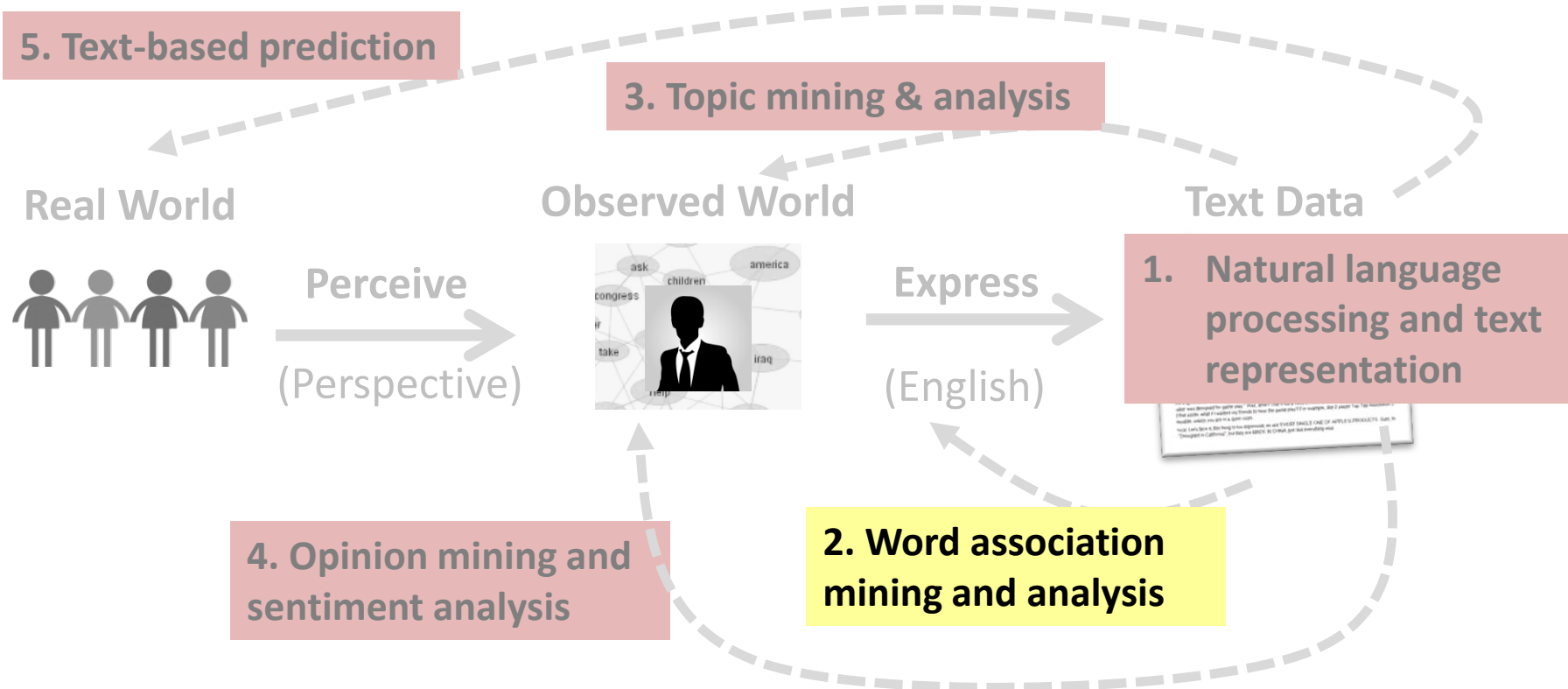


Paradigmatic Relation Discovery

Parts 1-3

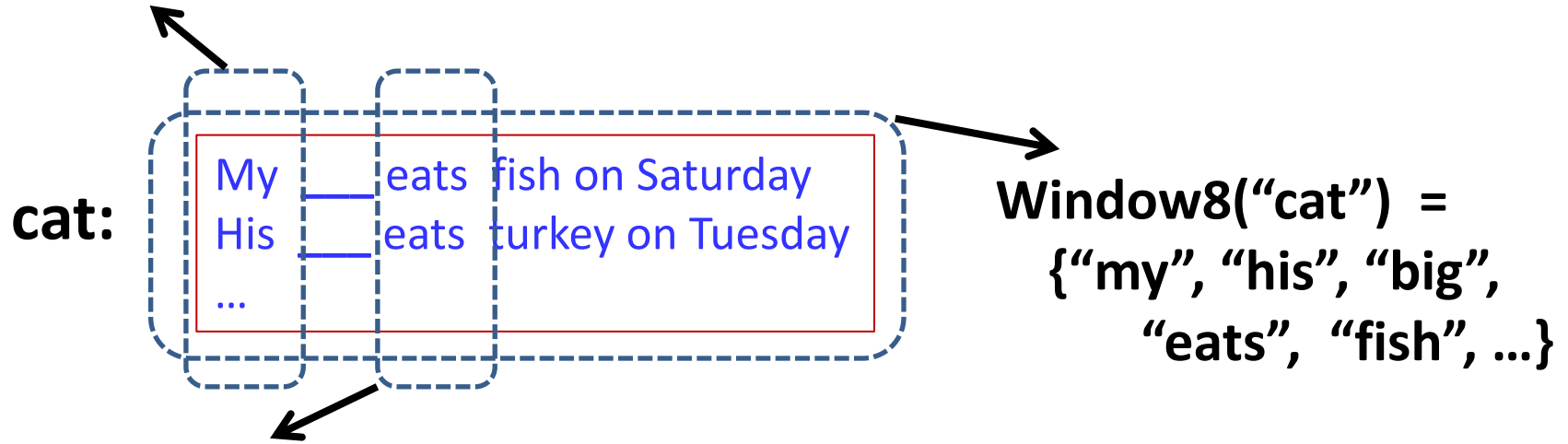
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Paradigmatic Relation Discovery



Word Context as “Pseudo Document”

$\text{Left1}(\text{"cat"}) = \{\text{"my"}, \text{"his"}, \text{"big"}, \text{"a"}, \text{"the"}, \dots\}$



$\text{Right1}(\text{"cat"}) = \{\text{"eats"}, \text{"ate"}, \text{"is"}, \text{"has"}, \dots\}$

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

Measuring Context Similarity

$\text{Sim}(\text{"Cat"}, \text{"Dog"}) =$

$\text{Sim}(\text{Left1}(\text{"cat"}), \text{Left1}(\text{"dog"}))$

$+ \text{Sim}(\text{Right1}(\text{"cat"}), \text{Right1}(\text{"dog"})) +$

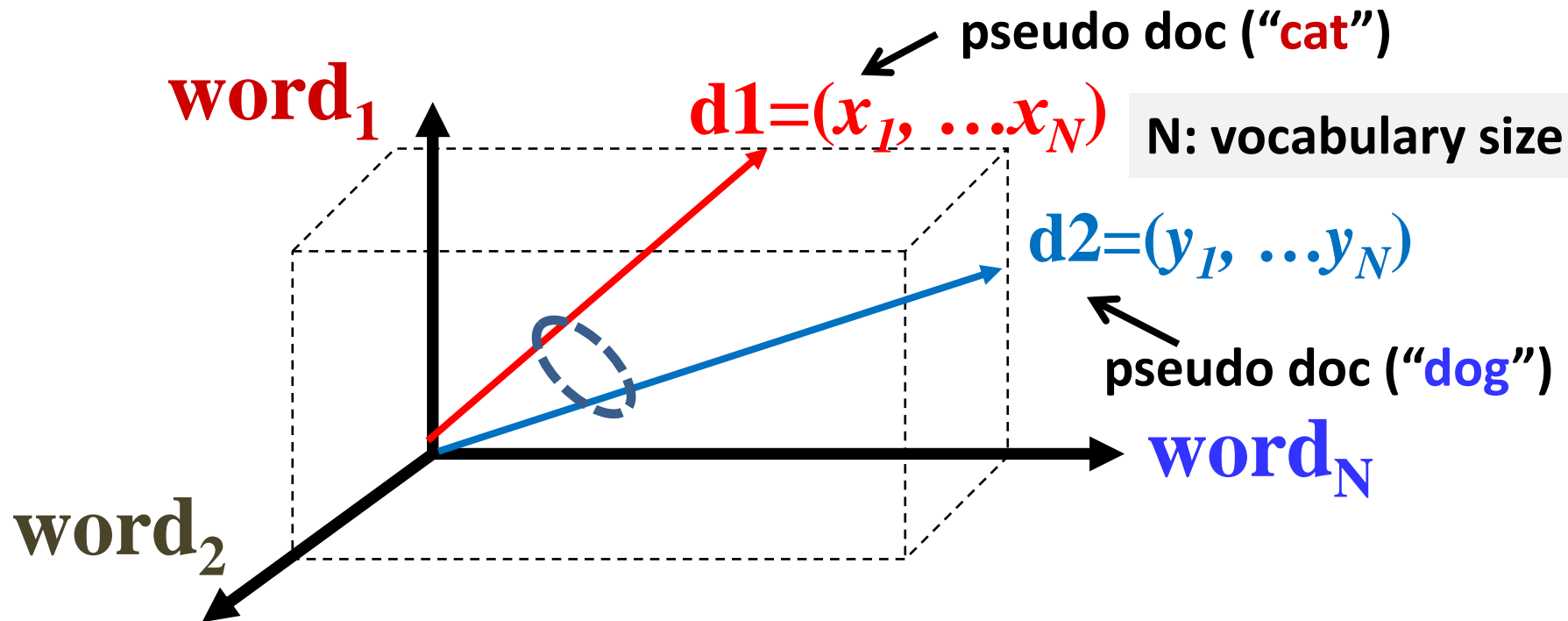
\dots

$+ \text{Sim}(\text{Window8}(\text{"cat"}), \text{Window8}(\text{"dog"})) = ?$

High $\text{sim}(\text{word1}, \text{word2})$

➔ word1 and word2 are **paradigmatically related**

Bag of Words \rightarrow 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?

word₁

$$\mathbf{d1} = (x_1, \dots, x_N) \quad x_i = ?$$

$$\mathbf{d2} = (y_1, \dots, y_N)$$

2. $\text{Sim}(\mathbf{d1}, \mathbf{d2}) = ?$

$$y_j = ?$$

word₂

word_N

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 w_i

Count of word w_i in $d1$

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

$$x_i = c(w_i, d1) / |d1|$$

$$d2 = (y_1, \dots, y_N)$$

$$y_i = c(w_i, d2) / |d2|$$

Total counts of
words in $d1$

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

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 w_i

Count of word w_i in $d1$

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$$y_i = c(w_i, d2) / |d2|$$

Total counts of
words in $d1$

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

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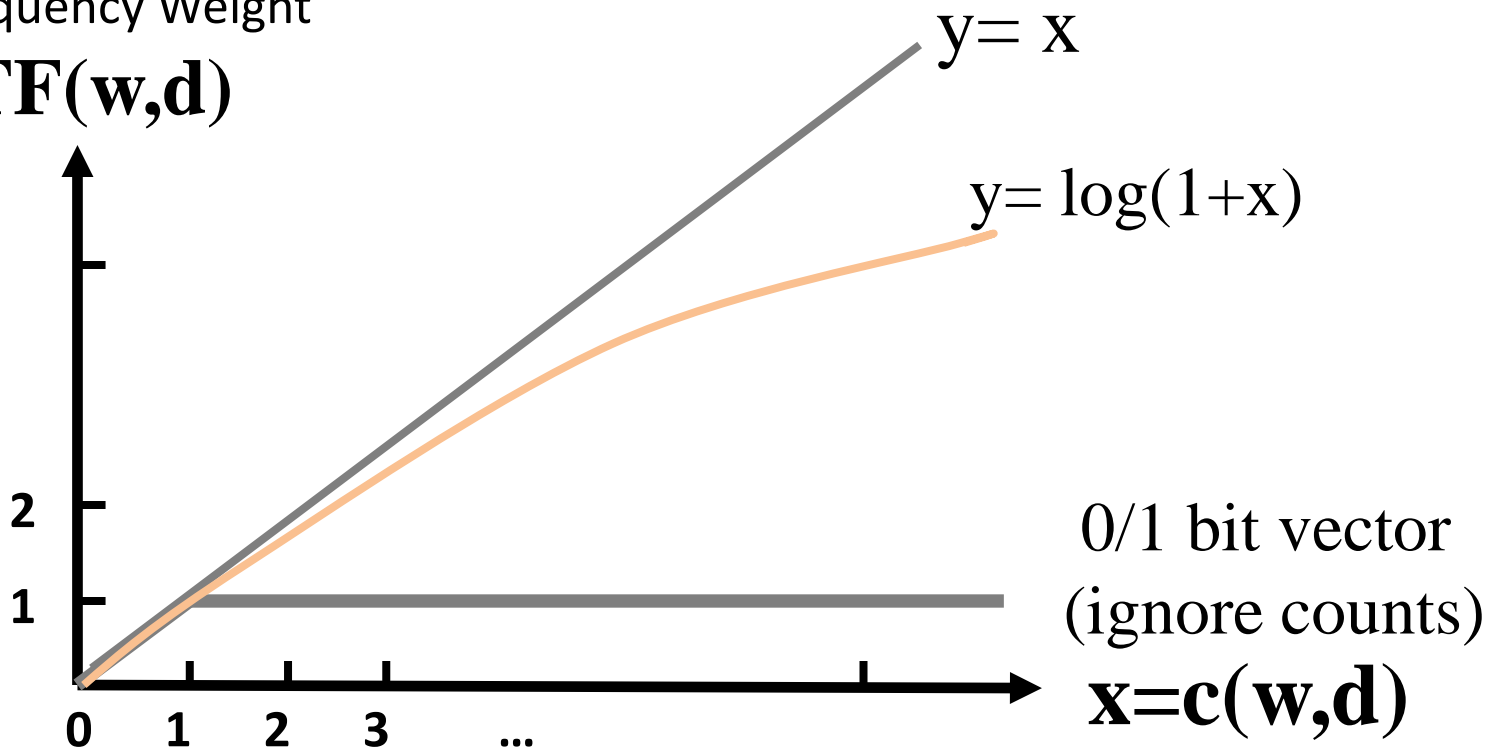
Improving EOWC with Retrieval Heuristics

- 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: $c(w,d) \rightarrow TF(w,d)$

Term Frequency Weight

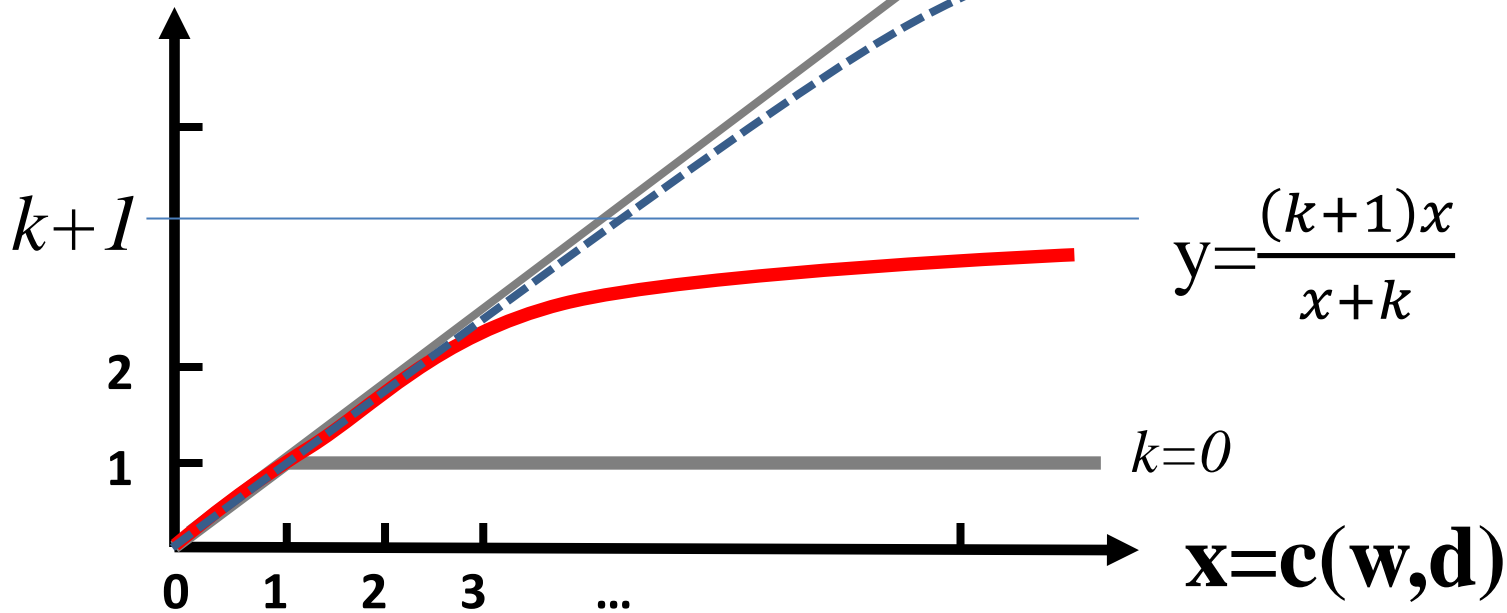
$$y = TF(w,d)$$



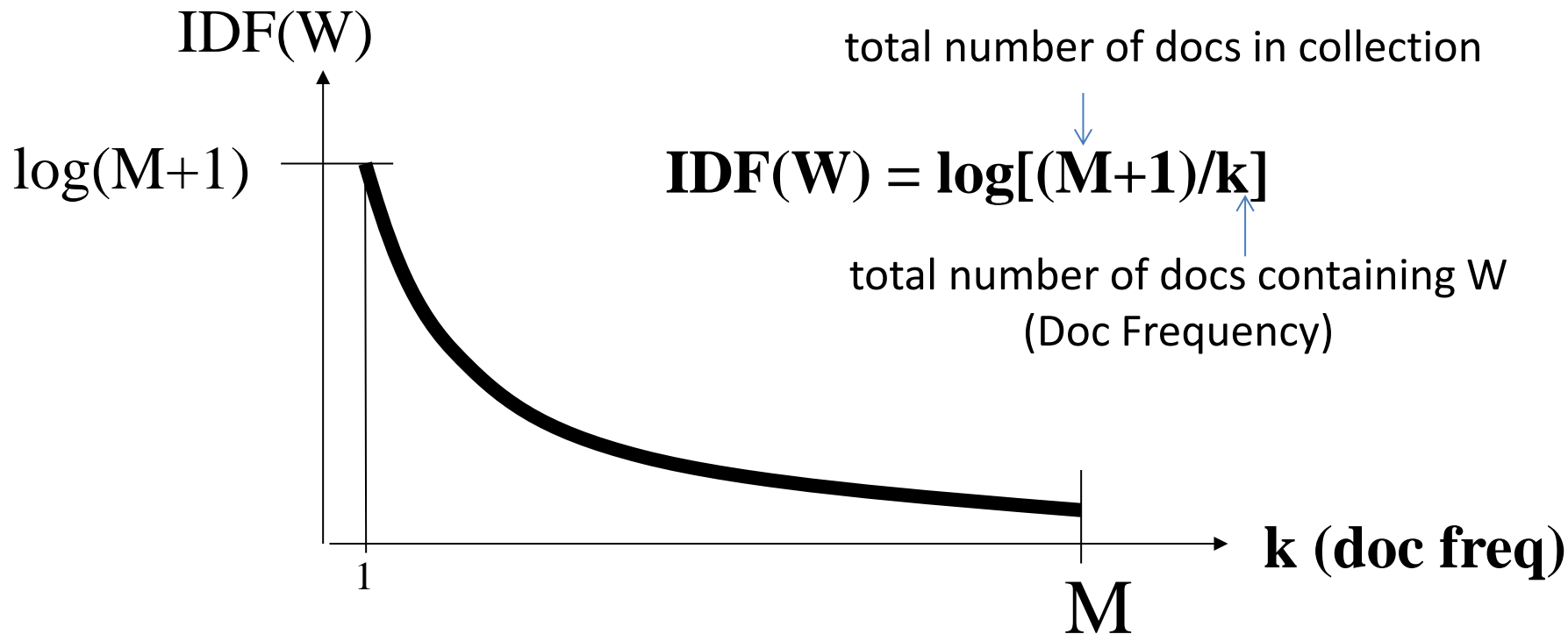
TF Transformation: BM25 Transformation

Term Frequency Weight

$$y = \text{TF}(\mathbf{w}, \mathbf{d})$$



IDF Weighting: Penalizing Popular Terms



Adapting BM25 Retrieval Model for Paradigmatic Relation Mining

$$\mathbf{d1}=(x_1, \dots x_N) \quad \text{BM25}(w_i, \mathbf{d1}) = \frac{(k+1)c(w_i, \mathbf{d1})}{c(w_i, \mathbf{d1}) + k(1-b+b*|\mathbf{d1}|/\text{avdl})}$$

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

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

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

$$\mathbf{d2}=(y_1, \dots y_N) \quad y_i \text{ is defined similarly}$$

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

BM25 can also Discover Syntagmatic Relations

$$d1=(x_1, \dots x_N) \quad \text{BM25}(w_i, d1) = \frac{(k+1)c(w_i, d1)}{c(w_i, d1) + k(1-b + b*|d1|/avdl)}$$

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

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

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

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”