R2RML Mappings in OBDA Systems: Enabling Comparison among OBDA Tools

Manuel Namici
DIAG, Sapienza, University of Rome
manuel.namici@gmail.com

Abstract

In today’s large enterprises there is a significant increasing trend in the amount of data that has to be stored and processed. To complicate this scenario the complexity of organizing and managing a large collection of data, structured according to a single, unified schema, makes so that there is almost never a single place where to look to satisfy an information need.

The Ontology-Based Data Access (OBDA) paradigm aims at mitigating this phenomenon by providing to the users of the system a unified and shared conceptual view of the domain of interest (ontology), while still enabling the data to be stored in different data sources, which are managed by a relational database. In an OBDA system the link between the data stored at the sources and the ontology is provided through a declarative specification given in terms of a set of mappings.

In this work we focus on comparing two of the available systems for OBDA, namely, Mastro and Ontop, by adopting OBDA specifications based on W3C recommendations. We first show how support for R2RML mappings has been integrated in Mastro, which was the last feature missing in order to enable the system to use specifications based solely on W3C recommendations relevant to OBDA. We then proceed in performing a comparison between these systems over two OBDA specifications, the NPD Benchmark and the ACI specification.

Keywords— Ontology-Based Data Access, R2RML, Mastro, Ontop

1 Introduction

In today’s large enterprises there is a significant increasing trend in the amount of data that has to be stored and processed. To complicate this scenario the complexity of organizing and managing a large collection of data, structured according to a single, unified schema, makes so that there is almost never a single place where to look to satisfy an information need.

The Ontology-Based Data Access (OBDA) paradigm aims at providing to the users of the system a unified and shared conceptual view of the domain of
interest (ontology), while still enabling the data to be stored in different data sources, which are managed by a relational database. In an OBDA system the link between the data stored at the sources and the ontology is provided through a declarative specification given in terms of a set of mappings.

The interest in the adoption of the OBDA paradigm has lead to the creation of prototype tools, that have evolved into full-fledged systems. Although, while these tools effectively enable to answer queries over the ontology, their use in industrial applications still represents a challenge due to the performance requirements that have to be met.

Several studies on the performance comparison among tools that enable semantic data integration have been performed, but to the best of our knowledge none of them focused on comparing fully-implemented systems designed to work in the OBDA setting, in order to gain insight on the advantages and disadvantages of each of the approach adopted, as this requires all the systems to be able to use completely-standard specifications.

In this work we focus on comparing two systems for OBDA, namely, Mastro\(^1\) and Ontop\(^2\).

In particular, we first enable the use of R2RML mappings in Mastro, a tool for Ontology-Based Data Access developed at Sapienza, University of Rome. R2RML is the W3C recommendation for expressing mappings in an OBDA specification, and was the last feature missing in order to enable Mastro to use a completely-standard specification. We then proceed in performing a comparison between these systems over two OBDA specifications, the NPD Benchmark and the ACI specification.

The rest of this work is organized as follows: In Section 2 we briefly describe the basic notions of the R2RML mapping language, and then show how such mappings can be interpreted for their use in Mastro. In Section 3 we discuss the comparison over the NPD Benchmark, a specification developed by the University of Oslo, and adapted for its use as a benchmark in the OBDA setting\(^3\). In Section 4 we discuss the comparison over an application of the OBDA paradigm, developed in collaboration between Sapienza University of Rome and ACI Informatica\(^4\), that is used in a real industrial setting to evaluate the benefits of the OBDA approach. Finally, in Section 5 we show some conclusions and present some possible future works.

2 Adding R2RML Support to Mastro

R2RML (RDB to RDF mapping language) is the W3C recommendation for expressing mappings from relational databases to RDF datasets\(^5\). Such
mappings provide the ability to view existing relational data as RDF graphs, expressed in a structure and target vocabulary of the mapping author’s choice.

Compared to other RDB to RDF mapping languages R2RML can be classified as a general purpose mapping language that allows to express customized, domain-specific mappings. An R2RML mapping is itself represented as an RDF graph. A system that makes use of an R2RML mapping to provide access to an RDF dataset from a relational database is called an R2RML processor. An R2RML processor could, for example, generate an RDF dump of the relational data, or it could offer a SPARQL endpoint over the virtual RDF dataset represented by the database and the R2RML mapping, through an interface that queries the underlying database without explicitly materializing the dataset. The latter scenario is particularly suitable in the case of a system that wants to realize the OBDA paradigm and is the reason why it as been considered as a solution to represent the mapping between the ontology and the data sources.

An overview of the main R2RML classes in the form of a UML class diagram is provided in Figure 1. Moreover, Listing 1 provides a complete example of an R2RML mapping that maps the example database shown in Figure 2 to the RDF dataset shown in Listing 2. For ease of presentation we denote with $rr$: the prefix for R2RML vocabulary terms, with $rdf$: the prefix for RDF vocabulary terms, and $ex$: the prefix for the specific target domain terms.

Figure 1: An overview of the R2RML classes
@prefix rr: <http://www.w3.org/ns/r2rml#> .
@prefix ex: <http://data.example.com/> .
ex:CustomersMap rr:logicalTable [
    rr:sqlQuery "SELECT C_ID, C_NAME FROM customers" ;
] ;
rr:subjectMap [
    rr:template "http://data.example.com/customer/{C_ID}" ;
    rr:class ex:Customer ;
] ;
rr:predicateObjectMap [
    rr:predicate ex:name ;
    rr:objectMap [ rr:column "C_NAME" ]
] .
ex:ProductsMap rr:logicalTable [ rr:tableName "products" ] ;
rr:subjectMap [
    rr:template "http://data.example.com/product/{P_ID}" ;
    rr:class ex:Product
] ;
rr:predicateObjectMap [
    rr:predicate ex:price ;
    rr:objectMap [ rr:column "P_PRICE" ]
] .
ex:OrdersMap rr:logicalTable [ rr:tableName "orders" ] ;
rr:subjectMap [
    rr:template "http://data.example.com/order/{O_ID}" ;
    rr:class ex:Order ;
] ;
rr:predicateObjectMap [
    rr:predicate ex:customer ;
    rr:objectMap [
        rr:parentTriplesMap ex:CustomersMap ;
        rr:joinCondition [
            rr:child "C_ID" ;
            rr:parent "C_ID" ;
        ]
    ] ;
rr:predicateObjectMap [
    rr:predicate ex:product ;
    rr:objectMap [
        rr:parentTriplesMap ex:ProductsMap ;
        rr:joinCondition [
            rr:child "P_ID" ;
            rr:parent "P_ID" ;
        ]
    ] ;
rr:predicateObjectMap [
    rr:predicate ex:quantity ;
    rr:objectMap [ rr:column "QUANTITY" ]
].

Listing 1: Example of a complete R2RML mapping
Listing 2: Example of the generated RDF dataset

| C_ID | C_NAME |
|------|--------|
| 3211 | Alice  |
| 3253 | Bob    |

| P_ID | P_PRICE |
|------|---------|
| 2532 | 12.00   |
| 2533 | 41.00   |

| O_ID | C_ID | P_ID | QUANTITY |
|------|------|------|----------|
| 4301 | 3211 | 2532 | 1        |
| 4302 | 3211 | 2533 | 1        |
| 4303 | 3253 | 2532 | 3        |

Figure 2: Example relational database
2.1 R2RML mappings in OBDA

Using Semantic Web technologies, the standard format for representing knowledge is through RDF triples. RDB to RDF languages such as R2RML allow to transform relational data into a set of RDF triples.

In OBDA the role of the mapping is to generate the set of membership assertions that form the extensional level of the ontology, and this can be represented by a virtual RDF graph when using these technologies.

We now show how an OBDA mapping can be expressed in R2RML, and then proceed in illustrating how this can be integrated into the Mastro system by showing how a set of R2RML triples maps can be converted into a set of mappings partitioned into view predicates and ontology predicate mappings, and a set of mappings in the latter form can be converted to a set of equivalent R2RML triples maps.

An OBDA mapping is represented by an expression of the form:

$$\Phi(\vec{x}) \Rightarrow \Psi(\vec{y}, \vec{t})$$

where $\Phi(\vec{x})$ is a conjunctive query over the source schema, with free variables $\vec{x}$, $\vec{y} \subseteq \vec{x}$, $\Psi(\vec{y}, \vec{t})$ is a conjunctive query over the ontology alphabet.

When trying to map the component of an OBDA mapping to the components of an R2RML triples map, we face two problems: The first issue is how to represent the query over the data source, that constitutes the left-hand side of the mapping. The second issue is how to represent the conjunction on the right-hand side, and how are the objects build from the values returned by the logical table rows.

For what regards the first issue the most appropriate solution is to use the effective SQL query of the logical table. This corresponds exactly to the meaning of the query in the mapping assertion.

For what regards the second issue, if we apply the procedure for generating RDF triples from a triples map, as defined by the standard, we obtain a set of triples, all having the same subject, corresponding to a conjunction of atoms composed by a unary atom for each class specified in the subject map, and a binary predicate for each of the predicate map-object map pair.
Example 2.1. Let’s consider, for example, the triples map `ex:CustomersMap` of Listing 1:

```
ex:CustomersMap rr:logicalTable [ 
  rr:sqlQuery "SELECT C_ID, C_NAME FROM customers" ; 
] ;
rr:subjectMap [ 
  rr:template "http://data.example.com/customer/{C_ID}" ; 
  rr:class ex:Customer ; 
] ;
rr:predicateObjectMap [ 
  rr:predicate ex:name ; 
  rr:objectMap [ rr:column "C_NAME" ] 
] .
```

This triples map specifies that, for each logical table row resulting from the evaluation of the SQL query:

```
SELECT C_ID, C_NAME FROM customers
```

the system should produce the following set of assertions in the virtual RDF graph:

```
ex:customer/{C_ID} rdf:type ex:Customer .
ex:customer/{C_ID} ex:name "{C_NAME}" .
```

where `{C_ID}` is replaced with the value of the column `C_ID`, and `{C_NAME}` is replaced with the value of the column `C_NAME` in the logical table row. This is equivalent to a mapping assertion of the form:

```
SELECT C_ID, C_NAME FROM customers ~> ex:Customer(cust(C_ID)), ex:name(cust(C_ID), C_NAME)
```

where we replaced the IRIs that represent the subjects with the function term `cust`. In fact, in R2RML, the role of the constructors of the individuals in the ontology from the values stored in the database is played by the string templates. This means that we can see each different string template in the mapping as a different function symbol, whose arity is the same as the number of placeholders in the template.

Additionally, in this setting, a mapping assertion of the previous form has been shown [16] to be equivalent to the following set of mappings:
Example 2.2. Let’s now see the case of a triples map of the form corresponding to the one of \texttt{ex:OrdersMap} in the example of Listing II.

\begin{verbatim}
rr:template "http://data.example.com/order/{O_ID}" ;
rr:class ex:Order ;
] ;
rr:predicateObjectMap [ rr:predicate ex:customer ;
rr:objectMap [ rr:parentTriplesMap ex:CustomersMap ;
rr:joinCondition [ rr:child "C_ID" ;
rr:parent "C_ID" ;
] ] ;
rr:predicateObjectMap [ rr:predicate ex:product ;
rr:objectMap [ rr:parentTriplesMap ex:ProductsMap ;
rr:joinCondition [ rr:child "P_ID" ;
rr:parent "P_ID" ;
] ] ] ;
rr:predicateObjectMap [ rr:predicate ex:quantity ;
rr:objectMap [ rr:column "QUANTITY" ]
].
\end{verbatim}

The logical table of this triples map specifies that the rows to consider are directly those of the relation \texttt{orders} in the input database schema. Moreover, the presence of the referencing object map imposes that, when generating the instances of the roles \texttt{ex:customer} and \texttt{ex:product}, we need to make sure that the objects we consider are only those that are subjects of the assertions generated by the \texttt{ex:CustomersMap} and \texttt{ex:ProductMap} respectively. We do this by using the joint SQL query of the referencing object map when generating the mappings. Similarly to the previous case, the set of mappings corresponding to this triples map are:
where we introduced two new function terms \( ord \) and \( prod \), corresponding to the string templates of the customers and products respectively.

### 2.2 Importing R2RML Mappings in Mastro

Up to now we have seen how a set of R2RML mappings are interpreted as a form of mappings that can be used in an OBDA system to generate the virtual ABox assertions.

In Mastro, the set of mappings is composed by a pair \( M = \langle M_v, M_o \rangle \), where:

- \( M_v \) is a set of assertions of the form:
  
  \[
  q_{DB}(\vec{x}) \leadsto v(\vec{x})
  \]

  where \( q_{DB} \) is an SQL query, and \( v \) is a view predicate.

- \( M_o \) is a set of assertions of the form:
  
  \[
  q_v(\vec{x}) \leadsto P(\vec{x}, \vec{t})
  \]

  where \( P \) is an atomic ontology predicate, built from function terms in \( \vec{t} \) applied over the variables in \( \vec{x} \).

The view predicates act as an intermediate level of abstraction and have a dual purpose: On one side they enable the database manager to focus on improving the efficiency of the database management system, by having a description of the relevant queries that will have to be performed. On the other side they free the ontology designer from having to consider the technical detail of the database schema.
In R2RML the closest notion to the views used in Mastro are the logical tables. Unfortunately, the R2RML language does not provide the vocabulary for expressing a logical table as an arbitrary conjunction of other logical tables (except when using referencing object maps, which are restricted to express foreign key relationships among logical tables), but relies completely on the queries at the SQL level. This does not really pose a problem when importing an R2RML mapping, as we can see each logical table as a view mapping, where the associated query is the effective SQL query of the logical table, and build the ontology mappings for each of the assertions generated by the triples map using this newly generated view mapping. The challenge is how to encode mappings that are expressed as arbitrary conjunction of view predicates in R2RML. The solution we adopt in order to capture the full semantics of the mappings in Mastro is to create a new logical table for each of this conjunctions, where the corresponding SQL query is the unfolding of the query over the views. In the following, we illustrate both processes by means of some examples.

**Example 2.3.** Starting from the example 2.1 from the previous section, in order to obtain a set of mappings in the form used by Mastro, we need to introduce an auxiliary view predicate, corresponding to the SQL query of the left-hand side of the original mapping, and substitute it in the left-hand side of the previously shown mappings:

- \( M_v \):
  ```sql
  SELECT C_ID, C_NAME
  FROM customers
  ⇝ customers_view(C_ID, C_NAME)
  ```

- \( M_o \):
  ```sql
  customers_view(C_ID, C_NAME) ⇝ ex:Customer(cust(C_ID))
  ```

  ```sql
  customers_view(C_ID, C_NAME) ⇝ ex:name(cust(C_ID), C_NAME)
  ```

**Example 2.4 (Importing a mapping from a referencing object map).** When translating R2RML mappings of the type shown in example 2.2 we can express the query of the referencing object map directly as queries over the view predicates:
where the join between the parent and child triples map is performed on the left-hand side of the mappings in $M_0$, by performing unification over the attributes stated in the join conditions.

### 2.3 Exporting Mastro Mappings in R2RML

The procedure for exporting a set of mappings expressed in the Mastro mapping format is the dual of the one previously described, with an important distinction: We need to introduce a new logical table for each of the conjunctions on the left-hand side of the ontology predicate mappings in order to be able to capture in R2RML the complete semantics that form the left-hand side of the mapping. This is because R2RML does not allow to express logical tables as arbitrary conjunctive queries of other logical tables. To obtain the SQL query of the generated logical table we unfold the query over the view predicates. During this translation all the constraints over the views, and the other optimizations expressed in the internal mapping format have to be discarded, as they cannot be expressed in R2RML.

**Example 2.5** (Exporting a mapping with a single view atom). Consider the case shown in example 2.3. In this case it is enough to generate a logical table
for the view customers_view, and a triples map for each of the mappings corresponding to the right-hand side of the ontology predicate mappings:

```
_:customer_view rr:sqlQuery " SELECT C_ID, C_NAME FROM customers "
ex:Customer rr:logicalTable _:customer_view
  rr:subjectMap [ rr:template "http://data.example.com/customer/{C_ID}" ; rr:class ex:Customer ]
ex:name rr:logicalTable _:customer_view
  rr:subjectMap [ rr:template "http://data.example.com/customer/{C_ID}" ]
  rr:predicateObjectMap [ rr:predicate ex:name ; rr:objectMap [ rr:column "C_NAME" ] ]
```

Example 2.6 (Exporting a mapping with a conjunction of view atoms). Now consider the mappings shown in example 2.4. The mappings for the roles ex:customer and ex:products are expressed as a conjunction of view predicates. Even though there may be cases where this type of assertion can be translated with the use of a referencing object map, we cannot assume that this is always the case. A general solution, that preserves the semantics of the mapping, is to transform the conjunction on the left-hand side of both roles into a new logical table, corresponding to the unfolding of the query over the views. This means generating triples maps in the following form:

```
ex:customerMap rr:logicalTable [ rr:sqlQuery ""
  SELECT v1.C_ID AS C_ID, v2.O_ID AS O_ID
  FROM
  (SELECT C_ID, C_NAME
   FROM customers) AS v1,
  (SELECT O_ID, C_ID
   FROM orders) AS v2
  WHERE v1.C_ID=v2.C_ID
""
  ];
  rr:subjectMap [ rr:template "http://data.example.com/order/{O_ID}" ];
  rr:predicateObjectMap [ rr:predicate ex:customer ; rr:objectMap [ rr:template "http://data.example.com/customer/{C_ID}" ] ]
```

12
3 Comparison on the NPD Benchmark

The increase in the rate of adoption of the OBDA paradigm has lead to the creation of several prototype tools. Although, while these tools effectively enable to answer queries over the ontology, their use in industrial applications still represents a challenge due to the performance requirements that have to be met.

Towards this direction, several benchmarks from the Semantic Web world have been proposed as a way of evaluating the performance of an OBDA system [10, 3].

Unfortunately, all these benchmarks lack a fundamental property, that is the presence of a complex and expressive ontology, which is required in order to effectively evaluate the performance of an OBDA system in an industrial application setting. For this purpose, recently a new benchmark has been proposed, based on the Norwegian Petroleum Directorate (NPD) FactPages.

The Norwegian Petroleum Directorate is a governmental organization whose main objective is to contribute to maximize the value that society can obtain from the oil and gas activities [12]. The NPD FactPages contains information regarding the petroleum activities on the Norwegian continental shelf. Such information is actively used by oil companies like Statoil. The Factpages are periodically synchronized with the NPD’s databases.

The NPD ontology has been mapped to the NPD FactPages and stored in a relational database. Together with the ontology, the benchmark is provided with a dump of the original database created from the NPD FactPages, the set of mappings expressed in the R2RML mapping language, and a set of queries that have been formulated by domain experts starting from an informal set of questions provided to the users of the NPD FactPages.

In the following we will first describe the main characteristics of what composes the NPD Benchmark specification, with respect to version 1.9. We will then proceed in illustrating the setup for our experimentation, with a presentation of the results obtained.

Ontology The NPD Ontology [20] describes activities on the Norwegian continental shelf (NCS), e.g., about companies that own or operate petroleum fields, results of tests taken during drilling, geographical data for physical installations and the areas of fields and seismic surveys, transfers of shares of fields between companies, and production results measured in volumes of petroleum [20]. The ontology has been created by the University of Oslo, and presents rich hierarchies of classes and properties, axioms that infer new objects, and disjointness assertions.

http://factpages.npd.no/factpages/
https://github.com/ontop/npd-benchmark
The ontology is specified in OWL and for the purpose of the benchmark it has been restricted to the fragment corresponding to the OWL 2 QL profile. Overall is composed by about 350 concepts, 142 roles and 238 attributes, with a maximum hierarchy depth of 10. This restriction is essential for its use in the context of OBDA as guarantees first-order rewritability for the class of union of conjunctive queries.

Mappings  The NPD specification provides a set of 1173 mapping assertions, characterized by an average of 1.7 joins per query. The mappings have been partially bootstrapped automatically from the database and the ontology, and partially created by hand, and are specified in the R2RML mapping language.

The mappings have purposely not optimized, to measure the efficiency of the optimization strategies employed by an OBDA system. This means that the number of mappings that refer to the same ontology predicate is in general very large, up to about 30 in some cases.

Query Set  The latest revision of the NPD benchmark devises 30 between real world and technical queries of different complexity, expressed in SPARQL, and defined by domain experts starting from an informal set of questions to the users of the NPD FactPages. Among the set of queries, some have been specifically generated to stress the efficiency of a system when reasoning with respect to existential variables.

Some of the characteristics of the queries are the presence of concepts with a rich hierarchy and the presence of aggregations. For the purpose of this experimentation, we are only interested in the subset of these SPARQL queries corresponding to the class of union of conjunctive queries, as this is the semantics for SPARQL queries that is adopted by Mastro. The only exception is that we make is for the use of duplicate elimination from the results. This requires to changes part of the query set.

In the following we present each individual query, together with its \( CQ \) restriction, the changes required, and a brief description of the query.
NPD query q1

```
SELECT DISTINCT ?licenceURI ?interest ?date 
WHERE {

?licenceURI a npdv:ProductionLicence .

[ ] a npdv:ProductionLicenceLicensee ;
npdv:dateLicenseeValidFrom ?date ;
npdv:licenseeInterest ?interest ;
npdv:licenseeForLicence ?licenceURI .
FILTER(?date > "1979-12-31T00:00:00"^^xsd:dateTime)
}
```

CQ query q1

```
SELECT DISTINCT ?licenceURI ?interest ?date 
WHERE {

?licenceURI a npdv:ProductionLicence .

[ ] a npdv:ProductionLicenceLicensee ;
npdv:dateLicenseeValidFrom ?date ;
npdv:licenseeInterest ?interest ;
npdv:licenseeForLicence ?licenceURI .
FILTER(?date > "1979-12-31T00:00:00"^^xsd:dateTime)
}
```

Modifications

No modification is required for query q1.

Description

Query q1 asks for the licenses, the interest applied to the respective licensees, and from when they are valid.

Listing 3: NPD Query q1
NPD query q2

```
SELECT ?licenceURI ?company ?date
WHERE {
  ?licenceURI a npdv:ProductionLicence .
  [ ] a npdv:ProductionLicenceOperator ;
  npdv:dateOperatorValidFrom ?date ;
  npdv:licenceOperatorCompany [ npdv:name ?company ] ;
  npdv:operatorForLicence ?licenceURI .
  FILTER(?date > "1979-12-31T00:00:00"^^xsd:dateTime)

} ORDER BY ?licenceURI
```

CQ query q2

```
SELECT ?licenceURI ?company ?date
WHERE {
  ?licenceURI a npdv:ProductionLicence .
  [ ] a npdv:ProductionLicenceOperator ;
  npdv:dateOperatorValidFrom ?date ;
  npdv:licenceOperatorCompany [ npdv:name ?company ] ;
  npdv:operatorForLicence ?licenceURI .
  FILTER(?date > "1979-12-31T00:00:00"^^xsd:dateTime)
}
```

Modifications

The CQ version of query q2 is obtained by removing the ORDER BY clause.

Description

Query q2 asks for the operators for licences whose contracts were started after 1980.

Listing 4: NPD Query q2
NPD query q3

```sql
SELECT ?licence ?dateGranted ?dateValidTo
WHERE {
    [ ] a npdv:ProductionLicence;
    npdv:name ?licence;
    npdv:dateLicenceGranted ?dateGranted;
    npdv:dateLicenceValidTo ?dateValidTo .
    FILTER(?dateValidTo > "1979-12-31T00:00:00"^^xsd:dateTime)
} ORDER BY ?licence
```

CQ query q3

```sql
SELECT ?licence ?dateGranted ?dateValidTo
WHERE {
    [ ] a npdv:ProductionLicence;
    npdv:name ?licence;
    npdv:dateLicenceGranted ?dateGranted;
    npdv:dateLicenceValidTo ?dateValidTo .
    FILTER(?dateValidTo > "1979-12-31T00:00:00"^^xsd:dateTime)
}
```

Modifications

The CQ version of query q3 is obtained by removing the ORDER BY clause with respect to the ?licence variable.

Description

Query q3 asks for the licences whose expiration dates were after 1980.

Listing 5: NPD Query q3
NPD query q4

SELECT ?licence ?company ?licenseeFrom
WHERE {
[ ? ] npdv:licenseeForLicence
[ a npdv:ProductionLicence ;
 npdv:name ?licence ];
 npdv:licenceLicensee [ npdv:name ?company ];
 npdv:dateLicenseeValidFrom ?licenseeFrom .
  FILTER(?licenseeFrom > "1979-12-31T00:00:00"^^xsd:dateTime)
}
ORDER BY ?licence ASC(?licenseeFrom)

CQ query q4

SELECT ?licence ?company ?licenseeFrom
WHERE {
[ ? ] npdv:licenseeForLicence
[ a npdv:ProductionLicence ;
 npdv:name ?licence ];
 npdv:licenceLicensee [ npdv:name ?company ];
 npdv:dateLicenseeValidFrom ?licenseeFrom .
  FILTER(?licenseeFrom > "1979-12-31T00:00:00"^^xsd:dateTime)
}

Modifications

The CQ of query q4 is obtained by removing the ORDER BY clause.

Listing 6: NPD Query q4
NPD query q5

```
SELECT  ?fr  ?OE  ?oil  ?gas  ?NGL  ?con
WHERE {
  ?fr a npdv:FieldReserve ;
  npdv:remainingCondensate  ?con ;
  npdv:remainingGas  ?gas ;
  npdv:remainingNGL  ?NGL ;
  npdv:remainingOil  ?oil ;
  npdv:remainingOilEquivalents  ?OE .
  FILTER(?gas < 100)
} ORDER BY DESC(?OE)
```

CQ query q5

```
SELECT  ?fr  ?OE  ?oil  ?gas  ?NGL  ?con
WHERE {
  ?fr a npdv:FieldReserve ;
  npdv:remainingCondensate  ?con ;
  npdv:remainingGas  ?gas ;
  npdv:remainingNGL  ?NGL ;
  npdv:remainingOil  ?oil ;
  npdv:remainingOilEquivalents  ?OE .
  FILTER(?gas < 100)
}
```

Modifications

The CQ of query q5 is obtained by removing the ORDER BY clause.

Listing 7: NPD Query q5
NPD query q6

```
SELECT DISTINCT ?wellbore (?length AS ?lengthM) ?company ?year
WHERE {
  ?wc npdv:coreForWellbore
  [ rdf:type npdv:Wellbore ;
    npdv:name ?wellbore ;
    npdv:wellboreCompletionYear ?year ;
    npdv:drillingOperatorCompany [ npdv:name ?company ]
  ] .
  { ?wc npdv:coresTotalLength ?length }
  FILTER(?year >= "2008"^^xsd:integer &&
         ?length > 50)
} ORDER BY ?wellbore
```

Description

This is a query that asks for the wellbores, their length, and the companies that completed the drilling of the wellbore after 2008, and sampled more than 50m of cores. The use of graph patterns of this form is not supported in Mastro, and so it has not been considered.

Listing 8: NPD Query q6
NPD query q7

```sparql
SELECT *
WHERE {
  [ ] a npdv:FieldMonthlyProduction ;
  npdv:productionYear ?year ;
  npdv:productionMonth ?month ;
  npdv:producedCondensate ?con ;
  npdv:producedGas ?gas ;
  npdv:producedNGL ?NGL ;
  npdv:producedOil ?oil ;
  npdv:producedOilEquivalents ?maxOE .
  FILTER(?gas < 100)
}
```

CQ query q7

```sparql
SELECT *
WHERE {
  [ ] a npdv:FieldMonthlyProduction ;
  npdv:productionYear ?year ;
  npdv:productionMonth ?month ;
  npdv:producedCondensate ?con ;
  npdv:producedGas ?gas ;
  npdv:producedNGL ?NGL ;
  npdv:producedOil ?oil ;
  npdv:producedOilEquivalents ?maxOE .
  FILTER(?gas < 100)
}
```

Modifications

No modification is required for query q7.

Listing 9: NPD Query q7
NPD query q8

```
SELECT *
WHERE {
  [ npdv:productionYear ?year ;
    npdv:productionMonth ?m ;
    npdv:producedGas ?g ;
    npdv:producedOil ?o
  ]
  FILTER (?year > 1999)
  FILTER(?m >= 1 && ?m <= 6 )
}
```

CQ query q8

```
SELECT *
WHERE {
  [ npdv:productionYear ?year ;
    npdv:productionMonth ?m ;
    npdv:producedGas ?g ;
    npdv:producedOil ?o
  ]
  FILTER (?year > 1999)
  FILTER(?m >= 1 && ?m <= 6 )
}
```

Modifications

No modification is required for query q8.

Listing 10: NPD Query q8
NPD query q9

```
SELECT *
WHERE {
    [ ] a npdv:Facility ;
    npdv:name ?facility ;
    npdv:registeredInCountry ?country;
    npdv:idNPD ?id .
    FILTER (?id > "400000"^^xsd:integer)
} ORDER BY ?facility
```

CQ query q9

```
SELECT *
WHERE {
    [ ] a npdv:Facility ;
    npdv:name ?facility ;
    npdv:registeredInCountry ?country;
    npdv:idNPD ?id .
    FILTER (?id > "400000"^^xsd:integer)
}
```

Modifications

The CQ version of q9 is obtained by removing the ORDER BY clause.

Listing 11: NPD Query q9
NPD query q10

```
SELECT DISTINCT *
WHERE {
    [] a npdv:DiscoveryWellbore ;
    npdv:name ?wellbore ;
    npdv:dateUpdated ?date .
    FILTER ( ?date > "2013-01-01T00:00:00.0"^^xsd:dateTime )
} ORDER BY ?wellbore
```

CQ query q10

```
SELECT DISTINCT *
WHERE {
    [] a npdv:DiscoveryWellbore ;
    npdv:name ?wellbore ;
    npdv:dateUpdated ?date .
    FILTER ( ?date > "2013-01-01T00:00:00.0"^^xsd:dateTime )
}
```

Modifications

The CQ version of q10 is obtained by removing the ORDER BY clause.

Listing 12: NPD Query q10
NPD query q11

```sql
SELECT DISTINCT ?wellbore (?length AS ?lengthM) ?company ?year
WHERE {
  ?wc npdv:coreForWellbore
  [ rdf:type npdv:Wellbore ;
    npdv:name ?wellbore ;
    npdv:wellboreCompletionYear ?year ;
    npdv:drillingOperatorCompany [ npdv:name ?company ] ] .
  { ?wc npdv:coresTotalLength ?length ;
    npdv:coreIntervalUOM °[m]°^^xsd:string .
  }
  FILTER(?year >= 2008 &&
    ?length > 50)
} ORDER BY ?wellbore
```

Description

Query q11 is a variation of q6 where the wellbore core length has a value expressed in meters.

Listing 13: NPD Query q11
NPD query q12

```sparql
SELECT DISTINCT ?wellbore (?length AS ?lenghtM) ?company ?year
WHERE {
  ?wc npdv:coreForWellbore
  [ rdf:type npdv:Wellbore ;
    npdv:name ?wellbore ;
    npdv:wellboreCompletionYear ?year ;
    npdv:drillingOperatorCompany [ npdv:name ?company ] ] .
  { ?wc npdv:coresTotalLength ?l ;
    npdv:coreIntervalUOM "[m]"^^xsd:string .
    BIND(?l AS ?length) }
  UNION
  { ?wc npdv:coresTotalLength ?l ;
    npdv:coreIntervalUOM "[ft]"^^xsd:string .
    BIND((?l * 0.3048) AS ?length) }
  FILTER(?year >= "2008"^^xsd:integer && ?length > 50)
} ORDER BY ?wellbore
```

Description

Query q12 is an extension of q6, and makes use of the SPARQL operator `BIND` and arithmetical operations on the results, which are not supported on Mastro.
NPD query q13

```
SELECT DISTINCT *
WHERE {
  ?x a npdv:SeismicSurvey .
  OPTIONAL {?x npdv:lengthCdpTotalKm ?cdpKM .}
  OPTIONAL {?x npdv:lengthBoatTotalKm ?boatKM .}
  FILTER (?cdpKM > 3660)
}
```

NPD query q14

```
SELECT DISTINCT *
WHERE {
  ?x a npdv:WellboreDrillingMudSample ;
  npdv:dateMudMeasured ?date .
  OPTIONAL {
    ?x npdv:mudType ?type .
    OPTIONAL {
      ?x npdv:mudWeight ?w ;
      npdv:mudMeasuredDepth ?d .
    }
  }
  FILTER (?date > "1986-08-25T00:00:00"^^xsd:dateTime)
}
```

Description

Queries q13 and q14 make use of the the SPARQL operators OPTIONAL and BIND which are not supported in the current version of Mastro.
NPD query q15

```sparql
SELECT ?licenceURI (AVG(?interest) AS ?vavg)
WHERE {
  ?licenceURI a npdv:ProductionLicence .
  [ ] a npdv:ProductionLicenceLicensee ;
  npdv:dateLicenseeValidFrom ?date ;
  npdv:licenseeInterest ?interest ;
  npdv:licenseeForLicence ?licenceURI .
  FILTER(?date >= "1979-12-31"^^xsd:date)
} GROUP BY ?licenceURI
```

CQ query q15

```sparql
SELECT ?licenceURI ?interest
WHERE {
  ?licenceURI a npdv:ProductionLicence .
  [ ] a npdv:ProductionLicenceLicensee ;
  npdv:dateLicenseeValidFrom ?date ;
  npdv:licenseeInterest ?interest ;
  npdv:licenseeForLicence ?licenceURI .
  FILTER(?date >= "1979-12-31"^^xsd:date)
}
```

Modifications

The CQ of query q15 is obtained by removing the aggregation over the ?licenceURI variable.

Description

Query q15 asks for the licenses, the interest applied to the respective licensees.

Listing 16: NPD Query q15
NPD query q16

SELECT ( COUNT(?licence ) AS ?licnumber) 
WHERE { 
[ ] a npdv:ProductionLicence ;
npdv:name ?licence ;
npdv:dateLicenceGranted ?dateGranted ;
FILTER(?dateGranted >= "1999-12-31"^^xsd:date) 
}

CQ query q16

SELECT ?licence 
WHERE { 
[ ] a npdv:ProductionLicence ;
npdv:name ?licence ;
npdv:dateLicenceGranted ?dateGranted ;
FILTER(?dateGranted >= "1999-12-31"^^xsd:date) 
}

Modifications

The CQ of query q16 is obtained by removing the COUNT operator.

Description

This query asks for the name of the licenses granted starting from year 2000.

Listing 17: NPD Query q16
NPD query q17

```
SELECT ?field (SUM(?g) AS ?gas)
WHERE {
  [ npdv:productionYear 2008 ;
    npdv:productionMonth ?m ;
    npdv:producedGas ?g ;
    npdv:productionForField
    [ rdf:type npdv:Field ;
      npdv:name ?field ;
      npdv:currentFieldOperator
      [ npdv:shortName "STATOIL PETROLEUM AS"^^xsd:string ]]
  ]
} GROUP BY ?field ORDER BY ?field
```

CQ query q17

```
SELECT ?field ?g
WHERE {
  [ npdv:productionYear 2008 ;
    npdv:productionMonth ?m ;
    npdv:producedGas ?g ;
    npdv:productionForField
    [ rdf:type npdv:Field ;
      npdv:name ?field ;
      npdv:currentFieldOperator
      [ npdv:shortName "STATOIL PETROLEUM AS"^^xsd:string ]]
  ]
}
```

Modifications

Query q17 is obtained by removing aggregation and the ordering over the ?field variable.
NPD query q18

```
SELECT ?field (AVG(?oil) AS ?avgOil)
WHERE {
  [ ] a npdv:FieldYearlyProduction ;
  npdv:productionForField [ npdv:name ?field ] ;
  npdv:producedOil ?oil ;
  npdv:productionYear ?year .
  FILTER (?year < 2013)
}
GROUP BY ?field
ORDER BY DESC(?avgOil)
```

CQ query q18

```
SELECT ?field ?oil
WHERE {
  [ ] a npdv:FieldYearlyProduction ;
  npdv:productionForField [ npdv:name ?field ] ;
  npdv:producedOil ?oil ;
  npdv:productionYear ?year .
  FILTER (?year < 2013)
}
```

Modifications

The CQ of query q18 is obtained by removing the aggregation over the ?field variable and the ordering over the averaged ?oil variable.

Listing 19: NPD Query q18
NPD query q19

SELECT ?field (SUM(?o) AS ?oil)
WHERE {
  [ npdv:productionYear 1993 ; npdv:productionMonth ?m ; npdv:producedOil ?o ; npdv:productionForField
    [ rdf:type npdv:Field ; npdv:name ?field ; npdv:currentFieldOperator
      [ npdv:shortName "STATOIL PETROLEUM AS"^^xsd:string ]] ]
  FILTER(?m >= 1 && ?m <= 6)
} GROUP BY ?field ORDER BY ?field

CQ query q19

SELECT ?field ?o
WHERE {
  [ npdv:productionYear 1993 ; npdv:productionMonth ?m ; npdv:producedOil ?o ; npdv:productionForField
    [ rdf:type npdv:Field ; npdv:name ?field ; npdv:currentFieldOperator
      [ npdv:shortName "STATOIL PETROLEUM AS"^^xsd:string ]] ]
  FILTER(?m >= 1 && ?m <= 6)
}

Modifications

The CQ of query q19 is obtained by removing the aggregation and ordering over the ?field variable.
**NPD query q20**

```
SELECT ?fr (Max(?g) AS ?max)
WHERE {
    ?fr npdv:productionYear ?year;
    npdv:productionMonth ?m;
    npdv:producedGas ?g .
    FILTER (?year > 2000)
} GROUP BY ?fr
```

**NPD query q21**

```
SELECT ?fr (Min(?g) AS ?min)
WHERE {
    ?fr npdv:productionYear ?year;
    npdv:productionMonth ?m;
    npdv:producedGas ?g .
    FILTER (?year > 2000)
} GROUP BY ?fr
```

**CQ query q20**

```
SELECT ?fr ?g
WHERE {
    ?fr npdv:productionYear ?year;
    npdv:productionMonth ?m;
    npdv:producedGas ?g .
    FILTER (?year > 2000)
}
```

**Modifications**

Query q20 and q21 differ only by the type of aggregation performed. For this reason after removing the aggregation only one of them has been considered.
NPD query q22

```
SELECT DISTINCT ?wc
WHERE {
  ?wc npdv:coreForWellbore [ rdf:type npdv:Wellbore ].
}
```

NPD query q23

```
SELECT DISTINCT ?member ?awc
WHERE {
  ?member npdv:member ?awc.
  ?awc npdv:coreForWellbore [ rdf:type npdv:Wellbore ].
}
```

NPD query q24

```
SELECT DISTINCT ?member
WHERE {
  ?member npdv:member ?awc.
  ?awc npdv:coreForWellbore [ rdf:type npdv:Wellbore ].
}
```

NPD query q25

```
SELECT DISTINCT ?licenssee
WHERE {
  ?licenssee npdv:licenseeForLicence ?licence.
}
```

Description

Queries q22 – 25 are already in the fragment of conjunctive queries, so no modification is required.

Listing 22: NPD Query q22-25
NPD query q26

```
SELECT DISTINCT ?licensee
WHERE {
    ?licensee npdv:licenseeForLicence
    [ npdv:licenceOperatorCompany ?company ]
}
```

NPD query q27

```
SELECT DISTINCT ?company
WHERE {
    ?licensee npdv:licenseeForLicence
    [ npdv:licenceOperatorCompany ?company ].
}
```

Description

Queries q26 – 27 are already in the fragment of conjunctive queries, so no modification is required.

Listing 23: NPD Query q26-27
NPD query q28

```
SELECT DISTINCT ?wellbore ?wc ?well
WHERE {
  ?wellbore npdv:wellboreForDiscovery ?discovery;
  npdv:belongsToWell ?well.
  ?wc npdv:coreForWellbore ?wellbore.
}
```

NPD query q29

```
SELECT DISTINCT ?wellbore ?wc ?well ?length
WHERE {
  ?wellbore npdv:wellboreForDiscovery ?discovery;
  npdv:belongsToWell ?well.
  ?wc npdv:coreForWellbore ?wellbore;
  npdv:coresTotalLength ?length;
  npdv:coreIntervalUOM "[ft ]"^^xsd:string . # feets
  FILTER (?length < 56796)
}
```

Description

Queries q28 – 29 are already in the fragment of conjunctive queries, so no modification is required.

Listing 24: NPD Query q28-29
### NPD query q30

```sparql
SELECT DISTINCT ?wellbore ?wc ?well ?length
WHERE {
  ?wellbore npdv:wellboreForDiscovery ?discovery;
  npdv:belongsToWell ?well.
  ?wc npdv:coreForWellbore ?wellbore.
  {
    ?wc npdv:coresTotalLength ?lMeters ;
    npdv:coreIntervalUOM "[m]"^^xsd:string .
    BIND(?lMeters AS ?length)
  }
  UNION
  {
    ?wc npdv:coresTotalLength ?lFeets ;
    npdv:coreIntervalUOM "[ft]"^^xsd:string .
    BIND((?lFeets * 0.3048) AS ?length)
  }
  FILTER (?length < 22337)
}
```

### Description

Query q30 is an extension of q12, and makes use of the SPARQL operator `BIND` and arithmetical operations on the results, which are not supported on Mastro.

Listing 25: NPD Query q30
Data generation  The original NPD databases is derived from the data published on the *Norwegian Petroleum Directorate FactPages*.

The data from FactPages has been translated from CSV files into a structured database. The generated schema consists of 70 tables with 276 distinct columns (about 1000 columns in total), and 94 foreign keys.

The schemas of the tables overlap in the sense that several attributes are replicated in several tables. In fact, there are tables with more than 100 columns. The total size of the initial database is about 60 MB.

Since OBDA are expected to work in the context of Big Data, the authors of the benchmark have provided a tool that enables the initial database instance to be scaled in order to obtain larger instances. The scaling process, implemented by the *Virtual Instances Generator (VIG)*\(^8\), is performed by taking into account the axioms in the ontology, the structure of the mappings, and the database constraints in order to preserve a set of similarity measures in the original database.

Compared to a random generation approach, the algorithm adopted by VIG preserves important factors, such as the ratio of column-based duplicates, null values ratios, and the ratio for join result sets. This is a requirement when the generation has to be performed in order to evaluate the performance of an OBDA system. Adopting a completely random approach would simply make the scaled database non-suitable for the evaluation of an OBDA system, since the number of joining columns in the mappings would be completely random and non-representative of the original instance.

Starting from this initial database, instances of different size have been created with the use of the VIG generator, and have been loaded into separate databases. Table 1 shows the scaling factor and the size for each of the generated databases that have been used in our experiment. The number of the database represents its scale with respect to the original instance.

| NAME  | SCALE FACTOR | SIZE       |
|-------|--------------|------------|
| NPD1  | 1            | 60 MB      |
| NPD10 | 10           | 710 MB     |
| NPD50 | 50           | 2570 MB    |
| NPD100| 100          | 5300 MB    |

Table 1: Generated databases

\(^7\)http://factpages.npd.no/factpages/

\(^8\)https://github.com/ontop/vig
Experimental Setup  We ran the NPD Benchmark on both the latest version of Mastro 1.0.2 and Ontop 3.0, on the same physical system using the same set of generated databases. The underlying DBMS is MySQL version 5.7.21, running locally on the testing machine.

The specifications of the platform used for the experiments are the following:

CPU  Intel Xeon E5-2670 running at 2.60GHz

RAM  16 GB DDR3 1600 MHz

OS  Ubuntu 17.10 running in a virtualized environment (4 cores)

The experimentation is performed in the following mode:

• We iterate over the set of queries. At each iteration we pick a random query from the set and evaluate it over the system. This is done in order to reduce the effect of the caching in the DBMS.

For each execution we store the results and the time it took to complete. We consider the combined time needed for evaluating the query and processing the set of results. Queries are executed sequentially through the use of a testing platform designed specifically for this task, which accesses directly the internal APIs of the systems.

• We repeat the process until all queries have been executed a fixed amount of time, in this case 5 executions were performed.

• Finally, we take the average of the execution times for each of the queries in the set.

In order to compare the systems under the same setting we enabled for both reasoning with respect to existential variables. Our metric of comparison is the total time taken to complete the execution of the query and to process the results. A comparison of the execution times for both systems for the database instances NPD1, NPD10, NP50, and NPD100 are shown respectively in Figure 3, 4, 5, and 6. Table 2 reports a summary of the average execution time for each query and database size.
Table 2: Query Answering Times over the generated databases (in seconds)

| QUERY | NPD1 |     | NPD10 |     | NPD50 |     | NPD100 |     |
|-------|------|-----|-------|-----|-------|-----|--------|-----|
|       | Mastro | Ontop |       | Mastro | Ontop |       | Mastro | Ontop |
| q1    | 0.364 | 0.692 | 3.320 | 3.627 | 14.277 | 36.657 | 37.107 | 159.733 |
| q2    | 0.316 | 0.098 | 0.201 | 0.078 | 1.302 | 2.944 | 2.939 | 6.762 |
| q3    | 0.117 | 0.064 | 0.279 | 0.485 | 0.900 | 2.304 | 1.939 | 9.450 |
| q4    | 0.620 | 0.996 | 2.815 | 3.779 | 69.200 | 34.961 | 32.037 | 76.069 |
| q5    | 0.082 | 0.024 | 0.115 | 0.043 | 0.108 | 0.090 | 0.134 | 0.074 |
| q7    | 0.788 | 0.258 | 0.694 | 0.425 | 0.464 | 5.793 | 0.656 | 19.252 |
| q8    | 0.141 | 0.076 | 0.250 | 0.197 | 0.395 | 0.394 | 0.612 | 0.651 |
| q9    | 0.937 | 0.125 | 1.176 | 2.096 | 7.284 | 5.788 | 7.012 | 18.753 |
| q10   | 0.161 | 0.250 | 0.600 | 2.523 | 3.401 | 17.849 | 6.207 | 33.731 |
| q15   | 0.288 | 0.111 | 1.161 | 0.586 | 19.688 | 5.454 | 22.683 | 43.994 |
| q16   | 0.093 | 0.011 | 0.093 | 0.011 | 0.116 | 0.023 | 0.172 | 0.085 |
| q17   | 2.121 | 0.004 | 2.287 | 0.006 | 2.167 | 0.006 | 2.213 | 0.004 |
| q18   | 0.071 | 0.009 | 0.074 | 0.004 | 0.082 | 0.005 | 0.074 | 0.004 |
| q19   | 2.024 | 0.005 | 2.043 | 0.005 | 2.138 | 0.004 | 3.051 | 0.004 |
| q20   | 0.249 | 0.113 | 2.901 | 1.579 | 15.146 | 11.898 | 44.538 | 118.329 |
| q22   | 0.457 | 0.565 | 3.421 | 5.408 | 14.808 | 28.372 | 26.425 | 55.841 |
| q23   | 0.752 | 0.243 | 6.065 | 2.363 | 42.884 | 22.180 | 65.265 | 46.621 |
| q24   | 0.562 | 0.114 | 3.546 | 0.715 | 18.224 | 3.640 | 39.278 | 7.772 |
| q25   | 0.745 | 0.284 | 6.551 | 2.985 | 61.744 | 19.048 | 94.802 | 35.893 |
| q26   | 0.088 | 0.004 | 0.086 | 0.006 | 0.094 | 0.003 | 0.109 | 0.007 |
| q27   | 0.089 | 0.003 | 0.082 | 0.002 | 0.107 | 0.003 | 0.114 | 0.004 |
| q28   | 13.496 | 1.648 | 49.303 | 20.641 | 220.932 | 133.396 | 438.149 | 319.339 |
| q29   | 6.001 | 0.155 | 8.211 | 0.440 | 27.770 | 9.396 | 58.841 | 18.525 |
Figure 3: Query Answering over NPD1 (Execution Time)

Figure 4: Query Answering over NPD10 (Execution Time)
Figure 5: Query Answering over NPD50 (Execution Time)

Figure 6: Query Answering over NPD100 (Execution Time)
Experimental results  We start our analysis by looking at some of the most interesting results. In particular, the queries where Ontop performs worse are those requiring reasoning with respect to the existential variables. Examples of these queries are \( q_9 \) and \( q_{10} \), which cause the system to produce rewritings consisting of unions of tens of sub-queries.

Queries \( q_1, q_2, q_3, q_4, q_7, q_{15}, q_{16}, q_{25} \) instead produce a simple SPJ rewriting, although the difference here is given by the fact that Ontop applies strictly the rules specified by the OWL 2 standard, performing the datatype casts and the generation of the IRIs directly at the SQL level, which causes a slowdown of the execution. Instead, Mastro adopts a less strict approach for dealing with datatypes, avoiding to perform casts and IRI-construction at the SQL level.

As for queries \( q_{24}-q_{25} \), and \( q_{28}-q_{29} \), it can be noted that in this case Mastro performs considerably slower than Ontop. This is due to the high number of mappings for the ontology predicates involved in these queries, that have to be unfolded by the system, and by the high number of sub-classes and sub-properties for the concepts and properties in the query, which cause the rewriting to grow exponentially in size. In Mastro, this phenomenon is mitigated with the addition of data constraints during the design of the views, in such a way that this redundancy is avoided. In this case, since view are generated automatically from the R2RML mapping, these constraints are not available to the system, effectively disabling all the optimizations that the system is capable of performing. Instead, in Ontop this problem is mitigated during the offline stage, when the mappings and the ontology are compiled to form the so-called \( T \)-mappings, using the database constraints to optimize the mappings.

Finally, queries \( q_{17}-q_{19} \), and \( q_{26}-q_{27} \) are less interesting, as they produce empty unfoldings (due to mismatching function names in the mappings), and their execution time does not depend on the database size. For these queries, it can be noted that moving part of the computation to an offline stage gives Ontop a big advantage, as the system has to check a small amount of mappings at query execution time.

4 Comparison on a full-fledged OBDA solution

While the use synthetic benchmarks can be a starting point in order to understand the type of performance that we can expect from a system, and allows to draw some conclusions about the effectiveness of the adopted approach, there is also the need to verify that such conclusions hold also when we move to real world applications.

The main problem with the specification that we presented in Section \( \text{X} \) is that while the ontology has been effectively designed to model accurately the conceptual reality of the domain of interest, the data sources did not
exist before and have been created specifically for the purpose of evaluating
the specification. Unfortunately, this means that they do not reflect what
is the real structure that can be found when attempting to experiment the
ontology-based data access approach in real world scenarios.

For this purpose we decided to use one of the specifications that is cur-
cently in development between Sapienza University of Rome and the Auto-
mobile Club d’Italia (ACI).

In this chapter we first give an overview of the specification, by describing
the ontology, the mappings and the data sources. Then, we proceed in
showing the experimentation that we performed, aimed at understanding
the usability of both Mastro and Ontop in such scenario. Finally, we present
the results and draw the conclusions.

Ontology The ontology comprises about 500 concepts, 200 roles and 200
attributes, and it is divided into 11 logically interconnected modules. Among
these modules some of the most important are represented by:

- The ontological module describing the concept of Vehicle (Veicolo),
  characterized as a central object in the ontology, modeling also its
  relevant state (Stato), that models the evolution of vehicles’ property
  over time.

- The ontological module describing the concept of Subject (Soggetto),
  modeling the possible roles played by the subjects (physical people or
  organizations) with respect to the taxation concerning vehicles.

- The ontological module describing the concept of Formality (Formalitá),
  and payment (Pagamento).

The ontology has been defined following rigorously the best practice for
ontology design, based on the analysis and definition of the domain of in-
terest through a series of interviews with the domain experts, so that the
ontology would reflect exactly the reality of the domain of interest, and not
the structure of the data sources. This characteristics of the ontology makes
so that the specification of the mappings is extremely complex, due to the
large semantic gap between the reality of the domain of interest and the se-
manics of the data sources, which are structured in such a way that enables
the applications that make use of them meet the efficiency requirements that
they need.

Moreover, the modeling of the ontology also describes the evolution in
time of its elements. For example, during its lifespan a vehicle can change
owner, license plate, and so on. This is captured by the notion of state of a
vehicle (Stato). This is a recurring aspect in the queries as we will show in
the following sections.
**Data source**  For this experiment the database is managed by an instance of Oracle 12c. The database is accessed remotely through the use of a VPN. The relevant portion of the data for our experiment is distributed across 6 schemas. These schemas are composed of hundreds of tables, but for what regards the portion of the domain that is of interest in this experiment we concentrate on about 90 relational tables, ranging from information regarding the domain of PRA (Pubblico Registro Automobilistico), to those regarding the taxation concerning the vehicles. Some of these tables count from 200 million tuples up to above 1 billion tuples in some cases, with a number of attributes ranging from 30 to 100. The overall size of the portion of interest of the data source is several gigabytes of data (an accurate estimate was not possible).

**Mappings**  The specification comprises 976 ontology mappings, composed from a set of about 110 views over the data source. About 300 of these ontology mappings are built from single view atoms, while the remaining are specified as conjunctive queries over the view predicates. For the purpose of our experimentation the mappings have been previously translated in R2RML through the use of the approach described in Section\textsuperscript{2} and then imported back into both systems. During the translation process the constraints over the view predicates are discarded, since they cannot be expressed in R2RML.

**Query Set**  In this section we describe the set of queries that have been defined to evaluate the usability of both systems. Query \(q_1\) to \(q_5\) are basic navigational queries, that span some of the relevant part of the ontology. The remaining queries \(q_6\) to \(q_{10}\) are derived the real queries used in the original experimentation of the project. These queries are built from a set of competency questions, defined by interviewing the domain experts over the practical questions that have to be posed to the system, and are used to validate the quality and the coherency of the specification.

Before showing the set of queries that have been used for our experimentation we have to point out that in order to comply with the time restrictions we were granted, these queries have been restricted to extracting information for single vehicles. In some cases this was already enough to fill the time slot that was allowed. In their real application, queries are used to build reports for several hundred of thousands of vehicles, that require several hours to complete.
ACI query q1

PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
SELECT ?veicolo ?stato ?proprieta
WHERE {
  ?veicolo aci:ID_veicolo "<id>"^^xsd:string.
  ?veicolo aci:ha_stato_di_veicolo ?stato.
  ?proprieta aci:proprieta_di ?veicolo.
}

Description

Query q1 asks for vehicles that have a state and their ownership.

Listing 26: ACI query q1

ACI query q2

PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>
SELECT ?veicolo ?stato ?proprieta ?formalita
WHERE {
  ?veicolo aci:ID_veicolo "<id>"^^xsd:string.
  ?veicolo aci:ha_stato_di_veicolo ?stato.
  ?proprieta aci:proprieta_di ?veicolo.
  ?formalita aci:formalita_presentata_per_veicolo ?veicolo.
}

Description

Query q2 asks for vehicles that have a state, their ownership, and the formalities.

Listing 27: ACI query q2
ACI query q3

```
PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?veicolo ?stato ?proprieta 
    ?accettazione ?anno ?descrizione 
WHERE { 
  ?veicolo aci:ID_veicolo "<id>"^^xsd:string. 
  ?veicolo aci:ha_stato_di_veicolo ?stato. 
  ?proprieta aci:proprieta_di ?veicolo. 
  ?formalita aci:formalita_presentata_per_veicolo ?veicolo. 
  ?formalita aci:data_accettazione_formalita ?accettazione. 
  ?formalita aci:anno_formalita ?anno. 
  ?formalita aci:descrizione_tipo ?descrizione. 
}
```

Description

Query q2 asks for vehicles that have a state, their ownership, and the formalities, with their acceptance dates, year of acceptance, and a description of the type of formality.

Listing 28: ACI query q3

47
**ACI query q4**

```
PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?veicolo ?stato ?proprieta ?accettazione ?descrizione ?anno ?certificato
WHERE {
    ?veicolo aci:ID_veicolo "<id>"^^xsd:string .
    ?veicolo aci:ha_stato_di_veicolo ?stato .
    ?proprieta aci:proprieta_di ?veicolo .
    ?formalita aci:formalita_presentata_per_veicolo ?veicolo .
    ?formalita aci:data_accettazione_formalita ?accettazione .
    ?formalita aci:anno_formalita ?anno .
    ?formalita aci:descrizione_tipo ?descrizione .
    ?formalita aci:emette_certificato ?certificato .
}
```

**Description**

Query q4 extends q3 with the certificate released for the formalities.

Listing 29: ACI query q4
ACI query q5

```
PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?veicolo ?stato ?proprieta ?accettazione ?descrizione ?anno ?certificato ?codiceCDP
WHERE {
  ?veicolo aci:ID_veicolo "<id>"^^xsd:string .
  ?veicolo aci:ha_stato_di_veicolo ?stato .
  ?proprieta aci:proprieta_di ?veicolo .
  ?formalita aci:formalita_presentata_per_veicolo ?veicolo .
  ?formalita aci:data_accettazione_formalita ?accettazione .
  ?formalita aci:anno_formalita ?anno .
  ?formalita aci:descrizione_tipo ?descrizione .
  ?formalita aci:emette_certificato ?certificato .
  ?certificato aci:codice_cdp ?codiceCDP .
}
```

Description

Query q5 extends q4 with the code of the certificate.

Listing 30: ACI query q5
ACI query q6

```
PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?veicolo ?stato
WHERE {
  ?veicolo aci:ID_veicolo "<id>"^^xsd:string.
  ?veicolo aci:ha_stato_di_veicolo ?stato.
  ?stato a aci:Stato_rappresentato_valido.
}
```

Description

Query q6 asks for vehicles that have a state which is valid.

Listing 31: ACI query q6
ACI query q7

PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?veicolo ?stato ?numeroTarga ?serieTarga
WHERE {
    ?veicolo aci:ID_veicolo "<id>"^^xsd:string.
    ?veicolo aci:ha_stato_di_veicolo ?stato.
    ?stato a aci:Stato_rappresentato_valido.
    ?stato aci:ha_targa ?targa.
    ?targa aci:numero_targa ?numeroTarga.
    ?targa aci:serie_targa ?serieTarga.
}

Description

Query q7 extends q6 with information about the license plate of the vehicles.

Listing 32: ACI query q7
ACI query q8

PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?veicolo ?stato ?numeroTarga ?serieTarga ?formalita ?codiceFormalita
WHERE {
  ?veicolo aci:ID_veicolo "<id>"^^xsd:string.
  ?veicolo aci:ha_stato_di_veicolo ?stato.
  ?stato a aci:Stato_rappresentato_valido.
  ?stato aci:ha_targa ?targa.
  ?targa aci:numero_targa ?numeroTarga.
  ?targa aci:serie_targa ?serieTarga.
  ?evento aci:determina_stato ?stato.
  ?formalita aci:formalita_genera_evento ?evento.
  ?formalita aci:codice_tipo ?codiceFormalita.
}

Description

Query q8 extends q7 with information about the events that determine the state.

Listing 33: ACI query q8
ACI query q9

PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?veicolo ?stato ?numeroTarga ?serieTarga
?inizioStato ?fineStato ?formalita
?codiceFormalita
WHERE {
  ?veicolo aci:ID_veicolo "<id>"^^xsd:string.
  ?veicolo aci:ha_stato_di_veicolo ?stato.
  ?stato a aci:Stato_rappresentato_valido.
  ?stato aci:ha_targa ?targa.
  ?targa aci:numero_targa ?numeroTarga.
  ?targa aci:serie_targa ?serieTarga.
  ?evento aci:determina_stato ?stato.
  ?formalita aci:formalita_genera_evento ?evento.
  ?formalita aci:codice_tipo ?codiceFormalita.
  ?stato aci:inizio_stato_del_mondo ?inizioStato.
  ?stato aci:fine_stato_del_mondo ?fineStato.
}

Description

Query q9 extends q8 with more informations about the state.

Listing 34: ACI query q9
ACI query q10

PREFIX aci: <http://www.aci.it/ontology#>
PREFIX xsd: <http://www.w3.org/2001/XMLSchema#>

SELECT ?veicolo ?stato ?numeroTarga ?serieTarga ?formalita ?codiceFormalita ?KW ?cilindrata ?classe
WHERE {
  ?veicolo aci:ID_veicolo "<id>"^^xsd:string.
  ?veicolo aci:ha_stato_di_veicolo ?stato.
  ?stato a aci:Stato_rappresentato_valido.
  ?stato aci:ha_targa ?targa.
  ?targa aci:numero_targa ?numeroTarga.
  ?targa aci:serie_targa ?serieTarga.
  ?evento aci:determina_stato ?stato.
  ?formalita aci:formalita_genera_evento ?evento.
  ?formalita aci:codice_tipo ?codiceFormalita.
  ?stato aci:kw ?KW.
  ?stato aci:cilindrata ?cilindrata.
  ?stato aci:classe_veicolo ?classe.
}

Description

Query q10 extends q9 with more informations about the state. This corresponds to one of the competency questions that are asked to the system, about technical data of the vehicles.

Listing 35: ACI query q10
**Experimental Setup**  For the purpose of the evaluation we ran the queries over both the latest version of Mastro 1.0.2 and Ontop version 3.0, using the same specification composed by the ontology and the mappings exported in R2RML. The database is managed by an instance of Oracle 12c, that is accessed remotely over a VPN connection.

The specifications of the platform used for the experiments are the following:

**CPU**  Intel Xeon E5-2670 running at 2.60GHz

**RAM**  16 GB DDR3 1600 MHz

**OS**  Ubuntu 17.10 running in a virtualized environment (4 cores)

The experimentation is performed in the following mode:

- We iterate over the set of queries. At each iteration we pick a random query from the set and evaluate it over the system. This is done in order to minimize the caching in the DBMS.

  For each execution we store the results and the time it took to complete. We consider the combined time needed for evaluating the query and processing the set of results. Queries are executed sequentially through the use of a testing platform designed specifically for this task, which accesses directly the internal APIs of the systems.

- We repeat the process until all queries have been executed a fixed amount of time, in this case 5 executions were performed.

- Finally, we take the average of the execution times for each of the queries in the set.

In order to compare the systems under the same setting we enabled for both reasoning with respect to existential variables. Our metric of comparison is the total time taken to complete the execution of the query and to the process the results. Due to restrictions in the amount of time we were allowed for experiments, the queries were executed with a timeout of 3 hours. As a reference, we report also the time needed by the Mastro system using the original mapping specification to evaluate the same set of queries. Figure 7 shows the overall execution times for both systems. Table 3 reports the execution times.
Table 3: Query Answering Times on the ACI Specification (in seconds)

| QUERY | MASTRO | MASTRO R2RML | ONTOP  |
|-------|--------|--------------|--------|
| q1    | 3.808  | 4.866        | 15.356 |
| q2    | 5.081  | 8.362        | 20.874 |
| q3    | 9.958  | 19.139       | 32.607 |
| q4    | 55.310 | 87.586       | 153.308|
| q5    | 56.452 | 85.284       | 398.358|
| q6    | 0.639  | 1.011        | – (> 3h)|
| q7    | 2.692  | 19.113       | – (> 3h)|
| q8    | 6.353  | 85.915       | – (> 3h)|
| q9    | 16.934 | 5894.621     | – (> 3h)|
| q10   | 16.104 | 9123.935     | – (> 3h)|

Figure 7: Query Answering over ACI (Execution Time)
**Experimental results**  There are several considerations that can be made by looking at the results of our experimentation, but the most important one is that in none of the queries based on the real competency questions that this solution is designed to answer, Ontop was able to complete in the time allowed, even though both systems are using the same specification. We identified three main reasons for this:

- The first reason is that, in the case of Ontop, the entire rewriting is executed as a single, complex SQL query, and the database management system is not able to compute an efficient query plan for such large queries.

- The second reason is that when the optimizations performed to reduce the size of the $T$-mappings fail, because there may be missing database constraints, or simply because the queries in the mappings contain complex conditions that don’t allow to apply such optimizations, the system produces rewriting containing complex sub-queries, composed of unions of several SPJ queries and these types of queries are not evaluated efficiently.

- The third reason is that, even though representing a very elegant solution, having the objects to be constructed directly at the level of the data sources, through the use inherently poorly performing operations such as string concatenation and type casts, is not feasible in real industrial applications.

This is due to the fact that the assumption at the base of the Ontop optimizations, that the axioms in the ontology duplicates the constraints on the database does not hold in this particular case. In this case the structure of the data sources reflects the application needs and not the conceptual reality of the domain of discourse. When this condition arises, the system is not able to optimize the queries in the mappings and causes it to produce rewritings that are too difficult to be dealt with efficiently by the DBMS, where the intermediate views are composed by complex unions of `select-project-join` queries.

On the other hand, the approach adopted in Mastro, of splitting the queries in several, simpler conjunctive queries, even if it can result in an exponential blowup in the size of the rewriting still enables the system to complete the task in the time allowed, even if in this case there are no optimizations performed, as the constraints over the views are not expressible in R2RML, which cause the time taken by the system to increase up to almost three orders of magnitude for the largest query.
5 Conclusions and Future Works

In this article we have worked on OBDA systems, and in particular, on the Mastro OBDA system, developed at Sapienza. For such system we have studied the support of the standard R2RML for realizing OBDA mappings. We have implemented software components to support such kind of mappings and our implementation is now part of the current release of Mastro. Interestingly, we have seen that we can translated any R2RML mapping into Mastro mappings, while the contrary is true only if it is acceptable to lose some efficiency.

Using R2RML mappings we have been able to compare various OBDA systems against fully standard specifications, where the ontology is specified in OWL 2, the queries are specified in SPARQL, and the mappings (to standard SQL DBs) are expressed in R2RML.

In fact, we have seen that only two systems have support fully the reasoning techniques needed for OBDA solutions: Mastro and Ontop. Hence, we have concentrated on such two systems.

Our comparison has focused on two benchmarks. The first one is NPD, a benchmark defined by the Ontop team. Specifically we have modified NPD queries focusing on the features that require reasoning support. The most important result in this case is that it shows how the idea of moving part of the optimization complexity during an offline stage can indeed provide an advantage, as it reduces the complexity of applying optimization algorithms entirely at query execution.

The second benchmark has been based on a full-fledged OBDA solution, developed within a contract between the department of DIAG at Sapienza, University of Rome, and ACI Informatica. In particular, we have used the real sources from ACI as well as the OWL 2 ontology developed by the department for them. With respect to the mappings, we have translate (losing some efficiency) the real Mastro mappings into R2RML, so as to allow the comparison with Ontop. Finally, as queries we used simplified versions of the actual queries used in the application. The results in this case are quite different. Most often, Ontop could not handle the queries, while Mastro could still complete the task in the allowed time slot. Instead, in the case of Mastro, the approach of separating the rewritings into single SPJ queries evaluated individually, still enables the system to complete the task within the allowed time slot, even without applying any optimization, as these are not expressible in R2RML.

This comparison lead to some interesting results, that can drive research for future works. In this section we highlight some of them:

Moving computation to an offline stage: We have seen how moving part of the computation to an offline stage can provide large benefits in some cases, not only because it could allow the system to produce
smaller rewritings by applying more extensive optimization techniques that would not be possible to execute during query evaluation due to their expensive cost in terms of complexity, but also because this enables these optimizations to be computed only once, without having to recompute them for every execution, effectively reducing the time spent during query evaluation. This has been already considered in Mastro, and a new optimization based on this idea is already under investigation.

**Improving R2RML support with database constraints:** Database constraints can alone represent a useful source of information that can be exploited for optimizations, as can be seen in the case of the NPD specification. A possible extension to the technique presented in this article for translating R2RML mappings into view and ontology mappings can take advantage of these constraints to automatically generate data constraints between view mappings.

**Combining both approaches:** In the case of Ontop, the idea compiling the ontology into the mappings, combined with the use of database constraints to simplify the resulting mappings, can be indeed a very effective technique when the database constraints reflect the knowledge expressed by the axioms of the ontology, as they can be combined with techniques that avoid the exponential blowup in the size of the produced CQ rewritings that can be generated by algorithms such as PerfectRef, and can be computed only once and used for all the unfoldings. Although, when such optimization fails to simplify the generated mapping, a better approach would be to treat each of the unions as a different mapping, and combine it into several, simpler SQL queries that can be treated separately, even if it can result in an exponential blowup in the number of rewritings, as it is done in Mastro. This would at least enable the queries in such case to be efficiently evaluated by the database management system.

**References**

[1] A. Acciarri, D. Calvanese, G. De Giacomo, D. Lembo, M. Lenzerini, M. Palmieri, and R. Rosati. Quonto: Querying ontologies. In *Proceedings, The Twentieth National Conference on Artificial Intelligence and the Seventeenth Innovative Applications of Artificial Intelligence Conference, July 9-13, 2005, Pittsburgh, Pennsylvania, USA*, pages 1670–1671, 2005.

[2] F. Baader, D. Calvanese, D. L. McGuinness, D. Nardi, and P. F. Patel-Schneider, editors. *The Description Logic Handbook: Theory, Implementation, and Applications*. Cambridge University Press, 2003.
[3] C. Bizer and A. Schultz. The berlin SPARQL benchmark. *Int. J. Semantic Web Inf. Syst.*, 5(2):1–24, 2009.

[4] D. Calvanese, B. Cogrel, E. G. Kalayci, S. Komla-Ebri, R. Kontchakov, D. Lanti, M. Rezk, M. Rodriguez-Muro, and G. Xiao. OBDA with the Ontop Framework. In *23rd Italian Symposium on Advanced Database Systems, SEBD 2015, Gaeta, Italy, June 14-17, 2015.*, pages 296–303, 2015.

[5] D. Calvanese, G. De Giacomo, D. Lembo, M. Lenzerini, A. Poggi, M. Rodriguez-Muro, and R. Rosati. Ontologies and Databases: The DL-Lite Approach. In *Reasoning Web. Semantic Technologies for Information Systems, 5th International Summer School 2009, Brixen-Bressanone, Italy, August 30 - September 4, 2009, Tutorial Lectures*, pages 255–356, 2009.

[6] D. Calvanese, G. De Giacomo, D. Lembo, M. Lenzerini, and R. Rosati. DL-Lite: Tractable Description Logics for Ontologies. In *Proceedings, The Twentieth National Conference on Artificial Intelligence and the Seventeenth Innovative Applications of Artificial Intelligence Conference, July 9-13, 2005, Pittsburgh, Pennsylvania, USA*, pages 602–607, 2005.

[7] D. Calvanese, G. De Giacomo, D. Lembo, M. Lenzerini, and R. Rosati. Tractable Reasoning and Efficient Query Answering in Description Logics: The DL-Lite Family. *J. Autom. Reasoning*, 39(3):385–429, 2007.

[8] D. Calvanese, G. De Giacomo, D. Lembo, M. Lenzerini, and R. Rosati. Data complexity of query answering in description logics. *Artif. Intell.*, 195:335–360, 2013.

[9] S. Das, S. Sundara, and R. Cyganiak. R2RML: RDB to RDF Mapping Language, 2012.

[10] Y. Guo, Z. Pan, and J. Heflin. LUBM: A benchmark for OWL knowledge base systems. *J. Web Sem.*, 3(2-3):158–182, 2005.

[11] J. Heflin and J. A. Hendler. A Portrait of the Semantic Web in Action. *IEEE Intelligent Systems*, 16(2):54–59, 2001.

[12] D. Lanti, M. Rezk, G. Xiao, and D. Calvanese. The NPD Benchmark: Reality Check for OBDA Systems. In *Proceedings of the 18th International Conference on Extending Database Technology, EDBT 2015, Brussels, Belgium, March 23-27, 2015.*, pages 617–628, 2015.

[13] D. Lanti, G. Xiao, and D. Calvanese. Data scaling in OBDA benchmarks: The VIG approach. *CoRR*, abs/1607.06343, 2016.
[14] M. Lenzerini. Data Integration: A Theoretical Perspective. In Proceedings of the Twenty-first ACM SIGACT-SIGMOD-SIGART Symposium on Principles of Database Systems, June 3-5, Madison, Wisconsin, USA, pages 233–246, 2002.

[15] F. D. Pinto, D. Lembo, M. Lenzerini, R. Mancini, A. Poggi, R. Rosati, M. Ruzzi, and D. F. Savo. Optimizing query rewriting in ontology-based data access. In Joint 2013 EDBT/ICDT Conferences, EDBT ’13 Proceedings, Genoa, Italy, March 18-22, 2013, pages 561–572, 2013.

[16] A. Poggi, D. Lembo, D. Calvanese, G. De Giacomo, M. Lenzerini, and R. Rosati. Linking Data to Ontologies. J. Data Semantics, 10:133–173, 2008.

[17] M. Rodriguez-Muro, R. Kontchakov, and M. Zakharyaschev. Ontology-Based Data Access: Ontop of Databases. In The Semantic Web - ISWC 2013 - 12th International Semantic Web Conference, Sydney, NSW, Australia, October 21-25, 2013, Proceedings, Part I, pages 558–573, 2013.

[18] M. Rodriguez-Muro and M. Rezk. Efficient SPARQL-to-SQL with R2RML mappings. J. Web Sem., 33:141–169, 2015.

[19] N. Shadbolt, T. Berners-Lee, and W. Hall. The semantic web revisited. IEEE Intelligent Systems, 21(3):96–101, 2006.

[20] M. G. Skjæveland, E. H. Lian, and I. Horrocks. Publishing the norwegian petroleum directorate’s factpages as semantic web data. In The Semantic Web - ISWC 2013 - 12th International Semantic Web Conference, Sydney, NSW, Australia, October 21-25, 2013, Proceedings, Part II, pages 162–177, 2013.

[21] W3C. OWL 2 Web Ontology Language Profiles (Second Edition), 11 2012. http://www.w3.org/TR/owl2-profiles/. 

61