



Beyond DL-Lite: Big Data meets Heavy Ontologies

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Applications: HCLS

- **SNOMED-CT** (Clinical Terms) ontology
 - provides common vocabulary for recording clinical data
 - used in healthcare systems of more than 15 countries, including Australia, Canada, Denmark, Spain, Sweden and the UK
 - “classified and checked for equivalencies” using ontology reasoners
- **OBO foundry** includes more than 100 biological and biomedical ontologies
 - “continuous integration server running **Elk and/or HermiT** 24/7 checking that multiple independently developed ontologies are mutually consistent”

Focus is mainly on **schema reasoning**

OBDA: Motivational Example

- **Statoil** use data to inform production and exploration management
 - Large and complex data sets are difficult and time consuming to use
- Ontology Based Data Access (OBDA) can **improve access** to relevant data
 - Intuitive queries over ontology
 - Answers reflect data and knowledge

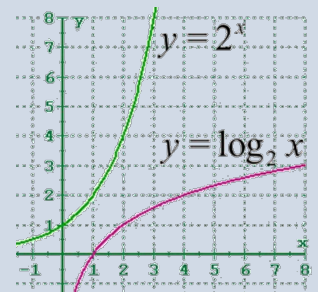
Focus is mainly on **query answering**



OBDA: Theory \rightsquigarrow Practice

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- Most ontologies use **OWL** ontology language
- OWL based on **description logic SROIQ**
 - ✓ Clear semantics
 - ✓ Well understood computational properties (e.g., decidability, complexity)
 - ✓ Simple goal directed reasoning algorithms
 - ✗ N2ExpTime-complete combined complexity
 - ✗ NP-hard data complexity (-v- logspace for databases)



How can we provide (robustly) scalable query answering?

OWL Profiles

OWL 2 defines language subsets, aka **profiles** that can be “more simply and/or efficiently implemented”

- **OWL 2 QL**

- Based on **DL-Lite**
- AC^0 data complexity (same as DBs)

- **OWL 2 EL**

- Based on **EL⁺⁺**
- PTime-complete for combined and data complexity

- **OWL 2 RL**

- Based on “**Description Logic Programs**” ($\approx DL \cap LP$)
- PTime-complete for combined and data complexity

OWL 2 QL and Query Rewriting

Given QL ontology \mathcal{O} query Q and mappings M :



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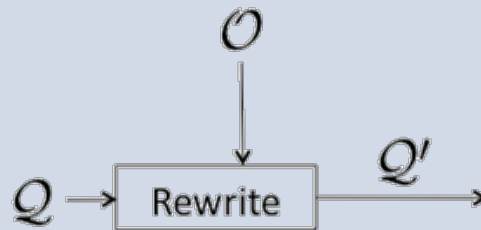
Optique



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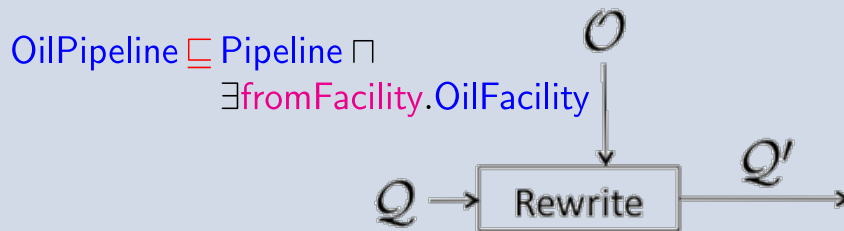
- **Rewrite** $Q \rightarrow Q^0$ s.t. answering Q^0 without \mathcal{O} equivalent to answering Q w.r.t. \mathcal{O} *for any dataset*



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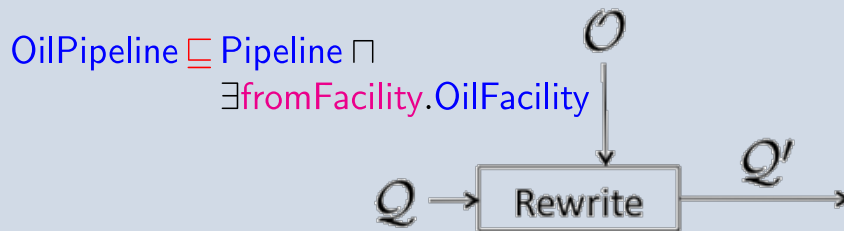


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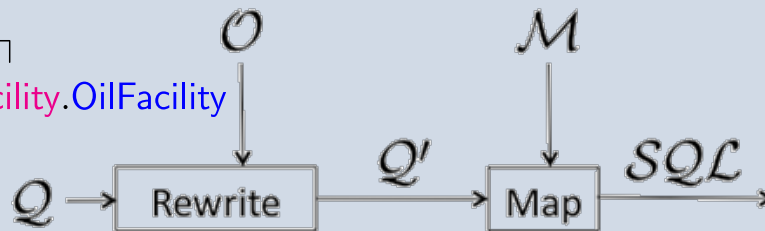
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$\text{OilPipeline} \sqsubseteq \text{Pipeline} \sqcap$
 $\exists \text{fromFacility}.\text{OilFacility}$



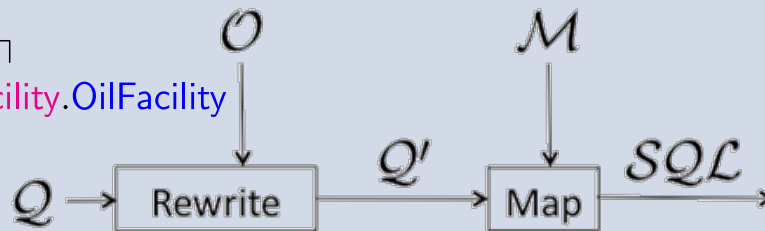
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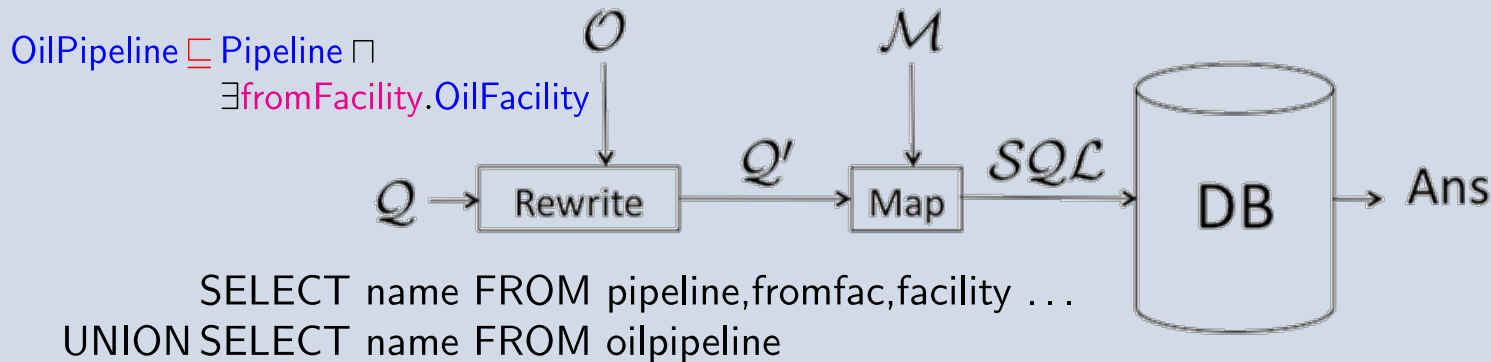


SELECT name FROM pipeline,fromfac,facility ...
UNION SELECT name FROM oilpipeline

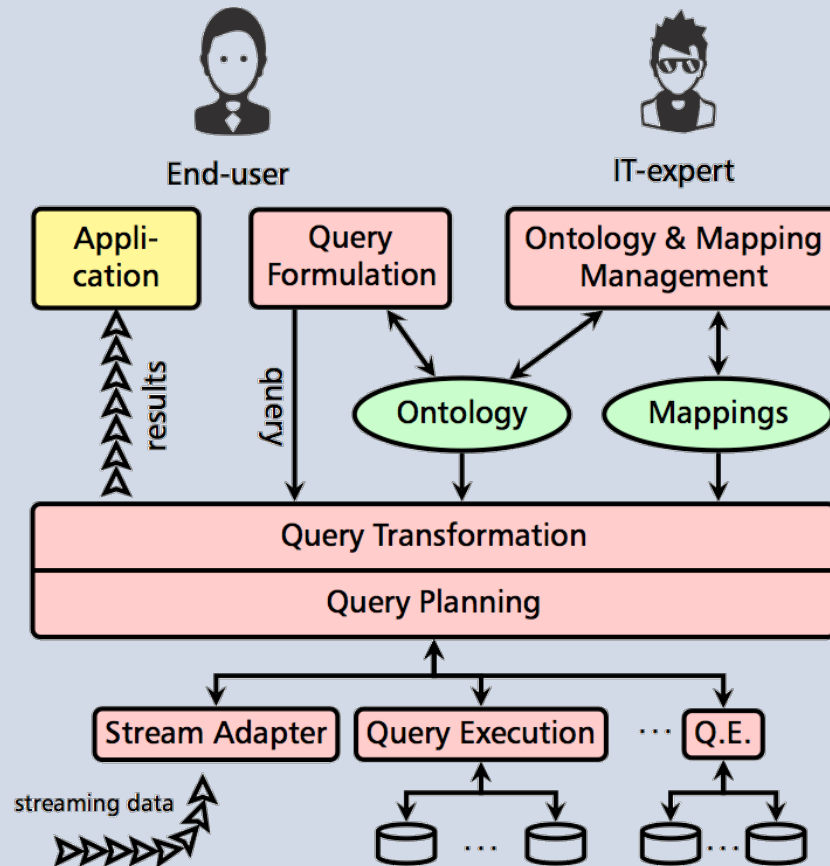
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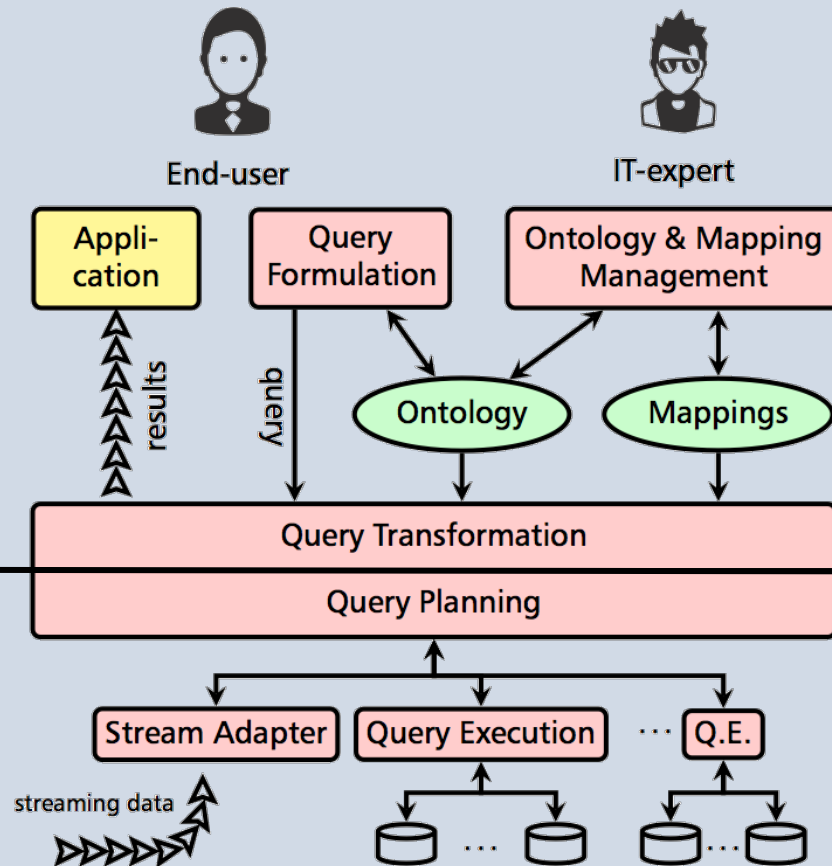
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- **Evaluate** (SQL) query against DB



Optique Platform Architecture



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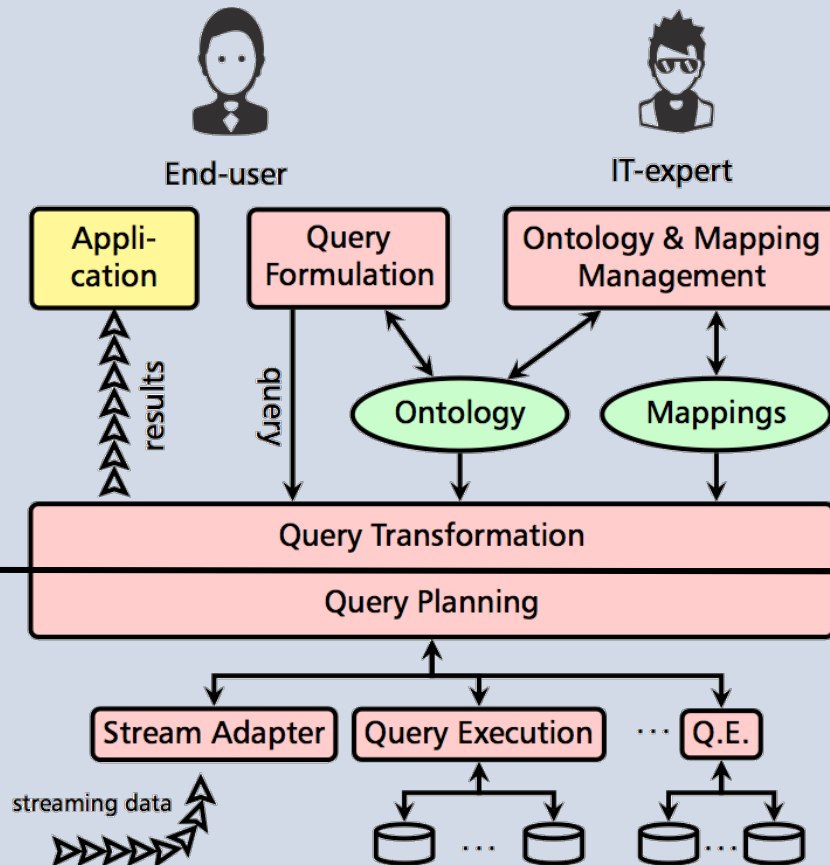


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Query rewriting:

- uses ontology & mappings
- computationally hard
- ontology & mappings small



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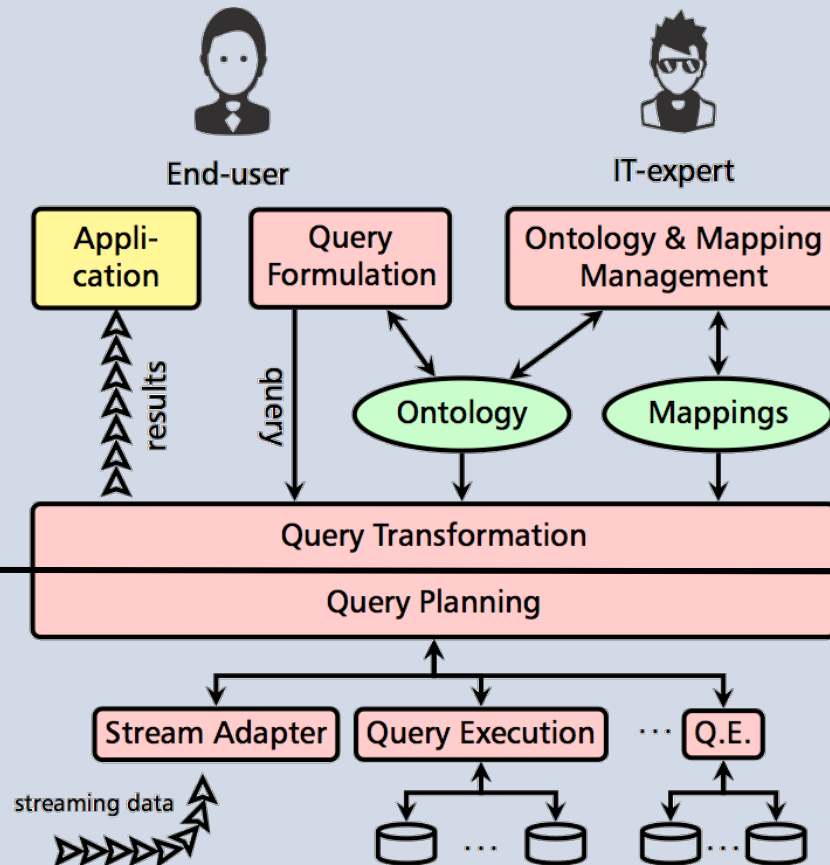
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Query evaluation:

- ind. of ontology & mappings
- computationally tractable
- data sets very large



Query Rewriting — Issues

1 Expressivity

- QL (necessarily) has (very) restricted expressive power

2 Rewriting

- May be large (worst case exponential in size of ontology)
- Queries may be hard for existing DBMSs

3 Mappings

- May be difficult to develop and maintain
- Relatively little work in this area to date

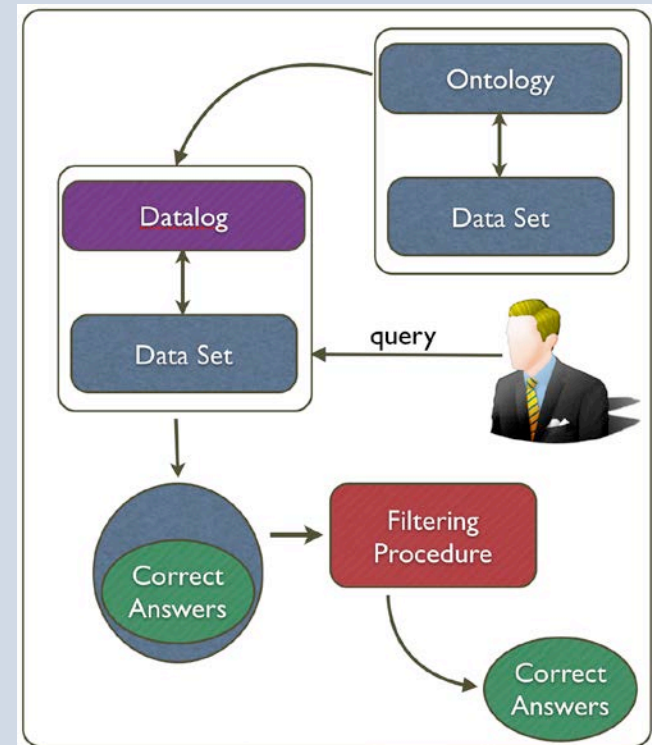
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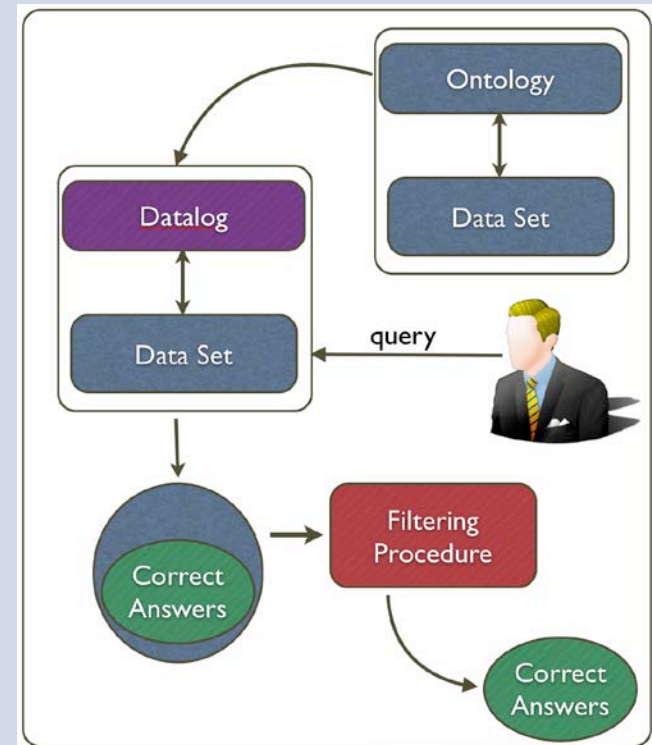
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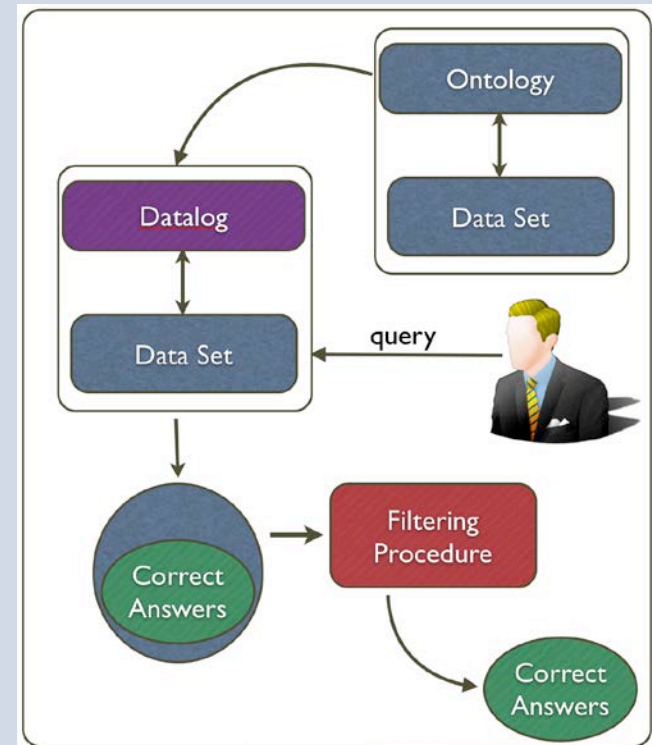
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Given (RDF) data DB, EL ontology O and query Q:

- **Over-approximate** O into Datalog program D
- **Evaluate** Q over D + DB
- **Filter** result to eliminate spurious answers



Combined Approach — Issues

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2 Scalability

- Dependent on performance of Datalog engine and/or blowup in size of data

OWL 2 RL and Materialisation

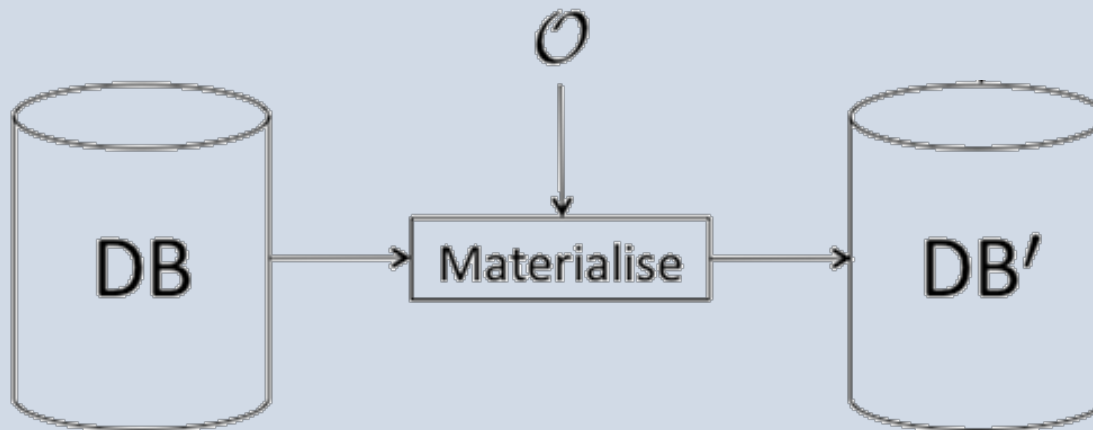
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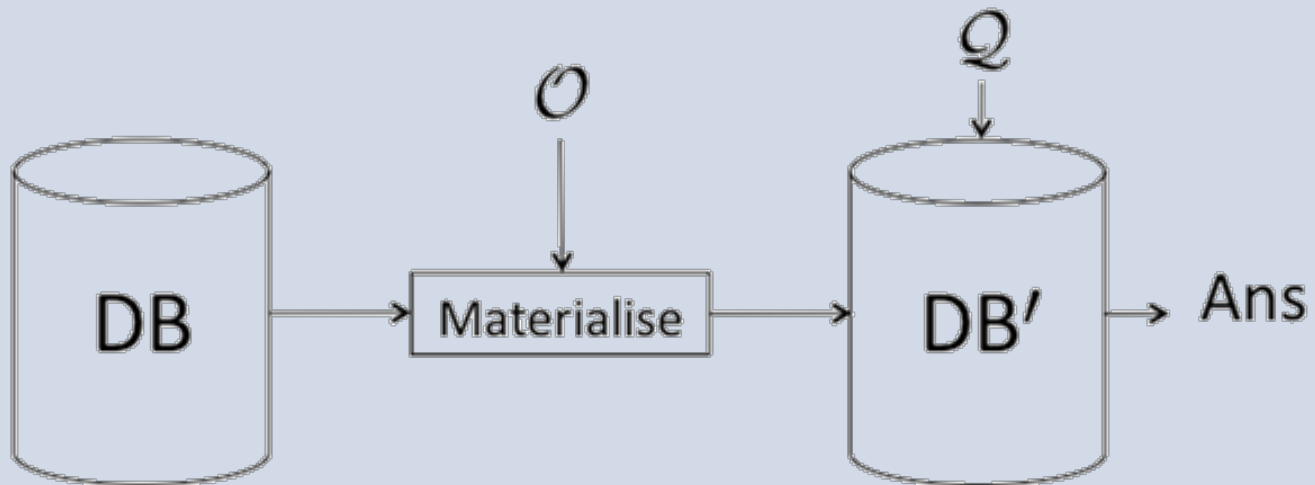
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 - nb: Closely related to **chase** procedure used with DB dependencies
- **Evaluate** Q against DB^0



Materialisation — Example

$\mathcal{O} \left\{ \begin{array}{l} \exists \text{treats.Patient} \sqsubseteq \text{Doctor} \\ \text{Consultant} \sqsubseteq \text{Doctor} \end{array} \right.$

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$$\rightsquigarrow \{d_2, d_1, c_1\}$$

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Scalability: RDFox Datalog Engine

- Efficient **Datalog/RL** engine critical for both RL and EL
- Existing approaches mainly focus on **map reduce**
 - high communication overhead
 - redundant computation
 - query answering over (distributed) materialized data is problematic
- **RDFox** is a new Datalog/RL engine with novel features
 - parallel materialization with **fine-grained load balancing**
 - highly optimized in-memory data storage with 'mostly' **lock-free parallel inserts**
 - £4,000 desktop with 128 GB can store around **2×10^9 triples**



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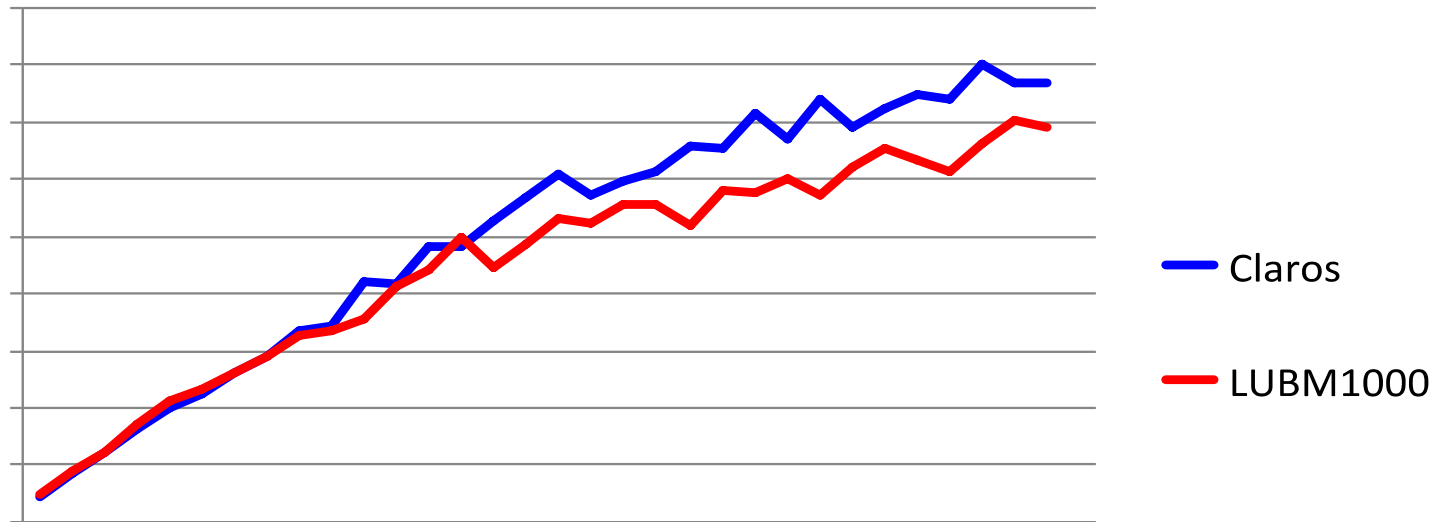


Scalability: RDFox Datalog Engine

	Claros	LUBM1000-UB
Memory Usage		
Base Triples	19M	134M
Base Mem	1GB	9GB
Mat. Triples	96M	333M
Mat. Mem	5GB	16GB
Time (16 cores)		
1 thread	2274s	942s
16 thread	180s	96s
32 thread	132s	66s

Scalability: RDFox Datalog Engine

Parallel Materialization (16 cores)



— Claros
— LUBM1000

Expressiveness: Chase Materialisation

- Applicable to **acyclic** ontologies
 - Acyclicity can be checked using, e.g., graph based techniques (weak acyclicity, **joint acyclicity**, etc.)
 - Many realistic ontologies turn out to be acyclic
- Given acyclic ontology \mathcal{O} , can apply chase materialisation:
 - Ontology translated into **existential rules** (aka dependencies)
 - Existential rules can introduce **fresh Skolem individuals**
 - **Termination guaranteed** for acyclic ontologies

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- Transform \mathcal{O} into **strictly stronger OWL RL ontology** \mathcal{O}^0
 - Transform ontology into Datalog ^{\pm, \forall} rules
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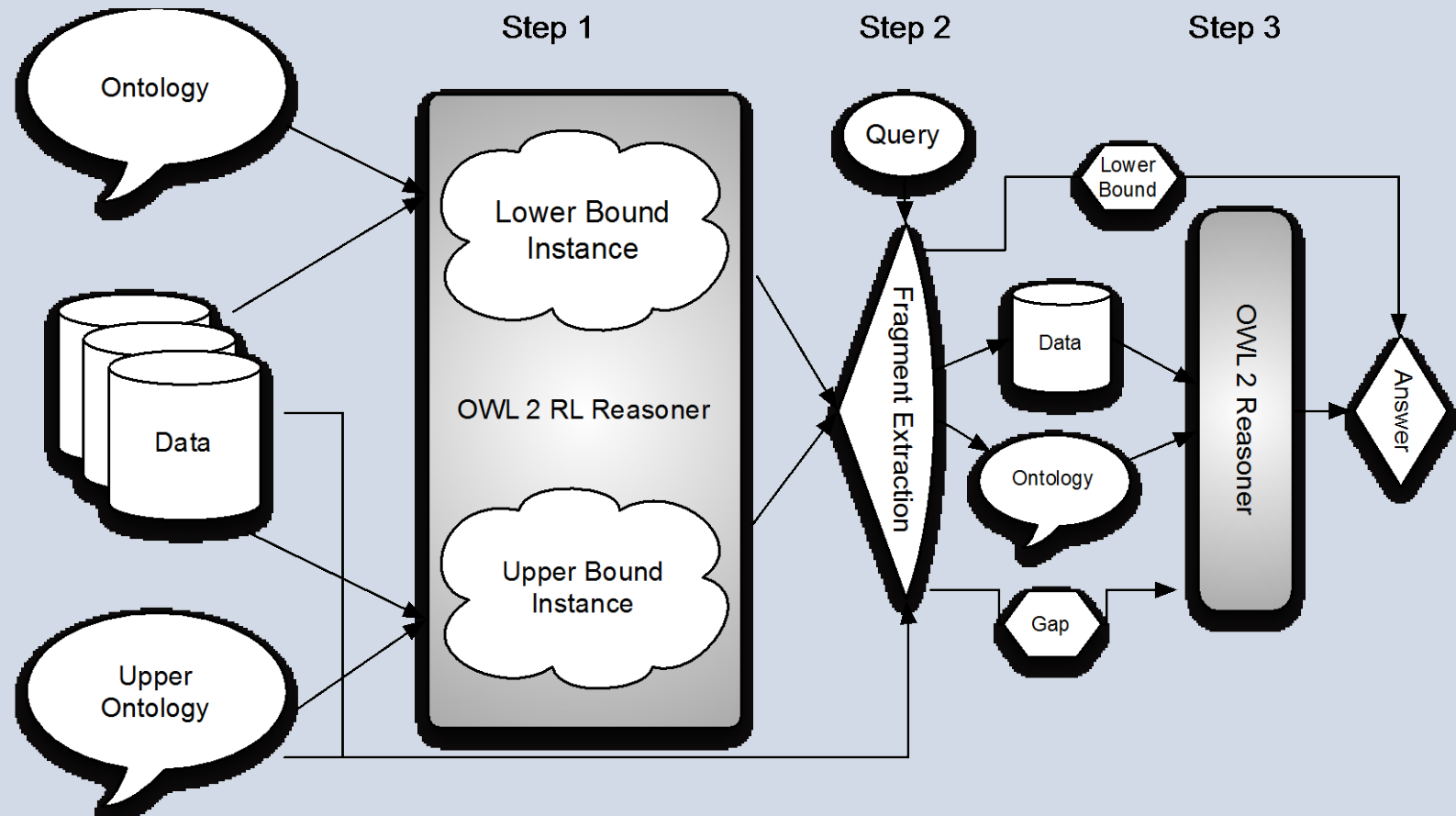
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- If $L = U$, then both answers are **sound and complete**
- If $L \neq U$, then $U \setminus L$ identifies a (small) set of “possible” answers
 - Delineates range of uncertainty
 - Can more efficiently check possible answers using, e.g., Hermit (but still infeasible if dataset is large)
 - Can use $U \setminus L$ to identify small(er) “relevant” subset of axioms/data needed to check possible answers

Expressiveness: Lower and Upper Bounds



Performance on LUBM 40

triples in the query \downarrow time to extract the fragment \downarrow Time to check all tuples in $U \setminus L$ by an OWL 2 reasoner using the fragment \downarrow

Query	$ V $	n	$ G $	t_f	$ O_f $	$ D_f $	t_{check}	t_{total}
M_1	2	3	39	36.4	6	29041	H: 23.3	H: 60.7
M_2	3	4	1	37.1	6	29004	H: 4.0	H: 42.1
M_3	4	6	16	38.2	6	29054	H: 8.4	H: 47.6
M_4	2	3	30	36.0	6	29032	H: 23.3	H: 60.2
M_5	3	4	4	39.4	6	29010	H: 24.0	H: 64.3
M_6	4	6	29	2,845.8	10	87209	H: 483.0	H: 3339.4
M_7	3	5	15	38.0	6	29033	H: 10.3	H: 49.3
M_8	3	5	14	39.3	6	29038	H: 11.9	H: 52.2
M_9	3	4	10	328.9	12	86785	H: 556.2	H: 886.7
S	1	2	39	310.0	12	86802	H: 1,780.0 P: 16,592.1	H: 2,126.5 P: 16,870.0

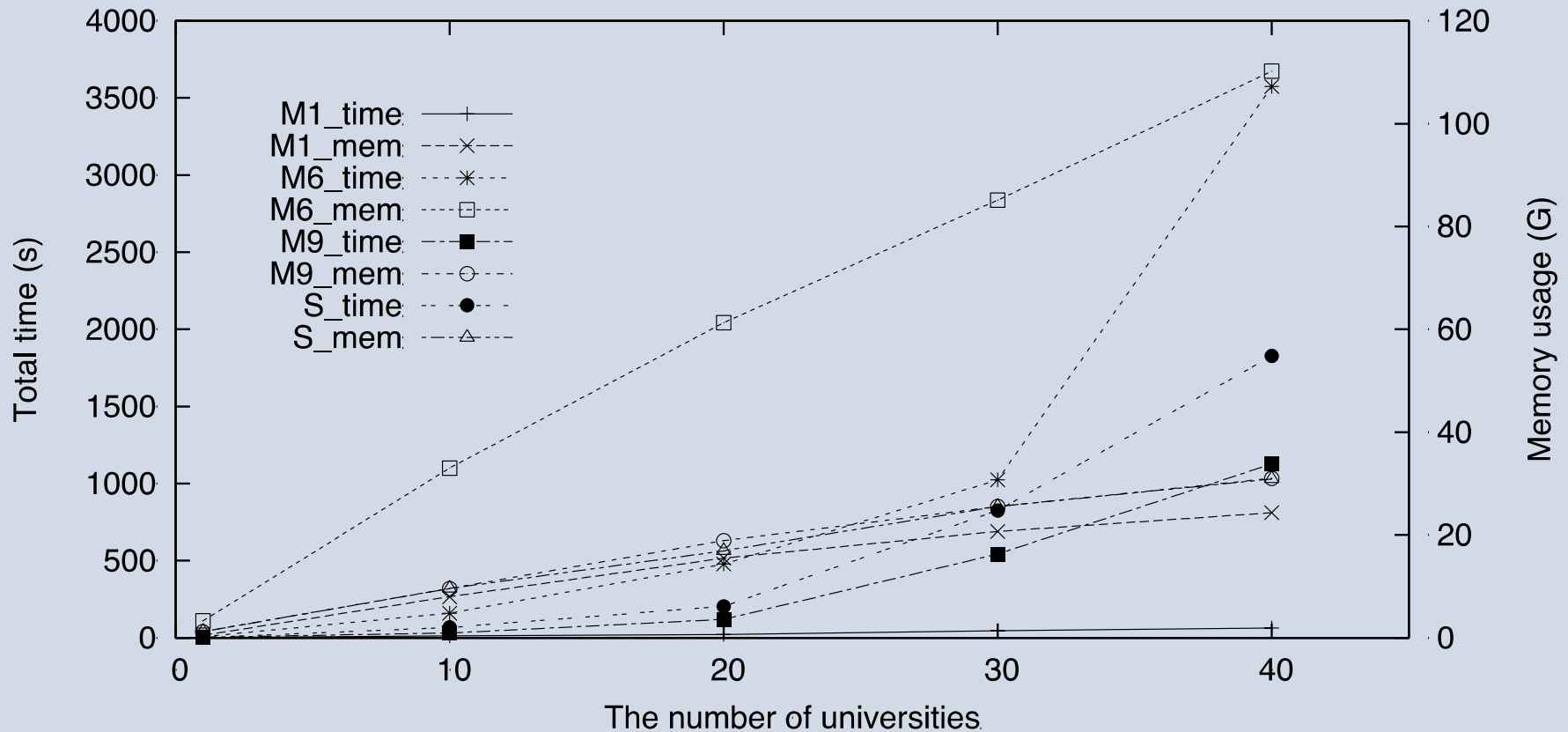
\uparrow variables in the query \uparrow answers in the gap $U \setminus L$ \uparrow total time to compute answers for the query

Performance on Fly

Query	$ V $	n	$ G $	t_f	$ O_f $	$ D_f $	$t_{\text{check}} \text{ (H)}$	t_{total}	t_{HermiT}
Q_1	2	3	803	108.9	224	4515	45.9	155.2	3,465.9
Q_2	3	5	342	97.7	224	4054	16.0	114.0	3,179.0
Q_3	1	1	28	91.0	217	3712	0.9	92.3	5,863.3
Q_4	2	3	25	94.3	233	3762	4.7	99.2	2,944.3
Q_5	2	2	518	100.3	222	3712	24.0	124.6	3,243.7

Time to check all tuples in $U \setminus L$ by an OWL 2 reasoner using the original ontology

Scalability on LUBM



Future Work

- Tighten lower and upper bounds
- Use Datalog reasoner to compute relevant subsets
- Hybrid approaches, e.g., exploiting ELHO filtering

Discussion

- QL-Rewriting has many advantages
 - Data can be left untouched and in legacy storage
 - Exploits existing DB infrastructure and scalability
 - ...

Discussion

- QL-Rewriting has many advantages
 - Data can be left untouched and in legacy storage
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 - ...
- But what if more expressiveness is needed?
 - Query answering for EL and RL still tractable (polynomial)
 - Critically depend on Datalog scalability – RDFox to the rescue!
 - Chase and LB/UB techniques offer potential for empirical scalability beyond EL and RL fragments

Acknowledgements



Engineering and Physical Sciences
Research Council



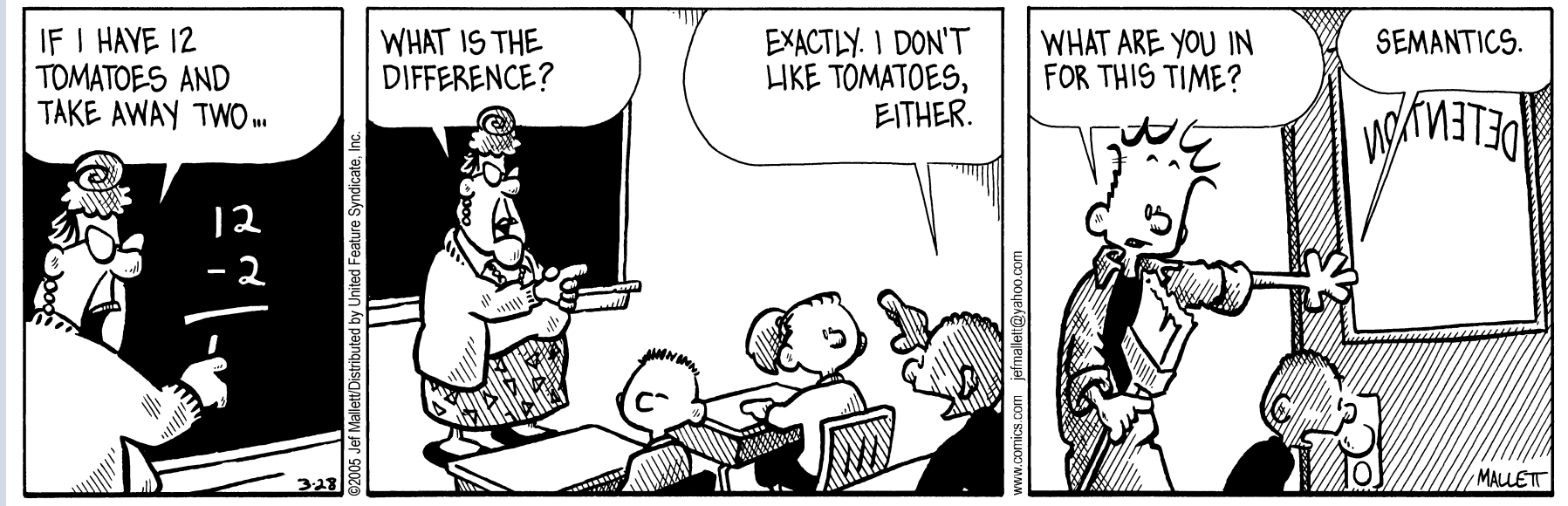
Optique



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Thank you for listening



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Any questions?