

# **Data-Intensive Distributed Computing**

CS 451/651 431/631 (Winter 2018)

Part 5: Analyzing Relational Data (1/3)

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These slides are available at <http://lintool.github.io/bigdata-2018w/>



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# Structure of the Course

Analyzing Text

Analyzing Graphs

Analyzing  
Relational Data

Data Mining

“Core” framework features  
and algorithm design

# Evolution of Enterprise Architectures

Next two sessions: techniques, algorithms, and  
optimizations for relational processing

users

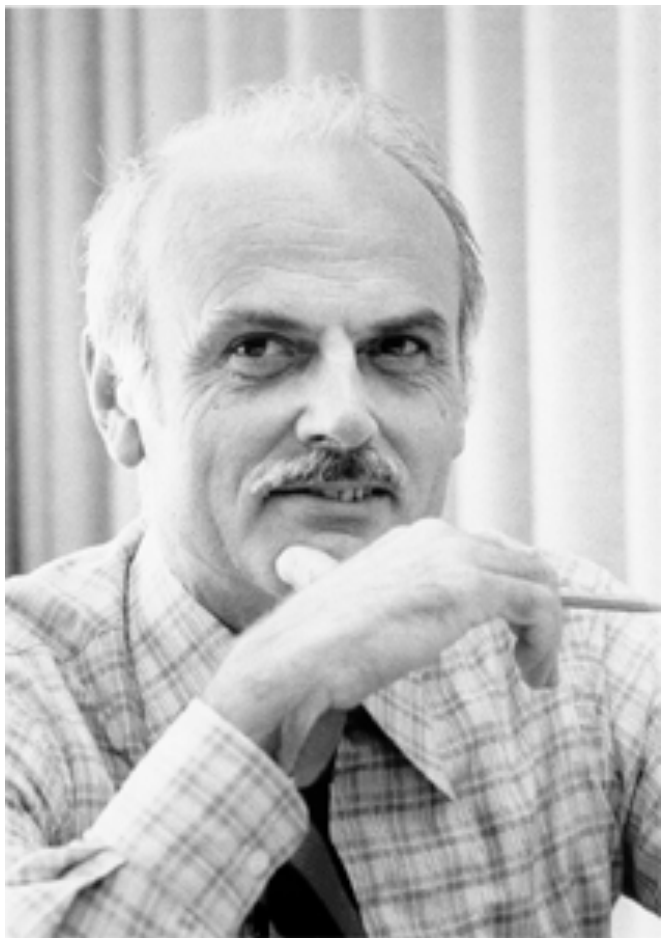
Monolithic  
Application

A diagram illustrating a monolithic application architecture. At the top, the word "users" is written. Below it, a light orange rectangular box with a thin brown border contains the text "Monolithic Application".

users

Frontend

Backend



users

Frontend

Backend

database

*Why is this a good idea?*

# 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!?**



users

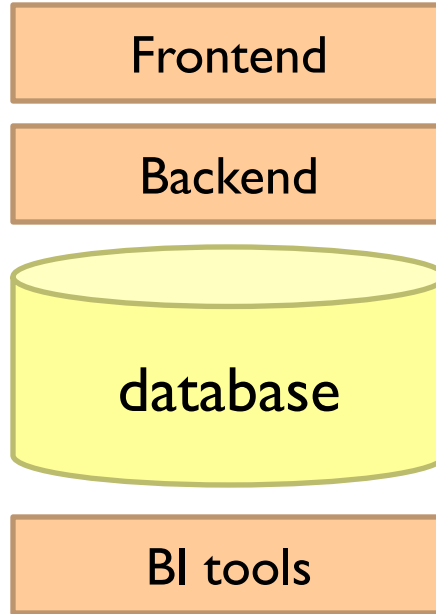
Frontend

Backend

database

BI tools

analysts



users

Frontend

Backend

database

BI tools

analysts



Why is my application so slow?

Why does my analysis take so long?



# 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 (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

# OLTP and OLAP Together?

Downsides of co-existing OLTP and OLAP workloads

Poor memory management  
Conflicting data access patterns  
Variable latency



users and analysts

**Solution?**



Build a data warehouse!



users

Frontend

Backend

OLTP database for  
user-facing transactions

OLTP  
database

ETL

(Extract, Transform, and Load)

OLAP database for  
data warehousing

Data  
Warehouse

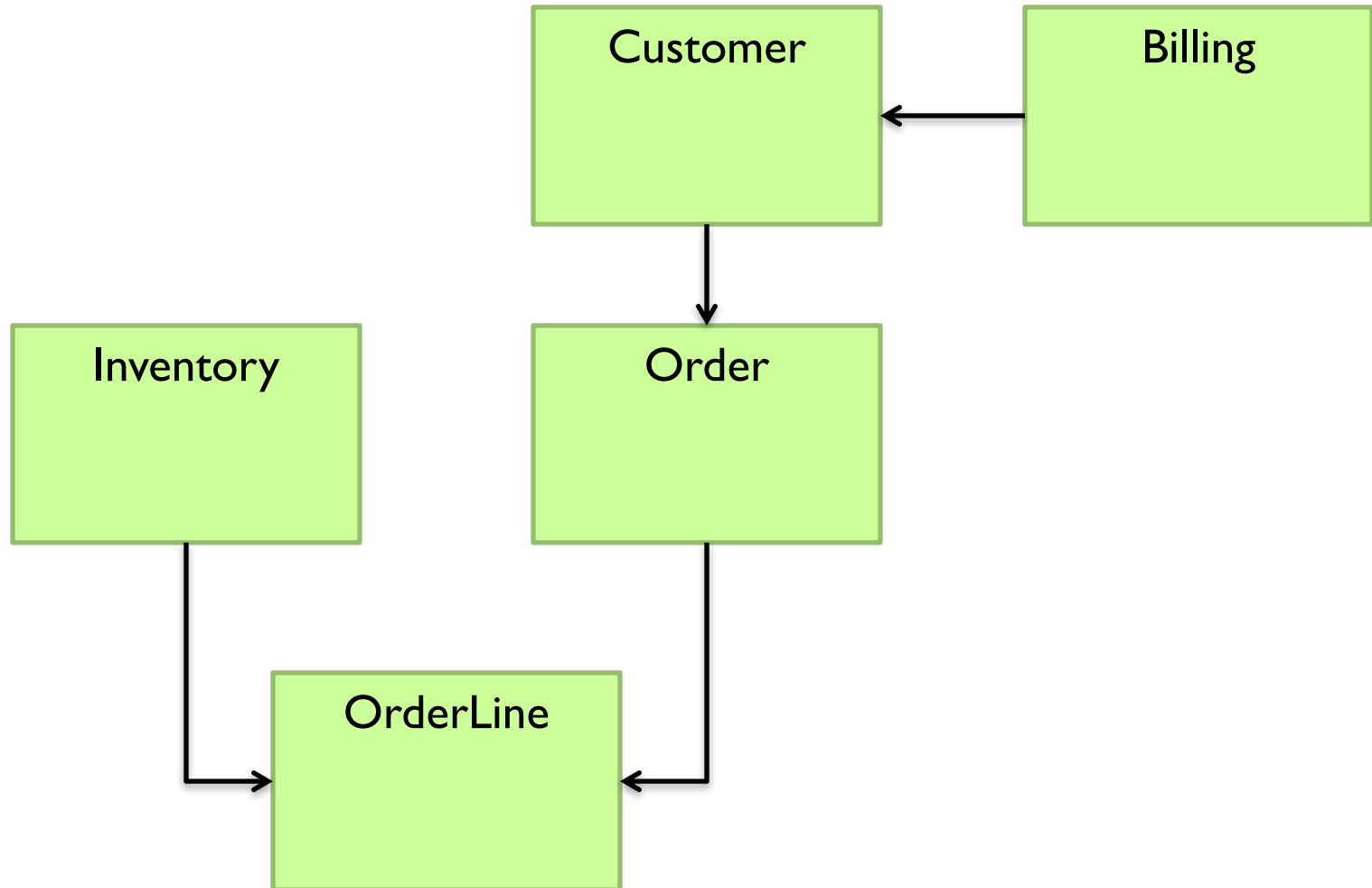
BI tools

analysts

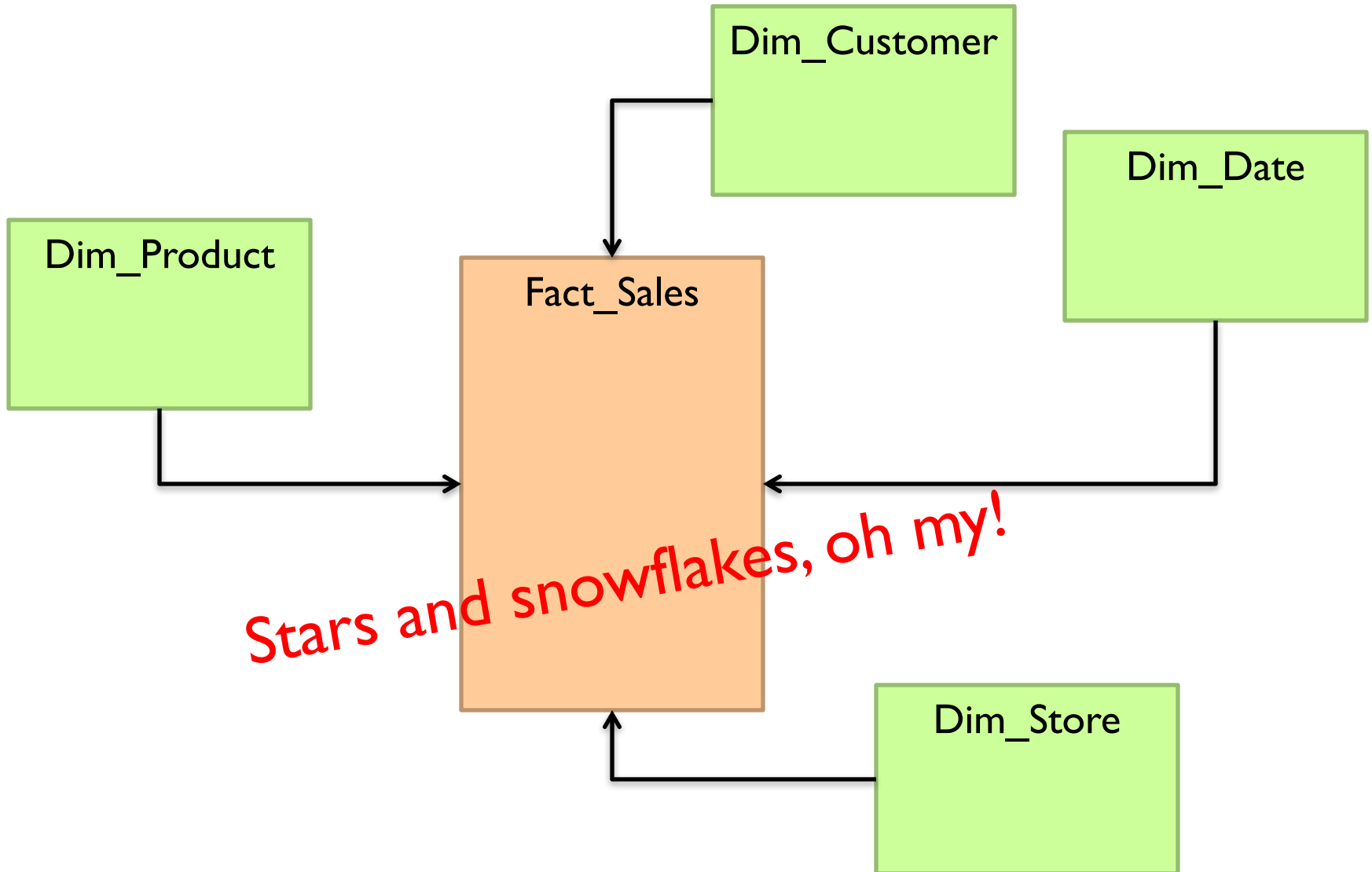


What's special about  
OLTP vs. OLAP?

# 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?



users

Frontend

Backend

OLTP  
database

ETL

(Extract, Transform, and Load)

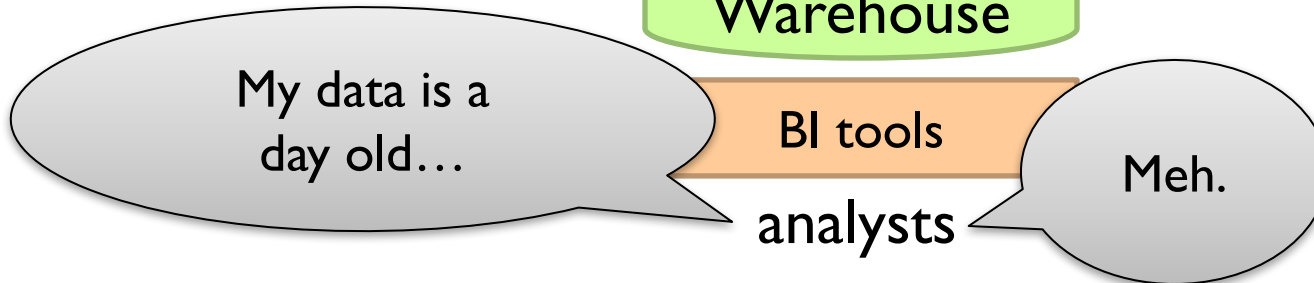
Data  
Warehouse

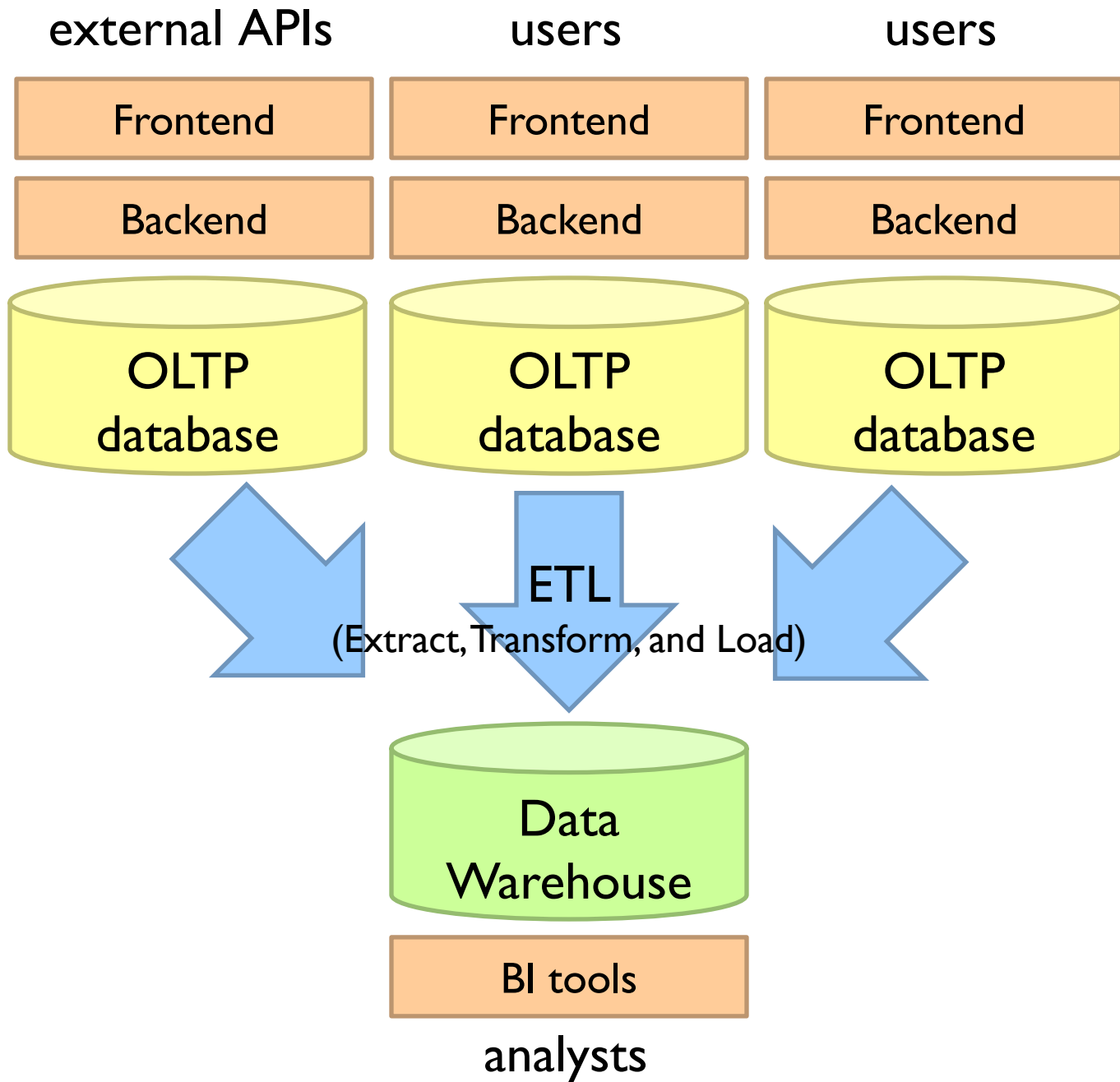
My data is a  
day old...

BI tools

analysts

Meh.





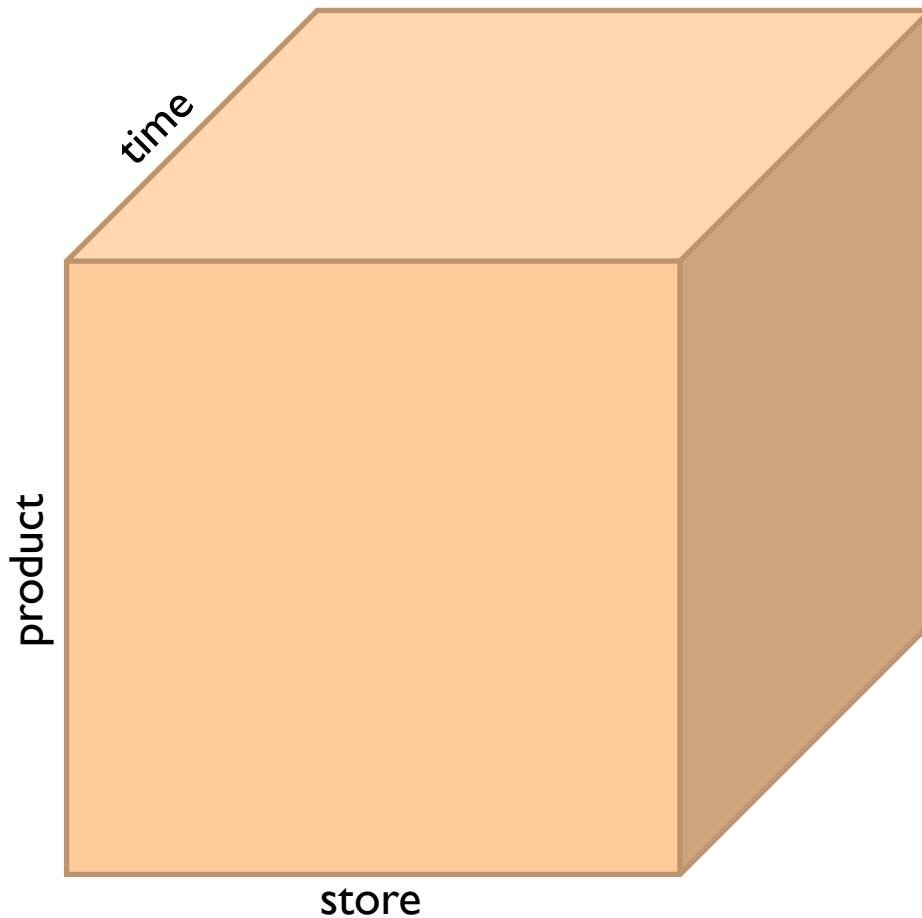
# What do you actually do?

Report generation

Dashboards

*Ad hoc* analyses

# OLAP Cubes



## Common operations

slice and dice

roll up/drill down

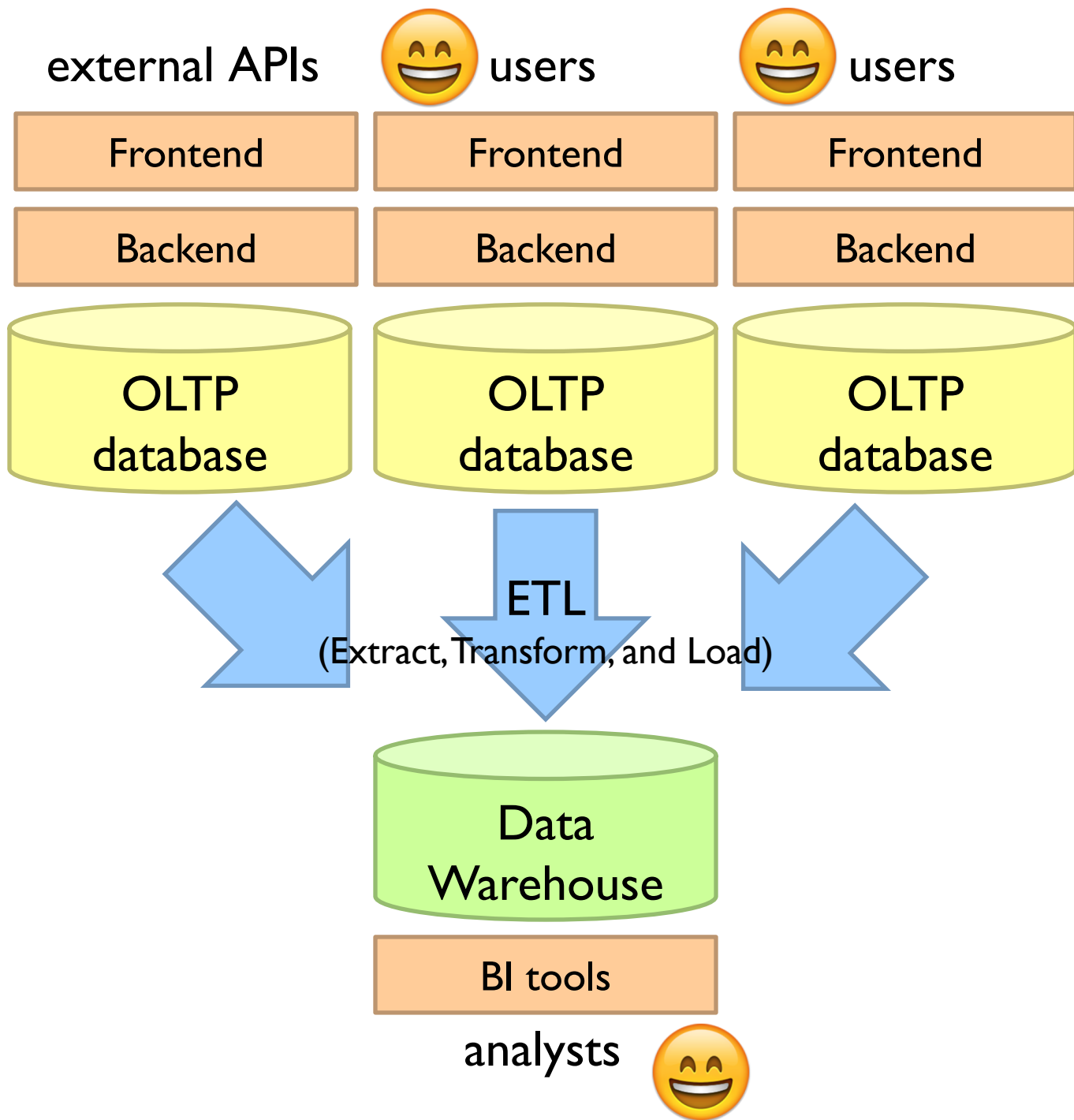
pivot

# 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.”

users

Frontend

Backend

OLTP  
database

Facebook context?

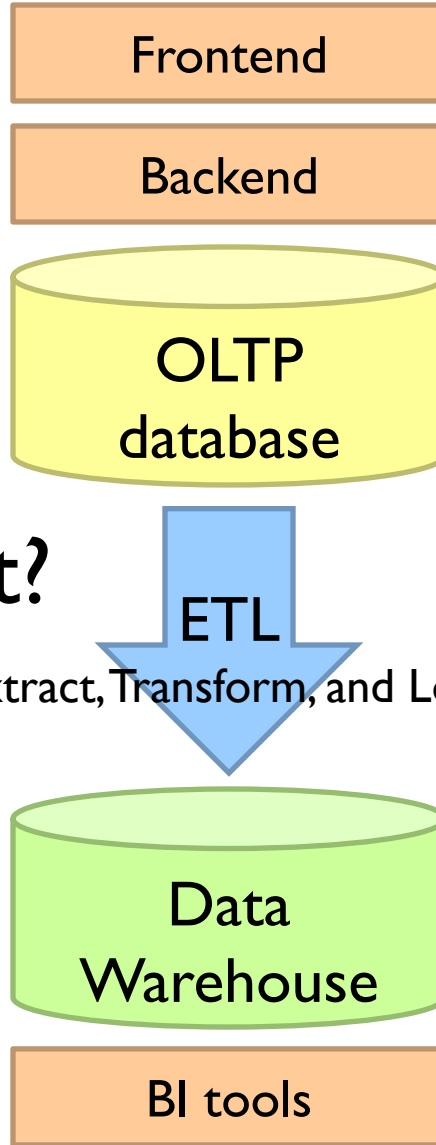
ETL

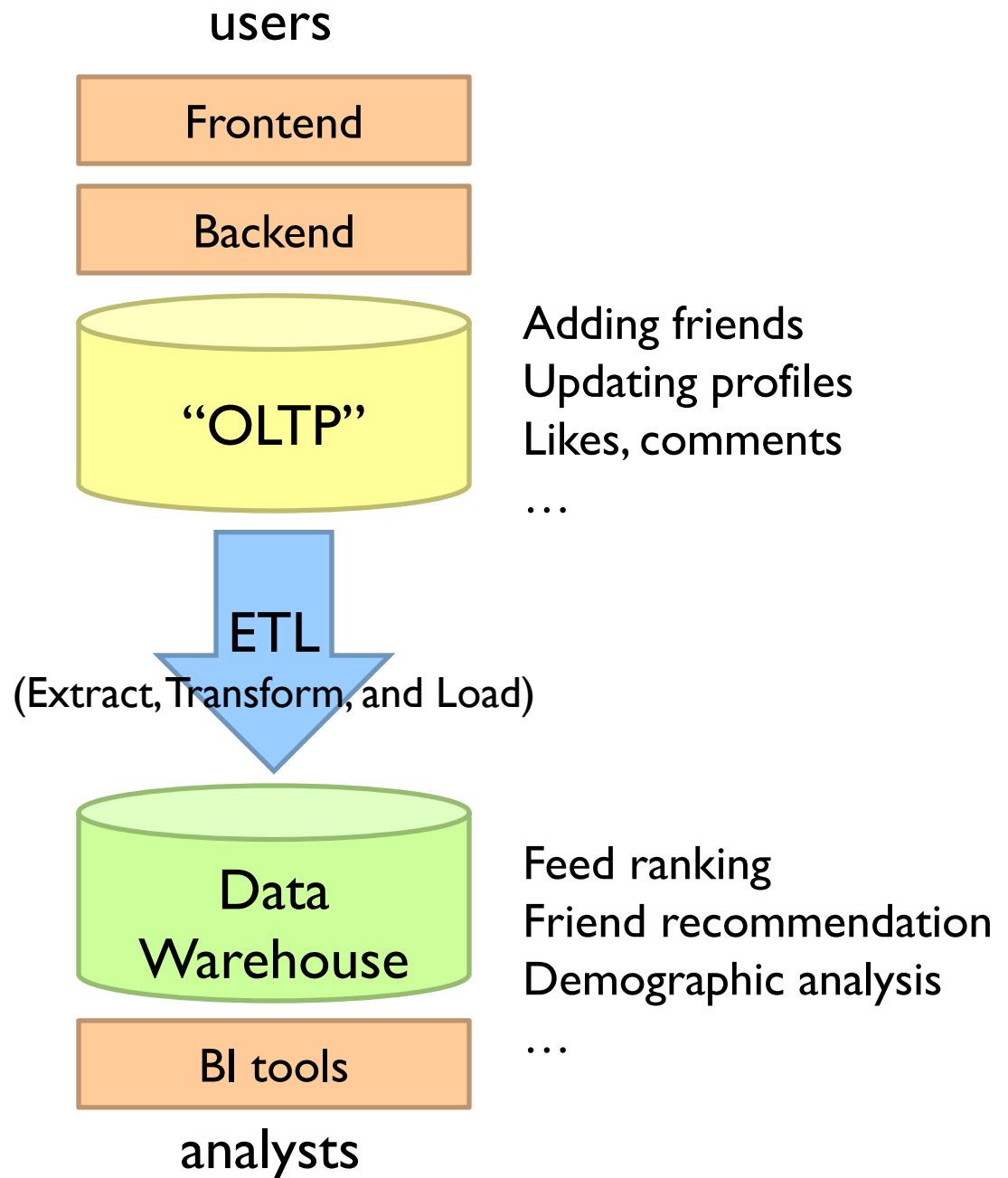
(Extract, Transform, and Load)

Data  
Warehouse

BI tools

analysts





users

Frontend

Backend

“OLTP”

PHP/MySQL

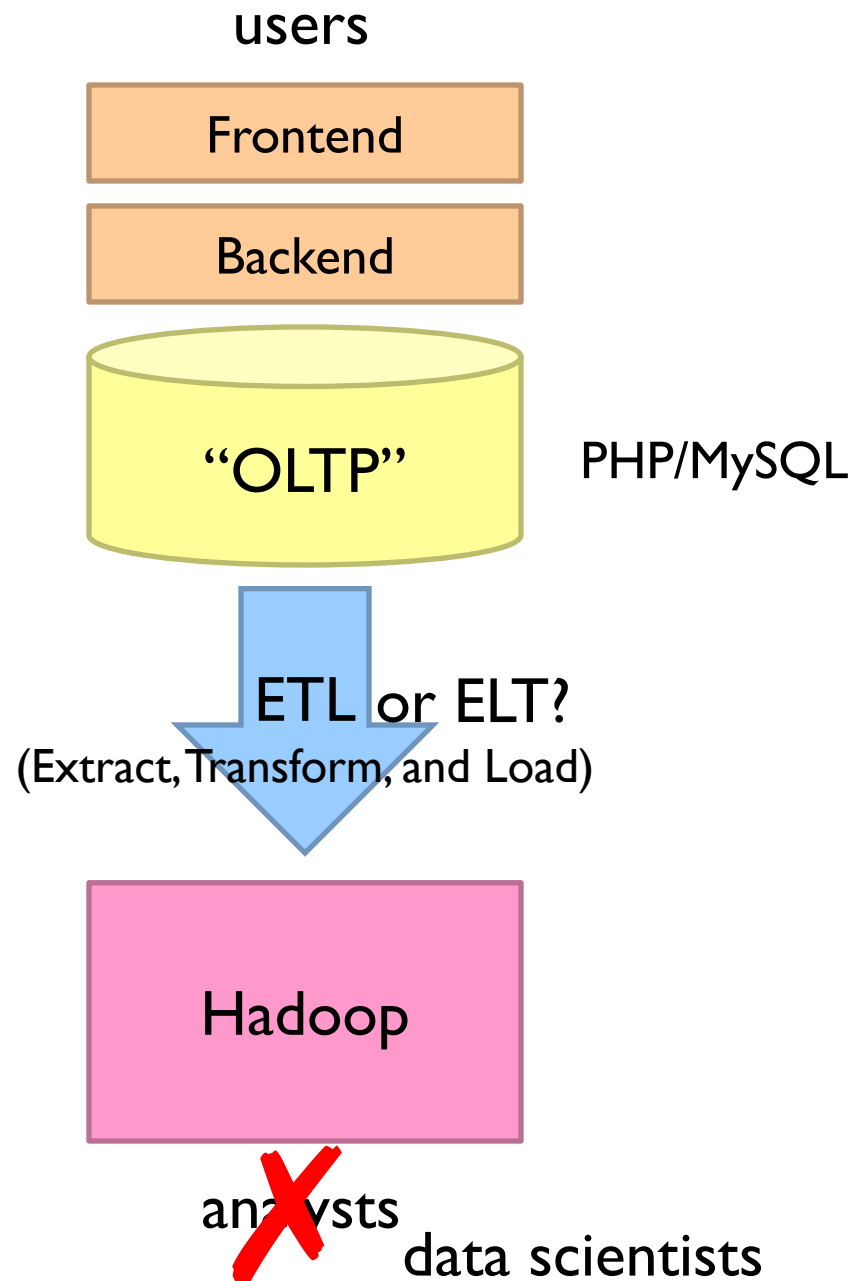
ETL or ELT?

(Extract, Transform, and Load)

Hadoop

~~analysts~~

data scientists



What?

Droppi

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

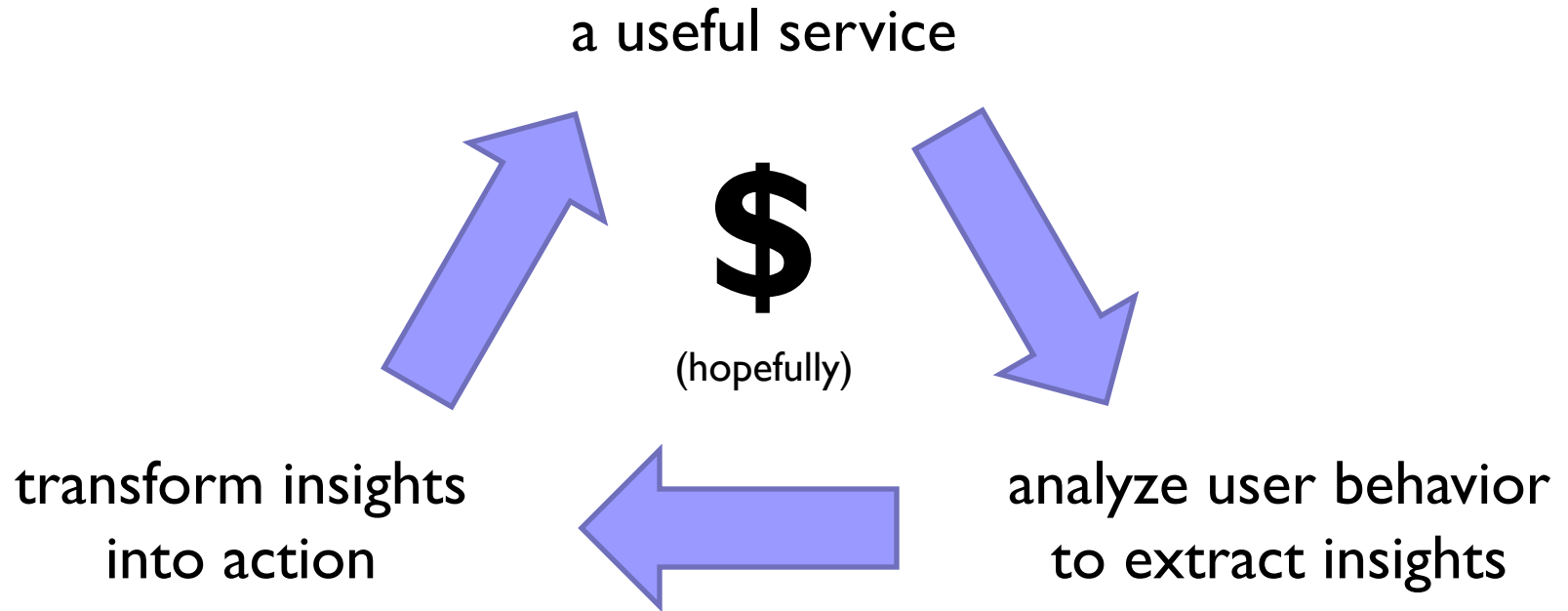
Rise of social media and user-generated content

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

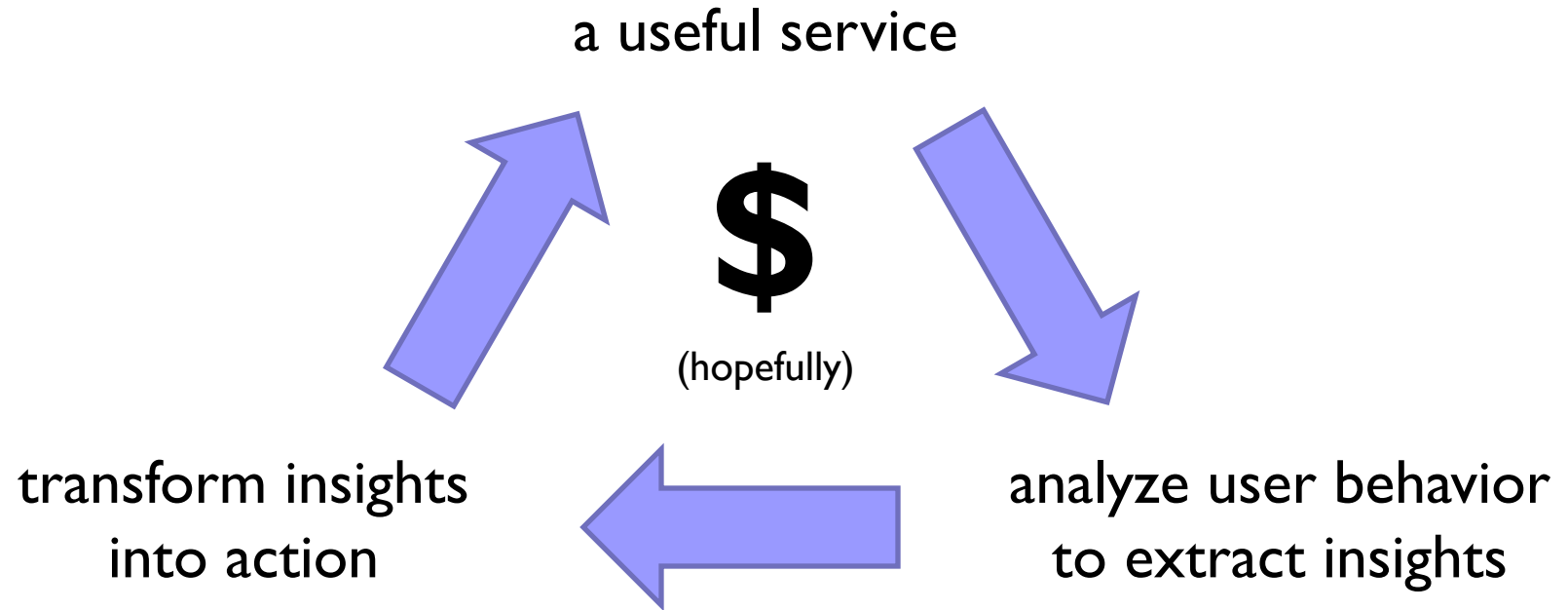
“Descriptive”

“Predictive”

Data products



# Virtuous Product Cycle



Google. Facebook. Twitter. Amazon. Uber.

**data products**

**data science**

# facebook®

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users

Frontend

Backend

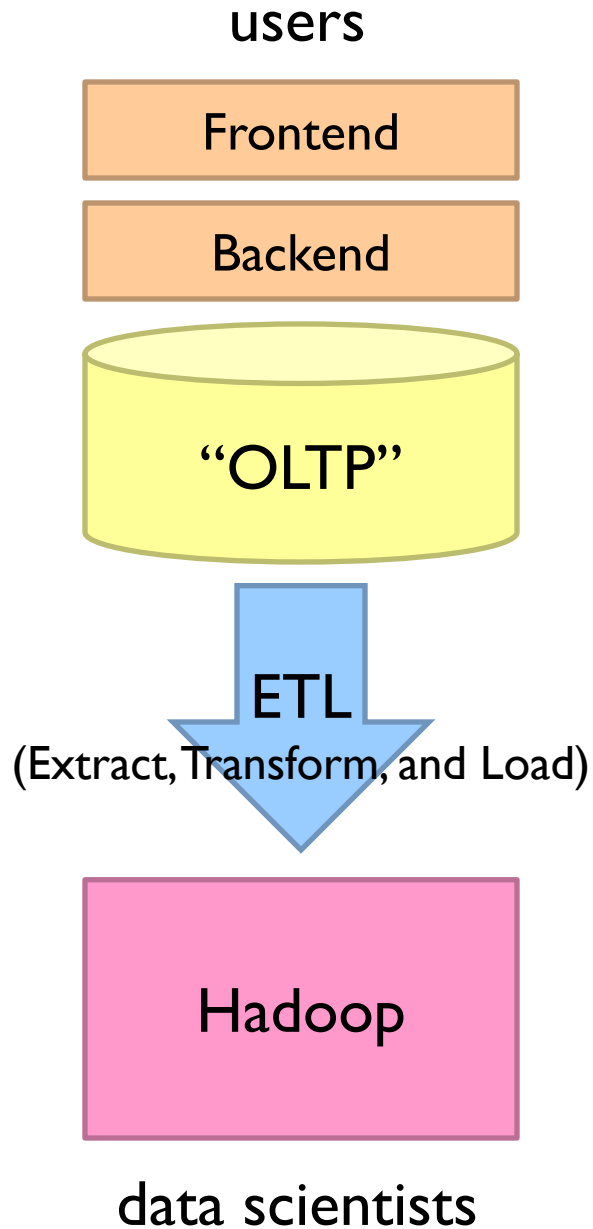
“OLTP”

ETL

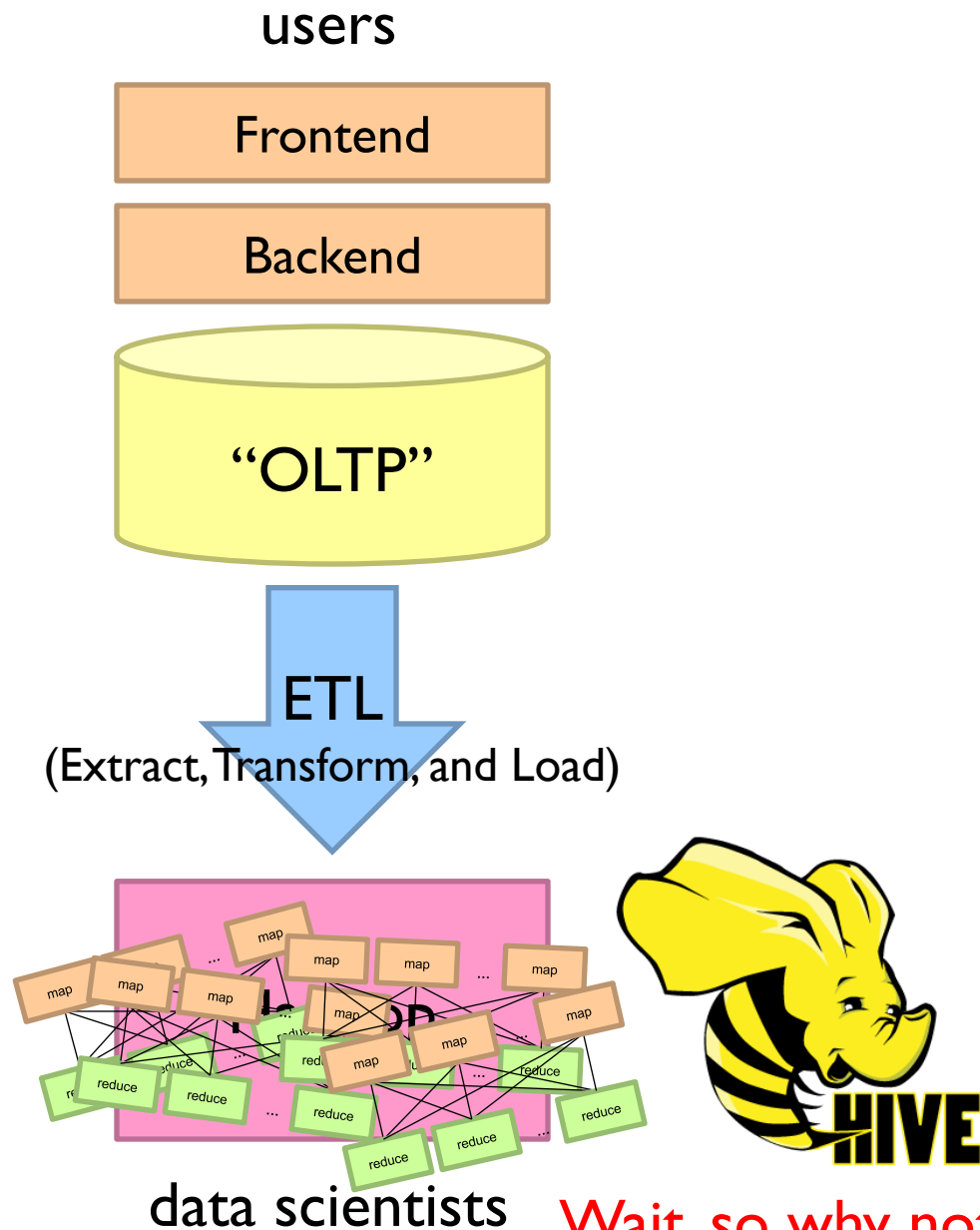
(Extract, Transform, and Load)

Hadoop

data scientists



# The Irony...



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

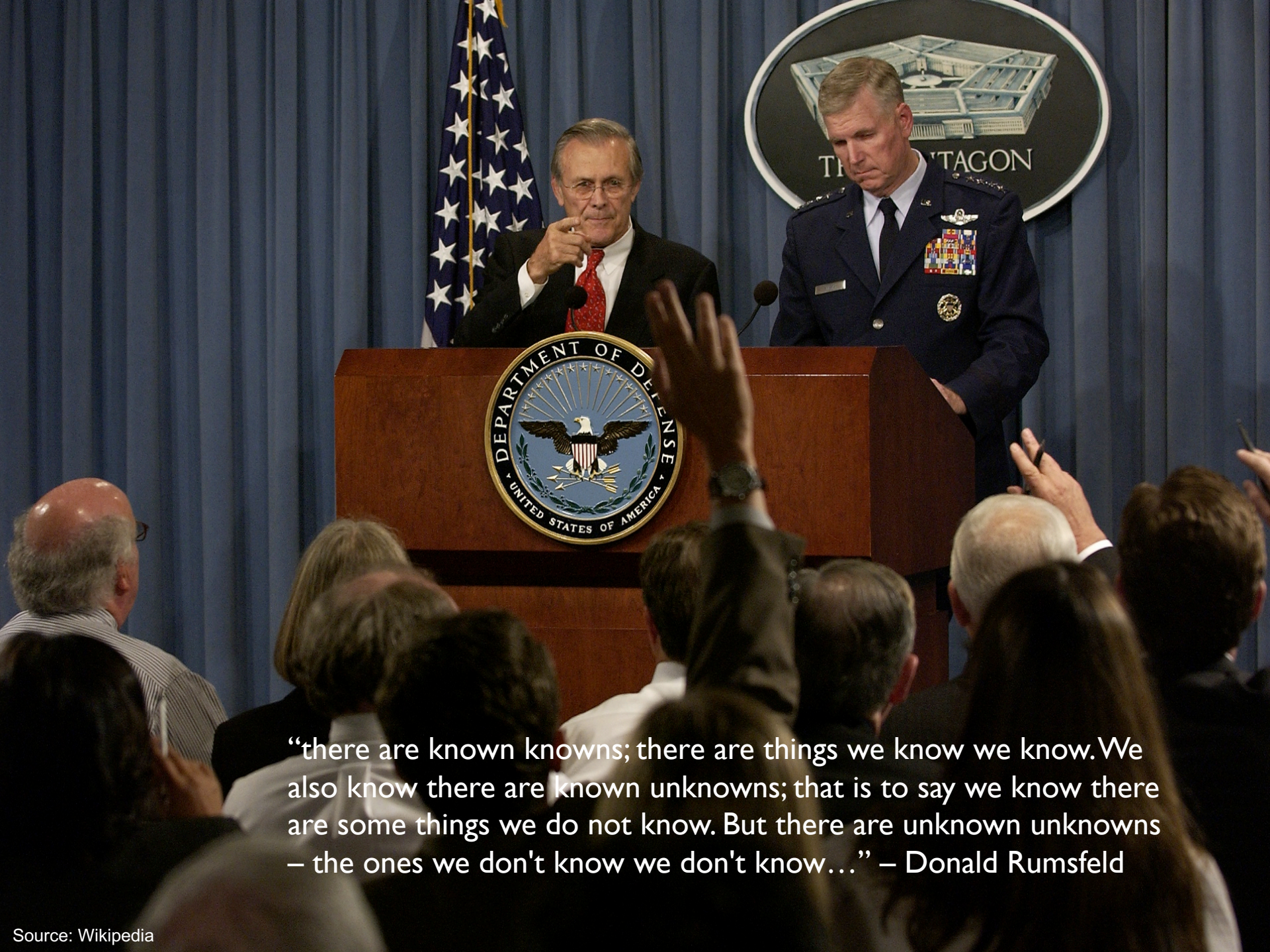
## Databases are not so great...

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

Much faster data ingest rate

# What do you actually do?

Report generation

Dashboards

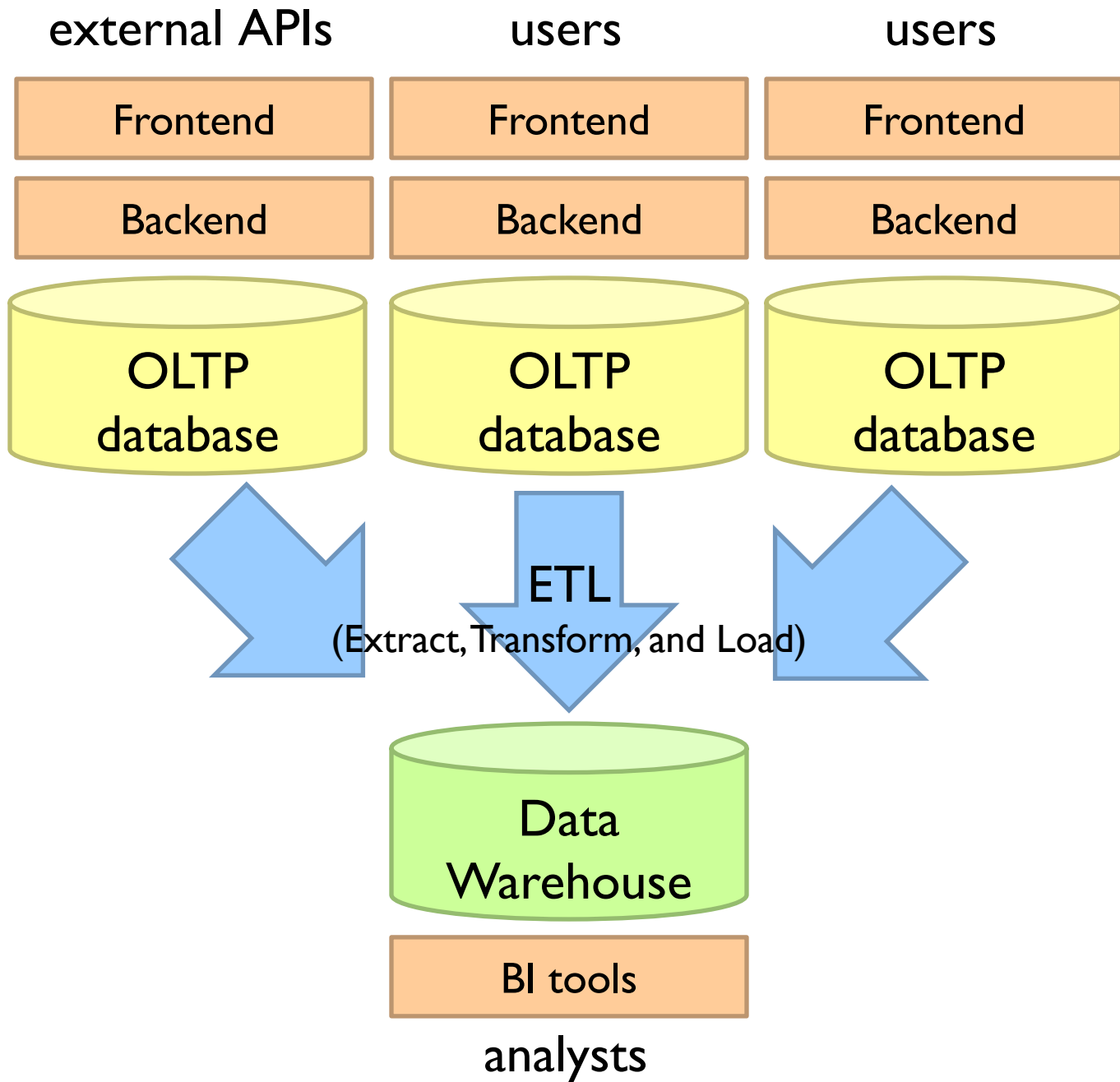
*Ad hoc* analyses

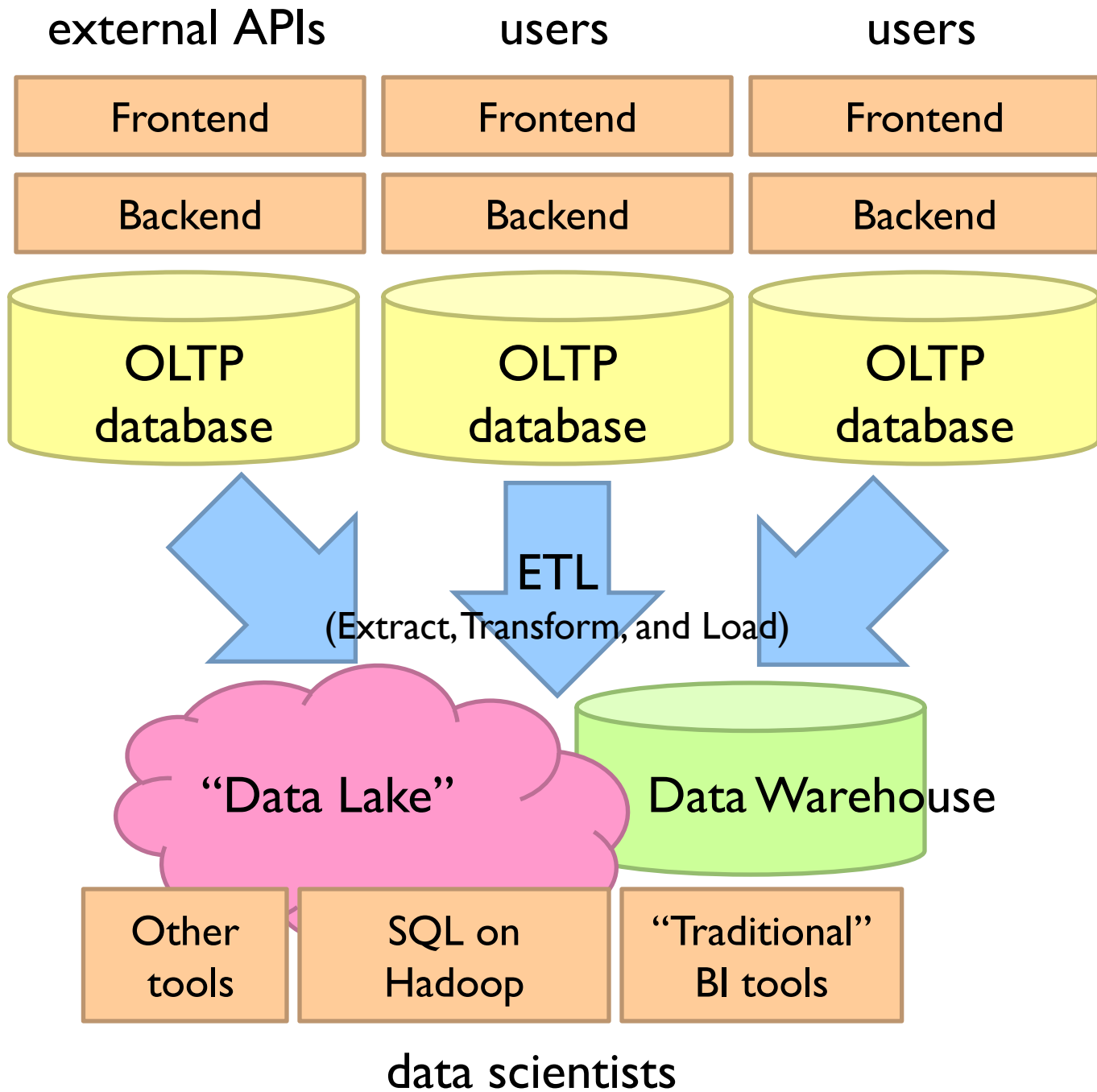
“Descriptive”

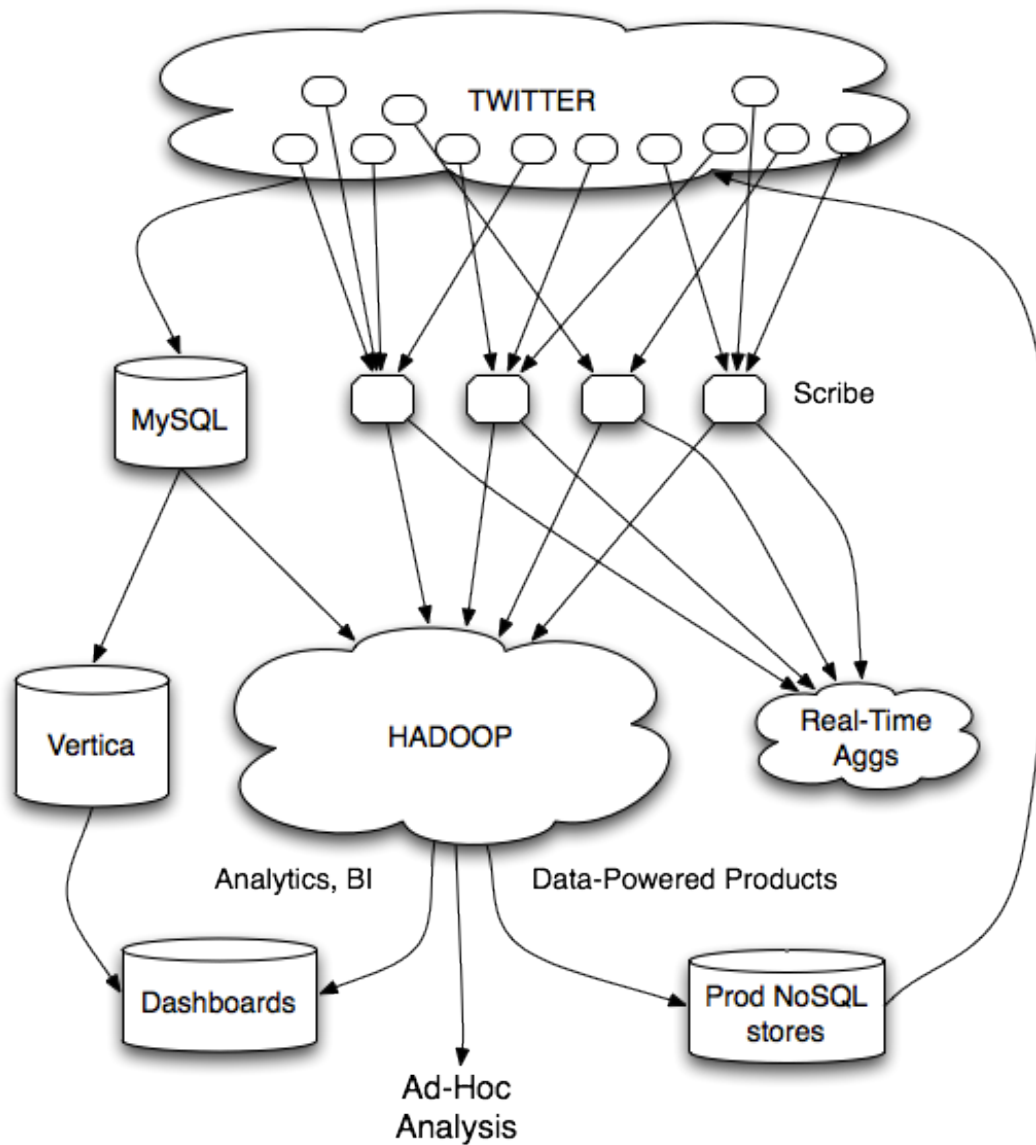
“Predictive”

Data products

Which are known unknowns and  
unknown unknowns?







Twitter's data warehousing architecture (circa 2012)

## **circa ~2010**

~150 people total

~60 Hadoop nodes

~6 people use analytics stack daily

## **circa ~2012**

~1400 people total

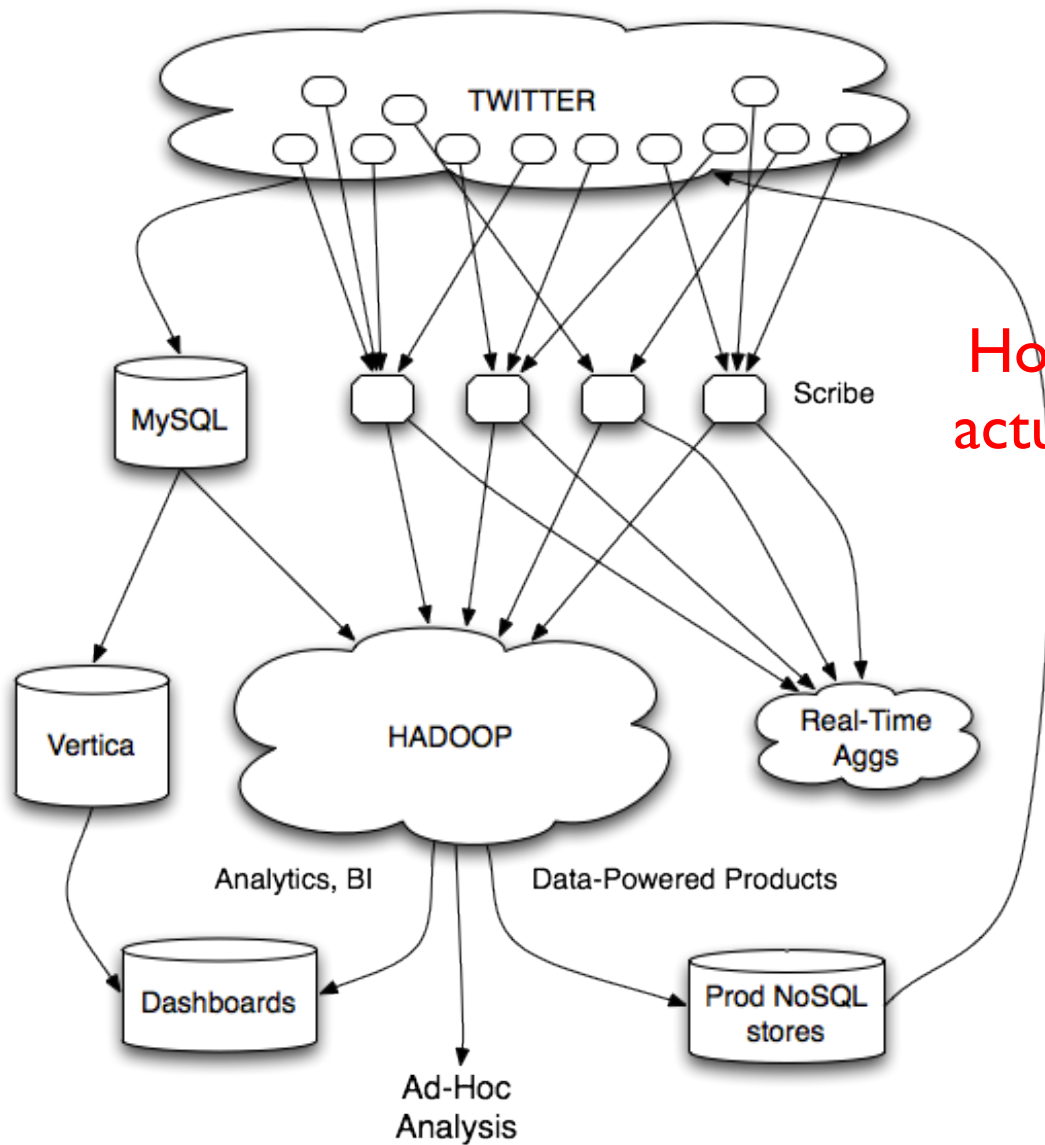
10s of Ks of Hadoop nodes, multiple DCs

10s of PBs total Hadoop DW capacity

~100 TB ingest daily

dozens of teams use Hadoop daily

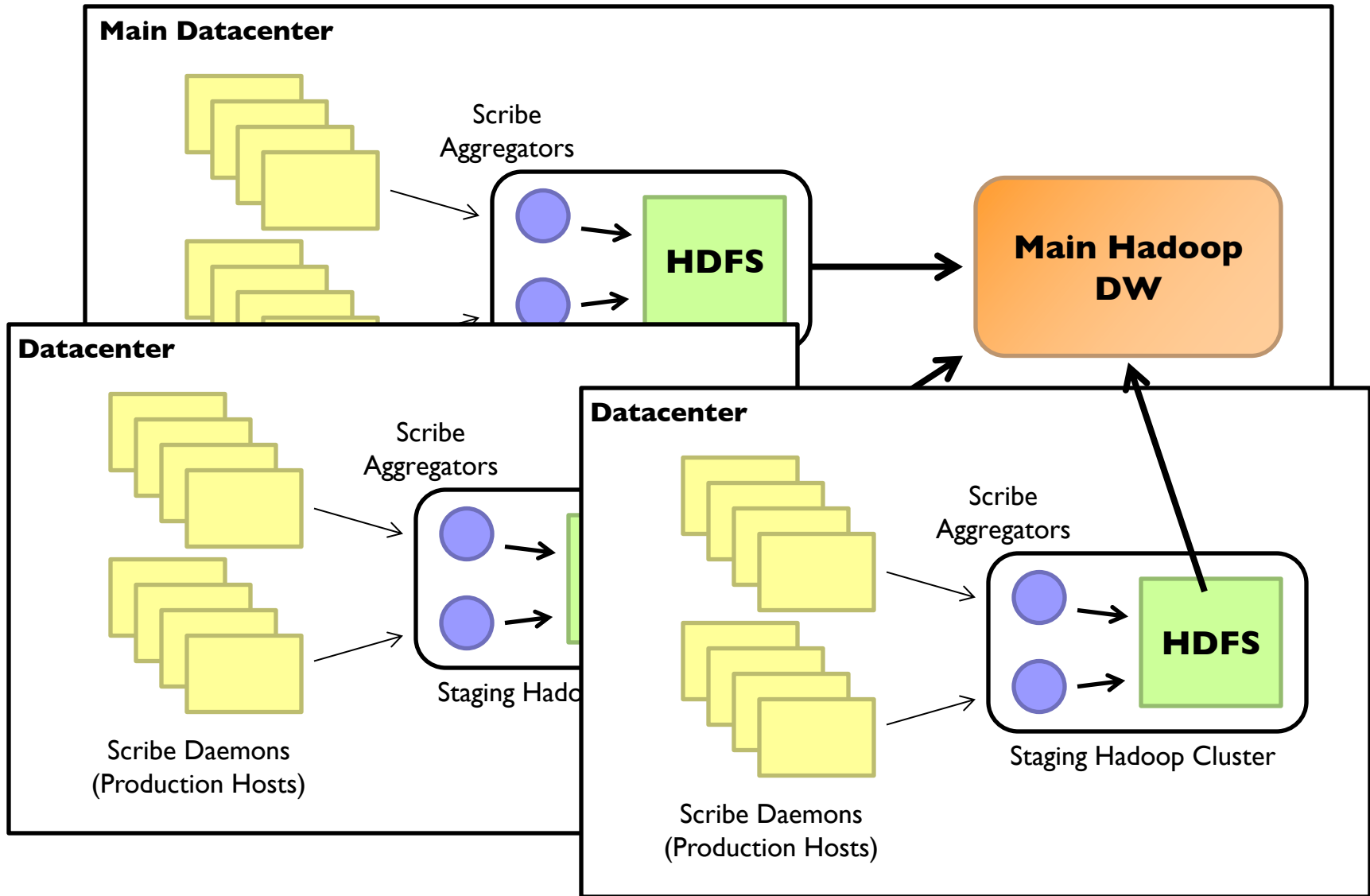
10s of Ks of Hadoop jobs daily



How does ETL  
actually happen?

Twitter's data warehousing architecture (circa 2012)

# Importing Log Data

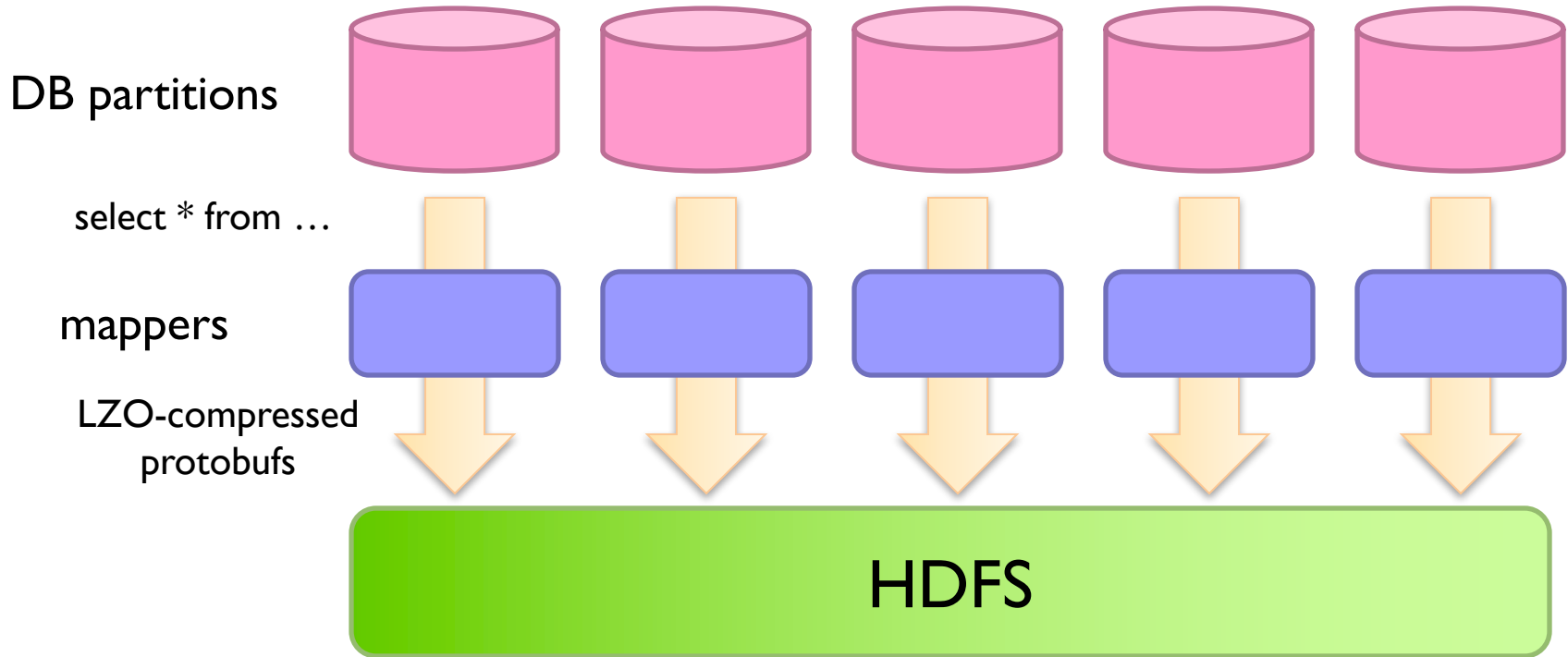




# Importing Log Data\*

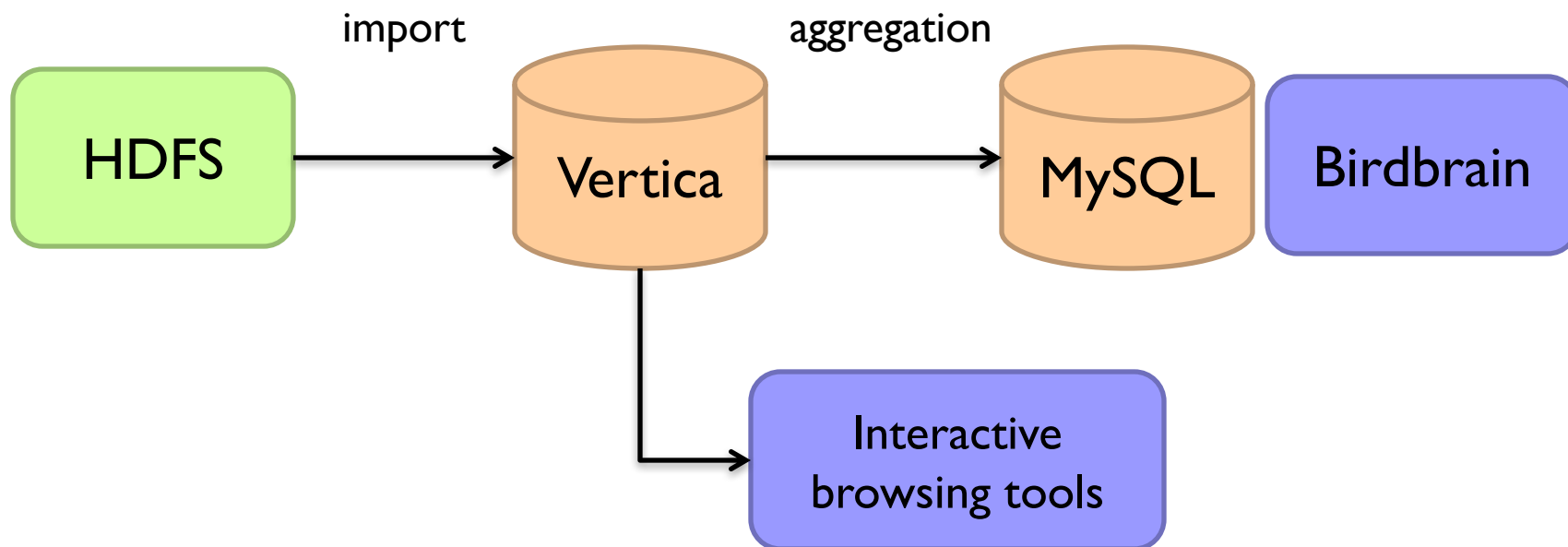
Tweets, graph, users profiles

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



**Important: Must carefully throttle resource usage...**

# Vertica Pipeline\*



Why?

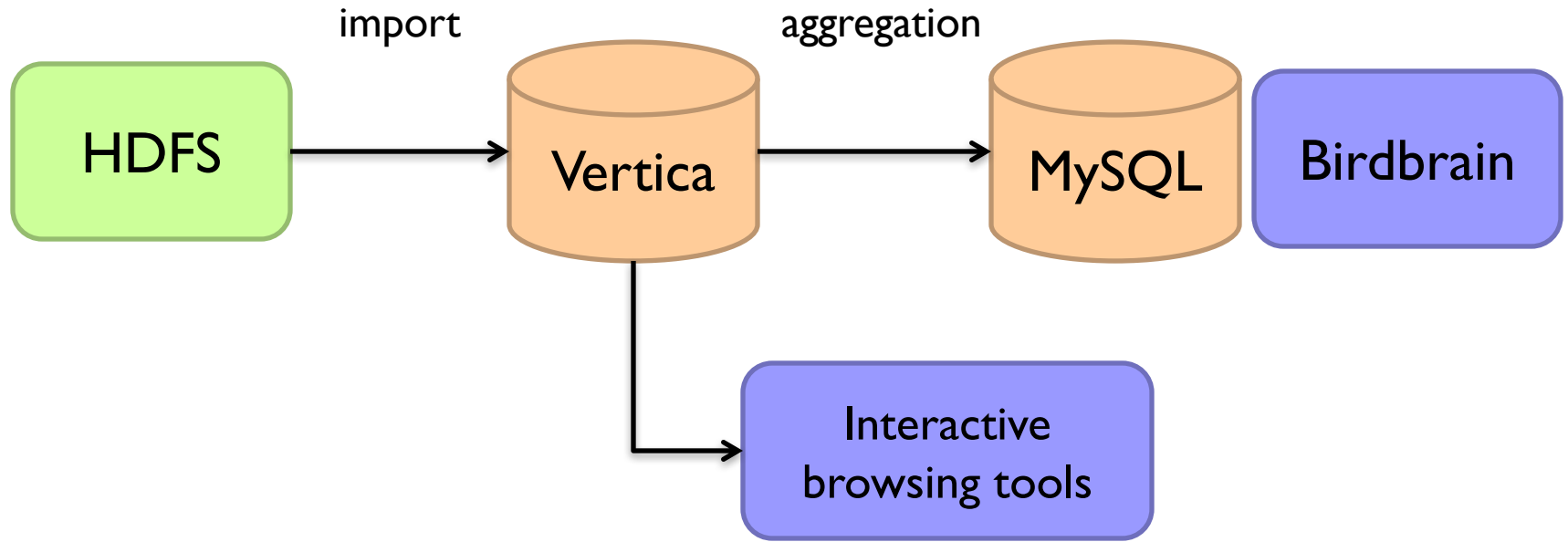
Vertica provides *orders of magnitude* faster aggregations!

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

@squarecog

\* Out of date – for illustration only

# Vertica Pipeline\*

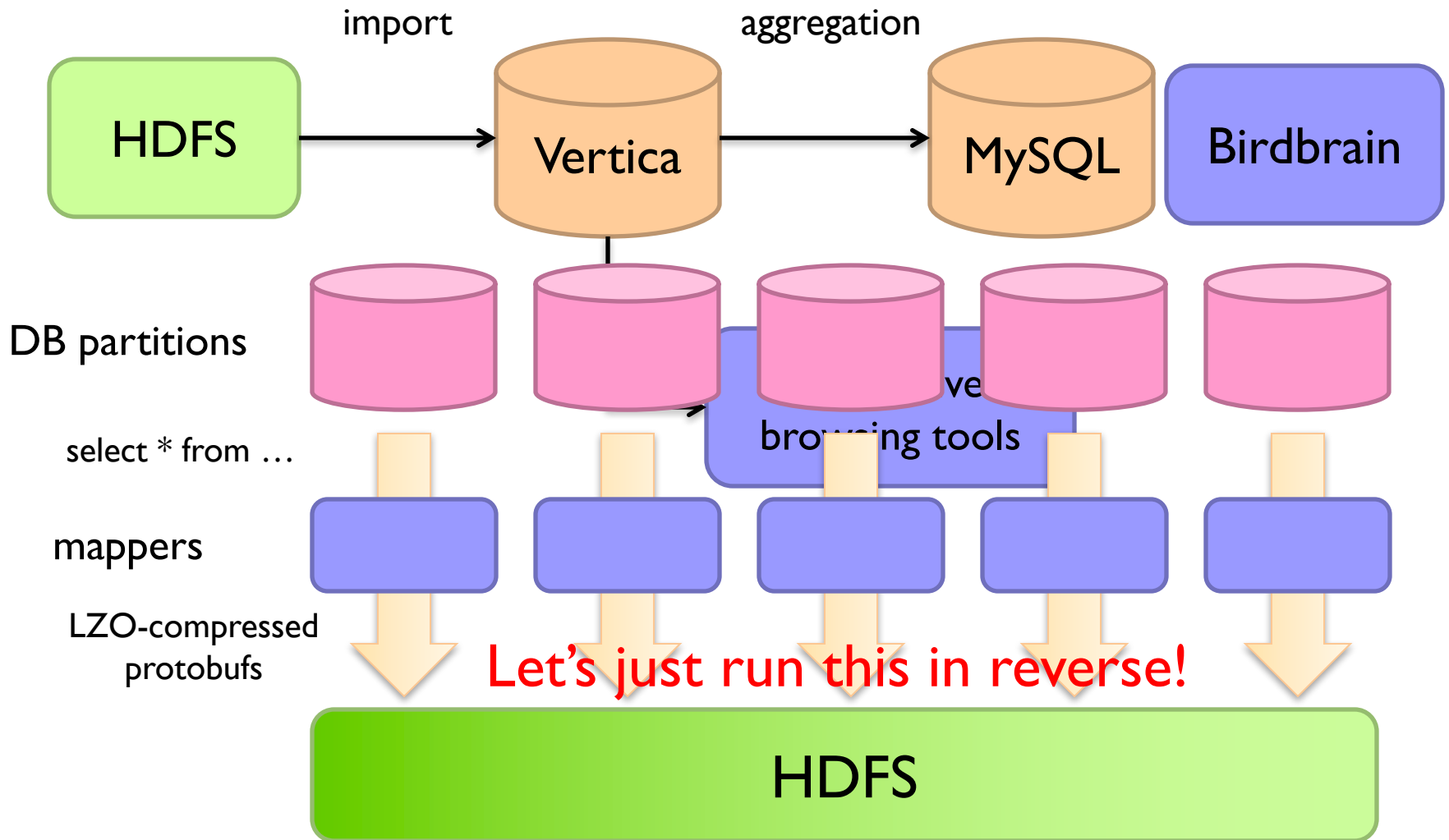


The catch...

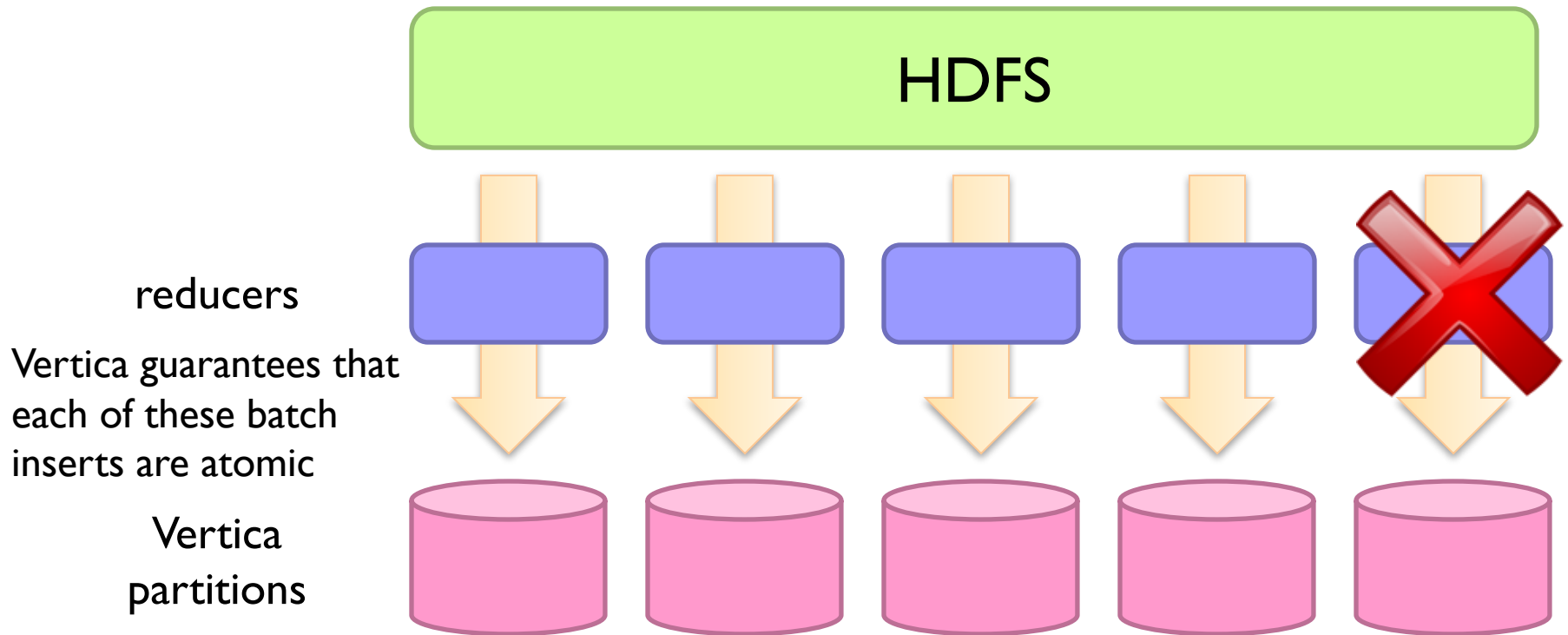
Performance must be balanced against integration costs

Vertica integration is non-trivial

# Vertica Data Ingestion



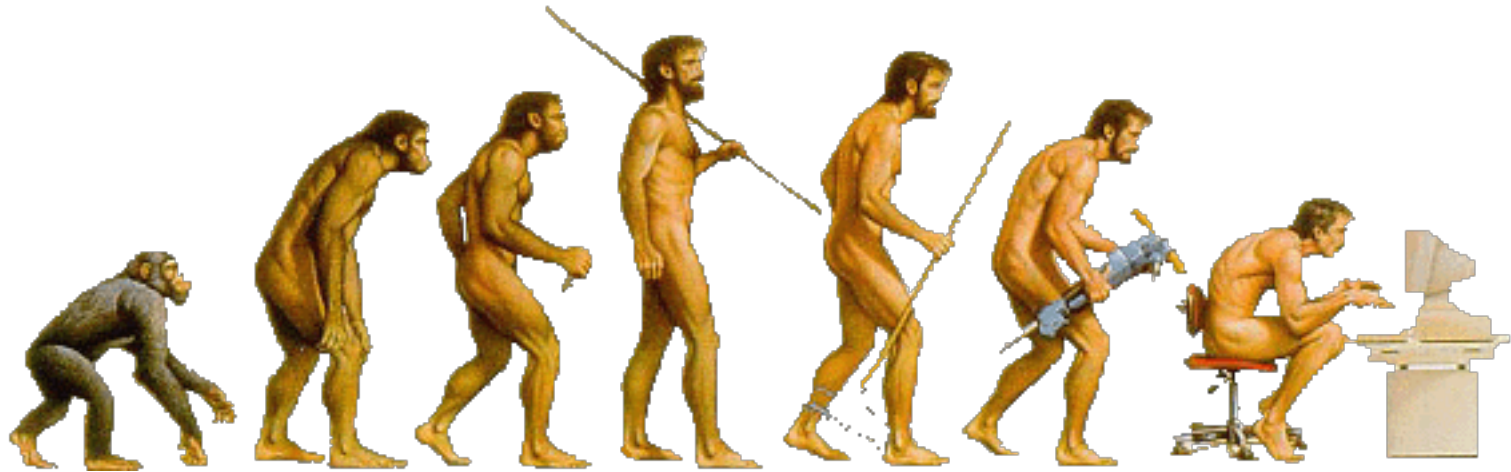
# Vertica Pig Storage\*



So what's the challenge?

Did you remember to turn off speculative execution?

What happens when a task dies?



# What's Next?

Two developing trends...

users

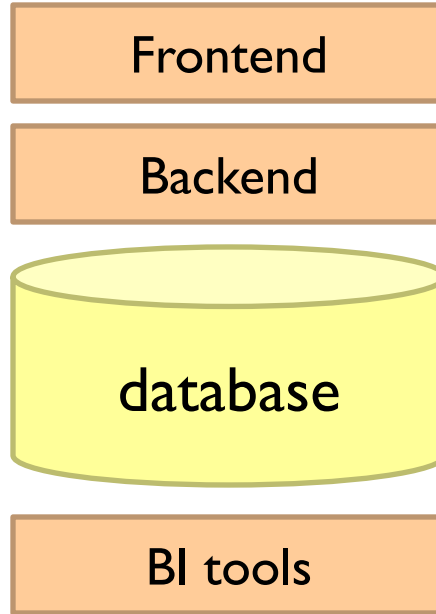
Frontend

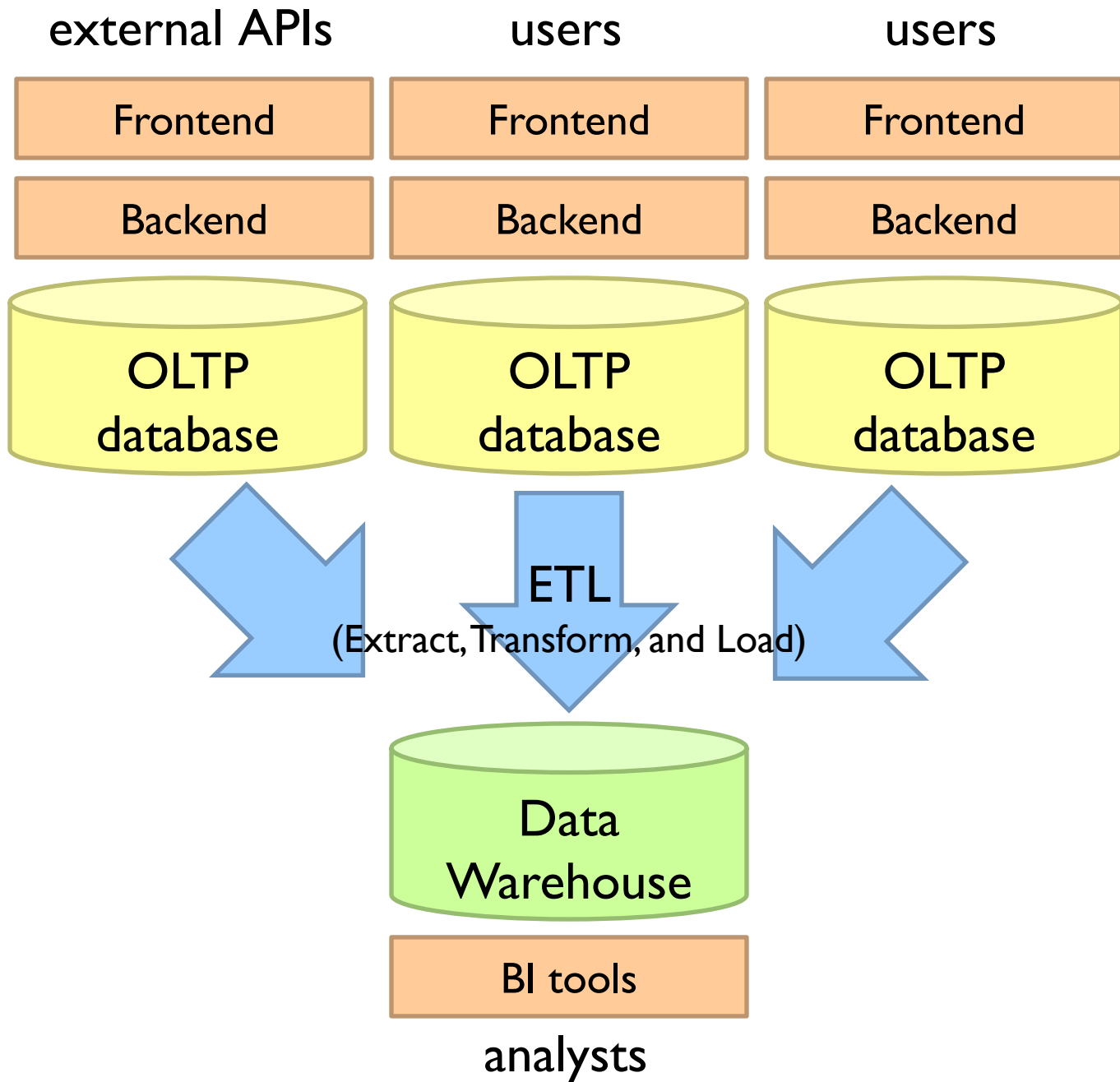
Backend

database

BI tools

analysts







external APIs

users

users

Frontend

Frontend

Frontend

Backend

Backend

Backend

OLTP  
database

OLTP  
database

OLTP  
database

ETL

(Extract, Transform, and Load)

“Data Lake”

Data Warehouse

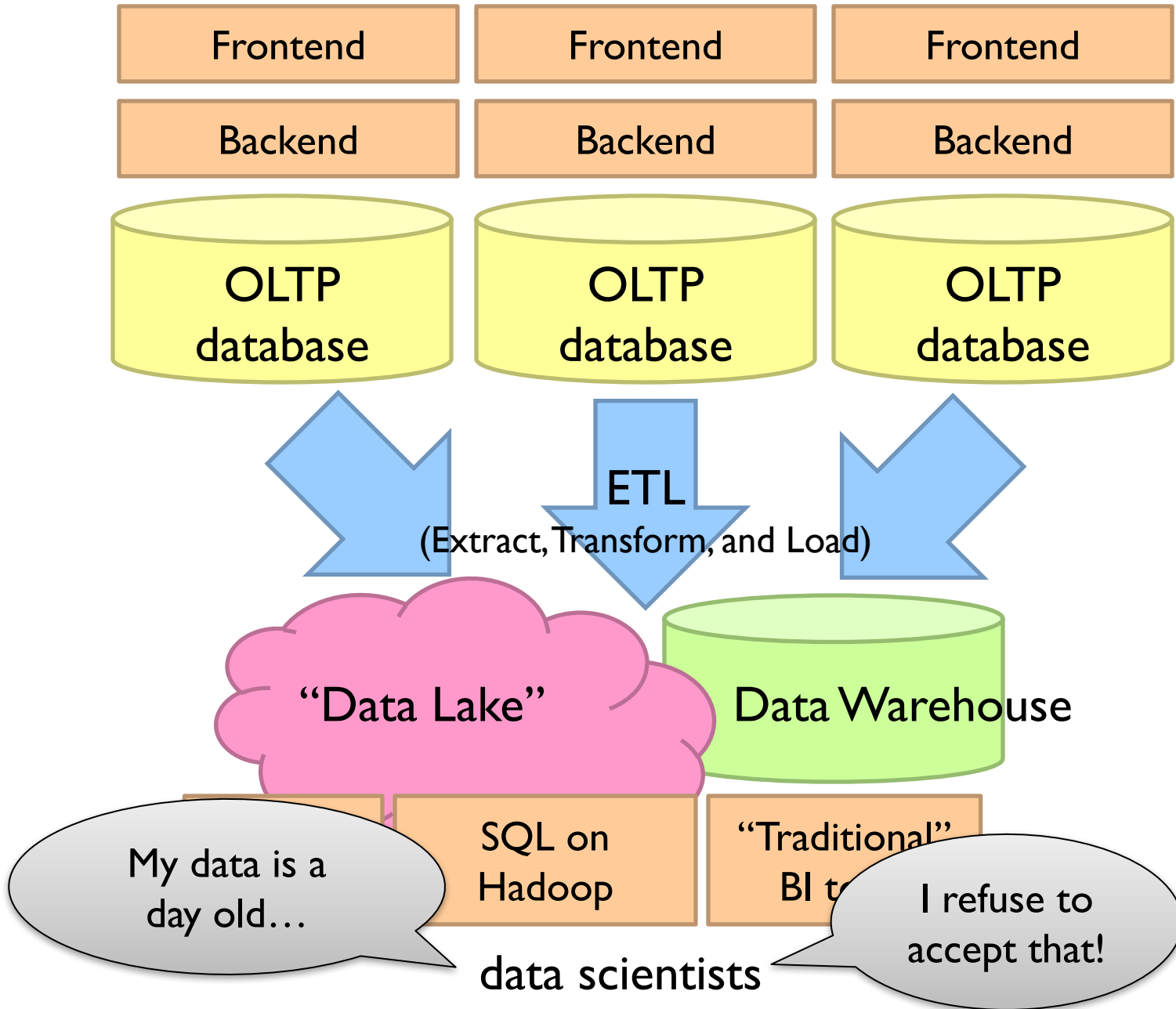
SQL on  
Hadoop

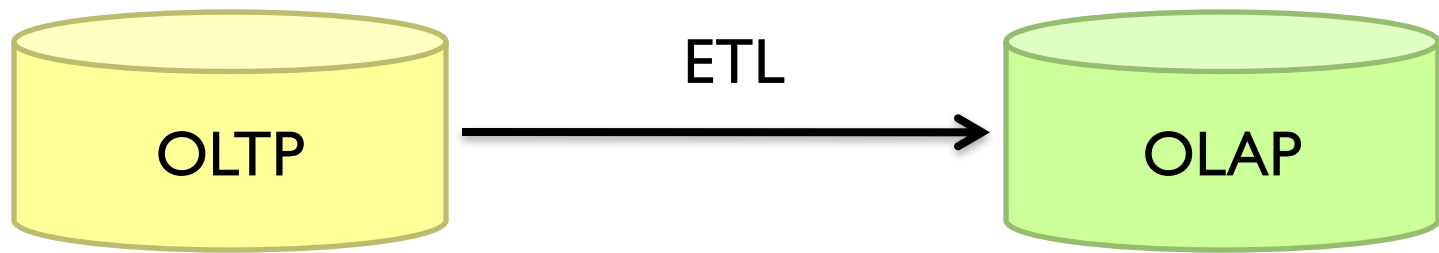
“Traditional”  
BI tool

My data is a  
day old...

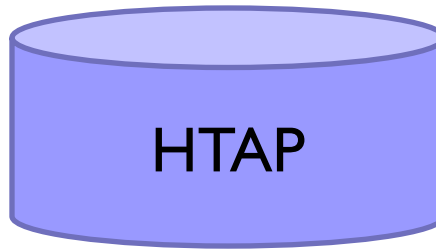
I refuse to  
accept that!

data scientists



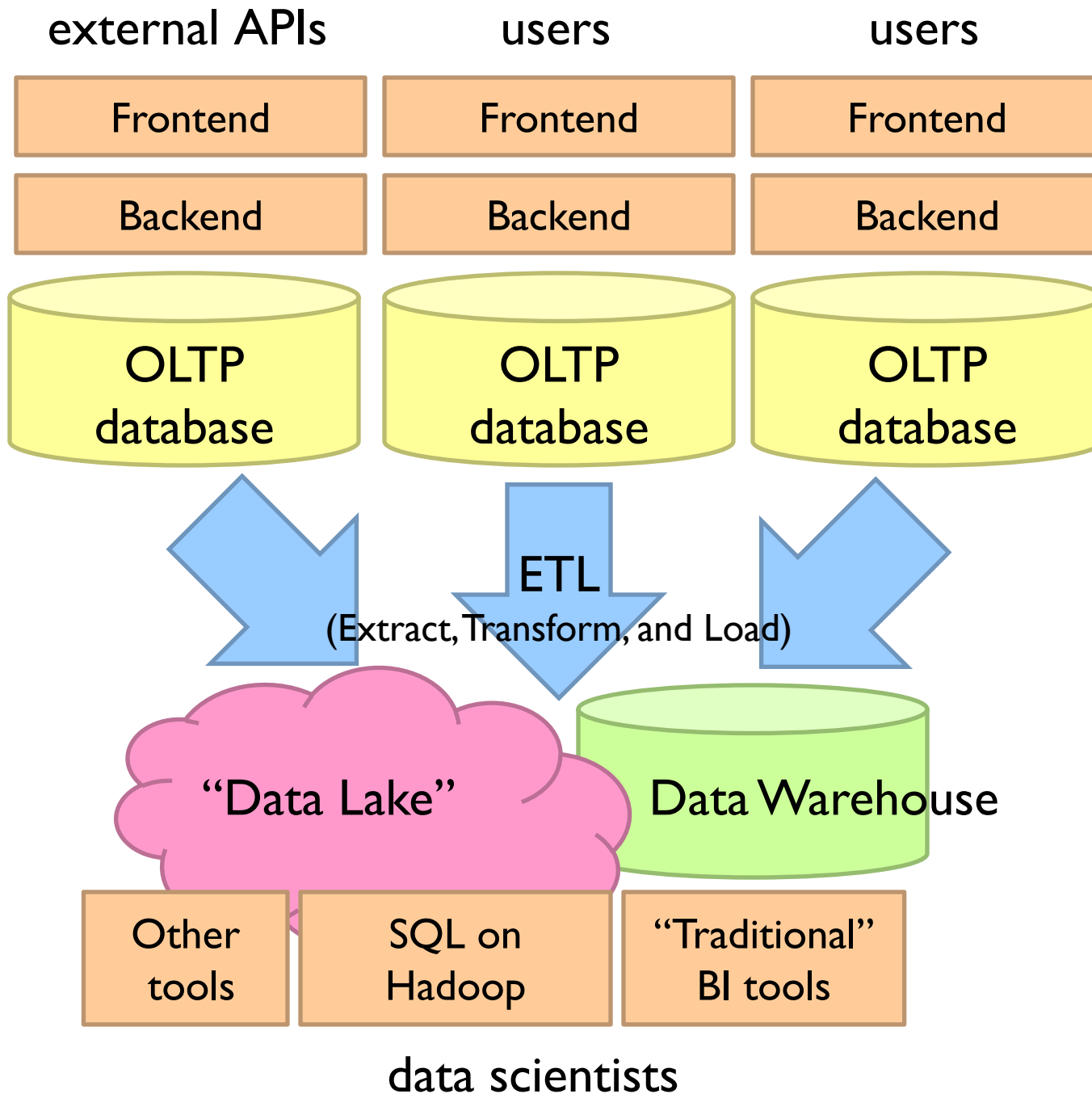


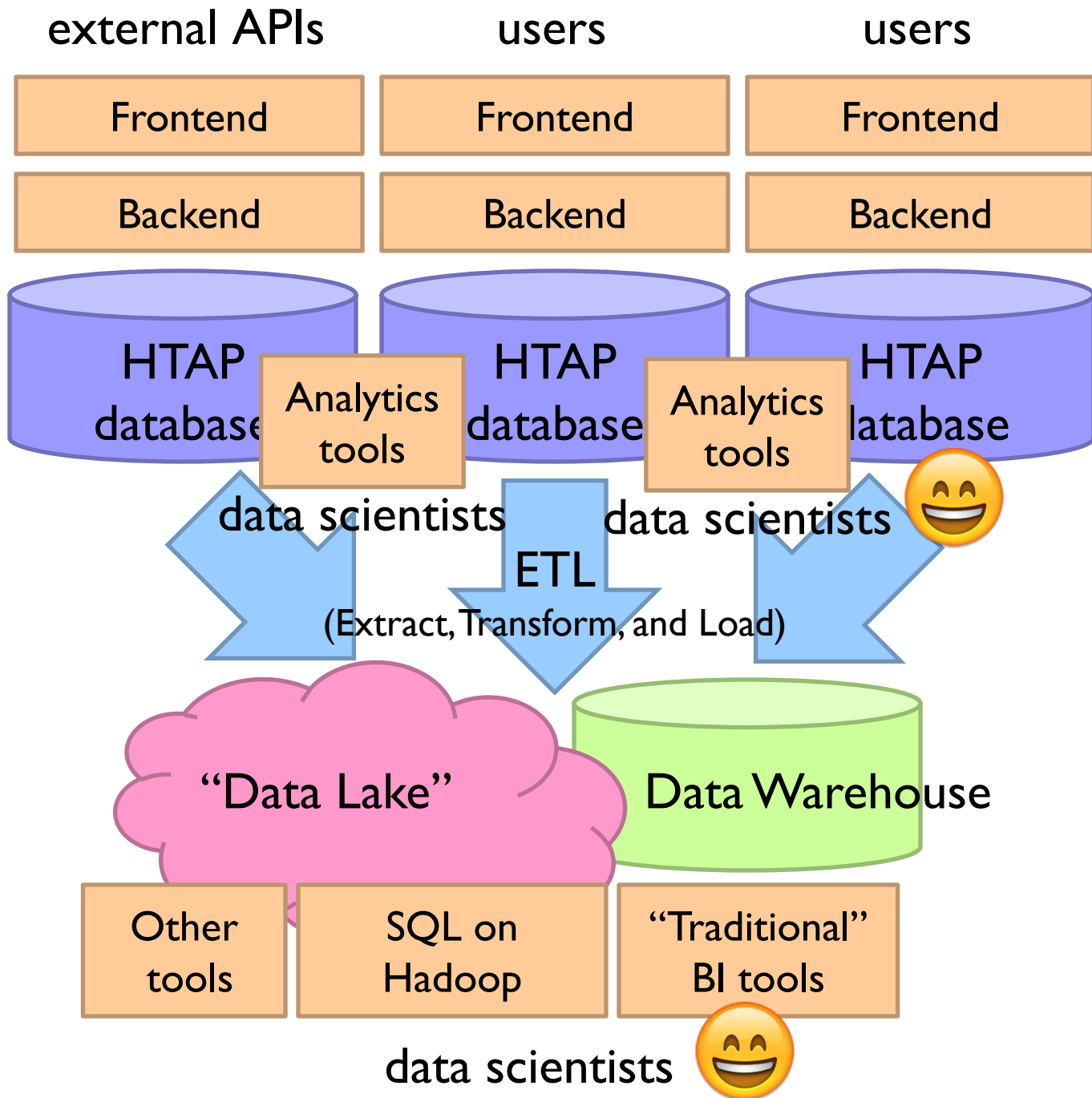
What if you didn't have to do this?

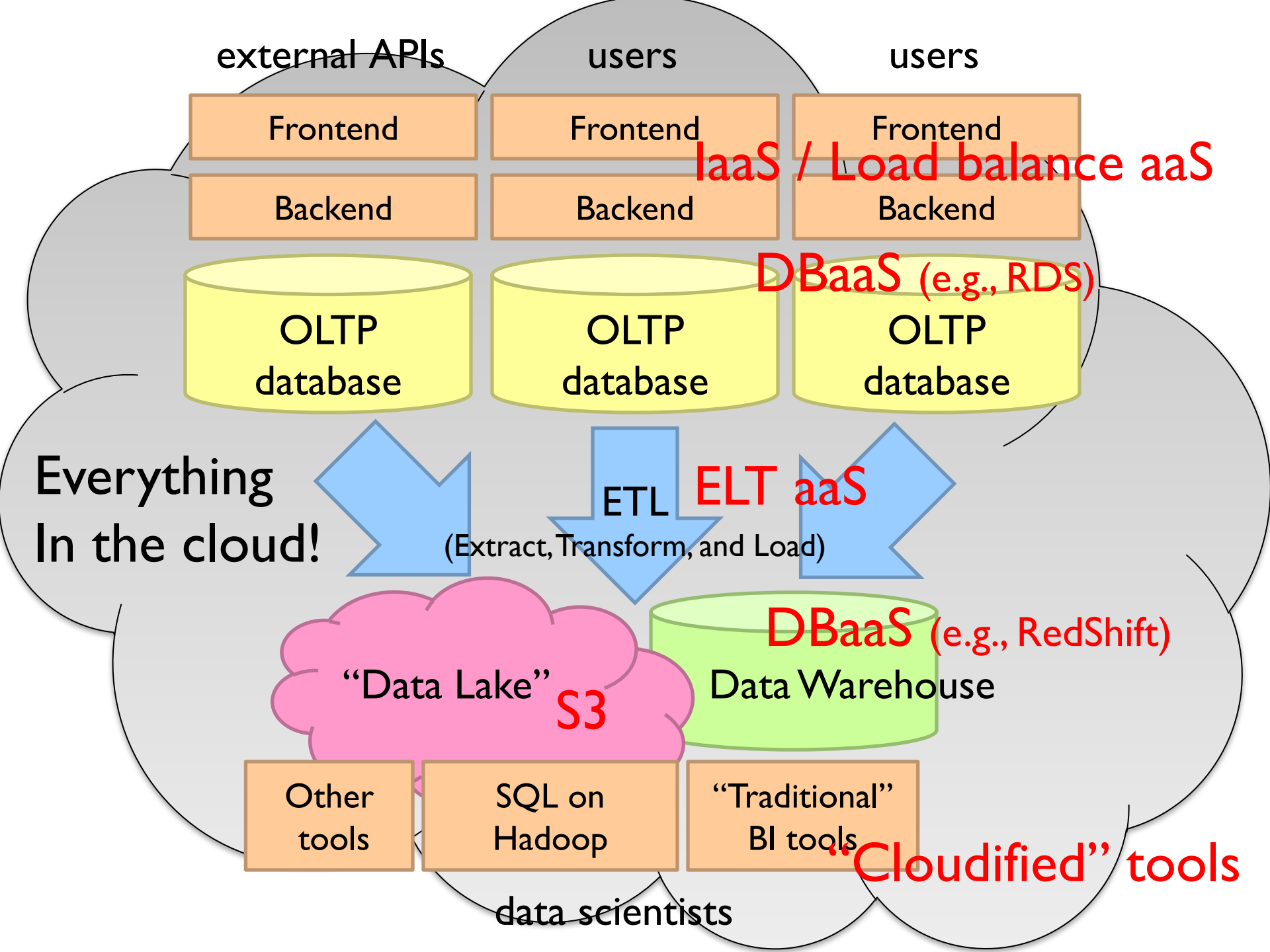


Hybrid Transactional/Analytical Processing (HTAP)

Coming back full circle?











# Questions?