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A Fine-Grained Evaluation of SPARQL Endpoint Federation Systems

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Abstract. The Web of Data has grown enormously over the last years. Currently, it comprises a large compendium of interlinked and distributed datasets from multiple domains. The abundance of datasets has motivated considerable work for developing SPARQL query federation systems, the dedicated means to access data distributed over the Web of Data. However, the granularity of previous evaluations of such systems has not allowed deriving of insights concerning their behavior in different steps involved during federated query processing. In this work, we perform extensive experiments to compare state-of-the-art SPARQL endpoint federation systems using the comprehensive performance evaluation framework FedBench. We extend the scope of the performance evaluation by considering additional criteria to the commonly used key criterion (i.e. the query runtime). In particular, we consider the number of sources selected, total number of SPARQL ASK requests used, and source selection time, the criteria which have not received much attention in the previous studies. Yet, we show that they have a significant impact on the overall query runtime of existing systems. Also, we extend FedBench to mirror a highly distributed data environment and assess the behavior of existing systems by using the same four criteria. As the result we provide a detailed analysis of the experimental outcomes that reveal novel insights for improving current and future SPARQL federation systems.

Keywords: SPARQL federation, Web of Data, RDF

1. Introduction

The transition from the Web of Documents to the Web of Data has resulted in a large compendium of interlinked datasets from diverse domains. Currently, the Linked Open Data (LOD) Cloud[1] contains over 60 billion triples available from 928 different datasets with large datasets [24] being added frequently. Due to the decentralized and linked architecture of LOD, answering complex queries often requires accessing and combining information from multiple datasets. Processing such queries, called *federated queries* [7,20,27,23], in a virtual integrated fashion is becoming increasingly popular. Given the importance of federated query processing over web of Linked Data, it is critical to provide fine-grained evaluations to assess the quality of state-of-the-art implementations of federated SPARQL query engines by comparing them against common criteria through an open benchmark. Such fine-grained evaluation results are valuable when positioning new federation systems against existing ones, and help application developers to choose appropriate systems by analyzing against given criteria of interest. Moreover, such fine-grained results provide useful insights for system developers and empower them to improve current federation systems as well as to develop better systems.

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[1] `http://stats.lod2.eu/`

Current evaluations [7,1,27,21,17,22,31] of SPARQL query federation systems compare some of the federation systems based on the central criterion of overall query runtime. While optimizing the query runtime of federation systems is the ultimate goal of the research performed on this topic, the granularity of current evaluations fails to provide results that allow understanding why the query runtimes of systems can differ drastically and thus insufficient to detect the components of systems that need to be improved. For example, key metrics such as smart source selection in terms of the *total number of data sources selected*, *total number of SPARQL ASK requests used*, and *source selection time* which has a direct impact on the overall query performance are not addressed in the existing evaluations. Furthermore, as pointed out by [18], the current testbeds [6,26,25,19] to evaluate, compare, and eventually improve SPARQL query federation systems still have some limitations. Especially, the *partitioning of data* as well as *the SPARQL clauses* used cannot be tailored sufficiently, although they are known to have a direct impact on the behaviour of SPARQL query federation systems.

The aim of this paper is to experimentally evaluate a large number of SPARQL query federation systems in a more fine-granular setting in which we can measure the time required to complete different steps of the SPARQL query federation process. Moreover, we want to address two weaknesses that is data partitioning and SPARQL clauses addressed in [18]. To achieve this goal, we first conducted a public survey[2] and collected information regarding 14 existing federated system implementations, their key features, and supported SPARQL clauses. Eight of the systems which participated in this survey are publicly available. However, two out of the eight with public implementation do not make use of the SPARQL endpoints and were thus not considered further in this study.

However, two out of the eight with public implementation do not make use of the SPARQL endpoints and were thus not considered further in this study. Given that we had to extend the systems to return their source selection time as well as the number of sources they selected, we only considered the six open-source systems in our fine-granular evaluation. Like in previous evaluations, we begin by comparing the remaining six systems [7,20,27,1,31,16] with respect to an *important unchanged performance criterion* (i.e., the query execution time) using the commonly used benchmark FedBench. In addition, we also compared these six systems with respect to their source selection approach in terms of the *total number of sources selected*, *total number of SPARQL ASK requests used,* and the *source selection time*. For the sake of completeness, we also performed a comparative analysis (based on the survey outcome) of the key functionality of the 14 systems which participated in our survey. The most important outcomes of this survey are presented in Section 3.[3]

To provide a quantitative analysis of the effect of *data partitioning* on the systems at hand, we extended both FedBench [25] and SP^{2}Bench [26] by distributing the data upon which they rely. To this end, we used the slice generation tool[4] described in [23]. This tool allows creating any number of subsets of a given dataset (called *slices*) while controlling the number of slices, the amount of overlap between the slices as well as the size distribution of these slices. The resulting slices were distributed across various data sources (SPARQL endpoints) to simulate a highly federated environment. In our experiments, we made use of both FedBench [25] and SP^{2}Bench [26] queries to ensure that we *cover the majority of the SPARQL query types and clauses*. Our aim here was to address the two weaknesses of current evaluations mentioned in previous works. Note that we used a dedicated network of local SPARQL endpoints to minimize the network latency.

Our main contributions are summarized as follow:

- We present the results of a public survey which allows us to provide a crisp overview of categories of SPARQL federation systems as well as provide their implementation details, features, and supported SPARQL clauses.
- We present (to the best of our knowledge) most comprehensive experimental evaluation of open-source SPARQL federations systems in terms of their source selection and overall query runtime using in two different evaluation setups.
- Along with the central evaluation criterion (i.e., the overall query runtime), we measure three sub-criteria, i.e., the total number of sources selected, the total number of SPARQL ASK requests used, and the source selection time. By these means,

[2]Survey: `http://goo.gl/iXvKVT`, Results: `http://goo.gl/CNW5UC`

[3]All survey responses can be found at `http://goo.gl/CNW5UC`.

[4]`https://code.google.com/p/fed-eval/wiki/SliceGenerator`

we obtain deeper insights into the behaviour of SPARQL federation systems.
- We extend both FedBench and SP^{2}Bench, well-known federated engines benchmarks, to mirror highly distributed data environments and test SPARQL endpoint federation systems for their parallel processing capabilities.
- We provide a detailed discussion of experimental results and reveal novel insights for improving existing and future federation systems.
- Our survey results provide useful research opportunities in the area of federated semantic data processing.

The rest of this paper is structured as follows: In Section 2, we provide an overview of state-of-the-art SPARQL federated query processing approaches. Section 3 provides a detailed description of the design of and the responses to our public survey of the SPARQL query federation. Section 4 provides an introduction to SPARQL query federation and selected approaches for experimental evaluation. Section 5 describes our evaluation framework and experimental results, including key performance metrics, a description of the used benchmarks (FedBench, SP^{2}Bench, SlicedBench), and the data slice generator. Section 6 provides our further discussion of the results. Finally, Section 7 concludes our work and gives an overview of possible future extensions.

2. Related work

In this section, we give an overview of existing works that are related to the two main areas of research covered in this paper: federates SPARQL query processing systems and benchmarks for SPARQL query processing engines.

2.1. Federation Systems

Rakhmawati et. al. [21] presents a survey of SPARQL endpoint federation systems, explaining the details of the query federation process and with a comparison of the query evaluation strategies used in these systems. Olaf et. al [10] provides a general overview of Linked Data federation. In particular, they introduce the specific challenges that need to be addressed and focus on possible strategies for executing Linked Data queries. However, both of these survey do not provide an experimental evaluation of the discussed SPARQL query federation systems. Umbrich et. al. [12] provides a detailed study of the recall and effectiveness of Link Traversal Querying for the Web of Data. Schwarte et. al. [28] present an experimental study of large-scale RDF federations on top of the Bio2RDF data sources using a particular federation system, i.e., FedX [27]. They focus on design decisions, technical aspects, and experiences made in setting up and optimizing the Bio2RDF federation. [5] identifies various drawbacks of federated Linked Data query processing. The authors propose that Linked Data as a service that has a potential to solve some of the identified problems. [9] presents limitations in Linked Data federated query processing and implications of these limitations. Moreover, this paper presents a query optimization approach based on semi-joins and dynamic programming. [14] identifies various strategies while processing federated queries over Linked Data. [30] provides an experimental evaluation of the different data summaries used in live query processing over Linked Data. [18] provides a detail discussion of the limitations of the existing testbeds used for the evaluation of SPARQL query federation systems. Some other experimental evaluations [7,1,27,31,17,22] of SPARQL query federation systems compare some of the federation systems based on their overall query runtime. Gorlitz et. al. [7] compare their approach with three other approaches ([27,20], AliBaba[5], and RDF-3X 0.3.4.22[8]. An extension of ANAPSID presented in [17] compare ANAPSID with FedX using 10 FedBench-additional complex queries. FedX [27] compare its performance with AliBaba and DARQ using a subset of FedBench queries. LHD [31] compare its performance with FedX, SPLENDID using Berlin SPARQL Benchmark (BSBM) [6].

All experimental evaluations (of SPARQL endpoint federation systems) above compare only a small number of SPARQL query federation systems using a subset of the queries available in current benchmarks with respect to a single performance criterion (query execution time). Consequently, they do not provide deeper insights into the behavior of these systems in different steps (e.g. source selection) required during the query federation. In this work, we evaluate six federated

[5] `SesameAliBaba:http://www.openrdf.org/alibaba.jsp`) using a subset of the queries from FedBench. Furthermore, they measure the effect of the information in VoiD[6] description on accuracy of their source selection. Acosta et. al. [1] compare their approach performance with respect to Virtuoso SPARQL endpoints, ARQ 2.8.8. BSD-style21[7]

[8] `http://www.mpi-inf.mpg.de/neumann/rdf3x/`

SPARQL query engines experimentally on two different evaluation frameworks. To the best of our knowledge, this is the largest evaluation of open-source SPARQL query federation systems. Furthermore, along with central performance criterion of query runtime, we compare these systems for their efficient source selection in terms of: (1) the total number of sources selected, (2) the total number of SPARQL ASK requests used, and (3) their source selection time. Our results show (section 5) that these criteria greatly affect the overall query runtime. Thus, the insights gained through our evaluation w.r.t to these criteria provide valuable insights for optimizing SPARQL query federation.

2.2. Benchmarks

Benchmarks for comparing SPARQL query processing systems have a rich literature as well. These include Berlin SPARQL Benchmark (BSBM), SP^{2}Bench, FedBench, Lehigh University Benchmark (LUBM), and the DBpedia Sparql Benchmark (DBPSB). Both BSBM and SP^{2}Bench are mainly designed for the evaluation of triple stores that keep their data in a single large repository. *BSBM* [6] was developed for comparing the performance of native RDF stores with the performance of SPARQL-to-SQL re-writers. *SP^{2}Bench* [26] mirrors vital characteristics (such as power law distributions or Gaussian curves) of the data in the DBLP bibliographic database. This benchmark comprises both a data generator for creating arbitrarily large DBLP-like documents and a set of carefully designed benchmark queries. FedBench [25] is designed explicitly to simulate SPARQL query federation tasks on real-world datasets with queries resembling typical requests on these datasets. Furthermore, this benchmark also includes a dataset and queries from SP^{2}Bench. LUBM [8] is designed to facilitate the evaluation of Semantic Web repositories in a systematic way. It is based on a customizable and repeatable synthetic data. DBPSB [19] includes queries from the DBpedia query log and aims to reflect the behavior of triple stores when confronted with real queries aiming to access native RDF data.

FedBench is the only (to the best of our knowledge) benchmark that encompasses real-world datasets, commonly used queries and distributed data environment. Furthermore, it is commonly used in the evaluation of SPARQL query federation systems [27,7,17,23]. Therefore, we choose this benchmark as a main evaluation benchmark in this paper. We also decided on using SP^{2}Bench in parts of our experiments to ensure that our queries cover most of SPARQL.

3. Federated engines public survey

In order to provide a comprehensive overview of existing SPARQL federation engines, we designed and conducted a survey of SPARQL query federation engines. In this section, we present the principles and ideas behind the design of the survey as well as its results and their analysis.

3.1. Survey Design

The aim of the survey was to compare the existing SPARQL query federation engines, regardless of their implementation or code availability. To reach this aim, we interviewed domain experts and designed a survey with three sections: system information, requirements, and supported SPARQL clauses.[9]

The system information section of the survey includes implementation details of the SPARQL federation engine such as:

- **URL of the paper, engine implementation:** Provides the URL of the related scientific publication or URL to the engine implementation binaries/-code.
- **Code availability:** Indicates the disclosure of the code to the public.
- **Implementation and licensing:** Defines the programming language and specific license.
- **Type of source selection:** Defines the source selection strategy used by the underlying federation system.
- **Type of join(s) used for data integration:** Shows the type of *joins* used to integrate sub-queries results coming from different data sources.
- **Use of cache:** Shows the usage of cache for performance improvement.
- **Support for catalog/index update:** Indicates the support for automatic index/catalog update.

The questions from the *requirements* section assess SPARQL query federation engines for the key features/requirements that a developer would require from such engines. These include:

- **Result completeness:** Given a SPARQL 1.0 query, can the federation engine retrieve all solutions for the given query (100% recall) or is it possible that it misses some of the solutions (for example due to the source selection or using an out-of-date index)?.

[9] The survey can be found at `http://goo.gl/iXvKVT`.

- **Privacy:** Most federation approaches target open data and do not provide means to take restrictions (according to different user access rights) on data access into account. Does the federation engine have the capability of taking privacy information (e.g., authentication, different graph-level access rights for different users, etc.) into account?
- **Support for partial results retrieval:** In some cases the query results can be too large and result completeness (i.e., 100% recall) may not be desired, rather partial but fast and/or quality query results are acceptable. Does the federation engine provide such functionality where a user can specify a desired recall (less than 100%) as a threshold for fast result retrieval? It is worth noticing that this is different from limiting the results using SPARQL LIMIT clause as it restricts the number of results to some fixed value while in partial result retrieval the number of retrieved results are relative to the actual total number of results.
- **Support for no-blocking operator/adaptive query processing:** SPARQL endpoints are sometimes blocked or down or exhibit high latency. Does the federation engine support non-blocking joins (where results are returned based on the order in which the data arrives, not in the order in which data being requested)?
- **Support for provenance information:** Usually, SPARQL query federation systems integrate results from multiple SPARQL endpoints without any provenance information, such as how many results were contributed by a given SPARQL endpoint or which of the results are contributed by each of the endpoint. Does the federation engine provide such provenance information?
- **Query runtime estimation:** In some cases a query may have a longer runtime (e.g., in the order of minutes). Does the federation engine provide means to approximate and display (to the user) the overall runtime of the query execution in advance?
- **Duplicate detection:** Due to the decentralized architecture of Linked Data Cloud, a sub-query might retrieve results that were already retrieved by another sub-query. For some applications, the former sub-query can be skipped from submission (federation) as it will only produce overlapping triples. Does the federation engine provide such a duplicate-aware SPARQL query federation? Note that this is the duplicate detection before sub-query submission to the SPARQL endpoints and the aim is to minimize the number of sub-queries submitted by the federation engine.
- **Top-K query processing:** Is the federation engine able to rank results based on the user's preferences (e.g., his/her profile, his/her location, etc.)?

The *supported SPARQL clauses* section assess existing SPARQL query federation engines w.r.t. the list of supported SPARQL clauses. The list of the SPARQL clauses is mostly based on the characteristics of the BSBM benchmark queries [6]. The summary of the used SPARQL clauses can be found in Table 3.

The survey was open and free for all to participate in. To contact potential participants, we used Google Scholar to retrieve papers that contained the keywords ŚPARQLánd qúery federation. After a manual filtering of the results, we contacted the main authors of the papers and informed them of the existence of the survey while asking them to participate. Moreover, we sent messages to the W3C Linked Open Data mailing list[10] and Semantic Web mailing list[11] with a request to participate. The survey was opened for two weeks.

3.2. Discussion of the survey results

Based on our survey results[12], existing SPARQL query federation approaches can be divided into three main categories (see Table 1)

Query federation over multiple SPARQL endpoints: In this type of approaches, RDF data is made available via SPARQL endpoints. The federation engine makes use of endpoint URLs to federate sub-queries and collect results back for integration. The advantage of this category of approaches is that queries are answered based on original, up-to-date data with no synchronization of the copied data required [10]. Moreover, the execution of queries can be carried out efficiently because the approach relies on SPARQL endpoints. However, such approaches are unable to deal with the data provided by the whole of LOD Cloud because sometimes data is not exposed through SPARQL endpoints.

Query federation over Linked Data: This type of approaches relies on the Linked Data principles[13] for query execution. The set of data sources which can contribute results is determined by using URI lookups

[10] public-lod@w3.org
[11] semantic-web@w3.org
[12] Available at http://goo.gl/CNW5UC
[13] http://www.w3.org/DesignIssues/LinkedData.html

Table 1

Overview of implementation details of federated SPARQL query engines (**SEF** = SPARQL Endpoints Federation, **DHTF** = DHT Federation, **LDF** = Linked Data Federation, **C.A.** = Code Availability, A.G.P.L. Affero General Public License, L.G.P.L. = Lesser General Public License, **S.S.T.** = Source Selection Type, **I.U.** = Index/catalog Update, (A+I) = SPARQL ASK and Index/catalog, (C+L) = Catalog and online discovery via Link-traversal), VENL = Vectored Evaluation in Nested Loop, NA = Not Applicable

Systems	Category	C.A	Implementation	Licencing	S.S.T	Join Type	Cache	I.U
FedX [27]	SEF	✓	Java	GNU A.G.P.L	index-free	bind (VENL)	✓	NA
LHD [31]	SEF	✓	Java	MIT	hybrid (A+I)	hash/ bind	✗	✗
SPLENDID [7]	SEF	✓	Java	L.G.P.L	hybrid (A+I)	hash/ bind	✗	✗
FedSearch [3]	SEF	✗	Java	GNU A.G.P.L	hybrid (A+I)	bind, pull based rank	✓	NA
GRANATUM [11]	SEF	✗	Java	yet to decide	index only	nested loop	✗	✗
Avalanche [4]	SEF	✗	Python, C, C++	yet to decide	index only	distributed, merge	✓	✗
DAW [23]	SEF	✗	Java	GNU G.P.L	hybrid (A+I)	based on underlying system	✓	✗
ANAPSID [1]	SEF	✓	Python	GNU G.P.L	hybrid (A+I)	AGJ, ADJ	✗	✓
ADERIS [16]	SEF	✓	Java	Apache	Index only	index-based nested loop	✗	✗
DARQ [20]	SEF	✓	Java	GPL	Index only	nested loop, bound	✗	✗
LDQPS [14]	LDF	✗	Java	Scala	hybrid (C+L)	symmetric hash	✗	✗
SIHJoin [15]	LDF	✗	Java	Scala	hybrid (C+L)	symmetric hash	✗	✗
WoDQA [2]	LDF	✓	Java	GPL	hybrid (A+I)	nested loop, bound	✓	✓
Atlas [13]	DHTF	✓	Java	GNU L.G.P.L	Index only	SQLite	✗	✗

during the query execution itself. Query federation over Linked Data does not require the data providers to publish their data as SPARQL endpoints. Instead, the only requirement is that the RDF data follows the Linked Data principles. A downside of these approaches is that they are less time-efficient than the previous approaches due to the URI lookups they perform.

Query federation on top of Distributed Hash Tables: This type of federation approaches stores RDF data on top of Distributed Hash Tables (DHTs) and use DHT indexing to federate SPARQL queries over multiple RDF nodes. This is a space-efficient solution and can reduce the network cost as well. However, many of the LOD datasets are not stored on top of DHTs.

SPARQL query federation approaches can be further divided into three sub-categories that are orthogonal to the ones used above (see Table 1).

Catalog/index-assisted solutions: These approaches utilize dataset summaries that have been collected in a pre-processing stage. These approaches may lead to more efficient query federation. However, the index needs to be constantly updated to ensure complete results retrieval. The index size should also be kept to a minimum to ensure that it does not significantly increase the overall query processing costs.

Catalog/index-free solutions: In these approaches, 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 starts. This approach promises that the results retrieved by the engine are complete and up-to-date. However, it may increase the query execution time, depending on the extra processing required for collecting and processing on-the-fly statistics.

Hybrid solutions: In these approaches, some of the data source statistics are pre-stored while some are collected on the fly, e.g., using SPARQL ASK queries.

Table 1 provides a classification along with the implementation details of the 14 systems which participated in the survey. Overall, we received responses mainly for systems which implemented the SPARQL endpoint federation and hybrid query processing paradigms in Java. Only Atlas [13] implements DHT federation whereas WoDQA [2], SIHJoin [15] and LDQPS [14] implement federation over linked data (LDF). Most of the surveyed systems provides "General Public Licences" with the exception of [14] and [15] which provides "Scala" licence whereas the authors of [11] and [4] have not yet decided which licence type will hold for their tools. Only 36% of the surveyed systems implement cashing mechanisms including [27], [3], [4], [23] and [2]. Only [1] and [2] (14% of the considered systems) provide

Table 2
Survey outcome: System's features (**R.C.** = Results Completeness, **P.R.R.** = Partial Results Retrieval, **N.B.O.** = No Blocking Operator, **A.Q.P.** = Adaptive Query Processing, **D.D.** = Duplicate Detection, **Q.R.E.** = Query Runtime Estimation, **Top-K.Q.P** = Top-K query processing)

Systems	R.C.	P.R.R.	N.B.O / A.Q.P.	D. D.	Privacy	Provenance	Q.R.E	Top-K.Q.P
FedX	✓	✗	✓	✗	✗	✗	✗	✗
DHT	✗	✗	✗	partial	✗	✗	✗	✗
LHD	✗	✗	✓	✗	✗	✗	✗	✗
SPLENDID	✗	✗	✗	✗	✗	✗	✗	✗
FedSearch	✓	✗	✓	✗	✗	✗	✗	✗
GRANATUM	✗	✗	✓	✗	partial	partial	✗	✗
Avalanche	✗	✓	✓	partial	✗	✗	✗	✗
DAW	✗	✓	✓	✓	✗	✗	✗	✗
LDQPS	✗	✗	✓	✗	✗	✗	✗	✗
SIHJoin	✗	✗	✓	✗	✗	✗	✗	✗
ANAPSID	✗	✗	✓	✗	✗	✗	✗	✗
ADERIS	✗	✗	✓	✗	✗	✗	✗	✗
QWIDVD	✓	✗	✗	✗	✗	✗	✗	✗
DARQ	✗	✗	✗	✗	✗	✗	✗	✗

Table 3
Survey outcome: System's Support for SPARQL Query Constructs (QP=Query Predicates, QS=Query Subjects)

SPARQL Cluase	FedX	DHT	LHD	SPLENDID	FedSearch	GRANATUM	Avalanche	DAW	LDQPS	SIHJoin	ANAPSID	ADERIS	QWIDVD	DARQ
SERVICE	✓	✗	✗	✗	✓	✓	✓	✓	✗	✗	✓	✗	✓	✗
FILTER	✓	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓	✓	✓	✓
Unbound QP	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✗
Unbound QS	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
OPTIONAL	✓	✗	✓	✓	✓	✓	✗	✓	✗	✗	✓	✗	✓	✓
DISTINCT	✓	✓	✓	✓	✓	✓	✓	✓	✗	✗	✓	✗	✓	✓
ORDER BY	✓	✗	✓	✓	✓	✓	✗	✓	✗	✗	✓	✗	✓	✓
UNION	✓	✓	✓	✓	✓	✓	✗	✓	✗	✗	✓	✗	✓	✓
NEGATION	✓	✗	✓	✓	✓	✓	✗	✓	✗	✗	✗	✗	✓	✓
REGEX	✓	✗	✓	✗	✓	✓	✗	✓	✗	✗	✓	✓	✓	✓
LIMIT	✓	✗	✓	✓	✓	✓	✓	✓	✗	✗	✓	✗	✓	✓
CONSTRUCT	✓	✗	✓	✗	✓	✓	✗	✓	✗	✗	✗	✗	✓	✗
DESCRIBE	✗	✗	✗	✗	✗	✓	✗	✗	✗	✗	✗	✗	✓	✗
ASK	✓	✗	✓	✗	✓	✓	✗	✓	✗	✗	✗	✗	✓	✗

support for catalog/index update whereas 14% do not require this mechanism by virtue of being index/catalog-free approaches.

Table 2 summarizes the survey outcome w.r.t. different features supported by systems. Only 21% of the systems ([27], [3] and QWIDVD) claim the completeness of the results and only Avalanche [4] and DAW [23] support partial results retrieval for their implementations. 71% of the considered systems support adaptive query processing with DHT, SPLENDID, QWIDVD and DARQ being the only systems that do not support this paradigm. Only DAW [23] supports Duplicate Detection Mechinism whereas DHT and Avalanche [4] claim to support partial duplicate detection. Granatum [11] is the only system that implements privacy and provenance. None of the considered systems implement top-k query processing or query runtime estimation.

Table 3 lists SPARQL clauses supported by the each of 14 systems. GRANATUM and QWIDVD are only two systems that support all of the query constructs used in our survey. It is important to note that most of these query constructs are based on query characteristics defined in BSBM.

4. Details of selected systems

After having given a general overview of SPARQL query federation systems, we present six SPARQL endpoints federation engines [7,20,27,1,31,16] with public implementation that were used within our experiments. We begin by presenting an overview of key concepts that underpin federated query processing and are used in the performance evaluation. We then use these key concepts to present the aforementioned six systems used in our evaluation in more detail.

4.1. Federated query processing

Given a SPARQL query $q \in Q$, where Q is a set of queries, the first step of federated SPARQL query

processing is to perform *triple pattern-wise source selection* or *source selection* for short. The goal of the *triple pattern-wise source selection* is to identify the set of data sources that contain relevant results against individual triple patterns of the query [23]. We call these sources *relevant* (also called capable) for the given triple pattern. The total number of triple pattern-wise selected sources N_s is the sum of the number of sources selected for individual query triple pattern. Later, in our evaluation, we will see that N_s has a direct impact on the query execution time. The source selection information is then used to decompose q into multiple sub-queries. Each sub-query is optimized to generate an execution plan. The sub-queries are forwarded to the relevant data sources according to the optimization plan. The results of each sub-query execution are finally joined to generate the result set of q.

4.2. Overview of the selected approaches

DARQ [20] makes use of an index known as *service description* to perform *source selection*. Each service description provides a declarative description of the data available in a data source, including the corresponding SPARQL endpoint along with statistical information. The *source selection* is performed by using distinct predicates (for each data source) recorded in the index as *capabilities*. 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 in the index. This means that DARQ is only able to answer queries with bound predicates. DARQ combines service descriptions, query rewriting mechanisms and a cost-based optimization approach to reduce the query processing time and the bandwidth usage.

SPLENDID [7] makes use of VoiD descriptions as index along with SPARQL ASK queries to perform the source selection step. A SPARQL ASK query is used when any of the subject or object of the triple pattern is bound. This query is forwarded to all of the data sources and those sources which pass the SPARQL ASK test are selected. A dynamic programming strategy [29] is used to optimize the join order of SPARQL basic graph patterns.

FedX [27] is an index-free SPARQL query federation system. The source selection relies completely on SPARQL ASK queries and a cache. The cache is used to store recent SPARQL ASK operations for relevant data source selection. As shown by our evaluation, the use of this cache greatly reduces the source selection and query execution time.

The publicly available implementation of LHD [31] only makes use of the VoiD descriptions to perform source selection. The source selection algorithm is similar to DARQ. However, it also supports query triple patterns with unbound predicates. In such cases, LHD simply selects all of the available data sources as relevant. This strategy often overestimates the number of capable sources and can thus lead to high overall runtimes. LHD performs a pipeline hash join to integrate sub-queries in parallel.

ANAPSID [1] is an adaptive query engine that adapts its query execution schedulers to the data availability and runtime conditions of SPARQL endpoints. This framework 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. ANAPSID makes use of both a catalog and ASK queries along with heuristics defined in [17] to perform the source selection step. This heuristic-based source selection can greatly reduce the total number of triple pattern-wise selected sources.

Finally, ADERIS [16] is an index-only approach for adaptive integration of data from multiple SPARQL endpoints. The source selection algorithm is similar to DARQ's. However, this framework also selects all of the available data sources for triple patterns with unbound predicates. ADERIS does not support several SPARQL 1.0 clauses such as UNION and OPTIONAL. For the data integration, the framework implements the pipelined index nested loop join operator.

5. Evaluation

In this section we present the data and hardware used in our evaluation. Moreover, we explain the key metrics underlying our experiments as well as the corresponding results.

5.1. Experimental setup

We used two settings to evaluate the selected federation systems. Within the first evaluation, we used the query execution time as central evaluation parameter and made use of the FedBench [25] federated SPARQL querying benchmark. In the second evaluation, we extended both FedBench and SP^2Bench to simulate a highly federated environment. Here, we focused especially on analyzing the effect of data partitioning on the

Table 4
SPARQL endpoints specification used in both FedBech and SlicedBench

EP	CPU(GHz)	RAM	Hard Disk
1	2.2, i3	4GB	300 GB
2	2.9, i7	16 GB	256 GB SSD
3	2.6, i5	4 GB	150 GB
4	2.53, i5	4 GB	300 GB
5	2.3, i5	4 GB	500 GB
6	2.53, i5	4 GB	300 GB
7	2.9, i7	8 GB	450 GB
8	2.6, i5	8 GB	400 GB
9	2.6, i5	8 GB	400 GB
10	2.9, i7	16 GB	500 GB

performance of federation systems. We call this extension *SlicedBench* as we created slices of each original datasets and distributed them among data sources. All of the selected performance metrics (explained in Section 5.2) remained the same for both evaluation frameworks. All experiments were carried out on a system with a 2.60 GHz i5 processor, 4GB RAM and 500GB hard disk. We executed each query 10 times and present the average values in the results. All of the data used in both evaluations can be downloaded from the project website.[14] The specification of the SPARQL endpoints used in both evaluations is given in Table 4.

5.1.1. First setting: FedBench

FedBench is commonly used to evaluate performance of the SPARQL query federation systems [27,7,17,23]. The benchmark is explicitly designed to represent SPARQL query federation on a real-world datasets. The datasets can be varied according to several dimensions such as size, diversity and number of interlinks. The benchmark queries resemble typical requests on these datasets and their structure ranges from simple star [23] and chain queries to complex graph patterns. The details about the FedBench datasets used in our evaluation along with some statistical information are given in Table 5.

The queries included in FedBench are divided into three categories: Cross-domain (CD), Life Sciences (LS), and Linked Data (LD). The distribution of the queries along with the result set sizes are given in Table 6. Details on the datasets and various advanced statistics are provided at the FedBench project page.[15]

In this evaluation setting, we selected all queries from CD, LS, and LD, thus performing (to the best of our knowledge) the first evaluation of SPARQL query federation systems on the complete benchmark data of FedBench. To ensure the reproducibility of our results as well as the reliability of the endpoints, we conducted our experiments on local copies of Virtuoso (version 20120802) SPARQL endpoints using the infrastructure provided by FedBench. For each dataset, a separate physical virtuoso server was created. To minimise the network latency we used a dedicated local network. All federation engines accessed the data sources via the SPARQL protocol.

5.1.2. Second setting: Sliced Bench

As pointed out in [18] the data partitioning can affect the overall performance of SPARQL query federation engines. To quantify this effect, we created 10 slices of each of the 10 datasets given in Table 5 and distributed this data across 10 local virtuoso SPARQL endpoints (one slice per SPARQL endpoint). Thus, every SPARQL endpoint contained one slice from each of the 10 datasets. This creates a highly fragmented data environment where a federated query possibly had to collect data from all of the 10 SPARQL endpoints. This characteristic of the benchmark stands in contrast to FedBench where the data is not highly fragmented. Moreover, each of the SPARQL endpoint contained a comparable amount of triples (load balancing). To facilitate the distribution of the data, we used the Slice Generator tool employed in [23]. This tool allows setting a discrepancy across the slices, where the *discrepancy* is defined as the difference (in terms of number of triples) between the largest and smallest slice:

$$discrepancy = \max_{1 \leq i \leq M} |S_i| - \min_{1 \leq j \leq M} |S_j|, \quad (1)$$

where S_i stands for the ith slice. The dataset D is partitioned randomly among the slices in a way that $\sum_i |S_i| = |D|$ and $\forall i \forall j \, i \neq j \rightarrow ||S_i| - |S_j|| \leq discrepancy$.

Table 7 shows the discrepancy values used for slice generation for each of the 10 datasets. Our discrepancy value varies with the size of the dataset. For the query runtime evaluation, we selected all of the seven queries both from CD and LS. Furthermore, we selected five queries from LD (2,4,6,10,11) and five from SP^{2}Bench given in Table 6: the reason for this selection was to cover majority of the SPARQL query clauses and types along with variable results size (from 1 to 40 million). For each of the CD, LS, and LD queries used in Sliced-

[14] https://code.google.com/p/fed-eval/
[15] http://code.google.com/p/fbench/

Table 5
Datasets statistics used in our benchmarks. (*only used in SlicedBench)

Collection	Dataset	version	#triples	#subjects	#predicates	#objects	#types	#links
Cross Domain	DBpedia subset	3.5.1	43.6M	9.50M	1063	13.6M	248	61.5k
	GeoNames	2010-10-06	108M	7.48M	26	35.8M	1	118k
	LinkedMDB	2010-01-19	6.15M	694k	222	2.05M	53	63.1k
	Jamendo	2010-11-25	1.05M	336k	26	441k	11	1.7k
	New York Times	2010-01-13	335k	21.7k	36	192k	2	31.7k
	SW Dog Food	2010-11-25	104k	12.0k	118	37.5k	103	1.6k
Life Sciences	KEGG	2010-11-25	1.09M	34.3k	21	939k	4	30k
	ChEBI	2010-11-25	7.33M	50.5k	28	772k	1	-
	Drugbank	2010-11-25	767k	19.7k	119	276k	8	9.5k
	DBpedia subset 3.5.1	43.6M	9.50M	1063	13.6M	248	61.5k	61.5k
SP^{2}Bench*	SP^{2}Bench 10M	v1.01	10M	1.7M	77	5.4M	12	-

Table 6
Query characteristics, (#TP = Total number of Triple patterns, #Res = Total number of query results, *only used in SlicedBench).

Linked Data (LD)			Cross Domain (CD)			Life Science (LS)			SP^{2}Bench*		
Query	#TP	#Res	Query	#TP	#Res	Query	#TP	#Res	Query	#TP	#Res
LD1	3	309	CD1	3	90	LS1	2	1159	SP2B-1	3	1
LD2	3	185	CD2	3	1	LS2	3	333	SP2B-2	10	500k
LD3	4	162	CD3	5	2	LS3	5	9054	SP2B-4	8	40M
LD4	5	50	CD4	5	1	LS4	7	3	SP2B-10	1	656
LD5	3	10	CD5	4	2	LS5	6	393	SP2B-11	1	10
LD6	5	11	CD6	4	11	LS6	5	28			
LD7	2	1024	CD7	4	1	LS7	5	144			
LD8	5	22									
LD9	3	1									
LD10	3	3									
LD11	5	239									

Bench, the number of results remained the same as given in Table 6. Analogously to FedBench, each of the SlicedBench data source is a virtuoso SPARQL endpoint.

5.2. Evaluation criteria

We selected four metrics for our evaluation: (1) *total triple pattern-wise sources selected*, (2) total number of SPARQL ASK requests used during source selection, (3) *source selection time* (i.e. the time taken by the process in the first metric), and (4) *query execution time*.

The total number of triple pattern-wise selected sources for a query is calculated as follows: Let $D_i = \{s_1, s_2 \dots s_m\}$ be the set of sources capable of answering a triple pattern tp_i and M is the total number of available (physical) sources. Then, for a query q with n triple patterns, $\{tp_1, tp_2, \dots tp_n\}$, the total number of triple pattern-wise sources is the sum of the magni-

Table 7
Dataset slices used in SlicedBench

Collection	#Slices	Discrepancy
DBpedia subset 3.5.1	10	280,000
GeoNames	10	600,000
LinkedMDB	10	100,000
Jamendo	10	30,000
New York Times	10	700
SW Dog Food	10	200
KEGG	10	35,000
ChEBI	10	50,000
Drugbank	10	25,000
SP^{2}Bench	10	150,000

SELECT o1, o2
WHERE
{
?s p1 ?o1. //tp_1
?s p2 ?o2. //tp_2
}
	D_1 = {s_1, s_2, s_4 }
	D_2 = {s_1, s_3, s_5, s_9 }
	$\|D_1\|$ = 3
	$\|D_2\|$ = 4
	Total TP. Sources = $\|D_1\|$ + $\|D_2\|$
	= 7

Fig. 1. Total triple pattern-wise selected sources example. (TP. = triple pattern-wise selected)

tude ($|D_i|$) of capable sources set for individual triple patterns. An example of the triple pattern-wise source selection is given in Figure 1 considering there are three sources capable of answering the first triple pattern tp_1 and four sources capable of answering tp_2 summing up to a total triple pattern-wise selected sources equal to seven.

An overestimation of triple pattern-wise selected sources increases the source selection time and thus the the query execution time. Furthermore, such an overestimation increases the number of irrelevant results which are excluded after joining the results of the different sources, therewith increasing both the network traffic and query execution time. In the next section we explain how such overestimations occur in the selected approaches.

5.3. Experimental results

5.3.1. Triple pattern-wise selected sources

Table 8 shows the total number of triple pattern-wise sources (TP sources for short) selected by each approach both for the FedBench and SlicedBench queries. ANAPSID is the most accurate system in terms of TP sources followed by both FedX and SPLENDID whereas similar results are achieved by the other three systems, i.e., LHD, DARQ, and ADERIS. Both FedX and SPLENDID select the optimal number of TP sources for individual query triple patterns. This is because both make use of ASK queries when any of the subject or object is bound in a triple pattern. However, they do not consider whether a source can actually contribute results after performing a join between results with other query triple patterns. Therefore, both can overestimate the set of capable sources that can actually contribute results. ANAPSID uses a catalog and ASK queries along with heuristics [17] about triple pattern joins to reduce the overestimation of sources. LHD (the publicly available version), DARQ, and ADERIS are index-only approaches and do not use SPARQL ASK queries when any of the subject or object is bound. Consequently, these three approaches tend to overestimate the TP sources per individual triple pattern. It is important to note that DARQ does not support queries where any of the predicates in a triple pattern is unbound (e.g., CD1, LS2) and ADERIS does not support queries which feature FILTER or UNION clauses (e.g., CD1, LS1, LS2, LS7). In case of triple patterns with unbound predicates (such as CD1, LS2) both LHD and ADERIS simply select all of the available sources as relevant. This overestimation can significantly increase the overall query execution time.

The effect overestimation can be clearly seen by taking a fine-granular look at how the different systems process FedBench query CD3 given in Listing 1. The optimal number of TP sources for this query is 5. This query has a total of five triple patterns. To process this query, FedX sends a SPARQL ASK query to all of the 10 benchmark SPARQL endpoints for each of the triple pattern summing up to a total of 50 (5*10) SPARQL ASK operations. As a result of these operations, only one source is selected for each of the first four triple pattern while eight sources are selected for last one, summing up to a total of 12 TP sources. SPLENDID utilizes its index and ASK queries for the first three and index-only for last two triple pattern to select exactly the same number of sources selected by FedX. LHD, ADERIS, and DARQ only makes use of predicate lookups in their catalogs to select nine sources for the first, one source each for the second, third, fourth, and eighth for the last triple pattern summing up to a total of 20 TP sources. The later three approaches overestimate the number of sources for first triple pattern by 8 sources. This is due to the predicate $rdf : type$ being likely to be used in all of RDF datasets. However, triples with $rdf : type$ as predicate and the bound object $dbp : President$ are only contained in the DBpedia subset of FedBench. Thus, the only relevant data source for the first triple pattern is DBpedia subset. Interestingly, even FedX and SPLENDID overestimate the number of data sources that can contribute for the last triple pattern. There are eight FedBench datasets which contain $owl : sameAs$ predicate. However, only one (i.e., New York Times) can actually contribute results after a join of the last two triple patterns is carried out. ANAPSID makes use of a catalog and SPARQL-ASK-assisted Star Shaped Group Multiple (SSGM) endpoint selection heuristic [17] to select the optimal (i.e., five) TP sources for this query. However, ANAPSID also overestimates the TP sources in some cases. For query CD6 of FedBench, ANAPSID selected a total of 10 TP sources while only 4 is the

Table 8
Comparison of triple pattern-wise total number of sources selected for FedBench and SlicedBench. NS stands for "not supported", RE for "runtime error", SPL for SPLENDID, ANA for ANAPSID and ADE for ADERIS. Key results are in **bold**.

FedBench							SlicedBench						
Query	FedX	SPL	LHD	DARQ	ANA	ADE	Query	FedX	SPL	LHD	DARQ	ANA	ADE
CD1	11	11	**28**	NS	3	NS	CD1	17	17	**30**	NS	8	NS
CD2	3	3	10	10	3	10	CD2	12	12	24	24	12	24
CD3	**12**	**12**	**20**	**20**	**5**	**20**	CD3	31	31	38	38	31	38
CD4	19	19	20	20	5	20	CD4	32	32	34	34	32	34
CD5	11	11	11	11	4	11	CD5	19	19	19	19	9	19
CD6	**9**	**9**	**10**	**10**	**10**	**10**	CD6	31	31	40	40	31	40
CD7	13	13	13	13	6	13	CD7	40	40	40	40	40	40
LS1	**1**	**1**	**1**	**1**	**1**	NS	LS1	3	3	3	3	3	NS
LS2	**11**	**11**	**28**	NS	**12**	NS	LS2	16	16	**30**	NS	16	NS
LS3	12	12	20	20	5	20	LS3	19	19	26	26	19	26
LS4	7	7	15	15	7	15	LS4	25	25	27	27	14	27
LS5	10	10	18	18	7	18	LS5	30	30	37	37	20	37
LS6	9	9	17	17	5	17	LS6	19	19	27	27	17	27
LS7	6	6	6	6	7	NS	LS7	13	13	13	13	13	NS
LD1	8	8	11	11	3	11	LD2	20	20	28	28	20	28
LD2	3	3	3	3	3	3	LD4	30	30	47	47	5	47
LD3	16	16	16	16	4	16	LD6	38	38	38	38	38	38
LD4	5	5	5	5	5	5	LD10	23	23	23	23	23	23
LD5	5	5	13	13	3	13	LD11	31	31	32	32	31	32
LD6	14	14	14	14	14	14	SP2B-1	10	10	28	28	RE	28
LD7	3	3	4	4	2	4	SP2B-2	90	90	92	92	RE	NS
LD8	15	15	15	15	9	15	SP2B-4	62	62	66	66	RE	NS
LD9	3	3	6	6	3	6	SP2B-10	7	7	**12**	NS	RE	**12**
LD10	10	10	11	11	3	11	SP2B-11	10	10	10	10	RE	NS
LD11	15	15	15	15	5	15							
Total	**242**	**242**	**336**	**283**	**134**	**273**		**628**	**628**	**764**	**692**	**382**	**520**

optimal sources that actually contributes to the final result set. This behavior leads us to our first insight: Optimal TP source selection is not sufficient to detect the optimal set of sources that should be queried.

In the SlicedBench results, we can clearly see the TP values are increased for each of the FedBench queries which mean a query spans more data sources, thus simulating a highly fragmented environment suitable to test the federation system for effective parallel query processing. The highest number of TP sources are reported for the second SP^{2}Bench query where up to a total of 92 TP sources are selected. This query contains 10 triple patterns and index-free approaches (e.g., FedX) need 100 (10*10) SPARQL ASK queries to perform the source selection operation. Using SPARQL ASK queries with no caching for such a highly federated environment can be very expensive. From the results shown in Table 8, it is noticeable that hybrid (catalog + SPARQL ASK) source selection approaches (ANAPSID, SPLENDID) perform an more accurate

```
SELECT ?president ?party ?page
WHERE {
?president rdf:type dbp:President .
?president dbp:nationality dbp:US .
?president dbp:party ?party .
?x nyt:topicPage ?page .
?x owl#sameAs ?president .
}
```

Listing 1: FedBench CD3. Prefixes are ignored for simplicity

Table 9
Comparison of number of SPARQL ASK requests used for source selection both in FedBench and SlicedBench. NS stands for "not supported", RE for "runtime error", SPL for SPLENDID, ANA for ANAPSID and ADE for ADERIS. Key results are in **bold**.

FedBench							SlicedBench						
Query	FedX	SPL	LHD	DARQ	ANA	ADE	Query	FedX	SPL	LHD	DARQ	ANA	ADE
CD1	27	27	0	NS	20	NS	CD1	30	30	0	NS	25	NS
CD2	27	18	0	0	1	0	CD2	30	20	0	0	29	0
CD3	45	18	0	0	2	0	CD3	50	20	0	0	46	0
CD4	45	9	0	0	3	0	CD4	50	10	0	0	34	0
CD5	36	9	0	0	1	0	CD5	40	10	0	0	14	0
CD6	36	9	0	0	11	0	CD6	40	10	0	0	40	0
CD7	36	9	0	0	5	0	CD7	40	10	0	0	40	0
LS1	18	0	0	0	0	NS	LS1	20	0	0	0	3	NS
LS2	27	27	0	NS	30	NS	LS2	30	30	0	NS	30	NS
LS3	45	9	0	0	13	0	LS3	50	10	0	0	30	0
LS4	63	18	0	0	1	0	LS4	70	20	0	0	15	0
LS5	54	9	0	0	4	0	LS5	60	10	0	0	27	0
LS6	45	18	0	0	13	0	LS6	50	20	0	0	26	0
LS7	45	9	0	0	2	NS	LS7	50	10	0	0	12	NS
LD1	27	9	0	0	1	0	LD2	30	10	0	0	29	0
LD2	27	9	0	0	0	0	LD4	50	20	0	0	25	0
LD3	36	9	0	0	2	0	LD6	50	10	0	0	38	0
LD4	45	18	0	0	0	0	LD10	30	10	0	0	23	0
LD5	27	18	0	0	2	0	LD11	50	10	0	0	32	0
LD6	45	9	0	0	12	0							
LD7	18	9	0	0	4	0	SP2B-1	30	20	0	0	RE	0
LD8	45	9	0	0	7	0	SP2B-2	100	10	0	0	RE	NS
LD9	27	18	0	0	3	0	SP2B-4	80	20	0	0	RE	NS
LD10	27	9	0	0	4	0	SP2B-10	10	10	0	NS	RE	0
LD11	45	9	0	0	2	0	SP2B-11	10	0	0	0	RE	NS
Total	**918**	**315**	**0**	**0**	**143**	**0**		**1050**	**330**	**0**	**0**	**518**	**0**

source selection than index/catalog-only approaches (i.e., DARQ, LHD, and ADERIS).

5.3.2. Number of SPARQL ASK requests

Table 9 shows the total number of SPARQL ASK requests used to perform source selection for each of the queries of FedBench and SlicedBench. Index-only approaches (DARQ, ADERIS, LHD) only make use of their index to perform source selection. Therefore, they do not necessitate any ASK requests to process queries. As mention before, FedX only makes use of ASK requests (along with a cache) to perform source selection. The results presented in Table 9 are for FedX(cold or first run), where the FedX cache is empty. This is basically the lower bound of the performance of FedX. For FedX(100% cached), the complete source selection is performed by using cache entries only. Hence, in that case, the number of SPARQL ASK requests is zero for each query. This is the upper bound of the performance of FedX on the data at hand. The results clearly shows that index-free (e.g., FedX) approaches can be very expensive in terms of SPARQL ASK requests used. This can greatly affect the source selection time and overall query execution time if no cache is used. For FedBench, ANAPSID is the most efficient hybrid approach in terms of SPARQL ASK requests consumed during source selection. On the other hand, SPLENDID is the most efficient hybrid approach for SlicedBench. The reason for higher number of ASK requests is due to the logic behind SSGM heuristics [17] used in ANAPSID's source selection algorithm. This heuristic computes the set of namespaces and predicates used in data sources (SPARQL endpoints in our case). For SlicedBench, all data sources are likely contains the same set of distinct predicates and namespaces (because each data source contains at least one slice from each data dump). SSGM heuristics are bound to perform poorly when faced with such a data distribution.

It is important to note that ANAPSID combines more than one triple pattern into a single SPARQL ASK query. The time required to execute these more complex SPARQL ASK operations are generally higher than SPARQL ASK queries having a single triple pattern as used in FedX and SPLENDID. Consequently, even though ANAPSID require less SPARQL ASK requests, its source selection time is greater than all other selected approaches. This behavior will be further elaborated upon in the subsequent section. Tables 8 and 9 clearly show that using SPARQL ASK queries for source selection leads to an efficient source selection in terms of TP sources selected. However, in the next section we will see that they increase both source selection and overall query runtime. A smart source selection approach should select fewer number of TP sources while using minimal number of SPARQL ASK requests.

5.3.3. Source selection time

Figure 2 shows the source selection time for each of the selected approach and for both FedBench and SlicedBench. For ANAPSID, the results presented in this figure shows the query decomposition time instead of pure source selection time. This is because the source selection and query decomposition phases are intermingled in ANAPSID. Thus, it was not possible to get the pure source selection time[16].

Compared to the TP results, the index-only approaches require less time than the hybrid approaches even though they overestimated the TP sources in comparison with the hybrid approaches. This is due to index-only approaches not having to send any SPARQL ASK queries during the source selection process. The index being usually pre-loaded into the memory before the query execution means that the runtime the predicate look-up in index-only approaches is minimal. Consequently, we observe a trade-off between the intelligent source selection and the time required to perform this process. To reduce the costs associated with ASK operations, FedX implements a cache to store the results of the recent SPARQL ASK operations. Figure 2 shows that source selection time of FedX with cached entries is significantly smaller than FedX's first run with no cached entries.

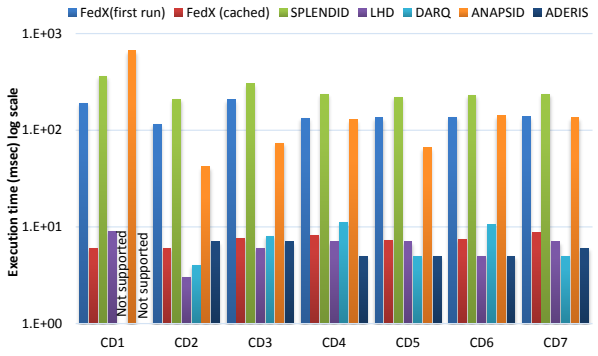
As expected the source selection time for FedBench queries is smaller than that for SlicedBench, particularly in hybrid approaches. This is because the number of TP sources for SlicedBench queries are increased due to data partitioning. Consequently, the number of SPARQL ASK requests grows and increases the overall source selection time. As mentioned before, an overestimation of TP sources in highly federated environments can greatly increase the source selection time. For example, consider query LD4. SPLENDID selects the optimal (i.e., five) number of sources for FedBench and the source selection time is 218 ms. However, it overestimates the number of TP sources for SlicedBench by selecting 30 instead of 5 sources. As a result, the source selection time is significantly increased to 1035 ms which directly affects the overall query runtime. The effect of such overestimation is even worse in SP2B-2 and SP2B-4 queries for the SlicedBench.

Lessons learned from the evaluation of the first three metrics is that using ASK queries for source selection leads to smart source selection in term of total TP sources selected. On the other hand, they significantly increase the overall query runtime where no caching is used. FedX makes use of an intelligent combination of parallel ASK query processing and caching to perform the source selection process. This parallel execution of SPARQL ASK queries is more time-efficient than the ASK query processing approaches implemented in both ANAPSID and SPLENDID. Nevertheless, the source selection of FedX could be improved further by using heuristics such as ANAPSID's to reduce the overestimation of TP sources.

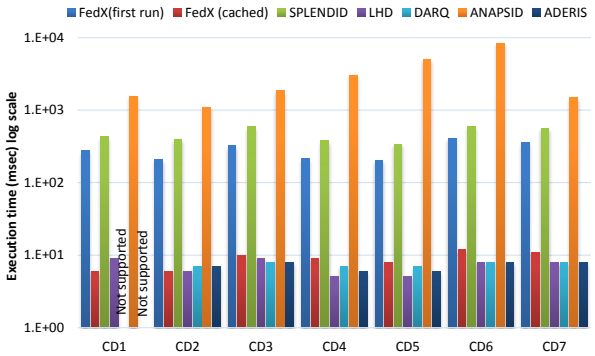
5.3.4. Query execution time

Figure 3 shows the query execution time for both experimental setups. FedX(cached) outperforms all of the remaining approaches in majority of the queries. FedX(cached) is followed by FedX(first run) which is further followed by SPLENDID, LHD, ANAPSID, ADERIS, and DARQ. Deciding between DARQ and ADERIS is a difficult task because the latter does not produce results for most queries. Several factors can influence the overall query execution time of a federated engine, including the join type, the join order selection, the level of parallelism as well as block and buffer sizes. However, one of the main reasons for FedX's small query execution times is the source selection caching which leads to 49% improvement in the average query execution for FedBech and 52% in SlicedBench. Hence, our results suggest that a smart source selection, both in term of TP sources and execution time, is a key metric to be considered while developing SPARQL query federation systems. This point is further supported by a comparison of the the pure (excluding source selection

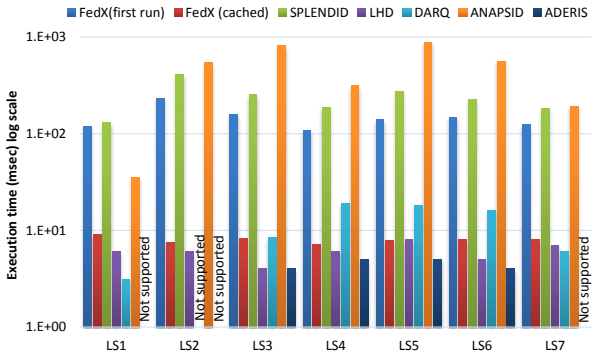
[16]This issue was confirmed by the corresponding authors of ANAPSID.



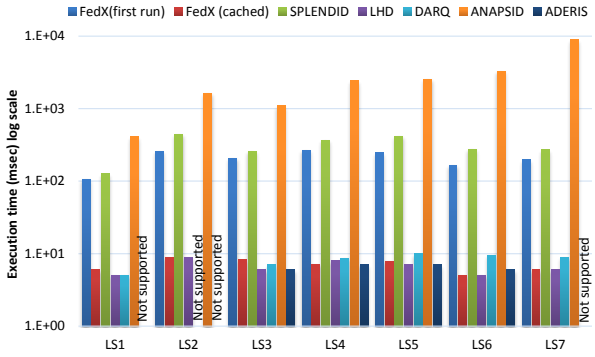
(a) FedBench: CD queries



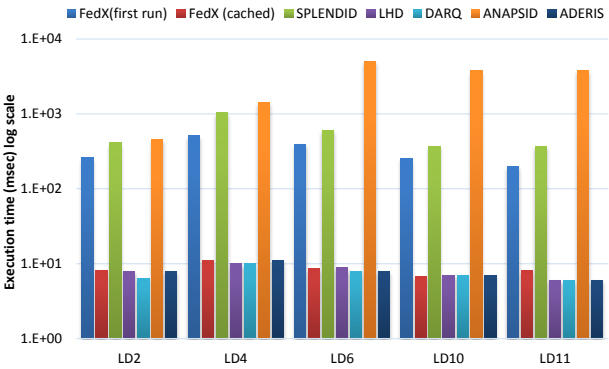
(b) SlicedBench: CD queries



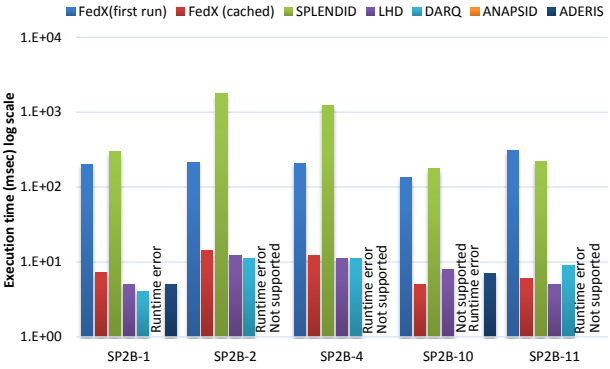
(c) FedBench: LS queries



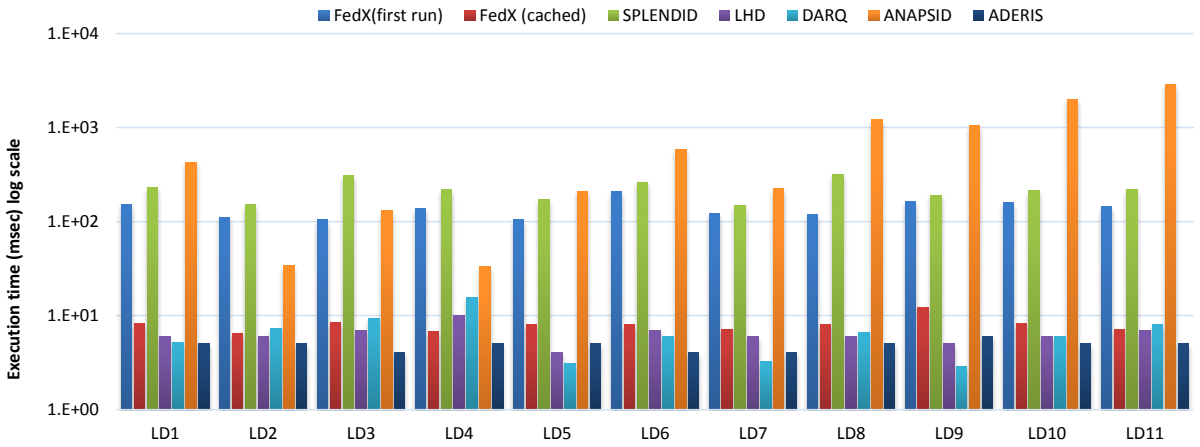
(d) SlicedBench: LS queries



(e) SlicedBench: LD queries

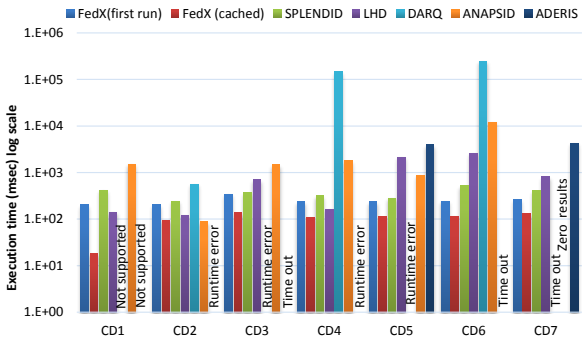


(f) SlicedBench: SP^{2}Bench queries

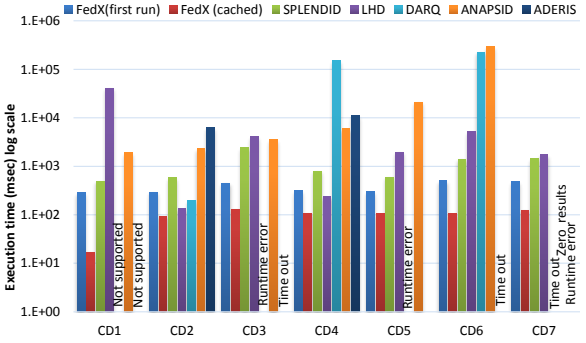


(g) FedBench: LD queries

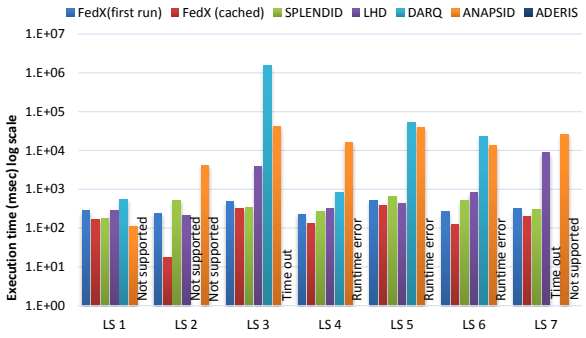
Fig. 2. Comparison of source selection time for FedBench and SlicedBench. The results for ANAPSID are based on query decomposition phase



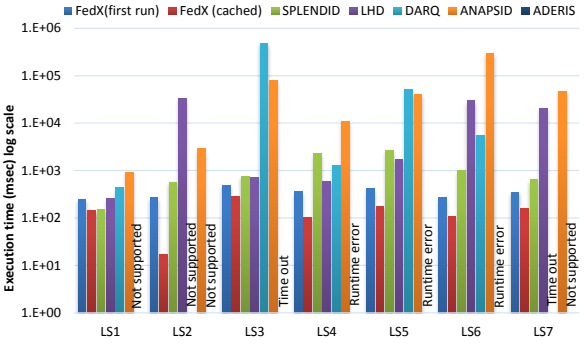
(a) FedBench: CD queries



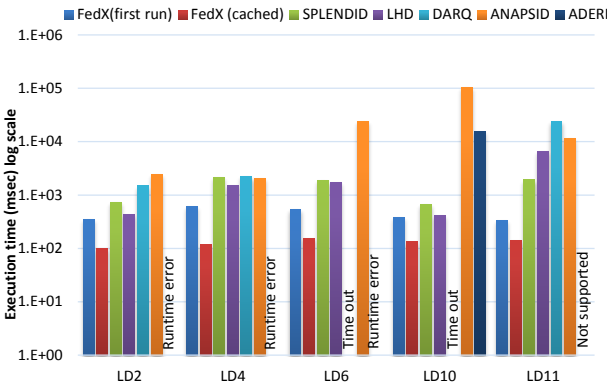
(b) SlicedBench: CD queries



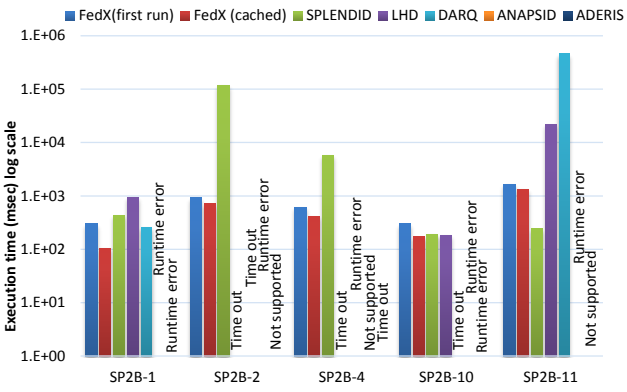
(c) FedBench: LS queries



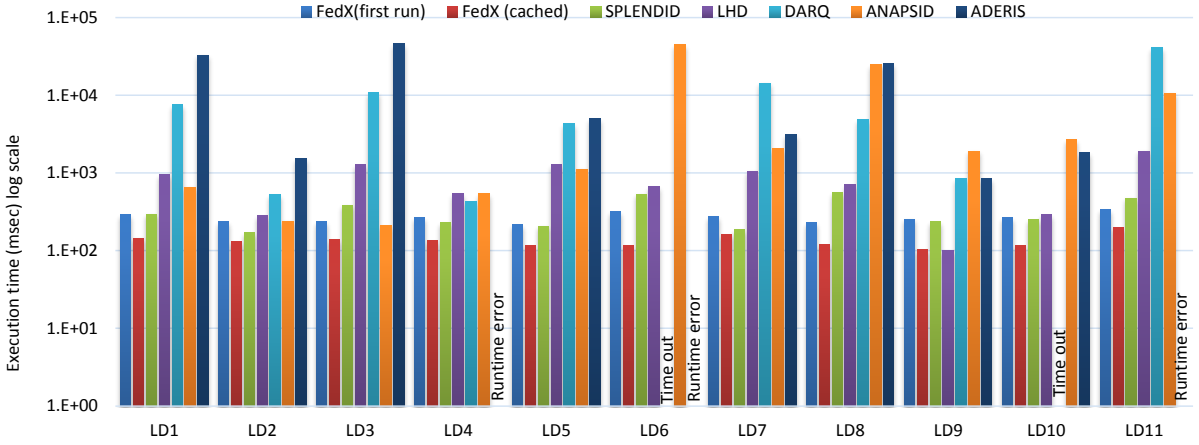
(d) SlicedBench: LS queries



(e) SlicedBench: LD queries



(f) SlicedBench: SP^{2}Bench queries



(g) FedBench: LD queries

Fig. 3. Comparison of query execution time for FedBench and SlicedBench

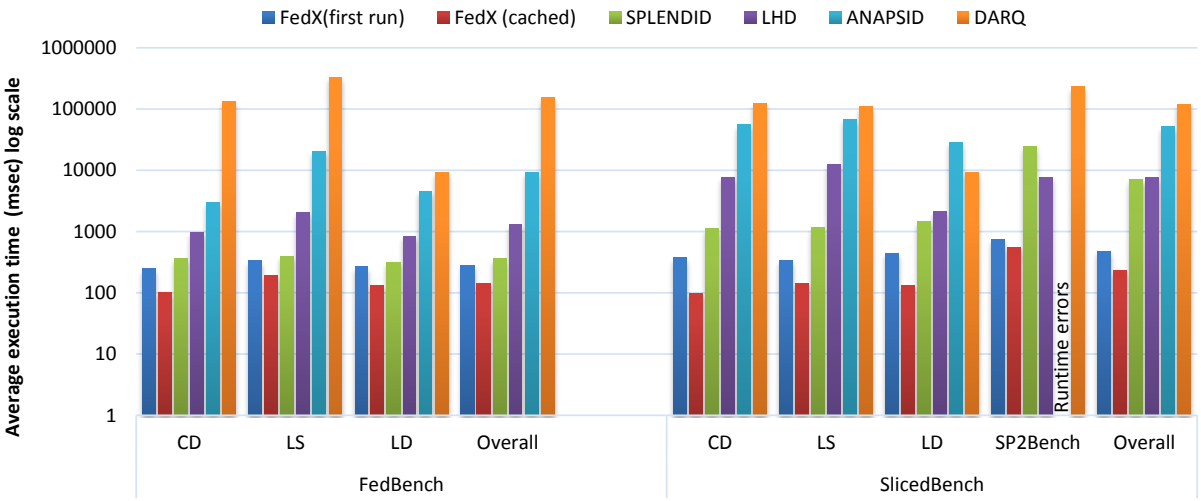


Fig. 4. Overall performance evaluation (ms)

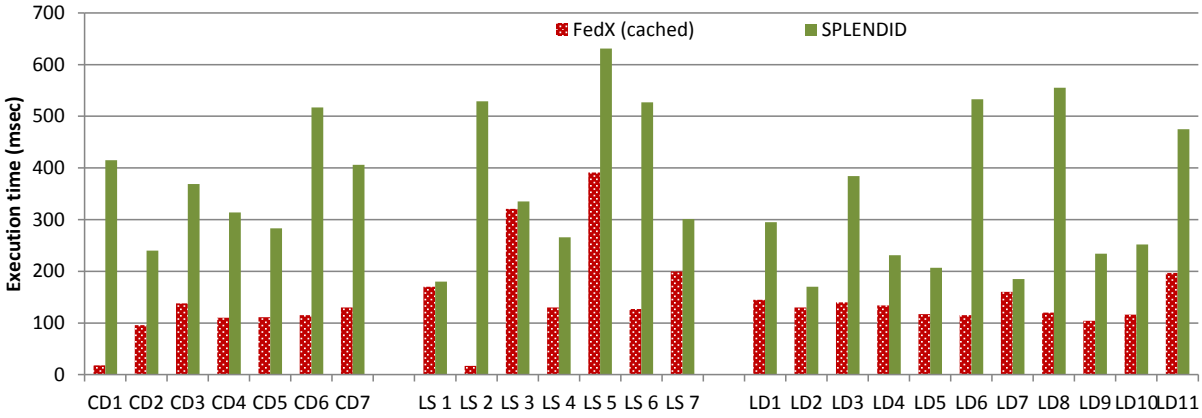
time) query execution time of FedX and SPLENDID (ref. Section 6).

The effect of the overestimation of the TP sources on query execution can be observed in majority of the queries for different systems. For instance, for LD4 query during FedBench SPLENDID selects optimal number of TP sources (i.e., five) and the query execution time is 231 ms of which 218 ms are used for selecting sources. For SlicedBench, SPLENDID overestimates the TP sources by 25 (i.e., selects 30 instead of 5 sources), resulting in a query execution of 2155 ms, of which 1035 ms are spent in source selection process. Consequently, the pure query execution time of this query is only 13 ms for FedBench (231-218) and 1120 ms (2155-1035) for SlicedBench. This means that an overestimation of TP sources does not only increase the source selection time but also produces results which are excluded after performing join operation between query triple patterns. These retrieval of irrelevant results increases the network traffic and thwarts the query execution plan. For example, both FedX and SPLENDID considered 285412 irrelevant triples due to the overestimation of 8 TP sources only for $owl:sameAs$ predicate in CD3 of FedBench. Another example of TP source overestimation can seen in CD1, LS2. LHD's overestimation of TP sources on SlicedBench (e.g., 22 for CD1, 14 for LS2) leads to its query execution time jumping from 141 ms to 40738 ms for CD1 and 211 ms to 33868 ms for LS2.

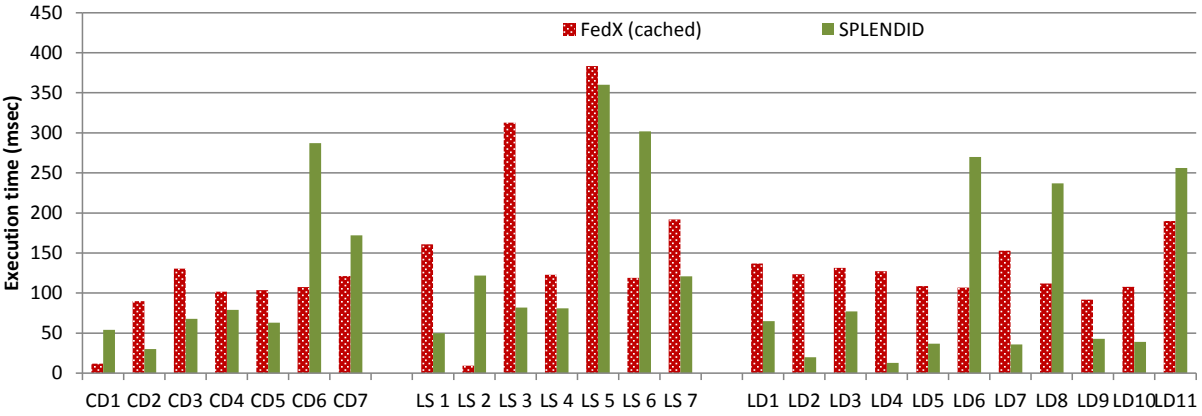
In queries such as CD4, CD6, LS3, LD11 and SP2B-11 we observe that the query execution time for DARQ is more than 2 minutes. In some cases, it even reaches the 30 minute timeout used in our experiments. The reason for this behaviour is that the simple nested loop join it implements overfloods SPARQL endpoints by submitting too many endpoint requests. FedX overcomes this problem by using a block nested loop join where the number of endpoints requests are dependent upon the block size. Furthermore, we can see that many systems do not produce results for SP^{2}Bench queries. A possible reason for this is the fact that SP^{2}Bench queries contain up to 10 triple patterns with different SPARQL clauses such as DISTINCT, ORDER BY, and complex FILTERS.

5.3.5. *Overall performance evaluation*

The comparison of overall performance of each approach is summarised in Figure 4, where we show the average query execution time for the queries in CD, LS, LD, and SP^{2}Bench sub-groups. As an overall performance evaluation based on FedBench, FedX(cached) outperformed FedX first run) in all of the 25 queries which in turn outperformed SPLENDID in 16 out of 25 queries. SPLENDID is better than LHD in 19 of the FedBench queries. LHD outperformed ANAPSID in 16 out of 24 queries while ANAPSID outperforms DARQ in 13 out of 22 commonly supported queries. For SlicedBench, FedX(cached) outperformed FedX(first run) in all 25 queries. In turn FedX(first run) outperformed SPLENDID in 23 out of 25 queries. SPLENDID is better than LHD in 15 out of the total SlicedBench queries. LHD outperformed ANAPSID in 14 out of 17 which in turn outperformed DARQ in 13 out of 17 commonly supported queries. We do not include ADERIS into this section because we could not retrieve results for the ma-



(a) Query execution time including source selection time



(b) Query execution time excluding source selection time

Fig. 5. Effect of the source selection time on overall query execution time: FedX(cached) vs SPLENDID on FedBench

jority of the queries. For complete results, please visit the downloads section of the project's home page[17]. The most noticeable fact here is that caching improves FedX's performance by decreasing the total query execution time by approximately half in both experimental setups as shown in Figure 4.

6. Discussion

The subsequent discussion of our findings can be divided into two main categories.

6.1. Effect of the source selection time

To the best of our knowledge, the effect of the source selection runtime has not been considered in SPARQL query federation system evaluations [7,1,27,21,17] so far. However, after analysing all of the results presented above, we noticed that this metric greatly affects the overall query execution time. To show this effect, we compared SPLENDID and FedX on FedBench w.r.t. their (1) overall query execution time including source selection time and their (2) pure query execution time excluding source selection time. To calculate the pure query execution time, we simply subtracted the source selection time from the overall query execution and plot the execution time (without including source selection time) in Figure 5b.

In Figure 5a, we can see that the overall query execution time (including source selection) of FedX is better than SPLENDID in all of the 25 FedBench queries. However, Figure 5b suggests that SPLENDID is better in 17 out of the 25 queries in terms of the pure query execution time. This means that the use of a cache

[17] https://code.google.com/p/fed-eval/

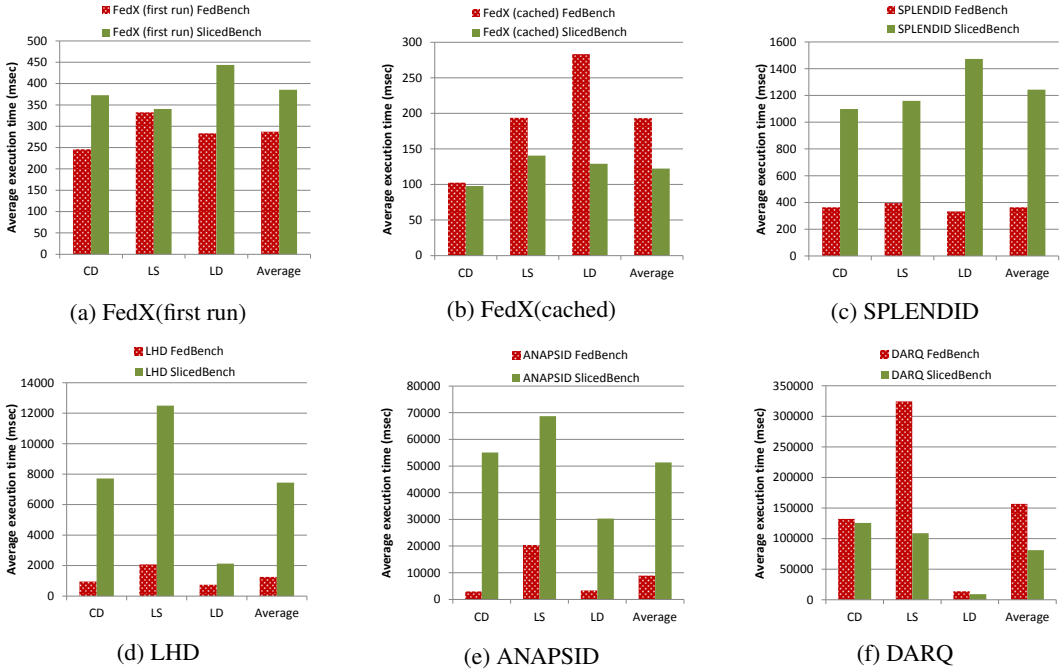


Fig. 6. Effect of the data partitioning

in FedX greatly improves the overall query execution. Furthermore, our results also suggest that the use of SPARQL ASK queries for source selection is very expensive without caching. On average, SPLENDID's source selection time is 66.44% of the overall query runtime for FedBench and 35.5% for SlicedBench. On the other hand, FedX (cached)'s source selection time is only 5.5% resp. 3.5% of the total query runtime for FedBench resp. SlicedBench.

6.2. *Effect of the data partitioning*

In our SlicedBench experiments, we extended FedBench to test the federation systems behaviour in highly federated data environment. This extension can also be utilized to test the capability of parallel execution of queries in SPARQL endpoint federation system. To show the effect of data partioning, we calculated the average for the query execution time of LD, CD, and LS for both the benchmarks and compared the effect on each of the selected approach. The performance of FedX(cached) and DARQ is improved with partitioning while the performance of FedX(first run), SPLENDID, ANAPSID, and LHD is reduced. As an overall evaluation result, FedX(first run)'s performance is reduced by 34%, FedX(cached)'s is improved by 37%, SPLENDID's is reduced by 240%, LHD's is reduced by 492%, ANAPSID's is reduced by 477%, and DARQ's is improved by 48%. The performance improvement for DARQ occurs due to the fact that the overflooding of endpoints with too many nested loop requests to a particular endpoint is now reduced. This reduction is due to the different distribution of the relevant results among many SPARQL endpoints. The increase in FedX (cached)'s performance is simply due to the use of a cache. One of the reasons for the performance reduction in LHD is its significant overestimation of TP sources in SlicedBench. The reduction of both SPLENDID's and ANAPSID's performance is due to an increase in ASK operations in SlicedBench and due to the increase in triple pattern-wise selected sources which greatly affects the overall performance of the systems when no cache used.

7. Conclusion

In this paper, we evaluated six SPARQL endpoint federation systems based on extended performance metrics and evaluation framework. We kept the main experimental metric (i.e. query execution time) unchanged and showed that the three other metrics (i.e. total triple pattern-wise selected sources, total number of SPARQL ASK request used during source selection, and source

selection time), which did not receive much attention so far, can significantly affect the main metric. We also measured the effect of the data partitioning on these systems to test the effective parallel processing in each of the federation system. Overall, our results suggest that a combination of caching and ASK queries with accurate heuristics for source selection (as implemented in ANAPSID) has the potential to lead to a significant improvement of the overall runtime of federated SPARQL query processing systems.

In future work, we will aim to get access to and evaluate the systems from our survey which do not provide a public implementation. We will also measure the effect of a range of various features (e.g., result completeness and duplicate detection) on the overall runtime of federated SPARQL engine. Furthermore, we will assess these systems on big data SPARQL query federation benchmark.

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