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.

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

- 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

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 $\vec{d}$.

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)

$float\ Scores[N] = 0$
$float\ Length[N]$
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 ⇒ *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)
- Then for ranking, don't need to normalize query vector
  - Simpler version of algorithm from last week

Faster cosine: unweighted query

```
FastCosineScore(q)
 float Scores[N] = 0
 for each d
 do Initialize Length[d] to the length of doc d
 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
     do add wf_{t,d} to Scores[d]
 Read the array Length[d]
 for each d
 do Divide Scores[d] by Length[d]
 return Top K components of Scores[]
```

No expensive multiplication; now just addition

Figure 7.1 A faster algorithm for vector space scores.

Efficient cosine ranking

- Find the *K* docs in the collection "nearest" to the query ⇒ *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?

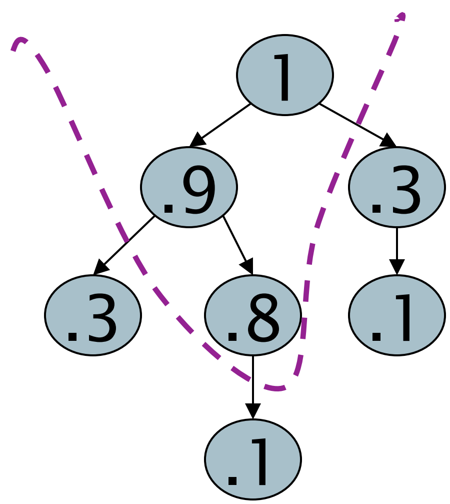
- Formal Problem Specification:
  Let *J* = number of docs with nonzero cosines.
  Then we seek the *K* best of these *J*

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



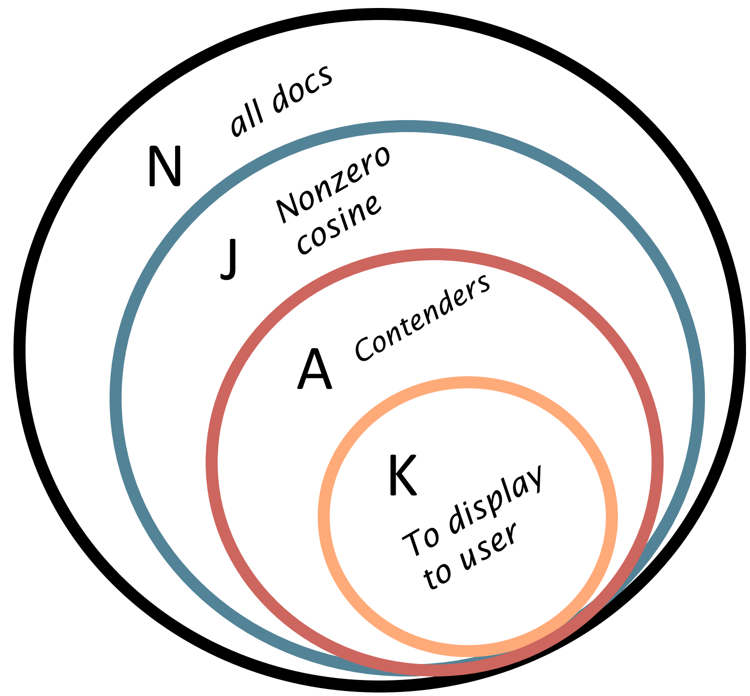
Blanks on slides, you may want to fill in

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 $K < |A| << N$
  - *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 only 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 <u>don't alter rank-ordering much</u>
- Benefit:
  - Postings of low idf terms have many docs → 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

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.

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

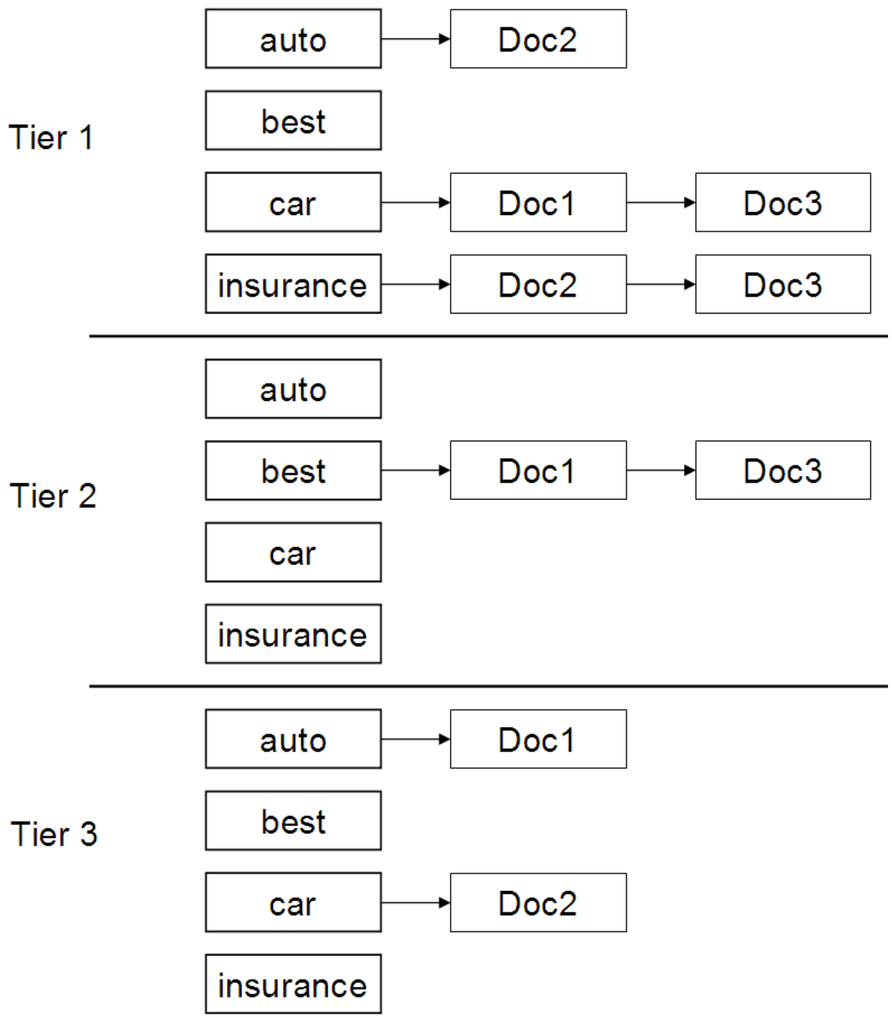
Tiered indexes

- 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
- Generalization of high-low lists

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 every other doc, pre-compute nearest leader
  - Docs attached to a leader: its *followers;*
  - Likely: each leader has ~ $\sqrt{N}$ followers.

Why choose leaders at random?

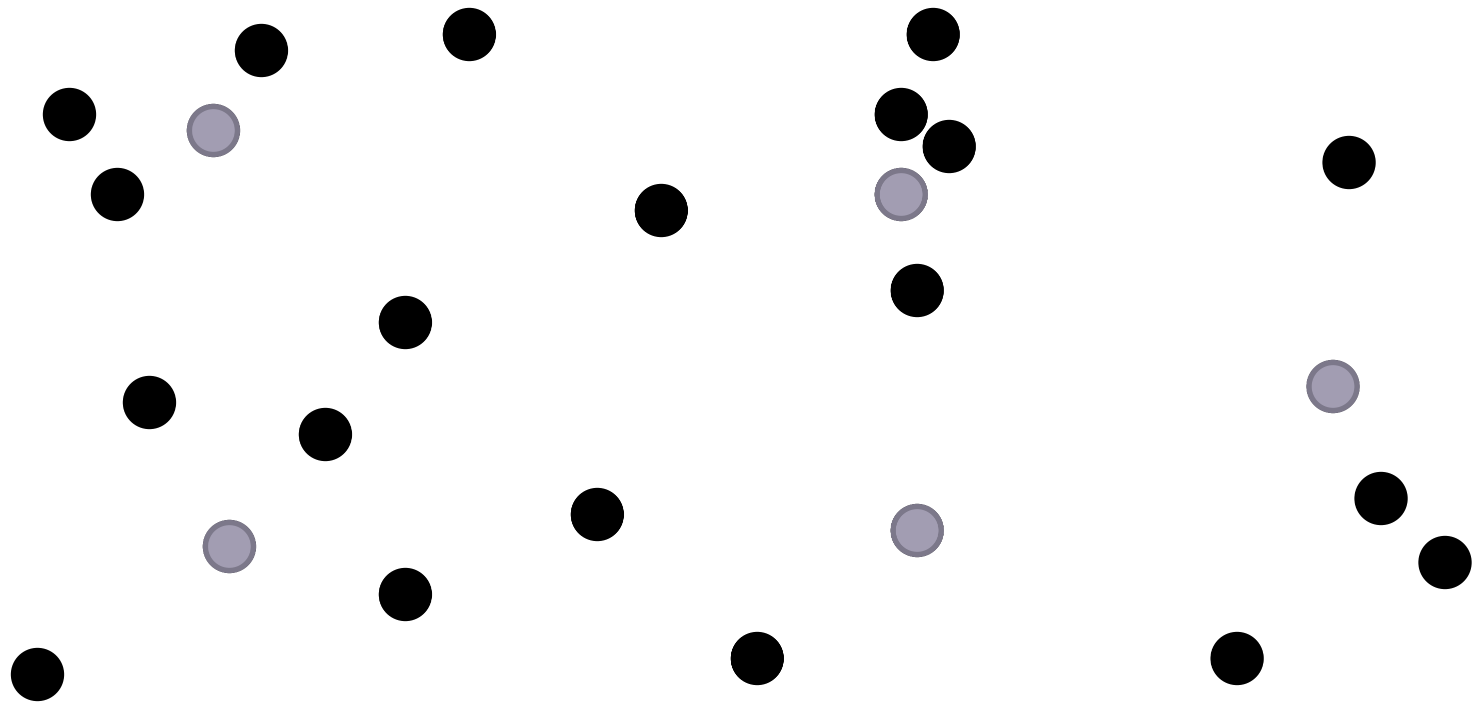
- Fast
- Leaders reflect data distribution

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.

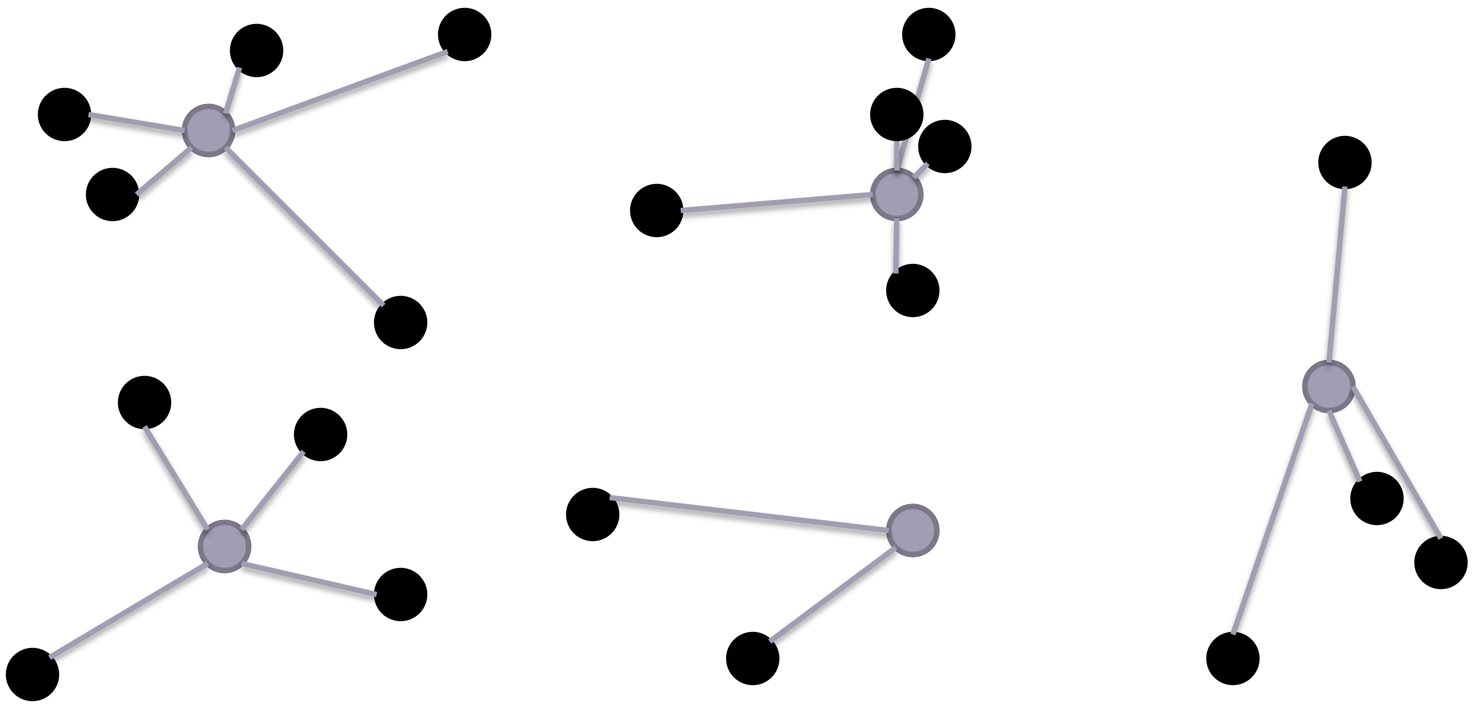
Cluster Pruning Visualization

1. Offline: Choose sqrt(n) leaders



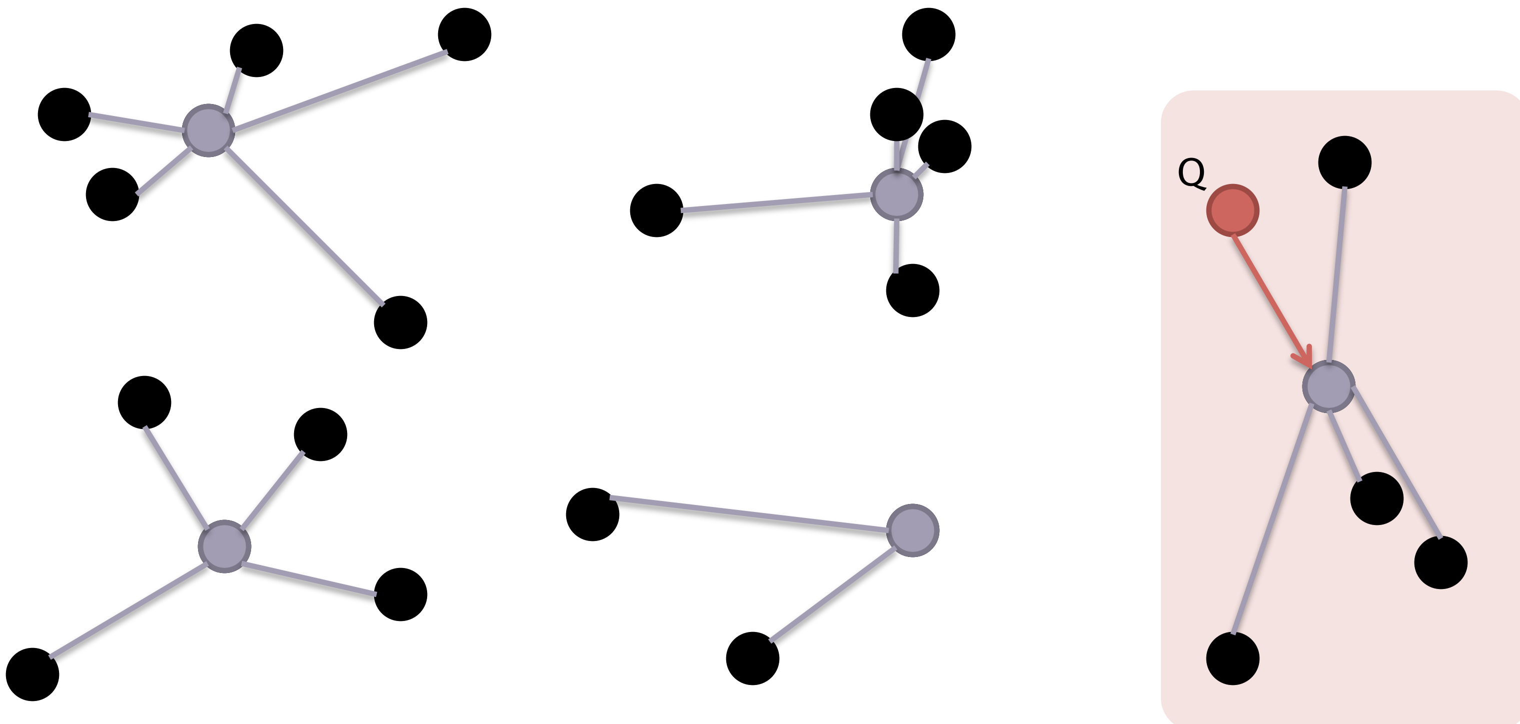
Cluster Pruning Visualization

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 *b1* nearest leaders
- From query, find *b2* nearest leaders and their followers

- b1 affects preprocessing step at indexing time
- b2 affects query processing step at run time

To think about: How do these parameters affect precision and recall?

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* <u>quality score</u> 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

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

  - 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 <u>net score</u>

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

  - Short of computing scores for all docs in postings

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-idf$_{t,d}$ instead of just tf-idf$_{t,d}$
- Seek top-*K* results from only the docs in these champion lists

Parametric and zone indexes

(Back to Chapter 6 skipped last week)

- 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 William Shakespeare in the year 1601, containing *alas poor Yorick*

Fields

Will be used in HW#4

- 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 (B-tree) trees (e.g., for dates)
- Field query typically treated as conjunction
  - (doc *must* be authored by shakespeare)

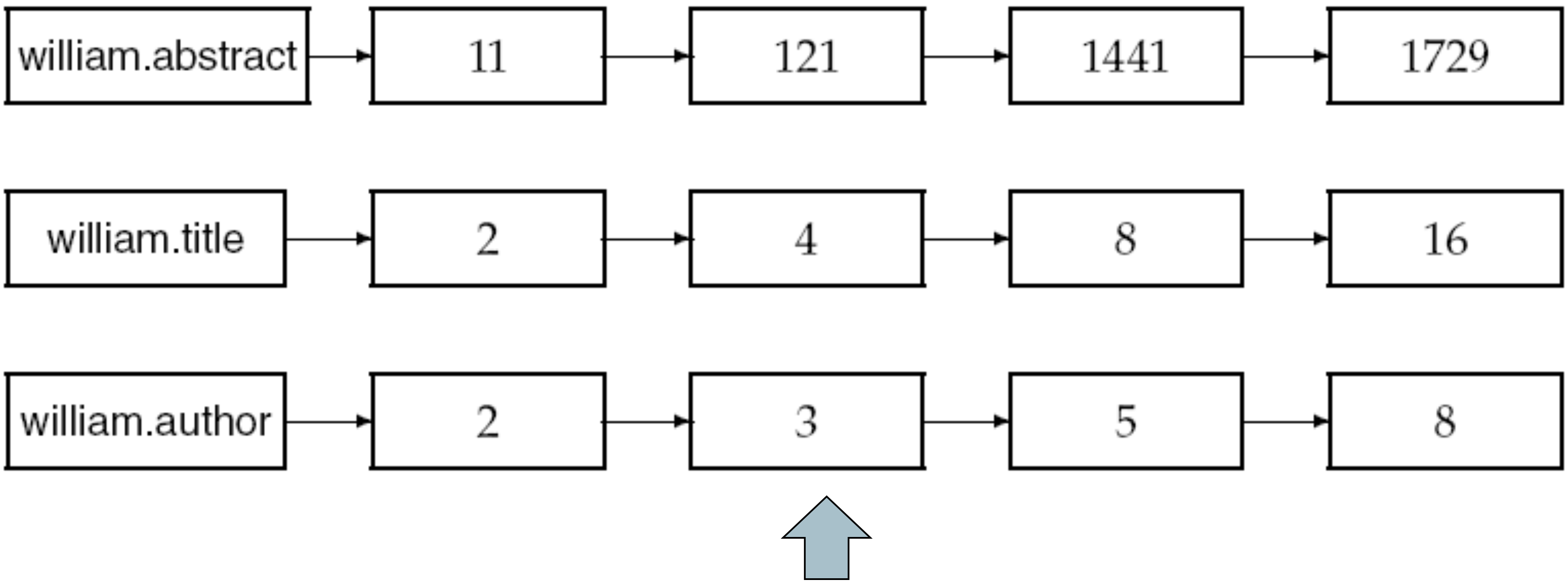
Zone

Also used in HW#4

- A <u>zone</u> 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*"

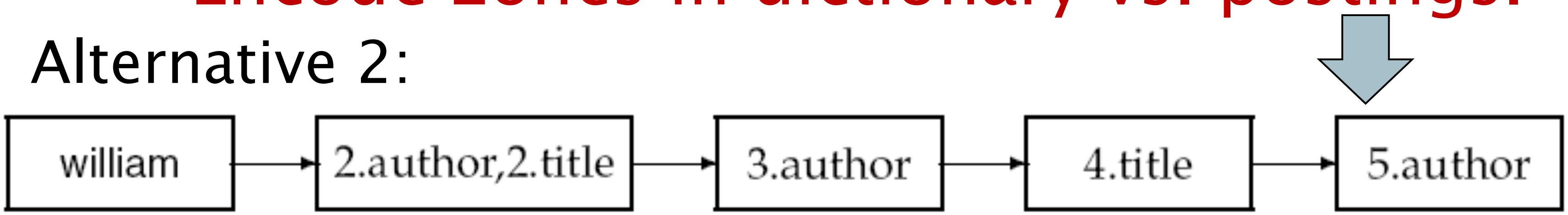
Two methods for zone indexing

Alternative 1:



Encode zones in dictionary vs. postings.

Alternative 2:



Query term proximity

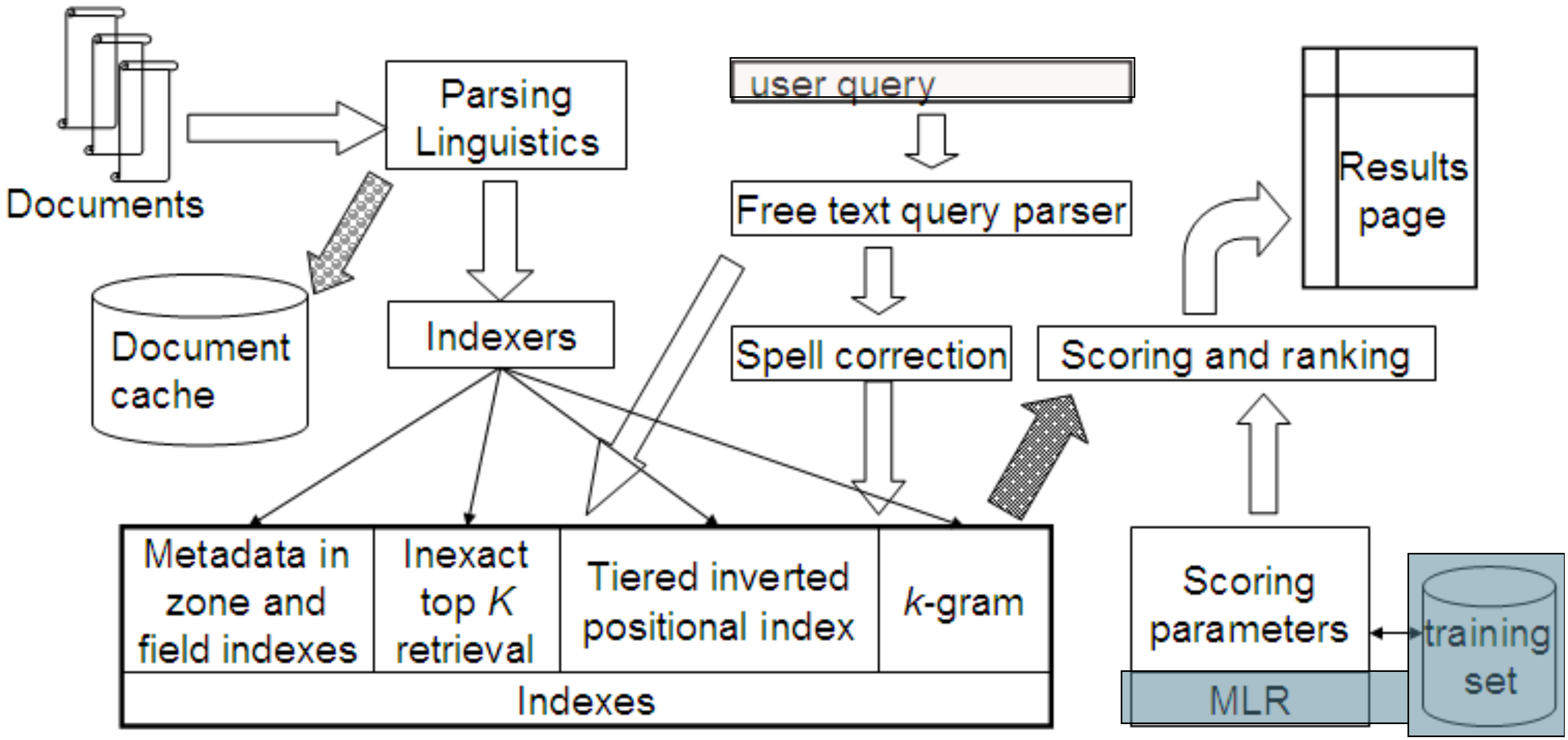
- Free text queries: just a set of terms typed into the query box – common on the web
- Users prefer docs where the query terms occur close to each other

- Let *w* be the smallest window in a doc containing all query terms, e.g.,
- For the query *strained mercy* the smallest window in the doc *The quality of mercy is not strained* is 4.

Query parsers

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

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