Introduction to
Information Retrieval

CS276
Information Retrieval and Web Search
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Efficient scoring

Today's focus

- Retrieval – get docs matching query from inverted index
- Scoring+ranking
  - Assign a score to each doc
  - Pick *K* highest scoring docs
- Our emphasis today will be on doing each of these efficiently, rather than on the quality of the ranking
  - We'll consider the impact of the scoring function – whether it's simple, complicated etc.
  - In turn, some "efficiency tricks" will impact the ranking quality

Background

- Score computation is a large (10s of %) fraction of the CPU work on a query
  - Generally, we have a tight budget on latency (say, 250ms)
  - CPU provisioning doesn't permit exhaustively scoring every document on every query
- Today we'll look at ways of cutting CPU usage for scoring, without compromising the quality of results (much)
- Basic idea: avoid scoring docs that won't make it into the top *K*

Recap: Queries as vectors

- We have a weight for each term in each doc
- Key idea 1: Do the same for queries: represent them as vectors in the space
- Key idea 2: Rank documents according to their cosine similarity to the query in this space
- Vector space scoring is
  - Entirely query dependent
  - Additive on term contributions – no conditionals etc.
  - Context insensitive (no interactions between query terms)
- We'll later look at scoring that's not as simple …

TAAT vs DAAT techniques

- TAAT = "Term At A Time"
  - Scores for all docs computed concurrently, one query term at a time
- DAAT = "Document At A Time"
  - Total score for each doc (incl all query terms) computed, before proceeding to the next
- Each has implications for how the retrieval index is structured and stored

Efficient cosine ranking

- Find the *K* docs in the collection "nearest" to the query ⇒ *K* largest query-doc cosines.
- Efficient ranking:
  - Computing a single cosine efficiently.
  - Choosing the *K* largest cosine values efficiently.
    - Can we do this without computing all *N* cosines?

Safe vs non-safe ranking

- The terminology "safe ranking" is used for methods that guarantee that the K docs returned are the K absolute highest scoring documents
  - (Not necessarily just under cosine similarity)
- Is it ok to be non-safe?
- If it is – then how do we ensure we don't get too far from the safe solution?
  - How do we measure if we are far?

SAFE RANKING

We first focus on safe ranking

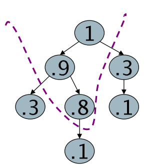
- Thus when we output the top K docs, we have a proof that these are indeed the top K
- Does this imply we always have to compute all N cosines?
  - We'll look at pruning methods
- Do we have to sort the resulting cosine scores? (No)

Computing the K largest cosines: selection vs. sorting

- Typically we want to retrieve the top K docs (in the cosine ranking for the query)
  - not to totally order all docs in the collection
- Can we pick off docs with K highest cosines?
- Let J = number of docs with nonzero cosines
  - We seek the K best of these J

Use heap for selecting top K

- Binary tree in which each node's value > the values of children
- Takes $2J$ operations to construct, then each of K "winners" read off in 2log J steps.
- For J=1M, K=100, this is about 10% of the cost of sorting.



WAND scoring

- An instance of DAAT scoring
- Basic idea reminiscent of branch and bound
  - We maintain a running *threshold* score – e.g., the K^{th} highest score computed so far
  - We prune away all docs whose cosine scores are guaranteed to be below the threshold
  - We compute exact cosine scores for only the un-pruned docs

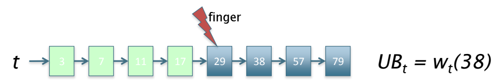
Broder et al. Efficient Query Evaluation using a Two-Level Retrieval Process.

Index structure for WAND

- Postings ordered by docID
- Assume a special iterator on the postings of the form "go to the first docID greater than *X*"
- Typical state: we have a "finger" at some docID in the postings of each query term
  - Each finger moves only to the right, to larger docIDs
- Invariant – all docIDs lower than any finger have already been *processed,* meaning
  - These docIDs are either pruned away or
  - Their cosine scores have been computed

Upper bounds

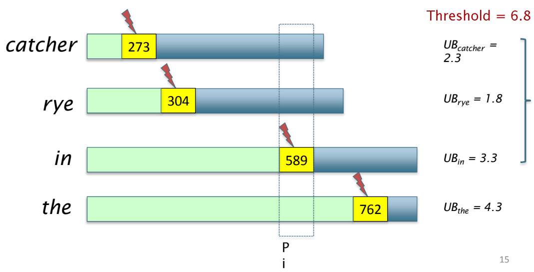
- At all times for each query term *t*, we maintain an *upper bound* UB_t on the score contribution of any doc to the right of the finger
  - Max (over docs remaining in *t's* postings) of w_t(doc)



As finger moves right, *UB* drops

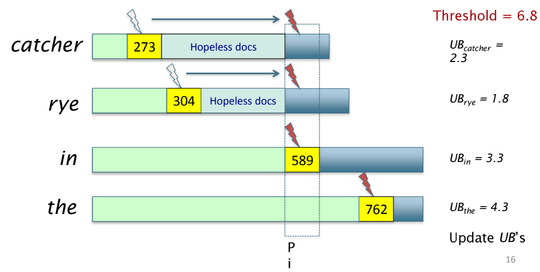
Pivoting

- Query: *catcher in the rye*
- Let's say the current finger positions are as below



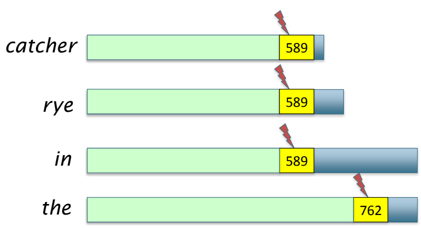
Prune docs that have no hope

- Terms sorted in order of finger positions
- Move fingers to 589 or right



Compute 589's score if need be

- If 589 is present in enough postings, compute its full cosine score – else some fingers to right of 589
- Pivot again …



WAND summary

- In tests, WAND leads to a 90+% reduction in score computation
  - Better gains on longer queries
- Nothing we did was specific to cosine ranking
  - We need scoring to be *additive* by term
- WAND and variants give us safe ranking
  - Possible to devise "careless" variants that are a bit faster but not safe (see summary in Ding+Suel 2011)
  - Ideas combine some of the non-safe scoring we consider next

NON SAFE RANKING

We'll speak of cosine scores, but most of these ideas are general and a recap of the Coursera video

Non-safe (cosine) ranking

- Return *K* docs whose cosine similarities to the query are high
  - Relative to the safe top *K*
  - Reminiscent of normalization in NDCG
- Can we prune more aggressively?
- Yes, but may sometimes get it wrong
  - a doc *not* in the top *K* may creep into the list of *K* output docs
  - Is this such a bad thing?

Cosine similarity is only a proxy

- User has a task and a query formulation
- Cosine matches docs to query
- Thus cosine is anyway a proxy for user happiness
- If we get a list of *K* docs "close" to the top *K* by cosine measure, should be ok
- All this is true for just about any scoring function

Generic approach

- Find a set *A* of *contenders*, with $K < |A| << N$
  - *A* does not necessarily contain the top *K*, but has many docs from among the top *K*
  - Return the top *K* docs in *A*
- Think of *A* as pruning non-contenders
  - Unlike WAND, pruning here can be *lossy*
- The same approach is also used for other (non-cosine) scoring functions
- Will look at several schemes following this approach
- Often *A* may not be explicitly spelled out a priori

Index elimination

- Basic cosine computation algorithm only considers docs containing at least one query term
- Take this further:
  - Only consider high-idf query terms
  - Only consider docs containing many query terms

High-idf query terms only

- For a query such as *catcher in the rye*
- Only accumulate scores from *catcher* and *rye*
- Intuition: ***in*** and ***the*** contribute little to the scores and so don't alter rank-ordering much
- Benefit:
  - Postings of low-idf terms have many docs → these (many) docs get eliminated from set *A* of contenders

Docs containing many query terms (DAAT)

- Any doc with at least one query term is a candidate for the top *K* output list
- For multi-term queries, only compute scores for docs containing several of the query terms
  - Say, at least 3 out of 4
  - Imposes a "soft conjunction" on queries seen on web search engines (early Google)
- Easy to implement in postings traversal

Champion lists

- Precompute for each dictionary term *t*, the *r* docs of highest weight in *t*'s postings
  - Call this the champion list for *t*
  - (aka fancy list or top docs for *t*)
- Note that *r* has to be chosen at index build time
  - Thus, it's possible that $r < K$
- At query time, only compute scores for docs in the champion list of some query term
  - Pick the *K* top-scoring docs from amongst these

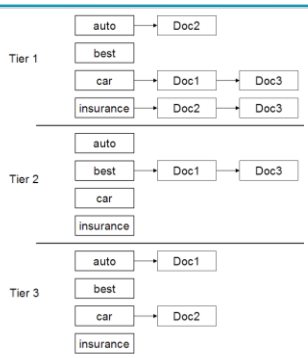
High and low lists

- For each term, we maintain two postings lists called *high* and *low*
  - Think of *high* as the champion list
- When traversing postings on a query, only traverse *high* lists first
  - If we get more than *K* docs, select the top *K* and stop
  - Else proceed to get docs from the *low* lists
- A means for segmenting index into two tiers

Tiered indexes

- Break postings up into a hierarchy of lists
  - Most important
  - …
  - Least important
- Inverted index thus broken up into tiers of decreasing importance
- At query time use top tier unless it fails to yield *K* docs
  - If so drop to lower tiers
  - Common practice in web search engines

Example tiered index



RECAP OF SOME FINAL SCORING IDEAS

Document dependent scoring

- Sometimes we'll have scoring functions that don't add up term-wise scores
- We'll look at two instances here, but industry practice is rife with these
  - Static document goodness measures
  - Term proximity

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Static quality scores

- We want top-ranking documents to be both *relevant* and *authoritative*
- *Relevance* is being modeled by cosine scores
- *Authority* is typically a query-independent property of a document
- Examples of authority signals
  - Wikipedia among websites
  - Articles in certain newspapers
  - A paper with many citations
  - Many bitly's, likes or social referrals marks
  - (Pagerank)

Quantitative

Introduction to Information Retrieval Sec. 7.1.4

Modeling authority

- Assign to each document a *query-independent* quality score in [0,1] to each document *d*
  - Denote this by *g(d)*
- Thus, a quantity like the number of citations is scaled into [0,1]

Introduction to Information Retrieval Sec. 7.1.4

Net score

- Consider a simple total score combining cosine relevance and authority
- net-score(*q,d*) = *g(d)* + cosine(*q,d*)
  - Can use some other linear combination
  - Indeed, any function of the two "signals" of user happiness – more later
- Now we seek the top *K* docs by net score

Introduction to Information Retrieval Sec. 7.1.4

Top *K* by net score – fast methods

- First idea: Order all postings by *g(d)*
- Key: this is a common ordering for all postings
- Thus, can concurrently traverse query terms' postings for
  - Postings intersection
  - Cosine (or other) score computation

Introduction to Information Retrieval Sec. 7.1.4

Why order postings by *g(d)*?

- Under *g(d)*-ordering, top-scoring docs likely to appear early in postings traversal
- In time-bound applications (say, we have to return whatever search results we can in 50 ms), this allows us to stop postings traversal early
  - Short of computing scores for all docs in postings

Champion lists in *g(d)*-ordering

- Can combine champion lists with *g(d)*-ordering
- Maintain for each term a champion list of the *r* docs with highest $g(d)$ + tf-idf$_{td}$
- Seek top-*K* results from only the docs in these champion lists
- Combine with other heuristics we've seen …

Different idea – Query term proximity

- Free text queries: just a set of terms typed into the query box – common on the web
- Users prefer docs in which query terms occur within close proximity of each other
- Let *w* be the smallest window in a doc containing all query terms, e.g.,
- For the query *strained mercy* the smallest window in the doc *The quality of mercy is not strained* is 4 (words)
- Would like scoring function to take this into account – how?

Scoring factors

- The ideas we've seen are far from exhaustive
- But they give some of the principal components in a typical scoring function
  - They reflect some intuition of how users phrase queries, and what they expect in return
- Scoring goes beyond adding up numbers
  - E.g., if we get too few hits – how should we increase recall on the fly?
  - If it's an obvious "nav query" how do we cut recall?

Non-additive scoring

- Free text query from user may in fact spawn one or more queries to the indexes, e.g., query *rising interest rates*
  - Run the query as a phrase query
  - If <*K* docs contain the phrase *rising interest rates*, run the two phrase queries *rising interest* and *interest rates*
  - If we still have <*K* docs, run the vector space query *rising interest rates*
  - Rank matching docs by vector space scoring
- This sequence is issued by a query handler