CIKM 2018

Multi-model Databases and Tightly Integrated Polystores

Current Practices, Comparisons, and Open Challenges

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Outline

- Motivation and multiple model examples (30')
- Theoretical foundations (30')
- Multi-model data storage (25')
- Questions and discussion (5’)

Session break

- Multi-model data query languages (10')
- Multi-model query processing (10')
- Overview on tightly integrated polystores (20')
- Query processing in tightly integrated polystores (15')
- Advanced aspects of tightly integrated polystores (15')
- Comparison of multi-model databases and tightly integrated polystores (5')
- Open problems and challenges (10')
- Questions and discussion (5’)

A grand challenge on Variety

- Big data: Volume, Variety, Velocity, Veracity
- Variety: hierarchical data (XML, JSON), graph data (RDF, property graphs, networks), tabular data (CSV), etc

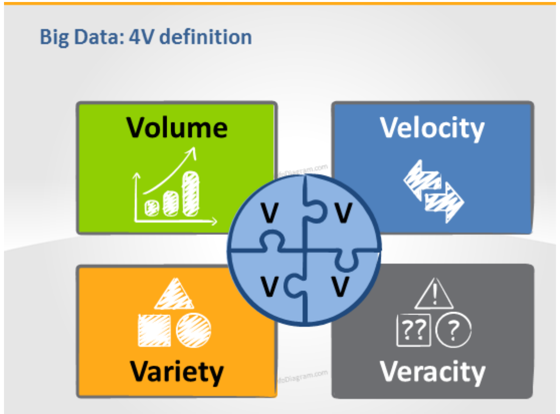
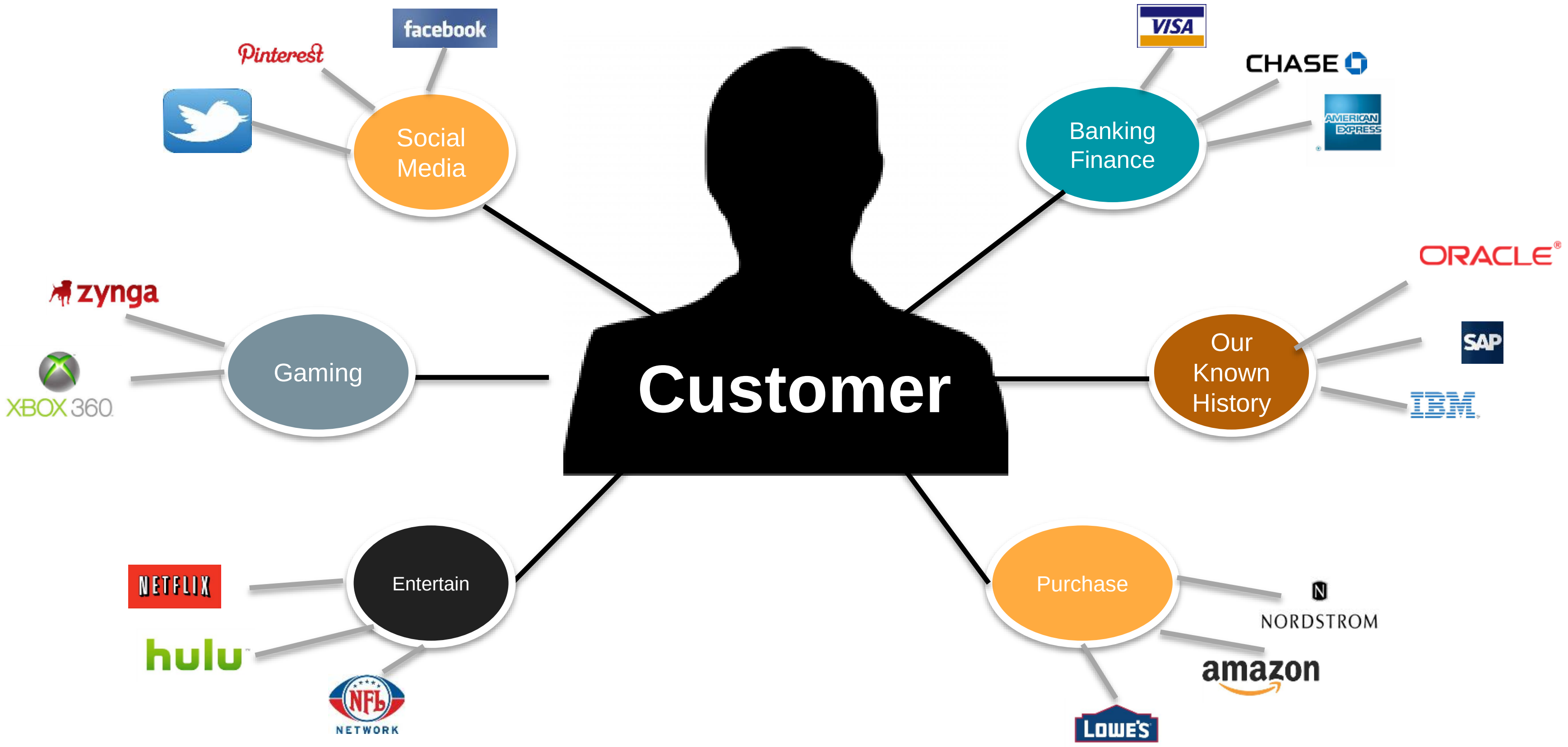


Photo downloaded from: https://blog.infodiagram.com/2014/04/visualizing-big-data-concepts-strong.html

Motivation: E-commerce



Motivation: one application to include multi-model data

- Relational data: customer databases
- Graph data: social networks
- Hierarchical data: catalog, product
- Text data: Customer Review
- ......

An E-commerce example with multi-model data

Two solutions

1. Polystores

   Using jointly multiple data storage technologies, chosen based upon the way data is being used by individual applications.

1. Multi-model databases

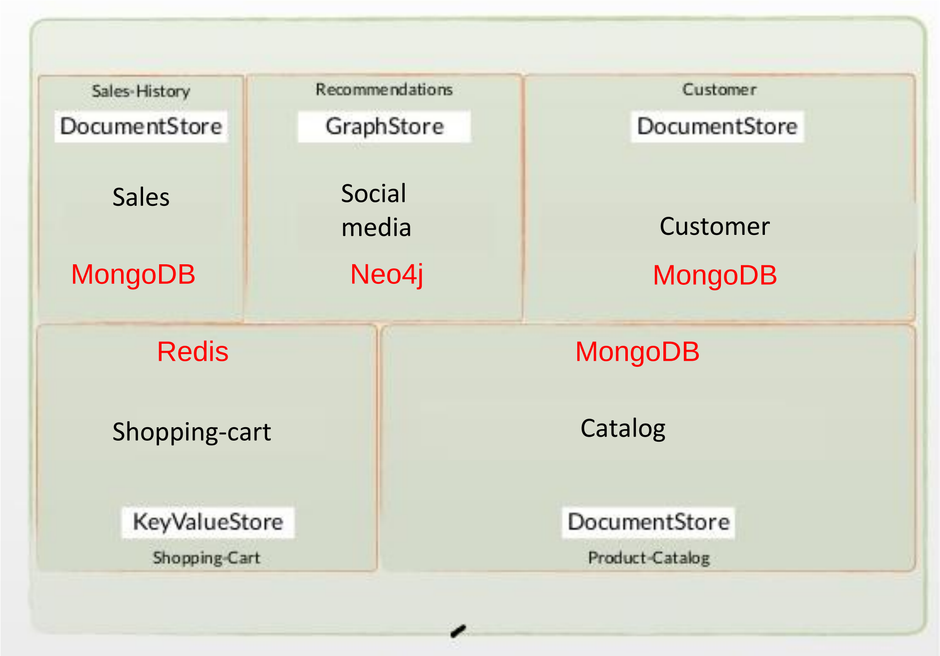
   Using one single, integrated backend.

Polystores

- Use the right tool for (each part of) the job
- If you have structured data with some differences
  - Use a document store
- If you have relations between entities and want to efficiently query them
  - Use a graph database
- If you manage the data structure yourself and do not need complex queries
  - Use a key-value store

Glue everything together...

Multiple NoSQL databases



Pros and Cons of Polystores

- Handle multi-model data
- Help your apps to scale well
- A rich experience

- Requires the company to hire people to integrate different databases
- Implementers need to learn different databases
- It is a challenge to handle cross-model query and transaction

Three types of polystore systems*

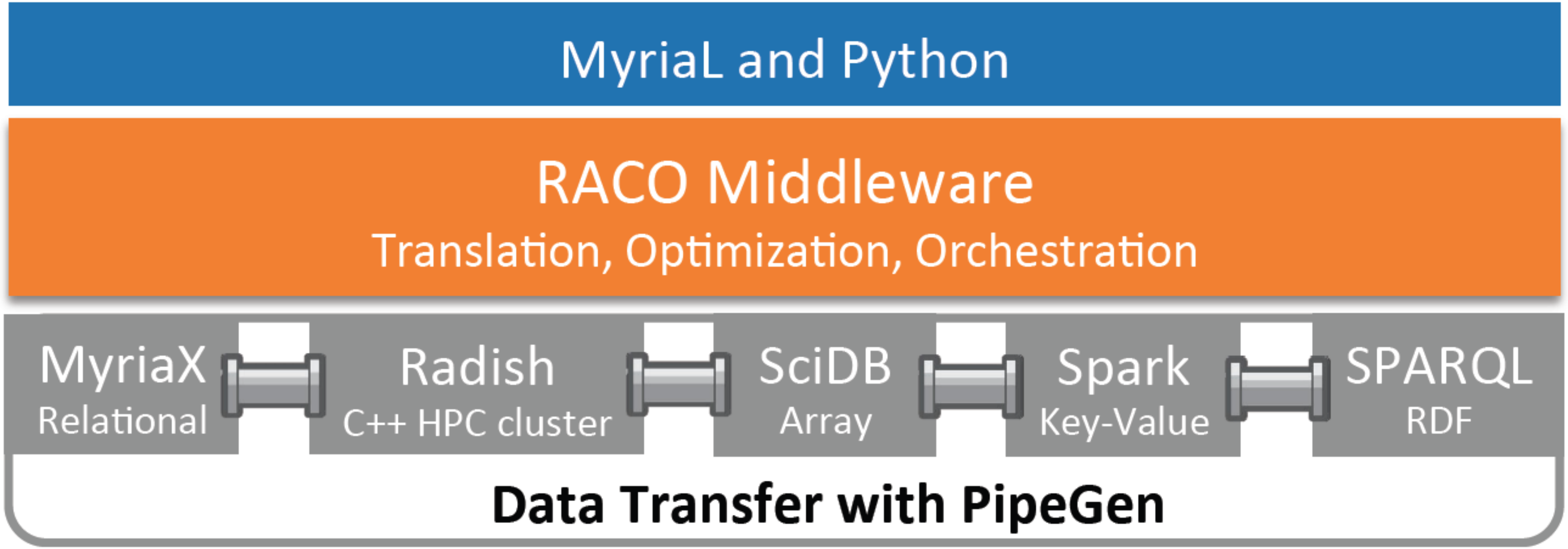
- Loosely-coupled systems
  - Similar to mediator / wrapper
  - Common interfaces
  - Autonomy of local stores
- Tightly-coupled systems
  - Trade autonomy for performance with materialized views and indexes
- Hybrid
  - Compromise between loosely-coupled and tightly

* Bondiombouy, Carlyna, and Patrick Valduriez. "Query processing in multistore systems: an overview." International Journal of Cloud Computing 5.4 (2016): 309-346

Polystore	Special modules	Schema mgt	Query processing	Query optimization
Loosely-coupled				
BigIntegrator (Uppsala U.)	Importer, absorber, finalizer	LAV	Access filters	Heuristics
Forward (UC San Diego)	Query processor	GAV	Data store capabilities	Cost-based
QoX (HP Labs)	Dataflow engine	No	Data/ function shipping, operation decomposition	Cost-based
Tightly-coupled				
Polybase (Microsoft)	HDFS bridge	GAV	Query splitting	Cost-based
HadoopDB (Yale U.)	SMS planer, dbconnector	GAV	Query splitting	Heuristics
Estocada (Inria)	Storage advisor	Materialized views	View-based query rewriting	Cost-based
Hybrid				
SparkSQL (UCB)	Catalyst extensible optimizer	Dataframes	In-memory caching using columnar storage	Cost-based
BigDAWG (MIT)	Island query processors	GAV within islands	Function/ data shipping	Heuristics

An overview of polystores https://slideplayer.com/slide/13365730/

Polystore example - Myria



http://myria.cs.washington.edu/

Two solutions

1. Polystores

   Using jointly multiple data storage technologies, chosen based upon the way data is being used by individual applications.

1. Multi-model databases

   Using one single, integrated backend

Multi-model DB

- One unified database for multi-model data

Multi-model DB

Multi-model databases

- A multi-model database is designed to support multiple data models against a single, integrated backend.

- Document, graph, relational, and key-value models are examples of data models that may be supported by a multi-model database.

Multi-model databases:
One size fits multi-data-model

ORACLE

mongoDB

MariaDB

ArangoDB

OrientDB

APACHE DRILL

FOUNDATIONDB

MarkLogic

AsterixDB

InterSystems CACHÉ

...

Most of DBs became multi-model databases in 2017

- By 2017, all leading operational DBMSs will offer multiple data models, relational and NoSQL, in a single DBMS platform.

--- Gartner report for operational databases 2016

Three examples of multi-model databases

ORACLE®

OrientDB®

ArangoDB

Oracle database provides a long list of supported data models that can be used and managed inside Oracle database:

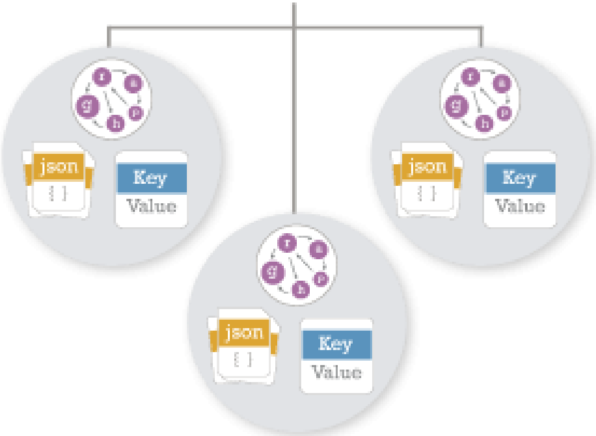
- JSON document
- Spatial and Graph Data
- XML DB data
- Text data
- Multimedia data

Example: Data transformation by views between JSON and relation data

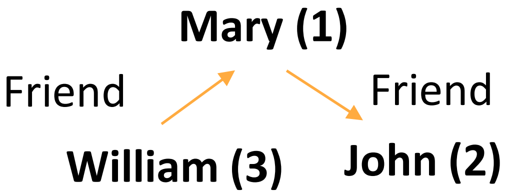
Tasks	SQL/JSON language
Construct JSON View from relational content	*CREATE JSON_VIEW AS SELECT JSON {"Staff" : {"STAFF_ID" : e.staff_id, "First" : e.first, "Last" : e.last, "Mgr" : e.mgr, {"Dept" : {"Dept_ID" :d.dept_id, "Names" : d.name, "Head" : d.head }} } FROM Employee e, department d WHERE e.dep_id = d.dep_id*
Construct relational view of employee from JSON	*CREATE EMPLOYEE_REL_VIEW AS SELECT * FROM JSON_VIEW f, JSON_TABLE (f.Staff COLUMNS (Staff_ID, First, Last, Mgr)*

ArangoDB

ArangoDB is designed as a native multi-model database, supporting key/value, document and graph models.



An example of multi-model data and query

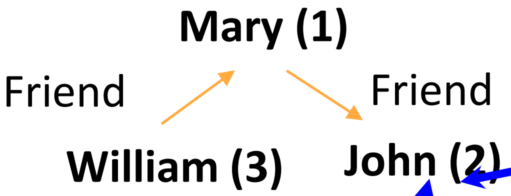



```
"1" -- > "34e5e759"
"2"-- > "0c6df508"
```

Customer_ID	Name	Credit_limits
1	Mary	5,000
2	John	3,000
3	William	2,000

```
{"Order_no":"0c6df508",
 “Orderlines": [
    { "Product_no":"2724f”
      “Product_Name":“Toy",
      "Price":66 },
    { "Product_no":“3424g”,
      "Product_Name":“Book",
      "Price":40 } ]
}
```

An example of multi-model data and query



"1" -- > "34e5e759"
"2"-- > "0c6df508"

```
{"Order_no":"0c6df508",
 "Orderlines": [
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     "Product_Name":"Toy",
     "Price":66 },
   { "Product_no":"3424g",
     "Product_Name":"Book",
     "Price":40 } ]
}
```

Customer_ID	Name	Credit_limits
1	Mary	5,000
2	John	3,000
3	William	2,000

Q: Return all products which are ordered by a friend of a customer whose credit limit is over 3000

Mary (1)

Friend　　　　Friend

William (3)　　**John (2)**

Customer_ID	Name	Credit_limits
1	Mary	5,000
2	John	3,000
3	William	2,000

```
"1" -- > "34e5e759"
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     "Price":66 },
   { "Product_no":“3424g”,
     "Product_Name":“Book",
     "Price":40 } ]
}
```

An example of multi-model query (ArangoDB)

```
Let CustomerIDs =(FOR Customer IN Customers FILTER
Customer.CreditLimit > 3000 RETURN Customer.id)

Let FriendIDs=(FOR CustomerID in CustomerIDs FOR
Friend IN 1..1 OUTBOUND CustomerID Knows return
Friend.id)

For Friend in FriendIDs

For Order in 1..1 OUTBOUND Friend Customer2Order

Return Order.orderlines[*].Product_no
```

Recommendation query:

Return all products which are ordered by a friend of a customer whose credit limit is over 3000.

- Supporting graph, document, key/value and object models.
- It supports schema-less, schema-full and schema-mixed modes. Queries with SQL extended for graph traversal.

```
Select
expand(out("Knows").Orders.orderlines
.Product_no) from Customers where
CreditLimit > 3000
```

Recommendation query:
Return all products which are ordered by any friend of a customer whose credit limit is over 3000.

What is the difference between Multi-model and Multi-modal

- Multi-model: graph, tree, relation, key-value,…
- Multi-modal: video, image, audio, eye gaze data, physiological signals,…

Three arguments on multi-model data management

- 1. One size cannot fit all

- 2. One size can fit all

- 3. One size fits a bunch

One size cannot fit all

“SQL analytics, real-time decision support, and data warehouses cannot be supported in one engine.”

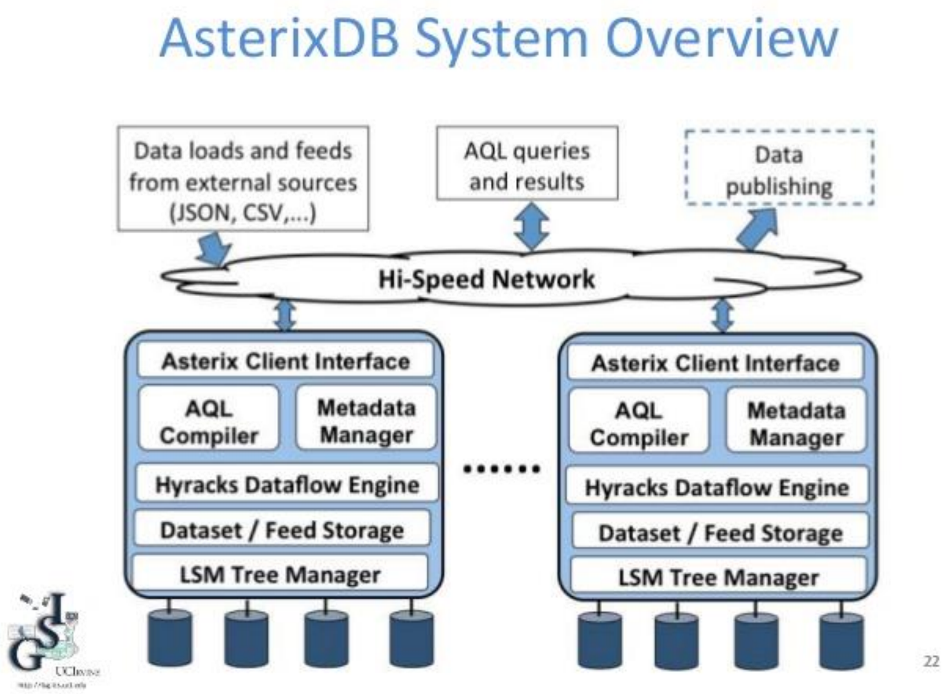
M. Stonebraker and U. Cetintemel. ”One Size Fits All”: An Idea Whose Time Has Come and Gone (Abstract). In ICDE, 2005.

One size can fit all

- OctopusDB suggests a unified, one size fits all data processing architecture for OLTP, OLAP, streaming systems, and scan-oriented database systems.

Jens Dittrich, Alekh Jindal: Towards a One Size Fits All Database Architecture. CIDR 2011: 195-198

One size can fit a bunch: AsterixDB



Providing Hadoop-based query platforms, key-value stores and semi-structured data management

AsterixDB: A Scalable, Open Source BDMS. PVLDB 7(14): 1905-1916 (2014)

A simple survey

How many of you agree that (You can choose both or all or none of them)

1. One size cannot fit all

2. One size can fit all

3. One size fits a bunch

4. ???

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Theoretical foundation for multi-model management

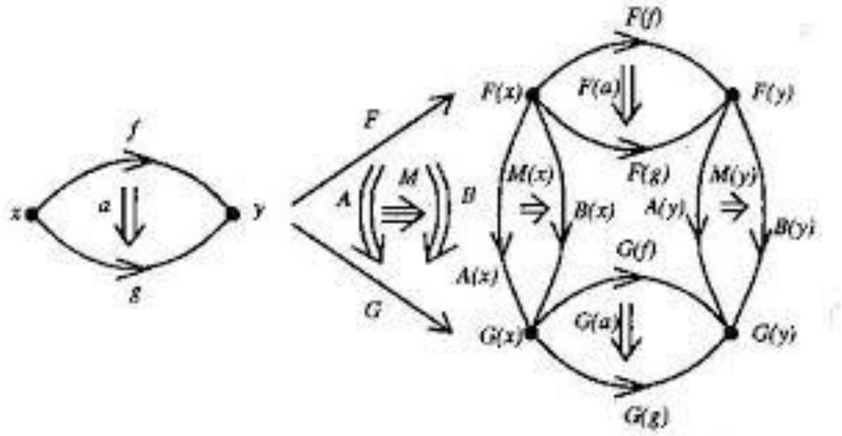


Diagram to illustrate 2-category

Challenge: a new theory foundation

Call for a unified model and theory for multi-model data!

The theory of relations (150 years old) is not adequate to mathematically describe modern (NoSQL and multi-model) DBMS.

Two possible theoretical models

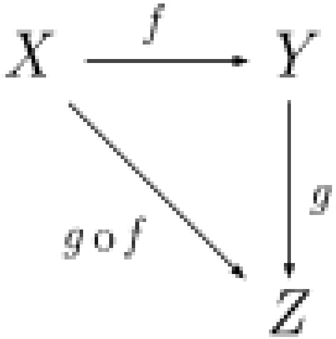
- **Category theory**
- **Associative array**

One possible theory foundation: category theory

- Introduced to mathematics world by Samuel Eilenberg and Sauders MacLane in 1944
- Found as part of their work in topology
- Category theory becomes the theoretical foundation on functional programming : Haskell

Categories Defined

- A category C is ….
  - a collection of objects ob(C) .. {X,Y, Z ….}
  - a collection of morphisms {f, g ….}
    - A set of morphisms from object a into b is denoted by $Hom_c(a, b)$ or $a \rightarrow b$.



Categories Defined (con't)

- The category must satisfy the following rules
  - associativity
    - $(h \circ g) \circ f = h \circ (g \circ f)$ [a,b,c,d Є ob(C), f Є $Hom_c(a, b)$, g Є $Hom_c(b, c)$, h Є $Hom_c(c, d)$]
  - unit laws
    - $f \circ 1_a = f = 1_b \circ f$

- Think of it like a graph: the nodes are objects and the arrows are relationships

Relational category

- A relational category C
  - an ob(C) is a table
  - a morphisms a→b means that a has the relational homomorphism with b

$$\begin{tikzcd} a \arrow[d] \\ b \end{tikzcd}$$

Table A

Staff_ID	First	Last
100	John	Smith

Table B

Staff_ID	Name
100	John Smith
101	James William

JSON category

- A JSON category J
  - an ob(J) is a JSON file
  - a morphisms a→b means that a has a tree homomorphism with b

$$
\begin{tikzcd}
a \arrow[d] \\
b
\end{tikzcd}
$$

JSON A

{Staffs:
{“Staff_ID”:”100”,”First”:”John”,
“Name”: “John Smith”, }
}

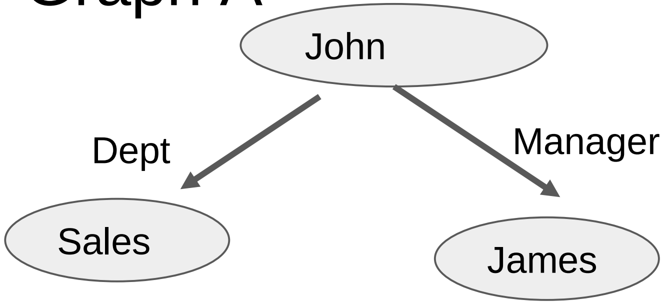
JSON B

{Staffs: {“Staff_ID”:”100”,”First”:”John”,
“Last”: “Smith”, “First”: “John”}
{“Staff_ID”:”101”,”First”:”James”,”Last”:”Willia
m”}}

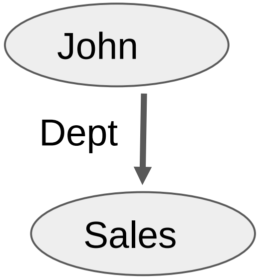
Graph category

- A Graph category G
  - an ob(J) is a graph
  - a morphisms a→b means that a has a graph homomorphism with b

Graph A

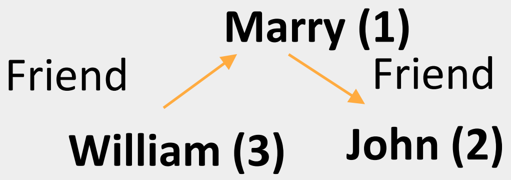


Graph B



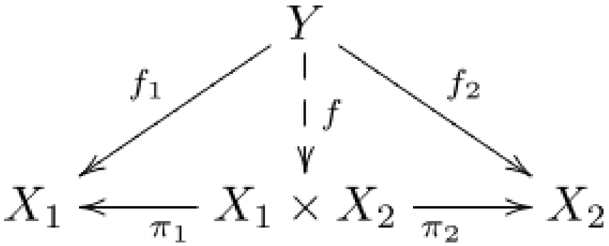
A single object can contain multi-model data

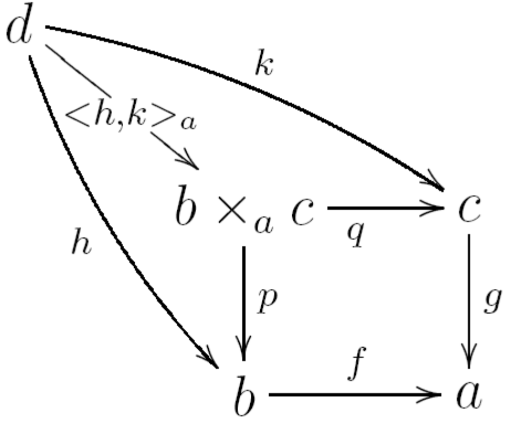
Customer_ID	Name	Credit_limits
1	Mary	5,000
2	John	3,000
3	William	2,000



One object in a category contains both graph and table data.

Product and Pull-back in categories



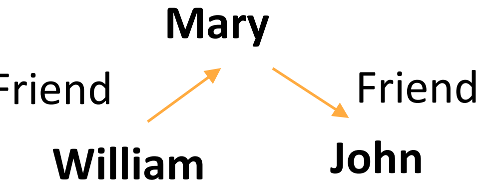


Product

Pull-back

An example of Product

G



T

Name	Credit_limits
Mary	5,000
John	3,000
William	2,000

G X T

Name	Credit_limits	G.Name
Mary	5,000	Mary
John	3,000	Mary
William	2,000	Mary

Friend

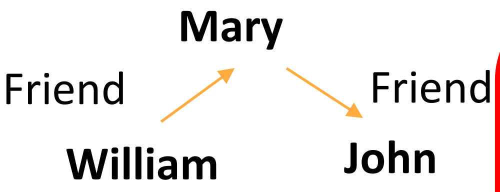
Friend

Name	Credit_limits	G.Name
Mary	5,000	William
John	3,000	WIlliam
William	2,000	William

Name	Credit_limits	G.Name
Mary	5,000	John
John	3,000	John
William	2,000	John

An example of Push-back

G



T

Name	Credit_limits
Mary	5,000
John	3,000
William	2,000

G X T

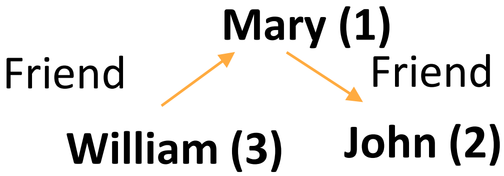
Name	Credit_limits	G.Name
Mary	5,000	Mary

Name	Credit_limits	G.Name
William	2,000	William

Name	Credit_limits	G.Name
John	3,000	John

An example of multi-model data and query

G



K

```
"1" -- > "34e5e759"
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```

T

Customer_ID	Name	Credit_limits
1	Mary	5,000
2	John	3,000
3	William	2,000

J

```
{"Order_no":"0c6df508",
 “Orderlines": [
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     “Product_Name":“Toy"
,
     "Price":66 },
   {
"Product_no":“3424g”,
     "Product_Name":“Book
",
     "Price":40 } ]
}
```
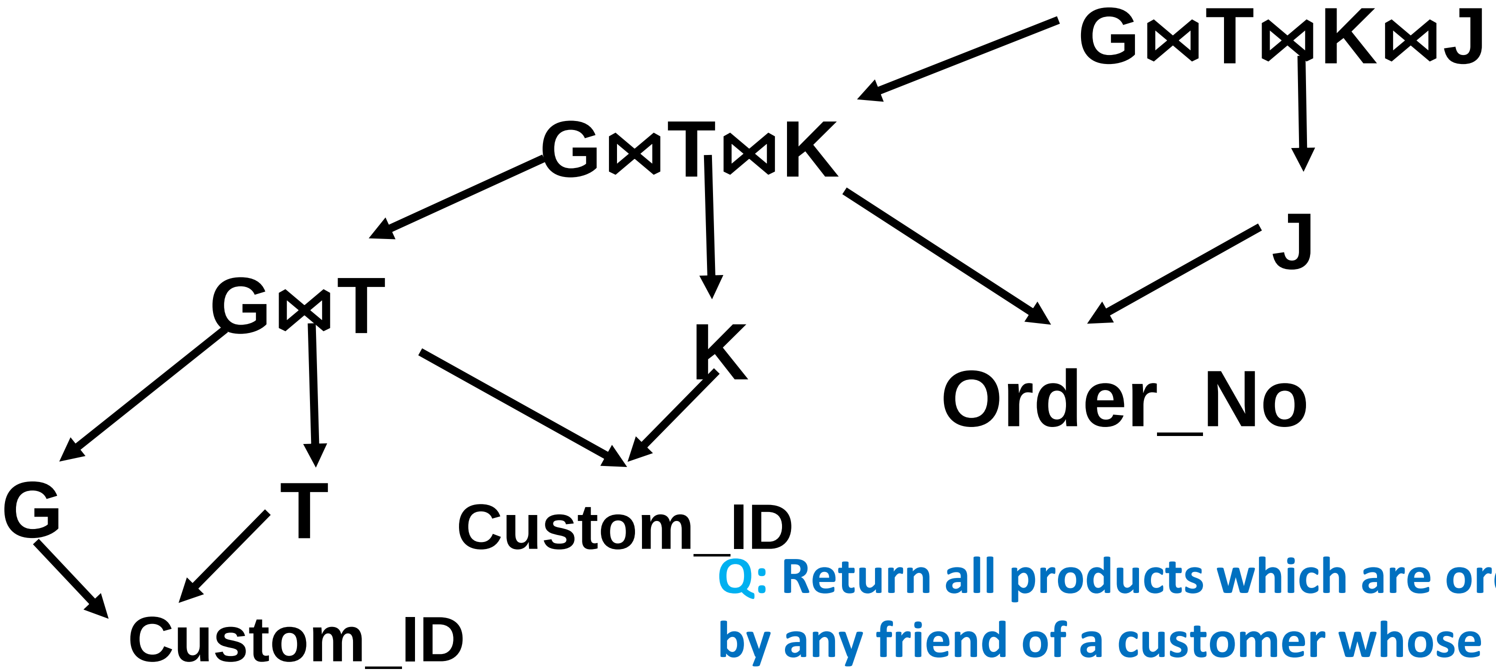
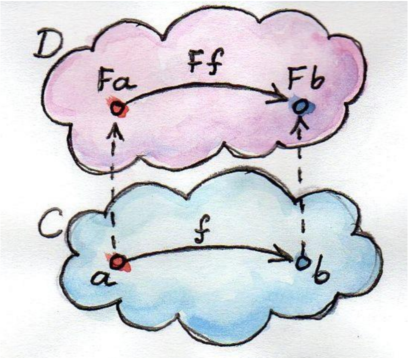

Join with four models of data by Pull-back



Q: Return all products which are ordered by any friend of a customer whose credit_limit>3000

Functors

- a “category of categories”
  - objects are categories, morphisms are mappings between categories
  - preserves identity and composition properties



Functors for data transformation

Table A

Dep_ID	Name
D2	Sales

JSON A

{Depts: {“Dep_ID”:”D2”,”Name”:”Sales”,}
}

Table B

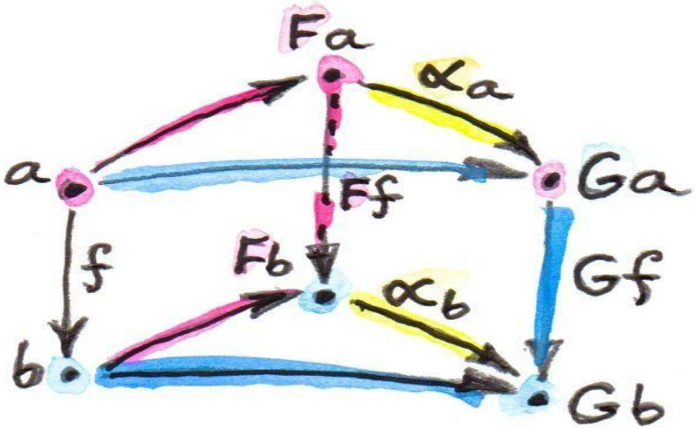
Dep_ID	Name	Head
D2	Sales	101
D3	Production	102

JSON B

{Depts:
{“Dep_ID”:”D2”,”Name”:”Sales”,
“Head”: “101”}
{“Dep_ID”:”D3”,”Name”:”Producti
on”,”Head”:”102”}}

Natural transformation

- A natural transformation provides a way of transforming one functor into another



Natural transformation example

Functor F

JSON A

{Depts: {“Dep_ID”:”D2”,”Name”:”Sales”,
Head: {“ID”: “101”, “Name”:”John”}}
{“Dep_ID”:”D3”,”Name”:”Production”,Head:{
”ID”:”102”, “Name”:”James”}}

Table A1

Dep_ID	Name	Head_I D	Head_ Name
D2	Sales	101	John
D3	Product ion	102	Jame

Functor G

Tables A2

DepID	Name	Head
101	Sales	H01
102	Production	H02

ID	Head_I D	Head_N ame
H01	101	John
H02	102	Jame

Category theory: mathematical foundation for MMDB

1, Category object: an abstract definition of object in multi-model databases: including relation, tree, graph, key-value pair

2. Query semantics: product, pull-back, limits in category theory

3. Proof of the equivalence of declarative and procedural syntaxes over the above definitions: functor and natural transformation

4. Proof of data instance equivalence for multi-model data

Two possible theoretical model

- **Category theory**

- **Associative array**

Associative arrays

Associative arrays could provide a mathematical model for polystores to optimize the exchange of data and execution queries.

Definition: $A:\{1,...,m\} \times \{1,...,n\} \rightarrow V$

Associative array for relations and graphs

A(row1,Name)=”Mary”

A(row2,Name)=”John”

A(row3,Name)=”William”

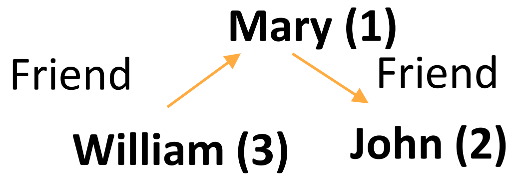
B(Edge1, start)=”William” ,

B(Edge1, end)=”Mary”

B(Edge2, start)=”Mary”

B(Edge2, end)=”John”

Customer_ID	Name	Credit_limits
1	Mary	5,000
2	John	3,000
3	William	2,000

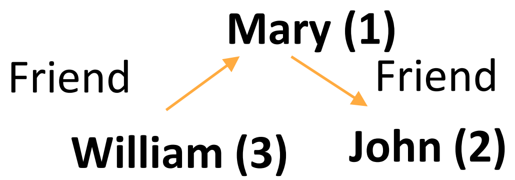


Associative array example

Customer_ID	Name	Credit_limits
1	Mary	5,000
2	John	3,000
3	William	2,000

Matrix A

$\bowtie$



Matrix B

$$C = PB \oplus PP^{T}A$$

$$\mathbf{P} = \mathbb{I}_{\mathbf{A}} \ (\mathbf{A} \oplus.\otimes \mathbf{B}^{\mathsf{T}}) \ \mathbb{I}_{\mathbf{B}}$$
$$= \mathbb{I}_{\mathbf{A}} \ (\mathbf{A} \ \&.= \ \mathbf{B}^{\mathsf{T}}) \ \mathbb{I}_{\mathbf{B}}$$

C(row3, start)=”William”

C(row1, end)=”Mary”

C(row1, start)=”Mary”

C(row2, end)=”John”

From SQL to Associative algebra

SELECT $J(1),\ldots,J(n)$ FROM $\mathbf{A}$ $\Rightarrow$ $\mathbf{A}_{.J(1),\ldots,J(n)}$

SELECT $*$ FROM $\mathbf{A}$ UNION SELECT $*$ FROM $\mathbf{B}$ $\Rightarrow$ $\mathbf{A} \oplus \mathbf{B}$

SELECT $*$ FROM $\mathbf{A}$ INTERSECT SELECT $*$ FROM $\mathbf{B}$ $\Rightarrow$ $\mathbf{PB}$ or $\mathbf{P}^{\mathsf{T}}\mathbf{A}$

SELECT $*$ FROM $\mathbf{A}$, $\mathbf{B}$ WHERE $\theta(\mathbf{A}_{.J(1),\ldots,J(n)}, \mathbf{B}_{.J'(1),\ldots,J'(n)})$ $\Rightarrow$ $\mathbf{PB} \oplus \mathbf{PP}^{\mathsf{T}}\mathbf{A}$

Comparison between Category theory and Associative array

	Category theory	Associative array
Abstraction level	High	Low
Operation	No concrete definition	Linear algebra operation
Extensibility	High, generalized to more data types	Focus on relation and graph

References on theoretical foundation (1)

Category theory

1.Multi-Model Database Management Systems-a Look Forward
ZH Liu, J Lu, D Gawlick, H Helskyaho, G Pogossiants, Z Wu, VLDB workshop Poly 2018

2.Henrik Forssell, Håkon Robbestad Gylterud, David I. Spivak: Type Theoretical Databases. LFCS 2016: 117-129

3. Patrick Schultz, David I. Spivak, Christina Vasilakopoulou, Ryan Wisnesky: Algebraic Databases. CoRR abs/1602.03501 (2016)

4. David I. Spivak: Simplicial Databases. CoRR abs/0904.2012 (2009)
. DBPL 2015: 21-28

References on theoretical foundation (2)

Associative array

1. Hayden Jananthan et al.: Polystore mathematics of relational algebra. BigData 2017: 3180-3189
2. Jeremy Kepner, et al:Associative array model of SQL, NoSQL, and NewSQL databases. HPEC 2016: 1-9
3. J. Kepner et al., “Dynamic Distributed Dimensional Data Model (D4M) Database and Computation System,” ICASSP (International Conference on Accoustics, Speech, and Signal Processing, 2012, Kyoto, Japan

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- Overview on tightly integrated polystores (20')
- Query processing in tightly integrated polystores (15')
- Advanced aspects of tightly integrated polystores (15')
- Comparison of multi-model databases and tightly integrated polystores (5')
- Open problems and challenges (10')
- Questions and discussion (5’)

Multi-model data storage

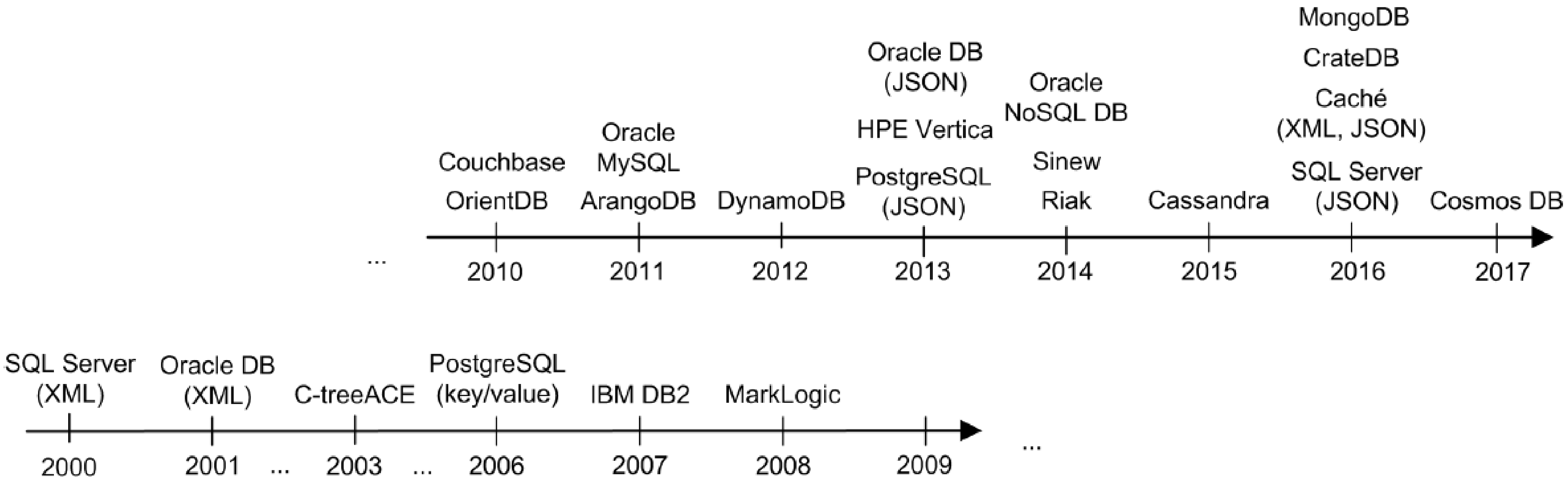
Classification

- Basic approach: on the basis of original (or core) data model

Original Type	Representatives
Relational	PostgreSQL, SQL Server, IBM DB2, Oracle DB, Oracle MySQL, Sinew
Column	Cassandra, CrateDB, DynamoDB, HPE Vertica
Key/value	Riak, c-treeACE, Oracle NoSQL DB
Document	ArangoDB, Couchbase, MongoDB, Cosmos DB, MarkLogic
Graph	OrientDB
Object	Caché
Other	Not yet multi-model – NuoDB, Redis, Aerospike Multi-use-case – SAP HANA DB, Octopus DB

Timeline

- When a particular system became multi-model
  - Original data format (model) was extended
  - First released directly as a multi-model DBMS



Extension towards Multiple Models

Types of strategies:

1. Adoption of a completely new storage strategy suitable for the new data model(s)
   - e.g., XML-enabled databases

sometimes hard to decide

2. Extension of the original storage strategy for the purpose of the new data model(s)
   - e.g., ArangoDB - special edge collections bear information about edges in a graph
3. Creating of a new interface for the original storage strategy
   - e.g., MarkLogic - stores JSON data in the same way as XML data
4. No change in the original storage strategy
   - Storage and processing of data formats simpler than the original one

Approach	**DBMS**	**Type**
New storage strategy	PostgreSQL	relational
	SQL server	relational
	IBM DB2	relational
	Oracle DB	relational
	Cassandra	column
	CrateDB	column
	DynamoDB	column
	Riak	key/value
	Cosmos DB	document
Extension of the original storage strategy	MySQL	relational
	HPE Vertica	column
	ArangoDB	document
	MongoDB	document
	OrientDB	graph
	Caché	object
New interface for the original storage strategy	Sinew	relational
	c-treeACE	key/value
	Oracle NoSQL Database	key/value
	Couchbase	document
	MarkLogic	document

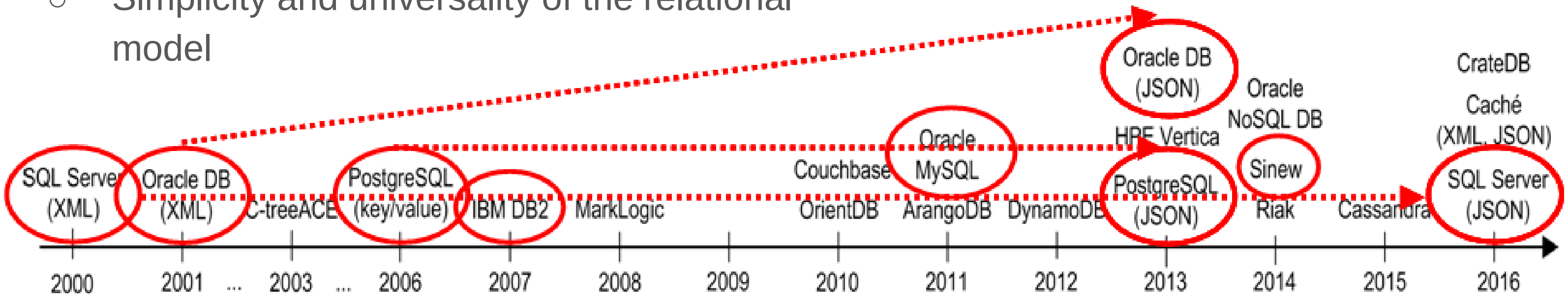
Overview of Supported Data Models

Type	DBMS	Relational	Column	Key/value	Document (JSON)	XML	Graph	Nested data/UDT/object
Relational	PostgreSQL	√		√	√	√		
	SQL Server	√			√	√		
	IBM DB2	√				√		
	Oracle DB	√			√	√		
	Oracle MySQL	√		√				
	Sinew	√		√				
Column	Cassandra		√					√
	CrateDB	√	√		√			
	DynamoDB		√	√	√			
	HPE Vertica		√		√			
Key/value	Riak			√	√	√		
	c-treeACE	√		√				
	Oracle NoSQL DB	√		√				
Document	ArangoDB			√	√		√	
	Couchbase			√	√			
	MongoDB			√	√		√	
	Cosmos DB		√	√	√		√	
	MarkLogic				√	√		
Graph	OrientDB			√	√		√	√
Object	Caché	√			√	√		√

Relational Stores

- Representatives: PostgreSQL, SQL Server, IBM DB2, Oracle DB, Oracle MySQL, Sinew
- Biggest set of multi-model databases
  - The most popular type of databases
  - SQL has been extended towards other data formats (e.g, SQL/XML)
  - Simplicity and universality of the relational model

Type	DBMS	Relational	Column	Key/value	Document (JSON)	XML	Graph	Nested data/UDT/object
Relational	PostgreSQL	√		√	√	√		
	SQL Server	√			√	√		
	IBM DB2	√				√		
	Oracle DB	√			√	√		
	Oracle MySQL	√		√				
	Sinew	√		√				



```sql
CREATE TABLE customer (
  id      INTEGER PRIMARY KEY,
  name    VARCHAR(50),
  address VARCHAR(50),
  orders  JSONB
);
```

```sql
INSERT INTO customer
VALUES (1, 'Mary', 'Prague',
 '{"Order_no":"0c6df508",
   "Orderlines":[
        {"Product_no":"2724f", "Product_Name":"Toy", "Price":66},
        {"Product_no":"3424g", "Product_Name":"Book", "Price":40}]
  }');
INSERT INTO customer
VALUES (2, 'John', 'Helsinki',
 '{"Order_no":"0c6df511",
   "Orderlines":[
        { "Product_no":"2454f", "Product_Name":"Computer", "Price":34 }]
  }');
```

id integer	name character varying (50)	address character varying (50)	orders jsonb
1	Mary	Prague	{"Orderlines":[{"Price":66,"Product_Name":"Toy","Product_no":"2724f"},{"Price":40,"Product_Name":...
2	John	Helsinki	{"Orderlines":[{"Price":34,"Product_Name":"Computer","Product_no":"2454f"}],"Order_no":"0c6df511"}

```sql
SELECT json_build_object('id',id,'name',name,'orders',orders)
FROM customer;
```

json_build_object json
{"orders":{"Orderlines":[{"Price":66,"Product_Name":"Toy","Product_no":"2724f"},{"Price":40,"Product_Name":"Book","Product_no":"3...
{"orders":{"Orderlines":[{"Price":34,"Product_Name":"Computer","Product_no":"2454f"}],"Order_no":"0c6df511"},"id":2,"name":"John"}

```sql
SELECT jsonb_each(orders) FROM customer;
```

jsonb_each record
(Order_no,"""0c6df508""")
(Orderlines,"[{""Price"": 66, ""Product_no"": ""2724f"", ""Product_Name"": ""To...
(Order_no,"""0c6df511""")
(Orderlines,"[{""Price"": 34, ""Product_no"": ""2454f"", ""Product_Name"": ""Co...

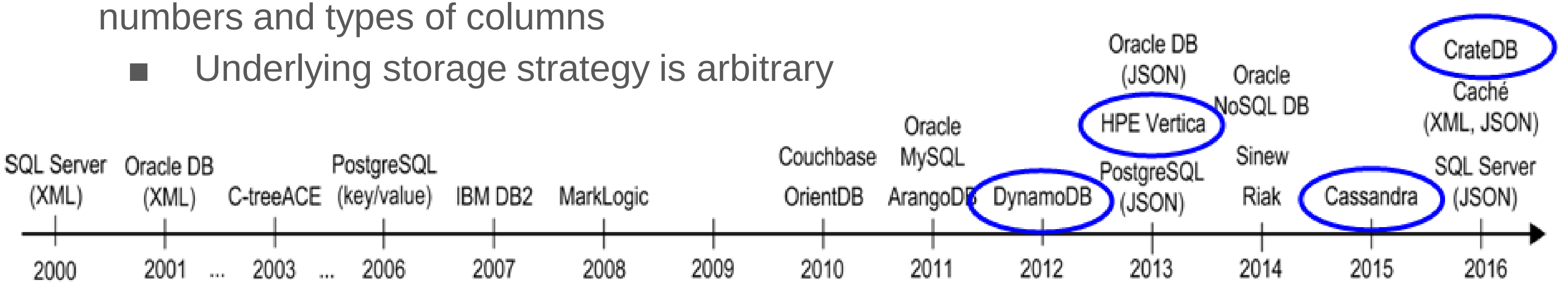
```sql
SELECT jsonb_object_keys(orders) FROM customer;
```

jsonb_object_keys text
Order_no
Orderlines
Order_no
Orderlines

Column Stores

- Representatives: Cassandra, CrateDB, DynamoDB, HPE Vertica
- Two meanings:
  - Column-oriented (columnar, column) DBMS stores data tables as columns rather than rows
    - Not necessarily NoSQL
  - Column-family (wide-column) DBMS = a NoSQL database which supports tables having distinct numbers and types of columns
    - Underlying storage strategy is arbitrary

Type	DBMS	Relational	Column	Key/value	Document (JSON)	XML	Graph	Nested data/UDT/object
Column	Cassandra		√					√
	CrateDB	√	√		√			
	DynamoDB		√	√	√			
	HPE Vertica		√		√			



```
create keyspace myspace
WITH REPLICATION = { 'class' : 'SimpleStrategy', 'replication_factor' : 3 };
CREATE TYPE myspace.orderline (
   product_no text,
   product_name text,
   price float
   );
CREATE TYPE myspace.myorder (
   order_no text,
   orderlines list<frozen <orderline>>
   );
CREATE TABLE myspace.customer (
   id INT PRIMARY KEY,
   name text,
   address text,
   orders list<frozen <myorder>>
   );
```

```
INSERT INTO myspace.customer JSON
' {"id":1,
   "name":"Mary",
   "address":"Prague",
   "orders" : [
   { "order_no":"0c6df508",
          "orderlines":[
          { "product_no" : "2724f",
            "product_name" : "Toy",
       "price" : 66 },
          { "product_no" : "3424g",
       "product_name" :"Book",
       "price" : 40 } ] } ]
  }';
```

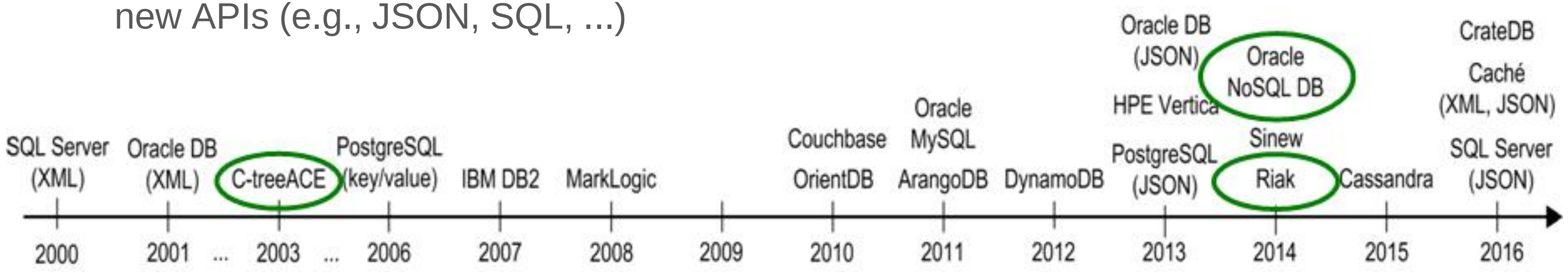
```
INSERT INTO myspace.customer JSON
' {"id":2,
   "name":"John",
   "address":"Helsinki",
   "orders" : [
   { "order_no":"0c6df511",
          "orderlines":[
     { "product_no" : "2454f",
            "product_name" :
"Computer",
            "price" : 34 } ] } ]
      }';
```

```
CREATE TABLE myspace.users (
   id text PRIMARY KEY,
   age int,
   country text
   );

INSERT INTO myspace.users (id, age, state)
VALUES ('Irena', 37, 'CZ');

SELECT JSON * FROM myspace.users;
[json]
-------------------------------------------
{"id": "Irena", "age": 37, "country": "CZ"}
```

Key/Value Stores

- Representatives: Riak, c-treeACE, Oracle NoSQL DB
- The simplest type of NoSQL database
  - Get / put / delete + key
  - Often extended with more advanced features
- Multi-model extensions:
  - More complex indices over the value part + new APIs (e.g., JSON, SQL, ...)

Type	DBMS	Relational	Column	Key/value	Document (JSON)	XML	Graph	Nested data/UDT/object
Key/value	Riak			√	√	√		
	c-treeACE	√		√				
	Oracle NoSQL DB	√		√				



```
create table Customers (
  id integer,
  name string,
  address string,
  orders array (
         record (
      order_no string,
      orderlines array (
         record (
      product_no string,
      product_name string,
      price integer ) ) )
         ),
  primary key (id)
);

import -table Customers
-file customer.json
```

customer.json:

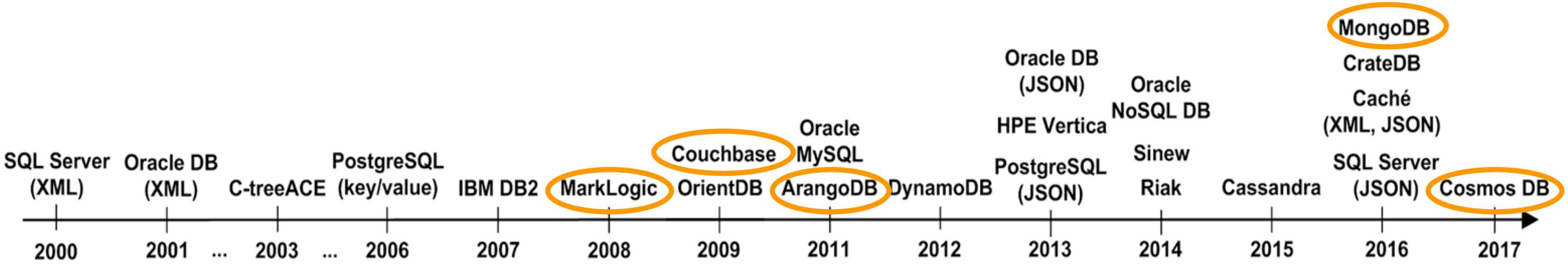
```
{   "id":1,
    "name":"Mary",
    "address":"Prague",
    "orders" : [
          { "order_no":"0c6df508",
          "orderlines":[
          { "product_no" : "2724f",
          "product_name" : "Toy",
          "price" : 66 },
          { "product_no" : "3424g",
          "product_name"  :"Book",
          "price" : 40 } ] } ]
}
{   "id":2,
    "name":"John",
    "address":"Helsinki",
    "orders" : [
          {"order_no":"0c6df511",
          "orderlines":[
          { "product_no" : "2454f",
          "product_name" : "Computer",
          "price" : 34  } ] } ]
}
```

```
sql-> select * from Customers
   -> ;
 +----+------+----------+-----------------------------+
 | id | name | address  |            orders           |
 +----+------+----------+-----------------------------+
 |  2 | John | Helsinki | order_no         | 0c6df511 |
 |    |      |          | orderlines                   |
 |    |      |          |     product_no   | 2454f    |
 |    |      |          |     product_name | Computer |
 |    |      |          |     price        | 34       |
 +----+------+----------+-----------------------------+
 |  1 | Mary | Prague   | order_no         | 0c6df508 |
 |    |      |          | orderlines                   |
 |    |      |          |     product_no   | 2724f    |
 |    |      |          |     product_name | Toy      |
 |    |      |          |     price        | 66       |
 |    |      |          |                              |
 |    |      |          |     product_no   | 3424g    |
 |    |      |          |     product_name | Book     |
 |    |      |          |     price        | 40       |
 +----+------+----------+-----------------------------+
```

Document Stores

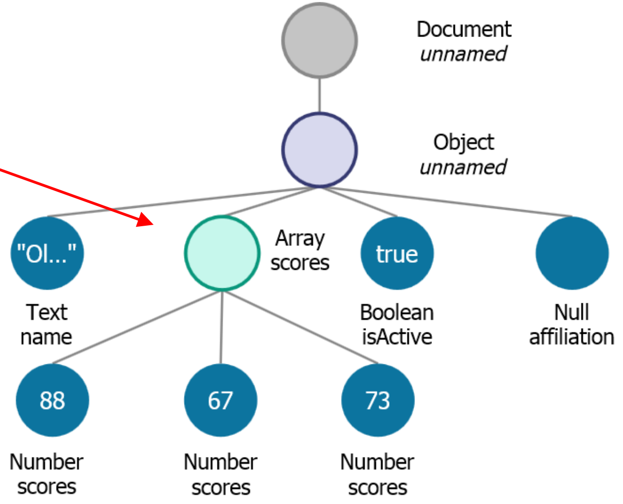
- Representatives: ArangoDB, Couchbase, MongoDB, Cosmos DB, MarkLogic
- Distinct strategies:
  - ArangoDB: special edge collection
  - MarkLogic: stores JSON data as XML

Type	DBMS	Relational	Column	Key/value	Document (JSON)	XML	Graph	Nested data/UDT/object
Document	ArangoDB			√	√		√	
	Couchbase			√	√			
	MongoDB			√	√		√	
	Cosmos DB		√	√	√		√	
	MarkLogic				√	√		



MarkLogic

```
{
   "name": "Oliver",
   "scores": [88, 67, 73],
   "isActive": true,
   "affiliation": null
}
```



JavaSript:

```
declareUpdate();
xdmp.documentInsert("/myJSON1.json",
{
   "Order_no":"0c6df508",
    "Orderlines":[
         { "Product_no":"2724f",
         "Product_Name":"Toy",
         "Price":66 },
         {"Product_no":"3424g",
         "Product_Name":"Book",
         "Price":40}]
}
);
```

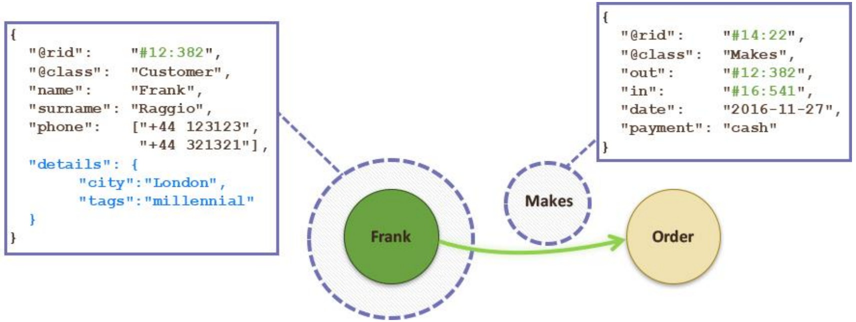
XQuery:

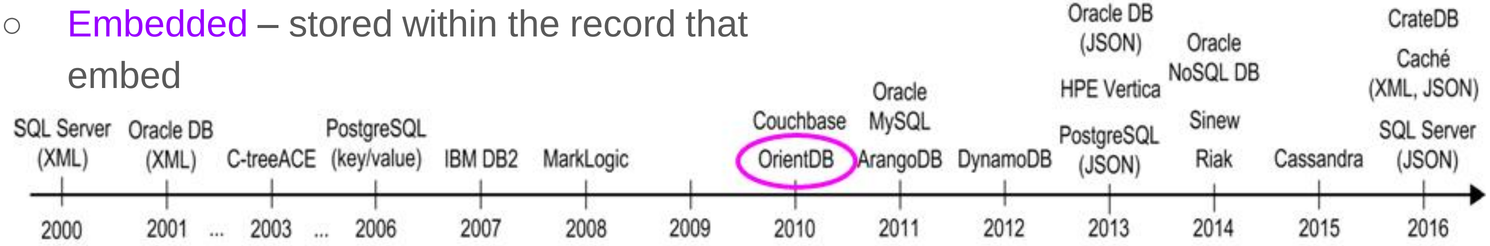
```
xdmp:document-insert("/myXML1.xml",
<product no="3424g">
  <name>The King's Speech</name>
  <author>Mark Logue</author>
  <author>Peter Conradi</author>
</product>
);
```

Graph Stores

- Representatives: OrientDB
- Based on an object database = native support for multiple models
  - Element of storage = record = document / BLOB / vertex / edge
- Classes – define records
- Classes can have relationships:
  - Referenced – stored similarly to storing pointers between two objects in memory
  - Embedded – stored within the record that embed

Type	DBMS	Relational	Column	Key/value	Document (JSON)	XML	Graph	Nested data/UDT/object
Graph	OrientDB			√	√		√	√



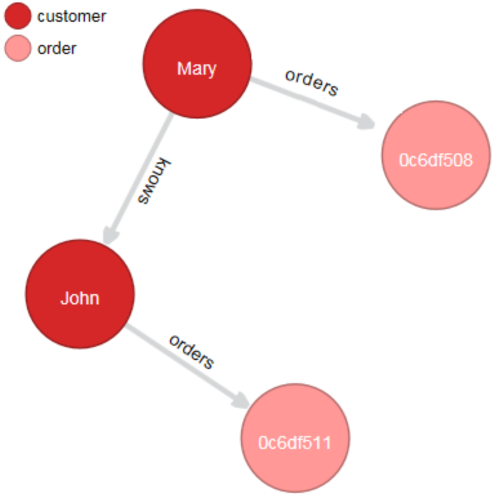


```
CREATE CLASS orderline EXTENDS V
CREATE PROPERTY orderline.product_no STRING
CREATE PROPERTY orderline.product_name STRING
CREATE PROPERTY orderline.price FLOAT

CREATE CLASS order EXTENDS V
CREATE PROPERTY order.order_no STRING
CREATE PROPERTY order.orderlines EMBEDDEDLIST orderline

CREATE CLASS customer EXTENDS V
CREATE PROPERTY customer.id INTEGER
CREATE PROPERTY customer.name STRING
CREATE PROPERTY customer.address STRING

CREATE CLASS orders EXTENDS E

CREATE CLASS knows EXTENDS E
```

```
CREATE VERTEX order CONTENT {
    "order_no":"0c6df508",
    "orderlines":[
         { "@type":"d",
           "@class":"orderline",
           "product_no":"2724f",
           "product_name":"Toy",
           "price":66 },
         { "@type":"d",
           "@class":"orderline",
           "product_no":"3424g",

"product_name":"Book",
           "price":40}]
}
```

```
CREATE VERTEX order CONTENT {
    "order_no":"0c6df511",
    "orderlines":[
         { "@type":"d",
           "@class":"orderline",
           "product_no":"2454f",
           "product_name":"Computer",
           "price":34 }]
}
CREATE VERTEX customer CONTENT {
   "id" : 1,
   "name" : "Mary",
   "address" : "Prague"
   }
CREATE VERTEX customer CONTENT {
   "id" : 2,
   "name" : "John",
   "address" : "Helsinki"
   }
```

```
CREATE EDGE orders FROM
    (SELECT FROM customer WHERE name = "Mary")
    TO
    (SELECT FROM order WHERE order_no = "0c6df508")
CREATE EDGE orders FROM
    (SELECT FROM customer WHERE name = "John")
    TO
    (SELECT FROM order WHERE order_no = "0c6df511")

CREATE EDGE knows FROM
    (SELECT FROM customer WHERE name = "Mary")
    TO
    (SELECT FROM customer WHERE name = "John")
```




Question


Break

Outline

- Motivation and multiple model examples (30')
- Theoretical foundations (30')
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- Questions and discussion (5’)

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Multi-model data query languages

Multi-model Query Languages

1. Simple API
   - Store, retrieve, delete data
     - Typically key/value, but also other use cases
   - DynamoDB – simple data access + querying over indices using comparison operators
2. SQL Extensions and SQL-Like Languages
   - Most common
   - In most types of systems (relational, column, document, …)

Type	DBMS	SQL extension
Relational	PostgreSQL	Getting an array element by index, an object field by key, an object at a specified path, containment of values/paths, top-level key-existence, deleting a key-value pair / a string element / an array element with specified index / a field / an element with specified path, ...
	SQL Server	JSON: export relational data in the JSON format, test JSON format of a text value, JavaScript-like path queries SQLXML: SQL view of XML data + XML view of SQL relations
	IBM DB2	SQL/XML + embedding SQL queries to XQuery expressions
	Oracle DB	SQL/XML + JSON extensions (`JSON_VALUE`, `JSON_QUERY`, `JSON_EXISTS`, ...)
Document	Couchbase	Clauses `SELECT`, `FROM` (multiple buckets), ... for JSON
	Cosmos DB	Clauses `SELECT`, `FROM` (with inner join), `WHERE` and `ORDER BY` for JSON
	ArangoDB	key/value: insert, look-up, update document: simple QBE, complex joins, functions, ... graph: traversals, shortest path searches
Key/value	Oracle NoSQL DB	SQL-like, extended for nested data structures
	c-treeACE	Simple SQL-like language
Column	Cassandra	`SELECT`, `FROM`, `WHERE`, `ORDER BY`, `LIMIT` with limitations
	CrateDB	Standard ANSI SQL 92 + nested JSON attributes
Graph	OrientDB	Classical joins not supported, the links are simply navigated using dot notation; main SQL clauses + nested queries
Object	Caché	SQL + object extensions (e.g. object references instead of joins)

PostgreSQL

id integer	name character varying (50)	address character varying (50)	orders jsonb
1	Mary	Prague	{"Orderlines":[{"Price":66,"Product_Name":"Toy","Product_no":"2724f"},{"Price":40,"Product_Name":...
2	John	Helsinki	{"Orderlines":[{"Price":34,"Product_Name":"Computer","Product_no":"2454f"}],"Order_no":"0c6df511"}

```
{"Order_no":"0c6df508",
 "Orderlines":[
        { "Product_no":"2724f",
      "Product_Name":"Toy",
         "Price":66 },
        { "Product_no":"3424g",
         "Product_Name":"Book",
         "Price":40}]
}
```

```sql
SELECT name,
  orders->>'Order_no' AS Order_no,
  orders#>'{Orderlines,1}'->>'Product_Name'
AS Product_Name
FROM customer
WHERE orders->>'Order_no' <> '0c6df511';
```

name character varying (50)	order_no text	product_name text
Mary	0c6df508	Book

```
sql-> select * from Customers
   -> ;
 +----+-------+----------+---------------------------+
 | id | name  | address  |          orders           |
 +----+-------+----------+---------------------------+
 |  2 | John  | Helsinki | order_no       | 0c6df511 |
 |    |       |          | orderlines               |
 |    |       |          |     product_no   | 2454f   |
 |    |       |          |     product_name | Computer |
 |    |       |          |     price        | 34      |
 +----+-------+----------+---------------------------+
 |  1 | Mary  | Prague   | order_no       | 0c6df508 |
 |    |       |          | orderlines               |
 |    |       |          |     product_no   | 2724f   |
 |    |       |          |     product_name | Toy     |
 |    |       |          |     price        | 66      |
 |    |       |          |                           |
 |    |       |          |     product_no   | 3424g   |
 |    |       |          |     product_name | Book    |
 |    |       |          |     price        | 40      |
 +----+-------+----------+---------------------------+
```

ORACLE NOSQL DATABASE

```
sql-> SELECT c.name, c.orders.order_no, c.orders.orderlines[0].product_name
   -> FROM customers c
   -> where c.orders.orderlines[0].price > 50;
 +------+----------+--------------+
 | name | order_no | product_name |
 +------+----------+--------------+
 | Mary | 0c6df508 | Toy          |
 +------+----------+--------------+

sql-> SELECT c.name, c.orders.order_no,
   -> [c.orders.orderlines[$element.price >35]]
   -> FROM customers c;
 +------+----------+-------------------------+
 | name | order_no |        Column_3         |
 +------+----------+-------------------------+
 | Mary | 0c6df508 | product_no   | 2724f    |
 |      |          | product_name | Toy      |
 |      |          | price        | 66       |
 |      |          |                         |
 |      |          | product_no   | 3424g    |
 |      |          | product_name | Book     |
 |      |          | price        | 40       |
 +------+----------+-------------------------+
 | John | 0c6df511 |                         |
 +------+----------+-------------------------+
```

ORACLE
NOSQL DATABASE

Multi-model Query Languages

3. SPARQL Query Extensions
   - e.g., IBM DB2 - SPARQL 1.0 + subset of features from SPARQL 1.1
     - SELECT, GROUP BY, HAVING, SUM, MAX, …
     - Probably no extension for relational data
       - But: RDF triples are stored in a table = SQL queries can be used over them too
4. XML Query Extensions
   - MarkLogic – JSON can be accessed using XPath
     - Tree representation like for XML
     - Can be called from XQuery and JavaScript
5. Full-text Search
   - In general quite common
   - e.g., Riak – Solr index + operations
     - Wildcards, proximity search, range search, Boolean operators, grouping, …

JavaSript:

```
declareUpdate();
xdmp.documentInsert("/myJSON1.json",
{
  "Order_no":"0c6df508",
   "Orderlines":[
        { "Product_no":"2724f",
          "Product_Name":"Toy",
          "Price":66 },
        { "Product_no":"3424g",
          "Product_Name":"Book",
          "Price":40}]
}
);
```

XQuery:

```
xdmp:document-insert("/myXML1.xml",
<product no="3424g">
  <name>The King's Speech</name>
  <author>Mark Logue</author>
  <author>Peter Conradi</author>
</product>
);
```

XQuery:

```
let $product := fn:doc("/myXML1.xml")/product
let $order := fn:doc("/myJSON1.json")
  [Orderlines/Product_no = $product/@no]
return $order/Order_no
Result: 0c6df508
```

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Multi-model query processing

Query Processing Approaches

- Depend highly on the way the system was extended
  - No change
  - New interface
    - e.g., MarkLogic
  - Extension of the original storage strategy
    - e.g. ArangoDB
  - A completely new storage strategy
    - e.g. Oracle native support for XML

changes in the query processing approaches

- General tendencies:
  - Exploit the existing storage strategies as much as possible
  - Exploit the verified approaches to query optimization

JavaSript:

```
declareUpdate();
xdmp.documentInsert("/myJSON1.json",
{
  "Order_no":"0c6df508",
   "Orderlines":[
        { "Product_no":"2724f",
          "Product_Name":"Toy",
          "Price":66 },
        { "Product_no":"3424g",
          "Product_Name":"Book",
          "Price":40}]
}
);
```

XQuery:

```
xdmp:document-insert("/myXML1.xml",
<product no="3424g">
  <name>The King's Speech</name>
  <author>Mark Logue</author>
  <author>Peter Conradi</author>
</product>
);
```

XQuery:

```
let $product := fn:doc("/myXML1.xml")/product
let $order := fn:doc("/myJSON1.json")
  [Orderlines/Product_no = $product/@no]
return $order/Order_no
Result: 0c6df508
```

MarkLogic Multiple Models

- Indexes both XML and JSON data in the same way
- Schema-less data
- Universal index - optimized to allow text, structure and value searches to be combined into
    - Word indexing
    - Phrase indexing
    - Relationship indexing
    - Value indexing
- Other user-defined indexes
    - Range indexing
    - Word lexicons
    - Reverse indexing
    - Triple index

ArangoDB

Social network graph

Marry (1)

Friend　　Friend

William (3)　　**John (2)**

graph - key-value join

Key/value pairs
(Customer_ID , Order_no)

"1" -- > "34e5e759"

"2"-- > "0c6df508"

key/value - JSON document join

relation - graph join

Order JSON document

```
{"Order_no":"0c6df508",
 "Orderlines": [
   { "Product_no":"2724f"
     "Product_Name":"Toy",
     "Price":66 },
   { "Product_no":"3424g",
     "Product_Name":"Book",
     "Price":40 } ]
}
```

relation Customers

Customer_ID	Name	Credit_limits
1	Mary	5,000
2	John	3,000
3	William	2,000

ArangoDB

```
LET CustomerIDs = (
  FOR Customer IN Customers
  FILTER Customer.CreditLimit > 3000
  RETURN Customer.id )
LET FriendIDs = (
  FOR CustomerID IN CustomerIDs
    FOR Friend IN 1..1 OUTBOUND CustomerID Knows
    RETURN Friend.id )
FOR Friend IN FriendIDs
  FOR Order IN 1..1 OUTBOUND Friend Customer2Order
  RETURN Order.orderlines[*].Product_no
```

Return all products which are ordered by a friend of a customer whose credit limit is over 3000.

ArangoDB Multiple Models

- Supported models:
  - Document - original
  - Key/value - special type of document without complex value part
  - Tables - special type of document with regular structure
  - Graph - relations between documents
    - Edge collection – two special attributes _from and _to
- So we still need to efficiently process queries over documents
- Indexes
  - Primary = hash index for document keys
  - Edge = hash index, which stores the union of all _from and _to attributes
    - For equality look-ups
  - User-defined - (non-)unique hash/skiplist index, (non-)unique sparse hash/skiplist index, geo, fulltext, ...

Query Optimization Strategies

- B-tree/B+-tree index - the most common approach
  - Typically in relational databases
- Native XML index - support of XML data
  - Typically an ORDPATH-based approach
- Hashing - can be used almost universally
- ...
- But: still no universally acknowledged optimal or sub-optimal approach
  - Approaches are closely related to the way the system was extended

Optimization	DBMS	Type
Inverted index	PostgreSQL	relational
	Cosmos DB	document
B-tree, B+-tree	SQL server	relational
	Oracle DB	relational
	Oracle MySQL	relational
	Cassandra	column
	Oracle NoSQL DB	key/value
	Couchbase	document
	MongoDB	document
Materialization	HPE Vertica	column
Hashing	DynamoDB	column
	ArangoDB	document
	MongoDB	document
	Cosmos DB	document
	OrientDB	graph
Bitmap index	Oracle DB	relational
	Caché	object
Function-based index	Oracle DB	relational
Native XML index	Oracle DB	relational
	SQL server	relational
	DB2	relational
	MarkLogic	document

Outline

- Motivation and multiple model examples (30')
- Theoretical foundations (30')
- Multi-model data storage (25')
- Questions and discussion (5’)

Session break

- Multi-model data query languages (10')
- Multi-model query processing (10')
- Overview on tightly integrated polystores (20')
- Query processing in tightly integrated polystores (15')
- Advanced aspects of tightly integrated polystores (15')
- Comparison of multi-model databases and tightly integrated polystores (5')
- Open problems and challenges (10')
- Questions and discussion (5’)

Overview on tightly integrated polystores

No one size fits all…

- Heterogenous analytics: data processing frameworks (MR, Spark, Flink), NoSQL
- ETL is very expensive towards a single model (may degrade performance), adapts poorly to changes in data / application requirements

Polystore idea: package together multiple query engines: union (federation) of different specialized stores, each with distinct (native) data model, internal capabilities, language, and semantics → Holy grail: platform agnostic data analytics

- Use the right store for (parts of) each specialized scenario
- Possibly rely on middleware layer to integrate data from different sources
- Read-only queries as distributed transactions over different data stores is hard !

Dimensions of polystores *

- Heterogeneity – different data models / query models, semantic expressiveness / query engines
- Autonomy – association, execution, evolution
- Transparency – location (data may even span multiple storage engines), transformation / migration
- Flexibility – schema, interfaces, architecture
- Optimality – federated plans, data placement

* Tan et al. “Enabling query processing across heterogeneous data models: A survey”. BigData 2017

Tightly integrated polystores (TIPs)

- Heterogeneity moderate
- Autonomy low
- Transparency high
- Flexibility low
- Optimality high
- Semantic expressiveness high

TIPs

- Trade autonomy for efficient querying of diverse kinds of data for BD analytics
  - data stores can only be accessed through the multi-store system (slaves)
  - less uncertainty with extended control over the various stores
  - stores accessed directly through their local language
- Query processor directly uses the local language and local interfaces
- Efficient / adaptive data movement across data stores
- Number of data stores that can be interfaced is typically limited
- Extensibility ? Good to have…

Arguably the closest we can get to multi-model DBs, while having several native stores “under the hood”.

Loosely integrated polystores

Reminiscent of multidatabase systems, follow mediator-wrapper architecture (one wrapper per datastore), one global common language

- Notable examples: BigIntegrator, Forward/SQL++, QoX
- Data mediation SQL engines: Apache Drill, Spark SQL, SQL++ allow different sources to be plugged in by wrappers, then queried via SQL

General approach

- Split a query into subqueries (per datastore, still in common language)
- Send to wrapper, translate, get results, translate to common format, integrate

Hybrid polystores

Rely on tight coupling for some stores, loose coupling for others, following the mediator-wrapper architecture, but the query processor can also directly access some data stores

- Notable examples: BigDawg (next), SparkSQL, CloudMdsQL

BigDawg – Big Data Analytics Working Group*

- One key abstraction: island of information, a collection of data stores accessed with a single query language
- BigDawg relies on a variety of data islands (relational, array, NoSQL, streaming, etc)
- No common data model, query language / processor (each island has its own)
- Wrappers (shims) mapping the island query to the native one
- CAST: explicit operators for moving intermediate datasets between islands

- Subqueries for multi-island query processing

* https://bigdawg.mit.edu/

Historical perspective

Multi-database systems (federated systems, data integration systems)

- mediator-wrapper architecture, declarative SQL-like language, single unified global schema (GAV, LAV)
- key principle: query is sent to store that owns the data
- focus on data integration

The reference federated databases: Garlic, Tsimmis

- even multi-model settings, but the non-relational stores did not support their own declarative query language (being wrapped to provide an SQL API)
- no cross-model rewriting

Polystores:

- higher expectations in terms of data heterogeneity
- allow the direct exploitation of the datasets in their native language (but not only)

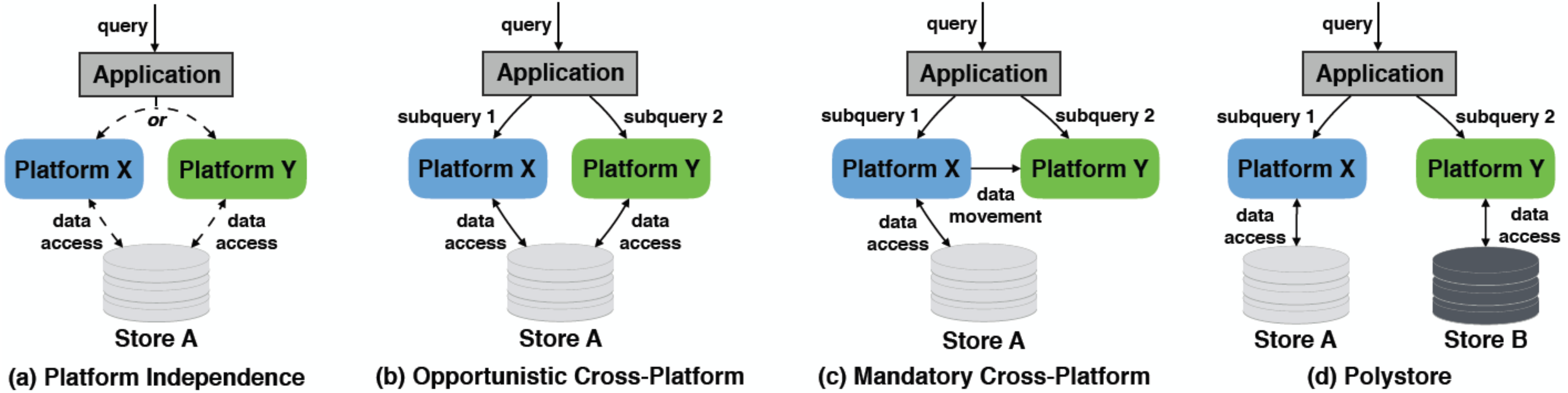
Another classification for polystores / multistores*

- Federated systems: collection of homogeneous data stores and features a single standard query interface
- Polyglot systems: collection of homogeneous data stores and exposes multiple query interfaces to the users
- Multistore systems: data across heterogeneous data stores, while supporting a single query interface
- Polystore systems: query processing across heterogeneous data stores and supports multiple query interfaces

* Tan et al. “Enabling query processing across heterogeneous data models: A survey”. BigData 2017

Scenarios for polystores*

- Platform independence
- Data analysis spanning stores (polystore)
- Query acceleration / opportunistic cross-platform
- Mandatory cross-platform



* Z. Kaoudi and J.-A. Quiané-Ruiz. Cross-Platform Data Processing: Use Cases and Challenges. ICDE 2018

In summary - goals of TIPs

- Focus on efficiency and transparency
- Exploit mature, focused technologies, good fits for different workloads
- Integrated, transparent access to data stores through one or more query languages (semantic expressiveness)
- Exploit the full expressive power of the native query languages
- Ease of use / develop apps

In summary - goals of TIPs (cont’d)

- Cross-model data migration, automated scheduling, self tuning (transparent)
- Cross-platform / multi-model query planning and optimizer
  - automatic query reformulation, inter-platform parallelism, …
- Potential goal: internally, unified storage abstraction
  - cross-model view (internal) over the native data

Main TIPs aspects discussed

- Architecture
- Data models / storage
- Query languages
- Query processing

Systems: HadoopBD, Polybase, Estocada/Tatooine, Odyssey/MISO, Myria, RHEEM

HadoopDB* - introduction

	Scalability*	High Performance**
MapReduce	✓	✗
Parallel Databases	✗	✓
What we need	✓	✓

Main idea:

- Query RDBMS from Hadoop
- use MR as communication layer

Schema: GAV

Queries: SQL-like system (HiveQL)

Objective: the best of parallel DBMS and MR systems, gets efficiency of PDBMS and scalability, fault-tolerance of MR

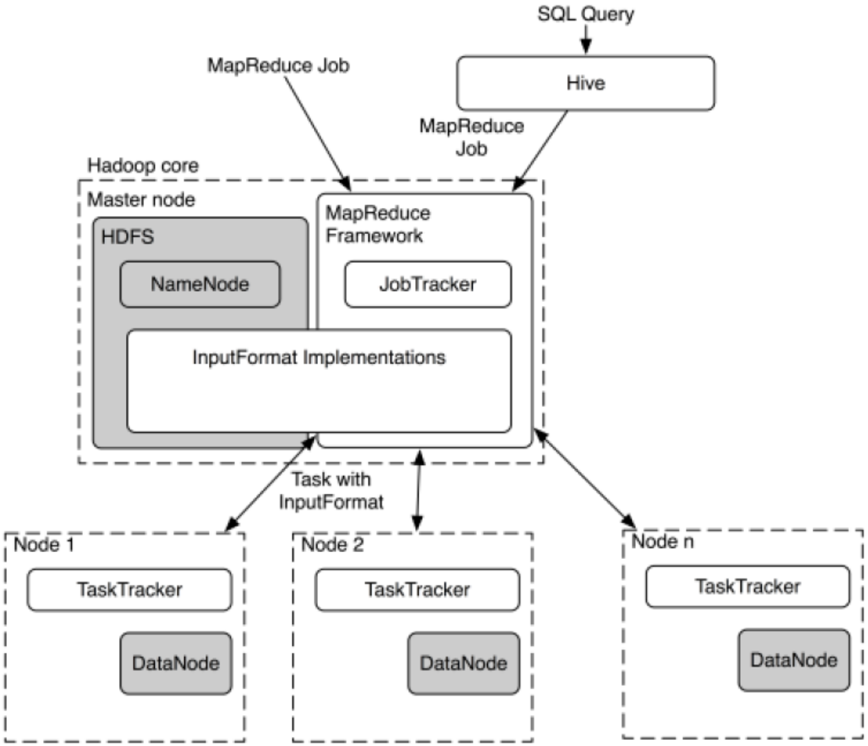
- Extends HIVE (Facebook) to push down operations into single node DBMS

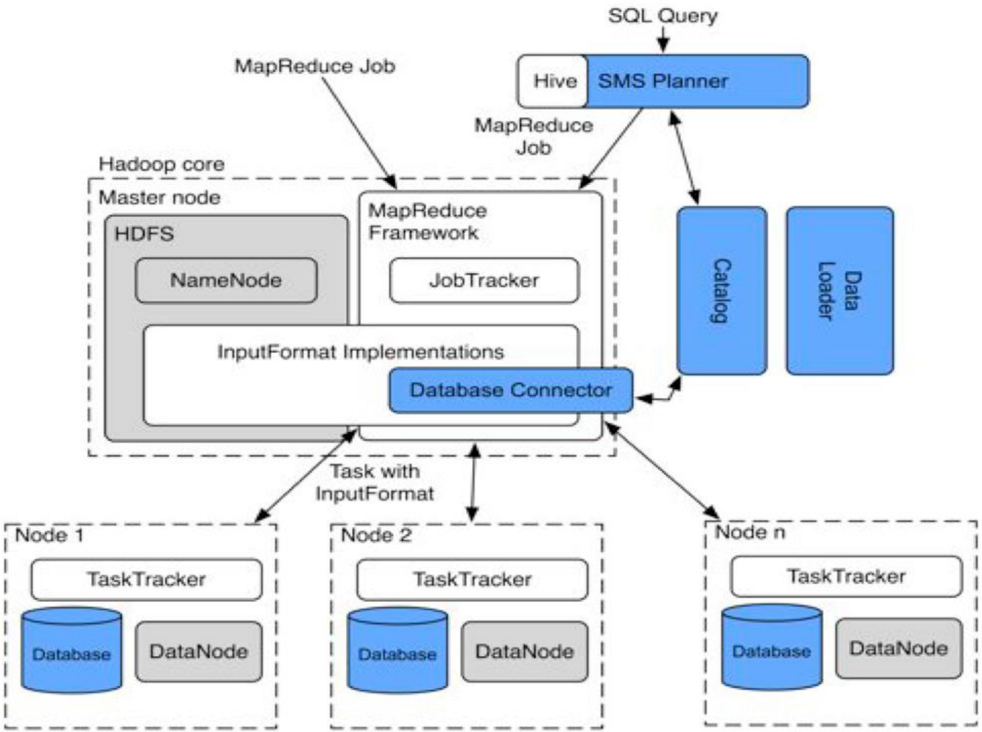
* http://dslam.cs.umd.edu/hadoopdb/hadoopdb.html

HadoopDB - introduction (cont’d)

- Multiple single-node RDBMs (PostgreSQL, VectorWise) coupled with HDFS/MR, deployed in a shared-nothing cluster
- Extensions to Hadoop: DB connector, catalog, data loader
- SQL-MR-SQL planner: extends HIVE, HiveQL → MR → SQL
- Data is partitioned both in RDMS tables and in HDFS files

HadoopDB - big picture





HadoopDB data and query model

- Raw data (text / binary), transformed into key-value pairs for Map tasks
  - Data globally repartitioned on a given key
  - Building and bulk-loading data chunks in the single-node DBs
- Relational data (column store or row store) → rows also hash partitioned across BD instances

Queries expressed as SQL (front end, extends HIVE)

- translated into MR, work pushed to single node DBMSs

Polybase* - introduction

Main idea:

- querying Hadoop (unstructured data) from RDBMS (structured)
- SQL Server Parallel Data Warehouse (shared nothing parallel) + Hadoop

Schema: GAV

Queries: SQL queries and distributed SQL execution plans

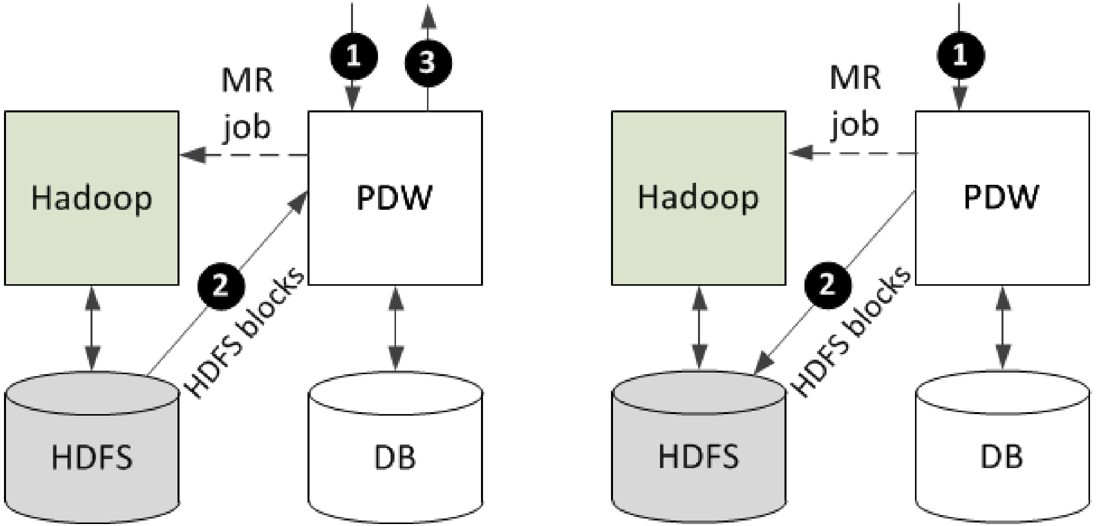
Objective: data in Hadoop (people just don’t see the value of clean, schema, load… or are more comfortable writing procedural code)

- Minimize data imported to PDW, maximize MR processing capability

*DeWitt et al. “Split Query Processing in Polybase”. SIGMOD 2013.

Polybase - introduction (cont'd)

- HDFS data can be imported / exported to / from SQL Server PDW
- HDFS referenced as « external tables », manipulated together with PDW native tables
- Takes advantage of PDW's data movement service (DMS), extended with HDFS bridge



(a) PDW query in, results out (b) PDW query in, results stored in HDFS

Polybase data and query model

- Raw data files (text / binary) - unstructured data with relational view
- Relational data - structured
- Queries expressed as SQL over relational tables (including external ones)
  - Translates SQL operators into MR jobs for data in HDFS

```
CREATE EXTERNAL TABLE hdfsCustomer
  ( c_custkey       bigint not null,
    c_name          varchar(25) not null,
    c_address       varchar(40) not null,
    c_nationkey     integer not null,
    c_phone         char(15) not null,
    c_acctbal       decimal(15,2) not null,
    c_mktsegment    char(10) not null,
    c_comment       varchar(117) not null)
WITH (LOCATION='/tpch1gb/customer.tbl',
FORMAT_OPTIONS (EXTERNAL_CLUSTER = GSL_CLUSTER,
EXTERNAL_FILEFORMAT = TEXT_FORMAT));
```

Estocada* - introduction

Main idea: self-tuning platform supporting natively various models

Schema: LAV

Queries: Access to each dataset in its native format

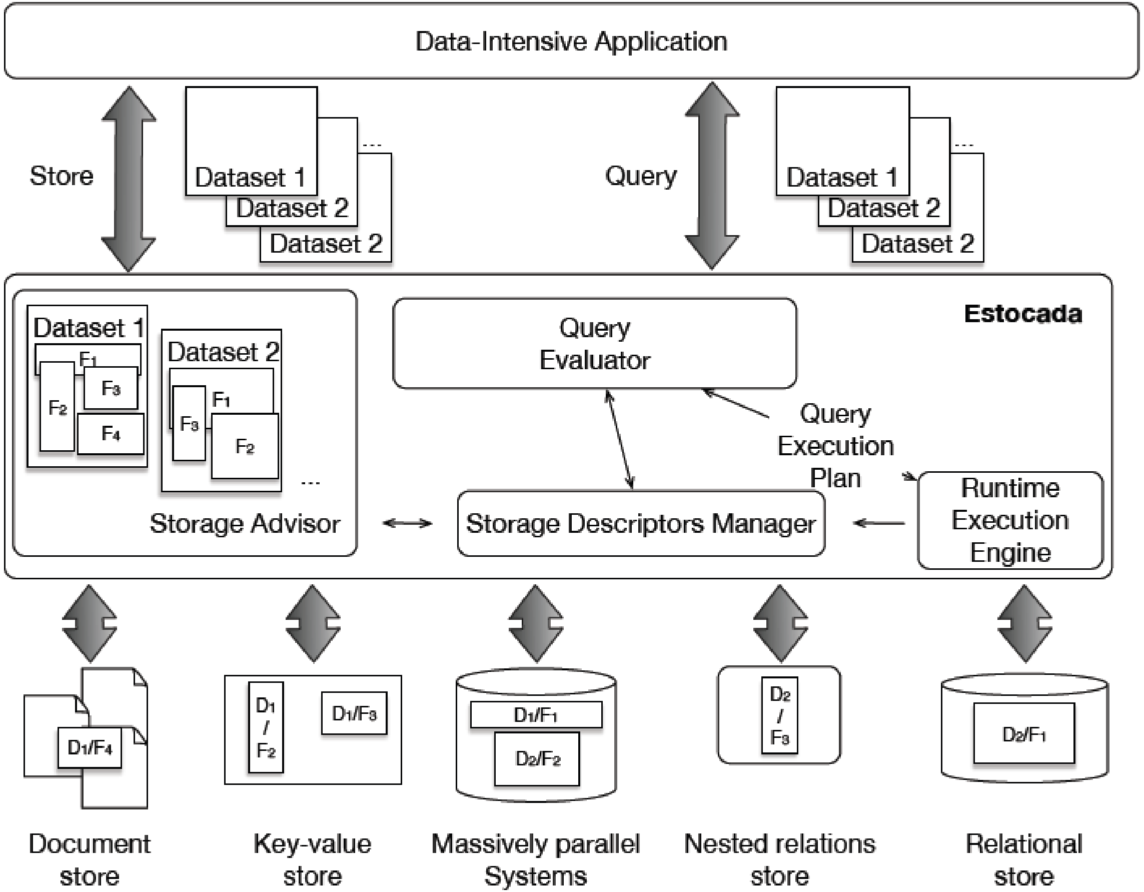
- no common query language / data model on top

Objectives: allow any data model, at both application and view level

- fragment based store, transparent to users
  - automatically distribute / partition the data into fragments
- although accessed natively, data internally may reside in different formats
  - pivot language: relational with prominent use of constraints

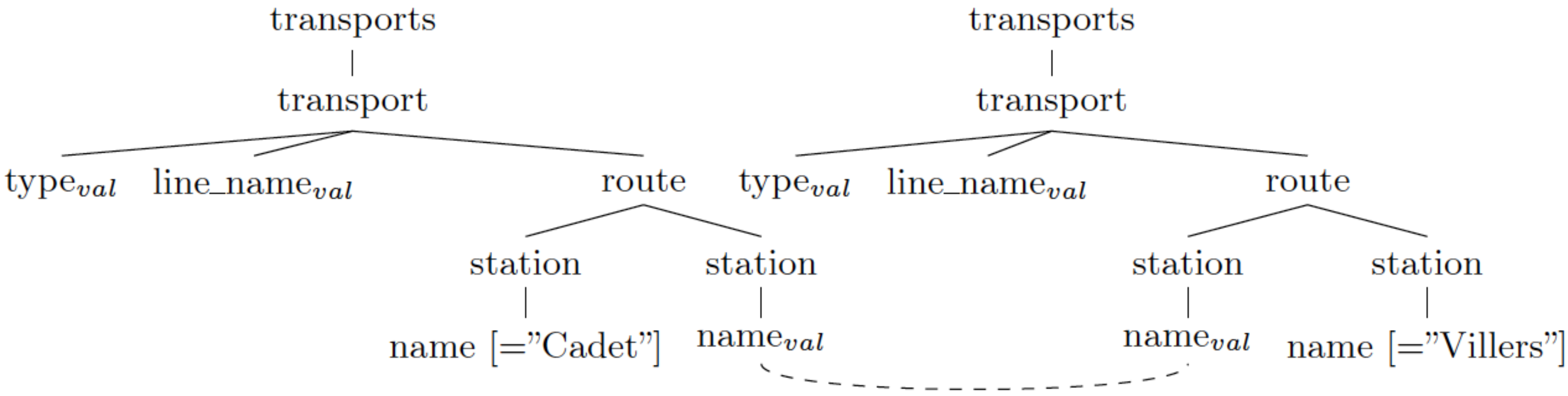
* Bugiotti et al. “Invisible Glue: Scalable Self-Tunning Multi-Stores”. CIDR 2015

Estocada - big picture



Estocada - data and query model

- (Nested) relational data, NoSQL (graphs, key-value, document)
- Queries expressed natively (e.g., over JSON data, below), translated into pivot language → relational algebra



Tatooine* - introduction

Main idea: use ontologies to mediate relational and non-relational sources

- RDF model as “glue” between all other models

Schema: GAV

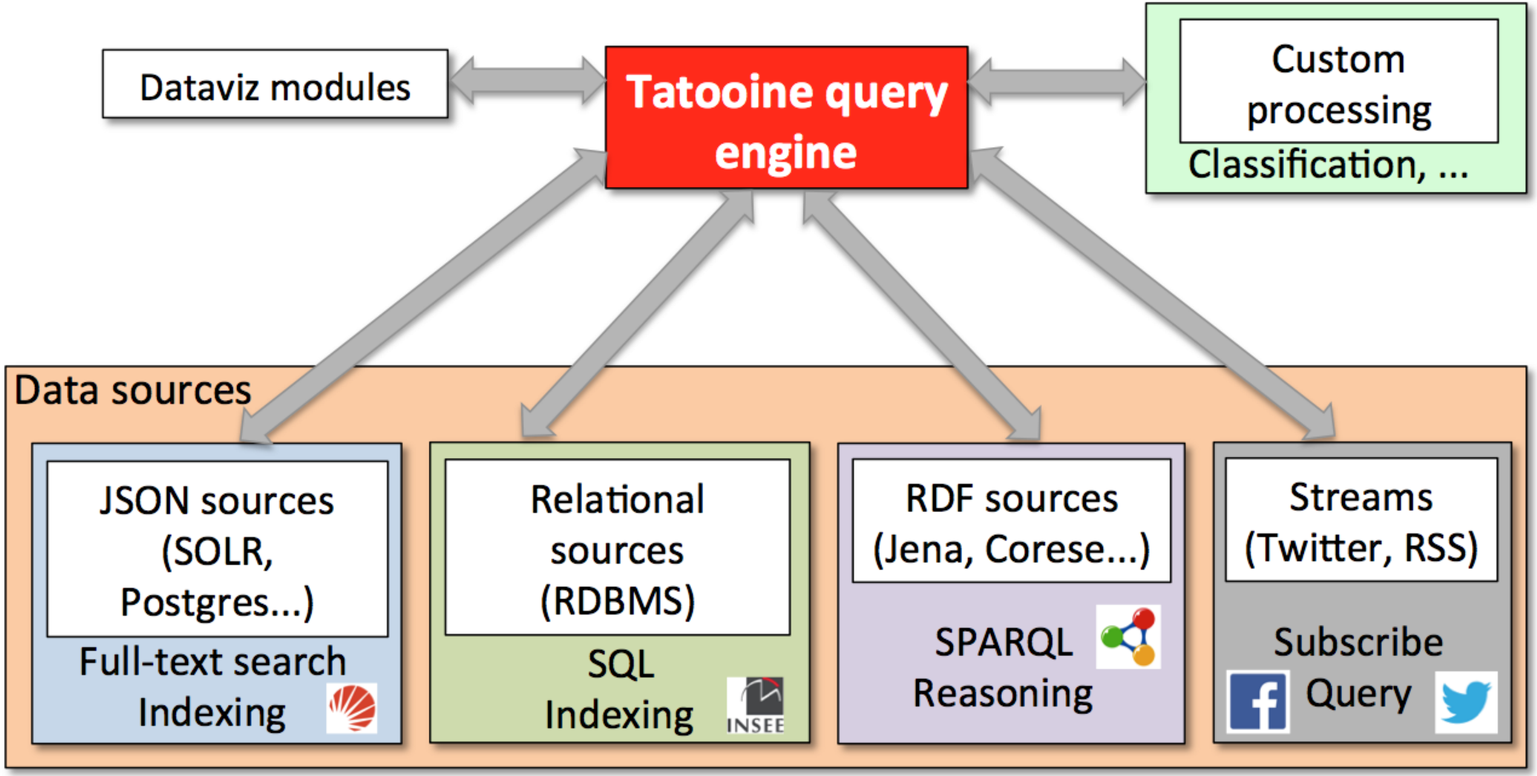
Queries: Conjunctive Mixed Queries (CMQ) - variation over the SPARQL subset of conjunctive queries (a.k.a. Basic Graph Pattern Queries - BGPs)

Objectives: lightweight integration over multiple native stores (mixed data instance), with focus on querying with a unified view

- a specific architecture and usage scenario for data journalism
- custom (application dependent) RDF graph, including ontology / triples, acting as bridge between different stores, based on common / repeated values (URIs)

* Bonaque et al. “Mixed-instance querying: a lightweight integration architecture for data journalism”. PVLDB 2016

Tatooine - big picture



Odyssey / Miso* - introduction

Main idea: self-tuning polystore on different analytic engines (parallel OLAP, Hadoop)

- enables storing and querying in HDFS and relational stores, using opportunistic materialized views

Schema: LAV

Queries: SQL-like (HiveQL) posed on HDFS, RDBMS used as query accelerator

Objectives: focus on time-to-insight / evolutionary analytics

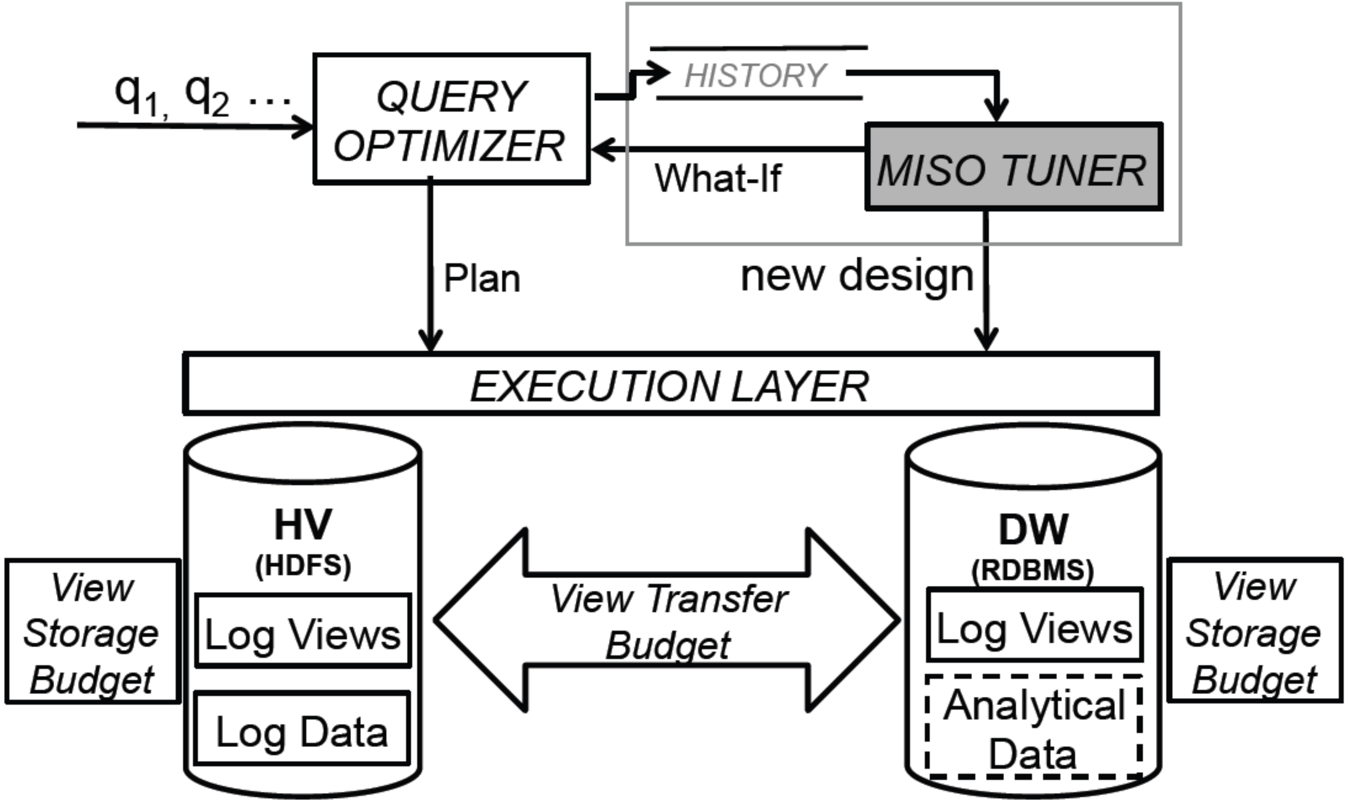
- which dataset should we move, where, when → method for tuning the physical design (MISO), decide in which data store the data should reside

* LeFevre et al. “MISO: souping up big data query processing with a multistore system”. SIGMOD 2014
Hacigümüs et al. “Odyssey: A Multi-Store System for Evolutionary Analytics”. PVLDB 2013

Odyssey / Miso - introduction (cont’d)

- Insight: single query optimization over multi-stores brings limited benefits; workload optimization instead
- Claim: physical design tuning is key
- Continuously monitors the workloads, online analysis to decide which views to materialize (share computation across queries)

Odyssey / Miso - big picture



Odyssey - data and query model

- Structured (relational) and unstructured data (large log files, text-based data stored as flat HDFS files)

- HiveQL queries: declarative language on top of MR
  - relational operators and arbitrary code (UDFs)
  - UDFs executed as MR jobs

Myria* - introduction

Main idea: A federated data analytics system, over data held by multiple backend systems (including MyriaX, SciDB, PostgreSQL, RDF, Spark key-value store)

Schema: LAV

Queries: MyriaL - a hybrid declarative / imperative language (relational query language with imperative extensions) (or Python)

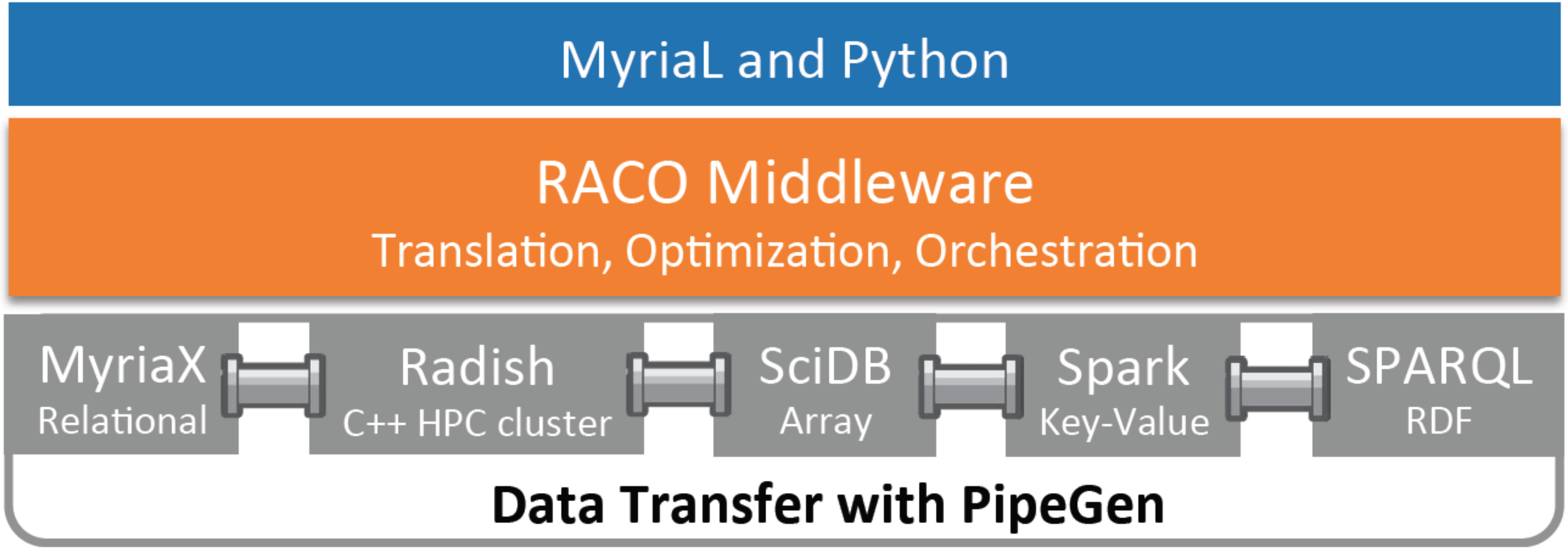
Objectives: “relational at the core approach”, focus on efficiency and usability, delivering the performance of specialized systems with the convenience of general purpose systems

- hides the data model differences between the various backends

* http://myria.cs.washington.edu/

Myria - big picture

- MyriaX (a parallel shared nothing DBMS) - query execution engine
- PipeGen: automatic data migration between stores, in support of query plans across engine boundaries
- RACO: Relational Algebra Compiler (locality-aware, rule based)



Myria - data and query model

- Relations, arrays, graphs, key-value pairs → the relational data model is used for translation and optimization
    - Observation: fundamentally isomorphic
- Queries expressed as SQL with imperative statements (similar to PL/SQL):
    - Relational semantics defined for operators of non-relational systems
    - Rules to translate such operators properly

```
E = scan(Graph); -- Graph(x, y) is an edge table
V = select distinct x from E;
CC = [from V emit x as node_id, x as comp_id];
do
  newCC = CC + [from E, CC where E.x = CC.node_id
                emit E.y, CC.comp_id];
  newCC = [from newCC emit
           newCC.node_id, min(new_CC.comp_id) as comp_id];
  delta = diff(CC, newCC);
  CC = newCC;
while [from delta emit count(*) > 0];
components = [from CC emit CC.comp_id, count(CC.node_id)];
store(components, ConnectedComponents);
```

RHEEM* - introduction

Main idea: general purpose cross-platform data processing system (DBMS, MR, NoSQL) -- data natively resides on different storage platforms

Schema: LAV

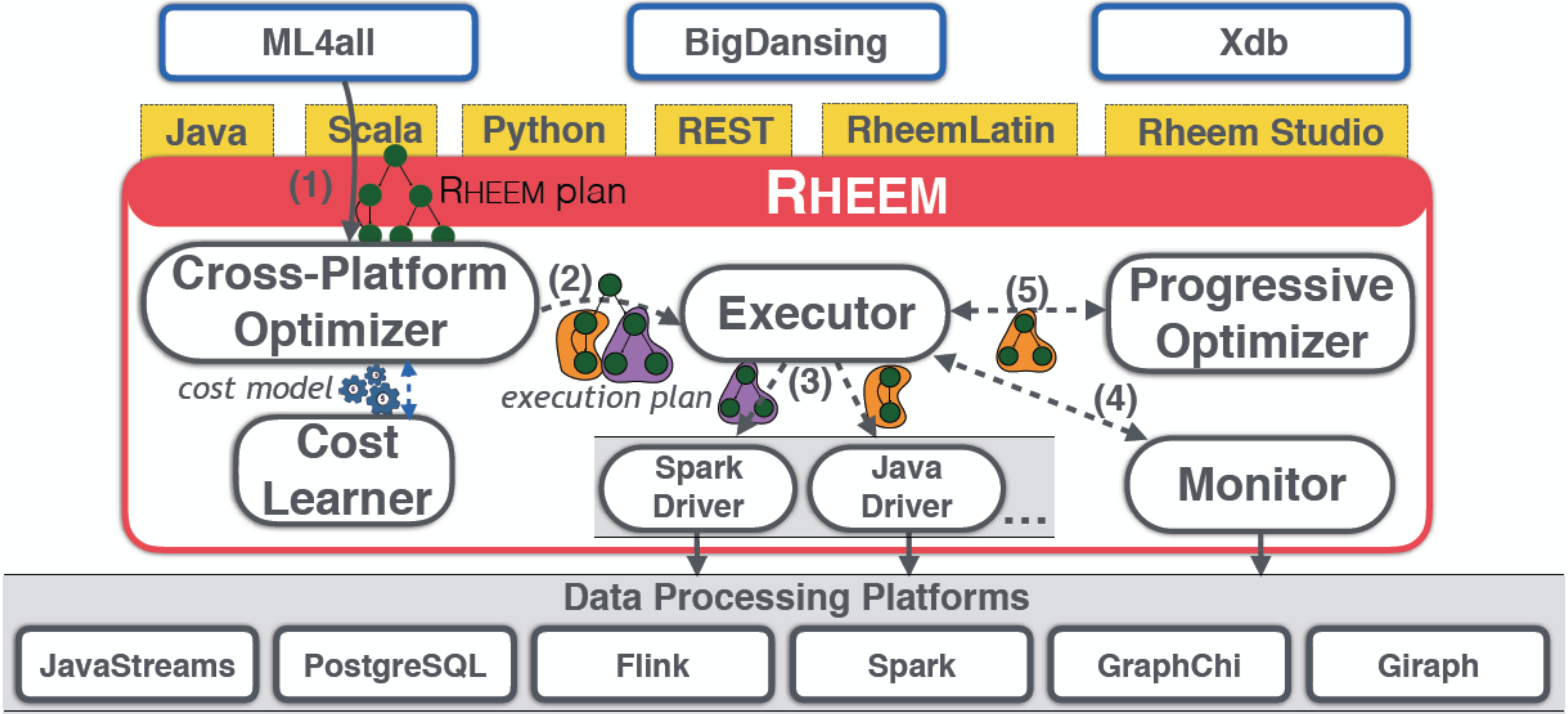
Queries: logic of the app in imperative form

Objectives: Decouple applications from underlying platforms → multi-platform task execution and data storage independence

- platform independent task specification
- transparent multi-platform optimization & execution (cost-based / learned)
- data storage and data movement optimization
- data processing and storage abstraction for adaptability / extensibility

* http://da.qcri.org/rheem/

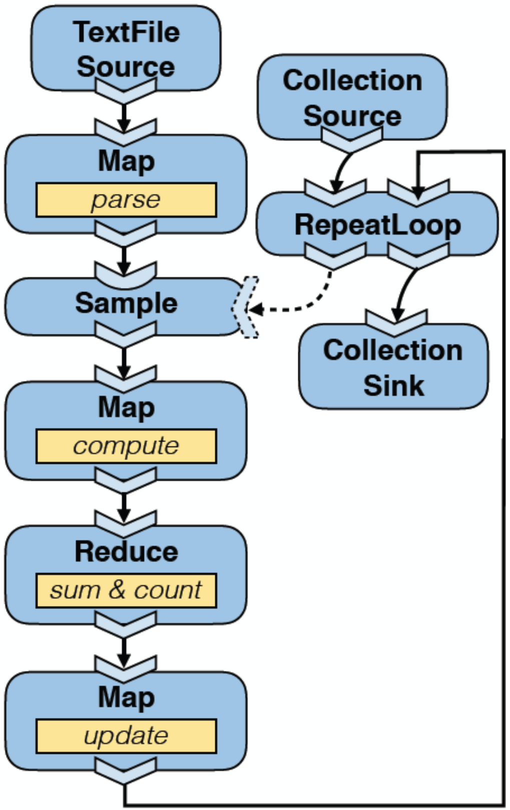
RHEEM - big picture



RHEEM - data and query model

- Data quanta abstraction (for database tuples, graph edges, full document content, etc)
- Procedural data-flow queries (Rheem plan)
  - Rheem Latin (based on Pig Latin grammar), Rheem Studio
  - Data-flow graph, vertices being platform agnostic operators
  - One or several data source

```
import '/sgd/udfs.class' AS taggedPointCounter;
lines = load 'hdfs://myData.csv';
points = map lines -> {taggedPointCounter.parsePoints(lines)};
weights = load taggedPointCounter.createWeights();
final_weights = repeat 50 {
    sample_points = sample points -> {taggedPointCounter.getSample()}
            with broadcast weights;
    gradient = map sample_points ->
            {taggedPointCounter.computeGradient()};
    gradient_sum_count = reduce gradient -> {gradient.sumcount()};
    weights = map gradient_sum -> {gradient_sum_count.average()} with
            platform 'JavaStreams';}
store final_weights 'hdfs://output/sgd';
```



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Query processing in TIPs

HadoopDB

Query processing: split MR/DB joins, referential partitioning, post-join aggregation
Query optimization: heuristics

Queries expressed as SQL (front end, extends HIVE), translated into MR, work pushed to single node DBMSs

- Query processing is simple: HiveQL query decomposed into QEP of relational operators, which are translated into MR jobs
- Leaf nodes are transformed into SQL to query the RDBMS instances
- Joins: easy if corresponding partitions collocated on same physical node

HadoopDB (cont'd) - SMS planner (extending Hive)

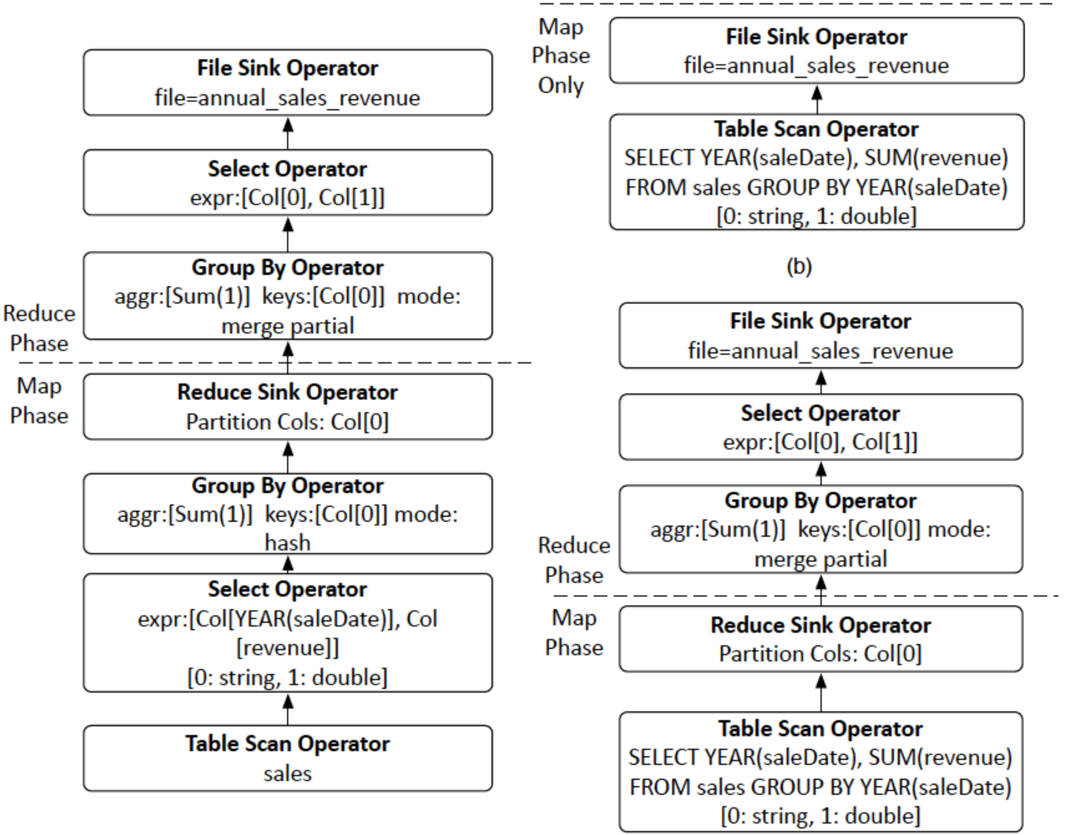
SELECT YEAR(date) AS year,

SUM(price)

FROM sales GROUP BY year

SMS Planner extensions, before execution:

- Retrieve data fields to determine partitioning keys
- Traverse DAG bottom-up (rule based SQL generator)



Polybase

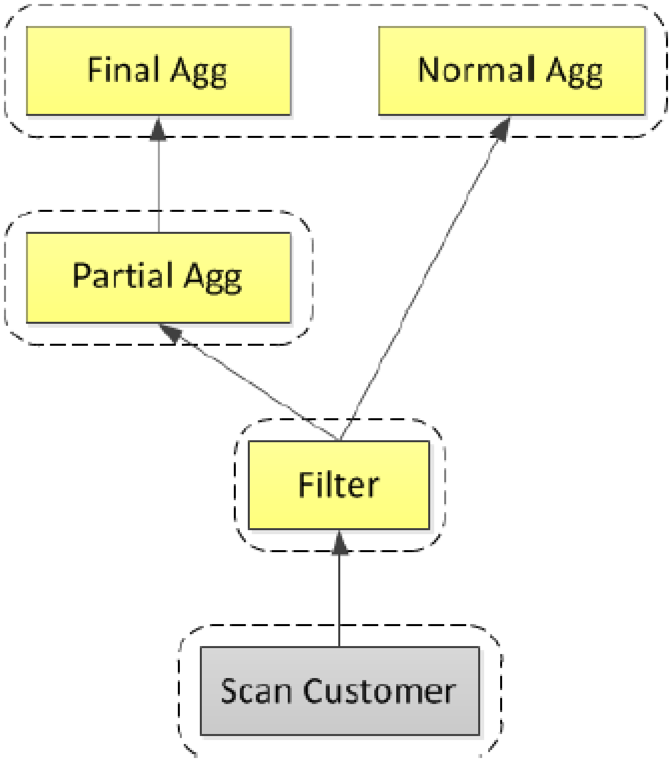
- Query plans: search space with 2 parts
  - MR jobs
  - regular relational operators
- Cost-based query optimizer: decide when good to push SQL to HDFS (statistics on external tables)
  - selects and projects on external tables (by MR jobs)
  - joins of 2 external tables (only when both tables are stored in HDFS)
  - indexes built on HDFS-resident data, stored inside PDW → use as pre-filter, lazily updated
- Query processing: query splitting

Polybase example

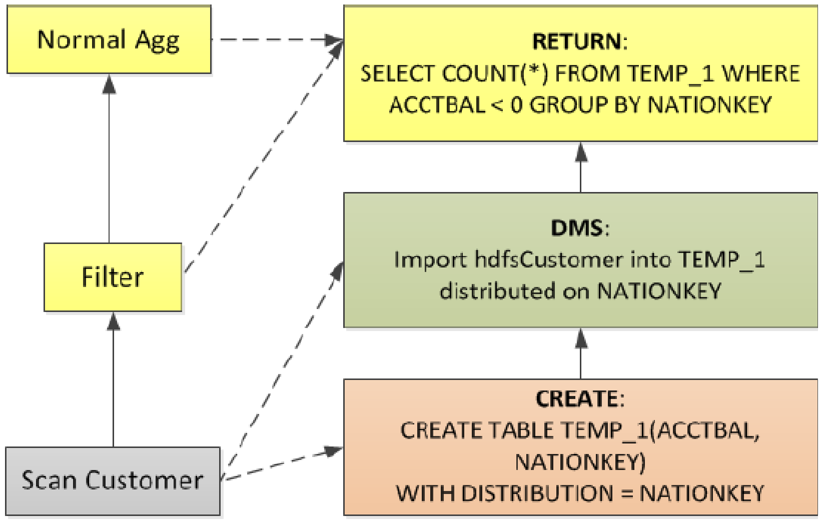
SELECT count (*) from Customer

WHERE acctbal < 0

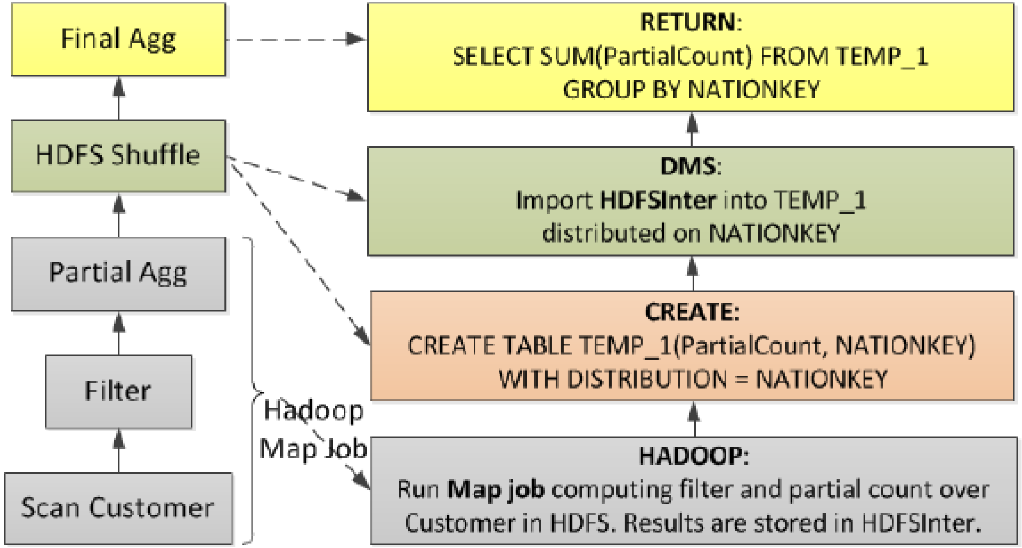
GROUP BY nationkey



Polybase example (cont'd)



(a) Optimized query plan (b) Corresponding DSQL plan



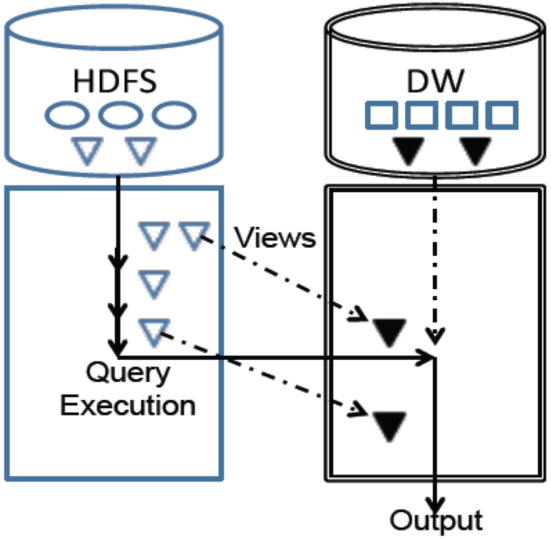
(a) Alternative query plan (b) Corresponding DSQL plan

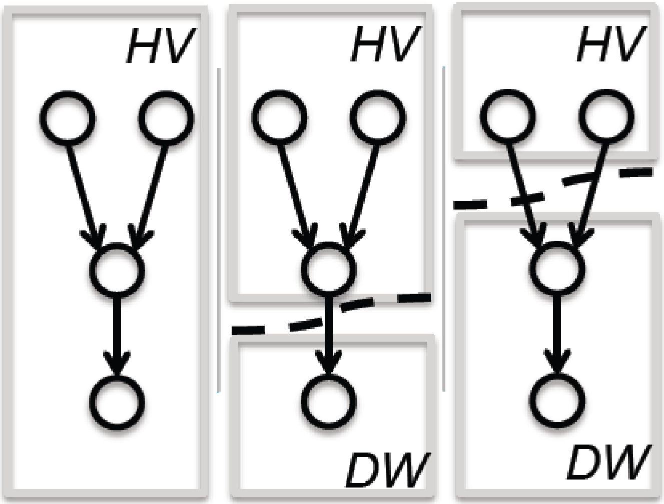
Estocada

- Recall: fragment based store, automatically distributes / partition the data into fragments → each data partition described as a materialized view
- View-based query processing: with conjunctive queries + constraints
- Query optimization: cost based
- Query → logical QEP on possibly multiple data stores → physical QEP based on relational algebra
  - leafs being translated into queries accessing the stores natively
  - work divided between the native stores and Estocada's own runtime engine
- Cross model / language storage advising (akin to automatic view selection)

MISO / Odyssey

- Optimization for entire workloads, using opportunistic materialized views
    - Shared intermediate results: opportunistic materialized views (useful if used repeatedly)
- Normalized cost-based optimization
    - cost in HV
    - cost in DW
    - cost of transfer between stores
- Annotated (by views) Query Plans
    - Stores in which sub-expressions are computed depends on the multistore physical design (views)





Myria

- Relational algebra compiler (RACO) is the query optimizer and federated query executor
- MyriaX takes as input RACO query plans
- RACO uses rule-based optimization
  - default: each leaf assigned to where data resides
  - iterates bottom up adding data movement operators wherever needed
  - rewrite rules determine the platform that each operator should run on

Myria RACO optimizer

- Graph of operators (including cycles, for iterative processing)
    - including relational operators + iterative processing, flatmap, stateful apply
- Query plans are organized into fragments and are fully pipelined
- Efficient join query evaluation (for large tables)
- Data movement during federated execution: if a query spans engine boundaries, intermediate results must move across systems
    - via HDFS, in a common format (CVS), or
    - new interconnection operators for each pair of systems, or...
    - PipeGen: enables automatically optimized data transfer between arbitrary pairs of systems

RHEEM

- Input: query – logic of the app in imperative form
- System ultimately decides on which platform to execute each task

For each RHEEM operator list all the alternatives for the optimizer to choose from: inflated RHEEM plan (each operator + all all its execution alternatives)

Three layer decoupled optimization

- Logical operators (application optimization layer)
- Physical operators (core optimization layer)
- Execution operators (platform optimization layer)

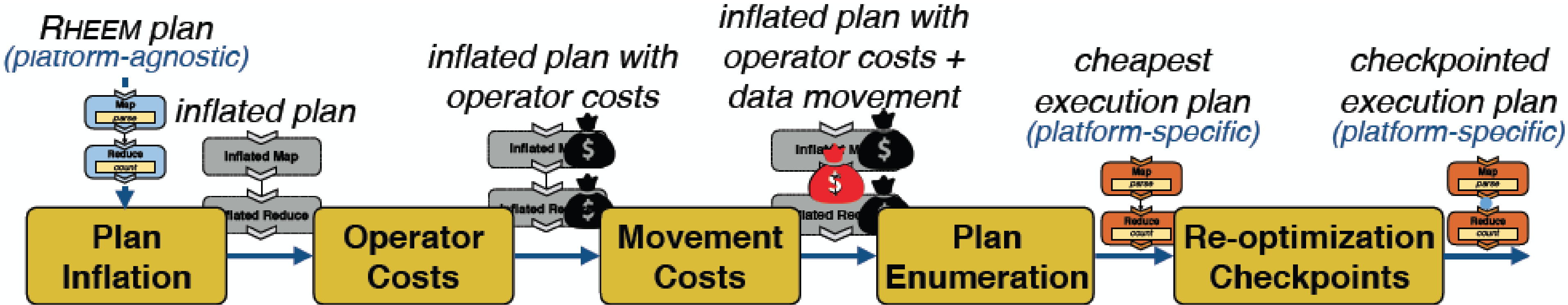
RHEEM execution plan

Cost-based optimizer outputs a RHEEM execution plan, also a data flow graph, but

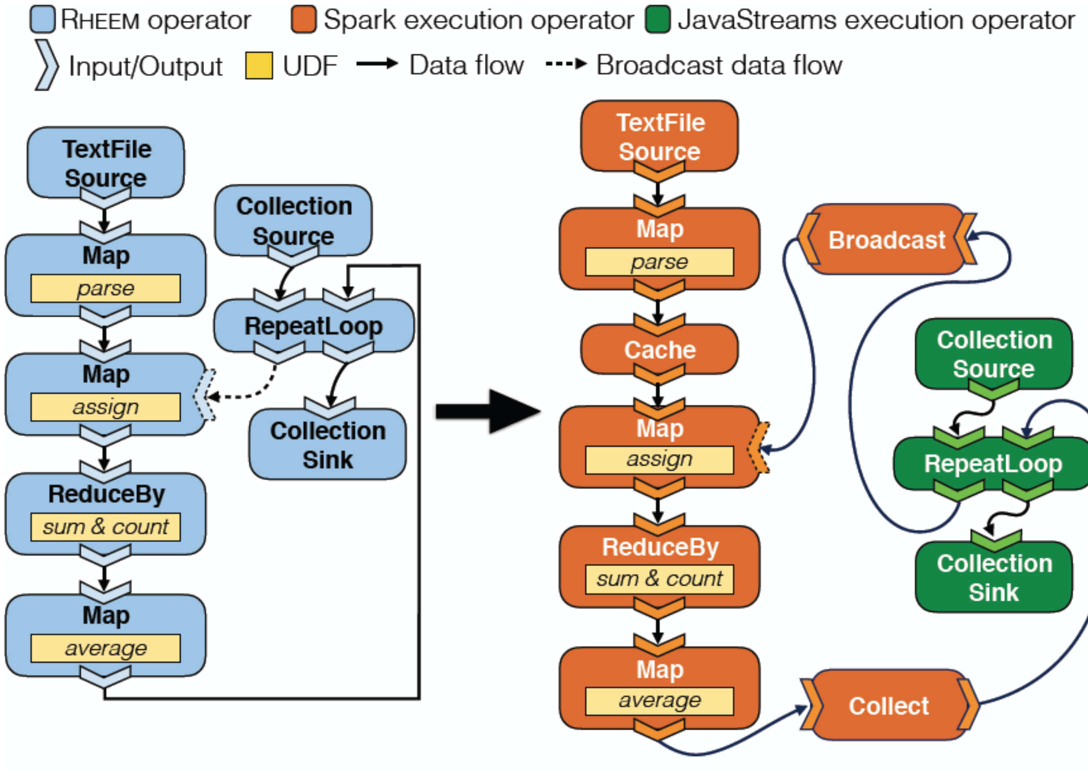
- vertices are platform specific execution operators
- may include operators for data movement across platforms

Cost model:

- each execution operator has an estimated cost, based on resource usage and unit cost, data cardinality → user hints, learned from logs, progressive optimization
- data movement: planning and assessing for cost model optimization
    - channel conversion graph (CCG): space of possible communication steps

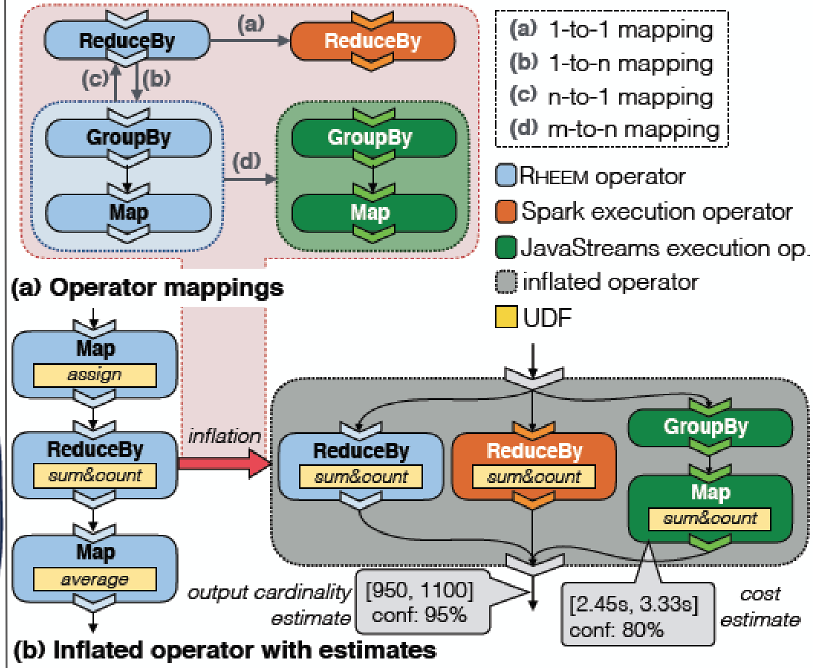


RHEEM - inflated execution plans



(a) RHEEM plan

(b) Execution plan



Outline

- Motivation and multiple model examples (30')
- Theoretical foundations (30')
- Multi-model data storage (25')
- Questions and discussion (5’)

Session break

- Multi-model data query languages (10')
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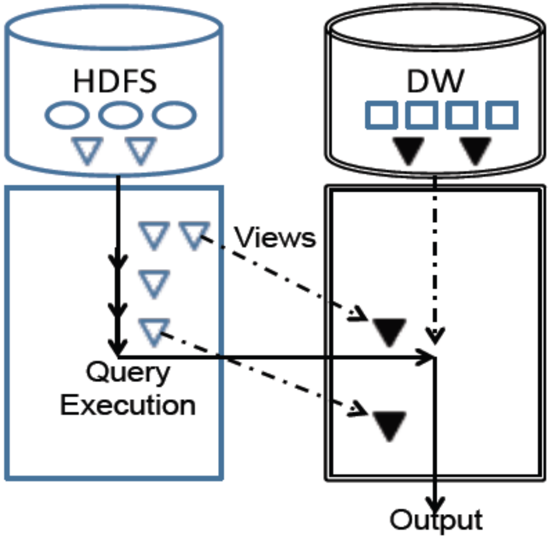
Advanced Aspects of TIPs

Tuning (MISO example)



- Physical design: materialized views
  - View storage budget
  - View migration budget
- Reorganization phase (workload history)
- Computationally hard problem
  - Heuristic approach: variant of the knapsack problem
  - Additional complexity: 2 physical design pbs, each with 2 dimensions

Multistore Design Problem. Given an observed query stream, a multistore design $\mathcal{M} = <\mathcal{V}_h , \mathcal{V}_d>$, and a set of design constraints $\mathcal{B}_h , \mathcal{B}_d , \mathcal{B}_t$ compute a new multistore design $\mathcal{M}^{new} = <\mathcal{V}_h^{new}, \mathcal{V}_d^{new}>$, where $\mathcal{V}_h^{new}, \mathcal{V}_d^{new}$ in $\mathcal{V}_h \cup \mathcal{V}_d$, that satisfies the constraints and minimizes future workload cost.

MISO tuner algorithm

Algorithm 1 MISO Tuner algorithm

function MISO_TUNE($\langle V_h, V_d \rangle, W, B_h, B_d, B_t$)

  $V \leftarrow V_h \cup V_d$

  $P \leftarrow$ COMPUTEINTERACTINGSETS(V)

  $V_{cands} \leftarrow$ SPARSIFYSETS(P)

  $V_d^{new} \leftarrow$ M-KNAPSACK(V_{cands}, B_d, B_t)

  $B_t^{rem} \leftarrow B_t - \sum_{v \in V_h \cap V_d^{new}} sz(v)$

  $V_h^{new} \leftarrow$ M-KNAPSACK($V_{cands} - V_d^{new}, B_h, B_t^{rem}$)

  $\mathcal{M}^{new} \leftarrow \langle V_h^{new}, V_d^{new} \rangle$

  return $\mathcal{M}^{new}$

end function

Extensibility - RHEEM

RHEEM brings an additional level of abstraction

- Data quanta
- Platform agnostic data transformation operators (RHEEM plans)

When a new platform is added

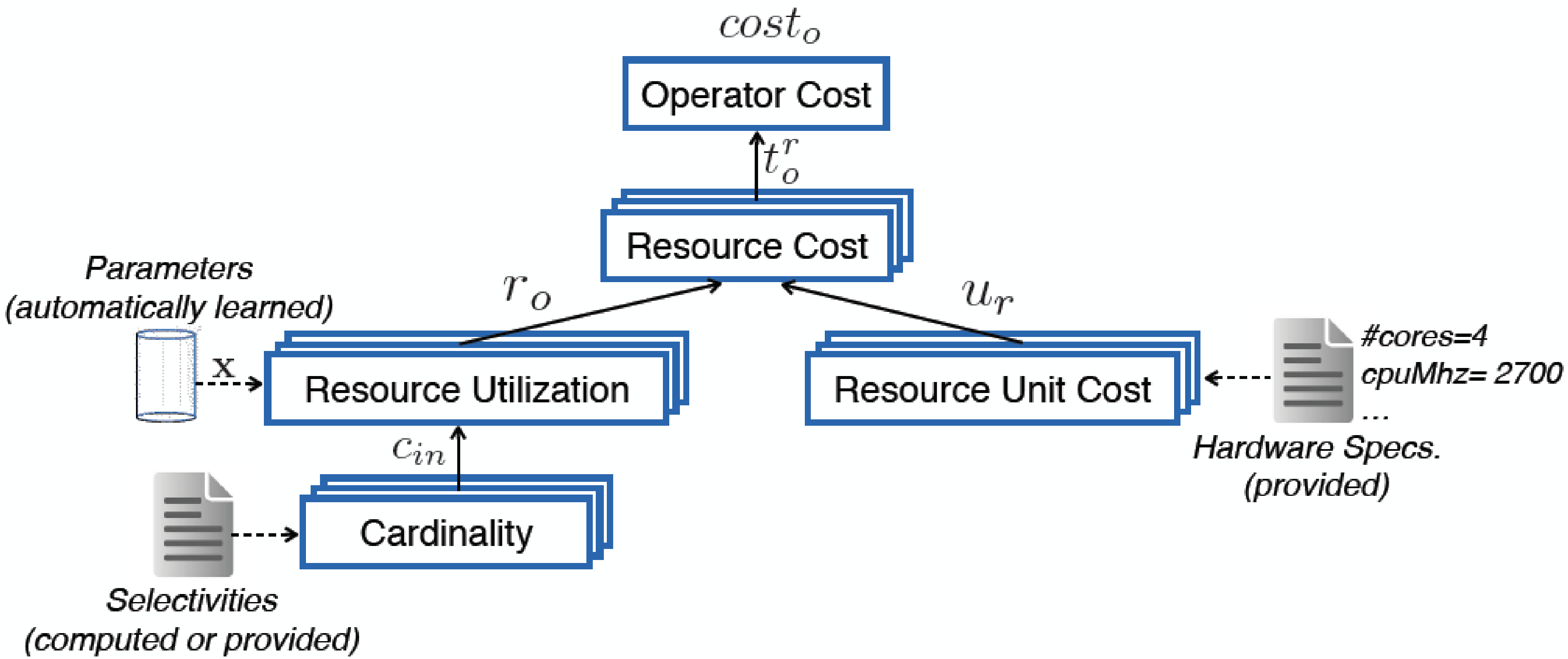
- New execution operators
- Their mappings to RHEEM operators
- Data quantum specification
- Communication channels (at least one)

Extensibility - Myria

When a new platform is added:

- An AST describing the API / query language supported
- rewrite rules / mappings of logical algebra into AST
- rule ordering
- set of administrative functions (querying the catalog, issuing a query, extracting results)

RHEEM cost model learner



RHEEM cost model learner (cont’d)

Parameters for a given operator and ressource:

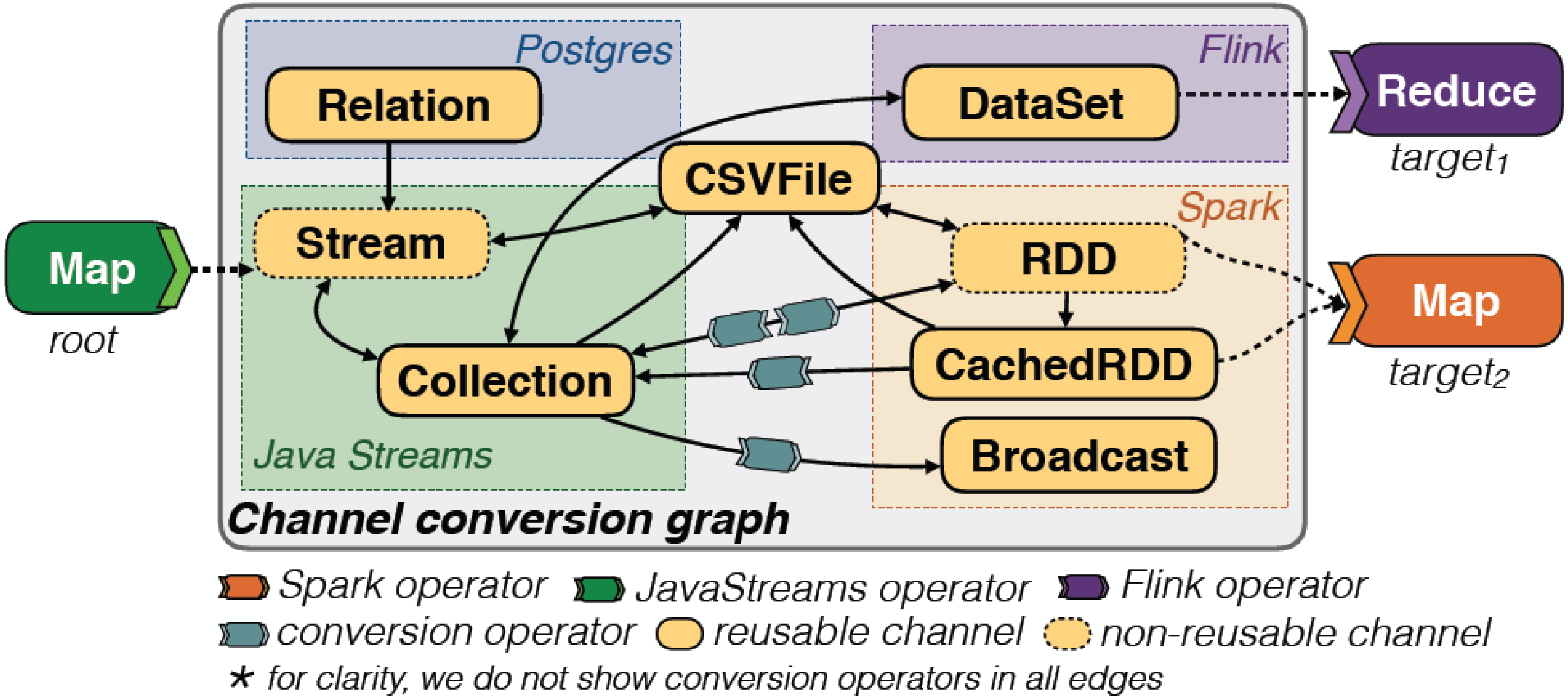
- α : number of required CPU cycles for each input data quantum in operator
- β : number of required CPU cycles for each input data quantum in UDF
- γ : fixed overhead for the operator start-up / scheduling

Logs used to learn these parameters: the cost of individual execution operators is modeled as a regression problem.

- difficulty: in logs, runtimes of stages (not individual operators)
- execution stage: $\{(o_1;C_1); (o_2;C_2); \ldots ; (o_n;C_n)\}; t)$
- $f_i(x,C_i)$ total cost function for executing operator o,
- finding $x_{min} = argmin_x\ loss(t, \Sigma^n_{i=1} f_i(x, C_i)$
- Genetic algorithm to find x_{min}

Data movement in RHEEM

Channel conversion graph (CCG)



Data movement in RHEEM

CCG: the space of possible communication steps

- vertices: data structure types (communication channels)
- edges: conversions from one structure to another (conversion operators)

Finding the most efficient communication path among execution operators: a new graph problem of finding a *minimum conversion tree* (similar to the Group Steiner Tree - GST problem).

- NP-hard problem, however, exp. time algorithm performs well in practice

Data movement in Myria - PipeGen

- PipeGen automatically enables optimized data transfer between arbitrary pairs of database systems
- Not dealing with schema matching / focus on “mechanics” of data movement
- Relies on DBMS capacity to ingest / export data to / from file system (CSV, JSON)
- Requires as input the DBMSs source code, unit tests exercising import / export
- Replaces that functionality with highly optimized version that sends data over a network socket

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Comparison of multi-model databases and tightly integrated polystores

Common features

- Support for multiple data models
- Global query processing
- Cloud support

Comparison

	Multi-model DBMSs	**TIPs**
Engine	single engine, backend	multiple databases (native)
Maturity	lower	higher
Usability	Read, write and update	read-only
Transactions	global transaction supported	unsupported
Holistic query optimizations	Open problem	challenging
Community	industry-driven	academia-driven (recently)
Data migration	difficult	simple

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Open problems and challenges

Multi-model databases

1. Schema design and optimization
    - NoSQL databases - usually schemaless
        - But we still need to model the target domain at least roughly
        - e.g. an application which stores data partially in JSON, XML and relational model => a user-friendly modeling tool which enables to model both the flat relations and semi-structured hierarchical data + relationships
    - Schema design influences query evaluations
        - Relational: minimum redundancy vs. NoSQL: materialized views
        - Relational: normalization vs. NoSQL: de-normalization
    - Schema inference
        - Approaches for single-models need to be extended
            - to support references amongs models
            - to benefit from information extracted from related data with distinct models

Multi-model databases

2. Query processing and optimization
    - Query languages are immature
        - Limited expressive power, limited coverage of models, …
    - The best query plan for queries over multi-model data
        - New dynamic statistics techniques for changing schema of the data
    - Indexing structures defined for single models + results are combined
        - e.g., relational: B-tree, XML: XB-tree, graph: gIndex, ...
        - How to index multiple data models with a single structure?
            - To accelerate cross-model filtering and join
    - In-memory technologies challenge disk-based solutions
        - A just-in-time multi-model data structure is a challenge

Multi-model databases

3. Evolution management
    - Schema evolution + propagation of changes
        - Adaptation of data instances, queries, indexes, or even storage strategies
        - Difficult task in general
    - Smaller applications = skilled DBA
        - Error-prone, demanding
    - Intra-model - re-use of an existing solution
    - Inter-model - distinct models cover separate parts of reality interconnected using references, foreign keys, …
        - Propagation across multiple models and their connections
4. Extensibility
    - Intra-model - extending one of the models with new constructs
    - Inter-model - new constructs expressing relations between the models
    - Extra-model - adding a whole new model

Tightly integrated polystores

Many challenges: query optimization, query execution, extensibility, interfaces, cross-platform transactions, self-tuning, data placement / migration, benchmarking.

- High degree of uncertainty even in TIPs
- Transparency: do not require users to specify where to get / store data, where to run queries / subqueries
    - Explain and allow user hints
- More than ever need for automation, adaptiveness, learning on the fly

Tightly integrated polystores

Many challenges: query optimization, query execution, extensibility, interfaces, cross-platform transactions, self-tuning, data placement / migration, benchmarking.

Query optimization:

- Query-based vs. workload based optimization
- Workload driven data partitioning, indexing, controlled degree of parallelism
- Progressive optimization → control over underlying platforms
- View-based query rewriting at large scale
- Cost based reformulation under constraints at large scale
- Cost-based optimizations across-platforms: uniformization, common cost unit, normalization → hard even in tightly coupled systems
- Computation costs vs data transfer costs

Tightly integrated polystores

Many challenges: query optimization, query execution, extensibility, interfaces, cross-platform transactions, self-tuning, data placement / migration, benchmarking.

Query execution:

- Data exploration in cross-platform settings
- Efficiently support fault tolerance across platforms
- Different query semantics / data typing

Extensibility: add new platforms automatically / easily

- Data abstractions / query abstractions

Query interfaces / internal common models / foundations:

- Expressiveness vs. declarative
- Limitations of the relational “glue” (algebra, imperative vs. Datalog-based) ?

More materials:

- Slides download: http://udbms.cs.helsinki.fi/?tutorials/CIKM2018
- UniBench: Towards Benchmarking Multi-Model DBMS http://udbms.cs.helsinki.fi/?projects/ubench
- Helsinki Multi-Model Dataset Repository: http://udbms.cs.helsinki.fi/?datasets
  - Collects and integrates publicly available datasets

Conclusion

- Big Data V-characteristics bring many challenges
- Variety requires concurrent storage and management of data with distinct formats
- Two sides of the same coin ?
  - Multi-model databases
  - Tightly-coupled polystores
- Still there is a long journey towards robust solutions


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spas
teşekkür ederim
Баярлалаа
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kia ora
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mahalo
tapadh leat
спасибо
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thank you
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kam sah hamnida
rahmat
তোমাকে ধন্যবাদ
감사합니다
xièxie
ευχαριστώ
merci


Question?