Introduction to Information Retrieval
http://informationretrieval.org

IIR 7: Scores in a Complete Search System

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2008.05.27
Overview

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

1. Recap
2. Why rank?
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Term frequency weighting

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

$$w_{t,d} = \begin{cases} 1 + \log_{10} tf_{t,d} & \text{if } tf_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$$

- Score for a document-query pair: sum over terms $t$ in both $q$ and $d$:

$$\text{matching-score} = \sum_{t \in q \cap d} (1 + \log \text{tf}_{t,d})$$
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:

$$idf_t = \log_{10} \frac{N}{df_t}$$

- idf is a measure of the informativeness of the term.
The tf-idf weight of a term is the \textbf{product of its tf weight and its idf weight}.

\[
    w_{t,d} = (1 + \log \text{tf}_{t,d}) \cdot \log \frac{N}{\text{df}_t}
\]

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

\[ \vec{v}(d_1) \]
\[ \vec{v}(q) \]
\[ \vec{v}(d_2) \]
\[ \vec{v}(d_3) \]
tf-idf example: ltn.lnc

Query: “best car insurance”. Document: “car insurance auto insurance”.

<table>
<thead>
<tr>
<th>word</th>
<th>tf-raw</th>
<th>tf-wght</th>
<th>df</th>
<th>idf</th>
<th>weight</th>
<th>tf-raw</th>
<th>tf-wght</th>
<th>weight</th>
<th>n’lized</th>
<th>product</th>
</tr>
</thead>
<tbody>
<tr>
<td>auto</td>
<td>0</td>
<td>0</td>
<td>5000</td>
<td>2.3</td>
<td>0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.52</td>
<td>0</td>
</tr>
<tr>
<td>best</td>
<td>1</td>
<td>1</td>
<td>50000</td>
<td>1.3</td>
<td>1.3</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>car</td>
<td>1</td>
<td>1</td>
<td>10000</td>
<td>2.0</td>
<td>2.0</td>
<td>1</td>
<td>1</td>
<td>1</td>
<td>0.52</td>
<td>1.04</td>
</tr>
<tr>
<td>insurance</td>
<td>1</td>
<td>1</td>
<td>1000</td>
<td>3.0</td>
<td>3.0</td>
<td>2</td>
<td>1.3</td>
<td>1.3</td>
<td>0.68</td>
<td>2.04</td>
</tr>
</tbody>
</table>

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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2 Why rank?

3 More on cosine

4 Implementation

5 The complete search system
Why is ranking so important?

- Last lecture: Problems with unranked retrieval
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  - Users want to look at a few results – not thousands.
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- Even for expert searchers
  → 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 look at 1, 2, or 3 results.
Empirical investigation of the effect of ranking

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- The following slides are from Dan Russell’s JCDL talk
Empirical investigation of the effect of ranking

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

Short / Nav

Topic exploration

Topic switch

Methodical results exploration

Query reform

Multitasking

Task 2

Stacking behavior
How many links do users view?

Total number of abstracts viewed per page

Mean: 3.07  Median/Mode: 2.00

Dip after page break
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

![Graph showing probability of click for normal and swapped orders]

- More relevant
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).
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  - ...but $d_2$ is more relevant than $d_3$. 
Query \( q \): “anti-doping rules Beijing 2008 olympics”

Compare three documents

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What ranking do we expect in the vector space model?

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- . . . but \( d_2 \) is more relevant than \( d_3 \).

What can we do about this?
Cosine normalization produces weights that are too large for short documents and too small for long documents (on average).
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- Note that “pivoted” scores are no longer bounded by 1.
Predicted and true probability of relevance
Pivot normalization

\[ \text{Cosine Normalization} \]

\[ \text{Pivoted Normalization} \]

\[ \alpha \]

\[ \text{slope} = \tan(\alpha) \]

source: Lillian Lee
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Now we also need term frequency in the index

<table>
<thead>
<tr>
<th>Name</th>
<th>Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brutus</td>
<td>1,2</td>
</tr>
<tr>
<td></td>
<td>7,3</td>
</tr>
<tr>
<td></td>
<td>83,1</td>
</tr>
<tr>
<td></td>
<td>87,2</td>
</tr>
<tr>
<td></td>
<td>...</td>
</tr>
<tr>
<td>Caesar</td>
<td>1,1</td>
</tr>
<tr>
<td></td>
<td>5,1</td>
</tr>
<tr>
<td></td>
<td>13,1</td>
</tr>
<tr>
<td></td>
<td>17,1</td>
</tr>
<tr>
<td></td>
<td>...</td>
</tr>
<tr>
<td>Calpurnia</td>
<td>7,1</td>
</tr>
<tr>
<td></td>
<td>8,2</td>
</tr>
<tr>
<td></td>
<td>40,1</td>
</tr>
<tr>
<td></td>
<td>97,3</td>
</tr>
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<tr>
<th>Term</th>
<th>Frequency</th>
</tr>
</thead>
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<tr>
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term frequencies
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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

term frequencies

We also need positions. Not shown here.
Term frequencies in the inverted index

- In each posting, store $tf_{t,d}$ in addition to docID $d$
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- In each posting, store $tf_{t,d}$ in addition to docID $d$
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- Why?
Term frequencies in the inverted index

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- As an integer frequency, not as a (log-)weighted real number
  - ... because real numbers are difficult to compress.
- Unary code is effective for encoding term frequencies.
- Why?
- Overall, additional space requirements are small: much less than a byte per posting.
How do we compute the top $k$ in ranking?

- In many applications, we don’t need a complete ranking.
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**What’s bad about this?**
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- What’s bad about this?
- Alternative?
Use heap for selecting the top $k$

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

Schütze: Scores in a complete search system
Binary max heap
Even more efficient computation of top $k$?

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- Ideas?
- What we’re doing in effect: solving the $k$-nearest neighbor (kNN) problem for the query vector (= query point).
Even more efficient computation of top $k$?

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- Optimizations reduce the constant factor, but they are still $O(N)$.
- Are there sublinear algorithms?
- Ideas?
- What we’re doing in effect: solving the $k$-nearest neighbor (kNN) problem for the query vector (= query point).
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- We will revisit this issue when we do kNN classification in IIR 14.
Non-docID ordering of postings lists

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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?
Document-at-a-time processing

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- Alternative: term-at-a-time processing
Weight-sorted postings lists

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- ... and so forth
- 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**($q$)

1. $\text{float } \text{Scores}[N] = 0$
2. $\text{float } \text{Length}[N]$
3. for each query term $t$
4. do calculate $w_{t,q}$ and fetch postings list for $t$
5. for each pair($d$, $tf_{t,d}$) in postings list
6. do $\text{Scores}[d] += w_{t,d} \times w_{t,q}$
7. Read the array $\text{Length}$
8. for each $d$
9. do $\text{Scores}[d] = \text{Scores}[d]/\text{Length}[d]$
10. return Top $k$ components of $\text{Scores}[]$

The elements of the array “Scores” are called **accumulators**.
Computing cosine scores

- For the web (20 billion documents), an array of accumulators $A$ in memory is infeasible.
Computing cosine scores

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- 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

<table>
<thead>
<tr>
<th>Name</th>
<th>Scores</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brutus</td>
<td>1,2 7,3 83,1 87,2 ...</td>
</tr>
<tr>
<td>Caesar</td>
<td>1,1 5,1 13,1 17,1 ...</td>
</tr>
<tr>
<td>Calpurnia</td>
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- For query: “Brutus Caesar”: 

Schütze: Scores in a complete search system
Accumulators

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For query: “Brutus Caesar”:
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- Don’t need accumulators for 8, 40, 97
Removing bottlenecks

- Use heap / priority queue as discussed earlier
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- . . . because only $d_1$ contains both words.
Outline

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

- Basic idea:
Tiered indexes

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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.
Tiered index

Tier 1
- auto → Doc2
- best
- car → Doc1 → Doc3
- insurance → Doc2 → Doc3

Tier 2
- auto
- best → Doc1 → Doc3
- car
- insurance

Tier 3
- auto → Doc1
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Tiered indexes

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(along with PageRank, use of anchor text and proximity constraints)
Complete search system

- Documents
- Parsing Linguistics
- Indexers
- Metadata in zone and field indexes
- Inexact top K retrieval
- Tiered inverted positional index
- k-gram
- Scoring parameters MLR
- Training set
- Results page
- User query
- Free text query parser
- Spell correction
- Scoring and ranking
- Indexes
Components we have introduced thus far

- Document preprocessing (linguistic and otherwise)
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- 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)
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- Machine-learned ranking functions
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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)
Components we haven’t covered yet: Query parser

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- The two-term query *London tower* (without quotes) may be interpreted as the phrase query “*London tower*”.
- 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.?
Vector space retrieval: Complications

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Resources

- Chapters 6 and 7 of IIR
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- Resources at http://ifnlp.org/ir
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- Yahoo SearchMonkey: Opens up the search engine to developers. For example, you can rerank search results.