

# MANAGING AND PROCESSING LARGE DATASETS

Christian Kaestner

Required watching: Molham Aref. [Business Systems with Machine Learning](#). Guest lecture, 2020.

Suggested reading: Martin Kleppmann. [Designing Data-Intensive Applications](#). O'Reilly. 2017.

# WHERE WE ARE

## Fundamentals of Engineering AI-Enabled Systems

**Holistic system view:** AI and non-AI components, pipelines, stakeholders, environment interactions, feedback loops

### Requirements:

- System and model goals
- User requirements
- Environment assumptions
- Quality beyond accuracy
- Measurement
- Risk analysis
- Planning for mistakes

### Architecture + design:

- Modeling tradeoffs
- Deployment architecture
- Data science pipelines
- Telemetry, monitoring
- Anticipating evolution
- Big data processing
- Human-AI design

### Quality assurance:

- Model testing
- Data quality
- QA automation
- Testing in production
- Infrastructure quality
- Debugging

### Operations:

- Continuous deployment
- Contin. experimentation
- Configuration mgmt.
- Monitoring
- Versioning
- Big data
- DevOps, MLOps

**Teams and process:** Data science vs software eng. workflows, interdisciplinary teams, collaboration points, technical debt

## Responsible AI Engineering

Provenance,  
versioning,  
reproducibility

Safety

Security and  
privacy

Fairness

Interpretability  
and explainability

Transparency  
and trust

Ethics, governance, regulation, compliance, organizational culture



# LEARNING GOALS

- Organize different data management solutions and their tradeoffs
- Understand the scalability challenges involved in large-scale machine learning and specifically deep learning
- Explain the tradeoffs between batch processing and stream processing and the lambda architecture
- Recommend and justify a design and corresponding technologies for a given system

# CASE STUDY

← search icon trees ×

Today



Fri, Oct 25





## Speaker notes

- Discuss possible architecture and when to predict (and update)
- in may 2017: 500M users, uploading 1.2billion photos per day (14k/sec)
- in Jun 2019 1 billion users

# ADDING CAPACITY



*Stories of catastrophic success?*

# **DATA MANAGEMENT AND PROCESSING IN ML- ENABLED SYSTEMS**

# KINDS OF DATA

- Training data
- Input data
- Telemetry data
- (Models)

*all potentially with huge total volumes and high throughput*

*need strategies for storage and processing*

# DATA MANAGEMENT AND PROCESSING IN ML-ENABLED SYSTEMS

- Store, clean, and update training data
- Learning process reads training data, writes model
- Prediction task (inference) on demand or precomputed
- Individual requests (low/high volume) or large datasets?
  
- Often both learning and inference data heavy, high volume tasks

# SCALING COMPUTATIONS

Efficient Algorithms

Faster Machines

More Machines

# DISTRIBUTED X

- Distributed data cleaning
- Distributed feature extraction
- Distributed learning
- Distributed large prediction tasks
- Incremental predictions
- Distributed logging and telemetry

# RELIABILITY AND SCALABILITY CHALLENGES IN AI-ENABLED SYSTEMS?



# DISTRIBUTED SYSTEMS AND AI-ENABLED SYSTEMS

- Learning tasks can take substantial resources
- Datasets too large to fit on single machine
- Nontrivial inference time, many many users
- Large amounts of telemetry
- Experimentation at scale
- Models in safety critical parts
- Mobile computing, edge computing, cyber-physical systems

# REMINDER: T-SHAPED PEOPLE



"I-shaped"  
Expert at one thing



Generalist  
Capable in a lot of things  
but not expert in any



"T-shaped"  
Capable in a lot of things  
and expert in one of them

Go deeper with: Martin Kleppmann. [Designing Data-Intensive Applications](#).  
O'Reilly. 2017.

# EXCURSION: DISTRIBUTED DEEP LEARNING WITH THE PARAMETER SERVER ARCHITECTURE

Li, Mu, et al. "Scaling distributed machine learning with the parameter server." OSDI, 2014.

# RECALL: BACKPROPAGATION

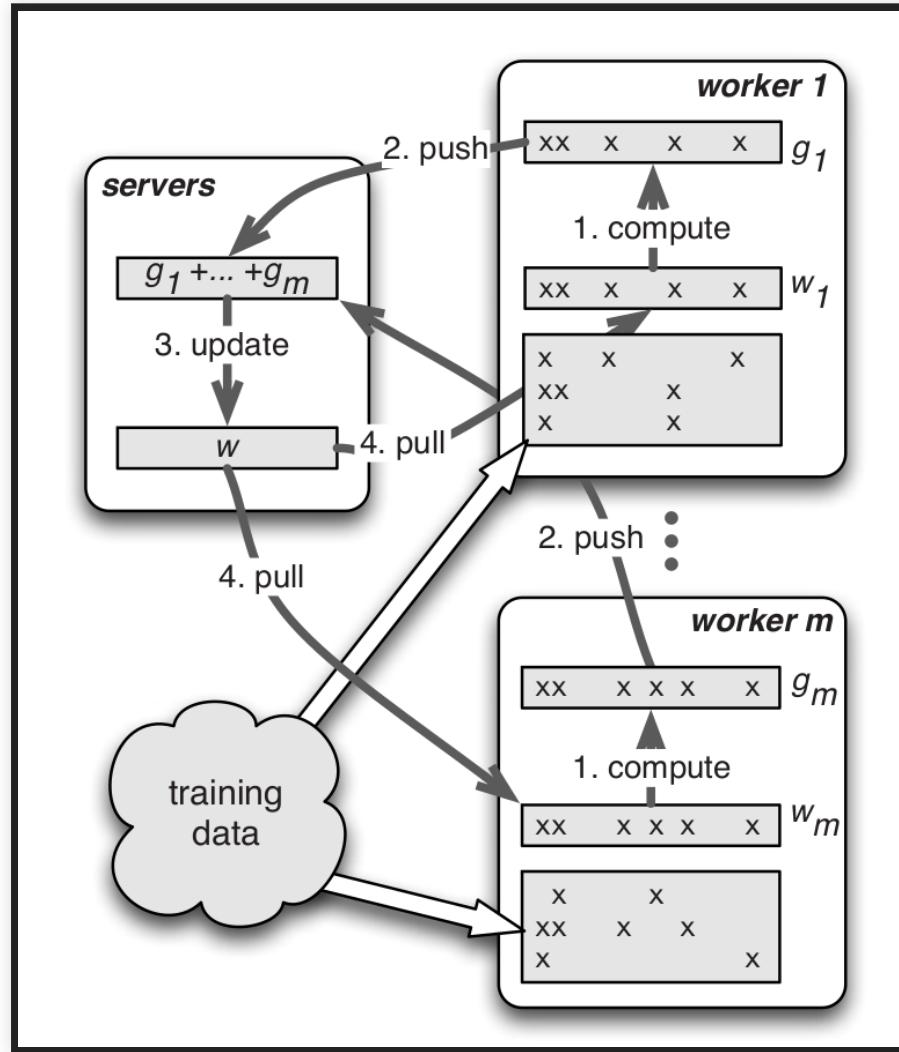


# TRAINING AT SCALE IS CHALLENGING

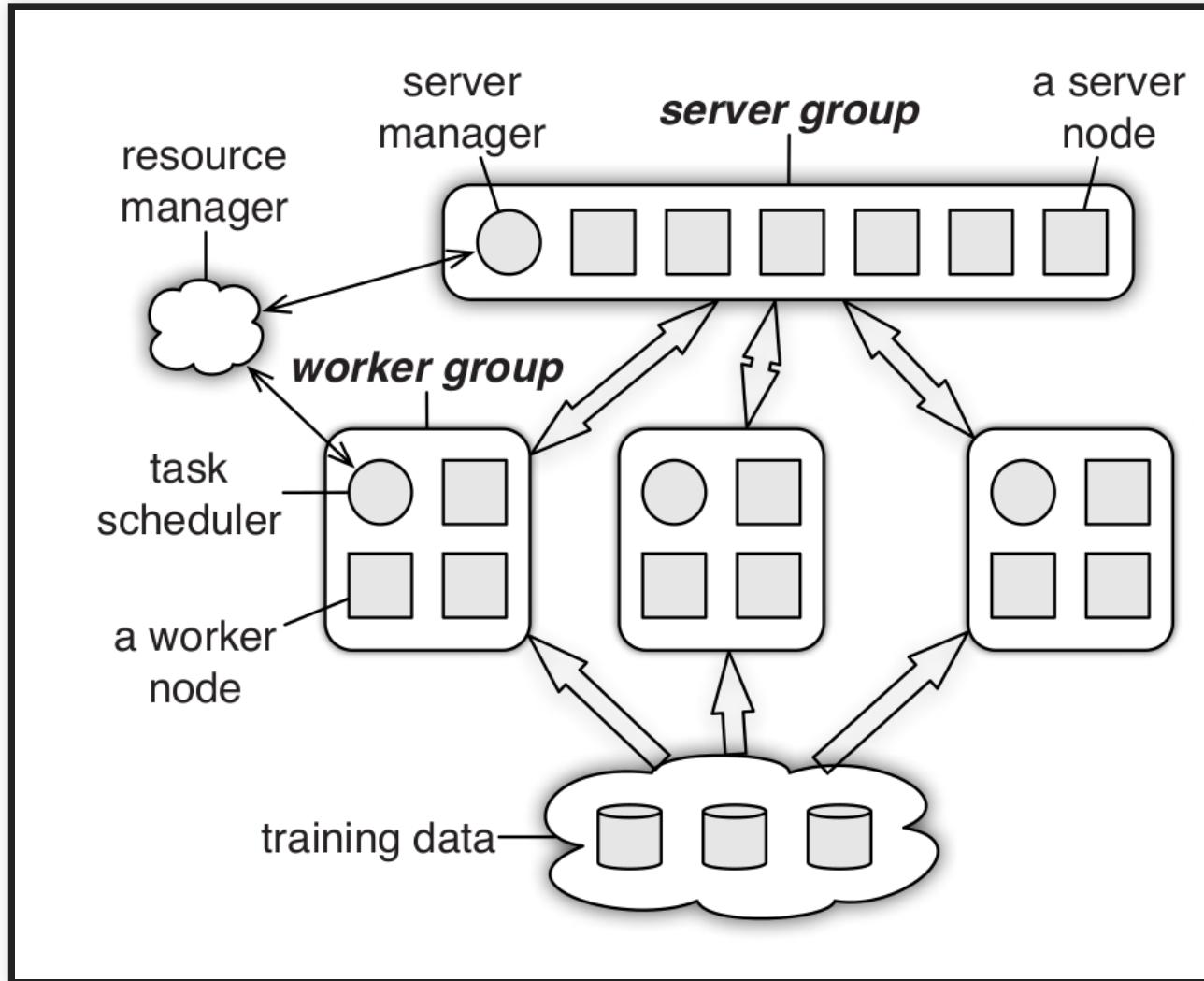
- 2012 at Google: 1TB-1PB of training data,  $10^9 – 10^{12}$  parameters
- Need distributed training; learning is often a sequential problem
- Just exchanging model parameters requires substantial network bandwidth
- Fault tolerance essential (like batch processing), add/remove nodes
- Tradeoff between convergence rate and system efficiency

Li, Mu, et al. "[Scaling distributed machine learning with the parameter server](#)." OSDI, 2014.

# DISTRIBUTED GRADIENT DESCENT



# PARAMETER SERVER ARCHITECTURE



## Speaker notes

Multiple parameter servers that each only contain a subset of the parameters, and multiple workers that each require only a subset of each

Ship only relevant subsets of mathematical vectors and matrices, batch communication

Resolve conflicts when multiple updates need to be integrated (sequential, eventually, bounded delay)

Run more than one learning algorithm simultaneously

# SYSML CONFERENCE

Increasing interest in the systems aspects of machine learning

e.g., building large scale and robust learning infrastructure

<https://mlsys.org/>

# DATA STORAGE BASICS

- Relational vs document storage
- 1:n and n:m relations
- Storage and retrieval, indexes
- Query languages and optimization

# RELATIONAL DATA MODELS

## Photos:

| photo_id  | user_id | path                    | upload_date              | size | camera_id | camera_setting               |
|-----------|---------|-------------------------|--------------------------|------|-----------|------------------------------|
| 133422131 | 54351   | /st/u211/1U6uFl47Fy.jpg | 2021-12-03T09:18:32.124Z | 5.7  | 663       | f/1.8; 1/120; 4.44mm; ISO271 |
| 133422132 | 13221   | /st/u11b/MFxL1FY8V.jpg  | 2021-12-03T09:18:32.129Z | 3.1  | 1844      | f/2, 1/15, 3.64mm, ISO1250   |
| 133422133 | 54351   | /st/x81/ITzhcSmv9s.jpg  | 2021-12-03T09:18:32.131Z | 4.8  | 663       | f/1.8; 1/120; 4.44mm; ISO48  |

## Users:

| user_id | account_name | photos_total | last_login               |
|---------|--------------|--------------|--------------------------|
| 54351   | ckaestne     | 5124         | 2021-12-08T12:27:48.497Z |
| 13221   | eva.burk     | 3            | 2021-12-21T01:51:54.713Z |

## Cameras:

| camera_id | manufacturer | print_name      |
|-----------|--------------|-----------------|
| 663       | Google       | Google Pixel 5  |
| 1844      | Motorola     | Motorola MotoG3 |

```
select p.photo_id, p.path, u.photos_total
from photos p, users u
where u.user_id=p.user_id and u.account_name = "ckaestne"
```

# DOCUMENT DATA MODELS

```
{  
    "_id": 133422131,  
    "path": "/st/u211/1U6uFl47Fy.jpg",  
    "upload_date": "2021-12-03T09:18:32.124Z",  
    "user": {  
        "account_name": "ckaestne",  
        "account_id": "a/54351"  
    },  
    "size": "5.7",  
    "camera": {  
        "manufacturer": "Google",  
        "print_name": "Google Pixel 5",  
        "settings": "f/1.8; 1/120; 4.44mm; ISO271"  
    }  
}
```

```
db.getCollection('photos').find( { "user.account_name": "ckaestne" })
```

# LOG FILES, UNSTRUCTURED DATA

```
02:49:12 127.0.0.1 GET /img13.jpg 200
02:49:35 127.0.0.1 GET /img27.jpg 200
03:52:36 127.0.0.1 GET /main.css 200
04:17:03 127.0.0.1 GET /img13.jpg 200
05:04:54 127.0.0.1 GET /img34.jpg 200
05:38:07 127.0.0.1 GET /img27.jpg 200
05:44:24 127.0.0.1 GET /img13.jpg 200
06:08:19 127.0.0.1 GET /img13.jpg 200
```

# LOG FILES, UNSTRUCTURED DATA

```
2020-06-25T13:44:14, 601844, GET /data/m/goyas+ghosts+2006/17.mpg
2020-06-25T13:44:14, 935791, GET /data/m/the+big+circus+1959/68.mp
2020-06-25T13:44:14, 557605, GET /data/m/elvis+meets+nixon+1997/17
2020-06-25T13:44:14, 140291, GET /data/m/the+house+of+the+spirits+
2020-06-25T13:44:14, 425781, GET /data/m/the+theory+of+everything+
2020-06-25T13:44:14, 773178, GET /data/m/toy+story+2+1999/59.mpg
2020-06-25T13:44:14, 901758, GET /data/m/ignition+2002/14.mpg
2020-06-25T13:44:14, 911008, GET /data/m/toy+story+3+2010/46.mpg
```

# TRADEOFFS



# DATA ENCODING

- Plain text (csv, logs)
- Semi-structured, schema-free (JSON, XML)
- Schema-based encoding (relational, Avro, ...)
- Compact encodings (protobuf, ...)

# **DISTRIBUTED DATA STORAGE**

# REPLICATION VS PARTITIONING



# PARTITIONING

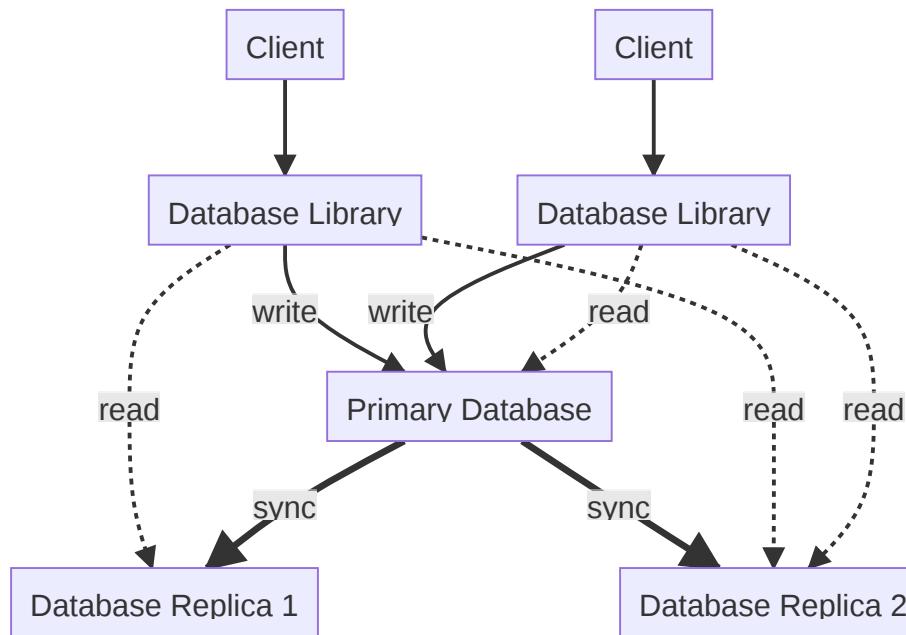
Divide data:

- Horizontal partitioning: Different rows in different tables; e.g., movies by decade, hashing often used
- Vertical partitioning: Different columns in different tables; e.g., movie title vs. all actors

Tradeoffs?



# REPLICATION STRATEGIES: LEADERS AND FOLLOWERS



# REPLICATION STRATEGIES: LEADERS AND FOLLOWERS

- Write to leader
  - propagated synchronously or async.
- Read from any follower
- Elect new leader on leader outage; catchup on follower outage
- Built in model of many databases (MySQL, MongoDB, ...)

**Benefits and Drawbacks?**

# MULTI-LEADER REPLICATION

- Scale write access, add redundancy
- Requires coordination among leaders
  - Resolution of write conflicts
- Offline leaders (e.g. apps), collaborative editing

# LEADERLESS REPLICATION

- Client writes to multiple replica, propagate from there
- Read from multiple replica (quorum required)
  - Repair on reads, background repair process
- Versioning of entries (clock problem)
- e.g. Amazon Dynamo, Cassandra, Voldemort



# TRANSACTIONS

- Multiple operations conducted as one, all or nothing
- Avoids problems such as
  - dirty reads
  - dirty writes
- Various strategies, including locking and optimistic+rollback
- Overhead in distributed setting

# DATA PROCESSING (OVERVIEW)

- Services (online)
  - Responding to client requests as they come in
  - Evaluate: Response time
- Batch processing (offline)
  - Computations run on large amounts of data
  - Takes minutes to days
  - Typically scheduled periodically
  - Evaluate: Throughput
- Stream processing (near real time)
  - Processes input events, not responding to requests
  - Shortly after events are issued

# MICROSERVICES

# MICROSERVICES



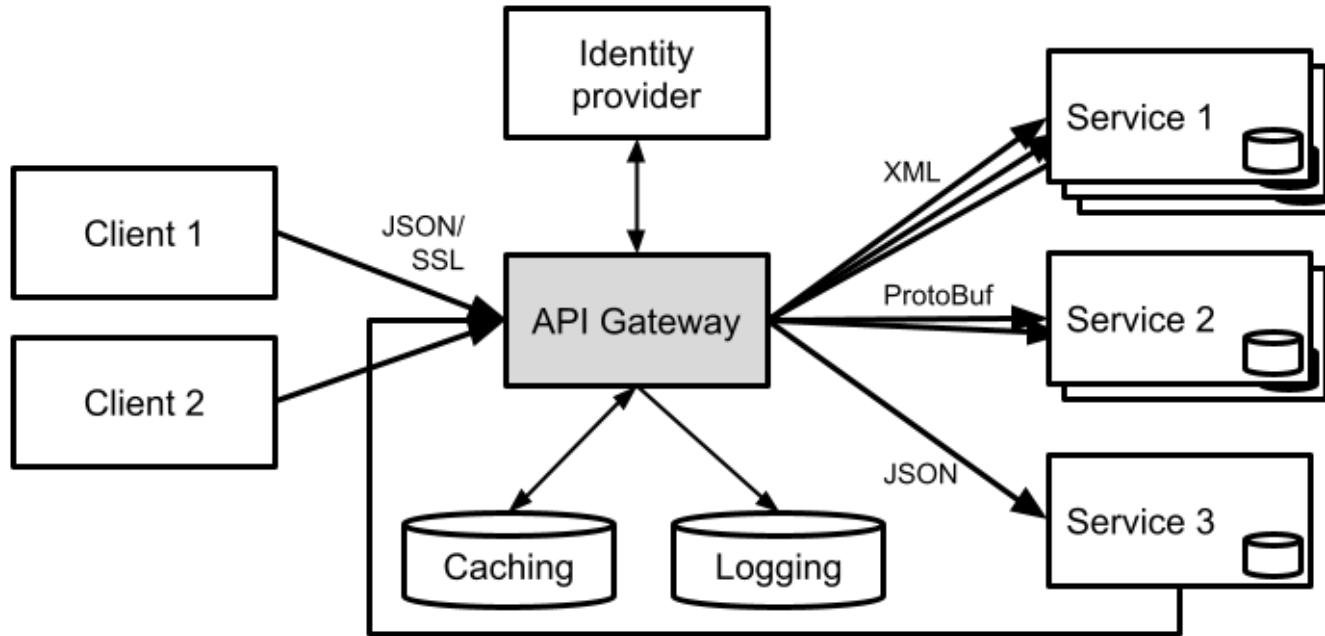
Figure based on Christopher Meiklejohn. [Dynamic Reduction: Optimizing Service-level Fault Injection Testing With Service Encapsulation](#). Blog Post 2021

# MICROSERVICES

- Independent, cohesive services
  - Each specialized for one task
  - Each with own data storage
  - Each independently scalable through multiple instances + load balancer (autoscaling infrastructure available)
- Remote procedure calls
- Different teams can work on different services independently (even in different languages)
- Substantial complexity from distributed system nature
  - Various network failures
  - Latency from remote calls
- Avoid microservice complexity unless really needed for scalability

# API GATEWAY PATTERN

Central entry point, authentication, routing, updates, ...



# BATCH PROCESSING

# LARGE JOBS

- Analyzing TB of data, typically distributed storage
- Filtering, sorting, aggregating
- Producing reports, models, ...

```
cat /var/log/nginx/access.log |  
awk '{print $7}' |  
sort |  
uniq -c |  
sort -r -n |  
head -n 5
```

Partitioned data storage      Map      Shuffle      Reduce      Result



```
02:49:12 127.0.0.1 GET /img13.jpg 200  
02:49:35 127.0.0.1 GET /img27.jpg 200  
  
03:52:36 127.0.0.1 GET /main.css 200  
04:17:03 127.0.0.1 GET /img13.jpg 200  
  
05:04:54 127.0.0.1 GET /img34.jpg 200  
05:38:07 127.0.0.1 GET /img27.jpg 200  
  
05:44:24 127.0.0.1 GET /img13.jpg 200  
06:08:19 127.0.0.1 GET /img13.jpg 200
```

```
/img13, 1  
/img27, 1  
  
/img13, 1  
  
/img34, 1  
/img27, 1  
  
/img13, 1  
/img13, 1
```

```
/img13, 1  
/img13, 1  
/img13, 1  
/img13, 1  
  
/img27, 1  
/img34, 1  
/img27, 1
```

```
/img13, 4  
/img27, 2  
/img34, 1
```

# DISTRIBUTED BATCH PROCESSING

- Process data locally at storage
- Aggregate results as needed
- Separate plumbing from job logic

*MapReduce* as common framework

# MAPREDUCE -- FUNCTIONAL PROGRAMMING STYLE

- Similar to shell commands: Immutable inputs, new outputs, avoid side effects
- Jobs can be repeated (e.g., on crashes)
- Easy rollback
- Multiple jobs in parallel (e.g., experimentation)

# MACHINE LEARNING AND MAPREDUCE



## Speaker notes

Useful for big learning jobs, but also for feature extraction

# DATAFLOW ENGINES (SPARK, TEZ, FLINK, ...)

- Single job, rather than subjobs
- More flexible than just map and reduce
- Multiple stages with explicit dataflow between them
- Often in-memory data
- Plumbing and distribution logic separated

# KEY DESIGN PRINCIPLE: DATA LOCALITY

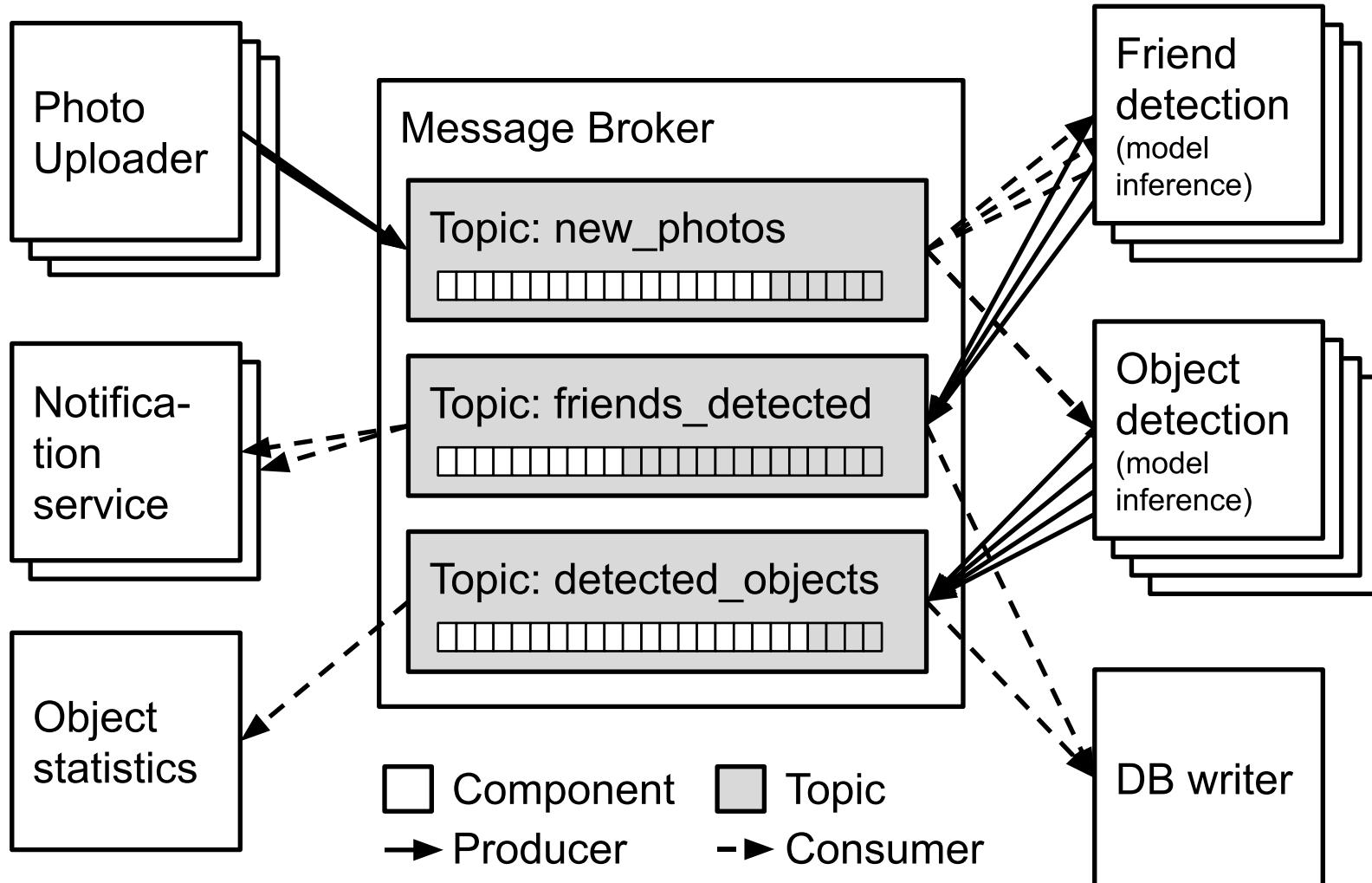
*Moving Computation is Cheaper than Moving Data --  
[Hadoop Documentation](#)*

- Data often large and distributed, code small
- Avoid transferring large amounts of data
- Perform computation where data is stored (distributed)
- Transfer only results as needed
  
- "The map reduce way"

# STREAM PROCESSING

Event-based systems, message passing style, publish subscribe

# STREAM PROCESSING (E.G., KAFKA)

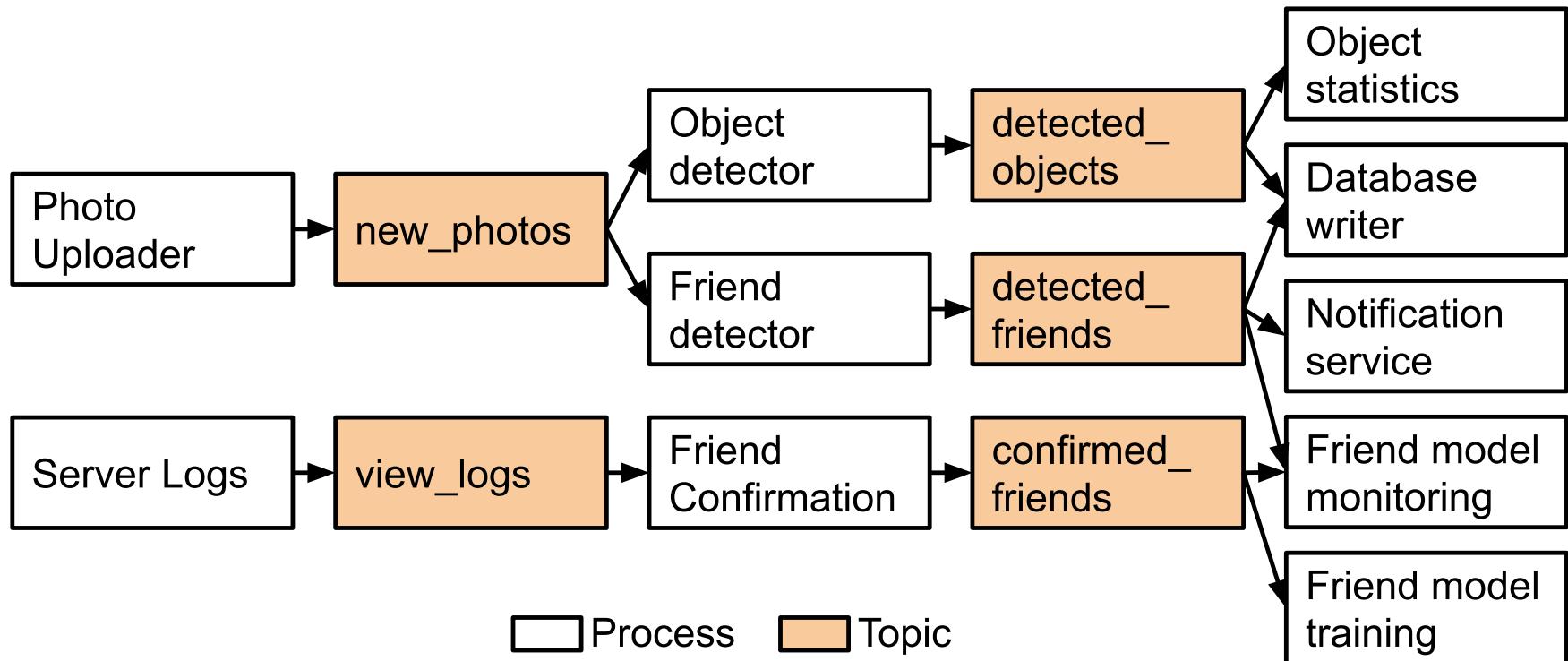


# MESSAGING SYSTEMS

- Multiple producers send messages to topic
- Multiple consumers can read messages
- Decoupling of producers and consumers
- Message buffering if producers faster than consumers
- Typically some persistency to recover from failures
- Messages removed after consumption or after timeout
- With or without central broker
- Various error handling strategies (acknowledgements, redelivery, ...)

# COMMON DESIGNS

Like shell programs: Read from stream, produce output in other stream. Loose coupling



# STREAM QUERIES

- Processing one event at a time independently
- vs incremental analysis over all messages up to that point
- vs floating window analysis across recent messages
- Works well with probabilistic analyses

# CONSUMERS

- Multiple consumers share topic for scaling and load balancing
- Multiple consumers read same message for different work
- Partitioning possible

# DESIGN QUESTIONS

- Message loss important? (at-least-once processing)
- Can messages be processed repeatedly (at-most-once processing)
- Is the message order important?
- Are messages still needed after they are consumed?

# STREAM PROCESSING AND AI-ENABLED SYSTEMS?



## Speaker notes

Process data as it arrives, prepare data for learning tasks, use models to annotate data, analytics

# EVENT SOURCING

- Append only databases
- Record edit events, never mutate data
- Compute current state from all past events, can reconstruct old state
- For efficiency, take state snapshots
- Similar to traditional database logs

```
addPhoto(id=133422131, user=54351, path="/st/u211/1U6uF147Fy.jpg"
updatePhotoData(id=133422131, user=54351, title="Sunset")
replacePhoto(id=133422131, user=54351, path="/st/x594/vipxBMF1LF
deletePhoto(id=133422131, user=54351)
```

# BENEFITS OF IMMUTABILITY (EVENT SOURCING)

- All history is stored, recoverable
- Versioning easy by storing id of latest record
- Can compute multiple views
- Compare *git*

*On a shopping website, a customer may add an item to their cart and then remove it again. Although the second event cancels out the first event from the point of view of order fulfillment, it may be useful to know for analytics purposes that the customer was considering a particular item but then decided against it. Perhaps they will choose to buy it in the future, or perhaps they found a substitute. This information is recorded in an event log, but would be lost in a database that deletes items when they are removed from the cart.*

Source: Greg Young. [CQRS and Event Sourcing](#). Code on the Beach 2014 via Martin Kleppmann. Designing Data-Intensive Applications. O'Reilly. 2017.

# DRAWBACKS OF IMMUTABLE DATA



## Speaker notes

- Storage overhead, extra complexity of deriving state
- Frequent changes may create massive data overhead
- Some sensitive data may need to be deleted (e.g., privacy, security)

# THE LAMBDA ARCHITECTURE

# LAMBDA ARCHITECTURE: 3 LAYER STORAGE ARCHITECTURE

- Batch layer: best accuracy, all data, recompute periodically
- Speed layer: stream processing, incremental updates, possibly approximated
- Serving layer: provide results of batch and speed layers to clients
  
- Assumes append-only data
- Supports tasks with widely varying latency
- Balance latency, throughput and fault tolerance

# LAMBDA ARCHITECTURE AND MACHINE LEARNING



- Learn accurate model in batch job
- Learn incremental model in stream processor

# DATA LAKE

- Trend to store all events in raw form (no consistent schema)
- May be useful later
- Data storage is comparably cheap



# DATA LAKE

- Trend to store all events in raw form (no consistent schema)
  - May be useful later
  - Data storage is comparably cheap
- 
- Bet: *Yet unknown future value of data is greater than storage costs*

# REASONING ABOUT DATAFLOWS

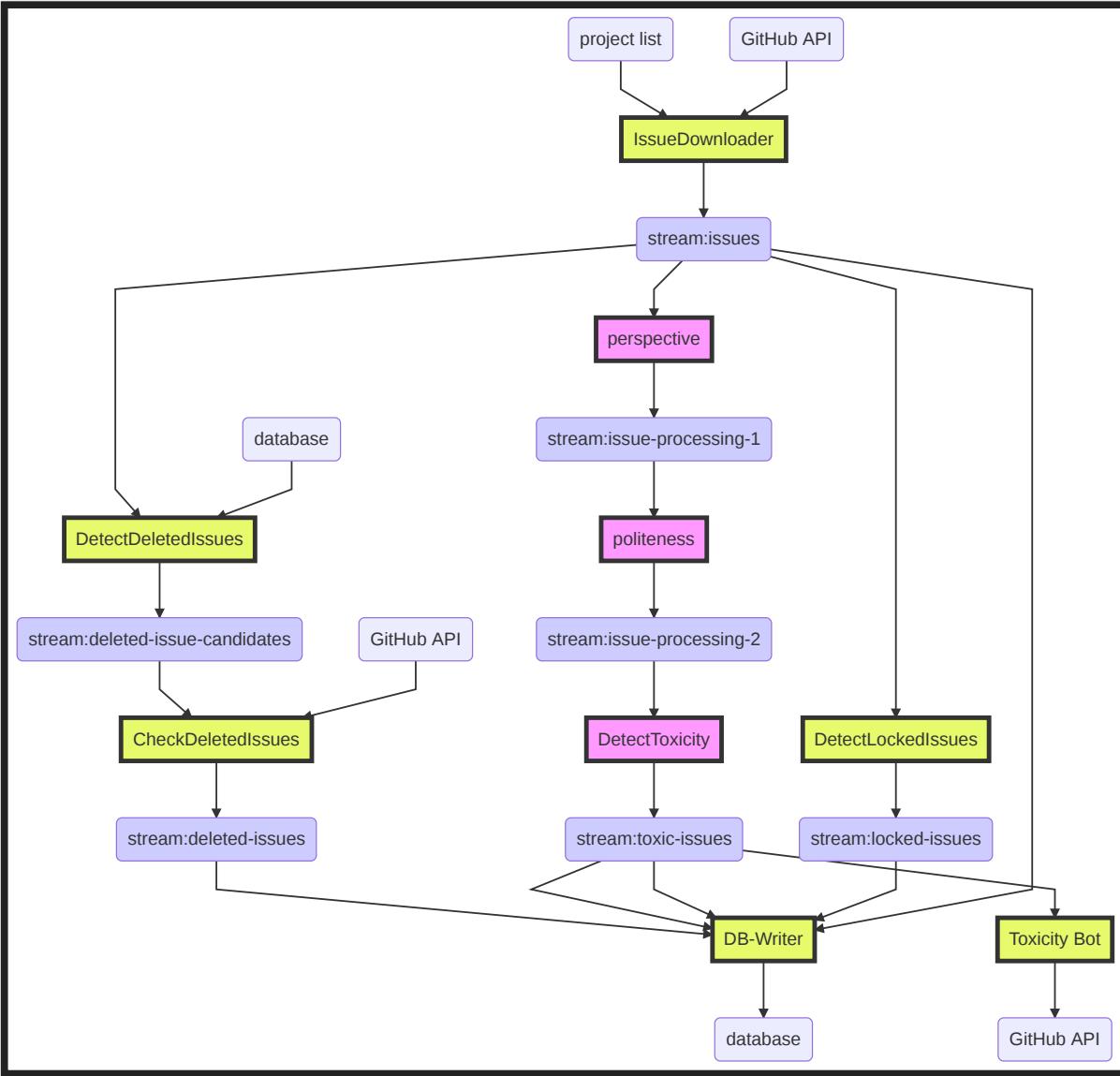
Many data sources, many outputs, many copies

Which data is derived from what other data and how?

Is it reproducible? Are old versions archived?

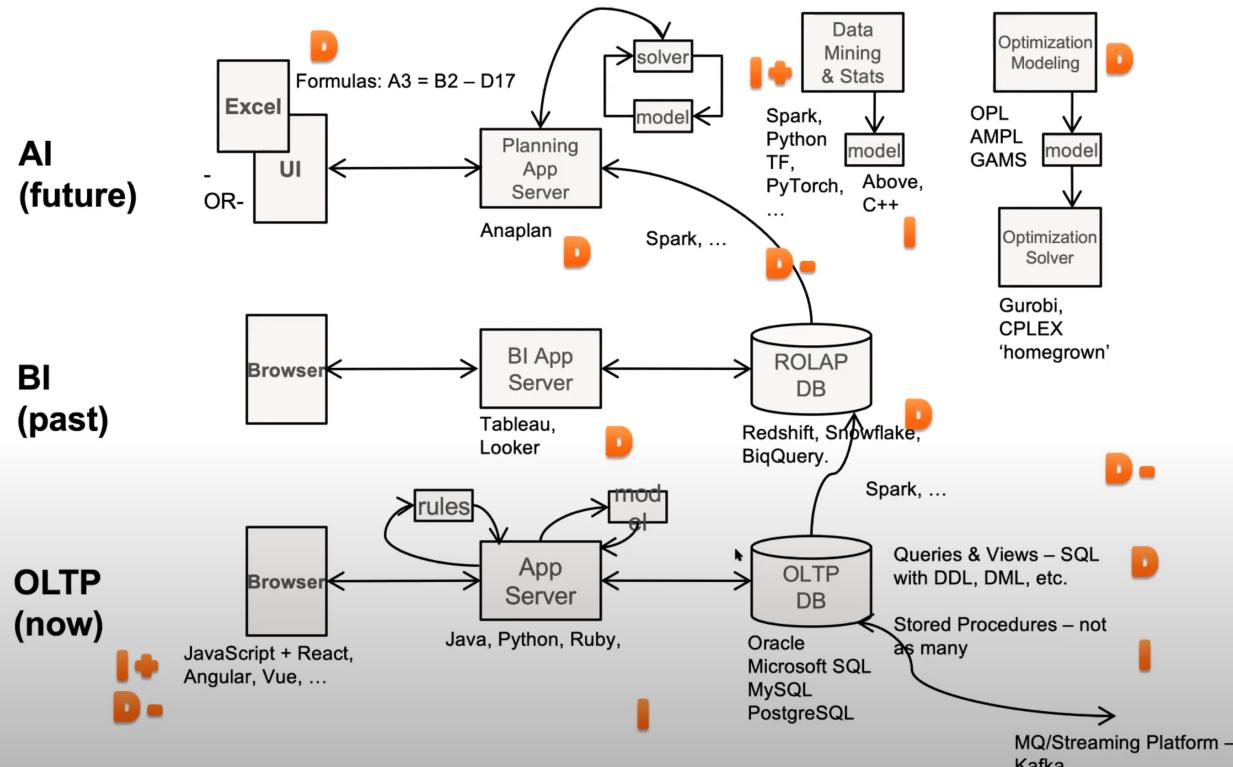
How do you get the right data to the right place in the right format?

**Plan and document data flows**





## Enterprise Tech Stack – Now isn't much different



Molham Aref "Business Systems with Machine Learning"

# BREAKOUT: VIMEO VIDEOS

In groups, discuss in slack #lecture:

- How to distribute storage:
- How to design scalable copy-right protection solution:
- How to design scalable analytics (views, ratings, ...):

**230M+**

users

**1.6M**

paid subscribers

**190+**

countries

**350K**

new videos added per day

**100B+**

video views

**1,100+**

employees around the world

# EXCURSION: ETL TOOLS

Extract, transform, load

The data engineer's toolbox

# DATA WAREHOUSING (OLAP)

- Large denormalized databases with materialized views for large scale reporting queries
- e.g. sales database, queries for sales trends by region
- Read-only except for batch updates: Data from OLTP systems loaded periodically, e.g. over night



## Speaker notes

Image source: [https://commons.wikimedia.org/wiki/File:Data\\_Warehouse\\_Feeding\\_Data\\_Mart.jpg](https://commons.wikimedia.org/wiki/File:Data_Warehouse_Feeding_Data_Mart.jpg)

# ETL: EXTRACT, TRANSFORM, LOAD

- Transfer data between data sources, often OLTP -> OLAP system
- Many tools and pipelines
  - Extract data from multiple sources (logs, JSON, databases), snapshotting
  - Transform: cleaning, (de)normalization, transcoding, sorting, joining
  - Loading in batches into database, staging
- Automation, parallelization, reporting, data quality checking, monitoring, profiling, recovery
- Often large batch processes
- Many commercial tools

Examples of tools in [several lists](#)

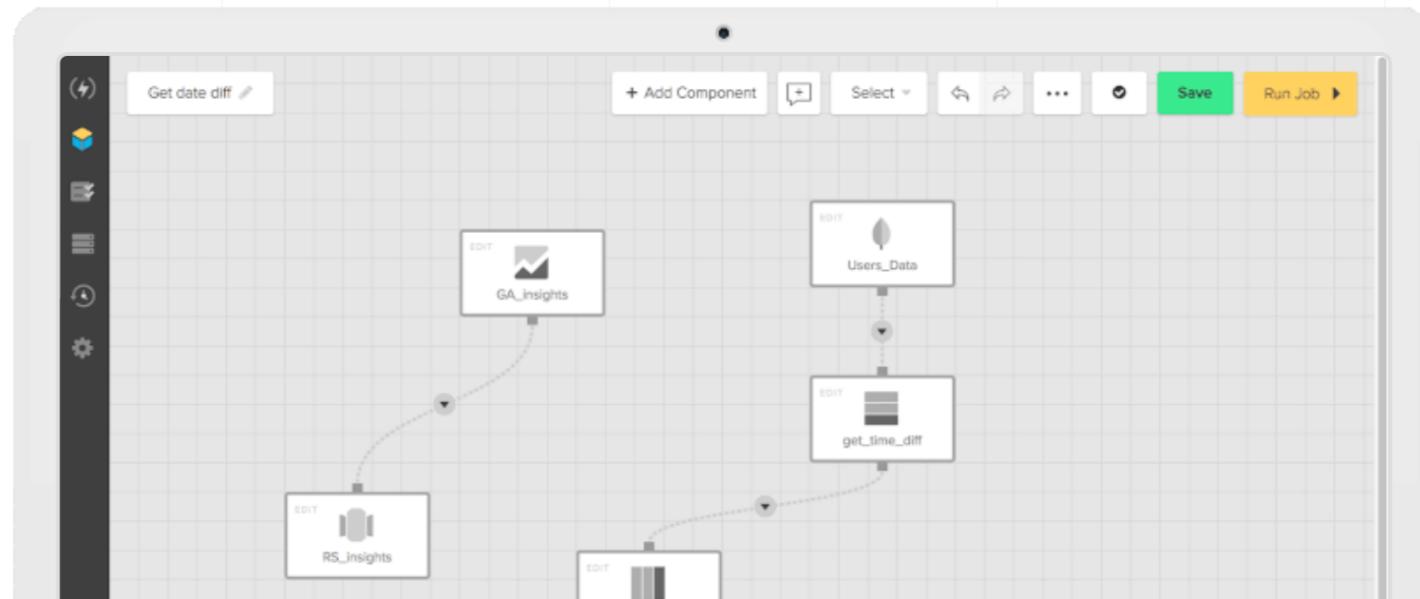




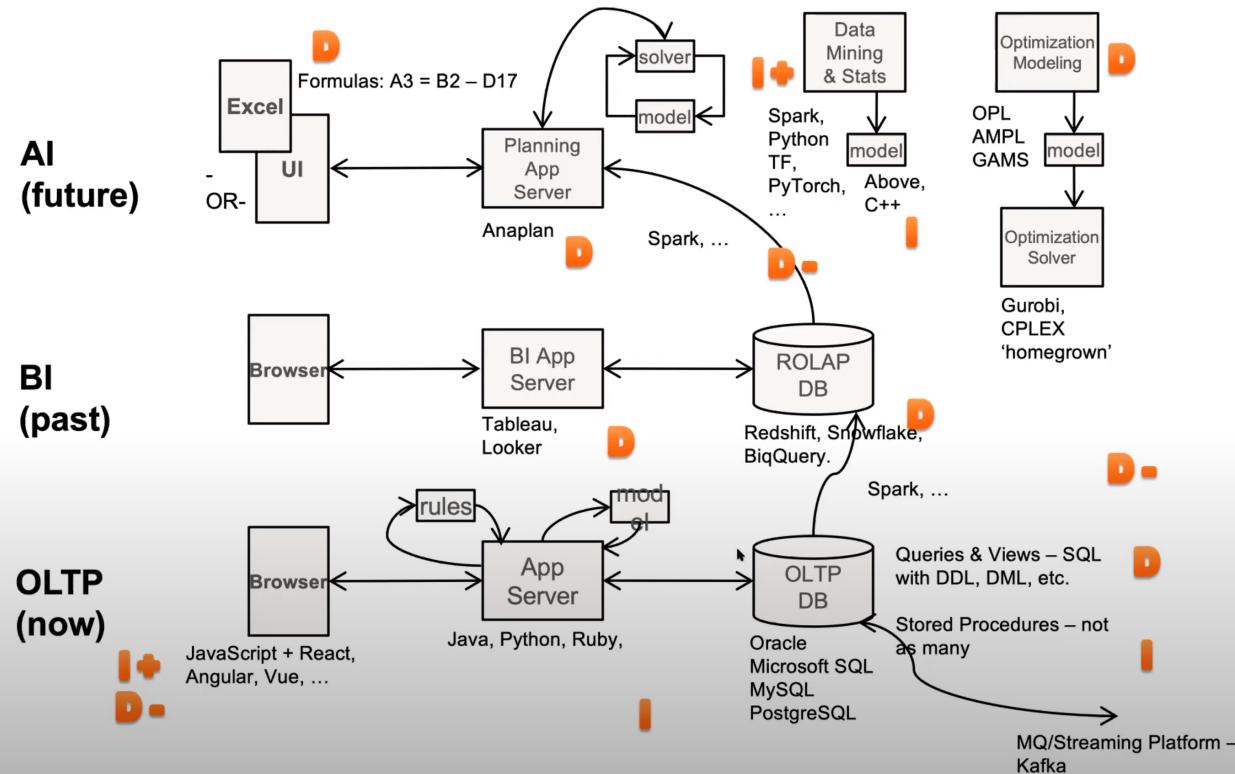
# The leading data integration platform to bring all your data sources together.

Create simple, visualized data pipelines to your data warehouse or data lake.

GET STARTED



## Enterprise Tech Stack – Now isn't much different



Molham Aref "Business Systems with Machine Learning"

# **COMPLEXITY OF DISTRIBUTED SYSTEMS**

A problem has been detected and windows has been shut down to prevent damage to your computer.

DRIVER\_IRQL\_NOT\_LESS\_OR\_EQUAL

If this is the first time you've seen this Stop error screen, restart your computer. If this screen appears again, follow these steps:

Check to make sure any new hardware or software is properly installed. If this is a new installation, ask your hardware or software manufacturer for any Windows updates you might need.

If problems continue, disable or remove any newly installed hardware or software. Disable BIOS memory options such as caching or shadowing. If you need to use Safe Mode to remove or disable components, restart your computer, press F8 to select Advanced Startup Options, and then select Safe Mode.

Technical information:

\*\*\* STOP: 0x00000001 (0x0000000c, 0x00000002, 0x00000000, 0xF86B5A89)

\*\*\* g\3.sys - Address F86B5A89 base at F86B5000, DateStamp 3dd991eb

Beginning dump of physical memory

Physical memory dump complete.

Contact your system administrator or technical support group for further assistance.

# COMMON DISTRIBUTED SYSTEM ISSUES

- Systems may crash
- Messages take time
- Messages may get lost
- Messages may arrive out of order
- Messages may arrive multiple times
- Messages may get manipulated along the way
- Bandwidth limits
- Coordination overhead
- Network partition
- ...

# TYPES OF FAILURE BEHAVIORS

- Fail-stop
- Other halting failures
- Communication failures
  - Send/receive omissions
  - Network partitions
  - Message corruption
- Data corruption
- Performance failures
  - High packet loss rate
  - Low throughput
  - High latency
- Byzantine failures

# COMMON ASSUMPTIONS ABOUT FAILURES

- Behavior of others is fail-stop
- Network is reliable
- Network is semi-reliable but asynchronous
- Network is lossy but messages are not corrupt
- Network failures are transitive
- Failures are independent
- Local data is not corrupt
- Failures are reliably detectable
- Failures are unreliably detectable

# STRATEGIES TO HANDLE FAILURES

- Timeouts, retry, backup services
  - Detect crashed machines (ping/echo, heartbeat)
  - Redundant + first/voting
  - Transactions
- 
- Do lost messages matter?
  - Effect of resending message?

# TEST ERROR HANDLING

- Recall: Testing with stubs
- Recall: Chaos experiments

# **PERFORMANCE PLANNING AND ANALYSIS**

# PERFORMANCE PLANNING AND ANALYSIS

- Ideally architectural planning upfront
  - Identify key components and their interactions
  - Estimate performance parameters
  - Simulate system behavior (e.g., queuing theory)
- Existing system: Analyze performance bottlenecks
  - Profiling of individual components
  - Performance testing (stress testing, load testing, etc)
  - Performance monitoring of distributed systems

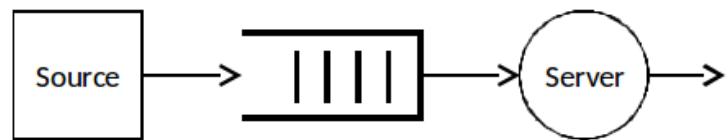
# PERFORMANCE ANALYSIS

- What is the average waiting?
  - How many customers are waiting on average?
  - How long is the average service time?
  - What are the chances of one or more servers being idle?
  - What is the average utilization of the servers?
- 
- Early analysis of different designs for bottlenecks
  - Capacity planning

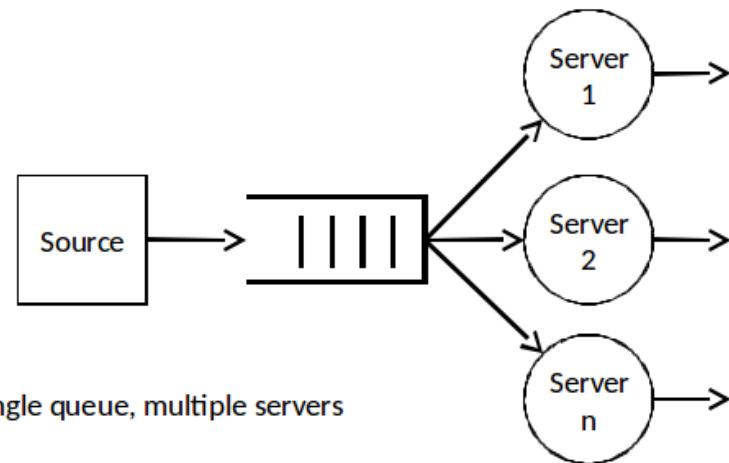
# QUEUEING THEORY

- Queuing theory deals with the analysis of lines where customers wait to receive a service
  - Waiting at Quiznos
  - Waiting to check-in at an airport
  - Kept on hold at a call center
  - Streaming video over the net
  - Requesting a web service
- A queue is formed when request for services outpace the ability of the server(s) to service them immediately
  - Requests arrive faster than they can be processed (unstable queue)
  - Requests do not arrive faster than they can be processed but their processing is delayed by some time (stable queue)
- Queues exist because infinite capacity is infinitely expensive and excessive capacity is excessively expensive

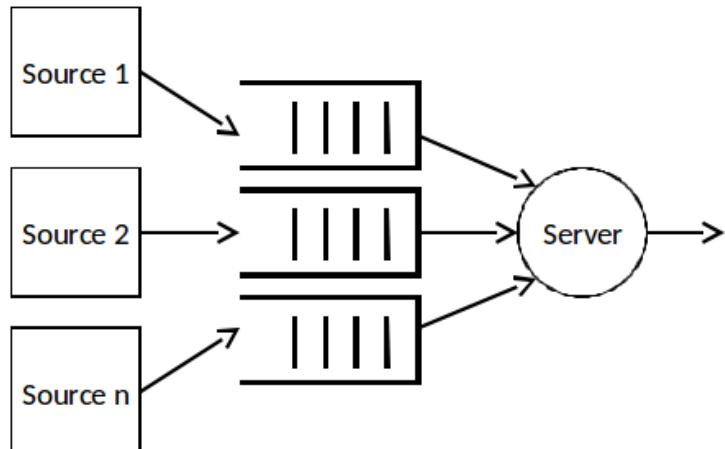
# QUEUEING THEORY



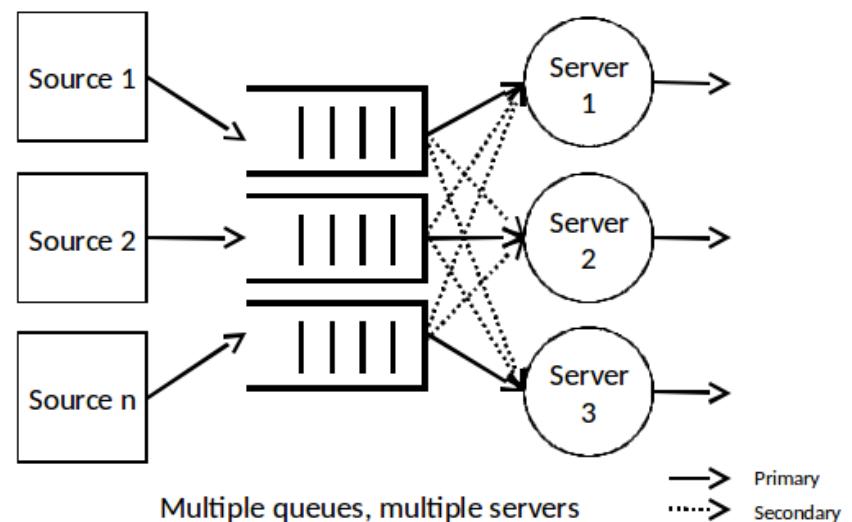
Single queue, single server



Single queue, multiple servers



Multiple queues, single server



Multiple queues, multiple servers

→ Primary  
.....→ Secondary

# ANALYSIS STEPS (ROUGHLY)

- Identify system abstraction to analyze (typically architectural level, e.g. services, but also protocols, datastructures and components, parallel processes, networks)
- Model connections and dependencies
- Estimate latency and capacity per component (measurement and testing, prior systems, estimates, ...)
- Run simulation/analysis to gather performance curves
- Evaluate sensitivity of simulation/analysis to various parameters ('what-if questions')

# **SIMULATION (E.G., JMT)**

# JMODEL - Advanced queuing network design tool

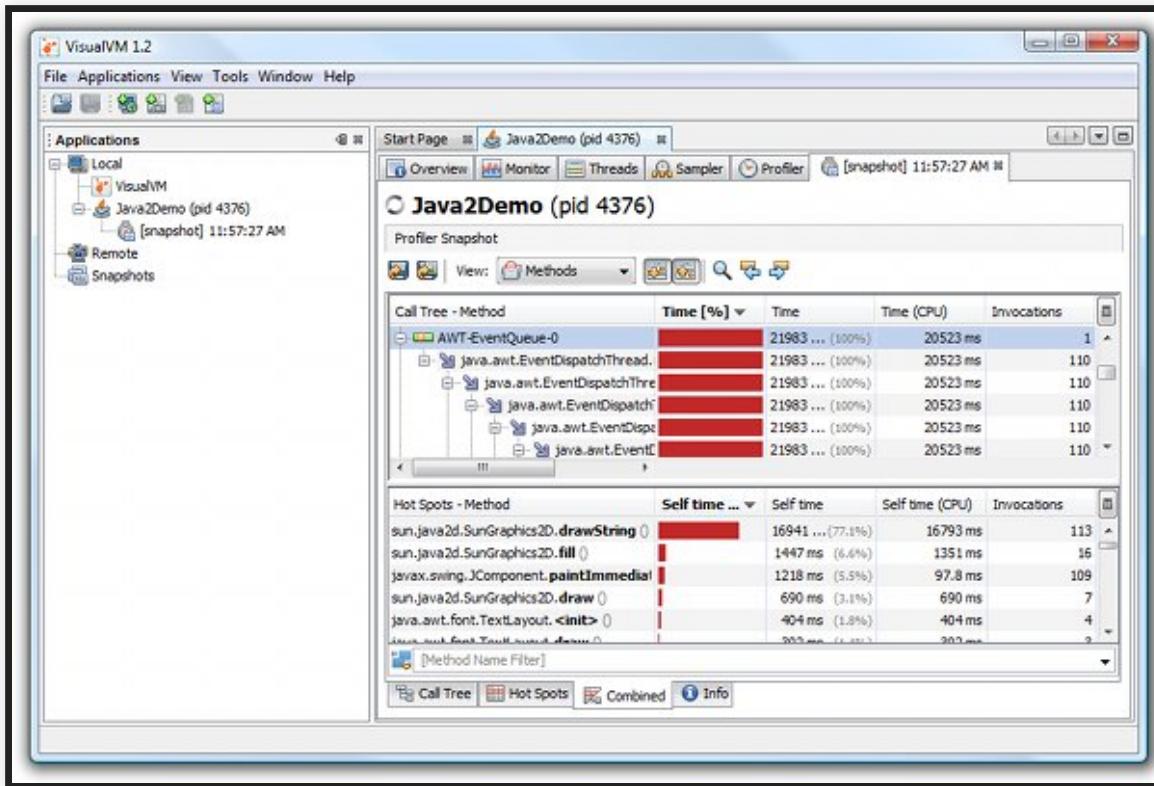


File Edit Define Solve Help



# PROFILING

Mostly used during development phase in single components



# PERFORMANCE TESTING

- Load testing: Assure handling of maximum expected load
- Scalability testing: Test with increasing load
- Soak/spike testing: Overload application for some time, observe stability
- Stress testing: Overwhelm system resources, test graceful failure + recovery
  
- Observe (1) latency, (2) throughput, (3) resource use
- All automateable; tools like JMeter

# PERFORMANCE MONITORING OF DISTRIBUTED SYSTEMS



Source: <https://blog.appdynamics.com/tag/fiserv/>



# PERFORMANCE MONITORING OF DISTRIBUTED SYSTEMS

- Instrumentation of (Service) APIs
- Load of various servers
- Typically measures: latency, traffic, errors, saturation
  
- Monitoring long-term trends
- Alerting
- Automated releases/rollbacks
- Canary testing and A/B testing

# SUMMARY

- Large amounts of data (training, inference, telemetry, models)
- Distributed storage and computation for scalability
- Common design patterns (e.g., batch processing, stream processing, lambda architecture)
- Design considerations: mutable vs immutable data
- Distributed computing also in machine learning
- Lots of tooling for data extraction, transformation, processing
- Many challenges through distribution: failures, debugging, performance, ...

Recommended reading: Martin Kleppmann. [Designing Data-Intensive Applications](#). O'Reilly. 2017.