# 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 $\mathrm{df}_t$ 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

$\vec{v}(d_2)$

$\vec{v}(d_3)$

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

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- 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.

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

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

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

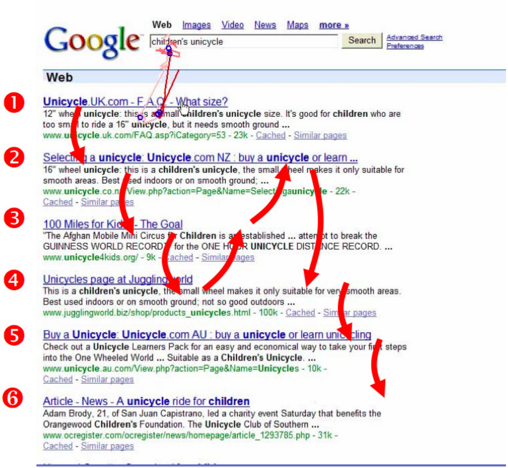
To be honest, 1800-flowers is what I'm familiar with and why I went there next even though I kind of assumed they wouldn't have $20 flowers

**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.


Google
Web Images Video News Maps more »
children's unicycle
Search
Advanced Search
Preferences
Web
1
Unicycle.UK.com - F.A.Q. - What size?
12" wheel unicycle: this is a small children's unicycle size. It's good for children who are too small to ride a 16" unicycle, but it needs smooth ground ...
www.unicycle.uk.com/FAQ.asp?iCategory=53 - 23k - Cached - Similar pages
2
Selecting a unicycle: Unicycle.com NZ : buy a unicycle or learn ...
16" wheel unicycle: this is a children's unicycle, the small wheel makes it only suitable for smooth areas. Best used indoors or on smooth ground; ...
Cached - Similar pages
3
100 Miles for Kids - The Goal
"The Afghan Mobile Mini Circus for Children is an established ... attempt to break the GUINNESS WORLD RECORD for the ONE HOUR UNICYCLE DISTANCE RECORD. ...
www.unicycle4kids.org/ - 9k - Cached - Similar pages
4
Unicycles page at Juggling World
This is a children's unicycle, the small wheel makes it only suitable for very smooth areas. Best used indoors or on smooth ground; not so good outdoors ...
www.jugglingworld.biz/shop/products_unicycles.html - 100k - Cached - Similar pages
5
Buy a Unicycle: Unicycle.com AU : buy a unicycle or learn unicycling
Check out a Unicycle Learners Pack for an easy and economical way to take your first steps into the One Wheeled World ... Suitable as a Children's Unicycle. ...
www.unicycle.au.com/View.php?action=Page&Name=Unicycles - 10k -
Cached - Similar pages
6
Article - News - A unicycle ride for children
Adam Brody, 21, of San Juan Capistrano, led a charity event Saturday that benefits the Orangewood Children's Foundation. The Unicycle Club of Southern ...
www.ocregister.com/ocregister/news/homepage/article_1293785.php - 31k -
Cached - Similar pages

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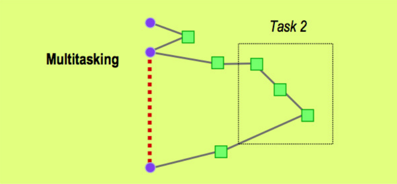


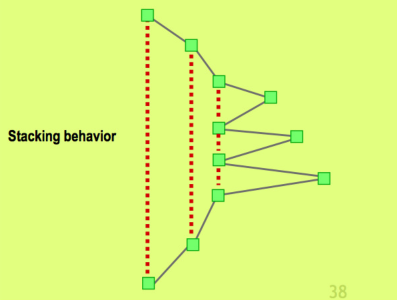

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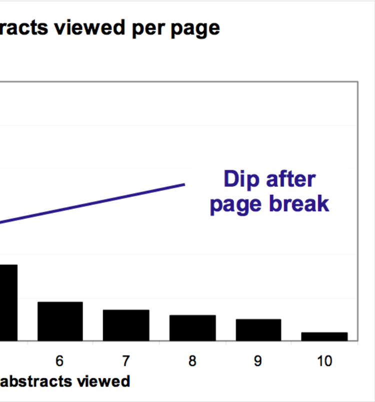
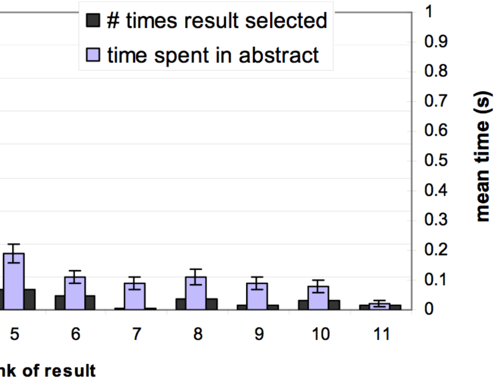



7 **Median/Mode: 2.00**




and two more often / thoroughly

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# esults

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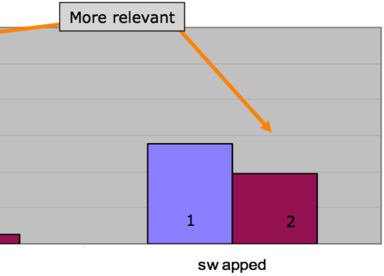

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# Outline

# Why distance is a bad idea

*q*: *[rich poor]*

$d_2$: *Rich poor gap grows*

POOR

RICH

$d_1$: *Ranks of starving poets swell*

$d_3$: *Record baseball salaries in 2010*

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.

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- What can we do about this?

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- 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.

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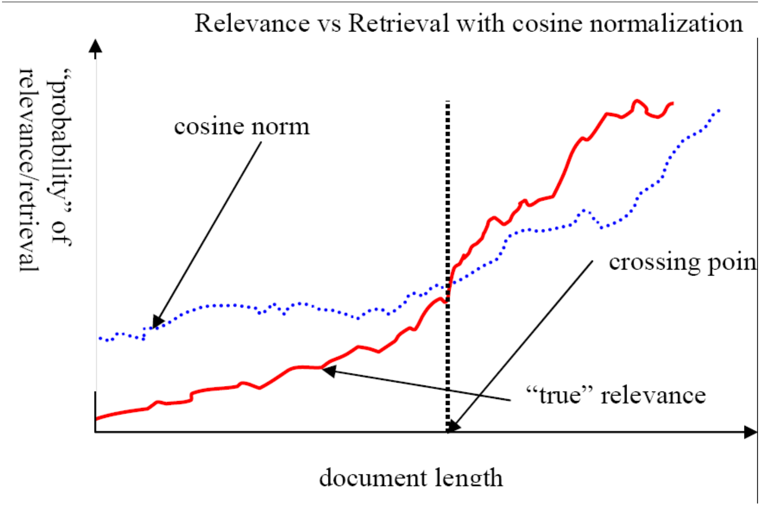


source: Lillian Lee

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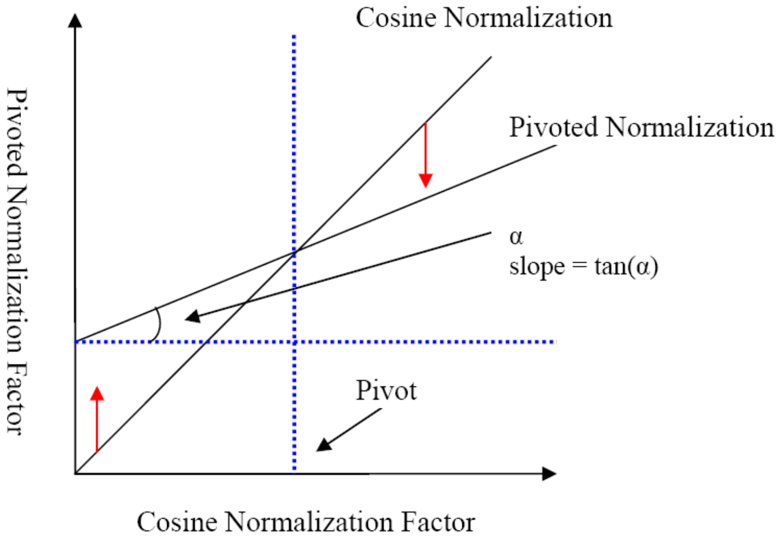


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# Pivoted normalization: Amit Singhal's experiments

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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)

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| | | | | | | |
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| BRUTUS | $\longrightarrow$ | 1,2 | 7,3 | 83,1 | 87,2 | ... |
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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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- Alternative: min heap

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

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  - If $s' > h_m$ heap-delete-root ($O(\log k)$)

# 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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- Alternative: term-at-a-time processing

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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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$\text{COSINESCORE}(q)$

*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$(d, \mathrm{tf}_{t,d})$ 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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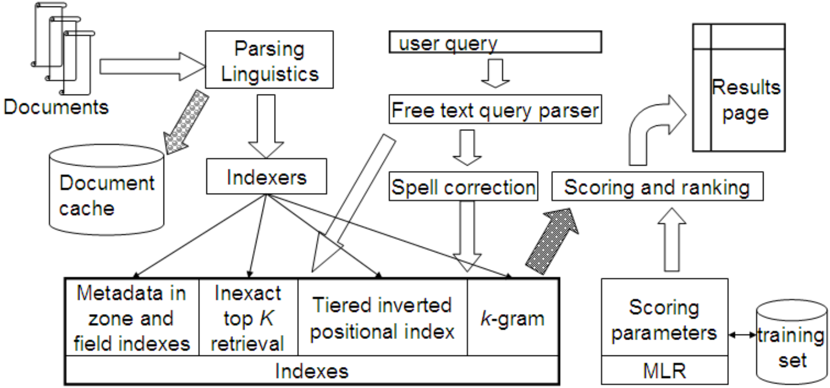
- . . . because only $d_1$ contains both words.

# Outline

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

# Complete search system



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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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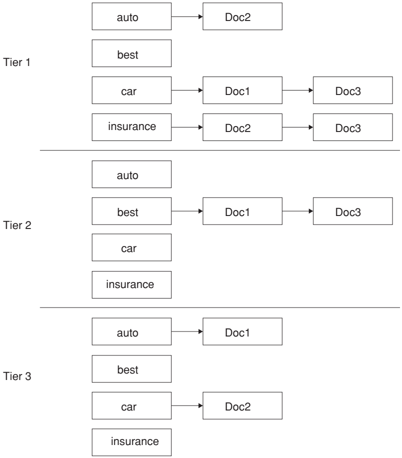

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- (along with PageRank, use of anchor text and proximity constraints)

# Exercise

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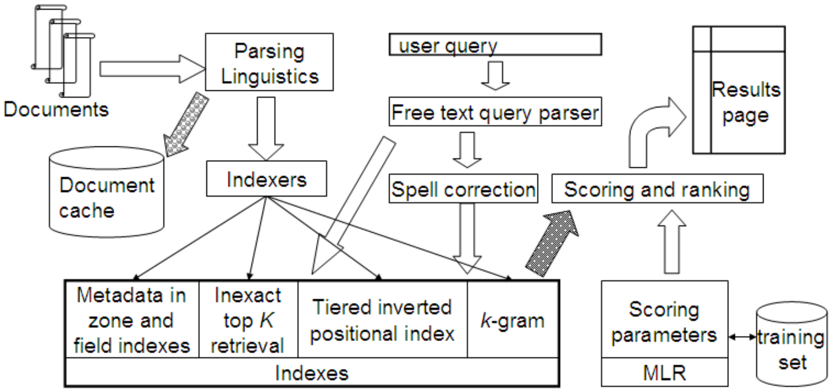
- Design criteria for tiered system
  - Each tier should be an order of magnitude smaller than the next tier.
  - The top 100 hits for most queries should be in tier 1, the top 100 hits for most of the remaining queries in tier 2 etc.
  - We need a simple test for "can I stop at this tier or do I have 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?

# 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
- Term-at-a-time processing

# 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

# Take-away today

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

# Resources

- Chapters 6 and 7 of IIR
- Resources at `http://ifnlp.org/ir`
  - 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