Distributed RDF Graph Management

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Outline

1. Background
2. Scale-out Systems
3. Federated Systems
4. Conclusions

Part 1

Background

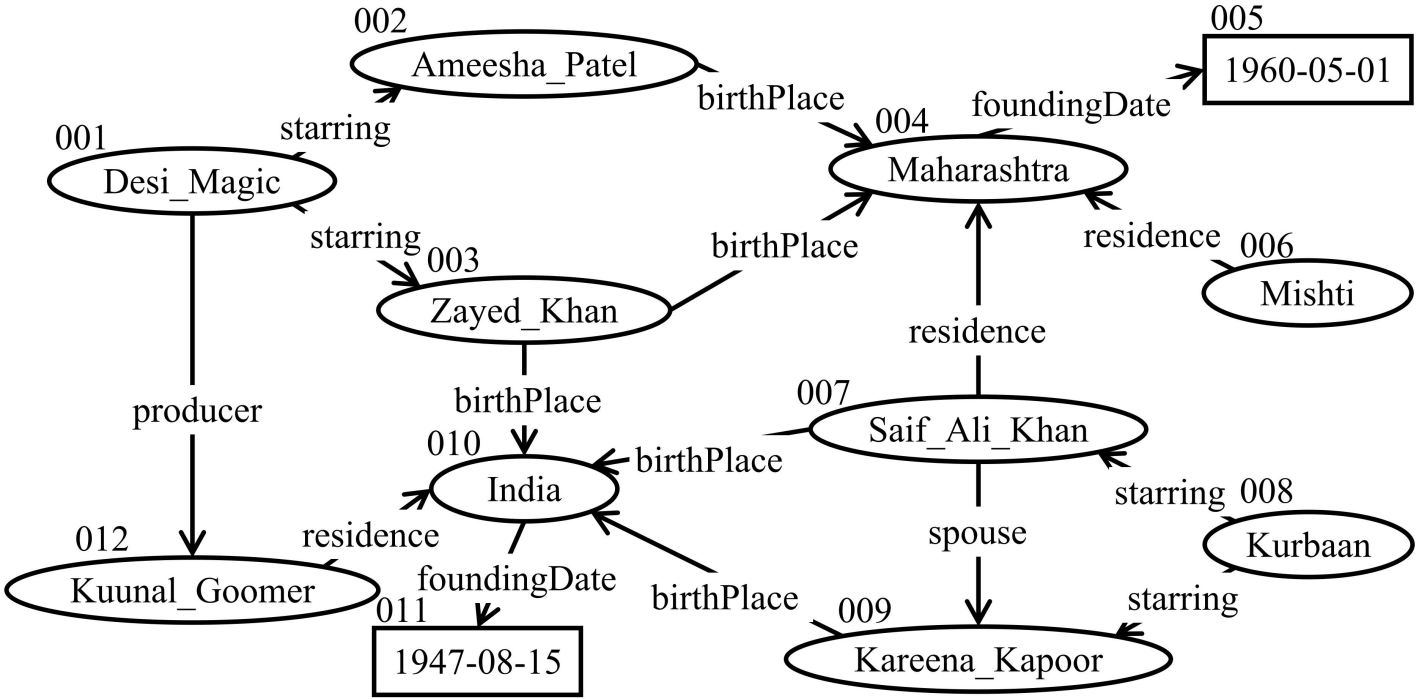
RDF Introduction

Resource Description Framework

- It is a data model proposed widely used for knowledge bases
- Everything is an uniquely named resource
- Properties of resources can be defined
- Relationships with other resources can be defined

RDF Graph

An RDF dataset can be represented as a graph

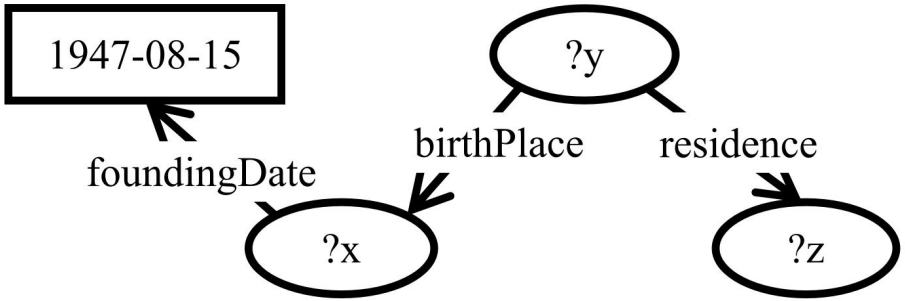


RDF Query Model

Query Model - SPARQL Protocol and RDF Query Language

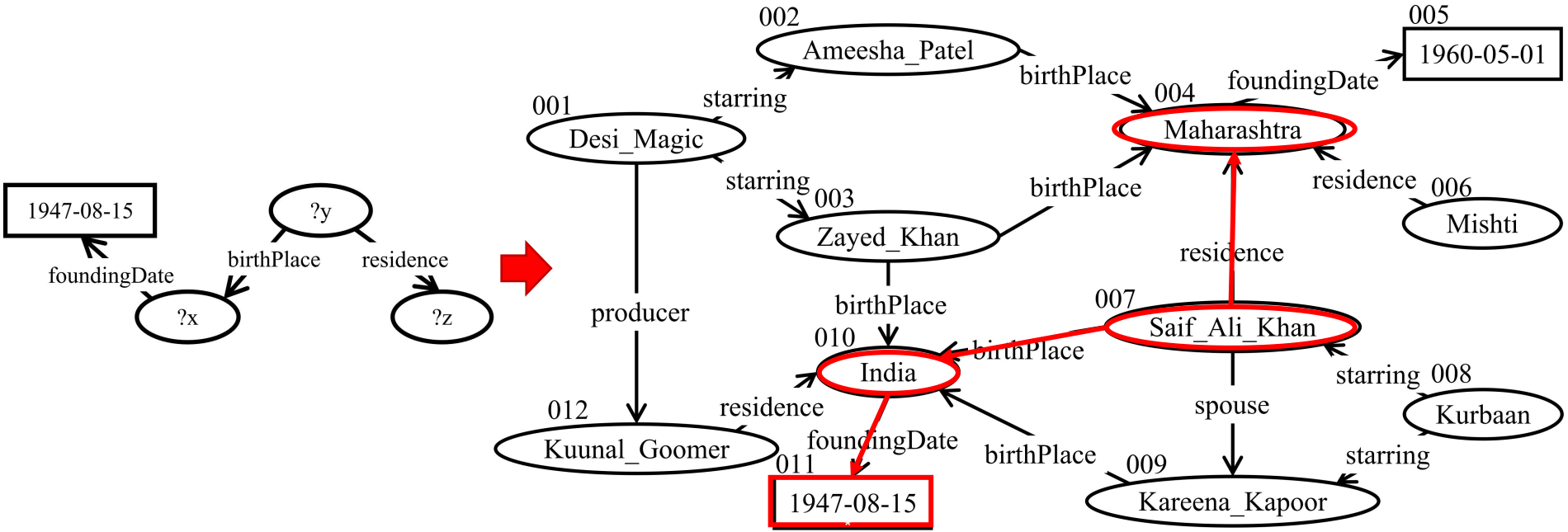
A SPARQL query is a set of triple patterns with variables

```
Select ?x where {
  ?y residence        ?z .
  ?y birthPlace       ?x .
  ?x foundingDate     1947-08-15 . }
```



RDF Query Model

Answering SPARQL query = subgraph matching using homomorphism



Large RDF Graphs

Now, RDF datasets become larger and larger

Max-Planck-Institute

284 million triples

Metaweb Company
acquired by Google in 2010

2.4 billion triples

Leipzig University
University of Mannheim
OpenLink Software

9.5 billion triples

It is important to design a distributed RDF system to manage the large RDF dataset.

Part 2

Scale-out Systems

Scale-out Systems

Partitioning-based Appoarches

- Workload-agnostic Appoarches
- Workload-aware Appoarches

Partitioning-agnostic Approaches

- gStore^{D}

Scale-out Systems

Partitioning-based Appoarches

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- Workload-aware Appoarches

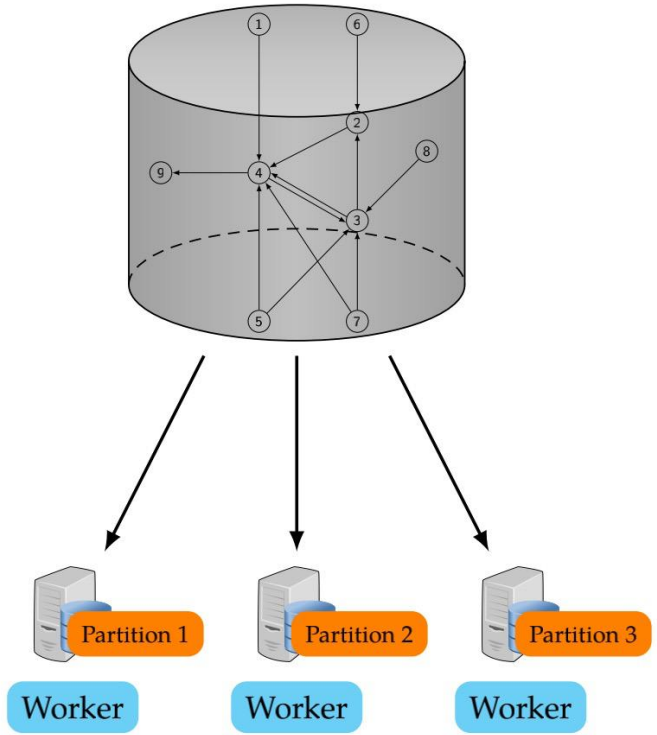
Partitioning-agnostic Approaches

- gStore^{D}

Distributed RDF System Architecture

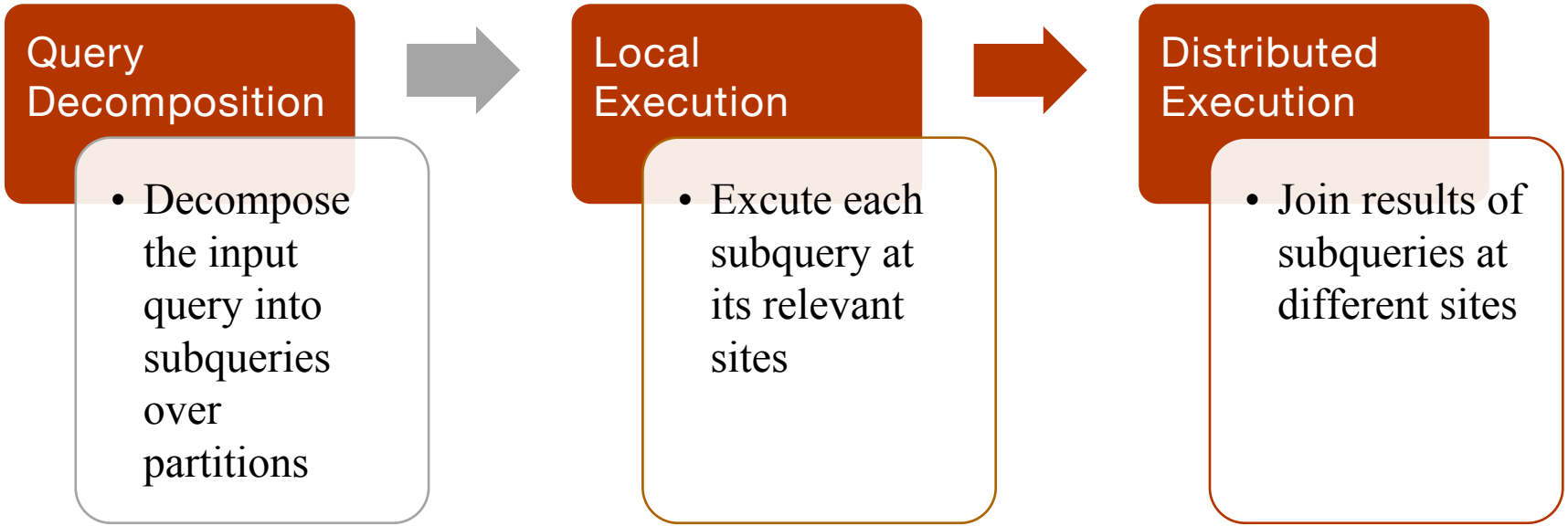
Partitioning–based Architecture

- An RDF graph is partitioned through different sites
- Objective: Parallelize query processing with as little inter-site communication as possible.



Distributed Query Execution Model

Partition the data and the query in such a way to minimize the inter-partition joins



Related Work

RDF graph partitioning approaches can be classified into three types:

- Vertex-disjoint: Put each vertex in one partition
  - Existing methods' objective is to minimize edge-cuts, rather than minimize the inter-partition joins
- Edge-disjoint: Put each edge in one partition
  - Existing methods are widely used in many cloud-based systems to prune irrelevant partitions and avoid too many scans in the cloud, but do not focus on avoiding inter-partition joins
- Other: Consider extra information, such as workloads

H-RDF-3X [Huang et al., VLDB 2011]

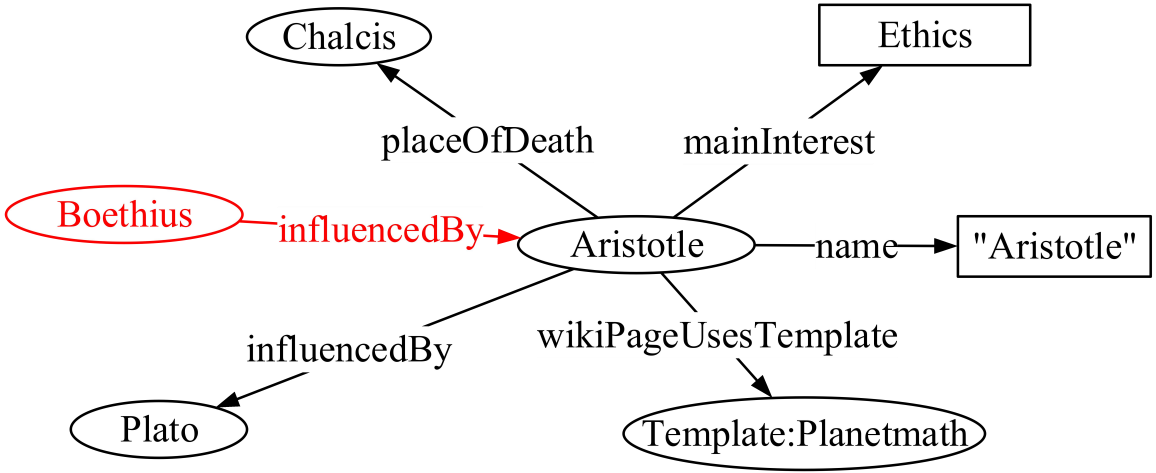
- Data is partitioned using METIS
- Replicate vertices using n-hop guarantee
- If the radius of Q is not larger than n, Q can be locally evaluated n each site
- If the radius of Q is larger than n, Q is decomposed into several subqueries Qi that can be independently evaluated; then their results are joined

SHAPE [Lee et al., VLDB 2013]

- Generate triple groups based on common subject or object
- Semantic hashing triple groups: URI references usually have a path hierarchy and URI references having a common ancestor are often connected together, so SHAPE places such URI references (vertices) in the same partition
- Allow some data replication between different partitions

Example Triple Groups

- Black subgraph is a subject-based triple group
- Red subgraph is an object-based triple group
- The whole graph is a subject-object-based triple group



Characteristics of RDF Graphs

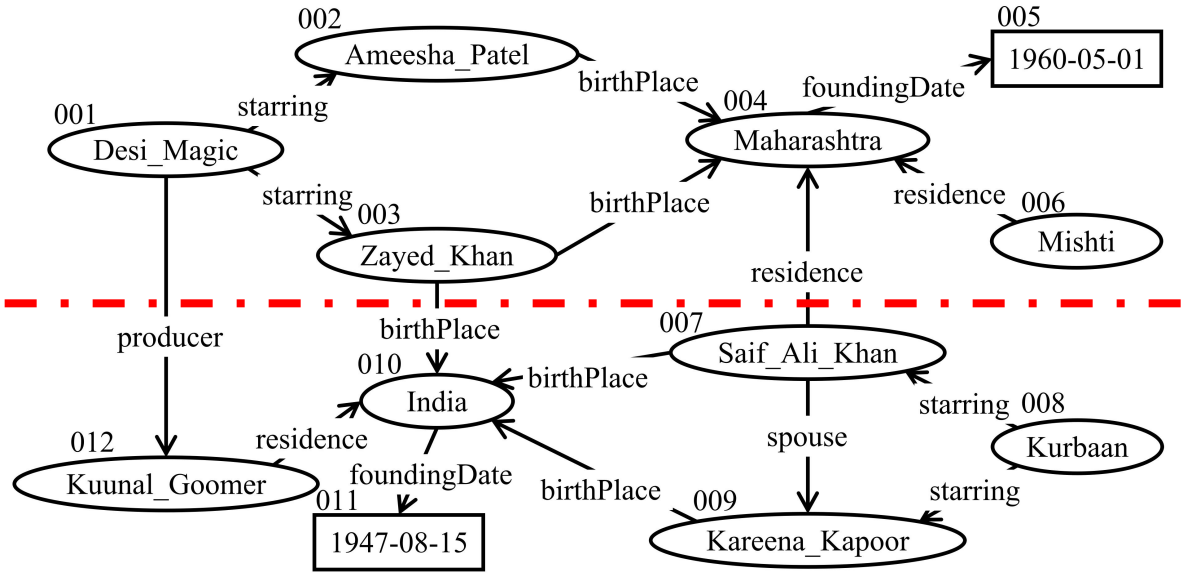
- LUBM is a benchmark that adopts an ontology for the university domain, and can generate synthetic RDF datasets of arbitrary sizes
- The URI references in LUBM are URLs with http as their schema, such as http://www.Department1.University2.edu/FullProfessor2/Publication14
- Then, all entities with the similar URI hierarchy are put into the same partition

Minimum Property-Cut [Peng et al., ICDE 2022]

- We propose a novel vertex-disjointed RDF Graph partitioning scheme, minimum property-cut (MPC), for distributed SPARQL query evaluation

Internal & Crossing Properties

- A property is called a crossing property if and only if there is at least one crossing edge with that property; otherwise, it is called an internal property

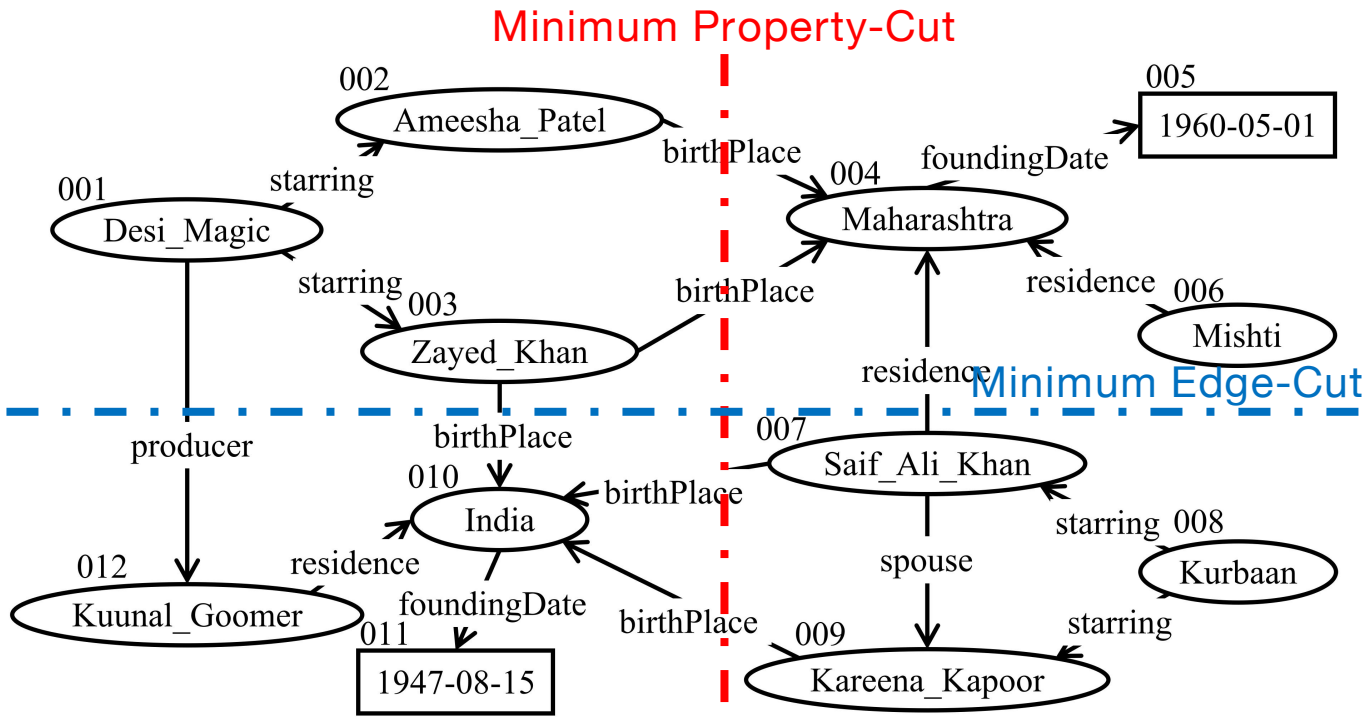


Motivations

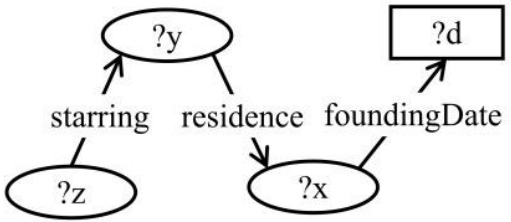
- The main performance bottleneck in distributed SPARQL execution is inter-partition joins
  - If all properties in a query are internal → execute independently over each partition without inter-partition join

- Objective: Partition to maximize the number of internal properties
  - May increase edge-cuts, but minimizes number of unique property-cuts

Example for Comparison of Different Partitionings



Example Partitionings



Example Query

Problem Definition

- Given an RDF graph G and a positive integer k, the minimum property-cut (MPC) partitioning of G is a partitioning $F = \{F_1, F_2, ..., F_k\}$ such that
  1. the number of crossing properties $|L_{cross}|$ is minimized (i.e. the number of internal properties $|L_{in}|$ is maximized);
  2. the size of F_i (i.e. $|V_i|$) is not larger than $(1 + \varepsilon) \times |V|/k$ for each F_i, where ε is a user-defined maximum imbalance ratio of a partitioning (i.e., how much difference can be in the relative sizes of partitions).

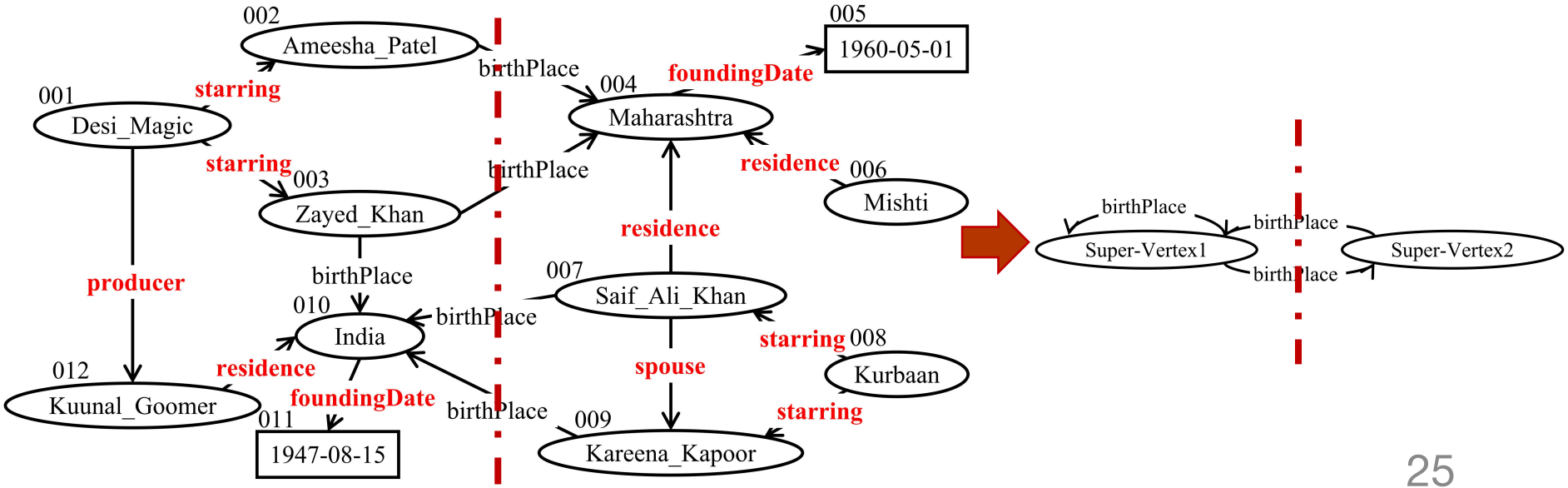
Hardness of MPC

Theorem: The MPC partitioning problem is NP-complete.

Proof: We reduce the NP-complete minimum edge-cut problem to the MPC problem by assigning each edge in an instance of minimum edge-cut graph partitioning with a distinct property

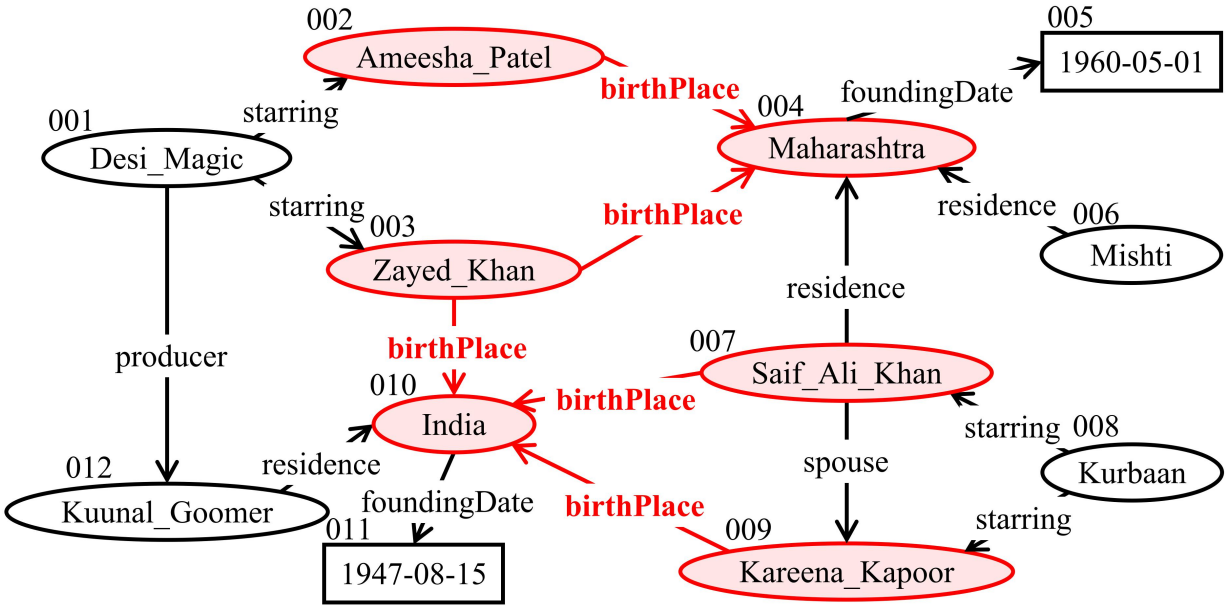
Framework of Minimize Predicate-Cuts

Selecting Internal Properties → Coarsening → Partitioning Coarsened Graph → Uncoarsening



Constraint of Internal Properties

If a property p is an internal property, any two vertices in a weakly connected component of p's induced graph should be in one partition.



If we want birthPlace to be an internal property, all the six vertices should be in one partition

Selecting Internal Property Cost

Given a set of properties L', the cost of selecting them as internal properties is defined as the size of the largest WCC in the property induced subgraph G[L']

$$Cost(L') = \max_{c \in WCC(G[L'])} |c|$$

where c is a weakly connected component in WCC(G[L']]) and |c| denotes the number of vertices in c.

Internal Property Selection Algorithm

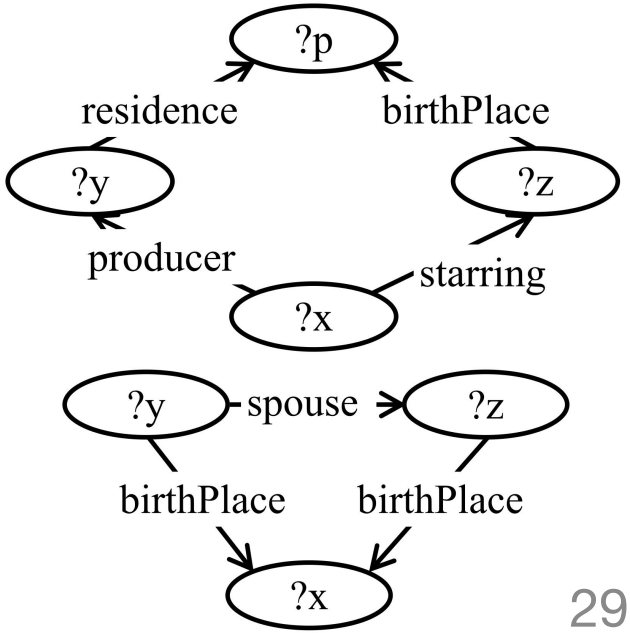
1. First, we initialize an empty set, L_{in}, for internal properties, and compute the WCCs of the property-induced subgraphs for each property
2. We iteratively select a property p that minimizes Cost($L_{in} \cup \{p\}$) and inserted it into L_{in}. These steps are repeated until no more property can be selected

To compute and merge the WCCs, we propose to use the disjoint-set forest data structure

Independently Executable Queries

Independently executable queries (IEQs) are those that are "local" to a partition and can be executed without a join with another partition

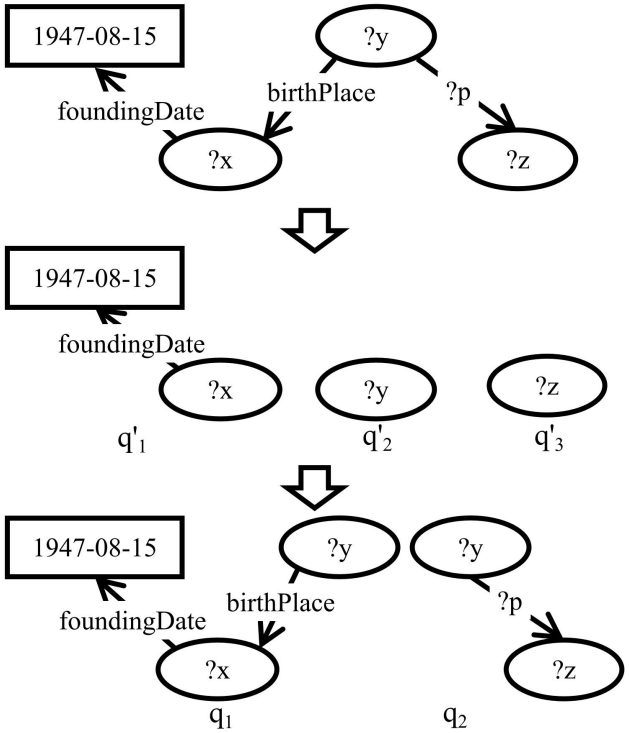
- Internal IEQs: Queries not containing any crossing properties
- Extended IEQs: Queries connected when crossing predicate edges are removed



Query Decomposition

Non-IEQ: We decompose into a set of IEQs and join the results

- Remove crossing property edges & edges with variables
- Form subqueries
- Add crossing property edges & edges with variables to subqueries



Query Execution

- When a non-IEQ Q is received, it is decomposed into a set of subqueries $\{q_1, q_2, ..., q_y\}$, and they are sent to each partition for independent execution

- Then, the subqueries' matches are joined to obtain the final result

Setting

- Datasets:

Dataset	#Entities	#Triples	#Properties
LUBM 100M	17,473,142	106,909,064	18
LUBM 1B	173,891,493	1,069,331,221	18
LUBM 10B	1,737,718,408	10,682,013,023	18
WatDiv 100M	5,212,745	108,997,714	86
WatDiv 1B	52,120,745	1,099,208,068	86
WatDiv 10B	521,200,745	10,987,996,562	86
YAGO2	21,073,153	284,417,966	98
Bio2RDF	804,671,979	4,426,591,829	1,581
DBpedia	139,493,254	1,111,481,066	124,034
LGD	311,153,753	1,292,933,812	33,348

- Competitors: Subject_Hash, METIS and VP
- Environment: 8 machines running Linux at Alibaba Cloud

Partitioning Quality

- $|L_{cross}|$ & $|E^c|$:

Datasets	MPC $\|L_{cross}\|$	MPC $\|E^c\|$	Subject_Hash $\|L_{cross}\|$	Subject_Hash $\|E^c\|$	METIS $\|L_{cross}\|$	METIS $\|E^c\|$
LUBM	5	29,971,560	14	62,377,786	13	21,853,766
WatDiv	17	95,497,642	31	95,786,527	31	58,100,544
YAGO2	5	128,758,514	45	142,274,454	43	58,912,138
Bio2RDF	36	2,044,500,633	398	2,184,075,117	-*	-
DBpedia	64	504,897,118	33,966	681,734,289	17,807	171,944,344
LGD	6	518,035,967	2,012	676,620,154	2,010	296,443,817

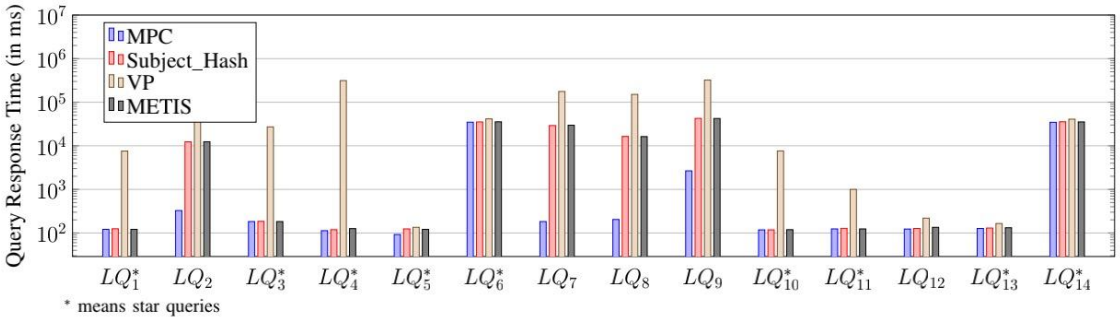
* - means that data size is beyond the capacity of METIS.

- Percentage of IEQs:

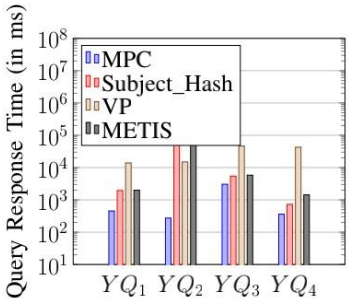
	MPC	VP	Subject_Hash / METIS	Subject_Hash+	METIS+
LUBM	100%	28.57%	71.43%	71.43%	71.43%
WatDiv	60%	0%	50%	50%	50%
YAGO2	100%	0%	0%	0%	0%
Bio2RDF	100%	40%	80%	80%	80%
DBpedia	75.19%	24.25%	46.87%	51.87%	51.90%
LGD	99.95%	83.51%	96.95%	96.98%	96.98%

Online Performance Comparison

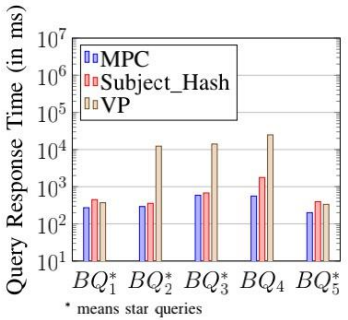
- On Benchmark Queries:



(a) LUBM

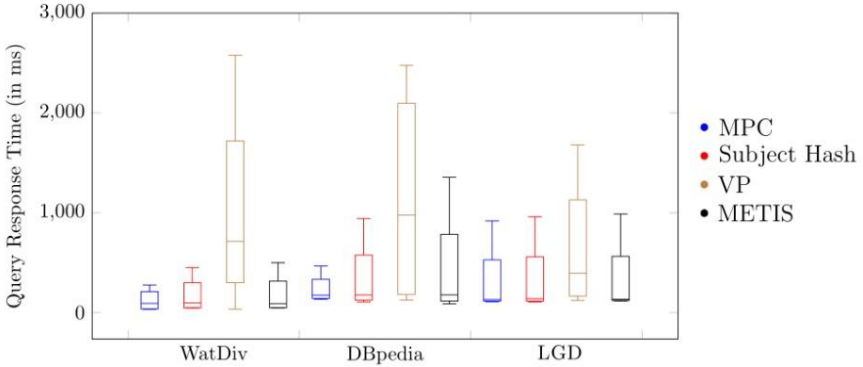


(b) YAGO2



(c) Bio2RDF

- On Real Query Logs:



Scale-out Systems

Partitioning-based Appoarches

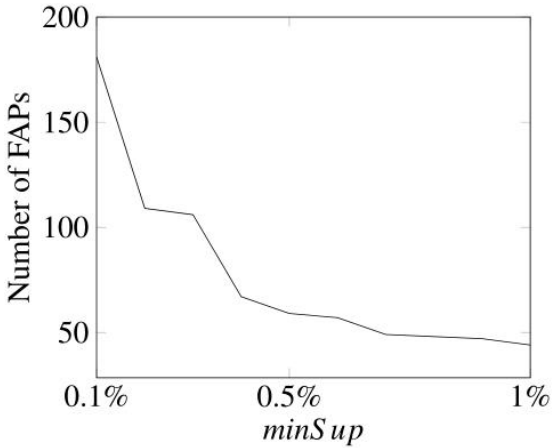
- Workload-agnostic Appoarches
- Workload-aware Appoarches

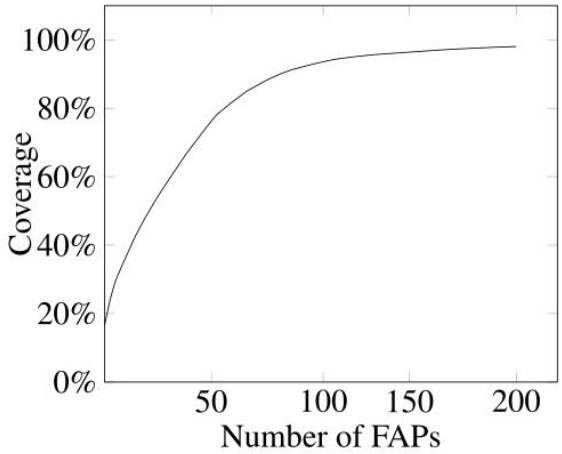
Partitioning-agnostic Approaches

- gStore^{D}

Why Query Workload Matters ?

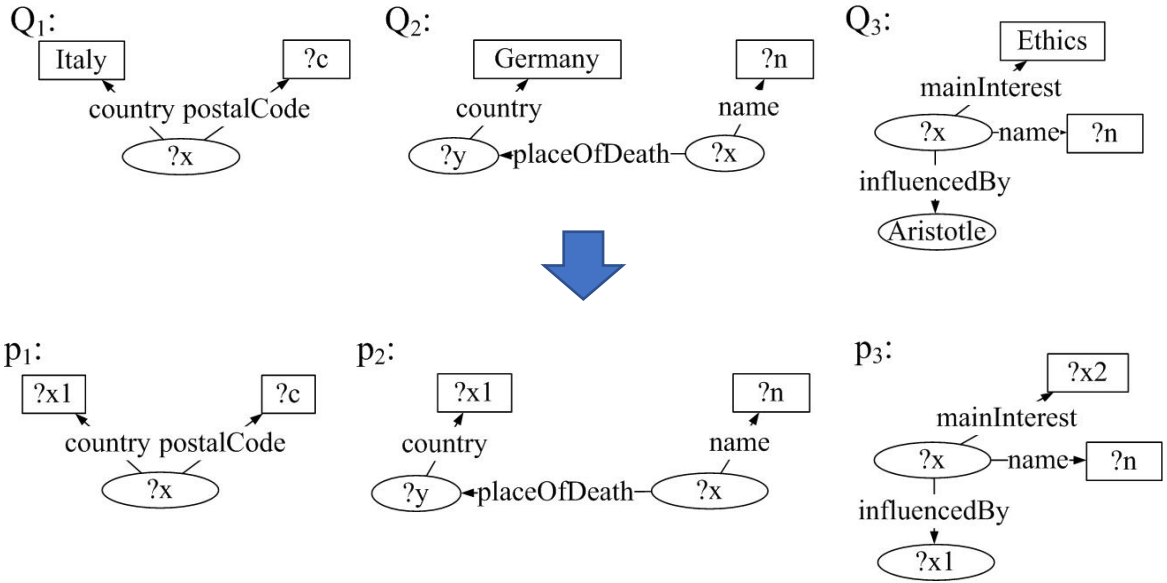
- A few pattern can cover most queries in the real query log





Normalization of the Workload

- Before frequent access pattern mining, we normalize all SPARQL queries in the workload to avoid overfitting



Access Frequency

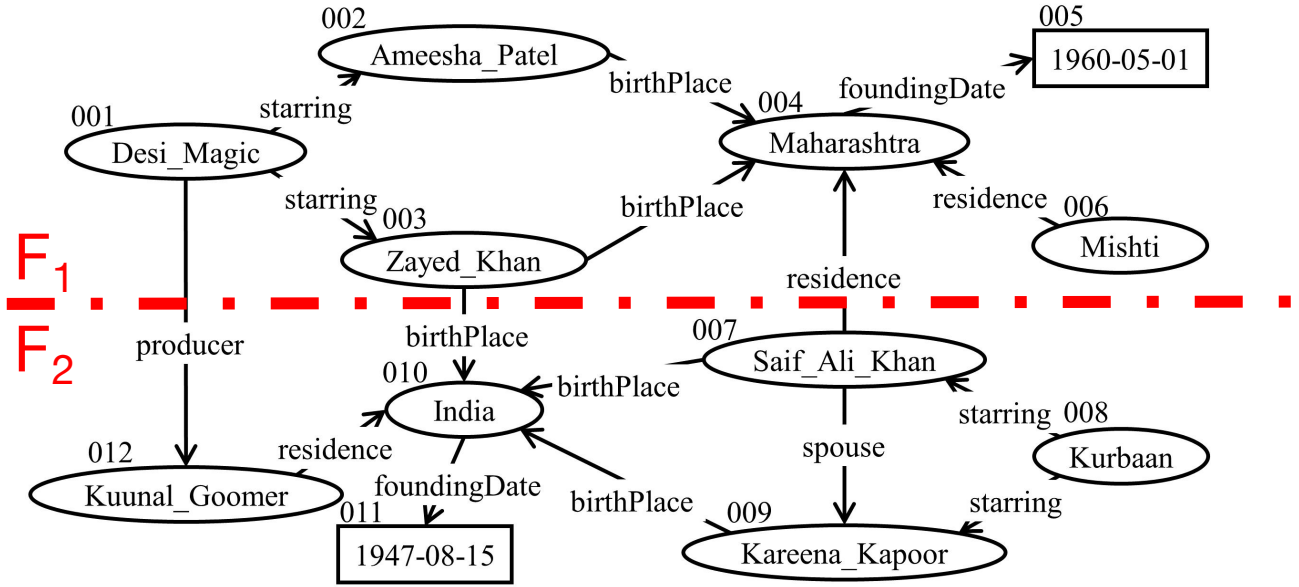
- The access frequency of a pattern p is the number of queries in a workload $\mathcal{Q}$, where a pattern p is a subgraph
- A pattern p is frequent access pattern if its access frequency is no less than a threshold, minSup.
- Most workload-aware appoarches are based on frequent access patterns

WARP [Hose et al., ICDE Workshops 2013]

- WARP proposes a distributed SPARQL engine that combines a graph partitioning technique with workload-aware replication of triples across partitions

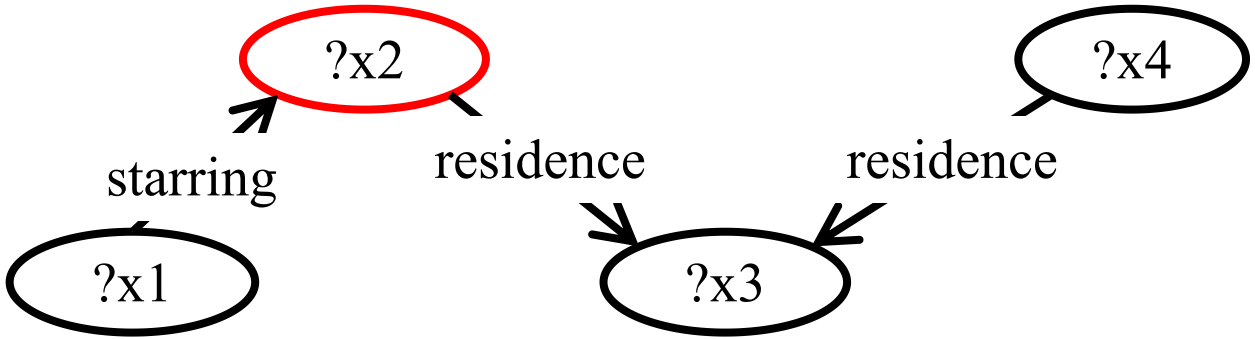
WARP

- First, WARP partitions the RDF graph using METIS



WARP

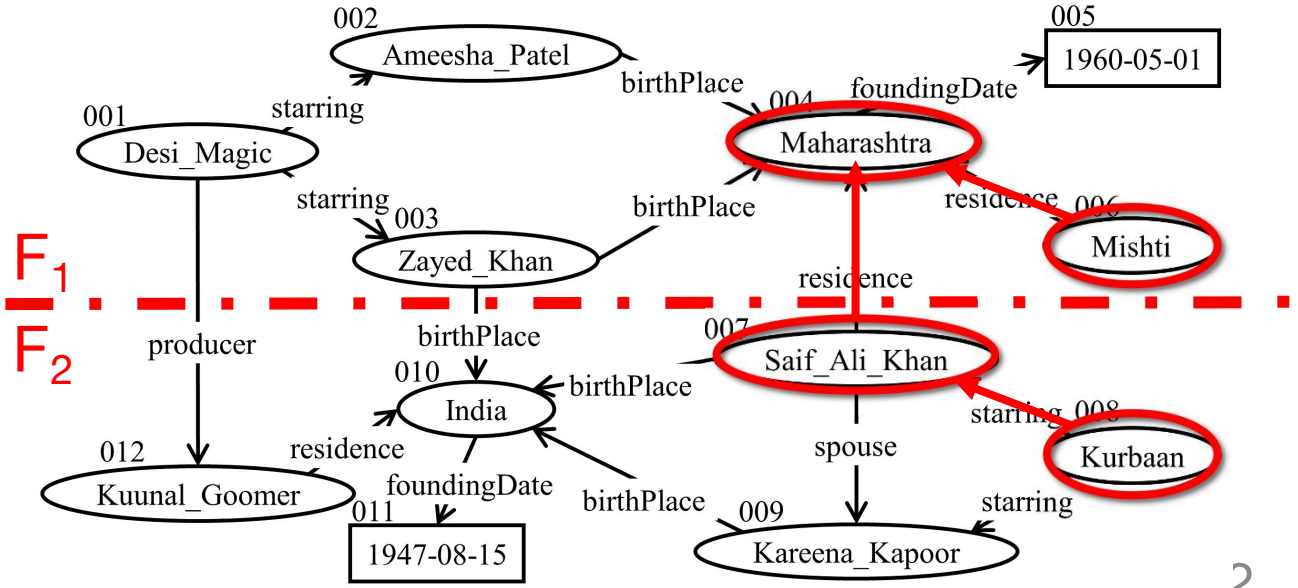
- Second, WARP find some frequent query patterns that are not independently executable and select one query vertex as seed



WARP

- Last, WARP replicate the matches of pattern at the partition that the mapping of the seed is at

Seed vertex ?x2 is mapped to 007, so the match is replicated at F_2



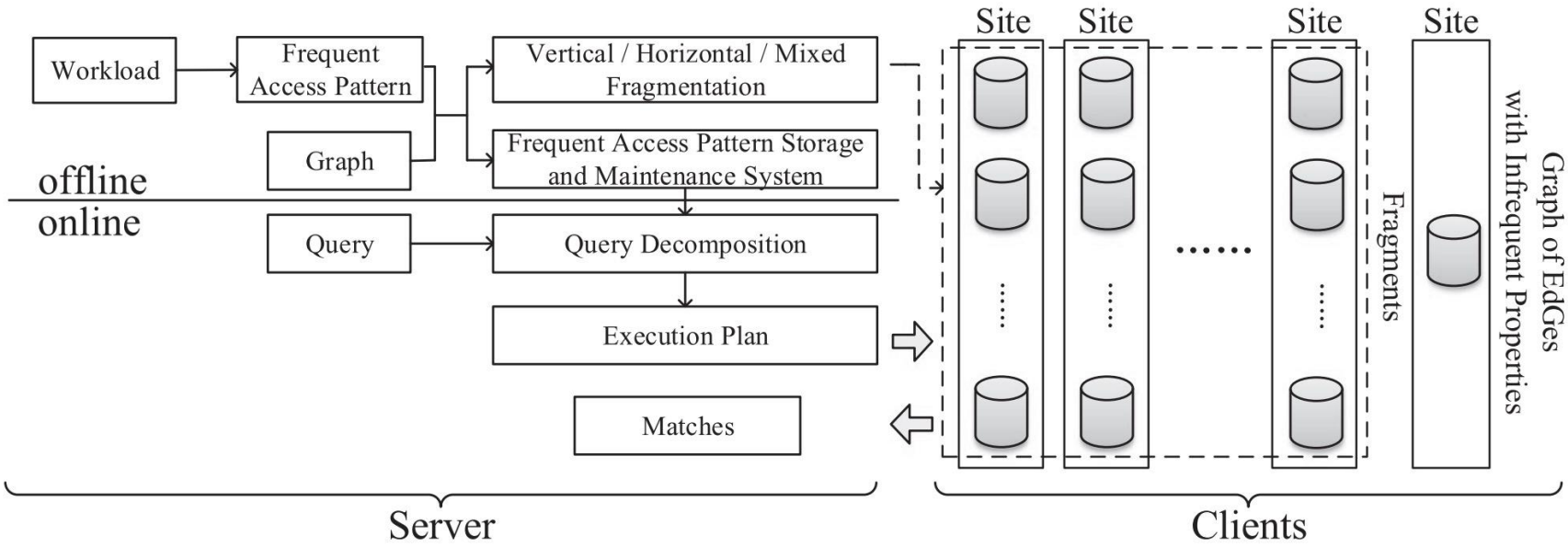
WARP

- Advantages: if a query is isomorphic to the frequent query pattern, there is no inter-partition join and the query performance is very high

VF, HF & MF [Peng et al., EDBT 2016, TKDE 2019]

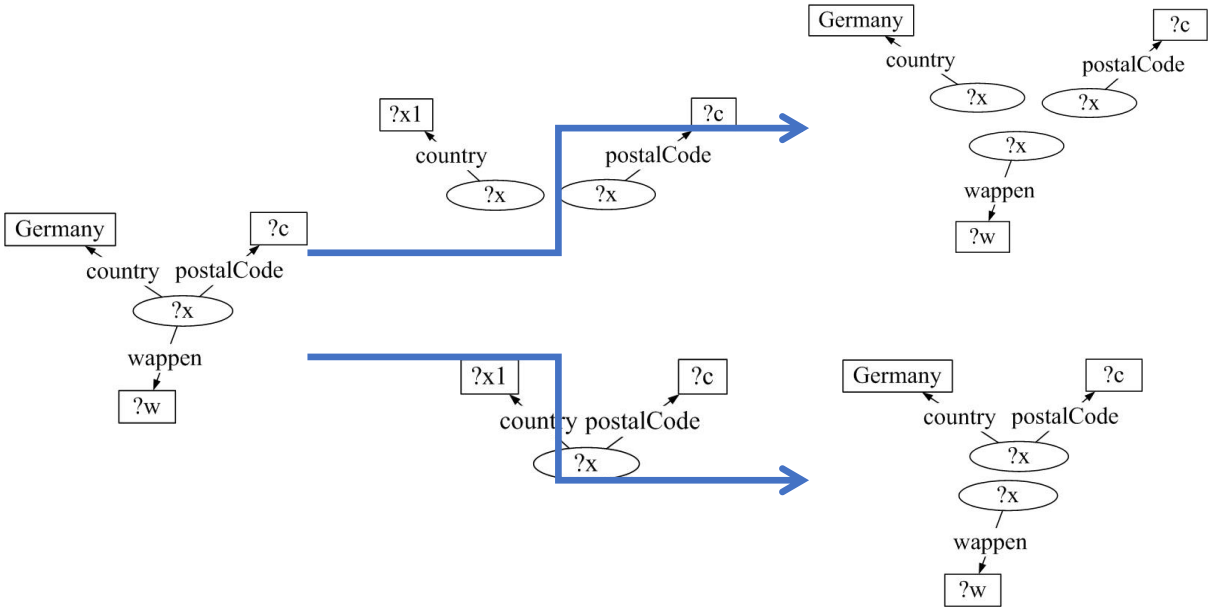
- We first mine and select frequent subgraph patterns, named frequent access patterns, in the query workload
- We propose three fragmentation strategies, vertical, horizontal and mixed fragmentation, based on these patterns and an allocation algorithm to distribute the fragments to the sites in the distributed system
- We propose a cost-aware query optimization method to evaluate a SPARQL query

Framework


Workload
Frequent Access Pattern
Graph
Vertical / Horizontal / Mixed Fragmentation
Frequent Access Pattern Storage and Maintenance System
offline
online
Query
Query Decomposition
Execution Plan
Matches
Server
Site
Site
Site
Site
Fragments
Graph of EdGes with Infrequent Properties
Clients

Frequent Access Pattern Selection

- Not all patterns need to be selected
- Larger patterns have large benefits



Size-increasing Benefit

- The benefit of selecting frequent access pattern p for hitting the query Q is

$$Benefit(p,Q) = |E(p)| \times use(Q,p)$$

where use(Q,p)=1 if pattern p is a subgraph of Q

- Given a set of frequent access patterns P' over the workload $\mathcal{Q}$, its benefit is

$$Benefit(P,\mathcal{Q}) = \sum_{Q_i \in \mathcal{Q}, i=1,\ldots,r} \max_{p \in P}\{Benefit(p,Q_i)\}$$

Storage Constraint

- We normalize a storage constraint to a value SC

$$\sum_{p \in P'} |E([\![p]\!]_G)| \leq SC$$

where $E([\![p]\!]_G)$ means the size of all subgraph matches in G homomorphic to p

Problem Hardness

- Finding a set of frequent access patterns with the largest benefit while subject to the storage constraint is NP-hard

- Thus, we propose a heuristic algorithm which can guarantee the data integrity

Frequent Access Pattern Selection Algorithm

Select all patterns with one edge to guarantee data integrity

Greedy selection of frequent access pattern

The approximation ratio is

$$\min\{\frac{1}{\max_{p\in P}|E(p)|}, \frac{1}{2}(1-\frac{1}{e})\}$$

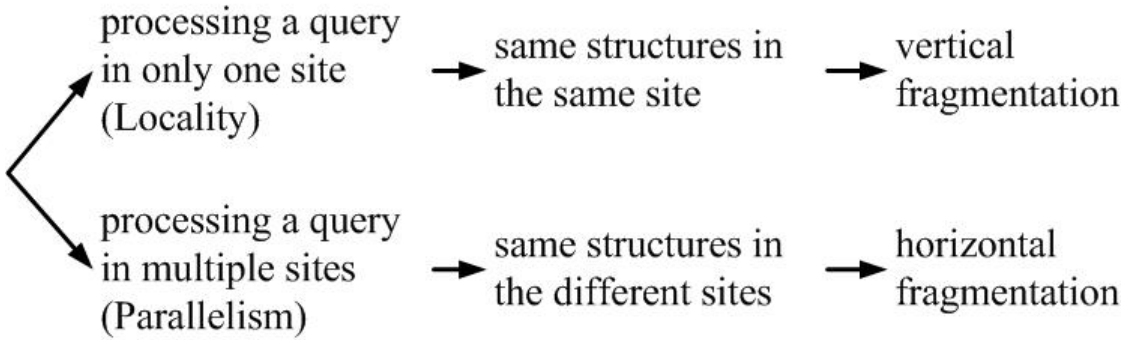
Algorithm 1: Frequent Access Pattern Selection Algorithm

Input: A set of frequent access patterns $P = \{p_1, p_2, ..., p_x\}$
Output: A set $P' \subseteq P$ to generate fragments

1 $P' \leftarrow \emptyset$;
2 $TotalSize \leftarrow 0$;
3 **for** *each* $p \in P$ *and* p *has only one edge* **do**
4 $\quad P' \leftarrow P' \cup \{p\}$;
5 $\quad P \leftarrow P - \{p\}$;
6 $\quad TotalSize \leftarrow TotalSize + |E([\![p]\!]_G)|$;
7 $P_1 \leftarrow argmax\{\frac{Benefit(\{p_i\},Q)}{|E([\![p_i]\!]_G)|} : p_i \in P, |E([\![p_i]\!]_G)| + TotalSize \leq SC \wedge |E(p)| > 1\}$;
8 $P_2 \leftarrow \emptyset$;
9 $TotalSize' \leftarrow 0$;
10 **while** $TotalSize' \leq SC - TotalSize$ **do**
11 $\quad$ Find the frequent access pattern $p' \in P - P'$ with the largest additional value of $\frac{Benefit(\{p'\}\cup P',Q)-Benefit(P',Q)}{|E([\![p']\!]_G)|}$;
12 $\quad P_2 \leftarrow P_2 \cup \{p'\}$;
13 $\quad P \leftarrow P - \{p'\}$;
14 $\quad TotalSize' \leftarrow TotalSize' + |E([\![p']\!]_G)|$;
15 **if** $Benefit(P' \cup P_1, Q) \geq Benefit(P' \cup P_2, Q)$ **then**
16 $\quad$ Return $P' \cup P_1$;
17 Return $P' \cup P_2$;

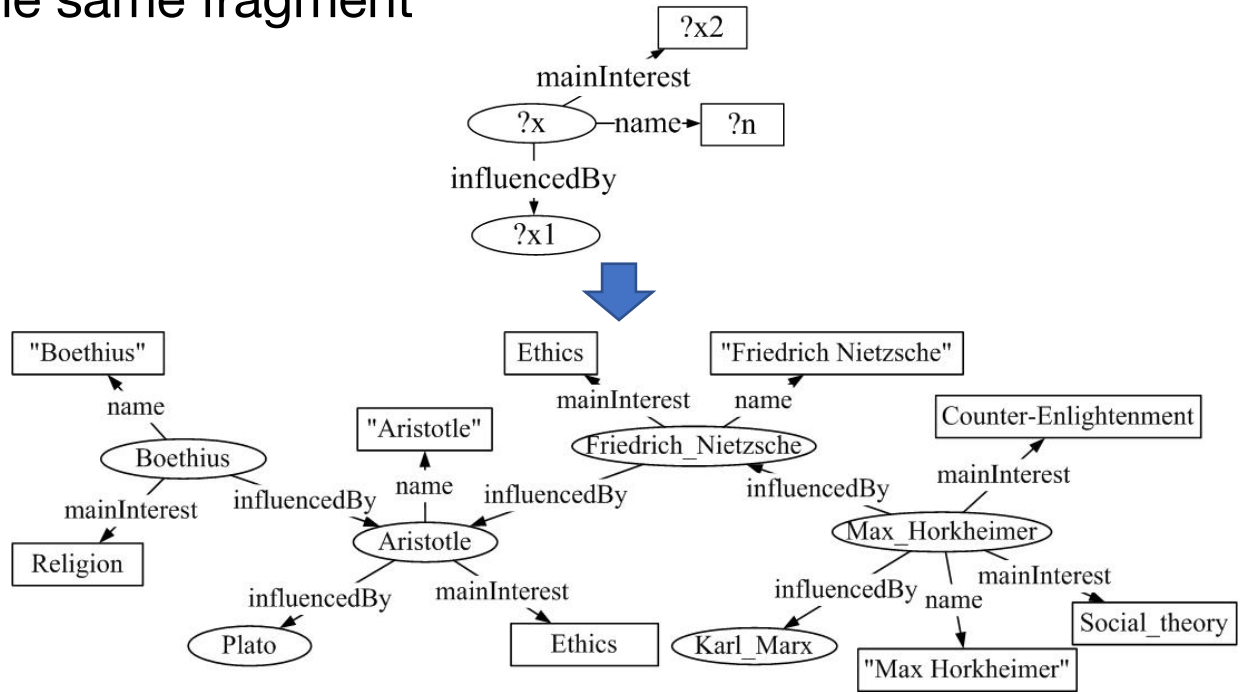
Fragmentation Framework

- In this paper, we present two fragmentation strategies: vertical and horizontal



Vertical Fragmentation

- All matches homomorphic to the same frequent access pattern into the same fragment



Fragmentation Framework

- We put matches of one frequent access pattern into the different fragments

- We extend the concepts of simple predicate and minterm predicate divide the RDF graph horizontally.

Structural Simple Predicate

- Given a frequent access pattern p with variables set $\{var_1, var_2, ..., var_n\}$, a structural simple predicate sp defined on Q_c, has the following form.

$$sp : p(var_i)\ \theta\ Value$$

where $\theta \in \{=, \neq\}$ and Value is a constant constraint for var_i chosen from a query containing p in Q_c.

Structural Minterm Predicate

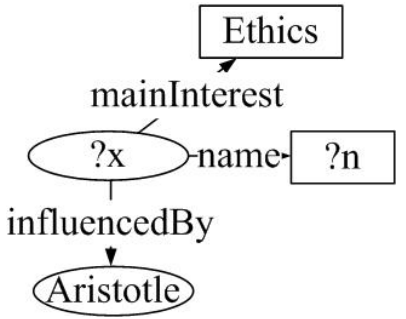
- Given a set of structural simple predicates SP = {sp_1, sp_2, ..., sp_y}

  for frequent access pattern p, a structural minterm predicate mp_i is

$$mp_i = \bigwedge_{sp_k \in SP} sp_k, 1 \le k \le y$$

  where $sp_k{}^* = sp_k$ or $sp_k{}^* = \neg sp_k$

Example Structural Simple and Minterm Predicates



$$sp_1 : p(?x1) = Aristotle;$$

$$sp_2 : p(?x1) \neq Aristotle;$$

$$sp_3 : p(?x2) = Ethics;$$

$$sp_4 : p(?x2) \neq Ethics.$$

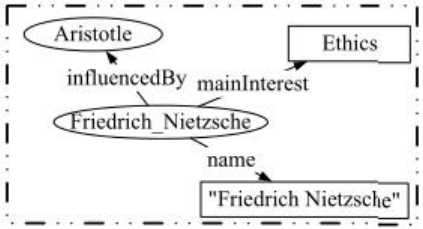
$$mp_1 : p(?x0) = Aristotle \wedge p(?x1) = Ethics;$$

$$mp_2 : p(?x0) = Aristotle \wedge p(?x1) \neq Ethics;$$

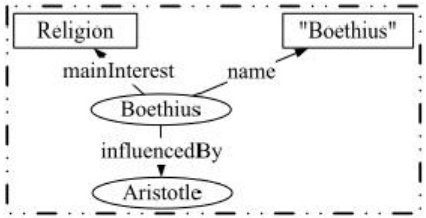
$$mp_3 : p(?x0) \neq Aristotle \wedge p(?x1) = Ethics;$$

$$mp_4 : p(?x0) \neq Aristotle \wedge p(?x1) \neq Ethics.$$

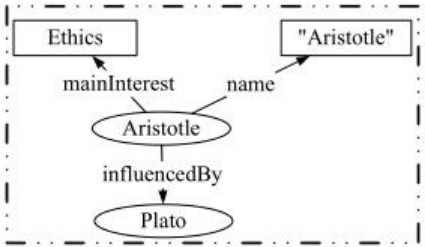
Example Horizontal Fragments



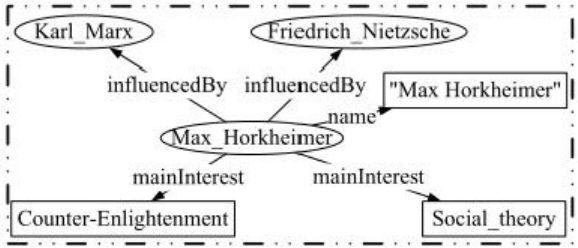
(a) Example Horizontal Fragment Generated from mp_1



(b) Example Horizontal Fragment Generated from mp_2



(c) Example Horizontal Fragment Generated from mp_3



(d) Example Horizontal Fragment Generated from mp_4

Mixed Fragmentation

- In our mixed fragmentation, we keep some frequent access patterns (P^v) for the vertical fragmentation but others (P^h) are designed for horizontal fragmentation

Classification of Frequent Access Patterns

- Given a frequent pattern p, let M(p) denote all structural minterm predicates that are derived from pattern p.
- The classification strategy is based on the access frequencies of the FAPs and corresponding structural minterm predicates to divide M(p) into two subsets:

$$M'(p) = \{mp | mp \in M(p) \wedge acc(mp) \geq minSup\}$$
$$M''(p) = \{mp | mp \in M(p) \wedge acc(mp) < minSup\}$$

Mixed Fragmentation Strategy

- Given a selected frequent access pattern p, we have the following fragmentation strategy:
  1. If $\sum_{mp \in M''(p)} ac(mp) \geq$ minSup, we vertically partition the RDF graph based on pattern p, i.e., $p \in P^v$;
  2. If $\sum_{mp \in M''(p)} ac(mp) <$ minSup, we horizontally partition the RDF graph based on frequent structural minterm predicates M'(p) that are derived from pattern p, i.e., $p \in P^h$.

Allocation

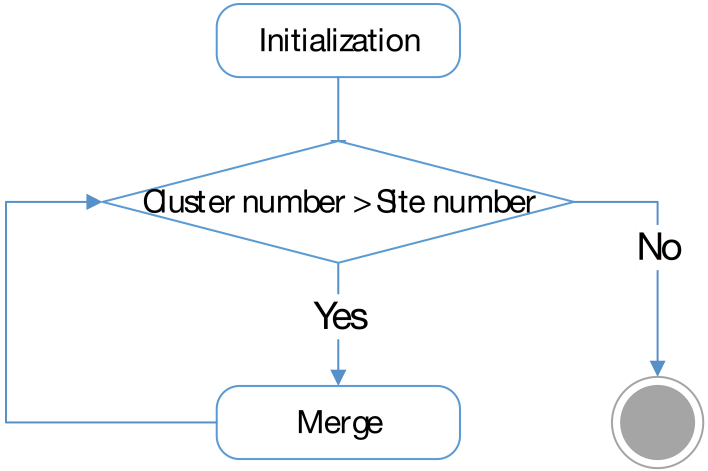
- Two fragments should be placed in one site if they are often accessed together

Fragment Affinity Metric

- The fragment affinity metric between two fragments F and F' with respect to the workload $Q = \{Q_1, Q_2, ..., Q_r\}$ is defined as follows
  1. Given two vertical fragments F and F' generated from frequent access patterns p and p', $aff(F, F') = \sum_{k=1}^{r} use(Q_k, p) \times use(Q_k, p')$;
  2. Given two horizontal fragments F and F' generated from structural minterm predicates mp and mp', $aff(F, F') = \sum_{k=1}^{r} use(Q_k, mp) \times use(Q_k, mp')$;
  3. Given two fragments F and F' in mixed fragmentation generated from FAP p and structural minterm predicate mp, if mp is not generated from p, $aff(F, F') = \sum_{k=1}^{r} use(Q_k, p) \times use(Q_k, mp)$; otherwise, $aff(F, F') = 0$

Allocation Algorithm

- We extend a clustering algorithm, PNN, to cluster all fragments

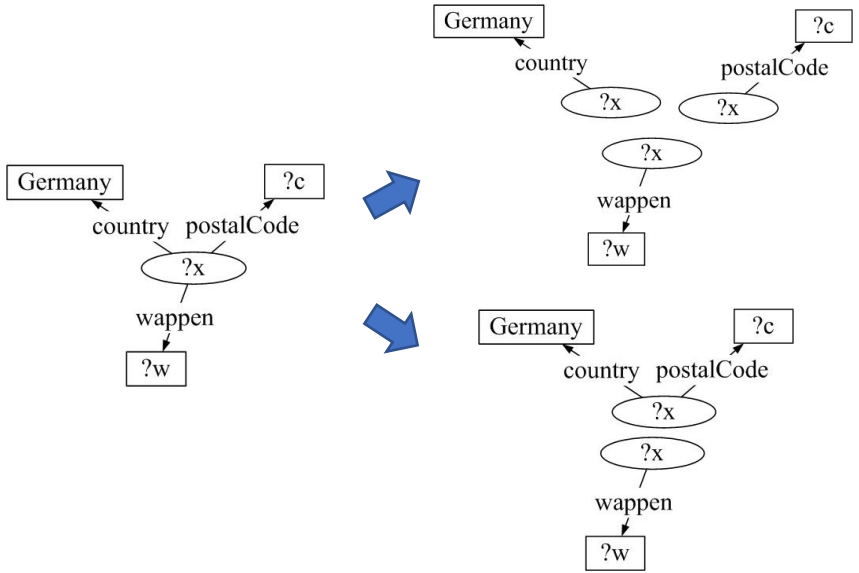


Data Dictionary

- The global statistics of fragmentation and allocation need to be stored and maintained in data dictionary
  1. fragment definitions
  2. fragment sizes
  3. site mappings
  4. access frequencies
  5. ……

Query Decomposition

- During query evaluation, we first decompose the query based on the frequent access patterns



Cost of Query Decomposition

- The cost of a decomposition is

$$\cos t(D) = \prod_{q \in D} card(q_i)$$

where D is a decomposition result and card(q_i) is the number of matches for q_i

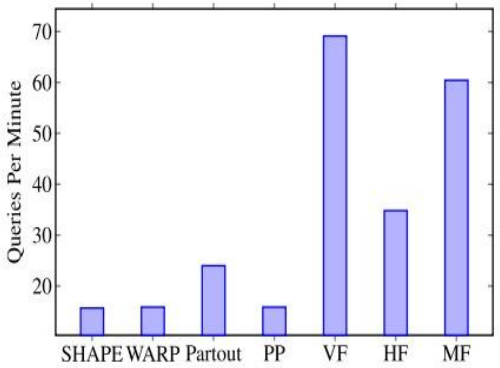
Query Optimization and Execution

- We extend the algorithm of System-R to find the optimal execution plan for joining the results of all subqueries
- Each subquery is executed in the corresponding sites in parallel
- We join them together according to the optimal execution plan

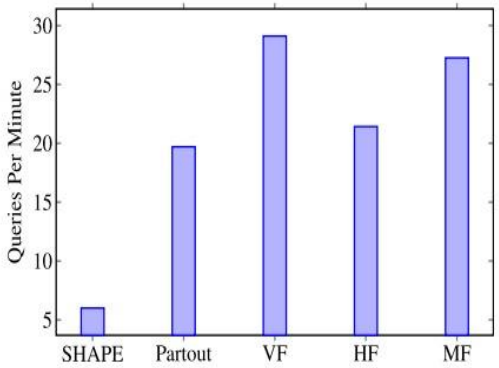
Experiments

- Datasets: DBPedia (about 330 millions triples) and WatDiv (50 millions to 250 million triples)
- Workload: 8 millions queries of DBPedia and 2 thousands queries of WatDiv
- Competitor: WARP and SHAPE
- Environment: 10 machines running Linux in a LAN

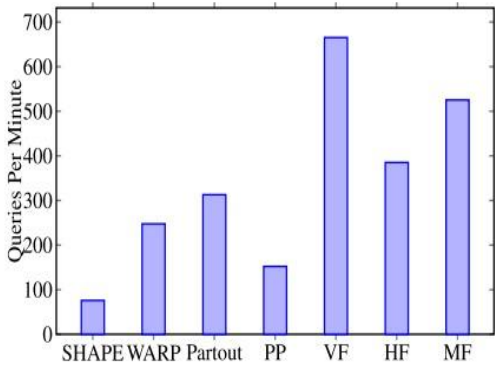
Throughput



(a) **DBpedia**

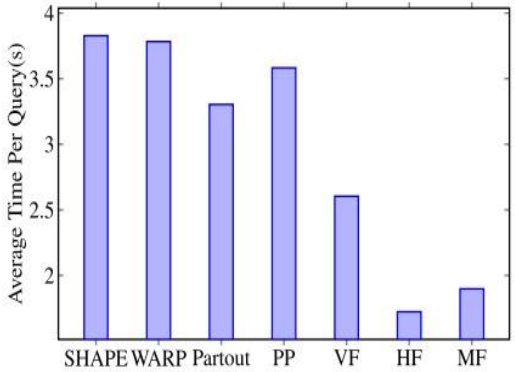


(b) **LinkedGeoData**

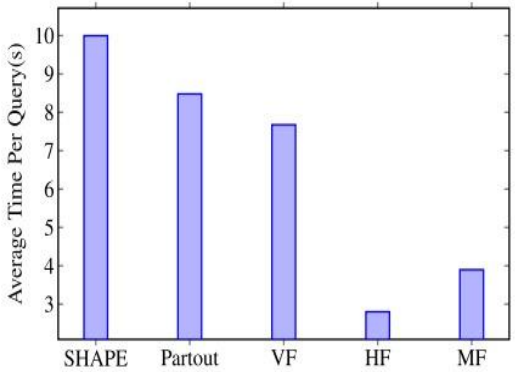


(c) **WatDiv**

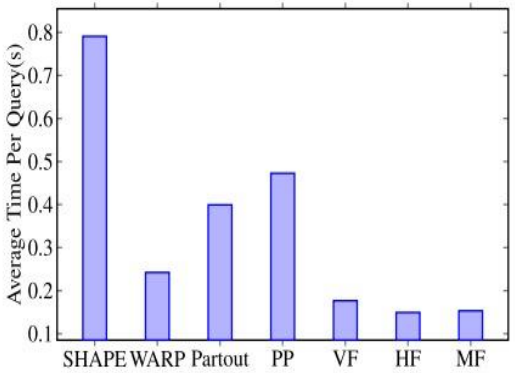
Response Time



(a) **DBpedia**



(b) **LinkedGeoData**



(c) **WatDiv**

Scale-out Systems

Partitioning-based Appoarches

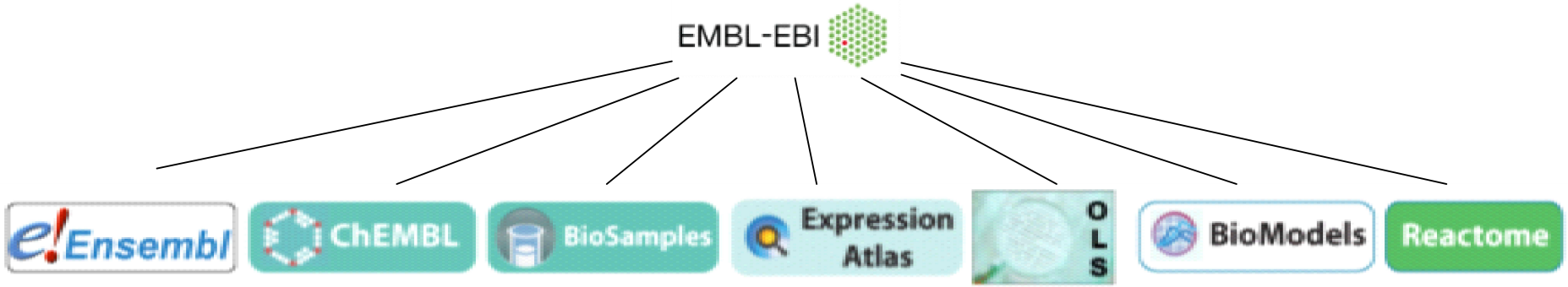
- Workload-agnostic Appoarches
- Workload-aware Appoarches

Partitioning-agnostic Approaches

- gStore^{D}

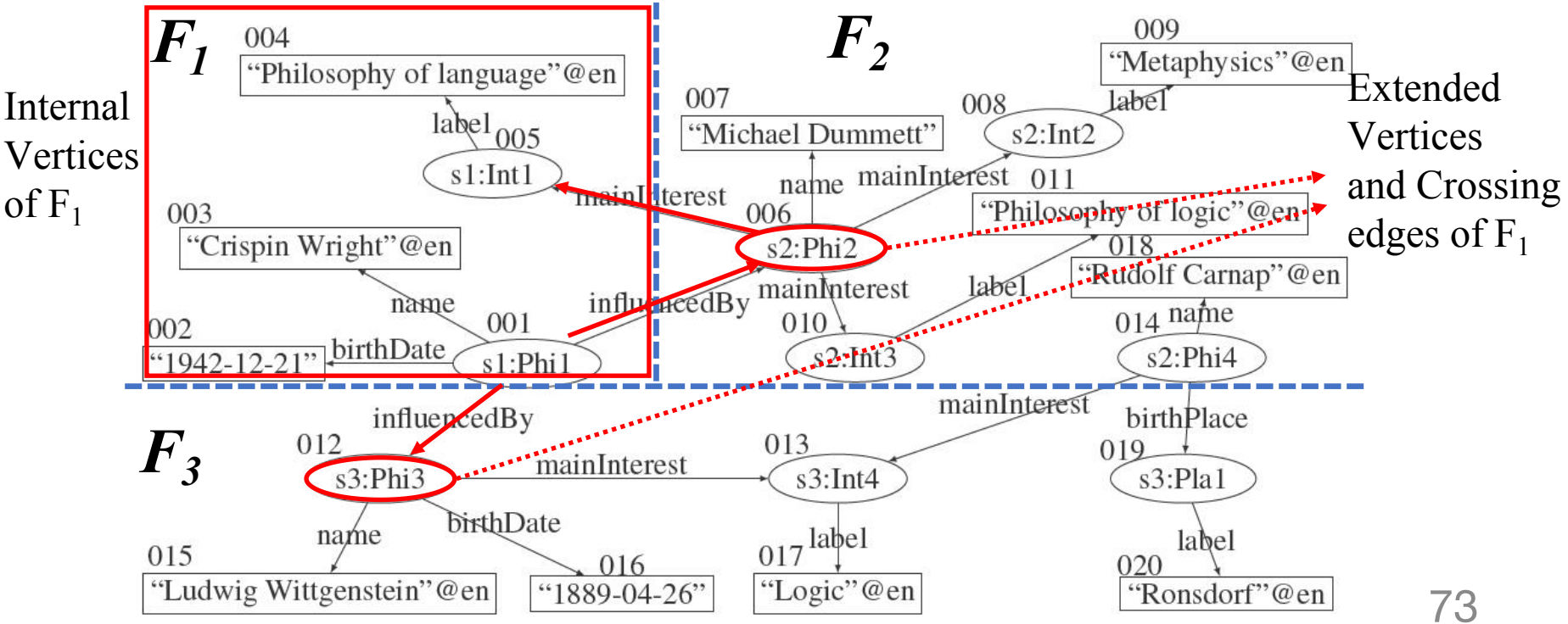
Partitioning-agnostic Application

- In some applications, the RDF graph partitioning strategy is not controlled by the distributed RDF system itself



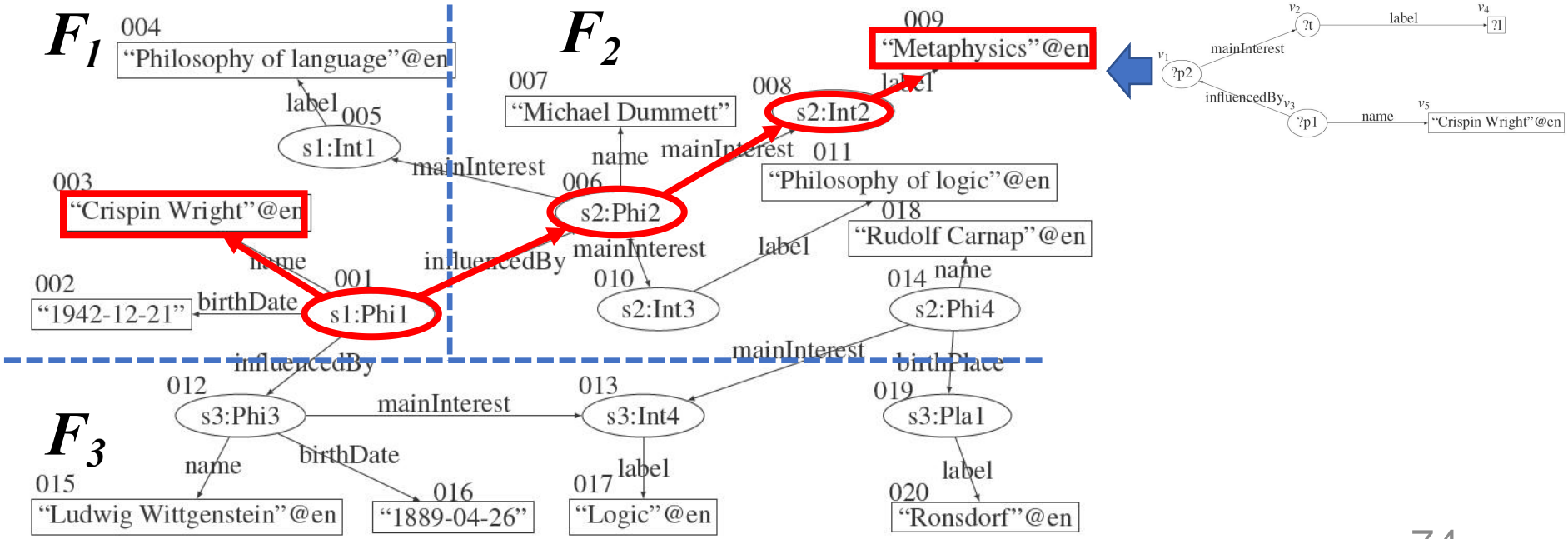
Distributed RDF Graphs

- An RDF graph is vertex-disjoint partitioned through different sites



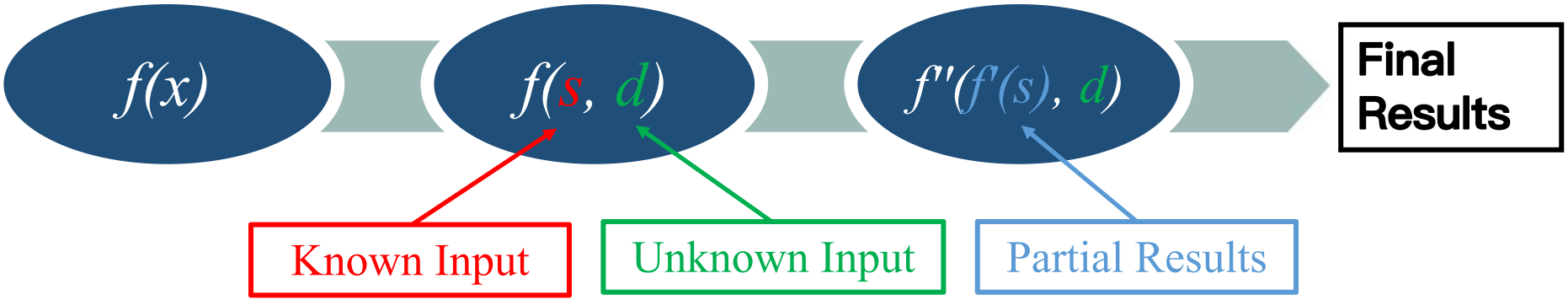
Partial Evaluation

- "Partial evaluation" framework is used for distributed SPARQL query evaluation



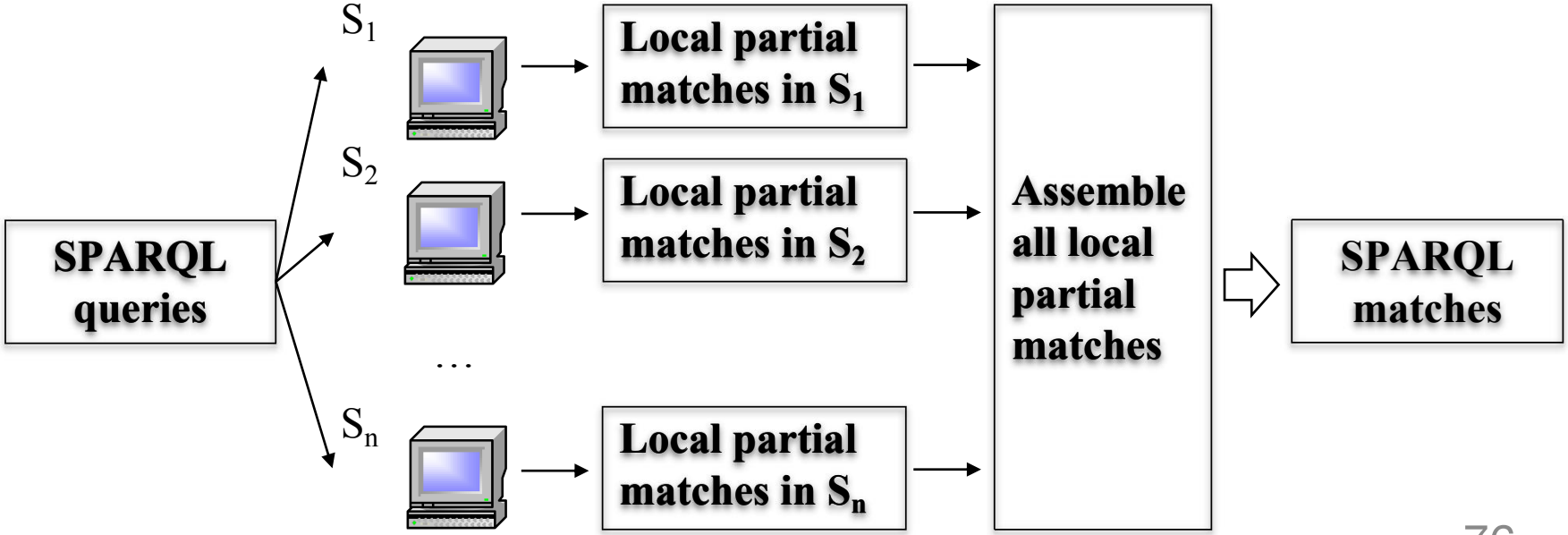
Partial Evaluation

- Partial Evaluation is a framework widely used for evaluating queries on distributed graphs



Partial Evaluation Framework [Peng et al., VLDBJ 2016, ICDE 2019]

- We propose a distributed RDF system, named gStore^D, to evaluate SPARQL queries in a "partial evaluation" framework.

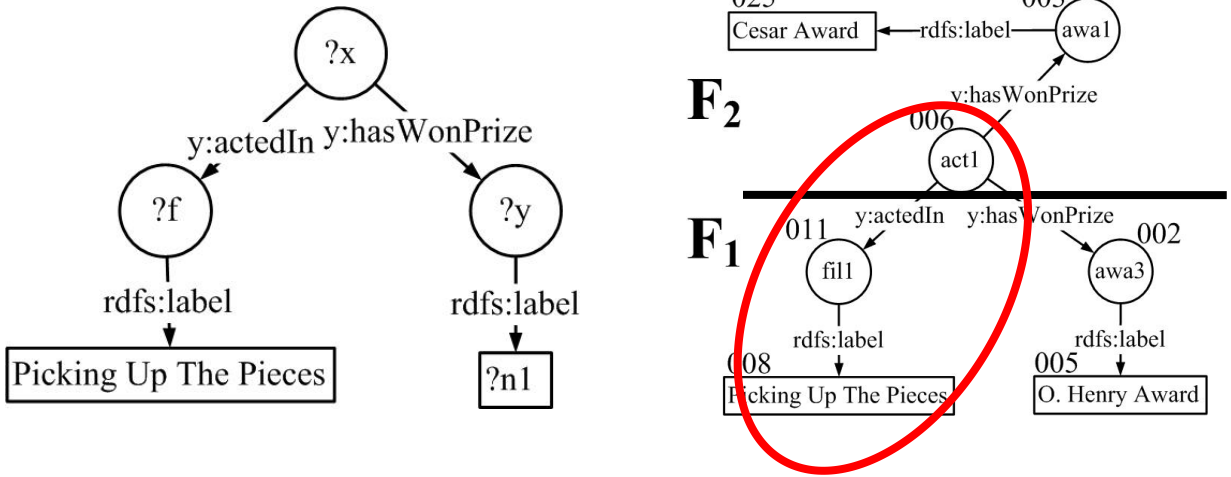


Definition of Local Partial Match

- Given a query Q with n vertices $\{v_1, ..., v_n\}$ and a subgraph PM with m vertices $\{u_1, ..., u_m\}$ ($m \leq n$) in a fragment F_k, PM is a local partial match in fragment F_k if and only if there exists a function $f : \{v_1, ..., v_n\} \rightarrow \{u_1, ..., u_m\} \cup \{NULL\}$, where the following conditions hold:
  1. If $f(v_i)$ is an internal vertex in F_k and v_j is a neighbor, $f(v_j) \neq NULL$;
  2. If $f(v_i)$ and $f(v_j)$ are both internal vertices in PM, then there exists a weakly connected path π between v_i and v_j in Q and each vertex in π maps to an internal vertex of F_k in PM.

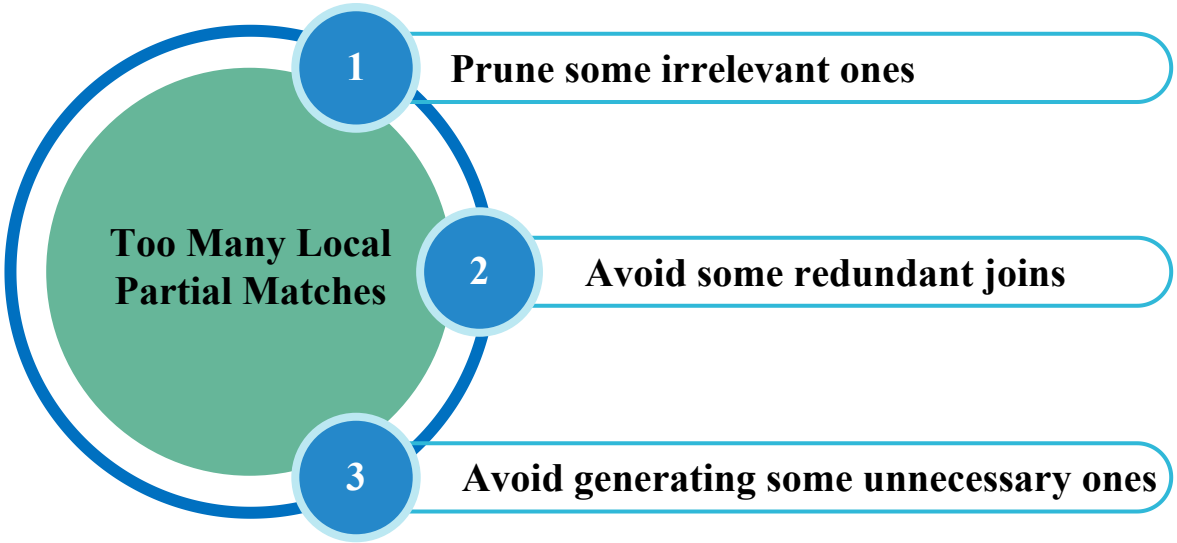
Example Local Partial Matches

- We propose a distributed RDF system, named gStore^D, to evaluate SPARQL queries in a “partial evaluation” framework.



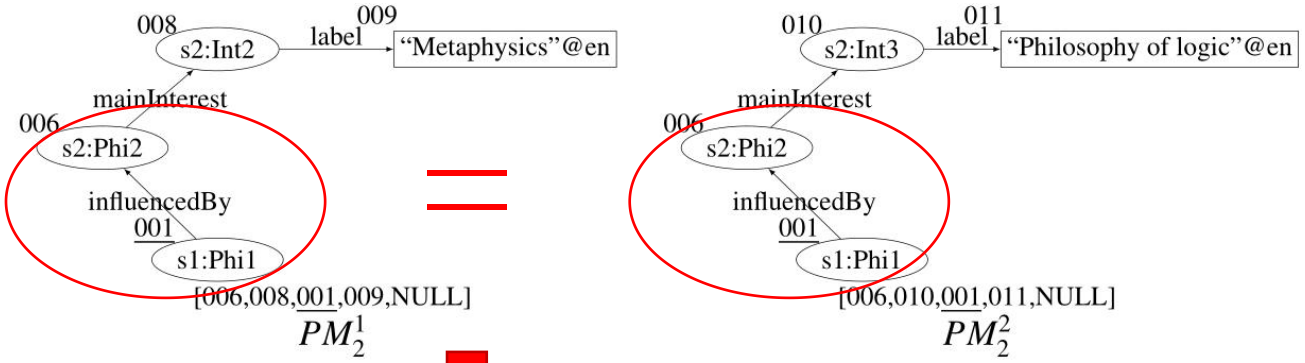
There may be too many local partial matches!!!

Three Optimizations



Properties of Local Partial Matches

- Two local partial matches of the same crossing edges from the same fragment have the same structures.



Local Partial Match Equivalence Class (LEC)

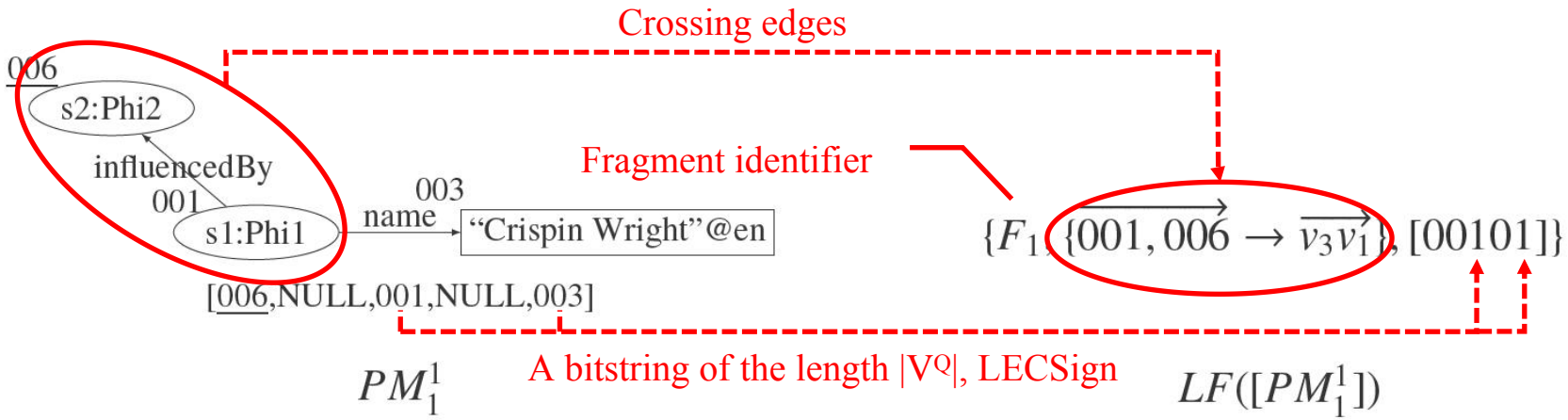
- All local partial matches of the same crossing edges from the same fragment are put into the same class

$$PM_2^1 \sim PM_2^2$$

$$[PM_2^1] = \{PM_2^i \mid PM_2^i \sim PM_2^1\}$$
$$= \{PM_2^1, PM_2^2\}$$
$$= [PM_2^2]$$

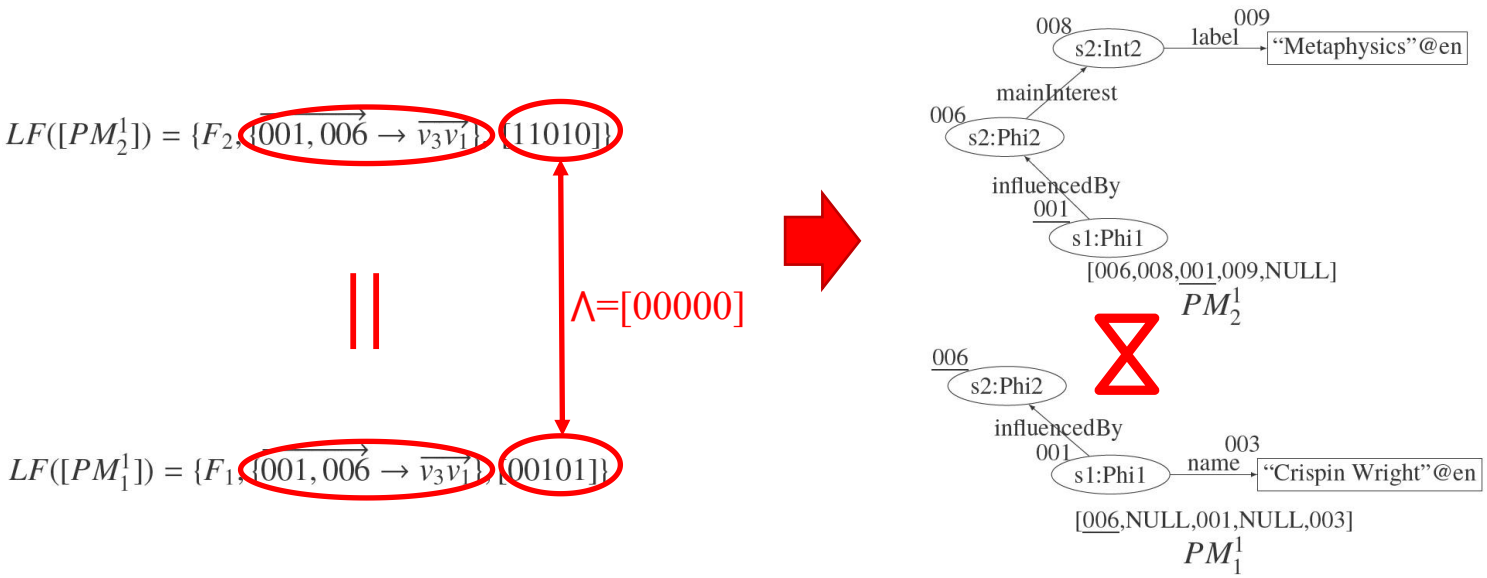
LEC Feature

- The structural information of a LEC is maintained in a compact data structure called LEC feature



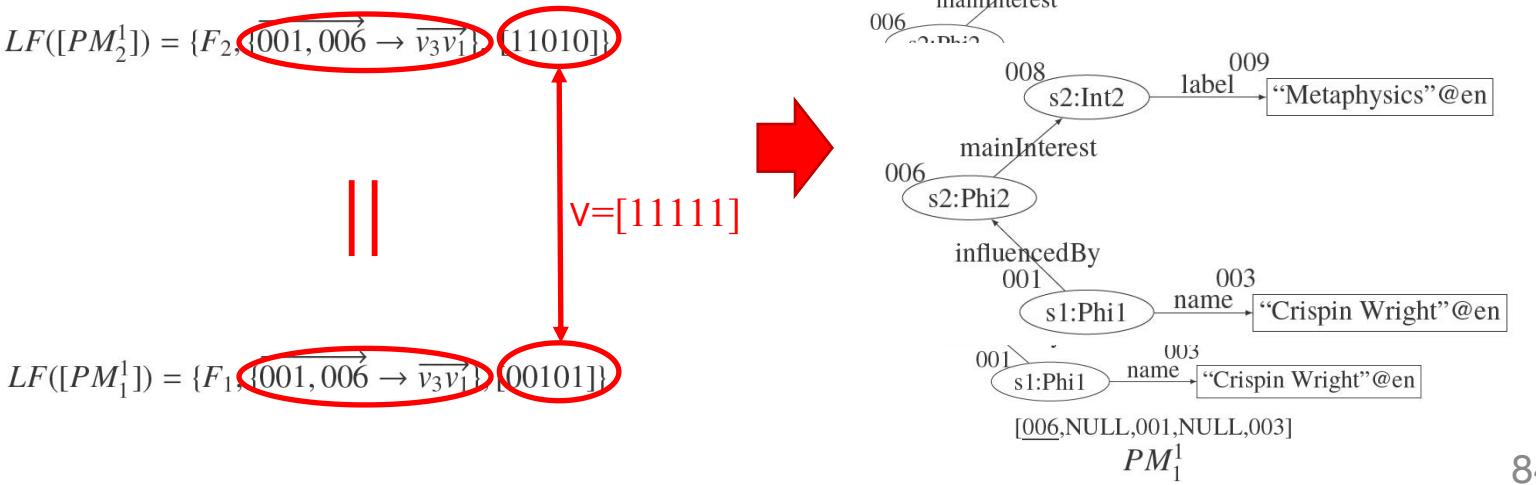
Joinable

- Two LEC features can join if they share the same crossing edges and all bits in the AND result of their LECSigns are 0

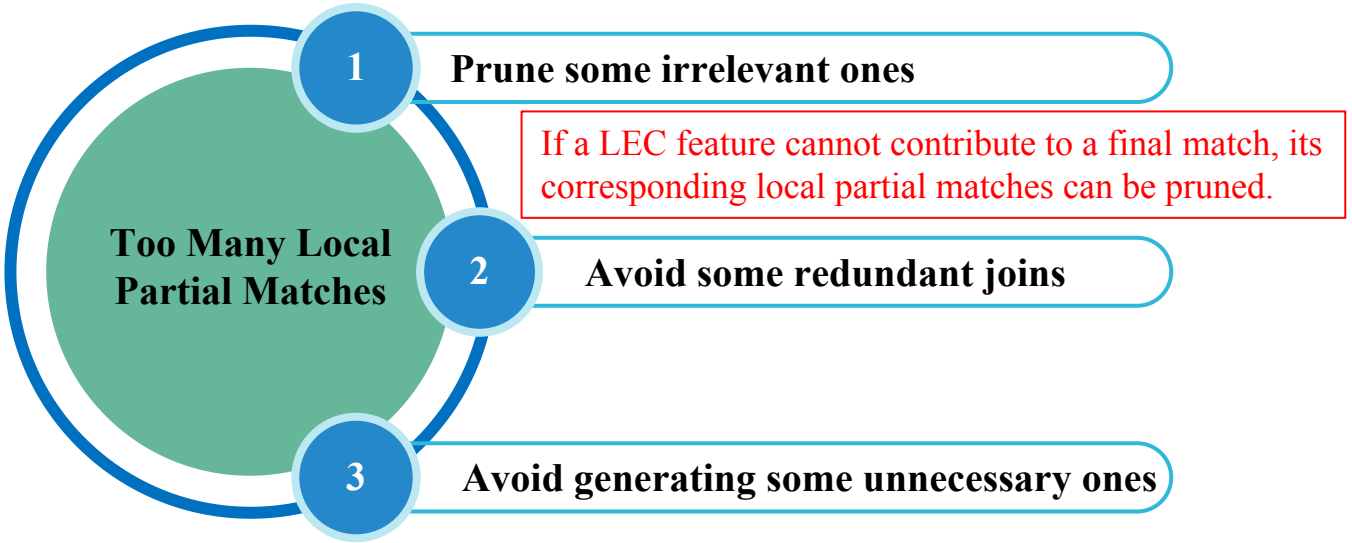


Joinable

- A local partial match can contribute to a final match if its LEC feature can join with some LEC features and all bits in the OR result of their LECSigns are 1



Optimizations based on LEC Features



The optimization is partition bounded in both response time and data shipment

LEC Feature-based Local Partial Match Group

- If the LECSigns of two local partial matches are the same, they cannot join together

Group 2

$$LF([PM_1^1]) = \{F_1, \{\overrightarrow{001, 006} \rightarrow \overrightarrow{v_3v_1}\}, [00101]\}$$
$$LF([PM_1^2]) = \{F_1, \{\overrightarrow{001, 012} \rightarrow \overrightarrow{v_3v_1}\}, [00101]\}$$

$$LF([PM_1^3]) = \{F_1, \{\overrightarrow{006, 005} \rightarrow \overrightarrow{v_1v_2}\}, [01010]\}$$

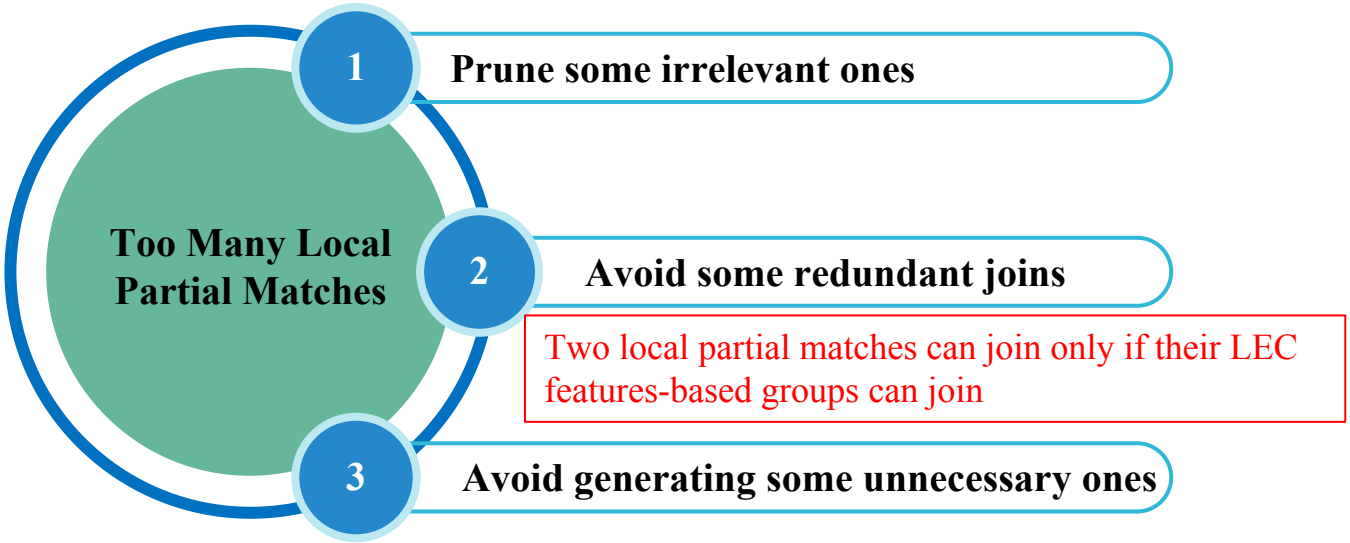
Group 1

Group 3

$$LF([PM_2^1]) = \{F_2, \{\overrightarrow{001, 006} \rightarrow \overrightarrow{v_3v_1}\}, [11010]\}$$
$$LF([PM_3^1]) = \{F_3, \{\overrightarrow{001, 012} \rightarrow \overrightarrow{v_3v_1}\}, [11010]\}$$

$$LF([PM_3^2]) = \{F_3, \{\overrightarrow{014, 013} \rightarrow \overrightarrow{v_1v_2}\}, [01010]\}$$

Optimizations based on LEC Feature-based Group



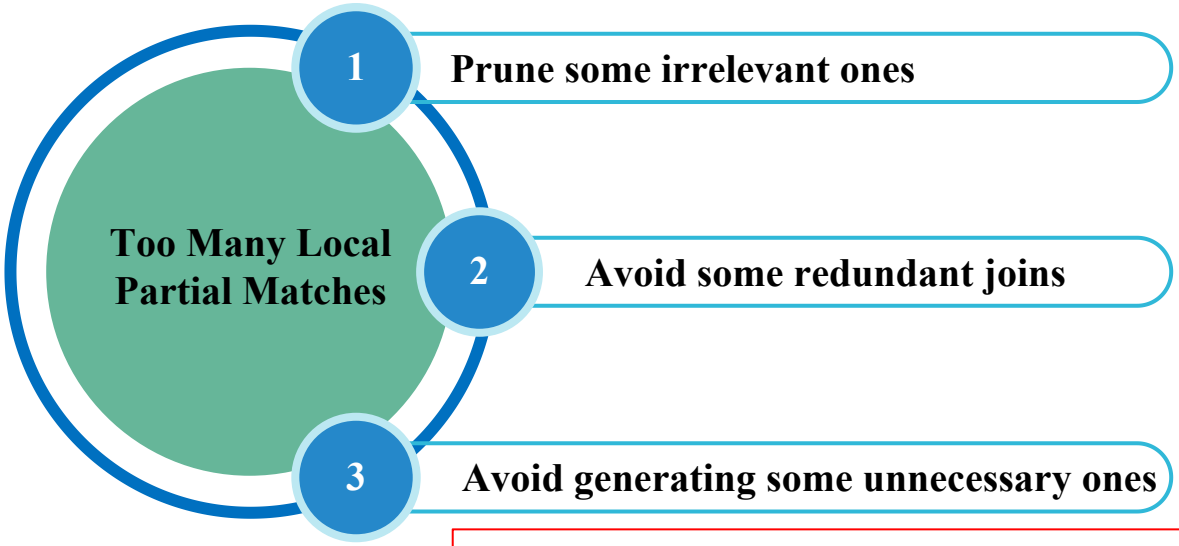
Assembling Internal Candidates

A vertex occurring in a final match must be an internal vertex of a fragment

We can prune a candidate of a variable that is only an extended vertex of fragments

We can avoid generating the local partial matches from the above candidates

Optimizations based on Internal Candidates

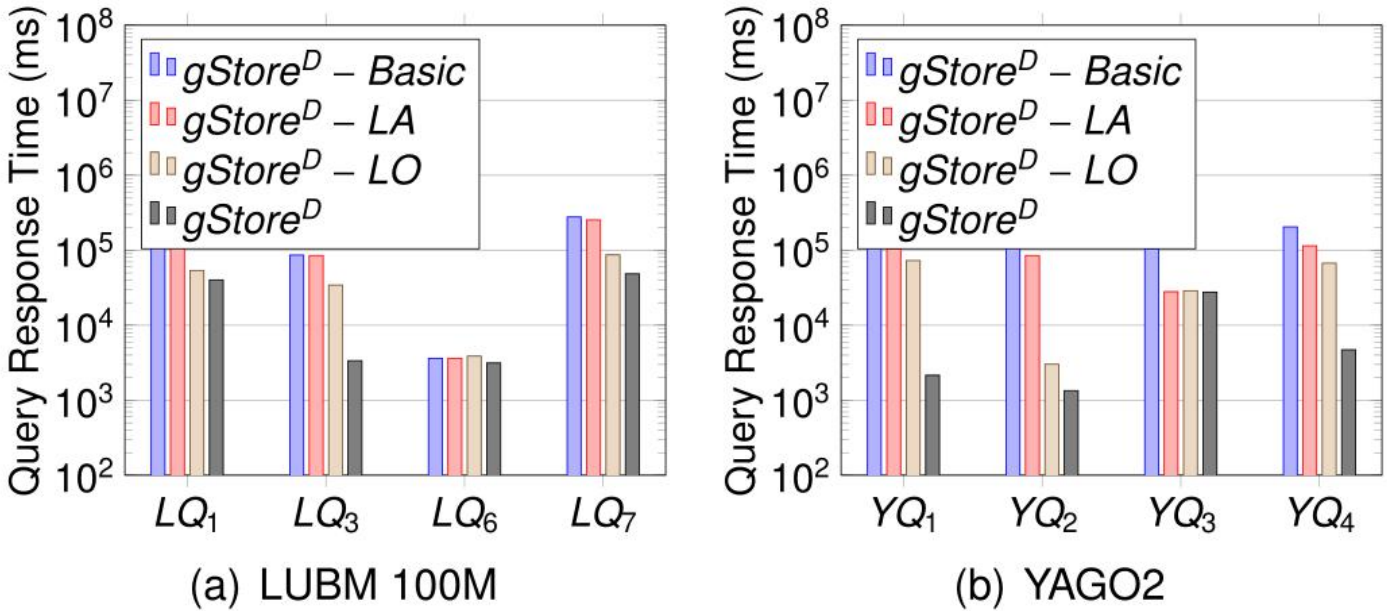


We use the internal candidates of all variables in each site to filter out some false positives.

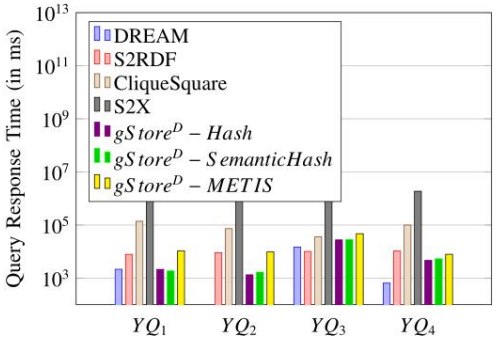
Experiments

- Datasets: YAGO2 (about 284 millions triples), BTC (about 1 billion triples) and LUBM (100 millions to 1 billion triples)
- Competitor: DREAM, S2X, S2RDF and CliqueSquare
- Environment: 12machines running Linux in a LAN

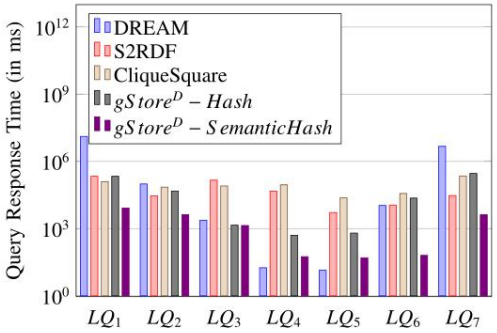
Evaluation of Different Optimizations



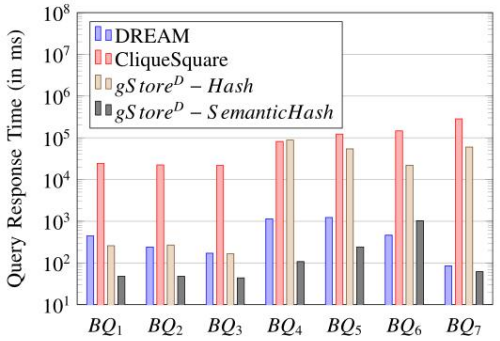
Online Performance Comparison



(a) YAGO2



(b) LUBM 1B



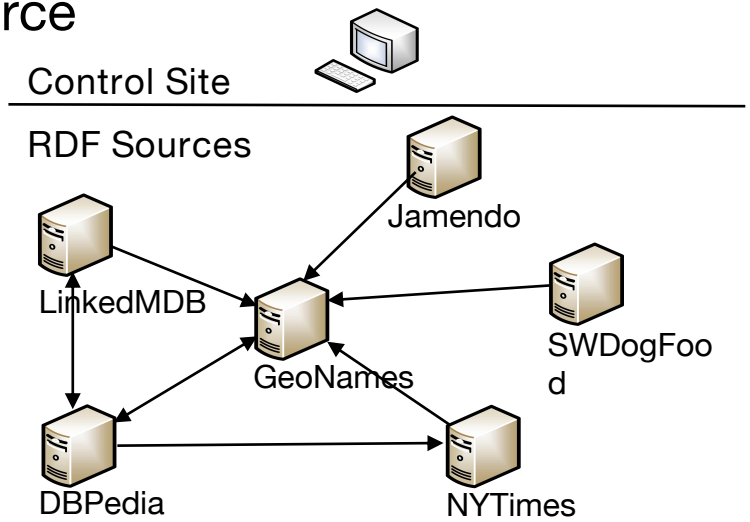
(c) BTC

Part 3

Federated Systems

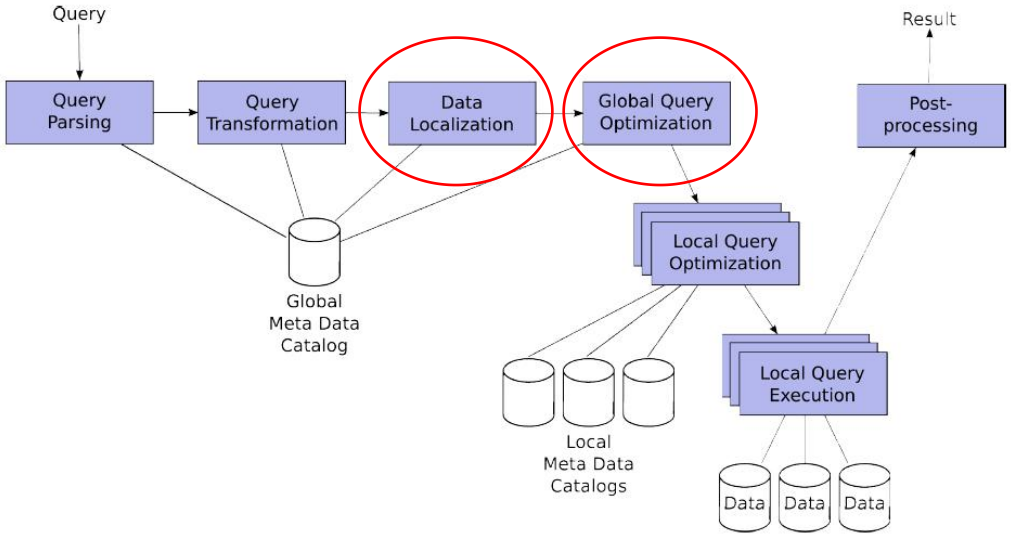
Federated RDF Systems

- A federated RDF system consists of multiple "autonomous" sites which store their own RDF data and provide SPARQL query interfaces. Here, an autonomous site with a SPARQL interface is called an RDF source

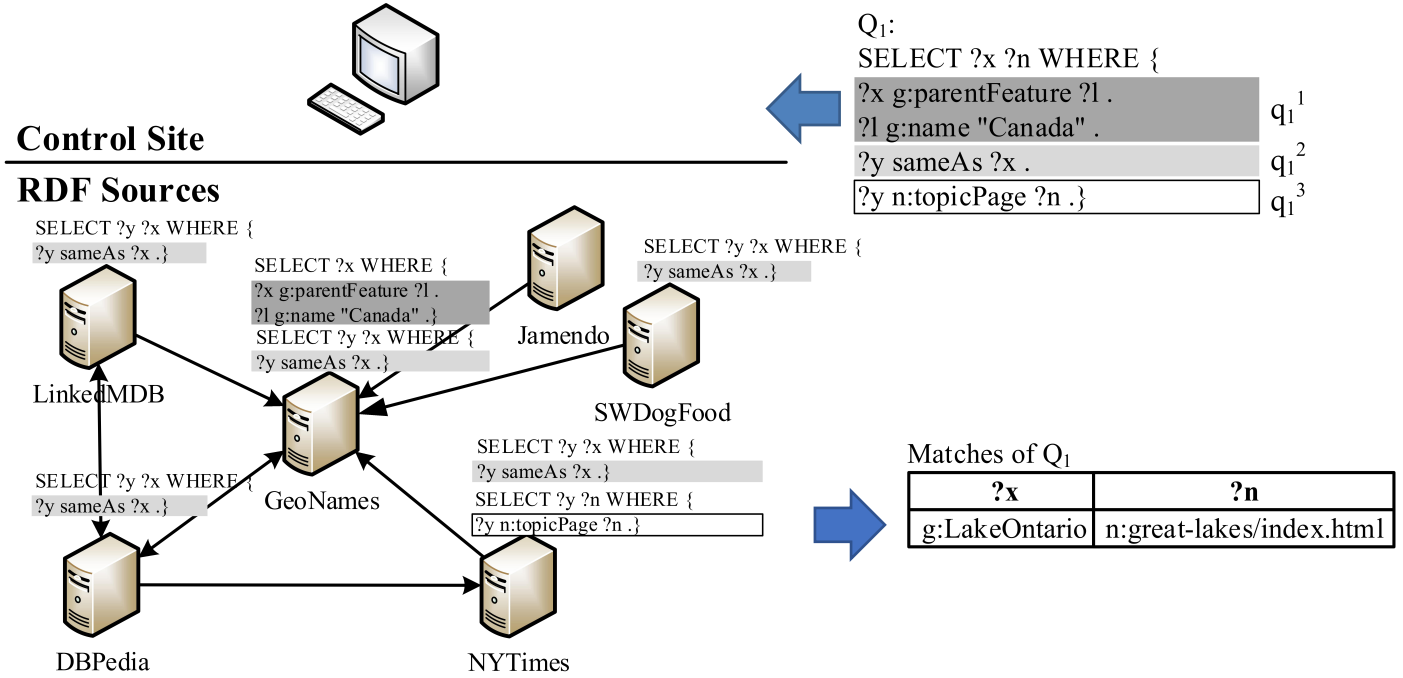


Existing Approaches

- Most of them focus on query decomposition and source selection



Federated SPARQL Query Processing



Federated RDF Systems

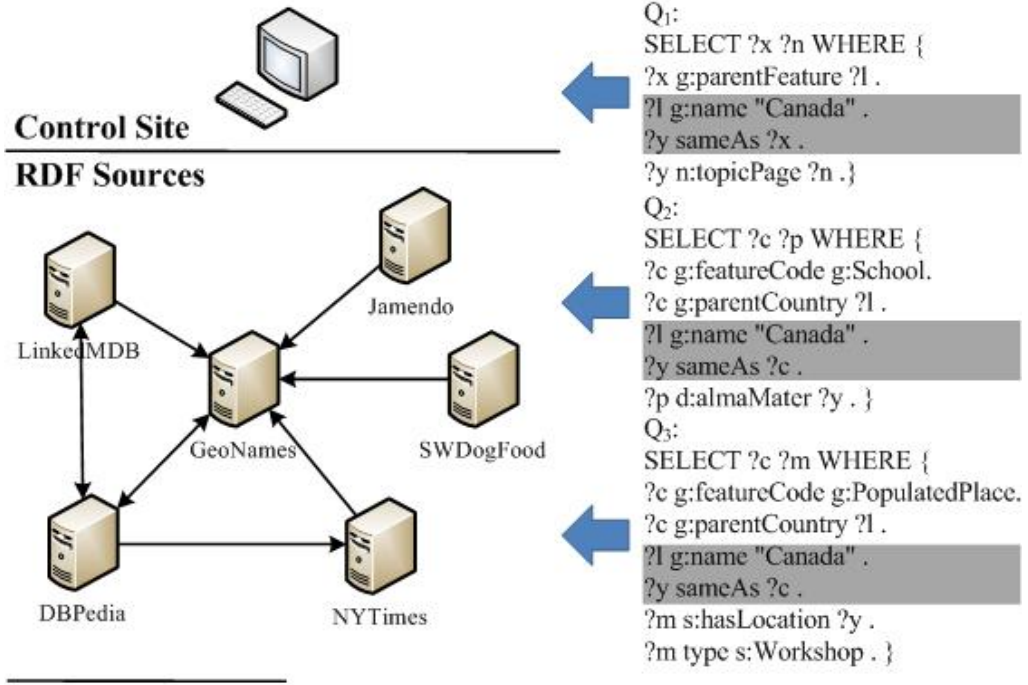
Metadata-based approaches

- Use the metadata to determine which sources are relevant
  - DARQ [Quilitz & Leser, ESWC 2008]
  - QTree [Harth et al., WWW 2010; Prasser et al., EDBT 2012]
  - . . .

ASK query-based approach

- Asking whether or not a triple pattern has an answer at a source
  - FedX [Schwarte et al., ISWC 2011]

Multi-Query Optimization [Peng et al., DASFAA 2018, TKDE 2021]

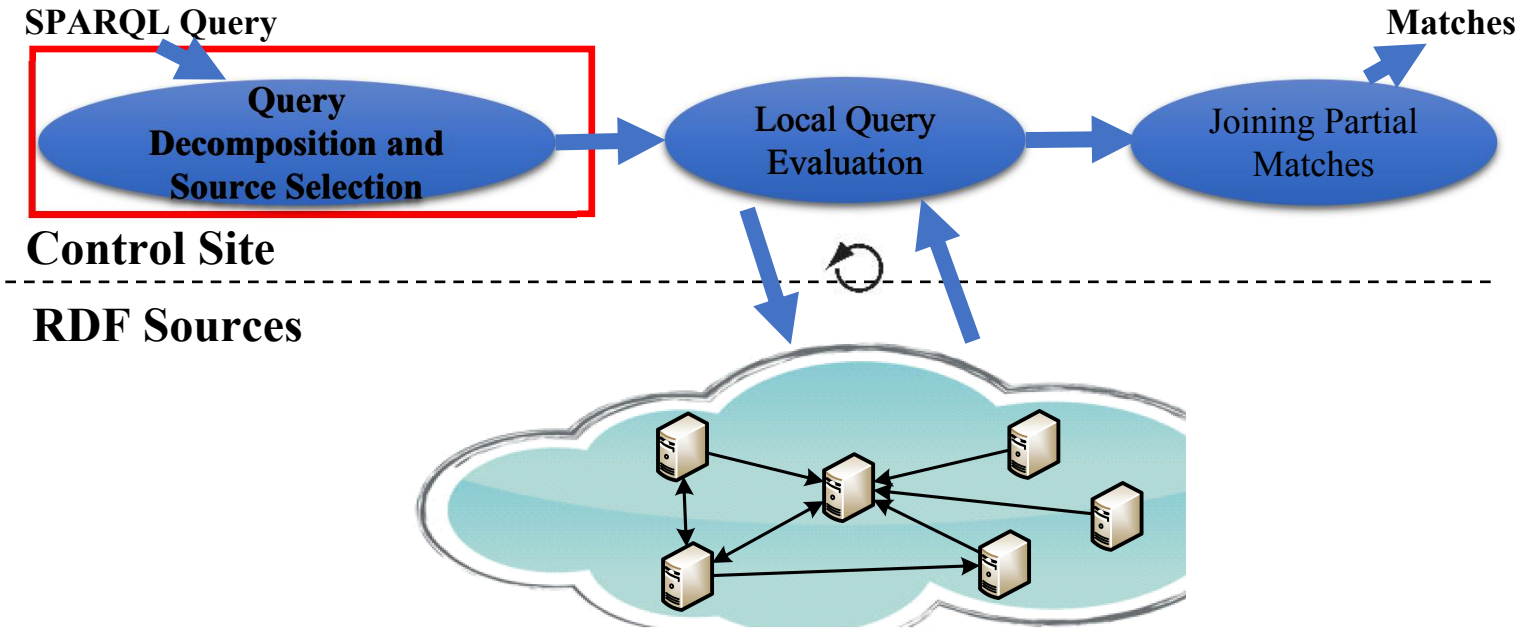


The shaded triple patterns correspond to the common subgraph during each iteration.

Main Ideas

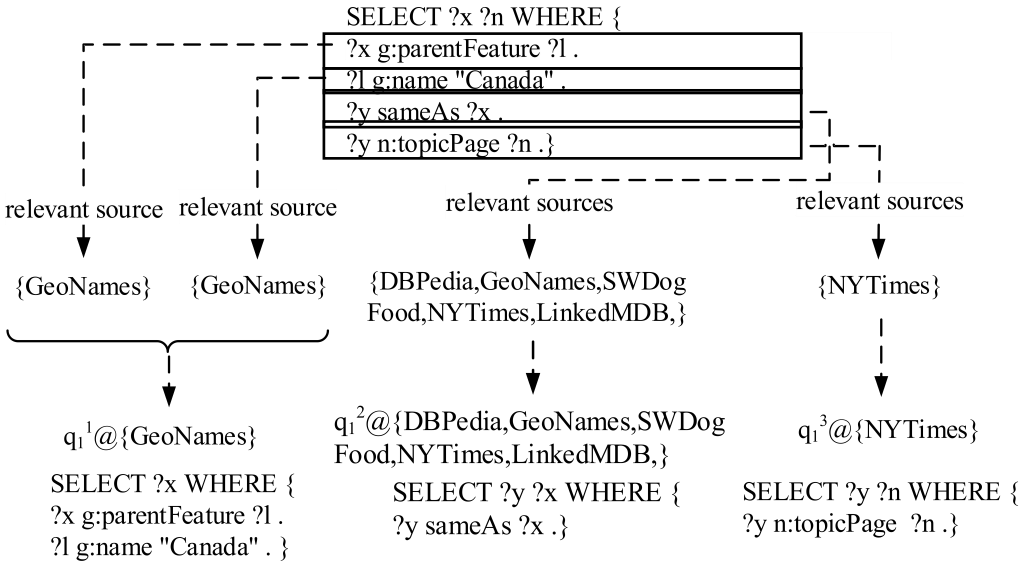
- A query rewriting-based approach for query evaluation on RDF sources while considering the cost of both query evaluation and data shipment
- An effective method to use the interconnection topology between RDF sources to filter out irrelevant sources
- An efficient method to share the common computation of intermediate results joining.

Framework

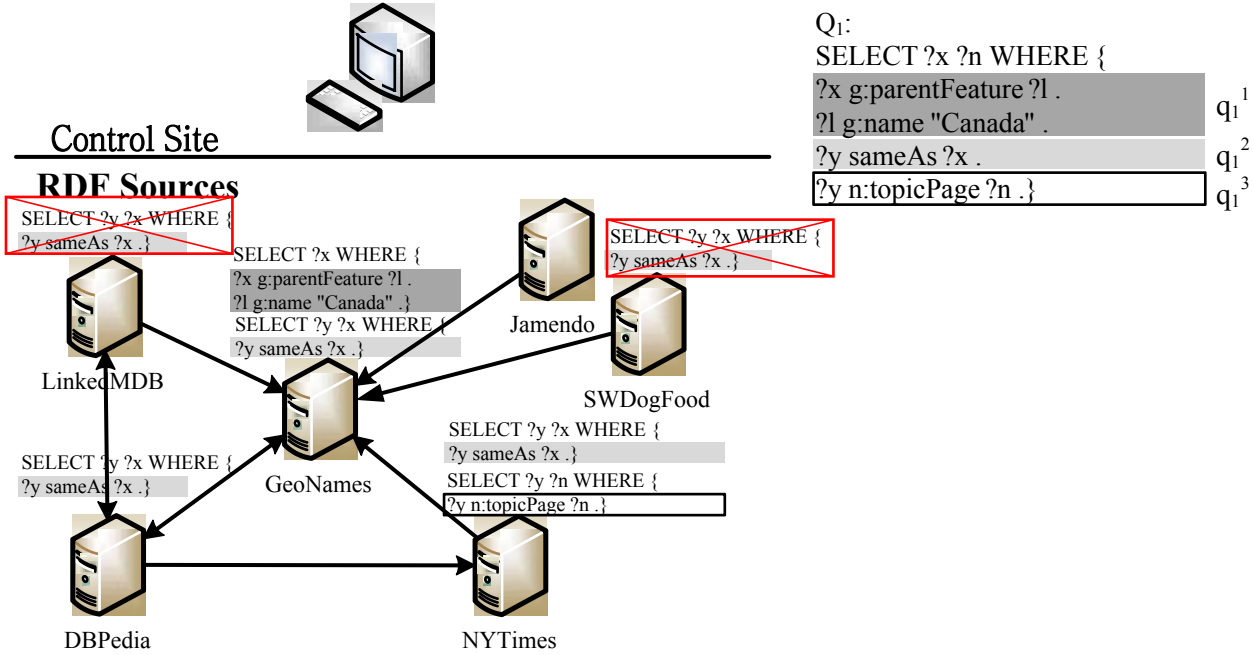

SPARQL Query
Matches
Query Decomposition and Source Selection
Local Query Evaluation
Joining Partial Matches
Control Site
RDF Sources

Basic Query Decomposition and Source Selection

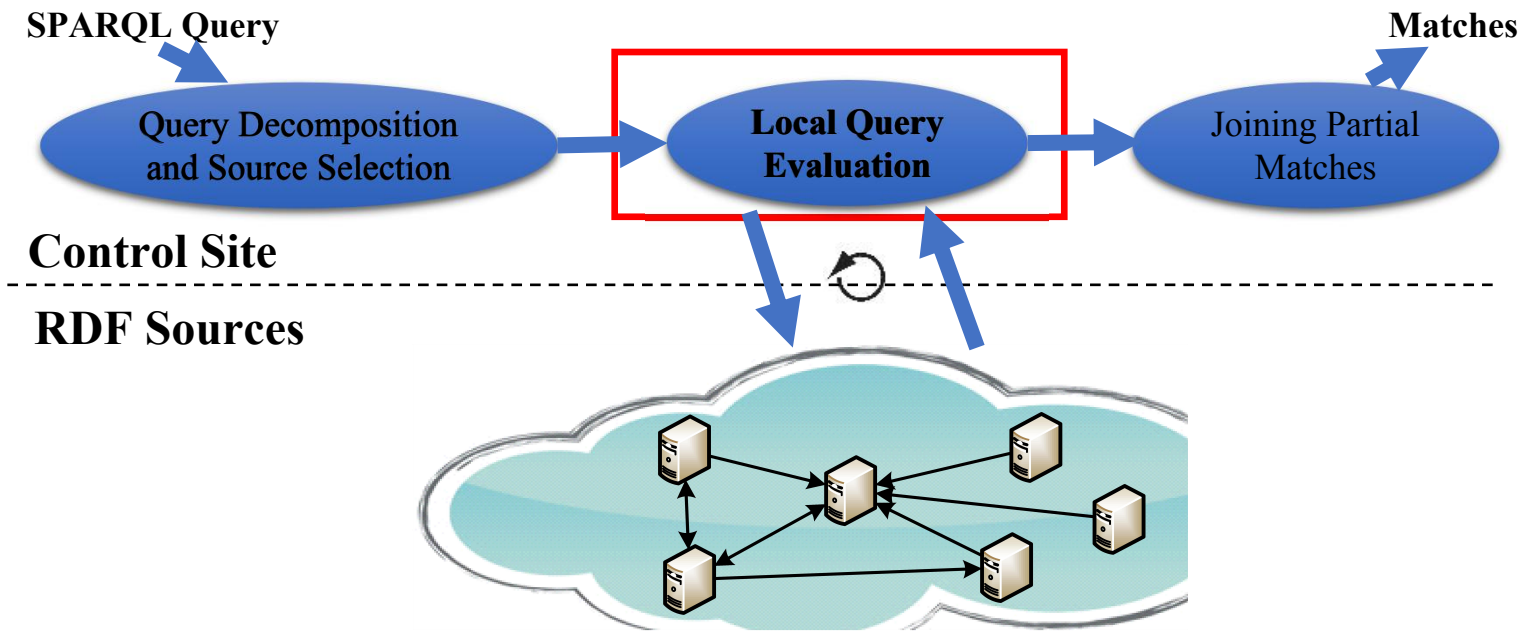
- Most existing solutions decompose the input query based on the triple patterns



Source Topology-based Query Decomposition and Source Selection



Framework


SPARQL Query
Query Decomposition and Source Selection
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Matches
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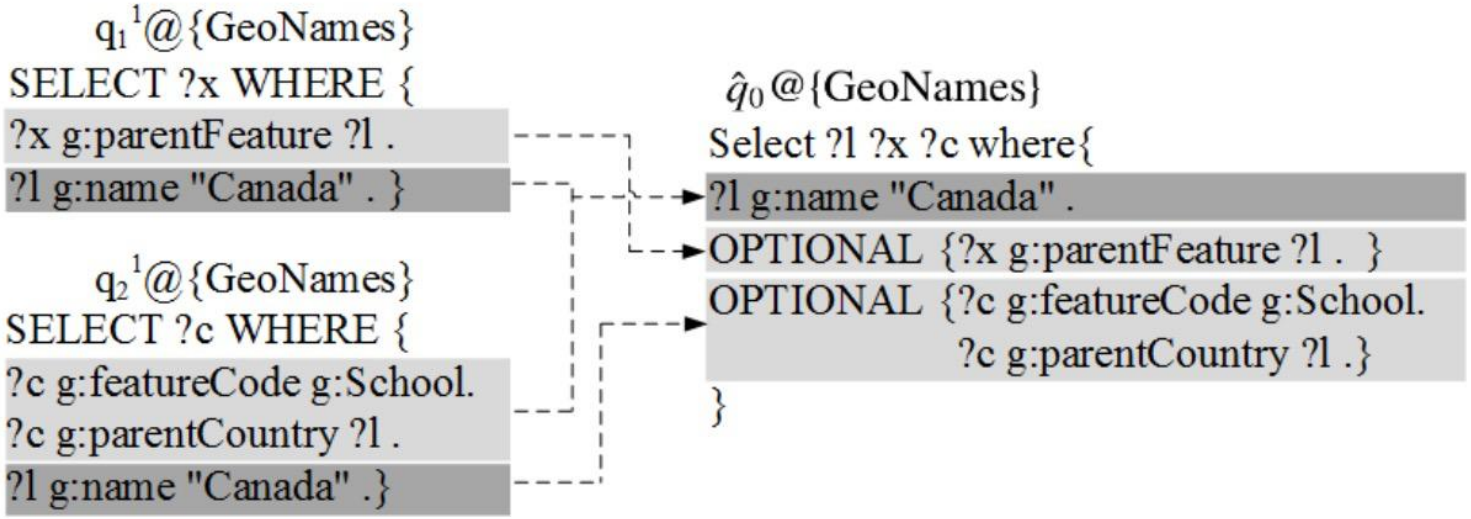
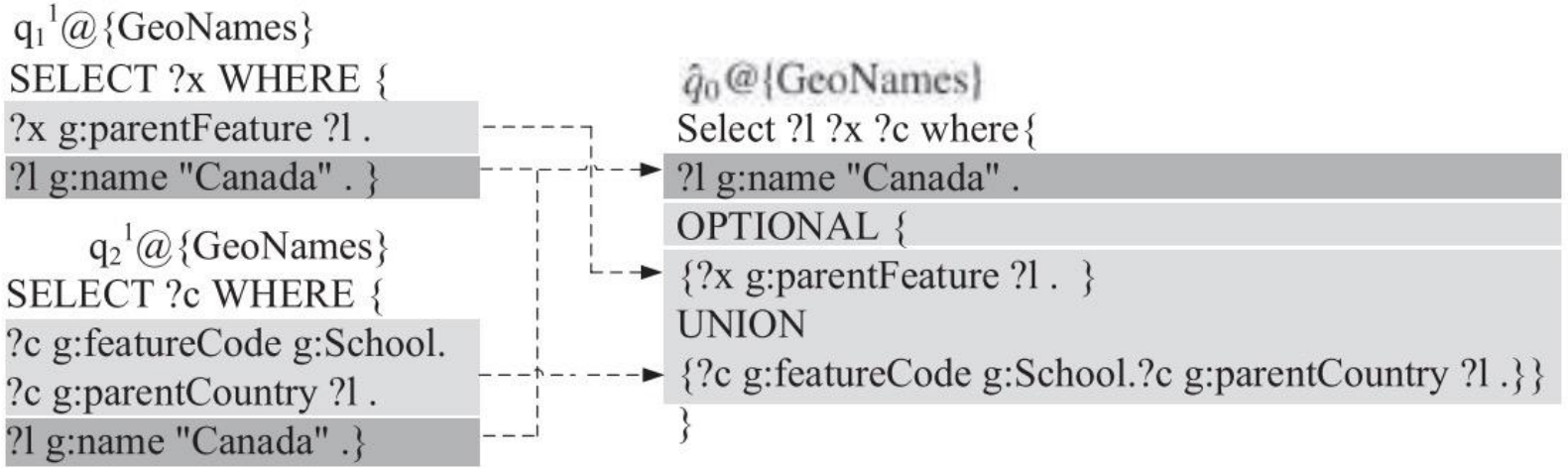
Local Query Evaluation

- When multiple SPARQL queries are posed simultaneously, there is room for sharing computation when executing these queries
- We proposes a cost-driven query rewriting scheme to rewrite them (at the control site) into fewer SPARQL queries, which can reduce the number of remote requests and improve the performances

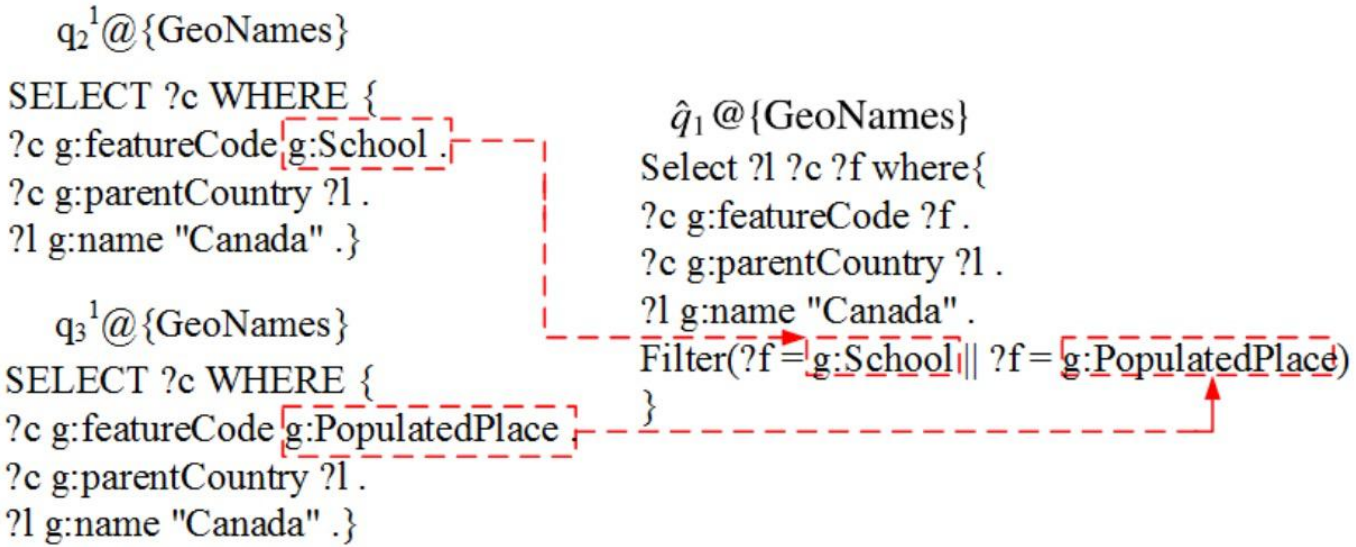
OPTIONAL-Based Rewriting



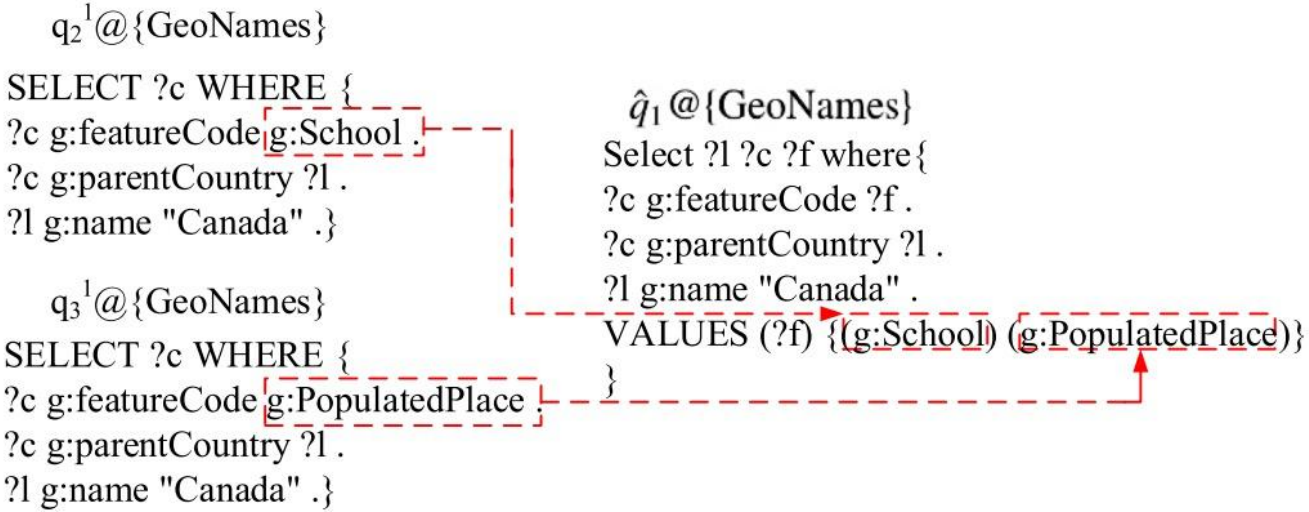
OPTIONAL-UNION-Based Rewriting



FILTER-based Rewriting



VALUES-based Rewriting

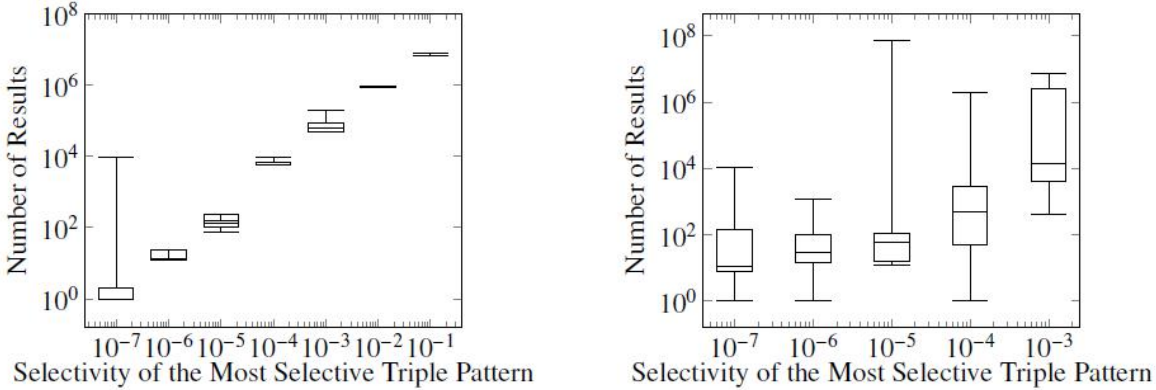


Cost Model for BGPs

- The cardinality of evaluating a basic graph pattern Q is as follows.

$$card(Q) = min_{e \in E(Q)}\{sel(e)\}$$

where sel(e) is the selectivity of triple pattern e in Q.



(a) DBPedia (b) WatDiv 10M

Fig. 6. Relationship Between the Cardinality and the Most Selective Triple Pattern

Cost Model for Data Shipment

- Based on the above, the cost of data shipment for a given query is as follows

$$cost_{DS}(\hat{q}) = card(\hat{q}) \times T_{MSG} = \min_{e \in p}\{sel(e)\} \times T_{MSG}$$

where T_{MSG} is the unit time to transmit a data unit.

Cost Model for Query Rewriting

- Hence, given a SPARQL Q, its cost $cost_{LE}(Q)$ for local evaluation is defined as follows

$$card(Q) = \begin{cases} \min_{e \in E(Q)}\{sel(e)\} & if\ Q\ is\ a\ BGP; \\ \min\{card(Q_1), card(Q_2)\} & if\ Q = Q_1\ AND\ Q_2; \\ card(Q_1) + card(Q_2) & if\ Q = Q_1\ UNION\ Q_2; \\ card(Q_1) + \Delta_1 & if\ Q = Q_1\ OPT\ Q_2; \\ card(Q_1) + \Delta_2 & if\ Q = Q_1\ FILTER\ F; \\ \min\{card(Q), |D|\} & if\ Q = VALUES\ \overrightarrow{W}\ D; \end{cases}$$

where T_{CPU} is the CPU unit time to construct a result, and $\triangle_3$ and $\triangle_4$ are empirically trivial values

Cost Model for Query Rewriting

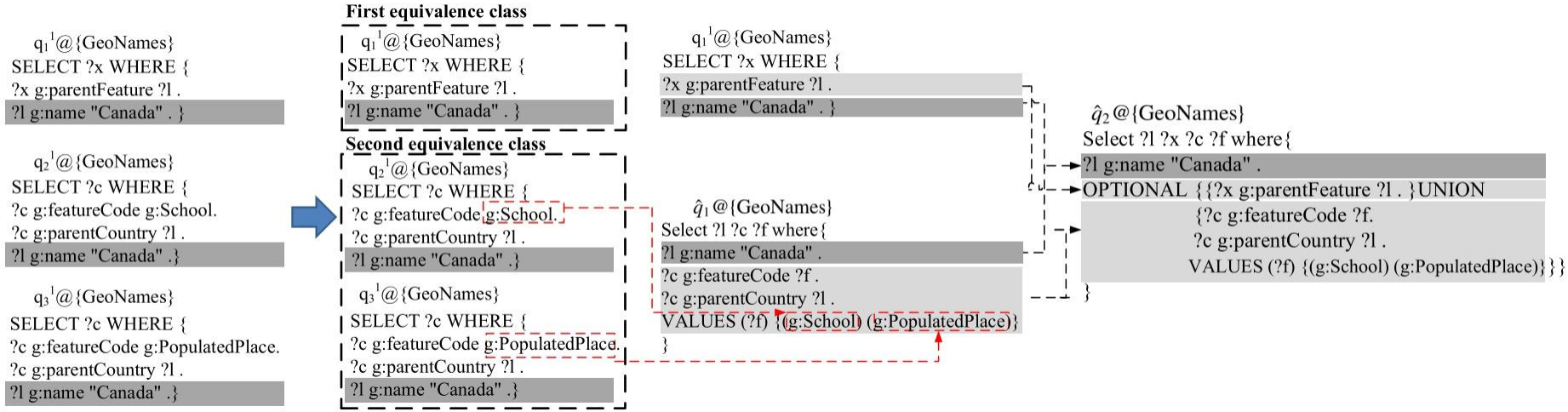
- Given a set of subqueries on a RDF source, if p is their common subgraph among these queries, we rewrite them into a SPARQL query. The cost of the rewriting is the cost of the rewritten query is as follows.

$$cost(\mathbf{Q}, \hat{q}) = cost(\hat{q}) = cost_{LE}(\hat{q}) + cost_{DS}(\hat{q}) = \min_{e \in p}\{sel(e)\} \times (|OPT_{\hat{q}}| \times T_{CPU} + T_{MSG})$$

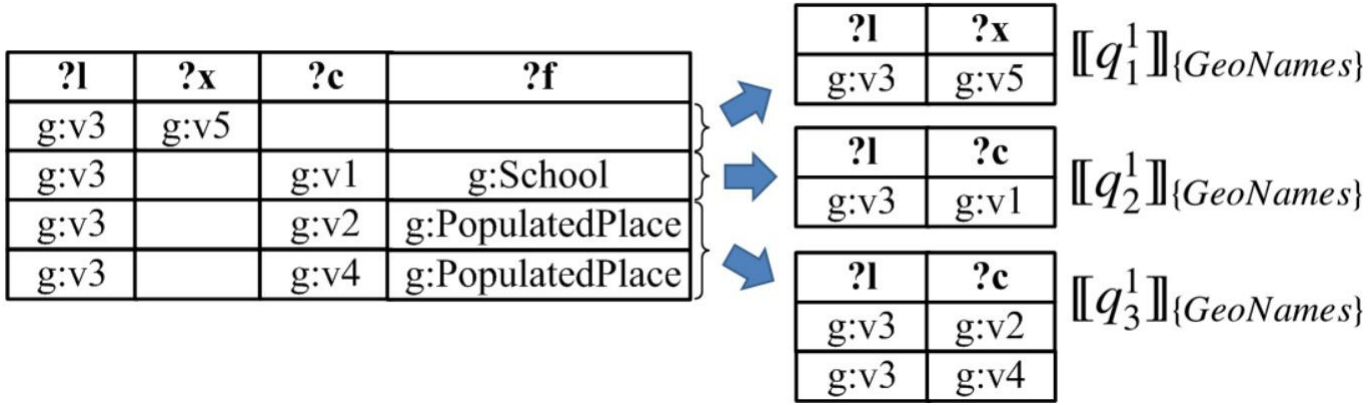
Query Rewriting

- Given a set of n subqueries, the objective is to find the set of m rewritten queries (m $\leq n$) with the smallest rewriting cost.
- We can prove that finding the optimal set of rewritten queries is NP-complete, and propose a greedy heuristic algorithm to find an approximately optimal solution

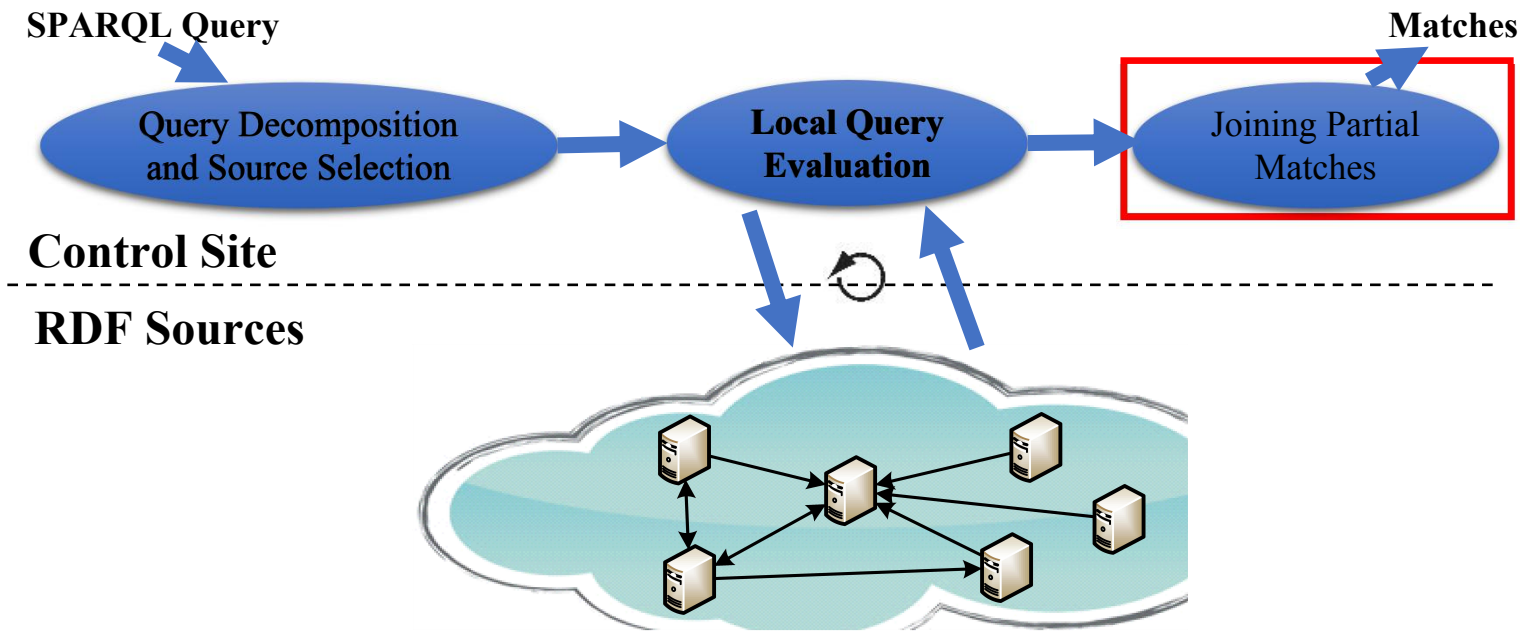
Query Rewriting Example



Postprocessing



Framework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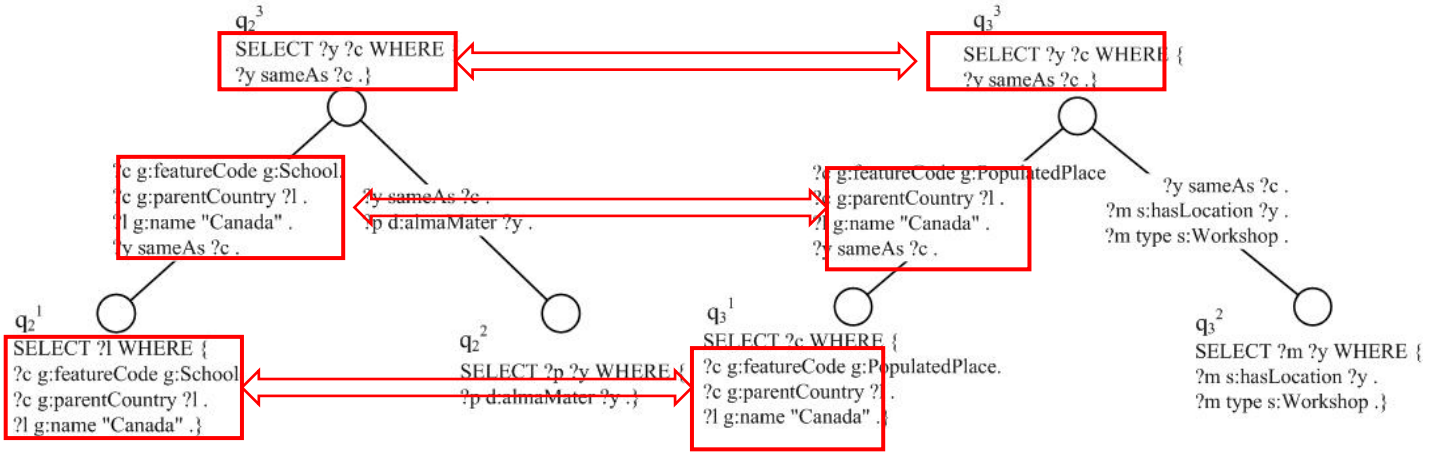
Joining Partial Matches

- There may exist some common computation in joining partial matches of different queries



Joining Partial Matches

- Formally,

$$[\![q_2^1]\!] \bowtie [\![q_2^3]\!]$$

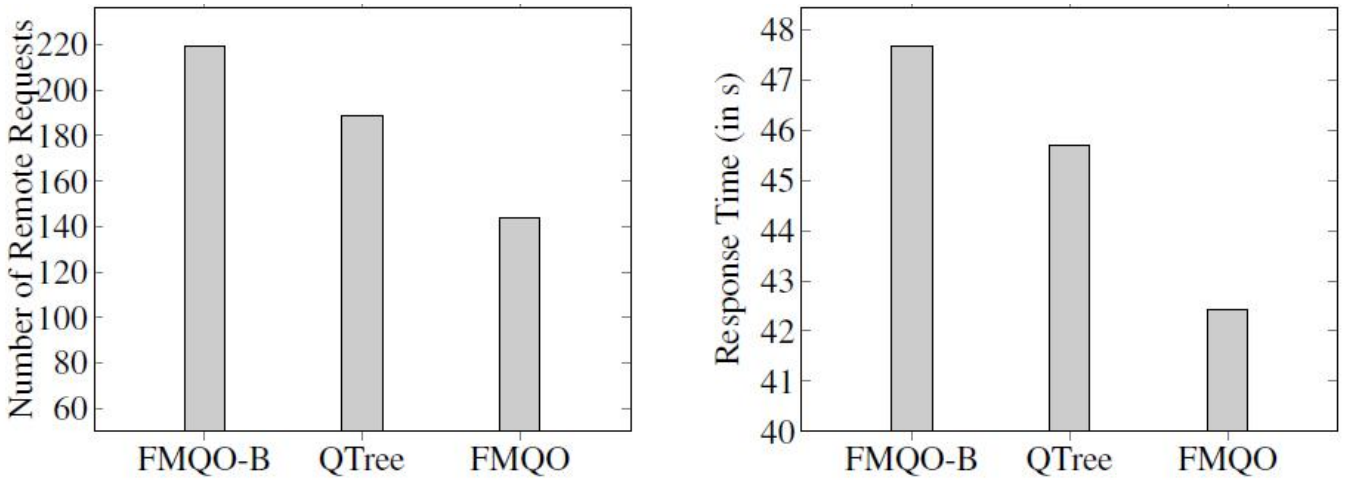
$$[\![q_3^1]\!] \bowtie [\![q_3^3]\!]$$

$$\Rightarrow ([\![q_2^1]\!] \cup [\![q_3^1]\!]) \bowtie ([\![q_2^3]\!] \cup [\![q_3^3]\!])$$

Experiments

- Datasets: WatDiv, FedBench and LargeRDFBench
- Competitor: FedX, SPLENDID and HiBISCuS
- Environment: a cluster of machines running Linux, each of which installs Sesame 2.7 to build up an RDF source.

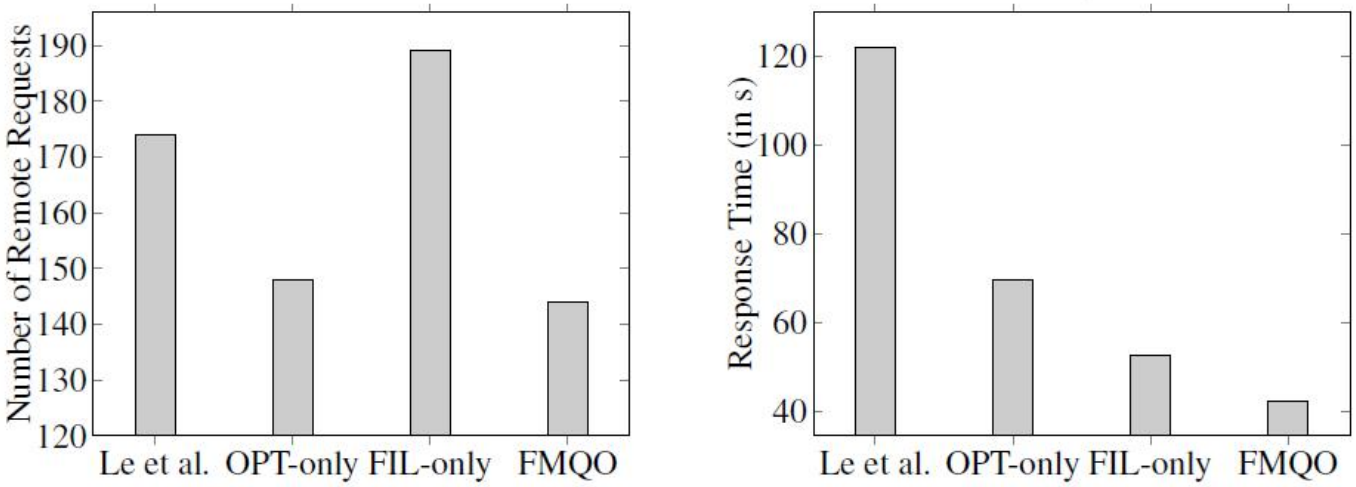
Effect of the Query Decomposition and Source Selection Technique



(a) Number of Remote Requests (b) Response Time

Fig. 8. Evaluating Source Topology-based Source Selection Technique

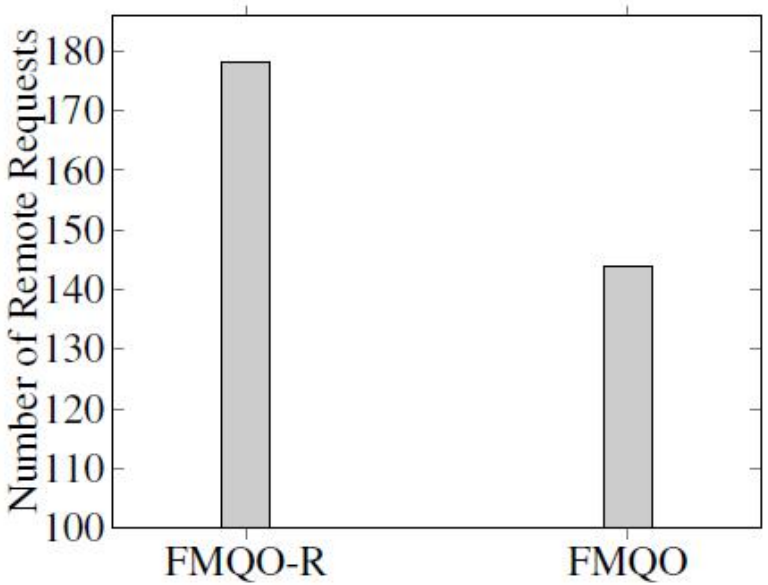
Effect of the Rewriting Strategies



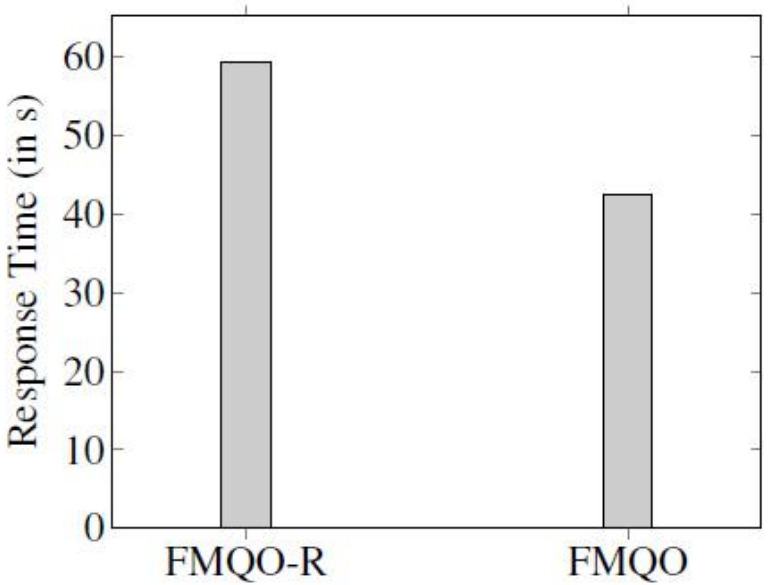
(a) Number of Remote Requests (b) Response Time

Fig. 9. Evaluating Different Rewriting Strategies

Evaluation of the Cost Model



(a) Number of Remote Requests



(b) Response Time

Effect of Optimization Techniques for Joins

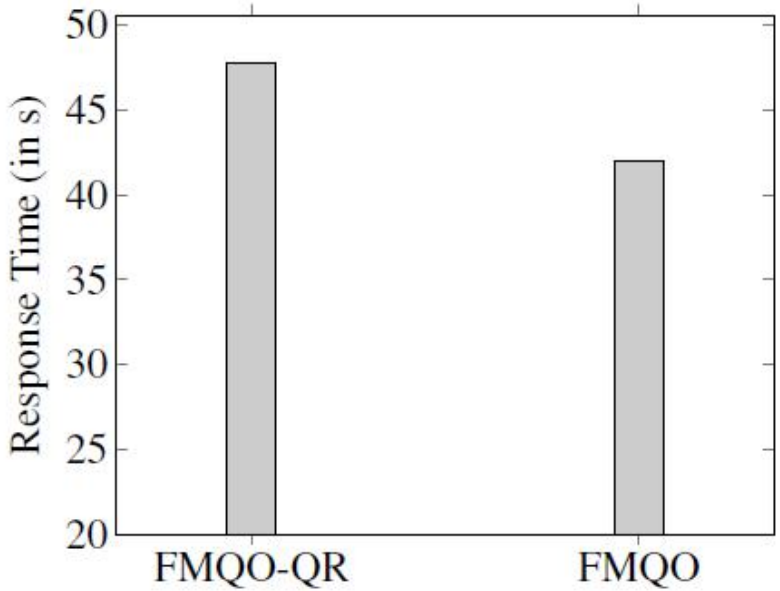
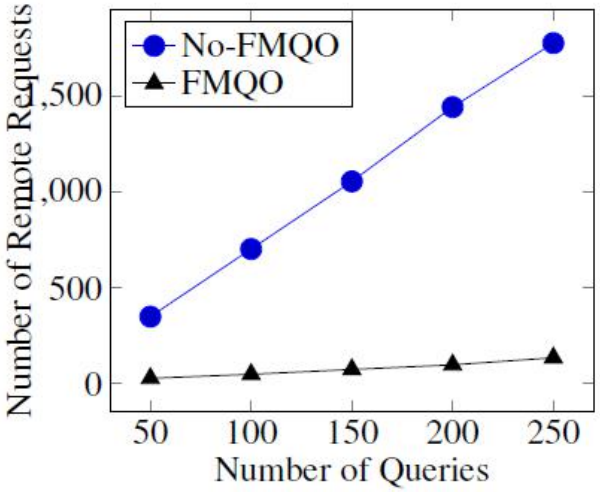
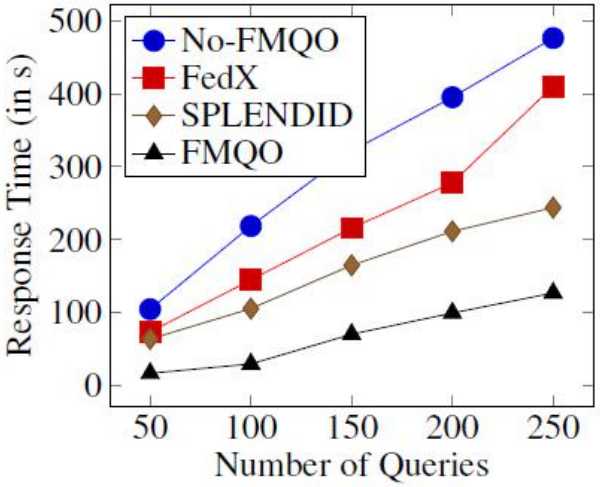


Fig. 11. Effect of Optimization Techniques for Joins

FedBench (Cross Domain)

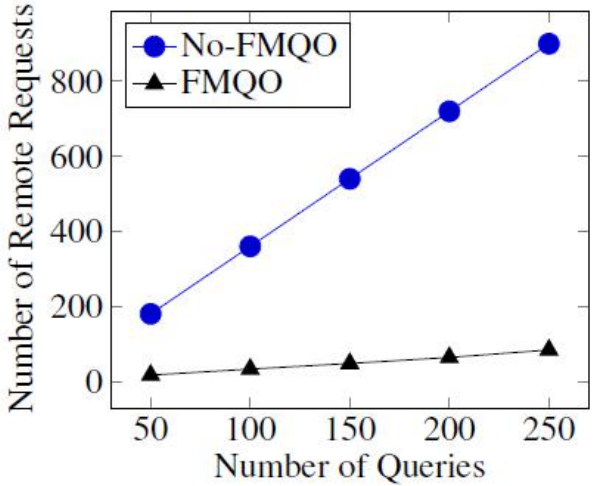


(a) Number of Remote Requests

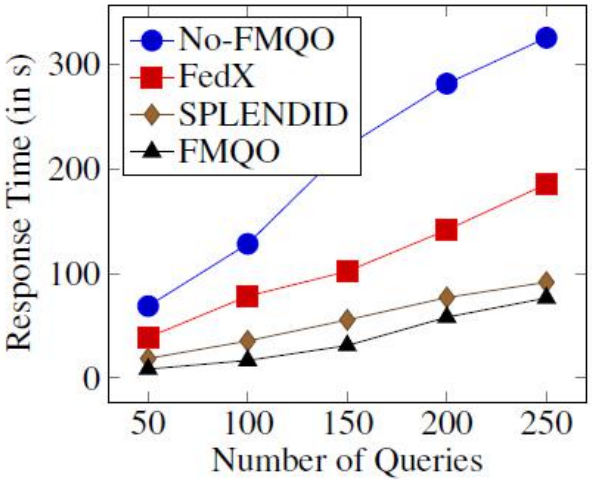


(b) Response Time

FedBench (Life Science)



(a) Number of Remote Requests



(b) Response Time

Part 4

Conclusions

Conclusions

- We introduce scale-out distributed RDF systems and classify them into two categories: partitioning-based and partitioning-agnostic approaches
- We introduce federated RDF systems and discuss how to optimize multi-query processing in federated RDF systems

Future Work

- There are many distributed database managment system architectures which are further used for RDF graphs
  1. Parallel Computing
  2. Edge Computing

  .....

THANK YOU

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