CS3245

Information Retrieval

8

Lecture 8: A complete search system – Scoring and results assembly

Live Q&A
https://pollev.com/jin

Last Time: tf-idf weighting

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

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

- Best known weighting scheme in information retrieval
  - One of the easy but important things you should remember for IR
  - Increases with the number of occurrence within a document
  - Increases with the rarity of the term in the collection

Last Time: Vector Space Model

- Key idea 1: represent both d and q as vectors
- Key idea 2: Rank documents according to their proximity (similarity) to the query in this space

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

cos(q, d) is the cosine similarity of *q* and *d* … or, equivalently, the cosine of the angle between *q* and *d*.

Computing cosine scores, redux

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

$\textsc{CosineScore}(q)$

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 $Scores[d] = \boxed{Scores[d]/Length[d]}$
return $\boxed{\text{Top } K}$ components of $Scores[]$

Consider only the terms appearing in both q and d.

Dot product

Normalize by the (pre-computed) document length only.

Normalization

Today

Goal

- Speeding up and shortcutting ranking
- Incorporating additional ranking information into VSM

Efficient cosine ranking

- Key observations
  - Users only checks the top results.
  - There are probably too many (relevant) documents in the first place.
- Given a collection of *N* documents and a query
  - Find *K* (<< *N*) docs that are (likely to be) the "nearest" to the query based on cosine similarity.
- Efficient ranking
  - Simplify the processing
  - Possibly less accurate / exact

Faster cosine: unweighted query

- To simplify the computation of a single cosine, we can…
- Assume each query term has weight 1
  - i.e., $w_{t,q} = 1$ (no *tf*, nor *idf* factor; just Boolean presence)
  - Before: Scores[d] += $w_{t,d}$ x $w_{t,q}$
  - After: Scores[d] += $w_{t,d}$

No expensive multiplication, only addition

- But the bigger bottleneck is to process all N documents in the collection…

Let's shrink the collection…

- Full collection = N documents
- Documents that do not contain any query terms have zero cosine values
  - Q: emperor
  - Doc1: queen, Doc2: the emperor, …
  - Score (Q, Doc1) = 0
- Such documents can be safely ignored…Let's call the remaining collection of documents J.

Optimizing the selection process

- What we need: Select **K** best out of **J**
  - Typically, K << J
  - Query: emperor
  - J (i.e., docs containing emperor) = 1M, but K could be just 100

- Sort and output top K = O(J log J + K)

- Can we do better?

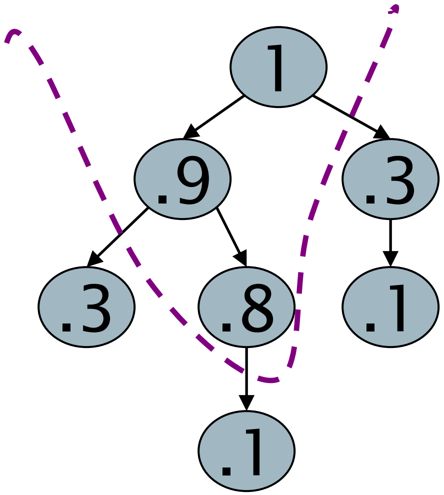
Use heaps for selecting top *K*

- Heap = Binary tree in which

  each node's value > the values of its children

- Takes O(J) operations to construct, then each of K "winners" read off in O(logJ) steps = O(J+K*logJ)

- For *J* = 1M, *K* = 100, this is about 5% of the cost of sorting and outputting (with log base 2)



Blanks on slides, you may want to fill in

Bottlenecks

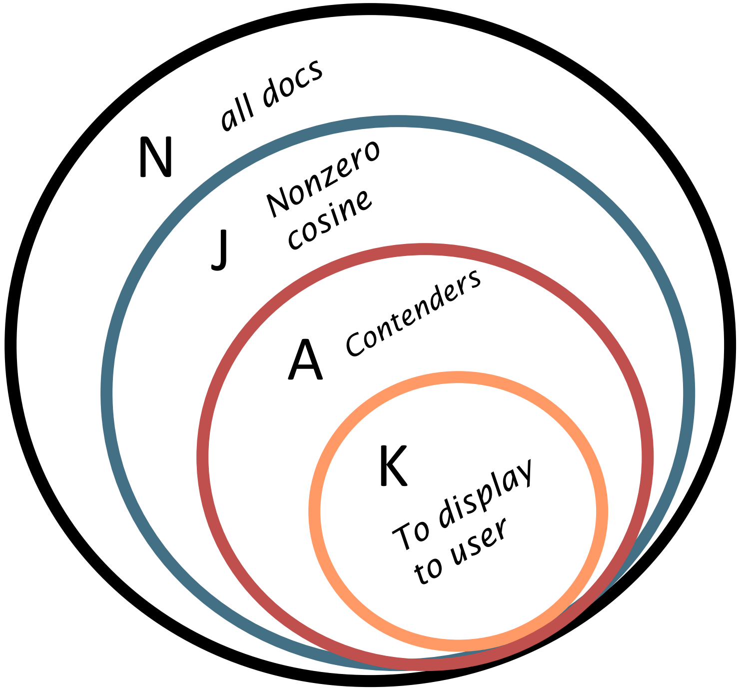
- Primary computational bottleneck in scoring: <u>cosine computation</u>

- Can we avoid doing this computation for all docs in J?
  - Yes, we need to do some pruning.

- We may get it wrong sometimes but it is ok if we are not missing too many.
  - It is unlikely that the user really want **all** relevant documents.

Generic approach

- Find a set *A* of contenders, with *K* < |*A*| << |*J*| << *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 can also be used for other (non-cosine) scoring functions.



Blanks on slides, you may want to fill in

Heuristic 1: Index elimination

- Basic algorithm: FastCosineScore of Fig 7.1 considers docs containing at least one query term (i.e., set J)

```
for each query term t
do calculate w_{t,q} and fetch postings list for t
    for each pair(d, tf_{t,d}) in postings list
```

- J will be large and the computation will be slow if

- We can in fact ignore part of the index (i.e., postings lists) based on the query.

1a. High-idf query terms only

- E.g., given a query such as ***catcher in the rye*** only accumulate scores from *catcher* and *rye*
- It is usually not important to match **in** and **the** anyway since they have low idfs.

- Benefit:
  - Postings of low *idf* terms have many docs → these (many) docs get eliminated from set *A* of contenders
  - Similar in spirit to stop word removal

1b. Docs containing many query terms

- Any doc with at least one query term is a candidate from the top *K* output list, but …
- For multi-term queries, only compute scores for docs containing several of the query terms
  - Say, at least 3 out of 4 query terms
- Easy to implement in postings traversal

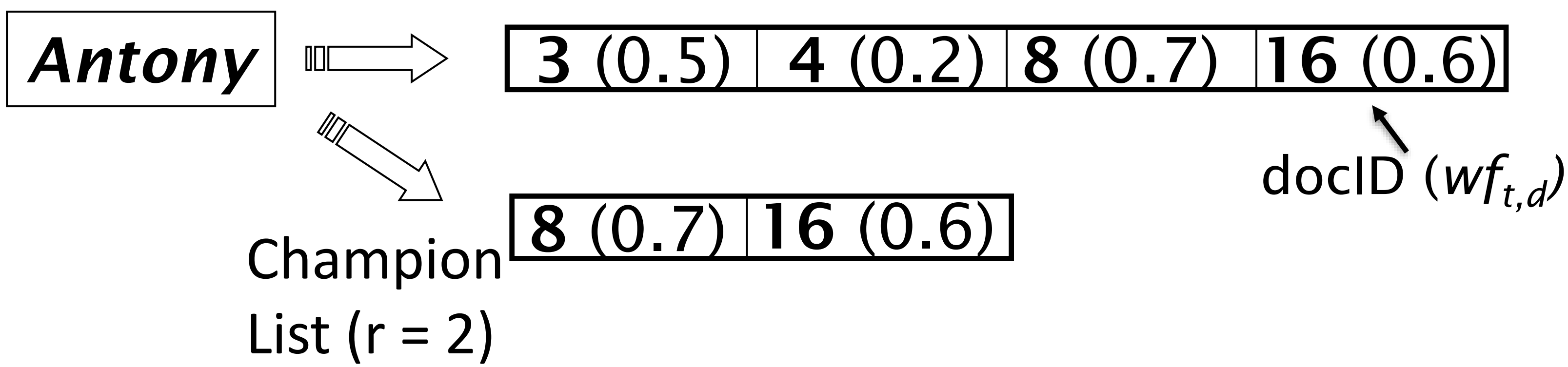
Example: Requiring 3 of 4 query terms

Antony	3	4	8	16	32	64	128	
Brutus	2	4	8	16	32	64	128	
Caesar	1	2	3	5	8	13	21	34
Calpurnia	13	16	32					

Scores only computed for docs 8, 16 and 32.

Heuristic 2: Champion lists

- Precompute for each dictionary term *t*, the *r* docs of highest weight in *t*'s postings
  - Call this the <u>champion list</u> for *t*
    (a.k.a. <u>fancy list</u> or <u>top docs</u> for *t*)



Heuristic 2: Champion lists

- 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

- Note that *r* has to be chosen at the indexing stage
  - Thus, it's possible that $r < K$

High and low lists

- For each term, we maintain two postings lists called *high* and *low*
  - Think of *high* as the champion list

Antony → 3 (0.5) | 4 (0.2) | 8 (0.7) | 16 (0.6)

docID ($wf_{t,d}$)

High List → 8 (0.7) | 16 (0.6)

Low List → 3 (0.5) | 4 (0.2)

High and low lists

- 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

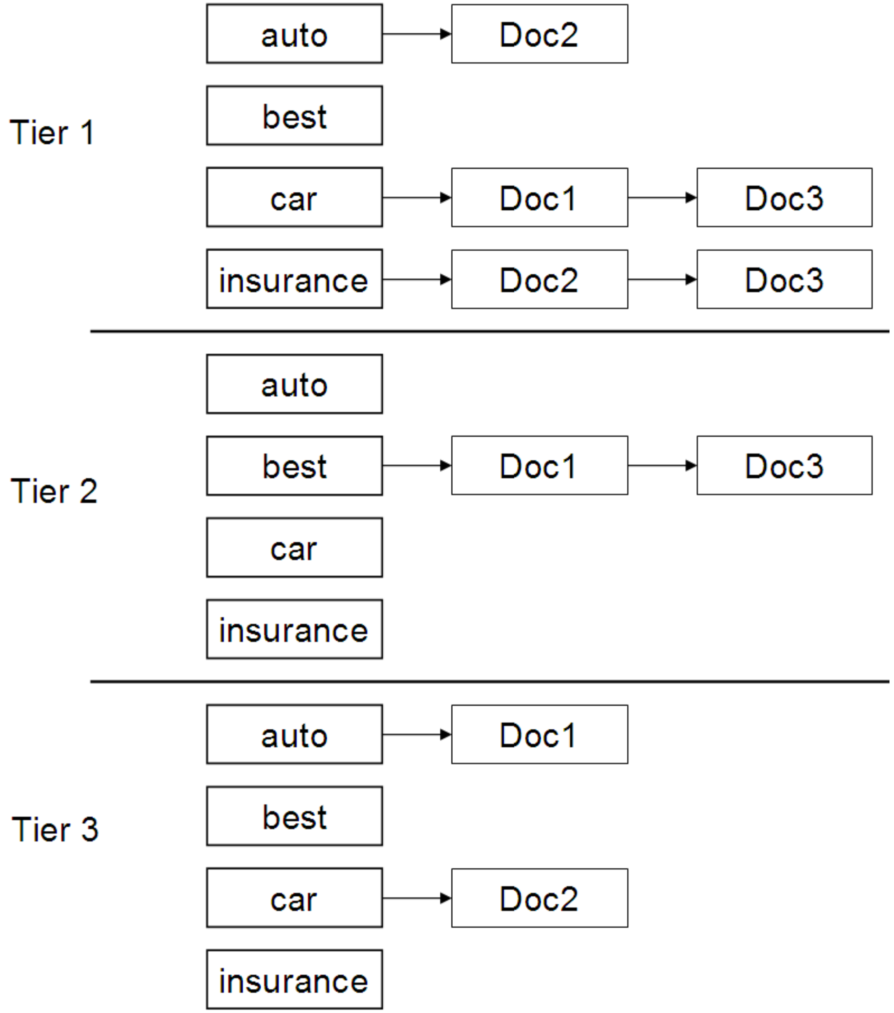
- Generalizing high-low lists into tiers
- Break postings up into a hierarchy of lists

Most important
…
Least important

- Inverted index thus broken up into tiers of decreasing importance
- At query time, use only top tier unless insufficient to get K docs

  If so, drop to lower tiers

Example tiered index



To think about: What information would be useful to use to determine tiers?

Heuristic 3: 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 $wf_{t,d}$

docID ($wf_{t,d}$)

Before sorting: ***Antony*** →

3 (0.5)	**4** (0.2)	**8** (0.7)	**16** (0.6)

After sorting: ***Antony*** →

8 (**0.7**)	16 (**0.6**)	3 (**0.5**)	4 (**0.2**)

3a. Early termination

Antony	→	8 (**0.7**)	16 (**0.6**)	3 (**0.5**)	4 (**0.2**)

- When traversing *t*'s postings (sorted by $wf_{t,d}$), stop early after either
  - a fixed number of *r* docs
  - $wf_{t,d}$ drops below some threshold

The score contribution ($wf_{t,d}$ * $wf_{t,q}$) is likely to be too low beyond these.

- Take the union of the resulting sets of docs
  - One set from the postings of each query term
- Compute only the scores for docs in this union

3b. idf-ordered query terms

- Consider the postings of query terms in order of decreasing *idf*
  - Query: *story Caesar Antony*
  - Order of processing: *Antony Caesar story*
- Skip low-idf query terms completely (e.g., ignore *story*) ← Similar to 1a
- Move on to the next query term once the score contribution ($wf_{t,d} * wf_{t,q}$) is low (e.g., <= 0.5)

Antony ⇨

8 (**0.7**)	16 (**0.6**)	3 (**0.5**)	4 (**0.2**)

E.g., if the query term weight of Anthony is **0.9**, skip to Caesar after checking the 3rd document.

Heuristic 4: Cluster pruning – preprocessing

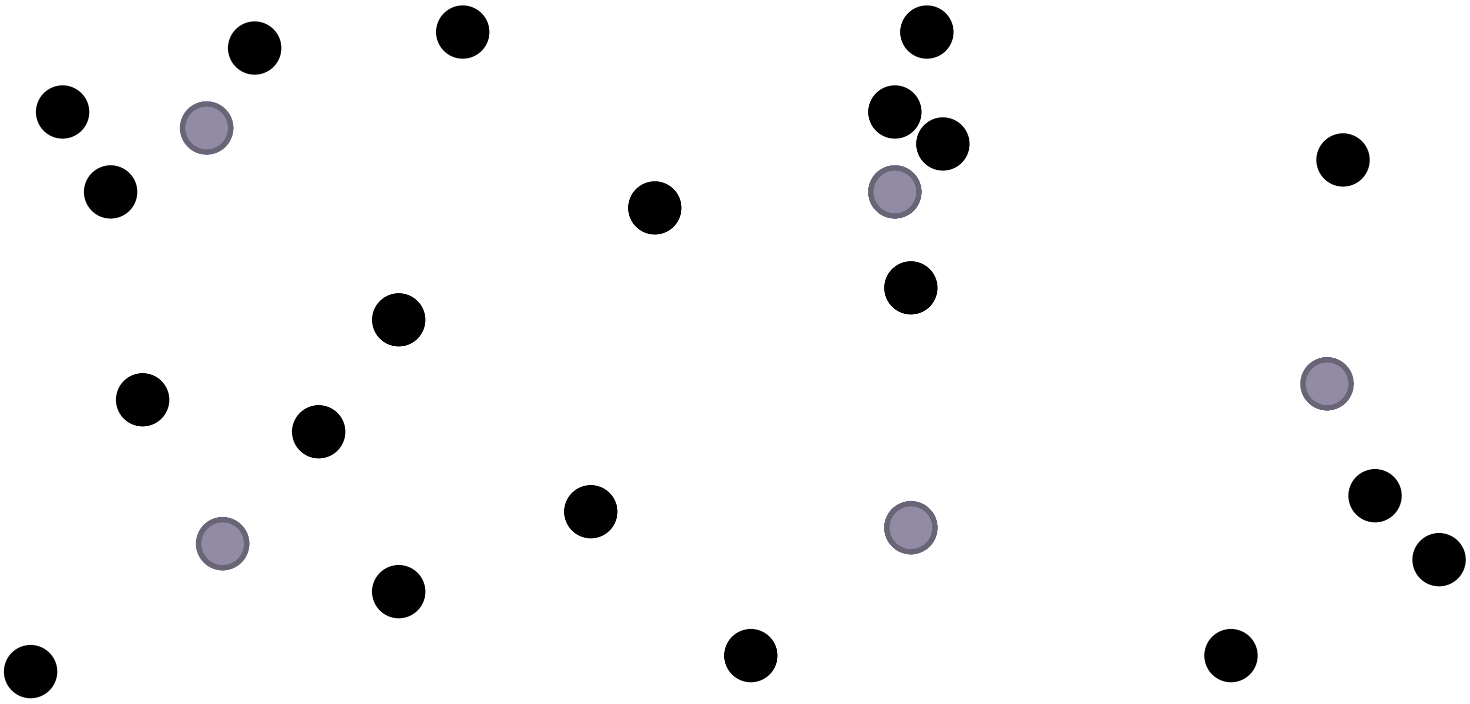
- Pick $\sqrt{N}$ docs at random, call these *leaders*
- For other docs, pre-compute nearest leader
  - Docs attached to a leader are its followers
  - Likely: each leader has $\sqrt{N}$ followers.

Why choose leaders at random?

- Fast
- Leaders reflect data distribution

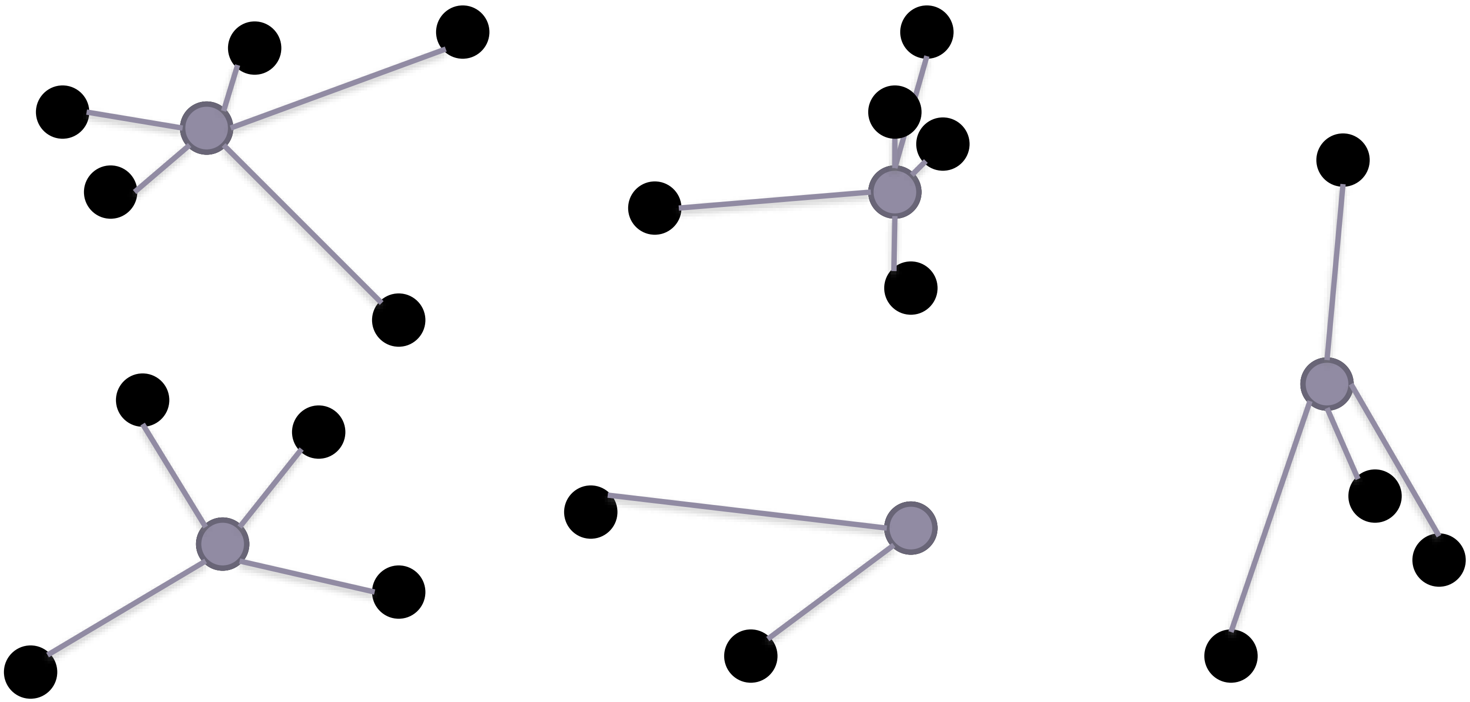
Cluster pruning visualization

1. Offline: Choose $\sqrt{N}$ leaders



Cluster pruning visualization

2. Associate documents to leaders to form clusters

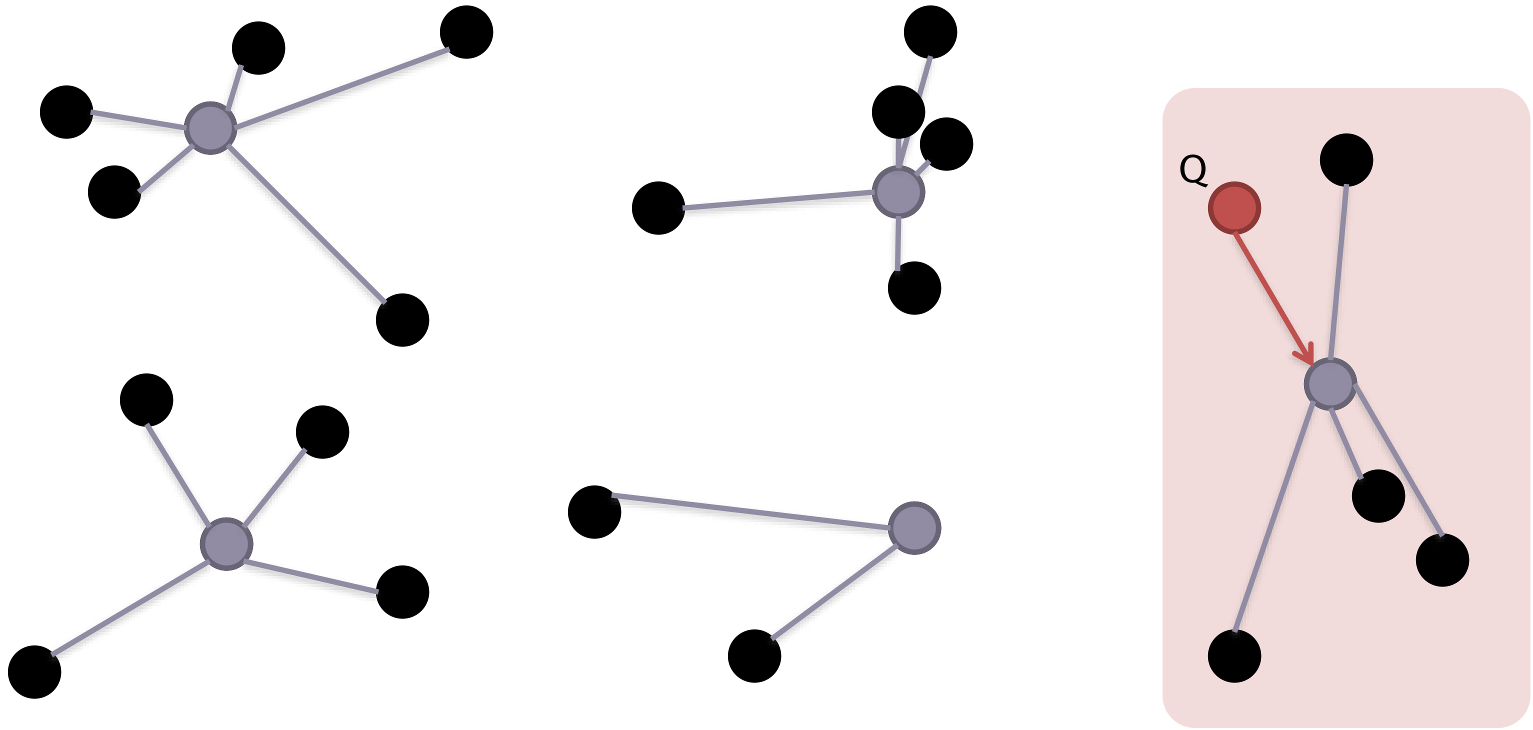


Cluster pruning – query processing

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

Cluster pruning visualization

3. Online: Associate query to a leader (cluster)



Clustering pruning variants

- Have each follower attached to b_1 nearest leaders
- From query, find b_2 nearest leaders and their followers

- b_1 affects preprocessing step at indexing time
- b_2 affects query processing step at run time

To think about: How do these parameters affect the retrieval results?

Incorporating Additional Information: Static quality scores

- We want top-ranking documents to be both *relevant* and *authoritative*
  - *Relevance* is being modeled by cosine scores
  - *Quality* is typically a query-independent property of a document
- Examples of quality signals
  - Wikipedia among websites
  - Articles in certain newspapers
  - A paper with many citations
  - Many views, retweets, favs, bookmark saves
  - PageRank score

Quantitative

Net score

- Assign to each document a quality score g(d) in [0,1]
  - E.g., PageRank
- Combine cosine relevance and quality

$$\textit{net-score}(q,d) = g(d) + \cos(q, d)$$

  - Can use some other linear combination than an equal weighting
- Now we seek the top *K* docs by net-score

Incorporating Additional Information: Query term proximity

- Free text queries: just a set of terms typed into the query box – common on the web
- Users prefer docs where the query terms occur close to each other
- Let *w* be the smallest window in a document containing all query terms, e.g.,
  - Given the query *open day*:
    - For the document *open the next day*, the size of *w* is 4.
    - For the document *national day open house*, the size of *w* is 2.

Query term proximity

- Collect candidates by running one or more queries to the indexes, and then rank.

- e.g., *NUS open day*
  1. Run it as a phrase query (e.g., using a positional index)
  2. If < *K* docs contain the phrase *NUS open day*, run the two phrase queries *"NUS open"* and *"open day"*
  3. If we still have < *K* docs, run the vector space query *NUS open day*
  4. Rank matching docs by vector space scoring combining all information (possibly including proximity score *w*)

Incorporating Additional Information: Parametric and zone indexes

Documents often have multiple parts, with different semantics:

- Author, Title, Date of publication, etc.

These constitute the metadata about a document.

We sometimes wish to search by these metadata.

- E.g., find docs authored by T.S. Raffles in the year 1818, with *Dutch East India Company* in the title

Fields

- Year = 1818 is an example of a field
  - Also, author = T.S. Raffles, etc
  - with **a finite set** of possible values
- Field or parametric index
  - Postings for each field value
  - Sometimes build range (B-tree) trees (e.g., for dates)
- Field query typically treated as conjunction
  - find docs authored by T.S. Raffles in the year 1818... =
  - doc *must* be authored by T.S. Raffles AND in the year 1818.

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 Dutch East India Company in the title

Two methods for zone indexing

Alternative 1:

william.abstract → 11 → 121 → 1441 → 1729

william.title → 2 → 4 → 8 → 16

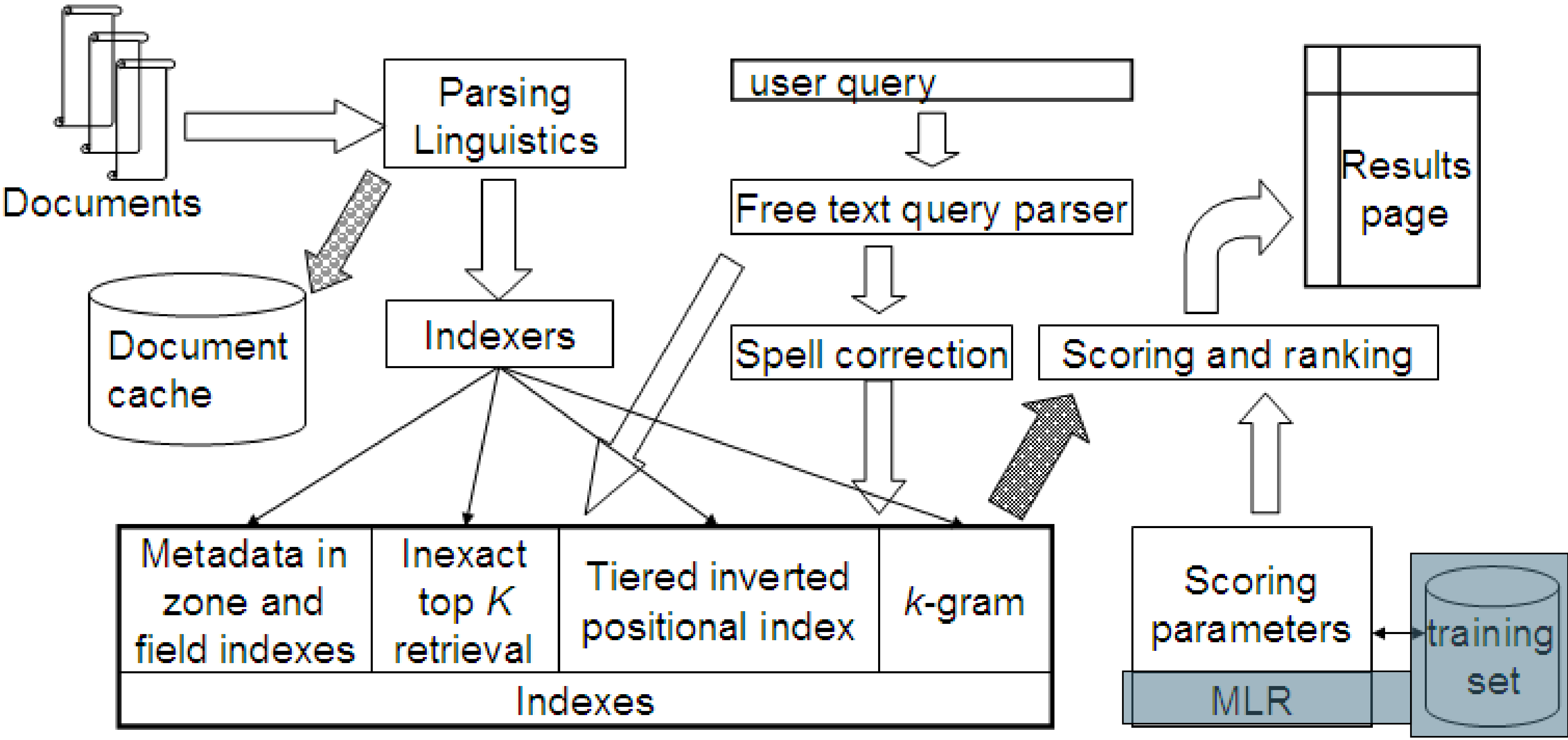
william.author → 2 → 3 → 5 → 8

Encode zones in dictionary vs. postings.

Alternative 2:

william → 2.author,2.title → 3.author → 4.title → 5.author

Putting it all together



Won't be covering these blue modules in this course

Summary

- Making the Vector Space Model more effective and efficient to compute
- Incorporating additional information

Resources for today

- IIR 7, 6.1