Word Association Mining and Analysis

Instructor: Junghye Lee

February 28th 2018

Outline

- What is a word association?
- Why mine word associations?
- How to mine word associations?

Basic Word Relations: Paradigmatic vs. Syntagmatic

- Paradigmatic: A & B have paradigmatic relation if they can be substituted for each other (i.e., A & B are in the same class)
  - E.g., “cat” and “dog”; “Monday” and “Tuesday”
- Syntagmatic: A & B have syntagmatic relation if they can be combined with each other (i.e., A & B are related semantically)
  - E.g., “cat” and “sit”; “car” and “drive”
- These two basic and complementary relations can be generalized to describe relations of any items in a language

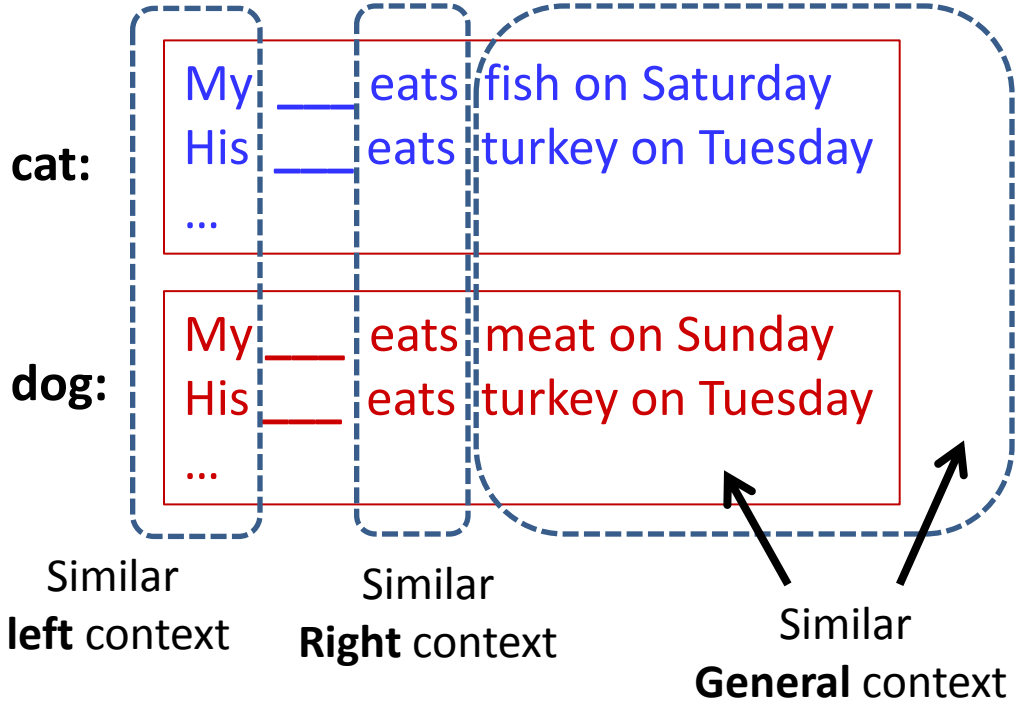
Why Mine Word Associations?

- They are useful for improving accuracy of many NLP tasks
  - POS tagging, parsing, entity recognition, acronym expansion
  - Grammar learning
- They are directly useful for many applications in text retrieval and mining
  - Text retrieval (e.g., use word associations to suggest a variation of a query)
  - Automatic construction of topic map for browsing: words as nodes and associations as edges
  - Compare and summarize opinions (e.g., what words are most strongly associated with “battery” in positive and negative reviews about iPhone 6, respectively?)

Mining Word Associations: Intuitions

Paradigmatic: similar context

My **cat** eats fish on Saturday
His **cat** eats turkey on Tuesday
My **dog** eats meat on Sunday
His **dog** eats turkey on Tuesday
…

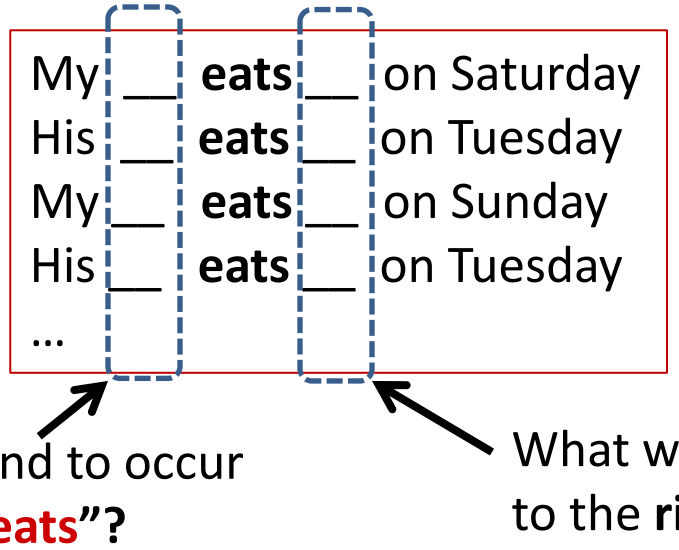


How similar are context ("cat") and context ("dog")?
How similar are context ("cat") and context ("computer")?

Mining Word Associations: Intuitions

Syntagmatic: correlated occurrences

My cat **eats** fish on Saturday
His cat **eats** turkey on Tuesday
My dog **eats** meat on Sunday
His dog **eats** turkey on Tuesday
…



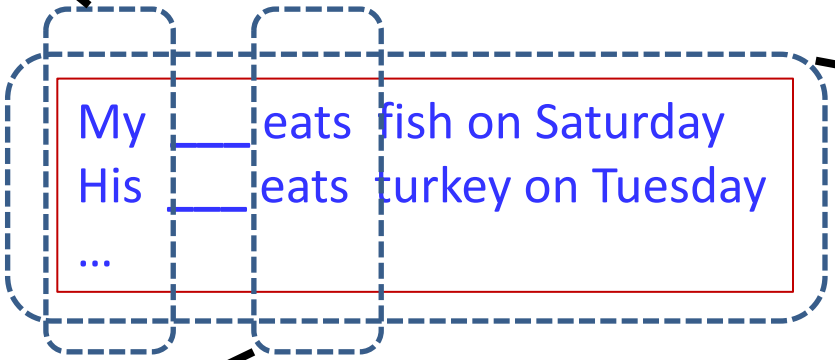
Whenever "**eats**" occurs, what **other words** also tend to occur?
How helpful is the occurrence of "**eats**" for predicting occurrence of "**meat**"?
How helpful is the occurrence of "**eats**" for predicting occurrence of "**text**"?

Mining Word Associations: General Ideas

- **Paradigmatic**
  - Represent each word by its context
  - Compute context similarity
  - Words with **high context similarity** likely have paradigmatic relation
- **Syntagmatic**
  - Count how many times two words occur together in a context (e.g., sentence or paragraph)
  - Compare their co-occurrences with their individual occurrences
  - Words with **high co-occurrences but relatively low individual occurrences** likely have syntagmatic relation
- Paradigmatically related words tend to have syntagmatic relation with the same word ➔ **joint discovery** of the two relations
- These ideas can be implemented in many different ways!

Word Context as “Pseudo Document”

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



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”)) +

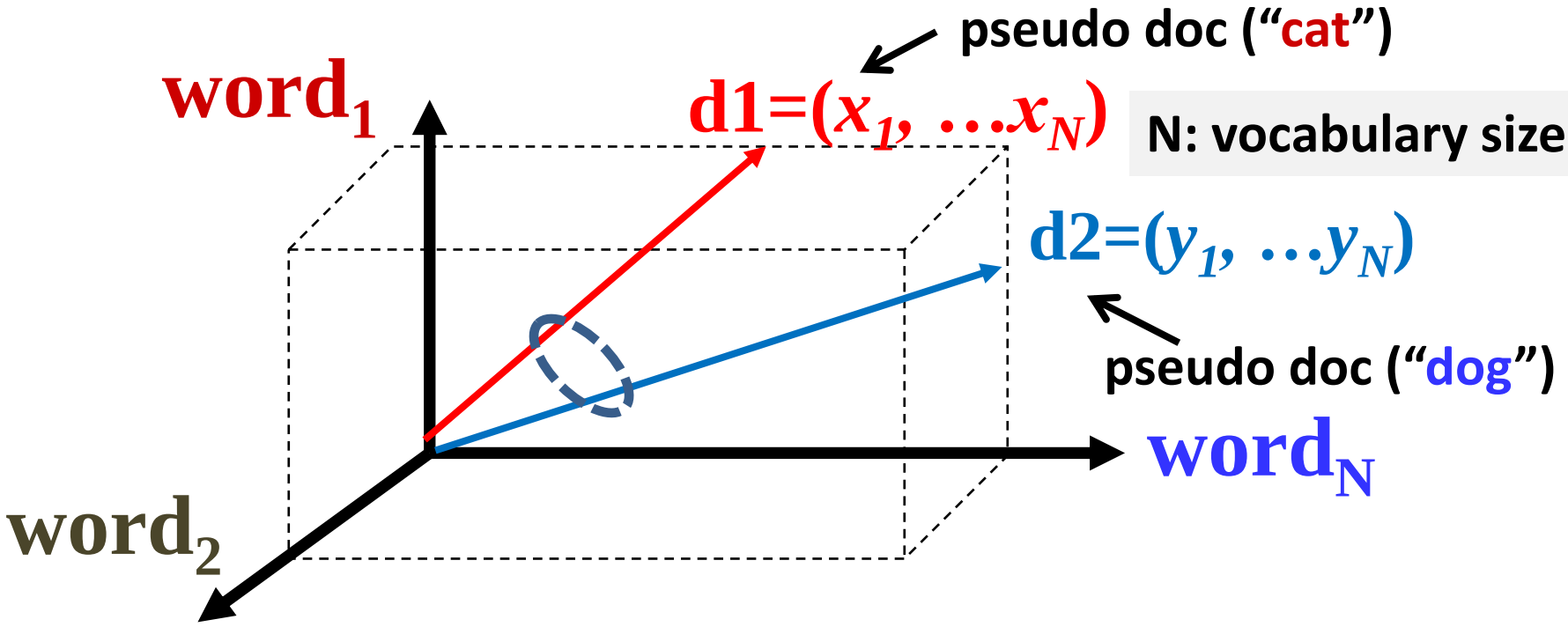
…

+ Sim(Window8(“cat”), Window8(“dog”))=?

High sim(word1, word2)

➔ word1 and word2 are **paradigmatically related**

Bag of Words ➔ Vector Space Model (VSM)

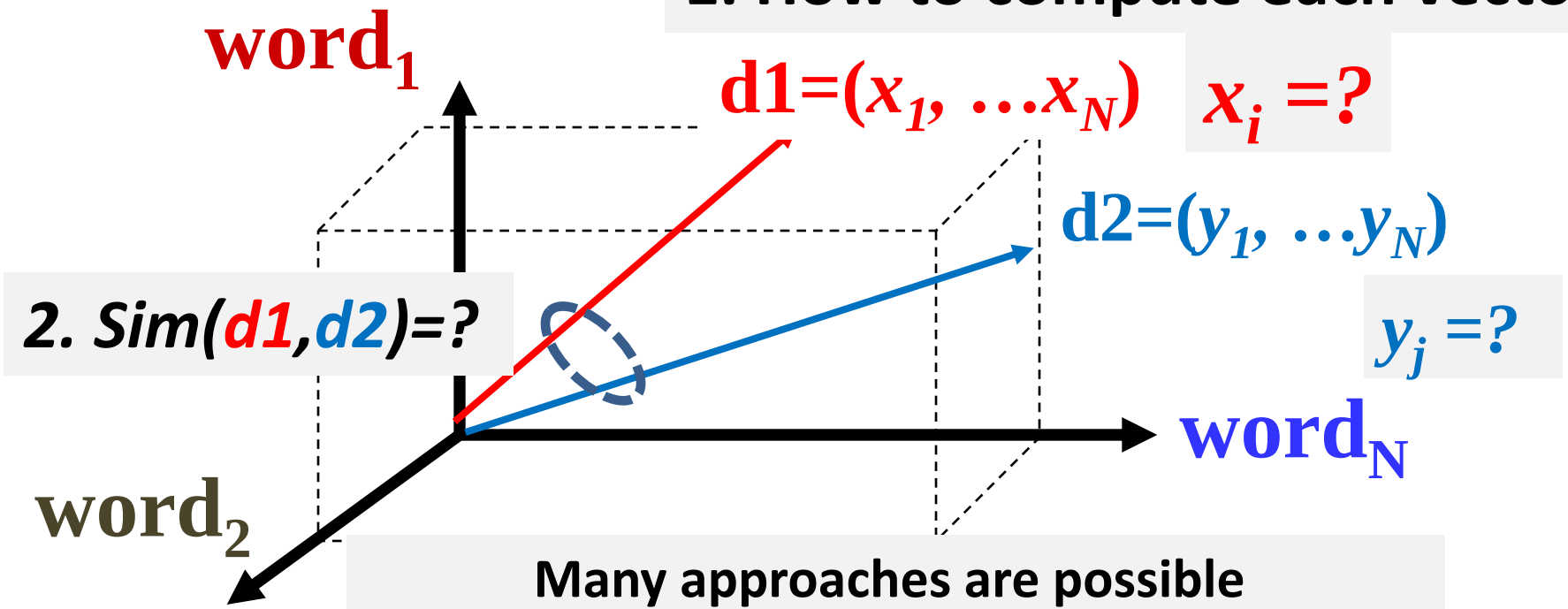


Terms: "eats" "ate" "is" "has" ….

Vector: (5, 3, 10, 3 ….)

VSM for Paradigmatic Relation Mining

1. How to compute each vector?



Many approaches are possible (most developed originally for text retrieval).

Expected Overlap of Words in Context (EOWC)

Probability that a randomly picked word from d1 is wi

Count of word wi in d1

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

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

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”).

Expected Overlap of Words in Context (EOWC)

Probability that a randomly picked word from d1 is wi

Count of word wi in d1

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

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

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.

Improving EOWC with Retrieval Heuristics

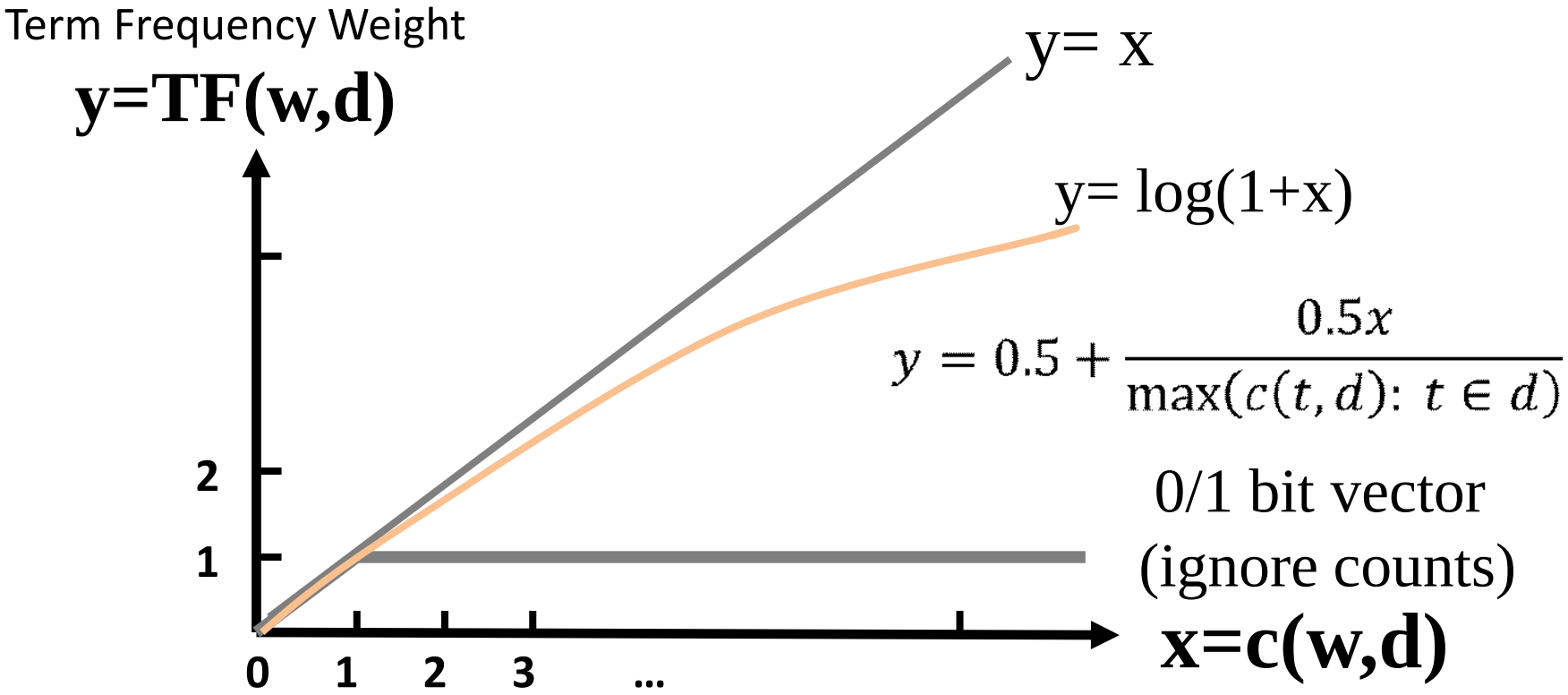
- It favors matching one frequent term very well over matching more distinct terms.

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

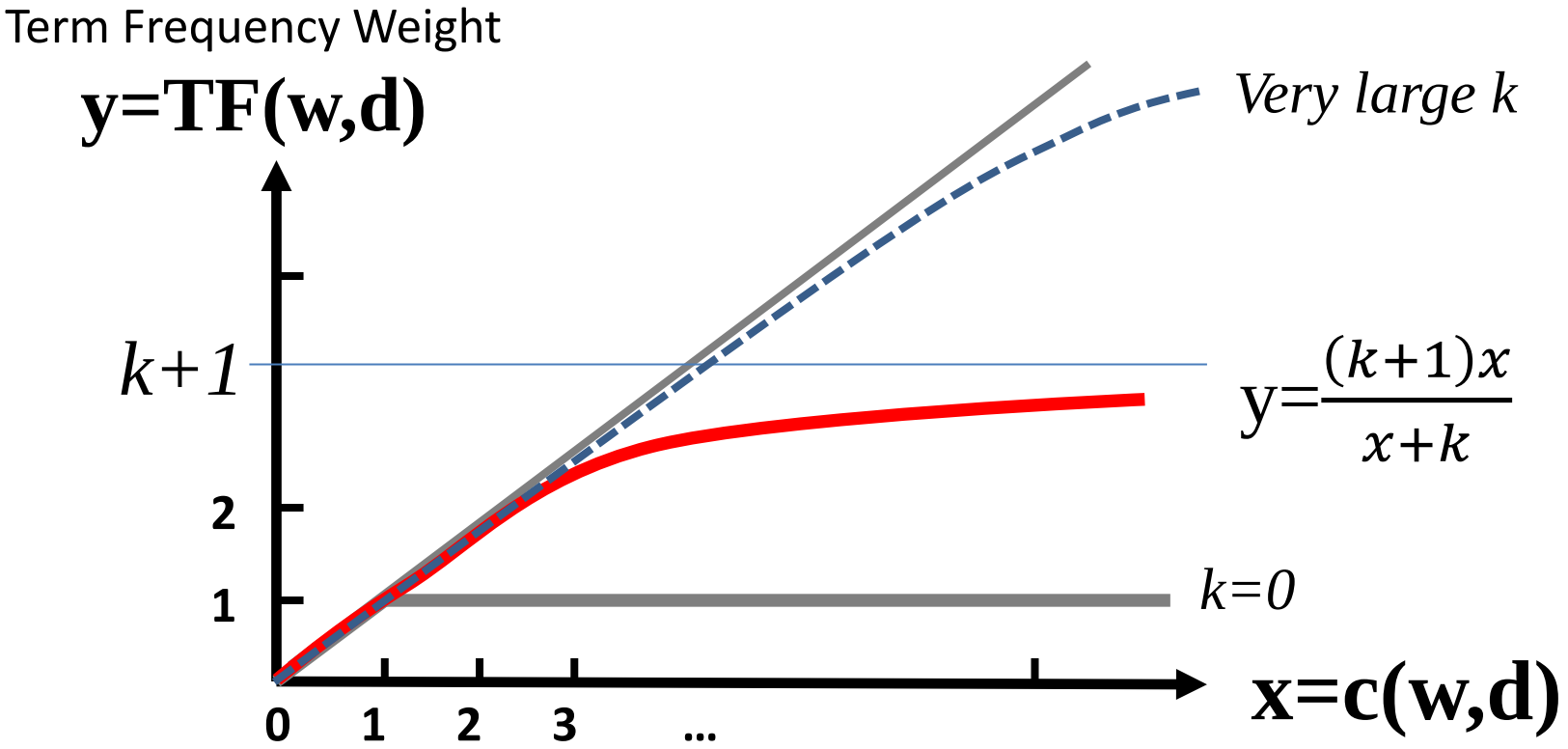
- It treats every word equally (overlap on “the” isn’t as so meaningful as overlap on “eats”).

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

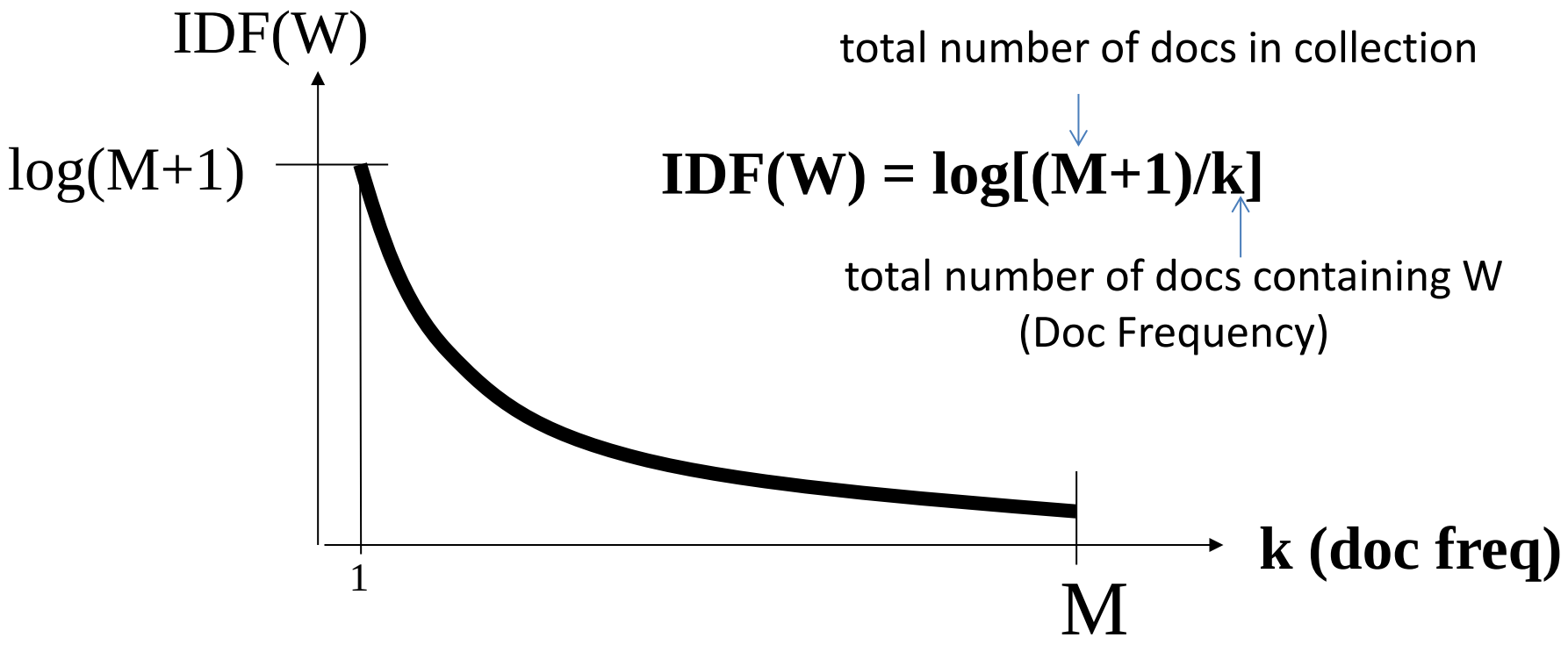
TF Transformation: c(w,d)➔TF(w,d)



TF Transformation: BM25 Transformation



IDF Weighting: Penalizing Popular Terms



Adapting BM25 Retrieval Model for Paradigmatic Relation Mining

$d1=(x_1, \ldots x_N)$

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

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

$b \in [0,1]$

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

b = 0.75

k = 1.2~2.0

$d2=(y_1, \ldots y_N)$

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

$d1=(x_1, \ldots x_N)$

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

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

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

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

IDF-weighted $d1=(x_1 * IDF(w_1), \ldots, x_N * IDF(w_N))$

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

Recommended Readings

- C. Zhai and S. Massung, Text Data Management and Analysis: A Practical Introduction to Information Retrieval and Text Mining. ACM and Morgan & Claypool Publishers, 2016. Chapters 1-4, Chapter 13.
- Chris Manning and Hinrich Schütze, Foundations of Statistical Natural Language Processing. MIT Press. Cambridge, MA: May 1999. (Chapter 5 on collocations)
- Chengxiang Zhai, Exploiting context to identify lexical atoms: A statistical view of linguistic context. Proceedings of the International and Interdisciplinary Conference on Modelling and Using Context (CONTEXT-97), Rio de Janeiro, Brazil, Feb. 4-6, 1997. pp. 119-129.
- Shan Jiang and ChengXiang Zhai, Random walks on adjacency graphs for mining lexical relations from big text data. Proceedings of IEEE BigData Conference 2014, pp. 549-554.