Information Retrieval & Text Mining

Paradigmatic Relation Discovery

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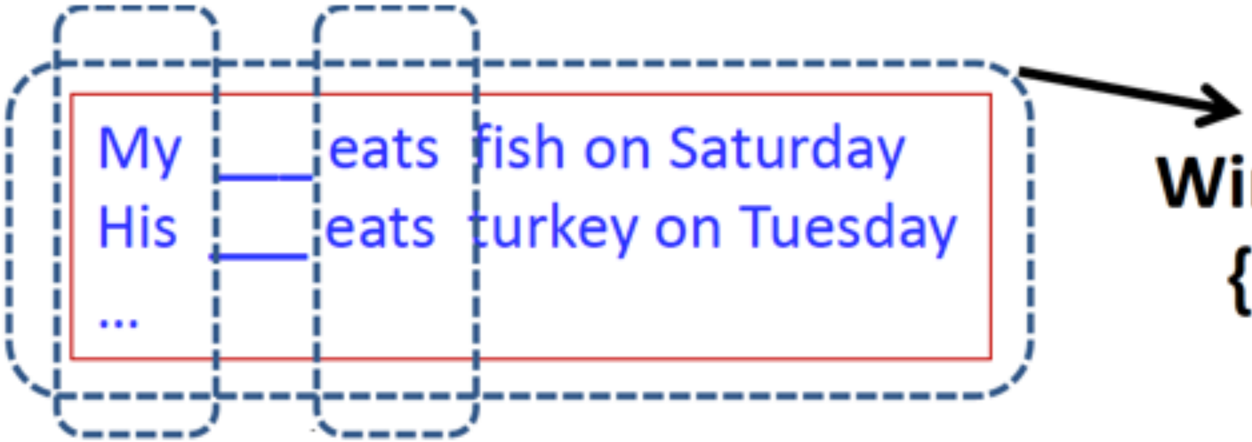
Word Context as "Pseudo Document"

cat:

My ___ eats fish on Saturday
His ___ eats turkey on Tuesday
...

Word Context as "Pseudo Document"

cat:



Window8("cat") =
{"my", "his", "big",
"eats", "fish", ...}

Word Context as “Pseudo Document”

Left1(“cat”) = {“my”, “his”, “big”, “a”, “the”,…}

cat:

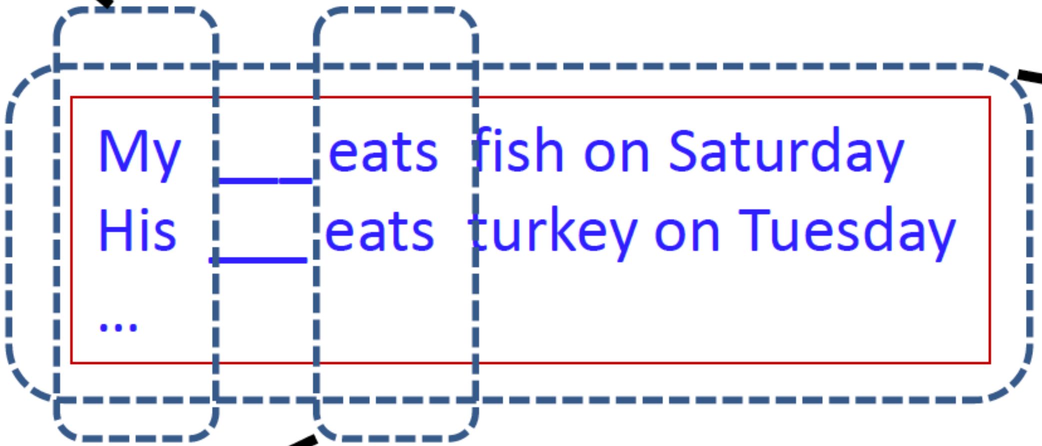
My ___ eats fish on Saturday
His ___ eats turkey on Tuesday
…

Window8(“cat”) =
{“my”, “his”, “big”,
“eats”, “fish”, …}

Word Context as “Pseudo Document”

Left1(“cat”) = {“my”, “his”, “big”, “a”, “the”,…}

cat:



Window8(“cat”) = {“my”, “his”, “big”, “eats”, “fish”, …}

Right1(“cat”) = {“eats”, “ate”, “is”, “has”, ….}

Context = pseudo document = “bag of words”
Context may contain adjacent or non-adjacent words

Measuring Context Similarity

Sim("Cat", "Dog") =

Sim(Left1("cat"), Left1("dog"))

+ Sim(Right1("cat"), Right1("dog")) +

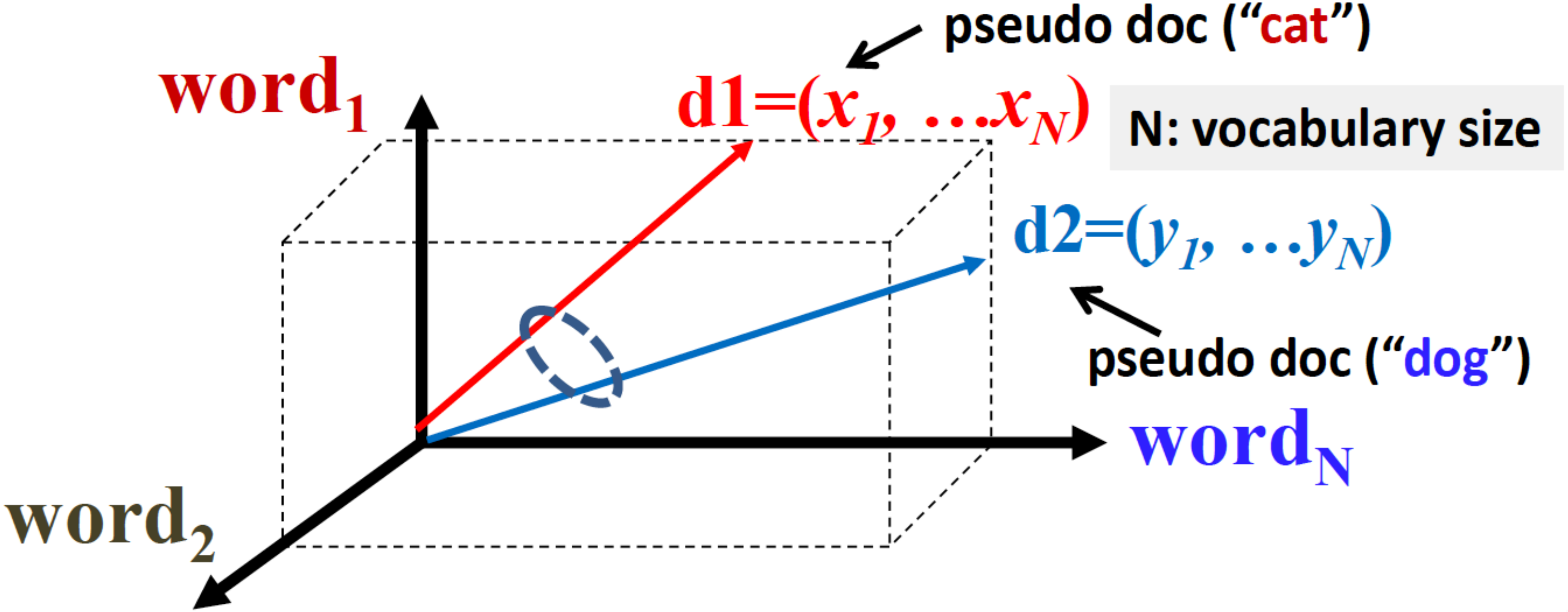
…

+ Sim(Window8("cat"), Window8("dog"))=?

High sim(word1, word2)

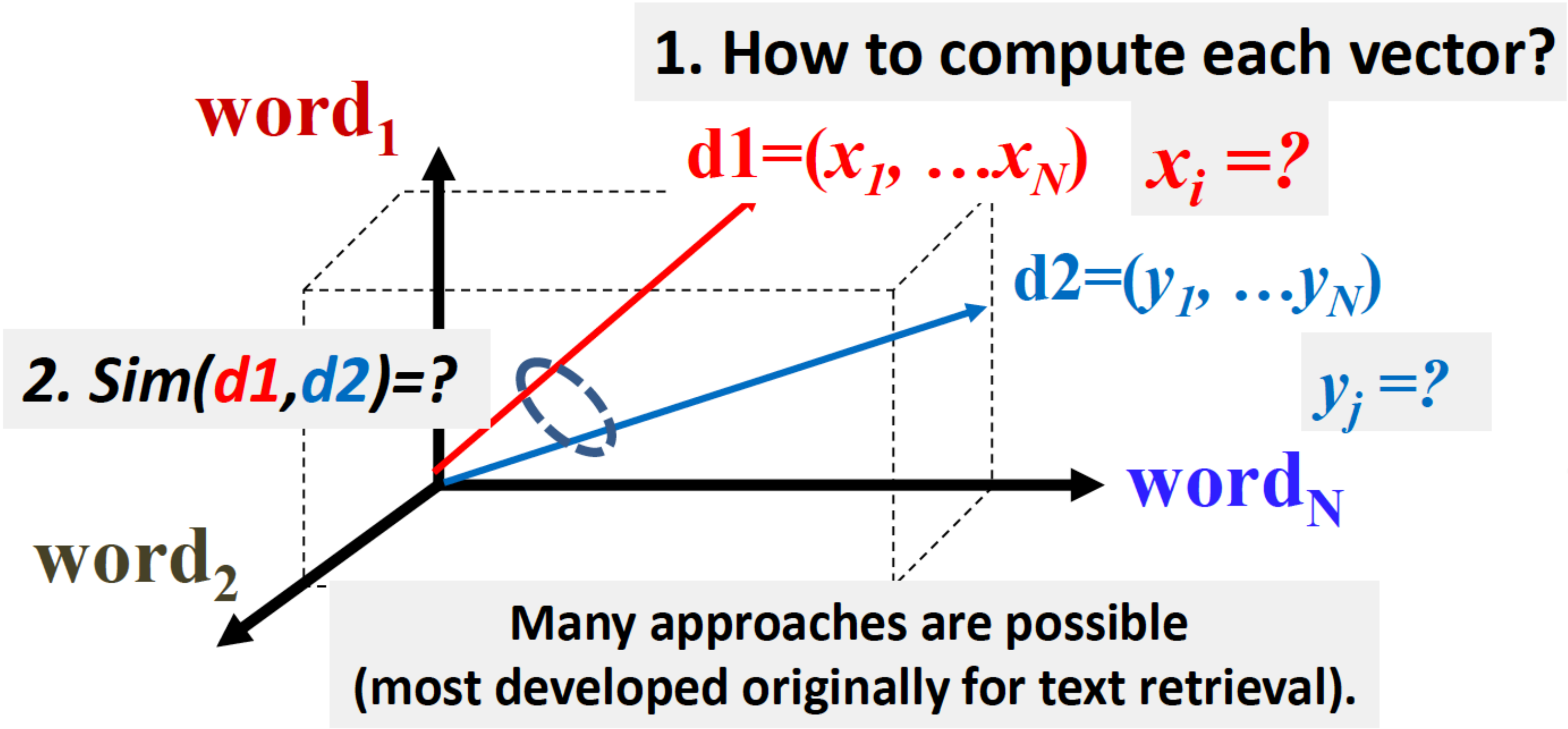
➔ word1 and word2 are **paradigmatically related**

Bag of Words → Vector Space Model (VSM)



Terms:	"eats"	"ate"	"is"	"has"	....
Vector:	(5,	3,	10,	3	....)

VSM for Paradigmatic Relation Mining



Expected Overlap of Words in Context (EOWC)

Probability that a randomly picked word from d1 is wi

Count of word wi in d1

$d1 = (x_1, \ldots x_N)$ $\quad x_i = c(w_i, d1)/|d1|$

$d2 = (y_1, \ldots y_N)$ $\quad y_i = c(w_i, d2)/|d2|$

Total counts of words in d1

$$Sim(d1, d2) = d1.d2 = x_1 y_1 + \ldots + x_N y_N = \sum_{i=1}^{N} x_i y_i$$

Probability that two randomly picked words from d1 and d2, respectively, are identical.

Would EOWC Work Well?

- Intuitively, it makes sense: The more overlap the two context documents have, the higher the similarity would be.
- However:
  - It favors matching one frequent term very well over matching more distinct terms.
  - It treats every word equally (overlap on “the” isn’t as so meaningful as overlap on “eats”).

Improving EOWC with Retrieval Heuristics

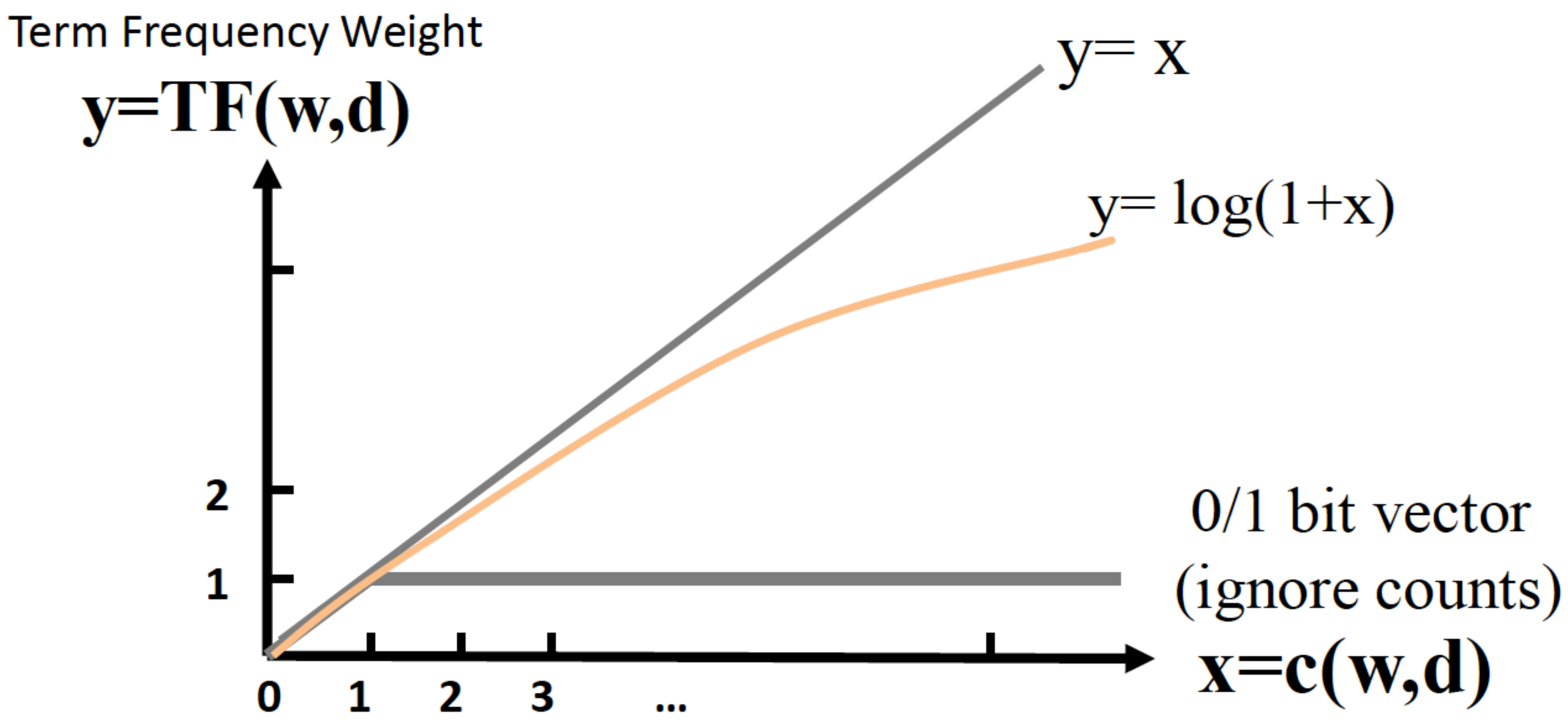
- It favors matching one frequent term very well over matching more distinct terms.

➔ **Sublinear transformation of Term Frequency (TF)**

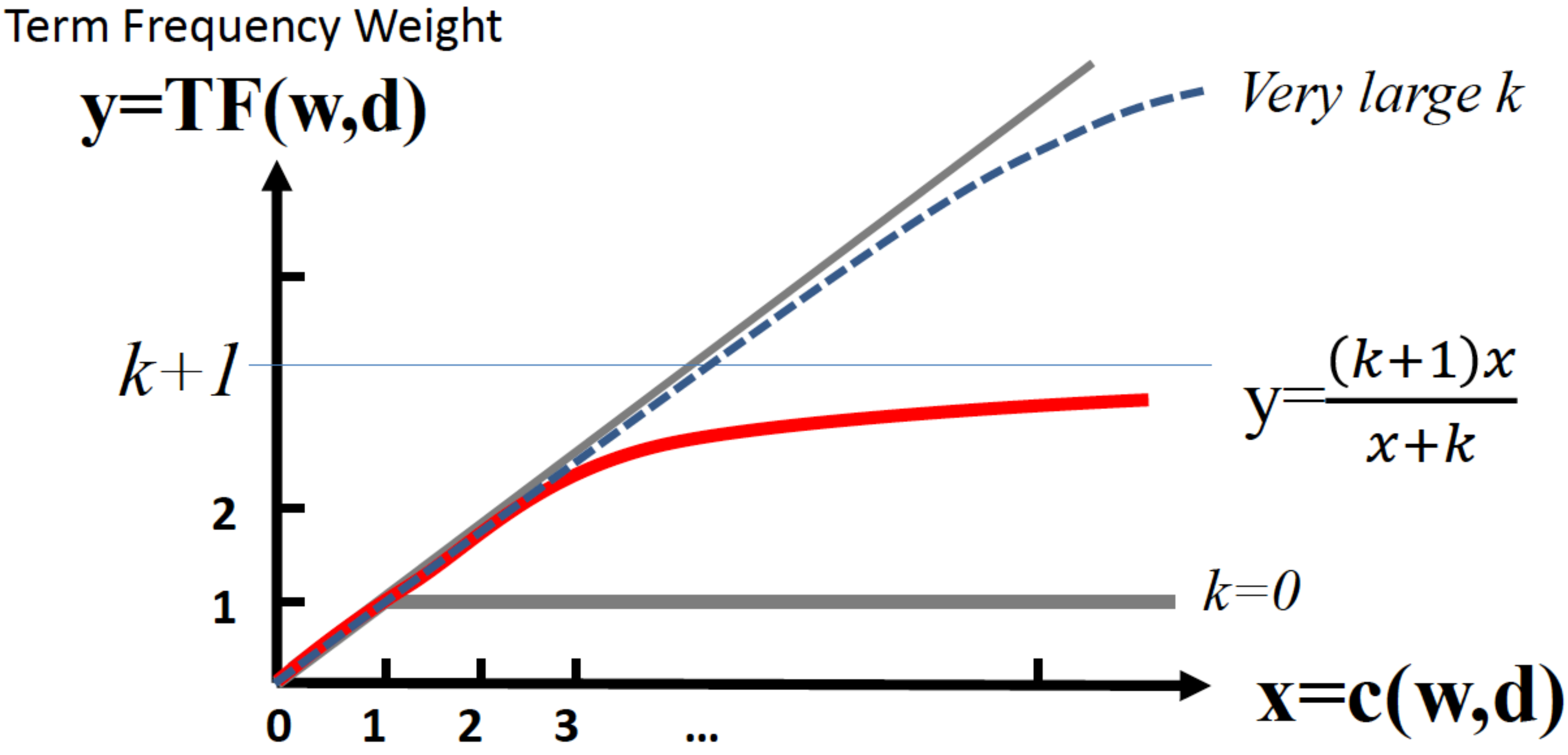
- It treats every word equally (overlap on “the” isn’t as so meaningful as overlap on “eats”).

➔ **Reward matching a rare word: IDF term weighting**

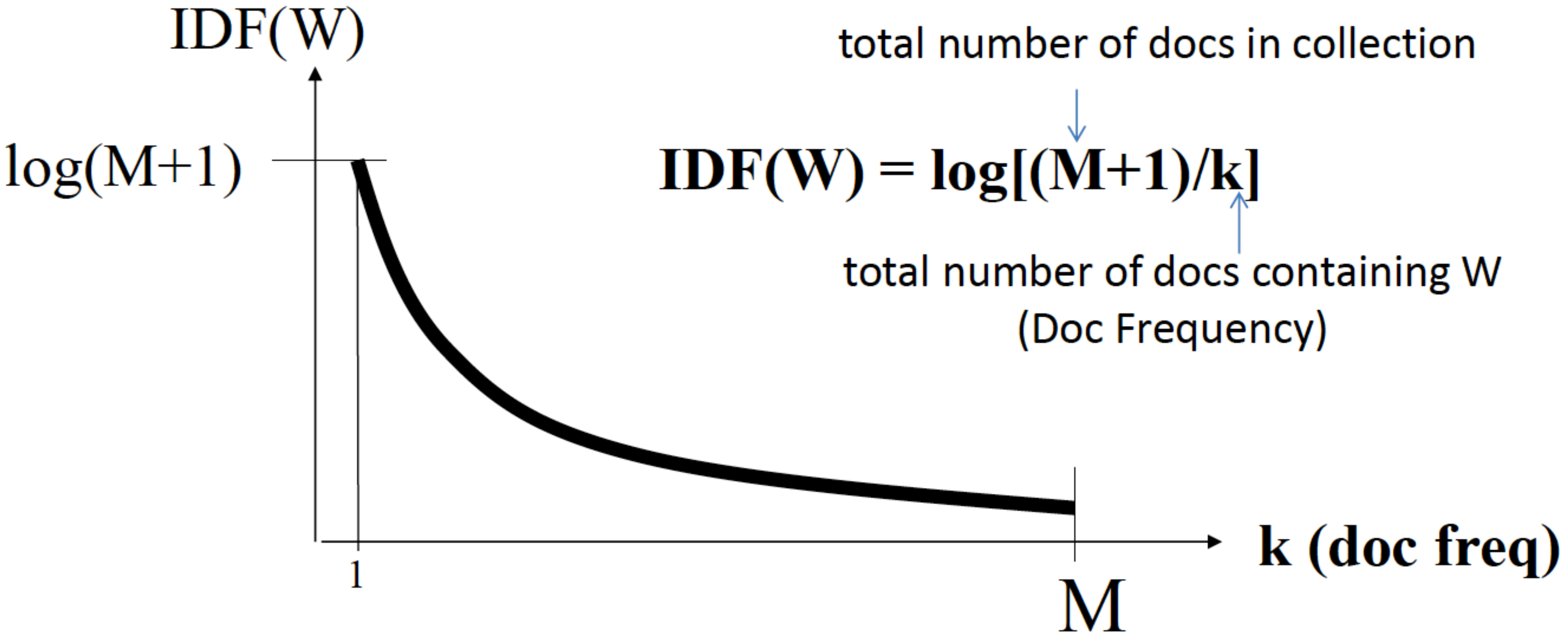
TF Transformation: c(w,d)➔TF(w,d)



TF Transformation: BM25 Transformation



IDF Weighting: Penalizing Popular Terms



Adapting BM25 Retrieval Model for Paradigmatic Relation Mining

$d1=(x_1, \ldots x_N)$ $\quad \mathrm{BM25}(w_i, d1) = \dfrac{(k+1)c(w_i, d1)}{c(w_i, d1) + k(1 - b + b^* |d1| / avdl)}$

$$x_i = \frac{\mathrm{BM25}(w_i, d1)}{\sum_{j=1}^{N} \mathrm{BM25}(w_j, d1)}$$

$b \in [0,1]$

$k \in [0,+\infty)$

$d2=(y_1, \ldots y_N)$ $\quad$ **y_i is defined similarly**

$$Sim(d1,d2)=\sum_{i=1}^{N} IDF(w_i)\, x_i\, y_i$$

BM25 can also Discover Syntagmatic Relations

$d1=(x_1, \ ...x_N)$

$$BM25(w_i, d1) = \frac{(k+1)c(w_i, d1)}{c(w_i, d1) + k(1 - b + b^* | d1 | / avdl)}$$

$$x_i = \frac{BM25(w_i, d1)}{\sum_{j=1}^{N} BM25(w_j, d1)}$$

$b \in [0,1]$

$k \in [0,+\infty)$

IDF-weighted $d1=(x_1{}^*IDF(w_1), \ ..., \ x_N{}^*IDF(w_N))$

The highly weighted terms in the context vector of word w are likely syntagmatically related to w.

Summary

- Main idea for discovering paradigmatic relations:
  – Collecting the context of a candidate word to form a pseudo document (bag of words)
  – Computing similarity of the corresponding context documents of two candidate words
  – Highly similar word pairs can be assumed to have paradigmatic relations
- Many different ways to implement this general idea
- Text retrieval models can be easily adapted for computing similarity of two context documents
  – BM25 + IDF weighting represents the state of the art
  – Syntagmatic relations can also be discovered as a "by product"