# ONTOLOGY-MEDIATED QUERY ANSWERING WITH OWL 2 QL ONTOLOGIES 

Succinctness and Complexity Landscapes

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## ONTOLOGY-MEDIATED QUERY ANSWERING (OMQA)



## ONTOLOGY-MEDIATED QUERY ANSWERING (OMQA)



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patient data
"Melanie has listeriosis"
"Paul has Lyme disease"

medical knowledge
"Listeriosis \& Lyme disease are bacterial infections"

user query bacterial infections" expected answers: Melanie, Paul

## 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 FOR TODAY'S TALK

Conjunctive queries (CQs) $\sim$ select-project-join queries in SQL conjunctions of atoms, some variables can be existentially quantified

## $\exists y . \operatorname{Faculty}(x) \wedge \operatorname{Teaches}(x, y)$

(find all faculty members that teach something)

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OWL 2 QL ontologies

- W3C standardized ontology language
- based upon DL-Lite $\mathcal{R}_{\mathcal{R}}$ description logic
- designed for querying large datasets
- simple yet useful language


## OWL 2 QL ONTOLOGIES

A (somewhat simplified) definition in FOL syntax
Ontology = finite set of FOL sentences (called axioms) of the forms:

$$
\begin{array}{ll}
\forall x\left(\tau(x) \rightarrow \tau^{\prime}(x)\right) & \forall x\left(\tau(x) \wedge \tau^{\prime}(x) \rightarrow \perp\right) \\
\forall x, y\left(\varrho(x, y) \rightarrow \varrho^{\prime}(x, y)\right) & \forall x, y\left(\varrho(x, y) \wedge \varrho^{\prime}(x, y) \rightarrow \perp\right) \\
\forall x \varrho(x, x) & \forall x(\varrho(x, x) \rightarrow \perp)
\end{array}
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where the formulas $\tau(x)$ and $\varrho(x, y)$ are defined by the grammars

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\begin{array}{lll}
\tau(x) & ::=A(x) \mid \exists y \varrho(x, y) & \text { (A unary predicate) } \\
\varrho(x, y) & ::=P(x, y) \mid P(y, x) & \text { (P binary predicate) }
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## EXAMPLE AXIOMS

Professors and fellows are subclasses of faculty

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Being head of a team/lab/dept implies being a member

$$
\text { HeadOf( } x, y) \rightarrow \text { MemberOf }(x, y)
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- function. ${ }^{\mathcal{I}}$ maps each unary predicate $A$ to $A^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}}$, each binary predicate $R$ to $R^{\mathcal{I}} \subseteq \Delta^{\mathcal{I}} \times \Delta^{\mathcal{I}}$, and each constant $a$ to $a^{\mathcal{I}} \in \Delta^{\mathcal{I}}$
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Certain answers of query $q$ w.r.t. KB $(\mathcal{O}, \mathcal{D})$ :

- tuples of constants $\vec{a}$ (of same arity as $q$ ) such that $q(\vec{a})$ holds in every model of $(\mathcal{O}, \mathcal{D})$
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Ontology-mediated query answering: computing certain answers

## OMQA EXAMPLE

Ontology:

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Dataset:
\{Prof(anna), Fellow(tom), Teaches(tom, cs101)\}

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## Query: $q(x)=\exists y . \operatorname{Faculty}(x) \wedge$ Teaches $(x, y)$

Get the following certain answers:

- anna

$$
\operatorname{Prof}(\text { anna })+\operatorname{Prof}(x) \rightarrow \operatorname{Faculty}(x)+\operatorname{Prof}(x) \rightarrow \exists y \text { Teaches }(x, y)
$$

- tom Fellow(tom) + Fellow $(x) \rightarrow$ Faculty $(x)+$ Teaches(tom, cs101)


## CANONICAL MODELS

For Horn ontologies (no form of disjunction) like OWL 2 QL: enough to consider a single canonical model

- idea: exhaustively apply ontology axioms to dataset
- possibly infinite $(A(x) \rightarrow \exists y R(x, y), R(x, y) \rightarrow A(y))$
- forest-shaped (dataset + new tree structures for $\exists$-axioms)
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> OMQA in OWL 2 QL = finding ways to map the query into the canonical model

## COMPLEXITY OF OMQA

OMQA viewed as a decision problem (yes-or-no question): Input: An $n$-ary query $q$, a dataset $\mathcal{D}$, a ontology $\mathcal{O}$, and a candidate answer tuple $\vec{a}$
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Combined complexity: in terms of size of whole input
Data complexity: in terms of size of $\mathcal{D}$ only

- view rest of input as fixed (of constant size)
- motivation: data typically much larger than rest of input
data complexity $\leq$ combined complexity


## QUERY REWRITING

Idea: reduce OMQA to database query evaluation

- rewriting step: ontology $\mathcal{O}+$ query $q \rightsquigarrow$ first-order (SQL) query $q^{\prime}$
- evaluation step: evaluate query $q^{\prime}$ using relational DB system

Advantage: harness efficiency of relational database systems

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## Key notion: first-order (FO) rewriting

- FO query $q^{\prime}$ is an FO-rewriting of OMQ $(\mathcal{O}, q)$ iff for every dataset $\mathcal{D}$ :

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\mathcal{O}, \mathcal{D} \models q(\vec{a}) \quad \Leftrightarrow \quad D B_{\mathcal{D}}=q^{\prime}(\vec{a})
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Good news: every CQ and OWL 2 QL ontology has an FO-rewriting

## EXAMPLE: QUERY REWRITING

Reconsider the ontology $\mathcal{O}$ :

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Evaluating the rewritten query over the earlier dataset \{Prof(anna), Fellow(tom), Teaches(tom, cs101)\}
produces the two certain answers: anna and tom

## QUERY REWRITING: THEORY AND PRACTICE

Data-independent reduction of OMQA to DB query evaluation - inherit low data complexity ( $\mathrm{AC}_{0} \subsetneq$ PTIME) of FO query evaluation

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This raises the following questions:
Succinctness When can we guarantee polynomial-size rewritings?
Complexity More generally, when is OMQA tractable?
Optimality Can query rewriting achieve optimal complexity?

## SUCCINCTNESS OF REWRITINGS

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- Query: $A_{1}^{0}(x) \wedge \ldots \wedge A_{n}^{0}(x)$
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- Rewriting: $\bigvee_{\left(i_{1}, \ldots, i_{n}\right) \in\{0,1\}} A_{1}^{i_{1}^{1}}(x) \wedge A_{1}^{i_{1}^{1}}(x) \wedge \ldots \wedge A_{1}^{i_{1}}(x)$


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To get positive results, need to go beyond UCQs

## DIFFERENT FORMS OF REWRITINGS

PE-rewritings: positive existential queries (only $\exists, \wedge, \vee$ )
$(r(x, y) \vee s(y, x)) \wedge(A(x) \vee(B(x) \wedge \exists z p(x, z))) \wedge(A(y) \vee(B(y) \wedge \exists z p(y, z)))$

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NDL-rewritings: non-recursive Datalog queries

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What if we replace UCQs by PE / NDL / FO?
Do we get polysize rewritings?

Exponential blowup unavoidable for PE / NDL-rewritings

Formally: sequence of CQs $q_{n}$ and OWL 2 QL ontologies $\mathcal{O}_{n}$ such that

- PE- and NDL-rewritings of $\left(\mathcal{O}_{n}, q_{n}\right)$ exponential in $\left|q_{n}\right|+\left|\mathcal{O}_{n}\right|$
- FO-rewritings of ( $\mathcal{O}_{n}, a_{n}$ ) superpolynomial unless $N P /$ poly $\subseteq N C^{1}$


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Key proof step: reduce CNF satisfiability to OMQA

- ontology generates full binary tree, leaves represent 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
* tree-shaped (acyclic) = undirected graph induced by query is a tree

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- no polysize FO-rewritings unless NP/poly $\subseteq$ NC ${ }^{1}$


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- no polysize PE- or NDL-rewritings
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- but: polysize PE-rewritings for tree-shaped queries


## MAP OF RESULTS SO FAR

no poly PE but poly NDL
no poly FO unless NL /poly $\subseteq \mathrm{NC}^{1}$

## COMPLETING THE LANDSCAPE



## COMPLETING THE LANDSCAPE

Strong negative result for PE-rewritings

- no polysize PE-rewritings for depth 2 ontologies + linear CQs


## Conditional negative results for FO-rewritings

- polysize FO-rewritings exist iff

$$
\begin{aligned}
& \cdot S A C^{1} \subseteq N C^{1} \\
& \cdot \\
& \cdot N L / \text { poly } \subseteq N C^{1}
\end{aligned}
$$

bounded depth + bounded treewidth CQs bounded-leaf tree-shaped CQs

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## Conditional negative results for FO-rewritings

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```
- SAC }\mp@subsup{\}{}{1}\subseteqN\mp@subsup{C}{}{1
- NL/poly \subseteqNC1
bounded depth + bounded treewidth CQs bounded-leaf tree-shaped CQs
```

Positive results for NDL-rewritings

- bounded depth ontology + bounded treewidth CQs
- bounded-leaf tree-shaped CQs (+ arbitrary ontology)

Takeaway: NDL good target language for rewritings

## BRIEF GLIMPSE AT PROOF TECHNIQUES (1)

Standard computational complexity not the right tool

- can be used to show no polytime-computable rewriting
... but not that no polysize rewriting exists


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- branch of complexity that classifies Boolean functions wrt. size / depth of Boolean circuits / formulas that compute them
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## Example: function REACH $n_{n}$

- input: a Boolean vector representing the adjacency matrix of a directed graph $G$ with $n$ vertices including special vertices $s$ and $t$
- output: 1 iff encoded graph $G$ contains a directed path from $s$ to $t$


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No family of polysize mon. Boolean formulas computing REACH $n$

## BRIEF GLIMPSE AT PROOF TECHNIQUES (2)

Types of rewritings $\rightsquigarrow$ ways of representing Boolean functions
PE-rewritings monotone Boolean formulas ( $\wedge, \vee$ )
NDL-rewritings
FO-rewritings
monotone Boolean circuits ( $\vee$ - and $\wedge$-gates) Boolean formulas ( $\wedge, \vee, \neg$ )

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Associate Boolean functions with ontology-mediated query $(\mathcal{O}, q)$

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Associate Boolean functions with ontology-mediated query $(\mathcal{O}, q)$
'Lower bound' function $f_{\mathcal{O}, q}^{\llcorner\mathrm{B}} \Rightarrow$ lower bounds on rewriting size

- transform rewriting of $(\mathcal{O}, q)$ into formula / circuit that computes $f_{\mathcal{O}, q}^{\llcorner B}$
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Exploit circuit complexity results about (in)existence of small formulas / circuits computing different classes of Boolean functions

- which functions expressible as $f_{q, \mathcal{O}}^{\llcorner\mathrm{B}} / f_{q, \mathcal{O}}^{\mathrm{UB}}$ for given OMQ class?
- intermediate computational model: hypergraph programs


## HYPERGRAPH PROGRAMS

A hypergraph program (HGP) is a hypergraph $H=(V, E)$, where:

- vertices labelled by 0,1 , or literal ( $\neg) p_{i}$
- input: valuation of $p_{0}, \ldots, p_{n}$
- outputs $1 \Leftrightarrow$ set of non-overlapping hyperedges that 'covers all zeros' (i.e. contains all vertices whose label evaluates to 0 )

Restricted HGPs: monotone, bounded degree, tree / linear

Hypergraph associated with ontology-mediated query $(\mathcal{O}, q)$ :

- vertices = atoms in q
- hyperedges = subqueries of $q$ 'relevant' for $\mathcal{O}$
- roughly: can be satisfied by tree-shaped structure of canonical model


## BACK TO GLIMPSE AT PROOF TECHNIQUES



## BACK TO GLIMPSE AT PROOF TECHNIQUES

$\mathbf{C}=$ OMQs with bounded-leaf CQs
Upper bound function for class C of OMQs
 (monotone)
linear HGPs = bounded-leaf HGPs

Class of hypergraph programs
characterizes

Circuit
(m) NL/poly
$\mathbf{C}=$ OMQs with linear CQs, depth 2 ontologies
Lower bound function for class C of OMQs

Positive result for NDL
$\mathrm{mNL} /$ poly $\rightsquigarrow$ polysize mon. circuit

Negative result for PE
REACH $\in \mathrm{mNL} /$ poly
REACH $\notin \mathrm{mNC}^{1}$

## COMPLEXITY AND OPTIMALITY

## WHAT DOES ALL THIS MEAN FOR THE COMPLEXITY OF OMQA?

Small rewritings do not guarantee low combined complexity

- need to consider cost of producing and evaluating the rewriting

Large rewritings do not guarantee high combined complexity

- maybe query rewriting is not the most efficient approach


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- maybe query rewriting is not the most efficient approach

Motivated the study of the complexity landscape of query answering

Focus on combined complexity (data complexity same in all cases)

## combined complexity landscape for dl-Lite [BKp15], [bKKpz18]


$N L \subseteq L O G C F L \subseteq P T I M E \subseteq N P$

## COMPARING SUCCINCTNESS \& COMPLEXITY LANDSCAPES

Size of rewritings
Combined complexity of OMQA

polysize NDL-rewritings ~ polynomial (LOGCFL / NL) complexity

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Size of rewritings
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polysize NDL-rewritings ~ 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 $C \in\{N L, L O G C F L\}$ the complexity of the OMQ class

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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
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Take-away: optimal complexity achievable via query rewriting

## CONCLUSION

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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)
- existence of FO and Datalog rewritings (automata, CSP)
- other tools: parameterized complexity, word rewriting

Active area with lots left to explore!

## Questions?

## REFERENCES: SUCCINCTNESS \& OPTIMALITY OF REWRITINGS

[KKPZ12] S. Kikot, R. Kontchakov, V. Podolskii, and M. Zakharyaschev: Exponential Lower Bounds and Separation for Query Rewriting. 39th International Colloquium on Automata, Languages, and Programming (ICALP'12), 2012.
[GS12] G. Gottlob and T. Schwentick: Rewriting Ontological Queries into Small Nonrecursive Datalog Programs. 13th International Conference on the Principles of Knowledge Representation and Reasoning (KR'12), 2012.
[GKKPSZ14] G. Gottlob, S. Kikot, R. Kontchakov, V. Podolskii, T. Schwentick, and M. Zakharyaschev: The Price of Query Rewriting in Ontology-based Data Access. Artificial Intelligence (AIJ), 2014.
[KKPZ14] S. Kikot, R. Kontchakov, V. Podolskii, and M. Zakharyaschev: On the Succinctness of Query Rewriting over Shallow Ontologies. 29th Annual ACM/IEEE Symposium on Logic in Computer Science (LICS'14), 2014.

## REFERENCES: SUCCINCTNESS \& OPTIMALITY OF REWRITINGS

[BKP15] M. Bienvenu, S. Kikot, V. Podolskii: Tree-like Queries in OWL 2 QL: Succinctness and Complexity Results. 30th Annual ACM/IEEE Symposium on Logic in Computer Science (LICS'15), 2015.
[BKKPRZ17] M. Bienvenu, S. Kikot, R. Kontchakov, V. Podolskii, V. Ryzhikov and M. Zakharyaschev: The Complexity of Ontology-Based Data Access with OWL 2 QL and Bounded Treewidth Queries. Proceedings of the 36th ACM SIGMOD-SIGACT-SIGAI Symposium on Principles of Database Systems (PODS'17), 2017.
[BKKPZ18] M. Bienvenu, S. Kikot, R. Kontchakov, V. Podolskii, and M. Zakharyaschev: Ontology-Mediated Queries: Combined Complexity and Succinctness of Rewritings via Circuit Complexity. Journal of the ACM (JACM), 2018.

## WHAT IS LOGCFL?

Original definition: class of decision problems logspace-reducible to the membership problem for context-free languages

Characterization in terms of circuits: solvable by uniform family of polysize, logarithmic-depth circuits, whose AND gates have fan-in 2
(called SAC ${ }^{1}$ circuits)

Yet another definition: problems solvable by non-deterministic polytime logspace-bounded TM augmented with a stack

Relationship to other classes:

$$
L O G S P A C E \subseteq N L \subseteq L O G C F L \subseteq N C^{2} \subseteq P \subseteq N P
$$

Considered highly parallelizable

## LOGCFL MEMBERSHIP FOR BOUNDED-LEAF QUERIES

Devise procedure that can be implemented by non-deterministic polytime logspace-bounded TM augmented with a stack

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Idea: guess homomorphism into canonical model, use stack to store word part w of domain element aw in canonical model

## LOGCFL MEMBERSHIP FOR BOUNDED-LEAF QUERIES

Devise procedure that can be implemented by non-deterministic polytime logspace-bounded TM augmented with a stack

Idea: guess homomorphism into canonical model, use stack to store word part $w$ of domain element aw in canonical model

## Difficulty: need to store several words, but have only one stack!

Solution: ‘synchronize’ traversal of different branches


## LOGCFL-HARDNESS FOR LINEAR QUERIES

## Reduction from SAC ${ }^{1}$ acceptance problem:

decide whether an input of length $n$ is accepted by the $n$th circuit of a logspace-uniform family of SAC ${ }^{1}$ circuits

Use characterization of acceptance in terms of proof trees:

- associate skeleton proof tree Skel ${ }_{C}$ to each circuit C
- label each node in skeleton with gate from C
- circuit $C$ accepts input $\sigma \Leftrightarrow$ valid labelling of Skelc
- labelling respects the structure of $C$
- leaves in Skelc mapped to input gates which are 1 under $\sigma$


## EXAMPLE: SAC ${ }^{1}$ CIRCUIT AND SKELETON PROOF TREE



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- labelling respects the structure of $C$
- leaves in Skelc mapped to input gates which are 1 under $\sigma$

Sketch of reduction:

- TBox generates tree-unfolding of circuit C, input gates marked 1, 0
- linear query corresponds to depth-first traversal of Skelc
- query holds $\Leftrightarrow$ valid labelling of Skelc

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

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Is it possible to do better?

- formally: fixed-parameter tractable (FPT)?

$$
f(d, \ell) \cdot p(|q|,|\mathcal{T}|,|\mathcal{A}|)
$$

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Parameterized complexity of answering tree-shaped OMQs $(\mathcal{T}, q)$ :

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

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Parameterized complexity of answering tree-shaped OMQs $(\mathcal{T}, q)$ :

- parameters: depth $d$ of $\mathcal{T}$, number $\ell$ of leaves in CQs
- not FPT if depth $d$ taken as parameter
- not FPT if number of leaves $\ell$ taken as parameter

W[2]-hard
W[1]-hard

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

