise query execution plan. The generation of MIPs statistical information is explained in the next section.

4.2 MIPS

Min-Wise Independent Permutations (MIPs) assumes that the set elements can be ordered (which is trivial for integer keys) and computes N random permutations of the elements. Each permutation uses a linear hash function of the form hi(x) : = ai* x + i mod U where U is a big prime number and ai, bi are fixed random numbers. By ordering the resulting hash values, we obtain a random permutation. For each of the N permutations, the MIPs technique determines the minimum hash value, and stores it in an N-dimensional vector, thus capturing the minimum set element under each of these random permutations. The technique is illustrated with an example in figure 3 taken from [13]. Its fundamental rationale is that each element has the same probability of becoming the minimum element under a random permutation. By using sufficiently many different permutations, we can approximate the set cardinality.

An unbiased estimate of the pair-wise resemblance of sets using their N-dimensional MIPs vectors is obtained by counting the number of positions in which the two vectors have the same number and dividing this by the number of permutations N. Essentially, this holds as the matched numbers are guaranteed to belong to the intersection of the sets.

For a predicate p∈ D, the set elements are all triples T ∈ D with predicate p and computes N random permutations. The resulting MIP vector is stored against each capability of the service description. MIP vector statistics is used during source selection and sub-query generating algorithm for efficient, duplicate free query execution plan.

4.3 Index construction

To find the set of relevant servers and decompose the user query into multiple sub-queries, the query engine needs information about the different data sets available at different servers. We call this catalog the **service description directory**. Each service description provides a declarative description of the data available from a server along with statistical information. The statistical information are used for query optimization. However, the directory size should be small enough and must contain sufficient information to enable sub-query generation, optimization and pre-processing dataset overlap estimation. Moreover, the directory should be dynamically updated for up to date data retrieval and accurate overlap detection.

In the initial stage, we only store the *server url*, and for each distinct predicate **p** we record *predicate name, MIPs Vector,* and *total number of triples* having predicate **p**. The MIPs vectors are used to estimate the dataset overlap before query execution. The other statistical information is used during sub-query generation and optimization. During this work, we are planning to use other statistical information

such as subject/object selectivity, histograms, links across the knowledge bases and ontology matching data. In addition, we will use a mediator to constantly update the service description directory. A sample service description for Galway geo data is given in the listing 1.

4.4 Source Selection

A SPARQL query contains one or more filtered basic graph patterns of which each contains the actual triple patterns. The query planning step is performed separately for each filtered basic graph pattern. The algorithm used in DARQ for finding the relevant data sources for a query simply matches all triple patterns against the capabilities of the data sources. The matching compares the predicate in a triple pattern with the predicate defined for a capability and evaluates the constraint for subject and object. Let BGP be a set of triple patterns in a filtered basic graph pattern. The result of the source selection is a set of data sources Dj for each triple pattern.

* need to include the source selection

We extended the DARQ source selection algorithm by comparing different MIP vectors for similarity. For a triple pattern, we compare the MIP vectors of all the relevant data sources for possible similarity. A specific source D is only added to the set of capable sources j, if D is able to produce new results above a specific threshold value defined for similarity. For a triple T in dataset D, if the resemblance value is less than the threshold, D is ignored from set Dj.

4.5 Source Ranking

Result set estimation

4.6 Subquery generation

We need an efficient algorithm for sub-query generation using the service description directory. In the initial stage we are using the sub-query generating algorithm of DARQ given in figure 2. We represent a sub-query as triple (T,C, d), where T is a set of triple patterns, C is a set of value constraints and d is the data source that can answer the sub-query. Algorithm 1 shows how the sub-queries are generated. If a triple pattern matches exactly one data source (Di = {d}) the triple will be added to the set of a sub-query for this data source. All triples in this set can later be sent to the data source in one sub-query. If a triple matches multiple data sources the triple must be sent individually to all matching data sources in separate sub-queries.

Algorithm 1 Sub-query generation

Require: $T = \{t_1, .., t_n\}$, // set of triple patterns
$D = \{D_1, .., D_n\}$ // sets of data sources matching to the triple patterns
1: $queries = \emptyset$, $separateQueries = \emptyset$
2: **for** each $t_i \in T$ **do**
3: **if** $D_i = \{d\}$ **then**
4: $q = queries.getQuery(d)$
5: **if** q not null **then**
6: $q.T = q.T + t_i$
7: **else**
8: $queries = queries + (\{t_i\}, \{\}, d)$
9: **end if**
10: **else**
11: **for** each $d_j \in D_i$ **do**
12: $separateQueries = separateQueries + (\{t_i\}, \{\}, d_j)$
13: **end for**
14: **end if**
15: **end for**
16: **return** $queries \cup seperateQueries$ // Return all queries

Figure 3: Sub-query Generating Algorithm

5. EXPERIMENTS AND RESULTS (AN)

5.1 Experimental Setup (AN)

5.1.1 Datasets (3 datasets)

5.1.2 Queries (6 types)

5.1.3 Metrics (MSE)

5.2 Results (AN)

5.2.1 Ranking Error

5.2.2 Result Set Estimation Error

5.2.3 Execution Time

5.2.4 Size of MIPS vectors (on largest dataset)

6. DISCUSSION (AN)

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