

CSE 4/535

Information Retrieval

Sayantan Pal
PhD Student, Department of CSE
338Z Davis Hall



Department of CSE

Before we start

1. Project 1 due 29th September, 11:59 PM (Hope it helps)
2. Join office hours if you have questions (Thursday 8-10 AM)
3. Today's lecture
 - a. Efficient Scoring in a Complete Search System
 - b. Speeding up vector space ranking
4. Upto Today's lecture - Syllabus for Mid Term
5. Last 10 mins of class - Mid Term Discussion

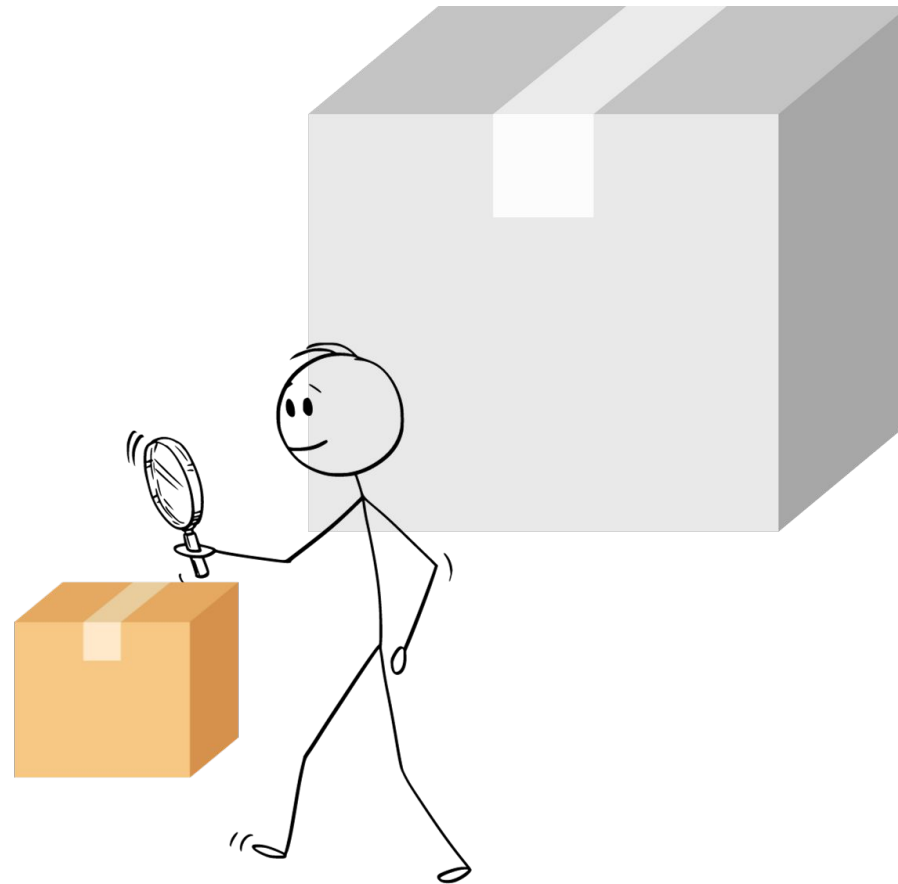


Recap - Previous Class

1. Term Frequency (TF)
2. Inverse Document Frequency (IDF)
3. TF-IDF score
4. VSM



Restricting the Search space





Parametric search

- Most documents have, in addition to text, some “meta-data” in fields e.g.,

- Language = French

Field → Format = pdf ← Value

- Subject = Physics etc.
- Date = Feb 2000

- A parametric search interface allows the user to combine a full-text query with selections on these field values e.g.,
 - language, date range, etc.

Parametric search example

CarFinder.com 

Over one million fictional vehicles to choose from!

We can add text search.

Choose your search criteria from the drop down menus:

Number of results to display: 50

Make Model Category Year
 City Color Price Description

Make	Model	Year	City	Mileage	Price	Category	Description	Color
BMW	5-Series	1997	San Francisco	14300	13100	Luxury	5-speed, heavy-duty suspension, extra wide tires. Well-maintained by mechanic-owner. Cloth seats and upgraded stereo system.	White
BMW	5-Series	1997	San Francisco	14600	13100	Luxury	Is that price for real? You bet it is. Fully loaded with all factory options. Former floor model.	Beige
BMW	5-Series	1997	San Francisco	14900	13100	Luxury	Fun to drive. Manual 5-speed transmission, turbo charger. Garaged all winter and pampered the rest of the year. This is a steal!	Orange
BMW	5-Series	1997	San Francisco	14800	13200	Luxury	Fully loaded, automatic transmission. Power everything. Anti-lock brakes and full safety features. Must test drive. Price firm.	Green
BMW	5-Series	1997	San Francisco	14300	13200	Luxury	Formerly an executive's vehicle. Interior has been professionally maintained, engine factory serviced every 3000 miles. Great gas mileage. Price negotiable.	Maroon
BMW	5-Series	1997	San Francisco	15000	13200	Luxury	Sun roof, air, CD player, driver side air bag. 10% deposit required. Owner financing available. Best offer by end of weekend buys it.	Red



Zones

- A zone is an identified region within a doc
- E.g., Title, Abstract, Bibliography
- Generally culled from marked-up input or document metadata (e.g., powerpoint)
- Contents of a zone are free text
- Not a “finite” vocabulary
- Indexes for each zone -allow queries like
- `sorting in Title AND smith in Bibliography AND recur* in Body`

Boosting

- Supported by Solr
- What to boost Query terms
 - E.g. terms appearing in title more important those those in body of document
 - Named entities
- Documents
 - E.g. more recent documents

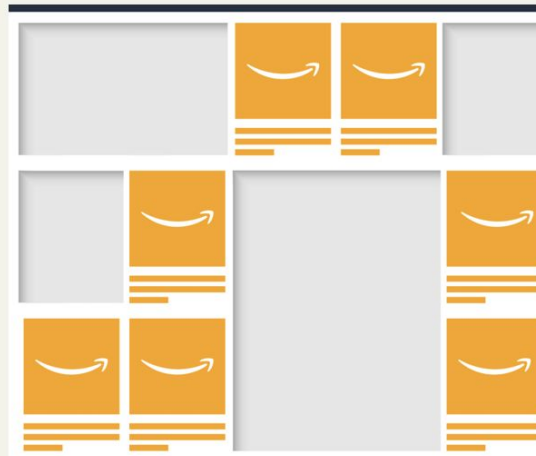


Amazon Product Search (Sept 2019)

◆ WSJ NEWS EXCLUSIVE

Amazon Changed Search Algorithm in Ways That Boost Its Own Products

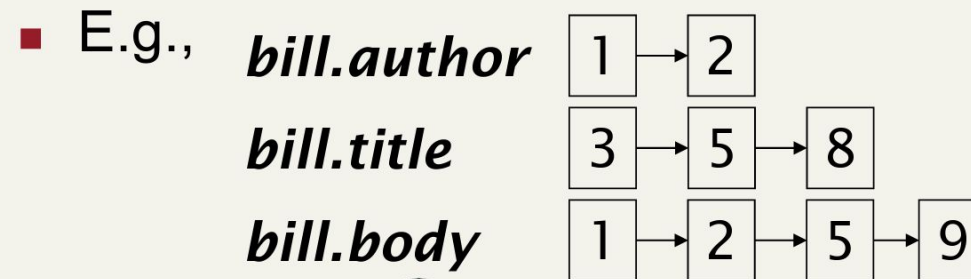
The e-commerce giant overcame internal dissent from engineers and lawyers, people familiar with the move say





Index support for zone combinations

- In the simplest version we have a separate inverted index for each zone
- Variant: have a single index with a separate dictionary entry for each term and zone



Of course, compress zone names like author/title/body.



Zone combinations index

- The above scheme is still wasteful: each term is potentially replicated for each zone
- In a slightly better scheme, we encode the zone in the postings:

bill 1.author, 1.body → 2.author, 2.body → 3.title

As before, the zone names get compressed.

Speeding up vector space ranking





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[]
  
```

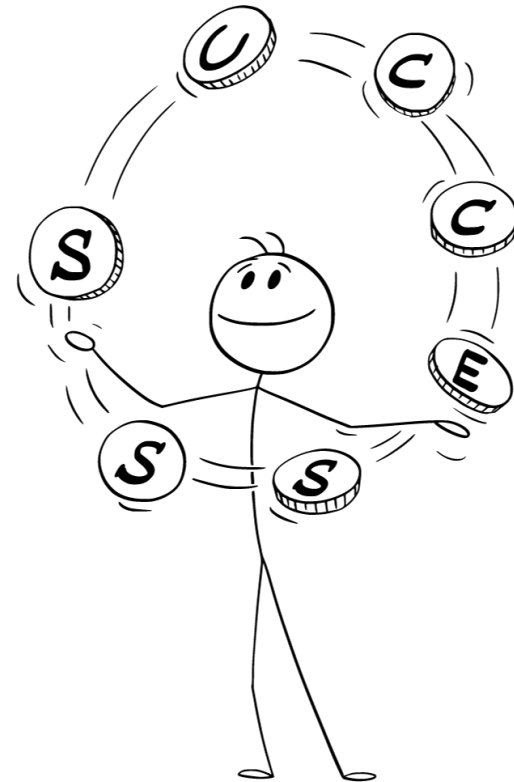
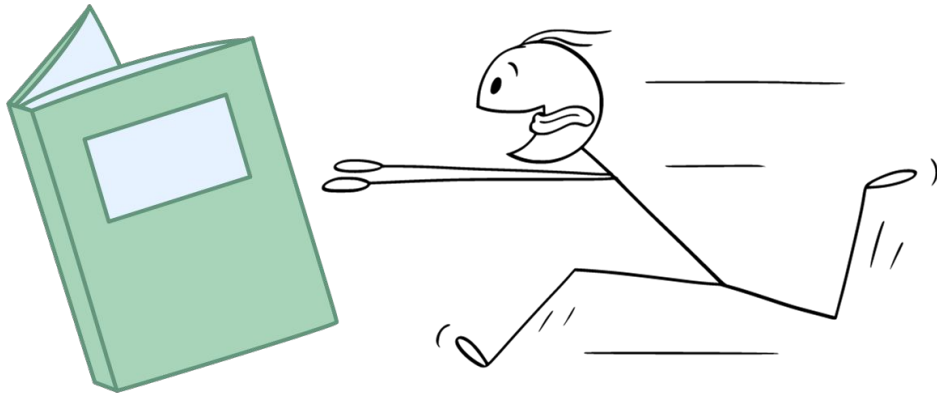
Scoring

DOT PRODUCT

LENGTH NORMALIZATION

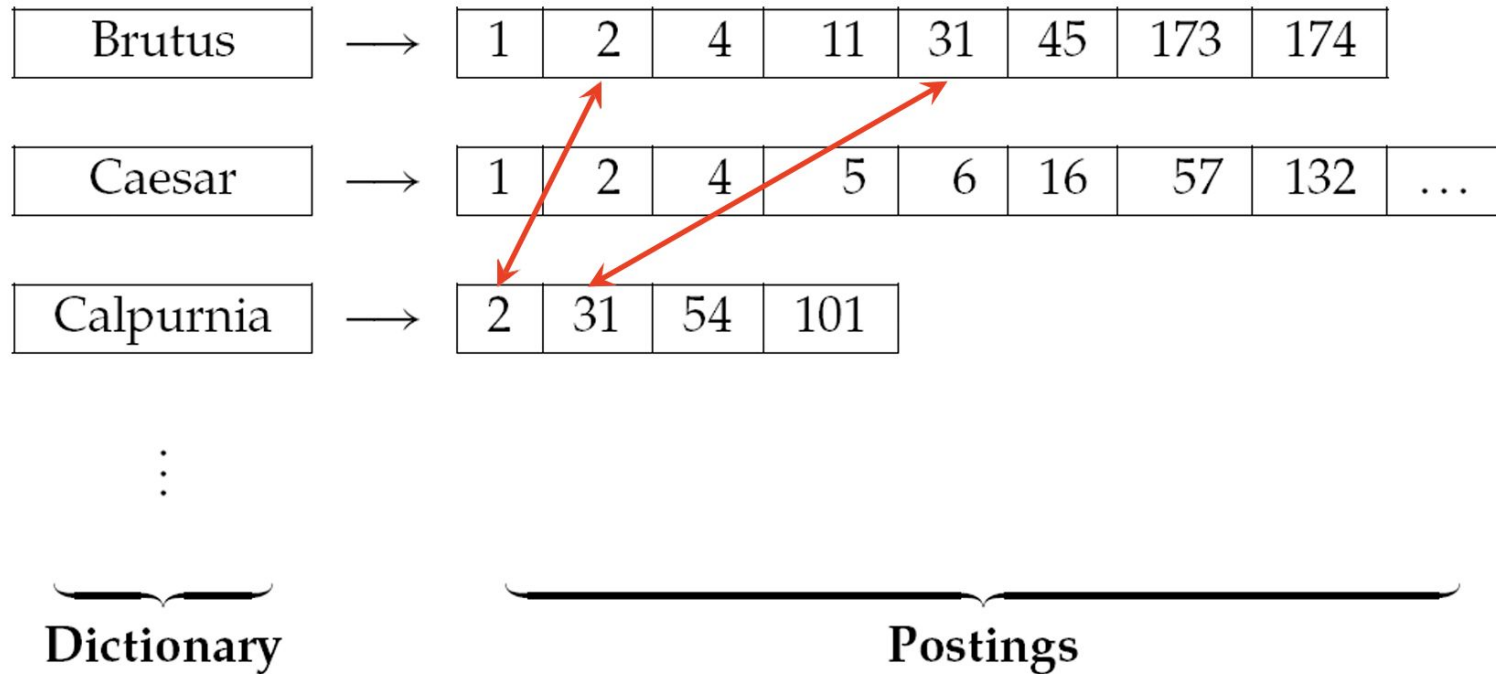
Finding the Best

Document-at-a-Time (DaaT) vs Term-at-a-Time (TaaT) scoring



Inverted Indexes

Query “Brutus” AND “Calpurnia”





Document-at-a-time Evaluation

- The conceptually simplest query answering method

Query	salt	1:1				4:1
	water	1:1	2:1			4:1
	tropical	1:2	2:2	3:1		
score		1:4	2:3	3:1		4:2

Algorithm

procedure DOCUMENTATATIME RETRIEVAL(Q, I, f, g, k)

$L \leftarrow \text{Array}()$

$R \leftarrow \text{PriorityQueue}(k)$

for all terms w_i in Q do

$l_i \leftarrow \text{InvertedList}(w_i, I)$

$L.\text{add}(l_i)$

end for

Find posting lists

for all documents $d \in I$ do

for all inverted lists l_i in L do

if l_i points to d then

$s_D \leftarrow s_D + g_i(Q)f_i(l_i)$

▷ Update the document score

$l_i.\text{movePastDocument}(d)$

end if

end for

$R.\text{add}(s_D, D)$

end for

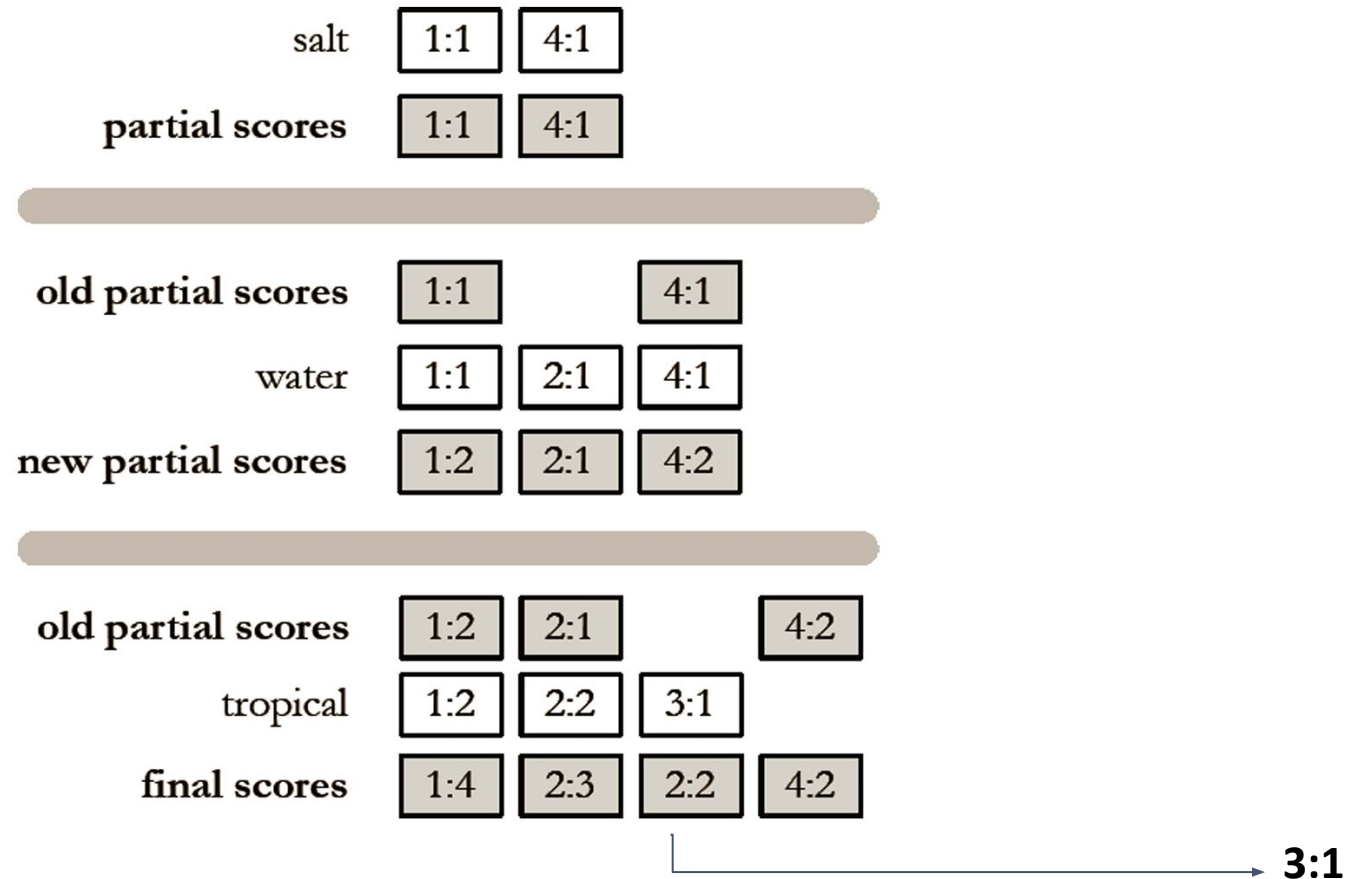
return the top k results from R

end procedure

Can be implemented efficiently by
keeping the top-k list at anytime



Term-at-a-time Evaluation



Algorithm

```

procedure TERMATATIMERETRIEVAL( $Q, I, f, g, k$ )
   $A \leftarrow \text{HashTable}()$ 
   $L \leftarrow \text{Array}()$ 
   $R \leftarrow \text{PriorityQueue}(k)$ 
  for all terms  $w_i$  in  $Q$  do
     $l_i \leftarrow \text{InvertedList}(w_i, I)$ 
     $L.\text{add}(l_i)$ 
  end for
  for all lists  $l_i \in L$  do
    while  $l_i$  is not finished do
       $d \leftarrow l_i.\text{getCurrentDocument}()$ 
       $A_d \leftarrow A_d + g_i(Q)f(l_i)$ 
       $l_i.\text{moveToNextDocument}()$ 
    end while
  end for
  for all accumulators  $A_d$  in  $A$  do
     $s_D \leftarrow A_d$ 
     $R.\text{add}(s_D, D)$ 
  end for
  return the top  $k$  results from  $R$ 
end procedure

```

Compute scores on
 one term

\triangleright Accumulator contains the document score

Can be implemented efficiently by keeping the
 top-k list at anytime



Comparison

- Memory usage
 - The document-at-a-time **only needs to maintain a priority queue R of a limited number of results**
 - The term-at-a-time needs to store the **current scores for all documents**
- Disk access
 - The document-at-a-time needs **more disk seeking** and buffers for seeking since multiple lists are read in a synchronized way
 - The term-at-a-time reads through each inverted list from start to end-requiring **minimal disk seeking** and buffer

EFFICIENT SCORING and SELECTING



Efficient cosine ranking

- Find the K docs in the collection “nearest” to the query => 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?



Efficient cosine ranking

- Special case
 - unweighted queries
- No weighting on query terms
- Assume each query term occurs only once
 - Then for ranking, don't need to normalize query vector

cosine(query,document)

$$\begin{array}{c}
 \boxed{\text{Dot product}} \qquad \boxed{\text{Unit vectors}} \\
 \cos(\vec{q}, \vec{d}) = \frac{\vec{q} \bullet \vec{d}}{|\vec{q}| |\vec{d}|} = \frac{\vec{q}}{|\vec{q}|} \bullet \frac{\vec{d}}{|\vec{d}|} = \frac{\sum_{i=1}^{|V|} q_i d_i}{\sqrt{\sum_{i=1}^{|V|} q_i^2} \sqrt{\sum_{i=1}^{|V|} d_i^2}}
 \end{array}$$

q_i is the weight of term i in the query
 d_i is the weight of term i in the document



Computing the K largest cosines:

- 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 get docs with K highest cosines?

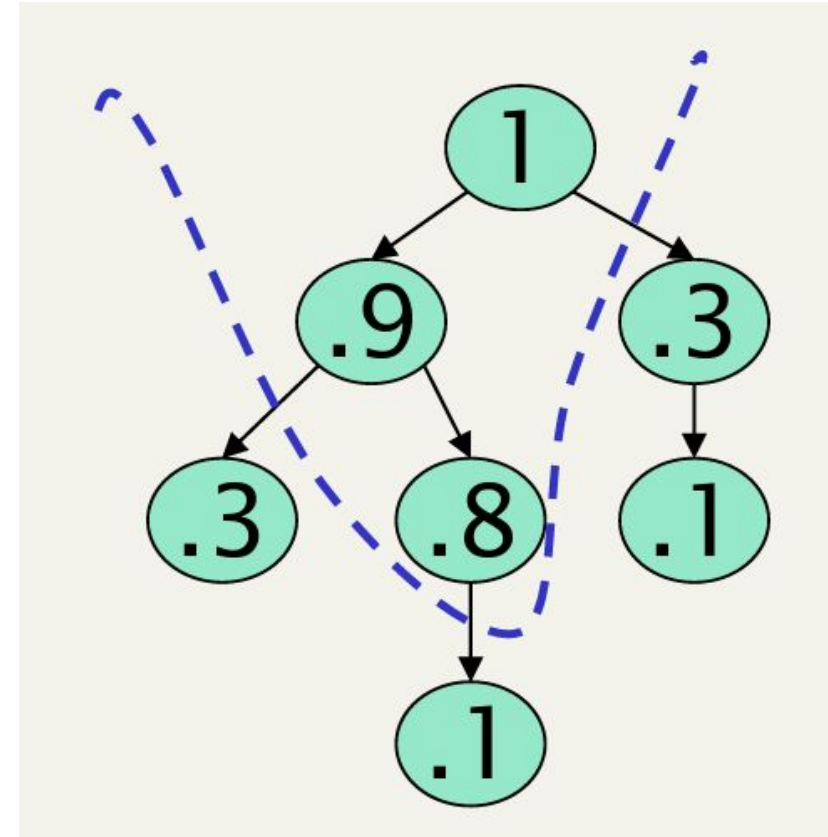


Computing the K largest cosines: selection vs. sorting

- 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 non-zero cosines
 - We seek the K best of these J

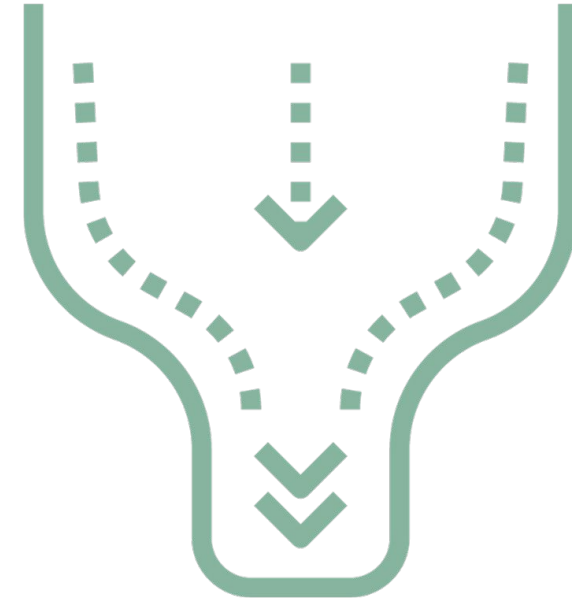
Use heap for selecting top K

- 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

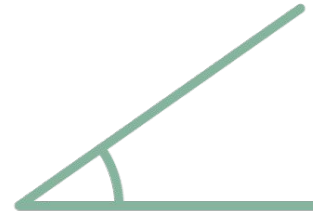
- Primary computational bottleneck in scoring: **cosine computation**
- Can we avoid all this computation?
- Yes, but may sometimes get it wrong
 - a doc not in the top K may creep into the list of K output docs
 - Is this **such a bad thing**?





Cosine similarity is only a proxy

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





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 is also used for other (non-cosine) scoring functions
- Will look at several schemes following this approach





Index elimination

- 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 don't alter rank-ordering much
 - Benefit: **Postings of low-idf terms have many docs -> these (many) docs get eliminated from A**

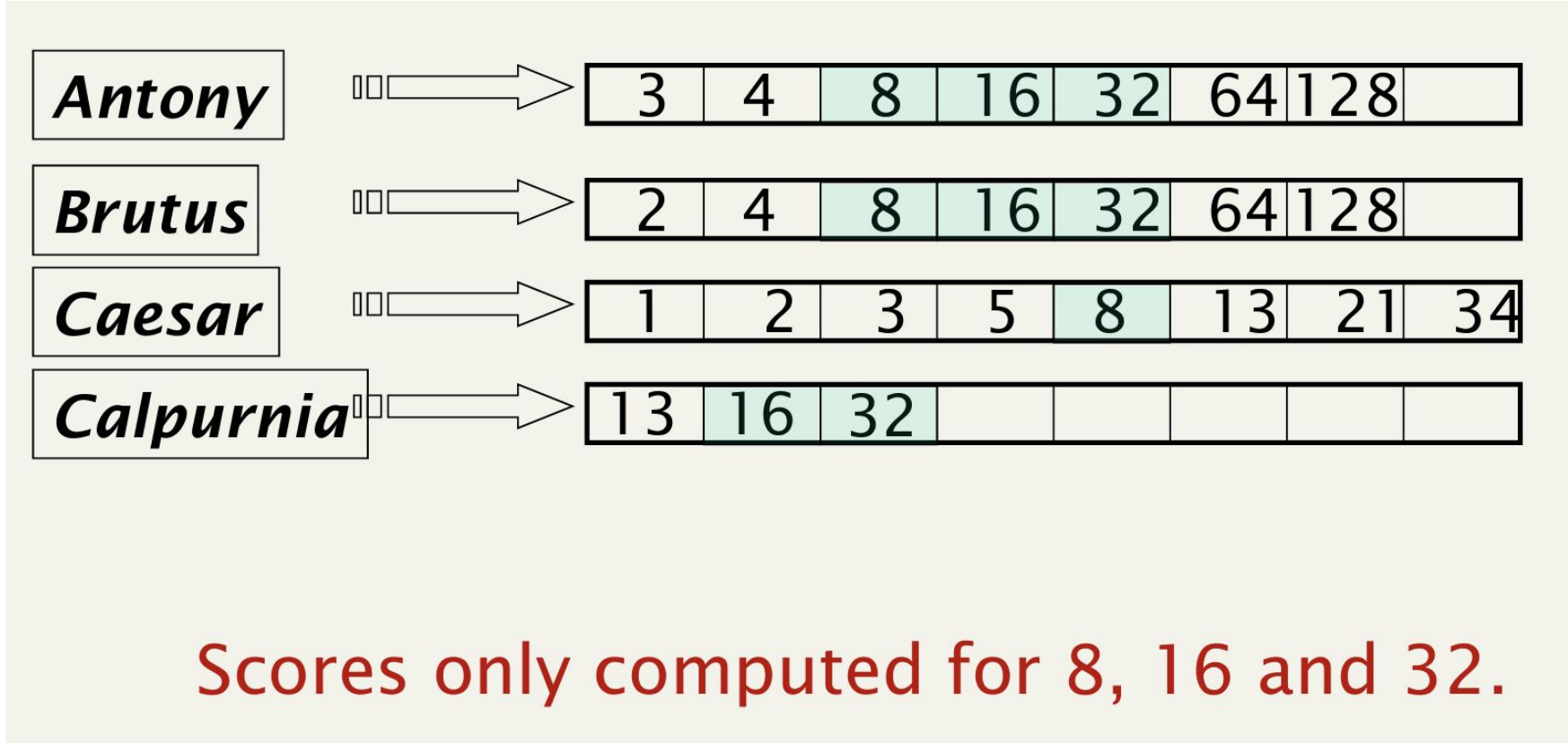


Docs containing many query terms

- 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



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 time
- At query time, only compute scores for docs in the union of the champion lists of query term
 - Pick the K top-scoring docs from amongst these



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
 - How many likes
 - (Pagerank)





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 $[0,1]$



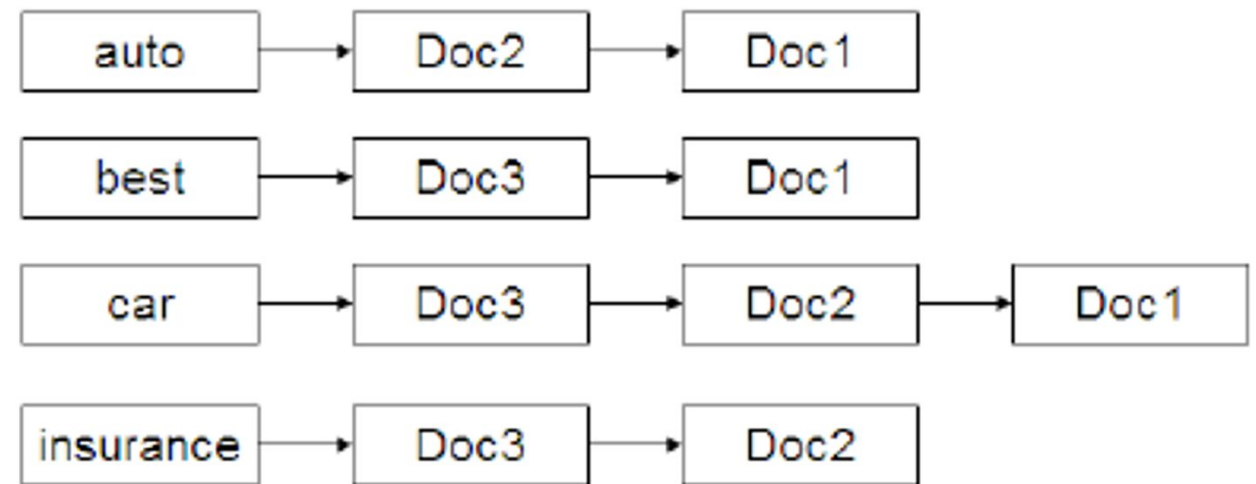
Net score

- Consider a simple total score combining cosine relevance and authority
- **$\text{Net-score}(q,d) = g(d) + \text{cosine}(q,d)$**
 - Can use some other linear combination than an equal weighting
 - Indeed, any function of the two “signals” of user happiness –more later
- 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
 - Document-at-a-time scoring
- Use accumulators to get the scores



► **Figure 7.2** A static quality-ordered index. In this example we assume that Doc1, Doc2 and Doc3 respectively have static quality scores $g(1) = 0.25$, $g(2) = 0.5$, $g(3) = 1$



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 $g(d) + \text{tf-idf}$ (List is still sorted by common order, either by document id, or by static score)
- Seek top-K results from only the docs in these champion lists
 - find documents in union of these champion lists
 - Compute scores and return k highest ones



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



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



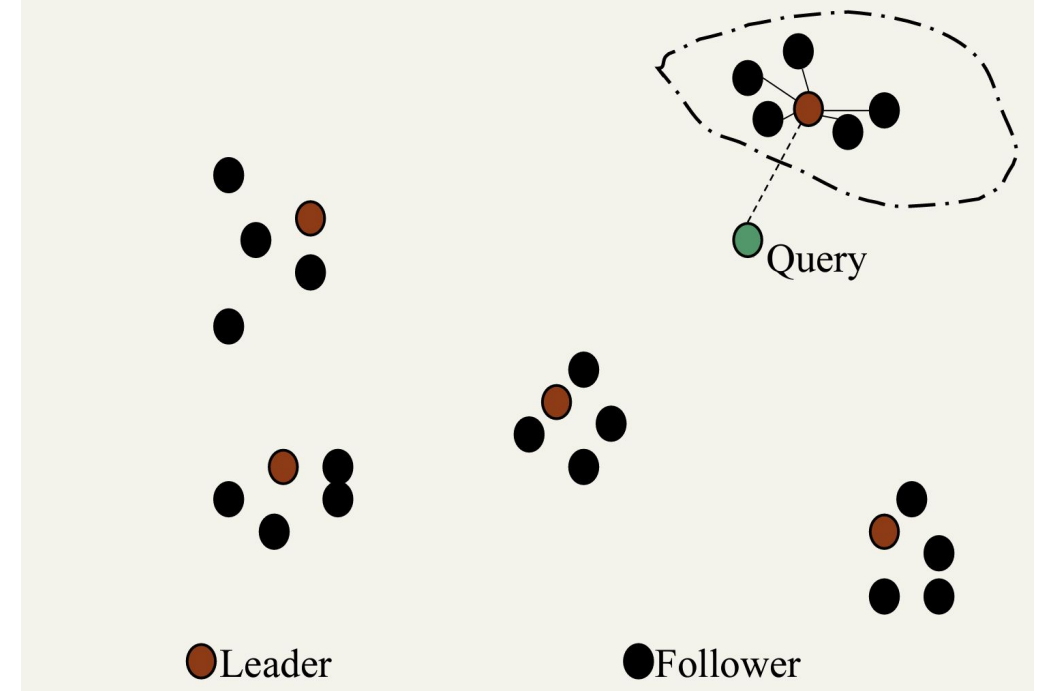
2. idf-ordered terms

- 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

Cluster pruning: preprocessing

- Pick \sqrt{N} docs: call these leaders
- For every other doc, pre-compute nearest leader
 - Docs attached to a leader: its followers
 - Likely: each leader has $\sim \sqrt{N}$ followers.
- Process a query as follows:
 - Given query Q , find its nearest leader L .
 - Seek K nearest docs from among L 's followers.

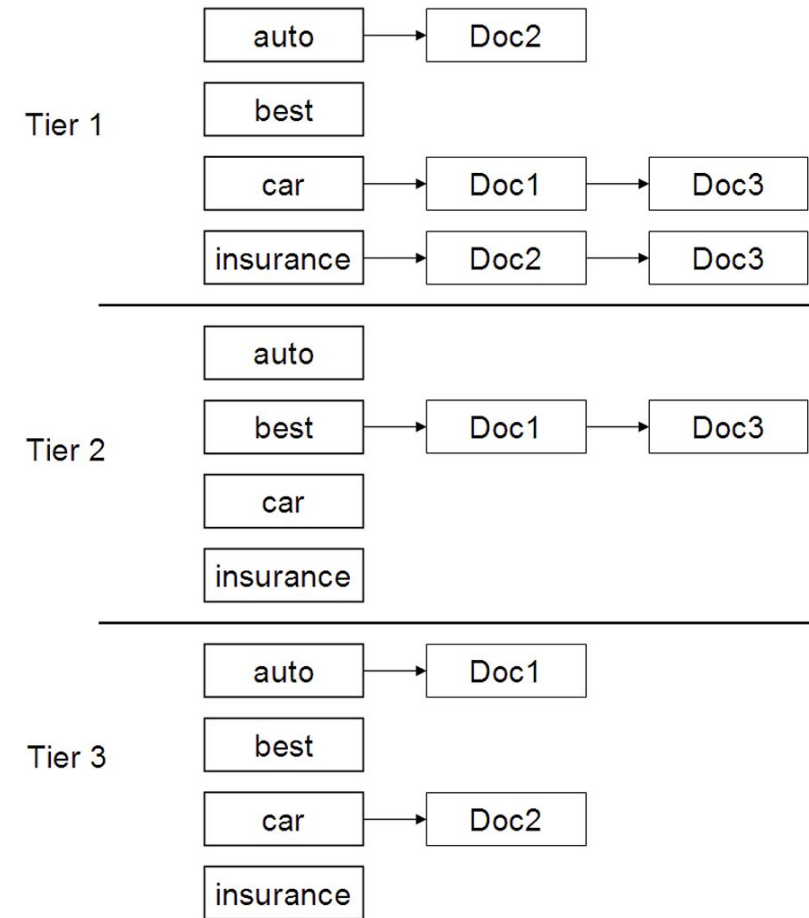
Visualization





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



References

1. Slides provided by Sougata Saha (Instructor, Fall 2022 - CSE 4/535)
2. Materials provided by Dr. Rohini K Srihari
3. <https://nlp.stanford.edu/IR-book/information-retrieval-book.html>