

Big Data Infrastructure

CS 489/698 Big Data Infrastructure (Winter 2016)

Week 6: Analyzing Relational Data (1/3)

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These slides are available at <http://lintool.github.io/bigdata-2016w/>

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Structure of the Course

Analyzing Text

Analyzing Graphs

Analyzing
Relational Data

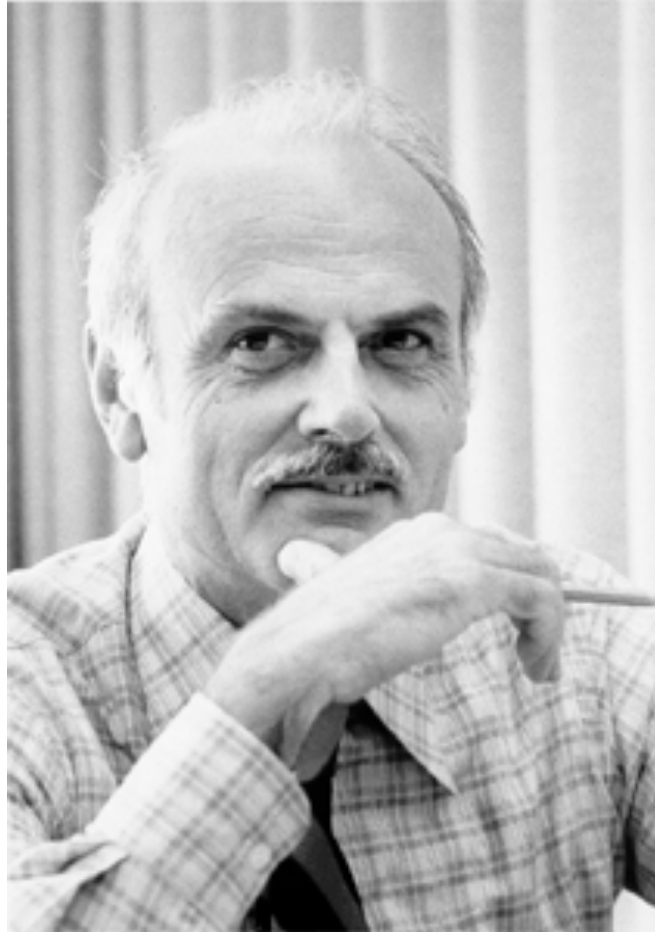
Data Mining

“Core” framework features
and algorithm design

Business Intelligence

An organization should retain data that result from carrying out its mission and exploit those data to generate insights that benefit the organization, for example, market analysis, strategic planning, decision making, etc.

Duh!?



Database Workloads

- OLTP (online transaction processing)
 - Typical applications: e-commerce, banking, airline reservations
 - User facing: real-time, low latency, highly-concurrent
 - Tasks: relatively small set of “standard” transactional queries
 - Data access pattern: random reads, updates, writes (involving relatively small amounts of data)
- OLAP (online analytical processing)
 - Typical applications: business intelligence, data mining
 - Back-end processing: batch workloads, less concurrency
 - Tasks: complex analytical queries, often ad hoc
 - Data access pattern: table scans, large amounts of data per query

An organization should retain data that result from carrying out its mission and exploit those data to generate insights that benefit the organization, for example, market analysis, strategic planning, decision making, etc.

One Database or Two?

- Downsides of co-existing OLTP and OLAP workloads
 - Poor memory management
 - Conflicting data access patterns
 - Variable latency
- Solution: separate databases
 - User-facing OLTP database for high-volume transactions
 - Data warehouse for OLAP workloads
 - How do we connect the two?

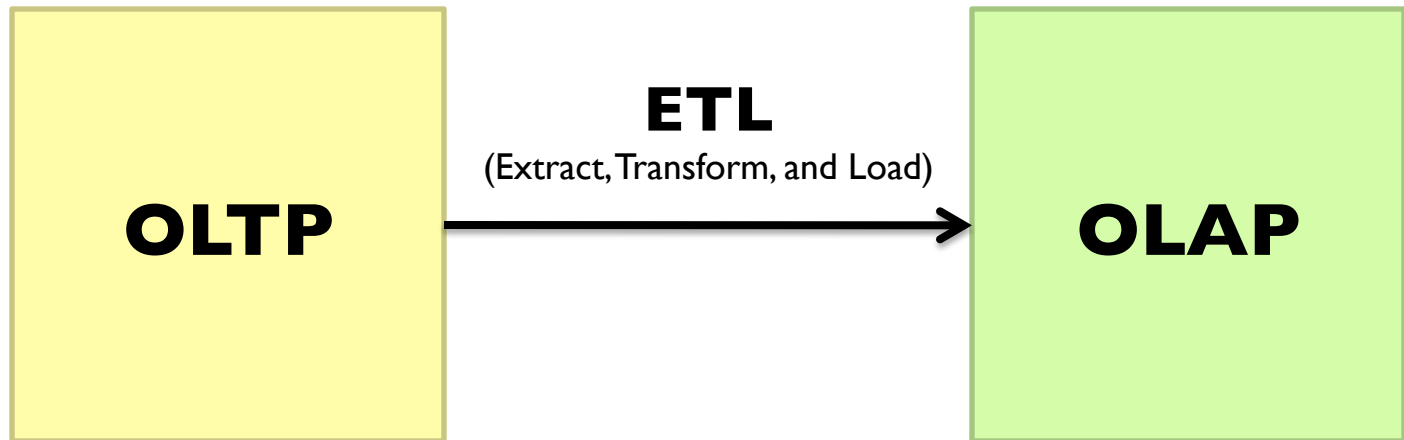


Data Warehousing

OLTP/OLAP Integration

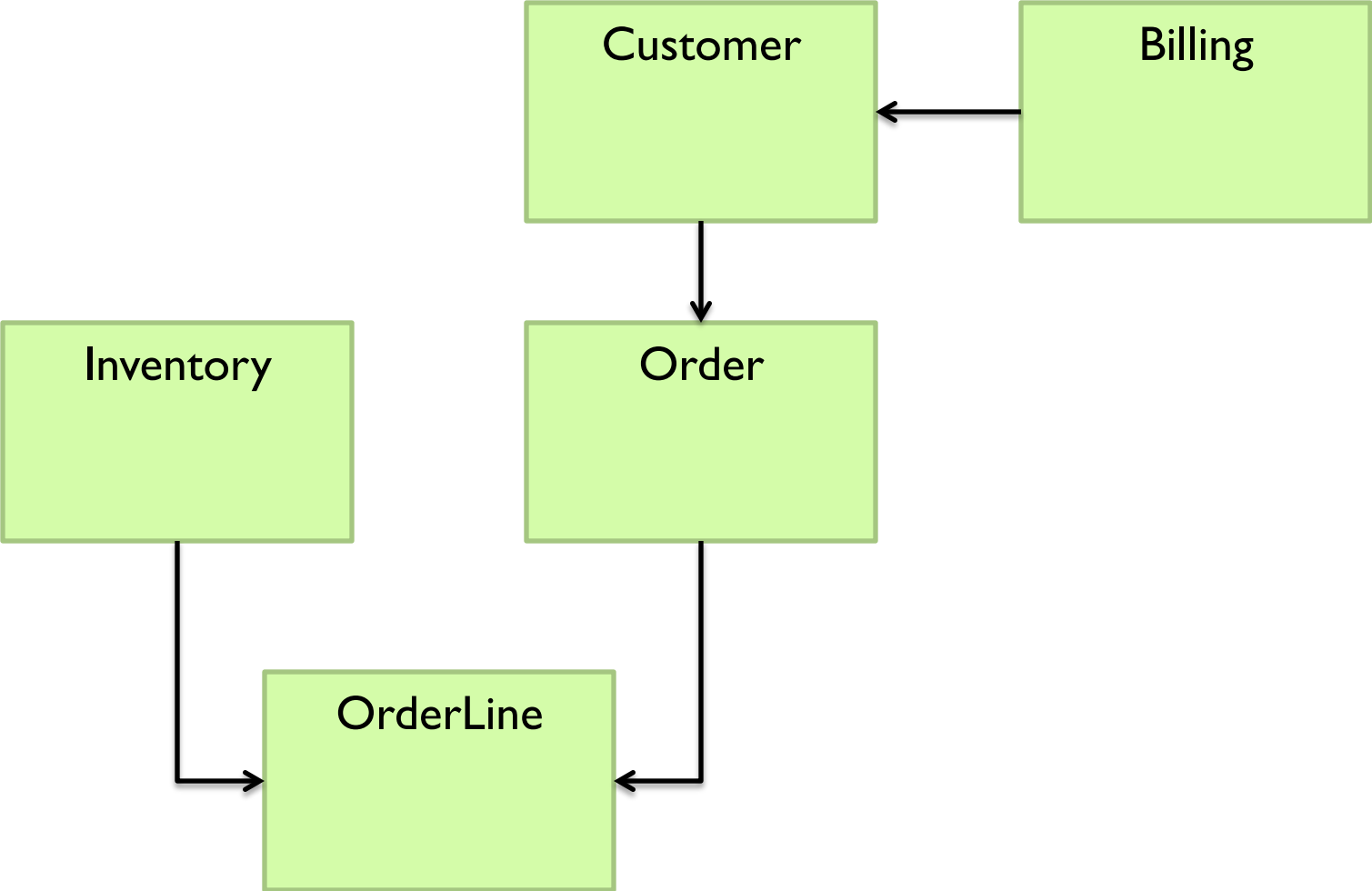
- OLTP database for user-facing transactions
- Extract-Transform-Load (ETL)
- OLAP database for data warehousing

OLTP/OLAP Architecture

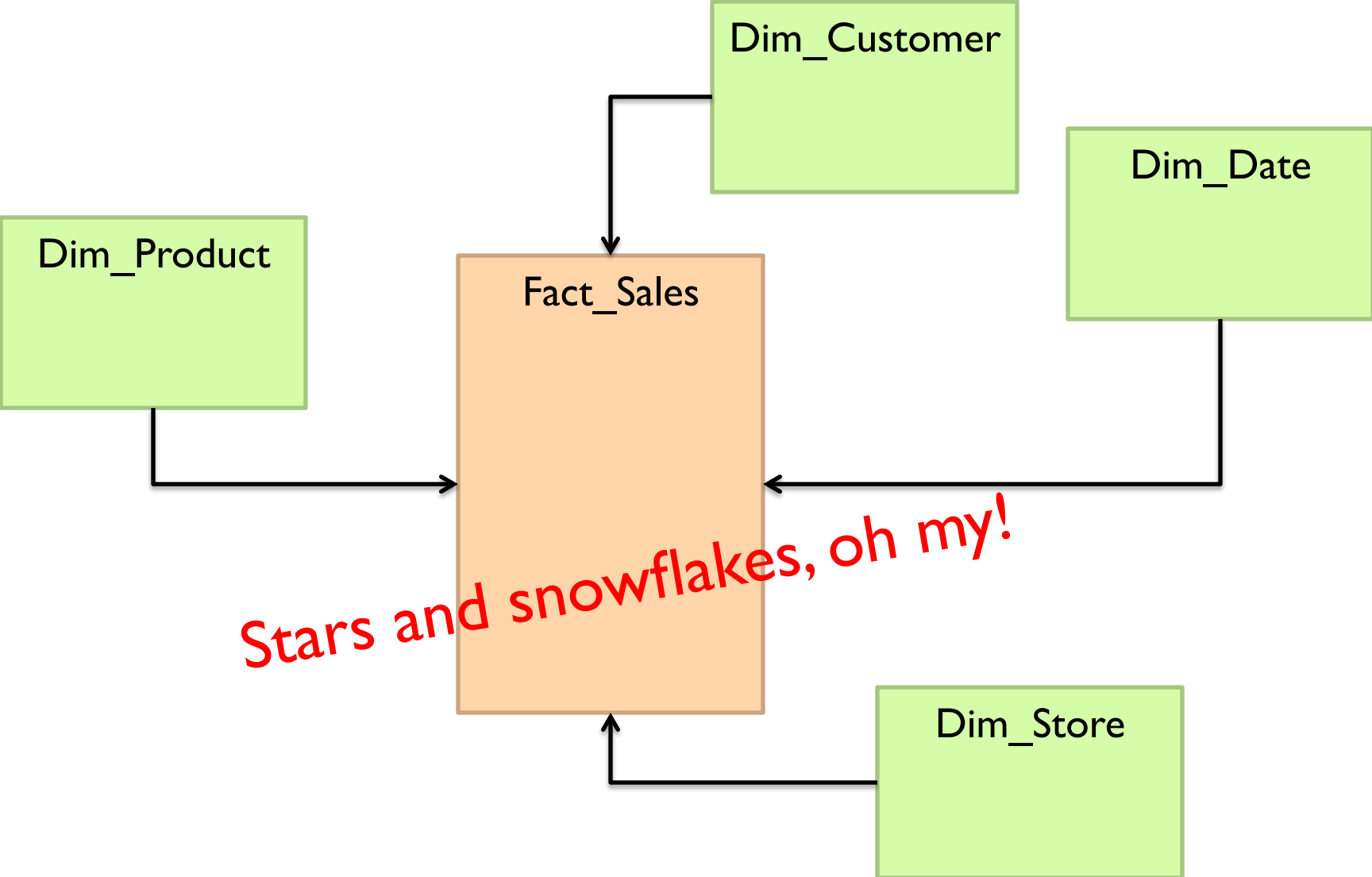


A simple example to illustrate...

A Simple OLTP Schema



A Simple OLAP Schema



ETL

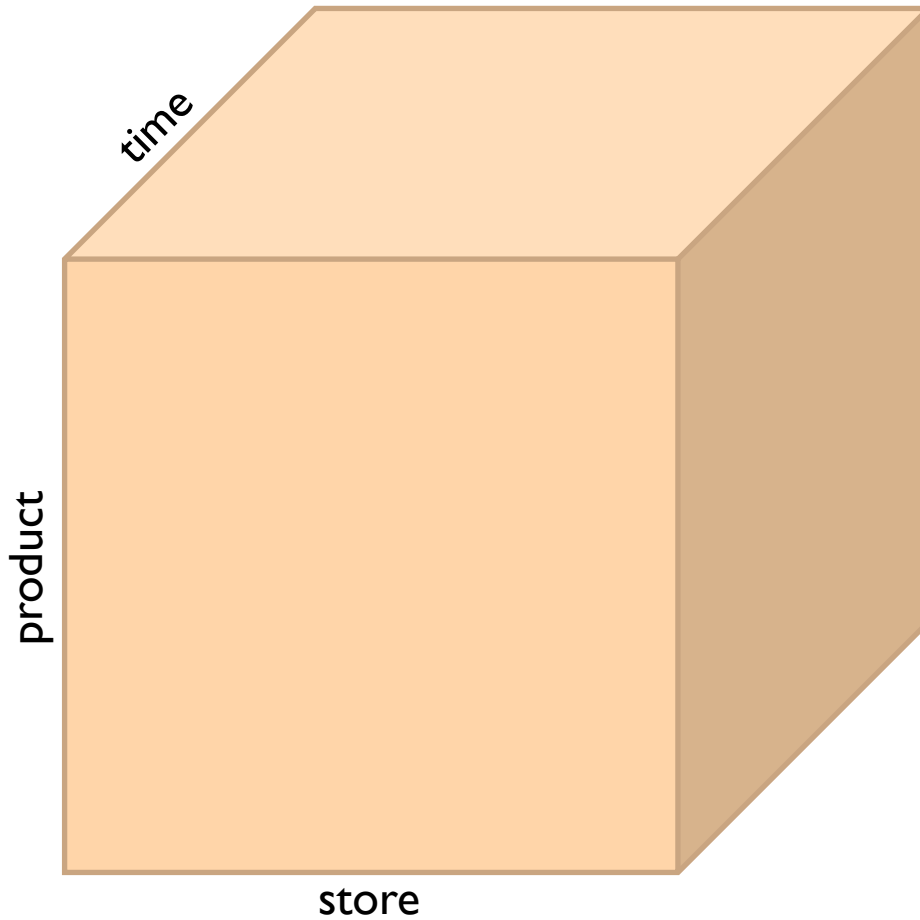
- Extract
- Transform
 - Data cleaning and integrity checking
 - Schema conversion
 - Field transformations
- Load

When does ETL happen?

What do you actually do?

- Report generation
- Dashboards
- *Ad hoc* analyses

OLAP Cubes



Common operations

slice and dice

roll up/drill down

pivot

OLAP Cubes: Challenges

- Fundamentally, lots of joins, group-bys and aggregations
 - How to take advantage of schema structure to avoid repeated work?
- Cube materialization
 - Realistic to materialize the entire cube?
 - If not, how/when/what to materialize?

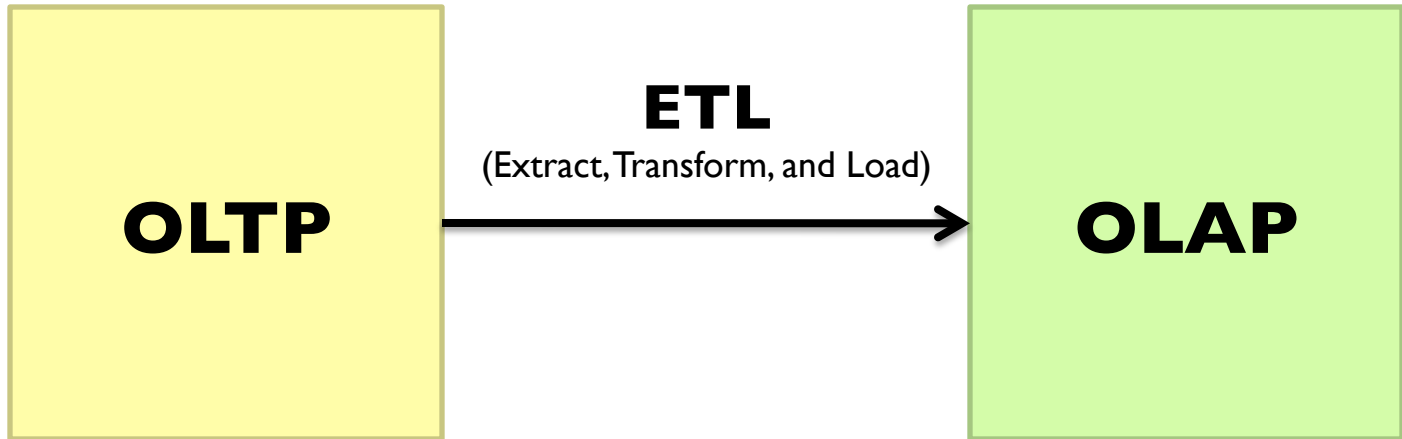
Fast forward...

facebook®

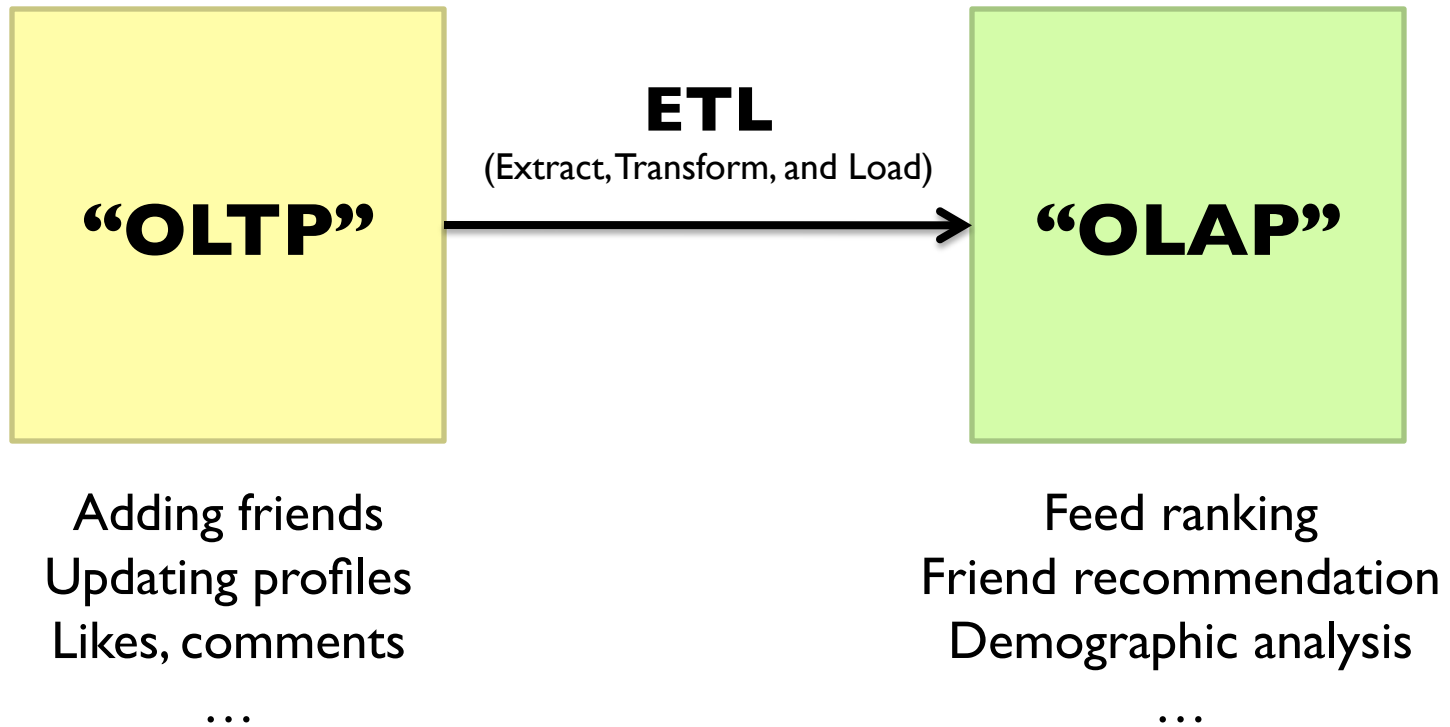
Jeff Hammerbacher, Information Platforms and the Rise of the Data Scientist.
In, *Beautiful Data*, O'Reilly, 2009.

“On the first day of logging the Facebook clickstream, more than 400 gigabytes of data was collected. The load, index, and aggregation processes for this data set really taxed the Oracle data warehouse. Even after significant tuning, we were unable to aggregate a day of clickstream data in less than 24 hours.”

OLTP/OLAP Architecture



Facebook Context



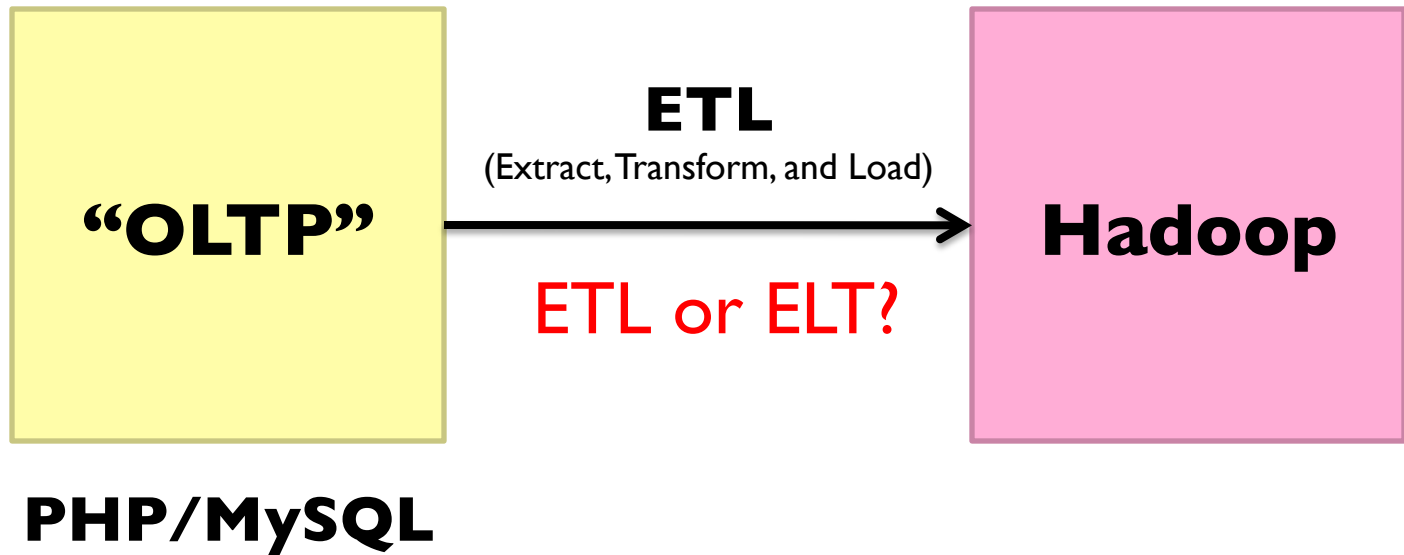
Facebook Technology



“OLTP”

PHP/MySQL

Facebook's Datawarehouse



What's changed?

- Dropping cost of disks
 - Cheaper to store everything than to figure out what to throw away

What's changed?

- Dropping cost of disks
 - Cheaper to store everything

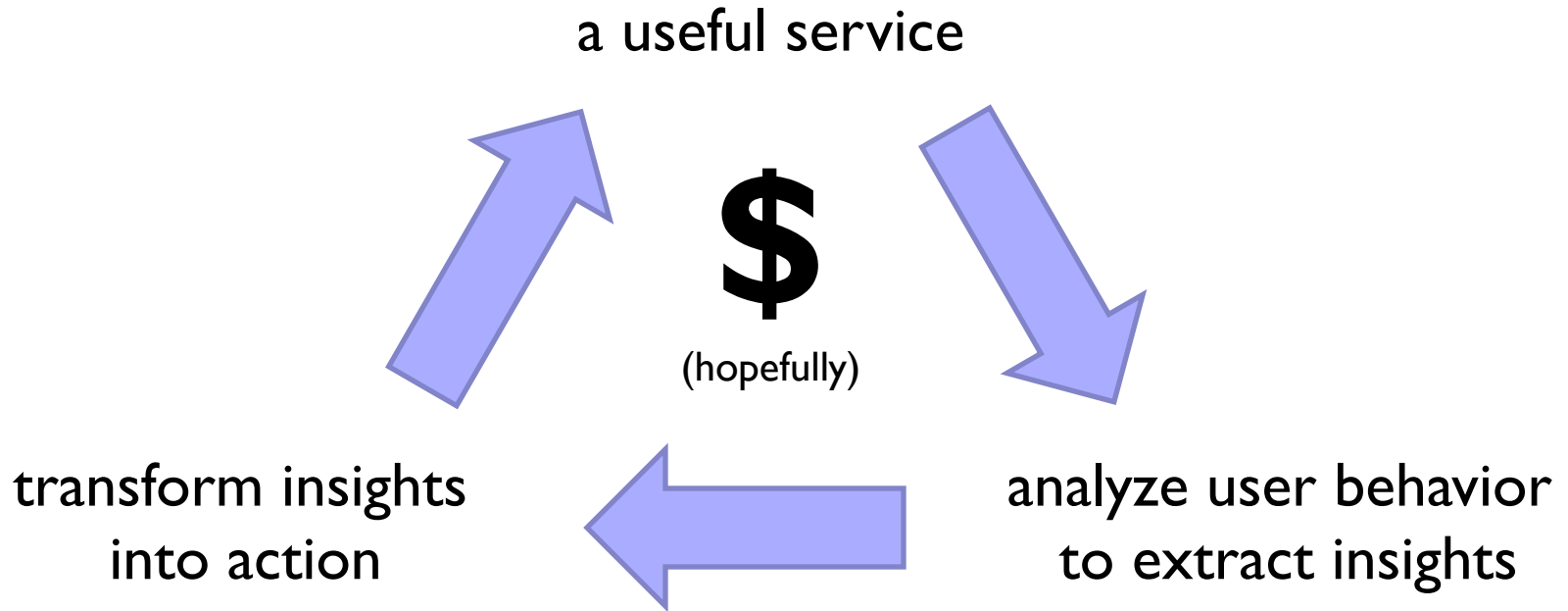


5 MB hard drive in 1956

What's changed?

- Dropping cost of disks
 - Cheaper to store everything than to figure out what to throw away
- Types of data collected
 - From data that's *obviously* valuable to data whose value is less apparent
- Rise of social media and user-generated content
 - Large increase in data volume
- Growing maturity of data mining techniques
 - Demonstrates value of data analytics

Virtuous Product Cycle

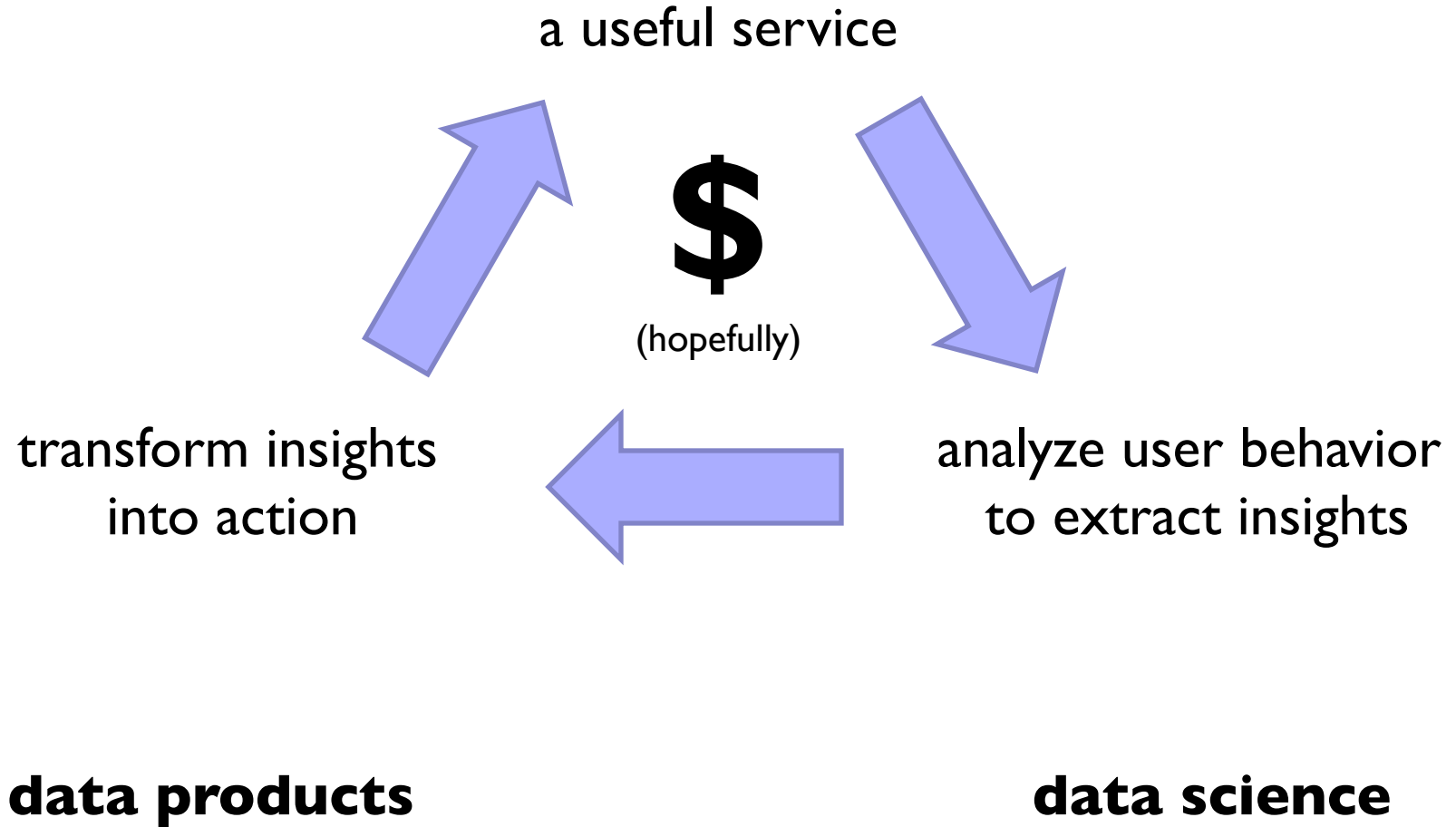


Google. Facebook. Twitter. Amazon. Uber.

What do you actually do?

- Report generation
- Dashboards
- *Ad hoc* analyses
 - “Descriptive”
 - “Predictive”
- Data products

Virtuous Product Cycle



facebook®

Jeff Hammerbacher, Information Platforms and the Rise of the Data Scientist.
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The Irony...

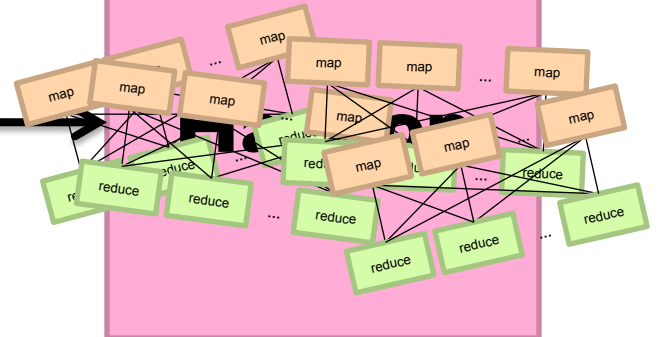


SQL



“OLTP”

ELT



PHP/MySQL

Wait, so why not use a database to begin with?

Why not just use a database?

SQL is awesome

Scalability. Cost.

Databases are great...

If your data has structure (and you know what the structure is)

If your data is reasonably clean

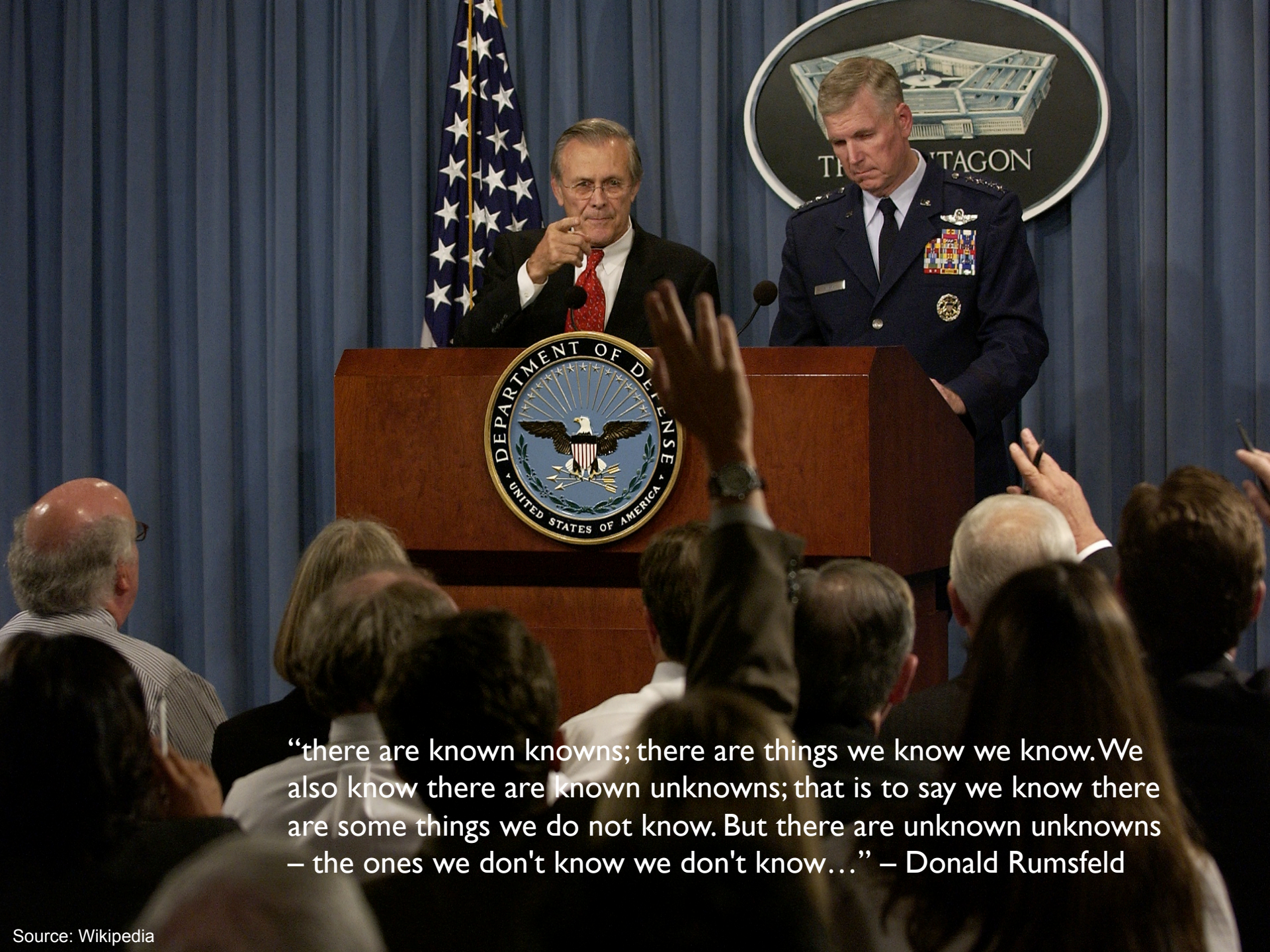
If you know what queries you're going to run ahead of time

Databases are not so great...

If your data has little structure (or you don't know the structure)

If your data is messy and noisy

If you don't know what you're looking for



“there are known knowns; there are things we know we know. We also know there are known unknowns; that is to say we know there are some things we do not know. But there are unknown unknowns – the ones we don't know we don't know...” – Donald Rumsfeld

Databases are great...

If your data has structure (and you know what the structure is)

If your data is reasonably clean

If you know what queries you're going to run ahead of time

Known unknowns!

Databases are not so great...

If your data has little structure (or you don't know the structure)

If your data is messy and noisy

If you don't know what you're looking for

Unknown unknowns!

Advantages of Hadoop dataflow languages

Don't need to know the schema ahead of time

Raw scans are the most common operations

Many analyses are better formulated imperatively

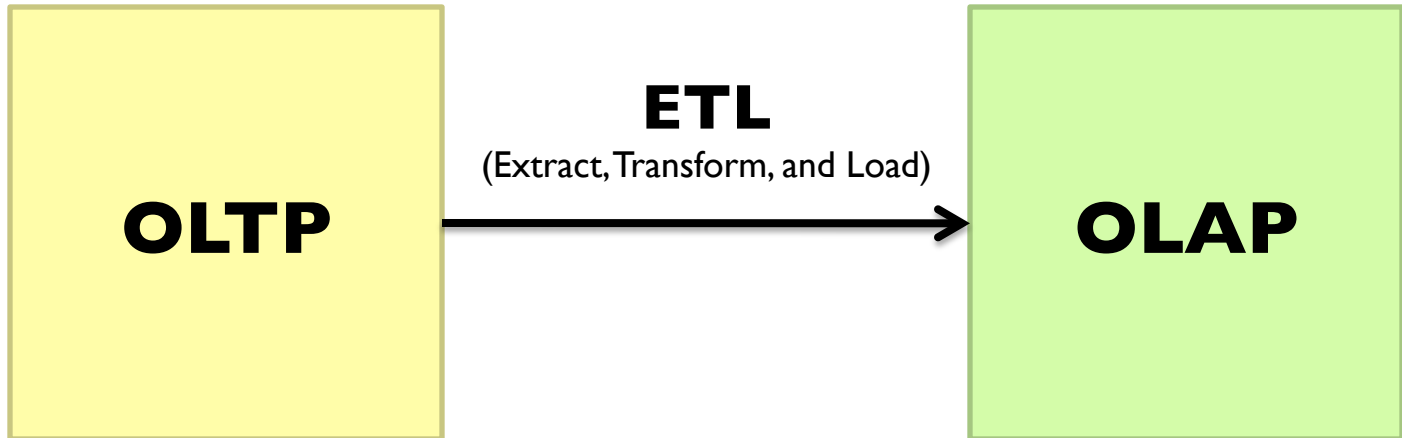
Also compare: data ingestion rate

What do you actually do?

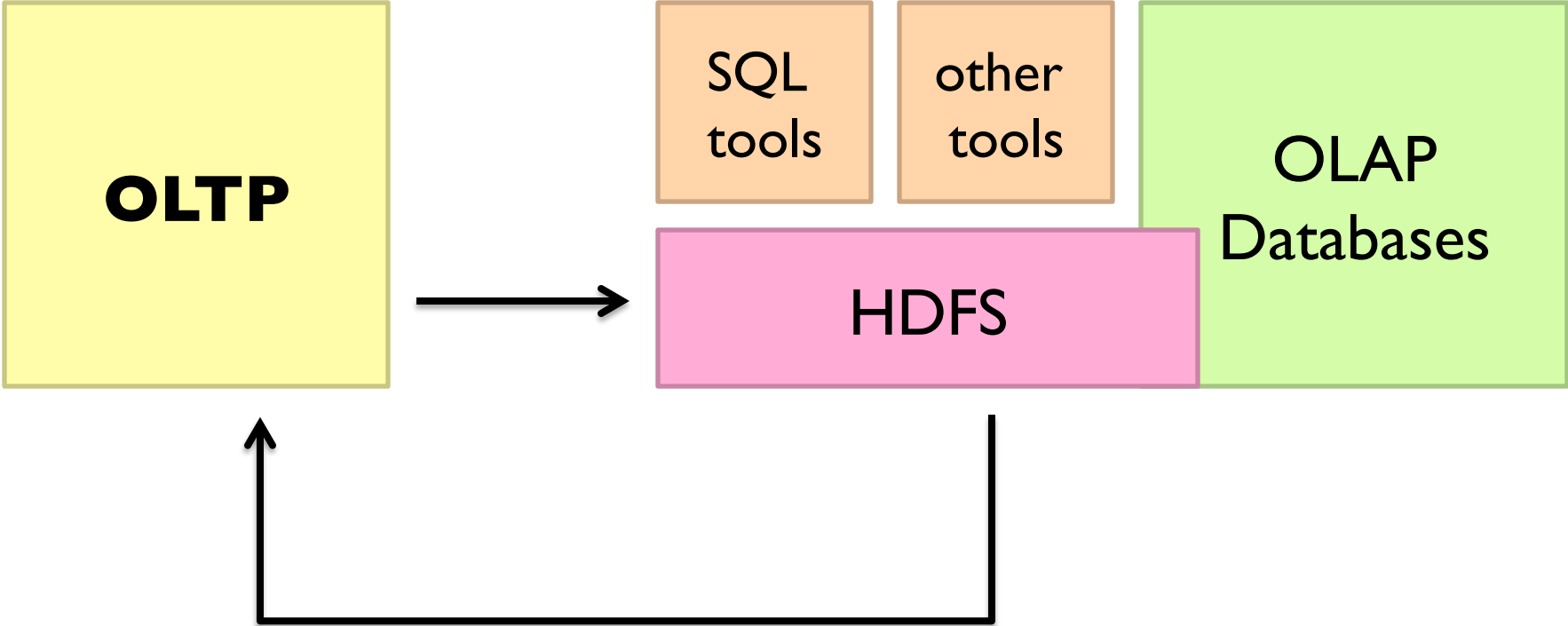
- Dashboards
- Report generation
- *Ad hoc* analyses
 - “Descriptive”
 - “Predictive”
- Data products

Which are known unknowns
and unknown unknowns?

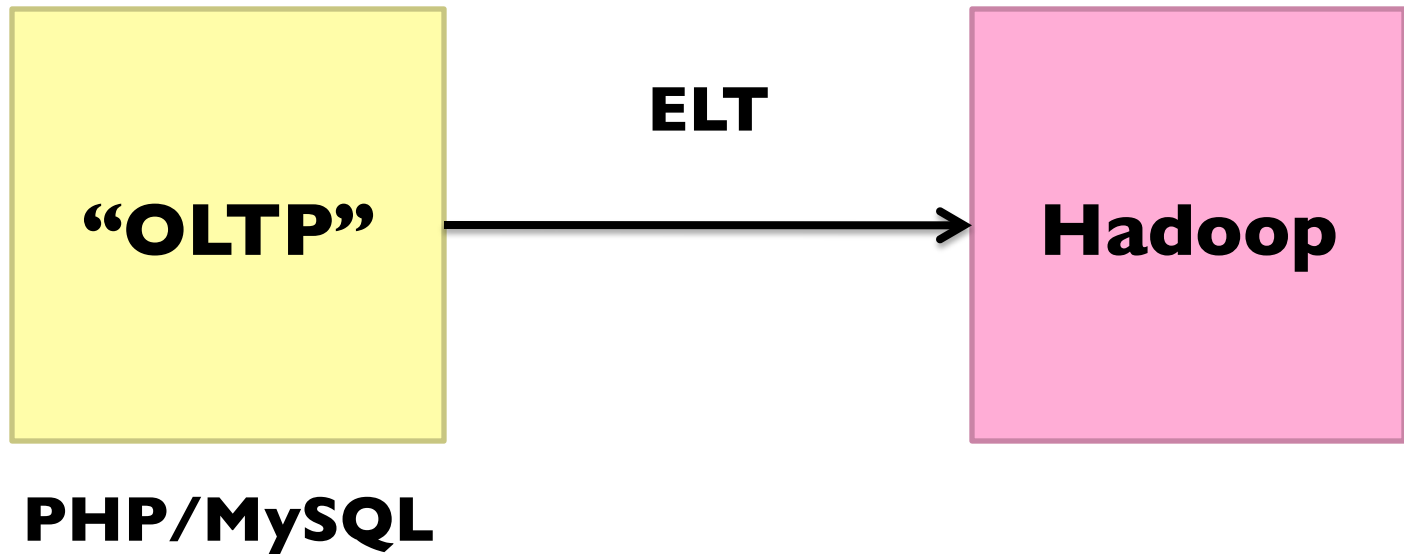
OLTP/OLAP Architecture



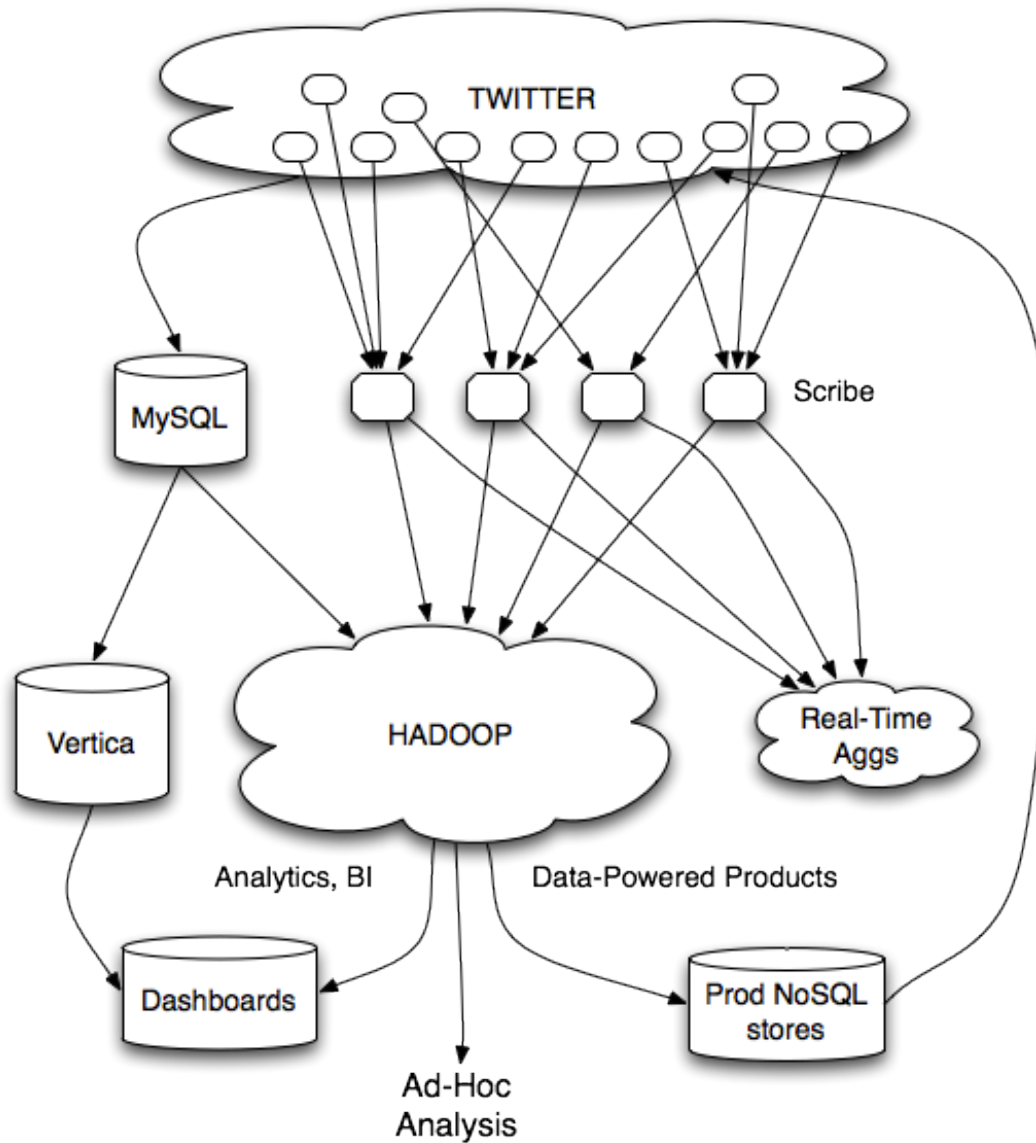
Modern Datawarehouse Ecosystem



Facebook's Datawarehouse



How does this actually happen?



Twitter's data warehousing architecture

circa ~2010

~150 people total

~60 Hadoop nodes

~6 people use analytics stack daily

circa ~2012

~1400 people total

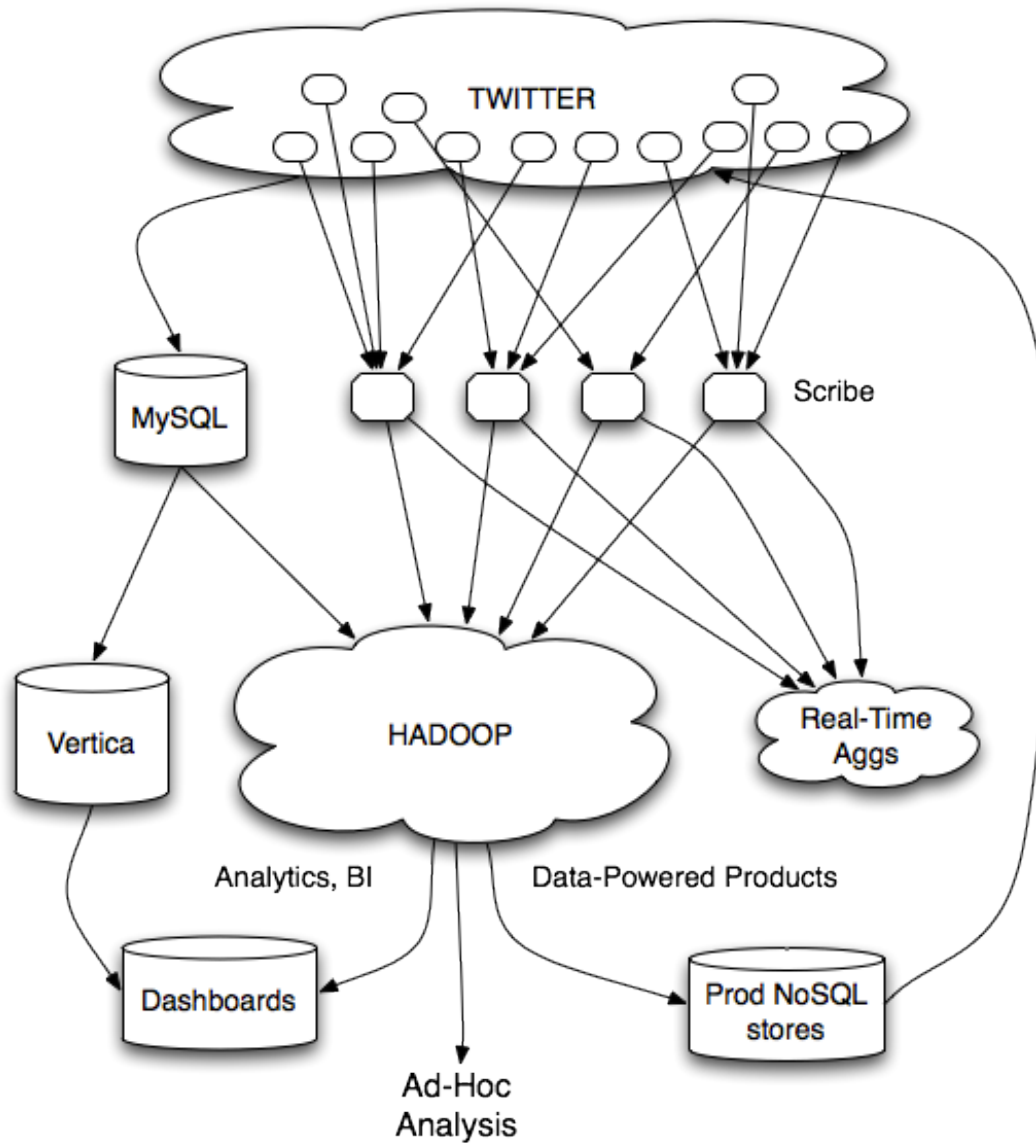
10s of Ks of Hadoop nodes, multiple DCs

10s of PBs total Hadoop DW capacity

~100 TB ingest daily

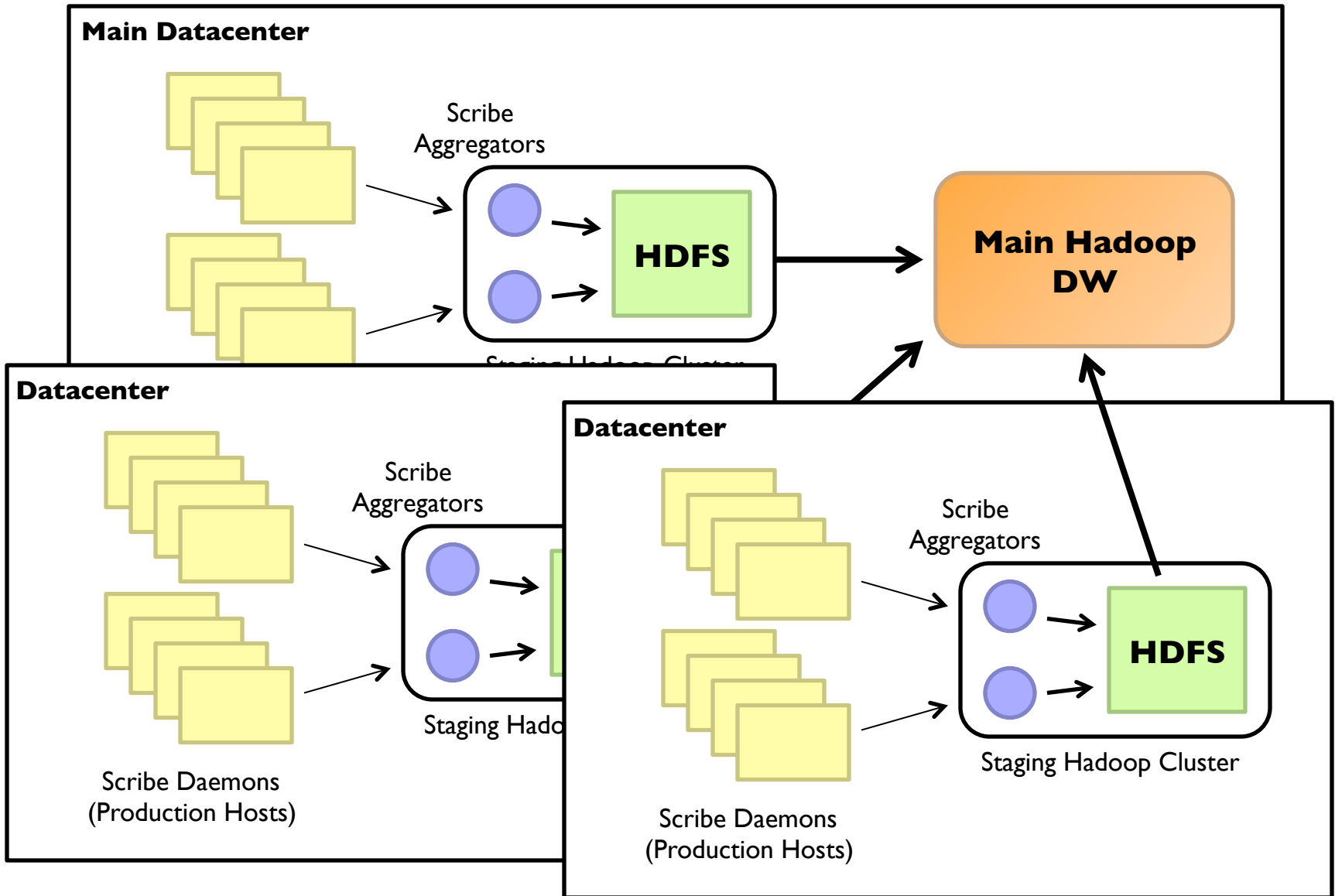
dozens of teams use Hadoop daily

10s of Ks of Hadoop jobs daily



Twitter's data warehousing architecture

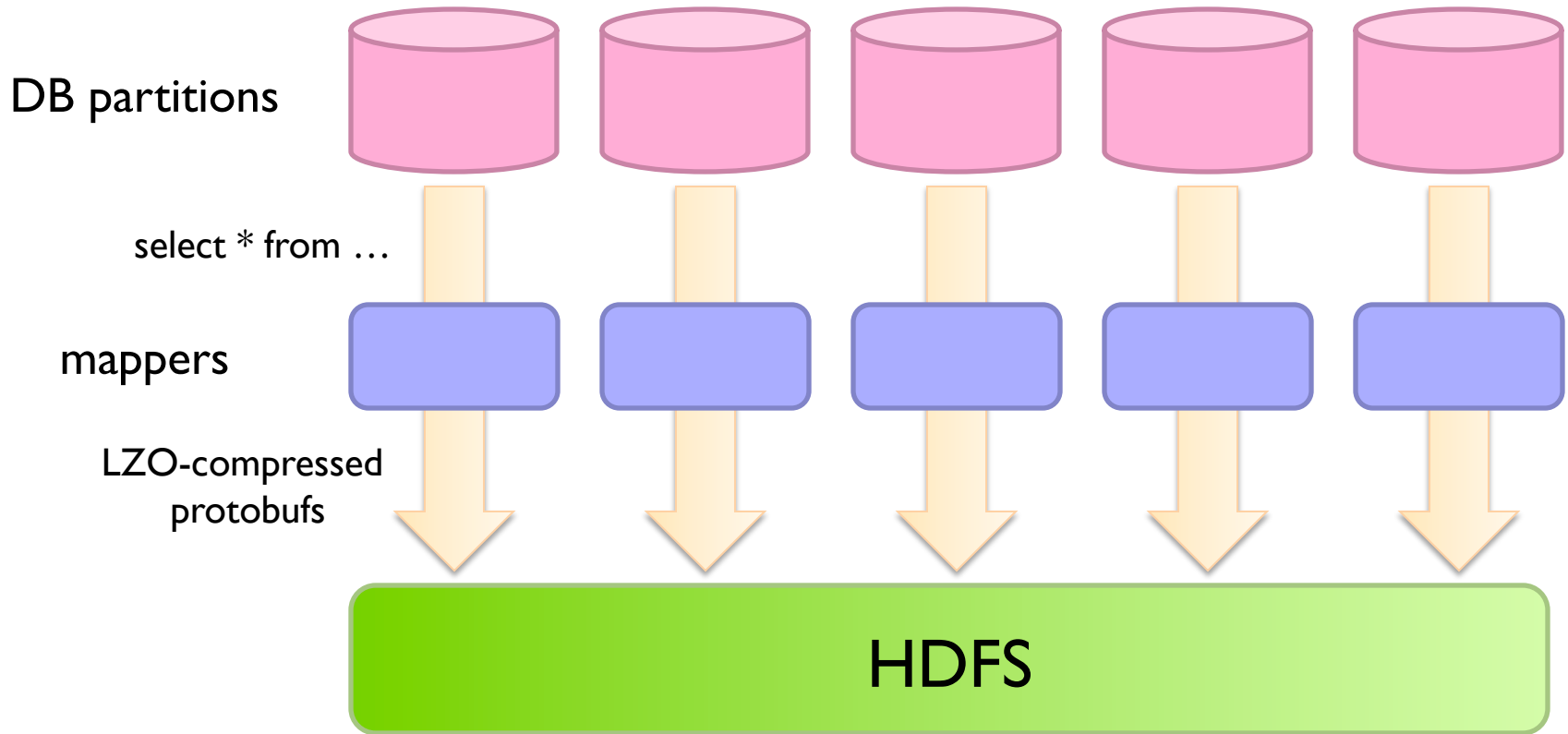
Importing Log Data



Importing Structured Data*

Tweets, graph, users profiles

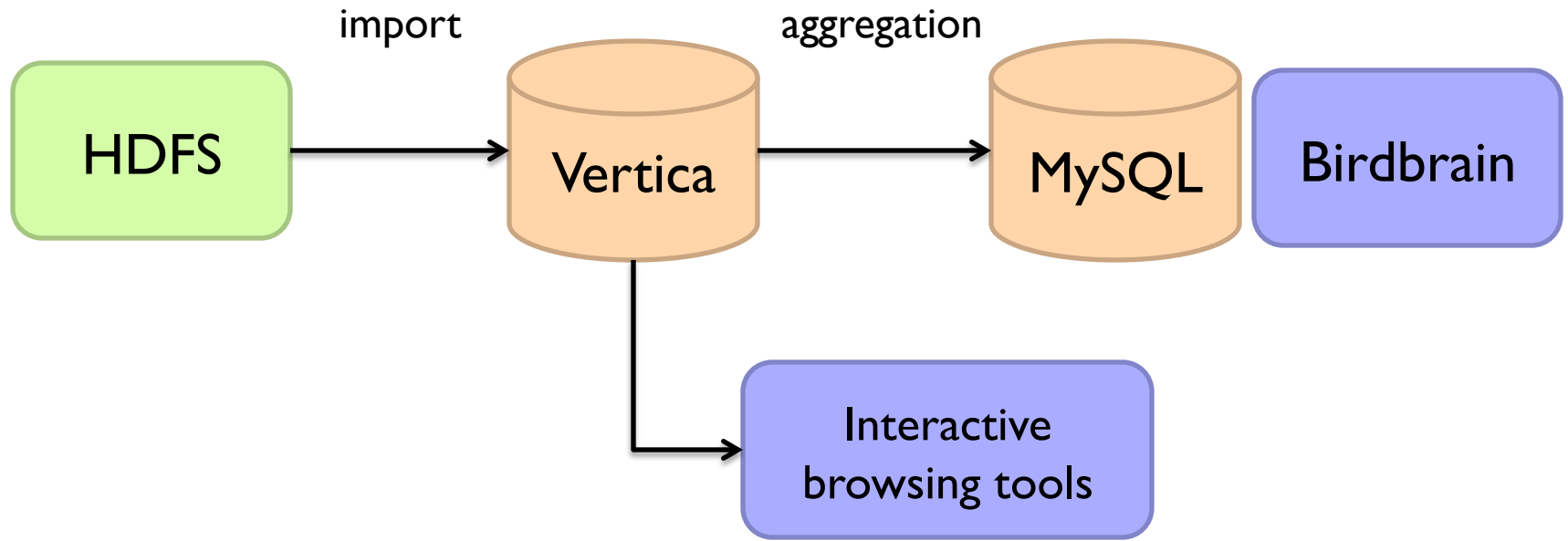
Different periodicity (e.g., hourly, daily snapshots, etc.)



Important: Must carefully throttle resource usage...

* Out of date – for illustration only

Vertica Pipeline



Why?

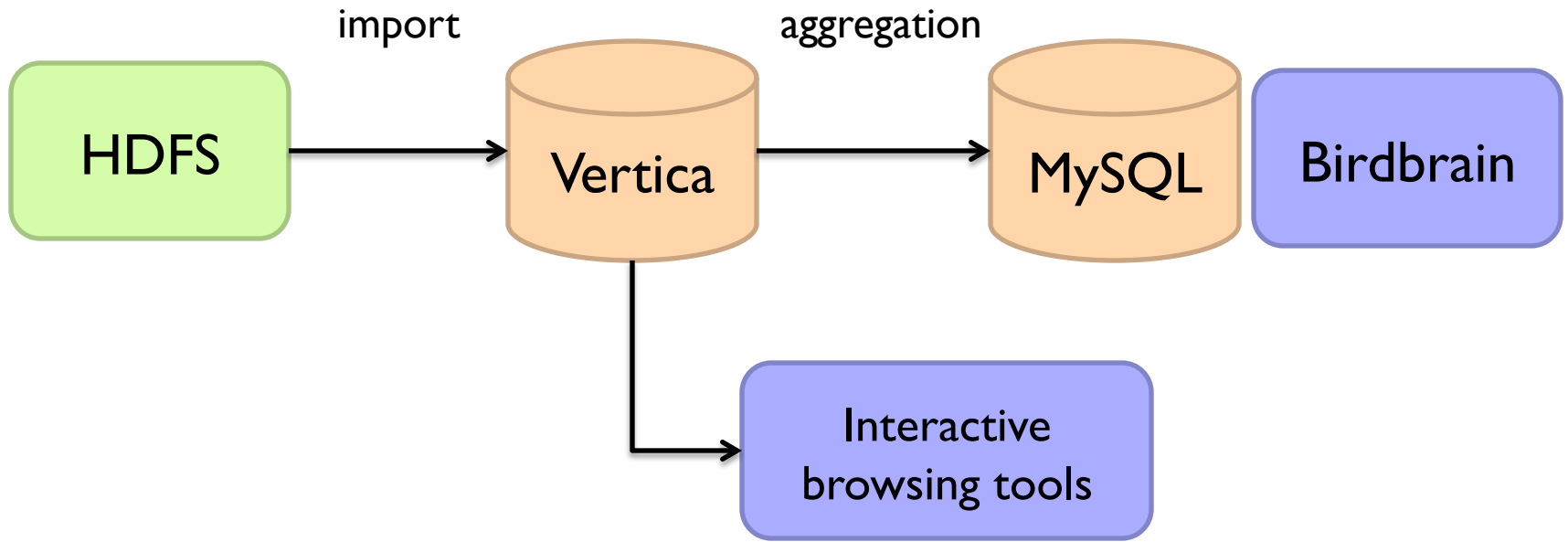
Vertica provides *orders of magnitude* faster aggregations!

“Basically, we use Vertica as a cache for HDFS data.”

@squarecog

* Out of date – for illustration only

Vertica Pipeline

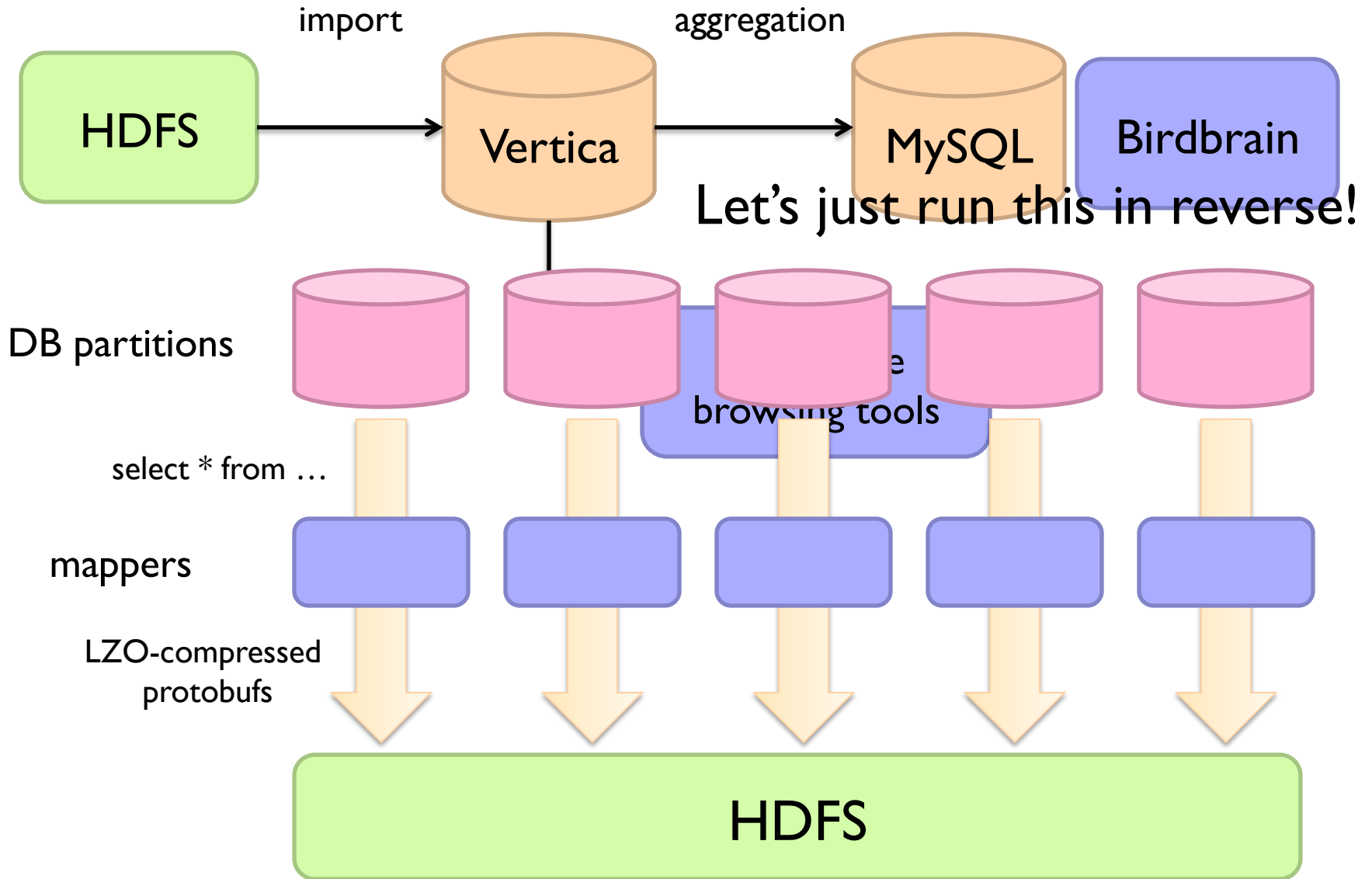


The catch...

Performance must be balanced against integration costs

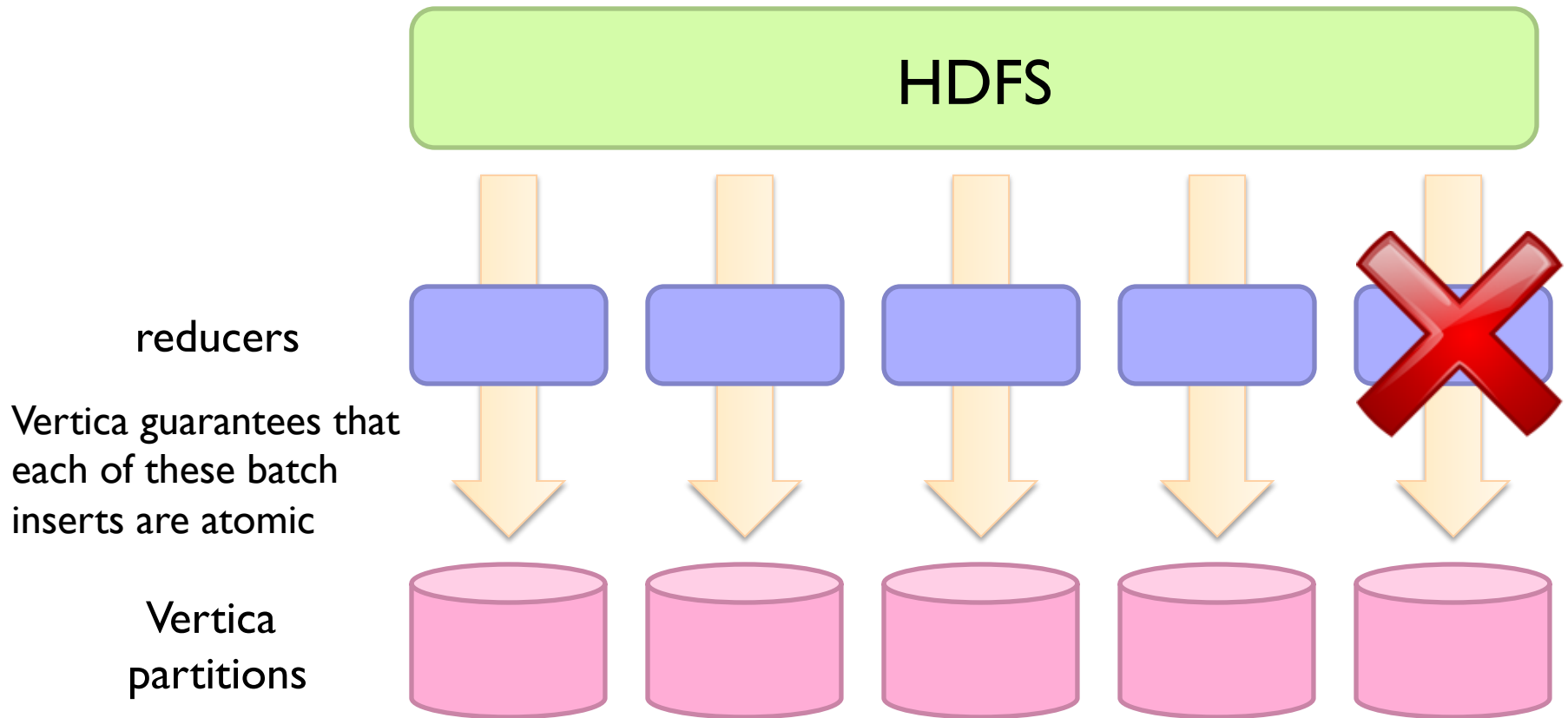
Vertica integration is non-trivial

Vertica Pipeline



* Out of date – for illustration only

Vertica Pig Storage

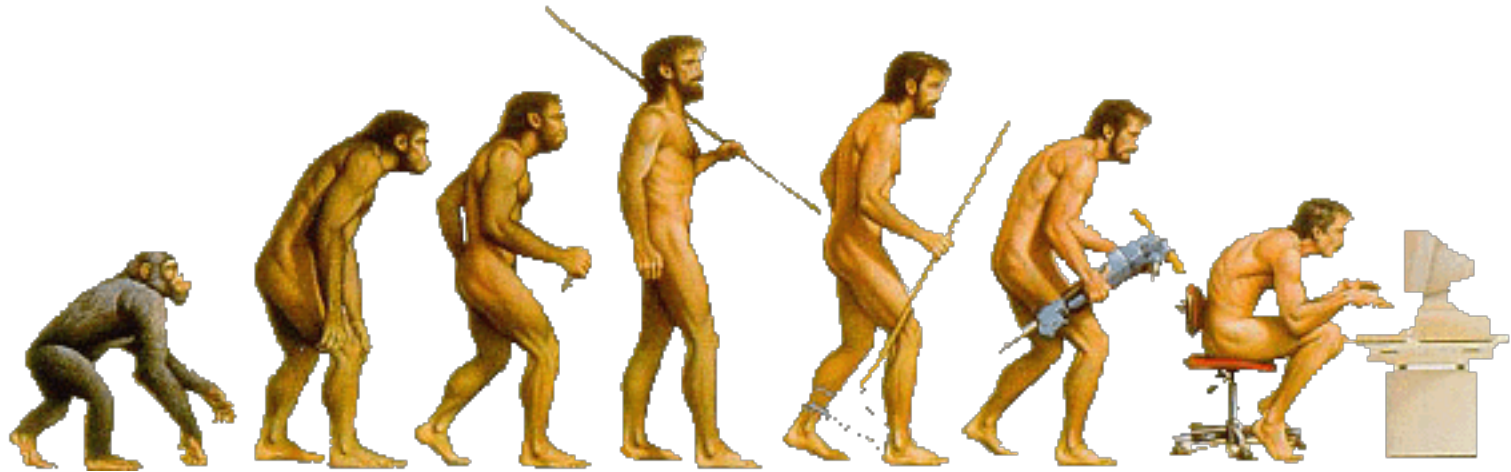


So what's the challenge?

Did you remember to turn off speculative execution?

What happens when a task dies?

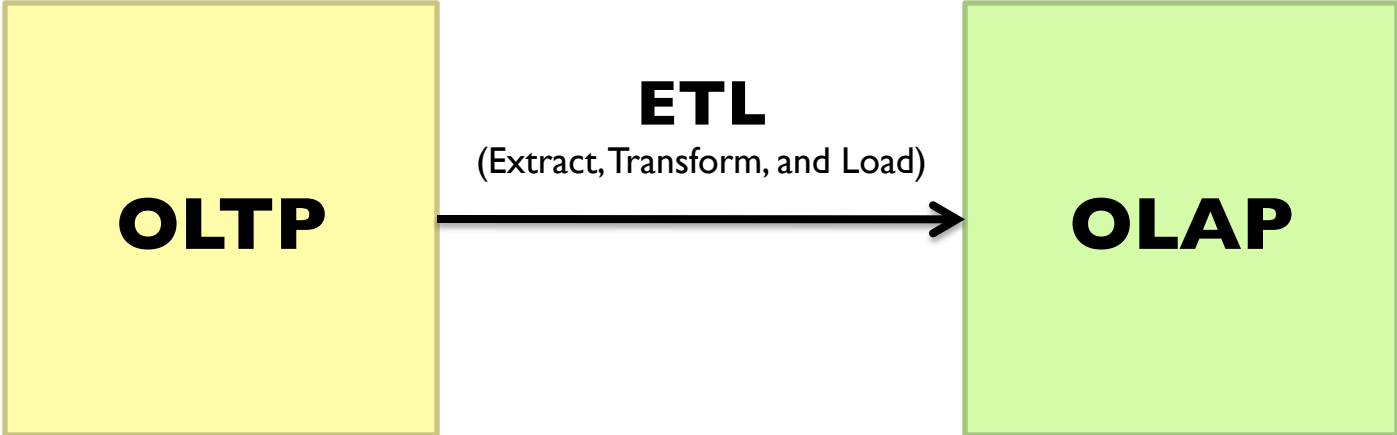
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What's Next?



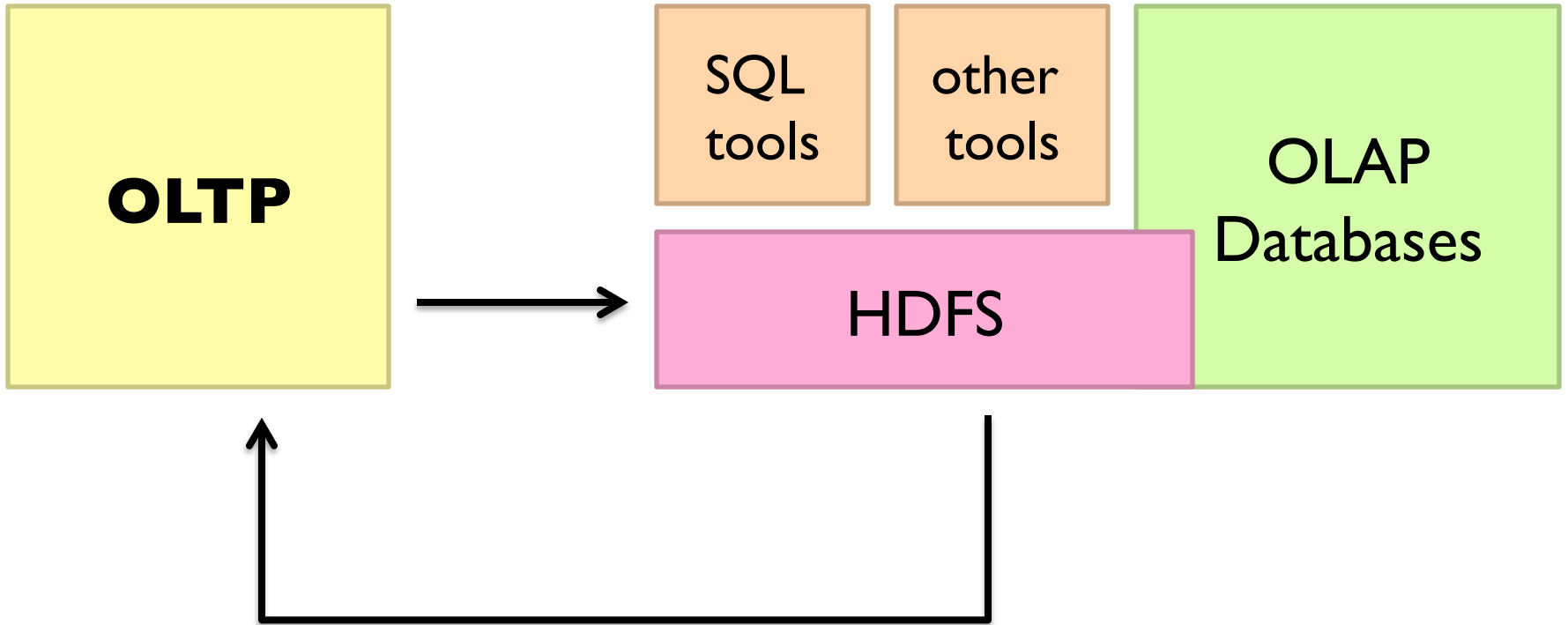
RDBMS

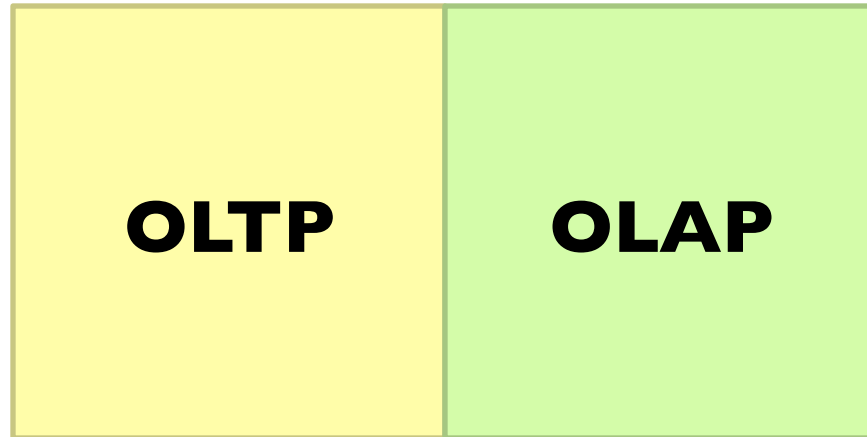




ELT







Hybrid Transactional/Analytical Processing (HTAP)

Coming back full circle?



Questions?