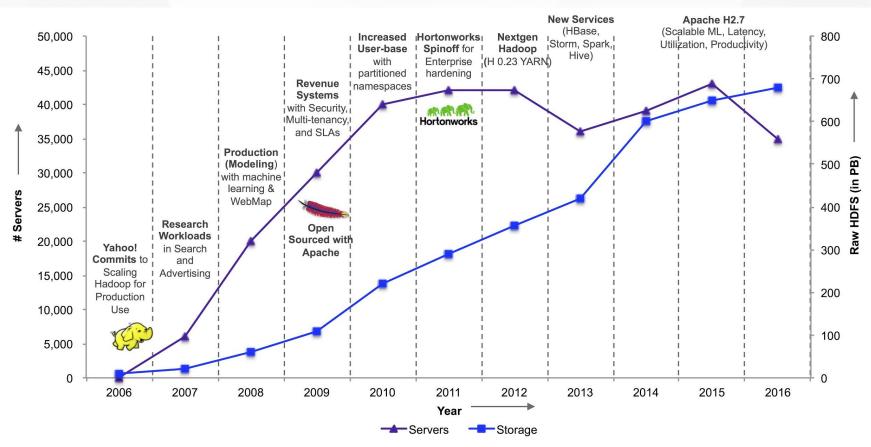


Andy Feng Yahoo

Hadoop at Yahoo



Real-time Processing at Yahoo

Big-Data Applications

Weather App



Beauty

> Computational assessed

• Relevant

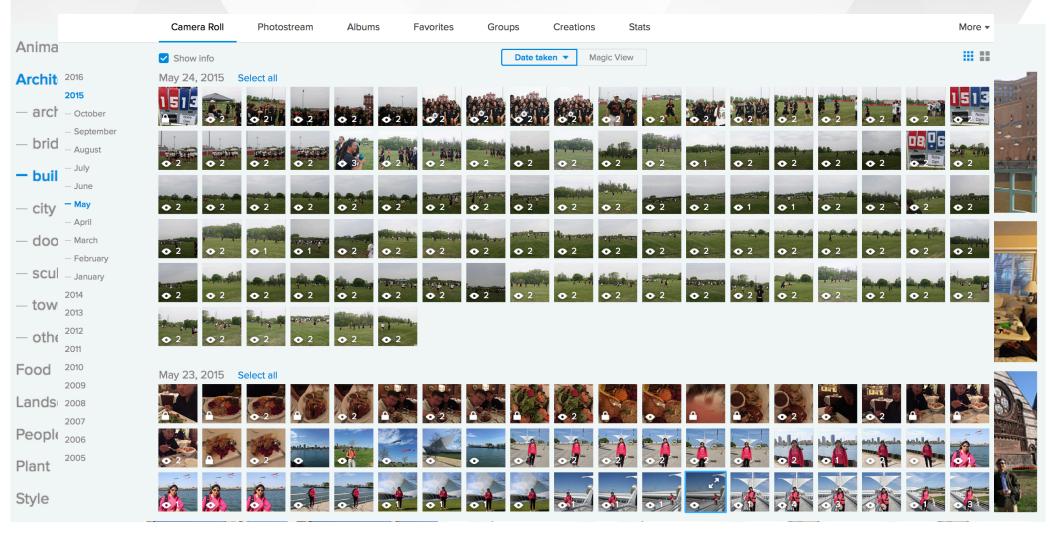
- > Location
- > Time
- > Cloudy
- > Shower
- > ...



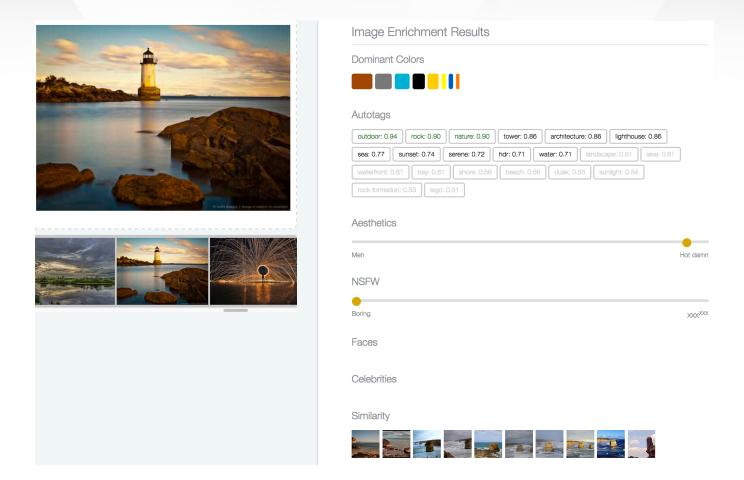
Yahoo Weather App



Flickr flickr.com/cameraroll

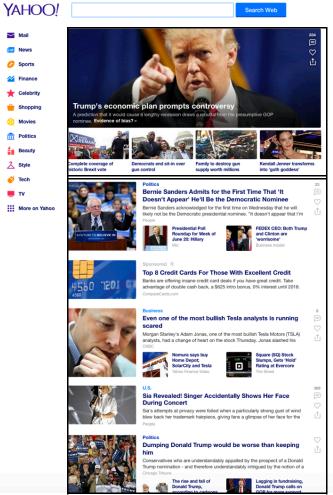


Yahoo Vision Kit









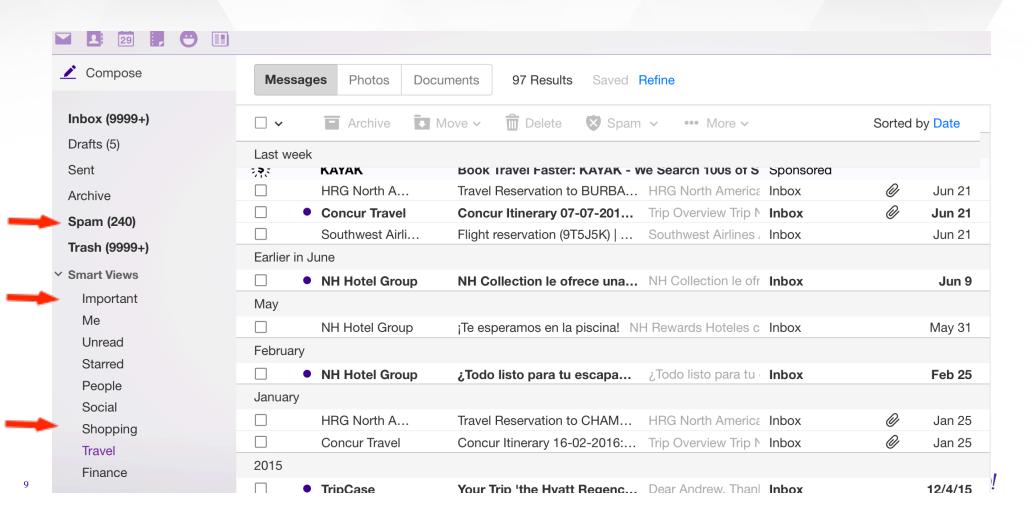


Content augmentation
User profiling
Recommendation

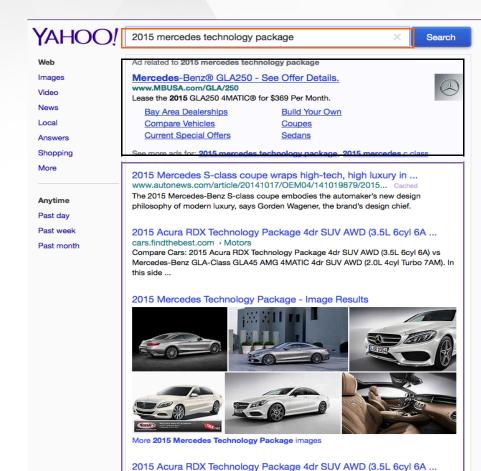




Mail Smart Views



Search



Compare Cars: 2015 Acura RDX Technology Package 4dr SUV AWD (3.5L 6cyl 6A) vs Mercedes-Benz GLK-Class GLK350 4MATIC 4dr SUV AWD (3.5L 6cyl 7A). See all the ...

cars.findthebest.com > Motors

See more ads for: 2015 mercedes technology package 2015 mercedes c class disney world vacation packages

Andrew Corp

mercedes benz gla 2015

disney vacation packages 2015

Ads

2015 Mercedes-Benz S550 FleetRates.com

mercedes gla 2015

New Rebate Now \$699/mo \$82,275 Low Prices Nationwide Delivery

2015 Mercedes

Edmunds.com

www.Edmunds.com

*** 78 reviews

Research, Reviews, Pricing & More. Edmunds.com® - Ask the Car People!

Top-Rated SUVs 2015

educatehow.com/Savings

Explore the Best New SUVs for 2015. Compare Prices & Specs.

Query intention

Page ranking

Ads matching



Yahoo Search2Vec: Big Data & Machine Learning http://bit.ly/28SLdjU

Bucket Tests	Query Coverag e	Auction Depth	Revenue per Search
Simple model vs. Baseline	+1.14%	+2.13%	+7.07%
Large model vs. Baseline	+3.61%	+4.57%	+17.12%

Big-Data Innovations

Technology Stack

Scalable Database	·	Scalable Inalytics	Scala Machi Learn	ine	Scalable Deep Learning
Batch Compu Hadoop	te:	Iterative Compute: Spark		Real-Time Compute: Storm	
CPUs (CORE-17) YARN GPUS (CORE-17) GPUS					
		НС)FS [

Flickr Pipeline: 10B photos, 8M per day

(1) (2) (3) (4) (5) Feature Non-deep **Product** Deep **Apply** Engineering Learning Learning Model Integration @ Scale @ Scale @ Scale @ Scale @ Scale



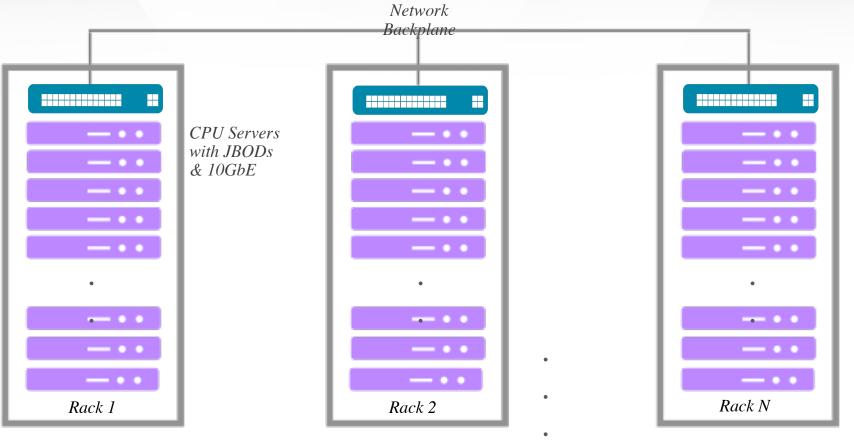




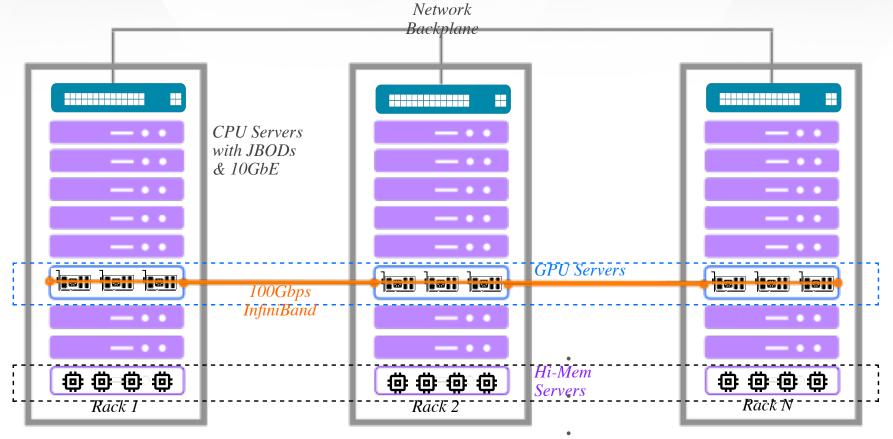


* http://bit.ly/1KIDfof by Pierre Garrigues, Deep Learning Summit 2015

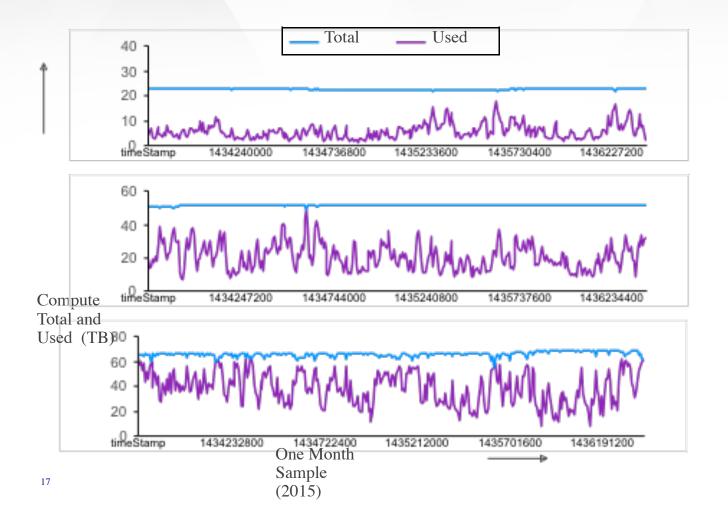
System Configuration: Homogenous Clusters



System Configuration: Heterogeneous Clusters http://bit.ly/295RNbU



Resource Allocation: Early Days



Cluster 1 (2,000 servers)

HDFS 12 PB Memory 23 TB Avg. Util: 26%

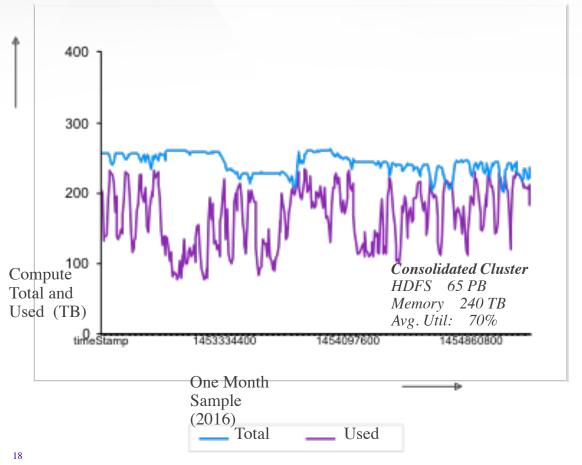
Cluster 2 (3,100 servers)

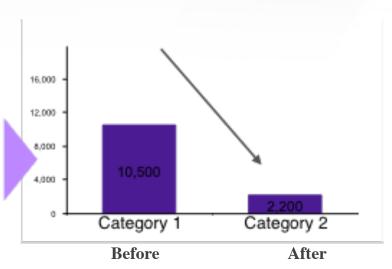
HDFS 21 PB Memory 52 TB Avg. Util: 40%

Cluster 3 (5,400 servers)

HDFS 36 PB Memory 70 TB Avg. Util: 59%

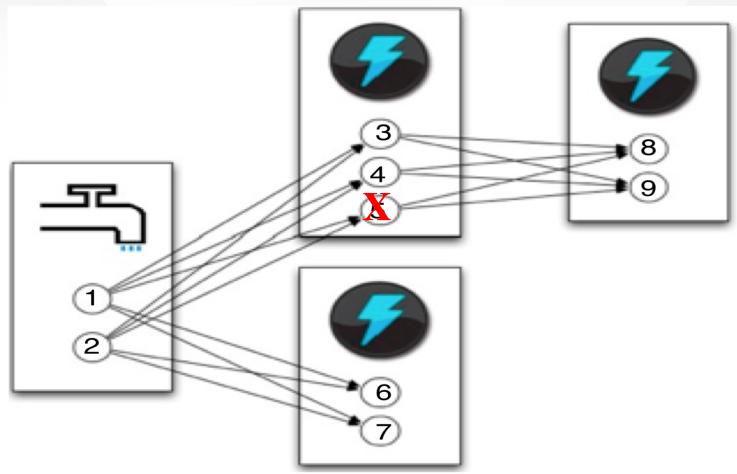
Resource Allocation: 40% decrease in TCO http://bit.ly/295RNbU



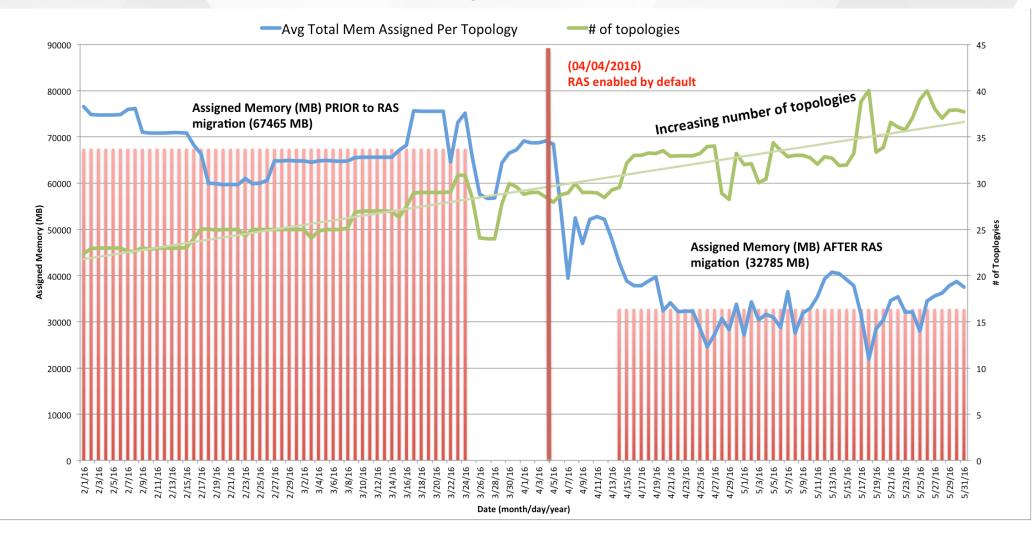


65% increase in compute capacity50% increase in avg. utilization

Apache Storm: Real-time Processing https://storm.apache.org

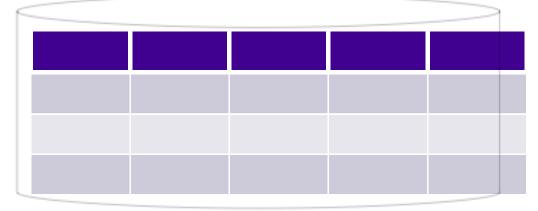


Resource Aware Scheduling: 100% increase utilization



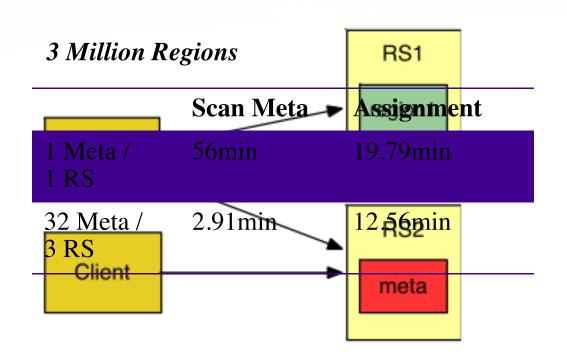
Apache HBase: NoSQL Database for Hadoop https://hbase.apache.org

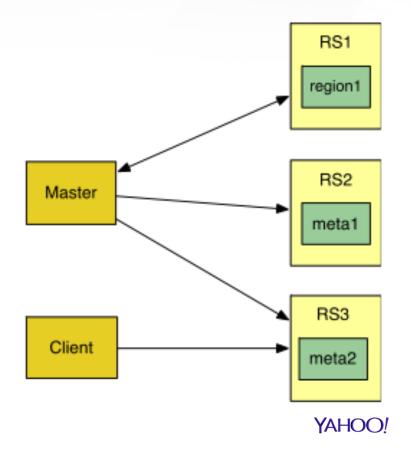




- Several million regions (partitions of tables)
- 800 region servers

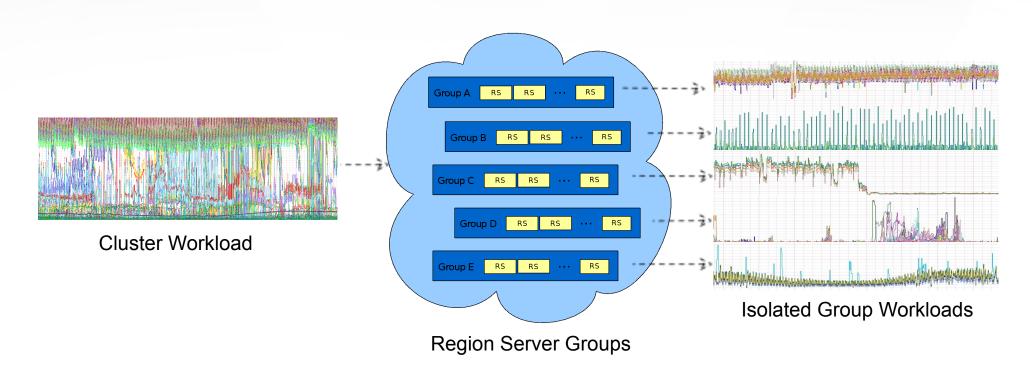
Support Millions of Regions http://bit.ly/29hlLFW





22

HBase Multi-tenancy & Isolation http://bit.ly/28YK4a7



Apache Omid: Transactions for NoSQL DB http://omid.incubator.apache.org



- Multi-row/multi-table transactions
- Snapshot isolation
- Lock-free

Omid: Transactional HBase App

```
TransactionManager tm = HBaseTransactionManager.newBuilder().build();

Transaction tx = tm.begin();

Put row1 = new Put(Bytes.toBytes("EXAMPLE_ROW1"));

row1.add(family, qualifier, Bytes.toBytes("VALUE_1"));

tt.put(tx, row1);

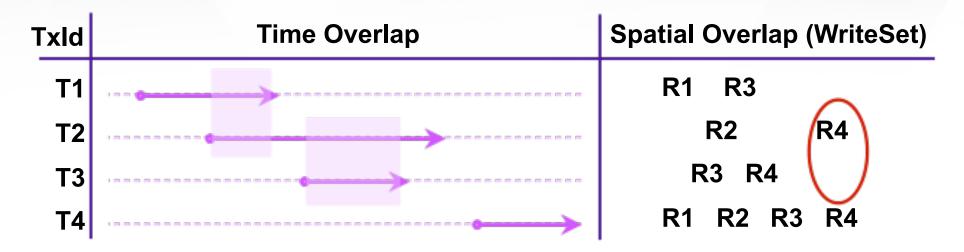
Put row2 = new Put(Bytes.toBytes("EXAMPLE_ROW2"));

row2.add(family, qualifier, Bytes.toBytes("VALUE_2"));

tt.put(tx, row2);

tm.commit(tx);
```

Omid: Snapshot Isolation http://bit.ly/28YZvQF



- T2 overlaps in time with T1 & T3, but
- Spatially T1 \cap T2 = \varnothing \rightarrow T1 and T2 can both commit.
- Spatially $T2 \cap T3 = \{R4\}$ \rightarrow T2 or T3 will abort.

Machine Learning: Search2Vec http://bit.ly/28SLdjU

Input: Training Data

gas_caps gas_cap_replacement_for_car slc_679f037d
 gas_door_replacement_for_car slc_466145af1 fuel_door_covers
 adid_28540536 slc_348709d7 autozone_auto_parts adid_33183157
 auoto_zone slc_8dcdab5d slc_58f979b6

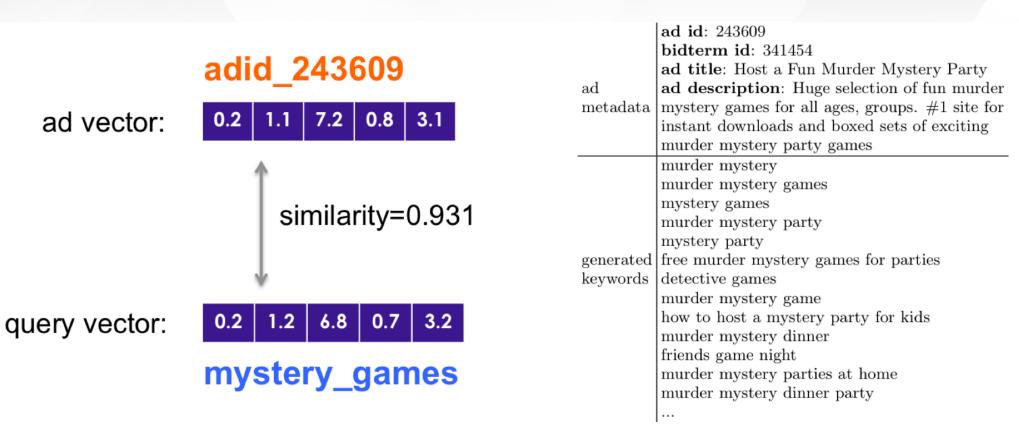
S2: hoka_running shoe_reviews adid_22830711 hoka_shoes_for_bad_feet hoka_shoes_amazon slc_231gfaw zappos_shoes slc_7c126f71 hoka_walking_shoes

\$\frac{1}{2}\$: \text{king_tut_exhibit_king_tut_exhibit_seattle_2015 slc_726y6j51 charlies_seattle_adid_55774014}\$

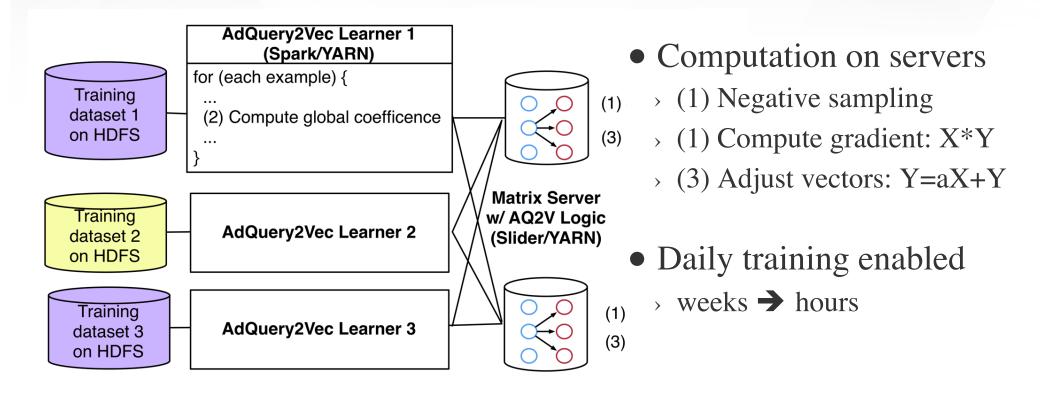
Output: Numeric Vectors aueries & ads

Of queries & ads Vector("san jose weather") ≈ Vector("weather 95113") ≈ Vector(ad123)

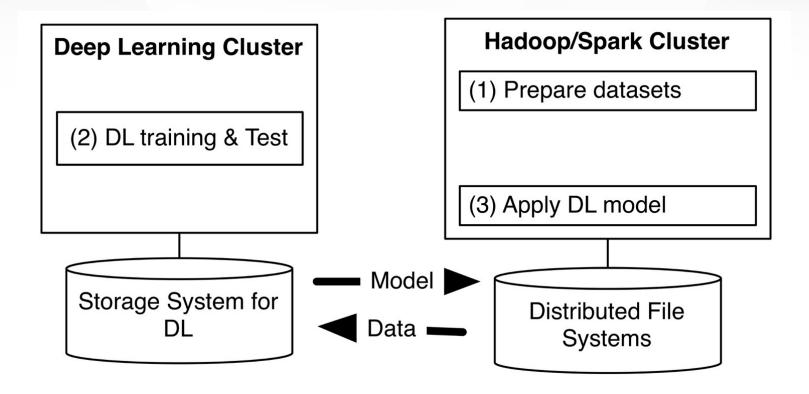
Search2Vec: Cosine similarity b/w ads and queries



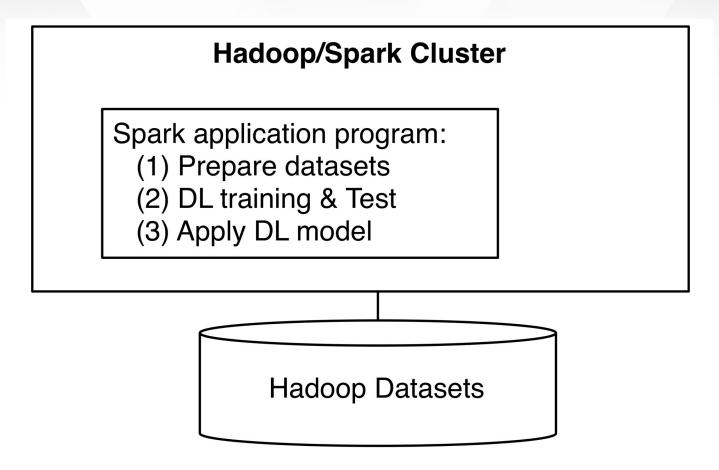
Search2vec: 300M Unique Queries/Ads/Links



Deep Learning: Previous Practice



Scalable Deep Learning for Big Data



CaffeOnSpark Open Sourced



github.com/yahoo/CaffeOnSpark

- Released in Feb. 2016
 - Apache 2.0 license
- Distributed deep learning
 - GPU or CPU
 - Ethernet or InfiniBand
- Easily deployed on public cloud or private cloud

CaffeOnSpark: One Notebook http://bit.ly/1REZ0cN

File Edit View Insert Cell Kernel Help Python 2 O

Logistic Regression using MLlib

```
In [57]: from pyspark.mllib.linalg import Vectors
         from pyspark.mllib.regression import LabeledPoint
         from pyspark.mllib.classification import LogisticRegressionWithLBFGS
In [58]: data = f.map(lambda row: LabeledPoint(row.label[0], Vectors.dense(row.ip1)))
In [59]: lr = LogisticRegressionWithLBFGS.train(data, numClasses=10, iterations=10)
In [60]: predictions = lr.predict(data.map(lambda pt : pt.features))
In [61]: predictions.take(5)
Out[61]: [7, 2, 1, 0, 4]
                       [1.0] [1.3683326, -0.0,... [2.0906663, 1.048... [2.0]]
           000000001
                       [1.0] [1.5641443, -0.0, ...] [-0.773368, 10.61...] [1.0]
           00000002
           000000031
                       [1.0] [-0.0, 1.9505613, ...] [16.46351, -6.917...] [0.0]
                       [1.0] [0.5979191, 0.075... [-0.48371825, -2.... [4.0]]
           00000004
In [45]: dl train source = DataSource(sc).getSource(cfg,True)
In [46]: cos.train(dl train source)
```

Datasets for YOU

Data, Data, Data.

- Machine learning is all about data
- More data → Better model
- Industrial researchers work on large-scale data
- Academic researchers need data, too ⊗

Yahoo Webscope Datasets

Categories	datatype	# of datasets
L: Language Data	1	25
G: Graph and Social Data	g	8
R: Ratings and Classification Data	r	10
A: Advertising and Market Data	a	4
C: Competition Data	c	3
S: Computing Systems Data	S	4
I: Image Data	i	5

- Ex. https://webscope.sandbox.yahoo.com/catalog.php?datatype=r
- Non-commercial use by academics and scientists: 8,000+

L5 - Query Vectors

- 8M query vectors trained using our search2vec system
- May serve as a testbed for query rewriting task
 - > IR research
 - > Word and sentence similarity task in NLP research

Method	oAUC	Macro NDCG@5
word2vec	0.817	0.929
search2vec	0.880	0.959

I3 - Flickr Creative Commons

- 100M Flickr photos & videos
- Largest public multimedia dataset ever released
- ImageNet ... 14M images
- Metadata
- Tags, title, des & geo
- 68M photos have at least one tag
- Comments, favorites, social network data queried via Flickr API



Tags: Ocean Beach, San Francisco, Pacific, Surf, surfing, waves, green, water, man, surfer, January, océan, le surf, vagues, mer, sea Description: "My soul is full of longing for the secret of the sea,

and the heart of the great ocean sends a thrilling pulse through me." — Henry Wadsworth

Summary

- Big-data technologies and continued innovation are critical for Yahoo business.
- Yahoo continues open source contribution ever since our donation of Hadoop to Apache
 - > Apache Spark/Storm/Hbase/Omid, CaffeOnSpark
 - > Webscope datasets

YAHOO:

Thanks!
yahoohadoop.tumblr.com
bigdata@yahoo-inc.com

