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Information Retrieval

Vector Space Models

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The ranking problem

Given

- Some evidence of the user's need

Produce

- A list of matching information items
- In decreasing order of relevance

The ranking problem

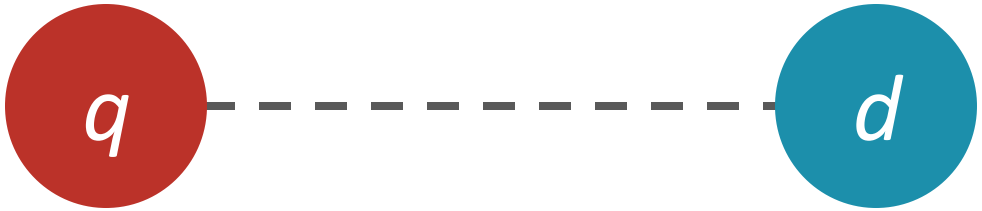
Given

- Some ~~evidence of the user’s need~~ ***query***

Produce

- A list of matching ~~information items~~ ***documents***
- In decreasing order of relevance

The ranking problem

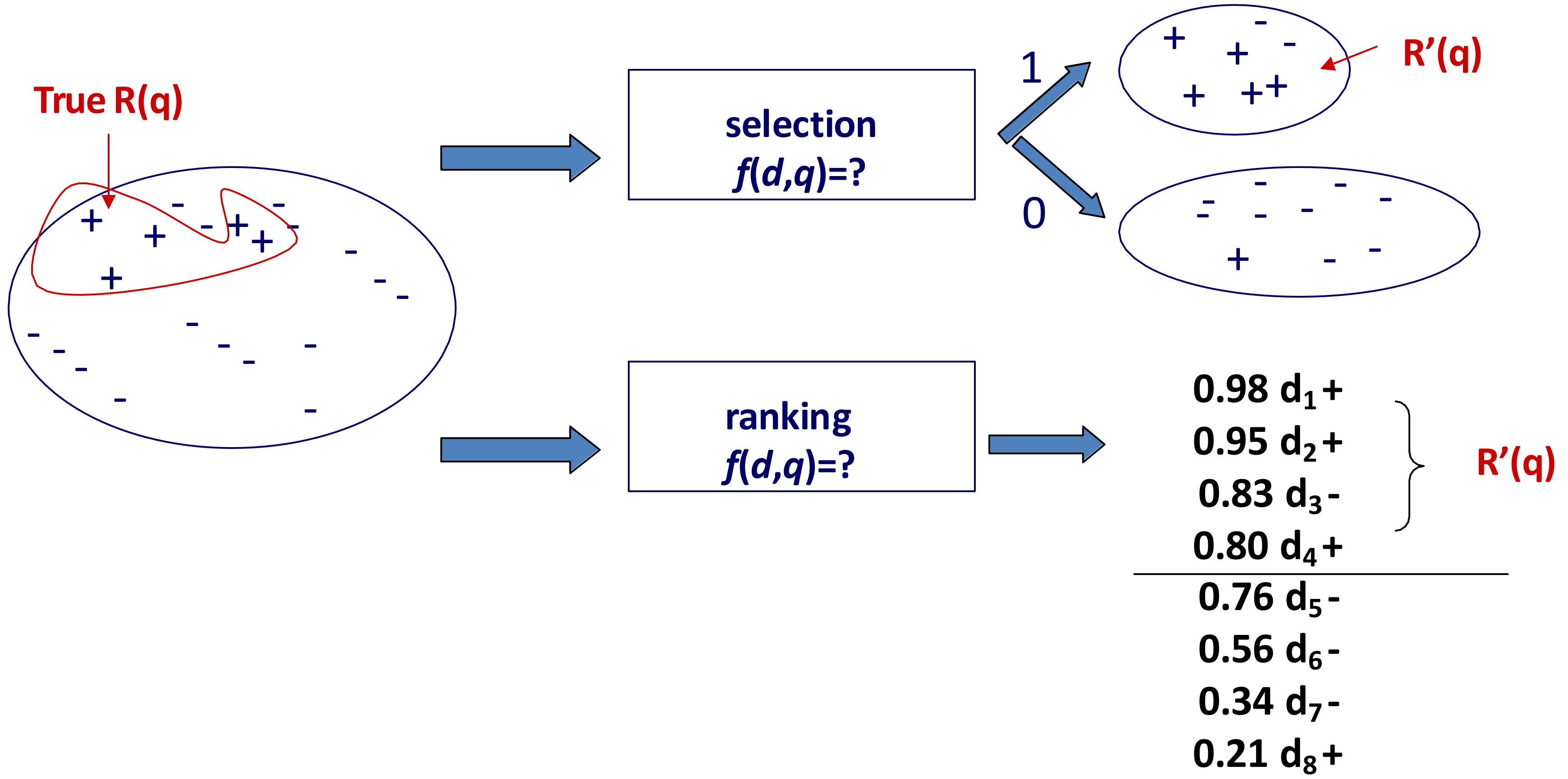


$$f(q,d)$$

Why rank?

Couldn't ***f*(*q*,*d*)** be just an indicator function?

Document selection vs. ranking



Why not select?

The classifier is unlikely accurate

- Over-constrained: no relevants returned
- Under-constrained: too many relevants returned
- Hard to find an appropriate threshold

Not all relevant documents are equally relevant!

- Prioritization is needed

Probability Ranking Principle (PRP)

“

Ranking documents by decreasing probability of relevance results in optimal effectiveness, provided that probabilities are estimated (1) with certainty and (2) independently.

- Robertson, 1977

Ranking effectiveness

Effectiveness is about doing the right thing; it's about finding documents that are relevant to the user

Relevance is influenced by many factors

- Topical relevance vs. user relevance
- Task, context, novelty, style

Ranking models define ***a view of*** relevance

Ranking models

Provide a mathematical framework for ranking

- Each model builds upon different assumptions

Progress in ranking models has corresponded with improvements in effectiveness

- An effective model should score relevant documents higher than non-relevant documents

Fundamental elements

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)

Many classical models

Similarity-based models: $f(q,d) = \mathrm{sim}(q,d)$

- Vector space models

Probabilistic models: $f(d,q) = p(R = 1|d,q)$

- Classic probabilistic models
- Language models
- Information-theoretic models

Many extended models

Structural models

- Beyond bags-of-words

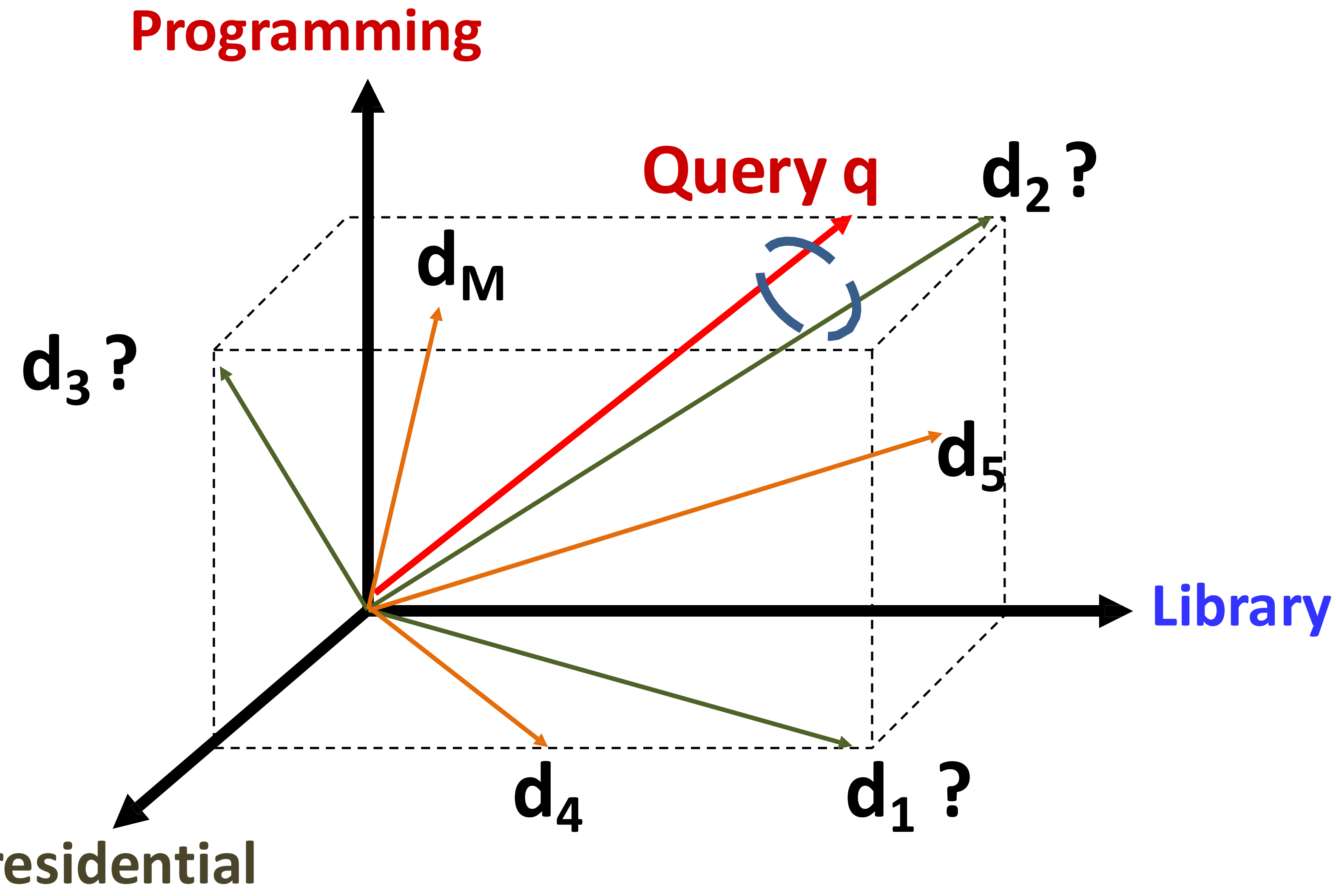
Semantic models

- Beyond lexical matching

Contextual models

- Beyond queries

Vector Space Model (VSM)



VSM is a framework

Queries and documents as term vectors

- Term as the basic concept (e.g., word or phrase)

A vocabulary V defines a $|V|$-dimensional space

- Vector components as real-valued term weights

Relevance estimated as $f(q,d) = \mathrm{sim}(q,d)$

- $q = \left(x_1, \dots, x_{|V|}\right)$ and $d = (y_1, \dots, y_{|V|})$

What VSM doesn't say

How to define vector dimensions

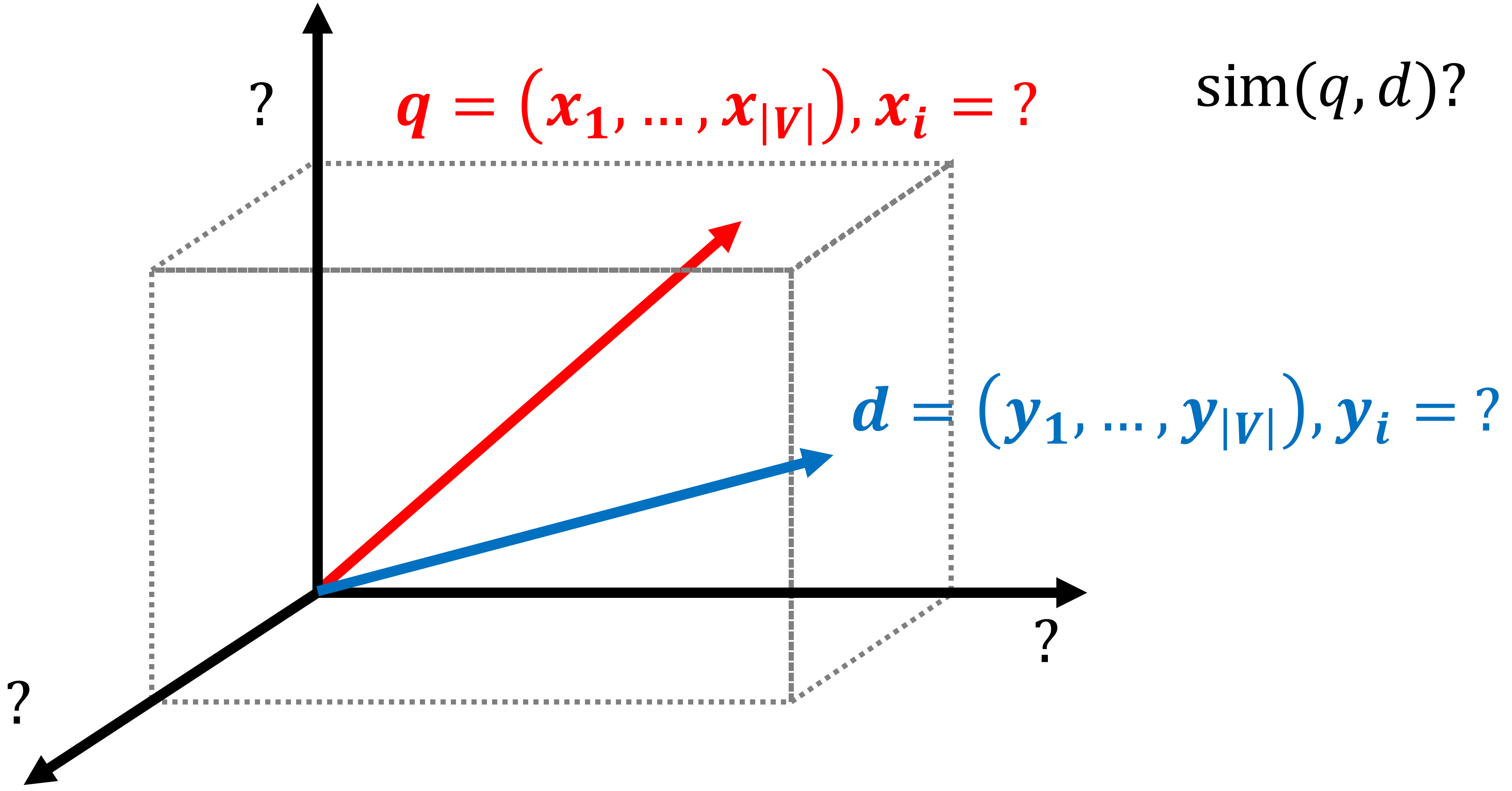
- Concepts are assumed to be orthogonal

How to place vectors in the space

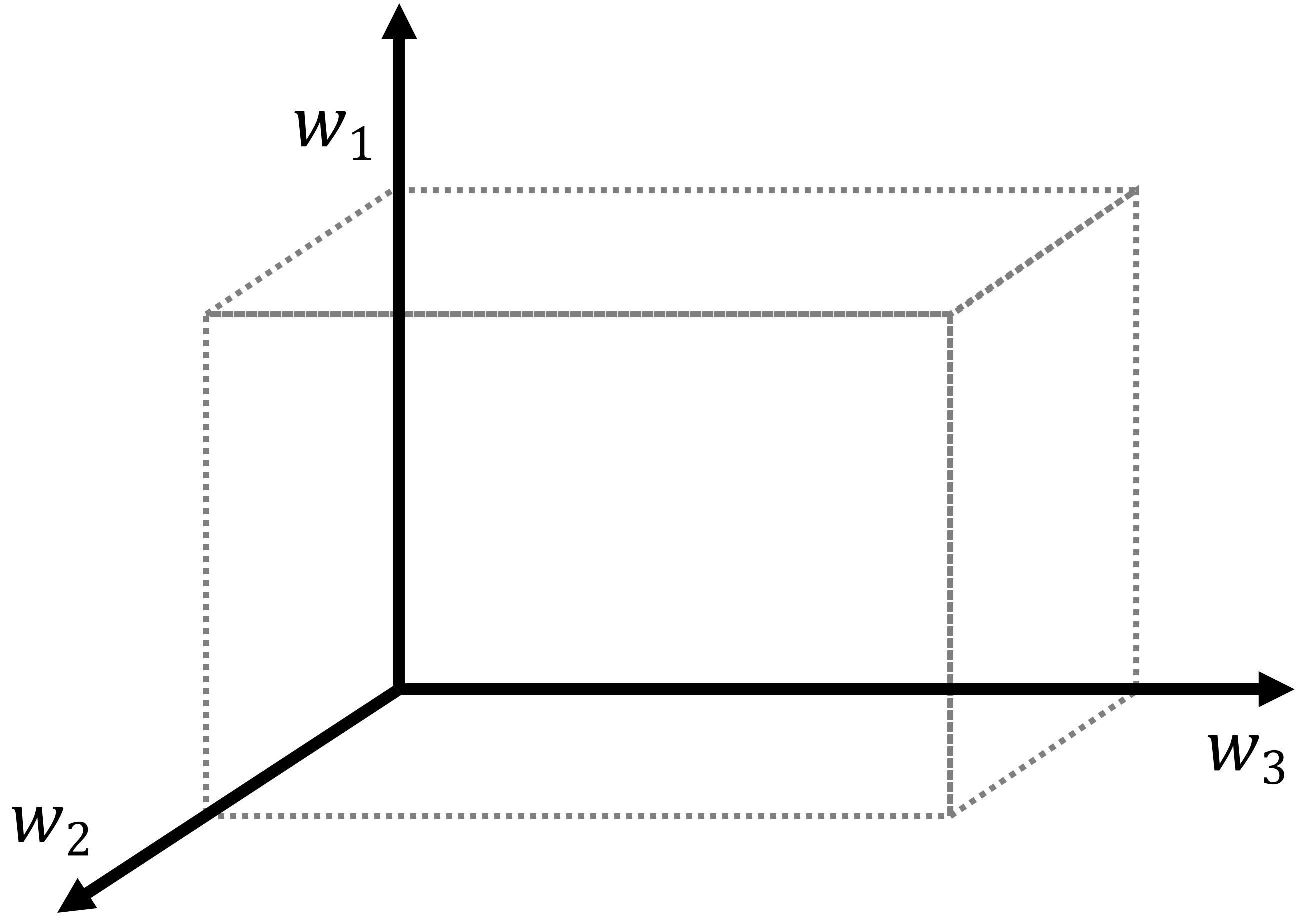
- Term weight in query indicates importance of term
- Term weight in document indicates topicality

How to define the similarity measure

What VSM doesn't say



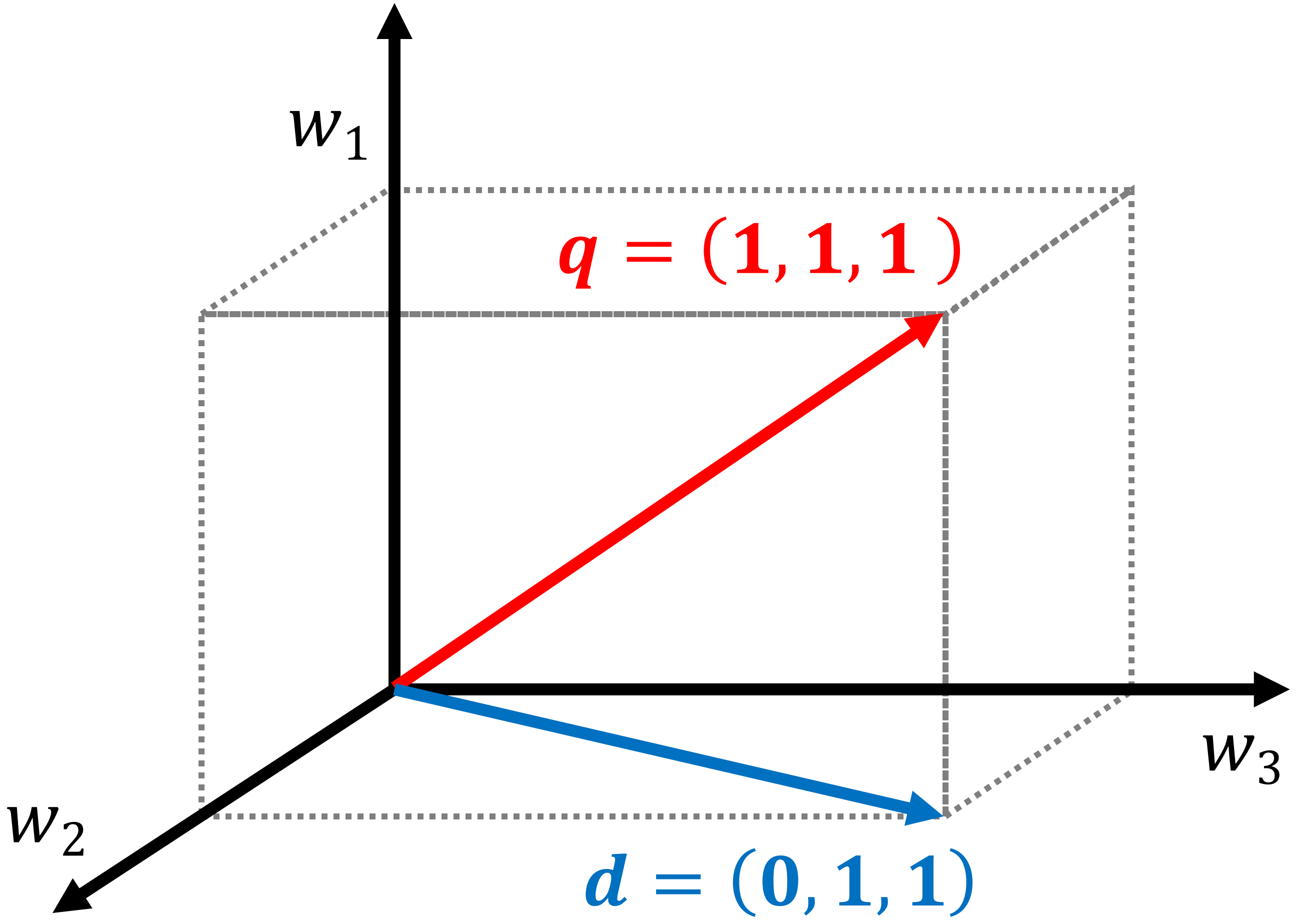
Dimensions as a bag of words (BOW)



Vocabulary

$V = (w_1, \ldots, w_{|V|})$

Vectors placed as bit vectors

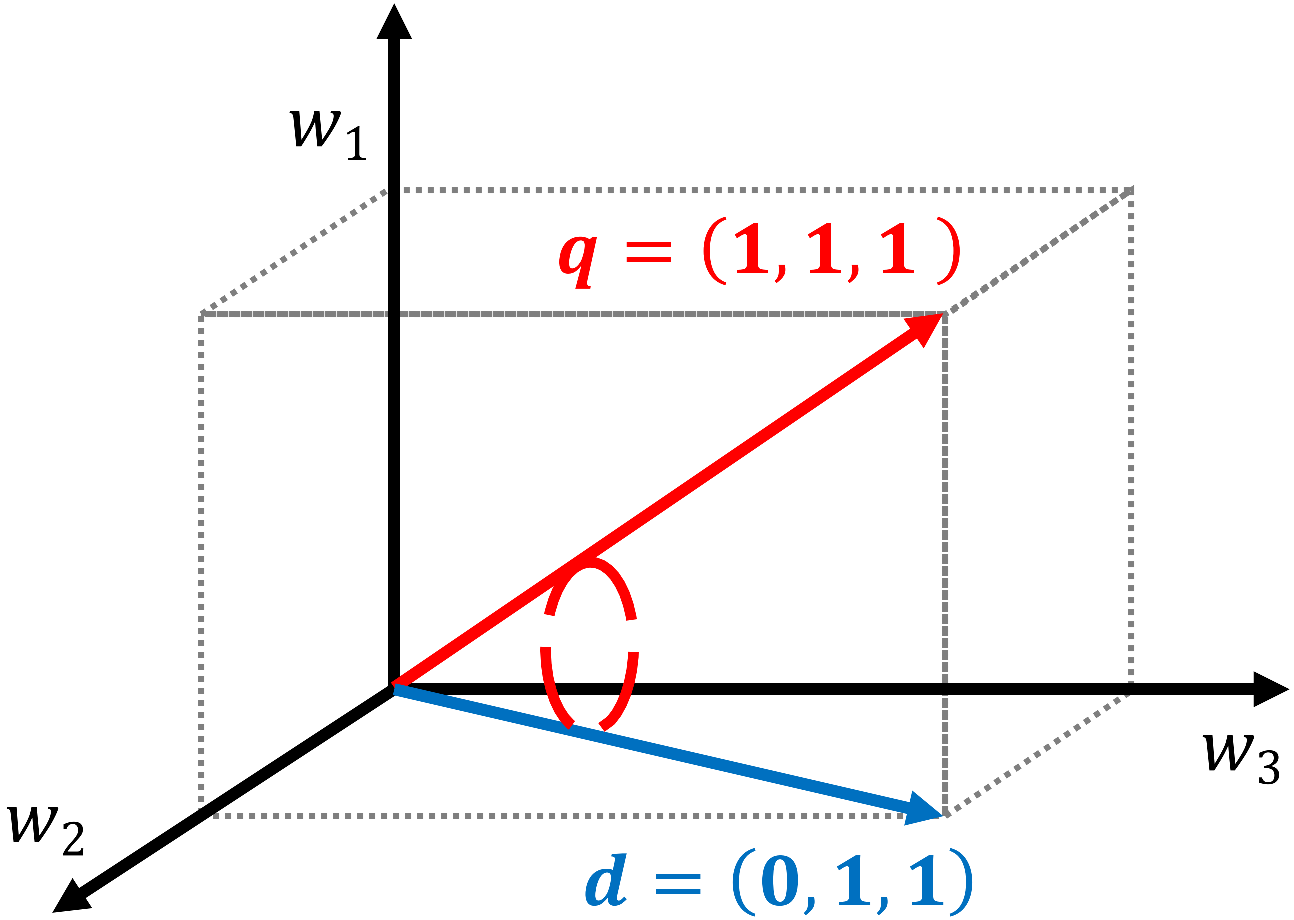


$x_i, y_i \in \{0,1\}$

1: word w_i is present

0: word w_i is absent

Similarity as dot product



$$\mathrm{sim}(q, d)$$
$$= q \cdot d$$
$$= x_1 y_1 + \cdots + x_{|V|} y_{|V|}$$
$$= \sum_{i=1}^{|V|} x_i y_i$$

Simplest VSM = BOW + bit vectors + dot

$\boldsymbol{q} = (\boldsymbol{x_1}, \dots, \boldsymbol{x_{|V|}})$

$\boldsymbol{d} = (\boldsymbol{y_1}, \dots, \boldsymbol{y_{|V|}})$

$x_i, y_i \in \{0,1\}$

1: word w_i is present

0: word w_i is absent

$$\begin{aligned} &\mathrm{sim}(q, d) \\ &= q \cdot d \\ &= x_1 y_1 + \cdots + x_{|V|} y_{|V|} \\ &= \sum_{i=1}^{|V|} x_i y_i \end{aligned}$$

What does this ranking function intuitively capture?

Is this a good ranking function?

How would you rank these documents?

q = [news about presidential campaign]

		ideal
d_1	… **news about** …	d_4 +
d_2	… **news about** organic food **campaign**…	d_3 +
d_3	… **news** of **presidential campaign** …	d_1 −
d_4	… **news** of **presidential campaign** … … **presidential** candidate …	d_2 −
d_5	… **news** of organic food **campaign**… **campaign**…**campaign**…**campaign**…	d_5 −

Ranking using the simplest VSM

q = [news about presidential campaign]

d_1	… **news about** …
d_3	… **news** of **presidential campaign** …

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

$$q = (1, 1, 1, 1, 0, \dots)$$

$$d_1 = (1, 1, 0, 0, 0, \dots) \qquad \mathrm{sim}(q, d_1) = 2$$

$$d_3 = (1, 0, 1, 1, 0, \dots) \qquad \mathrm{sim}(q, d_3) = 3$$

Is it effective?

q = [news about presidential campaign]		***f*(*q*,*d*)**	**ranking**	**ideal**
d_1	... **news about** ...	2	d_2	d_4 +
d_2	... **news about** organic food **campaign**...	3	d_3	d_3 +
d_3	... **news** of **presidential campaign** ...	3	d_4	d_1 −
d_4	... **news** of **presidential campaign** ... ... **presidential** candidate ...	3	d_1	d_2 −
d_5	... **news** of organic food **campaign**... **campaign**...**campaign**...**campaign**...	2	d_5	d_5 −

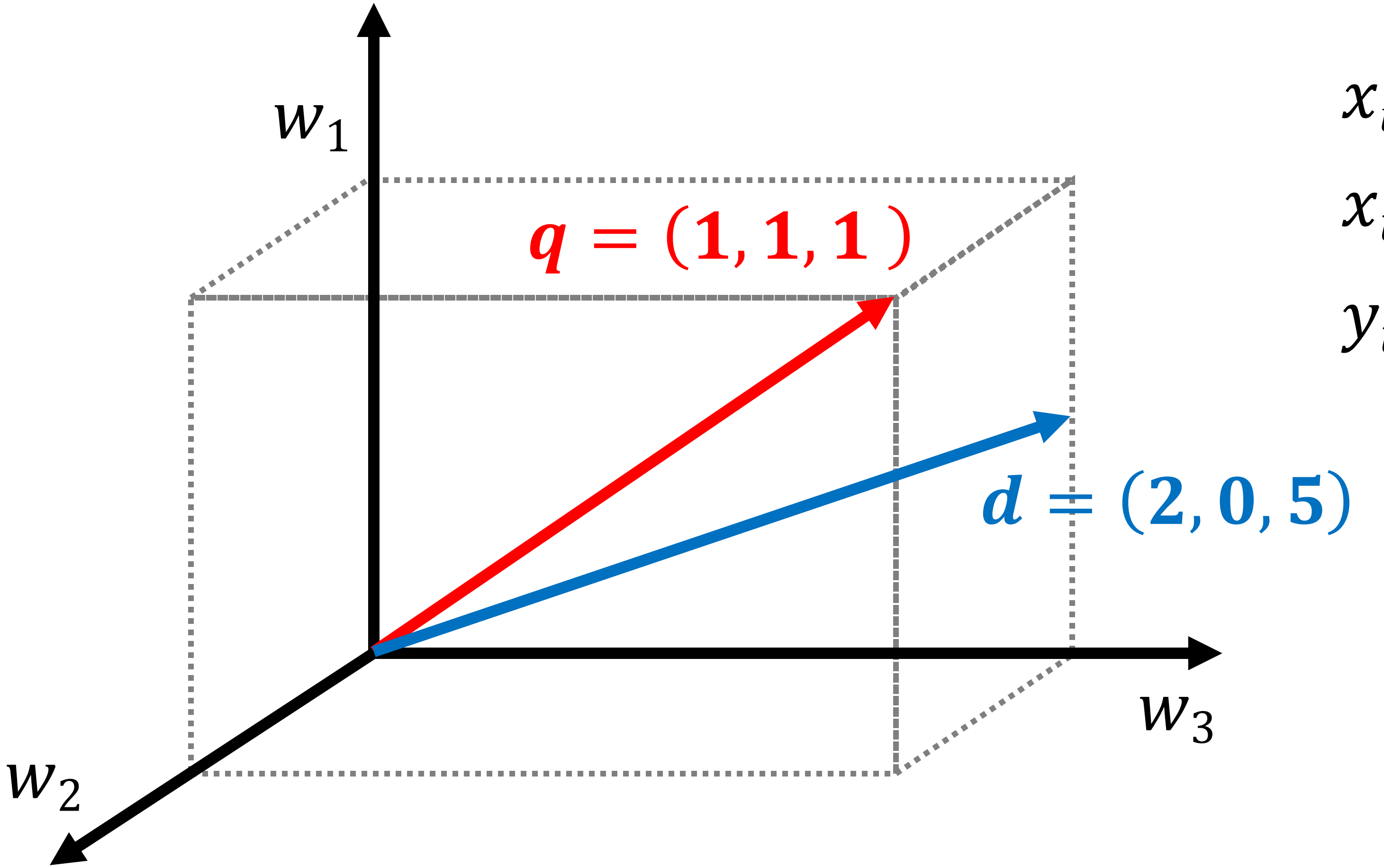
What's wrong with it?

q = [news about presidential campaign]

	$f(q,d)$	ranking	ideal
		d_2	d_4 +
		d_3	d_3 +
d_3: … **news** of **presidential campaign** …	3	d_4	d_1 −
d_4: … **news** of **presidential campaign** … … **presidential** candidate …	3	d_1	d_2 −
		d_5	d_5 −

Matching "presidential" ***more times*** *deserves more credit!*

Vectors placed as tf vectors



$x_i, y_i \in \mathbb{N}$

$x_i: \mathrm{tf}_{w_i,q}$

$y_i: \mathrm{tf}_{w_i,d}$

Ranking using VSM with tf vectors

q = [news about presidential campaign]

d_3	… **news** of **presidential campaign** …
d_4	… **news** of **presidential campaign** … … **presidential** candidate …

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

$$q = (1, 1, 1, 1, 0, \ldots)$$

$$d_3 = (1, 0, 1, 1, 0, \ldots) \qquad \mathrm{sim}(q, d_3) = 3$$

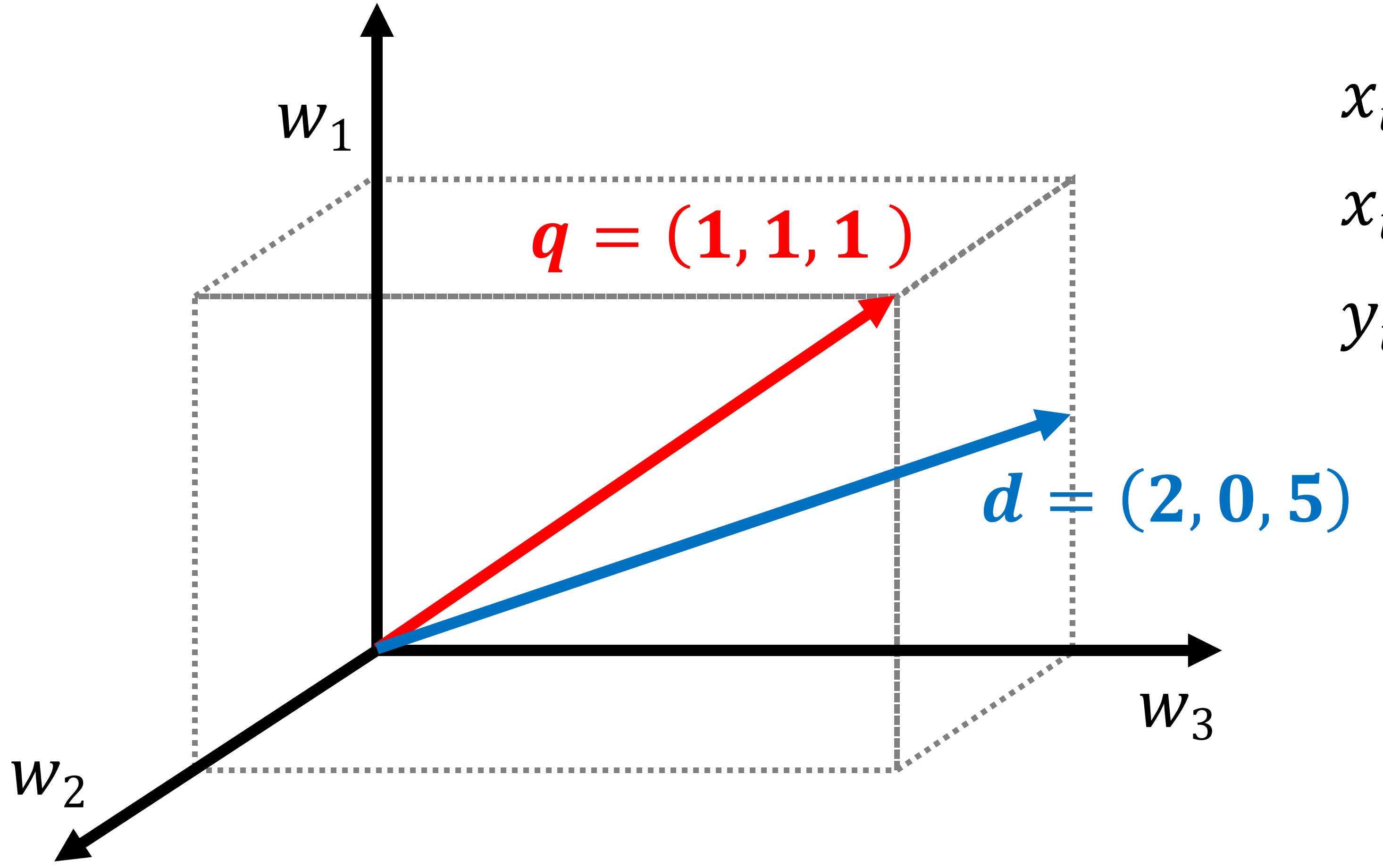
$$d_4 = (1, 0, 2, 1, 0, \ldots) \qquad \mathrm{sim}(q, d_4) = 4$$

What's wrong with it?

q = [news about presidential campaign]	***f*(*q*,*d*)**	**ranking**	**ideal**
		d_2	$d_4 +$
d_2 … **news about** organic food **campaign**…	3	d_3	$d_3 +$
d_3 … **news** of **presidential campaign** …	3	d_4	$d_1 -$
		d_1	$d_2 -$
		d_5	$d_5 -$

*Matching "presidential" is **more important** than matching "about"!*

Vectors placed as tf-idf vectors



$x_i, y_i \in \mathbb{R}$

x_i: $\mathrm{tf}_{w_i,q}\ \mathrm{idf}_{w_i}$

y_i: $\mathrm{tf}_{w_i,d}\ \mathrm{idf}_{w_i}$

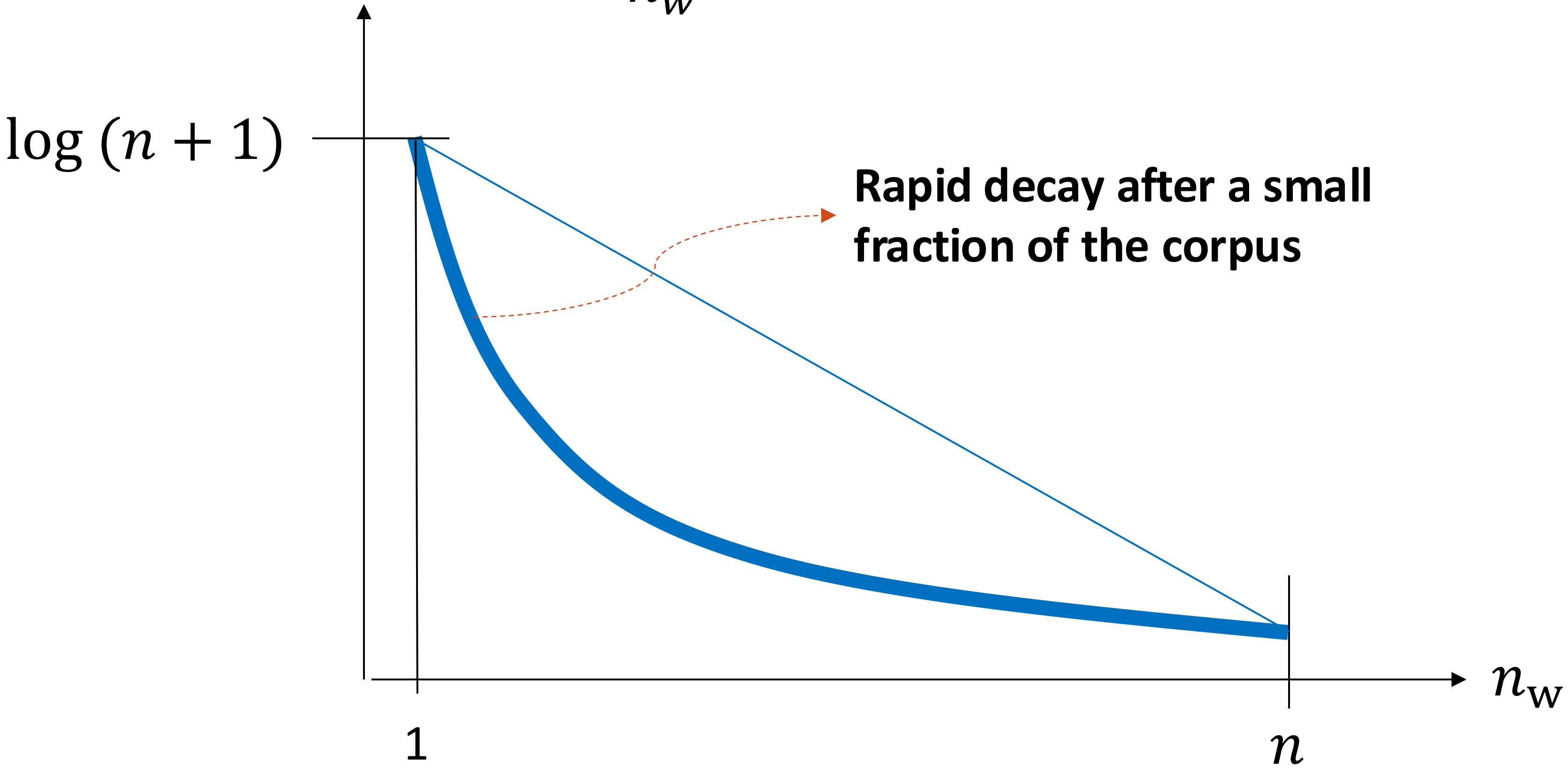
Inverse document frequency (idf)

$$\mathrm{idf}_{\mathrm{w}} = \log \frac{n+1}{n_w}$$

- n: number of documents in the corpus
- n_w: number of documents where w appears

Why a log-based penalization?

$$\mathrm{idf}_{\mathrm{w}} = \log \frac{n+1}{n_w}$$



Ranking using VSM with tf-idf vectors

q = [news about presidential campaign]

d_2	… **news about** organic food **campaign**…
d_3	… **news** of **presidential campaign** …

V = { news, about, presidential, campaign, food, … }
idf = (1.5, 1.0, 2.5, 3.1, 1.8, …)

$$q = (1, 1, 1, 1, 0, \dots)$$

$$d_2 = (1 * 1.5, 1 * 1.0, 0, 1 * 3.1, 0, \dots) \qquad \mathrm{sim}(q, d_2) = 5.6$$

$$d_3 = (1 * 1.5, 0, 1 * 2.5, 1 * 3.1, 0, \dots) \qquad \mathrm{sim}(q, d_3) = 7.1$$

Is it effective?

q = [news about presidential campaign]		$f(q,d)$	ranking	ideal
d_1	… **news about** …	2.5	d_5	d_4 +
d_2	… **news about** organic food **campaign**…	5.6	d_4	d_3 +
d_3	… **news** of **presidential campaign** …	7.1	d_3	d_1 −
d_4	… **news** of **presidential campaign** … … **presidential** candidate …	9.6	d_2	d_2 −
d_5	… **news** of organic food **campaign**… **campaign**…**campaign**…**campaign**…	13.9	d_1	d_5 −

Is it effective?

q = [news about presidential campaign]

$f(q,d)$	ranking	ideal
2.5	d_5	d_4 +
5.6	d_4	d_3 +
7.1	d_3	d_1 −
9.6	d_2	d_2 −
13.9	d_1	d_5 −

d_4	… **news** of **presidential campaign** … … **presidential** candidate …
d_5	… **news** of organic food **campaign**… **campaign**…**campaign**…**campaign**…

Ranking using VSM with tf-idf vectors

q = [news about presidential campaign]

d_4	… **news** of **presidential campaign** … … **presidential** candidate …
d_5	… **news** of organic food **campaign**… **campaign**…**campaign**…**campaign**…

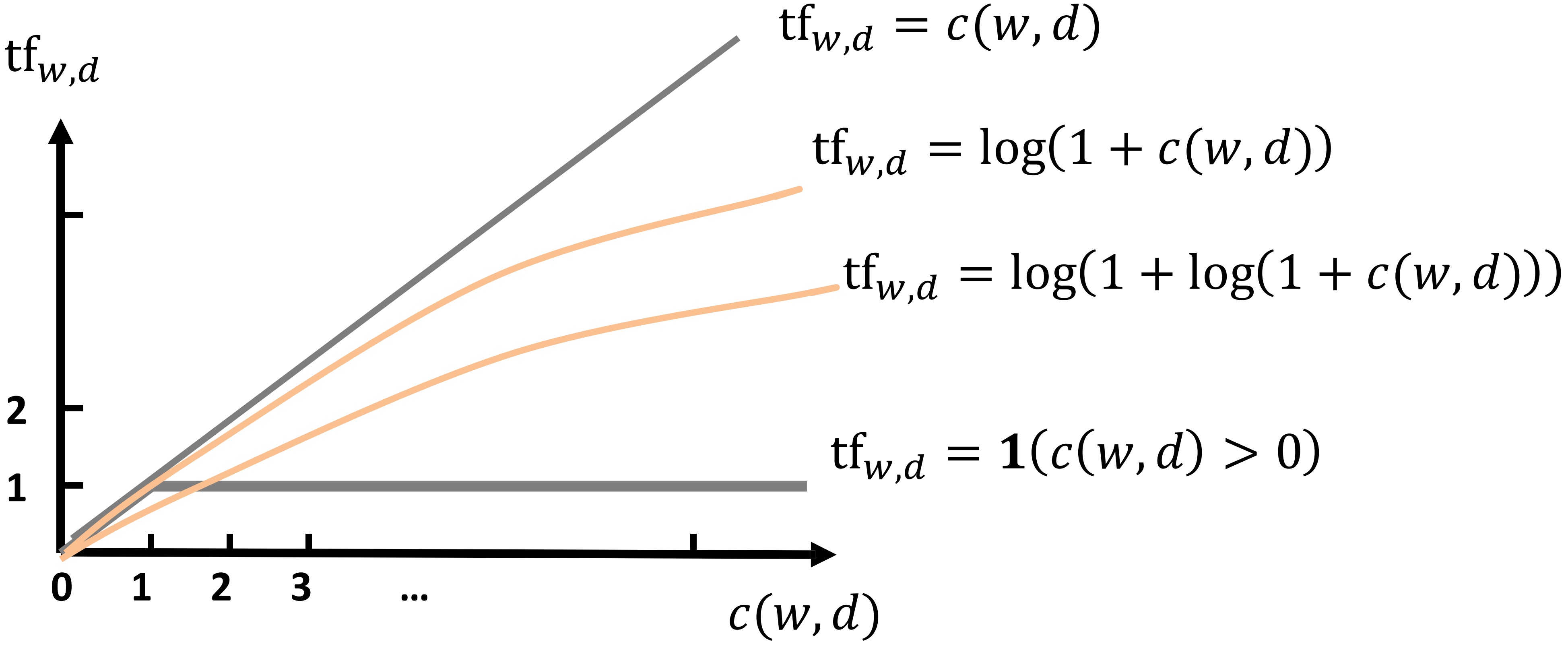
V = { news, about, presidential, campaign, food, … }
idf = (1.5, 1.0, 2.5, 3.1, 1.8, …)

$$q = (1, 1, 1, 1, 0, \dots)$$

$$d_4 = (1 * 1.5, 0, 2 * 2.5, 1 * 3.1, 0, \dots) \qquad \mathrm{sim}(q, d_4) = 9.6$$

$$d_5 = (1 * 1.5, 0, 0, 4 * 3.1, 1 * 1.8, \dots) \qquad \mathrm{sim}(q, d_5) = 13.9$$

Transforming tf



What about document length?

q = [news about presidential campaign]

d_4	... **news** of **presidential campaign** ... ... **presidential** candidate ...	**100 words**
d_6	... **campaign**......... **campaign**.................. ....**news**.. .... **news**..... .... **presidential** ......**presidential**......	**5000 words**

$$f(q, d_6) > f(q, d_4)?$$

Document length normalization

Penalize long documents

- Avoid matching by chance
- Must also avoid over-penalization

A document is long because

- It uses more words → more penalization
- It has more content → less penalization

Pivoted length normalization (pln)

$$\text{pln}_d = (1 - b) + b\,\frac{|d|}{\text{avdl}}$$

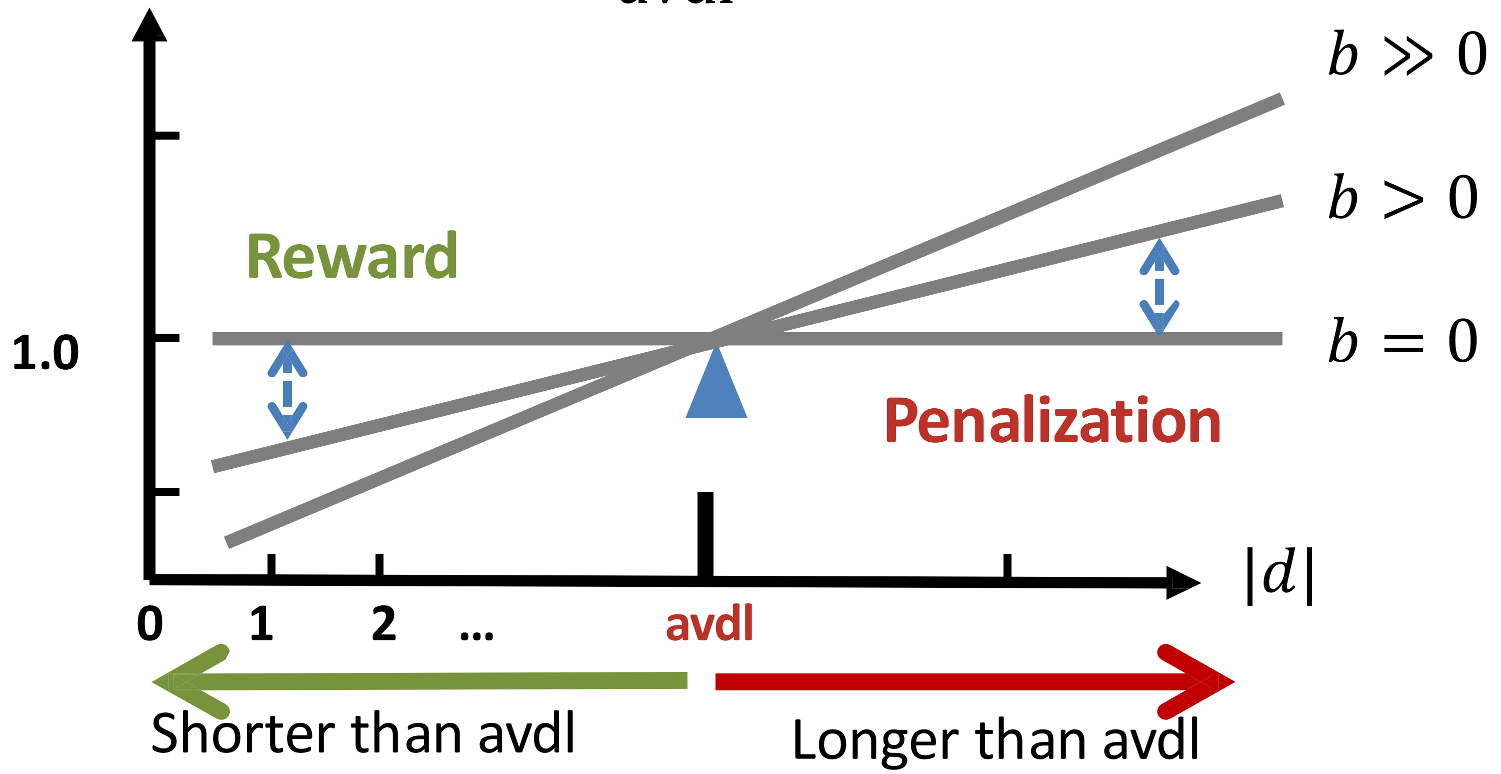
◦ $|d|$: document length in tokens

◦ avdl: average document length in the corpus

◦ $b \in [0,1]$: parameter

Pivoted length normalization (pln)

$$\text{pln}_d = (1 - b) + b\,\frac{|d|}{\text{avdl}}$$



State-of-the-art VSM ranking

Pivoted length normalization VSM [Singhal et al. 1996]

- $f(q,d) = \sum_{w \in q} c(w,q) \frac{\ln(1+\ln(1+c(w,d)))}{(1-b)+b\frac{|d|}{avdl}} \log \frac{n+1}{n_w}$

Okapi/BM25 [Robertson and Walker, 1994]

- $f(q,d) = \sum_{w \in q} c(w,q) \frac{(k_1+1)\, c(w,d)}{c(w,d)+k_1\left((1-b)+b\frac{|d|}{avdl}\right)} \log \frac{n+1}{n_w}$

Summary

Fundamental ranking components

- Term and document frequency
- Document length

VSM is a framework

- Components as term and document weights
- Relevance as query-document similarity

Summary

Lack of theoretical justification

- Axiomatic approaches, probabilistic approaches

Room for further improvement

- Structure, semantics, feedback, context
- Feature-based models

References

Text Data Management: A Practical Introduction to Information Retrieval and Text Mining, Ch. 6
Zhai and Massung, 2016

Search Engines: Information Retrieval in Practice, Ch. 7
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Robertson and Walker, SIGIR 1994

The probability ranking principle in IR
Robertson, J. Doc. 1977

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Coming next...

Language Models

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