# RDF Data Management & SPARQL Query Processing

#### **Federico Ulliana** UM, LIRMM, INRIA GraphIK

Slides collected from Martin Theobald, Katja Hose, Ralf Schenkel, and Stratos Idreos

# **NOSQL** Umbrella

#### (RDF and SPARQL are the only standardized languages)

- Key-value databases are systems are about as simple as databases get, being in essence variations on the theme of a persistent hash table. Current examples include MemcacheDB, Tokyo Cabinet, Redis and SimpleDB.
- Document databases are key-value stores that treat stored values as semistructured data instead of as opaque blobs. Prominent examples at the moment include CouchDB, MongoDB and Riak.
- Wide-column databases tend to draw inspiration from Google's BigTable model. Open-source examples include Cassandra, HBase and Hypertable.
- Graph databases include generic solutions like Neo4j, InfoGrid and HyperGraphDB as well as all the numerous RDF-centric solutions out there: AllegroGraph, 4store, Virtuoso, and many, many others.

# Objectifs du cours

Comprendre le fonctionnement des systèmes d'interrogation de données RDF

Implémenter un mini-moteur d'évaluation de requêtes qui incorpore les idées vues en cours

Conduire des expériences permettant d'analyser les performances du système réalisé

# Plan

RDF and SPARQL

RDF Row-stores

RDF Column-stores

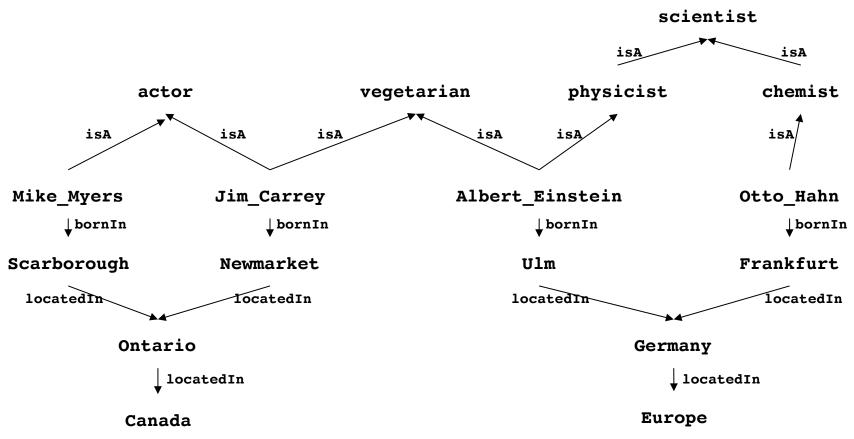
RDF Graph-stores

# **RDF Triples**

```
<Albert_Einstein, isA, physicist>
<Albert_Einstein, bornIn, Ulm>
<Albert_Einstein, isA, vegetarian> ...
```

# **Graph Notation**

```
<Albert_Einstein, isA, physicist>
<Albert_Einstein, bornIn, Ulm>
<Albert_Einstein, isA, vegetarian> ...
```



# RDF is strictly more than a Graph Database

```
<Albert Einstein, isA, physicist>
<isA, rdfs:subPropertyOf, rdfs:subClassOf>
SELECT ?x ?y
WHERE {
     ?x ?p ?y .
     ?p rdfs:subPropertyOf, rdf:subClassOf}
}
```

# RDF is strictly more than a Graph Database

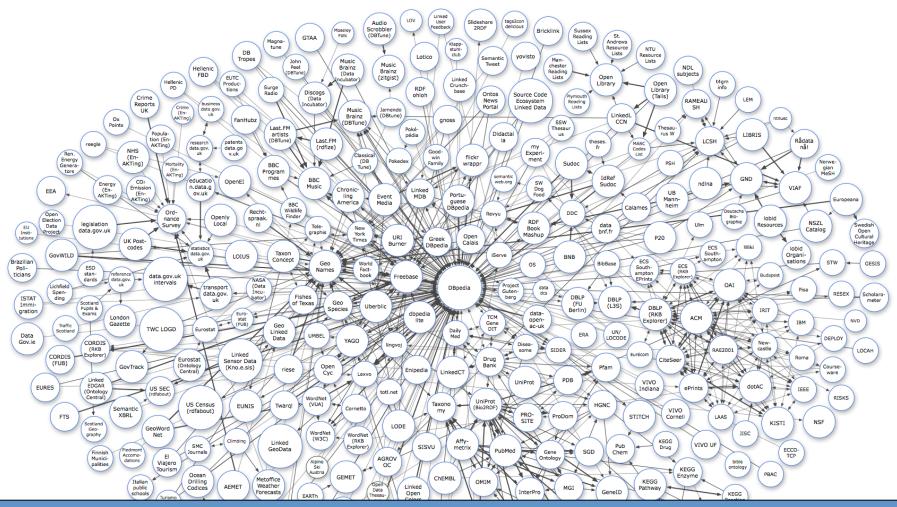
```
<Albert Einstein, isA, physicist>
<isA, rdfs:subPropertyOf, rdfs:subClassOf>
                                 property are
                                 also values
SELECT ?x ?y
WHERE {
     ?x ?p ?y .
     ?p rdfs:subPropertyOf, rdf:subClassOf}
}
```

# RDF is strictly more than a Graph Database

```
<Albert Einstein, (isA), physicist>
<isA, rdfs:subPropertyOf, rdfs:subClassOf>
                                   property are
                                   also values
SELECT ?x ?y
                                  properties can
WHERE {
                                   be gueried
      ?x
         (?p)?y
      ?p rdfs:subPropertyOf, rdf:subClassOf}
}
```

Sources: linkeddata.org wikipedia.org

# Why caring about RDF data? Open Data are gaining momentum!



More than 30 billion triples in more than 200 sources across the LOD cloud DBPedia: 3.4 million entities, 1 billion triples

# Queries can be complex, too

```
SELECT DISTINCT ?a ?b ?lat ?long WHERE
{ ?a dbpedia:spouse ?b.
  ?a dbpedia:wikilink dbpediares:actor.
  ?b dbpedia:wikilink dbpediares:actor.
  ?a dbpedia:placeOfBirth ?c.
  ?b dbpedia:placeOfBirth ?c2.
  ?c owl:sameAs ?c2.
  ?c2 pos:lat ?lat.
  ?c2 pos:long ?long.
```

# SPARQL 1.0 / 1.1

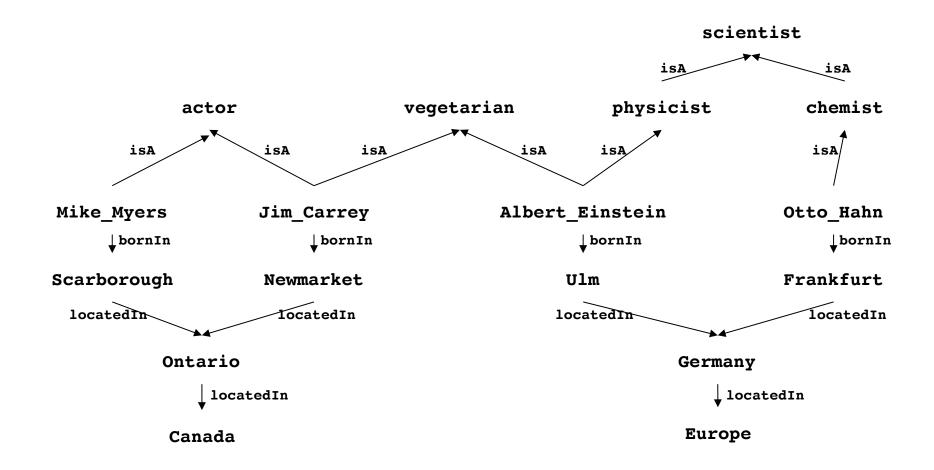
- Query language for RDF suggested by the W3C
- SPARQL main building block:triple patterns

Like select-project-join for relational databases

### SPARQL - Example

#### **Example query:**

Find all actors from Ontario (that are in the knowledge base)

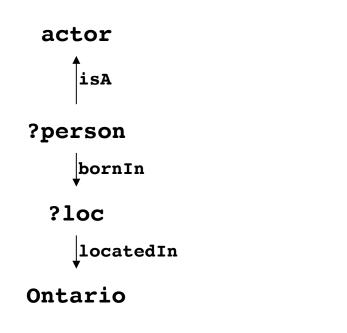


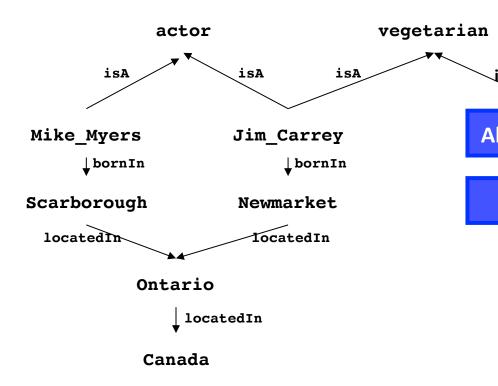
#### SPARQL - Example

#### **Example query:**

Find all actors from Ontario (that are in the knowledge base)

#### Find **subgraphs** of this form:



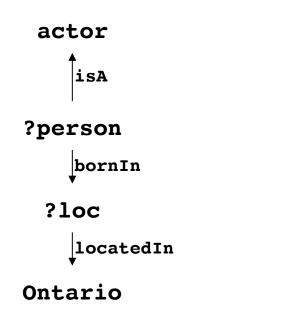


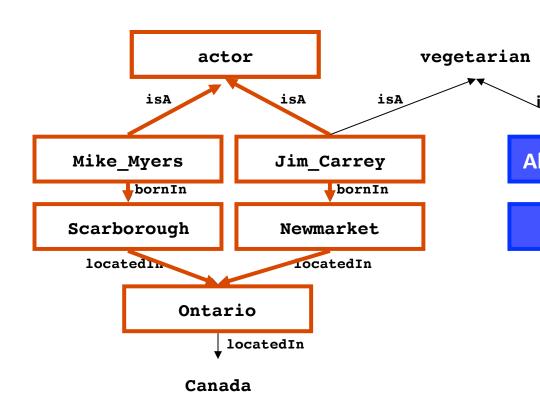
### SPARQL - Example

#### **Example query:**

Find all actors from Ontario (that are in the knowledge base)

#### Find **subgraphs** of this form:





# Questions

How to store RDF data?

How to query RDF data?

- We will study three main approaches
  - Row-stores
  - Column-stores
  - Graph-stores

# **ROW-STORES**

#### Row-store

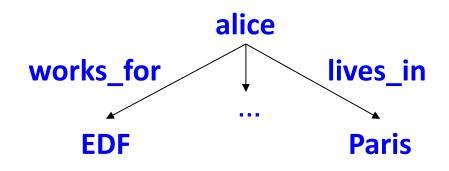
Classic relational database, storing relations by <u>rows</u>. (Postgres, Oracle, DB2, MySQL, ...)

product	country	sales
car	US	40K
bike	US	7K
	•••	



row1 car@US@40K row2 bike@US@7K ...

#### RDF in a Relational Row-store



1 triple = 1 edge in the RDF Graph

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	



s for@EDF

row1 alice@work row2 alice@live sIn@Paris

# Giant-Table (Jena, HexaStore, RDF-3X)

- 1. Store triples in one **giant** 3-attribute table
- 2. Convert SPARQL to equivalent SQL
- 3. Magic: the database will do the rest

subject	predicate	object	Giant
alice	works_for	EDF /	1 Billion Triples
alice	lives_in	Paris	= 1 Billion
	•••		lines

# Conversion of SPARQL to SQL

triple pattern → FROM/WHERE

Shared variables  $\rightarrow$  (self)JOIN conditions

Constants  $\rightarrow$  WHERE conditions

FILTER conditions  $\rightarrow$  WHERE conditions

OPTIONAL clauses → OUTER JOINS

UNION clauses  $\rightarrow$  UNION expressions

# Conversion of Triple Patterns (with Constants)

```
SPARQL >
SELECT ?x WHERE {?x lives_in ?y}
```

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of Triple Patterns (with Constants)

```
SPARQL >
   SELECT ?x WHERE {?x lives_in ?y}

SQL >
   SELECT subject FROM Giant-Table
   WHERE predicate = "lives_in"
```

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of Shared Variables

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of Shared Variables

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of FILTER conditions

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of FILTER conditions

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of UNION clauses

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of UNION clauses

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of OPTIONAL clauses

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# Conversion of OPTIONAL clauses

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

# From SQL to Relational Algebra

```
SELECT L.subject, L.object, W.object
FROM Giant-Table as L, Giant-Table as W
WHERE L.predicate = "lives_in"
AND W.predicate = "works_for"
AND L.subject = W.subject
```

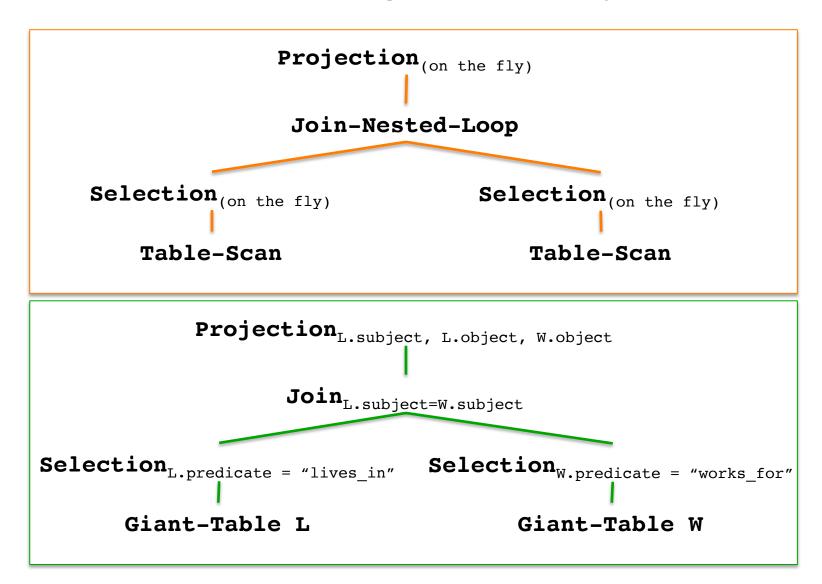
```
Projection<sub>L.subject</sub>, L.object, W.object

Join<sub>L.subject=W.subject</sub>

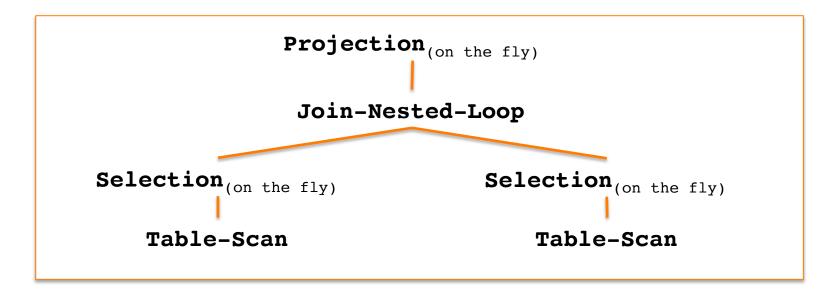
Selection<sub>L.predicate = "lives_in"</sub> Selection<sub>W.predicate = "works_for"</sub>

Giant-Table L Giant-Table W
```

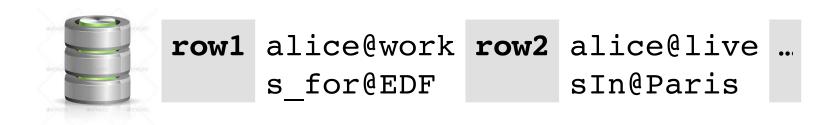
# From Relational Algebra to Physical Plan



# From Relational Algebra to Physical Plan



• Now, performances depend on the row-store.



# Is that all?

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#### Well, no.

- Which other logical schemas can we use?
- Which indexes should be built? (to support efficient evaluation of triple patterns)
- How can we reduce storage space?
- How can we find the best execution plan?

### Is that all?

### Well, no.

- Which other logical schemas can we use?
- Which indexes should be built? (to support efficient evaluation of triple patterns)
- How can we reduce storage space?
- How can we find the best execution plan?

### **Existing databases need modifications:**

- flexible, extensible, generic storage not needed here
- cannot deal with multiple self-joins of a single table
- often generate bad execution plans

# EXPLORING ALTERNATIVE RELATIONAL SCHEMAS

### Problems with **Giant-Table**

Too many joins, over a too large table.

Alternative = many tables instead of one

- Property-Tables
- Clustered Property-Tables
- Property-Class

## **Property-Tables**

A relational table for each single RDF property.

Giant-Table

subject	predicate	object	
alice	works_for	EDF	
alice	lives_in	Paris	
	•••		

works\_for

subject	object
alice	EDF
•••	

lives\_in

subject	object
alice	Paris
•••	

### The former conversion ...

subject	predicate	object	
alice	works_for	EDF	
alice	lives_in	Paris	
	•••		

## ... now goes as follows

#### works\_for

subject	object	
alice	EDF	
•••		

#### lives\_in

subject	object
alice	Paris
•••	

### ... now goes as follows

subject	object
alice	EDF
•••	

subject	object			
alice	Paris			
•••				

## **Property-Tables**

- Syntactically, we get smaller WHERE conditions
- Operationally, we avoid to self join a huge table
  - Keeping intermediary join result small is the key for efficiency in <u>any</u> database system

works for

subject	object
alice	EDF
•••	·

lives\_in

subject	object
alice	Paris
•••	r

## But properties can be correlated

YAGO: A Large Ontology from Wikipedia and WordNet

Group 1	Group 2	Group 3	Group 4	Group 5	Group 6
hasWebsite	isLocatedIn	hasGender	isCitizenOf	owns	created
isLocatedIn	isConnectedTo	isAffiliatedTo	wasBornIn	created	directed
owns	type	playsFor	livesIn	participatedIn	acted
created		wasBornIn		locatedIn	
	subClassOf		diedIn		influences

#### **Examples**

BMW	Los Angeles Airport	Alex Ferguson Jhon Belushi	Apple INC	Charlie Chaplin
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## **Clustered Properties**

### sport\_man\_property\_cluster

subject	isAffiliatedTo	playsFor	hasGender	wasBornIn
Ferguson	Manchester	Manchester	Male	Scotland
Ronaldo	UNICEF	Inter	Male	Brazil
		•••		

### employee\_property\_cluster

subject	works_for	lives_in	
alice	EDF	Paris	
	•••		

## Recall the previous conversion ...

subject	object
alice	EDF
alice	Paris
•••	

subject	object
alice	EDF
alice	Paris
•••	

## now it goes as follows

subject	works_for	lives_in
alice	EDF	Paris
	•••	

## Clustered Property-Tables

- Syntactically, we get even less join conditions
- Operationally, we avoid even more joins when properties are within a cluster
  - but we may still have to join two clusters!!

works for lives in cluster

subject	works_for	lives_in
alice	EDF	Paris
	•••	

## Correlations do not <u>always</u> hold

<pre><http: isaffiliatedto="" resource="" yago-knowledge.org=""></http:></pre>	2.635.440
<pre><http: playsfor="" resource="" yago-knowledge.org=""></http:></pre>	2.575.219
<http: hasgender<="" resource="" td="" yago-knowledge.org=""><td>345.794</td></http:>	345.794
<http: resource="" wasbornin="" yago-knowledge.org=""></http:>	172.541

- Only 172.541 resources have a value for all properties.
- Clustering properties may waste a lot of storage (nulls)

## Correlations do not <u>always</u> hold

<pre><http: isaffiliatedto="" resource="" yago-knowledge.org=""></http:></pre>	2.635.440
<http: playsfor="" resource="" yago-knowledge.org=""></http:>	2.575.219
<http: hasgender<="" resource="" td="" yago-knowledge.org=""><td>345.794</td></http:>	345.794
<http: resource="" wasbornin="" yago-knowledge.org=""></http:>	172.541

#### many\_properties\_cluster

subject	isAffiliatedTo	playsFor	hasGender	wasBornIn
				null
			null	null
			null	null
		null	null	null

## Attributes can have multiple values

#### many\_properties\_cluster

subject	isAffiliatedTo	playsFor	hasGender	wasBornIn
Ferguson	Manchester	Manchester	Male	Scotland
Ronaldo	UN	Inter	Male	Brazil
		•••		

## Attributes can have multiple values

many\_properties\_cluster

subject	isAffiliatedTo	playsFor	hasGender	wasBornIn
Ferguson	Manchester	Manchester	Male	Scotland
Ronaldo	UNICEF	Inter	Male	Brazil
Ronaldo	UNICEF	Milan	Male	Brazil
Ronaldo	UNICEF	Barcelona	Male	Brazil
Ronaldo	UNICEF	RealMadrid	Male	Brazil
Ronaldo	UNICEF	Flamenco	Male	Brazil
		•••		

 Note: by the way, the 4<sup>th</sup> normal form has been introduced exactly to avoid this.

## **Leftover Triples**

- Clustered Property Tables induce leftover triples
  - with none of the properties in a cluster
  - belonging to no class
  - extra joins between leftover-triples and clusters

leftover-triples

subject	predicate	object
alice	born_in	NY
EDF	located_in	Paris
	•••	

### The clustered-property table dilemma

- They are complex to design
  - If narrow: reduces nulls, increases unions/joins
  - If wide: reduces unions/joins, increases nulls

## Class-Property Tables

- A table contains all properties of the instances of a given class
- Has all inconvenients of the former method

class:Book

subject	title	author	year
ID1	XYZ	Joe Fox	2001
ID3	MNP	null	null
ID6	null	null	2004

### Property Tables: Pros and Cons

### **Advantages:**

- More in the spirit of existing relational systems
- Saves many self-joins over triple tables

### Disadvantages (mostly for clusters):

- Potentially many NULL values
- Multi-value attributes problematic
- Schema changes very expensive

**HEXASTORES: INDEXING IN RDF-3X** 

### Hexastores

RDF Systems introducing 6 indexing on triples

- SPO,PSO,OSP
  - to access data by subject, property, or object

- SOP, POS, OPS
  - to cover all permutations

### Indexes

- Indexes are data-structures that allow a fast (~constant time) access to the stored data
- One can simply add them to boost the performance of any relational schemas
  - warning: an index can be larger than a database!
    - the real question is: when to stop indexing??
- We look at a more original approach (RDF3X) that completely eliminates the schema design.

### Preprocessing: build a Dictionary for Strings

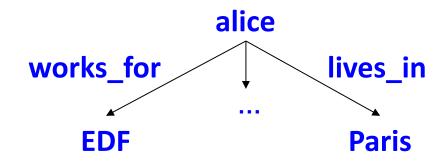
Map strings to unique integers (e.g., via hashing)

- Regular size (4-8 bytes), much easier to handle
- Dictionary usually kept in main memory

```
http://example.fr/Alice→ 1960
http://example.fr/Bob→ 3795
http://example.fr/Charles→ 4634
```

If not build carefully, this dictionnary may break the original lexicographic sorting order

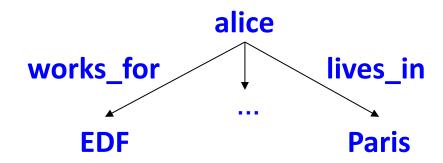
⇒ FILTER conditions may be more expensive!



### dictionary

id	string	
1	alice	
2	works_for	
3	lives_in	
4	EDF	
5	Paris	

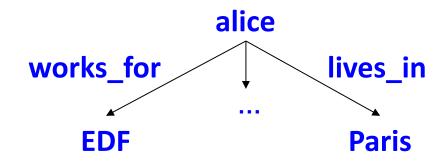
subject	pred.	object
1		



### dictionary

id	string	
1	alice	
2	works_for	
3	lives_in	
4	EDF	
5	Paris	

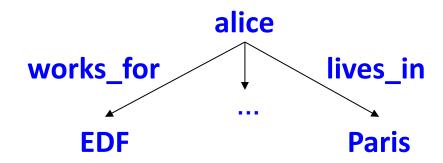
subject	pred.	object
1	2	



### dictionary

id	string	
1	alice	
2	works_for	
3	lives_in	
4	EDF	
5	Paris	

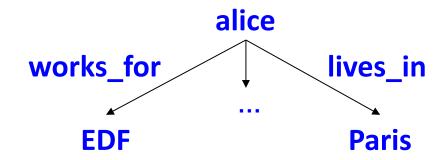
subject	pred.	object
1	2	4



### dictionary

id	string	
1	alice	
2	works_for	
3	lives_in	
4	EDF	
5	Paris	

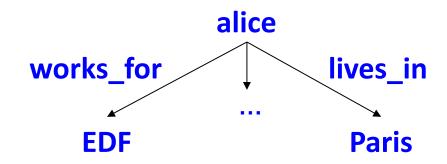
subject	pred.	object
1	2	4
1		



### dictionary

id	string
1	alice
2	works_for
3	lives_in
4	EDF
5	Paris

subject	pred.	object
1	2	4
1	3	



#### dictionary

id	string	
1	alice	
2	works_for	
3	lives_in	
4	EDF	
5	Paris	

#### Giant-Table

subject	pred.	object
1	2	4
1	3	5

up to 10x faster!!

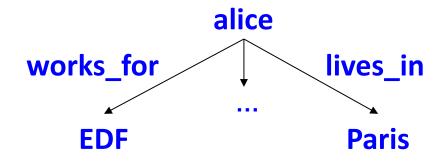
## RDF3X Storage and Indexing

 Giant-Table model + ad-hoc implementation (no RDBMs as we have seen before)

 Ad-hoc implementation here means that the Giant-Table is actually fused with indexes (we will see this next) What triple patterns are found in queries?

```
(s p o)
(s p ?x)
(s ?x o)
(?x p o)
(s ?x ?y)
(?x p ?y)
(?x ?y o)
(?x ?y ?z)
```

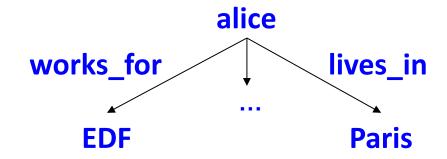
## So we can store triples pattern-wise



#### Giant-Table<SPO>

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris

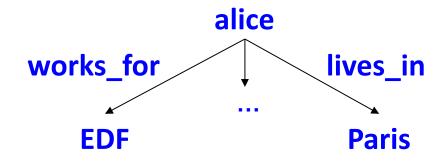
## So we can store triples pattern-wise



#### Giant-Table<SOP>

subject	object	predic	ate
alice	EDF	works_	for
alice	Paris	lives	_in

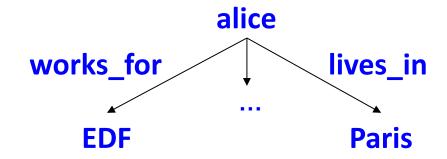
## So we can store triples pattern-wise



#### Giant-Table<OPS>

object	predicate	subject
EDF	works_for	alice
Paris	lives_in	alice

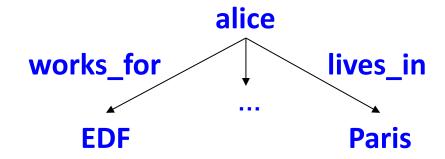
#### So we can store triples pattern-wise



Giant-Table<POS>

predic	ate	object	subject
works_	for	EDF	alice
lives	_in	Paris	alice

#### So we can store triples pattern-wise



#### Giant-Table<PSO>

predicate	subject	object
works_for	alice	EDF
lives_in	alice	Paris

#### Why? Because we deal with row-stores

Giant-Table<SPO>

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris

Easier to match (s p ?x) patterns if stored as

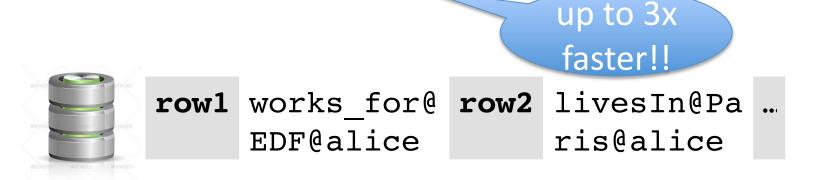


#### Why? Because we deal with row-stores

Giant-Table<POS>

predicate	object	subject
works_for	EDF	alice
lives_in	Paris	alice

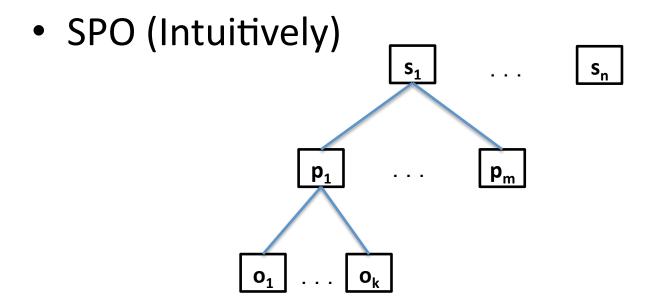
Easier to match (?x p o) patterns if stored as



#### RDF3X Storage and Indexing

Similarly RDF3X create 6 indexes

– SPO; SOP; PSO; POS; OSP; OPS

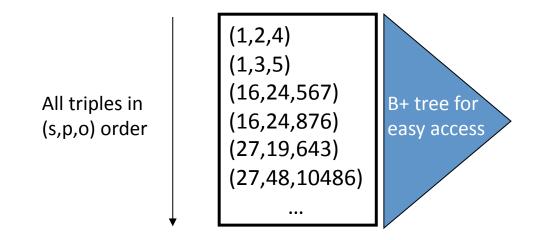


#### RDF3X Storage and Indexing

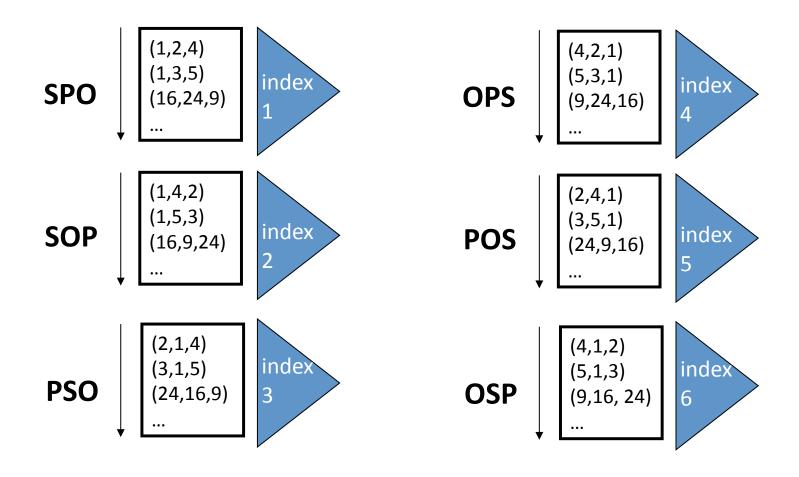
Similarly RDF3X create 6 indexes

— SPO; SOP; PSO; POS; OSP; OPS

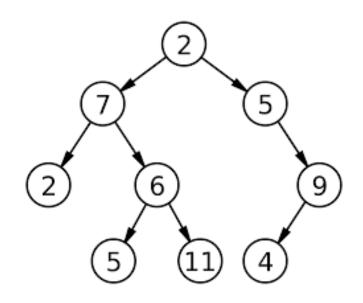
• SPO (in reality): (B+)-trees over triples



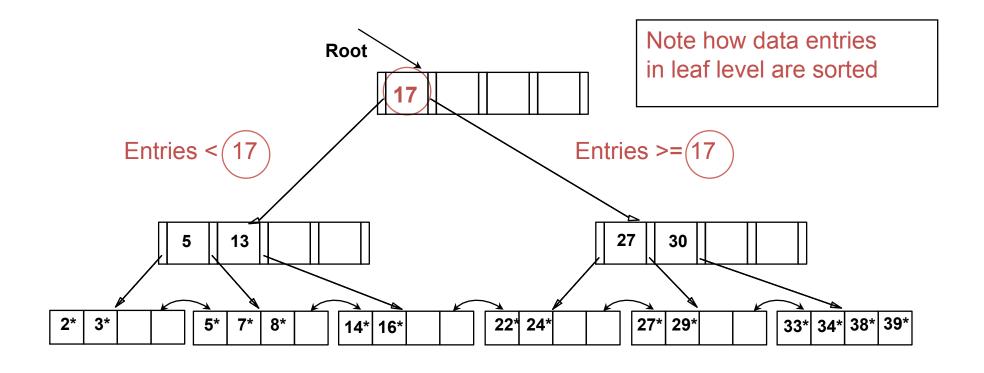
#### RDF3X 6 indexes (Hexastore)



## Binary trees are not enough

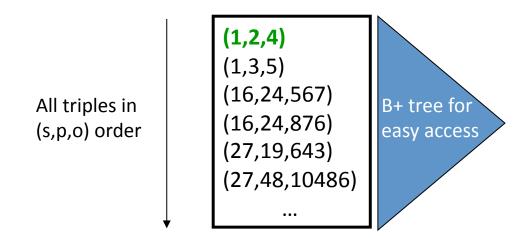


#### B+ Tree



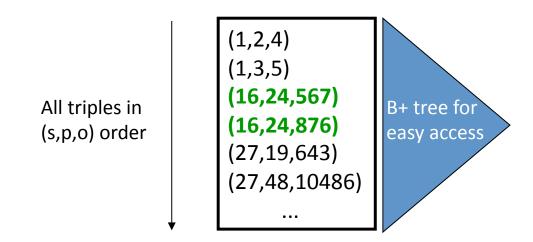
#### RDF3X Query Processing

```
SELECT ?x where { alice, lives_in, ?x }
• Lookup ids: alice→ 1, lives_in→ 2
• Read results while prefix (1,2) matches: (1,2,4)
```



#### RDF3X Query Processing

```
SELECT ?x where { Einstein, invented, ?x }
Lookup ids Einstein → 16, invented sorted
Read prefix matches (16,24): (16,24,567) (16,24,876)
```



### RDF3X Storage and Indexing

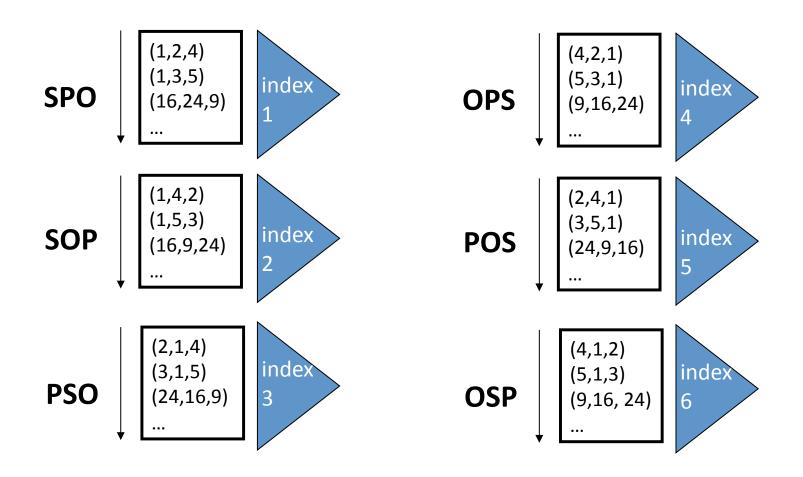
Build clustered indexes for all six permutations

SPO, POS, OSP to cover all possible triple patterns

 SOP, OPS, PSO to have all sort orders for patterns with two variables

Triple table no longer needed, all triples in each index

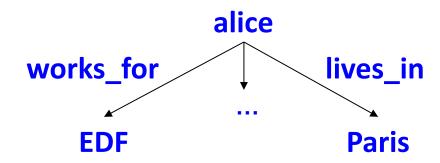
#### How do the indexes work together?



#### Now, how join two (2) triple patterns?

 Naïve-way: evaluate one triple pattern at-atime and then join (=intersect) the results

# **Recall Dictionnary**



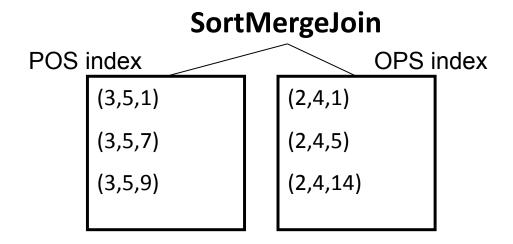
#### dictionary

id	string	
1	alice	
2	works_for	
3	lives_in	
4	EDF	
5	Paris	

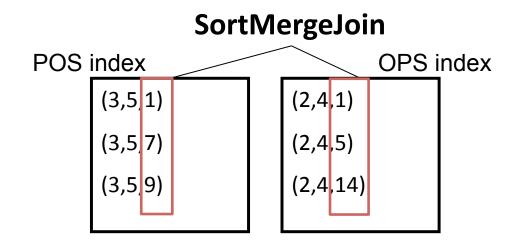
#### Giant-Table

subject	pred.	object
1	2	4
1	3	5

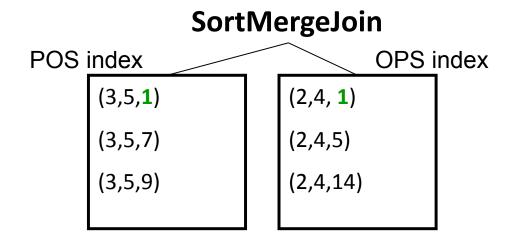
- For example, we decide to use POS & OPS index for 1<sup>st</sup> & 2<sup>nd</sup> pattern, respectively.
  - we will see next why we did this choice



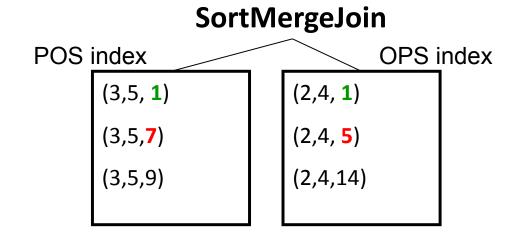
- Scan both inputs: join matching values OR skip
- Idea: advance pointer with <u>lower</u> value



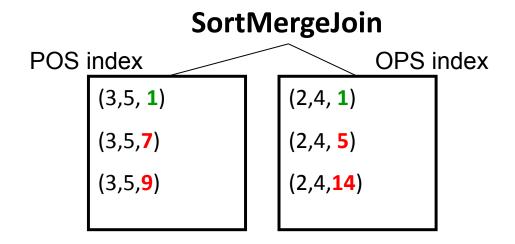
- We access POS[3.5.1] and OPS[2.4.1]
  - we find 1 on both sides -> query result



- We access POS [3.5.7]
  - then we know that OPS[2.4.{2..6}] are not results

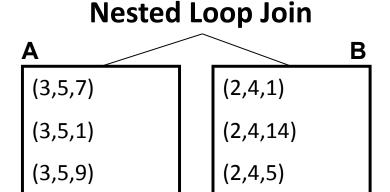


 We access OPS[2.4.14] then we know that PSO[3.5.{6..13}] are not results



#### For unsorted triples? Nested Loop

for each element  $\boldsymbol{x}$  of  $\boldsymbol{A}$ for each element  $\boldsymbol{y}$  of  $\boldsymbol{B}$ compare  $\boldsymbol{x}$  with  $\boldsymbol{y}$ 



#### RDF3X Query Evaluation

How to join n-triple patterns t<sub>1</sub>...t<sub>n</sub>?

```
SELECT ?x where { ?x, lives_in, ?y . t<sub>1</sub>
?x, works_for, ?z . t<sub>2</sub>
?y, isLocatedIn, "US" . t<sub>3</sub>
?z, isLocatedIn, "US" . t<sub>4</sub>
}
```

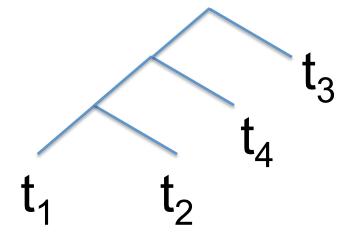
Classical relational problem: chose a left-deep join order, like

```
((t_1 Join t_2) Join t_4) Join t_3)
```

#### RDF3X Query Evaluation

Classical problem: chose a left-deep plan, like

 $((t_1 Join t_2) Join t_4) Join t_3)$ 



# Scenario 1: no triples using property lives in

then

```
((t_1 Join t_2) Join t_4) Join t_3)
```

is optimal as it immediately discovers that the query has no answer

```
SELECT ?x where { ?x, lives_in, ?y . t<sub>1</sub> ?x, works_for, ? . t<sub>2</sub> ?y, isLocatedIn, "US" . t<sub>3</sub> ?z, isLocatedIn, "US" . t<sub>4</sub> }
```

# Scenario 2: no triples using property isLocatedIn

then

```
((t_1 Join t_2) Join t_4) Join t_3)
```

is **not** optimal as it computes (t<sub>1</sub> Join t<sub>2</sub>) before understanding that the query is empty

```
SELECT ?x where {  ?x, \ lives\_in, \ ?y \qquad . \qquad t_1 \\ ?x, \ works\_for, \ ?z \qquad . \qquad t_2 \\ ?y, \ isLocatedIn, \ "US" \qquad . \qquad t_3 \\ ?z, \ isLocatedIn, \ "US" \qquad . \qquad t_4 \\ \}
```

# Scenario 3: isLocatedIn is very rare and lives\_in is more frequent than works\_for

then

```
(t<sub>4</sub> Join t<sub>2</sub>) Join (t<sub>3</sub> Join t<sub>1</sub>)
```

is optimal (in average) as it is likely to keep intermediate results low (but this plan is not left deep!!!)

```
SELECT ?x where {  ?x, \ lives\_in, \ ?y \qquad . \qquad t_1 \\ ?x, \ works\_for, \ ?z \qquad . \qquad t_2 \\ ?y, \ isLocatedIn, \ "US" \qquad . \qquad t_3 \\ ?z, \ isLocatedIn, \ "US" \qquad . \qquad t_4 \\ \}
```

#### Selectivity Estimates

 How do we know which property, or object or subject is more frequent in a query?

#### Selectivity Estimates

 Example: take the index OPS and (pre-)compute for how many values holds

?x isLocatedIn "US"

selectivity = #occurrences\_pattern / #triples

can be for example 1.000 out of 100.000 (1%)

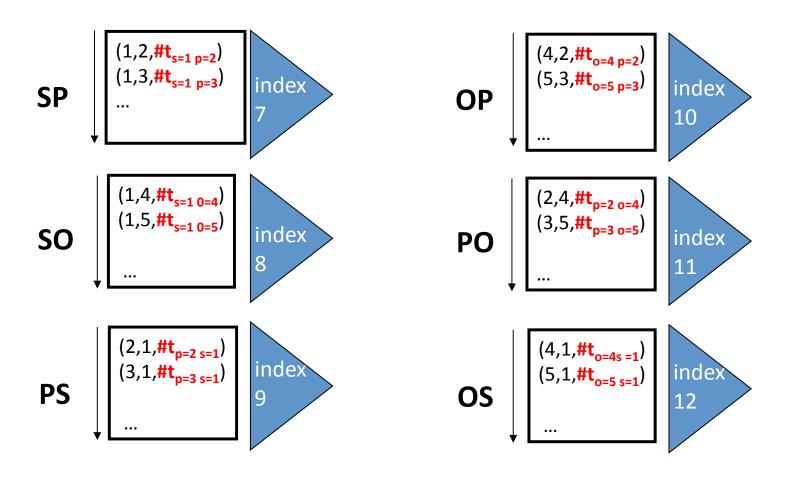
## Selectivity Estimates

Goal: skip non-matching triples asap

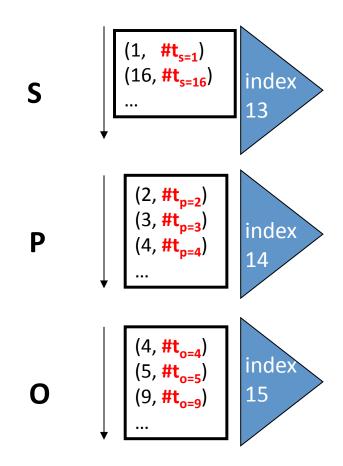
- Choose OPS instead of POS whenever the object
   "O" is more selective than property "P"
- Example (extreme): social graph whit 1 property
  - goal : match P only when O is what we are looking for
  - O can be a user or a value. So: match O first, then P.

#### RDF3X binary index with counters

 $\#t_{s=n} = number$  of triples with subject n and property m



#### RDF3X unary indexes with counters



## In reality

 Binary and unary indexes can be fused with the other indexes

### **Selectivity Estimation**

selectivity of t = (Obama,knows,-)

SP 
$$\begin{pmatrix} (1,2,\#t_{s=1 p=2}) \\ (1,3,\#t_{s=1 p=3}) \\ ... \end{pmatrix}$$
 index 7

selectivity of t = (-, -, "US")

Core ingredients of a good query optimizer are selectivity estimators for triple patterns (index scans) and joins

#### How to use selectivity estimation?

```
?x, lives in, US . ?x, works for, US
```

- We want to estimate the size of the result. Assume :
  - 10<sup>6</sup> triples in the database
  - Selectivity of the first pattern is 1%
  - Selectivity of the second pattern is 2%

```
Join |2*10<sup>2</sup>|

Selection<sub>pred;ob</sub> = "lives_in;us" |10<sup>4</sup>| Selection<sub>pred;ob</sub> = "works_for;us" |2*10<sup>4</sup>|

Giant-Table |10<sup>6</sup>| Giant-Table |10<sup>6</sup>|
```

## Selectivity Estimation (1)

The size of t1 Join t2, denoted |t1 Join t2|, is estimated as

```
|t1 Join_{\{\}}| t2| \cong |t1| * |t2| = Cart(t1,t2)
```

where |t1| = |DB| \* selectivity(t1) (same for |t2|)

- if t1 and t2 have no common variables
  - eg. ?x lives\_in US and ?z works\_for IBM

# Selectivity Estimation (2)

• The size of t1 Join t2, denoted |t1 Join t2|, is estimated as independence hypothesis!!

```
|t1 Join<sub>2x</sub> t2| = |DB| * selectivity(t1) * selectivity(t2)
```

- if t1 and t2 have a common variable
  - eg. ?x lives\_in US and ?x works for IBM

The size of Q<sub>1</sub> Join Q<sub>2</sub> is *estimated* as

```
| Q_1 Join_{2x} Q_2 | \sim | Q_2 | *1 = | Q_2 |
```

- if  $Q_1$  and  $Q_2$  are two (possibly) complex sub-queries with common variables and 2x is a key for  $Q_1$
- Since ?x is a key for  $Q_1$  then one line of  $|Q_2|$  is joined with at most one line of  $|Q_1|$

The size of Q<sub>1</sub> Join Q<sub>2</sub> is *estimated* as

```
|Q_1| Join Q_2| ~ min(|Q_1|, |Q_2|)
```

- if Q<sub>1</sub> and Q<sub>2</sub> are two (possibly) complex sub-queries with common variables
- in reality the formula is a bit more complex

If is not a key ?x for  $Q_1$  or  $Q_2$ 

$$| Q_1 Join_{?x} Q_2 |$$
 ~  $| Q_2 |$  \*  $| Q_1 |$  /  $V(?x,Q_1)$ 

If is not a key ?x for Q<sub>1</sub> or Q<sub>2</sub>

how many tuples with same value

$$| Q_1 Join_{?x} Q_2 |$$
 ~  $| Q_2 |$  \*  $| Q_1 |$  /  $| V(?x,Q_1)$ 

If is not a key ?x for Q<sub>1</sub> or Q<sub>2</sub>

how many tuples with same value

$$\mid Q_1 \operatorname{Join}_{?x} Q_2 \mid$$
 ~  $\mid Q_2 \mid$  \*  $\mid Q_1 \mid$  /  $\mid V(?x,Q_1) \mid$  more than 1 tuple

If is not a key ?x for  $Q_1$  or  $Q_2$ , more precisely

If is not a key ?x for  $Q_1$  or  $Q_2$ , finally

```
\mid Q_1 \text{ Join}_{?x} Q_2 \mid
```

- if impossible (or too expensive) to compute  $V(?x,Q_1)$  take for instance  $V(?x,Q_1) = |Q_1|$ 
  - this means that  $|Q_1| = Q_2 | \sim \min(|Q_1|, |Q_2|)$
- if more than one variable, take the min among all variables,  $|Q_1| * |Q_2| / V(?x,Q_2)$

## Why off-the-shelf relational database estimation over a **Giant-Table** cannot work well?

|t1 Join t2| = applies formula for queries as just seen

instead of

independence hypothesis!!

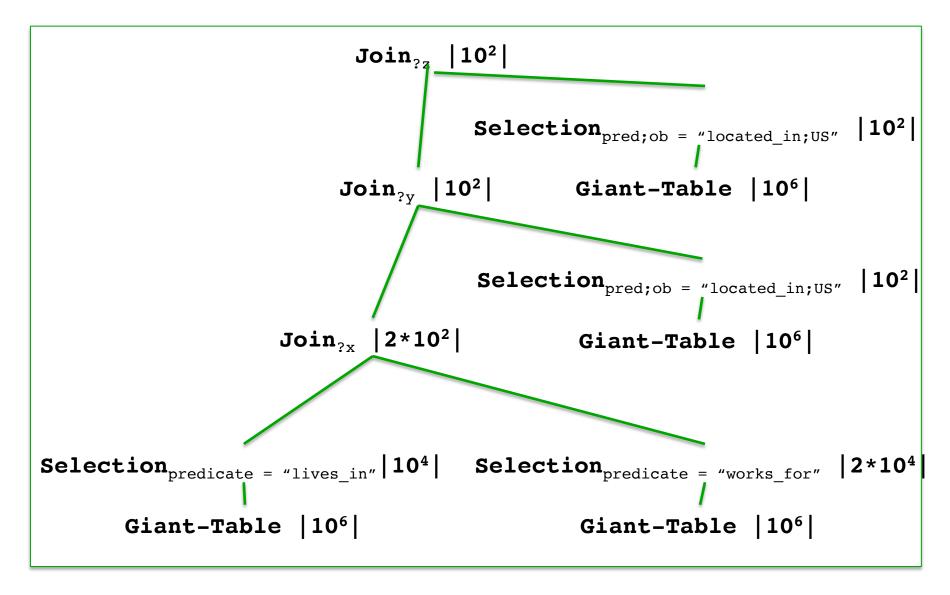
|t1 Join t2| = |DB| \* selectivity(t1) \* selectivity(t2)

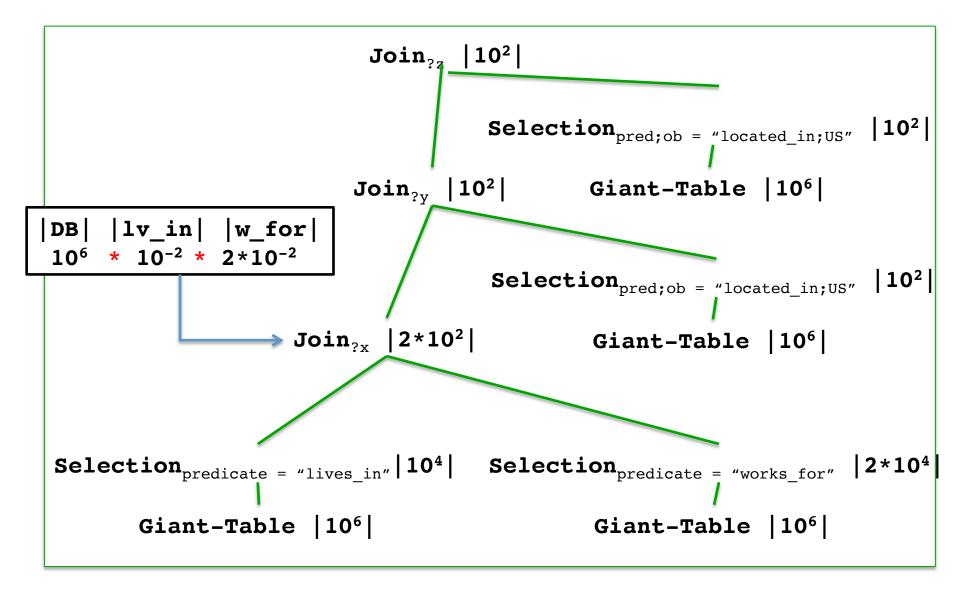
### Back to our query

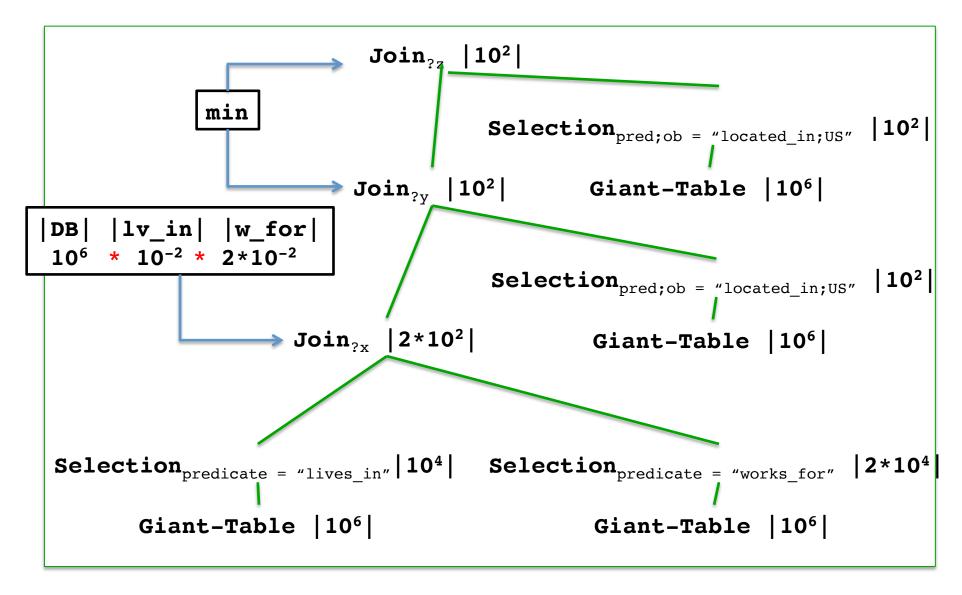
```
triple
pattern
selectivity
```

```
SELECT ?x where {  ?x, \ lives\_in, \ ?y \ . \ t_1 \ 10^{-2} \\ ?x, \ works\_for, \ ?z \ . \ t_2 \ 2*10^{-2} \\ ?y, \ isLocatedIn, \ "US" \ . \ t_3 \ 10^{-4} \\ ?z, \ isLocatedIn, \ "US" \ . \ ) \ t_4   (t_1 \ Join \ t_2) \ Join \ t_3) \ Join \ t_4
```

- Which plan is better?
  - smaller the intermediary results --> faster the joins



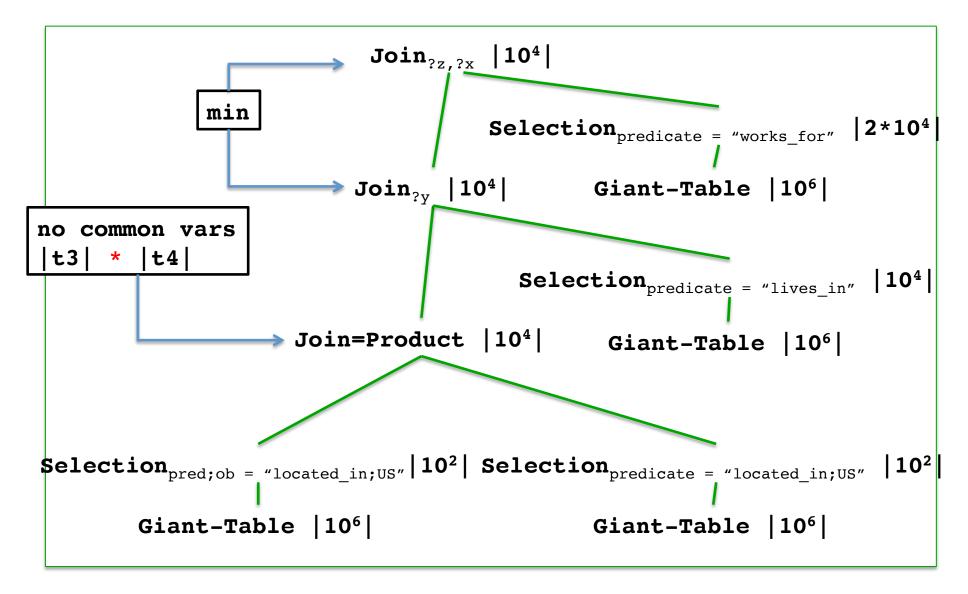




### Back to our query

```
triple
pattern
selectivity
```

- (t<sub>4</sub> Join t<sub>3</sub>) Join t<sub>2</sub>) Join t<sub>1</sub>
- Which plan is better?
  - smaller the intermediary results --> faster the joins



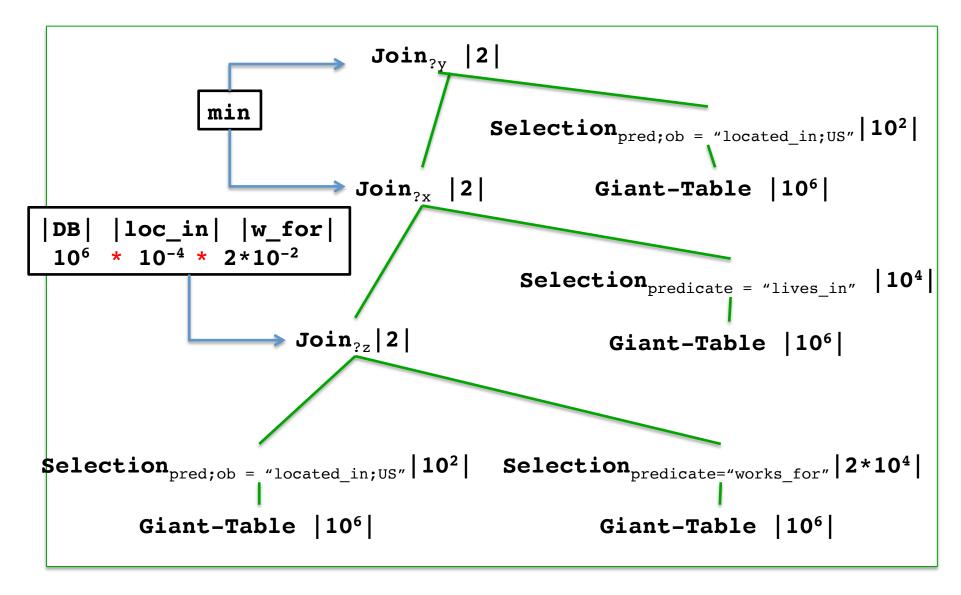
### Back to our query

```
triple
pattern
selectivity
```

```
SELECT ?x where {  ?x, \ lives\_in, \ ?y \ . \ t_1 \ 10^{-2} \\ ?x, \ works\_for, \ ?z \ . \ t_2 \ 2*10^{-2} \\ ?y, \ isLocatedIn, \ "US" \ . \ t_3 \ 10^{-4} \\ ?z, \ isLocatedIn, \ "US" \ . \ t_4
```

```
(t<sub>4</sub> Join t<sub>2</sub>) Join t<sub>1</sub>) Join t<sub>3</sub>
```

- Which plan is better?
  - smaller the intermediary results --> faster the joins

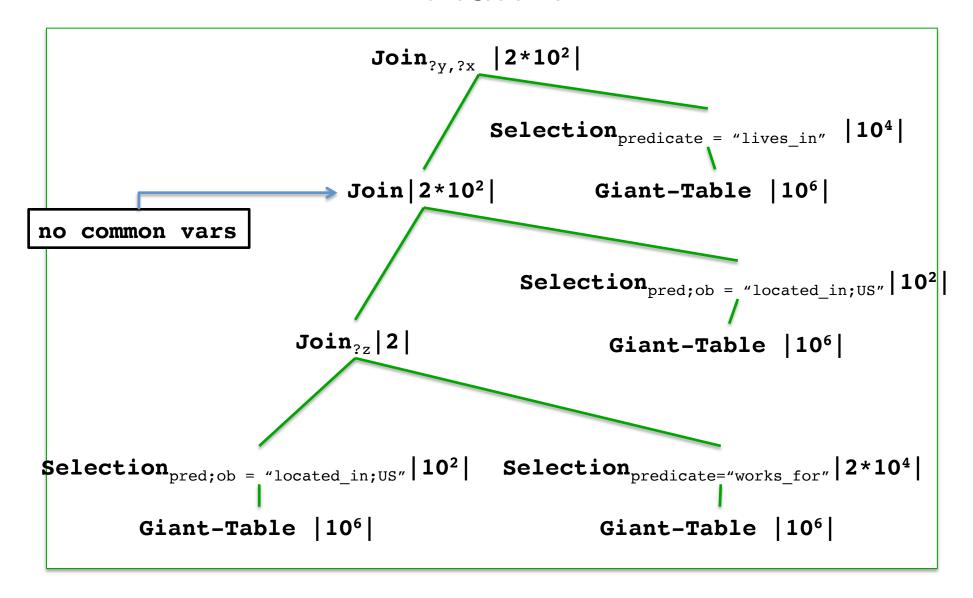


#### Back to our query

```
triple
pattern
selectivity
```

```
SELECT ?x where {  ?x, \ lives\_in, \ ?y \ . \ t_1 \ 10^{-2} \\ ?x, \ works\_for, \ ?z \ . \ t_2 \ 2*10^{-2} \\ ?y, \ isLocatedIn, \ "US" \ . \ t_3 \ 10^{-4} \\ ?z, \ isLocatedIn, \ "US" \ . \ ) t_4   (t_4 \ Join \ t_2) \ Join \ t_3 \ ) \ Join \ t_1
```

- Which plan is better?
  - smaller the intermediary results --> faster the joins



### Summing Up

 Choosing the join ordering between triple patterns is crucial for efficient query evaluation

 This heavily relies on selectivity estimators for triple patterns (index scans) and joins

## RDF3X: What we skipped

Compression Scheme

Selectivity estimation of correlated properties via sampling

 Query optimization for very complex queries based on dynamic programming

#### **COLUMN-STORES**

#### Column-store

Relational database, storing relations as columns. (C-Store, MonetDB and VectorWise, Ingres, IBM&MS Analytics)

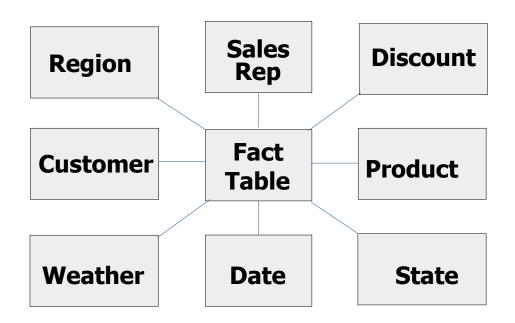
product	country	sales
car	US	40K
bike	US	7K
	•••	



col1 car@bike col2 US@US col3 40K@7K .

# Today, any Relational Datawarehouse is a Column-Store

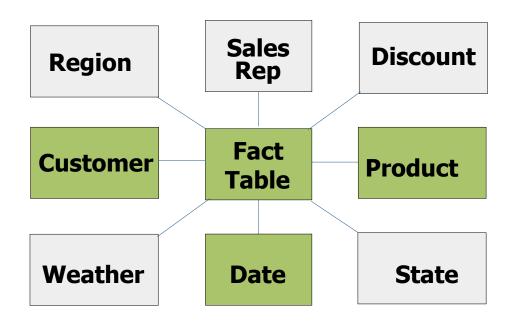
«Do not call them column-stores, just modern DB systems.»
 Stratos Idreos



Tables in a DW can have more than ten dimensions

# Today, any Relational Datawarehouse is a Column-Store

«Do not call them column-stores, just modern DB systems.»
 Stratos Idreos



Analytical query just uses a few of them

#### Rows become crowded



row1

idl@customer1@
region1@sales\_
repl@discount1
@product1
@weather1@date
1@state1...

row2 id2@customer2@
region2@sales\_
rep2@discount2
@product2
@weather2@date
2@state2

#### Worst case: visit whole row

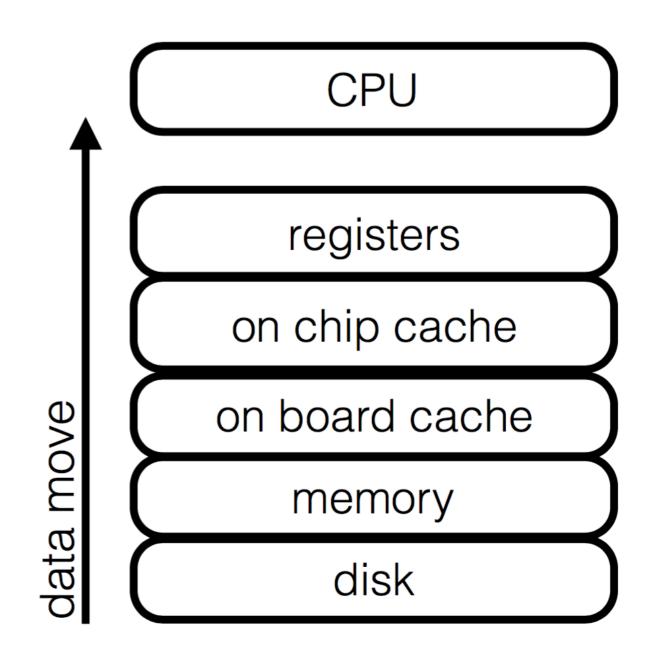


row1

id1@customer1@
region1@sales\_
rep1@discount1
@product1
@weather1@date
1@state1...

row2 id2@customer2@ ...
region2@sales\_
rep2@discount2
@product2
@weather2@date
2@state2

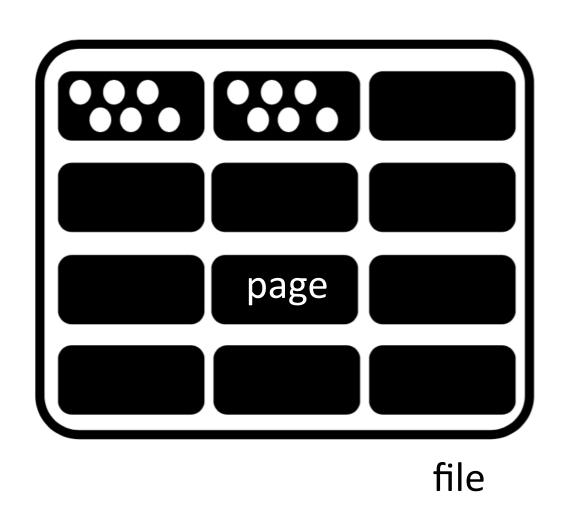
- Not only a reading-problem: entire sets of rows have to be loaded into memory from disk!
  - This wastes bandwidth



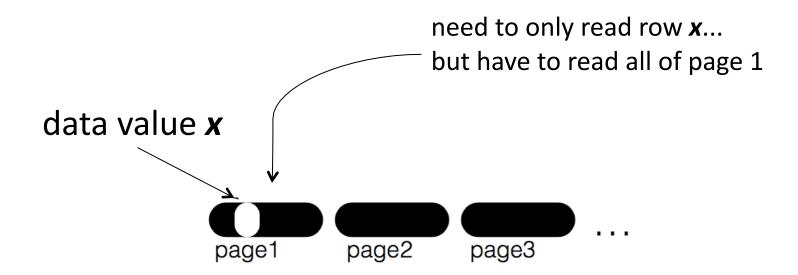
## Rows are stored in pages

page

## Pages are stored within files



#### Constraint: Pages are read as a whole!



## Better to « pay as you go »!

erven	4		-	erivi
	-			
eyo.		yello		ejmç
erwate		remetro		Jerwo

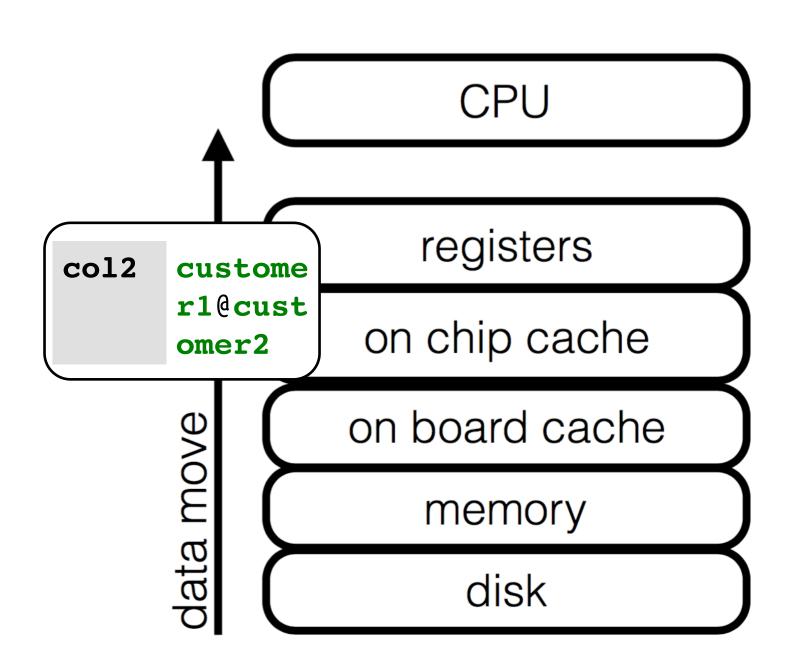
coll	idl@id2	col2	custom er1@cu stomer 2	col3	region 1@regi on2
col4	sales_r ep1@sal es_rep2	col5	discou nt1@di scount 2@	col6	produc t@1pro duct12
col7	weather 1@weath er2	col8	date1@ date2	col9	state1 @state 2

## Store columns on separate pages!



COII	1 <b>d</b> 1 <b>@</b> 1 <b>d</b> 2	col2	custom er1@cu stomer 2	co13	region 1@regi on2
col4	sales_r ep1@sal es_rep2	col5	discou nt1@di scount 2@	col6	produc t@1pro duct12
col7	weather 1@weath er2	col8	date1@ date2	col9	state1 @state 2

col3 col1 id1@id2 col2 custome region r1@cust 1@regi on2 omer2 col6 produc col4 discount sales r col t@1pro ep1@sal 5 1@discou duct12 es\_rep2 nt2@ col7 weather col9 state1 col8 date1@ 1@weath @state date2 er2 file



#### Column Stores

#### The state of the art solution for

- 1. analytical
- 2. read-mostly queries
- 3. on wide-relations
- 4. supporting only batch-updates

#### But wait...

- This does not mean that columnstores will automatically work well for RDF data..
  - for example, RDF property-tables are not wide, cluster-tables are wide however

Let's see...

# Logical Model for RDF ColumnStores: Property-Tables

A relational table for each single RDF property.

Giant-Table

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	•••	

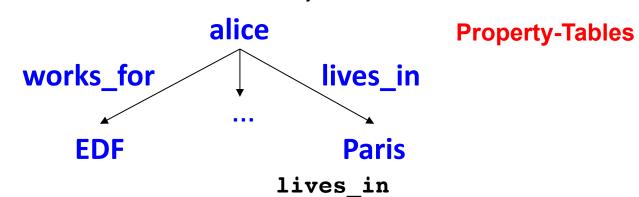
works\_for

subject	object
alice	EDF
•••	

lives\_in

subject	object
alice	Paris
•••	

# RDF in a Column-store (MonetDB, C-Store, Virtuoso)



works\_for

subject	object
alice	EDF
bob	SFR
•••	

subject	object
bob	Lyon
alice	Paris
•••	

# Property-Tables (Virtuso, C-Store)

- 1. Store triples in property tables
- 2. Convert SPARQL to equivalent SQL
- 3. Magic: the database will do the rest

What is the consequence of employing column stores?

#### RDF Column Stores (Virtouso, C-Store)

#### **Observations and assumptions:**

- Not too many different predicates
- Triple patterns usually have fixed predicate
- Need to access all triples with one predicate

#### **Design consequence:**

Use one two-attribute table for each predicate

### Neat advantage: column-projection

 Fast queries if only subject or object of a triple are accessed, not both

SQL> SELECT subject FROM lives\_in

```
lives_in col1 alice@... col2 Paris@...
```

All results can be found in the first column

# Advantages of using column stores

Allows for a very compact representation

Exploits merge joins

 A column contains "homogeneous" values, where many values repeat and thus compression is more effective



col1 car@bike col2 US@US col3 40K@7K .

### Disadvantages of using column stores

Need to recombine columns if subject and object are accessed



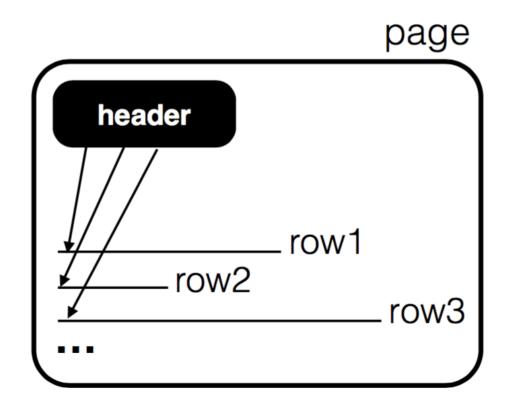
- Inefficient for triple patterns with predicate variable
   <alice ?p bob>
- Big question: when to reconstruct a tuple?
   (alap)

#### Advantages of Column Stores

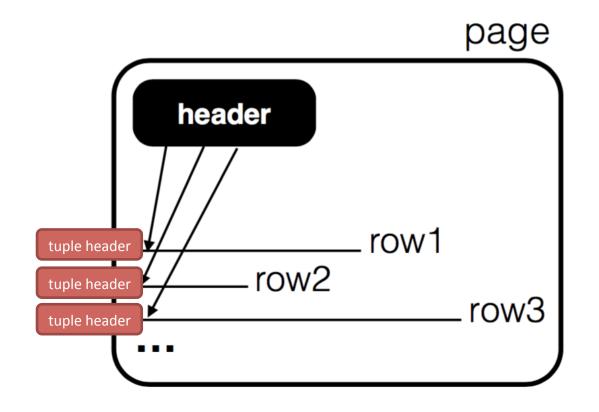
- 1. Tuple Headers Stored Separately
- 2. Optimizations for fixed-length tuples
- 3. Column-oriented data compression
- 4. Carefully optimized merge-join code

#### **TUPLE HEADERS**

# Page headers in Rowstores



### Tuple headers in Rowstores



| tuple header | >> |row<sub>of size 2</sub>|

### Tuple headers

- Metadata at the beginning of the row
  - Insert transaction timestamp
  - number of attributes in tuple (useless for RDF)
  - NULL flags

 Postgres: 27 byte tuple header + 8 bytes twocolumn tables

| header | >> | row<sub>of size 2</sub> |

# Postgres Tuple Header

Field	Туре	Length	Description
t_xmin	TransactionId	4 bytes	insert XID stamp
t_xmax	TransactionId	4 bytes	delete XID stamp
t_cid	CommandId	4 bytes	insert and/or delete CID stamp (overlays with t_xvac)
t_xvac	TransactionId	4 bytes	XID for VACUUM operation moving a row version
t_ctid	ItemPointerDa ta	6 bytes	current TID of this or newer row version number of attributes,
t_infomask2	int16	2 bytes	plus various flag bits
t_infomask	uint16	2 bytes	various flag bits
t_hoff	uint8	1 byte	offset to user data
null bitmap		optional	
object id		optional	

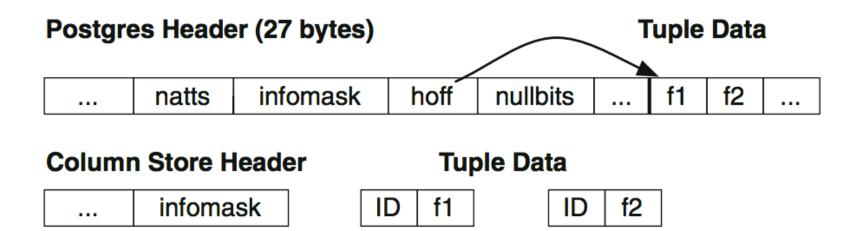
### Postgres Tuple Header

- Some information on visibility of a tuple for current transaction snapshot or newer version (needed for snapshot isolation algorithm)
  - t\_xmin TransactionId 4 bytes insert XID stamp
  - t\_xmax TransactionId 4 bytes delete XID stamp
  - t\_cid CommandId 4 bytes insert CID stamp (actual a UNION struct)
  - t\_ctid ItemPointerData 6 bytes current TID of this or newer row version
- How long is this row? Is it variable length? Does it have NULLs?
  - t natts int16 2 bytes number of attributes
  - t\_infomask uint16 2 bytes various flag bits
    - e.g. HAS\_NULL | HASVARWIDTH | HASOID | locks(!)
- t\_hoff uint8 1 byte /\* sizeof header incl. bitmap, padding \*/
- null bitmap (optional)
- object id(optional)

# Tuple headers in Columnstores

- Puts header information in separate columns and can selectively ignore it
  - #attributes is always two
  - in some cases, NULL values are totally avoided
- Column-store effective tuple width: ~8 bytes
- Reading a tuple takes 4-5 times less time than Postgres (27 + 8bytes), so does a simple table scan.

#### Rowstore vs Columnstore Headers



# OPTIMIZATIONS FOR FIXED-LENGTH TUPLES

#### Optimizations for variable-length tuples

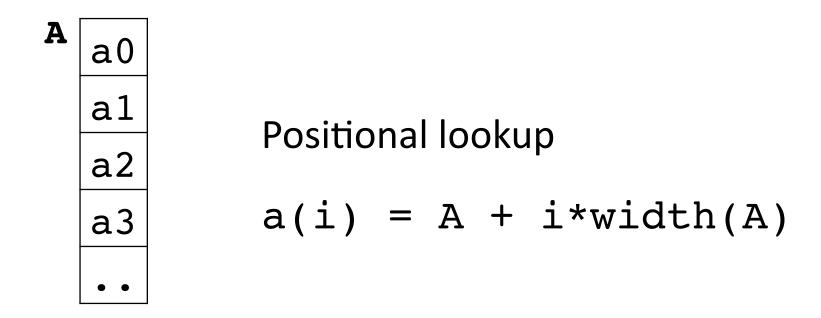
- 1 attribute variable length => the whole tuple is
- Common case: row-stores designed for this

row1 idcustomer1@fistname1@lastname1@...

 Tuples located/iterated via pointers in the page header (instead of address offset calculation)

#### Optimizations for fixed-length tuples

 In columnstores, with a dictionnary encoding, fixed length val. are stored/accessed as arrays



#### Optimizations for fixed-length tuples

Every RDF property table has two columns

subject	object	
alice	EDF	
•••		

- Store each on disk in a page (eg, 64K)
  - in SW-Store, they found this suboptimal for queries accessing both values

# Hybrid Storage (SW-Store)

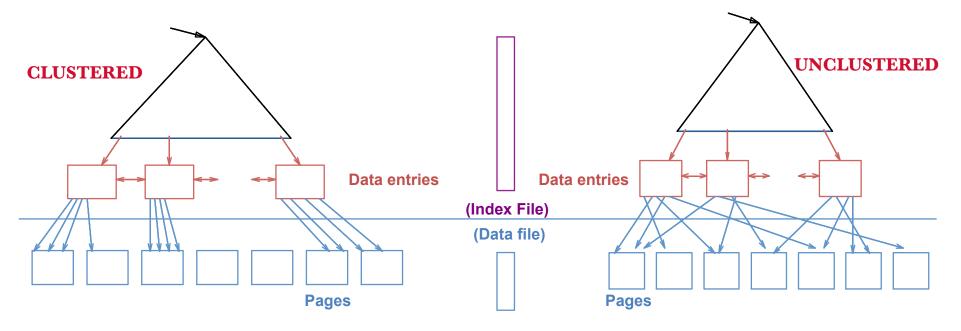
A page slot contains data from both columns

P	s0	00
	s1	o1
	s2	02
	s3	03
	• •	• •

```
o(i) = P + i *(width(S) + width(O)) + width(S)
```

### +Index on hybrid Column (SW-Store)

- clustered B+ tree index on subject
- unclustered B+ tree index on object.



#### Clustered/unclustered

- Clustered = records close in index are close in data
- Unclustered = records close in index may be far in data

# More optimizations: Id-Table

 Maintain a single-column table that contains all triple subjects (much better if ordered)

Id-Table id<sub>Obama</sub>
id<sub>Alice</sub>
id<sub>Paris</sub>

#### **Id-Table**

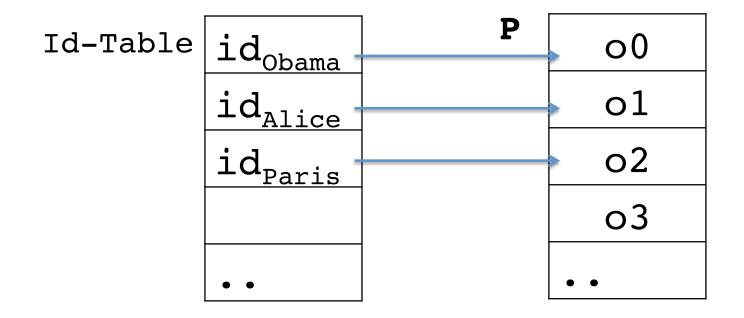
If property P is NOT multivalued (eg. birthday)
 we can avoid to store subject id

Id-Table id<sub>Obama</sub>
id<sub>Alice</sub>
id<sub>Paris</sub>

P 00o1o2o3

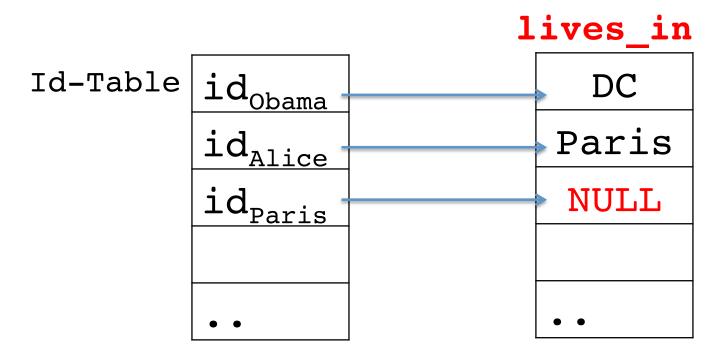
#### **Id-Table**

If property P is NOT multivalued (eg. birthday)
 we can avoid to store subject id



#### Nulls are back!

If property P is NOT multivalued (eg. birthday)
 we can avoid to store subject id



# Id-Table: Dealing with Nulls

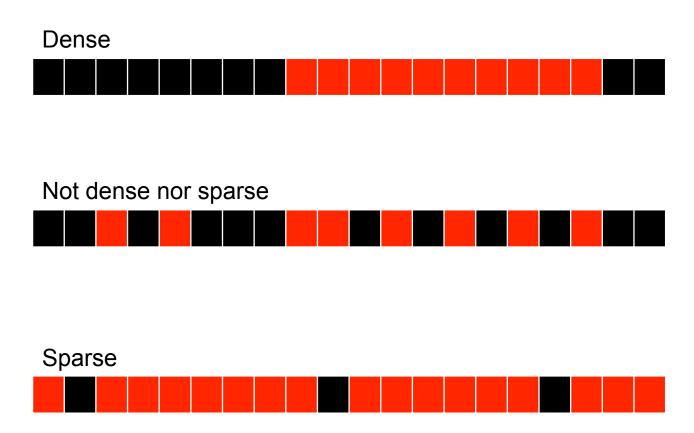
Goal: remove nulls from the column

There is not a single optimal solution

- The point is to find a tradeoff between the size and manegeability of the compressed column
  - this depends only on the data-distribution

# It's matter of « density »

D. Abadi Column-Stores For Wide and Sparse Data



#### Case 1: «dense» data and long null sequences

Title		Tanguaga	
11616	t1	Language	NULL
	t2		FR
	t3		EN
	t4		NULL
	NULL		NULL

#### Case 1: Low overhead for «dense» data

Store indexes of non-null values

t1
t2
t3
t4
NULL

Title t1 Range[1-4]
t2 t3 t4

#### Case 1: Low overhead for «dense» data

Store indexes of non-null elements

Language
NULL
FR
EN
NULL
NULL

Language FR EN

#### Case 1: Low overhead for «dense» data

Store indexes of non-null elements

• If data is dense, then

|range information | << |nulls |

#### Case 2: data not «dense» nor «sparse»

Store a bitmap index (0=NULL)

Copyright

2001

NULL

1985

NULL

1995

#### Case 2: data not «dense» nor «sparse»

Store a bitmap index (0=NULL)

Copyright Bit:101011

2001

NULL

1985

NULL

1995

#### Case 2: data not «dense» nor «sparse»

Store a bitmap index (0=NULL)

Copyright Bit:101011

Overhead = 1bit per value

2001

NULL

1985

NULL

1995

# Case 3 : sparse data

Store the list of non-null ids

Author
Hugo
NULL
NULL
NULL
NULL

Artist
NULL
Dylan
NULL
NULL
NULL

# Case 3 : sparse data

Store the list of non-null ids

NULL

Hugo
NULL
NULL

Author

Author List:1 Hugo

# Case 3 : sparse data

• Store the list of non-null ids

Artist
NULL
Dylan
NULL
NULL
NULL

Artist
<sub>List:2</sub> Dylan

# Case 3 : sparse data

Store the list of non-null ids

If data is sparse

|List| << |nulls|

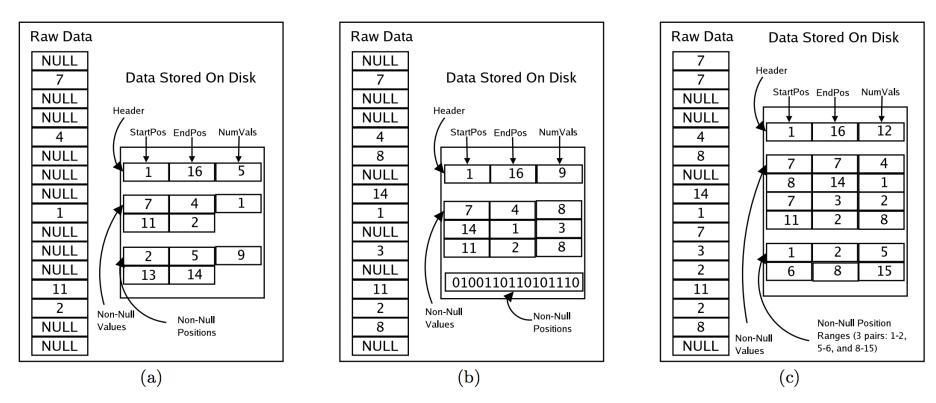


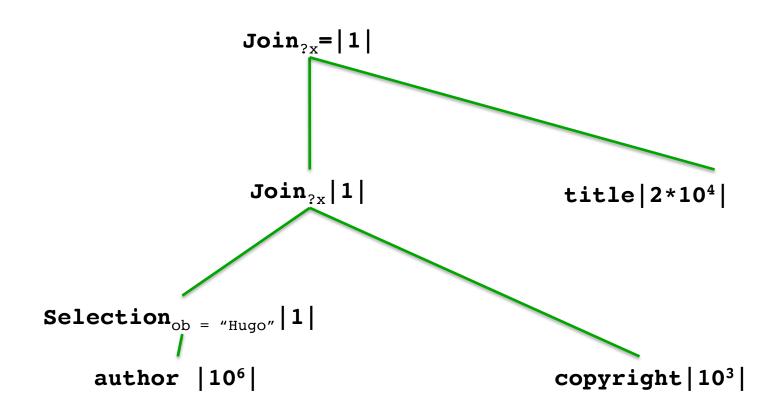
Figure 1: Positions represented using a list (a), a bit-string (b), and as ranges (c) for sparse columns

# Back to Query Evaluation

triple

(t<sub>1</sub> Join t<sub>3</sub>) Join t<sub>2</sub>

# Plan



### Author

List:1

#### Author

### Copyright

List:1

Bit:110011

Hugo

2001

id=1

1985

NULL

NULL

1995

2004

Author

Copyright

Title

List:1

Bit:110011

Range[1-5]

Hugo

id=1 → 2001

**----**

id=1

t1

t2

t3

t4

NULL

1985

NULL

1995

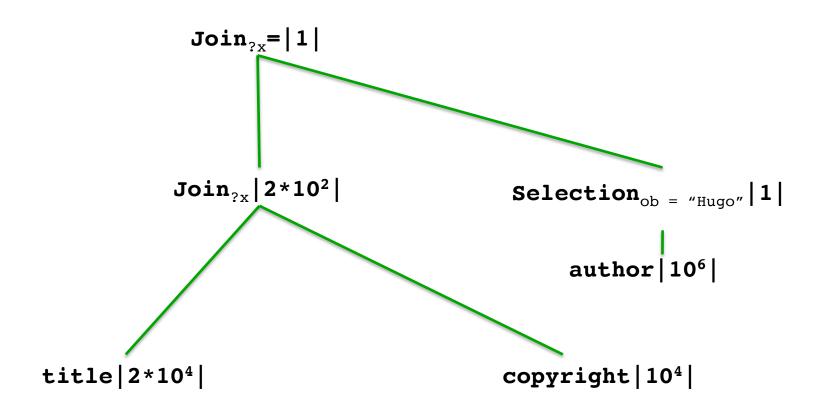
2004

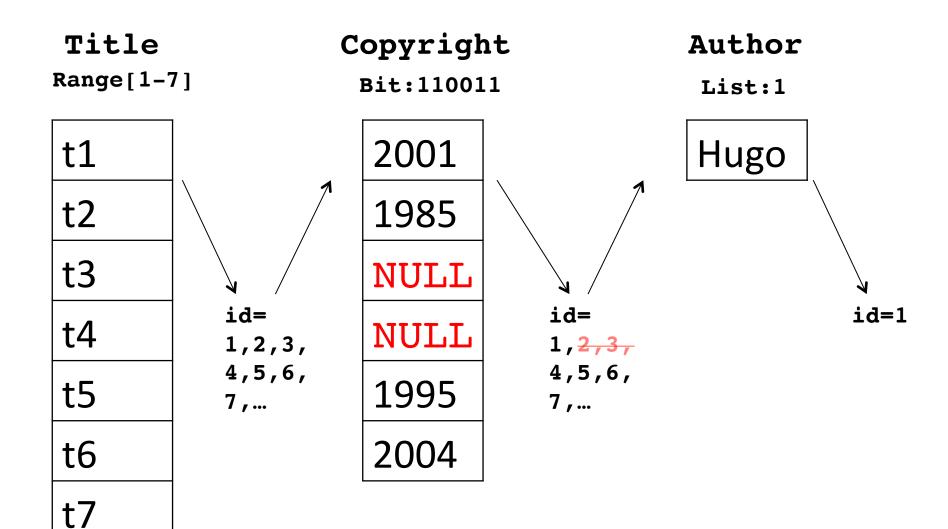
## Query

(t<sub>2</sub> Join t<sub>3</sub>) Join t<sub>1</sub>

triple pattern selectivity

# Plan





# COLUMN-ORIENTED DATA COMPRESSION

# Column-oriented data compression

- Since each attribute is stored separately (even within a slot), it can be compressed separately using the best algorithm
  - for example, the subject ID column, a monotonically increasing array of integers
  - data from the same domain tend to show locality
- It is often possible also to operate directly on compressed representations
  - Bandwidth requirements are reduced when transferring compressed data

# SO FAR SO GOOD. NOW WHO WINS?

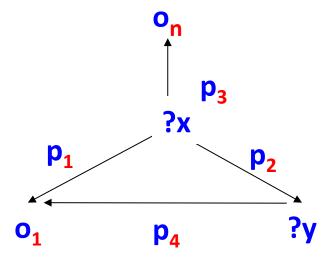
# There is no single winner

	RDF.3x	$Vos_{[6,1]}$	Vos (7.1)	$M_{Onet}D_{B}$	$^{4S_{tor_{\Theta}}}$
% of queries for which tested system is fastest	20.9%	0.0%	22.6%	56.5%	0.0%
Total workload execution time (hours)	27.1	20.9	20.8	38.6	72.2
Mean (per query) execution time (seconds)	7.8	6.0	6.0	11.1	20.8

Table 1.1: Summary of results over WatDiv 100M RDF triples, 12500 SPARQL queries.

# Mini-Projet: Moteur RDF (Partie 1)

- Implémenter un moteur de requêtes pour données RDF utilisant l'une des approches vues en cours :
  - Hexastore, Columnstore, Graphstore



# Mini-Projet: Moteur RDF (Partie 2)

- Évaluer les performances du système réalisé
  - comparer avec 1 autre système + Jena

 Fournir un système fonctionnel à ses collègues (dans les délais) fait partie de l'évaluation