The “Big Data” Ecosystem at LinkedIn

19-1-28

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Presenter: Camilo Muñoz

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Paper Background

- Lack of literature on productionizing machine learning workflows
- Data analytics and warehousing → Hive
- Ingress → Scribe (Twitter), Chukwa (Yahoo)
- Egress → Hbase, PNUTS (Yahoo)

Introduction

- LinkedIn +200 million users
- Data-driven features → collaborative filtering (*wisdom of the crowd*)
- Hadoop provides a rich ecosystem → horizontal scalability, fault tolerance, and multitenancy
- How to make life easier for machine learning researchers and data scientists

Let's talk Apache

The Data Ecosystem

- Online – Offline – Online. HDFS acts as the sink for all the data
- 2 types of incoming data → event data and core database snapshots
- From ETL Hadoop instance to dev and prod
- Researchers and DS define workflows to play with the data
- Data delivery → Key-value, Data Streams, and Analytics/OLAP
- Avro as the standard serialization format

Ingress

- Challenge to make data available without manual intervention → large datasets, diverse data, evolving functionalities, and data quality
- Kafka allows data publishers interact with consumers through topics
- Distribution of logical consumers for large data feeds → Zookeper

Ingress: Data Evolution

- Unstructured vs structured data
- LinkedIn uses a schema registry to map topics to schemas

Ingress: Hadoop Load

- Data pulled from Kafka brokers into Hadoop every 10 minutes
- Replication → from ETL cluster to prod and dev cluster
- LinkedIn maintains topics historic data
- 2 Kafka clusters for event data → primary (online services) and secondary (offline prototyping and data loading into Hadoop). Use of mirroring process for sync
- 100 TB = 300 topics
- 15 billion messages writes, 55 billion messages reads

Ingress: Monitoring

- Audit trail → assessment of correctness and latency
- Audit data: topic, machine name, time window, number of events
- Continuous audit → Programmed to alert if completeness is not reached in a fixed time

Workflows

- Workflow → Chain of MapReduce jobs. DAG
- Primary interfaces → Hive, Pig, and native MapReduce
- Common functionalities between workflows → creation of wrappers to read and write time-partitioned data

Workflows: Azkaban

- Configuration and dependencies for jobs are maintained as files of simple key-value pairs
- Researchers can edit, deploy, monitor, restart, setup notifications, and even capture logs and statistics
- Example: ML application → Each feature becomes an individual Azkaban job followed by a join of the output of these jobs into a feature vector.
- ADEV → test period → production review → APROD

Egress: Key-value access (70%)

- Voldemort → distributed key-value store with a simple get(key) and put(key, value) interface.
- Tuples are grouped into logical stores (tables). Keys are replicated. Nodes are split into logical partitions → A key is mapped to multiple partitions (hashing).

Serving Large-scale Batch Computed Data with Project Voldemort

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LinkedIn

Abstract

Current serving systems lack the ability to bulk load massive immutable data sets without affecting serving performance. The performance degradation is largely due to index creation and modification as CPU and memory resources are shared with request serving. We have extended Project Voldemort, a general-purpose distributed storage and serving system inspired by Amazon's Dynamo, to support bulk loading terabytes of read-only data. This extension constructs the index offline, by leveraging the fault tolerance and parallelism of Hadoop. Compared to MySQL, our compact storage format and data deployment pipeline scales to twice the request throughput while maintaining sub 5 ms median latency. At LinkedIn, the largest professional social network, this system has been running in production for more than 2 years and serves many of the data-intensive social features on the site.

You May Know" feature on LinkedIn runs on hundreds of terabytes of offline data daily to make these predictions.

Due to the dynamic nature of the social graph, this derived data changes extremely frequently—requiring an almost complete refresh and bulk load of the data, while continuing to serve existing traffic with minimal additional latency. Naturally, this batch update should complete quickly to engender frequent pushes.

Interestingly, the nature of this complete cycle means that live updates are not necessary and are usually handled by auxiliary data structures. In the collaborative filtering use case, the data is purely static. In the case of "People You May Know", dismissed recommendations (marked by clicking "X") are stored in a separate data store with the difference between the computed recommendations and these dismissals calculated at page load.

This paper presents read-only extensions to Project Voldemort, our key-value solution for the final serving

Egress: Stream-oriented access (20%)

- Useful for applications that need a change log of the underlying data.
- Hadoop OutputFormat

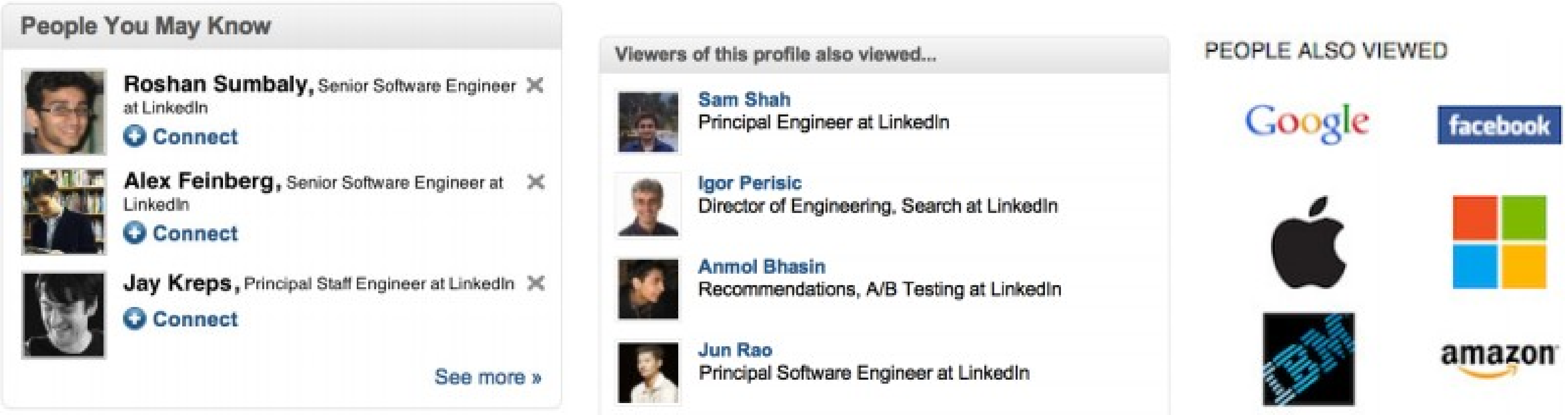
Egress: OLAP access (10%)

- Avatara separates cube generation (high throughput) and query serving (low latency)
- Large cubes are split into ‘small cubes’ using shard key

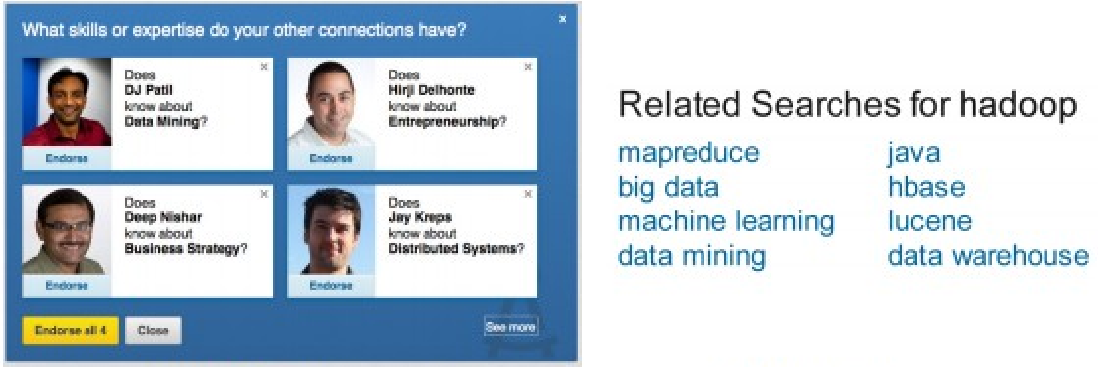
Applications: Key-value

- People You May Know → Link prediction problem. Key = member ID, Value = list of member ID, score
- Collaborative Filtering → Association rule mining, member-to-member, member-to-company. Key = <entity ID, entity type>, Value = top related entity pairs.
- Skill Endorsements → Def inion of a Taxonomy (e.g., "Rails" is the same as "Ruby on Rails"). Key = member ID, Value = <member ID, skill ID, score>.
- Related Searches → Member search activity. Key = <term ID, local>, Value = search term

Applications: Key-value



(a) "People You May Know" (b) Collaborative Filtering



(c) Skill Endorsements (d) Related Searches

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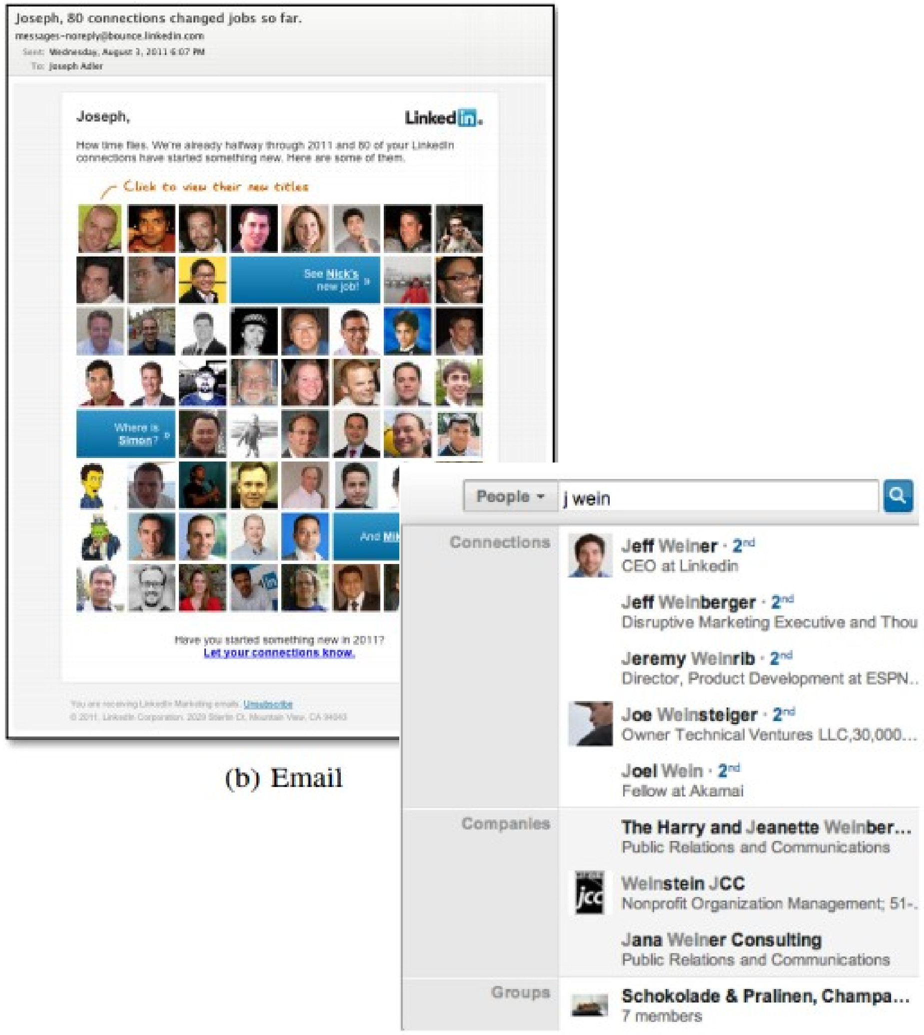
Applications: Streams

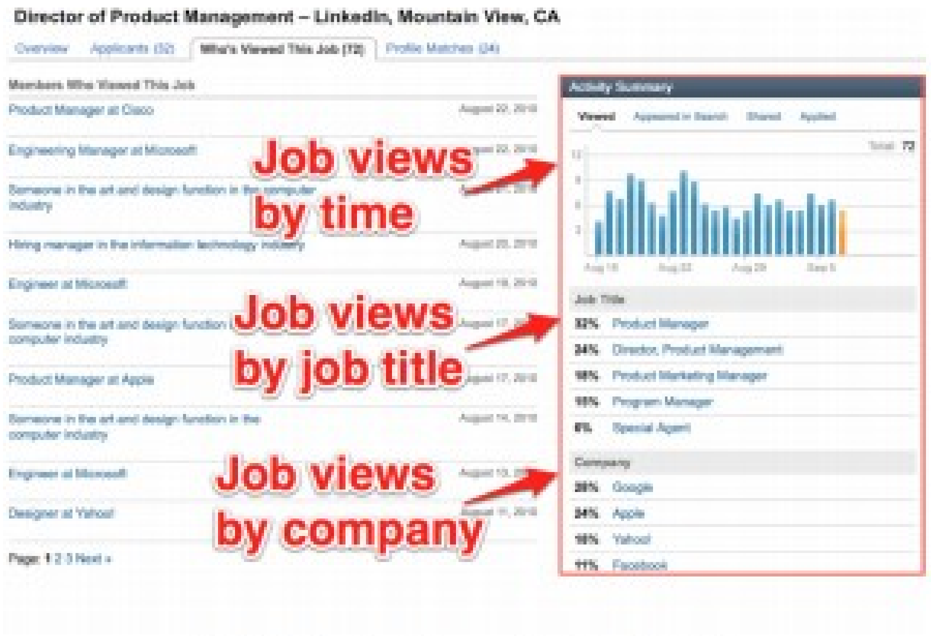
- News Feed Updates → A connection updates her profile, company that most of a member's former coworkers now work for
- Email → Online or offline. Examples: password recovery, joining a group, weekly digest.
- Relationship Strength → LinkedIn's social graph edge scoring. Examples: best path in the graph, search typeahead, search suggestions



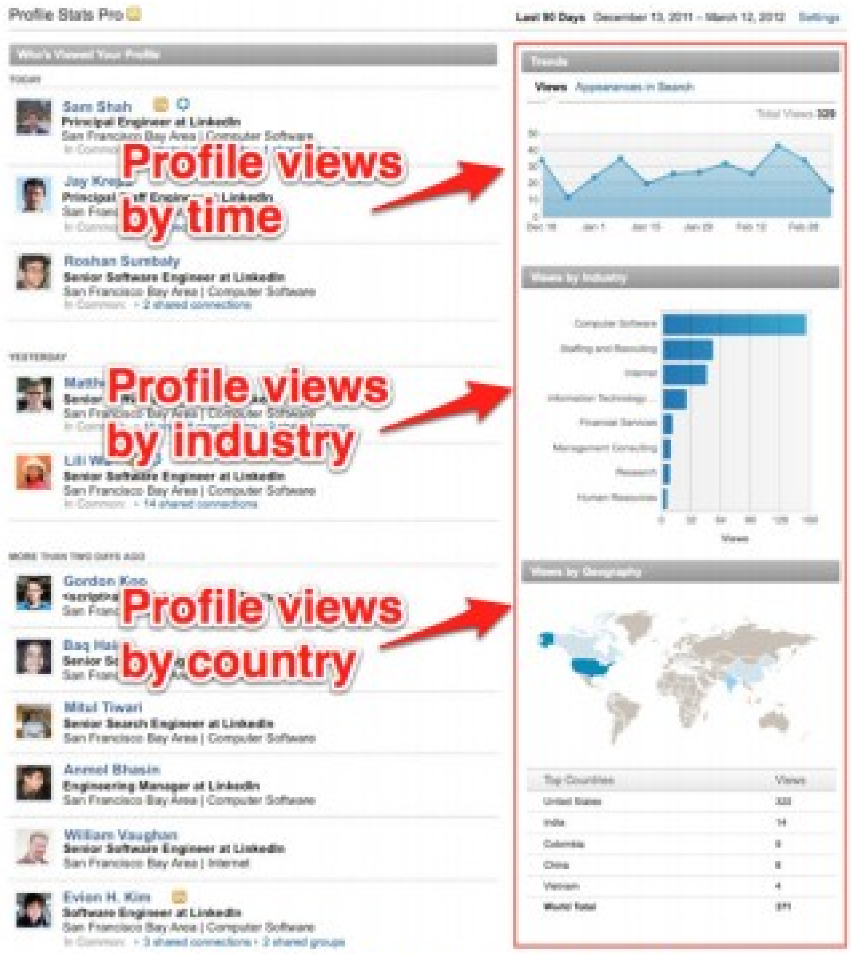
(b) Email
(c) Typeahead

Applications: OLAP

- Who’s Viewed My Profile?
- Who’s Viewed This Job?



(b) "Who’s Viewed This Job?"



(a) "Who’s Viewed My Profile?"

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Key Take away

A rich developer ecosystem empowers machine learning researchers and data scientists to productionize their work → Their focus is to build data products

Big Data Ecosystem at Linked

Mitul Tiwari • PREMIUM

Staff Research Engineer and Engineering Manager at LinkedIn

San Francisco Bay Area | Computer Software

Current	LinkedIn
Previous	Kosmix, Google, Microsoft
Education	The University of Texas at Austin

Big 2015 at WWW

Outline

- Data Ingress
  - Moving data from online to offline system
- Data Processing
  - Batch processing using Hadoop, Azkaban, Cubert
  - Stream processing using Samza
  - Iterative processing using Spark

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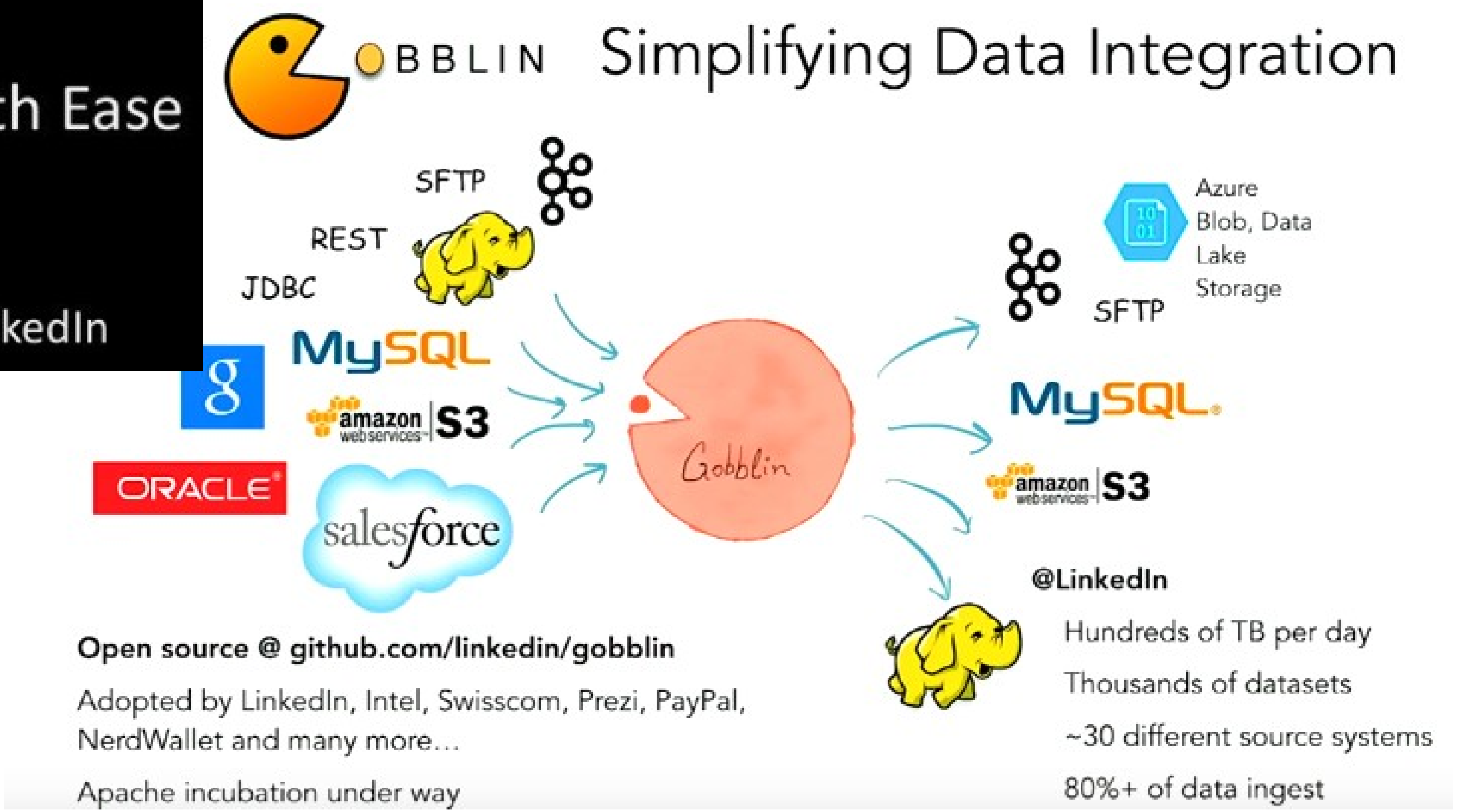
OBBLIN
Gobblin’ Big Data with Ease
Lin Qiao
Data Analytics Infra @ LinkedIn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Hundreds of TB per day
Thousands of datasets
~30 different source systems
80%+ of data ingest
Open source @ github.com/linkedin/gobblin
Adopted by LinkedIn, Intel, Swisscom, Prezi, PayPal, NerdWallet and many more…
Apache incubation under way

Discussion

- How about empowering prototyping and feature testing?
- Trade-off between in-house infrastructure and on the cloud infrastructure
- Is there a better replication schema than ETL+Dev+Prod?