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DIAERESIS: RDF Data Partitioning and Query Processing on SPARK

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Abstract. The explosion of the web and the abundance of linked data demand effective and efficient methods for storage, management, and querying. Apache Spark is one of the most widely used engines for big data processing, with more and more systems adopting it for efficient query answering. Existing approaches exploiting Spark for querying RDF data, adopt partitioning techniques for reducing the data that need to be accessed in order to improve efficiency. However, simplistic data partitioning fails, on one hand, to minimize data access and on the other hand to group data usually queried together. This is translated into limited improvement in terms of efficiency in query answering. In this paper, we present DIAERESIS, a novel platform that accepts as input an RDF dataset and effectively partitions it, minimizing data access and improving query answering efficiency. To achieve this, DIAERESIS first identifies the top-k most important schema nodes, i.e., the most important classes, as centroids and distributes the other schema nodes to the centroid they mostly depend on. Then, it allocates the corresponding instance nodes to the schema nodes they are instantiated under. Our algorithm enables fine-tuning of data distribution, significantly reducing data access for query answering. We experimentally evaluate our approach using both synthetic and real workloads, strictly dominating existing state-of-the-art, showing that we improve query answering in several cases by orders of magnitude.

Keywords: RDF, data partitioning, Spark, query answering

1. Introduction

The prevalence of Linked Open Data, and the explosion of available information on the Web, have led to an enormous amount of widely available RDF datasets [8]. To store, manage and query these ever increasing RDF data, many RDF stores and SPARQL engines have been developed [3] whereas in many cases other non RDF specific big data infrastructures have been leveraged for query processing on RDF knowledge graphs. Apache Spark is a big-data management engine, with an ever increasing interest in using it for efficient query answering over RDF data [2]. The platform uses in-memory data structures that can be used to store RDF data, offering increased efficiency, and enabling effective, distributed query answering.

The problem. The data layout plays an important role for efficient query answering in a distributed environment. The obvious way of using Spark for RDF query answering is to store all triples as a single large file in HDFS, loaded at query answering in the main memory search for the corresponding answers. However, using this approach, query answering usually needs to access a large volume of data for retrieving the required information. This results in poor query answering performance.

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The elusive solution: simplified horizontal and vertical partitioning. As this problem has already been recognized by the research community, many approaches have responded, by offering solutions that partition data, trying to minimize data access when answering SPARQL queries [2]. To achieve this, most of the Spark-based RDF query answering approaches exploit simplistic horizontal and/or vertical partitioning of triples (e.g. hashing triples based on their subject, creating a partition for every predicate, precomputing and storing one join step). The idea behind all those approaches is that they try to minimize data access and to collocate data that are usually queried together. However, although the aforementioned partitioning techniques are successful in optimizing fragments or certain categories of SPARQL queries, they fail to have a wider impact on all query categories, resulting in poor overall performance improvement for query answering.

Our solution. To address these problems, we introduce DIAERESIS, showing how to effectively partition data, balancing data distribution among partitions and reducing the size of the data accessed for query answering and thus, drastically improve query answering efficiency. The core idea is to identify important schema nodes as centroids, then to distribute the other nodes to the centroid that they mostly depend on, and, finally, assign the instance nodes to the corresponding schema nodes. Finally, a vertical sub-partinioning step further minimizes the accessed data during query answering.

More specifically our contributions are the following:

- We introduce DIAERESIS, a novel platform that accepts as input an RDF dataset, and effectively partitions data, by significantly reducing data access during query answering.
- We view an RDF dataset as two distinct and interconnected graphs, i.e. the schema and the instance graph. Since query formulation is usually based on the schema, we primarily generate partitions based on schema. To do so, we first select the top-k most important schema nodes as centroids and assign the rest of the schema nodes to the centroid they mostly depend on. Then, individuals are instantiated under the corresponding schema nodes producing the final dataset partitions.
- To identify the most important nodes, we use the notion of *betweenness* as it has been shown to effectively identify the most frequently queried nodes [22], adapting it to consider the individual characteristics of the RDF dataset as well. Then, to assign the rest of the schema nodes to a centroid, we define the notion of *dependence*. Using dependence, we assign each schema node to the partition with the maximum dependence between that node and the corresponding partition's centroid. In addition, the algorithm tries to balance the distribution of data in the available partitions. This method in essence tries to put together the nodes that are usually queried together, while maintaining a balanced data distribution.
- Based on the aforementioned partitioning method, we implement a vertical sub-partitioning scheme further splitting instances in the partition into vertical partitions - one for each predicate, further reducing data access for query answering. An indexing scheme on top ensures quick identification of the location of the queried data.
- Then, we provide a query execution module, that accepts a SPARQL query and exploits the generated indexes along with data statistics for query formulation and optimization.
- Finally, we perform an extensive evaluation using both synthetic and real workloads, showing that our method strictly outperforms existing approaches in terms of efficiency for query answering and size of data loaded for answering these queries. In several cases, we improve query answering by orders of magnitude when compared to competing methods.

Overall in this paper we present a new partitioning technique for SPARK, which has been designed specifically for improving query answering efficiency by reducing data visited at query answering. We experimentally show that indeed our approach leads to superior query answering performance. The remaining of this paper is structured as follows: In Section 2, we elaborate on preliminaries, and in Section 3, we present related work. We define the metrics used for partitioning in Section 4. In Section 5 we describe our methodology for partitioning and query answering. Section 6 presents our experimental evaluation, and finally Section 7 concludes the paper.

2. Preliminaries

2.1. RDF & RDF Schema

In this work, we focus on datasets expressed in RDF, as RDF is among the widely-used standards for publishing and representing data on the Web. Those datasets are based on triples of the form of $(s\ p\ o)$, which record that $subject\ s$ is related to $object\ o$ via property p. Formally, representation of RDF data is based on three disjoint and infinite sets of resources, namely: URIs (U), literals (L) and blank nodes (B). A key concept for RDF is that of URIs or Unique Resource Identifiers; these can be used in either of the s, p and o positions to uniquely refer to some entity, relationship, or concept. Literals (constants) are also allowed in the o position. Blank nodes in RDF allow representing a form of incomplete information for unknown constants or URIs. As such, a triple is a tuple $(s\ p\ o)$ from $(U \cup B) \times U \times (U \cup L \cup B)$.

In order to impose typing on resources, we consider three disjoint sets of resources: classes $(C \subseteq U \cup B)$, properties $(P \subseteq U)$, and individuals $(I \subseteq U \cup B)$. The set C includes all classes and the set P includes all properties. The set I includes all individuals. Additionally, RDF datasets have attached semantics through RDFS. RDFS is the accompanying W3C proposal of a schema language for RDF. It is used to describe classes and relationships between classes (such as inheritance). Further, it allows specifying properties, and relationships that may hold between pairs of properties, or between a class and a property. RDFS statements are also represented by triples.

An RDF graph can be represented as a labeled directed graph. Given a set A of labels, we denote by $G = (V, E)$ an A-edge labeled directed graph whose vertices are V, and whose edges are $E \subseteq V \times A \times V$. In the graph nodes represent subjects or objects and labeled directed edges represent properties.

In this work, we separate between the schema and the instances of an RDF dataset, represented in separate graphs (G_S and G_I, respectively). The schema graph contains all triples of the RDF Schema, which consists of all classes and the properties the classes are associated with (via the properties domain/range specification); multiple domains/ranges per property are allowed, by having the property URI be a label on the edge, via a labeling function λ, rather than the edge itself. The instance graph contains all individuals, and the instantiations of schema properties; the labeling function λ applies here as well for the same reasons. In addition, to state that a resource r is of a type τ, a triple of the form "r rdf:type τ" is used. Since this triple is about the resource r (not about the class τ), it is viewed as a data triple.

Formally:

Definition 1. ***(RDF dataset)*** *An RDF dataset is a tuple $V =< G_S, G_I, \lambda, \tau_c >$, where:*

- *The schema graph G_S is a labeled directed graph $G_S = (V_S, E_S)$ such that V_S, E_S are the nodes and edges of G_S, respectively, and $V_S \subseteq C \cup L$.*
- *The instance graph G_I is a labeled directed graph $G_I = (V_I, E_I)$ such that V_I, E_I are the nodes and edges of G_I, respectively, and $V_I \subseteq I \cup L$.*
- *A labeling function $\lambda : E_S \cup E_I \mapsto 2^P$ determines the property URI that each edge corresponds to (properties with multiple domains/ranges may appear in more than one edge).*
- *A function $\tau_c : I \mapsto 2^C$ associating each individual with the classes that it is instantiated under.*

Next, we denote as $p(v_1, v_2)$, an edge $e \in E_S$ in G_S (where $v_1, v_2 \in V_S$), or in G_I (where $v_1, v_2 \in V_I$), from node v_1 to node v_2 such that $\lambda(e) = p$.

Definition 2. ***(Schema and Instance Node)*** *Given an RDF dataset $V =< G_S, G_I, \lambda, \tau_c >$, $G_S = (V_S, E_S)$, $G_I = (V_I, E_I)$ we call schema node a node $v \in V_S$, and instance node a node $u \in I \cap V_I$.*

Moreover, we use $|v|$, where $v \in C \cap V_S$, to denote the number of instances that belong to the class node v in the dataset. Next, we define a path in V_S.

Definition 3. ***(Path)*** *A path from $v_1 \in V_S$ to $v_2 \in V_S$, i.e. $path(v_1, v_2)$, is the finite sequence of edges, which connect a sequence of nodes, starting from the node v_1 and ending in the node v_2.*

Moreover, we denote with $|path(v_1, v_2)|$ the length of the path, i.e., the number of edges in it. In our approach, we consider all instance triples of the RDF dataset to be fully described by the schema graph. Similarly to other works in the area [7], if a dataset is not fully described by the schema graph, we use a schema discovery tool to infer it. Specifically, in our case, we use Hint [17], our state-of-the-art schema discovery tool, exploiting LSH and clustering techniques for efficiently and effectively discovering the corresponding schema graph.

2.2. Querying

For querying RDF datasets, W3C has proposed SPARQL [1]. Essentially, SPARQL is a graph-matching language. A SPARQL query Q defines a graph pattern P that is matched against an RDF graph G. This is done by replacing the variables in P with elements of G such that the resulting graph is contained in G. The most basic notion in SPARQL is a triple pattern $tp = (s', p', o')$ with $s' \in \{s, ?s\}$, $p' \in \{p, ?p\}$, and $o' \in \{o, ?o\}$, i.e., a triple where every part is either an RDF term or a variable. A set of triple patterns forms a basic graph pattern (BGP). Two example BGP queries are presented in the sequel, the first one asking for the persons with their advisors and persons that those advisors teach, whereas the second one asks for the persons with their advisors and also the courses that those persons take.

```
Q1: SELECT * WHERE{?x advisor ?w. ?w teacherOf ?y.}
Q2: SELECT * WHERE{?x advisor ?w. ?x takesCourse ?y.}
```

The result of a BGP is a bag of solution mappings where a solution mapping is a partial function from variable names to RDF terms. On top of these basic patterns, SPARQL also provides more relational-style operators like *optional* and *filter* to further process and combine the resulting mappings. Nevertheless, it is commonly acknowledged that the most important aspect for efficienq SPARQL query answering is the efficient evaluation of the BGPs [25], on which we focus on this paper, leaving the remaining fragments for future work.

Common types of BGP queries are *star* queries and *chain* queries. *Star* queries are the ones characterized by triple patterns sharing the same variable on the subject position. Q2 of the previous example is a star query. On the other hand, *chain* queries are formulated using triple patterns where the object variable in one triple pattern appears as a subject in the other, and so on. For example, the join variable can be on the object position in one triple pattern, and on the subject position in the other, as shown in Q1. *Snowflake* queries are combinations of several star shapes connected by typically short paths, whereas as *complex*, we characterize queries that combine the aforementioned query types.

2.3. Apache Spark

Apache Spark [29] is an in-memory distributed computing platform designed for large-scale data processing. Spark proposes two higher-level data access models, GraphX and Spark SQL, for processing structured and semi-structured data. Spark SQL [4] is Spark's interface that enables querying data using SQL.

It also provides a naive query optimizer for improving query execution. The naive optimizer pushes down in the execution tree the filtering conditions and additionally performs join reordering based on the statistics of the joined tables. However, as we will explain in the sequel in many cases the optimizer was failing to return an optimal execution plan and we implemented our own procedure.

Applying Spark SQL on RDF requires a suitable storage format for triples and a translation procedure from SPARQL to SQL. The storage format for RDF triples is straightforward and usually refers to a three-column table $(s\ p\ o)$ stored in the HDFS, using HIVE or parquet format. Spark GraphX [28] is a library enabling graph processing by using the property graph as its graph data model, i.e. a directed multigraph with user-defined objects attached to each vertex and edge. A directed multigraph is a directed graph with potentially multiple parallel edges sharing the same source and destination vertex.

Spark by default implements no indexing at all. It loads the entire data file in main memory splitting then the work into multiple map-reduce tasks.

3. Related Work

In the past, many approaches have focused on efficiently answering SPARQL queries for RDF graphs. Based on the storage layout they adopt, a recent survey [7], classifies them to a) the ones using a large table storing all triples (e.g., Virtuoso, DistRDF); b) the ones that use a property table (e.g., Sempala, DB2RDF) that usually contains one column to store the subject (i.e. a resource) and a number of columns to store the corresponding properties of the given subject; c) approaches that partition vertically the triples (e.g., CliqueSquare, Prost, WORQ) adopting two column tables for the representation of triples; d) the ones being graph based (e.g., TRiaD, Coral); d) and the ones adopting custom layouts for data placement (e.g. Allegrograph, SHARD, H2RDF). For a complete view on the systems currently available in the domain the interested reader is forwarded to the relevant surveys [3, 7].

As in this work we specifically focus on moving a step forward the solutions on top of Spark, in the remainder of this section we only focus on approaches that try to exploit Spark for efficient query answering over RDF datasets. A preliminary survey on that area is also available in the domain [2].

Using default Spark policy. Many of the works available for Spark, adopt the naive policy of storing the entire dataset in a big file and focusing on the query optimization step. P-Spar(k)ql [11] tries to optimize and parallelize the query plan using GraphX, whereas Bahrami et al. [5] use GraphFrames for pruning the query-specific search space. S2X [24] is another approach that uses GraphX, where the basic idea is that every vertex in the graph stores the variables of a query where it is a possible candidate for and query evaluation proceeds by matching all triple patterns of a BGP independently, and then exchange messages between adjacent vertices to validate the match candidates. Although DIAERESIS also implements query optimization based on data statistics, our main contribution lies in the intelligent data partitioning scheme implemented.

Implementing partitioning schemes. HAQWA [10] was the first approach that tried to process RDF data on top of Apache Spark. Data allocation is performed based on a two-step procedure. In the first step, hash-based partitioning is executed on the triple subjects. This fragmentation ensures that star-shaped queries can be computed locally, but no guarantees are provided for other query types. In the second step, data are allocated according to the analysis of frequent queries executed over the dataset. At query time, the system decomposes a query pattern into a set of local sub-queries that can be locally evaluated.

In SPARQLGX [12], RDF datasets are vertically partitioned. As such, a triple *(s p o)* is stored in a file named *p* whose content keeps only *s* and *o* entries. By following this approach, the memory footprint is reduced and the response time is minimized when queries have bound predicates. As an optimization in query execution, triple patterns are reordered based on data statistics.

S2RDF [25] presents an extended version of the classic vertical partitioning technique, called ExtVP. Each ExtVP table is a set of sub-tables corresponding to a vertical partition (VP) table. The sub-tables are generated by using right outer joins between VP tables. More specifically, the partitioner pre-computes semi-join reductions for subject-subject (SS), object-subject (OS) and subject-object (SO). For query processing, S2RDF uses Jena ARQ to transform a SPARQL query to an algebra tree and then it traverses this tree to produce a Spark SQL query. As an optimization, an algorithm is used that reorders sub-query execution, based on the table size and the number of bound variables.

Another work that is focusing on query processing is [21] that analyzes two distributed join algorithms, partitioned join and broadcast join offering a hybrid strategy. More specifically, the authors exploit a data partitioning scheme that hashes triples, based on their subject, to avoid useless data transfer and use compression to reduce the data access cost for self-join operations.

PRoST [9] stores RDF data twice, partitioned in two different ways, both as Vertical Partitioning and Property Tables. It takes the advantage of both storage techniques with the cost of additional storage overhead. Specifically, the advantage of the property tables, when compared to the vertical partitioning, is that some joins can be avoided when some of the triple patterns in a query share the same subject -star queries. It does not maintain any additional indexes. SPARQL queries are translated into Join Tree format in which every node represents the VP table or PT's subquery's patterns. It makes use of a statistics-based query optimizer. The authors of PRoST report/show that PRoST achieves similar results to S2RDF. More precisely, S2RDF outperforms in all query categories since its average execution times are better in all categories. In most of the cases (query categories), S2RDF is three times faster than PRoST.

Table 1
Characteristics of the Spark-based RDF systems.

System	**Query Processing**	**Partitioning**
S2X [24]	Graph Iterations	Default
Bahrami et al. [5]	Pruning Query Space	Default
P-Spar(k)ql [11]	Parallel Query Plan	Default
HAQWA [10]	RDD API	Hash / Query Aware
SPARQLGX [12]	RDD API	Vertical
S2RDF [25]	Spark SQL	Extended Vertical
Naacke et. al [21]	Hybrid	Hash-sbj
WORQ [19]	Dataset API	Workload Join Keys
S3QLRDF [14, 15]	Spark SQL	Subset Property Table & Vertical
DIAERESIS	**Spark SQL**	**Dependency Aware + Vertical**

More recently, WORQ [19] presents a workload-driven partitioning of RDF triples. The approach tries to minimize the network shuffling overhead based on the query workload. It is based on bloom joins using bloom filters, to determine if an entry in one partition can be joined with an entry in a different one. Further, the bloom filters used for the join attributes, are able to filter the rows in the involved partitions. Then, the intermediate results are materialized as a reduction for that specific join pattern. The reductions can be computed in an online fashion and can be further cached in order to boost query performance. However, this technique focuses on known query workloads that share the same query patterns. As such, it partitions the data triples by the join attributes of each subquery received so far.

Finally, Hassan & Bansal [14] propose a relational partitioning scheme called subset property table that partitions property tables into subsets of tables to minimize query input and join operations. In addition, they combine subset property tables with vertical partitions to further reduce access to data. For query processing, an optimization step is performed based on the number of bound values in the triple queries and the statistics of the input dataset.

Comparison with DIAERESIS. The general goal of all approaches mentioned before is to improve query performance by exploiting in-memory data parallelization. To this purpose, most of the works end-up using simplistic vertical or horizontal partitioning schemes. However, simplistic partitioning schemes do not succeed to reduce significantly the data access on a query and to exploit the fact that usually many nodes are queried together. This has been recognized by latest works in the area, such as S2RDF [25], WORQ[19] and S3QLRDF [14, 15]. WORQ is based on known workloads in order to keep together nodes that are frequently accessed together, whereas DIAERESIS is workload agnostic and works independently of the available workload. S2RDF keeps join reductions up to a data size threshold, which is simple but not effective enough and can easily lead to a large storage overhead. On the other hand, S3QLRDF approach is optimized for star queries, in essence, pre-computing large fragments of star queries. However, the result tables are sparse containing many NULL values which can on one hand significantly increase data size and on the other hand introduce delays in query evaluation (in many complex queries as shown in [14] S3QLRDF falls behind S2RDF).

To the best of our knowledge, DIAERESIS is the only Spark-based system able to effectively collocate data that are frequently accessed together, minimizing data access, keeping a balanced distribution, while boosting query answering performance, without requiring the knowledge of the query workload. An overview of all aforementioned approaches is shown in Table 1, showing the query processing technology and the partitioning method adopted. In addition, we added DIAERESIS in the last line of the table, to be able to directly compare other approaches with it.

4. Identifying Centroids & Dependence (First-Level Partition)

To achieve efficient query answering, distributed systems attempt to parallelize the computation effort required. Instead of accessing the entire dataset, targeting the specific data items required for each computational node can further optimize query answering efficiency. Among others, recent approaches try to accomplish this by employing data partitioning methods in order to minimize data access at querying, or precomputing intermediate results so as

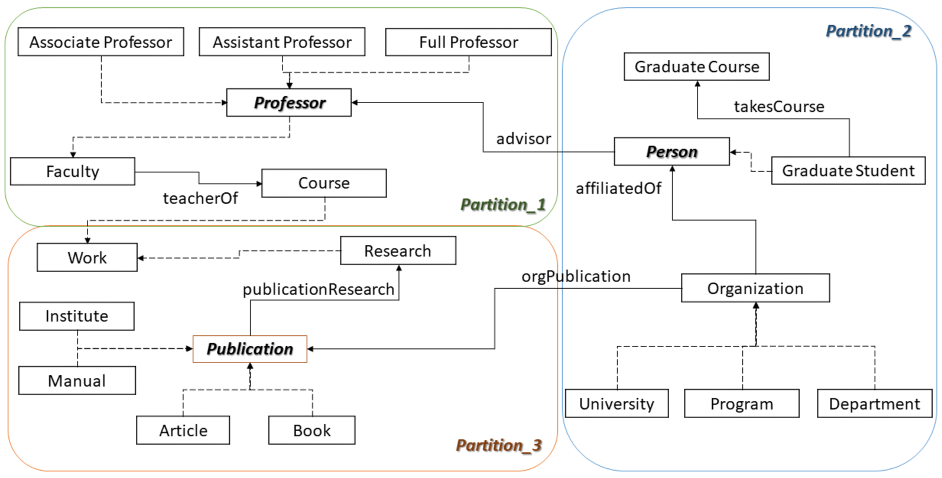


Fig. 1. Dependence aware partitioning example for LUBM subset.

to reduce the number of computational tasks. In this work we focus on the former, providing a highly effective data partitioning technique.

Since query formulation is usually based on schema information, our idea for partitioning the data starts there. The schema graph is split into sub-graphs, i.e., first-level partitions. Our partition strategy follows the K-Medoids method [18], selecting the most important schema nodes as centroids of the partitions, and assigning the rest of the schema nodes to the centroid they mainly depend on in order to construct the partitions. Then we assign the instances in the instance graph in the partition that they are instantiated under.

To identify the most important schema nodes, we exploit the Betweenness Centrality in combination with the number of instances allocated to a specific schema node. Then, we define *dependence*, which is used for assigning the remaining schema nodes (and the corresponding instances) to the appropriate centroid in order to formulate the partitions.

Example 4.1. *As a running example, Figure 1 presents a fragment from the LUBM ontology and shows the three partitions that are formulated ($k = 3$). The first step is to select the three most important schema nodes (the ones in boldface) as centrdois and then to assign to each centroid, the schema nodes that depend on it. Based on this partitioning of the schema graph, the individuals are assigned to the partitions that they are instantiated under. In the sequel we present in detail the methods for identifying the most important schema nodes and for calculating dependence.*

4.1. Importance Measure for Identifying Centroids in the Schema Graph

Many measures have been produced for assessing the importance of the nodes in a knowledge graph and various notions of importance exist. When trying to group nodes from an RDF dataset, that are frequently queried together, according to our past exploration on centrality measures, the Betweenness Centrality (*BC*) has already shown an excellent performance [22]. As the Betweenness Centrality was originally developed for generic graphs, approaches focusing on the schema graph of RDF datasets, i.e. [27], adapted this measure by combing it with the number of instances that belong to a schema node. Following the same idea, we initially identify the k most central schema nodes in a schema graph, combining Betweenness Centrality with the number of their instances, calculating the Importance Measure (IM) for each schema node.

In detail, the Betweenness Centrality of a schema node is equal to the number of the shortest paths from all schema nodes to all others that pass through that schema node. Formally:

Definition 4. ***(Betweenness Centrality)*** *Let $G_S = (V_S, E_S)$ be an RDF schema graph with V_S nodes and E_S edges. The Betweenness of a node $v \in V_S$ is defined as:*

$$BC(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{1}$$

where σ_{st} is the total number of shortest paths from node s to node t and $\sigma_{st}(v)$ is the number of those paths that pass through v.

Calculating the Betweenness for all nodes in a graph requires the computation of the shortest paths between all pairs of nodes. The complexity of the Brandes algorithm [6] for calculating it, is $O(|V_S| \times |E_S|)$ for an RDF schema graph $G_S = (V_S, E_S)$.

As data distribution should also play a key role in estimating the importance of a schema node [27], we combine the value of BC, with the number of instances of the corresponding schema node in order to assess its importance. To do so, we normalize first the BC value of each schema node v on a scale between 0 and 1 using the following equation:

$$normal(BC(v)) = \frac{BC(v) - \min(BC(u))}{\max(BC(u)) - \min(BC(u))}, \quad u \in V_S \tag{2}$$

$BC(v)$ is the Betweenness Centrality value of a node $v \in V_S$, $min(BC(u))$ and $max(BC(u))$ are the minimum and the maximum BC value respectively in the schema graph. Similarly, we normalize the number of instances for each schema node v:

$$normalInst(v) = \frac{|v| - \min(|u|)}{\max(|u|) - \min(|u|)}, \quad u \in V_S \tag{3}$$

As such, the importance (IM) of each schema node is defined as the sum of the normalized values of BC and the number of instances.

Definition 5. ***(Importance Measure)*** *Let $V =< G_S, G_I, \lambda, \tau_c >$ be an RDF Dataset, $G_S = (V_S, E_S)$. The Importance Measure of a schema node $v \in V_S$, i.e., the $IM(v)$, is defined as:*

$$IM(v) = normal(BC(v)) + normalInst(v)) \tag{4}$$

For calculating the number of instances of all nodes, we should visit all instances once, and as such the complexity of this part is $O(|V_I|)$. Overall, the complexity for calculating IM for all schema nodes in an RDF dataset is $O(|V_I|) + O(|V_S| \times |E_S|)$.

4.2. *Assigning Nodes to Centroids using Dependence*

Having a way to assess the importance of the schema nodes using IM, we are next interested in identifying to which partition, the remaining schema nodes should be assigned. In order to define how dependent two schema nodes are, we introduce the Dependence measure.

Our first idea in this direction comes from the classical information theory, where infrequent words are more informative than frequent ones. The idea is also widely used in the field of instance matching [26]. The basic hypothesis here is that the greater the influence of a property on identifying a corresponding node, the fewer times the range of the property is repeated. According to this idea, we define Cardinality Closeness (CC) as follows:

Definition 6. ***(Cardinality Closeness of two adjacent schema nodes)*** *Let $V =< G_S, G_I, \lambda, \tau_c >$ be an RDF dataset, $G_S = (V_S, E_S)$ and $G_I = (V_I, E_I)$. Let $v_k, v_m \in V_S$ be two adjacent schema nodes connected through an edge e where $\lambda(e) = p$. The Cardinality Closeness of $p(v_k, v_m)$, namely the $CC(p(v_k, v_m))$, is defined as:*

$$CC(p(v_k, v_m)) = \begin{cases} \frac{1+|V_S|}{|V_S|}, & when\ |v_k| = 0 \\ \frac{1+|V_S|}{|V_S|} + \frac{DistinctObjects(p(v_k,v_m))}{|v_k|}, & when\ |v_k| \neq 0 \end{cases} \tag{5}$$

where $|V_S|$ is the total number of nodes in the schema graph, and $DistinctObjects(p(v_k, v_m))$ is the number of distinct instances of v_m connected with the instances of v_k through p.

The constant $\frac{1+|V_S|}{|V_S|}$ is added in order to have a minimum value for CC in case of no available instances.

Example 4.2. *Assume for example the schema nodes Person, $Professor$ connected through the property advisor. Moreover, there are instances of the theses two schema nodes connected through the same property. Assume that there are ten instances of Person that are connected through the property advisor with only two distinct instances of $Professor$. In essence, only two professors advise 10 persons. We would like to calculate $CC(advisor(Professor, Person))$ knowing that the total number of schema nodes is $|V_S| = 20$, $DistinctObjects(advisor(Professor, Person)) = 2$ that are connected with the ten instances of Person. As such $CC(advisor(Professor, Person)) = ((1 + 20)/20) + 2/10 = 1.05 + 0.2 = 1.25$.*

Having defined the Cardinality Closeness of two adjacent schema nodes, we proceed further to identify the dependence. As such, we calculate the Dependence between two schema nodes, combining their Cardinality closeness, the IM of the schema nodes and the number of edges between them. Formally:

Definition 7. ***(Dependence between two schema nodes)*** *Let $V =< G_S, G_I, \lambda, \tau_c >$ be an RDF dataset with $G_S = (V_S, E_S)$ be the RDF schema graph with V_S schema nodes. The dependence between two schema nodes v_s, $v_e \in V_S$, i.e. $Dependence(v_s, v_e)$, is defined as:*

$$Dependence(v_s, v_e) = \frac{1}{|path(v_s, v_e)|^2} * \left(IM(v_s) - \sum_{i=s+1}^{e} \frac{IM(v_i)}{CC(p(v_{i-1}, v_i))} \right) \tag{6}$$

Intuitively, as we move away from a node, the dependence becomes smaller by calculating the differences of IM across the path with the minimum distance in the graph. We further penalize dependence, by dividing using the length of the path of the two nodes. The highest the dependence of a path, the more appropriate the first node characterizes the final node of the path, i.e., the final node of the path highly depends on the first one.

Example 4.3. *Note also, that $Dependence(v_s, v_e)$ is different than $Dependence(v_e, v_s)$. For example, Dependence(Publication, Book) $\geqslant$ Dependence(Book, Publication). This is reasonable, as the dependence of a more important node toward a less important one is higher than the other way around, although they share the same cardinality closeness.*

5. DIAERESIS Partitioning and Query Answering

Figure 2 presents an overview of the DIAERESIS architecture, along with its internal components. Starting from the left side of the figure, the input RDF dataset is fed to the DIAERESIS Partitioner in order to partition it. For each one of the generated first-level partitions, vertical partitions are created and stored in the HDFS. Along with the partitions and vertical partitions, the necessary indexes are produced as well. Based on the available partitioning scheme, the DIAERESIS Query Processor receives and executes input SPARQL queries exploiting the available indexes. We have to note that although schema information is used to generate the first-level partitions, in the sequel the entire graph is stored in the system including both the instance and the schema graph. In the sequel, we will analyze in detail the building blocks of the system.

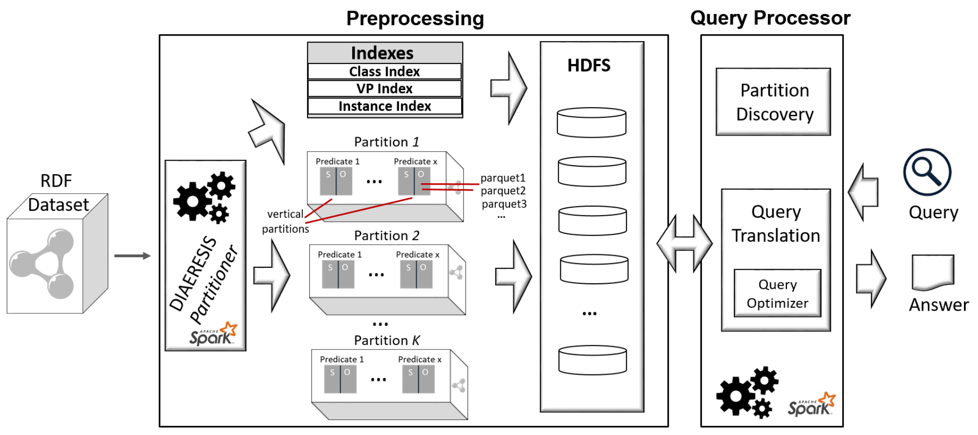


Fig. 2. DIAERESIS overview.

5.1. *The DIAERESIS Partitioner*

This component undertakes the task of partitioning the input RDF dataset, initially into first-level partitions, then into vertical partitions, and finally to construct the corresponding indexes to be used for query answering. Specifically, the Partitioner uses the Dependency Aware Partitioning (DAP) algorithm in order to construct the first-level partitions of data focusing on the structure of the RDF dataset and the dependence between the schema nodes. In the sequel, based on this first-level partitioning, instances are assigned to the various partitions, and the vertical partitions and the corresponding indexes are created.

5.1.1. *Dependency Aware Partitioning Algorithm*

The Dependency Aware Partitioning (DAP) algorithm, given an RDF dataset V and a number of partitions k, splits the input dataset into k first-level partitions. The partitioning starts from the schema and then the instances follow. The algorithm splits the schema graph into sub-graphs, called first-level partitions, and then assigns the individuals in the partitions that they are instantiated under. Specifically, it uses the *Importance Measure (IM)* for identifying the partition's centroids, and the *Dependence* for assigning nodes to the centroids where they belong. Depending on the characteristics of the individual dataset (e.g. it might be the case that most of the instances fall under just a few schema nodes), data might be accumulated into one partition, leading to data access overhead at query answering, as large fragments of data should be examined. DAP tries to achieve a balanced data distribution by reducing data access and maintaining a low replication factor.

The algorithm is shown in Algorithm 1 and starts by calculating the importance of all schema nodes (lines 1-3) based on the importance measure (IM) defined in Section 4.1, combining the betweenness centrality and the number of instances for the various schema nodes. Then, the k most important schema nodes are selected, to be used as centroids in the formulated partitions (line 4). The selected nodes are assigned to the corresponding partitions (lines 5-7). Next, the algorithm examines the remaining schema nodes in order to determine to which partition they should be placed based on their dependency on the partitions' central nodes.

Initially, for each schema node, the dependence between the selected node and all centroids is calculated by the *selectPartionBalanced* procedure (line 9). However, in order to achieve a more balanced data distribution, the *selectPartionBalanced* procedure calculates a space-bound for all partitions based on the number of triples in the dataset and the number of partitions k. Until this bound is reached each partition is filled with the most dependent schema nodes. Afterward, as this space bound is reached for a partition, the procedure selects the next partition with enough space that maximizes the dependence to allocate the selected schema node. Note that for calculating the space available, the schema nodes along with the number of instances available for that nodes are assessed.

However, we are not only interested in placing the selected schema node to the identified partition, but we also assign to that partition, all schema nodes contained in the path which connects the schema node with the selected centroid (line 10).

Algorithm 1 DAP(V, k)

```
Input: An RDF dataset $V =< G_S, G_I, \lambda, \tau_c >$, the number of partitions $k$
Output: A set of partitions $V_1$, ..., $V_k$.
 1: for each schema node $v_i \in G_S$ do
 2:     $IM_{v_i} = caclulateImportance(G_S, v_i)$
 3: end for
 4: $top_k = selectTopKNodes(IM, k)$
 5: for each schema node $v_i \in top_k$ do
 6:     $V_i = V_i \cup v_i$
 7: end for
 8: for each schema node $v_i \in G_S, v_i \notin top_k$ do
 9:     $j = selectPartitionBalanced(v_i, top_k, G_S)$
10:     $V_j = V_J \cup schemaNodesInPathWithMaxDependence(v_i, v_j)$
11: end for
12: for each schema node $v_i \in V_j, 1 \leqslant j \leqslant k$ do
13:     $V_j = V_j \cup getNeighborsAndProperties(v_i)$
14:     $V_j = V_j \cup instances(v_i)$
15: end for
16: return $V_1$, ..., $V_k$
```

Then, we add the direct neighbors of all schema nodes in each partition along with the properties that connect them (line 13). Finally, instances are added to the schema nodes they are instantiated under (line 14). The algorithm terminates by returning the generated list of first-level partitions (line 16) containing the corresponding triples that their subject and object are located in the specific partitions.

Note that the aforementioned algorithm introduces replication (lines 12-15) that comes from the edges/properties that connect the nodes located in the different partitions. Specifically, besides allocating a schema node and the corresponding instances to a specific partition, it also includes its direct neighbors that might originally belong to a different partition. This step reduces access to different partitions for joins on the specific node.

Complexity. To identify the complexity of the algorithm, we should first identify the complexity of the various components involved. Assume $|V_S|$ is the number of schema nodes, $|E_S|$ is the number of edges of the schema graph, $|V_I|$ is the number of instances, and $|E_I|$ are their connections. For identifying the cardinality closeness of the edges, we should visit all instances' edges once, hence the complexity of this step is $O(|E_I|)$. Then, for calculating the betweenness centrality for all schema nodes, we use a Spark implementation [16] with complexity $O(V_S)$. Next, we have to sort all nodes according to their IM and select the top_k ones with cost $O(|V_S| \times log|V_S|)$. To calculate the dependence of each node, we should visit each node once per selected node ($O(k \times |V_S|)$), whereas to identify the path maximizing the dependence, we use the weighted Dijkstra algorithm with cost $O(|V_S|^2)$. Finally, we should check once all instances for identifying the partitions to be assigned with cost $O(|E_I|)$. Overall, the time complexity of the algorithm is polynomial $O(|E_I| + |E_S| + |V_S|) + O(|V_S| \times log|V_S|) + O(k \times |V_S|) + O(|V_S|^2) + O(|E_I|) \leqslant O(|V_S|^2 + |E_S| + |E_I|)$.

5.1.2. *Vertical Partitioning*

Besides first-level partitioning, the DIAERESIS Partitioner also implements vertical sub-partitioning to further reduce the size of the data touched. Thus, it splits the triples of each partition produced by the DAP algorithm, into multiple vertical partitions, one per predicate, generating one file per predicate. Each vertical partition contains the subjects and the objects for a single predicate, enabling at query time a more fine-grained selection of data that are usually queried together. The vertical partitions are stored as parquet files in HDFS (see Figure 2). A direct effect of this choice is that when looking for a specific predicate, we do not need to access the entire data of the first-level partition storing this predicate, but only the specific vertical partition with the related predicate. As we shall see in the sequel, this technique minimizes data access, leading to faster query execution times.

5.1.3. *Number of First-Level Partitions*

As already presented in Section 5.1.1, the DAP algorithm receives as an input the number of first-level partitions (k). This determines data placement and has a direct impact on the data access for query evaluation and the replication factor.

According to the DAP algorithm, as the number of first-level partitions increases, the average data located in each partition is reduced or at least stays the same since there are more partitions for data to be distributed in. Further, the data in the vertical sub-partitions decreases as well.

Theorem 1. *Let $V =< G_S, G_I, \lambda, \tau_c >$ be an RDF dataset and $G_S = (V_S, E_S)$. Let also $DAP(V, k) = V_1, ..., V_k$, and $triples(V_i)$ be the number of triples in the partition i, $1 \leqslant i \leqslant k$. Then it holds that:*

$$\sum_{i=1}^{k} triples(V_i) \leqslant \sum_{j=1}^{k+1} triples(V_j) \tag{7}$$

where $V_i \in DAP(V, k)$, $V_j \in DAP(V, k+1)$, and $k \leqslant |V_S|$.

Proof. The theorem is immediately proved by construction (Lines 12-15 of the algorithm) as increasing the k will result in more schema nodes being split between the increased number of partitions, replicating all instances that span across the partitions. □

The above theorem tells us that as the number of partitions increases, the triples in the dataset might increase as well due to the replication of the triples that have domain/range in different partitions. Interestingly:

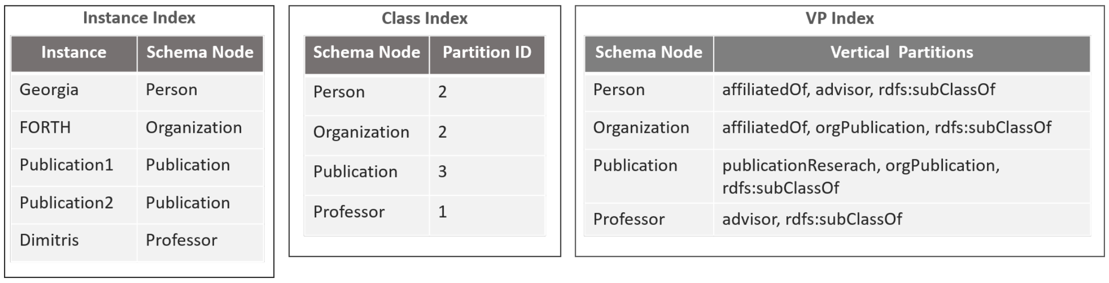
Theorem 2. *Let $V =< G_S, G_I, \lambda, \tau_c >$ be an RDF dataset and $G_S = (V_S, E_S)$. Let also $DAP(V, k) = V_1, ..., V_k$, and B_m be a vertical sub-partition, $B_m \in V_i$, $1 \leqslant i \leqslant k$. Then it holds that:*

$$AVG_{B_m \in V_i}(triples(B_m)) \geqslant AVG_{B_n \in V_j}(triples(B_n)) \tag{8}$$

where $V_i \in DAP(V, k)$, $V_j \in DAP(V, k+1)$, and $k \leqslant |V_S|$.

Proof. (sketch) In order to prove this theorem, assume a partitioning for an RDF dataset $V =< G_S, G_I, \lambda, \tau_c >$, produced by $DAP(V, k)$ splitting V into $V_1, ..., V_k$ and let B_m be the vertical sub-partitions distributed in the various partitions. For the vertical sub-partitions we don't know a priori their exact number, however, we know that for every predicate of the schema nodes in a first-level partition, we have one vertical sub-partition. In this layout for example we have $|V_S|$ schema nodes distributed in the k partitions and we can assume that there are p non-distinct predicates in the k partitions. As such we can safely assume that for B_m it holds that $1 \leqslant j \leqslant p$. Assume now a random schema node SC in the partition V_i, $1 \leqslant i \leqslant k$. SC is the domain of z properties which leads into z vertical sub-partitions for SC. Note that other schema nodes might exist sharing the same predicates as SC. As such, in the vertical sub-partitions of SC, instances of other schema nodes might also exist. Next assume that we run the DAP algorithm for $k+1$, increasing by one the number of the partitions to be produced. Now $DAP(V, k+1)$ splits V into $V_1, ..., V_{k+1}$ first-level partitions. In the new configuration, the centroids of the $V_1, ..., V_k$ partitions are exactly the same as in the $DAP(V, k)$, however now we select the $k+1$ schema node with the highest IM to be placed as the centroid of the V_{k+1} partition. Now we distinguish the following two cases:

1. *SC is placed in a partition where more schema nodes have one or more of the same predicates as SC.* In this case, the number of triples of the vertical sub-partitions increases as more triples are added by the other schema nodes which have the same properties. However, although this happens locally, the schema node that is now in the same partition as SC is removed from the partition it was in the $DAP(V, k)$ configuration. So when compared to the $DAP(V, k)$ configuration, in total the overall number of triples for the sub-partitions of



Instance Index

Instance	Schema Node
Georgia	Person
FORTH	Organization
Publication1	Publication
Publication2	Publication
Dimitris	Professor

Class Index

Schema Node	Partition ID
Person	2
Organization	2
Publication	3
Professor	1

VP Index

Schema Node	Vertical Partitions
Person	affiliatedOf, advisor, rdfs:subClassOf
Organization	affiliatedOf, orgPublication, rdfs:subClassOf
Publication	publicationReserach, orgPublication, rdfs:subClassOf
Professor	advisor, rdfs:subClassOf

Fig. 3. Instance, Class and VP indexes for our running example.

the same properties is not increased. On the contrary, as the partitioning is refined, and schema nodes are split into different partitions the number of triples appearing in the sub-partitions is gradually reduced. Specific attention should be paid here on cut-edges as they will introduce replication in the vertical sub-partitions. Still, in that case, the number of instances is at most doubled for each cut-edge; however, the average number of instances in the two vertical sub-partitions generated because of that is reduced in half, which shows why our theorem still holds.

2. *SC is placed in a partition where fewer or the same schema nodes have one or more of the same predicates as SC*. In this case, the number of triples of the vertical sub-partitions for SC is reduced or at least stays the same as in the $DAP(V,k)$.

□

The aforementioned theorem has a direct impact on query evaluation as it actually tells us that if we increase k, the average data stored in the vertical sub-partitions, will be reduced or at least stay the same. Thus, as k increases the data access for a query decreases or at least stays the same. This is verified also in the experimental evaluation (Section 6.2.3) showing the direct impact of k on both data replication and data access and as a result in query efficiency.

5.1.4. Indexing

Next, in order to speed up the query evaluation process, we generate appropriate indexes, so that the necessary sub-partitions are directly located during query execution. Specifically, as our partitioning approach is based on the schema of the dataset and data is partitioned based on the schema nodes, initially, we index for each schema node the first-level partitions (*Class Index*) it is primarily assigned to and also the vertical partitions (*VP Index*) it belongs. For each instance, we index also the schema nodes under which it is instantiated (*Instance Index*). The *VP Index* is used in case of a query with unbound predicates, in order to identify which vertical partitions should be loaded, avoiding searching all of them in a first-level partition.

The aforementioned indexes are loaded in the main memory of Spark as soon as the query processor is initialized. Specifically, the *Instance Index*, and the *VP Index* are stored in the HDFS as parquet files and loaded in the main memory. The *Class Index* is stored locally (txt file) since the size of the index/file is usually small and is also loaded in main memory at query processor initialization.

Example 5.1. *Figure 3 presents example indexes for our running example. Assuming that we have five instances in our dataset, the Instance Index, shown in the figure (left), indexes for each instance the schema node to which it belongs. Further, the Class Index records for each schema node the first-level partitions it belongs, as besides the one that is primarily assigned, it might also be allocated to other partitions as well. Finally, the VP Index contains the vertical partitions that the schema nodes are stored into (for each first-level partition). For example, the schema node Organization (along with its instances) is located in Partition-2 and specifically its instances are located in the vertical partitions affiliatedOf, orgPublication and rdfs:subClassOf.*

Algorithm 2 PartitionDiscovery(query, classIndex, instanceIndex, VPIndex, stats)

```
Input: The input $query$, the $classIndex$, the $instanceIndex$, the $VPIndex$, Statistics $stats$ about each partition
Output: $queryIndex$
 1: $queryIndex.Partitions = queryIndex.VP = variablesTypes = \emptyset$
 2: $triplePatterns = extractTriplePatterns(query)$
 3: for each $tp_i : p(v_{i.1}, v_{i.2}) \in triplePatterns$ do
 4:   $nodeClasses = partitions = fPartartition = \emptyset$
 5:   $nodeURIs = findURI(v_{i.1}, v_{i.2})$ //Extracts available URIs
 6:   $vars = findVariable(v_{i.1}, v_{i.2})$ //Extracts available variables
 7:   if $p ==$ rdf:type & $v_{i.2} \in nodeURIs$ then
 8:     $nodeClasses = \{v_{i.2}\}$
 9:     if $v_{i.1} \in vars$ then
10:       $variablesTypes = variablesTypes \cup \{v_{i.1} \rightarrow nodeClasses\}$
11:     end if
12:   else
13:     $nodeClasses = getSchemaNodes(nodeURIs, variablesTypes, instanceIndex)$
14:   end if
15:   for each $class \in nodeClasses$ do
16:     $partitions = partitions \cup classIndex[class]$
17:   end for
18:   $finalPart = smallestPartition(partitions, stats)$
19:   $queryIndex.Partitions = queryIndex.Partitions \cup \{tp_i \rightarrow fPartartition\}$
20:   if $isVariable(p)$ then
21:     $queryIndex.VP = queryIndex.VP \cup \{tp_i \rightarrow VPIndex[nodeClasses]\}$ //Unbound Predicate
22:   else
23:     $queryIndex.VP = queryIndex.VP \cup \{tp_i \rightarrow p\}$
24:   end if
25: end for
26: return $queryIndex$
```

5.2. *Query Processor*

In this section, we focus on the query processor module, implemented on top of Spark. An input SPARQL query is parsed and then translated into an SQL query automatically. To achieve this, first, the *Query Processor* detects the first-level and vertical partitions that should be accessed for each triple pattern in the query, creating a *Query Partitioning Information Structure*. This procedure is called *partition discovery*. Then, this *Query Partitioning Information Structure* is used by the *Query Translation* procedure, to construct the final SQL query. Our approach translates the SPARQL query into SQL in order to benefit from the Spark SQL interface and its native optimizer which is enhanced to offer better results.

5.2.1. *Partition Discovery*

In the partition discovery module, we create automatically an index of the partitions that should be accessed for answering the input query, called *Query Partitioning Information Structure*. Specifically, we detect the fist-level partitions and the corresponding vertical partitions that include information to be used for processing each triple pattern of the query, exploiting the available indexes.

The corresponding algorithm, shown in Algorithm 2, takes as input a query, the indexes (presented in Section 5.1.4), and statistics on the size of the first-level partitions estimated during the partitioning procedure and returns an index of the partitions (first-level and vertical partitions) that should be used for each triple pattern.

The algorithm starts by initializing the variables *queryIndex.Partitions*, *queryIndex.VP* used for storing the first-level and the vertical partitions and the *variablesTypes* which keeps track of the types (*rdf:type*) of the variables in the various triple patterns (line 1).Then it extracts from the input query all triple patterns in a list (line 2).

For each triple pattern the following variables are initialized (line 4): *nodeClasses* stores the schema nodes identified for the specific triple pattern since they lead to the first-level partitions, *partitions* stores the list of the first-level partitions that could be associated to a triple patter and $finalPart$ is the first-level partition finally selected for that triple pattern.

While parsing each triple pattern, the node URIs ($nodeURIs$) and the variables (var) are extracted from the subject or object positions of the triple (lines 5-6). If the predicate of the current triple pattern is *rdf:type* and its object is an URI, then the $nodeClasses$ of this triple pattern is that URI (line 8) since the object is a schema node. Moreover, if the subject of this triple pattern is a variable, we should remember that this variable refers to specific schema nodes and as such the association between the variable and the schema nodes is added to the $variablesTypes$ (line 10). This is happening as every triple pattern that shares this variable should be mapped to the same partition, as it refers to the same schema node. Overall, for each triple pattern we identify a list of schema nodes based on the available URIs and the variables in it. We exploit $variablesTypes$ for keeping track the variables with known types already. When the URIs (uri) do not correspond to schema nodes, the *Instance Index* is used to obtain the schema nodes that the instances are instantiated under (line 13). Then, by using the *Class Index*, we obtain the corresponding partitions ($partitions$) that can be used for that triple pattern (lines 15-17). Based on statistics stored during the partitioning procedure, the smallest partition is selected for the specific triple pattern (line 18) and is added in the $queryIndex.Partitions$ structure (line 19).

A step further, the triple pattern is located in the vertical partition identified by the predicate of the triple pattern (lines 20-24). Specifically, in the case that the predicate of the triple pattern is a variable (we have an unbound predicate), the *VP Index* is used to obtain the set of vertical partitions based on the schema nodes ($nodeClasses$) that we have already identified for that triple pattern (line 21). Otherwise, the predicate is added in the $queryIndex.VP$ since it specifies the vertical partition in which the triple pattern is located (line 23). Finally, *Query Partitioning Information Structure* is returned (line 26) consisting of the structures $queryIndex.Partitions$ and $queryIndex.VP$ that include information about the fist-level and vertical partitions that each triple pattern can be located at.

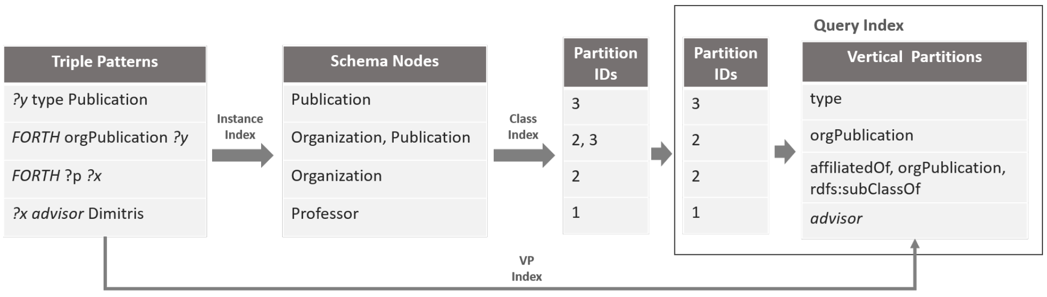


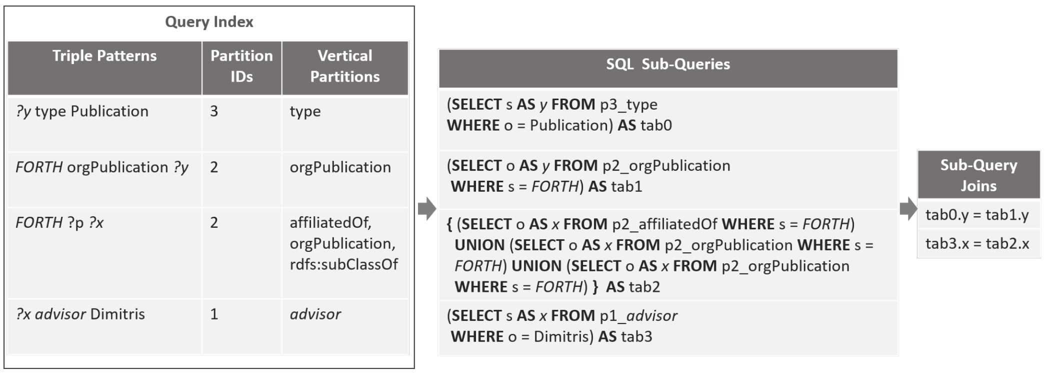
Fig. 4. Constructing Query Partitioning Information Structure.

Example 5.2. *The creation of Query Partitioning Information Structure for a query is a three-step process depicted in Figure 4. On the left side of the Figure, we can see the four triple patterns of the query. The first step is to map every triple pattern to its corresponding schema nodes. If a triple pattern contains an instance then the Instance Index is used to identify the corresponding schema nodes. Next by using the Class Index (Figure 3), we find for each schema node the partitions where it is located in (Partitions IDs in Figure 4). Finally we select the smallest partition in terms of size, for each schema node based on statistics collected for the various partitions. For example, for the second triple pattern (FORTH orgPublication ?y) we only keep the partition 2 since it is smaller than partition 3. For each one of the selected partitions, we finally identify the vertical partitions that should be accessed, based on the predicates of the corresponding triple patterns. In case of an unbound predicate, such as in the third triple pattern of the query (FORTH ?p ?x) in Figure 4, the VP Index is used to identify the vertical partitions in which this triple pattern could be located based on its first-level partition (Partition ID:2). The result Query Partitioning Information Structure for our running example is depicted on the right of Figure 4.*

5.2.2. Query Translation & Optimization

In order to produce the final SQL query, each triple pattern is translated into one SQL sub-query. Each one of those sub-queries specifically involves a vertical sub-partitioning table based on the predicate name - the table name in the *"FROM"* clause of the SQL query. For locating this table the *Query Partitioning Information Structure* is used. Afterward, all sub-queries are joined using their common variables.

Finally, in order to optimize query execution we disabled default query optimization by Spark as in many cases the returned query plans were not efficient and we implemented our own optimizer. Our optimizer exploits statistics recorded during the partitioning phase, to push joins on the smallest tables - in terms of rows - to be executed first, further boosting the performance of our engine. The query translation and optimization procedures are automatic procedures performed at query execution.



Query Index

Triple Patterns	Partition IDs	Vertical Partitions
?y type Publication	3	type
FORTH orgPublication *?y*	2	orgPublication
FORTH ?p *?x*	2	affiliatedOf, orgPublication, rdfs:subClassOf
?x advisor Dimitris	1	*advisor*

SQL Sub-Queries
(**SELECT** s **AS** *y* **FROM** p3_type **WHERE** o = Publication) **AS** tab0
(**SELECT** o **AS** *y* **FROM** p2_orgPublication **WHERE** s = *FORTH*) **AS** tab1
{ (**SELECT** o **AS** *x* **FROM** p2_affiliatedOf **WHERE** s = *FORTH*) **UNION** (**SELECT** o **AS** *x* **FROM** p2_orgPublication **WHERE** s = *FORTH*) **UNION** (**SELECT** o **AS** *x* **FROM** p2_orgPublication **WHERE** s = *FORTH*) } **AS** tab2
(**SELECT** s **AS** *x* **FROM** p1_*advisor* **WHERE** o = Dimitris) **AS** tab3

Sub-Query Joins
tab0.y = tab1.y
tab3.x = tab2.x

Fig. 5. Query Translation.

Example 5.3. *In Figure 5, an example is shown of the query processor module in action. The input of the translation procedure is the Query Partitioning Information Structure of Figure 4. Each triple pattern is translated into an SQL query, based on the corresponding information for the first-level and vertical partitions (SQL Sub-Queries in Figure 5) that should be accessed. The name of the table of each SQL query is the concatenation of the first-level and the vertical partitions. In case of an unbound predicate, such as the third triple pattern, the sub-query asks for more than one table based on the vertical partitions that exist in the Query Partitioning Information Structure for the specific triple pattern. Finally, sub-queries are reordered by the DIAERESIS optimizer that pushes joins on the smallest tables to be executed first - in our example the p3_type is first joined with p2_orgPublication.*

6. Evaluation

In this section, we present the evaluation of our system. We evaluate our approach in comparison to three query processing systems based on Spark, i.e., SPARQLGX [12], S2RDF [25], and WORQ [19], using two real-world RDF datasets and four versions of a synthetic dataset, scaling up to 1 billion triples.

6.1. System Setup

LUBM. The Lehigh University Benchmark (LUBM) [13] is a widely used synthetic benchmark for evaluating semantic web repositories. For our tests, we utilized the LUBM synthetic data generator to create four datasets of 100, 1300, 2300, and 10240 universities (LUBM100, LUBM1300, LUBM2300, LUBM10240) occupying 2.28GB, 30.1GB, 46.4GB, 223.2GB, and consisting of 13.4M triples, 173.5M triples, 266.8M triples, and 1.35B triples respectively. LUBM includes 14 classes and 18 predicates. We used the 13 queries provided by the benchmark for our evaluation, each one ranging between one to six triple patterns. We classify them into three categories, namely, star, chain, snowflake, and complex queries.

SWDF. The Semantic Web Dog Food (SWDF) [20] is a real-world dataset containing Semantic Web conference metadata about people, papers, and talks. It contains 126 classes, 185 predicates, and 304,583 triples. The dataset occupies 50MB of storage. To evaluate our approach, we use a set of 278 BGP queries generated by the FEASI-

BLE benchmark generator [23] based on real query logs. In the benchmark workload, all queries include unbound predicates. Although our system is able to process them, no other system was able to execute them. As such, besides the workload with the unbound predicates (noted as SWDB(u)), we also replaced the unbound predicates with predicates from the dataset (noted as SWDF(b)) to be able to compare our system with the other systems, using the aforementioned workload.

DBpedia. Version 3.8 of DBpedia, contains 361 classes, 42,403 predicates, and 182,781,038 triples. The dataset occupies 29.1GB of storage. To identify the quality of our approach, we use a set of 112 BGP queries generated again by the FEASIBLE benchmark generator based on real query logs. As it is based on real query logs the query workload here is closer to the queries of real users instead of focusing on the system's choke points - usually the focus in synthetic benchmarks.

All information about the datasets is summarized in Table 2. Further, all workloads along with the code of the system are available in our GitHub repository[1].

Table 2
Dataset Statistics

Dataset	#Triples	Size (.nt)	#Classes	#Predicates
LUBM 100	13,405,381	2.28 GB	14	18
LUBM 1300	173,546,369	30.1 GB	14	18
LUBM 2300	266,814,882	46.4 GB	14	18
LUBM 10240	1,340,300,979	223.2 GB	14	18
SWDF	304,583	49.2 MB	126	185
DBpedia	182,781,038	29.1 GB	361	42,403

6.1.1. *Setup.*

Our experiments were conducted using a cluster of 4 physical machines that were running Apache Spark (3.0.0) using Spark Standalone mode. Each machine has 400GB of SSD storage, and 38 cores, running Ubuntu 20.04.2 LTS, connected via Gigabit Ethernet. In each machine, 10GB of memory was assigned to the memory driver, and 15GB was assigned to the Spark worker for querying. For DIAERESIS, we configured Spark with 12 cores per worker (to achieve a total of 48 cores), whereas we left the default configuration for other systems.

6.1.2. *Competitors*

Next, we compare our approach with three state-of-the-art query processing systems based on Spark, i.e., the SPARQLGX [12], S2RDF [25], and WORQ[19]. In their respective papers, these systems have been shown to greatly outperform SHARD, PigSPARQL, Sempala and Virtuoso Open Source Edition v7 [25]. We also made a consistent effort to get S3QLRDF [14, 15] in order to include it in our experiments, however access to the system was not provided.

SPARQLGX implements a vertical partitioning scheme, creating a partition in HDFS for every predicate in the dataset. In the experiments we use the latest version of SPARQLGX 1.1 that relies on a translation of SPARQL queries into executable Spark code that adopts evaluation strategies to the storage method used and statistics on data. S2RDF, on the other hand, uses Extended Vertical Partitioning (ExtVP), which aims at table size reduction,when joining triple patterns as semijoins are already precomputed. In order to manage the additional storage overhead of ExtVP, there is a selectivity factor (SF) of a table in ExtVP, i.e. its relative size compared to the corresponding VP table. In our experiments, the selectivity factor (SF) for ExtVP tables is 0.25 which the authors propose as an optimal threshold to achieve the best performance benefit while causing only a little overhead. Moroever, the latest version of S2RDF 1.1 is used that supports the use of statistics about the tables (VP and ExtVP)) for the query generation/evaluation. Finally, WORQ [19] (version 0.1.0) reduces sets of intermediate results that are common for certain join patterns, in an online fashion, using Bloom filters, to boost query performance.

[1]https://github.com/isl/DIAERESIS

Regarding compression, all systems use parquet files to store VP (ExtVP) tables that enable better compression, and also WORQ uses dictionary compression.

DIAERESIS, S2RDF, and WORQ exploit the caching functionality of Spark SQL. As such, we do not include caching times in our reported query runtimes as it is a one-time operation not required for subsequent queries accessing the same table. SPARQLGX, on the other hand, loads the necessary data for each query from scratch so the reported times include both load time and query execution times. Further, we experimentally determined the number of partitions *k* that achieves an optimal trade-off between storage replication and query answering time. More details about the number of first-level partitions and how it affects the efficiency of query answering and the storage overhead can be found in Section 6.2.3. As such LUBM 100, LUBM 1300, LUBM 2300, and SWDF were split into 4 first-level partitions, LUBM 10240 into 10 partitions, and DBpedia into 8 partitions. Finally, note that a time-out of one week was selected for all the experiments, meaning that after one week without finishing the execution, each individual experiment was stopped.

Table 3

Preprocessing Dimensions.

System	**Preprocessing Time**	**Output Storage**	**Replication Factor**
LUBM 100 (13.4M triples)			
SPARQLGX	0.73 min	101.52 MB	0.33
S2RDF	8.21 min	332.3 MB	1.10
WORQ	2.16 min	73.19 MB	0.24
DIAERESIS	8.12 min	336.07 MB	1.12
LUBM 1300 (173.5M triples)			
SPARQLGX	4.91 min	1.48 GB	0.35
S2RDF	25.76 min	4.39 GB	1.05
WORQ	21.71 min	0.86 GB	0.21
DIAERESIS	124.31 min	4.74 GB	1.14
LUBM 2300 (266.8M triples)			
SPARQLGX	7.55 min	2.30 GB	0.35
S2RDF	36.63 min	6.84 GB	1.06
WORQ	33.96 min	1.32 GB	0.21
DIAERESIS	130.07 min	6.89 GB	1.06
LUBM 10240 (1.35 billion triples)			
SPARQLGX	64.6 min	12.42 GB	0.38
S2RDF	175.61 min	33.99 GB	1.04
WORQ	275.49 min	9.54 GB	0.29
DIAERESIS	187.44 min	44.32 GB	1.36
SWDF (304K triples)			
SPARQLGX	0.45 min	5.38 MB	0.40
S2RDF	15 min	44.58 MB	3.31
WORQ	2.3 min	6.05 MB	0.45
DIAERESIS	2.5 min	11.59 MB	0.86
DBpedia (182M triples)			
SPARQLGX	3.7 min	3.7 GB	0.41
S2RDF	Timeout	-	-
WORQ	Timeout	-	-
DIAERESIS	273.56 min	16.7 GB	2.41

6.1.3. Preprocessing

In the preprocessing phase, the main dimensions for evaluation are the time needed to partition the given dataset and the storage overhead that every system introduces in terms of the Replication Factor (RF). Specifically, RF is the number of copies of the input dataset each system outputs in terms of raw compressed parquet file sizes. Table 3 presents the results for the various datasets and systems.

Preprocessing time. Focusing, initially, on the time needed for each system to partition the dataset, we can observe that SPARQLGX has almost in all cases the fastest preprocessing time. This is due to the fact that it implements the most naive preprocessing procedure, as it aggregates data by predicates and then creates a compressed folder for every one of these predicates. However, exactly due to this simplistic policy, large fragments of data are required for query answering as we will show in Section 6.2.1. S2RDF partitions 13.4M triples (LUMB 100) faster than 304K (SWDF) ones. This happens as LUBM, being a synthetic dataset, has only 18 predicates, compared to SWDF which has 185. Regarding preprocessing time for the other LUBM datasets, S2RDF shows an almost linear increase. In the case of DBpedia, which has 42,403 predicates and is relatively big, both S2RDF and WORQ fail to preprocess it. More precisely, S2RDF was returning an error failing to process the complex structure of DBpedia, whereas the WORQ preprocessing stage was running for more than a week without returning results. Besides DBpedia, WORQ has relatively good preprocessing time for the remaining datasets showing also an almost linear increase in preprocessing time as the data grow. DIAERESIS requires more preprocessing time to finish, since it employs a more sophisticated algorithm. However, it is not stalled by complex datasets, such as WORQ and S2RDF. Nevertheless preprocessing is a task that is only executed once and offline for all systems before starting to answer queries.

Replication. By further examining the results shown in Table 3, SPARQLGX has no replication overhead since, as already explained, it is implementing a naive vertical partitioning schema. In fact, as information is omitted from the generated vertical partitions (i.e. the predicates), the result dataset is even smaller than the input. S2RDF, on the other hand, precomputes both the VP tables and every other possible semi-join combination of the dataset (up to a limit). This results in storage overhead. Regarding WORQ, again the result of preprocessed data is smaller than the initial dataset since it uses dictionary compression.

Looking at Table 3, for the LUBM datasets, the replication factor of SPARQLGX is around 0.35, for WORQ ranges between 0.21 and 0.29, for S2RDF is around 1.05, whereas for our approach it ranges between 1.05 and 1.36.

For the SWDF dataset, we see that SPARQLGX and WORQ have a replication factor of around 0.4, S2RDF has a replication factor of 3.31 due to the big amount of predicates contained in the dataset, whereas our approach has 0.86, achieving a better replication factor than S2RDF in this dataset, however falling behind the simplistic partitioning methods of SPARQLGX. That is, placing dependent nodes together, sacrifices storage overhead, for drastically improving query performance.

Overall, SPARQLGX wins in terms of storage overhead and preprocessing time in most of the cases due to its simplistic partitioning policy, however with a drastic overhead in query execution as we shall see in Section 6.2.1. On the other hand, S2RDF and WORQ fail to finish partitioning on a complex real dataset.

Nevertheless, we argue that preprocessing is something that can be implemented offline without affecting overall system performance and that a small space overhead is acceptable for improving query performance.

6.2. *Query Execution*

Next, we evaluate the query execution performance for the various systems. The times reported are the average of 10 executions of each set of queries.

6.2.1. *LUBM*

In this experiment, we show how the performance of the systems changes as we increase the dataset size using the four LUBM datasets - ranging from 13 million to 1.35 billion triples.

Figure 6 compares the average query execution time of different systems for the LUBM datasets. We can observe that in all cases, our system strictly dominates the other systems. More importantly, as the size of the dataset increases, the difference in the performance between DIAERESIS and the other systems increases as well. Specifically, our system is one order of magnitude faster than all competitors for LUBM100 and LUBM10240. For LUBM1300, DIAERESIS is two times faster than the most efficient competitor, whereas for LUBM2300, DIAERESIS is 40% faster than the most efficient competitor.

DIAERESIS continues to perform better than the other systems in terms of average query execution time across all versions, enjoying the smallest increase in execution times, compared to the other systems, as the dataset grows.

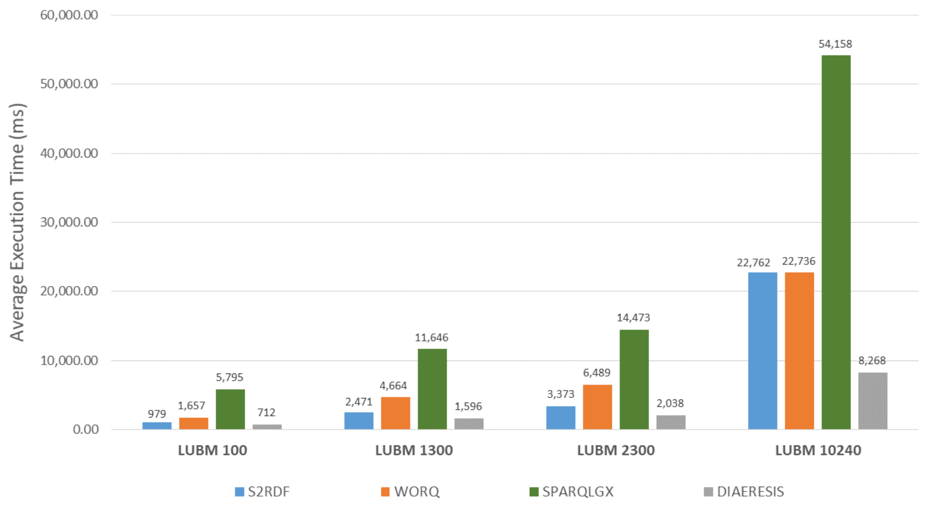


Fig. 6. Query execution for LUBM datasets and systems.

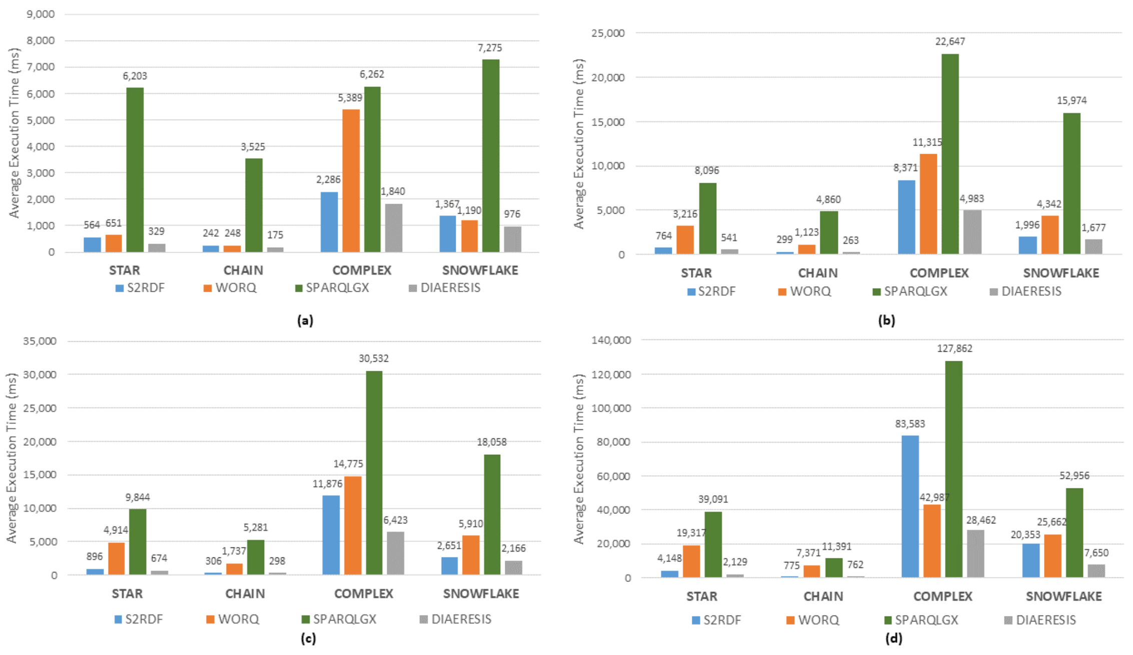


Fig. 7. Query execution for (a) LUBM 100, (b) LUBM 1300, (c) LUBM 2300, (d) LUBM 10240

For the largest dataset, i.e., LUBM10240, our system outperforms the other systems, being almost three times faster than the most efficient competitor. This demonstrates the superiority of DIAERESIS in big datasets. We conclude that as expected, the size of the dataset affects the query execution performance. Generally, SPARQLGX has the worst performance since it employs a really naive partitioning scheme, followed by S2RDF and WORQ - only in LUBM1024, WORQ is better than S2RDF. In contrast, the increase in the dataset size has the smallest impact for DIAERESIS, which dominates competitors.

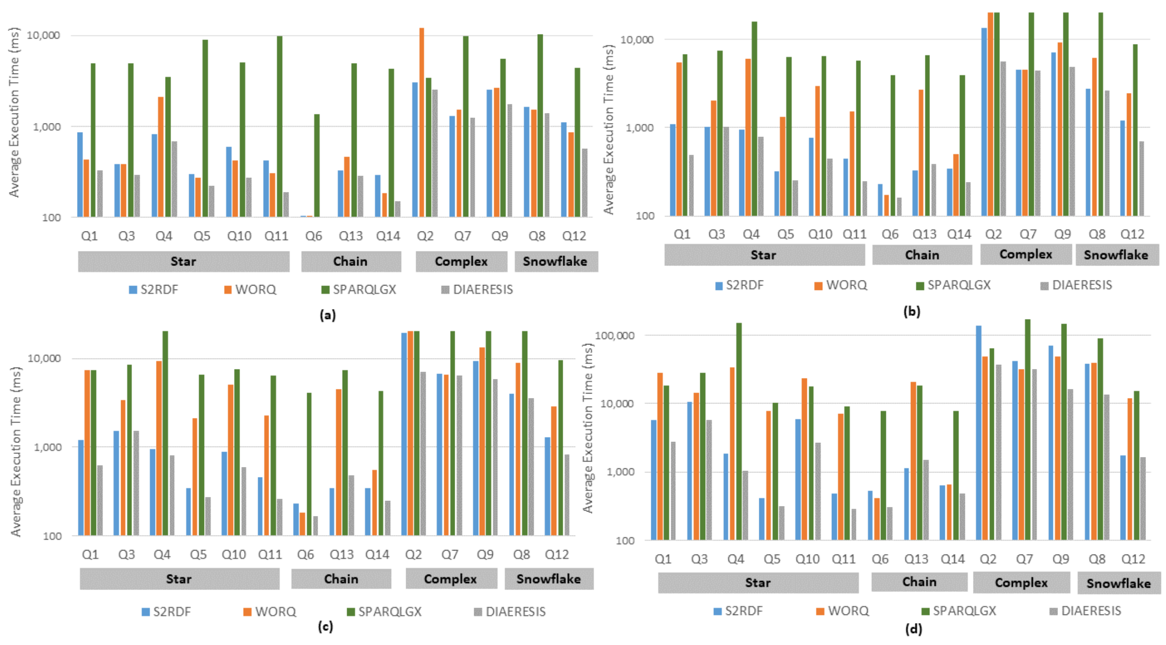


Fig. 8. Query execution for (a) LUBM 100, (b) LUBM 1300, (c) LUBM 2300, (d) LUBM 10240

Query Categories. Next, we study separately the four types of queries available, i.e., star, chain, snowflake, and complex queries. Their execution times are presented in Figure 7. Regarding star queries, we notice that for all LUBM datasets, DIAERESIS has the best performance followed by S2RDF, WORQ, and in the end SPARQLGX with a major difference. S2RDF performs better than WORQ due to the materialized join reduction tables since it uses fewer data to answer most of the queries than WORQ, as we will see in Section . Since our system places together dependent fragments of data that are usually queried together, it is able to reduce data access for query answering, performing significantly better than competitors.

For chain queries (Figure 7), the competitors perform quite well except for SPARQLGX which performs remarkably worse. More precisely, S2RDF performs slightly better than WORQ except for the LUBM100, the smallest LUBM dataset, where the difference is negligible. Still, DIAERESIS delivers a better performance than the others systems in this category for all LUBM datasets.

The biggest difference between DIAERESIS and the competitors is observed in complex queries for all LUBM datasets (Figure 7). Our system is able to lead to significantly better performance, despite the fact that this category contains the most time-demanding queries, with the bigger number of query triple patterns, and so joins. The difference in the execution times between our system and the rest becomes larger as the size of the dataset increases. S2RDF has the second better performance followed by WORQ and SPARQLGX in LUBM100, LUBM1300 and LUBM2300. However in LUBM10240 S2RDF comes third since WORQ is quite faster and SPAQGLGX is the last one. S2RDF performs better than WORQ due to the materialized join reduction tables since S2RDF uses fewer data to answer the queries than WORQ in all cases However, as the data grow, i.e., in LUBM10240, the complex queries with many joins, perform better in WORQ than S2RDF due to the increased benefit of the bloom filters.

Finally, in snowflake queries, again we dominate all competitors, whereas S2RDF in most cases comes second, followed by WORQ and SPAQLGX. Only in the smallest dataset, i.e. LUBM100, WORQ has a better performance. Again SPARQLGX has the worst performance in all cases.

The value of our system is that it reduces substantially the accessed data in most of the cases as it is able to retain the same partition dependent schema nodes that are queried together along with their corresponding instances. This will be subsequently presented in the section related to the data access reduction.

Individual Queries. Examining closely the individual queries and their execution times (Figure 8), for the star queries, DIAERESIS dominates other systems in all star queries for all LUBM datases. On the other hand, S2RDF wins WORQ in all LUBM datesets, except LUBM100 that it performs worse in five queries out of the total six star queries - except Q4 which is the only one in this category that has three joins while the others have one join.

Regarding chain queries, DIAERESIS outperforms the competitors on all individual chain queries, except Q13 in LUBM1300, LUBM2300 and LUBM 10240 where S2RDF is slightly better. This happens as S2RDF has already precomputed the two joins required for query answering and as such despite the fact that DIAERESIS loads fewer data (according to Fig. 9) the time spent in joining those data is higher than just accessing a bigger number of data. For Q6, WORQ performs better than S2RDF in all LUBM datasets. However, for Q14, S2RDF wins WORQ in LUBM1300, LUBM230, and slightly in LUBM10240, while WORQ is significantly faster than S2RDF in LUBM100.

Complex and snowflake queries put a heavy load on all systems since they consist of many joins (3-5 joins). DIAERESIS continues to demonstrate its superior performance and scalability since it is faster than competitors to all individual queries for all LUBM datasets. Competitors on the other hand do not show stability in their results. S2RDF comes second followed by WORQ and then SPARQLGX, in terms of execution time for most of the queries of the complex category, except LUBM10240. Specifically, for the biggest LUBM dataset, WORQ wins S2RDF in all complex queries apart from one. In the snowflake category, WORQ is better in LUBM100 and in LUBM10340 but not in the rest.

Data Access Reduction. Moving to explain the large performance improvement of our system, we present next the reduction in the size of the data accessed for query answering for all systems when compared to DIAERESIS for each individual query for LUBM10240 (refer to Figure 9). We only present LUBM10240 as the graphs for the other versions are similar. As shown, our system consistently outperforms all competitors, and in many cases to a great extent. DIAERESIS accesses 99% less data than WORQ for answering Q4, whereas for many queries the reduction is over 90%. For S2RDF on the other hand, the reduction in most of the cases is more than 60%. In only one case (Q12), our system loads 8.12% more data than S2RF, as the reduction tables used by S2RDF are smaller than the subpartitions loaded by DIAERESIS. However, even at that case, DIAERESIS performs better in terms of query execution time due to the most effective query optimization procedures we adopt, as shown already in Figure 8. Note that although in five cases the data access reduction of S2RDF, WORQ and SPARQLGX when compared to DIAERESIS seems to be the same (Q1, Q3, Q10, Q6, Q14) as shown in Figure 9, S2RDF performs better that

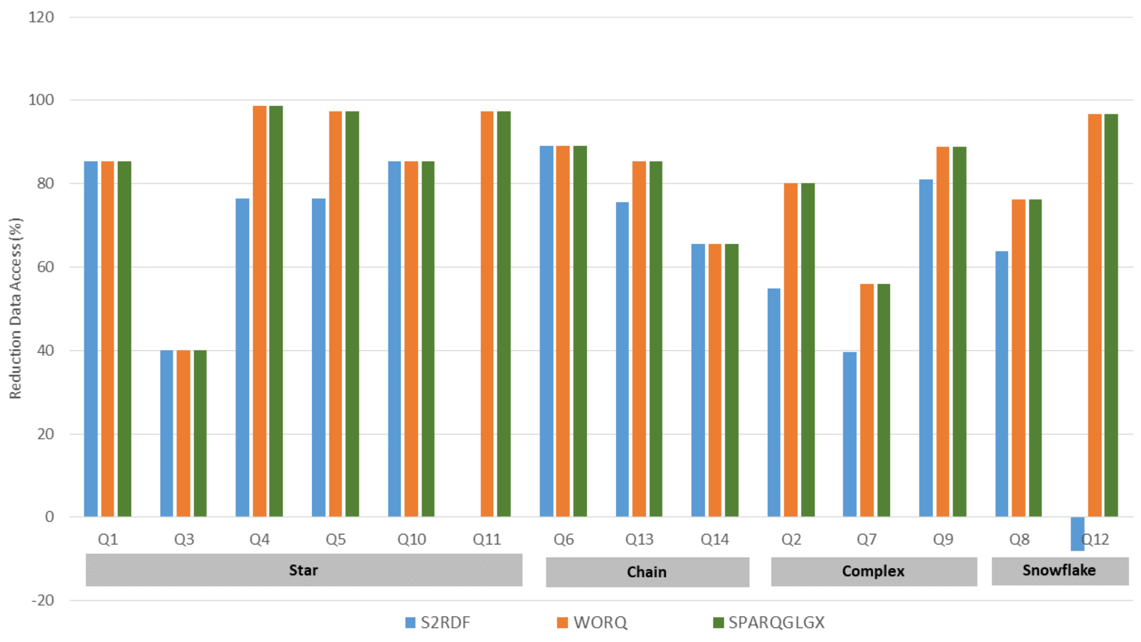


Fig. 9. Reduction of Data Access for LUBM10240

WORQ and SPARQLGX due to the query optimization it performs. Regrading SPARQLGX, in the most of the cases, the percentage of the reduction is over 80%, and in many cases over 90%.

Overall we can conclude that DIAERESIS boosts query performance, while effectively reducing the data accessed for query answering.

6.2.2. *Real-World Datasets*

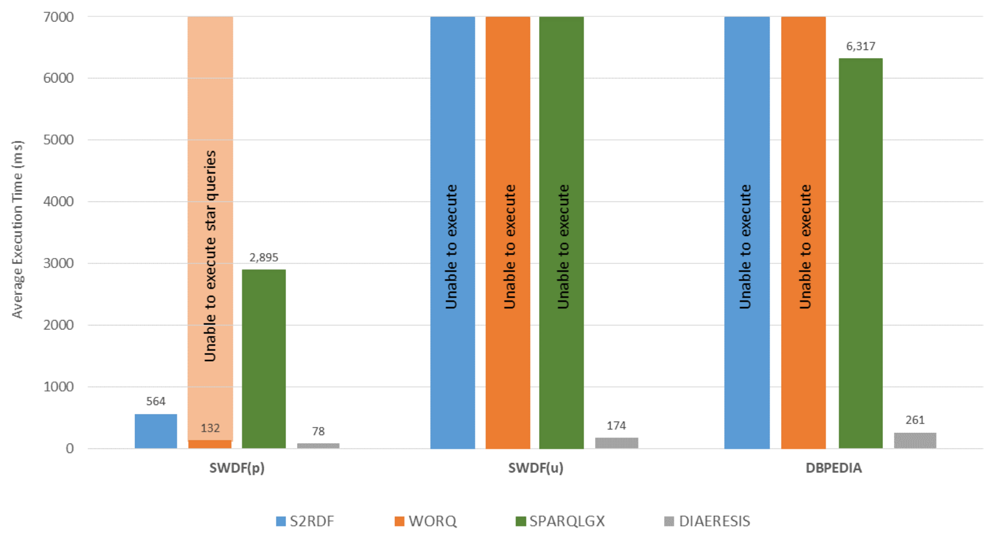


Fig. 10. Query execution for Real-World Datasets and systems

Apart from the synthetic LUBM benchmark datasets, we evaluate our system against the competitors over two real-world datasets, i.e., SWDF (unbound and bound) and DBpedia (Figure 10).

As already mentioned, no other system is able to execute queries with unbound predicates (i.e., SWDF(u)) in Figure 10), whereas for the SWDF workload with bound predicates (277 queries) (i.e., SWDF(b) in Figure 10) our system is one order of magnitude faster than competitors. WORQ was not able to execute star queries (147 queries) in this dataset, since the triples of star queries for this specific dataset should be joined through constants instead of variables as usual. Regarding DBpedia (Figure 10), both S2RDF and WORQ failed to finish the partitioning procedure due to the large number of predicates contained in the dataset and the way that the algorithms of the systems use this part.

Query Categories. Examining each query category in Figure 11, we can verify again that DIAERESIS strictly dominates other systems in all query categories as well. More specifically, DIAERESIS is one order of magnitude faster in star and complex queries than the fastest competitor able to process these datasets. The SWDF workload did not contain complex queries, whereas for the DBpedia dataset for complex queries, DIAERESIS is again one order of magnitude faster than SPARQLGX.

Overall, the evaluation clearly demonstrates the superior performance of DIAERESIS in real datasets as well, when compared to the other state-of-the-art partitioning systems, for all query types. DIAERESIS does not favour any specific query type, achieves consistent performance, dominating all competitors in all datasets.

6.2.3. *Impact of the number of the first-level partitions*

In this subsection, we experimentally investigate the influence of the number of first-level partitions on storage overhead, data access for query evaluation, and query efficiency verifying the theoretical results presented in Section 5.1.3.

For this experiment, we focus on the largest synthetic and real-world datasets, i.e. LUBM10240 and DBpedia, since their large size enables us to better understand the impact of the number of first-level partitions on the data

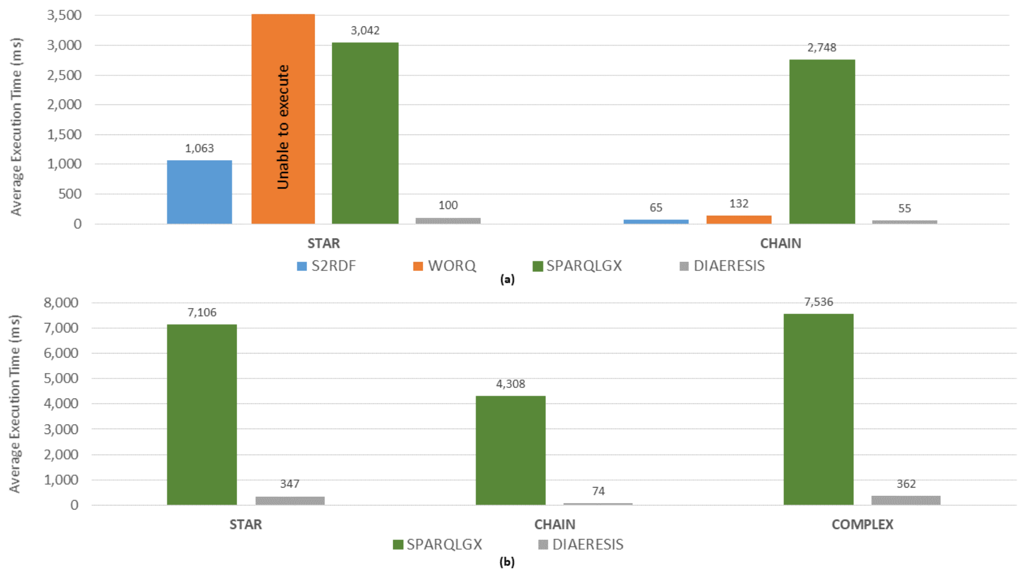


Fig. 11. Query execution for (a) SWDF(p), (b) DBpedia

layout and the query evaluation. We compare the replication factor, the total amount of data accessed for answering all queries in the workload in terms of number of rows, and the total query execution time varying the number of first-level partitions between four and ten for the two datasets.

The results are presented in Table 4 for the various DIAERESIS configurations and we also include the competitors able to run in these datasets. For both datasets, we notice that as the number of first-level partitions increases, the replication factor increases as well, which is in line with Theorem 1 (Section 4). The rate of the increase in terms of storage is larger in DBpedia than in LUBM10240 since the number of properties in DBpedia is quite larger compared to LUBM10240 (42.403 vs 18). The larger number of properties in DBpedia result in more properties spanning between the various partitions and as such increasing the replication factor more.

Further, looking at the total data access for query answering, we observe as well that the larger the number of partitions the smaller the data required to be accessed for answering all queries. Again this is in line with Theorem 2. The reduced data access has also a direct effect on query execution which is reduced as k increases.

Compering DIAERESIS performance with the other competitors, we can also observe that they access a larger fragment of data for answering queries in all cases, which is translated into a significantly larger execution time.

6.2.4. *Overall comparison*

Summing up, DIAERESIS strictly outperforms state-of-the-art systems in terms of query execution, for both synthetic and real-world datasets. SPARQLGX aggregates data by predicates and then creates a compressed folder for every one of those predicates, failing to effectively reduce data access. High volumes of data need to be touched at query time, with significant overhead in query answering. S2RDF implements a more advanced query processor, by pre-computing joins and performing query optimization using table statistics. WORQ, on the other hand, focuses on caching join patterns which can effectively reduce query execution time. However, in both systems, the data required to answer the various queries are not effectively collocated leading to missed optimization opportunities. Our approach, as we have experimentally shown, achieves significantly better performance by effectively, reducing data access, which is a major advantage of our system. Finally, certain flaws have been identified for other systems: no other system actually supports queries with unbounded predicates, S2RDF and WORQ fail to preprocess DBpedia, and WORQ fails to execute the star queries in the SWDF workload.

Overall our system is better than competitors in both small and large datasets across all query types. This is achieved by the hybrid partitioning of the triples as they are split by both the domain type and the name of the property leading to more fine-grained sub-partitions. As the number of partitions is increased the sub-partitions

Table 4
Comparing DIAERESIS and competitors for different number of first-level partitions (k).

System	**Partitions**	**Replication Factor**	**Data Access (M rows)**	**Execution Time**
LUBM 10240				
DIAERESIS	4	1.32	2,531	179,357 ms
DIAERESIS	6	1.35	2,509	160,189 ms
DIAERESIS	8	1.35	1,460	147,203 ms
DIAERESIS	10	1.36	1,406	116,908 ms
SPARQLGX		0.38	7,510	758,218 ms
S2RDF		1.04	4,348	318,668 ms
WORQ		0.29	7,510	318,299 ms
DBpedia				
DIAERESIS	4	1.83	353	37,731 ms
DIAERESIS	6	2.20	242	32,635 ms
DIAERESIS	8	2.41	184	20,777 ms
DIAERESIS	10	2.50	145	18,650 ms
SPARQLGX		0.41	925	599,134 ms

become even smaller as the partitioning scheme also decomposes the corresponding instances, however with an impact on the overall replication factor which is a trade-off of our solution.

7. Conclusions

In this paper, we focus on effective data partitioning for RDF datasets, expoiting schema information and the notion of importance and dependence, enabling efficient query answering, strictly dominating existing partitioning schemes of other Spark-based solutions. We experimentally show that DIAERESIS strictly outperforms, in terms of query execution, state of the art systems, for both synthetic and real-world workloads, and in several cases by orders of magnitude. This is achieved due to the significant reduction of data access required for query answering. Our results are completely in line with findings from other papers in the area [25].

Limitations. We have to note that our approach assumes that datasets are static and do not evolve over time, an assumption that might not always be true. In such a scenario, the pre-processing cost is something you only pay once at the configuration phase in order to enjoy the benefits at querying time.

Future work. As future work, an interesting direction would be to apply our techniques to schema-less datasets and to explore how to update partitioning as the RDF/S KB evolves.Another interesting direction would be to explore further query optimization techniques based on additional statistics (e.g based on selectivities).

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