Ontop: Answering SPARQL Queries over Relational Databases

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Abstract. In this paper we present *Ontop*, an open-source Ontology-Based Data Access (OBDA) system that allows for querying relational data sources through a conceptual representation of the domain of interest, provided in terms of an ontology, to which the data sources are mapped. Key features of *Ontop* are its solid theoretical foundations, a virtual approach to OBDA, which avoids materializing triples and is implemented through the query rewriting technique, extensive optimizations exploiting all elements of the OBDA architecture, its compliance to all relevant W3C recommendations (including SPARQL queries, R2RML mappings, and OWL 2 QL and RDFS ontologies), and its support for all major relational databases.

Keywords: Ontop, OBDA, Databases, RDF, SPARQL, Ontologies, R2RML, OWL

1. Introduction

Over the past 20 years we have moved from a world where most companies operated with one all-knowing, self-contained, central database to a world where companies buy and sell their data, interact with several data sources, and analyze patterns and statistics coming from all of them. The challenge is shifting from obtaining information to finding the *right* information. It has always been the case that information is power but today *attention* rather than information becomes the scarce resource, and those who can distinguish valuable information from background clutter gain power [22]. To separate the wheat from the chaff, companies need a comprehensive understanding of their data and the ability to cope with diversity in the data.

Since the mid 2000s, *Ontology-Based Data Access* (OBDA) has become a popular approach for tackling this problem [34]. In OBDA, a conceptual layer is given in the form of an *ontology* that defines a shared

vocabulary, models the domain, hides the structure of the data sources, and enriches incomplete data with background knowledge. Then, queries are posed over this high-level conceptual view, and the users no longer need an understanding of the data sources, the relation between them, or the encoding of the data. Queries are translated by the OBDA system into queries over potentially very large (usually relational and federated) data sources. The ontology is connected to the data sources through a declarative specification given in terms of mappings that relate symbols in the ontology (classes and properties) to (SQL) views over the data. The W3C standard R2RML [15] was created with the goal of providing a language for the specification of mappings in the OBDA setting. The ontology together with the mappings exposes a virtual RDF graph, which can be queried using SPARQL, the standard query language in the Semantic Web community. This virtual RDF graph can be materialized, generating RDF triples to be used with RDF triplestores, or alternatively it can be kept virtual and queried only

during query execution. The virtual approach avoids the cost of materialization and can profit from more than 30 years' maturity of relational systems (efficient query answering, security, robust transaction support, etc.).

To illustrate these concepts and the different notions in this paper, we will use the following running example. All the material needed to run this example in the OBDA system *Ontop* (and a complementary tutorial) can be found online¹.

Example 1.1 (Hospital Database). We consider a hospital database with a single table <code>tbl_patient</code> that contains information about lung cancer patients. The table has 4 attributes: the patient identifier (pid), his/her name, the type of cancer (tumor), and its stage. The lung cancer can be of two types: Non-Small Cell Lung Carcinoma (NSCLC) and Small Cell Lung Carcinoma (SCLC), which are encoded in the table by a boolean value <code>type</code> as follows:

- false for NSCLC, and true for SCLC.

The stage of the cancer is encoded by a positive integer value stage as follows:

- 1-6 for NSCLC stages I, II, III, IIIa, IIIb, and IV;
- 7-8 for SCLC stages Limited and Extensive.

Finally, our sample table contains the following data:

<u>pid</u>	name	type	stage
1	'Mary'	false	4
2	'John'	true	7

Suppose we need a simple piece of information from this database: "Give me the names of patients with a tumor of stage IIIa". Even this simple query in this tiny database already presents some challenges, because in order to formulate the query and to understand and analyze the results we need to know how the information is encoded in the data. In this paper, we describe how to use the *Ontop* system to address this challenge by enhancing the database with a semantic layer.

We present the OBDA system *Ontop*², a mature open-source system, which is currently being used in a number of projects. *Ontop* supports all the W3C recommendations related to OBDA: OWL 2 QL, R2RML, SPARQL, SWRL, and the OWL 2 QL entail-

ment regime in SPARQL. The system is available as a Protégé plugin, a SPARQL endpoint through Sesame Workbench, and a Java library supporting OWL API and Sesame API.

The structure of the paper is as follows. Section 2 presents a high-level overview of the architecture of *Ontop*. Section 3 surveys additional tools that can be used with *Ontop* for creating, deploying, and querying OBDA systems. Section 4 describes the SPARQL query answering techniques implemented in *Ontop*. Section 5 outlines the applications of *Ontop*, in particular the Statoil and Siemens use cases in the context of the *Optique* project. Related SPARQL query answering systems are surveyed in Section 6. Section 7 is a retrospective on the development of *Ontop* over the past five years. Finally, Section 8 concludes the paper.

2. Architecture of Ontop

Ontop is an open-source³ OBDA system released under the Apache license, developed at the Free University of Bozen-Bolzano. The Ontop system exposes relational databases as virtual RDF graphs by linking the terms (classes and properties) in the ontology to the data sources through mappings. This virtual RDF graph can then be queried using SPARQL by translating the SPARQL queries into SQL queries over the relational databases. This translation process is transparent to the user.

The architecture of *Ontop*, which is illustrated in Fig. 1, can be divided in four layers: (i) the inputs, i.e., the domain-specific artifacts such as the ontology, database, mappings, and queries; (ii) the core of the system in charge of query translation, optimization, and execution; (iii) the APIs exposing standard Java interfaces to users of the system; and (iv) the applications that allow end-users to execute SPARQL queries over databases.

We explore each of these components in turn.

2.1. Inputs: Ontology, Mappings, Queries, and Databases

To the best of our knowledge, *Ontop* is the first OBDA system that supports all the W3C recommendations related to OBDA: OWL 2 QL, R2RML, SPARQL, SWRL, and the OWL 2 QL entailment

Ihttps://github.com/ontop/ontop-examples/
tree/master/swj-2015

²http://ontop.inf.unibz.it/

³http://github.com/ontop/ontop/

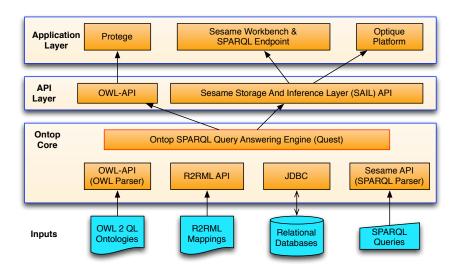


Fig. 1. Architecture of the Ontop system

regime in SPARQL⁴. In addition, it supports all the major commercial and open-source relational databases.

Ontology. Ontop allows for RDFS [7] and OWL 2 QL [31] as ontology languages. OWL 2 QL is based on the *DL-Lite* family of lightweight description logics [10,3], which guarantees that queries over the ontology can be rewritten into equivalent queries over the databases. Recently *Ontop* has been extended to support also a fragment of SWRL [53].

Example 2.1. The following ontology captures the domain knowledge of our running example. It describes the concepts of cancer and cancer patient with the following OWL axioms:

```
:NSCLC rdfs:subClassOf :LungCancer.
:SCLC rdfs:subClassOf :LungCancer.
:LungCancer rdfs:subClassOf :Neoplasm.
:hasNeoplasm rdfs:domain :Patient.
:hasNeoplasm rdfs:range :Neoplasm.
:hasName rdf:type owl:DatatypeProperty.
:hasStage rdf:type owl:ObjectProperty.
```

In particular, classes: NSCLS and: SCLC are both subclasses of: LungCancer (that is, both are types of lung cancer), which in turn is a subclass of: Neoplasm. The object property: hasNeoplasm has class: Patient as its domain and: Neoplasm as its range (in other words, it relates patients to neoplasms).

We also have a datatype property : has Name and an object property : has Stage. \Box

Mappings. Ontop supports two mapping languages: the W3C RDB2RDF Mapping Language (R2RML), which is a widely used standard; and the native Ontop mapping language, which is easier to learn and use. Ontop allows users to convert native mappings into R2RML mappings and vice-versa. Intuitively, a mapping assertion consists of a source, which is an SQL query retrieving values from the database, and a target, which defines RDF triples with values from the source.

Example 2.2. The ontology in Example 2.1 can be populated from the database in Example 1.1 by means of the following mappings: (To ease readability we use a slightly simplified version of the *Ontop* native mapping syntax.)

In this example, IRIs like :hasStage and rdf:type

⁴SWRL and the OWL 2 QL entailment regime are currently supported experimentally.

represent the constant components of the RDF triples. IRIs :db1/{pid} and :db1/neoplasm/{pid} are constructed using values from the database: in both cases {pid} is the value of the attribute pid in the respective SQL query. Similarly, {name} is the literal whose value is taken from the attribute name in the SQL query of the mapping. Note that there are individuals that represent patients, :db1/{pid}, and individuals that represent their tumors, :db1/neoplasm/{pid}. This allows for a better modeling of the domain and allows the user to query specific properties of the tumor independently of the patient.

Mappings are also used for data integration. To model an entity, for instance a patient, that is represented by different objects in different datasources, there are in principle two options. First, one can virtually merge different objects representing the same entity by generating for them the same URI. Second, when the first option is not available, one can use owl:sameAs in the target of the mappings to explicitly state the equality between objects, as shown in [11].

Queries. Ontop supports essentially all features of SPARQL 1.0 and the OWL 2 QL entailment regime of SPARQL 1.1 [28]. Support for other features of SPARQL 1.1 (e.g., aggregates, property path queries, and negation) is ongoing work.

Example 2.3. Recall our information need in Example 1.1: the names of all the patients who have a neoplasm (tumor) at stage IIIa. This can be represented by the following SPARQL query:

```
SELECT ?name WHERE {
    ?p rdf:type :Patient .
    ?p :hasName ?name .
    ?p :hasNeoplasm ?tumor .
    ?tumor :hasStage :stage-IIIa .}
```

On our sample database, the query would return 'Mary'. Observe that the vocabulary is more domain-oriented and independent of the encoding done in the database, e.g., there is no need anymore to be aware of the specific values that encode types or stages in the database.

Databases. Ontop supports many relational database engines via JDBC. These include all major commercial relational databases (DB2, Oracle, and MS SQL Server) and the most popular open-source databases (PostgreSQL, MySQL, H2, and HSQL). In addition,

Ontop can be used with federated databases (e.g., Teiid⁵ or Exareme⁶, formerly called ADP [51]) to support multiple data sources (e.g., relational databases, XML, CSV, and Web Services).

2.2. Ontop Core

The core of *Ontop* is the SPARQL engine *Quest*, which is in charge of rewriting SPARQL queries over the virtual RDF graph into SQL queries over the relational database (see Section 4).

2.3. API Layer

To allow developers building systems using *Ontop* as a Java library, *Ontop* implements two widely used Java APIs, which are also available as Maven artifacts:

- OWL API [20] is a reference implementation for creating, manipulating, and serializing OWL ontologies. We extended the OWLReasoner interface to support SPARQL query answering.
- Sesame [8] is a de-facto standard framework for processing RDF data. Ontop implements the Sesame Storage And Inference Layer (SAIL) API supporting inferencing and querying over relational databases.

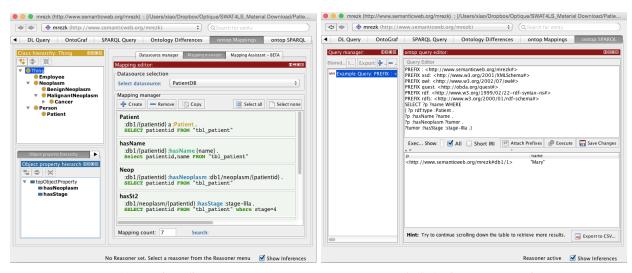
2.4. Application Layer

Ontop is available through a simple command line interface, and also through several applications accessing it via the above mentioned APIs. We describe three such applications, which we have been developing and maintaining together with Ontop over the past years.

- Protégé. Ontop implements a Plugin for Protégé 5 based on OWL API. The plugin provides a graphical interface for various key functionalites related to OBDA: editing mappings, executing SPARQL queries, checking consistency of the ontology, automatically bootstrapping ontologies and mappings from the database, importing and exporting R2RML mappings, materializing RDF triples, etc. Figure 2 shows two screenshots of the Ontop Protégé plugin for creating mappings and answering SPARQL queries from the running examples.

⁵http://teiid.jboss.org/

⁶http://www.exareme.org/



(a) Mapping editor

(b) SPARQL query answering

Fig. 2. Screenshots of the Ontop Protégé Plugin

- Sesame Workbench and SPARQL Endpoint. Sesame OpenRDF Workbench is a web application for administrating Sesame repositories. We extended the Workbench to create and manage Ontop repositories using SAIL API. Such repositories can then be used as standard SPARQL endpoints. Figure 3 shows a screenshot of creating an Ontop repository in Sesame Workbench.
- *Optique Platform*. The Optique Platform complements *Ontop* by adding an intuitive visual query builder, tools for ontology and mapping management, a friendly query answering interface, and a database federation tool, among other features [17]. *Ontop* is the core of the Optique Platform and is in charge of the query transformation module. The platform can exploit massive parallelism in the backend whenever possible, and it can also query streaming data⁷.

3. Ecosystem

Complementary to *Ontop*'s core functionalities, there are additional tools that support the tasks involved in creating and deploying OBDA systems. We now provide a brief overview of some of these tools for bootstrapping mappings and ontologies, for federating datasources at SQL and SPARQL levels, and for formulating queries.



Fig. 3. Screenshot of the Ontop Sesame Workbench

3.1. Mapping Bootstrapping

The process of creating mappings is probably the most complex step in setting up an OBDA system. It involves writing individual queries for each table and each column that needs to be aligned with the ontology's vocabulary. To support this task, the community has produced a number of tools, so-called *mapping bootstrappers*, that automatically create mappings from database schemas. *Ontop* itself includes a bootstrapper, which is available as a command line

⁷In the streaming scenario, *Ontop* is only used for query rewriting.

tool and as part of the Protégé plugin. Most of the existing tools generate mappings that follow the *Direct Mapping*⁸ specification, a W3C recommendation that specifies a default way for creating RDF triples from SQL databases. The specification contains guidelines on (i) how to use the values of primary, foreign, and unique keys to create IRIs for subjects and objects, (ii) how to use table names to define classes for rdf:type triples, and (iii) how to use table/column names to define the properties of the triples. The specification also defines low-level issues, such as casting SQL values to RDF literals, handling null values, etc. While the Direct Mapping is not a mapping by itself, it is used by many mapping bootstrappers as a guideline for mapping generation.

It is important to note, however, that a direct mapping is usually not sufficient to capture the semantics of the database, such as the encoding of hierarchies in columns with codes or IDs (e.g., type = false indicates small cell lung cancer), or the conditions that indicate that a value in a row identifies the object(s) in that row as belonging to a certain class (e.g., a patient with stage 1 to 4 is a high risk patient). To support the automatic generation of this kind of more complex mappings there are systems like MIRROR [16] or BootOX [21], which exploit the common patterns that schema managers use to encode part of the semantics of the database domain into the relational database.

Once mappings have been generated with any of these tools, any query engine for virtual RDF graphs like *Ontop* can use them.

Similar to mapping bootstrapping systems, there are systems such as Karma⁹ that provide a simple interface for building mappings and semi-automatically suggest new mappings by analyzing existing ones.

3.2. Ontology Bootstrapping

As we described in the previous section, it is possible to generate a base vocabulary of classes and properties from the table and column names of a database. However, this vocabulary lacks axioms that describe its semantics. *Ontology bootstrappers* are tools that allow to extract these axioms using schema information (such as keys or constraints) and/or the data in the database to generate RDFS or OWL axioms. For instance, BootOX [21] can also be used for ontology bootstrapping.

3.3. SQL Federation

One way in which *Ontop* supports data integration scenarios is through SQL federation. A *federated database* is a DBMS that maps multiple independent databases into a single *virtual* schema. The designer of a federated database chooses how to map the independent databases into the virtual schema by, e.g., creating one-to-one mappings, renaming elements of the schema, or creating virtual tables from SQL views. Some federated databases also allow for the use of wrappers for non-SQL databases (e.g., XML) to provide a uniform user interface for the client. SQL execution is coordinated by the federated database, which exploits techniques for planning and executing crossdatabase joins with guarantees of concurrency and transaction control.

Creating mappings for a federated schema involves the same processes as for a regular schema. *Ontop* is able to query the federated schema as long as the SQL dialect supported by the federated database is supported by *Ontop*.

Most major DBMSs provide support for federated schemas that integrate independent servers of their own kind, e.g., MySQL is able to create federated schemas over independent MySQL servers; similarly for PostgreSQL, Oracle, DB2, etc. Federated schemas with databases from multiple vendors are supported by systems like UnityJDBC, IBM's Websphere, MS SQL Server, and Oracle; open-source solutions are provided by JBoss's Teild and Exareme, both of which are supported by *Ontop*.

3.4. SPARQL Federation

Another setup in which *Ontop* can be used in data integration scenarios is through SPARQL federation. As with federated SQL databases, SPARQL federation involves multiple and independent SPARQL endpoints that are queried through a single entry point. We distinguish two forms of federation that are available today, *seamless* federation and SPARQL 1.1 *SERVICE* federation.

Seamless federation is very similar to SQL federation. That is, a system manager creates a federated SPARQL end-point where she configures access to independent and remote end-points. Clients submit plain SPARQL queries to the federated end-point, unaware of the existence of the remote end-points. As with SQL federation, the federation system is responsible of finding the most efficient way to execute these queries. In

 $^{^{8}}$ http://www.w3.org/TR/rdb-direct-mapping/

⁹http://usc-isi-i2.github.io/karma/

particular, it is extremely important for these systems to minimize the volume of data that is sent to/from the remote end-points. Examples of these systems are Anapsid [2] and FedX [47].

In contrast, SPARQL 1.1 SERVICE federation involves a direct reference to the remote end-points within the SPARQL query using the SERVICE keyword, which is used to scope a subgraph to a particular end-point. For example:

```
SELECT ?s {
    ?s a foaf:Person .
    SERVICE ex:endpoint {
        ?s foaf:knows ?o
    }
}
```

When a SERVICE keyword is encountered, the SPARQL engine delegates the evaluation of the enclosed graph pattern to the SPARQL end-point specified in the SERVICE call. The result will be retrieved by the local SPARQL engine and used to continue the evaluation of the SPARQL query. SPARQL federation through SERVICE calls is available in most SPARQL 1.1 compliant engines.

In contrast to seamless federation, using the SERVICE keyword does not require the federation engine to know about the remote end-points *a priori*. In fact, the URL end-point itself can be a variable in the query, getting values as the query gets executed.

Ontop can be used in both of these setups by deploying an *Ontop* SPARQL end-point (see Section 2.4).

3.5. Ontology-based Query Interface

The task of formulating SPARQL queries can be challenging for end-users. There are several ontology-based visual query interfaces to ease this task, e.g., Optique VQS [50], Query VOWL [19], SEWASIE VQS [13], and Faceted search [52]. These tools can be used together with *Ontop*. In particular, Optique VQS serves as the query interface in the *Optique* platform.

4. Answering SPARQL Queries

Ontop answers end-user's SPARQL queries by rewriting them into SQL queries and delegating their execution to the data sources. With this approach there is no need to apply rules to the datasources to generate all the facts entailed by the ontology. The workflow of Ontop can be divided into an off-line and an online

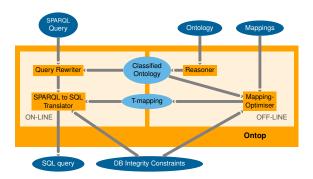


Fig. 4. The Ontop workflow

stage, and is illustrated in Fig. 4. The most critical task during start-up (the off-line stage) is compiling the ontology into the mappings and generating the so-called T-mappings [41]. During query execution (the online stage), *Ontop* transforms input SPARQL queries into optimized SQL queries exploiting the T-mappings and the database integrity constraints. We now explain each of the two stages.

4.1. Off-line Stage: Ontology and Mapping Compilation

The off-line stage of *Ontop* processes the ontology, mappings, and database integrity constraints. This stage can be thought of as consisting of three phases: (1) ontology classification, (2) T-mapping construction, and (3) T-mapping optimization. In the implementation of *Ontop*, however, the last two phases are performed simultaneously.

In Phase 1, the ontology is loaded through OWL API and is classified using the built-in reasoner. The resulting complete hierarchy of properties and classes is stored in memory as a directed acyclic graph. For example, in the ontology in Example 2.1, both :NSCLC and :SCLC are subclasses of :LungCancer, which in turn is a subclass of :Neoplasm. It follows that every NSCLC and every SCLC is a form of neoplasm:

```
:NSCLC rdfs:subClassOf :Neoplasm.
:SCLC rdfs:subClassOf :Neoplasm.
```

The classification algorithm is based on a variant of graph reachability [37] (a similar procedure was later described in [30]).

In Phase 2, T-mappings are constructed by composing the complete class and property hierarchies with the mappings [41,43]. For example, consider concept :Neoplasm in Example 2.1. Although it has no mappings defined by the user, the two class inclusions derived above give rise to the following

rules in the T-mapping:

Finally, in Phase 3, the T-mappings are optimized by using disjunction (OR) and interval expressions in SQL and by applying semantic query optimization (SQO) techniques (which will be described in Section 4.2.2). For instance, using disjunction, *Ontop* transforms the two rules above into the following single rule:

Such optimizations are known to be relatively expensive (for example, SQO is based on an NP-complete conjunctive query containment check) but are performed only once, during the off-line stage of *Ontop*, and therefore have a negligible effect on query processing. On the other hand, the resulting T-mappings define all the RDF triples that can be inferred from the database and the ontology and so, during the online stage, the T-mappings are used as the basis for the translation of individual triple patterns in SPARQL queries into SQL.

4.2. Online Stage: Query Answering

The online stage takes a SPARQL query and translates it into SQL by using the T-mappings. We focus only on the translation of SELECT queries (ASK and DESCRIBE queries are treated analogously). In this process *Ontop* also optimizes the SQL query by applying SQO techniques [14,27]. To ease the presentation we distinguish three phases in the query answering process:

- (1) The SPARQL query is translated into SQL using T-mappings.
- (2) The resulting SQL query is optimized for efficient execution by the database engine.
- (3) The optimized SQL query is then executed by the database engine, and the result set is translated into the answer to the original SPARQL query by creating the necessary RDF terms.

Phases 1 and 2 are handled together in the implementation of *Ontop* (we, however, distinguish them here for the sake of clarity). We elaborate now on the three phases of query answering.

4.2.1. From SPARQL to SQL

Ontop internally represents the SPARQL query as a tree corresponding to the SPARQL algebra expression (generated by the Sesame SPARQL parser). Each node of the tree is transformed into the respective SQL expression. To illustrate the transformation, we continue with the running example.

Example 4.1. Consider the fragment of the query in Example 2.3 that retrieves all tumors of stage IIIa:

```
SELECT ?tumor WHERE {
   ?tumor rdf:type :Neoplasm ;
   :hasStage :stage-IIIa . }
```

(We note that the triple pattern ?tumor rdf:type: Neoplasm was not needed in Example 2.3: indeed, Ontop can infer it from ?p:hasNeoplasm ?tumor because the range of:hasNeoplasm is:Neoplasm.)

The above query is represented by the following tree:

Next we explain how to produce the SQL expression from a SPARQL query using T-mappings. Algorithm 1

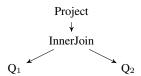
```
Algorithm 1. Translating SPARQL into SQL
    Input: SPARQL Query Q, T-mappings \mathcal{M}_{\mathcal{T}}
    Output: SQL Expression
 1: S \leftarrow \text{List of nodes in } Q \text{ in a bottom-up topological order}
 2: sqlM \leftarrow a map from nodes to SQL expressions
 3: for node n \in S do
 4:
         if n is triple pattern then
                                           ▶ Translating leaves
 5:
            sqlM[n] \leftarrow replace-Tmap-def(n, \mathcal{M}_{\mathcal{T}})
 6:
                                  7:
            if n = JOIN(n_1, n_2) then
 8:
                 sqlM[n] \leftarrow InnerJoin(sqlM[n_1], sqlM[n_2])
            else if n = OPTIONAL(n_1, n_2, e) then
 9:
10:
                 sqlM[n] \leftarrow LeftJoin(sqlM[n_1], sqlM[n_2], e)
            else if n = \text{UNION}(n_1, n_2) then
11:
12:
                 sqlM[n] \leftarrow Union(sqlM[n_1], sqlM[n_2])
13:
            else if n = FILTER(n_1, e) then
                 sqlM[n] \leftarrow Filter(sqlM[n_1], e)
14:
15:
             else if n = PROJECT(n_1, p) then
16:
                 sqlM[n] \leftarrow Project(sqlM[n_1], p)
17:
             end if
         end if
18:
19: end for
```

20: **return** sqlM[S.last()]

is a simplified version of the process. It iterates over the nodes of the SPARQL algebra tree in a bottom-up fashion; more precisely, it goes through the list S of nodes in the SPARQL query Q in the topological sorting order. In our running example this list is $[T_1, T_2, JOIN, PROJECT]$. So, the algorithm starts by replacing each leaf of the tree, that is, a triple pattern of the form (s, p, o), by the union of the SQL queries defining its predicate in the T-mapping (lines 4–5). In this step, the algorithm implicitly considers two cases: (i) when p is an object or data property, such as :hasStage or :hasName, or (ii) when p is rdf:type and o is a class, such as :Patient.

Once it finishes processing the leaves, it continues to the upper levels in the tree (lines 7–17), where the SPARQL operators (JOIN, OPTIONAL, UNION, FILTER, and PROJECT) are translated into the corresponding SQL operators (InnerJoin, LeftJoin, Union, Filter, and Project, respectively). Once the root is translated the process is finished and the resulting SQL expression is returned.

Example 4.2. *Ontop* translates the SPARQL query in Example 4.1 into an SQL query (shown in Fig. 5a) with the following structure:



The leaves, Q_1 and Q_2 , are respectively the SQL definitions of the concept : Neoplasm and of the property : hasStage in the T-mapping rules constructed during the off-line stage (see Section 4.1). Observe that without the T-mapping optimizations in the off-line stage, the resulting SQL would contain a union in place of Q_1 . This would increase the complexity of the SQL query and so, have a negative effect on the query evaluation time.

For the sake of simplicity we do not describe the translation of filter expressions and OPTIONALs (an optimal translation of unions and empty expressions in the second argument is particularly challenging) and how to handle data types and functions in SQL expressions. Instead, we refer the interested reader to [45,28].

4.2.2. Optimizing the generated SQL queries

The generated SQL queries can already be executed by the DB engine but they are not necessarily efficient: they often contain subqueries, redundant self-

```
SELECT Q1.x FROM

((SELECT concat(":db1/neoplasm/", pid) AS x FROM tbl_patient

WHERE type = false OR type = true) Q1

JOIN

(SELECT concat(":db1/neoplasm/", pid) AS x FROM tbl_patient WHERE stage = 4) Q2

ON Q1.x = Q2.x)
```

(a) Non-optimized generated SQL query

```
SELECT concat(":db1/neoplasm/", Q.pid) AS x
FROM
  (SELECT T1.pid
   FROM tb1_patient T1 JOIN tb1_patient T2
      ON T1.pid = T2.pid
WHERE (T1.type = false OR T1.type = true)
   AND T2.stage = 4) Q
```

(b) SQL query after the structural optimization

```
SELECT concat(":db1/neoplasm/", Q.pid) AS x
FROM
  (SELECT pid
   FROM tb1_patient
  WHERE (type = false OR type = true)
    AND stage = 4) Q
```

(c) SQL query after the self-join elimination

```
SELECT concat(":db1/neoplasm/", pid) AS x
FROM tbl_patient
WHERE (type = false OR type = true)
    AND stage = 4
```

(d) SQL query after the second structural optimization

Fig. 5. Example of SQL translation and optimization

joins, and joins over complex expressions (such as string concatenations). Observe that joins over complex expressions, for instance, prevent the database engine from using indexes. To improve performance, *Ontop* employs a number of structural and semantic optimizations.

Structural Optimizations. Ontop applies three main structural optimizations: (a) pushing the joins inside the unions, (b) pushing the functions as high as possible in the query tree, and (c) eliminating sub-queries. Returning to the running example, the SQL query obtained by these optimizations is shown in Fig. 5b: optimizations (b) and (c) convert the join over the complex expressions into a join over the attributes of the relations (effectively de-IRIing the join) and subsequently remove the subqueries.

Semantic Optimization. Ontop adopts techniques from the area of SQO [14,27]. In general, SQO refers to a set of techniques that perform the semantic analysis of SQL queries and transform them into a more efficient form, e.g., by removing redundant self-joins, and detecting unsatisfiable or trivially satisfiable conditions. SQO techniques often use database dependencies, such as primary and foreign keys, to reduce the size and complexity of the query. In our running example, these optimizations eliminate the self-join, which is redundant because pid is the primary key of tbl_patient; the result is shown in Fig. 5c. Observe that it has a subquery that could not be eliminated before, but because of SQO we can apply structural optimization (c) again, to obtain an even simpler SQL query, shown in Fig. 5d.

Observe that these optimizations complement and interact with each other. The optimization step is critical [29] and nontrivial. This simple example is meant to provide an intuition. The translation of more complex queries is more involved and implies tackling the gap between the SQL and SPARQL semantics. The interested reader is referred to [28,45].

4.2.3. Executing the Query over the Database

Since different database engines support slightly different SQL dialects, we have to adjust the SQL syntax accordingly. For instance, the operator for string concatenation is || in Postgres and concat in MySQL; in MySQL, one cannot cast a value to Integer, so we cast it to Signed instead; Postgres internally changes unquoted identifiers (both column and alias names) to lowercase, while Oracle and H2 change unquoted identifiers to uppercase¹⁰.

Finally, *Ontop* sends the optimized SQL query to the database engine and translates the result into RDF terms (URIs or literals) to construct the answers to the SPARQL query. In the implementation, *Ontop* wraps the result set obtained from the database via JDBC and creates corresponding Java objects for OWL API or Sesame API.

4.2.4. Performance

The cost of query answering in *Ontop* can be split into three parts: (i) the cost of generating the SQL query, (ii) the cost of execution by the RDBMS, and (iii) the cost of fetching and transforming the SQL results into RDF terms. We have studied the performance of *Ontop* using several benchmarks (e.g., BSBM, Fish-

Mark, LUBM, and NPD) and settings (e.g., different DB engines, number of clients, dataset size) [28,46,29, 43]. The obtained results suggest that the performance of Ontop depends more on the complexity of the combination of ontology and mappings than on the size of the dataset. This is in line with the well-known theoretical results that state that the translation from SPARQL to SQL is exponential in the worst case [18]. In benchmarks like BSBM, FishMark, and LUBM, where the number of mappings and the number of ontological terms are small and the datasets range from 25 to 200 million triples, Ontop outperforms its competitors by orders of magnitude [46,28,43]. This performance is the result of (i) the fast SPARQL-to-SQL translation (around 4–15ms); (ii) the efficient optimization of the SQL; and (iii) the well-known efficiency of relational DB engines. For instance, in BSBM with 200 million triples, Ontop can run more than 400.000 queries per hour (44k query mixes per hour).

To better understand the performance of OBDA systems, we developed a more challenging benchmark, the NPD Benchmark [29], which reveals the strengths and pitfalls of OBDA. The benchmark comes with thousands of axioms in the ontology and rules in mappings, and a dataset containing up to 4 billion triples. The query set was obtained by interviewing users of the NPD FactPages dataset [49], and thus provides a realistic account of the information needs in the modeled scenario.

The results comparing Ontop and Stardog on the NPD Benchmark show that the approach is scalable but that more work is needed to optimize the generated SQL queries. Indeed, while the optimizations currently implemented in Ontop are very effective for most of the queries, which are translated into efficient SQL, in some cases an effective translation into SQL is still challenging. Ontop outperforms Stardog whenever the SPARQL query is translated into a small SQL query. On the other hand, in those cases where the generated SQL queries are unions of a large number of subqueries, Stardog outperforms Ontop by orders of magnitude. These results confirm that the worst-case exponential blow-up of the translation into SQL is a major source of performance loss in modern OBDA systems. We are currently working on different techniques for tackling this issue.

5. Industrial Applications

The adoption of *Ontop* by the community has been growing steadily in the last five years: in 2014, *On-*

¹⁰See https://github.com/ontop/ontop/wiki/
Case-sensitivity-for-SQL-identifiers.

top got 500 new registrations, the webpage got 7000 hits, and the mailing list in excess of 120 threads. Nowadays, *Ontop* is the core of the *Optique* Platform, which is developed in the *Optique* EU project [17] and commercialized by fluid Operations (fluidOps)¹¹. *Ontop* is actively being used in academia¹² (e.g., in Semantic Mediator [6], for accessing electronic health records [38], and for querying temporal and streaming data in OBDA [33]) and being experimented within industry.

In this section we describe the use cases of the two major industrial partners in the *Optique* project, namely Statoil [24] and Siemens [33], and what role *Ontop* plays there.

Statoil. Statoil is an international energy company with main activities in gas and oil extraction. It is headquartered in Norway and present in over 30 countries around the world. Geologists at Statoil access several databases on a daily basis, of which one of the most relevant is the Exploration and Production Data Store (EPDS). EPDS is a large SQL database comprising over 1500 tables with information about historical exploration data (e.g., layers of rocks, porosity), production logs, and maps, among others. It also contains business information such as license areas and companies. The schema is organized in such a way that the direct data access by engineers (and geologists in particular) often becomes challenging or even impossible. The main problem lies not only in the size of the schema and the data but also in the obscure structure of this legacy database. The solution currently adopted by Statoil relies on tools that enable domain experts to combine different pre-defined queries. However, these pre-defined queries are often too specific, or too general, or cannot be easily combined to obtain the desired results.

Siemens. Siemens Energy is one of the four sectors of Siemens AG corporation. It is in charge of generating and delivering power from numerous sources. Siemens Energy runs several service centers for power plants. Each center monitors thousands of devices related to power generation, including gas and steam turbines, compressors, and generators. Each device is monitored by different sensors. All dynamic (observational) data from the sensors is stored in one large relational database (PostgreSQL) using more than 150 tables per device. About 30 GB of new sensor and

event data is generated every day, resulting in a total of 100 TB of timestamped data. One of the main tasks of service engineers monitoring these devices is to promptly solve issues detected by gathering the relevant sensor data and analyzing it. Nowadays, the data gathering phase is the bottleneck of the process because it takes about 80% of the time spent by engineers. The reason why the gathering phase is critical partially resides in the complexity and quantity of the data to be analyzed. Ideally the engineers should be able to access the data directly, by creating and combining queries in a way that is compatible with their knowledge. However, the data is often organized to better serve the applications rather than in a most intuitive way for the domain experts.

In scenarios such as those at Statoil and Siemens, the OBDA approach to solving the problems encountered in data access consists in enriching the legacy databases with an ontology that uses a terminology familiar to the engineers. The ontology helps the engineers in formulating their own queries autonomously using the domain vocabulary [17,25], thus effectively mediating between the engineers and the data. The role of Ontop (and Optique) is to make the OBDA approach feasible, by automating the process of translating the queries that the engineers pose over the ontology into queries over the legacy databases that are executed efficiently. Observe that in the Siemens scenario, where it is required to handle historical and streaming data, Ontop is only used for query reformulation, while query execution is delegated to another system.

6. Related SPARQL Query Answering Systems

We now briefly review the most popular SPARQL query answering systems, which can be categorized into two major types: OBDA systems and triplestores. Their main features are summarized in Table 1.

Triplestores provide a flexible generic logical model that allows them to accept and store any set of RDF triples. However, if the triples are generated from external sources (e.g., relational databases) then an intermediate ETL (Extract, Transform, and Load) process must be set up between these external sources and the triplestore. The ETL process can be expensive, especially when datasources are updated frequently.

OBDA systems, on the other hand, are set up over existing relational datasources and exploit their domain-specific schemas. By using ontologies and

¹¹http://www.fluidops.com/en/

 $^{^{12} \}mathrm{https://github.com/ontop/ontop/wiki/UseCases}$

Table 1
Feature matrix of SPARQL query answering systems

Туре	System	Reasoning	Mapping support	License	Starting year
Triplestore	Virtuoso	RDFS*	Native, R2RML*	GPL 2, Commercial	1999
	GraphDB	OWL 2 RL	_	Commercial	2005
	Stardog	OWL 2 */ SWRL*	_	Commercial	2012
	RDFox	OWL 2 RL / SWRL / Datalog	-	Academic	2013
OBDA	D2RQ	No	D2RQ Mapping, R2RML*	Apache 2	2004
	Mastro	OWL 2 QL	R2RML*	Academic	2006
	Ultrawrap	RDFS-Plus	Native, R2RML	Commercial	2012
	Morph-RDB	No	R2RML	Apache 2	2013
	Ontop	OWL 2 QL / SWRL*	Ontop Mapping, R2RML	Apache 2	2010

^{(*} indicates limited support)

mappings, they expose the database as a virtual RDF graph that can be queried using SPARQL. No additional ETL process is thus required.

Some triplestores and OBDA systems have reasoning capabilities. The most common strategy for triplestores is forward-chaining, which consists in extending the set of RDF triples by means of inferences according to a given set of rules. Thus, the OWL 2 RL profile of OWL 2 (and similar rule-based ontology languages) are most suitable for triplestores. Forward-chaining has some drawbacks: the inferences can be costly in terms of both time and space; moreover, updates and deletions of triples require additional book-keeping for incremental reasoning. Also, this approach cannot be adopted without giving up completeness of query answering, when the ontology is expressed in a language, such as OWL 2 QL, that allows for inferring an unbounded number of new individuals in the data.

In contrast to triplestores, the most common strategy for OBDA systems is query rewriting, and so the profile of OWL that is most suitable for this setting is OWL 2 QL. To guarantee rewritability, certain features, such as recursion and property chains, are not allowed in OWL 2 QL.

In the remainder of this section, we review various implementations of the two types.

6.1. Triplestores

Virtuoso Universal Server¹³ is a hybrid DBMS that can be used as a relational database, a triplestore, or an OBDA system. It has two editions, an open-source and a commercial one. From the perspective of answering SPARQL queries, Virtuoso is used mostly as a

triplestore. It supports SPARQL 1.1 and, in this mode, it offers some backward- (by default) and forward-chaining capabilities for a limited subset of RDFS and OWL. When Virtuoso is used as a regular DBMS, it can be extended into an OBDA system by setting up mappings in its own mapping language. However, this OBDA mode has several limitations: no reasoning capabilities are available and only a small fragment of R2RML is supported. Virtuoso can be accessed through the Sesame and Jena APIs.

GraphDB, ¹⁴ previously known as OWLIM [5], is a commercial triplestore developed by Ontotext. It fully supports SPARQL 1.1. OWL reasoning support is based on the forward-chaining rule-based materialization approach. This strategy naturally fits with the OWL 2 RL profile but is incomplete for OWL 2 QL [4]. GraphDB is accessible through the Sesame API.

Stardog¹⁵ is a commercial triplestore developed by Clark&Parsia (now Complexible Inc¹⁶). It supports SPARQL 1.1 and several reasoning levels: RDFS, the three profiles (OWL 2 QL, OWL 2 EL, OWL 2 RL), and OWL 2 DL (however, completeness in OWL 2 DL is guaranteed only for schema reasoning). The reasoning level can be chosen by the user at query time. Stardog avoids eager materialization and the reasoning is partly based on query rewriting. It can be accessed through the Sesame API.

*RDFox*¹⁷ is an in-memory triplestore developed at the University of Oxford. It implements a novel shared-

¹³http://virtuoso.openlinksw.com/

¹⁴http://ontotext.com/products/ontotext-graphdb/

¹⁵http://stardog.com/

 $^{^{16}}$ http://complexible.com/

¹⁷http://www.cs.ox.ac.uk/isg/tools/RDFox/

memory parallel Datalog reasoning algorithm and supports OWL 2 RL reasoning by materialization [32]. The system is a cross-platform software written in C++ and comes with a Java wrapper supporting OWL API.

6.2. OBDA Systems

D2RQ¹⁸ is one of the pioneering OBDA systems, developed at the Free University of Berlin and DERI. This query rewriting system provides some query optimizations but these have often been reported as insufficient: for instance, the generated SQL queries can contain an excessive number of joins [36]. It provides its own mapping language, D2RQ, and supports only a fragment of R2RML. No inference mechanism is included. This software (last release in 2012) is available under an open-source license.

*Mastro*¹⁹ is an OBDA system that shares common origins with *Ontop*. This query rewriting system supports reasoning over OWL 2 QL ontologies. Unlike other OBDA systems mentioned here, it supports only a restricted fragment of SPARQL that corresponds to unions of conjunctive queries. Mastro is available only for demonstration, testing, and evaluation purposes.

*Ultrawrap*²⁰ is an OBDA system commercialized by Capsenta. It was recently extended to support inference over an extension of RDFS with inverse and transitive properties [48]. Ultrawrap uses an analogue of T-mappings of *Ontop*, which are called saturated mappings and which are used for creating regular and materialized views in the relational database.

Morph-RDB,²¹ formerly called ODEMapster, is an open-source OBDA system supporting the R2RML and Direct Mappings standards. This system implements a number of query optimizations techniques such as the self-join elimination [36]. However, it has no inference capability.

7. A Retrospective

Ontop has its roots in our initial work on the QuOnto and Mastro [1,9] systems (2006), in the OBDA plugin for Protégé [35], and in our DIG extension for Mastro [40]. QuOnto is a reasoner for the description logic

DL-Lite with plain conjunctive query (CQ) answering. Mastro extends QuOnto with support for GAV (global as view) mappings for relational databases [34]. Both systems are maintained by the Sapienza University of Rome. Our work enabled the use of these systems through the ontology editor Protégé 3 and the DIG reasoner API.

Using these tools we interacted with third parties to develop several OBDA applications [12,9,23,44,39] (for a full list, see [39]). Such interactions allowed us to test both the performance of the state-of-the-art query rewriting techniques and the feasibility of applying this technology in data integration and data access. The insights we obtained concern techniques and optimization issues on the one hand, and issues related to APIa and required features on the other hand. These two paths of development characterized our work from then on. We now briefly elaborate on them.

Reasoning, Optimization, and Performance. The main issue initially was the large number of CQs generated by the rewriting technique implemented in QuOnto (the PerfectRef algorithm [10]), which sometimes, even for simple ontologies and mappings, produces in the order of hundreds of thousands of CQs. And although DBMSs do perform very well in general, they have problems with automatically generated queries (and this applies to both commercial and noncommercial database engines). To deal with the issue, we extended the PerfectRef algorithm by a Semantic Query Optimization (SQO) component, which removes redundant CQs and eliminates redundant selfjoins using database dependencies (foreign and primary keys) [39].

The work in this direction materialized in the first version of Ontop (2010), which at the time was called Quest (the name now refers only to the query answering engine). Quest focused on RDFS and OWL 2 QL (instead of *DL-Lite*) as ontology languages, and SPARQL (instead of CQs) as query language. This required a new mapping language suitable for these ontology languages. Quest is capable of working in two modes: (i) the virtual mode supports virtual RDF graphs via mappings, and (ii) the RDF triplestore mode stores triples directly in a relational database. Two further ideas were developed for improving performance: T-mappings for the virtual mode [41,28] (c.f. Section 4.1) and the Semantic Index for the RDF triplestore mode [42]. The tree-witness query rewriting algorithm [26] was implemented to drastically reduce the size of rewritings and take advantage of the T-

 $^{^{18}}$ http://d2rq.org/

 $^{^{19} {\}rm http://www.dis.uniromal.it/{\sim}mastro/}$

²⁰http://capsenta.com

²¹https://github.com/oeg-upm/morph-rdb

mappings and the Semantic Index. We also studied the execution of the SQL queries produced by *Ontop* and observed [39] that the generic database-centric SQO was not sufficient and other techniques were required for the issues specific to the context of mappings and ontologies (e.g., join conditions can be simplified by de-IRIing, and the resulting joins can be eliminated, as explained in Section 4.2.2).

The more recent lines of research in *Ontop* include the formalization of SPARQL in the context of OBDA [45], under the OWL 2 QL/RDFS entailment regimes [28], and the support of SWRL with limited forms of recursion, handled by SQL Common Table Expressions [53].

API, Features, and Accessibility. With the first version of Ontop, we shifted our focus from the Description Logic domain to Semantic Web technologies, gradually increasing our support for RDF, RDFS, OWL 2 QL, and SPARQL. To support the OWL community, we included the OWL API and Protégé 4 (and more recently Protégé 5) interfaces for Ontop. To support the Linked Data community, we created the Sesame API interface for Ontop, as well as an HTTP SPARQL endpoint. With the publication of R2RML as the official W3C RDB2RDF mapping language, we extended Ontop to support it.

Ontop was initially released under a noncommercial use license before adopting the permissive Apache 2.0 license in 2013. In addition, the project is now hosted in GitHub so that anybody can easily download and contribute to it. On the software engineering side, to facilitate integration, building, testing, and distribution, Ontop was repackaged as a Maven project and has been available from the official Maven repository since 2013. We gradually introduced project-wide testing, starting with functional tests for the reasoning modules, query answering modules (including the DAWG tests for SPARQL 1.0), and virtual RDF modules (including the DAWG tests for R2RML). Now most JUnit tests (~2000) are automatically run with Travis-CI whenever new changes are pushed to GitHub.

8. Conclusion

In this paper we presented *Ontop*, a mature opensource OBDA system. It allows users to access relational databases through a conceptual representation of the domain of interest in terms of an ontology. The system is based on solid theoretical foundations and has been designed and implemented towards compliance with relevant W3C standards. It supports all major relational databases and implements multiple optimization techniques to offer a good level of performance. *Ontop* has been adopted in several academic and industrial use cases.

In the future, we plan to extend *Ontop* in the following directions:

- In order to further improve performance, we will investigate data-dependent optimizations.
- We plan to support larger fragments of the SPARQL (e.g., aggregation, negation, and path queries) and R2RML (e.g., named graphs) standards.
- For end-users, we will improve the GUI and add utilities to make *Ontop* even more user-friendly.
- We plan to go beyond relational databases and support other kinds of data sources (e.g., graph and document databases).

Acknowledgements. This paper is supported by the EU under the large-scale integrating project (IP) Optique (*Scalable End-user Access to Big Data*), grant agreement n. FP7-318338.

References

- [1] Andrea Acciarri, Diego Calvanese, Giuseppe De Giacomo, Domenico Lembo, Maurizio Lenzerini, Mattia Palmieri, and Riccardo Rosati. QUONTO: Querying ONTOlogies. In Proc. of the 20th Nat. Conf. on Artificial Intelligence (AAAI), pages 1670–1671, 2005.
- [2] Maribel Acosta, Maria-Esther Vidal, Tomas Lampo, Julio Castillo, and Edna Ruckhaus. ANAPSID: An adaptive query processing engine for SPARQL endpoints. In *Proc. of the* 10th Int. Semantic Web Conf. (ISWC), volume 7031 of Lecture Notes in Computer Science, pages 18–34. Springer, 2011.
- [3] Alessandro Artale, Diego Calvanese, Roman Kontchakov, and Michael Zakharyaschev. The DL-Lite family and relations. J. of Artificial Intelligence Research, 36:1–69, 2009.
- [4] Barry Bishop and Spas Bojanov. Implementing OWL 2 RL and OWL 2 QL rule-sets for OWLIM. In Proc. of the 8th Int. Workshop on OWL: Experiences and Directions (OWLED), volume 796 of CEUR Electronic Workshop Proceedings, 2011.
- [5] Barry Bishop, Atanas Kiryakov, Damyan Ognyanoff, Ivan Peikov, Zdravko Tashev, and Ruslan Velkov. OWLIM: A family of scalable semantic repositories. *Semantic Web J.*, 2(1):33– 42, 2011.
- [6] Béatrice Bouchou and Cheikh Niang. Semantic mediator querying. In Proc. of the 18th Int. Database Engineering & Applications Symposium (IDEAS), pages 29–38. ACM Press, 2014.

- [7] Dan Brickley and R. V. Guha. RDF vocabulary description language 1.0: RDF Schema. W3C Recommendation, World Wide Web Consortium, February 2004. Available at http: //www.w3.org/TR/rdf-schema/.
- [8] Jeen Broekstra, Arjohn Kampman, and Frank van Harmelen. Sesame: A generic architecture for storing and querying RDF and RDF schema. In Proc. of the 1st Int. Semantic Web Conf. (ISWC), volume 2342 of Lecture Notes in Computer Science, pages 54–68. Springer, 2002.
- [9] Diego Calvanese, Giuseppe De Giacomo, Domenico Lembo, Maurizio Lenzerini, Antonella Poggi, Mariano Rodriguez-Muro, Riccardo Rosati, Marco Ruzzi, and Domenico Fabio Savo. The Mastro system for ontology-based data access. Semantic Web J., 2(1):43–53, 2011.
- [10] Diego Calvanese, Giuseppe De Giacomo, Domenico Lembo, Maurizio Lenzerini, and Riccardo Rosati. Tractable reasoning and efficient query answering in description logics: The *DL-Lite* family. *J. of Automated Reasoning*, 39(3):385–429, 2007.
- [11] Diego Calvanese, Martin Giese, Dag Hovland, and Martin Rezk. Ontology-based integration of cross-linked datasets. In Proc. of the 14th Int. Semantic Web Conf. (ISWC), volume 9366 of Lecture Notes in Computer Science, pages 199–216. Springer, 2015.
- [12] Diego Calvanese, C. Maria Keet, Werner Nutt, Mariano Rodriguez-Muro, and Giorgio Stefanoni. Web-based graphical querying of databases through an ontology: the WONDER system. In *Proc. of the 25th ACM Symposium on Applied Com*puting (SAC), pages 1388–1395, 2010.
- [13] Tiziana Catarci, Paolo Dongilli, Tania Di Mascio, Enrico Franconi, Giuseppe Santucci, and Sergio Tessaris. An ontology based visual tool for query formulation support. In *Proc. of the* 16th Eur. Conf. on Artificial Intelligence (ECAI), pages 308– 312. IOS Press, 2004.
- [14] Upen S. Chakravarthy, John Grant, and Jack Minker. Logic-based approach to semantic query optimization. ACM Trans. on Database Systems, 15(2):162–207, 1990.
- [15] Souripriya Das, Seema Sundara, and Richard Cyganiak. R2RML: RDB to RDF mapping language. W3C Recommendation, World Wide Web Consortium, September 2012. Available at http://www.w3.org/TR/r2rml/.
- [16] Luciano Frontino de Medeiros, Freddy Priyatna, and Oscar Corcho. MIRROR: Automatic R2RML mapping generation from relational databases. In Proc. of the 15th Int. Conf. on Web Engineering (ICWE), volume 9114 of Lecture Notes in Computer Science, pages 326–343. Springer, 2015.
- [17] Martin Giese, Peter Haase, Ernesto Jiménez-Ruiz, Davide Lanti, Özgür Özçep, Martin Rezk, Riccardo Rosati, Ahmet Soylu, Guillermo Vega-Gorgojo, Arild Waaler, and Guohui Xiao. Optique – zooming in on big data access. *IEEE Computer*, Accepted for publication, 2015.
- [18] Georg Gottlob, Stanislav Kikot, Roman Kontchakov, Vladimir V. Podolskii, Thomas Schwentick, and Michael Zakharyaschev. The price of query rewriting in ontology-based data access. Artificial Intelligence, 213:42–59, 2014.
- [19] Florian Haag, Steffen Lohmann, Stephan Siek, and Thomas Ertl. QueryVOWL: A visual query notation for linked data. In Proc. of the 3rd Int. Workshop on Human Semantic Web Interaction (HSWI). ESWC 2015 Satellite Events, volume 9341 of Lecture Notes in Computer Science, pages 387–402. Springer, 2015.
- [20] Matthew Horridge and Sean Bechhofer. The OWL API: A Java

API for OWL ontologies. Semantic Web J., 2(1):11–21, 2011.
[21] Ernesto Jimenez-Ruiz, Evgeny Kharlamov, Dmitriy
Thelegopyelogy Jon Hornockey Christoph Pickel Martin C.

- [21] Ernesto Jimenez-Ruiz, Evgeny Kharlamov, Dmitriy Zheleznyakov, Ian Horrocks, Christoph Pinkel, Martin G. Skjæveland, Evgenij Thorstensen, and Jose Mora. BootOX: Practical mapping of RDBs to OWL 2. In Proc. of the 14th Int. Semantic Web Conf. (ISWC), volume 9367 of Lecture Notes in Computer Science, pages 113–132. Springer, 2015.
- [22] Joseph S. Nye Jr. The benefits of soft power. Technical report, Harvard University Business School, 2004. Available at http://hbswk.hbs.edu/archive/4290.html.
- [23] C. Maria Keet, Ronell Alberts, Aurona Gerber, and Gibson Chimamiwa. Enhancing web portals with ontology-based data access: the case study of South Africa's Accessibility Portal for people with disabilities. In Proc. of the 5th Int. Workshop on OWL: Experiences and Directions (OWLED), volume 432 of CEUR Electronic Workshop Proceedings, 2008.
- [24] Evgeny Kharlamov, Dag Hovland, Ernesto Jimenez-Ruiz, Davide Lanti, Hallstein Lie, Christoph Pinkel, Martin Rezk, Martin G. Skjæveland, Evgenij Thorstensen, Guohui Xiao, Dmitriy Zheleznyakov, and Ian Horrocks. Ontology based access to exploration data at Statoil. In Proc. of the 14th Int. Semantic Web Conf. (ISWC), volume 9367 of Lecture Notes in Computer Science, pages 93–112. Springer, 2015.
- [25] Evgeny Kharlamov, Nina Solomakhina, Özgür Lütfü Özçep, Dmitriy Zheleznyakov, Thomas Hubauer, Steffen Lamparter, Mikhail Roshchin, Ahmet Soylu, and Stuart Watson. How semantic technologies can enhance data access at Siemens Energy. In Proc. of the 13th Int. Semantic Web Conf. (ISWC), volume 8796 of Lecture Notes in Computer Science, pages 601– 619. Springer, 2014.
- [26] Stanislav Kikot, Roman Kontchakov, and Michael Zakharyaschev. Conjunctive query answering with OWL 2 QL. In Proc. of the 13th Int. Conf. on the Principles of Knowledge Representation and Reasoning (KR), pages 275–285, 2012.
- [27] Jonathan J. King. QUIST: A system for semantic query optimization in relational databases. In *Proc. of the 7th Int. Conf. on Very Large Data Bases (VLDB)*, pages 510–517. IEEE Computer Society, 1981.
- [28] Roman Kontchakov, Martin Rezk, Mariano Rodriguez-Muro, Guohui Xiao, and Michael Zakharyaschev. Answering SPARQL queries over databases under OWL 2 QL entailment regime. In Proc. of the 13th Int. Semantic Web Conf. (ISWC), volume 8796 of Lecture Notes in Computer Science, pages 552–567. Springer, 2014.
- [29] Davide Lanti, Martin Rezk, Guohui Xiao, and Diego Calvanese. The NPD benchmark: Reality check for OBDA systems. In *Proc. of the 18th Int. Conf. on Extending Database Technology (EDBT)*, pages 617–628. OpenProceedings.org, 2015
- [30] Domenico Lembo, Valerio Santarelli, and Domenico Fabio Savo. Graph-based ontology classification in OWL 2 QL. In Proc. of the 10th Extended Semantic Web Conf. (ESWC), volume 7882 of Lecture Notes in Computer Science, pages 320– 334. Springer, 2013.
- [31] Boris Motik, Bernardo Cuenca Grau, Ian Horrocks, Zhe Wu, Achille Fokoue, and Carsten Lutz. OWL 2 Web Ontology Language profiles (second edition). W3C Recommendation, World Wide Web Consortium, December 2012. Available at http://www.w3.org/TR/owl2-profiles/.
- [32] Boris Motik, Yavor Nenov, Robert Piro, Ian Horrocks, and Dan Olteanu. Parallel materialisation of Datalog programs in cen-

tralised, main-memory RDF systems. In *Proc. of the 28th AAAI Conf. on Artificial Intelligence (AAAI)*, pages 129–137. AAAI Press, 2014.

- [33] Özgür Lütfü Özçep and Ralf Möller. Ontology based data access on temporal and streaming data. In Reasoning Web. Reasoning on the Web in the Big Data Era 10th Int. Summer School Tutorial Lectures (RW), volume 8714 of Lecture Notes in Computer Science, pages 279–312. Springer, 2014.
- [34] Antonella Poggi, Domenico Lembo, Diego Calvanese, Giuseppe De Giacomo, Maurizio Lenzerini, and Riccardo Rosati. Linking data to ontologies. *J. on Data Semantics*, X:133–173, 2008.
- [35] Antonella Poggi, Mariano Rodríguez-Muro, and Marco Ruzzi. Ontology-based database access with DIG-Mastro and the OBDA Plugin for Protégé. In Kendall Clark and Peter F. Patel-Schneider, editors, Proc. of the 4th Int. Workshop on OWL: Experiences and Directions (OWLED DC), 2008.
- [36] Freddy Priyatna, Oscar Corcho, and Juan Sequeda. Formalisation and experiences of R2RML-based SPARQL to SQL query translation using Morph. In Proc. of the 23rd Int. World Wide Web Conf. (WWW), pages 479–490, 2014.
- [37] S. Pugacs. Efficient query answering with semantic indexes. BSc thesis, KRDB Research Centre for Knowledge and Data, Free University of Bozen-Bolzano, 2011.
- [38] Alireza Rahimi, Siaw-Teng Liaw, Jane Taggart, Pradeep Ray, and Hairong Yu. Validating an ontology-based algorithm to identify patients with type 2 diabetes mellitus in electronic health records. *Int. J. of Medical Informatics*, 83(10):768–778, 2014.
- [39] Mariano Rodriguez-Muro. Tools and Techniques for Ontology Based Data Access in Lightweight Description Logics. PhD thesis, KRDB Research Centre for Knowledge and Data, Free University of Bozen-Bolzano, 2010.
- [40] Mariano Rodriguez-Muro and Diego Calvanese. Towards an open framework for ontology based data access with Protégé and DIG 1.1. In Proc. of the 5th Int. Workshop on OWL: Experiences and Directions (OWLED), volume 432 of CEUR Electronic Workshop Proceedings, 2008.
- [41] Mariano Rodríguez-Muro and Diego Calvanese. Dependencies: Making ontology based data access work in practice. In Proc. of the 5th Alberto Mendelzon Int. Workshop on Foundations of Data Management (AMW), volume 749 of CEUR Electronic Workshop Proceedings, 2011.
- [42] Mariano Rodriguez-Muro and Diego Calvanese. High performance query answering over *DL-Lite* ontologies. In *Proc. of the 13th Int. Conf. on the Principles of Knowledge Representation and Reasoning (KR)*, pages 308–318, 2012.
- [43] Mariano Rodriguez-Muro, Roman Kontchakov, and Michael Zakharyaschev. Ontology-based data access: Ontop of databases. In Proc. of the 12th Int. Semantic Web Conf. (ISWC),

- volume 8218 of *Lecture Notes in Computer Science*, pages 558–573. Springer, 2013.
- [44] Mariano Rodriguez-Muro, Lina Lubyte, and Diego Calvanese. Realizing ontology based data access: A plug-in for Protégé. In Proc. of the ICDE Workshop on Information Integration Methods, Architectures, and Systems (IIMAS), pages 286–289. IEEE Computer Society Press, 2008.
- [45] Mariano Rodriguez-Muro and Martin Rezk. Efficient SPARQL-to-SQL with R2RML mappings. J. of Web Semantics, 33:141–169, 2015.
- [46] Mariano Rodriguez-Muro, Martin Rezk, Josef Hardi, Mindaugas Slusnys, Timea Bagosi, and Diego Calvanese. Evaluating SPARQL-to-SQL translation in Ontop. In Proc. of the 2nd Int. Workshop on OWL Reasoner Evaluation (ORE), volume 1015 of CEUR Electronic Workshop Proceedings, pages 94–100, 2013.
- [47] Andreas Schwarte, Peter Haase, Katja Hose, Ralf Schenkel, and Michael Schmidt. FedX: A federation layer for distributed query processing on linked open data. In *Proc. of the 8th Ex*tended Semantic Web Conf. (ESWC), volume 6644 of Lecture Notes in Computer Science, pages 481–486. Springer, 2011.
- [48] Juan F. Sequeda, Marcelo Arenas, and Daniel P. Miranker. OBDA: Query rewriting or materialization? In practice, both! In Proc. of the 13th Int. Semantic Web Conf. (ISWC), volume 8796 of Lecture Notes in Computer Science, pages 535–551. Springer, 2014.
- [49] Martin G. Skjæveland and Espen H. Lian. Benefits of publishing the Norwegian Petroleum Directorate's FactPages as Linked Open Data. In Proc. of Norsk informatikkonferanse (NIK 2013). Tapir, 2013.
- [50] Ahmet Soylu, Evgeny Kharlamov, Dmitriy Zheleznyakov, Ernesto Jimenez-Ruiz, Martin Giese, and Ian Horrocks. Ontology-based visual query formulation: An industry experience. In Proc. of the 11th Int. Symposium on Visual Computing (ISVC), Lecture Notes in Computer Science. Springer, 2015.
- [51] Manolis M. Tsangaris, George Kakaletris, Herald Kllapi, Giorgos Papanikos, Fragkiskos Pentaris, Paul Polydoras, Eva Sitaridi, Vassilis Stoumpos, and Yannis E. Ioannidis. Dataflow processing and optimization on grid and cloud infrastructures. Bull. of the IEEE Computer Society Technical Committee on Data Engineering, 32(1):67–74, 2009.
- [52] Daniel Tunkelang. Faceted Search. Synthesis Lectures on Information Concepts, Retrieval, and Services. Morgan & Claypool Publishers, 2009.
- [53] Guohui Xiao, Martin Rezk, Mariano Rodriguez-Muro, and Diego Calvanese. Rules and ontology based data access. In Proc. of the 8th Int. Conf. on Web Reasoning and Rule Systems (RR), volume 8741 of Lecture Notes in Computer Science, pages 157–172. Springer, 2014.