Text Retrieval and Search Engines

Vector Space Retrieval Model: Improved Instantiation

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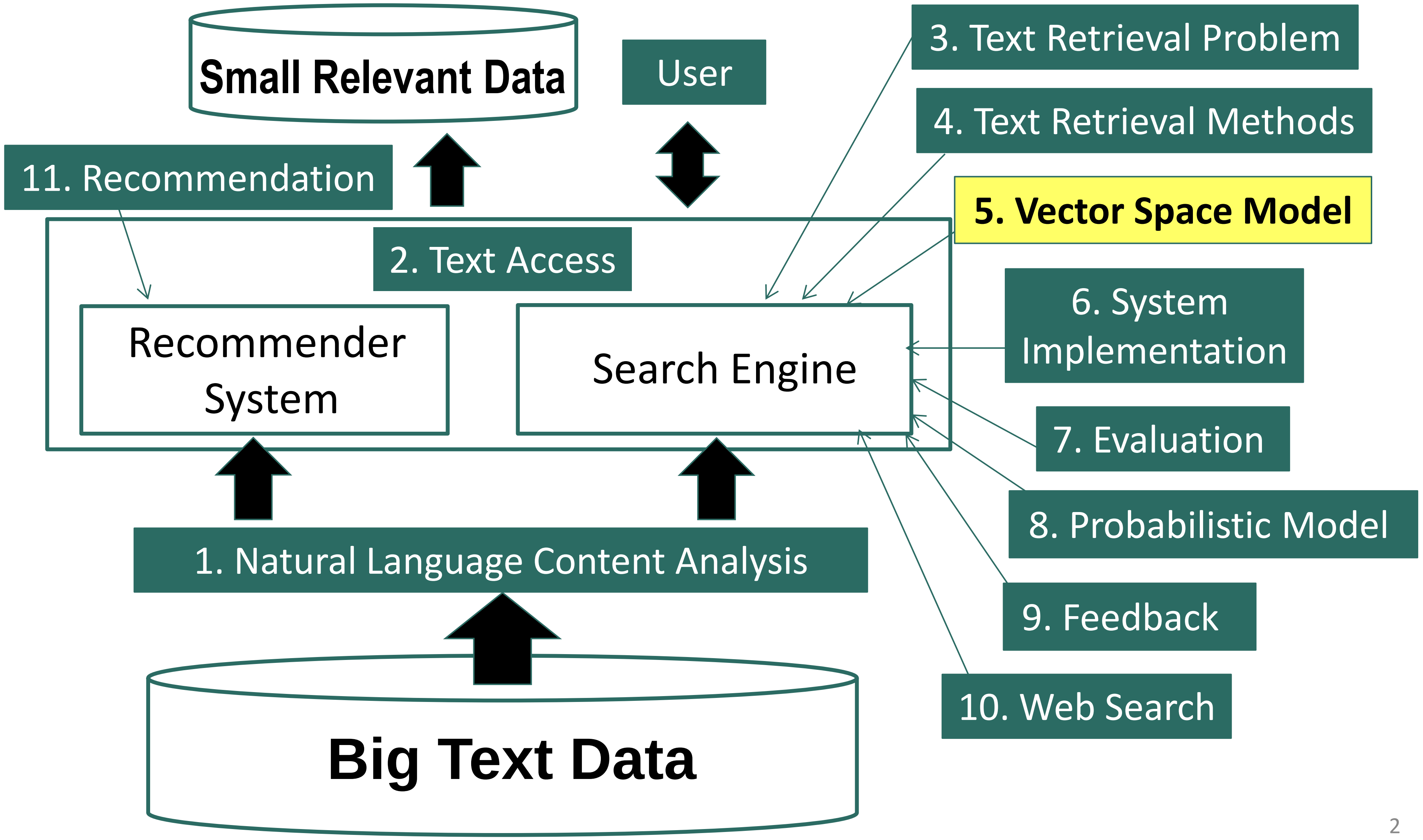
Course Schedule



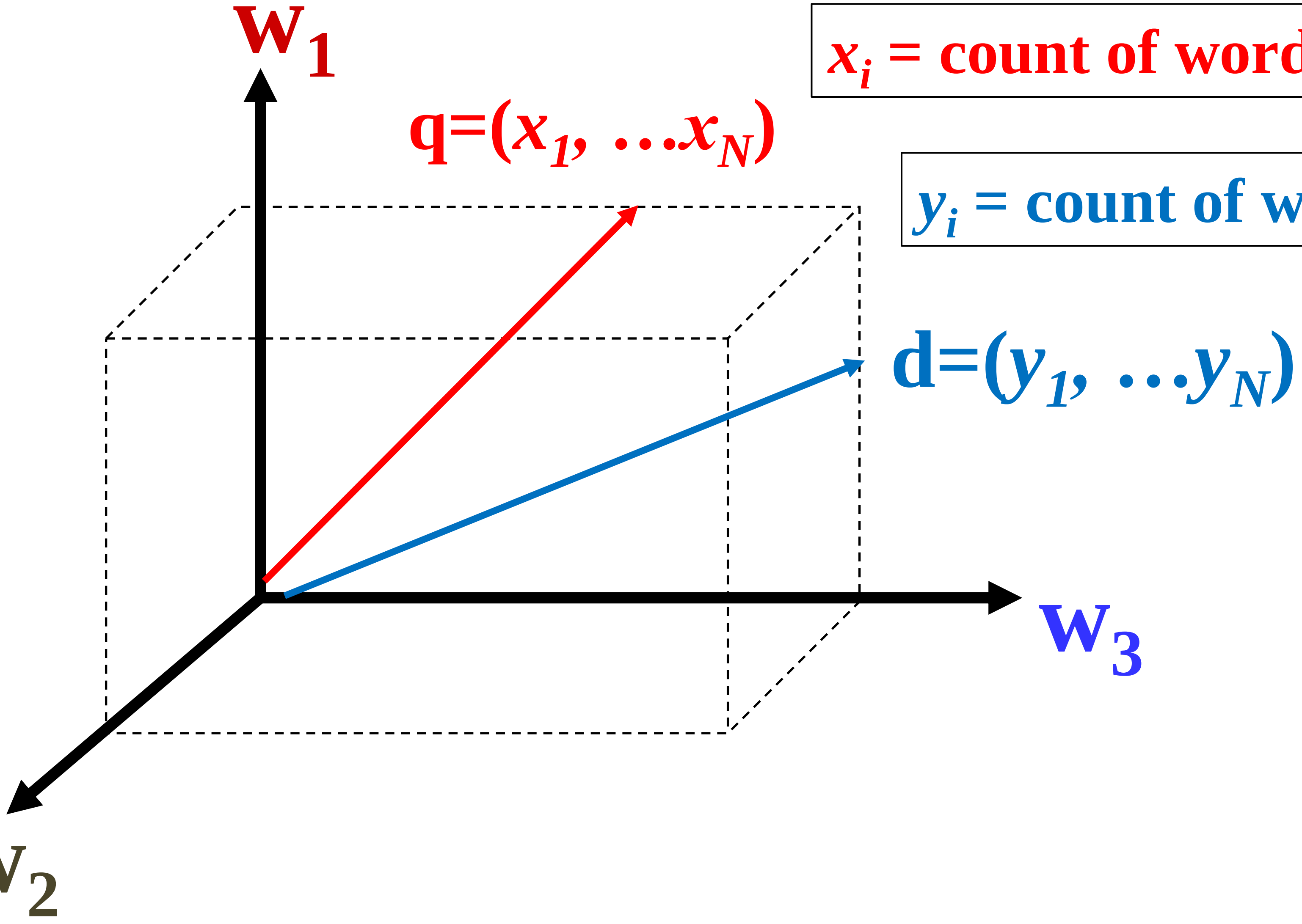
1. VSM Improved
Two Problems of the Simplest VSM

Query = "news about presidential campaign"

d2	… **news about** organic food **campaign**…	**f(q,d2)=3**
d3	… **news** of **presidential campaign** …	**f(q,d3)=3**
d4	… **news** of **presidential campaign** … … **presidential** candidate …	**f(q,d4)=3**

1. Matching "presidential" more times deserves more credit
2. Matching "presidential" is more important than matching "about"

Improved Vector Placement: Term Frequency Vector



x_i = count of word W_i in query

y_i = count of word W_i in doc

Improved VSM with Term Frequency Weighting

$q=(x_1, \ldots x_N)$

x_i = count of word W_i in query

$d=(y_1, \ldots y_N)$

y_i = count of word W_i in doc

$$Sim(q,d)=q.d= x_1 y_1 + \ldots + x_N y_N = {}^{N}_{i=1} x_i y_i$$

What does this ranking function intuitively capture?

Does it fix the problems of the simplest VSM?

Ranking Using Term Frequency (TF) Weighting

d2 … **news about** organic food **campaign**… f(q,d2)=3

q= (1, 1, 1, 1, 0, …)
d2= (1, 1, 0, 1, 1, …)

d3 … **news** of **presidential campaign** … f(q,d3)=3

q= (1, 1, 1, 1, 0, …)
d3= (1, 0, 1, 1, 0, …)

d4 … **news** of **presidential campaign** …
… **presidential** candidate … **f(q,d4)=4!**

q= (1, 1, 1, 1, 0, …)
d4= (1, 0, 2, 1, 0, …)

How to Fix Problem 2 (“presidential” vs. “about”)

d2	… **news about** organic food **campaign**…
d3	… **news** of **presidential campaign** …

V= {news, about, presidential, campaign, food …. }

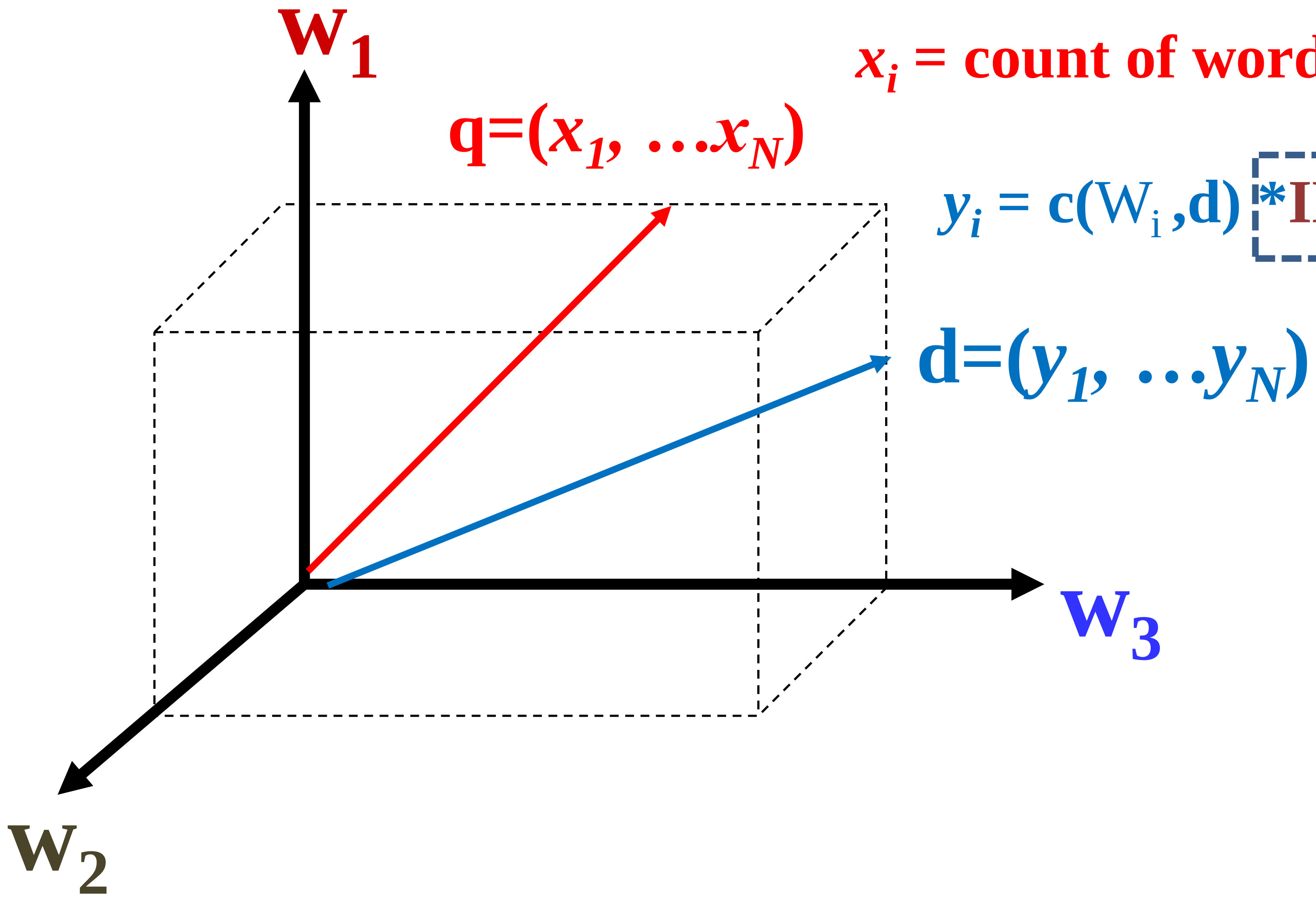
$$\begin{array}{lllllll}
 & \text{news} & \text{about} & \text{presidential} & \text{campaign} & \text{food} & \\
\mathbf{q}= & (\boxed{1,} & \boxed{1,} & 1, & \boxed{1,} & 0, & \ldots) \\
\mathbf{d2}= & (\boxed{1,} & \boxed{1,}\Downarrow & 0, & \boxed{1,} & 1, & \ldots)
\end{array}$$

f(q,d2)<3

f(q,d3)>3

$$\begin{array}{lllllll}
\mathbf{q}= & (\boxed{1,} & 1, & \boxed{1,} & \boxed{1,} & 0, & \ldots) \\
\mathbf{d3}= & (\boxed{1,} & 0, & \boxed{1,}\Uparrow & \boxed{1,} & 0, & \ldots)
\end{array}$$

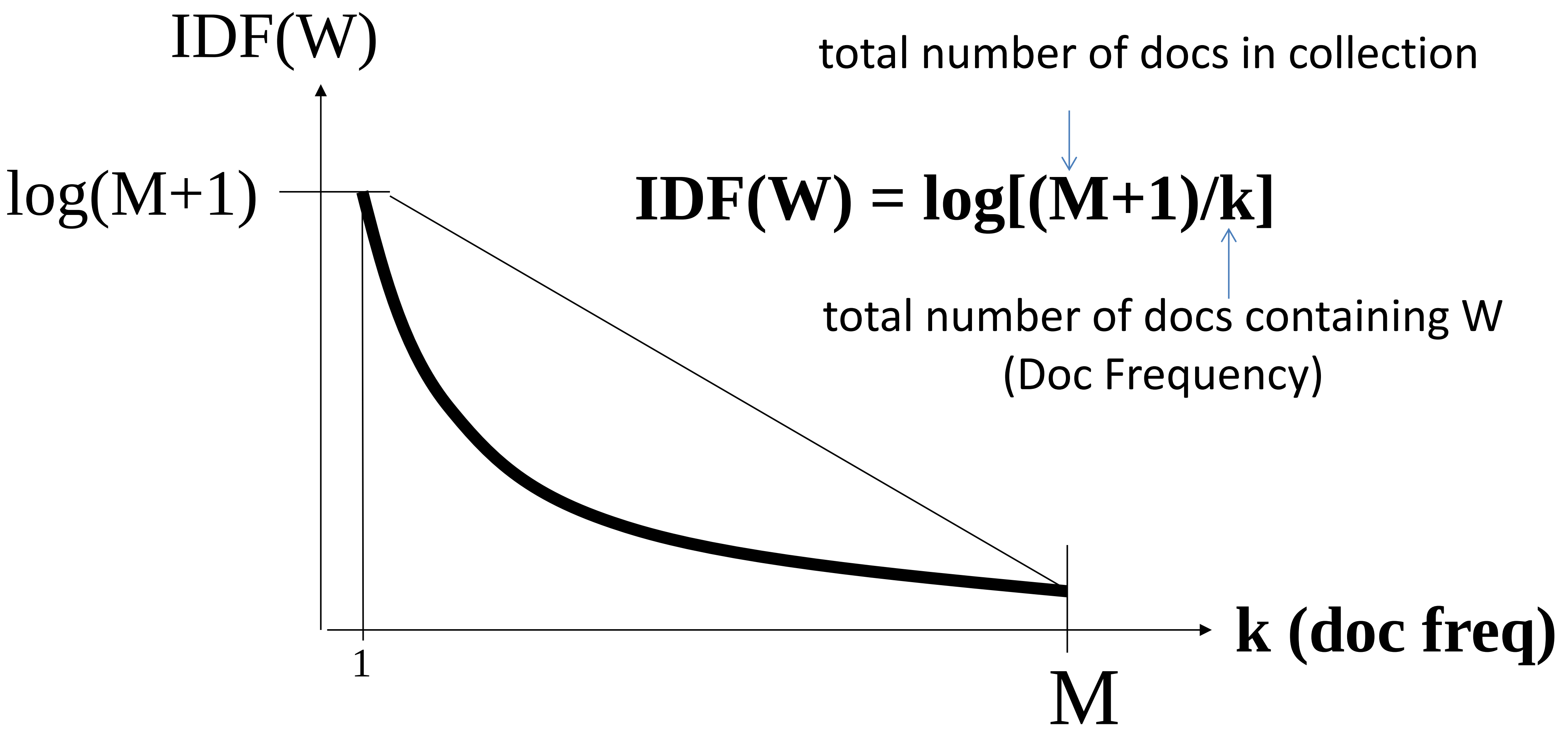
Further Improvement of Vector Placement: Adding Inverse Document Frequency (IDF)



x_i = count of word W_i in query

$y_i = c(W_i, d) \boxed{* IDF(W_i)}$

IDF Weighting: Penalizing Popular Terms



total number of docs in collection

$$\mathbf{IDF(W) = \log[(M+1)/k]}$$

total number of docs containing W (Doc Frequency)

Solving Problem 2 (“Presidential” vs “About”)

d2 … **news about** organic food **campaign**…

d3 … **news** of **presidential campaign** …

	V= {news,	about,	presidential,	campaign,	food …. }	
IDF(W)=	**1.5**	**1.0**	**2.5**	**3.1**	**1.8**	
q=	(1,	1,	1,	1,	0,	…)
d2=	(1*1.5,	1*1.0	0,	1*3.1,	0,	…)
q=	(1,	1,	1,	1,	0,	…)
d3=	(1*1.5,	0,	1*2.5	1*3.1,	0,	…)

f(q,d2) = 5.6 < f(q,d3)=7.1

How Effective Is VSM with TF-IDF Weighting?

Query = "news about presidential campaign"

d1	… **news about** …	f(q,d1)=2.5
d2	… **news about** organic food **campaign**…	f(q,d2)=5.6
d3	… **news** of **presidential campaign** …	f(q,d3)=7.1
d4	… **news** of **presidential campaign** … … **presidential** candidate …	f(q,d4)=9.6
d5	… **news** of organic food **campaign**… **campaign**…**campaign**…**campaign**…	**f(q,d5)=13.9!**

Summary

- Improved VSM
  - Dimension = word
  - Vector = TF-IDF weight vector
  - Similarity = dot product
  - Working better than the simplest VSM
  - Still having problems

2. TF Transformation
VSM with TF-IDF Weighting Still Has a Problem!

Query = “news about presidential campaign”

d1	… **news about** …	f(q,d1)=2.5
d2	… **news about** organic food **campaign**…	f(q,d2)=5.6
d3	… **news** of **presidential campaign** …	f(q,d3)=7.1
d4	… **news** of **presidential campaign** … … **presidential** candidate …	f(q,d4)=9.6
d5	… **news** of organic food **campaign**… **campaign**…**campaign**…**campaign**…	**f(q,d5)=13.9?**

Ranking Function with TF-IDF Weighting

Total # of docs in collection

$$f(q,d) = \sum_{i=1}^{N} x_i y_i = \sum_{w \in q \cap d} c(w,q)\underline{c(w,d)} \log \frac{M+1}{df(w)}$$

All matched query words in d

Doc Frequency

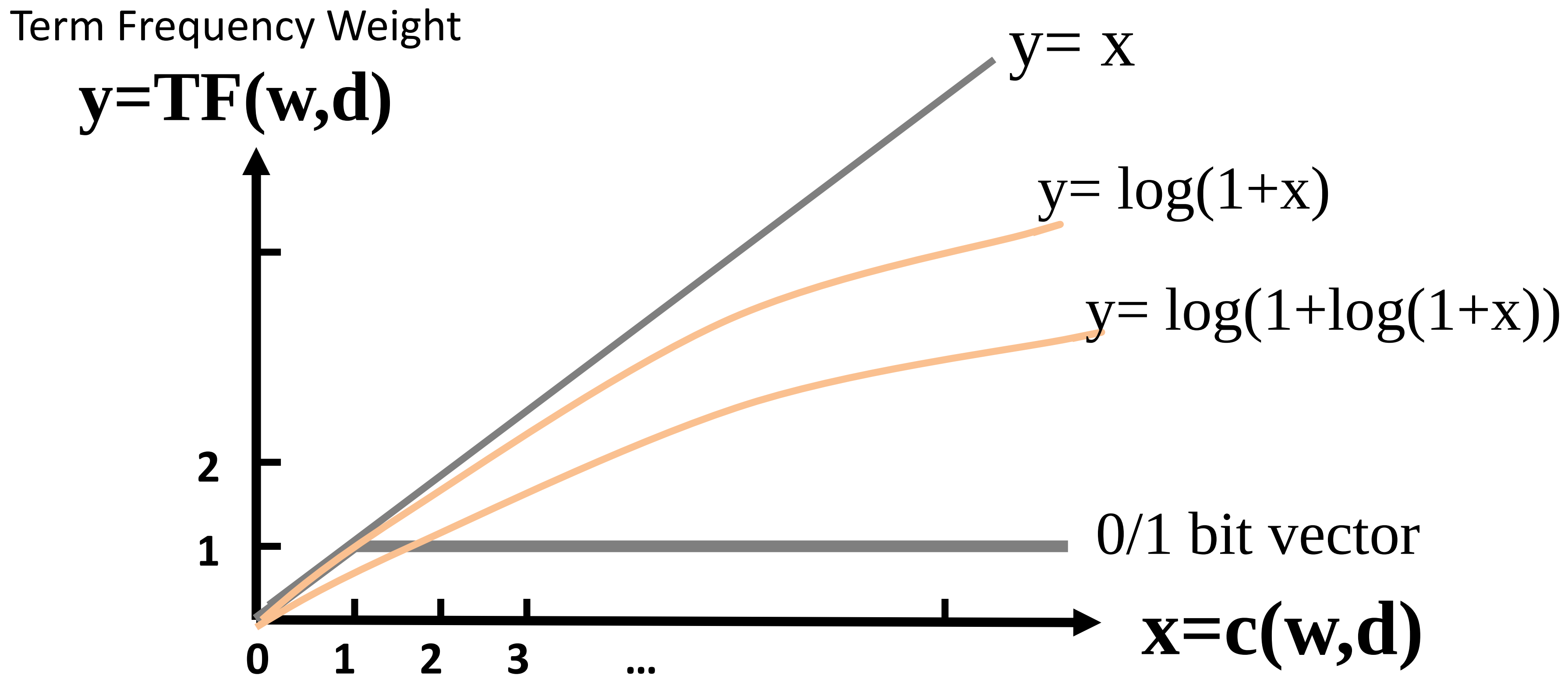
d5

… **news** of organic food **campaign**…
campaign…**campaign**…**campaign**…

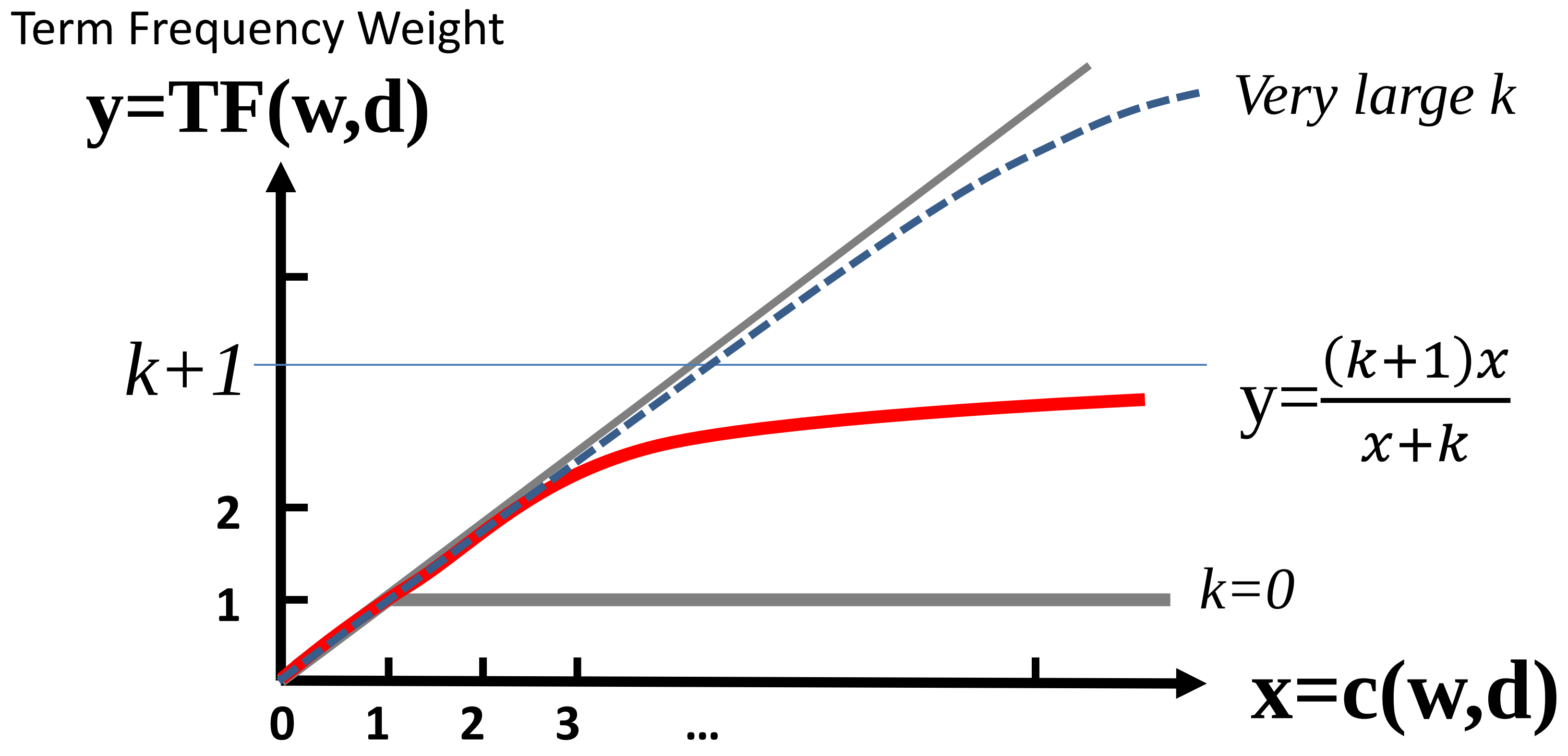
c("campaign",d5)=4

➔f(q,d5)=13.9?

TF Transformation: c(w,d)➔TF(w,d)



TF Transformation: BM25 Transformation



Summary

- Sublinear TF Transformation is needed to
  - capture the intuition of “diminishing return” from higher TF
  - avoid dominance by one single term over all others
- BM25 Transformation
  - has an upper bound
  - is robust and effective
- Ranking function with BM25 TF (k >=0)

$$f(q,d)=\sum_{i=1}^{N} x_i y_i = \sum_{w \in q \cap d} c(w,q)\frac{(k+1)c(w,d)}{c(w,d)+k}\log\frac{M+1}{df(w)}$$

3. Doc Length Normalization
What about Document Length?

Query = “news about presidential campaign”

d4

… **news** of **presidential campaign** …
… **presidential** candidate …

100 words

d6 > d4?

d6

… **campaign**……… **campaign**………………… **5000 words** …..
………………………………………………………
……….**news**…………………………………………………
………………………………………………………
……………………………………………… **news**…..
………………………………………………………
…………………………………… ………………………
…………………… **presidential** ……. **presidential**……

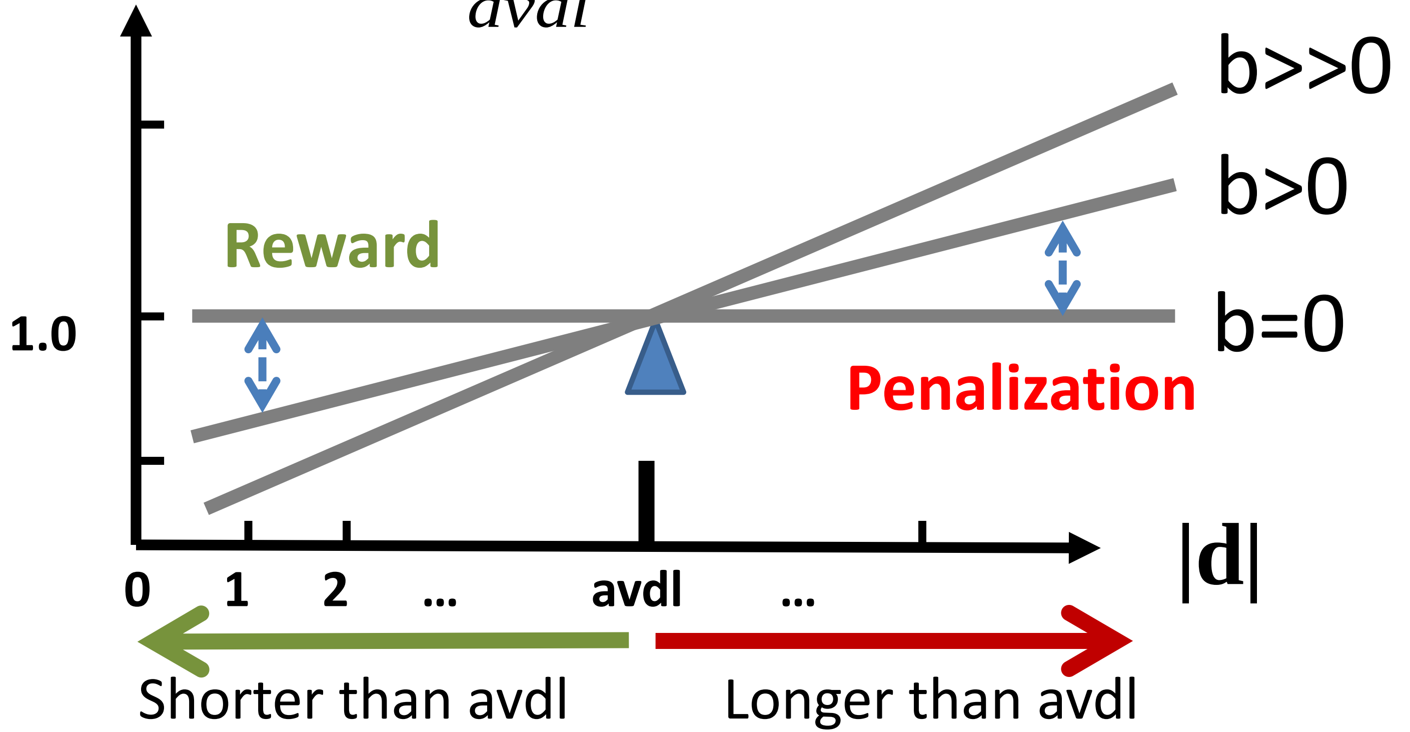
Document Length Normalization

- Penalize a long doc with a doc length normalizer
  - Long doc has a better chance to match any query
  - Need to avoid over-penalization
- A document is long because
  - it uses more words ➔ more penalization
  - it has more contents ➔ less penalization
- Pivoted length normalizer: average doc length as "pivot"
  - Normalizer = 1 if |d| =average doc length (avdl)

Pivoted Length Normalization

$$b \in [0,1]$$

$$normalizer = 1 - b + b\frac{|d|}{avdl}$$



State of the Art VSM Ranking Functions

- Pivoted Length Normalization VSM [Singhal et al 96]

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

- BM25/Okapi [Robertson & Walker 94]

$$b\in[0,1]$$
$$k_1,k_3\in[0,+\infty)$$

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

Further Improvement of VSM?

- Improved instantiation of **dimension?**
  - stemmed words, stop word removal, phrases, latent semantic indexing (word clusters), character n-grams, …
  - bag-of-words with phrases is often sufficient in practice
  - Language-specific and domain-specific tokenization is important to ensure “normalization of terms”
- Improved instantiation of **similarity function?**
  - cosine of angle between two vectors?
  - Euclidean?
  - dot product seems still the best (sufficiently general especially with appropriate term weighting)

Further Improvement of BM25

- BM25F [Robertson & Zaragoza 09]
  - Use BM25 for documents with structures (“F”=fields)
  - Key idea: combine the frequency counts of terms in all fields and then apply BM25 (instead of the other way)
- BM25+ [Lv & Zhai 11]
  - Address the problem of over penalization of long documents by BM25 by adding a small constant to TF
  - Empirically and **analytically** shown to be better than BM25

Summary of Vector Space Model

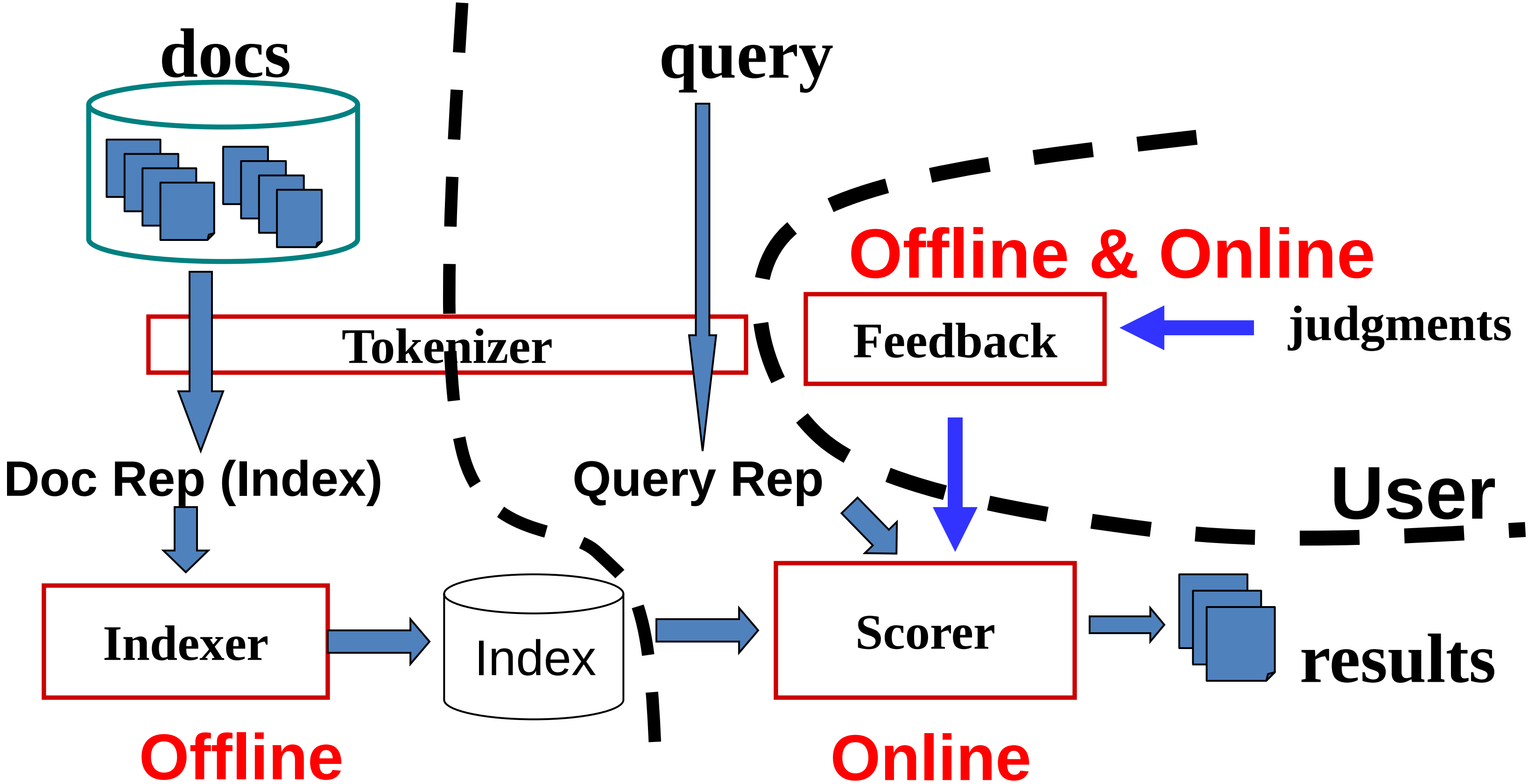
- Relevance(q,d) = similarity(q,d)
- Query and documents are represented as vectors
- Heuristic design of ranking function
- Major term weighting heuristics
  - TF weighting and transformation
  - IDF weighting
  - Document length normalization
- BM25 and Pivoted normalization seem to be most effective

Additional Readings

- A. Singhal, C. Buckley, and M. Mitra. Pivoted document length normalization. In *Proceedings of ACM SIGIR 1996.*
- S. E. Robertson and S. Walker. Some simple effective approximations to the 2-Poisson model for probabilistic weighted retrieval, *Proceedings of ACM SIGIR 1994*.
- S. Robertson and H. Zaragoza. The Probabilistic Relevance Framework: BM25 and Beyond, *Found. Trends Inf. Retr.* 3, 4 (April 2009).
- Y. Lv, C. Zhai, Lower-bounding term frequency normalization. In *Proceedings of ACM CIKM 2011.*

4. Implementation of TR Systems

Typical TR System Architecture



Tokenization

- Normalize lexical units: Words with similar meanings should be mapped to the same indexing term
- Stemming: Mapping all inflectional forms of words to the same root form, e.g.
  - computer -> compute
  - computation -> compute
  - computing -> compute
- Some languages (e.g., Chinese) pose challenges in word segmentation

Indexing

- Indexing = Convert documents to data structures that enable fast search (precomputing as much as we can)
- Inverted index is the dominating indexing method for supporting basic search algorithms
- Other indices (e.g., document index) may be needed for feedback

Inverted Index Example

doc 1

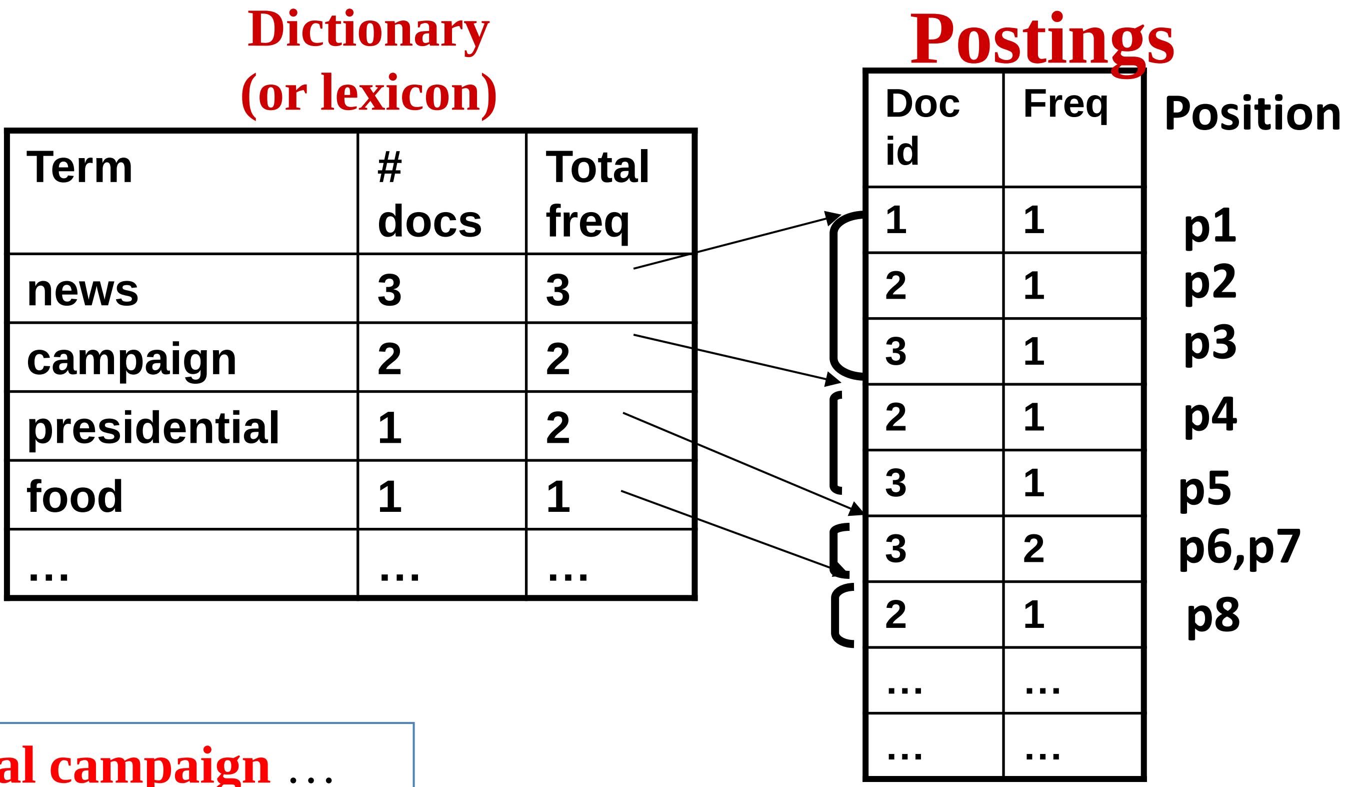
… **news about**

doc 2

… **news about** organic food **campaign**…

doc 3

… **news** of **presidential campaign** …
… **presidential** candidate …



Dictionary (or lexicon)

Term	# docs	Total freq
news	3	3
campaign	2	2
presidential	1	2
food	1	1
…	…	…

Postings

Doc id	Freq	Position
1	1	p1
2	1	p2
3	1	p3
2	1	p4
3	1	p5
3	2	p6,p7
2	1	p8
…	…	
…	…	

Inverted Index for Fast Search

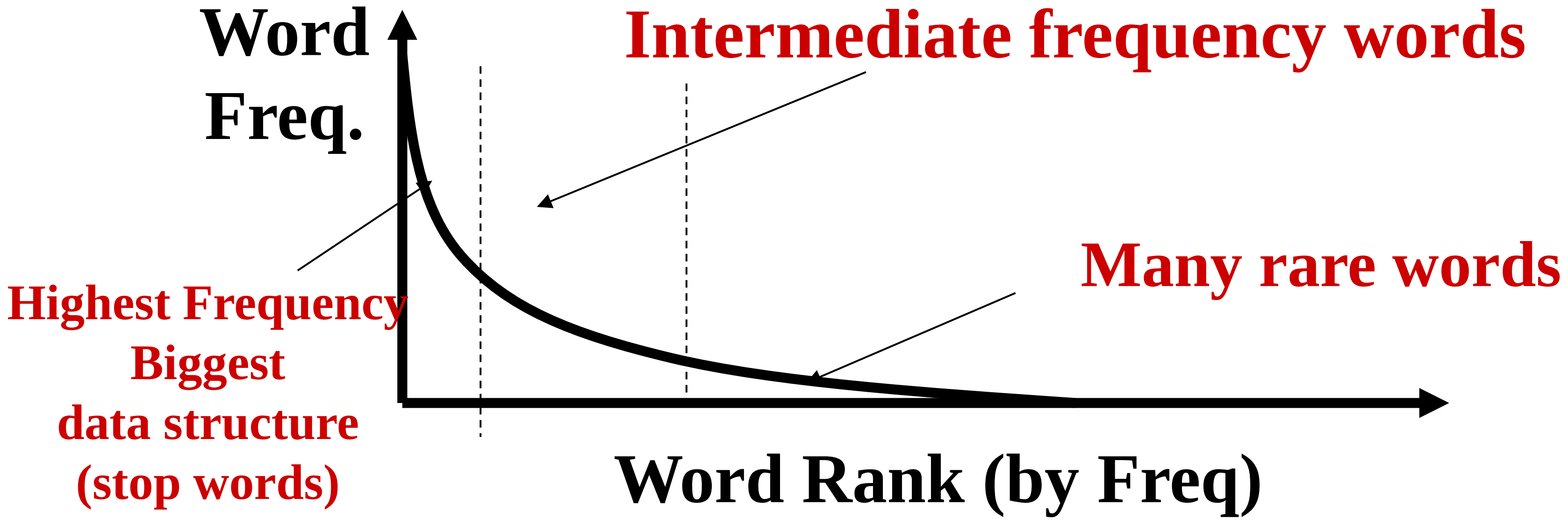
- Single-term query?
- Multi-term Boolean query?
  - Must match term “A” AND term “B”
  - Must match term “A” OR term “B”
- Multi-term keyword query
  - Similar to disjunctive Boolean query (“A” OR “B”)
  - Aggregate term weights
- More efficient than sequentially scanning docs (why?)

Empirical Distribution of Words

- There are stable language-independent patterns in how people use natural languages
- A few words occur very frequently; most occur rarely. E.g., in news articles,
  - Top 4 words: 10~15% word occurrences
  - Top 50 words: 35~40% word occurrences
- The most frequent word in one corpus may be rare in another

Zipf's Law

- rank * frequency ≈ constant $F(w) = \frac{C}{r(w)^{\alpha}} \quad \alpha \approx 1, C \approx 0.1$



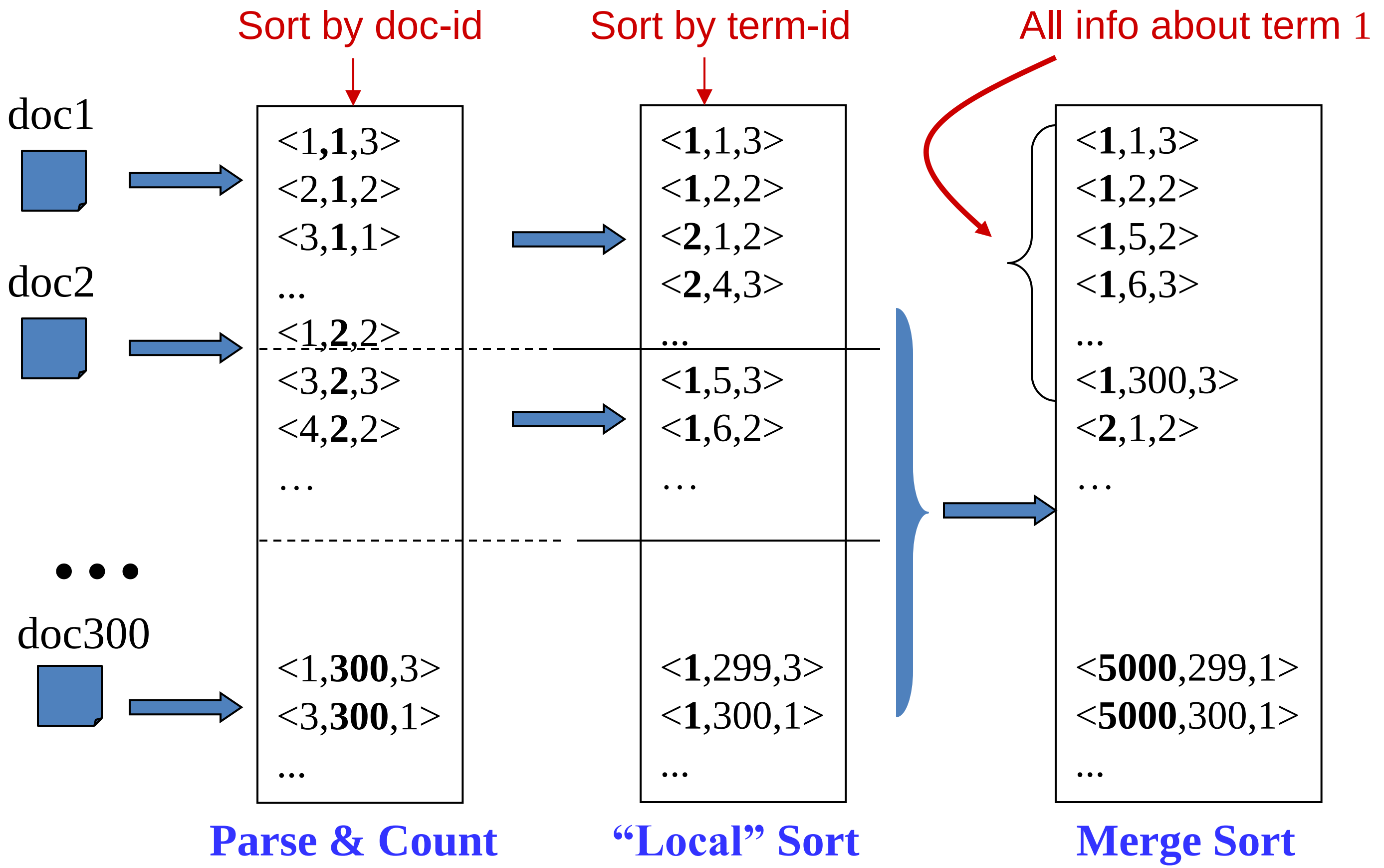
Data Structures for Inverted Index

- Dictionary: modest size
  - Needs fast random access
  - Preferred to be in memory
  - Hash table, B-tree, trie, …
- Postings: huge
  - Sequential access is expected
  - Can stay on disk
  - May contain docID, term freq., term pos, etc
  - Compression is desirable

5. Constructing Inverted Index

- The main difficulty is to build a huge index with limited memory
- Memory-based methods: not usable for large collections
- Sort-based methods:
  - Step 1: Collect local (termID, docID, freq) tuples
  - Step 2: Sort local tuples (to make “runs”)
  - Step 3: Pair-wise merge runs
  - Step 4: Output inverted file

Sort-based Inversion



Term Lexicon:

the 1
campaign 2
news 3
a 4
…

DocID Lexicon:

doc1 1
doc2 2
doc3 3
…

Inverted Index Compression

- In general, leverage skewed distribution of values and use variable-length encoding
- TF compression
  - Small numbers tend to occur far more frequently than large numbers (why?)
  - Fewer bits for small (high frequency) integers at the cost of more bits for large integers
- Doc ID compression
  - "d-gap" (store difference): d1, d2-d1, d3-d2,…
  - Feasible due to sequential access
- Methods: Binary code, unary code, γ-code, δ-code, …

Integer Compression Methods

- Binary: equal-length coding
- Unary: $x \geq 1$ is coded as x-1 one bits followed by 0, e.g., 3=> 110; 5=>11110
- γ-code: x=> unary code for $1+\lfloor \log x \rfloor$ followed by uniform code for $x-2^{\lfloor \log x \rfloor}$ in $\lfloor \log x \rfloor$ bits, e.g., 3=>101, 5=>11001
- δ-code: same as γ-code ,but replace the unary prefix with γ-code. E.g., 3=>1001, 5=>10101

Uncompress Inverted Index

- Decoding of encoded integers
  - Unary decoding: count 1’s until seeing a zero
  - γ-decoding
    - first decode the unary part; let value be k+1
    - read k more bits decode them as binary code; let value be r
    - the value of the encoded number is $\mathbf{2^k+r}$
- Decode doc IDs encoded using d-gap
  - Let the encoded ID list be x1, x2, x3, ….
  - Decode x1 to obtain doc ID1; then decode x2 and add the recovered value to the doc ID1 just obtained
  - Repeatedly decode x3, x4, …., and the recovered value to the previous doc ID.

6. How to Score Documents Quickly

General Form of Scoring Function

Final score **adjustment**

$$f(q,d) = f_a(\boldsymbol{h}(\,\boldsymbol{g}(\underline{\boldsymbol{t_1},\boldsymbol{d},\boldsymbol{q})}, \ldots, \boldsymbol{g}(\underline{\boldsymbol{t_k},\boldsymbol{d},\boldsymbol{q})}\,), f_d(d), f_q(q))$$

Weight **aggregation**

Weight a **matched** query term in d

A General Algorithm for Ranking Documents

$$\mathrm{f}(\mathrm{q},\mathrm{d}) = \mathrm{f_a}(\boldsymbol{h}(\,\boldsymbol{g}(\boldsymbol{t_1},\boldsymbol{d},\boldsymbol{q}),\ldots,\boldsymbol{g}(\boldsymbol{t_k},\boldsymbol{d},\boldsymbol{q})\,), f_d(d), f_q(q))$$

- $f_d(d)$ and $f_q(q)$ are pre-computed
- Maintain a score accumulator for each **d** to compute ***h***
- For each query term ***t$_i$***
  - Fetch the inverted list $\{(d_1,f_1),\ldots,(d_n,f_n)\}$
  - For each entry (d_j,f_j), compute **$g(t_i,d_j,q)$**, and update score accumulator for doc d_i to incrementally compute ***h***
- Adjust the score to compute **f_a**, and sort

An Example: Ranking Based on TF Sum

$\mathbf{f(d,q)=g(t_1,d,q)+\ldots+g(t_k,d,q)}$ where $g(t_i,d,q) = c(t_i,d)$

Query = **“info security”**

Info: (d1, 3), (d2, 4), (d3, 1), (d4, 5)
Security: (d2, 3), (d4,1), (d5, 3)

			Accumulators:	**d1**	**d2**	**d3**	**d4**	**d5**
				0	0	0	0	0
info	(d1,3)	=>		**3**	0	0	0	0
	(d2,4)	=>		3	**4**	0	0	0
	(d3,1)	=>		3	4	**1**	0	0
	(d4,5)	=>		3	4	1	**5**	0
security	(d2,3)	=>		3	**7**	1	5	0
	(d4,1)	=>		3	7	1	**6**	0
	(d5,3)	=>		3	7	1	6	**3**

Further Improving Efficiency

- Caching (e.g., query results, list of inverted index)
- Keep only the most promising accumulators
- Scaling up to the Web-scale? (need parallel processing)

Some Text Retrieval Toolkits

- Lucene: http://lucene.apache.org/
- Lemur/Indri: http://www.lemurproject.org/
- Terrier: http://terrier.org/
- MeTA: http://meta-toolkit.github.io/meta/
- More can be found at http://timan.cs.uiuc.edu/resources

Summary of System Implementation

- Inverted index and its construction
  - Preprocess data as much as we can
  - Compression when appropriate
- Fast search using inverted index
  - Exploit inverted index to accumulate scores for documents matching a query term
  - Exploit Zipf’s law to avoid touching many documents not matching any query term
  - Can support a wide range of ranking algorithms
- Great potential for further scaling up using distributed file system, parallel processing, and caching

Additional Readings

- Ian H. Witten, Alistair Moffat, Timothy C. Bell: Managing Gigabytes: Compressing and Indexing Documents and Images, Second Edition. Morgan Kaufmann, 1999.
- Stefan Büttcher, Charles L. A. Clarke, Gordon V. Cormack: Information Retrieval - Implementing and Evaluating Search Engines. MIT Press, 2010.