SP²Bench: A SPARQL Performance Benchmark

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Abstract— Recently, the SPARQL query language for RDF has reached the W3C recommendation status. In response to this emerging standard, the database community is currently exploring efficient storage techniques for RDF data and evaluation strategies for SPARQL queries. A meaningful analysis and comparison of these approaches necessitates a comprehensive and universal benchmark platform. To this end, we have developed SP²Bench, a publicly available, language-specific SPARQL performance benchmark. SP²Bench is settled in the DBLP scenario and comprises both a data generator for creating arbitrarily large DBLP-like documents and a set of carefully designed benchmark queries. The generated documents mirror key characteristics and social-world distributions encountered in the original DBLP data set, while the queries implement meaningful requests on top of this data, covering a variety of SPARQL operator constellations and RDF access patterns. As a proof of concept, we apply SP²Bench to existing engines and discuss their strengths and weaknesses that follow immediately from the benchmark results.

I. INTRODUCTION

The Resource Description Framework [1] (RDF) has become the standard format for encoding machine-readable information in the Semantic Web [2]. RDF databases can be represented by labeled directed graphs, where each edge connects a so-called *subject* node to an *object* node under label *predicate*. The intended semantics is that the *object* denotes the value of the *subject*'s property *predicate*. Supplementary to RDF, the W3C has recommended the declarative SPARQL [3] query language, which can be used to extract information from RDF graphs. SPARQL bases upon a powerful graph matching facility, allowing to bind variables to components in the input RDF graph. In addition, operators akin to relational joins, unions, left outer joins, selections, and projections can be combined to build more expressive queries.

By now, several proposals for the efficient evaluation of SPARQL have been made. These approaches comprise a wide range of optimization techniques, including normal forms [4], graph pattern reordering based on selectivity estimations [5] (similar to relational join reordering), syntactic rewriting [6], specialized indices [7], [8] and storage schemes [9], [10], [11], [12], [13] for RDF, and Semantic Query Optimization [14]. Another viable option is the translation of SPARQL into SQL [15], [16] or Datalog [17], which facilitates the evaluation

with traditional engines, thus falling back on established optimization techniques implemented in conventional engines.

As a proof of concept, most of these approaches have been evaluated experimentally either in user-defined scenarios, on top of the LUBM benchmark [18], or using the Barton Library benchmark [19]. We claim that none of these scenarios is adequate for testing SPARQL implementations in a general and comprehensive way: On the one hand, user-defined scenarios are typically designed to demonstrate very specific properties and, for this reason, lack generality. On the other hand, the Barton Library Benchmark is application-oriented, while LUBM was primarily designed to test the reasoning and inference mechanisms of Knowledge Base Systems. As a trade-off, in both benchmarks central SPARQL operators like OPTIONAL and UNION, or solution modifiers are not covered.

With the **SP**ARQL **P**erformance **Bench**mark (SP²Bench) we propose a language-specific benchmark framework specifically designed to test the most common SPARQL constructs, operator constellations, and a broad range of RDF data access patterns. The SP²Bench data generator and benchmark queries are available for download in a ready-to-use format.[1]

In contrast to application-specific benchmarks, SP²Bench aims at a comprehensive performance evaluation, rather than assessing the behavior of engines in an application-driven scenario. Consequently, it is not motivated by a single use case, but instead covers a broad range of challenges that SPARQL engines might face in different contexts. In this line, it allows to assess the generality of optimization approaches and to compare them in a universal, application-independent setting. We argue that, for these reasons, our benchmark provides excellent support for testing the performance of engines in a comprising way, which might help to improve the quality of future research in this area. We emphasize that such language-specific benchmarks (e.g., XMark [20]) have found broad acceptance, in particular in the research community.

It is quite evident that the domain of a language-specific benchmark should not only constitute a representative scenario that captures the philosophy behind the data format, but also leave room for challenging queries. With the choice of the DBLP [21] library we satisfy both desiderata. First, RDF has been particularly designed to encode metadata, which makes

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[1]http://dbis.informatik.uni-freiburg.de/index.php?project=SP2B

DBLP an excellent candidate. Furthermore, DBLP reflects interesting social-world distributions (cf. [22]), and hence captures the social network character of the Semantic Web, whose idea is to integrate a great many of small databases into a global semantic network. In this line, it facilitates the design of interesting queries on top of these distributions.

Our data generator supports the creation of arbitrarily large DBLP-like models in RDF format, which mirror vital key characteristics and distributions of DBLP. Consequently, our framework combines the benefits of a data generator for creating arbitrarily large documents with interesting data that contains many real-world characteristics, i.e. mimics natural correlations between entities, such as power law distributions (found in the citation system or the distribution of papers among authors) and limited growth curves (e.g., the increasing number of venues and publications over time). For this reason our generator relies on an in-depth study of DBLP, which comprises the analysis of entities (e.g. articles and authors), their properties, frequency, and also their interaction.

Complementary to the data generator, we have designed 17 meaningful queries that operate on top of the generated documents. They cover not only the most important SPARQL constructs and operator constellations, but also vary in their characteristics, such as complexity and result size. The detailed knowledge of data characteristics plays a crucial role in query design and makes it possible to predict the challenges that the queries impose on SPARQL engines. This, in turn, facilitates the interpretation of benchmark results.

The key contributions of this paper are the following.

- We present SP^{2}Bench, a comprehensive benchmark for the SPARQL query language, comprising a data generator and a collection of 17 benchmark queries.
- Our generator supports the creation of arbitrarily large DBLP documents in RDF format, reflecting key characteristics and social-world relations found in the original DBLP database. The generated documents cover various RDF constructs, such as blank nodes and containers.
- The benchmark queries have been carefully designed to test a variety of operator constellations, data access patterns, and optimization strategies. In the exhaustive discussion of these queries we also highlight the specific challenges they impose on SPARQL engines.
- As a proof of concept, we apply SP^{2}Bench to selected SPARQL engines and discuss their strengths and weaknesses that follow from the benchmark results. This analysis confirms that our benchmark is well-suited to identify deficiencies in SPARQL implementations.
- We finally propose performance metrics that capture different aspects of the evaluation process.

Outline. We next discuss related work and design decisions in Section II. The analysis of DBLP in Section III forms the basis for our data generator in Section IV. Section V gives an introduction to SPARQL and describes the benchmark queries. The experiments in Section VI comprise a short evaluation of our generator and benchmark results for existing SPARQL engines. We conclude with some final remarks in Section VII.

II. BENCHMARK DESIGN DECISIONS

Benchmarking. The Benchmark Handbook [23] provides a summary of important database benchmarks. Probably the most "complete" benchmark suite for relational systems is TPC^2, which defines performance and correctness benchmarks for a large variety of scenarios. There also exists a broad range of benchmarks for other data models, such as object-oriented databases (e.g., OO7 [24]) and XML (e.g., XMark [20]).

Coming along with its growing importance, different benchmarks for RDF have been developed. The Lehigh University Benchmark [18] (LUBM) was designed with focus on inference and reasoning capabilities of RDF engines. However, the SPARQL specification [3] disregards the semantics of RDF and RDFS [25], [26], i.e. does not involve automated reasoning on top of RDFS constructs such as subclass and subproperty relations. With this regard, LUBM does not constitute an adequate scenario for SPARQL performance evaluation. This is underlined by the fact that central SPARQL operators, such as UNION and OPTIONAL, are not addressed in LUBM.

The Barton Library benchmark [19] queries implement a user browsing session through the RDF Barton online catalog. By design, the benchmark is application-oriented. All queries are encoded in SQL, assuming that the RDF data is stored in a relational DB. Due to missing language support for aggregation, most queries cannot be translated into SPARQL. On the other hand, central SPARQL features like left outer joins (the relational equivalent of SPARQL operator OPTIONAL) and solution modifiers are missing. In summary, the benchmark offers only limited support for testing native SPARQL engines.

The application-oriented Berlin SPARQL Benchmark [27] (BSBM) tests the performance of SPARQL engines in a prototypical e-commerce scenario. BSBM is use-case driven and does not particularly address language-specific issues. With its focus, it is supplementary to the SP^{2}Bench framework.

The RDF(S) data model benchmark in [28] focuses on structural properties of RDF Schemas. In [29] graph features of RDF Schemas are studied, showing that they typically exhibit power law distributions which constitute a valuable basis for synthetic schema generation. With their focus on schemas, both [28] and [29] are complementary to our work.

A synthetic data generation approach for OWL based on test data is described in [30]. There, the focus is on rapidly generating large data sets from representative data of a fixed domain. Our data generation approach is more fine-grained, as we analyze the development of entities (e.g. articles) over time and reflect many characteristics found in social communities.

Design Principles. In the Benchmark Handbook [23], four key requirements for domain specific benchmarks are postulated, i.e. it should be (1) *relevant*, thus testing typical operations within the specific domain, (2) *portable*, i.e. should be executable on different platforms, (3) *scalable*, e.g. it should be possible to run the benchmark on both small and very large data sets, and last but not least (4) it must be *understandable*.

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^{2}See http://www.tpc.org.

For a language-specific benchmark, the relevance requirement (1) suggests that queries implement realistic requests on top of the data. Thereby, the benchmark should not focus on correctness verification, but on common operator constellations that impose particular challenges. For instance, two SP²Bench queries test negation, which (under closed-world assumption) can be expressed in SPARQL through a combination of operators OPTIONAL, FILTER, and BOUND.

Requirements (2) portability and (3) scalability bring along technical challenges concerning the implementation of the data generator. In response, our data generator is deterministic, platform independent, and accurate w.r.t. the desired size of generated documents. Moreover, it is very efficient and gets by with a constant amount of main memory, and hence supports the generation of arbitrarily large RDF documents.

From the viewpoint of engine developers, a benchmark should give hints on deficiencies in design and implementation. This is where (4) understandability comes into play, i.e. it is important to keep queries simple and understandable. At the same time, they should leave room for diverse optimizations. In this regard, the queries are designed in such a way that they are amenable to a wide range of optimization strategies.

DBLP. We settled SP²Bench in the DBLP [21] scenario. The DBLP database contains bibliographic information about the field of Computer Science and, particularly, databases.

In the context of semi-structured data one often distinguishes between data- and document-centric scenarios. Document-centric design typically involves large amounts of free-form text, while data-centric documents are more structured and usually processed by machines rather than humans. RDF has been specifically designed for encoding information in a machine-readable way, so it basically follows the data-centric approach. DBLP, which contains structured data and little free text, constitutes such a data-centric scenario.

As discussed in the Introduction, our generator mirrors vital real-world distributions found in the original DBLP data. This constitutes an improvement over existing generators that create purely synthetic data, in particular in the context of a language-specific benchmark. Ultimately, our generator might also be useful in other contexts, whenever large RDF test data is required. We point out that the DBLP-to-RDF translation of the original DBLP data in [31] provides only a fixed amount of data and, for this reason, is not sufficient for our purpose.

We finally mention that sampling down large, existing data sets such as U.S. Census[3] (about 1 billion triples) might be another reasonable option to obtain data with real-world characteristics. The disadvantage, however, is that sampling might destroy more complex distributions in the data, thus leading to unnatural and "corrupted" RDF graphs. In contrast, our decision to build a data generator from scratch allows us to customize the structure of the RDF data, which is in line with the idea of a comprehensive, language-specific benchmark. This way, we easily obtain documents that contain a rich set of RDF constructs, such as blank nodes or containers.

```
<!ELEMENT dblp
  (article|inproceedings|proceedings|book|
  incollection|phdthesis|masterssthesis|www)*>
<!ENTITY % field
  "author|editor|title|booktitle|pages|year|address|
  journal|volume|number|month|url|ee|cdrom|cite|
  publisher|note|crossref|isbn|series|school|chapter">
<!ELEMENT article (%field;)*>...<!ELEMENT www (%field;)*>
```

Fig. 1.   Extract of the DBLP DTD

III. THE DBLP DATA SET

The study of the DBLP data set in this section lays the foundations for our data generator. The analysis of frequency distributions in scientific production has first been discussed in [32], and characteristics of DBLP have been investigated in [22]. The latter work studies a subset of DBLP, restricting DBLP to publications in database venues. It is shown that (this subset of) DBLP reflects vital social relations, forming a "small world" on its own. Although this analysis forms valuable groundwork, our approach is of more pragmatic nature, as we approximate distributions by concrete functions.

We use function families that naturally reflect the scenarios, e.g. logistics curves for modeling limited growth or power equations for power law distributions. All approximations have been done with the *ZunZun*[4] data modeling tool and the *gnuplot*[5] curve fitting module. Data extraction from the DBLP XML data was realized with the MonetDB/XQuery[6] processor.

An important objective of this section is also to provide insights into key characteristics of DBLP data. Although it is impossible to mirror all relations found in the original data, we work out a variety of interesting relationships, considering entities, their structure, or the citation system. The insights that we gain establish a deep understanding of the benchmark queries and their specific challenges. As an example, $Q3a$, $Q3b$, and $Q3c$ (see Appendix) look similar, but pose different challenges based on the probability distribution of article properties discussed within this section; $Q7$, on the other hand, heavily depends on the DBLP citation system.

Although the generated data is very similar to the original DBLP data for years up to the present, we can give no guarantees that our generated data goes hand in hand with the original DBLP data for future years. However, and this is much more important, even in the future the generated data will follow reasonable (and well-known) social-world distributions. We emphasize that the benchmark queries are designed to primarily operate on top of these relations and distributions, which makes them realistic, predictable and understandable. For instance, some queries operate on top of the citation system, which is mirrored by our generator. In contrast, the distribution of article release months is ignored, hence no query relies on this property.

A. Structure of Document Classes

Our starting point for the discussion is the DBLP DTD and the February 25, 2008 version of DBLP. An extract of

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[3]http://www.rdfabout.com/demo/census/

[4]http://www.zunzun.com

[5]http://www.gnuplot.info

[6]http://monetdb.cwi.nl/XQuery/

the DTD is provided in Figure 1. The dblp element defines eight child entities, namely ARTICLE, INPROCEEDINGS, ..., and WWW resources. We call these entities *document classes*, and instances thereof *documents*. Furthermore, we distinguish between PROCEEDINGS documents, called *conferences*, and instances of the remaining classes, called *publications*.

The DTD defines 22 possible child tags, such as author or url, for each document class. They *describe* documents, and we call them *attributes* in the following. According to the DTD, each document might be described by arbitrary combination of attributes. Even repeated occurrences of the same attribute are allowed, e.g. a document might have several authors. However, in practice only a subset of all document class/attribute combinations occurs. For instance, (as one might expect) attribute pages is never associated with WWW documents, but typically associated with ARTICLE entities. In Table I we show, for selected document class/attribute pairs, the probability that the attribute describes a document of this class[7]. To give an example, about 92.61% of all ARTICLE documents are described by the attribute pages.

This probability distribution forms the basis for generating document class instances. Note that we simplify and assume that the presence of an attribute does not depend on the presence of other attributes, i.e. we ignore conditional probabilities. We will elaborate on this decision in Section VII.

Repeated Attributes. A study of DBLP reveals that, in practice, only few attributes occur repeatedly within single documents. For the majority of them, the number of repeated occurrences is diminishing, so we restrict ourselves on the most frequent *repeated attributes* cite, editor, and author.

Figure 2(a) exemplifies our analysis for attribute cite. It shows, for each documents with at least one cite occurrence, the probability (y-axis) that the document has exactly n cite attributes (x-axis). According to Table I, only a small fraction of documents are described by cite (e.g. 4.8% of all ARTICLE documents). This value should be close to 100% in real world, meaning that DBLP contains only a fraction of all citations. This is also why, in Figure 2(a), we consider only documents with at least one outgoing citation; when assigning citations later on, however, we first use the probability distribution of attributes in Table I to estimate the number of documents with at least one outgoing citation and afterwards apply the citation distribution in Figure 2(a). This way, we exactly mirror the distribution found in the original DBLP data.

Based on experiments with different function families, we decided to use bell-shaped Gaussian curves for data approximation. Such functions are typically used to model normal distributions. Strictly speaking, our data is not normally distributed (i.e. there is the left limit $x = 1$), however, these curves nicely fit the data for $x \geq 1$ (cf. Figure 2(a)). Gaussian curves are described by functions

$$p_{gauss}^{(\mu,\sigma)}(x) = \frac{1}{\sigma\sqrt{2\pi}}e^{-0.5(\frac{x-\mu}{\sigma})^2},$$

where $\mu \in \mathbb{R}$ fixes the x-position of the peak and $\sigma \in \mathbb{R}_{>0}$

[7]The full correlation matrix can be found in Table IX in the Appendix.

TABLE I
PROBABILITY DISTRIBUTION FOR SELECTED ATTRIBUTES

	Article	**Inproc.**	**Proc.**	**Book**	**WWW**
author	0.9895	0.9970	0.0001	0.8937	0.9973
cite	0.0048	0.0104	0.0001	0.0079	0.0000
editor	0.0000	0.0000	0.7992	0.1040	0.0004
isbn	0.0000	0.0000	0.8592	0.9294	0.0000
journal	0.9994	0.0000	0.0004	0.0000	0.0000
month	0.0065	0.0000	0.0001	0.0008	0.0000
pages	0.9261	0.9489	0.0000	0.0000	0.0000
title	1.0000	1.0000	1.0000	1.0000	1.0000

specifies the statistical spread. For instance, the approximation function for the cite distribution in Figure 2(a) is defined by $d_{cite}(x) \stackrel{def}{:=} p_{gauss}^{(16.82,10.07)}(x)$. The analysis and the resulting distribution of repeated editor attributes is structurally similar and is described by the function $d_{editor}(x) \stackrel{def}{:=} p_{gauss}^{(2.15,1.18)}(x)$.

The approximation function for repeated author attributes bases on a Gaussian curve, too. However, we observed that the average number of authors per publication has increased over the years. The same observation was made in [22] and explained by the increasing pressure to publish and the proliferation of new communication platforms. Due to the prominent role of authors, we decided to mimic this property. As a consequence, parameters μ and σ are not fixed (as it was the case for the distributions d_{cite} and d_{editor}), but modeled as functions over time. More precisely, μ and σ are realized by limited growth functions[8] (so-called logistic curves) that yield higher values for later years. The distribution is described by

$$d_{auth}(x, yr) \stackrel{def}{:=} p_{gauss}^{(\mu_{auth}(yr),\sigma_{auth}(yr))}(x), \text{ where}$$
$$\mu_{auth}(yr) \stackrel{def}{:=} \frac{2.05}{1+17.59e^{-0.11(yr-1975)}} + 1.05, \text{ and}$$
$$\sigma_{auth}(yr) \stackrel{def}{:=} \frac{1.00}{1+6.46e^{-0.10(yr-1975)}} + 0.50.$$

We will discuss the logistic curve function type in more detail in the following subsection.

B. Key Characteristics of DBLP

We next investigate the quantity of document class instances over time. We noticed that DBLP contains only few and incomplete information in its early years, and also found anomalies in the final years, mostly in form of lowered growth rates. It might be that, in the coming years, some more conferences for these years will be added belatedly (i.e. data might not yet be totally complete), so we restrict our discussion to DBLP data ranging from 1960 to 2005.

Figure 2(b) plots the number of PROCEEDINGS, JOURNAL, INPROCEEDINGS, and ARTICLE documents as a function of time. The y-axis is in log scale. Note that JOURNAL is not an explicit document class, but implicitly defined by the journal attribute of ARTICLE documents. We observe that inproceedings and articles are closely coupled to the proceedings and journals. For instance, there are always about 50-60 times more

[8]We make the reasonable assumption that the number of coauthors will eventually stabilize.
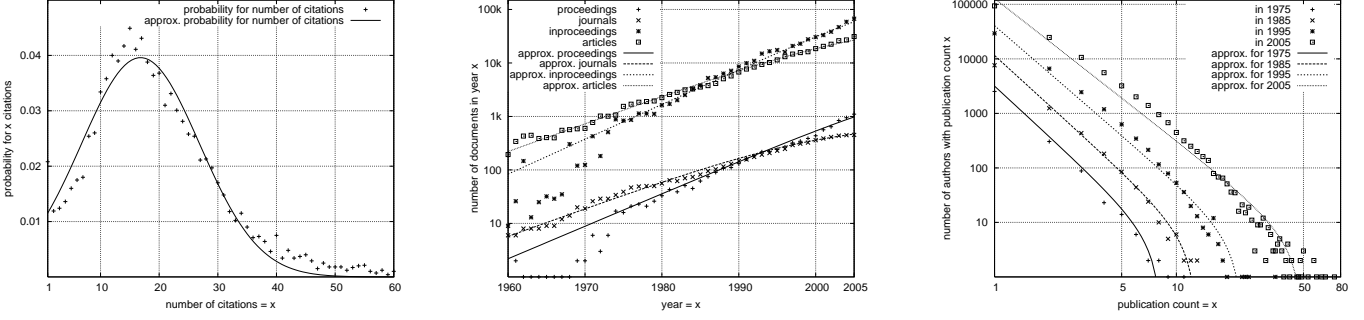
Fig. 2. (a) Distribution of citations, (b) Document class instances, and (c) Publication counts

inproceedings than proceedings, which indicates the average number of inproceedings per proceeding.

Figure 2(b) shows exponential growth for all document classes, where the growth rate of JOURNAL and ARTICLE documents decreases in the final years. This suggests a limited growth scenario. Limited growth is typically modeled by logistic curves, which describe functions with a lower and an upper asymptote that either continuously increase or decrease for increasing x. We use curves of the form

$$f_{logistic}(x) = \frac{a}{1+be^{-cx}},$$

where $a, b, c \in \mathbb{R}_{>0}$. For this parameter setting, a constitutes the upper asymptote and the x-axis forms the lower asymptote. The curve is "caught" in-between its asymptotes and increases continuously, i.e. it is S-shaped. The approximation function for the number of JOURNAL documents, which is also plotted in Figure 2(b), is defined by the formula

$$f_{journal}(yr) \stackrel{def}{:=} \frac{740.43}{1+426.28e^{-0.12(yr-1950)}}.$$

Approximation functions for ARTICLE, PROCEEDINGS, IN-PROCEEDINGS, BOOK, and INCOLLECTION documents differ only in the parameters. PHD THESES, MASTERS THESES, and WWW documents were distributed unsteadily, so we modeled them by random functions. It is worth mentioning that the number of articles and inproceedings per year clearly dominates the number of instances of the remaining classes. The concrete formulas look as follows.

$$
\begin{aligned}
f_{article}(yr) &\stackrel{def}{:=} \frac{58519.12}{1+876.80e^{-0.12(yr-1950)}} \\
f_{proc}(yr) &\stackrel{def}{:=} \frac{5502.31}{1+1250.26e^{-0.14(yr-1965)}} \\
f_{inproc}(yr) &\stackrel{def}{:=} \frac{337132.34}{1+1901.05e^{-0.15(yr-1965)}} \\
f_{incoll}(yr) &\stackrel{def}{:=} \frac{3577.31}{196.49e^{-0.09(yr-1980)}} \\
f_{book}(yr) &\stackrel{def}{:=} \frac{52.97}{40739.38e^{-0.32(yr-1950)}} \\
f_{phd}(yr) &\stackrel{def}{:=} random[0..20] \\
f_{masters}(yr) &\stackrel{def}{:=} random[0..10] \\
f_{www}(yr) &\stackrel{def}{:=} random[0..10]
\end{aligned}
$$

C. Authors and Editors

Based on the previous analysis, we can estimate the number of documents f_{docs} in yr by summing up the individual counts:

$$
\begin{aligned}
f_{docs}(yr) \stackrel{def}{:=}\ & f_{journal}(yr) + f_{article}(yr) + f_{proc}(yr) + \\
& f_{inproc}(yr) + f_{incoll} + f_{book}(yr) + \\
& f_{phd}(yr) + f_{masters}(yr) + f_{www}(yr),
\end{aligned}
$$

The *total number of authors*, which we define as the number of author attributes in the data set, is computed as follows. First, we estimate the number of documents described by attribute author for each document class individually (using the distribution in Table I). All these counts are summed up, which gives an estimation for the total number of documents with one or more author attributes. Finally, this value is multiplied with the expected average number of authors per paper in the respective year (implicitly given by d_{auth} in Section III-A).

To be close to reality, we also consider the number of distinct persons that appear as authors (per year), called *distinct authors*, and the number of *new authors* in a given year, i.e. those persons that publish for the first time.

We found that the number of distinct authors f_{dauth} per year can be expressed in dependence of f_{auth} as follows.

$$f_{dauth}(yr) \stackrel{def}{:=} \left(\frac{-0.67}{1+169.41e^{-0.07(yr-1936)}} + 0.84\right) * f_{auth}(yr)$$

The equation above indicates that the number of distinct authors relative to the total authors decreases steadily, from 0.84% to $0.84\% - 0.67\% = 0.17\%$. Among others, this reflects the increasing productivity of authors over time.

The formula for the number f_{new} of new authors builds on the previous one and also builds upon a logistic curve:

$$f_{new}(yr) \stackrel{def}{:=} \left(\frac{-0.29}{1749.00e^{-0.14(yr-1937)}} + 0.628\right) * f_{dauth}(yr)$$

Publications. In Figure 2(c) we plot, for selected year and publication count x, the number of authors with exactly x publications in this year. The graph is in log-log scale. We observe a typical power law distribution, i.e. there are only a couple of authors having a large number of publications, while lots of authors have only few publications.

Power law distributions are modeled by functions of the form $f_{powerlaw}(x) = ax^k + b$, with constants $a \in \mathbb{R}_{>0}$, exponent $k \in \mathbb{R}_{<0}$, and $b \in \mathbb{R}$. Parameter a affects the x-axis intercept, exponent k defines the gradient, and b constitutes a shift in y-direction. For the given parameter restriction, the functions decrease steadily for increasing $x \geq 0$.

Figure 2(c) shows that, throughout the years, the curves move upwards. This means that the publication count of the

leading author(s) has steadily increased over the last 30 years, and also reflects an increasing number of authors. We estimate the number of authors with x publications in year yr as

$$f_{awp}(x, yr) \overset{def}{:=} 1.50 f_{publ}(yr) x^{-f'_{awp}(yr)} - 5, \text{ where}$$

$$f'_{awp}(yr) \overset{def}{:=} \frac{-0.60}{1 + 216223 e^{-0.20(yr - 1936)}} + 3.08, \text{ and}$$

$f_{publ}(yr)$ returns the total number of publications in yr.

Coauthors. In analyzing coauthor characteristics, we investigated relations between the publication count of authors and the number of its total and distinct coauthors. Given a number x of publications, we (roughly) estimate the average number of total coauthors by $\mu_{coauth} := 2.12 * x$ and the number of its distinct coauthors by $\mu_{dcoauth} := x^{0.81}$. We take these values into consideration when assigning coauthors.

Editors. The analysis of authors is complemented by a study of their relations to editors. We associate editors with authors by investigating the editors' number of publications in (earlier) venues. As one might expect, editors often have published before, i.e. are persons that are known in the community. The concrete formula is rather technical and omitted.

D. Citations

In Section III-A we have studied repeated occurrences of attribute cite, i.e. outgoing citations. Concerning the *incoming* citations (i.e. the count of incoming references for papers), we observed a characteristic power law distribution: Most papers have few incoming citations, while only few are cited often. We omit the concrete power law approximation function.

We also observed that the number of incoming citations is smaller than the number of outgoing citations. This is because DBLP contains many untargeted citations (i.e. empty cite tags). Recalling that only a fraction of all papers have outgoing citations (cf. Section III-A), we conclude that the DBLP citation system is very incomplete.

IV. Data Generation

The RDF Data Model. From a logical point of view, RDF data bases are collections of so-called triples of knowledge. A triple (*subject*,*predicate*,*object*) models the binary relation *predicate* between *subject* and *object* and can be visualized in a directed graph by an edge from the *subject* node to an *object* node under label *predicate*. Figure 3(b) shows a sample RDF graph, where dashed lines represent edges that are labeled with rdf:type, and *sc* is an abbreviation for rdfs:subClassOf. For instance, the arc from node *Proceeding1* to node _:*John_Due* represents the triple (*Proceeding1*,*swrc:editor*,_:*John_Due*).

RDF graphs may contain three types of nodes. First, *URIs* (Uniform Resource Identifiers) are strings that uniquely identify abstract or physical resources, such as conferences or journals. *Blank nodes* have an existential character, i.e. are typically used to denote resources that exist, but are not assigned a fixed URI. We represent URIs and blank nodes by ellipses, identifying blank nodes by the prefix "_:". *Literals* represent (possibly typed) values and usually describe URIs or blank nodes. Literals are represented by quoted strings.

The RDF standard [1] introduces a base vocabulary with fixed semantics, e.g. defines URI rdf:type for type specifications. This vocabulary also includes containers, such as bags or sequences. RDFS [25] extends the RDF vocabulary and, among others, provides URIs for subclass (rdfs:subClassOf) and subproperty (rdf:subPropertyOf) specifications. On top of RDF and RDFS, one can easily create user-defined, domain-specific vocabularies. Our data generator makes heavy use of such predefined vocabulary collections.

The DBLP RDF Scheme. Our RDF scheme basically follows the approach in [31], which presents an XML-to-RDF mapping of the original DBLP data. However, we want to generate arbitrarily-sized documents and provide lists of first and last names, publishers, and random words to our data generator. Conference and journal names are always of the form "*Conference $i ($year)*" and "*Journal $i ($year)*", where $i is a unique conference (resp. journal) number in year *$year*.

Similar to [31], we use existing RDF vocabularies to describe resources in a uniform way. We borrow vocabulary from FOAF[9] for describing persons, and from SWRC[10] and DC[11] for describing scientific resources. Additionally, we introduce a namespace bench, which defines DBLP-specific document classes, such as bench:Book and bench:Article. Figure 3(a) shows the translation of attributes to RDF properties. For each attribute, we also list its range restriction, i.e. the type of elements it refers to. For instance, attribute author is mapped to dc:creator, and references objects of type foaf:Person.

The original DBLP RDF scheme neither contains blank nodes nor RDF containers. As we want to test our queries on top of such RDF-specific constructs, we use (unique) blank nodes "_:*givenname_lastname*" for persons (instead of URIs) and model outgoing citations of documents using standard rdf:Bag containers. We also enriched a small fraction of ARTICLE and INPROCEEDINGS documents with the new property bench:abstract (about 1%, keeping the modification low), which constitutes comparably large strings (using a Gaussian distribution with $\mu = 150$ expected words and $\sigma = 30$).

Figure 3(b) shows a sample DBLP instance. On the logical level, we distinguish between the *schema* layer (gray) and the *instance* layer (white). Reference lists are modeled as blank nodes of type rdf:Bag, i.e. using standard RDF containers (see node _:*references1*). Authors and editors are represented by blank nodes of type foaf:Person. Class foaf:Document splits up into the individual document classes bench:Journal, bench:Article, and so on. Our graph defines three persons, one proceeding, two inproceedings, one journal, and one article. For readability reasons, we plot only selected predicates. As also illustrated, property dcterms:partOf links inproceedings and proceedings together, while swrc:journal connects articles to their journals.

In order to provide an entry point for queries that access authors and to provide a person with fixed characteristics, we

| attribute	mapped to prop.	refers to
address	swrc:address	xsd:string
author	dc:creator	foaf:Person
booktitle	bench:booktitle	xsd:string
cdrom	bench:cdrom	xsd:string
chapter	swrc:chapter	xsd:integer
cite	dcterms:references	foaf:Document
crossref	dcterms:partOf	foaf:Document
editor	swrc:editor	foaf:Person
ee	rdfs:seeAlso	xsd:string
isbn	swrc:isbn	xsd:string
journal	swrc:journal	bench:Journal
month	swrc:month	xsd:integer
note	bench:note	xsd:string
number	swrc:number	xsd:integer
page	swrc:pages	xsd:string
publisher	dc:publisher	xsd:string
school	dc:publisher	xsd:string
series	swrc:series	xsd:integer
title	dc:title	xsd:string
url	foaf:homepage	xsd:string
volume	swrc:volume	xsd:integer
year	dcterms:issued	xsd:integer
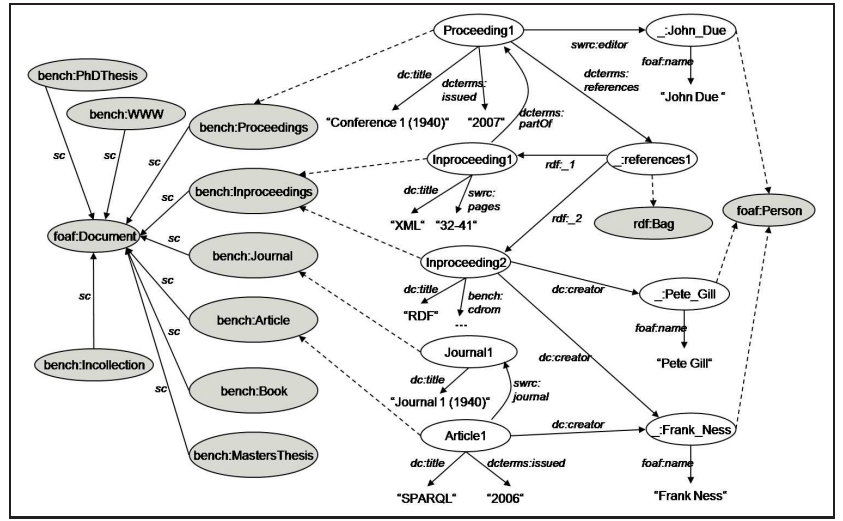
Fig. 3. (a) Translations of attributes, and (b) DBLP sample instance in RDF format

created a special author, named after the famous mathematician Paul Erdös. Per year, we assign 10 publications and 2 editor activities to this prominent person, starting from year 1940 up to 1996. For the ease of access, Paul Erdös is modeled by a fixed URI. As an example query consider $Q8$, which extracts all persons with *Erdös Number*[12] 1 or 2.

Data Generation. Our data generator was implemented in $C++$. It takes into account all relationships and characteristics that have been studied in Section III. Figure 4 shows the key steps in data generation. We simulate year by year and generate data according to the structural constraints in a carefully selected order. As a consequence, data generation is incremental, i.e. small documents are always contained in larger documents.

The generator offers two parameters, to fix either a triple count limit or the year up to which data will be generated. When the triple count limit is set, we make sure to end up in a "consistent" state, e.g. whenever proceedings are written, the corresponding conference will be included.

The generation process is simulation-based. Among others, this means that we assign life times to authors, and individually estimate their future behavior, taking into account global publication and coauthor characteristics, as well as the fraction of distinct and new authors (cf. Section III-C).

All random functions (which, for example, are used to assign the attributes according to Table I) base on a fixed seed. This makes data generation deterministic, i.e. the parameter setting uniquely identifies the outcome. As data generation is also platform-independent, we ensure that experimental results from different machines are comparable.

V. BENCHMARK QUERIES

The SPARQL Query Language. SPARQL is a declarative language and bases upon a powerful graph matching facility, allowing to match query subexpressions against the RDF input

[12]See http://www.oakland.edu/enp/.

```
foreach year:
    calculate counts for and generate document classes;
    calculate nr of total, new, distinct, and retiring authors;

    choose publishing authors;
    assign nr of new publications, nr of coauthors, and
    nr of distinct coauthors to publishing authors;
    // s.t. constraints for nr of publications/author hold

    assign from publishing authors to papers;
    // satisfying authors per paper/co authors constraints

    choose editors and assign editors to papers;
    // s.t. constraints for nr of publications/editors hold

    generate outgoing citations;
    assign expected incoming/outgoing citations to papers;

    write output until done or until output limit reached;
    // permanently keeping output consistent
```

Fig. 4. Data generation algorithm

graph. The very basic SPARQL constructs are triple patterns $(subject, predicate, object)$, where variables might be used in place of fixed values for each of the three components. In evaluating SPARQL, these patterns are mapped against one or more input graphs, thereby binding variables to matching nodes or edges in the graph(s). Since we are primarily interested in database aspects, such as operator constellations and access patterns, we focus on queries that access a single graph.

The SPARQL standard [3] defines four distinct query forms. SELECT queries retrieve all possible variable-to-graph mappings, while ASK queries return *yes* if at least one such mapping exists, and *no* otherwise. The DESCRIBE form extracts additional information related to the result mappings (e.g. adjacent nodes), while CONSTRUCT transforms the result mapping into a new RDF graph. The most appropriate for our purpose is SELECT, which best reflects SPARQL core evaluation. ASK queries are also interesting, as they might affect the choice of the query execution plan (QEP). In contrast, CONSTRUCT and DESCRIBE build upon the core evaluation of SELECT, i.e. transform its result in a post-processing step. This step

TABLE II

SELECTED PROPERTIES OF THE BENCHMARK QUERIES; SHORTCUTS ARE INDICATED BY BOLD FONT

	Query	1	2	3abc	4	5ab	6	7	8	9	10	11	12c
1	Operators: AND,FILTER,UNION,OPTIONAL	A	A,O	A,F	A,F	A,F	A,F,O	A,F,O	A,F,U	A,U	-	-	-
2	Modifiers: DISTINCT,LIMIT,OFFSET,ORDER bY	-	Ob	-	D	D		D	D	D	-	L,Ob,Of	-
4	Filter Pushing Possible?	-	-	✓	-	✓/-	✓	✓	✓	-	-	-	-
5	Reusing of Graph Pattern Possible?	-	-	-	✓	-	✓	✓	✓	✓	-	-	
6	Data Access: BLANK nodes,LITERALS,URIs, LARGE LITERALS,CONTAINERS	L,U	L,U,La	L,U	B,L,U	B,L,U	B,L,U	L,U,C	B,L,U	B,L,U	U	L,U	U

is not very challenging from a database perspective, so we focus on SELECT and ASK queries (though, on demand, these queries could easily be translated into the other forms).

The most important SPARQL operator is AND (denoted as "."). If two SPARQL expressions A and B are connected by AND, the result is computed by joining the result mappings of A and B on their shared variables [4]. Let us consider $Q1$ from the Appendix, which defines three triple patterns interconnected through AND. When first evaluating the patterns individually, variable *?journal* is bound to nodes with (1) edge rdf:type pointing to the URI bench:Journal, (2) edge dc:title pointing to the Literal "*Journal 1 (1940)*" of type string, and (3) edge dcterms:issued, respectively. The next step is to join the individual mapping sets on variable *?journal*. The result then contains all mappings from *?journal* to nodes that satisfy all three patterns. Finally SELECT projects for variable *?yr*, which has been bound in the third pattern.

Other SPARQL operators are UNION, OPTIONAL, and FILTER, akin to relational unions, left outer joins, and selections, respectively. For space limitations, we omit an explanation of these constructs and refer the reader to the SPARQL semantics [3]. Beyond all these operators, SPARQL provides functions to be used in FILTER expressions, e.g. for regular expression testing. We expect these functions to only marginally affect engine performance, since their implementation is mostly straightforward (or might be realized through efficient libraries). They are unlikely to bring insights into the core evaluation capabilities, so we omit them intentionally. This decision also facilitates benchmarking of research prototypes, which typically do not implement the full standard.

The SP²Bench queries also cover SPARQL solution modifiers, such as DISTINCT, ORDER BY, LIMIT, and OFFSET. Like their SQL counterparts, they might heavily affect the choice of an efficient QEP, so they are relevant for our benchmark. We point out that the previous discussion captures virtually all key features of the SPARQL query language. In particular, SPARQL does (currently) not support aggregation, nesting, or recursion.

SPARQL Characteristics. Rows 1 and 2 in Table II survey the operators used in the SELECT benchmark queries (the ASK-queries $Q12a$ and $Q12b$ share the characteristics of their SELECT counterparts $Q5a$ and $Q8$, respectively, and are not shown). The queries cover various operator constellations, combined with selected solution modifiers combinations.

One very characteristic SPARQL feature is operator OPTIONAL. An expression A OPTIONAL $\{B\}$ joins result mappings from A with mappings from B, but – unlike AND –

retains mappings from A for which no join partner in B is present. In the latter case, variables that occur only inside B might be unbound. By combining OPTIONAL with FILTER and function BOUND, which checks if a variable is bound or not, one can simulate *closed world negation* in SPARQL. Many interesting queries involve such an encoding (c.f. $Q6$ and $Q7$).

SPARQL operates on graph-structured data, thus engines should perform well on different kinds of graph patterns. Unfortunately, up to the present there exist only few real-world SPARQL scenarios. It would be necessary to analyze a large set of such scenarios, to extract graph patterns that frequently occur in practice. In the absence of this possibility, we distinguish between *long path chains*, i.e. nodes linked to each other node via a long path, *bushy patterns*, i.e. single nodes that are linked to a multitude of other nodes, and *combinations of these two patterns*. Since it is impossible to give a precise definition of "long" and "bushy", we designed meaningful queries that contain *comparably* long chains (i.e. $Q4$, $Q6$) and *comparably* bushy patterns (i.e. $Q2$) w.r.t. our scenario. These patterns contribute to the variety of characteristics that we cover.

SPARQL Optimization. Our objective is to design queries that are amenable to a variety of SPARQL optimization approaches. To this end, we discuss possible optimization techniques before presenting the benchmark queries.

A promising approach to SPARQL optimization is the *reordering of triple patterns* based on selectivity estimation [5], akin to relational join reordering. Closely related to triple reordering is FILTER *pushing*, which aims at an early evaluation of filter conditions, similar to projection pushing in Relational Algebra. Both techniques might speed up evaluation by decreasing the size of intermediate results. An efficient join order depends on selectivity estimations for triple patterns, but might also be affected by available data access paths. Join reordering might apply to most of our queries. Row 4 in Table II lists the queries that support FILTER pushing.

Another idea is to *reuse evaluation results of triple patterns* (or even combinations thereof). This might be possible whenever the same pattern is used multiple times. As an example consider $Q4$. Here, *?article1* and *?article2* in the first and second triple pattern will be bound to the same nodes. We survey the applicability of this technique in Table II, row 5.

RDF Characteristics and Storage. SPARQL has been specifically designed to operate on top of RDF [1] rather than RDFS [25] data. Although it is possible to access RDFS vocabulary with SPARQL, the semantics of RDFS [26] is ignored when evaluating such queries. Consider for example the rdfs:subClassOf property, which is used to model sub-

class relationships between entities, and assume that class `Student` is a subclass of `Person`. A SPARQL query like "*Select all objects of type* `Person`" then does *not* return students, although according to [26] each student is also a person. Hence, queries that cover RDFS inference make no sense unless the SPARQL standard is changed accordingly.

Recalling that persons are modeled as blank nodes, all queries that deal with persons access blank nodes. Moreover, one of our queries operates on top of the RDF bag container for reference lists ($Q7$), and one accesses the comparably large abstract literals ($Q2$). Row 6 in Table II provides a survey.

A comparison of RDF storage strategies is provided in [12]. Storage scheme and indices finally imply a selection of efficient *data access paths*. Our queries impose varying challenges to the storage scheme, e.g. test data access through RDF subjects, predicates, objects, and combinations thereof. In most cases, predicates are fixed and subject and/or object vary, but we also test more uncommon access patterns. We will resume this discussion when describing $Q9$ and $Q10$.

A. Benchmark Queries

The benchmark queries also vary in general characteristics like *selectivity*, *query and output size*, and *different types of joins*. We will point out such characteristics in the subsequent individual discussion of the benchmark queries.

In the following, we distinguish between *in-memory* engines, which load the document from file and process queries in main memory, and *native* engines, which rely on a physical database system. When discussing challenges to and evaluation strategies for native engines, we always assume that the document has already been loaded in the database before.

We finally emphasize that in this paper we focus on the SPARQL versions of our queries, which can be processed directly by real SPARQL engines. One might also be interested in the SQL-translations of these queries available at the SP^{2}Bench project page. We refer the interested reader to [33] for an elaborate discussion of these translations.

Q1. *Return the year of publication of "Journal 1 (1940)".*

This simple query returns exactly one result (for arbitrarily large documents). Native engines might use index lookups in order to answer this query in (almost) constant time, i.e. execution time should be independent from document size.

Q2. *Extract all inproceedings with properties* dc:creator, bench:booktitle, dcterms:issued, dcterms:partOf, rdfs:seeAlso, dc:title, swrc:pages, foaf:homepage, *and optionally* bench:abstract, *including their values.*

This query implements a bushy graph pattern. It contains a single, simple OPTIONAL expression, and accesses large strings (i.e. the abstracts). Result size grows with database size, and a final result ordering is necessary due to operator ORDER BY. Both native and in-memory engines might reach evaluation times that are almost linear to the document size.

Q3abc. *Select all articles with property (a)* swrc:pages, *(b)* swrc:month, *or (c)* swrc:isbn.

This query tests FILTER expressions with varying selectivity. According to Table I, the FILTER expression in $Q3a$ is not very selective (i.e. retains about 92.61% of all articles). Data access through a secondary index for $Q3a$ is probably not very efficient, but might work well for $Q3b$, which selects only 0.65% of all articles. The filter condition in $Q3c$ is never satisfied, as no articles have swrc:isbn predicates. Schema statistics might be used to answer $Q3c$ in constant time.

Q4. *Select all distinct pairs of article author names for authors that have published in the same journal.*

$Q4$ contains a rather long graph chain, i.e. variables *?name1* and *?name2* are linked through the articles the authors have published, and a common journal. The result is very large, basically quadratic in number and size of journals. Instead of evaluating the outer pattern block and applying the FILTER afterwards, engines might embed the FILTER expression in the computation of the block, e.g. by exploiting indices on author names. The DISTINCT modifier further complicates the query. We expect superlinear behavior, even for native engines.

Q5ab. *Return the names of all persons that occur as author of at least one inproceeding and at least one article.*

Queries $Q5a$ and $Q5b$ test different variants of joins. $Q5a$ implements an implicit join on author names, which is encoded in the FILTER condition, while $Q5b$ explicitly joins the authors on variable *name*. Although in general the queries are not equivalent, the one-to-one mapping between authors and their names (i.e. author names constitute primary keys) in our scenario implies equivalence. In [14], semantic optimization on top of such keys for RDF has been proposed. Such an approach might detect the equivalence of both queries in this scenario and select the more efficient variant.

Q6. *Return, for each year, the set of all publications authored by persons that have not published in years before.*

$Q6$ implements closed world negation (CWN), expressed through a combination of operators OPTIONAL, FILTER, and BOUND. The idea of the construction is that the block outside the OPTIONAL expression computes all publications, while the inner one constitutes earlier publications from authors that appear outside. The outer FILTER expression then retains publications for which *?author2* is unbound, i.e. exactly the publications of authors without publications in earlier years.

Q7. *Return the titles of all papers that have been cited at least once, but not by any paper that has not been cited itself.*

This query tests double negation, which requires nested CWN. Recalling that the citation system of DBLP is rather incomplete (cf. Section III-D), we expect only few results. Though, the query is challenging due to the double negation. Engines might reuse graph pattern results, for instance, the block ?class[i] rdf:type foaf:Document. ?doc[i] rdf:type ?class[i]. occurs three times, for empty [i], [i]=3, and [i]=4.

Q8. *Compute authors that have published with Paul Erdös or with an author that has published with Paul Erdös.*

Here, the evaluation of the second UNION part is basically "contained" in the evaluation of the first part. Hence, techniques like graph pattern (or subexpression) reusing might apply. Another very promising optimization approach is to decompose the filter expressions and push down its components, in order to decrease the size of intermediate results.

#triples	10^3	10^4	10^5	10^6	10^7	10^8	10^9
elapsed time [s]	0.08	0.13	0.60	5.76	70	1011	13306

Q9. *Return incoming and outgoing properties of persons.*

$Q9$ has been designed to test non-standard data access patterns. Naive implementations would compute the triple patterns of the UNION subexpressions separately, thus evaluate patterns where no component is bound. Then, pattern `?subject ?predicate ?person` would select all graph triples, which is rather inefficient. Another idea is to evaluate the first triple in each UNION subexpression, afterwards using the bindings for variable *?person* to evaluate the second patterns more efficiently. In this case, we observe patterns where only the *subject* (resp. the *object*) is bound. Also observe that this query extracts schema information. The result size is exactly 4 (for sufficiently large documents). Statistics about incoming/outgoing properties of *Person*-typed objects in native engines might be used to answer this query in constant time, even without data access. In-memory engines always must load the document, hence might scale linearly to document size.

Q10. *Return all subjects that stand in any relation to person "Paul Erdös".* In our scenario the query can be reformulated as *Return publications and venues in which* "Paul Erdös" *is involved either as author or as editor.*

$Q10$ implements an object bound-only access pattern. In contrast to $Q9$, statistics are not immediately useful, since the result includes subjects. Recall that "Paul Erdös" is active only between 1940 and 1996, so result size stabilizes for sufficiently large documents. Native engines might exploit indices and reach (almost) constant execution time.

Q11. *Return (up to) 10 electronic edition URLs starting from the 51th publication, in lexicographical order.*

This query focuses on the combination of solution modifiers ORDER BY, LIMIT, and OFFSET. In-memory engines have to read, process, and sort electronic editions prior to processing LIMIT and OFFSET. In contrast, native engines might exploit indices to access only a fraction of all electronic editions and, as the result is limited to 10, reach constant runtimes.

Q12. *(a) Return yes if a person occurs as author of at least one inproceeding and article, no otherwise; (b) Return yes if an author has published with Paul Erdös or with an author that has published with* "Paul Erdös", *and no otherwise.; (c) Return yes if person* "John Q. Public" *is present in the database.*

$Q12a$ and $Q12b$ share the properties of their SELECT counterparts $Q5a$ and $Q8$, respectively. They always return *yes* for sufficiently large documents. When evaluating such ASK queries, engines should break as soon as a solution has been found. They might adapt the QEP, to efficiently locate a witness. For instance, based on execution time estimations it might be favorable to evaluate the second part of the UNION in $Q12b$ first. Both native and in-memory engines should answer these queries very fast, independent from document size.
$Q12c$ asks for a single triple that is not present in the database. With indices, native engines might execute this query in constant time. Again, in-memory engines must scan (and hence, load) the whole document.

VI. EXPERIMENTS

All experiments were conducted under Linux ubuntu v7.10 gutsy, on top of an Intel Core2 Duo E6400 2.13GHz CPU and 3GB DDR2 667 MHz nonECC physical memory. We used a 250GB Hitachi P7K500 SATA-II hard drive with 8*MB* Cache. The Java engines were executed with JRE v1.6.0_04.

A. Data Generator

To prove the practicability of our data generator, we measured data generation times for documents of different sizes. Table III shows the performance results for documents containing up to one billion triples. The generator scales almost linearly with document size and creates even large documents very fast (the 10^9 triples document has a physical size of about 103*GB*). Moreover, it runs with constant main memory consumption (i.e., gets by with about 1.2*GB* RAM).

We verified the implementation of all characteristics from Section III. Table VIII shows selected data generator and output document characteristics for documents up to $25M$ triples. We list the size of the output file, the year in which simulation ended, the number of total authors and distinct authors contained in the data set (cf. Section III-C), and the counts of the document class instances (cf. Section III-B). We observe superlinear growth for the number of authors (w.r.t. the number of triples). This is primarily caused by the increasing average number of authors per paper (cf. Section III-A). The growth rate of proceedings and inproceedings is also superlinear, while the rate of journals and articles is sublinear. These observations reflect the yearly document class counts in Figure 2(b). We remark that – like in the original DBLP database – in the early years instances of several document classes are missing, e.g. there are no BOOK and WWW documents. Also note that the counts of inproceedings and articles clearly dominate the remaining document classes.

Table V surveys the result sizes for the queries on documents up to $25M$ triples. We observe for example that the outcome of $Q3a$, $Q3b$, and $Q3c$ reflects the selectivities of their FILTER attributes swrc:pages, swrc:month, and swrc:isbn (cf. Table I and VIII). We will come back to the result size listing when discussing the benchmark results later on.

B. Benchmark Metrics

Depending on the scenario, we will report on user time (`usr`), system time (`sys`), and the high watermark of resident memory consumption (`rmem`). These values were extracted from the *proc* file system, whereas we measured elapsed time (`tme`) through timers. It is important to note that experiments were carried out on a DuoCore CPU, where the linux kernel sums up the `usr` and `sys` times of the individual processor units. As a consequence, in some scenarios the sum `usr+sys` might be greater than the elapsed time `tme`.

We propose several metrics that capture different aspects of the evaluation. Reports of the benchmark results would, in the best case, include all these metrics, but might also ignore metrics that are irrelevant to the underlying scenario. We propose to perform three runs over documents comprising

$10k$, $50k$, $250k$, $1M$, $5M$, and $25M$ triples, using a fixed timeout of 30min per query and document, always reporting on the average value over all three runs and, if significant, the errors within these runs. We point out that this setting can be evaluated in reasonable time (typically within few days). If the implementation is fast enough, nothing prevents the user from adding larger documents. All reports should, of course, include the hardware and software specifications. Performance results should list `tme`, and optionally `usr` and `sys`. In the following, we shortly describe a set of interesting metrics.

1) SUCCESS RATE: We propose to separately report on the success rates for the engine on top of all document sizes, distinguishing between Success, Timeout (e.g. an execution time $> 30min$ as used in our experiments here), Memory Exhaustion (if an additional memory limit was set), and general Errors. This metric gives a good survey over scaling properties and might give first insights into the behavior of engines.

2) LOADING TIME: The user should report on the loading times for the documents of different sizes. This metric primarily applies to engines with a database backend and might be ignored for in-memory engines, where loading is typically part of the evaluation process.

3) PER-QUERY PERFORMANCE: The report should include the individual performance results for all queries over all document sizes. This metric is more detailed than the SUCCESS RATE report and forms the basis for a deep study of the results, in order to identify strengths and weaknesses of the tested implementation.

4) GLOBAL PERFORMANCE: We propose to combine the per-query results into a single performance measure. Here we recommend to list for execution times the arithmetic as well as the geometric mean, which is defined as the nth root of the product over n numbers. In the context of SP^{2}Bench, this means we multiply the execution time of all 17 queries (queries that failed should be ranked with $3600s$, to penalize timeouts and other errors) and compute the 17th root of this product (for each document size, accordingly). This metric is well-suited to compare the performance of engines.

5) MEMORY CONSUMPTION: In particular for engines with a physical backend, the user should also report on the high watermark of main memory consumption and ideally also the average memory consumption over all queries (cf. Table VI and VII).

C. Benchmark Results for Selected Engines

It is beyond the scope of this paper to provide an in-depth comparison of existing SPARQL engines. Rather than that, we use our metrics to give first insights into the state-of-the art and exemplarily illustrate that the benchmark indeed gives valuable hints on bottlenecks in current implementations. In this line, we are not primarily interested in concrete values (which, however, might be of great interest in the general case), but focus on the principal behavior and properties of engines, e.g. discuss how they scale with document size. We

will exemplarily discuss some interesting cases and refer the interested reader to the Appendix for the complete results.

We conducted benchmarks for (1) the Java engine **ARQ**[13] v2.2 on top of Jena 2.5.5, (2) the **Redland**[14] RDF Processor v1.0.7 (written in C), using the Raptor Parser Toolkit v.1.4.16 and Rasqal Library v0.9.15, (3) **SDB**[15], which link ARQ to an SQL database back-end (i.e., we used mysql v5.0.34) , (4) the Java implementation **Sesame**[16] v2.2beta2, and finally (5) OpenLink **Virtuoso**[17] v5.0.6 (written in C).

For Sesame we tested two configurations: $Sesame_M$, which processes queries in memory, and $Sesame_{DB}$, which stores data physically on disk, using the native *Mulgara* SAIL (v1.3beta1). We thus distinguish between the in-memory engines (ARQ, $Sesame_M$) and engines with physical backend, namely ($Redland$, SBD, $Sesame_{DB}$, $Virtuoso$). The latter can further be divided into engines with a native RDF store ($Redland$, $Sesame_{DB}$, $Virtuoso$) and a relational database backend (SDB). For all physical-backend databases we created indices wherever possible (immediately after loading the documents) and consider loading and execution time separately (index creation time is included in the reported loading times).

We performed three cold runs over all queries and documents of $10k$, $50k$, $250k$, $1M$, $5M$, and $25M$ triples, i.e. in-between each two runs we restarted the engines and cleared the database. We set a timeout of 30min (`tme`) per query and a memory limit of $2.6GB$, either using *ulimit* or restricting the JVM (for higher limits, the initialization of the JVM failed). Negative and positive variation of the average (over the runs) was $< 2\%$ in almost all cases, so we omit error bars. For SDB and $Virtuoso$, which follow a client-server architecture, we monitored both processes and sum up these values.

We verified all results by comparing the outputs, observing that SDB and $Redland$ returned wrong results for a couple of queries, so we restrict ourselves on the discussion of the remaining four engines. Table IV shows the success rates. All queries that are not listed succeeded, except for ARQ and $Sesame_M$ on the $25M$ document (either due to timeout or memory exhaustion) and Virtuoso on $Q6$ (due to missing standard compliance). Hence, $Q4$, $Q5a$, $Q6$, and $Q7$ are the most challenging queries, where we observe many timeouts even for small documents. Note that we did not succeed in loading the $25M$ triples document into the *Virtuoso* database.

D. Discussion of Benchmark Results

Main Memory. For the in-memory engines we observe that the high watermark of main memory consumption during query evaluation increases sublinearly to document size (cf. Table VI), e.g. for ARQ we measured an average (over runs and queries) of $85MB$ on $10k$, $166MB$ on $50k$, $318MB$ on $250k$, $526MB$ on $1M$, and $1.3GB$ on $5M$ triples. Somewhat

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[13]http://jena.sourceforge.net/ARQ/
[14]http://librdf.org/
[15]http://jena.sourceforge.net/SDB/
[16]http://www.openrdf.org/
[17]http://www.openlinksw.com/virtuoso/

TABLE IV

SUCCESS RATES FOR QUERIES ON RDF DOCUMENTS UP TO $25M$ TRIPLES. QUERIES ARE ENCODED IN HEXADECIMAL (E.G., 'A' STANDS FOR $Q10$). WE USE THE SHORTCUTS +:=SUCCESS, T:=TIMEOUT, M:=MEMORY EXHAUSTION, AND E:=ERROR.

	ARQ	Sesame$_M$	Sesame$_{DB}$	Virtuoso

Query	123 45 6789ABC
	   abc ab
		123 45 6789ABC
		   abc ab
			123 45 6789ABC
			   abc ab
				123 45 6789ABC
				   abc ab

10k	++++++++++++++++	++++++++++++++++	++++++++++++++++	+++++++E++++++++
50k	++++++++++++++++	++++++++++++++++	++++++++++++++++	+++++++E++++++++
250k	+++++T++++++++++	++++++T+T++++++++	++++++T+TT+++++++	+++++TT+E++++++++
1M	+++++TT+TT+++++++	++++++T+TT+++++++	++++++T+TT+++++++	+++++TTTET+++++++
5M	+++++TT+TT+++++++	+++++TT+TT+++++++	+++++MT+TT+++++++	+++++TTTET+++++++
25M	TTTTTTTTTTTTTTTTT	MMMMMMMTMMMMMTMMT	+++++TT+TT+++++++	(loading of document failed)

TABLE V

NUMBER OF QUERY RESULTS ON DOCUMENTS UP TO 25 MILLION TRIPLES

Query	Q1	Q2	Q3a	Q3b	Q3c	Q4	Q5a	Q5b	Q6	Q7	Q8	Q9	Q10	Q11
10k	1	147	846	9	0	23226	155	155	229	0	184	4	166	10
50k	1	965	3647	25	0	104746	1085	1085	1769	2	264	4	307	10
250k	1	6197	15853	127	0	542801	6904	6904	12093	62	332	4	452	10
1M	1	32770	52676	379	0	2586733	35241	35241	62795	292	400	4	572	10
5M	1	248738	192373	1317	0	18362955	210662	210662	417625	1200	493	4	656	10
25M	1	1876999	594890	4075	0	n/a	696681	696681	1945167	5099	493	4	656	10

TABLE VI

ARITHMETIC AND GEOMETRIC MEANS OF EXECUTION TIME (T_a/T_g) AND ARITHMETIC MEAN OF MEMORY CONSUMPTION (M_a) FOR THE IN-MEMORY ENGINES

	ARQ			Sesame$_M$		
	T_a[s]	T_g[s]	M_a[MB]	T_a[s]	T_g[s]	M_a[MB]
250k	491.87	56.35	318.25	442.47	28.64	272.27
1M	901.73	179.42	525.61	683.16	106.38	561.79
5M	1154.80	671.41	1347.55	1059.03	506.14	1437.38

TABLE VII

ARITHMETIC AND GEOMETRIC MEANS OF EXECUTION TIME (T_a/T_g) AND ARITHMETIC MEAN OF MEMORY CONSUMPTION (M_a) FOR THE NATIVE ENGINES

	Sesame$_{DB}$			Virtuoso		
	T_a[s]	T_g[s]	M_a[MB]	T_a[s]	T_g[s]	M_a[MB]
250k	639.86	6.79	73.92	546.31	1.31	377.60
1M	653.17	10.17	145.97	850.06	3.03	888.72
5M	860.33	22.91	196.33	870.16	8.96	1072.84

surprisingly, also the memory consumption of the native engines *Virtuoso* and *Sesame$_{DB}$* increased with document size.

Arithmetic and Geometric Mean. For the in-memory engines we observe that *Sesame$_M$* is superior to *ARQ* regarding both means (see Table VI). For instance, the arithmetic (T_a) and geometric (T_g) mean for the engines on the $1M$ document over all queries[18] are $T_a^{SesM} = 683.16s$, $T_g^{SesM} = 106.84s$, $T_a^{ARQ} = 901.73s$, and $T_g^{ARQ} = 179.42s$.

For the native engines on $1M$ triples (cf. Table VII) we have $T_a^{SesDB} = 653.17s$, $T_g^{SesDB} = 10.17s$, $T_a^{Virt} = 850.06s$, and $T_g^{Virt} = 3.03s$. The arithmetic mean of *Sesame$_{DB}$* is superior, which is mainly due to the fact that it failed only on 4 (vs. 5) queries. The geometric mean moderates the impact of these outliers. *Virtuoso* shows a better overall performance for the success queries, so its geometric mean is superior.

In-memory Engines. Figure 5 (top) plot selected results for in-memory engines. We start with $Q5a$ and $Q5b$. Although both compute the same result, the engines perform much better for the explicit join in $Q5b$. We may suspect that the implicit join in $Q5a$ is not recognized, i.e. that both engines compute

[18]We always penalize failure queries with $3600s$.

the cartesian product and apply the filter afterwards.

$Q6$ and $Q7$ implement simple and double negation, respectively. Both engines show insufficient behavior. At the first glance, we might expect that $Q7$ (which involves double negation) is more complicated to evaluate, but we observe that *Sesame$_M$* scales even worse for $Q6$. We identify two possible explanations. First, $Q7$ "negates" documents with incoming citations, but – according to Section III-D – only a small fraction of papers has incoming citations at all. In contrast, $Q6$ negates arbitrary documents, i.e. a much larger set. Another reasonable cause might be the non-equality filter subexpression ?yr2 < ?yr inside the inner FILTER of $Q6$.

For ASK query $Q12a$ both engines scale linearly with document size. However, from Table V and the fact that our data generator is incremental and deterministic, we know that a "witness" is already contained in the first $10k$ triples of the document. It might be located even without reading the whole document, so both evaluation strategies are suboptimal.

Native Engines. The leftmost plot at the bottom of Figure 5 shows the loading times for the native engines *Sesame$_{DB}$* and *Virtuoso*. Both engines scale well concerning usr and sys, essentially linear to document size. For *Sesame$_{DB}$*, however,
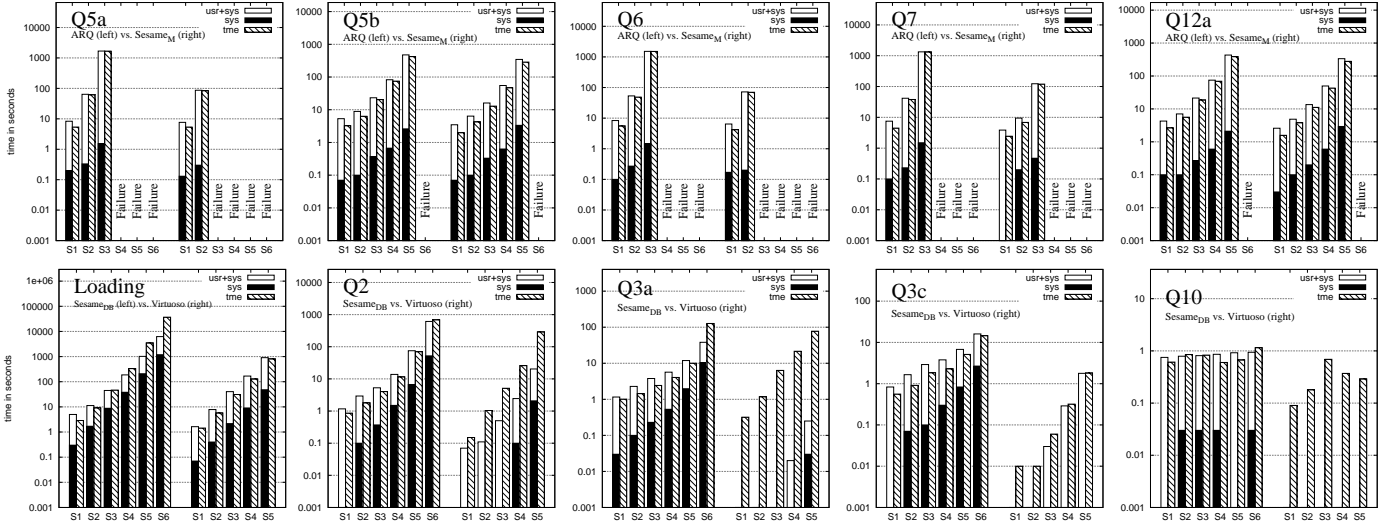
Fig. 5. Results for in-memory engines (top) and native engines (bottom) on S1=10k, S2=50k, S3=250k, S4=1M, S5=5M, and S6=25M triples

tme grows superlinearly (e.g., loading of the $25M$ document is about ten times slower than loading of the $5M$ document). This might cause problems for larger documents.

The running times for $Q2$ increase superlinear for both engines (in particular for larger documents). This reflects the superlinear growth of inproceedings and the growing result size (cf. Tables VIII and V). What is interesting here is the significant difference between usr+sys and tme for *Virtuoso*, which indicates disproportional disk I/O. Since *Sesame* does not exhibit this peculiar behavior, it might be an interesting starting point for further optimizations in the *Virtuoso* engine.

Queries $Q3a$ and $Q3c$ have been designed to test the intelligent choice of indices in the context of FILTER expressions with varying selectivity. *Virtuoso* gets by with an economic consumption of usr and sys time for both queries, which suggests that it makes heavy use of indices. While this strategy pays off for $Q3c$, the elapsed time for $Q3a$ is unreasonably high and we observe that $Sesame_M$ scales better for this query.

$Q10$ extracts subjects and predicates that are associated with *Paul Erdös*. First recall that, for each year up to 1996, *Paul Erdös* has exactly 10 publications and occurs twice as editor (cf. Section IV). Both engines answer this query in about constant time, which is possible due to the upper result size bound (cf. Table V). Regarding usr+sys, *Virtuoso* is even more efficient: These times are diminishing in all cases. Hence, this query constitutes an example for desired engine behavior.

VII. CONCLUSION

We have presented the SP²Bench performance benchmark for SPARQL, which constitutes the first methodical approach for testing the performance of SPARQL engines w.r.t. different operator constellations, RDF access paths, typical RDF constructs, and a variety of possible optimization approaches.

Our data generator relies on a deep study of DBLP. Although it is not possible to mirror *all* correlations found in the original DBLP data (e.g., we simplified when assuming independence between attributes in Section III-A), many aspects

TABLE VIII
CHARACTERISTICS OF GENERATED DOCUMENTS

#Triples	10k	50k	250k	1M	5M	25M
file size [MB]	1.0	5.1	26	106	533	2694
data up to	1955	1967	1979	1989	2001	2015
#Tot.Auth.	1.5k	6.8k	34.5k	151.0k	898.0k	5.4M
#Dist.Auth.	0.9k	4.1k	20.0k	82.1k	429.6k	2.1M
#Journals	25	104	439	1.4k	4.6k	11.7k
#Articles	916	4.0k	17.1k	56.9k	207.8k	642.8k
#Proc.	6	37	213	903	4.7k	24.4k
#Inproc.	169	1.4k	9.2k	43.5k	255.2k	1.5M
#Incoll.	18	56	173	442	1.4k	4.5k
#Books	0	0	39	356	973	1.7k
#PhD Th.	0	0	0	101	237	365
#Mast.Th.	0	0	0	50	95	169
#WWWs	0	0	0	35	92	168

are modeled in faithful detail and the queries are designed in such a way that they build on exactly those aspects, which makes them realistic, understandable, and predictable.

Even without knowledge about the internals of engines, we identified deficiencies and reasoned about suspected causes. We expect the benefit of our benchmark to be even higher for developers that are familiar with the engine internals.

To give another proof of concept, in [33] we have successfully used SP²Bench to identify previously unknown limitations of RDF storage schemes: Among others, we identified scenarios where the advanced vertical storage scheme from [12] was slower than a simple triple store approach.

With the understandable DBLP scenario we clear the way for coming language modifications. For instance, SPARQL update and aggregation support are currently discussed as possible extensions.[19] Updates, for instance, could be realized by minor extensions to our data generator. Concerning aggregations, the detailed knowledge of the document class counts and distributions (cf. Section III) facilitates the design of challenging aggregate queries with fixed characteristics.

[19]See http://esw.w3.org/topic/SPARQL/Extensions.

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```
SELECT ?yr                                            Q1
WHERE {
 ?journal rdf:type bench:Journal.
 ?journal dc:title "Journal 1 (1940)"^^xsd:string.
 ?journal dcterms:issued ?yr }
```

```
SELECT ?inproc ?author ?booktitle ?title             Q2
        ?proc ?ee ?page ?url ?yr ?abstract
WHERE {
  ?inproc rdf:type bench:Inproceedings.
  ?inproc dc:creator ?author.
  ?inproc bench:booktitle ?booktitle.
  ?inproc dc:title ?title.
  ?inproc dcterms:partOf ?proc.
  ?inproc rdfs:seeAlso ?ee.
  ?inproc swrc:pages ?page.
  ?inproc foaf:homepage ?url.
  ?inproc dcterms:issued ?yr
  OPTIONAL { ?inproc bench:abstract ?abstract } }
} ORDER BY ?yr
```

```
(a) SELECT ?article                                  Q3
    WHERE { ?article rdf:type bench:Article.
            ?article ?property ?value
            FILTER (?property=swrc:pages) }
(b) Q3a, but "swrc:month" instead of "swrc:pages"
(c) Q3a, but "swrc:isbn" instead of "swrc:pages"
```

```
SELECT DISTINCT ?name1 ?name2                         Q4
WHERE { ?article1 rdf:type bench:Article.
        ?article2 rdf:type bench:Article.
        ?article1 dc:creator ?author1.
        ?author1 foaf:name ?name1.
        ?article2 dc:creator ?author2.
        ?author2 foaf:name ?name2.
        ?article1 swrc:journal ?journal.
        ?article2 swrc:journal ?journal
        FILTER (?name1<?name2) }
```

```
(a) SELECT DISTINCT ?person ?name                     Q5
    WHERE { ?article rdf:type bench:Article.
            ?article dc:creator ?person.
            ?inproc rdf:type bench:Inproceedings.
            ?inproc dc:creator ?person2.
            ?person foaf:name ?name.
            ?person2 foaf:name ?name2
            FILTER(?name=?name2) }
(b) SELECT DISTINCT ?person ?name
    WHERE { ?article rdf:type bench:Article.
            ?article dc:creator ?person.
            ?inproc rdf:type bench:Inproceedings.
            ?inproc dc:creator ?person.
            ?person foaf:name ?name }
```

```
SELECT ?yr ?name ?doc                                 Q6
WHERE {
  ?class rdfs:subClassOf foaf:Document.
  ?doc rdf:type ?class.
  ?doc dcterms:issued ?yr.
  ?doc dc:creator ?author.
  ?author foaf:name ?name
  OPTIONAL {
    ?class2 rdfs:subClassOf foaf:Document.
    ?doc2 rdf:type ?class2.
    ?doc2 dcterms:issued ?yr2.
    ?doc2 dc:creator ?author2
    FILTER (?author=?author2 && ?yr2<?yr) }
  FILTER (!bound(?author2)) }
```

```
SELECT DISTINCT ?title                                Q7
WHERE {
  ?class rdfs:subClassOf foaf:Document.
  ?doc rdf:type ?class.
  ?doc dc:title ?title.
  ?bag2 ?member2 ?doc.
  ?doc2 dcterms:references ?bag2
  OPTIONAL {
    ?class3 rdfs:subClassOf foaf:Document.
    ?doc3 rdf:type ?class3.
    ?doc3 dcterms:references ?bag3.
    ?bag3 ?member3 ?doc
    OPTIONAL {
      ?class4 rdfs:subClassOf foaf:Document.
      ?doc4 rdf:type ?class4.
      ?doc4 dcterms:references ?bag4.
      ?bag4 ?member4 ?doc3 }
    FILTER (!bound(?doc4)) }
  FILTER (!bound(?doc3)) }
```

```
SELECT DISTINCT ?name                                 Q8
WHERE {
  ?erdoes rdf:type foaf:Person.
  ?erdoes foaf:name "Paul Erdoes"^^xsd:string.
  { ?doc dc:creator ?erdoes.
    ?doc dc:creator ?author.
    ?doc2 dc:creator ?author.
    ?doc2 dc:creator ?author2.
    ?author2 foaf:name ?name
    FILTER (?author!=?erdoes &&
            ?doc2!=?doc &&
            ?author2!=?erdoes &&
            ?author2!=?author)
  } UNION {
    ?doc dc:creator ?erdoes.
    ?doc dc:creator ?author.
    ?author foaf:name ?name
    FILTER (?author!=?erdoes) } }
```

```
SELECT DISTINCT ?predicate                            Q9
WHERE {
  { ?person rdf:type foaf:Person.
    ?subject ?predicate ?person } UNION
  { ?person rdf:type foaf:Person.
    ?person ?predicate ?object } }
```

```
SELECT ?subj ?pred                                    Q10
WHERE { ?subj ?pred person:Paul_Erdoes }
```

```
SELECT ?ee                                            Q11
WHERE { ?publication rdfs:seeAlso ?ee }
ORDER BY ?ee LIMIT 10 OFFSET 50
```

```
(a) Q5a as ASK query                                  Q12

(b) Q8 as ASK query

(c) ASK {person:John_Q_Public rfd:type foaf:Person}
```
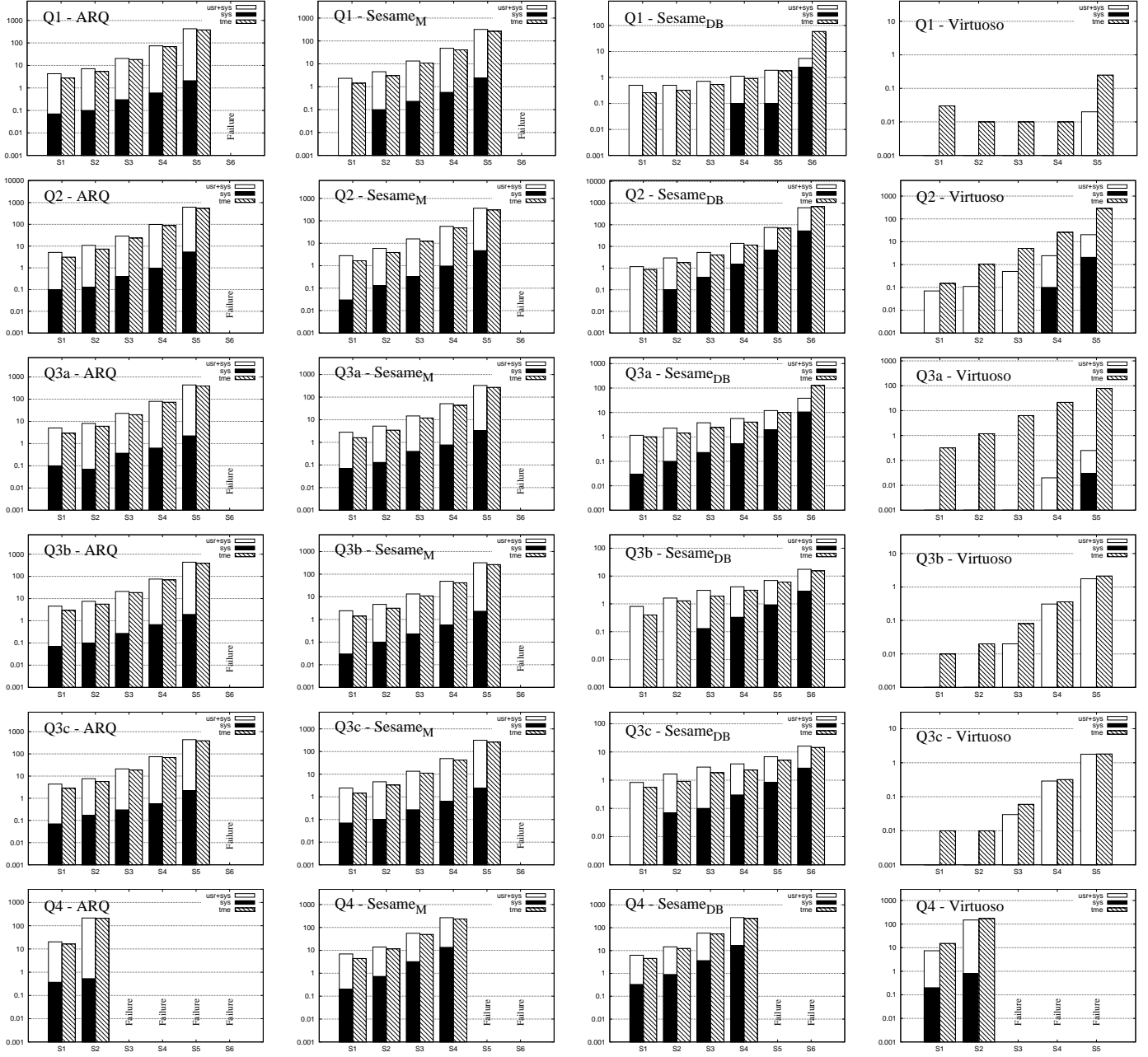
Fig. 6. Query evaluation results on S1=10k, S2=50k, S3=250k, S4=1M, S5=5M, and S6=25M triples
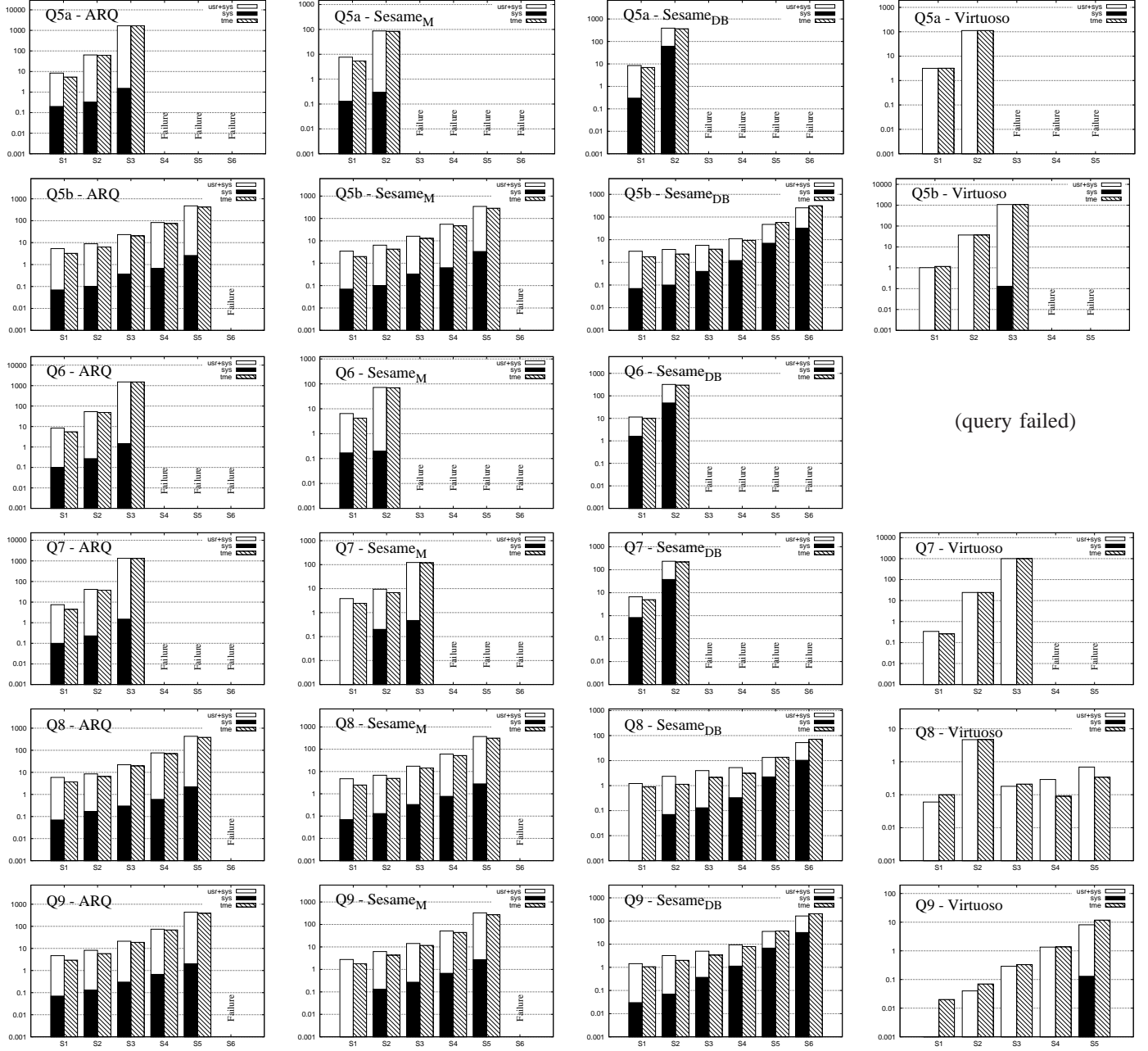
Fig. 7. Query evaluation results on S1=10k, S2=50k, S3=250k, S4=1M, S5=5M, and S6=25M triples
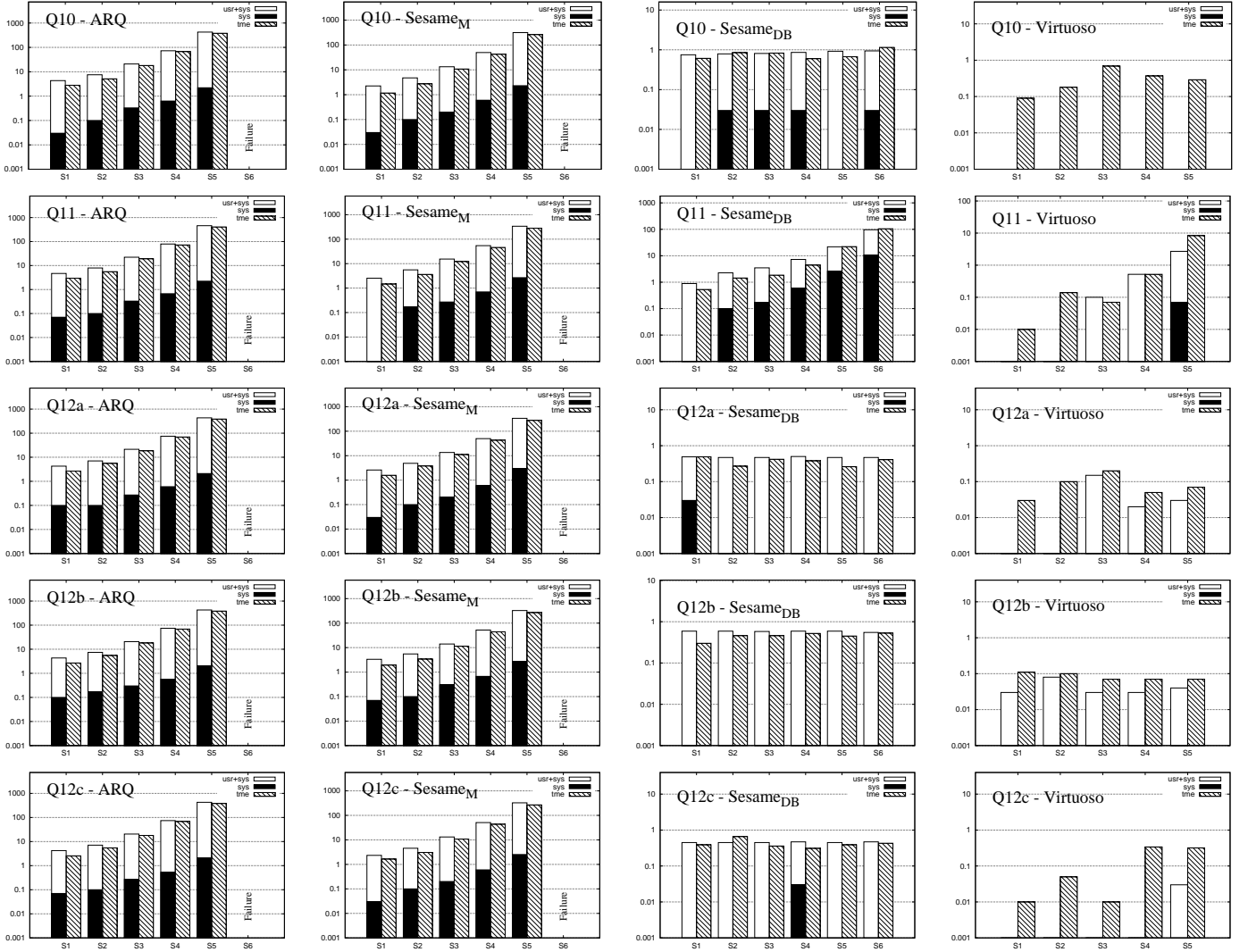
Fig. 8. Query evaluation results on S1=10k, S2=50k, S3=250k, S4=1M, S5=5M, and S6=25M triples

TABLE IX

PROBABILITY DISTRIBIBUTION FOR ATTRIBUTES AND DOCUMENT CLASSES

	Article	Inproc.	Proc.	Book	Incoll.	PhDTh.	MastTh.	WWW
address	0.0000	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000
author	0.9895	0.9970	0.0001	0.8937	0.8459	1.0000	1.0000	0.9973
booktitle	0.0006	1.0000	0.9579	0.0183	1.0000	0.0000	0.0000	0.0001
cdrom	0.0112	0.0162	0.0000	0.0032	0.0138	0.0000	0.0000	0.0000
chapter	0.0000	0.0000	0.0000	0.0000	0.0005	0.0000	0.0000	0.0000
cite	0.0048	0.0104	0.0001	0.0079	0.0047	0.0000	0.0000	0.0000
crossref	0.0006	0.8003	0.0016	0.0000	0.6951	0.0000	0.0000	0.0000
editor	0.0000	0.0000	0.7992	0.1040	0.0000	0.0000	0.0000	0.0004
ee	0.6781	0.6519	0.0019	0.0079	0.3610	0.1444	0.0000	0.0000
isbn	0.0000	0.0000	0.8592	0.9294	0.0073	0.0222	0.0000	0.0000
journal	0.9994	0.0000	0.0004	0.0000	0.0000	0.0000	0.0000	0.0000
month	0.0065	0.0000	0.0001	0.0008	0.0000	0.0333	0.0000	0.0000
note	0.0297	0.0000	0.0002	0.0000	0.0000	0.0000	0.0000	0.0273
number	0.9224	0.0001	0.0009	0.0000	0.0000	0.0333	0.0000	0.0000
pages	0.9261	0.9489	0.0000	0.0000	0.6849	0.0000	0.0000	0.0000
publisher	0.0006	0.0000	0.9737	0.9992	0.0237	0.0444	0.0000	0.0000
school	0.0000	0.0000	0.0000	0.0000	0.0000	1.0000	1.0000	0.0000
series	0.0000	0.0000	0.5791	0.5365	0.0000	0.0222	0.0000	0.0000
title	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000
url	0.9986	1.0000	0.986	0.2373	0.9992	0.0222	0.3750	0.9624
volume	0.9982	0.0000	0.567	0.5024	0.0000	0.0111	0.0000	0.0000
year	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	1.0000	0.0011