Introduction to

Information Retrieval

CS276

Information Retrieval and Web Search

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Systems issues

Background

- Score computation is a large (10s of %) fraction of the CPU work on a query
  - Generally, we have a tight budget on latency (say, 250ms)
  - CPU provisioning doesn't permit exhaustively scoring every document on every query
- Today we'll look at ways of cutting CPU usage for scoring, without compromising the quality of results (much)
- Basic idea: avoid scoring docs that won't make it into the top *K*

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
- Is it ok to be non-safe?

Ranking function is only a proxy

- User has a task and a query formulation
- Ranking function matches docs to query
- Thus the ranking function is anyway a proxy for user happiness
- If we get a list of K docs "close" to the top K by the ranking function measure, should be ok

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, measured by cosine similarity

Efficient cosine ranking

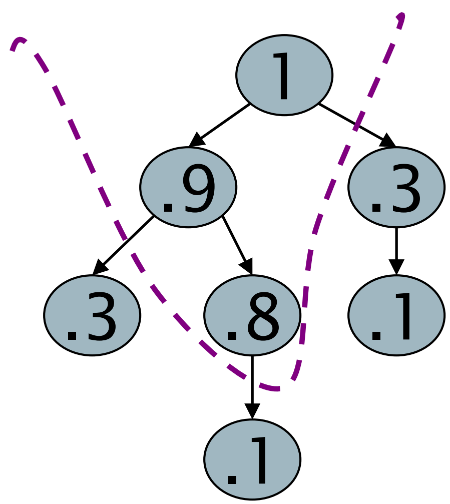
- Find the K docs in the collection "nearest" to the query $\Rightarrow$ K largest query-doc cosines.
- Efficient ranking:
  - Computing a single cosine efficiently.
  - Choosing the K largest cosine values efficiently.
    - Can we do this without computing all N cosines?

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 $2\log J$ 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
  - As noted earlier, this may not be a bad thing

SPEEDING COSINE COMPUTATION BY PRUNING

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 <u>pruning</u> 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 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 <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

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

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.

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 can Champion Lists be implemented in an inverted index?

QUERY-INDEPENDENT DOCUMENT SCORES

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 bitlys, likes, or bookmarks
  - Pagerank

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]
  - 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
- 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

CLUSTER PRUNING

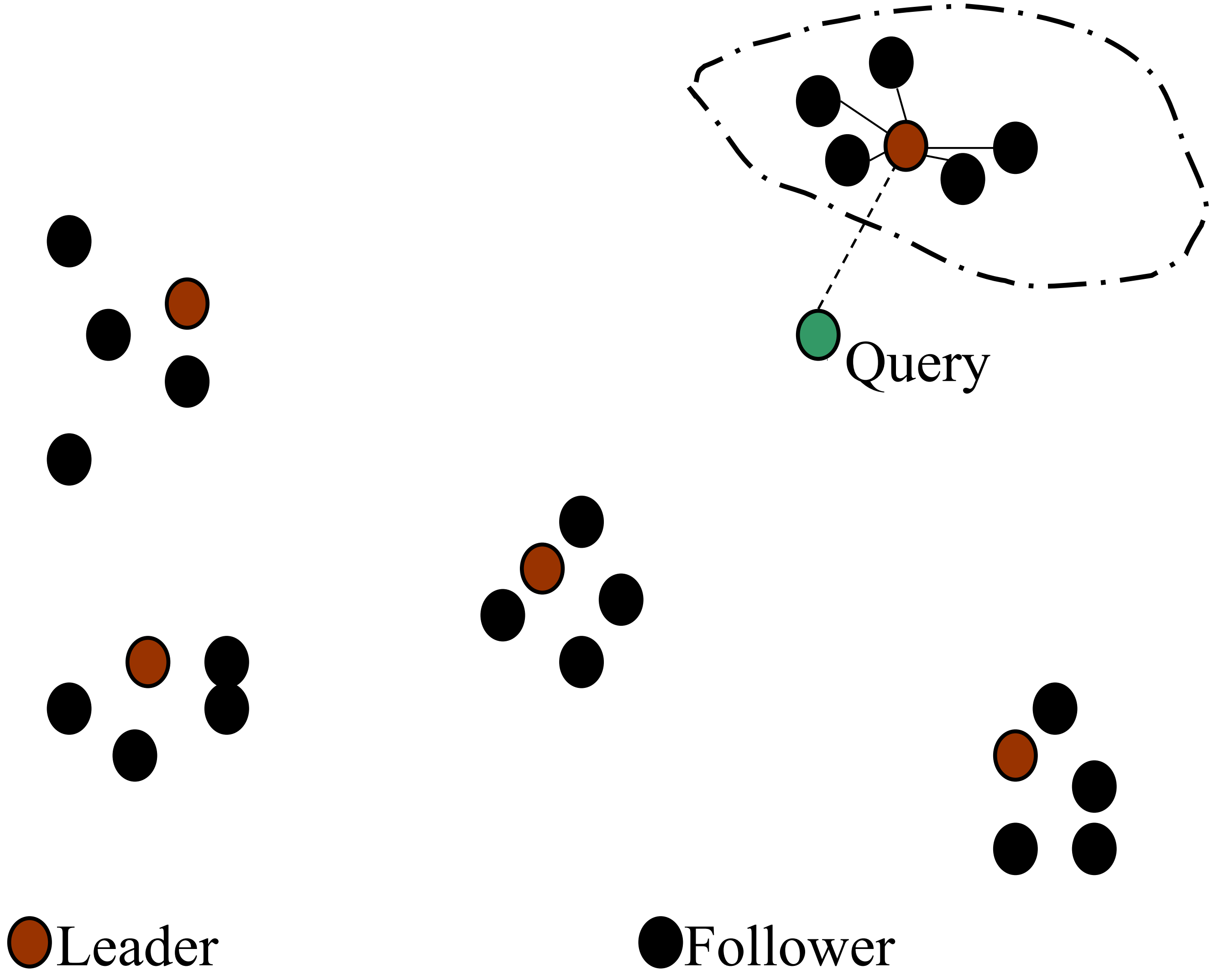
Cluster pruning: preprocessing

- 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.

TIERED INDEXES

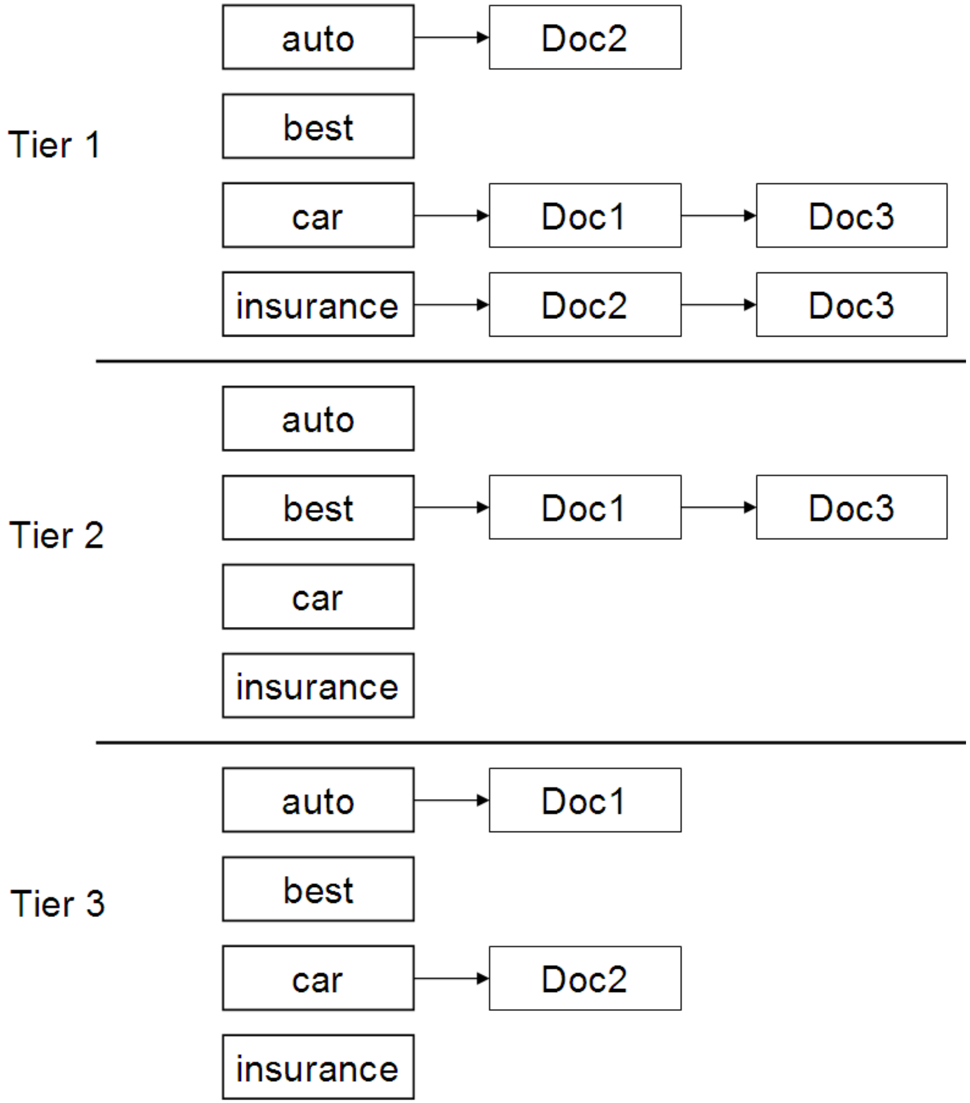
High and low lists

- 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
- 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



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

SAFE RANKING

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)

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

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

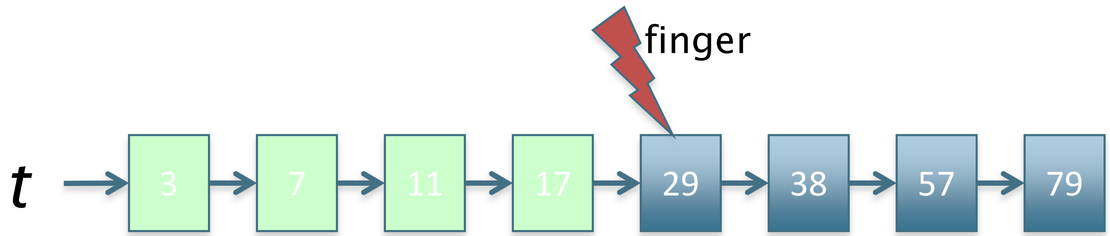
Broder et al. Efficient Query Evaluation using a Two-Level Retrieval Process.

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 $w_t(\text{doc})$

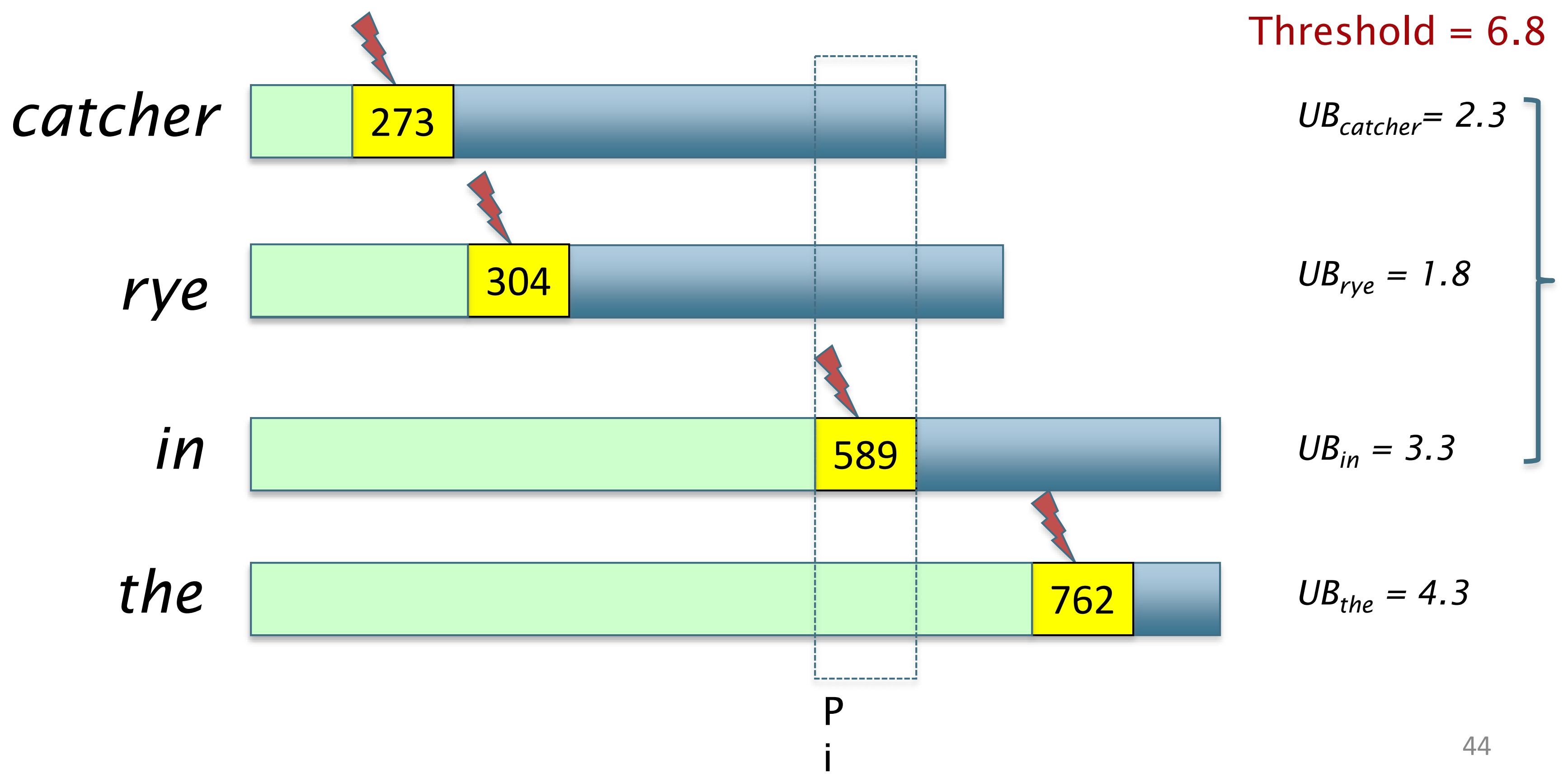


$UB_t = w_t(38)$

As finger moves right, *UB* drops

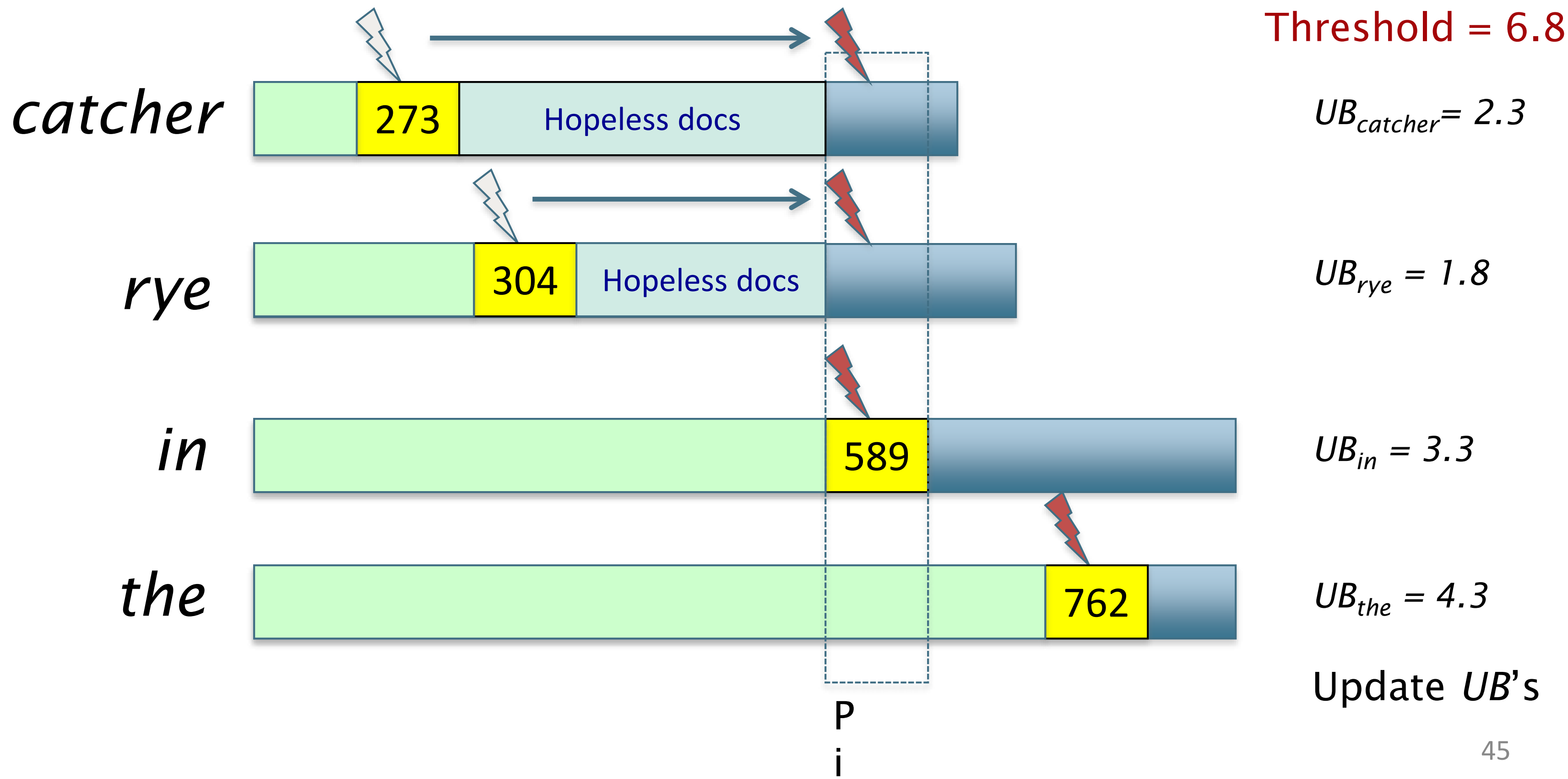
Pivoting

- Query: *catcher in the rye*
- Let's say the current finger positions are as below



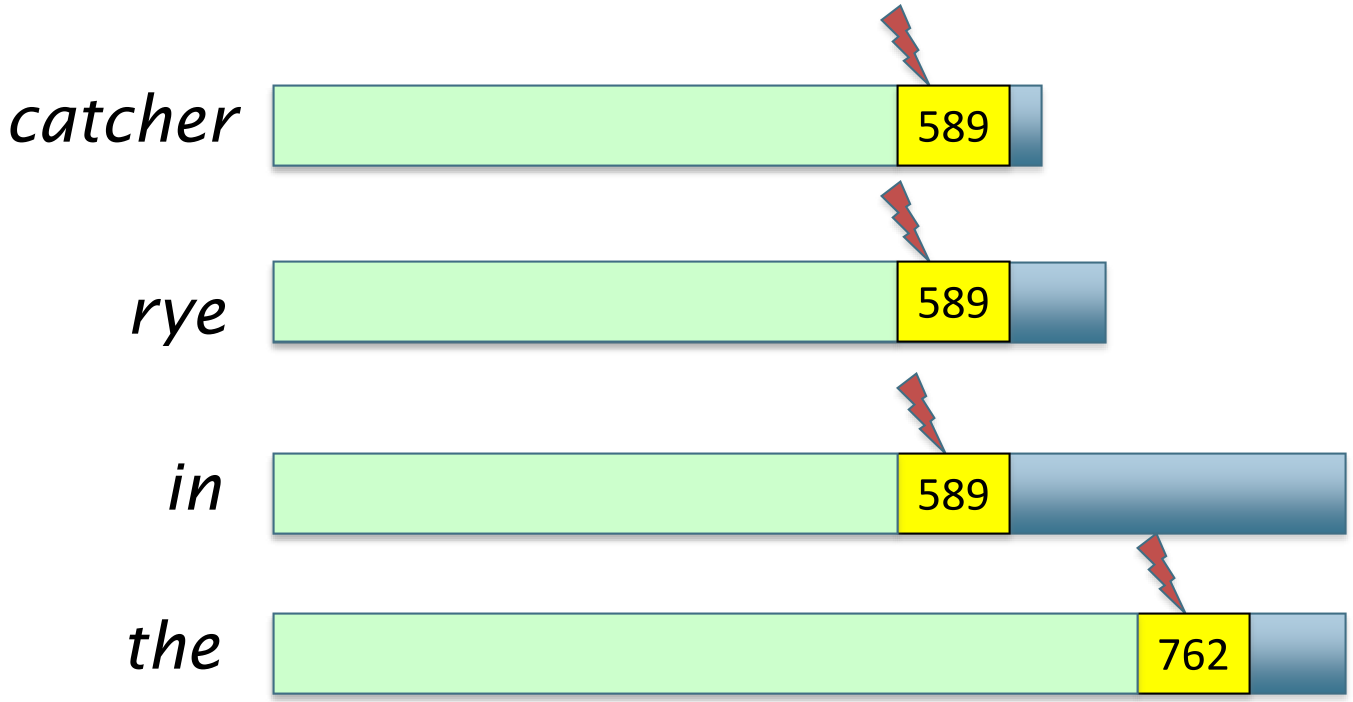
Prune docs that have no hope

- 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 <u>safe ranking</u>
  - 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

FINISHING TOUCHES FOR A COMPLETE SCORING SYSTEM

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 <u>query parser</u>

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

Putting it all together