Understanding and Querying Data Regardless of the Data Model

Ioana Manolescu

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Plan

1. Motivation: Data Heterogeneity
2. ESTOCADA: Heterogeneous Polystore Performance Through Views
   - How database geeks conquer heterogeneity
3. ABSTRA: Understanding Data of Any Data Model
   - How absolute newbies conquer heterogeneity

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2. View-Based Data Integration
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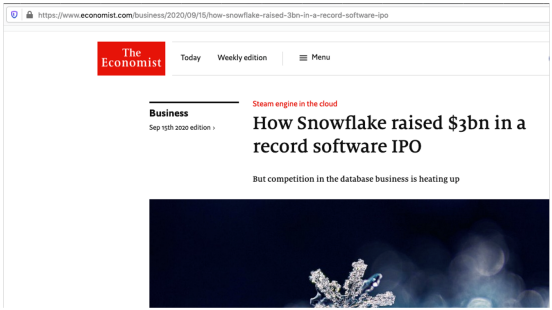
Part I

Motivation: Heterogeneous Data

Motivation: large-scale data management

Data management: a billion $ market

- Industry, trade, telecom, health, government, social, ...
- Data publishing, sharing, reusing



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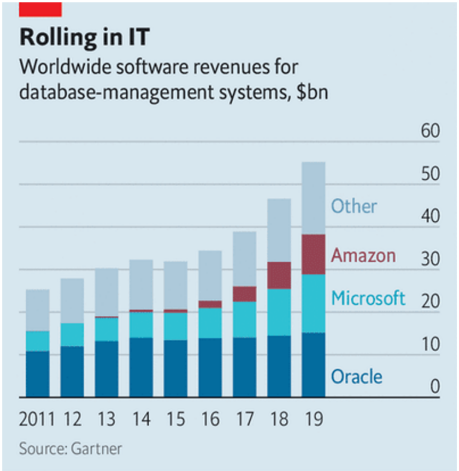

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- Industry, trade, telecom, health, government, social, ...
- Data publishing & sharing

Data heterogeneity

- Different **data formats**: relational, XML, JSON, RDF, property graphs, ...
- Replace but also frequently co-exist with other models

Data model heterogeneity: relational, XML

Relational model (also **CSV**): tables

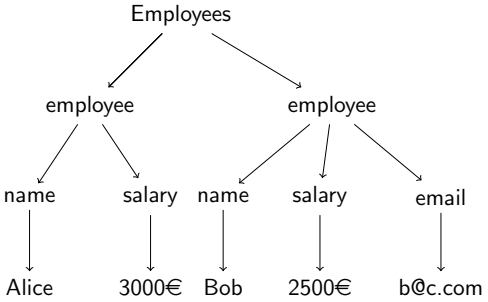
Employees

ID	name	salary
1	Alice	3000
2	Bob	2500

Query language: SQL (ISO Standard)

Most of the world's DB $

Tree-structured models: **XML** trees



Query languages: XPath, XQuery, XSLT
Great for: Web (XHTML), structured documents: finance, chemistry... medieval (TEI)

Data model heterogeneity: relational, XML

Relational model (also **CSV**): tables

Employees

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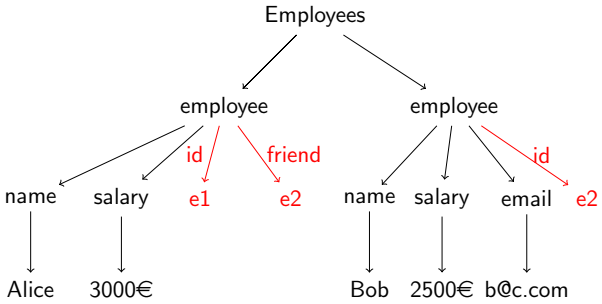
Tree-structured models: **XML** trees

```
<Employees>
   <employee> <name>Alice</name>
      <salary>3000€</salary>
   </employee>
   <employee> <name>Bob</name>
      <salary>2500€</salary>
      <email>b@c.com</email>
   </employee>
</Employees>
```

XML documents: not always trees

1. XML elements may have attributes

```
<Employees>
   <employee id="e1" friend="e2">
      <name>Alice</name>
      <salary>3000€</salary>
   </employee>
   <employee id="e2">
      <name>Bob</name>
      <salary>2500€</salary>
      <email>b@c.com</email>
   </employee>
</Employees>
```



XML documents: not always trees

2. An schema (Document Type Description or XML Schema) may state that id is a PK, and id is a FK

```
<Employees>
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      <name>Alice</name>
      <salary>3000€</salary>
   </employee>
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```
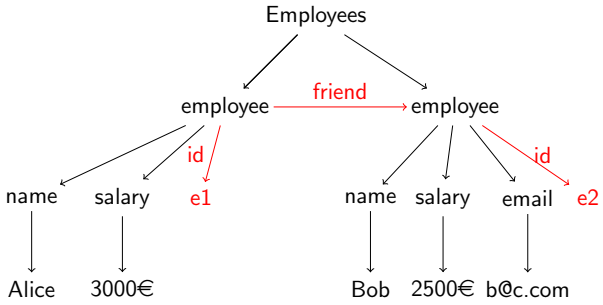
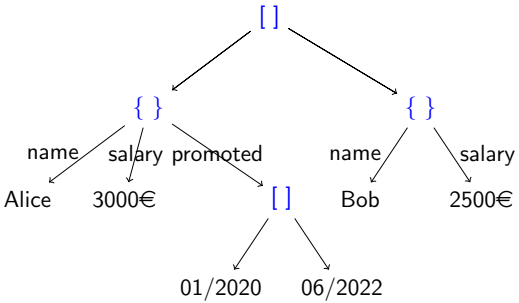



Data model heterogeneity: JSON

Tree-structured model

```
[
  {"id": "1", "name": "Alice",
   "salary": "3000",
   "promoted": ["01/2020", "06/2022"]},
  {"id": "2", "name": "Bob",
   "salary": "2500"},
]
```



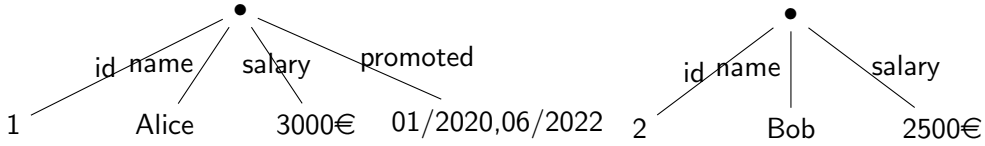
Java**S**cript **O**bject **N**otation

Compact format for heterogeneous tree-structured data

Some confusion in the use of [ ] vs. { }

Key-value pairs are simplified JSON (maps only)

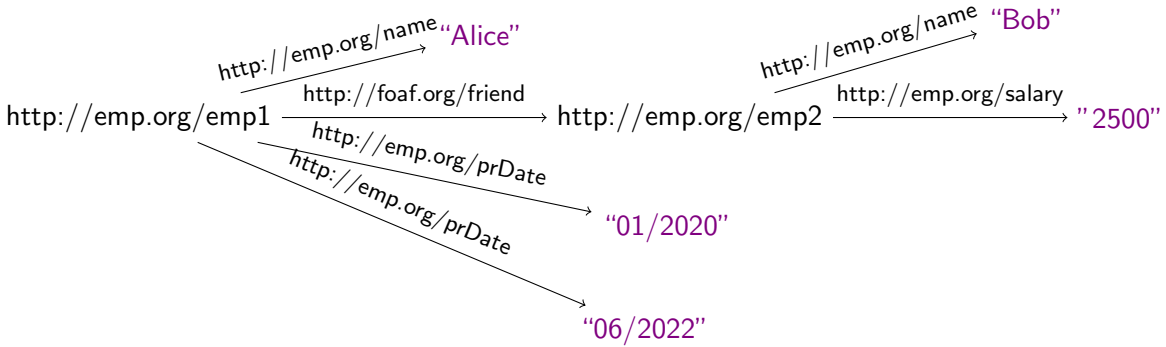
Among the simplest imaginable data models. No order.
No schema, no query language. Put/get API.



Very good for: (very) large, potentially heterogenous, tables, e.g., GoogleTables.

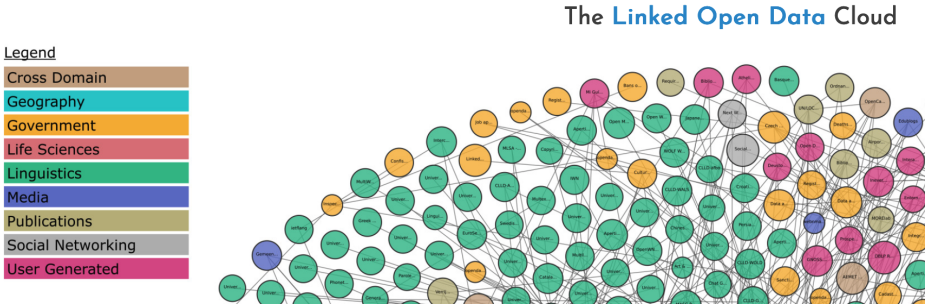
Data model heterogeneity: RDF graphs

RDF: **R**esource **D**escription **F**ramework, World Wide Web (W3C) standard (like XML, XPath, XQuery, etc.)
Resources identified by International Resource Identifiers (IRIs, previously URIs)
Resources described by properties (IRIs) w/ atomic values. A value can be an IRI or a literal.



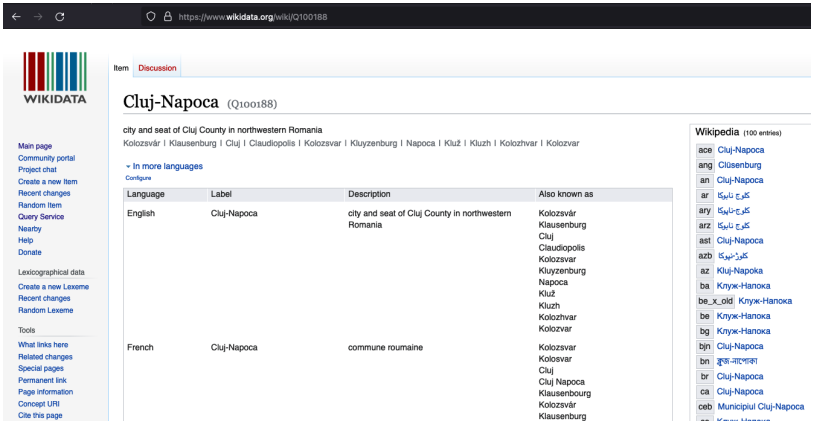
RDF graphs

RDF: **R**esource **D**escription **F**ramework, World Wide Web (W3C) standard
Self-describing, unordered, semistructured
Best practice for sharing data, thus very present in the Open Data movement
Query language: SPARQL



RDF graphs

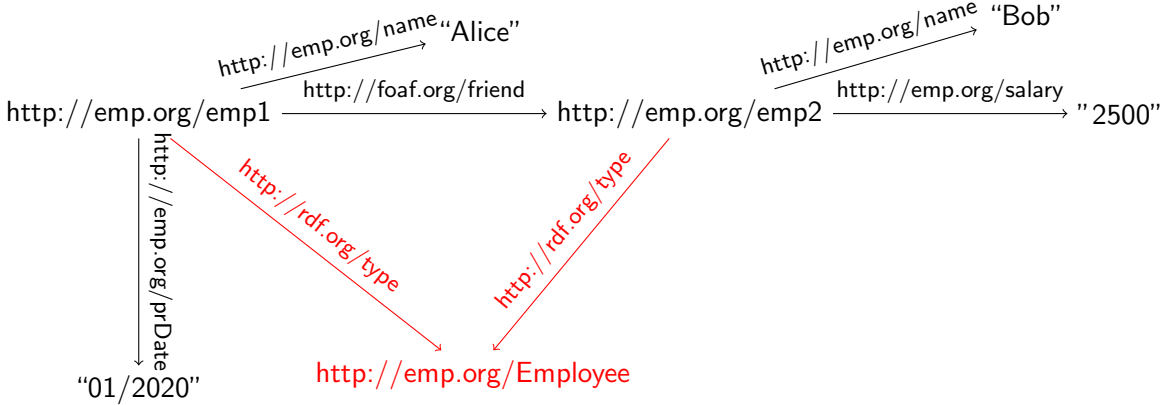
Best practice for sharing data, thus very present in the Open Data movement
Used in knowledge graphs, e.g., DBPedia, Yago, WikiData
E.g., Cluj is https://www.wikidata.org/wiki/Q100188



Adding meaning to RDF graph: types

They are optional

A resource can have zero or more types which can be related or not



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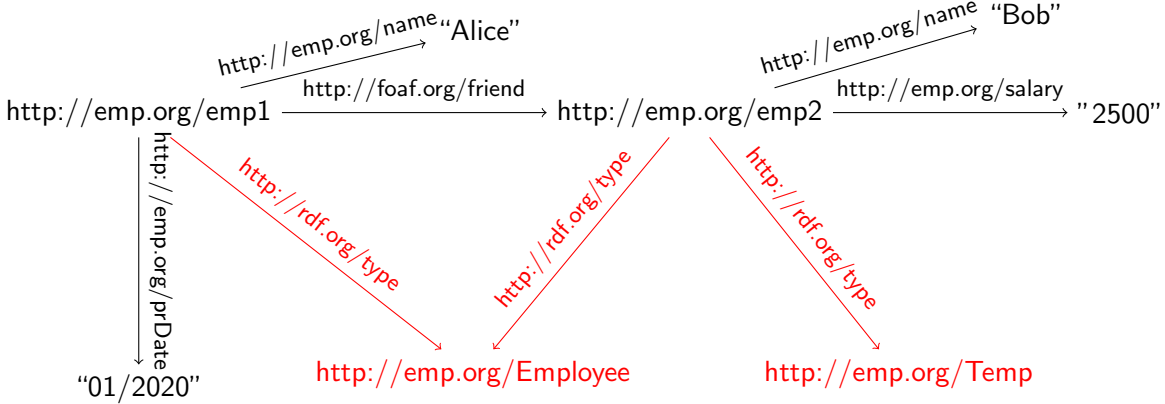
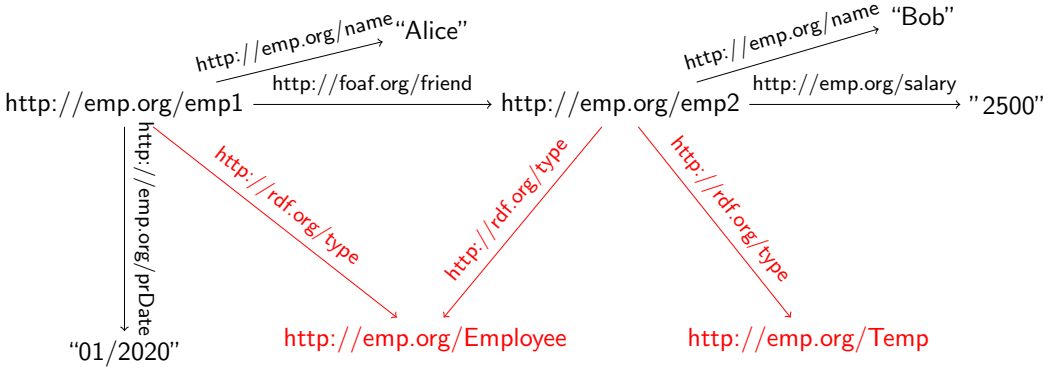


Adding meaning to RDF graphs: ontologies

Optional, allow describing how types and properties are related. Simplest examples:

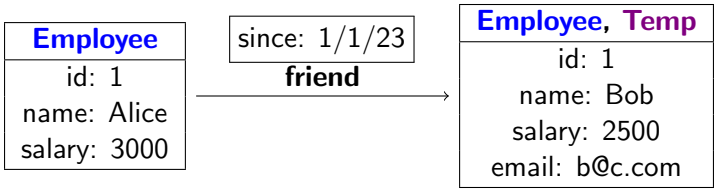
- http://emp.org/Temp is a subclass of http://emp.org/Employee'
- any resource having a http://emp.org/salary is an http://emp.org/Employee



Property graphs

Unlike RDF nodes, PG nodes contain their attributes.
Nodes can have zero or more labels. Relationships can also have attributes.

Industry first (Neo4J), then research, then (painfully, now) standards [11]



Data model heterogeneity: wrap-up

Models and strengths:

- **Tables** CSV, relational (most mature; most regular ⇒ optimization)
- **Trees** JSON, XML, K-V: Web content, structured documents, data exchange
- **Graphs** RDF: Open Data; PGs: latest iteration of heterogeneous databases

Data model heterogeneity: wrap-up

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Support:

	Tables	XML	JSON	KV	RDF	PGs
Relational databases	✓	✓	✓	✓	✓	✓
XML databases		✓				
JSON databases			✓	✓		
KV stores				✓		
RDF databases					✓	✓
PG databases					✓	✓

Data model heterogeneity: support (https://db-engines.com)

419 systems in ranking, July 2023

Rank Jul 2023	Rank Jun 2023	Rank Jul 2022	DBMS	Database Model	Score Jul 2023	Score Jun 2023	Score Jul 2022
1.	1.	1.	Oracle	Relational, Multi-model	1256.01	+24.54	-24.28
2.	2.	2.	MySQL	Relational, Multi-model	1150.35	-13.59	-44.53
3.	3.	3.	Microsoft SQL Server	Relational, Multi-model	921.60	-8.47	-20.53
4.	4.	4.	PostgreSQL	Relational, Multi-model	617.83	+5.01	+1.96
5.	5.	5.	MongoDB	Document, Multi-model	435.49	+10.13	-37.49
6.	6.	6.	Redis	Key-value, Multi-model	163.76	-3.59	-9.86
7.	7.	7.	IBM Db2	Relational, Multi-model	139.81	-5.07	-21.40
8.	8.	8.	Elasticsearch	Search engine, Multi-model	139.59	-4.16	-14.74
9.	9.	9.	Microsoft Access	Relational	130.72	-3.73	-14.37
10.	10.	10.	SQLite	Relational	130.20	-1.02	-6.48
11.	11.	↑ 13.	Snowflake	Relational	117.69	+3.55	+18.53
12.	12.	↓ 11.	Cassandra	Wide column	106.53	-2.03	-7.88
13.	13.	↓ 12.	MariaDB	Relational, Multi-model	96.10	-1.21	-16.42
14.	14.	14.	Splunk	Search engine	87.12	-2.34	-11.09
15.	↑ 16.	15.	Microsoft Azure SQL Database	Relational, Multi-model	78.96	-0.01	-5.94
16.	↓ 15.	16.	Amazon DynamoDB	Multi-model	78.81	-1.10	-5.13
17.	17.	17.	Hive	Relational	72.87	-2.65	-6.61
18.	18.	↑ 22.	Databricks	Multi-model	68.47	+2.65	+17.25
19.	19.	↓ 18.	Teradata	Relational, Multi-model	60.25	-2.39	-10.67
20.	20.	↑ 24.	Google BigQuery	Relational	55.42	+0.78	+6.53
21.	21.	↑ 23.	FileMaker	Relational	53.32	-1.06	+2.12
22.	22.	↓ 19.	Neo4j	Graph	52.06	-0.71	-6.36

Data model heterogeneity: can we eliminate it?

Short realist's answer:

It didn't happen so far! 

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Existing data Specific datasets that we need to work with come in specific formats due to industry or company standards.

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Data doesn't die It is organizationally very hard to accept data deletion [16].

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Migration is a pain Model conversion may lose some features, needs to invent others, is error-prone, leads to spaghetti systems.

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Migration is a pain Model conversion may lose some features, needs to invent others, is error-prone, leads to spaghetti systems.

Variety has merit It makes sense to experiment with new systems, especially if/when they have better performance for specific tasks. We'll hear more about this.

Data heterogeneity: how to live with it?

Data integration: leverage data from several stores (sources)

- Sources may have different data models
- Sources may have different schemas (or no schema at all)
- Sources may have different query processing capabilities
- An individual source may be distributed

Main questions to be addressed in data integration systems

- What unified schema/interface do users get?
- How do we automatically process queries over this schema?
- How do we do so efficiently, taking best advantage of the available computation capabilities?

Part II

View-Based Data Integration

Views in Relational Databases

Relation Named set (or bags, in SQL) of tuples **data!**

Query First-order logic formula (or SQL query): computes some answers from the data.

View Named query.

- **Virtual view**: associates a name to a query. It can then be queried.
- **Materialized view**: the query result is computed and stored on disk. It can be used like any other table. **data!**

Schema A set of relations and/or views.

Virtual views in SQL

Base table:

Hotel

city	street	name	descr	price
Paris	Odéon	Flora	"Historic"	200
Bastia	Corniche	Hippocampe	"Modern"	175

View definition:

create view ParisHotels as select street, name, price from Hotel where city='Paris' and price $<$ 210

Then:

select name from ParisHotels returns:

name
Flora

Views for data integration

View allow defining another (possibly virtual) schema based on an existing schema.

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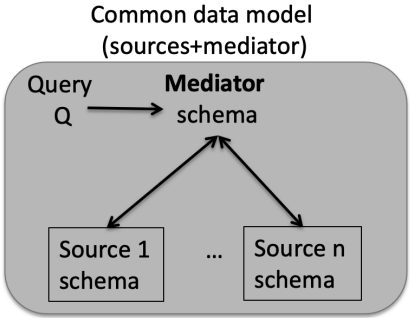
Data integration system

- A set of **data sources**, each with: data model, query language, and schema (also called source schemas).
- A **mediator** with its own DM, QL and global schema
- Queries are asked against the global schema
- **Wrappers** interface the sources to the mediator's model



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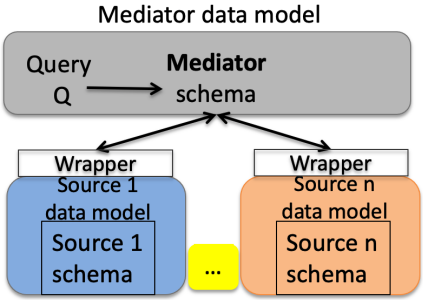
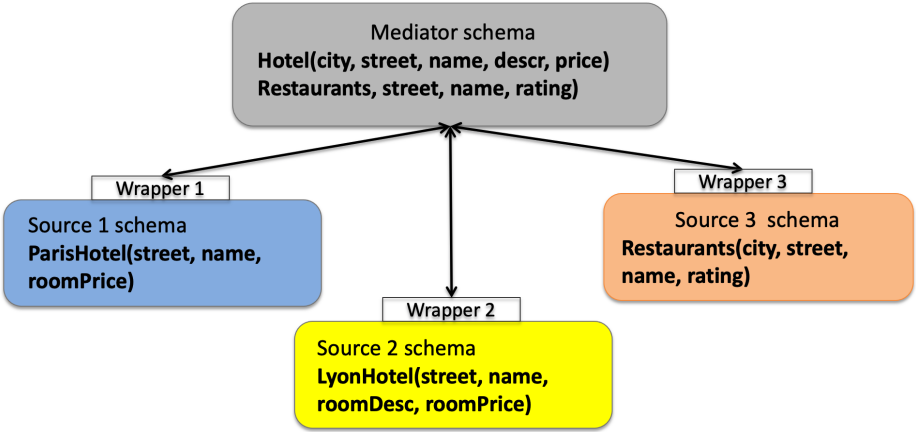


Connecting the source schemas to the global schema

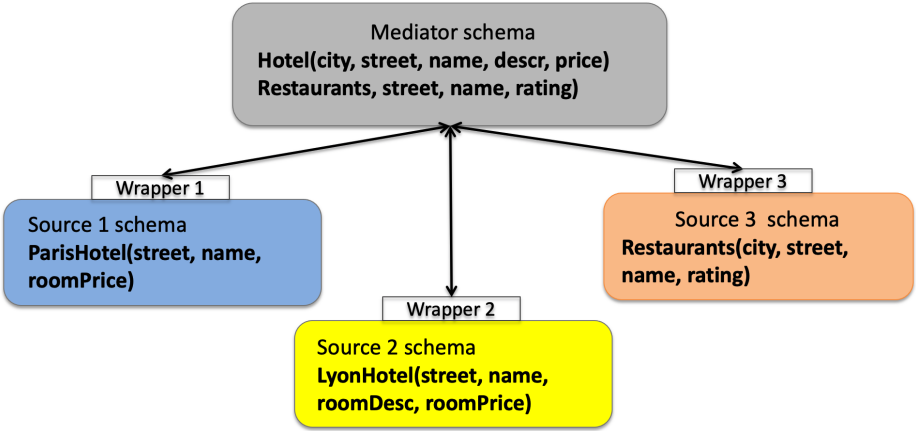
Sample scenario:



Connecting the source schemas to the global schema

Data only exists in the sources.

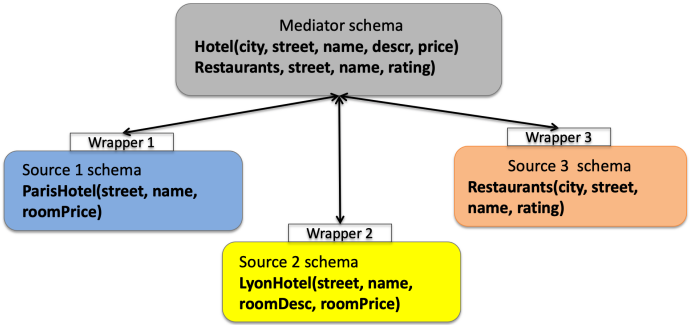
Applications can only query the global schema.



Connecting the source schemas to the global schema

How to **specify the relation** between

- The global schema acccessible to applications, and...
- the source schemas reflecting the data...
- so that a query over the global schema can be **automatically translated** into a query over the source schemas ?



Connecting the source schemas to the global schema: Global-as-View (GAV)

Source 1	s1:ParisHotels(street, name, roomPrice)
Source 2	s2:LyonHotel(street, name, roomDesc, roomPrice)
Source 3	s3:Restaurant(city, street, name, rating)
Global	Hotel(city, street, name, descr, price), Restaurant(city, street, name, rating)

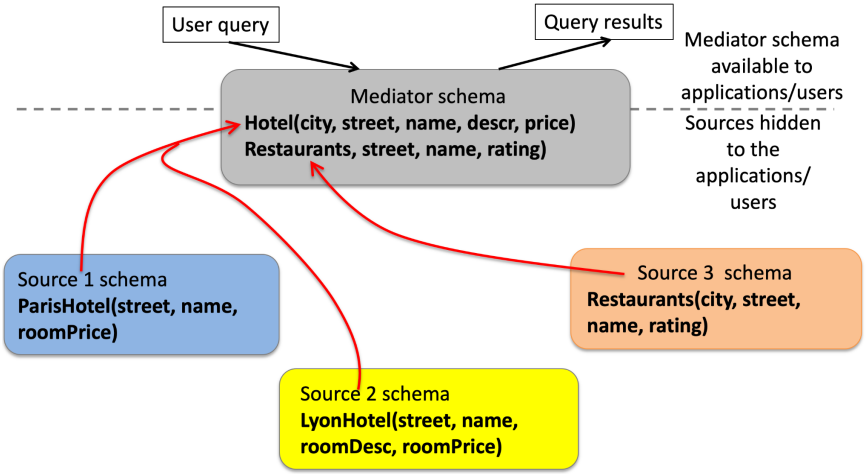
Defining Hotel as a view over the source schemas:

```
define view Hotel as   select 'Paris' as city, street, name, null as descr, roomPrice as price
                       from s1:ParisHotels
                       union all
                       select 'Lyon' as city, street, name, roomDesc as descr, price
                       from s2:LyonHotel
```

Defining Restaurant as a view over the source schemas:

```
define view Restaurant as   select * from s3:Restaurant
```

Connecting the source schemas to the global schema: Global-as-View (GAV)



Query processing in global-as-view (GAV) (1)

```
define view Hotel as   select 'Paris' as city, street, name, null as descr, roomPrice as price
                       from s1:ParisHotels
                       union all
                       select 'Lyon' as city, street, name, roomDesc as descr, price
                       from s2:LyonHotel
```

Query:

select * from Hotel where city='Paris' and price < 200	becomes:
select * from (select 'Paris' as city... union... select 'Lyon' as city...) where city='Paris' and price < 200	which becomes:
select * from (select 'Paris' as city...) where city='Paris' and price < 200	which becomes:
select * from s1:ParisHotels where price < 200	**Source-only!**

Query processing in global-as-view (GAV) (2)

define view **Hotel** as select 'Paris' as city, street, name, null as descr, roomPrice as price
from s1:ParisHotels
union all
select 'Lyon' as city, street, name, roomDesc as descr, price
from s2:LyonHotel

define view **Restaurant** as select * from s3:Restaurant

Query:

---

select h.street, r.rating from Hotel h, Restaurant r
where h.city=r.city and r.city='Lyon' and h.street=r.street and h.price<200 becomes:

---

select h.street, r.rating
from (select 'Paris' as city... from s1:ParisHotels union all select 'Lyon' as
city... from s2:LyonHotel) h, (select * from s3:Restaurant) r
where h.city=r.city and r.city='Lyon' and h.street=r.street and h.price<200 which becomes:

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define view Restaurant as   select * from s3:Restaurant
```

Query:

```
select h.street,r.rating
from (select ... from s2:LyonHotel) h, s3:Restaurant r
where r.city='Lyon' and h.street=r.street and h.price<200          which becomes:
```

```
select h.street, r.rating from s2:LyonHotel h, s3.Restaurant r
where r.city='Lyon' and h.price<200 and h.street=r.street
```

Query processing in global-as-view (GAV) (2)

Query:

select h.street, r.rating from Hotel h, Restaurant r where h.city=r.city and r.city='Lyon' and h.street=r.street and h.price<200 has become:
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Query:

select h.street, r.rating from Hotel h, Restaurant r where h.city=r.city and r.city='Lyon' and h.street=r.street and h.price<200 has become:
select h.street, r.rating from s2:LyonHotel h, s3.Restaurant r where r.city='Lyon' and h.price<200 and h.street=r.street

How do we process this?

- s2 evaluates: select h.street from s2:LyonHotel h where h.price<200
- s3 evaluates: select r.rating, r.street from s3.Restaurant r where r.city='Lyon'
- Mediator joins the results, applies final projection

Concluding remarks on global-as-view (GAV)

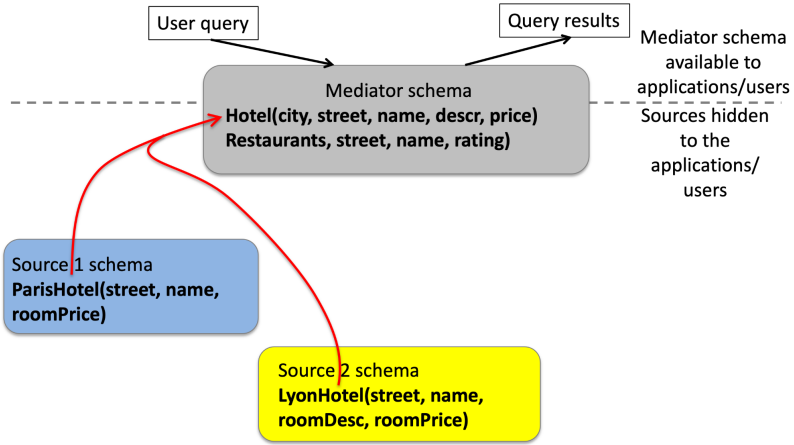
Query processing = view unfolding

- Just like querying views in a database
- Heuristic: push as many operators (select, project, join; navigate...) on the sources as possible

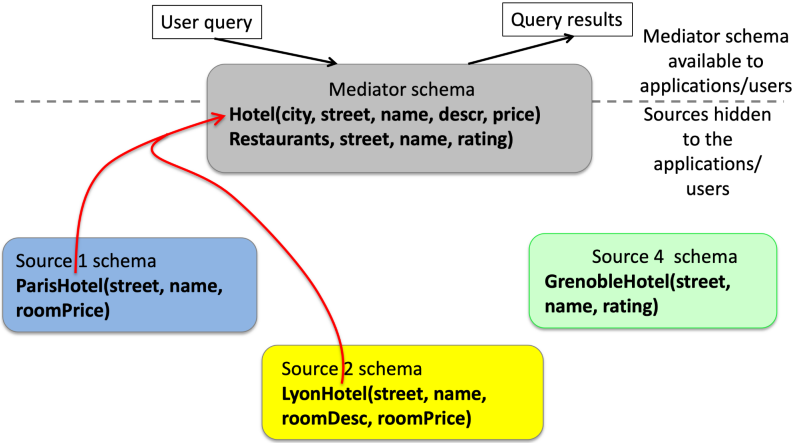
Weakness: source changes impact the global schema

- The global schema may need to change as parts of it may become invalid (undefined)
- As a consequence, applications may need to be rewritten!

Global-as-view: adding a new source



Global-as-view: Adding a new source



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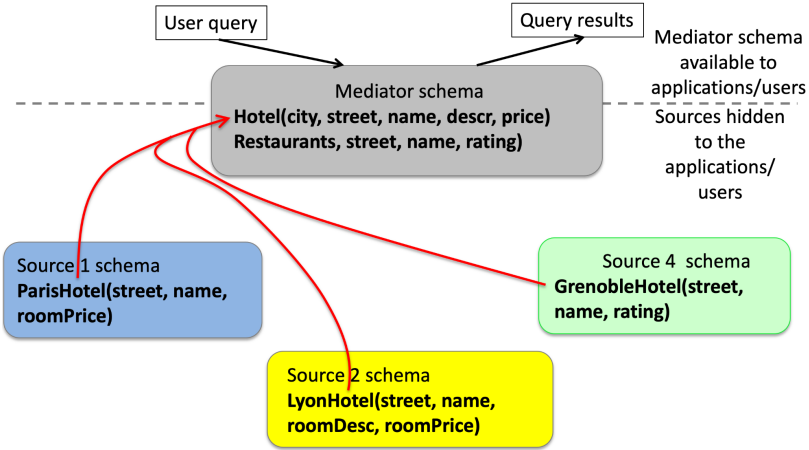
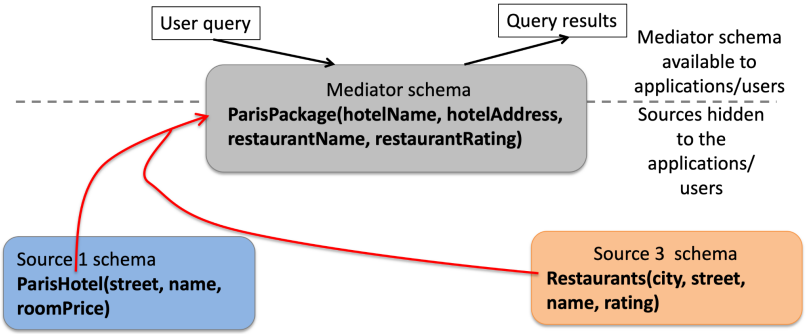
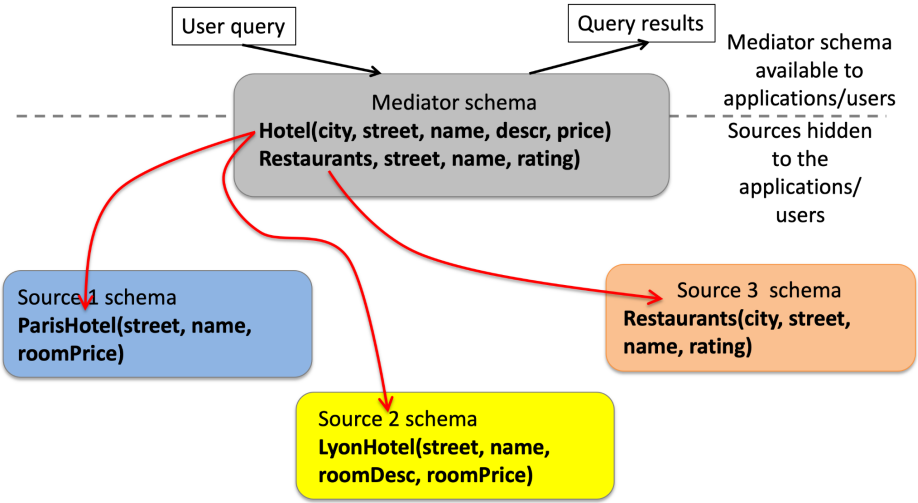


Global-as-view: removing a source



- If Source3.Restaurant withdraws, the ParisPackage relation in the global schema becomes empty.
- Applications cannot even access Source1.ParisHotels, even though it is still available.

Connecting the source schemas to the global schema: Local-as-view (LAV)



Connecting the source schemas to the global schema: Local-as-view (LAV)

s1:ParisHotel(street, name, roomPrice)
s2:LyonHotel(street, name, roomDesc, roomPrice)
s3:Restaurant(city, street, name, rating)
Global: Hotel(city, street, name, descr, price), Restaurant(city, street, name, rating)

Defining the sources as views over the global schema:

define view s1:ParisHotels as	select street, name, price as roomPrice from Hotel where city='Paris'
define view s2:LyonHotel as	select street, name, descr as roomDesc, price as roomPrice from Hotel where city='Lyon'
define view s3:Restaurant as	select * from Restaurant

GAV and LAV have different expressive power

Some GAV scenarios cannot be expressed in LAV

create view ParisPackage as
select ph.name as hotelName, ph.street as hotelAddress,
r.name as restaurantName, r.rating as restaurantRating
from s1:ParisHotel ph, s3:Restaurants r
where r.city='Paris' and r.street=ph.street

- Only (hotel, restaurant) pairs that are on the same street in Paris
- Not expressible in LAV which describes each source individually w.r.t. the global schema, not in correlation with data from other sources

GAV and LAV have different expressive power

Some LAV scenarios cannot be expressed in GAV

- s3:MHotel(city, street, name, price) only has data about Marseille hotels
- s4:WHotel(city, street, name price) has only data about Wien hotels
- Hotel is defined as:

  select * from MHotel union all select * from WHotel
- A query about hotels in Rome will also be sent to s3 and s4, although it will bring no results

Query processing in Local-as-View (LAV)

define view s1:ParisHotels as
select street, name, price as roomPrice
from Hotel where city='Paris'

---

define view s2:LyonHotel as
select street, name, descr as roomDesc, price as roomPrice
from Hotel where city='Lyon'

---

define view s3:Restaurant as select * from Restaurant

Query:

select h.street, h.price, r.rating
from Hotel h, Restaurant r
where r.city=h.city and h.street=r.street

Query processing in Local-as-View (LAV)

define view s1:ParisHotels as... from Hotel where city='Paris'

define view s2:LyonHotel as... from Hotel where city='Lyon'

define view s3:Restaurant as select * from Restaurant

Rewriting of the query using the views:

```
select h1.street, h1.price, r3.rating
from s1:ParisHotels h1, s3:Restaurant r3
where h1.city=h3.city and h1.street=r3.street
union all
select h2.street, h2.price, r3.rating
from s2:LyonHotels h2, s3:Restaurant r3
where h2.city=h3.city and h2.street=r3.street
```

Query processing in Local-as-View (LAV)

define view s1:ParisHotels as... from Hotel where city='Paris'

define view s2:LyonHotel as... from Hotel where city='Lyon'

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Rewriting of the query using the views:

```
select h1.street, h1.price, r3.rating
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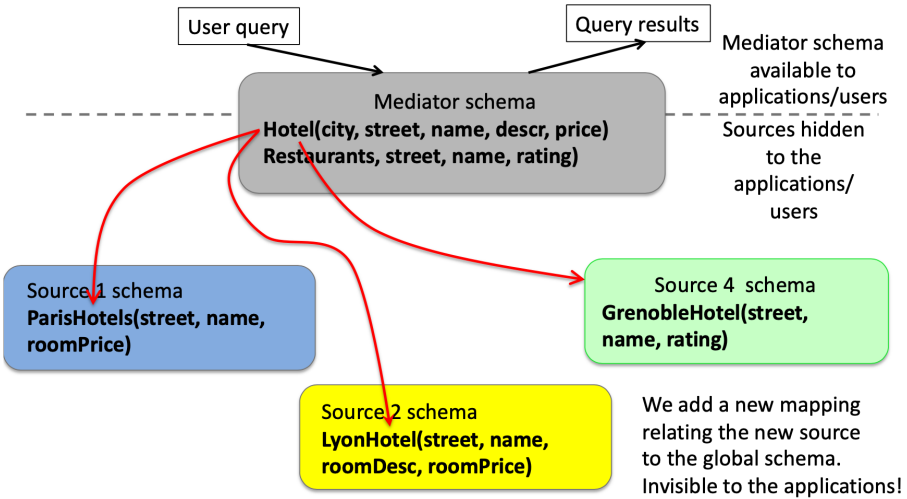
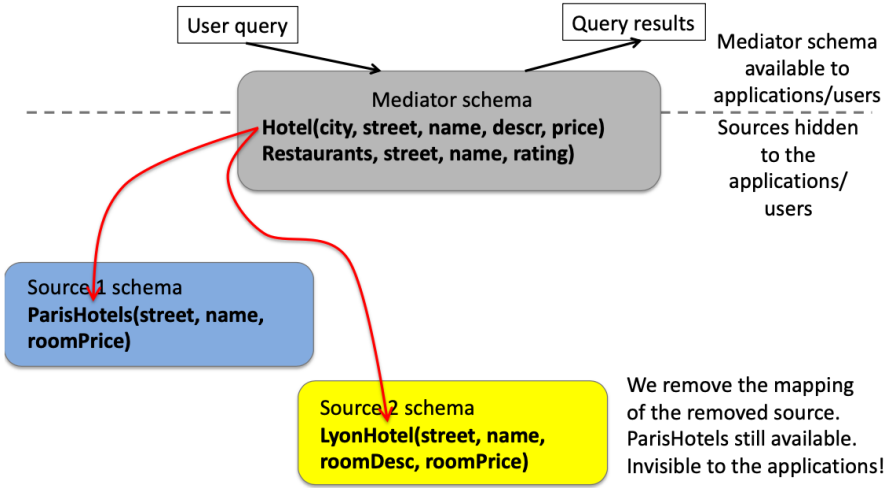
where h1.city=h3.city and h1.street=r3.street
union all
select h2.street, h2.price, r3.rating
from s1:ParisHotels h2, s3:Restaurant r3
where h2.city=h3.city and h2.street=r3.street
```

How do we find this?
It's more complicated
NP-hard problem [14]
in the size of views + query

Local-as-View: adding a new source



Local-as-View: removing a source



Concluding remarks on Local-as-View

Query processing: finding the query rewriting is significantly more complex

- NP-hard in the size of views + query, but...
- These are many orders of magnitude smaller than the data
- Practical algorithms have been proposed, in particular using chase and back-chase [15], improved since [2, 4], within ESTOCADA (see next)

The connection between sources and global schema is much more robust

- Sources can be added and/or removed with no impact on global schema
- Thus, no impact on applications.

Applicability to (any) distributed data management scenario

Views capture logical relationship between stored data collections and/or global schema (if any)

- Horizontal & vertical partitioning of a relation are just particular cases
  - Store FR sale in Paris, RO sale data in Cluj
  - Store current orders in Berlin, order history in Dublin
- Key-based distribution is just a particular case
  - Store on node i the records such that $h(k) = i$

Rewriting with Integrity Constraints

Integrity Constraints: express human knowledge about a domain.

- *IC*: "Every restaurant has a sanitary license".

View	Query	Rewriting
"All restaurants"	"All restaurants with a license"	?

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- Knowing *IC*, the view is a perfect rewriting.

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View	Query	Rewriting
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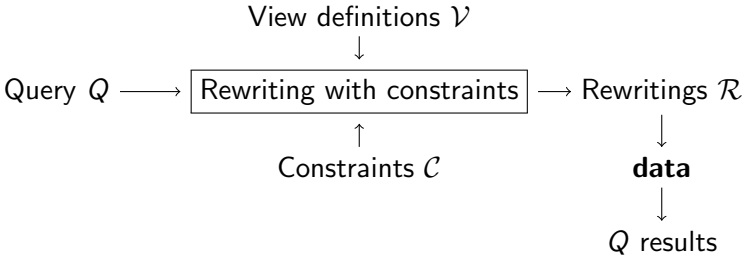
- Without IC, the view may return wrong answers (restaurants without a license)!
- Knowing IC, the view is a perfect rewriting.
- How do we find this? Provenance-Aware Chase & Backchase [15], LAV style

Rewriting with integrity constraints using an algorithm such as PACB [15]



Part III

ESTOCADA: View-Based Rewriting for Polystores

Joint work with: Rana Al-Otaibi (UCSD, now Microsoft Research), Alin Deutsch (UCSD), Bogdan Cautis (U. Paris-Saclay), D. Bursztyn, S. Zampetakis (Inria)

Polystores: modern heterogeneous Big Data management systems

- A set of data stores, each supporting one or several data models
  - PostgreSQL supports relational, XML, JSON
- Each store can evaluate queries in some language / dialect
- Each store may have better performance on some operations
  - SOLR extremely good at full-text search; no $\bowtie$
  - PostgreSQL good at σ, π, $\bowtie$, grouping; some JSON, XML querying
  - Redis good at key-value look-up; no $\bowtie$

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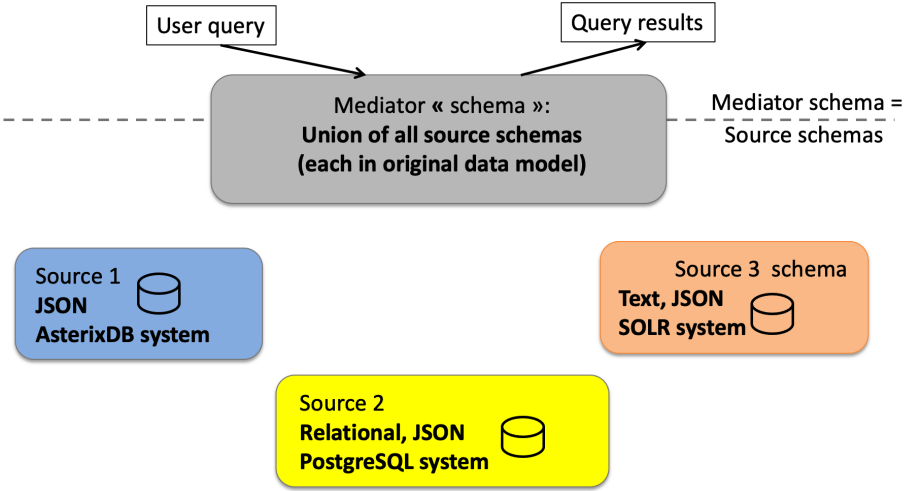
ESTOCADA [2, 3, 4]: How to **leverage the best performance available in the system?**

Connecting the source schemas to the global schema: ESTOCADA



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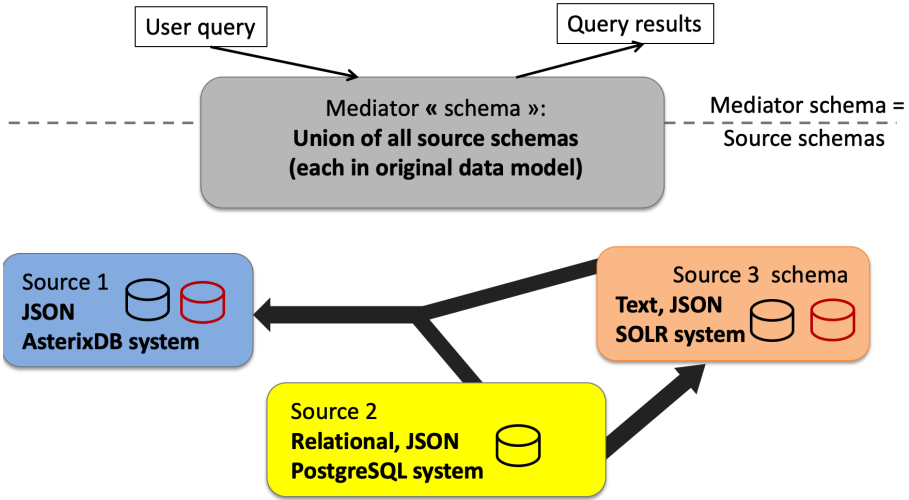
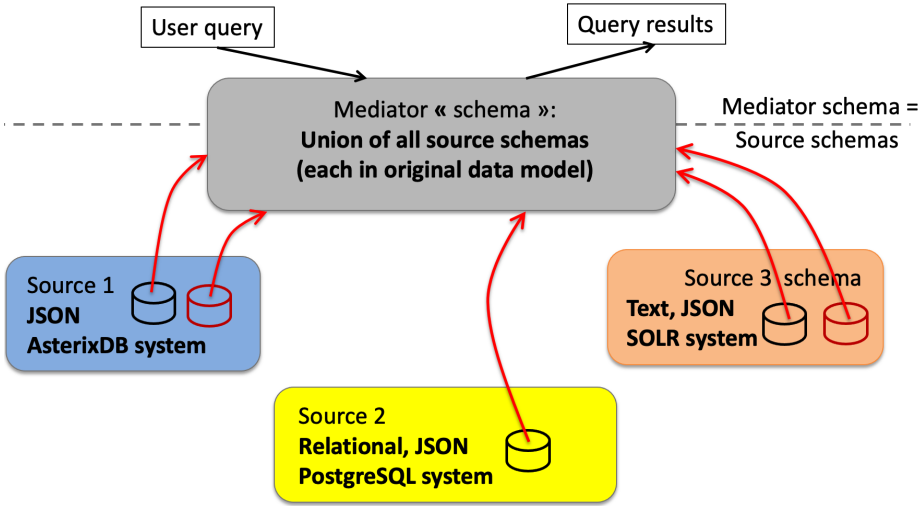
ESTOCADA [2, 3]: How to **leverage the best performance across all stores?**

1. **Move (migrate) data from one store to another**, since they all cooperate
   - Materialize, in one store, view(s) over data from other store(s)

Connecting the source schemas to the global schema: ESTOCADA



Connecting the source schemas to the global schema: ESTOCADA (LAV)



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How to write views and queries across data models?

Query Block Trees (QBT) cross-model query language: select from some data model(s), return in another data model

```
View V1:
FOR AJ:{SELECT  M.patientID AS patientID,
                A.admissionID AS admissionID,
                A.report AS report
         FROM  MIMIC M, M.admissions A}
RETURN SJ:{"patientID":patientID,
           "admissionID":admissionID,
           "report":report}
View V2:
FOR AJ:{SELECT  M.patientID AS patientID,
                A.admissionID AS admissionID,
                A.admissionLoc AS admissionLoc
                A.admissionTime AS admissionTime
          FROM  MIMIC M, M.admissions A}
RETURN PR:{patientID,admissionID,
           admissionLoc,admissionTime}
```

- AJ: AsterixDB's JSON query language
- SJ: SOLR's JSON query language
- PR: PostgreSQL SQL
- ... add your own!
- QBT resembles CloudMDSQL [17] + nesting

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                A.admissionTime AS admissionTime
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RETURN PR:{patientID,admissionID,
           admissionLoc,admissionTime}
```

One QBT block: FOR ... RETURN ...

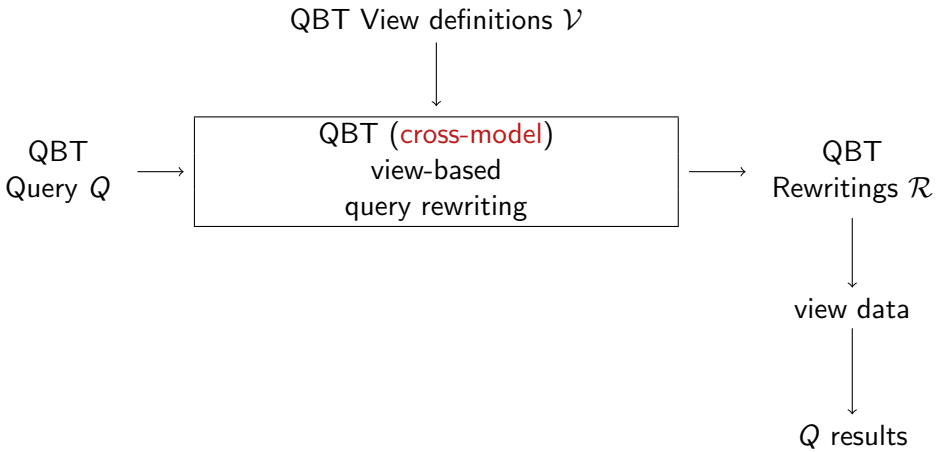
- One QBT block: FOR ... RETURN ...
- QBTs can be arbitrarily nested

Sample query against JSON data originally stored in AsterixDB

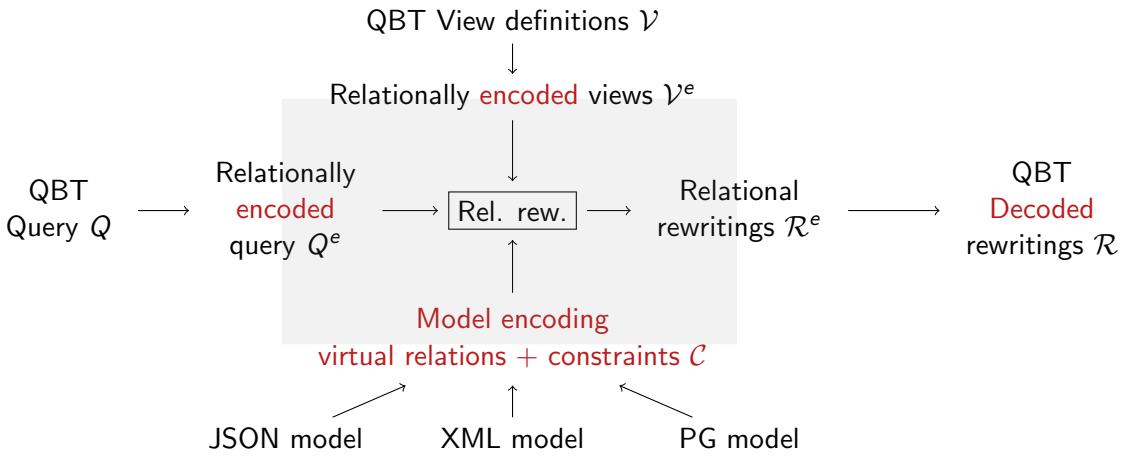
How to rewrite it using PostgreSQL and SOLR views?

```
FOR AJ:{SELECT M.patientID AS patientID,
               A.admissionLoc AS admissionID,
               A.admissionTime AS admissionTime,
               P.drug AS drug
        FROM   LABITEM L, MIMIC M, M.admissions A,
               A.labevents LE, A.prescriptions P
        WHERE  L.itemID=LE.labItemID AND
               L.category='blood' AND  L.flag ='abnormal' AND
               P.drugtype='additive' AND
               contains(report,'coronary artery')}
RETURN AJ:{"patientID":patientID, "drug":drug,
           "admissionLoc":admissionLoc,
           "admissionTime":admissionTime}
```

ESTOCADA view-based query rewriting



ESTOCADA view-based rewriting approach



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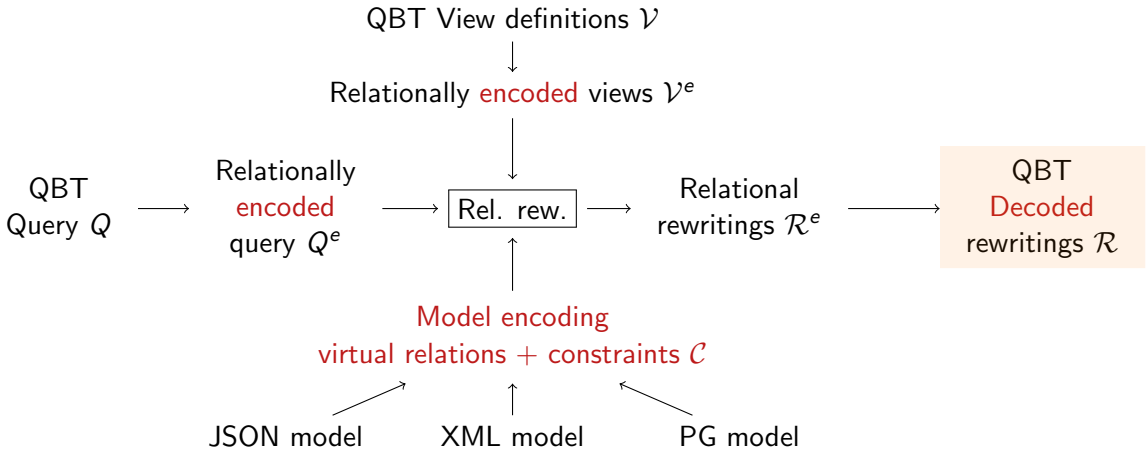
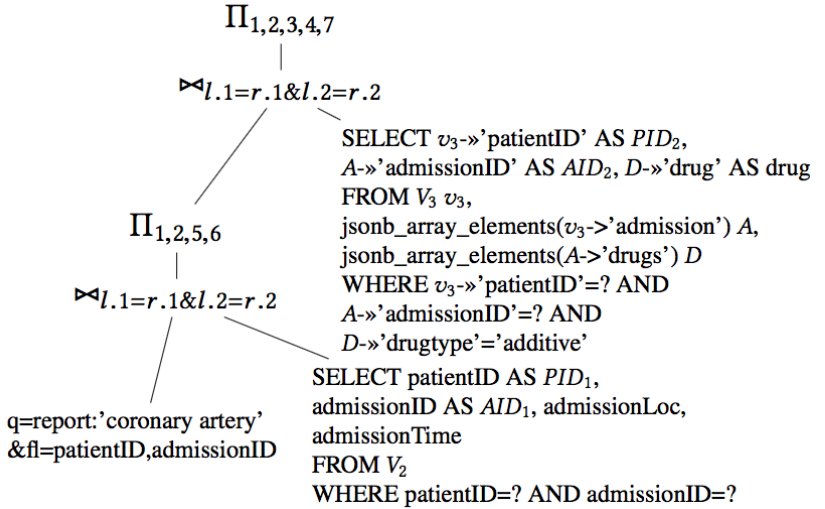
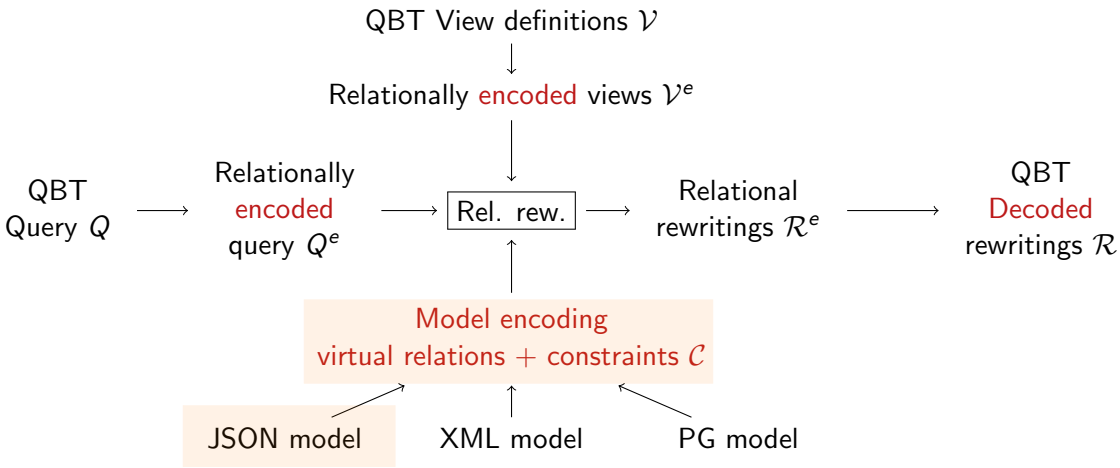


Our target: QBT decoded rewriting $\mathcal{R}$



- Each leaf is a source query
- Top $\bowtie, \Pi$ evaluated by a mediator [10]

ESTOCADA view-based rewriting approach



Encoding the JSON data model in ESTOCADA

Virtual Relational Encoding of JSON (VREJ) schema and integrity constraints

Describing the data:

$Collection_J(name, id)$
$Child_J(pId, cId, key, type)$

Needed for modelling:

$Eq_J(x, y)$
$Value_J(x, y)$

Constraints:

$$Collection_J(n, x) \wedge Collection_J(n, y) \rightarrow x = y \quad (1)$$

$$Child_J(p, c_1, k, t) \wedge Child_J(p, c_2, k, t) \rightarrow c_1 = c_2 \quad (2)$$

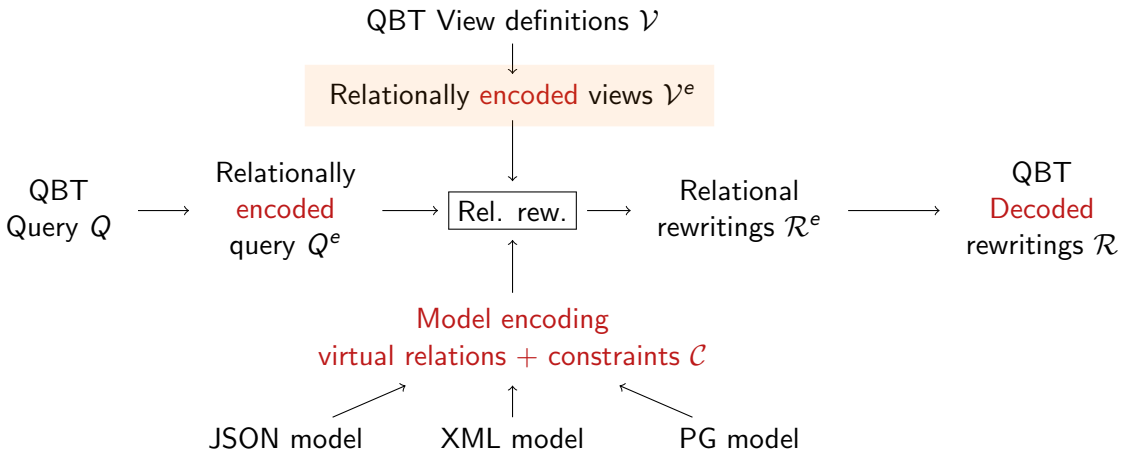
$$Eq_J(x, y) \rightarrow Eq_J(y, x) \quad (3)$$

$$Eq_J(x, y) \wedge Eq_J(y, z) \rightarrow Eq_J(x, z) \quad (4)$$

$$Eq_J(p, p') \wedge Child_J(p, c, k, t) \rightarrow \exists c' \; Eq_J(c, c') \wedge Child_J(p', c', k, t) \quad (5)$$

$$Value_J(i, v_1) \wedge Value_J(i, v_2) \rightarrow v_1 = v_2 \quad (6)$$

ESTOCADA view-based rewriting approach



Relational encoding of cross-model view V_2

```
View V2:
FOR AJ:{SELECT  M.patientID AS patientID,
                A.admissionID AS admissionID,
                A.admissionLoc AS admissionLoc
                A.admissionTime AS admissionTime
         FROM  MIMIC M, M.admissions A}
RETURN PR:{patientID,admissionID,
           admissionLoc,admissionTime}
```

MIMIC(M),
$Child_J$(M,patientID,"patientID","o"),
$Child_J$(M,A,"admissions","o"),
$Child_J$(A,admissionID,"admissionID","o"),
$Child_J$(A,admissionLoc,"admissionLoc","o"),
$Child_J$(A,admissionTime,"admissionTime","o"),
$Child_J$(A,report,"reports","o") $\rightarrow$
V_2(patientID,admissionID,admissionLoc,admissionTime)

"o": object (or map) type

Sample experimental benefits [2]

Dataset: Medical Information Mart for Intensive Care (MIMIC-III), real-life, JSON (46 GB)
Query: for the patients with "coronary artery" issues, and abnormal blood test results, find the date/time of admission, their previous location (e.g., emergency room, clinic referral), and the drugs of type "additive" prescribed

Single-system (JSON) evaluation

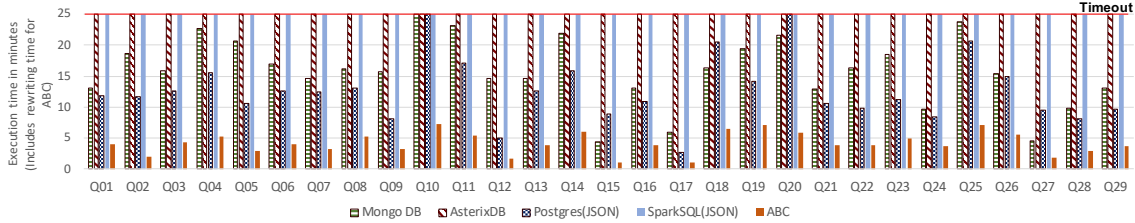
AsterixDB	SparkSQL	MongoDB	PostgreSQL JSON
25 min	$>$ 60 min	16 min	12.6 min

Materialized views:

- V_1 (SOLR): IDs of patients and their hospital admission data, caregivers' reports, notes on the patients' stay — full-text search for "coronary artery"
- V_2 (Postgres): patients metadata, hospital admission information (admission time and patients' location) — great join algos
- V_3 (Postgres JSON): drugs prescribed for each patient with "abnormal blood" test results

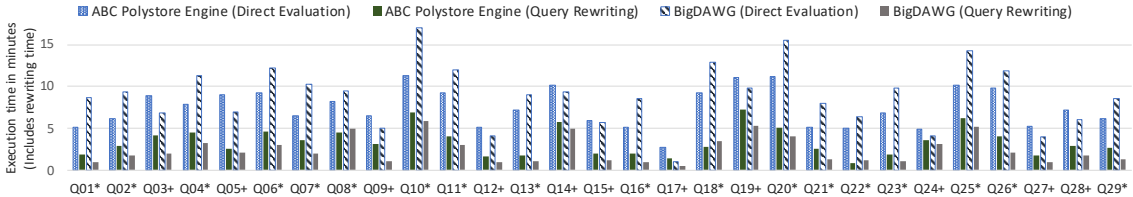
Execution using mat. views filter(V_1) $\bowtie$ V_3 $\bowtie$ V_2: 5.7 min

Query speed-up: comparison with single-store [2]



ESTOCADA: Relational and JSON views in Postgres, JSON views in SOLR

Query speed-up: comparison with BigDawg [12] polystore



ESTOCADA wrap-up

- In any setting, **materialized views** have the biggest potential for performance improvement
- In a polystore setting, **unequal source capabilities and performance** further motivate moving (or copying) parts of the data across sources
- Rewrite a query into a QBT over one or more sources and/or view, distribute computation across sources
- Efficient rewriting w/formal guarantees distinguishing from comparable systems, e.g., [1]
- The same benefits extend to mixed RA ($\sigma, \mathit{join}, \pi$) - LA ($+, \times, {}^T, \ldots$) workloads DB/ML [3, 4].
- Demo in Docker instance at:
  `https://gitlab.inria.fr/cedar/estocada-public/-/tree/master/estocada-MDD-tutorial`
- Automatic recommendation of materialized views ongoing

Part IV

ABSTRA: Abstracting Data of Any Model

Joint work with Nelly Barret (Inria), Prajna Upadhyay (Inria, now IIT Khanpur)

Data management for investigative journalists and fact-checking

I was born in communist Romania, then a dictatorship. Estimated victims 1945-1989: 500.000 to 2M (`https://ro.wikipedia.org/wiki/Rom%C3%A2nia_comunist%C4%83`)

Data management for investigative journalists and fact-checking

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Fall of communism in Romania: 1142 dead, 3138 wounded.
No one has been tried / convicted for that.

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Functional free press is an important ingredient for **democracy**

- To debate and express dissent
- To analyze and expose society's functioning

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Functional free press is an important ingredient for **democracy**

- To debate and express dissent
- To analyze and expose society's functioning

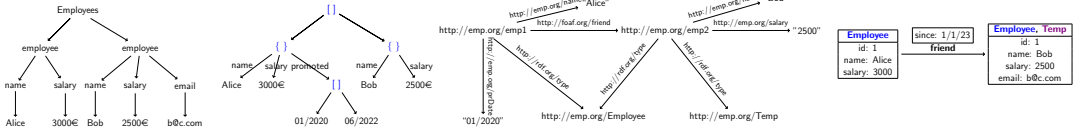
Overall, low IT use/literacy in newsrooms

- Writers, not geeks
- Yet data skills needed more than ever

Research projects with Le Monde, radiofrance since 2015

Data analysis needs for journalism

- The application domain follows the topic of interest: news cycle, or investigation topic.
- Journalists use whatever data they can get their hands on. Different data models! (All that we discussed + text, Office, etc.)



- Journalists are familiar with text and documents > spreadsheet ≫ anything else
- Data producers often uncollaborative ⇒ documentation, schema missing

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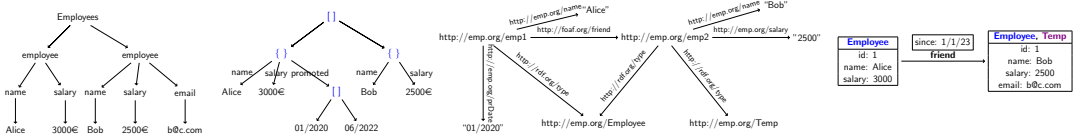

- Journalists are familiar with text and documents > spreadsheet ≫ anything else
- Data producers often uncollaborative ⇒ documentation, schema missing
- Data understanding conditions even the earliest stages of journalistic work!

How to help journalists understand heterogeneous data

Focus on (semi)structured data formats: RDBs, CSV, JSON, XML, RDF, PGs, ...

Core principles

1. Do not expose data model details.

How to help journalists understand heterogeneous data

Focus on (semi)structured data formats: RDBs, CSV, JSON, XML, RDF, PGs, ...

Core principles

1. Do not expose data model details.
2. Any application dataset (tabular/RDB, tree- or graph-oriented) contains some entities connected by some relationships. Find and (graphically) show these!

How to help journalists understand heterogeneous data

Focus on (semi)structured data formats: RDBs, CSV, JSON, XML, RDF, PGs, ...

Core principles

1. Do not expose data model details.
2. Any application dataset (tabular/RDB, tree- or graph-oriented) contains some entities connected by some relationships. Find and (graphically) show these!
   - Entities may have nested structure

How to help journalists understand heterogeneous data

Focus on (semi)structured data formats: RDBs, CSV, JSON, XML, RDF, PGs, ...

Core principles

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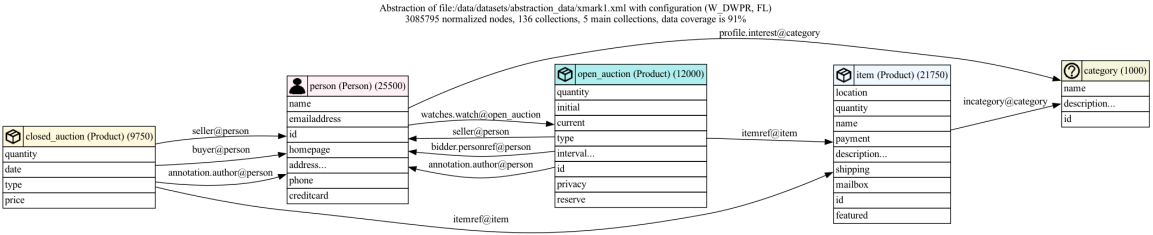
   - Entities may have nested structure
3. Let users control on how much information they want.

ABSTRA project [7, 8, 9]. Code and (many) examples:

`https://team.inria.fr/cedar/projects/abstra/`

Sample abstraction of an XMark XML document



Application benchmark: online auctions site

3M nodes, 80 different labels, on 124 labeled paths

Dataset abstraction stages

1. Turn any dataset into a graph
   - Based on ConnectionLens [5, 6]
   - Addition of extracted entity nodes
2. Summarize the graph: equivalent nodes grouped in collections
3. Identify (nested) entities:
   - Select some collections as entity roots
   - Determine each entity's boundaries
4. Classify entities: assign a human-understandable name
5. Identify relationships between entities

Relational data conversion into graph

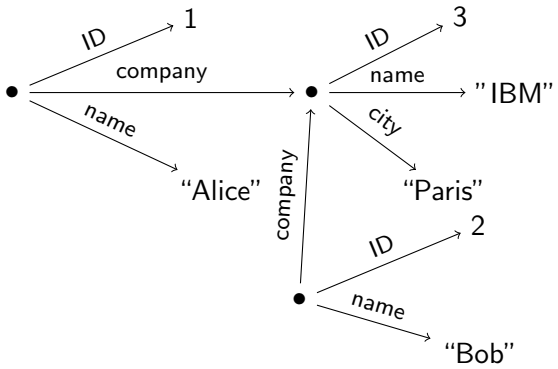
Relational model (also **CSV**): tables

Employees

ID	name	company
1	Alice	3
2	Bob	3

Companies

ID	name	city
3	IBM	Paris



XML, **JSON**, **RDF**: direct translation; **PGs**: similar to relational + nodes for relationships

Normalized graph: make all edges unlabeled

Data graph summarization: which groups of nodes are equivalent?

Reverse each data model's guidelines for representing "similar things":

- Relations all nodes representing tuples of the same table

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- XML: all XML elements w/ same name

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- **JSON** all nodes on the same path from the root

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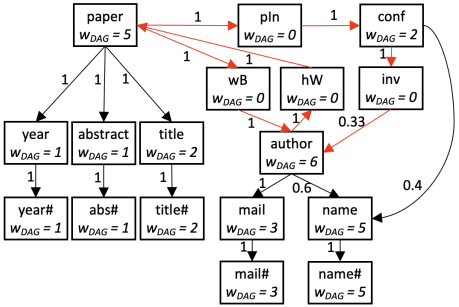
And: for all $x_1 \equiv x_2$ and label a, if $x_1 \xrightarrow{a} y_1, x_2 \xrightarrow{a} y_2$ and y_1, y_2 are leaves, then $y_1 \equiv y_2$.

Graph summarization result: collection graph

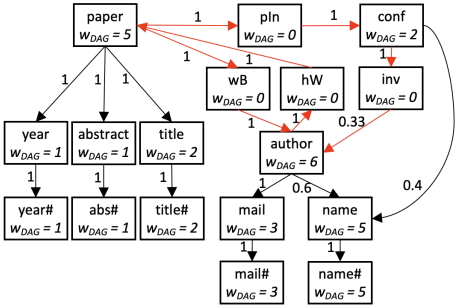
Each set of equivalent nodes is a collection; collections make up the collections graph



Red edges belong to cycles

year# is the collection of values of the nodes in the year collection

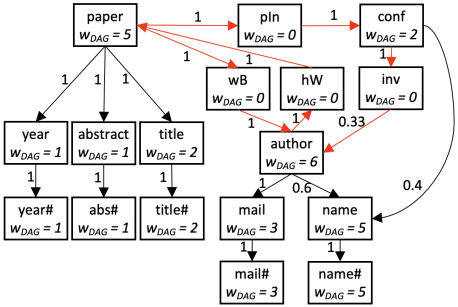
Selecting entities and their boundaries



We need to:

- Select some collections as entity roots;
- For each selected entity root, determine which other collections are in its boundary
- Until we identify k entities and/or $f\%$ of the data is reflected in the returned entities.

Which collections make good entity roots?



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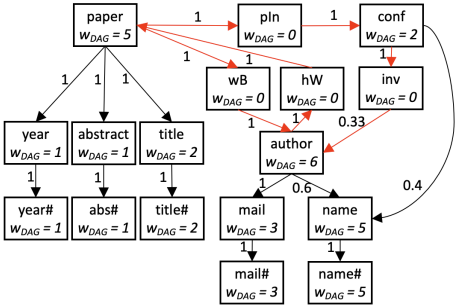

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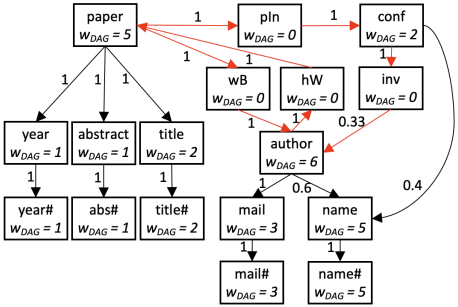

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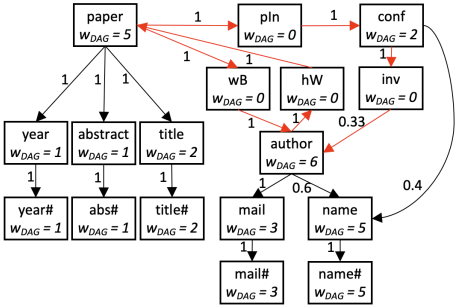

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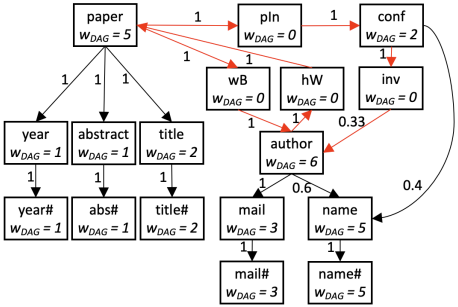

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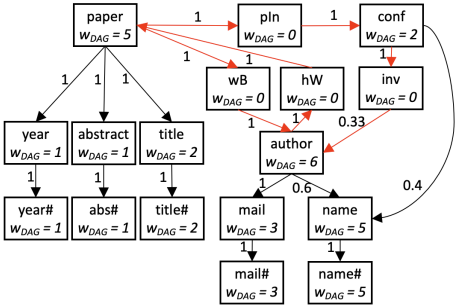

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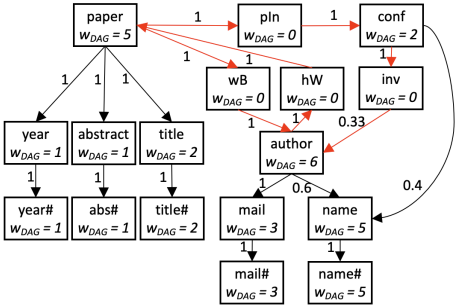

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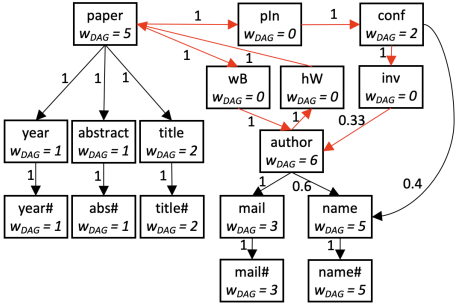
Assume **paper** is selected.

What to include in an entity boundary?



In the boundary of the entity rooted in c, we include any other collection c'

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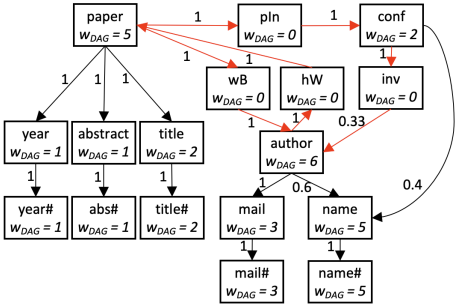

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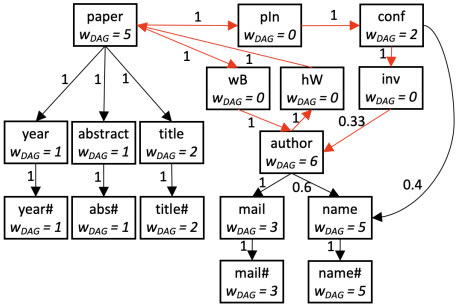

In the boundary of the entity rooted in c, we include any other collection c'

- Such that there is a path $c \rightsquigarrow c'$ with no in-cycle edges
- And along this path, each edge $c_i \rightarrow c_j$ satisfies:
  - Each node in c_i as at most one child in c_j; and/or
  - At least $x\%$ of the nodes in c_j have a parent in c_i.

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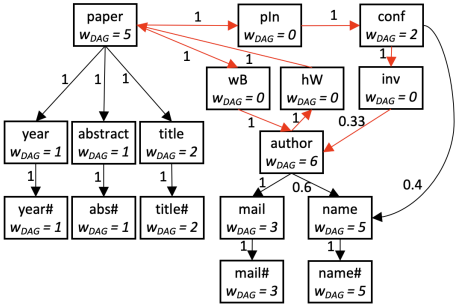

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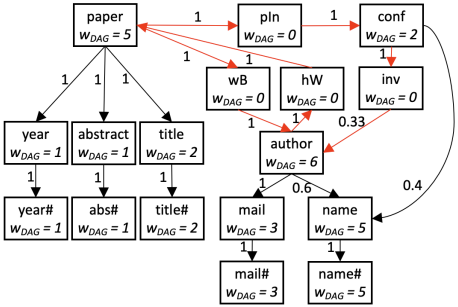
  - At least x% of the nodes in c_j have a parent in c_i.

The **paper** entity includes: year, abstract, title (allowing in-cycle edges: all the collections)

Selecting the entities

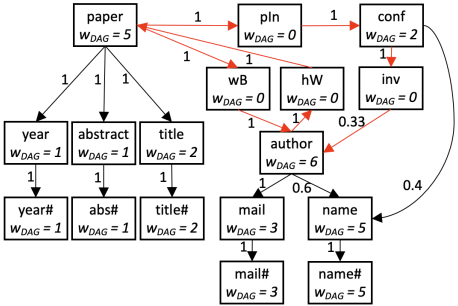


repeat

- Compute PageRank on collection graph
- Highest-rank node $\rightarrow$ root of next entity e
- Assign other collections in e's boundary
- Update the collection graph:
  - remove e's root + outgoing edges
  - remove every collection in e's boundary that contributed only to it
  - reduce the weights of the other collections in e's boundary

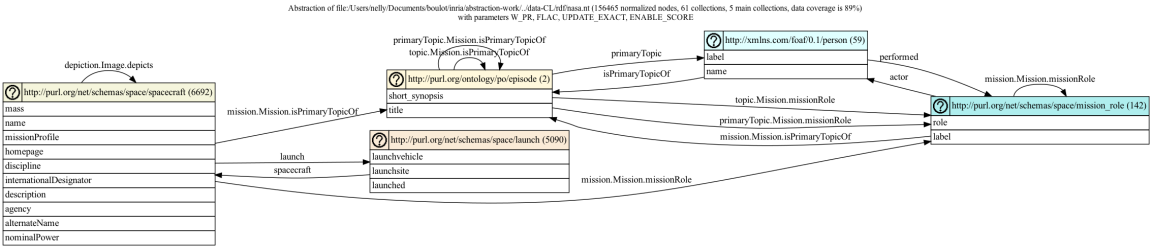
until k entities selected and/or f% of the data is reflected

Finding the relationships

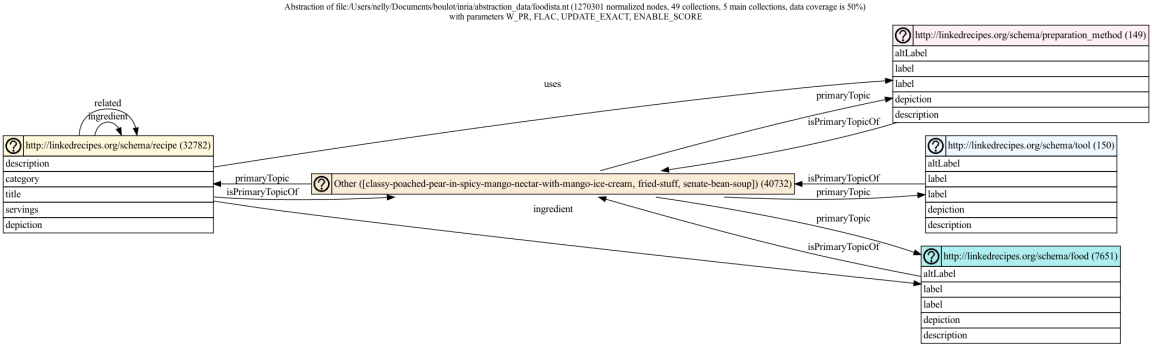


- For each c_1, root of entity e_1
  - For each path $c_1 \rightsquigarrow c_2$ where c_2 is the root of e_2
  - Create a relationship $e_1 \rightarrow e_2$ with the labels on the path

Abstraction of NASA RDF graph



Abstraction of Foodista RDF graph



General Conclusion

- Data heterogeneity is here to stay.
  - Each model is particularly good for some things... and many applications need several of these
  - Relational leads to most efficient evaluation but is rigid.
  - Nested formats, e.g., JSON, much more flexible.
- Many systems support several models, but not with the same performance
  - Your full-text search predicate could kill you
  - JSON index available at 1st but not at 2nd nesting level...
  - Poor RDF reasoning support in IBM DB2
  - "Export" Spark computations in Java streams, etc.
- ESTOCADA: View-based rewriting allows to deploy data fragments where they are most efficiently processed
- ABSTRA: Beyond the heterogeneity, find entities and relationships in application datasets.

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