Large-Scale Click-stream and transaction log mining in practice

Uwe Mayer, Nish Parikh, Gyanit Singh

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BIG DATA SCIENCE

Best Practices

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Key Ideas

- Big Data Sets
- Big Data Properties
- Challenges in working with big data
- Practical Solutions
- Leveraging Hadoop
- Case Studies

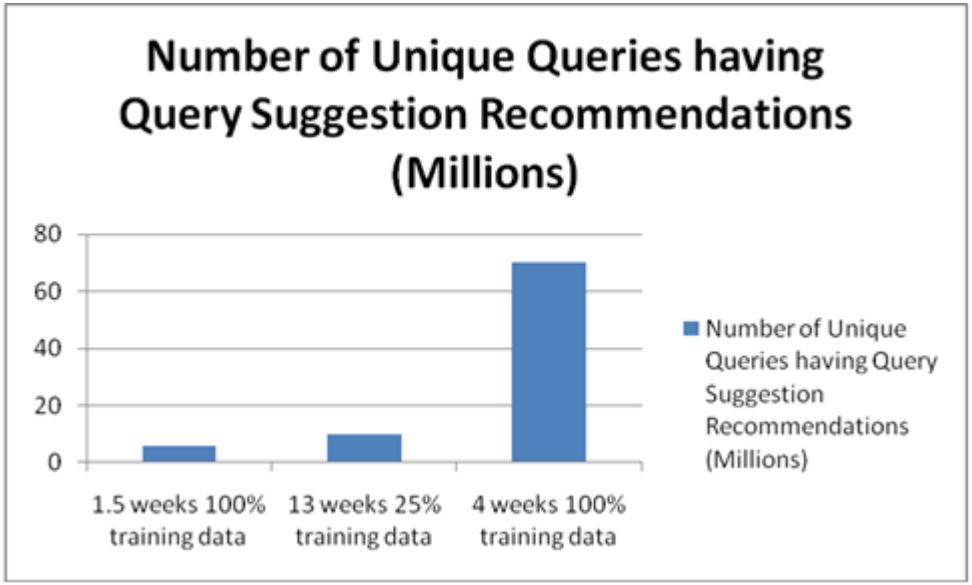
Types of Data Used in this Tutorial

- Click-stream logs
  - PetaByte Scale
- Transactional Data
  - TeraByte Scale
  - More than ½ B items for sale

BEST PRACTICES USED IN PRESENTED CASE STUDIES

- Data Cleaning
  - Taking care of bad data
  - Importance of domain knowledge
- Data Sampling
  - Reservoir sampling
- De-duplication
- Normalization
- Handling Idiosyncrasies of long-tail data
- Understanding Tractability of Algorithms
- Efficiency at scale
- Bucketing data in the right way
- Bias Removal
  - System bias
  - Platform bias
  - User bias
- Handling curse of dimensionality

More Data is Good



But it needs to be used carefully

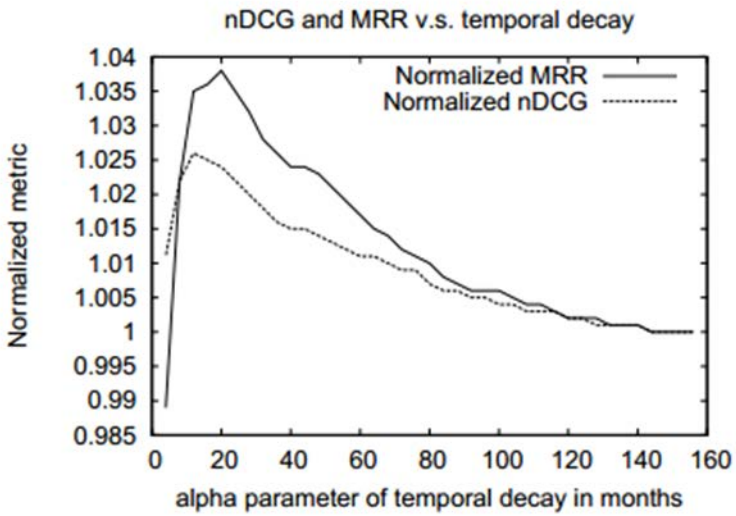


Figure 3: Describes the effect of the parameter α on nDCG and MRR. The peak is for the value of 12 months. The metrics obtained by using temporal decay are normalized against those obtained without using temporal decay. The early dip shows that as we increase lookback into history we get better coverage and precision upto a certain point. We observe that using large corpuses of historical data leads to better coverage for intent inference. Also, the best prediction accuracy is achieved, when the past one year data is considered to be highly and equally relevant (α = 12 months) and the data beyond the one year period is weighted by decaying exponentially ($\beta = 25$). α and β are chosen through heuristical parameter sweeping techniques maximizing the prediction metrics over queries in Q_{low}.

QUERY SUGGESTIONS

At Scale over Hadoop

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Query Suggestions on the web

Something different

yahoo
altavista
lycos
excite
hotbot

Searches related to **google**

google **translate**
google **desktop**
google **jobs**
google **maps**
google **docs**
google **images**
google **search**
google **voice**

RELATED SEARCHES

Warren Buffett **Personal Holdings**
Warren Buffett **Interview**
Warren Buffett **Family**
Warren Buffett **Email**
Warren Buffett **Taxes**
Warren Buffett **Stocks**
Oprah Winfrey
Berkshire Hathaway

Related Searches

guild wars
abyssal chronicles
diablo iii
blizzard
sclegacy

"ansel adams"

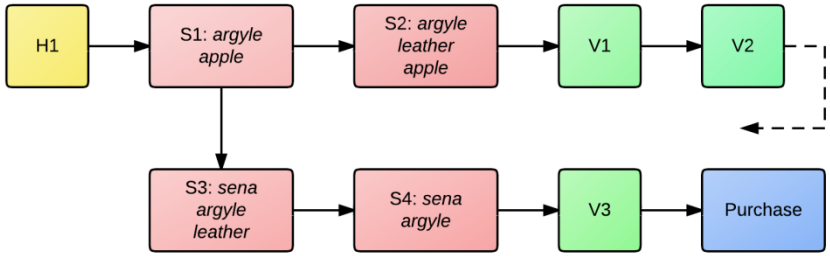
Related Searches: ansel adams framed prints, ansel adams poster, ansel adams prints.

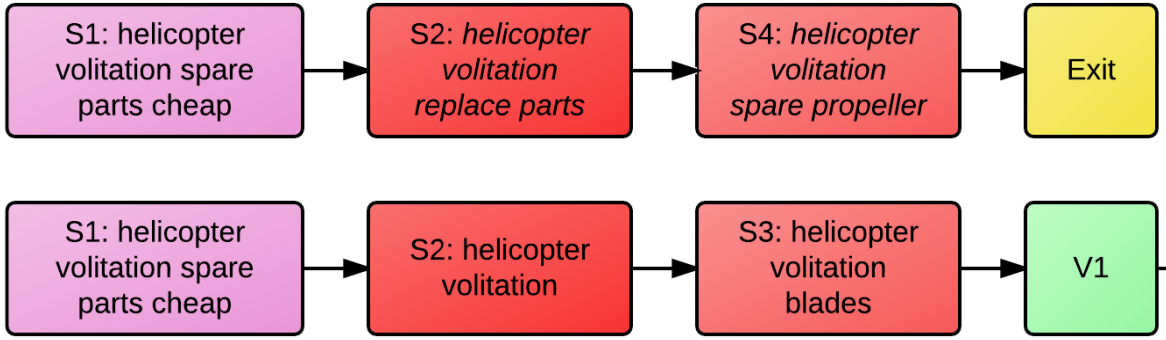
Query Suggestions at eBay

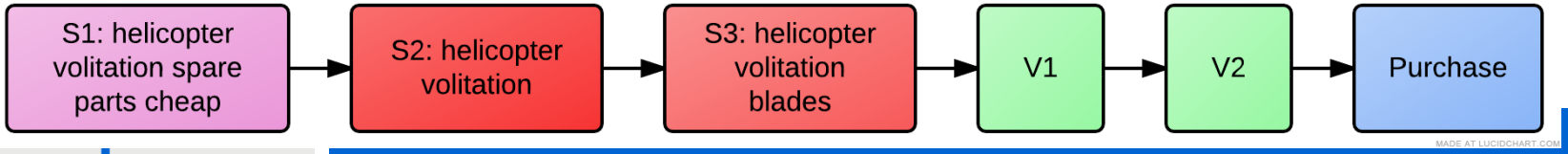
- Enable users to broaden or narrow searches.
- Lead users to related products or brands.
- Optimize the buying experience.

Query Suggestion Algorithms

- Various algorithms in literature
  - Agglomerative clustering
  - Query Similarity Measures (Linguistic, Latent)
  - Query Flow Graphs
- Our approach primarily based on user trails.







Challenges

- Large-scale data
  - 100M+ users.
  - 30TB+ click-stream logs.
  - 1B+ user sessions.
  - Several billion searches.
- Noisy Data
  - Robots
  - API Calls
  - Crawlers, spiders
  - Tools and scripts
  - User Bias

Raw association data	De-duplicated user association data
fluke, texas instrument adding machine, pocket knife, ti 84, scientific calculator	casio calculator, scientific calculator, calculator hp, texas instrument, ti84, adding machine

Query Suggestions for the query ‘calculator’.

Challenges

- Long Tail
- Dynamic Inventory

Suggestions are more useful for tail queries.

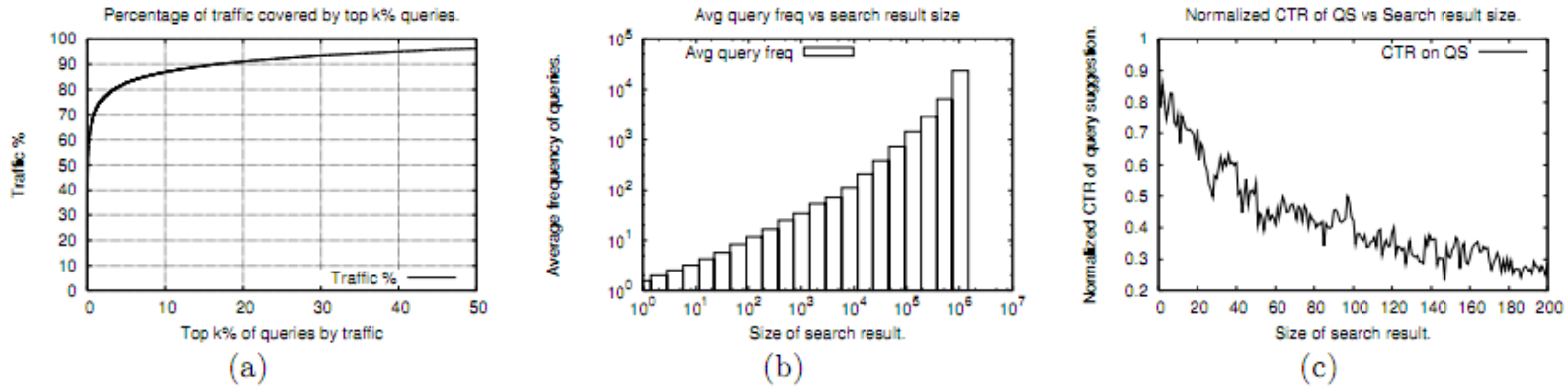


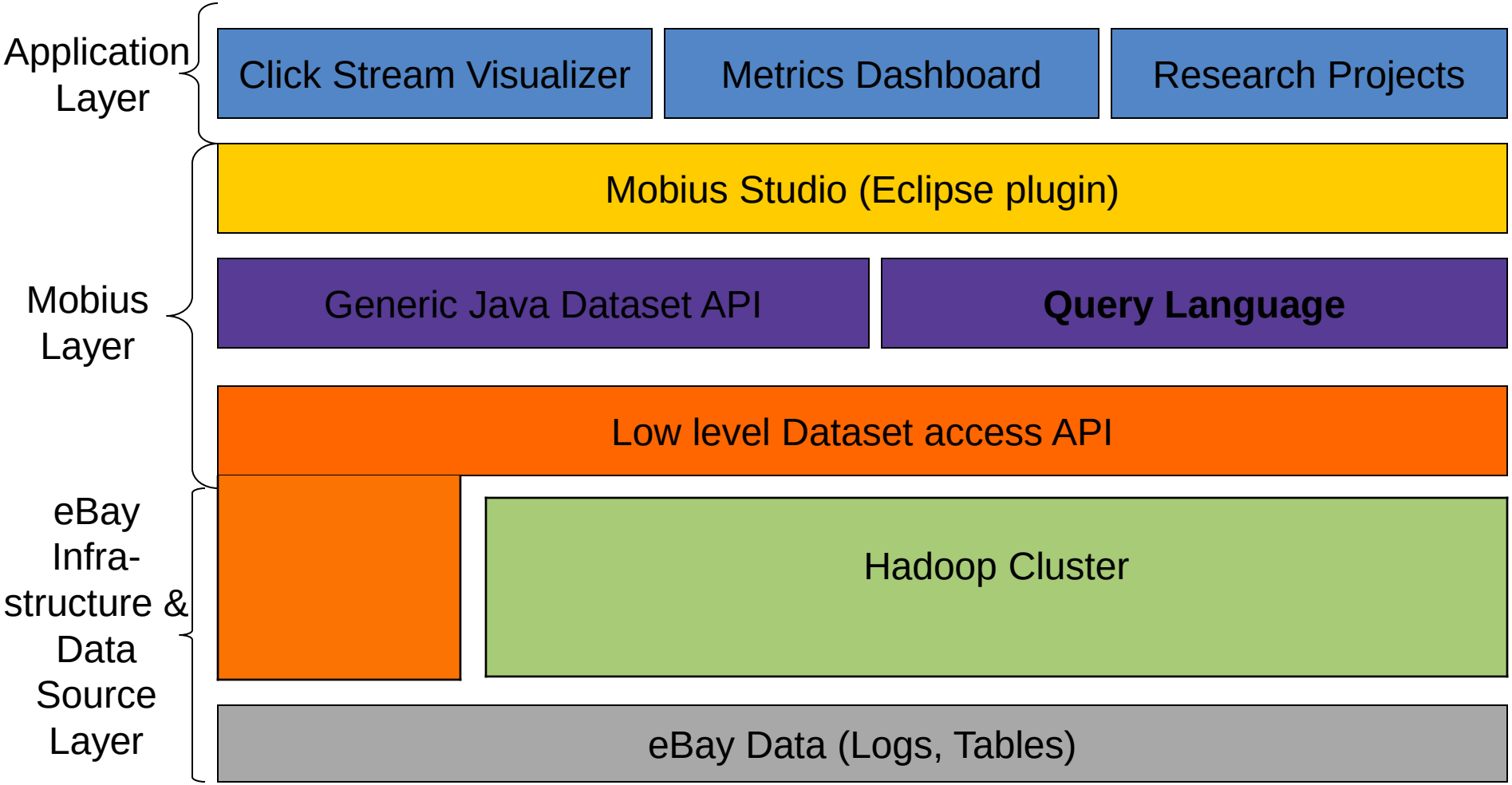
Figure 2: (a) Long tail distribution of eBay search queries (b) Relation between query frequency and search result-set size (c) Related search click-through for different result-set size.

HADOOP TO THE RESCUE

Hadoop Cluster at eBay (One of several)

- Nodes
  - Cent OS 4 64 Bit
  - Intel Dual Hex Core Xeon 2.4 GHz
  - 72 GB RAM
  - 2 * 12 (24TB) HDD
  - SSD for OS
- Network
  - TOR 1Gbps
  - Core Switches uplink 40 Gbps
- Cluster
  - 532n – 1008n
  - 4000+ cores – 24000 vCPUs
  - 5 – 18 PB

Mobius – Computation Platform



Sundaresan et al. Scalable Stream Processing & Map Reduce, HadoopWorld, 2009.

Data Cleaning

- Data is cleaned during the processing phase.
- User Bias Removal
  - Filter information from robots, API calls, spiders and crawlers.
  - De-duplicate signals from the same user.
- Platform Bias Removal
  - Treat signals from different platforms like mobile phones, game consoles, computers differently.
- System Bias Analysis
  - Treat searches typed in by users differently from searches issued through user clicks on features.

Recommendation Computation – Phase 1

Input: User Click-stream data

Mapper

- Data Cleaning.
- Query Pair and Behavioral Frequency extraction.
- Query normalization.

Key: user, originating query
Value: Recommendation query and behavioral frequencies.

Reducer

- User de-duplication.
- Computation of behavioral features.

Output: Query pair and behavioral features per user

Recommendation Computation – Phase 2

Input: Query pairs, behavioral features per user

Mapper

- Identity Mapper

Key: query, recommendation

- Query pairs with non-trivial textual similarity tend to have non-zero behavioral frequencies.
- Textual similarities computed only for 200M query pairs instead of several trillion.

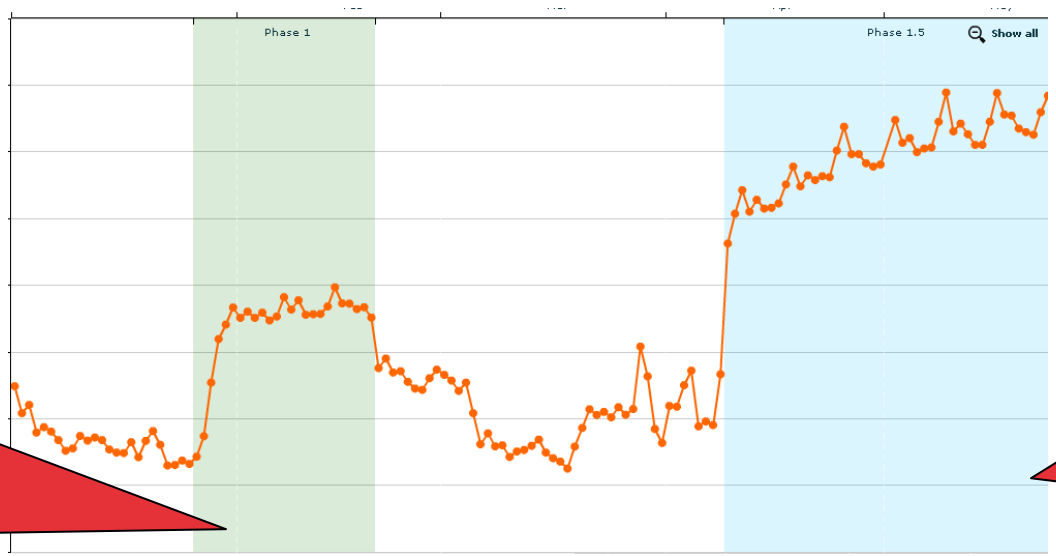
Reducer

- Compute textual features for query pair

Output: Query pair, behavioral features, textual features

Results

Evaluation Metrics	Baseline	Experiment I	Experiment II
# of unique queries with suggestions	4.8M	9.8M	22.6M
Impression Rate	1	1.12	1.22
Click-through Rate	1	1.41	1.13



CTR Increase due to better data cleaning algorithm

CTR Increase attributable to better weighting of behavioral trail data.

Live Site Experiments

Remarks

- Log Mining algorithms are parallelizable.
- Easy to scale such algorithms using Hadoop.
- Hadoop empowers us to look at data-sets spanning larger time-frames.
- Hadoop enables us to iterate faster and hence run more user-facing experiments.

TIME SERIES MINING

Mining Large Scale Temporal Dynamics over Hadoop

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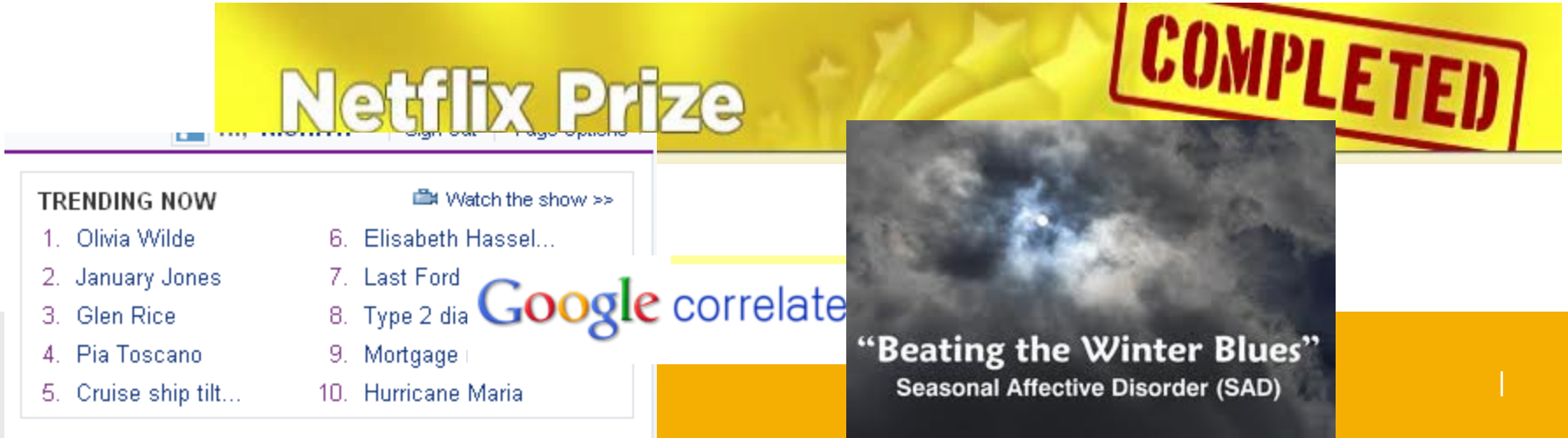
Why study temporal dynamics?

- Stock Markets
- Bio-Medical Signals
- Traffic, Weather and Network Systems
- Web Search & Ranking
- Recommender Systems
- eCommerce…



Challenges

- Large Scale data
  - 100M+ users
  - Petabytes of click-stream logs
  - Billions of user sessions
  - Billions of unique queries
- Noisy Data
  - Robots
  - API Calls
  - Crawlers, Spiders
  - Tools, Scripts
  - Data Biases
- Data spread across long time frames
  - Differences in collection methodologies
- Complexity of certain algorithms

Mobius – Generic JAVA Dataset API

- Java-based, high-level data processing framework built on top of Apache Hadoop.
- Tuple oriented.
- Supports job chaining.
- Supports high level operators such as join (inner or outer) or grouping.
- Supports filtering.
- Used internally at eBay for various data science applications.
- https://github.com/gysingh/openmobius

Hadoop – Handling External Code

- Pre-compiled Java code can easily be used with Apache Hadoop
- User code needs to be assembled into one or more jar files
- Jars can be copied to the task nodes on the Hadoop cluster with the -libjar option (takes a comma-separated list of local jar names)
- The Hadoop software will add the contents from the Jar file(s) to the classpath on the task nodes

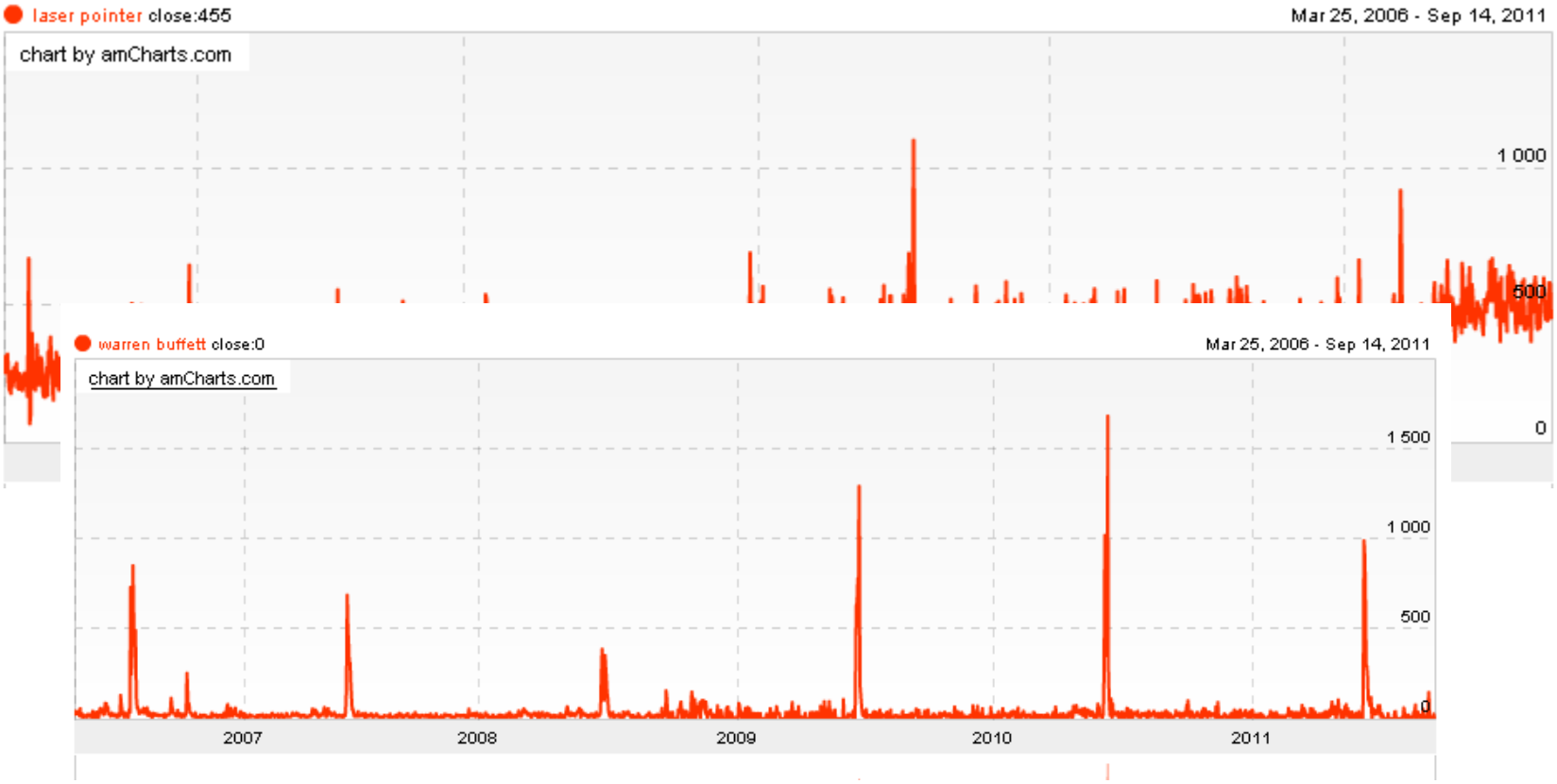
Mobius – Grouping

```
@Override
public int run(String[] args) throws Exception {
        Dataset order = TSVDatasetBuilder.newInstance(this, "orders",
                        new String[]{"O_Id", "OrderNo", "P_Id"})
                .addInputPath(new Path("$INPUT_PATH"))
        .build();

        Dataset grouping_result = this
                .group(order).by("P_ID")
                .save(this,
                                new Path("$OUTPUT_PATH"),
                                new Column(order, "P_ID"),
                                new Counts(new Column(order, "O_Id"))
                );
        return 0;
}
```

Mining Temporal Data

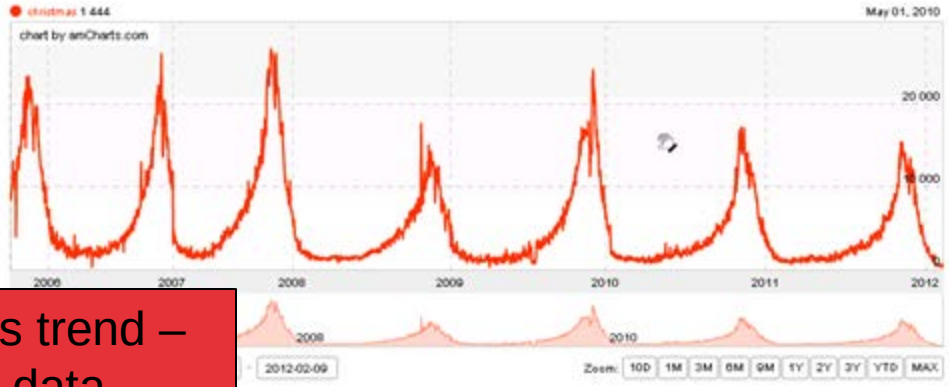
- When it's in your mind, it's in the Query Logs!
  - Queries as a proxy for demand



Mining Temporal Data

- Data Preparation
  - Robot Filtering
  - Session Log Analysis
- Data Cleaning
  - Normalization
  - De-duplication

Christmas trend – raw data



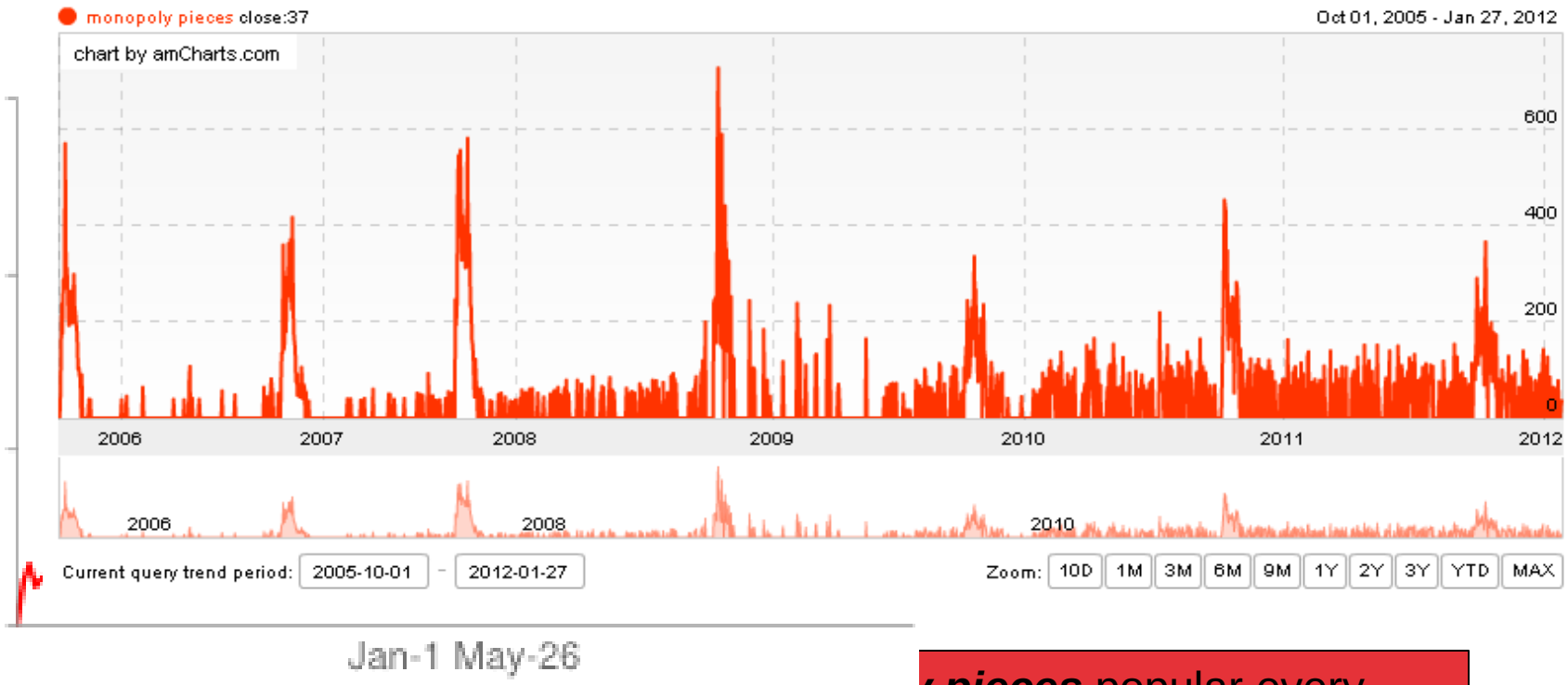
Christmas trend – prepared data

Mining Temporal Data – What's Buzzing?

- Automatic Buzz Detection

Mining Temporal Data – Does History Repeat Itself?

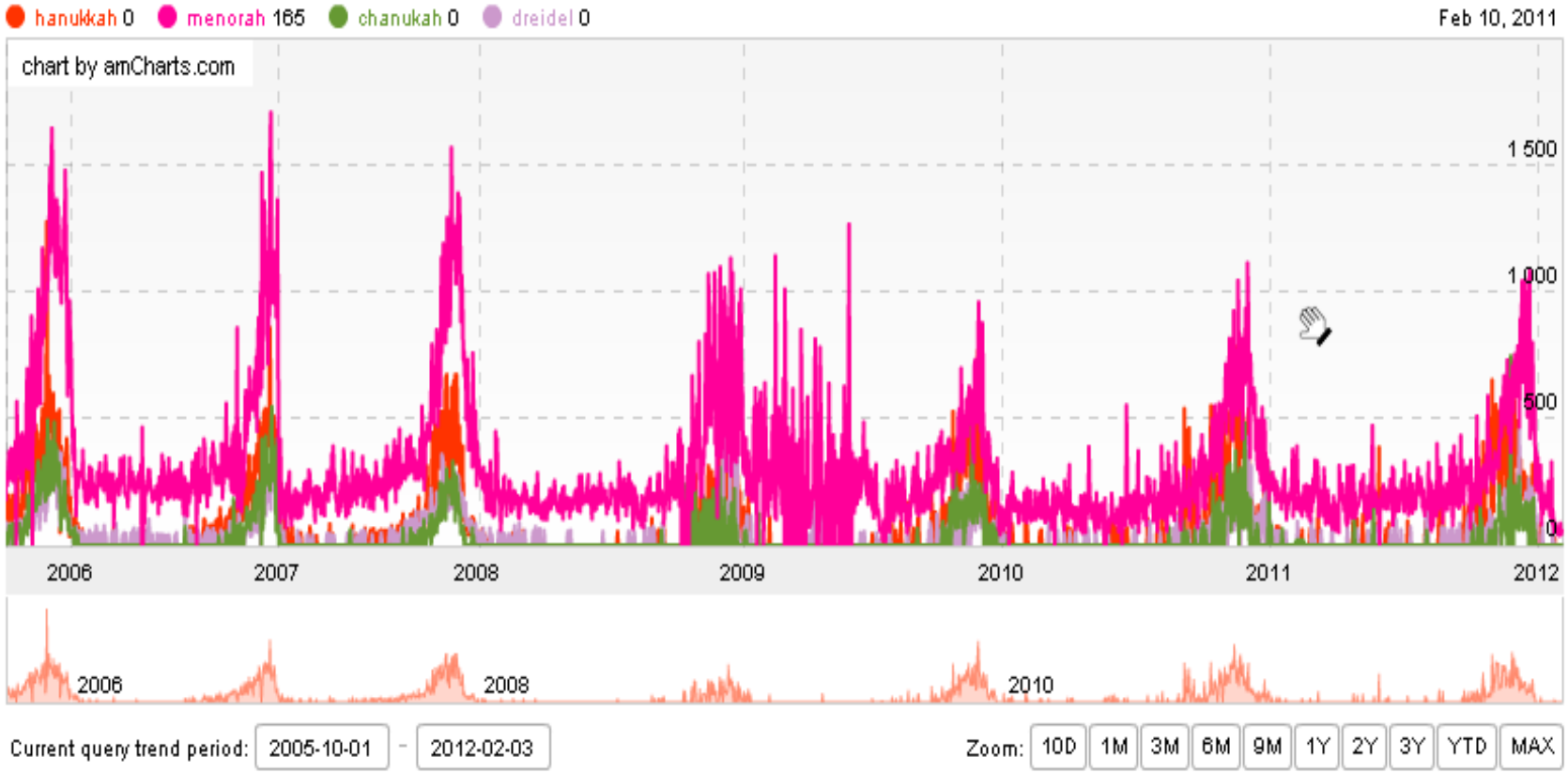
- Seasonality and Trend Prediction



Why are searches related to ***monopoly pieces*** popular every October?

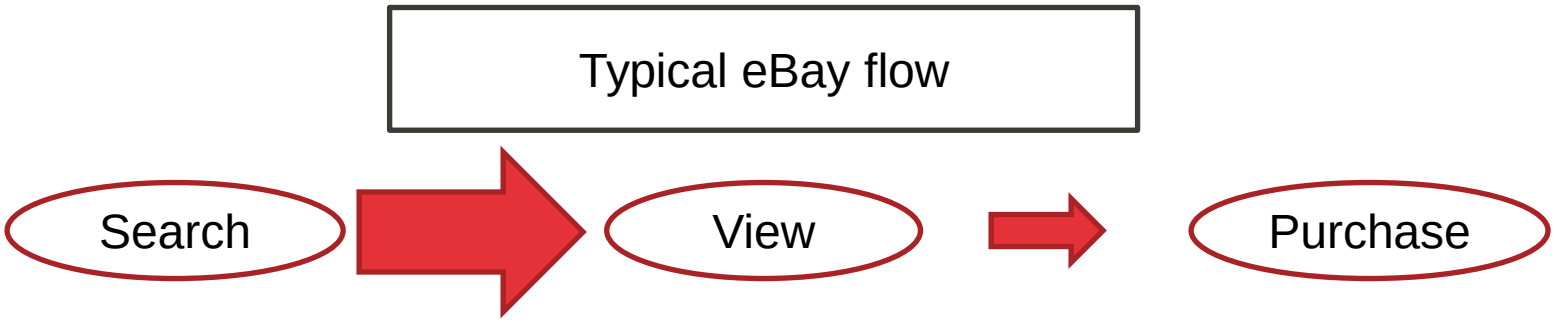
Air

Mining Temporal Data – Temporal Similarity



Similar patterns for queries related to ***Hanukkah***

Preparing Data – Getting Queries from User Sessions



- **Search**: specify a query, with optional constraints
- **View**: click on an item shown on search results page
- **Purchase**: buy a fixed-price item or place winning bid on an auction item

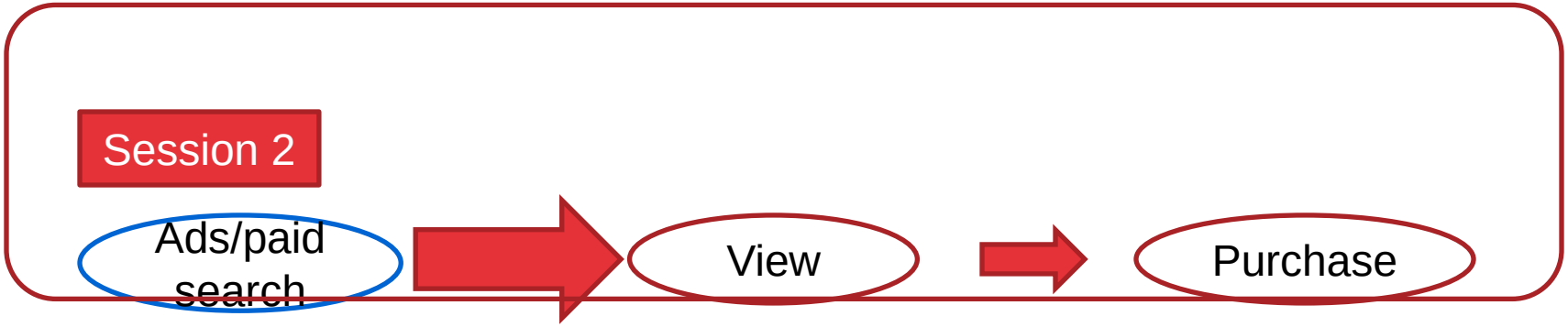
Consider only queries typed in by humans. Ignore page views from robots or views from paid advertisements, campaigns or natural search links.

Cleaning Data

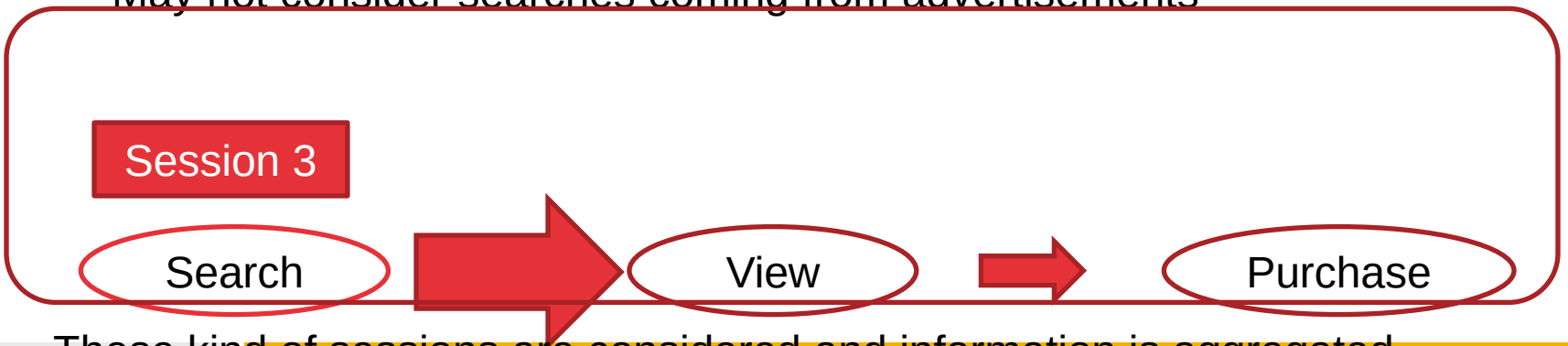
- Apply default robot detection and removal algorithm
  - Based on IP, number of actions per day, agent information.
- Find the right flows from the sessions.
  - Filter out noisy search events.
  - Remove anomalies due to outlier users.
  - Limit the impact a single user can have on aggregated data (de-duplication).

Finding the right flow in the session

May not consider flows without any interesting activity like clicks

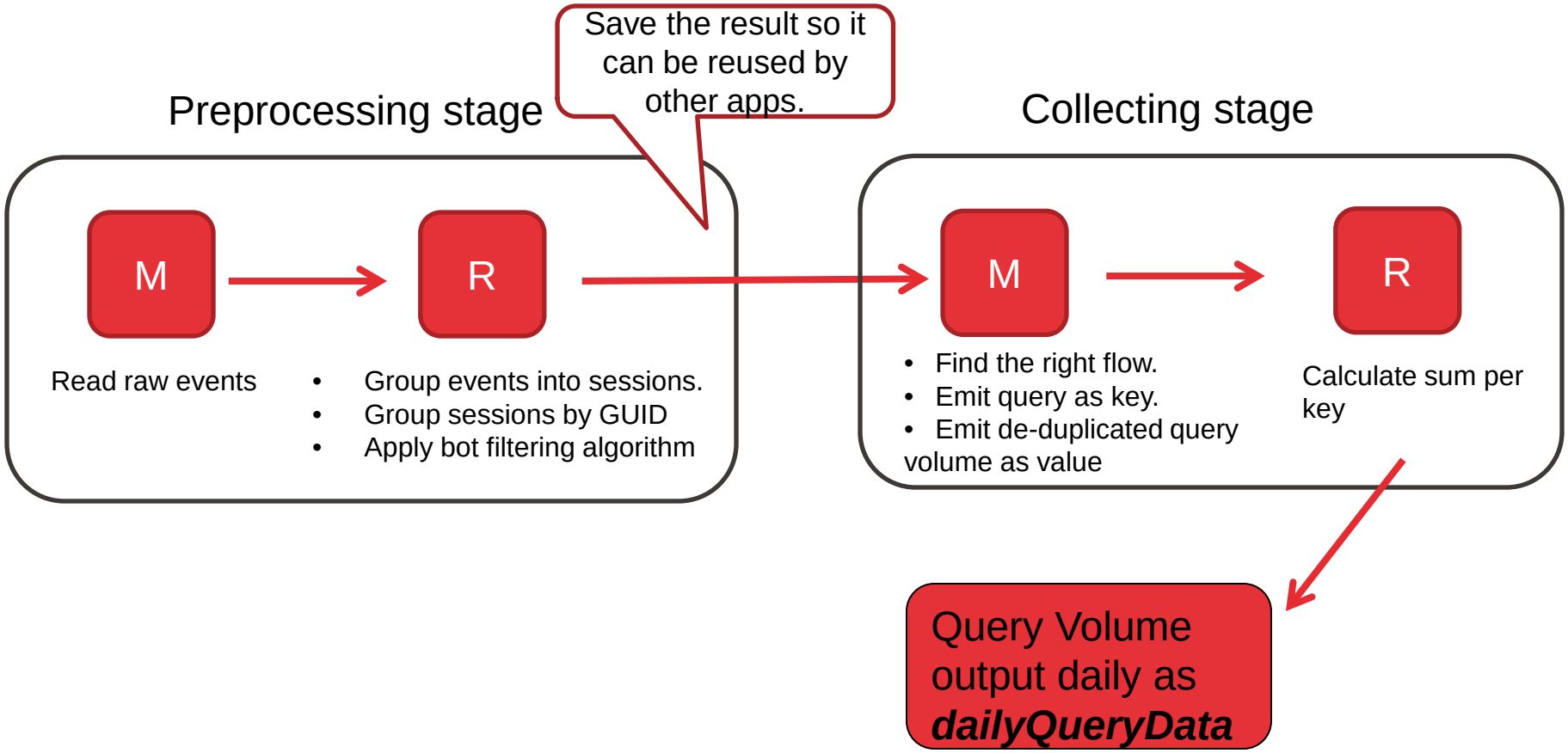


May not consider searches coming from advertisements



These kind of sessions are considered and information is aggregated.

Data Preparation - Map Reduce Flow



Time Series Generation

Input: ***dailyQueryData*** for multi-year time-frames

Mapper

- Data Cleaning.
- Query normalization.

oakley sunglasses	1458	1526	1521	890	1482	1473	1462	**17**	1312	**-1**	1316	978
swarovski	2597	2780	2571	1790	2497	2172	2525	**30**	3514	**-1**	4961	3658
Total Daily Volume	8366370	9349924	9424618	6339503	9127210	9257522	9153950	**267455**	9599864	**-1**	11120926	8463873

Data not to scale and only shown as an example

Reducer

- Time Series formation for all unique queries
- Time Series indicating total daily activity volume

Output: Vectors of Query → Volume Time Series

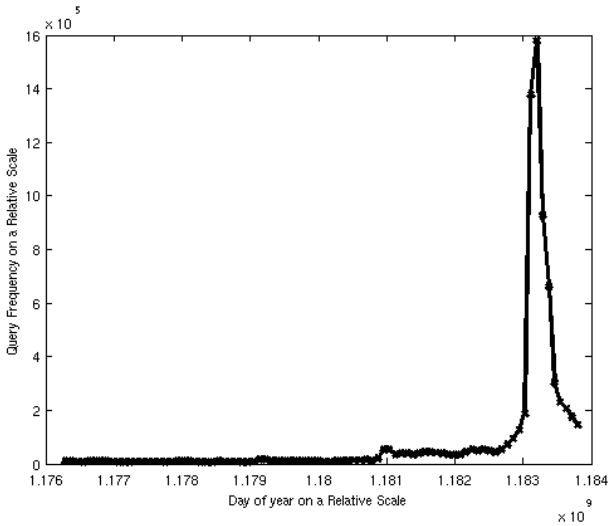
Buzz Detection – 2 state automaton model

- Arrival of queries as a stream.
- "low rate" state (q_0) and a "high rate" state (q_1).
- $f_0(x) = \alpha_0 e^{-\alpha_0 x}$ $f_1(x) = \alpha_1 e^{-\alpha_1 x}$ where $\alpha_1 > \alpha_0$.
- The automaton changes state with probability p ε (0, 1) between query arrivals.
- Let *Q* = *(qi1, qi2… qin)* be a state sequence. Each state sequence *Q* induces a density function f_Q over sequences of gaps, which has the form

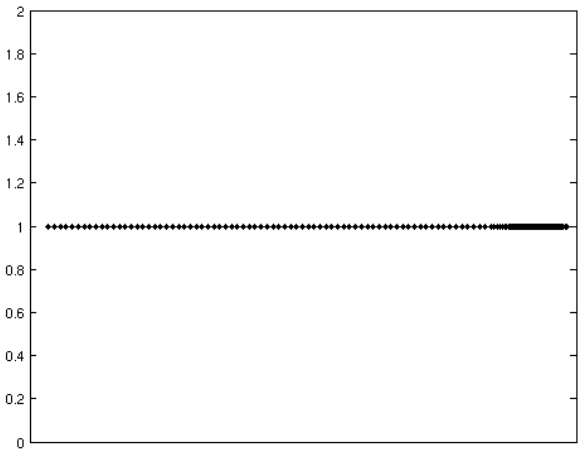
$$f_Q(x1, x2 \ldots xn) = \prod_{t=1}^{n} f_{i_t}(x_t)$$

N. Parikh, N. Sundaresan. KDD 2008.
Scalable and Near Real-time Burst Detection from eCommerce Queries.

Buzz Detection – Modeling Queries as a Stream



Frequency of Query



Gaps between arrival times for queries

Buzz Detection – 2 state automaton model

- If number of state transitions in sequence Q are denoted as *b*
- Prior probability of Q is given as

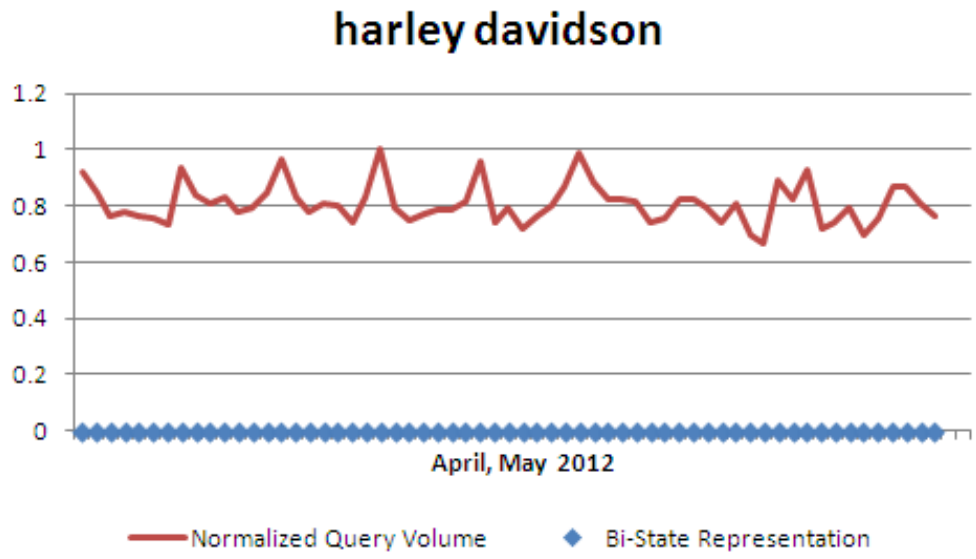
$$\left(\prod_{i_t \neq i_{t+1}} p\right)\left(\prod_{i_t = i_{t+1}} 1-p\right) = p^b (1-p)^{n-b} = \left(\frac{p}{1-p}\right)^b (1-p)^n$$

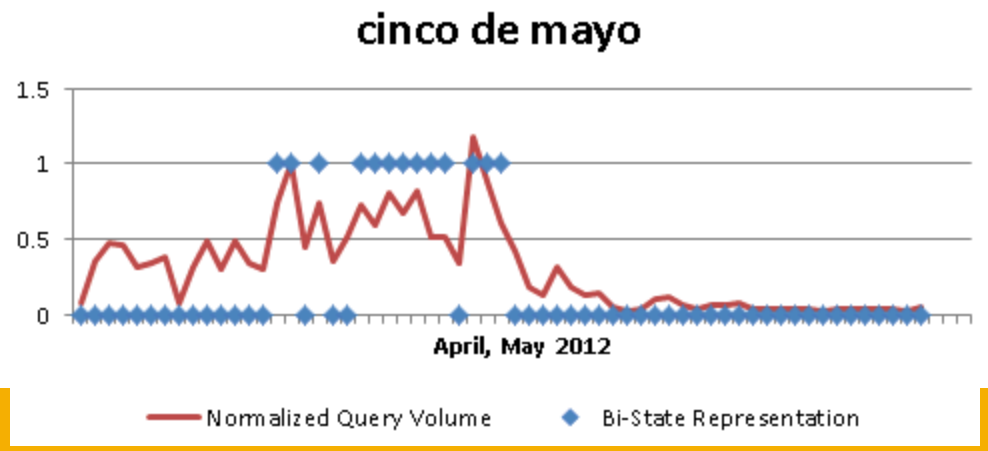
- Using Bayes theorem, the cost equation is

$$C(Q \mid X) = b.\ln\left(\frac{1-p}{p}\right) + \left(\sum_{t=1}^{n} -\ln f_{i_t}(x_t)\right)$$

- Sequence that minimizes the cost would depend on
  - Ease of jumps between 2 states.
  - How well the sequence conforms to the rate of query arrivals.
- Configurable Parameters for model are α_0, α_1 and cost p.
  - α_0, α_1 are calculated from data in the MR job.
  - Heuristically determined value of p = 0.38 is used.

Query Volume Time Series – 2 State Representation





Time Series Normalization and Buzz Detection

Nov-Jan	Winter	snowboarding pants, cashmere gloves, fleece lined jeans. mens ugly christmas sweater
Nov	Thanksgiving	Thanksgiving decorations, thanksgiving tablecloth, thanksgiving dress, vintage thanksgiving
Dec-Jan	Orange Bowl	Orange bowl,
Jan-Feb	Superbowl	Super bowl tickets, superbowl tickets, ahmad bradshaw, ny giants jersey
Jun	Father's Day	Father's day, father's day gifts
Dec	Kwanzaa	kwanzaa

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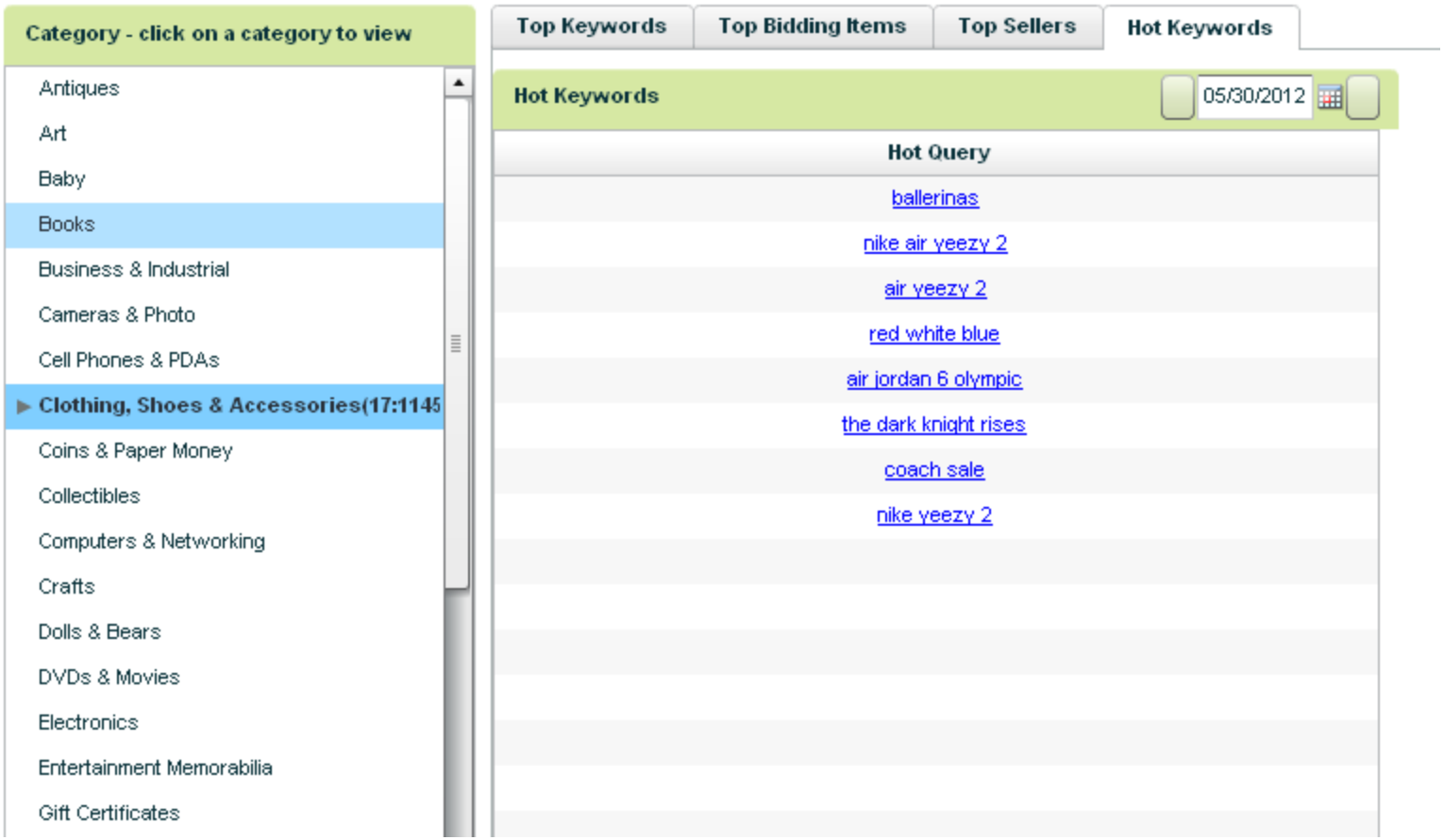
Output: time frame → Queries buzzing during that time period

Catman – http://labs.ebay.com/Catman/

Tre



Binary data structure generation from MR job

- Created new FileOutputFormat
- Write time series data to two files
  - Binary File with fixed sized records indicating time series volume
  - Text file mapping each unique query string to binary file and offset
- Index created by reducers directly loaded by custom servers written in C++.
- Used for an internal Query Trends Application

Query Trends

Research Labs

trends on eBay

monopoly pieces

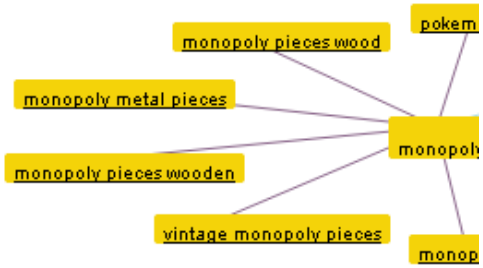
Search

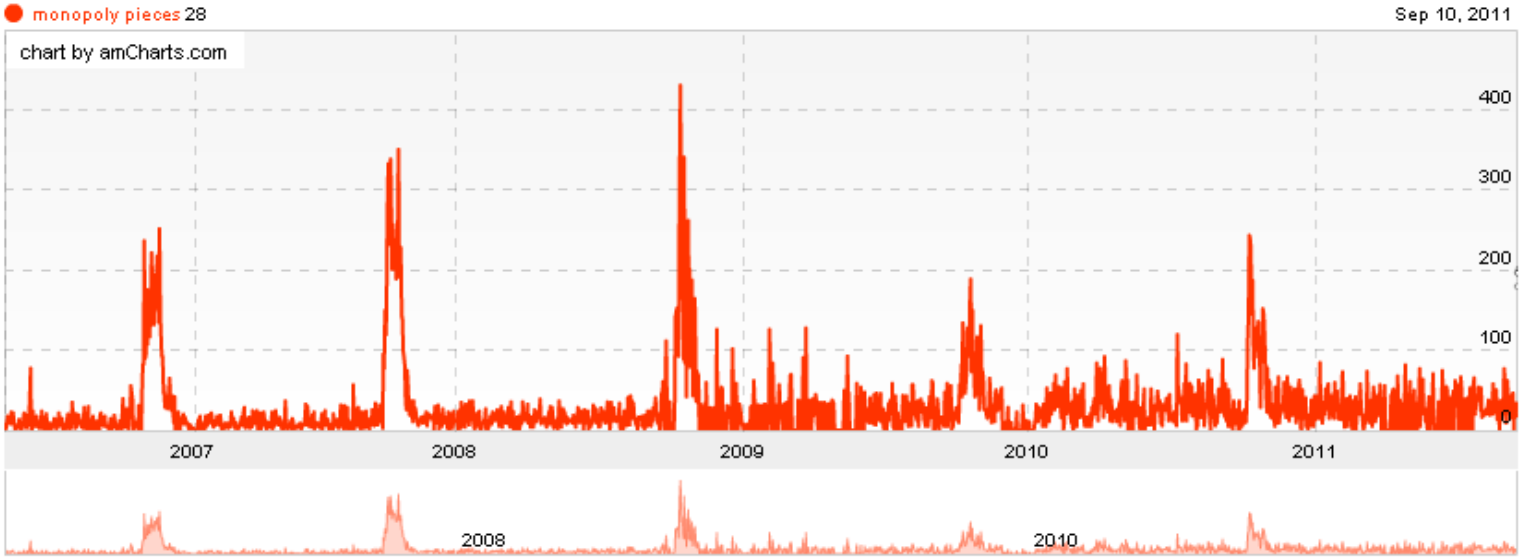
Popular Queries:

vintage anthropologie prada

Trending Queries:

an minnie mouse costume louis vuittons shoes wo





Current query trend period: 2006-03-23 - 2011-09-12

Zoom: 10D 1M 3M 6M 9M 1Y 2Y 3Y YTD MAX

Query Trends – Mapping to External Events

Research Labs trends on eBay

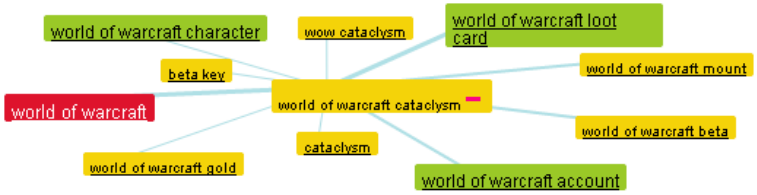
world of warcraft cataclysm Search

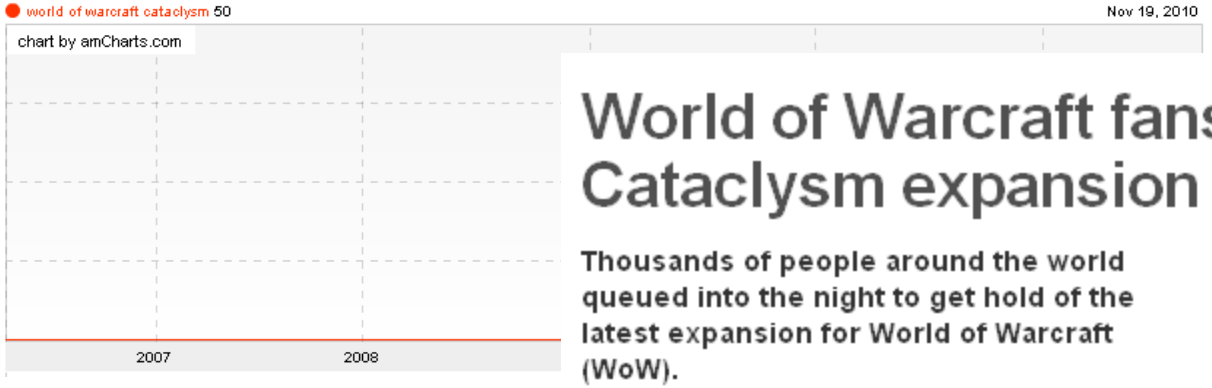
Popular Queries:

star wars ralph lauren nike

Trending Queries:

ɔmber uggs yoda stuart weitzman minnie mo





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World of Warcraft: Cataclysm (PC)

World of Warcraft fans queue to buy Cataclysm expansion

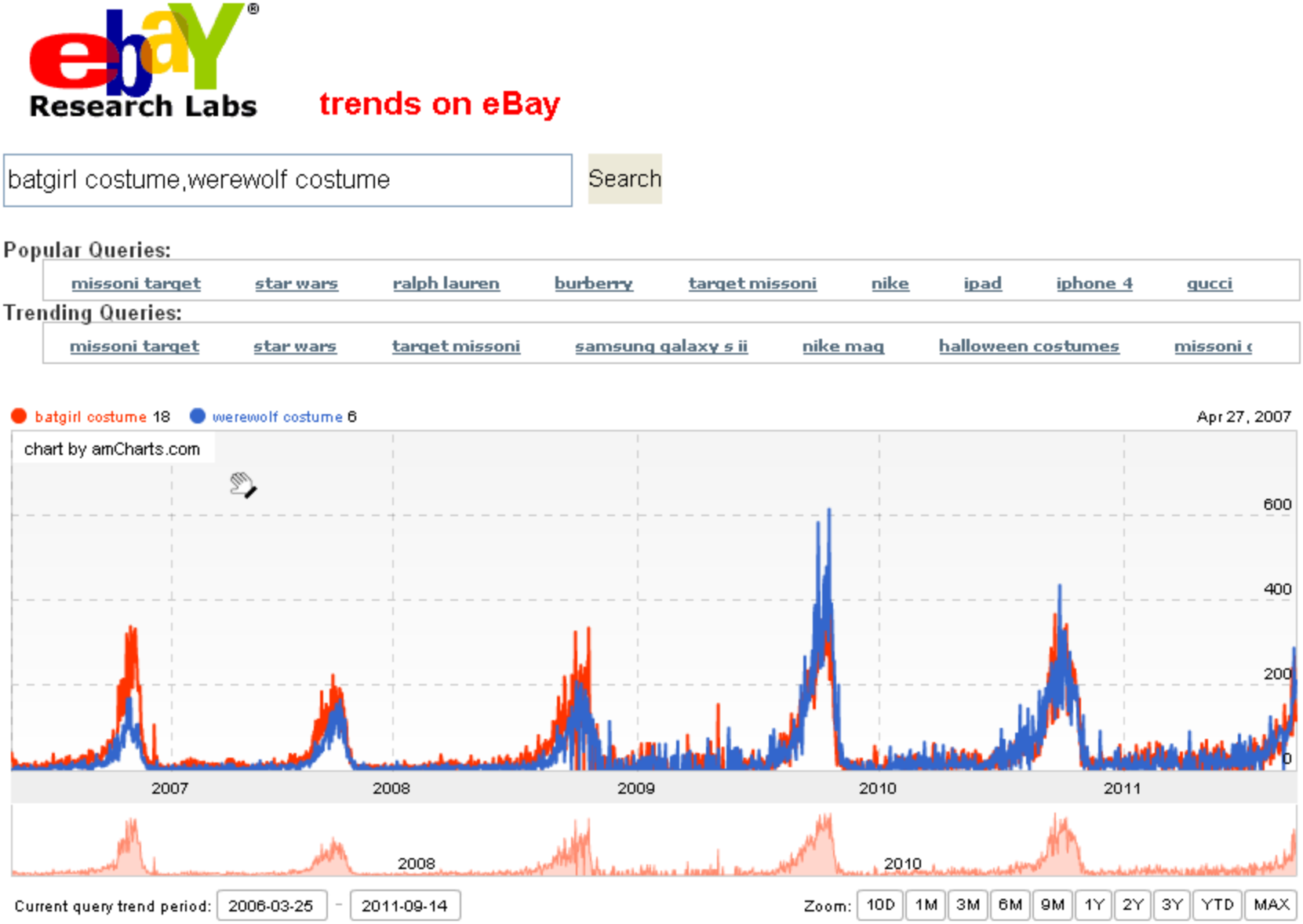
Thousands of people around the world queued into the night to get hold of the latest expansion for World of Warcraft (WoW).

The expansion, called Cataclysm, is the first for two years and makes big changes to the game.

The expansion re-makes the world in which WoW is set and rips up the geography of many familiar places.

Many shops opened up in the early morning to sell the Cataclysm expansion

Trends – Comparing Queries



Temporal Similarity

- 1+ Billion Queries
- Naïve Algorithm – Quadratic Complexity
- Pearson's Correlation

$$\frac{1}{d}\sum_{i}\left(\frac{X_{p,i}-\mu(X_p)}{\sigma(X_p)}\right)\left(\frac{X_{q,i}-\mu(X_q)}{\sigma(X_q)}\right)$$

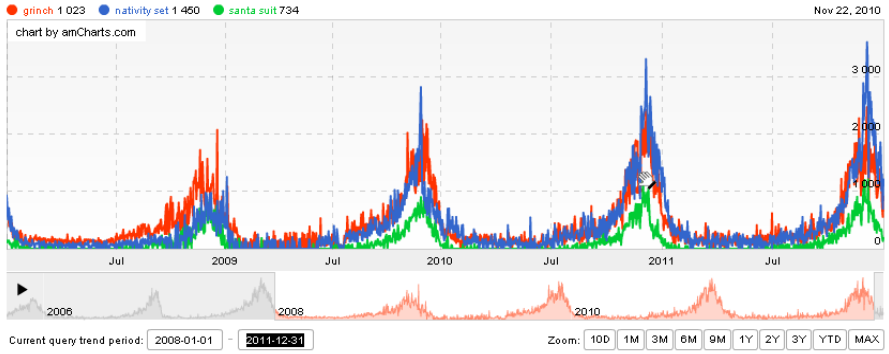
- Candidate Set Reduction
  - Correlations useful only for event-based or seasonal queries
  - Correlations useful in applications only for head and torso queries
  - These filters reduce candidate space from B+ to a few M.

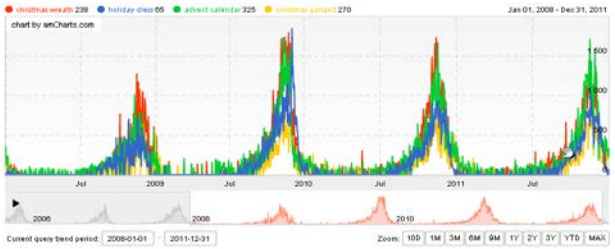
$$\tilde{X}_{p,i} = \frac{1}{\sqrt{d}}\frac{X_{p,i}-\mu(X_p)}{\sigma(X_p)}$$

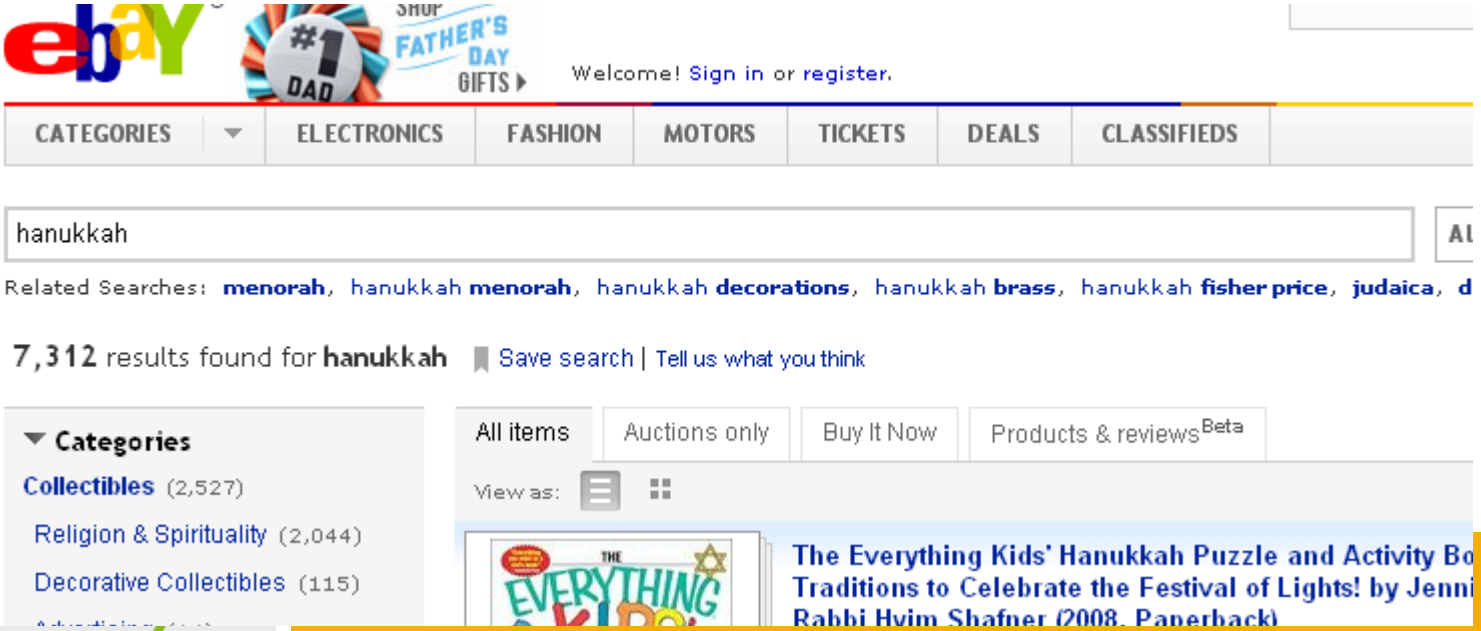
Exact Correlations amongst candidates – All pairs similarity on Reduced Set

Number of Mappers = M
Number of Iterations of the job = K
In every iteration, every mapper m pre-loads $\frac{N}{K}$ queries in RAM
Every mapper is then streamed $\frac{N}{M}$ queries
Every mapper in a single iteration computes $\frac{N}{M} \times \frac{N}{K}$ correlations
In a single iteration all mappers together compute $\frac{N}{M} \times \frac{N}{K} \times M = \frac{N \times N}{K}$ correlations
In K iterations $N \times N$ correlations are computed
As correlation is commutative $\tau_{p,q} = \tau_{q,p}$ we compute $\tau_{p,q}$ only when $p < q$ as an optimization
To save disk space only useful correlations ($\tau > T$) are stored
Parameters we use; $M = 5000, R = 100\ or\ 0, K = 100, T = 0.7$
Exact correlations for all pairs in reduced set can be computed and used in practice

Applications of Temporal Correlations – Query Suggestions







Remarks

- Log Mining and Time Series mining algorithms are parallelizable.
- Easy to scale such algorithms using Hadoop.
- Hadoop empowers us to look at data-sets spanning years and years.
- Hadoop enables us to iterate faster and hence run more user-facing experiments.

SHIPPING RECOMMENDATIONS

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Outline

- Introduction to selling on eBay
- Shipping suggestion opportunity
- Data to the rescue
- Shipping suggestions: Base approach
- Inhomogeneous category problem
- Improved data mining to the rescue
- Shipping suggestions: Current approach

Listing an item for sale on eBay

- Specify listing title
- Accept / override suggested listing category
- Upload one or more pictures
- Specify item condition (eg, New, Used)
- Type in item description
- Set start price or fixed price, and listing duration
- Specify shipping (service, cost, who pays: buyer / seller)
- Specify accepted payment methods

Shipping on eBay

- eBay would like to help sellers choose a shipping method
- Many different and unique items are offered on eBay
- Weight and dimensions are usually unknown
- Asking sellers to type in weight and dimensions creates friction
- Would like an automatic approach

Data to the rescue

- Sellers on eBay often buy their postage labels through eBay's label printing platform
- Many different shipping services are offered through eBay label printing (from US Postal Service, FedEx)
- Shipping labels usually include weight and dimensions to determine pricing
- While items are often unique, all items are assigned to categories during listing

Data to the rescue (cont.)

- Approach: aggregate past shipping label data by category
- Run statistics on the weight and dimension data for each category
- Derive a usable data-driven estimate on weight and dimensions
- Choose a suitable service and carrier, and make a suggestion

Label data at eBay

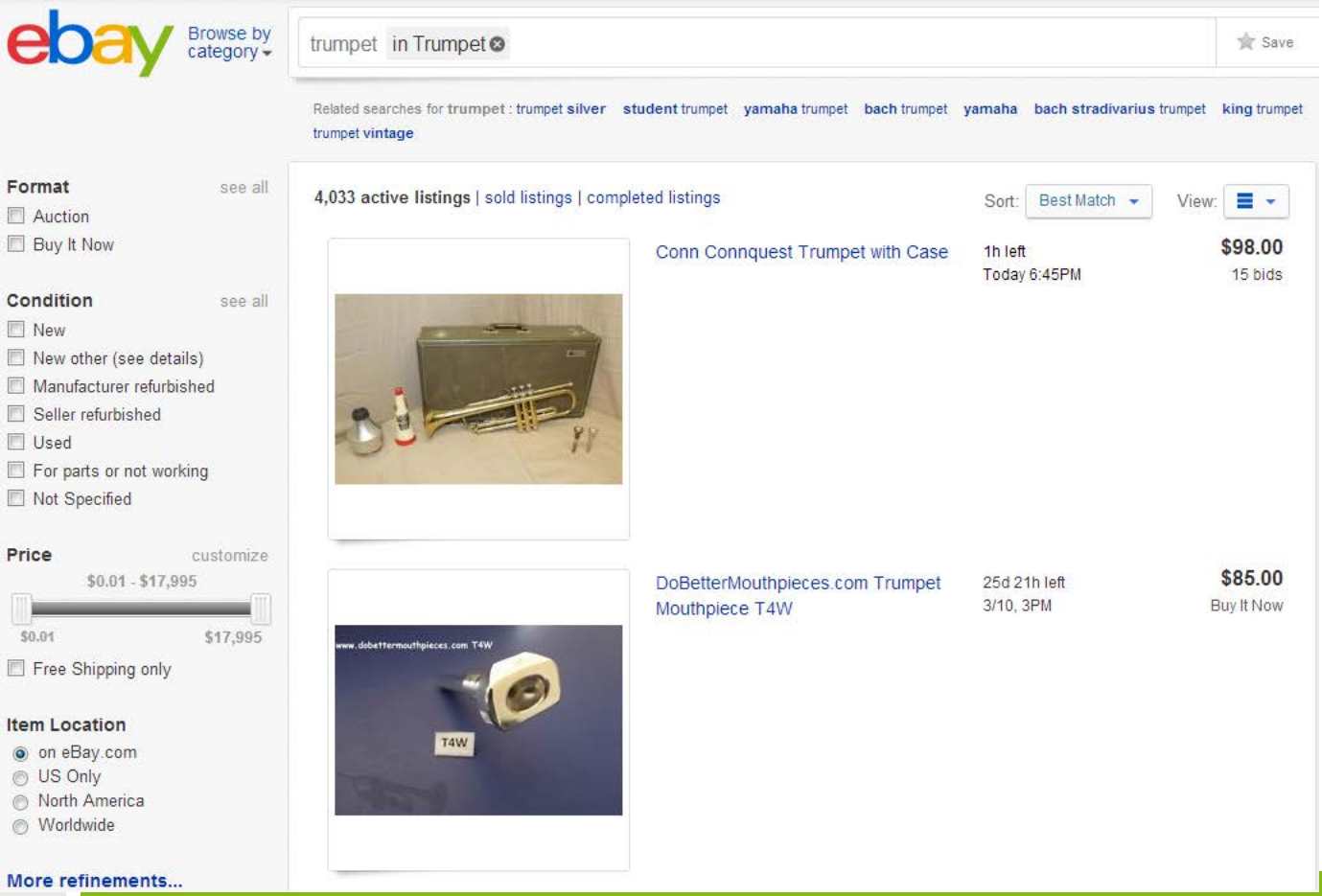
- eBay has at any given time more than 350 million listings worldwide
- Many millions of shipping labels for the US are printed through eBay every year
- Thousands of categories

Processing of label data with Hadoop

- Use Mappers to extract desired fields (weight, dimensions)
- Use Mappers for filtering (eg, exclude USPS flatrate)
- Mapper output key = category, value = weight and dimensions
- Use Reducers to perform statistical evaluation
- Reducer output key = category, value = suggested weight and dimensions
- Pick a suitable carrier and service for each category

Opportunities for Improvement

- Many categories contain a wide variety of items



Improved Approach

- Differentiate items within a category into light and heavy
- Light vs. heavy:
  - “trumpet” category: mouthpiece vs. trumpet with case
  - “dinnerware” category: single plate vs. dinnerware set
  - “computer accessories” category : mouse vs. keyboard
- Besides the listing category use the listing title
- Different words are important for different categories

Improved Approach: What precisely is “heavy”?

- Each category has its own separation into light and heavy
- Some categories are uniform and have no such separation
- Attempt to cluster items by weight in each category into precisely two clusters
- Split the category if both the light and the heavy clusters have sufficient items

Improved Approach: Bag of title words

- Each category has its own collection of title words indicating light and heavy items
- Preselect words important for each category
- Fit a statistical model on the title words that for each listing produces a probability that the item is heavy (or light)

Improved Approach with Hadoop

- Use Mappers to extract desired fields (weight, dimensions, title)
- Use Mappers for filtering (eg, exclude USPS flatrate)
- Mapper output key = category, value = weight, dimensions, and title
- Use Reducers to perform machine learning
  - Clustering to determine light / heavy cut-off
  - Title word selection
  - Title word model fitting

Sampling

- Categories have very different numbers of listings
  - Searching on 2013/09/23 on ebay.com yields:
  - **2,576,202** results for ”dvd”
  - **487** results for ”Climbing Holds”
- Above results are “active items”, if using historical data then some categories’ data will be too large to fit into a single reducer
- The reducer does not know ahead of time how large the category is (records are streamed by Hadoop)
- Use reservoir sampling in case leaf category is too large to fit into a single reducer (hundreds of thousands of records)

Modeling Details

- K-means for clustering of weights, K=2
- Discard clustering if almost all records are in larger cluster or too few records in smaller cluster
- For each category, fit a binary Maximum Entropy model (aka Logistic Regression) on item titles predicting light vs. heavy using standard public-domain Java software
- Perform cross-validation

Improved Approach with Hadoop (cont)

- Reducer also performs data-driven validation and testing of goodness of model fits
- Reducer output key = category, value = model words, model word parameters, and suggested weight / dimensions for light and heavy, model performance statistics

Final System

- Thousands of categories with title models to have suggestions for light and heavy items
- For thousands more rarely used categories have the baseline suggestions
- All transparent to the seller, no additional input required
- Sellers can override if they want
- Abandoning rate of listing flow at shipping stage is significantly improved

Example: Trumpet Mouthpiece

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Switch to advanced tool | Save for later | Help | Listing fees: $0.00

Describe it ✓ | Set price ✓ | **Select shipping** | Review

trumpet mouthpiece

Condition: **Used** Auction starts at: **$0.99**

* Required field

Select the shipping option most sellers use

Service	Package	Cost
USPS First Class Package 2 to 5 business days	**Package (or thick envelope)** 6oz. 10.0in. x 7.0in. x 5.0in.	**$2.58 paid by buyer** ☐ Offer free shipping to attract buyers

Create your own shipping option

☐ **Add international shipping** ?

Previous | Next

Example: Trumpet with Case and extra Mouthpiece

ebay

Switch to advanced tool | Save for later | Help | Listing fees: $0.00

Describe it ✓ | Set price ✓ | **Select shipping** | Review

trumpet with case and extra mouthpiece

Condition: **Used** Auction starts at: **$0.99**

* Required field

◉ **Select the shipping option most sellers use**

Service	Package	Cost
USPS Priority Mail 2 to 3 business days	**Package (or thick envelope)** 11lbs. 0oz. 24.0in. x 14.0in. x 11.0in.	**$13.50-$48.15 paid by buyer** varies by buyer's location ☐ Offer free shipping to attract buyers

○ **Create your own shipping option**

☐ **Add international shipping** ?

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Questions