Syntactic Parsing

Human Language from a Computational Perspective
April 25, 2018

Language models reminder

Use an *n*-gram model to predict the next token:

* ~~My only **wish I**~~

  My only **wish is**

Bigram counts (starting with wish):

wish I	**8**
wish is	6
wish they	4
wish was	4
wish that	2
wish you	1

Lexical ambiguity

The word WISH is ambiguous

WISH (verb): **לבקש, לאחל**

WISH (noun): **משאלה**

Some context helps

Verb:

How I **wish** you were here

Careful what you **wish** for

Wish you a happy birthday

Noun:

Your **wish** is my command

If you could have one **wish**

Make a **wish**

But sometimes it doesn't

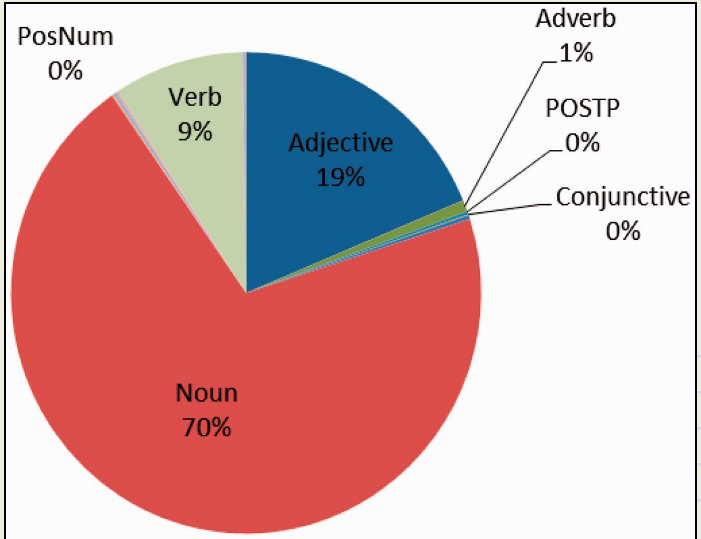
Squad helps dog **bite** victim

Eye **drops** off shelf

Reagan wins on budget, but more **lies** ahead

Parts of speech (POS)

Words can roughly be divided into **distributional categories** based on their **syntactic roles**.



Part-of-speech hierarchy

Open classes

Nouns

- Proper: Hebrew, John
- Common: arrival, pencils

Verbs

- Main: went, write
- Modals: would, shall

Adjectives
tall

Adverbs
quickly

Numbers
2015, 1/2, billion, one

...

Closed classes

- Determiners some, the
- Conjunctions and, or
- Pronouns you, my, us
- Prepositions to, in, by

...

Part-of-speech tags

Tag	Description	Example	Tag	Description	Example
CC	Coordin. Conjunction	*and, but, or*	SYM	Symbol	+,%, &
CD	Cardinal number	*one, two, three*	TO	"to"	*to*
DT	Determiner	*a, the*	UH	Interjection	*ah, oops*
EX	Existential 'there'	*there*	VB	Verb, base form	*eat*
FW	Foreign word	*mea culpa*	VBD	Verb, past tense	*ate*
IN	Preposition/sub-conj	*of, in, by*	VBG	Verb, gerund	*eating*
JJ	Adjective	*yellow*	VBN	Verb, past participle	*eaten*
JJR	Adj., comparative	*bigger*	VBP	Verb, non-3sg pres	*eat*
JJS	Adj., superlative	*wildest*	VBZ	Verb, 3sg pres	*eats*
LS	List item marker	*1, 2, One*	WDT	Wh-determiner	*which, that*
MD	Modal	*can, should*	WP	Wh-pronoun	*what, who*
NN	Noun, sing. or mass	*llama*	WP$	Possessive wh-	*whose*
NNS	Noun, plural	*llamas*	WRB	Wh-adverb	*how, where*
NNP	Proper noun, singular	*IBM*	$	Dollar sign	$
NNPS	Proper noun, plural	*Carolinas*	#	Pound sign	#
PDT	Predeterminer	*all, both*	"	Left quote	(' or ")
POS	Possessive ending	*'s*	"	Right quote	(' or ")
PP	Personal pronoun	*I, you, he*	(	Left parenthesis	([, (, {, <)
PP$	Possessive pronoun	*your, one's*	)	Right parenthesis	( ],), }, >)
RB	Adverb	*quickly, never*	,	Comma	,
RBR	Adverb, comparative	*faster*	.	Sentence-final punc	(. ! ?)
RBS	Adverb, superlative	*fastest*	:	Mid-sentence punc	(: ; ... – -)
RP	Particle	*up, off*			

Tag guide:
https://catalog.ldc.upenn.edu/docs/LDC99T42/tagguid1.pdf

Penn Treebank Part-of-Speech Tags for English

Language variations

AD	adverb	还
AS	aspect marker	着
BA	把 in ba-construction	把, 将
CC	coordinating conjunction	和
CD	cardinal number	一百
CS	subordinating conjunction	虽然
DEC	的 in a relative-clause	的
DEG	associative 的	的
DER	得 in V-de const. and V-de-R	得
DEV	地 before VP	地
DT	determiner	这
ETC	for words 等, 等等	等, 等等
FW	foreign words	ISO
IJ	interjection	啊
JJ	other noun-modifier	另, 共同
LB	被 in long bei-const	被, 给
LC	localizer	里
M	measure word	个
MSP	other particle	所

NN	common noun	书
NR	proper noun	美国
NT	temporal noun	今天
OD	ordinal number	第一
ON	onomatopoeia	哈哈, 哗哗
P	preposition excl. 被 and 把	从
PN	pronoun	他
PU	punctuation	、？。
SB	被 in short bei-const	被, 给
SP	sentence-final particle	吗
VA	predicative adjective	红
VC	是	是
VE	有 as the main verb	有
VV	other verb	走

Penn Treebank Part-of-Speech Tags

for Mandarin Chinese

Part-of-speech tagging

Tag the following text for POS:

ALICE	WAS	BEGINNING	TO	GET	VERY	TIRED
NNP	VBD	VBG	TO	VB	RB	JJ

Statistical POS tagging

We can use counts from the corpus to tag text for POS,

but it requires **annotation**:

just the text is not enough.

Annotated corpus example

Alice/NNP was/VBD beginning/VBG to/TO get/VB very/RB tired/JJ of/IN sitting/VBG by/IN her/PRP$ sister/NN on/IN the/DT bank/NN ,/, and/CC of/IN having/VBG nothing/NN to/TO do/VB ./. Once/RB or/CC twice/RB she/PRP had/VBD peeped/VBN into/IN the/DT book/NN her/PRP$ sister/NN was/VBD reading/VBG ,/, but/CC it/PRP had/VBD no/DT pictures/NNS or/CC conversations/NNS in/IN it/PRP ,/, "/" and/CC what/WDT is/VBZ the/DT use/NN of/IN a/DT book/NN ,/, "/" thought/VBD Alice/NNP ,/, "/" without/IN pictures/NNS or/CC conversations/NNS ?/. "/" So/CC she/PRP

Word/tag counts

Simple method: count the times each word occurred with each POS in the corpus

THE	DT	1527
WELL	RB	37
WELL	NN	3
SLEEP	NN	4
SLEEP	VBP	2
THAT	IN	197
THAT	DT	50

Algorithm to count word/tag

```
count(L, T):                            ▹ L: list of tokens, T: list of correct tags
    Cwt ← [0]                           ▹ create a table of zeros
    i ← 1                               ▹ assign 1 to i
    while i ≤ len(L):                   ▹ repeat while i is at most len(L)=len(T)
        Cwt[L[i], T[i]] ← Cwt[L[i], T[i]] + 1     ▹ increment count
        i ← i + 1                       ▹ increment i
    return Cwt                          ▹ output is the counts table
```

POS tagging algorithm

Find POS sequence of token sequence

[BOB WENT OUT FOR A SWIM .] $\longrightarrow$ [NNP VBD IN IN DT NN .]

This is the wanted result, but no algorithm is perfect

POS tagging algorithm 1

```
tag1(L, Cwt):                                  ▷ L: tokens, Cwt: word-tag counts
    T ← []                                     ▷ create empty list of tags
    i ← 1                                      ▷ initialize i to 1
    while i ≤ len(L):                          ▷ repeat for all tokens
        T[i] ← argmax(Cwt[L[i], ·])            ▷ most common tag for L[i]
        i ← i + 1                              ▷ increment i
    return T                                   ▷ output is list of tags
```

POS tagging algorithm 1

```
tag1(L, Cwt):                              ▷ L: tokens, Cwt: word-tag counts
    T ← []                                 ▷ create empty list of tags
    i ← 1                                  ▷ initialize i to 1
    while i ≤ len(L):                      ▷ repeat for all tokens
        T[i] ← argmax(Cwt[L[i], ·])        ▷ most common tag for L[i]
        i ← i + 1                          ▷ increment i
    return T                               ▷ output is list of tags
```

The same algorithm as prediction with bigram

Surprising accuracy

This simple approach actually gets about 90% of the POS tags correctly!

Most words almost always appear with the same POS.

Problem 1: variability

Use the most common POS for each word

THE	FISH	SLEEP	IN	THAT	WELL
DT	~~NN~~	~~NN~~	IN	~~IN~~	~~RB~~

But the correct tags are:

DT	NNS	VBP	IN	DT	NN

State of the art

The best methods today get slightly more than 97% accuracy, so 90% is not so bad.

Problem 2: unknown words

'T	WAS	BRILLIG	,	AND	THE	SLITHY	TOVES
?	VBD	?	,	CC	DT	?	?

DID	GYRE	AND	GIMBLE	IN	THE	WABE	;
VBD	?	CC	?	IN	DT	?	:

ALL	MIMSY	WERE	THE	BOROGOVES	,
DT	?	VBD	DT	?	,

AND	THE	MOME	RATHS	OUTGRABE	.
CC	DT	?	?	?	.

First stanza of *Jabberwocky* from *Through the Looking-Glass, and What Alice Found There* (1871) by Lewis Carroll

Solutions

- Context (above the word level)
- Morphology (below the word level)

Transition counts

Count the times each tag follows another tag.

These are **tag bigram** counts (transition counts).

NN	NN	312
NN	IN	690
NN	DT	113
IN	NN	262
DT	NN	1256
PRP	VBD	847
VBD	DT	464

Algorithm to count tag pairs

```
count(T):                                          ▹ T: list of correct tags from corpus
    Ct2 ← [0]                                      ▹ create a table of zeros
    i ← 2                                          ▹ assign 2 to i
    while i ≤ len(L):                              ▹ repeat while i is at most len(L)
        Ct2[T[i − 1], T[i]] ← Ct2[T[i − 1], T[i]] + 1    ▹ increment
        i ← i + 1                                  ▹ increment i
    return Ct2                                     ▹ output is the counts table
```

The same algorithm as for counting word bigrams

POS tagging algorithm 2

```
tag2(L, Cwt, Ct2):                          ▷ L: tokens, Cwt: word-tag counts,
                                                ▷ Ct2: tag bigram counts
    T ← []
    T[1] ← argmax(Cwt[L[1], ·])             ▷ most common tag for first token
    i ← 2                                   ▷ initialize i to 2
    while i ≤ len(L):                       ▷ repeat for all tokens
        T[i] ← argmax(Cwt[L[i], ·] × Ct2[T[i − 1], ·])  ▷ multiply counts
        i ← i + 1                           ▷ increment i
    return T                                ▷ output is list of tags
```

POS tagging algorithm 2

```
tag2(L, Cwt, Ct2):                          ▷ L: tokens, Cwt: word-tag counts,
                                                  ▷ Ct2: tag bigram counts
  T ← []
  T[1] ← argmax(Cwt[L[1], ·])               ▷ most common tag for first token
  i ← 2                                     ▷ initialize i to 2
  while i ≤ len(L):                         ▷ repeat for all tokens
    T[i] ← argmax(Cwt[L[i], ·] × Ct2[T[i − 1], ·])   ▷ multiply counts
    i ← i + 1                               ▷ increment i
  return T                                  ▷ output is list of tags
```

Multiply corresponding elements in the two tables

Combining counts

Cwt

THE	DT	1527
WELL	RB	37
WELL	NN	3
SLEEP	NN	4
SLEEP	VBP	2

Ct2

NN	NN	312
NN	IN	690
NN	RB	113
IN	NN	262
DT	NN	1256

Tag the short sentence: SLEEP WELL

Combining counts

Cwt

THE	DT	1527
WELL	RB	37
WELL	NN	3
SLEEP	NN	4
SLEEP	VBP	2

Ct2

NN	NN	312
NN	IN	690
NN	RB	113
IN	NN	262
DT	NN	1256

Tag the short sentence: SLEEP WELL

NN

Combining counts

Cwt

THE	DT	1527
WELL	RB	37
WELL	NN	3
SLEEP	NN	4
SLEEP	VBP	2

Ct2

NN	NN	312
NN	IN	690
NN	RB	113
IN	NN	262
DT	NN	1256

NN: 3×312=936

RB: 37×113=4181

Tag the short sentence: SLEEP WELL

NN RB

Phrases

Parts of speech are for single words, but multi-word phrases may have similar syntactic roles.

Noun phrases (NP)

I saw a [dog]

[small dog]

[small dog with a black tail]

Verb phrases (VP)

I [walk]

I [walk home]

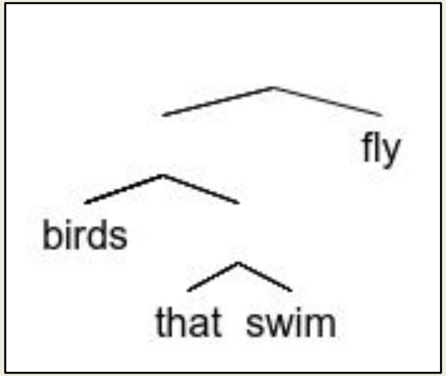
I [walk home quickly but surely]

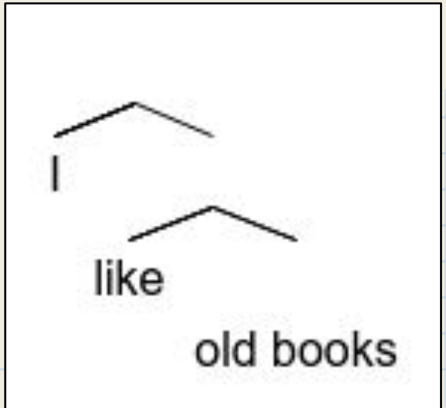
Bracketing

A hierarchy of **constituents**

[[BIRDS [THAT SWIM]] FLY]

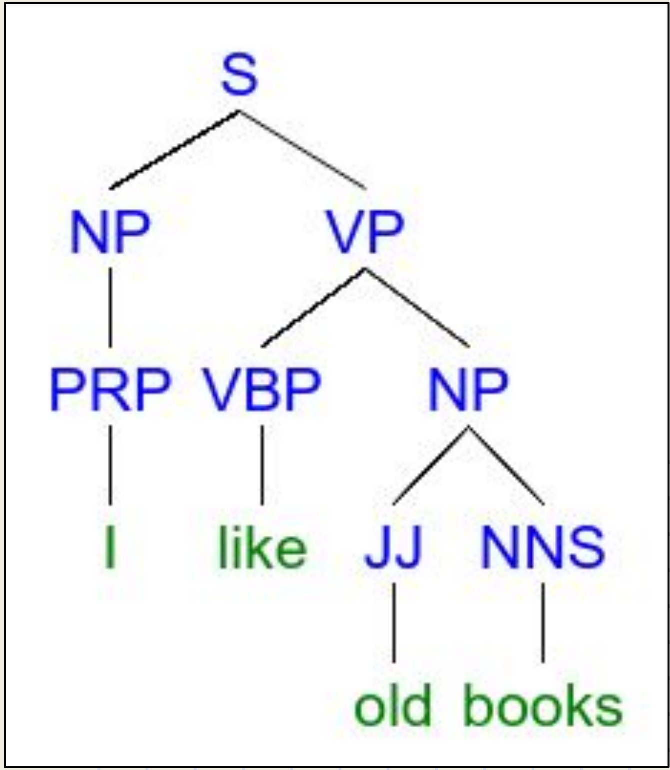
[I [LIKE [OLD BOOKS]]]





Phrase structure

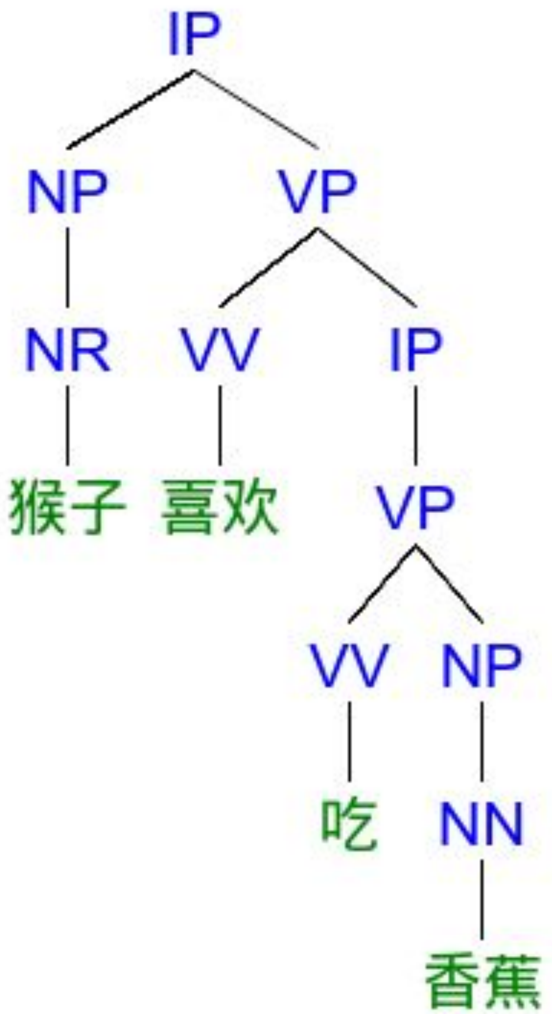
Represents text structure as a **tree**: tokens are leaves



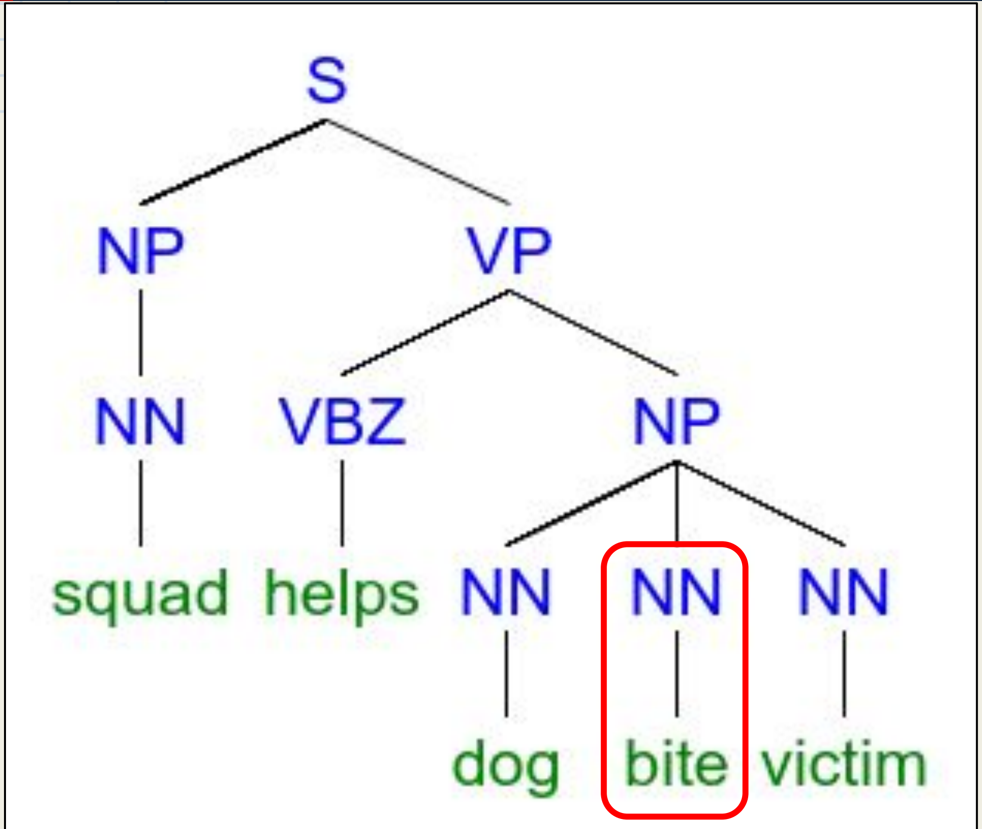
mshang.ca/syntree

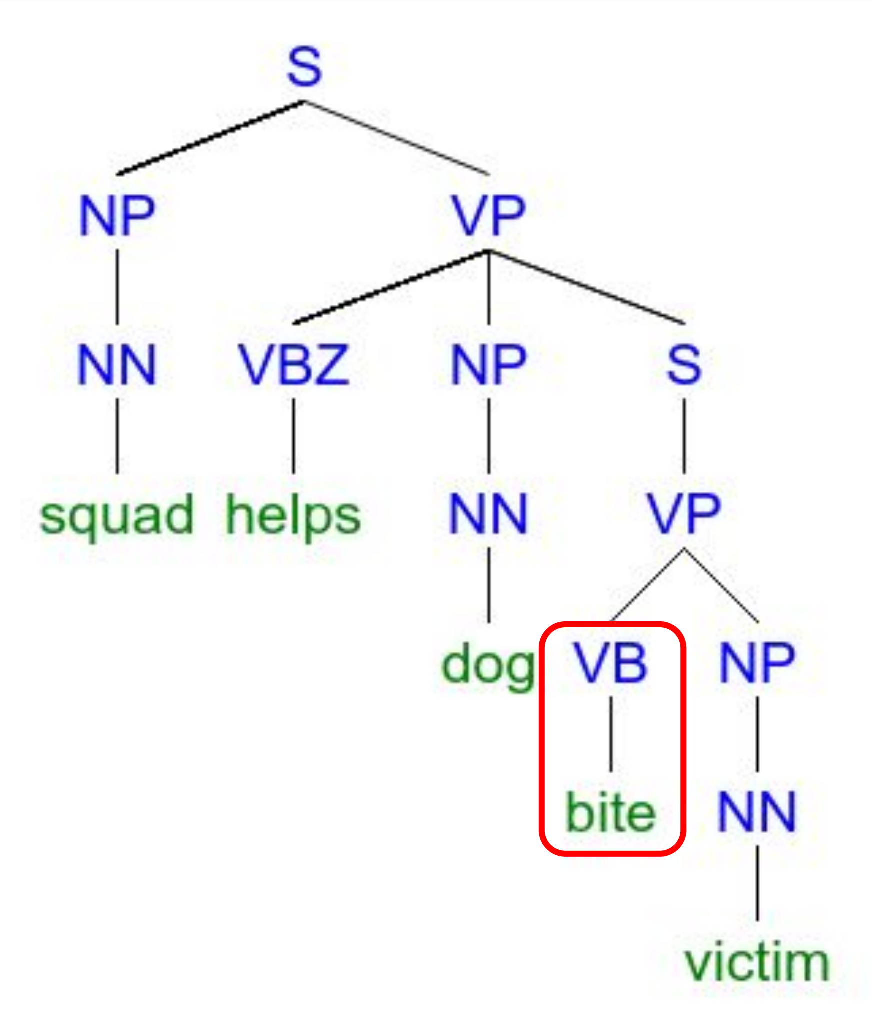
Chinese example

Different rules/labels are used for different languages



Lexical ambiguity





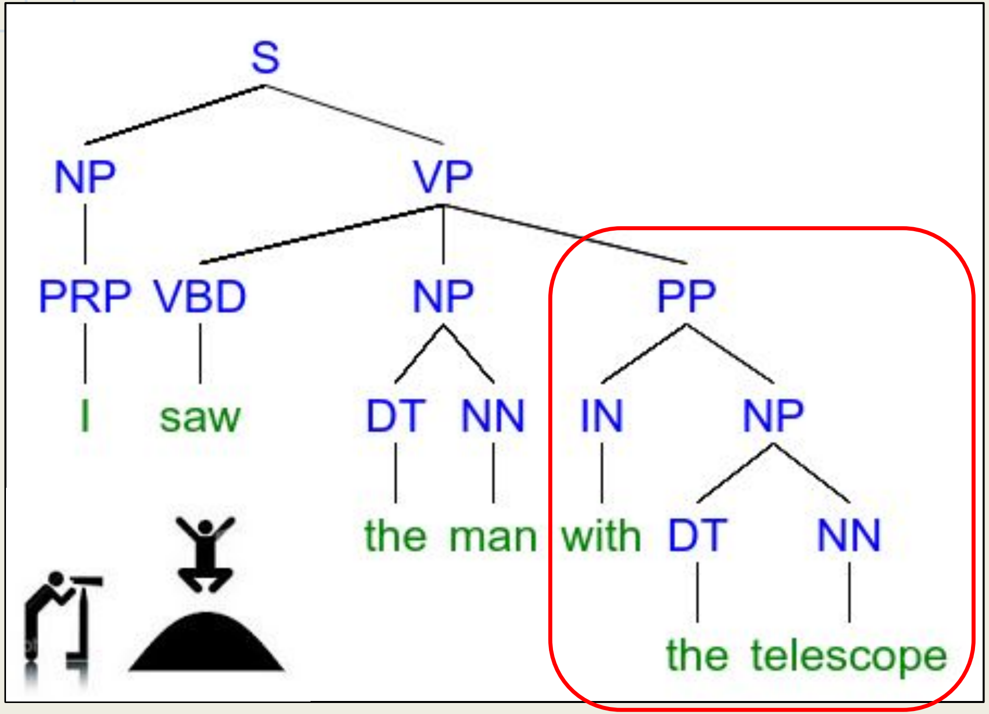
Prepositional phrases (PP)

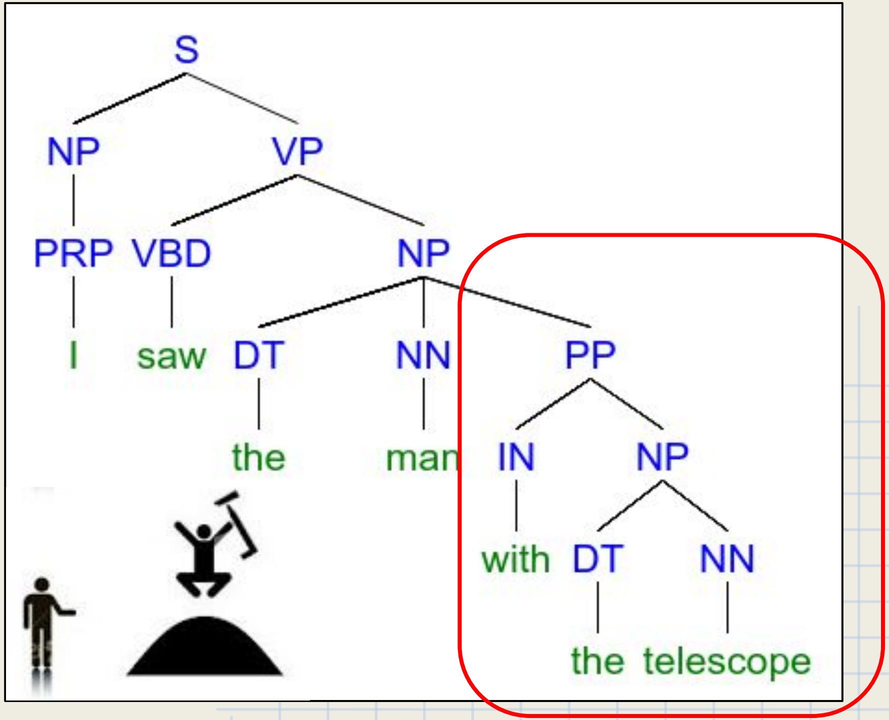
Cats fall [on their feet]

I'm wearing the shirt [from Italy]

I'm taking the bus [from Tel Aviv]

Syntactic ambiguity





Adjective phrases (AP)

This car is [fast]

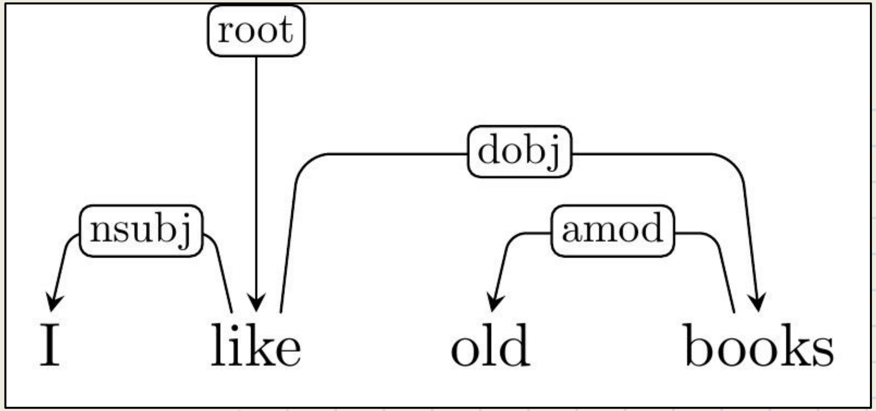
This car is [really very fast]

This car is [faster than my old one]

Dependency parsing

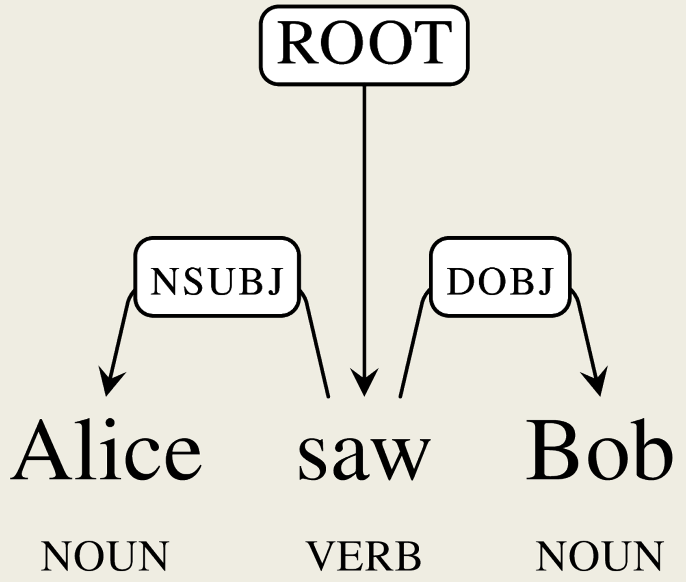
Represents text structure as a **tree**:

tokens are all the nodes (not just leaves)

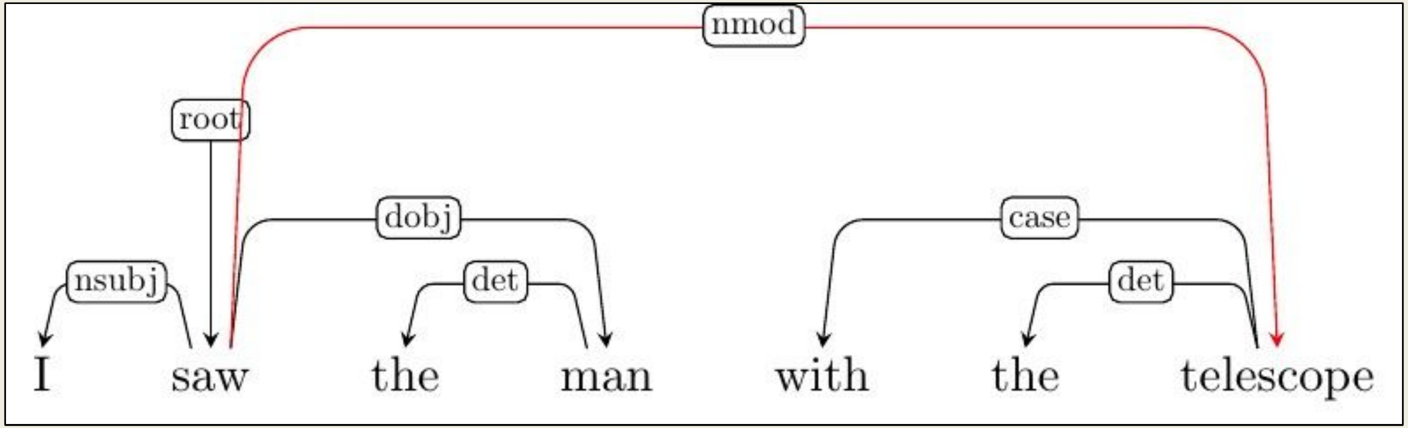


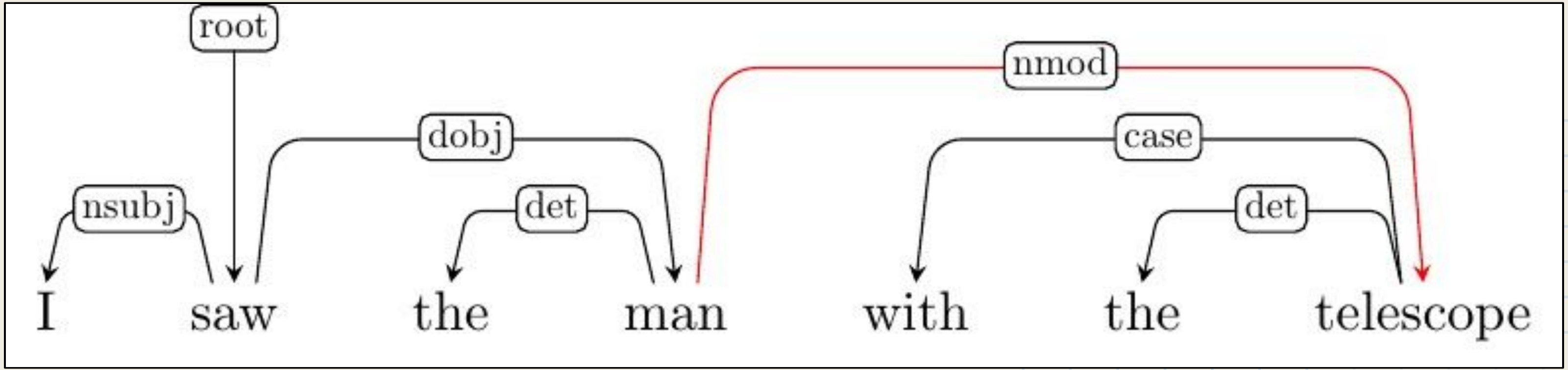
googleresearch.blogspot.co.il/2016/05/announcing-syntaxnet-worlds-most.html

Dependency Parsing

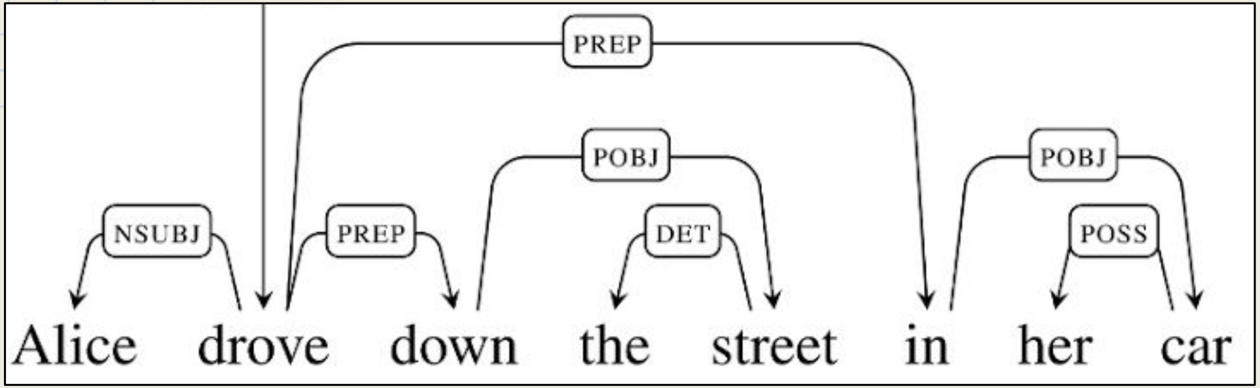


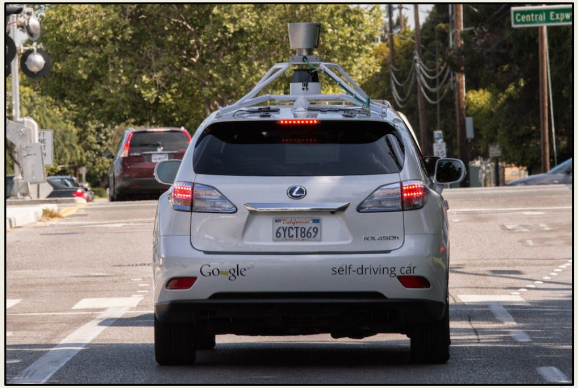
Syntactic ambiguity

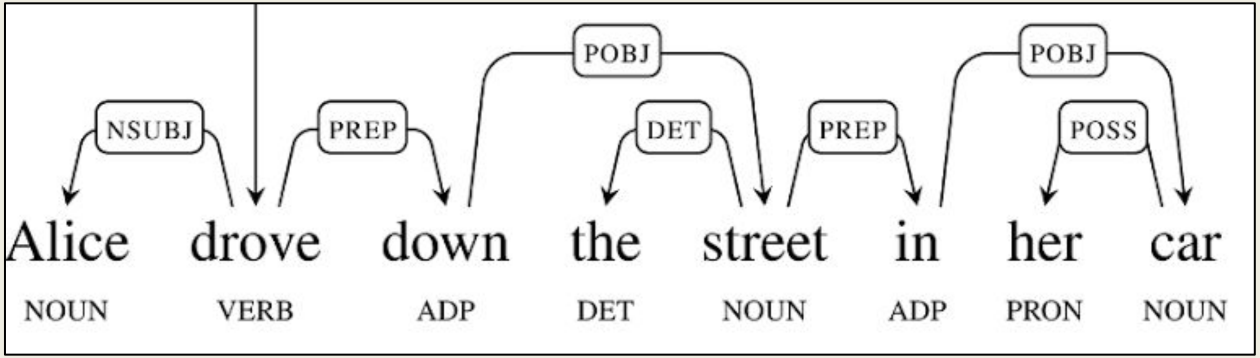




Syntactic Ambiguity

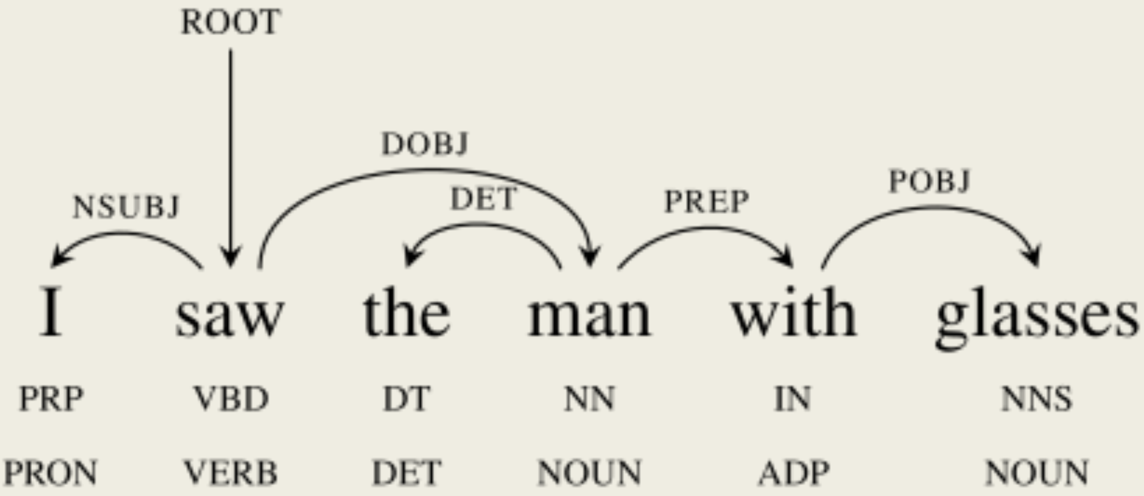






github.com/tensorflow/models/tree/master/syntaxnet

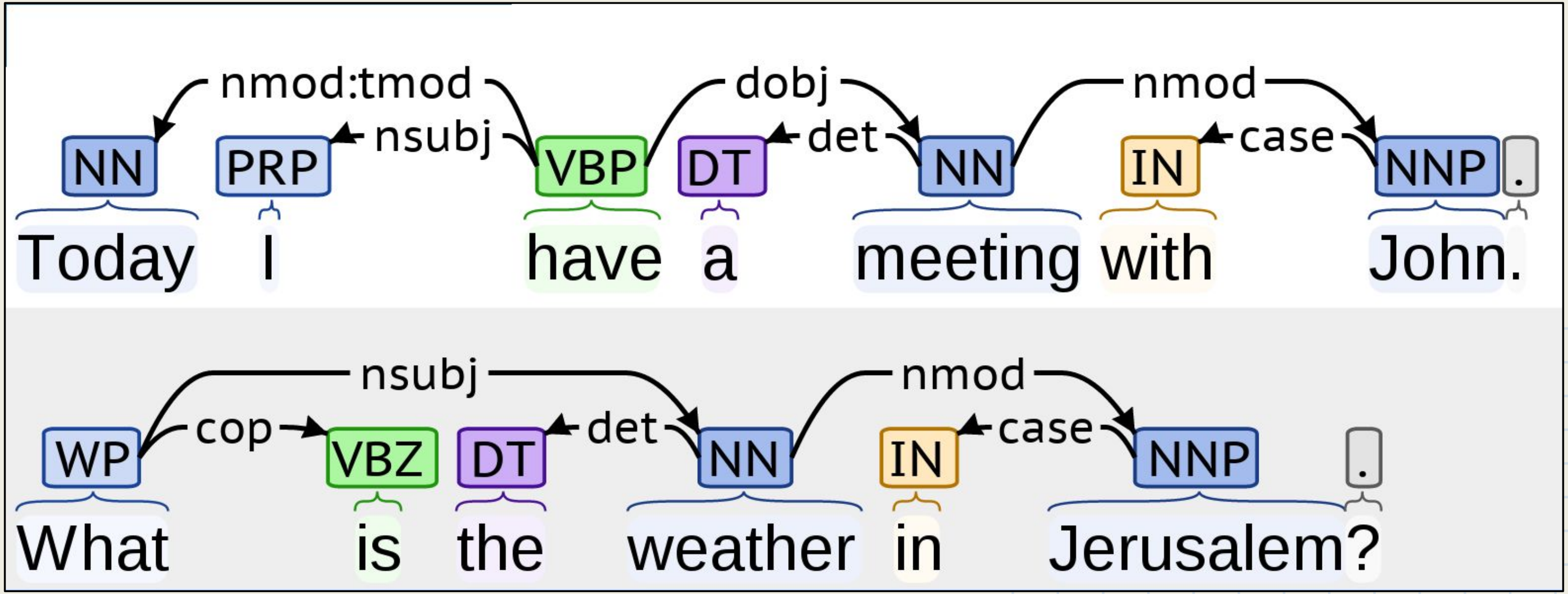
Syntactic Ambiguity



Who had the glasses?

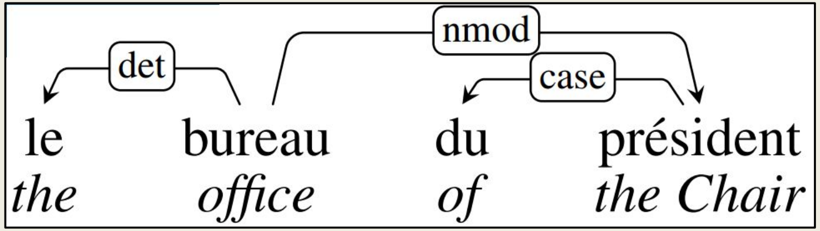
Representation

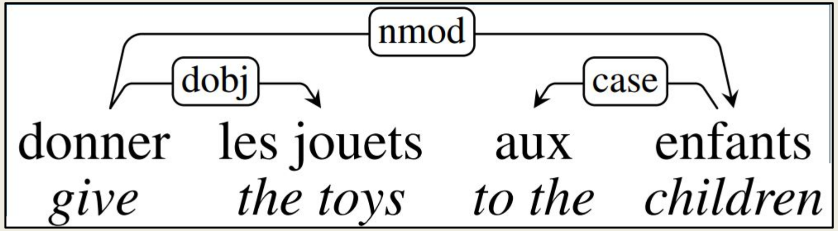
Natural Language Understanding: who did what to whom and where and when and how and why?



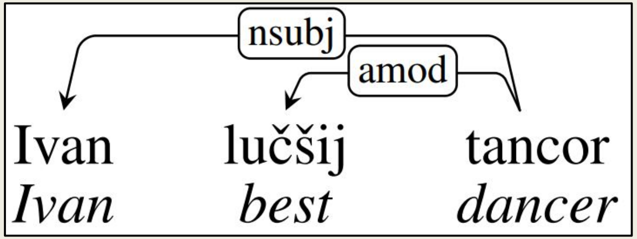
Cross-Linguistic Examples

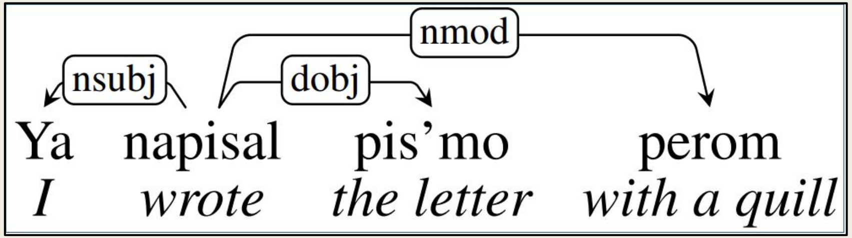
French



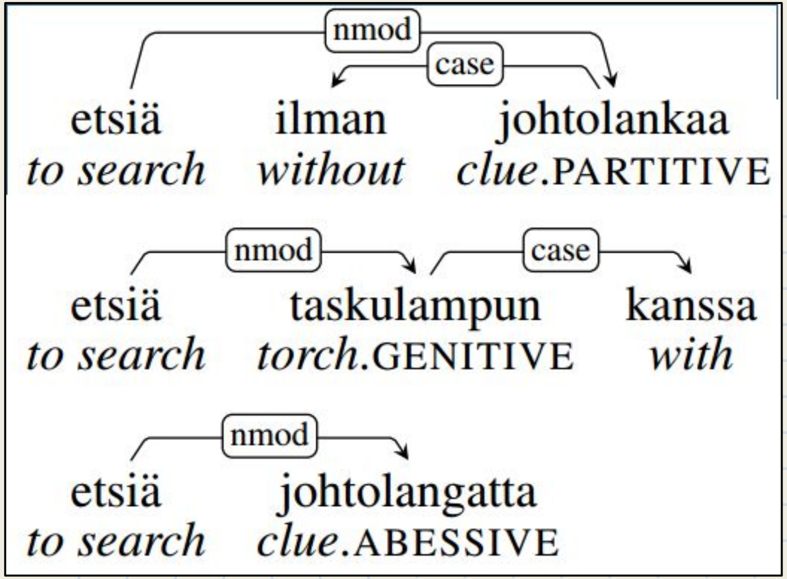


Russian





Finnish



lindat.mff.cuni.cz/services/pmltq/#!/treebanks

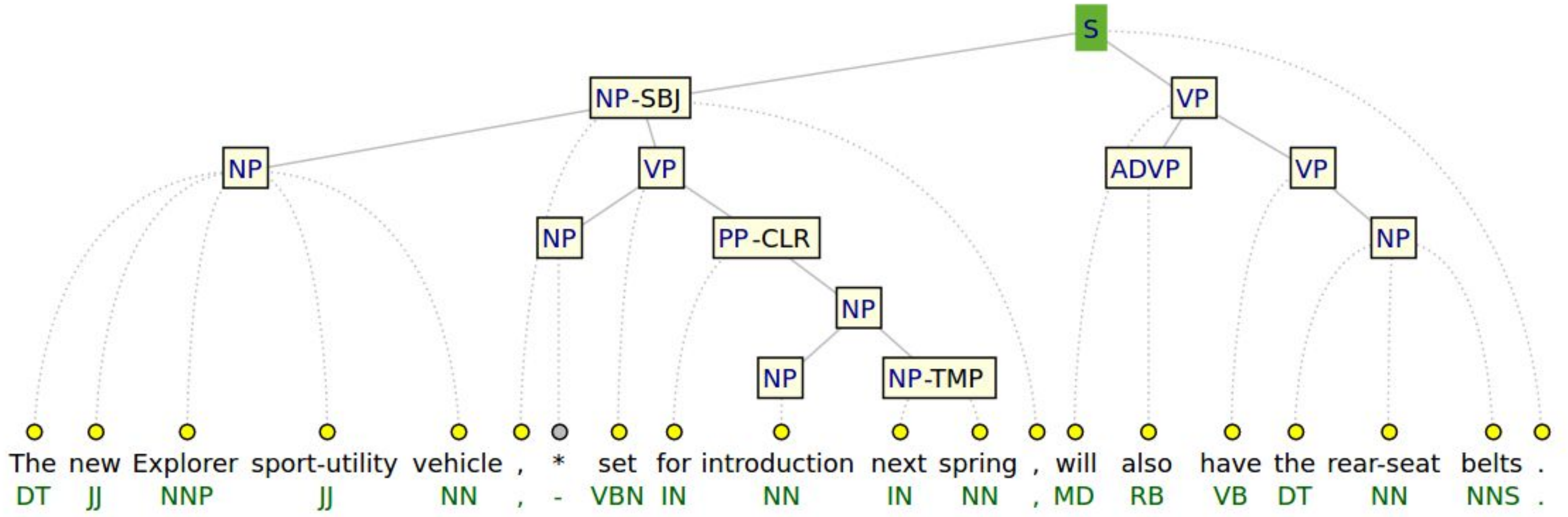
Resources: Treebanks

- Many text corpora parsed by humans
- Used for training automatic parsers

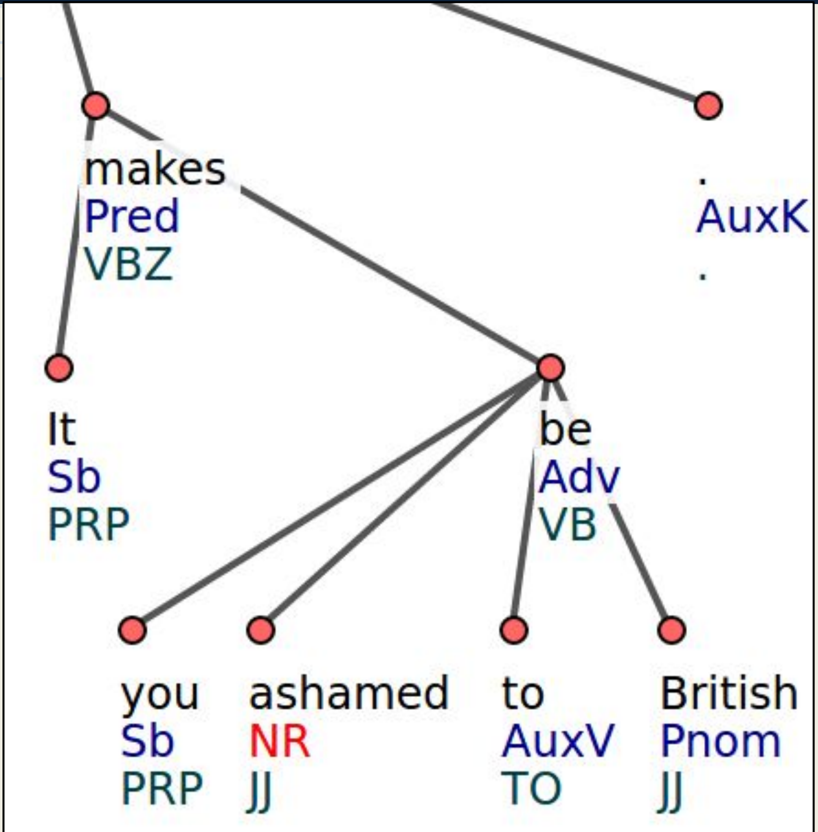
LANGUAGES: Ancient Greek 3 · Arabic 2 · Basque 1 · Bengali 1 · Bulgarian 2 · Catalan 2 · Chinese 3 · Croatian 1 · Czech 11 · Danish 1 · Dutch 2 · English 11 · Estonian 2 · Finnish 2 · French 1 · German 4 · Gothic 1 · Greek 1 · Hebrew 1 · Hindi 3 · Hungarian 1 · Indonesian 1 · Irish 1 · Italian 1 · Japanese 2 · Latin 7 · Norwegian 1 · Old Church Slavonic 1 · Persian 2 · Polish 2 · Portuguese 2 · Romanian 1 · Russian 1 · Slovak 1 · Slovenian 3 · Spanish 3 · Swedish 2 · Tamil 2 · Telugu 2 · Turkish 1

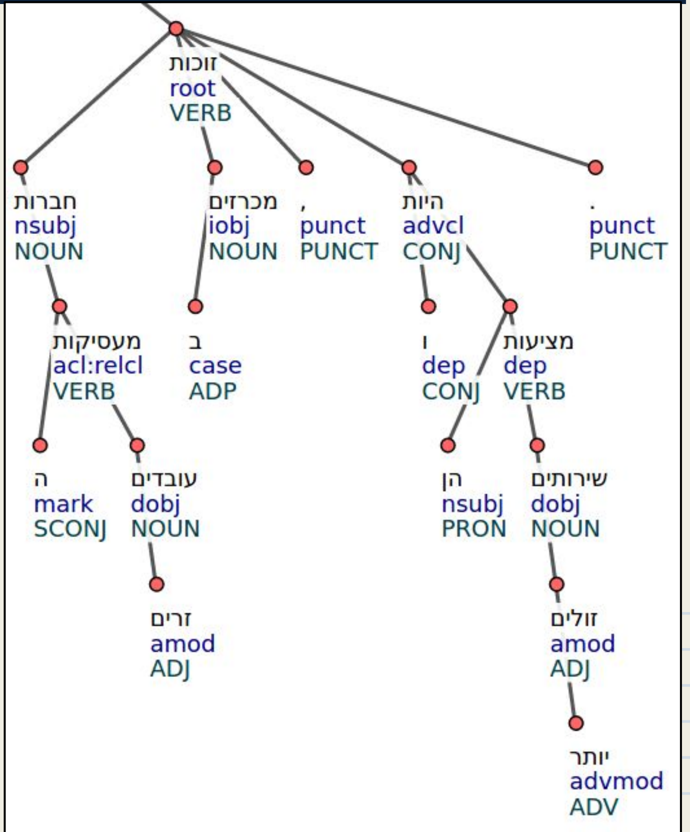
TAGS: CoNLL 8 · HamleDT 24 · PDT 3 · Penn Treebank 6 · Treex 1 · Universal Dependencies 35 www.cis.upenn.edu/~treebank

Penn Treebank (Constituency)



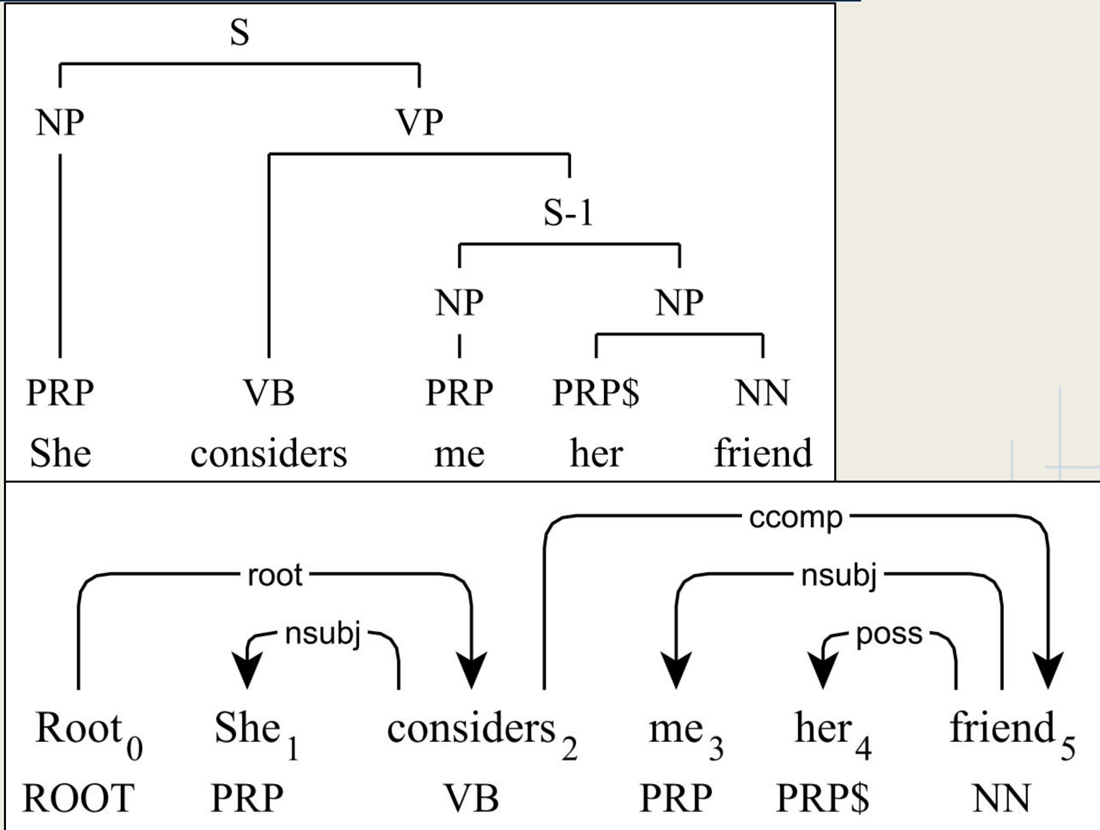
Dependency Treebanks





Converted Treebanks

Trees can be automatically converted to save manual work



Evaluation

Labeled Attachment Score (LAS):

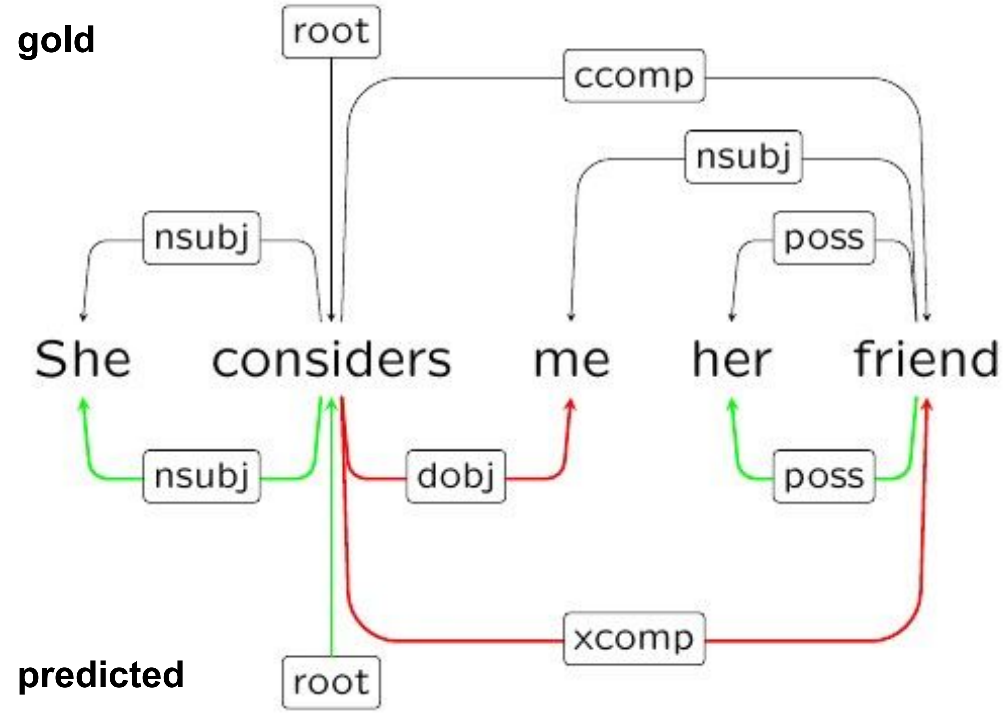
% of edges both in predicted tree and in gold tree

Unlabeled Attachment Score (UAS):

same as LAS, but ignoring edge label

$0 \leq \text{LAS} \leq \text{UAS} \leq 100\%$

Evaluation Example



$$\mathbf{LAS} = \frac{3}{5} = 60\%$$

$$\mathbf{UAS} = \frac{4}{5} = 80\%$$

Parser Scores

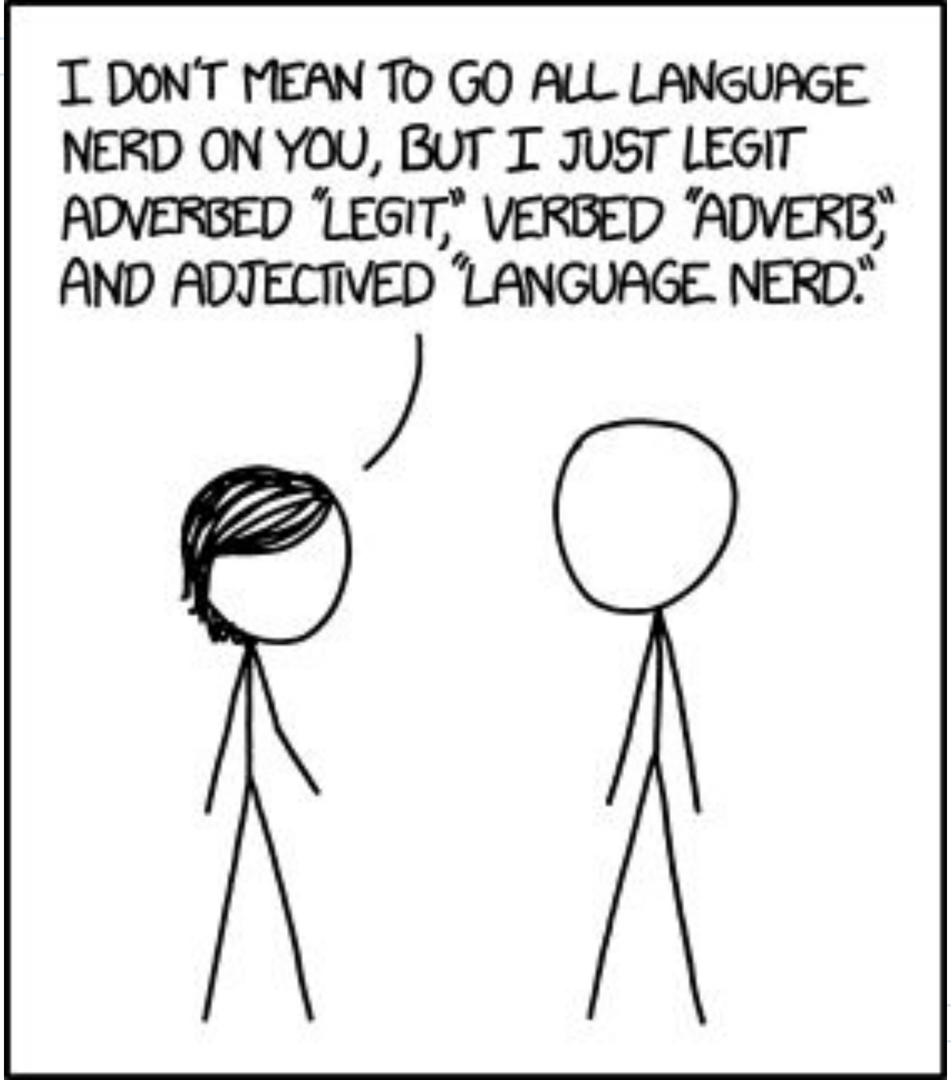
Parser	UAS	LAS
MaltParser	90.93	88.95
MSTParser	92.17	89.86
ZPar	92.93	91.28
TurboParser	93.80	92.00
Parsey McParseface	94.41	92.55

Summary

	Dependency	Constituency
Structure	tree	tree
Tokens are	all nodes	only leaves
Labels on	edges	nodes

References

- NLP class on Coursera: class.coursera.org/nlp
- Parts of speech: en.wikipedia.org/wiki/Part_of_speech
- Jurafsky, Daniel, and James H. Martin. 2009. Speech and Language Processing: An Introduction to Natural Language Processing, Speech Recognition, and Computational Linguistics. 2nd edition. Prentice-Hall. Pg. 295.



xkcd.com/1443