## Vector Space Model Implementation

Presenter

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Slides are obtained from ChengXiang Zhai and Sean Massung book

#### **Outline**

- 1. Text Retrieval Problem
- 2. Vector Space Model
- 3. Vector Space Model Implementation
  - Term At A Time (TAAT) Query Processing
  - Document At A Time (DAAT) Query Processing

#### 1. Text Retrieval Problem

#### **Text Retrieval Problem**

- Query:  $q = q_1,...,q_m$ , where  $q_i \in V$
- **Document:**  $d = d_1,...,d_n$ , where  $d_i \in V$
- Ranking function:  $f(q, d) \in \Re$
- A good ranking function should rank relevant documents on top of non-relevant ones
- Key challenge: how to measure the likelihood that document d is relevant to query q
- Retrieval model = formalization of relevance (give a computational definition of relevance)

# Common Form of a Retrieval Function

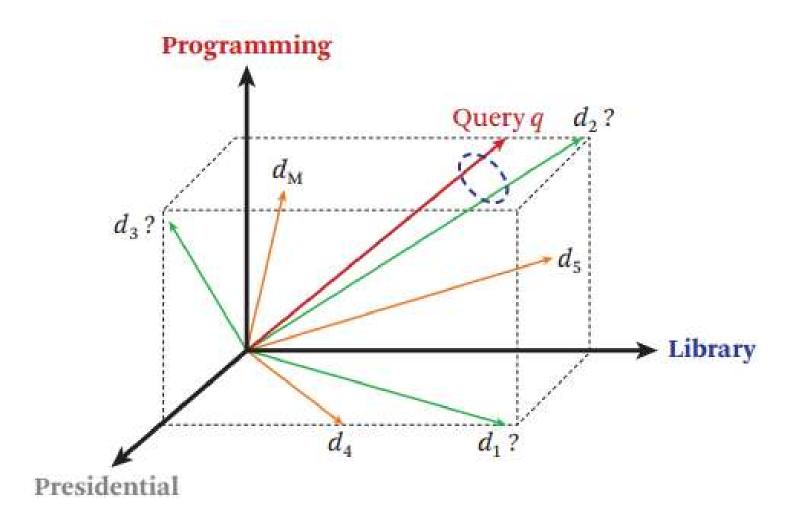
```
f(q = "presidential campaign news", d
                                                      "Bag of Words"
g("presidential", [d]) g("campaign", [d]) g("news", [d])
       How many times does "presidential" occur in d?
            Term frequency (TF): c ("presidential", d)
       How long is d? Document length: |d|
       How often do we see "presidential" in the entire collection?
            Document frequency: DF("presidential")
            P("presidential" | collection)
```

## 2. Vector Space Model

### **Vector Space Model (VSM)**

- Represent a document/query by a term vector
  - Term: basic concept, e.g., word or phrase
  - Each term defines one dimension
  - N terms define a high-dimensional space
  - Element of vector corresponds to term weight
  - E.g.,  $d = (x_1,...,x_N)$ ,  $x_i$  is "importance" of term i
- Measure relevance by the distance between the query vector and document vector in the vector space

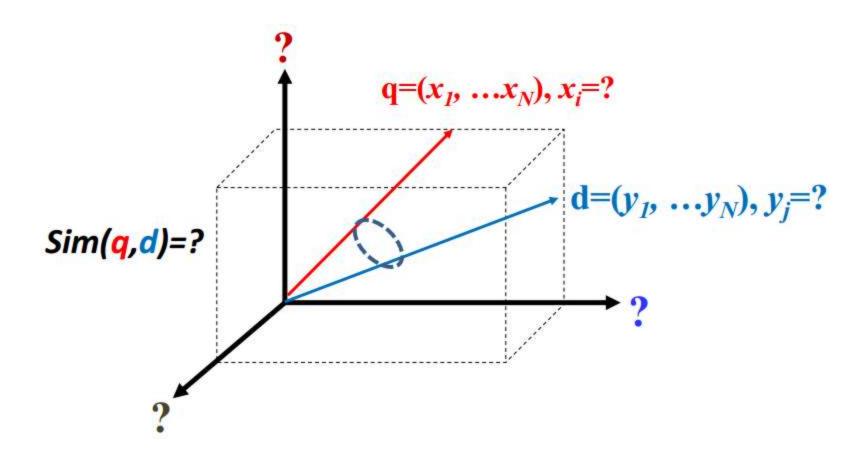
# Vector Space Model (VSM) Illustration



#### **VSM** is a Framework

- How to define/select the terms
  - Terms are assumed to be linearly independent
- How to assign term weights
  - Weight in query indicates importance of term
  - Weight in doc indicates how well the term characterizes the doc
- How to define the similarity/distance measure

### What VSM Doesn't Say



## Term weighting

- Major term weighting heuristics
  - TF weighting and transformation
  - IDF weighting
  - Document length normalization

Term frequency		Document frequency		Normalization	
n (natural)	$tf_{t,d}$	n (no)	1	n (none)	1
1 (logarithm)	$1 + \log(tf_{t,d})$	t (idf)	$\log \frac{N}{\mathrm{d} \mathrm{f}_t}$	c (cosine)	$\frac{1}{\sqrt{w_1^2 + w_2^2 + + w_M^2}}$
a (augmented)	$0.5 + \frac{0.5 \times tf_{t,d}}{max_t(tf_{t,d})}$	p (prob idf)	$\max\{0,\log\frac{N-\mathrm{d}f_t}{\mathrm{d}f_t}\}$	u (pivoted unique)	1/u (Section 6.4.4)
b (boolean)	$\begin{cases} 1 & \text{if } tf_{t,d} > 0 \\ 0 & \text{otherwise} \end{cases}$			b (byte size)	$1/\mathit{CharLength}^{\alpha}, \alpha < 1$
L (log ave)	$\frac{1 + \log(tf_{t,d})}{1 + \log(ave_{t \in d}(tf_{t,d}))}$				

https://nlp.stanford.edu/IR-book/html/htmledition/document-and-query-weighting-schemes-1.html

## State of the Art VSM Ranking Functions

Pivoted length normalization VSM

$$f(q,d) = \sum_{w \in q \cap d} c(w,q) \frac{\ln(1 + \ln(1 + c(w,d)))}{1 - b + b \frac{|d|}{avdl}} \log \frac{M+1}{\mathrm{df}(w)} \quad b \in [0,1]$$

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$$f(q,d) = \sum_{w \in q \cap d} c(w,q) \frac{(k+1)c(w,d)}{c(w,d) + k(1-b+b\frac{|d|}{avdl})} \log \frac{M+1}{\mathrm{df}(w)} \quad b \in [0,1], \ k \in [0,+\infty)$$

# 3. Vector Space Model Implementation

# Text Retrieval System Implementation

- Tokenizer
  - This determines how we represent a document
- Indexer
  - This convert documents to data structures that enable fast search
  - Compression when appropriate
- Scorer
  - This use inverted index for fast search

#### **Inverted Index**

- Fast access to all docs containing a given term (along with freq and pos information)
- For each term, we get a list of tuples (docID, freq, pos).
- Given a query, we can fetch the lists for all query terms and work on the involved documents.
  - Boolean query: set operation
  - Natural language query: term weight summing
- More efficient than scanning docs

### **Inverted Index Example**

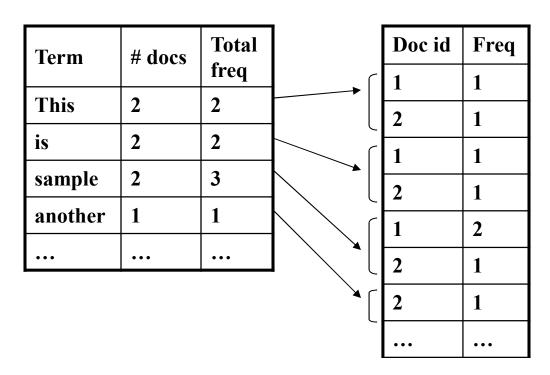
Doc 1

This is a sample document with one sample sentence

Doc 2

This is another sample document

**Dictionary** Postings



term | #docs | totalfreq | docID1:freq1;docID2:freq2;...

#### Positional Inverted Index Example

Doc 1

web retrieval web search information

#### Doc 2

search engine web ranking

#### Doc 3

web search course information search

#### **Dictionary**

Term	# docs	Total freq	
course	1	1	///
engine	2	1	// >
information	2	2	// *
ranking	1	1	
retrieval	1	1	/
search	3	4	
web	3	4	<b></b>
•••	•••	•••	

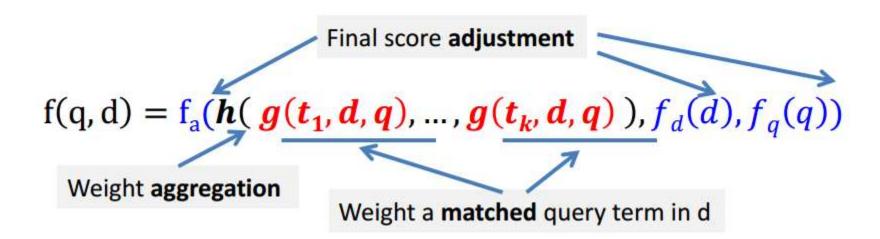
#### **Postings**

	Doc id	Freq	Pos
	3	1	2
	2	1	1
	1	1	4
	3	1	3
	2	1	3
	2	1	1
	1	1	3
	2	1	0
	3	2	1, 4
ſ	1	2	0, 2
	2	1	2
	3	1	1

term | #docs | totalfreq | docID1:freq1,pos1,pos2;docID2:freq2,pos3,pos4,pos5;...

## How to Score Documents Quickly with Inverted Index

#### **General Form of Scoring Function**



### **TAAT vs DAAT Query Processing**

- 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 (include all query terms)
     computed, before proceeding to the next
- Each has implications for how the retrieval index is structured and stored

- Read posting lists for query terms  $(t_1, ..., t_{|q|})$  successively
- Maintains an accumulator for each result document with value

$$acc(d) = \sum_{i \le j} score(t_i, d)$$

after the first j posting lists have been read

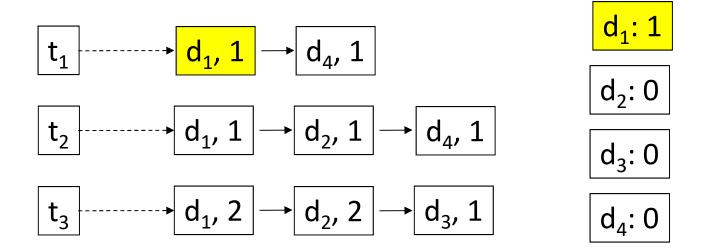
$$\begin{bmatrix} t_1 & \cdots & d_1, 1 \\ t_2 & \cdots & d_1, 1 \end{bmatrix} \rightarrow \begin{bmatrix} d_4, 1 \\ d_2, 1 \end{bmatrix} \rightarrow \begin{bmatrix} d_4, 1 \\ d_3; 0 \end{bmatrix}$$

$$\begin{bmatrix} t_3 & \cdots & d_1, 2 \\ d_1, 2 & \cdots & d_2, 2 \end{bmatrix} \rightarrow \begin{bmatrix} d_3, 1 \\ d_4; 0 \end{bmatrix}$$

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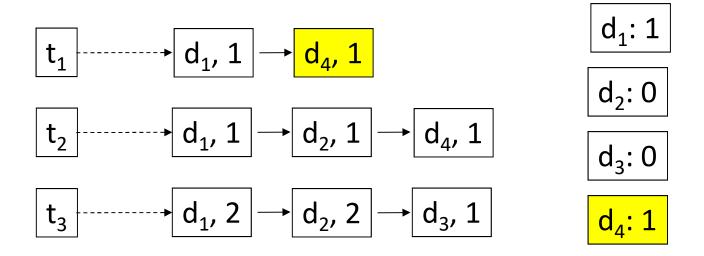
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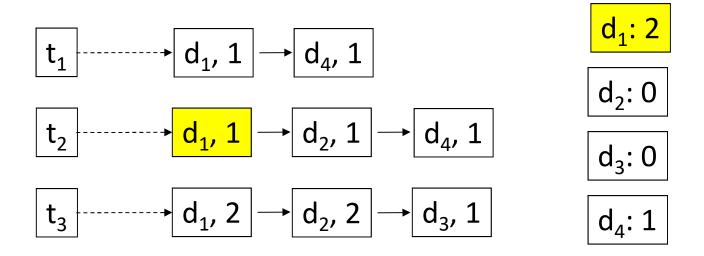
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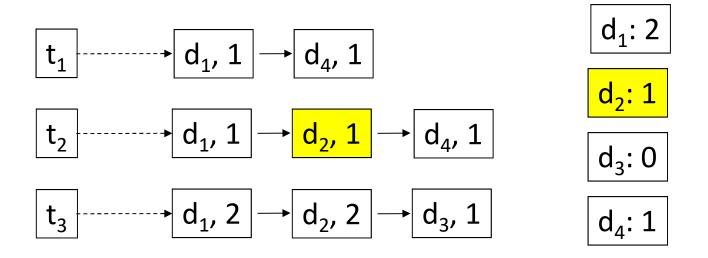
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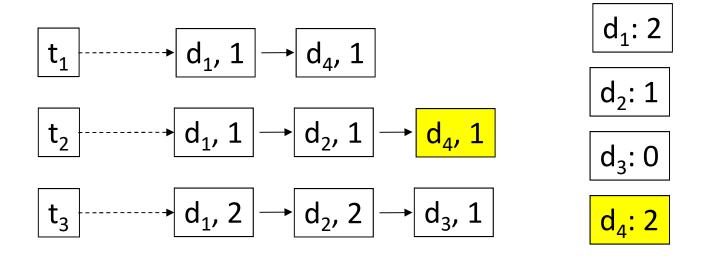
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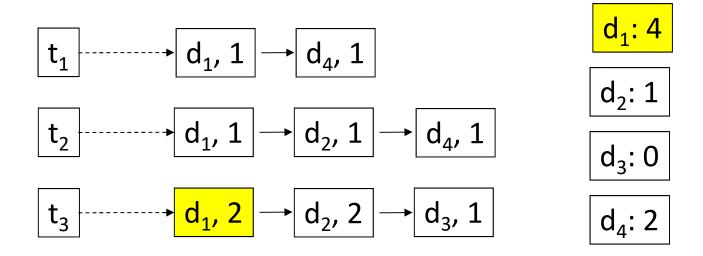
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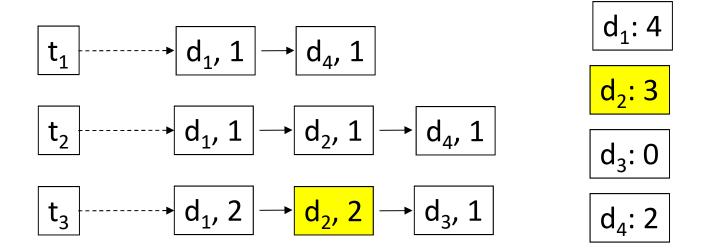
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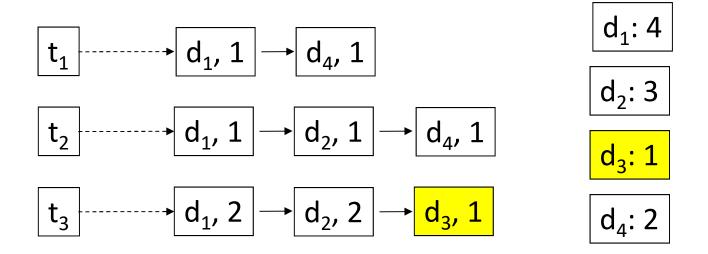
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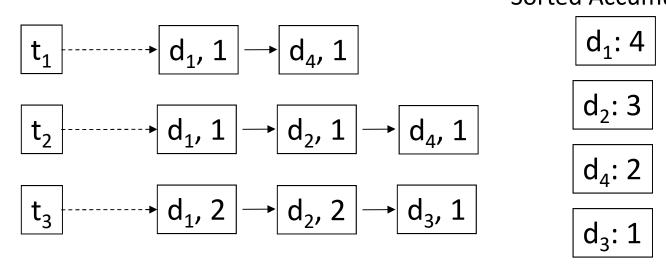


- Read posting lists for query terms  $(t_1, ..., t_{|q|})$  successively
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$$acc(d) = \sum_{i \le j} score(t_i, d)$$

after the first j posting lists have been read

 Top-k results can be determined by sorting accumulators at the end



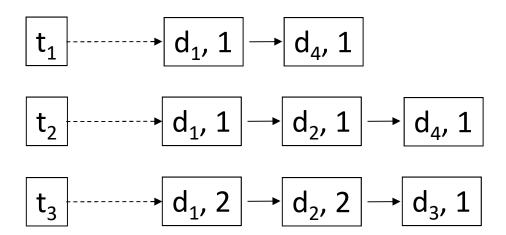
```
scores = {} // score accumulator maps doc IDs to scores
for w ∈ q do
    for d, count ∈ Idx.fetch_docs(w) do
        scores[d] = scores[d] + score_term(count)
    end for
end for
return top k documents from scores
```

# Disadvantage of term-at-a-time ranking

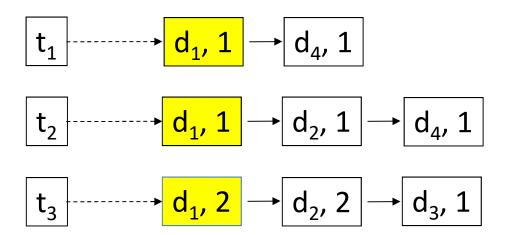
- The size of the score accumulators scores will be the size of the number of documents matching at least one term.
- This set is still large.

- Since most searches are top-k searches, we can only keep the top-k documents at any one time.
- We can hold the k best completely scored documents with a priority queue.

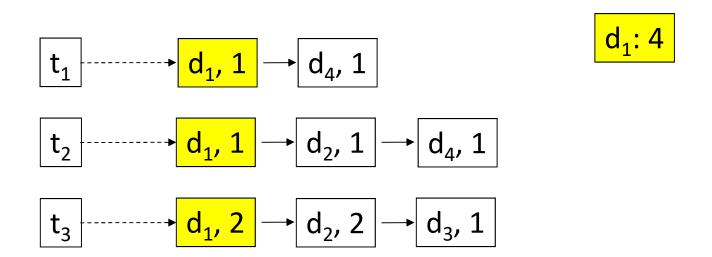
- Read posting lists for query terms  $(t_1, ..., t_{|q|})$  concurrently
- Computes score when same document is seen in one or more posting lists
- Always advances posting list with lowest current document id
- Top-k results can be determined by keeping results in priority queue



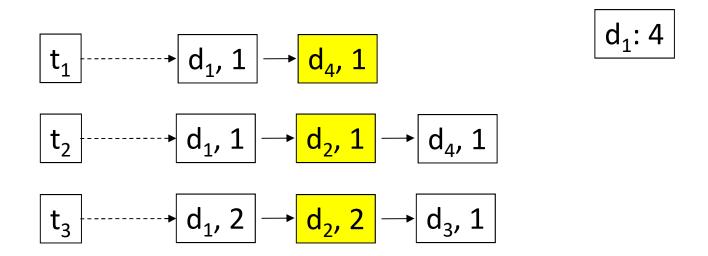
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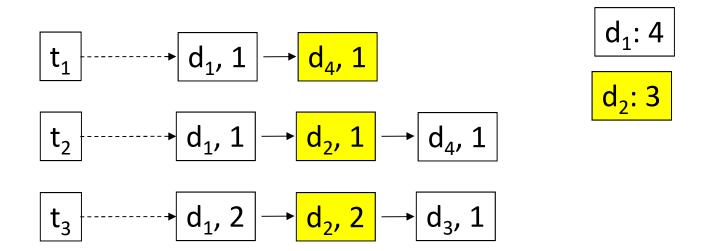
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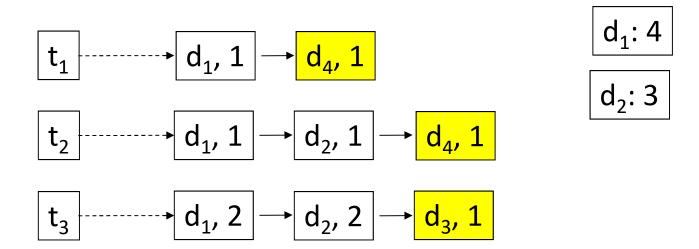
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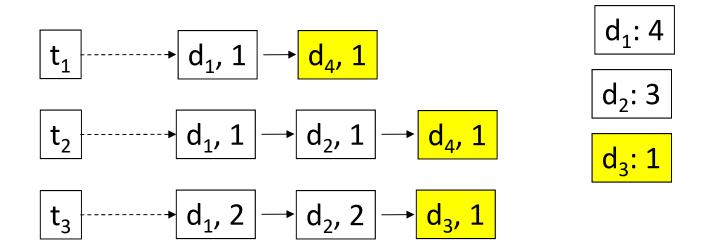
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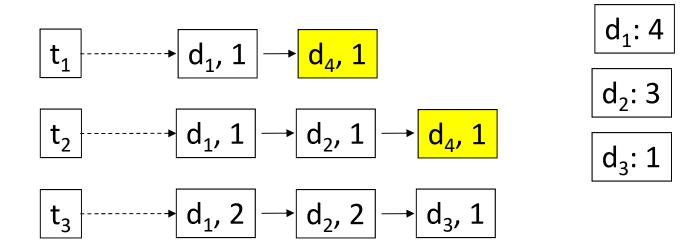
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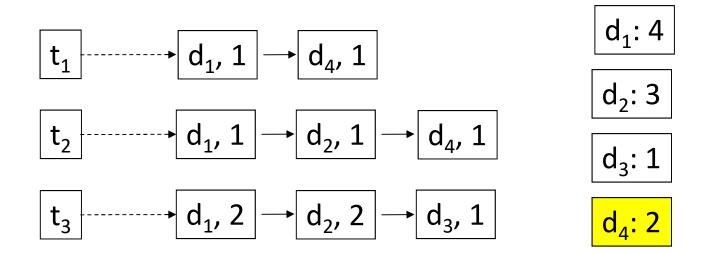
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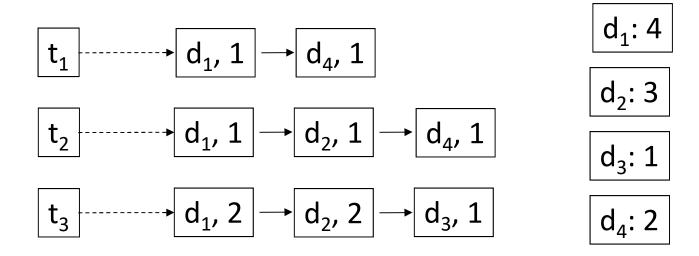
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```
// maps a document to a list of matching terms
context = \{\}
for w \in q do
   for d, count \in Idx.fetch\_docs(w) do
      context[d].append(count)
   end for
end for
priority_queue = {} // low score is treated as high priority
for d, term_counts \in context do
   score = 0
   for count \in term_counts do
      score = score + score\_term(count)
   end for
   priority_queue.push(d, score)
   if priority\_queue.size() > k then
      priority_queue.pop() // removes lowest score so far
   end if
end for
Return sorted documents from priority_queue
```

#### References

- ChengXiang Zhai and Sean Massung, Text Data Management and Analysis: A Practical Introduction to Information Retrieval and Text Mining, ACM Books, 2016.
  - Chapter 6, Section 6.1-6.3 (Vector space model)
  - Chapter 8, Section 8.1-8.3 (Vector space model implementation)

## Questions

