# Information Retrieval and Organisation

Dell Zhang

Birkbeck, University of London

2015/16

# Computing Scores in a Complete Search System

# Inexact Top-$k$ Retrieval

- We now consider schemes which produce $k$ documents that are likely to be among the $k$ highest scoring documents
  - We hope to dramatically lower the cost of computing the top-$k$ documents
  - Obviously, we don't want to alter the user's perceived relevance of the top-$k$ results significantly
- May not be such a bad thing as it sounds like
  - Cosine similarity is also only a proxy for the user's perceived relevance

# Inexact Top-$k$ Retrieval

- We'll now look at some ideas designed to eliminate a large number of documents without computing their cosine scores
- These heuristics follow a two-step scheme:
  1. Find a set $A$ of documents that are contenders, where $k < |A| \ll N$
     - $A$ does not necessarily contain all the $k$ top-scoring documents for the query, but there should be a large overlap
  2. Return the $k$ top-scoring documents in $A$

# Index Elimination

- We could only consider the terms whose idf exceeds a certain threshold
  - Low idf means that terms are not very relevant
  - These terms tend to have very long postings lists
- We could only consider the documents that contain many (or all) query terms
  - Only compute cosine values for these documents
  - The danger is that we could end up with $|A| < k$ (we'll come back to this in a moment)

# Champion Lists

- Pre-compute, for each term $t$ in the dictionary, the set of the $r$ documents with the highest tf-values for $t$. We call this set of $r$ documents the *champion list* for term $t$ (sometimes also called *fancy list* or *top docs*).
- We create $A$ by combining the champion lists of all terms in query $q$.
- Determining the parameter $r$ is crucial
  - As $r$ is determined when constructing the index, we might not know $k$ then
  - So we might choose an $r$ that is too small (ending up with $|A| < k$ again)

# Static Quality Scores

- In many search engines, a query-independent measure of quality is available
- The scores calculated based on such measures are called *static quality scores*
  - For example, the number of favourable reviews of news stories
- The matching-score is computed by combining the static quality $g(d)$ of a document $d$ with other query-dependent scores
  - A simple way to do this would be to add $g(d)$ to the cosine measure
- Such static quality scores can be used to build champion lists based on $g(d)$

# Impact Ordering

- The algorithm `COSINESCORE` in the last chapter applied a document-at-a-time processing
  - That means, for each $d$, $\mathrm{tf}_{t,d}$ pair we calculated the cosine measure
  - We have to accumulate the score for each document while the algorithm is running
- This is very inefficient:
  - We have to store scores for millions or even billions of documents
  - Most of those documents will never make it into the top-$k$

# Impact Ordering

- Naturally, we only want to compute cosine measures for serious contenders (the set $A$)
- So we allocate space for computing $|A|$ scores
- How do we make sure that we process the most important documents first?

# Impact Ordering

- Up to now we have implicitly assumed that postings lists are ordered by docIDs
- However, if we add term frequencies (or other scores such as $g(d)$) and want to do inexact top-$k$ retrieval, other orders might be better
- Let's assume that we have postings lists with term frequency values (each entry consists of (docID, tf-value)
  - e.g., `information`, 3: $\langle(1,3),(2,1),(5,2)\rangle$;
- We could order the postings lists in decreasing order of tf-values:
  - e.g., `information`, 3: $\langle(1,3),(5,2),(2,1)\rangle$;

# Impact Ordering

- We access the postings lists of all the terms contained in the query
- Then we process the items in the lists in decreasing tf-value order
  - Heuristic: documents in the top-$k$ are likely to occur early in these ordered lists
- We can also extend this scheme with idf-values, i.e. multiply each tf-value with the idf-value of the term before deciding on the order
- The first $|A|$ documents encountered get their total scores computed

# Impact Ordering

- Here's an example for three postings lists (and simplified tf-idf-values):
  - `information`, idf=1; 3: $\langle$ (1,3), (5,2), (2,1) $\rangle$;
  - `line`, idf=3; 2: $\langle$ (2,6), (1,2) $\rangle$;
  - `computer`, idf=2; 5: $\langle$ (3,7), (5,4), (2,3), (1,2), (4,1) $\rangle$;
- Start with document 2, term `line`
  - ($3 \times 6 = 18$; largest tf-idf value)
- Continue with document 3, term `computer`
  - ($2 \times 7 = 14$; second-larges tf-idf value)
- and so on ...

# Storing TF values

- Storing the tf-values for all documents will take up considerable space
  - The first problem we face is: how do we store the tf-values efficiently?
  - As it turns out, unary coding is quite good at this.

| method | bits per tf-value | | | |
|---|---|---|---|---|
| | Bible | GNUBib | Comact | TREC |
| Unary | 1.27 | 1.16 | 1.74 | 2.49 |
| Gamma | 1.38 | 1.23 | 1.88 | 2.13 |

# Storing TF values

- However, when sorting by tf-values we have problems with compressing docIDs (as gap encoding relies on sorted docIDs)
  - For example, the list $\langle 5 : (1, 2), (2, 2), (3, 5), (4, 1), (5, 2) \rangle$ would be sorted like this $\langle 5 : (3, 5), (1, 2), (2, 2), (5, 2), (4, 1) \rangle$
- Solution: organize items in "tf-blocks" $(\mathrm{tf}, k : d_1, \ldots, d_k)$, where $k$ is the number of documents for a certain tf-value and the $d_i$s are sorted docIDs
  - So for the above example, we would get: $\langle 5 : (5, 1 : 3), (2, 3 : 1, 2, 5), (1, 1 : 4) \rangle$
  - Needs slightly more memory than a docID-sorted list, but still efficient

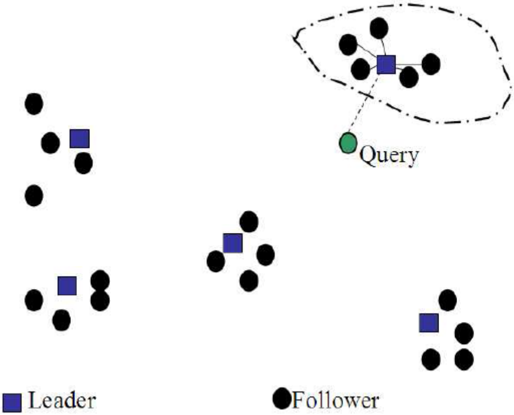
# Cluster Pruning

- In *cluster pruning*, we have a preprocessing step during which we cluster the document vectors
  - Pick $\sqrt{N}$ documents at random from the collection, we call these *leaders*.
  - For each document that is not a leader, we compute its nearest leader.
  - We refer to documents that are not leaders as *followers*.
  - The expected number of followers for each leader is roughly $N/\sqrt{N} = \sqrt{N}$
- We'll talk about more advanced text clustering techniques later in the module

# Cluster Pruning

- At query time, we only compute cosine measures for a small number of documents
  - Given a query $q$, find the leader $L$ closest to $q$ (this entails computing cosine similarities from $q$ to each of the $\sqrt{N}$ leaders)
  - The candidate set $A$ consists of $L$ together with its followers (this entails computing cosine similarities from $q$ to each of the $\sqrt{N}$ followers)

# Cluster Pruning



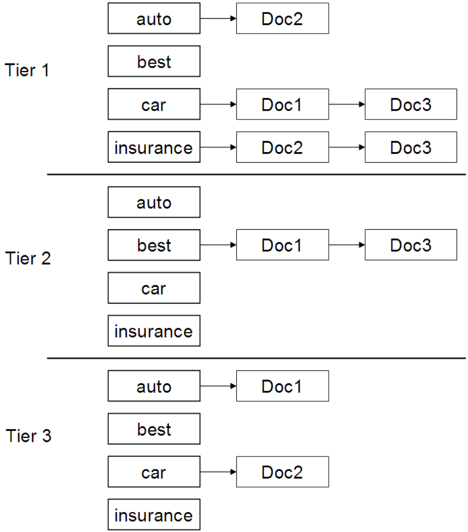
# Tiered Indexes

- Create several tiers of indexes, corresponding to importance of indexing terms
- During query processing, start with the highest-tier index
- If we get $\geq k$ hits: stop and return the results to user
- If we get $< k$ hits: repeat for the next index in tier cascade

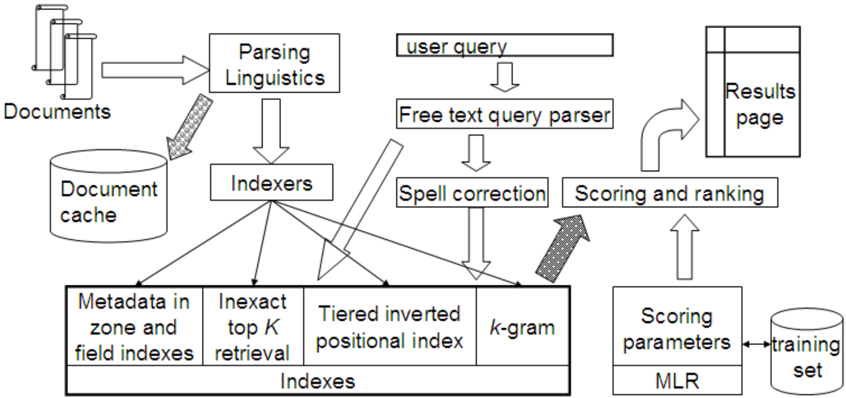
# Tiered Indexes

- Example: two-tier system
  - Tier 1: Index of all titles
  - Tier 2: Index of the rest of documents
  - As pages containing the search words in the title are usually better hits than pages containing the search words in the body of the text.
- Could be expanded to three-tier system
  - Tier 1: Index of all titles
  - Tier 2: Index of all abstracts
  - Tier 3: Index of the rest of documents

# Tiered Indexes



# Putting It All Together



# What Have We Covered So 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

# What Is Yet To Come?

- Document cache
  - e.g., for generating snippets (dynamic summaries)
- Zone indexes
  - 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
  - see next slide

# Query Parser

- IR systems often guess what the user intended
  - The two-term query *London tower* (without quotes) may be interpreted as the phrase query *"London tower"* or even *"Tower of London"*.
  - 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.?

# Summary

- Different variants for computing scores
- How to compute scores efficiently (inexact top-$k$ retrieval)
- How a complete retrieval system looks like