Introduction to Information Retrieval

http://informationretrieval.org

IIR 7: Scores in a Complete Search System

Hinrich Schütze

Center for Information and Language Processing, University of Munich

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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

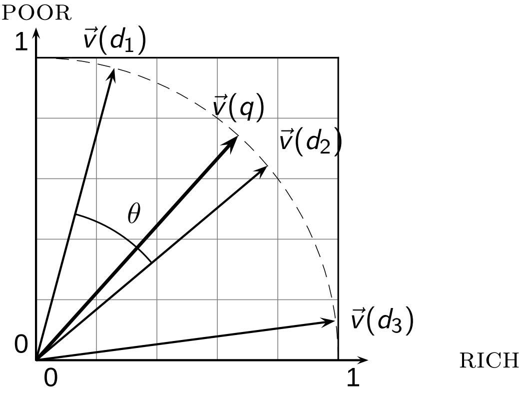
- The tf-idf weight of a term is the product of its tf weight and its idf weight.
- $$w_{t,d} = (1 + \log \mathrm{tf}_{t,d}) \cdot \log \frac{N}{\mathrm{df}_t}$$

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

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- Length normalization: Pivot normalization

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- Implementation of ranking

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- Next: More data on "users only look at a few results"

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  - 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

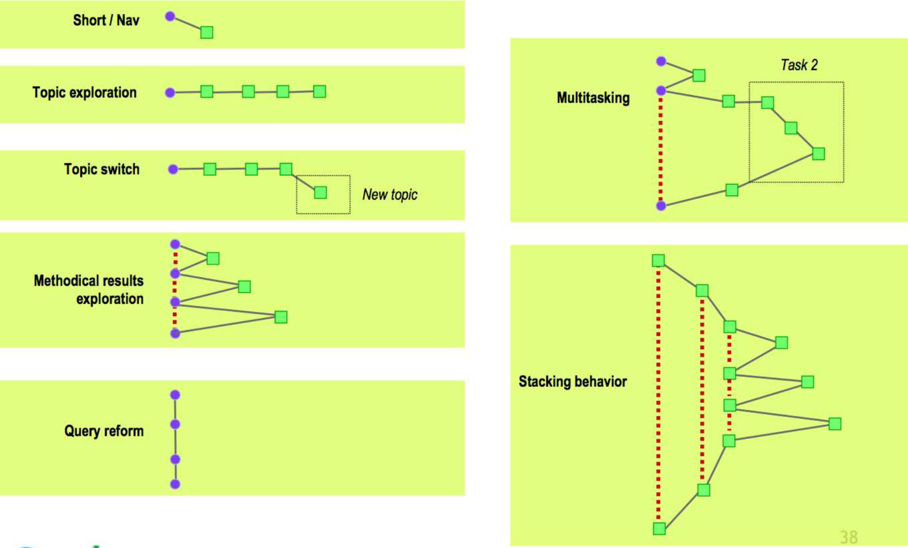
Note scan pattern:

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

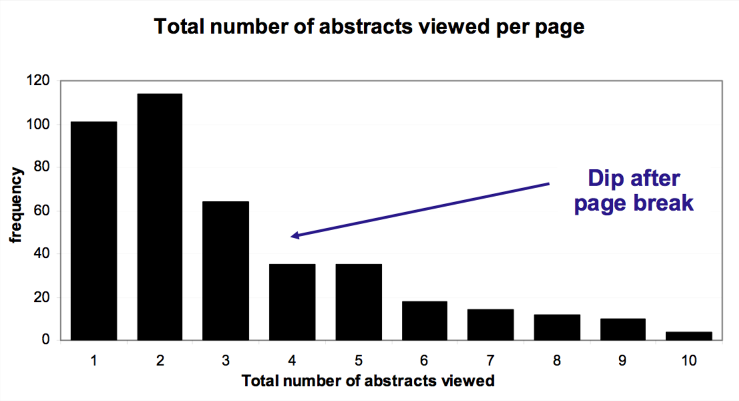
Q: Why do this?

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

Kinds of behaviors we see in the data

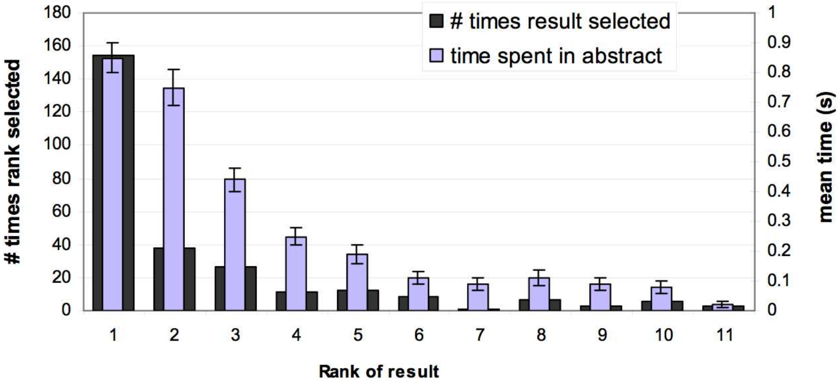


How many links do users view?



Mean: 3.07 Median/Mode: 2.00

Looking vs. Clicking

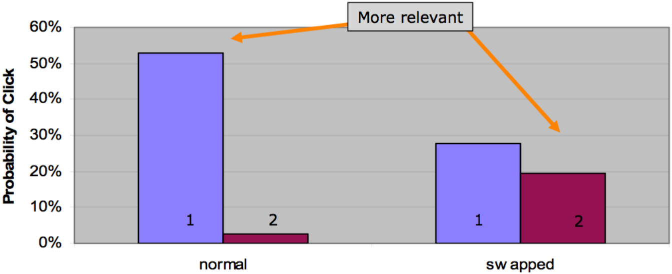


- Users view results one and two more often / thoroughly
- Users click most frequently on result one

Google

Presentation bias – reversed results

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



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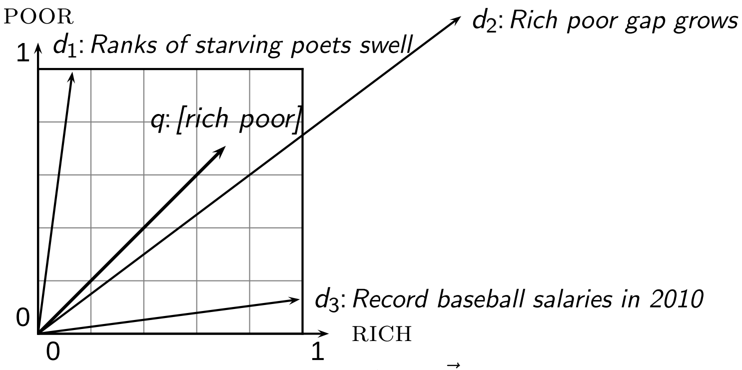
Exercise

- 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?

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- This removes the unfair advantage that short documents have.

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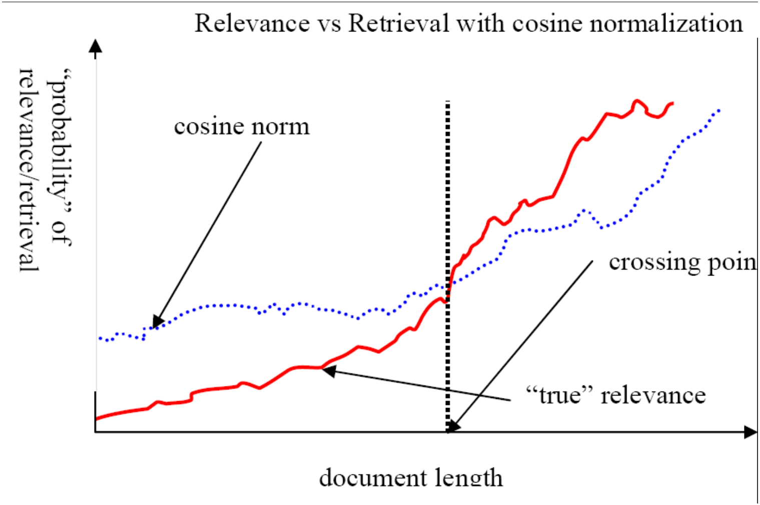

source: Lillian Lee

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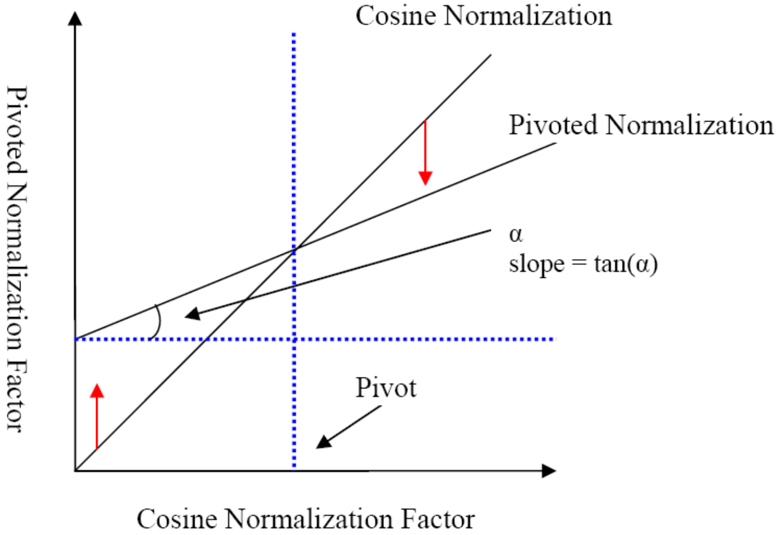

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Pivoted normalization: Amit Singhal's experiments

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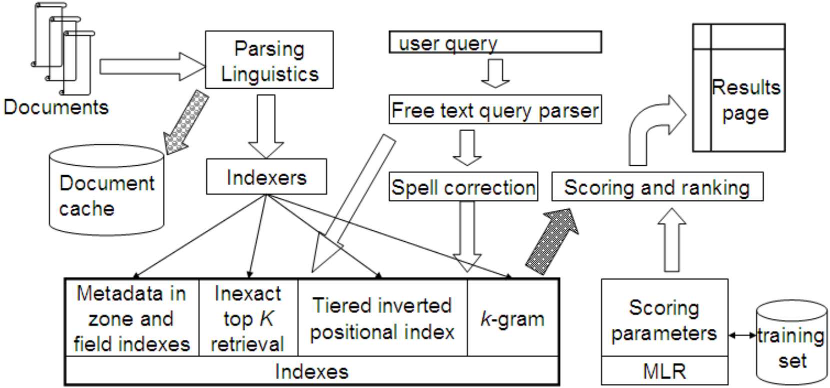
Cosine	Pivoted Cosine Normalization				
	Slope				
	0.60	0.65	0.70	**0.75**	0.80
6,526	6,342	6,458	6,574	**6,629**	6,671
0.2840	0.3024	0.3097	0.3144	**0.3171**	0.3162
Improvement	+ 6.5%	+ 9.0%	+10.7%	**+11.7%**	+11.3%

(relevant documents retrieved and (change in) average precision)

Outline

Complete search system



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  - Tier 1: Index of all titles
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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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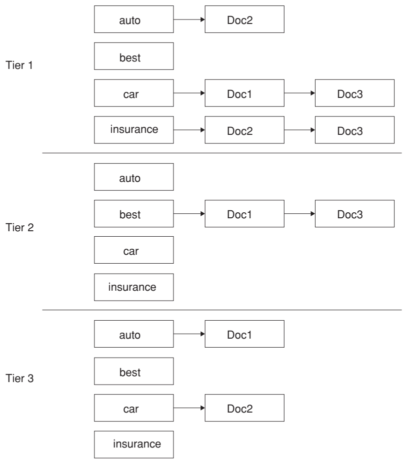

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- (along with PageRank, use of anchor text and proximity constraints)

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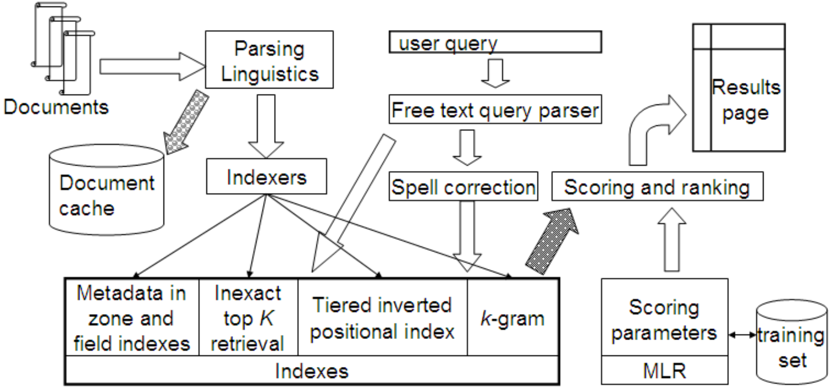

Components we have introduced thus far

- 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

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- 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?

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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	

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term frequencies

We also need positions. Not shown here.

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

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  - Return the top k

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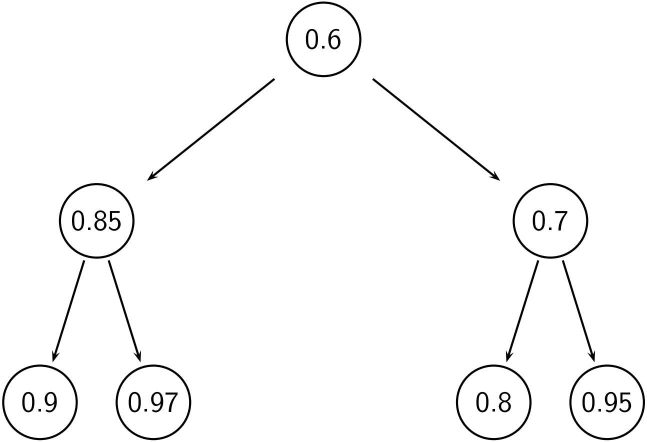
- ...then read off k winners in $O(k \log k)$ steps

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' ($O(\log k)$)

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- 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.

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  - For this, we'll need the concepts of document-at-a-time processing and term-at-a-time processing.

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

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- Questions?

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- But:
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  - We no longer can employ document-at-a-time processing.

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- . . . and so forth

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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$(d, \text{tf}_{t,d})$ in postings list
    do $Scores[d] += w_{t,d} \times w_{t,q}$
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.

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- . . . because only d_1 contains both words.

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- In most applications, the vast majority of documents have similarity score 0 for a given query → 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