Natural Language Processing

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Overview

- Applications and advances
- Language as data
- Language models
- Part of speech
- Morphology
- Sentences and parsing
- Semantics

What is Language?

- **Nouns** — to describe things in the world
- **Verbs** — to describe actions
- **Adjectives** — to describe properties

\+ glue to tie all this together

Why is Language Hard?

- **Ambiguity** on many levels
- **Sparse data** — many words are rare
- No clear understand how humans process language

Words

This is a simple sentence **WORDS**

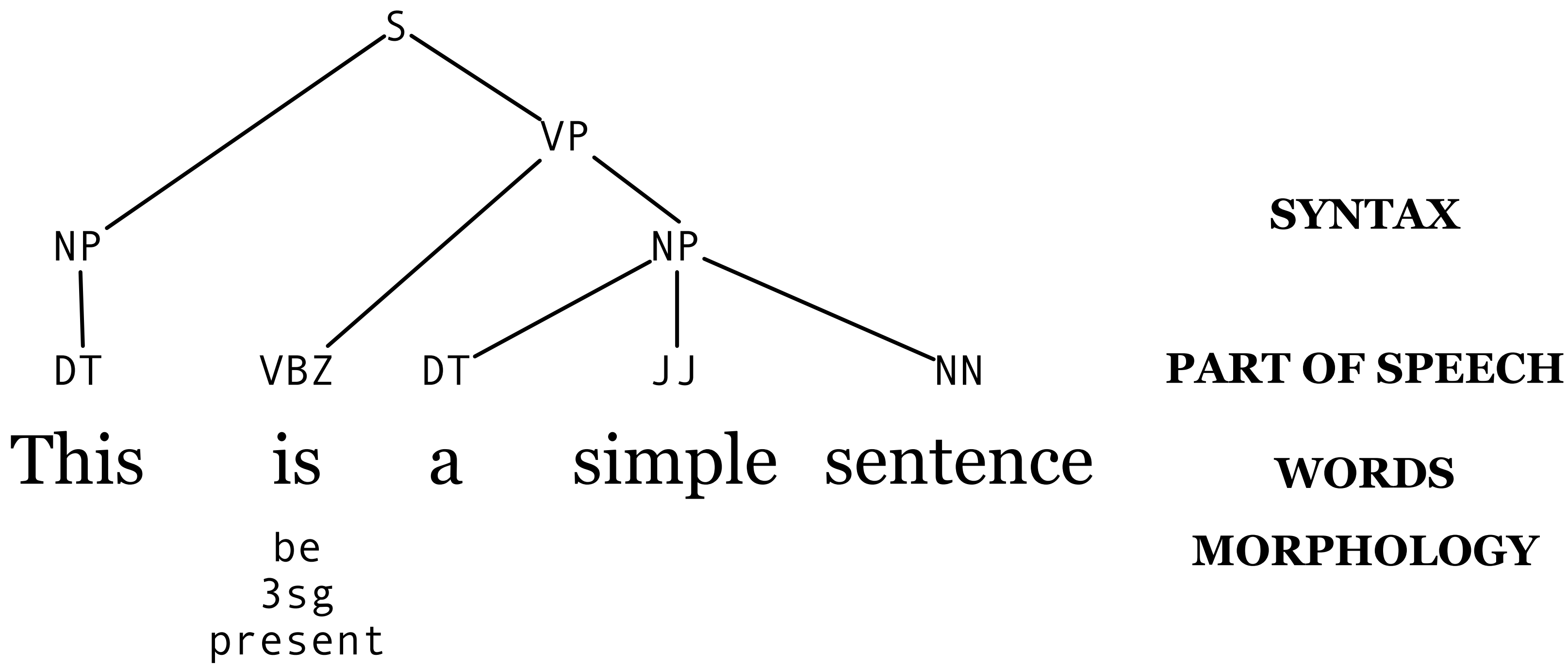
Morphology

This	is	a	simple	sentence	WORDS
	be 3sg present				MORPHOLOGY

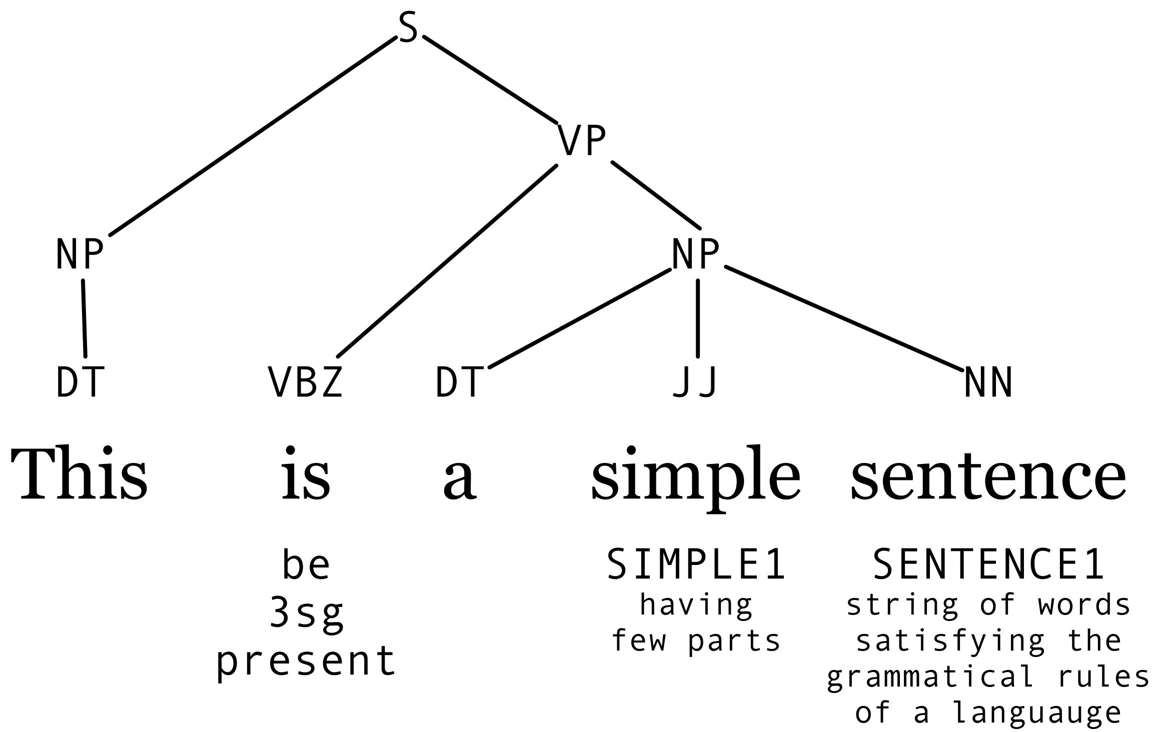
Parts of Speech

DT	VBZ	DT	JJ	NN	**PART OF SPEECH**
This	is	a	simple	sentence	**WORDS**
	be 3sg present				**MORPHOLOGY**

Syntax


S
VP
NP
NP
DT
VBZ
DT
JJ
NN
This
is
a
simple
sentence
be
3sg
present
SYNTAX
PART OF SPEECH
WORDS
MORPHOLOGY

Semantics



SYNTAX

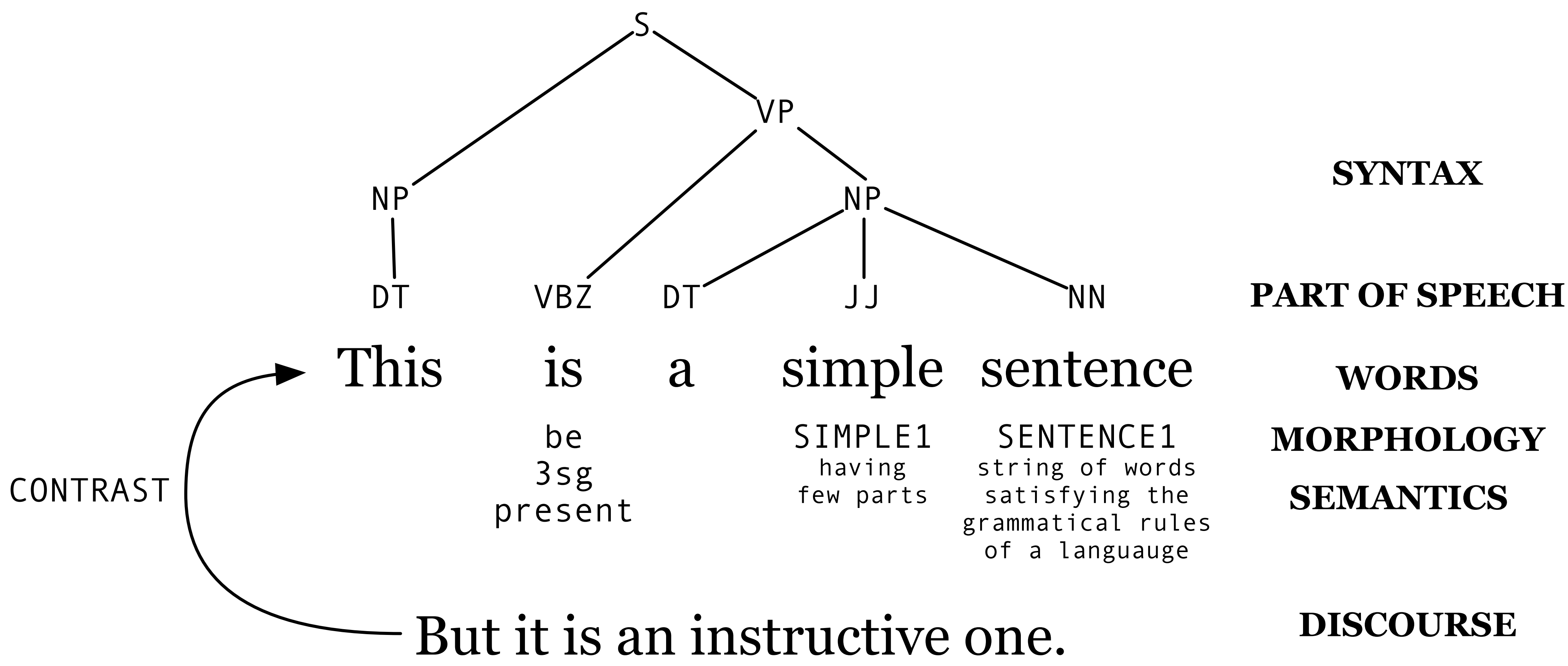
PART OF SPEECH

WORDS

MORPHOLOGY

SEMANTICS

Discourse


S
VP
NP
NP
DT
VBZ
DT
JJ
NN
This
is
a
simple
sentence
be
3sg
present
SIMPLE1
having
few parts
SENTENCE1
string of words
satisfying the
grammatical rules
of a languauge
CONTRAST
But it is an instructive one.
SYNTAX
PART OF SPEECH
WORDS
MORPHOLOGY
SEMANTICS
DISCOURSE

Recent Advances

Spoken dialogue devices
(Siri, Google Now, Echo, ...)

IBM Watson wins Jeopardy

Google machine translation

Web-scale question answering

IBM Watson

- IBM built a computer that won Jeopardy in 2011
- Question answering technology built on 200 million text pages, encyclopedias, dictionaries, thesauri, taxonomies, ontologies, and other databases

Machine Translation: Chinese

海军南海舰队战备巡逻远海训练编队２１日在南海某海域开展立体抢滩登陆训练。参加这次训练的是来自井冈山舰兵力群的陆战队、航空兵等百余名官兵。围绕抢滩登陆Ｄ岛，部队进行了两栖破障、掠海突击、垂直突击等课目的训练。

South China Sea Fleet combat patrol far-sea training formation on the 21st stereoscopic beach landing training carried out in the South China Sea waters. To participate in the training, Marines, Air Force, more than 100 officers and men from Jinggangshan ship troops group. Around the beach landing D Island, forces amphibious barrier-breaking, the sea skimming assault, vertical assault subjects training.

Machine Translation: French

La recette était simple. L'austérité budgétaire allait ramener la confiance, et celle-ci la croissance. On aurait l'équilibre des comptes publics et le retour de l'activité. Bon vieux bon sens britannique ! Ainsi parlait George Osborne, le péremptoire et sémillant chancelier de l'Echiquier. Il n'en n'a rien été. Depuis l'arrivée au pouvoir de David Cameron en 2010, l'impitoyable politique d'austérité budgétaire conduite à Londres n'a pas plus rétabli la croissance qu'elle n'a assaini les finances de l'Etat.

The recipe was simple. The austerity budget would restore confidence, and this growth. It would balance the public accounts and the return of the activity. Good old British common sense! Thus spoke George Osborne, the peremptory and spirited Chancellor of the Exchequer. It does not happen. Since coming to power in 2010 David Cameron, the relentless austerity policy London to conduct no more restored the growth it has cleaned up the finances of the State.

Eliza

Joseph Weizenbaum wrote the computer program **Eliza** in 1969 to demonstrate how easily people can be fooled into thinking that machines have some deep understanding.

young woman: Men are all alike.
eliza: In what way?
young woman: They're always bugging us about something specific or other.
eliza: Can you think of a specific example?
young woman: Well, my boyfriend made me come here.
eliza: Your boyfriend made you come here?
young woman: He says I'm depressed much of the time.
eliza: I am sorry to hear you are depressed.
young woman: It's true. I'm unhappy.
eliza: Do you think coming here will help you not to be unhappy?

Online demo: `http://www-ai.ijs.si/eliza-cgi-bin/eliza_script`

A Concrete Goal

- We would like to build
  - a machine that answers questions in natural language.
  - may have access to knowledge bases
  - may have access to vast quantities of English text
- Basically, a smarter Google
- This is typically called **Question Answering**

Example Question

- Question

  When was Barack Obama born?

- Text available to the machine

  Barack Obama was born on August 4, 1961

- This is easy.
  - just phrase a Google query properly:
    `"Barack Obama was born on *"`
  - syntactic rules that convert questions into statements are straight-forward

Example Question (2)

- Question

  What kind of plants grow in Maryland?

- Text available to the machine

  A new chemical plant was opened in Maryland.

- What is hard?
  - words may have different meanings
  - we need to be able to disambiguate between them

Example Question (3)

- Question

  Does the police use dogs to sniff for drugs?

- Text available to the machine

  The police use canines to sniff for drugs.

- What is hard?
  - words may have the same meaning (synonyms)
  - we need to be able to match them

Example Question (4)

- Question

  What is the name of George Bush's poodle?

- Text available to the machine

  President George Bush has a terrier called Barnie.

- What is hard?
  - we need to know that poodle and terrier are related, so we can give a proper response
  - words need to be group together into semantically related classes

Example Question (5)

- Question

  Which animals love to swim?

- Text available to the machine

  Ice bears love to swim in the freezing waters of the Arctic.

- What is hard?
  - some words belong to groups which are referred to by other words
  - we need to have database of such **A is-a B** relationships, so-called ontologies

Example Question (6)

- Question

  Did Poland reduce its carbon emissions since 1989?

- Text available to the machine

  Due to the collapse of the industrial sector after the end of communism in 1989, all countries in Central Europe saw a fall in carbon emmissions.

  Poland is a country in Central Europe.

- What is hard?

  - we need more complex semantic database
  - we need to do inference

language as data

Data: Words

- Definition: strings of letters separated by spaces

- But how about:
  - punctuation: commas, periods, etc. typically separated (tokenization)
  - hyphens: high-risk
  - clitics: Joe's
  - compounds: website, Computerlinguistikvorlesung

- And what if there are no spaces:
  伦敦每日快报指出,两台记载黛安娜王妃一九九七年巴黎死亡车祸调查资料的手提电脑,被从前大都会警察总长的办公室里偷走.

Word Counts

Most frequent words in the English Europarl corpus

any word

Frequency in text	Token
1,929,379	the
1,297,736	,
956,902	.
901,174	of
841,661	to
684,869	and
582,592	in
452,491	that
424,895	is
424,552	a

nouns

Frequency in text	Content word
129,851	European
110,072	Mr
98,073	commission
71,111	president
67,518	parliament
64,620	union
58,506	report
57,490	council
54,079	states
49,965	member

Word Counts

But also:

There is a large tail of words that occur only once.

33,447 words occur once, for instance

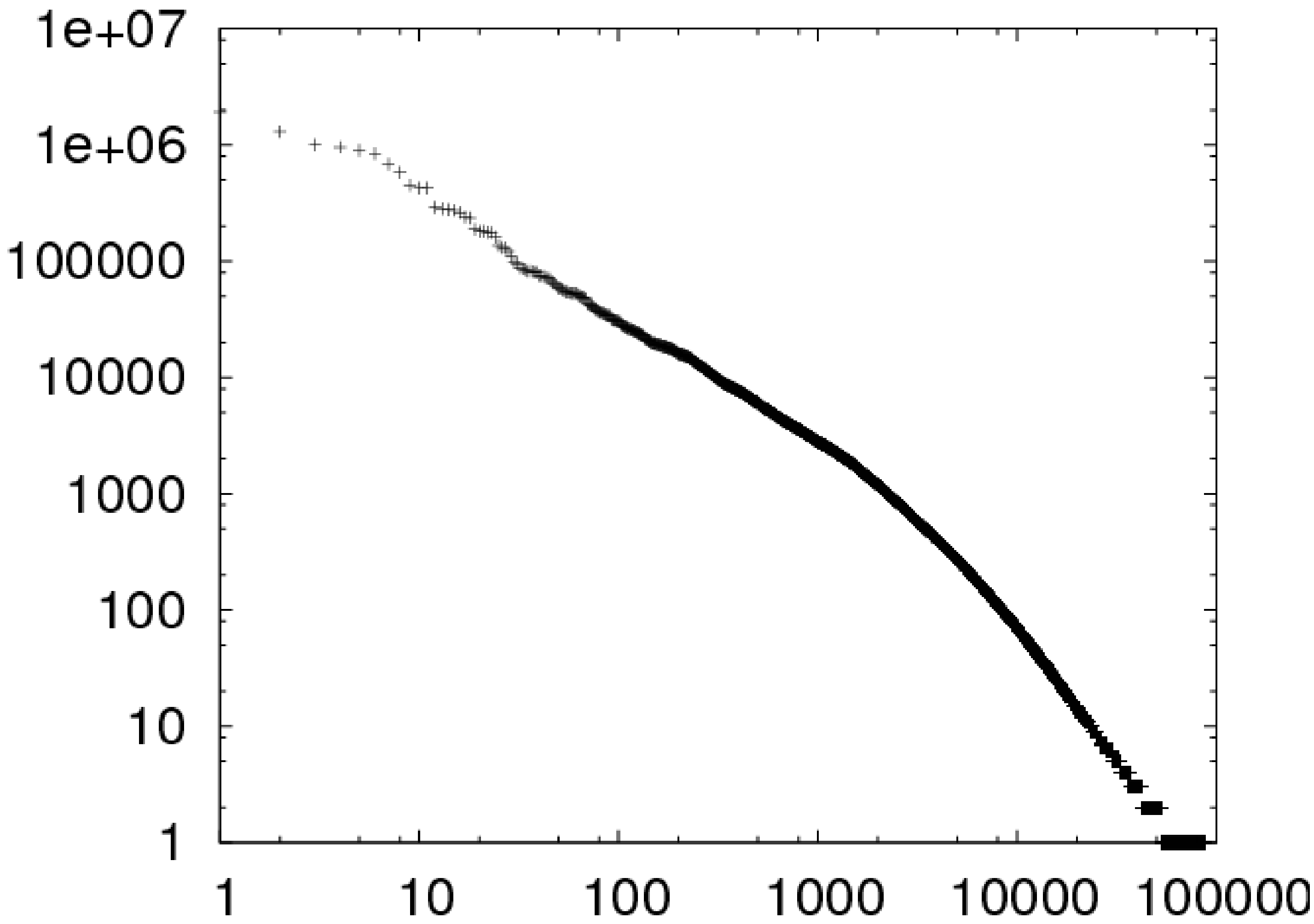
- cornflakes
- mathematicians
- Tazhikhistan

Zipf's Law

$$f \times r = k$$

f = frequency of a word
r = rank of a word (if sorted by frequency)
k = a constant

Zipf's Law as a Graph



why a line in log-scales? $fr = k \Rightarrow f = \frac{k}{r} \Rightarrow \log f = \log k - \log r$

language models

Language models

- **Language models** answer the question:

  How likely is a string of English words good English?

- Help with reordering

$$p_{\mathsf{LM}}(\text{the house is small}) > p_{\mathsf{LM}}(\text{small the is house})$$

- Help with word choice

$$p_{\mathsf{LM}}(\text{I am going home}) > p_{\mathsf{LM}}(\text{I am going house})$$

N-Gram Language Models

- Given: a string of English words $W = w_1, w_2, w_3, ..., w_n$
- Question: what is $p(W)$?
- Sparse data: Many good English sentences will not have been seen before

$\rightarrow$ Decomposing $p(W)$ using the chain rule:

$$p(w_1, w_2, w_3, ..., w_n) = p(w_1)\ p(w_2|w_1)\ p(w_3|w_1, w_2)...p(w_n|w_1, w_2, ...w_{n-1})$$

(not much gained yet, $p(w_n|w_1, w_2, ...w_{n-1})$ is equally sparse)

Markov Chain

- **Markov assumption**:
  - only previous history matters
  - limited memory: only last k words are included in history (older words less relevant)
  - → k**th order Markov model**

- For instance 2-gram language model:

$$p(w_1, w_2, w_3, ..., w_n) \simeq p(w_1)\ p(w_2|w_1)\ p(w_3|w_2)...p(w_n|w_{n-1})$$

- What is conditioned on, here w_{i-1} is called the **history**

Estimating N-Gram Probabilities

- Maximum likelihood estimation

$$p(w_2|w_1) = \frac{\text{count}(w_1, w_2)}{\text{count}(w_1)}$$

- Collect counts over a large text corpus
- Millions to billions of words are easy to get
  (trillions of English words available on the web)

Example: 3-Gram

- Counts for trigrams and estimated word probabilities

the green (total: 1748)

word	c.	prob.
paper	801	0.458
group	640	0.367
light	110	0.063
party	27	0.015
ecu	21	0.012

the red (total: 225)

word	c.	prob.
cross	123	0.547
tape	31	0.138
army	9	0.040
card	7	0.031
,	5	0.022

the blue (total: 54)

word	c.	prob.
box	16	0.296
.	6	0.111
flag	6	0.111
,	3	0.056
angel	3	0.056

- 225 trigrams in the Europarl corpus start with the red
- 123 of them end with cross

→ maximum likelihood probability is $\frac{123}{225} = 0.547$.

How good is the LM?

- A good model assigns a text of real English W a high probability

- This can be also measured with cross entropy:

$$H(W) = \frac{1}{n} \log p(W_1^n)$$

- Or, **perplexity**

$$\text{perplexity}(W) = 2^{H(W)}$$

Example: 3-Gram

prediction	p_{LM}	$-\log_2 p_{LM}$
p_{LM}(i|</s><s>)	0.109	3.197
p_{LM}(would|<s>i)	0.144	2.791
p_{LM}(like|i would)	0.489	1.031
p_{LM}(to|would like)	0.905	0.144
p_{LM}(commend|like to)	0.002	8.794
p_{LM}(the|to commend)	0.472	1.084
p_{LM}(rapporteur|commend the)	0.147	2.763
p_{LM}(on|the rapporteur)	0.056	4.150
p_{LM}(his|rapporteur on)	0.194	2.367
p_{LM}(work|on his)	0.089	3.498
p_{LM}(.|his work)	0.290	1.785
p_{LM}(</s>|work .)	0.99999	0.000014
	average	2.634

Comparison 1–4-Gram

word	unigram	bigram	trigram	4-gram
i	6.684	3.197	3.197	3.197
would	8.342	2.884	2.791	2.791
like	9.129	2.026	1.031	1.290
to	5.081	0.402	0.144	0.113
commend	15.487	12.335	8.794	8.633
the	3.885	1.402	1.084	0.880
rapporteur	10.840	7.319	2.763	2.350
on	6.765	4.140	4.150	1.862
his	10.678	7.316	2.367	1.978
work	9.993	4.816	3.498	2.394
.	4.896	3.020	1.785	1.510
</s>	4.828	0.005	0.000	0.000
average	8.051	4.072	2.634	2.251
perplexity	265.136	16.817	6.206	4.758

Core Challange

- How to handle low counts and unknown n-grams?
- Smoothing
  - adjust counts for seen n-grams
  - use probability mass for unseen n-grams
  - many discount schemes developed
- Backoff
  - if 5-gram unseen → use 4-gram instead
- Neural network models promise to handle this better

parts of speech

Parts of Speech

- **Open class words** (or content words)
  - nouns, verbs, adjectives, adverbs
  - refer to objects, actions, and features in the world
  - *open* class, new ones are added all the time (email, website).
- **Close class words** (or function words)
  - pronouns, determiners, prepositions, connectives, ...
  - there is a limited number of these
  - mostly functional: to tie the concepts of a sentence together

Parts of Speech

- There are about 30-100 parts of speech
  - distinguish between names and abstract nouns?
  - distinguish between plural noun and singular noun?
  - distinguish between past tense verb and present tense word?
- Identifying the parts of speech is a first step towards syntactic analysis

Ambiguous Words

- For instance: like
  - verb: I like the class.
  - preposition: He is like me.
- Another famous example: Time flies like an arrow
- Most of the time, the local context disambiguated the part of speech

Part-of-Speech Tagging

- Task: Given a text of English, identify the parts of speech of each word
- Example
  - Input: Word sequence
    Time flies like an arrow
  - Output: Tag sequence
    Time/NN flies/VB like/P an/DET arrow/NN
- What will help us to tag words with their parts-of-speech?

Relevant Knowledge for POS Tagging

- The word itself
  - Some words may only be nouns, e.g. arrow
  - Some words are ambiguous, e.g. like, flies
  - Probabilities may help, if one tag is more likely than another

- Local context
  - two determiners rarely follow each other
  - two base form verbs rarely follow each other
  - determiner is almost always followed by adjective or noun

Bayes Rule

- We want to find the best part-of-speech tag sequence T for a sentence S:

$$\text{argmax}_T \; p(T|S)$$

- Bayes rule gives us:

$$p(T|S) = \frac{p(S|T)\; p(T)}{p(S)}$$

- We can drop $p(S)$ if we are only interested in argmax_T:

$$\text{argmax}_T \; p(T|S) = \text{argmax}_T \; p(S|T)\; p(T)$$

Decomposing the Model

- The mapping $p(S|T)$ can be decomposed into

$$p(S|T) = \prod_i p(w_i|t_i)$$

- $p(T)$ could be called a *part-of-speech language model,* for which we can use an n-gram model (bigram):

$$p(T) = p(t_1)\, p(t_2|t_1)\, p(t_3|t_2) ... p(t_n|t_{n-1})$$

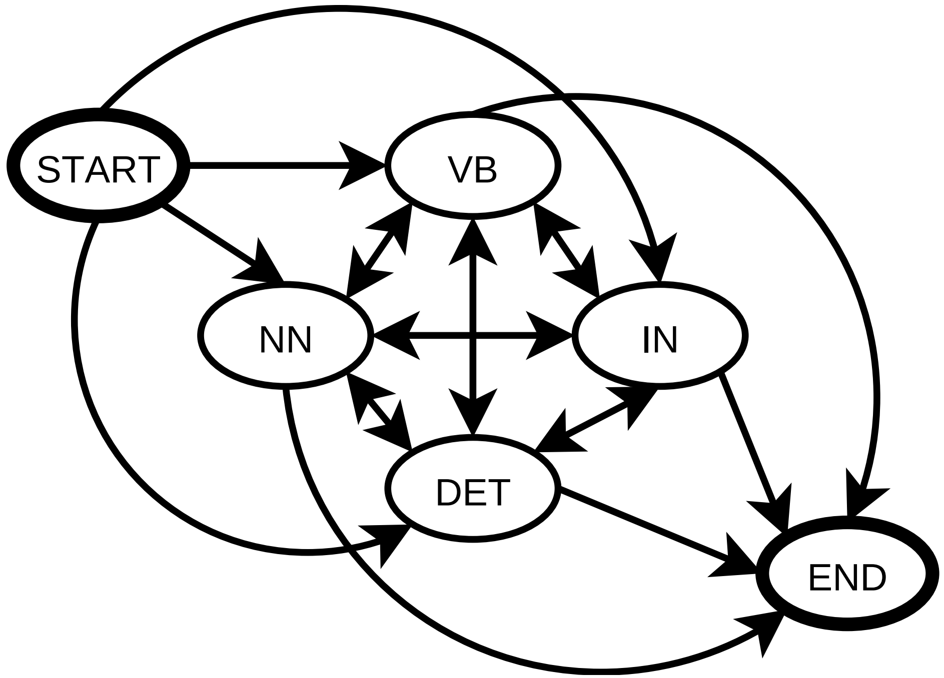
- We can estimate $p(S|T)$ and $p(T)$ with maximum likelihood estimation (and maybe some smoothing)

Hidden Markov Model (HMM)

- The model we just developed is a **Hidden Markov Model**
- Elements of an HMM model:
  - a set of states (here: the tags)
  - an output alphabet (here: words)
  - intitial state (here: beginning of sentence)
  - state transition probabilities (here: $p(t_n|t_{n-1})$)
  - symbol emission probabilities (here: $p(w_i|t_i)$)

Graphical Representation

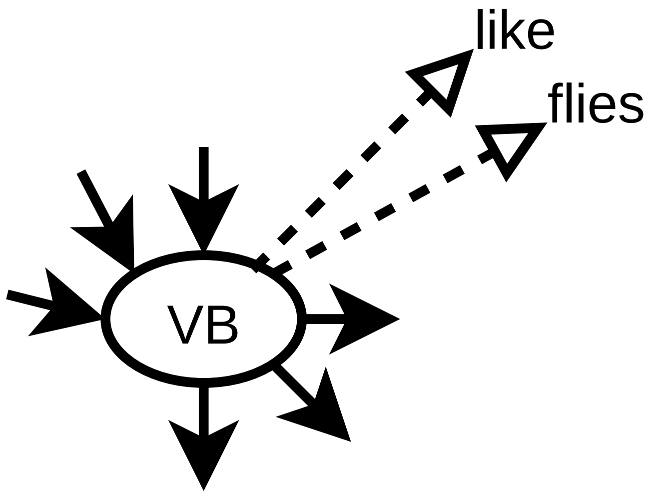
- When tagging a sentence, we are walking through the state graph:



- State transition probabilities: $p(t_n|t_{n-1})$

Graphical Representation

- At each state we emit a word:



- Symbol emission probabilities: $p(w_i|t_i)$

Search for the Best Tag Sequence

- We have defined a model, but how do we use it?
  - given: word sequence
  - wanted: tag sequence

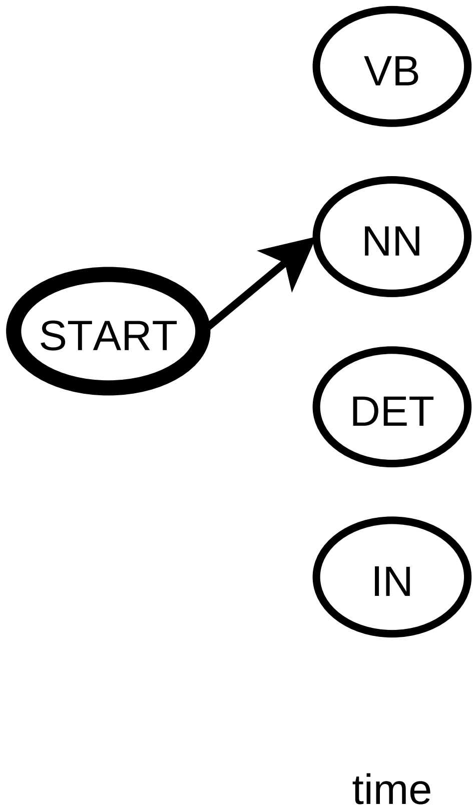
- If we consider a specific tag sequence, it is straight-forward to compute its probability

$$p(S|T)\, p(T) = \prod_i p(w_i|t_i)\, p(t_i|t_{i-1})$$

- Problem: if we have on average c choices for each of the n words, there are c^n possible tag sequences, maybe too many to efficiently evaluate

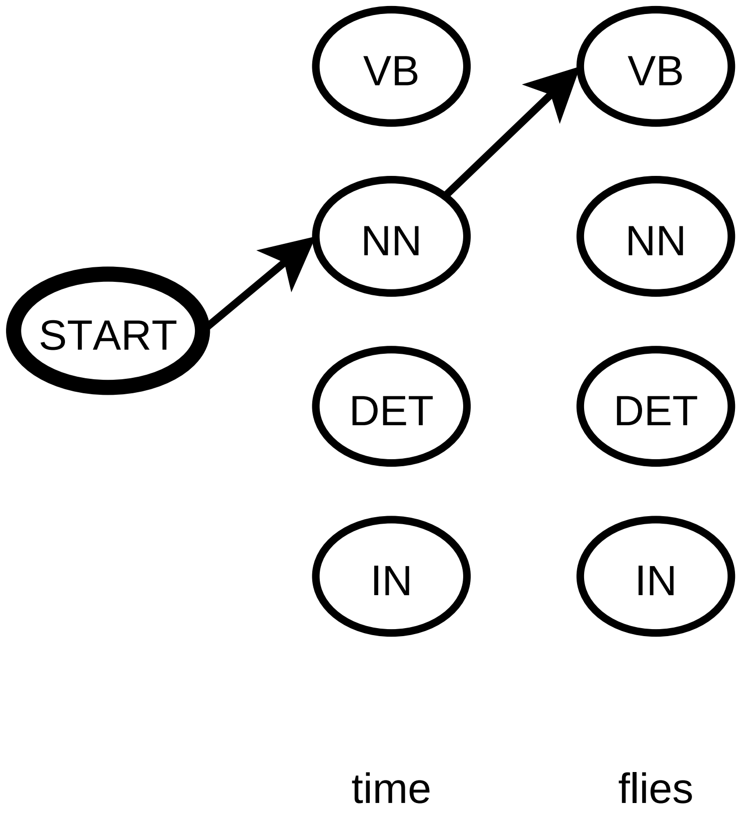
Walking Through the States

- First, we go to state NN to emit time:



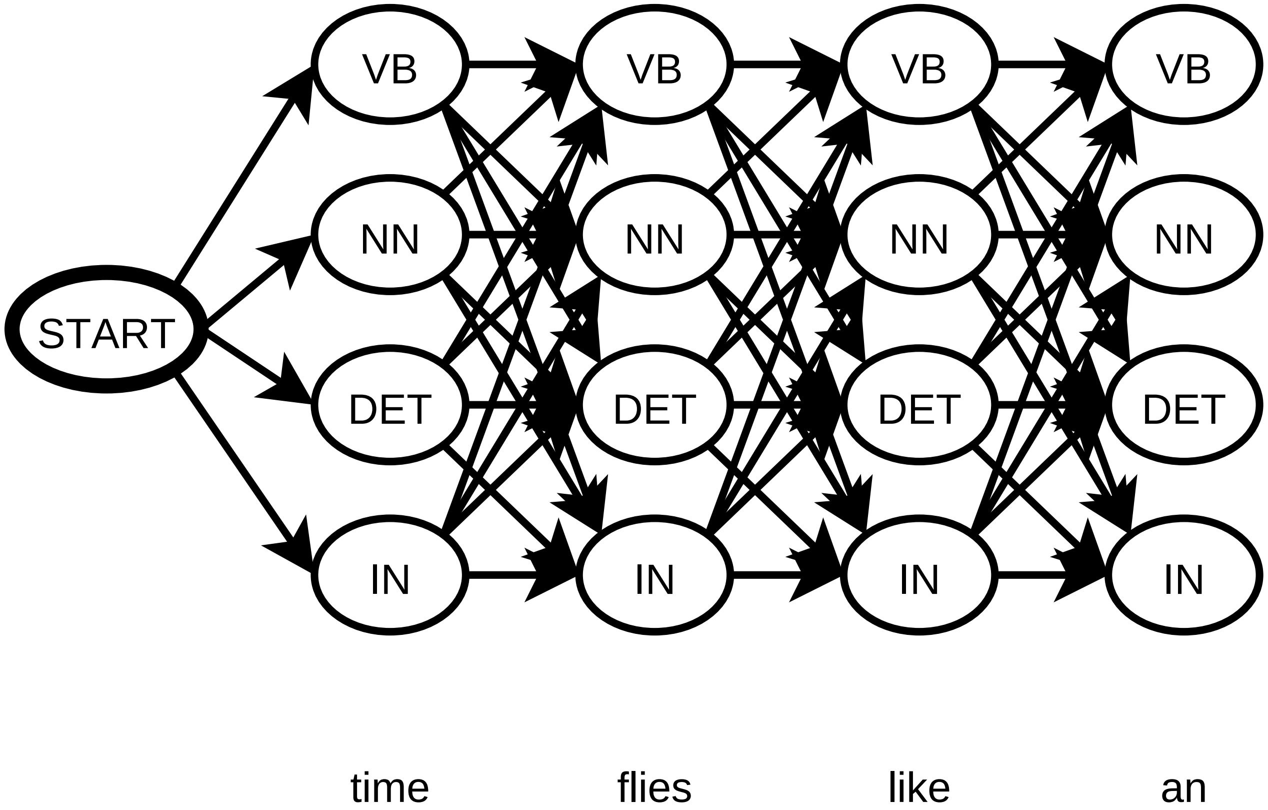
Walking Through the States

- Then, we go to state VB to emit flies:



Walking Through the States

- Of course, there are many possible paths:



Viterbi Algorithm

- Intuition: Since state transition out of a state only depend on the current state (and not previous states), we can record for each state the optimal path

- We record:
  - cheapest cost to state j at step s in $\delta_j(s)$
  - backtrace from that state to best predecessor $\psi_j(s)$

- Stepping through all states at each time steps allows us to compute
  - $\delta_j(s+1) \;=\; \max_{1\leq i\leq N} \delta_i(s)\, p(t_j|t_i)\, p(w_{s+1}|t_j)$
  - $\psi_j(s+1) = \text{argmax}_{1\leq i\leq N} \delta_i(s)\, p(t_j|t_i)\, p(w_{s+1}|t_j)$

- Best final state is $\text{argmax}_{1\leq i\leq N} \delta_i(|S|)$, we can backtrack from there

morphology

How Many Different Words?

10,000 sentences from the Europarl corpus

Language	Different words
English	16k
French	22k
Dutch	24k
Italian	25k
Portuguese	26k
Spanish	26k
Danish	29k
Swedish	30k
German	32k
Greek	33k
Finnish	55k

Why the difference? Morphology.

Morphemes: Stems and Affixes

- Two types of morphemes
  - stems: small, cat, walk
  - affixes: +ed, un+
- Four types of affixes
  - suffix
  - prefix
  - infix
  - circumfix

Suffix

- Plural of nouns

  cat+s

- Comparative and superlative of adjectives

  small+er

- Formation of adverbs

  great+ly

- Verb tenses

  walk+ed

- All inflectional morphology in English uses suffixes

Prefix

- In English: meaning changing particles

- Adjectives

  un+friendly
  dis+interested

- Verbs

  re+consider

- German verb pre-fix zer implies destruction

Infix

- In English: inserting profanity for emphasis

abso+bloody+lutely
unbe+bloody+lievable

- Why not:

ab+bloody+solutely

Circumfix

- No example in English

- German past participle of verb:

ge+sag+t (German)

Not that Easy...

- Affixes are not always simply attached
- Some consonants of the lemma may be changed or removed
  - walk+ed
  - frame+d
  - emit+ted
  - eas(–y)+ier
- Typically due to phonetic reasons

Irregular Forms

- Some words have irregular forms:
  - is, was, been
  - eat, ate, eaten
  - go, went, gone

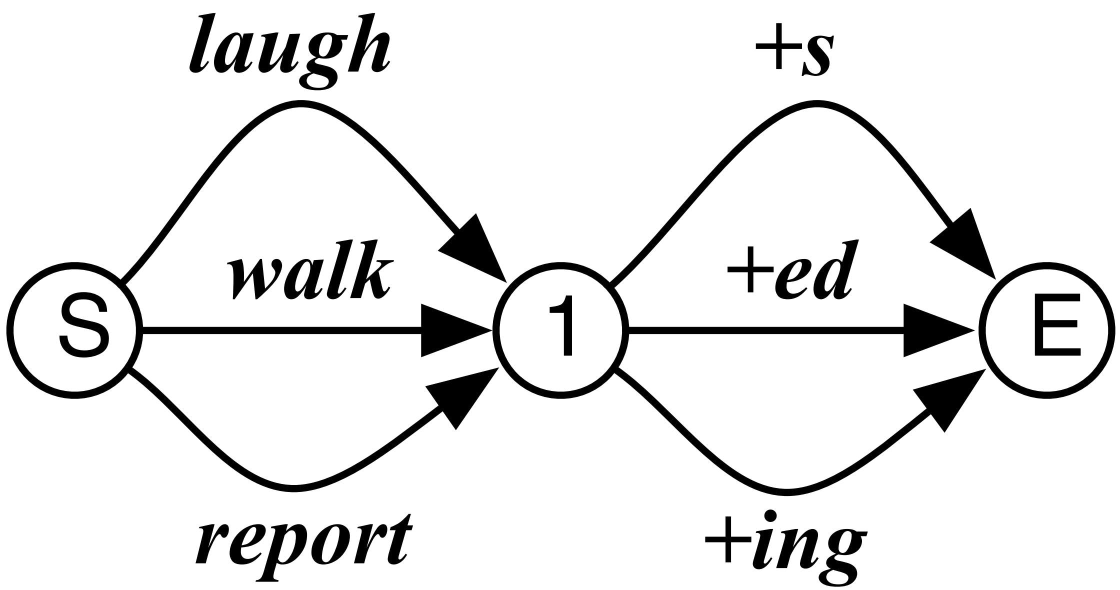
- Only most frequent words have irregular forms

- A failure of morphology:
  morphology reduces the need to create completely new words

Why Morphology?

- Alternatives
  - Some languages have no verb tenses
    → use explicit time references (yesterday)
  - Case inflection determines roles of noun phrase
    → use fixed word order instead
  - Cased noun phrases often play the same role as prepositional phrases
- There is value in redundancy and subtly added information...

Finite State Machines

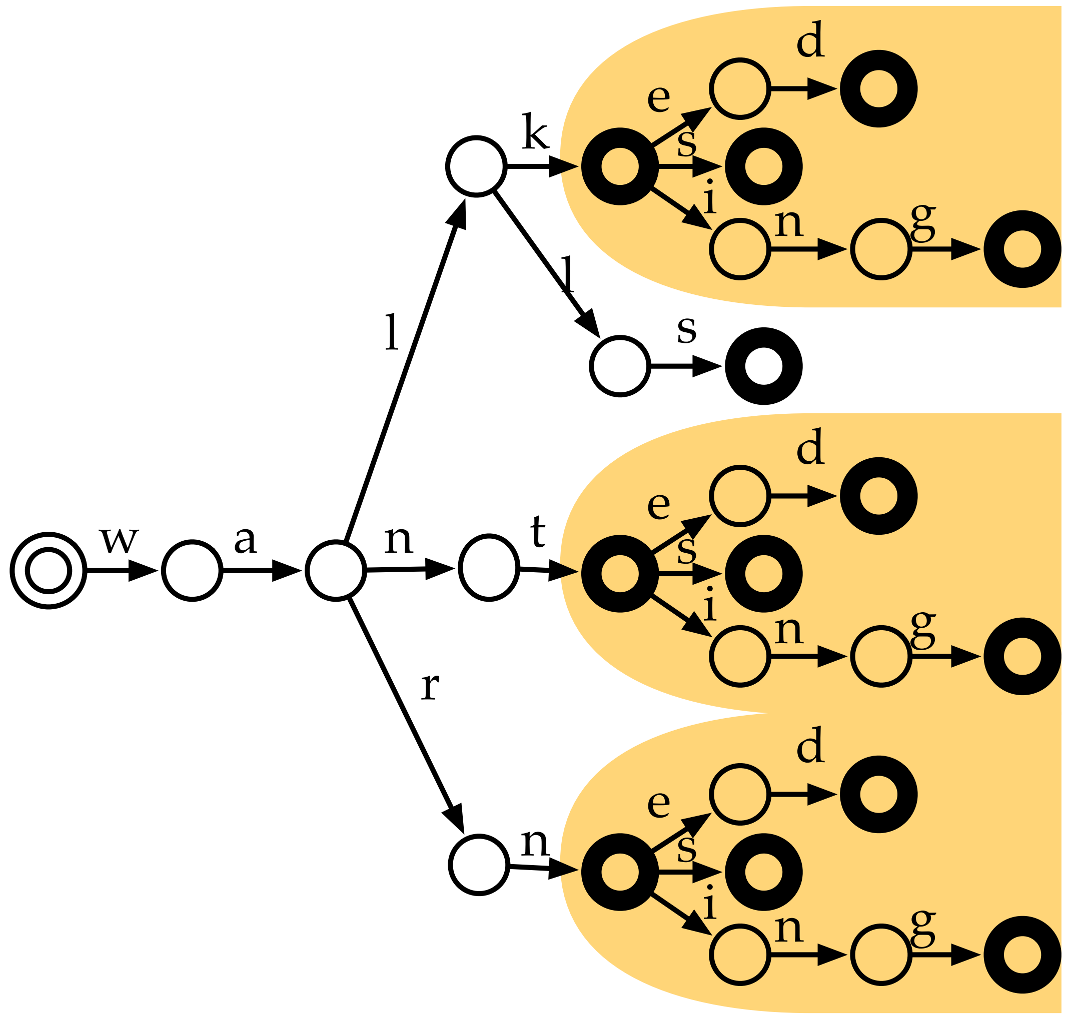


Multiple stems

- implements regular verb morphology

→ laughs, laughed, laughing
walks, walked, walking
reports, reported, reporting

Automatic Discovery of Morphology



syntax

The Path So Far

- Originally, we treated language as a *sequence of words*
  → n-gram language models

- Then, we introduced the notion of *syntactic properties of words*
  → part-of-speech tags

- Now, we look at *syntactic relations* between words
  → syntax trees

A Simple Sentence

I like the interesting lecture

Part-of-Speech Tags

I	like	the	interesting	lecture
PRO	VB	DET	JJ	NN

Syntactic Relations

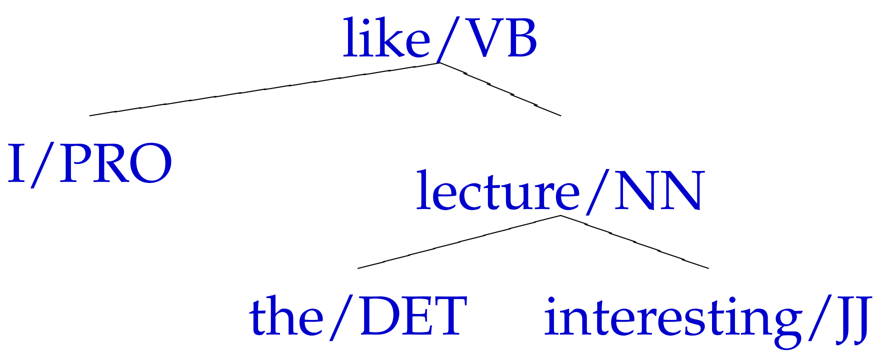
I	like	the	interesting	lecture
PRO	VB	DET	JJ	NN

- The adjective interesting gives more information about the noun lecture
- The determiner the says something about the noun lecture
- The noun lecture is the object of the verb like, specifying what is being liked
- The pronoun I is the subject of the verb like, specifying who is doing the liking

Dependency Structure

I	like	the	interesting	lecture
PRO	VB	DET	JJ	NN
↓		↓	↓	↓
like		lecture	lecture	like

This can also be visualized as a **dependency tree**:



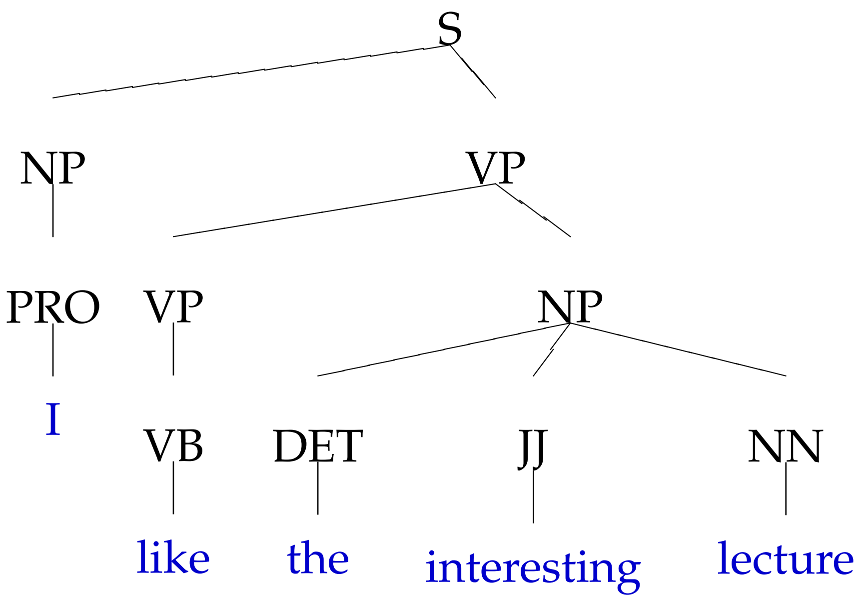
Dependency Structure

I	like	the	interesting	lecture
PRO	VB	DET	JJ	NN
↓		↓	↓	↓
subject		adjunct	adjunct	object
↓		↓	↓	↓
like		lecture	lecture	like

The dependencies may also be **labeled** with the type of dependency

Phrase Structure Tree

- A popular grammar formalism is **phrase structure grammar**
- Internal nodes combine leaf nodes into phrases, such as noun phrases (NP)



Building Phrase Structure Trees

- Task: **parsing**
  - *given:* an input sentence with part-of-speech tags
  - *wanted:* the right syntax tree for it

- Formalism: **context free grammars**
  - **non-terminal nodes** such as NP, S appear inside the tree
  - **terminal nodes** such as like, lecture appear at the leafs of the tree
  - **rules** such as NP → DET JJ NN

Context Free Grammars in Context

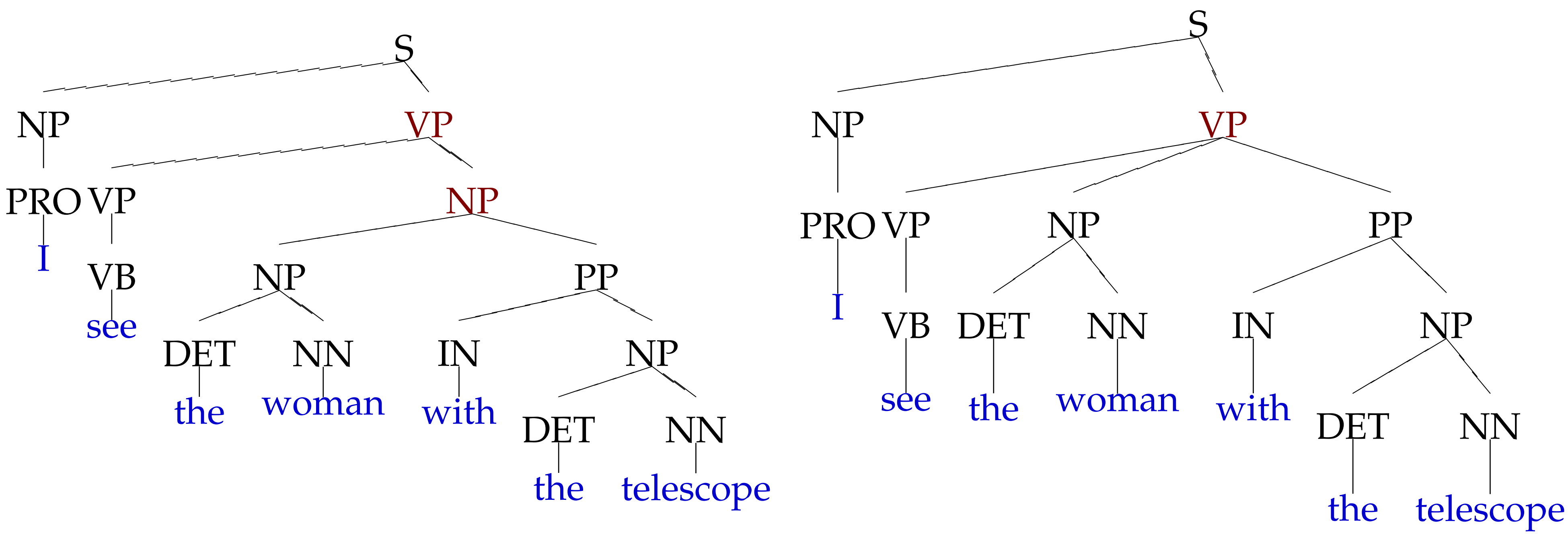
- **Chomsky hierarchy** of **formal languages**
  (terminals in caps, non-terminal lowercase)
  - **regular**: only rules of the form $A \rightarrow a$, $A \rightarrow B$, $A \rightarrow Ba$ (or $A \rightarrow aB$)
    Cannot generate languages such as $a^n b^n$
  - **context-free**: left-hand side of rule has to be single non-terminal, anything goes on right hand-side. Cannot generate $a^n b^n c^n$
  - **context-sensitive:** rules can be restricted to a particular context, e.g. $\alpha A \beta \rightarrow \alpha a B c \beta$, where α and β are strings of terminal and non-terminals

- Moving up the hierarchy, languages are more expressive and parsing becomes computationally more expensive

- Is natural language context-free?

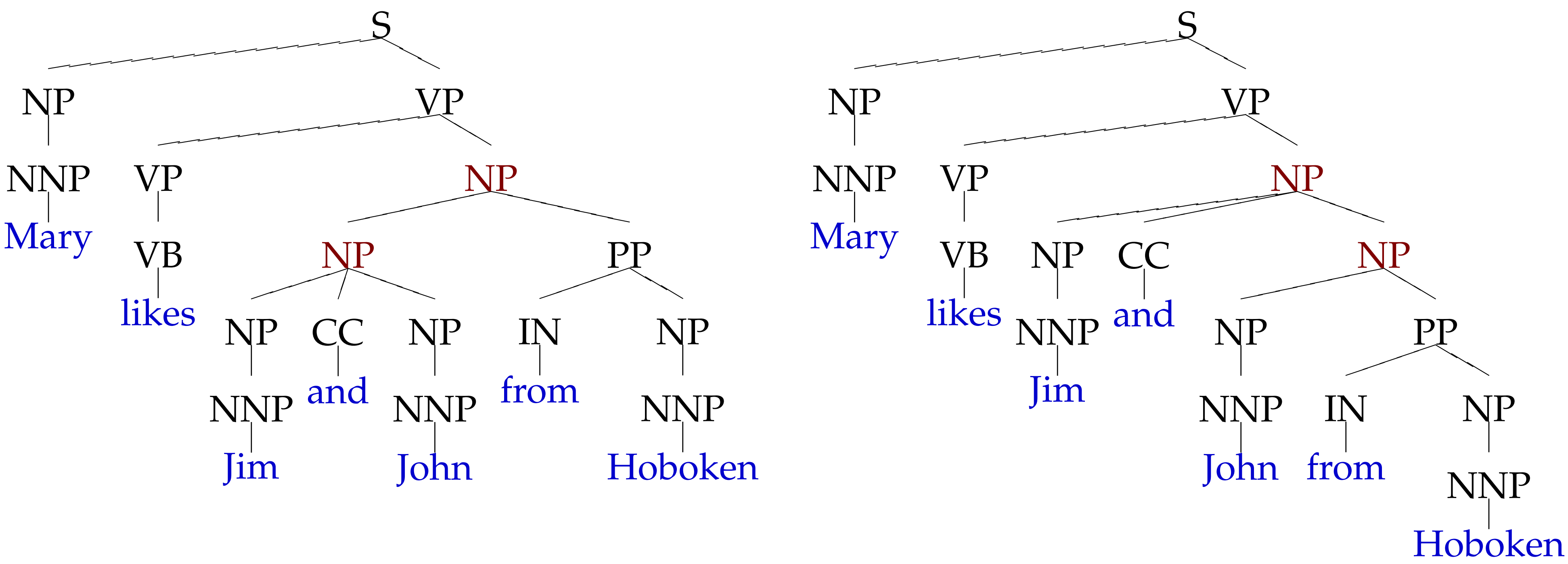
Why is Parsing Hard?

Prepositional phrase attachment: Who has the telescope?



Why is Parsing Hard?

Scope: Is Jim also from Hoboken?



CYK Parsing

- We have input sentence:
  I like the interesting lecture

- We have a set of context-free rules:
  $S \rightarrow NP\ VP$, $NP \rightarrow PRO$, $PRO \rightarrow$ I, $VP \rightarrow VP\ NP$, $VP \rightarrow VB$
  $VB \rightarrow$ like, $NP \rightarrow DET\ JJ\ NN$, $DET \rightarrow$ the, $JJ \rightarrow$, $NN \rightarrow$ lecture

- **Cocke-Younger-Kasami (CYK)** parsing
  - a **bottom-up** parsing algorithm
  - uses a **chart** to store intermediate result

Example

Initialize chart with the words

I	like	the	interesting	lecture
1	2	3	4	5

Example

Apply first terminal rule *PRO* → I

PRO				
I	like	the	interesting	lecture
1	2	3	4	5

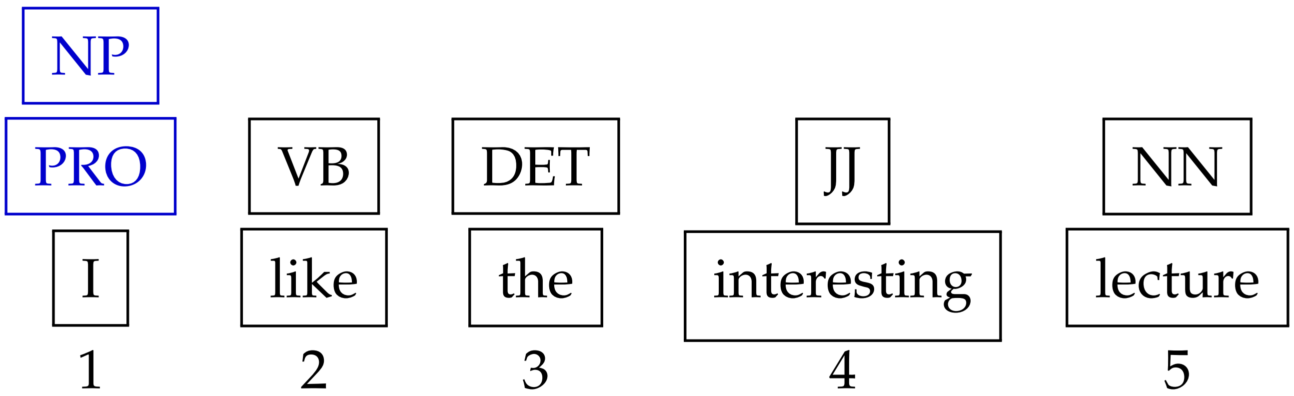
Example

... and so on ...

PRO	VB	DET	JJ	NN
I	like	the	interesting	lecture
1	2	3	4	5

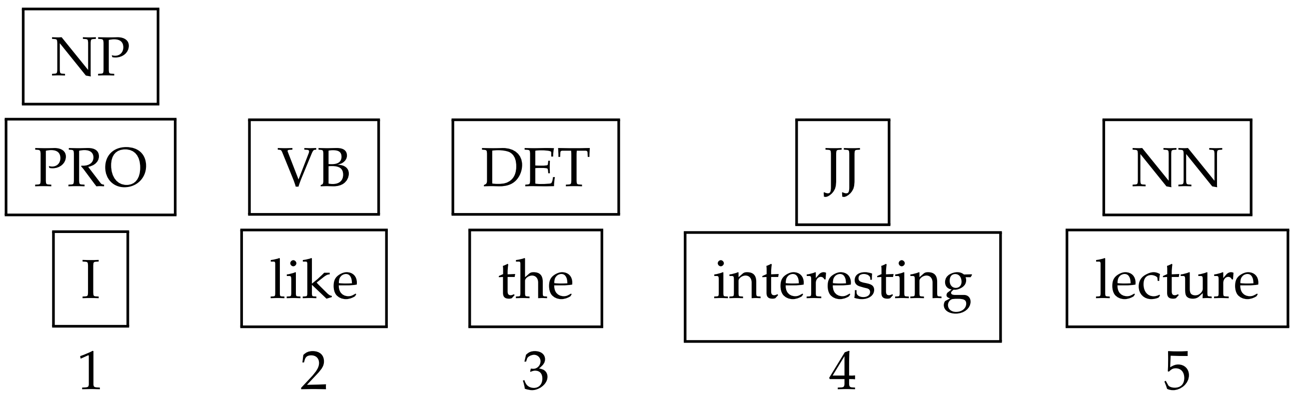
Example

Try to apply a non-terminal rule to the first word
The only matching rule is $NP \rightarrow PRO$



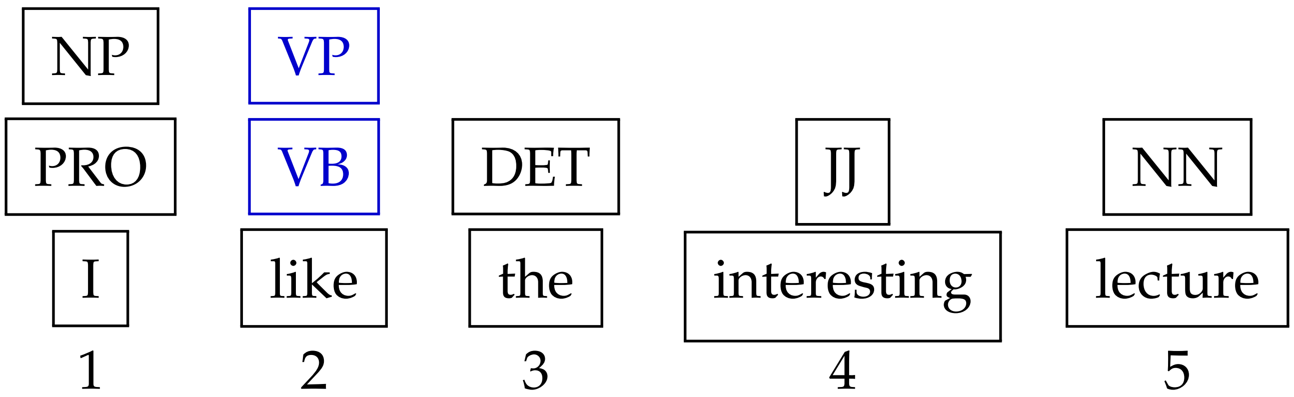
Example

Recurse: try to apply a non-terminal rule to the first word
No rule matches



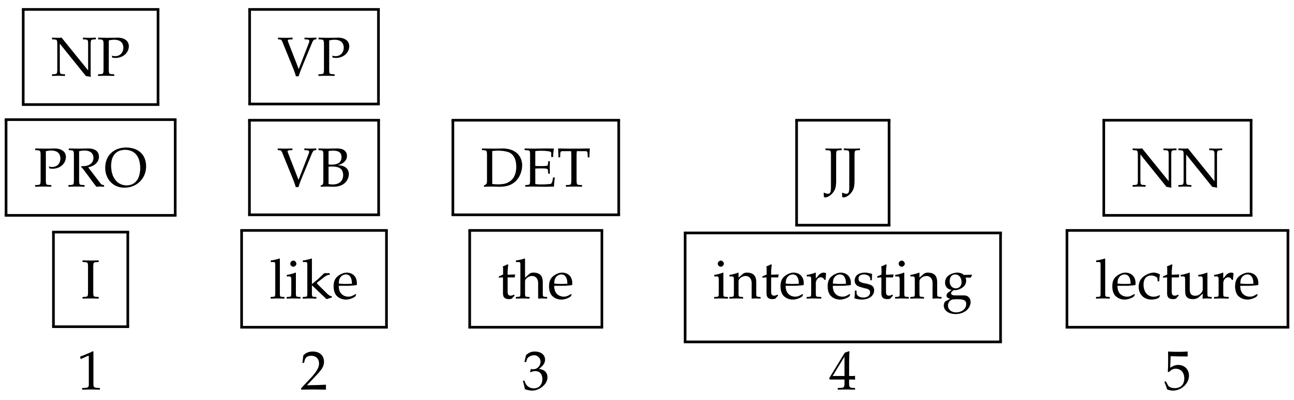
Example

Try to apply a non-terminal rule to the second word
The only matching rule is $VP \rightarrow VB$
No recursion possible, no additional rules match



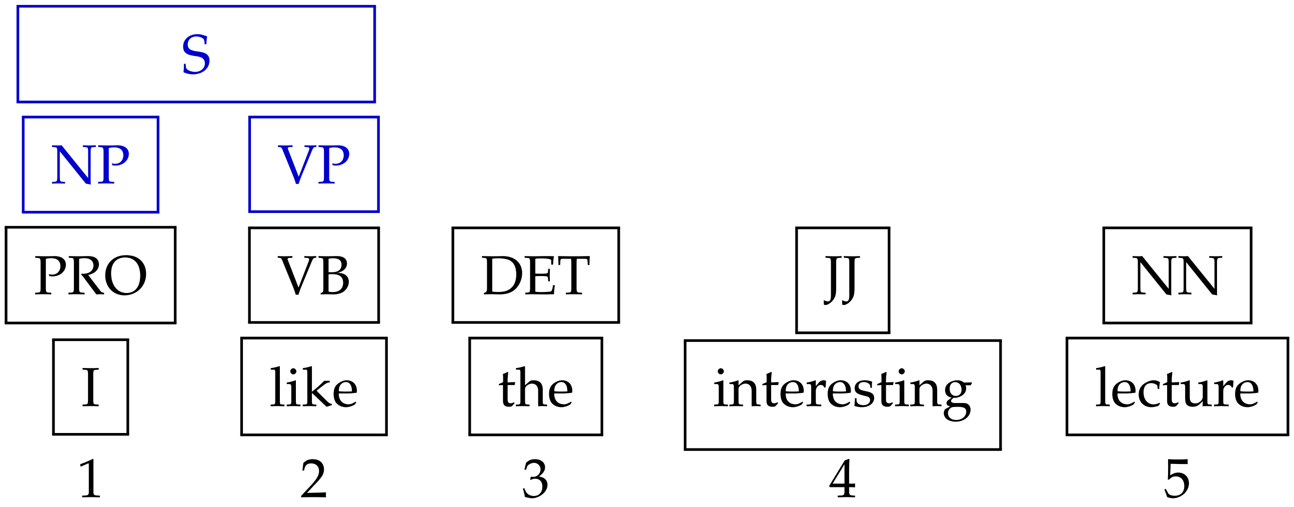
Example

Try to apply a non-terminal rule to the third word
No rule matches



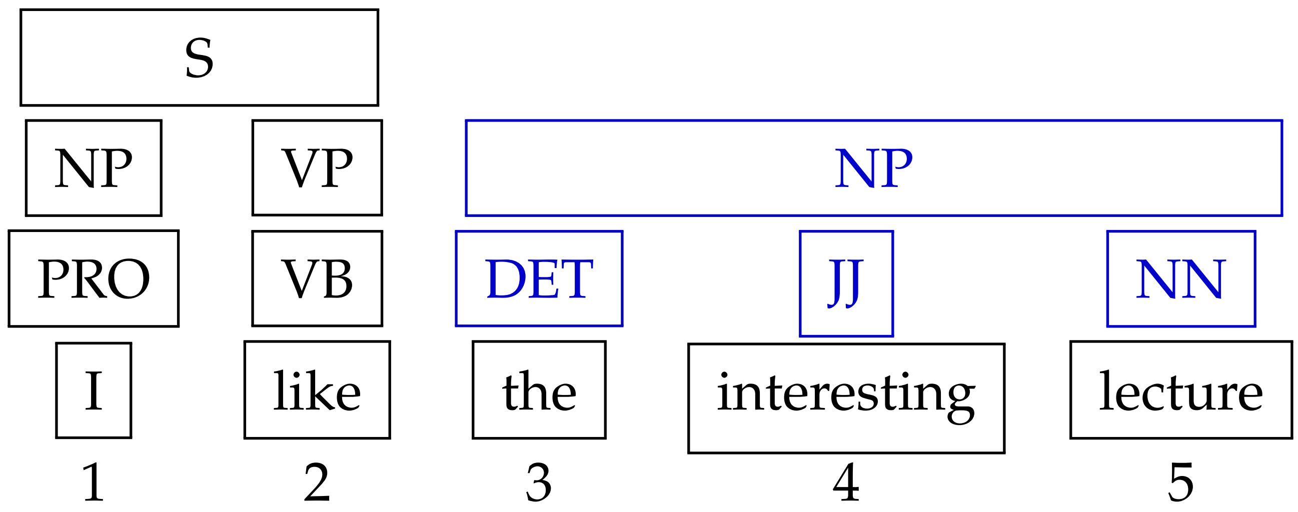
Example

Try to apply a non-terminal rule to the first two words
The only matching rule is $S \rightarrow NP\ VP$
No other rules match for **spans** of two words



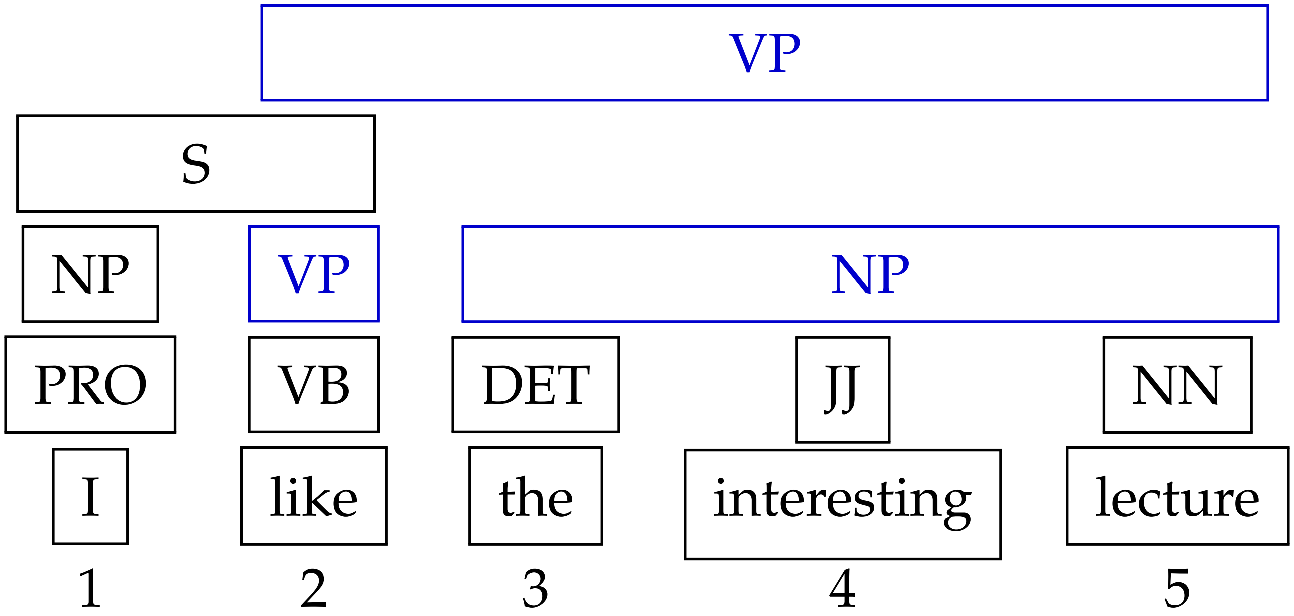
Example

One rule matches for a span of three words: *NP → DET JJ NN*



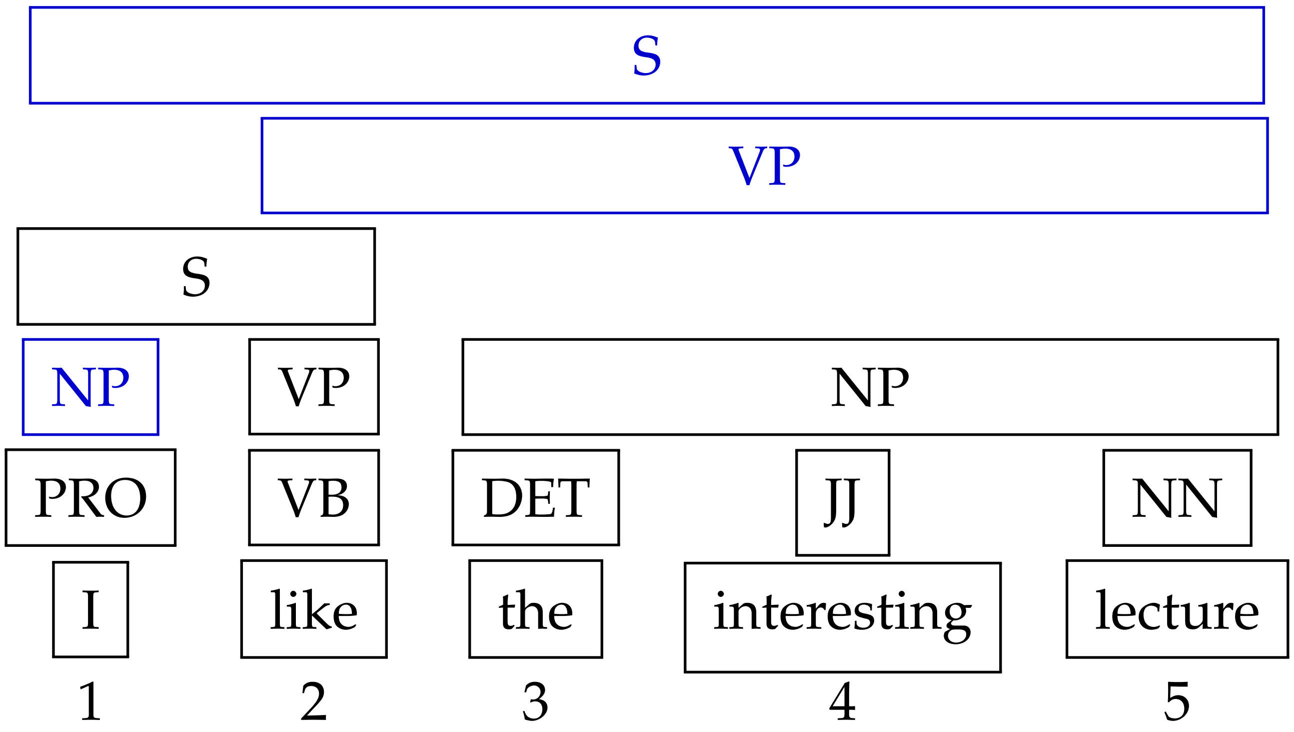
Example

One rule matches for a span of four words: *VP* → *VP NP*



Example

One rule matches for a span of five words: $S \rightarrow NP\ VP$



Statistical Parsing Models

- Currently best-performing syntactic parsers are statistical

- Assign each rule a probability

$$p(\text{tree}) = \prod_i p(\text{rule}_i)$$

- Probability distributions are learned from manually crafted treebanks

semantics

Word Senses

- Some words have multiple **meanings**
- This is called **Polysemy**
- Example: bank
  - financial institution: I put my money in the bank.
  - river shore: He rested at the bank of the river.
- How could a computer tell these senses apart?

How Many Senses?

- How many senses does the word interest have?
  - She pays 3% **interest** on the loan.
  - He showed a lot of **interest** in the painting.
  - Microsoft purchased a controlling **interest** in Google.
  - It is in the national **interest** to invade the Bahamas.
  - I only have your best **interest** in mind.
  - Playing chess is one of my **interests**.
  - Business **interests** lobbied for the legislation.
- Are these seven different senses? Four? Three?

Wordnet

- According to Wordnet, interest has 7 senses:
  - Sense 1: a sense of concern with and curiosity about someone or something, Synonym: involvement
  - Sense 2: the power of attracting or holding one's interest (because it is unusual or exciting etc.), Synonym: interestingness
  - Sense 3: a reason for wanting something done, Synonym: sake
  - Sense 4: a fixed charge for borrowing money; usually a percentage of the amount borrowed
  - Sense 5: a diversion that occupies one's time and thoughts (usually pleasantly), Synonyms: pastime, pursuit
  - Sense 6: a right or legal share of something; a financial involvement with something, Synonym: stake
  - Sense 7: (usually plural) a social group whose members control some field of activity and who have common aims, Synonym: interest group

Word Sense Disambiguation (WSD)

- For many applications, we would like to disambiguate senses
  - we may be only interested in one sense
  - searching for chemical plant on the web, we do not want to know about chemicals in bananas
- Task: Given a polysemous word, find the sense in a given *context*
- Popular topic, data driven methods perform well

WSD as Supervised Learning Problem

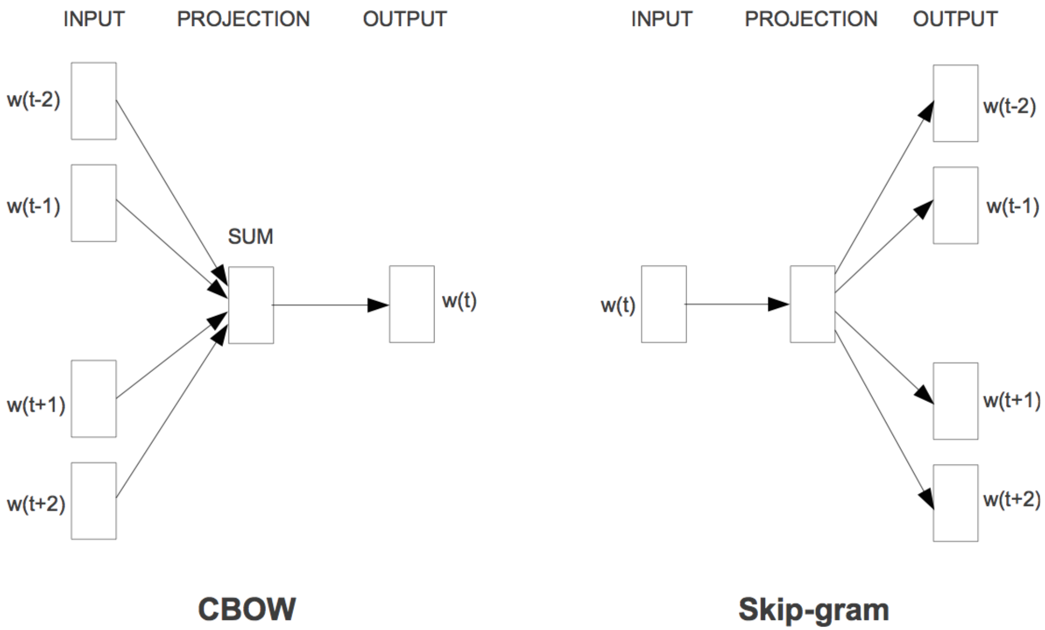
- Words can be labeled with their senses
  - A chemical **plant/PLANT-MANUFACTURING** opened in Baltimore.
  - She took great care and watered the exotic **plant/PLANT-BIOLOGICAL**.
- Features: directly neighboring words
  - **plant** life
  - manufacturing **plant**
  - assembly **plant**
  - **plant** closure
  - **plant** species
- More features
  - any content words in a 50 word window (animal, equipment, employee, ...)
  - syntactically related words, syntactic role in sense
  - topic of the text
  - part-of-speech tag, surrounding part-of-speech tags

Learning Lexical Semantics

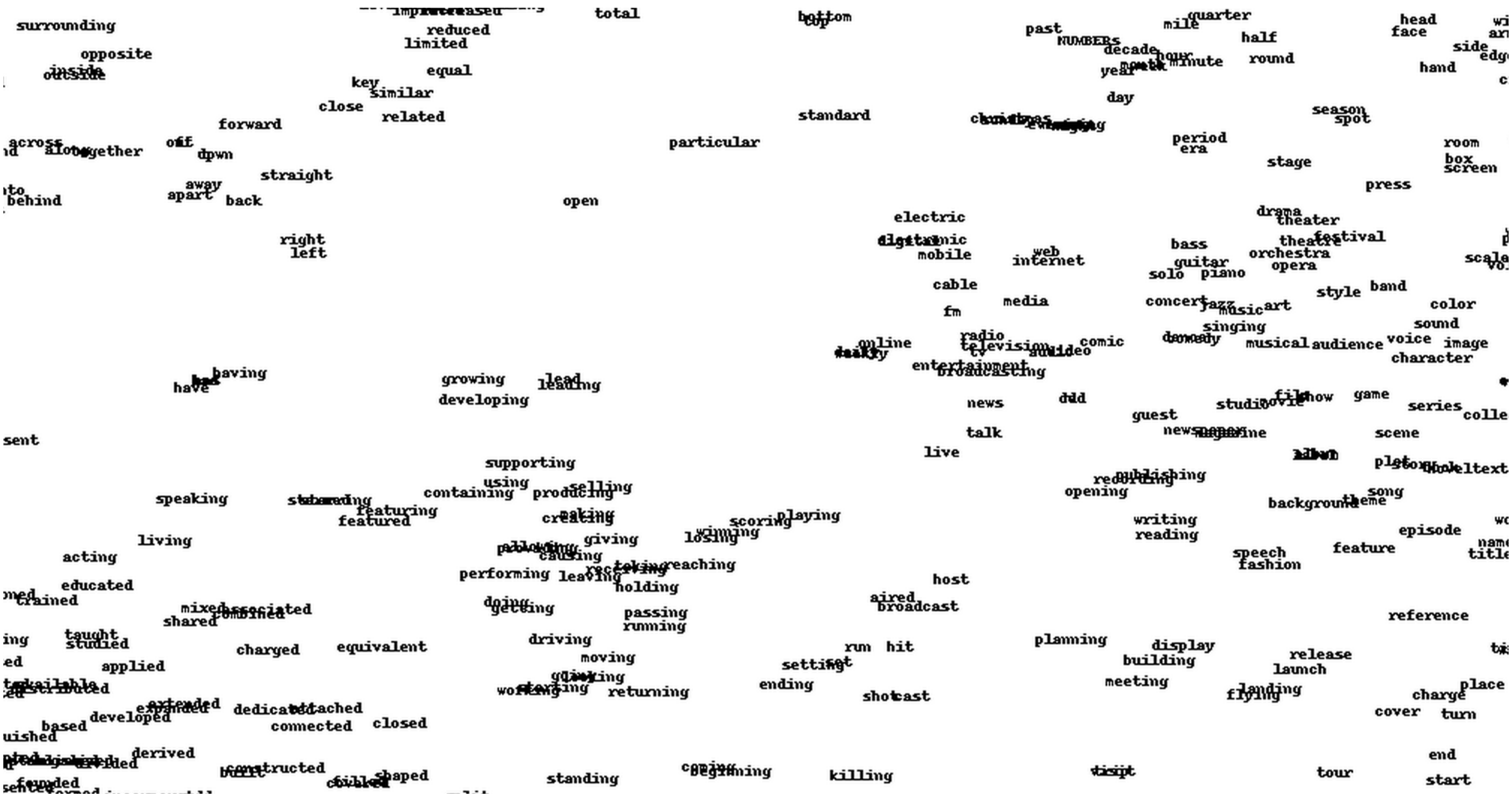
The meaning of a word is its use.
Ludwig Wittgenstein, Aphorism 43

- Represent context of a word in a vector
  → Similar words have similar **context vectors**

- Learning with neural networks



Word Embeddings



Word Embeddings

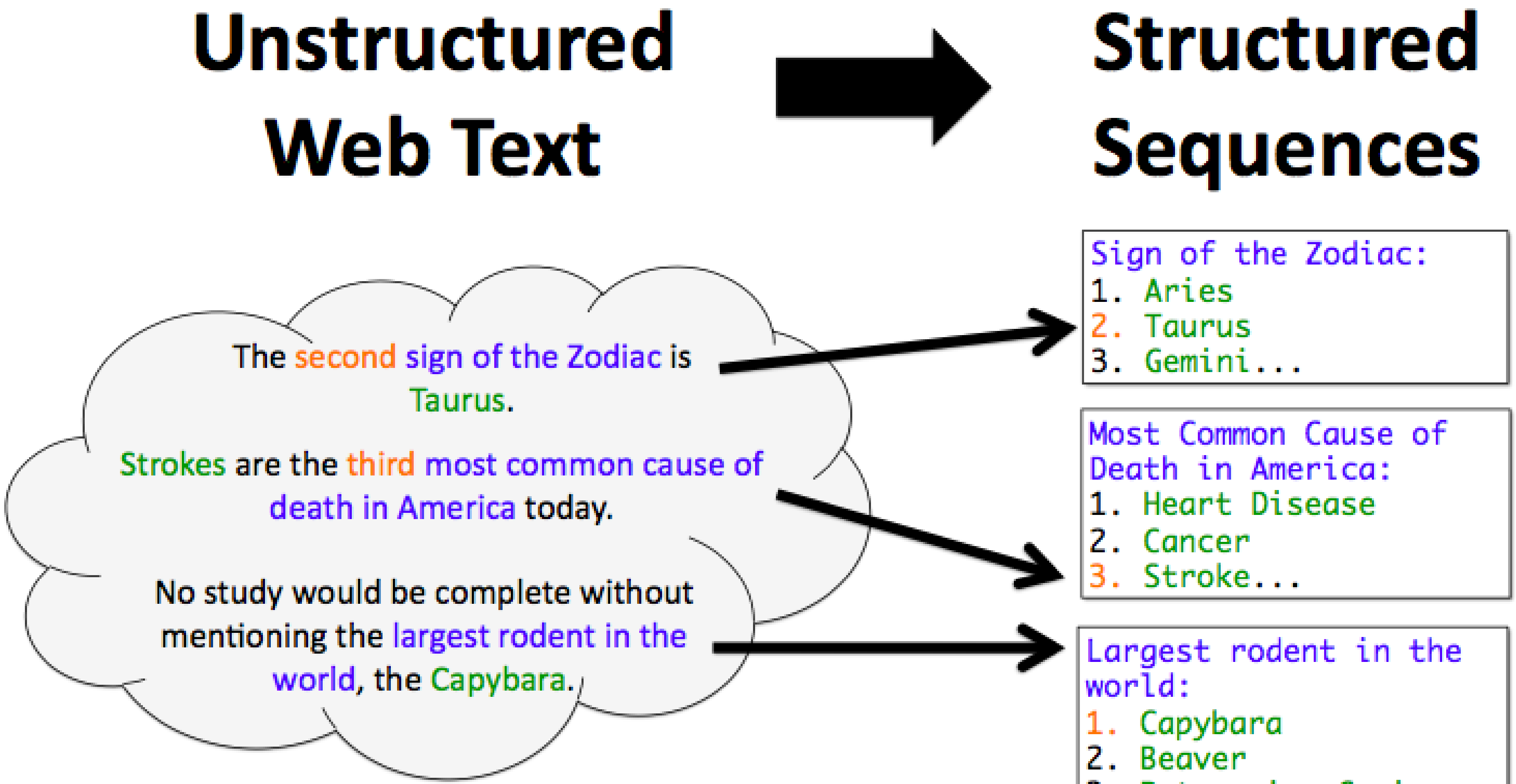
Thematic Roles

- Words play **semantic roles** in a sentence

$$\underbrace{\text{I}}_{\text{AGENT}} \text{ see } \underbrace{\text{the woman}}_{\text{THEME}} \underbrace{\text{with the telescope}}_{\text{INSTRUMENT}} .$$

- Specific verbs typically require **arguments** with specific thematic roles and allow **adjuncts** with specific thematic roles.

Information Extraction



questions?