Athena
Research Center

Cloud-based RDF data management

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SIGMOD 2014 Tutorial

History and acknowledgments

First presented at ICDE 2013 (short version: 1.5 hours)

Long version previously presented at the Workshop on Open Data (WOD) 2013

Companion paper:

"RDF in the clouds: A Survey", accepted for publication in the VLDB Journal (June 5)

Linked [Open] Data

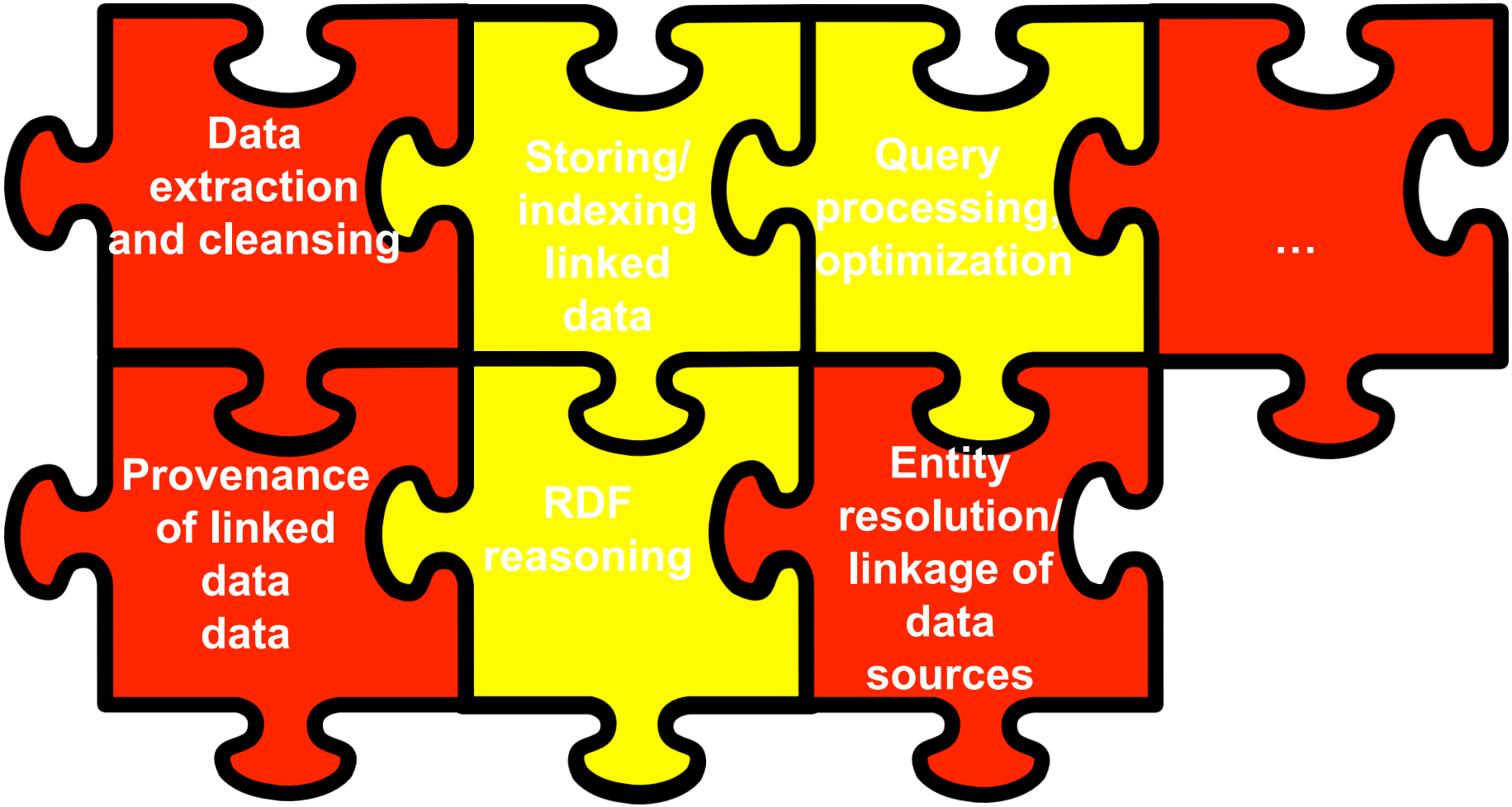
- Tim Berners-Lee in TED 2009 conference

  "Linked Data is the Semantic Web done right"

- Linked Data principles:
  - Use URIs to represent data
  - Use HTTP URIs (make data de-referenceable)
  - Give information for a piece of data using W3C standards
  - Include links to other URIs

- Linked Data Management → RDF data management

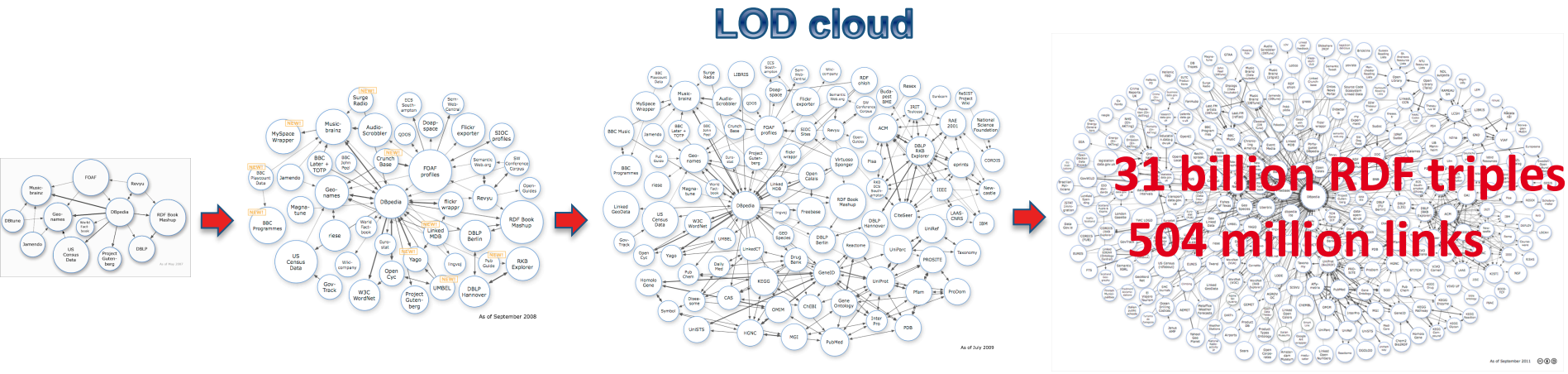
Linked data management tasks



Where is RDF found today?

- Many available open data sources in RDF

Linked data is growing

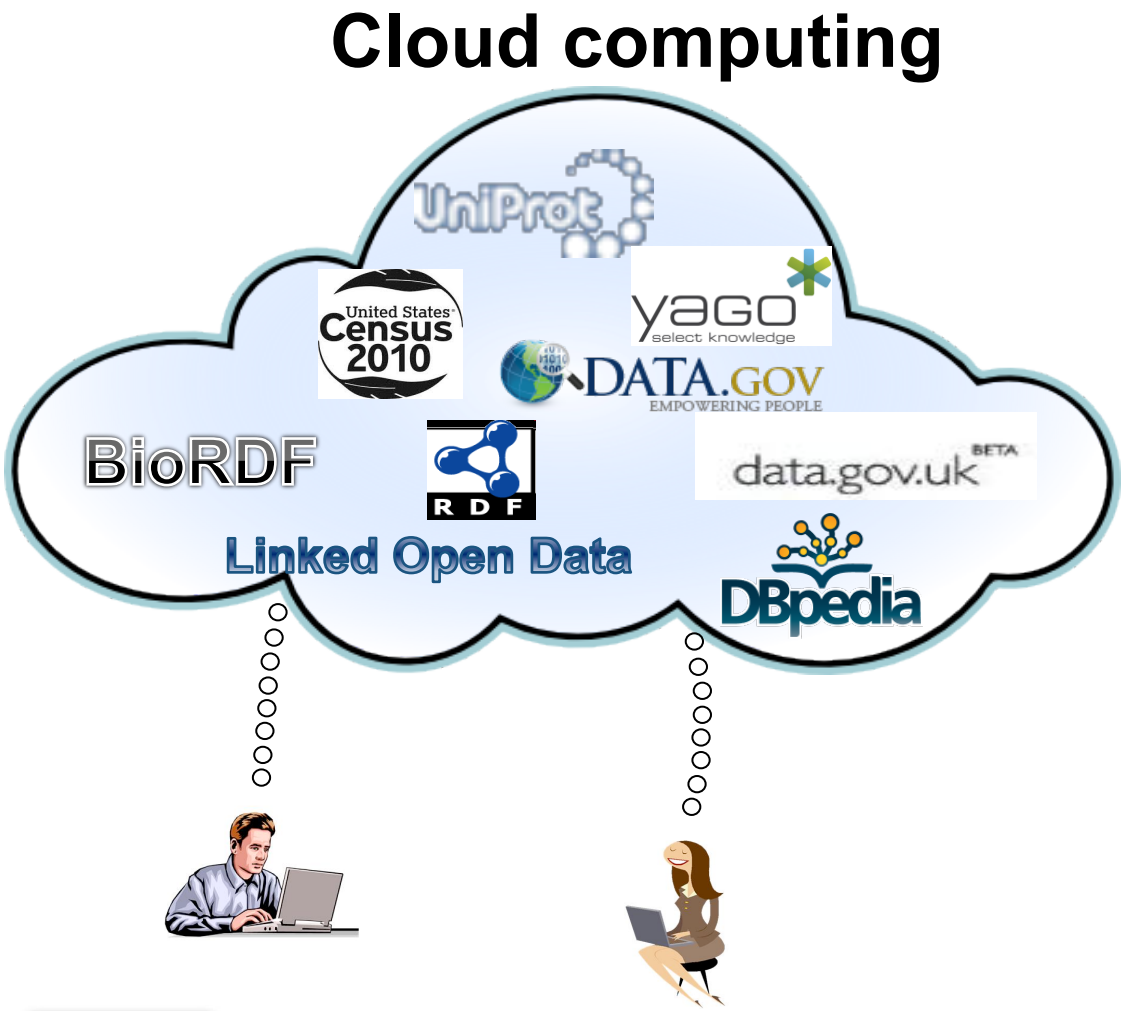


RDF data sources in numbers

LOD cloud	**Linked Open Data cloud**	**31 billion** triples, Sept.
DBpedia	RDF-encoded Wikipedia	1.89 billion triples
BioRDF	RDF-encoded biological data	2.7 billion triples
DATA.GOV EMPOWERING PEOPLE	US government data in RDF	5 billion triples
A new application award Semantic Web Challenge http://challenge.semanticweb.org	crawled Web data	2 billion triples
United States Census 2010	US population statistics	1 billion triples
yago select knowledge	facts from Wikipedia, Wordnet, Geonames	0.12 billion triples

… and many more … http://www.w3.org/wiki/DataSetRDFDumps
http://datahub.io/

Managing large volumes of RDF data



- Scalability
- Elasticity
- Fault-tolerance

What this seminar is about

RDF data management in the cloud
(*or: large-scale distributed repositories*)

- Storing RDF data in the cloud
- Evaluation of RDF queries in the cloud
- Inference of RDF data in the cloud

Outline

1. Introduction to RDF
2. Recall of Cloud platforms
3. Analysis of RDF systems in the cloud
   - Storage
   - Querying
   - Inference
4. Open issues

1

RDF BASICS

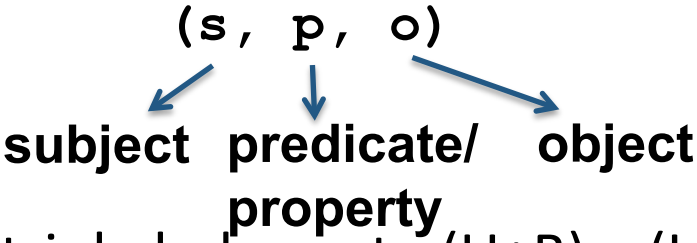
Resource Description Framework (RDF)

- RDF: representation of **resources** on the Web identified by Universal Resource Identifiers (**URIs**) **U**

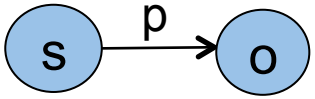
  http://live.dbpedia.org/page/Pablo_Picasso

- **Literals**: strings, numbers, dates, etc. **L**
- **Blank nodes**: existential identifiers **B**

- RDF data: facts = **triples**



- A *well-formed* triple belongs to (U+B) × (U+B) × (U+B+L)
- RDF as graphs



RDF Schema

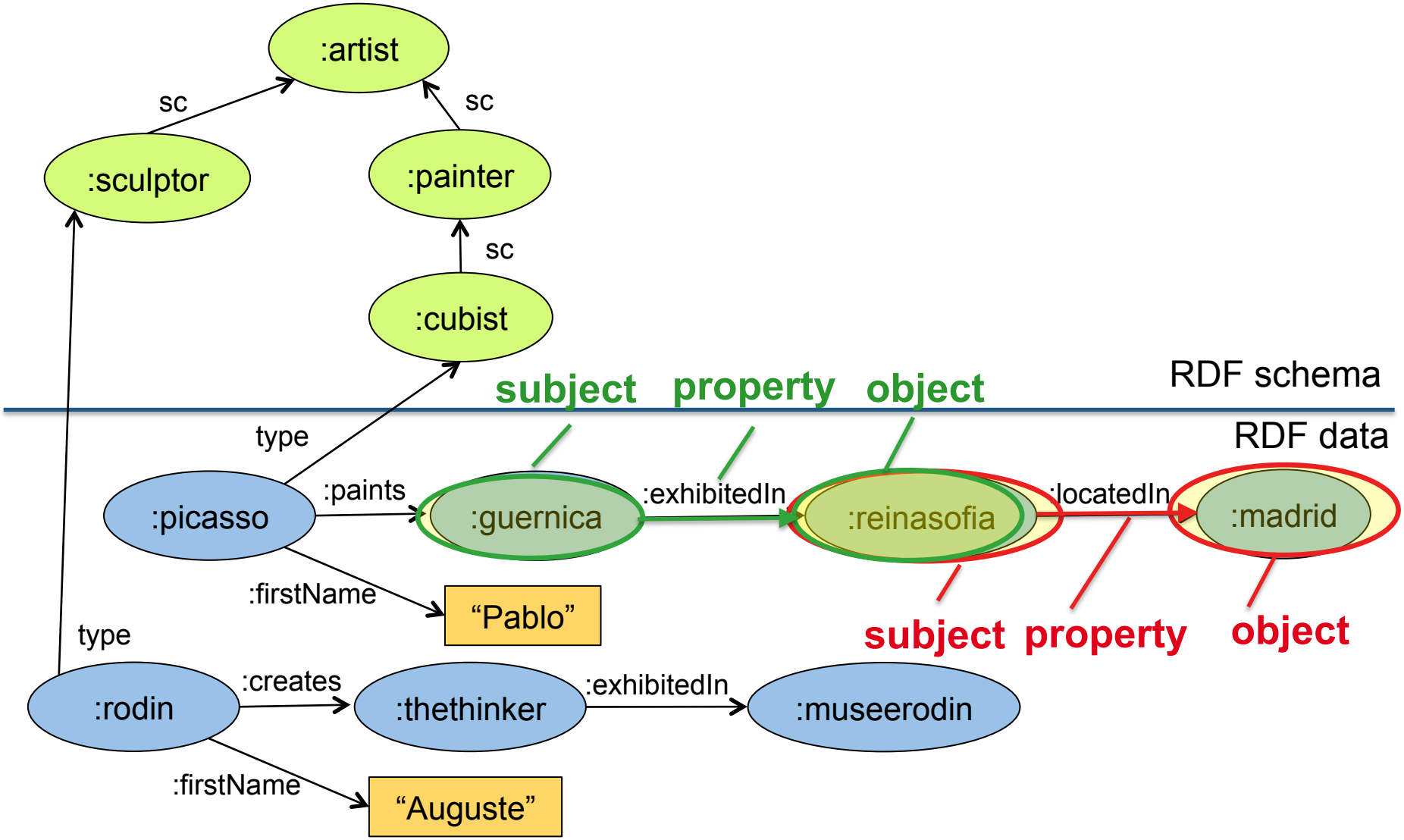
- RDF **schema** (RDFS): specifies concepts, properties and relationships between them
  - Concept/class: http://live.dbpedia.org/ontology/Artist
  - Property: http://dbpedia.org/property/birthPlace
  - Relationships:

```
(dbpedia-owl:Artist, rdfs:subClassOf, dbpedia-owl:Person)
(dbpprop:birthplace, rdfs:domain, dbpedia-owl:Person)
(dbpedia:Pablo_Picasso, rdf:type, dbpedia-owl:Artist)
```

We skip namespaces and use the following notation for rdf-specific terms:

```
(:Artist, sc, :Person)
(:birtplace, domain, :Person
(:Pablo_Picasso, type, :Artist)
```

Running example: RDF database



Running example: RDF database (triple syntax)

N-TRIPLE syntax

```
:picasso type :cubist .
:picasso :firstName "Pablo" .
:picasso :paints :guernica .
:guernica :exhibitedIn :reinasofia .
:reinasofia :locatedIn :madrid .
:rodin type :sculptor .
:rodin :firstName "Auguste" .
:rodin :creates :thethinker .
:thethinker :exhibitedIn :museerodin .
```

RDF data

```
:sculptor sc :artist .
:painter sc :artist .
:cubist sc :painter.
```

RDF Schema

SPARQL Query Language

- Basic building block
  - Triple pattern (s, p, o) from UBV × UBV × UBLV

constant or variable

U: URIs
B: blank nodes
L: literals
V: variables

- SQL-based syntax
  - Basic graph pattern (BGP) queries:

SELECT $?x_1$, $?x_2$, …, $?x_n$ → **distinguished variables**

WHERE {

s_1 p_1 o_1 .

…

s_k p_k o_k .

}

Conjunction of triple patterns

SPARQL Query Language

- BGP queries in conjunctive form:
  - $?x_1, ?x_2, \ldots, ?x_n : (s_1, p_1, o_1) \wedge \ldots \wedge (s_k, p_k, o_k)$

distinguished variables — **triple patterns**

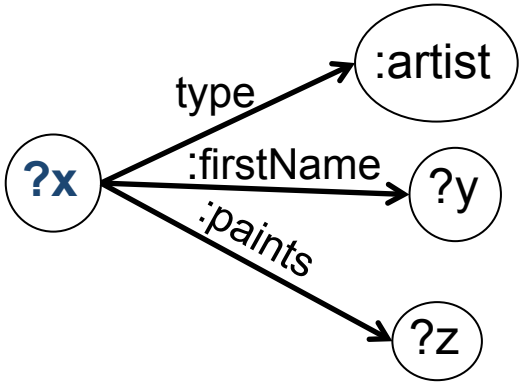
- BGP queries: Select-Project-Join fragment of relational algebra
  - Select → ?x: (?x, :paints, ?y)
  - Project → ?x: (?x, :paints, ?y)
  - Join → ?x: (?x, :paints, ?y) ∧ (?y, :exhibited, :reinasofia)

- More features in SPARQL 1.1: W3C recommendation, March 2013

Typical SPARQL query shapes

Star query

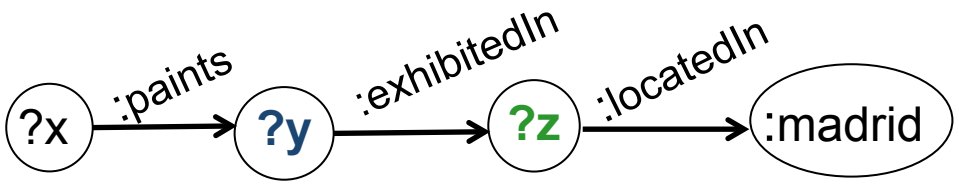
```
SELECT ?y ?z
WHERE {?x type :artist .
       ?x :firstName ?y .
       ?x :paints ?z .}
```



?y ?z: (?x type :artist ∧
(?x :firstName ?y) ∧
(?x :paints ?z)

Path query

```
SELECT ?x ?y ?z
WHERE {?x :paints ?y .
       ?y :exhibitedIn ?z .
       ?z :locatedIn :madrid.}
```



?x ?y ?z: (?x :paints ?y) ∧
(?y :exhibitedIn ?z) ∧
(?z :locatedIn :madrid)

Centralized RDF stores

- How to store RDF in a centralized setting?
- Approaches relying on RDBMs
  - Big **triple tables**

Triples

subject	property	object
:picasso	type	:cubist
:picasso	:firstName	“Pablo”
picasso	:paints	:guernica
:guernica	:exhibitedIn	:reinasofia
:reinasofia	:locatedIn	:madrid
:rodin	type	:sculptor
:rodin	:creates	:thethinker
…	…	…

Centralized RDF stores

- How to store RDF in a centralized setting?
- Approaches relying on RDBMs
  - Big triple tables
  - **Property tables** [Alexaki01, Wilkison06]

Artists

subject	type	firstName	paints	creates
:picasso	:cubist	"Pablo"	:guernica	null
:rodin	:sculptor	"Auguste"	null	:thethinker

Artifacts

subject	exhibitedIn
:guernica	:reinasofia
:thethinker	:museerodin

subject	…
…	…
…	…

Centralized RDF stores

- How to store RDF in a centralized setting?
- Approaches relying on RDBMs
  - Big triple tables
  - Property tables [Alexaki01, Wilkison06]
  - **Vertical partitioning** [Abadi07]

Benchmarking [Theoharis05]

type

subject	
:picasso	
:rodin	

paints

	object
	:guernica

Fits well in column-stores

firstName

subject	ob
:picasso	“Pablo”
:rodin	“Auguste”

edIn

	object
:guernica	:reinasofia
:thethinker	museerodin

subject	object
…	…

Centralized RDF stores

- How to store RDF in a centralized setting?
- Approaches relying on RDBMs
  - Big triple tables
  - Property tables [Alexaki01, Wilkison06]
  - Vertical partitioning [Abadi07]
- Native RDF stores
  - RDF-3X [Neumann10], Hexastore [Weiss08]
  - 6 indexes (1 for each permutation of s p o)
  - compressed indices
  - aggregated indices

Dictionary encoding

- RDF contains long strings of URIs

Size of triples

min	max	avg
80 bytes	2100 bytes	240 bytes

Source http://gromgull.net/blog/category/semantic-web/billion-triple-challenge/

Dictionary

id	resource
1	:picasso
2	:rodin
3	type
4	:cubist
5	:firstName
6	:guernica
…	…

Triples

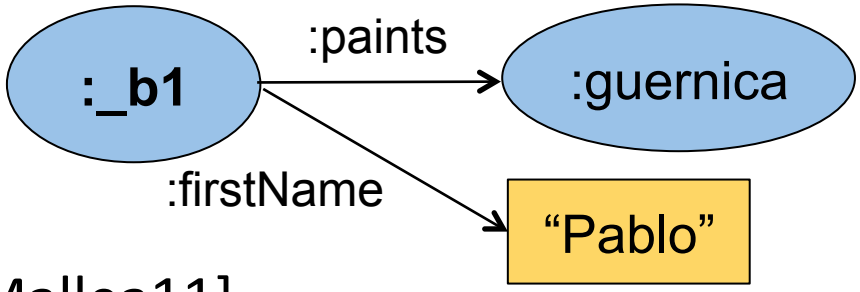
pro	
t	
:firs	
:p	
:exh	
:loc	
type	:sculptor
:creates	:thethinker
…	…

Triples

subject	property	object
1	3	4
1	5	10
1	7	6
6	12	9
…	…	…

RDF is not just a 3-attribute table

- Blank nodes
  - unknown/anonymous resources
  - existential variables



  - for more “On blank nodes” [Mallea11]
- Schema queries
  - ?x: (?x, sc, :artist) ⋀ (:paints, domain, ?x)
- Data and schema can be queried together
  - ?x: (?x, :paints, ?y) ⋀ (?x, type, ?z) ⋀ (?z, sc, :artist)

Data query

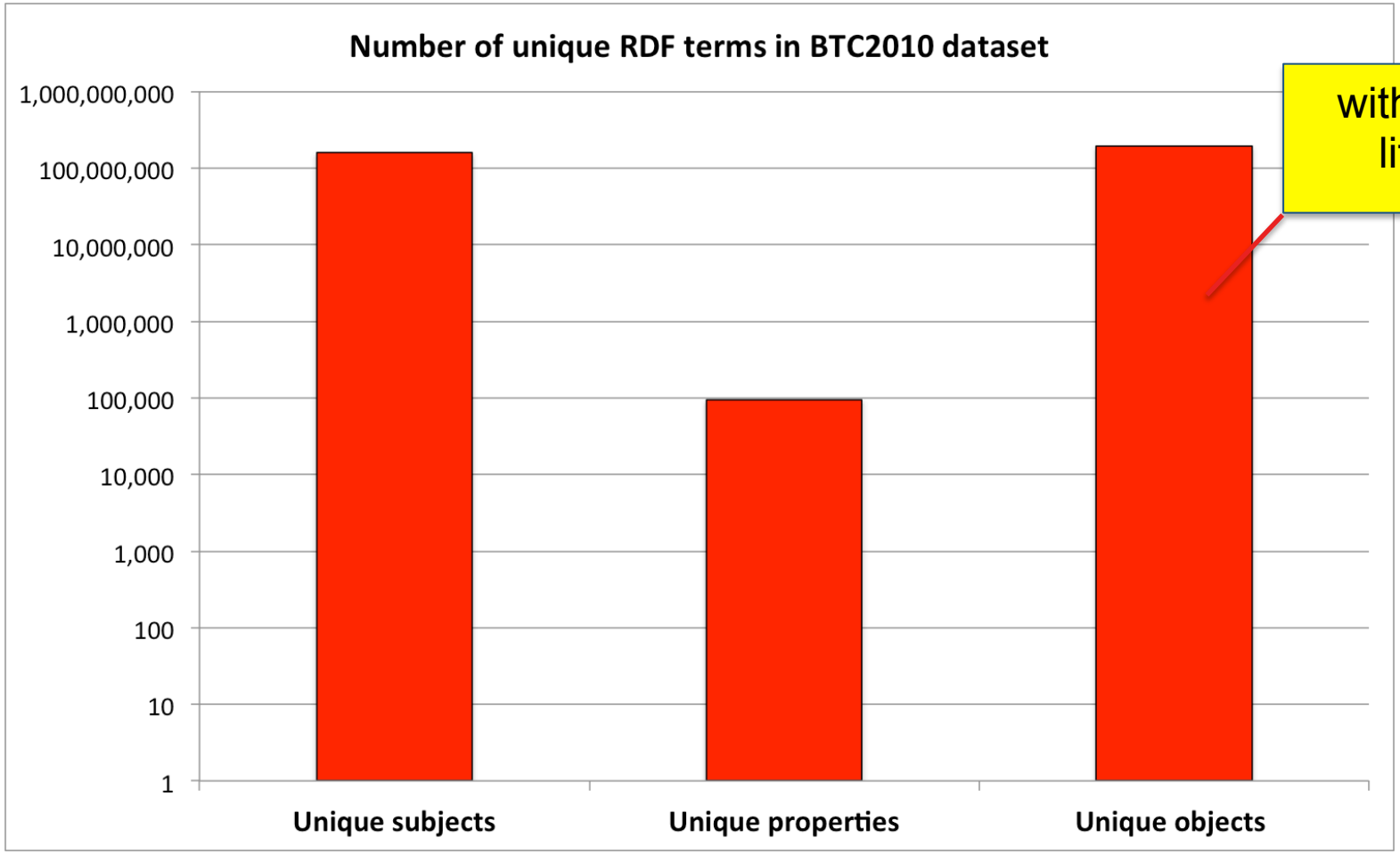
Schema query

RDF is not just a 3-attribute table

- Properties in RDF are treated as first class citizens (they are also resources)
  - `(:paints, domain, :painter)`
  - joins between properties and subjects/objects

    `?x: (?x, ?y, :guernica)` $\wedge$ `(?y, domain, :painter)`
- RDFS inference
- and more …

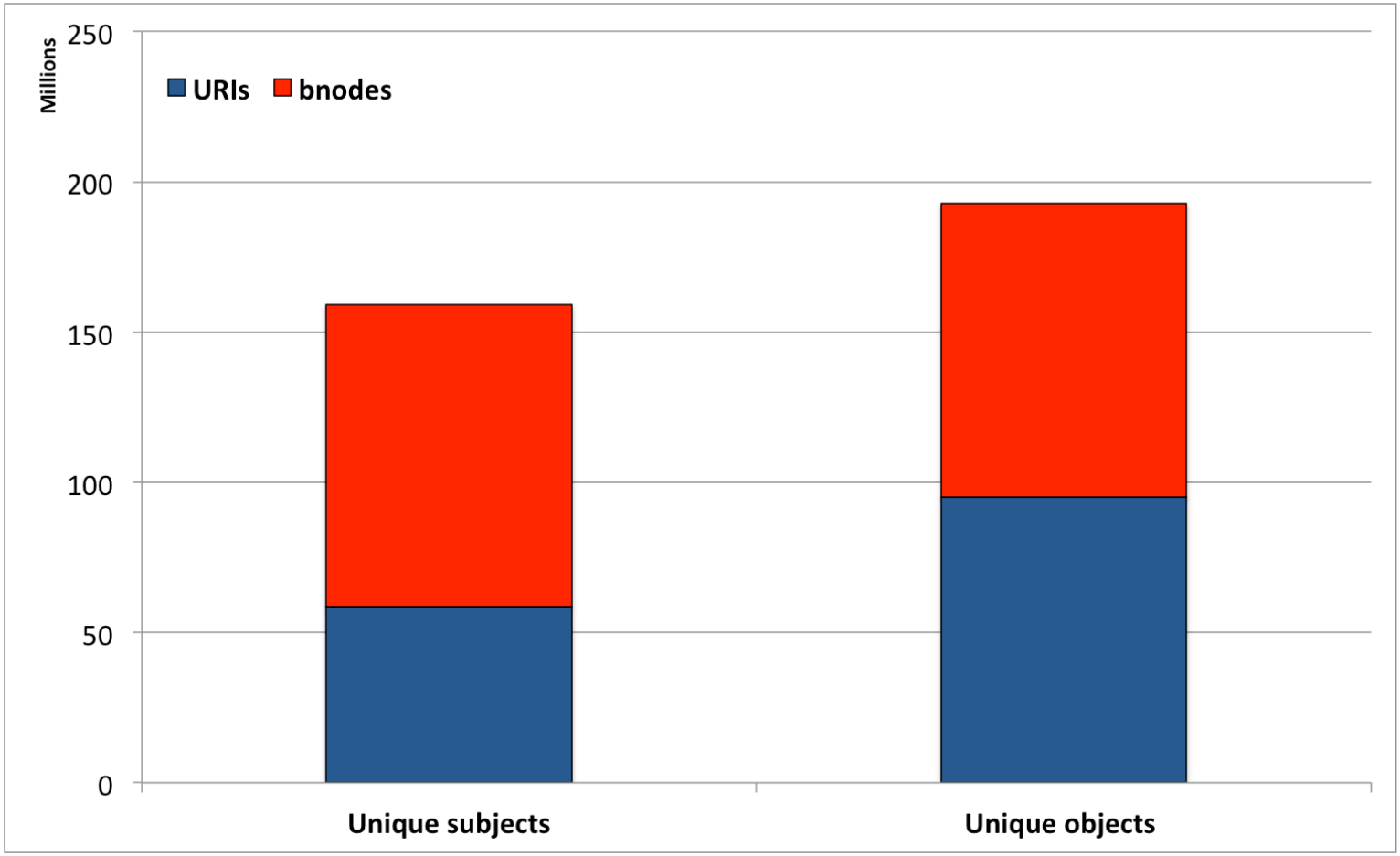
How does real RDF look?



Source: http://gromgull.net/blog/2010/09/btc2010-basic-stats/

How does real RDF look?

BTC2010 dataset



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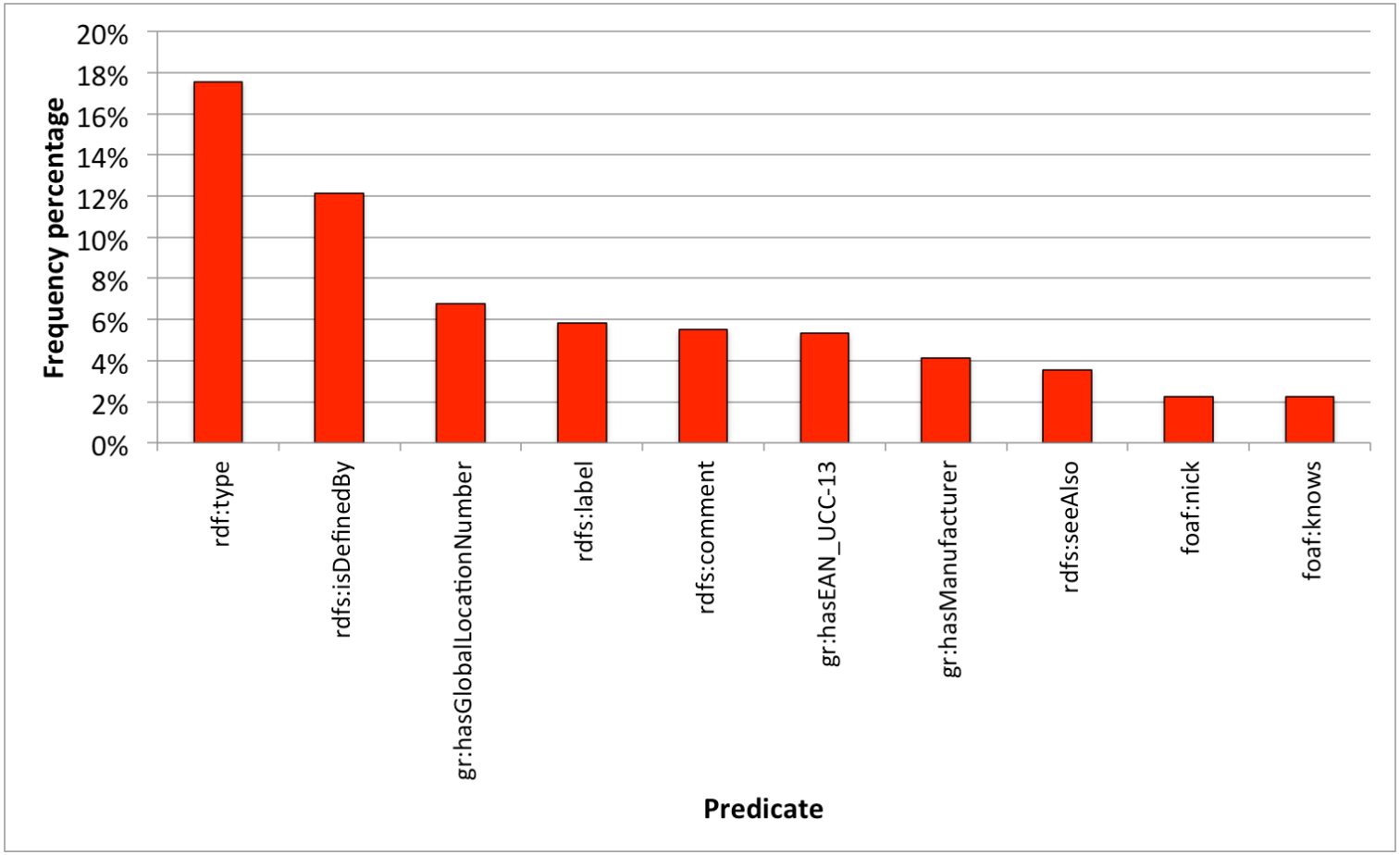
How does real RDF look?

BTC2010 dataset



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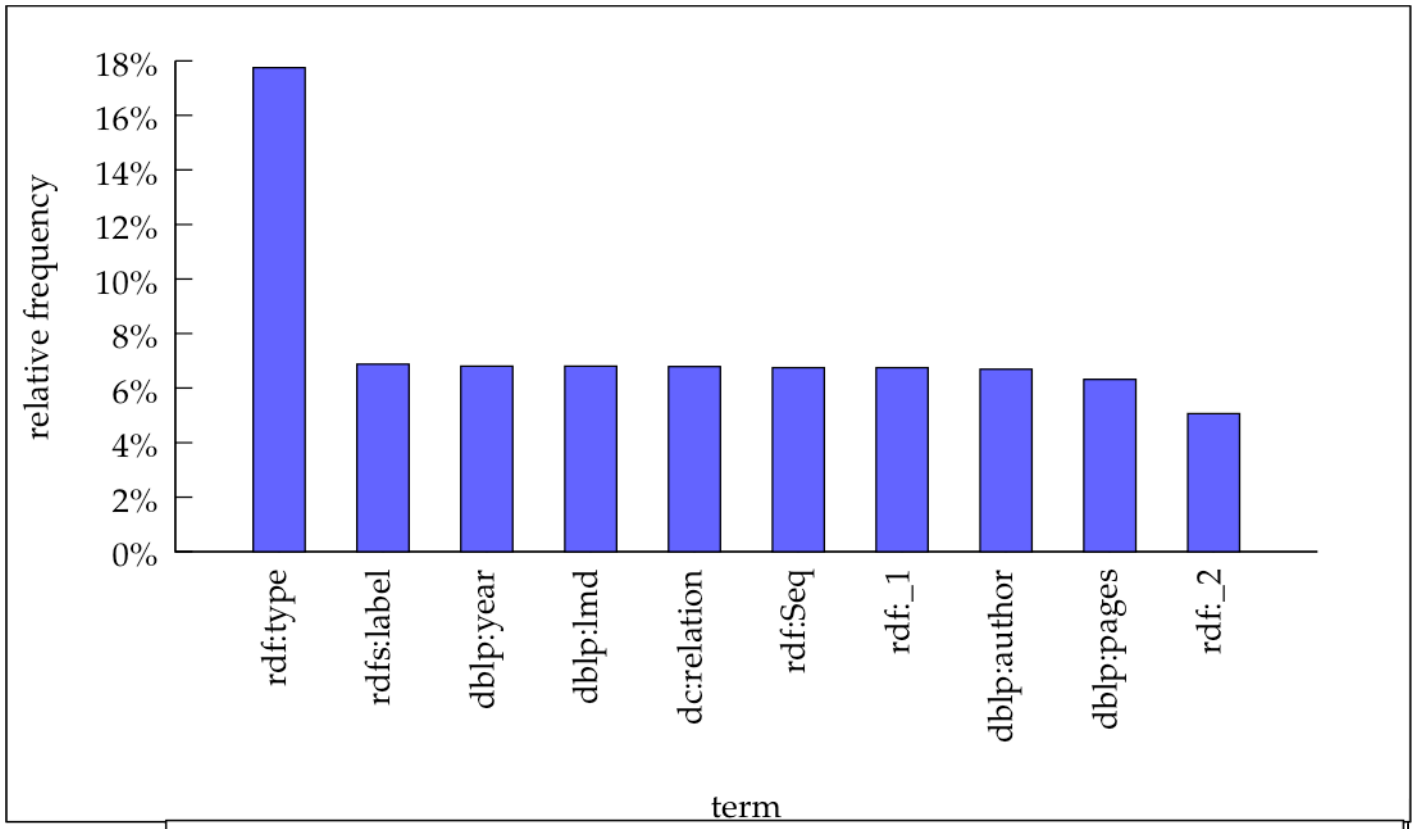
How does real RDF look?



Top-10 terms of SwetoDBLP [Kotoulas10]

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CLOUD BASICS

Cloud computing

The origin of the term cloud computing was derived from […] drawings of stylized clouds to denote networks […]
The cloud symbol was used to represent the Internet as early as 1994. [Wikipedia: http://en.wikipedia.org/wiki/Cloud_computing]

- Use of *computing resources as a service* over the network
- Technical advantages:
  - Scalability
  - Elasticity
  - Reliability
- Non-technical advantage:
  - Outsourcing system maintenance

Cloud computing service models

Google Apps

Software-as-a-Service (SaaS)

Applications

Windows Azure

web sites

Platform-as-a-Service (PaaS)

Platforms

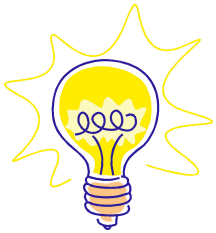
amazon web services™

Elastic Compute Cloud (EC2)

Infrastructure-as-a-Service (IaaS)

Hardware

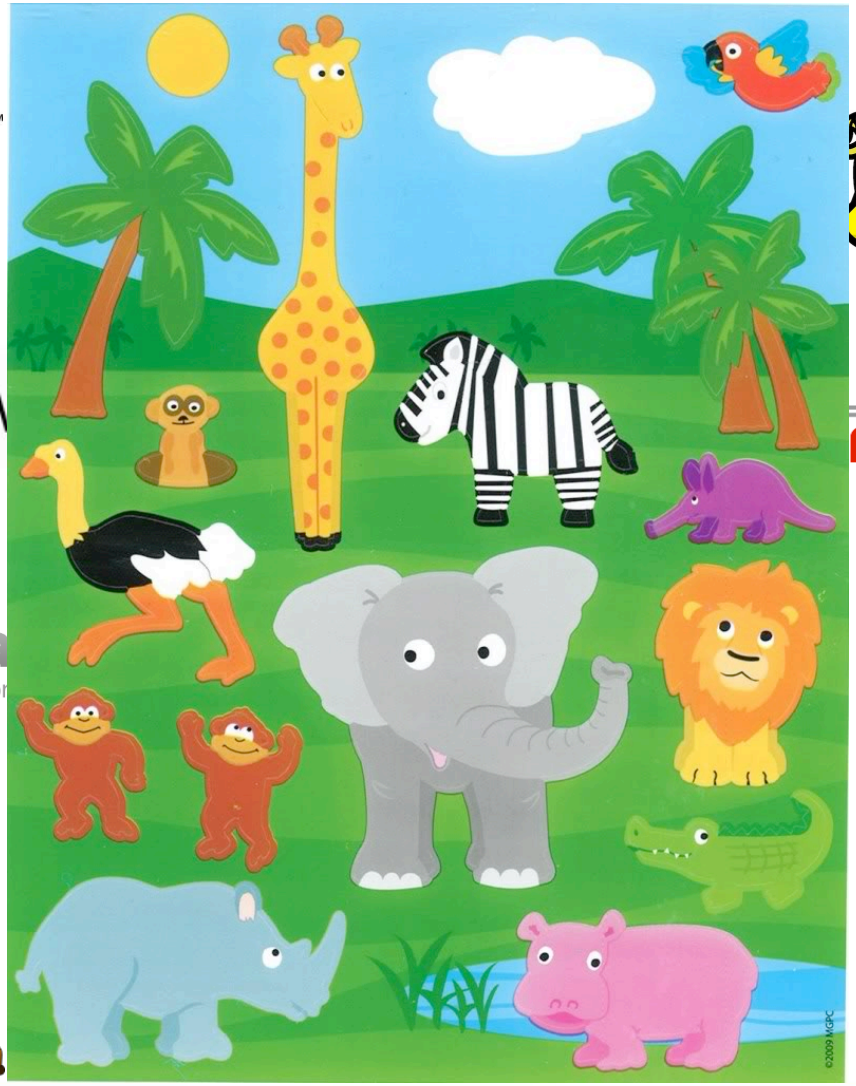
pay-per-use



Cloud computing and data management

- Relational databases in the cloud (DBaaS)
  - IBM DB2 on SmartCloud
  - Amazon RDS (MySQL, Oracle or SQL Server)
- NoSQL systems [Catell11]:
  - Key-value stores (memcached, DynamoDB, SimpleDB)
  - Extensible record stores (BigTable, Cassandra, HBase, Accumulo)
  - Document stores (MongoDB, CouchDB)
  - Graph databases (Pregel, Apache Giraph, Neo4J)
- Parallel data processing paradigms:
  - MapReduce (Hadoop, Amazon EMR), PACTs/Stratosphere, Spark

Cloud ecosystem



Cloud infrastructures considered here

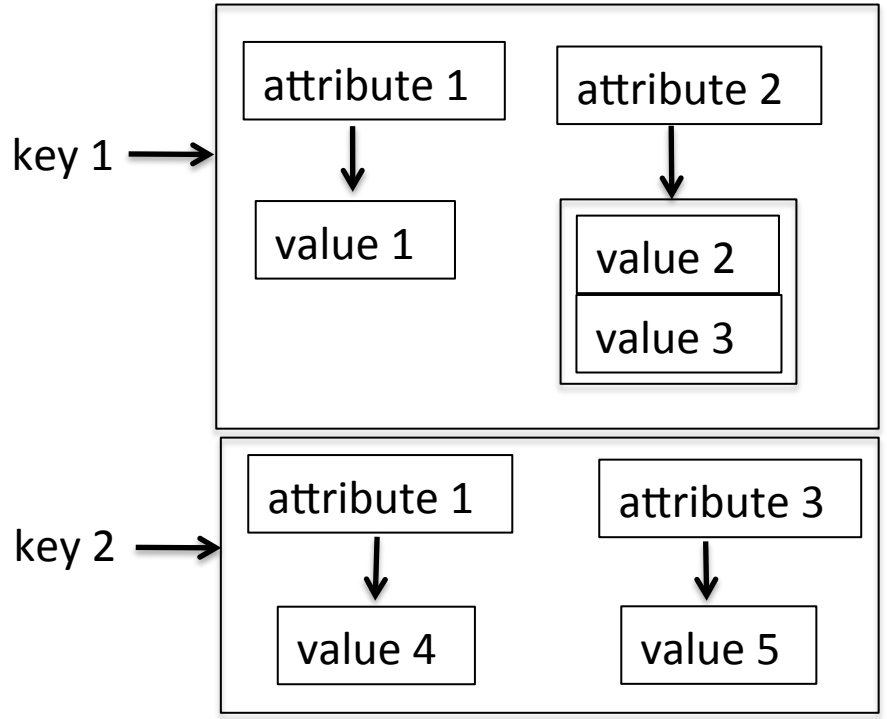
I. Distributed key-value stores

II. MapReduce-based parallel processing

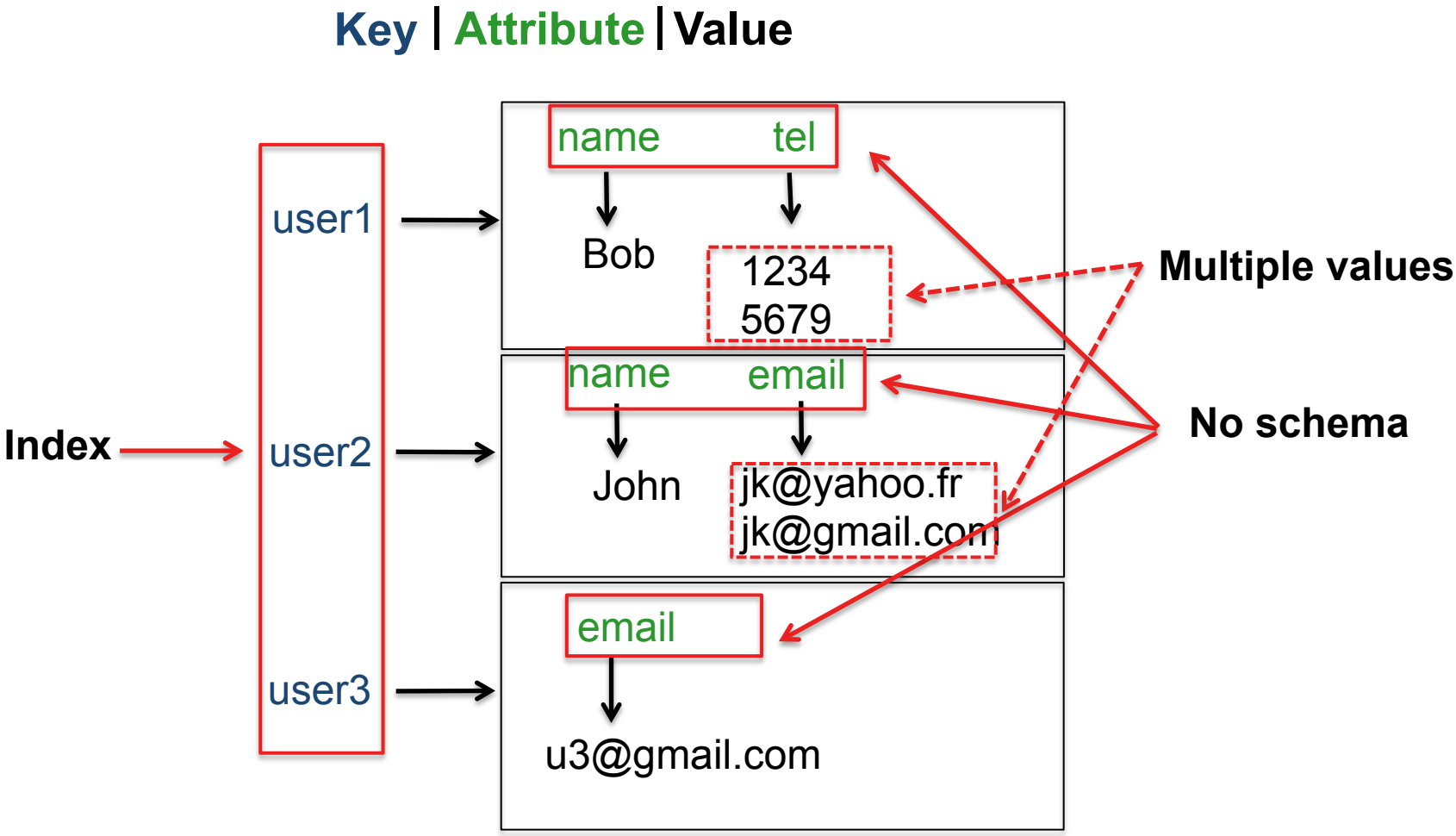
Distributed key-value stores

- Storing schema-less data in key-value pairs
- For each key there may be multiple (attribute-value) pairs
- Multi-valued attributes
- Index: Hash-based or lexicographically sorted on the key
- Basic APIs:

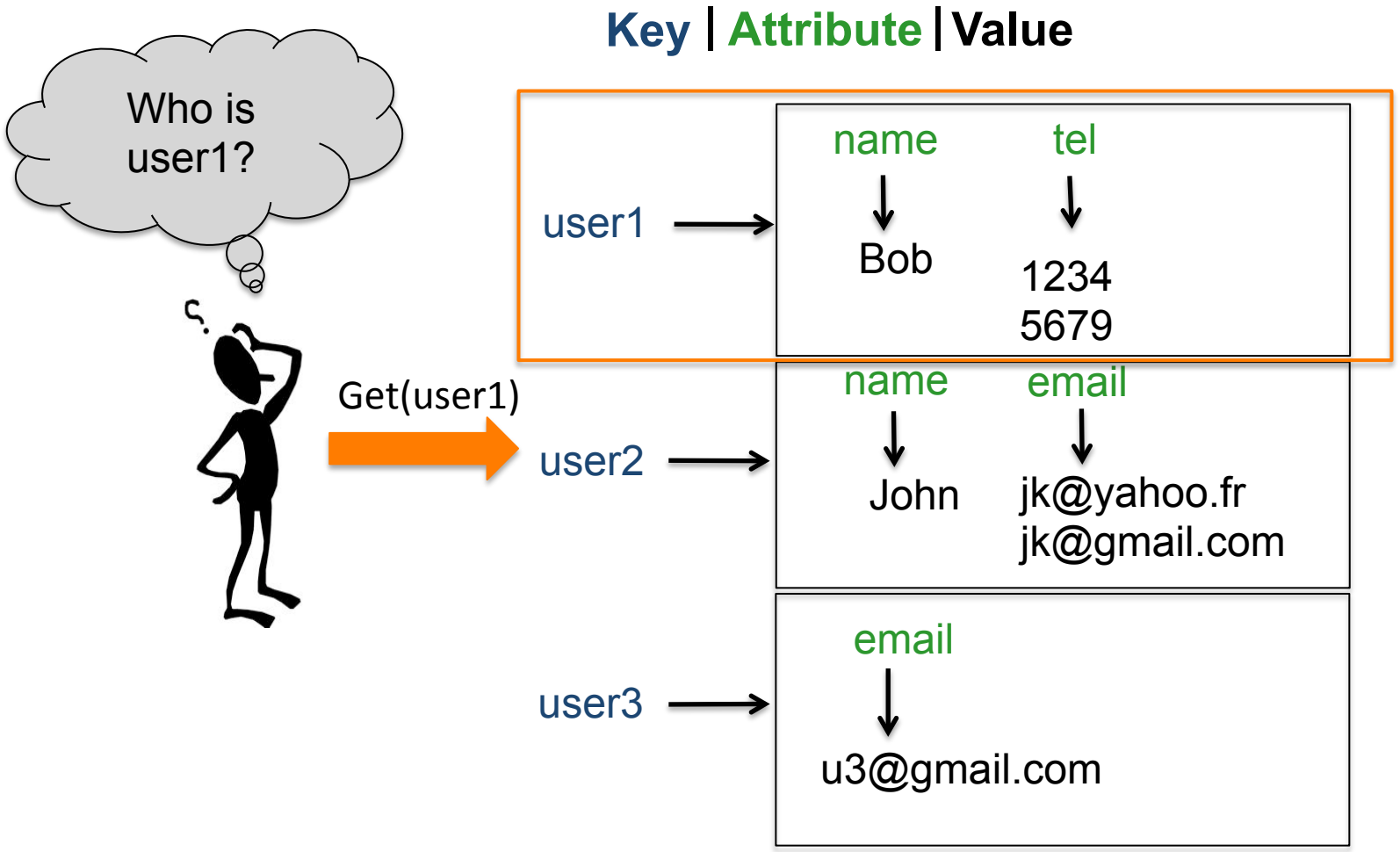
  Put(k, <a, v>), Get(k), Delete(k)
- No support for operations across tables (e.g., join!)



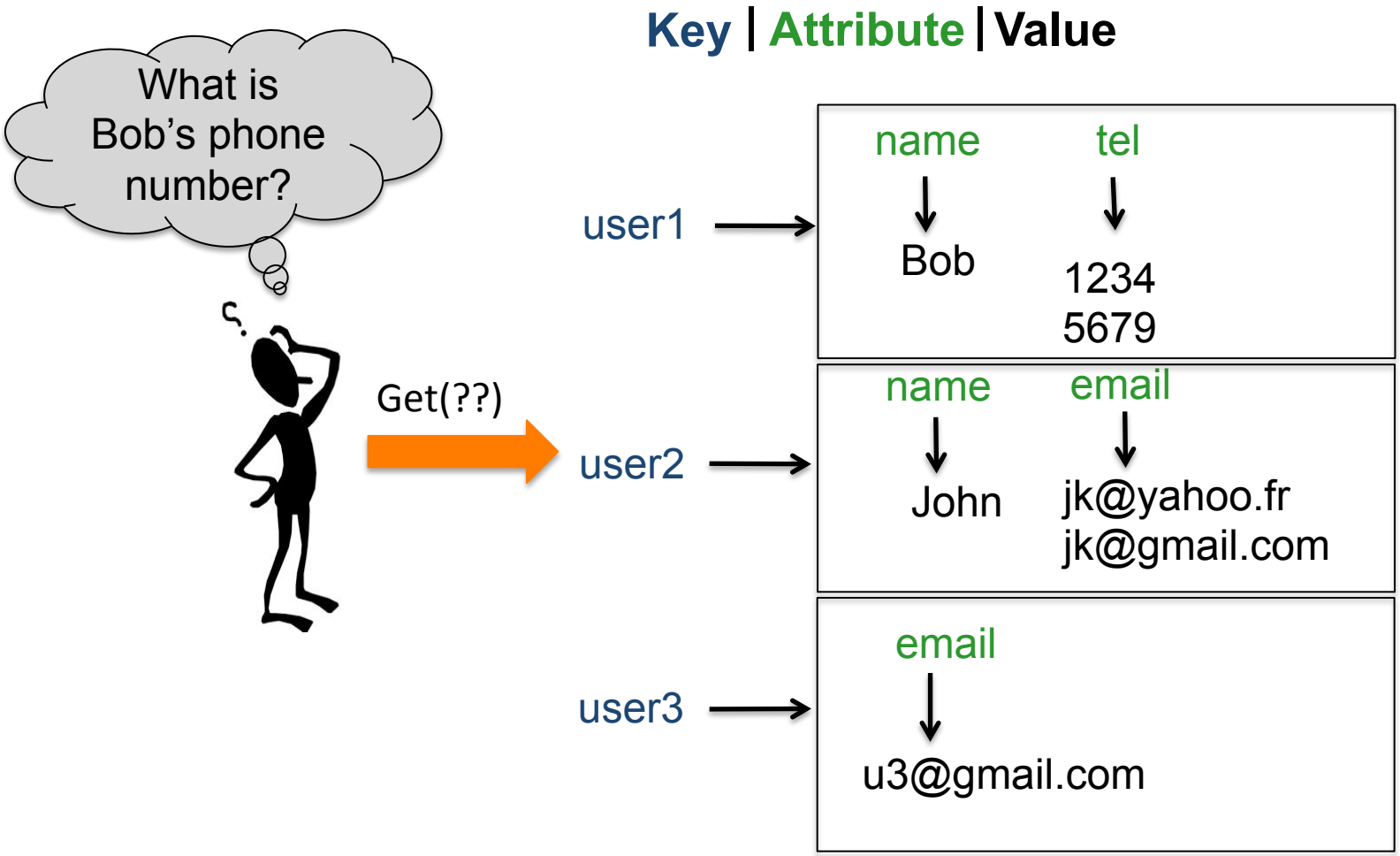
Distributed key-value stores



Distributed key-value stores

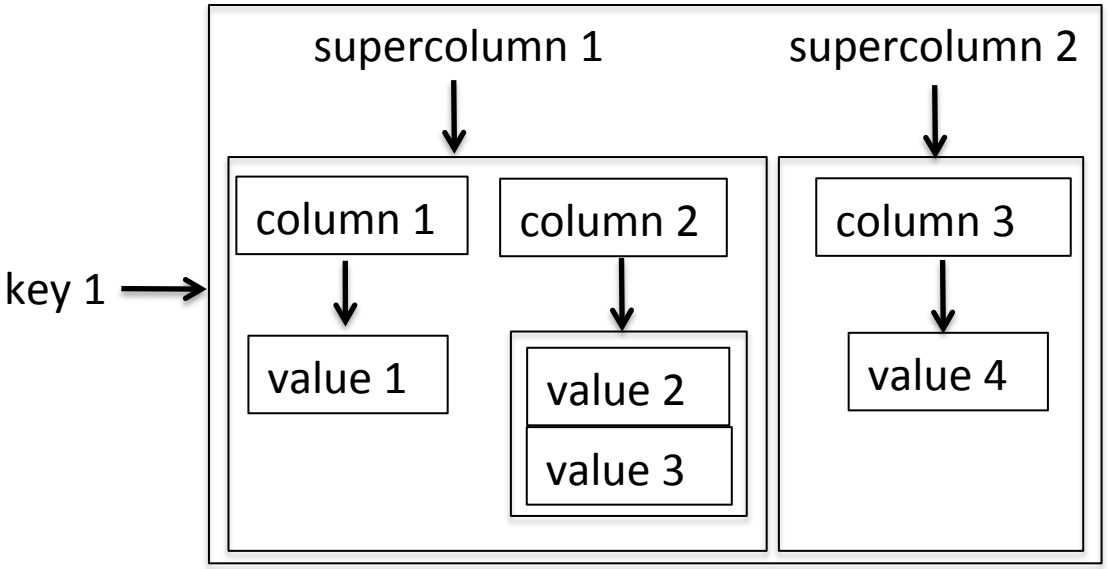


Distributed key-value stores



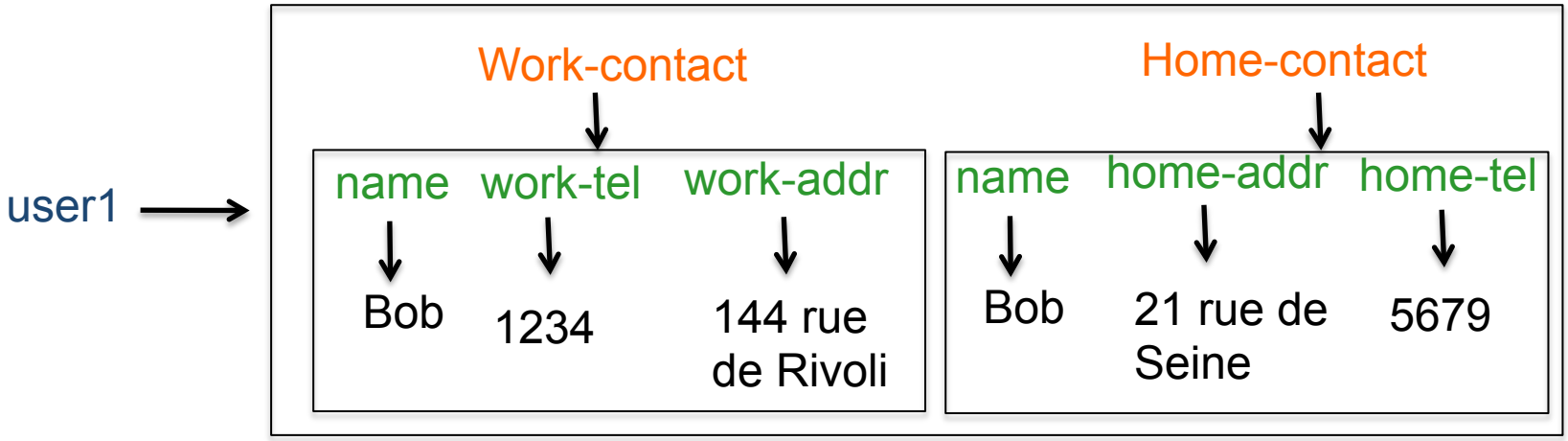
Extended key-value stores

- Google BigTable, Apache Cassandra
- Supercolumn: column container
  - K|SC|C|V
- Sorted index on the key
- Sorted index on the supercolumn
- Secondary index
  - maps values to keys



Extended key-value stores

Key | SuperColumn | Column | Value



Cloud infrastructures

I. Distributed key-value stores

II. MapReduce-based parallel processing

MapReduce in a nutshell

- Issued from Google [DG04]
- Massively parallel processing on commodity machines
- Master/slave architecture
- Input data is split horizontally into chunks
  - distributed file system (DFS)
- Simple API:
  - Map (*key*, *value*) → {*ikey*, *ivalue*}
  - Reduce (*ikey*, {*ivalues*}) → (*key'*, *value'*)

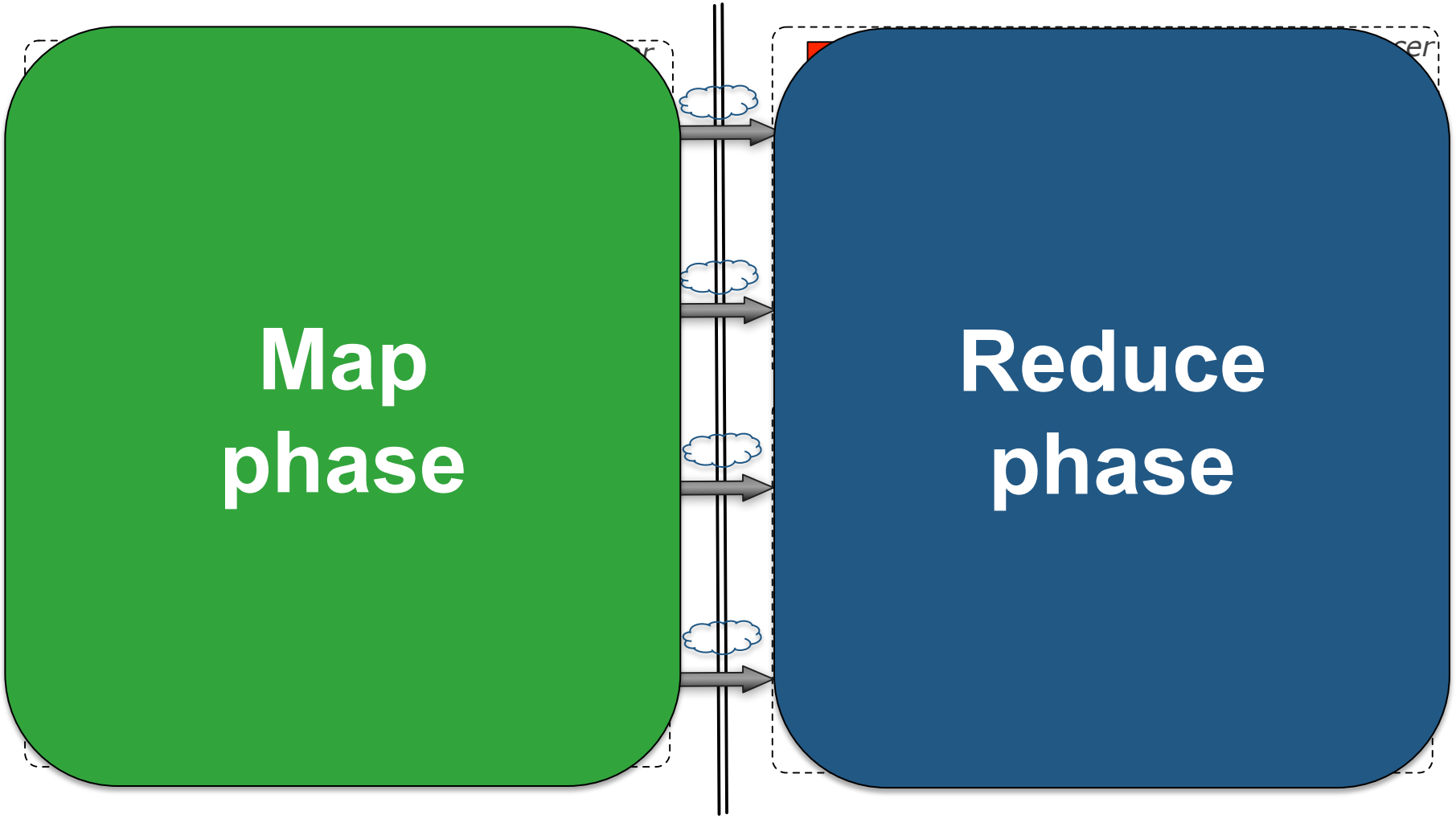
Many "more modern" extensions.

Extensively used in systems we cover.

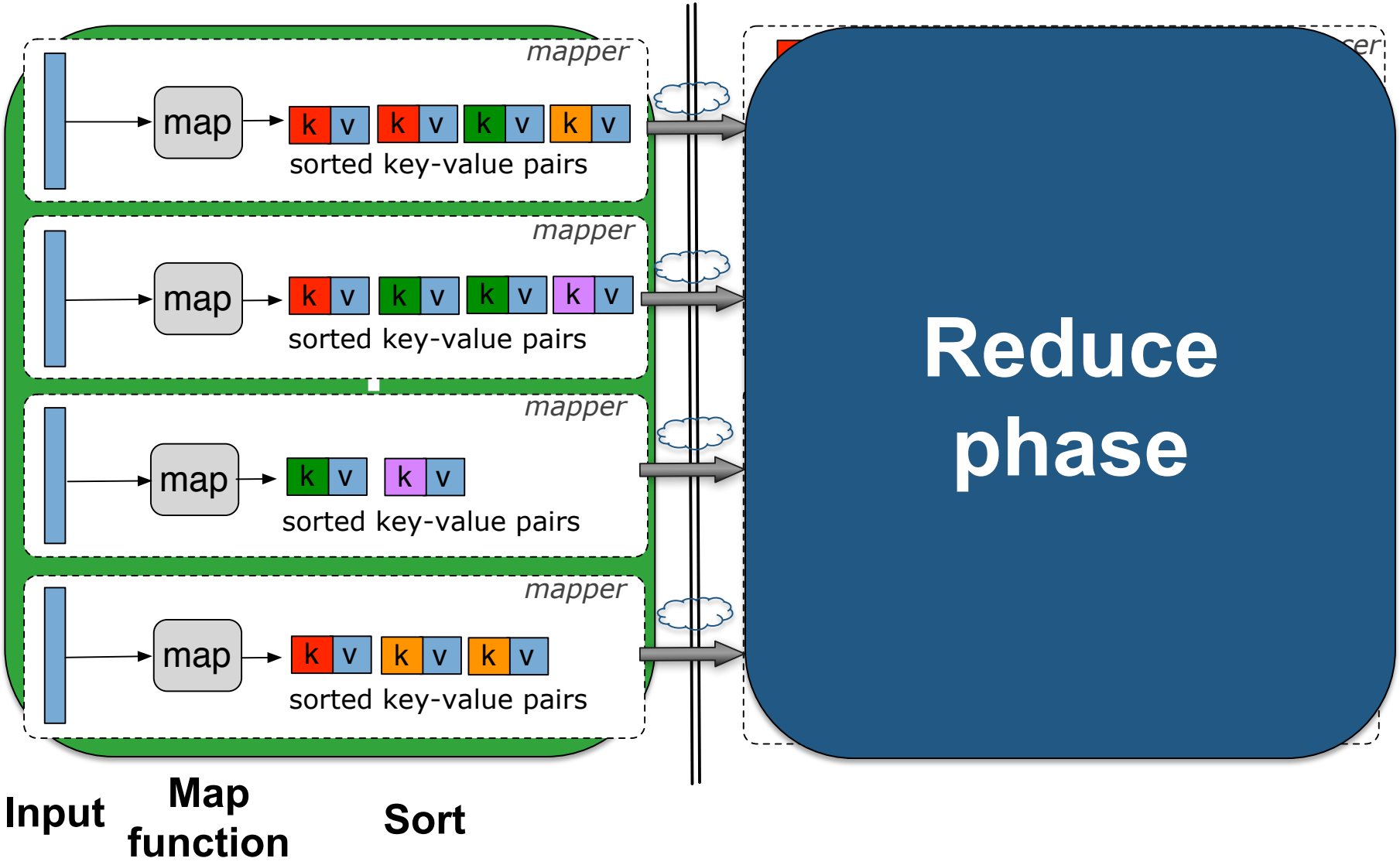
MapReduce in a nutshell

- **Map** phase: independent processes (mappers) which run in parallel
  - operate on the chunks of input data
  - output intermediate results
- **Shuffle** phase: Intermediate results are shuffled through the network
- **Reduce** phase: independent processes (reducers) which run in parallel
  - group intermediate results of the map phase
  - operate on the groups
  - output final results
- Key-value pairs with the same key *ikey* meet at the same reducer
  - e.g., hash(*ikey*) mod R
- Open source implementation: Hadoop and HDFS

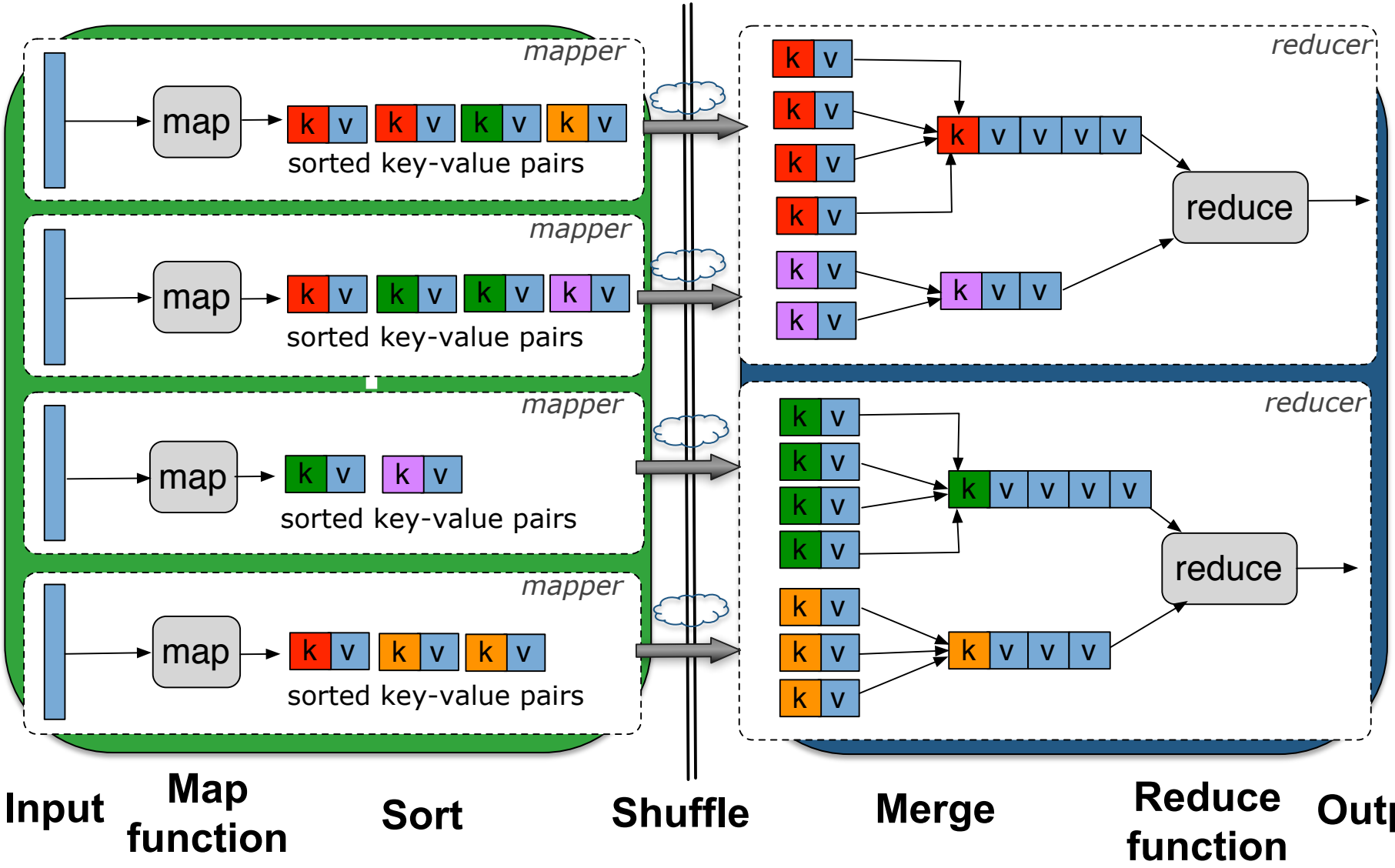
MapReduce illustration



MapReduce illustration

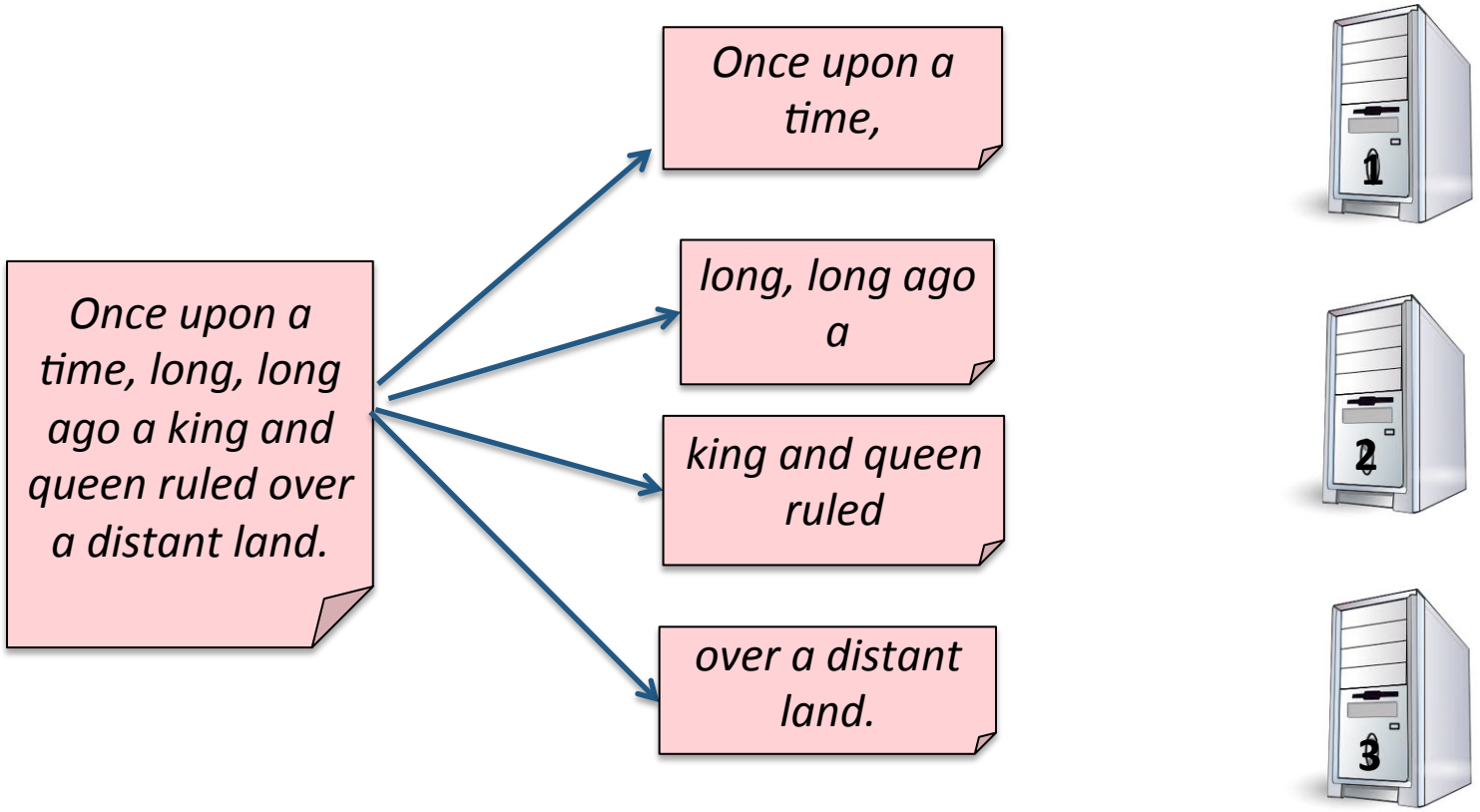


MapReduce illustration



MapReduce by words-count example

- *Count the number of words in parallel*

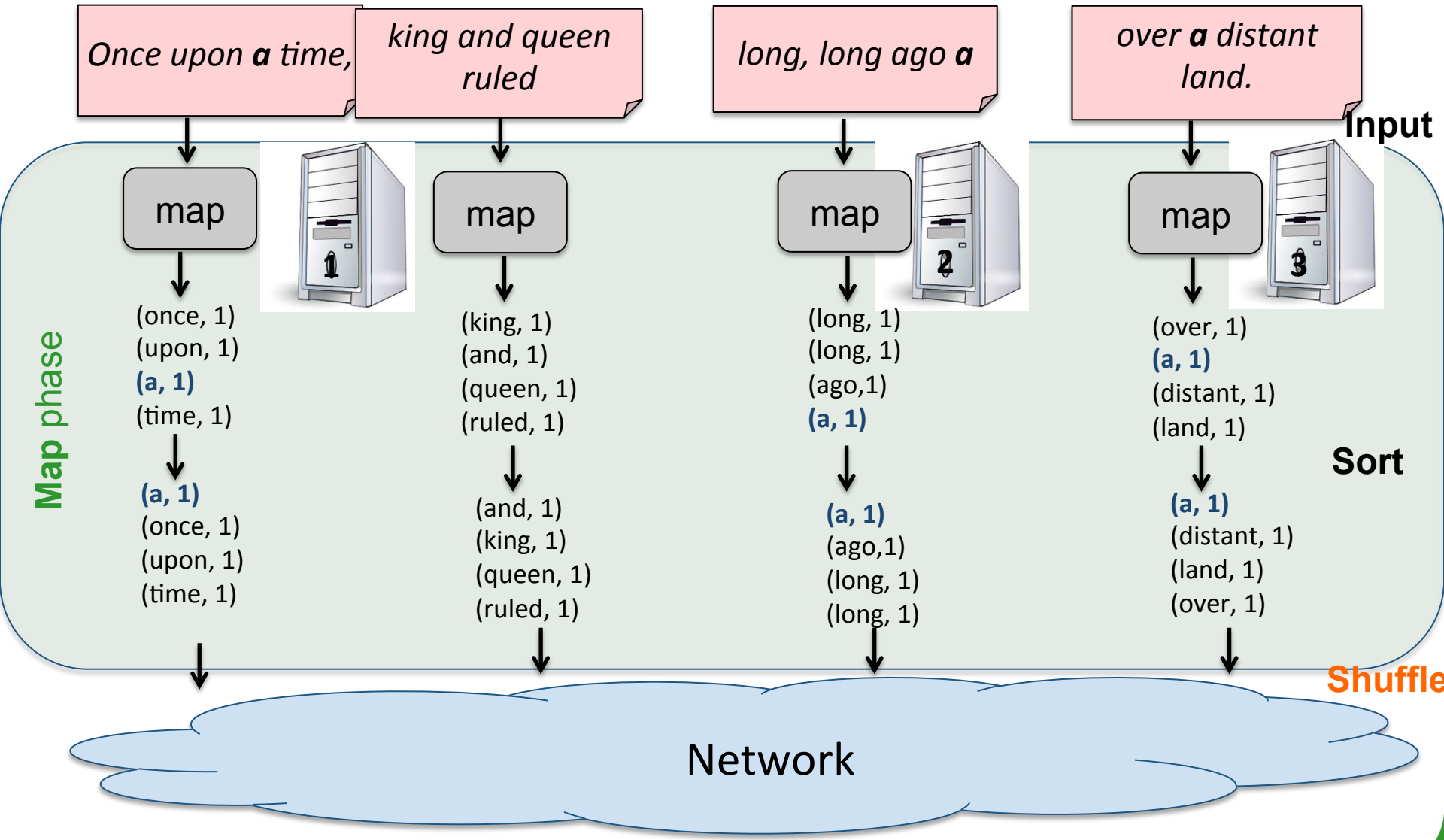


Initial file

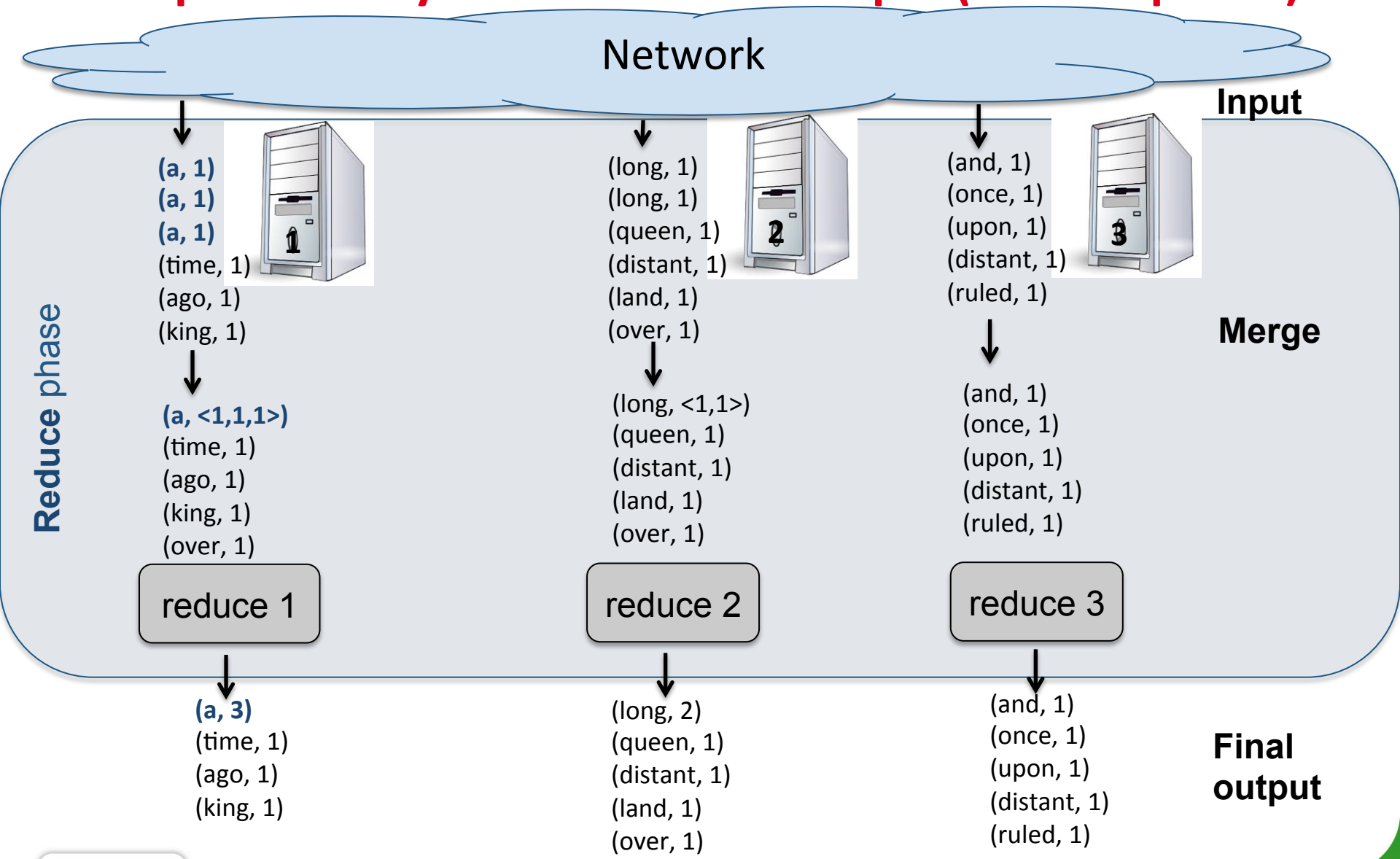
split by DFS in *data blocks*

3-nodes cluster

MapReduce by words-count example (Map phase)



MapReduce by words-count example (Reduce phase)



MapReduce code ☺

```
1 package org.myorg;
2
3 import java.io.IOException;
4 import java.util.*;
5
6 import org.apache.hadoop.fs.Path;
7 import org.apache.hadoop.conf.*;
8 import org.apache.hadoop.io.*;
9 import org.apache.hadoop.mapreduce.*;
10 import org.apache.hadoop.mapreduce.lib.input.FileInputFormat;
11 import org.apache.hadoop.mapreduce.lib.input.TextInputFormat;
12 import org.apache.hadoop.mapreduce.lib.output.FileOutputFormat;
13 import org.apache.hadoop.mapreduce.lib.output.TextOutputFormat;
14
15 public class WordCount {
16
17  public static class Map extends Mapper<LongWritable, Text, Text, IntWritable> {
18    private final static IntWritable one = new IntWritable(1);
19    private Text word = new Text();
20
21    public void map(LongWritable key, Text value, Context context) throws IOException, InterruptedException {
22      String line = value.toString();
23      StringTokenizer tokenizer = new StringTokenizer(line);
24      while (tokenizer.hasMoreTokens()) {
25        word.set(tokenizer.nextToken());
26        context.write(word, one);
27      }
28    }
29  }
30
31  public static class Reduce extends Reducer<Text, IntWritable, Text, IntWritable> {
32
33    public void reduce(Text key, Iterable<IntWritable> values, Context context)
34      throws IOException, InterruptedException {
35      int sum = 0;
36      for (IntWritable val : values) {
37        sum += val.get();
38      }
39      context.write(key, new IntWritable(sum));
40    }
41  }
42
43  public static void main(String[] args) throws Exception {
44    Configuration conf = new Configuration();
45
46      Job job = new Job(conf, "wordcount");
47
48    job.setOutputKeyClass(Text.class);
49    job.setOutputValueClass(IntWritable.class);
50
51    job.setMapperClass(Map.class);
52    job.setReducerClass(Reduce.class);
53
54    job.setInputFormatClass(TextInputFormat.class);
55    job.setOutputFormatClass(TextOutputFormat.class);
56
57    FileInputFormat.addInputPath(job, new Path(args[0]));
58    FileOutputFormat.setOutputPath(job, new Path(args[1]));
59
60    job.waitForCompletion(true);
61  }
62
63 }
```

http://wiki.apache.org/hadoop/WordCount

Only **63** lines for a distributed/parallel application!

MapReduce - pros/cons

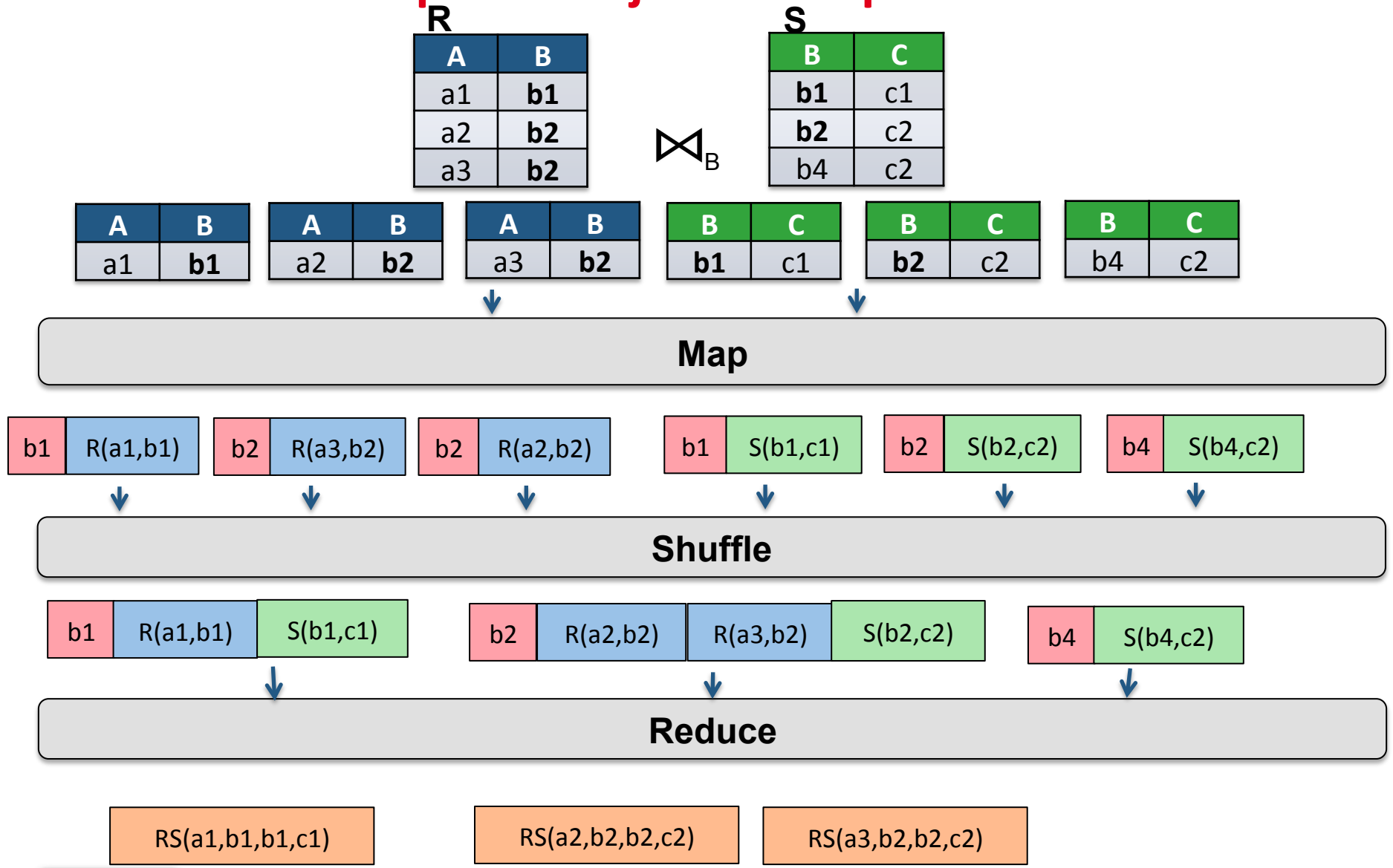
- ✚ High parallelization
- ✚ Scalable
  - number of nodes
  - size of data
- ✚ Fault-tolerant
  - replication of data
- ✚ Easy to implement

- ➖ Operates on only one input
- ➖ No indexes
  - scan of all data
- ➖ Blocking operations
  - e.g., reduce does not begin until all tasks have finished

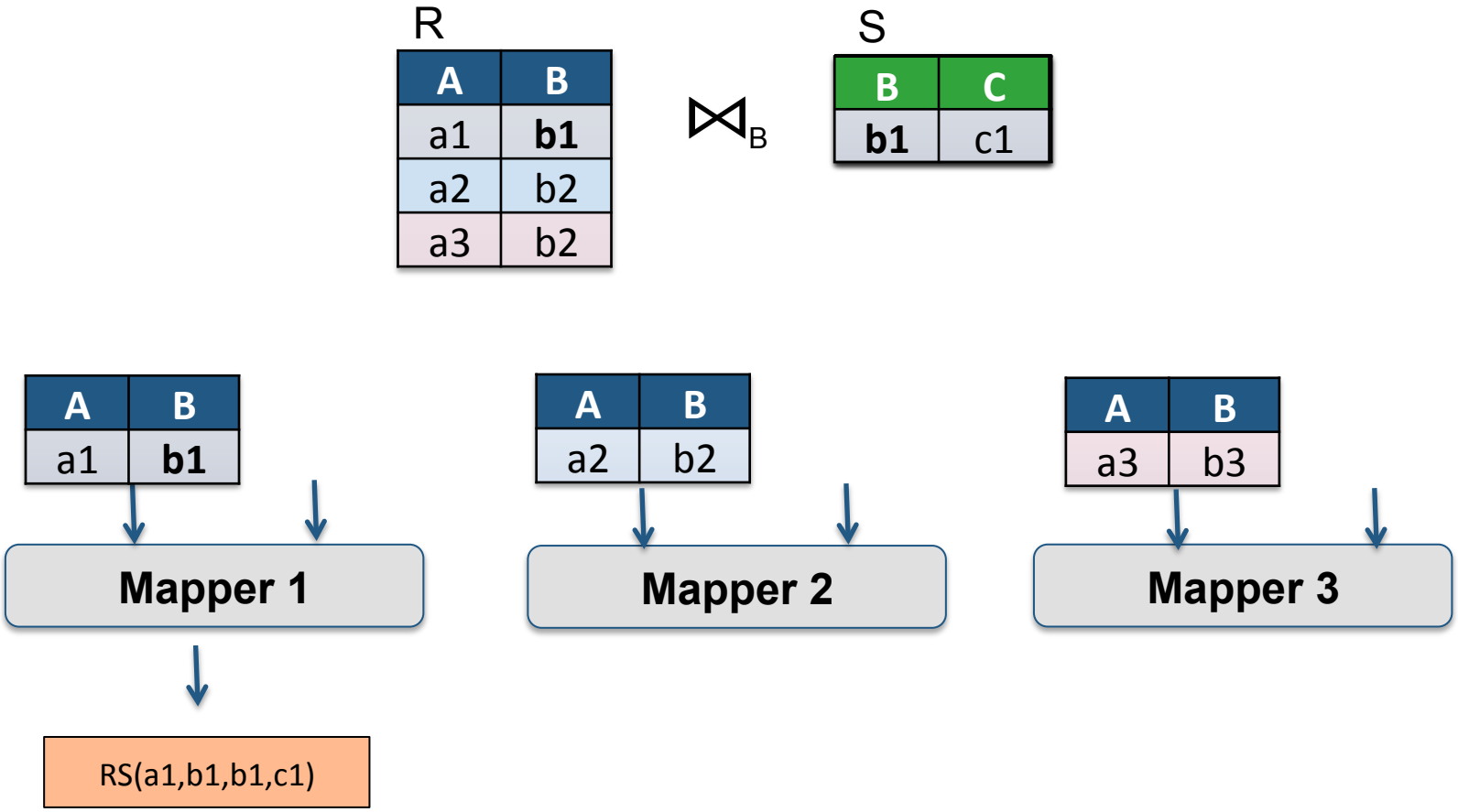
Joins in MapReduce

- Two main strategies:
  - symmetric hash join (repartition join)
  - replicated join (broadcast join)
- Representative works:
  - [Blanas10] on different join methods in MapReduce
  - [Afrati11] on optimizing multiway joins in MapReduce
  - [Wu11] on query optimization in MapReduce

Repartition join in MapReduce



Replicated (broadcast) join in MapReduce



Variability in the clouds

Cloud = performance variability [Schad10], [Iosup11]

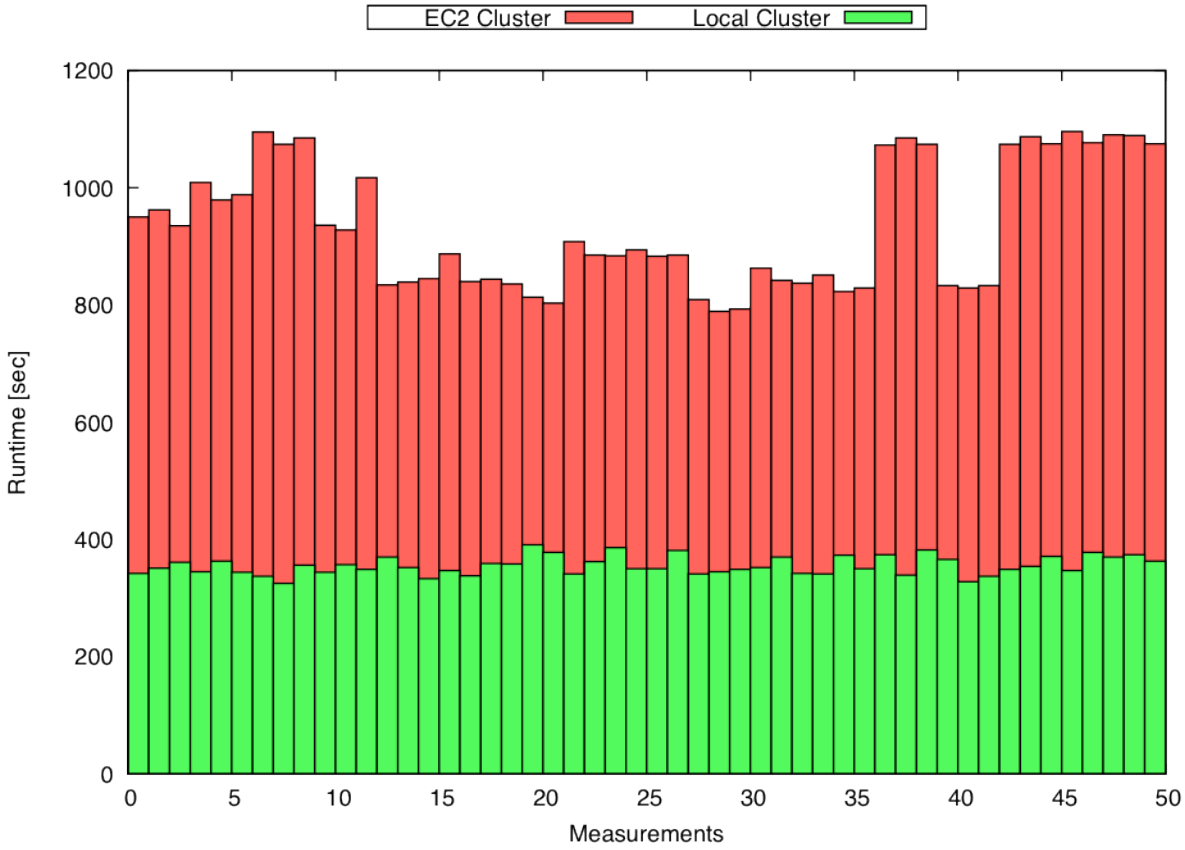


Figure 1: Runtime for a MapReduce job.

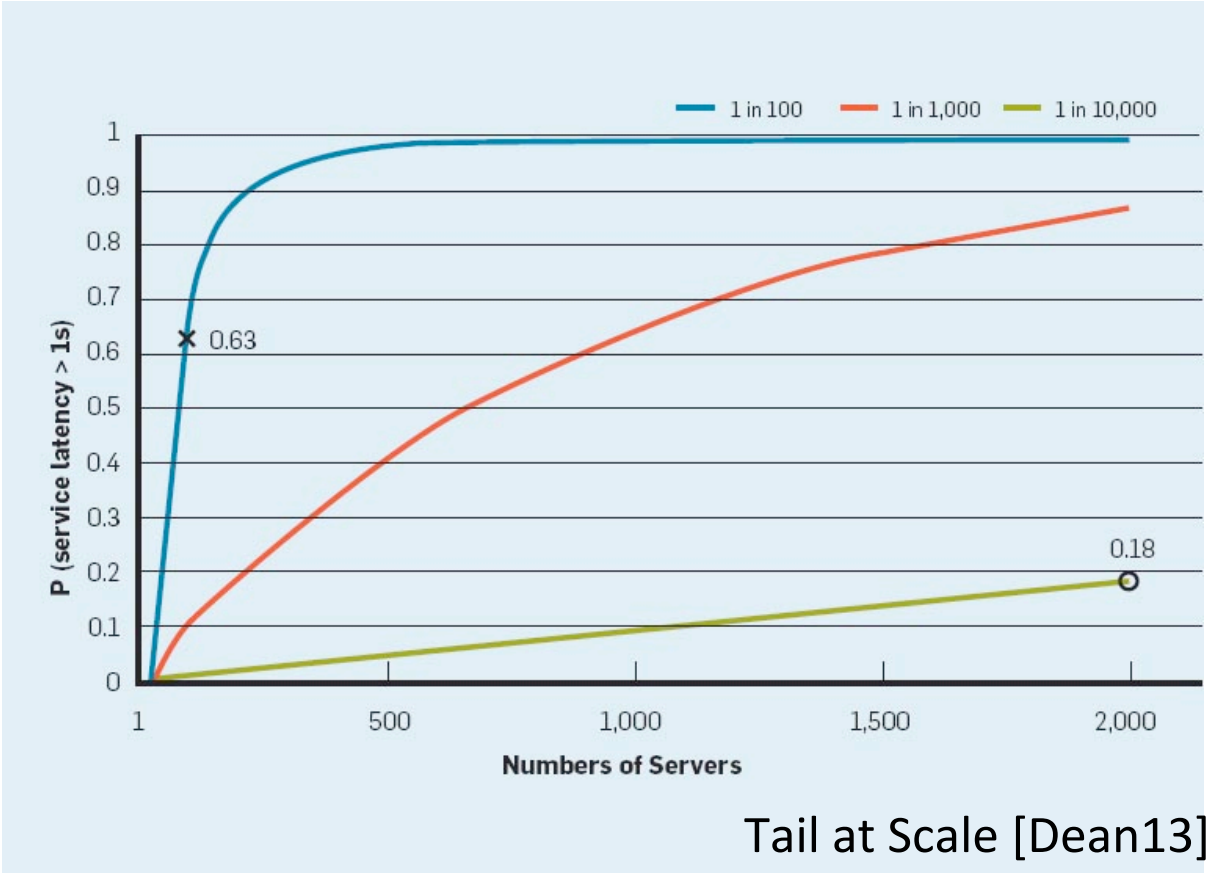
from [Schad10]

Why the variable performance?

- Software-based reasons:
  - Shared resources (cpu, memory, network bandwidth)
  - Daemons running in the background
  - Global resource sharing such as network switches and shared file systems
  - Maintenance activities running in the background
  - Multiple layers of queuing
- Hardware-based reasons:
  - Garbage collection for SSD
  - Energy management

Variability in the clouds

Variability is amplified by scale



Tail at Scale [Dean13]

3

ANALYSIS OF MASSIVELY DISTRIBUTED RDF DATA MANAGEMENT PLATFORMS

RDF systems in the cloud

- Relatively new and fast-growing research area

- Numerous systems
  - **AMADA** [Bugiotti11, Arandar12]
  - CumulusRDF [Ladwig11]
  - EAGRE [Zhang13]
  - **Graph partitioning** [Huang11]
  - H2RDF [Papailiou12]
  - **HadoopRDF** [Husain11]
  - MAPSIN [Schätzle12]
  - PigSPARQL [Schätzle11]
  - RAPID+ [Ravindra11]
  - **Rya** [Punnoose12]
  - Stratustore [Ladwig11]
  - **SHARD** [Rohloff10]
  - **TriAD** [Gurajada14]
  - **Trinity.RDF** [Zeng13]
  - **WebPie** [Urbani09]
  - QueryPie [Urbani11]
  - …

Analysis dimensions

1. Data storage

2. Query processing

3. RDFS entailment

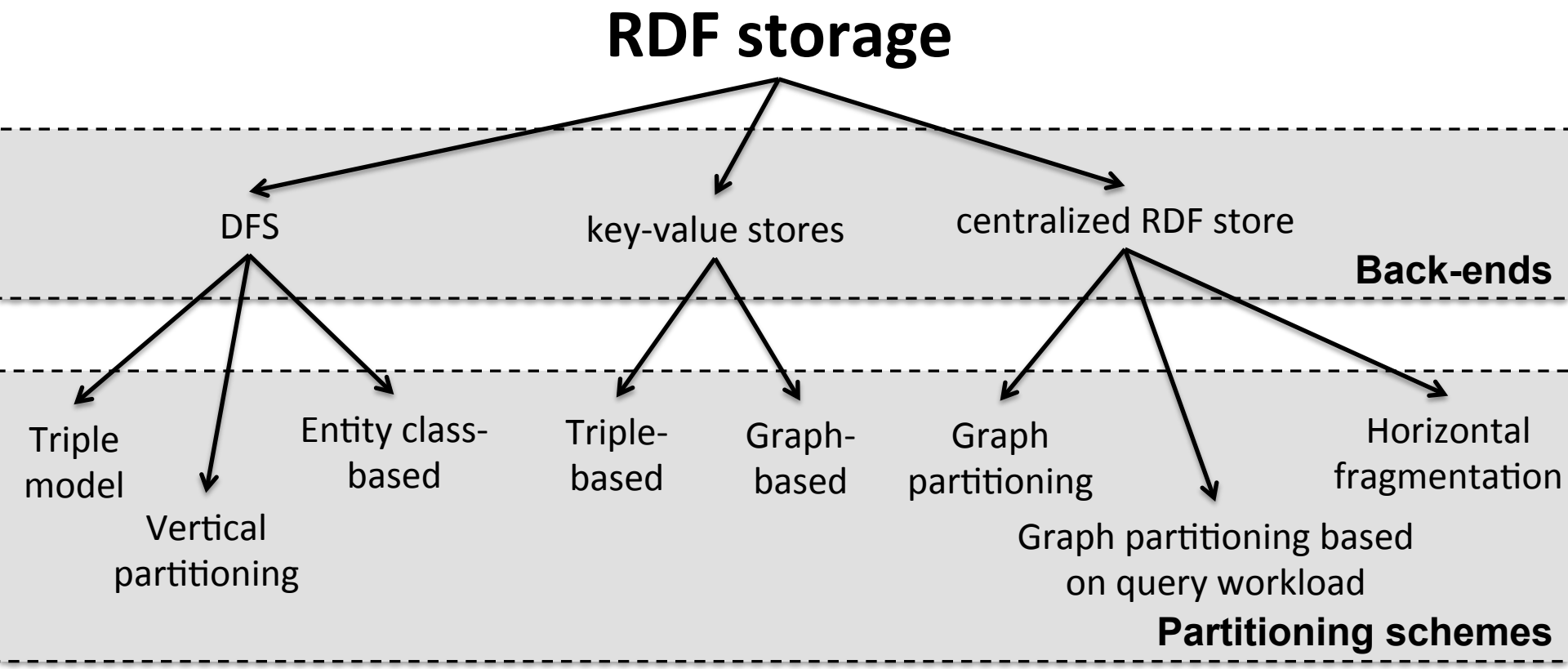
Analysis dimensions

1. Data storage

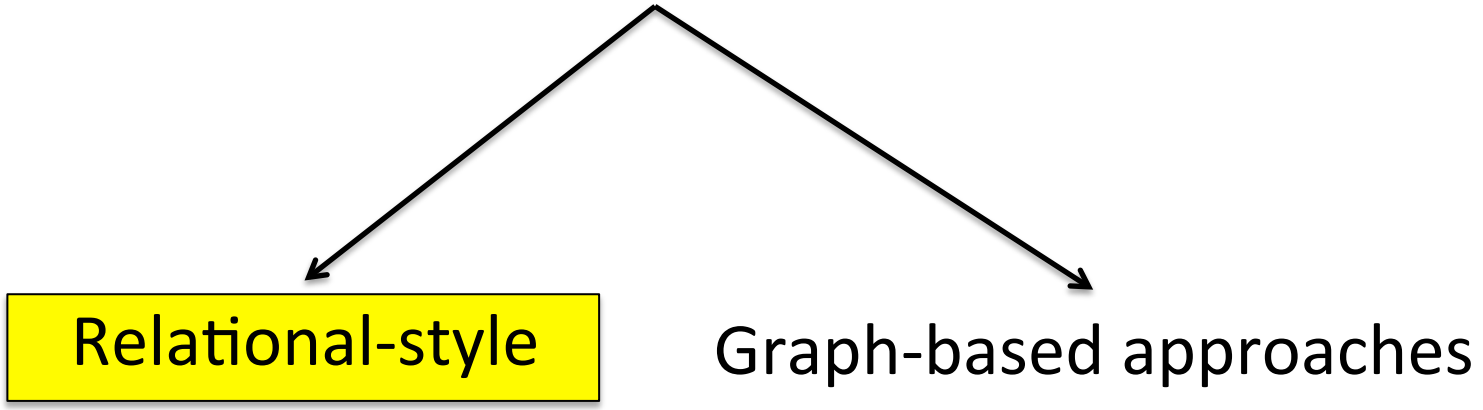
2. Query processing

3. RDFS entailment

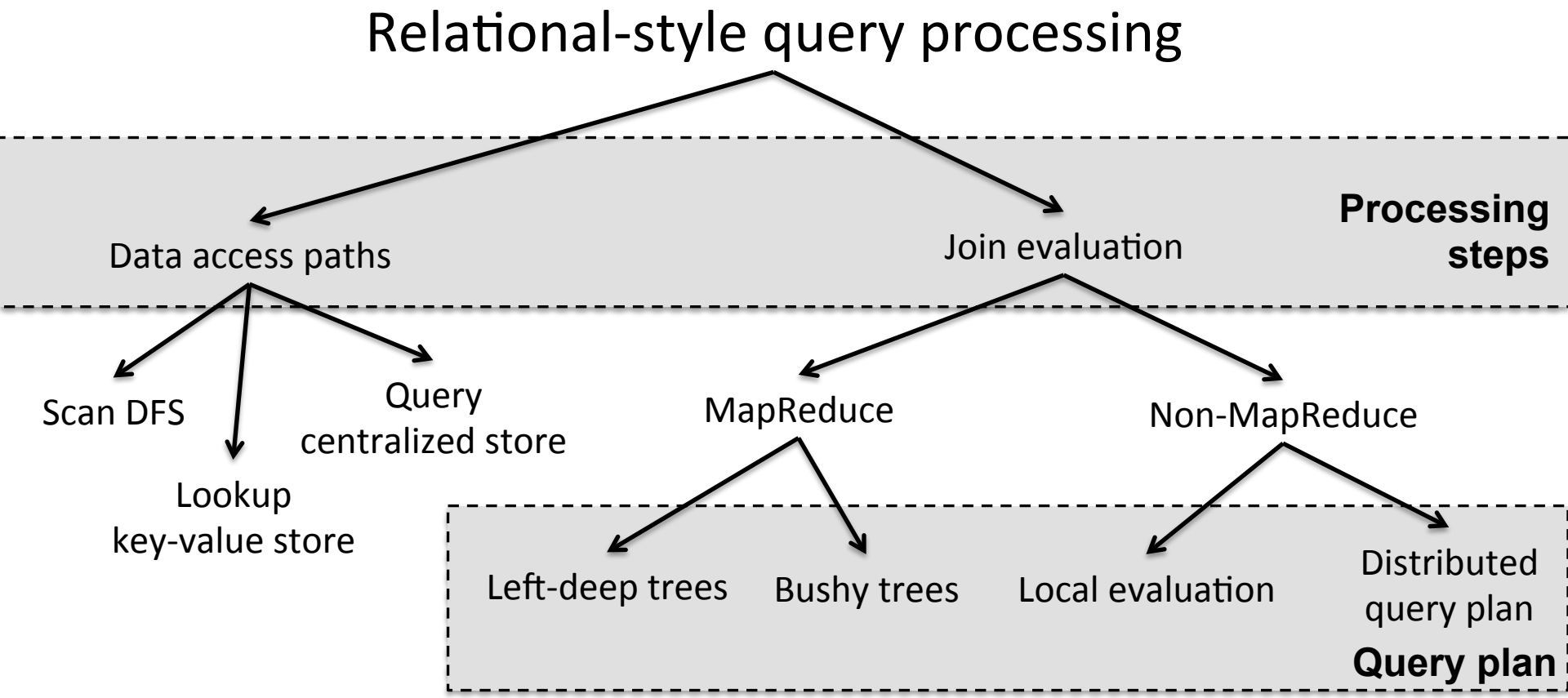
Data storage and partitioning schemes



Query processing



Query processing



Categorization based on storage and query processing

I. Based on MapReduce and DFS

II. Based on key-value stores

III. Based on graph platforms

IV. Based on multiple centralized (RDF) stores

V. Hybrid systems

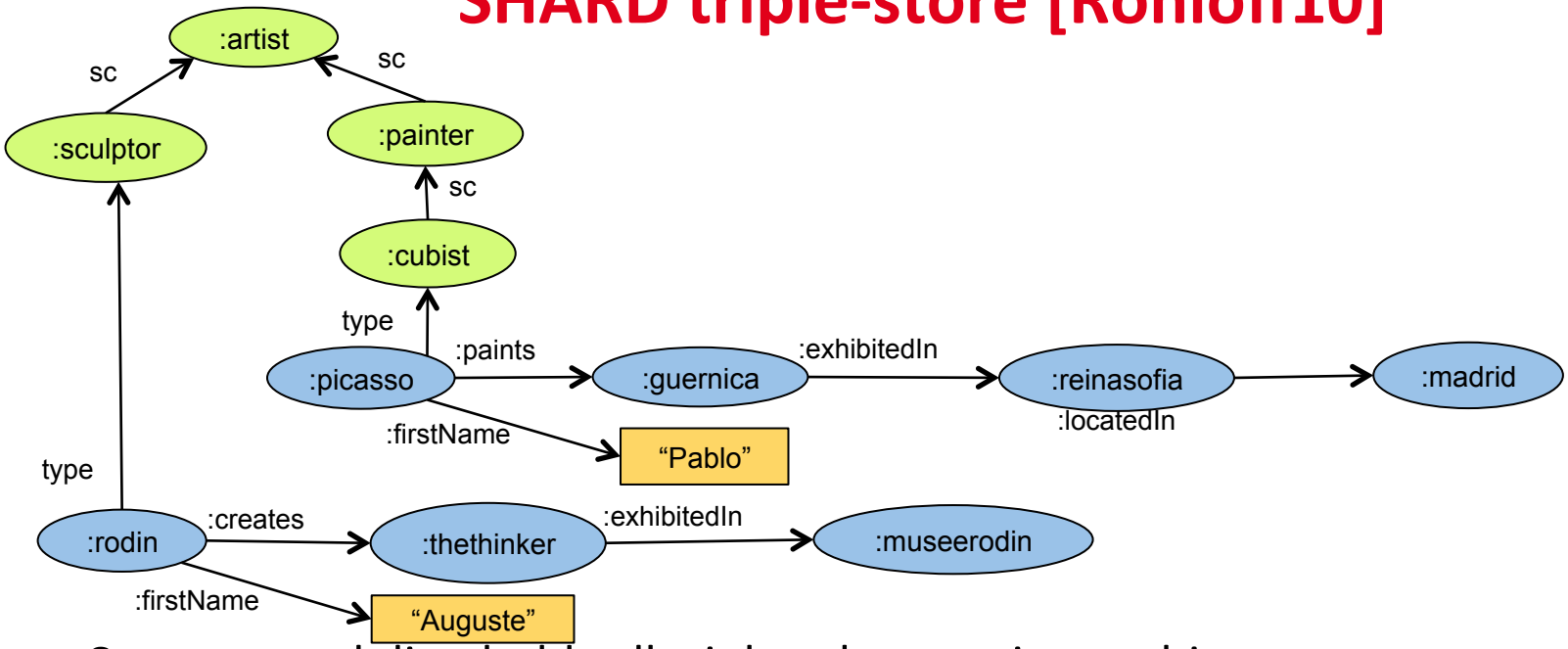
3.1

MapReduce/DFS-based approaches

I. MapReduce/DFS-based approaches

- Store RDF triples in DFS (usually HDFS)
- Translate the query to MapReduce jobs
- Run MapReduce to answer the queries (usually Hadoop)
- Representative works:
  - SHARD [Rohloff10]
  - HadoopRDF [Husain11]
  - RAPID+ [Ravindra11]
  - PigSPARQL [Schätzle11]
  - TriAD [Gujarada14]

SHARD triple-store [Rohloff10]



Storage: each line holds all triples about a given subject

File1.rdf

```
picasso type :cubist :paints :guernica :firstName "Pablo"
guernica :exhibitedIn :reinasofia
reinasofia :locatedIn :madrid
rodin type :sculptor :firstName
"Auguste" :creates :thethinker
thethinker :exhibitedIn :museerodin
```

File2.rdf

```
:sculptor sc :artist
:cubist sc :painter
:painter sc :artist
```

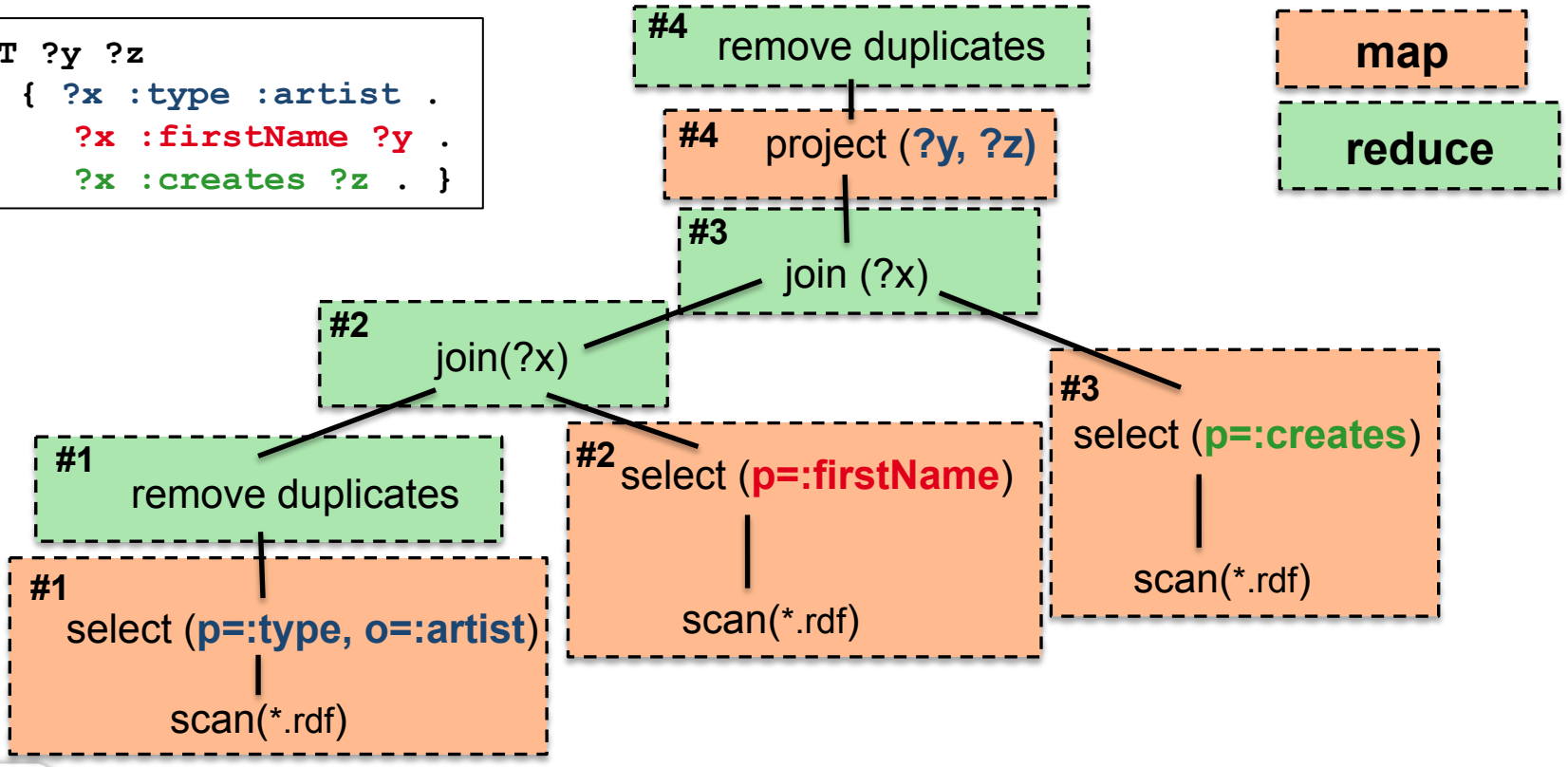
HDFS

SHARD triple-store [Rohloff10]

Query processing: Iterative MapReduce jobs

- 1 MapReduce job for each triple pattern + 1 for the projection at the end
- Map phase: match triple pattern by scanning all triples
- Reduce phase: join triple pattern with intermediate results from previous ones

```
SELECT ?y ?z
WHERE { ?x :type :artist .
        ?x :firstName ?y .
        ?x :creates ?z . }
```



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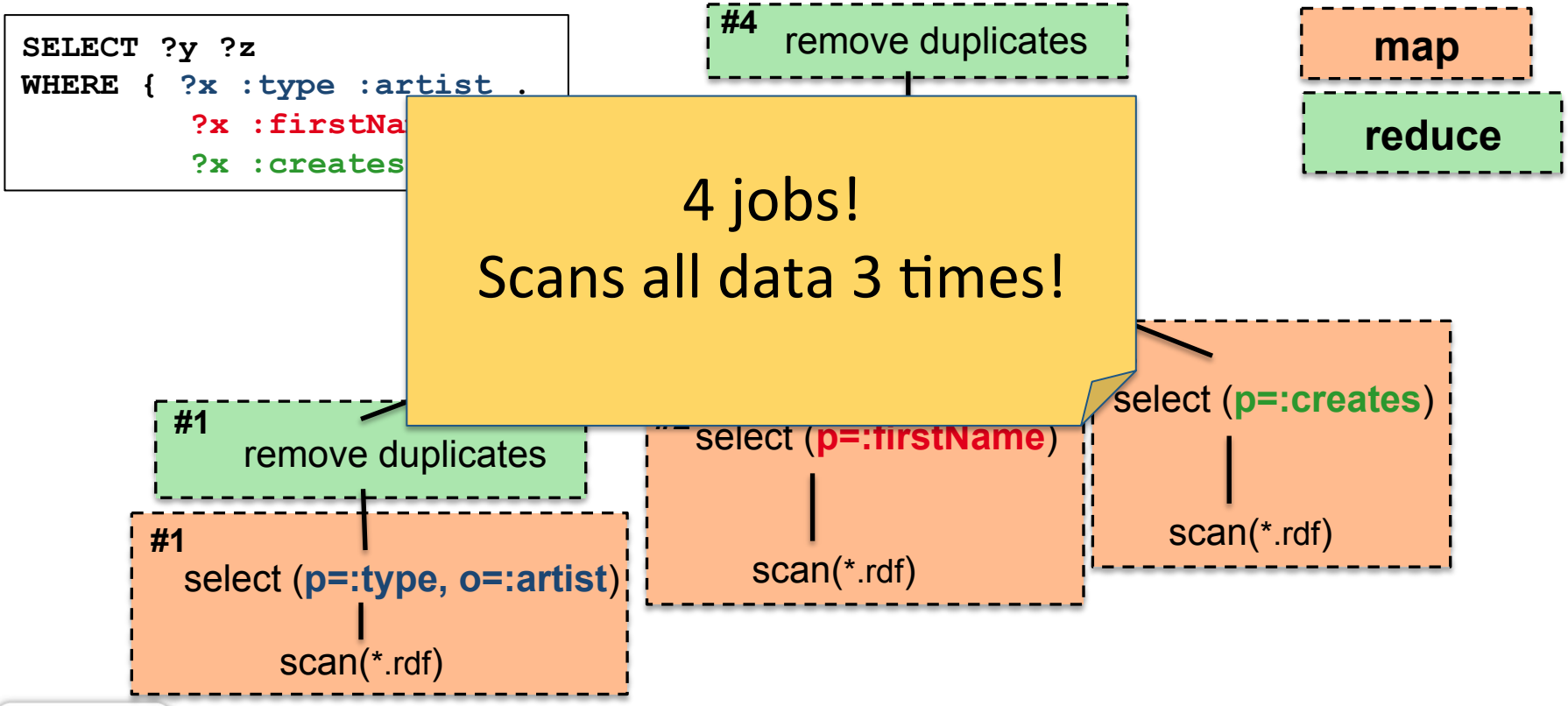
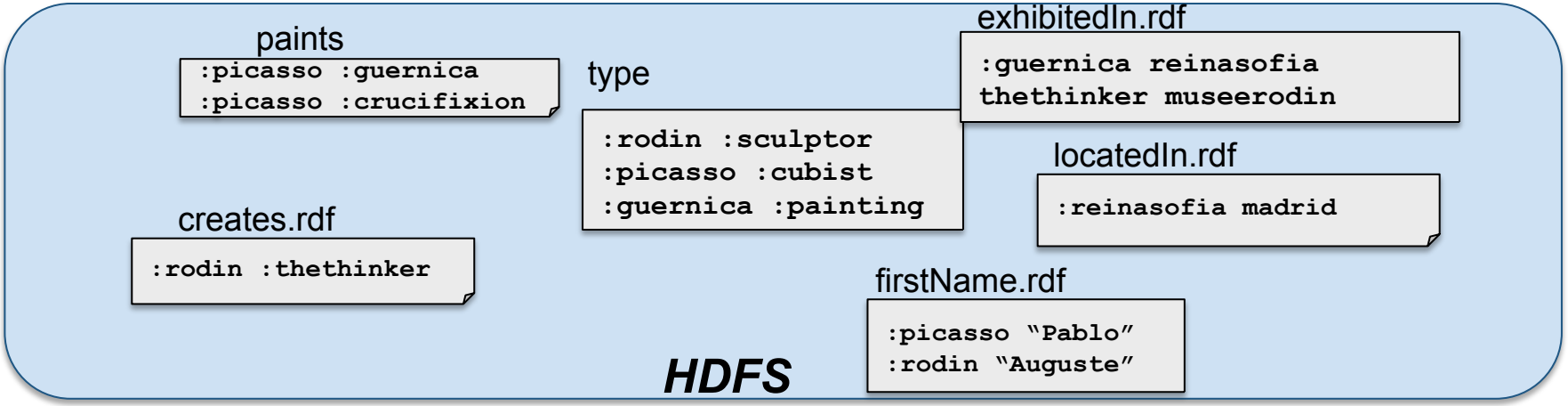


HadoopRDF - storage [Husain11]

- RDF triples grouped by the property names in files (vertical partitioning of centralized RDF stores)



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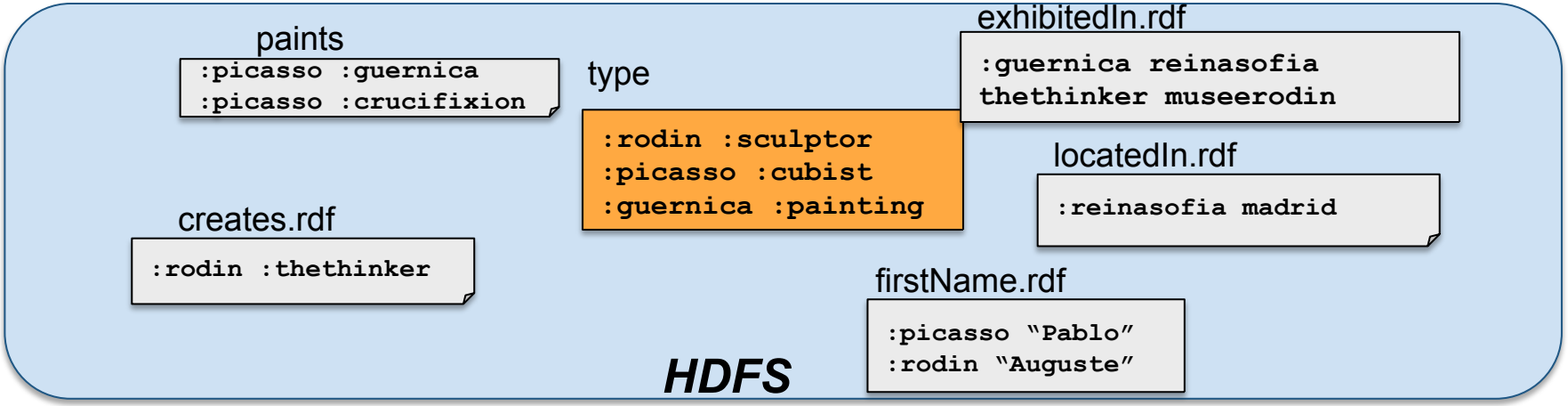
- The file for the property type partitioned based on the object value



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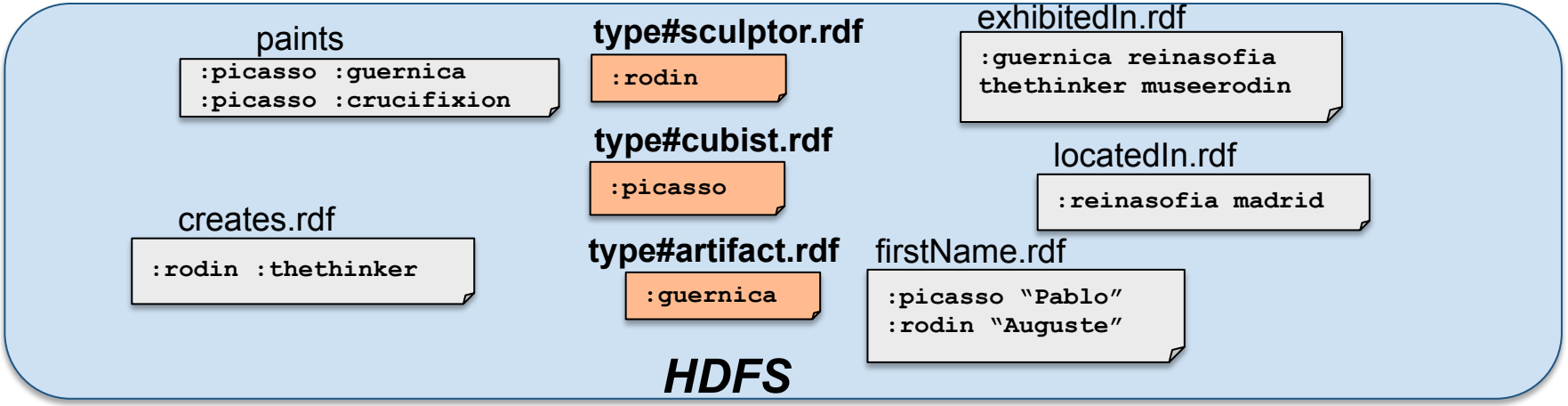
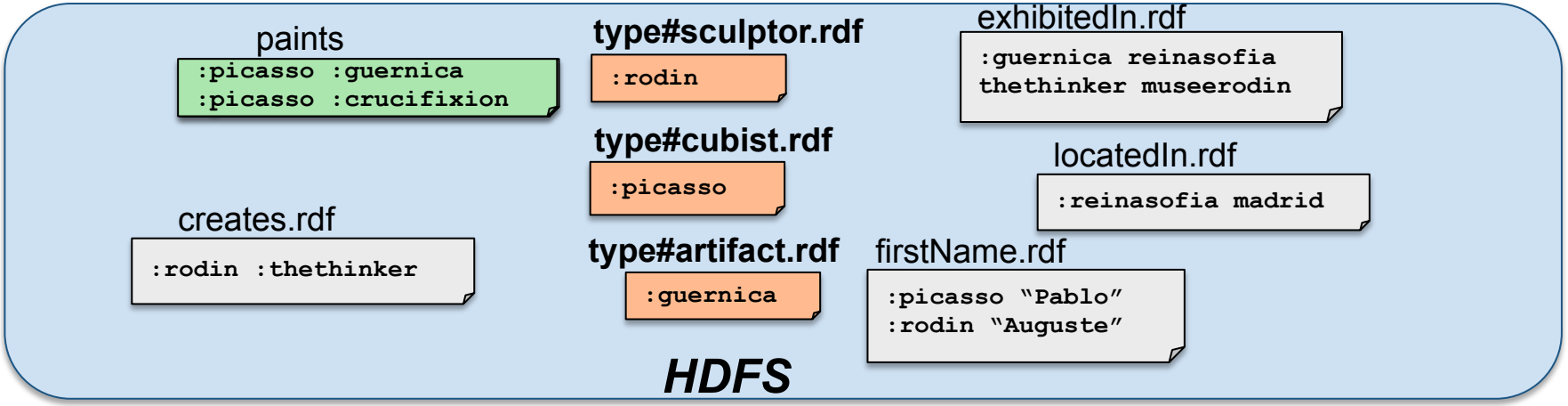


HadoopRDF storage

- RDF triples grouped by the property names in files (vertical partitioning of centralized RDF stores)
- The file for the property type partitioned based on the object value
- All other property files partitioned by their object type (if there is such information)



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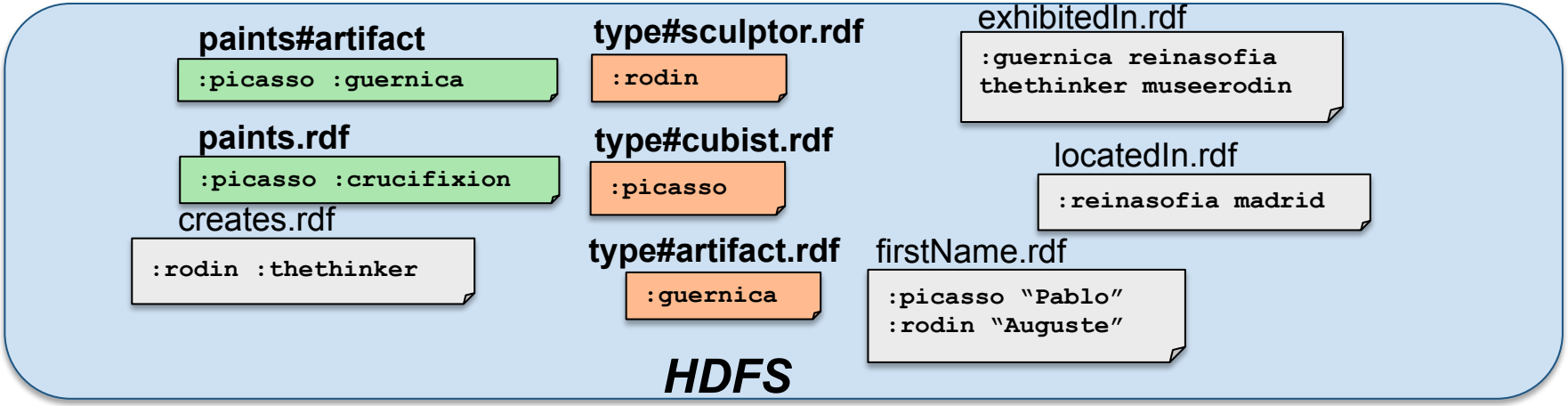


HadoopRDF storage features

- Space gains

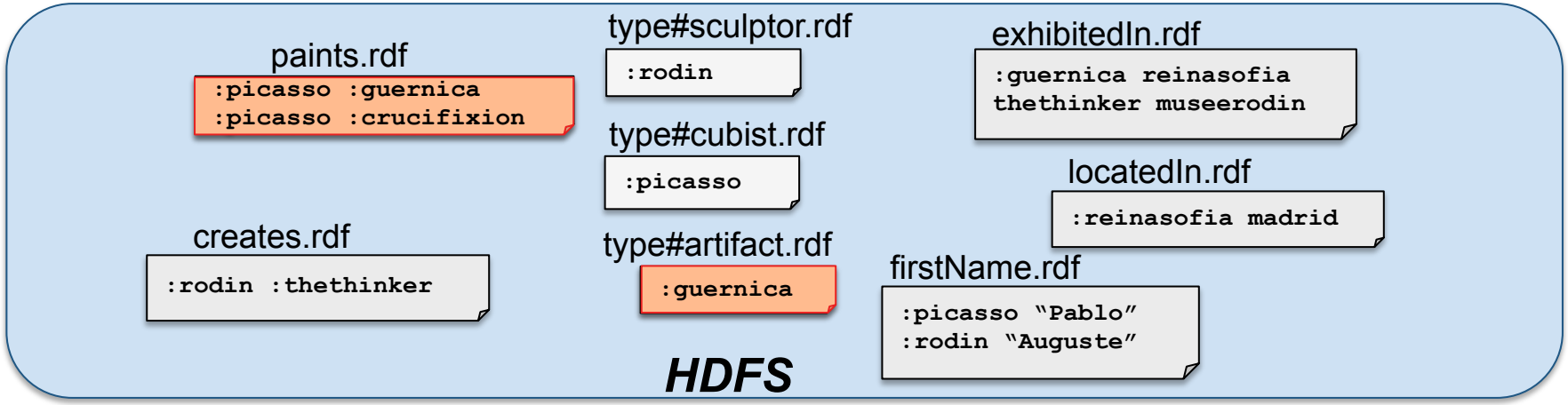
Step	Files	Size (GB)	Space Gain
N-Triples	20020	24	-
PS	17	7.1	70.42%
POS	41	6.6	7.04%

- Query optimization (minimization?)

```
SELECT ?x
WHERE { ?x :paints ?y .
        ?y type :artifact .}
```

Without object value partitioning, we would have to scan files:

{paints.rdf, type#artifact.rdf)



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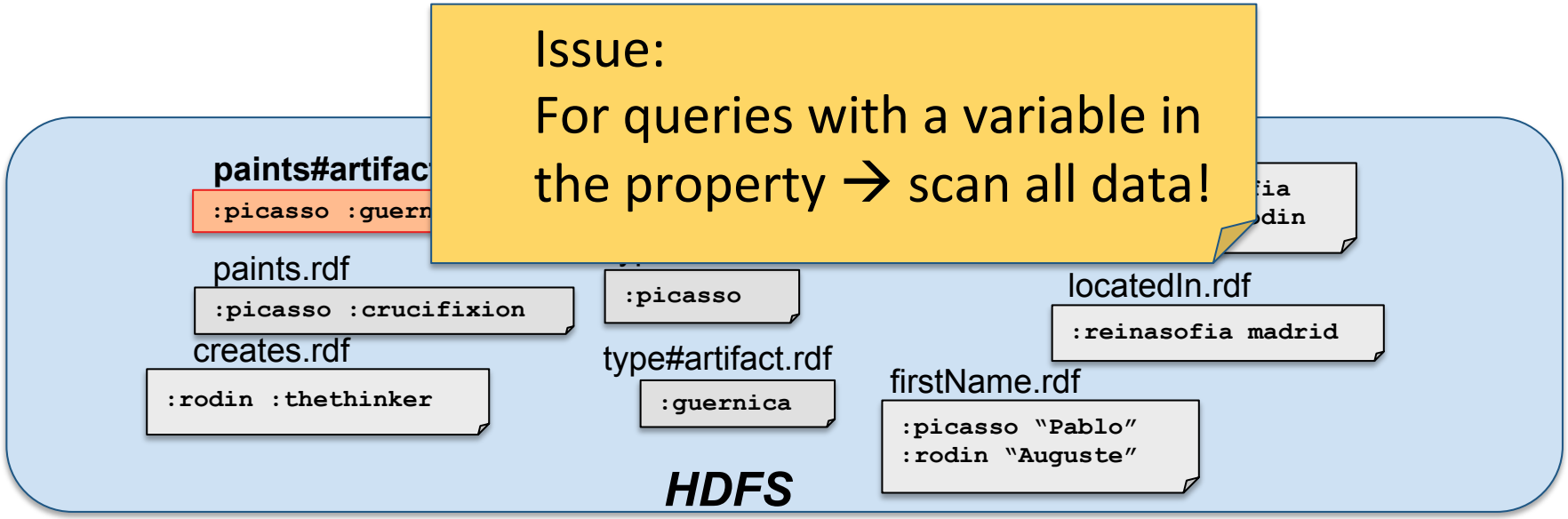
POS	41	6.6	7.04%

- Query optimization

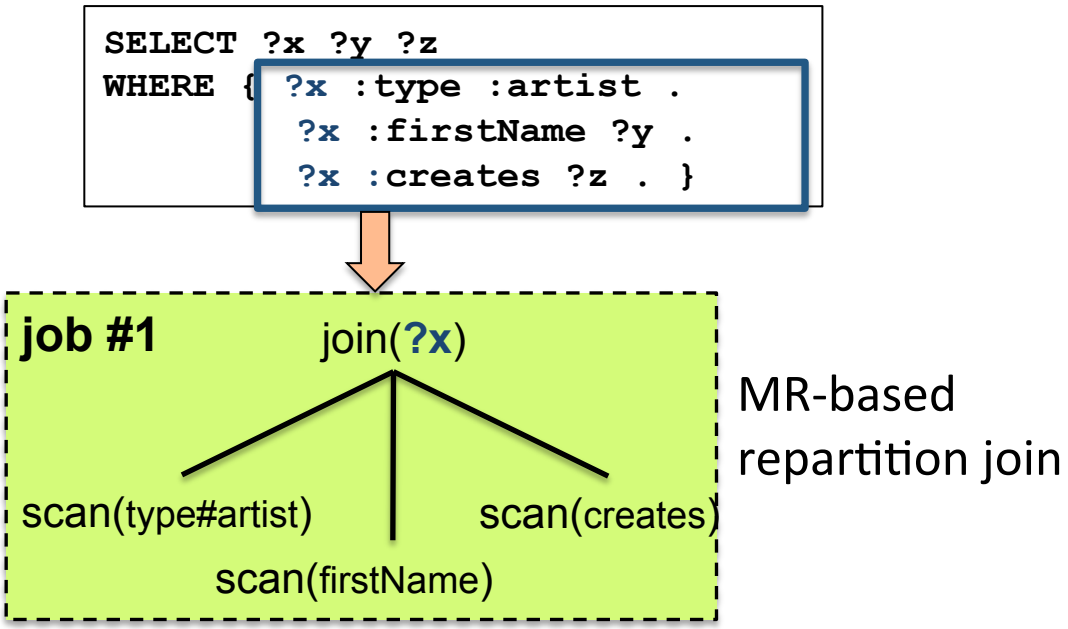
```
SELECT ?x
WHERE { ?x :paints ?y .
        ?y type :artifact .}
```

With object value partitioning, we only need to scan: {paints#artifact.rdf)



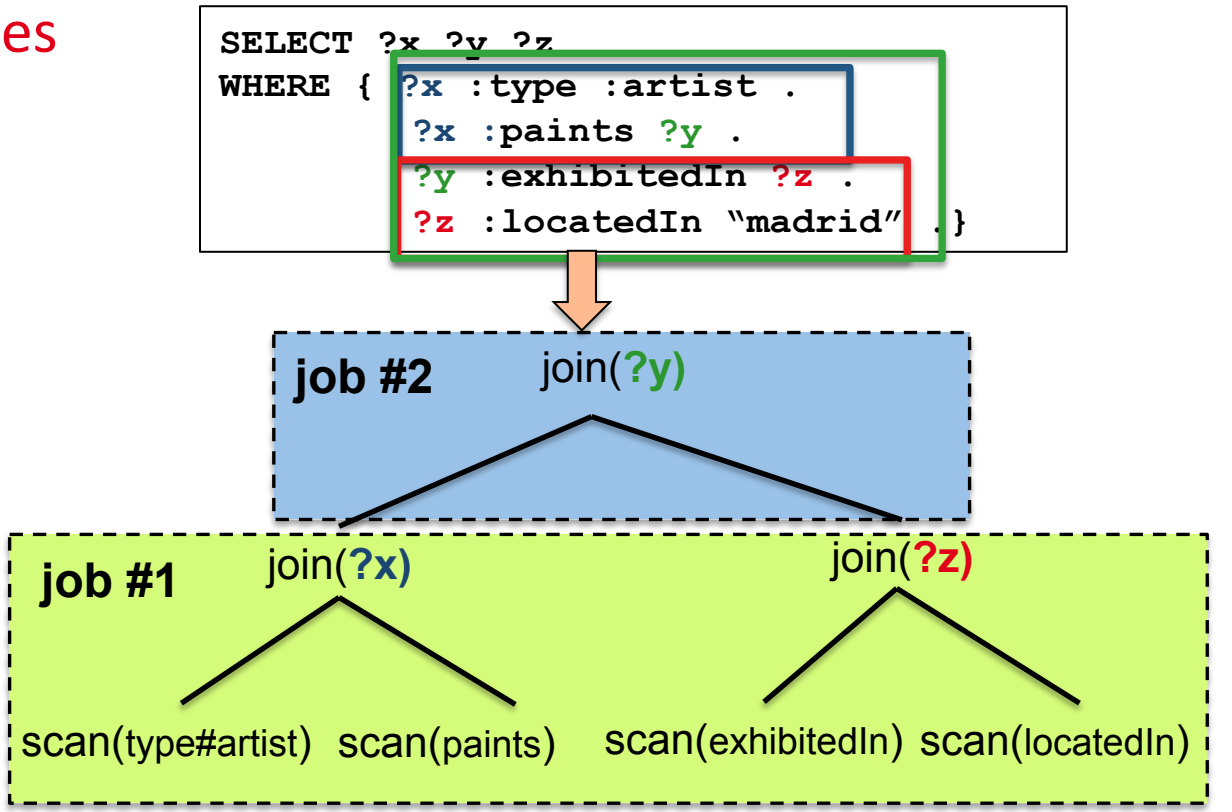
HadoopRDF - querying

- File selection based on the property (and object) of the triple
- Joining two or more triple patterns on the same variable



HadoopRDF querying

- File selection based on the property (and object) of the triple
- Joining two or more triple patterns on the same variable
- Several joins may be executed in parallel if they are on different variables



MR-based repartition joins

HadoopRDF query processing

How to decompose a query in elementary operations ?

What query plan to build ?

- Observations
  - Significant overhead when running a job
  - Traditional selectivity-based optimization techniques may result to plans with more jobs → bigger response times

Dataset	2 Job Plan	3 Job Plan	Difference
LUBM_10000	4920	9180	4260
LUBM_20000	31020	36540	5520
LUBM_30000	80460	93947	13487

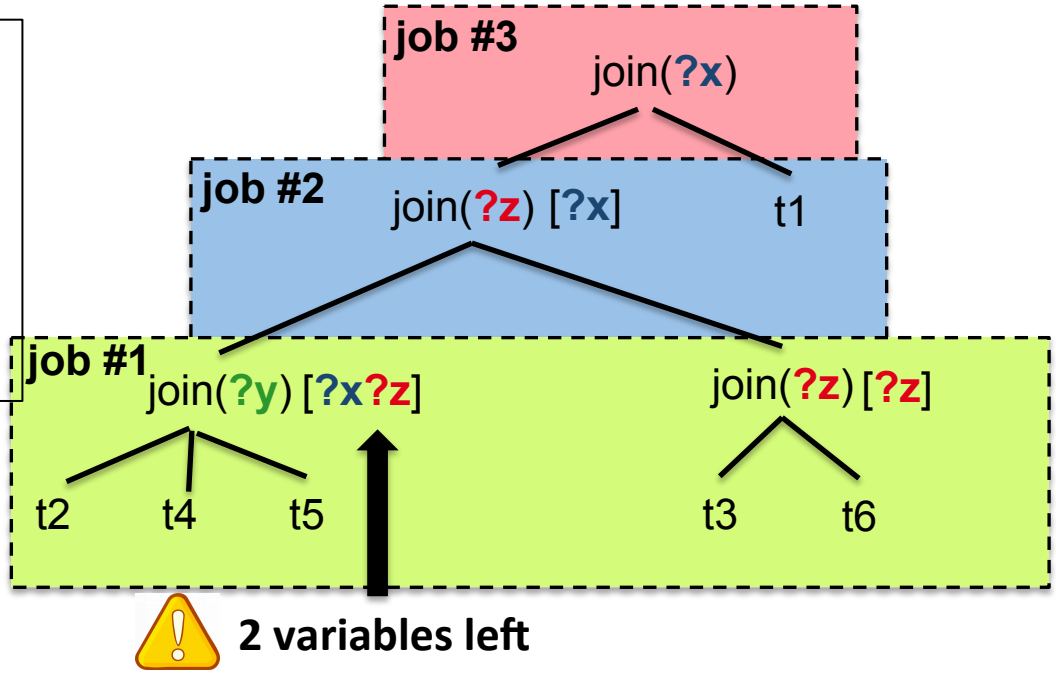
- Heuristic: Query decomposition to minimize the number of Hadoop jobs

HadoopRDF query planning

- Greedy algorithm
- As many joins as possible in one job
- Each triple pattern is used only once in each join
- Leave the least number of remaining variables to be joined

```
SELECT ?x ?y ?z
WHERE {?x type :artist .          (t1)
       ?y type :artifact .        (t2)
       ?z type :museum .          (t3)
       ?x :paints ?y .            (t4)
       ?y :exhibitedIn ?z .       (t5)
       ?z :locatedIn "madrid"     (t6)
}
```

"Complete variable elimination" of ?y



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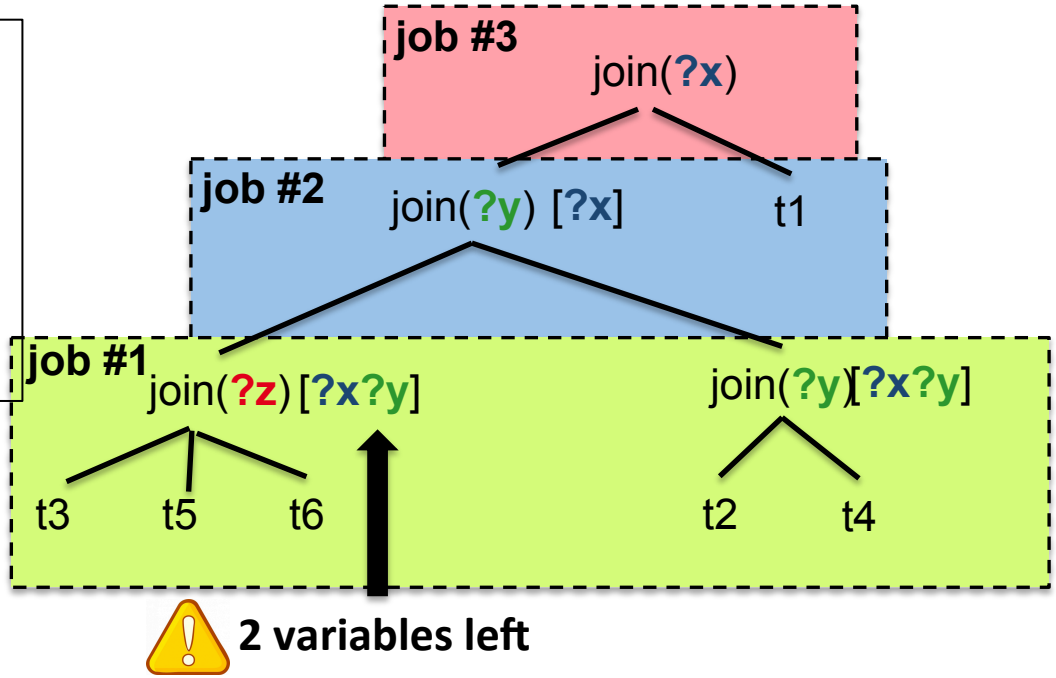
```

"Complete variable elimination" of ?z



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       ?x :paints ?y .
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}
```
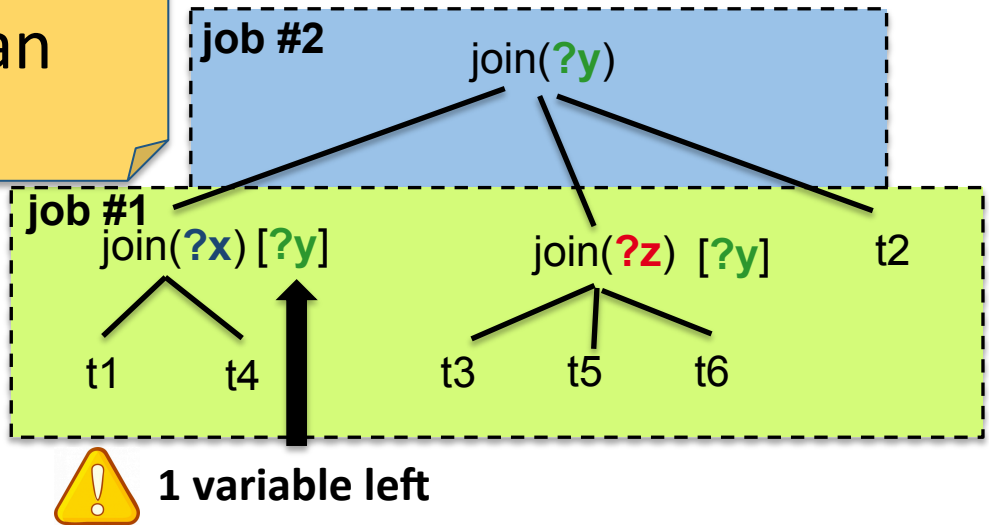

Best plan



"Complete variable elimination" of ?x and ?z

TriAD [Gurajada14]

Based not on MapReduce but on custom shared-nothing parallel processing framework using *asynchronous message passing*

- Advantage: asynchronous parallelism (join in stage N does not need to wait for join in stage N-1)

Storage: METIS partitioning (disjoint subgraphs)

Query processing:

- Custom distributed nested loops-, hash- and merge-joins
  - Layers « like MapReduce » but asynchronous execution
- Also:
  - Intra-node multi-threading
  - Optimizations to reduce intermediary results, …

Summary: MapReduce/DFS-based approaches

Pros	Cons
Scalability	No indexes – scan all data
Fault-tolerance	Shuffling of data
Fast data uploading	Semi-support for joins
Fast and easy to implement	Big initialization overhead
Good for “analytical” queries	High query response times

3.2

Approaches based on key-value stores

II. Approaches based on key-value stores

- Store RDF triples in a key-value store
  - Indexes on RDF triples
- Lookups in the key-value store for each query triple pattern
- How to perform the joins?
  - Centralized join
  - Use MapReduce
  - Graph exploration

II. Approaches based on key-value stores

- Representative works
  - CumulusRDF [Ladwig11]
  - Stratustore [Stein10]
  - Rya [Punnoose12]
  - AMADA [Bugiotti12]
  - H2RDF [Papailiou12]
  - H2RDF+[Papailiou13]
  - MAPSIN [Schätzle12]
  - Trinity.RDF [Zeng13]

Local query processing

MapReduce-based query processing

Graph exploration

Storing RDF in key-value stores

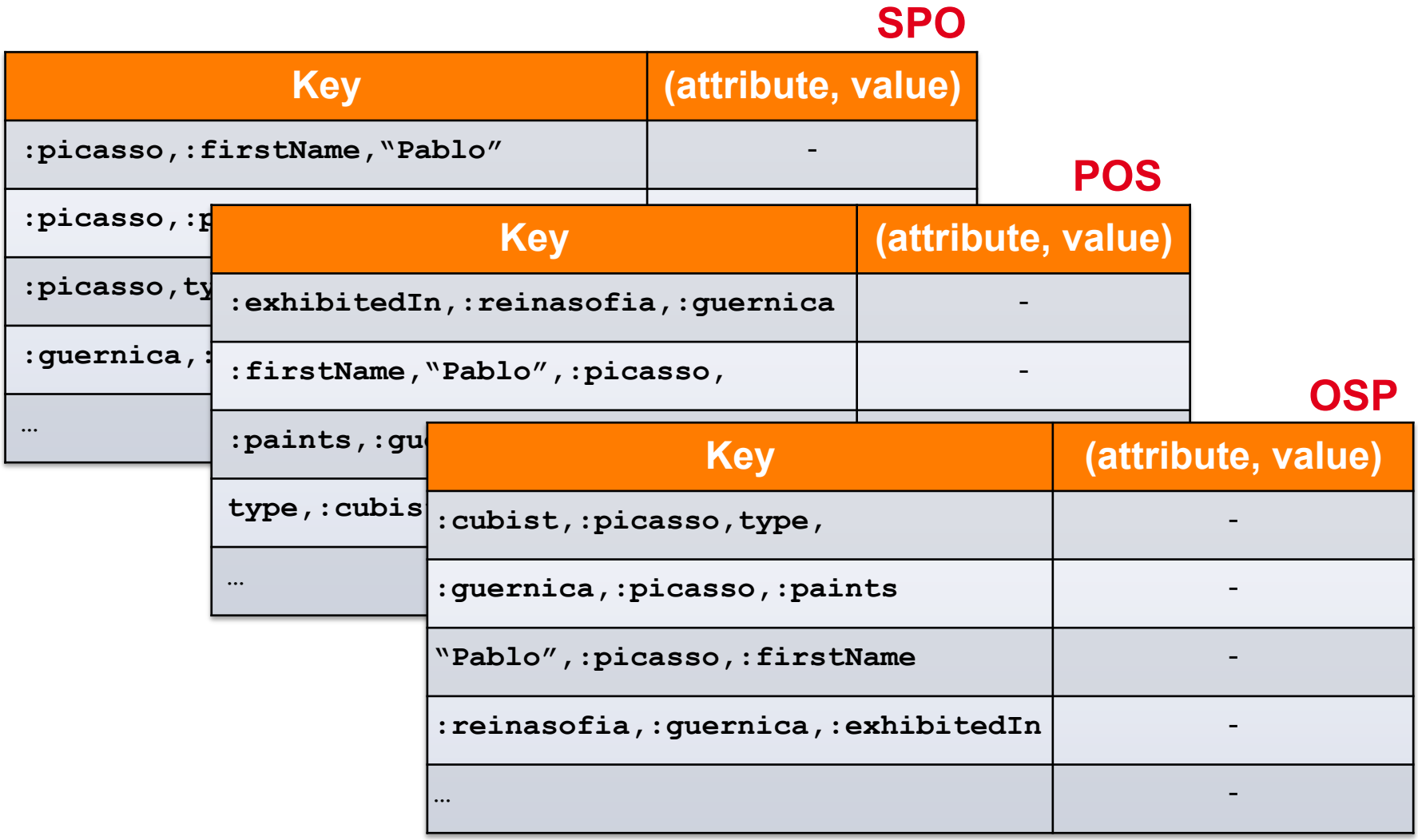
- Rya uses Apache Accumulo — **Sorted Index**
  - SPO|-|- POS|-|- OSP|-|-
- H2RDF uses Apache HBase — **Sorted Index**
  - SP|O|- PO|S|- OS|P|-
- AMADA uses Amazon DynamoDB — **Hash Index**
  - S|P|O P|O|S O|S|P
- MAPSIN uses Apache HBase — **Sorted Index**
  - S|P|O|- O|P|S|-
- Stratustore uses Amazon SimpleDB — **Hash Index**
  - S|P|O
- CumulusRDF uses Apache Cassandra — **Hash Index** **Sorted Index**
  - hierarchical layout: S|P|O|- P|O|S|- O|S|P|-
  - flat layout: S|PO|- PO|S|- PO|“P”| P O|SP|-

Storing RDF in key-value stores

- Rya uses Apache Accumulo — Sorted Index
  - SPO|-|- POS|-|- OSP|-|-
- H2RDF uses Apache HBase — Sorted Index
  - SP|O|- PO|S|- OS|P|-
- AMADA uses Am… — …dex
  - S|P|O P|…
- MAPSIN uses Apa… — …ndex
  - S|P|O|- O|…
- Stratustore uses Amazon SimpleDB — Hash Index
  - S|P|O
- CumulusRDF uses Apache Cassandra — Hash Index, Sorted Index
  - hierarchical layout: S|{P}O|- P|{O}S|- O|{S}P|-
  - flat layout: S|PO|- PO|S|- PO|"P"| P O|SP|-

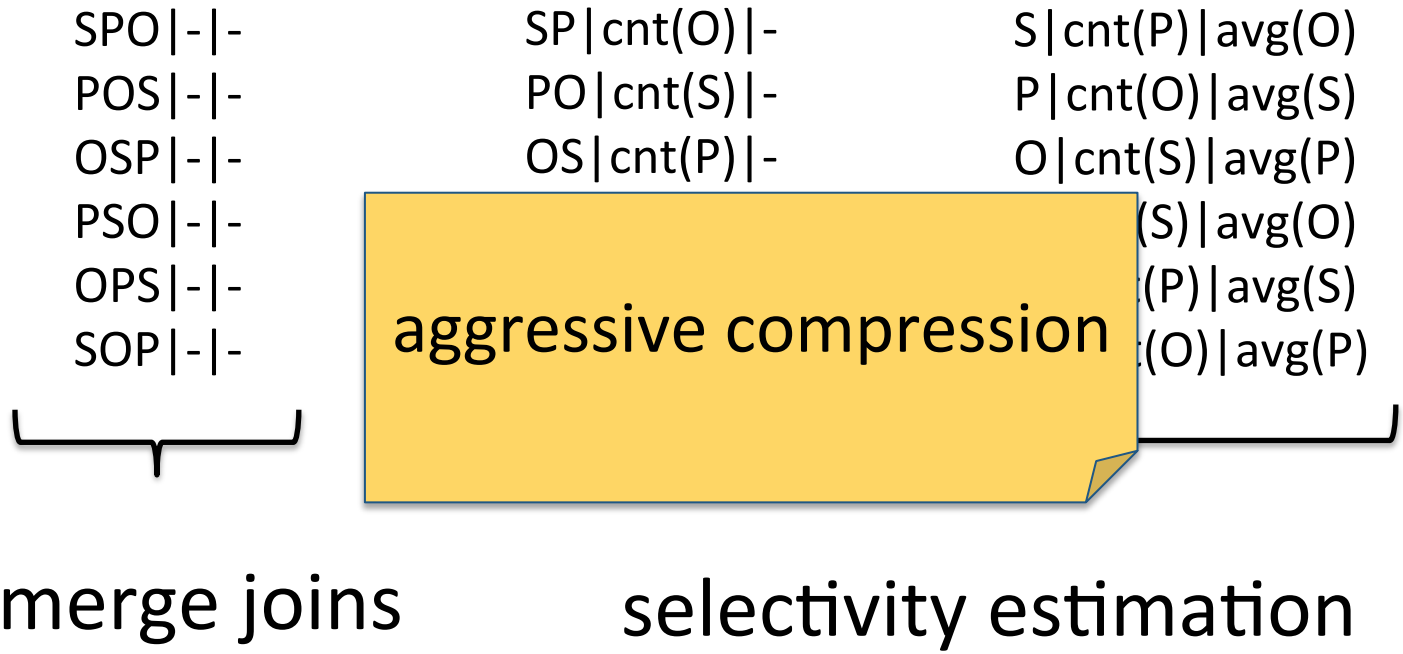
3 indexes:
SPO, POS, OSP

Rya storage - example



Aggressive indexing in key-value stores

- H2RDF+ (Apache HBase) **6** indices + **12** aggregated ones:



Strong point of key-value stores: selective data access

Different access paths for triple pattern matching

Triple pattern	Rya (Accumulo)	H2RDF (HBase)	AMADA (DynamoDB)	MAPSIN (HBase)
(s, p, o)	any lookup	any lookup + select	any lookup + select	any lookup + sselect
(s, p, ?o)	SPO range scan	SP|O lookup	S|P|O lookup + select	S|P|O lookup + sselect
(s, ?p, o)	OSP range scan	OS|P lookup	O|S|P lookup + select	O|S|P lookup + sselect
(s, ?p, ?o)	SPO range scan	SP|O range scan	S|P|O lookup	S|P|O lookup
(?s, p, o)	POS range scan	PO|S lookup	P|O|S lookup + select	O|S|P lookup + sselect
(?s, p, ?o)	POS range scan	PO|S range scan	P|O|S lookup	any scan + sselect
(?s, ?p, o)	OSP range scan	OS|P range scan	O|S|P lookup	O|S|P lookup
(?s, ?p, ?o)	any scan	any scan	any scan	any scan

select: filter on client side
sselect: filter on server side

Weak point of key-value stores: joins

Key-value stores do not support joins →

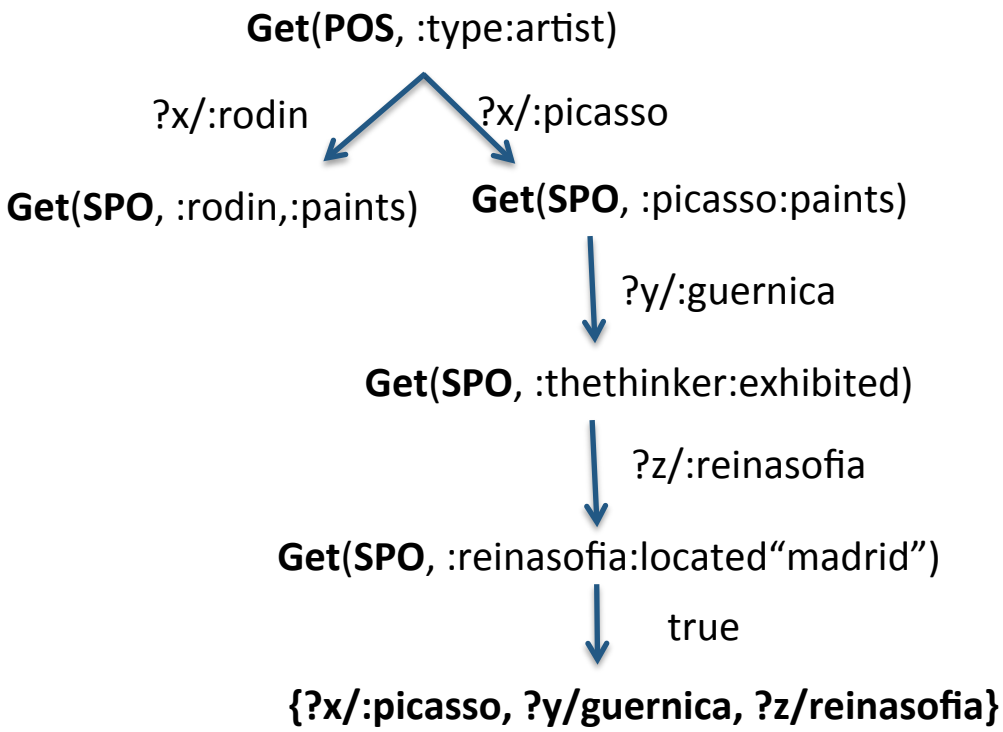
Look-ups in the store, joins out of the store

- **Rya**: index nested loops by query rewriting and lookups
- **H2RDF+**: 2 strategies
  - selective joins → centralized – sort-merge joins
  - non-selective → MapReduce (merge-join)
- **AMADA**: memory hash join
- **MAPSIN**: MapReduce (map phase only)
- **Stratustore**: SimpleDB SELECT query for each star-join and rest of the joins locally
- **CumulusRDF**: Only single triple pattern queries are supported

Rya joining strategy

- Index nested loops
- A lookup for the 1st triple pattern
- For each triple pattern t_i, use the n results from triple pattern t_{i-1} to rewrite t_i and then perform n lookups for the rewritten t_i

```
SELECT ?x ?y ?z
WHERE { ?x :type :artist .
        ?x :paints ?y .
        ?y :exhibitedIn ?z
        ?z :locatedIn "madrid".}
```



Rya joining strategy

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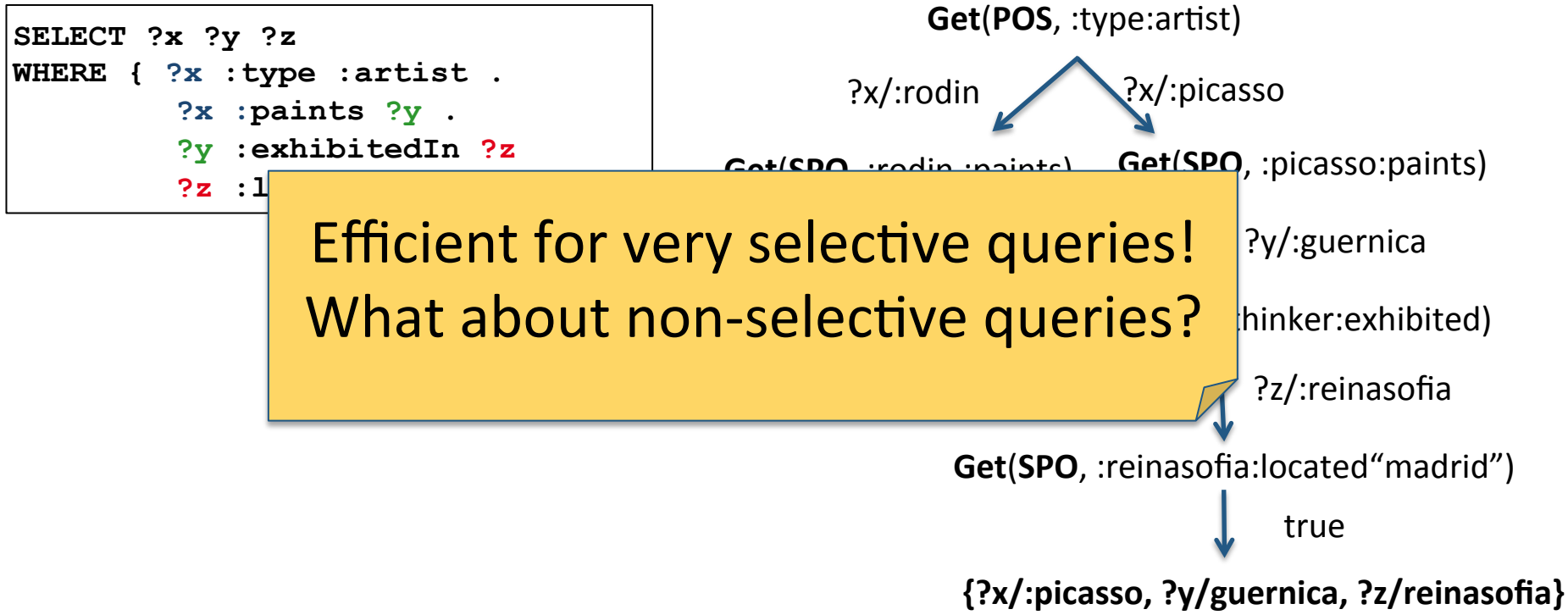
```
SELECT ?x ?y ?z
WHERE { ?x :type :artist .
        ?x :paints ?y .
        ?y :exhibitedIn ?z
        ?z :l
```



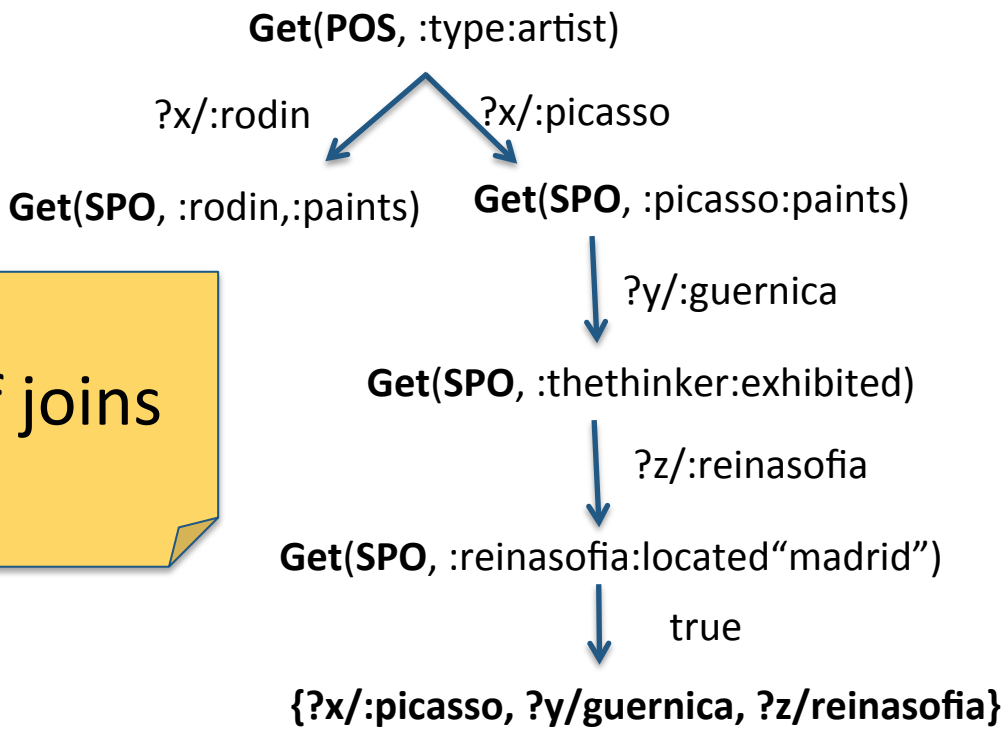
Efficient for very selective queries!
What about non-selective queries?

Rya: optimizations

- Index nested loops
- A lookup for the 1st triple pattern
- For each triple pattern t_i, use the n results from triple pattern t_{i-1} to rewrite t_i and then perform n lookups for the rewritten t_i

```
SELECT ?x ?y ?z
WHERE { ?x :type :artist .
        ?x :paints ?y .
        ?y :exhibitedIn ?z
        ?z :locatedIn "madrid".}
```

1. Parallelization of joins

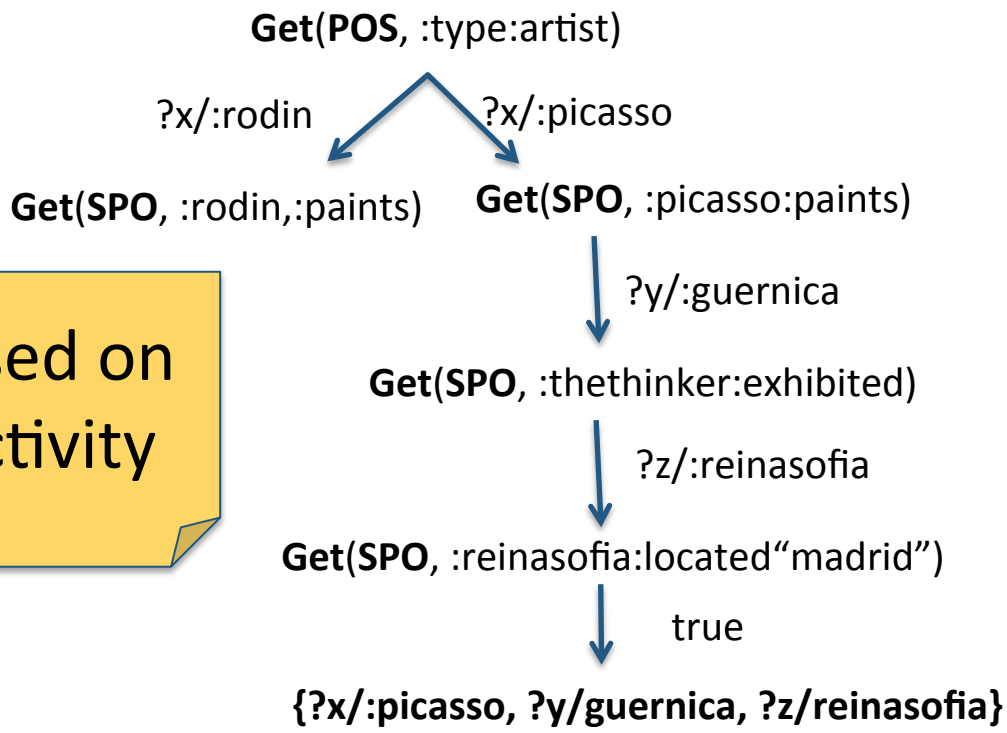


Rya: optimizations

- Index nested loops
- A lookup for the 1st triple pattern
- For each triple pattern t_i, use the n results from triple pattern t_{i-1} to rewrite t_i and then perform n lookups for the rewritten t_i

```
SELECT ?x ?y ?z
WHERE { ?x :type :artist .
        ?x :paints ?y .
        ?y :exhibitedIn ?z
        ?z :locatedIn "madrid".}
```

2. Join ordering based on triple pattern selectivity



Summary: Approaches based on key-value stores

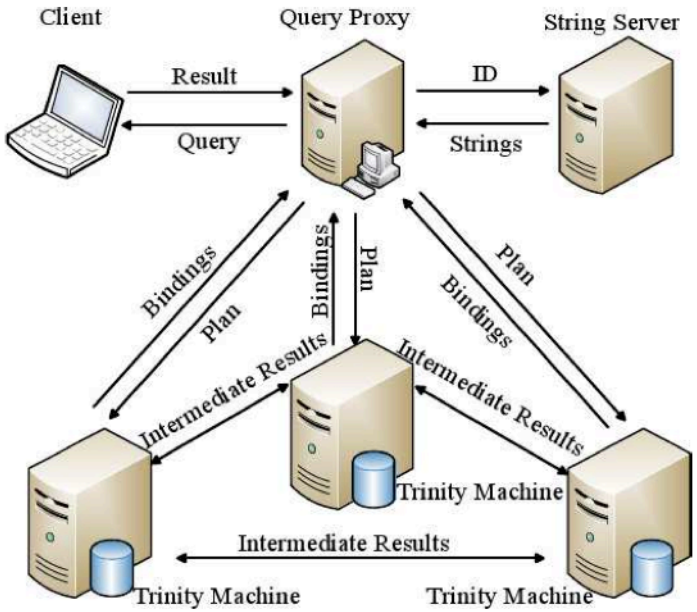
Pros	Cons
Scalability	Low schema expressivity
Fault-tolerance	Joins implemented by the user
Very fast lookups	Joins on the client-side
Efficient for selective queries	

3.3

Approaches based on graph platforms

Trinity.RDF [Zeng13]

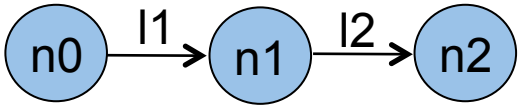
- Built on top of the Trinity in-memory key-value store
- Takes advantage of the graph-based model of RDF for query processing
- Graph exploration instead of joins (greedy pruning of candidate matches)
  - only if graph exploration can be implemented more efficiently than join
  - similar to index-nested-loops join



Trinity.RDF: RDF graph storage alternatives

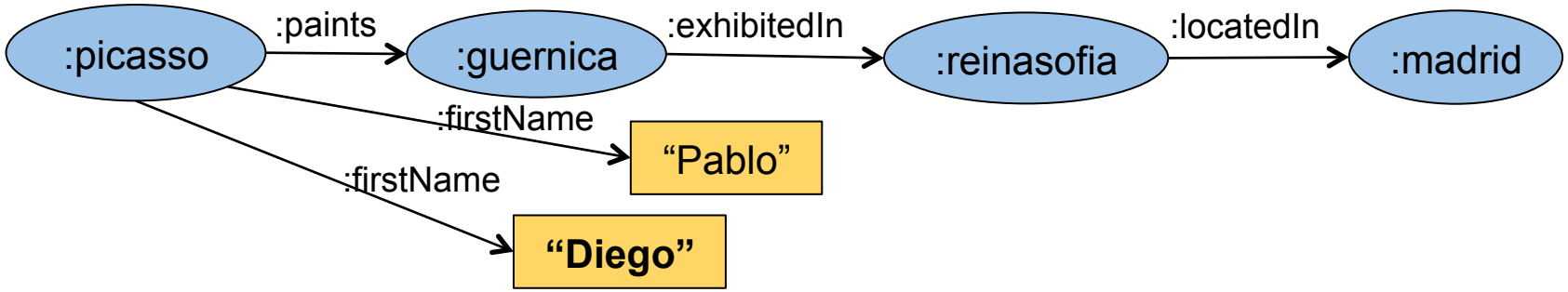
- Each node is assigned to a machine through hashing
- Two modeling choices
  - 1. (key, value) : (node_id, <in-adjacency-list, out-adjacency-list>)

(property, subject) (property, object)

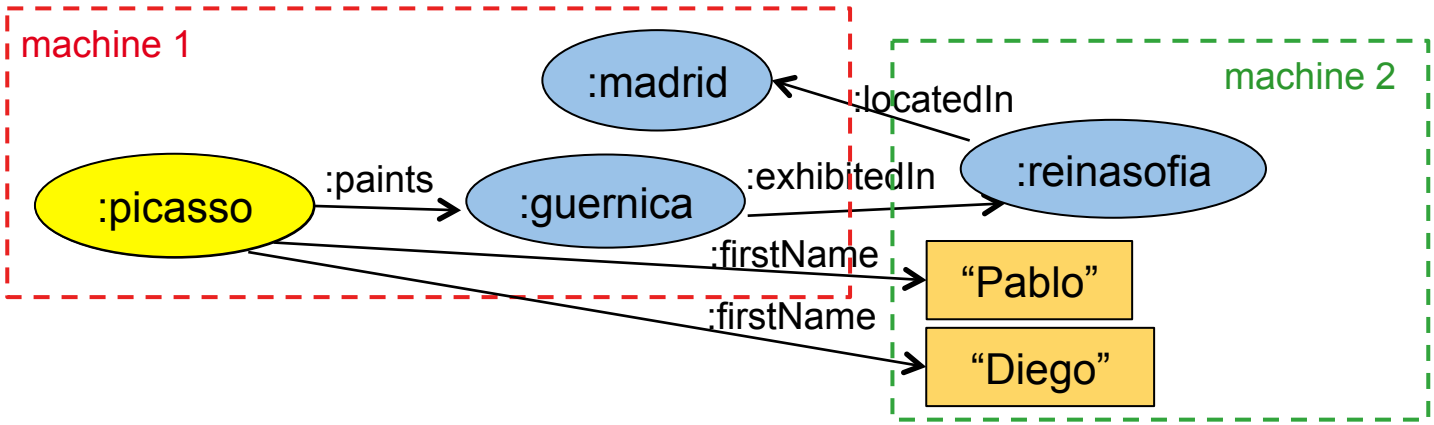


(n1, <{(l1, n0)} {(l2,n2)}>)
(n0, <{-} {(l1,n1)}>)
(n2, <{(l2,n2)} {-}>)

Trinity.RDF: RDF graph storage alternatives (1)



Trinity.RDF: RDF graph storage alternatives (1)



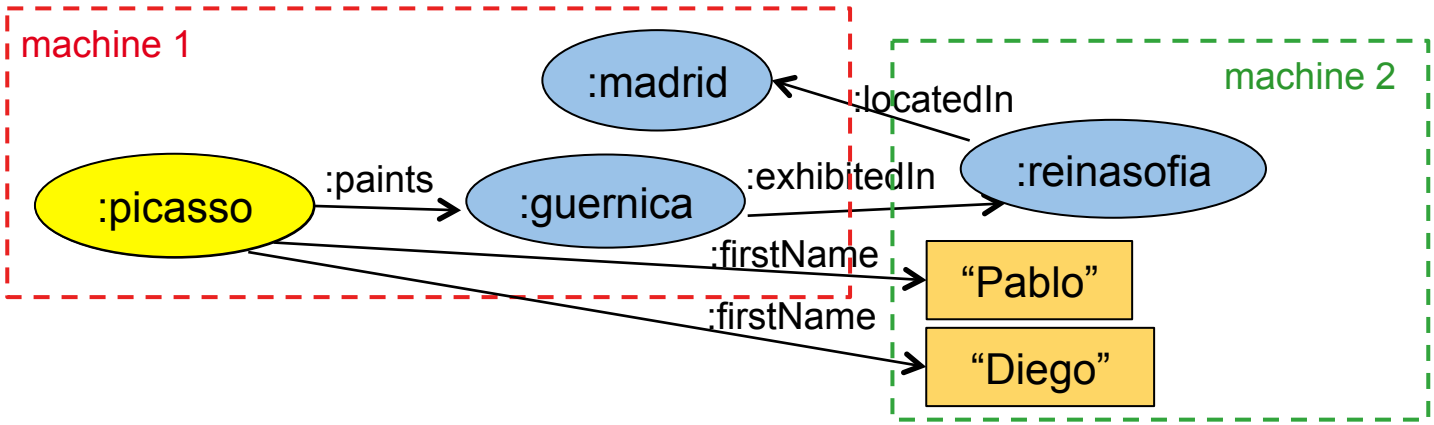
machine 1

Key	Value
:picasso	In: - Out: (:paints, :guernica) **Out: (:firstName, "Pablo")** **Out: (:firstName, "Diego")**
:guernica	In: (:paints, :picasso) **Out: (:exhibitedIn, :reinasofia)**
:madrid	**Out: (:locatedIn, :reinasofia)**

machine 2

Key	Value
:reinasofia	**In: (:exhibitedIn, :guernica)** **Out: (:locatedIn, :madrid)**
"Pablo"	**In: (:firstName, :picasso)**
"Diego"	**In: (:firstName, :picasso)**

Trinity.RDF: RDF graph storage alternatives (1)



machine 1

Key	Value
:picasso	In: - Out: (:paints, :guernica) **Out: (:firstName, "Pablo")** **Out: (:firstName, "Diego")**
:guernica	In: (:paints, :picasso) **Out: (:exhibitedIn, :reinasofia)**
:madrid	**Out: (:locatedIn, :reinasofia)**

machine 2

Key	Value
:reinasofia	**In: (:exhibitedIn, :guernica)** **Out: (:locatedIn, :madrid)**
"Pablo"	**In: (:firstName, :picasso)**
"Diego"	**In: (:firstName, :picasso)**

2 messages should be sent to continue the node exploration from *:picasso* through *:firstName*

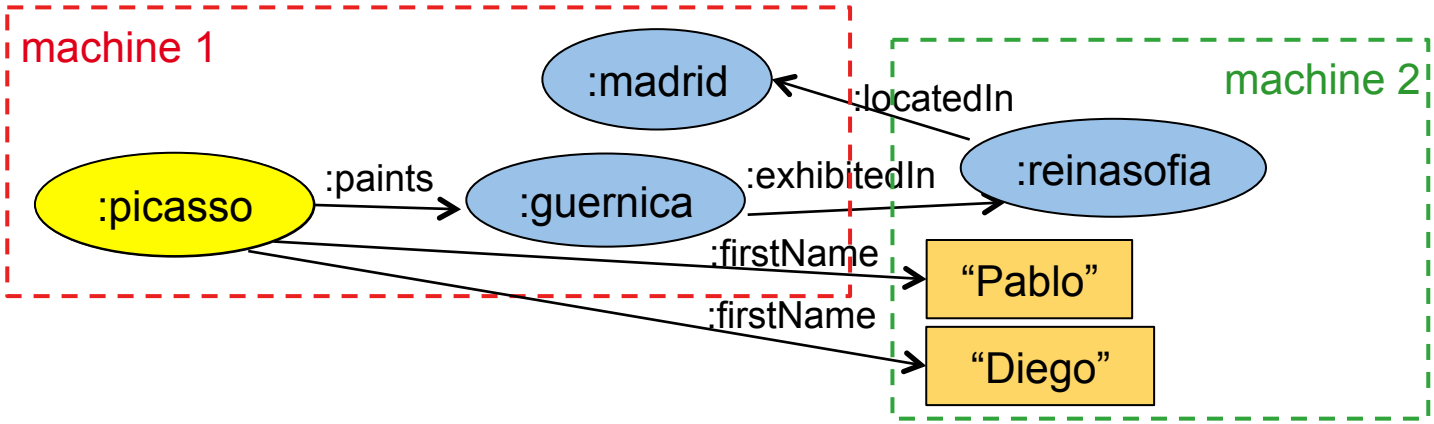
Trinity.RDF: RDF graph storage alternatives (2)

- Each node is assigned to a machine through hashing
- Two modeling choices
  - 1. (key, value) : (node_id, <in-adjacency-list, out-adjacency-list>)
  - 2. (key, value): (node_id, <in1, in2…., out1, out2…>)

    (in_i, in-adjacency-list$_i$): on the same machine i

    (out_i, out-adjacency-list$_i$): on the same machine i

Trinity.RDF: RDF graph storage alternatives (2)



machine 1

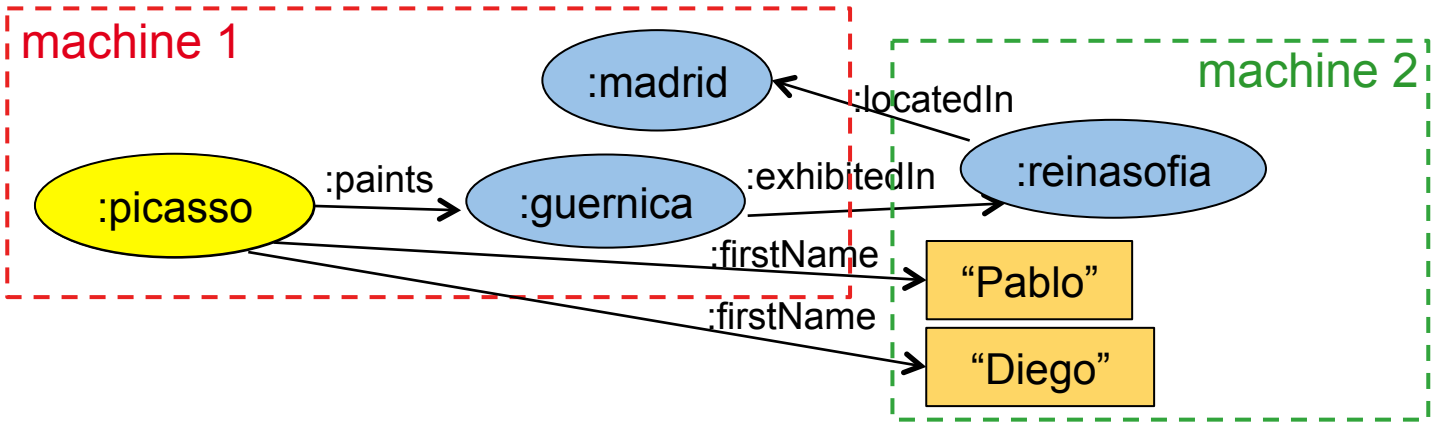
Key	Value
:picasso	out1 out2
:guernica	in1 out3
:madrid	out4
out1	(:paints, :guernica)
in1	(:paints, :picasso)
in2	(:exhibitedIn, :guernica)
out5	(:locatedIn, :madrid)
in3	(:firstName, :picasso)

machine 2

Key	Value
:reinasofia	in2 out5
"Pablo"	in3
out2	**(:firstName, "Pablo)** **(:firstName, "Diego")**
out3	(:exhibitedIn, :reinasofia)
out4	(:locatedIn, :reinasofia)

only 1 message needs to be sent

Trinity.RDF: RDF graph storage alternatives (2)



machine 1

Key	Value
:picasso	ou ou
:guernica	in ou
:madrid	ou
out1	(:paints, :guernica)
in1	(:paints, :picasso)
in2	(:exhibitedIn, :guernica)
out5	(:locatedIn, :madrid)
in3	(:firstName, :picasso)

machine 2

Key	Value
	2 5
	3
	ne, “Pablo) (:firstName, “Diego”)
out3	(:exhibitedIn, :reinasofia)
out4	(:locatedIn, :reinasofia)

No more than *#machines* messages are sent

only 1 message needs to be sent

Trinity.RDF: chosing between the storage alternatives

- Each node is assigned to a machine through hashing
- Two modeling choices
  - 1. (key, value) : (node_id, <in-adjacency-list, out-adjacency-list>)
  - 2. (key, value): (node_id, <in1, in2…., out1, out2…>)

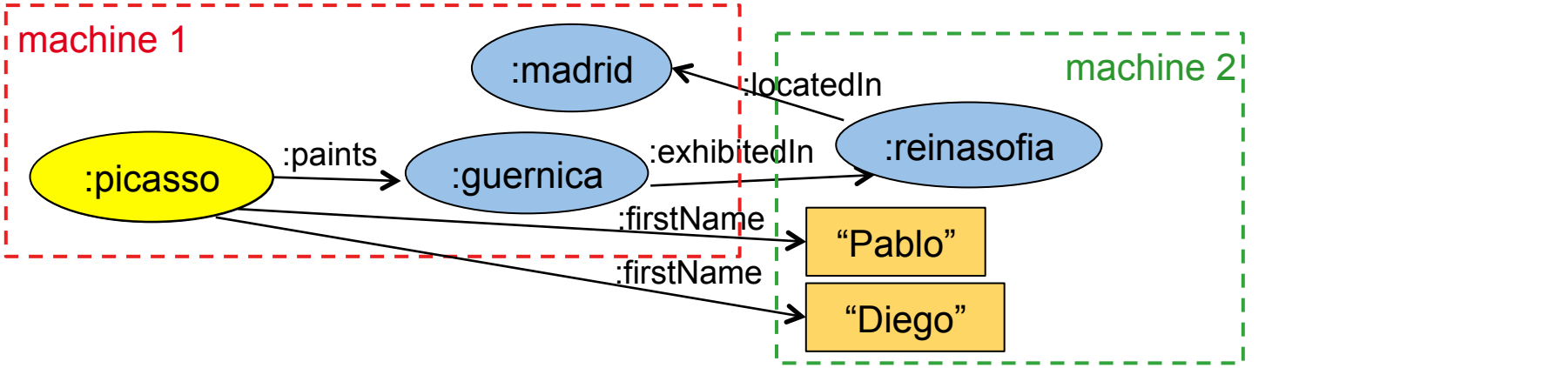
    (in_i, in-adjacency-list$_i$): on the same machine i

    (out_i, out-adjacency-list$_i$): on the same machine i
- Deciding whether to use model (1) or (2):
  - threshold on the number of neighbors of a node
- Local index on the predicate (in each machine)
- Aggregate index recording whether a node has a given predicate

Trinity.RDF: local predicate index

- To support queries of the form (?x, p, ?y):
- Global predicate indexing (predicate, ⟨subject-list$_i$, object-list$_i$⟩)

distinct subjects on machine i distinct objects on machine i



machine 1

Key	Value
:paints	{(:picasso)} {(:guernica)}
:firstName	{(:picasso)} {-}
:exhibitedIn	{(:guernica)} {-}
:locatedIn	{-} {(:madrid)}

machine 2

Key	Value
:firstName	{-} {("Pablo", "Diego")}
:exhibitedIn	{-} {(:reinasofia)}
:locatedIn	{(:reinasofia)} {-}

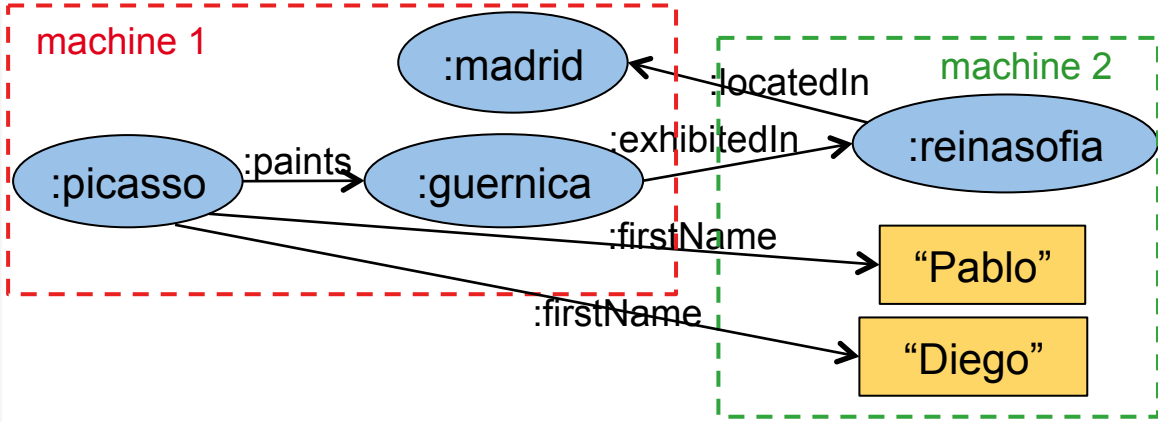
Trinity.RDF: triple pattern matching

- Single triple pattern (s, p, o)
  - s or o is constant → start exploring the graph from this node
  - s and o are variables →
    - Use POS to find the nodes that are connected by the edge p
    - For each node → graph exploration and filtering out edges that aren't p

Trinity.RDF: query processing example (1)

Key	Value
:picasso	In: - Out: (:paints, :guernica) **Out: (:firstName, "Pablo")** **Out: (:firstName, "Diego")**
:guernica	In: (:paints, :picasso) **Out: (:exhibitedIn, :reinasofia)**
:madrid	**Out: (:locatedIn, :reinasofia)**
:paints	{(:picasso)} {(:guernica)}
:firstName	{(:picasso)} {-}
:exhibitedIn	{(:guernica)} {-}
:locatedIn	{-} {(:madrid)}

Key	Value
:reinasofia	**In: (:exhibitedIn, :guernica)** **Out: (:locatedIn, :madrid)**
"Pablo"	**In: (:firstName, :picasso)**
"Diego"	**In: (:firstName, :picasso)**
:firstName	{-} {("Pablo", "Diego")}
:exhibitedIn	{-} {(:reinasofia)}
:locatedIn	{(:reinasofia)} {-}

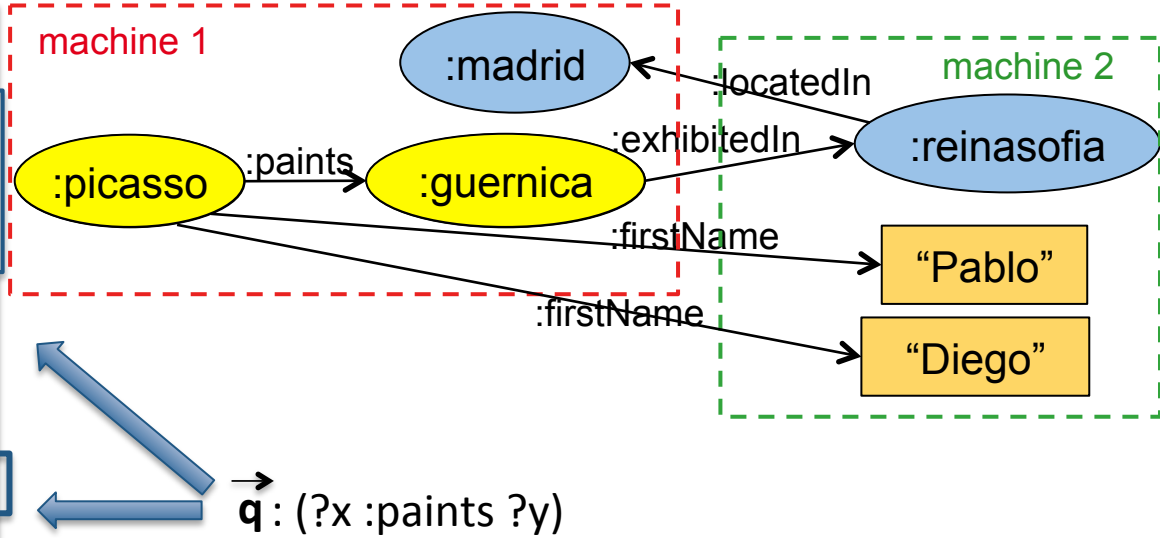


$\vec{q}$: (?x :paints ?y)

Trinity.RDF query processing example (1)

Key	Value
:picasso	In: - Out: (:paints, :guernica) **Out: (:firstName, "Pablo")** **Out: (:firstName, "Diego")**
:guernica	In: (:paints, :picasso) **Out: (:exhibitedIn, :reinasofia)**
:madrid	**Out: (:locatedIn, :reinasofia)**
:paints	{(:picasso)} {(:guernica)}
:firstName	{(:picasso)} {-}
:exhibitedIn	{(:guernica)} {-}
:locatedIn	{-} {(:madrid)}

Key	Value
:reinasofia	**In: (:exhibitedIn, :guernica)** **Out: (:locatedIn, :madrid)**
"Pablo"	**In: (:firstName, :picasso)**
"Diego"	**In: (:firstName, :picasso)**
:firstName	{-} {("Pablo", "Diego")}
:exhibitedIn	{-} {(:reinasofia)}
:locatedIn	{(:reinasofia)} {-}



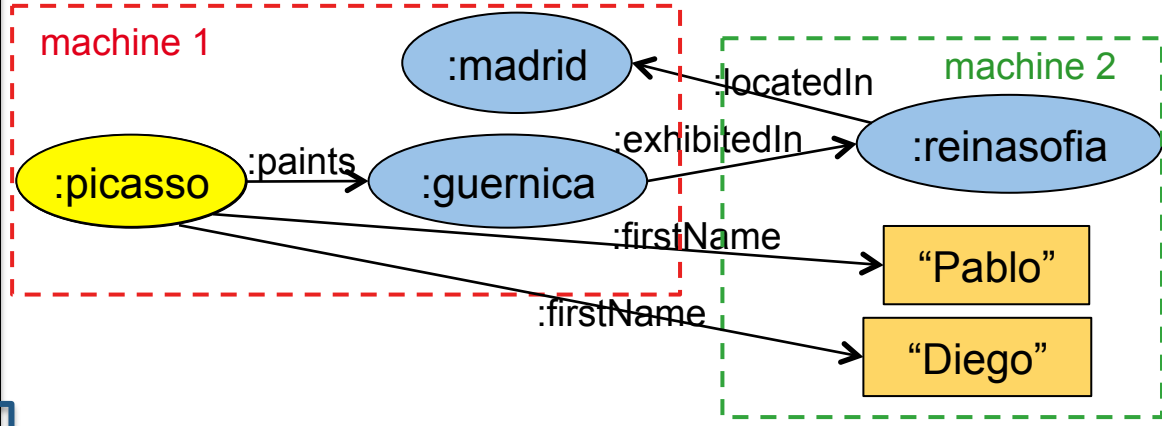
Trinity.RDF query processing

- Single triple pattern (s, p, o)
  - s or o is constant → start exploring the graph from this node
  - s and o is variable →
    - Use POS to find the nodes that are connected by the edge p
    - For each node → graph exploration and filtering out edges that aren't p
- Multiple triple patterns:
  - process sequentially by graph exploration
  - prune intermediate results

Trinity.RDF query processing example (2)

Key	Value
:picasso	In: - Out: (:paints, :guernica) **Out: (:firstName, "Pablo")** **Out: (:firstName, "Diego")**
:guernica	In: (:paints, :picasso) **Out: (:exhibitedIn, :reinasofia)**
:madrid	**Out: (:locatedIn, :reinasofia)**
:paints	{(:picasso)} {(:guernica)}
:firstName	{(:picasso)} {-}
:exhibitedIn	{(:guernica)} {-}
:locatedIn	{-} {(:madrid)}

Key	Value
:reinasofia	**In: (:exhibitedIn, :guernica)** **Out: (:locatedIn, :madrid)**
"Pablo"	**In: (:firstName, :picasso)**
"Diego"	**In: (:firstName, :picasso)**
:firstName	{-} {("Pablo", "Diego")}
:exhibitedIn	{-} {(:reinasofia)}
:locatedIn	{(:reinasofia)} {-}

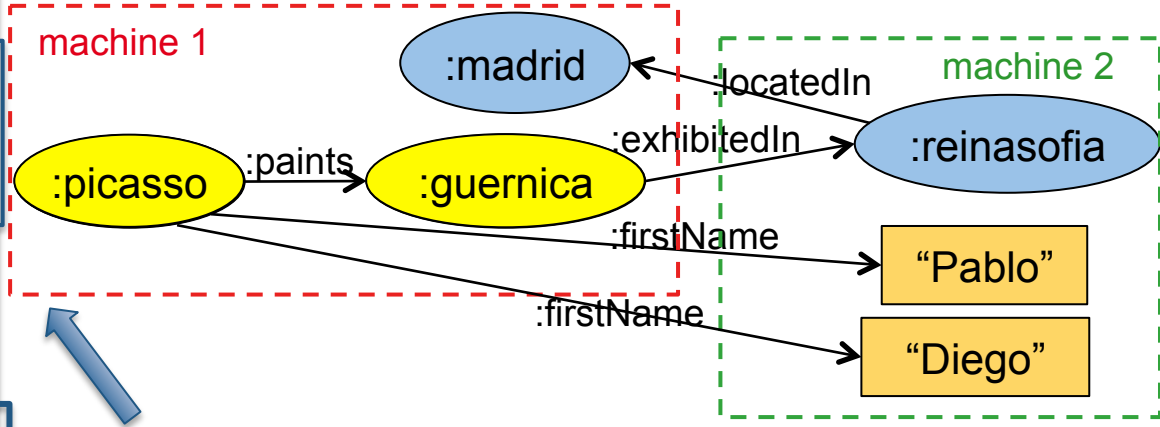


$\vec{q}$: (?x :paints ?y) ∧
(?y, exhibitedIn, ?z) ∧
(?z locatedIn, :madrid)

Trinity.RDF query processing example (2)

Key	Value
:picasso	In: - Out: (:paints, :guernica) **Out: (:firstName, "Pablo")** **Out: (:firstName, "Diego")**
:guernica	In: (:paints, :picasso) **Out: (:exhibitedIn, :reinasofia)**
:madrid	**Out: (:locatedIn, :reinasofia)**
:paints	{(:picasso)} {(:guernica)}
:firstName	{(:picasso)} {-}
:exhibitedIn	{(:guernica)} {-}
:locatedIn	{-} {(:madrid)}

Key	Value
:reinasofia	**In: (:exhibitedIn, :guernica)** **Out: (:locatedIn, :madrid)**
"Pablo"	**In: (:firstName, :picasso)**
"Diego"	**In: (:firstName, :picasso)**
:firstName	{-} {("Pablo", "Diego")}
:exhibitedIn	{-} {(:reinasofia)}
:locatedIn	{(:reinasofia)} {-}

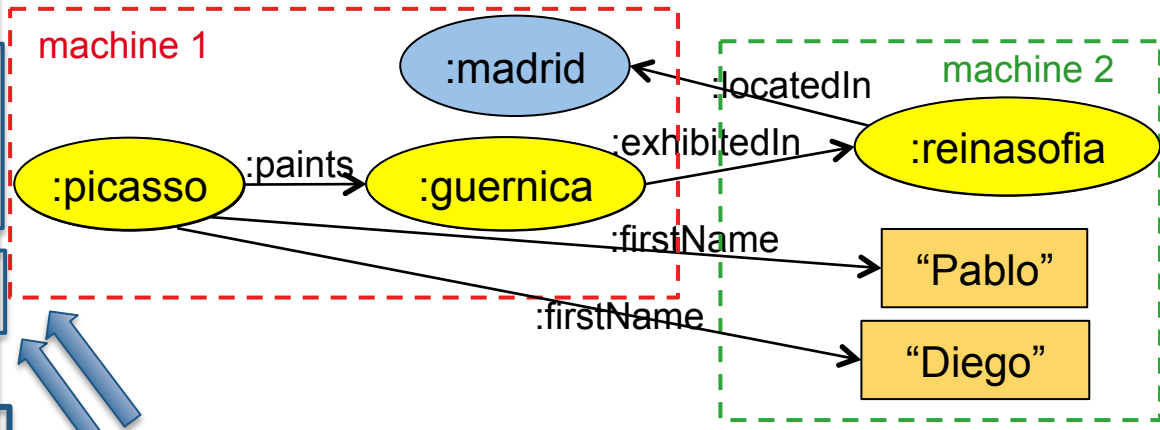


$\vec{q}$: (?x :paints ?y) ∧
(?y, exhibitedIn, ?z) ∧
(?z locatedIn, :madrid)

Trinity.RDF query processing example (2)

Key	Value
:picasso	In: - Out: (:paints, :guernica) **Out: (:firstName, "Pablo")** **Out: (:firstName, "Diego")**
:guernica	In: (:paints, :picasso) **Out: (:exhibitedIn, :reinasofia)**
:madrid	**Out: (:locatedIn, :reinasofia)**
:paints	{(:picasso)} {(:guernica)}
:firstName	{(:picasso)} {-}
:exhibitedIn	{(:guernica)} {-}
:locatedIn	{-} {(:madrid)}

Key	Value
:reinasofia	**In: (:exhibitedIn, :guernica)** **Out: (:locatedIn, :madrid)**
"Pablo"	**In: (:firstName, :picasso)**
"Diego"	**In: (:firstName, :picasso)**
:firstName	{-} {("Pablo", "Diego")}
:exhibitedIn	{-} {(:reinasofia)}
:locatedIn	{(:reinasofia)} {-}

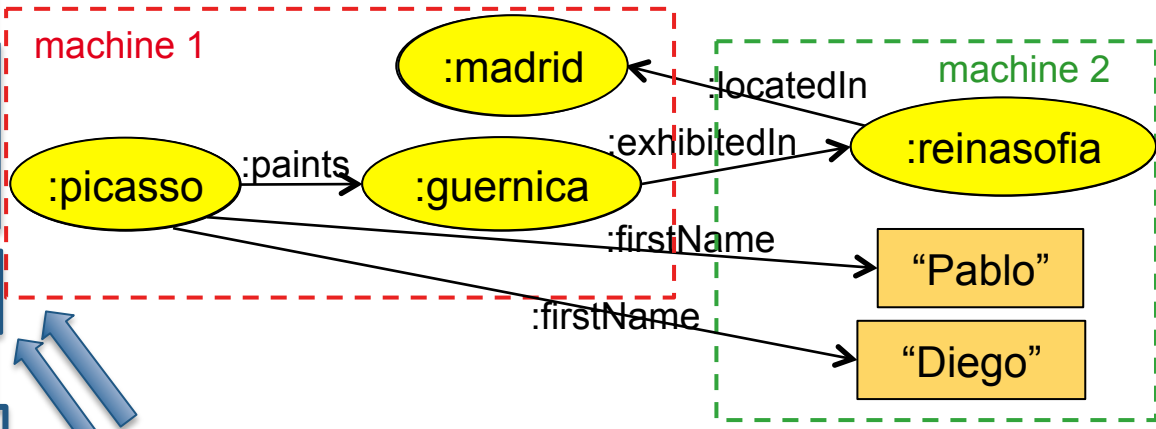


$\vec{q}$: (?x :paints ?y) ∧
(?y, exhibitedIn, ?z) ∧
(?z locatedIn, :madrid)

Trinity.RDF query processing example (2)

Key	Value
:picasso	In: - Out: (:paints, :guernica) **Out: (:firstName, "Pablo")** **Out: (:firstName, "Diego")**
:guernica	In: (:paints, :picasso) **Out: (:exhibitedIn, :reinasofia)**
:madrid	**Out: (:locatedIn, :reinasofia)**
:paints	{(:picasso)} {(:guernica)}
:firstName	{(:picasso)} {-}
:exhibitedIn	{(:guernica)} {-}
:locatedIn	{-} {(:madrid)}

Key	Value
:reinasofia	**In: (:exhibitedIn, :guernica)** **Out: (:locatedIn, :madrid)**
"Pablo"	**In: (:firstName, :picasso)**
"Diego"	**In: (:firstName, :picasso)**
:firstName	{-} {("Pablo", "Diego")}
:exhibitedIn	{-} {(:reinasofia)}
:locatedIn	{(:reinasofia)} {-}



$\vec{q}$: (?x :paints ?y) ∧
(?y, exhibitedIn, ?z) ∧
(?z locatedIn, :madrid)

Trinity.RDF query processing

- Single triple pattern (s, p, o)
  - s or o is constant → start exploring the graph from this node
  - s and o is variable →
    - Use POS to find the nodes that are connected by the edge p
    - For each node → graph exploration and filtering out edges that aren't p
- Multiple triple patterns:
  - process sequentially by graph exploration
  - prunes intermediate results
- Final join in a proxy for removing invalid results (small join)
- Ordering matters!

- In-memory system; hardware strongly impacts performance

Summary: Approaches based on graph stores

Pros	Cons
Replace joins by navigation	Replace joins by navigation Hard to enforce data locality

3.4

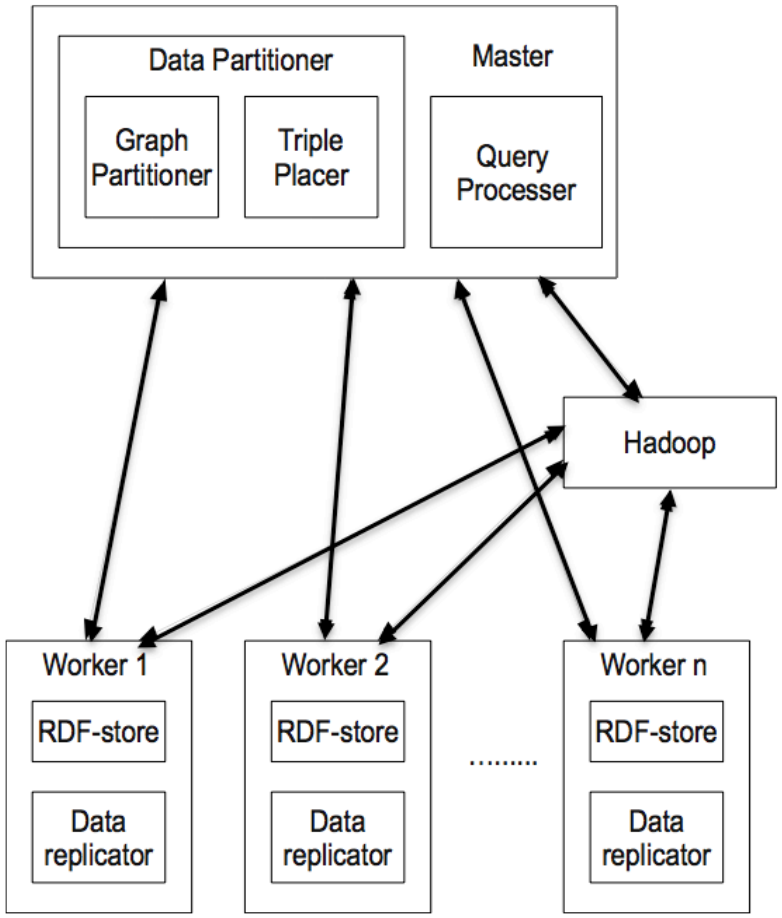
Multiple centralized (RDF) stores

IV. Multiple centralized (RDF) stores

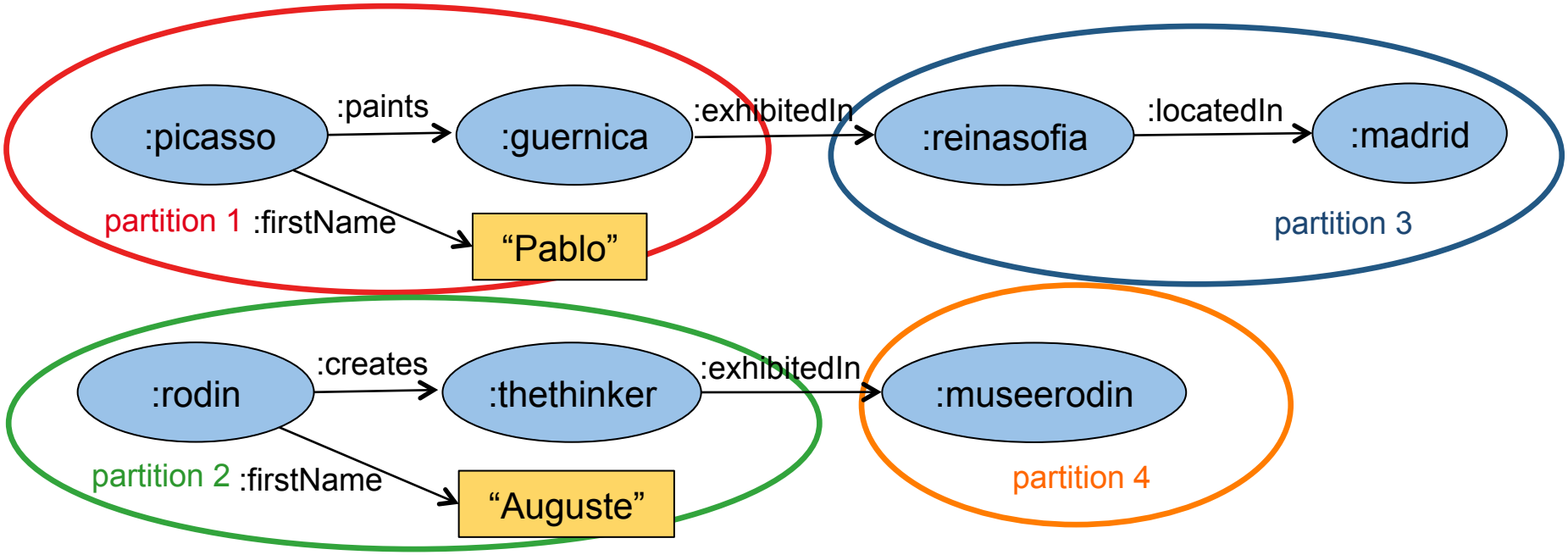
- Data partitioning using known graph tools
  - [Huang11] uses METIS: a graph partitioning tool
  - [Hose13] extends [Huang11] for known query workloads
- Data partitioning using hashing
  - SHAPE [Lee13] uses a semantic hashing method
- Horizontal fragmentation
  - Partout [Galarraga12]

Graph partitioning [Huang11]

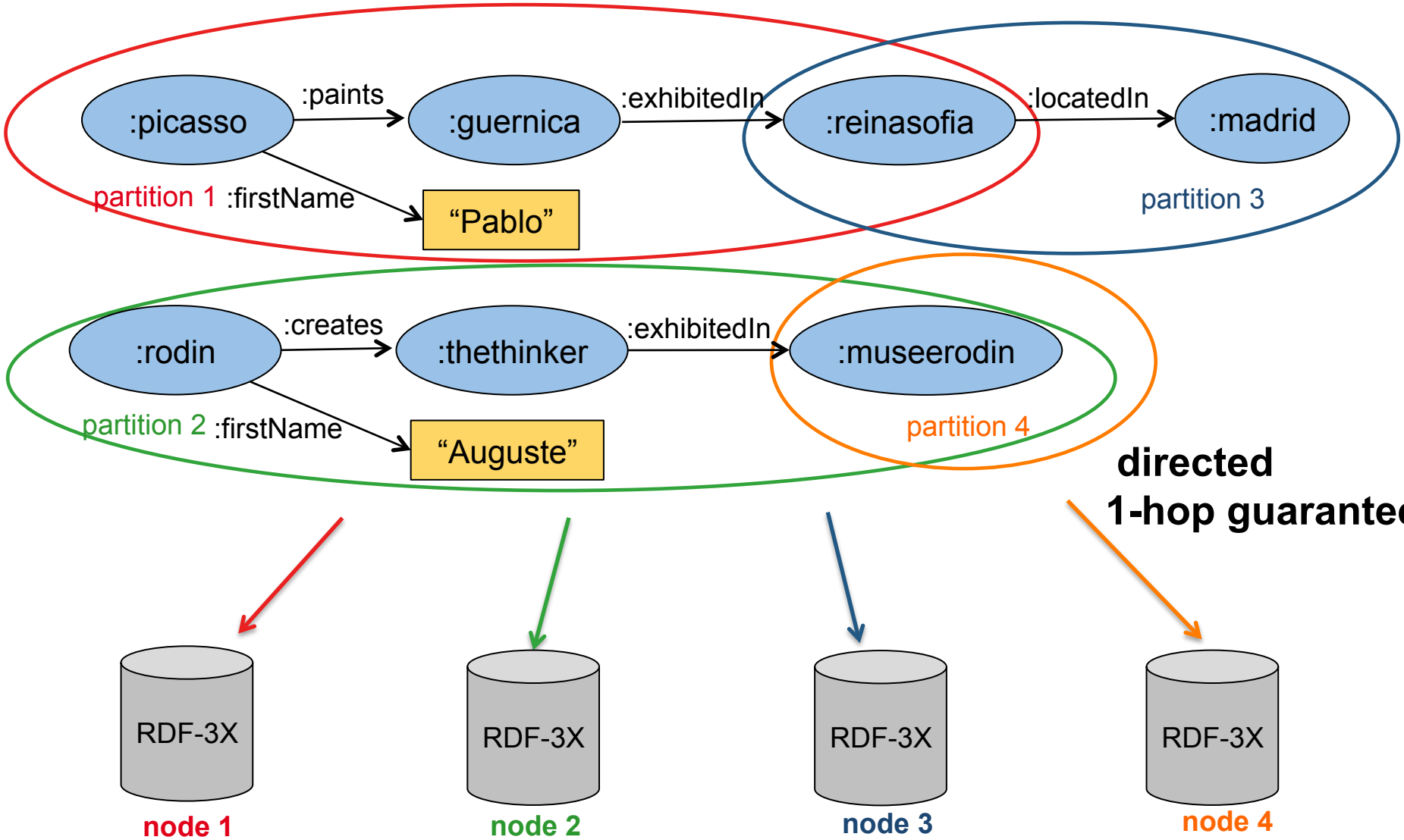
- Data partitioning
  - METIS graph partitioner [METIS]
  - vertex partitioning
  - #partitions = #machines
  - minimum edge cut
  - `type` triples are excluded from the partitioning process
- Data placement
  - partition triples by the subject
  - replication across the partitions
  - directed/undirected n-hop guarantee
- Data storage
  - each machine stores triples into RDF-3X



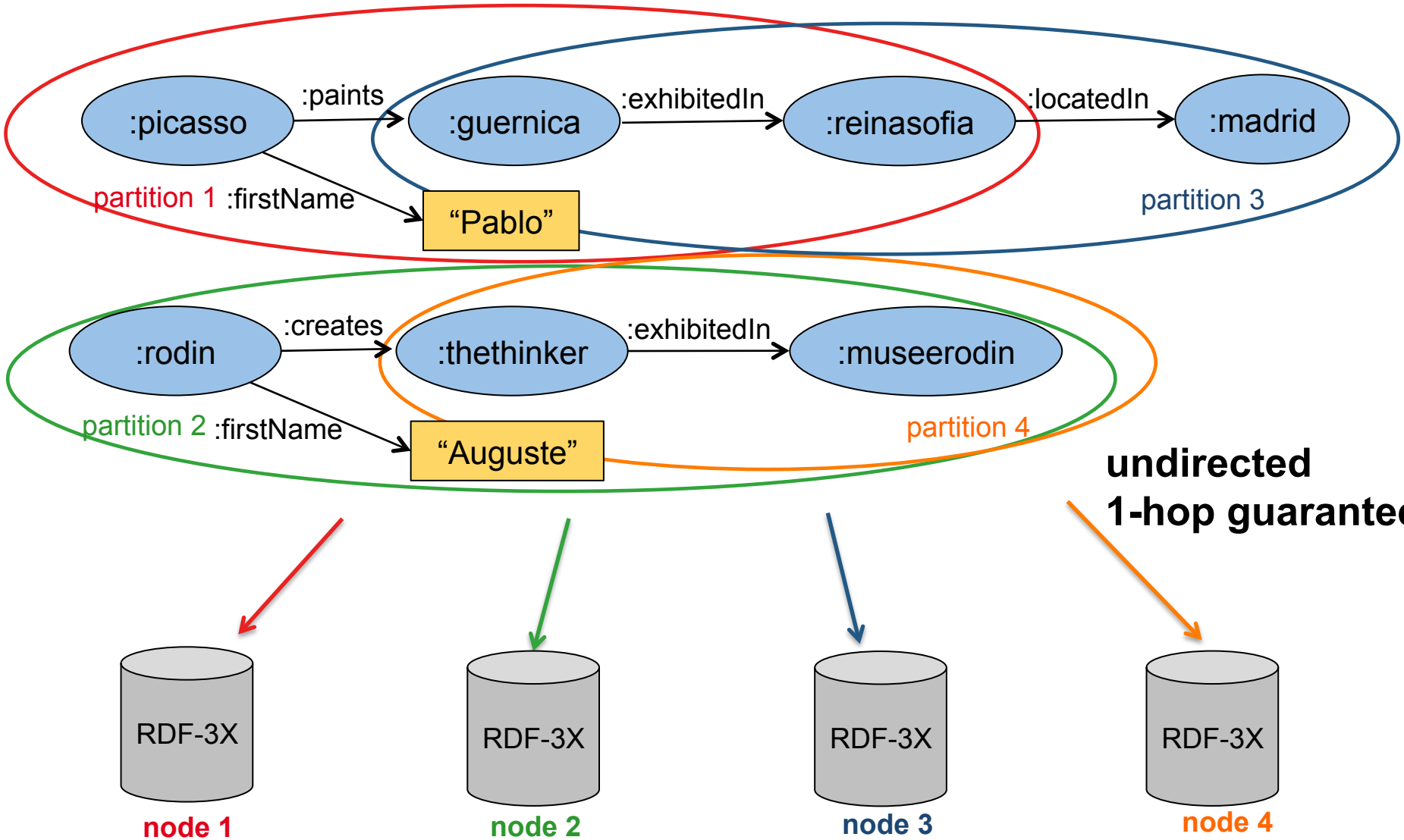
Graph partitioning [Huang11] - storage



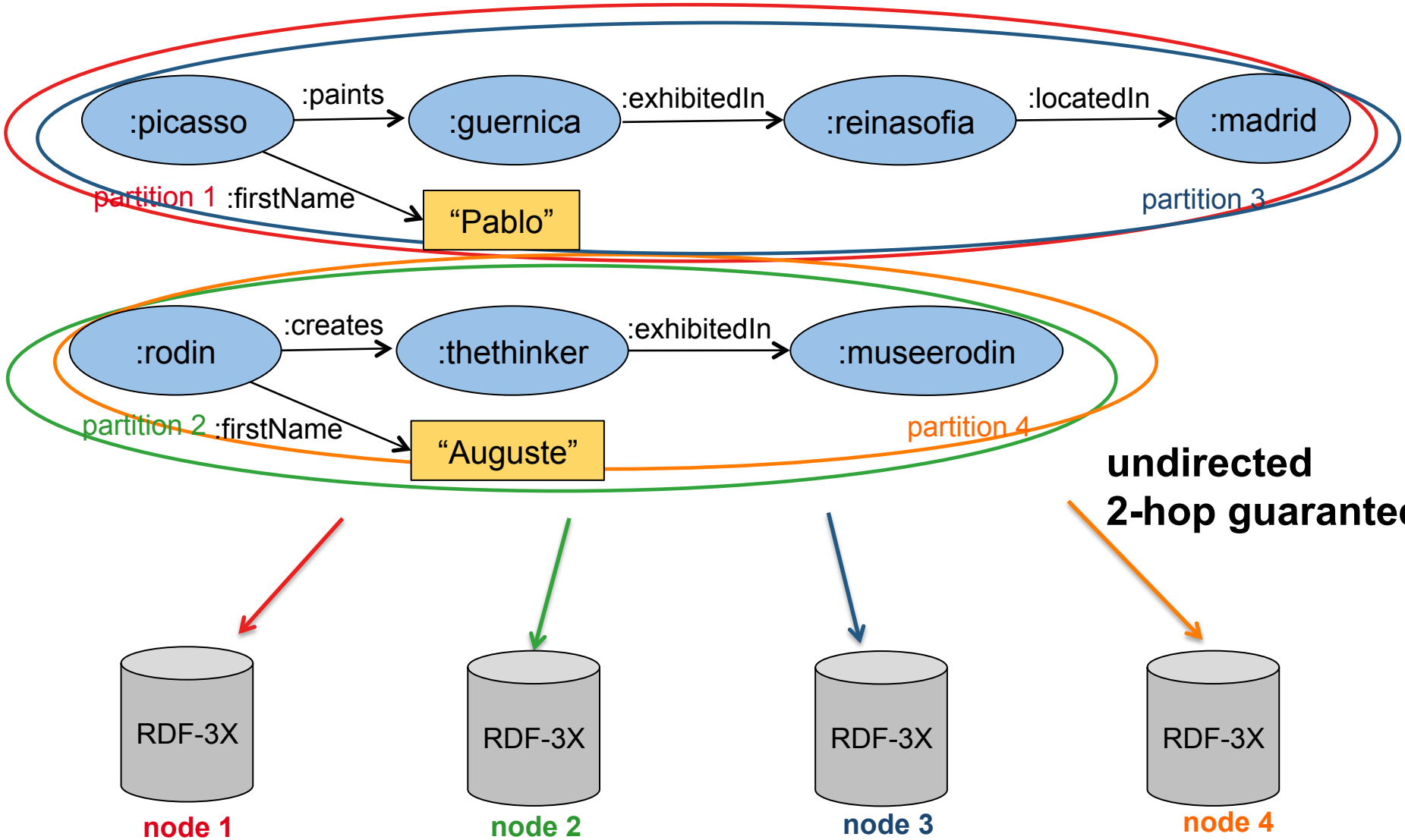
Graph partitioning [Huang11] - storage



Graph partitioning [Huang11] - storage

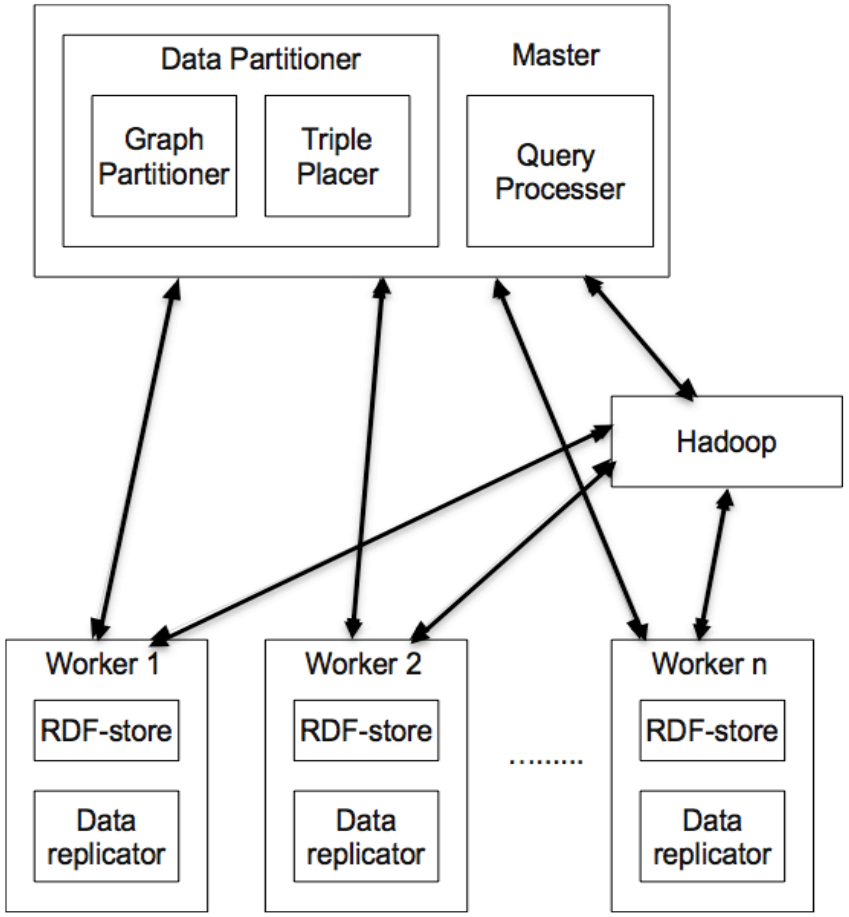


Graph partitioning [Huang11] - storage



Query processing [Huang11]

- Query decomposition for parallelization
- Check if q is PWOC (parallelizable without communication)
  - Yes: answer only from RDF-3X and union results
  - No: answer subqueries from RDF-3X and join them in Hadoop
- # jobs grows with # subqueries
- Heuristic optimization
  - decomposition so as to have minimum number of subqueries → minimal edge partitioning of the query graph into sub-graphs of bounded diameter

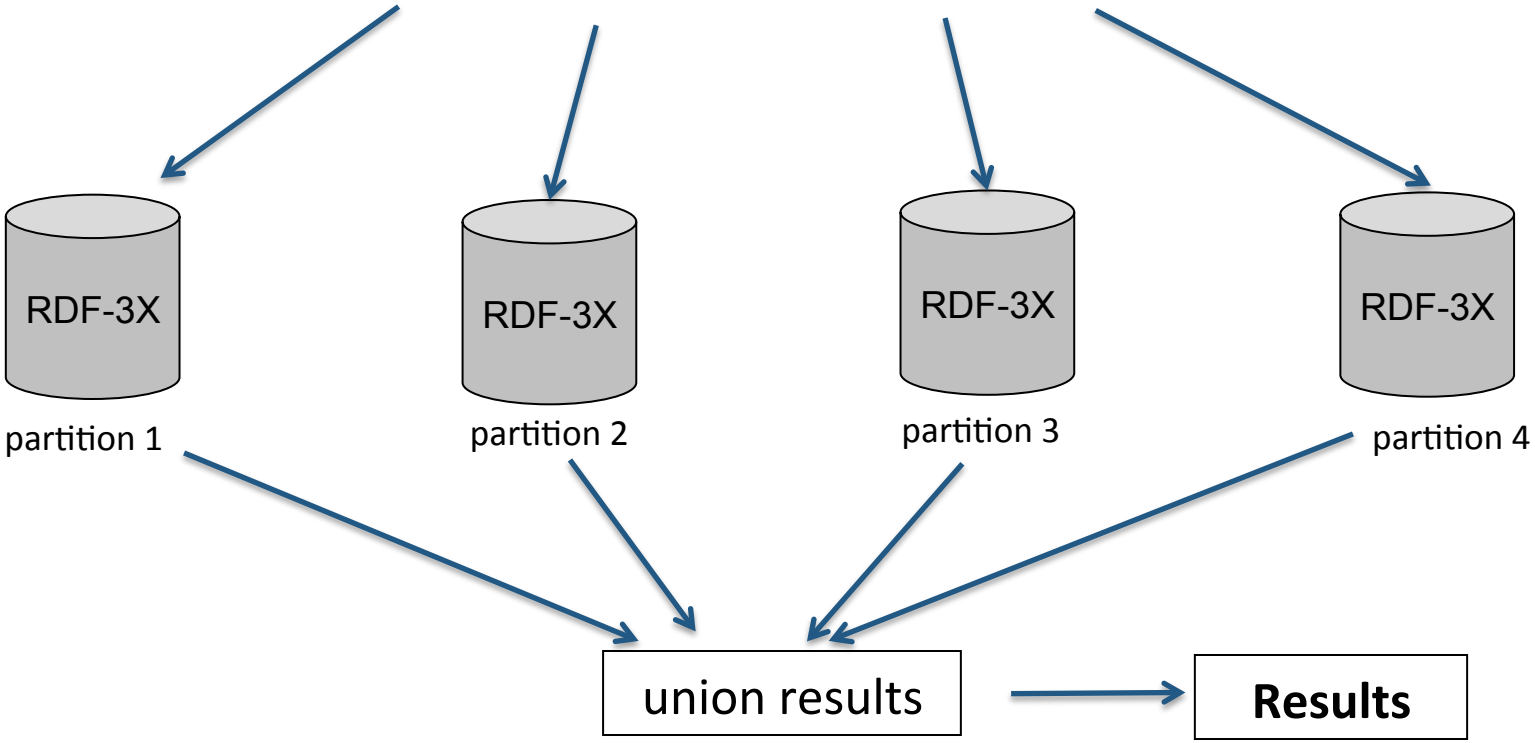


Query processing [Huang11]

Replication with
1-hop guarantee

PWOC query

```
SELECT ?x ?y ?z
WHERE {
        ?x type :artist .
        ?x :firstName ?y .
        ?x :creates ?z .}
```



Query processing [Huang11]

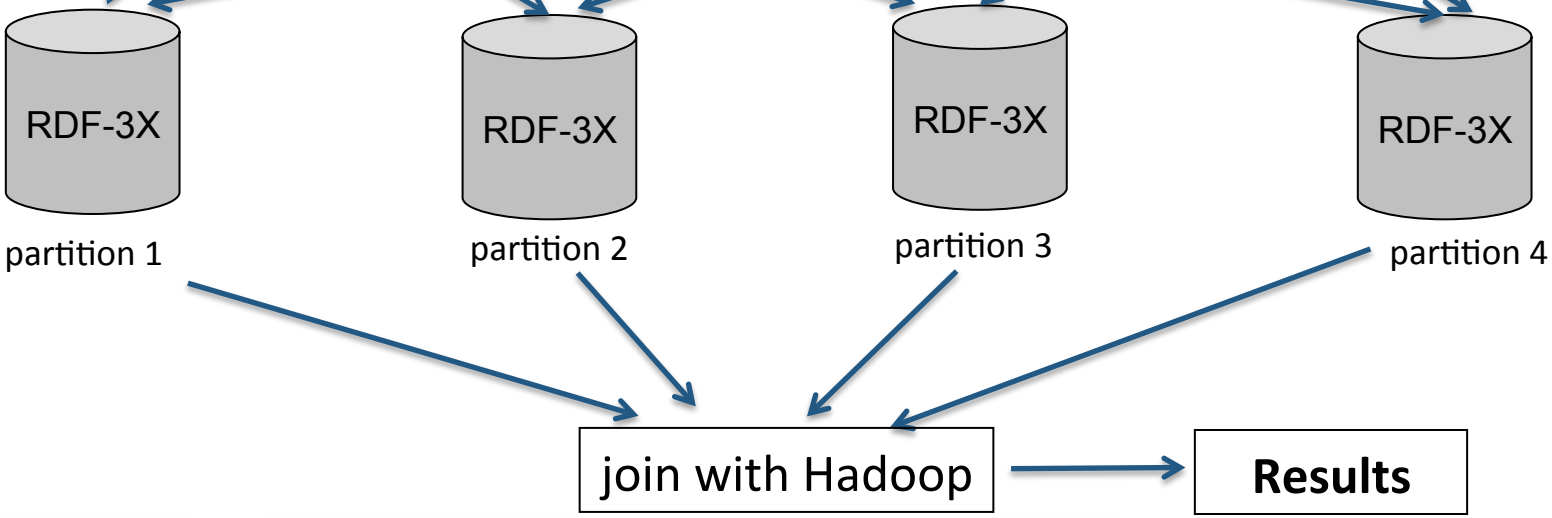
replication with
1-hop guarantee

non PWOC query

```
SELECT ?x ?y ?z
WHERE {  ?x :creates ?y .
         ?y :exhibitedIn ?z .
         ?z :locatedIn :paris .}
```

```
SELECT ?x ?y ?z
WHERE {  ?x :creates ?y .
         ?y :exhibitedIn ?z .}
```

```
SELECT ?z
WHERE {  ?z :locatedIn paris .}
```

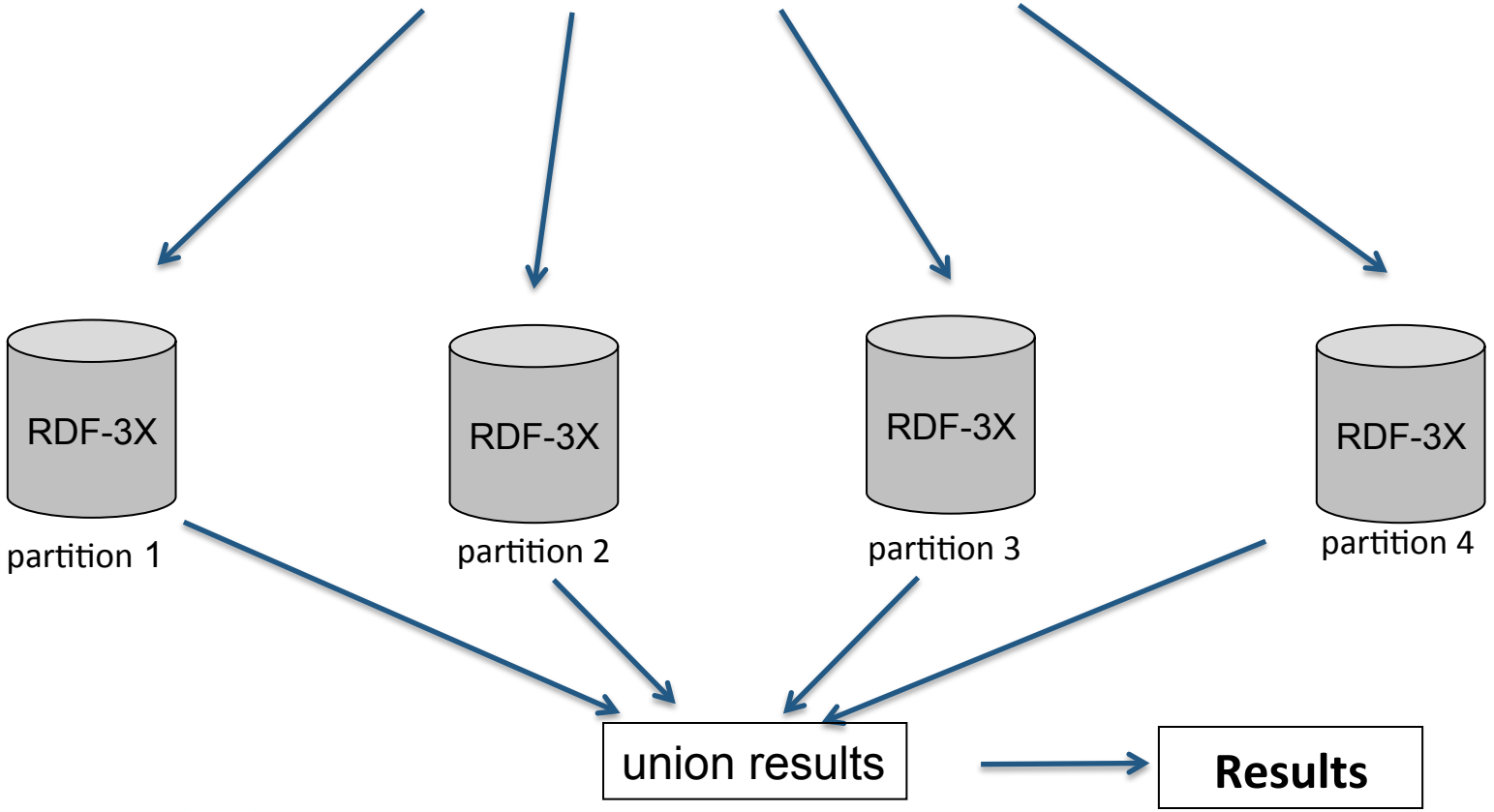


Query processing [Huang11]

replication with
2-hop guarantee

PWOC query

```
SELECT ?x ?y ?z
WHERE {  ?x :creates ?y .
         ?y :exhibitedIn ?z .
         ?z :locatedIn :paris .}
```



Concluding remarks [Huang11]

- ✚ Data fragmentation inspired by RDF structure
- ✚ Reduces shuffling

- ▬ Not scalable for big datasets (Metis is centralized)
- ▬ Sub-queries broadcast to all machines → significant total effort

SHAPE (Semantic HAsh Partitioning) [Lee13]

Introduces semantic hashing partitioning technique

1. Identify triple groups
   - Subject triple group (pairwise disjoint)
     - All triples have the same subject (group anchor)
     - Favors **subject-star** queries
   - Object triple groups (pairwise disjoint)
     - All triples have the same object (group anchor)
     - Favors **object-star** queries
   - Subject-object triple groups (each triple is in 2 groups)
     - All triples have the same subject and the same object (group anchor)
     - Favors **subject- and object-star** queries

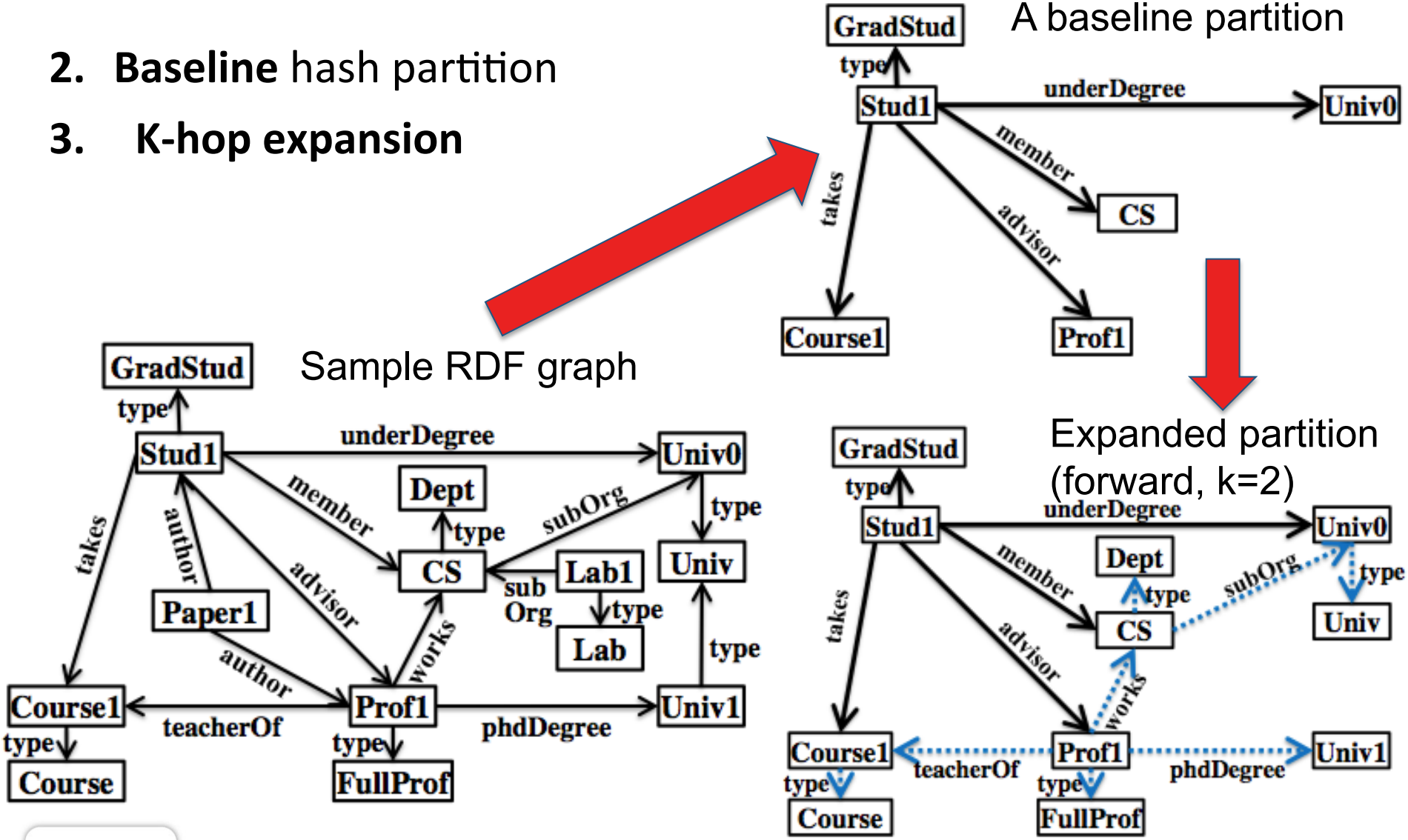
SHAPE (Semantic HAsh Partitioning)

Introduces semantic hashing partitioning technique

2. **Baseline** hash partition
   - Apply a hash function on each triple group anchor → baseline hash partitions for s (*or* o, *or* (s,o))
3. **K-hop expansion**
   - Add to each partition all the triples whose *shortest distance* to *any anchor* of the partition is *at most k* (e.g., k=2)
     - Distance can be measured forward (s→o), backward (o→s) or in any direction (minimum length between s→o and o→s)
   - The goal is to increase the chances of PWOC query evaluation

SHAPE (Semantic HAsh Partitioning)

2. **Baseline** hash partition
3. **K-hop expansion**



SHAPE (Semantic HAsh Partitioning)

1. Identify **triple groups** (based on s; o; or (s, o))
2. **Baseline** hash partition
   - Hash triple groups on s (*or* o, *or* (s,o))
3. **K-hop expansion**
   - Add to each partition all the triples whose *shortest distance* to *any anchor* of the partition is *at most k*
3. **Selective k-hop expansion**
   - Avoid some expansions which are « unlikely to help »
5. **URI-based optimization**
   - Idea: common URI prefix predicts correlated access
   - Hash on URI prefix of a group anchor, not on full URI

Each hash partition group = 1 RDF-3X server; joins on Hadoop

Summary: Multiple centralized (RDF) stores

Pros	Cons
Reduced shuffle cost	Fault tolerance must be implemented on top of the centralized servers
RDF-specific local operations	Scaling up the initial graph partitioning is non-trivial

3.5

Hybrid systems

V. Hybrid RDF stores

- AMADA [Bugiotti12, Aranda12]
  - Generic cloud-based architecture
  - Built on top of Amazon Web Services as a SaaS
  - Route the queries to a small subset of the data that are likely to have matches
  - Trade-offs between efficiency and monetary costs

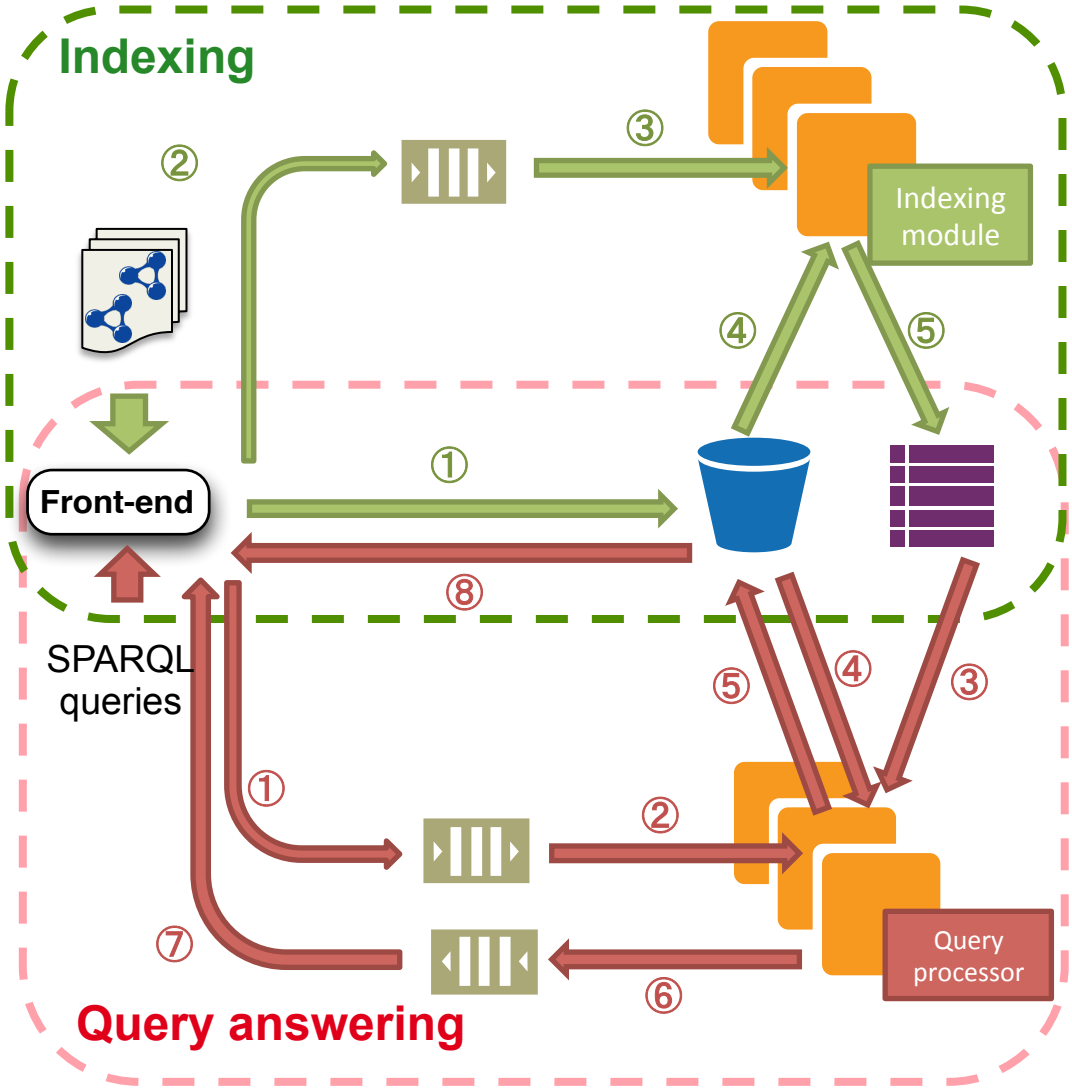
AMADA architecture

Key-value store
Ideal for indexing and querying small, structured data

Storage for raw data
Ideal for large files

Virtual machines
Resizable computing capacity in the cloud

Messaging queues
Queues for communication between distributed components



AMADA indexing and storage

S table

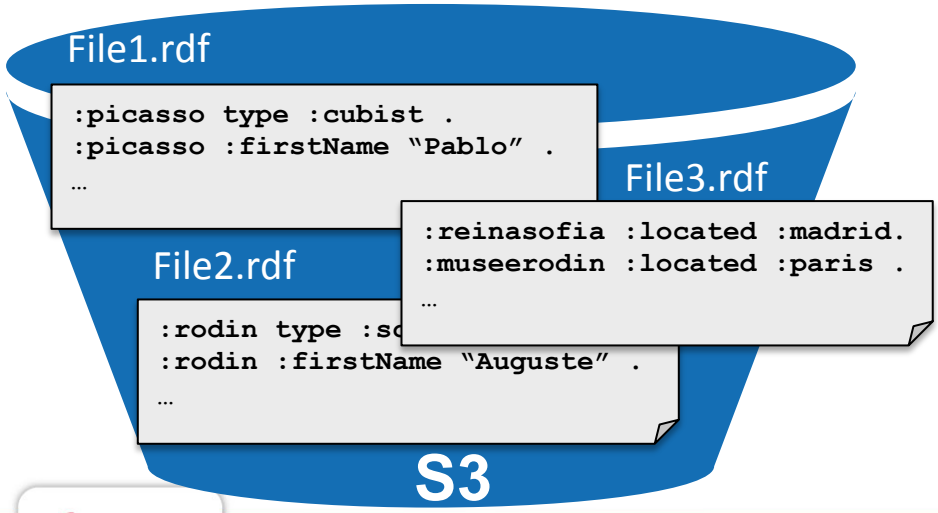
key	(attribute, value)
:picasso	(file1, -)
:guernica	(file1, -)
:reinasofia	(file1, -)
:rodin	(file2, -)
:thethinker	(file2, -)
:museerodin	(file2, -)
…	…

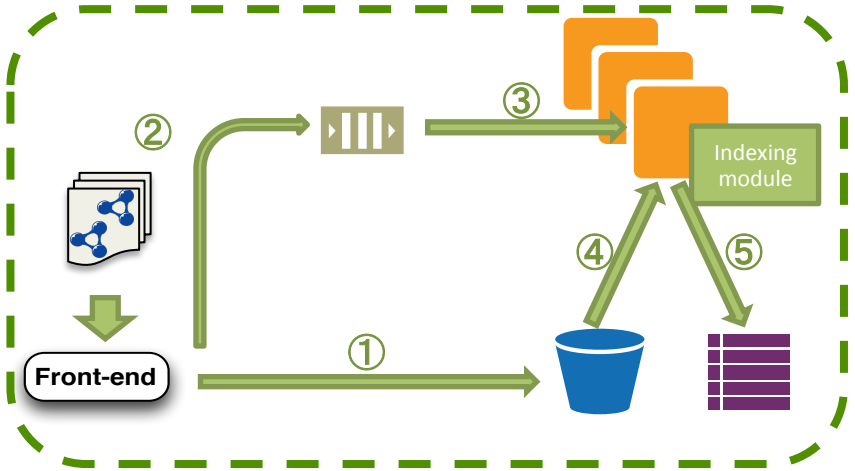
P table

key	(attribute, value)
type	(file1,-), (file2, -)
:firstName	(file1,-), (file2, -)
:paints	(file1,-)
:exhibitedIn	(file1,-), (file2, -)
:locatedIn	(file1,-)
:creates	(file2,-)
…	…

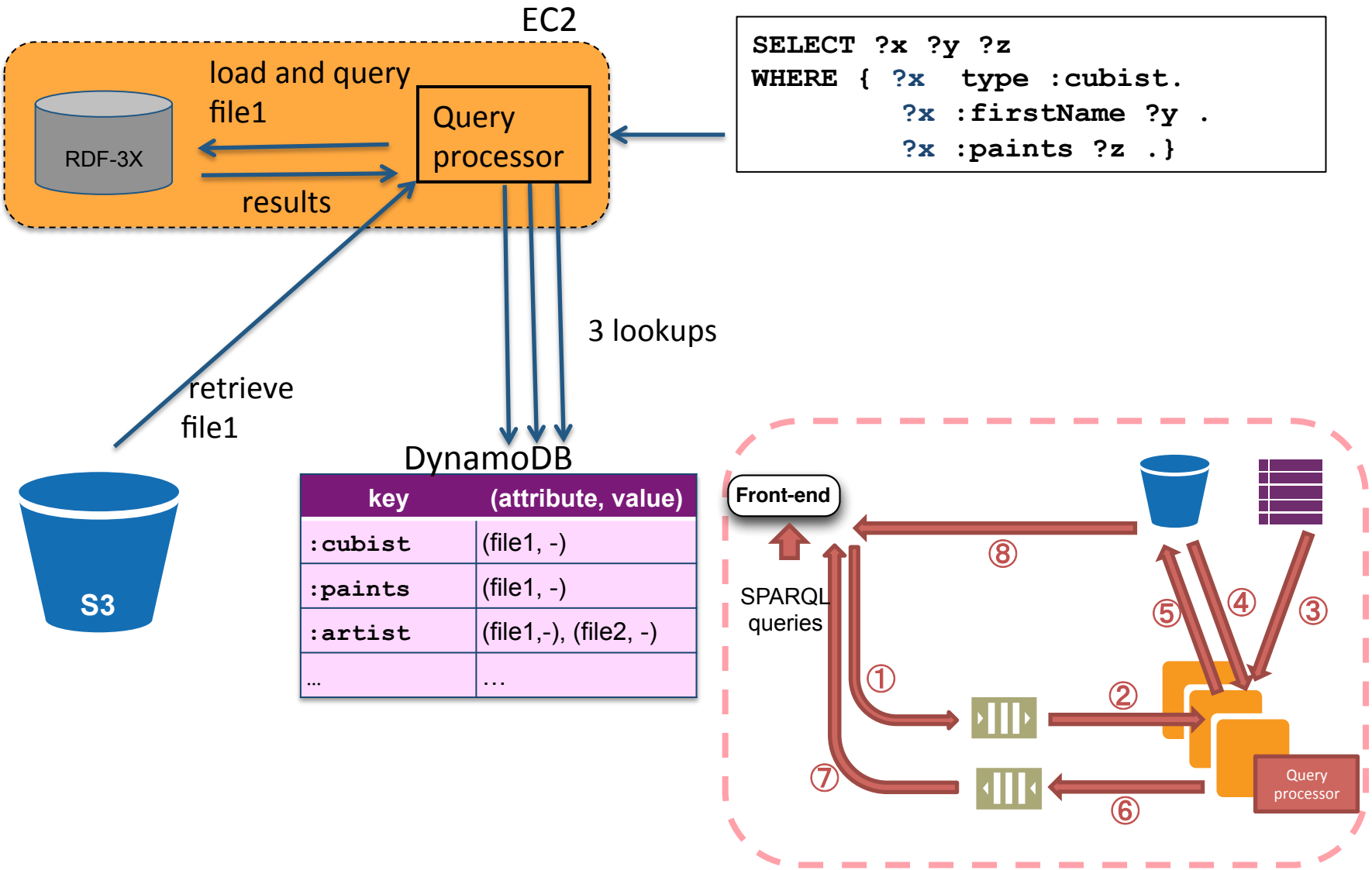
O table

key	(attribute, value)
:cubist	(file1,-)
:guernica	(file1,-)
"Pablo"	(file1,-)
:sculptor	(file2,-)
:thethinker	(file2,-)
:museerodin	(file2,-)
…	…





AMADA querying



AMADA indexing strategies

- Source indexing strategies
  - Identify files (F) that contribute an answer to a query
  - Term-based: T|F|- (T: URIs, literals etc. without caring if it's S, P, or O)
  - Attribute-based: S|F|- P|F|- O|F|-
  - Attribute-subset: S|F|- P|F|- O|F|- SP|F|- PS|F|- SO|F|- SPO|F|-
- Distributed data indexing (as in Part II)
  - RDF data itself is indexed in the key-value store
  - S|P|O P|O|S O|S|P
- Different trade-offs

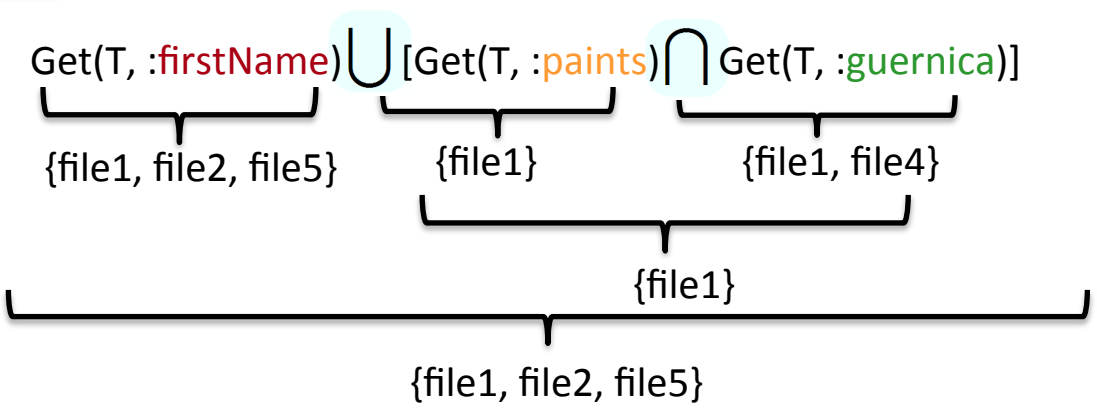
Term-based example

T table

key	(attribute, value)
:picasso	(file1, -)
:guernica	(file1, -), (file4, -)
:reinasofia	(file1, -)
:rodin	(file2, -)
:museerodin	(file2, -)
:firstName	(file1, -), (file2,-), (file5, -)
:paints	(file1,-)
…	…

```
SELECT ?y
WHERE {?x :firstName ?y .
       ?x :paints :guernica .}
```

Lookups



S3

file1.rdf
```
:picasso type :cubist .
:picasso :firstName "Pablo" .
…
```

file2.rdf
```
:rodin type :sculptor .
:rodin :firstName "Auguste" .
…
```

file3.rdf
```
:reinasofia :located :madrid.
:museerodin :located :paris .
…
```

file4.rdf
```
:guernica :exhibited :reinasofia.
:thethinker :exhibited :museerodin.
…
```

file5.rdf
```
:cubist sc :painter.
:firstName domain :artist .
…
```

Attribute-based example

S table

key	(attribute, value)
:picasso	(file1, -)
:guernica	(file4, -)
:reinasofia	(file1, -)
:rodin	(file2, -)
:thethinker	(file2, -)
:firstName	(file4, -)
…	…

P table

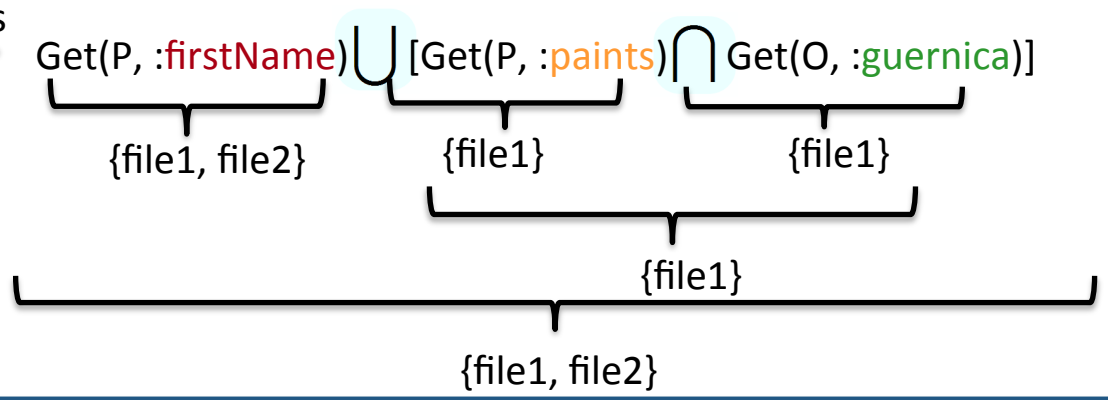
key	(attribute, value)
type	(file1,-), (file3, -), (file4, -)
:firstName	(file1,-), (file2, -)
:paints	(file1,-)
:exhibitedIn	(file1,-), (file2, -)
:locatedIn	(file1,-)
…	…

O table

key	(attribute, value)
:cubist	(file1,-)
:guernica	(file1,-)
"Pablo"	(file1,-)
:sculptor	(file2,-)
:thethinker	(file2,-)
…	…

```
SELECT ?y
WHERE {?x :firstName ?y .
       ?x :paints :guernica .}
```

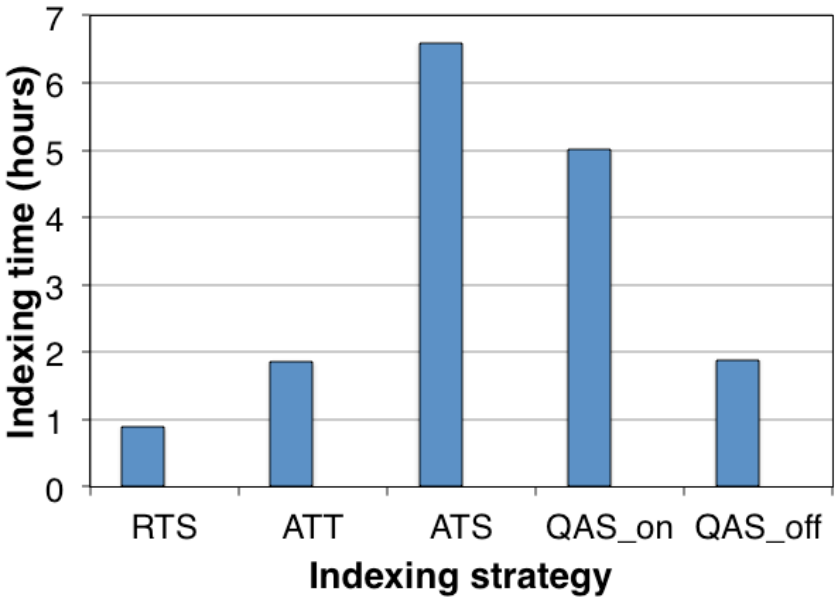
Lookups

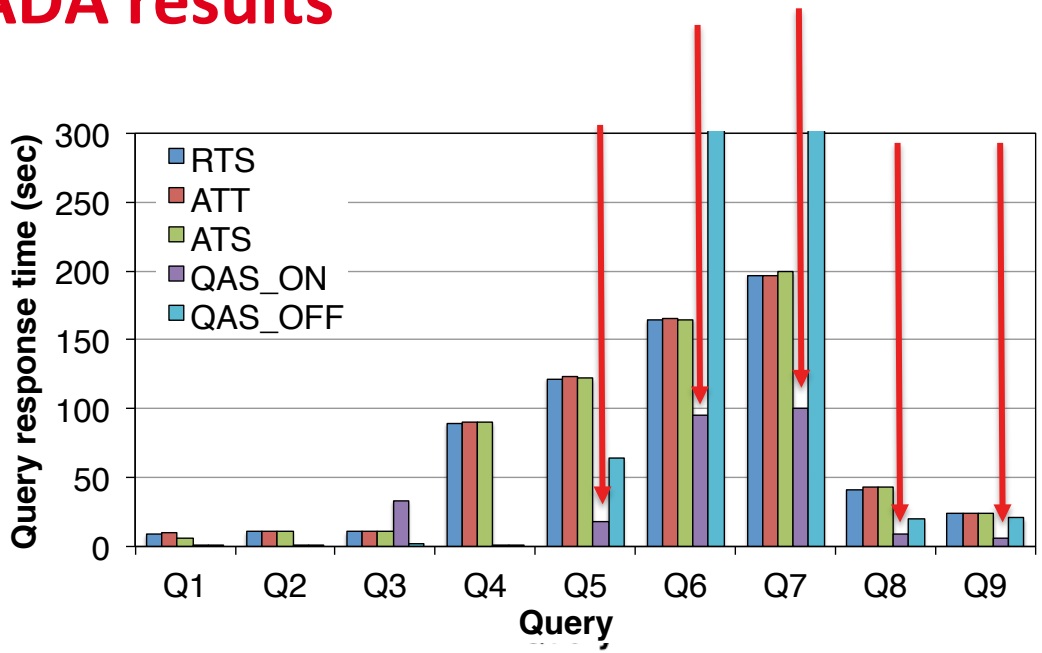


S3

file1.rdf	file2.rdf	file3.rdf	file4.rdf	file5.rdf
:picasso type :cubist . :picasso :firstName "Pablo" . … ✔	:rodin type :sculptor . :rodin :firstName "Auguste" . … ✔	:reinasofia :located :madrid. :museerodin :located :paris . …	:guernica :exhibited :reinasofia. :thethinker :exhibited :museerodin. …	:cubist sc :painter. :firstName domain :artist . …

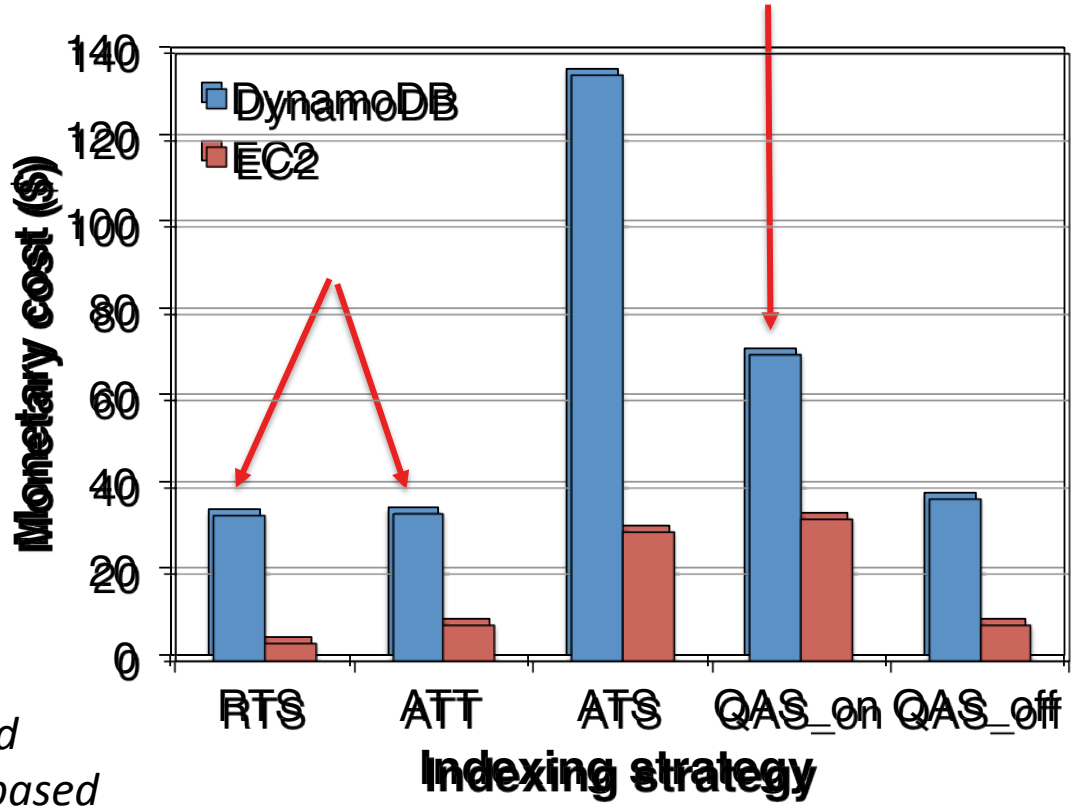
AMADA results





RTS: *term-based*
ATT: *attribute-based*
ATS: *attribute-subset*
QAS: *answering from the index*
on: *w compression*
off: *w/o compression*

What about the money spent?

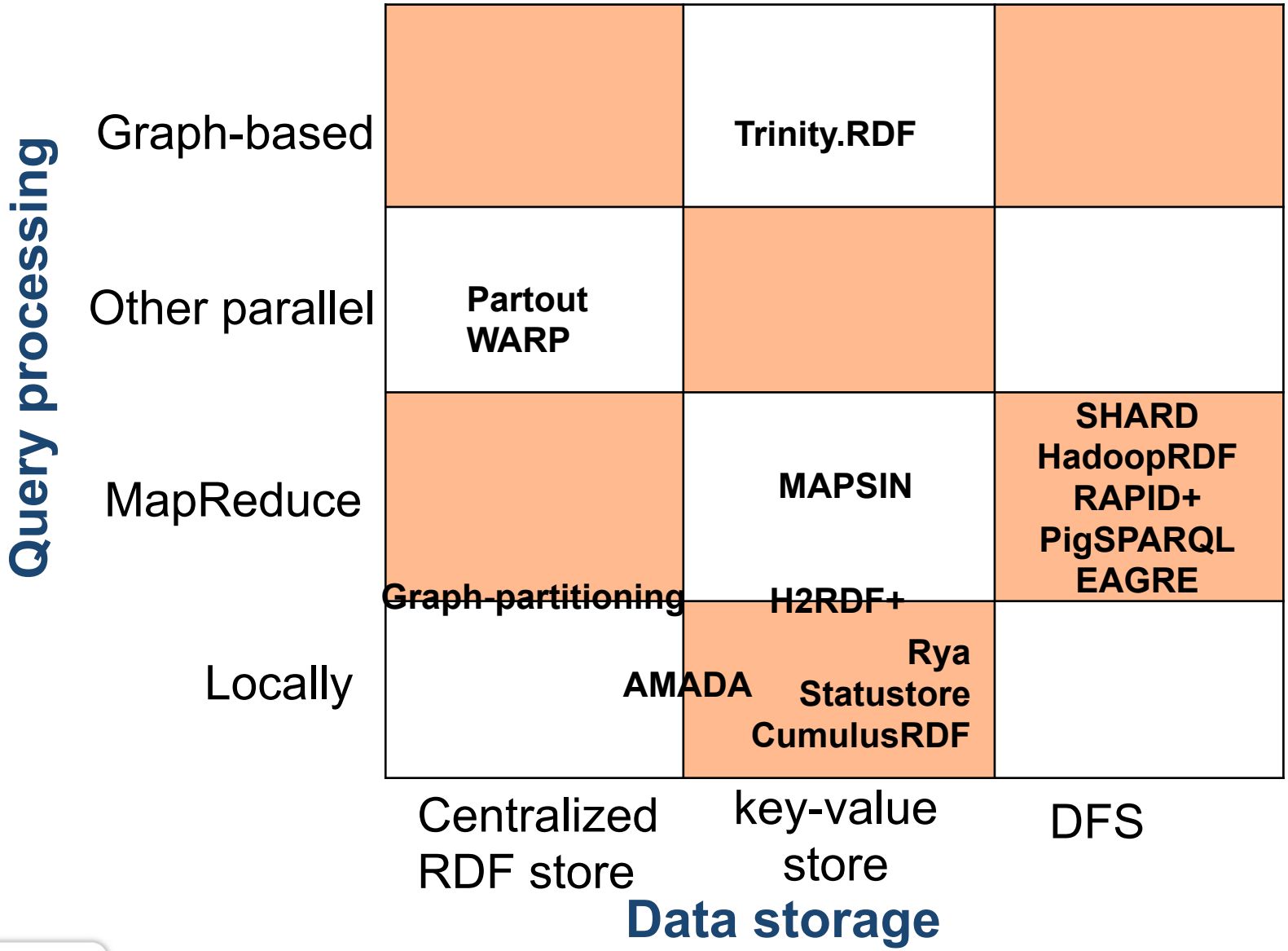


RTS: *term-based*
ATT: *attribute-based*
ATS: *attribute-subset*
QAS: *answering from the index*
on: *w compression*
off: *w/o compression*

Summary: Hybrid RDF stores

Pros	Cons
Scalability	Depends on data partitioning
Fault-tolerance	Separation between storage and processing services
Elastic allocation of resources	Low latency for non-selective queries
Inter-query parallelism	No control on the services
Benefit from higher-level services (PaaS)	

Classification of systems



Analysis dimensions

1. Data storage

- Key-value stores
- DFS (distributed file system)
- Single-site RDF stores or data storage services supplied by cloud providers

2. Query processing

- MapReduce-based
- Local processing (joins are usually performed at a single site)
- Distributed graph-based exploration

3. RDFS entailment

Analysis dimensions

1. Data storage

- Key-value stores
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- Distributed graph-based exploration

3. RDFS entailment

Entailment in RDF

- RDF schema statements and set of entailment rules lead to implicit (entailed) RDF data

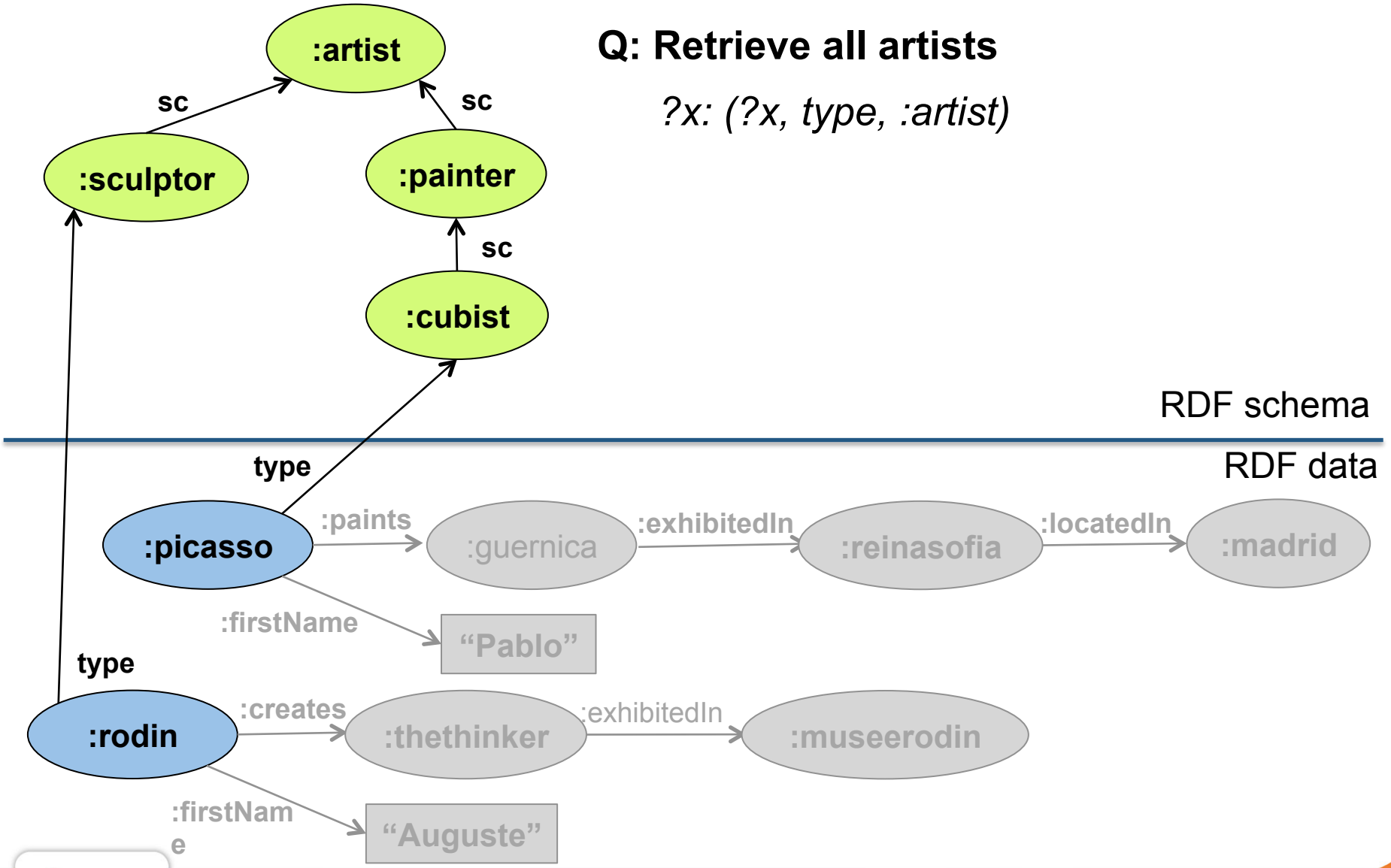
Sample rules

(X, type, A) ∧ (A, sc, B) → (X, type, B)
(X, P, O) ∧ (P, domain, A) → (X, type, A)

(:picasso, :paints, :guernica) ∧ (:paints, domain, :painter) → (:picasso, type, :painter)

- RDFS entailment : *Given an RDF(S) database DB and a triple t, is t entailed from DB (or does t logically follows from DB)?*

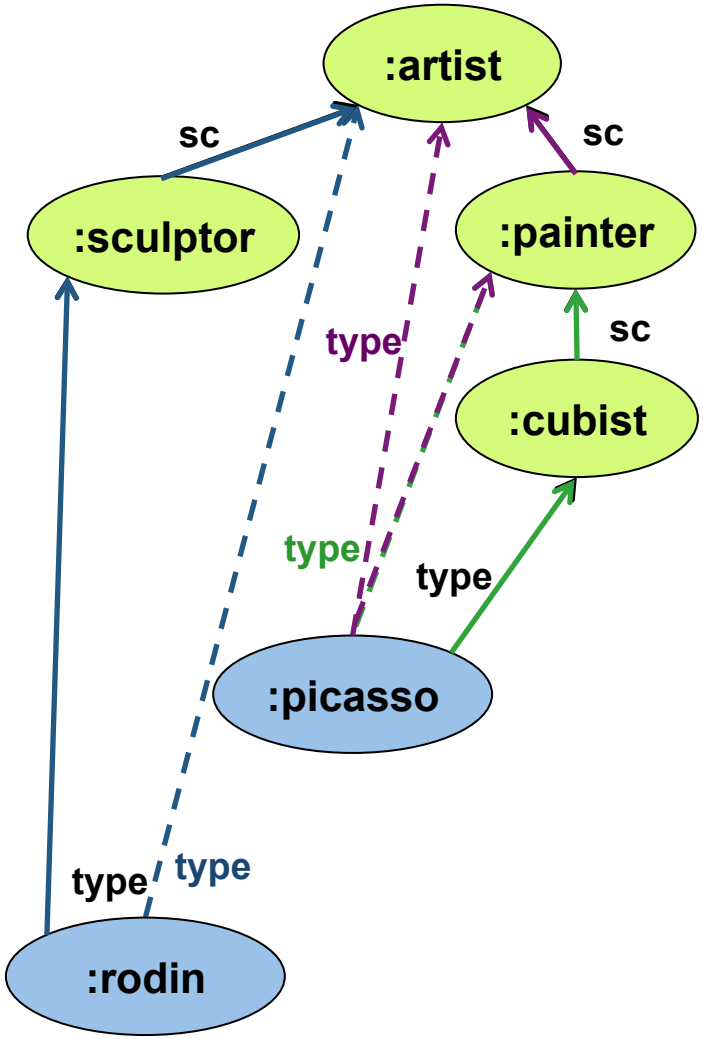
Entailed triples and RDF querying



Q: Retrieve all artists

?x: (?x, type, :artist)

Entailed triples and RDF querying



Q: Retrieve all artists *?x: (?x, type, :artist)*

A:

?x
-

no entailment

Rule:

(X, type, A) ∧ (A, sc, B) → (X, type, B)

Implicit / entailed triples

(:rodin, type, :artist)

(:picasso, type, :painter)

(:picasso, type, :artist)

A:

?x
:picasso
:rodin

with entailment

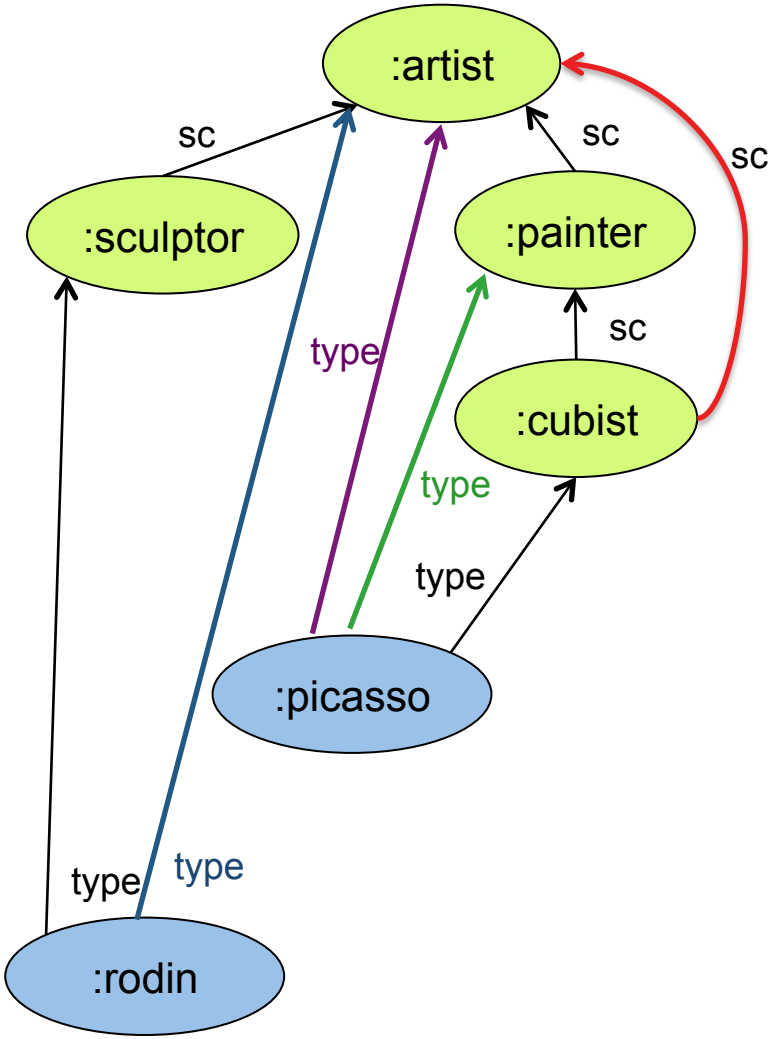
RDFS entailment techniques

- RDFS closure
  - compute all implicit triples and store/materialize them in the database
- Query reformulation
  - transform/rewrite the query so that you get all the answers (even the ones that come from implicit triples)
- Hybrid approaches
  - compute the schema closure, and then reformulate the query
  - magic sets: based on the queries, pre-compute and store only the implicit triples that are required for the answer

RDFS entailment – RDFS closure

Before querying

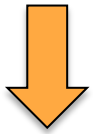
subject	property	object
:picasso	type	:cubist
:rodin	type	:sculptor
:sculptor	sc	:artist
:cubist	sc	:painter
:painter	sc	:artist
:cubist	sc	:painter
:rodin	type	:artist
:picasso	type	:painter
:picasso	type	:artist



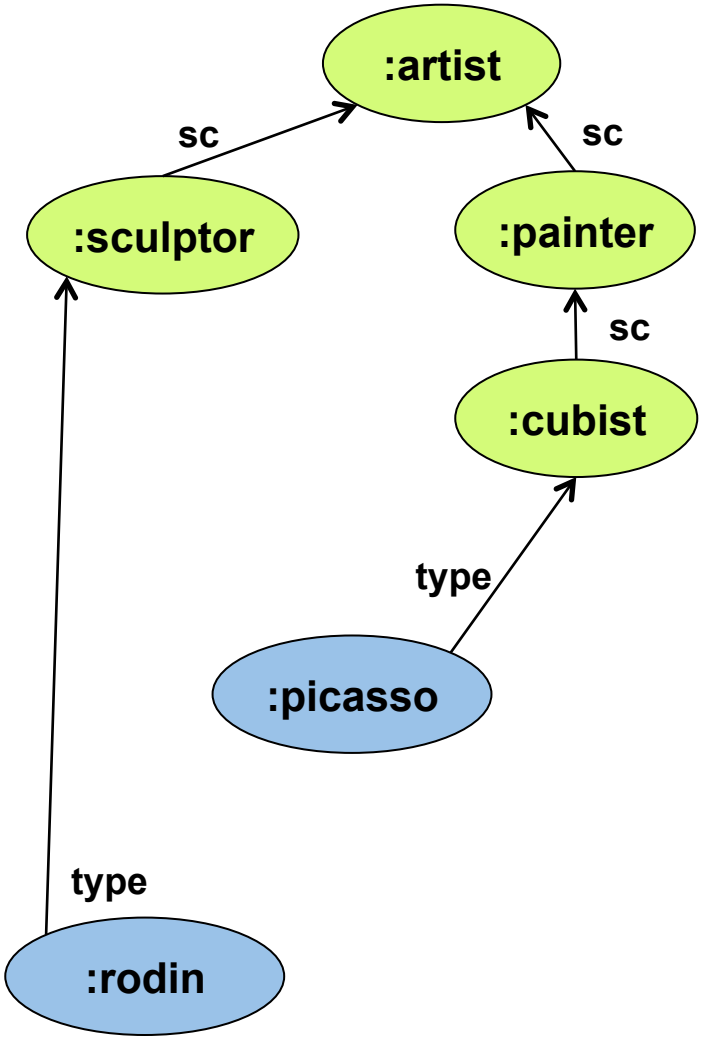
RDFS entailment – query reformulation

At query time

?x: (?x, type, :artist)



?x: (?x, type, :artist) ∨
(?x, type, :sculptor) ∨
(?y, type, :painter) ∨
(?x, type, :cubist)



RDFS entailment techniques

- RDFS closure
  - ✚ Simple query evaluation
  - ➖ Storage overhead
  - ➖ Maintenance costs upon updates
- Query reformulation
  - ✚ No storage overhead
  - ✚ Robust to data/schema changes
  - ➖ Evaluation inefficient for complex queries
- Hybrid approaches combine the two
- For a comparison on these techniques:
  - centralized [Goasdoué13] and distributed [Kaoudi13]

Categorization based on RDFS entailment

I. Computing RDFS closure

II. Approaches based on query reformulation

III. Hybrid approaches

I. Computing RDFS closure in the cloud

- RDFS closure computation in MapReduce Hadoop: **WebPie** [Urbani09]
  - RDF data is stored in HDFS
  - Compute all entailed triples using MapReduce
  - Optimization techniques

- Full RDFS closure computation in parallel (MPI-based) [Weaver09]
  - embarrassingly parallel algorithm
  - RDFS triples are kept in memory in each process

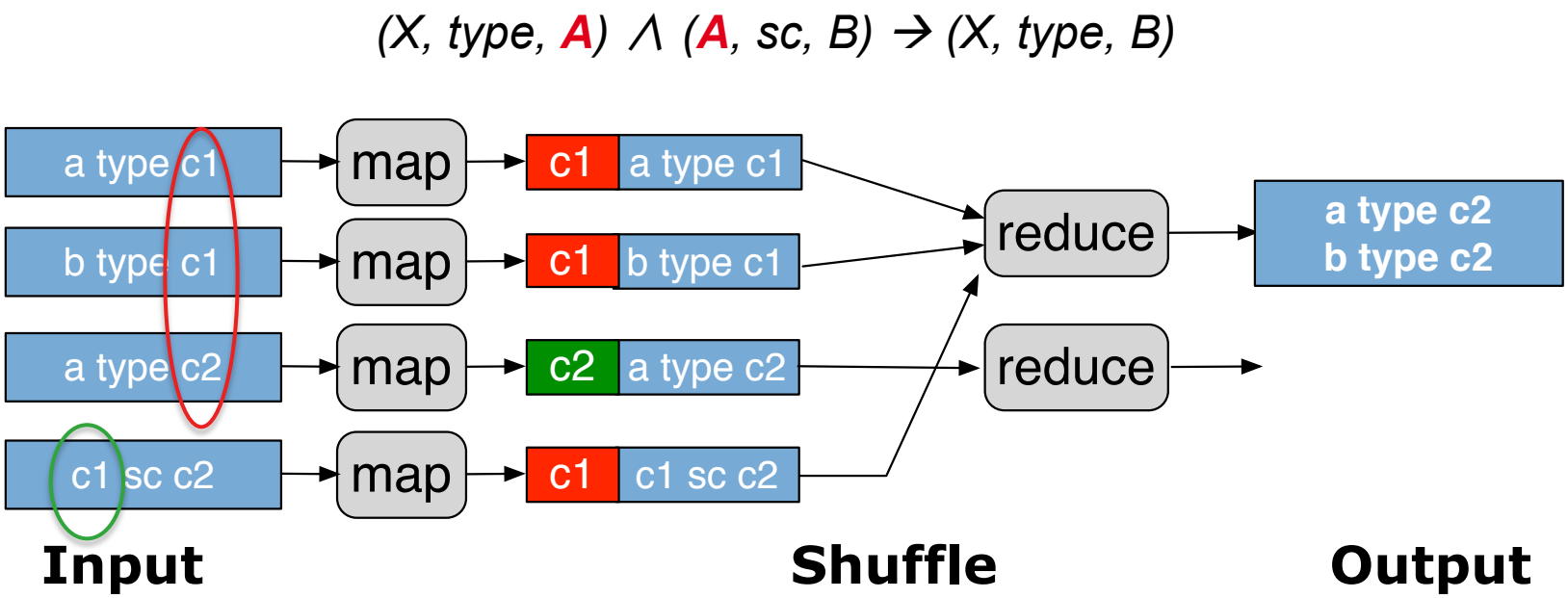
How do we execute the RDFS rules in MapReduce?

Rule Name	If E contains:	then add:
rdfs1	uuu aaa lll. where lll is a plain literal (with or without a language tag).	_:nnn rdf:type rdfs:Literal . where _:nnn identifies a blank node allocated to lll by rule rule lg.
rdfs2	aaa rdfs:domain xxx . uuu aaa yyy .	uuu rdf:type xxx .
rdfs3	aaa rdfs:range xxx . uuu aaa vvv .	vvv rdf:type xxx .
rdfs4a	uuu aaa xxx .	
rdfs4b	uuu aaa vvv.	
rdfs5	uuu rdfs:subPropertyOf vvv . vvv rdfs:subPropertyOf xxx .	
rdfs6	uuu rdf:type rdf:Property .	
rdfs7	aaa rdfs:subPropertyOf bbb . uuu aaa yyy .	
rdfs8	uuu rdf:type rdfs:Class .	uuu rdfs:subClassOf rdfs:Resource .
rdfs9	uuu rdfs:subClassOf xxx . vvv rdf:type uuu .	vvv rdf:type xxx .
rdfs10	uuu rdf:type rdfs:Class .	uuu rdfs:subClassOf uuu .
rdfs11	uuu rdfs:subClassOf vvv . vvv rdfs:subClassOf xxx .	uuu rdfs:subClassOf xxx .
rdfs12	uuu rdf:type rdfs:ContainerMembershipProperty .	uuu rdfs:subPropertyOf rdfs:member .
rdfs13	uuu rdf:type rdfs:Datatype .	uuu rdfs:subClassOf rdfs:Literal .

There is a common constant for rules with 2 atoms → Join

RDFS closure in MapReduce [Urbani09]

- Implement as a join in MapReduce each rule that has two atoms in its body



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rdfs2	aaa rdfs:domain xxx . uuu aaa yyy .	uuu rdf:type xxx .
rdfs3	aaa rdfs:range xxx . uuu aaa vvv .	vvv rdf:type xxx .
rdfs4a	uuu aaa xxx .	
rdfs4b	uuu aaa vvv.	
rdfs5	uuu rdfs:subPropertyOf vvv vvv rdfs:subPropertyOf xxx .	
rdfs6	uuu rdf:type rdf:Property	
rdfs7	aaa rdfs:subPropertyOf bbb uuu aaa yyy .	
rdfs8	uuu rdf:type rdfs:Class .	
rdfs9	uuu rdfs:subClassOf xxx . vvv rdf:type uuu .	vvv rdf:type xxx .
rdfs10	uuu rdf:type rdfs:Class .	uuu rdfs:subClassOf uuu .
rdfs11	uuu rdfs:subClassOf vvv . vvv rdfs:subClassOf xxx .	uuu rdfs:subClassOf xxx .
rdfs12	uuu rdf:type rdfs:ContainerMembershipProperty .	uuu rdfs:subPropertyOf rdfs:member .
rdfs13	uuu rdf:type rdfs:Datatype .	uuu rdfs:subClassOf rdfs:Literal .

Entailed triples are used as input in the rules → iterate jobs until no new data is produced (fixpoint)

RDFS closure in MapReduce [Urbani09]

- Optimizations

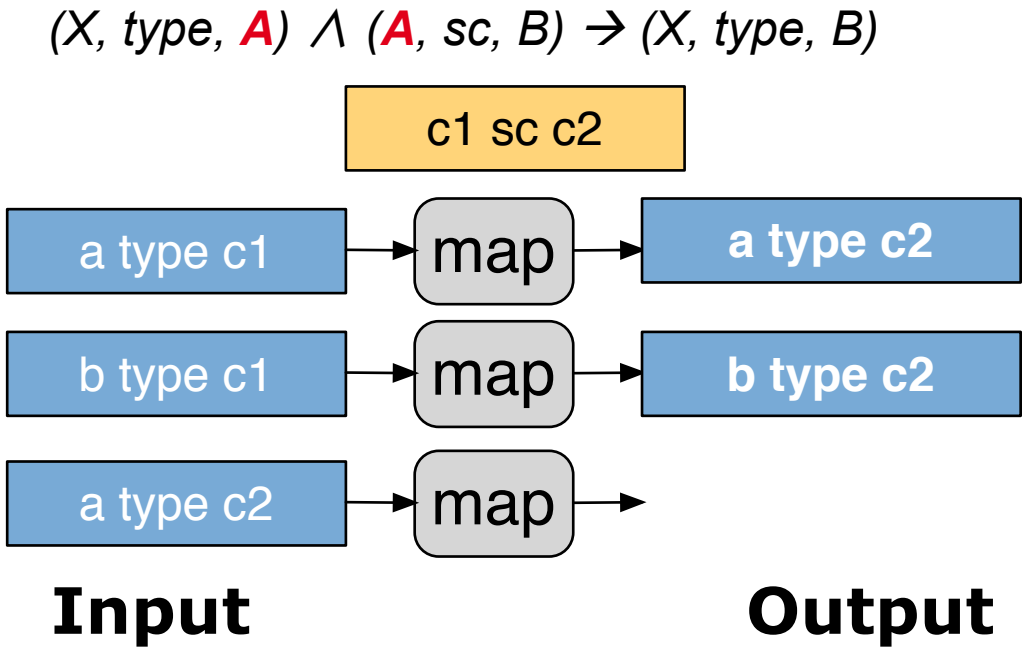
RDFS rules

Rule Name	If E contains:	then add:
rdfs1	uuu aaa lll. where lll is a plain literal (with or without a language tag).	_:nnn rdf:type rdfs:Literal . where _:nnn identifies a blank node allocated to lll by rule rule lg.
rdfs2	aaa rdfs:domain xxx . uuu aaa yyy .	uuu rdf:type xxx .
rdfs3	aaa rdfs:range xxx . uuu aaa vvv .	vvv rdf:type xxx .
rdfs4a	uuu aaa xxx .	uuu rdf:type rdfs:Resource .
rdfs4b	uuu aaa vvv.	vvv rdf:type rdfs:Resource .
rdfs5	uuu rdfs:subPropertyOf vvv . vvv rdfs:subPropertyOf xxx .	
rdfs6	uuu rdf:type rdf:Property .	
rdfs7	aaa rdfs:subPropertyOf bbb . uuu aaa yyy .	
rdfs8	uuu rdf:type rdfs:Class .	uuu rdfs:subClassOf rdfs:Resource .
rdfs9	uuu rdfs:subClassOf xxx . vvv rdf:type uuu .	vvv rdf:type xxx .
rdfs10	uuu rdf:type rdfs:Class .	uuu rdfs:subClassOf uuu .
rdfs11	uuu rdfs:subClassOf vvv . vvv rdfs:subClassOf xxx .	uuu rdfs:subClassOf xxx .
rdfs12	uuu rdf:type rdfs:ContainerMembershipProperty .	uuu rdfs:subPropertyOf rdfs:member .
rdfs13	uuu rdf:type rdfs:Datatype .	uuu rdfs:subClassOf rdfs:Literal .

At least 1 of the atoms is a schema triple!

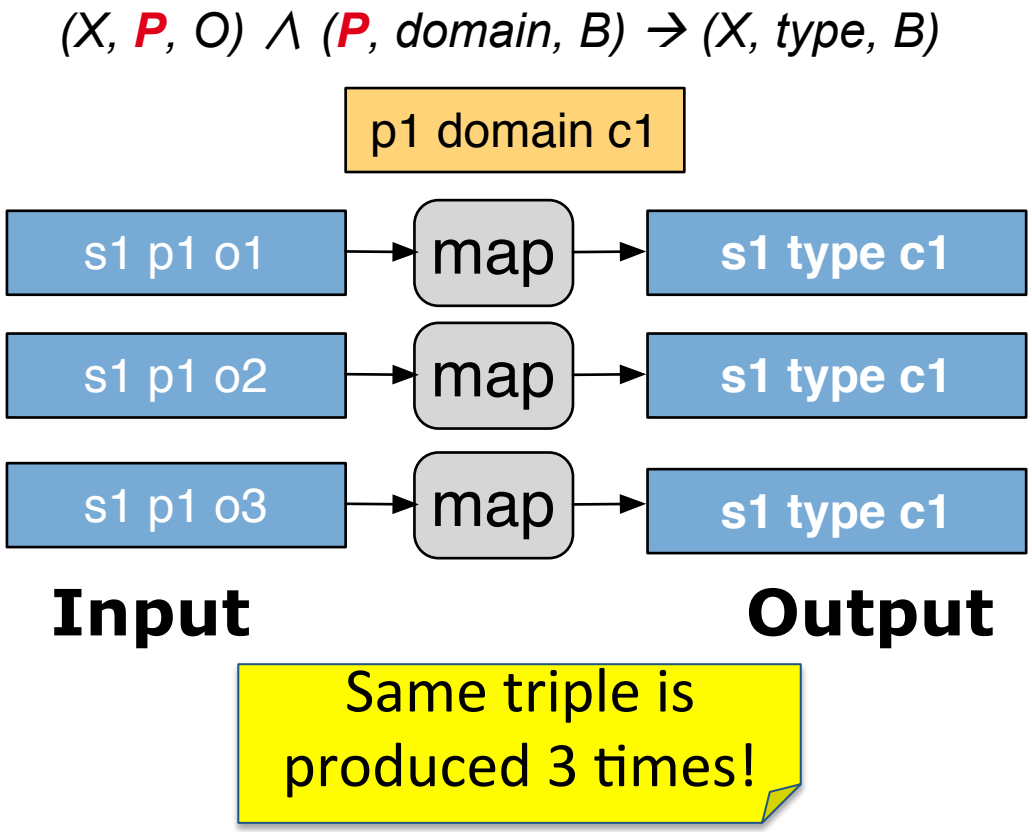
RDFS closure in MapReduce [Urbani09]

- Optimizations
  - Keep the RDF schema triples in memory of each node



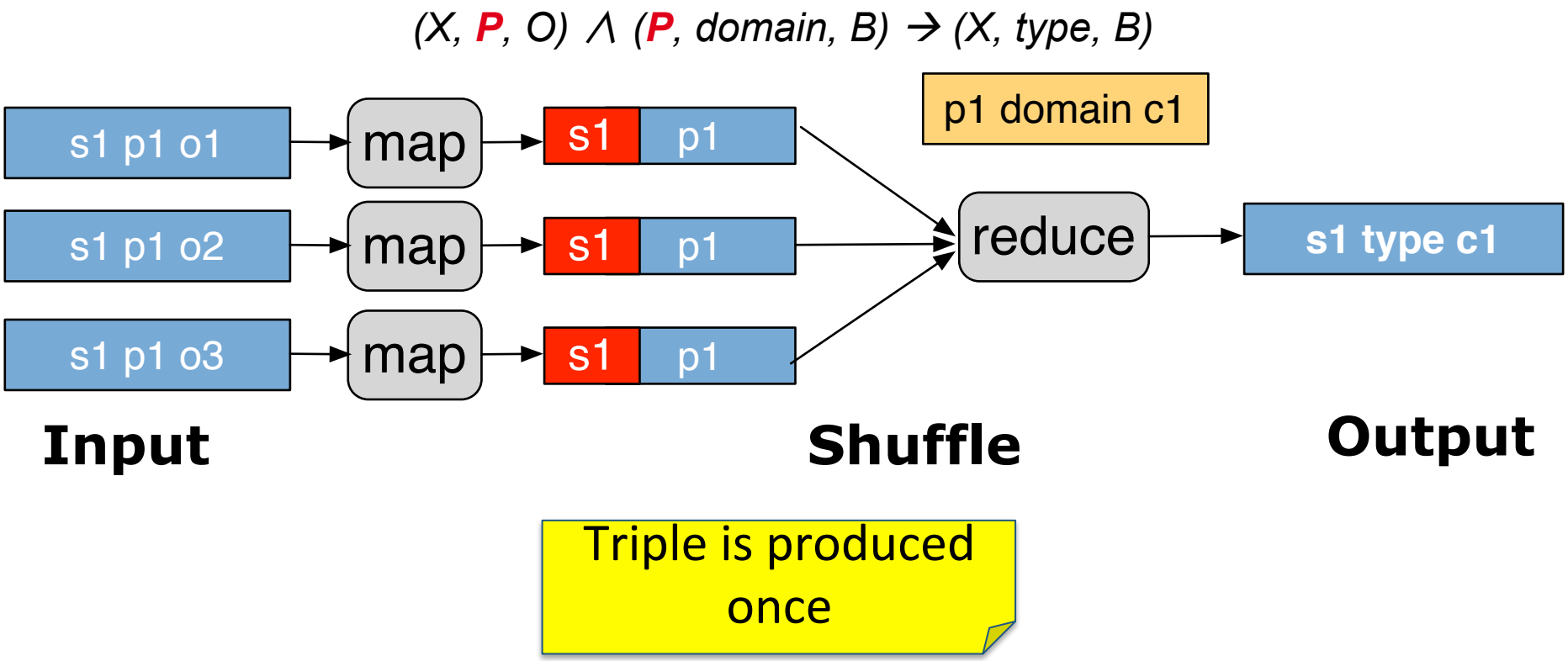
RDFS closure in MapReduce [Urbani09]

- Optimizations
  - Keep the RDF schema triples in memory of each node



RDFS closure in MapReduce [Urbani09]

- Optimizations
  - Keep the RDF schema triples in memory of each node
  - Data grouping to avoid duplicates



RDFS closure in MapReduce [Urbani09]

- Optimizations
  - Keep the RDF schema triples in memory of each node
  - Data grouping to avoid duplicates
  - Ordering of rules to limit iterations

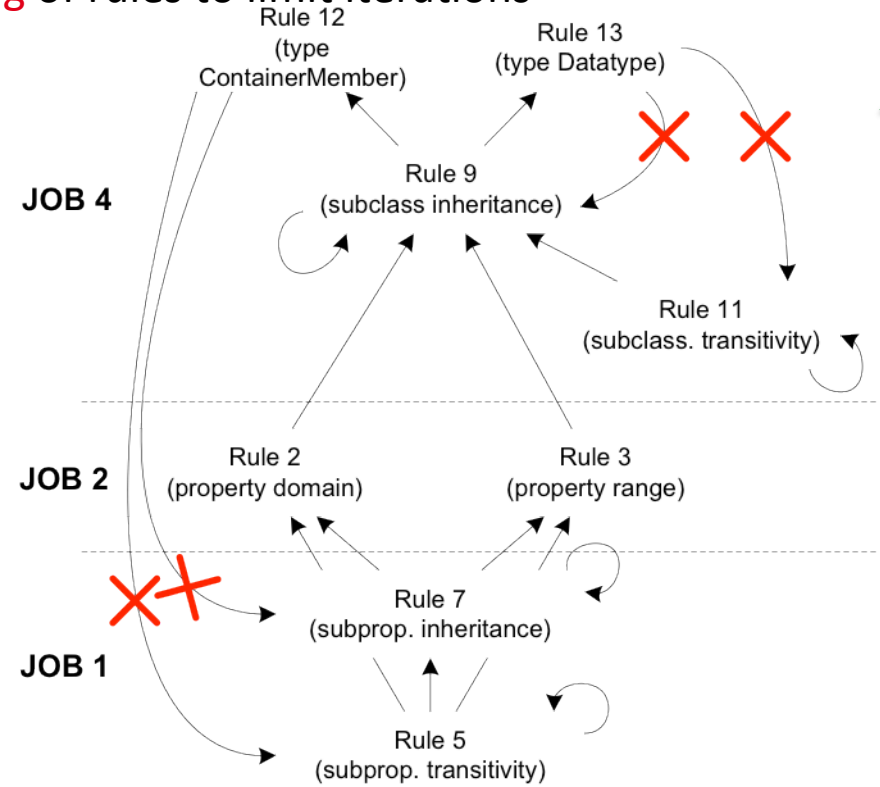


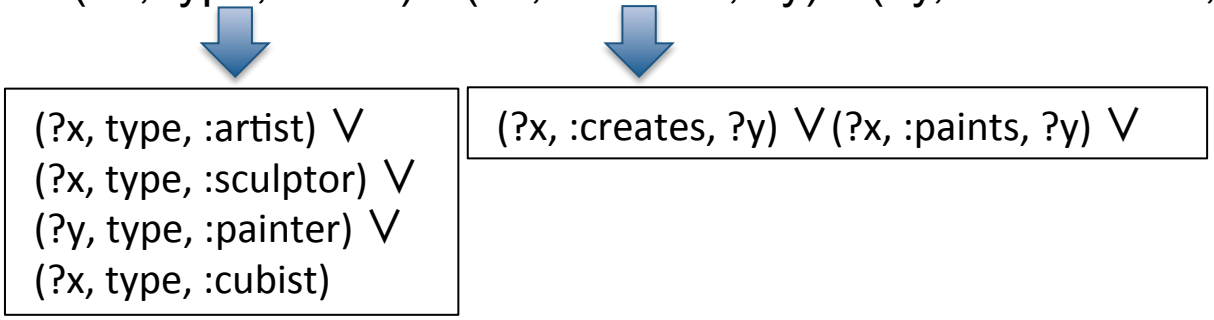
Fig. 3. Relation between the various RDFS rules

Process the rules only once in this order!

II. Query reformulation in the cloud

- Query rewriting of BGP queries may lead to complex queries

$$(?x, type, :artist) \wedge (?x, :creates, ?y) \wedge (?y, :exhibitedIn, ?z)$$



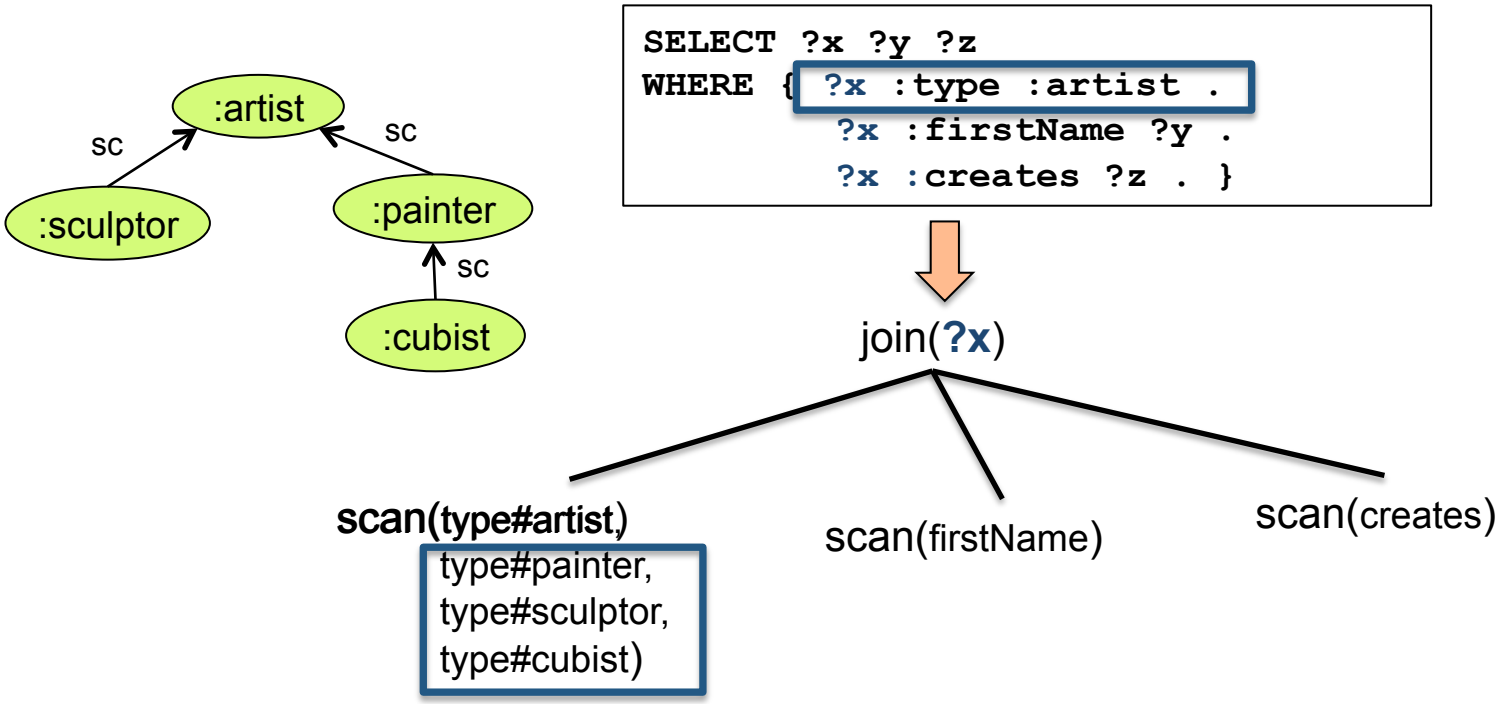
- Conjunction of unions of atomic queries
  - HadoopRDF [Husain11]
- Or union of conjunctive queries?

$$[(?x, type, :artist) \wedge (?x, :creates, ?y) \wedge (?y, :exhibitedIn, ?z)] \vee$$
$$[(?x, type, :artist) \wedge (?x, :paints, ?y) \wedge (?y, :exhibitedIn, ?z)] \vee$$
$$[(?x, type, :sculptor) \wedge (?x, :creates, ?y) \wedge (?y, :exhibitedIn, ?z)] \vee$$
$$[(?x, type, :sculptor) \wedge (?x, :paints, ?y) \wedge (?y, :exhibitedIn, ?z)] \vee$$
$$\ldots\ldots$$

- Transitive closure computation and recursive query processing in MapReduce [Afrati12, Bu12] may apply to RDFS reasoning

Query reformulation in HadoopRDF [Husain11]

- Query reformulation during the file selection of the query processing



III. Hybrid approaches

- Precompute the closure of the schema
  - Schema is usually much smaller than the data
  - Schema does not change often
  - It is always used in the RDFS rules
- Reformulate the query (faster reformulations)
- Representative works
  - QueryPie [Urbani11]
  - Rya [Punnoose12]

Analysis dimensions

1. Data storage

- Key-value stores
- DFS (distributed file system)
- Single-site RDF stores or data storage services supplied by cloud providers

2. Query processing

- MapReduce-based
- Local processing (joins are usually performed at a single site)
- Distributed graph-based exploration

3. RDFS entailment

- Materialization of RDFS closure
- Query reformulation
- Hybrid (only the schema closure is precomputed)

4

SUMMARY AND OPEN ISSUES

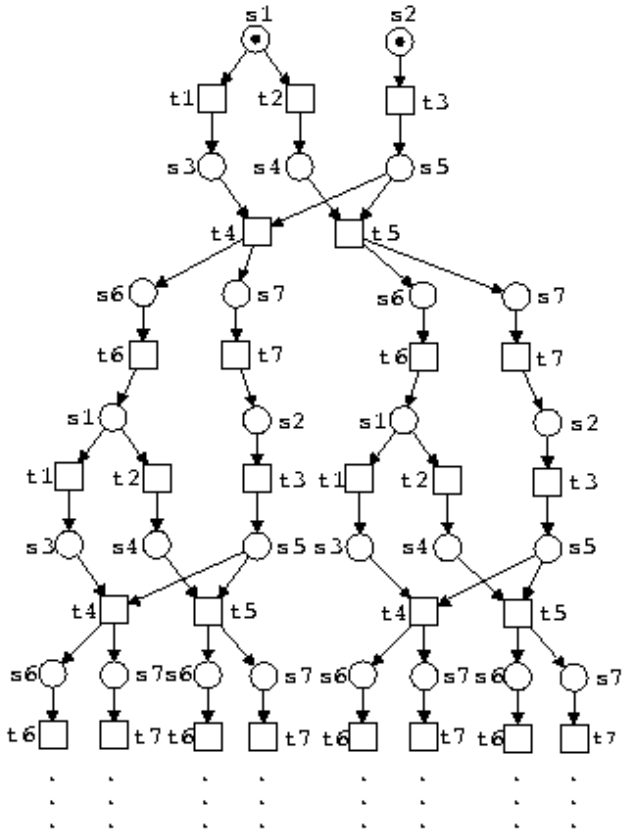
Summary

Main problems to be solved in a (distributed) RDF store

- Storage
- Query evaluation
- Reasoning (for query answering)

Plenty of techniques for centralized and distributed settings

- Oftentimes incomparable (partial order)
- Zoo!



Do we have a winner?

- No, at least not yet ☺
- Performance depends on data, workload…
  - Star queries or path queries?
  - Selective or analytics-style queries?
- Benchmarks on how real SPARQL queries look:
  - [Duan11]
  - [Arias11]
  - [Picalausa11]
  - Linked Data benchmark council (ldbc.eu)

Where do we go from here?

- Room for optimization
  - Improving query response time in the first place
  - Applying traditional optimization techniques (join ordering, statistics, etc.)?
- RDF data partitioning
  - Are the existing graph partitioning algorithms satisfactory?
- RDFS entailment
  - Query reformulation
- More SPARQL features
  - Blank nodes, optional, negation, property paths, etc.

Where do we go from here?

- RDF views/indexes in the cloud
- SPARQL multi-query optimization in the cloud
- RDF updates in the cloud
- RDF data analytics
- How does cloud variability affect RDF data management?

Thank you /Questions?

Companion paper:

"RDF in the clouds: A Survey", VLDB Journal

http://web.imis.athena-innovation.gr/~zoi/

http://pages.saclay.inria.fr/ioana.manolescu

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