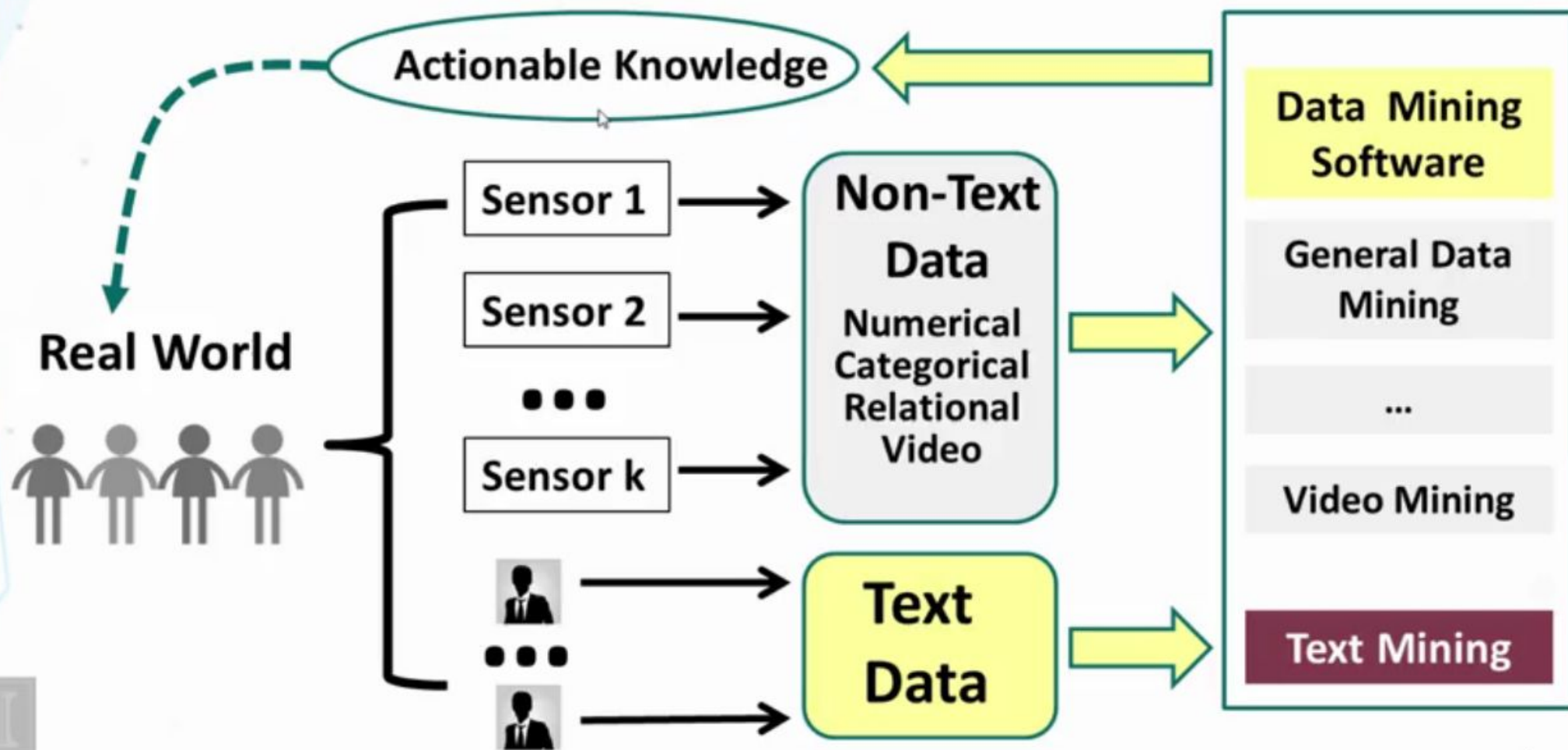


# Text Mining and Analytics

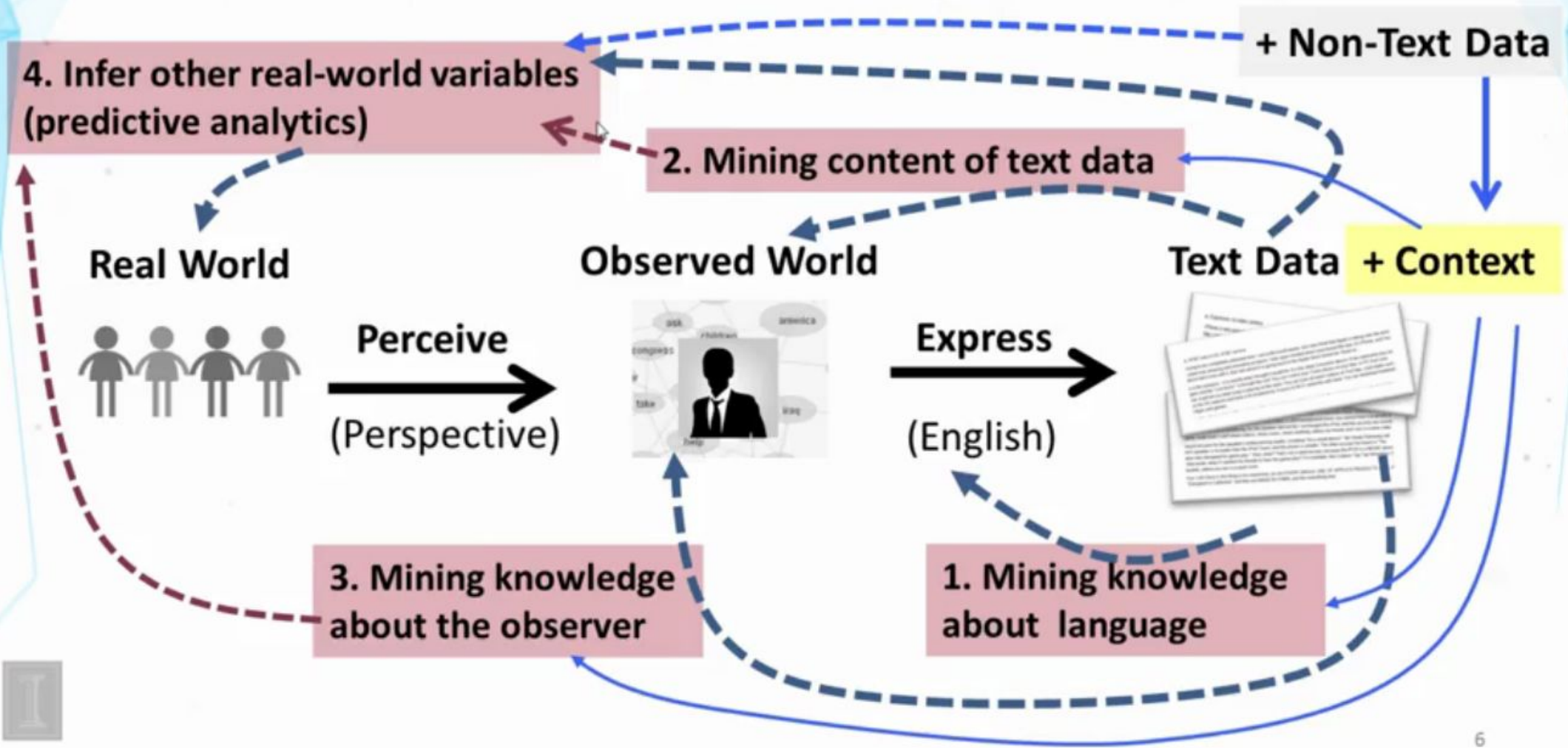
- Text mining  $\approx$  Text analytics
- Turn text data into **high-quality information** or **actionable knowledge**
  - **Minimizes human effort** (on consuming text data)
  - Supplies knowledge for **optimal decision making**
- Related to **text retrieval**, which is an essential component in any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



# The General Problem of Data Mining

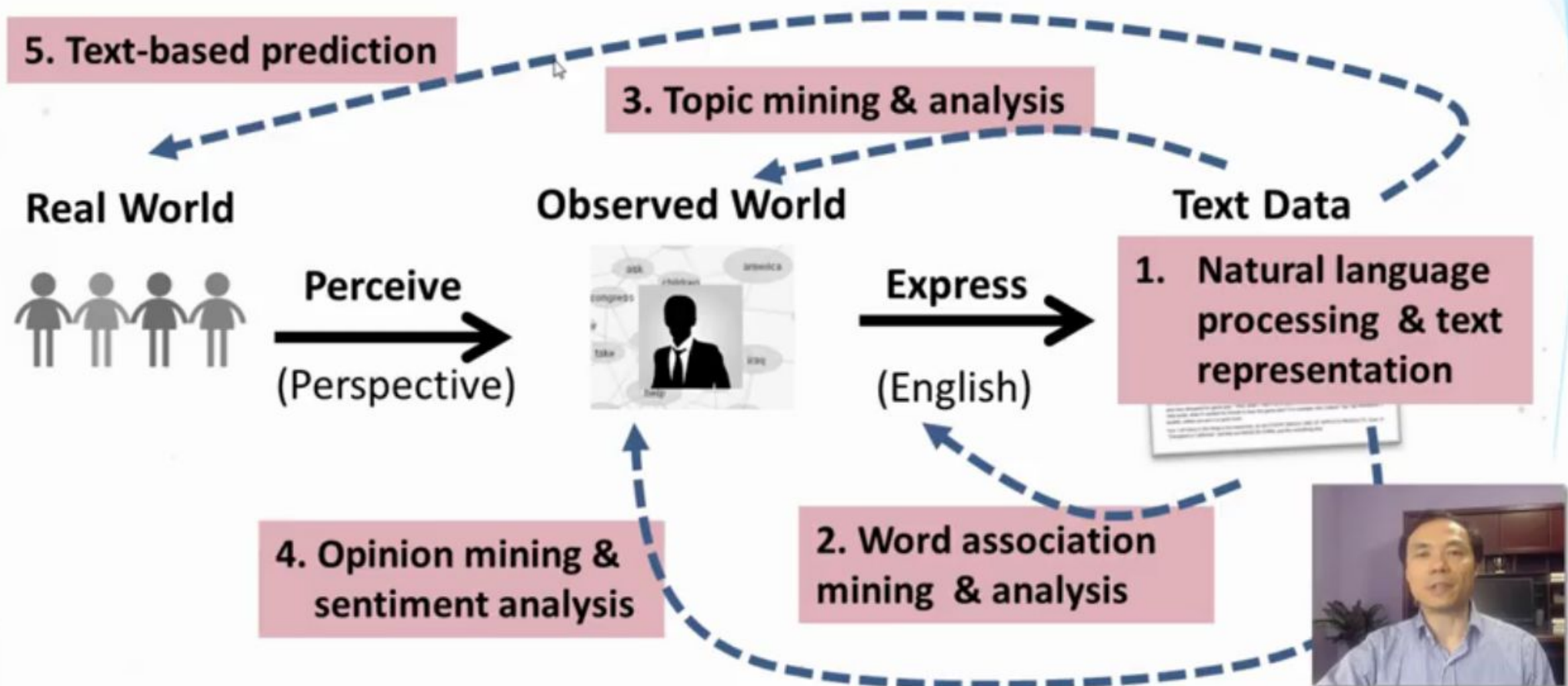


# Landscape of Text Mining and Analytics

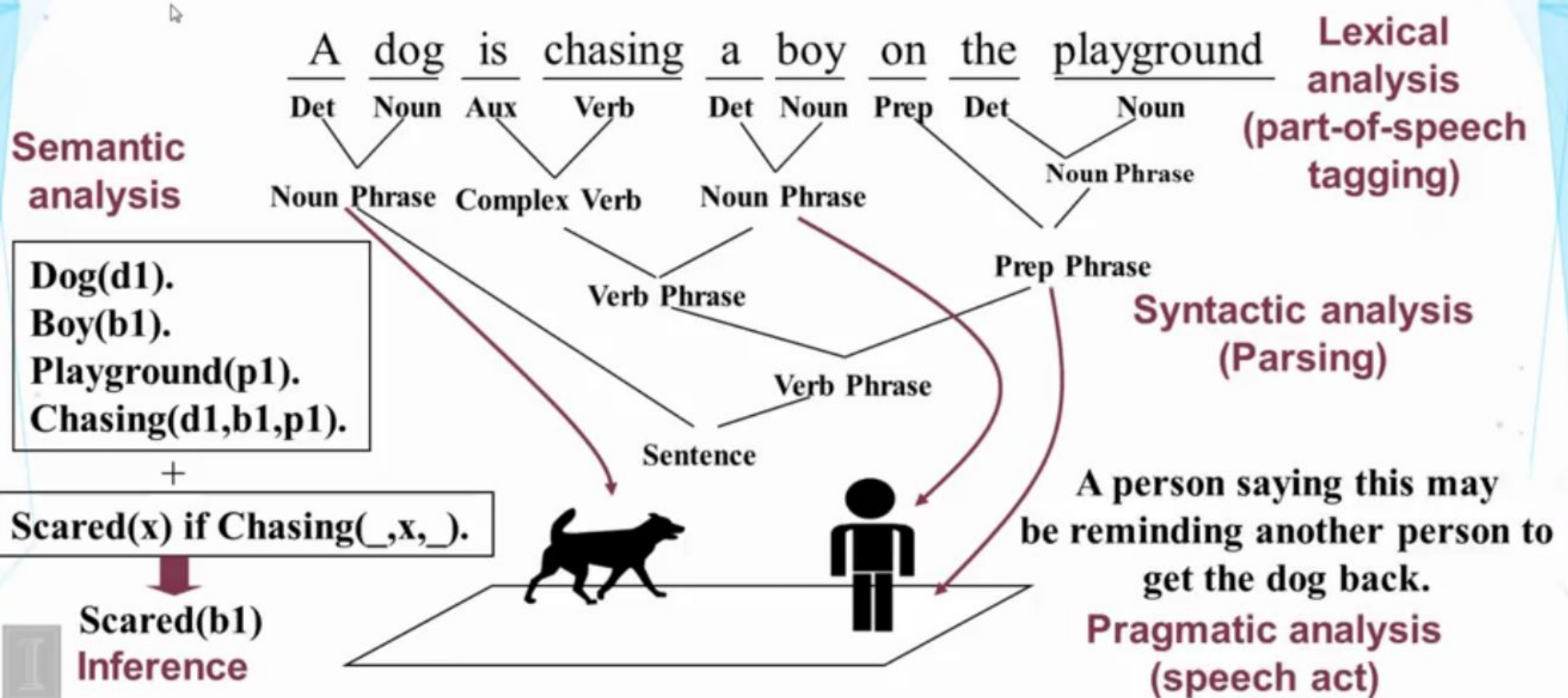




# Topics Covered in This Course



# Basic Concepts in NLP



# 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.



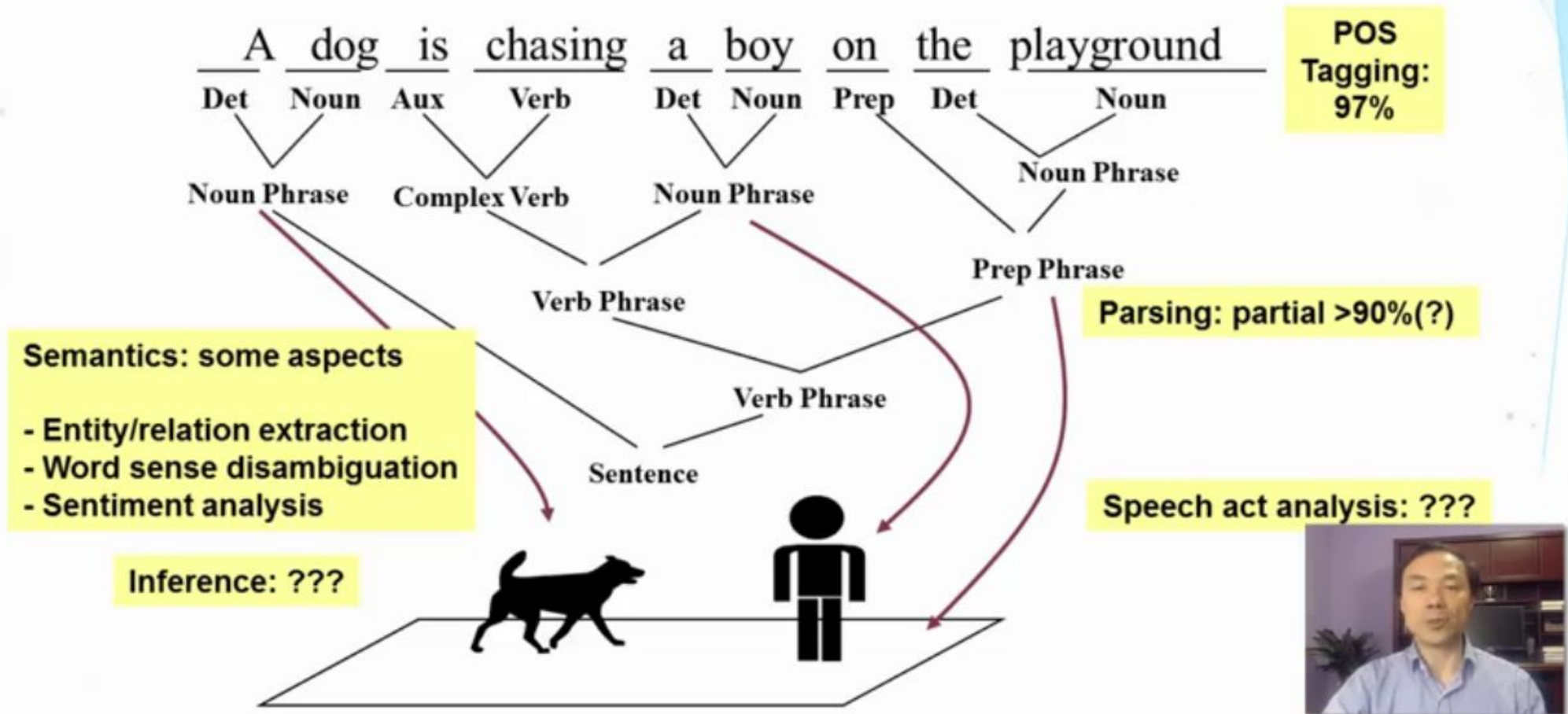
# Examples of Challenges

- 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.





# The State of the Art





# 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.**

# 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

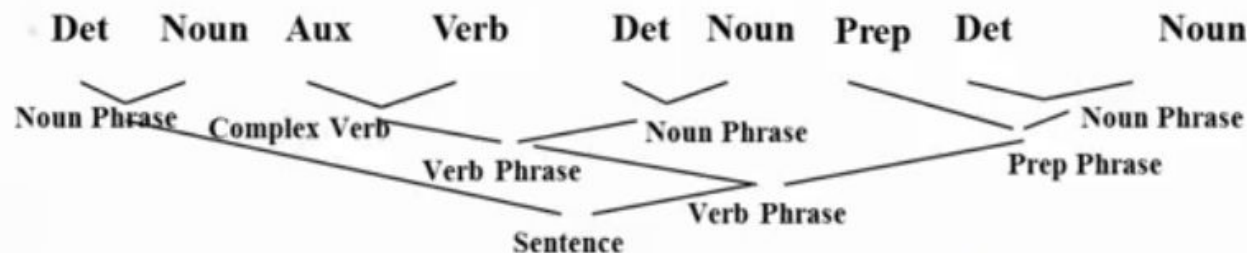
A dog is chasing a boy on the playground

**String of characters**

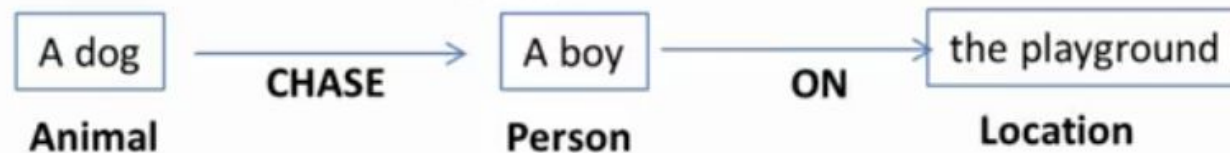
A dog is chasing a boy on the playground

**Sequence of words**

**+ POS tags**



**+ Syntactic structures**



**+ Entities and relations**

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

**+ Logic predicates**

Speech Act = REQUEST


**+ Speech acts**


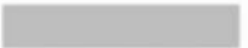



**Deeper NLP: requires more human effort; less accurate**

**Closer to knowledge representation**

# Text Representation and Enabled Analysis

This course



| Text Rep               | Generality  | Enabled Analysis   | Examples of Application                                     |
|------------------------|---|--|---|
| String                 |    | String processing  | Compression   |
| <b>Words</b>           |    | 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                          |

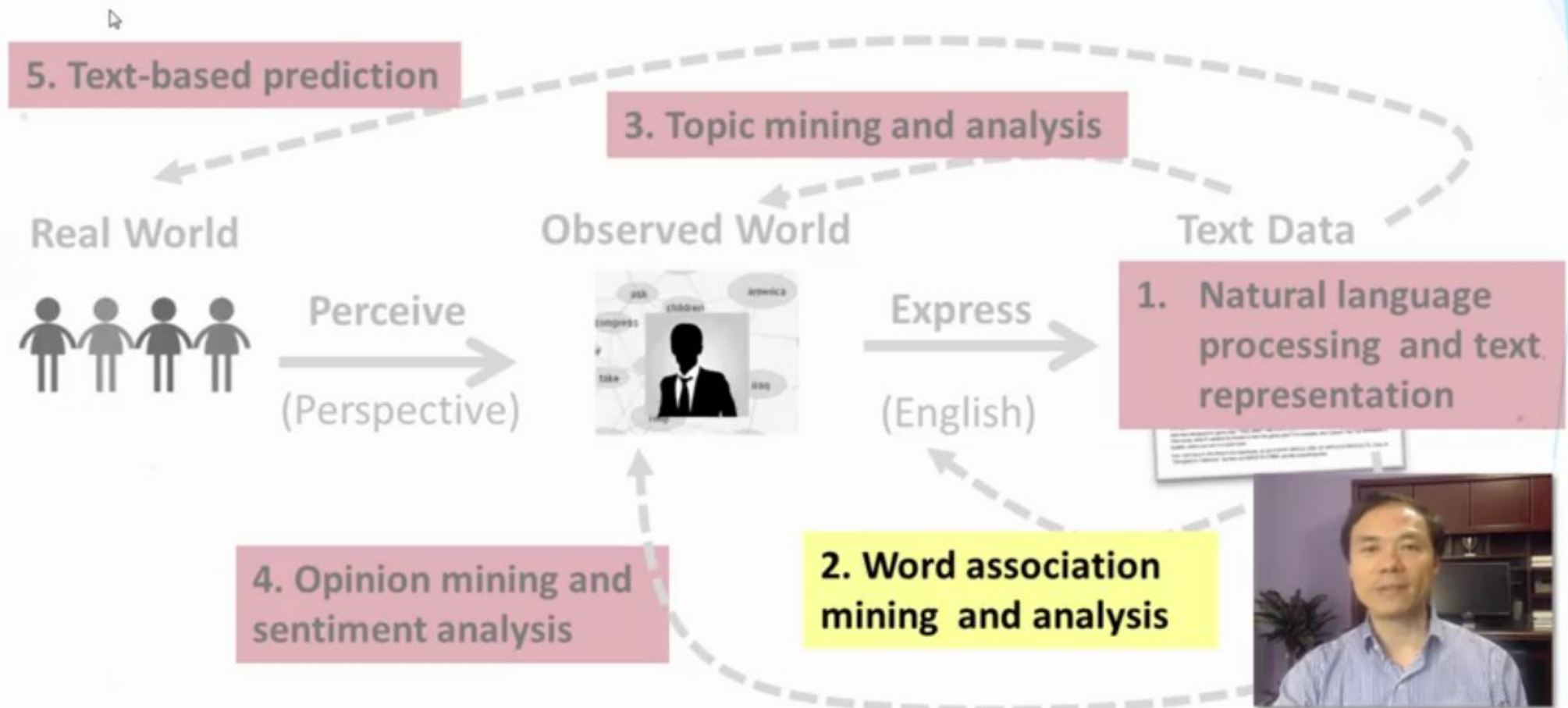


# Summary

- 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



# Word Association Mining & Analysis



# 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  
...

**cat:**

My \_\_\_ eats fish on Saturday  
His \_\_\_ eats turkey on Tuesday  
...

**dog:**

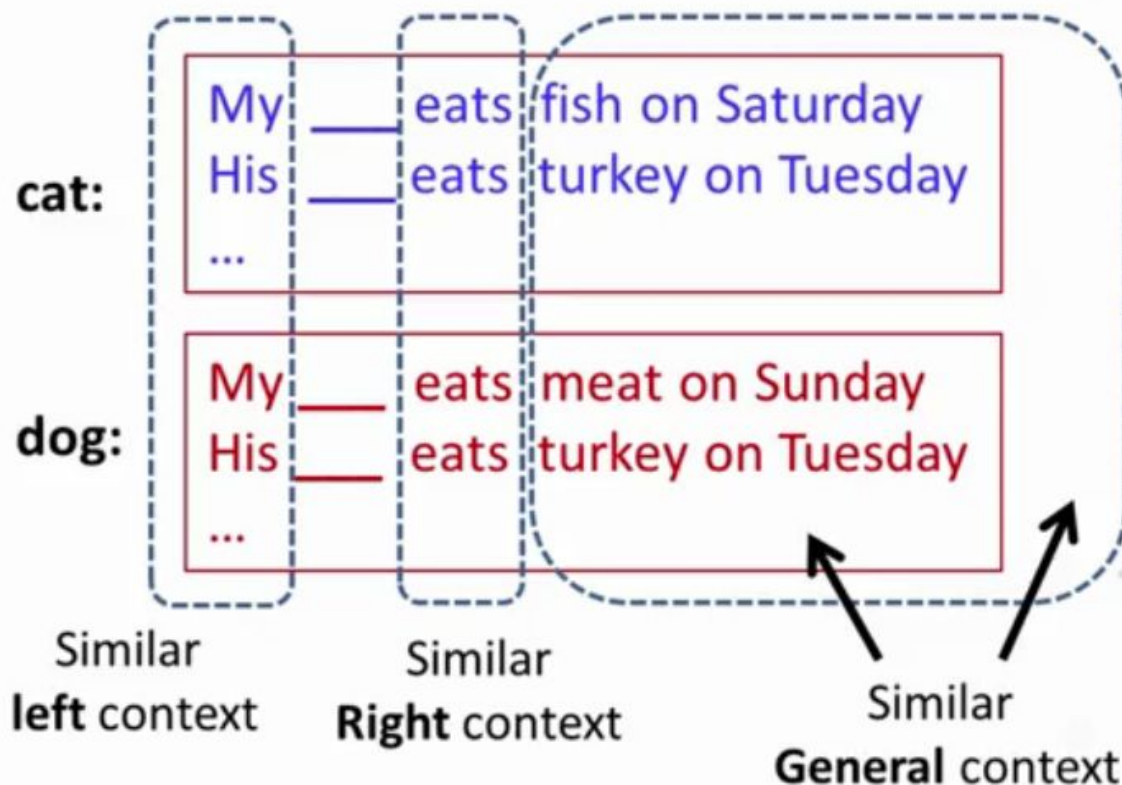
My \_\_\_ eats meat on Sunday  
His \_\_\_ eats turkey on Tuesday  
...



# 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  
...

|     |   |             |   |             |
|-----|---|-------------|---|-------------|
| My  | — | <b>eats</b> | — | on Saturday |
| His | — | <b>eats</b> | — | on Tuesday  |
| My  | — | <b>eats</b> | — | on Sunday   |
| His | — | <b>eats</b> | — | on Tuesday  |
| ... | — |             | — |             |

What words tend to occur  
to the **left** of “**eats**”?

What words  
to the **right**?

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**”?