Strategies for a Semantified Uniform Access to Large and Heterogeneous Data Sources

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"Who does not thank people does not thank God."

Prophet Muhammad PBUH

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To this great country Germany, *"Das Land der Ideen"* (the country of ideas). *Danke!*

Abstract

The remarkable advances achieved in both research and development of Data Management as well as the prevalence of high-speed Internet and technology in the last few decades have caused unprecedented data avalanche. Large volumes of data manifested in a multitude of types and formats are being generated and becoming the new norm. In this context, it is crucial to both leverage existing approaches and propose novel ones to overcome this data size and complexity, and thus facilitate data exploitation. In this thesis, we investigate two major approaches to addressing this challenge: Physical Data Integration and Logical Data Integration. The specific problem tackled is to enable querying large and heterogeneous data sources in an ad hoc manner.

In the Physical Data Integration, data is physically and wholly transformed into a canonical unique format, which can then be directly and uniformly queried. In the Logical Data Integration, data remains in its original format and form and a middleware is posed above the data allowing to map various schemata elements to a high-level unifying formal model. The latter enables the querying of the underlying original data in an ad hoc and uniform way, a framework which we call *Semantic Data Lake*, SDL. Both approaches have their advantages and disadvantages. For example, in the former, a significant effort and cost are devoted to pre-processing and transforming the data to the unified canonical format. In the latter, the cost is shifted to the query processing phases, e.g., query analysis, relevant source detection and results reconciliation.

In this thesis we investigate both directions and study their strengths and weaknesses. For each direction, we propose a set of approaches and demonstrate their feasibility via a proposed implementation. In both directions, we appeal to Semantic Web technologies, which provide a set of time-proven techniques and standards that are dedicated to Data Integration. In the Physical Integration, we suggest an end-to-end blueprint for the *semantification* of large and heterogeneous data sources, i.e., physically transforming the data to the Semantic Web data standard RDF (*Resource Description Framework*). A unified data representation, storage and query interface over the data are suggested. In the Logical Integration, we provide a description of the SDL architecture, which allows querying data sources right on their original form and format without requiring a prior transformation and centralization. For a number of reasons that we detail, we put more emphasis on the logical approach. We present the effort behind an extensible implementation of the SDL, called Squerall, which leverages state-of-the-art Semantic and Big Data technologies, e.g., RML (*RDF Mapping Language*) mappings, FnO (*Function Ontology*) ontology, and Apache Spark. A series of evaluation is conducted to evaluate the implementation along with various metrics and input data scales. In particular, we describe an industrial real-world use case using our SDL implementation. In a preparation phase, we conduct a survey for the Query Translation methods in order to back some of our design choices.

Contents

CHAPTER 1

Introduction

"You must be the change you wish to see in the world."

Mahatma Gandhi

The technology wheel has turned remarkably quickly in the last few decades. Advances in computation, storage and network technologies have led to the extensively digital-ized era we are living in today. At the center of the computation-storage-network triangle lays *data*. Data, which is an encoded information at its simplest, has become one of the most valuable human assets exploiting of which governments and industries are mobilized. Mathematician Clive Humby once said: "data is the new oil". Like oil, the exploitation process of data faces many challenges, of which we emphasis the following categories. First, the *large sizes* of data render simple computational tasks prohibitively time and resource-consuming. Second, the very *quick pace* at which modern high-speed and connected devices, sensors and engines generate data. Third, the *diverse formats* that are result of the diversification of data models and the proliferation of data management and storage systems. These three challenges, denoted Volume, Velocity and Variety, respectively form the 3-D Data Management Challenges put forward by Doug Laney [1], which was later adapted to the 3-V Big Data Challenges. Beyond the 3-V model, few other challenges have also been deemed significant and, thus, been incorporated, such as Veracity and Value. The former is raised when data is collected *en mass* with little to no attention dedicated to its quality and provenance. The latter is raised when a lot of data is collected but with no plausibly added value to its stakeholders or external users.

Nowadays, every agent, be it human or mechanical, is a contributor to the Big Data phenomenon. Individuals produce data through their connected handheld devices that they use to perform many of their daily life activities. For example, communicating with friends, surfing the Internet, partaking in large social media discourses, playing video games, traveling using GPS-empowered maps, even counting steps and heartbeats, etc. Industries are contributors through e.g., analyzing and monitoring the functionality of their manufactured products, health and ecological institutions through caring for the environment sanity and general human health, governments through providing inhabitants safety and well-being, etc.

Traditionally, data was stored and managed in the Relational Model [2]. The Relational Data Management is a well-established paradigm under which a large body of research, a wide array of market offerings and a broad standardization efforts have emerged. The Relational Data Management offers a great deal of system integrity, data consistency, and access uniformity, all

the while reducing the cost of system maintainability and providing advanced access control mechanisms. However, the advent of extremely large-scale Big Data applications revealed the weakness of Relational Data Management at dynamically and horizontally scaling the storage and querying of massive amounts of data. To overcome these limitations and extend application possibilities, a new breed of data management approaches have been suggested, in particular under the so-called NoSQL (Not only SQL) family. With the opportunities it brings, this paradigm shift contributes to broadening the *Variety* challenge.

Therefore, out of the five Big Data challenges, our main focus in this thesis is Variety with the presence of variably large volumes of data. Unlike Volume and Velocity problems that can be addressed in a *once-for-all* fashion, the Variety problem space is dynamic inherent to the dynamicity of data management and storage technologies it has to deal with. For example, data can be stored under a relational, hierarchical, or graph model; as it can also be stored in plain text, in more structured file formats, or under the various modern NoSQL models. Such data management and storage paradigms are in continuous development, especially under the NoSQL umbrella that does not cease to attract significant attention to this very day.

1.1 Motivation

Amid a dynamic, complex and large data-driven environment, enabling data stakeholders, analysts and users to maintain a uniform access to the data is a major challenge. A typical starting point for the exploration and analysis of the large repository of heterogeneous data is the *Data Lake*. Data Lake is named as an analogy to a natural lake. A lake is a large pool of water that is in its purest form, which different people frequent for various purposes. Professionals come to fish or mine, scuba-divers to explore, governments to extract water, etc. By analogy, the digital Data Lake is a pool of data that is in its original form accessible for various exploration and analysis purposes. This includes Querying, Search, Machine Learning, etc. Data Lake management is an integral part of many Cloud providers such as Amazon AWS, Microsoft Azure, and Google Cloud.

In the Querying use case, data in the Data Lake can directly be accessed, thus, maintaining data originality and freshness. Otherwise, data can be taken out of the Data Lake and transformed into another unique format, which then can be queried in a more uniform and straightforward way. Both approaches, direct and transformed access, have their merits and reasons to exist. The former (direct) is needed when data freshness is an uncompromisable requirement, or if for privacy or technical reasons, data cannot be transformed and moved to another environment. The latter (transformed) is needed if the previous requirements are not posed, if the query latency is the highest priority, or if there is a specifically desired quality in a certain data model or management system, in which case data is exhaustively transformed to that data model and management system.

In this thesis, we focus on enabling a uniform interface to access heterogeneous data sources. To this end, data has to be homogenized either physically or on-demand. The physical homogenization, or as commonly called Physical Integration, transforms data into a unique format, which then can be naturally queried in a uniform manner. The on-demand homogenization, or as commonly called Logical Integration, retrieves pieces of data from various sources and combines them in response to a query. Exploring the two paths, their approaches and methods, and in what context one can be superior to the other are what motivate the core of this thesis. Figure 1.1 illustrates the differences between the Virtual and Physical Integration. The latter

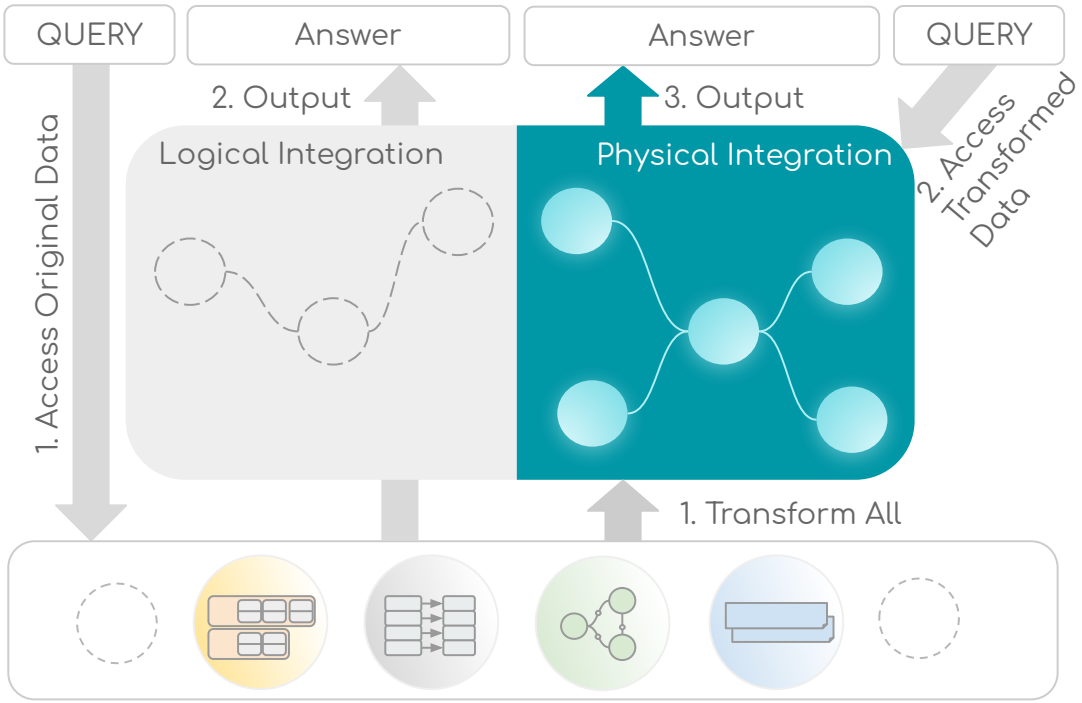


Figure 1.1: General overview. For Physical Integration (right side), all data is transformed then queried. For Virtual Integration (left side), data is not transformed; the query accesses (only) the relevant original data sources.

accesses all the data after being thoroughly transformed, while the former accesses directly the original data sources. Query execution details are hidden from the figure; it is to be found within the two big boxes of the figure, gray (left) and colored (right).

1.2 Problem Definition and Challenges

As stated in the Introduction (Chapter 1), the Variety challenge is still less adequately addressed in comparison to the other main Big Data dimensions Volume and Velocity. Further, observing the efforts that try to address the Variety challenge, cross-accessing large heterogeneous data sources is one of the least tackled sub-challenges (see Related Work, Chapter 3). On the other hand, traditional Data Integration systems fall short in embracing the new generation of data models and management systems. The latter are based on substantially different design principles and assumptions. For example, traditional Data Integration assumes a certain level of model uniformity that new Data Management systems comply against. Modern distributed database systems (e.g, NoSQL stores) opened the flour to more flexible models such as the document or wide columnar. Additionally, traditional Data Integration also assumes the centralized nature of all the accessed data, while modern Data Management systems are decentralized and distributed. For example, distributed file systems (e.g., HDFS [5]) invalidate the traditional assumption that data has to fit in memory or storage of a single machine in order for the various retrieval mechanisms (e.g., indexes) to be operational and effective. Such assumptions hinder the capability of traditional Data Integration systems to cater for the large scale and various types of the new Data Management paradigms.

Therefore, the general problem that this thesis addresses is providing a uniform access to heterogeneous data, with a focus on the large-scale distributed space of data sources. The specific challenges that the thesis targets are the following:

Challenge 1: Uniform querying of heterogeneous data sources

There are numerous approaches to access and interact with a data source, which we can categorize into APIs and query languages. APIs, for Application Programming Interfaces, expose programmatic methods allowing users to write, manipulate and read data using programming languages. A popular example is JDBC (Java Database Connectivity), which offers a standardized way to access databases. Programmatic methods can also be triggered distantly via a Web protocol (HTTP), turning an API into a *Web API*. There are two main approaches by which Web APIs receive commands from users. The first is by providing the method name to execute remotely, an approach called RPC (Remote Procedure Call). The second is by issuing more structured requests ultimately following a specific standard; an example of a prominent approach is REST (Representational State Transfer). As these methods are effectively executed by a Data Management system, they can only access its underlying data.

The second approach of interacting with a data source is via query languages. The range of options here is wider than APIs. Examples include SQL for accessing relational databases (e.g., SQL Server) or tabular data in a more general sense (e.g., Parquet files), SQL-derived languages (e.g., Cassandra Query Language, CQL), XPath/XQuery for XML data, JSON-based operations for Document stores, Gremlin and Cypher for graph data, etc. An access method that falls in between the two categories is GraphQL, which allows to run queries via a Web API. However, similarly to APIs, queries in these languages are only posed against a specific data source to interact with its underlying data. On the other hand, a few modern frameworks (e.g., Presto, Drill) have used SQL syntax to allow the explicit reference to heterogeneous data sources in the course of a single query, and then to retrieve the data from heterogeneous sources accordingly. However, the challenge is providing a method that accesses several sources at the same time in an ad hoc manner without having to explicitly *reference* the data sources, like if the user is querying a single database.

Challenge 2: Querying original data without prior data transformation

As mentioned earlier in this chapter, in order to realize a uniform access to heterogeneous data sources, data needs to be either physically or virtually integrated. Unlike the Physical Integration that unifies the data model in a pre-processing ingestion phase, the Virtual Integration requires to pose queries directly against the original data without prior transformation. The challenge here is incorporating an intermediate phase that plays three roles (1) *interpreter*, which analyses and translates the input query into requests over data sources, (2) *explorer*, which leverages metadata information to find the sub-set of data sources containing the needed sub-results, and (3) *combiner*, which collects and reconciles the sub-results forming the final query answer. As we are dealing with a disperse distributed data environment, an orthogonal challenge to the three-role middleware is to ensure the accuracy of the collected results. If it issues an incorrect request as *interpreter*, it will not detect the correct sources (false positives) as *explorer*, and, thus, will not return the correct sub-results as *combiner*. Similarly, if it detects incorrect links between query parts as *interpreter*, it will perform a join yielding no results as *combiner*.

Challenge 3: Coping with the lack of schema and semantics in data lakes

By definition, a Data Lake is a schema-less repository of original data sources. In the absence of a general schema or any mechanism that allows to deterministically transition from a query to a data source, there is no way to inter-operate, link and query data over heterogeneous data sources in a uniform manner. For example, a database or a CSV file uses a column that has no meaning, e.g., *col0* storing first names of customers. Also, different data sources can use different naming formats and conventions to denote the same schema concept. For example, a document database uses a field called *fname* to store customer's first names. The challenge is then to incorporate a mechanism that allows to (1) abstract away the semantic and syntactic differences found across the schemata of heterogeneous data sources, and (2) maintain a set of association links that allow detecting a data source given a query or a part of a query. The former mechanism relies on a type of domain definition containing abstract terms, which are to be used by the query. The latter mechanism maintains the links between these schema abstract terms and the actual attributes in the data sources. These mechanisms can be used to fully convert the data in a Physical Integration of query the original data on-the-fly in a Virtual Integration.

Challenge 4: Scalable processing of expensive query operations

As the scope of our work is mostly dealing with distributed heterogeneous data sources, the challenge is to provide a scalable query execution environment that can accommodate the expensive operations involving those data sources. The environment is typically based on the main memory of multiple compute nodes of a cluster. A query can be unselective, i.e., it requests a large set of results without filters, or with filters that do not significantly reduce the size of the results. For example, an online retailer is interested in knowing the age and gender of all customers who have purchased at least three items during November's promotional week of the last three years. Although we filtered on the year, month and number of purchased items, the result set is still expected to be large because promotional weeks are very attractive shopping periods. A query can also join data coming from multiple data sources, which is typical in heterogeneous environments such as the Data Lake. For example, the retailer asks to get the logistics company that shipped the orders of all the customers who purchased fewer items this year in comparison to the previous year and who left negative ratings about the shipping experience. This query aims at detecting which logistic companies have caused inconvenient shipping experience making certain customers rely less on the online retailer, and, thus, shop less therefrom. To do so, the query has to join between Logistics, Customers, Orders, and Ratings, which is expected to generate large intermediate results only containable and processable in a distributed manner.

Challenge 5: Enabling joinability of heterogeneous data sources

When joining various data sources, it is not guaranteed that identifiers on which join queries are posed match, and, thus, the join is successful and the query returns (the correct) results. The identifiers can be of a different shape or lay in a different value range. For example, given two data sources to join, values of the left join operand are in small letters and values of the right are in big letters; or values of the left side are prefixed and contains an erroneous extra character, and values of the right size are not prefixed and without any erroneous characters. The challenge is then to correct these syntactic value misrepresentations on the fly during query

execution, and not in a pre-processing phase generating a new version of the data, which then is queried.

1.3 Research Questions

To solve the above challenges we appeal in this thesis to Semantic technologies, which provide a set of primitives and strategies dedicated to facilitating Data Integration. Such primitives include ontologies, mapping language and a query language, with strategies for how these can collectively be used to uniformly integrate and access disparate data. These primitives and strategies allow to solve both Physical and Logical Data Integration problems. In the Physical Integration, data is fully converted under the Semantic Web data model, namely RDF [6]. In the Virtual Integration, data is not physically converted but integrated *on-demand* and accessed *as-is*. In both cases Semantic Web query language, SPARQL [7], is used to access the data.

We intend to start our study with a fully Physical Integration where data is exhaustively transformed into RDF, then we perform the necessary steps to bypass the transformation and directly access the original data. The advantage of this approach is twofold. First, it will reveal to us what are the necessary adaptations to transition from a physical off-line to a virtual on-line on-demand data access. Second, it will unveil the various trade-offs to make in each direction in order to reap the benefit of each. Finally and for the Virtual Integration in particular, data remains in its source only effectively accessible using its native query language. Therefore, it is necessary to ensure the suitability of SPARQL as a unified access interface, or a more efficient language exists to which SPARQL should be translated. Having clarified the context, our thesis work is based on the following research questions:

RQ1. What are the criteria that lead to deciding which query language can be most suitable as the basis for Data Integration?

As Data Integration entails a model conversion, either as physical or virtual, it is important to check the respective query language's suitability to act as a universal access interface. Since we are basing on Semantic Web data model RDF (introduced later in chapter 2) at the conceptual level, we default to using its query language SPARQL (also introduced in chapter 2) as the unified query interface. However, at the physical level, a different data model may be more suitable (e.g., space efficiency, query performance, technology-readiness, etc.), which requires the translation of the query in SPARQL to the data model's query language. An example of this can be adopting a tabular or JSON data model, in which case SPARQL query needs to be translated to SQL or a JSON-based query formalism, respectively. On the Virtual Data Integration side, we may resort to another language if it has conversions to more query languages, thus, enables access to more data sources. Therefore, we start our thesis by reviewing the literature of query translation approaches that exist between various query languages, including SPARQL.

RQ2. Do Semantic Technologies provide ground and strategies for solving Physical Integration in the context of Big Data Management i.e., techniques for the representation, storage and uniform querying of large and heterogeneous data sources?

To answer this, we investigate Semantic-based Data Integration techniques for ingesting and querying heterogeneous data sources. In particular, we study the suitability of its data model in capturing both the syntax and semantics found across the ingested data. We examine Semantic

techniques for the mapping between the data schema and the general schema that will guide the Data Integration. One challenge in this regard is the heterogeneous data models e.g., table and attributes in relational and tabular data, document and fields in document data, type and properties in graph data, etc. We aim at forming a general reusable blueprint that is based on Semantic Technologies and state-of-the-art Big Data Management technologies to enable the scalable ingestion and processing of large volumes of data. Since data will be exhaustively translated to the Semantic data model, we will dedicate special attention to optimizing the size of the resulted ingested data, e.g., by using partitioning and clustering strategies.

RQ3. Can Semantic Technologies be used to incorporate an intermediate middleware that allows to uniformly access original large and heterogeneous data sources on demand?

To address this question, we analyze the possibility of applying existing Semantic-based Data Integration techniques to provide a virtual, uniform and ad hoc access to *original* heterogeneous data. By *original*, we mean data as and where it was initially collected without requiring prior physical model transformation. By *uniform*, we mean using only one method to access all the heterogeneous data sources, even if the access method is based on a formalism that is different from that of one or more of the data sources. By *ad hoc*, we mean that from the user's perspective, the results should be derived directly starting from the access request and not by providing an extraction procedure. A uniform ad hoc access can be a query in a specific query language, e.g., SQL, SPARQL, XPath, etc. The query should also be *decoupled* from the data source specification, meaning that it should not explicitly state the data source(s) to access. Given a query, we are interested in analyzing the different mechanisms and steps that lead to forming the final results. This includes loading the relevant parts of the data into dedicated optimized data structures where they are combined, sorted or grouped distributedly in parallel.

RQ4. Can Virtual Semantic Data Integration principles and their implementation be applied to both synthetic and real-world use cases?

To answer this, we evaluate the implementation of the previously presented principles and strategies for Virtual Data Integration. We consider several metrics, namely data execution time, results accuracy, and resource consumption. We use both an existing benchmark with auto-generated data and queries, as well as a real-world use case and data. Such evaluations allow us to learn lessons that help improve the various implementations, e.g., performance pitfalls, recurrent SPARQL operations and fragments to enrich the supported fragment, new demanded data sources, etc.

1.4 Thesis Overview

In order to prepare the reader for the rest of this document, we present here an overview of the main contributions brought by the thesis, with references to the addressed research questions. We conclude with a list of publications and a glance at the structure of the thesis.

1.4.1 Contributions

In a nutshell, this thesis looks at *the techniques and strategies that enable the ad hoc and uniform querying of large and heterogeneous data sources.* Consequently, the thesis suggests multiple

methodologies and implementations that demonstrate its findings. With more details, the contributions are as follows:

1. **Contribution 1:** *A survey of Query Translation methods.* Querying heterogeneous data in a uniform manner requires a form of model adaptation, either permanently in the Physical Integration or temporary in the Virtual Integration of diverse data. For this reason, we conduct a survey on Query Transformation methods that exist in the literature and as published tools. We propose eight criteria according to which we classify translation methods from more than forty articles and published tools. We consider seven popular query languages (SQL, XPath/XQuery, Document-based, SPARQL, Gremlin, and Cypher) where popularity is judged based on a set of defined selection criteria. In order to facilitate the reading of our findings vis-à-vis the various survey criteria, we provide a set of graphical representations. For example, a historical timeline of the methods' emergence years, or star ratings to show the translation method's degree of maturity. The survey allows us to discover which translation paths are missing in the literature or that are not adequately addressed. It also allows us to identify gaps and learn lessons to support further research on the area. This contribution aims to answer **RQ1**.

2. **Contribution 2:** *A unified semantic-based architecture, data model and storage that are adapted and optimized for the integration of both semantic and non-semantic data.* We present a unified architecture that enables the ingestion and querying of both semantic and non-semantic data. The architecture presents a Semantic-based Physical Integration, where all input data is physically converted into the RDF data model. We suggest a set of requirements that the architecture needs to fulfill, such as the preservation of semantics and efficient query processing of large-scale data. Moreover, we suggest a scalable tabular data model and storage for the ingested data, which allows for efficient query processing. Under the assumption that the ingestion of RDF data may not be as straightforward as other flat models like relational or key-value, we suggest a partitioning scheme whereby an RDF instance is saved into a table representing its class, with the ability to capture also the other classes within the same class table if the RDF instance is multi-typed. We physically store the loaded data into a state-of-the-art storage format that is suitable for our tabular partitioning scheme, and that is queried in an efficient manner using large-scale query engines. We conduct an evaluation study to examine the performance of our implementation of the architecture and approaches. We also compare our implementation against a state-of-the-art triple store to showcase the implementation ability to deal with large-scale RDF data. This has answers to answer **RQ2**.

3. **Contribution 3:** *A virtual ontology-based data access to heterogeneous and large data sources.* We suggest an architecture for the Virtual Integration of heterogeneous and large data sources, which we call *Semantic Data Lake*, SDL. It allows to query original data sources without requiring to transform or materialize the data in a pre-processing phase. In particular, it allows to query the data in a distributed manner, including join and aggregation operations. We formalize the concepts that are underlying the SDL. The suggested Semantic Data Lake builds on the principles of Ontolog-Based Data Access, OBDA [8], hence mappings language and SPARQL query are cornerstones in the architecture. Furthermore, we allow users to declaratively alter the data on query time in order to enable two sources to join. This is done on two levels, the mappings and SPARQL query. Finally, we suggest a set of requirements that SDL implementations

have to comply with. We implement the SDL architecture and its underlying mechanisms using state-of-the-art Big Data technologies, Apache Spark and Presto. It supports several popular data sources, including Cassandra, MongoDB, Parquet, Elasticsearch, CSV and JDBC (experimented with MySQL, but many other data sources can be connected to via JDBC in the same way). This contribution aims to answer **RQ3**.

4. **Contribution 4:** *Evaluating the implementation of the Semantic Data Lake through a synthetic and a real-world industrial use case.* We explore the performance of our implementation in two use cases, one synthetic and one based on a real-world application from the Industry 4.0 domain. We are interested in experimenting with queries that evolve a different number of data sources to assess the ability to (1) perform joins and (2) the effect of increasing the number of joins on the overall query execution time. We breakdown the query execution time into its constituent sub-phases: query analyses, relevant data detection, and query execution time by the query processing engine (Apache Spark and Presto). We also experiment with increasing sizes of the data to evaluate the implementation scalability. Besides query-time performance, we measure results accuracy and we collect resource consumption information. For the former, we ensure 100% accuracy of the returned results; for the latter, we monitor data read/write, data transfer and memory usage. This contribution has answers to **RQ4**.

1.4.2 List of Publications

The content of this thesis is mostly based on scientific publications presented at international conferences and published within their respective proceedings. The following is an exhaustive list of these publications along with other publications that did not make part of the thesis. A comment is attached to the publications where I have a partial contribution, and to one publication (number 2) with another main author involvement. To the other publications, I have the major contribution, with the co-authors contributing mostly by reviewing the content and providing supervision advice.

- *Conference Papers*:

  3. **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer, Jens Lehmann. *Uniform Access to Multiform Data Lakes Using Semantic Technologies.* In Proceedings of the 21st International Conference on Information Integration and Web-based Applications & Services (iiWAS), 313-322. 2019. I conducted most of the study; co-author Damien Graux contributed to the performance evaluation (Obtaining and representing Resource Consumption figures, Chapter 8).
  4. **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer, Jens Lehmann. *Squerall: Virtual Ontology-Based Access to Heterogeneous and Large Data Sources.* In Proceeding of the 18th International Semantic Web Conference (ISWC), 229-245, 2019.
  5. Gezim Sejdiu, Ivan Ermilov, Jens Lehmann, **Mohamed Nadjib Mami**. *Distlodstats: Distributed computation of RDF dataset statistics.* In Proceedings of the 17th International Semantic Web Conference (ISWC), 206-222. 2018. This is a joint work with Gezim Sejdiu. I contributed to formulating and presenting the problem and solution, and in evaluating the complexity of the implemented statistical criteria.

6. Kemele M. Endris, Mikhail Galkin, Ioanna Lytra, **Mohamed Nadjib Mami**, Maria-Esther Vidal, Sören Auer. *MULDER: querying the linked data web by bridging RDF molecule templates.* In Proceedings of the 18th International Conference on Database and Expert Systems Applications (DEXA), 3-18, 2017. This is a joint work with Kemele M. Endris and Mikhail Galkin. I contributed to the experimentation, particularly preparing graph partitioning.
7. Farah Karim, **Mohamed Nadjib Mami**, Maria-Esther Vidal, Sören Auer. *Large-scale storage and query processing for semantic sensor data.* In Proceedings of the 7th International Conference on Web Intelligence, Mining and Semantics, 8, 2017. This is a joint work with Farah Karim. I contributed to describing, implementing and evaluating the tabular representation of RDF sensor data, including the translation of queries from SPARQL to SQL.
8. Sören Auer, Simon Scerri, Aaad Versteden, Erika Pauwels, **Mohamed Nadjib Mami**, Angelos Charalambidis, et al. *The BigDataEurope platform–supporting the variety dimension of big data.* In Proceedings of the 17th International Conference on Web Engineering (ICWE), 41-59, 2017. This is a project outcome paper authored by its technical consortium. I was responsible for describing the foundations of the Semantic Data Lake concept, including its general architecture. I also contributed to building the platform's high-level architecture.
9. **Mohamed Nadjib Mami**, Simon Scerri, Sören Auer, Maria-Esther Vidal. *Towards Semantification of Big Data Technology.* International Conference on Big Data Analytics and Knowledge Discovery (DaWaK), 376-390, 2016.

- *Journal Articles*:

1. Kemele M. Endris, Mikhail Galkin, Ioanna Lytra, **Mohamed Nadjib Mami**, Maria-Esther Vidal, Sören Auer. *Querying interlinked data by bridging RDF molecule templates.* In Proceedings of the 19th Transactions on Large-Scale Data-and Knowledge-Centered Systems, 1-42, 2018. This is a joint work with Kemele M. Endris and Mikhail Galkin. An extended version with the same contribution as the conference number 6 below.
2. **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Harsh Thakkar, Sören Auer, Jens Lehmann. *The query translation landscape: a survey.* In ArXiv, 2019. To be submitted to an adequate journal. I conducted most of this survey, including most of the review criteria and the collected content. Content I have not provided is the review involving Tinkerpop and partially Neo4J (attributed to Harsh Thakkar).

- *Demonstration Papers*:

12. **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer, Jens Lehmann. *How to feed the Squerall with RDF and other data nuts?.* In Proceeding of the 18th International Semantic Web Conference (ISWC), Demonstrations and Posters Track, 2019.
13. **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer. *Querying Data Lakes using Spark and Presto.* In Proceedings of the World Wide Web Conference (WWW), 3574-3578. Demonstrations Track, 2019.

14. Gezim Sejdiu, Ivan Ermilov, **Mohamed Nadjib Mami**, Jens Lehmann. *STATisfy Me: What are my Stats?*. In Proceedings of the 17th International Semantic Web Conference (ISWC), Demonstrations and Posters Track, 2018. This is a joint work with Gezim Sejdiu. I contributed to explaining the approach.

- *Industry Papers*:
  1. **Mohamed Nadjib Mami**, Irlán Grangel-González, Damien Graux, Enkeleda Elezi, Felix Lösch. *Semantic Data Integration for the SMT Manufacturing Process using SANSA Stack*. I contributed to deploying, applying and evaluating SANSA-DataLake (Squerall), and partially establishing the connection between SANSA-DataLake and another component of the project (Visual Query Builder).

1.5 Thesis Structure

The thesis is structured in nine chapters outlined as follows:

- *Chapter 1: Introduction.* This chapter presents the main motivation behind the thesis, describes the general problem it tackles and lists its challenges and main contributions.
- *Chapter 2: Background and Preliminaries.* This chapter lays the foundations for all the rest of the thesis, including the required background knowledge and preliminaries.
- *Chapter 3: Related Work.* This chapter examines the literature for related efforts in the topic of Big Data Integration. The reviewed efforts are classified into Physical Data Integration and Virtual Data Integration, each category is further divided into a set of sub-categories.
- *Chapter 4: Overview on Query Translation Approaches.* This chapter presents a literature review on the topic of Query Translation, with a special focus on the query languages involved in the thesis.
- *Chapter 5: Physical Big Data Integration.* This chapter describes the approach of Semantic-based Physical Data Integration, including a performance comparative evaluation.
- *Chapter 6: Virtual Big Data Integration - Semantic Data Lake.* This chapter describes the approach of Semantic-based Virtual Data Integration, also known as Semantic Data Lake.
- *Chapter 7: Semantic Data Lake Implementation: Squerall.* This chapter introduces an implementation of the Semantic-based Virtual Data Integration.
- *Chapter 8: Squerall Evaluation and Use Cases.* This chapter evaluates and showcases two applications of the SDL implementation, one synthetic and one from a real-world use case.
- *Chapter 9: Conclusion and Future Directions.* This chapter concludes the thesis revising the research questions, discussing lessons learned and outlining a set of future research directions.

CHAPTER 2

Background and Preliminaries

"The world is changed by your example, not by your opinion."

Paulo Coelho

In this chapter, we introduce the foundational concepts that are necessary to understand the rest of the thesis. We divide these concepts into Semantic Technologies, Big Data Management and Data Integration. We dedicate section 2.1 to Semantic Technologies concepts, including Semantic Web canonical data model RDF, its central concept of ontologies and its standard query language SPARQL. In section 2.2, we define Big Data Management related concepts, in particular concepts from distributed computing and from modern data storage and management systems. Finally, Data Integration concepts are introduced in section 2.3.

2.1 Semantic Technologies

Semantic Technologies are a set of technologies that aim to realize Semantic Web principles, i.e., let machines understand the meaning of data and interoperate thereon. In the following, we define the Semantic Web as well as its basic building blocks.

2.1.1 Semantic Web

The early proposal of the Web [9] as we know it today was defined as part of a *Linked Information Management* system presented by Tim Berners Lee to his employer CERN in 1989. The purpose of the system was to keep track of the growing information collected within the company, e.g., code, documents, laboratories, etc. The system was imagined to be a 'web' or a 'mesh' of information where a person can browse and traverse from one information source (e.g., reports, notes, documentation) to another. The traversal used a previously known mechanism called HyperText (1987) [10]. The proposal received encouragement, so Tim, together with colleague Robert Cailliau, expanded on the key concepts and presented a reformulated proposal entitled: "*WorldWideWeb: Proposal for a HyperText project*"[11] with focus on the Web. Years later, in 2001, Tim Berners Lee and colleagues suggested a transition from a Web of documents [12], as it was conceived, to a *Web of data* where textual information inside a document is given a meaning, e.g., athlete, journalist, city, etc. This meaning is specified using predefined vocabularies and taxonomies in a standardized format, which machines can understand and inter-operate on.

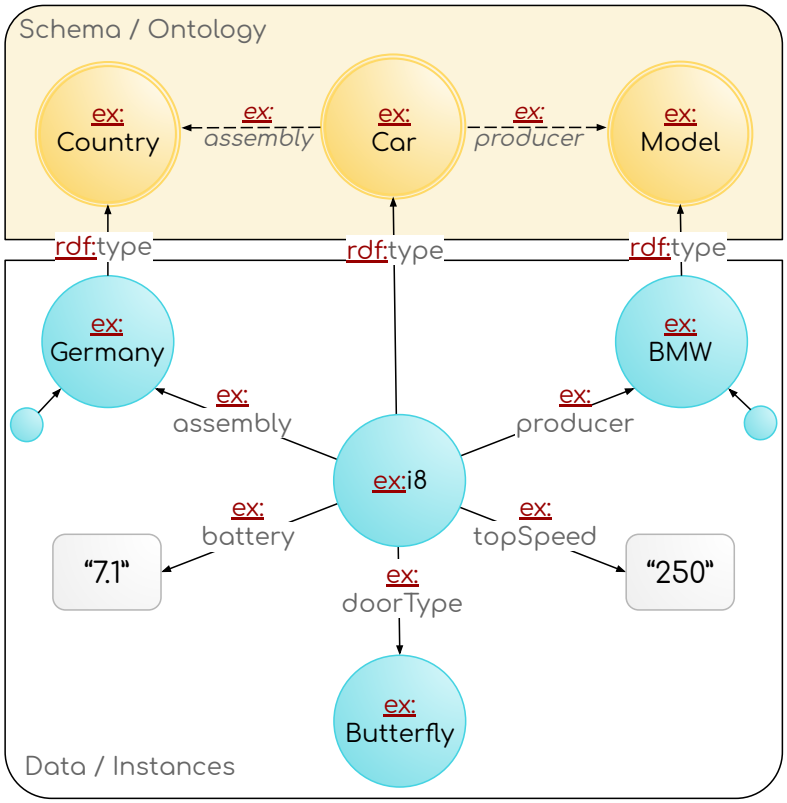


Figure 2.1: An example of RDF triples forming an RDF graph. Resources are denoted by circles and literals are denoted by rectangles. Instance resource circles are located on the lower box, and Schema resources are located on the upper box.

The new Web, called *Semantic Web*, has not only given *meaning* to previously plain textual information but also promoted data sharing and interoperability across systems and applications.

2.1.2 Resource Description Framework

To express and capture that meaning, Semantic Web made use of RDF, the *Resource Description Framework*, introduced earlier in 1998 by the W3C Consortium [6]. RDF is a standard for describing, linking and exchanging machine-understandable information on the Web. It denotes the entities inside Web pages as *resources* and encodes them using a triple model *subject-predicate-object*, similar to subject-verb-object of an elementary sentence. RDF triple can formally be defined as follows (Definition 2.1):

Definition 2.1: RDF Triple [13]

Let $\mathbf{I}$, $\mathbf{B}$, $\mathbf{L}$ be disjoint infinite sets of URIs, blank nodes, and literals, respectively. A tuple $(s, p, o) \in (\mathbf{I} \cup \mathbf{B}) \times \mathbf{I} \times (\mathbf{I} \cup \mathbf{B} \cup \mathbf{L})$ is denominated an RDF triple, where s is called the subject, p the predicate, and o the object.

Subject refers to a resource, object refers to a resource or a literal value, predicate refers to a relationship between the subject and the object. Figure 2.1 shows an example of a set

```
1  @prefix ex: <https://examples.org/automobile/> .
2  @prefix rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#> .
3
4  ex:Germany rdf:type     ex:Country .
5  ex:BMW     rdf:type     ex:Model .
6  ex:I8      rdf:type     ex:Car .
7  ex:I8      ex:assembly  ex:Germany .
8  ex:I8      ex:producer  ex:BMW .
9  ex:I8      ex:doorType  ex:Butterfly .
10 ex:I8      ex:topSpeed  "150"^^xsd:integer .
11 ex:I8      ex:battery   "7.1"^^xsd:float .
```

Listing 2.1: RDF triples represented by the graph in Figure 2.1.

of RDF triples, collectively forming an RDF *graph*. We distinguish between data or instance resources and schema resources[1]. Data resources are *instances* of schema resources. For example, in Figure 2.1, I8, BMW, Germany, and Butterfly are instances while Car, Model and country are schema resources, also called classes. I8, BMW and Germany are instances of Car, Model and Country classes, respectively. All resources of the figure belong to the ontology of namespace 'ex'. In the same figure, "7.1" and "250" are literals of type `float` and `integer` respectively.

Resources are uniquely identified using URIs (Uniform Resource Identifiers). Unlike URL (Uniform Resource Locator) that has necessarily to locate an existing Web page or a position therein, URI is a universal pointer allowing to uniquely identify an abstract or a physical resource [14] that does not necessarily have (although recommended) a representative Web page. For example, <http://example.com/automobile/Butterfly> and `ex:Butterfly` are URIs. In the latter, the prefix `ex` denotes a namespace [14], which uniquely identifies the scheme under which all related resources are defined. Thanks to the use of prefixes, the car door type `Butterfly` of URI `ex:Butterfly` defined inside the scheme `ex` can be differentiated from the insect `Butterfly` of URI `ins:Butterfly` defined inside the scheme `ins`. The triples of the RDF graph of Figure 2.1 are presented in Listing 2.1.

2.1.3 Ontology

Ontology is a specification of a common domain understanding that can be shared between people and applications. It promotes interoperability between systems and reusability of the shared understanding across disparate applications [15–17]. For example, ontologies define all the concepts underlying a medical or an ecological domain that enable medical and ecological institutions to universally share and interoperate over the same data. By analogy, an ontology to RDF data, among others, plays the role of a schema to relational data. Ontologies, however, are encoded using the same model as the data, namely the *subject-predicate-project* triple model. Further, ontologies are much richer in expressing the semantic characteristics of the data. For example, they allow to build hierarchies between classes (e.g., Car as sub-class of Vehicle) or between properties (e.g., topSpeed as sub-property of metric) or establishing relations between properties (e.g., inverse, equivalent, symmetric, transitive) by using a set of *axioms*. Axioms are partially similar to integrity constraints in relational databases, but with a richer expressivity. Ontologies can be shared with the community, in contrast to the

[1] Another common appellation is A-Box for instance resources and T-Box for schema resources.

relational schema and integrity constraints, both expressed using SQL query language, that only live inside and concern a specific database. A major advantage of sharing ontologies is allowing the collaborative construction of *universal schemata* or models that outlive the data they were initially describing. This characteristic complies with one of the original *Web of Data* and *Linked Open Data* principles [18]. Last but not least, ontologies are the driver of one of the most prominent Semantic Data applications, namely the Ontology-based Data Access (OBDA) [8]. An ontology can be formally defined as follows (Definition 2.2):

Definition 2.2: Ontology [19]

Let C be a conceptualization, and L a logical language with vocabulary V and ontological commitment K. An ontology O_K for C with vocabulary V and ontological commitment K is a logical theory consisting of a set of formulas of L, designed so that the set of its models approximates as well as possible the set of intended models of L according to K.

2.1.4 SPARQL Query Language

Both data and ontology are modeled after the triple model, RDF. Several query languages for querying RDF have been suggested since its conception. RQL, SeRQL, eRQL, SquishQL, TriQL, RDQL, SPARQL, TRIPLE, Versa [20, 21]. Among these languages, SPARQL has become a W3C standard and recommendation [7, 22]. SPARQL, for SPARQL Protocol and RDF Query Language, extracts data using pattern matching technique, in particular graph pattern matching. Namely, the query describes the data it needs to extract in the form of a set of patterns. These patterns are triples with some of their terms (subject, predicate or object) being variable, or as also called *unbound*. Triple patterns of a SPARQL query are organized into so-called Basic Graph Pattern and are formally defined as follows (Definition 2.3):

Definition 2.3: Triple Pattern and Basic Graph Patter [23]

Let U, B, L be disjoint infinite sets of URIs, blank nodes, and literals, respectively. Let V be a set of variables such that $V \cap (U \cup B \cup L) = \theta$. A triple pattern tp is a member of the set $(U \cup V) \times (U \cup V) \times (U \cup L \cup V)$. Let $tp_1, tp_2, \ldots, tp_n$ be triple patterns. A Basic Graph Pattern (BGP) B is the conjunction of triple patterns, i.e., $B = tp_1\ AND\ tp_2\ AND\ \ldots\ AND\ tp_n$

For convenience, SPARQL shares numerous common query operations with other query languages. For example, the following are operations that have identical syntax to SQL: `SELECT` / `WHERE` for projection and selection, `GROUP BY` / `HAVING` for grouping, `AVG|SUM|MEAN|MAX|MIN...` for aggregation, `ORDER BY ASC|DESC` / DISTINCT /`LIMIT` / `OFFSET` as solution modifiers (`SELECT` is also a modifier). However, SPARQL contains query operations and functions that are specific to RDF e.g., *blank nodes*, which are resources (subject or object) for which the URI is not specified, functions *isURI()*, *isLiteral()*, etc. Additionally, SPARQL allows other forms of queries than the conventional `SELECT` queries. For example, `CONSTRUCT` is used to return the results (matching triple patterns) in the form of an RDF graph, instead of a table like in SELECT queries. `ASK` is used to verify whether (`true`) or not (`false`) triple patterns can be matched against the data. `DESCRIBE` is used to return an RDF graph that describes a resource given its URI. See Listing 2.2 for a SPARQL query example, which is used to count the number

of cars that are produced by BMW, have butterfly doors and can reach a top speed of 180km/h or above.

```
PREFIX ex: <https://examples.org/automobile/>
PREFIX rdf: <http://www.w3.org/1999/02/22-rdf-syntax-ns#>

SELECT (COUNT(?car) AS ?count)
WHERE {
        ?car rdf:type ex:Car .
        ?car ex:producer ex:BMW .
        ?car ex:doorType ex:Butterfly .
        ?car ex:topSpeed ?topSpeed .
        FILTER (?topSpeed >= "180")
}
```

Listing 2.2: Example SPARQL Query.

2.2 Big Data Management

Data Management is a fundamental topic in the Computer Science field. The first so-called Data Management systems to appear in the literature dates to the sixties [24, 25]. Data Management is a vast topic grouping all disciplines that deal with the data. This ranges from data modeling, ingestion, governance, integration, curation, to processing, and more. Recently, with the emergence of Big Data phenomena, Big Data Management concept was suggested [26–29]. In the following, we define Big Data Management, BDM, and its underlying concepts.

2.2.1 BDM Definitions

Big Data can be seen as an umbrella term covering the numerous challenges that traditional centralized Data Management techniques faced when dealing with large, dynamic and diverse data. Big Data Management is a sub-set of Data Management addressing data management problems caused by the collection of large and complex datasets. Techopedia[2] defines Big Data Management as "The efficient handling, organization or use of large volumes of structured and unstructured data belonging to an organization.". TechTarget[3] defines it as "the organization, administration and governance of large volumes of both structured and unstructured data. Corporations, government agencies and other organizations employ Big Data management strategies to help them contend with fast-growing pools of data, typically involving many terabytes or even petabytes of information saved in a variety of file formats". Datamation[4] defines it as "A broad concept that encompasses the policies, procedures and technology used for the collection, storage, governance, organization, administration and delivery of large repositories of data. It can include data cleansing, migration, integration and preparation for use in reporting and analytics.".

2.2.2 BDM Challenges

The specificity of Big Data Management is, then, its ability to *address* the challenges that arise from processing large, dynamic and complex data. Examples of such challenges include:

[2] https://www.techopedia.com/dictionary
[3] https://whatis.techtarget.com
[4] https://www.datamation.com/

- The user base of a mobile app has grown significantly that the app started generating a lot of activity data. The large amounts of data eventually exhausted the querying ability of the underlying database and overflew the available storage space.
- An electronic manufacturing company improved the performance of its automated electronic mounting technology. The latter started to generate data at a very high pace handicapping the monitoring system ability to collect and analyze the data in a timely manner.
- Data is averagely large but the type and complexity of the analytical queries, which span a large number of tables became a bottleneck in generating the necessary dashboards.
- New application needs of a company required to incorporate new types of data management and storage systems, e.g., graph, document and key-value, which do not (straightforwardly) fit into the original system data model.

These challenges are commonly observed in many traditional Database Management Systems, e.g. the relational, or RDBMS. The latter was the *de facto* data management paradigm for four decades [30, 31]. However, the rapid growth of data in the last decade has revealed RDBMSs weakness at accommodating large volumes of data. The witnessed performance downgrade is the product of their strict compliance with ACID properties [32, 33], namely Atomicity, Consistency, Isolation and Durability. In a nutshell, Atomicity means that a transaction has to succeed as a whole or rolled back, Consistency means that any transaction should leave the database in a consistent state, Isolation means that transactions should not interfere, and Durability means that any change made has to persist. Although these properties guarantee data integrity, they introduce a significant overhead when performing lots of transactions over large data. For example, a write operation to a primary key attribute may be bottlenecked by checking the uniqueness of the value to be inserted. Other examples include checking the type correctness, or checking whether the value to be inserted in a foreign key attribute exists already as a primary key in another referenced table, etc. These challenges are hugely reduced by modern Data Management systems, thanks to their schema flexibility and distributed nature.

2.2.3 BDM Concepts and Principles

To mitigate these issues, approaches in BDM were suggested e.g., to relax the strict consistency and integrity constraints of RDBMSs and, thus, accelerate reading and writing massive amounts of data in a *distributed* manner. The following is a listing of concepts that contribute to solving the aforementioned challenges, which mostly stem from Distributed Computing field:

- **Distributed Indexing.** An index in traditional RDBMSs may itself become a source of overhead when indexing large volumes of data. In addition to the large storage space it occupies, maintaining a large index with frequent updates and inserts becomes an expensive process. Modern distributed databases cope with the large index size by distributing it across multiple nodes. This is mostly the case of hashing-based indexes, which are distribution-friendly. They only require an additional hash index that allows to tell in which node a requested indexed data item is located, then the local index is used to reach the exact item location. This additional hash index is generally a lot smaller than the data itself, and it can easily be distributed if needed. For example, an index created for a file stored in HDFS (Hadoop [34] Distributed File System) [5] can be hash-indexed to locate which file part is stored in which HDFS block (HDFS unit of storage

comprising the smallest split of a file, e.g., 128MB). Similarly, Cassandra, a scalable database, maintains a hash table to locate in which partition (sub-set of the data) a tuple should be written; the same hash value is used to retrieve that tuple given a query [35]. Traditional tree-based indexes, however, are less used in BDM, as tree data structures are less straightforward to split and distribute than hashing-based indexes. Just as indexes with conventional centralized databases, however, write operations (insert/update) can become slower when the index size grows. Moreover, the indexes in distributed databases are generally not as sophisticated as their centralized counterparts, e.g. secondary indexes [36]. In certain distributed frameworks, an index may have a slightly different meaning, e.g., in Elasticsearch search engine an index is the data itself to be queried [37].

- **Distributed Join.** Joining large volumes of data is a typical case where query performance can deteriorate. To join large volumes of data, distributed frameworks[5] typically try to use distributed versions of hash join. Using a common hash-based partitioner, the system tries to bring the two sides of a join into the same node, so the join can be partially performed locally and thus less data is transferred between nodes. Another common type of join in distributed frameworks is broadcast join, which is used when a side of the join is known to be small and thus loadable in the memory of every cluster node. This join type significantly minimizes data transfer as all data needed from one side of the join is guaranteed to be locally accessible. Sort-merge join is also used in cases where hash join involves significant data transfer.

- **Distributed Processing.** Performing computations e.g., query processing, in a distributed manner can be substantially different than in a single machine. For example, MapReduce [38] is a prominent distributed processing paradigm that solves computation bottlenecks by providing two simple primitives allowing to execute computational tasks in parallel. The primitives are *map*, which converts an input data item to a (key,value) pair, and *reduce*, which subsequently receives all the values attached to the same key and performs a common operation thereon. This allows to accomplish a whole range of computation, from as simple as counting error messages in a log file to as complex as implementing ETL integration pipelines. Alternative approaches are based on DAG (Directed Acyclic Graph) [39, 40] processing models, where several tasks (e.g., map, reduce, group by, order by, etc.) are chained and executed in parallel. These tasks operate on the same chunk of data; data is only transferred across the cluster if the output of multiple tasks needs to be combined (e.g., reduce, join, group by, etc.). Knowing the tasks order in the DAG, it is possible to recover from failure by resuming the failed task from the previous step, instead of starting from the beginning.

- **Partitioning.** It is the operation of slicing a large input data into disjoint sub-sets called *partitions*. These partitions can be stored in several compute nodes and, thus, be operated on in parallel. Partitions are typically duplicated and stored in different compute nodes to provide fault tolerance and improve system availability.

- **Data Locality.** It is a strategy, adopted by MapReduce and other frameworks, to run compute tasks on the node where the data needed is located. It aims at optimizing processing performance by reducing the amount of data transfer across the nodes.

[5] We mean here engines specialized in querying (e.g., Hive, Presto) or having query capabilities (e.g., Spark, Flink). Many distributed databases (e.g., MongoDB, Cassandra, HBase) lack the support of joins

- **BASE Properties.** A new set of database properties called BASE, by opposition to the traditional ACID, has been suggested [41]. BASE stands for Basic Availability, Soft state, and Eventually consistency, which can be described as follows:
  - **Basic Availability:** It states that the database is available, but it may occur that a read or a write operation makes the database state inconsistent. A write may not take effect in all the nodes and reads may not retrieve all the required data due to possible failures in the cluster.
  - **Soft State:** It states that the system is in constant change due to the write operations that take effect gradually, e.g., data duplication, recovering from failure by copying data from a healthy node to a recovering or newly joining node.
  - **Eventual Consistency:** It states that the system will be consistent at some time thanks to its soft state. Writes will be gradually duplicated and distributed across the cluster nodes, so a read operation on every node will eventually return the latest response.

  BASE properties have purposely a relaxed consistency semantics as to accelerate query performance. However, it is not to be implied that they are genuinely unreliable. Consistency may not be an issue in every application. An application requiring a higher degree of consistency can still enforce it at the application level by incorporating necessary checks when and where needed. For example, it is possible to check an ID to be inserted in a foreign key column whether it exists as a primary key in another table. Also, as by definition, BASE properties instructs that the database will still be consistent after all data has been distributed and/or duplicated across cluster nodes. This is a necessity in distributed environments.

  We give a few examples for how relaxing consistency relieves query performance. It is often the case that BASE-compliant databases, which are generally NoSQL stores, are schemaless or schema-flexible. This allows the underlying Data Management System to perform writs without checking the compliance of every element of every single entry with the predefined schema. A specific case is Cassandra database, which takes a few measures as to relief consistency check and, thus, accelerates query performance. For example, Cassandra does not check whether a value of a specific ID column exists in the database; if it exists it gets automatically overwritten, an operation called `upsert`. In a Big Data scale environment, lowering the level of consistency can yield a manifold improvement in data read and write performance. Conversely enforcing consistency at the Data Management level can easily lead to bottlenecks and failures.

2.2.4 BDM Technology Landscape

The two Big Data dimensions Volume and Variety are tightly related to the data type and storage properties. Data based on its type is classified into structured, semi-structured and unstructured. Data based on its storage properties can be classified into three categories:

- **Plain Files:** this represents the most basic form of storage, where data is written and read sequentially from a plain text file. Examples include CSV, JSON and XML files.
- **File formats:** this is a more sophisticated file-based storage, where data is stored following a specific schema that is optimized for data read and/or write. It consists of file partitions

and metadata that are utilized by processing engines during computation. Those files are not human-readable and require external capable processing engines to decode and process them. Examples include Parquet, ORC and Avro.

- **NoSQL Stores:** these are modern database systems that emerged to overcome the limitations of traditional, mainly relational, databases when dealing with large volumes and heterogeneous non-relational types of data. The term NoSQL stands for Not-only-SQL, meaning that other data formats and, thus, query formalities are possible. As a result, NoSQL stores have varied characteristics, in terms of their conceptual models, storage schemes and query languages. Based on those differences, they can be classified into four categories (see Figure 2.2 for a visual illustration of every category):
  - **Key-value:** the simplest of all, it stores data in the form of associations between a key and a value, e.g., (City -> "Berlin"). Values vary from atomic in primitive types to more sophisticated types, e.g., arrays, sets, maps, files. Key-value stores are useful in performing rapid scans and lookups of known values in e.g., indexes, hash maps, dictionaries. Their simple model allows them to scale very easily and efficiently. The key-value concept is the base of all the other NoSQL categories. Examples include Redis, Memcached and Riak.
  - **Document:** it represents data in the form of documents of variable schema, where every document is a set of key-value pairs in a JSON-like notation, e.g. `{City: "Berlin", Country: "Germany" }`. Like in key-value category, values can store more complex data types e.g., arrays, objects, etc. Every document can have a different set of keys (fields). Document stores are useful in writing and reading data in a JSON-like format with a flexible and nested schema. Examples of Document stores include MongoDB, Couchbase and MarkLogic.
  - **Wide Column:** the less trivial of the four, it conceptually organizes data into *sparse* wide tables called column families. A column family is a set of key-value pairs, where the key is a row ID and the values are a set of key-value pairs. In the latter, the key is equivalent to a table column and the value is equivalent to a column value in a conventional relational table. This allows every entry to include a different set of columns. Wide Column stores are useful in storing tabular data with records having variable schema. Examples of Wide Column stores include Cassandra, HBase and Bigtable.
  - **Graph:** the most varied of the four, it represents data in the form of a graph with nodes and relations between nodes. There are various models of graphs, two prominent types being Property Graphs and RDF Graphs. The latter, as we explained in subsection 2.1.2, build the graph starting from simple *statements* of subject-predicate-object, where subject and object are the nodes and predicate is the relationship edge. The former allows to store extra information about nodes and relationships in the form of key-value pairs called *properties*. Graph stores are difficult to horizontally scale due to their strong connected nature. They are useful in storing highly-interlinked data, suitable for applications like social network analysis, pattern matching, long path-traversals (multi-join in the relational model). Examples of Graph stores include Neo4J, OrientDB and Neptune.

With their significant data model differences, NoSQL stores have several characteristics

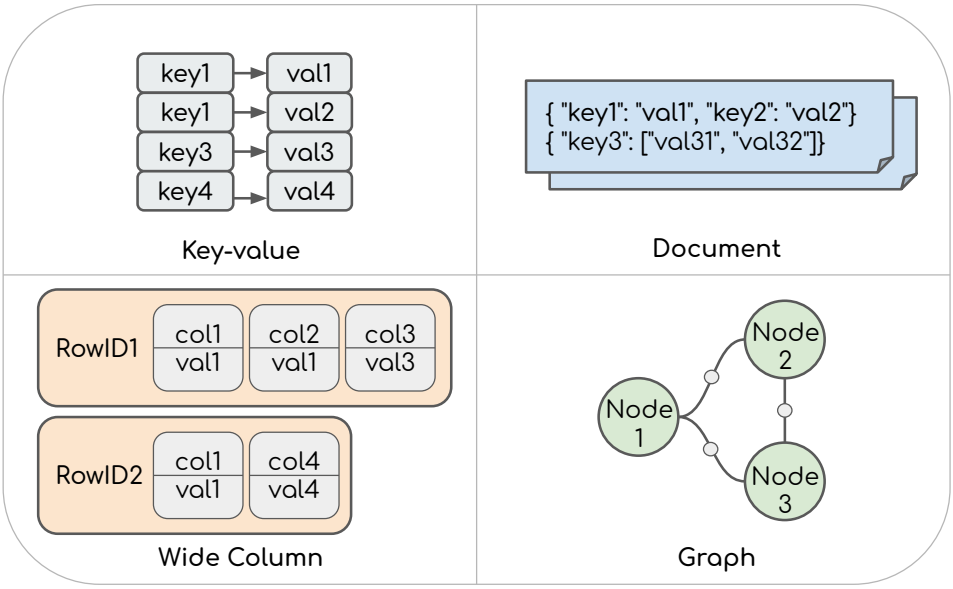


Figure 2.2: A categorization of the NoSQL database family.

that differentiate them from traditional RDBMSs:

- They do not adhere to the relational model, although they may use SQL for querying. Hence, the "only" in Not-only-SQL and their other *Non-Relational* appellation.
- They do not have or require a fixed pre-defined schema. For example, in a Document store, a collection may contain a varied number of fields and data types, or a Wide Column store may have tuples in the same column family with a varied schema.
- They have a distributed and horizontal scale-out architecture, i.e., they store and query data across a cluster of multiple nodes. When new data is inserted it is automatically distributed, often with duplication to provide resiliency to failures. When new nodes are added to the cluster to accommodate heavier processing, they are automatically used to store data, a property commonly called *Elasticity*.
- They trade-off several common query operations in favor of enhancing performance scalability. For example, Key-value stores allow no filtering on values, Document and Wide Column stores have no join operation. Joins and other dropped operations are left to the user to implement at the application level or are delegated to other processing frameworks also with user intervention. Furthermore, normalization, which is a fundamental principle in relational databases, is recommended against ([42]) by NoSQL experts to compensate for the lack of join operation. If there are lots of join use-cases then NoSQL graph database can be used; however, graph databases perform aggregation operations poorly in comparison to the other NoSQL databases.

2.3 Data Integration

These Data Management approaches and technologies have given applications a broader set of options, giving birth to new concepts like Polyglot Persistence [43] and Data Lakes [4]. Polyglot Persistence instructs that application data can be saved across multiple different

storage mediums, with possible duplication, to optimize for specific data processing types. For example, full-text search in a corpus of unstructured data can be achieved using Elasticsearch, analytical queries are applied on column-based file formats like Parquet, highly-interlinked data processing using a graph database, schema-flexible scenarios can benefit from HBase, etc.

Accessing these heterogeneous sources in a uniform manner is a Data Integration problem. At the conceptual level, Big Data Integration follows the same principles of a general Data Integration framework, with concepts like general schema, local schemata and mappings between them that are used during query processing, see Definition 2.4.

Definition 2.4: Data Integration System [44]

A data integration system IS is defined as a tuple <O, S, M>, where:

- O is the global schema, e.g., an RDF Schema, expressed in a language L_O over an alphabet A_O. The alphabet A_O consists of symbols for each element in O.
- S is the source schema, expressed in a language L_S over an alphabet A_S. The alphabet A_S contains symbols for each element of the sources.
- M is the mapping between O and S that is represented as assertions: $q_s \rightarrow q_o; q_o \rightarrow q_s$. Where q_s and q_o are two queries of the same arity, q_s is a query expressed in the source schema, q_o is a query expressed in the global schema. The assertions imply correspondence between global and source concepts.

We distinguish between two classes of Data Integration: Physical and Virtual, respectively described in the following two subsections.

2.3.1 Physical Data Integration

Physical Data Integration is the process of transforming the entire data from its original model to another unified canonical data model adopted by and for a given data-consuming application. Typically, Physical Integration involves three phases:

- **Model Conversion:** This includes performing model conversion or adaptation e.g., flattening if the destination data model is tabular. A common example of a purely Physical Data Integration is the Data Warehouses, where the destination model is relational and the data has to be loaded under a very specific schema optimized for analytical queries.
- **Data Migration:** Data is, next, loaded in accordance with the newly chosen and designed schema. This step typically follows the ETL process, Extact-Transfom-Load. In ETL, data may not be loaded as it is extracted but undergoes a series of transformations bringing it to the desired shape. Then it is loaded into the unified model in a corresponding Data Management System.
- **Query Processing:** Queries are posed against the newly designed model over the migrated and fully homogenized data. Thus, they are expressed in the native query language of the respective Data Management System or the access system in general.

2.3.2 Logical Data Integration

Logical Data Integration is the process of querying heterogeneous data sources without any prior data transformation. This means, unlike the Physical Integration, there is no physical model conversion or data migration involved. However, the complexity is shifted to the query processing, where three phases are involved:

- **Query Decomposition:** The query is analyzed and decomposed into sub-queries that each is responsible for retrieving a subset of the results.
- **Relevant Source Detection:** Sub-queries are analyzed with the help of metadata about the schema composition of the data sources. If a match between the sub-query and schema elements from a data source, the latter is declared as *relevant* to the query and accessed. Multiple approaches for querying the detected relevant data sources have been suggested in the literature. The sub-query can be translated to a query in the data source query language or in an intermediate abstract/meta language. It can also trigger other access mechanisms e.g., HTTPS requests (e.g., post/get), programmatic APIs (e.g., JDBC), etc.
- **Results Reconciliation:** The results from the sub-queries are combined in accordance with the query, e.g., aggregated, joined or union'ed.

2.3.3 Mediator/Wrapper Architecture

A popular architecture for Data Integration is the so-called Mediator/Wrapper [45, 46]. In essence, given a query, the architecture separates the tasks of data collection from the sources and the reconciliation of results into two layers. The latter being the *Mediator* and the former being the *Wrapper*. The Wrapper layer consists of a set of wrappers, which are components able to access specific data sources. The wrappers have access to source descriptions e.g. schema, statistics, cost information, access modality, etc. The Mediator layer, on the other hand, consists of a mediator component that interfaces with the wrappers. The mediator itself does not possess the required source descriptions to access data sources. Rather, it triggers multiple wrappers, which it detects as *relevant*, to extract sub-sets of the final results. The mediator combines the latter to form the final query answer using e.g., aggregate, group, join operations in accordance with the input query.

In its typical form, Mediator/Wrapper architecture consists of only one central mediator and several wrappers. However, other variations have been suggested, e.g., multiple mediators each responsible for a separate extract scenario. The Wrapper layer can also include one or more so-called *meta-wrappers* [47], which are intermediate wrappers transparently combining results from multiple basic wrappers and providing a unified output to the mediator. The underlying model of the mediator can be of any type [48], e.g. relational, object-oriented, JSON-based, XML-based, streaming, etc. Figure 2.3 shows a Mediator/Wrapper architecture withe multiple wrappers and a single mediator responsible for requesting data from the wrappers and reconciling their output afterwards to form the final query answer.

2.3.4 Semantic Data Integration

Using Semantic Technologies, we can implement the Data Integration architecture in the following way. Ontology serves at defining the general schema O. A set of mappings M between the ontology and data source schemata S_i expressed using a mapping language. Finally, the query

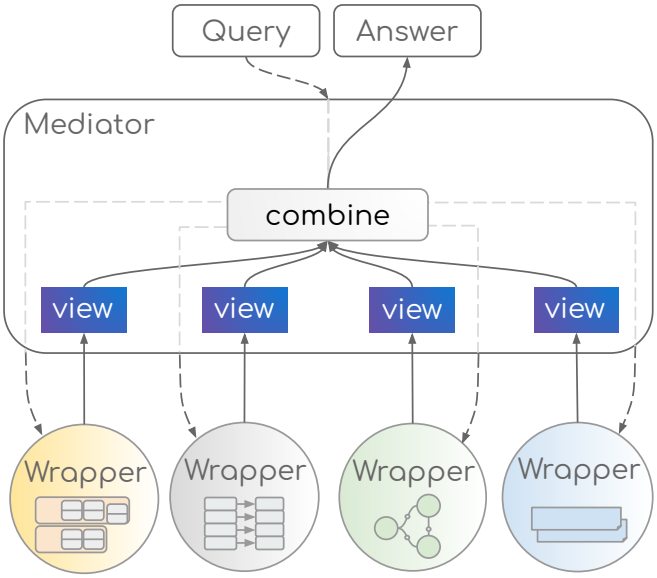


Figure 2.3: The dashed line is a request flow and the solid line is a data flow.

q_o is expressed in SPARQL and uses terms from the ontology O. It is the role of the mappings to navigate from the query to the correct relevant data sources, a common approach in the Data Integration literature called *Local-as-View* [49]. There are several ontology languages with different levels of expressivity, e.g., RDFS (RDF Schema), OWL (Ontology Web Language) that has a few variants e.g., OWL Lite, OWL DL (Description Language), OWL Full, OWL2. The minimum required definitions to achieve a Semantic-based Data Integration are *classes* and *properties*. Classes are mapped to entities (e.g., tables in a relational database) and properties are mapped to entity attributes (e.g., table columns in a relational database). The use of Ontology for Data Integration is called Ontology-Based Data Integration (OBDI), or Ontology-Based Data Access (OBDA) [8, 50], which is already an established paradigm in the literature [51]. In terms of Mediator/Wrapper architecture, the mediator analyzes the input query and uses the mappings to detect which data sources are relevant. Once identified, the respective mediator submits sub-queries to the respective wrappers. The wrappers, having knowledge of the source descriptions, retrieve sub-sets of the final results and return them in mediator's intermediate data model. The mediator combines the sub-results in accordance with the query, e.g., aggregate, group, order, join, etc. and returns the final query answer.

OBDA principles have been recently implemented on top of large scale data sources, e.g., NoSQL databases (See Related Work Chapter 3). The challenge is to support the emerging data types and mediums at the mappings, mediator and wrappers levels. For example, extend previous mapping languages to allow annotating the various NoSQL models, propose a specialized data model for the mediator that is adaptable to the NoSQL wrappers and vice-versa, formalize the access to the various data sources, etc.

2.3.5 Scalable Semantic Storage and Processing

Physical Semantic Data Integration of large and heterogeneous data sources results in voluminous RDF datasets, which need to be captured, stored and queried in an efficient manner. To this end, approaches from Distributed Computing data and Query Processing are incorporated and

adapted to RDF data model. A prominent example is MapReduce (earlier introduced in this chapter), which is a general-purpose framework for large-scale processing. As a reminder, it consists of *map* and *reduce* phases, *map* takes a line from an input data source and emits a key-value pair; *reduce* receives all values attached to the same key and applies certain processing thereon. Applied to RDF query processing, RDF triples are flown through one or more map and reduce phases in response to a query. For example, in the *map*, RDF subject goes into the key position and RDF predicate-object pair goes into the value. With this organization, star-shaped graph patterns can be answered in the *reduce* phase. Using Hadoop [34], MapReduce *de facto* implementation, data can only be accessed sequentially from its distributed file system, HDFS (earlier in introduced in this chapter). In order to provide faster random access, a NoSQL model and storage can be used instead. In this case, RDF triples are stored in a NoSQL database and queries are translated to the native query syntax of the NoSQL database. In order to optimize SPARQL query execution performance, several partitioning and storage schemes can be incorporated. The following are some of the most widely used in the literature (reviewed later in Chapter 3), illustrated in Figure 2.4:

- **Triple Tables:** RDF triples are stored in files or tables having as schema RDF's plain representation, i.e. (subject, predicate, object). It is the simplest scheme resulting in a very simple and straightforward ingestion phase. However, query processing can be complex as it may require a series of self-join. This scheme has been adopted by traditional single-machine RDBMS-based triple stores e.g., [52], relying heavily on indexes to speedup triple lookup. However, indexes in large-scale environments are not prevalent due to the significant cost to build, store, update and maintain.

- **Vertical Partitioning [53]:** RDF triples are split across several tables or files, one table or file per predicate. The table or file is bi-columnar, it contains only two columns to store RDF subject and object. This scheme enables querying a large class of queries as it is typical for SPARQL queries to have predicates bound [54]. Joins are reduced compared to Triple Table scheme, but they are still required to perform e.g., subject-object or object-subject joins. If the *typing* property, e.g., `rdf:type`, is present with every subject, possibly more than one type per subject, the typing table can be very large. Further splitting and balancing this table can alleviate the ingestion and query processing skew. Les typically, vertical partitioning can be based on the subject instead of the predicate, creating one table or file per subject with two columns: predicate and object. It can also be based on the object with two columns: subject and predicate. However, these models are likely to generate many more tables of much smaller size, as there are generally more (distinct) subjects and objects than predicates.

- **Property Tables [55]:** RDF triples are stored into tables where columns represent RDF properties and cells of these columns store objects. Subjects are stored as the primary key of the table. Several options as to what a table represents are posed in the literature. It can represent the RDF class of all the stored triples, or a grouping of properties that tend to be queried together, or triples distributed using a hashing function, or one universal table containing all the encountered predicates, etc. It is a more elaborate scheme resulting in a more complex ingestion task. However, it is more compact in terms of space, as subjects and predicates are stored only once, in contrast to the Vertical partitioning. This scheme can answer star-shaped queries more efficiently than the previous schemes, as we can obtain all the objects attached to one subject with only one table scan and without

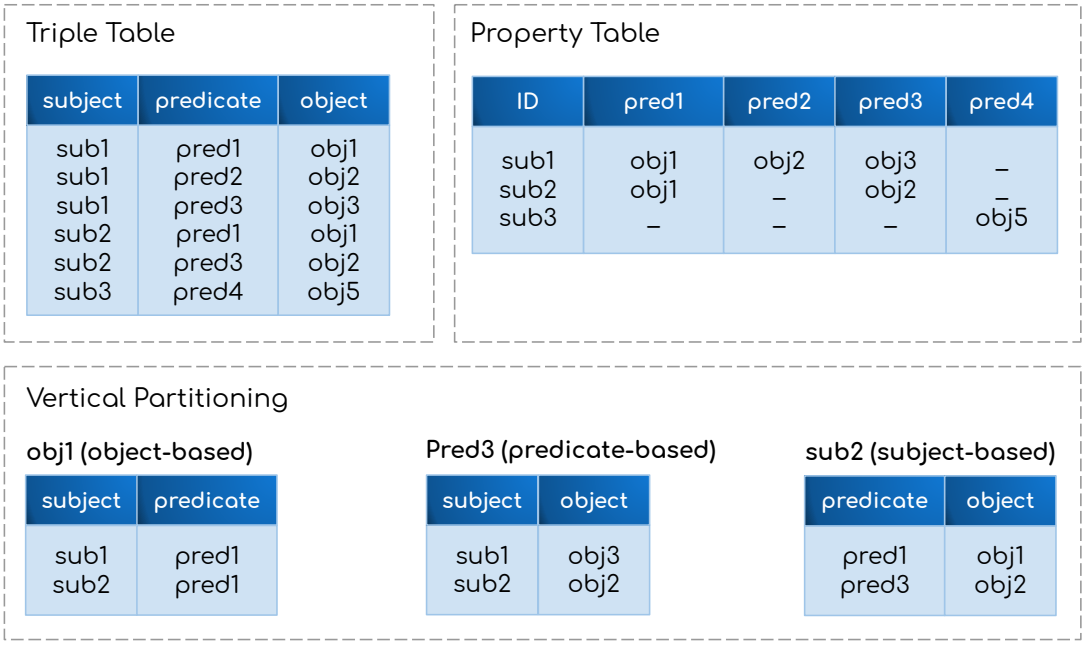


Figure 2.4: RDF Partitioning Schemes.

any join. Joins are till required if there are more than one star-shaped sub-BGPs.

These partitioning schemes can be used in combination; every scheme to optimize for a specific query type or shape. For example Triple Table when the predicate is unbound and predicate-based Vertical Partitioning for star-shaped sub-queries. Moreover, one partitioning scheme can be extended to store metadata information e.g., data type, language tag, timestamp, needed for various types of applications e.g., multilingual, time-series, etc.

CHAPTER 3

Related Work

"He who fears climbing mountains lives forever between the pits."

Aboul-Qacem Echebbi

In this chapter, we review existing approaches for Semantic-based Data Integration. We divide the efforts based on the integration type, either Physical or Logical. In the former, since data is physically materialized, a special focus is put on the loading the physical representation of data. In the latter, data is accessed as-is, so the focus is on the process of transitioning from the query to the (relevant) data sources.

3.1 Semantic-based Physical Integration

In Semantic-based Physical Data Integration, we generate, store and query RDF data by transforming heterogeneous large data sources. As a result, generated RDF data will have a large size, requiring the incorporation of scalable Data Management approaches. Therefore, we look at the efforts suggesting techniques and technologies for the storage and access to large RDF graphs. We classify these efforts into three main categories: MapReduce-based RDF Processing, SQL Query Engine for RDF Processing, and NoSQL-based RDF Processing. In the first category, only MapReduce paradigm is used, represented by its de facto implementation, Hadoop. In the second, specialized frameworks for SQL query processing are leveraged. In the third, NoSQL approaches are used both for storage and querying. This topic has been source for a large body of research, from which we review the following prominent efforts. Table 3.1 lists the efforts; extensive dedicated review studies have been conducted in the literature, which we reference in the discussion at the of the section.

3.1.1 MapReduce-based RDF Processing

The aim is to create a set of *map* and *reduce* phases given a SPARQL query. By design, intermediate results of the map phase are written to disk, then read, sorted and transferred to the reduce phase. Similarly, data between two MapReduce steps is materialized then read again. Therefore, efforts in this category try to reduce the I/O incurred during query execution by (1) minimizing the number of MapReduce involved, and (2) using only *map* phase whenever possible.

MapReduce-based RDF Processing
Jaql [56]
PigSPARQL [57]
HadoopRDF [58]
CliqueSquare [59]

SQL Query Engine for RDF Processing	
Work	**SQL Engine**
Sempala [62]	Impala
SPARQLGX [60]	Spark
S2RDF [64]	Spark
Sparklify [65]	Spark
HAQWA [66]	Spark

NoSQL-based RDF Processing	
Work	**NoSQL Framework**
Rya [73, 74]	Accumulo
H2RDF+ [75]	HBase
D-SPARQ [76]	MongoDB
ScalaRDF [77]	Redis
CumulusRDF [78]	Cassandra
AMADA [79–81]	DynamdoDB

Table 3.1: Reviewed efforts by their category. For the SQL Query Engine approaches, the adopted SQ engine is listed. Similarly for the NoSQL-based approaches, the adopted NoSQL framework is listed.

For example, join and aggregation often require a *reduce* phase to group RDF triples together. Additionally, indexing and partitioning techniques for large RDF data are investigated.

Authors in [56] present Jaql, a scripting language for processing large semi-structured data on top of Hadoop. RDF data is first ingested into HDFS as large JSON files with the triple structure `{"s": "subject", "p": "predicate" ,"o": "object"}`. Various partitioning techniques are then implemented. Horizontal Partitioning is implemented by creating a table for every RDF subject. Vertical Partitioning implemented by creating a JSON file for every RDF property. Clustered Property implemented by distributing RDF triples across various clusters. Inverted Indexes are created for every partitioning scheme. For querying, Jaql has operations that are equivalent to SPARQL query operations, e.g., `FILTER` -> `FILTER`, `JOIN` -> joins of triple patterns, `GROUP BY` -> `GROUP`, `ORDER BY` -> `SORT`.

PigSPARQL [57] is an effort to use another processing framework on top of Hadoop, called Pig. Data is loaded and queried using Pig's default data model and query engine. A triple table (subject, predicate, object) is created to store RDF triples. Then, SPARQL queries are translated into a sequence of Pig's query language (Pig Latin) commands. The latter include `LOAD`, `FILTER`, `JOIN`, `FOREACH`, `GENERATE`, `FILTER`, `JOIN`, `UNION`. Optimization techniques to reduce data transferred between *map* and *reduce* phases are suggested. For example, early execution of filters, rearranging the order of triple patterns based on their selectivity, using Pig multi-join operation to group joins on the same variable, optimizing data partitioning, etc.

HadoopRDF [58] is another effort to store large RDF graphs in HDFS; however, it uses Hadoop itself for query processing, i.e., MapReduce library. RDF files in N-Triples format (one triple per line) are stored following the Vertical Partitioning scheme. As mentioned in Chapter 2, this partitioning may produce abnormally very large files storing the *typing* predicate, e.g., `rdf:type`. HadoopRDF split this file by object, under the assumption that when a typing predicate is used, the object is typically bound to instruct what type it refers to. This generates as many object files, `type#object1`, `type#object2`, etc. Finally, the SPARQL query is translated into an internal representation following the adopted scheme. A heuristic is used to reduce MapReduce

jobs by combining as many joins as possible inside one MapReduce job.

CliqueSquare [59] proposes a novel portioning scheme that enables Hadoop to execute the most common types of queries, particularly joins, locally within the *map* phase. CliqueSquare adopts both Horizontal and Vertical Partitioning. Every triple is stored three times: in an *object partition* storing all triples having that object, in a *predicate partition* storing all predicates of that predicate, and similarly in an *object partition*. Furthermore, given a value, the subject, property, and object partitions of the value are stored in the same node. Finally, all *subject partitions* and *object partitions* of a given value are grouped by their properties. Similarly to HadoopRDF, typing table is also partitioned by object.

Summary. In addition to the common goal of reducing data written, read and transferred throughout MapReduce phases, efforts also try to optimize performance by sophisticating the underlying data representation and partitioning. This naturally comes at the price of a complex and expensive data ingestion phase, both in terms of loading time taken and disk space usage. This observation applies to all the reviewed efforts, and it goes in line with the authors' findings at [60]. Finally, we leave out other efforts that roughly share the same concepts we have already presented, and refer to the dedicated survey [61] for more details.

3.1.2 SQL Query Engine for RDF Processing

Recognizing MapReduce limitation at offering low latency query performances, other efforts suggest processing large RDF data using other in-memory frameworks with ad hoc SQL querying, e.g., Apache Spark, Impala. A variety of physical representations, partitioning schemes, and join patterns have also been suggested.

Sempala [62] suggests a SPARQL-over-SQL-on-Hadoop (Distributed File System) approach querying large RDF data using SQL as an intermediate query language. RDF triples are loaded into a fully denormalized *universal* Property Table consisting of all RDF properties found in the RDF data. The rationale is to reduce the number of joins required. In order to cope with the wideness and sparsity of the resulted table, the authors use a columnar file format called Parquet. The latter is queried using a Massively Parallel Processing (MPP) SQL engine called Impala [63]. Being column-based, Parquet stores data on disk by columns (common in NoSQL stores) instead of rows (common in RDBMSs), so if a SPARQL query requests a few predicates only those are read, not the entire record. The unified table is complemented with a Triple Table to address the class of queries with unbound predicates. Based on their algebraic representation, SPARQL queries are translated into Impala SQL queries following the suggested partitioning layout. A conversion methodology of SPARQL to SQL query operations is suggested, with `OPTIONAL` being translated to `LEFT OUTER JOIN`.

SPARQLGX [60] also starts from the observation that most SPARQL queries have their predicates bound [54], and builds their RDF internal data model accordingly. Thus, SPARQLGX focus is on SPARQL evaluation, which is based on converting SPARQL operations into Spark instructions (Scala code). It makes use of Spark transformations that are equivalent to SPARQL operations, e.g., `ORDER BY` -> `sortByKey`, `LIMIT` -> `take`, `UNION` -> `union`, `OPTIONAL` -> *leftOutJoin*. Finally, to optimize query time, the authors compute statistics about the data to reduce join intermediate results. Offline, they compute the number of distinct objects, predicates and objects, and attribute a selectivity count accordingly. Query triple patterns are organized based on their selectivity before the translation.

Authors of **S2RDF** [64] note that existing approaches in the literature are only optimized for certain forms of queries. Hence, they try to fill this gap by proposing an extension of the

Vertical Partitioning. The approach suggests to pre-computes all possible joins between predicate tables generated from applying Vertical Partitioning. This minimizes the number of scans and comparisons to do within a join, which has an impact on disk read, memory consumption and network. For every triple pattern, a pre-computed table is selected by noticing the correlation between the triple pattern and others; a selectivity factor is computed based on whichever choice is made. Selectivity factors are statistics computed during the loading phase. Finally, SQL queries are run to extract the triples from the various tables and execute the minimum needed joins. As optimization, similarly to SPARQLGX, S2RDF pays attention to the order of triple patterns as to reduce join intermediate results. This by joining triple patterns with the more bound variables first, and exploit table size statistics previously collected. Parquet is used for storage and Spark SQL for query processing.

Sparklify [65] is a recent addition to the literature, which is an extension of the previous Sparqlify SPARQL-to-SQL rewriter for RDBMSs. In a pre-processing phase and using Spark for parallel processing, Sparklify analyses RDF data triple by triple and creates virtual Vertical Partitioning-based *views* accordingly, taking into account data types and language tags. At this level, no data is materialized. After the SPARQL query is issued, the views are used to load data into Spark DataFrames (data structures specialized for parallel SQL processing), which are queried using SQL queries generated by Sparqlify rewriter. Optimizations happen at the query rewriting level, such us removing sub-queries that are known to yield empty results, e.g., joins based on URIs of disjoint namespaces, or joins between terms of different types, etc.

HAQWA [66] is similar to SPARQLGX in that it translates the SPARQL query into a set of Spark instructions. It incorporates fragmentation, allocation and encoding strategies. The fragmentation uses a hash-based partitioning on the RDF triple subjects to evaluate star-shaped queries locally. The allocation calculates the cost of transferring a triple into other partitions, where it may join with its local triples. HAQWA encodes RDF terms using integer type, which is more efficient to operate-on than strings.

Summary. We observe that most efforts focus on optimizing for a certain class of queries that are claimed to be the most common among SPARQL queries. The same observation was made by authors in [64]. However, the edge cases are dominant in certain applications, e.g., social network analysis where queries with a long chain of friend-of-a-friend are typical. On the other hand, here again, we make the observation that query performance is improved by pre-computing and storing data during the ingestion phase, e.g., pre-computing join results. We also note that many efforts compute statistics during the data loading phase. These significant pre-processing tasks result in a more complex and greedy data loading phase. Finally, we note that there is in most efforts (except a few e.g., [60] and to a degree [65]) no regard to the dynamicity of the data. This is an important overlooked aspect commonly found in production-level applications, where data is prone to new inserts either continually or in intervals. Although not impossible, a heavy ingestion phase with complex hardwired partitioning layouts, lots of pre-computed results, and fine-grain statistics collection can quickly become a serious bottleneck in large-scale settings. Finally, we leave out other efforts (e.g., [67–70]) that roughly share the same concepts as the efforts reviewed here, and refer to the dedicated surveys for more details [71, 72].

3.1.3 NoSQL-based RDF Processing

Despite their ability to provide up to a sub-second performance, data processing frameworks, e.g., Spark, Impala, Hive, are not designed to be used as databases. Hence, there will always be limitations at a certain level due to design incompatibilities. For example, they do not have

their own persistence storage backend as they purposely opt for the storage-compute separation. They also do not offer (efficient) indexes, they lack ad hoc querying optimizations as they do not own the data, they cannot keep consistent statistics, etc. Therefore, several efforts in the literature chose to leverage the query and storage capabilities of existing NoSQL databases.

Rya [73, 74] uses Accumulo as backend, a distributed column-oriented key-value store that uses HDFS to store its underlying data. Rya creates three Accumulo index following the Triple Table layout, storing (subject, Predicate, Object), (Predicate, Object, Subject) and (Object, Subject, Predicate). As Accumulo by default sorts and partitions all key-value pairs based on the Row ID of the key, Rya stores all RDF triples of the three indexes in the Row ID. Every triple pattern (eight possible cases) can be inserted using a range scan of one of the three tables. SPARQL query is evaluated locally using an index nested loop join. Here again, a MapReduce job is run to count the number of distinct subjects, predicates and objects and estimate triple patterns selectivity.

H2RDF+ [75] uses HBase as backend, a NoSQL store sitting on top of HDFS. HBase is similar to Accumulo in architecture and data model design being a column-based key-value. Similarly to Rya, H2RDF+ materializes several indexes; however, it does it for six permutations instead of three, namely [SP_O], [PS_O], [PO_S], [OP_S], [OS_P] and [SO_P]. Each table is sorted and range-partitioned (range of keys). Every triple pattern can be retrieved via a range scan of only one table of the six. These schemes allow joins between triple patterns to be executed using Merge Join. A cost model is suggested to estimate the cost of joins and suggests an optimal order. H2RDF+ has a hybrid adaptive execution model; according to query selectivity and estimated join cost, it decides whether to execute the query locally or in parallel using Hadoop MapReduce. Distributed (MapReduce-based) implementation of the traditional Multi-Way Merge join and Sort Merge join are presented and used for querying.

D-SPARQ [76] uses MongoDB as backend, a document-based NoSQL store. Starting from the input RDF data, a graph is constructed. Using a graph partitioning algorithm, partitions are created of the same number as the cluster nodes. Next, triples are distributed across the nodes by placing triples matching a graph vertex in the same partition as the vertex. As a replication mechanism, vertices along a path of n of a given vertex are added to the same partition as that vertex. As triples of the same subjects are co-located, star-shaped graph patterns on the subject can be efficiently answered. D-SPARQ leverages MongoDB **compound index**, by creating indexes for the pairs [SP] and [PO]. To enable parallel querying, it detects the following triple patters: patters sharing the same subject, patterns with object-subject, subject-object, and object-object join connections, and independent triple patterns sharing no variables. Finally and as other efforts, statistics are collected to compute triple pattern selectivity.

ScalaRDF [77] uses Redis as backend, an in-memory key-value NoSQL store. First, all RDF terms (subject, predicate, object) are stored as numeral IDs, so to save on the storage. The mappings between the ID and the original terms are stored in an auxiliary dictionary. Triples are indexes in six tables, [SP_O], [PO_S], [SO_P], [P_SO], [O_SP], and [S_PO], and distributed across the cluster in a Redis store using a consistent hashing protocol. This is the only work considering the deletion or update of the ingested RDF data, the explicit resizing of the cluster, and the data backup and node recovery. These features are necessary as ScalaRDF is composed of custom modules not benefiting from any existing resource management frameworks, unlike the other HDFS and NoSQL-based stores. Here again, the query is analyzed and triple patterns are reordered based on cardinality statistics collected at the ingestion phase.

CumulusRDF [78] uses Cassandra as a key-value store, where it stores its four indexes. Sesame query processor is used to translate SPARQL queries to index lookups on Cassandra indexes,

as well as to perform filtering and join on a single dedicated node. **AMADA** [79–81] uses DynamoDB as backend, a cloud key-value NoSQL store from Amazon. AMADA stores a different type of indexes; it does not index RDF triples themselves, but maps every RDF term (e.g., subject) to the datasets it is stored in. Given a query, the relevant index is detected, using which a set of relevant sub-datasets are located. The latter are loaded into a single-machine triple store and queried.

Summary. Efforts in this category take advantage of the opportunities offered by NoSQL Database Management Systems. They make use of more sophisticated indexes, statistics, more control over the storage layer, etc. However, the focus of most efforts is on the execution of triple patterns, i.e., retrieval of matching triples and joining them. Consideration for other common SPARQL operations, e.g., aggregation, union, optional, is lacking. Further, join is not always executed in parallel, but in most cases is delegated to a single node. The lack of common SPARQL operations and distributed join hinders the applicability of these approaches in real-world scenarios. Finally, we leave out a few more efforts that roughly share the same concepts as the effort reviewed here, and refer to dedicated surveys for more details [61, 72, 82, 83].

3.1.4 Discussion

In the following we highlight how our work aligns and differs from the existing reviewed efforts:

- Our work falls within the second category in that we neither use MapReduce framework for query processing nor a NoSQL database for storage and querying. Rather, we use a scalable processing engine with SQL query capabilities, Apache Spark, and an optimized file format in HDFS, Apache Parquet. We avoid MapReduce as it is a disk-based batch-oriented framework incurring a significant I/O and transfer overhead. Apache Spark, being memory-based, is more suitable for iterative and short-lived queries. It also provides other libraries that can extend the work and enrich RDF exploitation. For example, it has a library to ingest other data sources than RDF, which is desirable in our Data Integration work. Other libraries include Machine Learning, Stream Processing, and Graph Processing, which enable more opportunities e.g., ingesting streaming RDF data or perform analytics over the integrated data. Storage-wise, we avoid a NoSQL store as we want to simplify the stack to only one query engine and HDFS. HDFS, being a popular distributed file system, its contained data can be accessed by a much larger array of processing frameworks, in contrast to locking the data into one format and Data Management system (i.e., NoSQL).

- Our work particularly resembles Sempala at the processing layer (Impala instead of MapReduce) and storage layer (Parquet instead of NoSQL). It resembles Sempala and SPARQLGX in avoiding indexes and the manual distribution of RDF triples across cluster nodes. We just rely on the default data distribution and duplication of HDFS, and the efficient data compression of Parquet. However, our work diverges from existing work in the way it designs the Property Tables. We create a Property Table per RDF class with additional columns capturing the other classes if an RDF instance is of multiple types. In addition to saving on the disk space, this scheme makes query answering more intuitive and straightforward for the tabular-based querying (SQL) that we adopt. Refraining from the creation of indexes is a purposeful choice. Rational being (1) we want to accelerate the ingestion phase, which is a tedious and costly process in most reviewed efforts, and (2) we want to give consideration for dynamic data, where more data is expected to regularly

Work	Access Interface	Distributed Support	Join Support	Manual Wrapper	Nb. of Sources	Velocity Support
Squerall [84, 85]	Semantic	✔	✔	✗/✔	Multiple	✗
Optique [86]	Semantic	✔	✔	✔	Multiple	✔
Ontario [87]	Semantic	✔	✗	✔	2	✗
[88]	Semantic	✗	?	✔	2	✗
SparqlMap-M [89]	Semantic	✗	Indirect	✔	1	✗
[90]	Semantic	✗	✗	✔	1	✗
[91]	Relational	?	?	✔	2	✗
HybridDB [92]	JSON-based	✗	✗	✔	2	✗
[93–95]	CRUD/REST	✗	Indirect	✔	3	✗
SOS [96]	CRUD/API	✗	✗	✔	3	✗
Forward [97]	SQL/JSON	?	✔	✔	Multiple	✗
CloudMdsQL [95]	SQL-like	✔	?	✔	1	✗

Table 3.2: Information summary about reviewed efforts. Question mark (?) is used when information is absent or unclear. ✗/✔ under 'Manual Wrapper' means that wrappers are by default not manually created, but certain wrappers may be manually created. 'Distributed Support' means whether the work support the distributed processing of query operations. 'Nb. of Sources' is the number of supported data sources.

be added to the sources, which is also disregarded by most reviewed efforts. In fact, using an optimized (strong compression and fast random access) file format e.g., Parquet is a convenient alternative when indexing is not desired or not supported by the underlying query engine. Parquet, for example, offers *pseudo-indexes*, thanks to its default smart use of statistics, bloom filters, predicate-push down, compression and encoding techniques, etc.

In brief, we have not found any published work tackling the ingestion and querying of heterogeneous large-scale data sources into RDF format. Hence, our work is the first to propose a blueprint for an end-to-end semantified Big Data architecture, with an implementation that employs state-of-the-art extensible and scalable Big Data technologies.

3.2 Semantic-based Logical Data Integration

Data that is not physically transformed to RDF can also be queried on the fly. This is addressed by incorporating a unifying middleware and access interface to original heterogeneous data sources. In this second section of the literature, we review efforts following this integration pattern. Although Semantic-based Virtual Data Integration is an established research area in the literature, its applicability to the new Big Data technology space is still an emerging effort. Therefore, we do not review only Semantic-based Virtual integration but also involve other integration and access approaches, as illustrated in Figure 3.1. In Table 3.2, we summarize the information about the reviewed efforts along six criteria; a detailed review is subsequently presented.

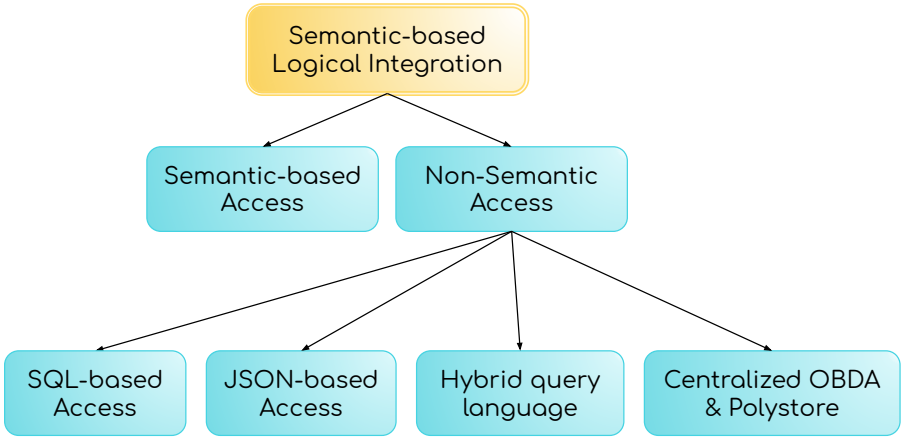


Figure 3.1: A visual representation of the reviewed related efforts.

3.2.1 Semantic-based Access

Optique [86] is an OBDA-based platform that accesses both static and dynamic data sources (streams). It makes a particular emphasis on semi-automatically extracting ontology and mappings (using R2RML, *RDB to RDF Mapping Language*) starting from analyzing data source schemata. An integral part of Optique is a visual query builder that allows non-experts to build queries by introducing and filtering concepts and properties. Offline, Ontop is used to map ontology axioms to relational queries (SQL). Online, a SPARQL query is generated, unfolded and transformed to SQL basing on Ontop mappings. Streaming data is queried using an extension of SPARQL called STARQL. Relational data sources are queried using SQL; other sources, e.g., CSV, XML, are queried using a separate parallel SQL query engine called Exareme. There is only a mention of NoSQL with no explicit description of how they can be accessed, and no mention of distributed file systems (e.g., HDFS). Although code-source of some individual used components (e.g. Ontop, Exareme) is separately available, code-source of the central Optique platform that is used to query a set of Big Data sources is not found.

Ontario [87] presents an implementation of a SDL, but lacking some of the requirements that we deem crucial in SDL implementations (subsection 6.1.2), e.g., supporting heterogeneous and large data sources, and distributed query execution. The emphasis is rather put on the query rewriting, planning, and federation, with a strong stress on RDF data as input. Query plans are built and optimized based on a set of heuristics. Ontario was evaluated in a centralized environment over small-sized RDF (via a SPARQL endpoint) and relational data (MySQL).

Authors of [88] motivate and advocate for the integration of OBDA technology over NoSQL stores. This involves the incorporation of a schema, the use of a high-level declarative query language and the support of integrity constraints. They suggested a preliminary approach for query processing focuses on star-shaped SPARQL queries. The prototype, which is lightly described, involves the query conversion from SPARQL to Java programs using MongoDB and Cassandra APIs. As it is a preliminary study, there is no discussion about the parallel and distributed execution of the queries, and no evaluation has been presented. Finally, the basis of the discussions was solely around Document and Columnar NoSQL stores.

SparqlMap-M [89] focuses on Document databases, MongoDB in particular, and enables querying them using SPARQL. It provides a relational view over Document databases. The effort extends a previous SPARQL-to-SQL translation method and uses R2RML as the mapping

language. Unions and joins, which are not supported by Document databases, reserve a special treatment. SPARQL queries are translated to union-free sub-queries. Intermediate results are materialized and pushed to an internal RDF triple store to perform the joins. The scope here is, however, narrower than what is considered in this thesis in terms of data source heterogeneity.

Ontop/MongoDB [90] proposes a formal generalization of the traditional OBDA framework to allow querying NoSQL stores. The SPARQL query is first translated to a high-level *intermediate query*, which is optimized (e.g., eliminating redundant self-join, replacing join of unions with union of joins) and then translated to the native query language of the data sources. An implementation of the presented approaches extending Ontop was described. SPARQL queries are translated to MongoDB Aggregate Queries, which are a set of procedure stages processing a MongoDB collection and returning a new modified collection. The implementation is demonstrated on a single MongoDB store with small data.

3.2.2 Non-Semantic Access

SQL-based Access

Motivated by the mainstream popularity of SQL query language, [91] poses a relational schema over NoSQL stores. A set of mapping assertions that associate the general relational schema with the data source schemata are defined. These mappings are expressed using a proposed mapping language. Authors state that most NoSQL stores do not have a declarative query language, rather a procedural access mechanism. For that, they suggest an intermediate query language called Bridge Query Language, BQL, which contains Java methods accessing the NoSQL databases. SQL queries supported are `SELECT-PROJECT-JOIN` conjunctive queries; other operations e.g., aggregations are not supported. The queries are translated to BQL using the mapping assertions, then to Java procedures using NoSQL stores' respective APIs. Cassandra and MongoDB APIs are used for demonstration. The underlying approach of join processing is not explained, and the prototype is not evaluated.

JSON-based Access

Authors in [92] propose a JSON-based general schema on top of RDBMSs and NoSQL stores. Schema semantic differences are captured using *alias*, similar to ontology properties in RDF ontologies. Queries are posed against the general schema and expressed using procedural calls including JSON-like notations. However, the access is only to single data sources; cross-source joins and aggregations can only be performed over JSON materialized query results. Further, the prototype is evaluated with only small data on a single machine.

CRUD API-based

ODBAPI [93] enables running CRUD (Create, Read, Update, Delete) operations over NoSQL stores and RDBMSs. It abstracts away the access syntax of the heterogeneous data sources by using common HTTPS requests *get*, *put*, *post* and *delete*. It aligns the concepts of three database categories: RDBMS (MySQL), Key-Value (Riak), and Document (CouchDB) into a unified conceptual model. Transparently, these requests trigger calls to the APIs of the respective data sources. Thus, more complex operations, e.g., joins, aggregations, are not supported. The authors extend their approach to support joins [94, 98], but not in a scalable way. The approach performs joins locally if involved data is located in the same database and the latter supports

join, otherwise, data is moved to another capable database. Naturally, moving data can become a bottleneck in large-scale settings.

Similarly to **ODBAPI**, **SOS** [96] suggests a generic programming model, a common interface and a *meta-layer* that collectively provide an abstraction on top of heterogeneous NoSQL and RDBMS sources. The programming model allows to directly access data sources using *get()*, *put()* and *delete()* methods, and, thus, simplifies application development. These methods are developed for every data source, using its official Java API. The Meta-layer consists of three components against which source schemata are aligned: *Set* (e.g., table), *Struct* (e.g., tuple), and *Attribute* (e.g., column). However, cross-databases join is not addressed. Three NoSQL data sources are considered, Key-value (Riak), Document (MongoDB) and Columnar (HBase).

Using a Hybrid Query Language

[97] suggests a generic query language that is based on SQL and JSON formalism, called **SQL++**. It tries to cover the capabilities of, among others, the heterogeneous NoSQL query syntax (Hive, Jaql, Pig, Cassandra, JSONiq, MongoDB, Couchbase, SQL, AsterixDB, BigQuery and UnityJDBC). SQL++ queries are translated to subqueries in the syntax of the source query language. However, only one NoSQL data source, MongoDB, is used to demonstrate the presented query conversion capabilities.

CloudMdsQL [95] proposes a SQL-like language, which contains invocations to the native query interfaces of NoSQL and RDMBS databases. The learning curve of this query language is higher than other efforts suggesting to query solely using plain (or minimally adapted) SPARQL, SQL, API calls, and JSON-based procedures. Its general architecture is distributed; however, we are not able to verify whether intra-source join is also distributed in the absence of the source-code.

In both efforts, users are expected to learn the syntax of other languages in addition to standard SQL.

Centralized OBDA and Polystores

There are two other categories that share with the Semantic Data Lake the ability to access heterogeneous stores. However, they differ in the scope of data sources to access and the access mechanism. The first family is represented by the solutions *mapping relational databases to RDF* [99], and *Ontology-Based Data Access over relational databases* [51], e.g., Ontop, Morph, Ultrawrap, Mastro, Stardog. These solutions are not designed to query large-scale data sources, e.g., NoSQL stores or HDFS. The second family is represented by the so-called *polystore* systems, which address large-scale heterogeneous data sources but require the movement of data across the data sources, or the data itself is duplicated across the sources, e.g., [100–102]. The task is to find which store answers best a given query (analytical, transactional, etc.) or which store to move all/part of the data to.

3.2.3 Discussion

The literature review revealed that providing a cross-source ad hoc uniform query interface and distributed query execution is generally not a central focus point. Further, the Virtual Integration literature is still less involved and advanced in comparison to the Physical Integration literature in the thesis topic. Hence, the gap we identified in the Virtual Integration is wider

and has more room for innovation. In particular, there seems to be no work that collectively meets the following criteria:

- Performing a fully distributed and parallel query processing including the join operation of disparate and heterogeneous data sources. The query execution manager in the reviewed efforts was a centralized component to which all intermediate results from the sub-queries is sent for reconciliation. This is clearly a bottleneck for many queries (e.g., unselective or aggregation queries) since data cannot be centrally accommodated or efficiently transferred across the network. In a disparate siloed data environment, joining heterogeneous distributed data sources is crucial.

- Making use of Semantic Web technologies that provide artifacts for a fully on-demand virtual query processing. For example, SPARQL allows to express queries that are agnostic to the underlying data sources. It also provides a flexible query model that supports the joining of disparate data sources, thanks to its concept of Basic Graph Patters. Ontologies and Mapping Languages provide convenient standardized means to link data to high-level general data models, abstracting away semantic differences found across the data schemata.

- Supporting many data sources from the state-of-the-art Big Data Management, all the while not solely basing on handcrafted wrappers. As of today, many Big Data query engines provide a rich set of connectors to dozens of popular and unpopular data sources. Resorting to manually creating wrappers is not only counterproductive but also often error-prone and rarely as effective and covering as the officially-provided wrappers/connectors. Exploiting these wrappers save the time for optimizing on the upper layers of the Data Integration, e.g., query decomposition, distributed query execution and results reconciliation.

Our work addresses the previous points by incorporating Semantic and Big Data Technologies. From Semantic Technologies, RDF is conceptually used as the underlying data model for the on-demand Data Integration. RML mapping language (*RDF Mapping Language*) is used to keep the links between data source entities and attributes with high-level ontology classes and properties. RML is extended with the FnO (Function) ontology, which allows to declare functions independently from the technical implementations. FnO functions are used to alter join keys on query-time and enable the connection between two data sources. SPARQL is used as the input query language and SQL as an intermediate query language given its omnipresence in the majority of Big Data processing engines. Among the latter, we leverage two popular frameworks, Spark and Presto. These engines provide facilities for distributed query execution including the ability to connect to a vast array of data sources without the need to manually creating wrappers for them.

CHAPTER 4

Overview on Query Translation Approaches

"Don't count the days, make the days count."

Muhammad Ali

A Data Integration process of heterogeneous data entails a model harmonization at a certain level. For the Physical Integration, all data is transformed to a unified model in a *pre-processing* phase. For the Virtual Integration, relevant data is loaded on *query-time* to a data model that is optimized for efficient query processing and that acts as an abstraction on top of the heterogeneous data sources. As the data model is followed by the query language, we set to conduct a survey of the literature on the topic of query translation methods. The survey reviews as many relevant criteria as possible to maximize its utility. However, in the context of this thesis we are interested in the following question:

RQ1. What are the criteria that lead to deciding which query language can be most suitable as input for the Data Integration?

To answer this, we observe how many languages can the input query be translated to. We take into consideration the semantic similarity between the input and destination query. A significant semantic difference may result in the impossibility to translate certain query constructs and operations or cause a loss in the retrieved results. Since we are solving the integration problem using Semantic Technologies, we start with the assumption that our input query would be in SPARQL. However, we keep the question open, such that if the survey reveals that more languages can be reached from another query language, then we can consider that language as a meta-language to which we translate the SPARQL query. Further, the choice of the query language follows the data model adopted by the Data Integration system. Since we are dealing with large-scale data, the choice of the model is critical as it can either optimize or hinder query processing performance. As an initial assumption, SQL and Document-based are good candidates, since several distributed processing engines adopt the tabular and Document/JSON as the central data model, e.g. Apache Spark, Apache Druid, Apache Drill. The survey has as secondary purpose the exploration of common translation strategies, e.g., query optimizations, storage-aware and schema-aware translation methods, mappings-based translation methods, etc. which we can leverage to guide our own approaches.

We consider six query languages chosen based on a set of criteria: SQL, SPARQL, Gremlin,

Document-based, XPath/XQuery. SQL was formally introduced in the early seventies [30] following the earlier proposed and well-received relational model [2]. SQL has influenced the design of dozens subsequent query languages, from several SQL dialects to object-oriented, graph, columnar, and the various NoSQL languages. SPARQL is the de facto standardized query language to query RDF data. XPath and XQuery are the de facto and standardized query languages for XML data. Document-based is not standardized but is commonly used with JSON formalism. All these query languages are used in a large variety of storage and Data Management systems. In order to leverage the advantages of each, companies and institutions are choosing to store their data under different representations, a phenomenon known as *Polyglot Persistence* [43]. As a result, large data repositories with heterogeneous data sources are being generated (also known as *Data Lakes* [4]), exposing various query interfaces to the user.

On the other hand, while computer scientists were looking for the holy grail of data representation and querying in the last decades, it is meanwhile accepted that no optimal data storage and query paradigm exist. Instead, different storage and query paradigms have different characteristics especially in terms of representation and query expressivity and scalability. Different approaches balance differently between expressivity and scalability in this regard. While SQL, for example, comprises a sophisticated data structuring and very expressive query language, NoSQL languages trades schema and query expressivity for scalability. As a result, since no optimal representation exists, different storage and query paradigms have their right to exist based on the requirements of various use-cases.

With the resulted high variety, the challenge is then how can the collected data sources be integrated and accessed in a uniform ad hoc way. Learning the syntax of their respective query languages is counterproductive as these query languages may substantially differ in both their syntax and semantics. A plausible approach is to develop means to map and translate between different storage and query paradigms. One way to achieve this is by leveraging the existing query translators, and building wrappers that allow the conversion of a query in a unique language to the various query languages of the underlying data sources. This has stressed the need for a better understanding of the translation methods between query languages.

Several studies investigating query translation methods exist in the literature. However, they typically tackle pair-wise translation methods between two specific types of query languages, e.g., [103] surveys XML languages-to-SQL query translations, [104–106] surveys SPARQL-to-SQL query translations. To the best of our knowledge, no survey has tackled the problem of universal translation across several query languages. Therefore, in this chapter, we take a broader view over the query translation landscape. We consider existing query translation methods that target many widely-used and standardized query languages. Those include query languages that have withstood the test of time and recent ones experiencing rapid adoption. The contributions of this article can be summarised as follows:

- We propose eight criteria shaping what we call a *Query Translation Identity Card*; each criterion represents an aspect of the translation method.
- We review the translation methods that exist between the most popular query languages, whereby popularity is judged based on a set of defined measures. We then categorize them based on the defined criteria.
- We provide a set of graphical representations of the various criteria in order to facilitate information reading, including a historical timeline of the query translation evolution.

- We discuss our findings, including the weakly addressed query translation paths or the unexplored ones, and report on some identified gaps and lessons learned.

This chapter is based on the following survey:

- **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Harsh Thakkar, Sören Auer, Jens Lehmann. *The query translation landscape: a survey.* In ArXiv, 2019. I conducted most of this survey, including most of the review criteria and the collected content. Content I have not provided is the review involving Tinkerpop and partially Neo4J (attributed to Harsh Thakkar).

4.1 Considered Query Languages

We chose the most popular query languages in four database categories: relational, graph, hierarchical and document-oriented databases. Popularity is based on the standardization efforts, number of citations to relevant publications, categorizations found in recently published works and technologies using the query languages. Subsequently, we introduce our chosen query languages and motivate the choice. We provide a query example for these query languages. Our example query corresponds to the following natural language question:

> Find the city of residence of all persons named Max.

4.1.1 Relational Query Language

SQL is the *de facto* relational query language first described in [30]. It has been an ANSI/ISO standard since 1986/1987 and is continually receiving updates, latest published in 2016 [107].

Example: `SELECT place FROM Person WHERE name = "Max"`

4.1.2 Graph Query Languages

The recently published work at the ACM Computing Surveys [108] features three query languages: SPARQL, Cypher and Gremlin. Further, a blog post [109] published by *IBM Developer* in 2017 sees those query languages as most popular[1].

SPARQL is the *de facto* language for querying RDF data. Of the three surveyed graph query languages, only SPARQL became a W3C standard in 2008 and is still receiving updates, the latest of which is SPARQL 1.1 [110] 2013. Research publications on SPARQL foundations [23, 111, 112] are among the most cited across all graph query languages.

Example: `SELECT ?c WHERE {?p :type :Person . ?p :name "Max" . ?p :city ?c }`

Cypher is Neo4j's query language developed in 2011 and open-sourced in 2015 under the OpenCypher project [113]. Cypher has been recently formally described in a scientific publication [114]. At the time of writing, Neo4j tops DB engine ranking [115] of Graph DBMS.

Example: `MATCH (p:Person) WHERE p.name = "Max" RETURN p.city`

[1] GraphQL is also mentioned, but it has far less scientific and technological adoption.

Gremlin [116] is the traversal query language of Apache TinkerPop [116]. It first appeared in 2009, predating Cypher. It also covers a wider range of graph query operations: *declarative* (pattern matching) and *imperative* (graph traversal). Thus, it has a larger technological adoption. It has libraries in more query languages: Java, Groovy, Python, Scala, Clojure, PHP, and JavaScript. It is also integrated into more renowned data processing engines (e.g., Hadoop, Spark), and graph databases (e.g., Amazon Neptune, Azure Cosmos, OrientDB, etc).

Example (*declarative*): `g.V().match(.as('a').hasLabel('Person').has('name','Max').as('p'),__.as('p').out('city').values().as('c')).select('c')`
Example (*imperative*): `g.V().hasLabel('Person').has('name','Max').out('city').values()`

4.1.3 Hierarchical Query Languages

This family is dominantly represented by XML query languages. XML appeared more than two decades ago and has been standardized in 2006 by W3C [117]; it is used mainly for data exchange between applications. W3C recommended XML query languages are XPath and XQuery.

XPath allows to define path expressions that navigate XML trees from a root parent to descendent children. XPath has been standardized by W3C in 1999 and is continually receiving updates, the latest of which published in 2017 [118].

Example: `//person[./name='Max']/city]`

XQuery is XML *de facto* query language. XQuery is also considered a functional programming language as it allows calling and writing functions to interact with XML documents. XQuery uses XPath for path expressions and can perform *insert*, *update* and *delete* operations. It was initially suggested in 2002 [119], standardized by W3C in 2007 and recently updated in 2017 [120].

Example: `for $x in doc("persons.xml")/person where $x/name='Max' return $x/city`

4.1.4 Document Query Languages

The representative document database that we choose is **MongoDB**. MongoDB, first released in 2009, is the document database that attracts the most attention both from academia and industry. At the time of writing, MongoDB tops Document stores ranking [115].

MongoDB operations. MongoDB does not have a proper query language like SQL or SPARQL but rather interacts with documents by means of *operation calls* and *procedures*.
Example: `db.product.find({name: "Max"}, {city: 1})`

4.2 Query Translation Paths

In this section, we introduce the various translation paths between the selected query languages. Figure 4.1 shows a visual representation, where the nodes correspond to the considered query languages and the directed arrows correspond to the translation direction; the thickness of the arrows reflects the number of works on the respective query translation path.

4.2.1 SQL ↔ XML Languages

The interest in using a relational database as a backbone for storing and querying XML has appeared as early as 1999 [121]. Even though XML model differs substantially from the relation model, e.g., multi-level data nesting, cycles, recursive graph traversals, etc., storing XML data in RDBMSs was sought to benefit from their query efficiency and storage scalability.

XPath/XQuery-to-SQL: XML documents have to be *flattened*, or *shredded*, into relations so they can be loaded into or mapped to relational tables. The ultimate goal is to hide the specificity of the back-end store and make users feel as if they are directly dealing with the original XML documents. In parallel, there are efforts to provide an XML view on top of relational databases. The rational is can be to unify the access using XML, or to benefit from XML querying capabilities, e.g., expressing path traversals and recursion.

SQL-to-XPath/XQuery: This covers approaches for storing XML in native XML stores, but adding an SQL interface to enable the querying of XML by SQL users. Metadata about how XML data is mapped to the relational model is required.

4.2.2 SQL ↔ SPARQL

SPARQL-to-SQL: Similarly to XML, the interest in bridging the gap between RDF model and the relational model emerged with RDF first days. This was motivated by multiple and various use cases. For example, RDBMSs were suggested to store RDF data [122, 123], even before SPARQL standardization. Also, the Semantic Web community suggested a well-received data integration proposal whereby disparate relational data sources are mapped to a unified ontology model and then queried uniformly [123, 124]. The concept evolved to become the popular OBDA, Ontology-Based Data Access [8], empowering many of applications today.

SQL-to-SPARQL: The other direction received less attention. The main two motivations presented were enhancing interoperability between the two worlds in general, and enabling reusability of the existing relation-oriented tools over RDF data, e.g, reporting and visualization.

4.2.3 SQL ↔ Document-based

The main motivation behind exploring this path was to enable SQL users and legacy systems to access the new class of NoSQL document databases with their sole SQL knowledge.

SPARQL-to-Document: The rationale here is identical to that of SPARQL-to-SQL, with one extra consideration: scalability. Native triple stores become prone to scalability issues when storing and querying significant amounts of RDF data. Users resorted to more scalable solutions to store and query the data [125]. The most studied database solution by the research community, we found, was MongoDB.

4.2.4 SQL ↔ Graph-based

SQL-to-Cypher: This path is considered for the same reasons as the SQL-to-Document, which is mainly attempting to help users with SQL knowledge to approach graph data stored in Neo4j.

Cypher-to-SQL: The rationale is to allow running graph queries over relational databases. It has also been advocated that using relational databases to store graph data can be beneficial in certain cases, benefiting from the efficient index-based retrieval typically offered by RDBMSs.

Gremlin-to-SQL: The aim here is to allow executing Gremlin traversals (without side effect steps) on top of relational databases in order to leverage the optimization techniques built into RDBMSs. To do so, the property graph data is represented and stored as relational tables.

SQL-to-Gremlin: The main motivation is to enable RDBMS users to migrate to graph databases in order to leverage the advantages of graph-based functions (e.g., depth-first search, shortest paths, etc.) and data analytical applications that require distributed graph data processing.

4.2.5 SPARQL ↔ XML Languages

SPARQL-to-XPath/XQuery: Similarly to SQL-to-XML paths, this path seeks to build interoperability environments between semantic and XML database systems. Moreover, it allows to add a semantic layer on top XML data and services for integration purposes.

XPath/XQuery-to-SPARQL: Enabling XPath traversal or XQuery functional programming styles on top of RDF data can be an interesting feature to equip native RDF stores with. This encourages new adopters from the XML world to embark on the Semantic Web world.

4.2.6 SPARQL ↔ Graph-based

SPARQL-to-Gremlin: This path aims to bridge the gap between the Semantic Web and Graph database communities by enabling SPARQL querying of property graph databases. Users well versed in SPARQL query language can avoid learning another query language, as Gremlin supports both OLTP and OLAP graph processors, covering a wide variety of graph databases.

4.3 Survey Methodology

Our study of the literature revealed a set of generic query translation patterns and common aspects that can be used to classify the surveyed query translation methods and tools. We refer to them as *translation criteria* and organize them into three categories.

I. Translation Properties

Describe the properties of the translation method divided into *type* and *coverage*.

1. **Translation Type:** Describes how the target query is obtained.
   a) **Direct:** The translation method generates the destination query starting from and by analyzing *only* the original query.
   b) **Intermediate/Meta Query Language-based:** The translation method generates the destination query by passing by an intermediate (meta-)language.
   c) **Storage Scheme-aware:** The translation generates queries depending on how data is internally structured or partitioned.

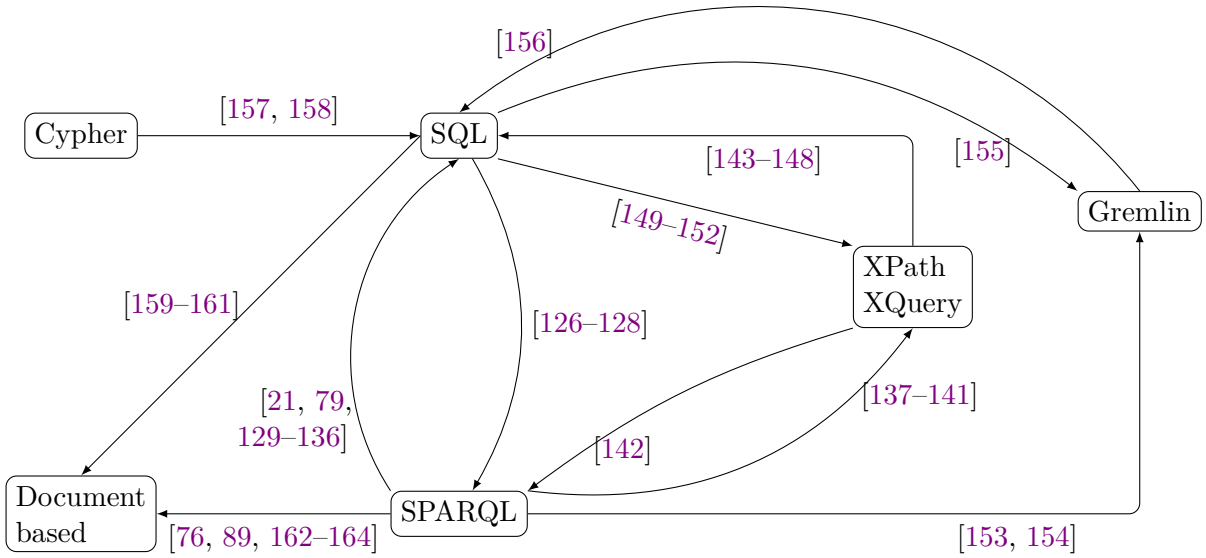


Figure 4.1: Query translation paths found and studied.

d) **Schema Information-aware:** The translation method depends mainly on the schema information of the underlying data.

e) **Mapping Language-based:** The translation method generates the destination query using a set of mapping rules expressed in an established/standardized third-party mapping language, e.g., R2RML [165].

2. **Translation Coverage:** Describes how much of the input query language syntax is covered. For example, projection and filtering preserved, joining and update dropped.

II. Translation Optimization

Describes the techniques used by the various approaches to improve query translation efficiency.

1. **Optimization Strategies:** Describes any optimization techniques applied during query translation, e.g., reordering joins in a query plan to reduce intermediate results.

2. **Translation Relationship:** Describes how many destination queries can be generated starting from the input query: one-to-one, one-to-many. Generally, it is desirable to reduce the number of destination queries to one, so we consider this an optimization aspect. We separate it from the previous point, however, as it has a different (discrete) value range.

III. Community Factors

Include different factors that can be used by interested users in deciding on the translation method value. For example, a method that is empirically evaluated, available for usage, adopted by other users and maintained have evidence for a well-founded method.

1. **Evaluation:** Assesses whether the translation method has been empirically evaluated. For example [149] evaluates the various schema options and their effect on query execution using the TPC-H benchmark.

2. **Availability:** Describes whether the translation method implementation or prototype is openly available. That can be known, for example, by checking if the reference to the source code repository or download page is still available.

3. **Impact:** Describes the influence made by the translation method among the community. This can be measured, for example, in terms of the number of research publications citing it.

4. **Metadata:** Provides some related information about the presented translation method, such as the date of first and last release/update. For example, this helps to obtain an indication of whether the solution is still maintained.

4.4 Criteria-based Classification

Scope definition. Given the broad scope tackled in this survey, it is important to limit the search space. Therefore, we take measures as to favor quality, high-influence and completeness, as well as preserve a certain level of novelty.

- We do not consider a work that describes the query translation very marginally or that has a broad scope with little focus on the query translation aspects.
- We only consider efforts proposed during the last fifteen years, i.e., after 2003. This applies in particular to XML-related translations; however, interested readers may refer to an existing survey covering older XML translation works [103].
- We do not consider efforts that are five years old and have no (external) citation.

It is also important to explicitly prune the scope in terms of what aspects are *not* considered in the survey:

- We do not address post-query translation steps, e.g., results formats and representations.
- As the aim of this survey is to explore the methods and capabilities, we do not comment on the results of empirical evaluations of the individual efforts. This is also due to the vast heterogeneity between the languages, data models and use cases.
- The translation method is summarized, which may entail that certain details are omitted. The goal is to allow the reader to discover the literature; interested readers are encouraged to visit the individual publications for the full details.

In the remainder of this survey, we refer to the articles and tools by citation and, when available, by name, then describe the respective query translation approaches. Further, it should not be inferred that the article or the tool presents solely query translation approaches, but often, other aspects are also addressed, e.g., data migration. These aspects are considered out-of-scope of the current survey. Finally, in order to give the survey a temporal context, efforts are listed in chronological order.

I. Translation Properties > 1. Translation Type

a) Direct

SQL-to-XPath/XQuery: **ROX** [149] aims at directly querying native XML stores using a SQL interface. The method consists of creating *relational* views, called NICKNAMEs, over a native XML store. The NICKNAME contains schema descriptions of the rows that would be returned starting from XML input data, including mappings between those rows and XML elements in form of XPath calls. Nested parent-child XML elements are caught, in the NICKNAME definition, by expressing primary and foreign keys between the corresponding NICKNAMEs. [150, 151] propose a set of algorithms enabling direct logical translations of simple SQL `INSERT`, `UPDATE`, `DELETE` and `RENAME` queries to statements in the XUpdate language[2]. In the case of `INSERT`, the SQL query has to be slightly extended to instruct in which position related to the context node (preceding/following) the new node has to be inserted.

SPARQL-to-SQL: [130] defines a set of primitives that allow to (a) extract the relation where triples matching a triple pattern are stored, (b) extract the relational attribute whose value may match a given triple pattern in a certain position (s,p,o), (c) generate a distinct name from a triple pattern variable or URI, (d) generate SQL conditions (`WHERE`) given a triple pattern and the latter primitive, and (e) generate SQL projections (`SELECT`) given a triple pattern and the latter three primitives. A translation function returns a SQL query by fusing and building up the previous primitives given a graph pattern. The translation function generates SQL joins from `UNION`s and `OPTIONAL`s between sub-graph patterns. **FSparql2Sql** [135] is an early work focusing on the various cases of `filter` in SPARQL queries. While RDF objects can take many forms e.g., IRIs (Internationalized Resource Identifier), literals with and without language and/or datatype tags, values stored in RDBMS are generally atomic textual or numeral values. Therefore, the various cases of RDF objects are assigned primitive data types, called "facets". For example, facets for IRIs, datatype tags and language tags are of primitive type *String*. As a consequence, filter operands become complex, so they need to be bound *dynamically*. To achieve that, SQL-92 `CASE WHEN ... THEN` expressions are exploited. [133] proposes several relational-based algorithms implementing different operators of a SPARQL query (algebra). In contrast to many existing efforts, this work aims to generate *flat/un-nested* SQL queries, instead of multi-level nested queries. The aim is to leverage the performance of common SQL query optimizers. SQL queries are generated using SQL *augmentations*, i.e., SPARQL operators gradually augment the SQL query instead of creating a new nested one. The algorithms implement *functions*, which generate parts of the final SQL query.

SQL-to-Document-based: **QueryMongo** [159] is a Web-based translator that accepts a SQL query and generates an equivalent MongoDB query. The translation is based solely on the SQL query syntax, i.e., not considering any data or schema. No explanation about the translation approach is provided. [166] is a library providing an API to translate SQL to MongoDB queries. The translation is based on the SQL query syntax only.

SPARQL-to-XPath/XQuery: [141] does not provide a direct translation of SPARQL to XQuery, rather SPARQL embedded inside XQuery. The method involves representing SPARQL

[2] XUpdate is an extension of XPath allowing to manipulate XML documents.

in the form of a *tree of operators*. There are operators for projection, filtering, joining, optional and union. These operators declare how the output (XQuery) of the corresponding operations are represented. The translation involves data translation from RDF to XML and the translation of the operators to corresponding XQuery queries. An XML element with three sub-elements is created for each triple term (s, p and o). The translation from an operator into XQuery constructs is based on transformation rules, which replace the embedded SPARQL constructs with XQuery constructs. The translation from an operator into XQuery constructs is based on transformation rules, which replace the embedded SPARQL constructs with XQuery constructs. In **XQL2Xquery** [140], variables of the query BGP (Basic Graph Patter) are mapped to XQuery values. A `for` loop and a path expression is used to retrieve subjects and bind any variables encountered. Then, nested under every variable, iterate over the predicates and bind their variables. In a similar way, nestedly iterate over objects. Next, BGP constants and filters are mapped to XQuery `where`. `OPTIONAL` is mapped to an XQuery *function* implementing a `left outer join`. For filters, XQuery value comparisons are employed (e.g., `eq`, `neq`). *ORDER BY* is mapped to `order by` in a *FLWOR* expression. `LIMIT` and `OFFSET` are handled using *position* on the results. `REDUCED` is translated into a `NO-OP`.

XPath/XQuery-to-SPARQL: [142] presents a translation method that includes data transformation from XML to RDF. During the data transformation process, XML nodes are annotated with information used to support all XPath axes. For example, type information, attributes, namespaces, parent-child relationships, information necessary for recursive XPath, etc. The above annotations conform to the structure of the generated RDF and are used to generate the final SPARQL query.

Gremlin-to-SQL: [156] proposes a direct mapping approach for translating Gremlin queries (without the side effect step) to SQL queries. The authors propose a generic technique to translate a subset of Gremlin queries (queries without side effect steps) into SQL leveraging the relational query optimizers. They propose techniques that make use of a novel scheme, which exploits both relational and non-relational storage for property graph data. This is achieved by combining relational with JSON storage for adjacency information and vertex and edge attributes respectively.

SPARQL-to-Gremlin: **Gremlinator** [153, 154] proposes a direct translation of SPARQL queries to Gremlin pattern matching traversals, by mapping each triple pattern within a SPARQL query to a corresponding single step in the Gremlin traversal language. This is made possible by the `match()`-step in Gremlink, which offers a SPARQL-style of declarative construct. Within a single `match()`-step, multiple single step traversals can be combined forming a complex traversal, analogous to how multiple basic graph patterns constitute a complex SPARQL query [167].

b) Intermediate/Meta Query Language-based

Type-ARQuE [132] uses an intermediate query language called AQL, Abstract Query Language, which is designed to stand between SQL and SPARQL. AQL extends from the relational algebra (in particular the join) and accommodates both SQL and SPARQL semantics. It is represented as a tree of expressions and joins between them, containing selects and orders.

The translation process consists of three stages: (1) SPARQL query parsed and translated to AQL, (2) AQL query undergoes a series of transformations (simplification) preparing it for SQL transformation, and (3) AQL query translated to the target SQL dialect, transforming AQL join tree to SQL join tree, along with the other selects and orders expressions. Example of stage 2 simplifications: type inference, nested join flattening, join inner joins with parents, etc. In [129], Datalog is used as an intermediate language between SPARQL and SQL. SPARQL query is translated into a semantics-similar Datalog program. The first phase is translating SPARQL query to a set of Datalog rules. The translation adopts a syntactic variation of the method presented in [168] by incorporating built-in predicates available in SQL and avoid negation, e.g., `LeftJoin`, `isNull`, `isNotNul`, `NOT`. The second phase is generating an SQL query starting from Datalog rules. Datalog atoms `ans`, `triple`, `Join`, `Filter` and `LeftJoin` are mapped to equivalent relational algebra operators. `ans` and `triple` are mapped to a projection, while `filter` and joins to equivalent relational filter and joins, respectively.

SPARQL-to-Document: In [164], a generic two-step SPARQL-to-X approach is suggested, with a showcase using MongoDB. The article proposes to convert the SPARQL query to a pivot intermediate query language called Abstract Query Language (AQL). The translation uses a set of mappings in a mapping language called xR2RML, which is an extension of RML [169]. These mappings describe how data in the target database is mapped into the RDF model, without converting data itself to RDF. AQL has a grammar that is similar to SQL both syntactically and semantically. The BGP part of a SPARQL query is decomposed into a set of expressions in AQL. Next, xR2RML mappings are checked for any maps matching the containing triple patterns. Those detected matching maps are used to translate individual triple patterns to *atomic abstract queries*. The latter are of the form "`FROM` query `PROJECT reference WHERE condition`". Where `query` is the concrete query over the database, which is a MongoDB query. Unsupported operations like `JOIN` in MongoDB are assumed left to a higher-lever query engine.

c) Storage scheme-aware

XPath/XQuery-to-SQL: In [148] **XTRON**, a relational XML management system is presented. The article suggests a Schema-oblivious way of storing and querying XML data. XML documents are stored uniformly in *identical* relational tables using a unified predefined relational model. Generated queries then have to abide by this fixed relational schema.

SPARQL-to-Document: **D-SPARQ** [76] focuses on the efficient processing of join operation between triple patterns of a SPARQL query. RDF data is physically materialized in a cluster of MongoDB stores, following a specific graph partitioning scheme. SPARQL queries are converted to MongoDB queries accordingly.

Cypher-to-SQL: **Cyp2sql** [158] is a tool for the automatic transformation of both data and queries from a Neo4j database to a relational database. During the transformation, the following tables are created: Nodes, Edges, Labels, Relationship types, as well as materialized views to store the adjacency list of the nodes. Cypher queries are then translated to SQL queries tailored to that data storage scheme.

SQL-to-Gremlin: SQL-Gremlin [155] is a proof-of-concept SQL-to-Gremlin translator. The translation requires that the underlying graph data is given a relational schema, whereby elements from the graph are mapped to tables and attributes. However, there is no reported scientific study that discusses the translation approach. **SQL2Gremlin** [170] is a tool for converting SQL queries to Gremlin queries. They show how to reproduce the effect of SQL queries using Gremlin traversals. A predefined graph model is used during the translation; as an example, Northwind relational data was loaded as a graph inside Gremlin.

d) Schema information-aware

XPath/XQuery-to-SQL: In [143], the process uses summary information on the relational integrity constraints computed in a pre-processing phase. An XML view is constructed by mapping elements from the XML schema to elements from the relational schema. The XML view is a tree where the nodes map to table names and the leaves to column names. An SQL query is built by going from the root to the leaves of this tree, a traversal from a node to a node is a join between the two corresponding tables. In [146], XML data is shredded into relations based on an XML schema (DTD) and saved in a RDBMS. The article extends XPath expressions to allow capturing recursive queries against a recursive schema. XPath queries with the extended expressions can, next, be translated into an equivalent sequence of SQL queries using a common RDBMS operator (LFP: Simple Least Fixpoint). Whereas [145] builds a virtual XML view on top of RDBMSs using XQuery, the focus of the article is on the optimization of the intermediate relational algebra.

SQL-to-SPARQL: **R2D** [127, 128] proposes to create a relational virtual normalized schema (view) on top of RDF data. Schema elements are extracted from RDF schema; if the schema is missing or incomplete, schema information is extracted by thoroughly exploring the data. *r2d:TableMap, r2d:keyField, r2d:refersToTableMap* denote a relational table, its primary key, and foreign key, respectively. A relational view is created using those schema constructs, against which SQL queries are posed. SQL queries are translated into SPARQL queries. In the SQL query, for every projected, filtered or aggregated (along with `GROUP BY`) variable, a variable is added to the *SELECT* of SPARQL query. SQL `WHERE` conditions are added to SPARQL `FILTER`, `LIKE` mapped to a `regex()`. Moreover, blank nodes are used in a number of cases. In **RETRO** [126], RDF data is exhaustively parsed to extract domain-specific relational schema. The schema corresponds to the Vertical Partitioning, i.e., one table for every extracted predicate, each table is composed of (subject object) attributes. Then, the translation algorithm parses the SQL query posed against the extracted relational schema and iteratively builds the SPARQL query.

SQL-to-Document-based: [160] requires the user to provide a MongoDB schema, expressed in a relational model using tables, procedures, and functions. [161] provides a JDBC access to MongoDB documents by building a representative schema, which is, in turn, constructed by sampling MongoDB data and fitting the least-general type representing the data.

SQL-to-XPath/XQuery: **AquaLogic Data Services Platform** [152] builds an XML-based layer on top of heterogeneous data sources and services. To allow SQL access to relational data,

a relational schema is mapped to AquaLogic DSP artifacts (internal data organization), e.g., service function to relational tables.

SPARQL-to-Document: In the context of OBDA, [163] suggests a two-step approach, whereby the relational model is used as an intermediate between SPARQL and MongoDB queries. Notions of MongoDB *type constrains* (schema) and *mapping assertions* are imposed on MongoDB data. These notions are used during the first step of the query translation to create relational views. Next, the schema is extracted from the data stored in MongoDB. MongoDB mappings relate MongoDB paths (e.g., `student.name`) to ontology properties. A SPARQL query is decomposed into a set of *translatable* sub-queries. Using MongoDB mappings, MongoDB queries are created. **OntoMongo** [162] proposes an OBDA on top of NoSQL stores, applied to MongoDB. Three artifacts are involved: an ontology, a conceptual layer, and mappings between the latter two. The conceptual layer adopts the object-oriented programming model, i.e., classes and hierarchy of classes. Data is accessed via ODM, Object-Document-Mapping, calls. SPARQL triple patterns are grouped by their shared subject variable (star-shaped). Each group of triples is assumed to be of one class defined in the mappings; the class name is denoted by the variable of the shared subject. MongoDB query can be created by mapping query classes to classes in the conceptual model, which then is used to call MongoDB terms via ODM. The lack of join operation in MongoDB is substituted with a combination of two *unwind* commands each concerning one side (class) of the join.

Cypher-to-SQL: **Cytosm** [157] presents a middleware allowing to execute graph queries directly on top of non-graph databases. The application relies on the so-called gTop (graph Topology) to build a form of schema on top of graph data. gTop consists of two components: (1) Abstract Property Graph model, and (2) a mapping to the relational model. It captures the structure of *property graphs* (node and edge types and their properties) and provides mapping between graph query language and the relational query language. The latter involves mapping nodes to table rows and edges to either fields of rows or a sequence of table-join operations. Query translation is twofold. First, Using gTop abstract model, Cypher path expressions (from `MATCH` clause) are visited and a set of *restricted* OpenCypher [114] queries are generated, denoted rOCQ. Restricted queries do not contain multi-hop edges and anonymous entities since those are not possible to translate in SQL. Second, rOCQ queries are parsed and an intermediate SQL-like query is generated, having one `SELECT` and `WITH SELECT` for each `MATCH`. `SELECT` variables are checked if they require information from the RDBMS and if they inter-depend. Then, the mapping part of gTop is used to map nodes to relational tables. Finally, edges are resolved into joins, also basing on gTop mappings.

SPARQL-to-XPath/XQuery: **SPARQL2XQuery** is described in a couple of publications [137–139]. The translation is based on a mapping model between OWL ontology (existing or user-defined) and XML Schema. Mappings can either be automatically extracted by analyzing the ontology and XML schema or manually curated by a domain expert. SPARQL queries are posed against the ontology without knowledge of the XML schema. The BGP (Basic Graph Pattern) of the SPARQL query is normalized into a form where each graph pattern is `UNION`-free, so each pattern can be processed independently and more efficiently. XPaths are bound to graph pattern variables; there are various forms of binding for various variable types. Next, graph patterns are translated into an equivalent XQuery expression using the mappings. For each

variable of a triple, a `For` or `Let` clause using the variable binding is created. **Ultrawrap** [136] implements an RDF2RDB mapping, allowing to execute SPARQL queries on top of existing RDBMSs. It creates an RDF ontology from the SQL schema, based on which it next creates a set of logical RDF views over the RDBMS. The views, called *Tripleviews*, are an extension of the famous *triple tables* (subject, predicate, object) with two additional columns: subject and object primary keys. Four Tripleviews are created: *types*, *varchar(size)*, *int* and *object properties*. These tables respectively store the subjects along with their types in the database, the textual attributes, the numeral attributes, and the join links between the tables. Given a SPARQL query, each triple pattern maps to a Tripleview.

e) Mapping language-based

SPARQL-to-SQL: In **SparqlMap** [134], triple patterns of a SPARQL query are individually examined to extract R2RML triple maps. Methods are applied to find the candidate set of triple maps, which is then pruned to produce a set that prepares for the query translation. Given a SPARQL query, a recursive query generation process yields a *single* but *nested* SQL query. Sub-queries are created for individual mapped triple patterns and for reconciling those via `JOIN` or `UNION` operations. Nested subqueries over RDBMS tables extract the columns as well as structural information e.g., term type (resource, literal, etc.); they also concatenate multiple columns to form IRIs, etc. To generalize the technique of [129] (Datalog as intermediate language) to arbitrary relational schema, R2RML is incorporated. For every R2RML *triple map*, a set of Datalog rules are generated reflecting the same semantics. A `triple` atom is created for every combination of *subject map*, *property map* and *object map* on a translated *logical table*. Finally, the translation process from Datalog to SQL is extended to deal with the new rules introduced by R2RML mappings. [79] extends a previously published translation method [130] to involve user-defined R2RML mappings. In particular, it incorporates R2RML mappings in α and β mappings as well as *genCondSQL()*, *genPRSQL()* and *trans()* functions. For each, an algorithm is devised, considering the various situations found in R2RML mappings like the absence of Reference Object Map. **SparqlMap-M** [89] enables querying document stores using SPARQL without RDF data materialization. It is based on a previous SPARQL-to-SQL translator, SparqlMap [134], so it adopts a relational model to virtually represent the data. Documents are mapped to relations using an extension of R2RML allowing to capture duplicate demoralized data, which is a common characteristic of document data. The lack of union and join capabilities is mitigated by a multi-level query execution, producing and reusing intermediate results. Projections (*SELECT*) are pushed to the document store, while the union and join are executed using an internal RDF store.

2. Translation coverage

By coverage, we mean the fragment of the query language that is supported by the translation method. We note the following before starting our review of the various efforts:

- The coverage of the translation method is extracted not only from the core of the respective article(s) but also from the evaluation section and from the online page of the implementation (when available). For example, [89, 136] evaluate using all 12 BSBM benchmark queries, which cover more scope than that of the article. Further, the corresponding online page of [136] mentions features that are both beyond the core and the evaluation sections of the article.

- We mention the supported query feature, but we do not assume its completeness, e.g., [162] supports filters but only for *equality* conditions. Interested users are encouraged to seek details from the corresponding article or tool.

- Some works, e.g., [130, 162] support only one feature. This does not necessarily imply insignificance, but it may reflect a choice made by the authors to reserve the full study to covering that particular feature, e.g., specific graph pattern shapes, `OPTIONAL` cases, etc.

SQL-to-X and SPARQL-to-X: See Table 4.1 and Table 4.2 for the translation methods and tools starting from SQL and SPARQL, respectively. For SQL, the `WHERE` clause is an essential part of most useful queries, hence its support by all methods. `GROUP BY` is the next commonly supported feature, as it enables a significant class of SQL queries: analytical and aggregational queries. To a lower extent supported is the sorting operation `ORDER BY`. Since `JOIN` and, to less extent, `UNION` are operations of typically high cost, they are among the least supported features. As most researched query categories are of retrieval nature (`SELECT`), update queries, e.g., `INSERT`, `UPDATE` and `DELETE`, are weakly addressed. `DISTINCT` and nested queries are rarely supported, which might also be attributed to their typical expensiveness. For example, typically, `DISTINCT` requires sorting, and nested-queries generate large intermediate results. `EXCEPT`, `UPSERT`, and `CREATE` are only supported by individual efforts. For SPARQL, query operation support is more prominent across the reviewed efforts. `FILTER`, `UNION` and `OPTIONAL` are the most commonly supported operations with up to 60% of the surveyed efforts. To less extent, `DISTINCT`, `LIMIT` and `ORDER BY` are supported by about half of the efforts. The remaining query operations are all only supported by a few efforts, e.g., `DESCRIBE`, `CONSTRUCT`, `ASK`, blank nodes, `datatype()`, `bound()`, `isLiteral()`, `isURI()`, etc. `GRAPH`, `SUB-GRAPH`, `BIND` are examples of useful query operations but only supported by individual efforts. In general, `DESCRIBE`, `CONSTRUCT` and `ASK` are far less prominent SPARQL query types in comparison to `SELECT`, which is present in all the efforts. `isURI()` and `isLiteral()` are SPARQL-specific functions with no direct equivalent in other languages.

XPath/XQuery-to-SQL: The queries that [143] focuses on are simple path expressions, including descendant axis traversal, i.e., //. [146] enables XPath recursive queries against a recursive schema. [145] focuses on optimizing relational algebra, where only a simple XPath query is used for the example. [147] covers simple ancestor, following, parent, following-sibling, descendant-or-self XPath queries. In [144], the supported XPath queries involve descendant/child axes with simple conditions. [148] translates XQuery queries with path expressions including decedent axis // XQuery queries, dereference operator => and FLWR expressions.

XPath/XQuery-to-SPARQL: Authors of [142] mention support for recursive XPath queries with descendant, following and preceding axes as well as for filters.

Cypher-to-SQL: Authors of [157] experiment with queries containing `MATCH`, `WITH`, `WHERE`, `RETURN`, `DISTINCT`, `CASE`, `ORDER BY`, `LIMIT`. They also consider simple patterns with known nodes and relationships, $->$ and $<-$ directions, and variable-length relationship. [158] is able to translate `MATCH`, `WITH`, `WHERE`, `RETURN`, `DISTINCT`, `ORDER BY`, `LIMIT`, `SKIP`, `UNION`, count(), collect(), exists(), label(), id(), and rich pattern cases, e.g., (a or empty)–()–(b or empty), [a or empty]-[b]-(c or empty), $->$ and $<-$, (a) $-->$ (b).

Work	DISTINCT	WHERE/ REGEX	JOIN	UNION	GROUP BY /HAVING	ORDER BY	LIMIT/ OFFSET	INSERT/ UPDATE	DELETE/ DROP	Nested queries	Others
SQL-to-XPath/XQuery											
[149]	?	✓/	?	?	✓/	✓	?	?	✓/	?	
[152]	?	✓/	✓	✓	?/	✓	?	?	?/	✓	
[150, 151]	?	✓/	?	?	?	?	?	✓/✓	✓/	?	RENAME
SQL-to-SPARQL											
[126]	?	✓/	✓	✓		?	?	?	?	?	EXCEPT
[127, 128]	?	✓/✓	?	?	✓/	?	?	?	?	?	
SQL-to-Document-based											
[159]	✓	✓/✓	✗	✗	✓/✓	✓	✓/	✗	✗	✗	
[160]	✓	✓/	?	?	✓/✓	✓	✓/✓	✓/	✓/	?	
[161]	?	✓/✓	✓	?	✓/	?	✓/✓	✓/✓	/✓	?	CREATE, DROP, UPSERT, *date, string, math fncts*
[166]	?	✓/✓	?	?	✓/	✓	?	?	✓/	?	some Boolean filters
[171]	?	✓/	✓	?	✓/	✓	?	?	?	?	
SQL-to-Gremlin											
[155]	✓	✓/✓	?	✓	✓/	✓	?	?	?	✓	

Table 4.1: SQL features supported in SQL-to-X query translations. ✓ is supported, ✗ is not supported, ? not (clearly) mentioned supported. *Others* are features provided only by individual efforts.

Work	DISTINCT /REDUCED	FILTER/ regex()	OPTIONAL	UNION	ORDER BY	LIMIT/ OFFSET	Blank nodes	datatype() /lang()	isURI() isLiteral()	DESCRIBE /bound()	CONSTRUCT /ASK	Others
SPARQL-to-SQL												
[132]	✔/–	?	?	✔	✘	✔/–	?	?	?	?	?	
[79]	?	?	?	?	?	?	?	?	?	?	?	
[133]	✔/–	?	✔	✔	✔	✔/–	✔	✔/–	✔	✔/–	✔/✔	GRAPH, FROM NAMED, *isBlank()*
[134]	?/–	?	✔	?	✔	?	?	?	?	?	?	
[153, 154]	✔/✘	✔/✔	✔	✔	✔	✔/✔	✔	?	?	✘/✘	✘/✘	GROUP BY, SUB-QUERY, REMOTE
[135]	?	✔	✔	✔	?	?	?	✔/–	✔	✔/–	?	
[136]	✔/–	✔/✔	✔	✔	✔	✔/✔	?	✔/–	?	✔/✔	?	BIND
[129]	✔/–	✔/–	✔	✔	✔	✔/✔	?	✔/–	?	?	?	
[130]	?	?	✔	?	?	?	?	?	?	?	?	
SPARQL-to-Document												
[162]	?	✔/–	?	?	?	?	?	?	?	?	?	
[89]	✔/–	✔/✔	✔	✔	✔	✔/✔	?	✔/–	?	✔/✔	✔/–	
[76]	?	✘	✘	?	✘	?	?		?	?	?	
[163]	?	✔/–	✘	?	✘	?	?	?	?	?	?	
SPARQL-to-XPath/XQuery												
[137–139, 172]	✔/✔	✔/✔	✔	✔	✔	✔/✔	✔	?	?	✔/–	✔/✔	DELETE, INSERT
[140]	✔/✔	✔/–	✔	✔	✔	✔/✔	?	?	?	?	?	
[141]	?	✔/✔	✔	✔	✔	?	?	?	?	?	?	

Table 4.2: SPARQL features supported in SPARQL-to-X query translations. See Table 4.1 for ✔ ✘ ?. *Others* are features provided only by individual efforts.

II. Translation Optimization

3. Optimization strategies

In this section, we present the various techniques, which are employed by the reviewed effort for the sake of improving query translation performance. We note that, in order to avoid repetition, we will use some terms that have previously been introduced in *Translation Type* (Section 4.4).

XPath/XQuery-to-SQL: [143] suggests to eliminate joins by eliminating unnecessary prefix traversals, i.e. first traversals from the root. [145] proposes a set of *rewrite rules* meant to detect and eliminate unnecessarily redundant joins in the relational algebra of the resulted SQL query. During query translation, [146] suggests an algorithm leveraging the structure of XML schema: pushing selections and projections into the LFP operator, (Simple Least Fixpoint). **PPFS+** [147] mainly seeks to leverage RDBMS storage of *shredded* XML data. Based on empirical evaluation, nested loop join was chosen to apply merge queries over the shredded XML. They try to improve query performance by generating *pipelined* plans reducing time to "first results". Authors try to abide by XPath semantics of order and uniqueness: XPath results should follow the order of the original XML document and have no duplicates. To meet these requirements, redundant orders (`ORDER BY`) are eliminated, and ordering operations are pushed down the query plan tree. As a physical optimization, the article resorts to indexed file organization for the shredded relations. Even though **XTRON** [148] is schema-oblivious by nature, some schema/structural information is used to speed up query response. That is by encoding simple paths of XML elements into *intervals* of real numbers using a specific algorithm (Reverse Arithmetic Encoder). The latter reduces the number of self-joins in the generated SQL query.

SQL-to-XPath/XQuery: **ROX** [149] suggests a cost-based optimization to generate optimal query plans, and physical indexes for quick node look-up; however, no details are given.

SPARQL-to-SQL: The method in [79] optimizes certain SQL query cases that negatively impact (some) RDBMSs. In particular, the query rewriting techniques Sub-Query Elimination and Self-Join Elimination, are applied. The former removes non-correlated sub-queries from the query by pushing down projections and selections, while the latter removes self-joins occurring in the query. [133] implements an optimization technique called Early Project simplification, which skips variables that are not needed during query processing from the `SELECT` clause. In **SparqlMap** [134], filter expressions are pushed to the graph patterns, and nested SQL queries are flattened to minimize self-joins. In **FSparql2Sql** [135], the translation method may generate an abnormal SQL query with a lot of `CASE` expressions and constants. The query is optimized by replacing complex expressions by simpler ones, e.g., by manipulating different logical orders or removing useless expressions. The translation approach in **Ultrawrap** [136] is expected to generate a view of a very large union of many `SELECT-FROM-WHERE` statements. To mitigate this, a strategy called Unsatisfiable Conditions Detection is used. It detects whether a query would yield empty results even before executing it. This can be the case in the presence of contradictions e.g., `WHERE` predicate equals two opposite values. The strategy also prunes unnecessary `UNION` sub-trees, e.g., by removing an empty argument from the `UNION` in case two attributes of the same table are projected or filtered individually, then joined. The generated SQL query in [129] may be sub-optimal due to the presence of e.g., joins of `UNION` sub-queries, redundant joins with respect to keys, unsatisfiable conditions, etc. Techniques from Logical Programming are

borrowed. The first is Partial Evaluation used to optimize Datalog rules dealing with `ans` and `triple` atoms, by iteratively filtering out options that would not generate valid answers. The second is Goal Derivation in Nested Atoms and Partial SDL-tree with `JOIN` and `LEFT JOIN` dealing with `join` atoms. Techniques from Semantic Query Optimization are applied to detect unsatisfiable queries, e.g., joins when equating two different constants, simplification of trivially satisfiable conditions like $x = x$. The generated query in [130] is optimized using *simplifications*, e.g., removing redundant projections that do not contribute to a join or conditions in sub-queries, removing *true* values from some conditions, reducing join conditions based on logical evaluations, omitting left outer joins in case of SPARQL `UNION` when union'ed relations have an identical schema, pushing projection to `SELECT` sub-queries, etc.

SPARQL-to-Document: Query optimization in **D-SPARQ** [76] is based on a "divide and conquer"-like principle. It groups triple patterns into independent *blocks* of triples, which can run more efficiently in parallel. For example, star-shaped pattern groups are considered as indivisible blocks. Within a star-shaped pattern group and for each triple predicate, patterns are ordered by the number of triples involving that predicate. This boosts query processing by reducing the selectivity of the individual patter groups. In the relational-based OBDA of [163], the intermediate relational query is simplified by applying structural optimization, e.g., replacing join of unions by union of joins, semantic optimization, e.g., redundant self-join elimination, etc. In [164], the generated MongoDB query is optimized by pushing filters to the level of triple patterns, and by self-join elimination through merging atomic queries that share the same `FROM` part, and by self-union elimination through merging `UNION`s of atomic queries that share the same `FROM` part.

Cypher-to-SQL: **Cyp2sql** [158] stores graph data following a specific tables scheme, which is designed to optimize specific queries. For example, *Label* table is created to overcome the problem of prevalent `NULL` values in the *Nodes* table. The query translator decides, on *query-time*, which relationship to use in order to obtain node information. Relationship data is stored in the *Edges* table (storing all relationships) as well as in their separate tables (duplicate). Further optimization is gained from using a couple of meta-files populated during schema conversion, e.g., a nodes property list per label type is used to narrow down the search for nodes.

SPARQL-to-XPath/XQuery: In [141], a logical optimization is applied to the operator tree in order to generate a reorganized equivalent tree with faster translation time (no more details are given). Next, a physical optimization aims to find the algorithm that implements the operator with the best-estimated performance.

Gremlin-to-SQL SQLGraph [156] proposes a translation optimization whereby a sequence of the non-selective pipe g.V (retrieve all vertices in g) or g.E (retrieve all edges in g) are replaced by a sequence of attribute-based filter pipes (filter pipes that select graph elements based on specific values). For example, the non-selective first pipe g.V is explicitly merged with the more selective filter `filterit.tag == 'w'` in the translation. For the query evaluation, optimization strategies from the RDBMS are leveraged.

Work	One-to-one	One-to-many
SQL-to-XPath/XQuery		
[149] ROX		✔
SPARQL-to-SQL		
[132] Type-ARQuE	✔	
[135] FSparql2Sql	✔	
SQL-to-SPARQL:		
[127, 128] R2D *SQL-to-SPARQL*	✔	
SQL-to-Document-based		
[159] QueryMongo	✔	
Gremlin-to-SQL		
[156] SQLGraph	✔	

Table 4.3: Query Translation relationship. The number of destination queries generated from one input query, one or many.

4. Translation relationship

A translation method that deterministically generates a single optimized query is more efficient than a one that generates several queries and leaves it to the user to decide on the most efficient. We note that this information is not always explicitly stated, and we cannot make assumptions based on the architectures or the algorithms. Therefore, we only report when there is a clear statement about the type of relationship. Information is collected in Table 4.3.

III. Community Factors

For better readability and structuring, we collect the information in Table 4.4. The last column rates the community effect using stars (★), which are to be interpreted as follows. ★: 'Implemented', ★★: 'Implemented and Evaluated' or 'Implemented and Available (for download)', '★★★: 'Implemented, Evaluated and Available (for download)'.

4.5 Discussions

In the next, we report on our findings with respect to the query translation scope in the reviewed efforts. We also report on the translation paths around which there is a few to no published efforts. Furthermore, we describe the gaps that we discovered as well as the lessons learned. Additionally, we conclude on the query language to use as input for the Data Integration. Finally, we project several relevant dates on a vertical timeline, highlighting when the involved query languages have appeared and when the reviewed efforts have been published.

Weakly addressed paths. Although one would presume that *SQL-to-Document-based* translation is a well-supported path given the popularity of SQL and document databases, there is still modest literature in this regard. Most of the efforts provide marginal contributions in addition to the more general SQL-to-NoSQL translation. Furthermore, the translation of this path in all cases is far from being complete and does not follow the systematic methodology observed by other efforts in this study. Some of these works are [173–175]. Similarly, despite the popularity of SQL and Gremlin, the *Gremlin-to-SQL* translation has also attracted little attention. That may

Paper/tool	Y_{FR}	Y_{LR}	n_R	n_C	Implementation Reference	Community
XPath/XQuery-to-SQL						
[143]				57		★
[146]	2005			37		★★
[145]	2006		1			★★
[147] PPFS+				40		★★
[144]				5		★★
[148] XTRON				23		★★
SQL-to-XPath/XQuery						
[150, 151]				1, 5		
[152] AquaLogic	2006	2008		22	*Acquired by Oracle and merged in its products*	★★
[149]				65		★★
SPARQL-to-SQL						
[131] Sparqlify	2013	2018	30	2	https://github.com/SmartDataAnalytics/Sparqlify	★★★
[132] Type-ARQuE		2010		6	http://www.cs.hut.fi/~skiminki/type-arque/index.html	★★
[79] Morph translator	2014	2018	37	74	*Part of Morph-RDB:* https://github.com/oeg-upm/morph-rdb	★★★
[130]				151		★★
[135]				28		★★
[133]				78		★★★
[134] SPARQLMap				22		★★★
[136] Ultrawrap				99	https://capsenta.com/ultrawrap	★★
[129]				52	*Part of Ontop: https://github.com/ontop/ontop*	★★
SQL-to-SPARQL						
[127, 128] R2D				19, 15		★★
[126]				14		
SQL-to-Document-based						
[159] Query Mongo						
[160] MongoDB Translator						★
[161] UnityJDBC						★
SPARQL-to-Document-based						
[76] D-SPARQ				11		★★
[89] SparqlMap-M	2015	2017	12	2	https://github.com/tomatophantastico/sparqlmap	★★★
[163]				19	*Extends Ontop but no reference found*	★
[162] OntoMongo		2017		1	https://github.com/thdaraujo/onto-mongo	★★
[164]	2014	2015	6	5	https://github.com/frmichel/morph-xr2rml/tree/query_rewrite	★★
Cypher-to-SQL						
[157] Cytosm		2017	1	2	https://github.com/cytosm/cytosm	★★★
[158] Cyp2sql	2017	2017		1	https://github.com/DTG-FRESCO/cyp2sql	★★
Gremlin-to-SQL						
[156] SQLGraph	2015			44		★★
SQL-to-Gremlin						
[155] SQL-Gremlin	2015	2016	1		https://github.com/twilmes/sql-gremlin	★
SPARQL-to-XPath/XQuery						
[137–139] SPARQL2XQuery				29, 11, 21	http://www.dblab.ntua.gr/~bikakis/SPARQL2XQuery.html	★★★
[141]				45		★★
[140] XQL2Xquery				6		★★
XPath/XQuery-to-SPARQL						
[142]				21		★★
SPARQL-to-Gremlin						
[153, 154] Gremlinator	2018			6	https://github.com/apache/tinkerpop/tree/master/sparql-gremlin	★★★

Table 4.4: Community Factors. $\mathbf{Y_{FR}}$ year of first release, $\mathbf{Y_{LR}}$ year of last release, $\mathbf{n_R}$ number of releases, $\mathbf{n_C}$ number of citations (from Google Scholar). If $\mathbf{n_R} = 1$ it is the first release and last release is last update.

be due to the large difference in the semantics of the Gremlin graph traversal model and the SQL relational model. In general, the work on translating between SQL and MongoDB and Gremlin languages is still in a relatively early stage. This is partially because of the lack of a strong formal foundation of the semantics and complexity of MongoDB document language as well as that of Gremlin. On the other hand, the path *XPath/XQuery-to-SPARQL* has significantly fewer methods than its reverse. This is possible because SPARQL is more frequently used for solving integration problems, e.g., as part of the OBDA framework, which involves translating various queries into SPARQL.

Missing paths. We have not found any published work or tool for the following paths: *SQL-to-Cypher*, *Gremlin-to-SPARQL*, *XPath/XQuery-to-Cypher* and vice versa, *XPath/XQuery-to-Gremlin* and vice versa, *Cypher-to-Document-based* and vice versa. We see opportunities in tackling those translation paths with rationals similar to those of the currently tackled translation paths. For example, although SPARQL and Gremlin fundamentally differ in their approaches to query graph data, one based on graph pattern matching and one on graph traversals, they are both graph query languages. A transition from one to the other not only allows the interoperability between systems supporting those languages but also makes data from one world available to the other without requiring to learn the other respective query language [181]. Similarly, since XML languages have a rooted notion of traversals, conversion to and from Gremlin is natural. In fact, according to [182], the early prototype of Gremlin used XPath for querying graph data.

Gaps and Lessons Learned. The survey allowed us to identify gaps and learn lessons, which we summarize in the following points:

- We noticed that the optimizations that are applied during the query translation process have more potential to improve the overall translation performance than the optimization applied to the generated query. This is because at query translation-time, optimizations from the system of the original query, e.g., statistics, can be leveraged to impact the resulted target query. This opportunity is not present once the query in the target language has been generated.

- Looking at the query translation scope, there seems to still be a lack in covering the more sophisticated operations of query languages, e.g., more join types and temporal functions in SQL, blank nodes, grouping and binding in SPARQL, etc. Such functions are motivated by and are at the core of many modern analytical and real-time applications. Indeed, some of those features are newly-introduced and some of the needs are only recently exposed. Therefore, we make the call to update the existing methods or suggest new approaches in order to embrace the new features and address the recent needs.

- Certain efforts present well-founded and defined query translation frameworks, from the query translation process to the various optimization strategies. However, the example queries effectively worked on are simple and would hardly represent real-world queries. Real-world use-case-driven translation methods would be more effective in revealing the useful query patterns and fragments, and in evaluating the underlying optimization techniques.

1974	Chamberlin et al. [30].	*SQL introduced.*
2002	Boag et al. [119].	*XQuery introduced.*
2003	Berglund et al. [176].	*XPath introduced.*
2004	Halverson et al. **ROX** [143, 177].	SQL-to-XPath/XQuery XPath/XQuery-to-SQL.
2005	Fan et al. [146].	XPath-to-SQL.
2006	Mani et al. [145].	XQuery-to-SQL.
2007	Droop et al. [142] Georgiadis et al. [147].	XPath/XQuery-to-SPARQL XPath/XQuery-to-SQL.
2008	Prudhommeaux [112] Hu et al. [144] Lu et al. [135] Min et al. **XTRON** [148].	*SPARQL introduced* XML-to-SQL SPARQL-to-SQL XQuery-to-SQL.
2009	Fan et al. [178] Vidhya et al. [151] Elliott et al. [133] Bikakis et al. [138, 139] Ramanujam et al.	XPath-to-SQL SQL-to-XPath SPARQL-to-SQL SPARQL-to-XQuery SQL-to-SPARQL.
2010	Vidhya et al. [150] Kiminki et al. **Type-ARQuE** [132].	SQL-to-XQuery SPARQL-to-SQL.
2011	Das **R2RML** [165] Atay et al. [179] Fischer et al. [140] Rachapalli et al. **RETRO** [126].	SQL-to-SPARQL XML-to-SQL SQL- and SPARQL-to-XQuery SQL-to-SPARQL.
2012	Rodrıguez-Muro et al. **Quest** [180] Unbehauen et al. **SPARQLMap** [134].	SPARQL-to-SQL SPARQL-to-SQL.
2013	Santos Ferreira et al.[173] Sequeda et al. **Ultrawrap** [136].	SQL-to-Document based SPARQL-to-SQL.
2014	Bikakis et al. [172] Priyatna et al. **Morph** [79] Lawrence [175].	SPARQL-to-XQuery SPARQL-to-SQL SQL-to-Document-based.
2015	Sun et al. **SQLGraph** [156] Bikakis et al. [137].	Gremlin-to-SQL SPARQL-to-XQuery.
2016	Unbehauen et al. **SparqlMap-M** [89].	SQL-to-Document-based.
2017	Steer et al. **Cytosm** [157].	Cypher-to-SQL.
2018	Thakkar et al. **Gremlinator** [153, 154].	SPARQL-to-Gremlin.

Table 4.5: Publication years Timeline of the considered query languages and translation methods.

- There is a wide variety in the evaluation frameworks used by each of the query translation methods. Following a unique standardized benchmark specialized in evaluating and assessing query translation aspects is paramount. Such a dedicated benchmark, unfortunately, does not exist at the time of writing.

Data Integration Query Language. After exploring the query translation literature, it appears that SQL and SPARQL are the most suitable languages to use as Data Integration canonical language, and, thus, RDF and relational/tabular as the internal underlying data model. They both have the most number of translations to other languages (see outgoing edges in Figure 4.1). Document-based query language, however, has no translation method to other languages. As a result, we retain SPARQL as the natural query language of our Semantic-based Data Integration.

Query Translation History. We project the surveyed efforts into a vertical timeline shown in Table 4.5. The visualization allows us to draw the following remarks. SPARQL was very quickly recognized by the community, as efforts translating to and from SPARQL started to emerge the same year it was suggested. We cannot make a similar judgment about the adoption of SQL, XPath and XQuery as these were introduced earlier than the time frame we consider in this study (2003-2020). Efforts on translating to and from SPARQL have continued to attract research efforts to date. Efforts translating to and from SQL is present in all the years of the timeline, except 2013. With lesser regularity, efforts translating to and from XPath/XQuery have also been continually published. However, despite their latest updates in 2017, we have not found any scientific publications (at least complying with our criteria) since 2015.

4.6 Summary

In this chapter, we have reported on our survey that we conduced reviewing more than forty articles and tools on the topic of Query Translation. The survey covered the query translation methods that exist between seven popular query languages. Although retrieving and organizing the information was a complicated and sensitive task, the study allowed us to extract eight common criteria according to which we categorized the surveyed works. The survey showed that both SQL and SPARQL are the most suitable options to act as the canonical query language for Data Integration scenarios. As our integration approach is Semantic-based, we opt for SPARQL. Naturally, SPARQL along with ontologies and mappings language constitute a more comprehensive framework for Data Integration. The survey has also served its second purpose; it helped us enrich our understanding of the various query translation strategies in general. For example, schema-aware translation, intermediate language usage, query optimization techniques, query rewriting and augmentation, etc. Finally, the survey allowed us to discover which translation paths are not sufficiently addressed and which ones are not addressed yet, as well as to observe gaps and learn lessons for future research on the topic.

CHAPTER 5

Physical Big Data Integration

"There are two ways of spreading light: to be the candle or the mirror that reflects it."

Edith Wharton

In this chapter, we focus on our Semantic Data Integration approach, namely physical integration of heterogeneous data sources using Semantic Technologies. Semantic Data Integration requires to convert to RDF all data coming from the input data sources, then to query the uniform output data using SPARQL. We propose an architecture for this integration, which we term SBDA, for *Semantified Big Data Architecture*. This chapter formally introduces the proposed architecture, suggests a set of requirements that it needs to meet, and describes it in the form of a reusable blueprint. An implementation of the blueprint is subsequently described and evaluated comparing it to a baseline native RDF triple store. In particular, we present our strategies for representing and partitioning the resulted to-be-queried RDF data. In this chapter, we address the following research question:

RQ2. Do Semantic Technologies provide ground and strategies for solving Physical Integration in the context of Big i.e., techniques for the representation, storage and uniform querying of large and heterogeneous data sources?

Contributions of this chapter can be summarized as follows:

- The definition of a blueprint for a Semantified Big Data Architecture that enables the ingestion, querying and exposure of heterogeneous data with varying levels of semantics (hybrid data), while ensuring the preservation of semantics.
- A proof-of-concept implementation, named SeBiDA, of the architecture using Big Data components such as Apache Spark and Parquet.
- Evaluation of the benefits of using Big Data technology for storing and querying hybrid large-scale data. In particular, we evaluate SeBiDA performance in ingesting and querying increasing data sizes, while comparing it to a centralized RDF triple store.

This chapter is based on the following publication:

- **Mohamed Nadjib Mami**, Simon Scerri, Sören Auer, Maria-Esther Vidal. *Towards Semantification of Big Data Technology*. International Conference on Big Data Analytics and Knowledge Discovery (DaWaK), 376-390, 2016.

5.1 Semantified Big Data Architecture

A Semantified Big Data Architecture, SBDA [183], allows for ingesting and processing heterogeneous data on a large scale. In the literature, there has been a separate focus on achieving efficient ingestion and querying of large RDF data and for other structured types of data. However, approaches for combining both RDF and non-RDF under one same architecture is overlooked. Our Semantic Data Integration approach addresses this gap through the introduction of (1) a unified data model and storage that is adapted and optimized for ingesting and integrating heterogeneous data using the RDF model, and (2) unified querying over all the ingested data.

5.1.1 Motivating Example

In order to facilitate the understanding of subsequent concepts and approaches, we start by introducing a simple motivating example. Suppose that a municipality is building a citizen-facing online service to manage the bus network. The municipality got hold of three data sources of various types, which they need to integrate and query in a uniform manner in order to improve the mobility service (see Figure 5.1):

1. Mobility: an RDF graph containing information about Buses circulating around the city, e.g., matriculation and size. Data is stored in NTriple files in HDFS.
2. Regions: JSON-encoded data containing information about the country's Regions where buses operate, e.g., name and surface, semantically described using ontology terms in JSON-LD format. Data is stored in a JSON format in HDFS.
3. Stop: a tabular data containing information about Stops e.g., names and coordinates, complying with GTFS specification [1]. Data is stored in a Cassandra database.

The problem to be solved is providing uniafied data model to *store* and *query* these datasets, independently of their dissimilar types. Once done, the three data sources can be queried in unity. For example, to investigate recurrent complaints about bus delays at a certain stop, the company suspects driver unpunctuality and retrieves all bus drivers that serve that stop. Another example, to increase bus frequency near to a recently opened university, the company tries to relocate certain buses from other regions to the new university region. To do so, the company retrieves the number of buses serving each region and sorts them in a descendant order.

5.1.2 SBDA Requirements

In order to fulfill its objectives, SBDA should meet the following requirements:

R1: Ingest semantic and non-semantic data. SBDA must be able to process arbitrary types of data. We should distinguish between semantic and non-semantic data. Semantic data is all data that is either originally represented according to the RDF data model or has an associated

[1] https://developers.google.com/transit/gtfs/

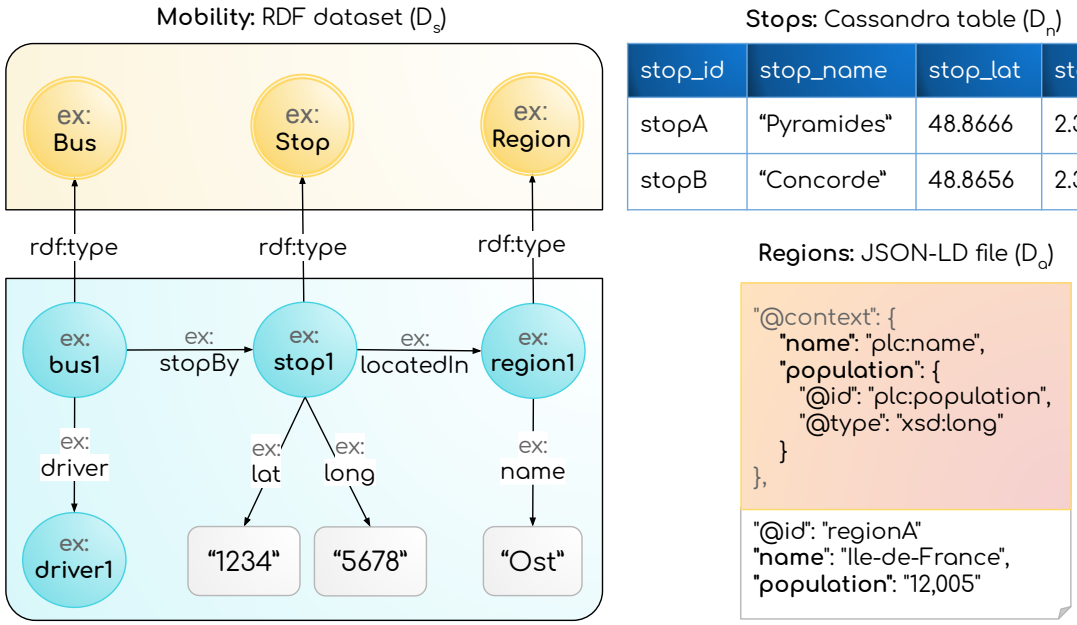


Figure 5.1: Motivating Example. MOBILITY: semantic RDF graph storing information about buses; REGIONS: semantically-annotated JSON-LD data about country's regions; and (3) STOP: non-semantic data about stops stored in a Cassandra table.

mapping, which allows to convert it to RDF. Non-semantic data is all data that is represented in other formalisms, e.g., tabular, JSON, XML. SBDA requires to lift non-semantic data to semantic data, which can be achieved through the integration of mapping techniques e.g., R2RM[2], CSVW[3] annotation models or JSON-LD contexts [4], RML [169]. This integration can lead to either a representation of the non-semantic data in RDF or its annotation with semantic mappings, which enable the conversion to RDF at a later stage. In our example, MOBILITY and REGIONS are semantic data. The former is originally in RDF model, while the latter is not in RDF model but has mappings associated that enables the conversion to RDF. STOPS, on the other hand, is a non-semantic dataset on which semantic lifting can be applied.

R2: Preserve semantics and metadata in Big Data processing chains. Once data is preprocessed, semantically enriched and ingested, it is paramount to preserve the semantic enrichment as much as possible. RDF-based data representations and mappings have the advantage (e.g., compared to XML) of using fine-grained formalisms (e.g., RDF triples or R2RML triple maps) that persist even when the data itself is significantly altered or aggregated. Semantics preservation can be reduced as follows:

- *Preserve URIs and literals.* The most atomic components of RDF-based data representation are URIs and literals [5]. Best practices and techniques to enable the storage and indexing of URIs (e.g., by separately storing and indexing namespaces and local names) and literals (along with their XSD or custom datatypes and language tags) need to be defined. In the dataset MOBILITY, the Literals "Alex Alion" and *"12,005"xsd:long*, and the URI

[2] http://www.w3.org/TR/r2rml
[3] http://www.w3.org/2013/csvw/wiki/Main_Page
[4] http://www.w3.org/TR/json-ld
[5] We disregard blank nodes, which can be avoided or replaced by IRIs [184].

'http://xmlns.com/foaf/0.1/name' (shortened foaf:name in the figure), should be stored in an optimal way in the big data storage. x²

- *Preserve triple structure.* Atomic URI and literal components are organized in triples. Various existing techniques can be applied to preserve RDF triple structures in SBDA components (e.g., HBase [185–187]). In the dataset MOBILITY, the triple (prs:Alex mb:drives mb:Bus1) should be preserved by adopting a storage scheme that keeps the connection between the subject *prs:Alex*, the predicate *mb:drives* and the object *mb:Bus1*.

Data may not be in RDF format but annotated using semantic models by means of mapping rules. The mappings are usually composed of fine-grained rules that define how a certain entity, attribute or value can be transformed to RDF. The preservation of such data structures throughout processing pipelines means that resulting views or query results can also be directly transformed to RDF. R2RML, RML, JSON-LD contexts, and CSV annotation models are examples of mapping languages. In REGIONS dataset of the motivating example (Figure 5.1), the semantic annotations defined by the JSON object *@context* would be persisted in association with the actual data it describes, *RegionA*.

R3: Scalable and Efficient Query Processing. Since the SBDA architecture targets large data sources, Data Management techniques like data caching, partitioning, indexing, query optimization have to be exploited to ensure the scalable and efficient performance of query processing. For example, cache in memory the triples that have the most frequently accessed predicates, partition on disk the data in a certain scheme that minimizes data transfer across compute nodes, index the data for fast retrieval of RDF objects when subject and predicate are known, query rewriting to reduce joins, etc.

5.1.3 SBDA Blueprint

We represent the SBDA architecture as a generic blueprint that can be instantiated using various processing and query technologies. The only fixed decision we made is the choice of the target data model, which we suggest to be tabular following the prevalence of this model in Big Data technologies. Historically, the relational data model and RDBMSs backed several state-of-the-art RDF centralized triple stores [188–190]. The tendency persists with the modern RDF distributed storage and processing systems, which we will review in the Related Work of this thesis (Chapter 3). In this section, we provide a formalisation of the various concepts underlying the SBDA blueprint.

Definition 1 (Heterogeneous Input Superset) *We define a heterogeneous input superset HIS, as the union of the following three types of datasets:*

- $D_n = \left\{d_{n_1}, \ldots, d_{n_m}\right\}$ *is a set of non-semantic, structured or semi-structured, datasets in any format (e.g., relational database, CSV files, Excel sheets, JSON files).*
- $D_a = \left\{d_{a_1} \ldots, d_{a_q}\right\}$ *is a set of semantically annotated datasets, consisting of pairs of non-semantic datasets with corresponding semantic mappings (e.g., JSON-LD context, metadata accompanying CSV).*
- $D_s = \left\{d_{s_1}, \ldots, d_{s_p}\right\}$ *is a set of semantic datasets consisting of RDF triples.*

In our motivating example, STOPS, REGIONS, and MOBILITY correspond to D_n, D_a, and D_s, respectively.

Definition 2 (Dataset Schemata) *Given HIS=$D_n \cup D_a \cup D_s$, the dataset schemata of D_n, D_a, and D_s are defined as follows:*

- $S_n = \{s_{n_1}, \ldots, s_{n_m}\}$ *is a set of* ***non-semantic schemata structuring*** D_n*, where each* s_{n_i} *is defined as follows:*

$$s_{n_i} = \{(T, A_T) \mid T \text{ is an entity type and } A_T \text{ is the set of all the attributes of } T\}$$

- $S_s = \{s_{s_1}, \ldots, s_{s_q}\}$ *is a set of the* ***semantic schemata behind*** D_s *where each* s_{s_i} *is defined as follows:*

$$s_{s_i} = \{(C, P_C) \mid C \text{ is an RDF class and } P_C \text{ is the set of all the properties of } C^{6}\}$$

- $S_a = \{s_{s_1}, \ldots, s_{s_p}\}$ *is a set of the* ***semantic schemata annotating*** D_a *where each* s_{s_i} *is defined the same way as elements of* S_s*.*

In the motivating example, the semantic schema of the dataset[7] MOBILITY is:
$s_{s_1} = \{(ex{:}Bus, \{ex{:}matric, ex{:}stopsBy\}), (ex{:}Driver, \{ex{:}name, ex{:}drives\})\}$

Definition 3 (Semantic Mapping) *A semantic mapping is a relation linking two semantically-equivalent schema elements. There are two types of semantic mappings:*

- $m_c = (e, c)$ *is a relation mapping an entity type e from* S_n *onto a class c.*
- $m_p = (a, p)$ *is a relation mapping an attribute a from* S_n *onto a predicate p.*

SBDA facilitates the lifting of non-semantic data to semantically annotated data by mapping non-semantic schemata to RDF vocabularies. The following are possible mappings: (*stop_name, rdfs:label*), (*stop_lat, geo:lat*), (*stop_long, geo:long*).

Definition 4 (Semantic Lifting Function) *Given a set of mappings M and a non-semantic dataset d_n, a semantic lifting function SL returns a semantically-annotated dataset d_a with semantic annotations of entities and attributes in d_n.*

In the motivating example, dataset STOPS can be semantically lifted using the following set of mappings: *{(stop_name, rdfs:label),(stop_lat, geo:lat), (stop_long, geo:long)}*, thus a semantically annotated dataset is generated.

Definition 5 (Ingestion Function) *Given an element $d \in HIS$, an ingestion function $In(d)$ returns a set of triples of the form (R_T, A_T, f), where:*

- *T an entity type or class for data on d,*
- *A_T is a set of attributes $A_1, \ldots, A_n$ of T,*

[6] A set of properties P_C of an RDF class C where: $\forall$ p $\in P_C$ (p rdfs:domain C).

[7] Here again, for simplicity, we use the exemplary namespace prefix *ex*, which can denote any given ontology. Multiple ontology namespace prefixes can also be used e.g., *ex1*, *ex2*.

- $R_T \subseteq type(A_1) \times type(A_2) \times \cdots \times type(A_n) \subseteq d$, *where* $type(A_i) = T_i$ *indicates that* T_i *is the data type of the attribute* A_i *in* d, *and*
- $f : R_T \times A_T \rightarrow \bigcup_{A_i \in A_T} type(A_i)$ *such that* $f(t, A_i) = t_i$ *indicates that* $t_i \in$ *tuple* t *in* R_T *is the value of the attribute* A_i.

The result of applying the ingestion function In *over all* $d \in HIS$ *is the final dataset that we refer to as Final Dataset* FD.

$$FD = \bigcup_{d_i \in HIS} In(d_i)\}$$

Definition 6 (Data Queries) *Let* q *be a relational query on relations* R_T *in* FD. *We define a Querying function* R *that generates a view* v *over the transformed dataset* FD *given a query* q:

$$R(FD, q) = r^{n \times w} = v$$

- r *is a matrix containing* n *rows, which represent the results, and* w *columns, which correspond to the query variables.*
- r_{prov} *is a metadata matrix containing provenance information (source dataset(s) links, acquisition timestamp) for each element of the resulting matrix.*
- q *is retained as the query generating* v.

The set of all views is denoted by V.

These concepts are visually illustrated in Figure 5.2. The SBDA blueprint handles a representation (FD) of the relations resulting from the ingestion of multiple heterogeneous datasets in HIS (d_s, d_a, d_n). The ingestion (In) generates relations or tables (denoted R_T) corresponding to the data, supported by a schema for interpretation (denoted T and A_T). The ingestion of semantic (d_s) and semantically-annotated (d_a) data is direct (denoted respectively by the solid and dashed lines), a non-semantic dataset (d_n) can be semantically lifted (SL) given an input set of mappings (M). Query processing can then generate a number ($|Q|$) of results over (FD).

5.2 SeBiDA: A Proof-of-Concept Implementation

We validate our blueprint through the description of a proof of concept implementation, called SeBiDA (for Semantified Big Data Architecture). It comprises the following three main components (Figure 5.3), which are subsequently detailed:

- *Schema Extractor*: It performs schema knowledge extraction from an input data source and performs semantic lifting based on a provided set of mappings.
- *Data Loader*: It creates tables based on the extracted schemata and loads input data accordingly.
- *Data Server*: It receives queries and generates results as tuples or RDF triples.

The first two components jointly realize the ingestion function In from subsection 5.1.3. The resulting tables FD can then be queried using the Data Server to generate the required views.

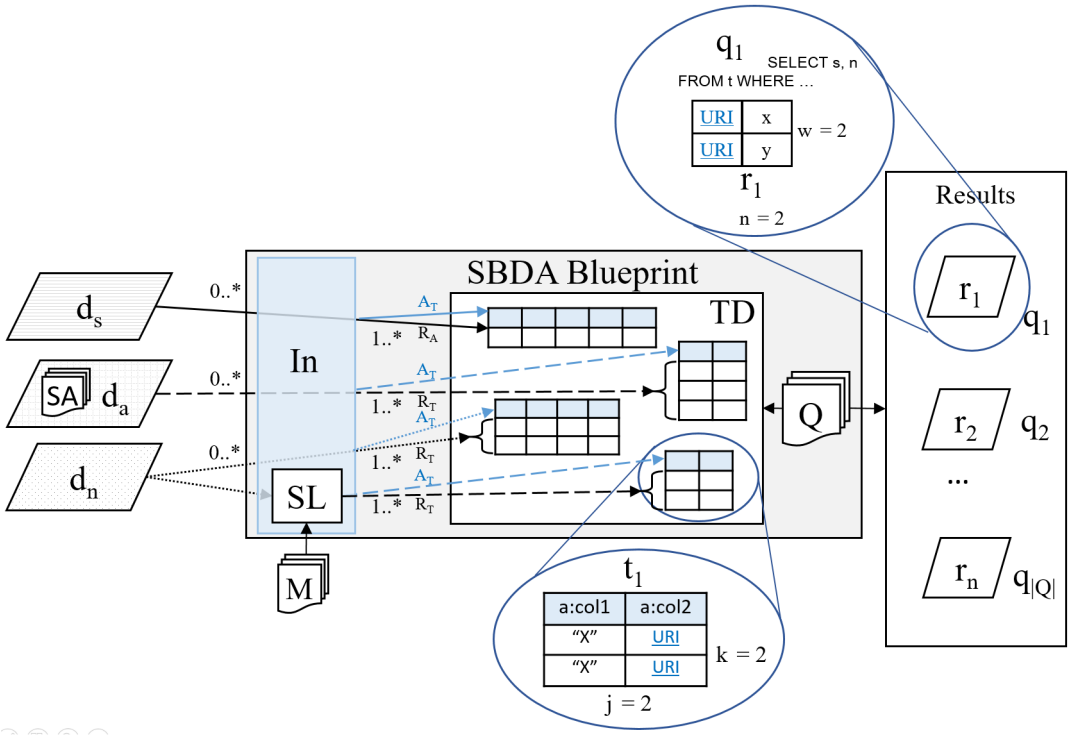


Figure 5.2: A Semantified Big Data Architecture Blueprint.

5.2.1 Schema Extractor

We extract the structure of both semantic and non-semantic data to transform it into the tabular model, an operation that is commonly called *flattening*. The schema extraction mechanism varies from a data source to the other:

(A) From the semantic or semantically-annotated input datasets (d_s or d_a), we extract *classes* and *properties* describing the data (see Definition 2). In the presence of RDF schema, classes and properties can be extracted by querying it. If not, schema information is extracted by exhaustively parsing the data. For example, this can be achieved by first reformatting RDF data into the following representation:

$$(\text{class}, (\text{subject}, (\text{predicate}, \text{object})^+)^+)$$

which reads: "Each class has one or more instances where each instance can be described using one or more (predicate, object) pairs", and then we retain the *classes* and *properties*. The XSD datatypes, if present, are leveraged to type the properties, otherwise[8] string is used.

(B) From each non-semantic input dataset (d_n), we extract *entities* and *attributes* (cf. Definition 2). For example, in relational and some NoSQL databases, *entities* and *attributes* correspond respectively to tables and columns, which can be retrieved by querying a set of default *metadata* tables. Another example, the entity and its attributes can be extracted from a CSV file's name and header, respectively. Whenever possible, attribute data types

[8] When the object is occasionally not typed or is a URL.

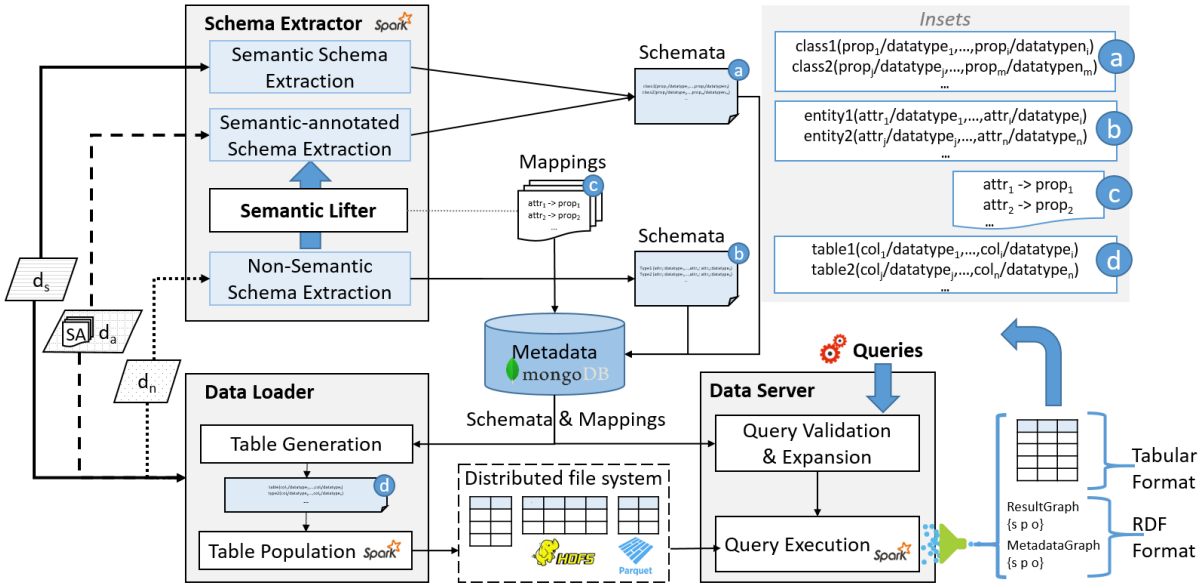


Figure 5.3: SeBiDA General Architecture. Data and work flows start from the left to the right. Insets are input sets: (a) semantic and semantically-annotated data schema, (b) non-semantic data schemata, (c) semantic mappings, (d) Final Dataset table schemata.

are extracted, otherwise, string is used. Schemata that do not natively have a tabular format (e.g., XML, JSON) also undergo flattening into entity-attributes pairs. Although principally different from the relational/tabular model, it is common to find non-tabular data organized into repeated schema-fixed tuples that can be extracted and saved into tables. For example, modern processing engines e.g., Apache Spark, do not accept the conventional single-rooted JSON files, but a variation called *JSON Lines*[9] where each line is a separate valid JSON value. This enables these engines to load JSON files and query them using their regular schema. The same is observed for XML files, which may contain a flat ordering of elements from which a regular schema can be extracted. One may not reinvent the wheel and use off-the-shelf some of the modern specialized processing engines that support the extraction of data from various sources. We use in our implementation Apache Spark[10] (see Figure 5.3) and it has wrappers[11] for many popular data sources, which can be used to extract schema information from JSON, XML, NoSQL databases, etc.

As depicted in Figure 5.3, schema extraction is performed independently and prior to data loading. Extracted schema information is saved in an independent metadata store. This is important because it allows the user to visualize the schema, navigate through it, and formulate queries accordingly. In our SeBiDA implementation, we use *MongoDB*[12], which is a flexible schema-less document-based store.

[9] http://jsonlines.org
[10] https://spark.apache.org
[11] https://spark-packages.org
[12] https://www.mongodb.org

Source	Target	Datatype
stop_name	http://xmlns.com/foaf/0.1/name	String
stop_lat	http://www.w3.org/2003/01/geo/wgs84_pos#lat	Double
stop_lon	http://www.w3.org/2003/01/geo/wgs84_pos#long	Double
parent_station	http://example.com/sebida/parent_station	String

Table 5.1: Mapping data attributes to ontology properties with datatype specification.

5.2.2 Semantic Lifter

In this step, SeBiDA targets the lifting of non-semantic entities/attributes to existing ontology classes/properties. The lifting process is semi-automated. We auto-suggest ontology terms based on the syntactical similarity with the entities/attributes. If semantic counterparts are undefined, internal URIs are created by attaching a base URI. Otherwise, the user can adjust the suggestions or incorporate custom ones. Table 5.1 shows a result of this process, where four attributes from the entity 'Stop'[13] have been mapped to existing vocabularies, where the forth converted to an internal URI. In our implementation, semantic mappings are stored in the same MongoDB metadata store in the form of simple one-to-one relationships, and thus can be visually explored. However, RDF-based mapping standards (e.g., R2RML [**das2011r2**], RML [169]) can also be used. The latter are even more favorable if more sophisticated mapping specification is required. Being in RDF, these standards also enable the interoperability across systems or implementations.

5.2.3 Data Loader

This component loads data from the source HIS into the final dataset FD. First, it generates tables following a tailored partitioning scheme. Then, it loads data into the tables accordingly.

Table Generation

Tables are generated following the previously extracted schema (subsection 5.2.1). For each *class*, a corresponding *table template* is created as follows:

(A) For Semantic Data, a table with the same label is created for each *class* (e.g. a table `` `ex:Bus` `` from the RDF class ex:Bus). A default column 'ID' (of type string) is created to store the triple's subject. For each *predicate* describing the class, an additional column is created typed according to the *predicate* extracted data type. This representation corresponds to the *Property Table* scheme [55], and more specifically its *class-based clustering* variant. In the latter, triples are distributed into tables based on their RDF type [189]. This Property Table partitioning scheme is used by traditional centralized triple stores e.g, Sesame, Jena2, RDFSuite and 4store [189]. A particularity in our approach is the ability to capture the classes of multi-typed RDF instances. For every table template, an extra column of array type called *"alsoType"* is added, which is intended to store every extra type found attached to one same RDF instance. Further, a boolean column called *type flag column* is added to the table template whenever an instance of an *otherType* is detected. In the previous example, two type flag columns are added *also_Electric* and *also_Mini-bus*. Observe the schema of the table in Figure 5.4.

[13] developers.google.com/transit/gtfs/reference

(B) For non-Semantic data, for each *entity*, a table is similarly created as above, taking the entity label as table name and creating a typed column for each attribute. We assume that multi-typing is only a prevalent property in semantic data, and thus we do not consider the problem of scattering data across several tables.

For RDF data, since not all instances have values to all the predicate, the tables may end up storing lots of null values, and thus reserving unnecessary storage space. However, this concern has largely been reduced following the emergence of modern NoSQL databases (e.g., HBase), and columnar storage formats (e.g., Apache Parquet), where the null values do not occupy a physical space. The particularity of columnar formats is that tuples are *physically* stored column-by-column instead of line-by-line. With this organization, all values of the same column are of the same type, in contrast to values of the same row that are of different types. This value homogeneity enables efficient *compression* e.g., by skipping the unnecessary `null` values (run-length encoding [191]). Another advantage of the columnar data layout is *schema projection*, whereby only projected columns are read and returned following a query. Using the columnar format for solving this so-called table *sparsity* problem is witnessed in the literature of centralized RDF stores, e.g., in [191]

In our implementation, we use Apache Spark to perform the data loading. We leverage its numerous wrappers to ingest as many data sources as possible. We only resort to building our custom reader when no wrapper is available, which is the case of RDF data. For storing the loaded data, we use the column-oriented tabular format Apache Parquet[14], which allows to overcome the sparsity problem. Parquet is suitable for storing RDF data from other respects. It also supports composed and nested columns, i.e., saving multiple values in one column and storing hierarchical data in one table cell. This is a common occurrence in RDF where one instance may use the same predicate several times, e.g., `_:authoredBy` predicate. Parquet also involves state-of-the-art encoding methods, e.g., bit-packing, run-length, and dictionary encoding. In particular, the latter can be useful to store long strings, which is the case of URIs. Finally, Parquet files are saved inside Hadoop Distributed Filesystem (HDFS), which is the *de facto* distributed file system for Big Data applications. This makes it so that other processing engines can inter-operate and query the same data generated by SeBiDA. This is not a design choice of ours, but rather a common understanding across modern Big Data applications leading to the emergence of so-called Hadoop Ecosystem [192]. In the latter, Hadoop Distributed File System is used as the central data repository from which the various processing frameworks read raw data.

Table Population

Once the table template is created, the table is populated as follows:

1. For each RDF extracted class (see subsection 5.2.1) iterate through its instances, a new row is inserted for each instance into the corresponding table. The instance *subject* is stored in the 'ID' column, whereas the corresponding *objects* are saved under the column representing the *predicates*. Multi-typed instances are stored following the design style described above (Table Generation). See Figure 5.4 for a visual illustration. If an instance is of *Bus*, *Electric* and *Mini-bus* types, it is stored in the *Bus* table, the other types are added to the *alsoType* array column, and `true` is set as the value to the type flags *also_Electric* and *also_Mini-bus*.

[14] https://parquet.apache.org

```
ex:bus1    rdf:type    ex:Bus ; ex:Electric ; ex:Mini-bus .
ex:bus1    ex:name     "600"^^xsd:integer .
ex:bus1    ex:driver   ex:driver1 .
ex:bus2    rdf:type    ex:bus ; ex:Electric .
ex:bus2    ex:name     "601"^^xsd:integer .
ex:bus2    ex:driver   ex:driver2 .
```

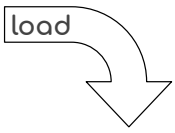


Table **ex:Bus**

ID *string*	ex:name *int*	ex:driver *string*	also_Electric *boolean*	also_Mini-bus *boolean*	alsoType *Array[String]*
ex:bus1	"600"	ex:driver2	true	true	["ex:Electric","ex:Mini-bus"]
ex:bus2	"601"	ex:driver2	true	false	["ex:Electric"]

Figure 5.4: Storing two RDF instances into `ex:Bus` table while capturing their multiple types. Data types are also captured, e.g., `xsd:integer` (XML Integer type) to table integer type.

In the presence of multiple types, we sort the types lexicographically and use the latest for the to-be-populated table. This way, instances of similar types end up in the same table, thus, we reduce data scattering. However, other types can be selected, e.g., the most used type or, in the presence of schema, the most specific or generic, etc. The most and generic types can be extracted from the class hierarchy, provided that an adequate RDF schema is available. The most and least used types can be obtained by computing statistics e.g., during the loading process. Each choice has its impact on data distribution and, thus, query performance. For example, using the most generic type from the class hierarchy (e.g., Bus) would result in a skewed large table containing potentially too many instances; however, the table would store all the data of that type and no union is required. If, however, a less generic class is used (e.g., Mini-bus) to build the table, and if a query asks for instances from the top-level generic class (e.g., Bus), a union with all the less generic tables is required.

2. Table population in the case of non-semantic data varies according to the data type. For example, we iterate through each CSV line and save its values into the corresponding column of the corresponding table. XPath and JSONPath [193] can be used to iteratively select the needed nodes in XML and JSON files, respectively. Technically, thanks to their versatility, many modern technologies allow to extract, transform and load (ETL) data. This makes the overall integration process simpler and more cost-effective since data is read and written without requiring intermediate data materialization. In our implementation, Apache Spark enables us to read data from the heterogeneous sources and load it under our unified partitioning and storage layout.

5.2.4 Data Server

Data loaded into tables following the unified tabular layout can be accessed in an *ad hoc* manner by means of queries. The Data Server is the component responsible for receiving and performing query processing and representing the final results.

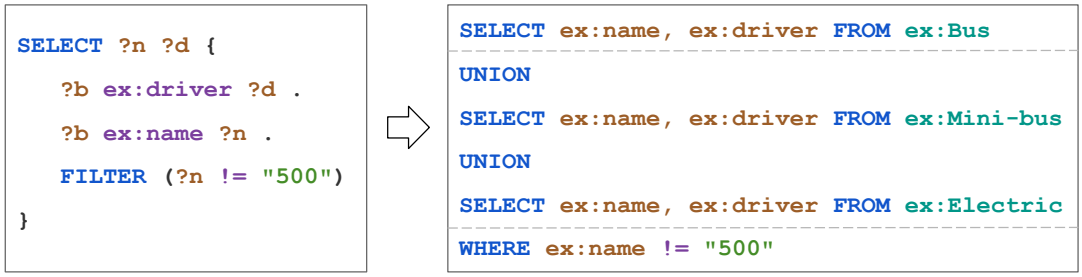


Figure 5.5: From SPARQL to SQL with SQL Query Expansion to involve instances of the same type scattered across multiple tables.

Querying Interface

Since our SBDA architecture and implementation propose a tabular-based model for representing the integrated data, the data itself is accessed using SQL query language. However, semantic data is more naturally accessed using SPARQL. Therefore, a custom SPARQL-to-SQL conversion method should be designed to access the data. SPARQL-to-SQL methods exist in the literature, but they cannot be adopted *as-is* to our custom data partitioning scheme, i.e., *Class-based Multi-Type-Aware Property Tables*. We generally follow a simple direct translation, similarly to [62], benefiting from the analogous semantics of several basic SQL and SPARQL (e.g., `SELECT`, `FILTER`, `ORDER BY`, `GROUP BY`, `LIMIT`). We differ from [62], however, in that we apply `UNION` whenever instances of the same type are scattered across multiple tables. To reconcile this scattered data, we use the Query Expansion algorithm described in Listing 5.1 and illustrated in Figure 5.5. We call the table addressed in the SQL query (after `FROM`) the Main Table, e.g., `ex:Bus` in Figure 5.5. The algorithm aims at performing a *query rewriting* to include the other tables where instances of the same type as the Main Table can be found. To decide on whether a union is needed and what are the complementary tables to union, the Data Server visits the schema and looks for any table that has the Main Table name as a flag column, i.e., *also_{MainTable}*, (Lines 7 and 8). This is one rationale behind keeping the schema separately stored as metadata. If a table is found, a `SELECT` query is added as a `UNION` with the `SELECT` of the input SQL query. If other tables are found, they are similarly added as `UNION` to the previous query, etc. (Lines 9 and 10). In SQL standard, there are two requirements for the `UNION` operator that have to be met:

1. The involved `SELECT` statements should include columns of analogous types. This condition is met as the user conceptually searches for the columns of the same entity, they are just physically found in disperse tables. The types are preserved by the Data Loader, which is the component responsible for populating the various tables containing instances of the same type.

2. The involved `SELECT` statements should have the same number of columns. This requirement is also met as the rewriting operation is done automatically by the Data Server without manual user intervention.

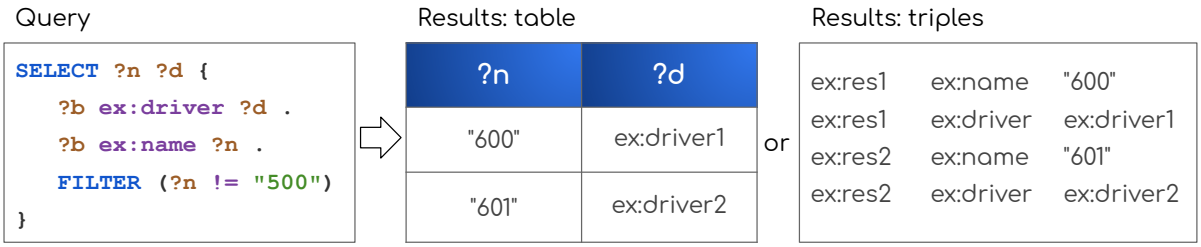


Figure 5.6: A SPARQL query (left) returning results represented in tables (middle) or triples (right).

```
Input: query, FD
Output: newQuery

mainTable = table(query)
newQuery = query // i.e., "SELECT ... FROM {mainTable} ..."

foreach table in FD
   if schema_columns(table) contains also_{mainTable}
      newQuery = newQuery + " UNION SELECT {columns} from {table} " +
                "WHERE alsoOfType_{table}=true"
```

Listing 5.1: Query Expansion rewriting to include all tables containing all instances of the same type.

Multi-Format Results

The Data Server can return the query results both as a table or as an RDF graph. The table is the default results representation stemming both from the underlying tabular data model and from the query engine used, Apache Spark. The process of *RDFisation* is achieved as follows: Create a triple from each projected column, using the column name and value as the triple predicate and object, respectively. For the triple subject, if the results include one table ID column, use its value as the triple subject. Otherwise, set the subject to <*base-URI*/res_{i}>, where the base URI is defined by the user, and i is an auto-incrementing integer. See Figure 5.6 for an example of a query and its two result formats, where *ex* is the prefix of an exemplary base URI *https://example.com/data*.

5.3 Experimental Study

The goal of this experimental study is to evaluate to what extent SeBiDA[15] meets the requirements **R1**, **R2**, and **R3** (see subsection 5.1.1). Namely, ingest both semantic and none-semantic data, preserve data semantics after the ingestion and during query processing, and exploiting the effect of BDM techniques, in particular caching, on query execution time.

5.3.1 Experimental Setup

Datasets

We use the Berlin Benchmark [194] to generate both semantic and non-semantic data. We use the formats N-Triple and XML, for semantic and non-semantic data respectively, both produced

[15] https://github.com/EIS-Bonn/SeBiDA

RDF Dataset	Size	Type	Scale Factor (# products)
Dataset_1	48.9GB	RDF	569,600 (200M)
Dataset_2	98.0GB	RDF	1,139,200 (400M)
Dataset_3	8.0GB	XML	284,800 (100M)

Table 5.2: Description of the Berlin Benchmark RDF Datasets. The original RDF data is in plain-text N-Triple serialization format.

RDF Dataset	Loading Time	New Size	Ratio
Dataset_1	3960 sec	389MB	1:0.008
Dataset_2	10440 sec	524MB	1:0.005
Dataset_3	1800 sec	188MB	1:0.023

Table 5.3: Data Loading performance. Shown are the loading times, the sizes of the obtained data, and the ratio between the new and the original sizes.

using BSBM data generator[16]. Table 5.2 describes the generated data in terms of the number of triples and file size.

Queries

We evaluate with all 12 BSBM *SQL* queries, which are slightly adapted to match the SQL supported syntax of the underlying query engine, Apache Spark. We use `LEFT OUTER JOIN` and inner queries instead of `OPTIONAL` and `NOT IN` sub-queries; the latter being unsupported [17]. We also omit time filter and RDF object language comparison, which are also not supported. Filtering based on the language tag is a specific function to the RDF data model, so not present at the SQL query.

Metrics

We measure the loading time of the datasets, the size of the datasets after the loading, as well as the query execution time over the loaded datasets. The queries are run both against a cold cache and a warm cache. Running on cold cache eliminates the impact of any possible previously computed intermediate results. Warm cache is running the five queries after having run the query once before, which reuses some temporary internal data during the subsequent runs of the same query. The query execution is run 10 times and the average time is reported, with a timeout of 300 seconds (5 minutes). Loading timeout is 43200 seconds (12 hours).

Environment

All queries are run on a cluster of three nodes having DELL PowerEdge R815, 2x AMD Opteron 6376 (16 cores) CPU and 256GB RAM, and 3 TB SATA RAID-5 disk. Queries are run in a cold cache and warm cache. To run on cold cache, we clear the cache before running each query[18].

[16] Using a command line: `./generate -fc -pc [scaling factor] -s [file format] -fn [file name]`, where file format is `nt` for semantic data and `xml` for non-semantic XML data.
[17] At the time of conducting these evaluations.
[18] Using a dedicated Linux system command: `sync; echo 3 > /proc/sys/vm/drop_caches`

Dataset$_1$													
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**	**Q10**	**Q11**	**Q12**	Geom. Mean
Cold Cache	3.00	2.20	1.00	4.00	3.00	0.78	11.3	6.00	16.00	7.00	11.07	11.00	4.45
Warm Cache	1.00	1.10	1.00	2.00	3.00	0.58	6.10	5.00	14.00	6.00	10.04	9.30	3.14
Diff.	2.00	1.10	0	2.00	0	0.20	**5.20**	1.00	2.00	1.00	1.03	1.70	1.31
Ratio	3.00	2.00	1.00	2.00	1.00	1.34	1.85	1.20	1.14	1.17	1.10	1.18	1.42
Dataset$_1$ ∪ Dataset$_3$													
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**	**Q10**	**Q11**	**Q12**	Geom. Mean
Cold Cache	3.00	2.94	2.00	5.00	3.00	0.90	11.10	7.00	**25.20**	8.00	11.00	11.5	5.28
Warm Cache	2.00	1.10	1.00	5.00	3.00	1.78	8.10	6.00	**20.94**	7.00	11.00	9.10	4.03
Diff.	1.00	1.84	1.00	0	0	-0.88	**3.00**	1.00	**4.26**	1.00	0	2.40	1.22
Ratio	1.50	2.67	2.00	1.00	1.00	0.51	1.37	1.17	1.20	1.14	1.00	1.26	3.70

Table 5.4: Benchmark Query Execution Times (seconds). in Cold and Warm Caches. Significant differences are highlighted in **bold**.

5.3.2 Results and Discussions

For data loading time, the results in Table 5.3 show that semantic data loading takes between 1 to 3 hours, whereas non-semantic XML data loading time takes 0.5 hours. In the absence of a schema, the loading of semantic data requires to exhaustively parse all the data and reorganize it to correspond with our tabular model (flattening). During this process, an inevitable large data movement occurs (Spark `collect` function), causing a significant network transfer and, thus, negatively impacting query performance. A small technique that we employed and that improved the loading time was reversing the URIs of RDF objects. It allowed for faster sorting and more balanced data distribution. The tables extracted from the semantic data are *product*, *offer*, *vendor*, *review*, *person* and `producer`, which correspond exactly to the main tables of the BSBM relational representation. Similar tables are retrieved from XML data, which are accessed using Spark XML reader[19] by means of XPath calls. However, we achieve a substantial gain in terms of data size due to the adopted data model that avoids data repetition (in case of RDF data) and the used file format (Parquet) that performs very efficient data compression (see subsection 5.2.3).

Table 5.4 reports on the results of executing Berlin Benchmark 12 queries against $Dataset_1$ (originally semantic), alone and in combination with $Dataset_3$ (originally non-semantic). Table 5.5 reports on the same but using $Dataset_2$ (originally semantic) instead of $Dataset_1$. Queries are run on cold cache and then on warm cache. The results show that all queries finished far below the specified threshold (300s), with the fastest query being Q6 finishing in 0.78s cold and 0.58s warm, and the slowest query being Q9 finished in 25.2s cold and 20.94s warm. Among the 12

[19] For more details: https://github.com/databricks/spark-xml

Dataset$_2$													
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**	**Q10**	**Q11**	**Q12**	Geom. Mean
Cold Cache	5.00	3.20	3.00	8.00	3.00	1.10	20.00	7.00	18.00	7.00	13.00	11.40	6.21
Warm Cache	4.00	3.10	2.00	7.00	3.00	1.10	18.10	6.00	17.00	6.00	12.04	11.2	5.55
Diff.	1	0.1	1	1	0	0	1.9	1	1	1	0.96	0.2	0.66
Ratio	1.25	1.03	1.50	1.14	1.00	1.00	1.10	1.17	1.06	1.17	1.08	1.02	1.12
Dataset$_2$ ∪ Dataset$_3$													
	Q1	**Q2**	**Q3**	**Q4**	**Q5**	**Q6**	**Q7**	**Q8**	**Q9**	**Q10**	**Q11**	**Q12**	Geom. Mean
Cold Cache	11.00	3.20	7.20	17.00	3.00	1.10	23.10	16.00	20.72	10.00	14.10	13.20	8.75
Warm Cache	4.00	3.20	2.00	8.00	3.00	1.10	21.20	8.00	18.59	7.00	12.10	11.10	5.96
Diff.	**7**	0	**5.2**	**9**	0	0	1.9	**8**	2.13	3	2	2.1	2.79
Ratio	2.75	1.00	3.60	2.13	1.00	1.00	1.09	2.00	1.11	1.43	1.17	1.19	1.47

Table 5.5: Benchmark Query Execution Times (seconds). in Cold and Warm Caches-Significant differences are highlighted in **bold**

queries, the most expensive queries are Q7 to Q12. Q7 is the most complex joining the largest number of tables (four), followed by Q9 and Q12 joining three tables producing a large number of intermediate results (in the absence of filters). Q8 and Q10 are similar in that they join two tables while sorting the final results. Q11 accesses the largest table (offer) filtering on a string value that does not exist in the data. Q1 to Q6 belong to the lower end of query execution time. Q1 query accesses only one table and has two selective filters. Q2 joins two tables, but one table is small in addition to filtering the results to a specific operand ID. Q3 and Q5 contain a self-join (one table), but largely limit the intermediate results by incorporating five and six filters, respectively. Q4 contains a union but accesses only one table with two filters. Q6 is the simplest and smallest query with only one filter. Note that for this query, the difference between the warm and cold cache execution is negative. This means that the query execution on the cold cache was faster than that on the warm cache. This is plausible with fast queries finishing within a second or two as there might be a variable overhead either from the system or the query engine that dominates the query execution time.

Further, the results in Table 5.4 and Table 5.5 suggest that caching can significantly improve query performance by up to 3 times saving up to 9 seconds (significant differences highlighted in bold). Thus, we obtain evidence of the benefits of using the cache stored during previous runs by the query engine, Spark. Finally, results also show that including data from (originally XML) $Dataset_3$ using `UNION` operator in the 12 queries does not deteriorate query performance. This is because the data effectively queried is in Parquet format generated during XML ingestion, which is the same format as $Dataset_1$ and $Dataset_2$. This is evidence that hybrid semantic and non-semantic data can be uniformly integrated and queried using a single query (**R1**). Further, we were able to capture the semantics of the data in our suggested RDF data partitioning

RDF Dataset	Loading Time	New Size	Ratio to Parquet S ize
Dataset_1	93min	21GB	55:1
Dataset_2	*Timed out*	-	-

Table 5.6: Loading Time of RDF-3X.

Engine	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12
SeBiDA	3.00	2.20	1.00	4.00	3.00	0.78	11.3	6.00	**16.00**	**7.00**	**11.07**	**11.00**
RDF-3X	0.01	1.10	**29.213**	0.145	**1175.98**	2.68	**77.80**	**610.81**	0.23	0.419	0.13	1.58

Table 5.7: SeBiDA vs. RDF-3X Query Execution Times (seconds). Cold Cache only on $Dataset_1$. Significant differences are highlighted in **bold**.

scheme (**R2**). Finally, the exploitation of caching and columnar-oriented format allowed us to optimize query performance (**Q3**).

5.3.3 Centralized vs. Distributed Triple Stores

We can regard SeBiDA as a distributed triple store as it can load and query semantic RDF data. Therefore, in the next series of evaluation, we compare SeBiDA's performance against the performance of a popular RDF store, RDF-3X [195][20]. We evaluate both the loading and querying of semantic data, the results of which are respectively shown in Table 5.6 and Table 5.7. Loading timeout is 43200 seconds (12 hours).

Loading time shows that RDF-3X loaded $Dataset_1$ within 93 minutes, compared to 66 minutes in SeBiDA. Loading $Dataset_2$, RDF-3X exceeded the timeout threshold and took up to 24 hours before we manually terminate it. The witnessed low loading performance in RDF-3X is attributed to the exhaustive creation of six triple indexes. These indexes also take a much larger disk footprint in comparison to SeBiDA with a factor of 55. SeBiDA, on the other hand, generates a much-reduced data thanks to its partitioning scheme and highly-compressed generated Parquet tables.

For query execution time, Table 5.7 reveals no definitive winner, but show that SeBiDA in all queries does not exceed the cap of 20s, while RDF-3X does in four queries (Q3, Q5, Q7, Q8) and even passes to the order of minutes. We do not report on the query time of $Dataset_2$ using RDF-3X as data was not loaded. This comparison practically supports the proposition we made in Chapter 2 that modern highly efficient and scalable formats, such as Parquet, can compensate for the lack of indexes in improving query execution by using optimized internal data structures and data encoding (**R3**).

5.4 Summary

The experimental series allows us to draw the following conclusions. The loading phase can be a bottleneck in the overall Data Integration process. Noticing the loading time of the Semantic data $Dataset_1$ and $Dataset_2$, there seems to be a proportionality between the data size and loading time. Namely, loading $Dataset_2$ took double the time taken by $Dataset_1$; similarly, the scale size of $Dataset_2$ is double that of $Dataset_1$. Loading larger datasets, e.g., billion triples,

[20] https://github.com/gh-rdf3x/gh-rdf3x

would clearly jeopardize the Data Integration process. For non-semantic data, loading the small XML $Dataset_3$ was also comparatively long. Although it has 16% of $Dataset_1$ size, it took 50% of its loading time. This adds to the price of reintegrating the data when the sources have received more data after the first integration. These costs include schema evolution and alignment in case the data has changed at the level of schema, data de-duplication to avoid inserting previously inserted data, synchronization in case the data itself has been altered, etc. A complex data loading phase hinders the adoption of the Physical Integration in many use cases, e.g., where data dynamicity and freshness are strong requirements.

Although our Class-based Multi-Type-Aware Property Table partitioning and clustering scheme optimizes for the loaded data footprint and query execution time, it cannot answer queries when the predicate is unbound. However, it has been shown in the literature that such queries are rare [54]; the same choice was made by other similar efforts as reported in the Related Work (chapter 3).

The data loading bottleneck provides the rationale behind the second part of this thesis, namely the Virtual Integration of heterogeneous and large data sources. A virtual integration implies that queries are posed against the original data on demand, without requiring any prior data transformation and loading. We hypothesize that a Virtual Integration will alleviate the ingestion overhead, but will shift the overhead to the query processing phase. This is because the underlying data is dissimilar in nature and disparate across multiple sources, in contrast to a fully homogeneous and centralized environment in the Physical Integration.

CHAPTER 6

Virtual Big Data Integration - Semantic Data Lake

"Do not go where the path may lead, go instead where there is no path and leave a trail."

Ralph Waldo Emerson

As previously mentioned (Introduction Chapter 1), multiple and diverse data models and distributed Data Management systems have emerged in recent years to alleviate the limitation of traditional centralized Data Management. A prominent example is the NoSQL non-relational family which includes models like Key-value, Document, Columnar, and Graph. Consequently, organizations are purposely converging towards these new models in order to capitalize on their individual merits. However, this paradigm shift poses challenges on the way of achieving a pure Physical Data Integration, such as:

- It is cumbersome to impossible migrating all the collected heterogeneous data to a single universal model without incurring data loss, both in structure and semantics. For example, nested and multi-valued array data in a document format cannot be converted in a flat tabular format. Similarly, graph data cannot be straightforwardly transformed into a document format without incorporating variable levels of normalization and denormalization.
- Data transformation and migration incurs a significant cost, both in time and resources. Migrating very large data volumes requires investing in more storage and network resources, adding to the already resource-consuming original large data.
- Many organizations are less likely to sacrifice data freshness especially with the advent of streaming and IoT technologies. Another data source added to the pool adds a complexity level to the overall Data Integration processes.

Further, we have witnessed some of the issues that arise from exhaustively transforming data following a purely Physical Data Integration process (reported in section 5.4). In the Logical Data Integration, heterogeneous data sources are accessed directly in their raw format without requiring prior data transformation and enforcing centralization. Keeping data in its raw format not only promises freshness but also makes data available to any type of processing

e.g., analytics, ad hoc querying, search, etc. The repository of heterogeneous data sources in their original formats is commonly referred to as *Data Lake* [196]. In this chapter, we describe our approach that leverages Semantic Web techniques to enable the *ad hoc* querying of Data Lakes, called Semantic Data Lake. In particular, we address the following research question:

RQ3. Can Semantic Technologies be used to incorporate an intermediate middleware that allows to uniformly access original large and heterogeneous data sources on demand?

Contributions of this chapter can be summarized as follows:

- We provide a thorough description of the concepts and components underlying the Semantic Data Lake.
- We suggest six requirements that need to be fulfilled by a system implementing the Semantic Data Lake.
- We detail the distributed query execution aspects of the Semantic Data Lake.

This chapter is based on the following publications:

- **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer, Jens Lehmann. *Uniform Access to Multiform Data Lakes Using Semantic Technologies*. In Proceeding of the 21st International Conference on Information Integration and Web-based Applications & Services Proceedings (iiWAS), 2019.
- **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer, Jens Lehmann. *Squerall: Virtual Ontology-Based Access to Heterogeneous and Large Data Sources*. In Proceeding of the 18th International Semantic Web Conference (ISWC) 229-245, 2019.
- **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer. *Querying Data Lakes using Spark and Presto*. In Proceedings of the World Wide Web Conference (WWW), 3574-3578. Demonstrations Track, 2019.
- Sören Auer, Simon Scerri, Aaad Versteden, Erika Pauwels, **Mohamed Nadjib Mami**, Angelos Charalambidis, et al. *The BigDataEurope platform–supporting the variety dimension of big data*. In Proceedings of the 17th International Conference on Web Engineering (ICWE), 41-59, 2017.

6.1 Semantic Data Lake

The term *Data Lake* [4] refers to the schema-less pool of heterogeneous and large data sources residing in their original formats on a horizontally-scalable cluster infrastructure. It typically consists of scale-out file/block storage infrastructure (e.g., Hadoop Distributed File System) or scalable databases (e.g., NoSQL stores). By definition, it requires dealing with the original data without requiring a physical transformation or pre-processing. After emerging in the industry, the concept has increasingly been discussed in the literature [197–199].

The integration of heterogeneous data is the key rationale behind the development of Semantic Technologies over the past two decades. Local data schemata are mapped to global *ontology*

terms using *mapping languages* that have been standardized for a number of popular data representations, e.g., relational data, JSON, CSV, XML, etc. Heterogeneous data can then be accessed in a *uniform* manner by means of queries in a standardized query language, *SPARQL* [200], employing terms from the ontology. Such data access is commonly referred to as Ontology-Based Data Access (OBDA) [8]. The application of these Semantic Technologies over the Data Lake led to the Semantic Data Lake concept, which we introduced in a series of publications [201–204] and detail in this thesis.

6.1.1 Motivating Example

In order to facilitate the understanding of subsequent definitions, we will use the SPARQL query in Listing 6.1 as a reference. `ns` denotes an example ontology where classes and properties are defined.

```
SELECT DISTINCT ?price ?page
WHERE {
        ?product    a               ns:Product .
        ?product    ns:hasType      ?type .
        ?product    ns:hasPrice     ?price
        ?product    ns:hasProducer  ?producer .
        ?producer   a               ns:Producer .
        ?producer   ns:homepage     ?page .
        FILTER (?price > 1200)
} ORDER BY ?type LIMIT 10
```

Listing 6.1: Example SPARQL Query.

6.1.2 SDL Requirements

The Semantic Data Lake, SDL, is then an extension of the Data Lake supplying it with a semantic middleware, which allows the uniform access to original heterogeneous large data sources. Therefore, an SDL-compliant system must meet the following requirements:

- **R1. It should be able to access large-scale data sources**. Typical data sources inside a Data Lake range from large plain files stored in a scale-out file/block storage infrastructure (e.g., Hadoop Distributed File System, Amazon S3) to scalable databases (e.g., NoSQL stores). Typical applications built to access a Data Lake are data- and compute-intensive. While a Data Lake may contain small-sized data, the primary focus of the Data Lake is, by definition [4], data and computations that grow beyond the capacity of single-machine deployments.

- **R2. It should be able to access heterogeneous sources**. The value of a Data Lake-accessing system increases with its ability to support as many data sources as possible. Thus, a SDL system should be able to access data of various forms. This includes plain-text files e.g., CSV, JSON, structured file formats, e.g., Parquet, ORC, databases, e.g., MongoDB, Cassandra, etc.

- **R3. Query execution should be performed in a distributed manner**. The following are scenarios highlighting this requirement. (1) Queries joining or aggregating only a sub-set of the data may incur large intermediate results that can only be computed and contained

by multiple nodes. (2) As original data is already distributed across multiple nodes, e.g., in HDFS or a high-availability MongoDB cluster, query intermediate results can only be stored distributedly and computed in parallel. (3) Many NoSQL stores, e.g., Cassandra and MongoDB, dropped the support for certain query operations [205], e.g., join, in favor of improving storage scalability and query performance. Thus, in order to join entities of even one same database, e.g., collections in MongoDB, they need to be loaded on-the-fly into an execution environment that supports join, e.g., Apache Spark [40].

- **R4. It should be able to query heterogeneous sources in a uniform manner**. One of the main purposes of adding a semantic layer on top of the various sources is to abstract away the structural differences found across Data Lake sources. This semantic middleware adds a schema to the originally schema-less repository of data, which can then be *uniformly* queried using a unique query language.
- **R5. It should query fresh original data without prior processing.** One of the ways the Data Lake concept contrasts with traditional Data Integration paradigms (e.g., Data Warehouse [206]) is that it does not enforce centralization by transforming the whole data into a new format and form. It rather queries directly the original data sources. Querying transformed data compromises data freshness, i.e., a query returns an outdated response when data has changed or been added to the Data Lake meanwhile. Such pre-processing also includes indexing; once new data is added to the Data Lake, queries will no longer access the original data but excludes the new yet un-indexed data. Besides Data Lake requirements, index creation in the highly scalable environment of the Data Lake is an expensive operation that requires both time and space resources.
- **R6. It should have a mechanism to enable the cross-source join of heterogeneous sources**. Data Lake is often created by dumping silos of data, i.e., data generated using separate applications but has the potential to be linked to derive new knowledge and drive new business decisions. As a result, Data Lake-contained data may not be readily joinable but requires introducing changes at *query-time* to enable the join operation.

6.1.3 SDL Building Blocks

In this section, we provide a formalisation for SDL underlying building blocks.

Definition 7 (Data Source) *A data source refers to any data storage medium, e.g., plain file, structured file or a database. We denote a data source by d and the set of all data sources by $D = \{d_i\}$.*

Definition 8 (Data Entities and Attributes) *Entities are collections of data that share a similar form and characteristics. These characteristics are described in the form of attributes. We denote an entity by $e_x = \{a_i\}$, where x is the entity name and a_i are its attributes. A data source consists of one or more entities, $d = \{e_i\}$.*

For example, 'Product' is an entity of relational form, and is characterized by (Name, Type, Producer) attributes.

Definition 9 (Ontology) *An ontology O is a set of terms that describe a common domain conceptualization. It principally defines classes C of concepts, and properties P about concepts, $O = C \cup P$.*

For example, `ns:Product` is the class of all products in an e-commerce system (`ns` is an ontology identifier or *namespace*), of which `ns:hasType`, `ns:hasPrice` and `ns:hasProducer` are properties and `ns:Book` is a sub-class.

Definition 10 (Semantic Mapping) *A semantic mapping is a relation linking two semantically-equivalent terms. We differentiate between two types of semantic mappings:*

- *Entity mappings:* $m^{en} = (e, c)$ *a relation mapping an entity* e *from* d *onto an ontology class* c. *For example, (ProductTable, ns:Product) is mapping the entity* `ProductTable` *from a Cassandra database to the class* `ns:Product` *of the ontology ns.* M^{en} *is the set of all entity mappings.*
- *Attribute mappings:* $m^{at} = (a, p)$ *a relation mapping an attribute* a *from a given* e *onto an ontology property* p.

For example, *(price, ns:hasPrice)* is mapping attribute `price` of a Cassandra table to the Ontology property `ns:hasPrice`. M^{at} is the set of all attribute mappings.

Definition 11 (Query) *a query* q *is a statement in a query language used to extract entities by means of describing their attributes. We consider SPARQL as a query language, which is used to query (RDF [6]) triple data (subject, property, object). In particular, we are concerned with the following fragment: the BGP (Basic Graph Pattern), which is a conjunctive set of triple patterns, filtering, aggregation and solution modifiers (projection, limiting, ordering, and distinct). Triple patterns are triples that are partially undefined e.g., (a, b, ?object).*

Definition 12 (Query Star) *Query star is a shorthand version of a subject-based star-shaped sub-BGP, a set of triple patterns sharing the same subject. We denote a star by* $st_x = \{t_i = (x, p_i, o_i) \mid t \in BGP_q\}$ *where* x *is the shared subject and* $BGP_q = \{(s_i, p_i, o_i) \mid p_i \in O\}$, *i.e., triple patterns of a star (thus of the BGP) use properties from the ontology. We call star variable the subject shared by the star's triples. A star is typed if it has a triple with the typing property (e.g.,* `rdf:type` *or* `a`*).*

For example, `(?product rdf:type ns:Product . ?product ns:hasPrice ?price . ?p ns:hasType ?type . ?product ns:hasProducer ?producer)` is a star that has variable *product* and type `ns:Product`.

Definition 13 (Query Star Connection) *A star* st_a *is connected to another star* st_b *if* st_a *has a tripe pattern (called connection triple) with the object being the variable of star* st_b, *i.e.,* $connected(st_a, st_b) \rightarrow \exists t_i = (s_i, p_i, b) \in st_a$.

For example, triple `(?product ns:hasProducer ?producer)` of $st_{product}$ connects $st_{product}$ with $st_{producer}$.

Definition 14 (Relevant Entities to Star) *An entity* e *is relevant to a star* st *if it contains attributes* a_i *mapping to every triple property* p_i *of the star i.e.,* $relevant(e, st) \rightarrow \forall p_i \in pred(st) \exists a_j \in e \mid (p_i, a_j) \in M^{at}$, *where pred is a relation returning the set of properties of a given star.*

Definition 15 (Distributed Execution Environment) *A Distributed Execution Environment, DEE, is the shared physical space where large data can be transformed, aggregated and joined. It has an internal data model with which the contained data comply. It is similar to the Staging Area of Data Warehouses [206], acting as an intermediate homogenization layer.*

For example, DEE can be a shared pool of memory in a cluster where data is organized in large distributed tables.

Definition 16 (ParSet (Parallel dataSet)) *A ParSet is a data structure that is partitioned and distributed, and that is queried in parallel. ParSet has the following properties:*

- *It is created by loading the star's relevant entities into the DEE.*
- *It has a well-defined data model, e.g., relational, graph, document, key-value, etc.*
- *It is populated on-the-fly and not materialized, i.e., used only during query processing then cleared.*

Its main purpose is to abstract away the schema semantic differences found across the varied data sources. We denote by PS_x the ParSet corresponding to the star st_x, the set of all ParSets is denoted PS.

Definition 17 (ParSet Schema) *ParSet has a schema that is composed of the properties of its corresponding star, plus an ID that uniquely identifies ParSet's individual elements. To refer to a property p of a ParSet, the following notation is used $PS_{star}.p$.*

For example, the schema of $PS_{product}$ is *{hasPrice, hasType, hasProducer, ID}*, its property *hasPrice* is referred to by $PS_{product}.hasPrice$.

Definition 18 (Joinable ParSets) *Two ParSets are joinable if their respective stars are connected (by a connection triple), i.e., $joinable(PS_a, PS_b) \iff connected(st_a, st_b)$. If the two ParSets have a relational model for example, two of their attributes may store inter-matching values. ParSets are incrementally joined following a query, results of which are called Results ParSet, denoted $PS^{results}$.*

For example, ParSet $PS_{product}$: *{hasPrice, hasType, hasProducer, ID}* is joinable with ParSet $PS_{producer}$: *{hasHomepage, ID}*, because the query contains the (connection) triple `(?product ns:hasProducer ?producer)`.

Definition 19 (Entity Wrapping) *Entity Wrapping is a function that takes one or more relevant entities to a star and returns a ParSet. It loads entity elements and organizes them according to ParSet's model and schema. $wrap(e_i) \rightarrow PS_x$.*

For example, a collection (entity) of a Document database is adapted (flattened) to a tabular model by mapping every document property to a table[1] column.

[1] Complex entities e.g., nested documents, may result in more than one table.

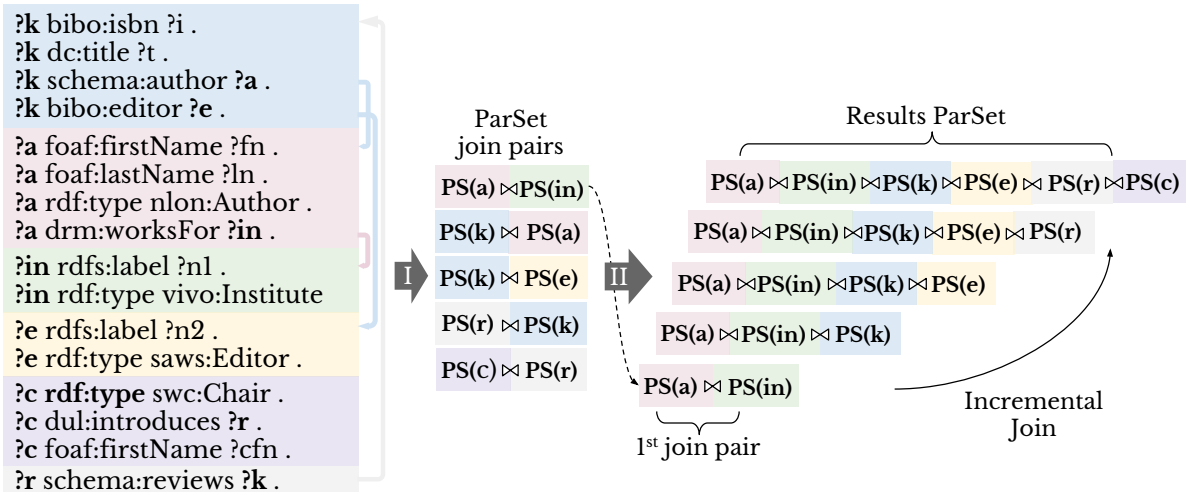


Figure 6.1: ParSets extraction and join (for clarity ParSet(x) is shortened to PS(x))

6.1.4 SDL Architecture

We envision an SDL *architecture* to contain four core components (see Figure 6.2): Query Decomposition, Relevant Source Detection, Data Wrapping and Distributed Query Processing. It accepts three inputs: the query, semantic mappings and access metadata. In the following, we describe the techniques and mechanisms underlying the architecture components.

Query Decomposition

Firstly, the input query is validated and analyzed to extract its contained query stars (Definition 12), as well as the connections between the stars (Definition 13). Query decomposition is subject-based (variable subjects) since the aim is bringing and joining entities from different sources. For example, in Figure 6.1 left, six stars have been identified (shown in distinct colored boxes) represented by their variables k, a, in, e, c and r. Similar decomposition methods are commonly found in OBDA and Query Federation systems (e.g., [207]).

Relevant Source Detection

For every star, the mappings are visited to find the relevant entities (Definition 14). If more than an entity is relevant, they are combined (union). If a star is typed with an ontology class, then only entities with 'entity mapping' to that class are extracted. For example, suppose a query with two joint stars (`?x _:hasAuthor ?y`) and (`?y foaf:firstName ?fn`, `?y foaf:lastName ?ln`). There exist, in the data, two entities about `authors` and `speakers`, both having the two attributes mapping to the predicates `foaf:firstName` and `foaf:lastName`, and an entity about `books`. As star y is untyped, and as both `authors` and `speakers` entities have attributes mapping to the predicates of star y, both will be identified as relevant data, and, thus, be joined with star `x` about books. Semantically, this yields wrong results as speakers have no relationship with books. Hence the role of the type in a star.

Data Wrapping

Relevant entities are loaded as ParSets, one ParSet per query star. This component implements the Entity Wrapping function (Definition 19), namely loading entities under ParSet's model and schema, e.g., the flattening of various data into tables. In the classical OBDA, the input SPARQL query has to be translated to queries in the language of each relevant data source. This is in practice hard to achieve with the highly heterogeneous Data Lake nature. Therefore, numerous recent publications (e.g., [89–91]) advocate for the use of an *intermediate* query language to interface between the SPARQL query and the data sources. In our case, the intermediate query language is the query language (e.g., SQL) corresponding to ParSet data model (e.g., tabular). The Data Wrapper generates data in ParSet model at query-time, which allows for the parallel execution of expensive query operations, e.g., join, or any unselective queries. There must exist *wrappers* to convert data entities from the source to ParSet data model. For each identified star by the Query Decomposition, exactly one ParSet is generated by the Data Wrapping. If more than an entity are relevant, the ParSet is formed as a *union*. Moreover, not the entirety of the entities is loaded, but *predicate push-down* optimization filters their content already at the data source level. This means that the only data loaded into ParSets is strictly what is needed to perform the join, and possibly the aggregations. An auxiliary metadata file (*Config*) is provided by the user, containing access information to guide the conversion process, e.g., authentication, deployment specifications, etc. More details are given in Section 6.2.

Distributed Query Execution

Connections between stars detected by Query Decomposition will be translated into joins between ParSets. Any operations on star properties (e.g., filtering) or results-wide operations (e.g., aggregation, sorting) are translated to operations on ParSets. Section 6.2 is reserved for detailing this component.

6.2 Query Processing in SDL

The pivotal property of SDL distinguishing it from traditional centralized Data Integration and Federation Systems is its ability to query large-scale data sources in a distributed manner. This requires the incorporation of adapted or new approaches, which are able to overcome the data scale barrier. In this section, we detail the various mechanisms and techniques underlying the distributed query execution in the SDL. Query Processing in SD stars by extracting stars from the SPARQL query, then forming ParSet from relevant data, then querying the ParSets. In this section, we first describe how ParSets are formed and interacted with (subsection 6.2.1), then how they are effectively queried (subsection 6.2.2).

6.2.1 Formation of and Interaction with ParSets

ParSets are the unit of computation in the SDL architecture. They are first loaded from relevant data source entities and then filtered, transformed, joined and aggregated as necessary in the course of a query. They can be seen as *views* that are populated from underlying data entities and are (only) available during the query execution time.

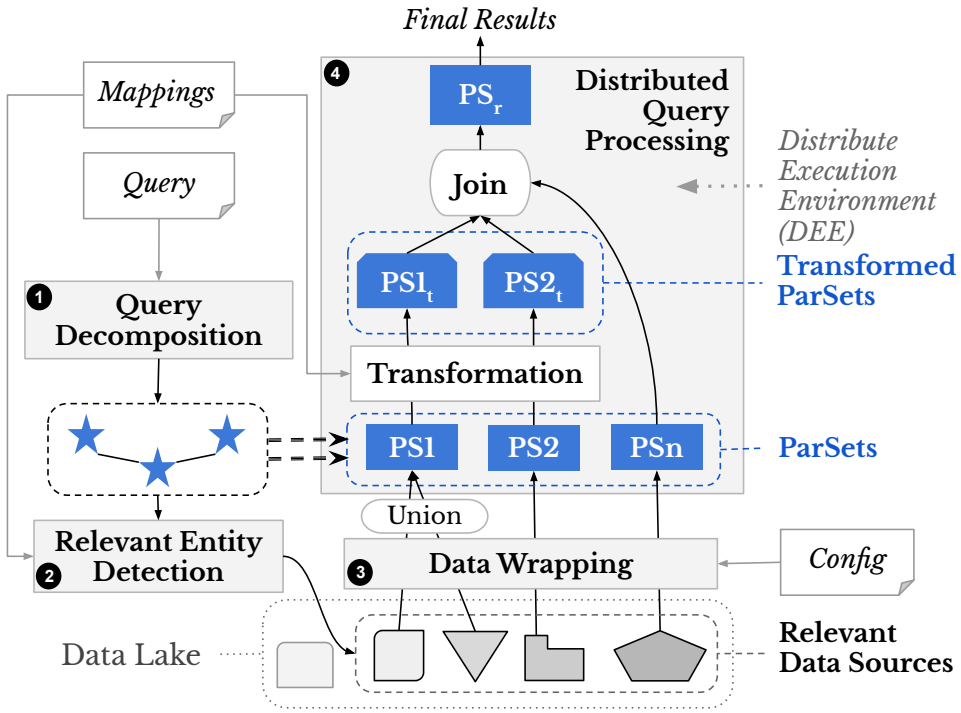


Figure 6.2: Semantic Data Lake Architecture (Mappings, Query and Config are user inputs).

From Data Source's Model to PatSet's Model

Retrieving data from a data source and populating the ParSet is performed by *wrappers*, which apply the necessary model transformation or adaptation. For example, if ParSet is of a tabular model and one data source is of a graph model, the source wrapper creates a tabular version by flattening the graph data structures. The data is retrieved using the source available access mechanisms. Several mechanisms were used in the literature ranging from programmatic APIs (e.g., `getter/setter` methods, ORM/OGM[2], query methods), Web APIs (e.g., `GET` requests, query endpoints), connectivity standards (JDBC, ODBC), etc.

ParSets Language as 'Intermediate' Query Language

ParSets have a specific data model and, thus, can be interacted with using a specific query language, e.g., tabular model and SQL. The query language of the ParSets can then be used as an *intermediate* query language. Using the latter, it becomes possible to convert SDL's unique query language (SPARQL in our case) to ParSet's unique query language (e.g., SQL), instead of the languages of every data source. Solving data integration problems using an intermediate or meta query language is an established approach in the literature. It has been used in recent works (e.g., [89, 90]) to access large and heterogeneous data sources.

Interaction Mechanisms with ParSets

Once ParSets are created, they are used in two different ways, detailed as follows.

[2] Object-Relational Mappings/Object-Grid Mappings

```
parset = wrapper(entity)
filter(parset)
aggregate(parset)
join(parset,otherParset)
```

Listing 6.2: ParSets manipulation. The ParSet is created from a data source entity by a specialized wrapper. The ParSet is then interacted with using a set of manipulation methods, here `filter`, then `aggregate`, then `join` with another ParSet.

```
SELECT C.type ... FROM cassandra.cdb.product C JOIN
mongo.mdb.producer M ON C.producerID = M.ID
WHERE M.page="www.site.com" ...
```

Listing 6.3: A self-contained SQL query. The query contains references to the required data sources and entities: a Cassandra table and a MongoDB collection.

- **Manipulated ParSets.** This is the case of wrappers generating ParSets in a format that users can manipulate. For example, if the model of the ParSet is tabular, the returned ParSet would be a table that users can interact with by means of SQL-like functions. This approach is more flexible as users have direct access to and control over the ParSets using an interaction language (e.g., Java). However, knowledge about the latter is, thus, a requirement. Listing 6.2 illustrates this mechanism.
- **Self-Contained Query.** This is the case where wrappers do not create ParSets in a data structure that users can control and manipulate. Users can only write one universal self-contained *declarative* query (i.e., ask for what is needed and not how to obtain it) containing direct references to the needed data sources and entities. An example of such a self-contained query in SQL is presented in Listing 6.3, where `product` and `producer` are two tables from Cassandra `cdb` and MongodB `mdb` databases, respectively.

This classification can categorize the various existing query engines that can implement the ParSet. For example, the first mechanism is applicable using Apache Spark or Flink[3], the second mechanism is applicable using Presto[4], Impala[5], Drill[6] or Drimio[7].

6.2.2 ParSet Querying

Once ParSets are produced by the wrappers, they are effectively queried to retrieve the sub-results that collectively form the final SPARQL query answer. The operations executed over ParSets correspond to SPARQL query operations. In the next, we describe how to deduce the list of operations and how they are executed.

From SPARQL to ParSet Operations

We remind that for every query star a ParSet is created, which has a schema that is composed of the properties of the corresponding star (Definition 17). In order to avoid property naming

[3] https://flink.apache.org
[4] https://prestosql.io
[5] https://impala.apache.org
[6] https://drill.apache.org
[7] https://docs.dremio.com

conflicts across multiple stars, we form the components of ParSet's schema using the following template: *{star-variable}_{property-name}_{property-namespace}*, e.g., `product_hasType_ns`. Then, the SPARQL query is translated into ParSet *operations* following the algorithm shown in Listing 6.5; ParSet operations are marked with an underline.

1. For each star, relevant entities are extracted (lines 5 to 7).
2. For each relevant entity, a ParSet (`oneParSet`) is loaded and changed in the following way. If the SPARQL query contains conditions on a star property, equivalent ParSet filtering operations are executed (lines 10 and 11). If there are joinability transformations [85] (Requirement 6, subsection 6.1.2), also equivalent transformation operations on ParSet are executed. If more than one entity is relevant, the loaded `oneParSet` is combined with the other ParSets relevant to the same star (line 14). Finally, add the changed and combined `starParSet` to a list of all ParSets (line 15).
3. Connections between query stars translate into joins between the respective ParSets, resulting in an array of join pairs e.g., *[(Product, Producer),(Product, Review)]* (line 17). As shown in the dedicated algorithm in Listing 6.6 (more detailed in Listing 6.7), results ParSet ($PS^{results}$) is created by iterating through the ParSet join pairs and incrementally join them (line 18).
4. Finally, if the SPARQL query contains results-wide query operations e.g. aggregations solution modifiers (project, limit, distinct or ordering) equivalent operations are executed on the results ParSet (lines 19 to 28).

Steps 1–3 are are illustrated in Table 6.1.

ParSet Operations Execution

Once ParSet operations are decided, their executed depends on the interaction mechanism of the implementing engine described in 6.2.1. For clarification purposes, we project some of the concepts on practical terms from current state-of-the-art query engines.

- **Manipulated ParSets.** This applies when ParSets are manually[8] loaded and manipulated using execution engine functions. This is the case of DataFrames, a possible implementation of ParSets in Spark, which undergo *Spark transformations*, e.g., `map`, `filter`, `join`, `groupByKey`, `sortByKey`, etc. If we consider `oneParset` of line 9 in Listing 6.5 as a DataFrame, then every ParSet operation can be implemented using an equivalent Spark transformation.
- **Self-Contained Query.** As in this case, a high-level declarative query is generated, there are no explicit operations to manually run in a sequence. Rather, ParSet operations of Listing 6.5 create and gradually *augment* a query, e.g., SQL query in Presto[9]. For example, in the query of Listing 6.1, there is a condition filter `?price > 1200`, ParSet operation of line 11 augments the query with `WHERE price > 1200`. Similarly, the query parts `ORDER BY ?type` and `LIMIT` represented by ParSet operations `order` (line 22) and

[8] By manual we do not mean the direct user interaction, but the implementation of these ParSets in a given SDL implementation. The only user interaction is via issuing SPARQL query.

[9] https://prestosql.io

```
1 SELECT DISTINCT C.type, C.price
2 FROM cassandra.cdb.product C
3 JOIN mongo.mdb.producer M ON C.producerID = M.ID
4 WHERE C.price > 1200 ORDER BY C.type LIMIT 10
```

Listing 6.4: Generated self-contained SQL Query.

```
1  Input: SPARQL query q
2  Output: resultsParSet
3
4  allParSets = new ParSet()
5  foreach s in stars(q)
6     starParSet = new ParSet()
7     relevant-entities = extractRelevantEntities(s)
8     foreach e in relevant-entities // one or more rlevant entities
9        oneParSet = loadParSet(e)
10       if containsConditions(s,q)
11          parSet = filter(oneParSet,conditions(s))
12       if containsTransformations(s,q)
13          parSet = transform(oneParSet,conditions(s))
14       starParSet = combine(starParSet,oneParSet)
15    allParSets += starParSet
16
17 parSetJoinsArray = detectJoinPoints(allParSets,q)
18 resultsParSet = joinAll(parSetJoinsArray)
19 if containsGroupBy(b)
20    resultsParSet = aggregate(resultsParSet,q)
21 if containsOrderBy(q)
22    resultsParSet = order(resultsParSet,q)
23 if containsProjection(q)
24    resultsParSet = project(resultsParSet,q)
25 if containsDistinct(q)
26    resultsParSet = distinct(resultsParSet,q)
27 if containsLimit(q)
28    resultsParSet = limit(resultsParSet,q)
```

Listing 6.5: ParSet Querying Process (simplified).

`limit` (line 28) augment the query by `ORDER BY C.type LIMIT 10`. Full generated SQL query of the query in Listing 6.1 is presented in Listing 6.4. Query Augmentation is a known technique in query translation literature, e.g., [133].

Optimization Strategies

In order to optimize query execution time, we have designed the query processing algorithm (Listing 6.5) in such a way that we reduce as much data as soon as possible, especially before the cross-ParSet join is executed. There are three locations where this is applied:

1. We push the query operations that affect only the elements of a single ParSet to the ParSet itself, not until obtaining *results ParSet*. Concretely, we execute the `filter` and `transform` operations before the `join`. Aggregation and the other solution modifiers are left to the final results ParSet, as those operations have a results-wide effect.

2. `Filter` operation runs before `transform` (line 11 then 13). This is because the transform

```
Input: ParSetJoinsArray // Pairs [(ParSet,ParSet)]
Output: ResultsParSet // ParSet joining all ParSets

ResultsParSet = ParSetJoinsArray[0] // 1st pair
foreach currentPair in ParSetJoinsArray
     if joinableWith(currentPair,ResultsParSet)
          ResultsParSet = join(ResultsParSet,currentPair)
     else
          PendingJoinsQueue += currentPair
// Next, iterate through PendingJoinsQueue
// similarly to ParSetJoinsArray
```

Listing 6.6: JoinAll - Iterative ParSets Join.

$\boldsymbol{Star_{product}}$:	**Mappings:**
?product a ns:Product . ?product ns:hasType ?type . ?product ns:hasPrice ?price .	Product → ns:Product type → ns:hasType price → ns:hasPrice
↳ $\boldsymbol{PS_{Product}}$: SELECT type AS product_hasType_ns, price AS product_hasPrice_ns	
$\boldsymbol{Star_{producer}}$:	**Mappings:**
?producer a ns:Producer . ?producer ns:homepage ?page .	Producer → ns:Producer website → ns:homepage
↳ $\boldsymbol{PS_{Producer}}$: SELECT website AS producer_homepage_ns	
$\boldsymbol{Star_{product}}$ (follow up) ?product ns:hasProducer ?producer	
$\boldsymbol{PS^{results}}$: Product JOIN Producer ON Product.product_hasProducer_ns = Producer.ID	

Table 6.1: ParSets generation and join from the SPARQL query and mappings. The join between $Star_{Product}$ and $Star_{Producer}$ enabled by the connection triple (`?product ns:hasProducer ?producer`) is represented by *ParSet(product).(ns:hasProducer) = ParSet(producer).(ID)* and translated to the SQL query shown under $PS^{results}$.

affects the attribute values (which will later participate in a join), so if they are reduced by the filter, fewer data will have to be transformed (then joined).

3. We leverage filter push-down optimization of the query engine. Namely, we allow the data sources themselves to filter data whenever possible (e.g., possible with Parquet and not with CSV) before loading them into ParSets. This reduces the data to be joined or aggregated later on.

6.3 Summary

In this chapter, we provided a formal description of the concepts and principles underlying the Semantic Data Lake architecture. We suggested six requirements that must be met for an implementation to be *SDL-compliant*. Most importantly, such implementation should be distributed, support joins and access as many original data sources as possible in an ad hoc

```
1  Input: ParSetJoinsArray // Pairs [(ParSet,ParSet)]
2  Output: resultsParSet // ParSet joining all ParSets
3
4  ps1 = ParSetJoinsArray[0].key
5  ps2 = ParSetJoinsArray[0].value
6
7  resultsParSet = ps1.join(ps2).on(ps1.var=ps2.var)
8  joinedParSets.add(ps1).add(ps2)
9
10 foreach currentPair in ParSetJoinsArray
11   ps1 = currentPair.key
12   ps2 = currentPair.value
13
14   if joinedParSets.contains(ps1) and !joinedParSets.contains(ps2)
15     resultsParSet = resultsParSet.join(ps2).on(resultsParSet.(ps1.var)=ps2.var)
16     joinedParSets.add(ps1).add(ps2)
17   else if !joinedParSets.contains(ps1) and joinedParSets.contains(ps2)
18     resultsParSet = resultsParSet.join(ps1).on(resultsParSet.(ps2.var)=ps1.var)
19     joinedParSets.add(ps1).add(ps2)
20   else if !joinedParSets.contains(ps1) and !joinedParSets.contains(ps2)
21     joinedParSets.enqueue((ps1,ps2))
22
23 while pending_joins.notEmpty do
24   join_pair = pending_join.hea
25   ps1 = join_pair.key
26   ps2 = join_pair.value
27   // Check and join similarily to lines 14-21
28   join_pair = pending_join.tail
```

Listing 6.7: JoinAll Detailed. Iterating over each join ParSet pair and check (both right and left side ParSet) if it can join with the previously and incrementally computed results. If a certain pair cannot join, it is added to a queue. After all pairs have been visited, the queue is iterated over in a simiar way as previously and the remaining ParSet pairs are joined with the results ParSet, then enqueued. The algorithm terminates when the queue is empty.

manner. Further, we provided detailed description of the SDL architecture and the various query execution mechanisms underlying the SDL. In particular, we detail how, given a SPARQL query, relevant data is organized into ParSets, and how equivalent query operations are derived from the SPARQL query. We showed the two main mechanisms by which ParSets are formed and queried. One is by manipulating ParSets in the form of operations on data structures, and one by augmenting a high-level declarative query in the language of the ParSet data model.

We dedicate the next two separate chapters to describe our implementation of the SDL (Chapter 7) and report on its empirical evaluation (Chapter 8), respectively.

CHAPTER 7

Semantic Data Lake Implementation: Squerall

"Tell me and I forget. Teach me and I remember. Involve me and I learn."

Benjamin Franklin

After describing the concepts, architecture and methodologies of the SDL, in this chapter, we provide details regarding our implementation of the SDL, called *Squerall* [202]. We focus on our choice of technologies for declaring mappings and query-time transformations and for implementing the various layers of the architecture. We also present Squerall-GUI, the graphical user interface that supports non-technical users in creating the necessary inputs. The GUI consists of three sub-interfaces for creating SPARQL queries, mappings and access metadata. Further, we present Squerall extensibility aspects, demonstrating source extensibility in particular with supporting access to RDF data. Finally, we describe Squerall integration into the SANSA Stack, a distributed framework for processing large-scale RDF data.

The main contribution of this chapter is then the description of Squerall, an extensible implementation of the SDL concept that:

- Allows *ad hoc* querying of large and heterogeneous data sources *virtually* without any data transformation or materialization.
- Allows the *distributed* query execution, in particular joining data from disparate heterogeneous data sources.
- Enables users to declare query-time *transformations* for altering join keys and thus making data *joinable* (definition below).
- Integrates state-of-the-art Big Data engines Apache Spark and Presto with the Semantic Technologies RML and FnO.

This chapter is based on the following publications:

- **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer, Jens Lehmann. *Squerall: Virtual Ontology-Based Access to Heterogeneous and Large Data Sources*. In Proceeding of the 18th International Semantic Web Conference (ISWC) 229-245, 2019.

- **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer, Jens Lehmann. *How to feed the Squerall with RDF and other data nuts?*. In Proceeding of the 18th International Semantic Web Conference (ISWC), Demonstrations and Posters Track, 2019.

7.1 Implementation

Squerall[1] (from Semantically query all) is our implementation of the Semantic Data Lake architecture. Squerall makes use of state-of-the-art Big Data technologies Apache Spark [40] and Presto [208] as query engines. Apache Spark is a general-purpose Big Data processing engine with modules for general Batch Processing, Stream Processing, Machine Learning and SQL Querying. Presto is a SQL query engine with a focus on the joint querying of heterogeneous data sources using a single SQL query. Both engines primarily base their computations in-memory. In addition to their ability to query large-scale data, Spark and Presto have wrappers allowing access to a wide array of data sources. Using those wrappers, we are able to avoid reinventing the wheel and only resort to manually building a wrapper for a data source for which no wrapper exists. We chose Spark and Presto because they offer a good balance between the number of connectors, ease of use and performance [209, 210]. For example, at the time of writing, we are able to easily check that Spark and Presto have the largest number of connectors than similar distributed SQL query engines by visiting their respective documentations.

Squerall is written using Scala and Java query language with a code base of around 6000 lines. We briefly list in the following the technologies backing every layer of the SDL architecture, details are given thereafter.

- **Query Decomposition:** We use Apache Jena to validate the syntax of the query and to extract the various SPARQL query components, e.g., BGP, projected variables, filtering, grouping, ordering, etc.

- **Source Mapping and Query-Time Transformation:** We use RML for mapping declaration combined with FnO ontology for query-time transformations declaration.

- **Data Wrapping and Distributed Query Processing:** We use Apache Spark [40] and Presto [208] to both retrieve the relevant entities and perform the query.

We provide a Sequence Diagram showing how Squerall is interacted with, what sequence of actions it takes to execute a query, and what major internal components are involved – see Figure 7.1.

7.2 Mapping Declaration

We distinguish between Data Mappings and Transformation Mappings. The former map schema elements to ontology terms and the latter map schema elements to functions altering their (schema elements) values.

[1] https://eis-bonn.github.io/Squerall

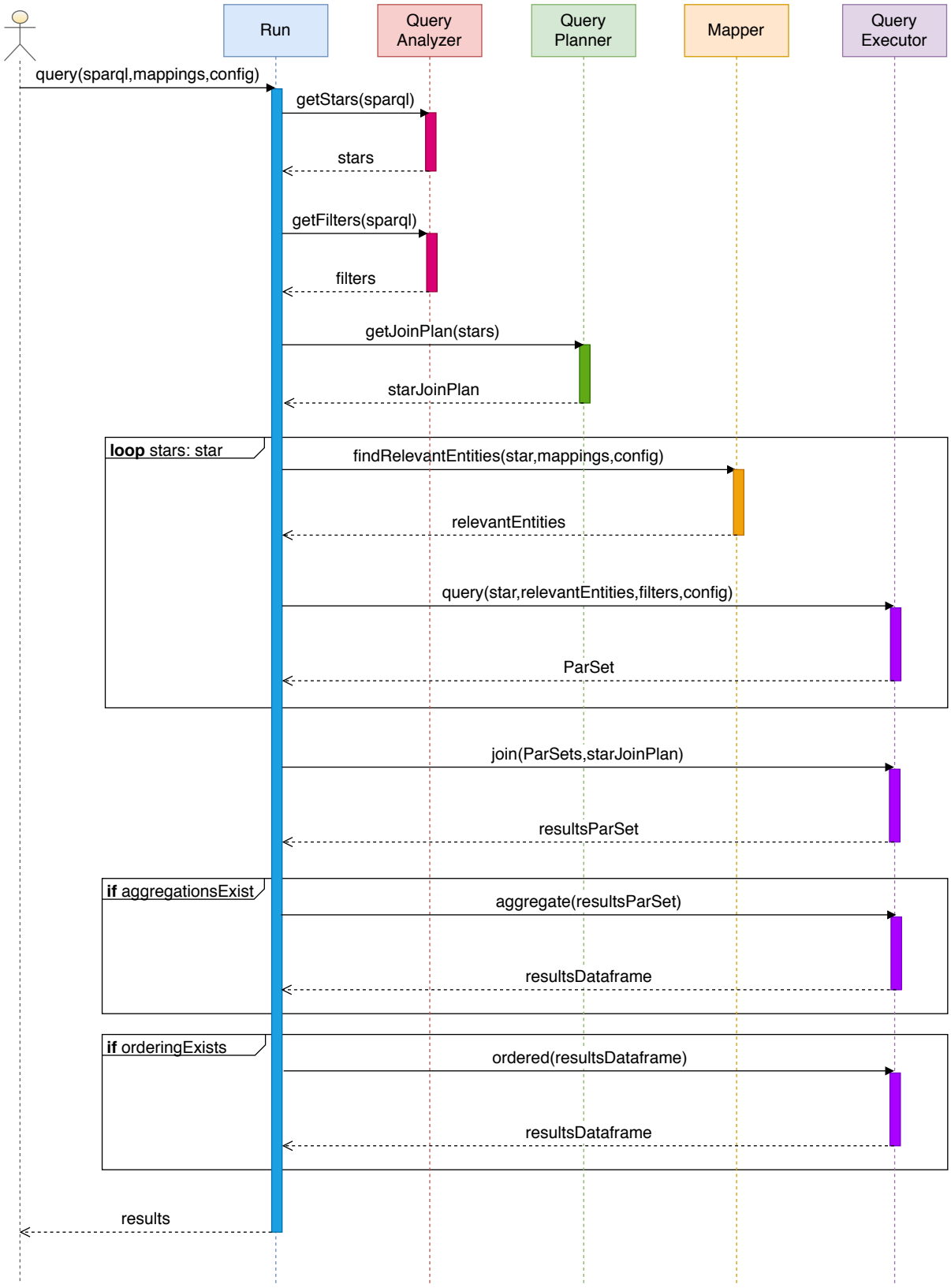


Figure 7.1: A Sequence Diagram of querying Squerall. ParSets in the join() call is a list of all ParSets accumulated during the preceding loop.

7.2.1 Data Mappings

Squerall accepts entity and attribute mappings declared in RML [169], a mapping language extending the W3C R2RML [211] to allow mapping heterogeneous sources. The following fragment is used (e.g., `#AuthorMap` in Listing 7.1):

- `rml:logicalsource` used to specify the entity source and type.
- `rr:subjectMap` used (only) to extract the entity ID (in brackets).
- `rr:predicateObjectMap` used to map an attribute using `rml:reference` to an ontology term using `rr:predicate`.

We complement RML with the property `nosql:store` (line 5) from our NoSQL ontology[2], to enable specifying the entity type, e.g., Cassandra, MongoDB, etc.

NoSQL Ontology. The ontology is built to fill a gap we found in RML, that is the need to specify information about NoSQL databases. The ontology namespace is `http://purl.org/db/nosql#` (suggested prefix `nosql`). It contains a hierarchy of NoSQL database: KeyValue, Document, Wide Column, Graph and Multimodal. Each class has several databases in sub-class, e.g., Redis, MongoDB, Cassandra, Neo4J and ArangoDB, for each class respectively. The ontology has a broader scope, it also groups the query languages for several NoSQL databases, e.g., CQL, HQL, AQL and Cypher. Further, miscellaneous categories about how each database calls a specific concept (e.g., indexes, primary keys, viewers), what is an entity in each database, .e.g., table, collection, data bucket, etc.

7.2.2 Transformation Mappings

Sometimes ParSets cannot be readily joined due to a syntactic mismatch between attribute values. We, therefore, suggest query-time *Transformations*, which are atomic operations declared by the user and applied to textual or numeral values. Two requirements should be met:

- **TR1.** Transformation specification should be decoupled from the technical implementation. In other words, they only contain high-level function definitions e.g., name, input parameters, output type, expected behavior. The implementations can be attached in the form of methods, modules or plugins.
- **TR2.** Transformations should be performed on-the-fly on *query-time*, not in a pre-processing phase physically materializing the altered values. This is important to retain the originality and freshness of the data sources (see SDL Requirement, Chapter 6 subsection 6.1.2).

Therefore, we suggest to declare those transformations at two different levels: Mappings Level and Query Level.

[2] URL: `http://purl.org/db/nosql#`.

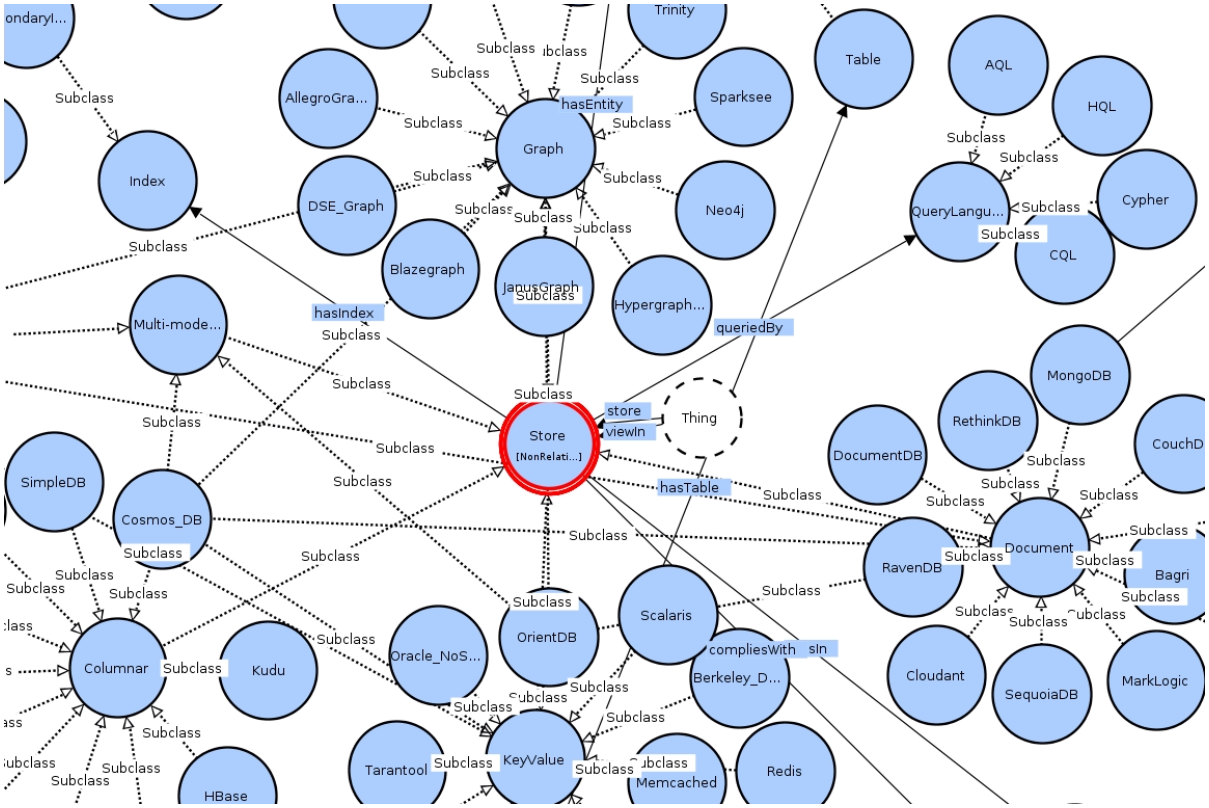


Figure 7.2: A portion of the NoSQL Ontology. It shows several NoSQL store classes under Key-value (bottom), Document (bottom right), Wide Column (bottom left), and Graph (top) NoSQL classes.

Mappings Level

We incorporate the Function Ontology (FnO, [212]), which allows to declare machine-processable high-level functions, abstracting from the concrete technology used (**TR1**). We use FnO in conjunction with RML similarly to the approach in [213] applied to the DBpedia Extraction Framework. However, we do not physically generate RDF triples but only apply FnO transformations on-the-fly at query-time (**TR2**). Instead of directly referencing an entity attribute `rml:reference` (e.g., line 7 Listing 7.1), we reference an FnO function that alters the values of the attribute (line 9 Listing 7.1). For example in Listing 7.1, the attribute `InID` (line 18) is indirectly mapped to the ontology term `drm:worksFor` via the `#FunctionMap`. This implies that the attribute values are to be transformed using the function represented by the `#FunctionMap`, `grel:string_toUppercase` (line 16). The latter sets the `InID` attribute values to uppercase.

Query Level

We propose to add a new clause called `TRANSFORM()` at the very end of a SPARQL query with the following syntax:

```
TRANSFORM([leftJoinVar][rightJoinVar].[l|r].[transformation]+))
```

`[leftJoinVar][rightJoinVar]` identifies the join to enable by referencing its two sides (stars). `[l|r]` is a *selector* to instruct which side of the join (star) is to be transformed. The selector has

```
<#AuthorMap>
rml:logicalSource [
        rml:source: "../authors.parquet" ; nosql:store nosql:parquet ] ;
        rr:subjectMap [
                rr:template "http://exam.pl/../{AID}" ;
                rr:class nlon:Author
        ] ;
        rr:predicateObjectMap [
                rr:predicate foaf:firstName ;
                rr:objectMap [rml:reference "Fname"]
        ] ;
        rr:predicateObjectMap [
                rr:predicate drm:worksFor ;
                rr:objectMap <#FunctionMap>
        ] .

<#FunctionMap>
fnml:functionValue [
        rml:logicalSource "../authors.parquet" ; # Same as above
        rr:predicateObjectMap [
                rr:predicate fno:executes ;
                rr:objectMap [
                        rr:constant grel:string_toUppercase
                ]
        ] ;
        rr:predicateObjectMap [
                rr:predicate grel:inputString ;
                rr:objectMap [rr:reference "InID"]
        ]
] . # Transform "InID" attribute using grel:string_toUppercase
```

Listing 7.1: Mapping an entity using RML and FnO.

```
?bk   schema:author   ?athr .
...
TRANSFORM(?bk?athr.l.skip(12*) && ?bk?athr.r.replc("id","1"))
```

Listing 7.2: An example of the TRANSFORM clause usage in a SPARQL query.

a special semantics: `l` refers to the RDF predicate used in the *connection triple* (Definition 13) of the left-hand star; `r` refers to the ID of the right-side star. `[transformation]+` is the list of one or many transformations to apply on the selected side to enable the join.

For example, in Listing 7.2 `?bk?athr` refers to the join between *ParSet(bk)* and *ParSet(athr)*. It translates to the ParSets join *ParSet(bk).(schema:author) = ParSet(athr).(ID)*, where *schema:author* is the predicate of the connection triple (`?bk schema:author ?athr`). The selector `.l` instructs to apply the transformation `skip(12*)` (skip all values beginning with 12) to the join attribute of *ParSet(athr)*. The selector `.r` instructs to apply the transformation `replc("id","1")` (replace string "id" with "1") to the join attribute of *ParSet(athr)*.

The Mappings Level transformation declaration is more encouraged as it makes use of existing standardized approaches. However, if the transformations are dynamic and change on a query-to-query basis, then Query Level transformation declaration is more practical.

Transformations to Application

Squerall visits the transformations on query-time and triggers specific Spark and Presto operations over the relevant entities. In Spark, a *map()* transformation is used and in Presto corresponding string or numeral SQL operations are used. For the *uppercase* example, in Spark `upper(column)` function inside a *map()* is used and in Presto the SQL `upper()` string function is used.

7.2.3 Data Wrapping and Querying

We implement Squerall query engine using two popular frameworks: Apache Spark and Presto. Spark is a general-purpose processing engine and Presto a distributed SQL query engine for interactive querying, both base their computations primarily in memory. We leverage Spark's and Presto's connector concept, which is a wrapper able to load data from an external source into their internal data structure, or ParSet, performing *flattening* of any non-tabular representations.

ParSet Implementations

Spark implements the Manipulated ParSet interaction mechanism (section 6.2.1). The implementation of ParSet in Spark is called *DataFrame*, which is a tabular distributed data structure. These DataFrames can be manipulated using various specialized Spark SQL-like operations, e.g., `filter`, `groupBy`, `orderBy`, `join`, etc. The DataFrame schema corresponds to the ParSet schema, *a column per star predicate*. As explained with ParSets, DataFrames are created from the relevant entities (fully or partially with predicate push-down), and incrementally joined. Presto, on the other hand, implements the Self-Contained Query interaction mechanism (section 6.2.1). The implementation of ParSet is an internal data structure that is not accessible by users. Presto, rather, accepts one self-contained SQL query with references to all the relevant data sources and entities, e.g., `SELECT cassandra.cdb.product C JOIN mongo.mdb.producer M ON C.producerID = M.ID`. ParSets, in this case, are represented by SELECT sub-queries, which we create, join and optimize similarly to DataFrames.

Wrapping Relevant Data Sources

Spark and Presto make using connectors very convenient, users only provide values to a predefined list of *options*. Spark DataFrames are created using the following formalism:

```
spark.read.format(sourceType).options(options).load
```

In Presto, options are added to a simple configuration file for each data source. Leveraging this simplicity, Squeral supports out-of-the-box six data sources: Cassandra, MongoDB, Parquet, CSV JDBC (MySQL tested), and Elasticsearch (experimental).

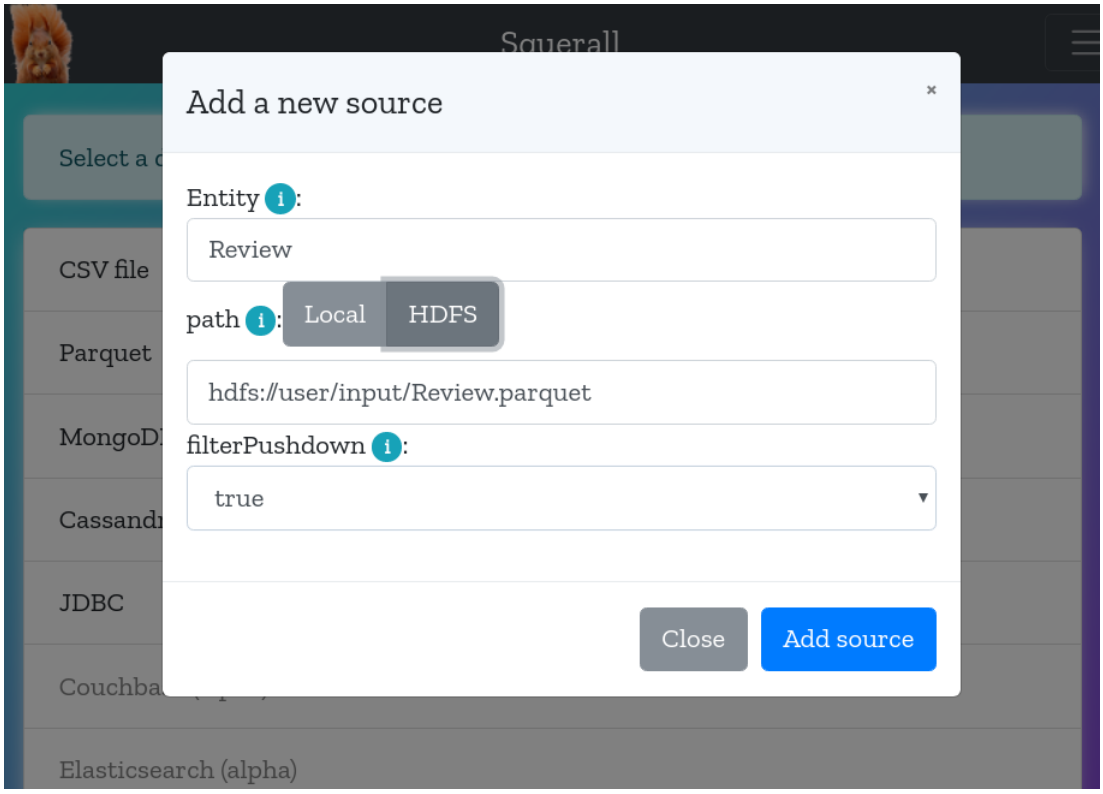


Figure 7.3: Config UI provides users with the list of options they can configure. Here are the options for reading a Parquet file. In the background can be seen other data sources.

7.2.4 User Interfaces

In order to guide non-technical users in providing the necessary inputs to Squerall, we have built[3] Squeral-GUI a set of visual interfaces that generate the access metadata, mappings and SPARQL query respectively described in the following.

Connect UI

This interface receives from users the required options that enable the connection to a given data source, e.g., credentials, cluster settings, optimization tuning options, etc. These options are specific to the query engine used, so in our case Spark and Presto. An example of such engine-specific options is `filterPushDown`, which takes `true` or `false` when using Spark to query a Parquet file (see Figure 7.3). To guarantee a persistent reliable storage, configuration options are internally stored in a lightweight embedded metadata store[4]. Reading from this metadata store, this interface produces the *Config* file with all user-provided access metadata, which will be used to wrap a data entity and load it for querying (see subsection 7.2.3).

[3] Using Play Framework and Scala programming language.
[4] A document database Nitrite https://www.dizitart.org/nitrite-database.html

Mapping UI

This interface uses the connection options collected using *Connect UI* to extract schema elements (entity and attributes) then maps them to ontology terms (class and predicates). The extracted schema elements are tentatively auto-mapped to ontology classes and predicates retrieved from the LOV (Linked Open Vocabularies) Catalog API[5]. If the auto-suggested mappings are not adequate, users can adjust them by searching for other terms from the same LOV catalog or introducing custom ones, see Figure 7.4 for an example. For certain data sources, e.g., Cassandra, Parquet, MySQL, etc, schema information can be extracted by running specific queries. However, other data sources do not provide such a facility, simply because NoSQL stores, by definition, do not necessarily adhere to a fixed schema. For example, this is the case of the document store MongoDB. As a workaround, for MongoDB, we have taken a sample of 100 documents and extracted their properties. When there is a certain regularity in the document properties, or if the documents have a fixed set of properties, or if there are less than or equal 100 documents this method suffices. If, otherwise, the documents have a deeply mixed schema and there are more than 100 documents, this method is not reliable. Therefore, we make it possible for users to manually complement the missing properties. Similarly to Config UI, mappings are persisted in the metadata store and can be exported as a file therefrom.

SPARQL UI

This interface guides non-SPARQL experts to build SPARQL queries by using a set of query widgets for different SPARQL operations, `SELECT`, `FILTER`, `GROUP BY`, `ORDER BY`, etc. Instead of hand-typing the query, users interact with the widgets and auto-generate a syntactically valid SPARQL query. The interface guides users to enter triple patterns describing an entity, one at a time, so they can easily and progressively build an image of the data they want based on these entities. For example, they star by entering the triple patterns describing a *product*, then the triple patterns of a *producer*, etc. The interface auto-suggests predicates and classes from the provided mappings. If a predicate or a class is not auto-suggested, users can predict that the results set will be empty as only mapped entities and attributes are retrievable. Figure 7.6 shows how an entity is described by entering its type (optional) and its predicate-object pairs. These descriptions generates at the end the query BGP.

7.3 Squerall Extensibility

The value of a Data Lake-accessing system lays in its ability to query as much data as possible. For this sake, Squerall was built from the ground up with extensibility in consideration. Squerall can be extended in two ways: supporting more query engines and supporting more data sources.

7.3.1 Supporting More Query Engines

Squerall code is *modular* by design, so it allows developers to incorporate their query engine of choice. Figure 7.7 shows Squerall code classes; the developers only implement a Query Executor (in color), all the other classes remain the same. This is achieved by implementing the set of common query operations of the Query Executor interface, e.g., projection, filtering, aggregation, etc. Spark and Presto are representative of two common types of engines. One queries the data

[5] https://lov.linkeddata.es/

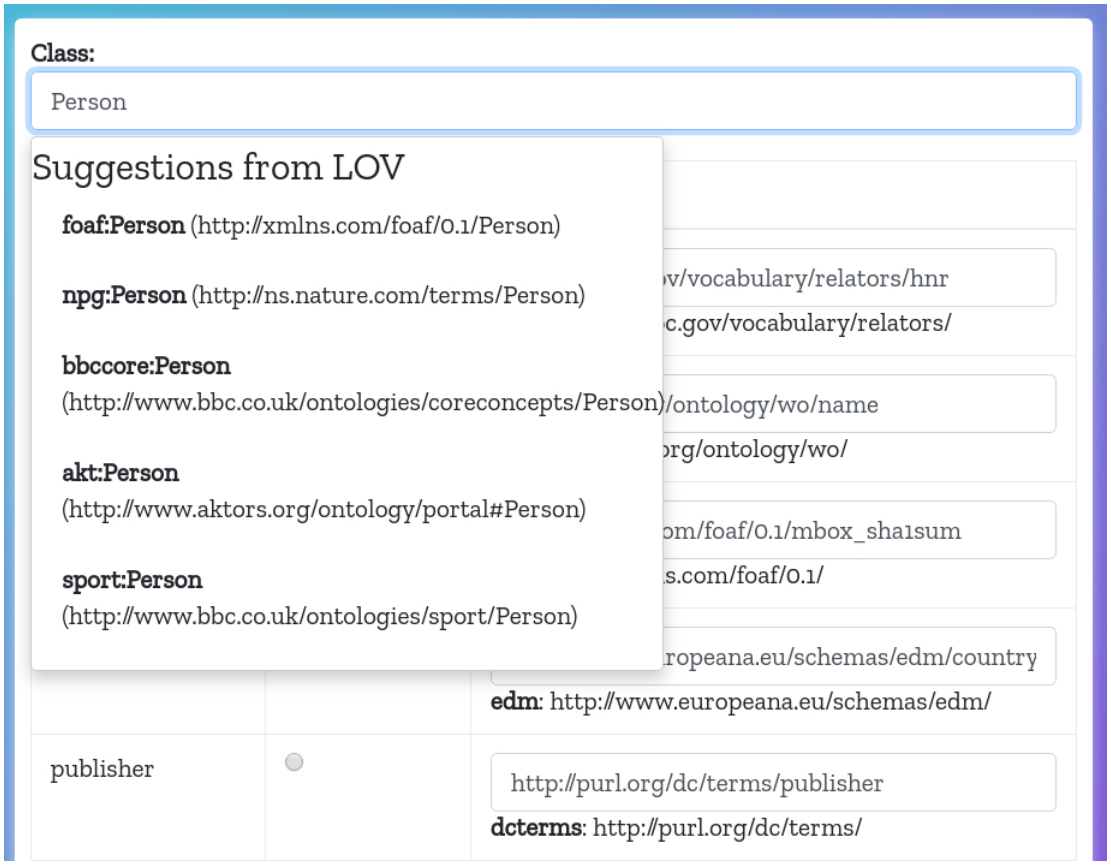


Figure 7.4: Mapping UI auto-suggests classes and properties, but users can adjust. Here we are searching for an RDF class to map a Person entity. The first column of the table contains the entity attributes and the third column contains the RDF predicates. The middle column contains a checkbox to state which predicate to use as the entity (later ParSet) ID.

by manipulating internal data structures using an API, and one queries the data using a single self-contained SQL query. Most other existing engines align with one of the two types, as we described in section 6.2.1. As a result, developers can largely be guided by Squerall existing Spark and Presto executors. For example, Flink is similar to Spark, and Drill and Dremio are similar to Presto.

7.3.2 Supporting More Data Sources

As we recognize the burden of creating wrappers for the variety of data sources, we chose not to reinvent the wheel and rely on the wrappers often offered by the developers of the data sources themselves or by specialized experts. The way a connector is used is dependent on the engine:

- **Spark:** The connector's role is to load a specific data entity into a DataFrame using *Spark SQL API*. It only requires providing access information inside a simple *connection template*:

```
spark.read.format(sourceType).options(options).load
```

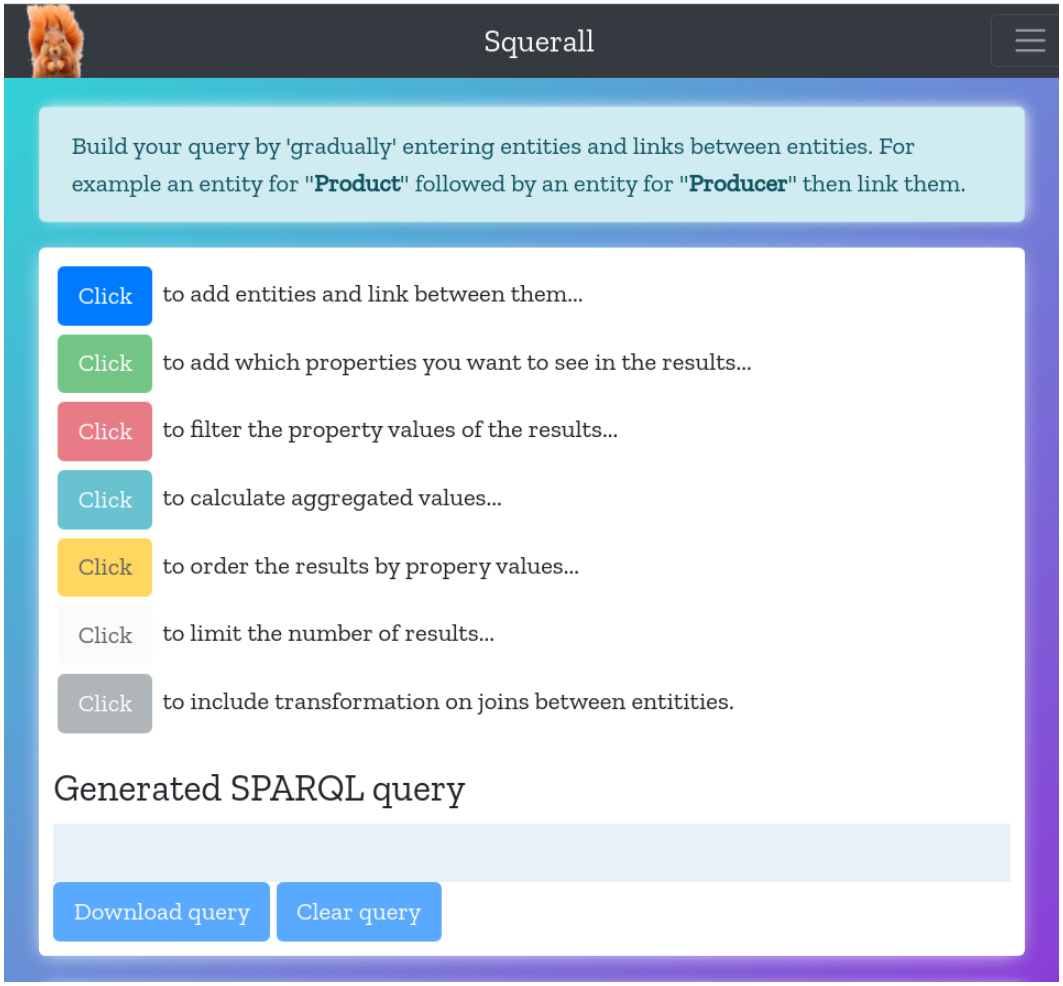


Figure 7.5: SPARQL UI, a general overview. Every button opens a query widget that adds a part (augmentation) to the query. For example, the blue button creates the BGP (`WHERE`) —also illustrated in Figure 7.6, the green creates the `SELECT` clause, the red creates the `FILTER` clause, etc. We avoid to use technical terms and substitute them with natural understandable directives, e.g., "limit the number of results" instead of e.g., "add the LIMIT modifier". The query will be shown in the button and can downloaded or reset.

`sourceType` designates the data source type to access and `options` is a simple key-value list storing e.g., username, password, host, cluster settings, optimization options, etc. The template is similar in most data source types. There are connectors[6] already available for dozens of data sources.

- **Presto:** The connector's role is to read a specific data entity into Presto's internal execution pipeline. It only requires providing access information in a key-value fashion inside a configuration text file. Presto uses directly an SQL query to access the heterogeneous data sources, e.g., `SELECT cassandra.cdb.product C JOIN mongo.mdb.producer M ON C.producerID = M.ID`, i.e., there is no direct interaction with the connectors via APIs.

[6] https://spark-packages.org/

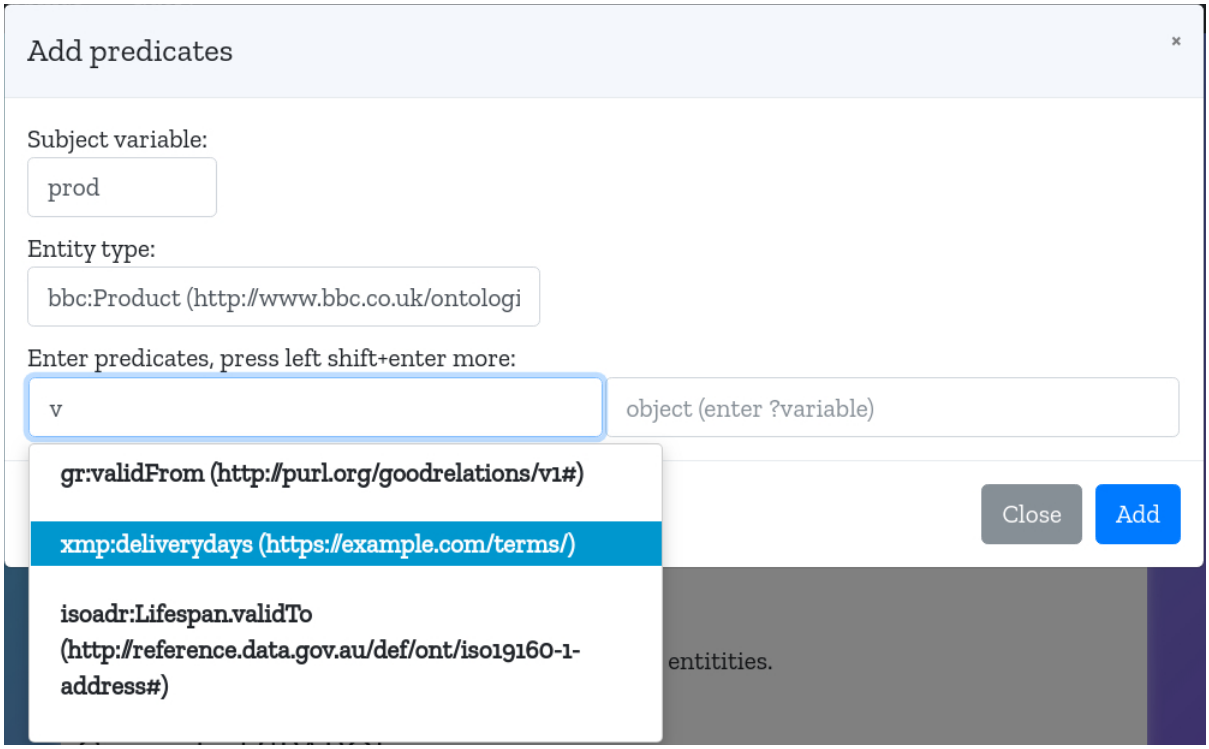


Figure 7.6: SPARQL UI auto-suggests classes and predicates.

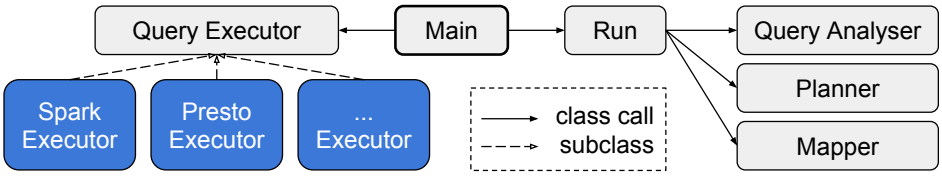


Figure 7.7: Squerall classes call hierarchy shows the modular design of Squerall. In color (blue) are the classes to provide for each query engine, the other classes (grey) remain the same.

Similarly to Spark, there are already several ready-to-use connectors for Presto[7].

To further support developers in extending Sqeruall, an online guide[8] has been made available for the exact steps needed with helpful pointers to the code-source.

7.3.3 Supporting a New Data Source: the Case of RDF Data

In case no connector is found for a given data source type, we show in this section the principles of supporting a new data source. The procedure concerns Spark as query engine, where the connector's role is to generate a DataFrame from an underlying data entity. Squerall did not previously have a wrapper for RDF data. With the wealth of RDF data available today as part of the Linked Data and Knowledge Graph movements, supporting RDF data is paramount. The role of our new Spark RDF connector is to flatten RDF data and save it as a DataFrame.

[7] https://prestosql.io/docs/current/connector.html
[8] https://github.com/EIS-Bonn/Squerall/wiki/Extending-Squerall

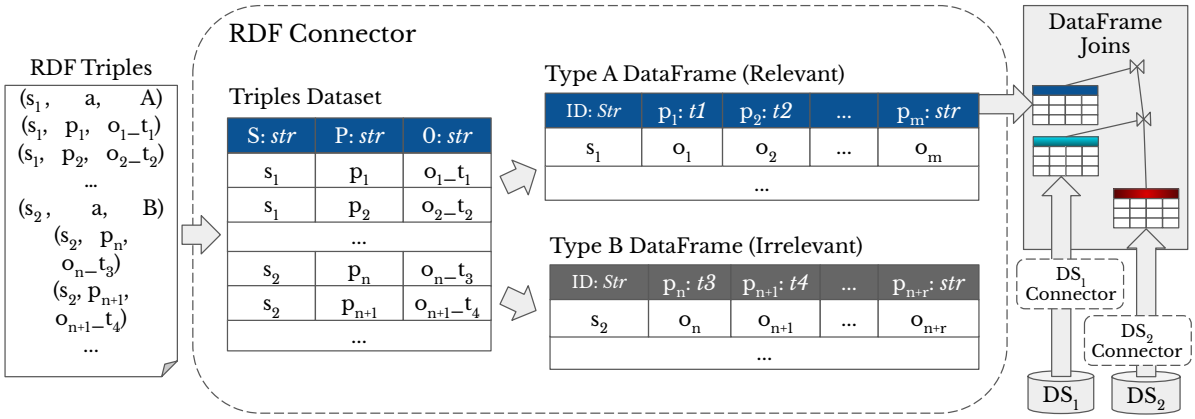


Figure 7.8: RDF Connector. A and B are RDF classes, t_n denote data types.

Contrary to the previously supported data sources, RDF does not require a schema. As a result, lots of RDF datasets are generated and published without schema. In this case, it is required to extract the schema by exhaustively parsing the data on-the-fly during query execution. Also, as per the Data Lake requirements, it is necessary not to apply any pre-processing and to directly access the original data. If an entity inside an RDF data is detected as relevant to a query star, a set of Spark transformations are carried out to flatten the (*subject*, *property*, *object*) triples and extract the schema elements needed to generate a DataFrame. The full procedure is shown in Figure 7.8 and is described as follows:

1. Triples are loaded into a Spark tabular distributed dataset (Called RDD[9]) of the schema *(s: String, p: String, o: String)*, for subject, predicate and object, respectively.

2. Using Spark *transformations*, we generate a new dataset in the following way. We map (s,p,o) triples to pairs: (s,(p,o)), then group pairs by subject: (s,(p,o)+), then find the RDF class from p (i.e., where p=`rdf:type`) and map the pairs to new pairs: (class,(s,(p,o)+])), then group them by class (class, (s, (p, o)+)+). The latter is read as follows: each class has one or more instances identified by 's' and contains one or more (p, o) pairs.

3. The new dataset is *partitioned* into a set of class-based DataFrames, columns of which are the predicates and tuples are the objects. This corresponds to the so-called Property Table partitioning [52].

4. The XSD data types, if present as part of the object, are detected and used to type the DataFrame attributes, otherwise string is used.

5. Only the relevant entity/ies (matching their attributes against the query predicates) detected using the mappings is/are retained, the rest are discarded.

This procedure generates a DataFrame that can join DataFrames generated using other data connectors from other data sources. The procedure is adapted from the RDF data loaded of SeBiDa (Chapter 5, section 5.2). We made the usage of the new RDF connector as simple as the other Spark connectors:

[9] Resilient Distributed Dataset

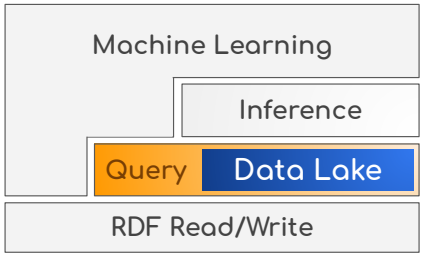


Figure 7.9: Squerall integrated into the SANSA Stack under SANSA-DataLake API.

```
val rdf = new NTtoDF()
df = rdf.options(options).read(filePath,sparkURI).toDF
```

`NTtoDF` is the connector's instance, `options` are the access information including RDF file path and the specific RDF class to load into the DataFrame.

7.4 SANSA Stack Integration

SANSA Stack [214] is a distributed framework for the scalable RDF data processing based on Apache Spark and Flink. It is composed of fours layers in the form of API libraries (used programmatically):

1. **RDF Read/Write Layer.** It allows the access to RDF data stored locally or in Hadoop Distributed File System. Data is loaded into Spark or Flink distributable data structures, e.g., RDDs, DataFrames, DataSets, following various partitioning schemes, e.g., Vertical Partitioning.

2. **Query API.** It allows to run SPARQL queries over large RDF datasets.

3. **Inference API.** It allows to apply inference over large-scale RDF data.

4. **Machine Learning API.** It allows to perform state-of-the-art Machine Learning algorithm on top of large-scale RDF data.

Squerall has been integrated as a sub-layer called SANSA-DataLake API under the SANSA-Query API. SANSA-DataLake broadens the scope of SANSA-Query, and thus SANSA itself, to also query heterogeneous non-RDF data sources. Figure 7.9 presents the SANSA Stack architecture including the SANSA-DataLake API.

7.5 Summary

In this chapter, we presented Squerall —a framework realizing the Semantic Data Lake, i.e., querying original large and heterogeneous data sources using Semantic We technologies. In particular, Squerall performs distributed query processing including cross-source join operation. It allows users to declare transformations that enable joinability on-the-fly at query-time. Squerall is built using state-of-the-art Big Data technologies Spark and Presto, and Semantic Web technologies SPARQL, (RML and FnO) mappings and ontologies. Relying on the query

engines connectors, Squerall relieves users from handcrafting wrappers —a major bottleneck in supporting data Variety throughout the literature. Thanks to its modular design, Squerall can also be extended to support a new query engine. As query and mappings creation can be a tedious task, we built a set of helping user interfaces to guide non-experts to generate the SPARQL query and the needed mappings.

CHAPTER 8

Squerall Evaluation and Use Cases

"The only impossible journey is the one you never begin."

Tony Robbins

In order to evaluate Squerall's query execution performance, we conduct an experimental study using both syntactic and real-world data. For the former, we base on the Berlin benchmark, where its data generator is used to populate five heterogeneous data sources, and its queries are adapted to access the populated data. For the latter, we evaluate the usage of Squerall in an internal use case of a manufacturing company, where both internal data and queries are used.

In this chapter, we address the following research question:

RQ4. Can Semantic Data Lake principles and their implementation Squerall be applied to both synthetic and real-world use cases?

The chapter provides quantifiable measures for the applicability of Squerall on both synthetic and real-world use cases. In particular, we make the following contributions:

- Evaluate Squerall's performance over synthetic data using the Berlin Benchmark, BSBM, where both its Spark and Presto engines are used.
- Report on the query execution time broken down into its constituting sub-phases.
- Assess the impact of the number of joins on the overall query execution time.
- Evaluate Squerall performance on a real-world data in an industrial use case.

This chapter is based on the following publications:

- **Mohamed Nadjib Mami**, Damien Graux, Simon Scerri, Hajira Jabeen, Sören Auer, Jens Lehmann. *Squerall: Virtual Ontology-Based Access to Heterogeneous and Large Data Sources*. In Proceeding of the 18th International Semantic Web Conference (ISWC) 229-245, 2019.
- **Mohamed Nadjib Mami**, Irlán Grangel-González, Damien Graux, Enkeleda Elezi, Felix Lösch. *Semantic Data Integration for the SMT Manufacturing Process using SANSA Stack*. Extended Semantic Web Conference (ESWC) Industry Track, 2020.

8.1 Evaluation Over Syntactic Data

In this section, we examine the performance of Squerall when applied to synthetic data. We set to answer the following questions:

- **Q1:** What is the query performance when Spark and Presto are used as the underlying query engine?
- **Q2:** What is the time proportion of query analysis and relevant source detection times to the overall query execution time?
- **Q3:** What is the performance of Squerall when increasing data sizes are queried?
- **Q4:** What is the impact of involving more data sources in a join query?
- **Q5:** What is the resource consumption (CPU, memory, data transfer) of Squerall running the various queries?

In the following, we describe the experimental protocol then discuss the experimental results.

8.1.1 Experimental Setup

Data

As we have explored in [85], there is still no dedicated benchmark for evaluating SDL implementations, i.e., querying original large and heterogeneous data sources in a uniform way using SPARQL, mappings and ontologies. Therefore, we resort to using and adapting the BSBM Benchmark [194], which is originally designed to evaluate the performance of RDF triple stores with SPARQL-to-SQL rewriters. As Squerall currently supports five data sources, Cassandra, MongoDB, Parquet, CSV, and JDBC, we have chosen to load five BSBM-generated tables into these data sources as shown in Table 8.1. The five data sources allow us to run queries of up to four joins between five distinct data sources. We generate three scales: 500k, 1.5M and 5M (in terms of number of products), which we will refer to in the following as *Scale 1*, *Scale 2* and *Scale 3*, respectively.

Queries

We have adapted the original BSBM queries, so they involve only the tables we have effectively used (e.g., *Vendor* table was not populated) and do not include unsupported SPARQL constructs e.g., `DESCRIBE`, `CONSTRUCT`. This resulted in nine queries[1], listed in Table 8.2, joining different tables and involving various SPARQL query operations.

Metrics

Our main objective is to evaluate the *Query Execution* time. In particular, we observe Squerall's performance with (1) increasing data sizes, (2) increasing data sources. We evaluate the effect of *Query Analyses* and *Relevant Source Detection* on the overall query execution time. We leave time markers at the beginning and end of each phase. Considering the distributed nature of Squerall, we also include a set of system-related metrics, following the framework presented

[1] Available at: https://github.com/EIS-Bonn/Squerall/tree/master/evaluation/input_files/queries

		Product	Offer	Review	Person	Producer
Scale	**Factor**	**Cassandra**	**MongoDB**	**Parquet**	**CSV**	**MySQL**
Scale 1	0.5M	0.5M	10M	5M	~26K	~10K
Scale 2	1.5M	1.5M	30M	15M	~77K	~30K
Scale 3	5M	5M	100M	50M	~2.6M	~100K

Table 8.1: Data loaded and the corresponding number of tuples. Scales factor is in number of products.

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q10
Tables joined									
Product	✔	✔	✔	✔	✔	✔	✔	✔	✔
Offer		✔		✔	✔	✔	✔		✔
Review	✔		✔	✔	✔	✔	✔	✔	
Person							✔	✔	
Producer	✔			✔				✔	✔
Query operations involved									
`FILTER`	✔ 1		✔ 2	✔ 1	✔ 3	✔ 1r	✔ 2	✔ 1	✔ 3
`ORDER BY`	✔		✔	✔	✔			✔	✔
`LIMIT`	✔		✔	✔	✔			✔	✔
`DISTINCT`	✔			✔	✔		✔	✔	✔

Table 8.2: Adapted BSBM Queries. The tick signifies that the query joins with the corresponding table or contains the corresponding query operation. Near to `FILTER` is the number of conditions involved, and r denotes a regex type of filter.

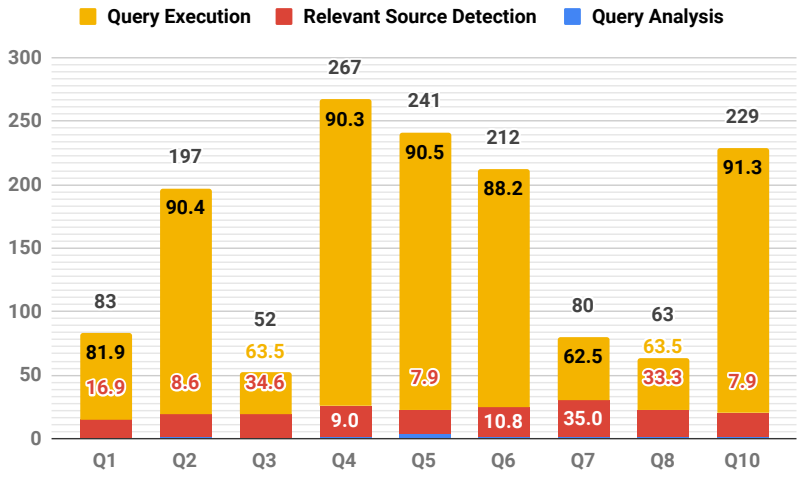
in [215], e.g., average CPU consumption and spikes, memory usage, data read from disk and transferred across the network. We run every query three times on a *cold cache*, clearing the cache before each run. As we report on the impact of every phase on the total query time, we cannot calculate the average of the recorded times. Rather, we calculate the sum of the overall query times of the nine queries of the three runs and take the run with the median sum value. Timeout is set to 3600s.

Environment

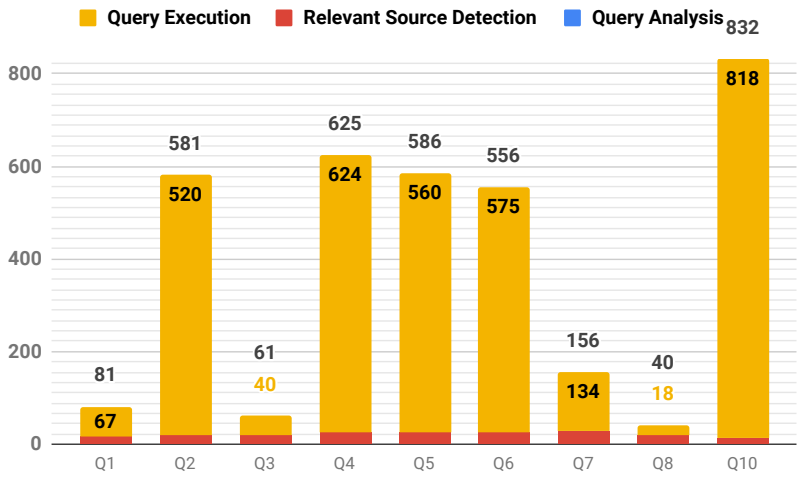
All queries are run on a cluster of three nodes having DELL PowerEdge R815, 2x AMD Opteron 6376 (16 cores) CPU and 256GB RAM, and 3 TB SATA RAID-5 disk. No caching or engine optimizations tuning were exploited.

8.1.2 Results and Discussions

Our extensive literature review reveals no single work that was openly available and that supported all the five sources and the SPARQL fragment that we support. Thus, we compare the performance of Squerall with both Spark and Presto as the underlying query engines. We also monitor and report on resource consumption by Squerall running the various queries.

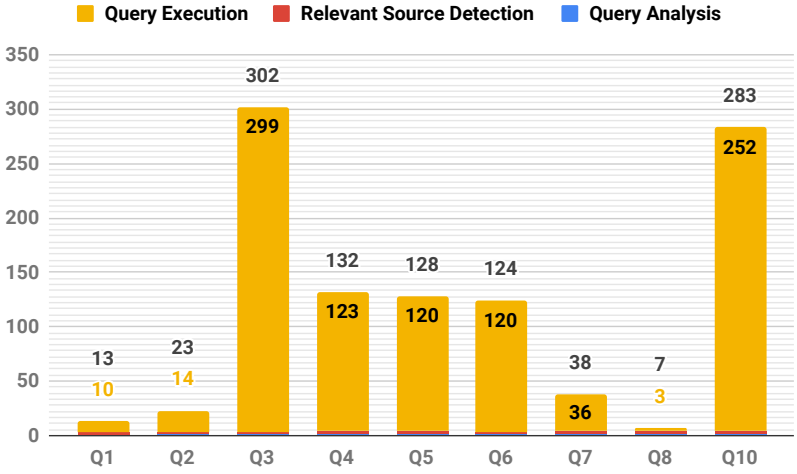


(a) Spark Scale 1.

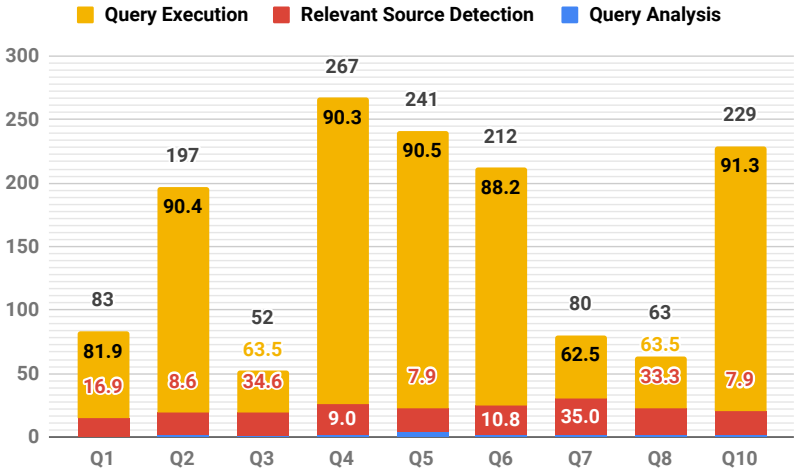


(b) Spark Scale 2.

Figure 8.1: Stacked view of the execution time phases on Presto (seconds). Bottom-up: Query Analyses, Relevant Source Detection, and Query Execution, the sum of which is the total Execution Time shown above the bars. Very low numbers are omitted for clarity.

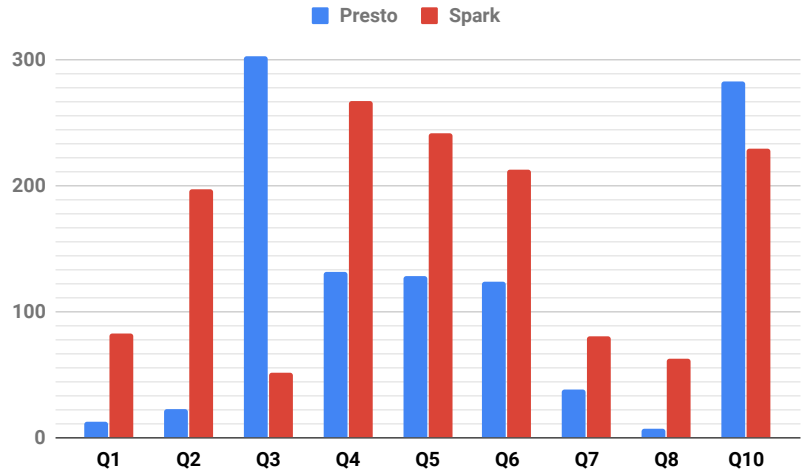


(a) Presto Scale 1.

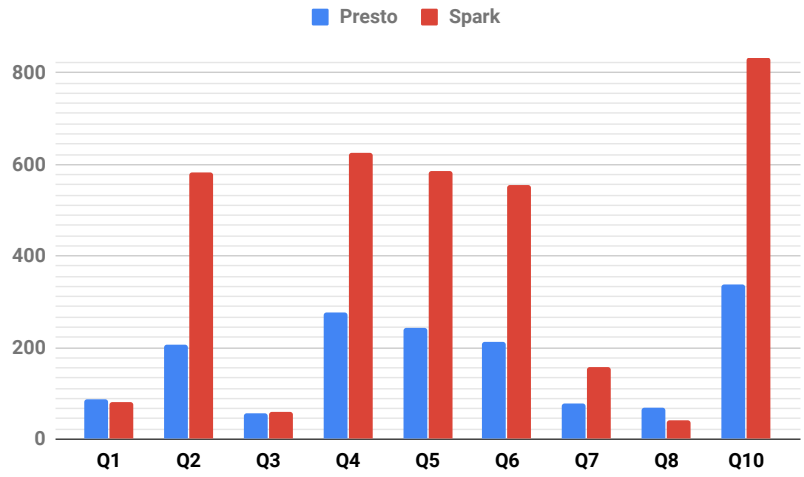


(b) Presto Scale 2.

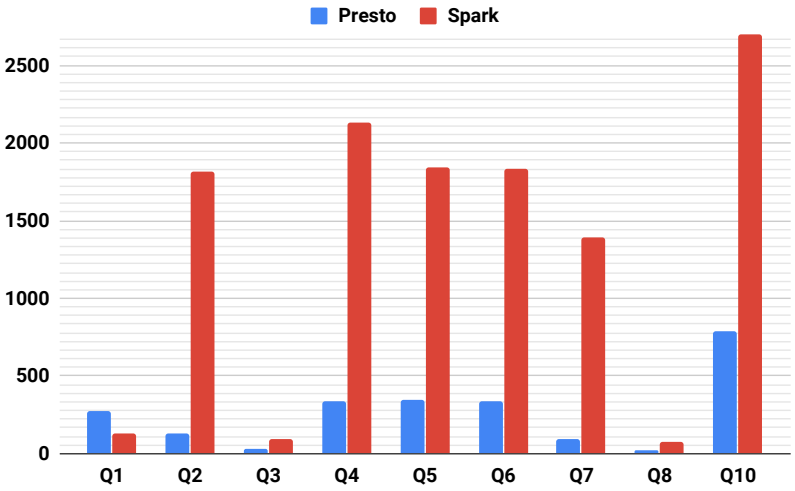
Figure 8.2: Stacked view of the execution time phases on Presto (seconds). Bottom-up: Query Analyses, Relevant Source Detection, and Query Execution, the sum of which is the total Execution Time shown above the bars. Very low numbers are omitted for clarity.



(a) Scale 1.



(b) Scale 2.



(c) Scale 3.

Figure 8.3: Query execution time (seconds). Comparing Spark-based vs. Presto-based Squerall.

Performance

The columns in Figure 8.1 and Figure 8.2 show the query execution times divided into three phases (each with distinct color):

1. **Query Analysis:** Time taken to extract the stars, joins between stars, and the various query operations linked to every star e.g., filtering, ordering, aggregation, etc.
2. **Relevant Source Detection:** Time taken to visit the mappings and find relevant entities by matching SPARQL star types and predicates against source entities and attributes.
3. **Query Execution:** Time taken by the underlying engine (Spark or Presto) to effectively query the (relevant) data sources and collect the results. This includes loading the relevant entities into ParSets (or a subset if filters are pushed down to the sources), performing query operations e.g., filtering, executing joins between ParSets, and finally performing results-wide operations e.g., order, aggregate, limit, etc.

The results[2] presented in Figures 8.1, 8.2 and 8.3 suggest the following:

- Presto-based Squarall is faster than Spark-based in most cases except for Q3 and Q10 at Scale 1. It has comparable to slightly lower performance in Q1 and Q8 at Scale 2. This superiority can be explained by Presto's nature that is precisely built and optimized for running cross-source *interactive* SQL queries. Spark, on the other hand, is a general-purpose engine with a SQL layer, which builds on Spark's core in-memory structures that are not originally designed for ad hoc querying. Unlike Spark, Presto does not load entities in blocks but streams them through a query execution pipeline [208]. However, Presto's speed comes at the cost of weaker query resiliency. Spark, on the other hand, is more optimized for fault tolerance and query recovery, making it more suitable for long-running complex queries. The latter are, however, not the case of our benchmark queries. **(Q1)**
- Query Analysis time is negligible; in all the cases it did not exceed 4 seconds, ranging from $< 1\%$ to 8% of the total execution time. Relevant Source Detection time varies with the query and scale. It ranges from 0.3% (Q3 Presto Scale 1) to 38.6% (Q8 Spark Scale 2). It is, however, homogeneous across the queries of the same scale and query engine. Query Execution time is what dominates the total query execution time in all the cases. It ranges from %42.9 (Q8 Presto Scale 1) to 99% (Q3 Spark Scale 2), with most percentages being about or above 90%, regardless of the total execution time. Both Query Analysis and Relevant Source Detection depend on the query and not the data, so their performance is not affected by the data size (hence the absence of numbers for Scale 3). **(Q2)**
- Increasing the size of the queried data did not deteriorate query performance. Co-relating query time and data scale indicates that performance is proprietorial to data size. Besides, all the queries finished within the threshold. **(Q3)**
- The number of joins did not have a decisive impact on query performance, it rather should be taken in combination with other factors, e.g., the size of involved data, the presence of filters, etc. For example, Q2 joins only two data sources but has comparable performance with Q5 and Q6 that join three data sources. This may be due to the presence of filtering in Q5 and Q6. Q7 and Q8 involve four data sources, yet they are among the fastest queries.

[2] Also available online at:https://github.com/EIS-Bonn/Squerall/tree/master/evaluation

Metrics	Spark			Presto		
	Node 1	Node 2	Node 3	Node 1	Node 2	Node 3
CPU Average (%)	4.327	7.141	4.327	2.283	2.858	2.283
Time Above 90% CPU (s)	9	71	9	0	2	0
Time Above 80% CPU (s)	19	119	19	0	5	0
Max Memory (GB)	98.4	100	98.4	99.5	99.7	99.5
Data Sent (GB)	4.5	6.3	4.5	5.4	8.5	5.4
Data Received (GB)	3.5	3.0	3.5	8.4	4.6	8.4
Data Read (GB)	9.6	5.6	9.6	1.9	0.2	1.9

Table 8.3: Resource Consumption by Spark and Presto across the three nodes on Scale 2.

This is because they involve the small entities *Person* and *Producer*, which significantly reduce the intermediate results to join. With four data sources, Q4 is among the most expensive. This can be attributed to the fact that the filter on products is not selective (`?p1 > 630`), in contrast to Q7 and Q8 (`?product = 9`). Although, the three-source join Q10 involves the small entity *Producer*, it is the most expensive; this can be attributed to the very unselective product filter it has (`?product > 9`). **(Q4)**

Resource Consumption

Resource consumption is visually represented in Figure 8.4 and reported in Table 8.3. We recorded (1) CPU utilization by calculating its average percentage usage as well as the number of times it reached 80% and 90%, (2) memory used in GB, (3) data sent across the network in GB, and (4) data read from disk in GB. We make the following observations **(Q5)**:

- Although the average CPU is low (below 10%), monitoring the 90% and 80% spikes shows that there were many instants where the CPU was almost fully used. The latter applies to Spark only, as Presto had far less 80%, 90% and average CPU usage, making it a lot less CPU-greedy than Spark.
- From the CPU average, it still holds that the queries overall are not CPU-intensive. CPU is in most of the time idle; the query time is rather used by the loading and transfer (shuffling) of the data between the nodes.
- The total memory reserved, 250GB per node, was not fully utilized; at most ≈100GB was used by both Spark and Presto.
- Presto reads less data from disk (Data Read), which can be due to one of the following. Presto does not read the data in full blocks but rather *streams* it through its execution pipelines. Presto might also be more effective at filtering irrelevant data and already starting query processing with reduced intermediate results.

Moreover, in Figure 8.4, we represent *as a function of time* the CPU utilization (in orange, top), the memory usage (in dashed red, bottom) and the data sent over the network[3] (in light blue, bottom) second by second during the complete run of the benchmark at Scale 2 with Spark. The noticed curve stresses correspond to the nine evaluated queries. We notice the following:

[3] For clarity reasons, we do not include Data Received traffic, since it is completely synchronized with Data Sent.

- CPU utilization curves change simultaneously with Data Sent curve, which implies that there is a constant data movement throughout query processing. Data movement is mainly due to the join operation that exists in all queries.
- Changes in all the three represented metrics are almost synchronized throughout all query executions, e.g., there is no apparent delay between Data Sent or Memory usage and the beginning of the CPU computation.
- Memory activity is correlated with the data activities (received and sent), all changes in memory usage levels are correlated with high network activity.
- Unexpectedly, the memory usage seems to remain *stable* between two consecutive query executions, which is in contradiction with our experimental protocol that applies cache clearing between each query. In practice, this can be attributed to the fact that even if some blocks of memory are *freed*, they remain shown as *used* as long as they are not used again[4].

8.2 Evaluation Over Real-World Data

Squerall has been evaluated internally in a large manufacturing industry[5]. An internal technology, called *Surface-Mount Technology*, generates fine-grained manufacturing data in a streaming fashion and stores it in local log files. Consequently, the resulted size of the data is considerable. Squerall is used to query this data joining distinct subsets thereof and computing aggregations over time intervals. In this section, we first describe the use case and technology involved, then detail how Squerall is used, then finally report on its querying performance.

8.2.1 Use Case Description

Surface-Mount Technology, SMT, is a process for mounting electronic components, e.g., microchips, resistors, capacitors, on print-circuit boards, PCBs. Several sub-processes are involved in producing these PCBs and are executed by specialized machines. We are interested in two sub-processes in particular: Surface Mount Devices, SMD, and Automatic Optical Inspection, AOI. The SMD places the electronic components on top of the PCBs, and the AOI inspects the boards for any error that could have occurred, e.g., misplaced or bad solder components. To be able to improve the SMT process in general and the error detection process at the end of the SMT line in particular, the semantics of the data generated by the machines should be harmonized. This can be achieved by posing a semantic model that unifies the interpretation of the different concepts. This allows to run *ad hoc* queries over the data generated by the two sub-processes in a uniform way. SMT and AOI data is available in Parquet format, other sub-processes generate data in CSV format, etc. In order to be able to access these heterogeneous data sources uniformly, Squerall has been used.

The SMT use case has the following requirements that need to be met by the access solution, which is Squerall in our case:

[4] For more details, see following the common UNIX strategy of memory management https://git.kernel.org/pub/scm/linux/kernel/git/torvalds/linux.git/commit/?id=34e431b0ae398fc54ea69ff85ec700722c9da773

[5] We are abide by not revealing identity, data or ontology.

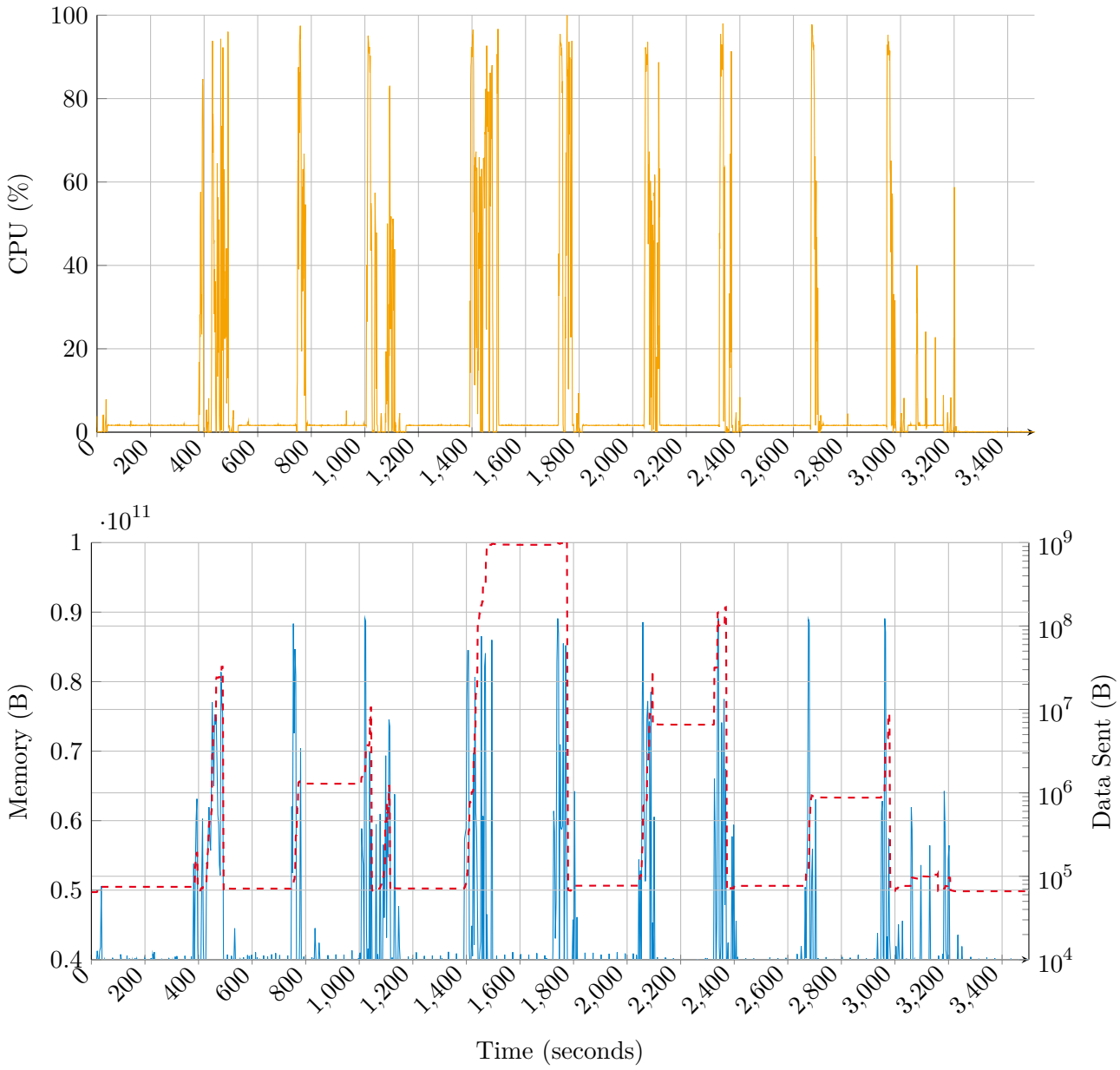


Figure 8.4: Resource consumption recorded on one cluster node (which we observed was representative of the other nodes) with Spark as query engine on Scale 2. Top is CPU percentage utilization. Bottom left dashed is RAM (in Bytes) recorded at instant t, e.g., $0.4\text{x}10^{11}B \approx 37GB$. Bottom right is Data Sent across the network (in Bytes) at instant t, e.g., $10^8B \approx 95MB$.

SMD Tables	AOI Data Tables
Event	aoiEvent
Machine	aoiFailures
ProcessedPanel	aoiProcessedPanel
ProcessedComponents	aoiComponents
Feeder	aoiComponentsPin
Nozzle	aoiClassifications
smdBoard	aoiMesLocation
Head	

Table 8.4: SMD and AOI provided tables.

- **R1.** Querying the data uniformly using SPARQL as query language exploiting data semantics that is encoded in the SMT ontology.
- **R2.** Querying should be scalable accessing the various provided data sizes.
- **R3.** Querying should support temporal queries (i.e., `FILTER` on the time), and aggregation queries (i.e. `GROUP BY` with aggregate functions, e.g., sum, average).

SMT-generated Data. SMT use case data consists of fifteen tables, eight pertaining to SMD sub-process and seven to AOI sub-process (see Table 8.4). For SMT, *Event* is the action performed (e.g. pick, place), *Machine* is the machine performing the action, *ProcessedComponents* are the components being moved (e.g., picked, placed), *Feeder* is a device from which the machine picks a component, *ProcessedPanel* and *Board* are respectively the panel and board where components get placed, *Head* is the mechanical arm moving the component, *Nozzle* is the end used to handle a specific type of component. For AOI, *Event* is the action during which the failure happened, *Failure* is the failure specification, *Component* and *ProcessedPanel* are respectively which component and panel the failure concerns, *MesLocation* is the panel location, and *CompoenentstPin* is the component connector on which the error was detected.

8.2.2 Squerall Usage

Thanks to Squerall's internal abstraction component (ParSets), data in its format heterogeneity can be represented and queried in a uniform manner. The target data of SMT use case is SMD and AOI, which both being stored in Parquet format. As such, data itself is not heterogeneous by nature, however, it benefits from Squerall *mediation* mechanism that supports the simultaneous access to multiple data sources. In other words, the query is run against the abstraction layer regardless of where data was originated from; all data being of Parquet format or other heterogeneous formats. The use case also principally benefits from Squerall scalability at querying large data sources, thanks to leveraging Big Data technologies. Limited to the available infrastructure at the premises of the use case company, only Apache Spark is used and not Presto.

As the data generated belongs to the same domain, the SMT use case does not require query-time transformation (to enable joinability). Hence, we omit query-time transformations from Squerall architecture and suggest a simplified version, which is presented in Figure 8.5. To interact with Squerall, the user issues a query on the command line where the results are

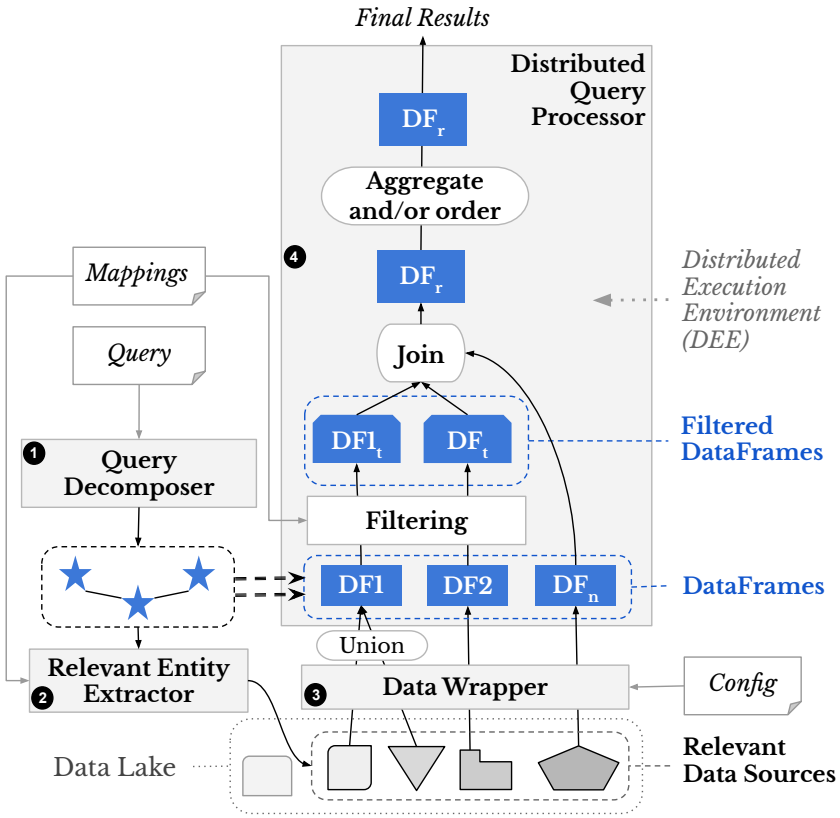


Figure 8.5: Squerall architecture variation excluding query-time transformations. ParSet is replaced by its implementation in Spark, namely DataFrame.

subsequently shown, see Figure 8.6. The output returned in the console first shows the query that is being executed, then the schema of the results table, then the results table itself, then the number of results and finally the time taken by the query execution.

8.2.3 Evaluation

In the following, we will report on the empirical study, which we have conducted to evaluate Squerall's performance querying SMT data. The research questions addressed are reduced to the following:

- **RQ1:** What is the performance of Spark-based Squerall accessing SMT data by means of join, aggregation and temporal queries?
- **RQ2:** What is the performance of Spark-based Squerall when *increasing* data sizes are queried?

Data and queries

Three sizes of SMT data are used for the evaluation, as shown in Table 8.5. SMT use case involves thirteen (13) queries, which have been evaluated using Squerall and reported in Table 8.6.

Scale 1	Scale 2	Scale 3
439M	3.8G	7.7G

Table 8.5: The sizes of the three data scales.

```
Going to execute the query:
PREFIX psmt: <                    /product#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?panel ?ts
WHERE {
  ?panel psmt:processedTimestamp ?ts .
 query execution: 1787 6-01T02:17:54+02:00')
  FILTER (?ts < '2018-06-02T07:04:14+02:00')
}
panel_processedTimestamp_psmt,panel
[2018-06-02 05:04:14.0,085079990009718060222610413 68]
[2018-06-02 17:23:56.0,085079990005818060222610413 39]
[2018-06-02 14:02:45.0,085089990058818060222610414 84]
[2018-06-02 16:41:24.0,085089990079918060222610414 84]
[2018-06-02 03:32:37.0,085089990013718060222610426 13]
[2018-06-02 14:51:50.0,085089990059518060222610414 84]
[2018-06-02 14:31:42.0,085079990016018060222610413 79]
[2018-06-02 20:31:42.0,085079990016618060222610414 13]
[2018-06-02 19:24:00.0,085089990007318060222610405 25]
[2018-06-02 05:52:56.0,085079990014818060222610413 68]
[2018-06-02 09:09:47.0,085089990015118060222610414 84]
[2018-06-02 12:21:54.0,085089990051718060222610414 84]
[2018-06-02 12:42:05.0,085079990011818060222610413 79]
[2018-06-02 23:08:04.0,085089990029918060222610426 13]
[2018-06-02 17:46:24.0,085089990085218060222610414 84]
[2018-06-02 09:15:44.0,085089990016418060222610414 84]
[2018-06-02 23:36:28.0,085089990033518060222610426 13]
[2018-06-02 15:50:10.0,085079990027418060222610413 79]
[2018-06-02 22:06:39.0,085079990004918060222610433 36]
[2018-06-02 17:28:03.0,085079990017218060222610413 39]
Number of results: 2106
Time of query execution: 1787
```

Figure 8.6: An example of the console output returned by Squerall running a query. It shows the issued query then the results then the execution time (seconds).

Discussion

Table 8.6 shows all the queries, along with their support status (supported by Squerall or not), their query execution time across the three data scales and a description of their content. All queries finished within the threshold of 300 seconds (5 minutes) in the three data scales, with no empty results set. Query times range from 0.25s minimum (Scale 1) to 129s maximum (Scale 3). Q1 and Q2 are the fastest queries; Q1 does not contain any join and filters the results to only one day of data. Q2 contains two joins but the filter significantly reduces the results to one specific `panelId`. Q5 and Q13 are the slowest queries as they involve two joins including both SMD and AOI data with no filter. Q13 is slower than Q5 with a factor of 2, as it does

Query	Supported?	Scl 1	Scl 2	Scl 3	Description
Q1	✔	1.28	2.15	2.02	No join, time filter
Q2	✔	0.27	3.26	3.74	2 joins, ID filter
Q3	✗ *(sub-q)*	/	/	/	/
Q4	✗ *(sub-q)*	/	/	/	/
Q5	✔	7.17	36.16	68.79	2 joins, SMT & AOI, ID filter
Q6	✗ *(sub-q)*	/	/	/	/
Q7	✗ *(obj-obj join)*	/	/	/	/
Q8	✔	2.78	9.85	29.98	1 join, time filter
Q9	✗ *(agg sub)*	/	/	/	/
Q10	✔	2.98	4.74	5.38	1 join, SMD & AOI, time filter, agg.
Q11	✔	4.68	5.34	11.77	2 joins, SMD & AOI, time filter, agg.
Q12	✗ *(agg sub)*	/	/	/	/
Q13	✔	14.51	79.52	129.59	2 joins, SMD & AOI

Table 8.6: Query Execution times (seconds). *sub-q* refers to a query containing a sub-query, *obj-obj join* refers to a query that contains joins at the object position, and *agg obj* refers to a query that contains an aggregation on the subject. Under Description, 'time filter' means that the query contains filter restricting the results inside a specific time interval, 'ID filter' means that the query contains a filter on a very specific panelID.

not contain any filter in contrast to Q5. Q10 and Q11 both involve join plus an aggregation, however, they are relatively fast as they involve filtering on a timestamp field limiting the results to only ten days worth of data. Q11 is slower than Q10 as it joins between three tables in contrast to two in Q10. Finally, Q8 falls in the middle of the query time range; although it contains a join, it filters the results to one day worth of data.

Table 8.6 also points to what queries are not supported. Squerall at the time of conducting the evaluation did not support SPARQL queries containing a sub-query, an object to object join, a filter between object variables, and aggregation on the subject position. See Figure 8.7 for unsupported query examples and explanations. This affects Q3 and Q6 (sub-query), Q7 and Q4 (object-object join), and Q9 and Q12 (aggregation on the subject position). When there is a filter comparing two object variables, the case of Q2 and Q4, the query is executed with the unsupported filter omitted.

8.3 Summary

In this chapter, we reported on our experience evaluating Squerall performance using both synthetic and real-world use cases. In the synthetic use case, we used Berlin Benchmark, both data and query. We used a subset of the data (tables) to populate the data sources that Squerall supports. We also used a subset of the queries (nine out of twelve) excluding unsupported query types (e.g., `DESCRIBE`). We evaluated Squerall accuracy, performance and query execution time breakdown into sub-phases: query analysis, relevant source detection and query execution. The results suggested that all queries exhibited 100% accuracy and that all queries were successful finishing within the threshold. The results also showed that query execution time was in the worst case proportional to the increasing data sizes. In the real-world use case, Squerall executed

```
?f fsmt:isFailureOf ?pin ;
   fsmt:failureType ?type .
?c psmt:hasPin ?pin .
   psmt:referenceDesignator ?r .
   psmt:hasSMDHead ?h .
```

(a) An example of object-object join from Q7 on variable `?pin` between the two stars `?f` and `?c`.

```
SELECT (COUNT(?failure) as ?failuresShape) ?shape
WHERE {
 ?component psmt:hasPin ?pin ;
            psmt:componentShape ?shape .
 ?failure a fsmt:Tombstoning ;
            fsmt:isFailureOf ?pin .
```

(b) An example of aggregation on object from Q12, `COUNT` on `?failure` object variable.

```
FILTER (?ts2 > ?ts)
FILTER (?panelId = "085079990025218062222261041592")
```

(c) An example of filter between object variables from Q2, between `?ts` and `ts2`.

Figure 8.7: Examples of unsupported SPARQL queries. The red font color highlights the unsupported operations. In (a) object-object join, in (b) aggregation on the abject variable, (c) filter including two variables. Queries (a) and (b) are discarded, query (c) is executed excluding the unsupported filter (strikethrough).

queries withing the threshold of five minutes along the three data sizes used. The use case included queries with unsupported SPARQL constructs e.g., sub-queries, in which case the queries were not executed. Supporting this constructs is planned for Squerall's next release.

CHAPTER 9

Conclusion

"A person who never made a mistake never tried anything new."

Albert Einstein

In this thesis, we investigated the problem of *providing an ad hoc uniform access to large and heterogeneous data sources using Semantic Web techniques and technologies*. We examined the applicability of existing Semantic-based Data Integration principles, notably, Ontology-Based Data Access, to the Big Data Management technology space. We studied both the Physical and Logical approaches of Data Integration, with more emphasis on the latter. We defined the tackled problem, challenges and contributions in Chapter 1. We presented the background and the necessary preliminaries in Chapter 2. We gave a state-of-the-art overview of the related efforts in Chapter 3. As model and query conversion was an integral part of our envisioned Data Integration approaches, we conducted a survey on the Query Translation approaches, reported in Chapter 4. The survey also supported us in the different design and optimization decisions we have made. Chapter 5 was dedicated to describing our Physical Data Integration approach, including the Semantified Big Data Architecture definition, its requirements, implementation and empirical evaluation. Chapter 6 was dedicated to describing our Logical Data Integration approach, including the Semantic Data Lake definition, its architecture as well as a set of requirements for its implementation. Our implementation of the Semantic Data Lake was detailed in Chapter 7. Finally, Chapter 8 presented two use cases of the latter implementation, one based on a synthetic benchmark and one based on a real-world industrial application.

9.1 Revisiting the Research Questions

In the introduction of the thesis (Chapter 1), we have defined four research questions that were intended to frame our core contributions of the thesis. In this conclusion, it is important to retrospectively revisit every research question and make a brief summary about how it was tackled. In particular, how our Physical and Logical approaches for Data Integration of heterogeneous and large data sources were conceptually defined and practically implemented.

RQ1. What are the criteria that lead to deciding which query language can be most suitable as the basis for Data Integration?

We have tackled this question by conducting an extensive literature review on the topic of Query Translation, reported in Chapter 4. As the topic was of a general interest and pertained to an essential aspect of data retrieval in general, the review was enriching and profitable. It covered both the syntactic and semantic considerations of query translation, query rewriting and optimization, and the different strategies of transitioning from an input to a target query, e.g., direct, via intermediate phase, using an (abstract) meta-language, etc. The survey had several motivations, summarized as follows. First, as model and query conversion is at the core of data integration, it was necessary to have a general overview of the existing query translation approaches. This helped us support the choices we made for the external query language (SPARQL), underlying meta query language (SQL), as well as the transition between the two in a query execution middleware. For example, SPARQL and SQL were the most translated to and from query languages, which makes them very suitable to act as a universal query language. Second, the feasibility and efficiency of a query translation method can only be evaluated within an operable data translation or migration system, which we wanted to leverage to make sound design decisions in our different integration approaches. As examples, the use of a meta-language, as well as query augmentation starting from iteratively analyzing the input query were both prevalent techniques from the literature, which we adopted. A side motivation was that, at the time of reviewing, there was no published survey addressing the query translation across multiple query languages. All that existed was aiming at pair-wise methods involving only two query languages. We reviewed more than forty query translation efforts, including tools only available in source hosting services with accompanying description. The survey allowed us to detect patterns and criteria, against which we classified the reviewed efforts. The criteria included translation type (direct, indirect), schema-aware or mappings-dependent translation, commonly used optimization techniques, query coverage as well as community adoption. Finally, through the survey, we were able to detect the translation paths for which there existed a few to no publications, as well as to learn some lessons for future research on the topic.

RQ2. Do Semantic Technologies provide ground and strategies for solving Physical Integration in the context of Big Data Management i.e., techniques for the representation, storage and uniform querying of large and heterogeneous data sources?

This question was addressed by the Semantic-based Physical Data Integration, detailed in Chapter 5. In the presence of heterogeneous data sources, classified as semantic and non-semantic, the aim was to access the data in a uniform way. First, we suggested a generic blueprint called SBDA, for *Semantified Big Data Architecture*, that supports the integration of hybrid semantic and non-semantic data, and the access to the integrated data. The architecture leveraged Semantic Web techniques and technologies, such as the RDF data model and SPARQL query language. RDF was used as the underlying data model under which all input data of different types is represented and physically converted. Data is then naturally queried in a uniform way using SPARQL. As we target the integration of large datasets, we proposed a data model and storage that is both space-efficient and scalable, i.e., accommodating increasing data sizes while keeping reasonable query performance. We suggested a partitioning scheme that is based on the popular *Property Table* under which RDF instances are stored into tables containing columns corresponding to the instance predicates, e.g., first name, last name and birth date of a person. The tables are clustered by type (RDF class), where all instances of the same type are stored in the same dedicated table. Further, multi-typed instances are captured within the same table via incorporating an extra column storing a list of all types that the

instance belongs to. The table also contains a column for every detected other type, which indicates whether or not (flag) an instance is also of that type. At the physical level, the tables are stored in a columnar-format where data is organized by columns instead of rows. This organization makes it very efficient to store tuples of a large number of columns while accessing only a subset of them. It also enables efficient compression as the data of the same column is homogeneous. These characteristics make this format particularly useful for storing RDF data under our scheme. A SPARQL query typically involves only a subset of the instance predicates. We also benefit from the compression efficiency as we target the integration of large datasets. Under this data partitioning and clustering scheme, input SPARQL query needs to be transparently rewritten to involve the other tables where instances of the same type can be found. A proof-of-concept implementation of the architecture was presented and evaluated for performance and generated data size. Both semantic data (RDF) and non-semantic data (XML) were integrated and queried. In particular, the implementation was compared against a popular RDF triple store and showed its superiority in terms of space usage and query performance when queries large data. State-of-the-art Big Data technologies, namely Apache Spark (ingestion and querying) and Parquet (columnar storage) were used.

RQ3. Can Semantic Technologies be used to incorporate an intermediate middleware that allows to uniformly access original large and heterogeneous data sources on demand?

This question was addressed by the Semantic-based Logical Data Integration, detailed in Chapter 6. Conversely to the Physical Integration, the aim here was to query the original data sources, without a prior transformation to a unique model. In this case, the complexity is shifted from the data ingestion to query processing. Given a query, it is required to detect the relevant data sources, retrieve the intermediate results and combine them to form the final query answer. We proposed an architecture called SDL, for *Semantic Data Lake*, which is based on the OBDA (Ontology-based Data Access) principles. We suggested a set of requirements that should be met when implementing the SDL. For example, the implementation should execute the queries, including multi-source joins, in a distributed manner to cope with data volume. In SDL, data schemata (organized into entities and attributes) are mapped to ontology terms (classes and predicates) creating a virtual semantic middleware against which SPARQL queries can uniformly be posed. The input query is analyzed to extract all the triple pattern groups that share the same subject. Additionally, the connections between these groups as well as any involved query operations (e.g., sorting, grouping, solution modifiers) are detected. The triple pattern predicates, assumed *bound*, are matched against the mappings to find the entities that have attributes matching every predicate. In distributed large-scale settings, two strategies of accessing the detected relevant data entities were described. In the first, the entities are loaded into distributed data structures that can be manipulated by the user. The data structures can be joined following the triple pattern group connections. As optimization, *predicate push-down* is applied to filter the entity at the data source level. The second strategy is when the SPARQL query is internally converted into an intermediate query language, e.g., SQL. The intermediate query is constructed in *augmentation* steps, by analyzing the input query (SPARQL). Once fully constructed, the query is submitted to a query engine that accesses the relevant entities. We presented an extensible implementation of the SDL, which uses RML and FnO for the mappings and Apache Spark and Presto for query execution. The two engines provide the data structures required to distribute the query processing, as well as many readily usable wrappers to enable the loading of data into their internal data structures. The implementation is built following a

modular design allowing it to be extended to support more data sources and incorporate new query engines. The implementation is detailed in a dedicated Chapter 7.

RQ4. Can Virtual Semantic Data Integration principles and their implementation be applied to both synthetic and real-world use cases?

Our SDL implementation was evaluated in two use cases based respectively on a synthetic benchmark and a real-world application from the Industry 4.0 domain. We described the evaluation framework and presented the results in Chapter 8. In the synthetic use case, we used the Berlin Benchmark, BSBM. We generated five datasets and loaded them into the five supported data sources: MongoDB, Cassandra, Parquet CSV, and MySQL. We adapted ten queries to use only the data we ingested and the supported SPARQL fragment. The queries have various numbers of joins, to which we paid special attention to assess the effect of joining multiple heterogeneous data sources. We reported on the query execution time, broken down into query analysis, relevant source detection and actual query execution time. We also examined the implementation scalability by running the queries against three increasing data scales. We reported on the query evaluation by, first, comparing the results cardinality against the results of loading and querying the same benchmark data into MySQL. For data sizes that are beyond MySQL limits, we resorted to comparing the cardinality when Spark and Presto are used as query engines. For the industrial use case, we have experimented with real-world data generated using a so-called *Surface-Mount Technology*. To evaluate the query performance and scalability, we ran the queries against three data scales. The use case involved thirteen SPARQL queries, which we ran and reported. Some queries involved unsupported constructs e.g., sub-queries and aggregation on the object position.

9.2 Limitations and Future Work

Data Integration poses challenges at various levels, from query analysis to data extraction to results reconciliation and representation. Thus, there are several avenues for improvement as well as for extending the current state of the work. In the following, we list a number of directions that the current work could take in the future, classified into Semantic-based Physical Integration and Semantic-based Logical Integration.

9.2.1 Semantic-based Physical Integration

Optimizing the Data Ingestion

In the Semantic-based Physical Integration, we focused our effort more on providing data model and storage schemes that support the integration of large amounts of data under the RDF standard. The most significant lesson learned was that the ingestion of the heterogeneous datasets under a chosen partitioning scheme is a laborious and costly task. The cost increases with the complexity of the partition scheme used. When we assume the absence of an RDF schema, which is not uncommon, the ingestion of RDF data requires exhaustively processing data triple by triple. With large RDF data, this operation becomes severely resource and time-consuming. Most of the existing work that we have reviewed had also incorporated a heavy data ingestion phase in order to pre-compute various joins optimizing for different query shapes and patterns. However, it is usually understated that the improved results were only

possible due to an intensive data ingestion phase, thus little to no attention was dedicated to its optimization. While we recognize the value of collecting statistics, indexing and partitioning the data during the loading time, we deem that a heavy data ingestion phase should be addressed with adequate optimization techniques. The problem is more apparent in our context of large-scale data-intensive environments. For example, statistics calculations could be done in a *lazy* fashion after data has been loaded. Data indexing can also be performed in a similar fashion. In distributed systems, the notion of *eventual consistency* [216] can be ported to having *eventual statistics* or *eventual indexing*. With this, the first queries may be slow but future runs of the same or other queries will eventually have an improved execution time. Data partitioning can also become challenging. If the data has to undergo fundamental model conversion or significant data transformation or adaptation, partitioning optimization possibilities become limited. One may benefit from applying traditional partitioning and scheduling algorithms at the data ingestion phase, e.g., Range partitioning, Hash partitioning, List partitioning, etc. For example, distributing RDF triples into compute nodes based on RDF subject or property. The latter can be useful for Vertical Partitioning schemes. However, this requires a deeper level of customization, which is not always evident if an existing processing engine is used, e.g. Hadoop MapReduce, Spark. In this regard, it is not always recommended to manipulate the underlying distribution primitives and data structures, as this may possibly conflict with the default ingestion and optimization strategies. For example in Hadoop MapReduce, a dedicated programming interface called `Partitioner` offers the possibility to impose a custom data distribution across the cluster nodes. Exploring these avenues is a viable future next-step for this thesis.

Expanding the Scope of Query Patterns

Our suggested Class-based Multi-Type-Aware Property Table scheme has some drawbacks. First, it not allow to answer SPARQL queries where the predicate is unbound. Although it has been reported that unbound predicates are uncommon in SPARQL queries [54], it is still a valid extension of the current querying coverage. This could be implemented by additionally storing the data under the Triple Table scheme *(subject, predicate, object)*. This, however, would add to both the data ingestion time and ingested data size. However, we could use the same columnar format (Parquet) to store this table and thus benefit from its efficient compression capability.

Incorporating Provenance Retention

In a Physical Integration environment, it comes naturally to think of incorporating provenance retention both at the data and query level. Provenance information includes the original source from which a data item was retrieved, the time of retrieval, the person or agent retrieving the information, the sources involved in the query results, the person or agent issuing the query, the query execution time, etc. At the data level, since the data ingestion is a supervised operation, one can easily record, for each ingested item, which data source it was retrieved from, when and by whom. For example, while ingesting RDF triples, it is possible to capture the provenance information at the triple level. It can accompany the triple itself, e.g., *(triple, source, time, user)*, or similarly if other partitioning schemes are used e.g., in Predicate-based Vertical Partitioning *(subject, object, source, time, user)*. Provenance information can also be saved in form of an auxiliary index where every triple is assigned an identifier (e.g., based on a hash function) and mapped to the provenance information e.g., *e.g., (recordID, source, time, user)*. An RDF

technique called *reification* could alternatively be used, whereby provenance information is encoded in the form of RDF statements about RDF statements.

At the query level, it is particularly important to record the query execution time and cardinality. This allows following how the results to the same query evolve over time. The results are timestamped once obtained and saved along with the query statement, the person or agent issuing the query, etc. If provenance information is attached to individual data elements, the query engine can automatically retrieve the provenance information along with the query results. Alternatively, a hash map can be populated during data ingestion, so it is possible to find the original data source by mapping data elements appearing in the results. Technically, distributed Key-value in-memory stores (e.g., Redis[1]) can be used to implement these hash maps. As the provenance information can escalate in size, such distributed Key-value stores can also be leveraged to optimize for disk usage by sharding (dividing) the provenance data across multiple nodes. Finally, Specialized provenance ontologies (e.g., W3C recommendation *PROV-O* [217]) accompanied with data catalog ontologies (e.g., W3C recommendation DCAT [218]) can be used to capture provenance information in the RDF model.

Diversifying Query Results Representation

The default SPARQL query answer is tabular, where every column corresponds to the projected RDF variable. However, when the query is of analytical nature, i.e., computing statistics using aggregation functions (`MAX`, `MIN`, `AVG`, etc.), the query results can also be represented using the W3C recommended *Data Cube* vocabulary [219]. In addition to enabling interoperability and contributing statistical RDF data that can be linked to or from, results can also be visualized using specialized tools e.g., CubeViz [220][2]. Consider the query *"Give me the number of buses per region and driver gender"*, each aggregation column (region and gender) corresponds to a *dimension*, the column of the computed statistical value (bus_number) is the *measure*, and the computed values themselves are the *observations*. Exposing various result formats is also a natural extension of the current Data Integration work.

9.2.2 Semantic-based Logical Integration

Supporting a Larger SPARQL Fragment

The SPARQL fragment that our SDL implementation, Squerall, supports has evolved thanks to the projects it was used in (raised by SANSA users and the I4.0 use case). However, there are still a few query patterns and operations that we find important to cover in the future. For example, sub-queries were common in the industrial use case we described in Chapter 8. Object-object join and aggregation on object variables were also requested. We also see `UNION` and `OPTIONAL` frequently discussed in the literature. While supporting nested sub-queries is challenging given that we map every query star to a ParSet (implemented in tabular format), the other features can be relatively straightforwardly addressed. In other words, the addressable operations and constructs are those that do not interfere with our *start-to-ParSet* principle. In our tabular-based implementation, this requirement is translated to keeping the query shape flat. For example, `UNION` can be addressable because it just requires combining two separate entities, and both our used engines Spark and Presto support an equivalent `UNION` operation.

[1] https://redis.io
[2] https://github.com/AKSW/cubeviz.ontowiki

`OPTIONAL` was less common in the use cases we were involved in, but it is generally translated to SQL *LEFT OUTER JOIN*. It is noteworthy, however, that we did not envision Squerall to be or become a fully-fledged RDF store. The use of SPARQL was more motivated by bridging between the query and the heterogeneous data sources, passing by the mappings. RDF-specific query operations and types such as blank nodes, named graphs, *isURI*, *isLiteral*, `ASK`, `CONSTRUCT`, etc. are considered out-of-the-scope.

Improving Extensibility

Reflected in both our suggested SDL architecture and our implementation of the architecture, we paid special attention to allowing for extension opportunities. In Squerall, we showcased how it can (programmatically) be extended to support more data sources and use other query engines along with the currently-used Spark and Presto. In the first extensibility aspect, our current work advocated for the reuse of data source wrappers from the existing underlying query engines, and thus avoid to each time reinvent the wheel as noticed in the literature. Not only creating wrappers is a laborious error-prone task, it was also observed in several efforts that the wrappers were limited in their ability to match data from the source to the data structure of the query engine. We had our own experience creating wrappers, e.g. MongoDB, and we faced similar difficulties. However, it is remained to state that there might well be other sources for which no wrapper exists. This means that the support for source heterogeneity of our default implementation is limited by the number of wrappers the adopted query engine supports. Although we demonstrated in this thesis the extensibility methodology for supporting new data sources (applied to RDF data), it is still an important manual work involvement, which we aim to partially alleviate by providing specialized guiding user interfaces and suggesting a set of best practices.

The second extensibility aspect is adding another query engine. In subsection 6.2.2 we showed that data can be queried either by manipulating ParSets or augmenting a self-contained internal query submitted as-is to the underlying query engine. The former strategy requires the implementation of common programmatic interfaces. As previously, programmatic challenges can be alleviated by providing graphical interfaces or recommended best practices. The latter strategy, on the other hand, has an intrinsic characteristic that can be levered to support more query engines straightforwardly. That is accepting self-contained queries not requiring any programmatic work. There exist other SQL query engines that can be interacted with using this strategy e.g., Drill, Dremio, Impala. In the future, we can extend our implementation to all these query engines using the *exact* same methods we have established for submitting queries to Presto. These methods generate a self-contained query, which can be submitted *as-is* to the other SQL query engines.

Comparing our SDL Implementation and Establishing an SDL Benchmark

We have not conducted any comparative evaluation against related efforts. We rather self-compared our strategies when both Spark and Presto are used. While we had interesting results for the community, not comparing to another related effort limits the value delivered by the conducted evaluation. In fact, there was no existing SDL implementation or similar that supported all or most of our supported sources. We found only two related efforts both of which supported a few data sources having only one data source in common with our implementation. Efforts for providing a SQL interface on top of NoSQL stores were also either limited in terms

of data sources supported or lack crucial query operations like join. We will continue reviewing the literature for any similar comparable work published. Alternatively, we might alter our benchmarking framework as to compare against single-source approaches (thus eliminating joins), or against SQL-based approaches by creating equivalent SQL queries to our SPARQL queries. Nonetheless, this would not be a valuable comparison for the community and the results would not advance the topic of the work in any significant way.

On the other hand, there is still no benchmark dedicated to comparing SDL implementations. Such a benchmark should be able to generate data that can be loaded into various heterogeneous data sources and generate a set of SPARQL queries. The data can be generated in a canonical format, e.g., relational, which can be saved into the different heterogeneous data sources. This can be achieved by leveraging the wrappers of existing distributed query engines, e.g., Spark. This is the method we have followed to generate BSBM relational data (SQL dumps) and save it into Cassandra, MongoDB, Parquet, CSV and MySQL. This method is straightforward and can exploit the available wrappers of dozens of data source types. The benchmark should also generate a set of mappings linking data schemata elements to ontology terms. The latter could be user-defined as they could be exemplary, which users can later adjust.

9.3 Closing Remark

In the scope of modern Big Data technologies, the topic of Semantic Data Integration, especially the Virtual Integration, is still in its infancy. At the time of writing, there is no production-ready openly-available solution that can be used for real-world use cases. For example, as mentioned previously, the efforts that are embarking on this domain lack a common ground that would allow them to be evenly compared. This can also be attributed to the high dynamicity of many of these systems that makes it very challenging to provide sustainable access mechanisms. To the same argument, the substantial model differences between many of the so-called NoSQL stores makes it virtually impossible to establish a standardized way to interface with these stores. This is a widely recognized issue that is a source of active ongoing research. Moreover, from our own experience during this thesis work, dealing with these modern storage and data management systems is a technically tedious task involving a lot of trial-and-error due to the lack of documentation and sufficient previous experiences. On the other hand, adopting the traditional OBDA systems may seem a reasonable direction given their maturity in processing RDF data and dealing with SPARQL specificities. However, Big Data has come with fundamentally different semantics and assumptions that would deeply alter the architecture of these traditional centralized OBDA systems. These range from dealing with large distributed data requiring parallel processing (e.g. distributed join) to supporting data sources that are very dissimilar in terms of their data model, query syntax and access modality.

The Physical and Logical Data Integration are two different approaches, which are also opposite in certain respects. They both have their application scope, merits and challenges. The Physical Data Integration is favored when it is explicitly desired to transform all input data into a unique data model and, thus, benefit from model uniformity advantages, e.g. improved query performance. However, data transformation and centralization is a challenge that worsens with the increased data volume and variety. The Logical Data Integration is favored if data freshness and originality are not to be compromised. However, disparate data needs to be individually accessed then, on-the-fly, homogenized and reconciled. This lowers the *time-to-query* (i.e., data is accessed directly) but raises the *time-to-results* (i.e., longer execution time). Our focus on the

Logical Data Integration in this thesis gives no recommendation for the latter over the former. It is a choice that we made after balancing between the technical challenge (a one that promises faster progress based on our practical experience) and scientific impact and significance (a one that is more recent and, thus, with more open issues and innovation opportunities).

In the end, it is our hope that this thesis will serve as a reference for future students and researchers in the topic of '*Semantic Web for Big Data Integration*', setting foundations for future research and development in the topic.

Bibliography

[1] D. Laney, *Deja VVVu: others claiming Gartner's construct for big data*, Gartner Blog, Jan **14** (2012) (cit. on p. 1).

[2] E. F. Codd, *A relational model of data for large shared data banks*, Communications of the ACM **13** (1970) 377 (cit. on pp. 1, 42).

[3] S. Baškarada and A. Koronios, *Unicorn data scientist: the rarest of breeds*, Program (2017).

[4] J. Dixon, *Pentaho, Hadoop, and Data Lakes*, Online; accessed 27-January-2019, 2010, URL: https://jamesdixon.wordpress.com/2010/10/14/pentaho-hadoop-and-data-lakes (cit. on pp. 22, 42, 84, 85).

[5] D. Borthakur et al., *HDFS architecture guide*, Hadoop Apache Project **53** (2008) 2 (cit. on pp. 3, 18).

[6] O. Lassila, R. R. Swick et al., *Resource description framework (RDF) model and syntax specification*, (1998) (cit. on pp. 6, 14, 87).

[7] E. Prud'hommeaux and A. Seaborne, *SPARQL Query Language for RDF*, W3C Recommentation, W3C, 2008, URL: http://www.w3.org/TR/rdf-sparql-query/ (cit. on pp. 6, 16).

[8] A. Poggi, D. Lembo, D. Calvanese, G. De Giacomo, M. Lenzerini and R. Rosati, "Linking data to ontologies", *Journal on Data Semantics X*, Springer, 2008 (cit. on pp. 8, 16, 25, 45, 85).

[9] T. J. Berners-Lee, *Information management: A proposal*, tech. rep., 1989 (cit. on p. 13).

[10] J. Conklin, *Hypertext: An introduction and survey*, computer (1987) 17 (cit. on p. 13).

[11] T. J. Berners-Lee and R. Cailliau, *WorldWideWeb: Proposal for a HyperText project*, (1990) (cit. on p. 13).

[12] T. Berners-Lee, J. Hendler, O. Lassila et al., *The semantic web*, Scientific american **284** (2001) 28 (cit. on p. 13).

[13] M. Arenas, C. Gutierrez and J. Pérez, "Foundations of RDF databases", *Reasoning Web International Summer School*, Springer, 2009 158 (cit. on p. 14).

[14] T. Berners-Lee, R. Fielding, L. Masinter et al., *Uniform resource identifiers (URI): Generic syntax*, 1998 (cit. on p. 15).

[15] D. Fensel, "Ontologies", *Ontologies*, Springer, 2001 11 (cit. on p. 15).

[16] M. Uschold and M. Gruninger, *Ontologies: Principles, methods and applications*, The knowledge engineering review **11** (1996) 93 (cit. on p. 15).

[17] P. Agarwal, *Ontological considerations in GIScience*,
International Journal of Geographical Information Science **19** (2005) 501 (cit. on p. 15).

[18] T. Berners-Lee, *Linked data-design issues*,
http://www. w3. org/DesignIssues/LinkedData. html (2006) (cit. on p. 16).

[19] N. Guarino, D. Oberle and S. Staab, "What is an ontology?", *Handbook on ontologies*,
Springer, 2009 1 (cit. on p. 16).

[20] J. Bailey, F. Bry, T. Furche and S. Schaffert,
"Web and semantic web query languages: A survey",
Proceedings of the First international conference on Reasoning Web,
Springer-Verlag, 2005 35 (cit. on p. 16).

[21] P. Haase, J. Broekstra, A. Eberhart and R. Volz,
"A comparison of RDF query languages", *International Semantic Web Conference*,
Springer, 2004 502 (cit. on pp. 16, 47).

[22] E. Prud'hommeaux and A. Seaborne, eds.,
SPARQL Query Language for RDF, W3C Recommendation, 2008,
URL: http://www.w3.org/TR/rdf-sparql-query/ (cit. on p. 16).

[23] J. Pérez, M. Arenas and C. Gutierrez, *Semantics and complexity of SPARQL*,
ACM Transactions on Database Systems (TODS) **34** (2009) 16 (cit. on pp. 16, 43).

[24] J. P. Fry, S. Bramson, D. C. Fried, W. P. Grabowsky and J. Jeffries Jr,
Data management systems survey, tech. rep., MITRE CORP MCLEAN VA, 1969
(cit. on p. 17).

[25] J. P. Fry and E. H. Sibley, *Evolution of data-base management systems*,
ACM Computing Surveys (CSUR) **8** (1976) 7 (cit. on p. 17).

[26] F. Almeida and C. Calistru, *The main challenges and issues of big data management*,
International Journal of Research Studies in Computing **2** (2013) 11 (cit. on p. 17).

[27] J. Chen, Y. Chen, X. Du, C. Li, J. Lu, S. Zhao and X. Zhou,
Big data challenge: a data management perspective,
Frontiers of Computer Science **7** (2013) 157 (cit. on p. 17).

[28] M. Xiaofeng and C. Xiang,
Big data management: concepts, techniques and challenges [J],
Journal of computer research and development **1** (2013) 146 (cit. on p. 17).

[29] A. Siddiqa, I. A. T. Hashem, I. Yaqoob, M. Marjani, S. Shamshirband, A. Gani and
F. Nasaruddin, *A survey of big data management: Taxonomy and state-of-the-art*,
Journal of Network and Computer Applications **71** (2016) 151 (cit. on p. 17).

[30] D. D. Chamberlin and R. F. Boyce, "SEQUEL: A structured English query language",
Proceedings of the 1974 ACM SIGFIDET (now SIGMOD) workshop on Data description, access and control, ACM, 1974 249 (cit. on pp. 18, 42, 43, 63).

[31] T. J. W. I. R. C. R. Division and G. Denny,
An introduction to SQL, a structured query language, 1977 (cit. on p. 18).

[32] J. Gray et al., "The transaction concept: Virtues and limitations", *VLDB*, vol. 81, 1981
144 (cit. on p. 18).

[33] T. Haerder and A. Reuter, *Principles of transaction-oriented database recovery*, ACM computing surveys (CSUR) **15** (1983) 287 (cit. on p. 18).

[34] T. White, *Hadoop: The definitive guide*, " O'Reilly Media, Inc.", 2012 (cit. on pp. 18, 26).

[35] E. Hewitt, *Cassandra: the definitive guide*, " O'Reilly Media, Inc.", 2010 (cit. on p. 19).

[36] A. H. Team, *Apache HBase reference guide*, Apache, version **2** (2016) (cit. on p. 19).

[37] C. Gormley and Z. Tong, *Elasticsearch: the definitive guide: a distributed real-time search and analytics engine*, " O'Reilly Media, Inc.", 2015 (cit. on p. 19).

[38] J. Dean and S. Ghemawat, *MapReduce: simplified data processing on large clusters*, Communications of the ACM **51** (2008) 107 (cit. on p. 19).

[39] P. Carbone, A. Katsifodimos, S. Ewen, V. Markl, S. Haridi and K. Tzoumas, *Apache flink: Stream and batch processing in a single engine*, Bulletin of the IEEE Computer Society Technical Committee on Data Engineering **36** (2015) (cit. on p. 19).

[40] M. Zaharia, M. Chowdhury, M. J. Franklin, S. Shenker and I. Stoica, *Spark: Cluster computing with working sets*, HotCloud **10** (2010) 95 (cit. on pp. 19, 86, 98).

[41] D. Pritchett, *Base: An acid alternative*, Queue **6** (2008) 48 (cit. on p. 20).

[42] E. Hewitt, *Cassandra: the definitive guide*, " O'Reilly Media, Inc.", 2010 (cit. on p. 22).

[43] P. J. Sadalage and M. Fowler, *NoSQL distilled: a brief guide to the emerging world of polyglot persistence*, Pearson Education, 2013 (cit. on pp. 22, 42).

[44] M. Lenzerini, "Data integration: A theoretical perspective", *Proceedings of the twenty-first ACM SIGMOD-SIGACT-SIGART symposium on Principles of database systems*, ACM, 2002 233 (cit. on p. 23).

[45] G. Wiederhold, *Mediators in the architecture of future information systems*, Computer **25** (1992) 38 (cit. on p. 24).

[46] M. J. Carey, L. M. Haas, P. M. Schwarz, M. Arya, W. F. Cody, R. Fagin, M. Flickner, A. W. Luniewski, W. Niblack, D. Petkovic et al., "Towards heterogeneous multimedia information systems: The Garlic approach", *Proceedings RIDE-DOM'95. Fifth International Workshop on Research Issues in Data Engineering-Distributed Object Management*, IEEE, 1995 124 (cit. on p. 24).

[47] M.-E. Vidal, L. Raschid and J.-R. Gruser, "A meta-wrapper for scaling up to multiple autonomous distributed information sources", *Proceedings. 3rd IFCIS International Conference on Cooperative Information Systems (Cat. No. 98EX122)*, IEEE, 1998 148 (cit. on p. 24).

[48] Y. Papakonstantinou, H. Garcia-Molina and J. Widom, "Object exchange across heterogeneous information sources", *Proceedings of the eleventh international conference on data engineering*, IEEE, 1995 251 (cit. on p. 24).

[49] A. Y. Halevy, *Answering queries using views: A survey*, The VLDB Journal **10** (2001) 270 (cit. on p. 25).

[50] D. Calvanese, G. De Giacomo, D. Lembo, M. Lenzerini, R. Rosati and G. A. Ruberti, *Ontology-Based Data Access and Integration.* 2018 (cit. on p. 25).

[51] G. Xiao, D. Calvanese, R. Kontchakov, D. Lembo, A. Poggi, R. Rosati and M. Zakharyaschev, "Ontology-based data access: A survey", IJCAI, 2018 (cit. on pp. 25, 38).

[52] K. Wilkinson, C. Sayers, H. Kuno and D. Reynolds, "Efficient RDF storage and retrieval in Jena2", *Proceedings of the First International Conference on Semantic Web and Databases*, Citeseer, 2003 120 (cit. on pp. 26, 109).

[53] D. J. Abadi, A. Marcus, S. R. Madden and K. Hollenbach, "Scalable semantic web data management using vertical partitioning", *Proceedings of the 33rd international conference on Very large data bases*, VLDB Endowment, 2007 411 (cit. on p. 26).

[54] M. Arias, J. D. Fernández, M. A. Martínez-Prieto and P. de la Fuente, *An empirical study of real-world SPARQL queries*, arXiv preprint arXiv:1103.5043 (2011) (cit. on pp. 26, 31, 82, 133).

[55] K. Wilkinson, *Jena Property Table Implementation*, SSWS (2006) (cit. on pp. 26, 73).

[56] Z. Nie, F. Du, Y. Chen, X. Du and L. Xu, "Efficient SPARQL query processing in MapReduce through data partitioning and indexing", *Web Technologies and Applications*, Springer, 2012 628 (cit. on p. 30).

[57] A. Schätzle, M. Przyjaciel-Zablocki, T. Hornung and G. Lausen, "PigSPARQL: A SPARQL Query Processing Baseline for Big Data.", *International Semantic Web Conference (Posters & Demos)*, 2013 241 (cit. on p. 30).

[58] J.-H. Du, H.-F. Wang, Y. Ni and Y. Yu, "HadoopRDF: A scalable semantic data analytical engine", *Intelligent Computing Theories and Applications*, Springer, 2012 633 (cit. on p. 30).

[59] F. Goasdoué, Z. Kaoudi, I. Manolescu, J. Quiané-Ruiz and S. Zampetakis, "CliqueSquare: efficient Hadoop-based RDF query processing", *BDA'13-Journées de Bases de Données Avancées*, 2013 (cit. on pp. 30, 31).

[60] D. Graux, L. Jachiet, P. Geneves and N. Layaı**********da, "Sparqlgx: Efficient distributed evaluation of sparql with apache spark", *International Semantic Web Conference*, Springer, 2016 80 (cit. on pp. 30–32).

[61] Z. Kaoudi and I. Manolescu, *RDF in the clouds: a survey*, The VLDB Journal—The International Journal on Very Large Data Bases **24** (2015) 67 (cit. on pp. 31, 34).

[62] A. Schätzle, M. Przyjaciel-Zablocki, A. Neu and G. Lausen, "Sempala: Interactive SPARQL Query Processing on Hadoop", *The Semantic Web–ISWC 2014*, Springer, 2014 164 (cit. on pp. 30, 31, 76).

[63] M. Kornacker, A. Behm, V. Bittorf, T. Bobrovytsky, C. Ching, A. Choi, J. Erickson, M. Grund, D. Hecht, M. Jacobs et al., "Impala: A Modern, Open-Source SQL Engine for Hadoop.", *Cidr*, vol. 1, 2015 9 (cit. on p. 31).

[64] A. Schätzle, M. Przyjaciel-Zablocki, S. Skilevic and G. Lausen,
S2RDF: RDF querying with SPARQL on spark,
Proceedings of the VLDB Endowment **9** (2016) 804 (cit. on pp. 30–32).

[65] C. Stadler, G. Sejdiu, D. Graux and J. Lehmann, "Sparklify: A Scalable Software Component for Efficient evaluation of SPARQL queries over distributed RDF datasets", *International Semantic Web Conference*, Springer, 2019 293 (cit. on pp. 30, 32).

[66] O. Curé, H. Naacke, M. A. Baazizi and B. Amann,
"HAQWA: a Hash-based and Query Workload Aware Distributed RDF Store.",
International Semantic Web Conference (Posters & Demos), 2015 (cit. on pp. 30, 32).

[67] L. H. Z. Santana and R. dos Santos Mello, "Workload-Aware RDF Partitioning and SPARQL Query Caching for Massive RDF Graphs stored in NoSQL Databases.", *SBBD*, 2017 184 (cit. on p. 32).

[68] M. Cossu, M. Färber and G. Lausen,
PRoST: distributed execution of SPARQL queries using mixed partitioning strategies,
arXiv preprint arXiv:1802.05898 (2018) (cit. on p. 32).

[69] M. Wylot and P. Cudré-Mauroux,
Diplocloud: Efficient and scalable management of rdf data in the cloud,
IEEE Transactions on Knowledge and Data Engineering **28** (2015) 659 (cit. on p. 32).

[70] M. Mammo and S. K. Bansal, "Presto-rdf: Sparql querying over big rdf data",
Australasian Database Conference, Springer, 2015 281 (cit. on p. 32).

[71] I. Abdelaziz, R. Harbi, Z. Khayyat and P. Kalnis, *A survey and experimental comparison of distributed SPARQL engines for very large RDF data*,
Proceedings of the VLDB Endowment **10** (2017) 2049 (cit. on p. 32).

[72] M. Wylot, M. Hauswirth, P. Cudré-Mauroux and S. Sakr,
RDF data storage and query processing schemes: A survey,
ACM Computing Surveys (CSUR) **51** (2018) 84 (cit. on pp. 32, 34).

[73] R. Punnoose, A. Crainiceanu and D. Rapp,
"Rya: a scalable RDF triple store for the clouds",
Proceedings of the 1st International Workshop on Cloud Intelligence, ACM, 2012 4
(cit. on pp. 30, 33).

[74] R. Punnoose, A. Crainiceanu and D. Rapp, *SPARQL in the cloud using Rya*,
Information Systems **48** (2015) 181 (cit. on pp. 30, 33).

[75] N. Papailiou, I. Konstantinou, D. Tsoumakos and N. Koziris,
"H2RDF: adaptive query processing on RDF data in the cloud.",
Proceedings of the 21st International Conference on World Wide Web, 2012 397
(cit. on pp. 30, 33).

[76] R. Mutharaju, S. Sakr, A. Sala and P. Hitzler,
D-SPARQ: distributed, scalable and efficient RDF query engine, (2013)
(cit. on pp. 30, 33, 47, 51, 57, 59, 61).

[77] C. Hu, X. Wang, R. Yang and T. Wo,
"ScalaRDF: a distributed, elastic and scalable in-memory RDF triple store", *2016 IEEE 22nd International Conference on Parallel and Distributed Systems (ICPADS)*,
IEEE, 2016 593 (cit. on pp. 30, 33).

[78] G. Ladwig and A. Harth,
"CumulusRDF: linked data management on nested key-value stores",
The 7th International Workshop on Scalable Semantic Web Knowledge Base Systems (SSWS 2011), 2011 30 (cit. on pp. 30, 33).

[79] F. Priyatna, O. Corcho and J. Sequeda, "Formalisation and experiences of R2RML-based SPARQL to SQL query translation using morph",
Proceedings of the 23rd international conference on World wide web, ACM, 2014 479 (cit. on pp. 30, 34, 47, 54, 57, 58, 61, 63).

[80] F. Bugiotti, J. Camacho-Rodríguez, F. Goasdoué, Z. Kaoudi, I. Manolescu and S. Zampetakis, *SPARQL Query Processing in the Cloud.* 2014 (cit. on pp. 30, 34).

[81] F. Bugiotti, F. Goasdoué, Z. Kaoudi and I. Manolescu,
"RDF data management in the Amazon cloud",
Proceedings of the 2012 Joint EDBT/ICDT Workshops, ACM, 2012 61 (cit. on pp. 30, 34).

[82] P. Cudré-Mauroux, I. Enchev, S. Fundatureanu, P. Groth, A. Haque, A. Harth, F. L. Keppmann, D. Miranker, J. F. Sequeda and M. Wylot,
"NoSQL databases for RDF: an empirical evaluation",
International Semantic Web Conference, Springer, 2013 310 (cit. on p. 34).

[83] N. M. Elzein, M. A. Majid, I. A. T. Hashem, I. Yaqoob, F. A. Alaba and M. Imran,
Managing big RDF data in clouds: Challenges, opportunities, and solutions,
Sustainable Cities and Society **39** (2018) 375 (cit. on p. 34).

[84] M. N. Mami, D. Graux, H. Thakkar, S. Scerri, S. Auer and J. Lehmann,
The query translation landscape: a survey, arXiv preprint arXiv:1910.03118 (2019) (cit. on p. 35).

[85] M. N. Mami, D. Graux, S. Scerri, H. Jabeen, S. Auer and J. Lehman,
Squerall: Virtual Ontology-Based Access to Heterogeneous and Large Data Sources,
Proceedings of 18th International Semantic Web Conference (2019) (cit. on pp. 35, 93, 114).

[86] M. Giese, A. Soylu, G. Vega-Gorgojo, A. Waaler, P. Haase, E. Jiménez-Ruiz, D. Lanti, M. Rezk, G. Xiao, Ö. Özçep et al., *Optique: Zooming in on big data*,
Computer **48** (2015) 60 (cit. on pp. 35, 36).

[87] K. M. Endris, P. D. Rohde, M.-E. Vidal and S. Auer,
"Ontario: Federated Query Processing Against a Semantic Data Lake",
International Conference on Database and Expert Systems Applications, Springer, 2019 379 (cit. on pp. 35, 36).

[88] O. Curé, F. Kerdjoudj, D. Faye, C. Le Duc and M. Lamolle,
On the potential integration of an ontology-based data access approach in NoSQL stores,
International Journal of Distributed Systems and Technologies (IJDST) **4** (2013) 17 (cit. on pp. 35, 36).

[89] J. Unbehauen and M. Martin,
"Executing SPARQL queries over Mapped Document Stores with SparqlMap-M",
12th International Conference on Semantic Systems Proceedings (SEMANTiCS 2016), SEMANTiCS '16, 2016 (cit. on pp. 35, 36, 47, 54, 57, 61, 63, 90, 91).

[90] E. Botoeva, D. Calvanese, B. Cogrel, J. Corman and G. Xiao,
"A Generalized Framework for Ontology-Based Data Access",
International Conference of the Italian Association for Artificial Intelligence,
Springer, 2018 166 (cit. on pp. 35, 37, 90, 91).

[91] O. Curé, R. Hecht, C. Le Duc and M. Lamolle,
"Data integration over NoSQL stores using access path based mappings",
International Conference on Database and Expert Systems Applications, Springer, 2011
481 (cit. on pp. 35, 37, 90).

[92] Á. Vathy-Fogarassy and T. Hugyák,
Uniform data access platform for SQL and NoSQL database systems,
Information Systems **69** (2017) 93 (cit. on pp. 35, 37).

[93] R. Sellami, S. Bhiri and B. Defude,
"ODBAPI: a unified REST API for relational and NoSQL data stores",
2014 IEEE International Congress on Big Data, IEEE, 2014 653 (cit. on pp. 35, 37).

[94] R. Sellami, S. Bhiri and B. Defude,
Supporting Multi Data Stores Applications in Cloud Environments.,
IEEE Trans. Services Computing **9** (2016) 59 (cit. on pp. 35, 37).

[95] B. Kolev, P. Valduriez, C. Bondiombouy, R. Jiménez-Peris, R. Pau and J. Pereira,
CloudMdsQL: querying heterogeneous cloud data stores with a common language.,
Distributed and Parallel Databases **34** (2016) 463 (cit. on pp. 35, 38).

[96] P. Atzeni, F. Bugiotti and L. Rossi,
"Uniform Access to Non-relational Database Systems: The SOS Platform.", *In CAiSE*,
ed. by J. Ralyté, X. Franch, S. Brinkkemper and S. Wrycza, vol. 7328, Springer, 2012
160, ISBN: 978-3-642-31094-2 (cit. on pp. 35, 38).

[97] K. W. Ong, Y. Papakonstantinou and R. Vernoux,
The SQL++ unifying semi-structured query language, and an expressiveness benchmark of SQL-on-Hadoop, NoSQL and NewSQL databases, CoRR, abs/1405.3631 (2014)
(cit. on pp. 35, 38).

[98] R. Sellami and B. Defude, *Complex Queries Optimization and Evaluation over Relational and NoSQL Data Stores in Cloud Environments.*,
IEEE Trans. Big Data **4** (2018) 217 (cit. on p. 37).

[99] D. Spanos, P. Stavrou and N. Mitrou,
Bringing relational databases into the semantic web: A survey, Semantic Web (2010) 1
(cit. on p. 38).

[100] V. Gadepally, P. Chen, J. Duggan, A. Elmore, B. Haynes, J. Kepner, S. Madden,
T. Mattson and M. Stonebraker, "The bigdawg polystore system and architecture",
High Performance Extreme Computing Conference, IEEE, 2016 1 (cit. on p. 38).

[101] M. Vogt, A. Stiemer and H. Schuldt, *Icarus: Towards a multistore database system*,
2017 IEEE International Conference on Big Data (Big Data) (2017) 2490 (cit. on p. 38).

[102] V. Giannakouris, N. Papailiou, D. Tsoumakos and N. Koziris,
"MuSQLE: Distributed SQL query execution over multiple engine environments",
2016 IEEE International Conference on Big Data (Big Data), IEEE, 2016 452
(cit. on p. 38).

[103] R. Krishnamurthy, R. Kaushik and J. F. Naughton,
"XML-to-SQL query translation literature: The state of the art and open problems",
International XML Database Symposium, Springer, 2003 1 (cit. on pp. 42, 48).

[104] F. Michel, J. Montagnat and C. F. Zucker,
A survey of RDB to RDF translation approaches and tools, PhD thesis: I3S, 2014
(cit. on p. 42).

[105] D.-E. Spanos, P. Stavrou and N. Mitrou,
Bringing relational databases into the semantic web: A survey,
Semantic Web **3** (2012) 169 (cit. on p. 42).

[106] S. S. Sahoo, W. Halb, S. Hellmann, K. Idehen, T. Thibodeau Jr, S. Auer, J. Sequeda and A. Ezzat,
A survey of current approaches for mapping of relational databases to RDF,
W3C RDB2RDF Incubator Group Report **1** (2009) 113 (cit. on p. 42).

[107] J. Michels, K. Hare, K. Kulkarni, C. Zuzarte, Z. H. Liu, B. Hammerschmidt and F. Zemke, *The New and Improved SQL: 2016 Standard*,
ACM SIGMOD Record **47** (2018) 51 (cit. on p. 43).

[108] R. Angles, M. Arenas, P. Barceló, A. Hogan, J. Reutter and D. Vrgoč,
Foundations of modern query languages for graph databases,
ACM Computing Surveys (CSUR) **50** (2017) 68 (cit. on p. 43).

[109] A. Mahmoud, *No more joins: An Overview of Graph Database Query Language*,
Accessed: 06-08-2019, 2017, URL: https://developer.ibm.com/dwblog/2017/overview-graph-database-query-languages/
(cit. on p. 43).

[110] P. Gearon, A. Passant and A. Polleres, *SPARQL 1.1 Update*,
W3C recommendation **21** (2013) (cit. on p. 43).

[111] J. Pérez, M. Arenas and C. Gutierrez, "Semantics and Complexity of SPARQL",
International semantic web conference, Springer, 2006 30 (cit. on p. 43).

[112] E. Prudhommeaux, *SPARQL query language for RDF*,
http://www. w3. org/TR/rdf-sparql-query/ (2008) (cit. on pp. 43, 63).

[113] A. Green, M. Junghanns, M. Kiessling, T. Lindaaker, S. Plantikow and P. Selmer,
openCypher: New Directions in Property Graph Querying, (2018) (cit. on p. 43).

[114] N. Francis, A. Green, P. Guagliardo, L. Libkin, T. Lindaaker, V. Marsault, S. Plantikow, M. Rydberg, P. Selmer and A. Taylor,
"Cypher: An evolving query language for property graphs",
Proceedings of the 2018 International Conference on Management of Data, ACM, 2018
1433 (cit. on pp. 43, 53).

[115] D.-E. Ranking, *DB-Engines Ranking*, Accessed: 06-08-2019, 2019,
URL: https://db-engines.com/en/ranking (cit. on pp. 43, 44).

[116] M. A. Rodriguez, "The gremlin graph traversal machine and language (invited talk)",
Proceedings of the 15th Symposium on Database Programming Languages, ACM, 2015 1
(cit. on p. 44).

[117] T. Bray, J. Paoli, C. M. Sperberg-McQueen, E. Maler and F. Yergeau, *Extensible Markup Language (XML).*, World Wide Web Journal **2** (1997) 27 (cit. on p. 44).

[118] M. Dyck, J. Robie, J. Snelson and D. Chamberlin, *XML Path Language (XPath) 3.1*, Accessed: 06-08-2019, 2017, URL: https://www.w3.org/TR/xpath-31/ (cit. on p. 44).

[119] S. Boag, D. Chamberlin, M. F. Fernández, D. Florescu, J. Robie, J. Siméon and M. Stefanescu, *XQuery 1.0: An XML query language*, (2002) (cit. on pp. 44, 63).

[120] J. S. Jonathan Robie Michael Dyck, *XQuery 3.1: An XML Query Language*, Accessed: 06-08-2019, 2017, URL: https://www.w3.org/TR/xquery-31/ (cit. on p. 44).

[121] J. S. K. T. G. He and C. Z. D. D. J. Naughton, *Relational databases for querying XML documents: Limitations and opportunities*, Very Large Data Bases: Proceedings **25** (1999) 302 (cit. on p. 45).

[122] S. Melnik, *Storing RDF in a relational database*, 2001 (cit. on p. 45).

[123] E. Prud'hommeaux, *Optimal RDF access to relational databases*, 2004 (cit. on p. 45).

[124] N. F. Noy, *Semantic integration: a survey of ontology-based approaches*, ACM Sigmod Record **33** (2004) 65 (cit. on p. 45).

[125] M. Hausenblas, R. Grossman, A. Harth and P. Cudré-Mauroux, *Large-scale Linked Data Processing-Cloud Computing to the Rescue?.*, CLOSER **20** (2012) 246 (cit. on p. 45).

[126] J. Rachapalli, V. Khadilkar, M. Kantarcioglu and B. Thuraisingham, *RETRO: a framework for semantics preserving SQL-to-SPARQL translation*, The University of Texas at Dallas **800** (2011) 75080 (cit. on pp. 47, 52, 56, 61, 63).

[127] S. Ramanujam, A. Gupta, L. Khan, S. Seida and B. Thuraisingham, "R2D: A bridge between the semantic web and relational visualization tools", *2009 IEEE International Conference on Semantic Computing*, IEEE, 2009 303 (cit. on pp. 47, 52, 56, 60, 61, 63).

[128] S. Ramanujam, A. Gupta, L. Khan, S. Seida and B. Thuraisingham, "R2D: Extracting relational structure from RDF stores", *Proceedings of the 2009 IEEE/WIC/ACM International Joint Conference on Web Intelligence and Intelligent Agent Technology-Volume 01*, IEEE Computer Society, 2009 361 (cit. on pp. 47, 52, 56, 60, 61).

[129] M. Rodriguez-Muro and M. Rezk, *Efficient SPARQL-to-SQL with R2RML mappings.*, J. Web Sem. **33** (2015) 141, URL: http://dblp.uni-trier.de/db/journals/ws/ws33.html#Rodriguez-%20MuroR15 (cit. on pp. 47, 51, 54, 57, 58, 61).

[130] A. Chebotko, S. Lu, H. M. Jamil and F. Fotouhi, *Semantics preserving SPARQL-to-SQL query translation for optional graph patterns*, tech. rep., 2006 (cit. on pp. 47, 49, 54, 55, 57, 59, 61).

[131] C. Stadler, J. Unbehauen, J. Lehmann and S. Auer, *Connecting Crowdsourced Spatial Information to the Data Web with Sparqlify*, tech. rep., Technical Report, University of Leipzig, Leipzig, 2013. Available at http://sparqlify.org/downloads/documents/2013-Sparqlify-Technical-Report.pdf, 2013 (cit. on pp. 47, 61).

[132] S. Kiminki, J. Knuuttila and V. Hirvisalo,
"SPARQL to SQL translation based on an intermediate query language",
The 6th International Workshop on Scalable Semantic Web Knowledge Base Systems (SSWS2010), 2010 32 (cit. on pp. 47, 50, 57, 60, 61, 63).

[133] B. Elliott, E. Cheng, C. Thomas-Ogbuji and Z. M. Ozsoyoglu,
"A complete translation from SPARQL into efficient SQL",
Proceedings of the 2009 International Database Engineering & Applications Symposium, ACM, 2009 31 (cit. on pp. 47, 49, 57, 58, 61, 63, 94).

[134] J. Unbehauen, C. Stadler and S. Auer,
"Accessing relational data on the web with sparqlmap",
Joint International Semantic Technology Conference, Springer, 2012 65
(cit. on pp. 47, 54, 57, 58, 61, 63).

[135] J. Lu, F. Cao, L. Ma, Y. Yu and Y. Pan,
"An effective sparql support over relational databases",
Semantic web, ontologies and databases, Springer, 2008 57
(cit. on pp. 47, 49, 57, 58, 60, 61, 63).

[136] J. F. Sequeda and D. P. Miranker, *Ultrawrap: SPARQL execution on relational data*, Web Semantics: Science, Services and Agents on the World Wide Web **22** (2013) 19
(cit. on pp. 47, 54, 57, 58, 61, 63).

[137] N. Bikakis, C. Tsinaraki, I. Stavrakantonakis, N. Gioldasis and S. Christodoulakis,
The SPARQL2XQuery interoperability framework, World Wide Web **18** (2015) 403
(cit. on pp. 47, 53, 57, 61, 63).

[138] N. Bikakis, N. Gioldasis, C. Tsinaraki and S. Christodoulakis,
"Querying xml data with sparql",
International Conference on Database and Expert Systems Applications, Springer, 2009
372 (cit. on pp. 47, 53, 57, 61, 63).

[139] N. Bikakis, N. Gioldasis, C. Tsinaraki and S. Christodoulakis,
"Semantic based access over xml data", *World Summit on Knowledge Society*,
Springer, 2009 259 (cit. on pp. 47, 53, 57, 61, 63).

[140] P. M. Fischer, D. Florescu, M. Kaufmann and D. Kossmann,
Translating SPARQL and SQL to XQuery, XML Prague (2011) 81
(cit. on pp. 47, 50, 57, 61, 63).

[141] S. Groppe, J. Groppe, V. Linnemann, D. Kukulenz, N. Hoeller and C. Reinke,
"Embedding sparql into XQuery/XSLT",
Proceedings of the 2008 ACM symposium on Applied computing, ACM, 2008 2271
(cit. on pp. 47, 49, 57, 59, 61).

[142] M. Droop, M. Flarer, J. Groppe, S. Groppe, V. Linnemann, J. Pinggera, F. Santner, M. Schier, F. Schöpf, H. Staffler et al., "Translating xpath queries into sparql queries",
OTM Confederated International Conferences" On the Move to Meaningful Internet Systems", Springer, 2007 9 (cit. on pp. 47, 50, 55, 61, 63).

[143] R. Krishnamurthy, R. Kaushik and J. F. Naughton,
"Efficient XML-to-SQL query translation: Where to add the intelligence?",
Proceedings of the Thirtieth international conference on Very large data bases-Volume 30,
VLDB Endowment, 2004 144 (cit. on pp. 47, 52, 55, 58, 61, 63).

[144] T.-l. Hu and G. Chen, *Adaptive XML to relational mapping: an integrated approach*, Journal of Zhejiang University-SCIENCE A **9** (2008) 758 (cit. on pp. 47, 55, 61, 63).

[145] M. Mani, S. Wang, D. Dougherty and E. A. Rundensteiner, *Join minimization in XML-to-SQL translation: an algebraic approach*, ACM SIGMOD Record **35** (2006) 20 (cit. on pp. 47, 52, 55, 58, 61, 63).

[146] W. Fan, J. X. Yu, H. Lu, J. Lu and R. Rastogi, "Query translation from XPath to SQL in the presence of recursive DTDs", *Proceedings of the 31st international conference on Very large data bases*, VLDB Endowment, 2005 337 (cit. on pp. 47, 52, 55, 58, 61, 63).

[147] H. Georgiadis and V. Vassalos, "Xpath on steroids: exploiting relational engines for xpath performance", *Proceedings of the 2007 ACM SIGMOD international conference on Management of data*, ACM, 2007 317 (cit. on pp. 47, 55, 58, 61, 63).

[148] J.-K. Min, C.-H. Lee and C.-W. Chung, *XTRON: An XML data management system using relational databases*, Information and Software Technology **50** (2008) 462 (cit. on pp. 47, 51, 55, 58, 61, 63).

[149] A. Halverson, V. Josifovski, G. Lohman, H. Pirahesh and M. Mörschel, "ROX: relational over XML", *Proceedings of the Thirtieth international conference on Very large data bases-Volume 30*, VLDB Endowment, 2004 264 (cit. on pp. 47–49, 56, 58, 60, 61, 63).

[150] P. Vidhya and P. Samuel, "Insert queries in XML database", *Computer Science and Information Technology (ICCSIT), 2010 3rd IEEE International Conference on*, vol. 1, IEEE, 2010 9 (cit. on pp. 47, 49, 56, 61, 63).

[151] P. Vidhya and P. Samuel, "Query translation from SQL to XPath", *Nature & Biologically Inspired Computing, 2009. NaBIC 2009. World Congress on*, IEEE, 2009 1749 (cit. on pp. 47, 49, 56, 61, 63).

[152] S. Jigyasu, S. Banerjee, V. Borkar, M. Carey, K. Dixit, A. Malkani and S. Thatte, "SQL to XQuery translation in the aqualogic data services platform", *Data Engineering, 2006. ICDE'06. Proceedings of the 22nd International Conference on*, IEEE, 2006 97 (cit. on pp. 47, 52, 56, 61).

[153] H. Thakkar, D. Punjani, Y. Keswani, J. Lehmann and S. Auer, *A Stitch in Time Saves Nine–SPARQL Querying of Property Graphs using Gremlin Traversals*, arXiv preprint arXiv:1801.02911 (2018) (cit. on pp. 47, 50, 57, 61, 63).

[154] H. Thakkar, D. Punjani, J. Lehmann and S. Auer, "Two for One: Querying Property Graph Databases using SPARQL via Gremlinator", *Proceedings of the 1st ACM SIGMOD Joint International Workshop on Graph Data Management Experiences & Systems (GRADES) and Network Data Analytics (NDA)*, ACM, 2018 12 (cit. on pp. 47, 50, 57, 61, 63).

[155] T. Wilmes, *SQL-Gremlin*, Accessed: 06-08-2019, 2016, URL: https://github.com/twilmes/sql-gremlin (cit. on pp. 47, 52, 56, 61).

[156] W. Sun, A. Fokoue, K. Srinivas, A. Kementsietsidis, G. Hu and G. Xie, "SQLGraph: an efficient relational-based property graph store", *Proceedings of the 2015 ACM SIGMOD International Conference on Management of Data*, ACM, 2015 1887 (cit. on pp. 47, 50, 59–61, 63).

[157] B. A. Steer, A. Alnaimi, M. A. Lotz, F. Cuadrado, L. M. Vaquero and J. Varvenne, "Cytosm: Declarative property graph queries without data migration", *Proceedings of the Fifth International Workshop on Graph Data-management Experiences & Systems*, ACM, 2017 4 (cit. on pp. 47, 53, 55, 61, 63).

[158] L. Carata, *Cyp2SQL: Cypher to SQL Translation*, Accessed: 06-08-2019, 2017, URL: https://github.com/DTG-FRESCO/cyp2sql (cit. on pp. 47, 51, 55, 59, 61).

[159] QueryMongo, *Query Mongo: MySQL to MongoDB Query Translator*, Accessed: 06-08-2019, 2019, URL: http://www.querymongo.com (cit. on pp. 47, 49, 56, 60, 61).

[160] R. Reddy, *MongoDB Translator - Teiid 9.0 (draft)*, Accessed: 06-08-2019, 2015, URL: https://docs.jboss.org/author/display/TEIID/MongoDB+Translator (cit. on pp. 47, 52, 56, 61).

[161] UnityJDBC, *UnityJDBC - JDBC Driver for MongoDB*, Accessed: 06-08-2019, 2017, URL: http://unityjdbc.com/mongojdbc/mongo_jdbc.php (cit. on pp. 47, 52, 56, 61).

[162] T. H. D. Araujo, B. T. Agena, K. R. Braghetto and R. Wassermann, "OntoMongo- Ontology-Based Data Access for NoSQL.", *ONTOBRAS*, ed. by M. Abel, S. R. Fiorini and C. Pessanha, vol. 1908, CEUR Workshop Proceedings, CEUR-WS.org, 2017 55, URL: http://dblp.uni-trier.de/db/conf/ontobras/%20ontobras2017.html#AraujoABW17 (cit. on pp. 47, 53, 55, 57, 61).

[163] E. Botoeva, D. Calvanese, B. Cogrel, M. Rezk and G. Xiao, "OBDA beyond relational DBs: A study for MongoDB", CEUR Workshop Proceedings, 2016 (cit. on pp. 47, 53, 57, 59, 61).

[164] F. Michel, C. F. Zucker and J. Montagnat, "A generic mapping-based query translation from SPARQL to various target database query languages", *12th International Conference on Web Information Systems and Technologies (WEBIST'16)*, 2016 (cit. on pp. 47, 51, 59, 61).

[165] S. Das, *R2RML: RDB to RDF mapping language*, http://www. w3. org/TR/r2rml/ (2011) (cit. on pp. 47, 63).

[166] V. Russell, *sql-to-mongo-db-query-converter*, Accessed: 15-10-2018, 2016, URL: https://github.com/vincentrussell/sql-to-mongo-db-query-converter (cit. on pp. 49, 56).

[167] H. Thakkar, D. Punjani, S. Auer and M.-E. Vidal, "Towards an Integrated Graph Algebra for Graph Pattern Matching with Gremlin", *International Conference on Database and Expert Systems Applications*, Springer, 2017 81 (cit. on p. 50).

[168] A. Polleres and J. P. Wallner, *On the relation between SPARQL1. 1 and answer set programming*, Journal of Applied Non-Classical Logics **23** (2013) 159 (cit. on p. 51).

[169] A. Dimou, M. Vander Sande, P. Colpaert, R. Verborgh, E. Mannens and R. Van de Walle, "RML: A Generic Language for Integrated RDF Mappings of Heterogeneous Data.", *LDOW*, 2014 (cit. on pp. 51, 67, 73, 100).

[170] SQL2Gremlin, *SQL2Gremlin*, Accessed: 06-08-2019, 2018, URL: http://sql2gremlin.com (cit. on p. 52).

[171] N. Website, *For Relational Database Developers: A SQL to Cypher Guide*, Accessed: 06-08-2019, 2019, URL: https://neo4j.com/developer/guide-sql-to-cypher (cit. on p. 56).

[172] N. Bikakis, C. Tsinaraki, I. Stavrakantonakis and S. Christodoulakis, *Supporting SPARQL update queries in RDF-XML integration*, arXiv preprint arXiv:1408.2800 (2014) (cit. on pp. 57, 63).

[173] G. dos Santos Ferreira, A. Calil and R. dos Santos Mello, "On providing DDL support for a relational layer over a document NoSQL database", *Proceedings of International Conference on Information Integration and Web-based Applications & Services*, ACM, 2013 125 (cit. on pp. 60, 63).

[174] G. A. Schreiner, D. Duarte and R. dos Santos Mello, "SQLtoKeyNoSQL: a layer for relational to key-based NoSQL database mapping", *Proceedings of the 17th International Conference on Information Integration and Web-based Applications & Services*, ACM, 2015 74 (cit. on p. 60).

[175] R. Lawrence, "Integration and virtualization of relational SQL and NoSQL systems including MySQL and MongoDB", *Computational Science and Computational Intelligence (CSCI), 2014 International Conference on*, vol. 1, IEEE, 2014 285 (cit. on pp. 60, 63).

[176] A. Berglund, S. Boag, D. Chamberlin, M. F. Fernández, M. Kay, J. Robie and J. Siméon, *Xml path language (xpath)*, World Wide Web Consortium (W3C) (2003) (cit. on p. 63).

[177] R. Krishnamurthy, V. T. Chakaravarthy, R. Kaushik and J. F. Naughton, "Recursive XML schemas, recursive XML queries, and relational storage: XML-to-SQL query translation", *null*, IEEE, 2004 42 (cit. on p. 63).

[178] W. Fan, J. X. Yu, J. Li, B. Ding and L. Qin, *Query translation from XPath to SQL in the presence of recursive DTDs*, The VLDB Journal **18** (2009) 857 (cit. on p. 63).

[179] M. Atay and A. Chebotko, "Schema-based XML-to-SQL query translation using interval encoding", *Information Technology: New Generations (ITNG), 2011 Eighth International Conference on*, IEEE, 2011 84 (cit. on p. 63).

[180] M. Rodrıguez-Muro, J. Hardi and D. Calvanese, "Quest: efficient SPARQL-to-SQL for RDF and OWL", *11th International Semantic Web Conference ISWC*, Citeseer, 2012 53 (cit. on p. 63).

[181] R. Angles, H. Thakkar and D. Tomaszuk,
"RDF and Property Graphs Interoperability: Status and Issues",
Proceedings of the 13th Alberto Mendelzon International Workshop on Foundations of Data Management, Asunción, Paraguay, June 3-7, 2019. 2019,
URL: http://ceur-ws.org/Vol-2369/paper01.pdf (cit. on p. 62).

[182] T. Lindaaker, *An overview of the recent history of Graph Query Languages*, 2018 (cit. on p. 62).

[183] M. N. Mami, S. Scerri, S. Auer and M.-E. Vidal,
"Towards semantification of big data technology",
International Conference on Big Data Analytics and Knowledge Discovery, Springer, 2016 376 (cit. on p. 66).

[184] A. Hogan, "Skolemising Blank Nodes while Preserving Isomorphism",
24th Int. Conf. on World Wide Web, WWW 2015, 2015,
URL: http://doi.acm.org/10.1145/2736277.2741653 (cit. on p. 67).

[185] V. Khadilkar, M. Kantarcioglu, B. Thuraisingham and P. Castagna,
"Jena-HBase: A distributed, scalable and efficient RDF triple store",
11th Int. Semantic Web Conf. Posters & Demos, ISWC-PD, 2012 (cit. on p. 68).

[186] J. Sun and Q. Jin, "Scalable rdf store based on hbase and mapreduce",
3rd Int. Conf. on Advanced Computer Theory and Engineering, IEEE, 2010 (cit. on p. 68).

[187] C. Franke, S. Morin, A. Chebotko, J. Abraham and P. Brazier,
"Distributed semantic web data management in HBase and MySQL cluster",
Cloud Computing (CLOUD), 2011, IEEE, 2011 105 (cit. on p. 68).

[188] S. Sakr and G. Al-Naymat, *Relational processing of RDF queries: a survey*,
ACM SIGMOD Record **38** (2010) 23 (cit. on p. 68).

[189] D. C. Faye, O. Cure and G. Blin, *A survey of RDF storage approaches*, (2012) (cit. on pp. 68, 73).

[190] Z. Ma, M. A. Capretz and L. Yan,
Storing massive Resource Description Framework (RDF) data: a survey,
The Knowledge Engineering Review **31** (2016) 391 (cit. on p. 68).

[191] D. J. Abadi et al., "Column Stores for Wide and Sparse Data.", *CIDR*, vol. 2007, 2007 292 (cit. on p. 74).

[192] J. Y. Monteith, J. D. McGregor and J. E. Ingram, "Hadoop and its evolving ecosystem",
5th International Workshop on Software Ecosystems (IWSECO 2013), vol. 50,
Citeseer, 2013 (cit. on p. 74).

[193] J. Friesen, *Java XML and JSON*, Springer, 2016 (cit. on p. 75).

[194] C. Bizer and A. Schultz, *The Berlin SPARQL benchmark*,
International Journal on Semantic Web and Information Systems (IJSWIS) **5** (2009) 1 (cit. on pp. 77, 114).

[195] T. Neumann and G. Weikum, *RDF-3X: a RISC-style engine for RDF*,
Proceedings of the VLDB Endowment **1** (2008) 647 (cit. on p. 81).

[196] J. Dixon, *Pentaho, Hadoop, and Data Lakes*, Online; accessed 27-January-2019, 2010, URL: https://jamesdixon.wordpress.com/2010/10/14/pentaho-hadoop-and-data-lakes (cit. on p. 84).

[197] C. Quix, R. Hai and I. Vatov, "GEMMS: A Generic and Extensible Metadata Management System for Data Lakes.", *CAiSE Forum*, 2016 129 (cit. on p. 84).

[198] N. Miloslavskaya and A. Tolstoy, "Application of Big Data, Fast Data, and Data Lake Concepts to Information Security Issues", *International Conference on Future Internet of Things and Cloud Workshops*, IEEE, 2016 148 (cit. on p. 84).

[199] C. Walker and H. Alrehamy, "Personal data lake with data gravity pull", *5th International Conf. on Big Data and Cloud Computing*, IEEE, 2015 160 (cit. on p. 84).

[200] S. Harris, A. Seaborne and E. Prud'hommeaux, *SPARQL 1.1 query language*, W3C recommendation **21** (2013) (cit. on p. 85).

[201] M. N. Mami, D. Graux, S. Scerri, H. Jabeen, S. Auer and J. Lehman, *Squerall: Virtual Ontology-Based Access to Heterogeneous and Large Data Sources*, Proceedings of 18th International Semantic Web Conference (2019) (cit. on p. 85).

[202] M. N. Mami, D. Graux, S. Scerri, H. Jabeen and S. Auer, "Querying Data Lakes using Spark and Presto", *The World Wide Web Conference*, ACM, 2019 3574 (cit. on pp. 85, 97).

[203] S. Auer, S. Scerri, A. Versteden, E. Pauwels, S. Konstantopoulos, J. Lehmann, H. Jabeen, I. Ermilov, G. Sejdiu, M. N. Mami et al., "The BigDataEurope platform–supporting the variety dimension of big data", *International Conference on Web Engineering*, Springer, 2017 41 (cit. on p. 85).

[204] M. N. Mami, D. Graux, S. Scerri, H. Jabeen, S. Auer and J. Lehman, *How to feed the Squerall with RDF and other data nuts?*, Proceedings of 18th International Semantic Web Conference (Poster & Demo Track) (2019) (cit. on p. 85).

[205] F. Michel, C. Faron-Zucker and J. Montagnat, "A mapping-based method to query MongoDB documents with SPARQL", *International Conference on Database and Expert Systems Applications*, Springer, 2016 52 (cit. on p. 86).

[206] R. Kimball and J. Caserta, *The data warehouse ETL toolkit: practical techniques for extracting, cleaning, conforming, and delivering data*, John Wiley & Sons, 2011 (cit. on pp. 86, 88).

[207] K. M. Endris, M. Galkin, I. Lytra, M. N. Mami, M.-E. Vidal and S. Auer, "MULDER: querying the linked data web by bridging RDF molecule templates", *Int. Conf. on Database and Expert Systems Applications*, Springer, 2017 3 (cit. on p. 89).

[208] R. Sethi, M. Traverso, D. Sundstrom, D. Phillips, W. Xie, Y. Sun, N. Yegitbasi, H. Jin, E. Hwang, N. Shingte et al., "Presto: SQL on Everything", *2019 IEEE 35th International Conference on Data Engineering (ICDE)*, IEEE, 2019 1802 (cit. on pp. 98, 119).

[209] M. S. Wiewiórka, D. P. Wysakowicz, M. J. Okoniewski and T. Gambin, *Benchmarking distributed data warehouse solutions for storing genomic variant information*, Database **2017** (2017) (cit. on p. 98).

[210] A. Kolychev and K. Zaytsev, *Research of The Effectiveness of SQL Engines Working in HDFS.*, Journal of Theoretical & Applied Information Technology **95** (2017) (cit. on p. 98).

[211] S. Das, S. Sundara and R. Cyganiak, *R2RML: RDB to RDF Mapping Language. Working Group Recommendation, W3C, Sept. 2012* (cit. on p. 100).

[212] B. De Meester, A. Dimou, R. Verborgh and E. Mannens, "An ontology to semantically declare and describe functions", *ISWC*, Springer, 2016 46 (cit. on p. 101).

[213] B. De Meester, W. Maroy, A. Dimou, R. Verborgh and E. Mannens, "Declarative data transformations for Linked Data generation: the case of DBpedia", *European Semantic Web Conference*, Springer, 2017 33 (cit. on p. 101).

[214] J. Lehmann, G. Sejdiu, L. Bühmann, P. Westphal, C. Stadler, I. Ermilov, S. Bin, N. Chakraborty, M. Saleem, A.-C. N. Ngomo et al., "Distributed semantic analytics using the sansa stack", *International Semantic Web Conference*, Springer, 2017 147 (cit. on p. 110).

[215] D. Graux, L. Jachiet, P. Geneves and N. Layaida, "A Multi-Criteria Experimental Ranking of Distributed SPARQL Evaluators", *2018 IEEE International Conference on Big Data (Big Data)*, IEEE, 2018 693 (cit. on p. 115).

[216] S. Burckhardt et al., *Principles of eventual consistency*, Foundations and Trends® in Programming Languages **1** (2014) 1 (cit. on p. 133).

[217] T. Lebo, S. Sahoo, D. McGuinness, K. Belhajjame, J. Cheney, D. Corsar, D. Garijo, S. Soiland-Reyes, S. Zednik and J. Zhao, *Prov-o: The prov ontology*, W3C recommendation **30** (2013) (cit. on p. 134).

[218] F. Maali, J. Erickson and P. Archer, *Data catalog vocabulary (DCAT)*, W3c recommendation **16** (2014) (cit. on p. 134).

[219] R. Cyganiak, D. Reynolds and J. Tennison, *The RDF data cube vocabulary*, World Wide Web Consortium (2014) (cit. on p. 134).

[220] M. Martin, K. Abicht, C. Stadler, A.-C. Ngonga Ngomo, T. Soru and S. Auer, "Cubeviz: Exploration and visualization of statistical linked data", *Proceedings of the 24th International Conference on World Wide Web*, 2015 219 (cit. on p. 134).

[221] J. Volz, C. Bizer, M. Gaedke and G. Kobilarov, *Silk-A Link Discovery Framework for the Web of Data.*, LDOW **538** (2009).

[222] A.-C. N. Ngomo and S. Auer, *Limes-a time-efficient approach for large-scale link discovery on the web of data*, integration **15** (2011) 3.

[223] N. Marz and J. Warren, *Big Data Principles and best practices of scalable realtime data systems*, April 2015.

[224] L. Douglas, *3d data management: Controlling data volume, velocity and variety*, Gartner. Retrieved **6** (2001) 6.

[225] D. L. Gartner, *The Importance of 'Big Data': A Definition*, = https://www.gartner.com/doc/2057415/importance-big-data-definition.

[226] N. Partners, *Big Data Executive Survey*, Survey, 2014: NewVantage Partners.

[227] C. Consulting, *Big Data Survey*, Survey, November 2014: Capgemini Consulting.

[228] D. of the Secretary of State - State of Main, ed., *Net Licenses In Force by type, gender and age*, 2012.

[229] N. L. Steve Harris and N. Shadbolt, *4store: The Design and Implementation of a Clustered RDF Store*, SSWS (2009).

[230] A. S. Alisdair Owens and N. Gibbins, *Clustered TDB: A Clustered Triple Store for Jena*, WWW (2009).

[231] O. Erling and I. Mikhailov, *Towards web scale RDF*, SSWS (2008).

[232] A. Schätzle, M. Przyjaciel-Zablocki, C. Dorner, T. Hornung and G. Lausen, *Cascading map-side joins over HBase for scalable join processing*, SSWS+ HPCSW (2012) 59.

[233] A. Gangemi, S. Leonardi and A. Panconesi, eds., *24th Int. Conf. on World Wide Web, WWW 2015*, ACM, 2015, ISBN: 978-1-4503-3469-3, URL: http://dl.acm.org/citation.cfm?id=2736277.

[234] M. Martin, K. Abicht, C. Stadler, A.-C. N. Ngomo, T. Soru and S. Auer, "CubeViz: Exploration and Visualization of Statistical Linked Data", *24th Int. Conf. on World Wide Web*, 2015, URL: http://doi.acm.org/10.1145/2740908.2742848.

[235] *Proceedings of the 24th International Conference on World Wide Web Companion, WWW 2015, Florence, Italy, May 18-22, 2015 - Companion Volume*, ACM, 2015, ISBN: 978-1-4503-3473-0, URL: http://dl.acm.org/citation.cfm?id=2740908.

[236] J. Euzenat, C. Meilicke, H. Stuckenschmidt, P. Shvaiko and C. Trojahn, "Ontology alignment evaluation initiative", *Journal on data semantics XV*, Springer, 2011.

[237] S. Ota, A. Morishima, N. Shinagawa and T. Amagasa, "C-Mapping: a flexible XML-RDB mapping method based on functional and inclusion dependencies.", *SAC*, ACM, 2012, ISBN: 978-1-4503-0857-1, URL: http://dblp.uni-trier.de/db/conf/sac/sac2012.html#OtaMSA12.

[238] M. A. Martinez-Prieto, C. E. Cuesta, M. Arias and J. D. Fernández, *The Solid architecture for real-time management of big semantic data*, Future Generation Computer Systems **47** (2015) 62.

[239] N. Papailiou, I. Konstantinou, D. Tsoumakos, P. Karras and N. Koziris, "H 2 RDF+: High-performance distributed joins over large-scale RDF graphs", *2013 IEEE International Conference on Big Data*, IEEE, 2013 255.

[240] O. Hartig and J. Zhao, "Publishing and consuming provenance metadata on the web of linked data", *Provenance and annotation of data and processes*, Springer, 2010 78.

[241] J. Debattista, C. Lange, S. Scerri and S. Auer,
"Linked'Big'Data: Towards a Manifold Increase in Big Data Value and Veracity",
Big Data Computing (BDC), 2015 IEEE/ACM 2nd International Symposium on,
IEEE, 2015 92.

[242] M. Burzańska,
New Query Rewriting Methods for Structured and Semi-Structured Databases,
Praca doktorska, Warsaw University, Department of Mathematics, Informatics and Mechanics, Warsaw, Poland **10** (2011) 125.

[243] R. Cyganiak, *A relational algebra for SPARQL*,
Digital Media Systems Laboratory HP Laboratories Bristol. HPL-2005-170 **35** (2005).

[244] N. Bikakis, C. Tsinaraki, N. Gioldasis, I. Stavrakantonakis and S. Christodoulakis,
"The XML and semantic web worlds: technologies, interoperability and integration: a survey of the state of the art", *Semantic Hyper/Multimedia Adaptation*, Springer, 2013 319.

[245] J. Clark, S. DeRose et al., *XML path language (XPath) version 1.0*, 1999.

[246] M. Dyck, J. Robie, J. Snelson and D. Chamberlin, *XML Path Language (XPath) 2.0*, 2009.

[247] A. Buccella, A. Cechich and N. R. Brisaboa, "Ontology-Based Data Integration",
Encyclopedia of Database Technologies and Applications, IGI Global, 2005 450.

[248] E. Prud'Hommeaux, A. Seaborne et al., *SPARQL query language for RDF*,
W3C recommendation **15** (2008), www.w3.org/TR/rdf-sparql-query/.

[249] W. S. W. Group et al., *SPARQL 1.1 Overview*,
W3C Recommendation. W3C (2013), http://www.w3.org/TR/sparql11-overview/.

[250] C. Tsinaraki and S. Christodoulakis, "Interoperability of XML schema applications with OWL domain knowledge and semantic web tools", *OTM Confederated International Conferences" On the Move to Meaningful Internet Systems"*, Springer, 2007 850.

[251] D. Laney, *Deja VVVu: others claiming Gartner's construct for big data*,
Gartner Blog, Jan **14** (2012).

[252] O. Curé, H. Naacke, M. A. Baazizi and B. Amann,
"HAQWA: a Hash-based and Query Workload Aware Distributed RDF Store.",
International Semantic Web Conference (Posters & Demos), 2015.

[253] O. Lassila, R. R. Swick et al.,
Resource description framework (RDF) model and syntax specification, (1998).

[254] B. Elliott, E. Cheng, C. Thomas-Ogbuji and Z. M. Ozsoyoglu,
"A complete translation from SPARQL into efficient SQL",
Proceedings of the International Database Engineering & Applications Symposium,
ACM, 2009 31.

[255] J. Lehmann, G. Sejdiu, L. Bühmann, P. Westphal, C. Stadler, I. Ermilov, S. Bin,
N. Chakraborty, M. Saleem and A.-C. N. Ngomo,
"Distributed Semantic Analytics using the SANSA Stack", *ISWC*, Springer, 2017 147.

[256] M. Saleem and A.-C. N. Ngomo,
"Hibiscus: Hypergraph-based source selection for SPARQL endpoint federation",
Ext. Semantic Web Conf. Springer, 2014.

[257] M. Gorman, *Understanding the Linux virtual memory manager*, Prentice Hall Upper Saddle River, 2004.

[258] R. Sellami and B. Defude, *Complex Queries Optimization and Evaluation over Relational and NoSQL Data Stores in Cloud Environments.*, IEEE Trans. Big Data **4** (2018) 217.

[259] O. Curé, R. Hecht, C. Le Duc and M. Lamolle, "Data integration over NoSQL stores using access path based mappings", *International Conference on Database and Expert Systems Applications*, Springer, 2011 481.

[260] M. Zaharia, M. Chowdhury, M. J. Franklin, S. Shenker and I. Stoica, *Spark: Cluster computing with working sets*, HotCloud **10** (2010) 95.

[261] N. Garg, *Apache Kafka*, Packt Publishing Ltd, 2013.

[262] D. E. O'Leary, *Embedding AI and crowdsourcing in the big data lake*, IEEE Intelligent Systems **29** (2014) 70.

[263] P. P. Khine and Z. S. Wang, "Data lake: a new ideology in big data era", *ITM Web of Conferences*, vol. 17, EDP Sciences, 2018 03025.

[264] J. Lehmann, G. Sejdiu, L. Bühmann, P. Westphal, C. Stadler, I. Ermilov, S. Bin, N. Chakraborty, M. Saleem and A.-C. N. Ngomo, "Distributed Semantic Analytics using the SANSA Stack", *ISWC*, Springer, 2017 147.

[265] Y. Jiang, G. Li, J. Feng and W.-S. Li, *String Similarity Joins: An Experimental Evaluation.*, PVLDB **7** (2014) 625.

[266] Y. Jiang, G. Li, J. Feng and W.-S. Li, *String similarity joins: An experimental evaluation*, Proceedings of the VLDB Endowment **7** (2014) 625.

[267] S. Chaudhuri and U. Dayal, *An overview of data warehousing and OLAP technology*, ACM Sigmod record **26** (1997) 65.

[268] A. Cassandra, *Apache Cassandra*, Google Scholar (2015).

[269] C. Bizer and A. Schultz, *The Berlin SPARQL benchmark*, International Journal on Semantic Web and Information Systems (IJSWIS) **5** (2009) 1.

[270] F. Chang, J. Dean, S. Ghemawat, W. C. Hsieh, D. A. Wallach, M. Burrows, T. Chandra, A. Fikes and R. E. Gruber, "Bigtable: A Distributed Storage System for Structured Data", *OSDI*, 2006 205.

[271] F. Chang, J. Dean, S. Ghemawat, W. C. Hsieh, D. A. Wallach, M. Burrows, T. Chandra, A. Fikes and R. E. Gruber, *Bigtable: A distributed storage system for structured data*, ACM Transactions on Computer Systems (TOCS) **26** (2008) 4.

[272] A. Poggi, D. Lembo, D. Calvanese, G. De Giacomo, M. Lenzerini and R. Rosati, "Linking data to ontologies", *Journal on Data Semantics X*, Springer, 2008.

[273] P. Hayes and B. McBride, *RDF Semantics*, W3C Rec. (2004).

[274] D. Calvanese, G. De Giacomo, D. Lembo, M. Lenzerini, A. Poggi, M. Rodriguez-Muro, R. Rosati, M. Ruzzi and D. F. Savo, *The MASTRO system for ontology-based data access*, Semantic Web **2** (2011) 43.

[275] C. Stadler, J. Unbehauen, P. Westphal, M. A. Sherif and J. Lehmann, "Simplified RDB2RDF Mapping.", *LDOW@ WWW*, 2015.

[276] H. Garcia-Molina, J. Ullman and J. Widom, *Database Systems – The Complete Book*, Prentice Hall, 2002.

[277] F. Michel, C. Faron-Zucker and J. Montagnat, "A mapping-based method to query MongoDB documents with SPARQL", *International Conference on Database and Expert Systems Applications*, Springer, 2016 52.

[278] V. Gadepally, P. Chen, J. Duggan, A. Elmore, B. Haynes, J. Kepner, S. Madden, T. Mattson and M. Stonebraker, "The bigdawg polystore system and architecture", *High Performance Extreme Computing Conference*, IEEE, 2016 1.

[279] M. Schmidt, T. Hornung, G. Lausen and C. Pinkel, "SP^{2}Bench: A SPARQL Performance Benchmark", *IEEE ICDE*, 2009.

[280] Y. Guo, Z. Pan and J. Heflin, *LUBM: A benchmark for OWL knowledge base systems*, Web Semantics **3** (2005) 158.

[281] M. Chevalier, M. E. Malki, A. Kopliku, O. Teste and R. Tournier, "Benchmark for OLAP on NoSQL technologies comparing NoSQL multidimensional data warehousing solutions", *RCIS*, IEEE, 2015 480, ISBN: 978-1-4673-6630-4.

[282] B. F. Cooper, A. Silberstein, E. Tam, R. Ramakrishnan and R. Sears, "Benchmarking cloud serving systems with YCSB", *Symposium on Cloud computing*, ACM, 2010 143.

[283] J. Klein, I. Gorton, N. Ernst, P. Donohoe, K. Pham and C. Matser, "Performance evaluation of NoSQL databases: a case study", *Proceedings of the 1st Workshop on Performance Analysis of Big Data Systems*, ACM, 2015 5.

[284] A. Gandini, M. Gribaudo, W. J. Knottenbelt, R. Osman and P. Piazzolla, "Performance evaluation of NoSQL databases", *European Workshop on Performance Engineering*, Springer, 2014 16.

[285] V. Abramova, J. Bernardino and P. Furtado, *Experimental evaluation of NoSQL databases*, International Journal of Database Management Systems **6** (2014) 1.

[286] S. Auer, C. Bizer, G. Kobilarov, J. Lehmann, R. Cyganiak and Z. Ives, "DBpedia: A nucleus for a web of open data", *The semantic web*, Springer, 2007 722.

[287] D. Spanos, P. Stavrou and N. Mitrou, *Bringing relational databases into the semantic web: A survey*, Semantic Web (2010) 1.

[288] G. Xiao, D. Calvanese, R. Kontchakov, D. Lembo, A. Poggi, R. Rosati and M. Zakharyaschev, "Ontology-based data access: A survey", IJCAI, 2018.

[289] Á. Vathy-Fogarassy and T. Hugyák, *Uniform data access platform for SQL and NoSQL database systems*, Information Systems **69** (2017) 93.

[290] E. Botoeva, D. Calvanese, B. Cogrel, J. Corman and G. Xiao,
"A Generalized Framework for Ontology-Based Data Access",
International Conference of the Italian Association for Artificial Intelligence,
Springer, 2018 166.

[291] O. Curé, F. Kerdjoudj, D. Faye, C. Le Duc and M. Lamolle,
On the potential integration of an ontology-based data access approach in NoSQL stores,
International Journal of Distributed Systems and Technologies (IJDST) **4** (2013) 17.

[292] P. Atzeni, F. Bugiotti and L. Rossi,
"Uniform Access to Non-relational Database Systems: The SOS Platform.", *In CAiSE*,
ed. by J. Ralyté, X. Franch, S. Brinkkemper and S. Wrycza, vol. 7328, Springer, 2012
160, ISBN: 978-3-642-31094-2.

[293] B. Kolev, P. Valduriez, C. Bondiombouy, R. Jiménez-Peris, R. Pau and J. Pereira,
CloudMdsQL: querying heterogeneous cloud data stores with a common language.,
Distributed and Parallel Databases **34** (2016) 463.

[294] M. Saleem and A.-C. N. Ngomo,
"Hibiscus: Hypergraph-based source selection for SPARQL endpoint federation",
Ext. Semantic Web Conf. Springer, 2014.

[295] J. Roijackers and G. H. L. Fletcher,
"On Bridging Relational and Document-Centric Data Stores.", *BNCOD*,
ed. by G. Gottlob, G. Grasso, D. Olteanu and C. Schallhart, vol. 7968,
Lecture Notes in Computer Science, Springer, 2013 135, ISBN: 978-3-642-39466-9.

[296] M. Giese, A. Soylu, G. Vega-Gorgojo, A. Waaler, P. Haase, E. Jiménez-Ruiz, D. Lanti,
M. Rezk, G. Xiao, Ö. Özçep et al., *Optique: Zooming in on big data*,
Computer **48** (2015) 60.

[297] J. Unbehauen and M. Martin,
"Executing SPARQL queries over Mapped Document Stores with SparqlMap-M",
12th Int. Conf. on Semantic Systems, 2016.

[298] K. W. Ong, Y. Papakonstantinou and R. Vernoux,
The SQL++ unifying semi-structured query language, and an expressiveness benchmark of SQL-on-Hadoop, NoSQL and NewSQL databases, CoRR (2014).

[299] K. W. Ong, Y. Papakonstantinou and R. Vernoux,
The SQL++ unifying semi-structured query language, and an expressiveness benchmark of SQL-on-Hadoop, NoSQL and NewSQL databases, CoRR, abs/1405.3631 (2014).

[300] M. Vogt, A. Stiemer and H. Schuldt, *Icarus: Towards a multistore database system*,
2017 IEEE International Conference on Big Data (Big Data) (2017) 2490.

[301] S. Auer, S. Scerri, A. Versteden, E. Pauwels, A. Charalambidis, S. Konstantopoulos,
J. Lehmann, H. Jabeen, I. Ermilov, G. Sejdiu et al.,
"The BigDataEurope platform–supporting the variety dimension of big data",
International Conference on Web Engineering, Springer, 2017 41.

[302] B. Reichert,
Franz's CEO, Jans Aasman to Present at the Smart Data Conference in San Jose,
Online; accessed 20-July-2018, 2015,
URL: https://franz.com/about/press_room/smart-data_5-22-2015.html.

[303] M. Zaharia, M. Chowdhury, T. Das, A. Dave, J. Ma, M. McCauley, M. J. Franklin, S. Shenker and I. Stoica, "Resilient distributed datasets: A fault-tolerant abstraction for in-memory cluster computing", *Proceedings of the 9th USENIX conference on Networked Systems Design and Implementation*, USENIX Association, 2012 2.

[304] G. G. Dodd, *Elements of data management systems*, ACM Computing Surveys (CSUR) **1** (1969) 117.

[305] R. Ramakrishnan and J. Gehrke, *Database management systems*, McGraw Hill, 2000.

[306] K. M. Endris, M. Galkin, I. Lytra, M. N. Mami, M.-E. Vidal and S. Auer, "Querying interlinked data by bridging RDF molecule templates", *Transactions on Large-Scale Data-and Knowledge-Centered Systems XXXIX*, Springer, 2018 1.

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