Building LinkedIn's Real-time Data Pipeline

Jay Kreps



Jay Kreps Principal Staff Engineer at LinkedIn Mountain View, California (San Francisco Bay Area) Internet

Current Principal Staff Engineer at LinkedIn

Past Principal Engineer and Engineering Manager at LinkedIn

Senior Software Engineer at LinkedIn Principal Software Engineer at LinkedIn

see all -

Education University of California, Santa Cruz

University of California, Santa Cruz

Recommendations 1 person has recommended Jay

Connections 500+ connections

Websites Blog

Project Voldemort

Apache Kafka

What is a data pipeline?

What data is there?

- Database data
- Activity data
 - Page Views, Ad Impressions, etc
- Messaging
 - JMS, AMQP, etc
- Application and System Metrics
 - Rrdtool, graphite, etc
- Logs
 - Syslog, log4j, etc

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

Michael Stonebraker
Computer Science and Artificial
Intelligence Laboratory, M.I.T., and
StreamBase Systems, Inc.
stonebraker@csail.mit.edu

Uğur Çetintemel
Department of Computer Science
Brown University, and
StreamBase Systems, Inc.
ugur@cs.brown.edu

Abstract

The last 25 years of commercial DBMS development can be summed up in a single phrase: "One size fits all". This phrase refers to the fact that the traditional DBMS architecture (originally designed and optimized for business data processing) has been used to support many data-centric applications with widely varying of multiple code lines causes various practical problems, including:

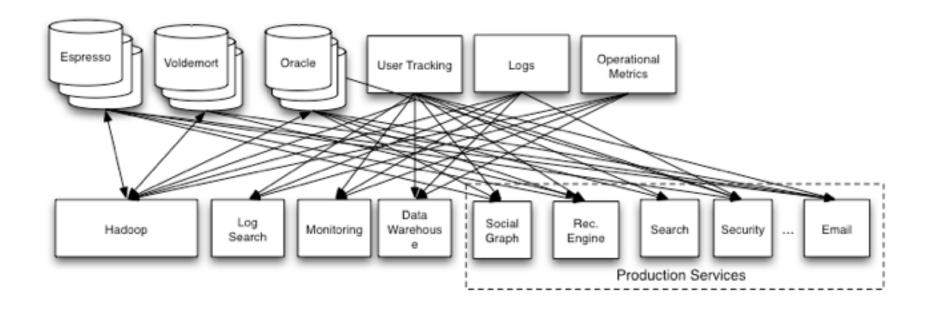
- a cost problem, because maintenance costs increase at least linearly with the number of code lines;
- a compatibility problem, because all applications have to run against every code line;
- a sales problem, because salespeople get confused

Data Systems at LinkedIn

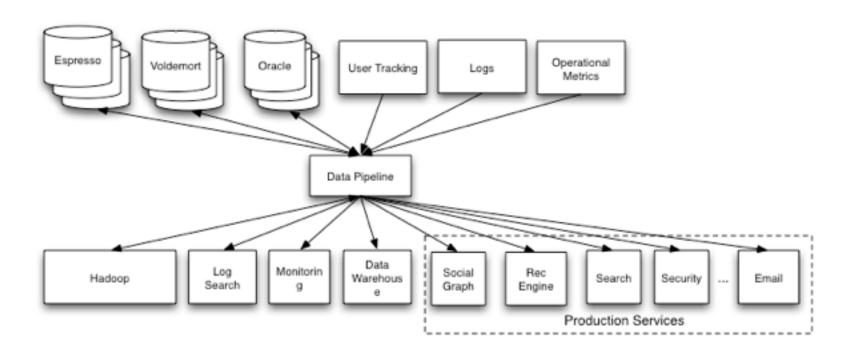
- Search
- Social Graph
- Recommendations
- Live Storage
- Hadoop
- Data Warehouse
- Monitoring Systems
- •

Problem: Data Integration

Point-to-Point Pipelines



Centralized Pipeline



How have companies solved this problem?

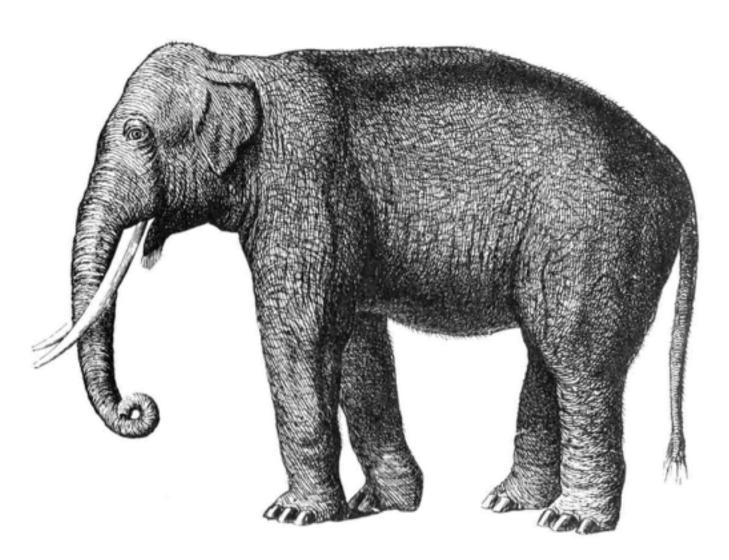
The Enterprise Data Warehouse



Problems

- Data warehouse is a batch system
- Central team that cleans all data?
- One person's cleaning...
- Relational mapping is non-trivial...

My Experience

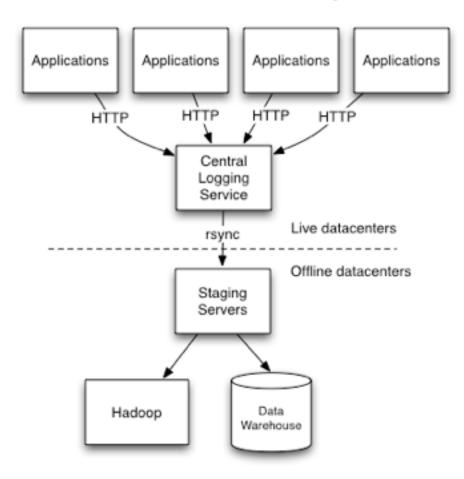


LinkedIn's Pipeline

LinkedIn Circa 2010

- Messaging: ActiveMQ
- User Activity: In house log aggregation
- Logging: Splunk
- Metrics: JMX => Zenoss
- Database data: Databus, custom ETL

2010 User Activity Data Flow



Problems

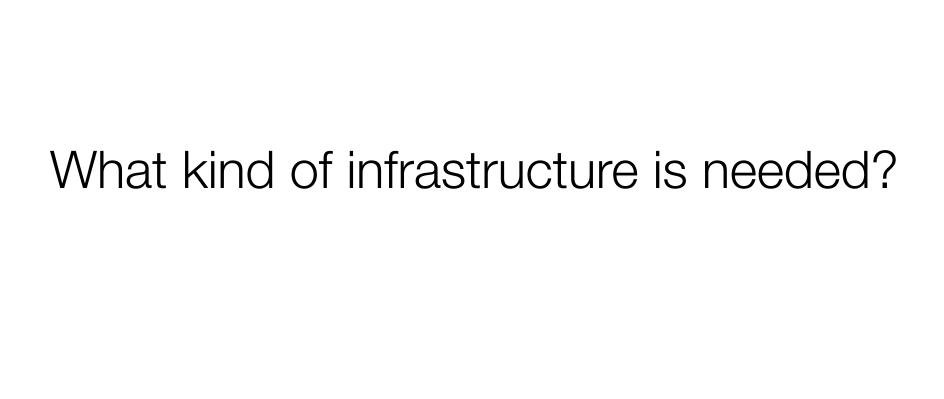
- Fragility
- Multi-hour delay
- Coverage
- Labor intensive
- Slow
- Does it work?

Four Ideas

- 1. Central commit log for all data
- 2. Push data cleanliness upstream
- 3. O(1) ETL
- 4. Evidence-based correctness

Four Ideas

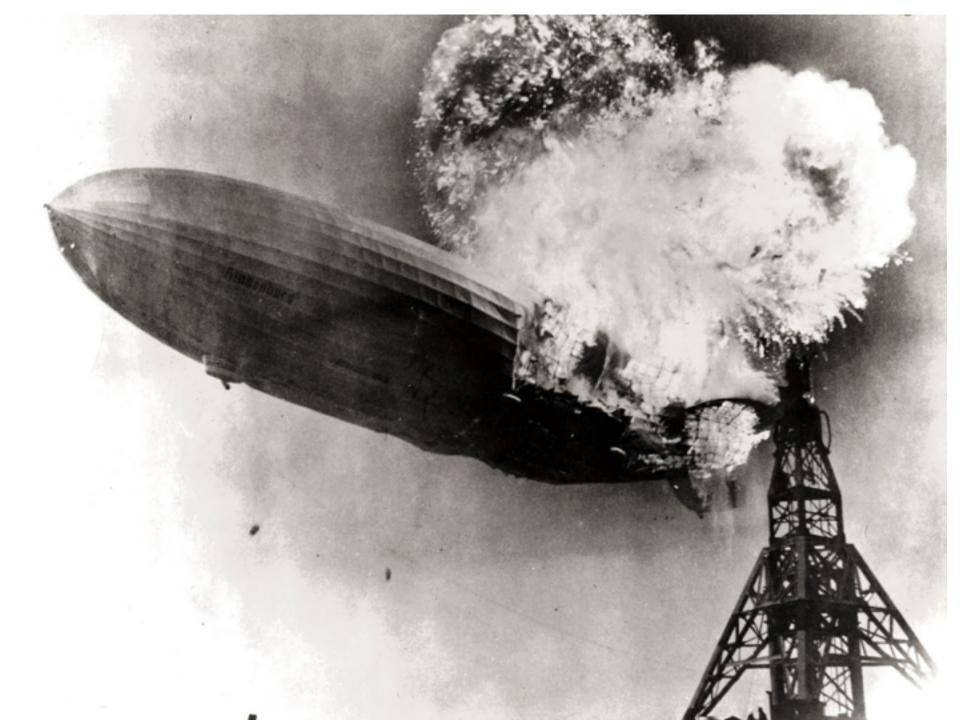
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Very confused

- Messaging (JMS, AMQP, ...)
- Log aggregation
- CEP, Streaming

First Attempt: Don't reinvent the wheel!



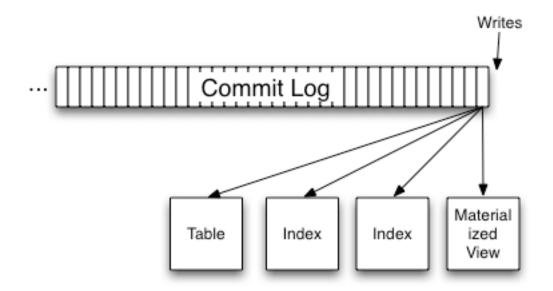
Problems With Messaging Systems

- Persistence is an afterthought
- Ad hoc distribution
- Odd semantics
- Featuritis

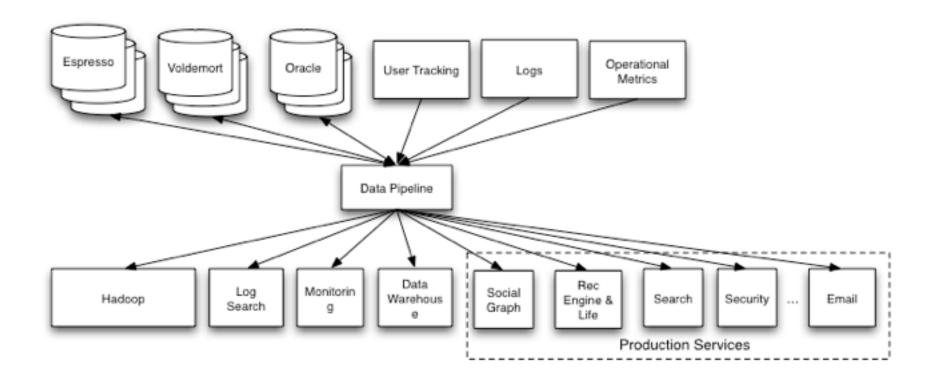
Second Attempt: Reinvent the wheel!

Idea: Central, Distributed Commit Log

What is a commit log?



Data Flow



Apache Kafka

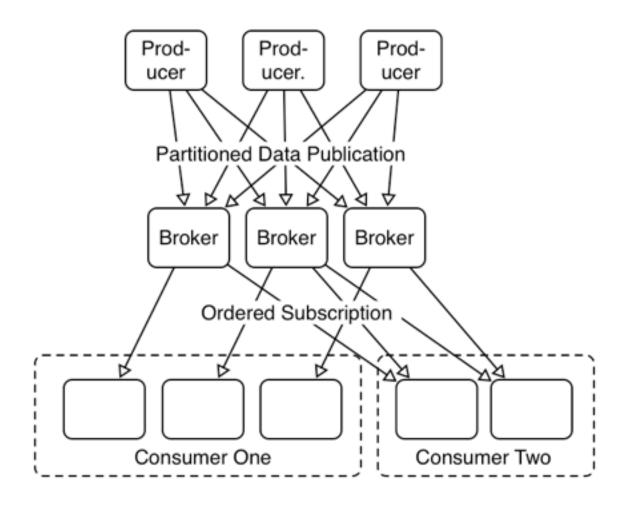
Some Terminology

- Producers send messages to Brokers
- Consumers read messages from Brokers
- Messages are sent to a Topic
- Each topic is broken into one or more ordered partitions of messages

APIs

- send(String topic, String key, Message message)
- Iterator<Message>

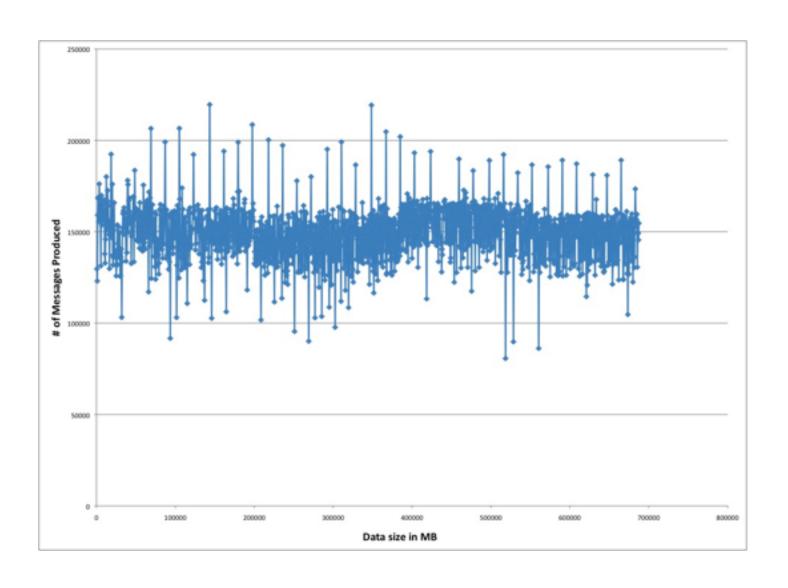
Distribution



Performance

- 50MB/sec writes
- 110MB/sec reads

Performance



Performance Tricks

- Batching
 - Producer
 - Broker
 - Consumer
- Avoid large in-memory structures
 - Pagecache friendly
- Avoid data copying
 - sendfile
- Batch Compression

Kafka Replication

- In 0.8 release
- Messages are highly available
- No centralized master

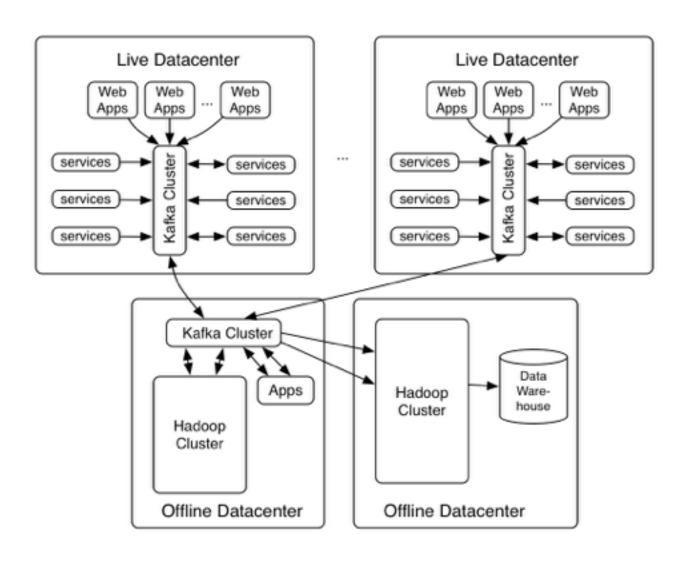
Kafka Info

http://incubator.apache.org/kafka

Usage at LinkedIn

- 10 billion messages/day
- Sustained peak:
 - 172,000 messages/second written
 - 950,000 messages/second read
- 367 topics
- 40 real-time consumers
- Many ad hoc consumers
- 10k connections/colo
- 9.5TB log retained
- End-to-end delivery time: 10 seconds (avg)

Datacenters



Four Ideas

- 1. Central commit log for all data
- 2. Push data cleanliness upstream
- 3. O(1) ETL
- 4. Evidence-based correctness

Problem

- Hundreds of message types
- Thousands of fields
- What do they all mean?
- What happens when they change?

Make activity data part of the domain model

Schema free?



LOAD 'student' USING PigStorage()
AS (name:chararray, age:int, gpa:float)

Schemas

- Structure can be exploited
 - Performance
 - Size
- Compatibility
- Need a formal contract

Avro Schema

- Avro data definition and schema
- Central repository of all schemas
- Reader always uses same schema as writer
- Programatic compatibility model



Workflow

- 1. Check in schema
- 2. Code review
- 3. Ship

Four Ideas

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Hadoop Data Load

- Map/Reduce job does data load
- One job loads all events
- Hive registration done automatically
- Schema changes handled transparently
- ~5 minute lag on average to HDFS

Four Ideas

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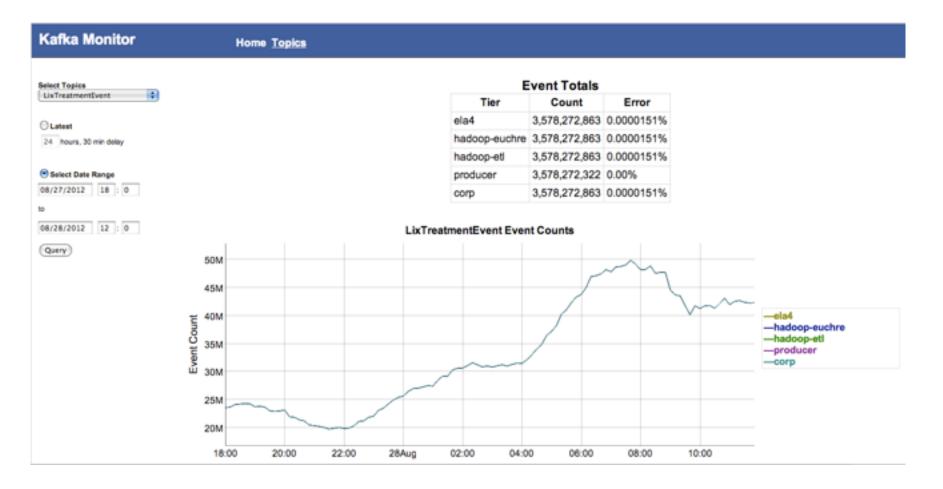
Does it work?

All messages sent must be delivered to all consumers (quickly)

Audit Trail

- Each producer, broker, and consumer periodically reports how many messages it saw
- Reconcile these counts every few minutes
- Graph and alert

Audit Trail



Questions?