Introduction to

Information Retrieval

CS276

Information Retrieval and Web Search

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Lecture 7: Scoring and results assembly

Lecture 6 – I introduced a bug

- In my anxiety to avoid taking the log of zero, I rewrote

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

as
$$w_{t,d} = \begin{cases} \log_{10}(1 + \mathrm{tf}_{t,d}), & \text{if } \mathrm{tf}_{t,d} > 0 \\ 0, & \text{otherwise} \end{cases}$$

In fact this was unnecessary, since the zero case is treated specially above; net the FIRST version above is right.

Recap: tf-idf weighting

- The tf-idf weight of a term is the product of its tf weight and its idf weight.

$$w_{t,d} = (1 + \log_{10} \mathrm{tf}_{t,d}) \times \log_{10}(N / \mathrm{df}_t)$$

- Best known weighting scheme in information retrieval
- Increases with the number of occurrences within a document
- Increases with the rarity of the term in the collection

Recap: Queries as vectors

- Key idea 1: Do the same for queries: represent them as vectors in the space
- Key idea 2: Rank documents according to their proximity to the query in this space
- proximity = similarity of vectors

Recap: cosine(query,document)

Dot product

Unit vectors

$$\cos(\vec{q},\vec{d}) = \frac{\vec{q} \bullet \vec{d}}{|\vec{q}||\vec{d}|} = \frac{\vec{q}}{|\vec{q}|} \bullet \frac{\vec{d}}{|\vec{d}|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2} \sqrt{\sum_{i=1}^{|V|} d_i^2}}$$

$\cos(\vec{q},\vec{d})$ is the cosine similarity of $\vec{q}$ and $\vec{d}$ … or, equivalently, the cosine of the angle between $\vec{q}$ and $\vec{d}$.

This lecture

- Speeding up vector space ranking
- Putting together a complete search system
  - Will require learning about a number of miscellaneous topics and heuristics

Computing cosine scores

CosineScore(q)
float $Scores[N] = 0$
float $Length[N]$
for each query term t
do calculate $w_{t,q}$ and fetch postings list for t
    for each pair(d, $\mathrm{tf}_{t,d}$) in postings list
    do $Scores[d] += w_{t,d} \times w_{t,q}$
Read the array *Length*
for each d
do $Scores[d] = Scores[d]/Length[d]$
return Top K components of $Scores[]$

Efficient cosine ranking

- Find the *K* docs in the collection "nearest" to the query $\Rightarrow$ *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?

Efficient cosine ranking

- What we're doing in effect: solving the *K*-nearest neighbor problem for a query vector
- In general, we do not know how to do this efficiently for high-dimensional spaces
- But it is solvable for short queries, and standard indexes support this well

Special case – unweighted queries

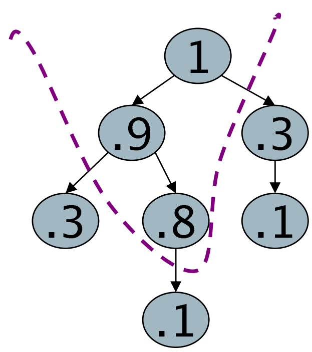
- No weighting on query terms
  - Assume each query term occurs only once
- Then for ranking, don’t need to normalize query vector
  - Slight simplification of algorithm from Lecture 6

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.



Bottlenecks

- Primary computational bottleneck in scoring: cosine computation
- Can we avoid all this computation?
- 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

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
- The same approach is also used for other (non-cosine) scoring functions
- Will look at several schemes following this approach

Index elimination

- Basic algorithm 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

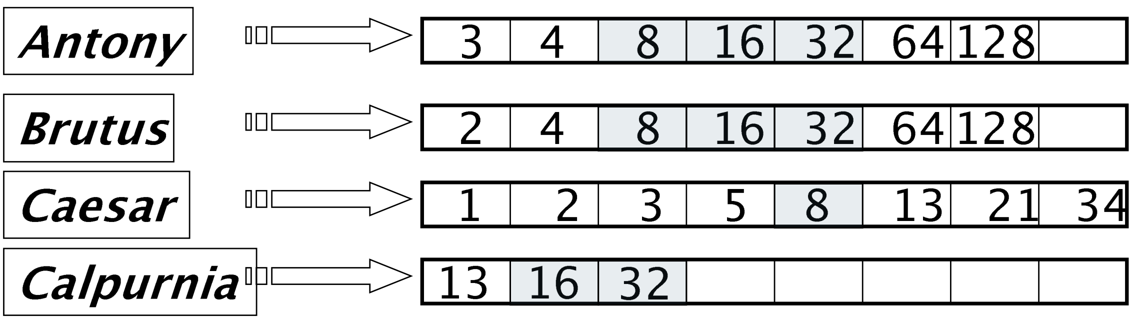
High-idf query terms only

- 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

- 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

3 of 4 query terms



Scores only computed for docs 8, 16 and 32.

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

Exercises

- How do Champion Lists relate to Index Elimination? Can they be used together?
- How can Champion Lists be implemented in an inverted index?
  - Note that the champion list has nothing to do with small docIDs

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, diggs or del.icio.us marks
  - (Pagerank)

Quantitative

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]
  - Exercise: suggest a formula for this.

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

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 score computation
- Exercise: write pseudocode for cosine score computation if postings are ordered by *g(d)*

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

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
- Can be used even for simple cosine scores, without global quality *g(d)*
- A means for segmenting index into two tiers

Impact-ordered postings

- We only want to compute scores for docs for which $wf_{t,d}$ is high enough
- We sort each postings list by $wf_{t,d}$
- Now: not all postings in a common order!
- How do we compute scores in order to pick off top *K?*
  - Two ideas follow

1. Early termination

- When traversing *t*'s postings, stop early after either
  - a fixed number of *r* docs
  - $wf_{t,d}$ drops below some threshold
- Take the union of the resulting sets of docs
  - One from the postings of each query term
- Compute only the scores for docs in this union

2. idf-ordered terms

- When considering the postings of query terms
- Look at them in order of decreasing idf
  - High idf terms likely to contribute most to score
- As we update score contribution from each query term
  - Stop if doc scores relatively unchanged
- Can apply to cosine or some other net scores

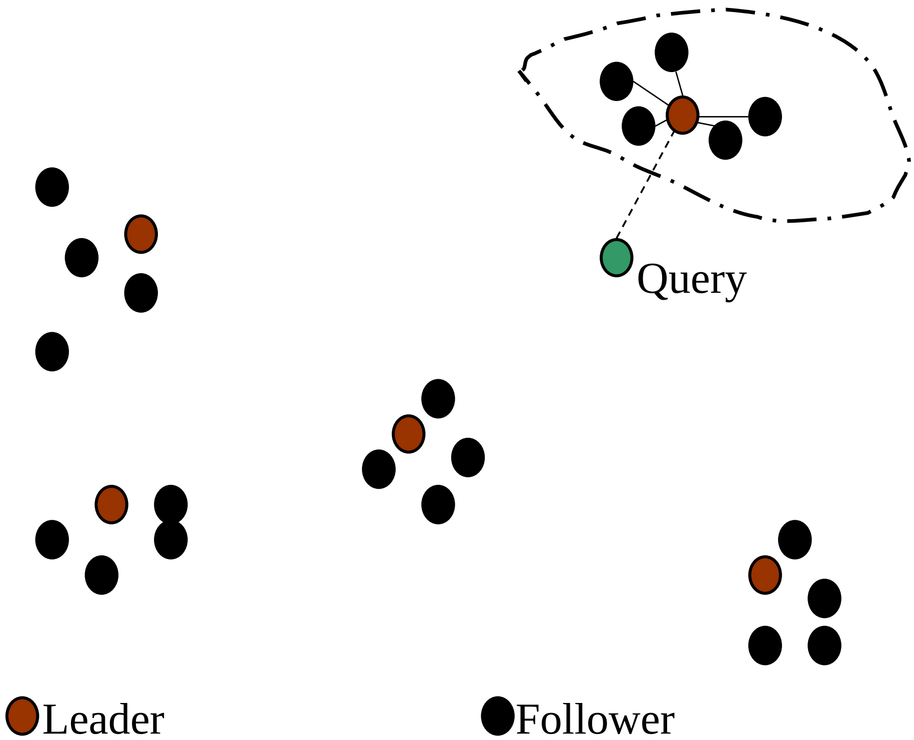
Cluster pruning: preprocessing

- Pick √N *docs* at random: call these *leaders*
- For every other doc, pre-compute nearest leader
  - Docs attached to a leader: its *followers;*
  - Likely: each leader has ~ √*N* followers.

Cluster pruning: query processing

- Process a query as follows:
  - Given query *Q*, find its nearest *leader L.*
  - Seek *K* nearest docs from among *L*'s followers.

Visualization



Why use random sampling

- Fast
- Leaders reflect data distribution

General variants

- Have each follower attached to *b1*=3 (say) nearest leaders.
- From query, find *b2*=4 (say) nearest leaders and their followers.
- Can recurse on leader/follower construction.

Exercises

- To find the nearest leader in step 1, how many cosine computations do we do?
  - Why did we have $\sqrt{N}$ in the first place?
- What is the effect of the constants *b1, b2* on the previous slide?
- Devise an example where this is *likely to* fail – i.e., we miss one of the *K* nearest docs.
  - *Likely* under random sampling.

Parametric and zone indexes

- Thus far, a doc has been a sequence of terms
- In fact documents have multiple parts, some with special semantics:
  - Author
  - Title
  - Date of publication
  - Language
  - Format
  - etc.
- These constitute the metadata about a document

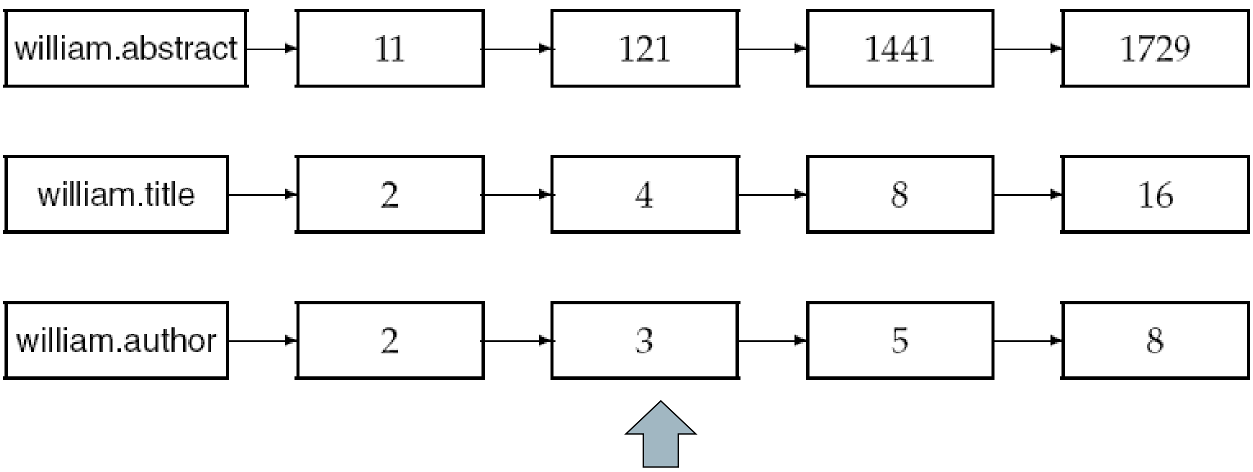
Fields

- We sometimes wish to search by these metadata
  - E.g., find docs authored by William Shakespeare in the year 1601, containing *alas poor Yorick*
- Year = 1601 is an example of a field
- Also, author last name = shakespeare, etc.
- Field or parametric index: postings for each field value
  - Sometimes build range trees (e.g., for dates)
- Field query typically treated as conjunction
  - (doc *must* be authored by shakespeare)

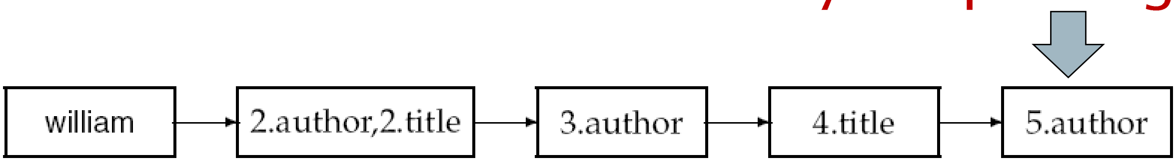
Zone

- A zone is a region of the doc that can contain an arbitrary amount of text, e.g.,
  - Title
  - Abstract
  - References …
- Build inverted indexes on zones as well to permit querying
- E.g., “find docs with *merchant* in the title zone and matching the query *gentle rain*”

Example zone indexes



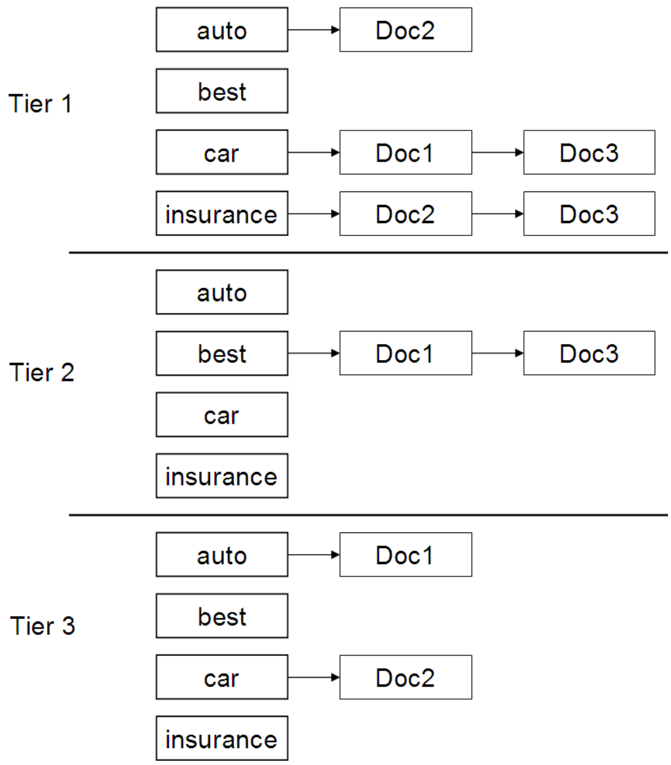
Encode zones in dictionary vs. postings.



Tiered indexes

- Break postings up into a hierarchy of lists
  - Most important
  - …
  - Least important
- Can be done by *g(d)* or another measure
- 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

Example tiered index



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?

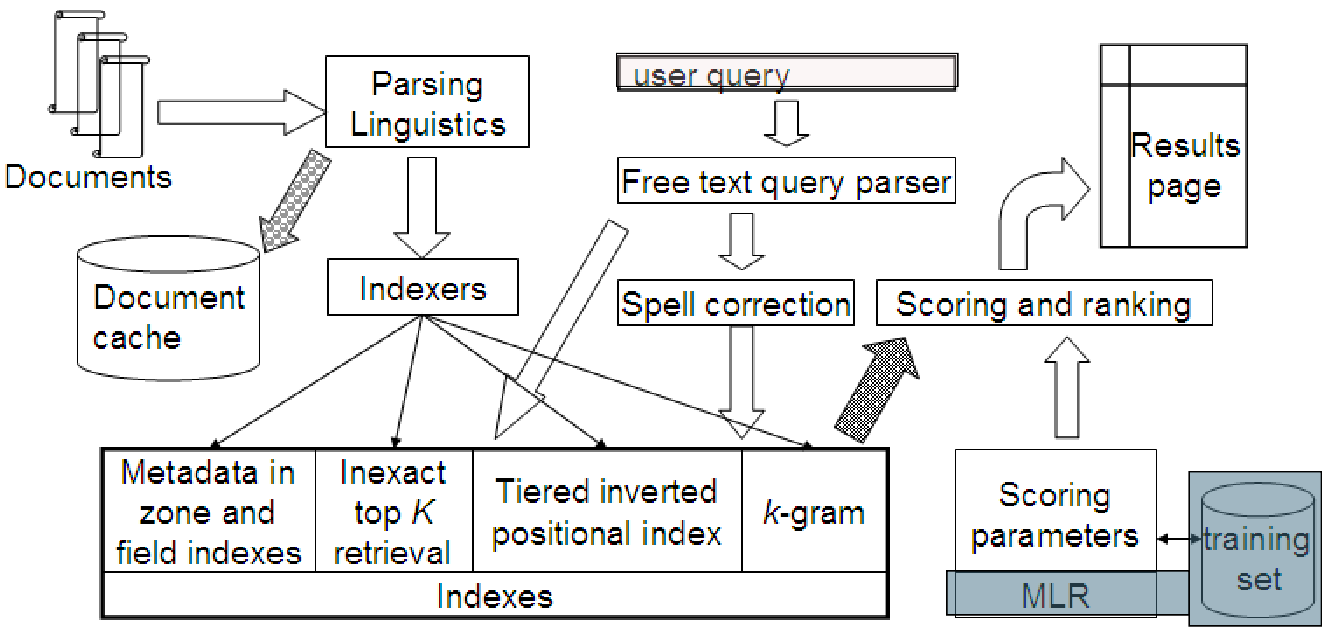
Query parsers

- 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 parser

Aggregate scores

- We've seen that score functions can combine cosine, static quality, proximity, etc.
- How do we know the best combination?
- Some applications – expert-tuned
- Increasingly common: machine-learned
  - See May 19th lecture

Putting it all together



Resources

- IIR 7, 6.1