Overview of Text Mining and Analytics

Text Mining and Analytics

- Text mining ≈ Text analytics
- Turn text data into **high-quality information** or **actionable knowledge**
  - **Minimizes human effort** (on consuming text data)
  - Supplies knowledge for **optimal decision making**
- Related to **text retrieval**, which is an essential component in any text mining system
  - Text retrieval can be a preprocessor for text mining
  - Text retrieval is needed for knowledge provenance

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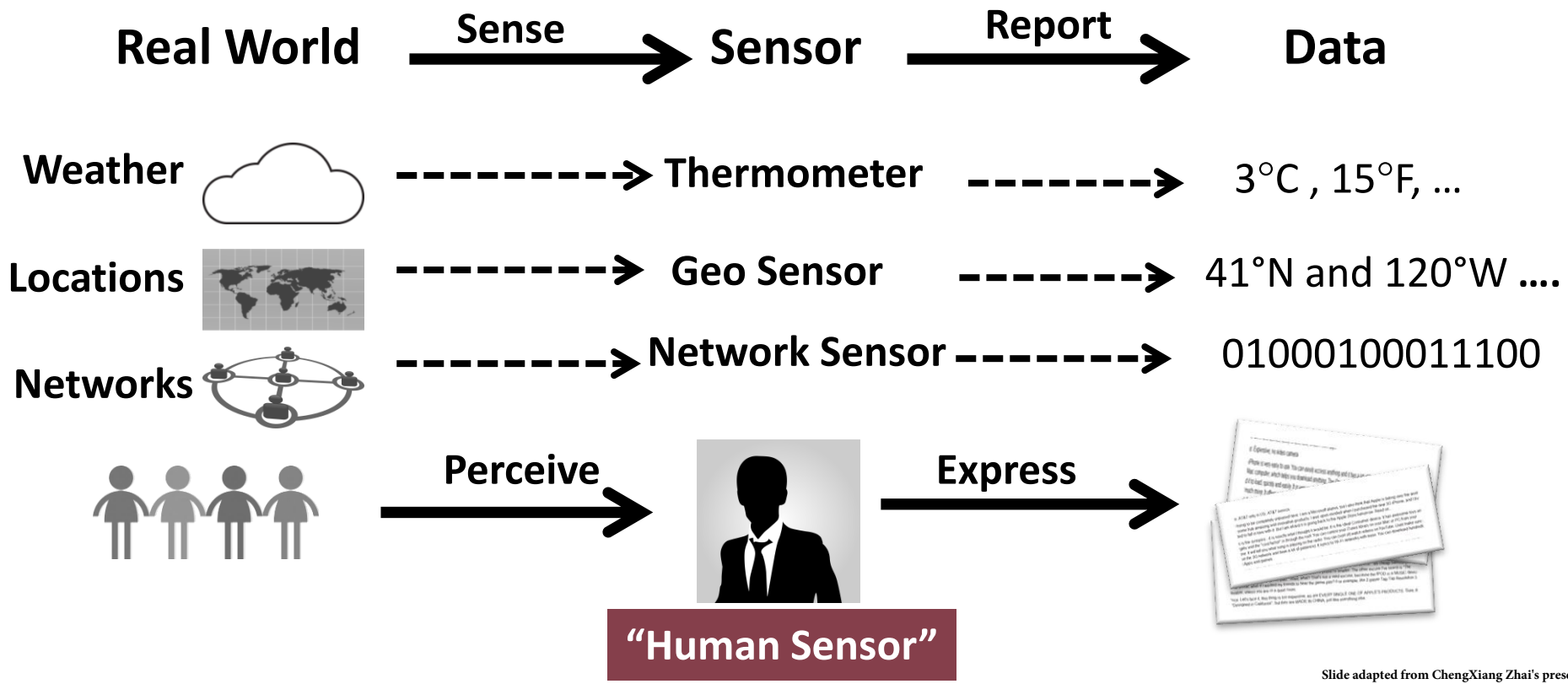
Text vs. Non-Text Data: Humans as Subjective "Sensors"



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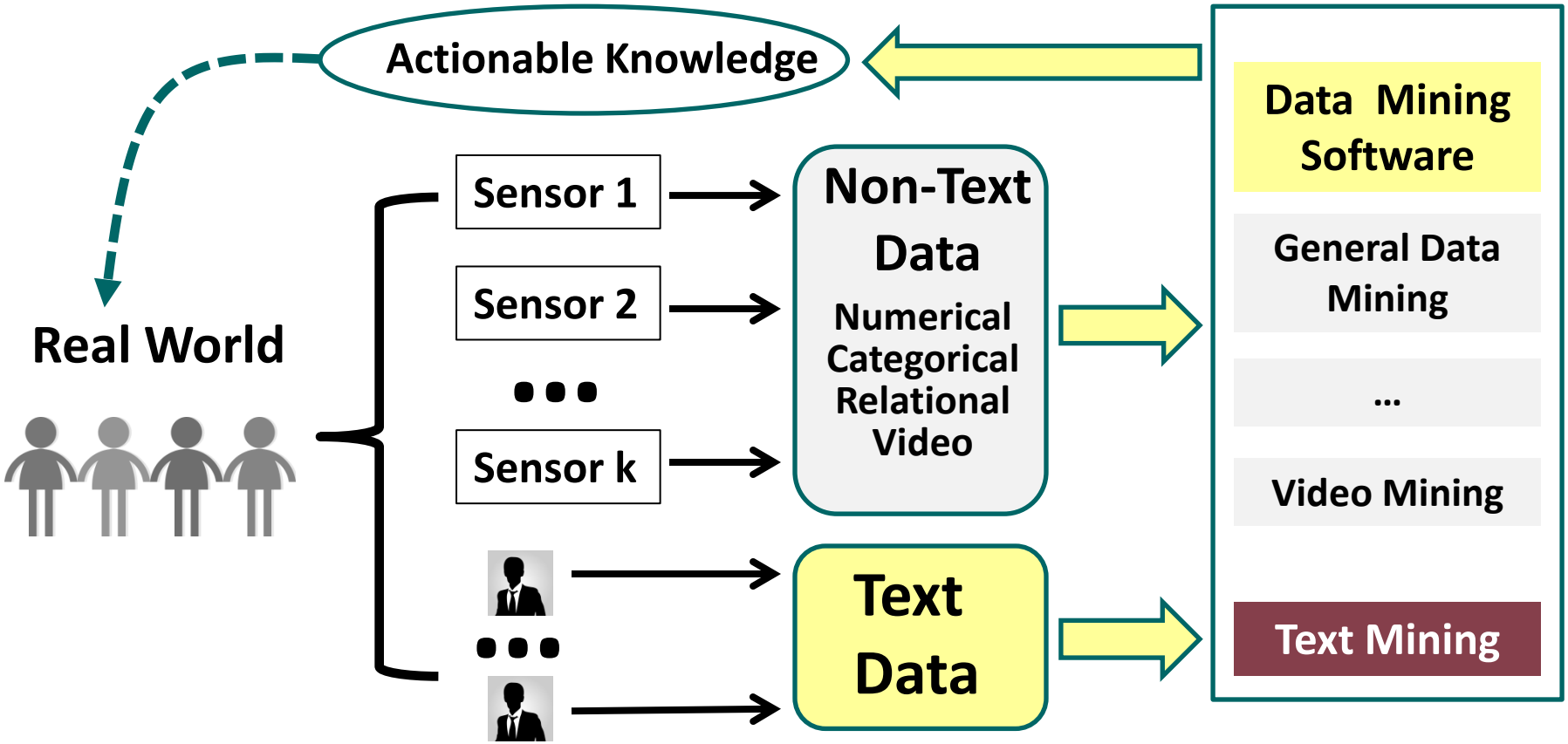
The General Problem of Data Mining



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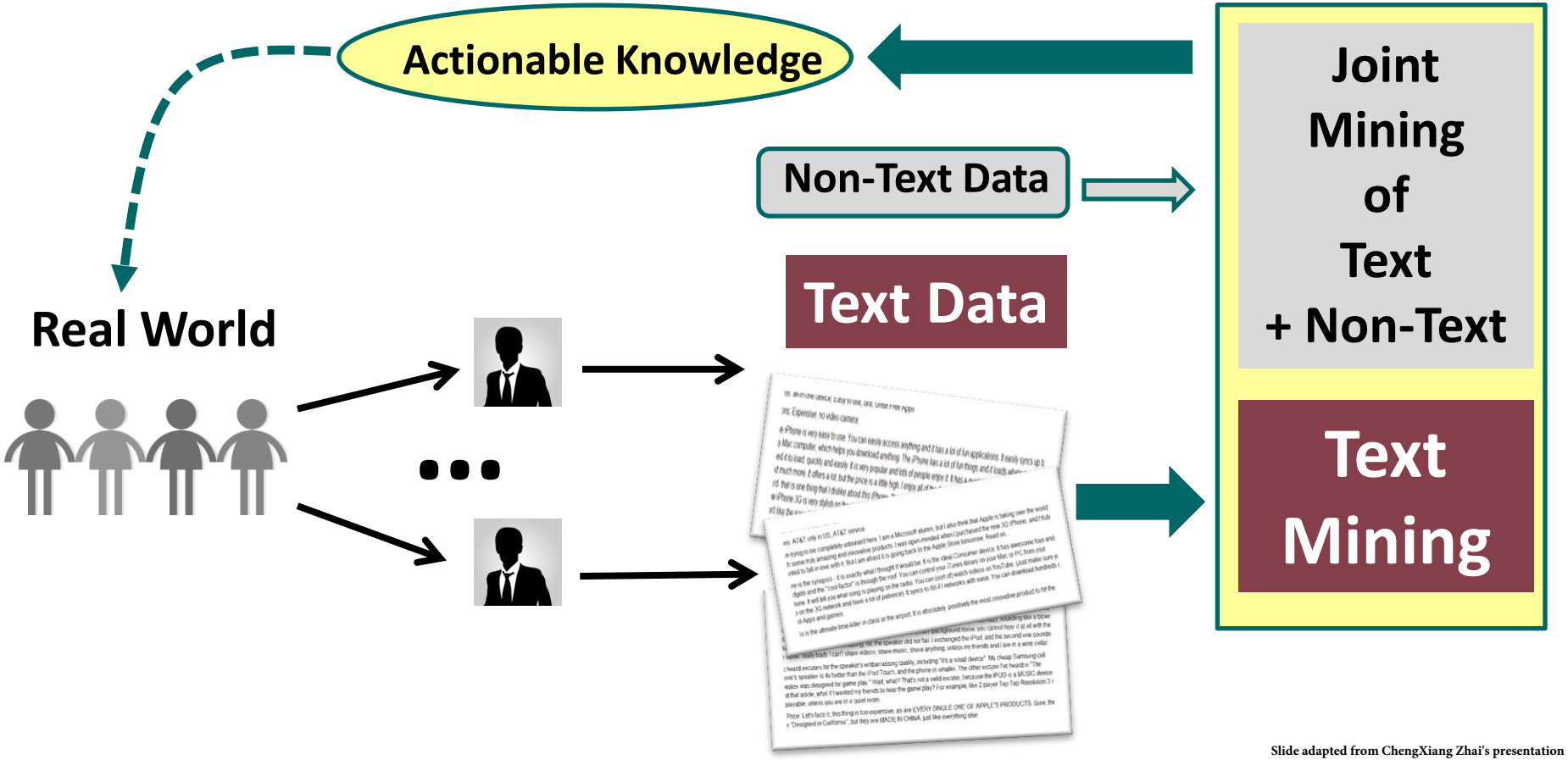
The Problem of Text Mining



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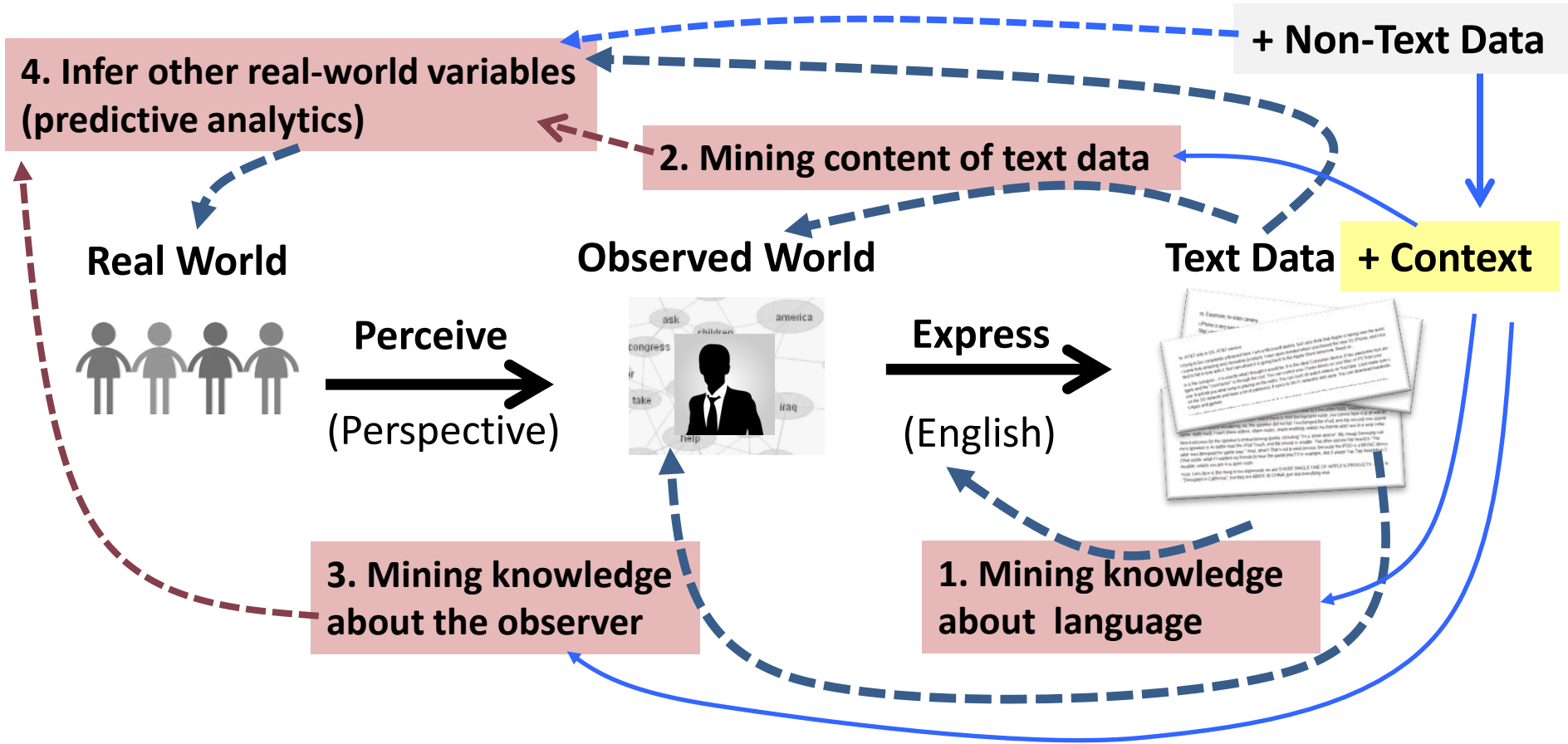
Landscape of Text Mining and Analytics



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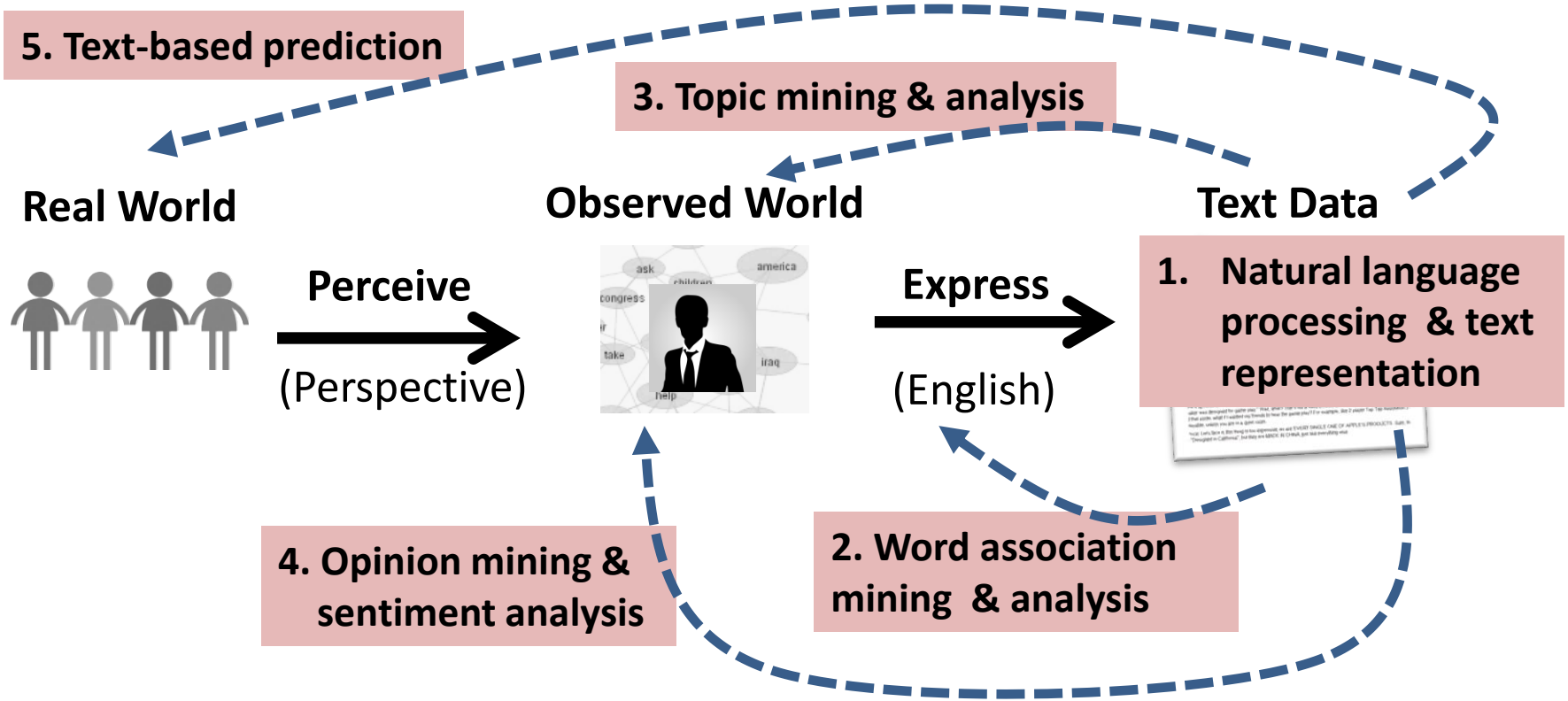
Topics Covered in This Course



Slide adapted from ChengXiang Zhai's presentation

Natural Language Content Analysis

Slide adapted from ChengXiang Zhai's presentation

Natural Language Content Analysis

5. Text-based prediction

3. Topic mining & analysis

Real World

Observed World

Text Data

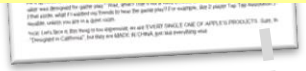
Perceive

(Perspective)

Express

(English)

1. **Natural language processing & text representation**

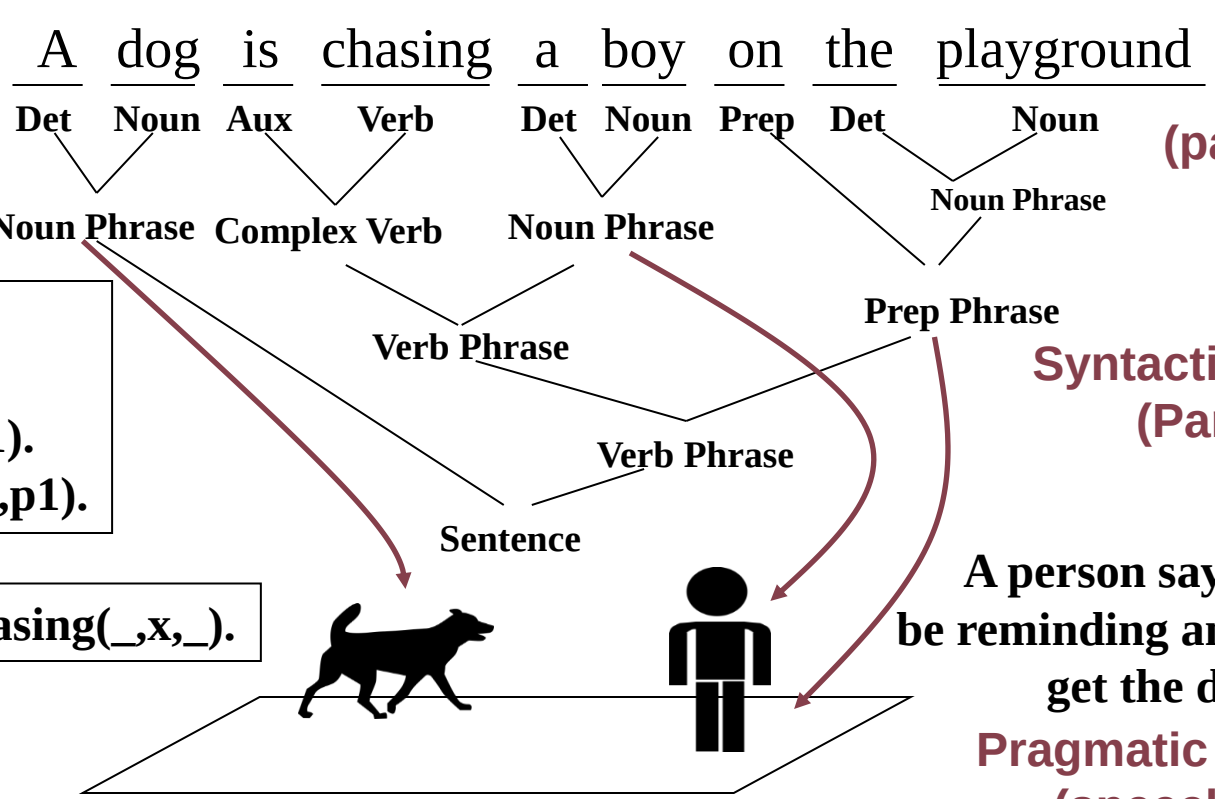


4. Opinion mining & sentiment analysis

2. Word association mining & analysis

Slide adapted from ChengXiang Zhai's presentation

Basic Concepts in NLP



Lexical analysis (part-of-speech tagging)

Syntactic analysis (Parsing)

Semantic analysis

Dog(d1).
Boy(b1).
Playground(p1).
Chasing(d1,b1,p1).

+

Scared(x) if Chasing(_,x,_).

Scared(b1)

Inference

A person saying this may be reminding another person to get the dog back.

Pragmatic analysis (speech act)

Slide adapted from ChengXiang Zhai's presentation

NLP Is Difficult!

- Natural language is designed to make human communication efficient. As a result,
  - we omit a lot of *common sense* knowledge, which we assume the hearer/reader possesses.
  - we keep a lot of ambiguities, which we assume the hearer/reader knows how to resolve.
- This makes EVERY step in NLP hard
  - Ambiguity is a *killer*!
  - Common sense reasoning is pre-required.

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Examples of Challenges

- Word-level ambiguity:
  - "design" can be a noun or a verb (ambiguous POS)
  - "root" has multiple meanings (ambiguous sense)
- Syntactic ambiguity:
  - "natural language processing" (modification)
  - "A man saw a boy *with a telescope*." (PP Attachment)
- Anaphora resolution: "John persuaded Bill to buy a TV for *himself*." (himself = John or Bill?)
- Presupposition: "He has quit smoking" implies that he smoked before.

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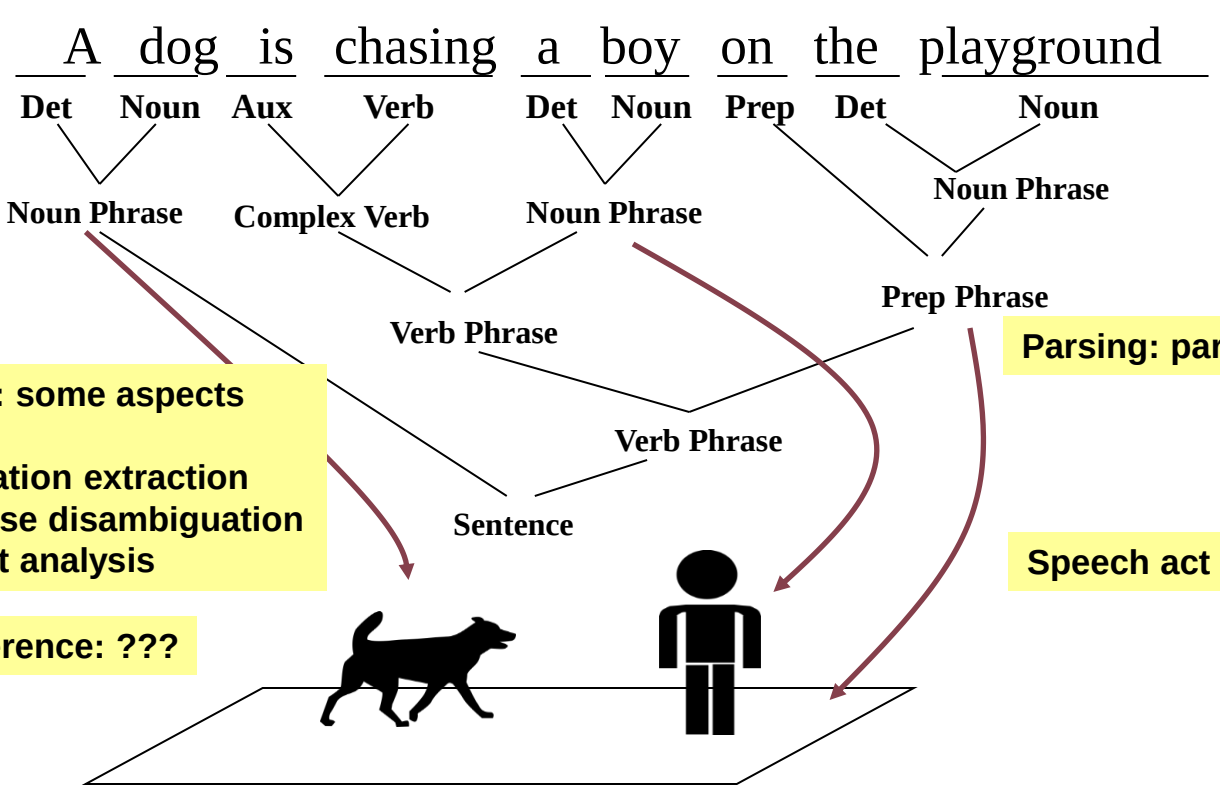
The State of the Art



POS Tagging: 97%

Parsing: partial >90%(?)

Semantics: some aspects

- **Entity/relation extraction**
- **Word sense disambiguation**
- **Sentiment analysis**

Speech act analysis: ???

Inference: ???

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What We Can't Do

- 100% POS tagging
  - "He turned off the highway." vs "He turned off the fan."
- General complete parsing
  - "A man saw a boy with a telescope."
- Precise deep semantic analysis
  - Will we ever be able to precisely define the meaning of "own" in "John owns a restaurant"?

Robust and general NLP tends to be *shallow* while *deep* understanding doesn't scale up.

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Summary

- NLP is the foundation for text mining
- Computers are far from being able to understand natural language
  - Deep NLP requires common sense knowledge and inferences, thus only working for very limited domains
  - Shallow NLP based on statistical methods can be done in large scale and is thus more broadly applicable
- In practice: statistical NLP as the basis, while humans provide help as needed

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Additional Reading

Manning, Chris and Hinrich Schütze. *Foundations of Statistical Natural Language Processing*. Cambridge: MIT Press, 1999.

Text Representation

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Text Representation

5. Text-based prediction

3. Topic mining & analysis

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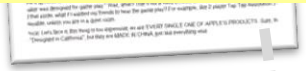
1. **Natural language processing & text representation**



4. Opinion mining & sentiment analysis

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Slide adapted from ChengXiang Zhai's presentation

A dog is chasing a boy on the playground

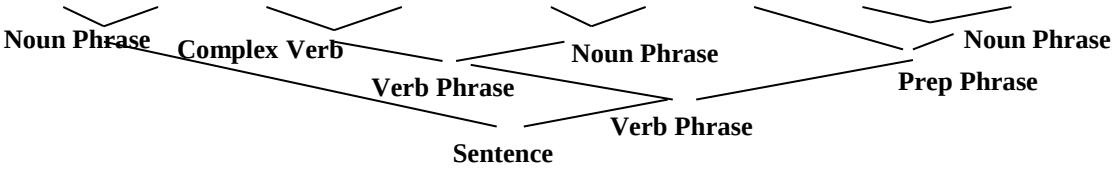
String of characters

A dog is chasing a boy on the playground

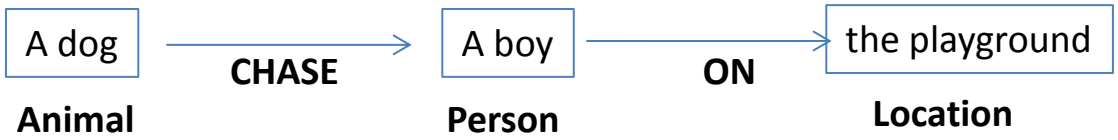
Sequence of words

Det Noun Aux Verb Det Noun Prep Det Noun

+ POS tags



+ Syntactic structures



+ Entities and relations

Dog(d1). Boy(b1). Playground(p1). Chasing(d1,b1,p1).

+ Logic predicates

Speech Act = REQUEST

+ Speech acts

Deeper NLP: requires more human effort; less accurate

Closer to knowledge representation

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Text Representation and Enabled Analysis

This course

Text Rep	Generality	Enabled Analysis	Examples of Application
String		String processing	Compression
Words		Word relation analysis; topic analysis; sentiment analysis	Thesaurus discovery; topic and opinion related applications
+ Syntactic structures		Syntactic graph analysis	Stylistic analysis; structure-based feature extraction
+ Entities & relations		Knowledge graph analysis; information network analysis	Discovery of knowledge and opinions about specific entities
+ Logic predicates		Integrative analysis of scattered knowledge; logic inference	Knowledge assistant for biologists

Slide adapted from ChengXiang Zhai's presentation

Summary

- Text representation determines what kind of mining algorithms can be applied
- **Multiple ways** of representing text are possible
  - string, words, syntactic structures, entity-relation graphs, predicates…
  - can/should be **combined** in real applications
- This course focuses on **word-based representation**
  - **General and robust**: applicable to any natural language
  - **No/little manual effort**
  - **"Surprisingly" powerful** for many applications (not all!)
  - **Can be combined** with more sophisticated representations

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Word Association Mining and Analysis

Word Association Mining & Analysis

5. Text-based prediction

3. Topic mining and analysis

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(Perspective)

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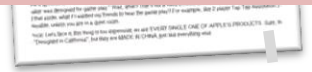
(English)

1. Natural language processing and text representation



4. Opinion mining and sentiment analysis

2. Word association mining and analysis

Slide adapted from ChengXiang Zhai's presentation

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

Slide adapted from ChengXiang Zhai's presentation

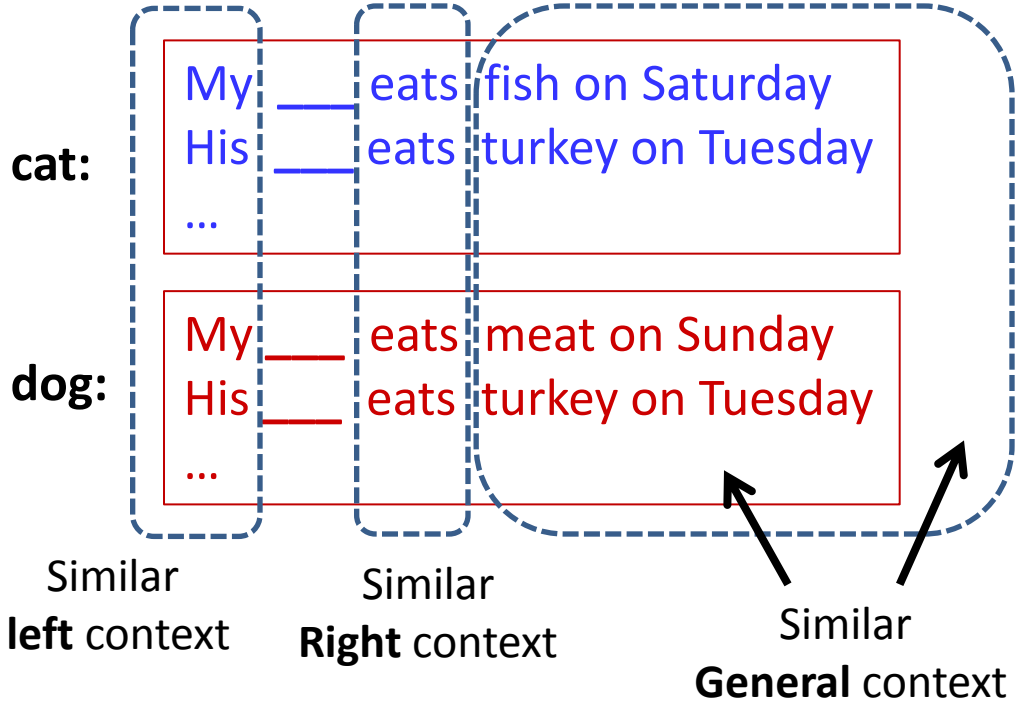
Why Mine Word Associations?

- 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")?

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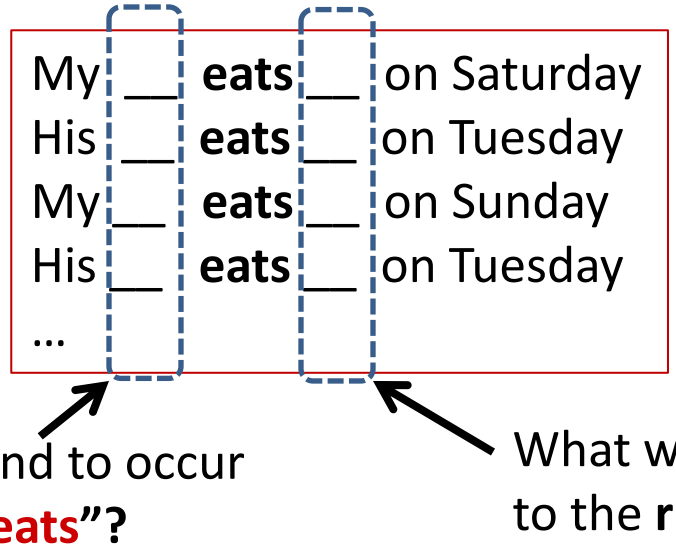
Mining Word Associations: Intuitions

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**"?

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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!

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Paradigmatic Relation Discovery: Part 1

Paradigmatic Relation Discovery

5. Text-based prediction

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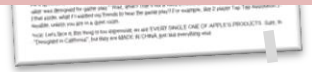
1. Natural language processing and text representation



4. Opinion mining and sentiment analysis

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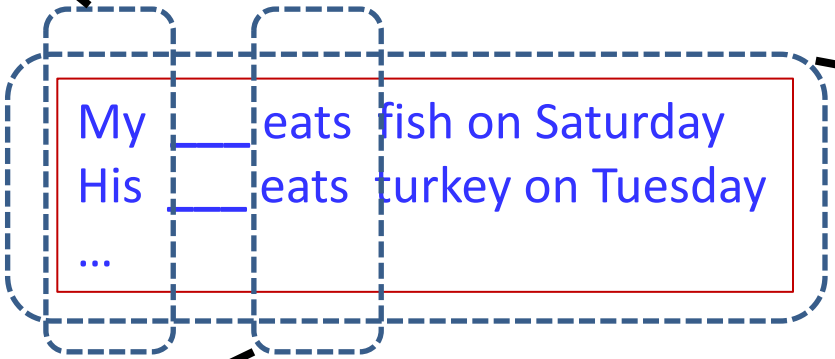
Word Context as “Pseudo Document”

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

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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**

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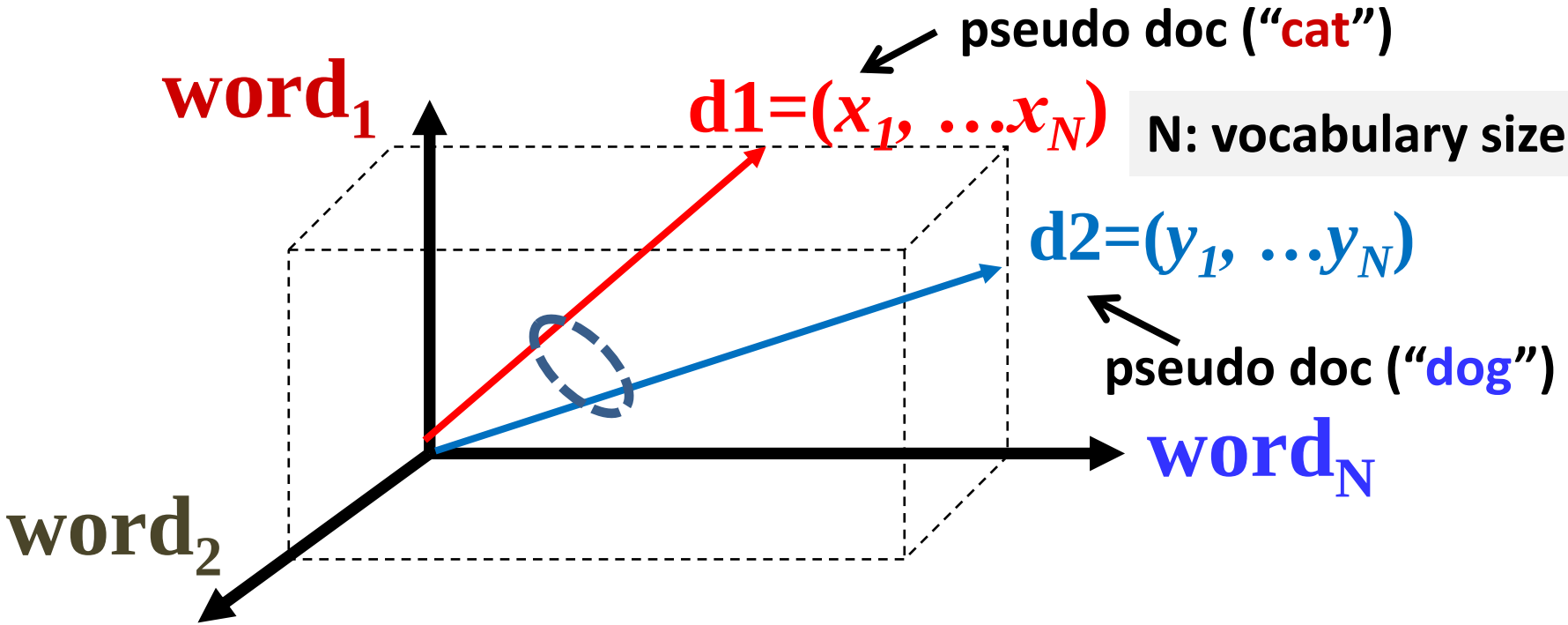
Bag of Words ➔ Vector Space Model (VSM)



Terms: "eats" "ate" "is" "has" ….

Vector: (5, 3, 10, 3 ….)

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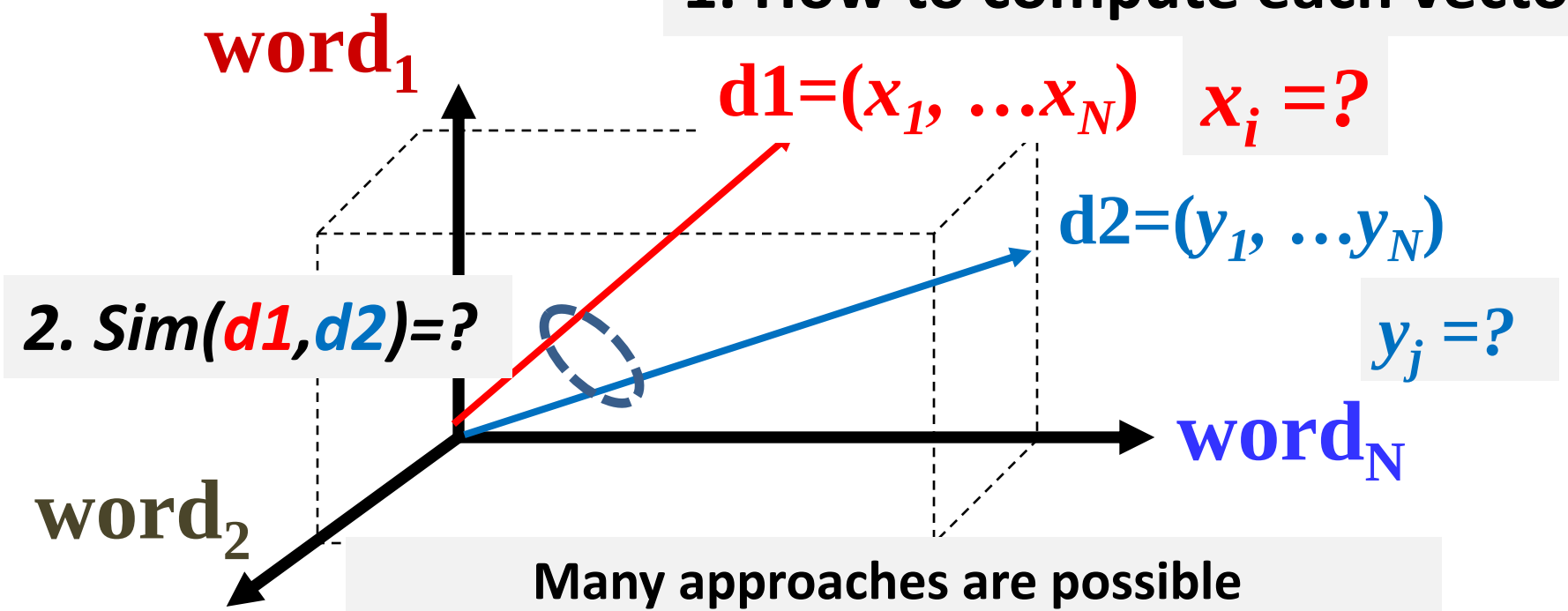
VSM for Paradigmatic Relation Mining

1. How to compute each vector?



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

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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.

Slide adapted from ChengXiang Zhai's presentation

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

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

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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.

Slide adapted from ChengXiang Zhai's presentation

Improving EOWC with Retrieval Heuristics

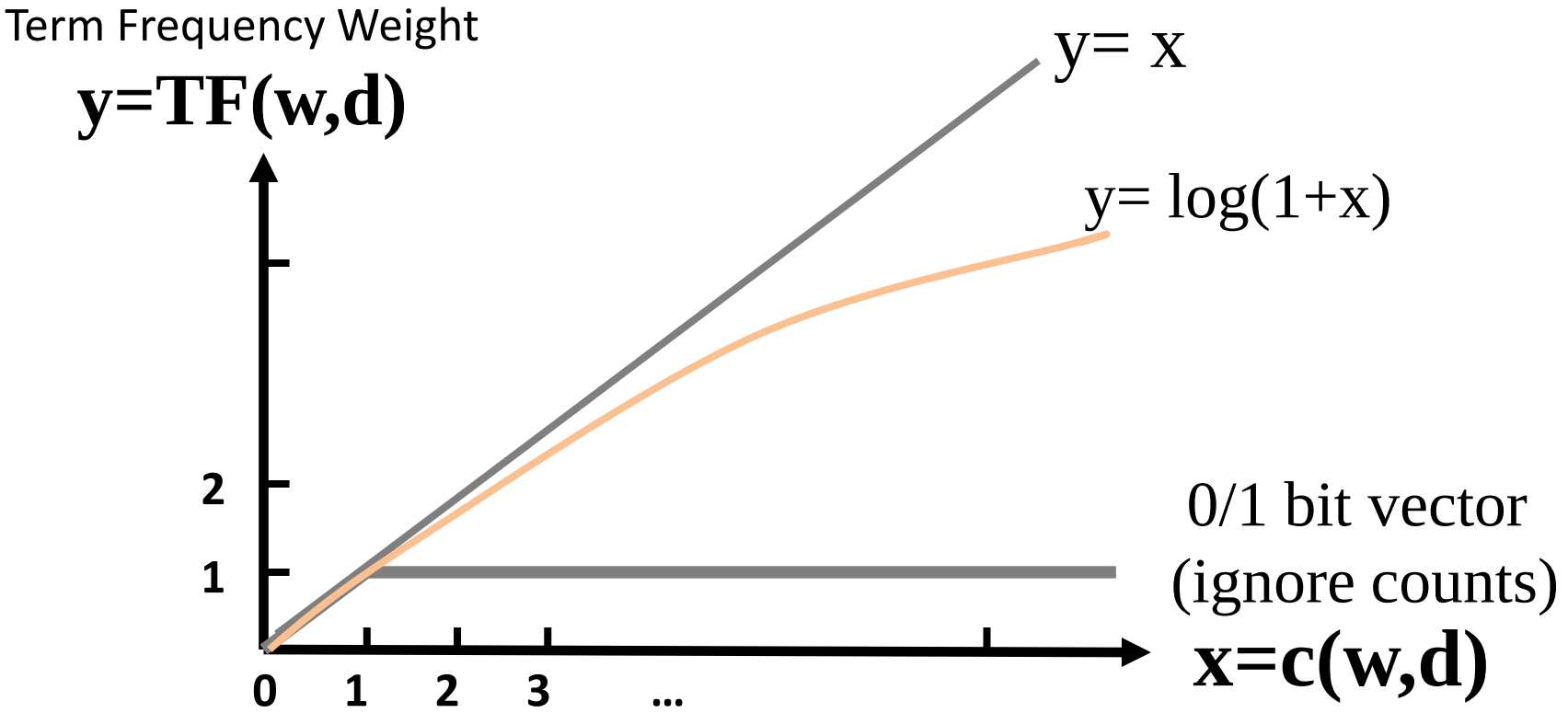
- It favors matching one frequent term very well over matching more distinct terms.

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

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

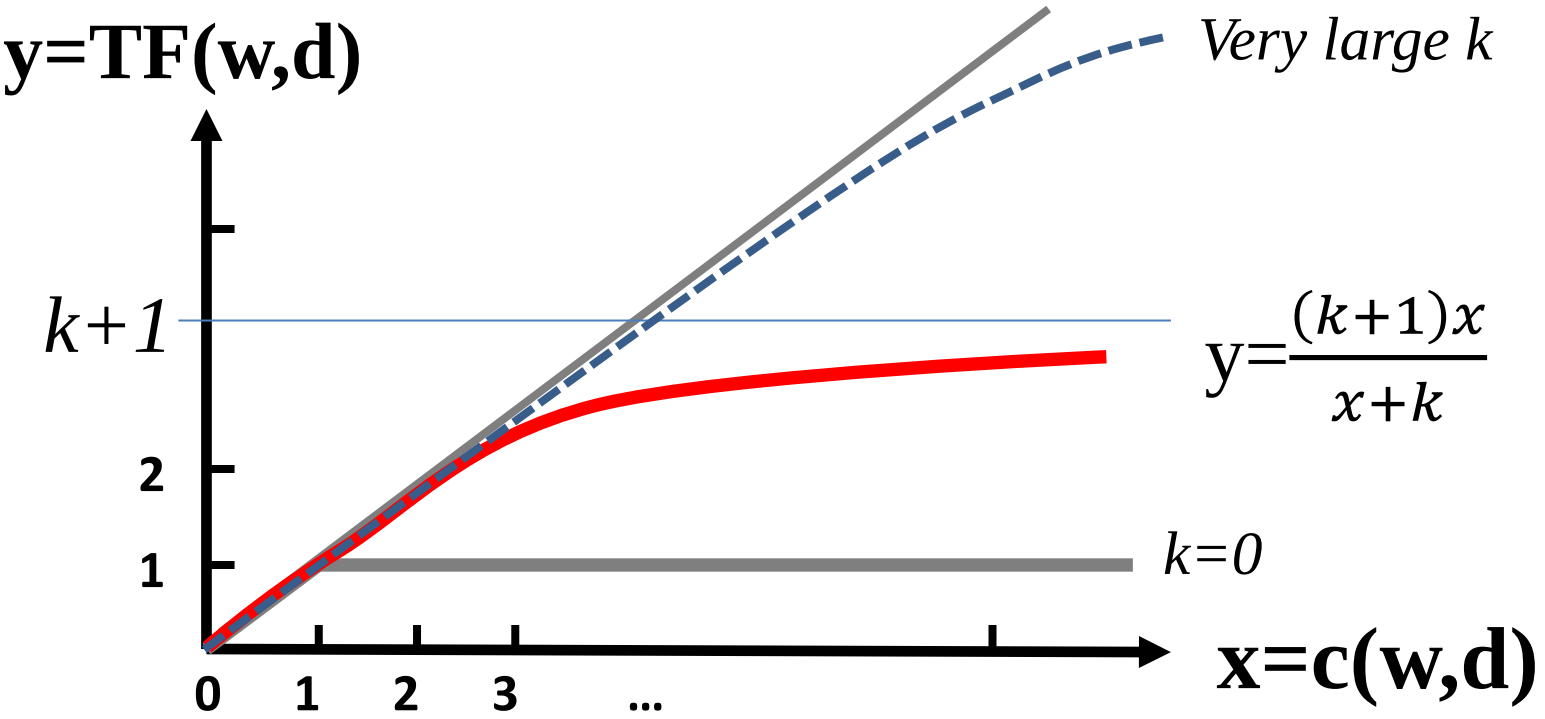
➔ **Reward matching a rare word: IDF term weighting**

TF Transformation: c(w,d)➔TF(w,d)



TF Transformation: BM25 Transformation

Term Frequency Weight



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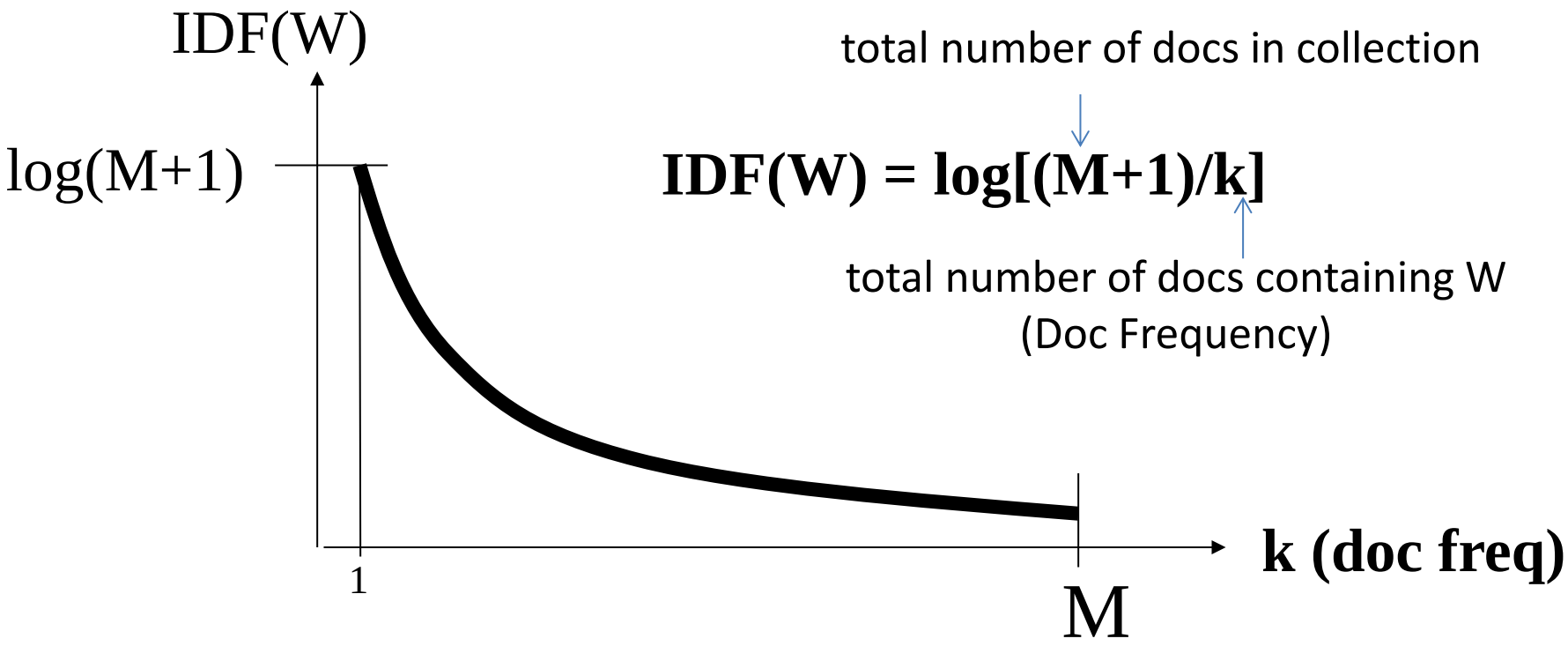
IDF Weighting: Penalizing Popular Terms



total number of docs in collection

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

total number of docs containing W
(Doc Frequency)

Adapting BM25 Retrieval Model for Paradigmatic Relation Mining

$d1=(x_1, \ldots x_N)$

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

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

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

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

$d2=(y_1, \ldots y_N)$

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, …x_N)

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

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

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

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

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.

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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”