Introduction to Information Retrieval
http://informationretrieval.org

IIR 7: Scores in a Complete Search System

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Overview

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

1 Recap

2 Why rank?

3 More on cosine

4 Implementation of ranking

5 The complete search system
Relevance feedback: Basic idea

- The user issues a (short, simple) query.
- The search engine returns a set of documents.
- User marks some docs as relevant, some as nonrelevant.
- Search engine computes a new representation of the information need – should be better than the initial query.
- Search engine runs new query and returns new results.
- New results have (hopefully) better recall.
Rocchio illustrated
Types of query expansion

- Manual thesaurus (maintained by editors, e.g., PubMed)
- Automatically derived thesaurus (e.g., based on co-occurrence statistics)
- Query-equivalence based on query log mining (common on the web as in the “palm” example)
Query expansion at search engines

Main source of query expansion at search engines: query logs

Example 1: After issuing the query [herbs], users frequently search for [herbal remedies].

→ “herbal remedies” is potential expansion of “herb”.

Example 2: Users searching for [flower pix] frequently click on the URL photobucket.com/flower. Users searching for [flower clipart] frequently click on the same URL.

→ “flower clipart” and “flower pix” are potential expansions of each other.
Take-away today

- The importance of ranking: User studies at Google
- Length normalization: Pivot normalization
- Implementation of ranking
- The complete search system
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Why is ranking so important?

- Last lectures: 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

- 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

- The following slides are from Dan Russell’s JCDL talk
- 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
  - New topic

- 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
Order of presentation influences where users look \textbf{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.
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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?
Pivot normalization

- 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

source: Lillian Lee
Pivot normalization

Cosine Normalization

Pivoted Normalization

Pivot

\[ \alpha \]

slope = \tan(\alpha)
Pivoted normalization: Amit Singhal’s experiments

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

(relevant documents retrieved and (change in) average precision)
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Now we also need term frequencies in the index

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 $d$
- 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?

- In many applications, we 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
```


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 (kNN) 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 $k$. 
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 $d$
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.
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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)
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?
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
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
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