Introduction to Information Retrieval

http://informationretrieval.org

IIR 7: Scores in a Complete Search System

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Overview

Outline

Term frequency weight

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

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

idf weight

- The document frequency df_t is defined as the number of documents that t occurs in.
- We define the idf weight of term t as follows:

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

- idf is a measure of the informativeness of the term.

tf-idf weight

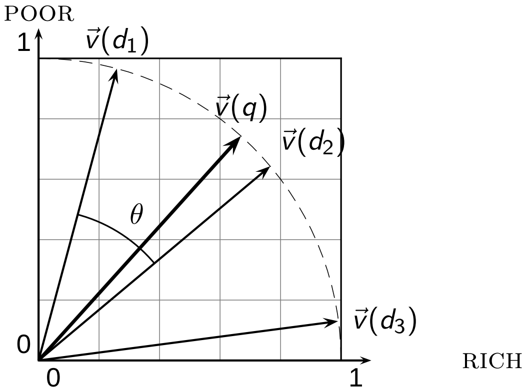
- The tf-idf weight of a term is the product of its tf weight and its idf weight.
- $$w_{t,d} = (1 + \log \mathrm{tf}_{t,d}) \cdot \log \frac{N}{\mathrm{df}_t}$$

Cosine similarity between query and document

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

- q_i is the tf-idf weight of term i in the query.
- d_i is the tf-idf weight of term i in the document.
- $|\vec{q}|$ and $|\vec{d}|$ are the lengths of $\vec{q}$ and $\vec{d}$.
- $\vec{q}/|\vec{q}|$ and $\vec{d}/|\vec{d}|$ are length-1 vectors ($=$ normalized).

Cosine similarity illustrated



tf-idf example: lnc.ltn

Query: "best car insurance". Document: "car insurance auto insurance".

word	query					document				product
	tf-raw	tf-wght	df	idf	tf-idf weight	tf-raw	tf-wght	tf-wght	n'lized	
auto	0	0	5000	2.3	0	1	1	1	0.52	0
best	1	1	50000	1.3	1.3	0	0	0	0	0
car	1	1	10000	2.0	2.0	1	1	1	0.52	1.04
insurance	1	1	1000	3.0	3.0	2	1.3	1.3	0.68	2.04

Key to columns: tf-raw: raw (unweighted) term frequency, tf-wght: logarithmically weighted

term frequency, df: document frequency, idf: inverse document frequency, weight: the final weight of the term in the query or document, n'lized: document weights after cosine normalization, product: the product of final query weight and final document weight

$\sqrt{1^2 + 0^2 + 1^2 + 1.3^2} \approx 1.92$
$1/1.92 \approx 0.52$
$1.3/1.92 \approx 0.68$ Final similarity score between query and

document: $\sum_i w_{qi} \cdot w_{di} = 0 + 0 + 1.04 + 2.04 = 3.08$

Take-away today

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

Outline

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"

Empirical investigation of the effect of ranking

- The following slides are from Dan Russell's JCDL 2007 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

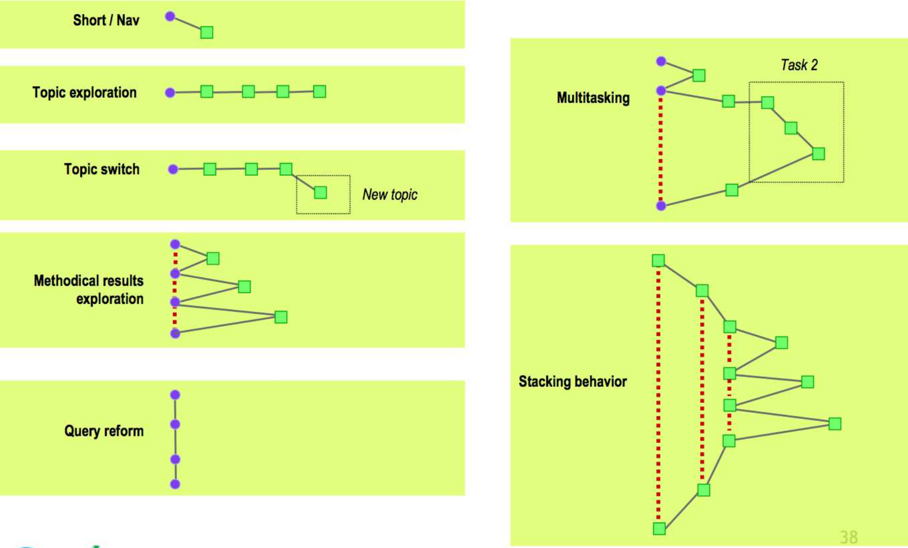
Note scan pattern:

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

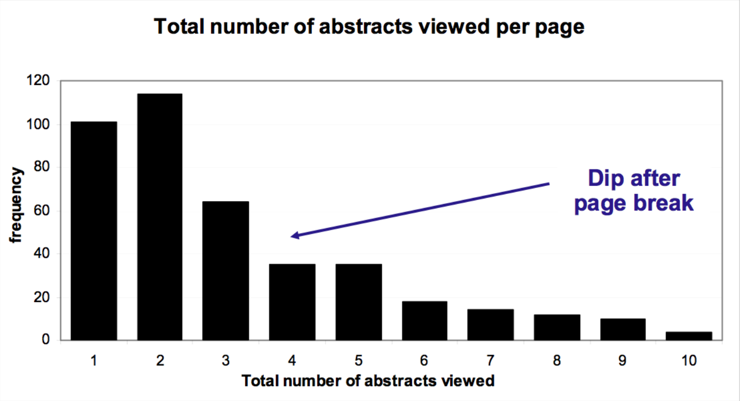
Q: Why do this?

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

Kinds of behaviors we see in the data



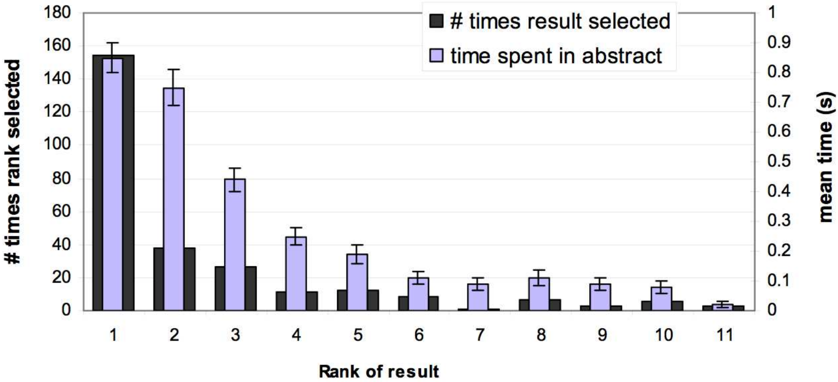
How many links do users view?



Mean: 3.07 Median/Mode: 2.00

Google

Looking vs. Clicking

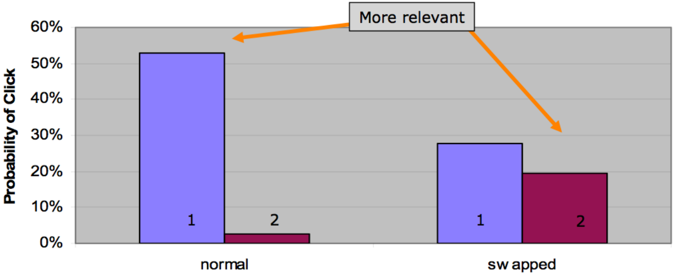


- Users view results one and two more often / thoroughly
- Users click most frequently on result one

Google

Presentation bias – reversed results

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



Importance of ranking: Summary

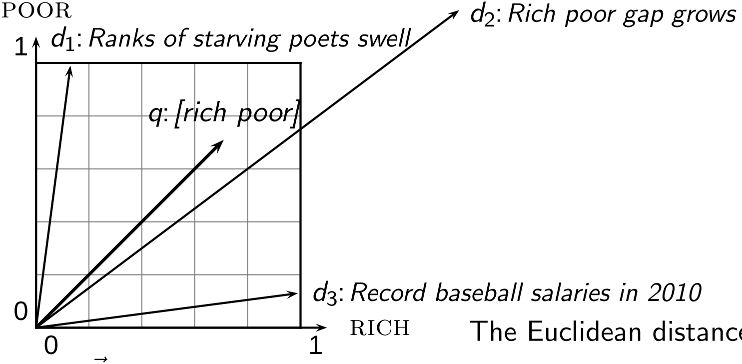
- Viewing abstracts: Users are a lot more likely to read the abstracts of the top-ranked pages (1, 2, 3, 4) than the abstracts of the lower ranked pages (7, 8, 9, 10).
- Clicking: Distribution is even more skewed for clicking
- In 1 out of 2 cases, users click on the top-ranked page.
- Even if the top-ranked 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?

Outline

Why distance is a bad idea



The Euclidean distance of $\vec{q}$ and $\vec{d_2}$ is large although the distribution of terms in the query q and the distribution of terms in the document d_2 are very similar. That's why we do length normalization or, equivalently, use cosine to compute query-document matching scores.

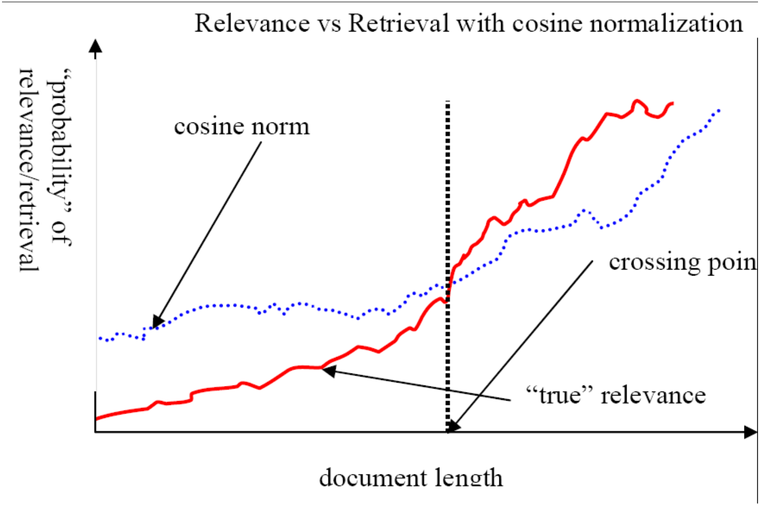
Exercise: A problem for cosine normalization

- Query q: "anti-doping rules Beijing 2008 olympics"
- Compare three documents
  - d_1: a short document on anti-doping rules at 2008 Olympics
  - d_2: a long document that consists of a copy of d_1 and 5 other news stories, all on topics different from Olympics/anti-doping
  - d_3: a short document on anti-doping rules at the 2004 Athens Olympics
- What ranking do we expect in the vector space model?
- What can we do about this?

Pivot normalization

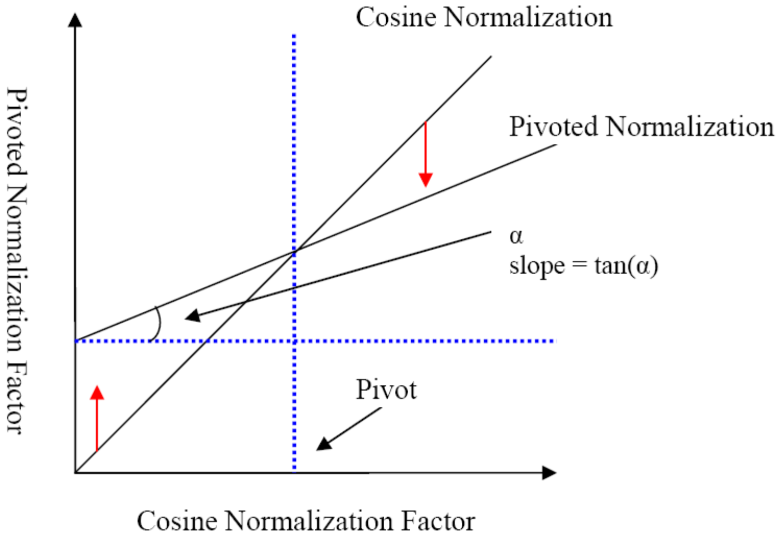
- Cosine normalization produces weights that are too large for short documents and too small for long documents (on average).
- Adjust cosine normalization by linear adjustment: "turning" the average normalization on the pivot
- Effect: Similarities of short documents with query decrease; similarities of long documents with query increase.
- This removes the unfair advantage that short documents have.

Predicted and true probability of relevance



source: Lillian Lee

Pivot normalization



source:
Lillian Le

Pivoted normalization: Amit Singhal's experiments

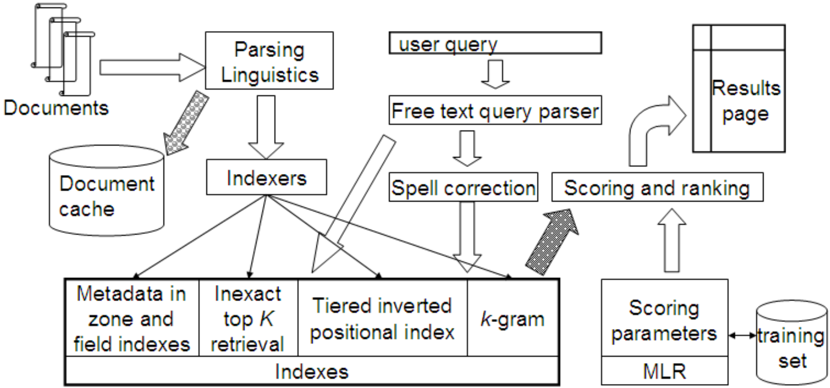
Cosine	Pivoted Cosine Normalization				
	Slope				
	0.60	0.65	0.70	**0.75**	0.80
6,526	6,342	6,458	6,574	**6,629**	6,671
0.2840	0.3024	0.3097	0.3144	**0.3171**	0.3162
Improvement	+ 6.5%	+ 9.0%	+10.7%	**+11.7%**	+11.3%

(relevant

documents retrieved and (change in) average precision)

Outline

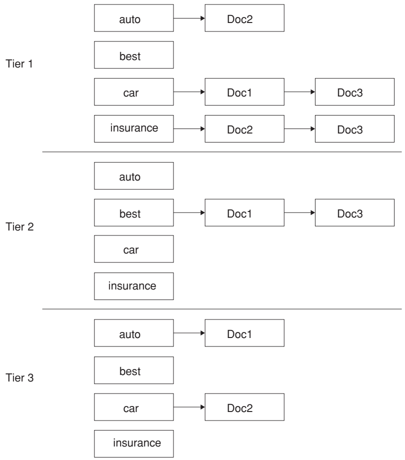
Complete search system



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.

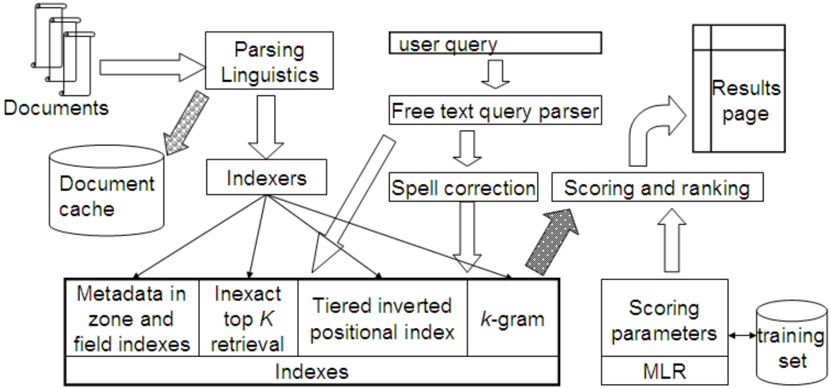
Tiered index



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)

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)
- 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
- Machine-learned ranking functions
- 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)
- Query parser

Vector space retrieval: Interactions

- How do we combine phrase retrieval with vector space retrieval?
- We do not want to compute document frequency / idf for every possible phrase. Why?
- How do we combine Boolean retrieval with vector space retrieval?
- For example: "+"-constraints and "-"-constraints
- Postfiltering is simple, but can be very inefficient – no easy answer.
- How do we combine wild cards with vector space retrieval?
- Again, no easy answer

Exercise

- Design criteria for tiered system
  - Each tier should be an order of magnitude smaller than the next tier.
  - 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.
- Consider a two-tier system where the first tier indexes titles and the second tier everything.
- 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?

Outline

Now we also need term frequencies in the index

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

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 ...
- ... because real numbers are difficult to compress.
- Overall, additional space requirements are small: a byte per posting or less

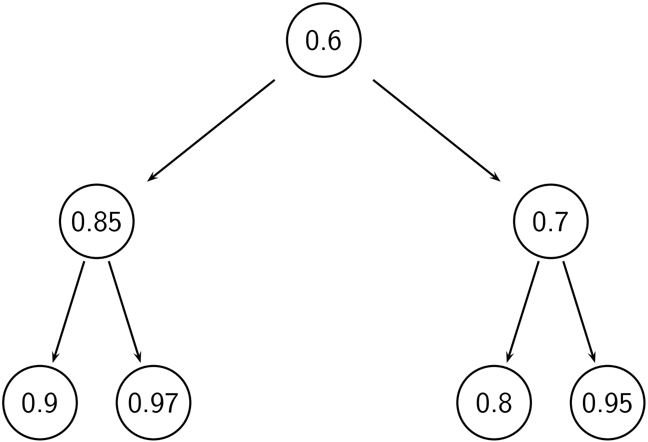
How do we compute the top k in ranking?

- 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.
- 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

Binary min heap



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?
- 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: Heuristics

- Idea 1: Reorder postings lists
  - Instead of ordering according to docID . . .
  - . . . order according to some measure of "expected relevance".
- Idea 2: Heuristics to prune the search space
  - Not guaranteed to be correct . . .
  - . . . but fails rarely.
  - In practice, close to constant time.
  - For this, we'll need the concepts of document-at-a-time processing and term-at-a-time processing.

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: $g(d_1) > g(d_2) > g(d_3) > \dots$
- 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)

- Order documents in postings lists according to PageRank: $g(d_1) > g(d_2) > g(d_3) > \dots$
- Define composite score of a document:

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

- Suppose: (i) $g \to [0, 1]$; (ii) $g(d) < 0.1$ for the document d we're currently processing; (iii) smallest top k score we've found so far is 1.2
- 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?

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.
- We complete computation of the query-document similarity score of document d_i before starting to compute the query-document similarity score of d_{i+1}.
- Alternative: term-at-a-time processing

Weight-sorted postings lists

- Idea: don't process postings that contribute little to final score
- Order documents in postings list according to weight
- Simplest case: normalized tf-idf weight (rarely done: hard to compress)
- Documents in the top k are likely to occur early in these ordered lists.
- $\rightarrow$ Early termination while processing postings lists is unlikely to change the top k.
- But:
  - We no longer have a consistent ordering of documents in postings lists.
  - We no longer can employ document-at-a-time processing.

Term-at-a-time processing

- Simplest case: completely process the postings list of the first query term
- Create an accumulator for each docID you encounter
- Then completely process the postings list of the second query term
- ... and so forth

Term-at-a-time processing

```
CosineScore(q)
float Scores[N] = 0
float Length[N]
for each query term t
do calculate w_{t,q} and fetch postings list for t
    for each pair(d, tf_{t,d}) in postings list
    do Scores[d] += w_{t,d} × w_{t,q}
Read the array Length
for each d
do Scores[d] = Scores[d]/Length[d]
return Top k components of Scores[]
```

The elements of the array "Scores" are called accumulators.

Accumulators

- For the web (20 billion documents), an array of accumulators A in memory is infeasible.
- Thus: Only create accumulators for docs occurring in postings lists
- This is equivalent to: Do not create accumulators for docs with zero scores (i.e., docs that do not contain any of the query terms)

Accumulators: Example

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	

- For query: [Brutus Caesar]:
- Only need accumulators for 1, 5, 7, 13, 17, 83, 87
- Don't need accumulators for 3, 8 etc.

Enforcing conjunctive search

- We can enforce conjunctive search (a la Google): only consider documents (and create accumulators) if all terms occur.
- Example: just one accumulator for [Brutus Caesar] in the example above . . .
- . . . because only d_1 contains both words.

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
- Length normalization: Pivot normalization
- The complete search system
- Implementation of ranking

Resources

- Chapters 6 and 7 of IIR
- Resources at `http://cislmu.org`
    - How Google tweaks its ranking function
    - Interview with Google search guru Udi Manber
    - Amit Singhal on Google ranking
    - SEO perspective: ranking factors
    - Yahoo Search BOSS: Opens up the search engine to developers. For example, you can rerank search results.
    - Compare Google and Yahoo ranking for a query
    - How Google uses eye tracking for improving search