Novel Developments in Ontology-Based Data Access and Integration: Part 1. Introduction to Semantic Technologies and Data Access

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Outline of the tutorial

Part 1: Introduction to ontology-based data access and integration (Diego, 60 mins)

- Motivations
- Structure of OBDA systems
- Relevant Semantic Web Technologies

Part 2: Systems and use cases (Guohui, 60 mins)

- OBDA/I Systems
- ② Use-cases for OBDA and OBDI
- 3 Demo of the OBDA system *Ontop*

Part 3: Latest advancements in OBDA and OBDI (Diego, 45 mins)

- Temporal OBDA
- 2 Accessing cross-linked data sources

Part 4: Demo of OBDI (Guohui, 30 mins)



Typical view of Big Data



In fact, data has a lot of structure



Motivation

Challenges in the Big Data era



The New York Stock Exchange captures 1 TR OF TRADE

Velocity

ANALYSIS OF

By 2016, it is projected there will be 18 9 RILLION NETWORK CONNECTIONS

- almost 2.5 connections per person on earth

Diego Calvanese, Guohui Xiao (unibz)

STREAMING DATA

The FOUR V's of Big Data

Velocity, Variety and Veracity

4.4 MILLION IT IORS



AS OT ZULL, the global size of data in healthcare was estimated to be 150 EXARYTES

30 BILLION are shared on Eacebook



420 MILLION WEARARIE WIRELESS HEALTH MONITORS **Variety** are watched on DIFFERENT

YouTube each month

4 RILLION+

By 2014, it's anticipated

there will be

1 IN 3 BUSINESS Poor data quality costs the US economy around don't trust the information they use to make decisions

FORMS OF DATA



Veracity UNCERTAINTY OF DATA

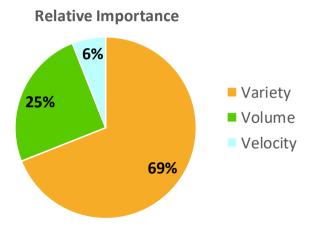
in one survey were unsure of how much of their data was inaccurate



Sources: McKinsey Global Institute Twitter Cisco, Gartner EMC SAS IRM MERTEC DAS

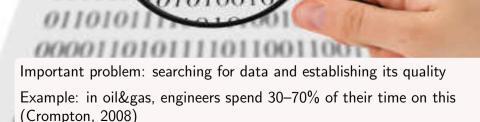
Variety, not volume, is driving Big Data initiatives

MIT Sloan Management Review (28 March 2016)





How much time is spent searching for the right data?





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Challenge: Accessing heterogeneous data



Problem: Translating information needs

Information need expressed by geologists

In my geographical area of interest, return all pressure data tagged with key stratigraphy information with understandable quality control attributes, and suitable for further filtering.

To obtain the answer, this needs to be translated into SQL¹:

- main table for wellbores has 38 columns (with cryptic names)
- to obtain pressure data requires a 4-table join with two additional filters
- to obtain stratigraphic information requires a join with 5 more tables



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¹BTW, SQL is the standard DB query language.

Problem: Translating information needs

We would obtain the following SQL query:

```
SELECT WELLBORE.IDENTIFIER. PTY PRESSURE.PTY PRESSURE S.
       STRATIGRAPHIC ZONE.STRAT COLUMN IDENTIFIER. STRATIGRAPHIC ZONE.STRAT UNIT IDENTIFIER
FROM WELLBORE.
     PTY PRESSURE.
     ACTIVITY FP DEPTH DATA
       LEFT JOIN (PTY_LOCATION_1D FP_DEPTH_PT1_LOC
           INNER JOIN PICKED_STRATIGRAPHIC_ZONES ZS
              ON ZS.STRAT_ZONE_ENTRY_MD <= FP_DEPTH_PT1_LOC.DATA_VALUE_1_O AND
                 ZS.STRAT ZONE EXIT MD >= FP DEPTH PT1 LOC.DATA VALUE 1 0 AND
                 ZS.STRAT_ZONE_DEPTH_UOM = FP_DEPTH_PT1_LOC.DATA_VALUE_1_OU
           INNER JOIN STRATIGRAPHIC_ZONE
              ON ZS.WELLBORE = STRATIGRAPHIC_ZONE.WELLBORE AND
                 ZS.STRAT_COLUMN_IDENTIFIER = STRATIGRAPHIC_ZONE.STRAT_COLUMN_IDENTIFIER AND
                 ZS.STRAT_INTERP_VERSION = STRATIGRAPHIC_ZONE.STRAT_INTERP_VERSION
                                                                                     AND
                ZS.STRAT ZONE IDENTIFIER = STRATIGRAPHIC ZONE.STRAT ZONE IDENTIFIER)
           ON FP DEPTH DATA.FACILITY S = ZS.WELLBORE AND
              FP_DEPTH_DATA.ACTIVITY_S = FP_DEPTH_PT1_LOC.ACTIVITY_S.
     ACTIVITY CLASS FORM PRESSURE CLASS
WHERE WELLBORE.WELLBORE S = FP_DEPTH_DATA.FACILITY_S AND
     FP DEPTH DATA.ACTIVITY S = PTY PRESSURE.ACTIVITY S AND
     FP DEPTH DATA.KIND S = FORM PRESSURE CLASS.ACTIVITY CLASS S AND
      WELLBORE.REF EXISTENCE KIND = 'actual' AND
      FORM PRESSURE CLASS.NAME = 'formation pressure depth data'
```

Problem: Translating information needs

We would obtain the following SQL query:

```
ON ZS.WELLBORE = STRATIGRAPHIC_ZONE.WELLBORE AND
ZO GTDAT COLUMN TRENTTETED - GTDATTCDADUTC ZONE GTDAT COLUMN TRENTTETED
```

This is also very costly!

ACTIV: Statoil loses **50.000.000€** per year only due to this problem!!

WELLBORE.REF_EXISTENCE_KIND = 'actual' AND

FORM_PRESSURE_CLASS.NAME = 'formation pressure depth data'

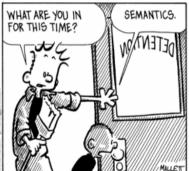
Idea: Exploit semantics of data

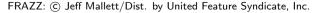


Spring 2015 issue of Al Magazine is devoted to Semantics for Big Data.











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Outline

- Motivation
- 2 Ontology-based Data Access
- 3 Representing Data in RDF and RDFS
- **4** OBDA Framework
- **5** Query Answering in OBDA

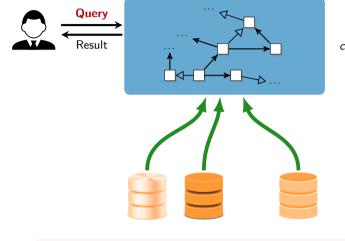


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Solution: Ontology-based data access (OBDA)



Ontology \mathcal{O}

conceptual view of data, convenient vocabulary

Mapping M how to populate the ontology from the data

Data Sources S autonomous and heterogeneous

Reduces the time for translating information needs into queries from days to minutes.



Challenges in OBDA

- How to instantiate the abstract framework?
- How to execute queries over the ontology by accessing data in the sources?
- How to address the expressivity efficiency tradeoff?
- How to optimize performance with big data and large ontologies?
- How to deal with heterogeneity in the data?
- How to deal with different types of data sources?
- How to provide automated support for key tasks during design and deployment?
- How to assess the quality of the constructed system?

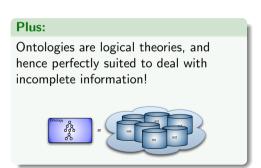


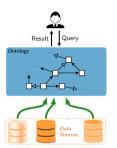
Incomplete information

We are in a setting of incomplete information!!!

Incompleteness is introduced:

- by data sources, in general assumed to be incomplete;
- by domain constraints encoded in the ontology.





Minus:

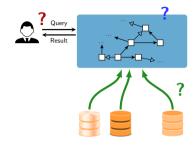
Query answering amounts to **logical inference**, and hence is significantly more challenging.



OBDA framework – Which languages to use?

The choice of the right languages needs to take into account the tradeoff between expressive power and efficiency of query answering.

Note: We are in a setting where data plays a prominent role, so **efficiency with respect to the data** is the key factor.



The W3C has standardized languages that are suitable for OBDA:

● Ontology O: expressed in OWL 2 QL [W3C Rec. 2012]

Q Query: expressed in **SPARQL** [W3C Rec. 2013] (v1.1)

3 Mapping \mathcal{M} : expressed in R2RML [W3C Rec. 2012]



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Resource Description Framework (RDF)

RDF provides a description of the domain of interest in terms of triples:



<http://slegger.gitlab.io/slegge-obda/ontology/subsurface-exploration#name>

Triple elements: resources denoted by **global identifiers** (IRIs)

- Subject: IRI of the described resource
- 2 Predicate: IRI of the property
- 3 Object: attribute value or IRI of another resource

Prefixes: useful abbreviations and/or references to external information

```
@prefix expl: <http://slegger.gitlab.io/slegge-obda/ontology/subsurface-exploration#>
@prefix : <http://slegger.gitlab.io/data#>
```

@base <http://slegger.gitlab.io/>

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@prefix expl: <http://slegger.gitlab.io/slegge-obda/ontology/subsurface-exploration#>
@prefix : <http://slegger.gitlab.io/data#>

@base <http://slegger.gitlab.io/>

RDF – Examples

We assume <code>@prefix</code> : .

Class membership:

Fact	:Wellbore(<i>pf2/WB-16/1-29-S</i>)	
RDF triple	<pf2 1-29-s="" wb-16=""> a :Wellbore</pf2>	

Note: This is an abbreviation for

RDF triple | <pf2/WB-16/1-29-S> rdf:type :Wellbore

Attribute of an individual:

Fact	:name(<i>pf2/WB-16/1-29-S</i> , "16/1-29-S")	
RDF triple	<pre><pf2 1-29-s="" wb-16=""> :name "16/1-29-S"</pf2></pre>	

Property of an individual:

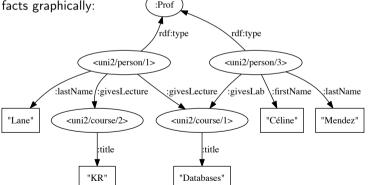
	:hasFormationPressure($pf2/WB-16/1-29-S$, $FP-1249$)		
RDF triple	<pre><pf2 1-29-s="" wb-16=""> :hasFormationPressure <fp-1249></fp-1249></pf2></pre>		



RDF graph – Example

```
<uni2/person/1> rdf:type :Prof
<uni2/person/1> foaf:lastName "Lane"
<uni2/person/1> :givesLecture <uni2/course/1>
...
```

We can represent such a set of facts graphically:





Additional RDF features

RDF has additional features that we do not cover here:

- blank nodes
- named graphs



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- OBDA Framework Ontology Language – OWL 2 QL Query Language – SPARQL Mapping Language – R2RML
- **5** Query Answering in OBDA



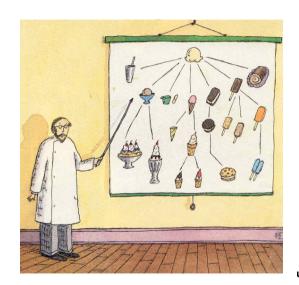
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 Query Language SPARQL
 Mapping Language R2RML
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What is an ontology?

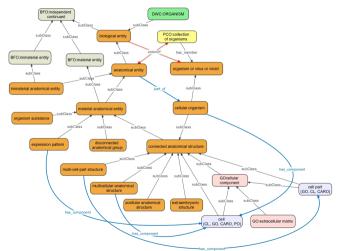
- An ontology conceptualizes a domain of interest in terms of concepts/classes, (binary) relations, and their properties.
- It typically organizes the concepts in a hierarchical structure.
- Ontologies are often represented as graphs.
- However, we consider an ontology as a logical theory, expressed in a suitable fragment of first-order logic, or better, in description logics.





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```
\forall x. \mathsf{Pressure}(x) \to \mathsf{Measurement}(x)
\forall x. \mathsf{Porosity}(x) \to \mathsf{Measurement}(x)
\forall x. \text{ Permeability}(x) \rightarrow \text{Measurement}(x)
\forall x. \mathsf{Temperature}(x) \to \mathsf{Measurement}(x)
\forall x. \mathsf{Pressure}(x) \to \neg \mathsf{Porosity}(x) \land \neg \mathsf{Permeability}(x) \land \neg \mathsf{Temperature}(x)
\forall x. \operatorname{Porosity}(x) \rightarrow \neg \operatorname{Permeability}(x) \wedge \neg \operatorname{Temperature}(x)
\forall x. \text{Permeability}(x) \rightarrow \neg \text{Temperature}(x)
\forall x. \, \mathsf{HvdrostaticPressure}(x) \to \mathsf{Pressure}(x)
\forall x. \, \mathsf{FormationPressure}(x) \to \mathsf{Pressure}(x)
\forall x. \mathsf{PorePressure}(x) \to \mathsf{Pressure}(x)
\forall x. \, \mathsf{HydrostaticPressure}(x) \to \neg \mathsf{FormationPressure}(x) \land \neg \mathsf{PorePressure}(x)
\forall x. \, \mathsf{FormationPressure}(x) \to \neg \mathsf{PorePressure}(x)
\forall x, y. \, \mathsf{hasFormationPressure}(x, y) \to \mathsf{Wellbore}(x) \land \mathsf{FormationPressure}(y)
\forall x, y, \mathsf{hasDepth}(x, y) \to \mathsf{FormationPressure}(x) \land \mathsf{Depth}(y)
\forall x. \, \mathsf{FormationPressure}(x) \to \exists u. \, \mathsf{hasDepth}(x, u)
\forall x, y. \text{ hasFormationPressure}(x, y) \rightarrow \text{hasMeasurement}(x, y)
\forall x, y. \mathsf{completionDate}_{\mathsf{Wellbore}}(x, y) \to \mathsf{Wellbore}(x) \land \mathsf{xsd}:\mathsf{dateTime}(y)
```

 $\forall x. \, \mathsf{Wellbore}(x) \to (\sharp \{y \mid \mathsf{completionDate}_{\mathsf{Wellbore}}(x,y)\} \le 1)$

 $\forall x. \, \mathsf{Wellbore}(x) \to (\sharp \{y \mid \mathsf{wellboreTrack}_{\mathsf{Wellbore}}(x,y)\} \leq 1)$

 $\forall x, y$. hasCoreSample $(x, y) \rightarrow \mathsf{Core}(x) \land \mathsf{CoreSample}(y)$ $\forall x$. CoreSample $(x) \rightarrow \exists y$. hasCoreSample $(y, x) \land \mathsf{Core}(y)$

 $\forall x,y. \, \mathsf{wellboreTrack}_{\ensuremath{\mathsf{Wellbore}}}(x,y) \to \ensuremath{\mathsf{Wellbore}}(x) \land \mathsf{xsd:string}(y)$

What is an ontology?

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Permeability [Temperature [Measurement Measurement Measurement Measurement ¬Porosity □ ¬Permeability □ ¬Temperature
Porosity	¬Permeability □ ¬Temperature ¬Temperature
HydrostaticPressure FormationPressure PorePressure HydrostaticPressure FormationPressure	Pressure Pressure ¬FormationPressure □ ¬PorePressure
∃hasFormationPressure ∃hasFormationPressure ∃hasDepth ∃hasDepth FormationPressure	FormationPressure FormationPressure Depth
hasFormationPressure [hasMeasurement
Wellbore	Wellbore xsd:dateTime $(\leq 1 \text{ completionDate}_{\text{Wellbore}})$



The OWL 2 QL ontology language

- OWL 2 QL is one of the three standard profiles of OWL 2. [W3C Rec. 2012]
- Derived from the DL-Lite_R description logic [Baader et al. 2003] of the DL-Lite-family:
 - Groups the domain into classes of objects with common properties.
 - Binary relations between objects are called object properties.
 - Binary relations from objects to values are called data properties.
- Is considered a lightweight ontology language:
 - controlled expressive power
 - efficient inference
- Optimized for accessing large amounts of data (i.e., for data complexity):
 - First-order rewritability of query answering: queries over the ontology can be rewritten into SQL queries over the underlying relational database.
 - Consistency checking is also first-order rewritable.



OWL 2 QL ontologies

- An OWL 2 QL ontology $\langle \mathcal{T}, \mathcal{A} \rangle$ is constituted by:
 - ullet a TBox ${\mathcal T}$, modeling the intensional level information (i.e., axioms), and
 - \bullet an ABox ${\cal A},$ modeling the extensional level information (i.e., facts).
- In the OBDA setting, the ABox is (usually) implicitly defined through the database and the mappings.
- Therefore, in the following, we use the term "ontology" to refer to the TBox only.



Constructs of OWL 2 QL/ *DL-Lite*_R

• Class hierarchies: rdfs:subClassOf

Property hierarchies: rdfs:subPropertyOf

• Property domain: rdfs:domain

• Property range: rdfs:range

• Inverse properties: owl:inverseOf

Class disjointness: owl:disjointWith

Mandatory participation: owl:someValuesFrom in superclass expression



RDF Schema (RDFS)

```
Class hierarchy: rdfs:subClassOf (A_1 \sqsubseteq A_2)

:FormationPressure rdfs:subClassOf :Pressure .

<FP-1249> a :FormationPressure .

\Rightarrow <FP-1249> a :Pressure .
```

```
Property hierarchy: rdfs:subPropertyOf (P_1 \sqsubseteq P_2)
```

```
Domain of properties: rdfs:domain \quad (\exists P \sqsubseteq A)
```

```
Range of properties: rdfs:range (\exists P^- \sqsubseteq A)
```



Other constructs of OWL 2 QL I

Mandatory participation: owl:someValuesFrom in the superclass expression $(A_1 \sqsubseteq \exists RA_2)$



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Other constructs of OWL 2 QL II

```
Class disjointness: owl:disjointWith (A_1 \sqsubseteq \neg A_2)

: Wellbore owl:disjointWith : Measurement .

<pf2/WB-16/1-29-S> a : Wellbore .
<pf2/WB-16/1-29-S> a : Measurement .

⇒ Inconsistent RDF graph
```



Semantics of an OWL 2 QL ontology

The **formal semantics** of OWL 2 QL is given in terms of first-order interpretations.

An interpretation $\mathcal{I} = (\Delta^{\mathcal{I}}, \cdot^{\mathcal{I}})$ consists of:

- a nonempty set $\Delta^{\mathcal{I}}$, called the interpretation domain (of \mathcal{I}), and
- an interpretation function $\cdot^{\mathcal{I}}$, which maps
 - each class nane A to a subset $A^{\mathcal{I}}$ of $\Delta^{\mathcal{I}}$
 - each property name P to a subset $P^{\mathcal{I}}$ of $\Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$
- The interpretation function is then extended to cover the OWL 2 QL constructs: $(P^{-})^{\mathcal{I}} = \{(u, w) \mid (w, w) \in P^{\mathcal{I}}\}$ $\exists P^{\mathcal{I}} = \{(w, w) \mid (w, w) \in P^{\mathcal{I}}\}$

$$(P^-)^{\mathcal{I}} = \{(y,x) \mid (x,y) \in P^{\mathcal{I}}\} \hspace{1cm} \exists P^{\mathcal{I}} = \{x \mid \text{there is some } y \text{ such that } (x,y) \in P^{\mathcal{I}}\}$$

The semantics of an ontology is given by specifying when \mathcal{I} satisfies an assertion α , denoted $\mathcal{I} \models \alpha$:

$$\mathcal{I} \models C_1 \sqsubseteq C_2$$
 if $C_1^{\mathcal{I}} \subseteq C_2^{\mathcal{I}}$; $\mathcal{I} \models R_1 \sqsubseteq R_2$ if $R_1^{\mathcal{I}} \subseteq R_2^{\mathcal{I}}$;

 \mathcal{I} satisfies an ABox fact, if the fact holds in \mathcal{I} .

An interpretation that satisfies all assertions of the ontology, is called a model of the ontology.

Representing OWL 2 QL ontologies as UML class diagrams/ER schemas

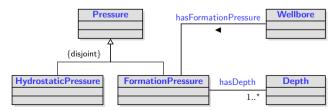
There is a close correspondence between OWL 2 QL and conceptual modeling formalisms [Lenzerini and Nobili 1990; Bergamaschi and Sartori 1992; Borgida 1995; C., Lenzerini, and Nardi 1999; Borgida and Brachman 2003; Berardi, C., and De Giacomo 2005; Queralt et al. 2012].

FormationPressure □ Pressure

disjointness domain range mandatory participation sub-association

subclass

An OWL 2 QL ontology can be visualized naturally as a UML class diagram or as an ER schema





Capturing UML class diagrams/ER schemas in OWL 2 QL

Modeling construct	DL-Lite	FOL formalization
ISA on classes	$A_1 \sqsubseteq A_2$	$\forall x (A_1(x) \to A_2(x))$
and on relations	$R_1 \sqsubseteq R_2$	$\forall x, y(R_1(x,y) \to R_2(x,y))$
Disjointness of classes	$A_1 \sqsubseteq \neg A_2$	$\forall x (A_1(x) \to \neg A_2(x))$
and of relations	$R_1 \sqsubseteq \neg R_2$	$\forall x, y(R_1(x,y) \to \neg R_2(x,y))$
Domain of relations	$\exists P \sqsubseteq A_1$	$\forall x(\exists y(P(x,y)) \to A_1(x))$
Range of relations	$\exists P^- \sqsubseteq A_2$	$\forall x(\exists y(P(y,x)) \to A_2(x))$
Mandatory participation	$A_1 \sqsubseteq \exists P$	$\forall x(A_1(x) \to \exists y(P(x,y)))$
(min card = 1)	$A_2 \sqsubseteq \exists P^-$	$\forall x (A_2(x) \to \exists y (P(y,x)))$

OWL 2 QL/ DL-Lite_R cannot capture:

- covering constraints This would require **disjunction**.
- identity between individuals This would owl:sameAs.
- functionality of roles This would require number restrictions.



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Ontology Language – OWL 2 QL

Query Language – SPARQL

Mapping Language – R2RML

5 Query Answering in OBDA



Query answering - Which query language to use

Querying under incomplete information

Query answering is not simply query evaluation, but a form of logical inference, and requires reasoning.



Two borderline cases for choosing the language for querying ontologies:

- 1 Use the **ontology language** as query language.
 - Ontology languages are tailored for capturing intensional relationships.
 - They are quite poor as query languages.
- 2 Use Full SQL (or equivalently, first-order logic).
 - Problem: in a setting with incomplete information, query answering is undecidable (FOL validity).

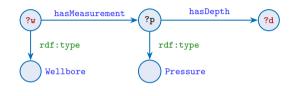
Conjunctive queries – Are concretely represented in **SPARQL**

A good tradeoff is to use conjunctive queries (CQs) or unions of CQs (UCQs), corresponding to SQL/relational algebra (union) select-project-join queries.

SPARQL query language

- Is the standard query language for RDF data. [W3C Rec. 2008, 2013]
- Core query mechanism is based on graph matching.

```
SELECT ?w ?d
WHERE { ?w rdf:type Wellbore .
     ?w hasMeasurement ?p .
     ?p rdf:type Pressure .
     ?p hasDepth ?d
}
```



Additional language features (SPARQL 1.1):

- UNION: matches one of alternative graph patterns
- OPTIONAL: produces a match even when part of the pattern is missing
- complex FILTER conditions
- GROUP BY, to express aggregations
- MINUS, to remove possible solutions
- property paths (regular expressions)



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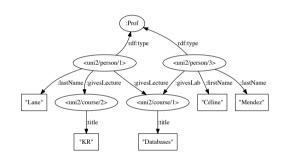
SPARQL Basic Graph Patterns

Basic Graph Pattern (BGP) are the simplest form of SPARQL query, asking for a pattern in the RDF graph.

```
Example: BGP

SELECT ?p ?ln ?c ?t
WHERE {
    ?p :lastName ?ln .
    ?p :givesLecture ?c .
    ?c :title ?t .
}
```

When evaluated over the RDF graph



... the query returns:

р	ln	С	t
<pre><uni2 1="" person=""></uni2></pre>	"Lane"	<pre><uni2 1="" course=""></uni2></pre>	"Databases"
<pre><uni2 1="" person=""></uni2></pre>	"Lane"	<pre><uni2 2="" course=""></uni2></pre>	"KR"



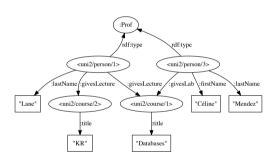
Projecting out variables in a SPARQL query

A query may also return only a subset of the variables used in the BGP.

```
Example: BGP with projection

SELECT ?ln ?t
WHERE {
    ?p :lastName ?ln .
    ?p :givesLecture ?c .
    ?c :title ?t .
}
```

When evaluated over the RDF graph



... the query returns:

ln	t
"Lane"	"Databases"
"Lane"	"KR"

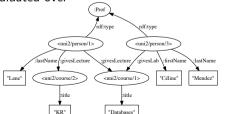


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Union of Basic Graph Patterns

```
Example: BGPs with UNION
```

When evaluated over



... the query returns:

p	ln	С
<pre><uni2 1="" person=""></uni2></pre>	"Lane"	<pre><uni2 1="" course=""></uni2></pre>
<pre><uni2 1="" person=""></uni2></pre>	"Lane"	<pre><uni2 2="" course=""></uni2></pre>
<pre><uni2 3="" person=""></uni2></pre>	"Mendez"	<pre><uni2 1="" course=""></uni2></pre>



BGPs vs. conjunctive queries

We can write queries using a more compact and abstract syntax, borrowed from database theory.

```
Example: BGP

SELECT ?p ?ln ?c ?t
WHERE {
    ?p :lastName ?ln .
    ?p :givesLecture ?c .
    ?c :title ?t .
}
```

```
vs. conjunctive query
```

```
\begin{aligned} \boldsymbol{q}(p, ln, c, t) &\leftarrow & \mathsf{lastName}(p, ln), \\ && \mathsf{givesLecture}(p, c), \\ && \mathsf{title}(c, t) \end{aligned}
```

```
A conjunctive query q has the form q(\vec{x}) \leftarrow p_1(\vec{y}_1), \dots, p(\vec{y}_k) where
```

- $q(\vec{x})$ is called the head of q,
- $p_1(\vec{y}_1), \ldots, p(\vec{y}_k)$ is a conjunction of atoms called the body of q,
- all variables \vec{x} in the head are among $\vec{y}_1, \dots, \vec{y}_k$, and
- the variables in $\vec{y}_1, \dots, \vec{y}_k$ that are not among \vec{x} are existentially quantified.

BGPs vs. conjunctive queries (cont.)

```
Example: BGP with projection

SELECT ?ln ?t
WHERE {
    ?p :lastName ?ln .
    ?p :givesLecture ?c .
    ?c :title ?t .
}
```

```
vs. conjunctive query q(ln,t) \leftarrow \mathsf{lastName}(p,ln),
```

givesLecture(p, c),

title(c, t)

```
But there is a difference in semantics when we have an ontology:
```

- In a SPARQL query, all variables, including those that are projected out, must match nodes of the RDF graph.
- In a conjunctive query, the existentially quantified variables can also match nodes that are existentially implied by the axioms of the ontology.



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SPARQL UNION vs. unions of CQs

```
Example: BGP with UNION
SELECT ?p ?ln ?c
WHERE {
  { ?p :lastName ?ln .
    ?p :givesLecture ?c .
  UNION
  { ?p :lastName ?ln .
    ?p :givesLab ?c .
```

```
vs. union of CQs (UCQ)
```

```
\begin{aligned} \boldsymbol{q}(p, ln, c) &\leftarrow & \mathsf{lastName}(p, ln), \\ && \mathsf{givesLecture}(p, c) \\ \boldsymbol{q}(p, ln, c) &\leftarrow & \mathsf{lastName}(p, ln), \\ && \mathsf{givesLab}(p, c) \end{aligned}
```

A UCQ is written as a set of CQs, all with the same head.



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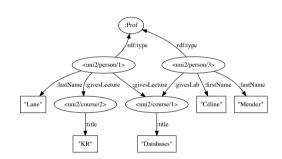
Extending BGPs with OPTIONAL

We might want to add information when available, but **not reject** a solution **when some part of the query does not match**.

```
Example: BGP with OPTIONAL

SELECT ?p ?fn ?ln
WHERE {
    ?p :lastName ?ln .
    OPTIONAL {
        ?p :firstName ?fn .
    }
}
```

When evaluated over the RDF graph



... the query returns:

р	fn	ln
<pre><uml2 1="" person=""></uml2></pre>		"Lane"
<pre><uml2 3="" person=""></uml2></pre>	"Céline"	"Mendez"



SPARQL algebra

We have seen the following features of the SPARQL algebra:

- Basic Graph Patterns
- UNION
- OPTIONAL

The overall algebra has additional features:

- more complex FILTER conditions
- GROUP BY, to express aggregations and support aggregation operators
- MINUS, to remove possible solutions
- FILTER NOT EXISTS, to test for the absence of a pattern



Outline

- 1 Motivation
- Ontology-based Data Access
- 3 Representing Data in RDF and RDFS
- 4 OBDA Framework
 Ontology Language OWL 2 QI
 Query Language SPARQL
 Mapping Language R2RML
- **5** Query Answering in OBDA



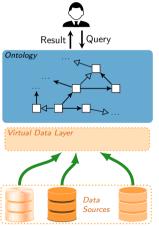
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Use of mappings

In OBDA, the mapping \mathcal{M} encodes how the data \mathcal{D} in the sources should be used to populate the elements of the ontology \mathcal{O} .

Virtual data layer $\mathcal{V} = \mathcal{M}(\mathcal{D})$ defined from \mathcal{M} and \mathcal{D}

- Queries are answered with respect to O and V.
- The data of \mathcal{V} is not materialized (it is virtual!).
- Instead, the information in O and M is used to translate queries over O into queries formulated over the sources.





Mismatch between data layer and ontology

Impedance mismatch

- Relational databases store values.
- Ontologies represent both objects and values.

We need to construct the ontology objects from the database values.



Proposed solution

The specification of **how to construct the ontology objects** that populate the virtual data layer from the database values **is embedded in the mapping** between the data sources and the ontology.

ORDA Framework

Mapping language

The **mapping** consists of a set of assertions of the form

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

where

- $\Phi(\vec{x})$ is the source query in SQL.
- $\Psi(\vec{t}, \vec{x})$ is the target query, consisting of atoms in the ontology vocabulary.

To address the impedance mismatch

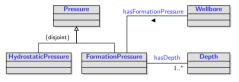
In the target query, we make use of a function iri, which constructs object identifiers (IRIs) from database values and string constants by concatenation.

We call a term making use of the iri function, an IRI-template.



Mapping language – Example

Ontology \mathcal{O} :



Database \mathcal{D} :

WELLBORE		
IDENTIFIER	REF_EXISTENCE_KIND	
16/1-29_S	actual	
30/8-5	actual	
33/10-12	planned	

Mapping \mathcal{M} :

We obtain the virtual data layer $\mathcal{M}(\mathcal{D})$: Wellbore(wb-16/1-29_S) Wellbore(wb-30/8-5)



Concrete mapping languages

Several proposals for concrete languages to map a relational DB to an ontology:

- They assume that the ontology is populated in terms of RDF triples.
- Some template mechanism is used to specify the triples to instantiate.

Examples: D2RQ², SML³, Ontop⁴

R2RML

- Most popular RDB to RDF mapping language
- W3C Recommendation 27 Sep. 2012, http://www.w3.org/TR/r2rml/
- R2RML mappings are themselves expressed as RDF graphs and written in Turtle syntax.

```
<sup>2</sup>http://d2rq.org/d2rq-language
```



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³http://sparqlify.org/wiki/Sparqlification_mapping_language

⁴https://github.com/ontop/ontop/wiki/ontopOBDAModel#Mapping_axioms

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Formalizing OBDA

OBDA specification $\mathcal{P} = \langle \mathcal{O}, \mathcal{M}, \mathcal{S} \rangle$ and **OBDA** instance $\langle \mathcal{P}, \mathcal{D} \rangle$

- O is an ontology (expressed in OWL 2 QL),
- \mathcal{M} is a set of (R2RML) mapping assertions,
- ullet ${\cal S}$ is a (relational) database schema with integrity constraints,
- \mathcal{D} is a database conforming to \mathcal{S} .

Semantics:

A first-order interpretation \mathcal{I} of the ontology predicates is a **model** of $\langle \mathcal{P}, \mathcal{D} \rangle$ if

However, for query answering, we do not need to compute such models.

- it satisfies all axioms in \mathcal{O} , and
- contains all facts in $\mathcal{M}(\mathcal{D})$, i.e., retrieved through \mathcal{M} from \mathcal{D} .

Note:

• In general, $\langle \mathcal{P}, \mathcal{D} \rangle$ has infinitely many models, and some of these might be infinite.



Query answering in OBDA – Certain answers

In OBDA, we want to answer queries formulated over the ontology, by using the data provided by the data sources through the mapping.

Consider our formalization of OBDA and an OBDA instance $\mathcal{J} = \langle \mathcal{P}, \mathcal{D} \rangle$.

Certain answers

Given an OBDA instance $\mathcal J$ and a query q over $\mathcal J$, the certain answers to q are those answers that hold in all models of $\mathcal J$.



First-order rewritability

To make computing certain answers viable in practice, OBDA relies on reducing it to evaluating SQL (i.e., first-order logic) queries over the data.

Consider an OBDA specification $\mathcal{P} = \langle \mathcal{O}, \mathcal{M}, \mathcal{S} \rangle$.

First-order rewritability

A query $r(\vec{x})$ is a **first-order rewriting** of a query $q(\vec{x})$ with respect to \mathcal{P} if, for every source DB \mathcal{D} , certain answers to $q(\vec{x})$ over $\langle \mathcal{P}, \mathcal{D} \rangle = \text{answers to } r(\vec{x}) \text{ over } \mathcal{D}$.

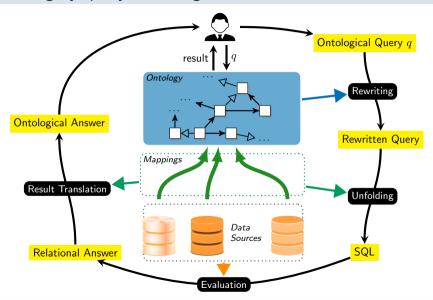
For OWL 2 QL ontologies and R2RML mappings, (core) SPARQL queries are first-order rewritable.

In other words, in OBDA, we can compute the certain answers to a SPARQL query by evaluating over the sources its rewriting, which is an SQL query.



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Query answering by query rewriting





res References

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