Scalable Multi-Query Optimization for SPARQL

Wangchao Le[1] Anastasios Kementsietsidis[2] Songyun Duan[2] Feifei Li[1]

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April 2, 2012

Outline

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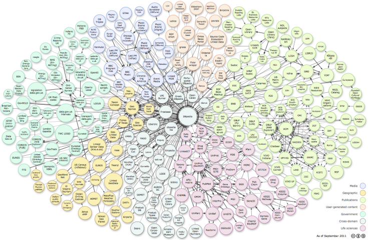

Internally ...

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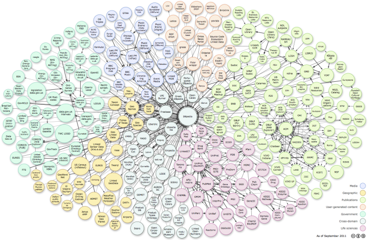

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Triple format:

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subject predicate object

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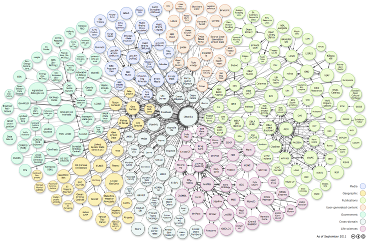
  - A large graph and encode rich semantics



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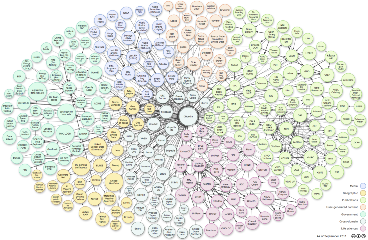

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Query language: SPARQL

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- Available engines to manage RDF data?
    - RDBMS: Migrate RDF, *e.g.*, Sesame, JenaSDB etc.
    - Generic RDF stores: *e.g.*, RDF3X, JenaTDB etc.

[VP07] D.J. Abadi, et al. Scalable semantic web data management using vertical partitioning. In *VLDB*, 2007.

[HEX08] C. Weiss, et al. Hexastore: sextuple indexing for semantic web data management. In *VLDB*, 2008.

[RDF3X] T. Neumann, G. Weikum. RDF-3X: a RISC-style engine for RDF. In *VLDB*, 2008.

[SJP09] T. Neumann, G. Weikum. Scalable Join Processing on Very Large RDF Graphs. In *SIGMOD*, 2009.

[BM10] M. Atre, et al. Matrix "Bit" loaded: A Scalable Lightweight Join Query Processor for RDF Data. In *WWW*, 2010.

[SSQ11] J. Huang, et al. Scalable SPARQL Querying of Large RDF Graphs. In *VLDB*, 2011.

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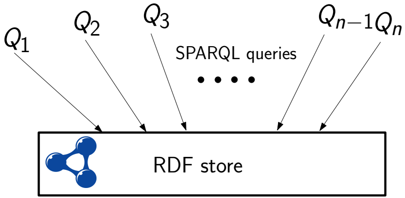
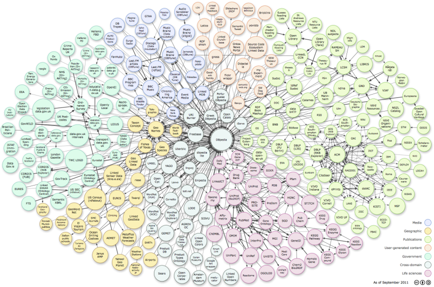
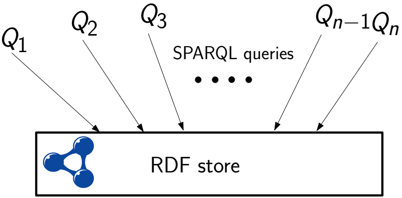
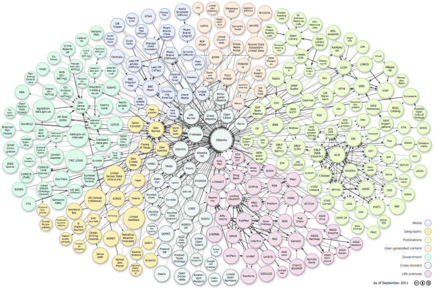




Introduction

- Observation: queries share common parts
- Multi-query optimization





Introduction

- A tempting choice: turn to MQO in relational databases [MQO88][MQO90][MQO00]
  - SPARQL$\leftrightarrow$relational algebra [EPS08][FSR07].
  - Exist quite a few relational solutions for RDF store.

[MQO90] T. Sellis, et al. On the Multiple-Query Optimization Problem. In *TKDE*, 1990.

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[MQO00] P. Roy, et al. Efficient and extensible algorithms for multi query optimization. In *SIGMOD*, 2000.

[EPS08] R. Angles, et al. The Expressive Power of SPARQL. In *ISWC*, 2008.

[FSR07] A. Polleres, et al. From SPARQL to rules (and back). In *WWW*, 2007.

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  - Conversion to SQL → a large number of joins
  - Store dependent solution

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p1	mbox	alice@home
p1	mbox	alice@work
p1	www	http://home/alice
p2	name	"Bob"
p2	zip	10001
p3	name	"Ella"
p3	zip	10001
p3	www	http://work/ella
p4	name	"Tim"
p4	zip	"11234"

(a) triple table D

```
SELECT ?name
WHERE { ?x name ?name, ?x zip 10001,

}
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(b) Example query Q_{OPT}

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(a) triple table D

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SELECT ?name , ?mail, ?hpage
WHERE  { ?x name ?name, ?x zip 10001,
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name	mail	hpage
"Alice"	alice@home	http://home/alice
"Alice"	alice@work	http://home/alice
"Bob"		
"Ella"		http://work/ella

(c) Output Q_{OPT}(D)

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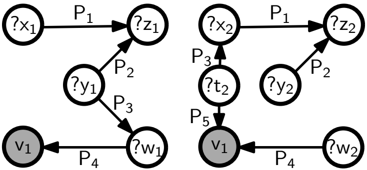
- Problem statement.
  - Input: a set $\mathcal{Q}$ of **Type 1** queries and a data graph G
  - Output: a set of rewritten queries, $\mathcal{Q}_{\mathrm{OPT}}$ of **Type 1** and **Type 2** queries
  - Requirements:
    - soundness and completeness: $\mathcal{Q}_{\mathrm{OPT}}(\mathrm{G}) \equiv \mathcal{Q}\ (\mathrm{G})$.
    - cost: $\frac{\mathcal{T}_r(\mathcal{Q})+\mathcal{T}_e(\mathcal{Q}_{\mathrm{opt}})}{\mathcal{T}_e(\mathcal{Q})} \leq 1$

Our approach

Motivating example



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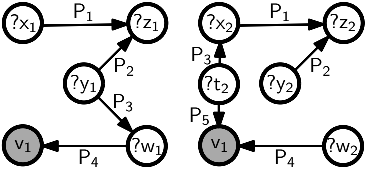

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: constant : variable

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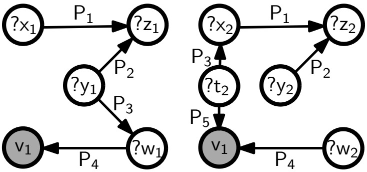

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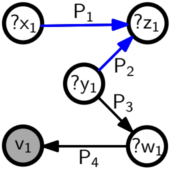

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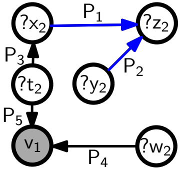
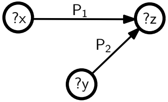


(b) Query Q_2

SELECT *
WHERE { $?x$ P_1 $?z$, $?y$ P_2 $?z$,

}



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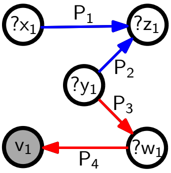

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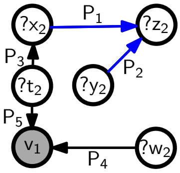

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SELECT *
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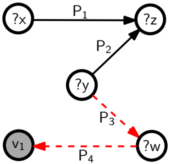

(I) Structure only Q_{OPT}

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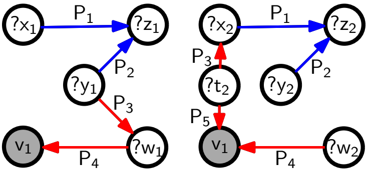

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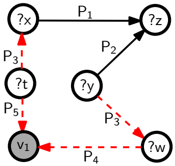

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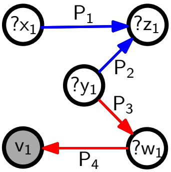

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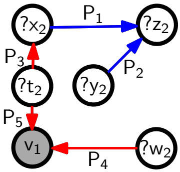

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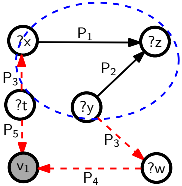
Evaluated once→potential saving



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OPTIONALs are evaluated on top of the common substructures (intermediate results cached by engine).

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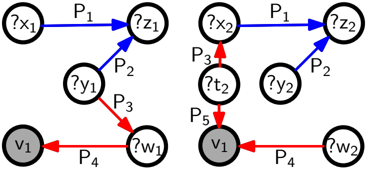

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pattern p	α(p)
$?x$ P_1 $?z$	30%
$?y$ P_2 $?z$	20%
$?y$ P_3 $?w$	18%
$?w$ P_4 v_1	1%
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*Max common subquery is not selective

(II) Using cost in optimization

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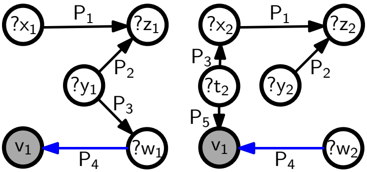

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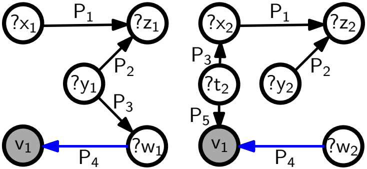

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(II) Using cost in optimization

Our approach

$$\mathcal{Q}=\{q_1, q_2, \ldots, q_n\}$$

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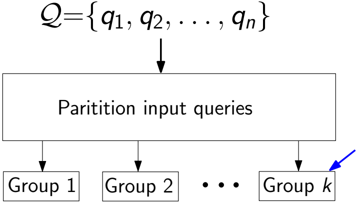

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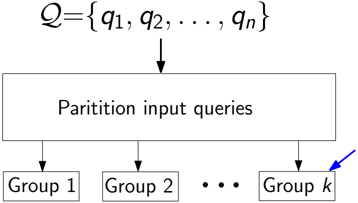

- Similar queries can be optimized together
  - finding structure similarity is expensive
  - group by predicates
  - distance: Jaccard similarity of predicate sets

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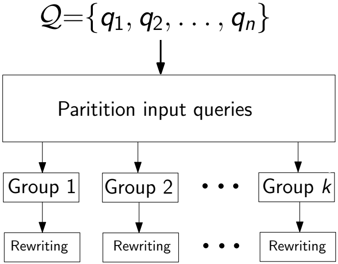

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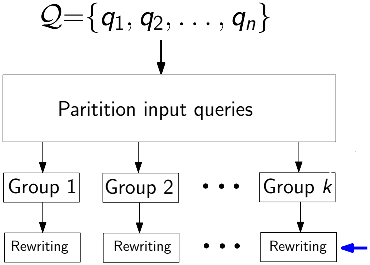

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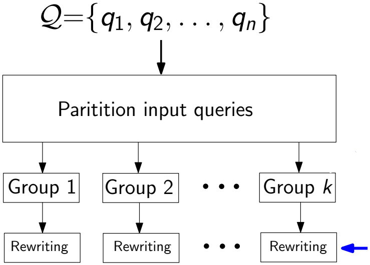

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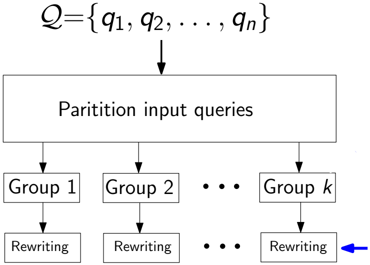

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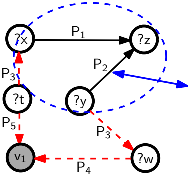

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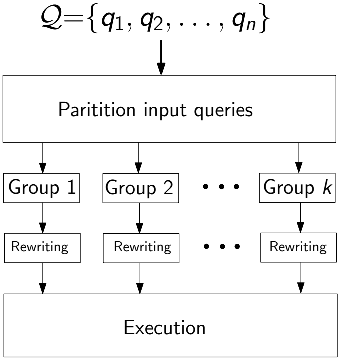

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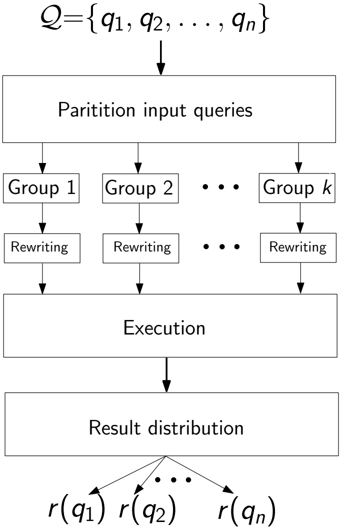

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- Related issues

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  - Distributing results, *i.e.*, **Type 2** query→**Type 1** queries

X	Y	Z
a		
b		c
d	e	
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RD of a **Type 1** query: e.g., X and Z

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columns from results of the **Type 2** rewriting

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columns from results of the **Type 2** rewriting

  - Soundness and completeness
  - Extensibility of the solution: more general queries
    - handle variable predicates
    - OPTIONAL queries

Experiments

- Implementation highlights
  - C++
  - 64-bit Linux, 2GHz Xeon(R) CPU, 4GB memory

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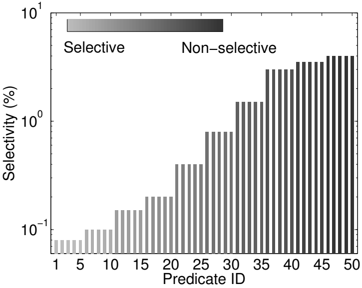

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  Ensure randomness in structure, e.g., star, chain and circle

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Parameter	Symbol	Default	Range
Dataset size	D	4M	3M to 9M
Number of queries	$\lvert\mathcal{Q}\rvert$	100	60 to 160
Size of query (num of triple patterns)	$\lvert Q\rvert$	6	5 to 9
Number of seed queries	κ	6	5 to 10
Size of seed queries	$\lvert q_{\text{cmn}}\rvert$	$\sim \lvert Q\rvert/2$	1 to 5
Max selectivity of patterns in Q	$\alpha_{max}(Q)$	random	0.1% to 4%
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- Rewriting w/ structure: MQO-S; rewriting w/ structure and cost: MQO

Experiments

- Time on rewriting
  MQO-S-C: structure based rewriting

  MQO-C: rewriting integrating with cost

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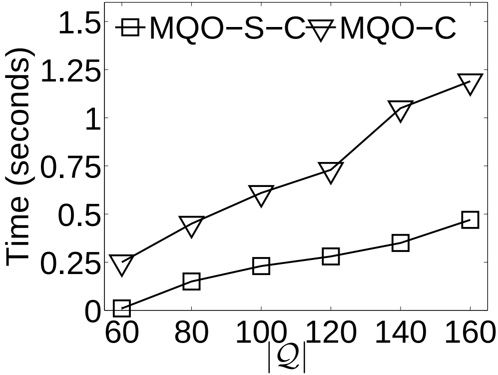

*Costly/bad rewritings are rejected
→more rounds of comparisons.

Experiments

- Time on distributing results
  MQO-S-P: parsing results from MQO-S
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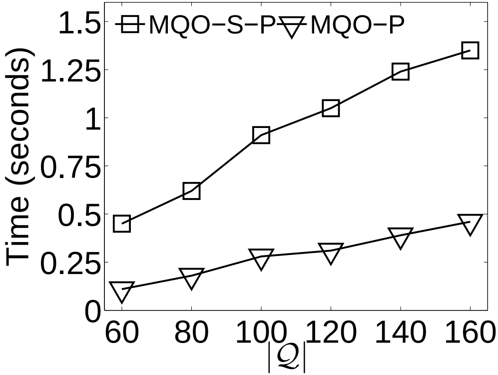

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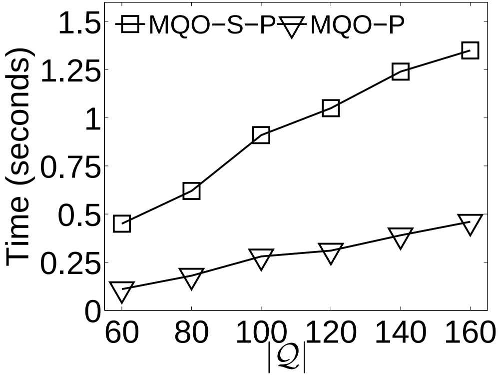

*Non-selective common subqueries increase the set of results.

*Both rewriting and parsing are efficiently doable

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- Varying num of queries in a batch
  No-MQO: no optimization
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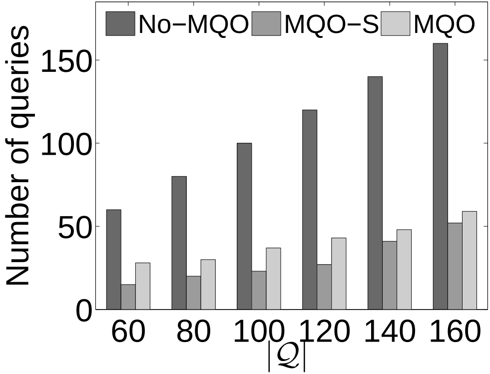

*Both reduce the num of queries to be exectued

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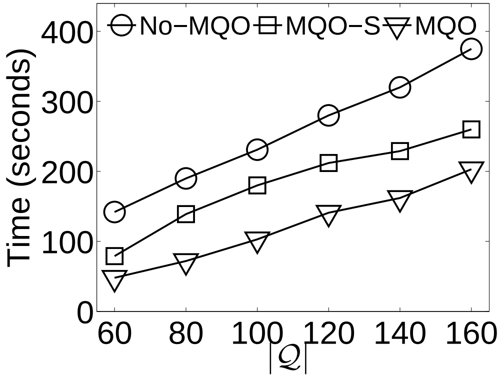

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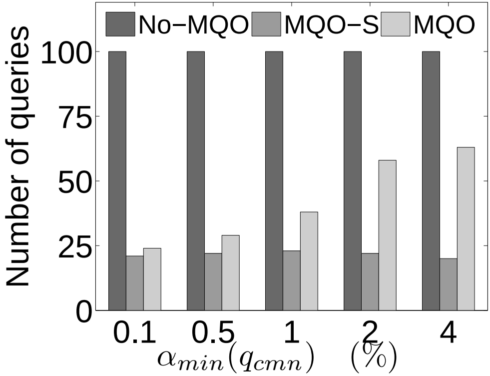

*MQO: reject more bad rewritings;
MQO-S: not sensitive

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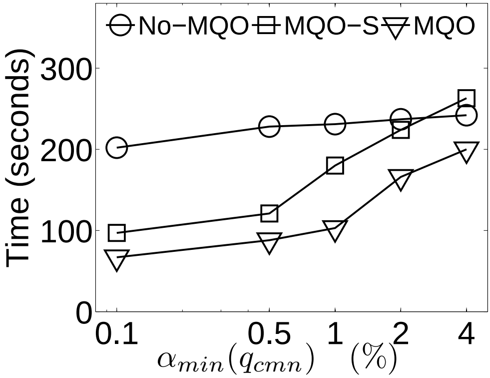

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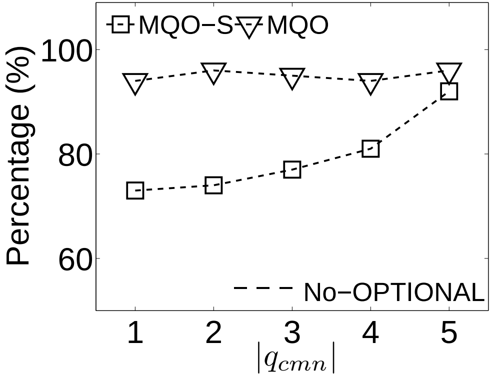

*MQO-S: up to 25% time on optional

Conclusions

- In dealing RDF data on the Web, store independency is important
- Combining SPARQL language and graph algorithms can achieve MQO, *i.e.*, by rewriting queries
- Cost must be taken in consideration during rewriting

Thank You

Q and A

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- Partition input queries

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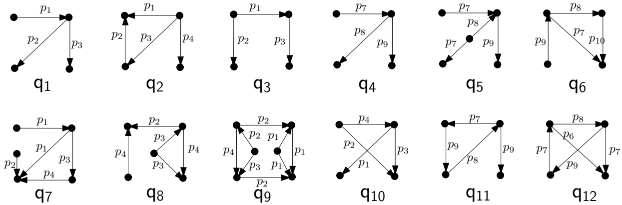

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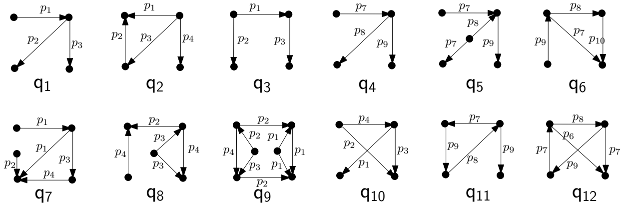

Distance: Jaccard similarity on predicates

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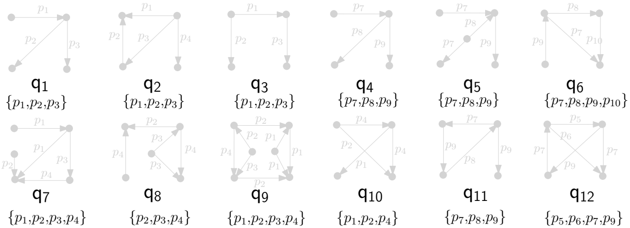

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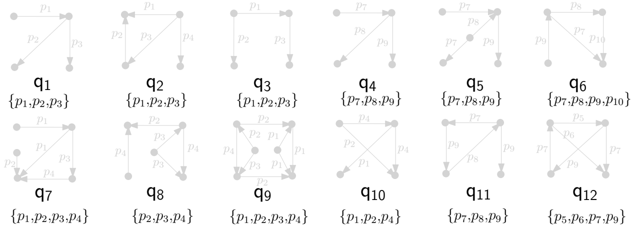

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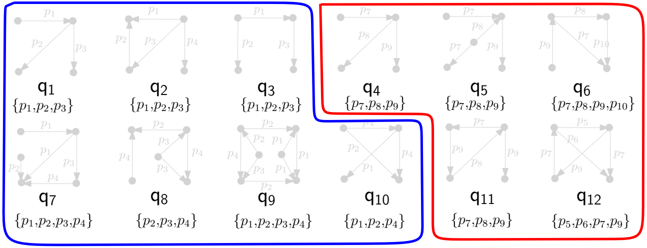

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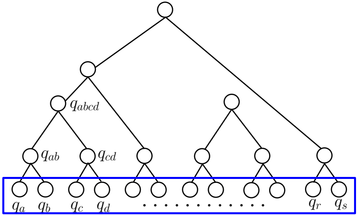

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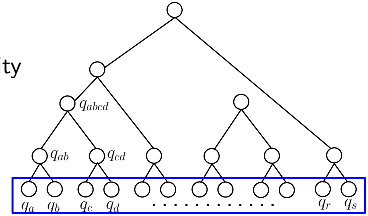

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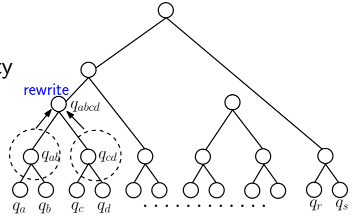

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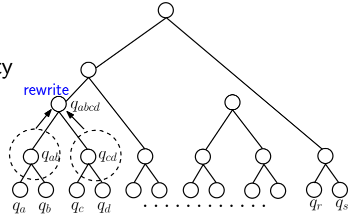

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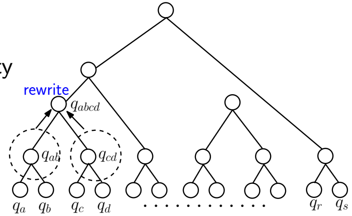

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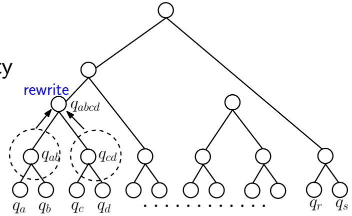

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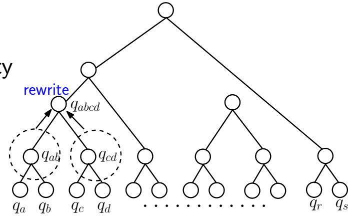

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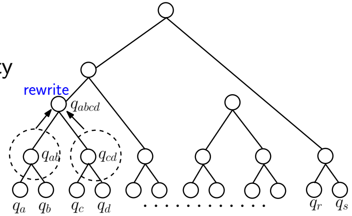

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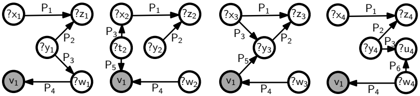

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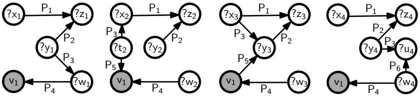

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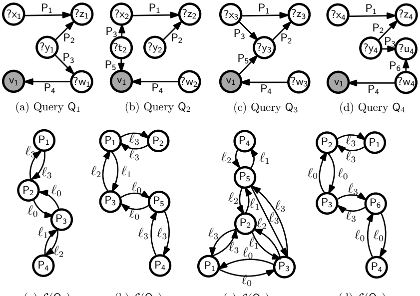

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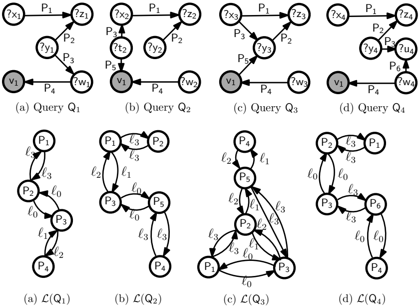

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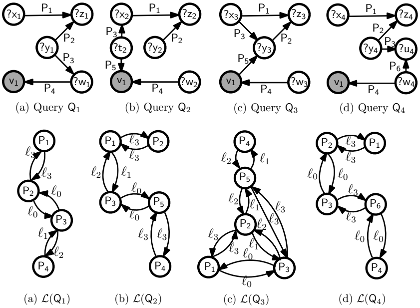

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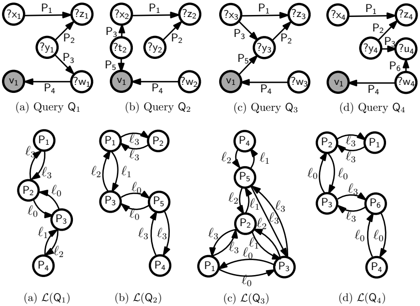

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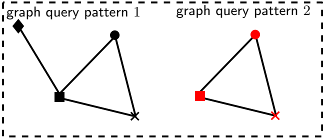

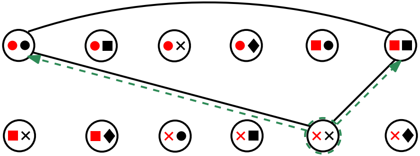

The triangle (clique) highlights the common subgraph composed by ■ × ●

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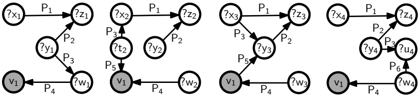

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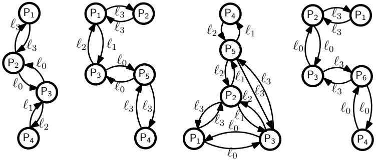

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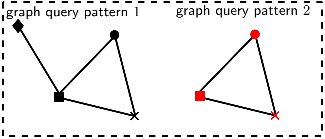

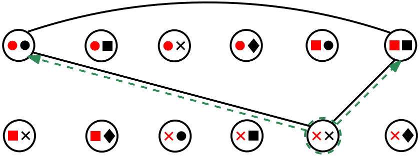

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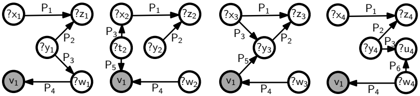

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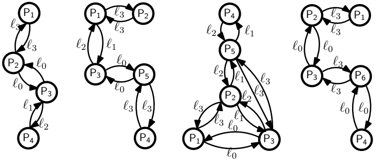

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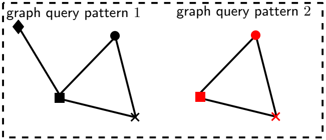
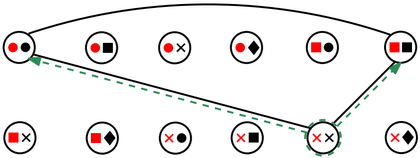
- optimize the product graph





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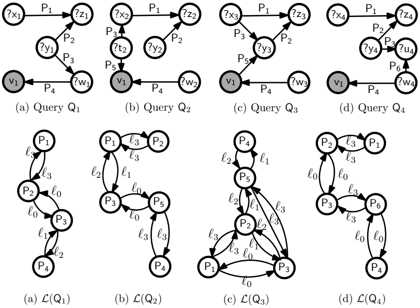

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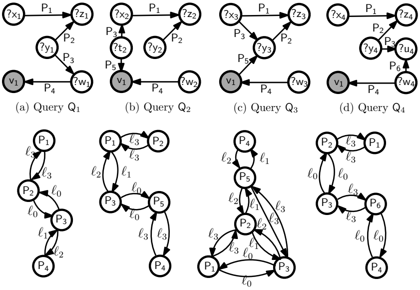
- sub—sub:ℓ_0, sub—obj:ℓ_1, obj—sub:ℓ_2, obj—obj:ℓ_3

- product graph: simultaneous walk
- blowup in size, esp. > 2 queries affect clique detection
- optimize the product graph

- prune non-common predicates
- check the constants

Our approach



(a) Query Q_1 (b) Query Q_2 (c) Query Q_3 (d) Query Q_4

(a) $\mathcal{L}(Q_1)$ (b) $\mathcal{L}(Q_2)$ (c) $\mathcal{L}(Q_3)$ (d) $\mathcal{L}(Q_4)$

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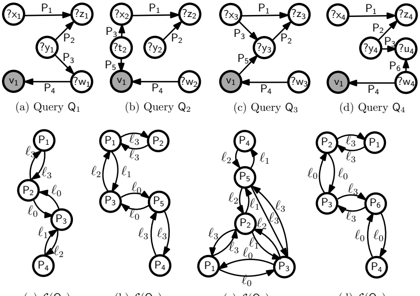

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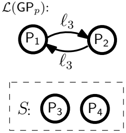

Our approach

- Find maximal cliques in the product graph [CLQ02][CLQ03]

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- Integrate cost into rewriting

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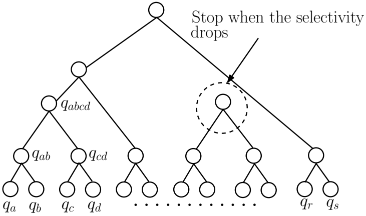

Our approach

- Related issues

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  - Distributing results, *i.e.*, **Type 2** query$\rightarrow$**Type 1** queries

name	mail	hpage
"Alice"	alice@home	http://home/alice
"Alice"	alice@work	http://home/alice
"Bob"		
"Ella"		http://work/ella

RD of a **Type 1** query

$\uparrow\downarrow$

columns from results of the **Type 2** rewriting

Our approach

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RD of a **Type 1** query

↑↓

columns from results of the **Type 2** rewriting

  - Soundness and completeness
  - Extensibility of the solution: more general queries
    - handle variable predicates
    - nested OPTIONALs