#### Systems

# Ontology Based Data Access

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> Acknowledgements: Diego Calvanese, Roman Kontchakov, Martin Rezk, Davide Lanti

### Outline

# 1 Motivation

- 2 Ontology Based Data Access
- **3** Ontologies and Description Logics
- **4** Queries

# **6** Mappings

Techniques
Query Rewriting
Combined Approach

#### Ø Systems

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- 6 Techniques Query Rewriting Combined Approach

#### **7** Systems

# The Problem: Information Need

# how to formulate the right question to find the right answer in the ocean of Big Data

# We are Living in the Era of Big Data





# Big Data in Industry



Ontologies and Description Logic

ueries l

Technique

System

# Big Data in Industry



# SIEMENS: Information Need

• Reactive diagnostics of turbines.



• Predictive analysis of turbine condition.



• Product engineering and maintenance support.

How Much Time is Spent Searching for Data?

Engineers in industry spend a significant amount of their time searching for data that they require for their core tasks. E.g., in the oil&gas industry, 30-70% of engineers time is spent looking for and assessing the quality of data (Crompton, 2008).

How Much Time/Money is Spent Searching for Data?

A user query in Statoil:

Show all norwegian wellbores with some aditional attributes (wellbore id, completion date, oldest penetrated age,result). Limit to all wellbores with a core and show attributes like (wellbore id, core number, top core depth, base core depth, intersecting stratigraphy). Limit to all wellbores with core in Brentgruppen and show key atributes in a table. After connecting to EPDS (slegge) we could for instance limit futher to cores in Brent with measured permeability and where it is larger than a given value, for instance 1 mD. We could also find out whether there are cores in Brent which are not stored in EPDS (based on NPD info) and where there could be permeability values. Some of the missing data we possibly own, other not.

System

#### How Much Time/Money is Spent Searching for Data?

A use

Show comp and s depth Brent (slegg perm could EPDS Some

SELECT [...] FROM db name.table1 table1. db\_name.table2 table2a, db\_name.table2 table2b, db name.table3 table3a. db name.table3 table3b. db\_name.table3 table3c, db\_name.table3 table3d, db\_name.table4 table4a, db name.table4 table4b. db\_name.table4 table4c, db name.table4 table4d, db\_name.table4 table4e, db name.table4 table4f. db\_name.table5 table5a, db\_name.table5 table5b, db\_name.table6 table6a, db name.table6 table6b. db name.table7 table7a. db\_name.table7 table7b, db\_name.table8 table8, db name.table9 table9. db\_name.table10 table10a, db\_name.table10 table10b, db name.table10 table10c. db name.table11 table11. db name.table12 table12. db\_name.table13 table13, db name.table14 table14. db\_name.table15 table15, db name.table16 table16 WHERE [...]

table2a.attr1='keyword' AND table3a.attr2=table10c.attr1 AND table3a.attr6=table6a.attr3 AND table3a.attr9='keyword' AND table4a.attr10 IN ('keyword') AND table4a.attr1 IN ('keyword') AND table5a.kinds=table4a.attr13 AND table5b.kinds=table4c.attr74 AND table5b.name='keyword' AND (table6a.attr19=table10c.attr17 OR (table6a.attr2 IS NULL AND table10c.attr4 IS NULL)) AND table6a attr14=table5b attr14 AND table6a.attr2='keyword' AND (table6b.attr14=table10c.attr8 OR (table6b.attr4 IS NULL AND table10c.attr7 IS NULL)) AND table6b.attr19=table5a.attr55 AND table6b.attr2='keyword' AND table7a.attr19=table2b.attr19 AND table7a attr17=table15 attr19 AND table4b.attr11='keyword' AND table8.attr19=table7a.attr80 AND table8.attr19=table13.attr20 AND table8.attr4='keyword' AND table9.attr10=table16.attr11 AND table3b attr19=table10c attr18 AND table3b.attr22=table12.attr63 AND table3b.attr66='keyword' AND table10a.attr54=table7a.attr8 AND table10a attr70=table10c attr10 AND table10a.attr16=table4d.attr11 AND table4c.attr99='keyword' AND table4c.attr1='keyword' AND

table11.attr10=table5a.attr10 AND table11.attr40='keyword' AND table11.attr50='keyword' AND table2b.attr1=table1.attr8 AND table2b.attr9 IN ('keyword') AND table2b.attr2 LIKE 'keyword'% AND table12.attr9 IN ('keyword') AND table7b.attr1=table2a.attr10 AND table3c attr13=table10c attr1 AND table3c.attr10=table6b.attr20 AND table3c.attr13='keyword' AND table10b.attr16=table10a.attr7 AND table10b attr11=table7b attr8 AND table10b attr13=table4b attr89 AND table13.attr1=table2b.attr10 AND table13.attr20=''keyword'' AND table13.attr15='keyword' AND table3d attr49=table12 attr18 AND table3d.attr18=table10c.attr11 AND table3d.attr14='keyword' AND table4d.attr17 IN ('keyword') AND table4d.attr19 IN ('keyword') AND table16.attr28=table11.attr56 AND table16.attr16=table10b.attr78 AND table16.attr5=table14.attr56 AND table4e.attr34 IN ('kevword') AND table4e.attr48 IN ('keyword') AND table4f.attr89=table5b.attr7 AND table4f.attr45 IN ('keyword') AND table4f.attr1='keyword' AND table10c.attr2=table4e.attr19 AND (table10c.attr78=table12.attr56 OR (table10c.attr55 IS NULL AND table12.attr17 IS NULL))

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#### How Much Time/Money is Spent Searching for Data?

	SELECT []	table2a.attr1='keyword' AND	table11.attr10=table5a.attr10 AND
	FROM	table3a.attr2=table10c.attr1 AND	table11.attr40='keyword' AND
	db_name.table1 table1,	table3a.attr6=table6a.attr3 AND	table11.attr50='keyword' AND
A use	db_name.table2 table2a,	table3a.attr9='keyword' AND	table2b.attr1=table1.attr8 AND
	db_name.table2 table2b,	table4a.attr10 IN ('keyword') AND	table2b.attr9 IN ('keyword') AND
	db_name.table3 table3a,	table4a.attr1 IN ('keyword') AND	table2b.attr2 LIKE 'keyword'% AND
	db_name.table3 table3b,	table5a.kinds=table4a.attr13 AND	table12.attr9 IN ('keyword') AND
	db_name.table3 table3c,	table5b.kinds=table4c.attr74 AND	table7b.attr1=table2a.attr10 AND
	db_name.table3 table3d,	table5b.name='keyword' AND	table3c.attr13=table10c.attr1 AND
Show	db_name.table4 table4a,	(table6a.attr19=table10c.attr17 OR	table3c.attr10=table6b.attr20 AND
	db_name.table4 table4b,	(table6a.attr2 IS NULL AND	table3c.attr13='keyword' AND
	db_name.table4 table4c,	table10c.attr4 IS NULL)) AND	table10b.attr16=table10a.attr7 AND
romn			

# In SIEMENS, it usually takes 4 to 6 weeks to formulate a query in SQL. SIEMENS loses up to **50.000.000**€ per year because of this!!

perm could EPDS Some uu\_inde:.table0 table0, db\_name.table0 table0, db\_name.table10 table10a, db\_name.table10 table10c, db\_name.table10 table10c, db\_name.table11 table11, db\_name.table12 table12, db\_name.table13 table13, db\_name.table14 table14, db\_name.table15 table15, db\_name.table16 table16 WHERE [...] table8.att19=table7.a.att70 AND table8.att19=table7.a.att70 AND table8.att719=table7.a.att70 AND table9.att710=table16.att71 AND table3b.att719=table10c.att71 AND table3b.att719=table10c.att71 AND table3b.att76=table7.a.att78 AND table10a.att76=table7.a.att78 AND table10a.att70=table10c.att71 AND table10a.att70=table10c.att71 AND table10a.att79='keyword' AND table4c.att79='keyword' AND tablei6.attr28=tablei1.attr56 AND tablei6.attr28=tablei0.attr78 AND tablei6.attr5=tablei0.attr78 AND table4.attr54 IN ('keyvord') AND table44.attr48 IN ('keyvord') AND table4f.attr48=table5b.attr7 AND table4f.attr45 IN ('keyvord') AND table4f.attr2=table4e.attr19 AND (table10c.attr78=table12.attr56 OR (table10c.attr75 IS NULL AND table10.

#### Need for Abstraction

We need to facilitate access to Data

- by abstracting away from how the data is stored, and
- by making use of high level views on the data, so called **ontologies**.

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#### Logical transparency in accessing data:

- 🔔 does not know where and how data is stored;
- <u>C</u> can only see a **conceptual view** of data.

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# Questions to be Addressed in OBDA

- What is the right ontology language?
- What is the right query language?
- What is the right mapping language?
- What are the available tools?

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A database is an organized collection of data 🔤

that can be accessed by a computer program to quickly select pieces of data.

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- axioms (formalization of how things are in the world), and of
- data 🔤 (facts about the world),

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Every patient must have a name, age	Non Small Cell Lung Cancer on stage 2.
and SSN.	

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In this tutorial, by **ontology** we mean the **axioms** part of knowledge bases. It is also referred to as intentional level, conceptual schema, domain structure.

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- Modal Logics
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- DDL (in Databases)

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In a description logic knowledge base,

- the **TBox**  $\mathcal{T}$  encodes axioms
- the ABox  $\mathcal{A}$  encodes data  $\square$ .

Thus, a knowledge base is a pair  $\langle \mathcal{T}, \mathcal{A} \rangle$ .

#### A DL KB talks about

- individuals (objects): mary, neoplasm1;
- concepts (classes): Patient, Cancer;
- roles (properties): hasNeoplasm, hasSSN.

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LungCancer ⊑ Cancer NSCLCancer ⊑ LungCancer Patient ⊑ ∃hasSSN

Patient(mary) hasNeoplasm(mary, neoplasm1) NSCLCancer(neoplasm1)

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### Why to use description logics?

- good trade-off between expressivity and computational complexity
- efficient reasoning algorithms
- concise syntax

 $\begin{array}{l} LungCancer \sqsubseteq Cancer \\ NSCLCancer \sqsubseteq LungCancer \\ Patient \sqsubseteq \exists hasSSN \end{array}$ 



# $\textit{DL-Lite}_{\mathcal{R}}$ at the Basis of OWL2QL

DL-Lite<sub>R</sub> provides the basis for the OWL 2 QL profile of OWL 2. It is specifically tailored to efficient **query answering**.

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A DL-Lite<sub> $\mathcal{R}$ </sub> TBox is a finite set of inclusion and disjointness axioms.



## A DL-Lite<sub>R</sub> ABox is a finite set of facts of the form A(c), P(c, d).

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DL-Lite<sub>R</sub>

LungCancer  $\Box$  Cancer

 $Patient \Box \exists hasSSN$ 

 $DL-Lite_{\mathcal{R}}$  in the OWL 2 and RDF Syntaxes

# appings Techniques System

OWL 2 Functional Style Syntax RDF/Turtle

SubClassOf(LungCancer, Cancer)

SubClassOf( Patient, ObjectSomeValuesFrom( hasSSN, owl:Thing)

∃hasNeoplasm<sup>−</sup> ⊑ Neoplasm

hasNeoplasm ⊑ hasCondition

Patient(mary)

hasNeoplasm( mary, neoplasm1) SubClassOf( ObjectSomeValuesFrom( ObjectInverseOf(hasNeoplasm), owl:Thing), Neoplasm

SubObjectPropertyOf( hasNeoplasm, hasCondition)

ClassAssertion(Patient, mary)

ObjectPropertyAssertion( hasNeoplasm, mary, neoplasm1) LungCancer rdfs:subClassOf Cancer .

Patient rdfs:subClassOf \_b1 . \_b1 rdf:type owl:Restriction ; owl:onProperty hasSSN ; owl:someValuesFrom owl:Thing .

\_b2 rdfs:subClassOf, Neoplasm ; rdf:type owl:Restriction ; owl:onProperty \_b22 ; owl:someValuesFrom owl:Thing . \_b22 owl:inverseOf hasNeoplasm .

hasNeoplasm rdfs:subPropertyOf hasCondition .

mary rdf:type Patient .

mary hasNeoplasm neoplasm1 .

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## Query Languages

Intuitively, a **query** is a question:

- have all patients diagnosed with cancer received chemotherapy?
- give me all patients diagnosed with cancer who have not received chemotherapy.
- give me all patients diagnosed with cancer.
- give me all patients diagnosed with lung or skin cancer.

Standard query languages:

• First-Order Queries ( $\approx$  SQL)

 $q() = \forall x, d((Patient(x) \land hasCondition(x, d) \land Cancer(d)) \rightarrow (\exists t.hadTreat(x, t) \land Chemo(t)))$ 

 $q(x) = \textit{Patient}(x) \land (\exists \textit{d.hasCondition}(x, \textit{d}) \land \textit{Cancer}(\textit{d})) \land (\neg \exists \textit{t.hadTreat}(x, t) \land \textit{Chemo}(t))$ 

• Conjunctive Queries (Select-Project-Join)

 $q(x) = \exists d.Patient(x) \land hasCondition(x, d) \land Cancer(d)$ 

• Unions of Conjunctive Queries (Union-of-Select-Project-Join)

$$q(x) = \begin{array}{l} \exists d.Patient(x) \land hasCondition(x, d) \land LungCancer(d) \\ \lor \\ \exists d.Patient(x) \land hasCondition(x, d) \land SkinCancer(d) \end{array}$$

Query Answering in Databases and in  $\textit{DL-Lite}_{\mathcal{R}}$ 

The Query Answering Problem: Is it true that c is an answer to a query q?

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```
Query Answering in Databases 🚔
```

Data is complete.

• Query answering amounts to query evaluation, which is computationally easy.



• Query answering amounts to logical inference, which is computationally costly.

# Query Evaluation Vs. Query Answering

- Axioms:LungCancer  $\sqsubseteq$  CancerPatient  $\sqsubseteq \exists hasSSN$ NSCLCancer  $\sqsubseteq$  LungCancerhasNeoplasm  $\sqsubseteq$  hasCondition
  - q<sub>1</sub>: Is Mary a patient?
  - q2: Does Mary have neoplasm that is NSCLCancer?
- Queries:  $q_3$ : Does Mary have neoplasm that is Cancer?
  - q4: Does Mary have neoplasm that is SkinCancer?
    - q<sub>5</sub>: Does Mary have condition that is NSCLCancer?
    - q<sub>6</sub>: Does Mary have SSN?



Data: (CWA)

Patient	hacNoonlasm	NSCI Cancer	$q_1$	$q_2$	$q_3$	$q_4$	$q_5$	$q_6$
mary •	nasiveopiasin	→● neop-12	Yes	Yes	No	No	No	No







## Data: (CWA)





#### Data: (CWA)

Patient mary •	hasNeoplasm	NSCLCancer →● neop-12	$\frac{q_1}{\text{Yes}}$	q <sub>2</sub> Yes	<i>q</i> 3 No	q <sub>4</sub> No	<i>q</i> 5 No	<i>q</i> 6 No
Data + Axio	ms = inferred	data						
Patient	hasNeoplasm	Cancer LungCancer NSCLCancer	$\frac{q_1}{\text{Yes}}$	q <sub>2</sub> Yes	q <sub>3</sub> Yes	<i>q</i> 4 <b>No</b>	q <sub>5</sub> Yes	q <sub>6</sub> Yes
hay has	hasCondition	→• neop-12		I	I	1	1	I
,	SN b							

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## Complexity of Query Answering in Databases and in $DL-Lite_{\mathcal{R}}$

	Databases	$DL\text{-}Lite_{\mathcal{R}}$ Knowledge Bases
FO	PSpace-complete in LogSpace	undecidable
CQs & UCQs	NP-complete in LogSpace	NP-complete in LogSpace in PTime

 $LogSpace \subseteq PTime \subseteq NP \subseteq PSpace$ 

**Combined** complexity: the **query**, the data (and the **TBox**) make the input. **Data** complexity: the **data** is the only input (the **query** and the **TBox** are fixed). **TBox** complexity: the **TBox** is the only input.

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#### What this table tells us

- Databases are able to perform well for queries of small size.
- Databases are able to perform well even if the data is huge.
- Answering UCQs over DL-Lite<sub>R</sub> KBs can be reduced to QE over Databases.

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# Connecting Inherently Different Domains

## Problem

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This is done by using values (normally, keys) to create object identifiers (think of **Uniform Resource Identifiers, URIs**).

A mapping has two parts:

Source Query: An SQL query over the data source



Target Query: An ABox template of the ontology  $\approx$  a CQ without existentially quantified variables

We assume a cancer patient database containing the table PATIENT:

PatientID	Name	Туре	Stage
12	Mary	true	2
34	John	false	7

• Type is: true for Non-Small Cell Lung Cancer, and false for Small Cell Lung Cancer

Mappings

• Stage is: 1-6 for NSCLC stages I,II,III,IIIa,IIIb,IV, and 7-8 for SCLC stages Limited,Extensive

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select  $\star$  from PATIENT where Type=true

Patient(pat-{PatientID})
hasNeoplasm(pat-{PatientID}, neop-{PatientID})
NSCLCancer(neop-{PatientID})



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We assume a cancer patient database containing the table PATIENT:

PatientID	Name	Туре	Stage
12	Mary	true	2
34	John	false	7

- Type is: true for Non-Small Cell Lung Cancer, and false for Small Cell Lung Cancer
- Stage is: 1-6 for NSCLC stages I,II,III,IIIa,IIIb,IV, and 7-8 for SCLC stages Limited,Extensive

#### A mapping has two parts:

Source Query: An SQL query over the data source select \* from PATIENT where Type=true Patient(pat-{PatientID}) hasNeoplasm(pat-{PatientID}, neop-{PatientID}) NSCLCancer(neop-{PatientID}) Target Query: An ABox template of the ontology ≈ a CQ without existentially quantified variables

If we were to materialize, we would obtain the following ABox from our database:



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 Target Query: An ABox template of the ontology ≈ a CQ without existentially quantified variables

If we were to materialize, we would obtain the following ABox from our database:

Patient	hasNeoplasm	NSCLCancer		
pat-12 •		$\longrightarrow \bullet$	neop-12	

However, the ABox is only virtual, and the objects are not materialized.

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Ontology Based Data Access

## The Standard Mapping Languages

**R2RML** is an RDB to RDF mapping language, a W3C recommendation http://www.w3.org/TR/r2rml/

**Direct mapping** is a default RDB to RDF mapping language, a W3C recommendation http://www.w3.org/TR/rdb-direct-mapping/

# Outline

## 1 Motivation

- 2 Ontology Based Data Access
- **3** Ontologies and Description Logics

#### **4** Queries

## 6 Mappings



#### **7** Systems

					Techniques	
Query Rewri	ting				Combined Ap	proach
Approad	ches					
How do	es OBDA actually wo	rk?				
• We	want to keep the Da	ta in the data sources.				
• We	embed reasoning eit	her into the query or int	to the D	ata.		

Query Rewriting	Combined Approach	Materialization

Niotivation Ontology Based Data Access	Ontologies and Description Logics		Techniques Systems
Query Rewriting			Combined Approach
Approaches			
How does OBDA actually	work?		
• We want to keep the	Data in the data sources.		
<ul> <li>We embed reasoning e</li> </ul>	either into the query or into	the Data.	
Query Rewriting	Combined Approach		Materialization
In practice:			
Query Rewriting			
the data is not manipute	ulated		
the axioms are embed	ded into the query		
the rewritten query is	translated to SQL		
the translated query is	answered by the DBMS		
Combined Approach			
• the data is partially co	ompleted (materialized) w.r	.t. the axioms	
2 the query is rewritten	w.r.t. the axioms		
3 the rewritten query is	translated to SQL		
the translated query is	answered by the DBMS		

Query Rewriting		Combined Approach	
Approaches			
How does OBDA actually	work?		
• We want to keep the	Data in the data sources.		
• We embed reasoning either into the query or into the Data.			
Query Rewriting	Combined Approach	Materialization	
In practice:			
Query Rewriting			
• the data is not manipulated			
$\boldsymbol{Q}$ the axioms are embedded into the query			
• the rewritten query is translated to SQL of strange shape and quite big size			
• the translated query is answered by the DBMS			
	answered by the DDING		
Combined Approach			
• the data is partially completed (materialized) w.r.t. the axioms			
the query is rewritten w.r.t. the axioms			
the rewritten query is translated to SQL			
the translated query is answered by the DBMS			
• ···· ······ ···· ···· ···· ···			

Technic

Query Rewriting		Combined Approach	
Approaches			
How does OBDA actually w	ork?		
<ul> <li>We want to keep the D</li> </ul>	ata in the data sources.		
<ul> <li>We embed reasoning ei</li> </ul>	ther into the query or into the Dat	ta.	
Query Rewriting	Combined Approach	Materialization	
In practice:			
Query Rewriting			
the data is not manipulated			
${f Q}$ the axioms are embedded into the query			
• the rewritten query is translated to SQL of strange shape and quite big size			
• the translated query is answered by the DBMS			
Combined Approach			
• the data is partially completed (materialized) w.r.t. the axioms			
the query is rewritten w.r.t. the axioms			
the rewritten query is translated to SQL hopefully of small size			
the translated query is answered by the DBMS			
-	•		

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Technic








## Query Answering by Query Rewriting



## Query Answering by Query Rewriting







# C is an answer to a query $oldsymbol{q}$ over a knowledge base $\langle \mathcal{T}, \mathcal{A} angle$

## if and only if

**C** is an answer to the **rewritten query**  $q_{\mathcal{T}}$  over the database  $\mathcal{A}$ 





#### Rewritten Query:

 $\exists y.hasNeoplasm(x,y) \land Cancer(y)$ q'(x) =



#### Rewritten Query:

 $\exists y.hasNeoplasm(x, y) \land Cancer(y) \\ \lor \\ q'(x) = \exists y.hasNeoplasm(x, y) \land LungCancer(y)$ 



#### Rewritten Query:

$$\exists y.hasNeoplasm(x, y) \land Cancer(y) \\ \lor \\ q'(x) = \exists y.hasNeoplasm(x, y) \land LungCancer(y) \\ \lor \\ \exists y.hasNeoplasm(x, y) \land NSCLCancer(y) \end{cases}$$



$$q(x) = \exists y.hasNeoplasm(x, y) \land Cancer(y)$$

#### Rewritten Query:

$$\exists y.hasNeoplasm(x, y) \land Cancer(y) \\ \lor \\ q'(x) = \exists y.hasNeoplasm(x, y) \land LungCancer(y) \\ \lor \\ \exists y.hasNeoplasm(x, y) \land NSCLCancer(y) \end{cases}$$

The answer is Yes: Mary is an answer to the query q' over data alone.





#### Rewritten Query:

 $\exists y.hasCondition(x, y) \land NSCLCancer(y)$ q'(x) =



#### Rewritten Query:

 $q'(x) = \begin{cases} \exists y.hasCondition(x, y) \land NSCLCancer(y) \\ \lor \\ \exists y.hasNeoplasm(x, y) \land NSCLCancer(y) \end{cases}$ 



#### Rewritten Query:

 $q'(x) = \begin{cases} \exists y.hasCondition(x, y) \land NSCLCancer(y) \\ \lor \\ \exists y.hasNeoplasm(x, y) \land NSCLCancer(y) \end{cases}$ 

The answer is Yes: Mary is an answer to the query q' over data alone.





**Rewritten Query:** 

q'(x) =

 $\exists y.hasSSN(x, y)$ 



 $q(x) = \exists y.hasSSN(x, y)$ 

#### Rewritten Query:

 $q'(x) = \bigvee_{\substack{Patient(x)}} \nabla q'(x) = \bigvee_{\substack{V \\ Patient(x)}} \nabla q'(x) = \nabla q'(x)$ 



 $q(x) = \exists y.hasSSN(x, y)$ 

Rewritten Query:

 $q'(x) = \bigvee_{\substack{\forall y.hasSSN(x, y) \\ \forall \\ Patient(x)}}$ 

The answer is Yes: Mary is an answer to the query q' over data alone.

					Techniques	
Query Rewriting				Combined Approach		
Query I	Rewriting Practic	al Issues				

- The rewritten query can be huge: exponential in the size of the original query.
- Databases are very bad at evaluating big queries.

### How to deal with that?

Employ various optimization techniques

- reduce the number of joins
- reduce the number of CQs in the big Union of CQs
- massage the query to a shape optimal for the database engine

























 $q(x) = \exists y.hasNeoplasm(x, y) \land Cancer(y)$ 



Rewritten Query:

q'(x) = q(x)



#### Rewritten Query:

q'(x)=q(x)

The answer is Yes: Mary is an answer to the query q' over partially completed data.





 $q(x) = \exists y.hasCondition(x, y) \land NSCLCancer(y)$ 

#### Rewritten Query:

q'(x)=q(x)



 $q(x) = \exists y.hasCondition(x, y) \land NSCLCancer(y)$ 

#### Rewritten Query:

q'(x)=q(x)

The answer is Yes: Mary is an answer to the query q' over partially completed data.



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Rewritten Query:

$$q'(x) = \frac{\exists y.hasSSN(x, y)}{\lor}$$

$$q'(x) = \frac{\forall y.hasSSN(x, y)}{\lor}$$

$$\forall x \in SN(x, y)$$


$$q'(x) = \frac{\exists y.hasSSN(x,y)}{\lor}$$

$$q'(x) = \frac{\forall}{Patient(x)}$$

The answer is Yes: Mary is an answer to the query q' over partially completed data.

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			Techniques	
Query Rewriting			Combined A	pproach

## Combined Approach Issues

- $\bullet$  in general does not work well for  $\textit{DL-Lite}_{\mathcal{R}}$
- however, it works well for  $\mathcal{EL}\approx \mathsf{OWL}\,2\,\mathsf{EL}$
- requires updating data sources, which might not be always possible

				Techniques	
Query Rewriting			Combined Ap		pproach
What I	Did Not Mention				

is how Query Unfolding is done:

how to obtain from an ontological query an SQL query

## Outline

#### 1 Motivation

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- **5** Mappings
- 6 Techniques Query Rewriting Combined Approach

#### Ø Systems

#### The Architecture of an OBDA System



#### The Architecture of an OBDA System



## The Existing OBDA Systems

- MASTRO
- Ultrawrap
- ontop / Quest
- . . .

#### -ontop-

-Ontop- is an OBDA framework developed at the Free University of Bozen-Bolzano. http://ontop.inf.unibz.it/

-Ontop- is freely available for download and comes as

- a plugin for Protege
- OWLAPI
- a SPARQL end-point

Let us see it at work!<sup>1</sup>

<sup>1</sup>We follow the tutorial that can be found here: https://github.com/ontop/ontop/wiki/Easy-Tutorial%3A-Using-Ontop-from-Protege Elena Botoeva(FUB) Ontology Based Data Access

# Thank you for your attention!

## QUESTIONS?

#### Recommended Reading

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