

Scoring & result assembly

CE-324: Modern Information Retrieval

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Most slides have been adapted from: Profs. Manning, Nayak & Raghavan (CS-276, Stanford)

Outline

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

Recap: Queries as vectors

- ▶ Vector space scoring
 - ▶ We have a weight for each term in each doc
 - ▶ Represent queries as vectors in the space
 - ▶ Rank documents according to their cosine similarity to the query in this space
 - ▶ Or something more complex: BM25, proximity, ...
- ▶ Vector space scoring is
 - ▶ Entirely query dependent
 - ▶ Additive on term contributions – no conditionals etc.
 - ▶ Context insensitive (no interactions between query terms)



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

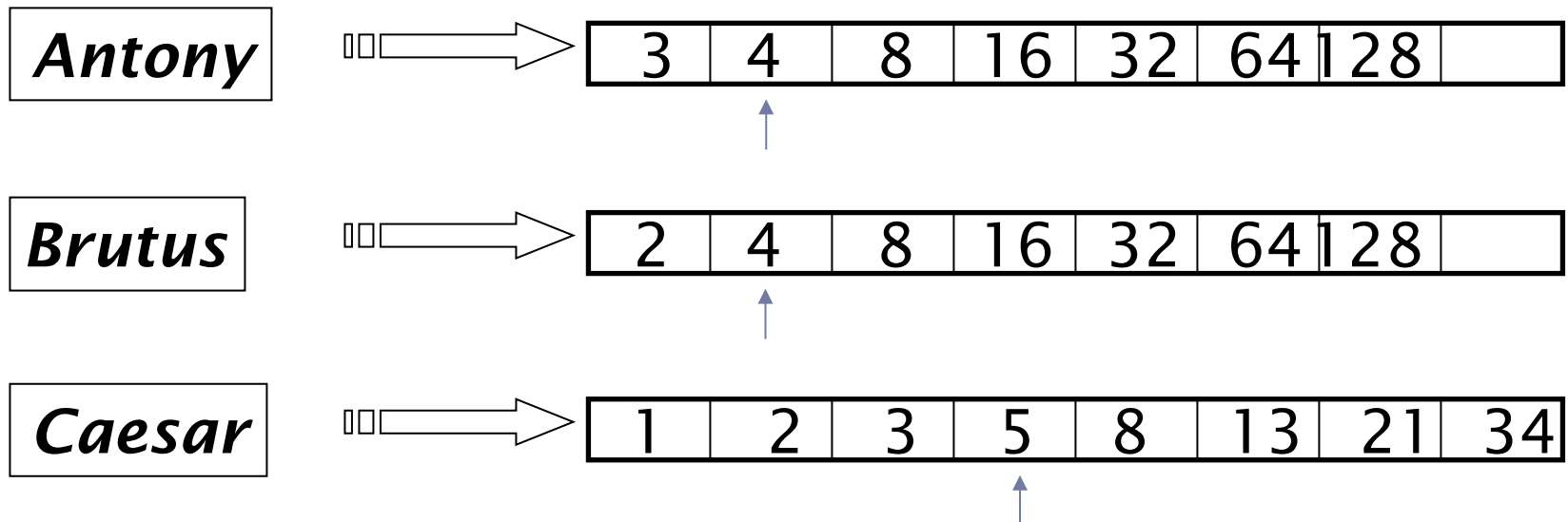
Computing cosine scores

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[ $d$ ] + =  $w_{t,d} \times w_{t,q}$ 
7  Read the array Length
8  for each  $d$ 
9  do Scores[ $d$ ] = Scores[ $d$ ] / Length[ $d$ ]
10 return Top  $K$  components of Scores[]
```

Term-at-a-time vs. doc-at-a-time processing

- ▶ Completely process the postings list of the first query term, then process the postings list of the second query term and so forth
- ▶ Doc-at-time



Efficient cosine ranking

- ▶ Find the K docs in the collection “nearest” to the query $\Rightarrow K$ largest query-doc cosines.
- ▶ Efficient ranking:
 - ▶ 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?

Non-safe ranking

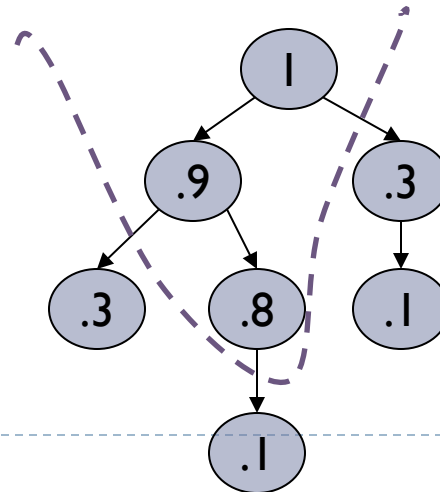
- ▶ Non-safe ranking may be okay
 - ▶ Ranking function is only a proxy for user happiness
 - ▶ Documents close to top K may be just fine
- ▶ Index elimination
- ▶ Champion lists
- ▶ High/low lists, tiered indexes
- ▶ Order postings by $g(d)$ (query-indep. quality score)

Computing the K largest cosines: selection vs. sorting

- ▶ Retrieve the top K docs
 - ▶ 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

- ▶ Construction: $2J$ operations
- ▶ K “winners”: $2K\log J$ operations
- ▶ For $J = 1M$, $K = 100$, this is about 10% of the cost of sorting.



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

Cosine similarity is only a proxy

- ▶ Cosine similarity is just a proxy for user happiness
 - ▶ If we get a list of K docs “close” to top K by cosine measure, it should be ok

Generic idea of inexact top k search

- ▶ 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
- ▶ Same approach is also used for other scoring functions
 - ▶ Will look at several schemes following this approach

Ideas for more efficient computation of top k

- ▶ Index elimination
- ▶ Champion lists
- ▶ Global ordering
- ▶ Impact ordering
- ▶ Cluster pruning

Index elimination for cosine computation

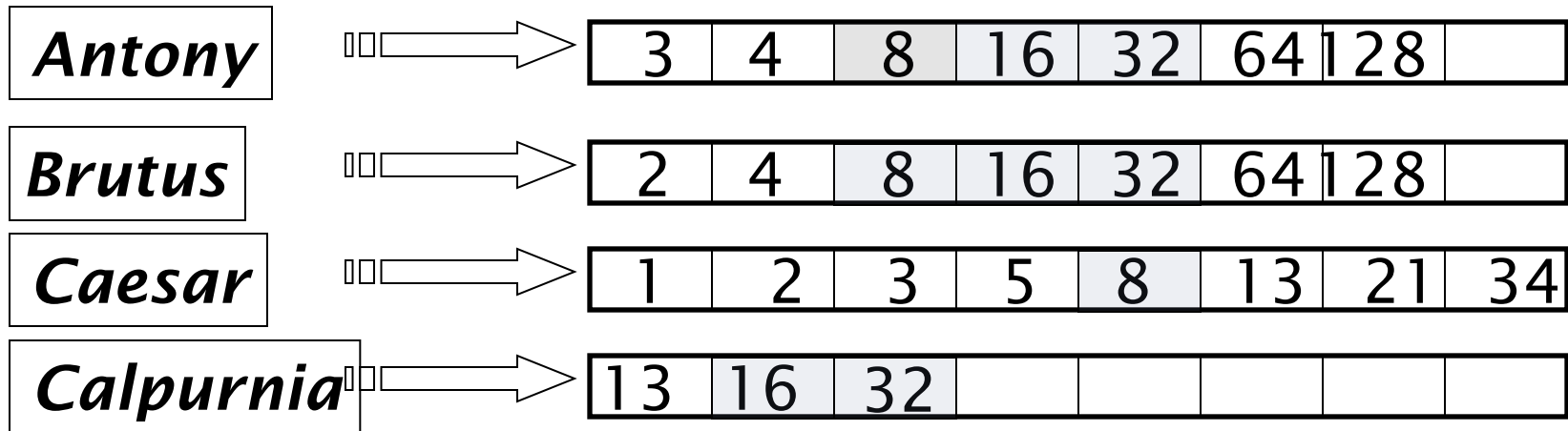
- ▶ Basic algorithm: considers docs containing at least one query term
- ▶ Extend this basic algorithm to:
 - ▶ Only consider docs containing many (or all) query terms
 - ▶ Only consider high-idf query terms

Docs containing many query terms

When we have 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)
 - ▶ May find fewer than k candidates
- ▶ Easy to implement in postings traversal

3 of 4 query terms



Scores only computed for docs 8, 16 and 32.

High-idf query terms only

- ▶ Query: ***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
 - ▶ → many docs are eliminated from set A of contenders

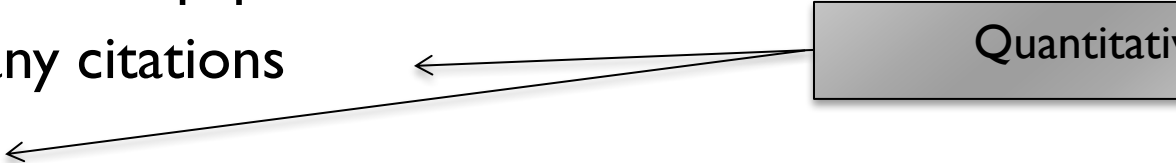
Champion lists

- ▶ r docs of highest weight in the posting list of each dictionary term
 - ▶ Call this the champion list for t
 - ▶ aka fancy list or top docs for t
- ▶ At query time, only compute scores for docs in the champion list of some (or all of) query terms
 - ▶ Pick the K top-scoring docs from amongst these
- ▶ Note that r has to be chosen at index build time
 - ▶ Thus, it's possible that the obtained list of docs contains less than K docs

High and low lists

- ▶ For each term, two postings lists high and low
 - ▶ High: like the champion list
 - ▶ Low: all other docs containing t
- ▶ Only traverse *high* lists first
 - ▶ If we get more than K docs, select top K and stop
 - ▶ Else proceed to get docs from *low* lists
- ▶ A means for segmenting index into two tiers

Static quality scores

- ▶ Top-ranking docs needs to be both relevant and authoritative
 - ▶ *Relevance*: modeled by cosine scores
 - ▶ *Authority*: typically a query-independent property of a doc
 - ▶ Examples of authority signals
 - ▶ Wikipedia among websites
 - ▶ Articles in certain newspapers
 - ▶ A paper with many citations
 - ▶ Pagerank
- 
- A gray rectangular box labeled "Quantitative" has two arrows pointing left. One arrow points to the text "Articles in certain newspapers" and the other points to the text "Pagerank".

Modeling authority

- ▶ Assign to each doc d a ***query-independent*** quality score in $[0,1]$ (called $g(d)$)
 - ▶ A quantity like the number of citations scaled into $[0,1]$

Net score

- ▶ Simple total score: combining cosine relevance and authority

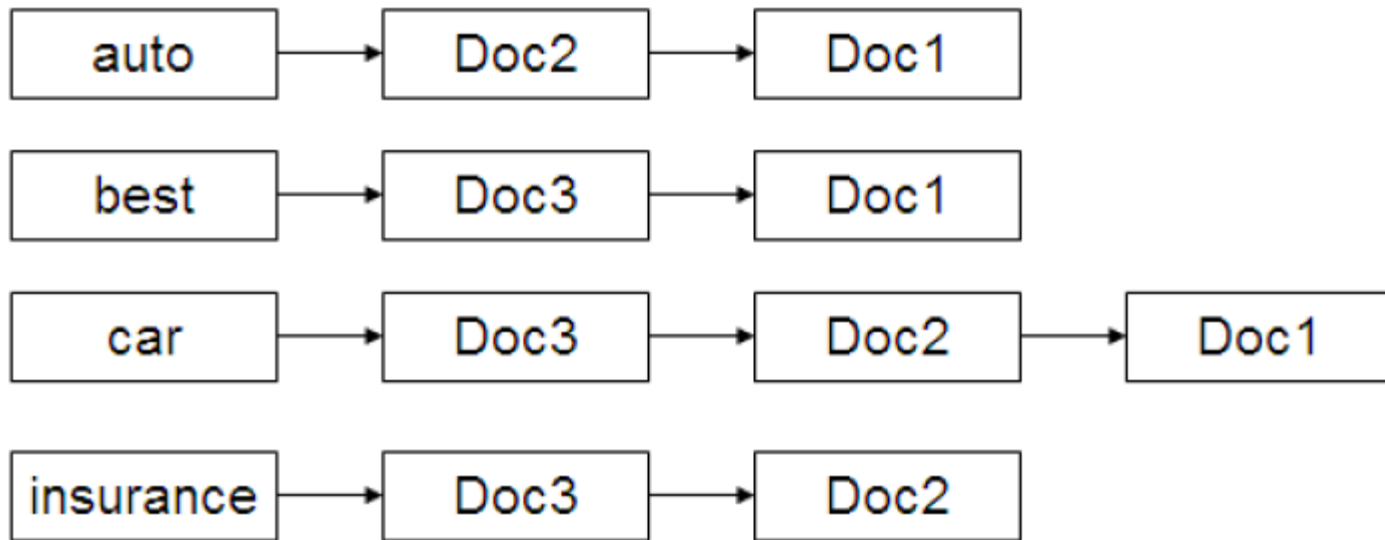
$$\text{NetScore}(q, d) = g(d) + \text{cosine}(q, d)$$

- ▶ Can use some other linear combination
- ▶ 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
 - ▶ All postings are ordered by a single common ordering
 - ▶ and the merge is then performed by a single pass through the postings
- ▶ Can concurrently traverse query terms' postings for
 - ▶ Postings intersection
 - ▶ Cosine score computation

Static quality-ordered index



$$g(1) = 0.25$$

$$g(2) = 0.5$$

$$g(3) = 1$$

Why order postings by $g(d)$?

- ▶ $g(d)$ -ordering: top-scoring docs likely to appear early in postings traversal
- ▶ In time-bound applications:
 - ▶ It allows us to stop postings traversal early
 - ▶ E.g., we have to return search results in 50 ms

Global champion lists

- ▶ Can combine champion lists with $g(d)$ -ordering?
- ▶ Maintain for each term a champion list of r docs with highest $g(d) + \text{tf.idf}_{td}$
 - ▶ Sorted by a common order $g(d)$
- ▶ Seek top- K results from only the docs in these champion lists

Impact-ordered postings

- ▶ If we have impact ordering
 - ▶ Docs in the top k are likely to occur early in the ordered lists.
- ▶ We sort each postings list according to weight $wf_{t,d}$
 - ▶ Simplest case: normalized tf-idf weight
 - ▶ \Rightarrow Early termination while processing postings lists is unlikely to change the top k.

Term-at-a-time processing

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  $Scores[]$ 
```

Impact-ordered postings

- ▶ Now: not all postings in a common order!
 - ▶ no longer a consistent ordering of docs in postings lists.
 - ▶ no longer can employ document-at-a-time processing
- ▶ Term-at-a-time processing
 - ▶ Create an accumulator for each docID you encounter
- ▶ How do we compute scores in order to pick off inexact top K ?
 - ▶ Early termination
 - ▶ idf-ordered terms

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

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 we can stop when doc scores are relatively unchanged
 - ▶ If the changes are minimal, we may omit accumulation from the remaining query terms
 - ▶ or alternatively process shorter prefixes of their postings lists.

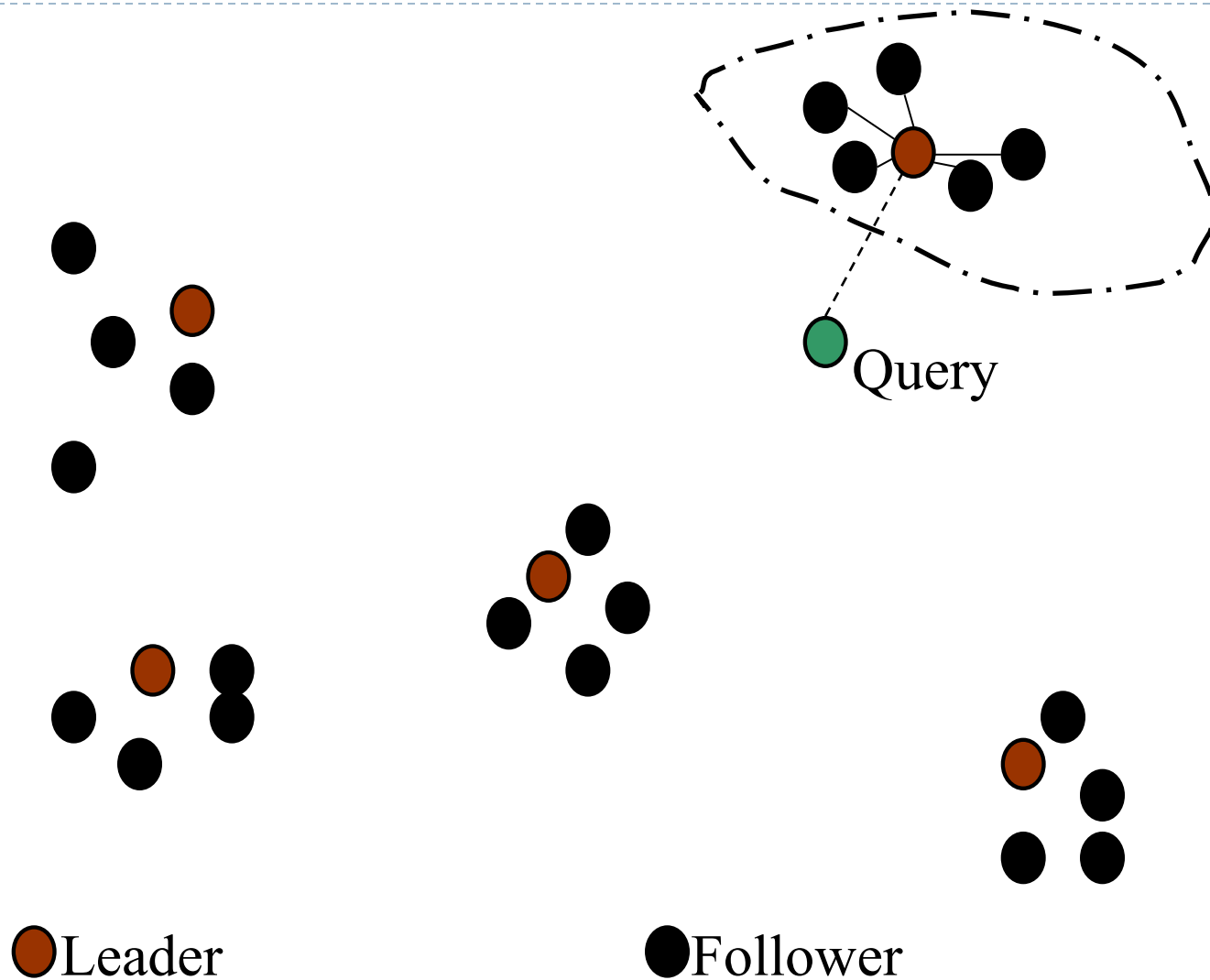
Cluster pruning: preprocessing

- ▶ *Leaders*: \sqrt{N} docs at random
- ▶ For every other doc, pre-compute nearest leader
 - ▶ *Followers*: Docs attached to a leader
 - ▶ Likely: each leader has $\sim \sqrt{N}$ followers.
- ▶ Why random sampling for finding leaders:
 - ▶ Fast approach
 - ▶ Leaders reflect data distribution

Cluster pruning: query processing

- ▶ Given query Q , find its nearest *leader* L .
- ▶ Seek K nearest docs from among L 's followers.

Visualization



General variants

- ▶ Have each follower attached to b_1 nearest leaders.
- ▶ From query, find b_2 nearest leaders and their followers.
- ▶ Can recurse on leader/follower construction.

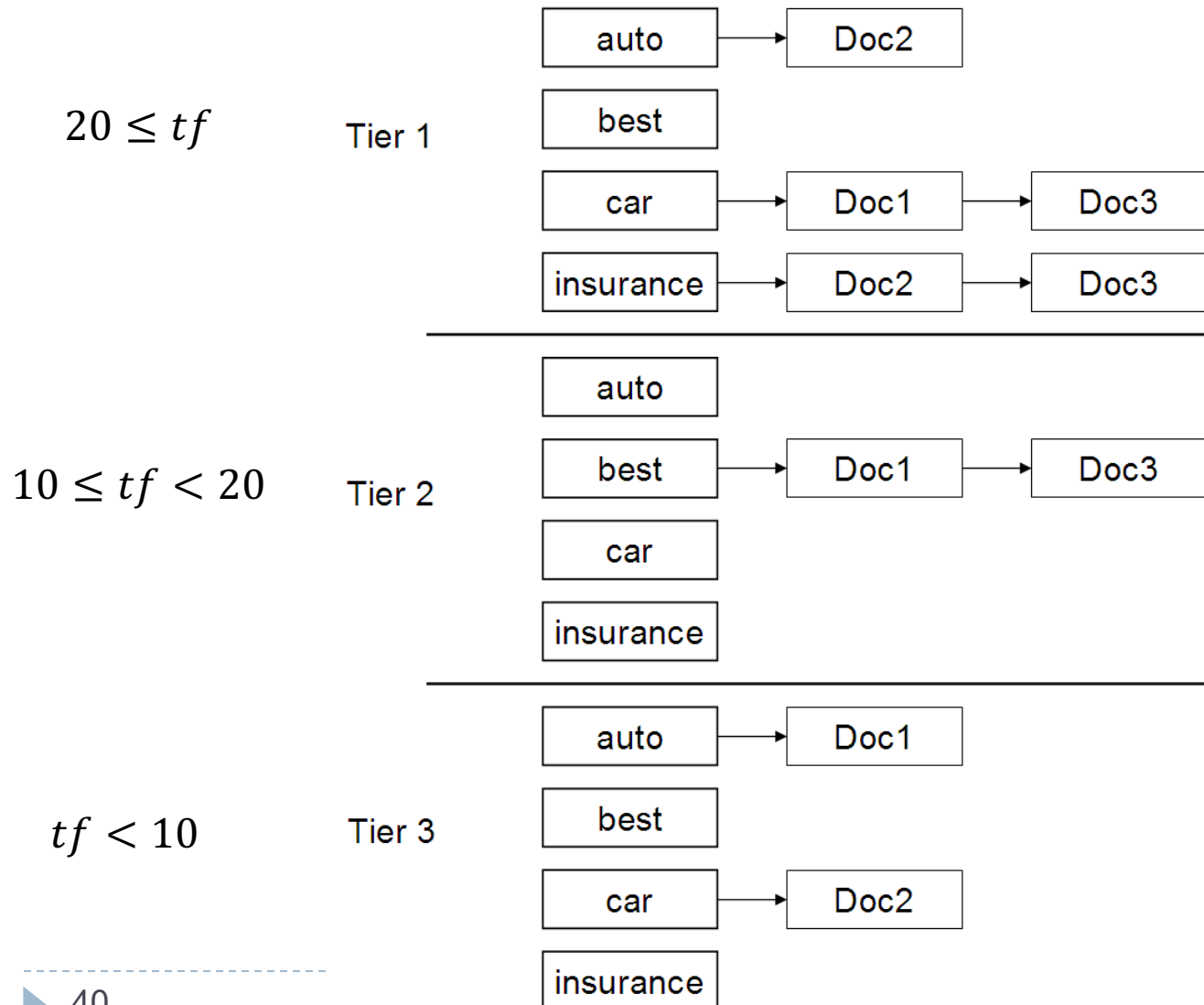
Tiered indexes

- ▶ **Basic idea:**
 - ▶ Create several tiers of indexes
 - ▶ During query processing, start with highest-tier index
 - ▶ If highest-tier index returns at least k (e.g., $k = 100$) results:
 - ▶ stop and return results to user
 - ▶ If we've only found $< k$ hits: repeat for next index in tier cascade

Tiered indexes

- ▶ Break postings up into a hierarchy of lists
 - ▶ Most important to least important
 - ▶ Can be done by $g(d)$ or another measure
- ▶ Inverted index \Rightarrow tiers of decreasing importance
- ▶ At query time use top tier unless it fails to yield K docs
 - ▶ If so drop to lower tiers
- ▶ Tiered indexes as one of the reasons for the success of early Google (2000/01)
 - ▶ along with PageRank, use of anchor text and proximity constraints

Example tiered index



Safe ranking

- ▶ 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
 - ▶ So we only fully score some J documents
- ▶ Do we have to sort the J cosine scores?

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

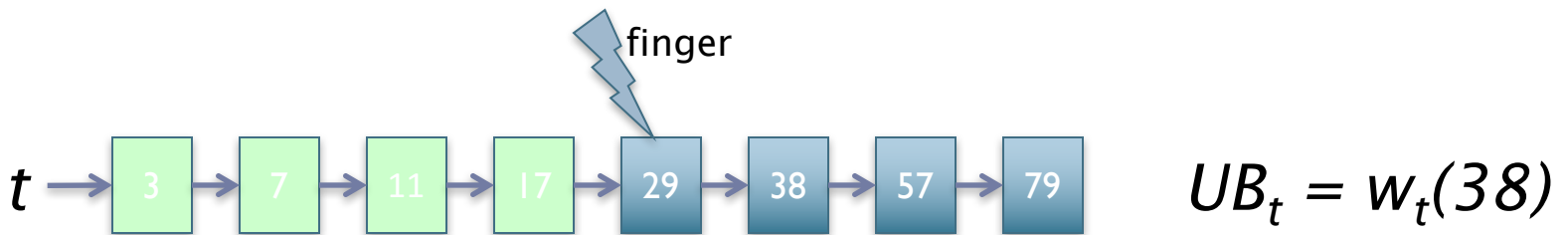
Broder et al. Efficient Query Evaluation using a Two-Level Retrieval Process.

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 or equal to 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

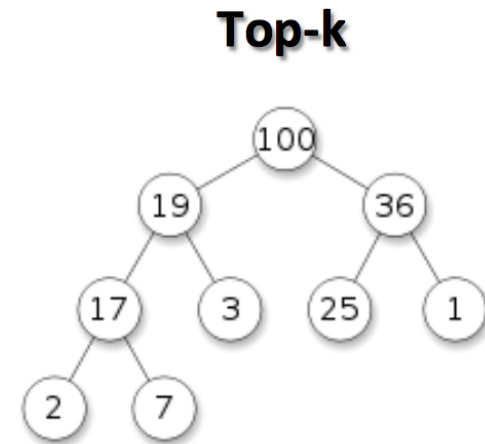
- ▶ At all times for each query term t , we maintain an *upper bound* UB_t on the score contribution of any doc to the right of the finger
 - ▶ Max (over docs remaining in t 's postings) of $w_t(\text{doc})$



As finger moves right, UB drops

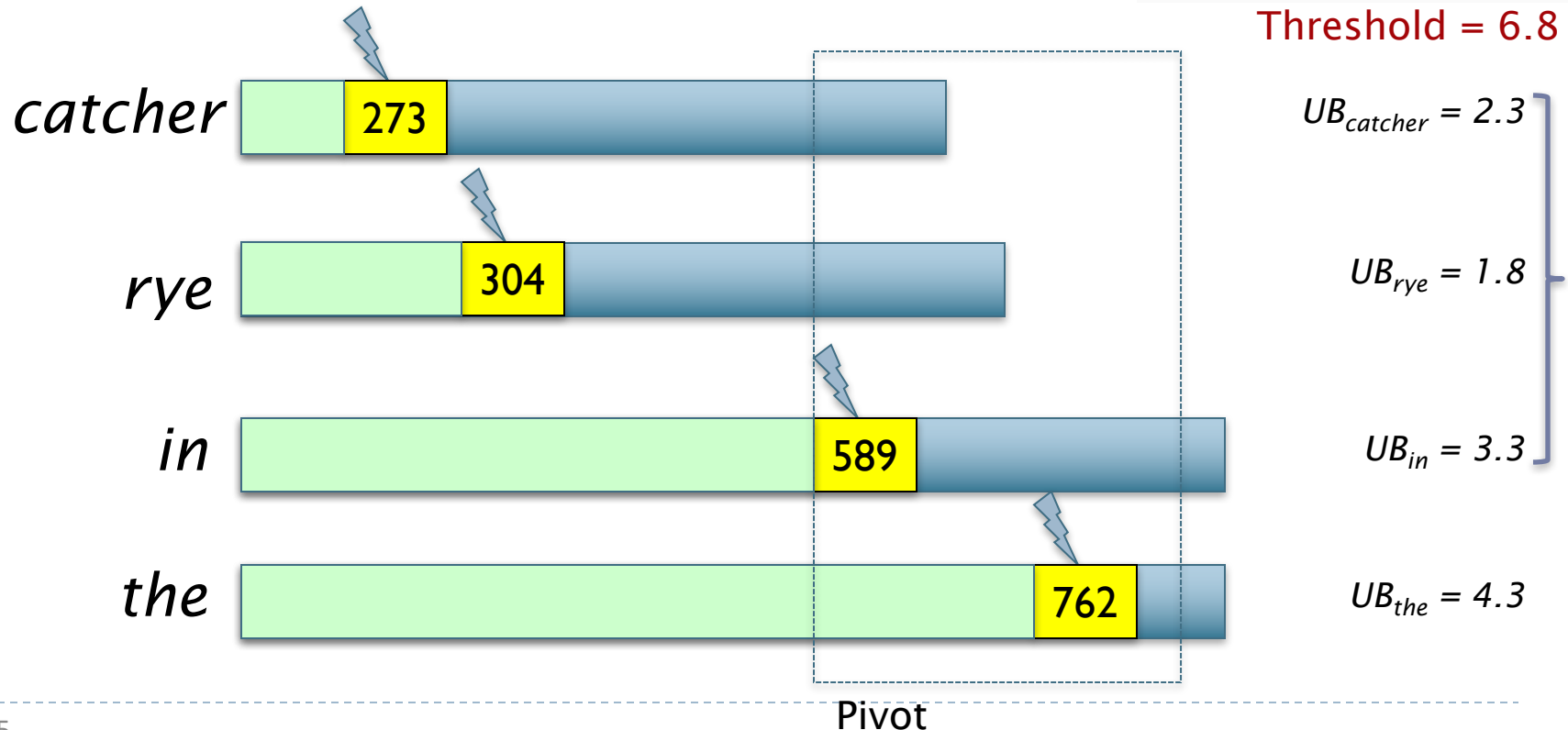
Pivoting

- ▶ Query: *catcher in the rye*
- ▶ The current finger positions are as below



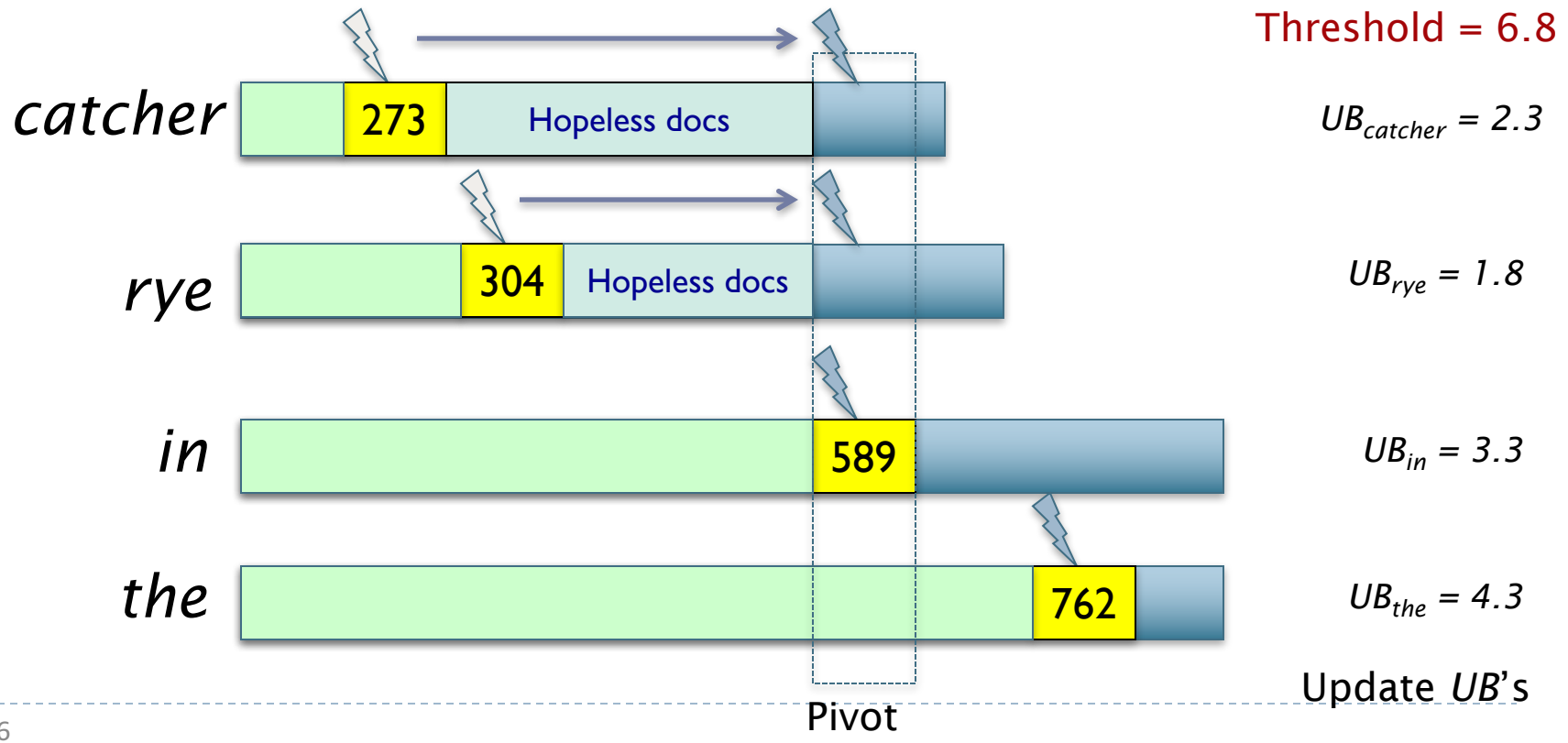
Scores ≥ 6.8

Threshold = 6.8



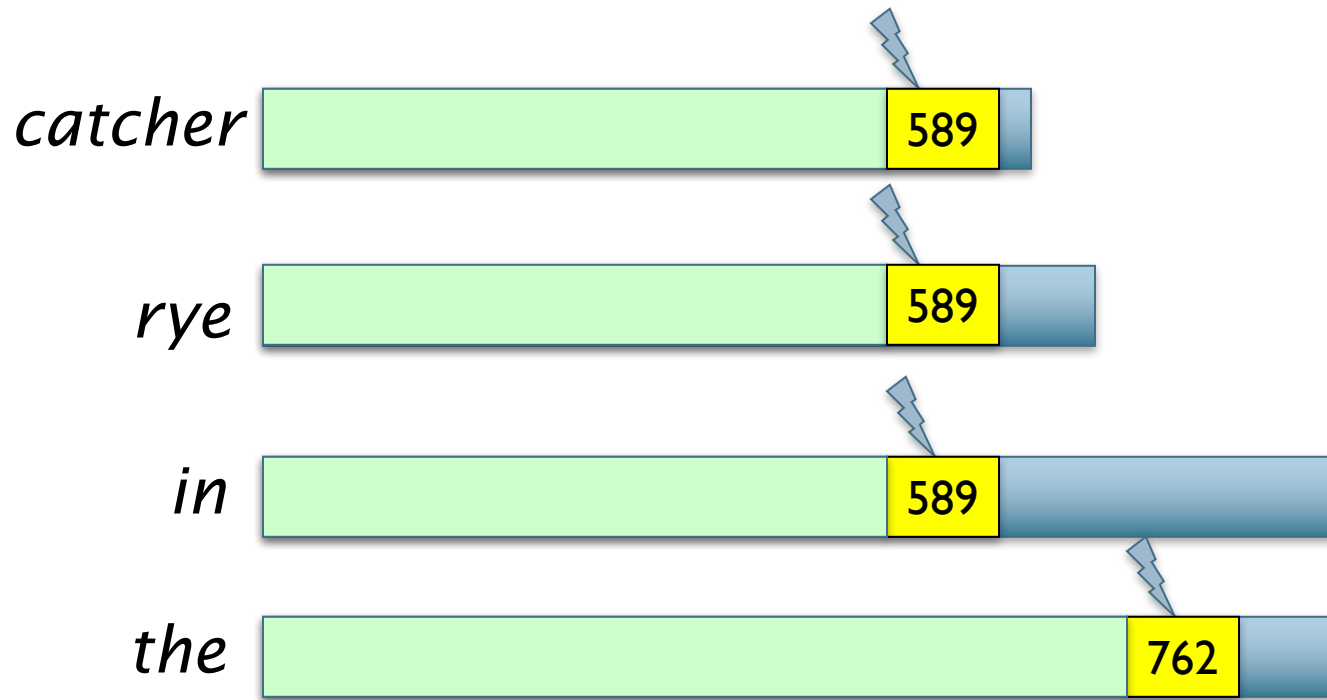
Prune docs that have no hope

- ▶ 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 ...



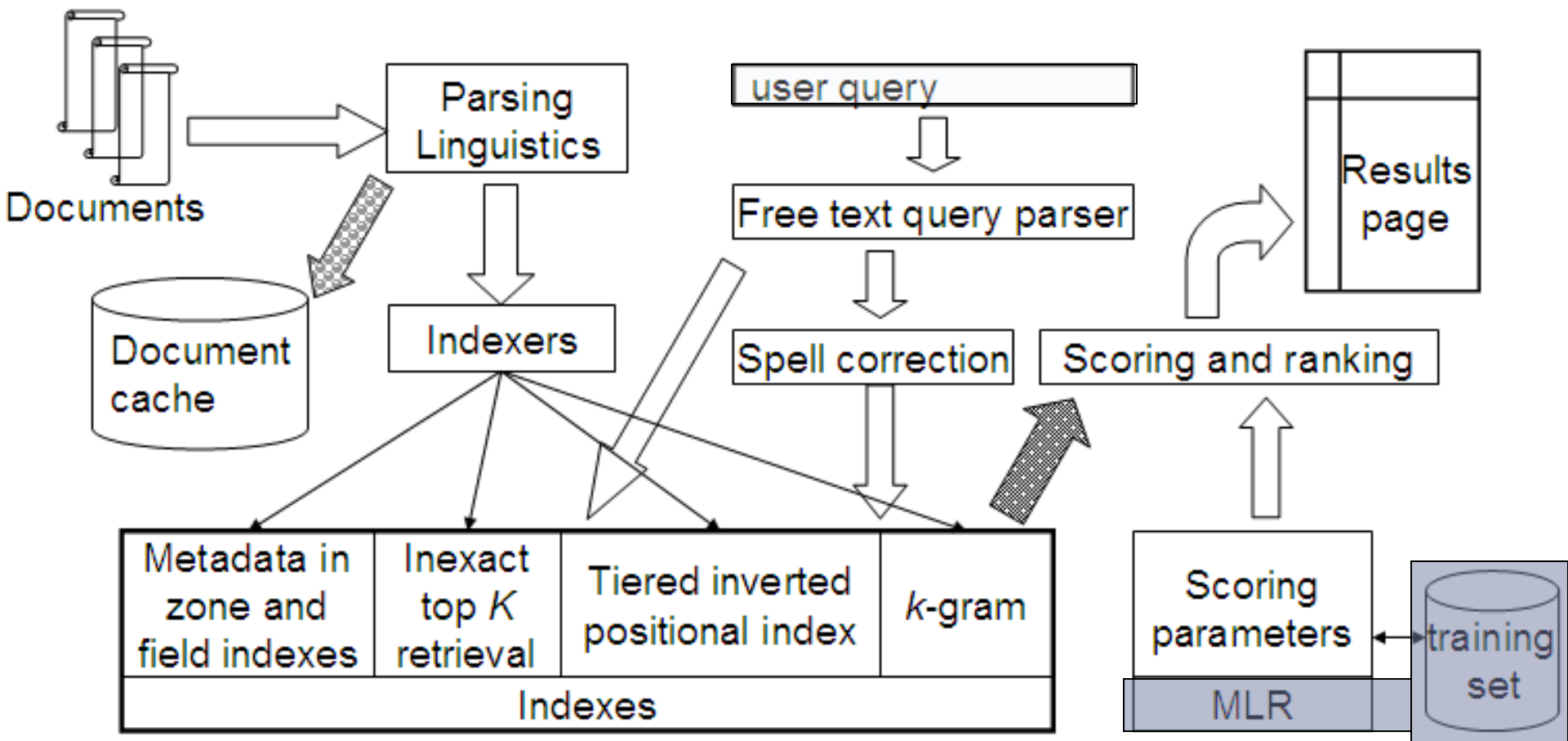
WAND summary

- ▶ 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 considered

Term frequencies in the inverted index

- ▶ In each posting, store $tf_{t,d}$ in addition to docID
 - ▶ As an integer frequency, not as a (log-)weighted real number
 - ▶ because real numbers are difficult to compress.
 - ▶ overall, additional space requirements are small: a byte per posting or less

Complete search system



Components we haven't covered yet

- ▶ Proximity ranking
 - ▶ rank docs in which the query terms occur in the same local window higher
- ▶ Query parser
- ▶ Zone indexes
- ▶ Document cache: we need this for generating snippets
- ▶ Machine-learned ranking functions

Query term proximity

- ▶ Free text queries: just a set of terms
 - ▶ Users may prefer docs in which query terms occur within close proximity of each other
 - ▶ w: smallest window in a doc containing all query terms
 - ▶ Query: **strained mercy**
 - ▶ Doc: “The quality of *mercy is not strained*”
 - ▶ w: 4 (words)
- ▶ Would like scoring function to take this into account – how?

Query parsers

- ▶ Free text query from user may spawn one or more queries to the indexes
 - ▶ Run the query as a phrase query
 - ▶ If $<K$ docs contain the phrase run smaller phrase queries
 - ▶ If we still have $<K$ docs, run the vector space query
 - ▶ Rank matching docs by vector space scoring
- ▶ This sequence is issued by a query parser

Query parsers

- ▶ Example:

- ▶ Query: ***rising interest rates***

- ▶ If $< K$ docs contain

- “***rising interest rates***”

- run queries

- “***rising interest***” and “***interest rates***”

- ▶ If we still have $< K$ docs, run the vector space query
rising interest rates

- ▶ We need aggregate scoring function that *accumulates evidence* of a doc's relevance from multiple sources

Aggregate scores

- ▶ Score functions can combine cosine, static quality, proximity, etc.
- ▶ How do we know the best combination?
 - ▶ Some applications – expert-tuned
 - ▶ Increasingly common: machine-learned

Vector space retrieval: Interactions

- ▶ Combining **Boolean retrieval** with vector space retrieval?
 - ▶ no easy way of combining vector space and Boolean queries
 - ▶ Postfiltering is simple, but can be very inefficient – no easy answer.
- ▶ Combining **phrase retrieval** with vector space retrieval?
 - ▶ no way of demanding a vector space score for a phrase query
 - ▶ can in some cases be combined usefully (query parser)
- ▶ Combining **wild cards** with vector space retrieval?

Parametric and zone indexes

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

Fields

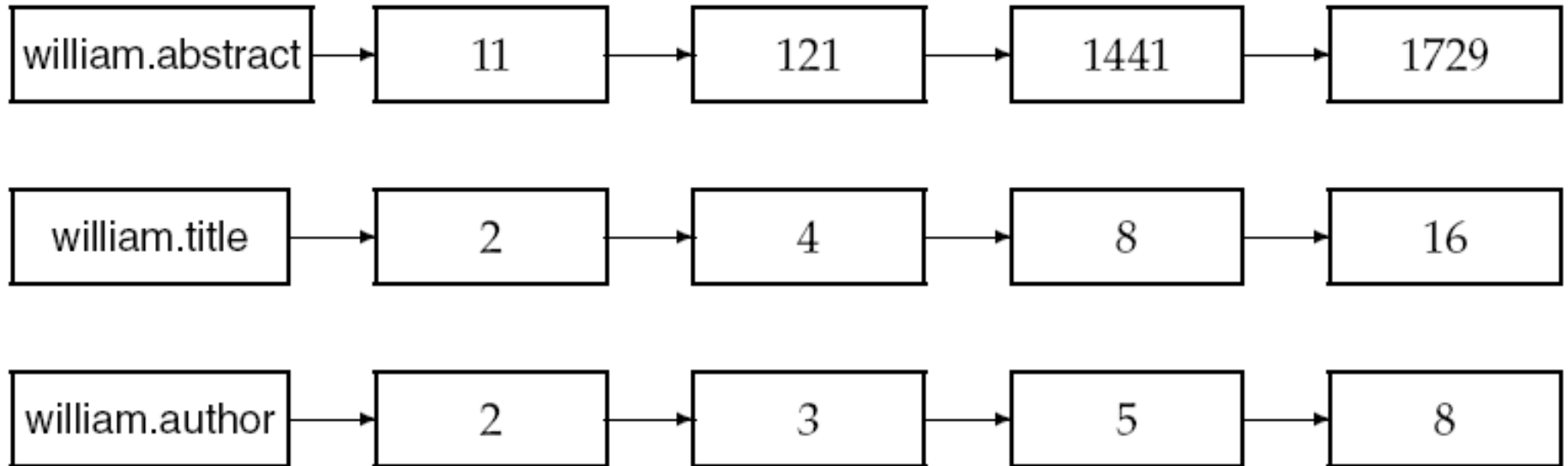
- ▶ We sometimes wish to search by these metadata
 - ▶ E.g., find docs authored by William Shakespeare in the year 1601, containing *alas poor Yorick*
 - ▶ Year = 1601 is an example of a field
 - ▶ Author last name = shakespeare
- ▶ Field or parametric index: postings for each field value
 - ▶ Sometimes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

Zone

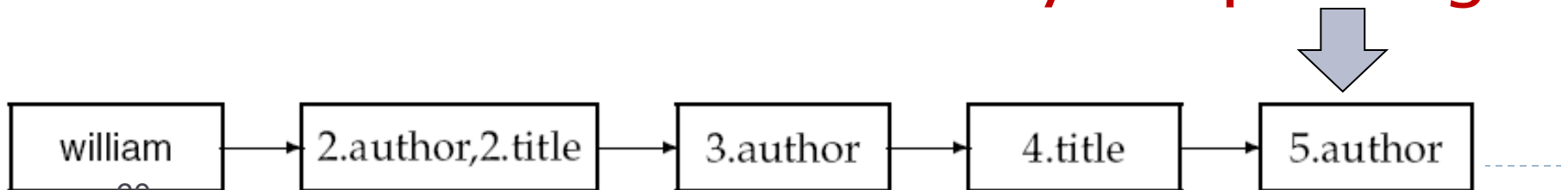
- ▶ A zone is a region of the doc that can contain an arbitrary amount of text, e.g.,
 - ▶ Title
 - ▶ Abstract
 - ▶ References ...
- ▶ Example: “find docs with *merchant* in the title zone and matching the query *gentle rain*”
- ▶ Build inverted indexes on zones (to permit querying)

Zone examples: the body of the doc, all highlighted text in the doc, anchor text, text in metadata fields

Example zone indexes



Encode zones in dictionary vs. postings.



Resources

- ▶ IIR 7, 6.1
- ▶ Resources at <http://ifnlp.org/ir>
 - ▶ How Google tweaks its ranking function
 - ▶ Interview with Google search guru Udi Manber
 - ▶ Amit Singhal on Google ranking
 - ▶ SEO perspective: ranking factors