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?

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Query answering in description logics: *DL-Lit* (3/56)

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

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Query answering in description logics: *DL-Lit* (4/56)

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).

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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{array}{l}
q(nf, af, nd) \;\leftarrow\; \exists f, c, d, ad. \\
\quad \text{worksFor}(f, c) \land \text{isHeadOf}(d, c) \land \text{name}(f, nf) \land \text{name}(d, nd) \land \\
\quad \text{age}(f, af) \land \text{age}(d, ad) \land af = ad
\end{array}
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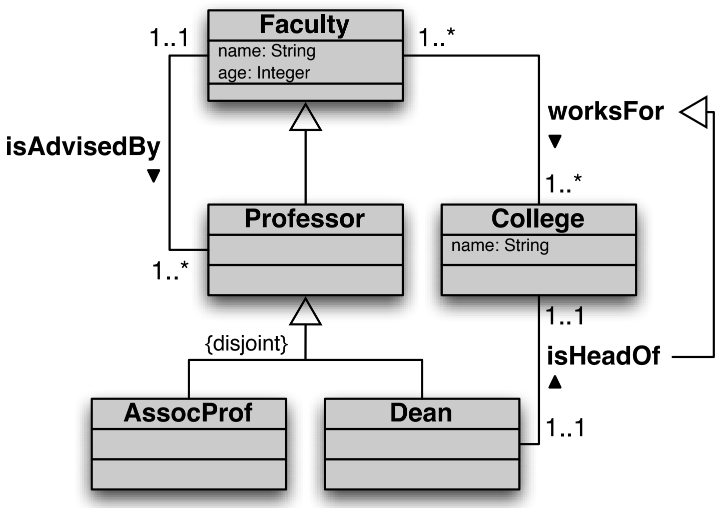

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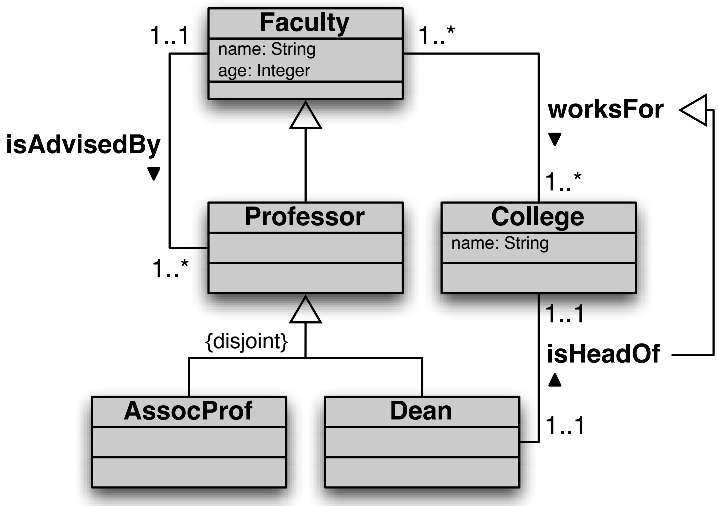

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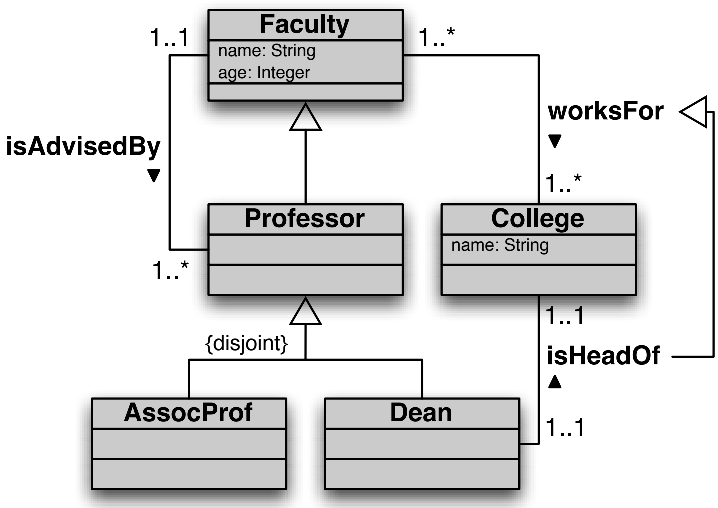

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Conjunctive queries and SQL – Example

Relational alphabet:
$\mathsf{worksFor}(\mathsf{fac}, \mathsf{coll})$, $\mathsf{isHeadOf}(\mathsf{dean}, \mathsf{coll})$, $\mathsf{name}(\mathsf{p}, \mathsf{n})$, $\mathsf{age}(\mathsf{p}, \mathsf{a})$

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

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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
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Conjunctive queries and SQL – Example

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

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Expressed as a CQ:

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\begin{aligned}
q(nf, af, nd) \leftarrow\ & \mathsf{worksFor}(f1, c1),\ \mathsf{isHeadOf}(d1, c2),\\
& \mathsf{name}(f2, nf),\ \mathsf{name}(d2, nd),\ \mathsf{age}(f3, af),\ \mathsf{age}(d3, ad),\\
& f1 = f2,\ f1 = f3,\ d1 = d2,\ d1 = d3,\ c1 = c2,\ af = ad
\end{aligned}
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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.

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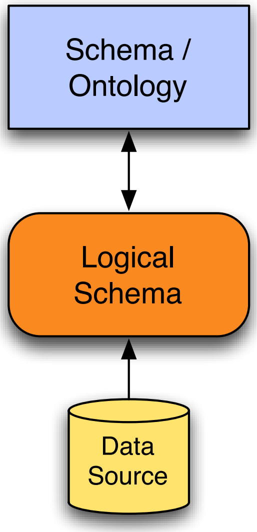
Query answering under the database assumption

- 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)



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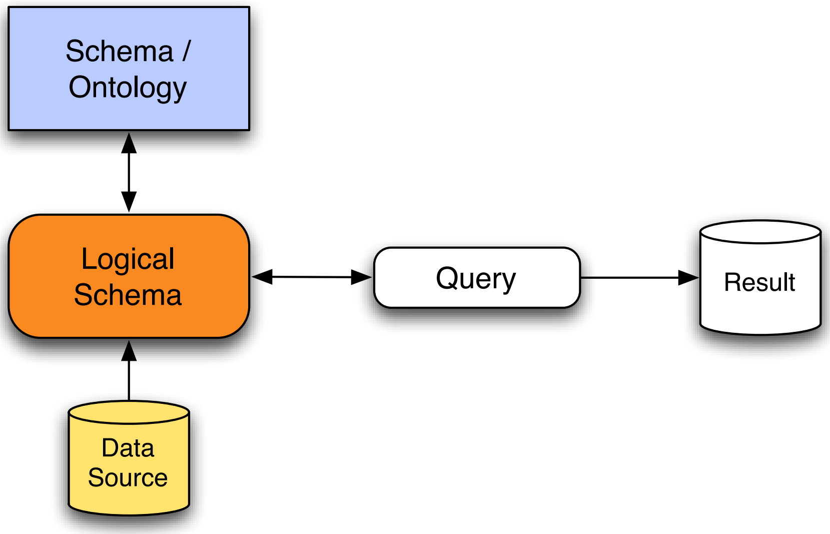

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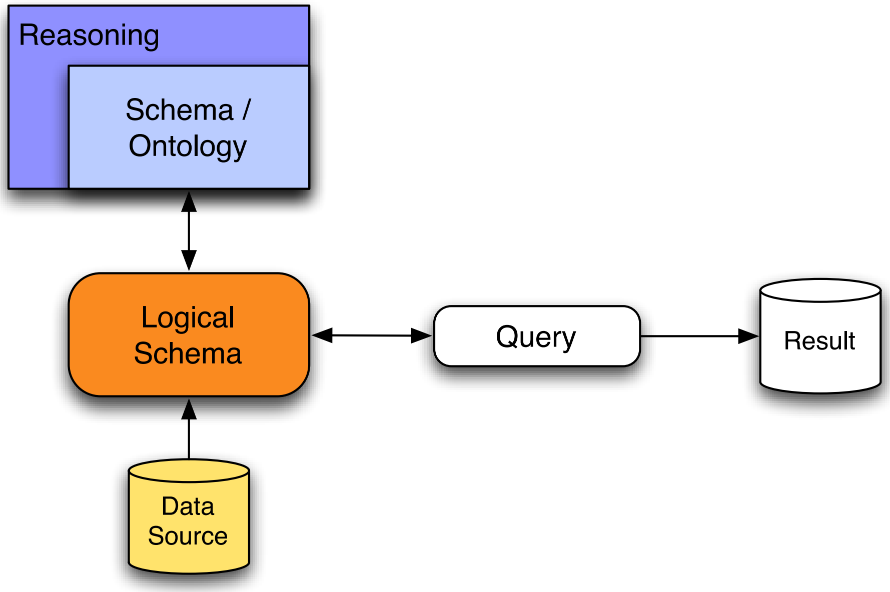

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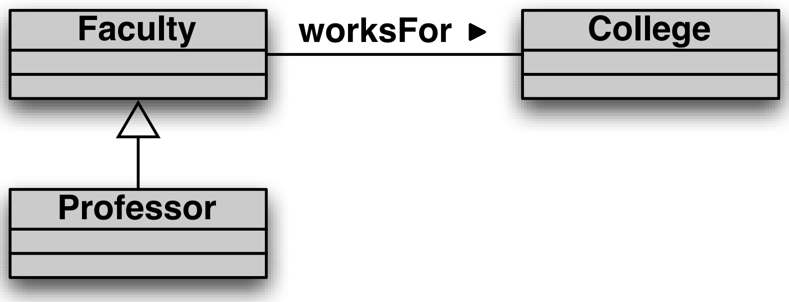

For each class/property we have a (complete) table in the database.

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

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

Answer: ???

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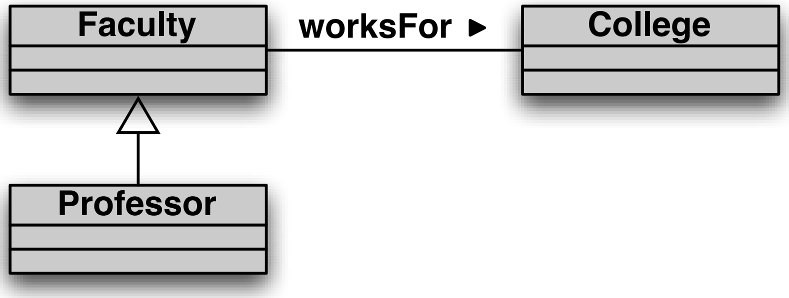

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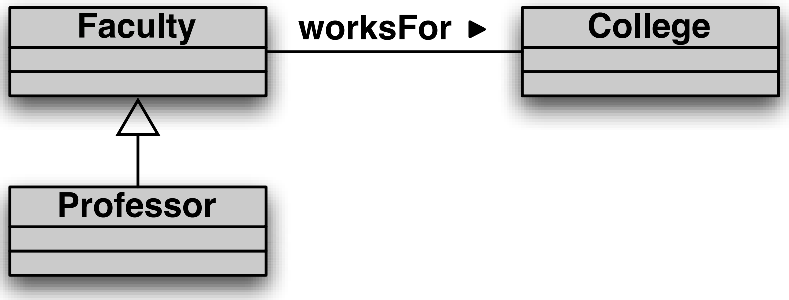

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Query: $q(x) \leftarrow \exists c.\, \text{Professor}(x), \text{College}(c), \text{worksFor}(x, c)$

Answer: { john }

Query answering under the KR assumption

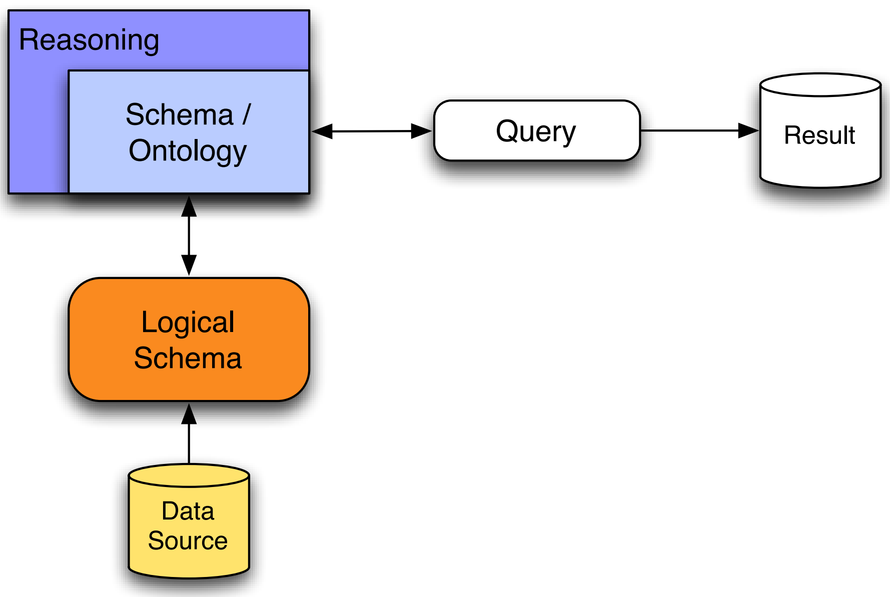
- An ontology imposes constraints on the data.
- Actual data may be incomplete or inconsistent w.r.t. such constraints.
- The system has to take into account the constraints during query answering, and overcome incompleteness or inconsistency.

$\rightsquigarrow$ 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)



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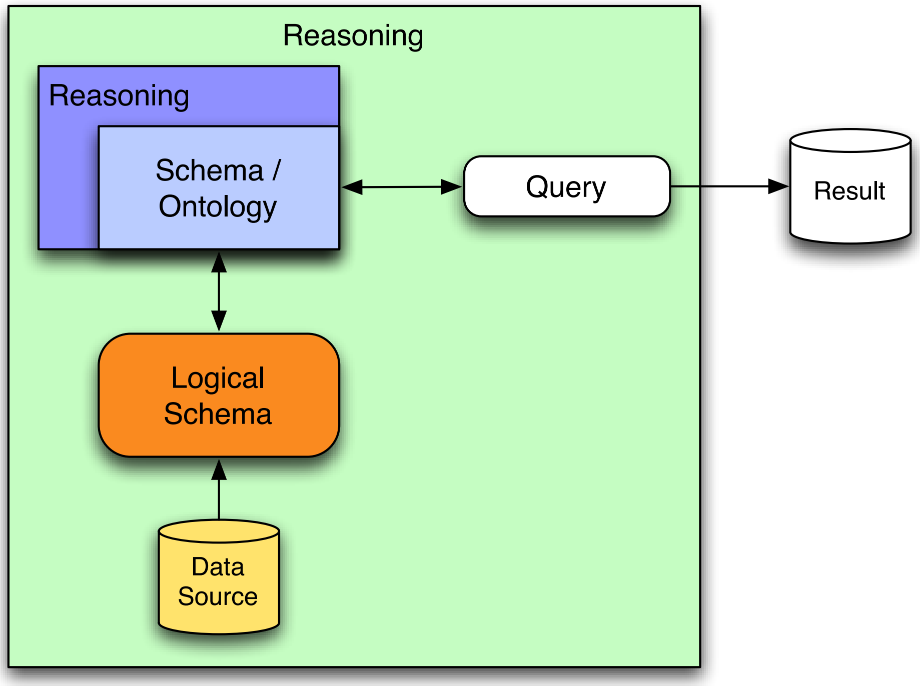

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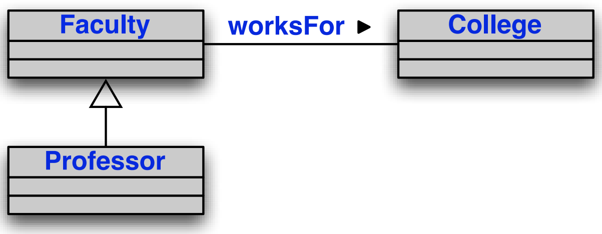

The tables in the database may be **incompletely specified**, or even missing for some classes/properties.

DB: Professor $\supseteq$ { `john`, `nick` }
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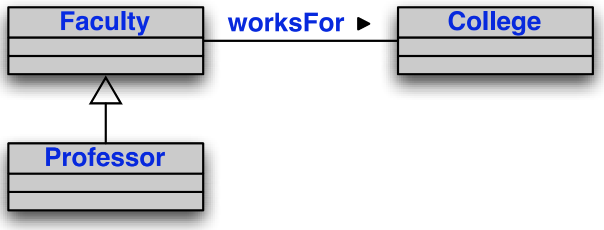
Query: $q(x) \leftarrow$ Faculty(x)

Answer: ???

Query answering under the KR assumption – Example



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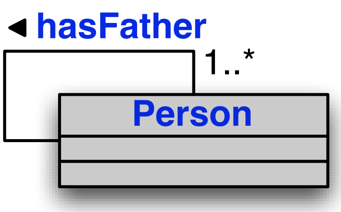
Query: $q(x) \leftarrow \text{Faculty}(x)$

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

Answers: to q_1: ???
to q_2: ???
to q_3: ???
to q_4: ???

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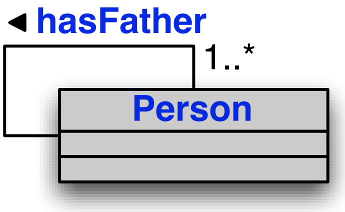

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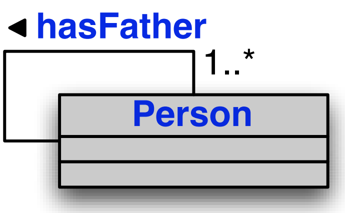

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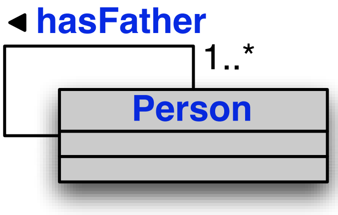

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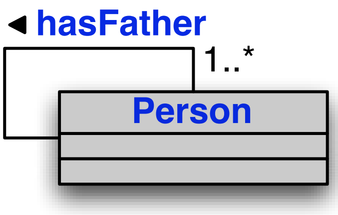
Answers: to q_1: { (john,nick), (nick,toni) }
to q_2: { john, nick, toni }
to q_3: { john, nick, toni }
to q_4: ???

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: $q_1(x, y) \leftarrow \text{hasFather}(x, y)$

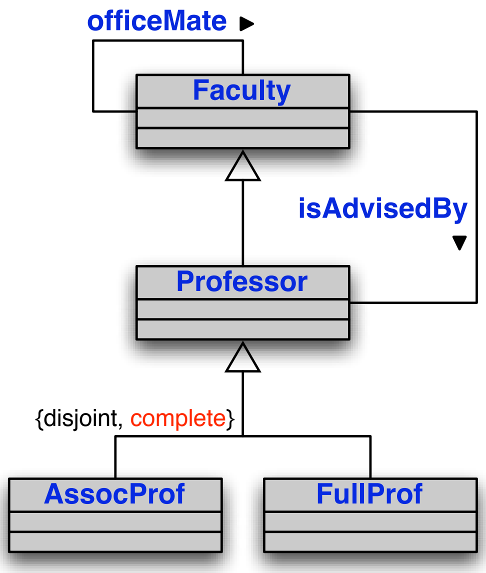
$q_2(x) \leftarrow \exists y.\, \text{hasFather}(x, y)$

$q_3(x) \leftarrow \exists y_1, y_2, y_3.\, \text{hasFather}(x, y_1), \text{hasFather}(y_1, y_2), \text{hasFather}(y_2, y_3)$

$q_4(x, y_3) \leftarrow \exists y_1, y_2.\, \text{hasFather}(x, y_1), \text{hasFather}(y_1, y_2), \text{hasFather}(y_2, y_3)$

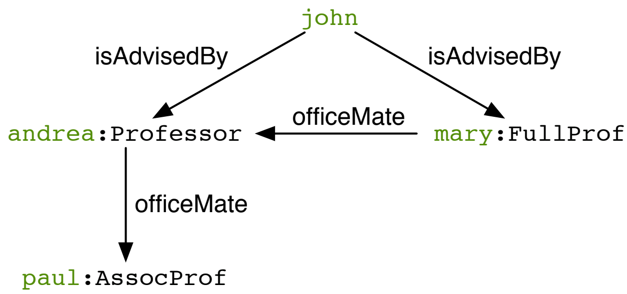
Answers: to q_1: { (john,nick), (nick,toni) }
to q_2: { john, nick, toni }
to q_3: { john, nick, toni }
to q_4: { }

QA under the KR assumption – Andrea's Example

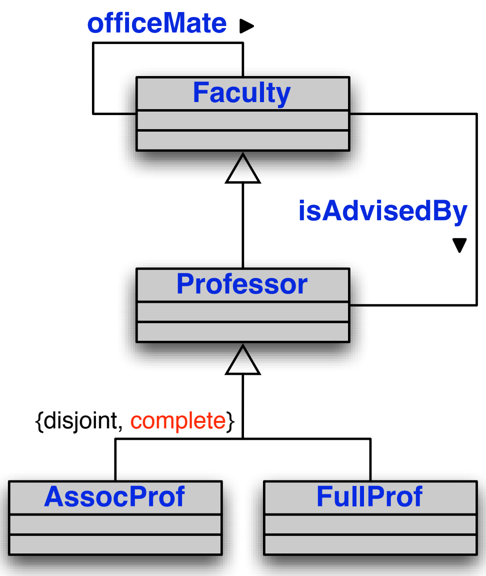


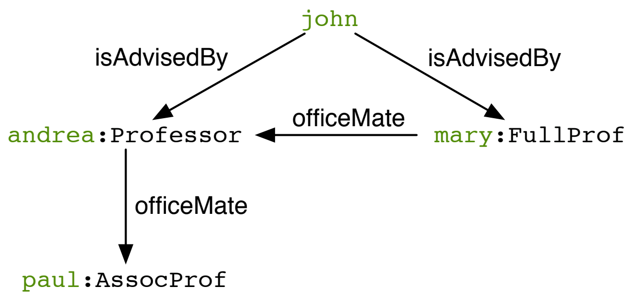
$$\text{Professor} \equiv \text{AssocProf} \sqcup \text{FullProf}$$

$$\begin{aligned}
\text{Faculty} &\supseteq \{\ \texttt{andrea}, \texttt{nick}, \texttt{mary}, \texttt{john}\ \} \\
\text{Professor} &\supseteq \{\ \texttt{andrea}, \texttt{nick}, \texttt{mary}\ \} \\
\text{AssocProf} &\supseteq \{\ \texttt{nick}\ \} \\
\text{FullProf} &\supseteq \{\ \texttt{mary}\ \} \\
\text{isAdvisedBy} &\supseteq \{\ (\texttt{john},\texttt{andrea}), (\texttt{john},\texttt{mary})\ \} \\
\text{officeMate} &\supseteq \{\ (\texttt{mary},\texttt{andrea}), (\texttt{andrea},\texttt{nick})\ \}
\end{aligned}$$



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

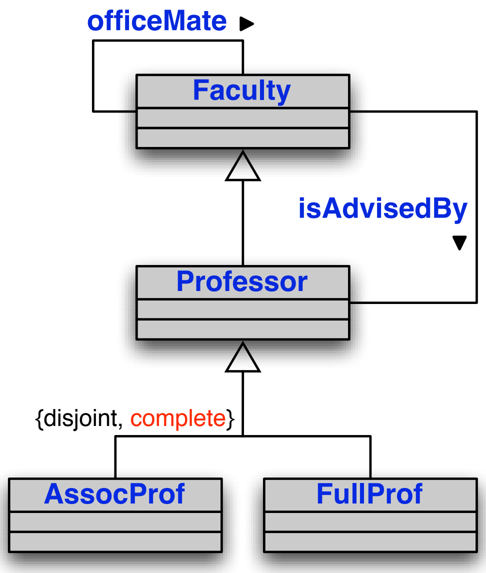


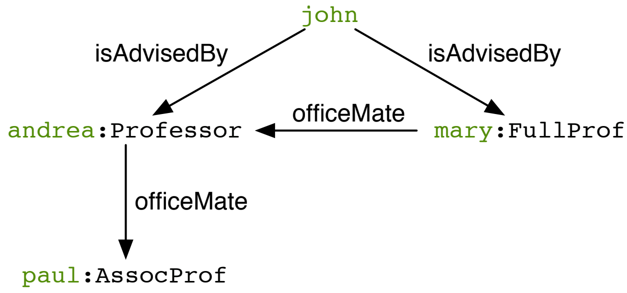


$$q() \leftarrow \exists y, z.\ \text{isAdvisedBy}(\texttt{john}, y),\ \text{FullProf}(y),\ \text{officeMate}(y, z),\ \text{AssocProf}(z)$$

Answer: yes or no?

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





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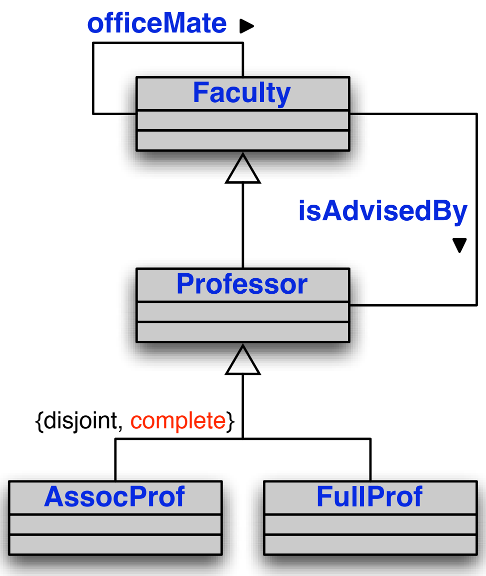

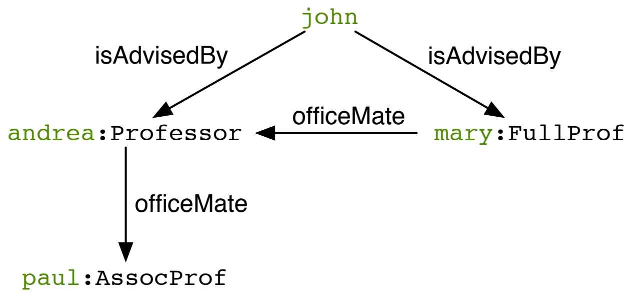

$$q() \leftarrow \exists y, z.\ \mathsf{isAdvisedBy}(\mathtt{john}, y),\ \mathsf{FullProf}(y),\ \mathsf{officeMate}(y, z),\ \mathsf{AssocProf}(z)$$

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 $cert(q, \mathcal{O})$

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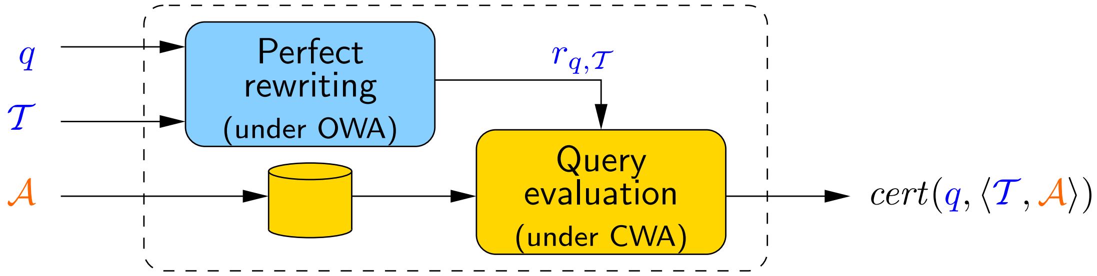
Inference in query answering

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

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

Query rewriting

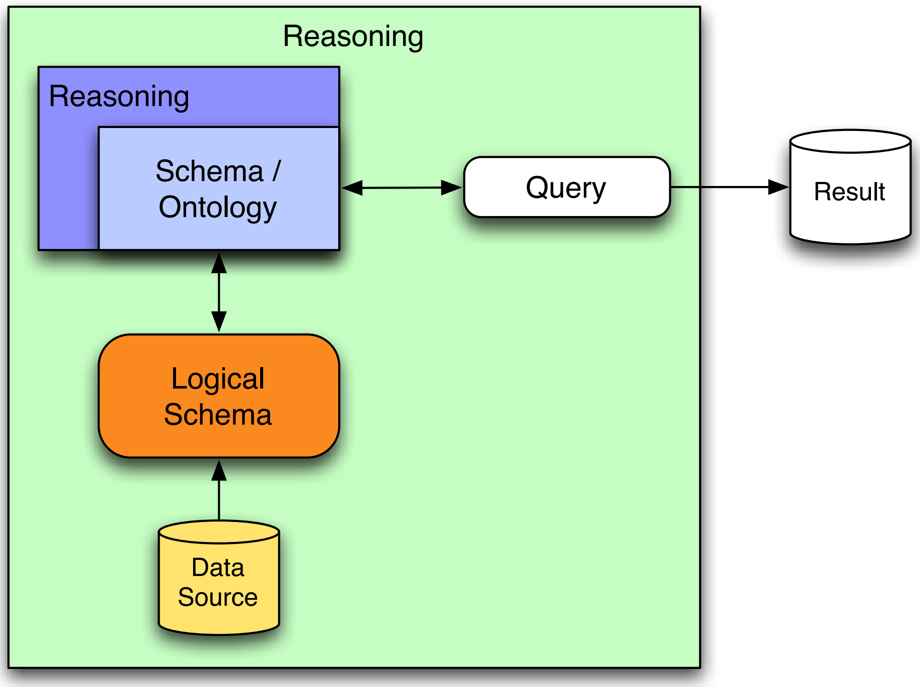


Query answering can **always** be thought as done in two phases:

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 $\mathcal{T}$).
   $\leadsto$ 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)



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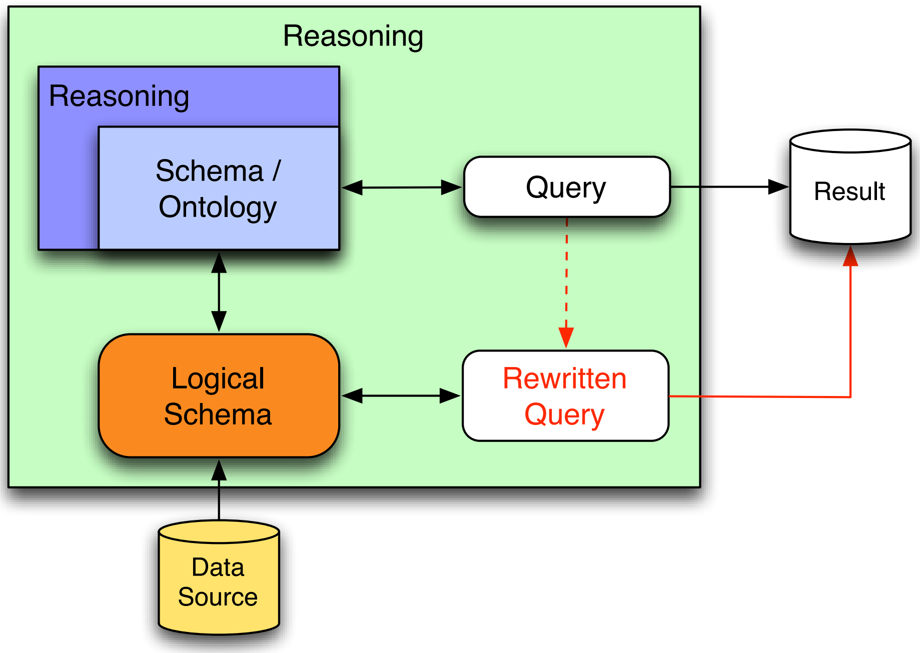

Language of the rewriting

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**.
  $\leadsto$ 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.
  $\leadsto$ Query evaluation requires (at least) linear recursion.
- When we can rewrite into a PTime-hard language.
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- When we can rewrite into a coNP-hard language.
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Query answering in description logics: *DL-Lit* (26/56)

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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?

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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 $\textit{DL-Lite}_{\mathcal{A}}$, an expressive member of the *DL-Lite* family.

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

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

TBox assertions:

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

$$\begin{array}{rcl} B & \longrightarrow & A \mid \exists Q \\ C & \longrightarrow & C \mid \neg C \end{array}$$

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

$$\begin{array}{rcl} Q & \longrightarrow & P \mid P^{-} \\ R & \longrightarrow & Q \mid \neg Q \end{array}$$

- Functionality assertions: $(\textbf{funct}\ Q)$
- **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.	$(\textbf{funct}\ Q)$	(**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.	$(\textbf{funct}\ U)$	(**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	$\exists P \sqsubseteq A_1 \qquad \exists P^- \sqsubseteq A_2$
Mandatory participation *(min card = 1)*	$A_1 \sqsubseteq \exists P \qquad A_2 \sqsubseteq \exists P^-$
Functionality of relations *(max card = 1)*	$(\textbf{funct}\ P) \qquad (\textbf{funct}\ P^-)$
ISA between properties	$Q_1 \sqsubseteq Q_2$
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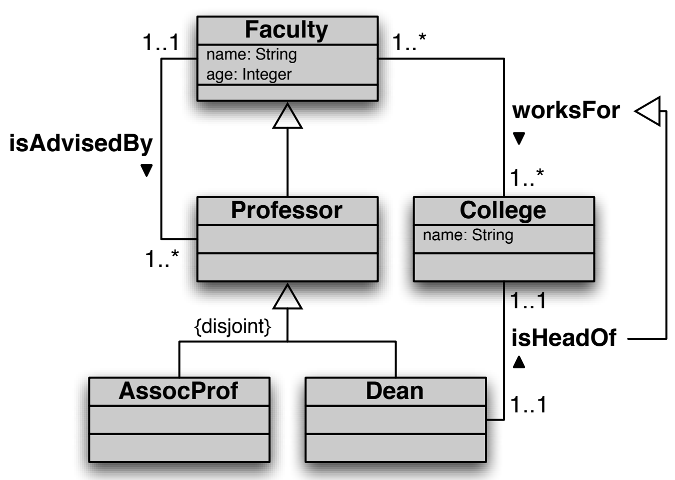
Example



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

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.

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Query answering in description logics: *DL-Lit* (34/56)

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.

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

TBox: $\mathsf{Professor} \sqsubseteq \exists\mathsf{worksFor}$
$\exists\mathsf{worksFor}^- \sqsubseteq \mathsf{College}$

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: $\mathsf{worksFor}(\mathtt{john}, \mathtt{collA})$ $\mathsf{Professor}(\mathtt{john})$
$\mathsf{worksFor}(\mathtt{mary}, \mathtt{collB})$ $\mathsf{Professor}(\mathtt{nick})$

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

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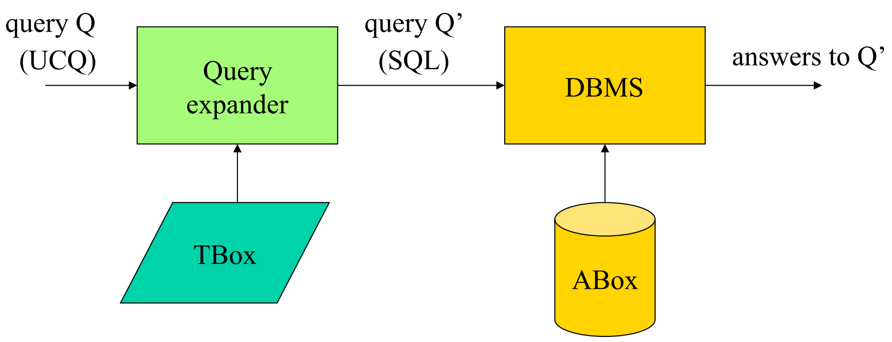


Example

TBox:

$\text{MALE} \sqsubseteq \text{PERSON}$ $\quad$ $\text{FEMALE} \sqsubseteq \text{PERSON}$

$\text{MALE} \sqsubseteq \neg\text{FEMALE}$

$\text{PERSON} \sqsubseteq \exists\text{hasFather}$ $\quad$ $\text{PERSON} \sqsubseteq \exists\text{hasMother}$

$\exists\text{hasFather}^{-} \sqsubseteq \text{MALE}$ $\quad$ $\exists\text{hasMother}^{-} \sqsubseteq \text{FEMALE}$

input query:

$q(x) \leftarrow \text{PERSON}(x)$

rewritten query:

$q'(x) \leftarrow \text{PERSON}(x) \lor$
$\text{FEMALE}(x) \lor$
$\text{MALE}(x) \lor$
$\text{hasFather}(y,x) \lor$
$\text{hasMother}(y,x)$

Example

rewritten query:

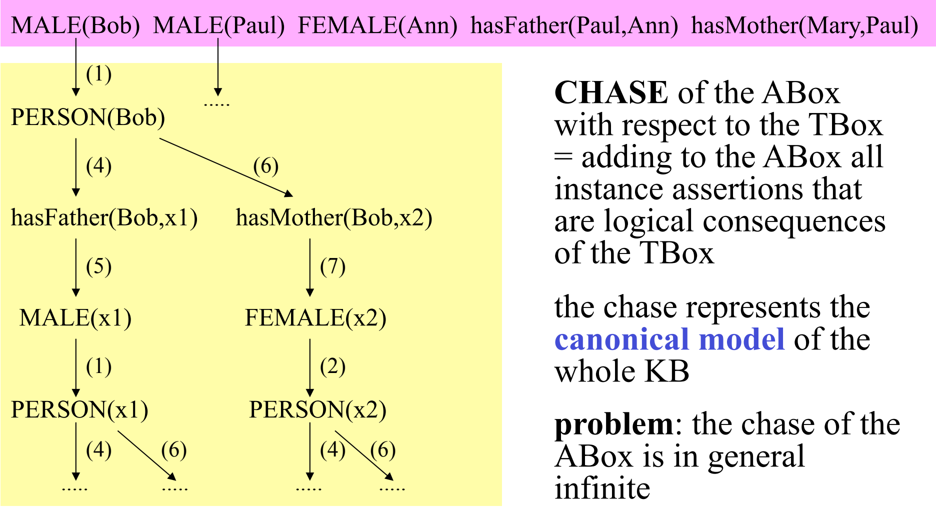
q'(x) ← PERSON(x) ∨
FEMALE(x) ∨
MALE(x) ∨
hasFather(y,x) ∨
hasMother(y,x)

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



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

$$\begin{array}{ccc} & q(x) \leftarrow PERSON(x) & \\ \swarrow & & \searrow \\ q(x) \leftarrow MALE(x) & & q(x) \leftarrow FEMALE(x) \\ \downarrow & & \downarrow \\ q(x) \leftarrow hasFather(y,x) & & q(x) \leftarrow hasMother(y,x) \end{array}$$

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)

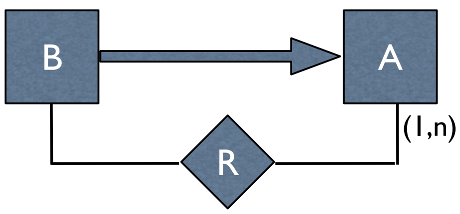
•**reduce**: takes two unifiable atoms of the conjunctive query and merges (unifies) them

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.

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

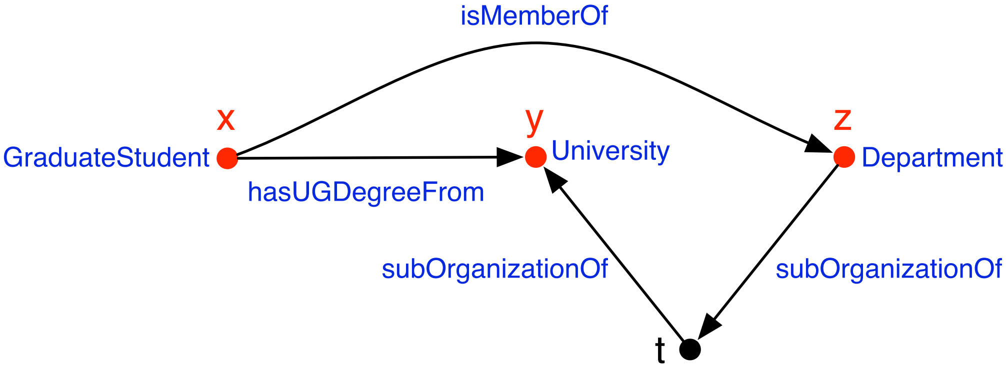
	lhs	rhs	funct.	Prop. incl.	Data complexity of query answering
0	*DL-Lite*$_\mathcal{A}$		$\surd^*$	$\surd^*$	in LOGSPACE
1	$A \mid \exists P.A$	A	–	–	NLOGSPACE-hard
2	A	$A \mid \forall P.A$	–	–	NLOGSPACE-hard
3	A	$A \mid \exists P.A$	$\surd$	–	NLOGSPACE-hard
4	$A \mid \exists P.A \mid A_1 \sqcap A_2$	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! $\leadsto$ **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
```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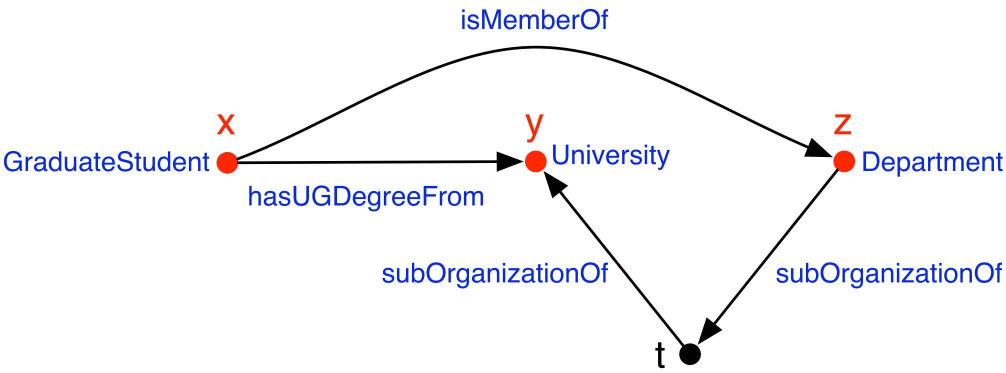


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  ?Z rdf:type 'Department'  .
  ?X :hasUndergraduateDegreeFrom ?Y  .  ?X :isMemberOf ?Z  .
  ?Z subOrganizationOf ?T  .  ?T subOrganizationOf ?Y
```

Query answering in description logics: *DL-Lit* (48/56)

Beyond union of conjunctive queries

Till now we have assumed that the client queries are UCQs (aka positive queries).
Can we go beyond UCQ? Can we go to full **FOL/SQL queries**?

- No! Answering FOL queries in presence of incomplete information is undecidable: Consider an empty source (no data), still a (boolean) FOL query may return *true* because it is valid! (FOL validity is undecidable)
- Yes! With some compromises:
  Query what the ontology **knows** about the domain, not what is **true** in the domain!
  On knowledge we have complete information, so evaluating FOL queries is LogSpace.

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SparSQL

Full **SQL**, but with relations in the FROM clause that are UCQs, expressed in **SPARQL**, over the ontology.

- **SPARQL** queries are used to query what is **true** in the domain.
- **SQL** is used to query what the ontology **knows** about the domain.

Example: negation

Return all known people that are neither known to be male nor known to be female.

```
SELECT persons.x
FROM SparqlTable(SELECT ?x
                 WHERE {?x rdf:type 'Person'}
                ) persons
EXCEPT  (
SELECT males.x
FROM SparqlTable(SELECT ?x
                 WHERE {?x rdf:type 'Male'}
                ) males
UNION
SELECT females.x
FROM SparqlTable(SELECT ?x
                 WHERE {?x rdf:type 'Female'}
                ) females
)
```

Example: aggregates

Return the people and the number of their known spouses, but only if they are known to be married to at least two people.

```
SELECT marriage.x, count(marriage.y)
FROM SparqlTable(SELECT ?x ?y
                 WHERE {?x :MarriedTo ?y}
                ) marriage
GROUP BY marriage.x
HAVING count(marriage.y) >= 2
```


SparSQL in $DL\text{-}Lite_{\mathcal{A}}$

Answering of SparSQL queries in $DL\text{-}Lite_{\mathcal{A}}$:

1. Expand and unfold the UCQs (in the SparqlTables) as usual in $DL\text{-}Lite_{\mathcal{A}}$ $\leadsto$ an SQL query over the ABox (seen as a database) for each SparqlTable in the FROM clauses.
2. Substitute SparqlTables with the new SQL queries. $\leadsto$ the result is again an SQL query over the ABox (seen as a database)!
3. Evaluate the resulting SQL query over the ABox (seen as a database)

Outline

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