Information Retrieval

Scores in a complete search system

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Introduction

1. We define term frequency weight of term t in document d as

$$tf_{t,d} = \sum_{x \in d} f_t(x) \text{ where } f_t(x) = \begin{cases} 1 & \text{if } x = t \\ 0 & \text{otherwise} \end{cases}$$

2. The log frequency weight of term t in d is defined as follows

$$\mathrm{w}_{t,d} = \begin{cases} 1 + \log_{10} \mathrm{tf}_{t,d} & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$$

3. We define the idf weight of term t as follows:

$$\mathrm{idf}_t = \log_{10} \frac{N}{\mathrm{df}_t}$$

4. We define the tf-idf weight of term t as product of its *tf* and *idf* weights.

$$w_{t,d} = (1 + \log \mathrm{tf}_{t,d}) \cdot \log \frac{N}{\mathrm{df}_t}$$

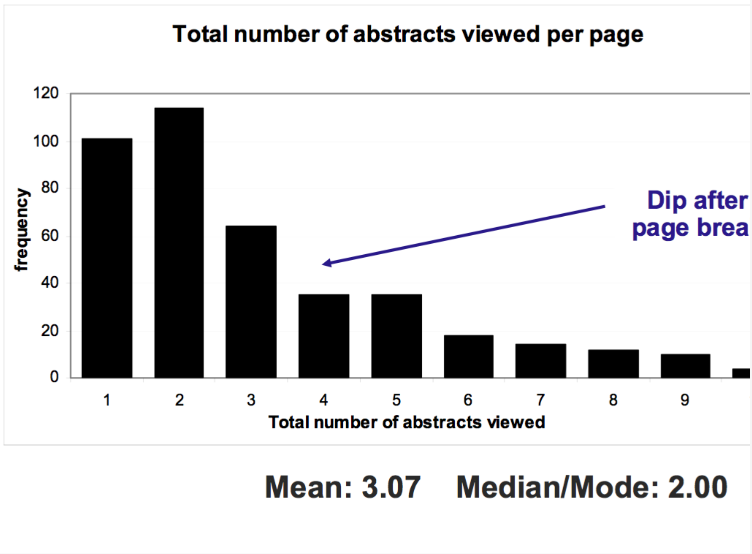
Cosine similarity between query and document

1. Cosine similarity between query q and document d is defined as

$$\cos(\vec{q}, \vec{d}) = \textsc{sim}(\vec{q}, \vec{d}) = \frac{\vec{q}}{|\vec{q}|} \cdot \frac{\vec{d}}{|\vec{d}|} = \sum_{i=1}^{|V|} \frac{q_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2}} \cdot \frac{d_i}{\sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

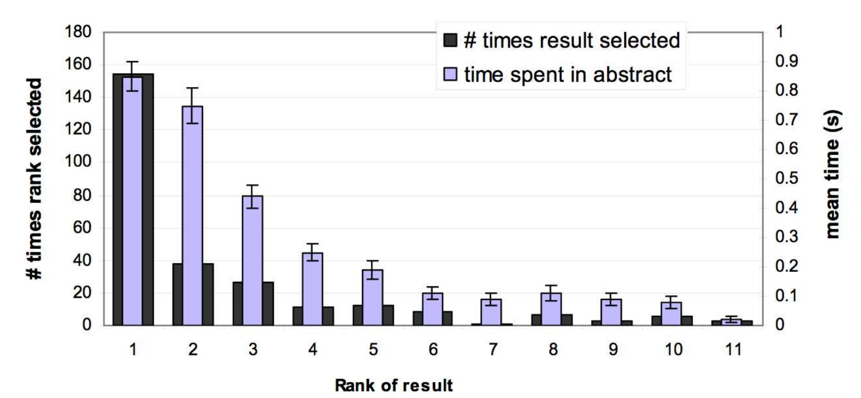
2. q_i is the tf-idf weight of term i in the query.
3. d_i is the tf-idf weight of term i in the document.
4. $|\vec{q}|$ and $|\vec{d}|$ are the lengths of $\vec{q}$ and $\vec{d}$.
5. $\vec{q}/|\vec{q}|$ and $\vec{d}/|\vec{d}|$ are length-1 vectors ($=$ normalized).
6. Computing the cosine similarity is time-consuming task.

How many links do users view?



Looking versus clicking

1. Users view results two more often/ thoroughly.
2. Users click most frequently on result one.



Importance of ranking

1. Viewing abstracts: Users are a lot more likely to read the abstracts of the top-ranked pages (1, 2, 3, 4) than the abstracts of the lower ranked pages (7, 8, 9, 10).
2. Clicking: Distribution is even more skewed for clicking
3. In 1 out of 2 cases, users click on the top-ranked page.
4. Even if the top-ranked page is not relevant, 30% of users will click on it.
    - Getting the ranking right is very important.
    - Getting the top-ranked page right is most important

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Speeding up document scoring

1. The scoring algorithm can be time consuming
2. Using heuristics can help saving time
3. Exact top-score vs approximative top-score retrieval
   We can lower the cost of scoring by searching for K documents that are likely to be among the top-scores
4. General optimization scheme:
   1. find a set of documents A such that $K < |A| << N$, and whose is likely to contain many documents close to the top-scores
   2. return the K top-scoring document included in A

Index elimination

1. While processing the query, only consider terms whose idf_t exceeds a predefined threshold
   Thus we avoid traversing the posting lists of high idf_t terms, lists which are generally long
2. Only consider documents where all query terms appear

Champion lists

1. We know which documents are the most relevant for a given term
2. For each term t, we pre-compute the list of the r most relevant (with respect to $w(t, d)$) documents in the collection
3. Given a query q, we compute

$$A = \bigcup_{t \in q} r(t)$$

r can depends on the document frequency of the term.

Static quality score

1. only consider documents which are considered as high-quality documents
2. Given a measure of quality $g(d)$, the posting lists are ordered by decreasing value of $g(d)$
3. Can be combined with champion lists, *i.e.* build the list of r most relevant documents wrt $g(d)$
4. Quality can be computed from the logs of users' queries

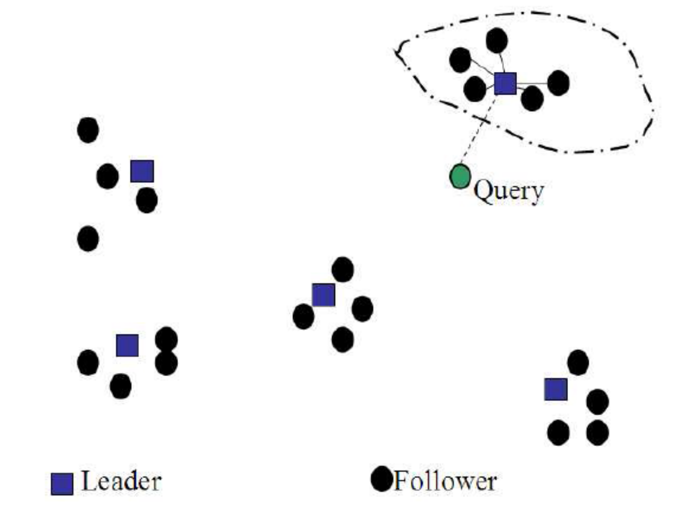
Impact ordering

1. Some sublists of the posting lists are of no interest
2. To reduce the time complexity:
   - query terms are processed by decreasing idf_t
   - postings are sorted by decreasing term frequency $tf_{t,d}$
   - Once idf_t gets low, we can consider only few postings
   - Once $tf_{t,d}$ gets smaller than a predefined threshold, the remaining postings in the list are skipped

Cluster pruning

1. The document vectors are gathered by proximity
2. We pick $\sqrt{N}$ documents randomly $\Rightarrow$ leaders
3. For each non-leader, we compute its nearest leader $\Rightarrow$ followers
4. At query time, we only compute similarities between the query and the leaders
5. The set A is the closest document cluster
6. The document clustering should reflect the distribution of the vector space

Cluster pruning



Tiered indexes

1. This technique can be seen as a generalization of champion lists
2. Instead of considering one champion list, we manage layers of champion lists, ordered in increasing size:

index 1	l most relevant documents
index 2	next m most relevant documents
index 3	next n most relevant documents

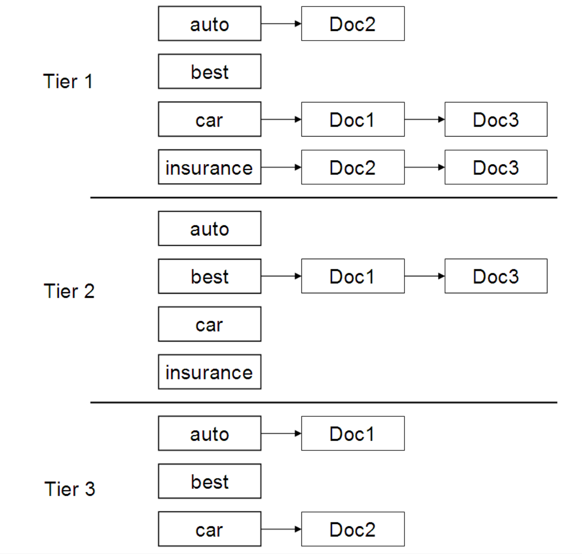
Indexed defined according to thresholds

Dictionary	$v(\vec{d}_1)$	$v(\vec{d}_2)$	$v(\vec{d}_3)$
affection	0.996	0.993	0.847
jealous	0.087	0.120	0.466
gossip	0.017	0	0.254

$$sim(d_1, d_2) = 0.999$$

$$sim(d_1, d_3) = 0.888$$

Tiered indexes



Query-term proximity

1. Priority is given to documents containing many query terms in a close window
2. Needs to pre-compute n-grams
3. And to define a proximity weighting that depends on the window size n (either by hand or using learning algorithms)

Scoring optimizations – summary

1. Index elimination
2. Champion lists
3. Static quality score
4. Impact ordering
5. Cluster pruning
6. Tiered indexes
7. Query-term proximity

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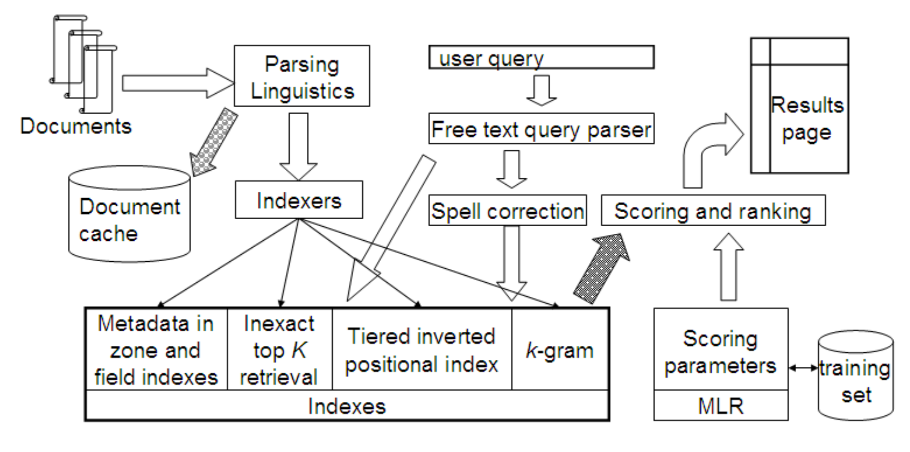
Putting it all together

1. Many techniques to retrieve documents (using logical operators, proximity operators, or scoring functions)
2. Adapted technique can be selected dynamically, by parsing the query
3. First process the query as a phrase query, if fewer than K results, then translate the query into phrase queries on bi-grams, if there are still too few results, finally process each term independently (real free text query)

A complete search engine



Reading

Please read chapter 7 of Information Retrieval Book.