Introduction to Information Retrieval
http://informationretrieval.org

IIR 7: Scores in a Complete Search System

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Overview

Outline

1. Recap
2. Why rank?
3. More on cosine
4. Implementation
5. The complete search system

Term frequency weighting

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

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

- Score for a document-query pair: sum over terms t in both q and d:
  matching-score $= \sum_{t \in q \cap d} (1 + \log \mathrm{tf}_{t,d})$

idf weight

- df_t is the document frequency, the number of documents that t occurs in.
- df is an inverse measure of the informativeness of the term.
- 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 weighting

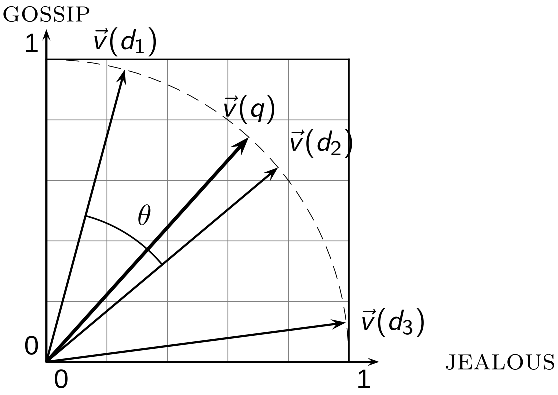
- The tf-idf weight of a term is the product of its tf weight and its idf weight.
- $$w_{t,d} = (1 + \log \mathrm{tf}_{t,d}) \cdot \log \frac{N}{\mathrm{df}_t}$$
- Best known weighting scheme in information retrieval

Cosine similarity between query and document

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

- 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 $\vec{d}$.

Cosine similarity illustrated



tf-idf example: ltn.lnc

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

word	query					document				product
	tf-raw	tf-wght	df	idf	weight	tf-raw	tf-wght	weight	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: $\sum_i w_{qi} \cdot w_{di} = 0 + 0 + 1.04 + 2.04 = 3.08$

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- Next: More data on "users only look at a few results"
- Actually, in the vast majority of cases they only look at 1, 2, or 3 results.

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- Dan Russell is the "Über Tech Lead for Search Quality & User Happiness" at Google.

Interview video

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…"

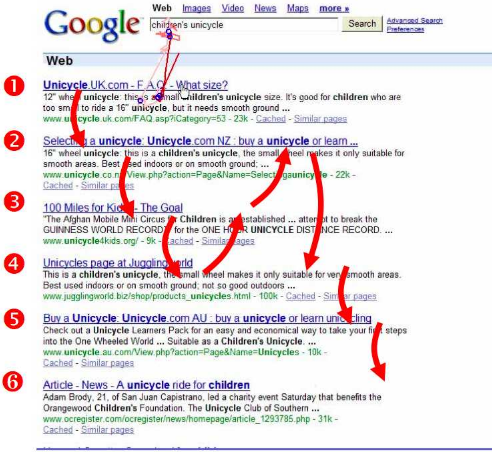
But you didn't notice the FTD?

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

Rapidly scanning the results

Note scan pattern:

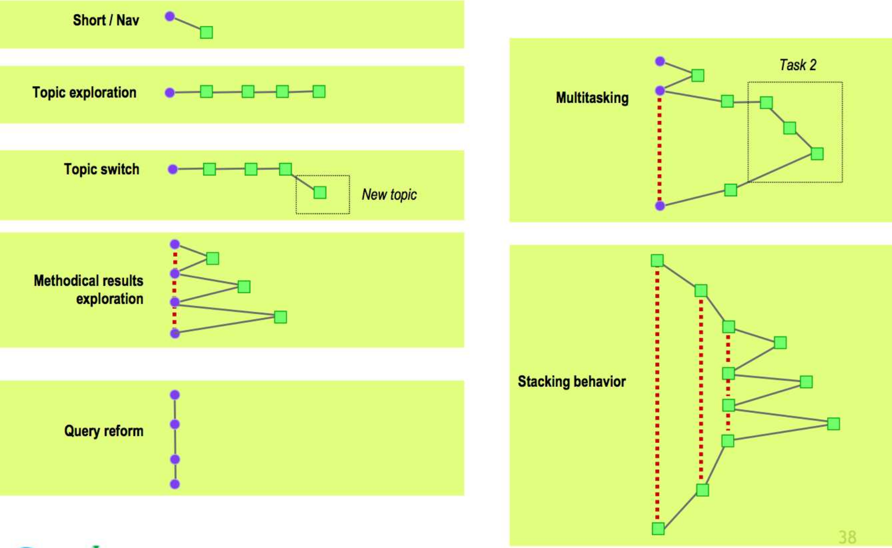
Page 3:	Result 1
	Result 2
	Result 3
	Result 4
	Result 3
	Result 2
	Result 4
	Result 5
	Result 6 <click>



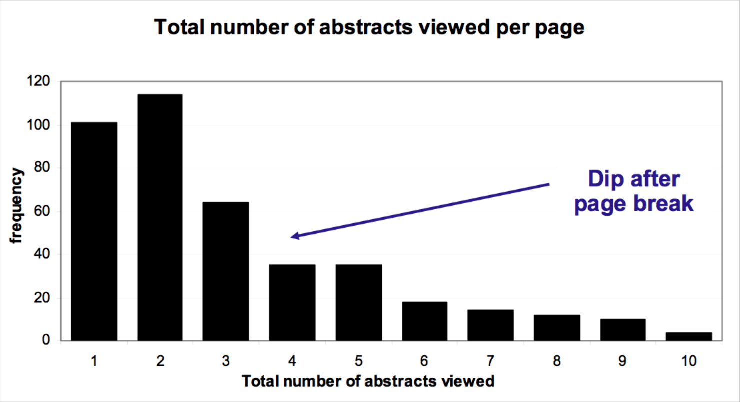
Q: Why do this?

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

Kinds of behaviors we see in the data



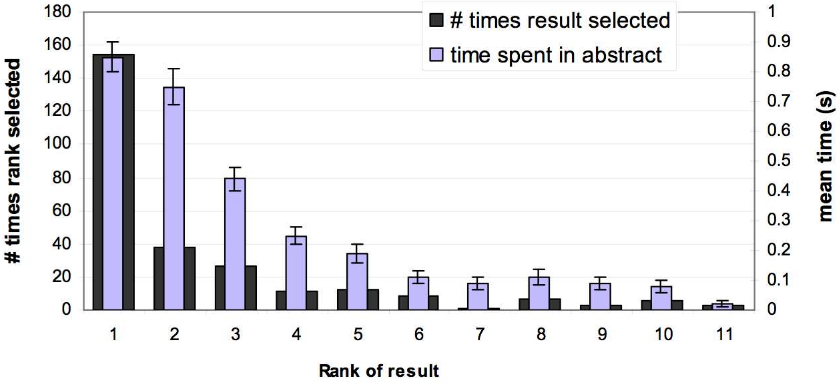
How many links do users view?



Mean: 3.07 Median/Mode: 2.00

Google

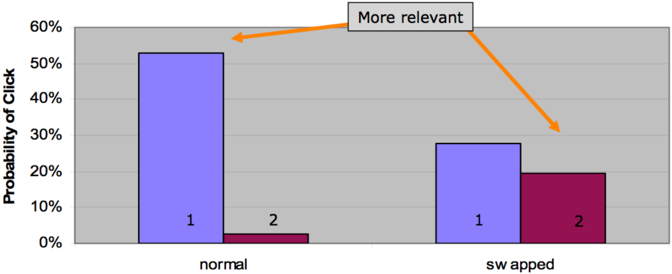
Looking vs. Clicking



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

Presentation bias – reversed results

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



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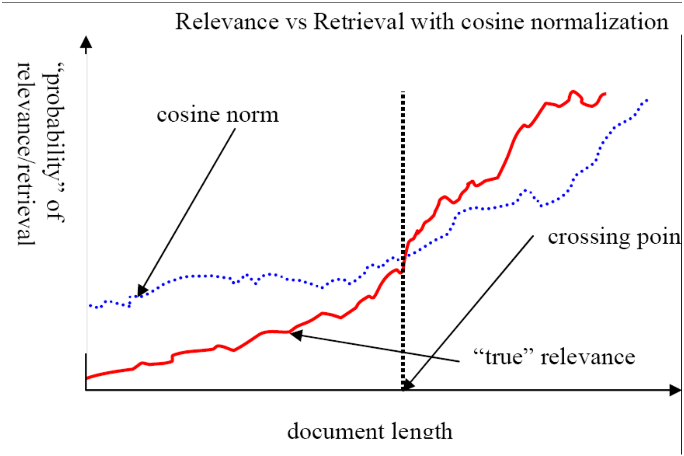
- Note that “pivoted” scores are no longer bounded by 1.

Predicted and true probability of relevance



source:
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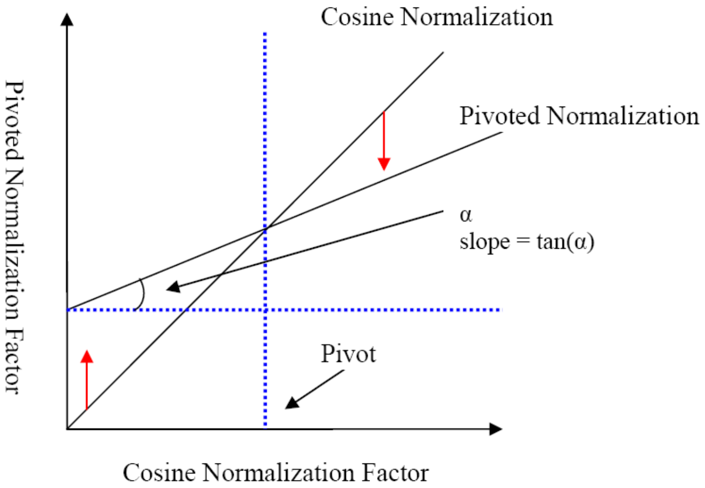

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We also need positions. Not shown here.

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- Why?
- Overall, additional space requirements are small: much less than a byte per posting.

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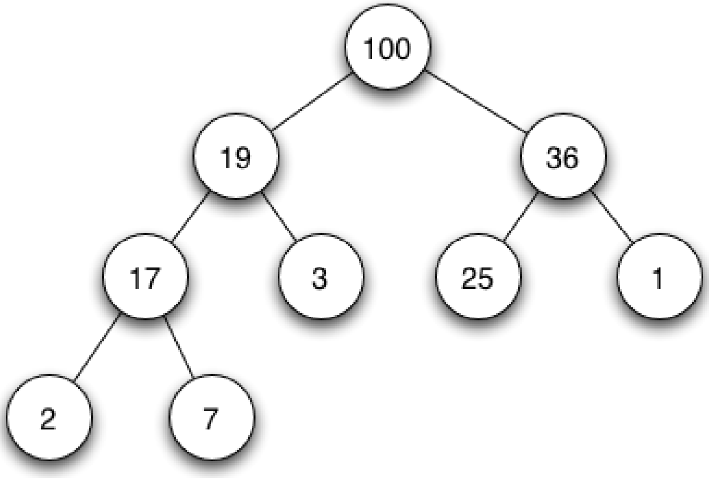
- Essentially linear in N for small k and large N.

Binary max heap



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- We will revisit this issue when we do kNN classification in IIR 14.

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- 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
- Order documents in postings lists according to PageRank: $g(d_1) > g(d_2) > g(d_3) > \dots$

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- Questions?

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- Alternative: term-at-a-time processing

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- For early termination in weight-sorted indexes, we can interleave term-at-a-time and document-at-a-time processing.

Term-at-a-time processing

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 $Scores[]$

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

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- 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

BRUTUS	$\longrightarrow$	1,2	7,3	83,1	87,2	...
CAESAR	$\longrightarrow$	1,1	5,1	13,1	17,1	...
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- ... because only d_1 contains both words.

Outline

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  - Pages containing the search words in the title are better hits than pages containing the search words in the body of the text.

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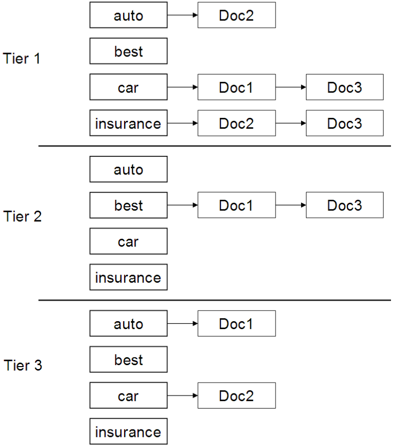

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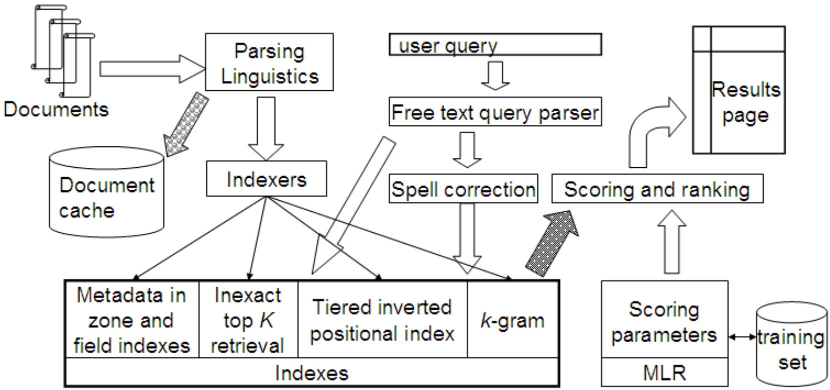
- (along with PageRank, use of anchor text and proximity constraints)

Complete search system



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- 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)

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- How do we "parse" the query and translate it into a formal specification containing phrase operators, proximity operators, indexes to search etc.?

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