“One Size Fits All”: An Idea Whose Time Has Come and Gone

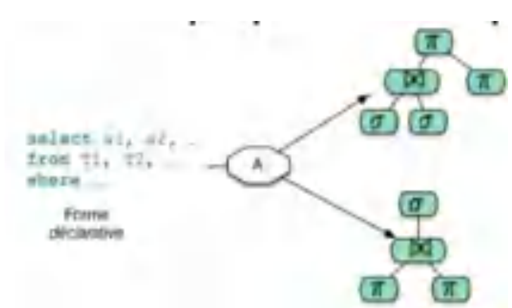
(M. Stonebraker)

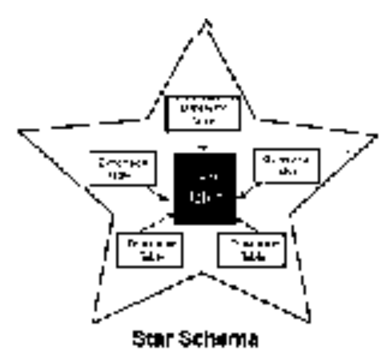
Christophe Menichetti (Hewlett-Packard, IBM)
Big-Data and Data-Science :
Problems, Challenges, Use-Cases

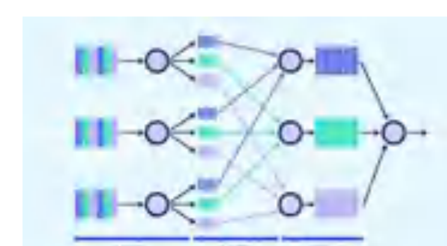
Query Optimization

Data Warehouses

Hadoop & Map/Reduce







Why this Class Matters !

(and how you can take the best out of it)

https://moodle.umontpellier.fr/course/section.php?id=141291

Vidéo ENT

Pourquoi ce cours est important?

Dans un monde où les données pilotent les décisions dans tous les secteurs, comprendre comment gérer et exécuter des traitements complexes sur des ensembles de données massifs n'est pas seulement utile : c'est essentiel.

Ce cours vous propose d'acquérir des connaissances sur la gestion et l'exploitation des données massives, vous dotant ainsi de compétences pratiques pour relever les défis du monde réel et, plus important encore, des connaissances pour vous adapter aux innovations de demain dans ce domaine.

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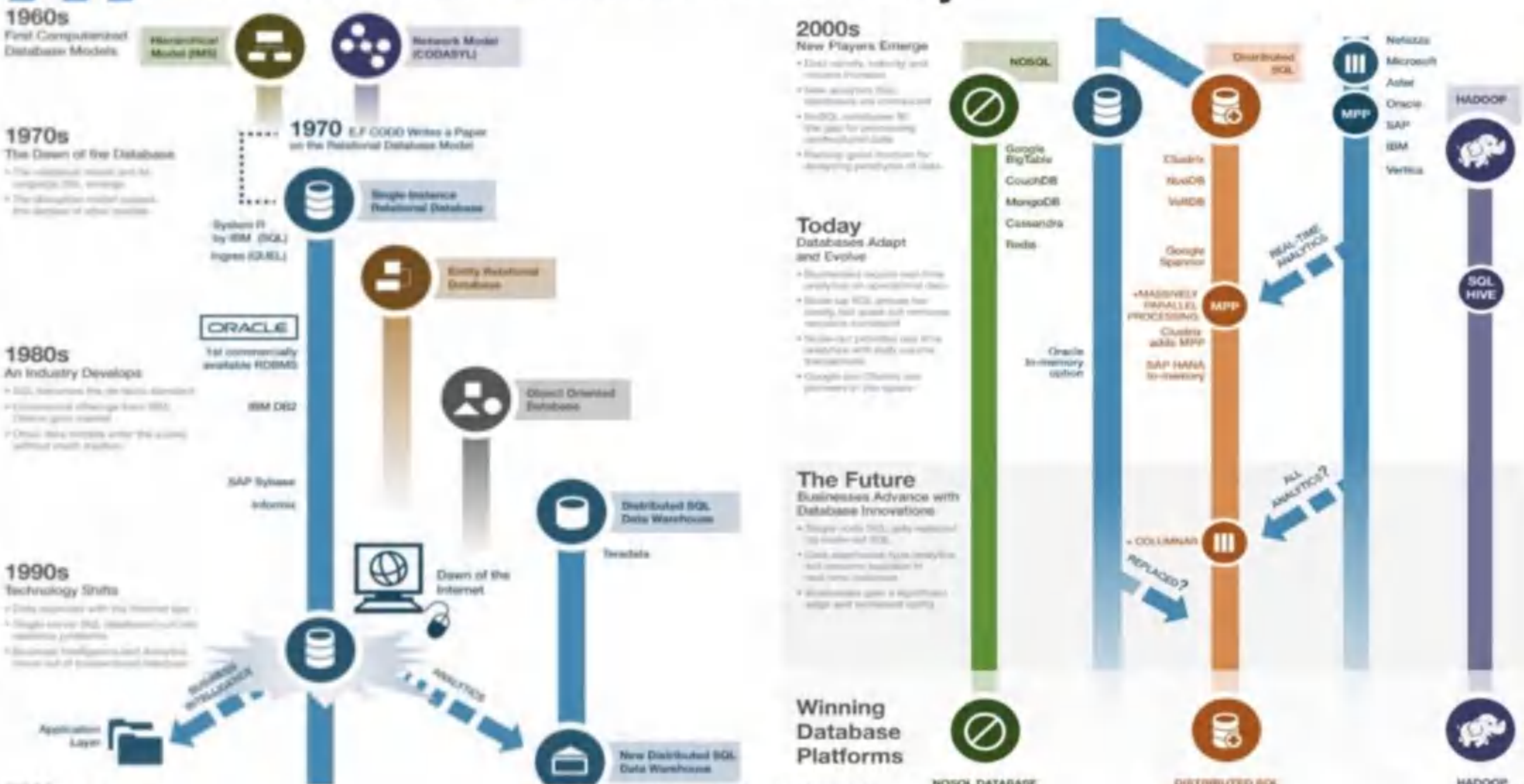
Database Evolution History



Source: Robin Purohit

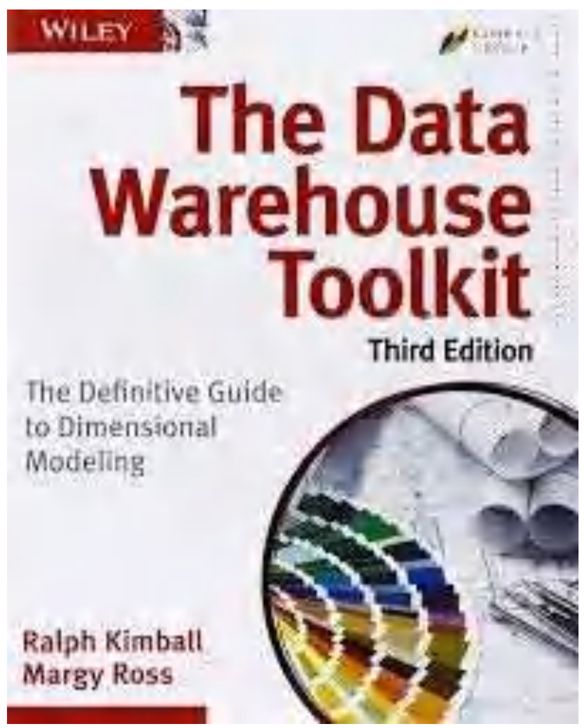
Today’s Questions

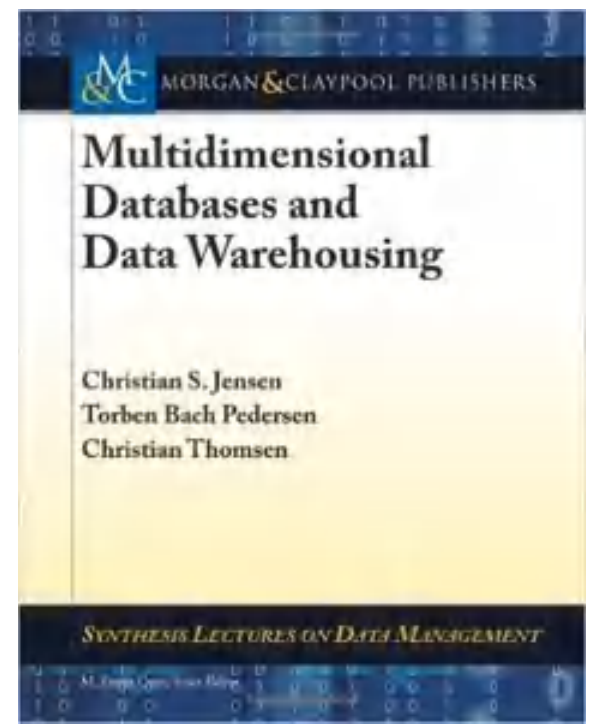
From Relational Databases to Data-Warehouses

- why RDB are insufficient for big-data analysis ?
- why do we need new models to *analyze* data ?
- which models do we need and
  how to conceive them ?

Resources

- Entrepôts de données, guide pratique de modélisation dimensionnelle. R.Kimball, M.Ross



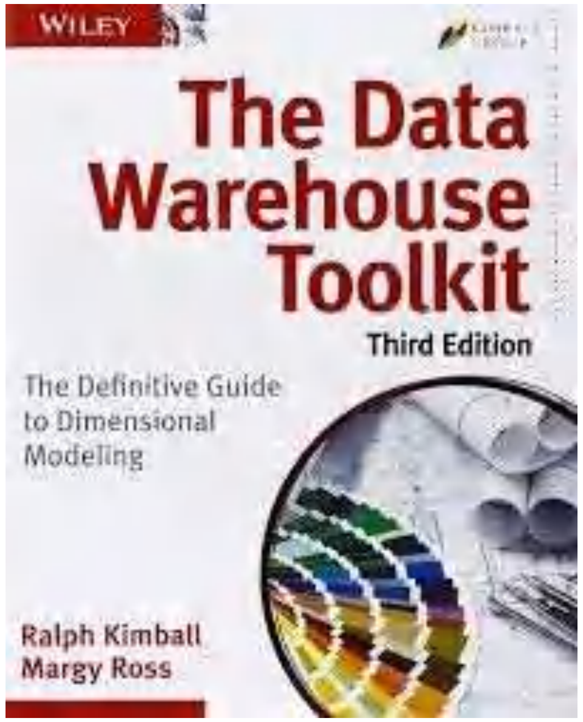


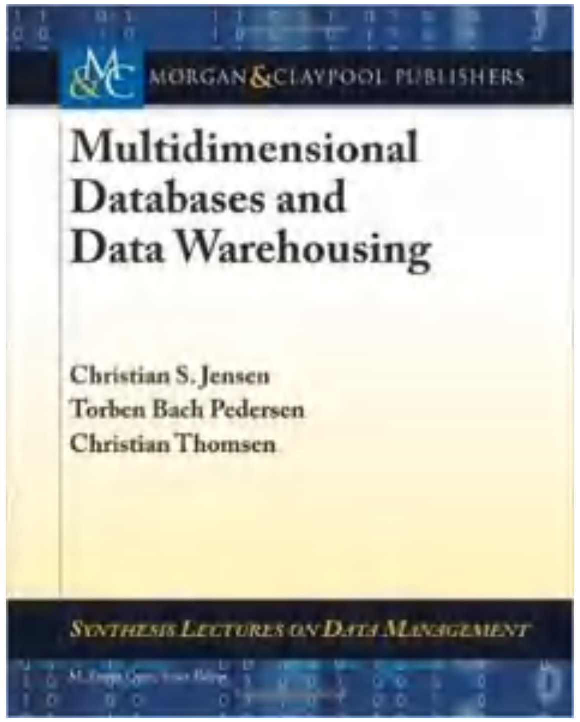
- Multidimensional databases and Data Warehousing C.S. Jensen, T.B.Pedersen and C.Thomsen

Resources

these slides cannot replace the textbooks by any means !

- Entrepôts de données, guide pratique de modélisation dimensionnelle. R.Kimball, M.Ross

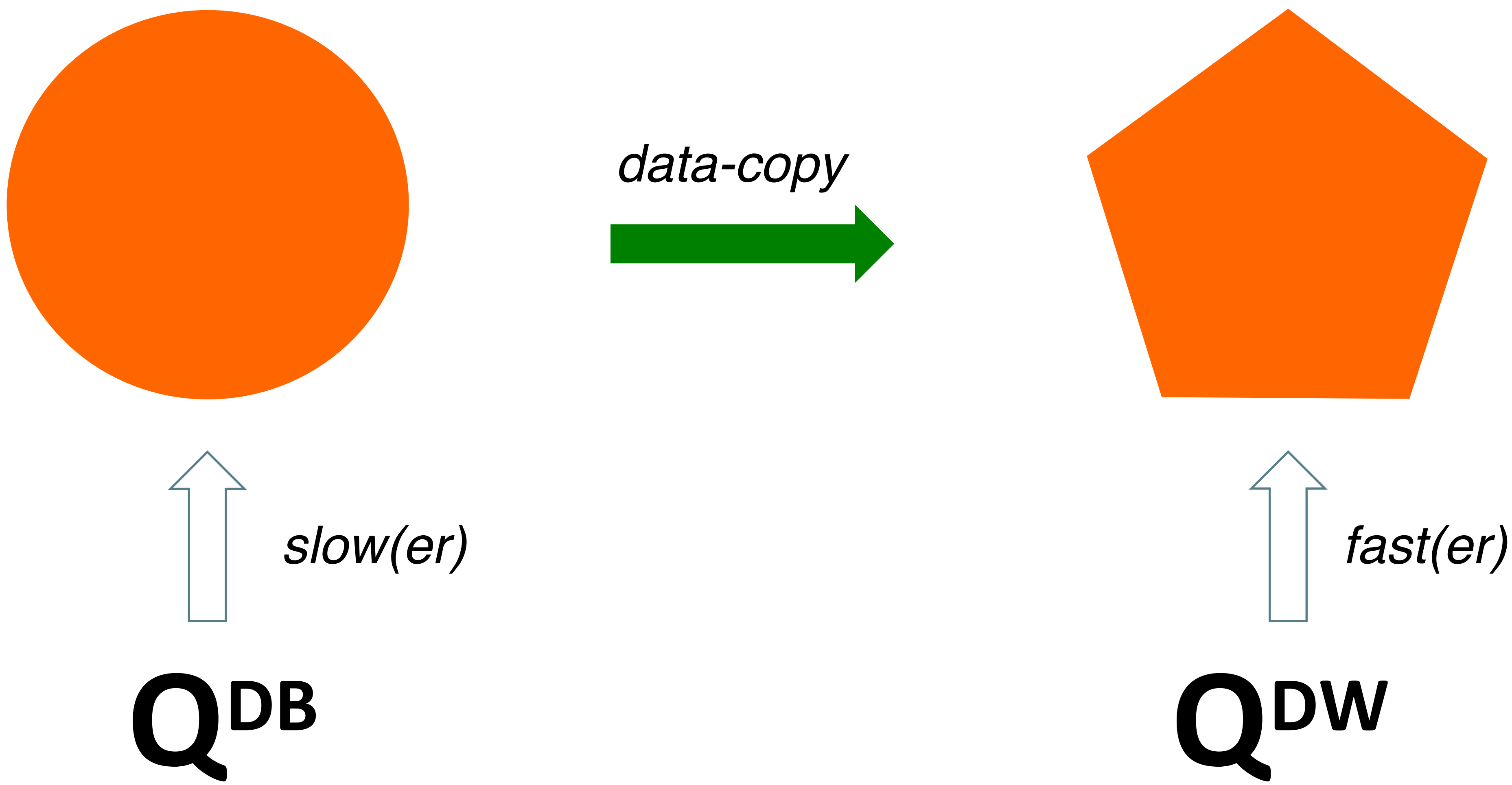




- Multidimensional databases and Data Warehousing C.S. Jensen, T.B.Pedersen and C.Thomsen

Datawarehouse

"a copy of transactional data specifically structured for analytical queries"



Why bothering with replicas of data ?

What are analytical queries and why are they different ?

Motivation Story

http://philip.greenspun.com/sql/data-warehousing.html

- '90 Bentonville (Arkansas)

- **Walmart**:''*I want to keep track of sales in all of my stores simultaneously.*"

- **Sybase** : "*You need our wonderful RDBMS software. You can stuff data in as sales are rung at cash registers and simultaneously query data right here in your office.*

  That's the beauty of concurrency control."

Motivation Story

http://philip.greenspun.com/sql/data-warehousing.html

- Walmart buys a $1M HP multi-CPU server and a $0.5M Sybase license, and builds a **normalized** database

- ```
  Sales( product_id,      store_id,
         quantity_sold,   date_time_of_sale)
  ```

- ```
  Products( product_id,         product_name,
            product_category,   manufacturer_id)
  ```

- `Stores(store_id, city_id, store_address, phone_num)`

- `Cities(city_id, city_name, state, population)`

Motivation Story

http://philip.greenspun.com/sql/data-warehousing.html

product

Products(product_id, product_name, product_category, manufacturer_id)

city

Cities(city_id, city_name, state, population)

store

Stores(store_id_city_id, store_address, phone_num)

sale

Sales(product_id, store_id, quantity_sold, date_time_of_sale)

Concurrency Control

sale

`Sales( product_id, store_id, quantity_sold, date_time_of_sale)`

Concurrency Control

```
INSERT INTO Sales
(1,1,10,12345678)
```

WRITE

```
INSERT INTO Sales
(1,2,10,12345758)
```

WRITE

```
SELECT COUNT(*)
FROM Sales
```

READ

```
INSERT INTO Sales
(3,4,10,12345768)
```

WRITE

sale

```
Sales( product_id,
store_id, quantity_sold,
   date_time_of_sale)
```

Concurrency Control

```
INSERT INTO Sales
(1,1,10,12345678)
```

WRITE

```
INSERT INTO Sales
(1,2,10,12345758)
```

WRITE

```
SELECT COUNT(*)
FROM Sales
```

READ

```
INSERT INTO Sales
(3,4,10,12345768)
```

WRITE

can we **WRITE** while we **READ** on the same table?

sale

```
Sales( product_id,
store_id, quantity_sold,
date_time_of_sale)
```

Concurrency Control

```
INSERT INTO Sales
(1,1,10,12345678)
```

WRITE

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```

WRITE

```
SELECT COUNT(*)
FROM Sales
```

READ

```
INSERT INTO Sales
(3,4,10,12345768)
```

WRITE

NO! **COUNT**(*)
may become
inconsistent :
table locking

sale

```
Sales( product_id,
store_id, quantity_sold,
date_time_of_sale)
```

Motivation Story

- Some time after…

- Walmart executive asks: *”I noticed that there was a Colgate promotion recently, directed at people who live in small towns.*
  *How much Colgate toothpaste did we sell in those towns **yesterday**?*
  *And how much on **the same day a month ago**?”*

- **Sybase** : *“Let me write the query!”*

Motivation Story

```
SELECT SUM(sales.quantity_sold)
FROM sales, products, stores, cities
WHERE products.manufacturer_id = 68  -- Colgate_id
AND products.product_category = 'toothpaste'
AND cities.population < 40000
AND sales.datetime_of_sale::date =
               'yesterday'::date
AND sales.product_id = products.product_id
AND sales.store_id = stores.store_id
AND stores.city_id = cities.city_id
```

Motivation Story

http://philip.greenspun.com/sql/data-warehousing.html

product

Products(product_id, product_name, product_category, manufacturer_id)

city

Cities(city_id, city_name, state, population)

store

Stores(store_id_city_id, store_address, phone_num)

sale

Sales(product_id, store_id, quantity_sold, date_time_of_sale)

Motivation Story

http://philip.greenspun.com/sql/data-warehousing.html

to test the condition on the city's population the 3NF schema obliges to add a join with **store**

Join

Selection

Join

Join

Selection

store

Motivation Story

```
INSERT INTO Sales
(1,1,10,12345678)
```

WRITE

```
INSERT INTO Sales
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```

WRITE

```
SELECT sum(sales.quantity_sold)
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AND sales.product_id = products.product_id
AND sales.store_id = stores.store_id
AND stores.city_id = cities.city_id
```

READ

Motivation Story

```
INSERT INTO Sales
(1,1,10,12345678)
```

WRITE

```
INSERT INTO Sales
(1,2,10,12345758)
```

WRITE

lock on 4 tables
sales, **products**, **stores**, **cities**

```
SELECT sum(sales.quantity_sold)
FROM sales, products, stores, cities
WHERE products.manufacturer_id = 68  -- Colgate_id
AND products.product_category = 'toothpaste'
AND cities.population < 40000
AND sales.datetime_of_sale::date = 'yesterday'::date
AND sales.product_id = products.product_id
AND sales.store_id = stores.store_id
AND stores.city_id = cities.city_id
```

READ

Motivation Story

- What can happen when you run joins on big-data :
  the query returns after **20**mins.
- Cash **registers over the country cannot process the sales** when the toothpaste query is run.

Motivation Story

- **Walmart**: *"We type in the toothpaste query and our system wedges."*

- **Sybase**: *"Of course it does!*
  You built an on-line transaction processing system.
  You can't ask analytic queries & expect things to work!"

- **Walmart**: *"But I thought the whole point of SQL and your RDBMS was that users could query and insert simultaneously."*

Motivation Story

- **Sybase**: *"Uh, not exactly. The system prevents simultaneous Writes and Reads to guarantee coherent information: this is called "<u>pessimistic locking</u>".*

- **Walmart**: *"Can you fix your system so that it doesn't lock up?"*

- **Sybase**: *" No.*
  But we made a great loader tool to copy everything from your transactional system into a separate decision support system at 100 GB/hour."

Analytical Query

Basically, a query which needs to access a

very large portion

of a database

for the sake of data analysis

(ex. compare sales per region on July)

Note : analytical query are also possible outside DW but as the example shows, they can just be inefficient

Main SQL construct : Group By (ex. Monoprix)

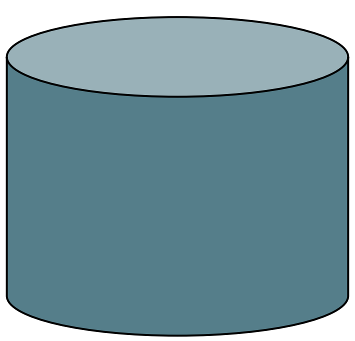
date	product	store	city	amount
1/12/2018	P1	Gare	Montpellier	2000
1/12/2018	P1	Antigone	Montpellier	3400
1/12/2018	P2	Port Marianne	Montpellier	1280
		.....		

```
SELECT    date, store, SUM(amount)
FROM      ventes
GROUP BY  date, store
```

Business Intelligence

(Big-Data before 2010)

Make strategic fact-based decisions

Aggregate Data	Present Data	Enrich Data	Inform a Decision
			
Database, Data Mart, Data Warehouse, ETL Tools, Integration Tools	Reporting Tools, Dashboards, Static Reports, Mobile Reporting, OLAP Cubes	Add Context to Create Information, Descriptive Statistics, Benchmarks, Variance to Plan or LY	Decisions are Fact-based and Data-driven

Transactional Vs **A**nalytical Systems

Aspect	Operational DB	DW
User	clerk	manager
Interaction	short (s)	long analyses (min,h)
Type of interaction	Insert, Update, Delete	Read,periodically (bulk) inserts
Type of query	many simple queries	few, but complex queries (typically drill-down, slice...)
Query scope	a few tuples (often 1)	many tuples (range queries)
Concurrency	huge (thousands)	limited (hundreds)
Data source	single DB	multiple independant DB...
Schema	query-independant (3NF)	based on queries
Data	original, detailed, dynamic	derived,consolidated, integrated,historicized,partially aggregated,stable
Size	MB,GB cost of redundancy	TB,PB
Availability	crucial	not so crucial
Architecture	3-tier (ANSI-SPARC)	adapted to data integration

Applications of Datawarehouses

Domains

- Retail
- E-business
- Banks
- Telecoms
- Logistics
- Travels
- Hotels Insurances
- Health
- Science
- Public Administration
- …

Retail (Walmart)

[Data Warehousing: Using the Wal-Mart Model,Westman]

- Pioneer: one of the largest (retail) warehouses since. Teradata solution.

	92	2001	2004	2008
size	1 TB	70 TB	>500 TB	2.5 PB

- $20M Prototype DW to analyze sales launched in ’90
  - **investment paid back in 6 months**
- A study over analysts estimated ROI per query at $12K

Retail (Casino)

Sources: http://www.mycustomer.com/topic/technology/casino-group-upgrades-teradata-data-warehouse http://fr.teradata.com/newsrelease.aspx?id=12338
http://www.lemagit.fr/actualites/2240197570/
Pour- harmoniser- ses- calculs- de- marge- Casino- sengage- dans- la- refonte- de- son- decisionnel

- One of the earliest DW in France. Teradata solution

	94	2002	2009
size	80 GB	10 TB	18 TB
users	50	1,500	3500
queries/day		25,000	600,000

- Saved millions when realized that Coca-Cola stocks were often low :
  - order more ! (better price (negotiate) / logistics)
  - sell more ! (reduce missed sales)

Retail (Casino)

Goals:

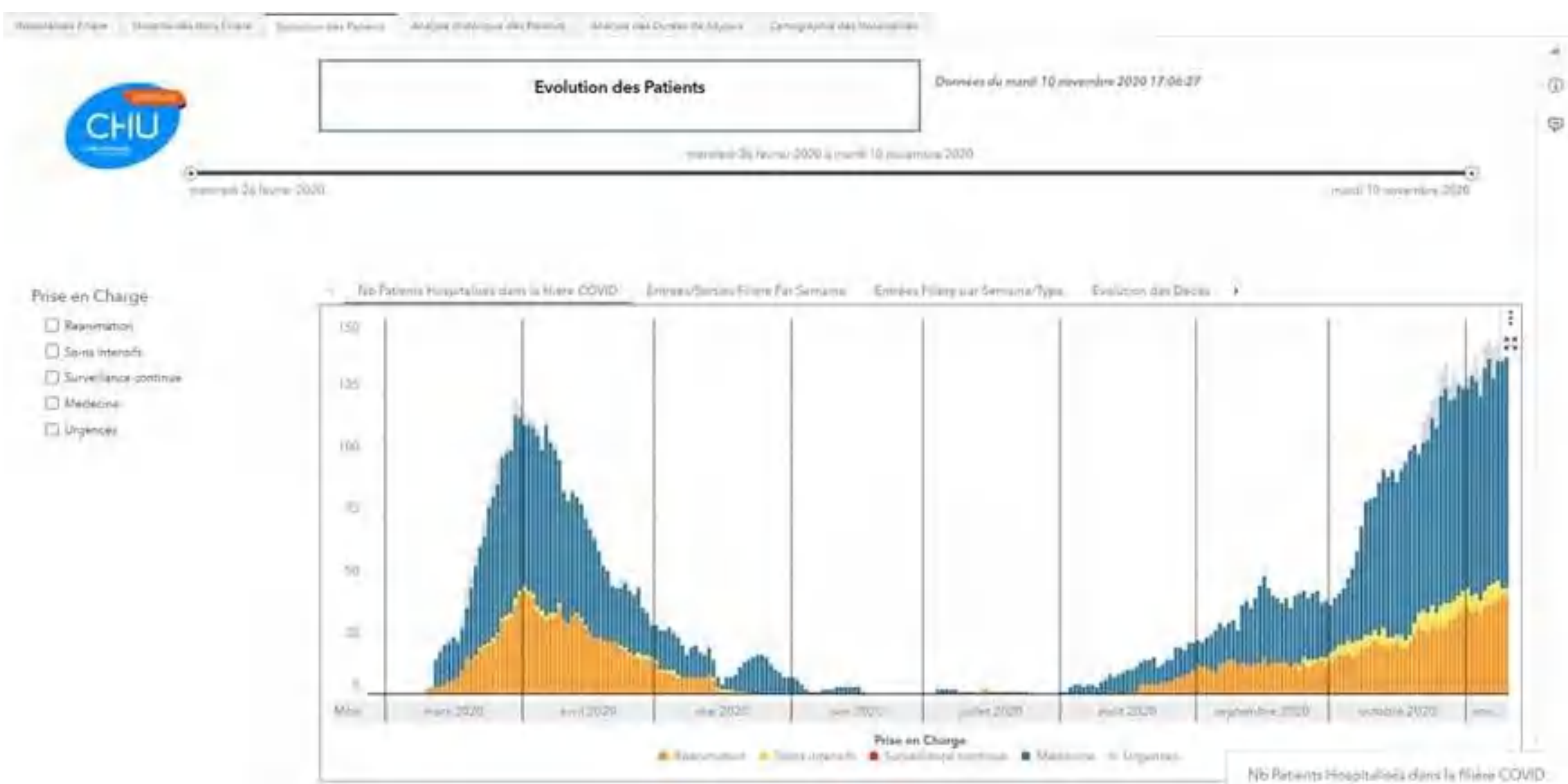
- improve sales
- product offerings
- optimize supply chain
- optimize promotions
- redesign store layouts
- customer retention

fidelity-cards are good or bad ???

DW 4 Health : CHU Montpellier

https://www.chu-montpellier.fr/fr/plateformes-recherche/eds

Entrepôt de Données de Santé du Languedoc



Main challenge : Making a datawarehouse is not science, is an art.

Datawarehouse Making

“Art” = combination of a set of best-practices

- Totally driven by the “industrial” case considered
- Neglects sensible parts of rel. theory : eg Normal Forms
- User-driven : make analytic **user-**queries easy

Problem #1

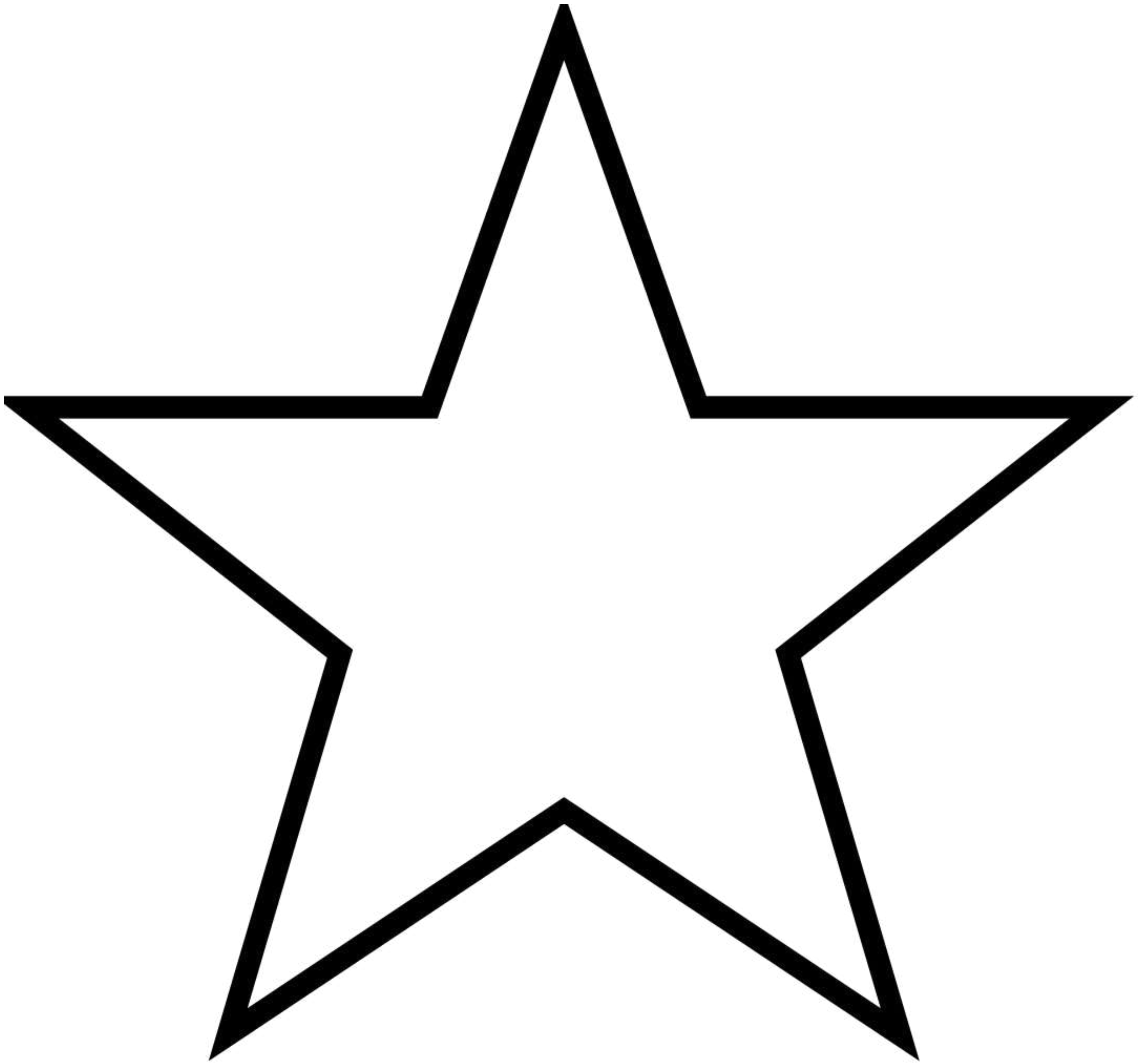
Aspect	Operational DB	DW
Interaction	short (s)	long analyses (min,h)

Analytical queries need to aggregate a lot of data, query time is thus typically higher than a transactional query

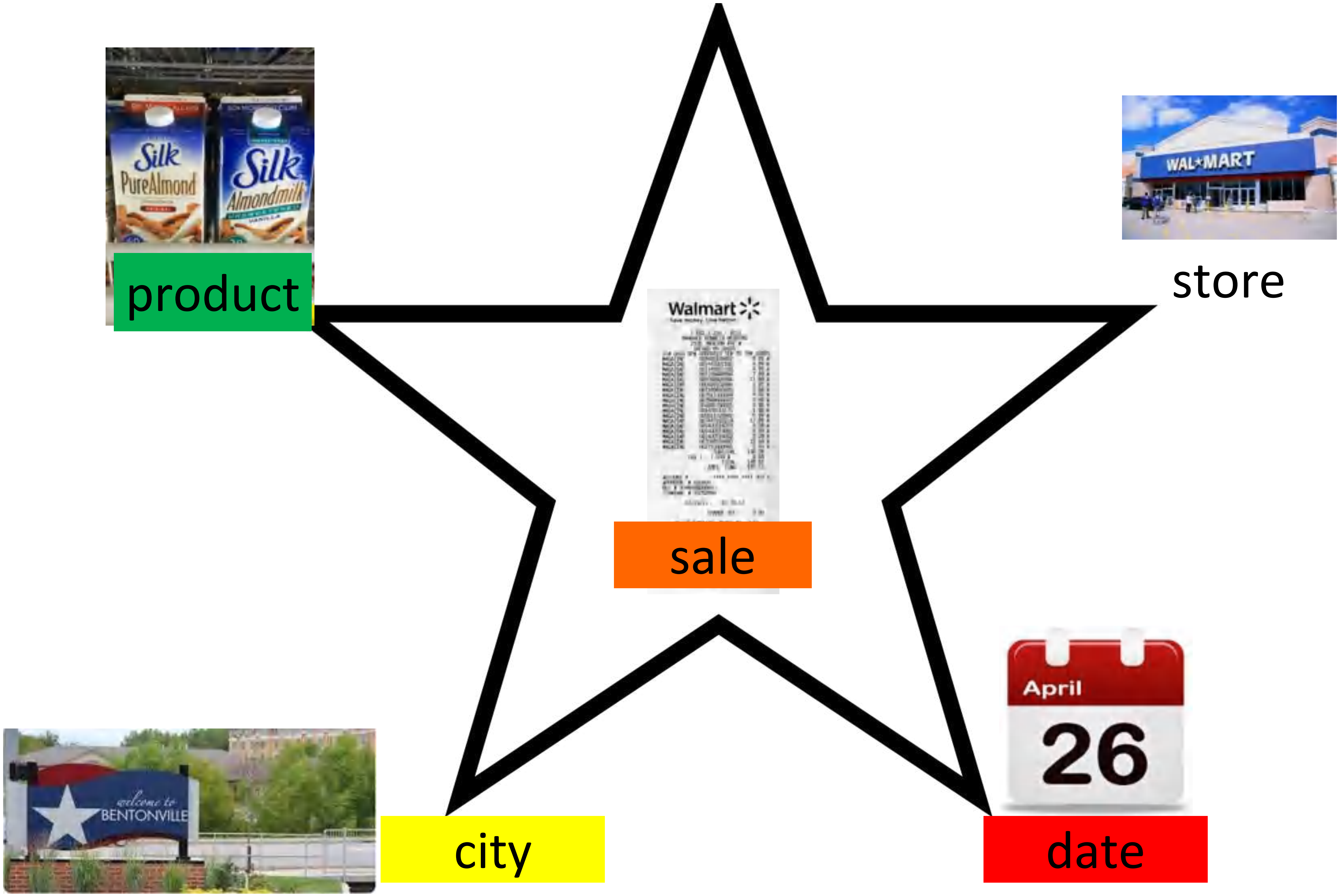
Solution : Star Schemas

- Conceived for two purposes
  - Query optimisation
    - Save joins (using redundant non-3NF schemas)
    - Joins over star-schema can be optimised
  - Make data understanding and query formulation easy

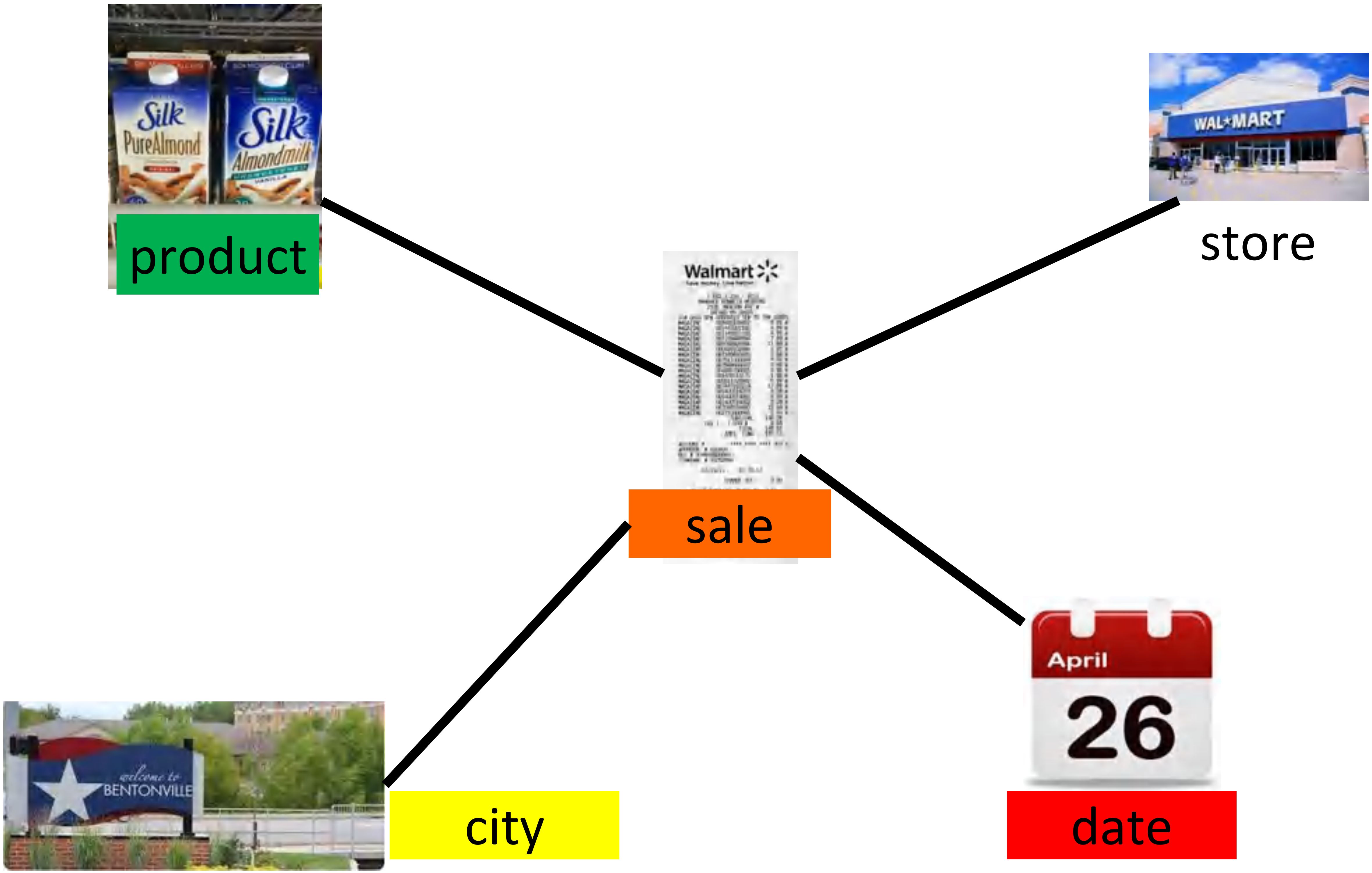
Relational Models for DW



Star Schemas



Star Schemas



Basic terminology : Fact

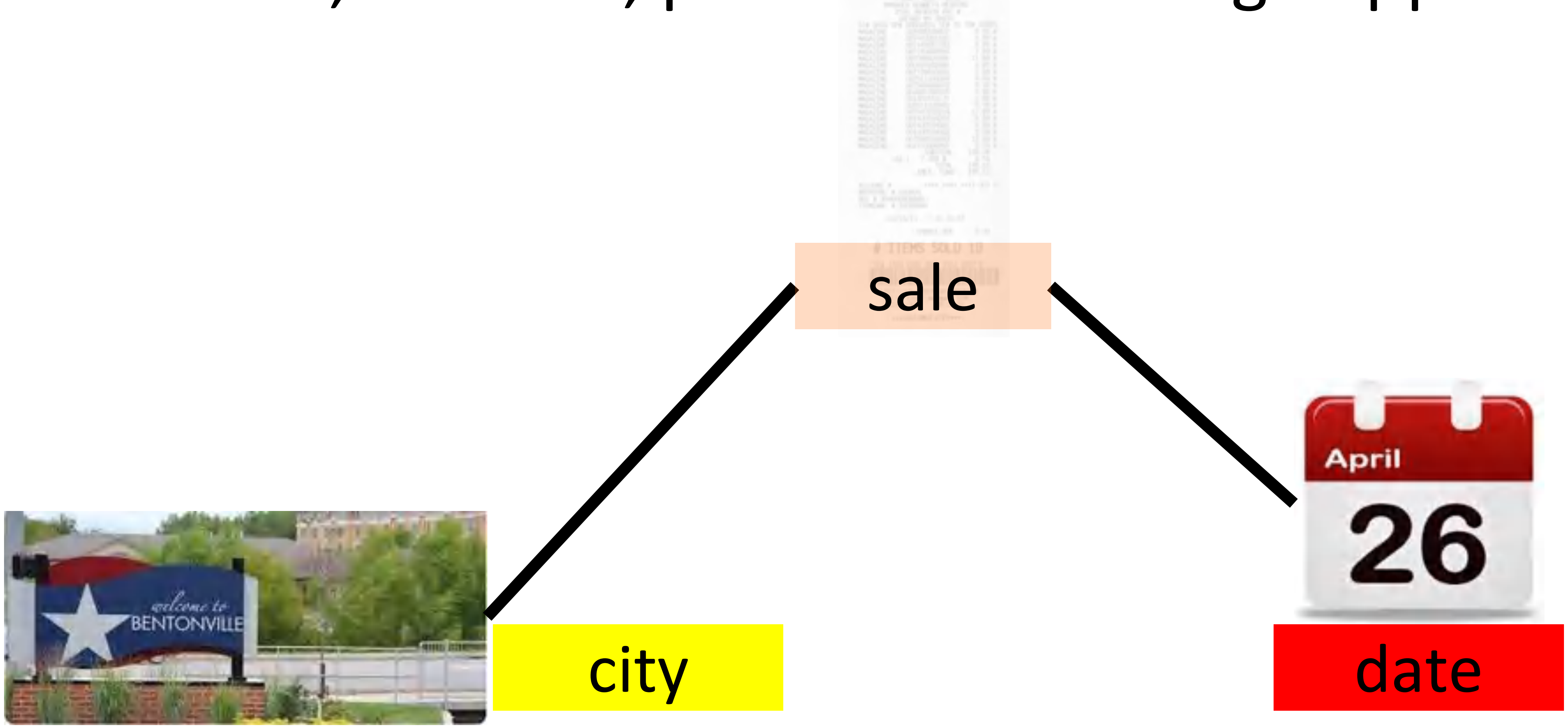
Fact = recording of an event occuring in the real world
(the center of the star)

- I sell an item

Basic terminology : Dimension

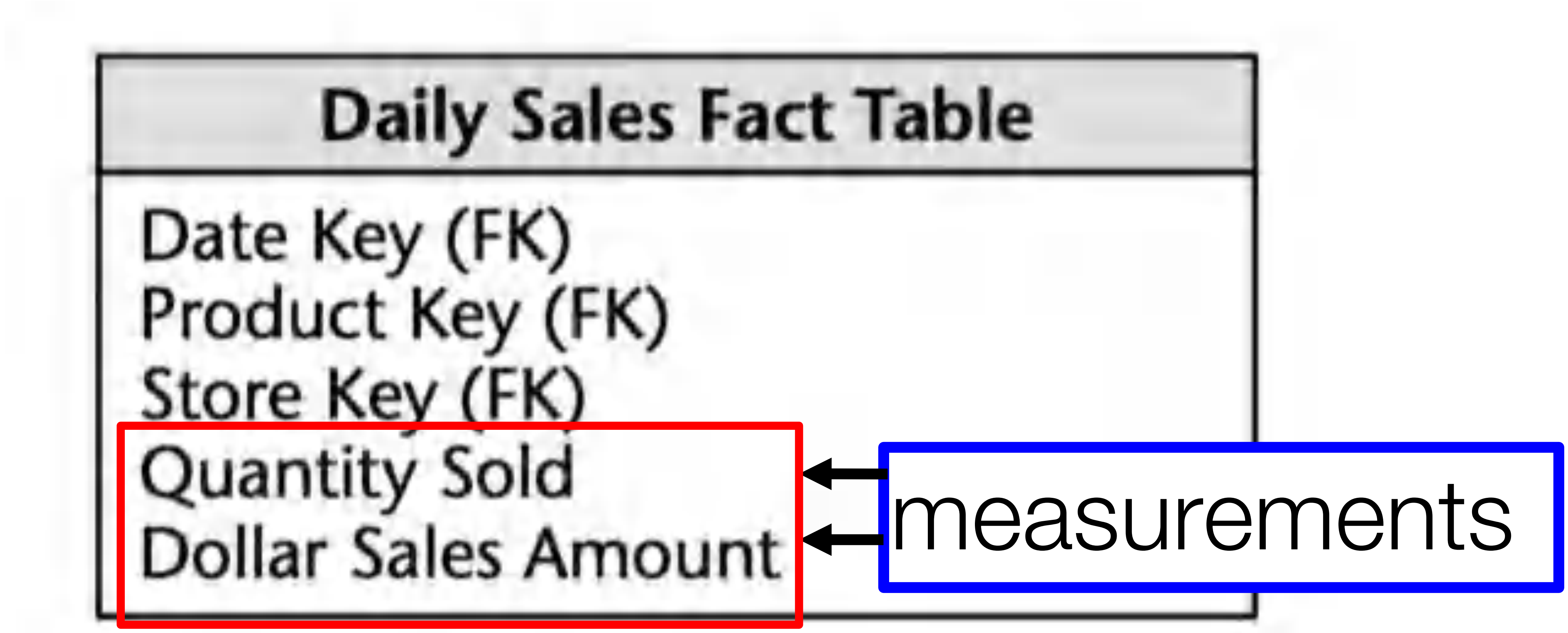
Dimension = a set of attribures describing the fact
(a vertex of the star)

- the date, location, place where selling happened



Fact Table

- Principal table in a datawarehouse
- Stores performance **measurements** of the business



Fact Table

- Principal table in a datawarehouse
- Stores performance **measurements** of the business

date	product	store	quantity	amount($)
1	3	1	11	45
1	21	2	65	1200
1	47	3	2332	15000
1	710	4	53	75

measurements

Numeric and Additive Facts

- most useful **measurements** are **numeric** and **additive**:

- **Additivity is crucial**

date	product	store	quantity	amount($)
1	3	1	11	45
1	21	2	65	1200
1	47	3	2332	15000
1	710	4	53	75

- **Text facts are rare**

measurements

Non-Additive Facts

- **%** (gross margin), **ratios** (movie rating) are nonadditive

date	product	store	quantity	amount($)	margin(%)
1	3	1	11	45	15
1	21	2	65	1200	35
1	47	3	2332	15000	20
1	710	4	53	75	50

non-additive

Non-Additive Facts

- **%** (gross margin), **ratios** (movie rating) are nonadditive

date	heure	film	note (num)	note (den)
1	11	1	1	5
1	23	1	4	5
1	47	3	5	5
1	70	4	5	5

ratios best practice for DW:
numerator & denominator
separately in fact table
ratio calculated on the fly
by the query

non-additive

Fact Table

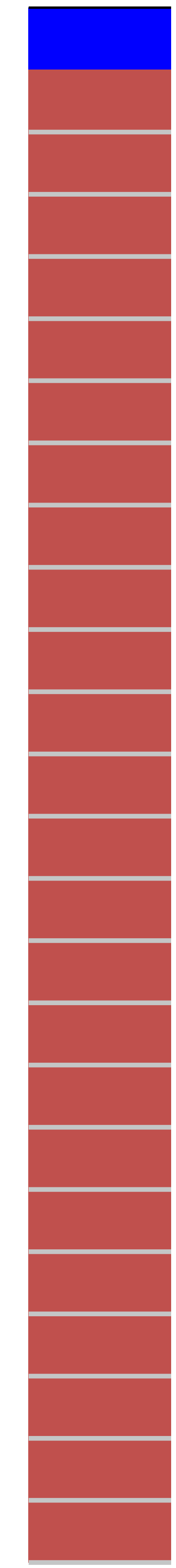
Fact tables usually make up **90% of the DW**
(can be billions of lines)

- **Deep** in the #rows (facts)

- **Narrow** in the #columns (dimensions)

NO sales activity (day, store, product) = NO rows

- Zero(s) saying nothing happening = space waste



Referential Integrity

- **Fact tables foreign keys** connect to the **dimension** tables primary keys   (this makes the "star")

Daily Sales Fact Table
Date Key (FK)
Product Key (FK)
Store Key (FK)
Quantity Sold
Dollar Sales Amount

Referential Integrity

- **Fact tables foreign keys** connect to the **dimension** tables primary keys   (this makes the "star")

date	product	store	quantity	amount($)
1	3	1	11	45
1	21	2	65	1200
1	47	3	2332	15000
1	710	4	53	75

- Fact table => has ***composite key*** made of foreign keys
  (a priori, no need for ROWID, **but** ...)

Marrying Facts and Dimensions (into star-schemas)

A list of dimensions defines the *grain* of the fact table.

All measurements in a fact table are at the same grain.

Dimension Table

- Has a single-attribute PK
- Contain as many textual descriptors of the business as possible (**50-100 : OK**)
- Usually shallow in terms of the number of row, has many large columns

Product Dimension Table
Product Key (PK)
Product Description
SKU Number (Natural Key)
Brand Description
Category Description
Department Description
Package Type Description
Package Size
Fat Content Description
Diet Type Description
Weight
Weight Units of Measure
Storage Type
Shelf LIfe Type
Shelf Width
Shelf Height
Shelf Depth
... and many more

Textual & Discrete Dimension = 👍

- No cryptic abbreviations
  Include a short description (10 to 15 characters),
  a long description (30 to 50 characters),
  a brand name,
  a category name,
  a packaging type,
  size (behaving like a a discrete and constant descriptor)

Product Key	Product Description	Brand Description	Category Description	Department Description
1	Baked Well Light Sourdough Fresh Bread	Baked Well	Bread	Bakery
2	Fluffy Sliced Whole Wheat	Fluffy	Bread	Bakery
3	Fluffy Light Sliced Whole Wheat	Fluffy	Bread	Bakery

Dimension Table

- Entry points into the fact table

- Example : first I choose a a brand (eg. Colgate), then I look for sellings of corresponding items

Product Dimension Table
Product Key (PK)
Product Description
SKU Number (Natural Key)
Brand Description
Category Description
Department Description
Package Type Description
Package Size
Fat Content Description
Diet Type Description
Weight
Weight Units of Measure
Storage Type
Shelf LIfe Type
Shelf Width
Shelf Height
Shelf Depth
... and many more

Dimension Table

10% of the DW **but, data analysis power** directly proportional to quality and depth of the dimension attributes

Compared to a **fact table** is :

Large(r) in the #colums (attributes)

Shallow(er) in the #rows (possible values) (<< 10^6 rows)

BACK TO QUERY OPTIMISATION

Cost of the Colgate Query on RDBMS

product

Products(product_id, product_name, product_category, manufacturer_id)

city

Cities(city_id, city_name, state, population)

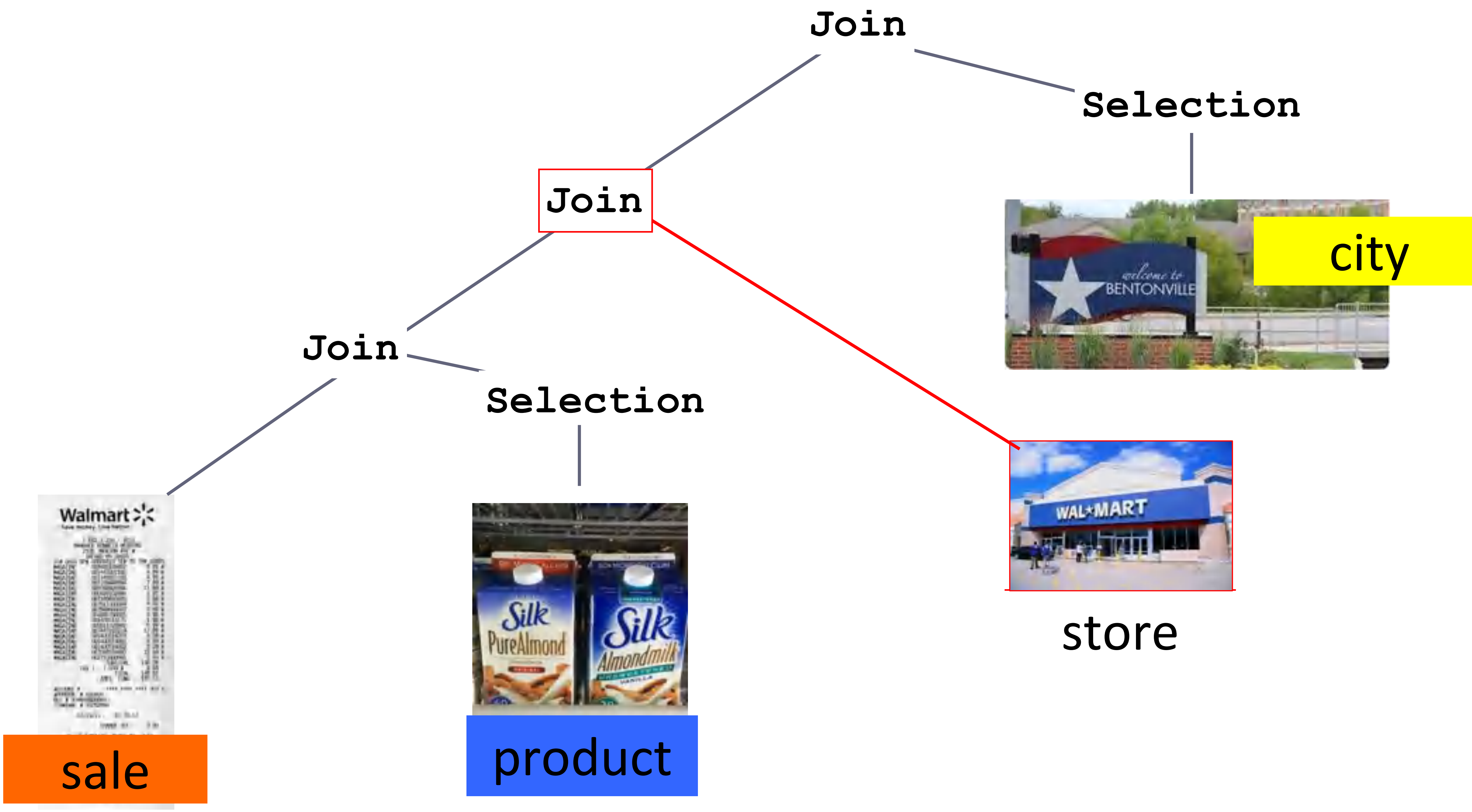
sale

Sales(product_id, store_id, quantity_sold, date_time_of_sale)

store

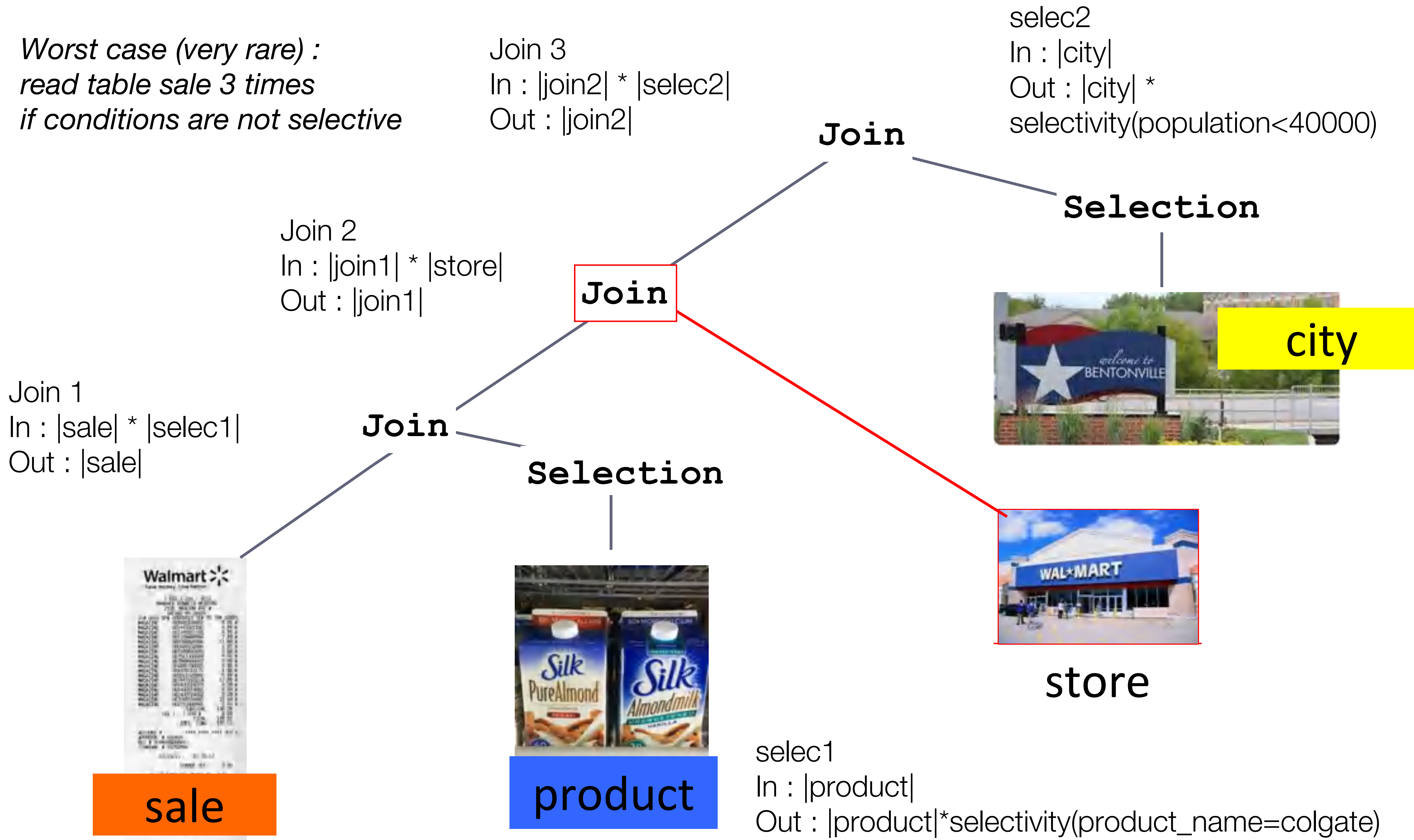
Stores(store_id_city_id, store_address, phone_num)

Estimating the Cost of the Colgate Query on RDBMS

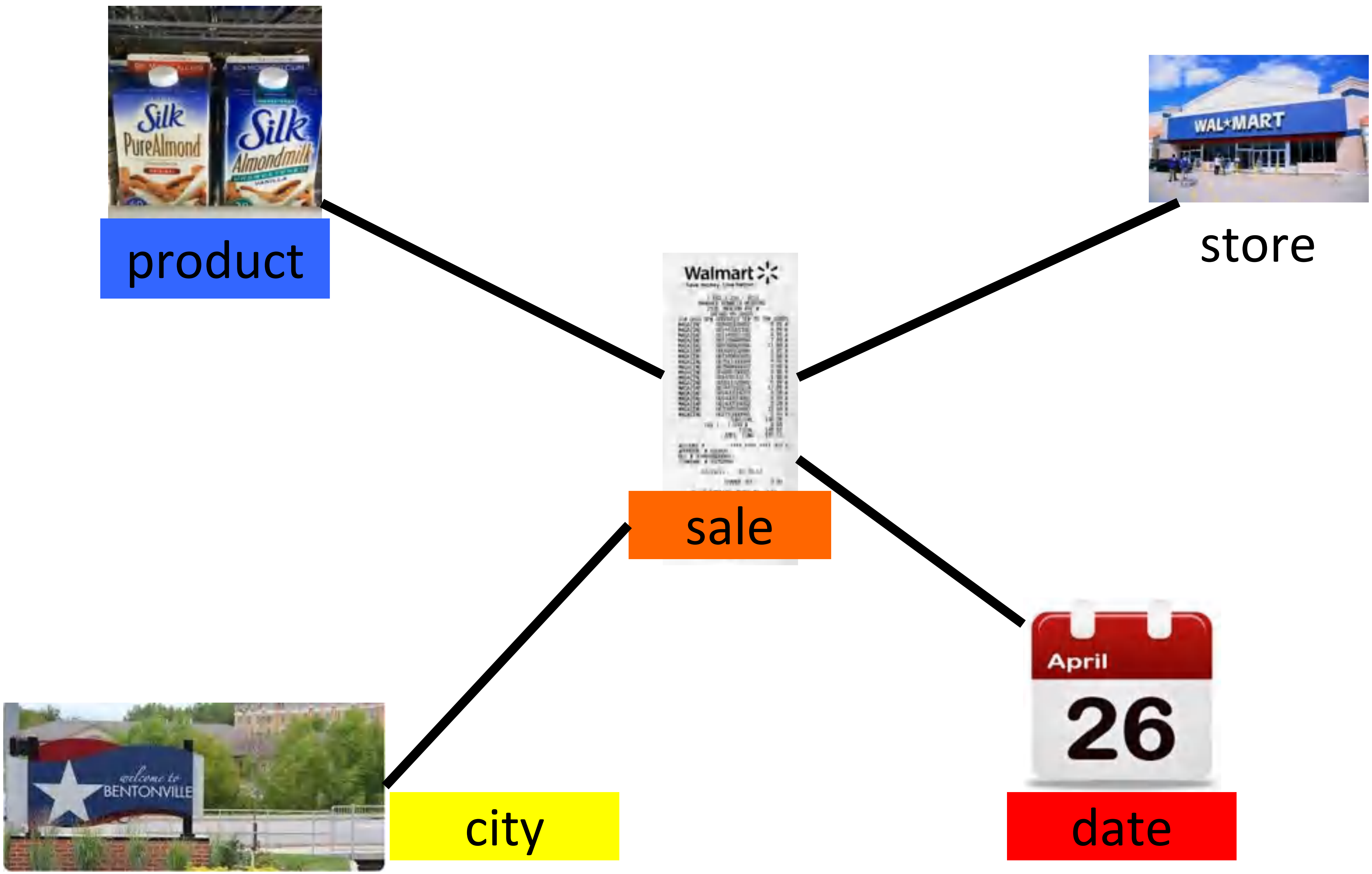


Estimating the Cost of the Colgate Query on RDBMS

Worst case (very rare) :
read table sale 3 times
if conditions are not selective



Estimating the Cost of the Colgate Query on a DW using a Star Schema



Estimating the Cost of the Colgate Query on a DW using a Star Schema

- Use the hypothesis that the query is a star query !

- First, scan all dimensions and apply filtering conditions

product

selec1
In : |product|
Out : |product| * selectivity(product_name=colgate)

city

selec2
In : |city|
Out : |city| * selectivity(population<40000)

- Then, read only once the Fact table !

Star-join
In : |sale|
Out : |sale| * selectivity(product_name=colgate) * selectivity(population<40000)

sale

Conclusion

- Queries over star schema are easier to optimise, and also to write

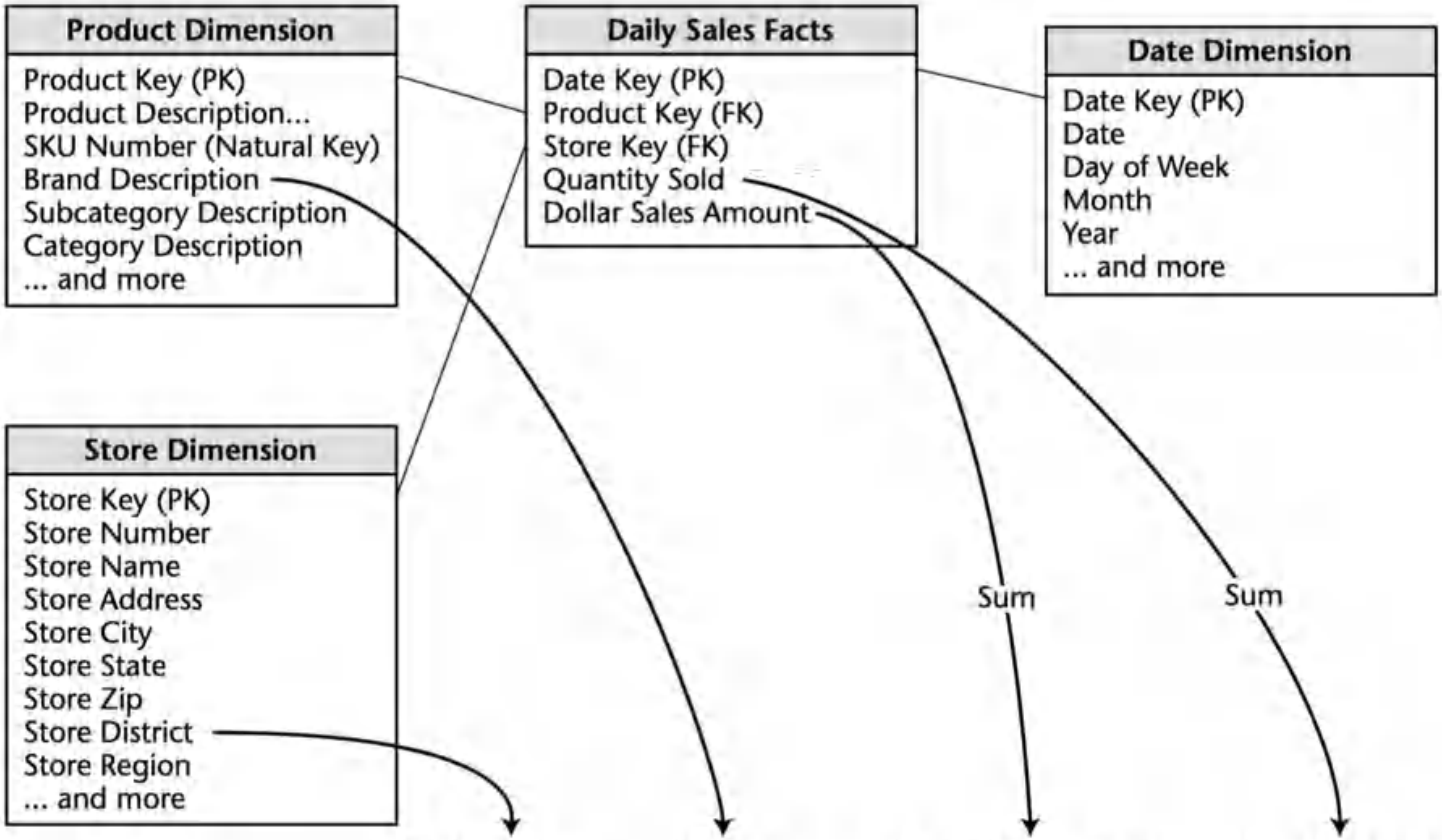
- We tried to give a numerical account for that by comparing the cost of the colgate query with two different cost-estimation models

  - One is for RDBMS, and accounts for the fact that RDBMS uses left-deep plans

  - One is for a relational DW, and accounts for the fact that it exploits the shape of star-schemas to optimise joins

SQL ANALYTICAL QUERIES

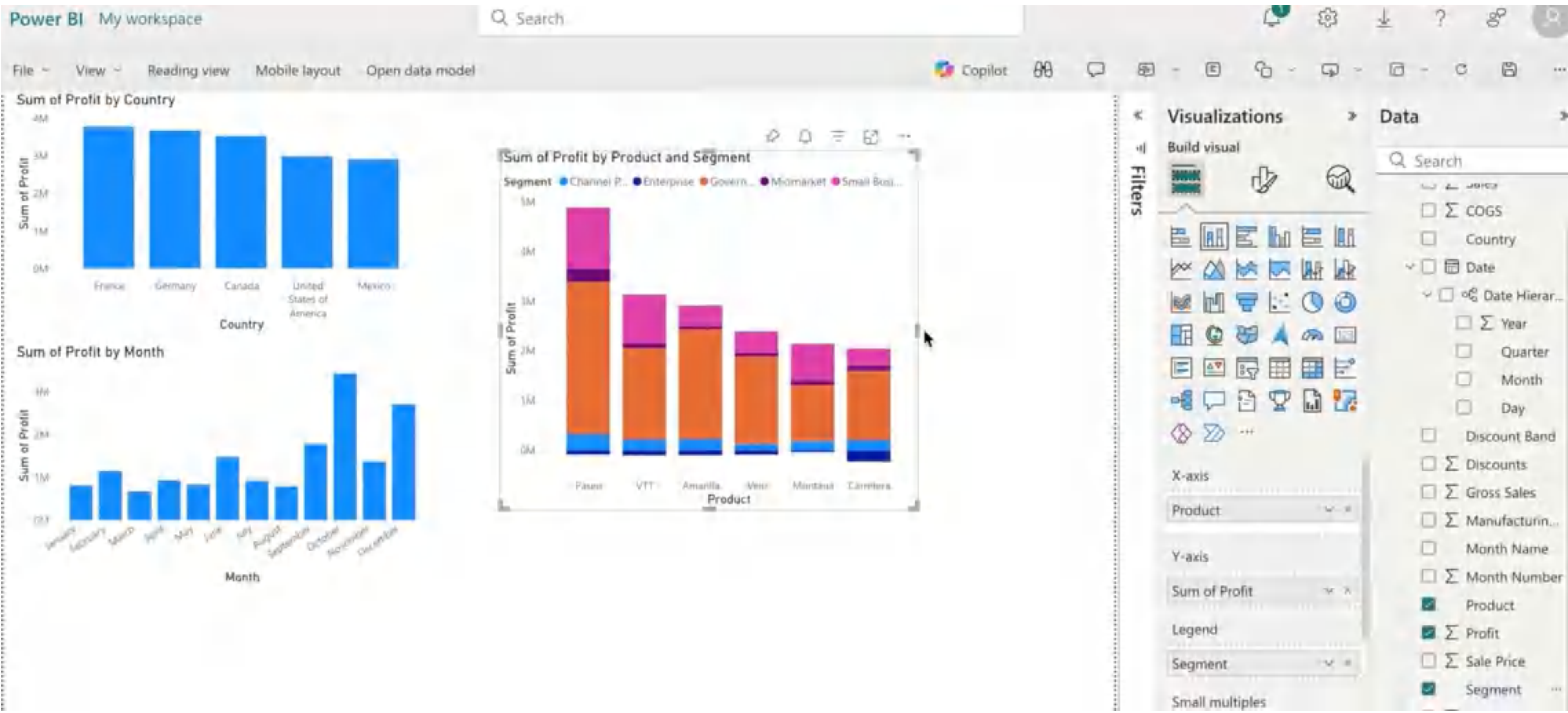
Ultimate Goal : Analytical Reports



District	Brand	Dollar Sales Amount	Quantity Sold
Atherton	Clean Fast	1,233	1,370
Atherton	More Power	2,239	2,035
Atherton	Zippy	848	707
Belmont	Clean Fast	2,097	2,330
Belmont	More Power	2,428	2,207
Belmont	Zippy	633	527

Example : Power BI (Microsoft)

https://moodle.umontpellier.fr/mod/videofile/view.php?id=896160



New Relational Operators

- `ROLLUP` operator
- `CUBE` operator

Group By

departement	**employee**	**manager**	**salaire**
D1	E1	M1	2000
D2	E2	M2	3400
D1	E3	M3	1280

```
SELECT    departement, AVG(salaire)
FROM      employees
GROUP BY  departement
```

Group By

departement	AVG(salaire)
D1	1640
D2	3400

```
SELECT    departement, AVG(salaire)
FROM      employees
GROUP BY  departement
```

`ROLLUP`

- `ROLLUP` is an extension to the `GROUP BY` clause.

- `ROLLUP` produces cumulative aggregates

Group By

departement	employee	manager	salaire
D1	E1	M1	2000
D2	E2	M2	3400
D1	E3	M3	1280

```
SELECT   departement, manager, AVG(salaire)
FROM     employees
GROUP BY departement,manager
```

ROLLUP

departement	manager	AVG(salaire)
D1	M1	2000
D1	M3	1280
D2	M2	3400

```
SELECT   departement, manager, AVG(salaire)
FROM     employees
GROUP BY departement,manager
```

ROLLUP

departement	manager	AVG(salaire)
D1	M1	2000
D1	M3	1280
D1		1640
D2	M2	3400
D2		3400
		2222.6

```
SELECT   departement, manager, AVG(salaire)
FROM     employees
GROUP BY   ROLLUP(departement,manager)
```

ROLLUP

departement	manager	AVG(salaire)
D1	M1	2000
D1	M3	1280
D1		1640
D2	M2	3400
D2		3400
		2222.6

Salaire par département par rapport à la moyenne.

Salaire par manager par rapport à la moyenne du département.

ROLLUP

```
SELECT    departement, manager, AVG(salaire)
FROM      employees
GROUP BY  departement, manager
                         ***
SELECT    departement, AVG(salaire)
FROM      employees
GROUP BY  departement
                         ***
SELECT    AVG(salaire) FROM    employees
```

~

```
SELECT   departement, manager, AVG(salaire)
FROM     employees
GROUP BY   ROLLUP(departement,manager)
```

CUBE

- `CUBE` is an extension to the `GROUP BY` clause.

- `CUBE` takes aggregation even further

```
SELECT   departement, manager, AVG(salaire)
FROM     employees
GROUP BY   CUBE(departement,manager)
```

CUBE

departement	manager	AVG(salaire)
		2226.6
	M1	2000
	M2	3400
	M3	1280
D1		1640
D1	M1	2000
D1	M3	1280
D2		3400
D2	M2	3400

```
SELECT   departement, manager, AVG(salaire)
FROM     employees
GROUP BY   CUBE(departement,manager)
```

CUBE

departement	**manager**	**AVG(salaire)**
		2226.6
	M1	2000
	M2	3400
	M3	1280
D1		1640
D1	M1	2000
D1	M3	1280
D2		3400
D2	M2	3400

```
SELECT   departement, manager, AVG(salaire)
FROM     employees
GROUP BY   CUBE(departement,manager)
```

CUBE

```
SELECT    departement, manager, AVG(salaire)
FROM      employees
GROUP BY  departement,manager
                                     ***
SELECT    manager, AVG(salaire)
FROM      employees
GROUP BY  manager
                                     ***
SELECT    departement, AVG(salaire)
FROM      employees
GROUP BY  departement
                                     ***
SELECT    AVG(salaire) FROM     employees
```

~

```
SELECT    departement, manager, AVG(salaire)
FROM      employees
GROUP BY   CUBE(departement,manager)
```

Summing up

- DW : **dedicated** systems for running analytical queries (heavy GROUP BY)

- Modelization : star-schemas (reduce joins; but don't use universal relations)

- Facts (hold numeric, mostly additive measurements)

- Dimensions (hold rich textual attribute information)