Query answering in description logics: *DL-Lite*$_{\mathcal{A}}$

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Outline

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Ontologies and data

- The best current DL reasoning systems can deal with moderately large ABoxes. $\rightsquigarrow 10^4$ individuals *(and this is a big achievement of the last years)!*
- But data of interests in typical information systems are much **larger** $\rightsquigarrow 10^6 - 10^9$ individuals
- The best technology to deal with large amounts of data are **relational databases**.

Question:
How can we use ontologies together with large amounts of data?

Challenges when integrating data into ontologies

Deal with well-known tradeoff between expressive power of the ontology language and complexity of dealing with (i.e., performing inference over) ontologies in that language.

Requirements come from the specific setting:

- We have to fully take into account the ontology.
  $\leadsto$ **inference**
- We have to deal very large amounts of data.
  $\leadsto$ **relational databases**
- We want flexibility in querying the data.
  $\leadsto$ **expressive query language**
- We want to keep the data in the sources, and not move it around.
  $\leadsto$ **map** data sourses to the ontology (cf. Data Integration)

Questions addressed in this part of the tutorial

1. Which is the "right" **query language**?
2. Which is the "right" **ontology language**?
3. How can we bridge the **semantic mismatch** between the ontology and the data sources?
4. How can **tools for ontology-based data access and integration** fully take into account all these issues?

Outline

Ontology languages vs. query languages

Which query language to use?

Two extreme cases:

1. Just classes and properties of the ontology $\rightsquigarrow$ instance checking
   - Ontology languages are tailored for capturing intensional relationships.
   - They are quite **poor as query languages**:
     Cannot refer to same object via multiple navigation paths in the ontology, i.e., allow only for a limited form of JOIN, namely chaining.
2. Full SQL (or equivalently, first-order logic)
   - Problem: in the presence of incomplete information, query answering becomes **undecidable** (FOL validity).

Conjunctive queries (CQs)

A **conjunctive query (CQ)** is a first-order query of the form

$$q(\vec{x}) \leftarrow \exists \vec{y}. R_1(\vec{x}, \vec{y}) \wedge \cdots \wedge R_k(\vec{x}, \vec{y})$$

where each $R_i(\vec{x}, \vec{y})$ is an atom using (some of) the free variables $\vec{x}$, the existentially quantified variables $\vec{y}$, and possibly constants.

We will also use the simpler Datalog notation:

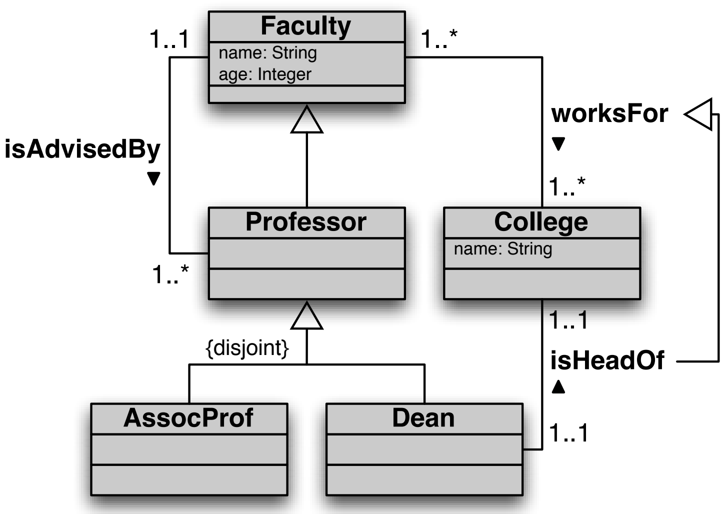
$$q(\vec{x}) \leftarrow R_1(\vec{x}, \vec{y}), \ldots, R_k(\vec{x}, \vec{y})$$

Note:

- CQs contain no disjunction, no negation, no universal quantification.
- Correspond to SQL/relational algebra **select-project-join (SPJ) queries** – the most frequently asked queries.
- They can also be written as **SPARQL** queries.

Example of conjunctive query

$$\begin{array}{rcl}
\text{Professor} & \sqsubseteq & \text{Faculty} \\
\text{AssocProf} & \sqsubseteq & \text{Professor} \\
\text{Dean} & \sqsubseteq & \text{Professor} \\
\text{AssocProf} & \sqsubseteq & \neg\text{Dean} \\
\text{Faculty} & \sqsubseteq & \exists\text{age} \\
\exists\text{age}^- & \sqsubseteq & \text{Integer} \\
\exists\text{worksFor} & \sqsubseteq & \text{Faculty} \\
\exists\text{worksFor}^- & \sqsubseteq & \text{College} \\
\text{Faculty} & \sqsubseteq & \exists\text{worksFor} \\
\text{College} & \sqsubseteq & \exists\text{worksFor}^- \\
 & \vdots &
\end{array}$$



$$\begin{aligned} q(nf, af, nd) \leftarrow\ & \exists f, c, d, ad. \\ & \text{worksFor}(f, c) \wedge \text{isHeadOf}(d, c) \wedge \text{name}(f, nf) \wedge \text{name}(d, nd) \wedge \\ & \text{age}(f, af) \wedge \text{age}(d, ad) \wedge af = ad \end{aligned}$$

Conjunctive queries and SQL – Example

Relational alphabet:
worksFor(fac, coll), isHeadOf(dean, coll), name(p, n), age(p, a)

Query: return name, age, and name of dean of all faculty that have the same age as their dean.

Expressed in SQL:

```
SELECT NF.name, AF.age, ND.name
FROM worksFor W, isHeadOf H, name NF, name ND, age AF, age AD
WHERE W.fac = NF.p   AND  W.fac = AF.p  AND
      H.dean = ND.p  AND  H.dean = AD.p  AND
      W.coll = H.coll  AND  AF.a = AD.a
```

Expressed as a CQ:

$$q(nf, af, nd) \leftarrow \text{worksFor}(f1, c1),\ \text{isHeadOf}(d1, c2),$$
$$\text{name}(f2, nf),\ \text{name}(d2, nd),\ \text{age}(f3, af),\ \text{age}(d3, ad),$$
$$f1 = f2,\ f1 = f3,\ d1 = d2,\ d1 = d3,\ c1 = c2,\ af = ad$$

Query answering under different assumptions

There are fundamentally different assumptions when addressing query answering in different settings:

- **traditional database assumption**
- **knowledge representation assumption**

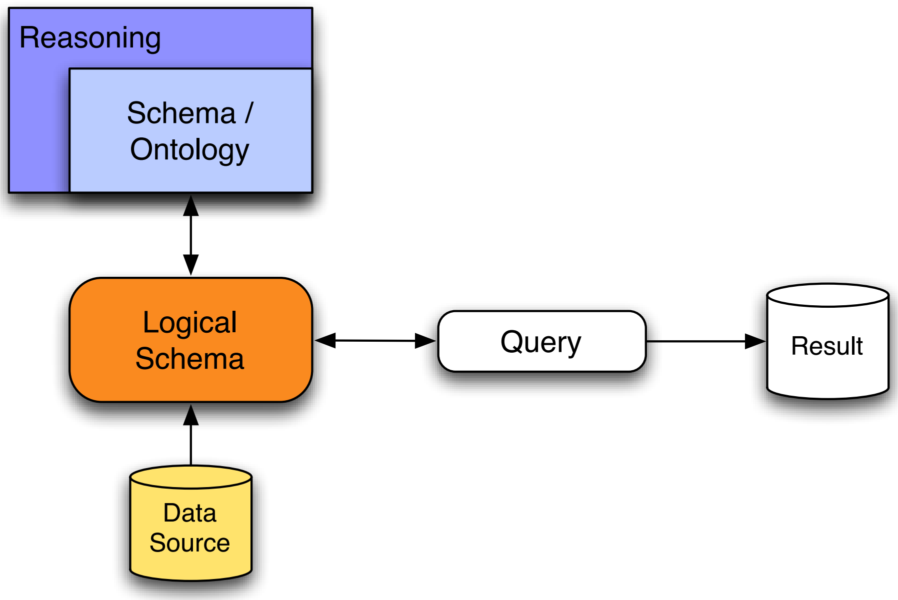
Note: for the moment we assume to deal with an ordinary ABox, which however may be very large and thus is stored in a database.

Query answering under the database assumption

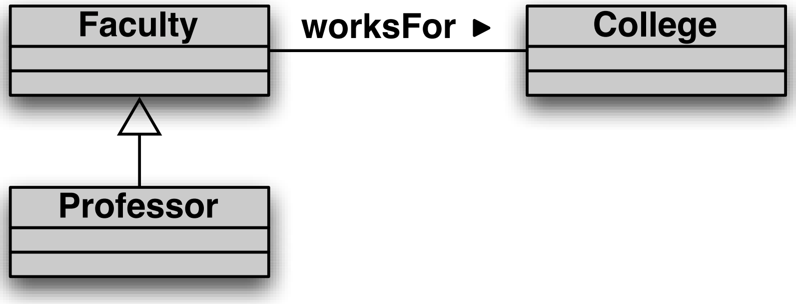
- Data are completely specified (CWA), and typically large.
- Schema/intensional information used in the design phase.
- At **runtime**, the data is assumed to satisfy the schema, and therefore the **schema is not used**.
- Queries allow for complex navigation paths in the data (cf. SQL).

$\rightsquigarrow$ Query answering amounts to **query evaluation**, which is computationally easy.

Query answering under the database assumption (cont'd)



Query answering under the database assumption – Example



For each class/property we have a (complete) table in the database.

DB: Faculty = { `john`, `mary`, `nick` }
Professor = { `john`, `nick` }
College = { `collA`, `collB` }
worksFor = { (`john`,`collA`), (`mary`,`collB`) }

Query: $q(x) \leftarrow \exists c.$ Professor(x), College(c), worksFor(x, c)

Answer: { `john` }

Query answering under the KR assumption

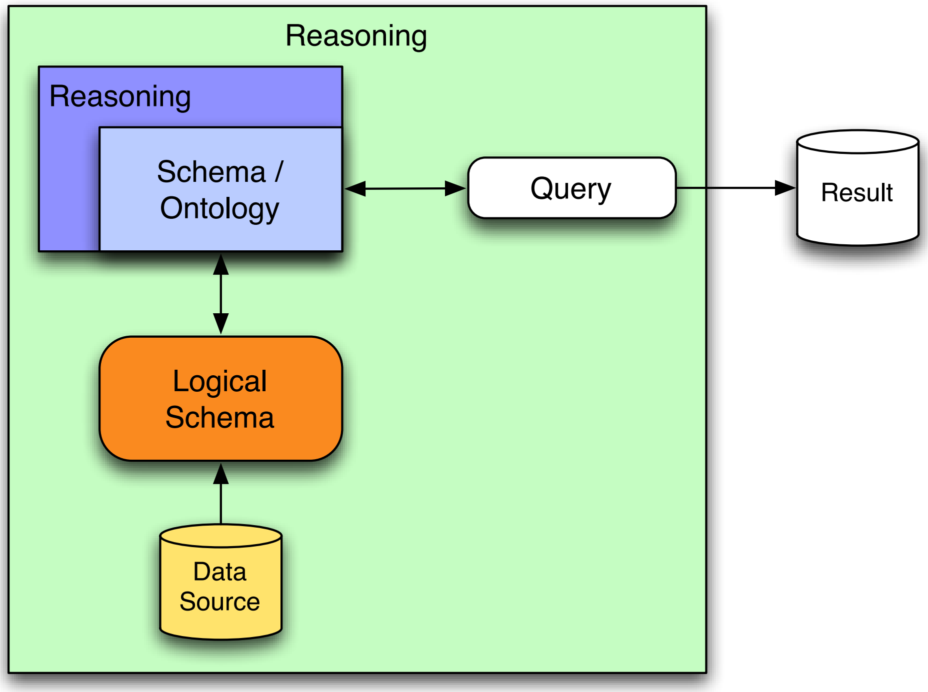
- An ontology imposes constraints on the data.
- Actual data may be incomplete or inconsistent w.r.t. such constraints.
- The system has to take into account the constraints during query answering, and overcome incompleteness or inconsistency.

⇝ Query answering amounts to **logical inference**, which is computationally more costly.

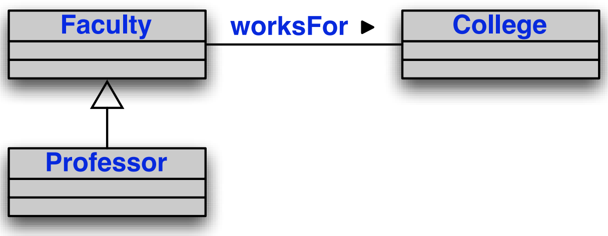
Note:

- Size of the data is not considered critical (comparable to the size of the intensional information).
- Queries are typically simple, i.e., atomic (a class name), and query answering amounts to instance checking.

Query answering under the KR assumption (cont'd)



Query answering under the KR assumption – Example



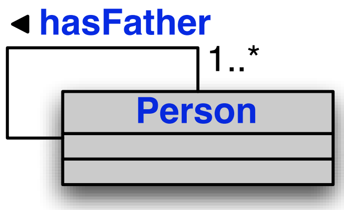
The tables in the database may be **incompletely specified**, or even missing for some classes/properties.

DB: Professor $\supseteq$ { john, nick }
College $\supseteq$ { collA, collB }
worksFor $\supseteq$ { (john,collA), (mary,collB) }

Query: $q(x) \leftarrow$ Faculty(x)

Answer: { john, nick, mary }

Query answering under the KR assumption – Example 2



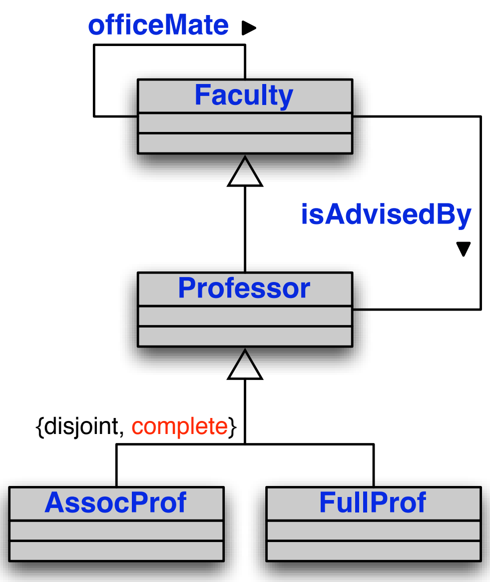
Each person has a father, who is a person.

DB: Person $\supseteq$ { john, nick, toni }
hasFather $\supseteq$ { (john,nick), (nick,toni) }

Queries: $q_1(x, y) \leftarrow$ hasFather(x, y)
$q_2(x) \leftarrow \exists y.$ hasFather(x, y)
$q_3(x) \leftarrow \exists y_1, y_2, y_3.$ hasFather(x, y_1), hasFather(y_1, y_2), hasFather(y_2, y_3)
$q_4(x, y_3) \leftarrow \exists y_1, y_2.$ hasFather(x, y_1), hasFather(y_1, y_2), hasFather(y_2, y_3)

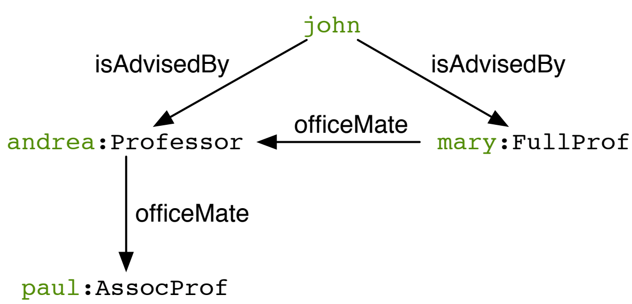
Answers: to q_1: { (john,nick), (nick,toni) }
to q_2: { john, nick, toni }
to q_3: { john, nick, toni }
to q_4: { }

QA under the KR assumption – Andrea's Example

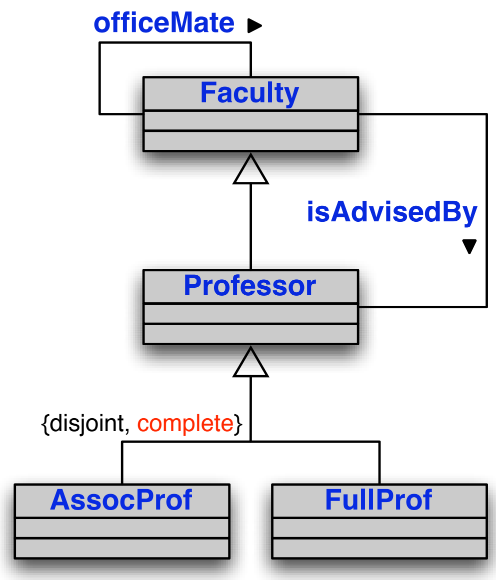


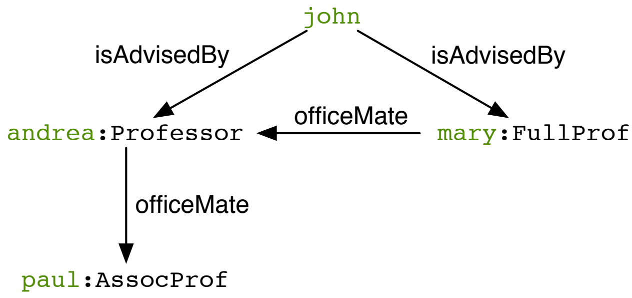
FullProf $\equiv$ AssocProf $\sqcup$ FullProf

Faculty $\supseteq$ { andrea, nick, mary, john }
Professor $\supseteq$ { andrea, nick, mary }
AssocProf $\supseteq$ { nick }
FullProf $\supseteq$ { mary }
isAdvisedBy $\supseteq$ { (john,andrea), (john,mary) }
officeMate $\supseteq$ { (mary,andrea), (andrea,nick) }



QA under the KR assumption – Andrea's Example (cont'd)





$$q() \leftarrow \exists y, z.\ \text{isAdvisedBy}(\texttt{john}, y),\ \text{FullProf}(y),\ \text{officeMate}(y, z),\ \text{AssocProf}(z)$$

Answer: **yes!**

To determine this answer, we need to resort to **reasoning by cases**.

Query answering when accessing data through ontologies

We have to face the difficulties of both DB and KB assumptions:

- The actual **data** is stored in external information sources (i.e., databases), and thus its size is typically **very large**.
- The ontology introduces **incompleteness** of information, and we have to do logical inference, rather than query evaluation.
- We want to take into account at **runtime** the **constraints** expressed in the ontology.
- We want to answer **complex database-like queries**.
- We may have to deal with multiple information sources, and thus face also the problems that are typical of data integration.

Certain answers to a query

Let $\mathcal{O} = \langle \mathcal{T}, \mathcal{A} \rangle$ be an ontology, $\mathcal{I}$ an interpretation for $\mathcal{O}$, and $q(\vec{x}) \leftarrow \exists \vec{y}.\, conj(\vec{x}, \vec{y})$ a CQ.

Def.: The **answer** to $q(\vec{x})$ over $\mathcal{I}$, denoted $q^{\mathcal{I}}$

. . . is the set of **tuples $\vec{c}$ of constants of $\mathcal{A}$** such that the formula $\exists \vec{y}.\, conj(\vec{c}, \vec{y})$ evaluates to true in $\mathcal{I}$.

We are interested in finding those answers that hold in all models of an ontology.

Def.: The **certain answers** to $q(\vec{x})$ over $\mathcal{O} = \langle \mathcal{T}, \mathcal{A} \rangle$, denoted $cert(q, \mathcal{O})$

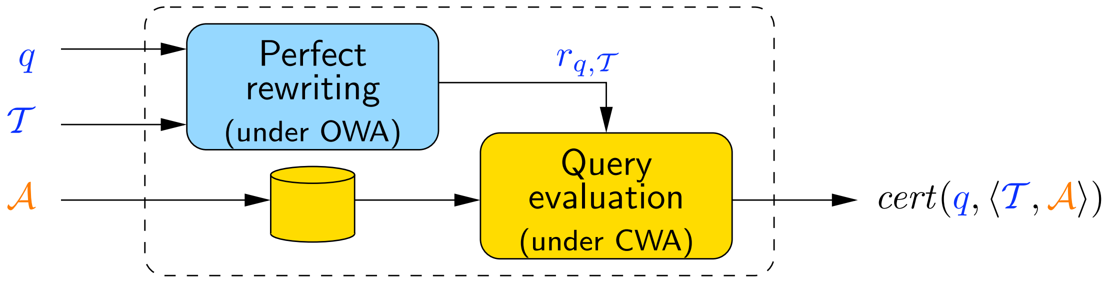
. . . are the **tuples $\vec{c}$ of constants of $\mathcal{A}$** such that $\vec{c} \in q^{\mathcal{I}}$, for every model $\mathcal{I}$ of $\mathcal{O}$.

Inference in query answering

To be able to deal with data efficiently, we need to separate the contribution of $\mathcal{A}$ from the contribution of q and $\mathcal{T}$.

$\leadsto$ Query answering by **query rewriting**.

Query rewriting

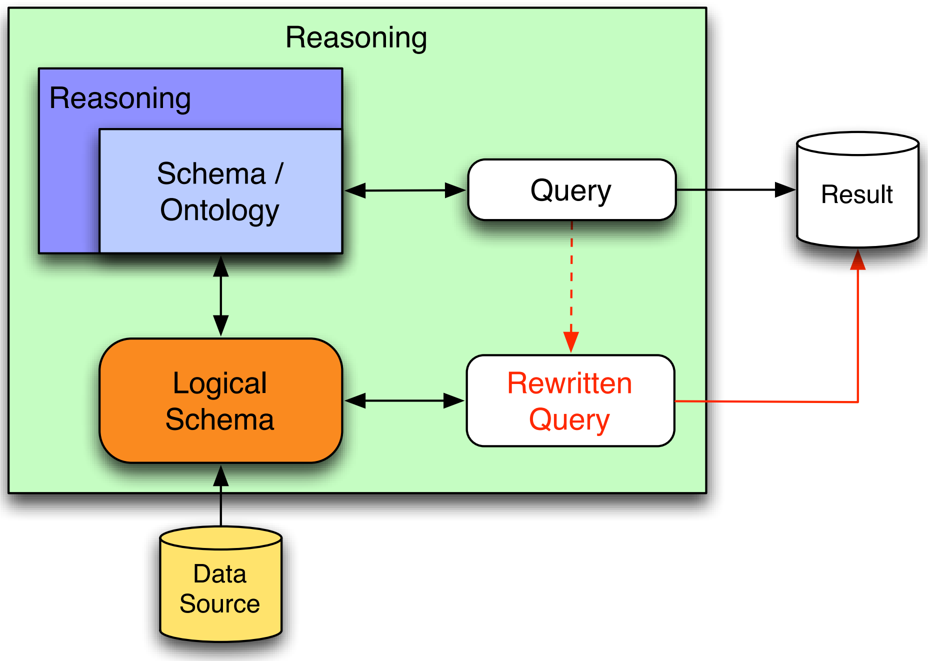


Query answering can **always** be thought as done in two phases:

1. **Perfect rewriting**: produce from q and the TBox $\mathcal{T}$ a new query $r_{q,\mathcal{T}}$ (called the perfect rewriting of q w.r.t. $\mathcal{T}$).
2. **Query evaluation**: evaluate $r_{q,\mathcal{T}}$ over the ABox $\mathcal{A}$ seen as a complete database (and without considering the TBox $\mathcal{T}$).
   $\rightsquigarrow$ Produces $cert(q, \langle\mathcal{T}, \mathcal{A}\rangle)$.

Note: The "always" holds if we pose no restriction on the language in which to express the rewriting $r_{q,\mathcal{T}}$.

Query rewriting (cont'd)



Language of the rewriting

The expressiveness of the ontology language affects the **query language into which we are able to rewrite CQs**:

- When we can rewrite into **FOL/SQL**.
  ⇝ Query evaluation can be done in SQL, i.e., via an **RDBMS** (*Note:* FOL is in LogSpace).
- When we can rewrite into an NLogSpace-hard language.
  ⇝ Query evaluation requires (at least) linear recursion.
- When we can rewrite into a PTime-hard language.
  ⇝ Query evaluation requires full recursion (e.g., Datalog).
- When we can rewrite into a coNP-hard language.
  ⇝ Query evaluation requires (at least) power of Disjunctive Datalog.

Complexity of query answering in DLs

Problem of rewriting is related to **complexity of query answering**.

Studied extensively for (unions of) CQs and various ontology languages:

	Combined complexity	Data complexity
Plain databases	NP-complete	in LogSpace [(2)]
OWL 2 (and less)	2ExpTime-complete	coNP-hard [(1)]

[(1)] Already for a TBox with a single disjunction (see Andrea's example).
[(2)] This is what we need to scale with the data.

Questions

- Can we find interesting families of DLs for which the query answering problem can be solved efficiently (i.e., in LogSpace)?
- If yes, can we leverage relational database technology for query answering?

Outline

The *DL-Lite* family

- A family of DLs optimized according to the tradeoff between expressive power and **complexity** of query answering, with emphasis on **data**.
- Carefully designed to have nice computational properties for answering UCQs (i.e., computing certain answers):
  - The same complexity as relational databases.
  - In fact, query answering can be delegated to a relational DB engine.
  - The DLs of the *DL-Lite* family are essentially the maximally expressive ontology languages enjoying these nice computational properties.
- We present *DL-Lite*$_\mathcal{A}$, an expressive member of the *DL-Lite* family.

DL-Lite$_\mathcal{A}$ provides robust foundations for Ontology-Based Data Access.

DL-Lite$_{\mathcal{A}}$ ontologies

TBox assertions:

- Class inclusion assertions: $B \sqsubseteq C$, with:

$$B \longrightarrow A \mid \exists Q$$
$$C \longrightarrow C \mid \neg C$$

- Property inclusion assertions: $Q \sqsubseteq R$, with:

$$Q \longrightarrow P \mid P^-$$
$$R \longrightarrow Q \mid \neg Q$$

- Functionality assertions: (**funct** Q)
- **Proviso:** functional properties cannot be specialized.

ABox assertions: $A(c)$, $P(c_1, c_2)$, with c_1, c_2 constants

Note: *DL-Lite*$_{\mathcal{A}}$ distinguishes also between object and data properties (ignored here).

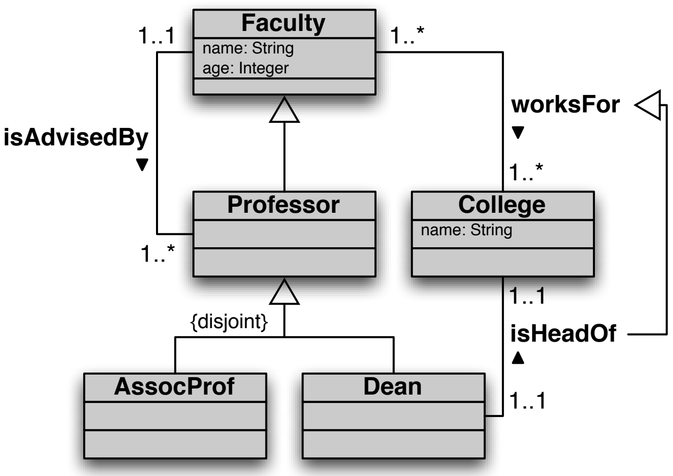
Semantics of the *DL-Lite*$_{\mathcal{A}}$ assertions

Assertion	Syntax	Example	Semantics
class incl.	$B \sqsubseteq C$	Father $\sqsubseteq$ $\exists$child	$B^\mathcal{I} \subseteq C^\mathcal{I}$
o-prop. incl.	$Q \sqsubseteq R$	father $\sqsubseteq$ anc	$Q^\mathcal{I} \subseteq R^\mathcal{I}$
v.dom. incl.	$E \sqsubseteq F$	ρ(age) $\sqsubseteq$ `xsd:int`	$E^\mathcal{I} \subseteq F^\mathcal{I}$
d-prop. incl.	$U \sqsubseteq V$	offPhone $\sqsubseteq$ phone	$U^\mathcal{I} \subseteq V^\mathcal{I}$
o-prop. funct.	(**funct** Q)	(**funct** father)	$\forall o, o, o''.(o, o') \in Q^\mathcal{I} \wedge (o, o'') \in Q^\mathcal{I} \rightarrow o' = o''$
d-prop. funct.	(**funct** U)	(**funct** ssn)	$\forall o, v, v'.(o, v) \in U^\mathcal{I} \wedge (o, v') \in U^\mathcal{I} \rightarrow v = v'$
mem. asser.	$A(c)$	Father(bob)	$c^\mathcal{I} \in A^\mathcal{I}$
mem. asser.	$P(c_1, c_2)$	child(bob, ann)	$(c_1^\mathcal{I}, c_2^\mathcal{I}) \in P^\mathcal{I}$
mem. asser.	$U(c, d)$	phone(bob, '2345')	$(c^\mathcal{I}, \mathit{val}(d)) \in U^\mathcal{I}$

Capturing basic ontology constructs in *DL-Lite*$_{\mathcal{A}}$

ISA between classes	$A_1 \sqsubseteq A_2$
Disjointness between classes	$A_1 \sqsubseteq \neg A_2$
Domain and range of properties	$\exists P \sqsubseteq A_1 \quad \exists P^- \sqsubseteq A_2$
Mandatory participation *(min card = 1)*	$A_1 \sqsubseteq \exists P \quad A_2 \sqsubseteq \exists P^-$
Functionality of relations *(max card = 1)*	$(\textbf{funct } P) \quad (\textbf{funct } P^-)$
ISA between properties	$Q_1 \sqsubseteq Q_2$
Disjointness between properties	$Q_1 \sqsubseteq \neg Q_2$

Example



$$
\begin{array}{rcl}
\text{Professor} & \sqsubseteq & \text{Faculty} \\
\text{AssocProf} & \sqsubseteq & \text{Professor} \\
\text{Dean} & \sqsubseteq & \text{Professor} \\
\text{AssocProf} & \sqsubseteq & \neg\text{Dean} \\
\\
\text{Faculty} & \sqsubseteq & \exists \textit{age} \\
\exists \textit{age}^- & \sqsubseteq & \texttt{xsd:int} \\
 & (\textbf{funct } \textit{age}) & \\
\\
\exists\text{worksFor} & \sqsubseteq & \text{Faculty} \\
\exists\text{worksFor}^- & \sqsubseteq & \text{College} \\
\text{Faculty} & \sqsubseteq & \exists\text{worksFor} \\
\text{College} & \sqsubseteq & \exists\text{worksFor}^- \\
\\
\exists\text{isHeadOf} & \sqsubseteq & \text{Dean} \\
\exists\text{isHeadOf}^- & \sqsubseteq & \text{College} \\
\text{Dean} & \sqsubseteq & \exists\text{isHeadOf} \\
\text{College} & \sqsubseteq & \exists\text{isHeadOf}^- \\
\text{isHeadOf} & \sqsubseteq & \text{worksFor} \\
 & (\textbf{funct } \text{isHeadOf}) & \\
 & (\textbf{funct } \text{isHeadOf}^-) & \\
 & \vdots &
\end{array}
$$

Note: *DL-Lite*$_{\mathcal{A}}$ cannot capture completeness of a hierarchy. This would require **disjunction** (i.e., **OR**).

Observations on *DL-Lite*$_{\mathcal{A}}$

- Captures all the basic constructs of **UML Class Diagrams** and of the **ER Model** . . .
- . . . **except covering constraints** in generalizations.
- Is **one of** the three candidate **OWL 2 Profiles**.
- Extends (the DL fragment of) the ontology language **RDFS**.
- Is completely symmetric w.r.t. **direct and inverse properties**.
- Does **not** enjoy the **finite model property**, i.e., reasoning and query answering differ depending on whether we consider or not also infinite models.

Query answering in *DL-Lite*$_{\mathcal{A}}$

Based on query reformulation: given an (U)CQ and an ontology:

1. **Compute its perfect rewriting**, which turns out to be a UCQ.
2. **Evaluate the perfect rewriting** on the ABox seen as a DB.

To compute the perfect rewriting, starting from the original (U)CQ, iteratively get a CQ to be processed and either:

- **expand** positive inclusions & **simplify** redundant atoms, or
- **unify** atoms in the CQ to obtain a more specific CQ to be further expanded.

Each result of the above steps is added to the queries to be processed.

Note: negative inclusions and functionalities play a role in ontology satisfiability, but not in query answering.

Query answering in *DL-Lite*$_{\mathcal{A}}$ – Example

TBox: Professor $\sqsubseteq$ $\exists$worksFor
$\exists$worksFor$^-$ $\sqsubseteq$ College

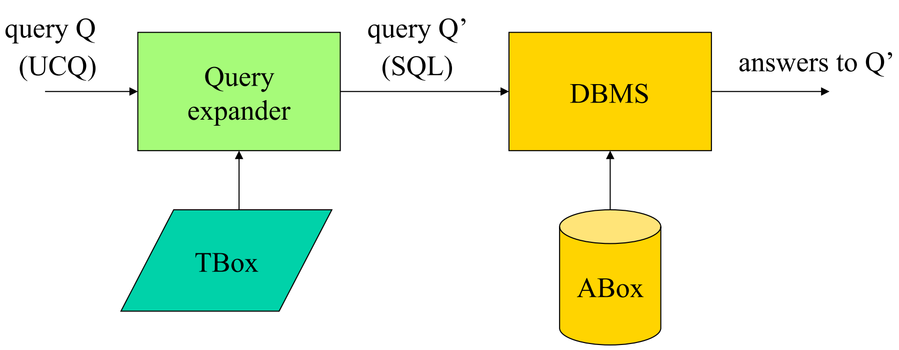
Query: $\mathsf{q}(x) \leftarrow \mathsf{worksFor}(x, y), \mathsf{College}(y)$

Perfect Reformulation:
$\mathsf{q}(x) \leftarrow \mathsf{worksFor}(x, y), \mathsf{College}(y)$
$\mathsf{q}(x) \leftarrow \mathsf{worksFor}(x, y), \mathsf{worksFor}(\_, y)$
$\mathsf{q}(x) \leftarrow \mathsf{worksFor}(x, \_)$
$\mathsf{q}(x) \leftarrow \mathsf{Professor}(x)$

ABox: worksFor(john, collA) Professor(john)
worksFor(mary, collB) Professor(nick)

Evaluating the last two queries over the ABox (seen as a DB) produces as answer {john, nick, mary}.

Query answering in DL-Lite



Riccardo Rosati - OWL profiles and DL-Lite 1

Example

TBox:

MALE $\sqsubseteq$ PERSON
FEMALE $\sqsubseteq$ PERSON
MALE $\sqsubseteq$ ¬FEMALE

PERSON $\sqsubseteq$ ∃hasFather
PERSON $\sqsubseteq$ ∃hasMother
$\exists hasFather^{-} \sqsubseteq$ MALE
$\exists hasMother^{-} \sqsubseteq$ FEMALE

input query:
q(x) ← PERSON(x)

rewritten query:
q'(x) ← PERSON(x) ∨
FEMALE(x) ∨
MALE(x) ∨
hasFather(y,x) ∨
hasMother(y,x)

Example

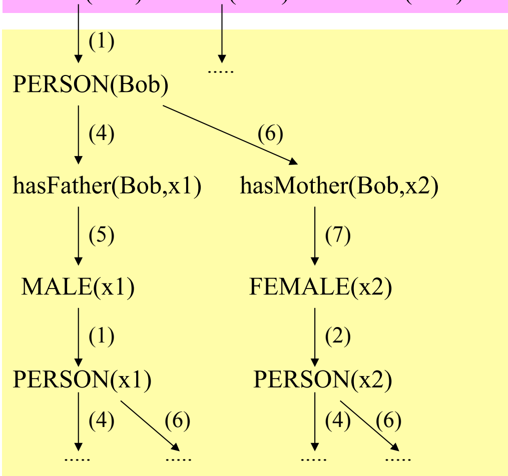
rewritten query:
q'(x) ← PERSON(x) ∨
FEMALE(x) ∨
MALE(x) ∨
hasFather(y,x) ∨
hasMother(y,x)

ABox:
MALE(Bob)
MALE(Paul)
FEMALE(Ann)
hasFather(Paul,Ann)
hasMother(Mary,Paul)

answers to query:
{ Bob, Paul, Ann, Mary }

Answering queries: chasing the ABox

MALE(Bob) MALE(Paul) FEMALE(Ann) hasFather(Paul,Ann) hasMother(Mary,Paul)

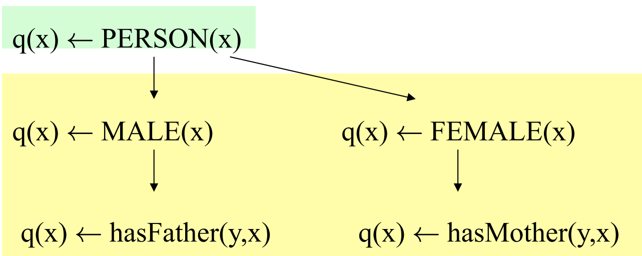


CHASE of the ABox with respect to the TBox = adding to the ABox all instance assertions that are logical consequences of the TBox

the chase represents the **canonical model** of the whole KB

problem: the chase of the ABox is in general infinite

Query rewriting algorithm for DL-Lite



how to avoid the infinite chase of the ABox?

CHASE of the query:

- inclusions are applied “from right to left”
- this chase always terminates
- this chase is computed independently of the ABox

Query rewriting algorithm for DL-Lite

The rewriting algorithm iteratively applies two rewriting rules:

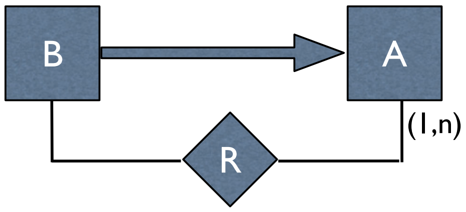
- **atom-rewrite**: takes an atom of the conjunctive query and rewrites it applying a TBox inclusion
  - the inclusion is used as a rewriting rule (right-to-left)
- **reduce**: takes two unifiable atoms of the conjunctive query and merges (unifies) them

Query rewriting algorithm for DL-Lite

```
Algorithm PerfectRef (q; 𝒯)
Input: conjunctive query q, DL-Lite TBox 𝒯
Output: union of conjunctive queries PR
PR := {q};
repeat
    PR0 := PR;
    for each q ∈ PR0 do
    (a) for each g in q do
          for each positive inclusion I  in 𝒯 do
            if I is applicable to g  then PR := PR ∪{q[g/gr(g,I)]};
    (b) for each g1, g2 in q  do
        if g1 and g2 unify then PR := PR ∪{f (reduce(q,g1,g2))}
until PR0 = PR;
return PR
```

KB

- TBOX:
  - A ISA SOME R
  - SOME R ISA A
  - SOME R^- ISA B
  - B ISA A



- ABOX:
  - B(c)
- QUERY:
  - q(x) :- R(x,y), R(y,z)

Query Answering

Expansion:

- q(x) :- R(x,y), R(y,z)
- q(x) :- R(x,y), R(y,_)
- q(x) :- R(x,y), A(y)
- q(x) :- R(x,y), B(y)
- q(x) :- R(x,y), R(_,y)
- q(x) :- R(x,y)
- q(x) :- R(x,_)
- q(x) :- A(x)
- q(x) :- B(x)

All queries empty except for the last!

Certain Answer: {c}

Complexity of reasoning in *DL-Lite*$_{\mathcal{A}}$

Ontology satisfiability and all classical DL reasoning tasks are:

- Efficiently tractable in the size of TBox (i.e., PTIME).
- Very efficiently tractable in the size of the ABox (i.e., LOGSPACE).

In fact, reasoning can be done by constructing suitable FOL/SQL queries and evaluating them over the ABox (**FOL-rewritability**).

Query answering for CQs and UCQs is:

- PTIME in the size of TBox.
- LOGSPACE in the size of the ABox.
- Exponential in the size of the **query** (NP-complete).
  Bad? ...not really, this is exactly as in relational DBs.

Can we go beyond *DL-Lite*$_{\mathcal{A}}$?

No! By adding essentially any additional constructor we lose these nice computational properties.

Beyond *DL-Lite*$_{\mathcal{A}}$: results on data complexity

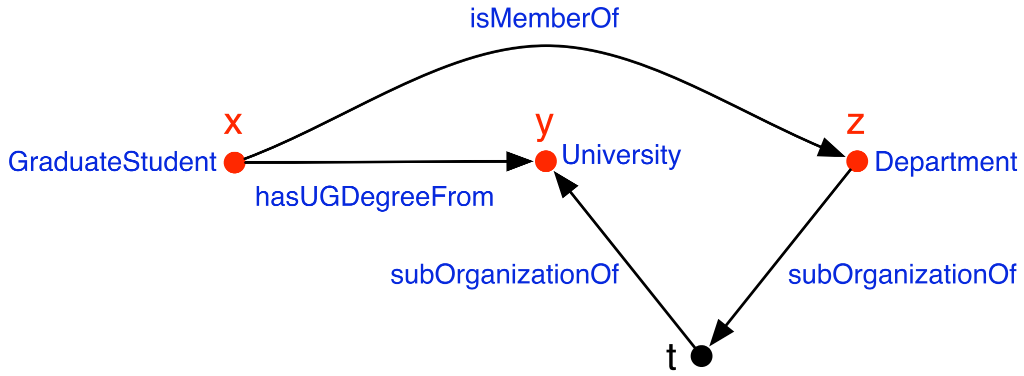
	lhs	rhs	funct.	Prop. incl.	Data complexity of query answering
0	*DL-Lite*$_{\mathcal{A}}$		$\surd$*	$\surd$*	in LOGSPACE
1	$A \mid \exists P.A$	A	–	–	NLOGSPACE-hard
2	A	$A \mid \forall P.A$	–	–	NLOGSPACE-hard
3	A	$A \mid \exists P.A$	$\surd$	–	NLOGSPACE-hard
4	$A \mid \exists P.A \mid A_1 \sqcap A_2$	A	–	–	PTIME-hard
5	$A \mid A_1 \sqcap A_2$	$A \mid \forall P.A$	–	–	PTIME-hard
6	$A \mid A_1 \sqcap A_2$	$A \mid \exists P.A$	$\surd$	–	PTIME-hard
7	$A \mid \exists P.A \mid \exists P^-.A$	$A \mid \exists P$	–	–	PTIME-hard
8	$A \mid \exists P \mid \exists P^-$	$A \mid \exists P \mid \exists P^-$	$\surd$	$\surd$	PTIME-hard
9	$A \mid \neg A$	A	–	–	**coNP-hard**
10	A	$A \mid A_1 \sqcup A_2$	–	–	**coNP-hard**
11	$A \mid \forall P.A$	A	–	–	**coNP-hard**

Notes:

- * with the "proviso" of not specializing functional properties.
- NLOGSPACE and PTIME hardness holds already for instance checking.
- For coNP-hardness in line 10, a TBox with a single assertion $A_L \sqsubseteq A_T \sqcup A_F$ suffices! $\rightsquigarrow$ **No** hope of including **covering constraints**.

Example of query

$$q(x, y, z) \leftarrow \text{GraduateStudent}(x),\ \text{University}(y),\ \text{Department}(z),\ \text{hasUndergraduateDegreeFrom}(x, y),\ \text{isMemberOf}(x, z),\ \text{subOrganizationOf}(z, t),\ \text{subOrganizationOf}(t, y)$$




```
SELECT ?X ?Y ?Z WHERE
  ?X rdf:type 'GraduateStudent'  .  ?Y rdf:type 'University' .
  ?Z rdf:type 'Department'  .
  ?X :hasUndergraduateDegreeFrom ?Y  .  ?X :isMemberOf ?Z  .
  ?Z subOrganizationOf ?T  .  ?T subOrganizationOf ?Y
```


Outline

1 Introduction

2 Querying data through ontologies

3 *DL-Lite*$_{\mathcal{A}}$: an ontology language for accessing data

4 Conclusions

5 References

Conclusions

- Ontology-based data access and integration is a challenging problem with great practical relevance.
- In this setting, the size of the data is the relevant parameter that must guide technological choices.
- Currently, scalability w.r.t. the size of the data can be achieved only by relying on commercial technologies for managing the data, i.e., relational DBMS systems and federation tools.
- In order to tailor semantic technologies so as to provide a good compromise between expressivity and efficiency, requires a thorough understanding of the semantic and computational properties of the adopted formalisms.
- We have now gained such an understanding, that allows us to develop very good solutions for ontology-based data access and integration.
- One of the three OWL 2 profiles, namely "OWL 2 QL", is directly based on this understanding.

Outline

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