

# Introduction to Information Retrieval

CS276  
Information Retrieval and Web Search  
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Efficient scoring

Introduction to Information Retrieval

## Today's focus

- **Retrieval** – get docs matching query from inverted index
- **Scoring+ranking**
  - Assign a score to each doc
  - Pick  $K$  highest scoring docs
- Our emphasis today will be on doing this efficiently, rather than on the quality of the ranking

2

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## 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  $K$

3

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Ch. 6

## 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)

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## 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

5

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Sec. 7.1

## 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?

7

## Non-safe ranking

- Covered in depth in Coursera video (number 7)
- 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
  - Only consider high-idf query terms
  - Only consider docs containing many query terms
- Champion lists
- High/low lists, tiered indexes
- Order postings by  $g(d)$  (query-indep. quality score)

8

## SAFE RANKING

9

## 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?

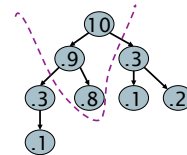
10

## 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  $O(\log J)$  steps.
- For  $J=1M$ ,  $K=100$ , this is about 10% of the cost of sorting.



## WAND scoring

- An instance of DAAT scoring
- Basic idea reminiscent of branch and bound
  - We maintain a running *threshold* score – e.g., the  $K^{\text{th}}$  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

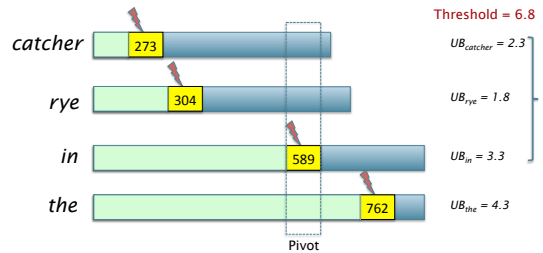
- At all times for each query term  $t$ , we maintain an *upper bound*  $UB_t$  on the score contribution of any doc to the right of the finger
  - Max (over docs remaining in  $t$ 's postings) of  $w_t(\text{doc})$



As finger moves right,  $UB$  drops

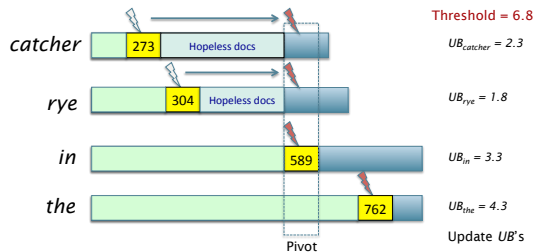
## Pivoting

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



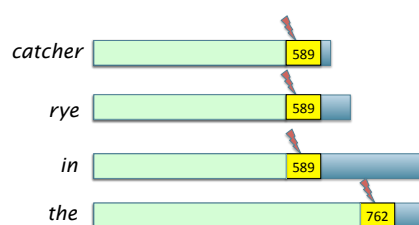
## Prune docs that have no hope

- 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

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- 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