On Enhancing Scalability for Distributed RDF/S Stores

George Tsatsanifos
School of Electrical & Computer Engineering
National Technical University of Athens
gtsat@dblab.ece.ntua.gr

Dimitris Sacharidis
Institute for the Management of Information Systems
R.C. "Athena"
dsachar@imis.athena-innovation.gr

Timos Sellis
Institute for the Management of Information Systems
R.C. "Athena"
timos@imis.athena-innovation.gr

ABSTRACT

This work presents MIDAS-RDF, a distributed P2P RDF/S repository that is built on top of a distributed multi-dimensional index structure. MIDAS-RDF features fast retrieval of RDF triples satisfying various pattern queries by translating them into multi-dimensional range queries, which can be processed by the underlying index in hops logarithmic to the number of peers. More importantly, MIDAS-RDF utilizes a labeling scheme to handle expensive transitive closure computations efficiently. This allows for distributed RDFS reasoning in a more scalable way compared to existing methods, as also demonstrated by our extensive experimental study. Furthermore, MIDAS-RDF supports a publish-subscribe model that enables remote peers to selectively subscribe to RDF content.

Categories and Subject Descriptors

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

General Terms

Algorithms

Keywords

RDF/S stores, P2P systems

1. INTRODUCTION

The main incentive for the Semantic Web is to allow the description of web resources through a formal language, e.g., creating metadata according to a formal representation, forming a mesh of information linked up in such a way as to be easily processable by machines, on a global scale. The Semantic Web community has developed a set of standards for expressing schemas that enable the creation and exchange of information among communities of different backgrounds (e.g., cultural heritage researchers, librarians, audio-visual content producers), and also facilitate the encoding, exchange, processing and reuse of resource metadata while each user community is free to specify its own description semantics in a standardized, interoperable human-readable manner.

The most prominent Semantic Web technology is the Resource Description Framework (RDF) data model, according to which information is represented as statements about resources. An RDF statement is represented as the triple `(subject, predicate, object)`, which signifies that the relationship denoted as `predicate` holds between the concepts denoted as `subject` and `object`, where predicate and object are resources or strings. The power and versatility of this model lies in its simplicity; e.g., relational and XML databases can be described by RDF triples. More importantly, the RDF data model offers the possibility to derive new knowledge from explicit and background knowledge.

Efficient and scalable management of RDF triples has become an important prerequisite for realizing the Semantic Web vision. Centralized RDF stores are empowered with traditional relational tools, e.g., indices, materialized views, to allow for efficient retrieval of RDF triples, and generation of new knowledge via reasoning rules. Motivated by the need to increase flexibility and ultimately allow any community to freely contribute its knowledge, a trend towards decentralized repositories has recently emerged. However, existing solutions fail to offer the scalability of their centralized counterparts. One reason is that single dimensional indices are used in distributed repositories, while RDF triples are inherently multi-dimensional. Moreover, existing algorithms for distributed reasoning based on transitive relationships must visit in sequence a large number of peers.

This work proposes a novel distributed RDF store, called MIDAS-RDF, that alleviates the problems typically encountered in existing solutions. Specifically, our store is based on a structured multi-dimensional index [38], which is able to process point and range queries with low latency, requiring only logarithmic, in the network size, number of hops. Building upon this functionality, MIDAS-RDF supports pattern queries, conjunctive and disjunctive queries, and transitivity queries. The most prominent feature of MIDAS-RDF, however, is that it implements a rigorous *inference model* that allows efficient identification and storage of new knowledge, by incorporating transitivity information using a labeling scheme. In addition, we propose an RDF publish-subscribe model that enables peers to selectively subscribe to RDF content. Unlike most distributed solutions that are restricted to specific topic-based subscriptions, MIDAS-RDF support general *content-based* subscriptions.

The remainder of this paper is organized as follows. Section 2 reviews relevant literature about distributed RDF repositories, introduces essential preliminaries, and overviews the underlying distributed index used in MIDAS-RDF. Section 3 describes our storage model and discusses RDF triple retrieval, and Section 4 presents the distributed inference algorithm. Section 5 discusses our decentralized publish-subscribe mechanism. Section 6 contains the experimental evaluation, while Section 7 concludes this work.

2. BACKGROUND AND RELATED WORK

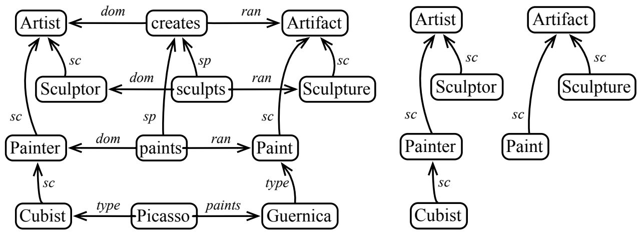
This section establishes the necessary background, reviews literature on distributed RDF stores and RDFS reasoning, and overviews the MIDAS distributed index.

2.1 RDF/S Concepts

The Semantic Web [14] is a group of methods and technologies to allow machines to understand the meaning — or "semantics" — of information on the World Wide Web. The term was coined by World Wide Web Consortium (W3C) [4] director Tim Berners-Lee, who defines the Semantic Web as "a web of data that can be processed directly and indirectly by machines". These technologies include the Resource Description Framework (RDF), a variety of data interchange formats (e.g., RDF/XML, N3, Turtle, N-Triples), and notations such as RDF Schema (RDFS) and the Web Ontology Language (OWL), all of which are intended to provide a formal description of concepts, terms, and relationships within a given knowledge domain.

The Resource Description Framework (RDF) data model [24] represents information as statements about resources. Any concept that can have a Universal Resource Identifier (URI) can be a resource. RDF consists of a set of named binary predicates, termed RDF statements, that are represented as triples. A `(subject, predicate, object)` triple implies that the relationship denoted as `predicate` holds between the concepts denoted as `subject` and `object`, where predicate and object are resources or strings.

A set of RDF triples defines an RDF graph. The set of nodes is the set of subjects and objects of the triples. A (u, α, v) triple defines a directed edge from the subject u to the object v labelled with the property α. Figure 1a shows an example RDF graph. The `(Picasso, paints, Guernica)` triple is represented as the edge labelled `paints` from node `Picasso` to `Guernica`. The set of all triples regarding a property α define the α subgraph of the RDF graph. For instance, Figure 1b depicts the subgraph for property `sc`. In a subgraph, a node u *subsumes* another v if there is a path from v to u. In Figure 1b, `Artist` subsumes `Sculptor`, `Painter` and `Cubist`.



(a) RDF graph (b) The *sc* subgraph

Figure 1: An RDF graph example

The RDF specification includes a mechanism, termed the RDF Schema (RDFS), that provides a type system for RDF models. It offers flexible features for representing domain knowledge. Abstraction is enabled by multiple class inheritance with the `rdfs:subClassOf` and `rdfs:subPropertyOf` core properties (abbreviated as `sc` and `sp` in Figure 1), and classification of resources `rdf:type` (abbreviated as `type`). Although RDFS does not provide elaborate mechanisms for defining property restrictions, one can declare simple domain and range restrictions through properties `rdfs:domain` and `rdfs:range` (abbreviated as `dom` and `ran` in Figure 1).

The semantics of RDFS is defined through a set of axiomatic triples and *entailment rules* [3], which determine the full set of valid inferences. These inference rules can be intuitively explained as follows. Each rule has a set of *premises* that conjunctively define its body. The premises represent "extended" RDF statements, where variables can occupy any of the three possible positions in the triple (that of a `subject`, of a `predicate`, or of an `object`). The head of the rule comprises of one or more *consequences*, each of which represents in its turn an RDF statement. Applying the entailment rules to RDF graphs infers new triples, which can be regarded as a logical consequence of the initial graph. The newly inferred triples can be denoted as inferred closure of the source graph. The only way to determine whether a specific statement can be inferred from an RDF graph is to check if it is a member of its inferred closure.

In simple rule-based systems, there are two main reasoning strategies. *Forward-chaining* involves applying the inference rules to the known facts to generate new facts. The rules can then be re-applied to the combination of original and inferred facts to produce yet more new facts. The process is iterative and continues until no new facts can be generated. The advantage of this approach is that when all inferences have been computed, query answering is extremely fast. The disadvantages are greater initialization costs (inference computed at load time) and space usage (especially when the number of inferred facts is very large).

On the other hand, *backward-chaining* involves starting with a fact to be proved or a query to be answered. Typically, the reasoner examines the knowledge base to see if the fact to be proved is present and if not it examines the rule set to see which rules could be used to prove it. Hence, a check is made to see what other supporting facts would need to be present to fire these rules. The reasoner searches for proofs of each of these supporting facts in the same way and iteratively maps out a search tree. The process terminates when either all of the leaves of the tree have proofs or no new candidate solutions can be found. Query processing is similar, but only stops when all search paths have been explored. The purpose in query answering is to find not just one, but all possible substitutions in the query expression. The advantages of this approach are that there are no inferencing costs at start-up and minimal space requirements. The disadvantage is that inference must be done each and every time a query is answered and for complex search graphs this can be computationally expensive and slow.

The prevalent language to query RDF data is SPARQL [2]. Similar to SQL in its syntax, it can be used to express queries across diverse data sources, whether the data is stored natively as RDF or viewed as RDF via middleware. It can also query required and optional graph patterns along with their conjunctions and disjunctions.

RDF stores, e.g., Hexastore [40], RDFSuite [10], 3store [27], DLDB [32, 33], KAON [39], are centralized engines, similar to the Database Management Systems (DBMS), that allow storing, querying, managing and reasoning on RDF graphs. The architectures enabling RDF stores include *giant triple table*, *property tables*, [42, 41] *vertical partitioning* [5, 19] and application specific indices.

2.2 Distributed RDF Storage and Reasoning

Table 1 overviews the features of the most well-known distributed RDF stores and MIDAS-RDF. Edutella [30] retains the structure of many independent RDF databases and connects them by an unstructured overlay network consisted of peers and super-peers. All data remain at their original location and queries are routed via flooding. Nonetheless, there is no guarantee that the queried content will eventually be retrieved, if at all. Compared to this work, MIDAS-RDF relies on a structured multi-dimensional distributed index that is known to support efficiently range search.

Crespo and Molina argue [20] that a classification hierarchy, resembling an ontology, should serve as the basis of the network formation. In Semantic Overlay Networks (SONs), nodes of semantically similar content are clustered together, establishing connections among them; a node is allowed to belong to more than one clusters at the same time. Queries are processed by identifying which SONs are better suited to answer it. Then, the query is sent to a node in those SONs to multi-cast it to the remaining members. On the other hand, MIDAS-RDF does not require a notion of semantic proximity and features efficient routing mechanisms.

RDFPeers [15] is one of the first efforts for structured peer-to-peer RDF stores. The key idea is to use a MAAN overlay [16] to index a triple three times, once based on the subject, another based on the predicate, and a final based on the object. There are a few shortcomings in this design. First, there is a replication factor of three for all triples. Furthermore, the RDF schema semantics are totally ignored during query routing. Due to its underlying storage layer, RDFPeers can in the worst case, e.g., for queries with low selectivity, require a linear number of hops with respect to the overlay size. Finally, RDFPeers is susceptible to load imbalances, as peers responsible for popular and reserved keywords quickly become overwhelmed. Note that MIDAS-RDF does not store duplicate triples, has efficient routing algorithms with logarithmic number of hops in the worst case, does not suffer from load balances due to popular keywords, and in addition supports reasoning.

Regarding distributed RDFS reasoning in particular, Fang et al. [23] propose an iterative forward-chaining procedure, though they do not address load-balancing issues. Kaoudi et al. [28] compare the two well-known approaches for RDFS reasoning, backward- and forward-chaining on top of distributed hash table based structure overlays, and conclude that backward-chaining is the most effective. Compared to this work, MIDAS also considers incremental updates, triple removals along with all their inferred triples, and prevents the inference of duplicate triples. Battré et al. [12] present a paradigm for performing reasoning over *locally stored* triples and introduce a policy to address load-balancing issues. On the other hand, our approach does not require from each peer to maintain multiple RDF databases for distinct purposes. Marvin [31] constitutes a parallel and distributed platform for processing large amounts of RDF data, on a network of loosely coupled peers. Also, this work presents an iterative procedure for computing the deductive closure of large datasets. Serafini and Tamilin propose in [36] a system that relies on manually created ontology mappings.

A different concept is presented in [35] that distributes the reasoning rules instead of the data, so that each node is responsible for performing a specific part of the reasoning process. However, this scheme is liable to imbalances and does not scale well. Piazza [26] relies on the mappings established between the individual peer schemes to route queries on semantically related peers, rather than on a distributed index of graph fragments. GridVine [7] realizes semantic overlays by separating a logical layer from a physical, applying the principle of data independence. The logical layer has operations to support semantic interoperability including attribute based search, schema inheritance, schema management and schema mapping. It also supports a schema reconciliation technique, known as semantic gossiping, for semantic interoperability in decentralized settings [6].

2.3 Labeling Schemes

In the following, we provide a succinct overview of labeling schemes for the Semantic Web; a detailed review can be found at [18] and [17]. These techniques can be divided into two categories, interval-based and prefix-based.

Agrawal et al. [9] propose an scheme that assigns intervals to nodes of a graph, so that an ancestry relationship between two nodes is checked by interval inclusion. First, spanning tree T is determined. A node u in T is labeled with $[\texttt{minpost}(u), \texttt{post}(u)]$, where $\texttt{post}(u)$ is the order of u in a postorder traversal of T, and $\texttt{minpost}(u)$ is the lowest $\texttt{post}$ among u's descendants. Finally, all nodes of the graph are examined in reverse topological order, and for each edge (u, v) all intervals associated with v are propagated to u. Based on this scheme, a node v is an ancestor of u, if all intervals of u are included in those of v. Note that to avoid frequent node relabeling and support incremental updates, gaps are typically left in the generated intervals.

Other interval schemes exhibit similar properties. In [21], [22], a node u in T is labeled with $[\texttt{pre}(u), \texttt{post}(u)]$, where $\texttt{post}(u)$ is the order of u in a preorder traversal of T. Similarly, Tsakalidis [37] shows that a node v is an ancestor to u iff $\texttt{pre}(v) \leq \texttt{pre}(u) \leq \texttt{post}(v)$, which leads to a labeling scheme with labels of size $2 \log n$. Peleg [34] proposes an $O(\log n)$ labeling scheme that given nodes u and v one can determine the lowest common ancestor of u and v.

Prefix-based schemes, such as [29], [11], [8], apply for trees. Consider an alphabet $\Sigma = \{\sigma_1, \cdots, \sigma_M\}$. Node labels can be defined recursively, as follows. Consider a node u with label $\texttt{id}(u) \in \Sigma^*$. Assuming an order on u's children, let node v be the k-th child of u. We have that $\texttt{label}(v) = \texttt{label}(u)\sigma_k$. One of the advantages of this approach is its ability to handle incremental updates efficiently. As long as the order among descendants is not important, one can always add a new child as the last, avoiding any relabeling. Note that to handle the general case of graphs, a child is allowed to have multiple labels, one per parent.

Checking whether a node v is an ancestor of u is equivalent to checking if $\texttt{label}(v)$ is a prefix of $\texttt{label}(u)$. Furthermore, given two nodes u and w, their nearest common ancestor is the node labeled with their longest common prefix, which can be easily computed in $O(\min\{\|\texttt{label}(u)\|, \|\texttt{label}(w)\|\})$, where $\|\texttt{label}(u)\|$ denotes the length of u's identifier.

	Storage Layer	Multi-Attribute	Load-Balancing	Reasoning
Edutella [30]	unstructured	N/A	No	No
SONs [20]	hierarchical	N/A	No	No
RDFPeers [15]	MAAN	No	No	No
Battre et al. [12]	Pastry	No	Yes	FC
Kaoudi et al. [28]	Pastry	No	No	BC
MARVIN [31]	Chord	No	No	FC
Piazza [26]	unstructured	N/A	No	Yes
GridVine [7]	P-Grid	No	Yes	Yes
MIDAS-RDF	MIDAS	Yes	Yes	FC

Table 1: Characteristics of different distributed RDF repositories.

2.4 The MIDAS Overlay

We present a brief overview of the MIDAS distributed multi-dimensional index [38], which forms the basis for out distributed RDF store. MIDAS is a distributed version of the k-d tree [13]. The k-d tree is a binary tree, where each node corresponds to an axis parallel rectangle; the root represents the entire space. Each internal node has always two children whose rectangles are obtained by splitting the parent's rectangle in two along some dimension. Each node is assigned a binary identifier corresponding to its path from the root, defined recursively. The root has the empty id $\varnothing$; the left (resp. right) child of an internal node has the id of its parent augmented with 0 (resp. 1). Figure 2 depicts a k-d tree of seven nodes with three splits and their ids. Due to the hierarchical splits, the rectangles of the leaf nodes in a k-d tree, shown in green, constitute a non-overlapping partition of the entire space.

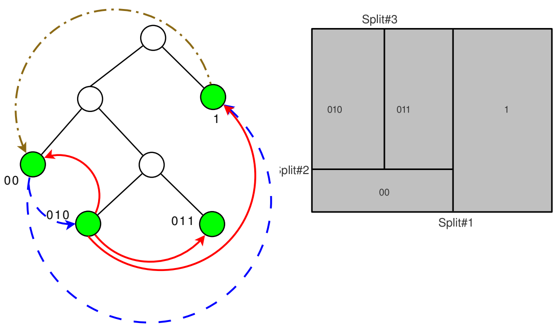


Figure 2: An example of a two-dimensional k-d tree.

A *peer* in MIDAS corresponds to a leaf of the k-d tree, and stores/indexes all tuples that reside in the leaf's rectangle. Peer joins and departures are handled by appropriately splitting and merging k-d tree nodes. Due to its routing mechanism and the locality preserving property of the underlying k-d tree, MIDAS can efficiently support multi-dimensional point and range queries. A point in the space (more accurately, the peer responsible for that point) can be retrieved in logarithmic number of hops, in the worst case. To process range queries, MIDAS is able to identify in parallel all peers whose rectangle overlaps with the given range. As a result, independently of the size of the range, MIDAS requires logarithmic number of hops in the worst case.

3. THE MIDAS-RDF DISTRIBUTED STORE

Section 3.1 describes how triples are stored and indexed, while Section 3.2 explains query evaluation in MIDAS-RDF.

3.1 Storage Model

The MIDAS-RDF system stores RDF triples and transitive information using the MIDAS distributed index. An RDF triple (u, α, v) is represented as a four dimensional key $\langle u, \alpha, v, \texttt{id}(v)\rangle$, where $\texttt{id}(v)$ encodes transitive information regarding object v in the subgraph of predicate α, which corresponds to the RDF graph associated with the triples with predicate α. We also assume a lexicographic ordering for the *subject*, *predicate* and *object* dimensions, and the natural ordering for *object subgraph identifiers*.

Consider a MIDAS-RDF key $\langle u, \alpha, v, \texttt{id}(v)\rangle$. The subgraph identifier of the object v, $\texttt{id}(v)$, can be set according to one of the schemes described in Section 2.3. When the interval-based scheme of [9] is used, $\texttt{id}(v)$ is $\texttt{post}(v)$, that is, v's order in a postorder traversal of a spanning tree of the α subgraph. On the other hand, when the prefix-based scheme of [29] is used, $\texttt{id}(v)$ corresponds to the prefix label $\texttt{label}(v)$ in a spanning tree of the α subgraph that includes the (u, v) edge.

Note that, when the interval-based scheme is used, $\texttt{post}(v)$ alone cannot encode the transitivity in the α subgraph. For this reason, with each $\langle u, \alpha, v, \texttt{post}(v)\rangle$ key, MIDAS-RDF associates a composite value that consists of all intervals associated with node v in the α subgraph. Therefore, in this case, a tuple in MIDAS-RDF has five dimensions, *subject*, *predicate*, *object*, *object subgraph identifier* and *intervals*. However, only the first four comprise the key indexed by MIDAS-RDF.

Figure 3 illustrates an example subgraph of some property that contains six nodes denoted symbols u through z; we assume that other nodes below x, y, z exist, but are not shown. For the interval-based scheme, the spanning tree contains all edges except the one drawn with dotter line. For easy reference, the node symbols also correspond to the identifiers according to the interval-based scheme, e.g., $\texttt{post}(u) = u$. The intervals associated with each node are shown in red. Observe that node w has two intervals, one from the spanning tree edge $[r, w]$, and another $[q, y]$, propagated from node y. The identifiers according to the prefix-based scheme are depicted on the edges and are shown in blue. Notice that node y has two prefix labels, 01 corresponding to the (v, y) edge, and 10 corresponding to the (w, y) edge.

Table 2 shows the attribute values of the tuples stored in MIDAS-RDF peers according to both labeling schemes. In this example, the predicate dimension is omitted since its common among all triples. In the prefix-based scheme, columns 1, 2 and 3 constitute the tuple keys, whereas in the interval-based scheme, columns 1, 2 and 4 constitute the tuple keys, and column 5 represents the value.

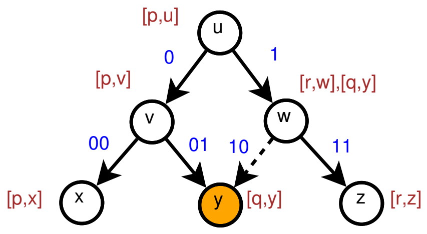


Figure 3: Identifiers for the two labeling schemes.

Subject	Object	Label	Post	Intervals
u	v	0	v	$[p, v]$
u	w	1	w	$[r, w], [q, y]$
v	x	00	x	$[p, x]$
v	y	01	y	$[q, y]$
w	y	10	y	$[q, y]$
w	z	11	z	$[r, z]$

Table 2: Triples stored as tuples for both labeling schemes.

3.2 RDF Queries

MIDAS-RDF straightforwardly supports RDF triple pattern queries. Consider the query types shown in Table 3. The notation $?s$ (and $?p$, $?o$) is borrowed from SPARQL [2], and denotes that variable $?s$ corresponds to possibly many subjects satisfying the pattern. Query type Q1 is evaluated in MIDAS-RDF as a point query requiring logarithmic, in the number of peers, hops. All other pattern queries, are evaluated as range queries in MIDAS-RDF, where an $?s$, $?p$, or $?o$ expression is translated as the range of the entire domain of subjects, predicates, or objects, respectively. For example, consider the RDF graph depicted in Figure 1a. The Q2 type query `SELECT ?paint WHERE {Picasso paints ?paint}` returns all paintings of Picasso. Note that a Q8 type query essentially retrieves all RDF triples. Due to the MIDAS overlay, such queries require only logarithmic hops.

Name	Subject	Predicate	Object
Q1	s	p	o
Q2	s	p	?o
Q3	s	?p	o
Q4	s	?p	?o
Q5	?s	p	o
Q6	?s	p	?o
Q7	?s	?p	o
Q8	?s	?p	?o

Table 3: Atomic triple pattern queries.

Disjunctive range queries can be resolved by issuing one query for each contiguous range and then computing the union of the results. Such a mechanism can be efficiently implemented by issuing simultaneously the atomic queries that constitute the disjunction. Conjunctive queries, such as `SELECT ?artifact WHERE {{?x type Sculptor} {?x type Painter} {?x creates ?artifact}}` returns the artifacts that were created by an artist that was a painter *and* a sculptor, e.g., Michelangelo's David. A simple way to support conjunctive queries is to invoke first the atomic query that constitutes the conjunction with the greater selectivity (assuming that such information exists, e.g., via histograms). Then, the result-set can be filtered appropriately in the peer that issued the request.

An important class of queries is those concerning transitive properties. For example, consider the *sc* subgraph of Figure 1b. A query for the concepts that subsume `Cubist` would retrieve `Painter` and `Artist`. Efficient processing of transitivity queries requires a labeling scheme. Posed such a query, MIDAS-RDF initially retrieves v's object subgraph identifier $\texttt{id}(v)$, if not known. Further, if the interval-based scheme is used, it also retrieves the labels associated with v. Based on this information it formulates a range query.

In the case of the prefix-based scheme, the start of the range is $\texttt{id}(v)$. The end of the range is open and is the id of v's next sibling if it exists; otherwise, it is the id of the next sibling of v's parent or of v's grandparent, and so on. For example, the nodes (concepts) that subsume v in Figure 3 have ids in the range $[0, 1)$; these are nodes x and y.

In the case of the interval-based scheme, a range query is issued for its interval associated with v. For example, the nodes that subsume v in Figure 3 have ids that belong in the range $[p, v]$. Note that, independently of the labeling scheme, transitivity queries are processed in logarithmic number of hops, as they are transformed into range queries.

4. RDFS REASONING IN MIDAS-RDF

Section 4.1 outlines the basic principles of the MIDAS-RDF inference model. Then, Section 4.2 details the implementations of RDFS entailment rules.

4.1 Inference Model

The RDF semantic document [3] describes how RDFS entailment can be seen as a set of rules which generate new RDF triples from existing ones. In this work, we focus on a subset of these rules, including the extensional entailment rules, depicted in Table 4, which contains the most computationally intensive ones. Properties `sp` and `sc` are shorthands for `subPropertyOf` and `subClassOf`, respectively.

Rule	Precondition	Generated Triple
rdfs2	$(\alpha, \texttt{domain}, x), (u, \alpha, v)$	$(u, \texttt{type}, x)$
rdfs3	$(\alpha, \texttt{range}, x), (u, \alpha, v)$	$(v, \texttt{type}, x)$
rdfs5	$(\alpha, \texttt{sp}, \beta), (\beta, \texttt{sp}, \gamma)$	$(\alpha, \texttt{sp}, \gamma)$
rdfs7	$(\alpha, \texttt{sp}, \beta), (u, \alpha, v)$	(u, β, v)
rdfs9	$(u, \texttt{sc}, v), (w, \texttt{type}, u)$	$(w, \texttt{type}, v)$
rdfs11	$(u, \texttt{sc}, v), (v, \texttt{sc}, w)$	$(u, \texttt{sc}, w)$
ext1	$(\alpha, \texttt{domain}, u), (u, \texttt{sc}, v)$	$(\alpha, \texttt{domain}, v)$
ext2	$(\alpha, \texttt{range}, u), (u, \texttt{sc}, v)$	$(\alpha, \texttt{range}, v)$
ext3	$(\alpha, \texttt{domain}, u), (\beta, \texttt{sp}, \alpha)$	$(\beta, \texttt{domain}, u)$
ext4	$(\alpha, \texttt{range}, u), (\beta, \texttt{sp}, \alpha)$	$(\beta, \texttt{range}, u)$

Table 4: RDFS entailment rules.

Unlike other approaches, MIDAS-RDF does not require ad-hoc splitting of the inference procedure in independent subparts. Contrary, peers autonomously partition the problem, as each operates on some subproblem to find partial solutions that are quickly made available to anyone. More precisely, MIDAS-RDF follows a forward chaining inference model. Each time a peer, i.e., a local store, receives a triple for storage, it generates all inferred triples and inserts them in MIDAS-RDF using the underlying network infrastructure. Naturally, the generated triples for some of the rules may trigger other rules to be executed.

In order to avoid creating duplicates, we adopt the policy that our methods are executed only once from one of the two peers containing the parts to be considered for entailment. Nevertheless, that part is selected to optimize specific factors that affect performance and scalability. Therefore, our design choices minimize the amount of exchanged messages and as a result the consumed bandwidth, which is arguably the most costly resource in a distributed environment.

Most importantly, our scheme enhances performance by utilizing a labeling scheme. For example, without such a scheme, the deductive closure of entailment rule *rdfs11* on a `subClassOf` subgraph of depth K, would require a sequence of at least K operations that cost $O(\log n)$ hops each. On the other hand, the labeling scheme, can process the deductive closure in a single operation of $O(\log n)$ cost that applies the rule to all qualifying nodes of the sub-graph. These nodes are efficiently retrieved by issuing an appropriate range query, as described in Section 3.2. To illustrate this, assume the RDF graph of Figure 1a and consider rule *rdfs9*. In MIDAS-RDF, a peer can generate triples `(Picasso, type, Painter)` and `(Picasso, type, Artist)` in a single step. As a result, the query `SELECT ?x WHERE {?x type Artist}` would also return the name of Picasso, which otherwise would not be part of the answer.

4.2 Implementation Details

We present the implementation of the rules depicted in Table 4, and also discuss the case of triple updates.

4.2.1 Applying rules rdfs2, rdfs3

Algorithm 1 produces new knowledge using entailment rules *rdfs2* and *rdfs3*. This method is called when a triple of the form $(\alpha, \texttt{domain}, u)$ or $(\alpha, \texttt{range}, v)$ is locally inserted. Such a triple must be associated with all triples of predicate α retrieved from remote peers by invoking a range query, so as to generate the triples dictated by the two rules.

The example illustrated in Table 5 concerns rule *rdfs2* and can be described by the following steps:

1. Peer p_2 examines local triple (u, α, v) and invokes a range query of the form $(\alpha, \texttt{domain}, ?X)$ to retrieve $(\alpha, \texttt{domain}, x)$ from p_1.
2. Peer p_2 processes the returned tuple using rule *rdfs2* and generates triple $(u, \texttt{type}, x)$.
3. Peer p_2 stores the generated tuples in the overlay using the network infrastructure. The peers that are responsible for the newly inserted triples will invoke Algorithm 5 to apply rule *rdfs9*.

Figure 5 also shows that an identical approach for rule *rdfs3* applies. Notice that Algorithm 5 handles triples that were just inserted in a peer. In order to prevent the creation of duplicates, we produce new triples when examining a predetermined part (for performance reasons) of the two required to apply an entailment rule. However, as new triples are inferred and inserted there is also the need to implement methods for handling entailment rules for the other part to be considered for entailment. As this is the case for Algorithm 5 and entailment rule *rdfs9*, we suggest very similar implementations with limited changes for the rules that are not presented both ways, such as *rdfs7*, *ext1* and *ext2*. In many ways both implementations are equivalent and our selections were made towards the more efficient and elegant.

Peer	Local Store	Generated Triples	Rule
p_1	$(\alpha, \texttt{domain}, x)$		
p_2	(u, α, v)	$(u, \texttt{type}, x), (v, \texttt{type}, z)$	*rdfs2,3*
p_3	$(\alpha, \texttt{range}, z)$		

Table 5: Inference example for *rdfs2* and *rdfs3*.

Algorithm 1 deduceRDFS2/3a: Inputs an RDF triple in the form (u, α, v), searches for associated triples by rules *rdfs2* and *rdfs3* and generates new triples to be stored.

```
1: /* Associated rule: RDFS2 */
2: $p$.rangeRDFquery $(\beta, \texttt{domain}, ?X)$
3: for all $x$ in $X$ do
4:     $p$.insert $(u, \texttt{type}, x)$
5: end for
6:
7: /* Associated rule: RDFS3 */
8: $p$.rangeRDFquery $(\beta, \texttt{range}, ?Y)$
9: for all $y$ in $Y$ do
10:    $p$.insert $(v, \texttt{type}, y)$
11: end for
```

Algorithm 2 deduceRDFS2b: Triggered upon an insertion of an RDF triple of the form $(\alpha, \texttt{domain}, u)$, searches for associated triples by rule *rdfs2* and generates new triples to be stored.

```
1: $p$.rangeRDFquery $(?X, \alpha, ?Y)$
2: for all $x$ in $X$ do
3:     $p$.insert $(x, \texttt{type}, u)$
4: end for
```

4.2.2 Applying rules rdfs5, rdfs7

Algorithms 3 and 4 justify the design choice of utilizing a labeling scheme in MIDAS-RDF, as they reduce the number of hops required from $O(K \log n)$ to $O(\log n)$. The example of Algorithm 3 depicted in Table 6 can be described by the following steps:

1. Peer p_1 examines $(\alpha, \texttt{subPropertyOf}, \beta)$ and acquires the local labels of the triples that correspond to the nodes that subsume β in the `subPropertyOf` sub-graph.
2. Peer p_1 retrieves all the triples that correspond to the obtained labels in $O(\log n)$ hops, from peers p_2 and p_3 triples $(\beta, \texttt{subPropertyOf}, \zeta), (\zeta, \texttt{subPropertyOf}, \xi)$.
3. Peer p_1 stores the generated tuples, by entailment rule *rdfs5*, $(\alpha, \texttt{subPropertyOf}, \zeta)$ and $(\alpha, \texttt{subPropertyOf}, \xi)$ in the overlay.
4. Likewise, peer p_2 checks triple $(\beta, \texttt{subPropertyOf}, \zeta)$ to retrieve $(\zeta, \texttt{subPropertyOf}, \xi)$ from p_3, and when rule *rdfs5* is applied it generates $(\beta, \texttt{subPropertyOf}, \xi)$ to store it in the overlay.
5. Peer p_3 examines $(\zeta, \texttt{subPropertyOf}, \xi)$ only to find out that there are no nodes that subsume ξ.
6. Peer p_2 acquires (u, α, v) (Alg. 3) and applies rule *rdfs7* with local labels of the nodes that subsume ζ.

7. Then, peer p_2, after invoking a range query for all relevant labels, retrieves $(\zeta, \texttt{subPropertyOf}, \xi)$ from p_3.
8. When rule *rdfs7* is applied, peer p_2 generates triples $(u, \zeta, v), (u, \xi, v)$ and stores them in the overlay.
9. The peers that are responsible for the newly inserted triples from peer p_2 will invoke Algorithm 1 for handling them according to etailment rules *rdfs2* and *rdfs3*.

Peer	Local Store	Generated Triples	Rule
p_1	$(\alpha, \texttt{sp}, \beta)$	$(\alpha, \texttt{sp}, \zeta), (\alpha, \texttt{sp}, \xi)$	*rdfs5*
p_2	$(\beta, \texttt{sp}, \zeta)$	$(\beta, \texttt{sp}, \xi), (u, \zeta, v), (u, \xi, v)$	*rdfs5,7*
p_3	$(\zeta, \texttt{sp}, \xi)$		
p_4	(u, β, v)		

Table 6: Inference example for *rdfs5* and *rdfs7*.

Instead of chasing pointers and issuing sequential queries, peer p_1 retrieves the subgraph with a simple range query based on a labeling scheme. In particular, peer p_4 would have to invoke 4 distinct queries in order to generate all possible triples regarding entailment rule *rdfs7* for its content. Most importantly, peer p_4 is in position of completing the closure of its statements without being aware of other peers' progress, in our case p_1, p_2, p_3, or waiting for their intermediate results.

4.2.3 Applying rules rdfs11, rdfs9

The example of Algorithm 4 shown in Table 7 is described in the following steps:

1. Peer p_1 examines $(u, \texttt{subClassOf}, v)$ and checks the labels of the nodes that subsume v.
2. Peer p_1 retrieves triples, $(v, \texttt{subClassOf}, w)$ from p_2 and $(w, \texttt{subClassOf}, y)$ from p_3.
3. Peer p_1 stores the generated tuples $(u, \texttt{subClassOf}, w)$ and $(u, \texttt{subClassOf}, y)$ in the overlay.
4. When peer p_2 examines $(v, \texttt{subClassOf}, w)$, it retrieves from p_3 triple $(w, \texttt{subClassOf}, y)$.
5. Peer p_2 stores the generated tuple $(v, \texttt{subClassOf}, y)$ in the overlay.
6. Peer p_3 examines $(w, \texttt{subClassOf}, y)$ only to find out that there are no nodes that subsume y. It also issues a range query for $(?X, \texttt{type}, w)$ and retrieves $(x, \texttt{type}, w)$ from p_4.
7. Peer p_3 applies rule *rdfs9* and generates $(x, \texttt{type}, y)$ that stores in the overlay.

Peer	Local Store	Generated Triples	Rule
p_1	$(u, \texttt{sc}, v)$	$(u, \texttt{sc}, w), (u, \texttt{sc}, y)$	*rdfs11*
p_2	$(v, \texttt{sc}, w)$	$(v, \texttt{sc}, y)$	*rdfs11*
p_3	$(w, \texttt{sc}, y)$	$(x, \texttt{type}, y)$	*rdfs9*
p_4	$(x, \texttt{type}, w)$		

Table 7: Inference example for *rdfs11* and *rdfs9*.

4.2.4 Applying rules ext1 and ext2

For the implementation of extentional entailment rules *ext1* and *ext2*, we follow an approach similar to the one adopted for *rdfs9*. The example shown in Table 8 is described as follows:

1. Peer p_2 checks $(u, \texttt{subClassOf}, v)$ and to apply *ext1* retrieves the triples that correspond to labels of the nodes that subsume v, in our case $(v, \texttt{subClassOf}, w)$.
2. When entailment rule *ext1* is applied for each of the returned triples (Alg. 4), p_2 generates and stores triples $(\alpha, \texttt{domain}, v)$ and $(\alpha, \texttt{domain}, w)$, after retrieving from p_1 $(\alpha, \texttt{domain}, u)$ with a range query.
3. The peers that are responsible for the newly inserted triples will invoke Algorithm 2 for handling *rdfs2*.
4. Likewise, p_3 applies *ext2* to $(\beta, \texttt{range}, v)$ that retrieves after $O(\log n)$ hops from p_4, to produce $(\beta, \texttt{range}, w)$.

Peer	Local Store	Generated Triples	Rule
p_1	$(\alpha, \texttt{domain}, u)$		
p_2	$(u, \texttt{sc}, v)$	$(\alpha, \texttt{domain}, v), (\alpha, \texttt{domain}, w)$	*ext1*
p_3	$(v, \texttt{sc}, w)$	$(\beta, \texttt{range}, w)$	*ext2*
p_4	$(\beta, \texttt{range}, v)$		

Table 8: Inference example for *ext1* and *ext2*.

4.2.5 Applying rules ext3 and ext4

Entailment rules *ext3* and *ext4* require a different approach. All previously described methods resolve a transitive relation whose results were combined with a fixed statement. Here, we compute the transitive closure for each statement we examine and we combine each element of the result with associated remote triples that *ext3* and *ext4* require. Next, we provide an intuition of the principle used in Algorithm 3 in the example of Table 9:

1. Peer p_3 examines $(\zeta, \texttt{subPropertyOf}, \beta)$ and uses local information for all labels of the nodes that subsume ζ in the subPropertyOf sub-graph.
2. Peer p_3 based on the local labeling information invokes the appropriate range query to retrieve statement $(\beta, \texttt{subPropertyOf}, \alpha)$ from peer p_2.
3. Peer p_3, for each subsuming node α, retrieves all triples of the form $(\alpha, \texttt{domain}, u)$, in our case from peer p_1 and $(\alpha, \texttt{range}, v)$ from peer p_4.
4. When peer p_3 applies *ext3* generates $(\zeta, \texttt{domain}, u)$ that stores in the overlay. Likewise, peer p_3 generates triple $(\zeta, \texttt{range}, v)$ from *ext4*.
5. The peers that are responsible for the newly inserted triples will invoke Algorithm 2 for handling rules *rdfs2* and *rdfs3* for $(\zeta, \texttt{domain}, u)$ and $(\zeta, \texttt{range}, v)$.
6. An identical procedure is followed by peer p_2 to produce $(\beta, \texttt{domain}, u)$ and $(\beta, \texttt{range}, v)$ for *ext3* and *ext4*.

Peer	Local Store	Generated Triples	Rule
p_1	$(\alpha, \texttt{domain}, u)$		
p_2	$(\beta, \texttt{sp}, \alpha)$	$(\beta, \texttt{domain}, u), (\beta, \texttt{range}, v)$	*ext3,4*
p_3	$(\zeta, \texttt{sp}, \beta)$	$(\zeta, \texttt{domain}, u), (\zeta, \texttt{range}, v)$	*ext3,4*
p_4	$(\alpha, \texttt{range}, v)$		

Table 9: Inference example for *ext3* and *ext4*.

4.2.6 Incremental updates

For a data-driven forward chaining based scheme, an update of triples naturally triggers an update of the inferred

Algorithm 3 deduceRDFS5/7/EXT3/4: Inputs an RDF triple in the form $(\beta, \mathtt{sp}, \alpha)$, searches for associated triples by rules *ext3*, *ext4* and generates new triples to be stored.

```
 1: $\Lambda = p$.getTriplesThatSubsume $(\alpha)$
 2: for all $(s, p, o)$ in $\Lambda$ do
 3:   /* Associated rule: RDFS5 */
 4:   $p$.insert $(\beta, \mathtt{subPropertyOf}, o)$
 5:
 6:   /* Associated rule: RDFS7 */
 7:   $p$.rangeRDFquery $(?U, \beta, ?V)$
 8:   for all $(u, v)$ in $(U, V)$ do
 9:     $p$.insert $(u, o, v)$
10:   end for
11:
12:   /* Associated rule: EXT3 */
13:   $p$.rangeRDFquery $(o, \mathtt{domain}, ?X)$
14:   for all $x$ in $X$ do
15:     $p$.insert $(\beta, \mathtt{domain}, x)$
16:   end for
17:
18:   /* Associated rule: EXT4 */
19:   $p$.rangeRDFquery $(o, \mathtt{range}, ?Y)$
20:   for all $y$ in $Y$ do
21:     $p$.insert $(\beta, \mathtt{range}, y)$
22:   end for
23: end for
```

tuples as well. In the process of reverting these changes we need to make sure that all the triples that we remove have been inferred with one of the RDFS entailment rules. Since there is no notion of data provenance, we follow the reverse procedure of our inference methods with the following additional consideration. Before removing any triple, we must make sure that no other triple exists that when combined under any of RDFS entailment rule would yield the candidate triple. This check can be supported at the cost of some additional steps and computation.

The example of Algorithm 6 in Table 10 applies to deletions of triples of the form $(\alpha, \mathtt{subPropertyOf}, \beta)$ or (u, α, v) from peers p_1, p_2, which raises the question of removing the (u, β, v) inferred triple produced by *rdfs7*. The problem is that the very same triple is inferred by peer p_4 when applying *rdfs7* to its content. Hence, as more than one combinations of rules and triples may lead to the same inferred rules, MIDAS-RDF must examine whether there are more ways of producing them. If this is the case, we proceed to the next inferred triple. For example, in Table 10 when (u, α, v) is deleted and (u, β, v) is examined we simultaneously issue the appropriate requests that would trace the conflict. First, we have to study all RDFS entailment rules and find those that produce triples of the form (u, β, v). Then, we will examine whether there are other triples that lead again to (u, β, v) for each relevant rule that is found. In our case, *rdfs7* is the unique rule that needs to be checked. This is done with a range query of the form $(u, ?\Gamma, v)$ that retrieves (u, γ, v) from peer p_3. Hence, we now need to check whether node β is an ancestor of γ in the `subPropertyOf` sub-graph, a simple task using a labeling scheme. For the prefix-based scheme, we simply check whether the label of node β is a prefix of the label of node γ. For the interval-based scheme, we check whether the postorder identifier of node γ is in any of the intervals of β. Apparently, the cost of this mechanism is not dramatic if we simultaneously try to resolve the possible conflicts from all relevant rules, as in a MIDAS disjunctive query. Thus, combined with this special feature, the aforementioned methods can easily be undone and all inferred triples be removed by replacing the p.`insert()` function-calls, in the algorithms presented earlier, with p.`delete()` function-call. Finally, update requests can be considered as a pair of a deletion of an old triple and a insertion of a triple with the updated values.

Peer	Local Store	Generated Triples	Rule
p_1	$(\alpha, \mathtt{sp}, \beta)$	(u, β, v)	*rdfs7*
p_2	(u, α, v)		
p_3	(u, γ, v)		
p_4	$(\gamma, \mathtt{sp}, \beta)$	(u, β, v)	*rdfs7*

Table 10: Inference example for *rdfs7*.

Algorithm 4 deduceRDFS11/9/EXT1/2: Inputs an RDF triple in the form $(u, \mathtt{sc}, v)$, searches for associated triples by rule *rdfs11* and generates new triples to be stored.

```
 1: $\Lambda = p$.getTriplesThatSubsume $(v)$
 2: $p$.rangeRDFquery $(?X, \mathtt{type}, u)$
 3: $p$.rangeRDFquery $(?A, \mathtt{domain}, u)$
 4: $p$.rangeRDFquery $(?B, \mathtt{range}, u)$
 5: for all $(s, p, o)$ in $\Lambda$ do
 6:   /* Associated rule: RDFS11 */
 7:   $p$.insert $(u, \mathtt{sc}, o)$
 8:
 9:   /* Associated rule: RDFS9 */
10:   for all $x$ in $X$ do
11:     $p$.insert $(x, \mathtt{type}, o)$
12:   end for
13:
14:   /* Associated rule: EXT1 */
15:   for all $\alpha$ in $A$ do
16:     $p$.insert $(\alpha, \mathtt{domain}, o)$
17:   end for
18:
19:   /* Associated rule: EXT2 */
20:   for all $\beta$ in $B$ do
21:     $p$.insert $(\beta, \mathtt{range}, o)$
22:   end for
23: end for
```

5. A PUBLISH-SUBSCRIBE MODEL

In this section, we present a distributed content-based publish-subscribe service that addresses needs pertaining to participants in the community that want to be quickly notified of specific new content, i.e, they have persistent queries expressing interest in certain topics that are constantly serviced. Content-based publish-subscribe systems allow more complex subscriptions by enabling restrictions on the event content. Most importantly, multiple predicates upon the subscription may be defined and only the events that fulfill the requirements are notified to the subscriber.

Our scheme constitutes a middleware for scalable dissemination of data events to subscribers dispersed across the network. In this context, an area of interest is described by a hyper-rectangle, and withal, a range along each dimension

Algorithm 5 deduceRDFS9b: Changes triggered by an insertion of a triple of the form $(x, \texttt{type}, u)$ regarding rule *rdfs9*.

```
1: p.rangeRDFquery $(u, \texttt{subClassOf}, ?V)$
2: for all $v$ in $V$ do
3:     $[\ell, h] = p$.getLabel $(u, \texttt{subClassOf}, v)$
4:     $\Lambda = p$.rangeLabelQuery $(\ell, h)$
5:     for all $(s, p, o)$ in $\Lambda$ do
6:         p.insert $(x, \texttt{type}, o)$
7:     end for
8: end for
```

Algorithm 6 deleteRDFS7: Changes triggered by a deletion of a triple of the form $(\alpha, \texttt{subProperty}, \beta)$ regarding rule *rdfs7*.

```
1: $\Lambda = p$.getTriplesThatSubsume $(\beta)$
2: for all $(s, p, o)$ in $\Lambda$ do
3:     /* Associated rule: RDFS7 */
4:     p.rangeRDFquery $(?\Gamma, \texttt{subPropertyOf}, \beta)$
5:     p.rangeRDFquery $(?U, \alpha, ?V)$
6:     for all $(u, v)$ in $(U, V)$ do
7:         if $\nexists \gamma \in \Gamma, \gamma \neq \alpha : (u, \gamma, v) \in KB$ then
8:             p.delete $(u, o, v)$
9:         end if
10:    end for
11: end for
```

is defined, to identify triples limited to a specific subject. Dimensions that are of no particular interest, are naturally rendered obsolete by declaring their range of domain values equal to the domain space of that particular dimension.

If a subscription needs to specify multiple predicates over the same attribute (for example conjunctive and disjunctive clauses), we can model such a subscription as a combination of multiple subscriptions, each of which specifies a continuous range over that attribute. Therefore, we treat a subscription request similar to a multi-dimensional range query. Peers may subscribe to a specified area whose responsibility might be distributed among several peers.

A subscriber does not know in advance what peers are responsible for the area it is interested in. Moreover, each peer maintains a local spatial index (e.g., an R-tree [25]) with all the subscriptions (hyper-rectangles) that overlap its area of responsibility. To elaborate, as a request is being forwarded recursively to more relevant subtrees of the distributed index, it becomes fragmented by the corresponding sub-regions, and withal, the subscription (hyper-rectangle) is stored in the local spatial indices of the overlapping peers. Henceforth, subscribers will be notified about the changes their areas of interest undergo. Consequently, our approach requires an additional hop for insertions/updates to inform the subscribers, as they instantly become aware of changes that take place (e.g., newly inserted tuples) in those specific areas. Otherwise, a peer would have to periodically invoke a request of a certain type, which would generate unnecessary load. Note that multiple notifications are prevented as duplicate events can be easily detected in the local index.

6. EXPERIMENTAL EVALUATION

Section 6.1 describes the experimental setting and Section 6.2 presents the results of our extensive evaluation.

6.1 Setting

We evaluate performance according to several metrics appearing. We measure query performance by *latency*, which is the maximum distance (in terms of hops) from the initial peer to any peer reached during query processing. Another important metric in distributed systems is network *congestion*, defined as the average number of queries processed at any node, when n uniformly random queries are issued. This actually resembles the average traffic a peers accepts when n queries are issued in the overlay by random peers. To quantify how fast an answer is retrieved, we use two metrics. *Recall* is the ratio between the number of accessed relevant peers to the number of peers that are relevant to the query for each simulation cycle. *Responsiveness* is the ratio between the number of retrieved qualifying tuples to the number of tuples are relevant.

Our experiments simulate a dynamic environment. They consist of a *growing* and a *shrinking* stage. Therefore, we are given the opportunity to study the course of those metrics, as overlay adapts dynamically to changes of the topology. In each step of the growing stage, a new peer joins the overlay network, whereas during the shrinking stage a peer is removed, selected at random with equal probability. In each figure, we depict the impact of both stages. All simulations initiate an overlay of 1K peers growing up to 100K peers, followed by the reverse procedure.

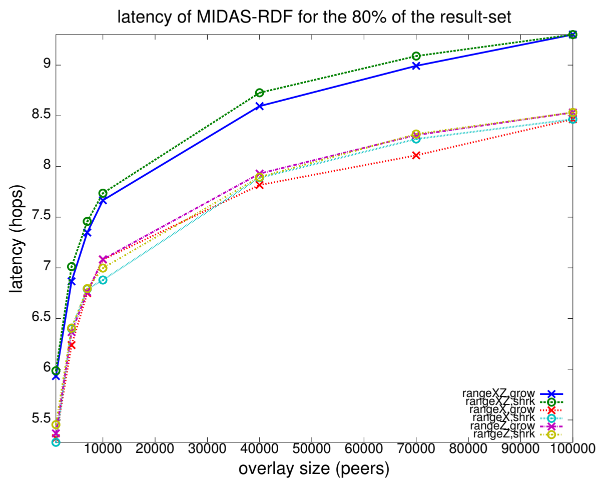
To evaluate transitivity computation and study how different techniques scale, we used synthetic RDF graphs of variable depth (up to 16). In these settings, we compare our labeling scheme based paradigm with traditional solutions based on an iterative forward-chaining procedure. Note that efficient management of transitive relations is of major significance as it is present in the vast majority of the RDFS entailment rules proposed by W3C [3]. The synthetic datasets consist of 1M triples.

Frequency	Relationships (in main relationships)
900,440	publication-has-author (author)
438,531	contained in proceedings (isIncludedIn)
112,303	cites publication
10,639	has-homepage (foaf:homepage)
10,461	has-publisher (dc:publisher)
7,308	has affiliation (foaf:workplaceHomepage)
5,850	in series

Table 11: Statistics summary of the DBLP dataset (Resource-to-Resource Triples: 3,740,438, Resource-to-Literal Triples: 7,274,180).

Furthermore, we evaluate range queries with a real dataset of approximately 11.2M triples. The DBLP dataset [1] is available in XML and contains a large number of bibliographic descriptions on major computer science journals and proceedings, more than half a million articles and several thousand links to home pages of computer scientists. For our evaluation, we use an RDF converted dataset from XML of the Proximity DBLP database, which is based on the DBLP dataset with additional preparation performed by the Knowledge Discovery Laboratory, University of Massachusetts Amherst. Specifically, the data in this dataset were derived from a snapshot of the bibliography in 2006.

Tables 11 and 12 indicate important characteristics of the DBLP dataset that prelude our results. In addition, there



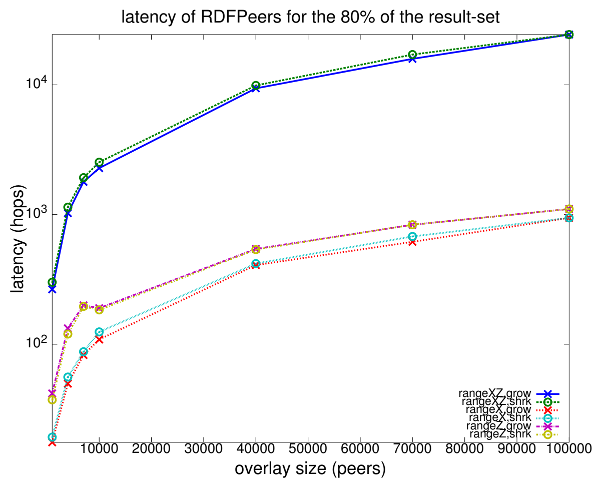
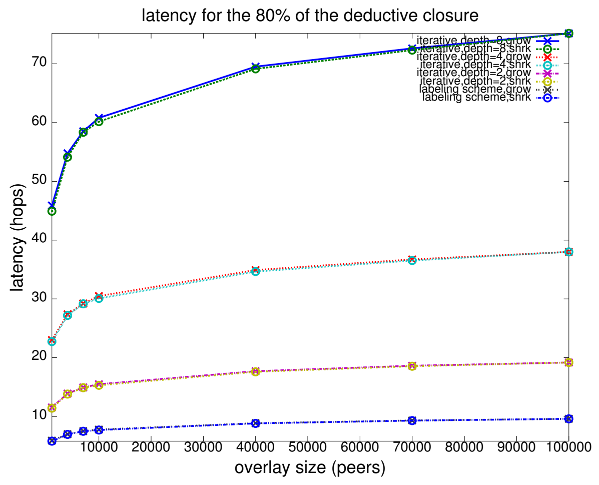


Figure 4: Latency of MIDAS-RDF, RDFPeers for *rangeXZ*, *rangeX*, *rangeZ* querysets on the DBLP dataset.



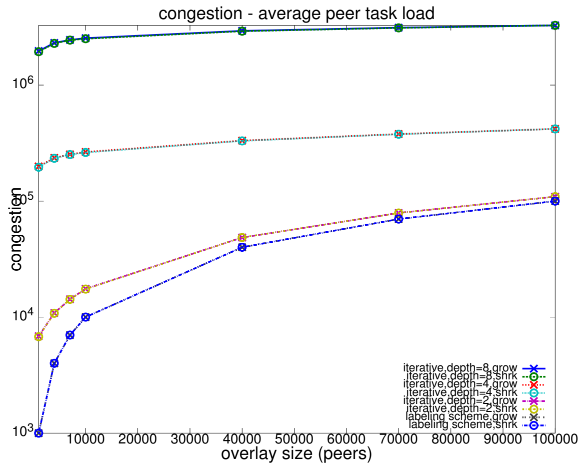


Figure 5: Latency and task-load for the computation of the deductive closure of synthetic graphs of variable depth for labeling and iterative based schemes.

Frequency	Entities (in main classes)
560,792	Person (foaf:Person)
561,895	Articles in Proceedings
340,488	Journal Articles
10,610	Webpages of persons
9,027	Proceedings
2,530	Book Chapters

Table 12: Statistics summary of the DBLP dataset (Resources: 2,395,467, Literals: 3,064,704).

are 2,425,830 triples with `<rdf:type>` as their property, another 1,708,988 with `<http://xmlns.com/foaf/0.1/name>`, just 1,689,330 triples with a `<dc:creator>` predicate, etc. In fact, only seven distinct predicates appear in the outlandish percentage of 72% of our triples. Consequently, considering the immense arising skew, the hitherto approach of earlier efforts that hash each triple separately by its subject, its predicate and its object is absolutely unjustified. Hence, when the size of the overlay exceeds the number of keywords used in a dataset, especially when some of those terms are also popular, like `type` and `Article`, load imbalances have an immense impact on all aspects of performance and scalability. Therefore, we made some enhancements in the design of one of our competitors, RDFPeers [15], and benefited its overlay infrastructure to support multi-attribute range queries and not hash triples separately for each of their attributes. Otherwise, a single peer in RDFPeers would easily be responsible for at least half the dataset, a critical impediment to the functional operation of a peer-to-peer system.

We evaluate MIDAS-RDF with various types of queries that were used in our inference methods. More specifically, with *rangeXZ* we denote querysets consisted of range queries of the form `SELECT ?publication ?author WHERE {?publication <dc:creator> ?person}`, where only the predicate has a fixed value as in Algorithm 2. With *rangeZ* querysets of range queries of the form `SELECT ?author WHERE {<http://www.w3.org/TR/xquery> <ex:editor> ?author}` where we want to retrieve triples of a specific subject and predicate, for example in Algorithm 1. Last, with *rangeX* we denote range queries of the form `SELECT ?id WHERE {?id date "2002-01-03"}`, to retrieve all possible subjects that appear with a specific predicate and object (Alg. 4). In our queryset, the queries were originated from the DBLP dataset. They are triples selected at random and processed appropriately. Their querysize and selectivity is not fixed and is associated with the frequency of the used terms. Our querysets consist of approximately 40K range queries. Last, in Figures 4 and 5 we draw the mean values of important metrics, for the 20 times that we run our experiments.

6.2 Results

In this section we present our results that validate our analytical claims. Figure 4 presents query performance aspects for various types of range search, namely *rangeX, rangeZ* and *rangeXZ*. Latency for MIDAS-RDF is bounded by $O(\log n)$ as expected. In terms of latency, the original version of RDFPeers performs equally good with our solution. Nonetheless, both data- and task-load fairness suffered severely in such a degree that commodity hardware would find it very difficult to cope with. On the other hand, our pure multi-dimensional scheme prevents similar phenomena as it takes load into consideration when assigning a zone to a new peer, and as a result, no peer is duly loaded. Regarding the altered version of RDFPeers that uses the protocol of MAAN to index triples, it is obvious that MIDAS-RDF outperforms it by more than an order of magnitude for all query types. Clearly, being strongly affected by query selectivity our competitor shows linear behavior as the overlay size increases, in contrast to MIDAS' logarithmic performance. More specifically, latency on MAAN is dominated by the number of peers relevant to the query, due to the adopted approach to look up for a bound of the range first, and then sequentially traverse all relevant neighboring peers. This also becomes apparent for the various types of range search where performance deteriorates as selectivity diminishes from *rangeX* to *rangeXZ*.

Figure 5 presents query performance aspects for resolving the transitive closure of a synthetic RDF graph of variable depth. We compare MIDAS-RDF and its incorporated labeling scheme with the traditional iterative approach that has been widely accepted by similar efforts on the subject to date. Regarding latency, our approach performs logarithmically and clearly outperforms the iterative procedure. In particular, the usage of labeling schemes ameliorates performance significantly, as it renders obsolete the impact of graph's depth parameter. Surprisingly enough, both labeling schemes we leverage, prefix and interval scheme, performed equally well with MIDAS.

When it comes to congestion, MIDAS-RDF outperforms the competition again. Apparently, resolving range queries is more efficient than the traditional iterative procedure of chasing pointers, some orders of magnitude analogous to the depth of the resolved graph. Also, note that this figure corresponds to the average peer message load when invoking n queries for retrieving the whole transitive hierarchy of an RDF graph that consists of 1M triples and variable depth.

Finally, Figures 6 and 7 illustrate in detail the progress of the transitive closure computation in MIDAS-RDF with time for the responsiveness and recall metrics.

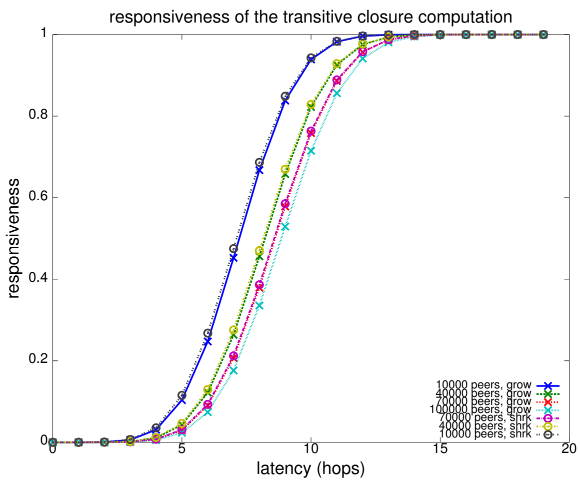


Figure 6: Responsiveness for transitivity computation.

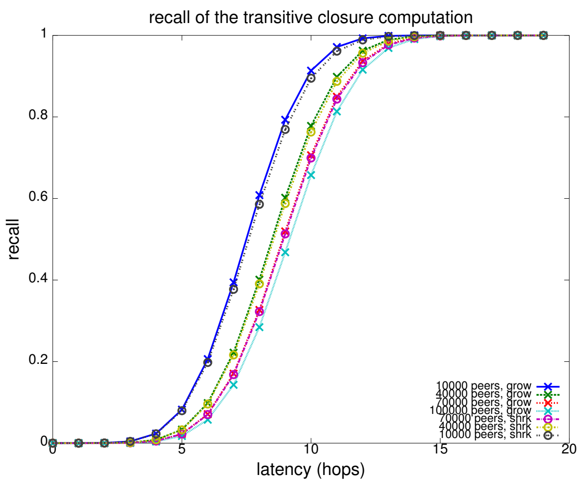


Figure 7: Recall for transitivity computation.

7. CONCLUSIONS

This paper presented MIDAS-RDF, a novel distributed RDF repository based on a pure multi-dimensional indexing scheme for large-scale decentralized networks. MIDAS-RDF is able to process various pattern queries in hops logarithmic to the number of peers. Furthermore, using labeling schemes, MIDAS-RDF implements a forward-chaining inference method that outperforms known approaches that rely on iterative procedures. Last but not least, MIDAS-RDF supports a publish-subscribe model that enables peers to selectively subscribe to RDF content.

8. ACKNOWLEDGMENTS

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9. REFERENCES

[1] The dblp data-set. `http://dblp.uni-trier.de/xml`.

[2] Sparql query language for rdf. `http://www.w3.org/TR/rdf-sparql-query/`.

[3] W3c rdfs rules of entailment. `http://www.w3.org/TR/rdf-mt/#rules`.

[4] World wide web consortium (w3c). `http://www.w3.org/`.

[5] D. J. Abadi, A. Marcus, S. Madden, and K. J. Hollenbach. Scalable semantic web data management using vertical partitioning. In *VLDB*, pages 411–422, 2007.

[6] K. Aberer, P. Cudré-Mauroux, and M. Hauswirth. The chatty web: emergent semantics through gossiping. In *WWW*, pages 197–206, 2003.

[7] K. Aberer, P. Cudré-Mauroux, M. Hauswirth, and T. V. Pelt. Gridvine: Building internet-scale semantic overlay networks. In *ISWC*, pages 107–121, 2004.

[8] S. Abiteboul, S. Alstrup, H. Kaplan, T. Milo, and T. Rauhe. Compact labeling scheme for ancestor queries. *SIAM J. Comput.*, 35(6):1295–1309, 2006.

[9] R. Agrawal, A. Borgida, and H. V. Jagadish. Efficient management of transitive relationships in large data and knowledge bases. In *SIGMOD Conference*, pages 253–262, 1989.

[10] S. Alexaki, V. Christophides, G. Karvounarakis, D. Plexousakis, and K. Tolle. The ics-forth rdfsuite: Managing voluminous rdf description bases. In *SemWeb*, 2001.

[11] S. Alstrup and T. Rauhe. Improved labeling scheme for ancestor queries. In *SODA*, pages 947–953, 2002.

[12] D. Battré, F. Heine, A. Höing, and O. Kao. On triple dissemination, forward-chaining, and load balancing in dht rdf stores. In *DBISP2P*, pages 343–354, 2006.

[13] J. L. Bentley. K-d trees for semidynamic point sets. In *Symposium on Computational Geometry*, pages 187–197, 1990.

[14] T. Berners-Lee, J. Hendler, and O. Lassila. The semantic web. The Scientific American, May, 17, 2001.

[15] M. Cai and M. R. Frank. Rdfpeers: a scalable distributed rdf repository based on a structured peer-to-peer network. In *WWW*, pages 650–657, 2004.

[16] M. Cai, M. R. Frank, J. Chen, and P. A. Szekely. Maan: A multi-attribute addressable network for grid information services. *J. Grid Comput.*, 2(1):3–14, 2004.

[17] V. Christophides, G. Karvounarakis, D. Plexousakis, M. Scholl, and S. Tourtounis. Optimizing taxonomic semantic web queries using labeling schemes. *J. Web Sem.*, 1(2):207–228, 2004.

[18] V. Christophides, D. Plexousakis, M. Scholl, and S. Tourtounis. On labeling schemes for the semantic web. In *WWW*, pages 544–555, 2003.

[19] G. P. Copeland and S. Khoshafian. A decomposition storage model. In *SIGMOD Conference*, pages 268–279, 1985.

[20] A. Crespo and H. Garcia-Molina. Semantic overlay networks for p2p systems. In *AP2PC*, pages 1–13, 2004.

[21] P. F. Dietz. Maintaining order in a linked list. In *STOC*, pages 122–127, 1982.

[22] P. F. Dietz and D. D. Sleator. Two algorithms for maintaining order in a list. In *STOC*, pages 365–372.

[23] Q. Fang, Y. Zhao, G. Yang, and W. Zheng. Scalable distributed ontology reasoning using dht-based partitioning. In *ASWC*, pages 91–105, 2008.

[24] C. Gutiérrez, C. A. Hurtado, and A. O. Mendelzon. Foundations of semantic web databases. In *PODS*, pages 95–106, 2004.

[25] A. Guttman. R-trees: A dynamic index structure for spatial searching. In *SIGMOD Conference*, pages 47–57, 1984.

[26] A. Y. Halevy, Z. G. Ives, P. Mork, and I. Tatarinov. Piazza: data management infrastructure for semantic web applications. In *WWW*, pages 556–567, 2003.

[27] S. Harris and N. Gibbins. 3store: Efficient bulk rdf storage. In *PSSS*, 2003.

[28] Z. Kaoudi, I. Miliaraki, and M. Koubarakis. Rdfs reasoning and query answering on top of dhts. In *ISWC*, pages 499–516, 2008.

[29] H. Kaplan, T. Milo, and R. Shabo. A comparison of labeling schemes for ancestor queries. In *SODA*, pages 954–963, 2002.

[30] W. Nejdl, B. Wolf, C. Qu, S. Decker, M. Sintek, A. Naeve, M. Nilsson, M. Palmér, and T. Risch. Edutella: a p2p networking infrastructure based on rdf. In *WWW*, pages 604–615, 2002.

[31] E. Oren, S. Kotoulas, G. Anadiotis, R. Siebes, A. ten Teije, and F. van Harmelen. Marvin: Distributed reasoning over large-scale semantic web data. *J. Web Sem.*, 7(4):305–316, 2009.

[32] Z. Pan and J. Heflin. Dldb: Extending relational databases to support semantic web queries. In *PSSS*, 2003.

[33] Z. Pan, X. Zhang, and J. Heflin. Dldb2: A scalable multi-perspective semantic web repository. In *Web Intelligence*, pages 489–495, 2008.

[34] D. Peleg. Informative labeling schemes for graphs. *Theor. Comput. Sci.*, 340(3):577–593, 2005.

[35] A. Schlicht and H. Stuckenschmidt. Distributed resolution for alc. In *Description Logics*, 2008.

[36] L. Serafini and A. Tamilin. Drago: Distributed reasoning architecture for the semantic web. In *ESWC*, pages 361–376, 2005.

[37] A. K. Tsakalidis. Maintaining order in a generalized linked list. *Acta Inf.*, 21:101–112, 1984.

[38] G. Tsatsanifos, D. Sacharidis, and T. Sellis. Midas: Multi-attribute indexing for distributed architecture systems.

[39] R. Volz, D. Oberle, S. Staab, and B. Motik. Kaon server - a semantic web management system. In *WWW (Alternate Paper Tracks)*, 2003.

[40] C. Weiss, P. Karras, and A. Bernstein. Hexastore: sextuple indexing for semantic web data management. *PVLDB*, 1(1):1008–1019, 2008.

[41] K. Wilkinson, C. Sayers, H. A. Kuno, and D. Reynolds. Efficient rdf storage and retrieval in jena2. In *SWDB*, pages 131–150, 2003.

[42] K. Wilkinson and K. Wilkinson. Jena property table implementation. In *SSWS*, 2006.