Evaluating Query and Storage Strategies for RDF Archives

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Abstract. There is an emerging demand on techniques addressing the problem of efficiently archiving and (temporal) querying different versions of evolving semantic Web data. While systems archiving and/or temporal querying are still in their early days, we consider this a good time to discuss benchmarks for evaluating storage space efficiency for archives, retrieval functionality they serve, and the performance of various retrieval operations. To this end, we provide theoretical foundations on the design of data and queries to evaluate emerging RDF archiving systems. Next, we instantiate these foundations along a concrete set of queries on the basis of a real-world evolving dataset. Finally, we perform an empirical evaluation of various current archiving techniques and querying strategies on this data. Our work comprises – to the best of our knowledge – the first benchmark for querying evolving RDF data archives.

1 Introduction

Nowadays, RDF data is ubiquitous. In less than a decade, and thanks to active projects such as the Linked Open Data (LOD) [3] effort or `schema.org`, researchers and practitioners have built a continuously growing interconnected Web of Data. In parallel, a novel generation of semantically enhanced applications leverage this infrastructure to build services which can answer questions not possible before (thanks to the availability of SPARQL [14] which enables structured queries over this data). As previously reported [27,15], this published data is continuously undergoing changes (on a data and schema level). These changes naturally happen without a centralized monitoring nor pre-defined policy, following the scale-free nature of the Web. Applications and businesses leveraging the availability of certain data over time, and seeking to track data changes or conduct studies on the evolution of data, thus need to build their own infrastructures to preserve and query data over time. Moreover, at the schema level, evolving vocabularies complicate re-use as inconsistencies may be introduced between data relying on a previous version of the ontology.

Thus, archiving policies of Linked Open Data (LOD) collections emerge as a novel – and open – challenge aimed at assuring quality and traceability of Semantic Web data over time. While sharing the same overall objectives with traditional Web archives,

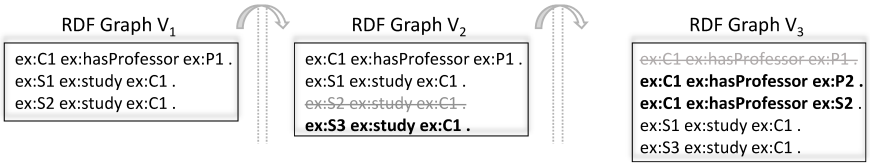


Fig. 1: Example of RDF graph versions.

such as the Internet Archive,[3] archives for the Web of Data should additionally offer capabilities for time-traversing structured queries.

In spite of initial works on RDF archiving policies/strategies [9], these are not implemented at large scale, and existing archiving infrastructures do not support structured and time-traversing queries in demand: for instance, knowing whether a dataset, or a particular entity has changed is neither natively supported by SPARQL nor by any of the existing temporal extensions of SPARQL [26,10,23,33].

This paper anticipates the development of definitive solutions for archiving and querying Semantic Web data, and discusses the problem of evaluating the efficiency of the required retrieval demands. To the best of our knowledge, no work has been proposed to systematically benchmark RDF archives. Existing RDF versioning and archiving solutions focus so far on providing feasible proposals for partial coverage of possible use case demands. Somewhat related, but not covering the specifics of (temporal) querying over archives, existing RDF/SPARQL benchmarks focus on static [1,4,24], federated [18] or streaming data [6] in centralized or distributed repositories: they do not cover the particularities of RDF archiving, where querying entity changes across time is a crucial aspect.

In order to fill this gap, our main **contributions** are: (i) Based on an analysis of current RDF archiving proposals (Section 2), we provide theoretical foundations on the design of benchmark data and queries for emerging RDF archiving systems (Section 3); (ii) we present a prototypical BEnchmark of RDF ARchives (referred to as *BEAR*), which makes use of real-world data snapshots extracted from the Dynamic Linked Data Observatory [15] (Section 4). We describe queries with varying complexity, covering a broad range of archiving use cases; finally, (iii) we implement RDF archiving systems based on different RDF stores, archiving and querying strategies, and evaluate them using BEAR to set an (extensible) baseline and illustrate our foundations (Section 5).

2 Preliminaries

We briefly summarise the necessary findings of our previous survey on current archiving techniques for dynamic Linked Open Data [9]. The use case is depicted in Figure 1, showing an evolving RDF graph with three versions V_1, V_2 and V_3: the initial version V_1 models two students *ex:S1* and *ex:S2* of a course *ex:C1*, whose professor is *ex:P1*. In V_2, the *ex:S2* student disappeared in favour of a new student, *ex:S3*. Finally, the former professor *ex:P1* leaves the course to a new professor *ex:P2*, and the former student *ex:S2* reappears also as a professor.

[3] http://archive.org/.

Type / Focus	Materialisation	Structured Queries	
		Single time	**Cross time**
Version	Version Materialisation *-get snapshot at time t_i*	Single-version structured queries *-lectures given by certain teacher at time t_i*	Cross-version structured queries *-subjects who have played the role of student and teacher of the same course*
Delta	Delta Materialisation *-get delta at time t_i*	Single-delta structured queries *-students leaving a course between two consecutive snapshots, i.e. between t_{i-1}, t_i*	Cross-delta structured queries *-evolution of added/deleted students across versions*

Table 1: Classification and examples of retrieval needs.

2.1 Retrieval Functionality

Given the relative novelty of archiving and querying evolving semantic Web data, retrieval needs are neither fully described nor broadly implemented in practical implementations (described below). First categorizations [9,25] are compiled in Table 1. This classification distinguishes six different types of retrieval needs, mainly regarding the query type (materialisation or structured queries) and the main focus (version/delta) of the query.

Version materialisation is a basic demand in which a full version is retrieved. In fact, this is the most common feature provided by revision control systems and other large scale archives, such as current Web archiving that mostly dereferences URLs across a given time point.[4]

Single-version structured queries are queries which are performed on one specific version. One could expect to exploit current state-of-the-art query resolution in RDF management systems, with the additional difficulty of maintaining and switching between all versions.

Cross-version structured queries, also called time-traversal queries, add a novel complexity since these queries must be satisfied across different versions.

Delta materialisation retrieves the differences (deltas) between two or more given versions. This functionality is largely related to RDF authoring and other operations from revision control systems (merge, conflict resolution, etc.). There exist several approaches to describe the deltas between two RDF versions; *low-level* deltas [30] at the level of triples, distinguishing between added (Δ^+) and deleted (Δ^-) triples, or *high-level* deltas [22] which are human-readable explanations (*e.g.* deltas can state that a class has been renamed, and this affects all the instances). *High-level* deltas are more descriptive and can be more concise, but this is at the cost of relying on an underlying semantics (such as RDFS or OWL), and they are more complex to detect and manage [31].

Single-delta structured queries and **cross-delta structured queries** are the counterparts of the aforementioned version-focused queries, but must be satisfied on change instances of the dataset.

2.2 Archiving Policies and Retrieval Process

Main research efforts addressing the challenge of RDF archiving fall in one of the following three storage strategies [9]: *independent copies (IC)*, *change-based (CB)* and *timestamp-based (TB)* approaches.

[4] See the Internet Archive effort, http://archive.org/web/.

Independent Copies (IC) [16,21] is a basic policy that manages each version as a different, isolated dataset. It is, however, expected that IC faces scalability problems as static information is duplicated across the versions. Besides simple retrieval operations such as version materialisation, other operations require non-negligible processing efforts. A potential retrieval mediator should be placed on top of the versions, with the challenging tasks of (i) computing deltas at query time to satisfy delta-focused queries, (ii) loading/accessing the appropriate version/s and solve the structured queries, and (iii) performing both previous tasks for the case of structured queries dealing with deltas.
Change-based approach (CB) [30,7,32] partially addresses the previous scalability issue by computing and storing the differences (deltas) between versions. For the sake of simplicity, in this paper we focus on low-level deltas (added or deleted triples). As stated, complementary works tackle high-level delta management [22,20] but they focus on materialisation retrieval [31]. A query mediator for this policy manages a materialised version and the subsequent deltas. Thus, CB requires additional computational costs for delta propagation which affects version-focused retrieving operations. Different alternatives have been proposed such as computing reverse deltas (storing a materialisation of the current versions and computing the changes with respect to this) or providing full version materialisation in some intermediate steps [7,25], at the cost of augmenting space overheads.
Timestamp-based approach (TB) can be seen as a particular case of time modelling in RDF [26,13,33], where each triple is annotated with its temporal validity. Likewise, in RDF archiving, each triple locally holds the timestamp of the version. In order to save space avoiding repetitions, practical proposals annotate the triples only when they are added or deleted. That is, the triples are augmented by two different fields: the created and deleted (if present) timestamps [19,28,11]. In these practical approaches, versions/deltas are managed under named/virtual graphs, so that the retrieval mediator can rely on existing solutions providing named/virtual graphs. Except for delta materialisation, all retrieval demands can be satisfied with some extra efforts given that (i) version materialisation requires to rebuild the delta similarly to CB, and (ii) structured queries may need to skip irrelevant triples [19].

3 Evaluation of RDF Archives: Challenges and Guidelines

Previous considerations on RDF archiving policies and retrieval functionality set the basis of future directions on evaluating the efficiency of RDF archives. The design of a benchmark for RDF archives should meet three requirements:

- First, the benchmark should be **archiving-policy agnostic** both in the dataset design/generation and the selection of queries to do a fair comparison of different archiving policies.
- Early benchmarks should mainly focus on simpler queries against an increasing number of snapshots and introduce complex querying once the policies and systems are better understood.
- While new retrieval features must be incorporated to benchmark archives, one should consider lessons learnt in previous recommendations on benchmarking RDF data management systems [1].

Besides these particular considerations, in general we briefly recall here the four most important criteria when designing a domain-specific benchmark [12]: Relevancy (to measure the performance when performing typical operations of the problem domain, i.e. archiving retrieval features), portability (easy to implement on different systems and architectures, i.e. RDF archiving policies), scalability (apply to small and large computer configurations, which should be extended in our case also to data size and number of versions), and simplicity.

We next formalize the most important features to characterize data and queries to evaluate RDF archives. Most of these features will be instantiated in the next section to provide a concrete experimental testbed.

3.1 Dataset Configuration

We first provide semantics for RDF archives and adapt the notion of *temporal RDF graphs* by Gutierrez et al. [13]. In this paper, we make a syntatic-sugar modification to put the focus on version labels instead of temporal labels. Note, that time labels are a more general concept that could lead to time-specific operators (intersect, overlaps, etc.), which is complementary –and not mandatory– to RDF archives. Let $\mathcal{N}$ be a set of version labels in which a total order is defined.

Definition 1 (RDF Archive). *A version-annotated triple is an RDF triple (s, p, o) with a label $i \in \mathcal{N}$ representing the version in which this triple holds, denoted by the notation $(s, p, o) : [i]$. An RDF archive graph $\mathcal{A}$ is a set of version-annotated triples.*

Definition 2 (RDF Version). *An RDF version of an RDF archive $\mathcal{A}$ at snapshot i is the RDF graph $\mathcal{A}(i) = \{(s, p, o) | (s, p, o) : [i] \in \mathcal{A}\}$. We use the notation V_i to refer to the RDF version $\mathcal{A}(i)$.*

As basis for comparing different archiving policies, we introduce four main features to describe the dataset configuration, namely *data dynamicity*, *data static core*, *total version-oblivious triples* and *RDF vocabulary*. The main objective is to precisely describe the important features of the benchmark data; although this blueprint could serve in the process of automatic generation of synthetic benchmark data, this is not addressed in this paper.

Data dynamicity. This feature measures the number of changes between versions, considering these differences at the level of triples (low-level deltas [32]) Thus, it is mainly described by the *change ratio* and the *data growth* between versions:

Definition 3 (Version change ratio). *Given two versions V_i and V_j, with $i < j$, let $\Delta^+_{i,j}$ and $\Delta^-_{i,j}$ two sets respectively denoting the triples added and deleted between these versions, i.e. $\Delta^+_{i,j} = V_j \setminus V_i$ and $\Delta^-_{i,j} = V_i \setminus V_j$. The change ratio between two versions denoted by $\delta_{i,j}$, is defined by*

$$\delta_{i,j} = \frac{|\Delta^+_{i,j} \cup \Delta^-_{i,j}|}{|V_i \cup V_j|}.$$

In turn, the insertion $\delta^+_{i,j} = \frac{|\Delta^+_{i,j}|}{|V_i|}$ and deletion $\delta^-_{i,j} = \frac{|\Delta^-_{i,j}|}{|V_i|}$ ratios provide further details on the proportion of inserted and add triples.

Definition 4 (Version data growth). *Given two versions V_i and V_j, having $|V_i|$ and $|V_j|$ different triples respectively, the data growth of V_j with respect to V_i, denoted by, $growth(V_i, V_j)$, is defined by*

$$growth(V_i, V_j) = \frac{|V_j|}{|V_i|}.$$

In archiving evaluations, one should provide details on three related aspects, $\delta_{i,j}$, $\delta^+_{i,j}$ and $\delta^-_{i,j}$, as well as the complementary version data growth, for all pairs of consecutive versions. Note that most archiving policies are affected by the frequency and also the type of changes. For instance, IC policy duplicates the static information between two consecutive versions V_i and V_j, whereas the size of V_j increases with the added information ($\delta^+_{i,j}$) and decreases with the number of deletions ($\delta^-_{i,j}$), given that the latter are not represented. In contrast, CB and TB approaches store all changes, hence they are affected by the general dynamicity ($\delta_{i,j}$).

Data static core. It measures the triples that are available in all versions:

Definition 5 (Static core). *For an RDF archive $\mathcal{A}$, the static core $\mathcal{C}_\mathcal{A} = \{(s,p,o)|\forall i \in \mathcal{N}, (s,p,o) : [i] \in \mathcal{A}\}$*

This feature is particularly important for those archiving policies that, whether implicitly or explicitly, represent such static core. In a change-based approach, the static core is not represented explicitly, but it inherently conforms the triples that are not duplicated in the versions, which is an advantage against other policies such as IC. It is worth mentioning that the static core can be easily computed taking the first version and applying all the subsequent deletions.

Total version-oblivious triples. This computes the total number of different triples in an RDF archive independently of the timestamp. Formally speaking:

Definition 6 (Version-oblivious triples). *For an RDF archive $\mathcal{A}$, the version-oblivious triples $\mathcal{O}_\mathcal{A} = \{(s,p,o)|\exists i \in \mathcal{N}, (s,p,o) : [i] \in \mathcal{A}\}$*

This feature serves two main purposes. First, it points to the diverse set of triples managed by the archive. Note that an archive could be composed of few triples that are frequently added or deleted. This could be the case of data denoting the presence or absence of certain information, e.g. a particular case of RDF streaming. Then, the total version-oblivious triples are in fact the set of triples annotated by temporal RDF [13] and other representations based on annotation (e.g. AnQL [33]), where different annotations for the same triple are merged in an annotation set (often resulting in an interval or a set of intervals).

RDF vocabulary. In general, we cover under this feature the main aspects regarding the different subjects (S_A), predicates (P_A), and objects (O_A) in the RDF archive $\mathcal{A}$. Namely, we put the focus on the RDF *vocabulary per version and delta* and the *vocabulary set dynamicity*, defined as follows:

Definition 7 (RDF vocabulary per version). *For an RDF archive $\mathcal{A}$, the vocabulary per version is the set of subjects (S_{V_i}), predicates (P_{V_i}) and objects (O_{V_i}) for each version V_i in $\mathcal{A}$.*

Definition 8 (RDF vocabulary per delta). *For an RDF archive $\mathcal{A}$, the vocabulary per delta is the set of subjects ($S_{\Delta^+_{i,j}}$ and $S_{\Delta^-_{i,j}}$), predicates ($P_{\Delta^+_{i,j}}$ and $P_{\Delta^-_{i,j}}$) and objects ($O_{\Delta^+_{i,j}}$ and $O_{\Delta^-_{i,j}}$) for all consecutive V_i and V_j in $\mathcal{A}$.*

Definition 9 (RDF vocabulary set dynamicity). *The dynamicity of a vocabulary set K, being K one of $\{S, P, O\}$, over two versions V_i and V_j, with $i < j$, denoted by $vdyn(K, V_i, V_j)$ is defined by*

$$vdyn(K, V_i, V_j) = \frac{|(K_{V_i} \setminus K_{V_j}) \cup (K_{V_j} \setminus K_{V_i})|}{|K_{V_i} \cup K_{V_j}|}$$

Likewise, $vdyn^+(K, V_i, V_j) = \frac{|K_{V_j} \setminus K_{V_i}|}{|K_{V_i} \cup K_{V_j}|}$ and $vdyn^-(K, V_i, V_j) = \frac{|K_{V_i} \setminus K_{V_j}|}{|K_{V_i} \cup K_{V_j}|}$ define the vocabulary set dynamicity for insertions and deletions respectively.

Note that the evolution (cardinality and dynamicity) of the vocabulary is specially relevant in RDF archiving, since traditional RDF management systems use dictionaries (mappings between terms and integer IDs) to efficiently manage RDF graphs.

3.2 Design of Benchmark Queries

As stated, there is neither a standard language to query RDF archives, nor an agreed way for the more general problem of querying temporal graphs. Nonetheless, most of the proposals (such as T-SPARQL [10] and SPARQL-ST [23]) are based on SPARQL modifications.

In general, previous experiences on SPARQL benchmarking show that benchmark queries should report on the query type, result size, graph pattern shape, and query atom selectivity. Conversely, for RDF archiving, one should put the focus on data dynamicity, without forgetting the strong impact played by query selectivity in most RDF triple stores and query planning strategies.

Let us briefly recall and adapt definitions of query cardinality and selectivity [2,1] to RDF archives. Given a SPARQL query Q, where we restrict to *BGP*s hereafter, the evaluation of Q over a general RDF graph $\mathcal{G}$ results in a bag of solution mappings $[[Q]]_G$, where Ω denotes its underlying set. The function $card_{[[Q]]_G}$ maps each mapping $\mu \in \Omega$ to its cardinality in $[[Q]]_G$. Then, for comparison purposes, we introduce three main features, namely *archive-driven result cardinality and selectivity*, *version-driven result cardinality and selectivity*, and *version-driven result dynamicity*, defined as follows.

Definition 10 (Archive-driven result cardinality). *The archive-driven result cardinality of Q over the RDF archive $\mathcal{A}$, is defined by*

$$CARD(Q, \mathcal{A}) = \sum_{\mu \in \Omega} card_{[[Q]]_A}(\mu).$$

In turn, the archive-driven query selectivity accounts how selective is the query, and it is defined by $SEL(Q, \mathcal{A}) = |\Omega|/|\mathcal{A}|$.

Definition 11 (Version-driven result cardinality). *The version-driven result cardinality of Q over a version V_i, is defined by*

$$CARD(Q, V_i) = \sum_{\mu \in \Omega_i} card_{[[Q]]_{V_i}}(\mu),$$

where Ω_i denotes the underlying set of the bag $[[Q]]_{V_i}$. Then, the version-driven query selectivity is defined by $SEL(Q, V_i) = |\Omega_i|/|V_i|$.

Definition 12 (Version-driven result dynamicity). *The version-driven result dynamicity of the query Q over two versions V_i and V_j, with $i < j$, denoted by $dyn(Q, V_i, V_j)$ is defined by*

$$dyn(Q, V_i, V_j) = \frac{|(\Omega_i \setminus \Omega_j) \cup (\Omega_j \setminus \Omega_i)|}{|\Omega_i \cup \Omega_j|}$$

Likewise, we define the version-driven result insertion $dyn^+(Q, V_i, V_j) = \frac{|\Omega_j \setminus \Omega_i|}{|\Omega_i \cup \Omega_j|}$ and deletion $dyn^-(Q, V_i, V_j) = \frac{|\Omega_i \setminus \Omega_j|}{|\Omega_i \cup \Omega_j|}$ dynamicity.

The archive-driven result cardinality is reported as a feature directly inherited from traditional SPARQL querying, as it disregards the versions and evaluates the query over the set of triples present in the RDF archive. Although this feature could be only of peripheral interest, the knowledge of this feature can help in the interpretation of version-agnostic retrieval purposes (e.g. ASK queries).

As stated, result cardinality and query selectivity are main influencing factors for the query performance, and should be considered in the benchmark design and also known for the result analysis. In RDF archiving, both processes require particular care, given that the results of a query can highly vary in different versions. Knowing the version-driven result cardinality and selectivity helps to interpret the behaviour and performance of a query across the archive. For instance, selecting only queries with the same cardinality and selectivity across all version should guarantee that the index performance is always the same and as such, potential retrieval time differences can be attributed to the archiving policy. Finally, the version-driven result dynamicity does not just focus on the number of results, but how these are distributed in the archive *timeline*.

In the following, we introduce five different, foundational query atoms to cover the broad spectrum of emerging retrieval demands in RDF archiving. Rather than providing a complete catalog, our main aim is to reflect basic atoms allowing to gain specific knowledge on RDF archiving, without harming neither the combination of them in order to serve more complex queries. We elaborate these atoms on the basis of related literature, with especial attention to the needs of the well-established *Memento Framework* [5], which can provide access to prior states of RDF resources using datetime negotiation in HTTP.

Version materialisation, $Mat(Q, V_i)$***:*** it provides the SPARQL query resolution of the query Q at the given version V_i. Formally, $Mat(Q, V_i) = [[Q]]_{V_i}$.

Within the Memento Framework, this operation is needed to provide mementos (URI-M) that encapsulate a prior state of the original resource (URI-R).

Delta materialisation, $Diff(Q, V_i, V_j)$***:*** it provides the different results of the query Q between the given V_i and V_j versions. Formally, let us consider that the output is a pair of mapping sets, corresponding to the results that are present in V_i but not in V_j, that is $(\Omega_i \setminus \Omega_j)$, and viceversa, i.e. $(\Omega_j \setminus \Omega_i)$.

A particular case of delta materialisation is to retrieve all the differences between V_i and V_j, which corresponds to the aforementioned $\Delta^+_{i,j}$ and $\Delta^-_{i,j}$.

Version Query, $Ver(Q)$***:*** it provides the results of the query Q *annotated* with the version label in which each of them holds. In other words, it facilitates the $[[Q]]_{V_i}$ solution for those V_i that contribute with results.

Cross-version join, $Join(Q_1, V_i, Q_2, V_j)$***:*** it serves the join between the results of Q_1 in V_i, and Q_2 in V_j. Intuitively, it is similar to $Mat(Q_1, V_i) \bowtie Mat(Q_2, V_j)$.

Change materialisation, $Change(Q)$***:*** it provides those consecutive versions in which the given query Q produces different results. Formally, $Change(Q)$ reports the labels i, j (referring to the versions V_i and V_j) $\Leftrightarrow Diff(Q, V_i, V_j) \neq \emptyset, i < j, !\exists k \in \mathcal{N} / i < k < j$.

Within the Memento Framework, change materialisation is needed to provide timemap information to compile the list of all mementos (URI-T) for the original resource, i.e. the basis of datetime negotiation handled by the timegate (URI-G).

3.3 Instantiation in a Concrete Query Language: AnQL

In order to "ground" the five concrete query cases outlined above, we herein propose the syntactic abstraction of AnQL [33], a query language that provides some syntactic sugar for (time-)annotated RDF data and queries on top of SPARQL. This abstraction helps us, as a tradeoff between concrete instantiation in SPARQL as a query language and implementation issues underneath, differentiating between IC, CB and TB as storage strategies from the viewpoint of an off-the shelf RDF store.

AnQL is a query language defined as - relatively straightforward - extension of SPARQL, where a SPARQL triple pattern t is allowed to be annotated with a (temporal[5]) label l as an *annotated triple pattern* of the form $t : l$. In our case, we assume for simplicity that the domain of annotations are simply (consecutive) version numbers, i.e. `:s :p :o` `:[`v_i`]` and `:s :p :o` `:[`v_i`,`v_j`]`, resp., would indicate that the triple pattern `:s :p :o` is valid in version v_i or, resp., between versions $v_i, v_j \in \mathbb{N}$, where s.t. $v_i \leq v_j$.

Moreover, for simplicity, we extend an AnQL BAP (basic annotated pattern), that is, a SPARQL Basic graph pattern (BGP) which may contain such annotated triple patterns as follows: Let P be a SPARQL graph pattern, then we write $P : l$ as a syntactic short cut for an annotated pattern such that each triple pattern $t \in P$ is replaced by $t : l$.

Using this notation, we can "instantiate" the queries from above as follows in AnQL.

- $Mat(Q, v_i)$:
  `SELECT * WHERE {` Q `:[`v_i`] }`

[5] Note that in [33] we also discuss various other annotation domains.

- $Diff(Q, v_i, v_j)$:
  SELECT * WHERE { { { {Q :[v_i]} MINUS {Q :[v_j]} } BIND (v_i AS ?V) } UNION { { {Q :[v_j] } MINUS {Q :[v_i]}} BIND (v_i AS ?V) }
  Here, the newly bound variable ?V is used to show which solutions appear only in version ?V but not in the other version, which is a simple way to describe the changeset [17].
- $Ver(Q)$:
  SELECT * WHERE { P :?V }
- $join(Q_1, v_i, Q_2, v_j)$:
  SELECT * WHERE { {Q :[v_i]} {Q :[v_j]} }
- $Change(Q)$:
  SELECT ?V1 ?V2 WHERE { {{P :?V1 } MINUS {P :?V2}}
  FILTER(abs(?V1-?V2) = 1) }

Based on these queries, a naive implementation of IC, CB and TB on top of an off-the-shelf triple store could now look as follows:

IC. All triples of each instance/version would be stored in named graphs with the version name being the graph name and respective metadate about the version number on the default graph. That is, a triple (:s :p :o) in version v_i would result in the respective graph being stored in graph :version_v1 plus a triple (:version_v1 :version_number v_i) in the default graph.

Then, each annotated pattern $P : l$ in the AnQL queries above could be translated into a native SPARQL graph pattern as GRAPH ?G1 { P } {?G1 :version_number l .

TB. All triples appearing in any instance/version could be stored as a single reified triple, with additional meta-information in which version the triple is true in disjoint from-to ranges to indicate the version ranges when a particular triple was true. That is, a triple (:s :p :o) which was true in versions v_i until v_j coud be represented as follows:

[:subject :s ; :predicate :p; :object :o; :valid [:start v_i; :end v_j]].

Note that this representation allows for a compact representation of several disjoint (maximal) validity intervals of the same triple, thus causing less overhead than the graph-based representation discussed for IC. The translation for annotated query patterns $P : l$ in the AnQL syntax could proceed by replacing each triple pattern $t =$ (:s :p :o) in P as follows, where ?t_start and ?t_end are fresh variables unique per t:

[:subject :s ; :predicate :p; :object :o; :valid [:start ?t_start; :end ?t_end]].
FILTER(l >= ?t_start && l <= ?t_end)

Unfortunately, this "recipe" does not work for $Ver(Q)$ and $Change(Q)$, since it would result in l being an unbound variable in the FILTER expression. Thus we provide

separate translations for $Ver(Q)$ and $Change(Q)$, where both would use the same replacement, but without the FILTER expression per triple pattern.

As for $Ver(Q)$ the overall result only holds, in case intersection of all [?t_start$_i$,?t_end$_i$] intervals is non-empty, an overall FILTER which checks this condition needs to be added for the whole BGP Q:

FILTER (max(?t_start$_1$, ..., ?t_start$_n$) <= min(?t_end$_1$, ..., ?t_end$_n$))

The respective interfals [max(?t_start$_1$, ..., ?t_start$_n$), min(?t_end$_1$, ..., ?t_end$_n$)] could then be returned by a BIND clause to indicate the version ranges where Q holds.[6] Finally, let us note that the implementation sketched here only works for Q being a BGP (as we originally assumed). As for more complex patterns such as OPTIONAL, MINUS, NOT EXISTS or patterns involving complex FILTERS or even aggregations, a simple translation like the one sketched here would not return correct results in the general case.

CB. We emphasize that a change-based storage of RDF triples has no trivial implementation in an off-the shelf RDF store. Again, change -deltas (triple additions and deletions between versions could be stored in separate graphs, starting with an original graph :version_v0_add and separate graphs labelled, e.g., :version_vi_add and :version_vi_del per new version, plus again metadata triples, e.g.

:version_v1_add :version_number v_i; a :Addition.
:version_v1_del :version_number v_i; a :Deletion.

in the default graph. Then the validity of a triple pattern t in a particular version v_i as follows, intuitively testing whether the triple has been added in a prior version and not been removed since:

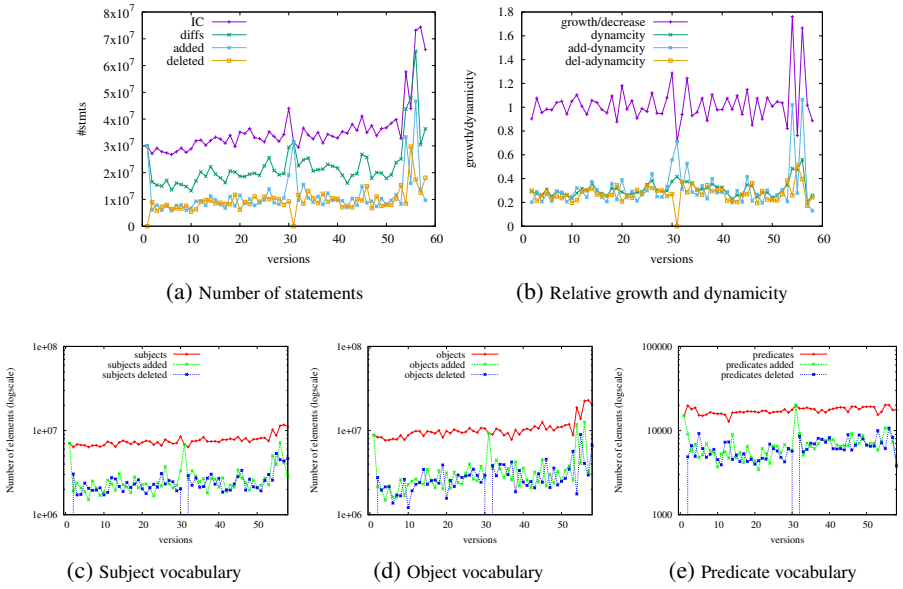
{ GRAPH ?GAdd { t } {?GAdd :version_number ?va; a :Addition. FILTER(?va <= v_i) } FILTER NOT EXISTS { GRAPH ?GDel { t } {?GDel:version_number ?vd; a :Deletion. FILTER(?vd >=?va && ?vd<= v_i) }}}

The translation of whole AnQL queries in the case of CB is therefore, by no means trivial, as this covers only single triple patterns.Whereas we do not provide the full translation for CB here, we hope that the sketch here, along with the translations for IC and TB above have served to illustrate that an implementation of RDF archives and queries in off-the-shelf RDF stores and using SPARQL is a non-trivial exercise – even the translated patterns for CB and IC sketched above would likely not scale to large archives of dynamic RDF data and complex queries. Therefore, in the following sections, we focus on tailored implementations using efficient optimized storage techniques to implement these features, using rather simple triple lookup queries rather than full SPARQL BGPs.

[6] Note that, unfortunately, the function min() and max() used here exist in SPARQL only as aggregates for subqueries and not as functions over value lists, so this expression would look in an off-the-shelf SPARQL implementation even more complicated, using either expressions involving e.g. the COALESCE function or aggregate subqueries).

versions	$\|V_0\|$	$\|V_{57}\|$	$\overline{growth}$	$\overline{\delta}$	$\overline{\delta^-}$	$\overline{\delta^+}$	$\mathcal{C}_\mathcal{A}$	$\mathcal{O}_\mathcal{A}$
58	30m	66m	101%	31%	32%	27%	3.5m	376m

Table 2: Dataset configuration



(a) Number of statements (b) Relative growth and dynamicity

(c) Subject vocabulary (d) Object vocabulary (e) Predicate vocabulary

Fig. 2: Dataset description.

4 BEAR: A Test Suite for RDF Archiving

This section presents BEAR, a prototypical (and extensible) test suite to demonstrate the new capabilities in benchmarking the efficiency of RDF archives using our foundations, and to highlight current challenges and potential improvements in RDF archiving. We first detail the dataset description and the query set covering basic retrieval needs. Next section evaluates BEAR on different archiving systems. The complete test suite (data corpus, queries, archiving system source codes, evaluation and additional results) are available at the BEAR repository[7].

4.1 Dataset Description

We build our RDF archive on the data hosted by the Dynamic Linked Data Observatory[8], monitoring more than 650 different domains across time and serving weekly crawls of these domains. BEAR data are composed of the first 58 weekly snapshots, i.e. 58 versions, from this corpus. Each original week consists of triples annotated with their RDF document provenance, in N-Quads format. In this paper we focus on archiving of

[7] https://github.com/webdata/BEAR.
[8] http://swse.deri.org/dyldo/.

QUERY SET	lookup position	$\overline{CARD}$	$\overline{dyn}$	#queries
Q^S_L-ϵ=0.2	subject	6.7	0.46	50
Q^P_L-ϵ=0.6	predicate	178.66	0.09	6
Q^O_L-ϵ=0.1	object	2.18	0.92	50
Q^S_H-ϵ=0.1	subject	55.22	0.78	50
Q^P_H-ϵ=0.6	predicate	845.3	0.12	10
Q^O_H-ϵ=0.6	object	55.62	0.64	50

Table 3: Overview of benchmark queries

a single RDF graph, so that we remove the context information and manage the resultant set of triples, disregarding duplicates. The extension to multiple graph archiving can be seen as a future work.

In order to describe our benchmark dataset, we compute and report the data configuration features (cf. Section 3) that are relevant for our purposes. Table 2 lists basic statistics of our dataset, further detailed in Figure 2, which shows the figures per version and the vocabulary evolution. Data growth behaviour (dynamicity) can be identified at a glance: although the number of statement in the last version ($|V_{57}|$) is more than double the initial size ($|V_0|$), the mean version data growth ($\overline{growth}$) between versions is almost marginal (101%).

A closer look to Figure 2 (a) allows to identify that the latest versions are highly contributing to this increase. Similarly, the version change ratios in Table 2 ($\overline{\delta}$, $\overline{\delta^-}$ and $\overline{\delta^+}$) point to the concrete adds and delete operations. Thus, one can see that a mean of 31% of the data change between two versions and that each new version deletes a mean of 27% of the previous triples, and adds 32%. Nonetheless, Figure 2 (b) points to particular corner cases (in spite of a common stability), such as V_{31} in which no deletes are present, as well as it highlights the noticeable dynamicity in the last versions.

Conversely, the number of version-oblivious triples ($\mathcal{O}_\mathcal{A}$), $376m$, points to a relatively low number of different triples in all the history if we compare this against the number of versions and the size of each version. This fact is in line with the $\overline{\delta}$ dynamicity values, stating that a mean of 31% of the data change between two versions. The same reasoning applies for the remarkably small static core ($\mathcal{C}_\mathcal{A}$), $3.5m$.

Finally, Figures 2 (c-e) show the RDF vocabulary (different subjects, predicates and objects) per version and per delta (adds and deletes). As can be seen, the number of different subjects and predicates remains stable except for the noticeable increase in the latests versions, as already identified in the number of statements per versions. However, the number of added and deleted subjects and objects fluctuates greatly and remain high (one order of magnitude of the total number of elements, except for the aforementioned V_{31} in which no deletes are present). In turn, the number or predicates are proportionally smaller, but it presents a similar behaviour.

4.2 Test Queries

BEAR provides triple pattern queries Q to test each of the five atomic operations defined in our foundations (Section 3). Note that, although BEAR queries do not cover the full spectrum of SPARQL queries, triple patterns (i) constitute the basis for more complex queries, (ii) are the main operation served by lightweight clients such as the Linked

Data Fragments [29] proposal, and (iii) they are the required operation to retrieve prior states of a resource in the Memento Framework. For simplicity, we focus on atomic lookup queries Q in the form (S??), (?P?), and (??O), which can then be extended to the rest of triple patterns (SP?), (S?O), (?PO), and (SPO)[9].

In order to provide comparable results, we consider entirely dynamic queries, meaning that the results always differ between consecutive versions. In other words, for each of our selected queries Q, and all the versions V_i and V_j ($i < j$), we assure that $dyn(Q, V_i, V_j) > 0$. To do so, we first extract subjects, predicates and objects that appear in all $\Delta_{i,j}$.

Then, we follow the foundations and try to minimise the influence of the result cardinality on the query performance. For this purpose, we sample queries which return, for all versions, result sets of similar size, that is, $CARD(Q, V_i) \approx CARD(Q, V_j)$ for all queries and versions. We introduce here the notation of a ϵ-stable query, that is, a query for which the min and max result cardinality over all versions do not vary by more than a factor of $1 \pm \epsilon$ from the mean cardinality, i.e., $\max_{\forall i \in \mathcal{N}} CARD(Q, V_i) \leq (1+\epsilon) \cdot \frac{\sum_{\forall i \in \mathcal{N}} CARD(Q, V_i)}{|\mathcal{N}|}$ and $\min_{\forall i \in \mathcal{N}} CARD(Q, V_i) \geq (1-\epsilon) \cdot \frac{\sum_{\forall i \in \mathcal{N}} CARD(Q, V_i)}{|\mathcal{N}|}$.

Thus, the previous selected dynamic queries are effectively run over each version in order to collect the result cardinality. Next, we split subject, objects and predicate queries producing low (Q^S_L, Q^P_L, Q^O_L) and high (Q^S_H, Q^P_H, Q^O_H) cardinalities. Finally, we filter these sets to sample at most 50 subject, predicate and object queries which can be considered ϵ-stable for a given ϵ. Table 3 shows the selected query sets with their epsilon value, mean cardinality and mean dynamicity. Although, in general, one could expect to have queries with a low ϵ (i.e. cardinalities are equivalent between versions), we test higher ϵ values in objects and predicates in order to have queries with higher cardinalities. Note that even with this relaxed restriction, the number of predicate queries that fulfil the requirements is just 6 and 10 for low and high cardinalities respectively.

5 Evaluation of RDF archiving systems

We illustrate the use of our foundations to evaluate RDF archiving systems. In particular, we implemented two systems on different RDF stores and archiving policies, and we use our prototypical BEAR to evaluate the influence of the concrete store and policy.

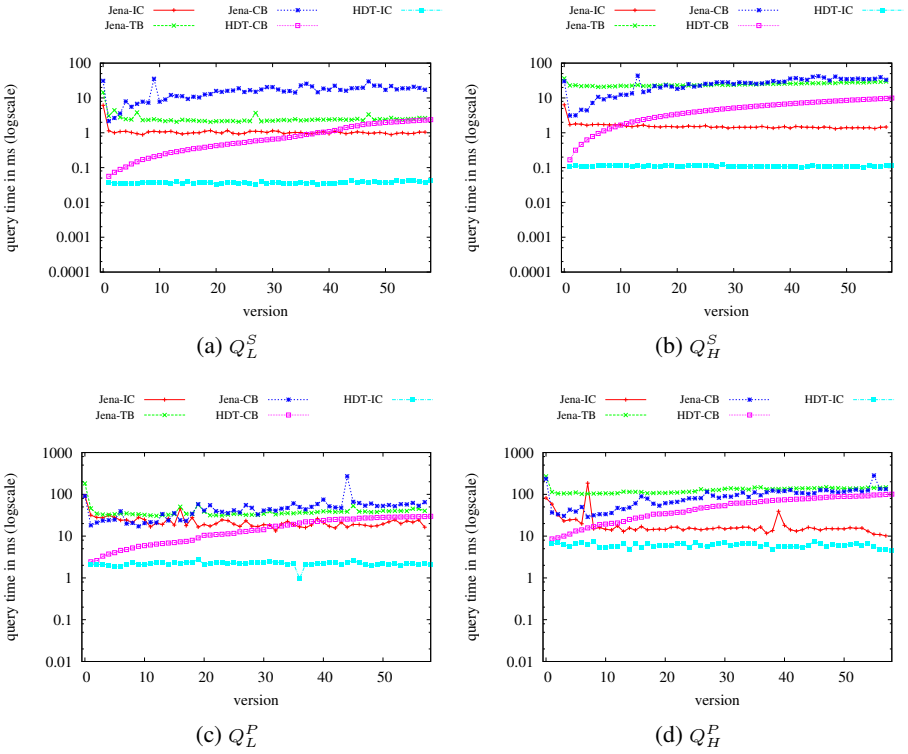
Archiving systems. We built two RDF archiving systems using the Jena's TDB store[10] (referred to as Jena hereinafter) and HDT [8], each of them considering different state-of-the-art archiving policies. First, we implemented the IC, CB and TB policies using Jena (referred to as Jena-IC, Jena-CB and Jena-TB). For the IC policy, we index each version in an independent TDB instance. Likewise, for the CB policy, we create an index for each added and deleted statements, again for each version and using an independent TDB store. Last, for the TB policy, we followed the approach of [28,11] and indexed all deltas using named graph in one single TDB instance. We follow the same

[9] The triple pattern (???) retrieves all the information, so no sampling technique is required.

[10] https://jena.apache.org/documentation/tdb/.

RAW DATA(GZIP)	DIFF (GZIP)	JENA TDB			HDT	
		IC	**CB**	**TB**	**IC**	**CB**
23 GB	14 GB	225 GB	196 GB	353 GB	46 GB	26 GB

Table 4: Space requirements for the different archiving systems and policies.



(a) Q_L^S (b) Q_H^S

(c) Q_L^P (d) Q_H^P

Fig. 3: Query times for Mat queries.

strategy to develop the IC and CB strategies in HDT [8] (referred to as HDT-IC, HDT-CB), which provides a compressed representation and indexing of RDF graphs. The TB policy cannot be implemented as current HDT implementations[11] do not support quads, hence triples cannot be annotated with the version.

5.1 Space Results

Table 4 shows the required on-disk space for the raw data of the corpus, the GNU diff of such data, and the space required by the Jena and HDT[12] archiving systems under the different policies. Raw gzipped data take roughly 23GB disk space, while storing the diffs information results just requires 14GB. A comparison of these figures against the size of the different systems and policies allows to describe their inherent overheads: the IC policy indexing in Jena requires roughly ten times more space than the raw data, mainly due to the data decompression and the built-in Jena indexes. In contrast, the

[11] We use the HDT C++ libraries available at http://www.rdfhdt.org/.

[12] We include the space overheads of the provided HDT indexes to solve all lookups.

compact HDT indexes in the IC policy just double the size of the gzipped raw data, serving the required retrieval operations in such compressed space. In turn, Jena-CB reduces the space needs w.r.t Jena-IC (13% less). In HDT, the CB policy produces stronger reductions (43% less than HDT-IC), being roughly the double of the gzipped diff data. Finally, TB policy in Jena reports the highest size as it requires 57% and 80% more space than Jena-IC and Jena-CB respectively. Note that, although CB and TB policies manage the same delta sets, TB uses a unique Jena instance and stores named graph for the triples, so additional "context" indexes are required.

These initial results confirm current RDF archiving scalability problems at large scale, where specific RDF compression techniques such as HDT emerges as an ideal solution [9]. Note that Jena-IC requires almost 5 times the size of HDT-IC, whereas Jena-CB takes more than 7 times the space required by HDT-CB.

5.2 Retrieval Performance

From our foundations, we chose three exemplary query operations: (i) version materialisation, (ii) delta materialisation and (iii) version queries, and we apply the selected BEAR queries (cf. Section 4.2) as the target query Q in each case.

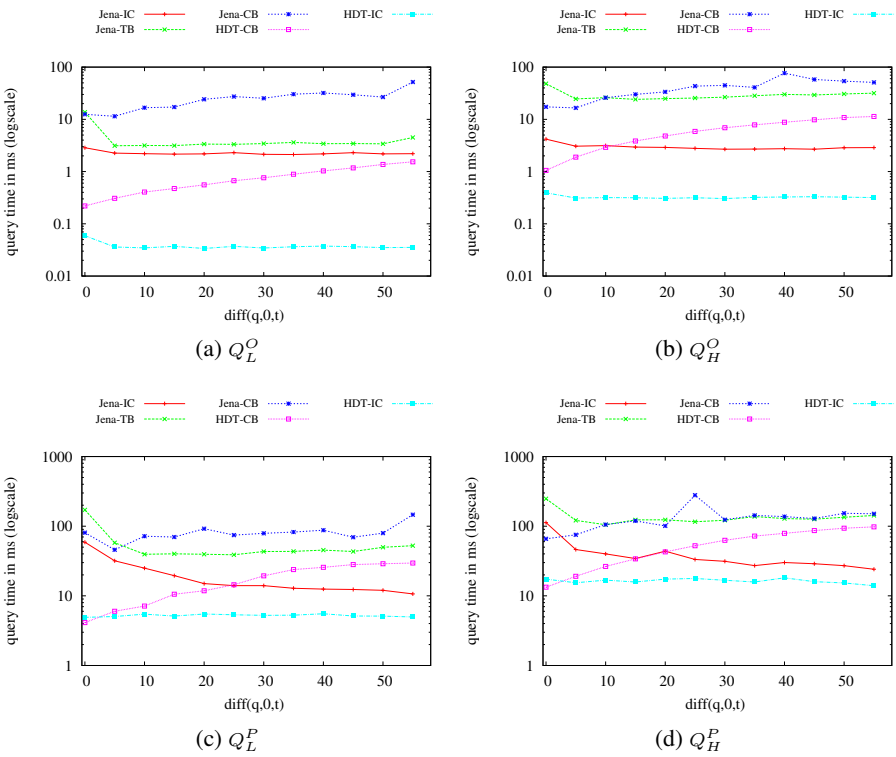
In general, our evaluation confirmed our assumptions about the characteristics of the policies (cf. Section 2), but also pointed out differences between the stores (Jena and HDT). The IC and TB policies show a very constant behaviour for all our tests, while the retrieval time of the CB policy increases if more deltas have to be queried. The main difference between IC and TB is the slightly higher retrieval time of TB due to the larger index size.ext, we present and discuss selected plots for each query operation.

Version materialisation. We measure and compute, for each version, the average query time[13] over all queries in the BEAR query set. The results for the version materialisation queries show very similar patterns for the subject and object query sets. As such, we present in Figure 3 only the results for the subject and predicate queries, as objects behaves similarly to subjects.

First, we can observe in all plots that the HDT archiving system generally outperforms Jena. In both systems, the IC policy provides the best and most constant retrieval time. In contrast, the CB policy shows a clear trend that the query performance decreases if we query a higher version since more deltas have to be queried and the adds and delete information processed.

The degradation of the performance highly depends on the system and the type of query. For instance the performance degradation in less skewed in predicate lookups for HDT-CB, shown in Figures 3 (c-d). The explanation of such behaviour is that predicate lookups are the most expensive query as it has a logarithmic cost in the number of different predicates in the dataset. Thus, given that the vocabulary of predicates in CB instances is much smaller than IC as shown in Figure 2 (e), HDT-CB predicate lookups are faster and improve the overall performance even if versions are materialized. This illustrates how archiving policies and internal RDF store design interact and affect the

[13] All reported (elapsed) times in the evaluation are the average of three independent executions deployed in an Intel Xeon E5-2650v2 @ 2.6 GHz (32 cores), RAM 256 GB, Debian 7.9.



(a) Q_L^O (b) Q_H^O

(c) Q_L^P (d) Q_H^P

Fig. 4: Query times for $Diff$ queries with increasing intervals.

results of archiving retrieval, and how benchmark design should consider such particularities.

The TB policy in Jena performs worse than the IC, as TB has to query more indexed data than the IC policy. In turn, CB and TB have similar performances if queries have higher cardinalities, as shown in Figure 3 (b).

Delta materialisation queries. We performed diffs between the initial version and increasing intervals of 5 versions, i.e., $diff(Q, V_0, V_i)$ for i in $\{5, 10, 15, \cdots, 55, 57\}$. Figure 4 shows again the plots for selected query sets, in this case the diff of objects and predicate lookups. We observe the expected constant retrieval performance of the IC policy which always needs to query only two version to compute the delta in-memory. The query time increases for the CB policy if the intervals of the deltas are increasing, given that more deltas have to be inspected.

Interestingly, HDT outperforms Jena under the same policy (IC or CB), i.e. HDT implements the policy more efficiently. However, an IC policy in Jena can be faster than a CB policy in HDT. Again, this behaviour highly depends on the query: Jena-IC outperforms HDT-CB after the 10th version in objects with high cardinality, shown in Figure 4 (b), and after the 25th and 15th version in predicates with low and high

QUERY SET	JENA TDB			HDT	
	IC	**CB**	**TB**	**IC**	**CB**
Q_L^S	55.70	122.44	27.32	**2.03**	2.73
Q_H^S	71.62	144.12	61.46	**6.57**	10.19
Q_L^P	304.67	412.17	237.83	128.20	**31.28**
Q_H^P	733.80	523.90	362.20	354.60	**104.57**
Q_L^O	40.54	91.92	22.78	**1.65**	2.89
Q_H^O	78.18	136.30	73.54	**8.37**	13.23

Table 5: Average query time (in ms) for ver(Q) queries

cardinality respectively, shown in Figures 4 (c-d). In turn the TB policy in Jena behaves similar than the Mat case given that it always inspects the full store.

Version queries. Table 5 reports the average query time over each $ver(Q)$ query per BEAR query set. As can be seen, HDT archiving system clearly outperforms Jena in all scenarios, taking advantages of its efficient indexing. Nonetheless, the policies plays an important role: HDT-IC outperforms HDT-CB (as expected once versions have to be materialized in CB) except for predicates lookups queries (Q_L^P and Q_H^P). The explanation of such behaviour is that predicate lookups in HDT have a logarithmic cost in the number of different predicates in the dataset, which is smaller in CB. In Jena the TB policy outperforms IC and CB policies in contrast to the previous Mat and $Diff$ experiments. This can be explained since both, IC and CB, require to query each version, while TB only requires a query over the full store and then splits the results by version.

6 Conclusions

RDF archiving is still in an early stage of research. Novel solutions should be driven by comparing the performance of archiving policies, storage schemes and querying stretegies. The introduction of a new dimension (the data version at different times) adds new challenges on top of traditional semantic benchmarks, plus, there are no specific data corpora for RDF archiving nor a "gold-standard" set of supported retrieval functionalities. To this end, we have provided foundations to guide future evaluation of RDF archives. First, we formalized dynamic notions of archives, allowing to effectively describe the data corpus. Then, we described the main retrieval facilities involved in RDF archiving, and have provided guidelines on the selection of relevant and comparable queries. We instantiate these foundations in a prototypical benchmark, BEAR, serving a clean, well-described data corpus and a basic, but extensible, query testbed. Finally, we have implemented state-of-the-art archiving policies (using independent copies, differential representation and timestamps) in two stores (Jena TDB and HDT) and ran BEAR over them. Results clearly confirm challenges (in terms of scalability) and strengths of current archiving approaches, guiding future developments. We currently focus on exploiting the presented blueprints as basis to generate diverse synthetic benchmark data. Furthermore, we work on novel archiving techniques, intelligently utilizing compression techniques.

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