RDF Data Management & SPARQL Query Processing

Cours développé par

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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 semi-structured 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

Organisation

- 29 Octobre : RDF Stores 2CM + 1TP (début mini-projet)
- 19 Novembre: 1TP
- 26 Novembre: 2TP
- 3 Décembre: 2TP
- 10 Décembre: 2TP

Plan

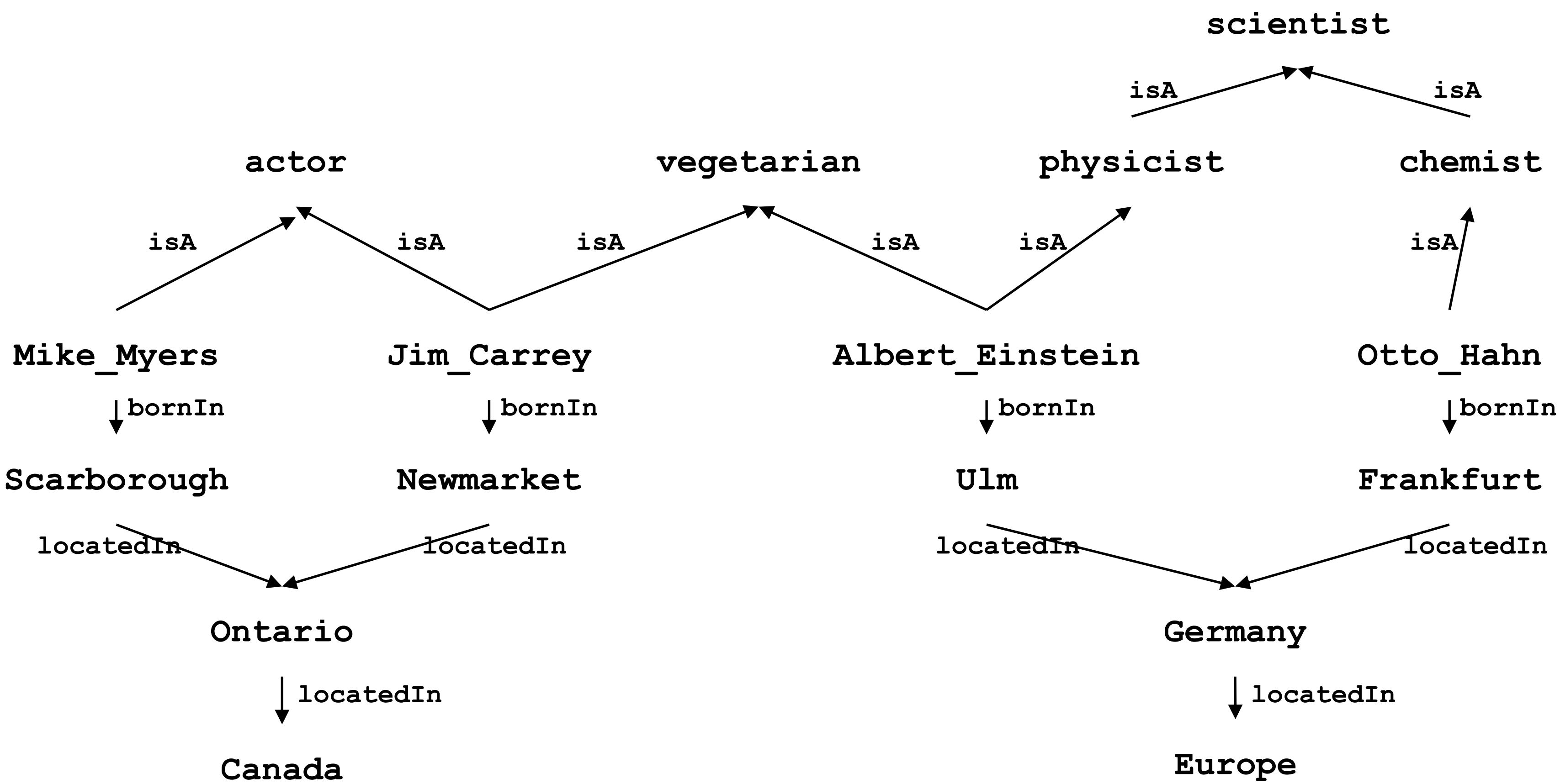
- **RDF and SPARQL**
- **RDF Row-stores**
- **RDF Column-stores**
- **RDF Graph-stores**

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 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 more than a Graph Database

```
<Albert_Einstein, isA, physicist>
<isA, rdfs:subPropertyOf, rdfs:subClassOf>
```

property are also reources

```
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>
```

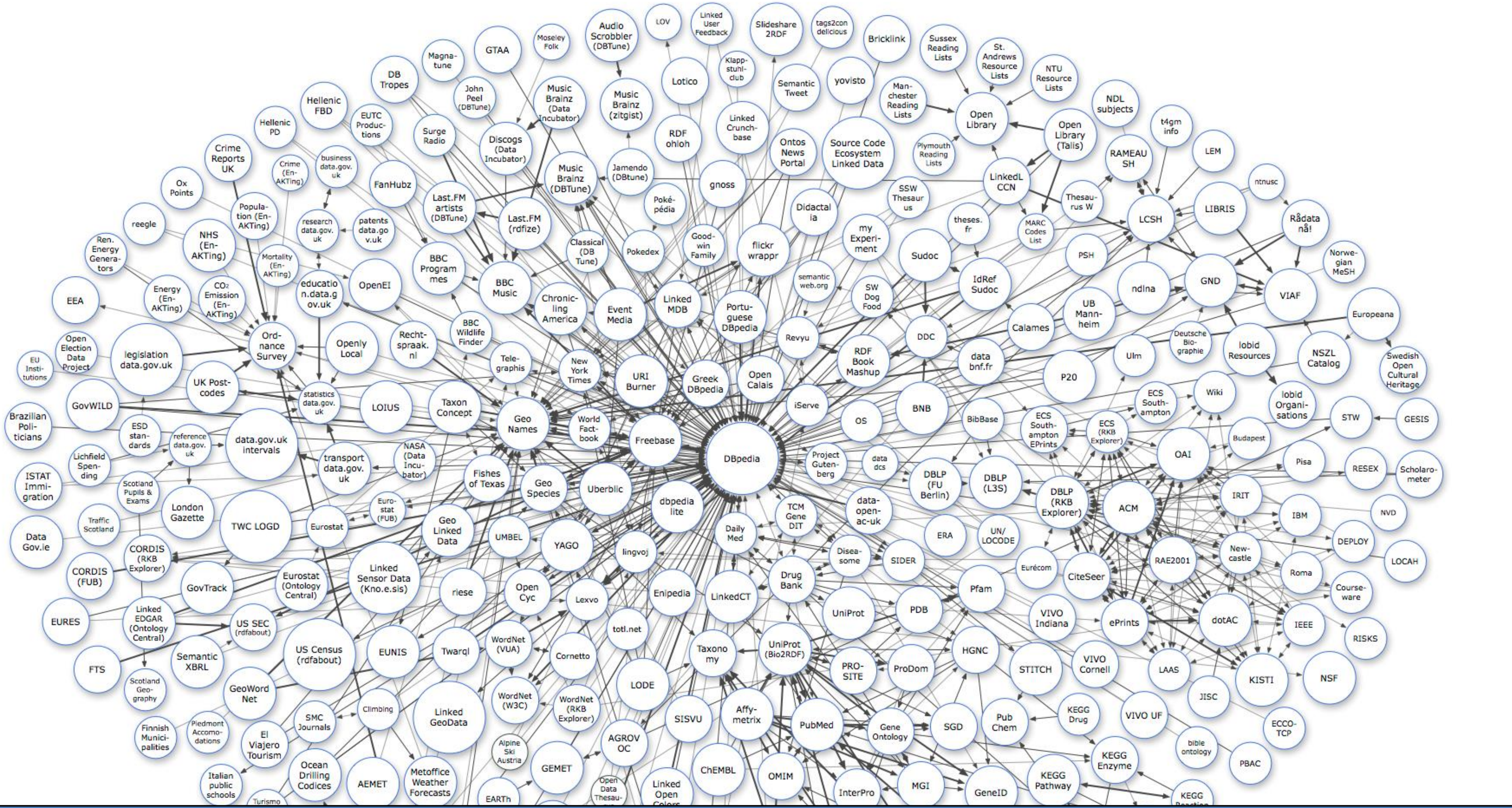
property are also resources

```
SELECT ?x ?y
WHERE {
      ?x ?p ?y .
      ?p rdfs:subPropertyOf, rdf:subClassOf}
}
```

properties can be queried

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**

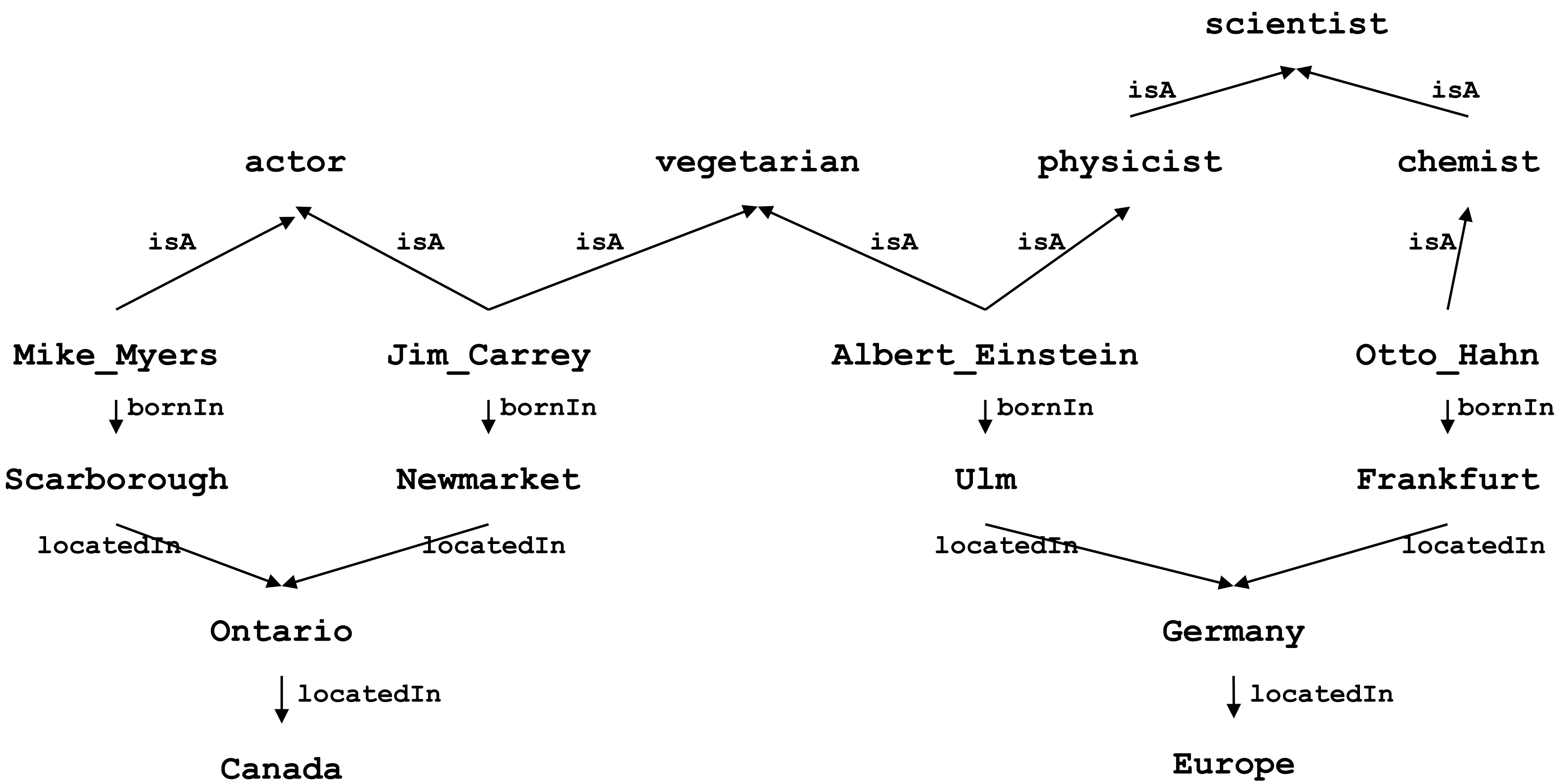
```
?x  wrote_book  ?y
```

- Like **select-project-join** for relational databases

SPARQL – Example

Example query:

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



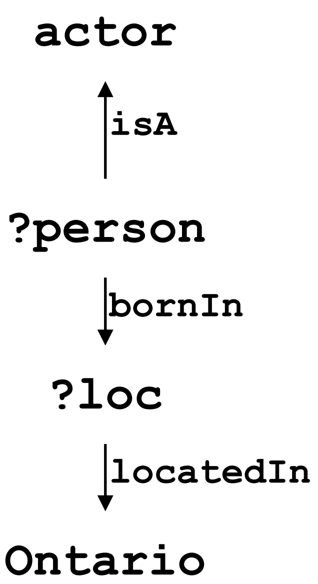
SPARQL – Example

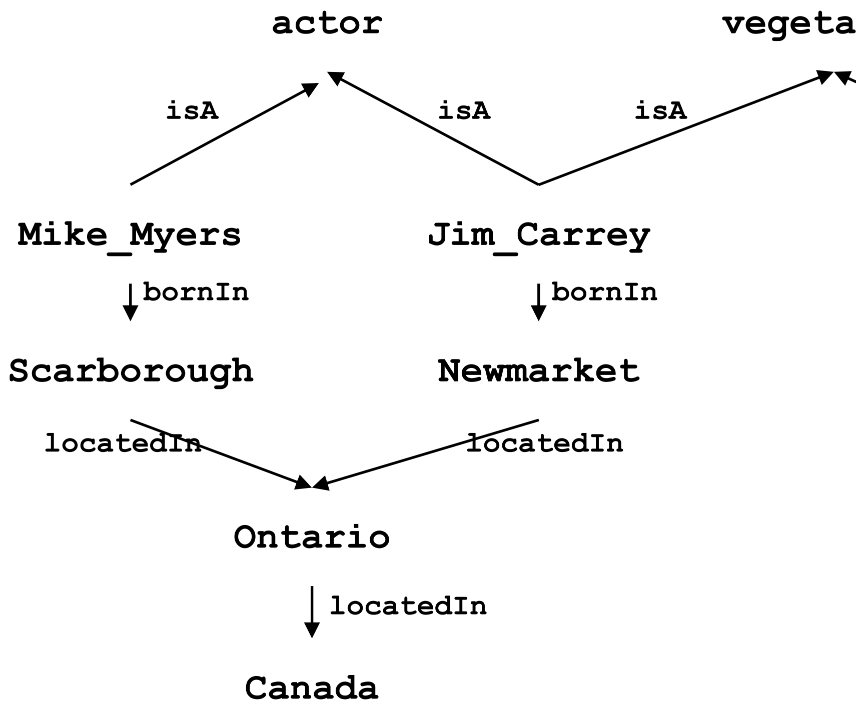
<u>Example query:</u>

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

```
SELECT ?person WHERE { ?person isA actor.
                       ?person bornIn ?loc .
                       ?loc locatedIn Ontario . }
```

Find **subgraphs** of this form:





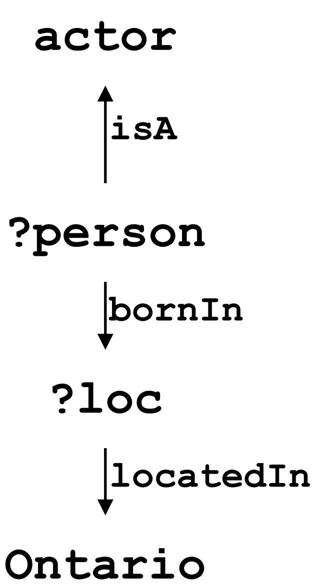
SPARQL – Example

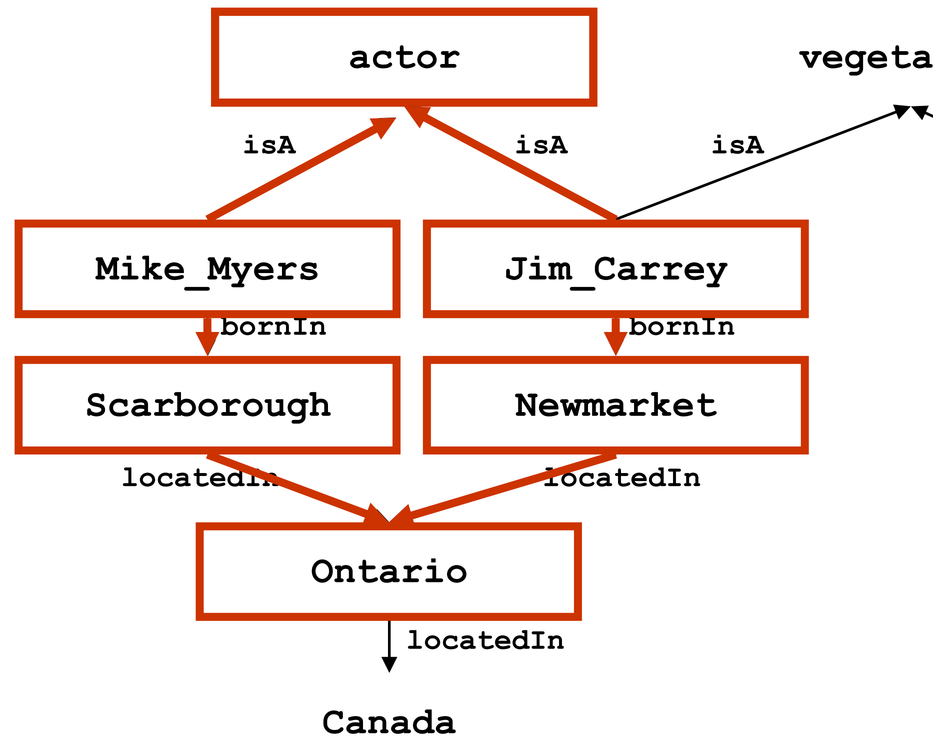
Example query:

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

```
SELECT ?person WHERE { ?person isA actor.
                       ?person bornIn ?loc .
                       ?loc locatedIn Ontario . }
```

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

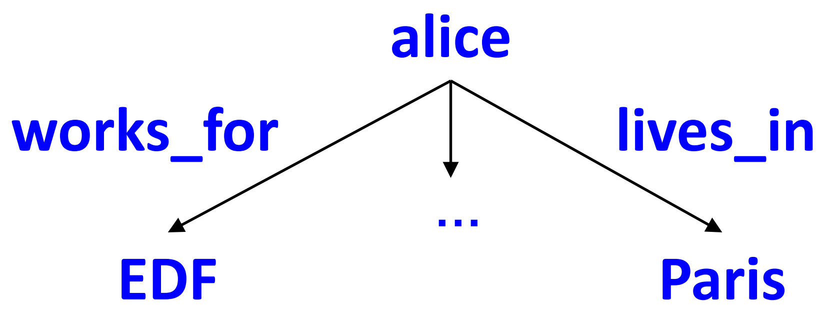
Classic relational database, storing relations by <u>rows</u>.

(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
	...	

row1	alice@works_for@EDF	**row2**	alice@livesIn@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**
alice	works_for	EDF
alice	lives_in	Paris
	…	

Giant

1 Billion Triples = 1 Billion lines

Conversion of SPARQL to SQL

triple pattern	→	FROM/WHERE
Shared variables	→	(self)JOIN conditions
Constants	→	WHERE conditions
FILTER conditions	→	WHERE conditions
OPTIONAL clauses	→	OUTER JOINS
UNION clauses	→	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

```
SPARQL >
  SELECT * WHERE { ?x lives_in ?y.
                   ?x works_for ?z }
```

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

Conversion of Shared Variables

SPARQL >

```
SELECT * WHERE { ?x lives_in ?y.
                 ?x works_for ?z }
```

SQL >

```
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
```

subject	**predicate**	**object**
alice	works_for	EDF
alice	lives_in	Paris
	...	

Conversion of FILTER conditions

```
SPARQL >
  SELECT ?x WHERE { ?x lives_in ?y .
                    FILTER(?y!="New York") }
```

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	…	

Conversion of FILTER conditions

SPARQL >

```
SELECT ?x WHERE { ?x lives_in ?y .
                  FILTER(?y!="New York") }
```

SQL >

```
SELECT subject
FROM Giant-Table
WHEREpredicate = "lives_in"
  ANDobject != "New York"
```

subject	**predicate**	**object**
alice	works_for	EDF
alice	lives_in	Paris
	…	

Conversion of UNION clauses

```
SPARQL >
  SELECT ?x WHERE {         { ?x lives_in ?y }
                     UNION  { ?x works_for ?z} }
```

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	…	

Conversion of UNION clauses

SPARQL >

```
SELECT ?x WHERE {        { ?x lives_in ?y }
                   UNION { ?x works_for ?z} }
```

SQL >

```
     SELECT   subject     FROM Giant-Table
     WHERE    predicate = “lives_in” )
  UNION
     SELECT   subject     FROM Giant-Table
     WHERE    predicate = “works_for”
```

subject	predicate	object
alice	works_for	EDF
alice	lives_in	Paris
	…	

Conversion of OPTIONAL clauses

SPARQL >

```
SELECT ?x WHERE { ?x lives_in ?y .
                  OPTIONAL { ?x works_for ?z} }
```

subject	**predicate**	**object**
alice	works_for	EDF
alice	lives_in	Paris
	…	

Conversion of OPTIONAL clauses

```
SPARQL >
  SELECT ?x WHERE { ?x lives_in ?y .
                    OPTIONAL { ?x works_for ?z} }
SQL >
   ( SELECT    subject     FROM Giant-Table
     WHERE     predicate = "lives_in" ) L
LEFT OUTER JOIN
   ( SELECT    subject     FROM Giant-Table
     WHERE     predicate = "works_for" ) W
ON (L.subject = W.subject)
```

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
```

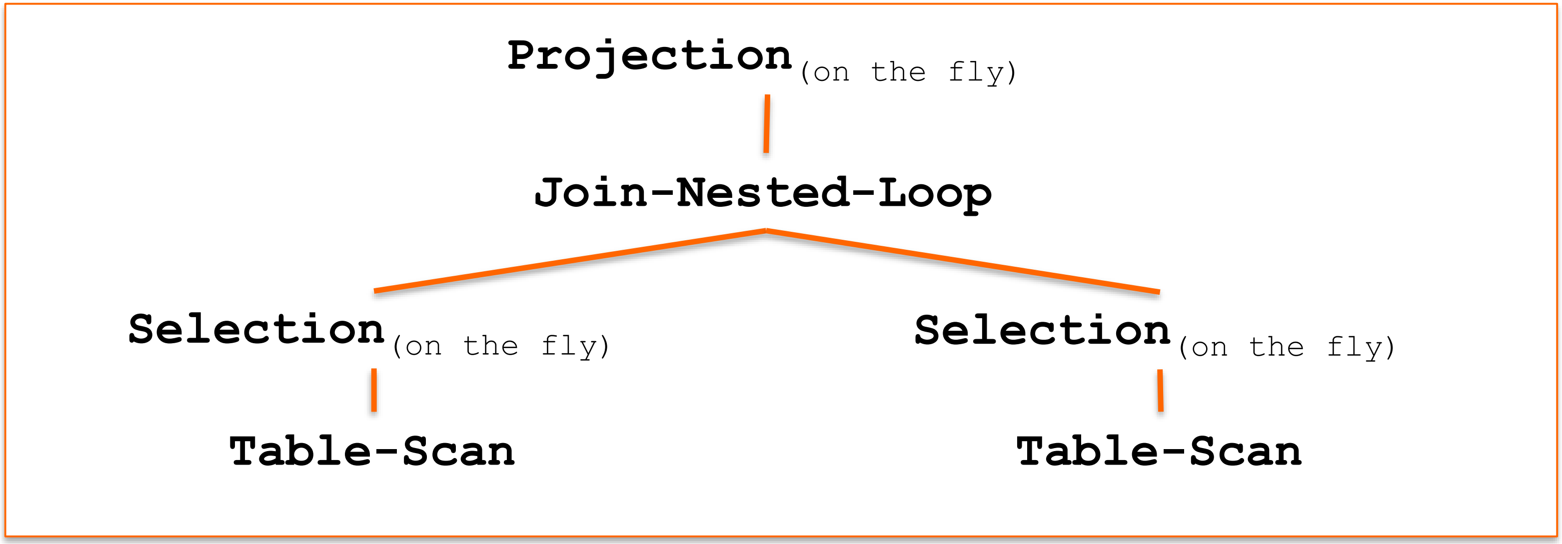
Projection$_{\texttt{L.subject, L.object, W.object}}$

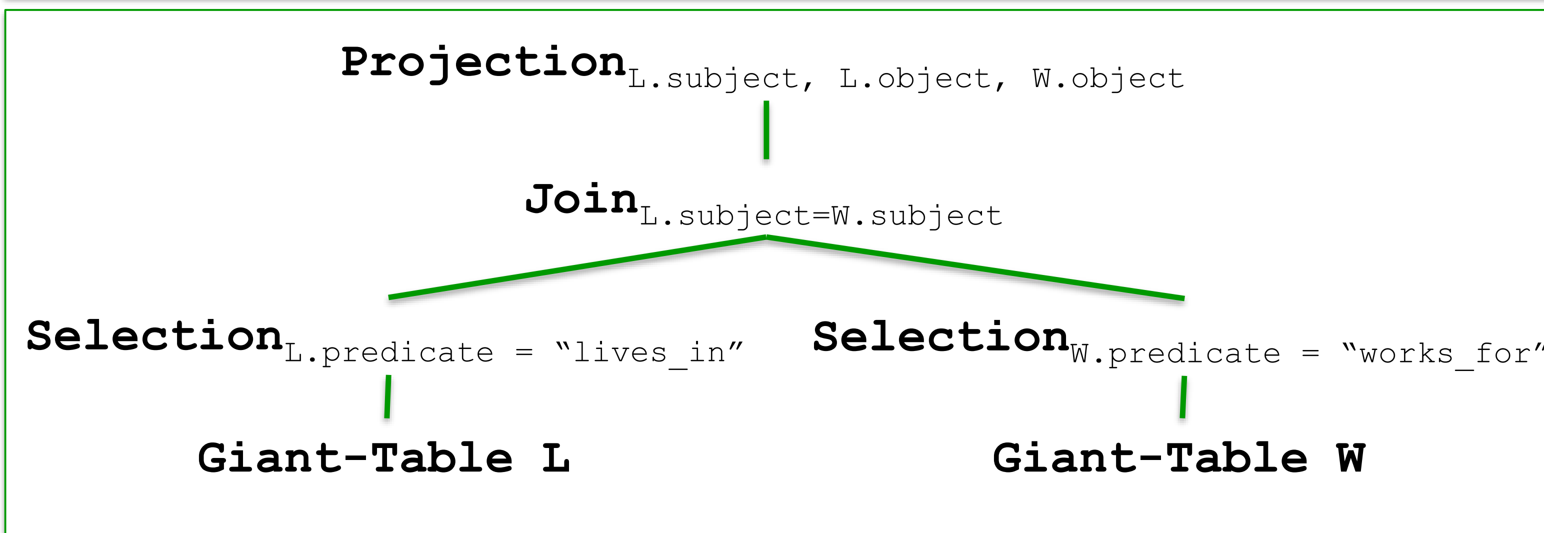
Join$_{\texttt{L.subject=W.subject}}$

Selection$_{\texttt{L.predicate = “lives\_in”}}$ **Selection**$_{\texttt{W.predicate = “works\_for”}}$

Giant-Table L **Giant-Table W**

From Relational Algebra to Physical Plan





From Relational Algebra to Physical Plan

Projection (on the fly)

Join-Nested-Loop

Selection (on the fly) **Selection** (on the fly)

Table-Scan **Table-Scan**

- Now, performance depend on the <u>row-store.</u>

row1	alice@works_for@EDF	**row2**	alice@livesIn@Paris	…

Is that all?

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**?

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 ...

SPARQL >

```
SELECT * WHERE { ?x lives_in ?y.
                 ?x works_for ?z }
```

SQL >

```
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
```

subject	**predicate**	**object**
alice	works_for	EDF
alice	lives_in	Paris
	…	

… now goes as follows

SPARQL >

```
SELECT * WHERE { ?x lives_in ?y.
                 ?x works_for ?z }
```

works_for

subject	**object**
alice	EDF
…	

lives_in

subject	**object**
alice	Paris
…	

… now goes as follows

SPARQL >

```
SELECT * WHERE { ?x lives_in ?y.
                 ?x works_for ?z }
```

SQL >

```
SELECT L.subject, L.object, W.object
FROM lives_in as L, works_for as W
WHERE  L.subject = W.subject
```

works_for

subject	object
alice	EDF
…	

lives_in

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 any database system

works_for

subject	object
alice	EDF
…	

lives_in

subject	object
alice	Paris
…	

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	subClassOf	wasBornIn	diedIn	locatedIn	influences

Examples

BMW	*Los Angeles Airport*	*Alex Ferguson*	*John Belushi*	*Apple INC*	*Charlie Chaplin*

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 …

SPARQL >

```
SELECT * WHERE { ?x lives_in ?y.
                 ?x works_for ?z }
```

SQL >

```
SELECT L.subject, L.object, W.object
FROM lives_in as L, works_for as W
AND  L.subject = W.subject
```

works_for

subject	object
alice	EDF
alice	Paris
…	

lives_in

subject	object
alice	EDF
alice	Paris
…	

now it goes as follows

SPARQL >

```
SELECT * WHERE {  ?x lives_in ?y.
                  ?x works_for ?z   }
```

SQL >

```
SELECT *
FROM employee_property_cluster
WHERE lives_in   IS NOT NULL
AND   works_for  IS NOT NULL
```

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 **always** hold

<http://yago-knowledge.org/resource/isAffiliatedTo>	**2.635.440**
<http://yago-knowledge.org/resource/playsFor>	**2.575.219**
<http://yago-knowledge.org/resource/hasGender	**345.794**
<http://yago-knowledge.org/resource/wasBornIn>	**172.541**

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

Correlations do not **always** hold

<http://yago-knowledge.org/resource/isAffiliatedTo>	**2.635.440**
<http://yago-knowledge.org/resource/playsFor>	**2.575.219**
<http://yago-knowledge.org/resource/hasGender	**345.794**
<http://yago-knowledge.org/resource/wasBornIn>	**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 4th 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 inconveniences 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

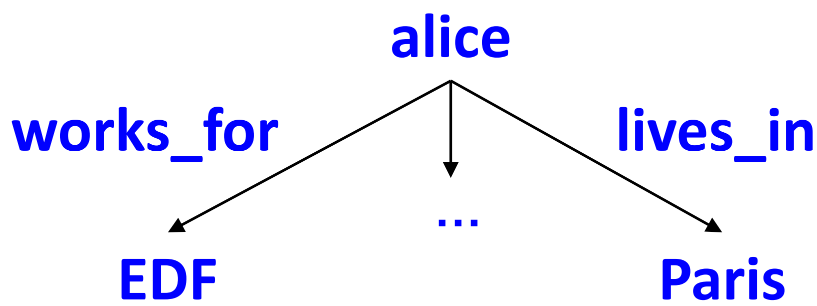
Map strings to unique integers (e.g., via hashing)

- 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!

Dictionnary



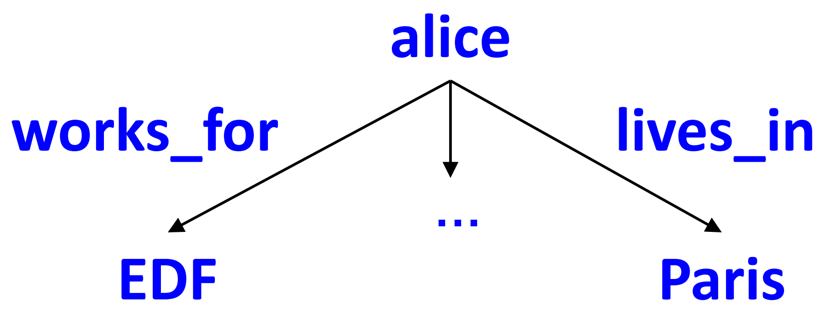
dictionary

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

Giant-Table

subject	pred.	object
1		

Dictionnary



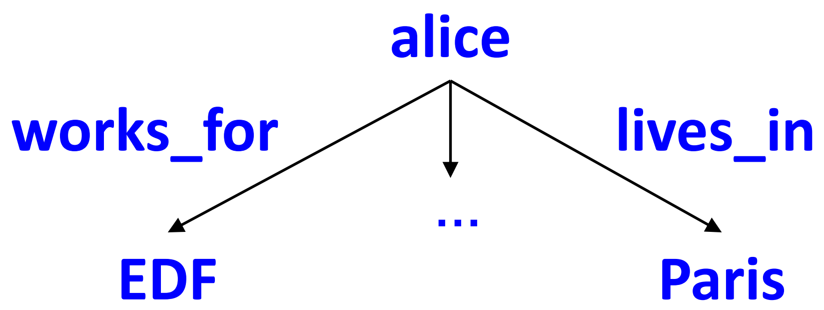
dictionary

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

Giant-Table

subject	pred.	object
1	2	

Dictionnary



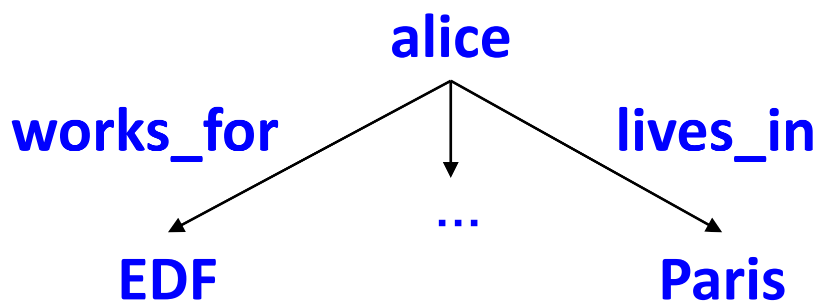
dictionary

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

Giant-Table

subject	pred.	object
1	2	4

Dictionnary



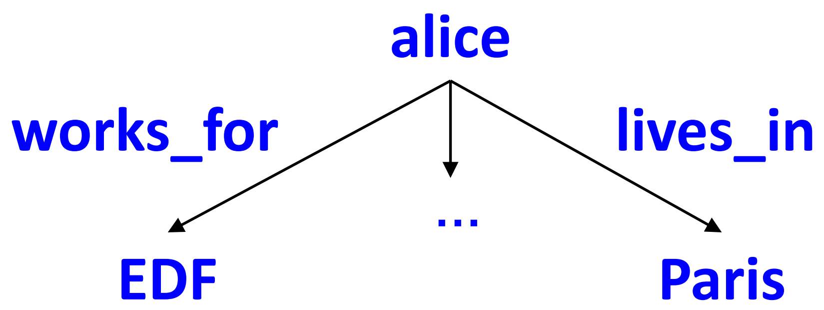
dictionary

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

Giant-Table

subject	pred.	object
1	2	4
1		

Dictionnary



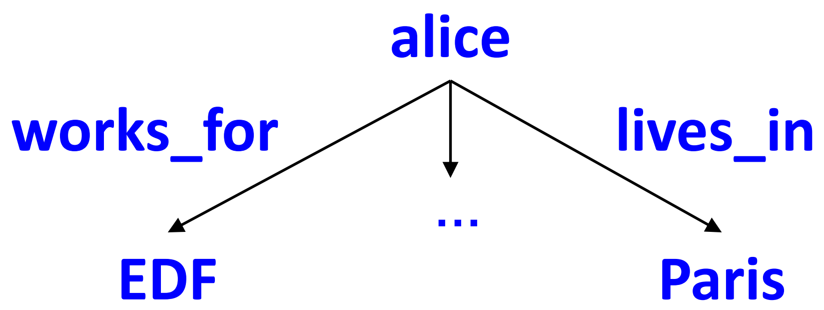
dictionary

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

Giant-Table

subject	pred.	object
1	2	4
1	3	

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

up to 10x faster!!

RDF3X Storage and Indexing

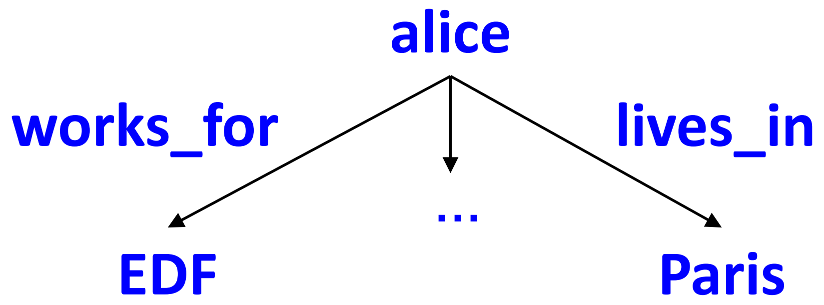
- Giant-Table model + ad-hoc implementation (no RDBMs as we have seen before)

- 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)
```

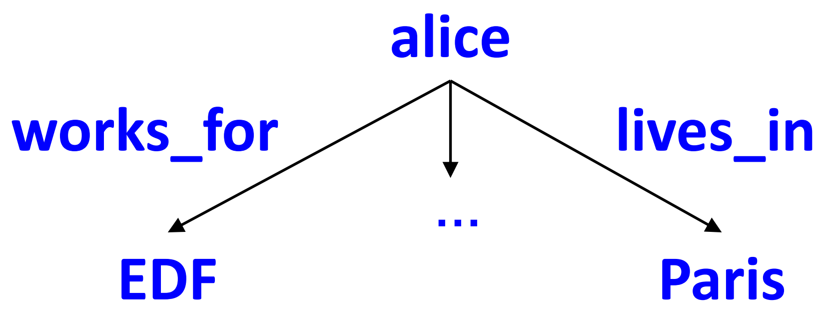
So we can store triples pattern-wise



`Giant-Table<SPO>`

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

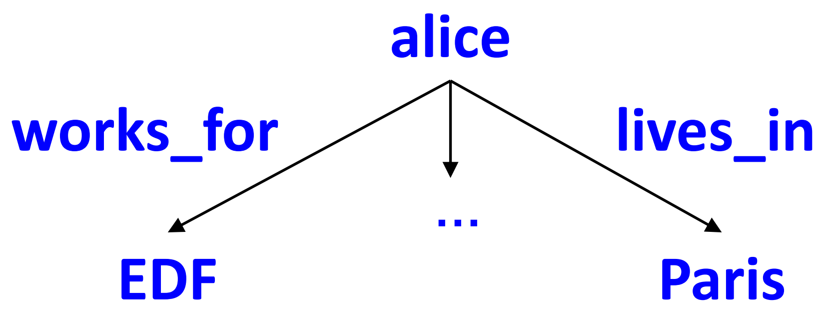
So we can store triples pattern-wise



Giant-Table<SOP>

subject	object	predicate
alice	EDF	works_for
alice	Paris	lives_in

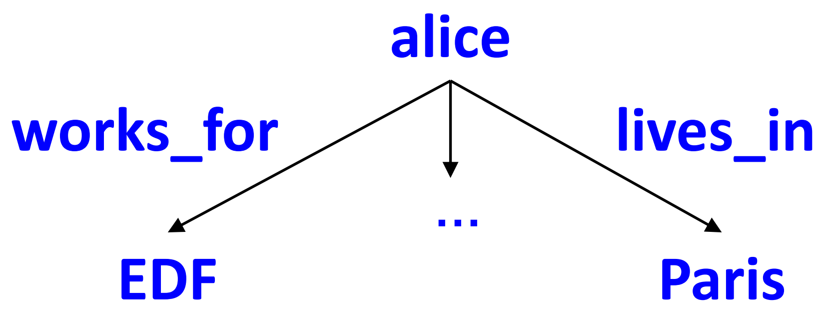
So we can store triples pattern-wise



Giant-Table<OPS>

object	predicate	subject
EDF	works_for	alice
Paris	lives_in	alice

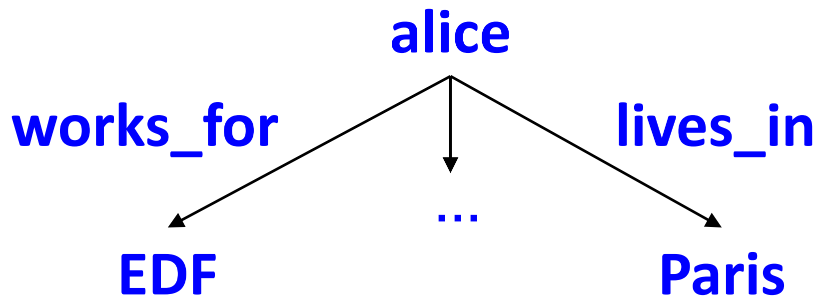
So we can store triples pattern-wise



Giant-Table<POS>

predicate	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

row1	alice@works_for@EDF	**row2**	alice@livesIn@Paris	…

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

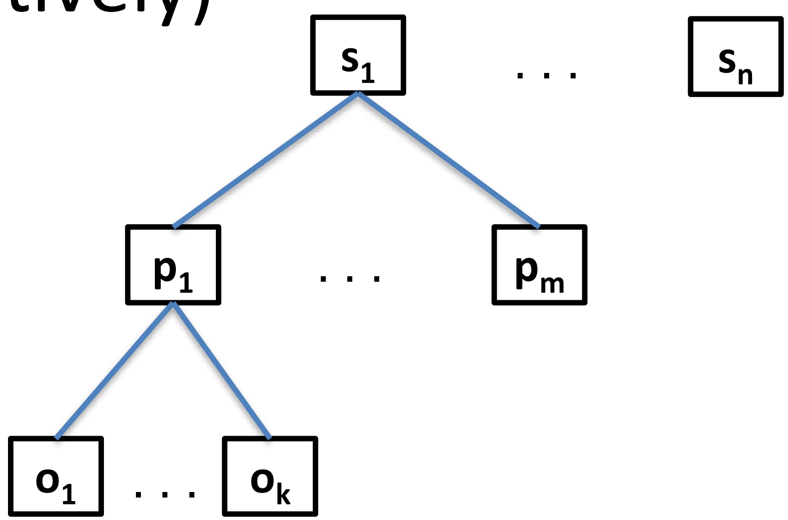
up to 3x faster!!

row1	works_for@EDF@alice	**row2**	livesIn@Paris@alice	…

RDF3X Storage and Indexing

- Similarly RDF3X create 6 indexes
  - SPO ; SOP ; PSO ; POS ; OSP ; OPS

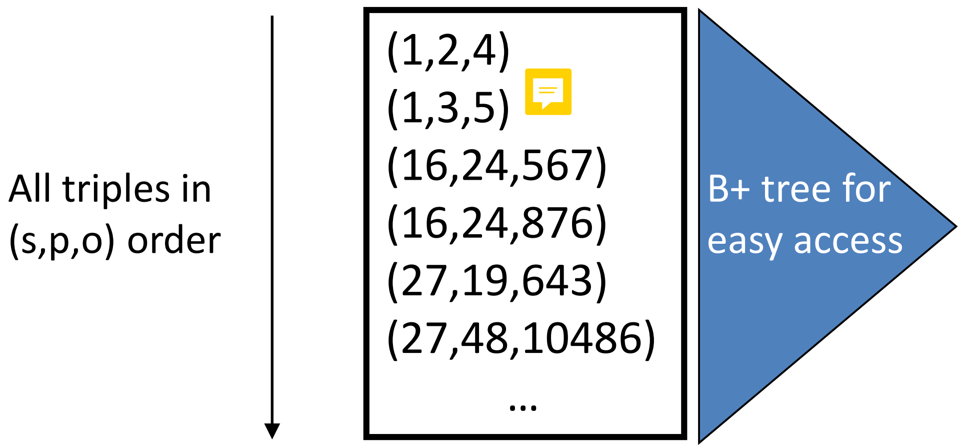
- SPO (Intuitively)



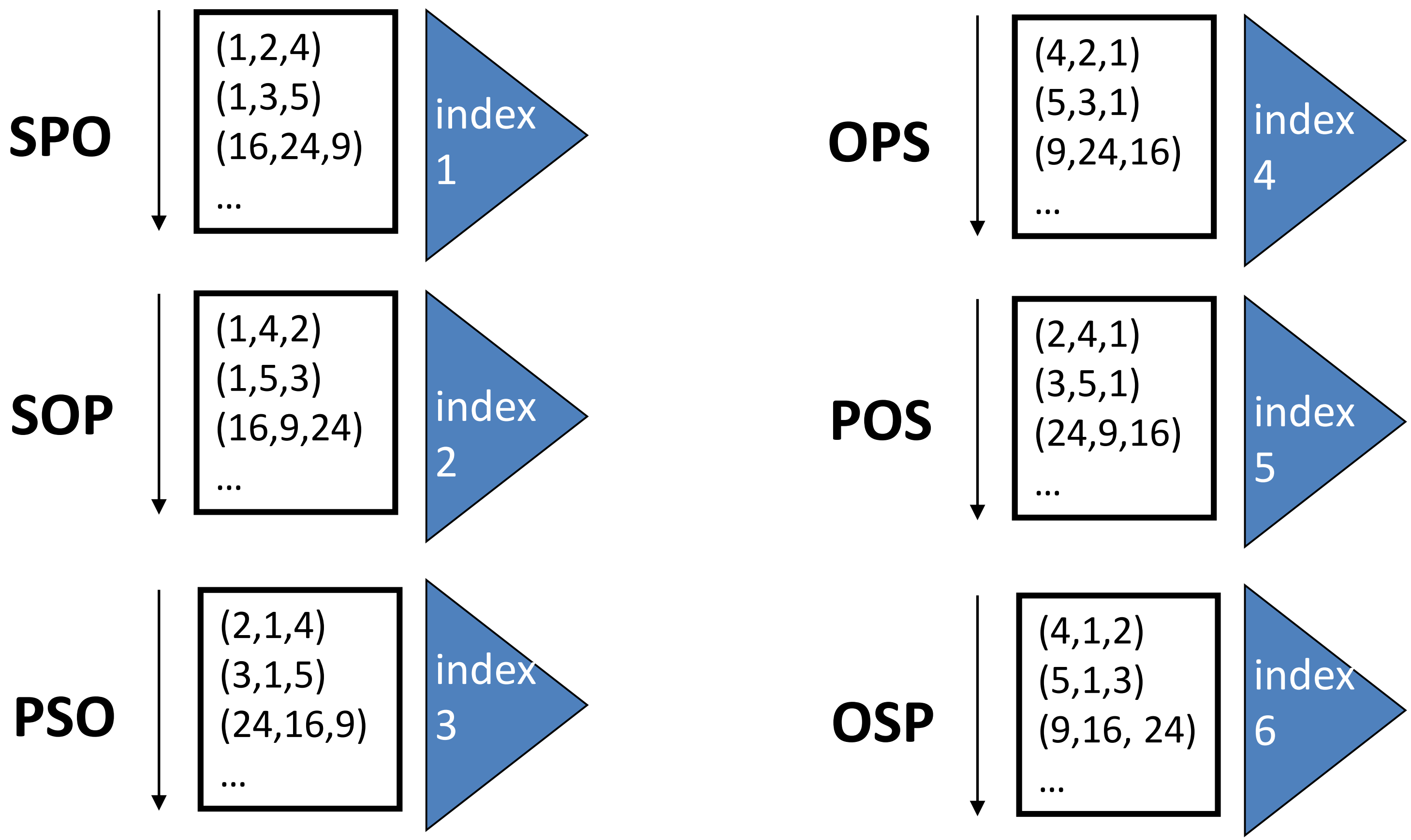
RDF3X Storage and Indexing

- Similarly RDF3X create 6 indexes
  - SPO ; SOP ; PSO ; POS ; OSP ; OPS

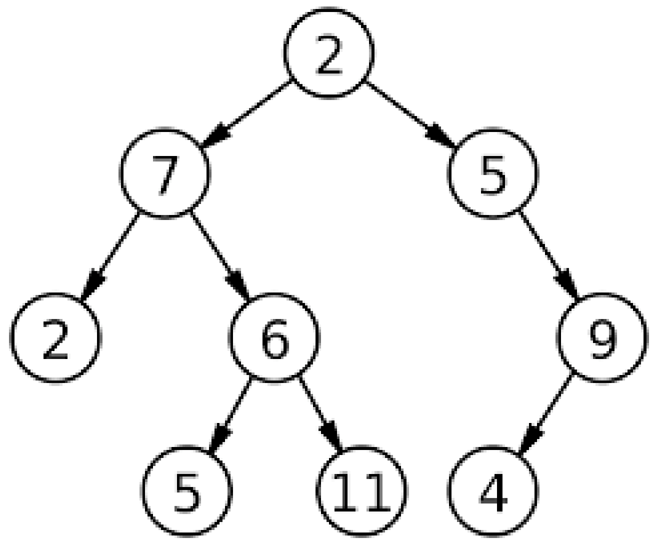
- SPO (in reality) : (B+)-trees over triples



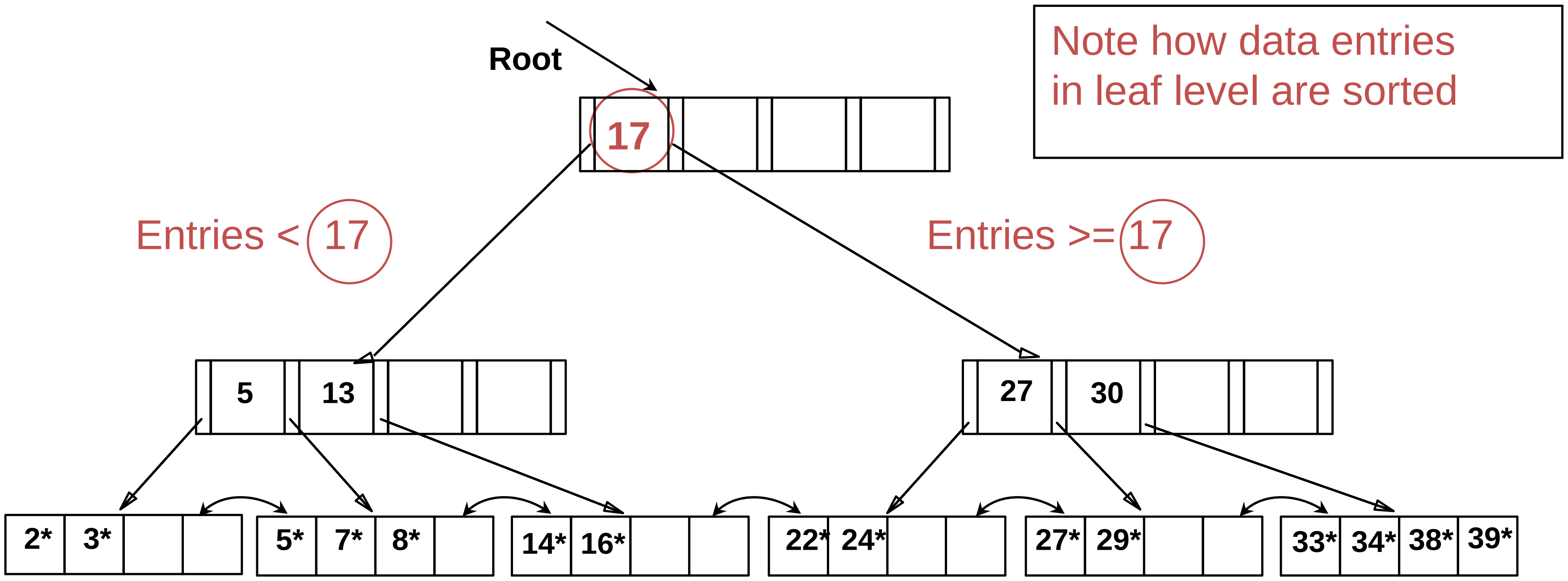
RDF3X 6 indexes (Hexastore)



Binary trees are not enough



B+ Tree

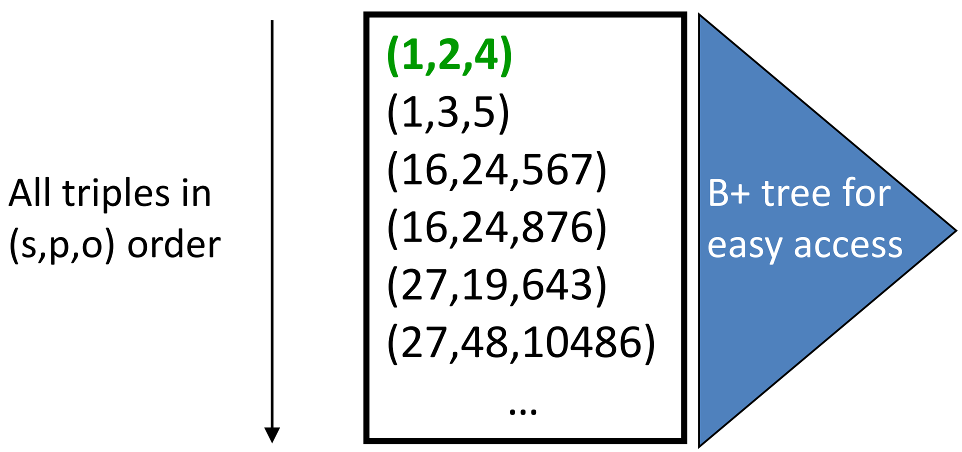


Root
17
Entries < 17
Entries >= 17
Note how data entries in leaf level are sorted
5
13
27
30
2*
3*
5*
7*
8*
14*
16*
22*
24*
27*
29*
33*
34*
38*
39*

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)**



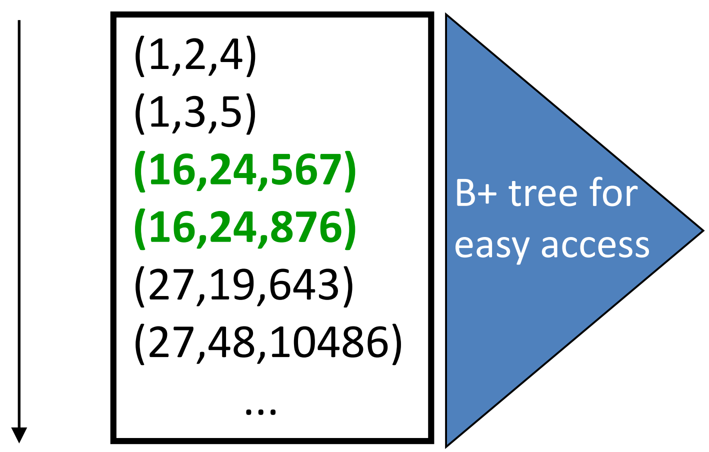
RDF3X Query Processing

```
SELECT ?x where { Einstein, invented, ?x }
```

- Lookup ids **Einstein**→ 16, **invented**
- Read prefix matches (16,24): **(16,24,567) (16,24,876)**

already sorted

All triples in (s,p,o) order



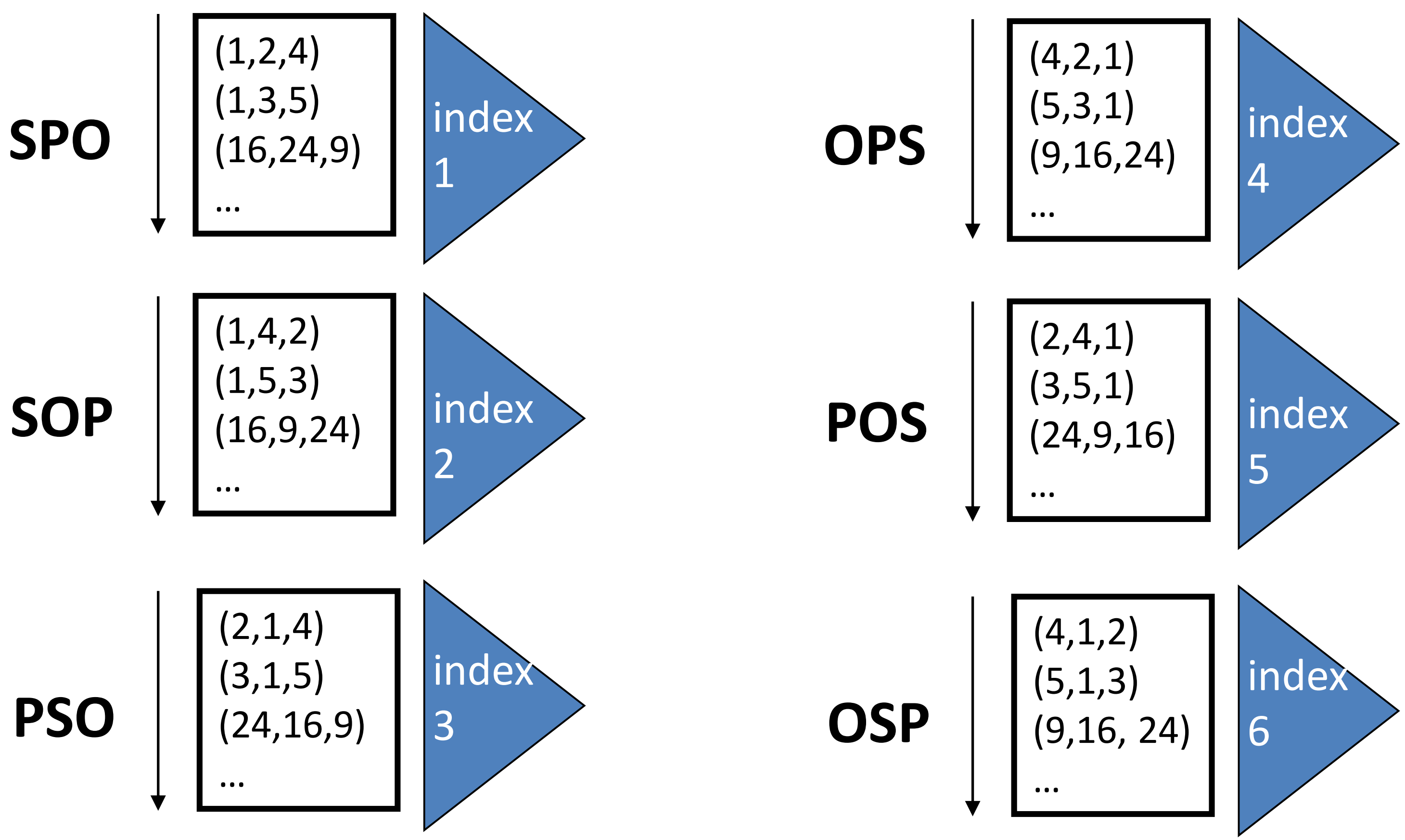
RDF3X Storage and Indexing

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 ?

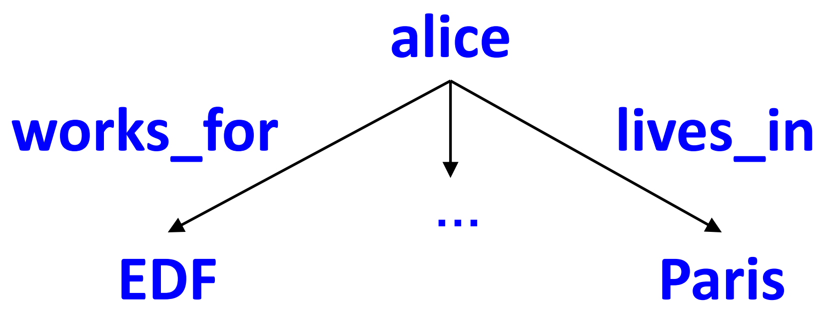


Now, how join two (**2**) triple patterns ?

```
SELECT ?x where {
                  ?x, lives_in, Paris.
                  ?x, works_for, EDF
                  }
```

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

Recall Dictionnary



dictionary

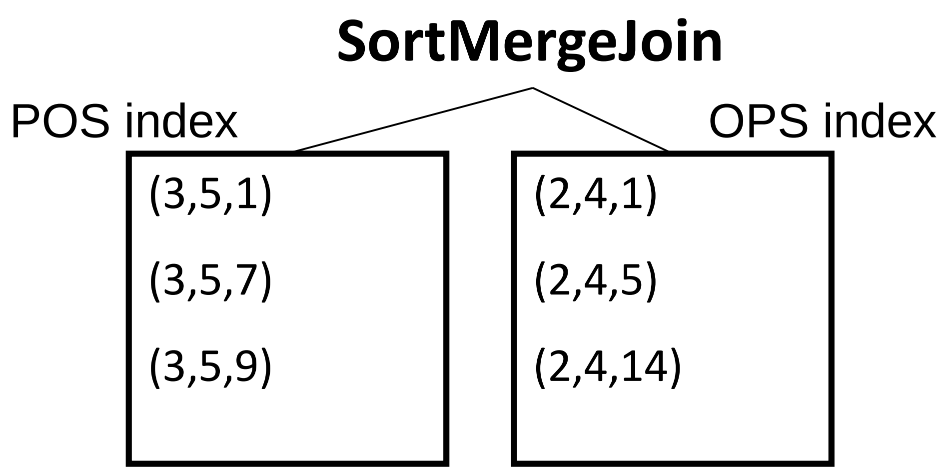
id	string
1	alice
2	works_for
3	lives_in
4	EDF
5	Paris

Giant-Table

subject	pred.	object
1	2	4
1	3	5

RDF3X : Sort-Merge-join

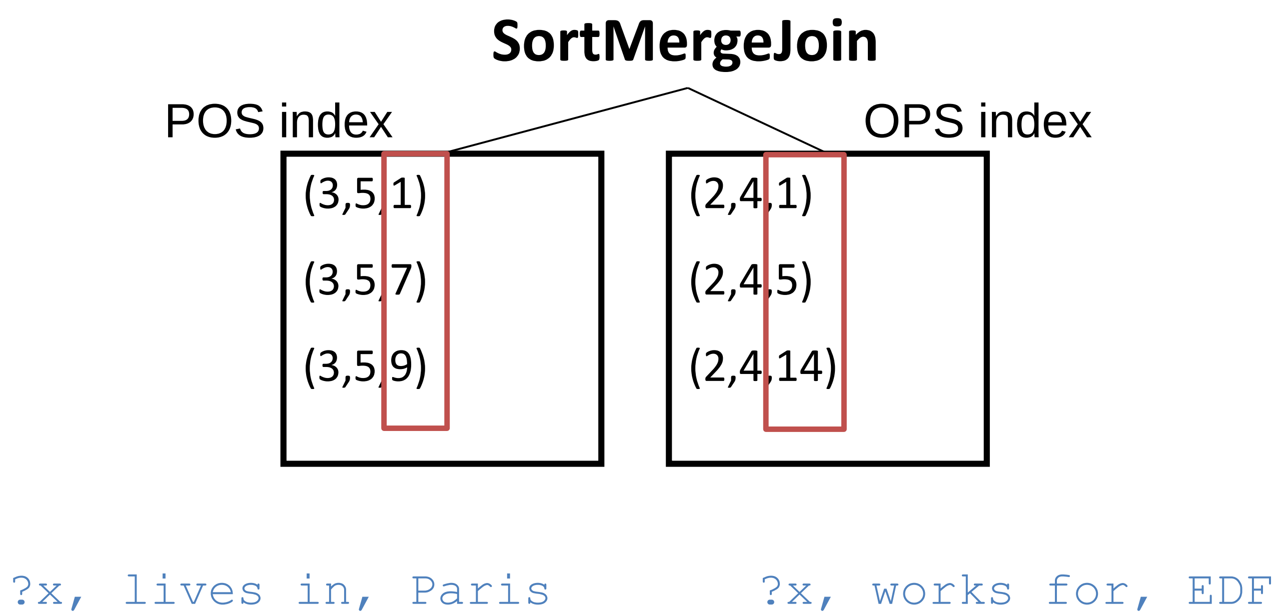
- For example, we decide to use POS & OPS index for 1^{st} & 2^{nd} pattern, respectively.
  – we will see next why we did this choice



`?x, lives_in, Paris`   `?x, works_for, EDF`

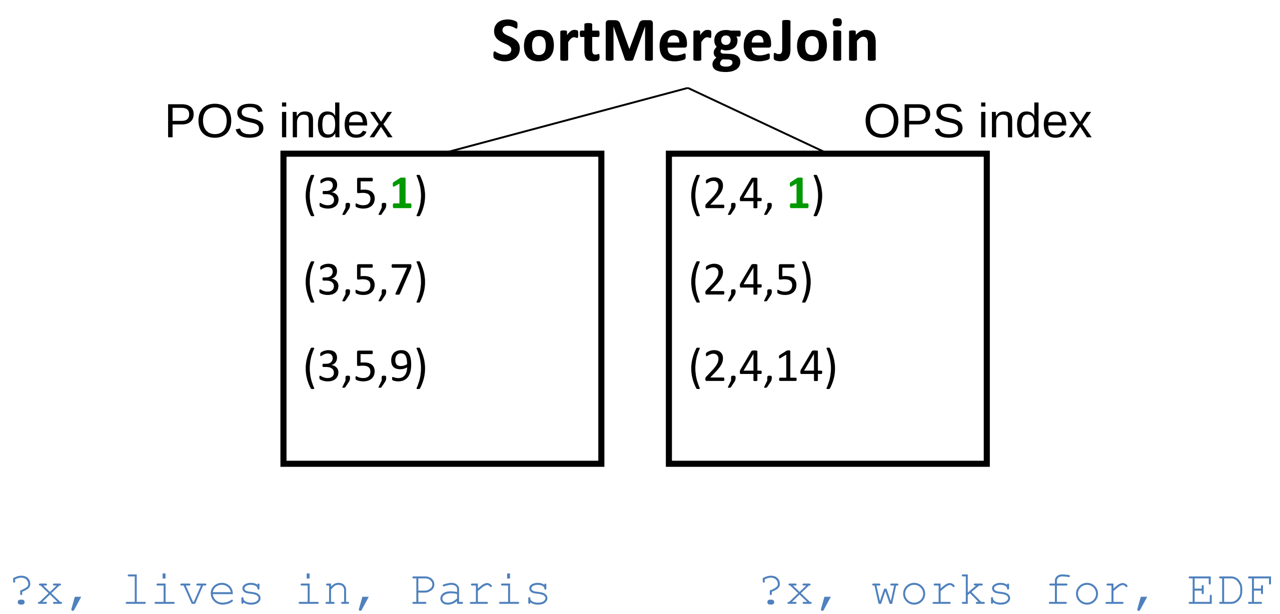
RDF3X : Sort-Merge-join

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



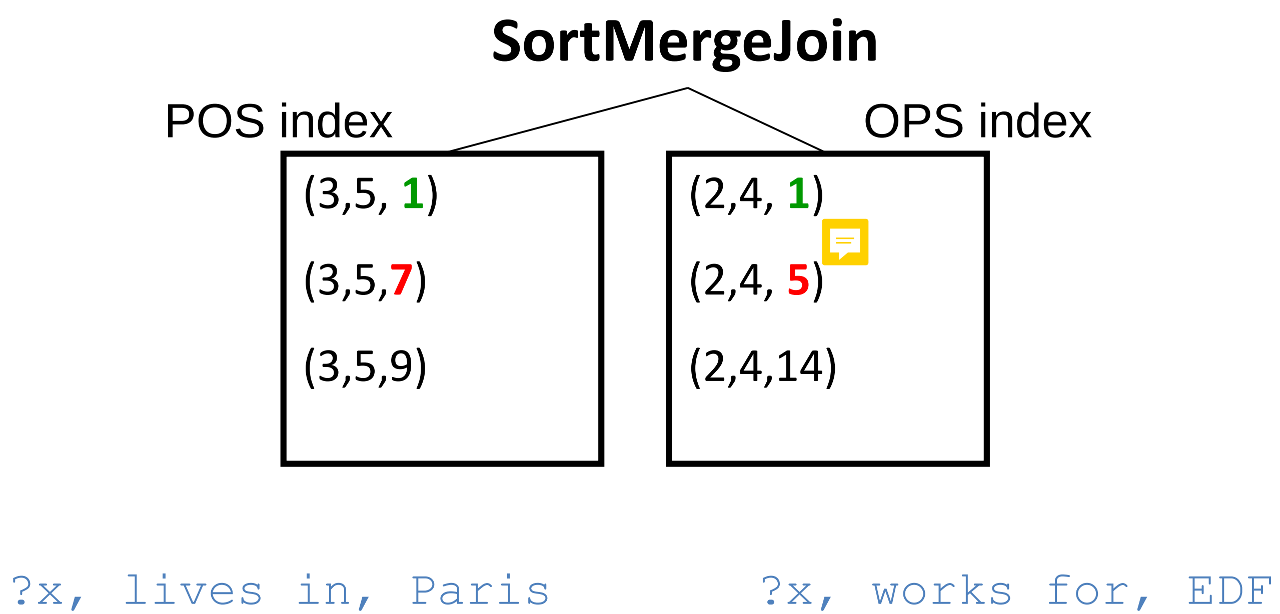
RDF3X : Sort-Merge-join

- We access POS[3.5.**1**] and OPS[2.4.**1**]
  - we find **1** on both sides -> query result



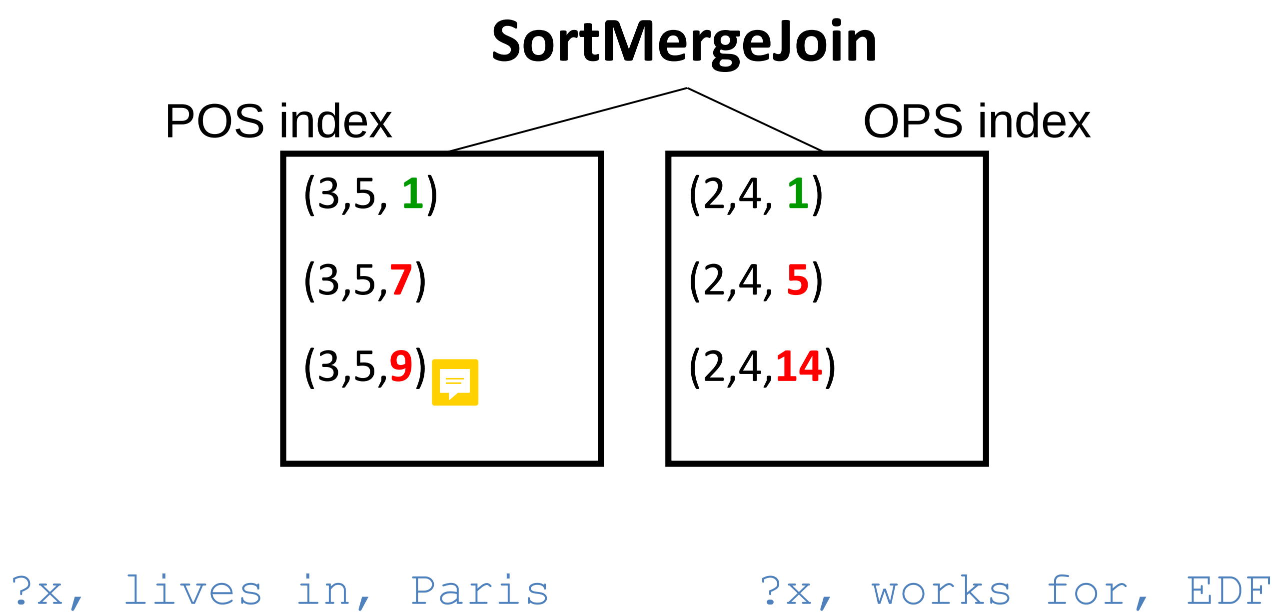
RDF3X : Sort-Merge-join

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



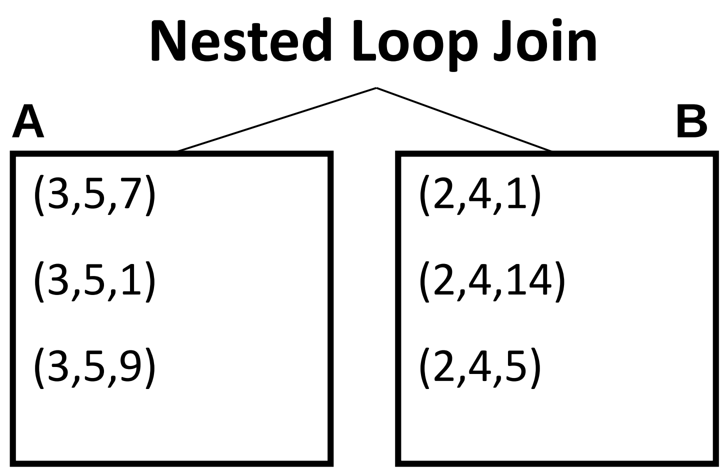
RDF3X : Sort-Merge-join

- 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 x of A
          for each element y of B
                  compare x with y
```



RDF3X Query Evaluation

- How to join n-triple patterns $t_1 \ldots t_n$?

```
SELECT ?x where {   ?x, lives_in, ?y             .  t1
                         ?x, works_for, ?z
    .  t2
                    ?y, isLocatedIn, "US"        .  t3
                    ?z, isLocatedIn, "US"           t4
                    }
```

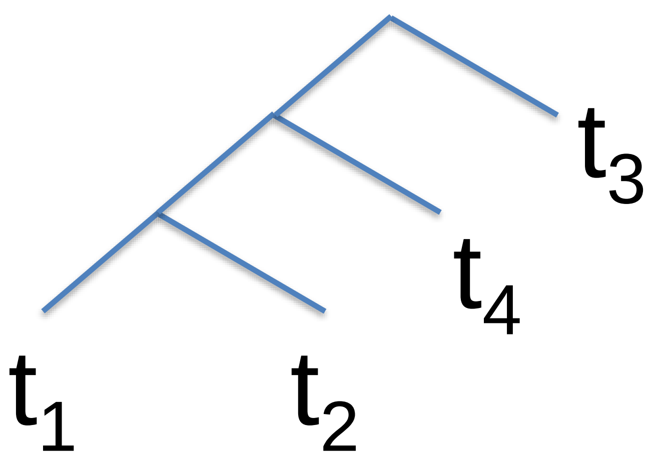
Classical relational problem: choose a left-deep join order, like

$$(\ (t_1 \text{ Join } t_2)\ \text{ Join }\ t_4)\ \text{ Join } t_3)$$

RDF3X Query Evaluation

Classical problem: chose a left-deep plan, like

$$(\ (t_1 \text{ Join } t_2) \ \text{ Join } \ t_4) \ \text{ Join } t_3)$$



Scenario 1 : no triples using property `lives_in`

- then

$$(\quad (t_1 \text{ Join } t_2) \quad \text{Join} \quad t_4) \quad \text{Join } t_3)$$

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

```
SELECT ?x where {   ?x, lives_in,   ?y        .      t1
                    ?x, works_for, ?          .      t2
                    ?y, isLocatedIn, "US" .          t3
                    ?z, isLocatedIn, "US"            t4
                    }
```

Scenario 2: no triples using property `isLocatedIn`

- then

$$((t_1 \text{ Join } t_2) \text{ Join } t_4) \text{ Join } t_3)$$

is **not** optimal as it computes (t_1 Join t_2) before understanding that the query is empty

```
SELECT ?x where {
                    ?x, lives_in,  ?y .          t1
                    ?x, works_for, ?z .          t2
                    ?y, isLocatedIn, “US” .      t3
                    ?z, isLocatedIn, “US”        t4
                    }
```

Scenario 3 : `isLocatedIn` is very rare and `lives_in` is more frequent than `works_for`

- then

$$(t_4 \text{ Join } t_2) \quad \text{Join} \quad (t_3 \text{ Join } t_1)$$

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          .     t1
                    ?x, works_for, ?z .              t2
                    ?y, isLocatedIn, "US"      .     t3
                    ?z, isLocatedIn, "US"            t4
                    }
```

COLUMN-STORES

Column-store

Relational database, storing relations as <u>columns</u>.

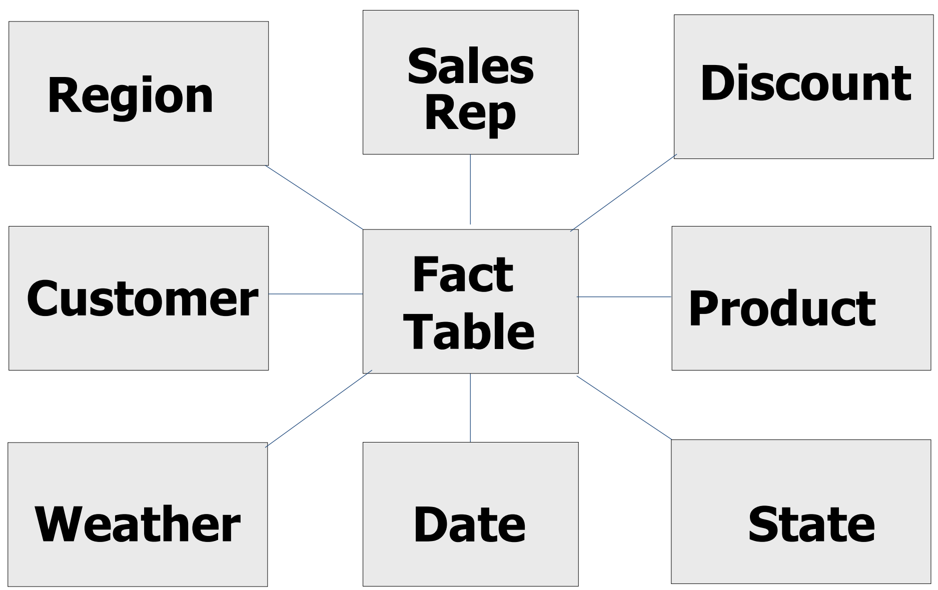
(C-Store, MonetDB and VectorWise, Ingres, IBM&MS Analytics)

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

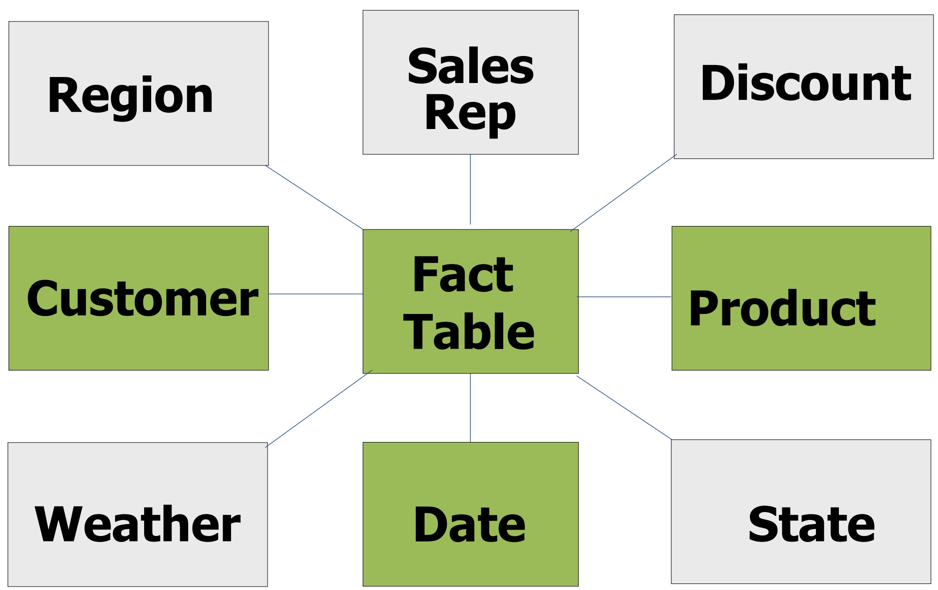
- *«Do not call them column-stores, just modern DB systems.»*
  Stratos Idreos



- 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

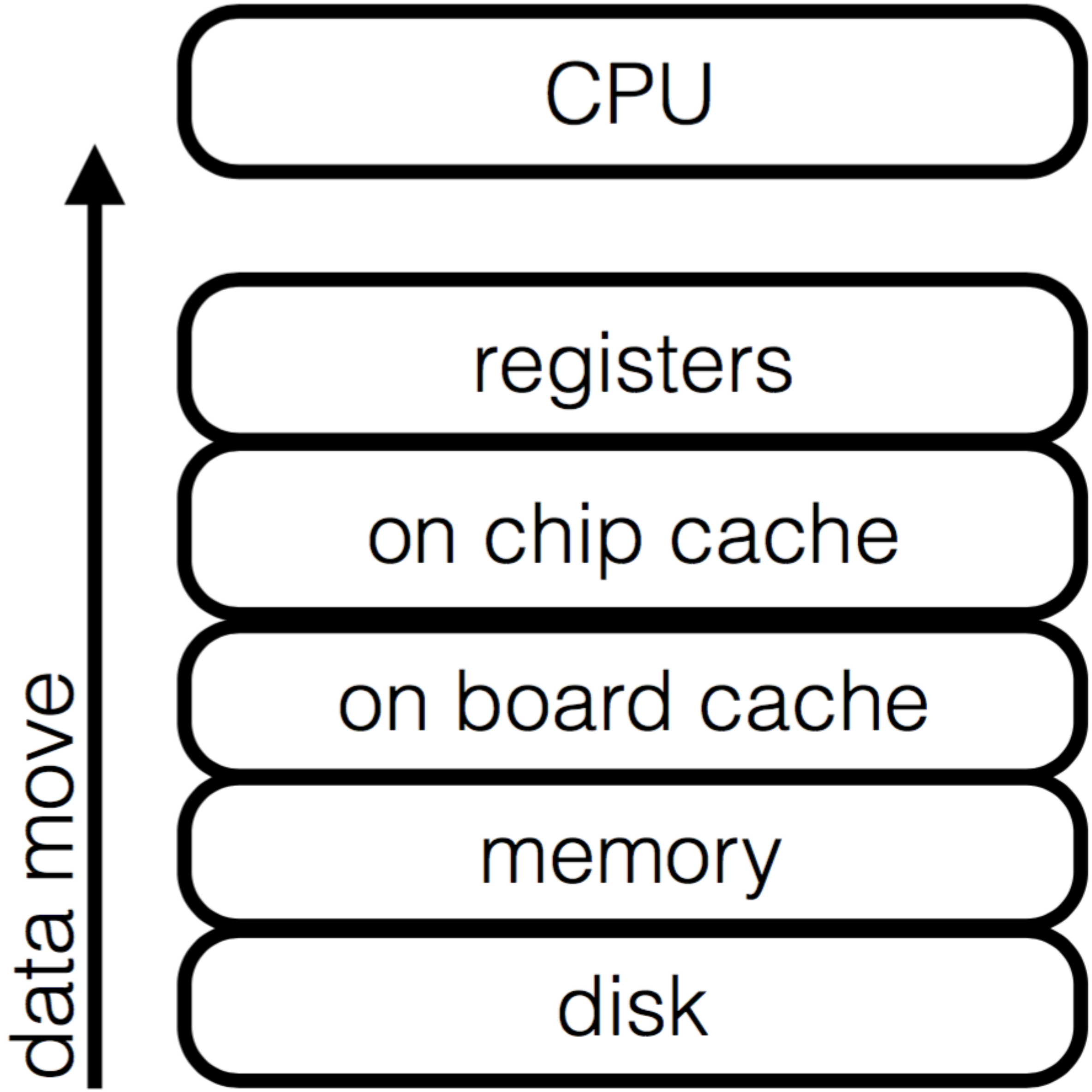
Rows become crowded

row1	id1@customer1@region1@sales_rep1@discount1@product1@weather1@date1@state1…	**row2**	id2@customer2@region2@sales_rep2@discount2@product2@weather2@date2@state2	…

Worst case : visit whole row

row1	**id1**@**customer1**@region1@sales_rep1@discount1@**product1**@weather1@**date1**@state1…	**row2**	**id2**@**customer2**@region2@sales_rep2@discount2@**product2**@weather2@**date2**@state2	…

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

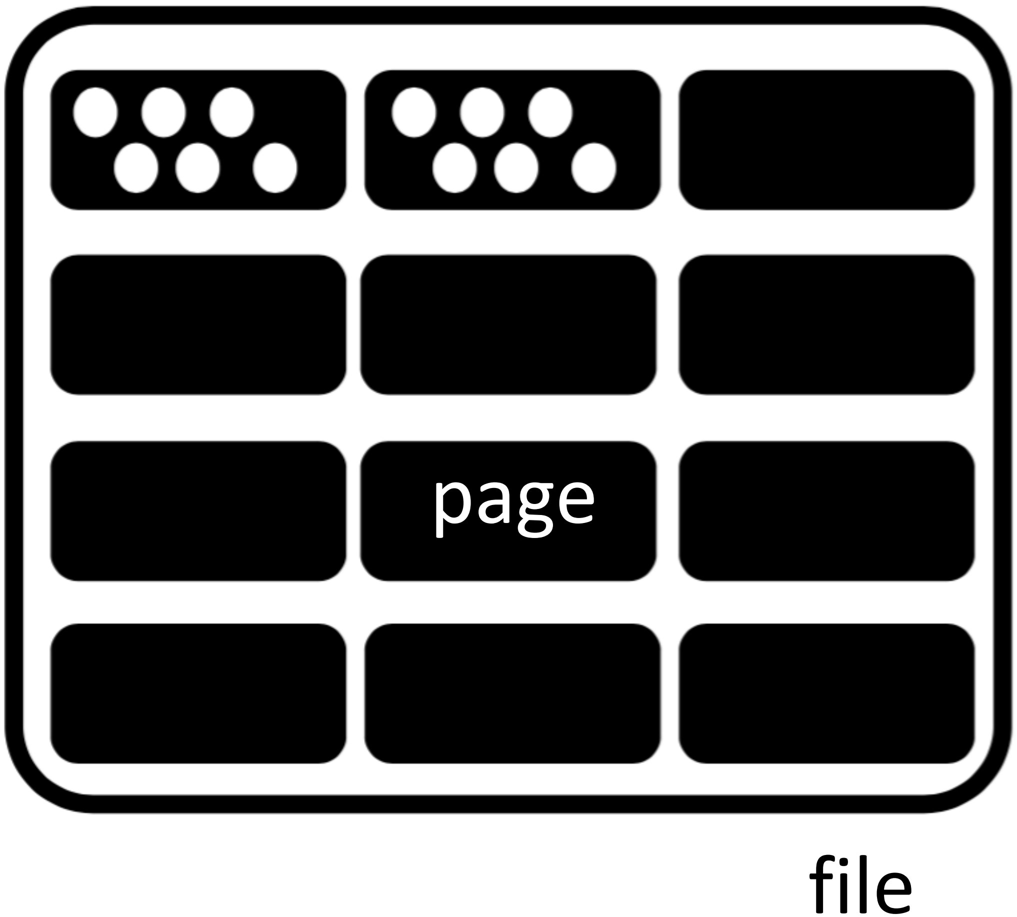

CPU
registers
on chip cache
on board cache
memory
disk
data move

Rows are stored in pages

row1	**id1**@**customer1**@region1@sales_rep1@discount1@**product1**@weather1@**date1**@state1…	**row2**	**id2**@**customer2**@region2@sales_rep2@discount2@**product2**@weather2@**date2**@state2	…

page

Pages are stored within files

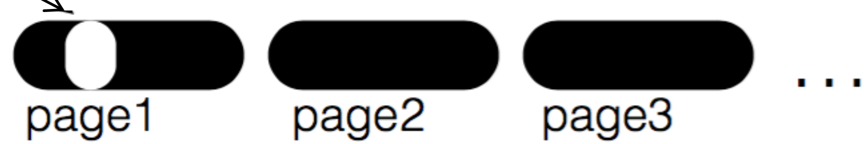


Constraint : Pages are read as a whole!

need to only read row ***x***...

but have to read all of page 1

data value ***x***

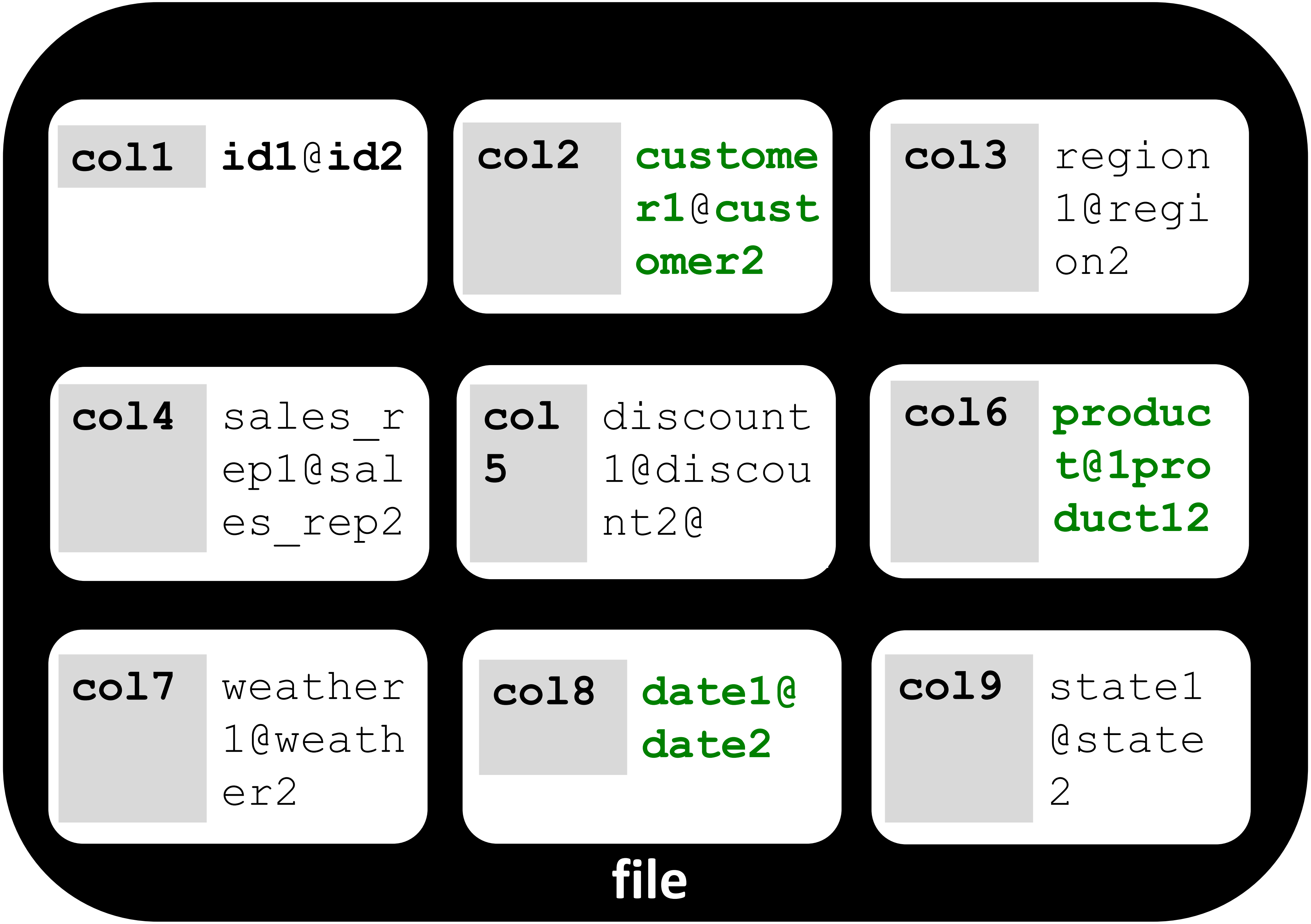


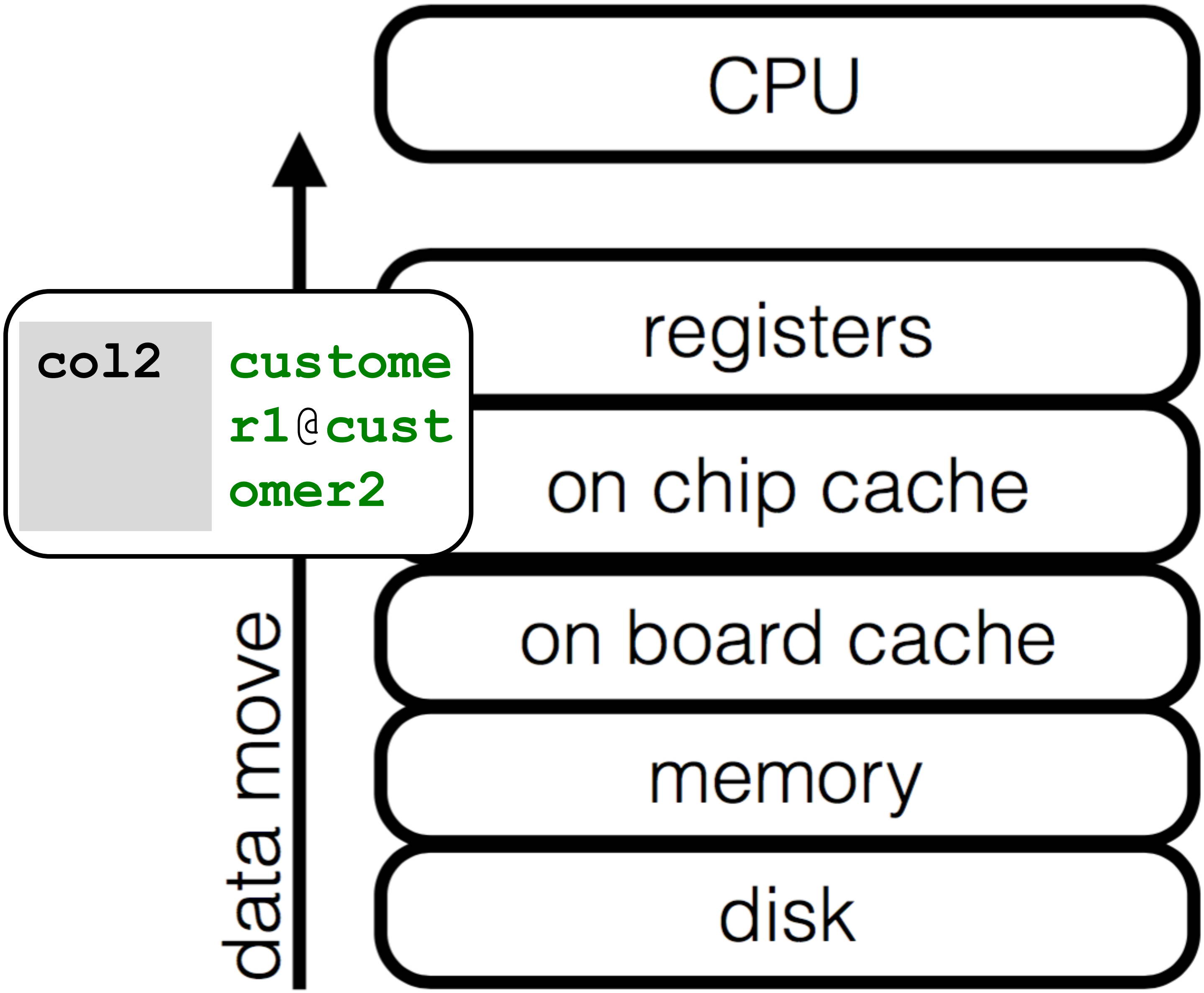
Better to « pay as you go »!

col1	**id1@id2**	**col2**	**customer1@customer2**	**col3**	region1@region2
col4	sales_rep1@sales_rep2	**col5**	discount1@discount2@	**col6**	**product@1product12**
col7	weather1@weather2	**col8**	**date1@date2**	**col9**	state1@state2

Store columns on separate pages!

col1	**id1@id2**	**col2**	**customer1@customer2**	**col3**	region1@region2
col4	sales_rep1@sales_rep2	**col5**	discount1@discount2@	**col6**	**product@1product12**
col7	weather1@weather2	**col8**	**date1@date2**	**col9**	state1@state2


col1
id1@id2
col2
customer1@customer2
col3
region1@region2
col4
sales_rep1@sales_rep2
col5
discount1@discount2@
col6
product@1product12
col7
weather1@weather2
col8
date1@date2
col9
state1@state2
file


CPU
registers
on chip cache
on board cache
memory
disk
data move
col2
custome
r1@cust
omer2

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
	…	

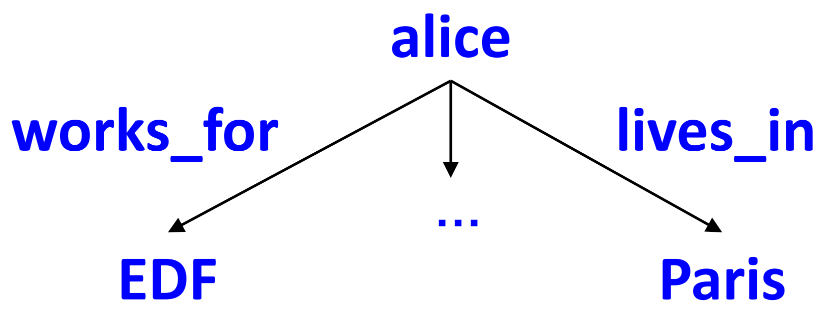
works_for

subject	object
alice	EDF
…	

lives_in

subject	object
alice	Paris
…	

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



Property-Tables

works_for

subject	object
alice	EDF
bob	SFR
...	

lives_in

subject	object
bob	Lyon
alice	Paris
...	

works_for	col1	alice@bob...	col2	EDF@SFR...
lives_in	col1	bob@alice...	col2	Paris@Lyon...

Neat advantage : column-projection

- Fast queries if only subject or object of a triple are accessed, <u>not both</u>

```
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

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

- Inefficient for triple patterns with predicate variable

  <alice **?p** bob>

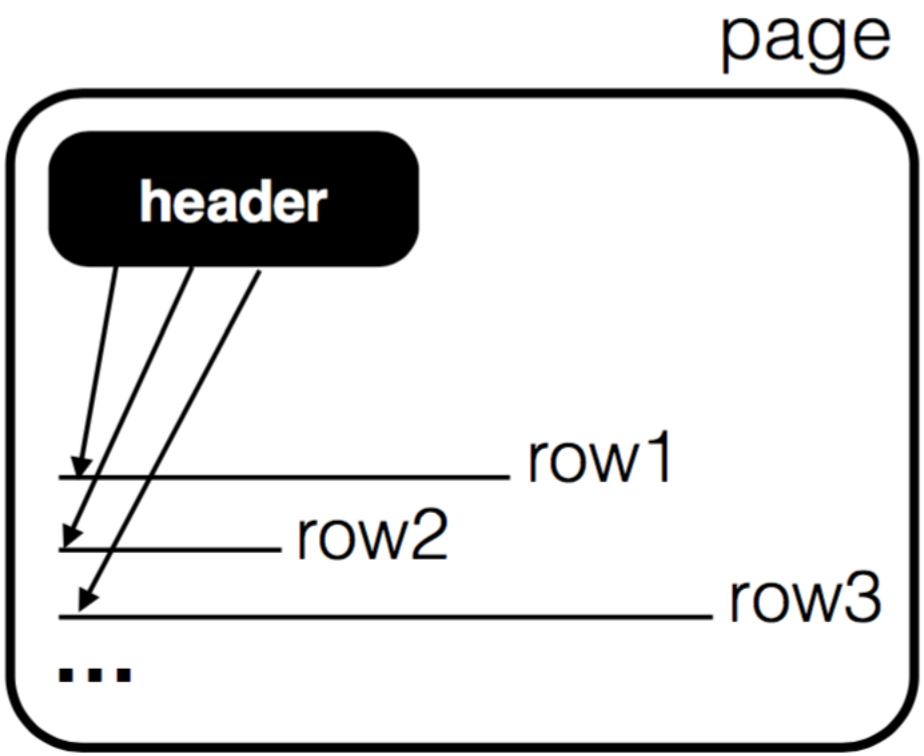
- Big question : when to reconstruct a tuple ? (alap)

Advantages of Column Stores

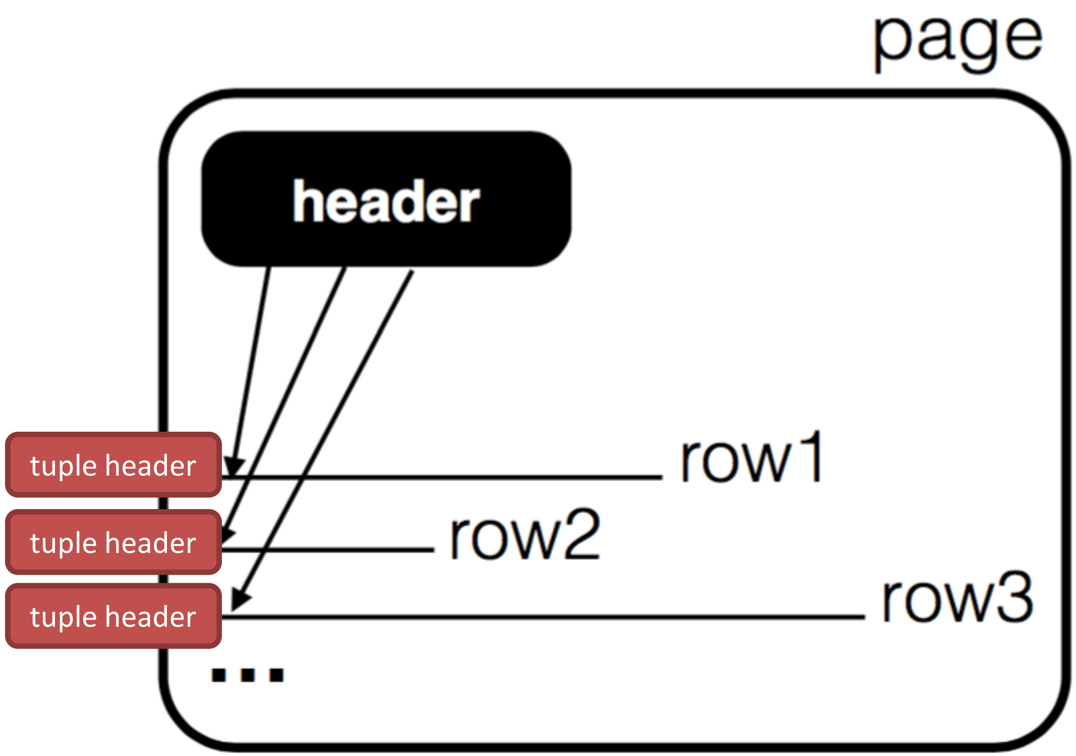
1. Tuple Headers Stored Separately
2. Optimizations for fixed-length tuples
3. Column-oriented data compression
4. Carefully optimized merge-join code

TUPLE HEADERS

Page headers in Rowstores



Tuple headers in Rowstores



$$|\text{ tuple header }| \gg |\text{row}_{\text{of size 2}}|$$

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 two-column tables

$$| \text{header} | \gg |\text{row}_{\text{of size 2}}|$$

Postgres Tuple Header

Field	Type	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	ItemPointerData	6 bytes	current TID of this or newer row version
t_infomask2	int16	2 bytes	number of attributes, 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	

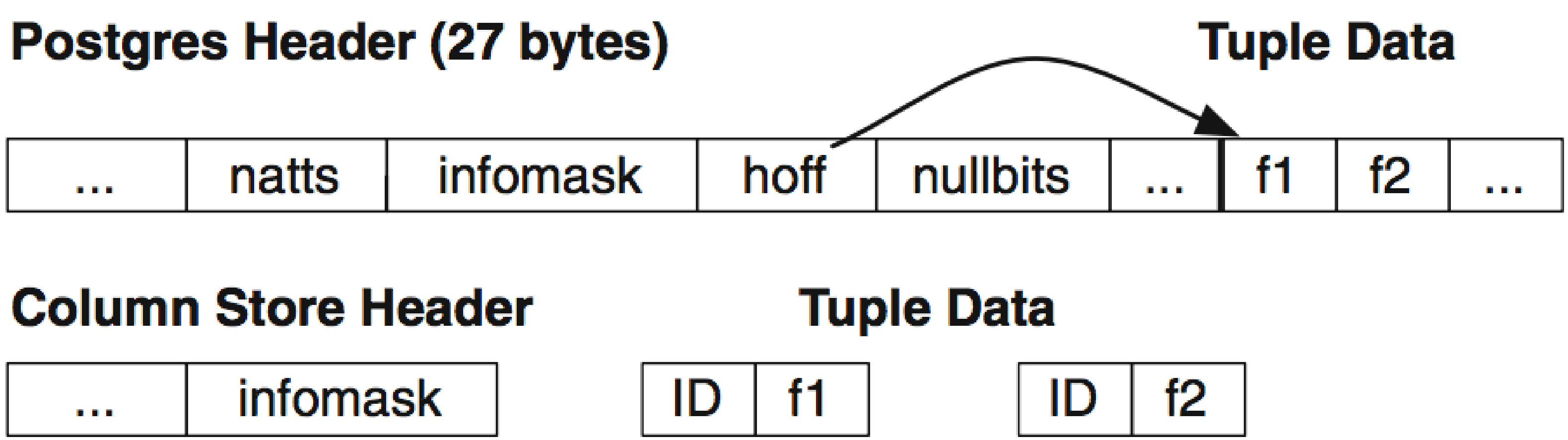
Postgres Tuple Header

- 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

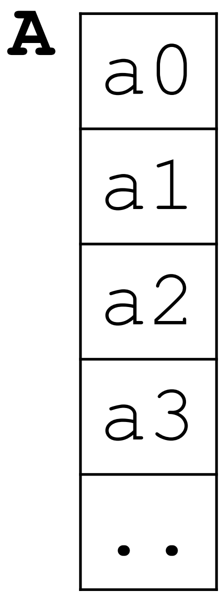
- 1 attribute variable length => the whole tuple is
- Common case: row-stores designed for this

```
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**



Positional lookup

`a(i) = A + i*width(A)`

Optimizations for fixed-length tuples

- Every RDF property table has two columns

`works_for`

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

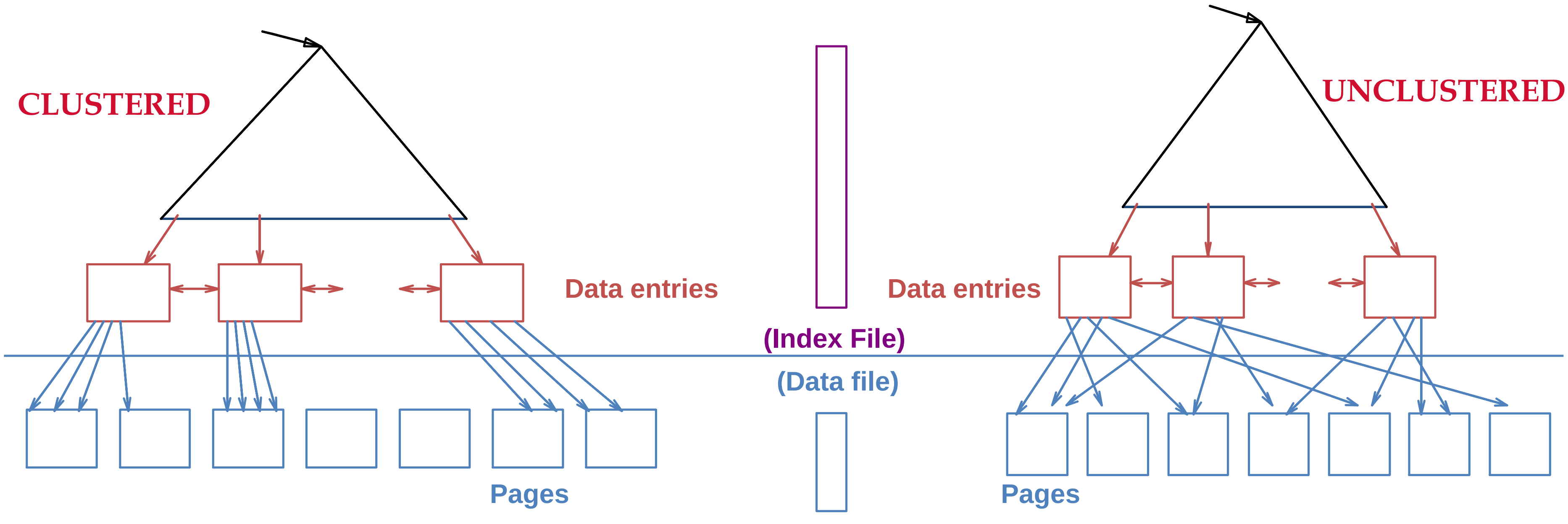
P

s0	o0
s1	o1
s2	o2
s3	o3
.. ..	

`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_{Obama}
id_{Alice}
id_{Paris}
..

Id-Table

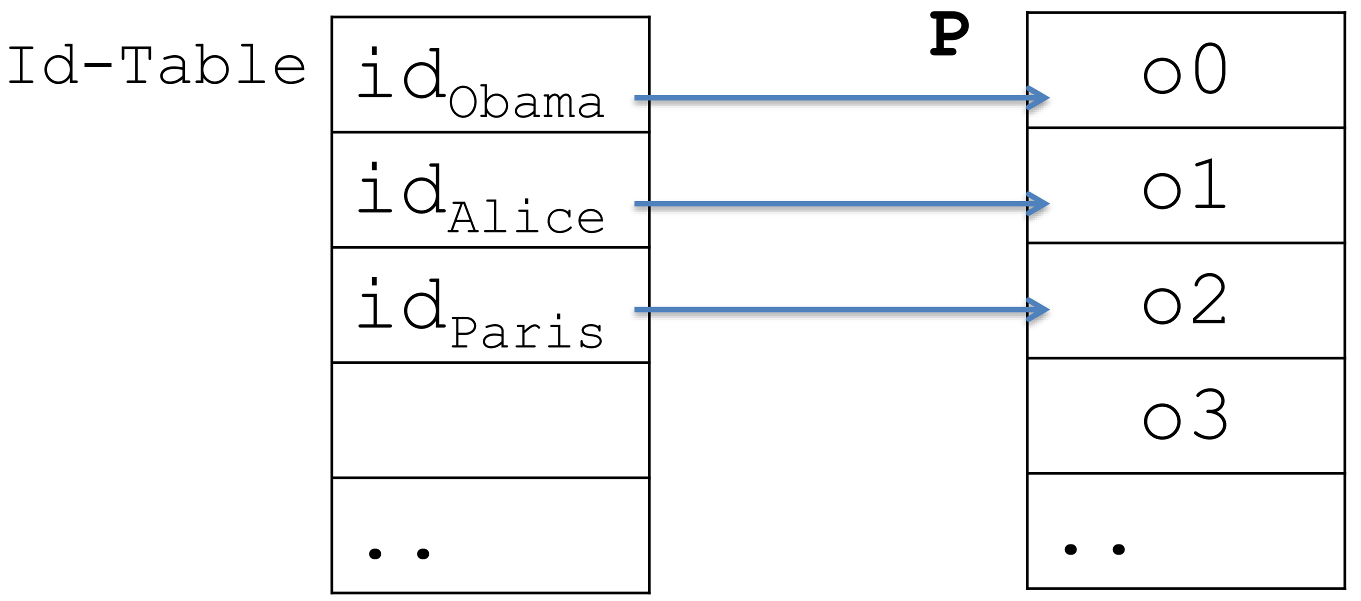
- If property **P** is <u>NOT</u> multivalued (eg. birthday) we can avoid to store subject id

Id-Table
id_{Obama}
id_{Alice}
id_{Paris}
..

P
o0
o1
o2
o3
..

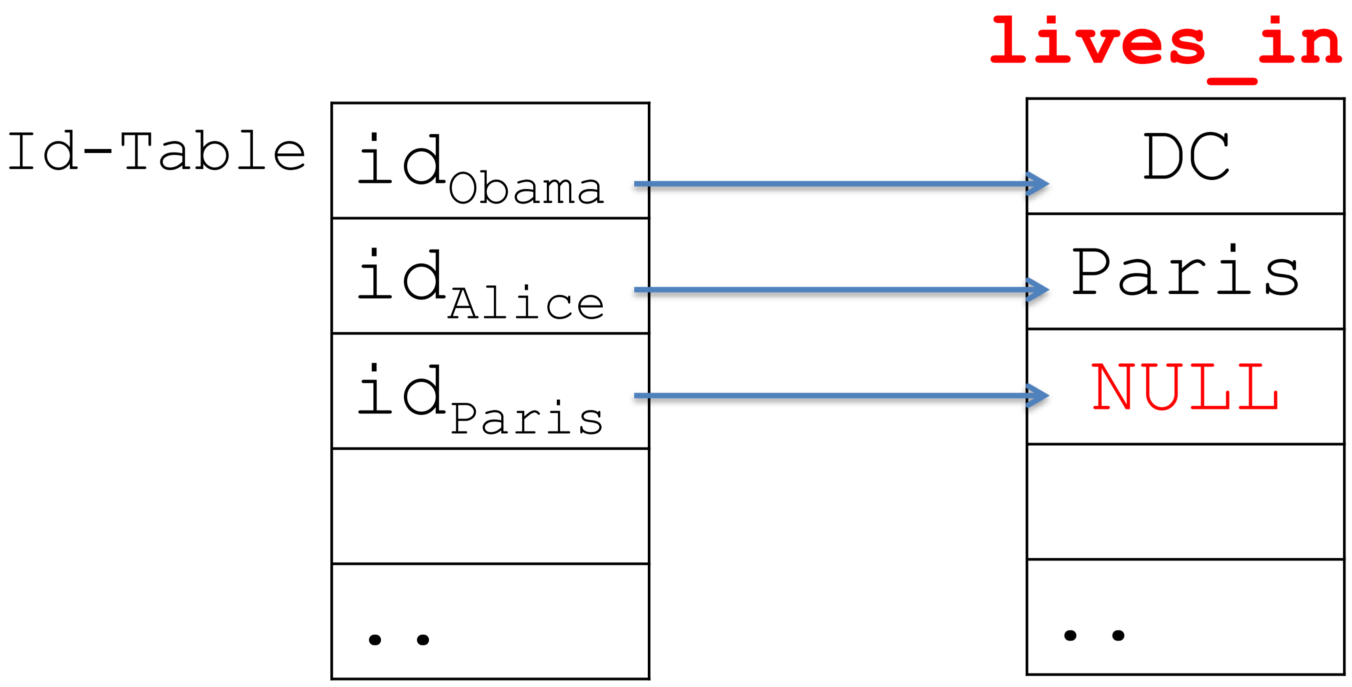
Id-Table

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



Nulls are back!

- If property **P** is <u>NOT</u> 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

Dense

Not dense nor sparse

Sparse

Case 1: «dense» data and long null sequences

Title

t1
t2
t3
t4
NULL

Language

NULL
FR
EN
NULL
NULL

Case 1: Low overhead for «dense» data

- Store indexes of non-null values

Title

t1
t2
t3
t4
NULL

Title Range[1-4]

t1
t2
t3
t4

Case 1: Low overhead for «dense» data

- Store indexes of non-null elements

Language
NULL
FR
EN
NULL
NUL

Language
FR
EN

Range[2-3]

Case 1: Low overhead for «dense» data

- Store indexes of non-null elements

- If data is dense, then

$$|\text{range information}| \ll |\text{nulls}|$$

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

2001
NULL
1985
NULL
1995

- Overhead = 1bit per value

Case 3 : sparse data

- Store the list of non-null ids

Author

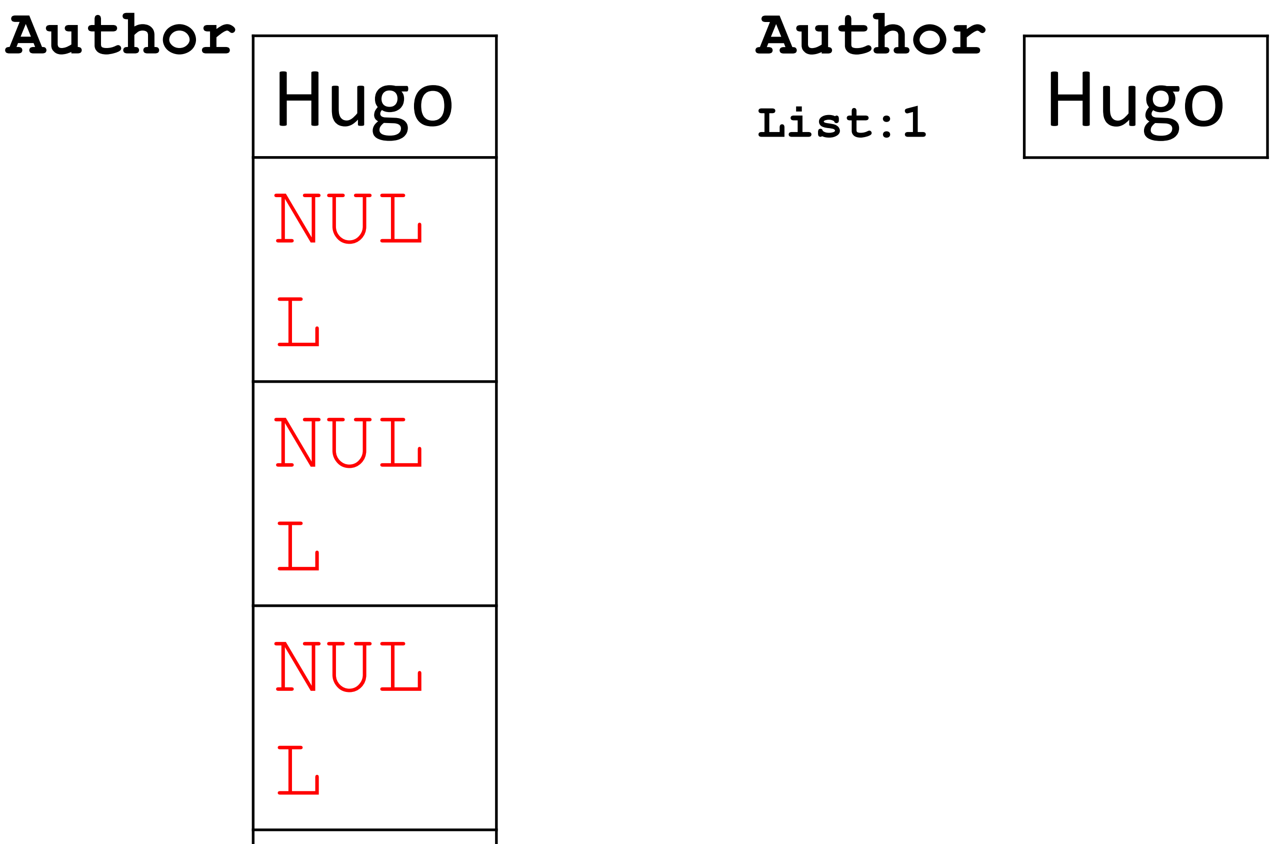
Hugo
NULL
NULL
NULL

Artist

NULL
Dylan
NULL
NULL

Case 3 : sparse data

- Store the list of non-null ids



Case 3 : sparse data

- Store the list of non-null ids

Artist

NULL
Dylan
NULL
NULL

Artist

List:2

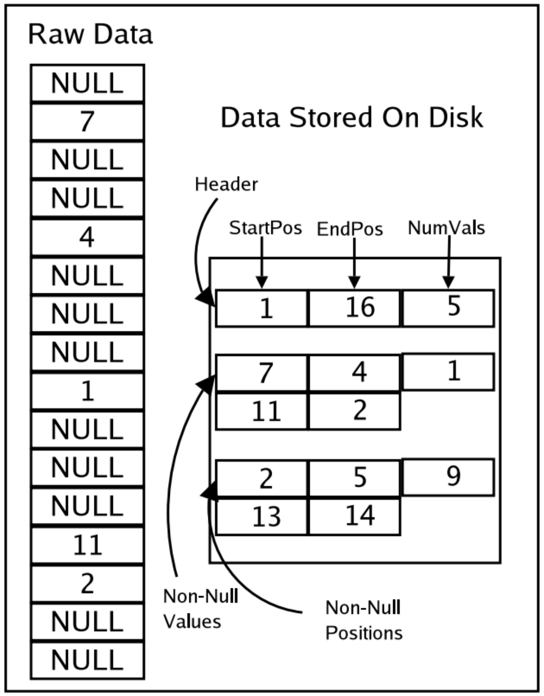
Dylan

Case 3 : sparse data

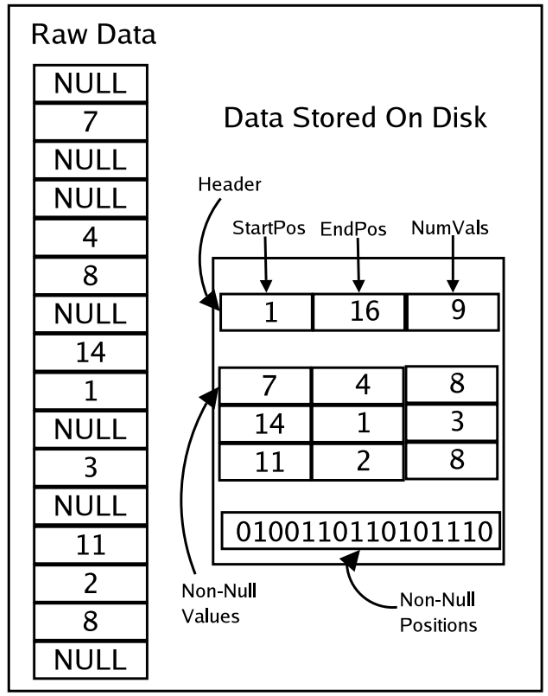
- Store the list of non-null ids

- If data is sparse

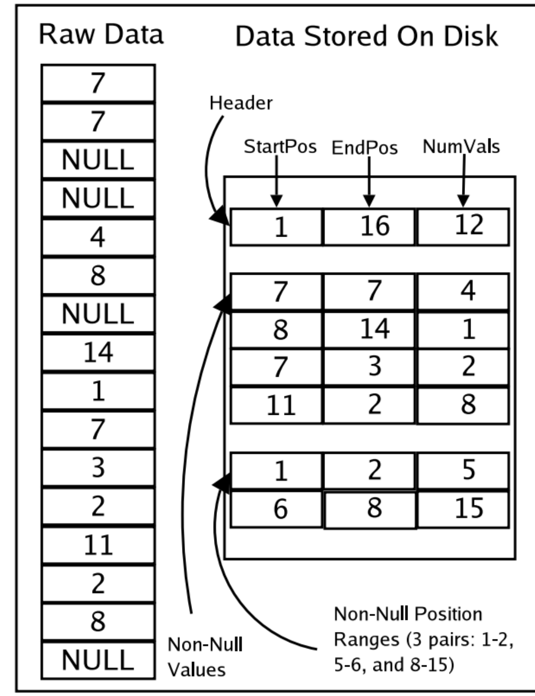
$$|List| << |nulls|$$



(a)



(b)



(c)

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

Back to Query Evaluation

triple pattern selectivity

```
SELECT ?y ?z where {
        ?x, author,  Hugo        .
        ?x, title, ?y            .
        ?x copyright ?z          .
        }
```

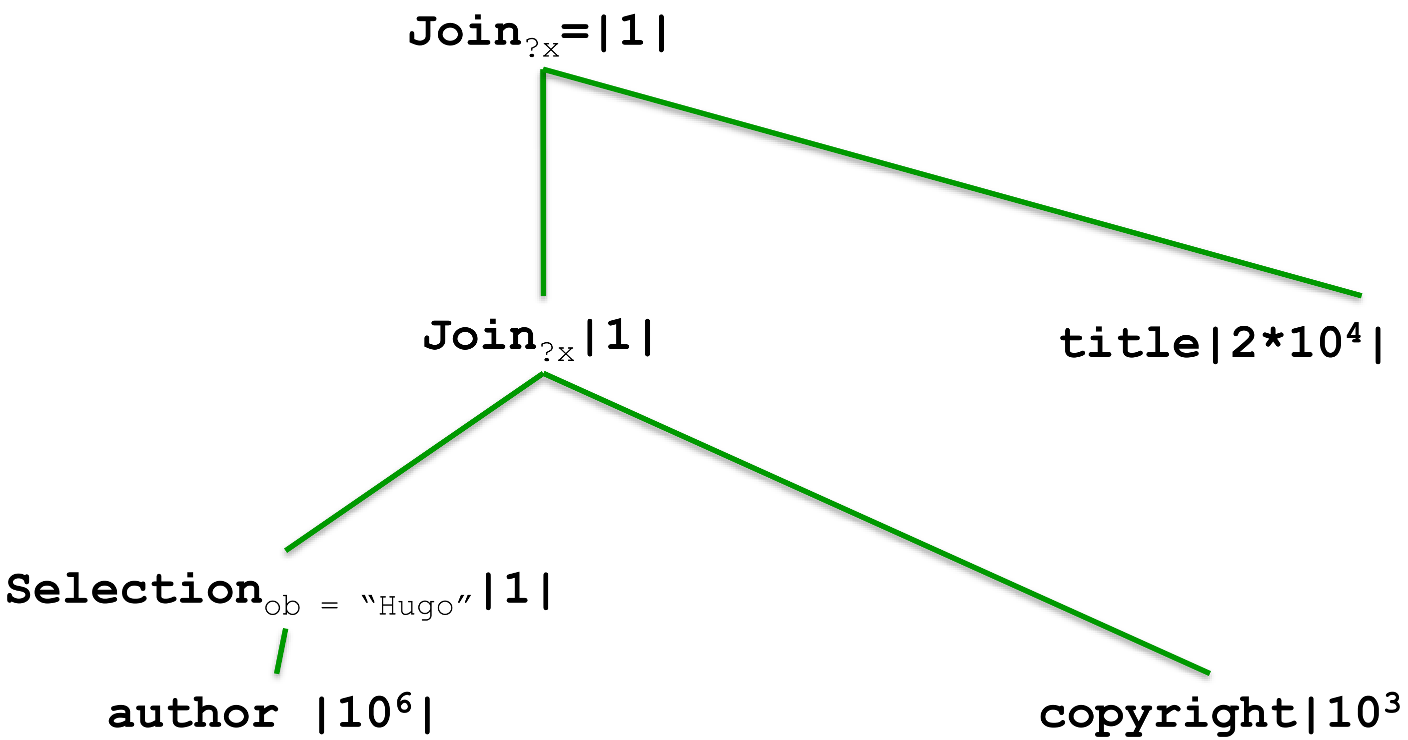
t_1 $\mathbf{10^{-6}}$

t_2 $\mathbf{2*10^{-2}}$

t_3 $\mathbf{10^{-3}}$

$(t_1 \text{ Join } t_3) \text{ Join } t_2$

Plan

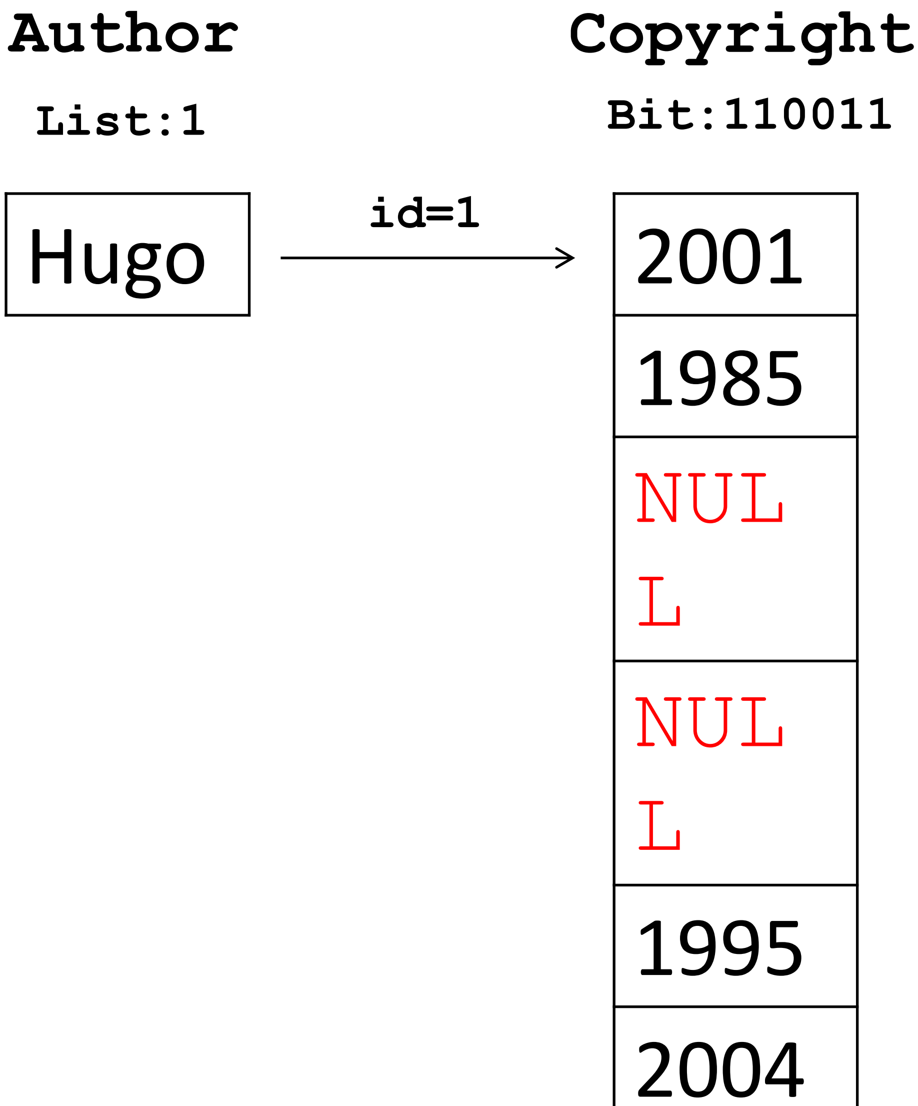


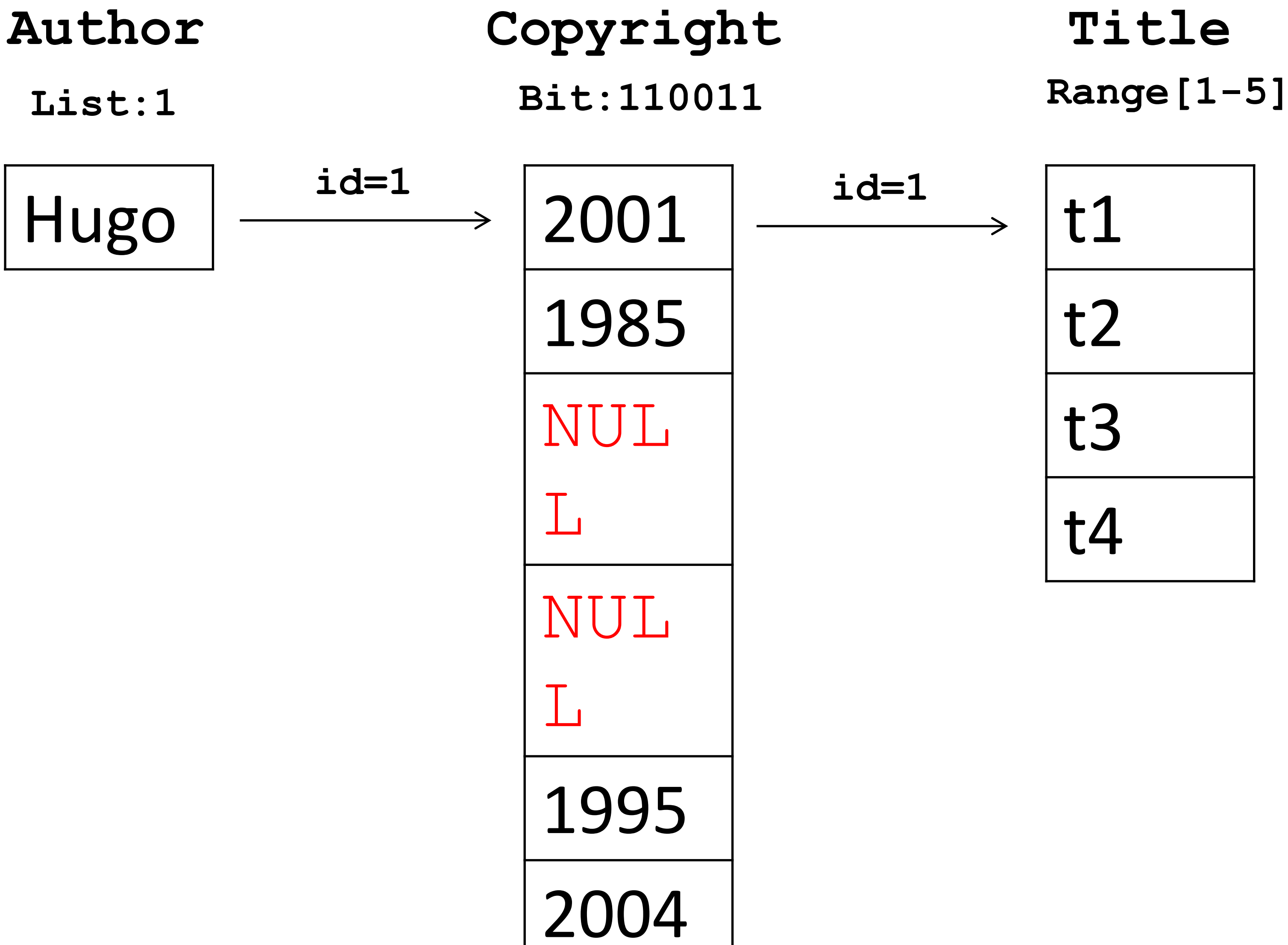
Join?x=|1|
Join?x|1|
title|2*10⁴|
Selectionob = "Hugo"|1|
author |10⁶|
copyright|10³|

Author

List:1

Hugo $\xrightarrow{\texttt{id=1}}$


Author
List:1
Hugo
id=1
Copyright
Bit:110011
2001
1985
NULL
NULL
1995
2004


Author
List:1
Hugo
id=1
Copyright
Bit:110011
2001
1985
NULL
NULL
1995
2004
id=1
Title
Range[1-5]
t1
t2
t3
t4

Query

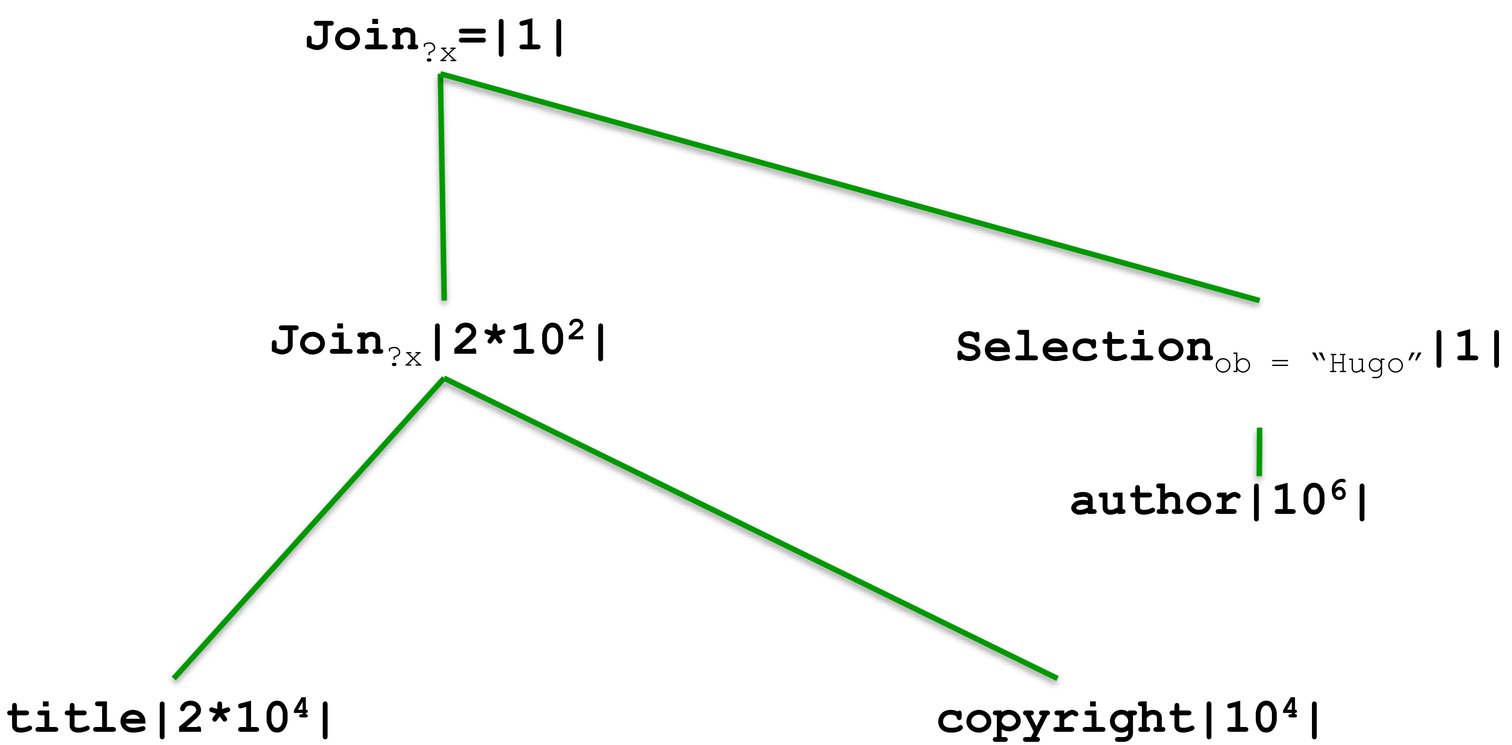
triple pattern selectivity

```
SELECT ?y ?z where {
            ?x, author,  Hugo          .
            ?x, title, ?y              .
            ?x copyright ?z            .
            }
```

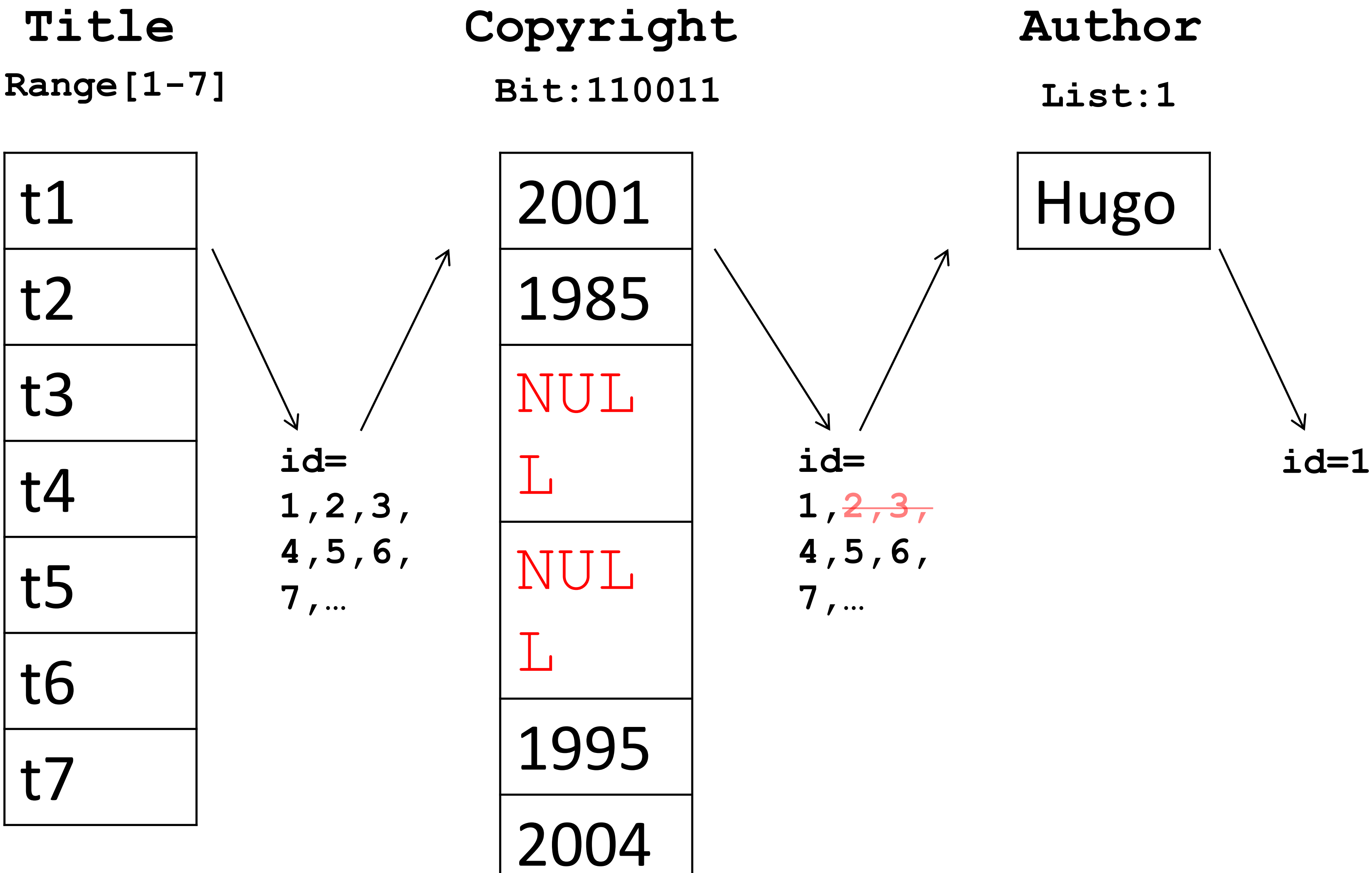
?x, author, Hugo	.	t_1	10^{-6}
?x, title, ?y	.	t_2	$2*10^{-2}$
?x copyright ?z	.	t_3	10^{-3}

$(t_2 \text{ Join } t_3) \text{ Join } t_1$

Plan



Join?x=|1|
Join?x|2*10²|
Selectionob = "Hugo"|1|
author|10⁶|
title|2*10⁴|
copyright|10⁴|


Title
Range[1-7]
t1
t2
t3
t4
t5
t6
t7
id=
1,2,3,
4,5,6,
7,…
Copyright
Bit:110011
2001
1985
NUL
L
NUL
L
1995
2004
id=
1,~~2,3,~~
4,5,6,
7,…
Author
List:1
Hugo
id=1

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?

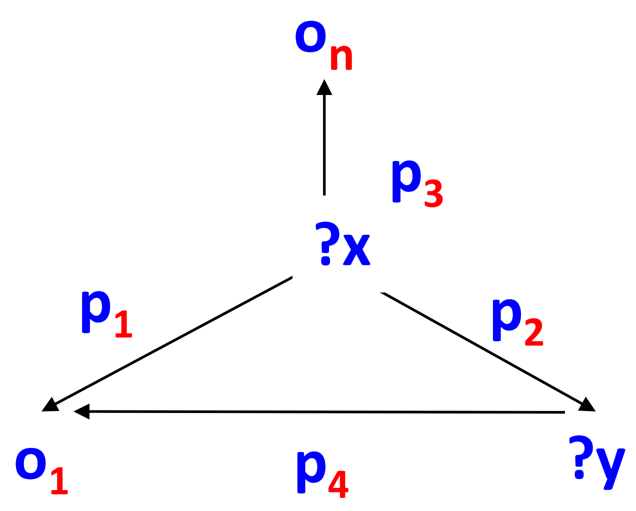
There is no single winner

	RDF-3x	VOS [6.1]	VOS [7.1]	MonetDB	4Store
% 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