Introduction to Information Retrieval

`http://informationretrieval.org`

IIR 7: Scores in a Complete Search System

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(Based on slides by Hinrich Schütze at `informationretrieval.org`)

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Overview

1. Why rank?
2. The complete search system
3. Implementation of ranking

Take-away today

- The importance of ranking: User studies at Google
- The complete search system
- Implementation of ranking

Outline

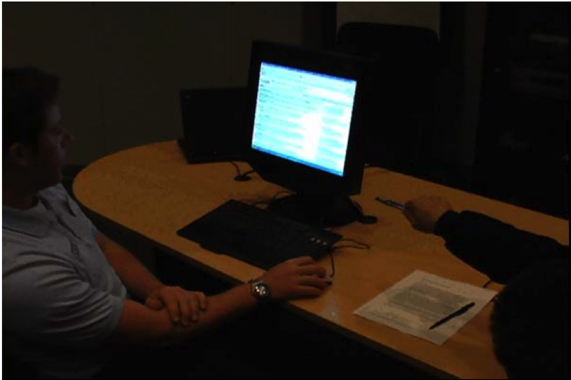
1. Why rank?
2. The complete search system
3. Implementation of ranking

Why is ranking so important?

- Last lecture: Problems with unranked retrieval
  - Users want to look at a few results – not thousands.
  - It's very hard to write queries that produce a few results.
  - Even for expert searchers
  - $\rightarrow$ Ranking is important because it effectively reduces a large set of results to a very small one.
- Next: More data on "users only look at a few results"
- Actually, in the vast majority of cases they only examine 1, 2, or 3 results.

Empirical investigation of the effect of ranking

- The following slides are from Dan Russell's JCDL talk
- Dan Russell was the "Über Tech Lead for Search Quality & User Happiness" at Google.
- How can we measure how important ranking is?
- Observe what searchers do when they are searching in a controlled setting
  - Videotape them
  - Ask them to "think aloud"
  - Interview them
  - Eye-track them
  - Time them
  - Record and count their clicks



So.. Did you notice the FTD official site?

To be honest, I didn't even look at that.

At first I saw "from $20" and $20 is what I was looking for.

To be honest, 1800-flowers is what I'm familiar with and why I went there next even though I kind of assumed they wouldn't have $20 flowers

And you knew they were expensive?

I knew they were expensive but I thought "hey, maybe they've got some flowers for under $20 here…"

But you didn't notice the FTD?

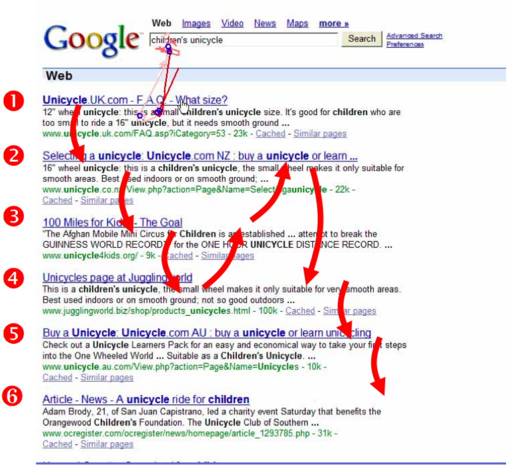
No I didn't, actually… that's really funny.

Interview video

Rapidly scanning the results

Note scan pattern:

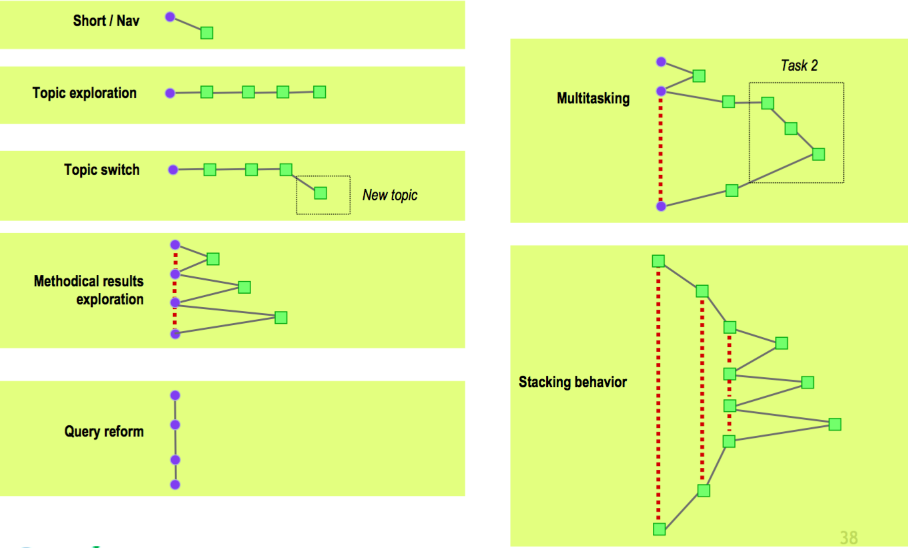
Page 3: Result 1
Result 2
Result 3
Result 4
Result 3
Result 2
Result 4
Result 5
Result 6 <click>



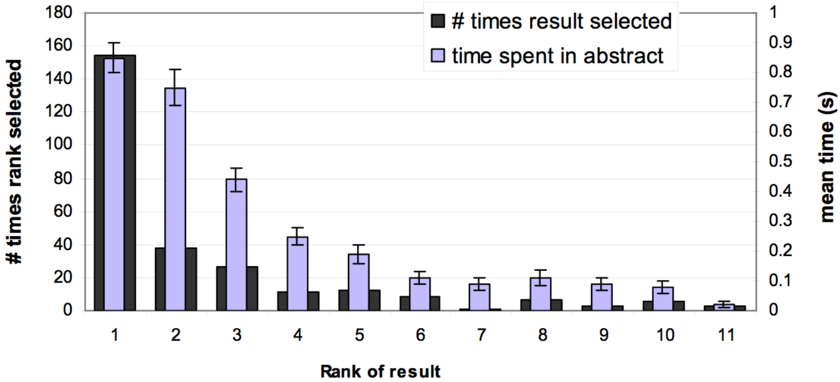
Q: Why do this?

A: What's learned later influences judgment of earlier content.

Kinds of behaviors we see in the data



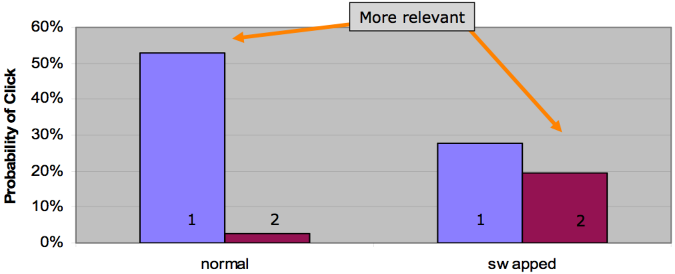
Looking vs. Clicking



- Users view results one and two more often / thoroughly
- Users click most frequently on result one

Presentation bias – reversed results

- Order of presentation influences where users look **AND** where they click



Importance of ranking: Summary

- 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).
- Clicking: Distribution is even more skewed for clicking
- In 1 out of 2 cases, users click on the top-ranked page.
- Even if the top-ranked page is not relevant, 30% of users will click on it.
- $\rightarrow$ Getting the ranking right is very important.
- $\rightarrow$ Getting the top-ranked page right is most important.

Exercise

- Ranking is also one of the high barriers to entry for competitors to established players in the search engine market.
- Why?

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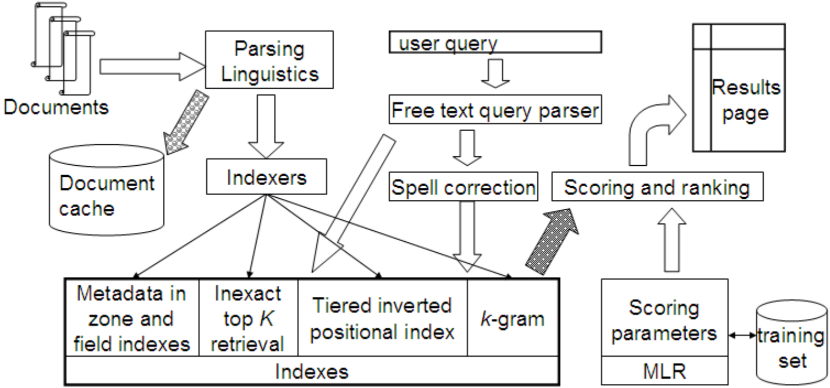
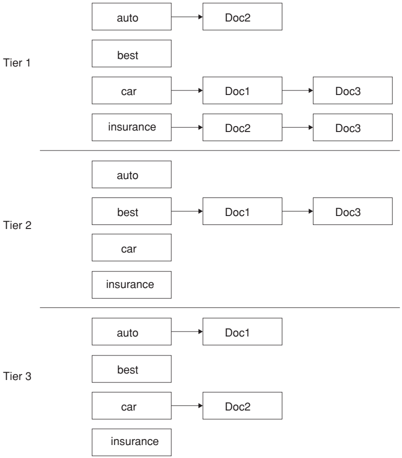
Complete search system



Tiered indexes

- Basic idea:
  - Create several tiers of indexes, corresponding to importance of indexing terms
  - During query processing, start with highest-tier index
  - If highest-tier index returns at least k (e.g., $k = 100$) results: stop and return results to user
  - If we've only found $< k$ hits: repeat for next index in tier cascade
- Example: two-tier system
  - Tier 1: Index of all titles
  - Tier 2: Index of the rest of documents
  - Pages containing the search words in the title are better hits than pages containing the search words in the body of the text.

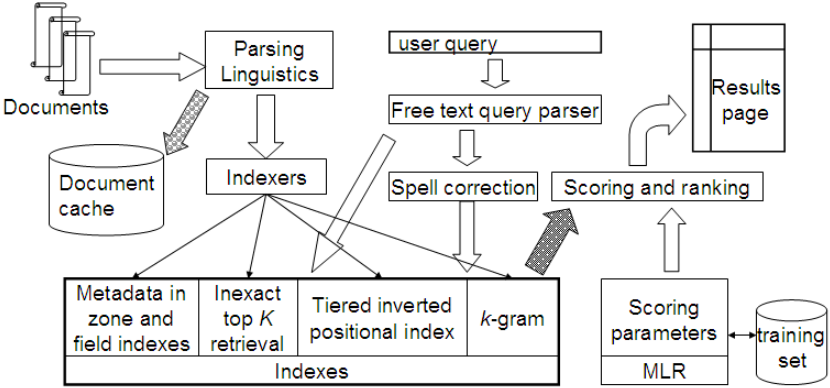
Tiered index: by term frequency



Tiered indexes

- The use of tiered indexes is believed to be one of the reasons that Google search quality was significantly higher initially (2000/01) than that of competitors.
- (along with PageRank, use of anchor text and proximity constraints)
  - What are these?

Complete search system



Components we have introduced thus far

- Document preprocessing (linguistic and otherwise)
- Positional indexes
- Tiered indexes
- Spelling correction
- k-gram indexes for wildcard queries and spelling correction
- Query processing
- Document scoring

Components we haven't covered yet

- Document cache: we need this for generating snippets (= dynamic summaries; see Lecture 8)
- Zone indexes: They separate the indexes for different zones: the body of the document, all highlighted text in the document, anchor text, text in metadata fields etc. Why?
- Proximity ranking (e.g., rank documents in which the query terms occur in the same local window higher than documents in which the query terms occur far from each other)
- The two issues above best covered using machine-learned (ML) ranking functions!
  - Google didn't use ML for ranking until 2016. Why?
- Query parser

Tiered indexes vs. zone indexes

- Tiered index: partitions the *collection of documents*
- Zone index: partitions *individual documents*
- What does Lucene support?

Components we haven't covered yet: Query parser

- IR systems often guess what the user intended.
- The two-term query *London tower* (without quotes) may be interpreted as the phrase query *"London tower"*. How?
- The query *100 Madison Avenue, New York* may be interpreted as a request for a map.
- How do we "parse" the query and translate it into a formal specification containing phrase operators, proximity operators, indexes to search etc.? Need query syntax language!
  - We have seen Lucene's, but actual search engines do a lot of natural language processing as well, e.g., to recognize addresses, definitional questions, etc.

Exercise: Interactions with vector space retrieval

- How do we combine phrase retrieval with vector space retrieval?
- How do we combine Boolean retrieval with vector space retrieval?
- How do we combine wild cards with vector space retrieval?
- What does Lucene implement?

Exercise: Better tiered system

- Design criteria for tiered system
  - Each tier should be an order of magnitude smaller than the next tier.
  - Roughly: the top 100 hits for most queries should be in tier 1, the top 100 hits for most of the remaining queries in tier 2 etc.
  - We need a simple test for "can I stop at this tier or do I have to go to the next one?"
    - There is no advantage to tiering if we have to hit most tiers for most queries anyway.
- Question: Can you think of a better way of setting up a multitier system? Which "zones" of a document should be indexed in the different tiers (title, body of document, others?)? What criterion do you want to use for including a document in tier 1?

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BRUTUS	$\longrightarrow$	1,2	7,3	83,1	87,2	. . .
CAESAR	$\longrightarrow$	1,1	5,1	13,1	17,1	. . .
CALPURNIA	$\longrightarrow$	7,1	8,2	40,1	97,3	

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term frequencies

We also need positions. Not shown here.

Term frequencies in the inverted index

- Thus: In each posting, store $\mathrm{tf}_{t,d}$ in addition to docID d.
- As an integer frequency, not as a (log-)weighted real number . . .

Term frequencies in the inverted index

- Thus: In each posting, store $\mathrm{tf}_{t,d}$ in addition to docID d.
- As an integer frequency, not as a (log-)weighted real number ...
- ... because real numbers are difficult to compress.
- Overall, additional space requirements are small: a byte per posting or less

Computing cosine: compare against the Boolean intersection!

CosineScore(q)

float Scores$[N] = 0$
float Length$[N]$
for each query term t
do calculate $\mathrm{w}_{t,q}$ and fetch postings list for t
  for each pair$(d, \mathrm{tf}_{t,d})$ in postings list
  do $Scores[d] += \mathrm{w}_{t,d} \times \mathrm{w}_{t,q}$
Read the array *Length*
for each d
do $Scores[d] = Scores[d]/Length[d]$
return Top k components of $Scores[]$

How do we compute the top k in ranking?

- We usually don't need a complete ranking.
- We just need the top k for a small k (e.g., $k = 100$).
- If we don't need a complete ranking, is there an efficient way of computing just the top k?
- Naive:
    - Compute scores for all N documents
    - Sort
    - Return the top k
- Not very efficient
- Alternative: min heap

Use min heap for selecting top k ouf of N

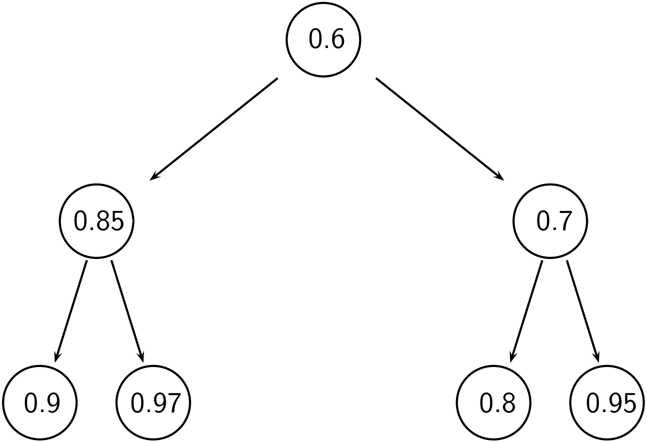
- A binary min heap is a binary tree in which each node's value is less than the values of its children.
- It is a complete tree: all levels are completely filled, except possibly the last one. If the last level is not complete, the leaves are filled from left to right.
- Takes $O(N \log k)$ operations to construct (where N is the number of documents) ...
- ...then read off k winners in $O(k \log k)$ steps

Inserting into a min heap

- Place the new element in the next available position in the leaves.
- Compare the new element with its parent. If the new element is smaller, than swap it with its parent.
- Continue this process until either
  - the new elements parent is smaller than or equal to the new element, or
  - the new element reaches the root.

(Text adapted from CMU's Introduction to Data Structures)

Binary min heap: insert 0.75

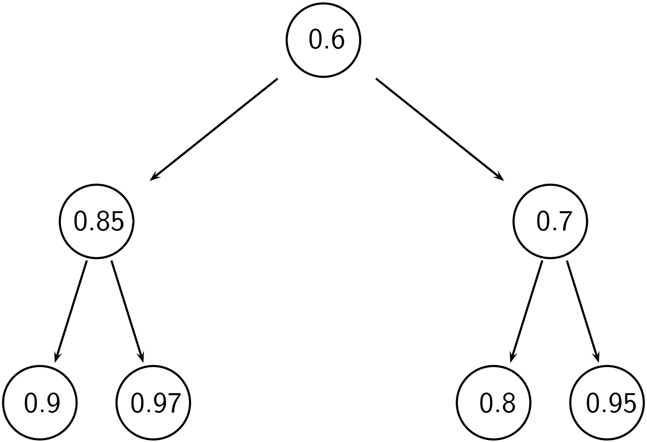


Removing the smallest element from the min heap

- Place the root element in a variable to return later.
- Remove the last element in the deepest level and move it to the root.
- While the moved element has a value greater than at least one of its children, swap this value with the smaller-valued child.
- Return the original root that was saved.

(Text adapted from CMU's Introduction to Data Structures)

Binary min heap: remove 0.6



Selecting top k scoring documents in $O(N \log k)$

- Goal: Keep the top k documents seen so far
- Use a binary min heap
- To process a new document d' with score s':
  - Get current minimum h_m of heap ($O(1)$)
  - If $s' \leq h_m$ skip to next document
  - If $s' > h_m$ heap-delete-root ($O(\log k)$)
  - Heap-add d'/s' ($O(\log k)$)

Even more efficient computation of top k?

- Ranking has time complexity $O(N)$ where N is the number of documents.
- Optimizations reduce the constant factor, but they are still $O(N)$, $N > 10^{10}$
- Are there sublinear algorithms?

Even more efficient computation of top k?

- Ranking has time complexity $O(N)$ where N is the number of documents.
- Optimizations reduce the constant factor, but they are still $O(N)$, $N > 10^{10}$
- Are there sublinear algorithms?
- What we're doing in effect: solving the k-nearest neighbor (kNN) problem for the query vector (= query point).
- There are no general solutions to this problem that are sublinear.

More efficient computation of top k: Three ideas (heuristics)

- Document-at-a-time processing
- Term-at-a-time processing
- Cluster pruning

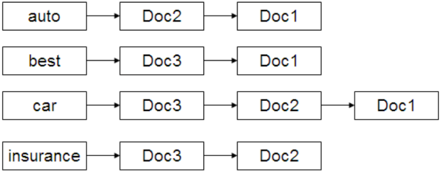
Non-docID ordering of postings lists

- So far: postings lists have been ordered according to docID.
- Alternative: a query-independent measure of "goodness" of a page
- Example: PageRank $g(d)$ of page d, a measure of how many "good" pages hyperlink to d (chapter 21)
- Order documents in postings lists according to PageRank: $g(d_1) > g(d_2) > g(d_3) > \ldots$
- Define composite score of a document:

$$\text{net-score}(q, d) = g(d) + \cos(q, d)$$

- This scheme supports early termination: We do not have to process postings lists in their entirety to find top k.

Non-docID ordering of postings lists (2)



► **Figure 7.2** A static quality-ordered index. In this example we assume that Doc1, Doc2 and Doc3 respectively have static quality scores $g(1) = 0.25, g(2) = 0.5, g(3) = 1$.

Postings no longer sorted by doId, but by g! Does it matter?

Non-docID ordering of postings lists (3)

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- Then all subsequent scores will be < 1.1.
- So we've already found the top k and can stop processing the remainder of postings lists.
- Questions?

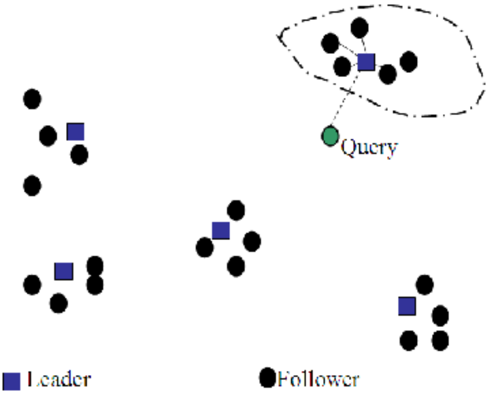
This was document-at-a-time processing

- Both docID-ordering and PageRank-ordering impose a consistent ordering on documents in postings lists.
- Computing cosines in this scheme is document-at-a-time
- This means we need to be careful to store intermediate results for all documents seen! (Remember the `Scores[]` variable in the cosine similarity algorithm?)
- Alternative: term-at-a-time processing

Term-at-a-time processing

- Idea 1 (sort postings):
  - Order the documents d in the postings list of term t by decreasing order of $tf_{t,d}$.
  - When traversing the postings list for a query term t, we stop either after a fixed number of documents r have been seen, or after the value of $tf_{t,d}$ has dropped below a threshold.
- Idea 2 (sort query):
  - Sort terms in query q in descending order of idf.
  - Stop after getting to terms with low idf values.

Cluster pruning



Cluster pruning: Algorithm

- At indexing time:
  - Pick $\sqrt{N}$ documents at random from the collection as *leaders*.
  - For each document that is not a leader, compute its closest leader. These are *followers*.
- At search time:
  - Given a query q, find the leader L that is closest to q.
  - The candidate set consists of L together with all its followers. We compute the cosine scores *only* for the documents in this set.

Implementation of ranking: Summary

- Ranking is very expensive in applications where we have to compute similarity scores for all documents in the collection.
- In most applications, the vast majority of documents have similarity score 0 for a given query $\rightarrow$ lots of potential for speeding things up.
- However, there is no fast nearest neighbor algorithm that is guaranteed to be correct even in this scenario.
- In practice: use heuristics to prune search space – usually works very well.

Take-away today

- The importance of ranking: User studies at Google
- The complete search system
- Implementation of ranking