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# Introduction to NLP

## Semantic Analysis

Dr. Paul Buitelaar  
Data Science Institute, University of Galway

Includes updates by Omnia Zayed



# Learning Objectives

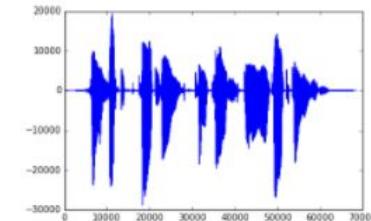
- Understand basic concepts and challenges in semantic analysis
- Understand and apply approaches to Word Sense Disambiguation
- Understand other tasks in semantic analysis: Semantic Role Labelling, Coreference Resolution



# Remember

In Lecture 2 on Linguistic Concepts, we discussed the different **linguistic levels of analysis**

Phonology - acoustic signal



Morphology – word structure

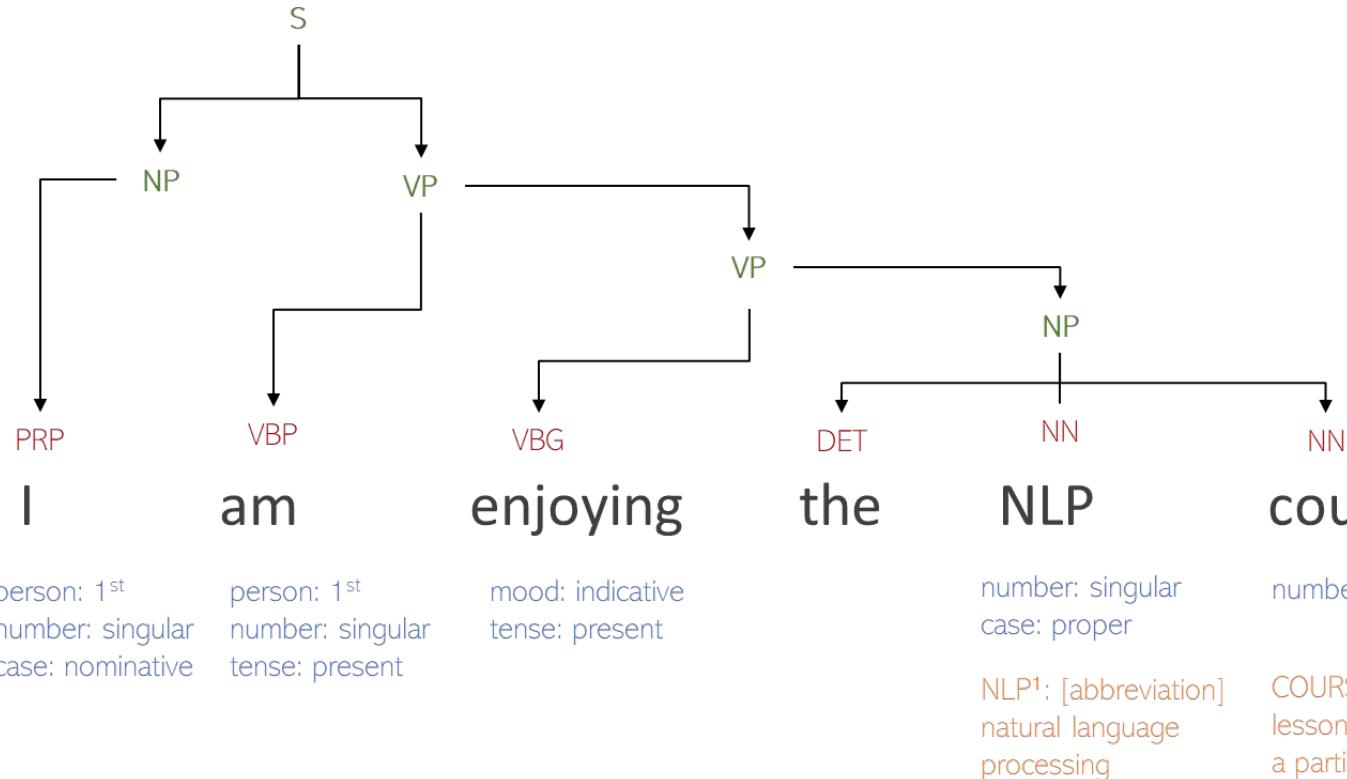
Syntax – sentence and phrase structure

Semantics – meaning and reference

Pragmatics - communication



# Remember



SYNTAX

PART OF SPEECH

WORDS

MORPHOLOGY

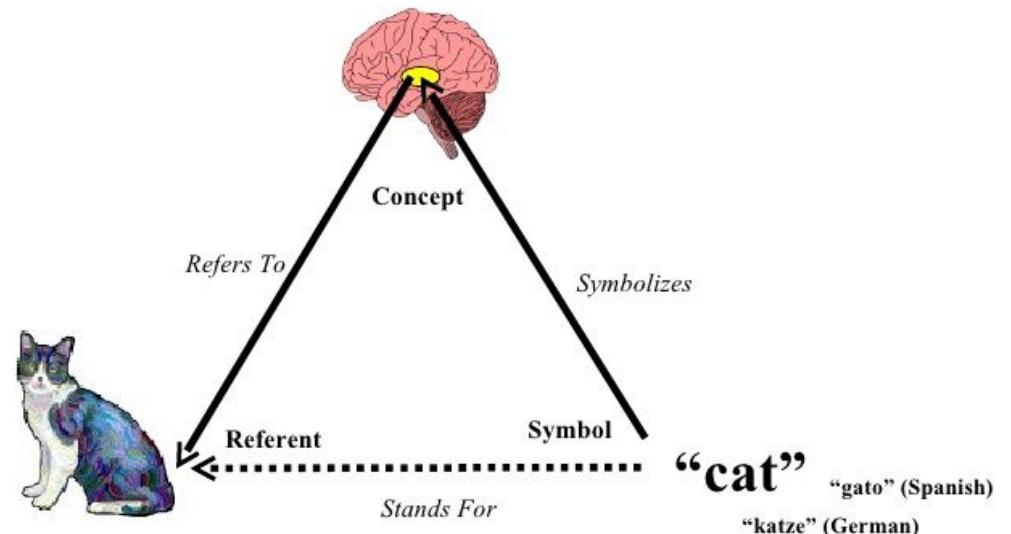
SEMANTICS



# Remember

Semantic analysis of language data is concerned with  
**how linguistic expressions/symbols** (words, phrases, sentences)  
**refer to concepts** (entities, relations, events)  
**about referents** (objects in the world)

***Semantic relation between linguistic symbols and concepts and how they refer to objects in the world is commonly referred to as ‘meaning’***



# Semantic Analysis

## Semantic Analysis in Linguistics

Analyse how **linguistic expressions** (words, phrases, sentences) refer to **meaning representations** (concepts about objects in the world)

## Semantic Analysis in NLP

Develop automatic methods for **constructing unambiguous meaning representations** for linguistic expressions



# Levels of Semantic Analysis

## Lexical Semantics

*XYZ corporation bought the **stock**.*

*She made gravy with a base of beef **stock**.*

*The store has a very low turnover of **stock**.*

**Word Sense Disambiguation:** identify correct word meaning or ‘sense’



# Levels of Semantic Analysis

## Compositional Semantics

*XYZ corporation bought the stock.*

*They sold the stock to XYZ corporation.*

*The stock was bought by XYZ corporation.*

*The purchase of the stock by XYZ corporation...*

*The stock purchase by XYZ corporation...*

**Semantic Role Labelling:** identify ‘semantic role’ for each word/phrase



# Levels of Semantic Analysis

## Discourse Semantics

*XYZ corporation bought the stock. They had the backing from their bank.*

*XYZ corporation bought the stock. It was valued rather high.*

**Coreference Resolution:** identify which words/phrases refer to the same ‘entity’ across sentences



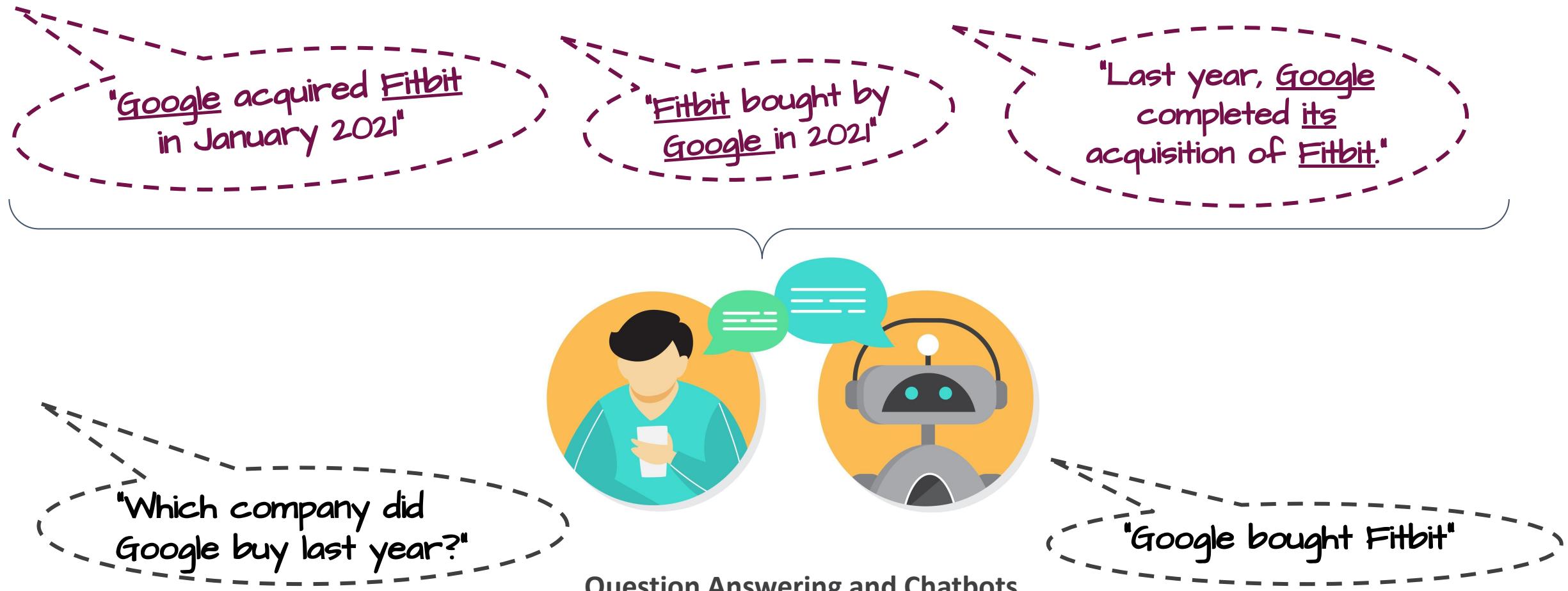


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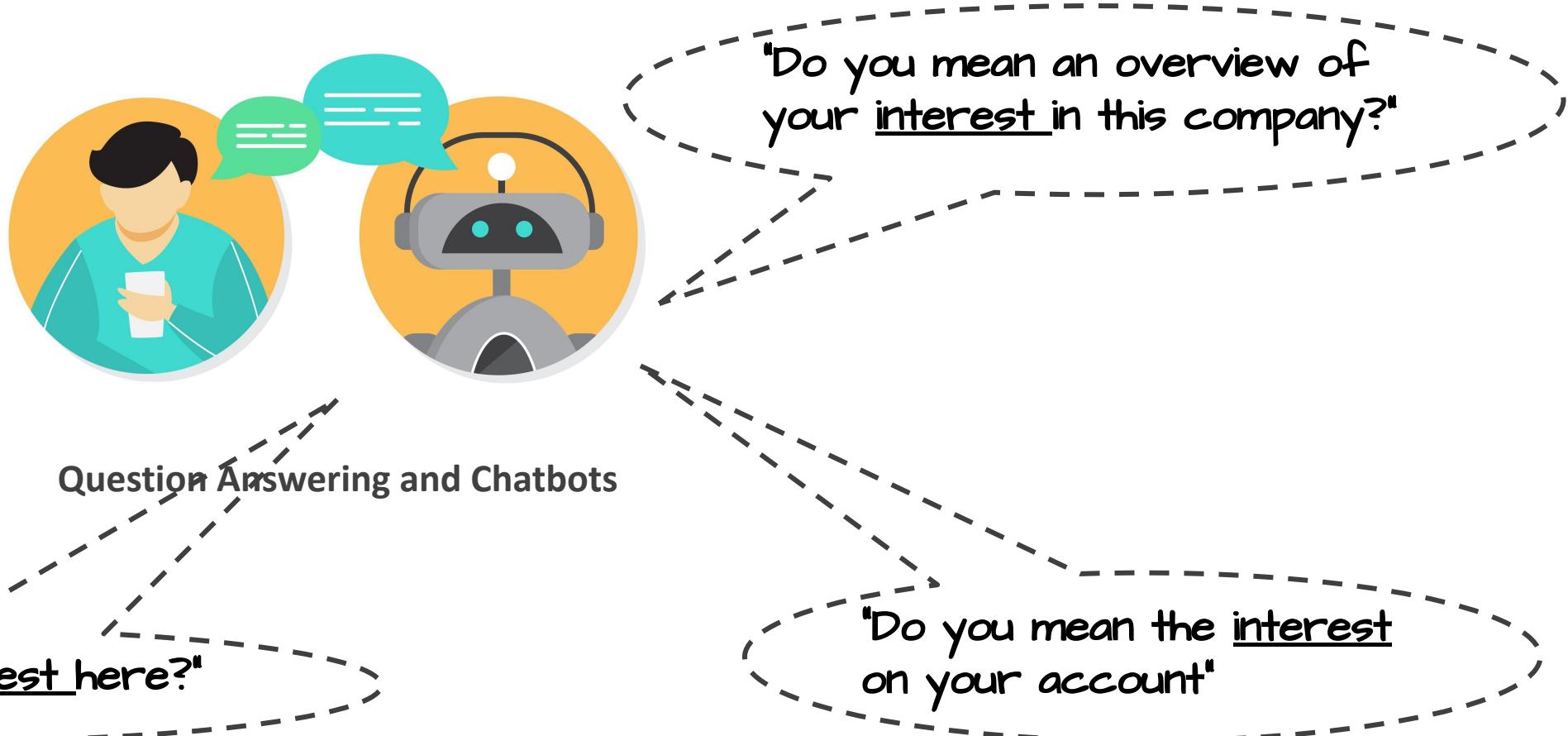
# Buzz Groups

Why do we need semantic analysis?

# Semantic Analysis in Applications - SRL, CR



# Semantic Analysis in Applications - WSD





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# Word Sense Disambiguation

# What is Word Sense Disambiguation?

Words can have different meanings due to **homonymy**



*table* in the interpretation of **furniture**

*table* in the interpretation of **data**

3 YEARS ACCOUNTING									
COST ITEM	DESCRIPTION	TOTAL BUDGET	HISTORIC	HISTORIC	HISTORIC	HISTORIC	HISTORIC	CURRENT	FOREC
			Q1	Q2	Q3	Q4	Q5	Q6	Q7
A1	Directly incurred: Staff	£1,000,000.00	£20,000.00	£50,000.00	£50,000.00	£100,000.00	£100,000.00	£1,300,00	
A2	Directly incurred: Travel & subsistence	£150,000.00	£6,000.00	£6,000.00	£6,000.00	£6,000.00	£6,000.00	£6,000.00	£6,000
A3	Directly incurred: Equipment	£1,500,000.00	£50,000.00	£50,000.00	£50,000.00	£50,000.00	£50,000.00	£50,000.00	£50,00
A4	Directly incurred: Other cost	£400,000.00	£20,000.00	£20,000.00	£20,000.00	£20,000.00	£20,000.00	£20,000.00	£20,00
A4a	Directly incurred: Exceptions Other	£100,000.00		£5,000.00			£20,000.00		
A5	Directly allocated: Investigators	£300,000.00	£30,000.00	£30,000.00	£30,000.00	£30,000.00	£30,000.00	£30,000.00	£30,00
A6	Directly allocated: Estates	£300,000.00	£10,000.00		£10,000.00		£10,000.00		£10,00
A7	Directly allocated: Other cost	£100,000.00							
A8	Indirect costs	£100,000.00	£15,000.00	£15,000.00	£15,000.00	£15,000.00	£15,000.00	£15,000.00	£15,00
A9	Exceptions: Staff	£20,000.00							
A10	Exceptions: Travel & Subsistence	£10,000.00		£2,000.00		£2,000.00		£2,000.00	
A11	Exceptions: Student Internships	£10,000.00							
A12	Exceptions: Other cost	£20,000.00							
Total Cost (for each claim)		£4,010,000.00	£151,000.00	£148,000.00	£181,000.00	£173,000.00	£251,000.00	£223,000.00	£1,431,0
Total Cost (cumulative)			£151,000.00	£299,000.00	£480,000.00	£653,000.00	£904,000.00	£1,127,000.00	£2,558,0

# Word Senses

*mouse*



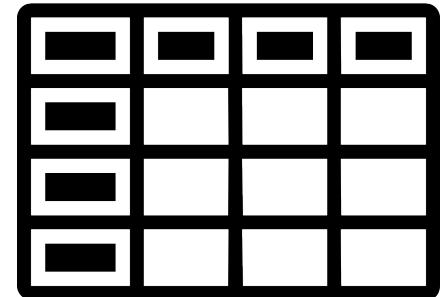
**mouse#1**  
**ANIMAL**

**mouse#2**  
**OBJECT**

*table*



**table#1**  
**FURNITURE**



**table#2**  
**DATA**

# Word Senses - Dictionary / Lexicon

## table

From Longman Dictionary of Contemporary English

Related topics: [Furniture](#), [Newspapers](#), [printing](#), [publishing](#)

**ta·ble<sup>1</sup>** /'teɪbəl/ ••• **S1** **W1** noun [countable]

1 **FURNITURE** a piece of furniture with a flat top supported by legs

The food was served on long tables.

→ **coffee table**, **dressing table**

2 **RESTAURANT** a table for people to eat at in a restaurant

I've booked a table for two.

3 → **snooker/billiard/ping-pong etc table**

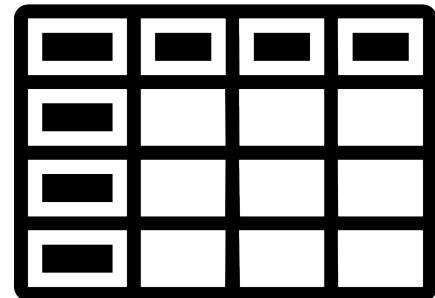
4 **LIST** a list of numbers, facts, or information arranged in rows across and down a page

**table of**

a table of results

the table of contents

the



**table#1**  
**FURNITURE**

**table#2**  
**DATA**



# Word Senses - Summary

- A sense, or **word sense**, is a discrete representation of one meaning of a word
- Words can have different meanings due to **homonymy** (same sound or spelling but different meaning)
- Word senses can be defined explicitly in a **semantic lexicon** such as WordNet



# Word Senses - Explicit vs. Implicit

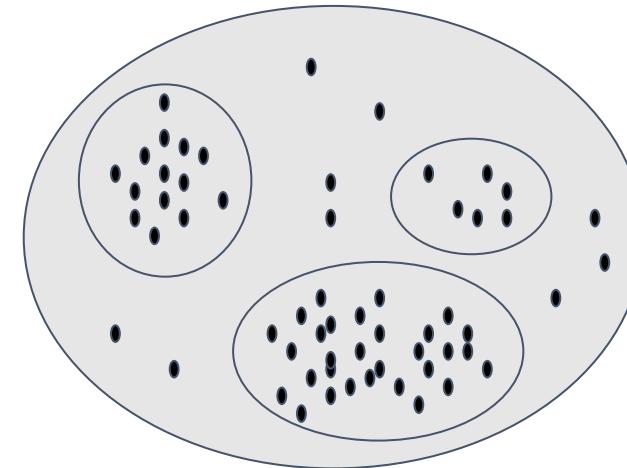
Use lists to define **explicit** word senses (symbolic)

Use clusters to define **implicit** word senses (sub-symbolic)

*table#1: FURNITURE*

*table#2: ACCOUNTING*

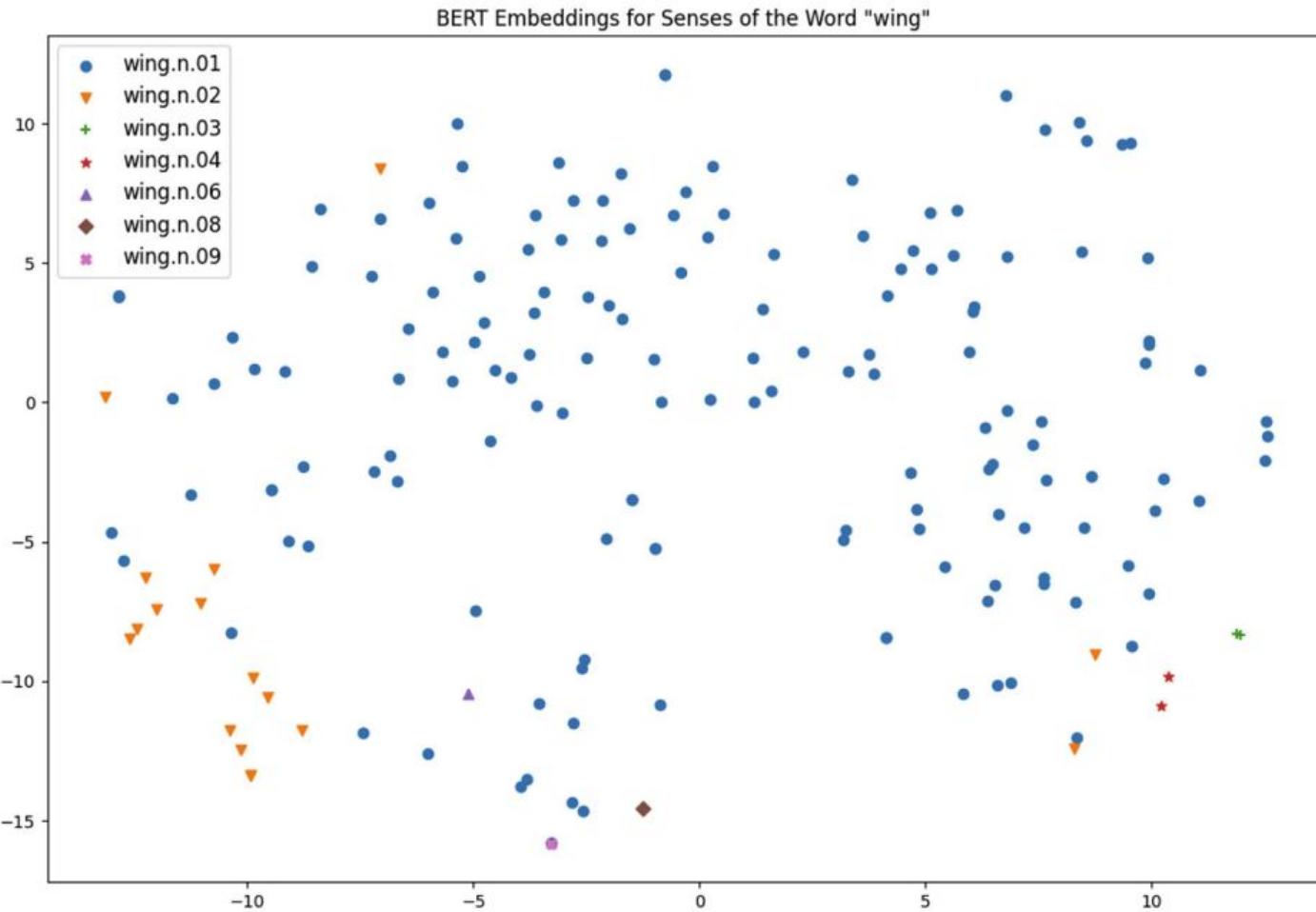
*table#3: GEOGRAPHICAL*



**Here we focus on explicitly defined (symbolic) word senses as in WordNet**



# Word Senses - Clustering



# Word Senses - not only Nouns

*They rarely **serve** red meat, preferring to prepare seafood.*

*He **served** as U.S. ambassador to Norway in 1976 and 1977.*

*He might have **served** his time, come out and led an upstanding life.*



# Word Senses in WordNet

Remember that WordNet uses ‘synsets’ to define word senses



# Word Senses in WordNet

*... drag the field to the **table** until you see an insertion point ...*

*... on the dining **table**, vases are a beautiful addition to any home ...*

- S: (n) **table#1**, tabular array#1 (a set of data arranged in rows and columns) "see *table 1*"
- S: (n) **table#2** (a piece of furniture having a smooth flat top that is usually supported by one or more vertical legs) "*it was a sturdy table*"
- S: (n) **table#3** (a piece of furniture with tableware for a meal laid out on it) "*I reserved a table at my favorite restaurant*"
- S: (n) mesa#1, table#4 (flat tableland with steep edges) "*the tribe was relatively safe on the mesa but they had to descend into the valley for water*"
- S: (n) **table#5** (a company of people assembled at a table for a meal or game) "*he entertained the whole table with his witty remarks*"
- S: (n) board#4, table#6 (food or meals in general) "*she sets a fine table*"; "*room and board*"



# Word Sense Disambiguation

... drag the field to the [table#1] until you see an insertion point ...

... on the dining [table#3], vases are a beautiful addition to any home ...

- S: (n) table#1, tabular array#1 (a set of data arranged in rows and columns) "see *table 1*"
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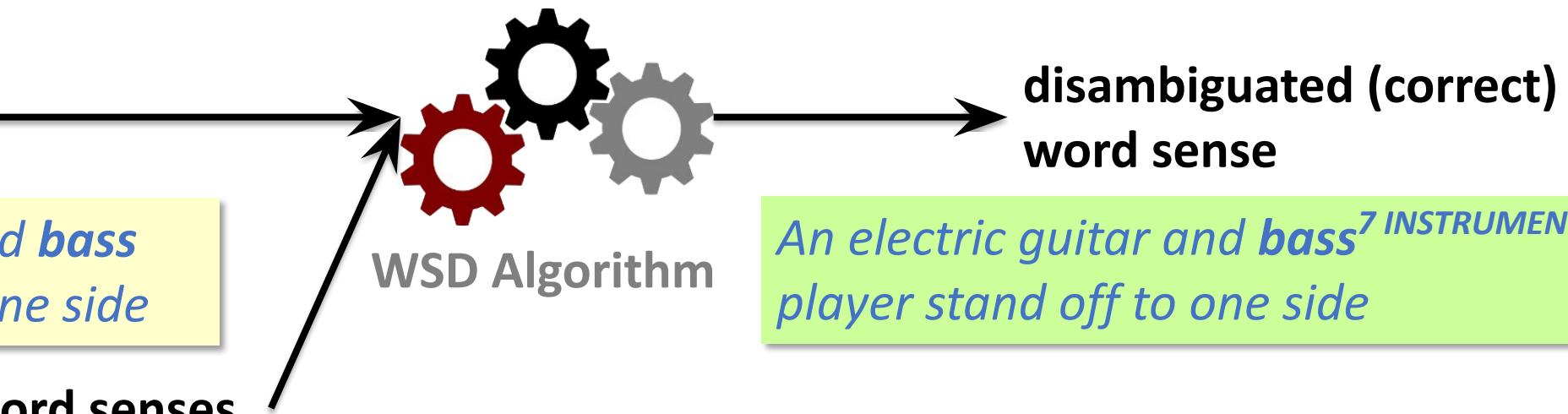
# WSD Task

a word in context

*An electric guitar and **bass** player stand off to one side*

fixed inventory of word senses

- S: (n) **bass#1** (the lowest part of the musical range)
- S: (n) **bass#2, bass\_part#1** (the lowest part in polyphonic music)
- S: (n) **bass#3, basso#1** (an adult male singer with the lowest voice)
- S: (n) sea bass#1, bass#4 (the lean flesh of a saltwater fish of the family Serranidae)
- S: (n) freshwater bass#1, bass#5 (any of various North American freshwater fish with lean flesh (especially of the genus Micropterus))
- S: (n) **bass#6, bass voice#1, basso#2** (the lowest adult male singing voice)
- S: (n) **bass#7** (the member with the lowest range of a family of musical instruments)
- S: (n) **bass#8** (nontechnical name for any of numerous edible marine and freshwater spiny-finned fishes)





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# Buzz Groups

Can you think of different approaches to WSD?

# Approaches to WSD

## Unsupervised

- Knowledge-based
- Graph-based

## Supervised

- Word Sense Annotated Corpora

## Semi-supervised

- Distant supervision



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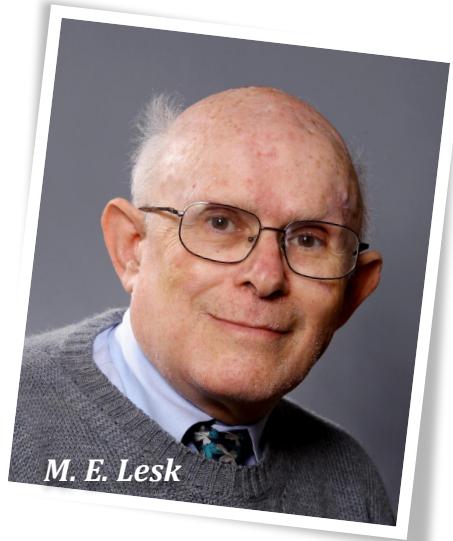


# Unsupervised WSD - Knowledge-based

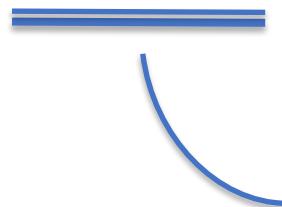
## Lesk

Oldest, most effective baseline **WSD algorithm**

Uses a dictionary (e.g. WordNet) as **knowledge base**



M. E. Lesk



Choose the sense that shares the most words in its signature (dictionary definition) with the context of the target word



# (Simplified) Lesk Algorithm

**function** SIMPLIFIED LESK(*word, sentence*) **returns** best sense of *word*

*best-sense*  $\leftarrow$  most frequent sense for *word*

*max-overlap*  $\leftarrow$  0

*context*  $\leftarrow$  set of words in *sentence*

**for each** *sense* **in** senses of *word* **do**

*signature*  $\leftarrow$  set of words in the gloss and examples of *sense*

*overlap*  $\leftarrow$  COMPUTE OVERLAP(*signature, context*)

**if** *overlap*  $>$  *max-overlap* **then**

*max-overlap*  $\leftarrow$  *overlap*

*best-sense*  $\leftarrow$  *sense*

**end**

**return**(*best-sense*)



# Lesk Algorithm – Example

*The toolbar includes a basic **table** drawing feature that lets you divide the canvas into rows and columns that you can use to organize your text.*



# Lesk Algorithm – WordNet Senses

*The toolbar includes a basic **table** drawing feature that lets you divide the canvas into rows and columns that you can use to organize your text.*

<b>Word</b>	<b>Sense</b>	<b>SynSets</b>
<i>table</i>	#1	table#1, tabular array#1
	#2	table#2



# Lesk Algorithm – Dictionary Definition

*The toolbar includes a basic **table** drawing feature that lets you divide the canvas into rows and columns that you can use to organize your text.*

**Word      Sense      dictionary definition - here WordNet gloss**

*table*      #1      ‘*a set of data arranged in rows and columns*’

                #2      ‘*a piece of furniture having a smooth flat top that is usually supported by one or more vertical legs*’



# Lesk Algorithm – Signature

*The toolbar includes a basic **table** drawing feature that lets you divide the canvas into rows and columns that you can use to organize your text.*

<b>Word</b>	<b>Sense</b>	<b>Signature (e.g. nouns in dictionary definition - here WordNet gloss)</b>
<i>table</i>	#1	<i>'a set of <u>data</u> arranged in <u>rows</u> and <u>columns</u>'</i>
	#2	<i>'a piece of <u>furniture</u> having a smooth flat <u>top</u> that is usually supported by one or more vertical <u>legs</u>'</i>



# Lesk Algorithm – Context/Signature Overlap

*The toolbar includes a basic **table** drawing feature that lets you divide the canvas into rows and columns that you can use to organize your text.*

Word	Sense	Signature	
<i>table</i>	#1	<i>data <u>rows</u> <u>columns</u></i>	2
	#2	<i>furniture top legs</i>	0



# Lesk Algorithm – Best Sense

*The toolbar includes a basic [table#1] drawing feature that lets you divide the canvas into rows and columns that you can use to organize your text.*

Word	Sense	SynSets
table	#1	table#1, tabular array#1
	#2	table#2



# Approaches to WSD

## Unsupervised

- Knowledge-based
- Graph-based

## Supervised

- Word Sense Annotated Corpora

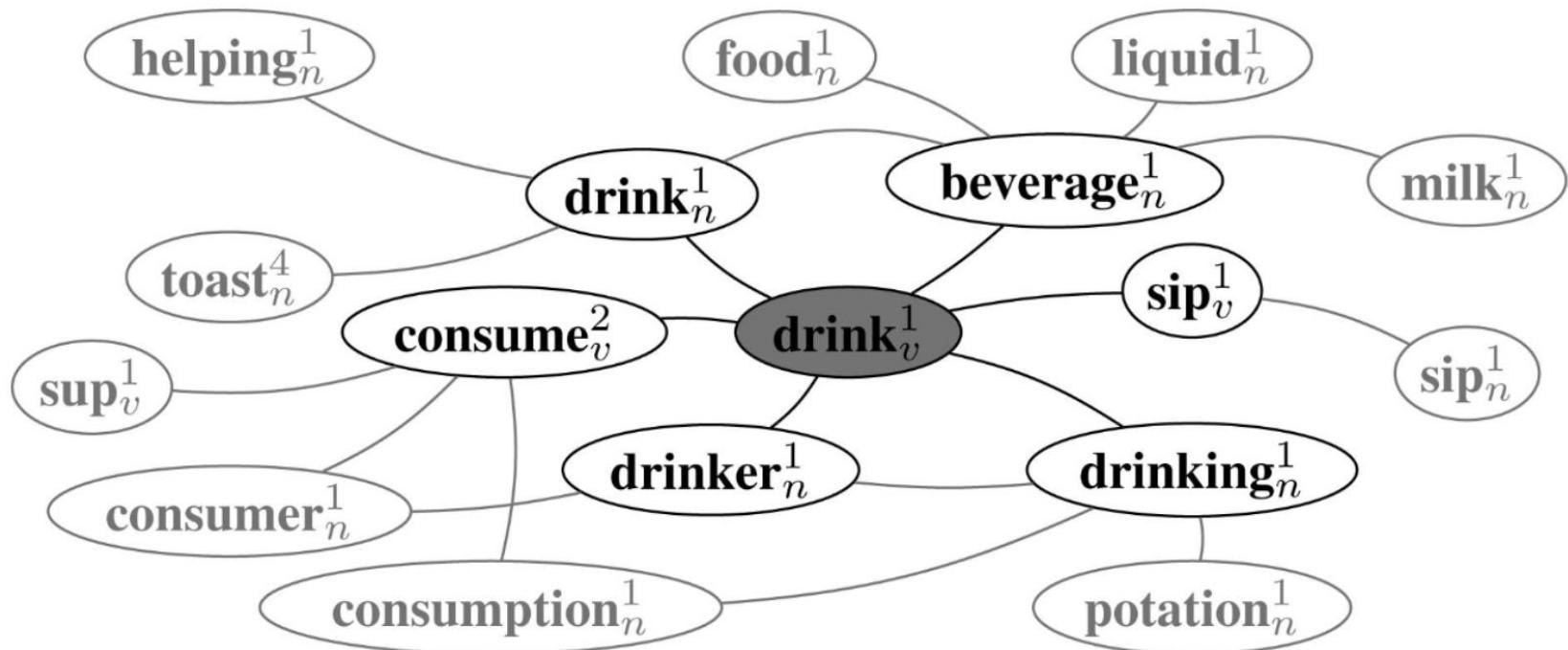
## Semi-supervised

- Distant supervision



# Unsupervised WSD using Graph Distance

WordNet graph for word sense **drink (verb) #1: 'take in liquids'**

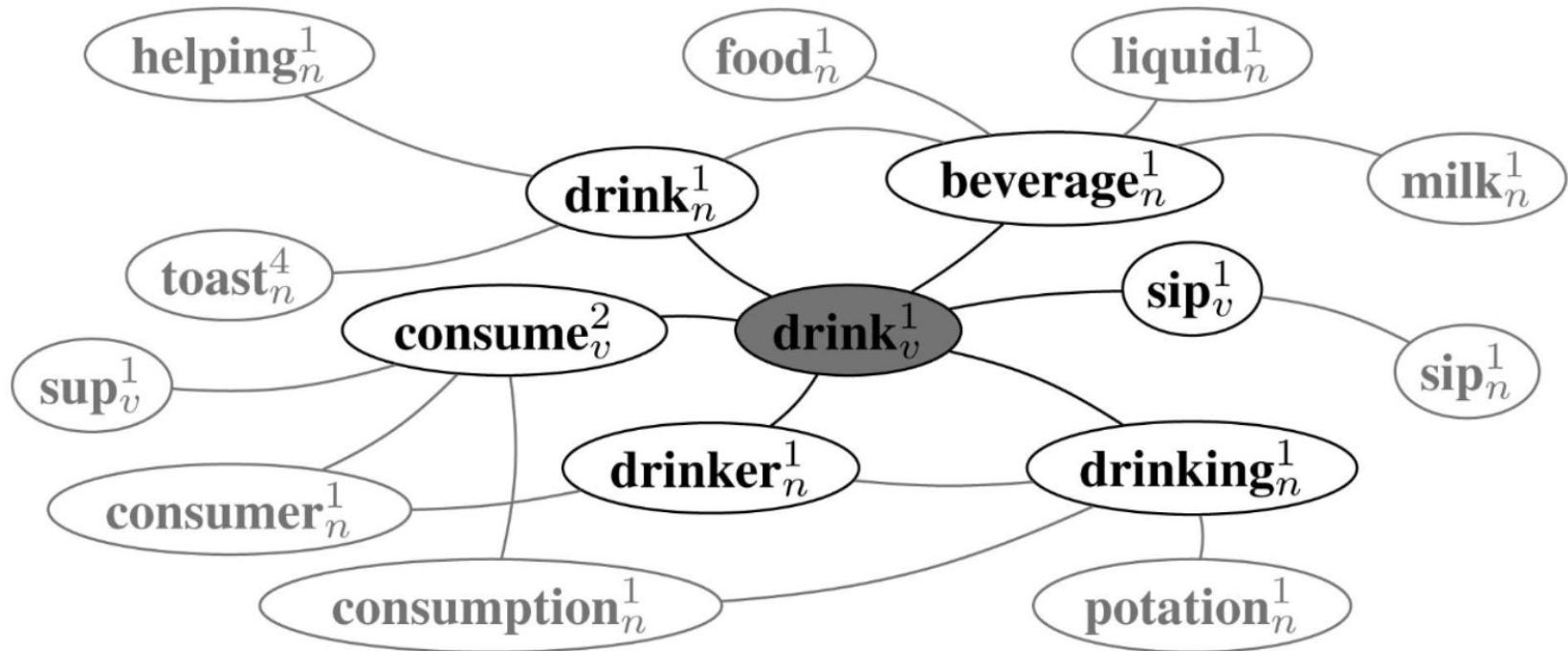


Navigli, R. and Lapata, M. (2010). An experimental study of graph connectivity for unsupervised word sense disambiguation. *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 32(4), 678–692



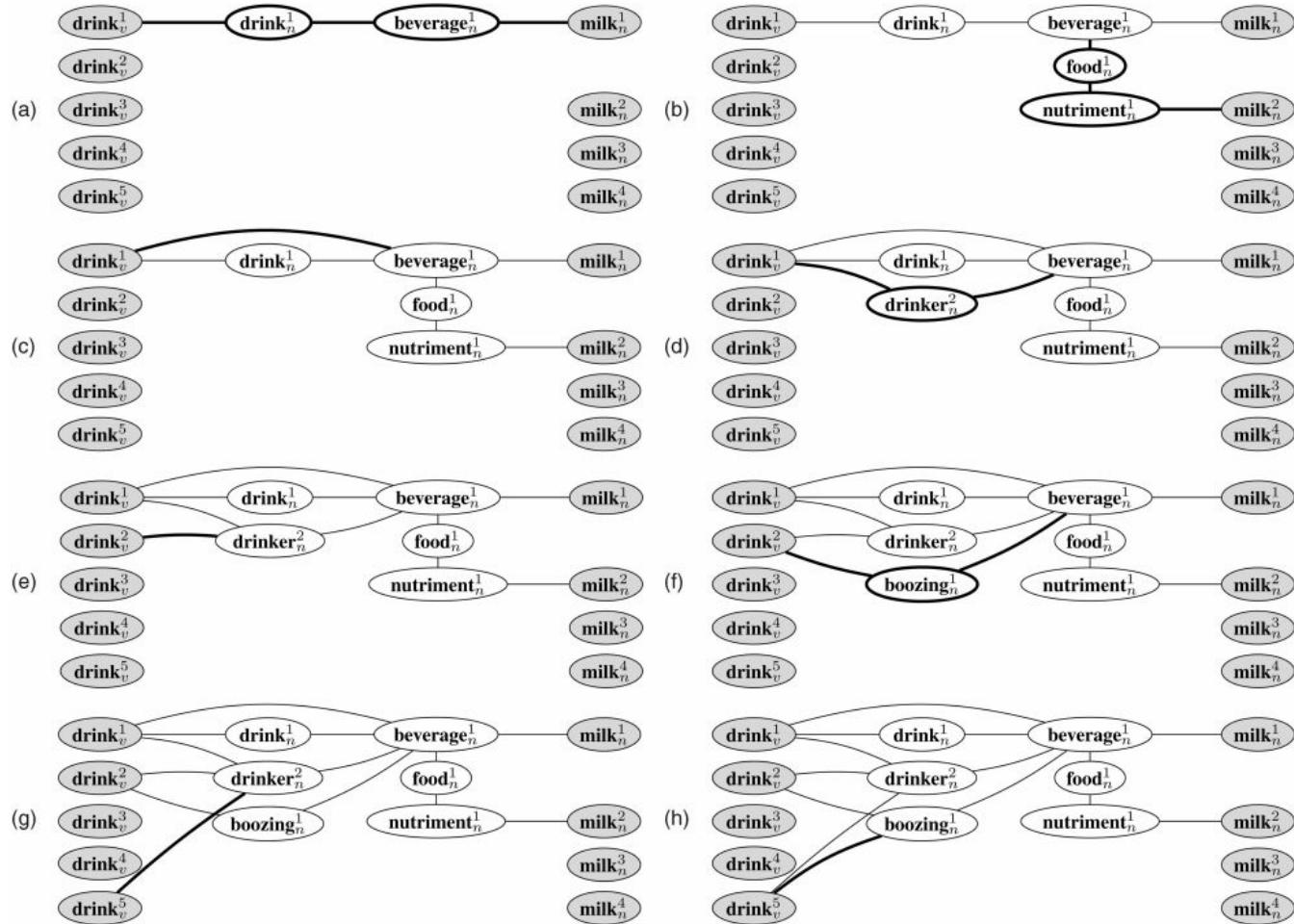
# Graph-based Methods for WSD

Can we use this graph to disambiguate words in the sentence “*She drank some milk.*”



# Graph Construction

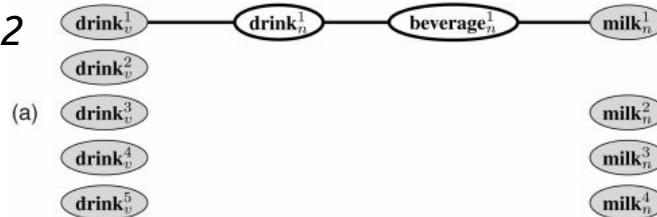
*“She drank some milk.”*



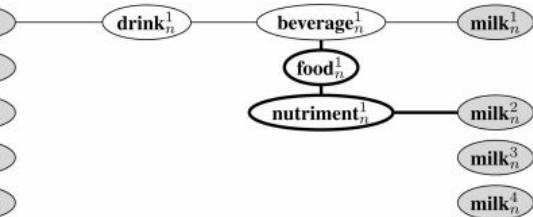
# Paths in the Graph with Distance

*“She drank some milk.”*

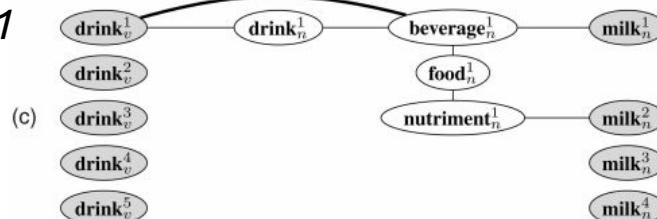
$$d(u,v) = 2$$



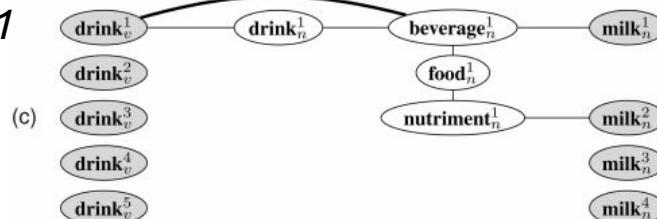
$$d(u,v) = 4$$



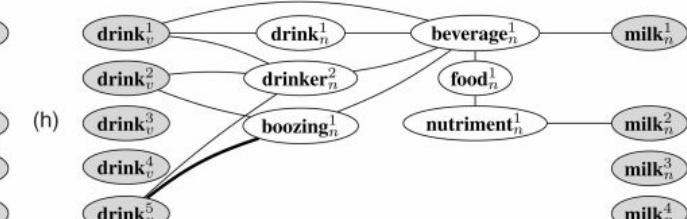
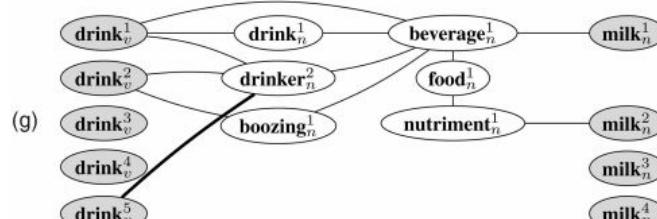
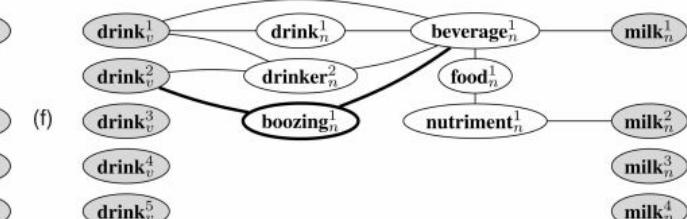
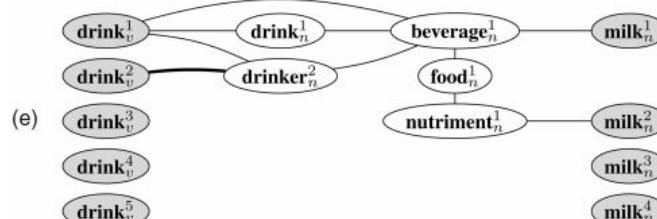
$$d(u,v) = 1$$



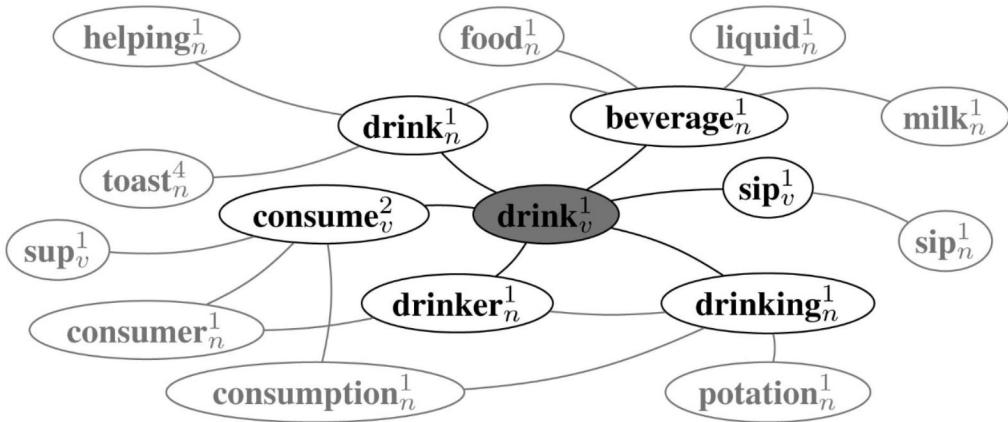
$$d(u,v) = 2$$



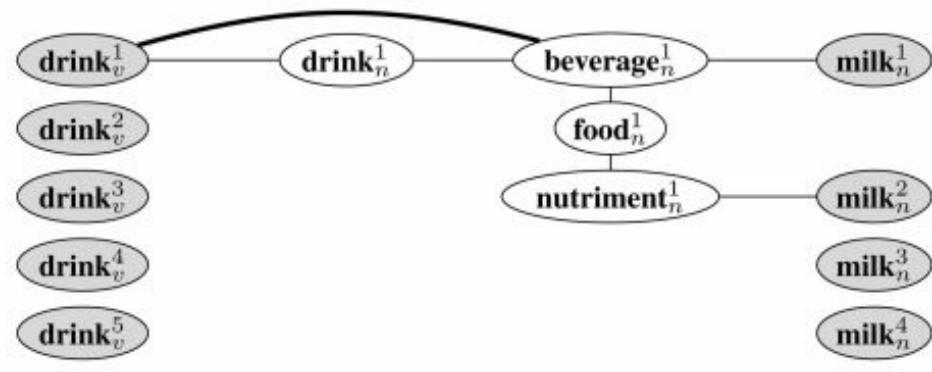
$$d(u,v) = 4$$



# Shortest Path



$$d(u, v) = 1$$



*"She [drank#1] some [milk#1]."*

# Approaches to WSD

## Unsupervised

- Knowledge-based
- Graph-based

## Supervised

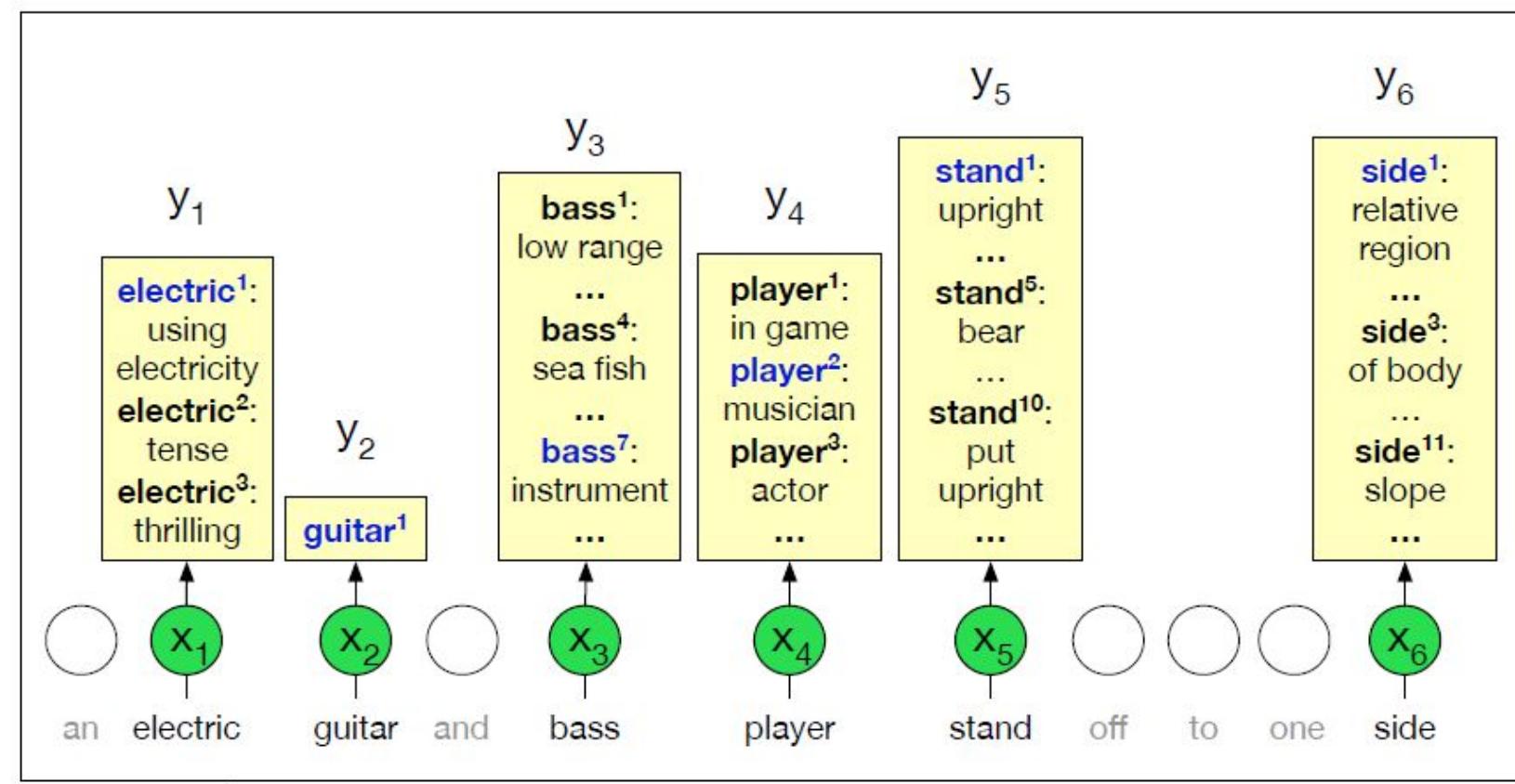
- Word Sense Annotated Corpora

## Semi-supervised

- Distant supervision



# Supervised WSD - Sense Annotated Corpora



# WSD - Vector Space Model

WSD target:

*To add columns and rows, drag the field to the **table** until you see an insertion point.*

Labeled (word sense annotated) corpus data:

*In addition to rows, you can also divide a **table#1** into columns.*

*This **table#2** is of the highest quality, crafted from solid wood.*

Vocabulary (nouns in WSD target and labeled data):

**[columns, rows, field, point, quality, wood]**



# WSD - Vector Space Model

WSD target:

*To add columns and rows, drag the field to the **table** until you see an insertion point.*

Labeled (word sense annotated) corpus data:

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*This **table#2** is of the highest quality, crafted from solid wood.*

Vocabulary (nouns in WSD target and labeled data):

**[columns, rows, field, point, quality, wood]**

Vectors (binary):

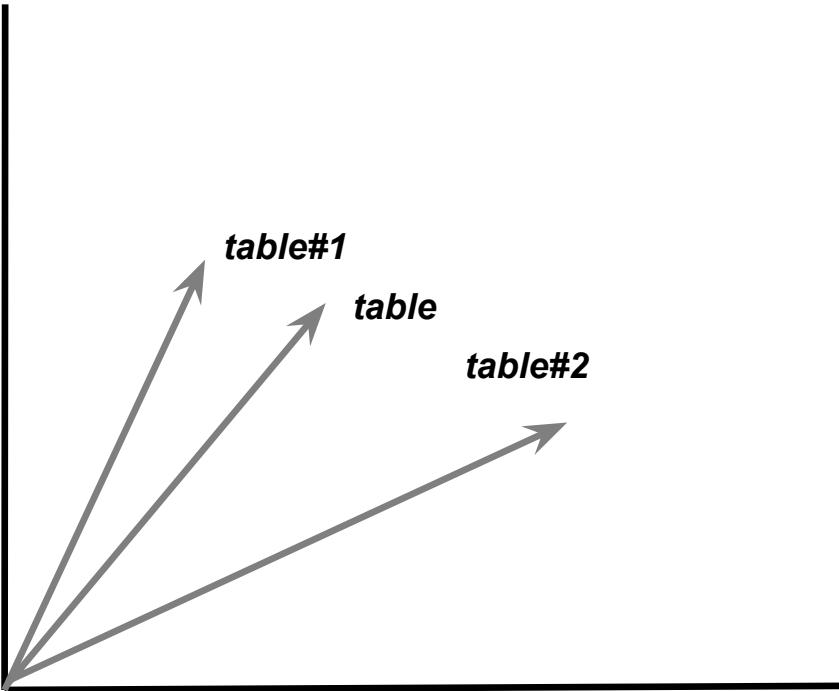
**table**      **[1,1,1,1,0,0]**

**table#1**      **[1,1,0,0,0,0]**

**table#2**      **[0,0,0,0,1,1]**



# WSD - Vector Space Model



# Supervised WSD - Features

SVM classifier using features of surrounding words (e.g. window of 2 on each side):

*An electric [guitar and bass player stand] off to one side.*

part-of-speech tags

*guitar, NN, and, CC, player, NN, stand, VB*

collocation features

*and guitar, player stand*

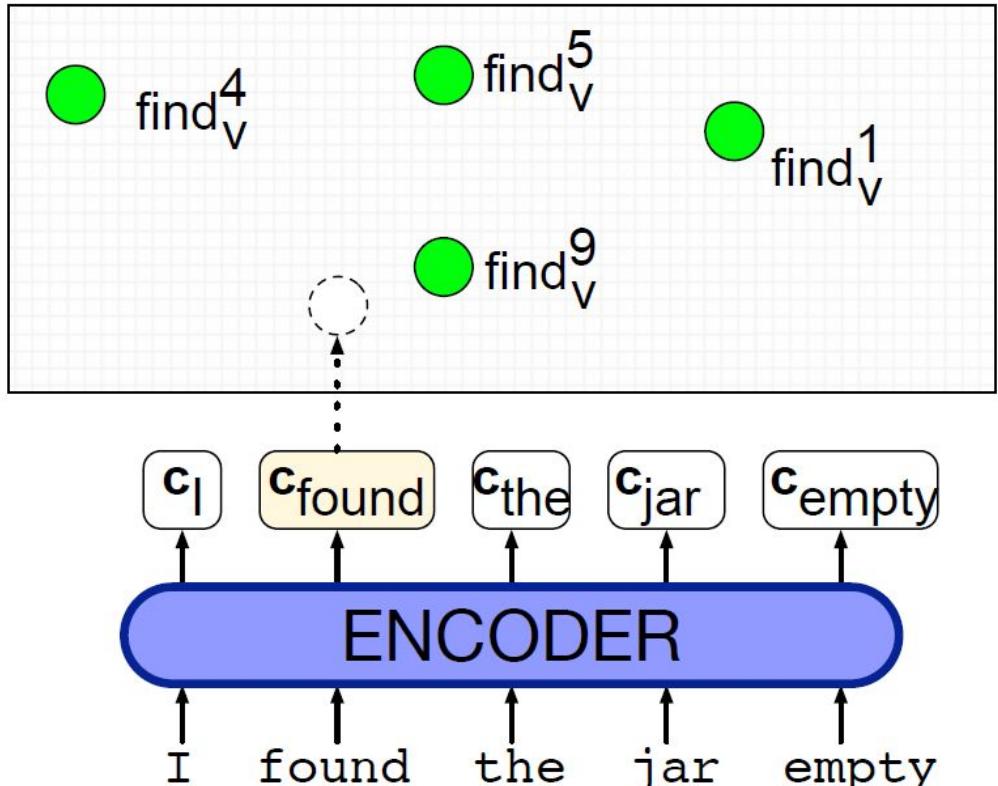
weighted sum  $g$  of embeddings

$g( E(\text{guitar}), E(\text{and}), E(\text{player}), E(\text{stand}) )$

$[ \text{guitar}, \text{NN}, \text{and}, \text{CC}, \text{player}, \text{NN}, \text{stand}, \text{VB}, \text{and guitar, player stand}, g( E(\text{guitar}), E(\text{and}), E(\text{player}), E(\text{stand}) ) ]$



# Supervised WSD - Nearest-Neighbor Algorithm



## WSD Training

- Pass each sentence in a word sense labeled dataset (e.g. SemCore: Miller et al 1993) through any contextual embedding (e.g., BERT)
- For each token of each sense of each word, average contextual representations to produce contextual sense embeddings

## WSD Application

- Compute contextual embedding for target (ambiguous) word and select nearest neighbor contextual sense embedding from training set





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# Buzz Groups

Can you think of a challenge in supervised WSD?

# Supervised WSD - Lack of Training Data

Only a **few sense annotated corpora exist**, even for English

No sense annotated corpora for most **other languages**

No sense annotated corpora for **domain-specific areas** (e.g. finance)

**Language use changes rapidly**, sense annotation may be outdated soon



# Approaches to WSD

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## Semi-supervised

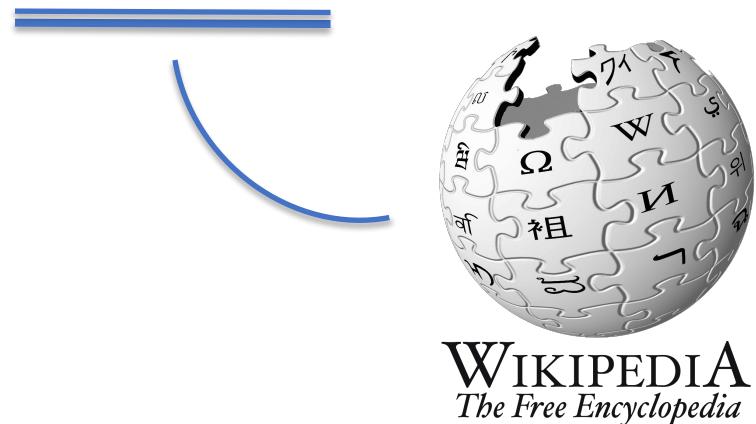
- Distant supervision



# Semi-Supervised WSD

Distant Supervision by use of Wikipedia as a source of sense-labeled data

We do not consider labeled data in a corpus but use **related data** at a ‘distance’ as  
‘weakly labeled data’



# Using Wikipedia Categories as WordNet Senses



WIKIPEDIA  
The Free Encyclopedia

Article Talk

Read Edit View hi

No

## Table

From Wikipedia, the free encyclopedia

For use of tables to display information in Wikipedia, see [Wikipedia:Tables](#).

"Tabular" redirects here. For the typewriter key, see [tab key](#). For the bone at the back of the skull, see [tabular bone](#).

Table may refer to:

- [Table \(furniture\)](#), a piece of furniture with a flat top and one or more legs
- [Table \(information\)](#), a data arrangement with rows and columns
- [Table \(database\)](#)
- [Calligra Tables](#), a spreadsheet application
- [Mathematical table](#)
- [Table \(landform\)](#)
- [Table \(parliamentary procedure\)](#)
- [Tables \(board game\)](#)
- [The Table](#), a volcanic tuya in British Columbia, Canada
- [Table](#), surface of the [sound board \(music\)](#) of a string instrument
- [Al-Ma'ida](#), the fifth *sura* of the Qur'an, usually translated as "The Table"
- [Water table](#)

- [S: \(n\) table#1, tabula, array#1](#) (a set of data arranged in rows and columns) "see [table 1](#)"
- [S: \(n\) table#2](#) (a piece of furniture having a smooth flat top that is usually supported by one or more vertical legs) "it was a sturdy table"
- [S: \(n\) table#3](#) (a piece of furniture with tableware for a meal laid out on it) "I reserved a table at my favorite restaurant"
- [S: \(n\) mesa#1, table#4](#) (flat tableland with steep edges) "the tribe was relatively safe on the mesa but they had to descend into the valley for water"
- [S: \(n\) table#5](#) (a company of people assembled at a table for a meal or game) "he entertained the whole table with his witty remarks"
- [S: \(n\) board#4, table#6](#) (food or meals in general) "she sets a fine table"; "room and board"



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<https://en.wikipedia.org/wiki/Table>

# Wikipedia Text as ‘weakly labeled sense data’

“A **table** is an arrangement of data in rows and columns, or possibly in a more complex structure. ... **Tables** appear in print media, handwritten notes, computer software, architectural ornamentation, traffic signs, and many other places. ... In books and technical articles, **tables** are typically presented apart from the main text in numbered and captioned floating blocks.” -  
[https://en.wikipedia.org/wiki/Table\\_\(information\)](https://en.wikipedia.org/wiki/Table_(information))

⇒ Align Wikipedia Category information with WordNet sense **table#1**

- ★ A **[table#1:information]** is an arrangement of data in rows and columns, or possibly in a more complex structure.
- ★ **[table#1:information]** appear in print media, handwritten notes, computer software, architectural ornamentation, traffic signs, and many other places.
- ★ In books and technical articles, **[table#1:information]** are typically presented apart from the main text in numbered and captioned floating blocks.



# Wikipedia Text as ‘weakly labeled sense data’

“A **table** is an item of furniture with a flat top and one or more legs, used as a surface for working at, eating from or on which to place things. ... There are also a range of specialized types of **tables**, such as drafting **tables**, used for doing architectural drawings, and sewing **tables**.” -

[https://en.wikipedia.org/wiki/Table\\_\(furniture\)](https://en.wikipedia.org/wiki/Table_(furniture))

⇒ Align Wikipedia Category furniture with WordNet sense **table#2**

- ★ A [**table#2:furniture**] is an item of furniture with a flat top and one or more legs, used as a surface for working at, eating from or on which to place things.
- ★ There are also a range of specialized types of [**table#2:furniture**], such as drafting [**table#2:furniture**], used for doing architectural drawings, and sewing [**table#2:furniture**].



# WSD - SemEval Tasks (Ideas for MSc Projects)

SemEval-2021 Task 2: Multilingual and Cross-lingual Word-in-Context Disambiguation: <https://competitions.codalab.org/competitions/27054>

SemEval 2020 Task 1: Unsupervised Lexical Semantic Change Detection:  
<https://competitions.codalab.org/competitions/20948>

SemEval-2015 Task 13: Multilingual All-Words Sense Disambiguation and Entity Linking: <https://alt.qcri.org/semeval2015/task13/>



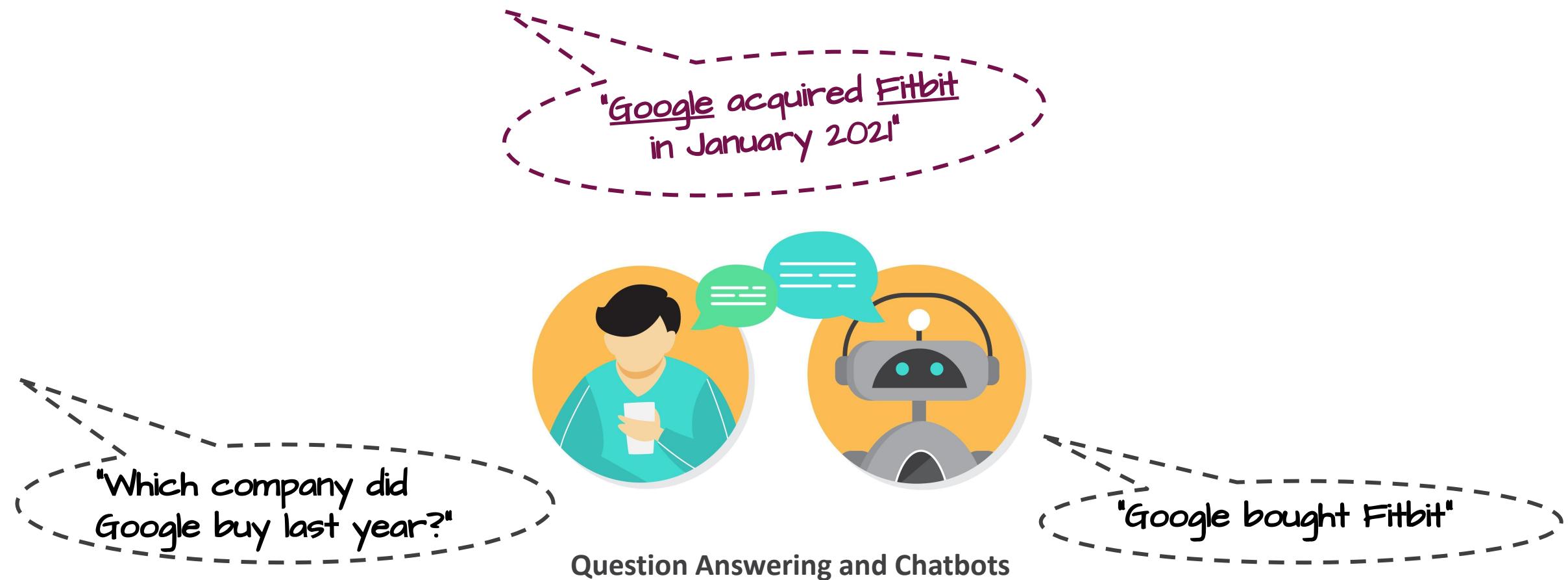


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# Semantic Role Labelling

# Remember: SRL in Applications



# What is Semantic Role Labelling (SRL)?

Process of understanding **who** did **what** to **whom**, **with what**, **where** ...

NLP task of **assigning labels to entities** (expressed by words or phrases) indicating their **semantic role in an event**

**For example:** several **entities** with different **semantic roles** in this *hitting* **event**:

[*Kristina AGT*] hit [*Scott EXP*] with [*a baseball INS*] .

**Where:** AGENT (**AGT**), EXPERIENCER (**EXP**), INSTRUMENT (**INS**)

**Note** that semantic roles remain the same across different sentences:

[*Kristina AGT*] hit [*Scott EXP*] with [*a baseball INS*] .

[*Scott EXP*] was hit with [*a baseball INS*] by [*Kristina AGT*] .

[*Scott EXP*] was hit by [*Kristina AGT*] with [*a baseball INS*] .



# Semantic Roles - Overview

Thematic Role	Definition
AGENT	The volitional cause of an event
EXPERIENCER	The experiencer of an event
FORCE	The non-volitional cause of the event
THEME	The participant most directly affected by an event
RESULT	The end product of an event
CONTENT	The proposition or content of a propositional event
INSTRUMENT	An instrument used in an event
BENEFICIARY	The beneficiary of an event
SOURCE	The origin of the object of a transfer event
GOAL	The destination of an object of a transfer event

**Figure 19.1** Some commonly used thematic roles with their definitions.

Thematic Role	Example
AGENT	<i>The waiter</i> spilled the soup.
EXPERIENCER	<i>John</i> has a headache.
FORCE	<i>The wind</i> blows debris from the mall into our yards.
THEME	Only after Benjamin Franklin broke <i>the ice</i> ...
RESULT	The city built a <i>regulation-size baseball diamond</i> ...
CONTENT	Mona asked “ <i>You met Mary Ann at a supermarket?</i> ”
INSTRUMENT	He poached catfish, stunning them <i>with a shocking device</i> ...
BENEFICIARY	Whenever Ann Callahan makes hotel reservations <i>for her boss</i> ...
SOURCE	I flew in <i>from Boston</i> .
GOAL	I drove <i>to Portland</i> .

**Figure 19.2** Some prototypical examples of various thematic roles.

**Note:** semantic roles are also referred to as ‘thematic roles’



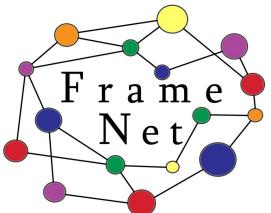
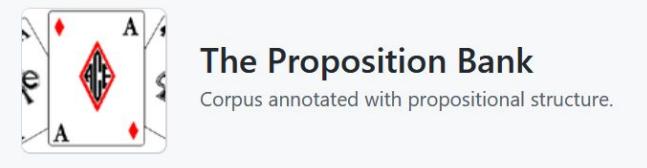
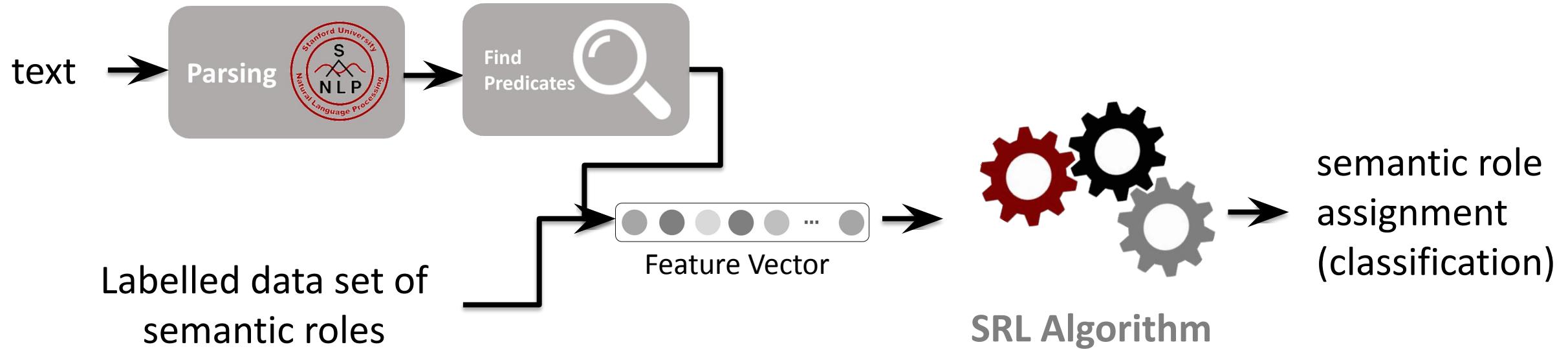
# Semantic Roles - Challenges

Semantic roles are **not very well defined** with different names and interpretations of roles across the literature

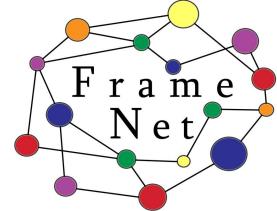
Automatic ‘semantic role labeling’ depends largely on supervised training with **limited labeled data available**



# SRL Approach



# Remember: FrameNet



Based on **Frame Semantics** (Fillmore 1968)

“frame [is] a description of a type of event ... and the participants in it”

Frames express Semantic Roles - for example:

- **cooking** typically relates to an **Apply\_Heat** event
- involving a person doing the cooking (**Cook**)
- the food that is to be cooked (**Food**)
- something to hold the food while cooking (**Container**)
- and a source of heat (**Heating\_instrument**)

Labeled Data:

“[John (**Cook**) [made **Apply\_Heat** event] [a great cake (**Food**)] [in the oven (**Heating\_instrument**)].”

# PropBank



The Proposition Bank  
Corpus annotated with propositional structure.

The Proposition Bank (or ‘PropBank’), is a corpus annotated with semantic roles (Palmer et al 2005)

Each sense of each verb has a specific set of roles, which are given only numbers rather than names: Arg0, Arg1, Arg2, and so on.

Labeled Data:

**“[A1B Arg0] [raised increase.01] [interest Arg1] [incrementally by 2% Arg2].”**

- **Arg0:** causer of increase
- **Arg1:** thing increasing
- **Arg2:** amount increased by

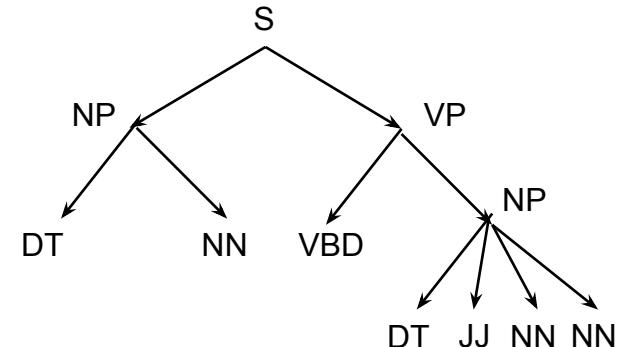


# SRL Features - Syntax

Use constituency parsing features

*The chancellor announced a new policy measure.*

(S  
  (NP (DT *The*) (NN *chancellor*))  
  (VP (VBD *announced*)  
    (NP (DT *a*) (JJ *new*) (NN *policy*) (NN *measure*))))



# SRL Features

## Labeled Data

[AGENT *The chancellor*] announced new policy measures.

## Feature Extraction

Predicate:

***announce***

Voice (whether predicate is active or passive):

**active**

Phrase Type (NP, PP, ...) of classified constituent:

**NP**

Minimal Path from classified constituent to predicate:

**NP $\uparrow$ S $\downarrow$ VP $\downarrow$ VBD**

Position (before/after) of classified constituent with regard to predicate:

**before**

Head Word of classified constituent:

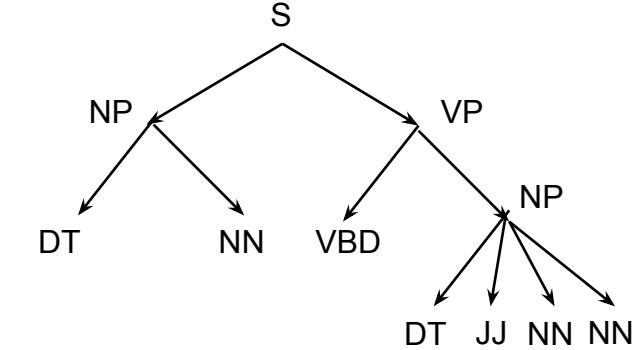
***chancellor***

Sub-categorization for parent of predicate:

**VP $\rightarrow$ VBD,NP**

## Feature Vector

AGENT: [announce, active, NP, NP $\uparrow$ S $\downarrow$ VP $\downarrow$ VBD, before, chancellor, VP $\rightarrow$ VBD,NP]



# SRL Algorithm

**function** SEMANTICROLELABEL(*words*) **returns** labeled tree

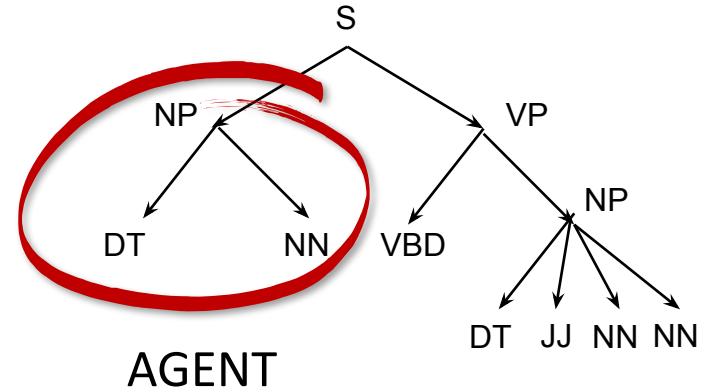
parse  $\leftarrow$  PARSE(*words*)

**for each** *predicate* **in** parse **do**

**for each** *node* **in** parse **do**

*featurevector*  $\leftarrow$  EXTRACTFEATURES(*node*, *predicate*, *parse*)

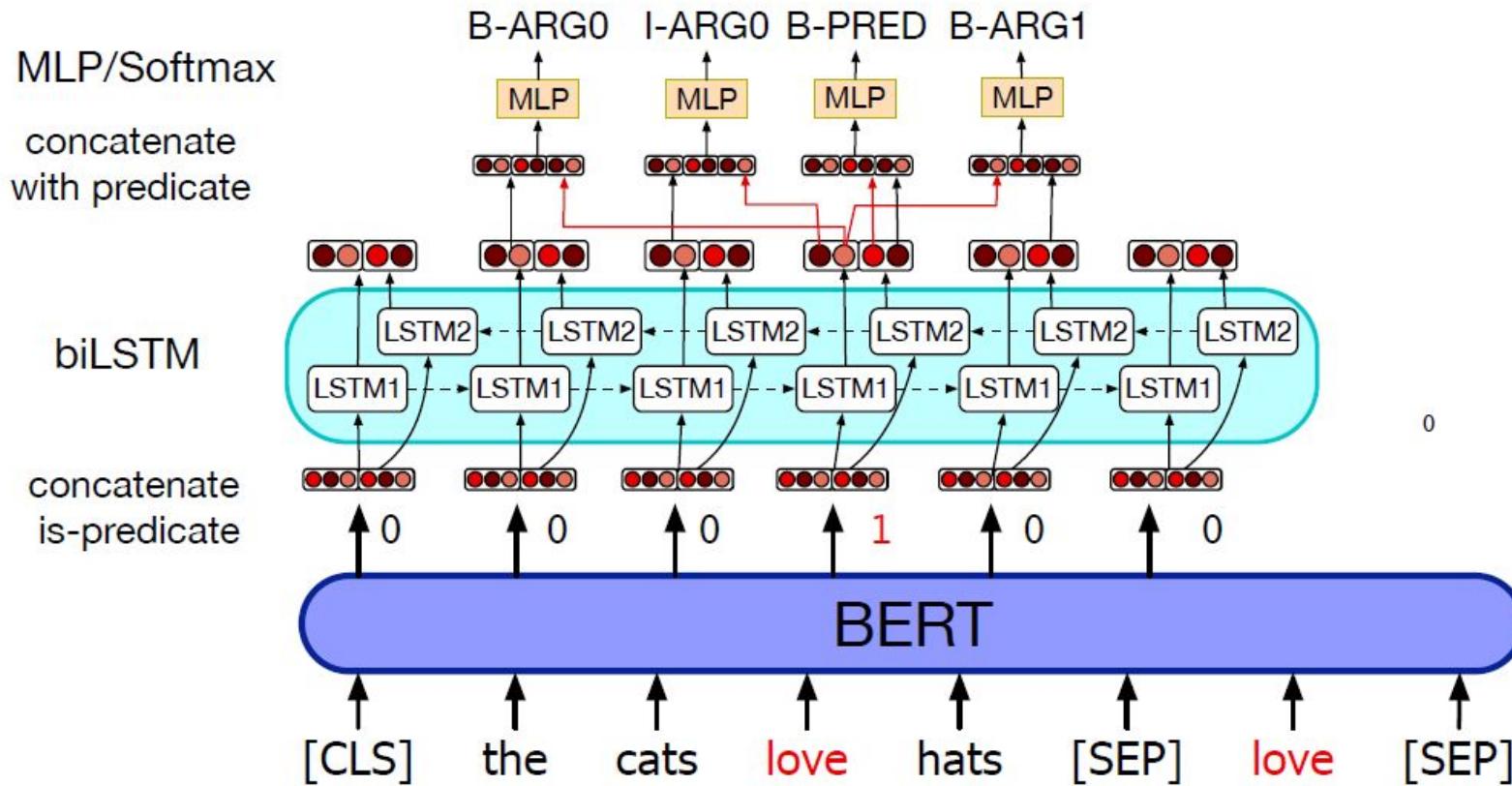
CLASSIFYNODE(*node*, *featurevector*, *parse*)



[announce, active, NP,  
NP  $\uparrow$  S  $\downarrow$  VP  $\downarrow$  VBD,  
before, chancellor,  
VP  $\rightarrow$  VBD, NP]



# Neural SRL Algorithm



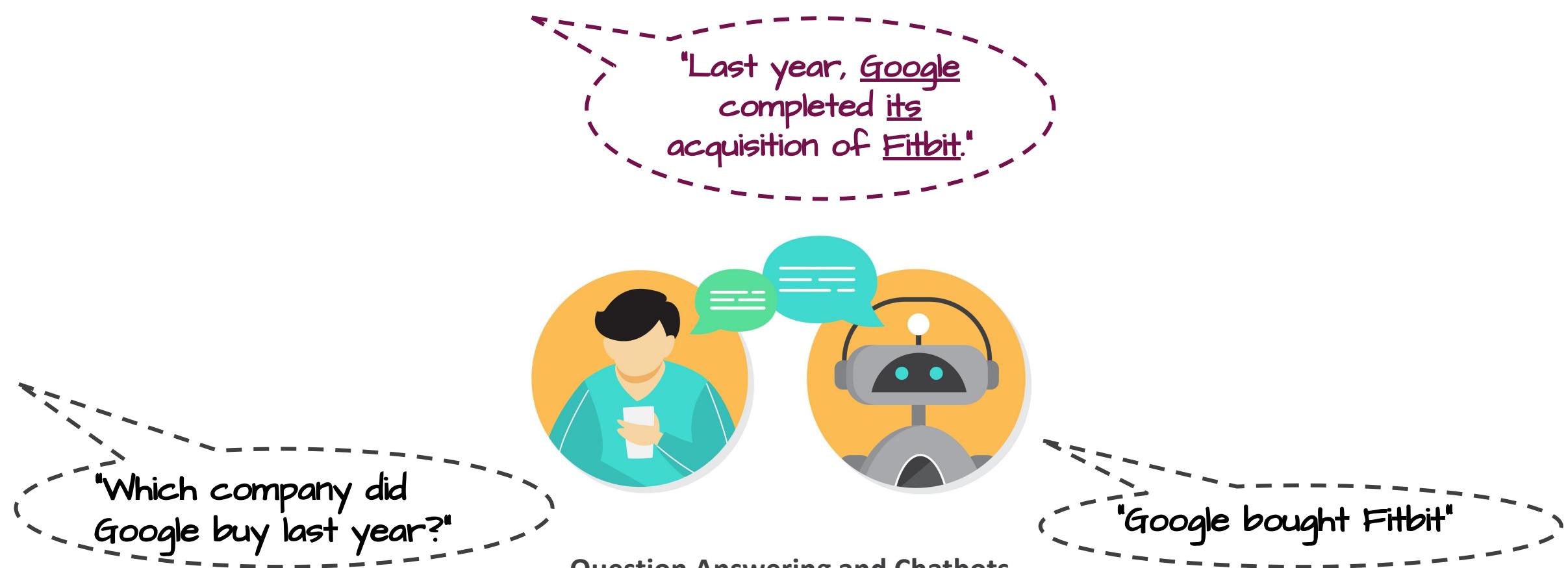


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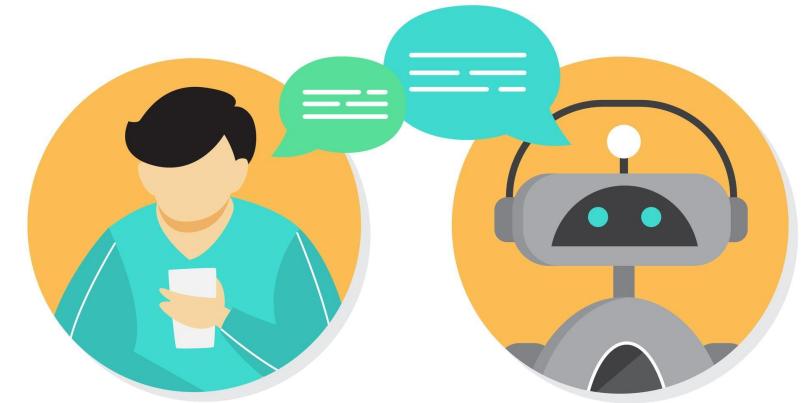
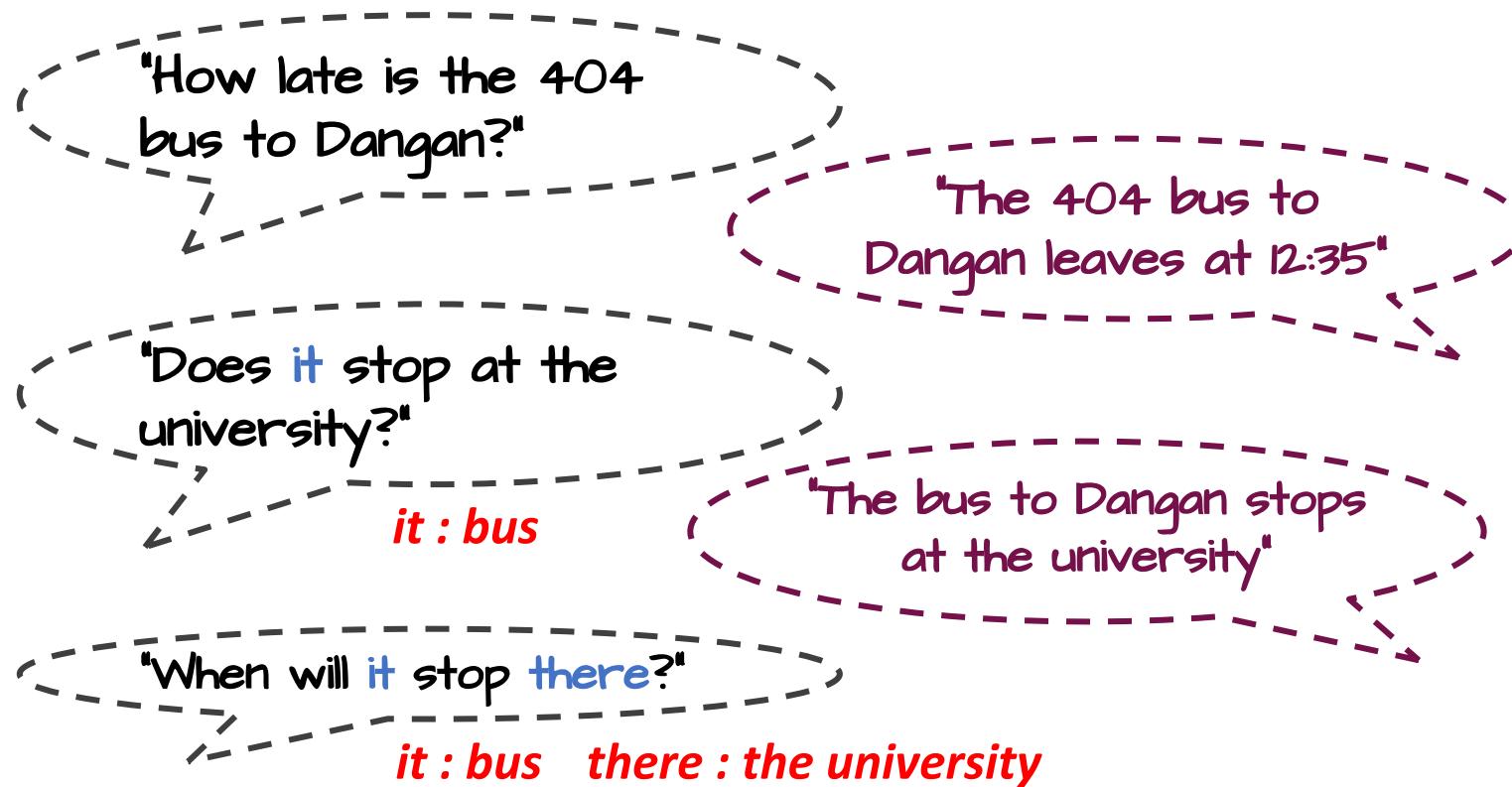


# Coreference Resolution

# Remember: CR in Applications



# CR in Applications - Other Example



Question Answering and Chatbots

# What is Coreference Resolution?

Task of identifying words and/or phrases referring to the same entity

Document

Barack Obama nominated Hillary Rodham Clinton as his secretary of state on Monday. He chose her because she had foreign affairs experience as a former First Lady.

Run Model

Model Output

Share

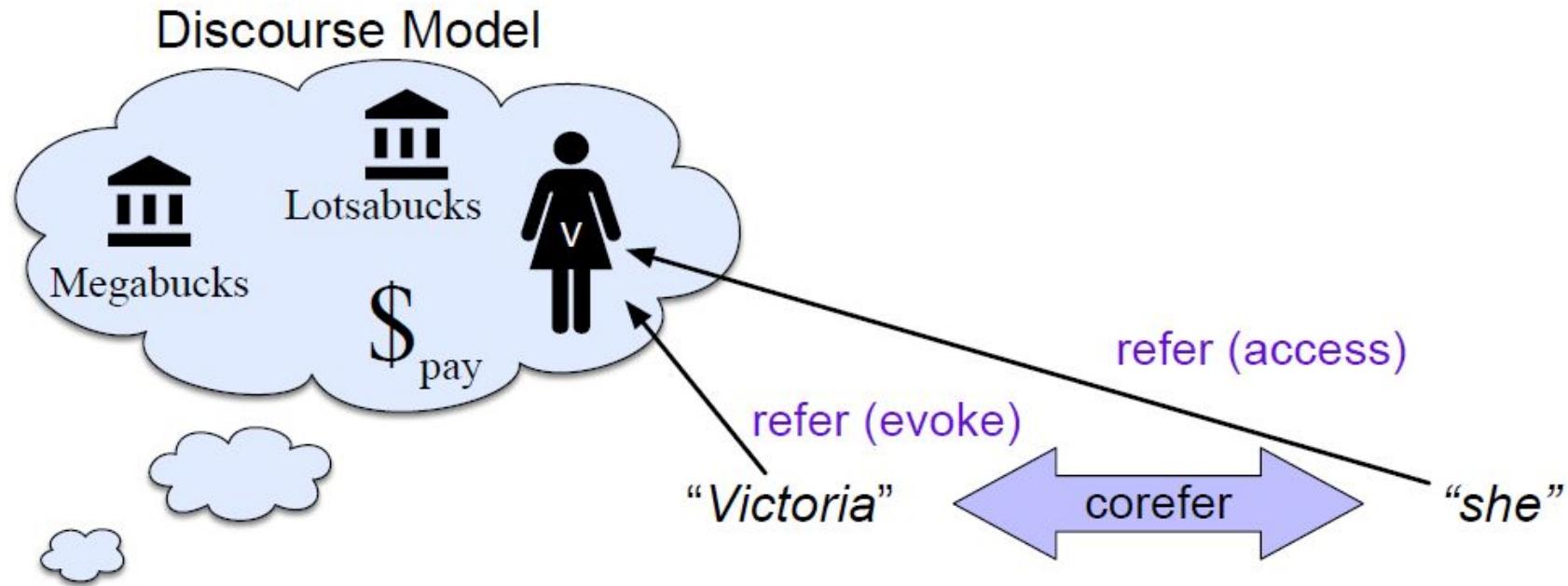
0 Barack Obama nominated 1 Hillary Rodham Clinton as 0 his secretary of state on Monday. 0 He chose 1 her  
because 1 she had foreign affairs experience as a former First Lady.



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<https://demo.allennlp.org/coreference-resolution/>

# Remember: Discourse Semantics



# Subtasks: Mention Detection & Clustering

*“Barack Obama nominated Hillary Rodham Clinton as his secretary of state on Monday. He chose her because she had foreign affairs experience as a former First Lady.”*

**Step 1:** Identify all **mentions** - coreference candidates

**“Barack Obama** nominated **Hillary Rodham Clinton** as **his secretary of state** on **Monday**.  
**He** chose **her** because **she** had **foreign affairs experience** as **a former First Lady.**”

} **Mention  
Detection**

**Step 2:** Identify all **mentions** that refer to the **same** real world entity

**“Barack Obama** nominated **Hillary Rodham Clinton** as **his secretary of state** on **Monday**.  
**He** chose **her** because **she** had **foreign affairs experience** as **a former First Lady.**”

} **Mention  
Clustering**

**“Barack Obama** nominated **Hillary Rodham Clinton** as **his secretary of state** on **Monday**.  
**He** chose **her** because **she** had **foreign affairs experience** as **a former First Lady.**”



# Mention Detection

## Kinds of Mentions

Mention is a **span of text referring to an entity**

There are **three kinds of mentions**:

- **Pronouns:** *I, your, it, she, him, ...*
- **Named Entities:** *person, location, organization, ...*
- **Noun Phrases:** *“a dog,” “the big fluffy cat stuck in the tree”*

## NLP Tools to Use

**Part-of-speech tagger**

**Named Entity Recognizer (NER)**

**Constituency (Phrase) parser**



# Mention Clustering – Features

**Recency** - more recently mentioned entities are preferred

*John went to a movie. Jack went as well. He was not busy.*

$\text{He} = \text{Jack}$  ( $\text{He} \neq \text{John}$ )

**Syntactic agreement**

*Jack gave Mary a gift. She was excited.*

$\text{She} = \text{Mary}$  ( $\text{She} \neq \text{Jack}$ )

**Other syntactic constraints**

*John bought him a new car.*

$\text{him} \neq \text{John}$

**Semantic compatibility**

*... the mining conglomerate ... the company ...  
conglomerate*

$\text{company} =$

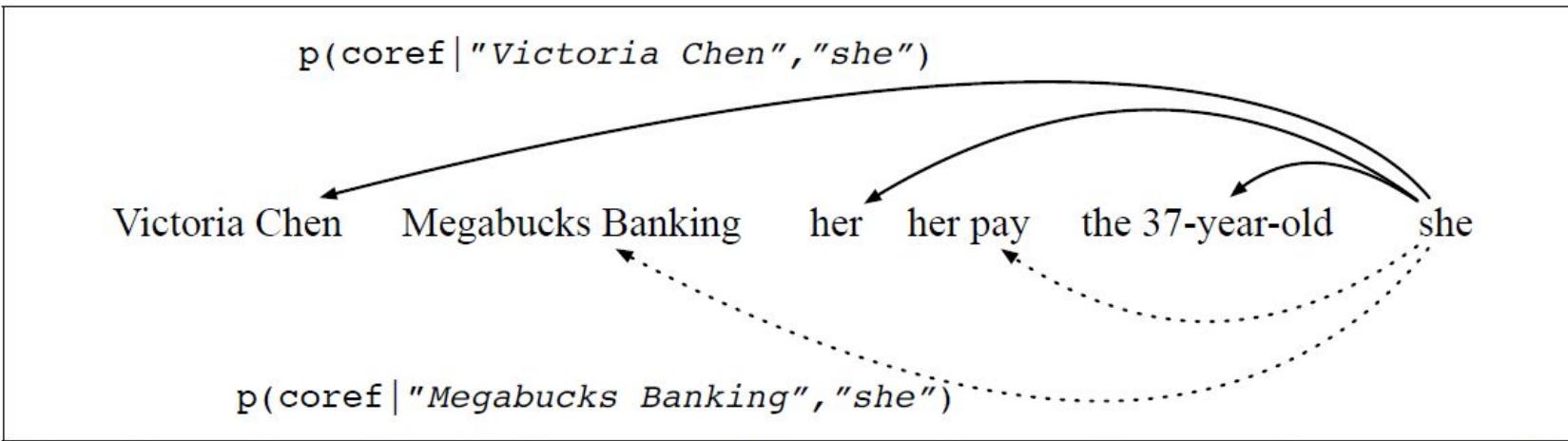
**Grammatical Role** - prefer entities in the subject position

*John went to a movie with Jack as he was not busy.*

$\text{He} = \text{John}$  ( $\text{He} \neq \text{Jack}$ )



# Mention Pair Architecture



**Figure 21.2** For each pair of a mention (like *she*), and a potential antecedent mention (like *Victoria Chen* or *her*), the mention-pair classifier assigns a probability of a coreference link.



# Learning Outcomes

After completing this topic, you should be able to:

- Explain semantic analysis in NLP
- Discuss various approaches to Word Sense Disambiguation
- Understand the core idea of and features used for Semantic Role Labeling & Coreference Resolution

External Sources:

***Chapters 18, 19 and 21*** in Jurafsky and Martin, SPEECH and LANGUAGE PROCESSING: An Introduction to Natural Language Processing, Computational Linguistics, and Speech Recognition, 3<sup>rd</sup> edition:  
<https://web.stanford.edu/~jurafsky/slp3/ed3book.pdf>



# Lab of this week

Practical application on WSD

