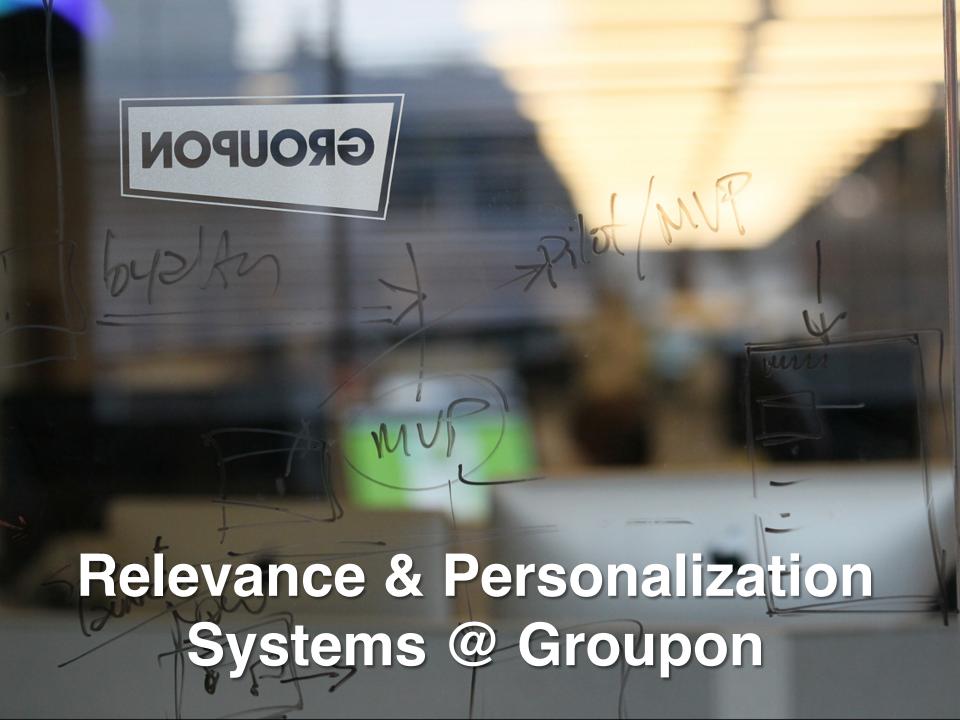


Deal Personalization Systems @ Groupon

GROUPON®

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What are Groupon Deals?



Our Relevance Scenario

Users





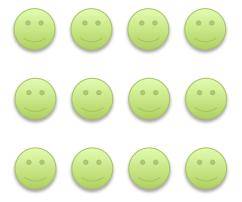






Our Relevance Scenario

Users



How do we surface relevant deals?

- Deals are perishable (Deals expire or are sold out)
- No direct user intent (As in traditional search advertising)
 - Relatively Limited User Information
 - Deals are highly local









Two Sides to the Relevance Problem

Algorithmic Issues

How to find relevant deals for individual users given a set of optimization criteria

Scaling Issues

How to handle relevance for all users across multiple delivery platforms



Developing Deal Ranking Algorithms

Exploring Data

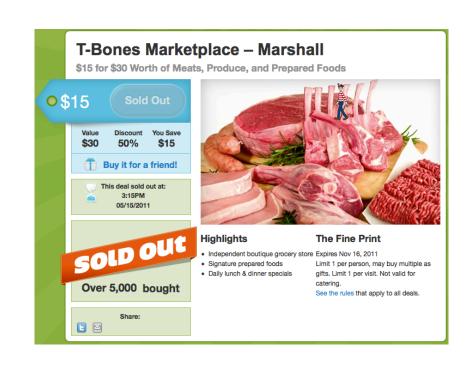
 Understanding signals, finding patterns

Building Models/Heuristics

 Employ both classical machine learning techniques and heuristic adjustments to estimate user purchasing behavior

Conduct Experiments

 Try out ideas on real users and evaluate their effect





Data Infrastructure

Growing Deals

2011



20 +

2012



400+

2013



2000 +

Growing Users

- 100 Million+ subscribers
- We need to store data like, user click history, email records, service logs etc. This tunes to billions of data points and TB's of data

Deal Personalization Infrastructure Use Cases

Deliver Personalized Emails

Deliver Personalized Website & Mobile Experience







Personalize billions of emails for hundreds of millions of users

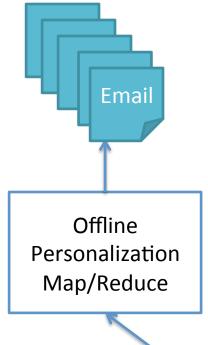
Personalize one of the most popular e-commerce mobile & web app for hundreds of millions of users & page views

Offline System

Online System



Earlier System

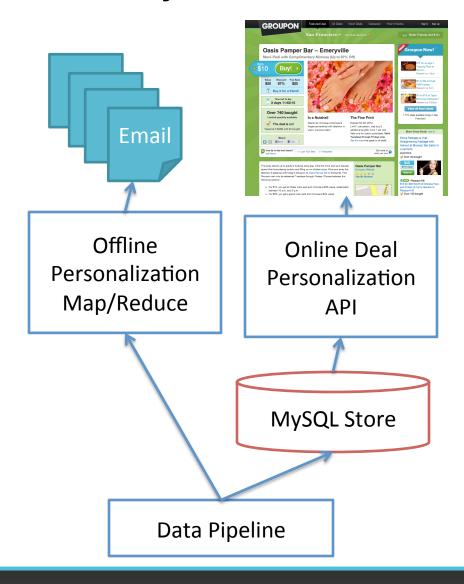




Data Pipeline (User Logs, Email Records, User History etc)



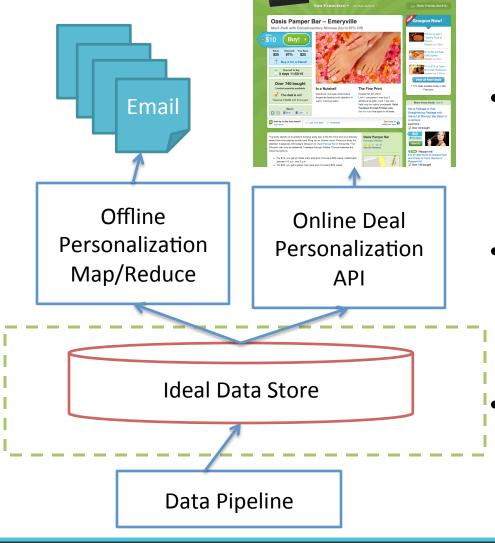
Earlier System



- Scaling MySQL for data such as user click history, email records was painful unless we shard data
- Need to maintain two separate data pipelines for essentially the same data.



Ideal System



- Common data store that serves data to both online and offline systems
- Data store that scales to hundreds of millions of records
- Data store that plays well with our existing hadoop based systems
- Data store that supports get() put() access patterns based on a key (User ID).

Why HBase?

- Open Source distributed map data store modeled after Google's Big Table
- Distributed Data Store: Store data on 1-700 node cluster. Linear scaling. Add capacity by adding more machines.
- Very light schema. Each row may have any number of columns. Columns need not be defined upfront.
 (Something like: Row1-> Map<byte[], byte[])

Why HBase?

- Consistent Database. Highly available. Automatically shards/ scales. Can scale to billions of rows and multi terabyte data sizes
- Writes: 1-10 ms, Reads 20-50 ms
- Tight out of the box integration with Hadoop and Map Reduce

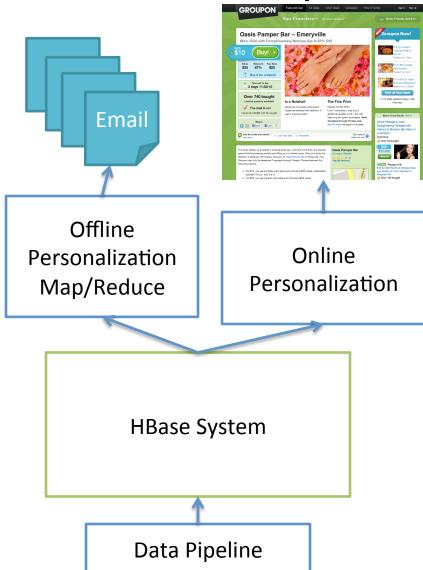


HBase Table

Row	Cf: <qual></qual>	Cf: <qual></qual>	••••	Cf: <qual></qual>
row1	Cf1:qual1	Cf1:qual2		
row11	Cf1:qual2	Cf1:qual22	Cf1:qual3	
row2	Cf2:qual1			
rowN				

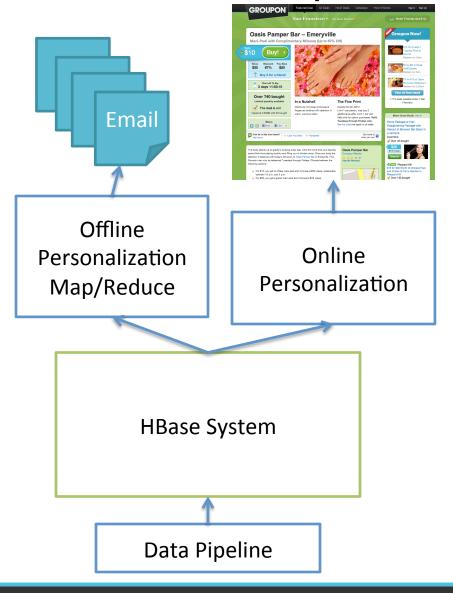


Architecture Options





Architecture Options



Pros

- Simple design
- Consolidated system that serves both online and offline personalization

Architecture Options



Offline
Personalization
Map/Reduce



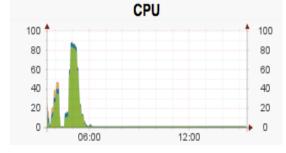
Online Personalization

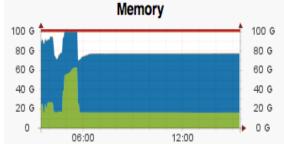
Cons

- We now have same uptime
 SLA on both offline and online
 system
- Maintaining online latency SLA for bulk writes and bulk reads is hard.

And here is why...

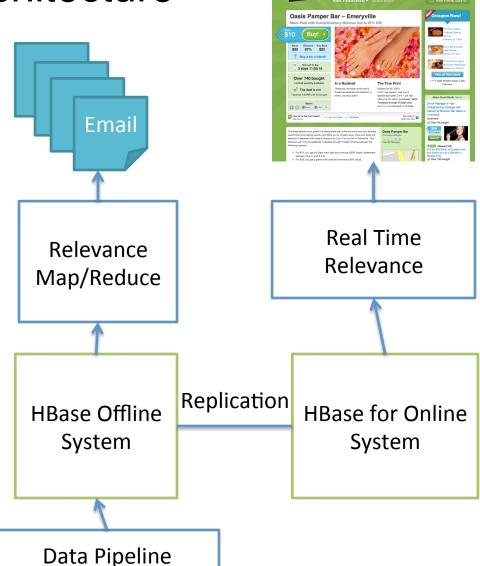
HBase System





Data Pipeline

Architecture



- We can now maintain different SLA on online and offline systems
- We can tune HBase cluster differently for online and offline systems



HBase Schema Design

User ID	Column Family 1	Column Family 2
Unique Identifier for Users	User History and Profile Information	Email History For Users

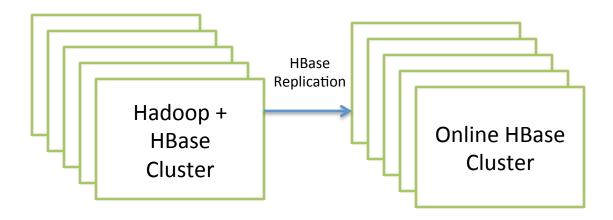
Overwrite user history and profile info

Append email history for each day as a separate columns. (On avg each row has over 200 columns)

- Most of our data access patterns are via "User Key"
- This makes it easy to design HBase schema
- The actual data is kept in JSON



Cluster Sizing



100+ machine Hadoop cluster, this runs heavy map reduce jobs The same cluster also hosts 15 node HBase cluster

10 Machine dedicated HBase cluster to serve real time SLA

- Machine Profile
- 96 GB RAM (HBase 25 GB)
- 24 Virtual Cores CPU
- 8 2TB Disks
- Data Profile
- 100 Million+ Records
- 2TB+ Data
- Over 4.2 Billion Data Points

Other Takeaways

- Choose data storage format carefully. (We are using JSON, but one can consider Avro, Protobufs etc)
- Always store compressed data. We use LZO, its easy to map reduce
- Always store processed data in HBase.
- HBase needs some tuning before it scales. Tuning garbage collection is important. So is various timeouts and caching parameters, cluster can be unstable without these tuning parameters.

Questions?

