CS3245

Information Retrieval

8

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

Last Time: tf-idf weighting

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

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

- Best known weighting scheme in information retrieval

  "One of the easy but important things you should remember about IR" – Min

  - Increases with the number of occurrences 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

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

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

Today

Goal

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

Method

- Heuristics

Recap:

- An overview of the complete search system

Recap: Computing cosine scores

```
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} × w_{t,q}
 7  Read the array Length
 8  for each d
 9  do Scores[d] = Scores[d]/Length[d]
10  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:
  1. Computing a single cosine efficiently

Simpler case – unweighted queries

- No weighting on query terms
  - Assume each query term has weight 1
  - i.e. $w_{t,q} = 1$
    (no tf, nor idf factor; just Boolean presence)

Faster cosine: unweighted query

```
FastCosineScore(q)
 1   float Scores[N] = 0
 2   for each d
 3   do Initialize Length[d] to the length of doc d
 4   for each query term t
 5   do calculate w_{t,q} and fetch postings list for t
 6      for each pair(d, tf_{t,d}) in postings list
 7      do add wf_{t,d} to Scores[d]
 8   Read the array Length[d]
 9   for each d
10   do Divide Scores[d] by Length[d]
11   return Top K components of Scores[]
```

Figure 7.1 A faster algorithm for vector space scores.

No expensive multiplication; now just addition

Efficient cosine ranking

- Find the K docs in the collection "nearest" to the query $\Rightarrow$ K largest query-doc cosines.
- Efficient ranking:
  1. Computing a single cosine efficiently.
  2. Choosing the K largest cosine values efficiently.

Can we do this without computing all N cosines?

Computing the K largest cosines: selection vs. sorting

- Typically we want to retrieve the top K docs (in the cosine ranking for the query)
  - Don't need total order for **all** docs

Can we pick off docs with K highest cosines?

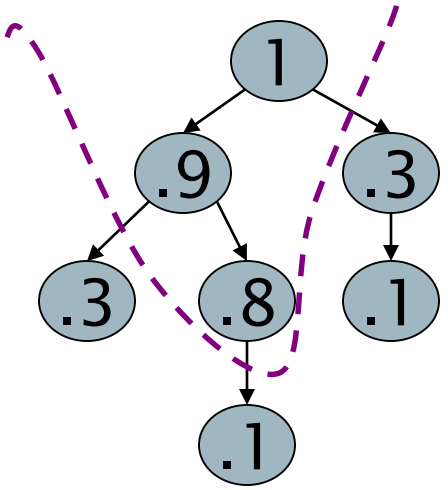
- Formal Problem Specification:
  Let J = number of docs with nonzero cosines.
  Then we seek the K best of these J

Use heaps for selecting top K

- Heap = Binary tree in which
  each node's value > the values of children

- Takes $O(J)$ operations to construct, then each of K "winners" read off in $O(\log J)$ steps.

- For $J = 1M$, $K = 100$, this is about 10% of the cost of sorting



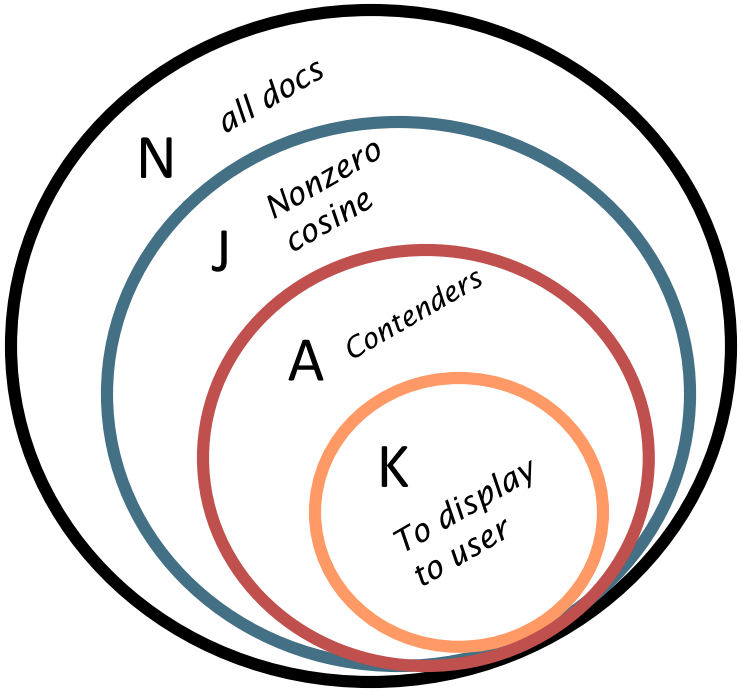
Blanks on slides, you may want to fill in

Bottlenecks

- Primary computational bottleneck in scoring: cosine computation
- Can we avoid doing this computation for all docs?
- **Yes**, but may sometimes get it wrong…
  - a doc *not* in the top K may creep into the list of K output docs, and vice versa
  - Is this such a bad thing?

Generic approach

- Find a set A of *contenders*, with $K < |A| \ll N$
  - 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 used for other (non-cosine) scoring functions



Heuristic 1: Index elimination

- Basic algorithm: FastCosineScore of Fig 7.1 considers docs containing at least one query term

- Extend this to a logical conclusion:

  A. Only consider high idf query terms
  B. Only consider docs containing many query terms

A. High-idf query terms only

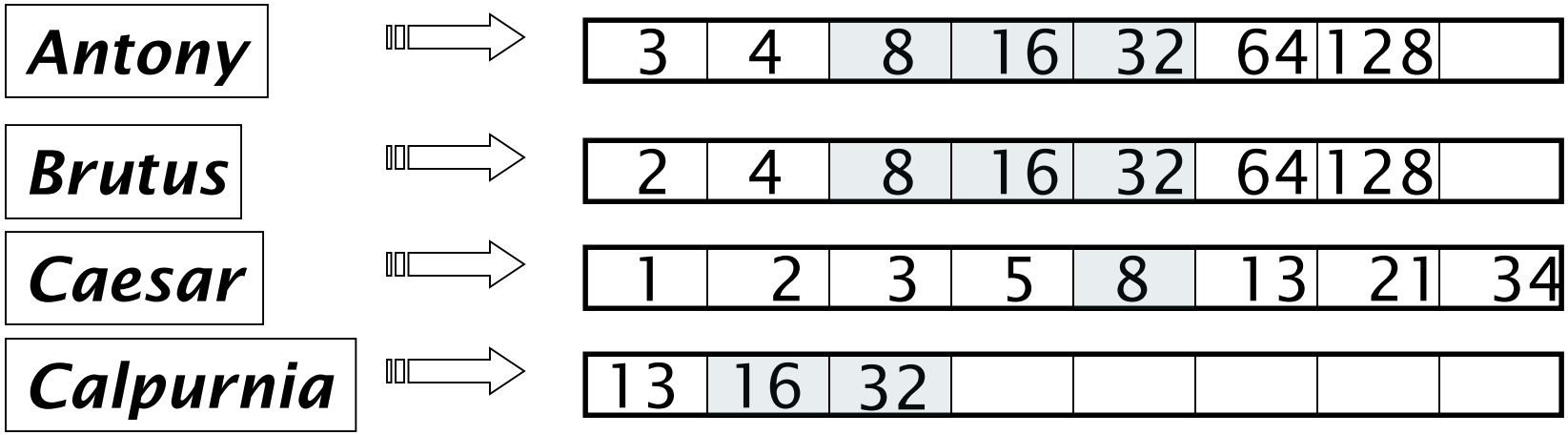
- E.g., given a query such as *catcher in the rye* only accumulate scores from *catcher* and *rye*
- Intuition: *in* and *the* contribute little to the scores and so don't alter rank-ordering much

- Benefit:
  - Postings of low idf terms have many docs $\rightarrow$ these (many) docs get eliminated from set A of contenders
  - Similar in spirit to stopwording

B. Docs containing many query terms

- Any doc with at least one query term is a candidate for 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
  - Imposes a "soft conjunction" on queries seen on web search engines (early Google)
- Easy to implement in postings traversal

Example: Requiring 3 of 4 query terms



Scores only computed for docs 8, 16 and 32.

Blanks on slides, you may want to fill in

Heuristic 2: 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)
  - For tf-idf weighting this just means
- 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
- Can be used even for simple cosine scores, without global quality $g(d)$
- A means for segmenting index into two tiers

Tiered indexes

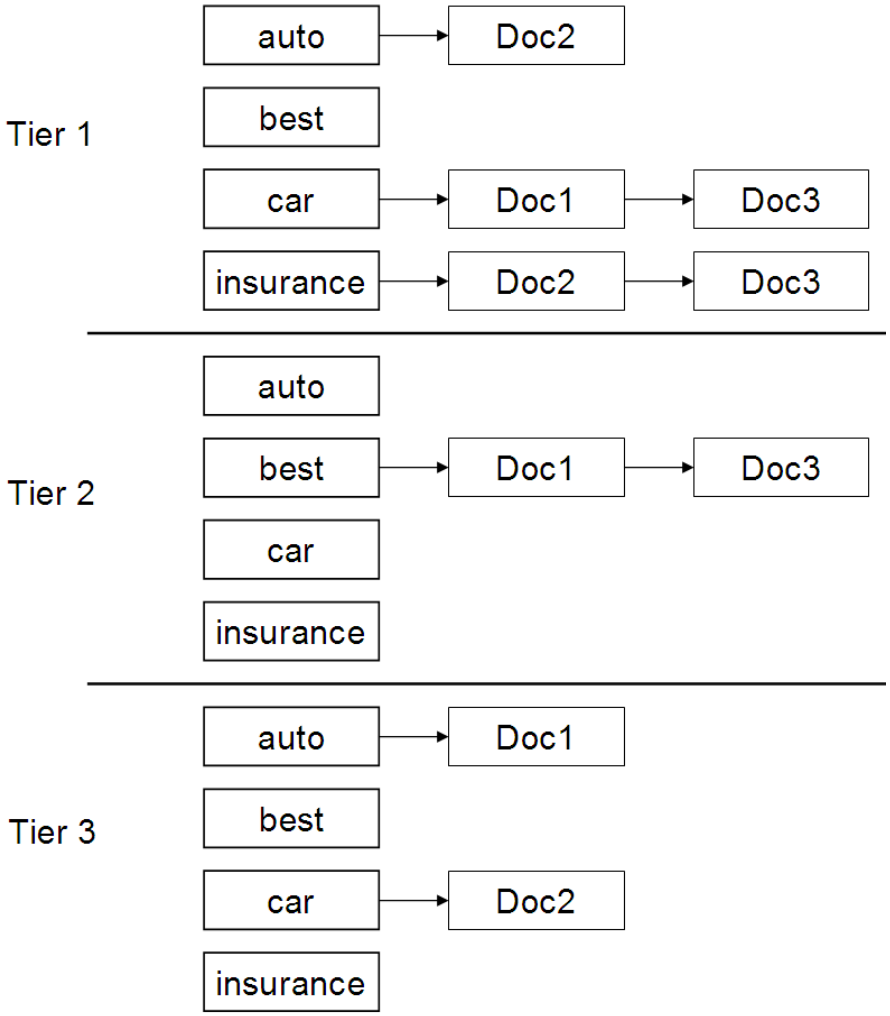
- Generalizing high-low lists into tiers
- Break postings up into a hierarchy of lists

  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 $wf_{t,d}$
- Problem: not all postings in a common order! (Concurrent traversal then not possible)

- How do we compute scores in order to pick off top K?
  Two ideas:
  A. Early Termination
  B. IDF Ordered Terms

A. Early termination

- Sort t's postings by descending $wf_{t,d}$ value
- 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

B. 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 weighting but also other net scores

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?

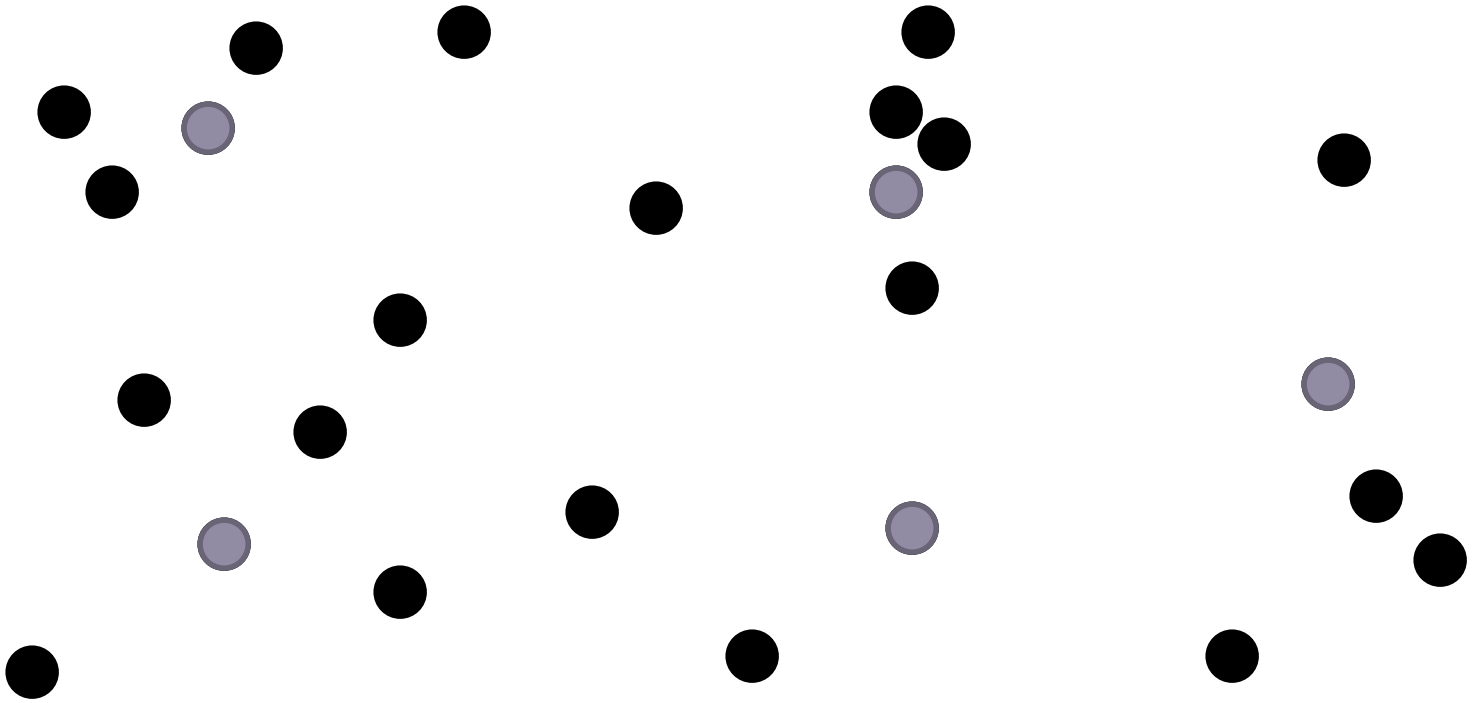
- Fast
- Leaders reflect data distribution

Cluster pruning – query processing

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

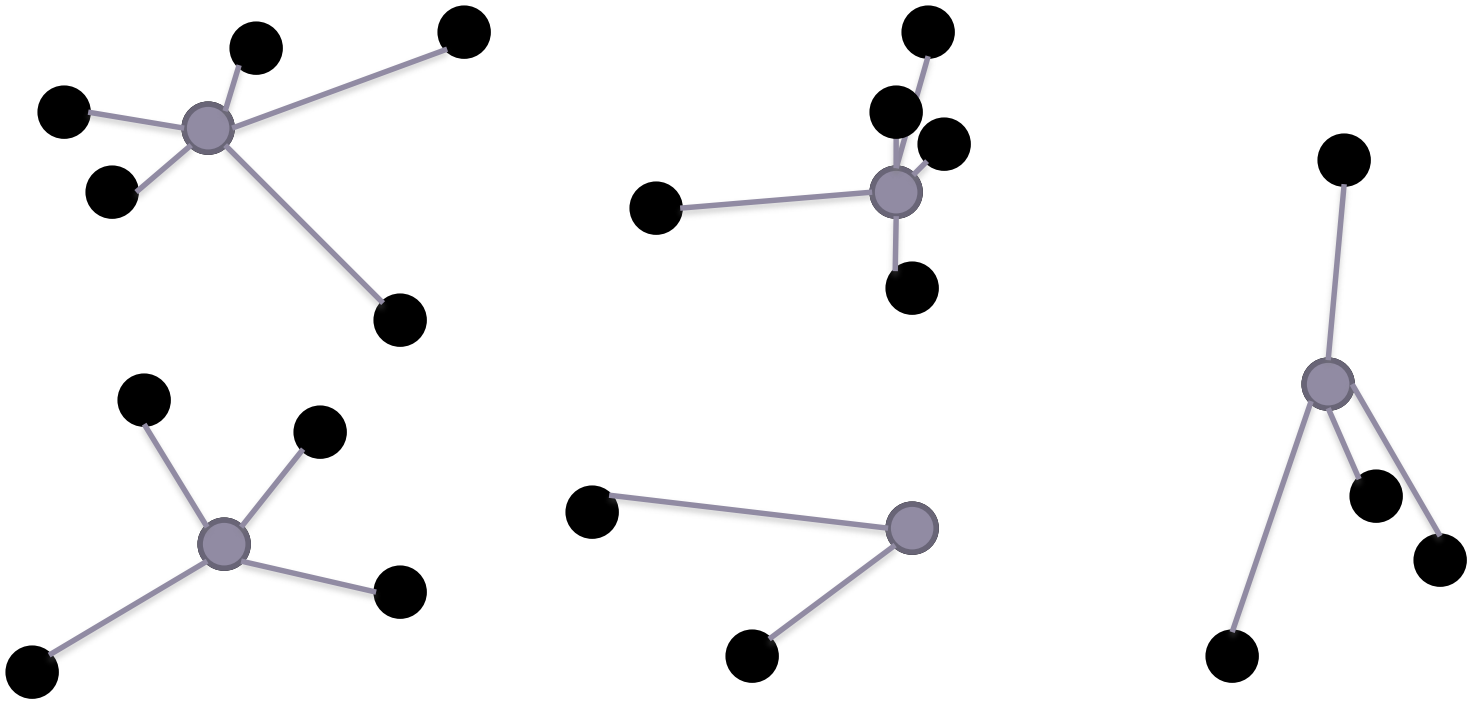
Cluster pruning visualization

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



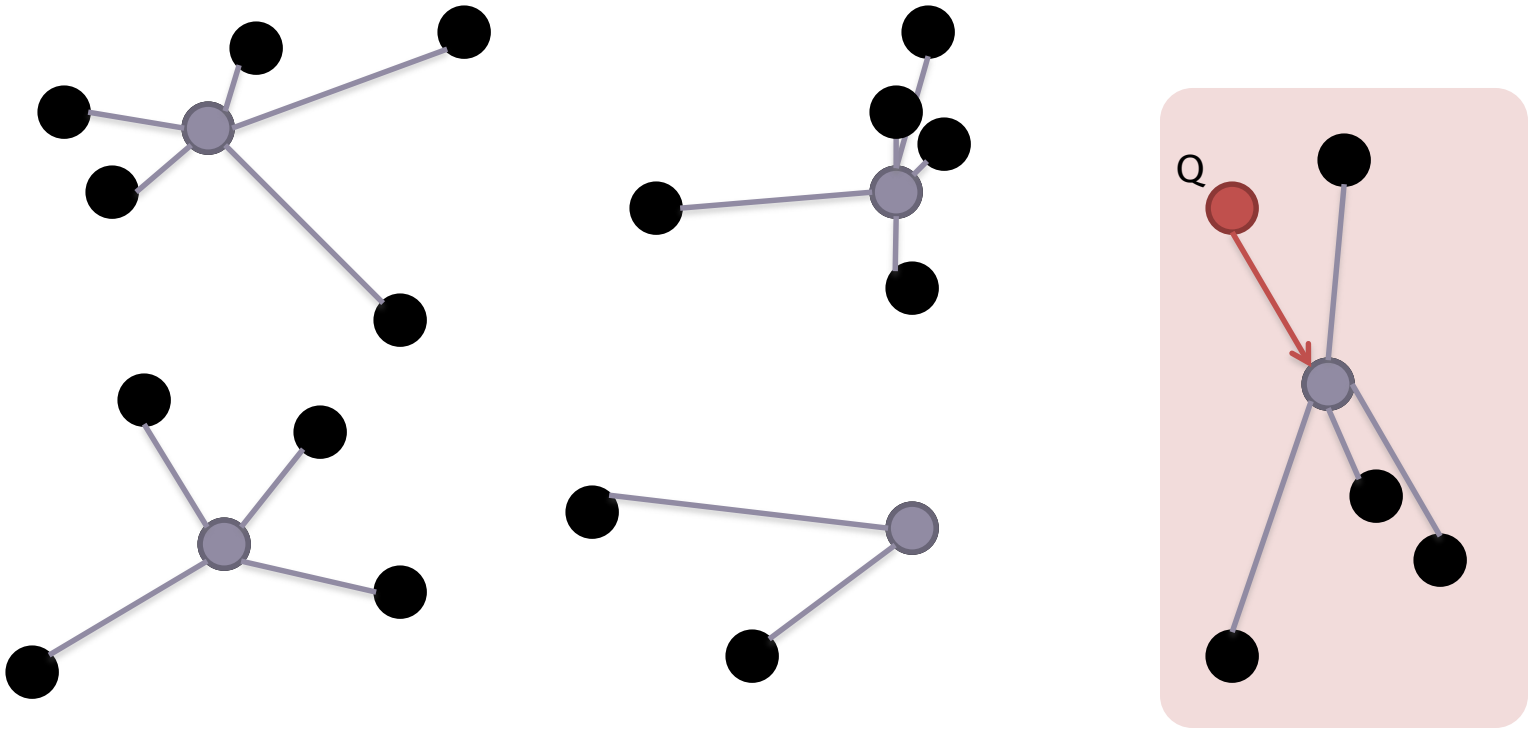
Cluster pruning visualization

2. Associate documents to leaders to form clusters



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
  - *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 views, retweets, favs, bookmark saves
  - PageRank score

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]

Net score

- Consider a simple total score combining cosine relevance and authority

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

  - Can use some other linear combination than an equal weighting
  - Indeed, any function of the two "signals" of user happiness

- 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

Wait a second. We previously said documents need to be in order of docID to be merged efficiently. Why does this not violate it?

- Thus, can concurrently traverse query terms' postings for
  - Postings intersection
  - Cosine score computation

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

Combining Ideas: 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 $g(d) + tf\text{-}idf_{t,d}$ instead of just $tf\text{–}idf_{t,d}$
- Seek top-K results from only the docs in these champion lists

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 doc containing all query terms, e.g.,
- For the query *open day* the smallest window in the doc Special *Special open box promo day* is 4.

Query parsers

- Free text query from user may spawn one or more queries to the indexes, e.g. *"NUS open day"*
  1. Run the query as a phrase query
  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
- This sequence is issued by a query parser

Parametric and zone indexes

(From Chapter 6.1 skipped last week [Week 7, slide 3])

Thus far, a doc has been a sequence of terms.

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, containing *Dutch East India Company*

Fields

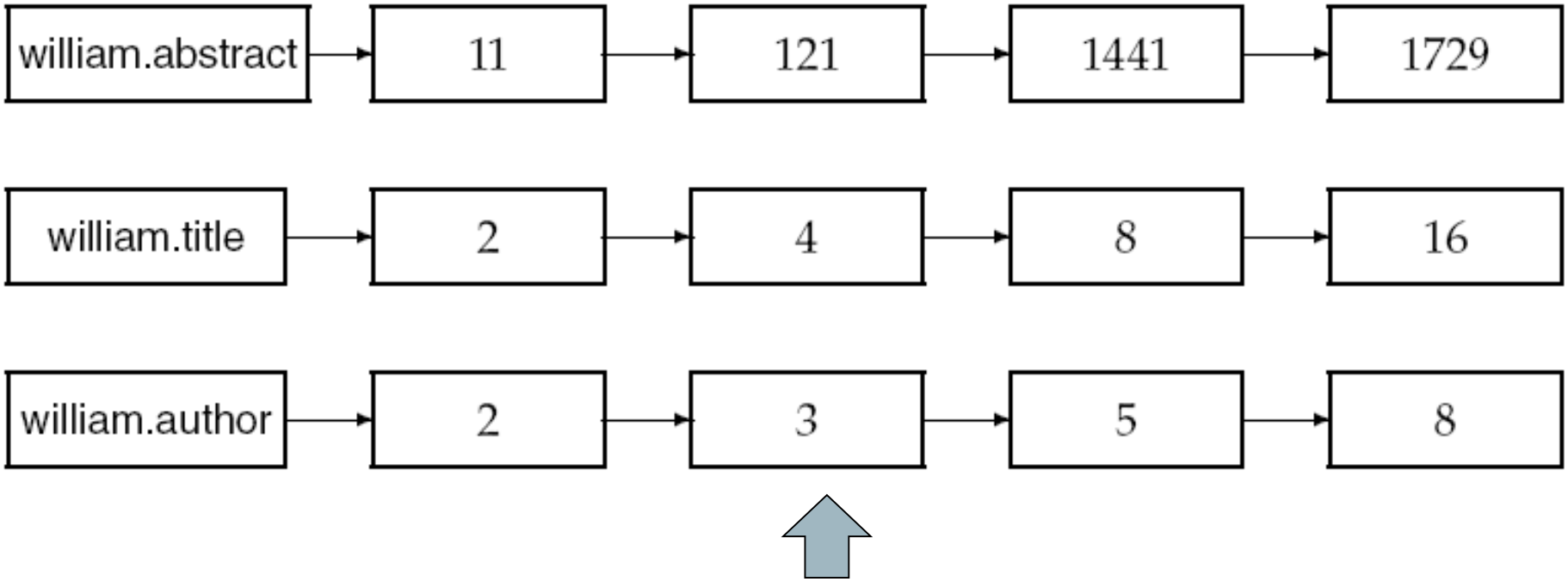
- Year = 1818 is an example of a field
- Also, author last name = Raffles, etc
- Field or parametric index: postings for each field value
  - Sometimes build range (B-tree) trees (e.g., for dates)
- Field query typically treated as conjunction
  - (doc *must* be authored by Raffles)

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* "

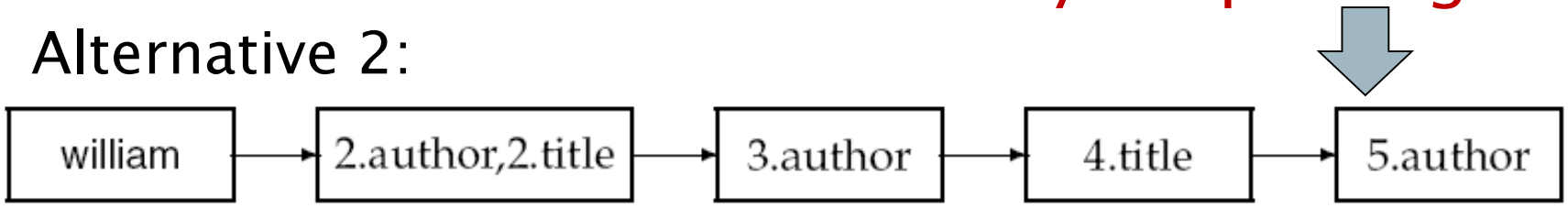
Two methods for zone indexing

Alternative 1:

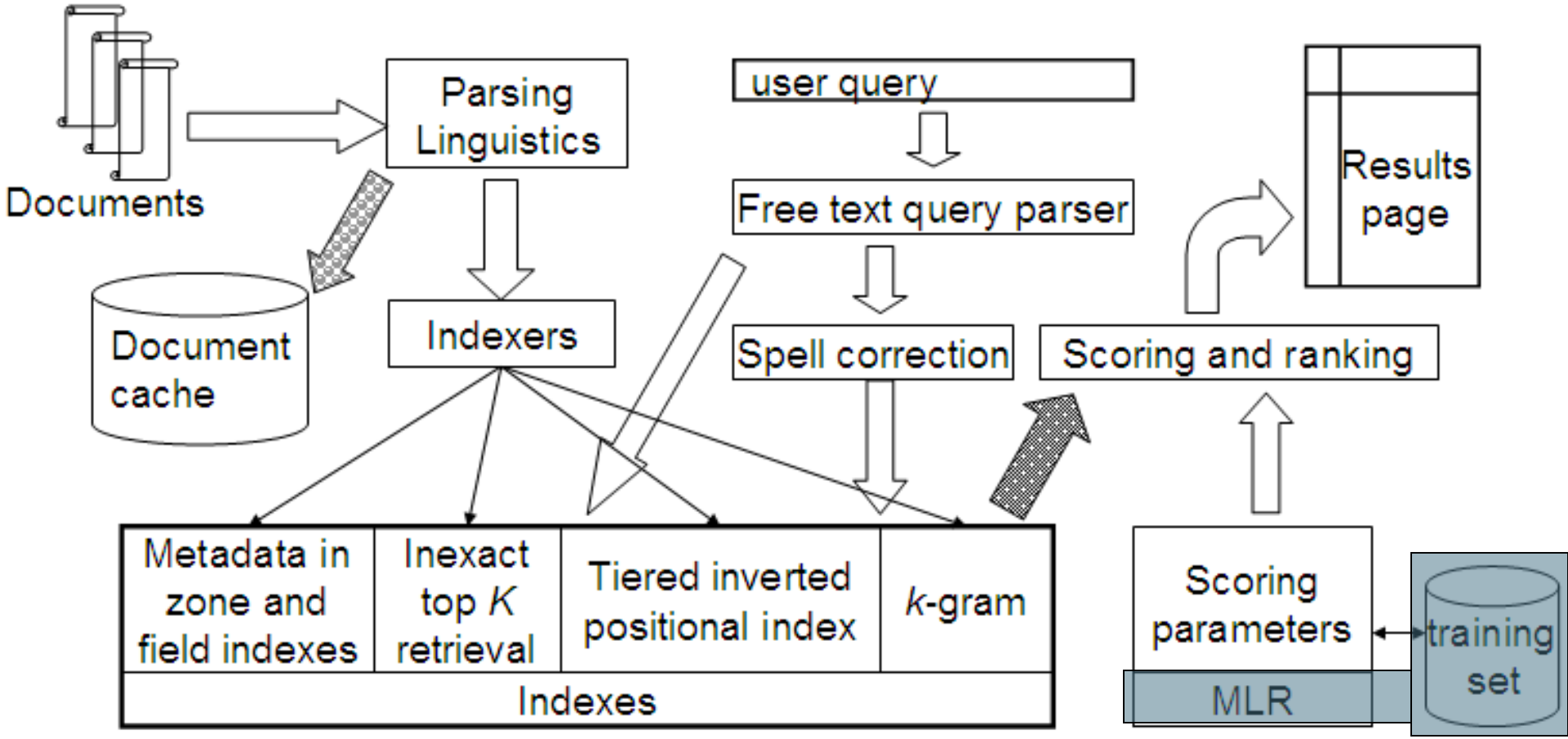


Encode zones in dictionary vs. postings.

Alternative 2:



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 other ranking information G(d)
- Approximating the actual correct results
- Skipping unnecessary documents

In actual data: dealing with zones and fields, query term proximity

Resources for today

- IIR 7, 6.1