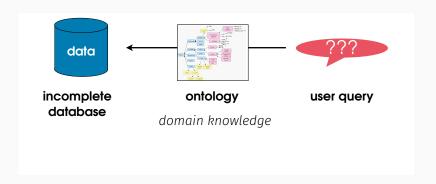
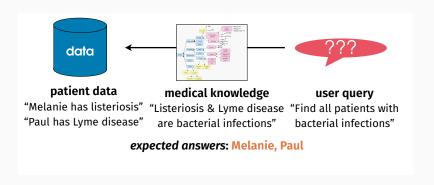
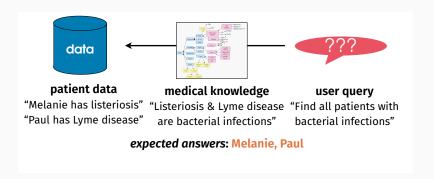
# QUERY REWRITING: Limits and Possibilities

Meghyn Bienvenu (CNRS, University of Montpellier, Inria)







# Why use an ontology?

- extend the vocabulary (making queries easier to formulate)
- provide a unified view of multiple data sources
- · obtain more answers to queries (by exploiting domain knowledge)

#### **SETTING WE CONSIDER**

Ontologies formulated using description logics (DLs):

- · family of decidable fragments of first-order logic
- · basis for OWL web ontology language (W3C)
- · range from fairly simple to highly expressive
- · complexity of query answering well understood

In this talk, mainly focus on three particular DLs:

· DL-Lite<sub>R</sub>,  $\mathcal{EL}$ ,  $\mathcal{ALC}$ 

Consider two types of queries:

- · conjunctive queries (CQs) aka select-project-join queries
- · instance queries (IQs)

# BRIEF INTRO TO DLS & OMQA

#### **DESCRIPTION LOGIC ALC**

In ALC, we have the following concept constructors:

- · top concept ⊤ (acts as a "wildcard", denotes set of all things)
- bottom concept ⊥ (denotes empty set)
- · conjunction ( $\sqcap$ ), disjunction ( $\sqcup$ ), negation ( $\neg$ )
- · restricted forms of existential and universal quantification  $(\exists, \forall)$

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An  $\mathcal{ALC}$  TBox (ontology) is a set of concept inclusions  $C \sqsubseteq D$ , where

$$C, D := \top \mid \bot \mid A \mid \neg C \mid C \sqcap D \mid C \sqcup D \mid \exists r.C \mid \forall r.C$$

where A is an atomic concept, r an atomic role.

Intuitively,  $C \sqsubseteq D$  means "everything that is a C is also a D"

#### **EXAMPLES OF TBOX AXIOMS**

Professors and lecturers are disjoint classes of faculty

 $Prof \sqsubseteq Faculty \quad Lect \sqsubseteq Faculty \quad Prof \sqsubseteq \neg Lect$ 

Every grad student is supervised by a professor

GradSt ⊑ ∃supervisedBy.Prof

Grad students are students, and they only take graduate courses

 $GradSt \sqsubseteq Student \sqcap \forall takesC.GradC$ 

FO translation:  $\forall x \; (GradSt(x) \rightarrow (Student(x) \land \forall y \; takesC(x,y) \rightarrow GradC(y))$ 

#### **DESCRIPTION LOGIC EL**

In  $\mathcal{EL}$ , complex concepts are constructed as follows:

$$C, D := \top \mid A \mid C \sqcap D \mid \exists r.C$$

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Advantage w.r.t. ALC: reasoning much simpler (PTIME vs. EXPTIME)

Despite lower expressivity,  $\mathcal{EL}$  very useful in practice

- · used for many biomedical ontologies, including SNOMED
- · importance witnessed by OWL 2 EL profile

Also consider  $\mathcal{ELI} = \mathcal{EL} + \text{inverse roles}(r^-)$ 

#### DESCRIPTION LOGIC DL-LITE

We present the dialect DL-Lite<sub>R</sub> (which underlies OWL 2 QL profile).

DL-Lite<sub>R</sub> TBoxes contain

- · concept inclusions  $B_1 \sqsubseteq B_2$ ,  $B_1 \sqsubseteq \neg B_2$
- · role inclusions  $S_1 \sqsubseteq S_2$ ,  $S_1 \sqsubseteq \neg S_2$

where 
$$B := A \mid \exists S$$
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## **Example TBox inclusions:**

- · Every professor teaches something: Prof 

  ∃teaches
- · Everything that is taught is a course: ∃teaches ☐ ☐ Course
- · Head of dept implies member of dept: headOf 

  memberOf

#### **QUERY LANGUAGES**

Instance queries (IQs): find instances of a given concept or role

Faculty(x)

teaches(x, y)

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Conjunctive queries (CQs)  $\sim$  SPJ queries in SQL, BGPs in SPARQL conjunctions of atoms, some variables can be existentially quantified

 $\exists y. \, \mathsf{Faculty}(x) \land \mathsf{teaches}(x,y)$ 

(find all faculty members that teach something)

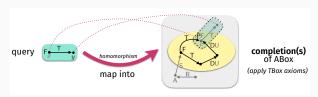
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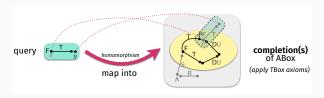
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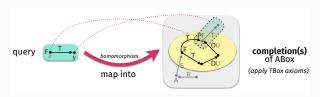


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**Certain answers**: tuples  $\vec{a}$  of individuals such that  $\mathcal{T}, \mathcal{A} \models q(\vec{a})$ 

Ontology-mediated query (OMQ): pair (T, q) with T a TBox, q a query

Idea: reduce OMQA to database query evaluation

- · rewriting step: OMQ  $(\mathcal{T},q) \rightsquigarrow$  first-order (SQL) query q'
- · evaluation step: evaluate query q' using relational DB system

Advantage: harness efficiency of relational database systems

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Key notion: first-order (FO) rewriting

FO query q' is an FO-rewriting of  $(\mathcal{T}, q)$  iff for every ABox  $\mathcal{A}$ :

$$\mathcal{T}, \mathcal{A} \models q(\vec{a}) \Leftrightarrow \mathsf{DB}_{\mathcal{A}} \models q'(\vec{a})$$

Informally: evaluating q' over A (viewed as DB) gives correct result

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Can also consider Datalog rewritings, defined analogously

Good news: every CQ and DL-Lite<sub>R</sub> ontology has FO-rewriting

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\textbf{TBox}~\mathcal{T} = \{~\exists supervises \sqsubseteq Prof~supervises \sqsubseteq involved~100S \sqsubseteq IntroC\}
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Query  $q_0 = Prof(x) \land involved(x, y) \land IntroC(y)$ 

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q_1 = \exists z \, supervises(x, z) \land involved(x, y) \land IntroC(y)
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 $q_2 = supervises(x, y) \land IntroC(y)$ 

 $q_3 = Prof(x) \wedge involved(x, y) \wedge 100S(y)$ 

 $q_5 = \exists z \, \text{supervises}(x, z) \land \text{involved}(x, y) \land 100S(y)$ 

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Note: existence of FO-rewritings  $\Rightarrow$  very low data complexity (AC<sub>0</sub>)

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- · Datalog program  $\Pi$ :  $r(x,y) \land A(x) \rightarrow A(y)$   $A(x) \rightarrow \text{goal}(x)$
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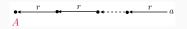
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**Note**: also get Datalog rewritings for many extensions of  $\mathcal{EL}$ 

## WHAT ABOUT ALC?

Neither FO nor Datalog rewritings need exist

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Encoding of non-3-colourability:

TBox axioms:

- $\cdot \top \sqsubseteq R \sqcup G \sqcup B$
- $\cdot B \sqcap \exists edge.B \sqsubseteq clash (same for R, G)$

Graph is 3-colourable  $\Leftrightarrow$  Boolean query  $\exists x.clash(x)$  not entailed

#### **UNDERSTANDING QUERY REWRITING**

To gain better understanding of query rewriting, we consider the following natural questions:

1. Size of rewritings

DL-Lite

· How large are the rewritten queries?

2. Optimality of rewritings

DL-Lite

· Can we achieve optimal complexity via query rewriting?

3. Existence of rewritings

beyond DL-Lite

· When is query rewriting applicable?

## SIZE OF REWRITINGS

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- . Query:  $A_1^0(x) \wedge \ldots \wedge A_n^0(x)$
- · Ontology:  $A_1^1 \sqsubseteq A_1^0$   $A_2^1 \sqsubseteq A_2^0$  ...  $A_n^1 \sqsubseteq A_n^0$
- · Rewriting:  $\bigvee_{(i_1,\ldots,i_n)\in\{0,1\}} A_1^{i_1}(x) \wedge A_1^{i_1}(x) \wedge \ldots \wedge A_1^{i_1}(x)$

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But: simple polysize FO-rewriting does exist!

$$\bigwedge_{i=1}^n (A_i^0(x) \vee A_i^1(x))$$

**PE**-rewritings: positive existential queries (only  $\exists$ ,  $\land$ ,  $\lor$ )

$$(r(x,y)\vee s(y,x))\wedge (A(x)\vee (B(x)\wedge \exists z\, p(x,z)))\wedge (A(y)\vee (B(y)\wedge \exists z\, p(y,z)))$$

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NDL-rewritings: non-recursive Datalog queries

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**FO**-rewritings: **first-order queries** (can also use ∀, ¬)

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FO-rewritings: first-order queries (can also use  $\forall$ ,  $\neg$ )

What if we replace UCQs by PE / NDL / FO?

Do we get polysize rewritings?

(Note: focus on so-called pure rewritings - no special constants)

## Exponential blowup unavoidable for PE / NDL-rewritings

Formally: sequence of CQs  $q_n$  and DL-Lite<sub>R</sub> TBoxes  $\mathcal{T}_n$  such that

- PE- and NDL-rewritings of  $(q_n \text{ and } \mathcal{T}_n \text{ are exponential in } |q_n| + |\mathcal{T}_n|$
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Key proof step: reduce CNF satisfiability to CQ answering in DL-Lite<sub>R</sub>

- · TBox generates full binary tree, leaves represent prop. valuations
  - · depth of tree = number of variables
- · tree-shaped query selects valuation, checks clauses are satisfied
  - · number of leaves / branches in query = number of clauses

maximum depth of generated trees in canonical model / chase

·  $\mathcal{T}$  has finite depth  $\leftrightarrow$  chase terminates for every KB  $(\mathcal{T}, \mathcal{A})$ 

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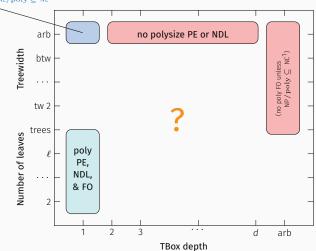
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- · no polysize PE- or NDL-rewritings
- · no polysize FO-rewritings unless NL/poly ⊆ NC<sup>1</sup>
- · but: polysize PE-rewritings for tree-shaped queries

#### MAP OF RESULTS SO FAR







#### Two dimensions:

- type of TBox
- · type of query

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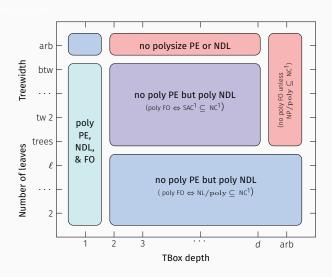
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What about tree-shaped queries & depth k TBoxes (k > 1)?

What about bounded treewidth queries?

What about restricted classes of tree-shaped queries?

- · linear queries
- tree-shaped queries with fixed number of leaves



#### Bounded depth TBox + bounded treewidth CQs

- · no polysize PE-rewritings
- · polysize NDL-rewritings do exist
- · no polysize FO-rewritings (unless  $SAC^1 \subseteq NC^1$ )

#### Tree-shaped CQs with bounded number of leaves

- · no polysize PE-rewritings
- · polysize NDL-rewritings do exist
- · no polysize FO-rewritings (unless  $NL/poly \subseteq NC^1$ )

Negative results hold already for: depth 2 + linear queries

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- · can be used to show no polytime-computable rewriting
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Associate Boolean functions with query-TBox pair  $(q,\mathcal{T})$ 

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# Primitive evaluation function $f_{q,\mathcal{T}}^{\,\mathsf{prim}}$

- · input vector  $\vec{u} \sim extstyle{ extstyle single-individual ABox} \, \mathcal{A}_{\vec{u}}$ 
  - ·  $p_A$  means concept A is present,  $p_r$  means r self-loop

$$f_{a,\mathcal{T}}^{\text{prim}}(\vec{u}) = 1 \text{ if } (\mathcal{T}, \mathcal{A}_{\vec{u}}) \models q(a, \dots, a)$$

ind a

Associate Boolean functions with query-TBox pair  $(q, \mathcal{T})$ 

# Primitive evaluation function $f_{q,\mathcal{T}}^{\,\mathsf{prim}}$

- · input vector  $\vec{u} \sim \text{single-individual ABox } \mathcal{A}_{\vec{u}}$ 
  - ·  $p_A$  means concept A is present,  $p_r$  means r self-loop

$$f_{q,\mathcal{T}}^{\mathsf{prim}}(\vec{u}) = 1 \mathsf{if}(\mathcal{T}, \mathcal{A}_{\vec{u}}) \models q(a, \ldots, a)$$

# Tree-witness hypergraph function $f_{q,T}^{tw}$ :

- · input vector  $\vec{u} \sim$  abstract description of how query mapped into canonical model
  - ·  $p_{\alpha}$  means atom  $\alpha$  mapped into ABox
  - $\cdot$   $p_t$  means tree-witness (subquery) t mapped to existential part
- $f_{q,\mathcal{T}}^{tw}(\vec{u}) = 1$  if  $\vec{u}$  describes a partition of the atoms in q

ind a

# Types of rewritings → ways of representing Boolean functions

PE-rewritings	monotone Boolean formulas
NDL-rewritings	monotone Boolean circuits
FO-rewritings	Boolean formulas

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### Primitive evaluation function ⇒ lower bounds on rewriting size

· transform rewriting of  $q,\mathcal{T}$  into formula / circuit that computes  $f_{q,\mathcal{T}}^{\,\mathrm{prim}}$ 

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Exploit circuit complexity results about (in)existence of small formulas / circuits computing different classes of Boolean functions

# OPTIMALITY OF REWRITINGS

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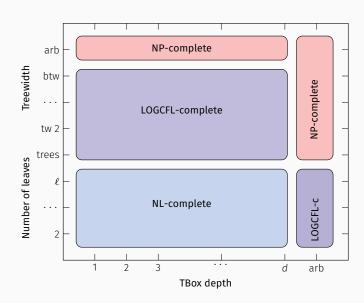
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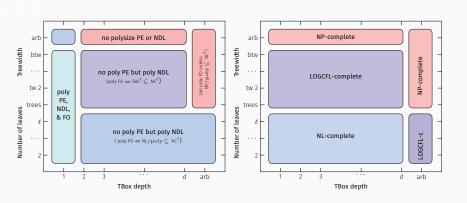
· maybe query rewriting is not the most efficient approach

Motivated the study of the complexity landscape of query answering

Consider combined complexity (data complexity is same in all cases)

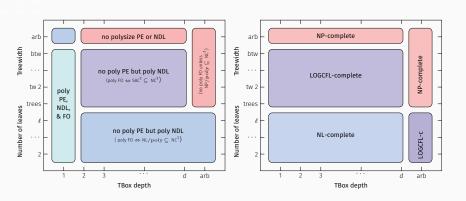


#### **COMPARING THE LANDSCAPES**



polysize NDL-rewritings  $\sim$  polynomial (LOGCFL / NL) complexity

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polysize NDL-rewritings  $\sim$  polynomial (LOGCFL / NL) complexity Can we marry the positive succinctness & complexity results?

For the three well-behaved classes of OMQs, define NDL-rewritings of optimal complexity:

- · rewriting can be constructed by  $L^{C}$  transducer
- evaluating the rewriting can be done in C with  $C \in \{NL, LOGCFL\}$  the complexity of the OMQ class

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· NL: linear NDL-programs of bounded width (# vars per rule)

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## Preliminary experiments with simple OMQs (depth 1, linear CQs):

- · compared with other NDL-rewritings (Clipper, Rapid, Presto)
- · our rewritings grow linearly with increasing query size
- · other systems produce rewritings that grow exponentially
- · our rewritings usually evaluated faster

· depth d / number of leaves  $\ell$  occur in the exponent

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## Is it possible to do better?

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## Parameterized complexity of answering tree-shaped OMQs (T, q):

· parameters: depth d of  $\mathcal{T}$ , number  $\ell$  of leaves in CQs

· not FPT if depth d taken as parameter W[2]-hard

· not FPT if number of leaves  $\ell$  taken as parameter W[1]-hard

Message: for good performance, want d and  $\ell$  small

# **EXISTENCE OF REWRITINGS**

#### QUERY REWRITING BEYOND DL-LITE

#### We have seen that:

- · for EL ontologies, FO-rewritings need not exist
- · for ALC ontologies, FO- and Datalog rewritings may not exist

#### But these are worst-case results

- · only say that some OMQ that does not have a rewriting
- possible that rewritings exist for many ontologies and queries encountered in practice

## To extend the applicability of query rewriting beyond DL-Lite:

- devise ways of identifying 'good cases'
- construct rewritings when they exist

#### **DECIDING EXISTENCE OF REWRITINGS**

Use  $(\mathcal{L}, \mathcal{Q})$  to denote set of **OMQs**  $(\mathcal{T}, q)$  where:

- $\cdot \mathcal{T}$  is an  $\mathcal{L}$ -TBox
- $\cdot$  q is a query from Q

 $\mathcal{Q} \in \{\mathsf{IQ},\mathsf{CQ}\}$ 

For example:  $(\mathcal{EL}, CQ)$ ,  $(\mathcal{ALC}, IQ)$ 

## FO-rewritability in $(\mathcal{L}, \mathcal{Q})$

- · Input: OMQ  $(\mathcal{T},q)$  from  $(\mathcal{L},\mathcal{Q})$
- · Problem: decide whether  $(\mathcal{T}, q)$  has an FO-rewriting

Datalog-rewritability decision problem can be defined analogously

We have the following results:

- · FO-rewritability is **Exp-complete** in  $(\mathcal{EL}, |Q)$  and  $(\mathcal{ELI}, |Q)$
- · FO-rewritability is **Exp-complete** in  $(\mathcal{EL}, CQ)$
- · FO-rewritability is **2Exp-complete** in  $(\mathcal{ELI}, CQ)$

#### What makes FO-rewritability so difficult?

Consider TBox 
$$\mathcal{T} = \{\exists r.A \sqsubseteq A, \exists r.\top \sqsubseteq A\}$$
 IQ  $A(x)$ 

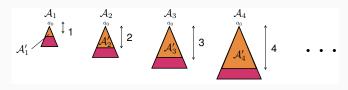
FO-rewriting exists:  $A(x) \lor \exists y \, r(x, y)$ 

Reason:  $\exists r. \top \sqsubseteq A$  cancels effect of recursive  $\exists r. A \sqsubseteq A$ 

· such cancellations can be quite complicated and difficult to detect

## Characterization of non-existence of FO-rewriting:

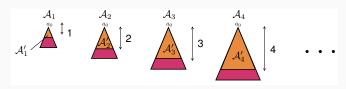
OMQ  $(\mathcal{T}, A(x))$  is not FO-rewritable iff there exist tree-shaped ABoxes



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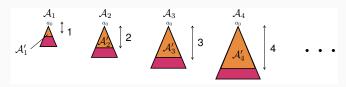
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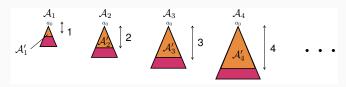
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Can generalize this technique to handle CQs as well

## Use existing backwards-chaining rewriting procedure

- · if FO-rewriting does exist, terminates and outputs UCQ-rewriting
- · to ensure termination in general: use characterization result

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- · allows for structure sharing
- produces (succinct) NDL-rewriting instead of UCQ-rewriting

## Experimental results are very encouraging:

- · terminates quickly, produced rewritings are typically small
- · suggests that in practice FO-rewritings do exist for majority of IQs

FO-rewritability and Datalog-rewritability of  $(\mathcal{ALC}, IQ)$  are both NEXPTIME-complete.

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Lower bound: reduction from exponential grid tiling problem

Upper bound: connection to constraint satisfaction problems (CSPs)

- · CSP( $\mathfrak{B}$ ): decide if homomorphism from input structure  $\mathcal{D}$  into  $\mathfrak{B}$
- · (Boolean) OMQs in (ALC, IQ) ~ (complement of) CSPs
- exponential reduction to problem of deciding whether a CSP is definable in FO / Datalog
- · use NP upper bounds for latter problems [LLT07] [FKKMMW09]

FO-rewritability of  $(\mathcal{ALC}, \mathsf{UCQ})$  is 2NEXPTIME-complete

Instead of CSP, uses MMSNP (monotone monadic strict NP): fragment of monadic second-order logic that generalizes CSP

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FO-expressibility of (co)MMSNP not studied in CSP literature

Recently: shown to be decidable and 2NEXPTIME-complete

# CONCLUDING REMARKS

#### CONCLUSION

## Ontology-mediated query answering:

- · new paradigm for intelligent information systems
- · offers many advantages, but also computational challenges

## Query rewriting promising algorithmic approach

Many interesting problems related to OMQA and query rewriting:

- succinctness of rewritings (Boolean functions, circuit complexity)
- · optimality of rewritings (Datalog fragments, param. complexity)
- · existence of FO and Datalog rewritings (automata, CSP / MMSNP)

#### Lots left to do!

- · experiment + optimize NDL-rewritings, evaluation strategies
- · develop practical algorithms going beyond  $\mathcal{EL}$  and IQs



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