Natural Language Processing (7)

Parsing (1): Constituency Parsing

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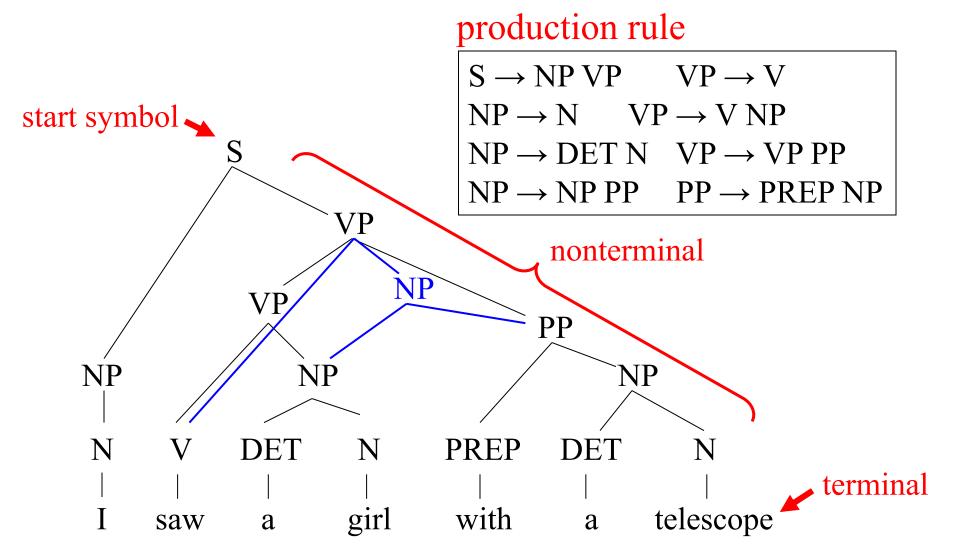
Lecture Plan

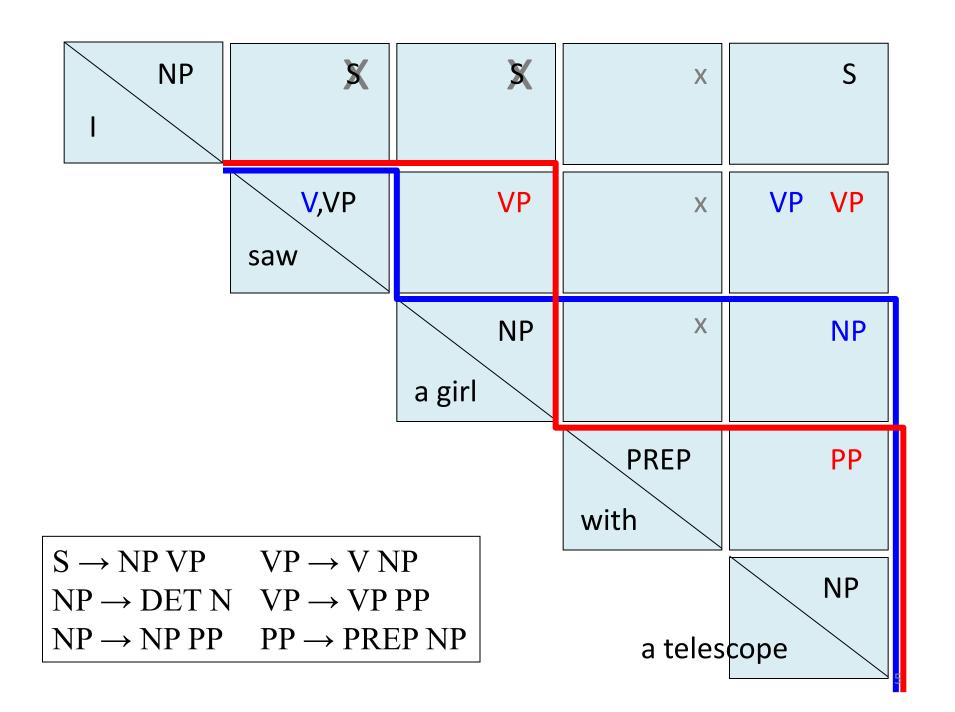
- 1. Overview of Natural Language Processing
- 2. Formal Language Theory
- 3. Word Senses and Embeddings
- 4. Topic Models
- 5. Collocations, Language Models, and Recurrent Neural Networks
- 6. Sequence Labeling and Morphological Analysis
- 7. Parsing (1)
- 8. Parsing (2)
- 9. Transfer Learning
- 10. Knowledge Acquisition
- 11. Information Retrieval, Question Answering, and Machine Translation
- 12. Guest Talk (1)
- 13. Guest Talk (2)
- 14. Project: Survey or Programming
- 15. Project Presentation

Table of Contents

- Review of CFG and CKY parsing
- Probabilistic CFG
- Treebanks
- Extensions
 - Lexicalization
 - History
 - Nonterminal Classification
- Evaluation criteria and SOTA of English parsing

CFG and Syntactic Structure





Probabilistic Context Free Grammar (PCFG)

- A set of terminals $\{w^k\}, k = 1,...,V$
- A set of nonterminals $\{N^i\}, i = 1,...,n$
- A designated start symbol N^1
- A set of rules $\{N^i \to \zeta^j\}$
- A corresponding set of probabilities on rules

$$\forall i \sum_{j} P(N^{i} \to \zeta^{j}) = 1$$

A simple PCFG

$S \rightarrow$	NP	VP	1.0
_ /		• •	

$$PP \rightarrow P NP 1.0$$

$$VP \rightarrow V NP 0.7$$

$$VP \rightarrow VP PP 0.3$$

$$P \rightarrow with$$
 1.0

$$V \rightarrow saw$$
 1.0

$NP \rightarrow NP PP$ 0.4

$$NP \rightarrow astronomers 0.1$$

$$NP \rightarrow ears$$
 0.18

$$NP \rightarrow saw$$
 0.04

$$NP \rightarrow stars$$
 0.18

$$NP \rightarrow telescopes$$
 0.1

Chomsky Normal Form

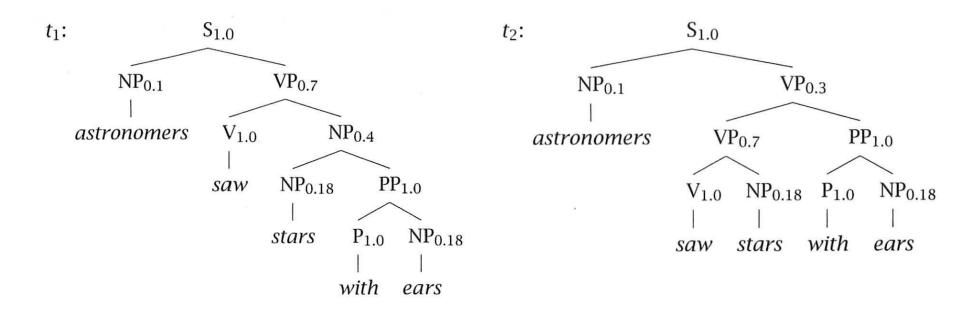
•
$$A \rightarrow BC$$

•
$$A \rightarrow \alpha$$

$$\Sigma P(NP \rightarrow *) = 1$$

Parse Trees

astronomers saw stars with ears



$$P(t_1) = 0.0009072$$

$$P(t_2) = 0.0006804$$

$$P(S) = P(t_1) + P(t_2) = 0.0015876$$

Probabilistic Context Free Grammar (PCFG)

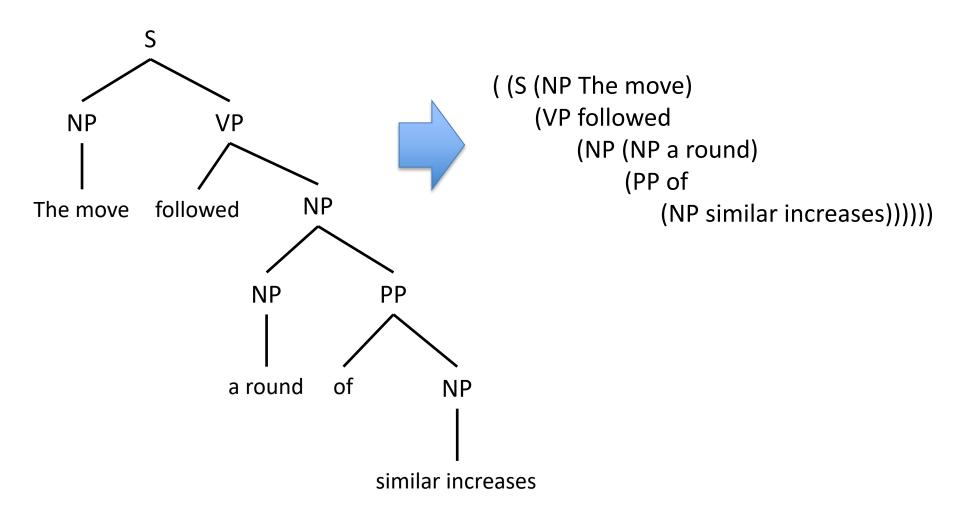
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Penn Treebank [Marcus+ 1993]

- An annotated corpus for English
 - Wall Street Journal (1 million words)
 - Brown Corpus
 - Switchboard Corpus (telephone conversation)
 - ATIS (Air Travel Information System) Corpus
- Released by LDC
- The de facto data for English parsing (training and evaluation)

A Penn Treebank Tree



Phrasal Categories of Penn Treebank

S	Simple clause (sentence)
SBAR	S' clause with complementizer
SBARQ	Wh-question S' clause
SQ	Inverted Yes/No question S' clause
SINV	Declarative inverted S' clause
ADJP	Adjective phrase
ADVP	Adverbial phrase
NP	Noun phrase
PP	Prepositional phrase
QP	Quantifier phrase (inside NP)
VP	Verb phrase
WHNP	Wh-noun phrase
WHPP	Wh-prepositional phrase

CONJP	Multiword conjunction phrase
FRAG	Fragment
INTJ	Interjection
LST	List marker
NAC	Not a consistent grouping
NX	Nominal constituent inside NP
PRN	Parenthetical
PRT	Particle
RRC	Reduced relative clause
UCP	Unlike coordinated phrase
X	Unknown or uncertain
WHADJP	Wh-adjective phrase
WHADVP	Wh-adverbial phrase

Exercise

```
((S (NP (NP (NNP Pierre) (NNP Vinken))
        (,,)
       (NP (NP (CD 61) (NNS years))
            (ADJP (JJ old)))
       (,,)
   (MD will)
   (VP (VB join)
       (NP (DT the) (NN board))
       (PP (IN as)
           (NP (DT a) (JJ nonexecutive) (NN director)))
       (ADVP (NP (NNP Nov.) (CD 29)))))
   (..)
```

Probabilistic Context Free Grammar (PCFG)

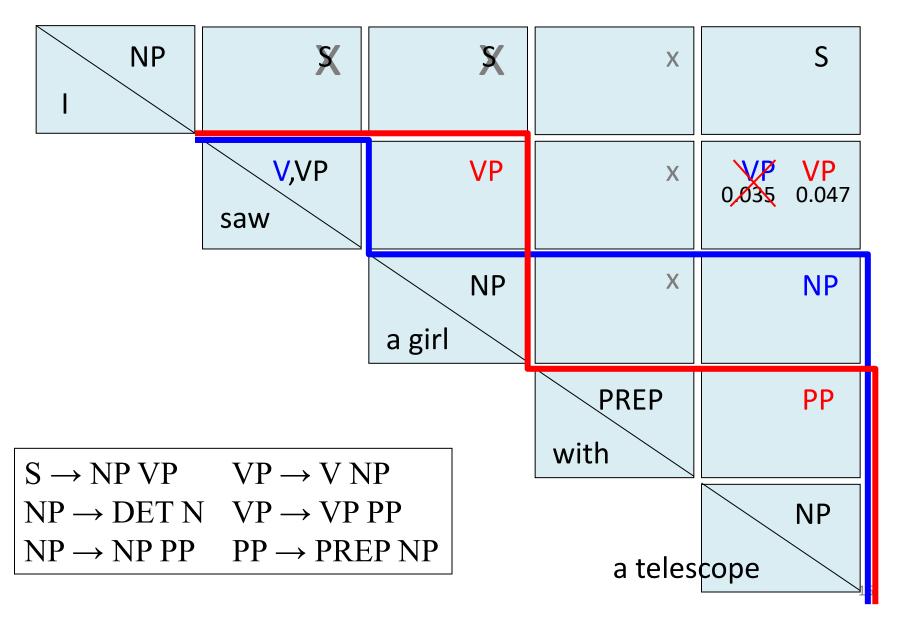
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$$\forall i \sum_{j} P(N^{i} \to \zeta^{j}) = 1$$

Maximum Likelihood Estimation using a treebank

$$\hat{P}(N^i \to \zeta^j) = \frac{C(N^i \to \zeta^j)}{C(N^i)}$$

A Dynamic Programming Algorithm

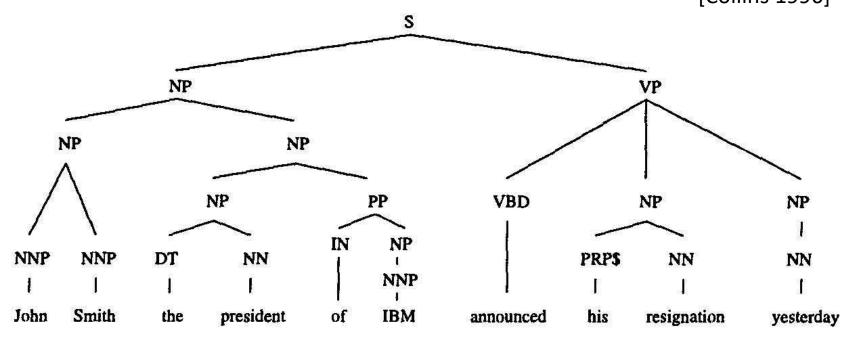


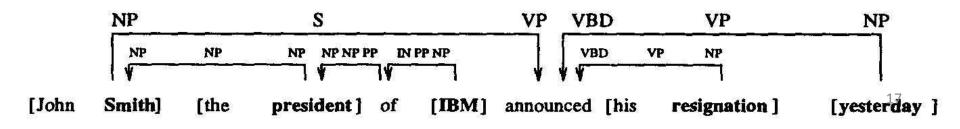
Extensions

- Lexicalization
 - → Use lexical information
- History
 - PCFG: too strong independence assumption
 - → Use history
- Nonterminal Classification

Lexicalization

A New Statistical Parser Based on Bigram Lexical Dependencies
[Collins 1996]



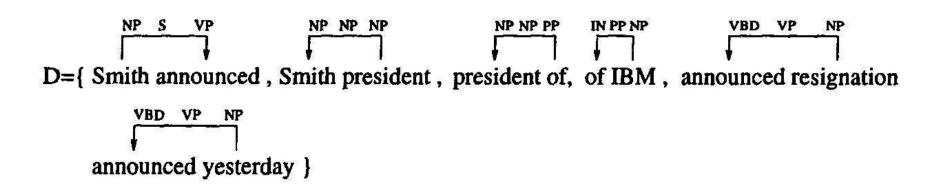


Lexicalization

A New Statistical Parser Based on Bigram Lexical Dependencies
[Collins 1996]

$$T_{best} = \arg\max_{T} P(T \mid S) = \arg\max_{T} P(B \mid S) \times P(D \mid S, B)$$
Base NP Model Dependency Model

B={ [John Smith], [the president], [IBM], [his resignation], [yesterday] }



Base NP Model

$$P(B \mid S) = \prod_{i=2...n} \hat{P}(G_i \mid w_{i-1}, t_{i-1}, w_i, t_i, c_i)$$

$$S(tart)$$

$$C(ontinue)$$

$$E(nd)$$

$$B(etween)$$

$$N(ull)$$

<u>S</u> John <u>C</u> Smith <u>B</u> the <u>C</u> president <u>E</u> of <u>S</u> IBM <u>E</u> announced ...

Dependency Model

$$P(D \mid S, B) = \prod_{j=1}^{m} P(AF(j) = (i, R_{j}) \mid S, B)$$

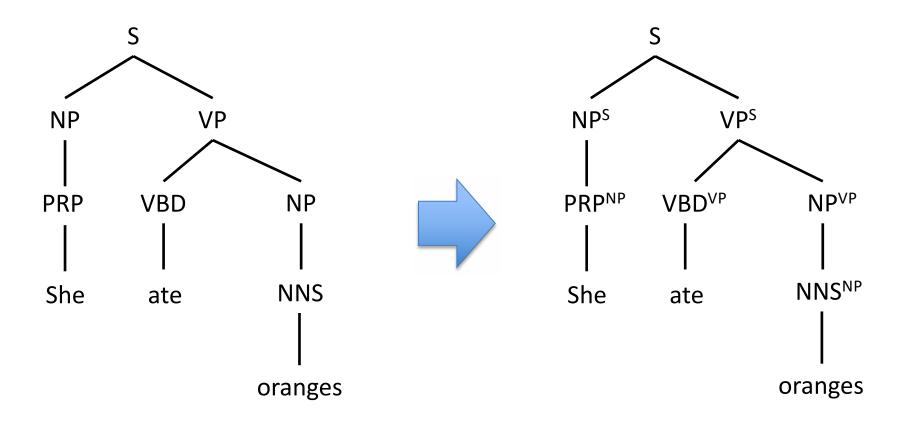
$$\text{e.g. } AF(1) = (5,)$$

$$= \prod_{j=1}^{m} \frac{F(R_{j} \mid < w_{j}, t_{j} >, < w_{i}, t_{i} >)}{\sum_{k=1...m, k \neq j, p \in P}}$$

$$F(R | ,) = C(R, ,) / C(,)$$
e.g.
$$\frac{C(, ,)}{C(,)}$$

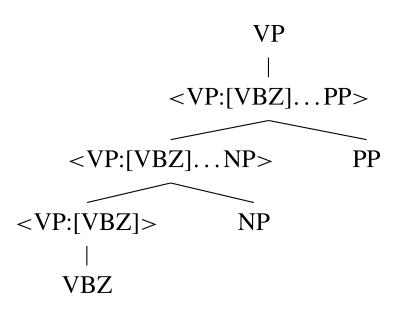
History: Parent Annotation

[Johnson 1998]



Vertical/Horizontal Markovization

[Klein & Manning 2003]



F1 and grammar size:

PCFG

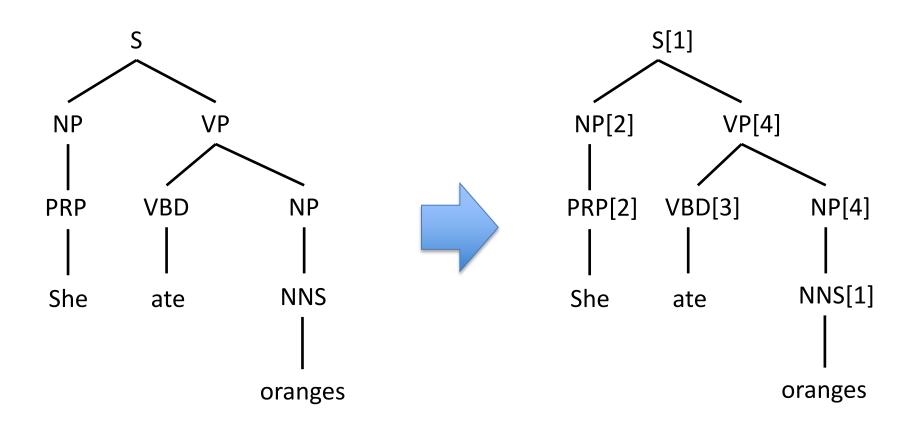
	Horizontal Markov Ord e r						
Vertical Order	h = 0	h = 1	$h \leq 2$	h=2	$h = \infty$		
v = 1 No annotation	71.27	72.5	73.46	72.96	72.62		
	(854)	(3119)	(3863)	(6207)	(9657)		
$v \le 2$ Sel. Parents	74.75	77.42	77.77	77.50	76.91		
	(2285)	(6564)	(7619)	(11398)	(14247)		
v = 2 All Parents	74.68	77.42	77.81	77.50	76.81		
	(2984)	(7312)	(8367)	(12132)	(14666)		
$v \leq 3$ Sel. GParents	76.50	78.59	79.07	78.97	78.54		
	(4943)	(12374)	(13627)	(19545)	(20123)		
v = 3 All GParents	76.74	79.18	79.74	79.07	78.72		
	(7797)	(15740)	(16994)	(22886)	(22002)		
<u> </u>							

v=1, h=1 markovization of "VP \rightarrow VBZ NP PP"

Parent Annotation

Nonterminal Classification

[Matsuzaki+ 2005] [Petrov+ 2006]

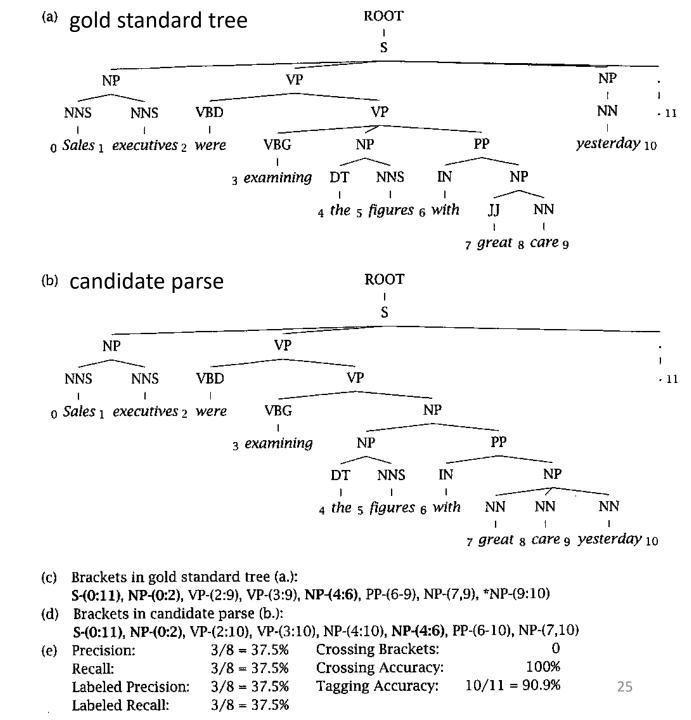


VBZ				DT					IN				
VBZ-0	gives	sells	takes	Ì	DT-0	the	The	a		IN-0	In	With	After
VBZ-1	comes	goes	works		DT-1	A	An	Another		IN-1	In	For	At
VBZ-2	includes	owns	is		DT-2	The	No	This		IN-2	in	for	on
VBZ-3	puts	provides	takes		DT-3	The	Some	These		IN-3	of	for	on
VBZ-4	says	adds	Says		DT-4	all	those	some		IN-4	from	on	with
VBZ-5	believes	means	thinks		DT-5	some	these	both		IN-5	at	for	by
VBZ-6	expects	makes	calls		DT-6	That	This	each		IN-6	by	in	with
VBZ-7	plans	expects	wants		DT-7	this	that	each		IN-7	for	with	on
VBZ-8	is	's	gets		DT-8	the	The	a		IN-8	If	While	As
VBZ-9	's	is	remains		DT-9	no	any	some		IN-9	because	if	while
VBZ-10	has	's	is		DT-10	an	a	the		IN-10	whether	if	That
VBZ-11	does	Is	Does		DT-11	a	this	the		IN-11	that	like	whether
	N	INP		•		(CD C			IN-12	about	over	between
NNP-0	Jr.	Goldman	INC.		CD-0	1	50	100		IN-13	as	de	Up
NNP-1	Bush	Noriega	Peters		CD-1	8.50	15	1.2		IN-14	than	ago	until
NNP-2	J.	E.	L.		CD-2	8	10	20		IN-15	out	up	down
NNP-3	York	Francisco	Street		CD-3	1	30	31	l '			RB	
NNP-4	Inc	Exchange	Co		CD-4	1989	1990	1988		RB-0	recently	previously	still
NNP-5	Inc.	Corp.	Co.		CD-5	1988	1987	1990		RB-1	here	back	now
NNP-6	Stock	Exchange	York		CD-6	two	three	five		RB-2	very	highly	relatively
NNP-7	Corp.	Inc.	Group		CD-7	one	One	Three		RB-3	so	too	as
NNP-8	Congress	Japan	IBM		CD-8	12	34	14		RB-4	also	now	still
NNP-9	Friday	September	August		CD-9	78	58	34		RB-5	however	Now	However
NNP-10	Shearson	D.	Ford		CD-10	one	two	three		RB-6	much	far	enough
NNP-11	U.S.	Treasury	Senate		CD-11	million	billion	trillion		RB-7	even	well	then
NNP-12	John	Robert	James			P	RP			RB-8	as	about	nearly
NNP-13	Mr.	Ms.	President		PRP-0	It	Не	I		RB-9	only	just	almost
NNP-14	Oct.	Nov.	Sept.		PRP-1	it	he	they		RB-10	ago	earlier	later
NNP-15	New	San	Wall		PRP-2	it	them	him		RB-11	rather	instead	because
		IJS		-	•	R	BR		•	RB-12	back	close	ahead
JJS-0	largest	latest	biggest		RBR-0	further	lower	higher		RB-13	up	down	off
JJS-1	least	best	worst		RBR-1	more	less	More		RB-14	not	Not	maybe
JJS-2	most	Most	least		RBR-2	earlier	Earlier	later		RB-15	n't	not	also

[Petrov+ 2006]

Evaluation

- Precision
- Recall
- Labeled Precision
- Labeled Recall



Performance on English (supervised)

	LP	LR	F1
[Magerman 1995]	84.0	84.3	84.2
[Charniak 1997]	86.7	86.6	86.7
[Collins 1997]	87.5	88.1	87.8
[Charniak 2000]	89.6	89.5	89.6
[Petrov&Klein 2007]	90.2	89.9	90.1
[Carreras+ 2008]	90.7	91.4	91.1
[Shindo+ 2012]			91.1
[Zhu+ 2013]	90.2	90.7	90.4

	LP	LR	F1
[Socher+ 2013]			90.4
[Watanabe+ 2015]			90.7
[Mi&Huang 2015]	90.7	90.9	90.8
[Cross&Huang 2016]	90.5	92.1	91.3
[Dyer+ 2016]			91.7
[Stern+ 2017]	90.6	93.0	91.8
[Stern+ 2017]	92.6	92.6	92.6
[Gaddy+ 2018]			92.1
[Kitaev&Klein 2018]	93.2	93.9	93.6

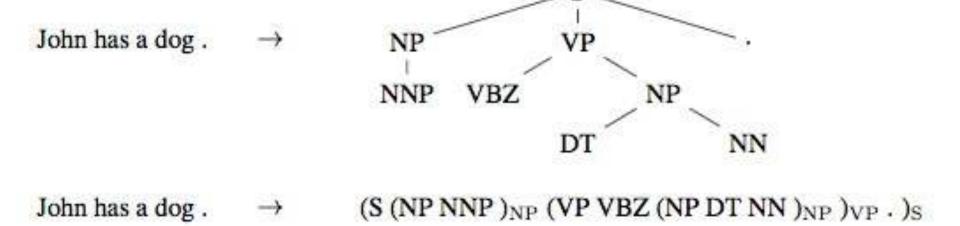
Performance on English (semi-supervised, reranking, etc.)

	F1	Note
[Charniak&Johnson 2005]	91.0	reranking
[McClosky+ 2006]	92.1	self-training
[Shindo+ 2012]	92.4	ensemble
[Vinyals+ 2015]	92.8	tri-training
[Dyer+ 2016]	92.4	reranking
[Choe&Charniak 2016]	93.8	tri-training
[Kuncoro+ 2017]	93.6	reranking
[Liu&Zhang 2017]	94.2	reranking/tri-training
[Fried+ 2017]	94.7	ensemble/reranking

Performance on English (pre-trained)

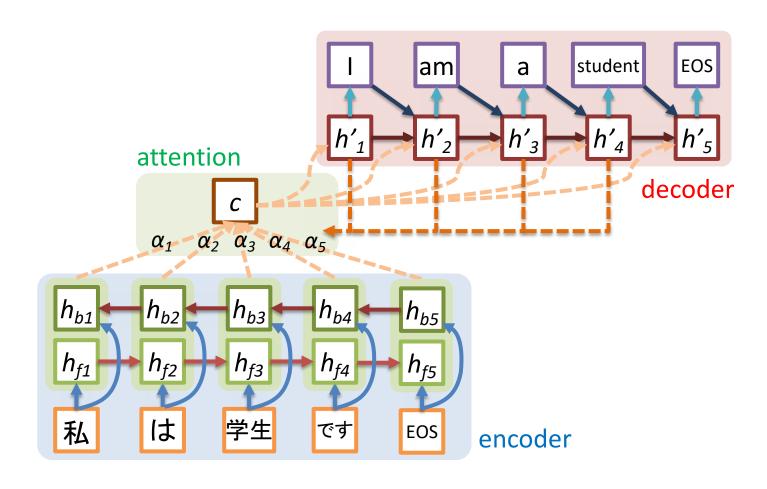
	F1	Note
[Kitaev&Klein 2018]	95.1	pre-train (ELMo)
[Kitaev+ 2019]	95.6	pre-train (BERT)
[Zhou&Zhao 2019]	96.3	pre-train (XLNet)
[Yang&Deng 2020]	96.3	pre-train (XLNet)
[Mrini+ 2020]	96.4	pre-train (XLNet)

Serialization [Vinyals+ 2015]



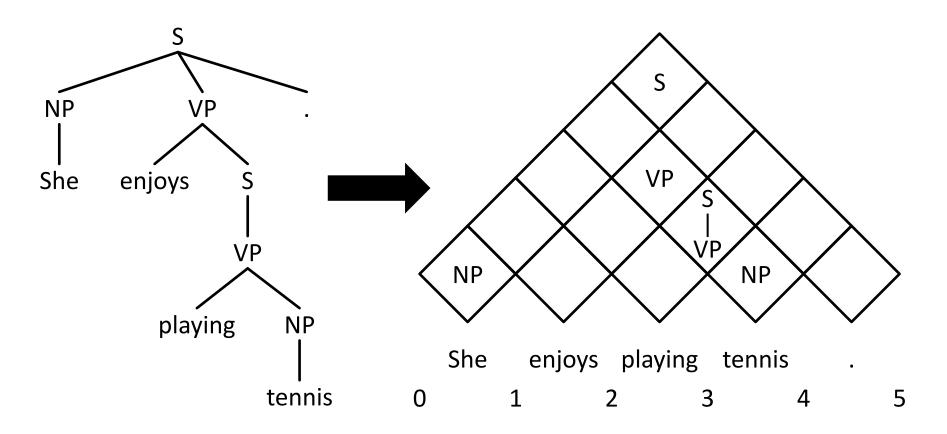
Attention-based Neural Machine Translation

[Bahdanau+ 2014]

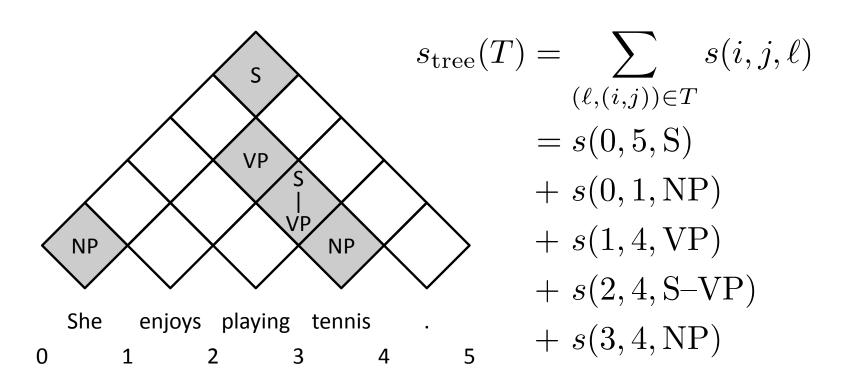


Neural Span Classification

[Stern+ 2017]

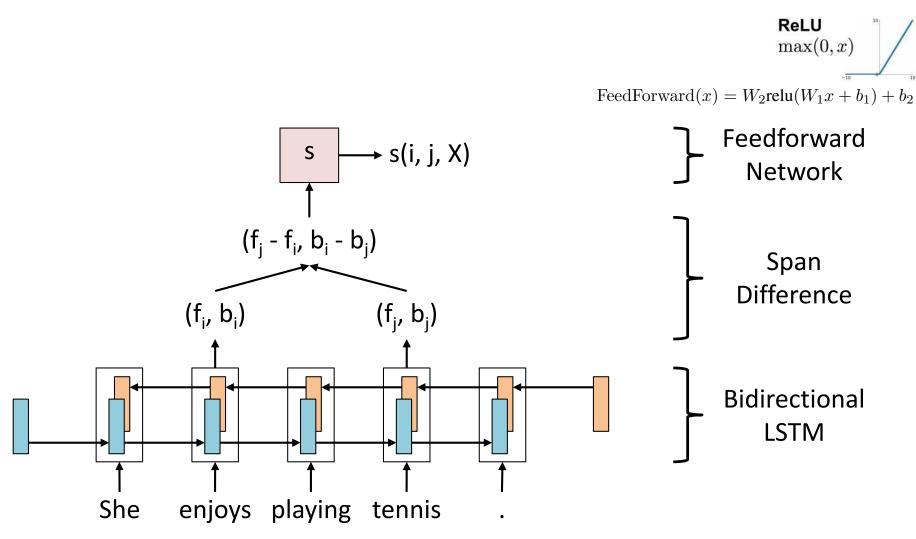


Neural Span Classification



$$s_{\text{best}}(i,j) = \max_{\ell}[s(i,j,\ell)] \ + \max_{k}[s_{\text{best}}(i,k) + s_{\text{best}}(k,j)]$$
 Pick best split point

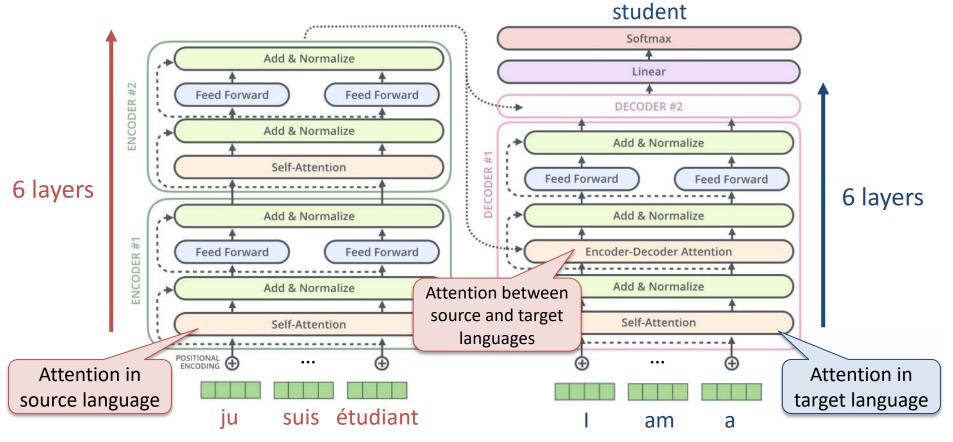
Neural Span Classification



Transformer: "Attention is All You Need"

[Vaswani+ 2017]

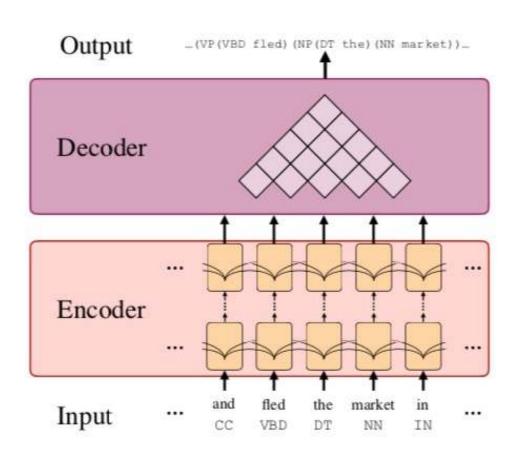
Output: next word in target language



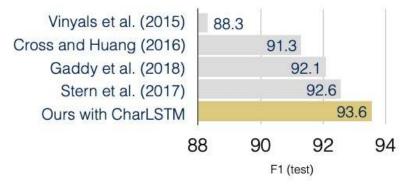
Input: sentence in source language Words previously generated

Using Self Attention

[Kitaev&Klein 2018]



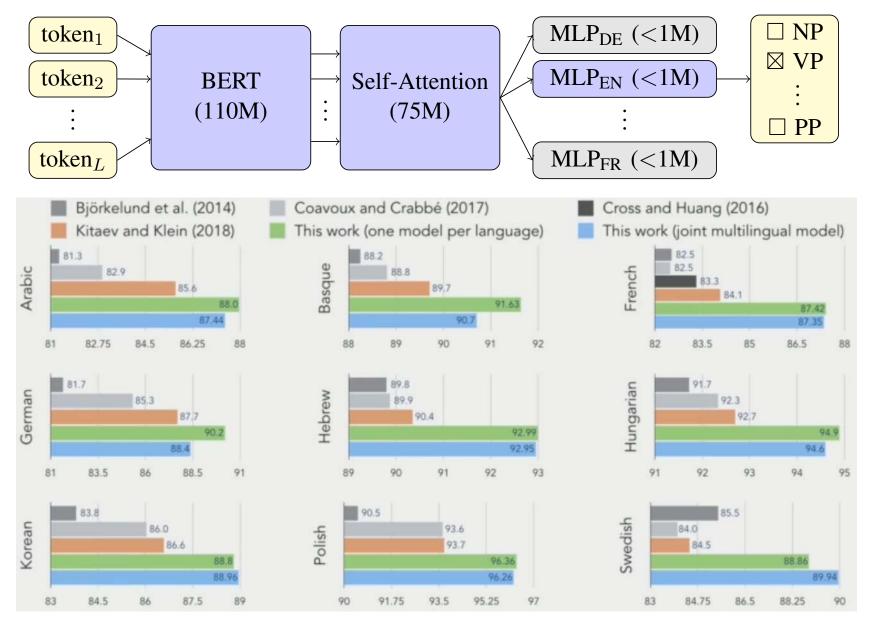
Single Model, WSJ Only



Multi-Model / External

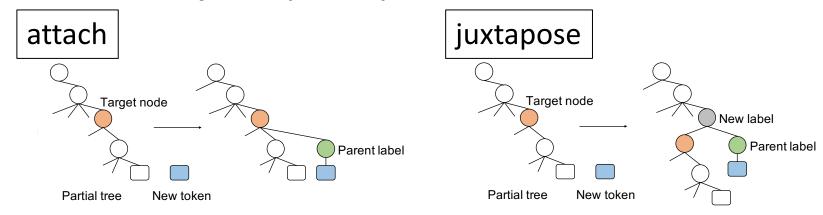


Joint Multilingual Span Classification [Kitaev+ 2019]

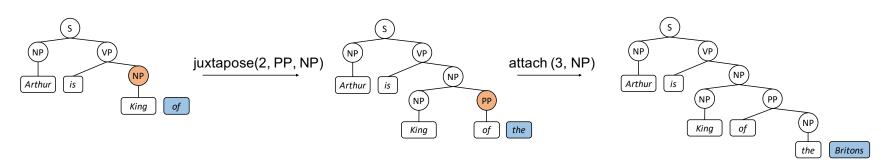


Transition-based Constituency Parsing

An attach-juxtapose parser [Yang&Deng 2020]

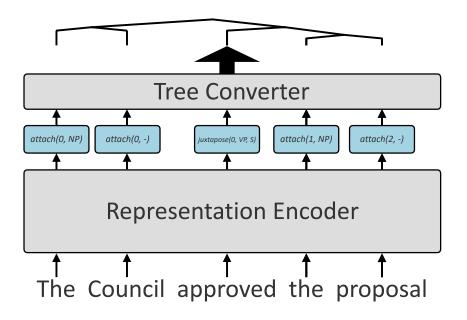


Example:

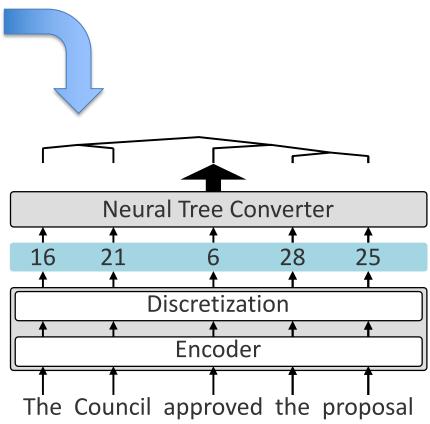


Learning Representations for Parsing

[Kitaev+ 2022]



	Encoder Type				
	Bi	Bi (↔)			
Representation	BERT	GPT-2	GPT-2		
Span Classification (Kitaev et al., 2019)	95.59	95.10 [†]	93.95 [†]		
Attach-Juxtapose (Yang and Deng, 2020)	95.79	94.53 [†]	87.66 [†]		
Learned (This work)	95.55	_	94.97		



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