

Duplicate-Aware Federated Query Processing over the Web of Data

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ABSTRACT

Over the last years, the Web of Data has developed into a large compendium of interlinked data sets from multiple domains. Due to this lack of coordination, several of these data sets contain duplicate or complementary data. Several federated querying approaches have been proposed to retrieve information from these data sources. Still, only little attention has been paid to the effect of duplicated and fragmented data on the processing of federated queries. This work presents a novel duplicate-aware approach to federated SPARQL querying based on Min-Wise Independent Permutations (MIPs) applied to RDF predicates. Our approach begins by parsing each input query for triple patterns. Then, for each of these triple patterns, it uses MIPs to approximate the amount of non-duplicate triples contained in each of the available data sources. This approximation is used to select and rank relevant data sources. Finally, the selected data sources are queried by means of the sub-queries contained in the user input. The ranking function implemented by our approach allows taking into account the overlap among the available data sources and can thus account for duplicates across the data sets. Moreover, our approach queries the data sources by using single triple patterns and can thus also retrieve results whose fragments are distributed across the Web of Data. We evaluate our approach on four datasets of different sizes by using 79 queries of various shapes. Our evaluation shows that our approach achieves significantly smaller mean squared errors than the state of the art with respect to the approximation of result set sizes as well as in the ranking of data sources. Moreover, it requires less

queries to achieve the same recall as existing approaches, thus improving both execution time and network traffic.

Categories and Subject Descriptors

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

General Terms

Algorithms, Experimentation, Theory

Keywords

Federated queries, SPARQL, Min-wise independent permutations

1. INTRODUCTION

Over the last years, the Data Web has developed into a large compendium of interlinked data sets from multiple domains [14]. 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 [20]. 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 queries, called *federated queries*, is of central importance for manifold applications such as question answering [?] and knowledge retrieval [?]. Due to the reuse of URIs and the independence of the data sources, 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 Linked-MDB. Authors of papers can be found in both the ACM and DBLP libraries. Similarly, we have noticed that the *DrugBank*¹ and *Neurocommons*² datasets are duplicated at *DERI health Care and Life Sciences Knowledge Base*³. A list of the mirrored SPARQL endpoints is given in the url⁴.

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¹<http://datahub.io/dataset/fu-berlin-drugbank>

²http://neurocommons.org/page/RDF_distribution

³<http://hcls.deri.org:8080/openrdf-sesame/repositories/hclskb>

⁴http://hcls.deri.org/RoadMapEvaluation/#Sparql_Endpoints

An analysis of Linked Open Data Cloud shows that duplicates are most common in life sciences domain. Examples of data sets which might contain the same triples across the life science domain is shown in Figure 1. 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 Permutations (MIPs). The use of statistical synopsis such as MIPs for overlap estimation is very common in the literature (as discussed in the next section), however these synopsis cannot be used alone in semantic web domain due to the diverse nature of SPARQL queries. For example, the synopsis estimation need to be completely changed if any of the subject or object becomes bound in the query triple. To address such issues, we combine MIPs synopsis with the data summaries statistics for more accurate overlap estimation.

By creating small summaries of the data found in the available knowledge bases, our approach is able to estimate the amount of new information contained in a knowledge base with a high accuracy, leading to a better performance with respect to source ranking, estimation of result set sizes, execution time and network traffic.

The main contributions of this paper are as follows:

1. We propose the (to the best of our knowledge) first duplicate-aware approach for federated SPARQL querying.
2. We combine data summaries statistics with MIPs to address the diversity in SPARQL queries.
3. We evaluate our approach against the state of the art on 79 queries and four datasets and show that we achieve better estimations of result set sizes and therefore a better ranking of data sources, lower execution times and consequently less network traffic.

The rest of this paper is organized as follows: We begin by giving a brief overview of the state of the art in federated query processing. In addition, we present different statistical synopsis approaches that can be used for the approximation of duplicate-free result set sizes. Thereafter, we elaborate on our novel duplicate-aware federated query processing approach and present the components of our approach in detail. Subsequently, we present a thorough evaluation of our approach against state of the art approaches. We finally conclude the paper with a discussion of our findings and an overview of future work.

2. RELATED WORK

2.1 Federated SPARQL Queries

The research work on federated query processing over the Data Web can be categorized into three 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

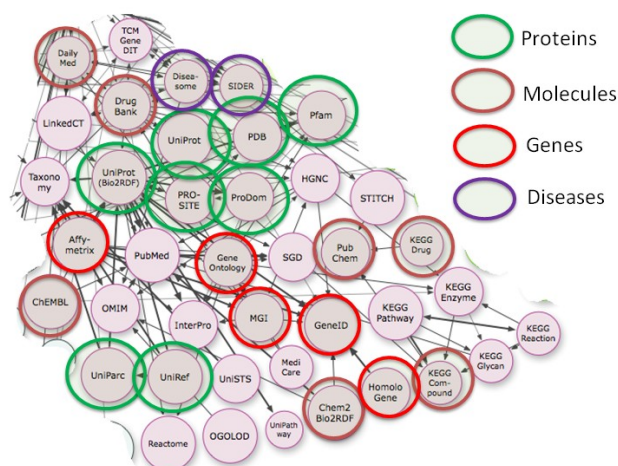


Figure 1: Possible duplicates in life sciences domain

may 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 cost.

- Index-free approaches, in which the query federation is performed without using any stored data summaries. The data source statistics can be collected on-the-fly before the query federation. This approach promises the up-to-date records retrieval however; it may increase or decrease the query execution time, depends on the extra processing required in collecting, processing on-the-fly statistics.
- Hybrid approaches, in which some of the data source statistics are pre-stored while some are collected on-the-fly.

All of the above approaches can be further divided into two categories (a) Query federation with complete result retrieval (100% recall), and (b) Query federation with partial (sufficient) record retrieval. In our work, we focus on index-assisted query federation which can be used both for complete and partial record retrieval.

Heiner et al. [1] describe 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] use 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 use a 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] propose a solution similar to DARQ using a mediator approach. The SPARQL endpoints need to register first with the mediator using HTTP POST requests with an RDF document attached. The mediator con-

tinuously monitors the SPARQL 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 use 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], propose a Qtree-based index structure which summarizes the content of data source for query execution over the Web of Data. Their approach is able to handle more expressive queries however; because of the complete-query based source ranking, it may skip querying many sources which are capable of answering a sub-set of the query triples. Schwarte et al. [7] propose 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 federated query processing over multiple heterogeneous sources. They make use of an OWL reasoner to answer queries over the selected sources and their corresponding ontologies. Kaoudi et al. [16] propose a federated query technique on top of distributed hash tables (DHT). The overall goal is to minimize the query execution time and the bandwidth consumption by reducing the cardinality of intermediate results. The DHT-based optimizer make use of three greedy optimization algorithms for best plan selection.

Ludwig and Tran [18] propose a mixed query engine that assumes some incomplete knowledge about the sources to select and discover new sources at run time. A Symmetric Hash Join is implemented to incrementally produce answers. This approach is extended to query both remote and local linked data [19].

Maribel et al. [21] present ANAPSID, an adaptive query engine that adapts query execution schedulers to SPARQL endpoints data availability and run-time conditions. ANAPSID provides physical SPARQL operators that detect when a source becomes blocked or data traffic is bursty. The operators produce results as quickly as data arrives from the sources. Amol et al. [17] present a survey of the adaptive query processing techniques, common issues, and the settings in which each piece of work is most appropriate. Avalanche [24] gathers endpoints dataset statistics and bandwidth availability on-the-fly before the query federation. The advantage of this technique is the live query execution over the Web of Data. However, on-the-fly statistics calculation can increase the overall query execution time. Olaf [25] propose a heuristics-based technique to minimize query intermediate results.

Other notable contributions such as LIMES [26], SILK [27], EAGLE [28] provides time-efficient approaches for link discovery using various distance measure techniques. The 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 specifications based on genetic programming. EAGLE generates highly accurate link specifications while reducing the annotation burden for the user.

Few other contributions address the problem of SPARQL query federation [22], [23] but none, to the best of our knowledge has taken into account the possibility of mutual overlap between different RDF datasets before query execution. Similar to DARQ engine, we use service descriptions for query federation. In addition, we store MIPs vector statistics for each of the indexed data source. Our query federator makes use of this special statistic information to estimate the possible overlap between the results of different sub-queries in order to avoid the retrieval of redundant information.

2.2 Dataset Overlap Estimation

Avoiding the retrieval of duplicate records is a crucial issue in large scale distributed datasets. As the SPARQL endpoints are autonomous, there is always the possibility of high mutual overlap between different datasets residing in different endpoints. It is thus likely that an optimized query execution plan contains a sub-query that retrieves records which are already retrieved by another sub-query from a different SPARQL endpoint. In this case it is not necessary to execute the later sub-query, as it would not only result in duplicate records being retrieved but also increase the total processing time.

Statistical synopsis like min-wise independent permutations [9], bloom filters [10], hash sketches [36], XSKETCH [37], fractional XSKETCH [38], and compressed bloom filters [11] have been extensively used in the literature to provide a compacted representation of data sets. Statistical synopsis allow to estimate a number of set operations such as overlap and union without having to compare the original sets directly. For example, Bender et al. [12] propose a technique for predicting the query-specific mutual overlap datasets in a peer to peer network. MIPs have proved to be the more accurate overlap estimation with small bandwidth consumption [9] therefore we have chosen them in our approach.

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 data sets is dubbed \mathcal{S} . 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 in the processing of federated queries as it is most commonly used to decide upon the ranking of data sources for a given

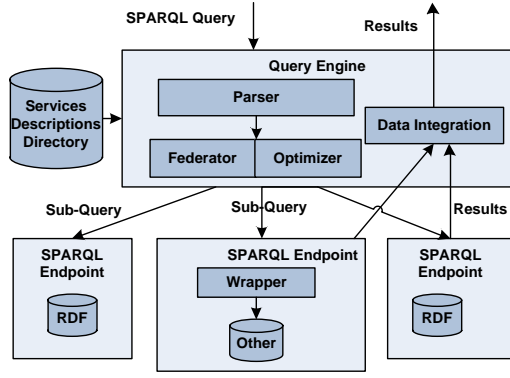


Figure 2: Duplicate-aware federated query processing architecture

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. DUPLICATE-AWARE FEDERATED QUERY PROCESSING

4.1 Overview

Given a query, it is first parsed, then sent to federator which makes use of the services descriptions directory/index to decompose the query into duplicate free multiple sub-queries. Each sub-query is optimized to generate an optimized execution plan. The optimized sub-queries are forwarded to the relevant SPARQL endpoints. The results of each sub-query execution are integrated and the final query result set is generated. This architecture for duplicate-aware federated query processing is shown in Figure 2. While this architecture is similar to other federated query systems, the federator in our system differ significantly from those of other approaches as it makes use of MIPs statistical information to generate duplicate-free query execution plans. The generation of MIPs statistical information is explained in the next section.

4.2 Service Description Directory

To find the set of relevant servers and generate the appropriate sub-queries, the federator needs information about the different data sets available at the different servers. We call the catalog containing such information the *service description directory*. Each service description provides a declarative description of the data available from a server along with statistical information.

For each server our *service description directory* stores *server url*, *graph name*, and for each distinct predicate *p* we record *predicate name*, *MIPs vector*, *subject selectivity*, *object selectivity*, and *total number of triples* having predicate *p*. The MIPs vectors are used to estimate the dataset overlap among the capable datasets before the sub-query distribution and it will be explained in detail in section 4.3. The *subject* and *object selectivity* are used to estimate the sub-query result set when *subject*, *object* are bound, respectively. We call the set $C_i = \{(p_i, mipsv_i, sbj sel_i, obj sel_i, totTrpl_i)\}$ as a *capability* of the data source. The total number of ca-

Listing 1: A Service Description Example

```
[ ] a sd:Service ;
sd:url <http://localhost:8890/sparql> ;
sd:graph "diseasome/DS1" ;
sd:capability
[
sd:predicate diseasome:name ;
sd:MIPv "-6908232 -7090543 -6892373 -7064247 ...";
sd:subjectSelectivity "0.0068" ;
sd:objectSelectivity "0.0069" ;
sd:triples 147 ;
] ;
sd:capability
[
sd:predicate diseasome:chromosomalLocation ;
sd:MIPv "-7056448 -7056410 -6845713 -6966021 ...";
sd:subjectSelectivity "0.0062" ;
sd:objectSelectivity "0.0072" ;
sd:triples 160 ;
] ;
```

pabilities of a data source is equal to the number of distinct predicate in that data source. A sample service description is given in the Listing 1.

It is very crucial to keep the directory size small to minimize the pre-query federation time. However, this directory must contain sufficient information to enable the generation of sub-query, the optimization, and the pre-processing dataset overlap estimation. Our index size is mostly depended upon the size of the MIPs vectors which can be adjusted to any length. In general MIPs can provide a good estimation of the overlap between sets with a few integer in length. Min-Wise Independent Permutations have been in the peer to peer networks literature [13, 39, 40].

4.3 Min-Wise Independent Permutations

MIPs assumes that the set elements can be ordered and computes N random permutations of the elements. Each permutation uses a linear hash function of the form $h_i(x) := a_i * x + b_i \text{ mod } U$ where U is a big prime number and a_i, b_i are fixed random numbers [13]. 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. 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.

Let S_A and S_B be the two MIPs set, the cardinality of the intersection is defined as the overlap between these two sets. The overlap and union of the two sets is given in Equation 1 and Equation 2, respectively.

$$Overlap(S_A, S_B) = |S_A \cap S_B| \quad (1)$$

$$Union(S_A, S_B) = |S_A \cup S_B| \quad (2)$$

An unbiased estimate of the pair-wise resemblance of the sets can be obtained by counting the number of positions in which the two MIPs 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. The resemblance formula is given in Equation 3.

$$Resemblance(S_A, S_B) = \frac{Overlap(S_A, S_B)}{Union(S_A, S_B)} \quad (3)$$

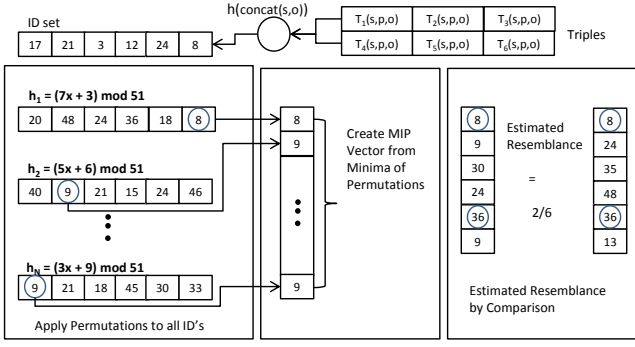


Figure 3: Min-Wise Independent Permutations

In our service descriptions the MIPs are used as follow: for a predicate $p \in S$, we create a MIPs vector representing all triples $T \in S$ having predicate p . We concatenate the *subject* and *object* of each triple in T and apply a hash function to get the *ID set*. Finally, we compute N random permutations of the *ID set*. The resulting MIPs vector is stored against each capability of the service description. Note that we are not applying hash function to the complete triple because the predicate is already stored with each service capability and source selection is bound by query predicate.

4.4 Source Selection

A SPARQL query contains one or more basic graph patterns. Similar to DARQ, our query planning step is performed separately for each basic graph pattern. The source selection algorithm used in DARQ 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. Let $S = \{(s_1, C_1), \dots, (s_n, C_n)\}$ be a set of all indexed data sources $s_1 \dots s_n$ and their capabilities $C_1 \dots C_n$, where $C_i = \{(p_i, mipsv_i, sbj sel_i, obj sel_i, totTrpl_i)\}$.

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 D_j for each triple pattern $t_j = (s_j, p_j, o_j) \in BGP$ such that

$$D_j = \{s | (s, C) \in S \wedge \exists p_j \in C\}$$

We extend the DARQ source selection algorithm by comparing MIPs vectors for duplicates. For a triple pattern, we compare the MIPs vectors of all the relevant data sources for possible duplicates. A specific source s is only added to the set of capable sources D_j , if it is able to produce a number of new results above a specific threshold value predefined for final source selection. For a triple $t \in BGP$ and a dataset $s \in S$, if the value of new results generated is less than the threshold, s is ignored from set D_j . For 100% recall the threshold value should be 1. Which means if a source is able to produce a single triple, it will be added to the set of capable sources. For sufficient (not complete) record retrieval the threshold can be fixed to any number greater than 1. For all of the 79 queries in this work, our threshold value is 1.

4.5 Source Ranking

To show the importance of the duplicate-aware data source ranking (based on the amount of duplicate-free records retrieved), suppose we have a triple pattern query q shown in

Listing 2 and ds_1, ds_2, ds_3 are the data sources capable of answering that query. If we apply DARQ source selection algorithm we will get all 4 dataset as the list of capable sources. Let ds_1 has a total of 50 triples satisfying q , ds_2 and ds_3 each has 40 triples satisfying the query. Further suppose that 25 of the ds_3 triples are duplicated at ds_1 while remaining 15 are duplicated at ds_2 . The DARQ sub-query generator will forward the query to all of the datasets and will be surprised with a complete duplicates from ds_3 . In this case the time consumed by the ds_3 to process the query q is extra added to the overall query execution time. Moreover, integration time is also increased as the ds_3 records need to be considered during the final result set compilation. Now if we apply duplicate-aware source ranking approach, which will select ds_1 as first, ds_2 as second in the rank and ds_3 will become out of the rank competition. Which means we only need two sub-queries and can skip querying ds_3 .

Similar to DARQ, our system make use of the triple-by-triple sub-query federation, therefore it is important to have a duplicate-aware triple pattern source ranking algorithm for sub-query escaping. We present this triple pattern source ranking algorithm in the next section.

Listing 2: A single triple pattern query

```
SELECT ?o
WHERE
{
  ?s <p1> ?o .
}
```

4.5.1 Triple Pattern Source Ranking

Algorithm 1 shows the single triple pattern source ranking. For a triple $t(s, p, o) \in T$ the set of capable data sources D is obtained using the source selection algorithm explained in previous section. The source $d \in D$ which has the highest $totTrpl$ value in the matched capability $C(p, mipsv, sbj sel, obj sel, totTrpl)$ is selected as first in the rank. The union and intersection of *MIPs Vectors* is explained in section 4.3. In order to get the accurate result set estimate, we multiply $sbj sel$, $obj sel \in C$ to the *original size* of the *MIPs Vectors* if *subject* or *object* of the triple pattern is bound respectively. The same is true for rank 1 dataset selection. However, the multiplication is performed with $totTrpl$ of matched capability instead of *original size*.

It is important to note that the number of elements in the MIPs vector may be different from its *original size*. The *original size* is the number of elements in the *ID set* over which we applied N random permutations to get the MIPs Vector as explained in MIPs section. In the line 24 we set the threshold value to 1 in order to get 100% recall. For each triple pattern $t_j = (s_j, p_j, o_j)$ in the query $q \in Q$, we apply the Algorithm 1 to get a set of selected capable data sources D_{s_j} which is used in sub-query generating algorithm explained in Section 4.6.

4.5.2 Join Source Ranking

As mentioned earlier, we perform individual triple based sub-query federation. Consequently, triple pattern source ranking is most important for sub-query escaping. The advantage of this approach is that if a data source is not capable of answering the complete query, it may produce enough results for a specific sub-set of query triples. For the comparison purpose we propose a complete query source ranking which works as follow: For a star shaped queries (described

Algorithm 1 triple pattern source ranking

Require: $t(s,p,o) \in T$ //triple pattern
1: $D = \text{getCapableSources}(t)$ //all sources capable of answering triple t
2: $\text{rank}_1\text{Source} = \text{getMaxSizeSource}(D,t)$
3: $\text{rnkNo} = 1$
4: $\text{unionMipv} = \text{rank}_1\text{Source}.\text{getMIPv}(t)$
5: $D_s[\text{rnkNo}] = \text{selectedSource}$
6: $D = D - \{\text{selectedSource}\}$
7: $\text{rnkNo} = \text{rnkNo} + 1$
8: **while** $D \neq \emptyset$ **do**
9: $\text{selectedSource} = \text{null}$
10: $\text{maxDistinctRecords} = 0$
11: **for each** $d_i \in D$ **do**
12: $\text{mipv} = d_i.\text{getMipv}(t)$
13: **if** s is bound in t **then**
14: $\text{mipv}.\text{originalSize} = \text{mipv}.\text{originalSize} * d_i.\text{getSbjSel}(t)$
15: **else if** o is bound in t **then**
16: $\text{mipv}.\text{originalSize} = \text{mipv}.\text{originalSize} * d_i.\text{getObjSel}(t)$
17: **end if**
18: $\text{overlap} = \text{unionMipv}.\text{intersectionSize}(\text{mipv})$
19: $\text{distinctRecords} = \text{mipv}.\text{getOriginalSize}() - \text{overlap}$
20: **if** $\text{distinctRecords} > \text{maxDistinctRecords}$ **then**
21: $\text{selectedSource} = d_i$
22: $\text{maxDistinctRecords} = \text{distinctRecords}$
23: **end if**
24: **end for**
25: **if** $\text{maxDistinctRecords} \geq 1$ **then**
26: $D_s[\text{rnkNo}] = \text{selectedSource}$
27: $\text{selectedMipv} = \text{selectedSource}.\text{getMipv}(t)$
28: $\text{unionMipv} = \text{unionMipv}.\text{union}(\text{selectedMipv})$
29: $\text{rnkNo} = \text{rnkNo} + 1$
30: **end if**
31: $D = D - \{\text{selectedSource}\}$
32: **end while**
33: **return** D_s //rank wise selected sources

in [5]), the overall result set is bound by the triple with lowest number of estimated records. Therefore, we perform the source ranking for that triple (using Algorithm 1) and use this as complete query ranking. The lowest records query triple can be estimated using the rank 1 source selection explained in previous section. However, this time we are looking for a source which has the lowest estimated value of all. For path shaped queries the total records are bound by the triple which has *subject* variable equal to the *object* of the previous query triple. For example the result set in the query given in Listing 3, is bound by the second triple in which the *object* variable in the first triple is used as *subject* in the second triple. Therefore, we perform the triple pattern ranking for second triple and use this as ranking for complete query.

Listing 3: A P-1 query example

SELECT ?o1
WHERE
{
?s <p1> ?o .
?o <p2> ?o1
}

4.6 Sub-query generation

The sub-query generation algorithm is similar to the one

Algorithm 2 sub-query generation

Require: $T = \{t_1, \dots, t_n\}$
 $S = \{D_{s_1}, \dots, D_{s_n}\}$ // sets of data sources obtained from algorithm 1
1: $\text{sub-queries} = \emptyset$, $\text{seperateSub-queries} = \emptyset$
2: **for each** $t_i \in T$ **do**
3: **if** $D_{s_j} = \{s\}$ **then**
4: $q = \text{queries}.\text{getQuery}(s)$
5: **if** q not null **then**
6: $q.T = q.T + t_i$
7: **else**
8: $\text{sub-queries} = \text{sub-queries} + (\{t_i\}, s)$
9: **end if**
10: **else**
11: **for each** $s_j \in D_{s_j}$ **do**
12: $\text{seperateSub-queries} = \text{seperateSub-queries} + (\{t_i\}, s)$
13: **end for**
14: **end if**
15: **end for**
16: **return** $\text{sub-queries} \cup \text{seperateSub-queries}$ //Return all sub-queries

presented in DARQ. However, instead of using all capable sources, we use selected data sources (obtained from Algorithm 1) for the sub-query generation. Let (T, s) be a sub-query, where T is a set of triple patterns, and s is the data source that can answer this sub-query. The sub-query generation is shown in Algorithm 2. If a triple pattern t_j matches exactly one data source ($D_{s_j} = \{s\}$) then the triple will be added to the set of sub-queries for this data source. All triples in this set will be sent to the data source in one sub-query. If a triple matches more than one data sources then the triple will be sent individually to all matching data sources in separate sub-queries. After the sub-queries are generated, the federator sends all of them to the optimizer for further optimization, before the federation. Our optimizer and data integrator module is similar to DARQ.

5. EXPERIMENTS AND RESULTS

The goal of our experiments was to assess how well our duplicate-aware solution performs in terms of result set recall, ranking of data sources and runtime. We compared our approach with DARQ, a well-known and widely used federated query execution engine. We also compared our approach with a simulation of the optimal duplicate-unaware (DU) approach, where (1) the result set estimation of carried is carried out regardless of the overlap between data source and each source containing an one relevant triple is queried. In the following, we describe our experimental setup in detail and contrast the results achieved by each of the approaches. All data used in this evaluation is either publicly available or can be found at the project webpage.⁵

5.1 Experimental Setup

5.1.1 Datasets

Within our experiments, we used the four datasets described in Table 1. The first data set, Diseasome, contains

⁵<http://???>

Dataset	BGP	S-1	S-2	P-1	P-2	P-3	Total
Diseasome	5	5	5	4	5	2	26
Geo	5	5	5	0	0	0	15
LinkedMDB	5	0	0	0	0	0	5
Publication	5	5	5	7	7	4	33
Total	20	15	15	11	12	6	79

Table 2: Distribution of query types across datasets

diseases and disease genes linked by disease-gene associations. The Publication data set was extracted from ??? and contains information on publications, venues and authors of publications. The Geo data set resulted from retrieving all ??? from DBpedia. Finally, LinkedMDB is the RDF version of IMDB and contains amongst others a large number of actors, movies and directors. We chose data sets of different data sizes to assess the scalability of our approach. The size of the MIPS vectors was set to achieve a compression ratio of 98%, which is greater than that used in the previous work [5].

Given that we wanted to emulate fragmented data sets distributed across several sources, we began by partitioning each of the data sets D across $n = 10$ data sources (which we also call “slices”): We set the parameter d , which we dubbed *discrepancy factor*. d controls the maximal size difference across the data source, ergo

$$d = \max_{1 \leq i \leq n} |S_i| - \min_{1 \leq j \leq n} |S_j|. \quad (4)$$

Then, we computed the sizes of the slices by assigning them random sizes such that $\sum_i |S_i| = D$ and $\forall i \forall j i \neq j \rightarrow ||S_i| - |S_j|| \leq d$. We then picked one of the n data sources randomly and redistributed its content across all 9 remaining data sources. We set d to values between ca 1.6% and 2.8% of the triples. Note that the value of d was increased with increasingly larger data sets.

The number of slices was set to 10 in all experiments.

5.1.2 Queries

We used three main types of queries. Simple basic graph pattern (BGP) queries consisted of exactly one triple pattern in the query. Star-shaped and path-shaped queries were defined as in [5]: star-shaped queries (denoted S-k) have one variable as subject and contained k triple patterns. Path-shaped queries, denoted P-k on the other hand were generated by using a random walk approach to generate a path of length k . Note that previous work has shown that these query shapes are the most common shapes found in real-world RDF queries [35]. Overall, our benchmark data consisted of 79 queries as shown in Table 2. Note that some query shapes could not be used on certain datasets due to the topology of the ontology underlying the datasets not being permissive for such queries. For example, S-2 queries could not be sent to LinkedMDB because

5.1.3 Metrics

We used two measures to compare our approach with the state of the art. First, we measured the mean squared error of each approach with respect to their result set evaluation as follows: For each query q_i , each source S_i contained a number $R_i(q_i)$ of non-duplicate results. Each of the approaches generated an approach $\tilde{R}_i(q_i)$ of $R_i(q_i)$. The mean squared error with respect to the result set size (short *RSMSE*) was

then computed as follows:

$$RSMSE = \frac{1}{|Q|} \sum_{q_i \in Q} |R_i(q_i) - \tilde{R}_i(q_i)|^2. \quad (5)$$

In addition to the MSERS, we also computed how well the approaches were able to rank the data sources with respect to the unseen triples they would return for a given query. Given the ideal ranking $rank(S_i, q_j)$ of each data source S_i for each query q_j , we computed the mean squared ranking error (short *RankMSE*) of an approach characterized by the the ranking function $\tilde{r}(S_i, q_j)$ by using the following formula:

$$RankMSE(q_j) = \frac{1}{|\mathcal{S}|} \sum_{S_i} |rank(S_i, q_j) - \tilde{r}(S_i, q_j)|^2. \quad (6)$$

$$RankMSE = \frac{1}{|Q|} \sum_{q_j \in Q} RankMSE(q_j). \quad (7)$$

For both measures, higher values are obviously worse.

5.2 Results

5.2.1 Result set estimation and ranking

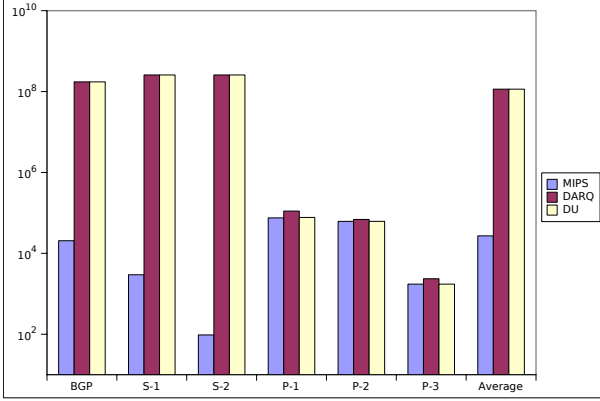
The RSMSE results are shown in Figures 4 while the ranking results are shown in Figure 5. In each figure, we compared the results of the approaches w.r.t. both the whole input query and to each of the triples patterns contained in the input queries. Our results clearly show that we outperform the state of the art w.r.t to both result set estimation and ranking. Especially, our estimation of the result set sizes is approximately 4 orders of magnitude better than DARQ’s or even DU’s. This is due to our approach being able to capture the existence of duplicates in the data sets and thus to better approximate the number of new results that can be expected from an endpoint. As expected, the ranking error for datasets decreases when carrying the ranking of data sources at triple pattern level instead of query level (see Figures 4b and 4a). This is simply due to the overall error increasing when combining the several triple patterns to a query. The same overall behavior is also displayed when considering the result set estimation error (see Figures 5b and 5a). Interestingly, the approximation of our approach is slightly poorer on star-shaped queries (approx. 0.2 on S-2 queries). This is a result of our approach to generating the estimations for whole query, which is carried out by using the lower bound of the estimation of single query patterns in the query. Small errors in the estimation of the size of the result size can thus lead to minor absolute errors.

As stated before, we used a compression ratio of approx. 98% across all experiments. The main advantage of such a high compression ratio is the small size of the index. Yet, the higher the compression ratio, the larger the error margin of the ranking function. When given a query whose sub-queries lead to very similar result set estimations, this larger error margin can lead to substantial *RankMSE* and *RSMSE* rates. We thus studied the effect of decreasing the compression ratio on the *RSMSE* and *RankMSE* for such a query. Our results in Table 3 suggest that MIPS vectors can successfully detect even small differences in the sizes of the result sets when given a sufficiently small compression ratio.

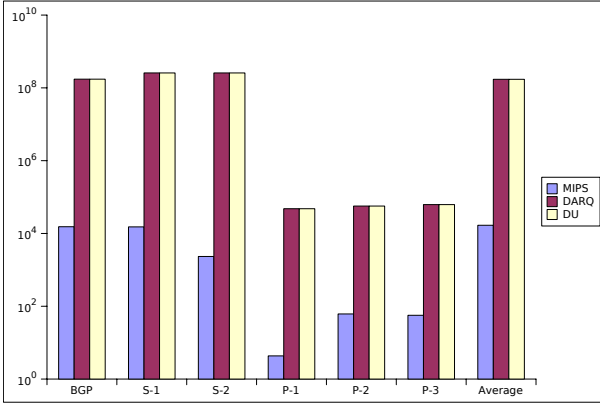
5.2.2 Recall and Runtime

Dataset	Size (MB)	Summary Size (MB)	CR (%)	Slices	Discrepancy	Duplicate Slices	Duplicate Datasets	Total Triples	Sum. Gen. Time (sec)
Disease	18.6	0.64	96	10	1,500	1	10	91,122	9
Publication	39.0	1.15	97	10	2,500	1	10	234,405	16
Geo	274.1	4.66	98	10	50,000	2	5,8	1,900,006	1302
LinkedMDB	448.9	7.9	97	10	100,000	1	2	3,579,616	1837

Table 1: Overview of datasets. CR stands for Compression Ratio.

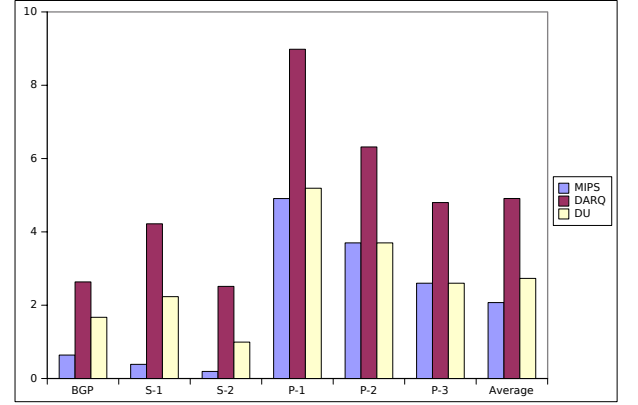


(a) RSMSE for query-wise selection (vertical log scale)

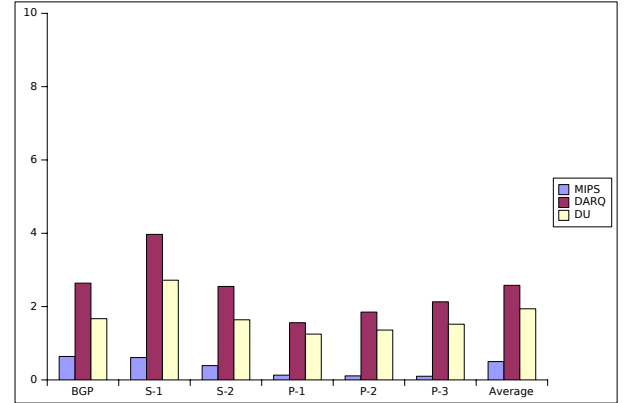


(b) RSMSE for subquery-wise selection (vertical log scale)

Figure 4: Mean squared errors with respect to result set evaluation



(a) RankMSE for query-wise selection



(b) RankMSE for subquery-wise selection

Figure 5: Mean squared errors with respect to ranking

Compression Ratio	<i>RSMSE</i>	<i>RankMSE</i>
97%	253.9×10^6	3.4
94%	33.3×10^6	0.6
91%	0	0

Table 3: Effect of compression ratio

Dataset	BGP	S-1	S-2	P-1	P-2	P-3	Total
Diseasome	7	21	21	8	20	12	89
Geo	10	15	23	0	0	0	48
LinkedMDB	5	0	0	0	0	0	5
Publication	1	2	5	0	0	0	8
Total	23	38	49	8	20	12	150

Table 5: Distribution of sub-query escaped by our approach

Table 4 shows the recall achieved by MIPS and DARQ in relation to the number of slices taken into consideration. Our results display the superiority of our ranking function, which is always able to achieve a recall of 1 by querying 9 from 10 data sources. In contrast, DARQ always has to visit all data sources to achieve a comparable recall. We measured the number of sub-query executions that could be escaped by our approach without any loss in recall. The results shown in Table 5 clearly display that our approach can effectively reduce the total number of queries executed overall. Especially, on BGP queries, we were able to escape up to 10 subqueries. Our approach was most successful on star-shaped queries, where up to 21 subqueries could be escaped. The better ranking function also leads to a superior overall runtime as shown in Figure 6. In average, our approach requires solely between 79.85% (S-2 queries) and 93.46% (P-1 queries) of the runtime of DARQ to retrieve the complete results to each query.

6. DISCUSSION

7. REFERENCES

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Rank	BGP		S1		S2		P1		P2		P3	
	MIPS	DARQ	MIPS	DARQ	MIPS	DARQ	MIPS	DARQ	MIPS	DARQ	MIPS	DARQ
1	29,22	19,22	26,53	24,42	30,69	30,69	18,12	15,67	24,60	21,99	31,60	29,30
2	49,61	39,50	46,20	39,67	52,15	49,70	34,04	31,49	38,84	38,56	43,78	45,02
3	67,48	61,78	60,90	54,78	66,48	59,96	50,28	49,23	55,74	53,16	61,86	56,76
4	78,44	72,68	70,75	63,86	76,60	71,49	65,71	64,04	72,25	69,11	80,17	73,72
5	85,65	79,26	79,76	74,32	83,64	80,54	77,24	79,87	83,04	86,11	90,45	91,74
6	90,54	84,00	86,67	79,59	89,90	86,76	82,28	83,75	87,69	89,95	94,48	95,70
7	94,68	87,25	92,94	85,61	94,88	90,22	85,56	87,17	89,99	92,08	95,59	96,73
8	99,40	89,38	98,62	89,98	99,35	93,43	87,71	89,29	91,47	93,31	95,70	97,53
9	100,00	97,95	100,00	96,52	100,00	97,06	100,00	94,97	100,00	97,15	100,00	99,26
10	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00	100,00

Table 4: Comparison of recall on top-k data sources

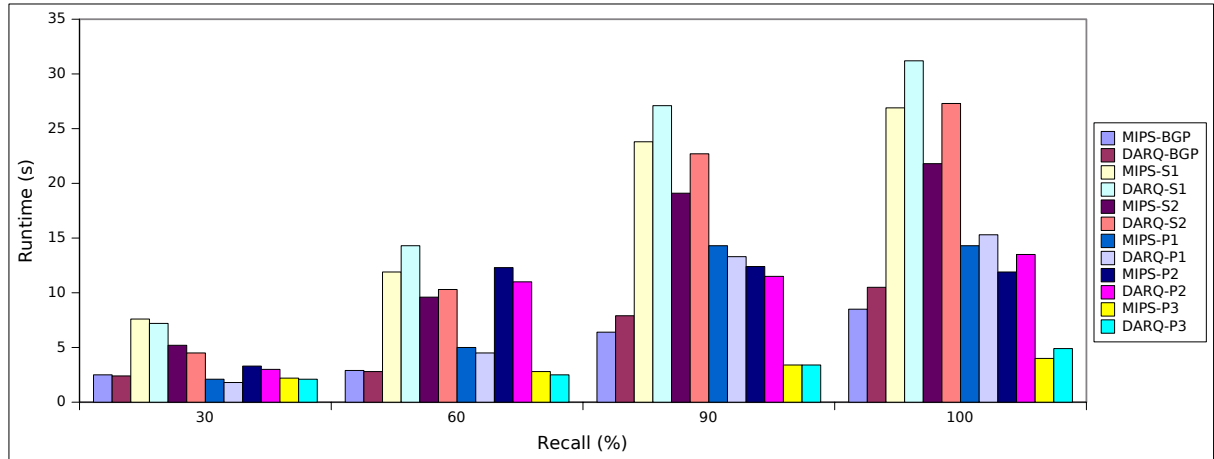


Figure 6: Comparison of runtimes for different recall values

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