Query Modelling

Autocompletions, Temporal profiling

Query Modelling

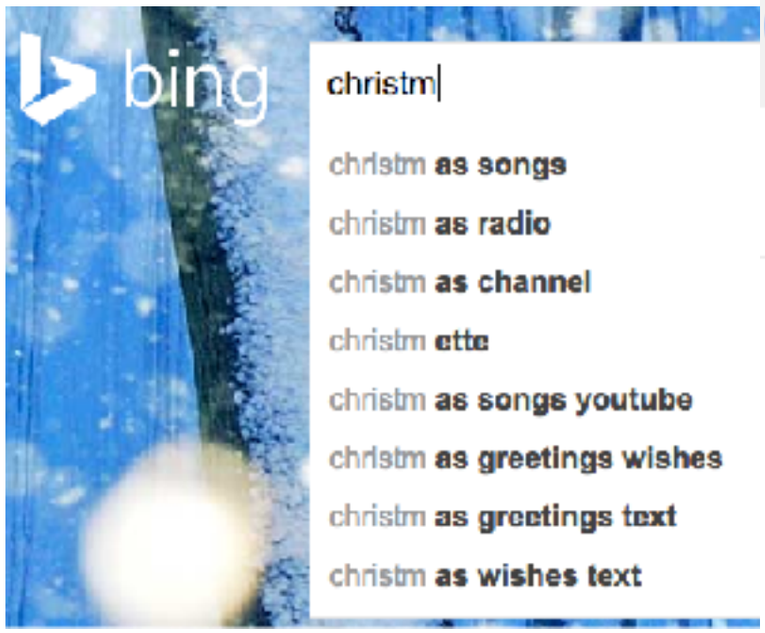
- Query modelling is used to better capture the users information need

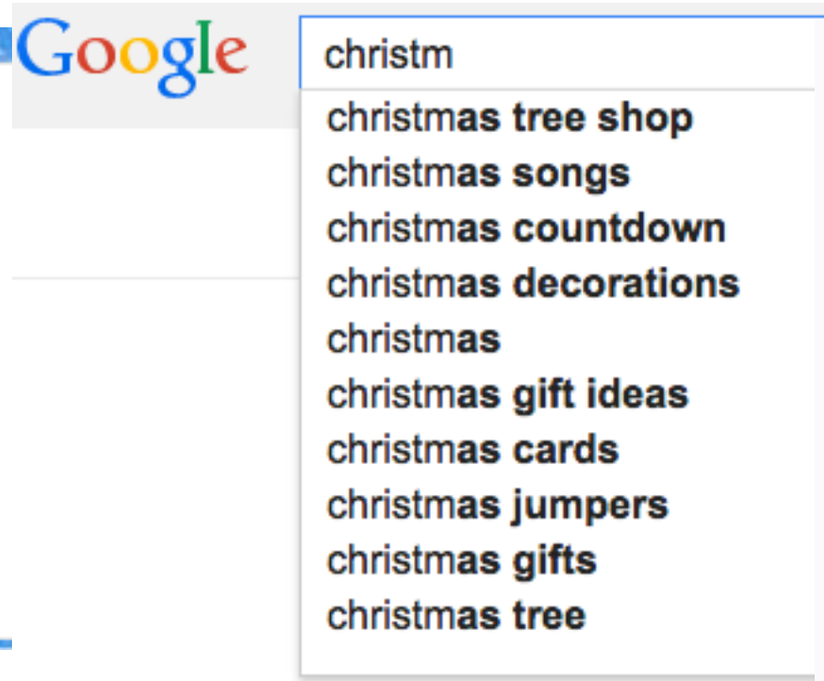
- Bridges the vocabulary gap between the query and the documents to be retrieved
  - bicycle vs bike, LOTUS vs POTUS vs president of US
  - EOS 1000D vs canon rebel series

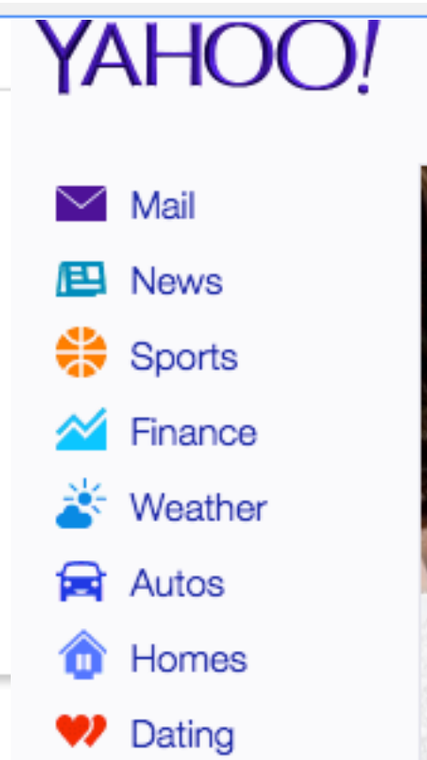
- Used in Query expansions, suggestions and auto-completions

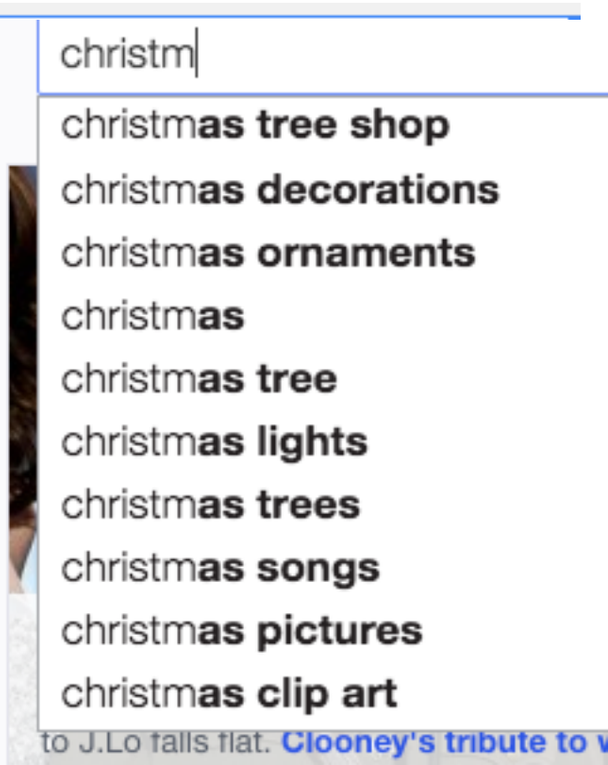
- Temporal Profiling for improving result quality

Query Modelling Applications - Auto-completions





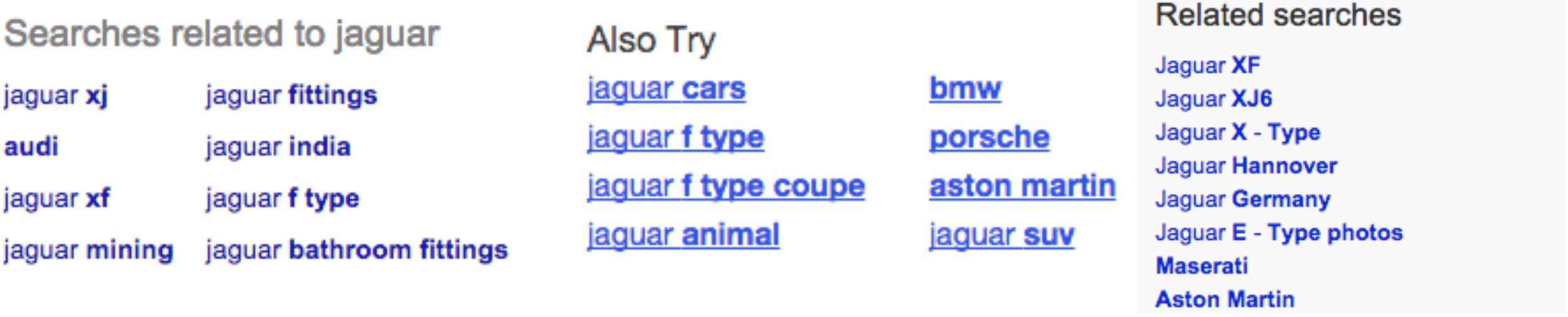




- Query Auto-completions : Given a prefix text suggest the most probable queries

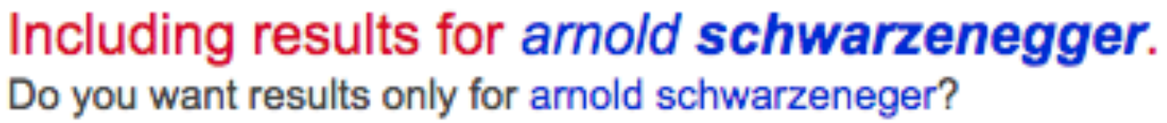
- Better auto-completions are based on better modelling user intents

Query Modelling Applications - Suggestions



- Query Suggestions : Given the complete query, try to guess related queries or what the user might be interested in

- spelling corrections are a subset of it



Query Modelling Applications - Expansions

- Autocompletions and suggestions are explicit
- To improve the quality of results the search engines implicitly enrich or expand queries
  - Input query: bike prices
  - Expanded query: bike prices OR bicycle price OR bicycle cost OR two-wheeler cost OR …

How can queries be modelled ?

How to use temporal information to better model queries?

Query Modelling - Ingredients

- **Query log mining:** Usage of query logs and behavioral statistics while interacting with the search engines

- Query logs are not always available especially query logs for a long duration of time

- Information about new and emerging topics are unavailable even in query logs

- **Pseudo-relevance feedback:** Assuming top documents retrieved by the search engine to be relevant

Query Logs

- **Query log mining:** Usage of query logs and behavioral statistics while interacting with the search engines

- Example of query logs and usage logs :

```
1326    coats tire equipment    2006-04-28 15:53:18
1326    coats tire equipment    2006-05-03 19:15:01
1326    verizon wireless        2006-05-09 00:09:22
1326    www.crazyradiodeals.com 2006-05-23 18:00:30
1337    uslandrecords.com       2006-03-01 11:50:34     1       http://www.seda-cog.org
1337    titlesourcein.com       2006-03-14 15:45:07
1337    titlesourceinc  2006-03-14 15:45:55     1       http://www.titlesourceinc.com
1337    select business services        2006-03-14 15:51:41
1337    select business services title  2006-03-14 15:52:10
1337    cbc companies   2006-03-14 15:52:44     2       http://www.cbc-companies.com
1337    cbc companies   2006-03-14 15:52:44     3       http://www.cbc-companies.com
1337    cbc companies   2006-03-14 15:52:44     4       http://www.mktgservices.com
1337    national real estate settlement services        2006-03-14 15:59:13     1       http://www.realtms.com
1337    national real estate settlement services        2006-03-14 15:59:13     7       http://dmoz.org
1337    pennsylvania real estate settlement services    2006-03-14 16:04:40
1337    pennsylvania real estate settlement services    2006-03-14 16:05:11
1337    sunbury pennsylvania real estate settlement services    2006-03-14 16:05:47
1337    sunbury pennsylvania real estate settlement services    2006-03-14 16:06:28     14      http://pa.optimuslaw.com
```

[10/09 06:53:30] Click: [webresult][q=home made halloween decorations][20]
http://www.halloween-magazine.com/

Query Auto-completions

- Candidate set generation for a given prefix p
- Candidates are ranked according to the *most popular completion* to the given prefix and top-k are presented as most promising
- A weight w(q) for each candidate **q** is estimated from the document collection of query log
- How are weights computed ?
  - Most popular query — based on query frequency or how many times has the query been issues

$$MPC(p) = arg\max_{q \in \mathcal{C}_p} w(q), \quad w(q) = \frac{f(q)}{\sum_{i \in \mathcal{Q}} f(i)}$$

Query Auto-completions

- Choose the top-k promising candidates

query frequency

$$MPC(p) = arg\max_{q \in C_p} w(q), \quad w(q) = \frac{f(q)}{\sum_{i \in Q} f(i)}$$

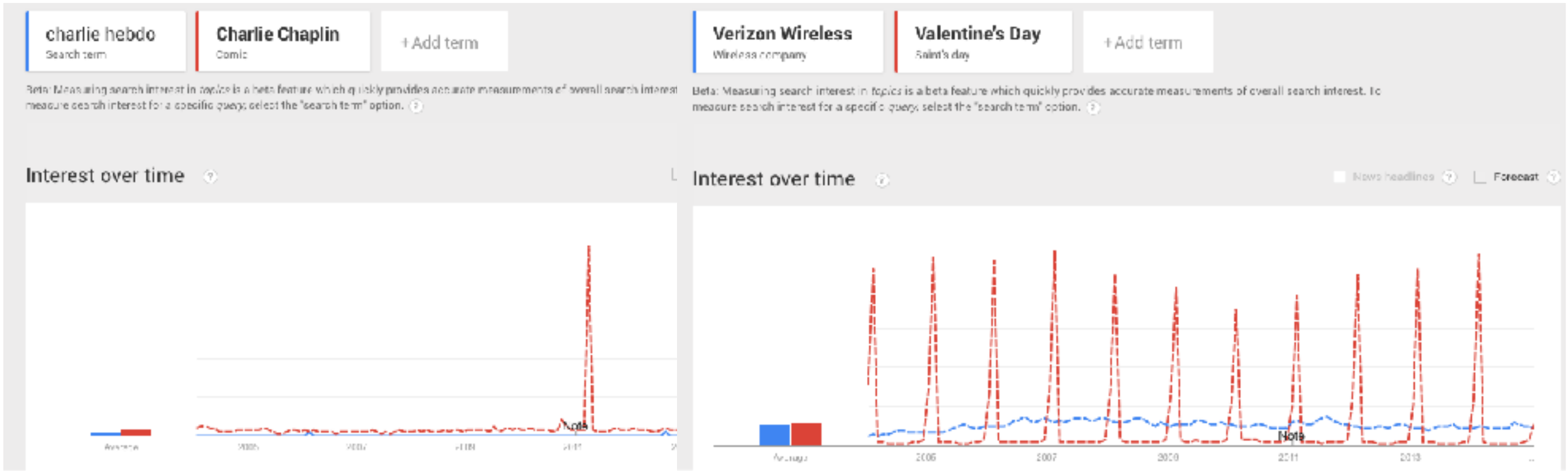
candidates for prefix p

candidate weight

query log

What is missed in such kind of a modelling approach ?

Temporal Query Auto-completions

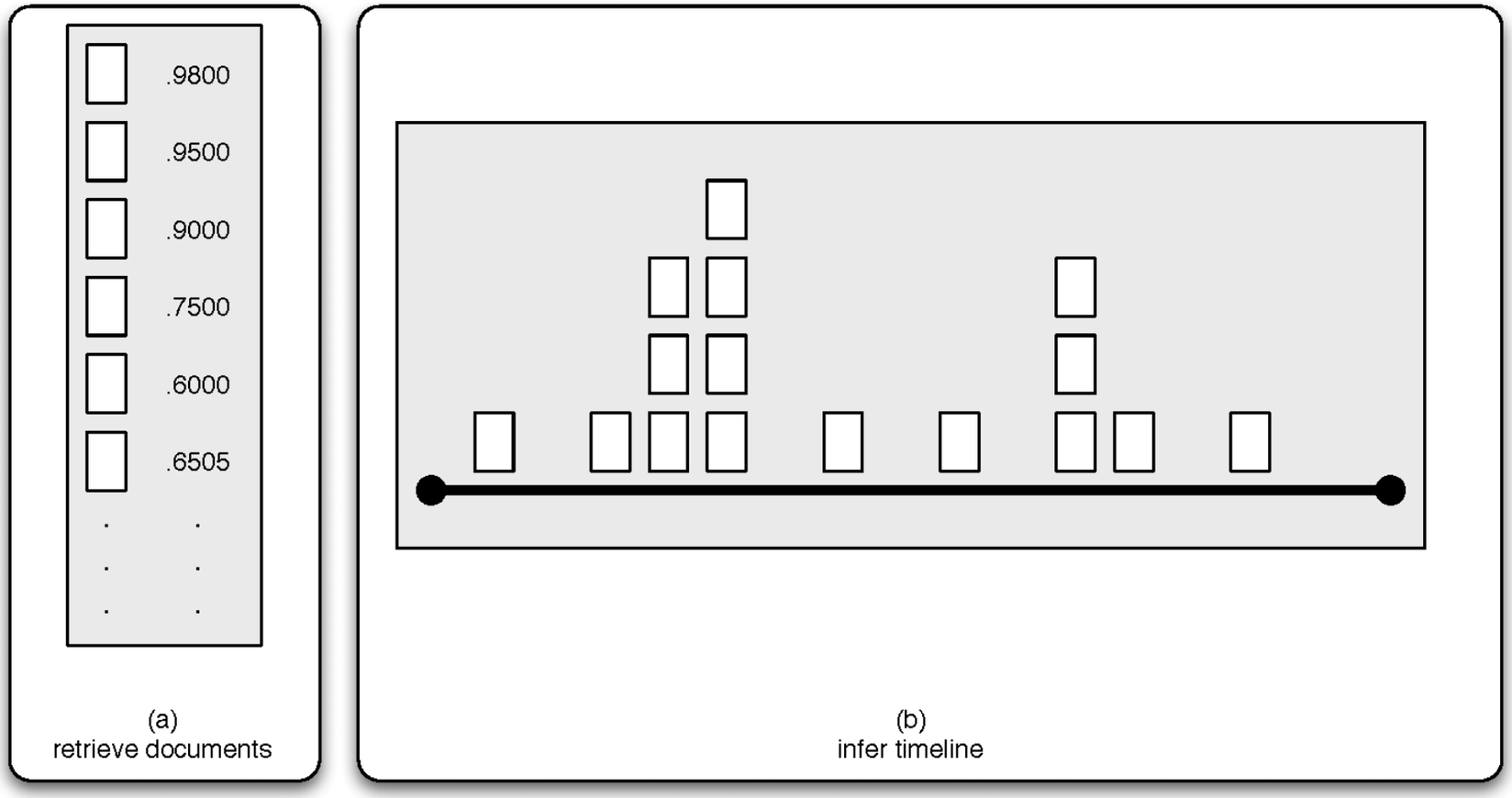


- Temporal aspect of popularity not taken into account
- Historically popular candidates might overpower recent trends
- Periodically popular queries might not be represented

Temporal Query Auto-completions

- Weights assigned to candidates should not only take into account absolute historical frequencies but also
  - Trends
  - periodicities
  - bursts
- Time series analysis techniques can be used to determine the forecast the popularity weight
  - Trends - double exponential smoothing
  - periodicities - triple exponential smoothing
  - burst - burst detection techniques

Pseuso-Relevance feedback

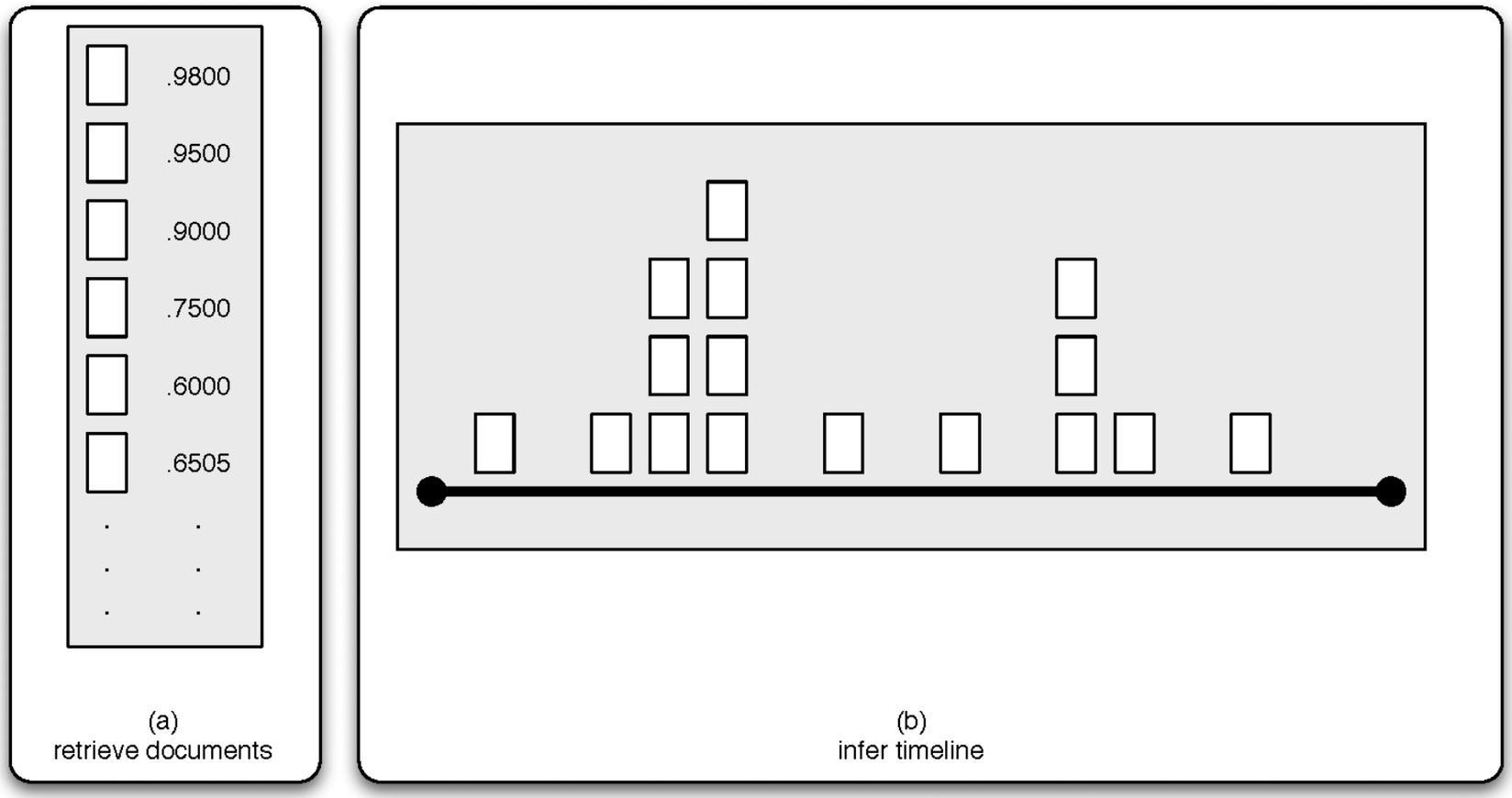


- Assume top-k documents to be relevant
- Use this set for query modelling or retrieval effectiveness

Temporal query profiles

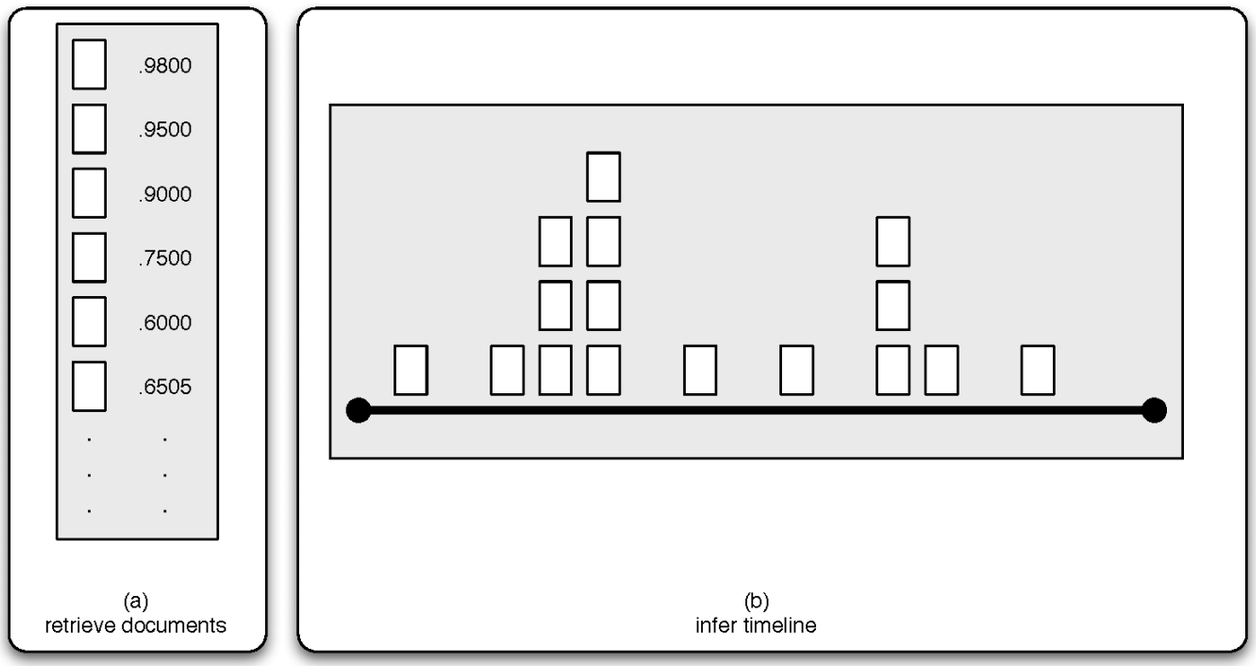
- Temporal profiles are constructed to determine how temporally relevant queries
- Queries can be classified into
  - Atemporal
  - Temporally Ambiguous
  - Temporally unambiguous
- Model the period of time relevant to the query

Temporal query profiles



- For a given query rank the documents according to the standard retrieval models (say LM as discussed in the previous lectures)
- Each document has a score and a publication time
- Plot the time lines which will then be analysed to find the query classes

Estimating Time Series Values

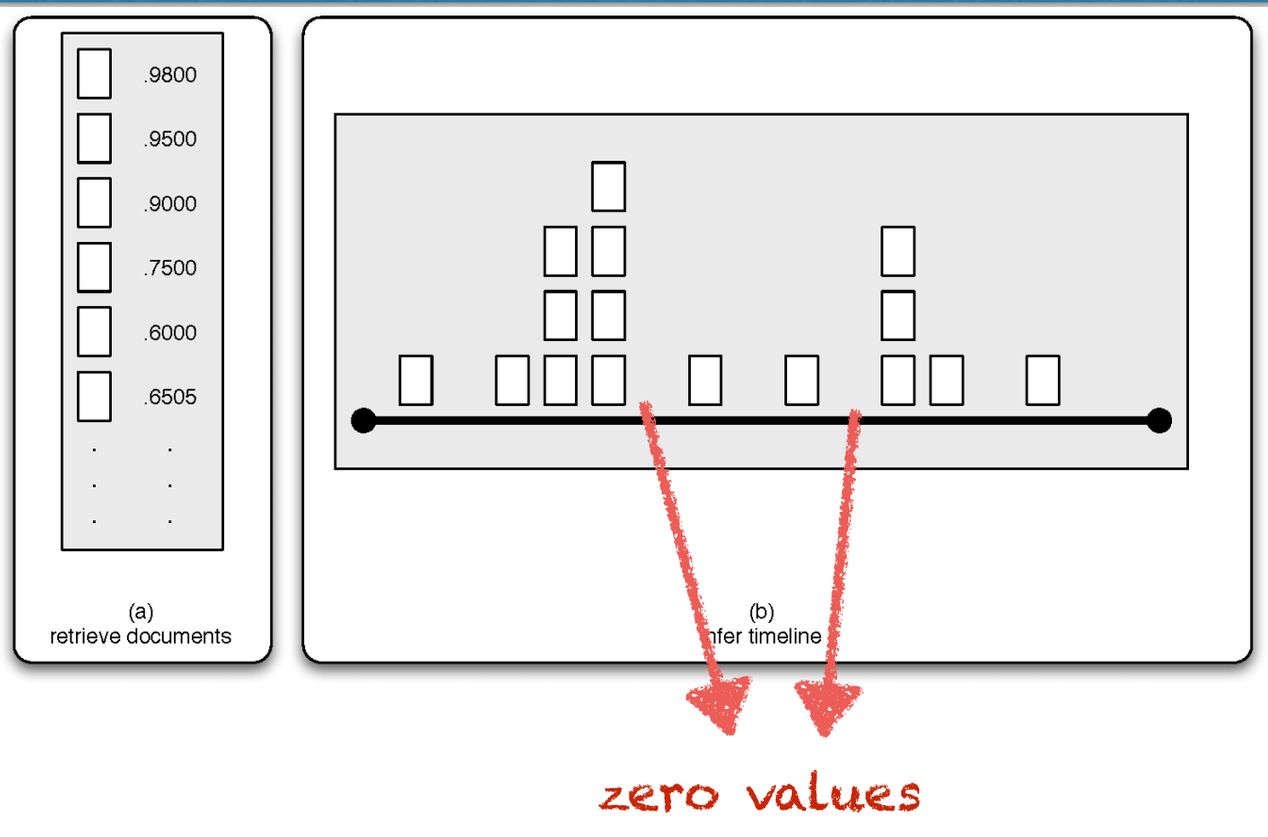


$$P(t|Q) = \sum_{D \in R} P(t|D) \frac{P(Q|D)}{\sum_{D' \in R} P(Q|D')}$$

1 is doc. is published in t, 0 otherwise

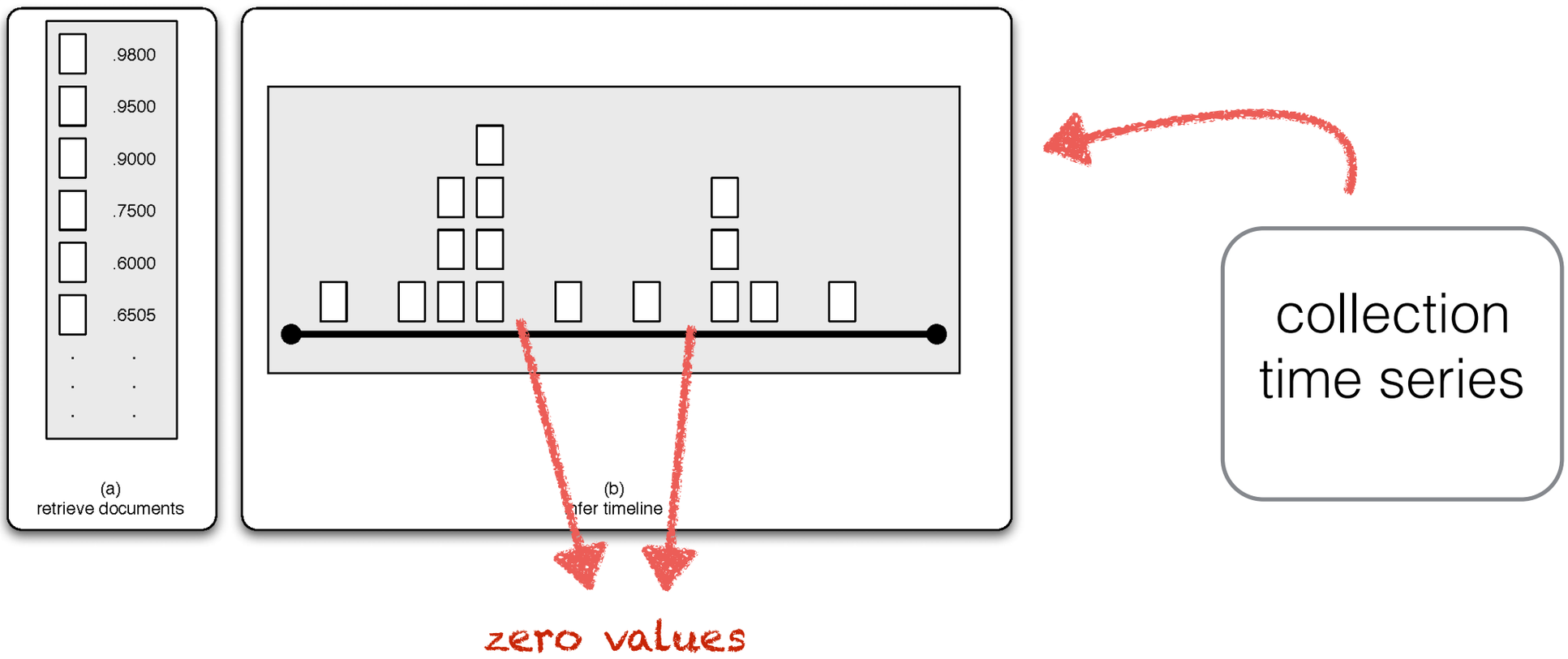
- What would be the value at a given time point ?
  - count of documents published at that time point (contribution of each doc same, i.e., 1.0)
  - sum of the scores of the documents (relevance score)
  - Language modelling approach to establish P(t|Q)

Smoothing the time series



- What about the time points with no documents published ?
  - Distribution of documents containing the query term irregular (vocabulary gap)
  - Neighbouring time points having high values increases the probability of have a non-zero value for a time point

Smoothing using Background Model



- Smoothing using language model
  - Take the distribution of the entire collection P(t | C)
  - What is the concentration of documents in the underlying distribution at t

Smoothing using Background Model

$$P'(t|Q) = \lambda P(t|Q) + (1-\lambda) P(t|c)$$

smoothing parameter

original score at t

collection score at t

$$P(t|Q) = \sum_{D \in R} P(t|D) \frac{P(Q|D)}{\sum_{D' \in R} P(Q|D')}$$

How do we incorporate information from neighbouring time points ?

- Use time series prediction methods like exponential smoothing

Features of Temporal Profiles

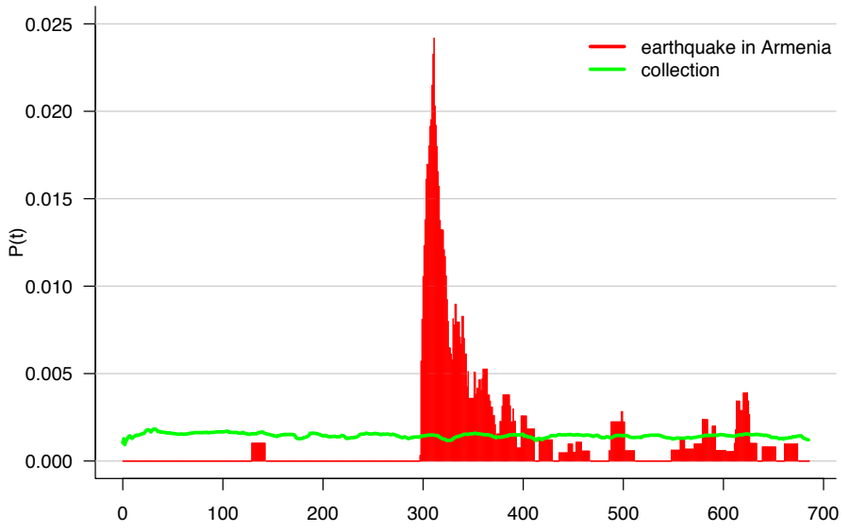
- How do we compare time series ?
- **Clarity** - Based on KL divergence between collection and query distribution
  - KL divergence is used to compare two distribution
  - The more the divergence the more clear the query is
- **Periodicity -** detect if the query time-series so obtained is periodic
  - Use auto-correlation or similar methods (discussed in lecture before)

Features of Temporal Profiles - II

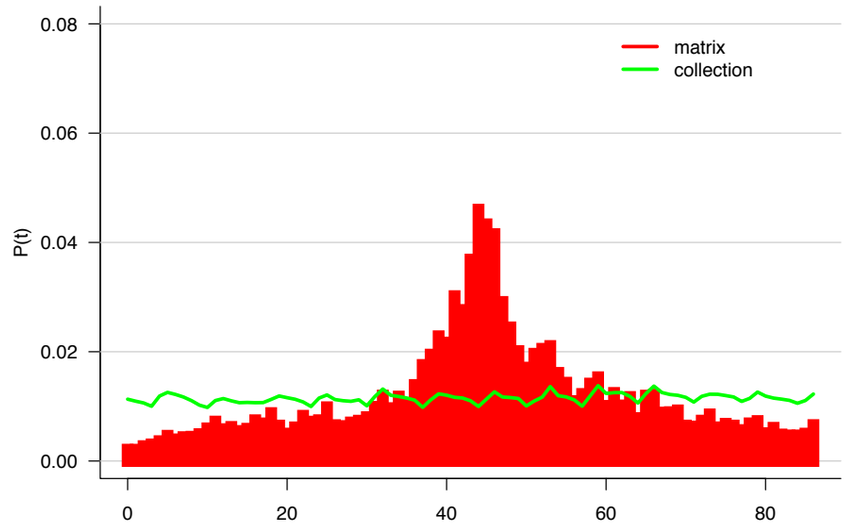
- **Statistics of Rank order**
  - How much of the power of the distribution contained in the peaks ?
  - To focus on peaks we use rank order of high peaks using the **Kurtosis** measure
- **Burst Model**
  - Identify the burstiness of a distribution using burst detection techniques
- Finally using these features classify the queries into the query classes

Temporal query profiles

Temporal Unambiguous Queries

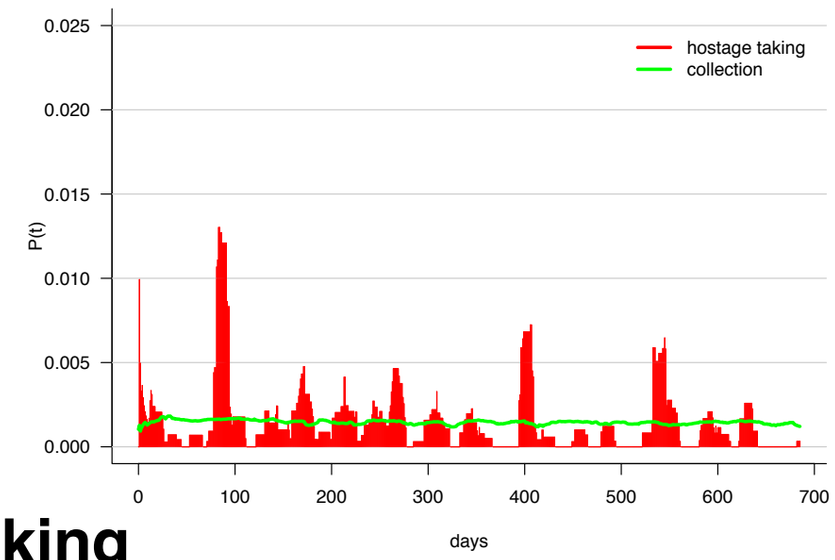


earthquake in armenia

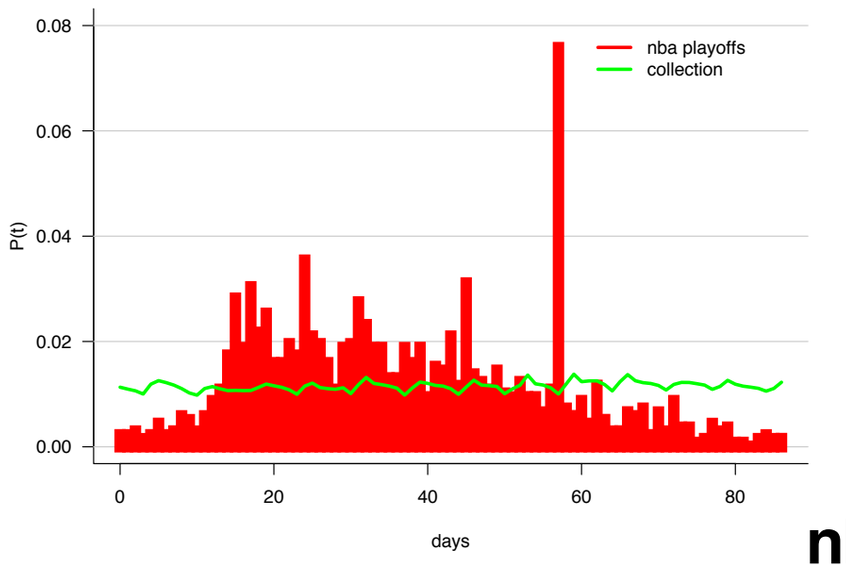


matrix

Temporal Ambiguous Queries



hostage taking



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References and Further Readings

- Jones, Rosie, and Fernando Diaz. “Temporal Profiles of Queries.” ACM Trans. Inf. Syst. 25, no. 3 (July 2007).

- Radinsky, Kira, Krysta M. Svore, Susan T. Dumais, Milad Shokouhi, Jaime Teevan, Alex Bocharov, and Eric Horvitz. “Behavioral Dynamics on the Web: Learning, Modeling, and Prediction.” ACM Trans. Inf. Syst. 31, no. 3 (August 2013)