Introduction to Information Retrieval
IIR 7: Scores in a Complete Search System

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Overview

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

1. Recap
2. Why rank?
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Term frequency weight

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

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

$$\text{idf}_t = \log_{10} \frac{N}{df_t}$$

$idf$ is a measure of the **informativeness** of the term.
The tf-idf weight of a term is the product of its tf weight and its idf weight.

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

Why rank? More on cosine The complete search system Implementation of ranking

Cosine similarity between query and document

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

- \(q_i\) 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

\[ \vec{v}(d_1) \]

\[ \vec{v}(q) \]

\[ \vec{v}(d_2) \]

\[ \vec{v}(d_3) \]

POOR

RICH

\[ \theta \]
tf-idf example: Inc.ltn

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

<table>
<thead>
<tr>
<th>word</th>
<th>query</th>
<th>document</th>
<th>product</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>tf-raw</td>
<td>df</td>
<td>idf</td>
</tr>
<tr>
<td>auto</td>
<td>0</td>
<td>5000</td>
<td>2.3</td>
</tr>
<tr>
<td>best</td>
<td>1</td>
<td>50000</td>
<td>1.3</td>
</tr>
<tr>
<td>car</td>
<td>1</td>
<td>10000</td>
<td>2.0</td>
</tr>
<tr>
<td>insurance</td>
<td>1</td>
<td>1000</td>
<td>3.0</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: \[ \sum_i w_{qi} \cdot w_{di} = 0 + 0 + 1.04 + 2.04 = 3.08 \]
Take-away today

- The importance of ranking: User studies at Google
- Length normalization: Pivot normalization
- The complete search system
- Implementation of ranking
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
  - → 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 examine 1, 2, or 3 results.
Empirical investigation of the effect of ranking

- The following slides are from Dan Russell’s JCDL 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.
Rapidly scanning the results

Note scan pattern:

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

New topic

Task 2

Stacking behavior
How many links do users view?

Total number of abstracts viewed per page

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
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.

→ Getting the ranking right is very important.

→ 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?
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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?
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

Relevance vs Retrieval with cosine normalization

“true” relevance

crossing point

cosine norm

document length

“probability” of relevance/retrieval

source: Lillian Lee
Pivot normalization

Cosine Normalization

Pivoted Normalization

\[ \alpha \]

slope = \tan(\alpha)

Pivot
Pivoted normalization: Amit Singhal’s experiments

<table>
<thead>
<tr>
<th>Cosine</th>
<th>Pivoted Cosine Normalization</th>
<th>Slope</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>0.60</td>
</tr>
<tr>
<td>6,526</td>
<td>6,342</td>
<td>6,458</td>
</tr>
<tr>
<td>0.2840</td>
<td>0.3024</td>
<td>0.3097</td>
</tr>
<tr>
<td>Improvement</td>
<td>+ 6.5%</td>
<td>+ 9.0%</td>
</tr>
</tbody>
</table>

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

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

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

Tier 3
- auto → Doc1
- best
- car → Doc2
- insurance
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)
Recap Why rank? More on cosine The complete search system Implementation of ranking

Complete search system

- Documents
  - Parsing Linguistics
  - Indexers
    - user query
    - Free text query parser
    - Spell correction
    - Scoring and ranking
  - Results page
  - Document cache
    - Metadata in zone and field indexes
    - Inexact top K retrieval
    - Tiered inverted positional index
    - k-gram

Indexes

Scoring parameters
- Scoring MLR
- training set

Gray: Scores in a 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?
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Now we also need term frequencies in the index

<table>
<thead>
<tr>
<th>Term</th>
<th>Values</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>
<td>7,1 8,2 40,1 97,3</td>
</tr>
</tbody>
</table>

term frequencies

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

- Thus: In each posting, store $tf_{t,d}$ 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 $k$ out 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

0.6

/  \
0.85  0.7

/  \
0.9  0.97  0.8  0.95

Gray: Scores in a complete search system
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 ($k$NN) 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: $g(d_1) > g(d_2) > g(d_3) > \ldots$
- 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:
  \[ g(d_1) > g(d_2) > g(d_3) > \ldots \]
- Define composite score of a document:
  \[
  \text{net-score}(q, d) = g(d) + \cos(q, d)
  \]
- Suppose: (i) \( g \rightarrow [0, 1] \); (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.
- 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**($q$)

1. float Scores[$N$] = 0
2. float 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 $Scores[d] += w_{t,d} \times w_{t,q}$
7. Read the array Length
8. for each $d$
9. do $Scores[d] = Scores[d]/Length[d]$
10. 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

<table>
<thead>
<tr>
<th>Brutus</th>
<th>→</th>
<th>1,2</th>
<th>7,3</th>
<th>83,1</th>
<th>87,2</th>
<th>...</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caesar</td>
<td>→</td>
<td>1,1</td>
<td>5,1</td>
<td>13,1</td>
<td>17,1</td>
<td>...</td>
</tr>
<tr>
<td>Calpurnia</td>
<td>→</td>
<td>7,1</td>
<td>8,2</td>
<td>40,1</td>
<td>97,3</td>
<td></td>
</tr>
</tbody>
</table>

- 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 → 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.