Natural Language Processing Syntactic parsing

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Credit to Yulia Tsvetkov for slides

Announcements

- A3 is out on gitlab!
- Quiz 6 goes out on Canvas today at the end of lecture
 - Available until Friday 2/24 at 2:20pm; you'll have 15 minutes to complete it once you start.
 - Remember that you can use your notes during the quiz
 - Will cover material from (last) Wednesday's lecture and (last) Friday's lecture (so, transformers and machine translation)

Wrapping up machine translation

What's our loss function?

Just cross-entropy loss at each output timestep for correct output word (either pretending we've gotten all previous tokens in the output correct, or not- see <u>this</u> <u>pytorch NMT tutorial</u> for details).



Where might we find this kind of parallel data?

Note that this seq2seq approach can apply to more tasks than NMT!



Evaluating an MT system: Adequacy, fluency

In the past, these were usually separately computed elements of a score.

They're still relevant today, but these days, they're sort of both rolled into...

These days: BLEU score, mostly.

For each instance in your test set, have a set of human-written reference translations.

$p_n = \frac{\text{number of } n \text{-grams appearing in both reference and hypothesis translations}}{\text{number of } n \text{-grams appearing in the hypothesis translation}}$

Once you've got reference translations for a test set, pretty cheap to compute.

Evaluating bias in MT systems

Translate

Turn off instant translation

Bengali	English	Hungarian	Detect language	*	$\stackrel{\leftarrow}{\to}$	English	Spanish	Hungarian	*	Translate
ő egy ő egy ő egy ő egy ő egy ő egy ő egy	ápoló. tudós. mérnök pék. tanár. esküvő vezérig	k. ii szervező jazgatója.	5.		×	she's he is a she's he is a She is he's a ☆ □	a nurse a scienti an engir a baker a teache s a wedo CEO.	ist. neer. er. ding organ	nizer.	
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See, for example, Stanovsky et al. 2019



Ambiguity

• I saw a girl with a telescope



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Syntactic Parsing

• INPUT:

• The move followed a round of similar increases by other lenders, reflecting a continuing decline in that market



A Supervised ML Problem

- Data for parsing experiments:
 - Penn WSJ Treebank = 50,000 sentences with associated trees
 - Usual set-up: 40,000 training, 2,400 test



Syntax

• The study of the patterns of formation of sentences and phrases from words

0 0 0	my dog the dog the cat	Pron N Det N Det N
0	and	Conj
0	the large cat the black cat	Det Adj N Det Adj N
0	ate a sausage	V Det N

Parsing

- The process of predicting syntactic representations
- Different types of syntactic representations are possible, for example:



Constituent (a.k.a. phrase-structure) tree

Constituent trees

- Internal nodes correspond to phrases
 - S a sentence
 - NP Noun Phrase: My dog, a sandwich, lakes,...
 - **VP** Verb Phrase: ate a sausage, barked, ...
 - **PP** Prepositional phrases: with a friend, in a car, ...



- Nodes immediately above words are PoS tags (aka preterminals)
 - PN pronoun
 - **D** determiner
 - \circ V verb
 - N noun
 - **P** preposition

Bracketing notation

• It is often convenient to represent a tree as a bracketed sequence



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Parsing

- The process of predicting syntactic representations
- Different types of syntactic representations are possible, for example:



Constituent (a.k.a. phrase-structure) tree

Dependency tree

Constituent trees



• Internal nodes correspond to phrases

- S a sentence
- NP (Noun Phrase): My dog, a sandwich, lakes,...
- VP (Verb Phrase): ate a sausage, barked, ...
- PP (Prepositional phrases): with a friend, in a car, ...

- Nodes immediately above words are PoS tags (aka preterminals)
 - PN pronoun
 - D determiner
 - V verb
 - \circ N noun
 - P preposition

Constituency Tests

- How do we know what nodes go in the tree?
- Classic constituency tests:
 - Replacement
 - Movement
 - Passive
 - Clefting
 - Preposing
 - Substitution by proform
 - Modification
 - Coordination/Conjunction
 - Ellipsis/Deletion



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Morphology/Syntax/Semantics

- Syntax: The study of the patterns of formation of sentences and phrases from word
 - Borders with semantics and morphology sometimes blurred

Afyonkarahisarlılaştırabildiklerimizdenmişsinizcesinee

in Turkish means "as if you are one of the people that we thought to be originating from Afyonkarahisar" [wikipedia]

English grammar



Product Details (from Amazon) Hardcover: 1779 pages Publisher: Longman; 2nd Revised edition Language: English ISBN-10: 0582517346 ISBN-13: 978-0582517349 Product Dimensions: 8.4 x 2.4 x 10 inches Shipping Weight: 4.6 pounds

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Context Free Grammar (CFG)

Context Free Grammar (CFG)

Grammar (CFG) $ROOT \rightarrow S$ $S \rightarrow NP VP$ $NP \rightarrow DT NN$ $NP \rightarrow NN NNS$ $NP \rightarrow NP PP$ $VP \rightarrow VBP NP$ $VP \rightarrow VBP NP$ $PP \rightarrow IN NP$

Lexicon

 $NN \rightarrow interest$ $NNS \rightarrow raises$ $VBP \rightarrow interest$ $VBZ \rightarrow raises$

. . .

Other grammar formalisms: LFG (Lexical functional grammar), HPSG (Head-driven phrase structure grammar), TAG (Tree adjoining grammar), CCG (Combinatory categorial grammar)...

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 $N \to girl$ $S \rightarrow NP \ VP$ $N \rightarrow telescope$ $VP \rightarrow V$ $N \rightarrow sandwich$ $VP \rightarrow V NP$ $PN \to I$ $VP \rightarrow VP PP$ $V \rightarrow saw$ $V \rightarrow ate$ $NP \rightarrow NP PP$ $P \rightarrow with$ $NP \rightarrow D N$ $P \rightarrow in$ $NP \rightarrow PN$ $D \to a$ $PP \rightarrow P NP$ $D \rightarrow the$

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 $N \to girl$ $S \rightarrow NP VP$ $N \rightarrow telescope$ $VP \rightarrow V$ $N \rightarrow sandwich$ $VP \rightarrow V NP$ $PN \to I$ $VP \rightarrow VP PP$ $V \rightarrow saw$ $V \rightarrow ate$ $NP \rightarrow NP PP$ $NP \rightarrow D N$ $P \rightarrow with$ $NP \rightarrow PN$ $P \rightarrow in$ $D \to a$ $PP \rightarrow P NP$ $D \rightarrow the$



$S \rightarrow NP \ VP$	N ightarrow girl
	$N \rightarrow telescope$
$VP \rightarrow V$	$N \rightarrow sandwich$
$VP \rightarrow V NP$	$PN \rightarrow I$
$VP \rightarrow VP PP$	$V \rightarrow saw$
$NP \rightarrow NP PP$	$V \rightarrow ate$
$NP \rightarrow D N$	$P \rightarrow with$
$NP \rightarrow PN$	$P \rightarrow in$
	$D \rightarrow a$
$PP \rightarrow P NP$	$D \rightarrow the$



 $N \to girl$ $S \rightarrow NP VP$ $N \rightarrow telescope$ $VP \to V \qquad N \to sandwich$ $VP \to V \quad NF \qquad PN \to I$ $PN \rightarrow I$ $VP \rightarrow VP PP$ $V \rightarrow saw$ $V \rightarrow ate$ $NP \rightarrow NP PP$ $NP \rightarrow D N$ $P \rightarrow with$ $NP \rightarrow PN$ $P \rightarrow in$ $D \to a$ $PP \rightarrow P NP$ $D \rightarrow the$



 $N \to girl$ $S \rightarrow NP VP$ $N \rightarrow telescope$ $VP \rightarrow V$ $N \rightarrow sandwich$ $VP \rightarrow V NP$ $PN \rightarrow I$ $VP \rightarrow VP PP$ $V \rightarrow saw$ 1 $V \rightarrow ate$ $NP \rightarrow NP PP$ $NP \rightarrow D N$ $P \rightarrow with$ $NP \rightarrow PN$ $P \rightarrow in$ $D \to a$ $PP \rightarrow P NP$ $D \rightarrow the$



 $N \to girl$ $S \rightarrow NP VP$ $N \rightarrow telescope$ $VP \rightarrow V$ $N \rightarrow sandwich$ $VP \rightarrow V NP$ $PN \to I$ $VP \rightarrow VP PP$ $V \rightarrow saw$ $NP \rightarrow NP PP$ $V \rightarrow ate$ ____ $NP \rightarrow D N$ $P \rightarrow with$ $NP \rightarrow PN$ $P \rightarrow in$ $D \rightarrow a$ $PP \rightarrow P NP$ $D \rightarrow the$



 $N \to girl$ $S \rightarrow NP VP$ $N \rightarrow telescope$ $VP \rightarrow V$ $N \rightarrow sandwich$ $VP \rightarrow V NP$ $PN \to I$ $VP \rightarrow VP PP$ $V \rightarrow saw$ $V \rightarrow ate$ $NP \rightarrow NP PP$ I $NP \rightarrow D N$ $P \rightarrow with$ $\bar{N}\bar{P} \rightarrow PN$ $P \rightarrow in$ $D \to a$ $PP \rightarrow P NP$ $D \rightarrow the$



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$S \rightarrow NP \ VP$	$N \to girl$
	$N \rightarrow telescope$
$VP \to V$	$N \rightarrow sandwich$
$VP \rightarrow V \ NP$ $VP \rightarrow VP \ PP$	$PN \rightarrow I$
	$V \rightarrow saw$
$NP \rightarrow NP PP$	$V \rightarrow ate$
$NP \rightarrow D N$	$P \rightarrow with$
$NP \rightarrow PN$	$P \rightarrow in$
	$D \rightarrow a$
$PP \rightarrow P NP$	$D \rightarrow the$

Treebank Sentences

```
( (S (NP-SBJ The move)
     (VP followed
         (NP (NP a round)
             (PP of
                 (NP (NP similar increases)
                     (PP by
                          (NP other lenders))
                      (PP against
                          (NP Arizona real estate loans)))))
         (S-ADV (NP-SBJ *)
                (VP reflecting
                    (NP (NP a continuing decline)
                         (PP-LOC in
                                 (NP that market))))))
     .))
```

Context-Free Grammars

- A context-free grammar is a 4-tuple <N, T, S, R>
 - N: the set of non-terminals
 - Phrasal categories: S, NP, VP, ADJP, etc.
 - Parts-of-speech (pre-terminals): NN, JJ, DT, VB
 - T: the set of terminals (the words)
 - S: the start symbol
 - Often written as ROOT or TOP
 - Not usually the sentence non-terminal S
 - R: the set of rules
 - Of the form $X \rightarrow Y_1 Y_2 \dots Y_k$, with $X, Y_i \in N$
 - Examples: $S \rightarrow NP VP$, $VP \rightarrow VP CC VP$
 - Also called rewrites, productions, or local trees

An example grammar

 $PP \rightarrow P NP$

 $N = \{S, VP, NP, PP, N, V, PN, P\}$ $T = \{girl, telescope, sandwich, I, saw, ate, with, in, a, the\}$ $S = \{S\}$ Called Inner rules R : $S \rightarrow NP VP$ (NP A girl) (VP ate a sandwich) $VP \rightarrow V$ $VP \rightarrow V NP$ (V ate) (NP a sandwich) (VP saw a girl) (PP with a telescope) $VP \rightarrow VP PP$ (NP a girl) (PP with a sandwich) $NP \rightarrow NP PP$ (D a) (N sandwich) $NP \rightarrow D N$ $NP \rightarrow PN$

(P with) (NP with a sandwich)



Why context-free?



Why context-free?


Ambiguities

Coordination ambiguity

• Here, the coarse VP and NP categories cannot enforce subject-verb agreement in number resulting in the coordination ambiguity





This tree would be ruled out if the context would be somehow captured (subject-verb agreement)

Why is parsing hard? Ambiguity

• Prepositional phrase attachment ambiguity





PP Ambiguity

Put the block in the box on the table in the kitchen

3 prepositional phrases, 5 interpretations:

- Put the block ((in the box on the table) in the kitchen)
- $\circ~$ Put the block (in the box (on the table in the kitchen))
- $\circ\,$ Put ((the block in the box) on the table) in the kitchen.
- $\circ~$ Put (the block (in the box on the table)) in the kitchen.
- $\circ\,$ Put (the block in the box) (on the table in the kitchen)

PP Ambiguity

Put the block in the box on the table in the kitchen

3 prepositional phrases, 5 interpretations:

- \circ Put the block ((in the box on the table) in the kitchen)
- \circ Put the block (in the box (on the table in the kitchen))

0 ...

A general case:

 \circ ((())) ()(()) ()()() (())() (()())

$$Cat_n = \binom{2n}{n} - \binom{2n}{n-1} \sim \frac{4^n}{n^{3/2}\sqrt{\pi}}$$
 Cata

Catalan numbers

 $1, 2, 5, 14, 42, 132, 429, 1430, 4862, 16796, 58786, \ldots$

A typical tree from a standard dataset (Penn treebank WSJ)



Canadian Utilities had 1988 revenue of \$ 1.16 billion , mainly from its natural gas and electric utility businesses in Alberta , where the company serves about 800,000 customers .

[from Michael Collins slides]

Syntactic Ambiguities I

- Prepositional phrases:
 - They cooked the beans in the pot on the stove with handles.
- Particle vs. preposition:
 - The puppy tore up the staircase.
- Complement structures
 - The tourists objected to the guide that they couldn't hear. She knows you like the back of her hand.
- Gerund vs. participial adjective
 - Visiting relatives can be boring. Changing schedules frequently confused passengers.

Syntactic Ambiguities II

- Modifier scope within NPs
 - impractical design requirements plastic cup holder
- Multiple gap constructions
 - The chicken is ready to eat.
 The contractors are rich enough to sue.
- Coordination scope:
 - Small rats and mice can squeeze into holes or cracks in the wall.

How to Deal with Ambiguity?

• We want to score all the derivations to encode how plausible they are



Put the block in the box on the table in the kitchen

Probabilistic Context Free Grammar (PCFG)

Probabilistic Context-Free Grammars

- A context-free grammar is a 4-tuple <N, T, S, R>
 - N: the set of non-terminals
 - Phrasal categories: S, NP, VP, ADJP, etc.
 - Parts-of-speech (pre-terminals): NN, JJ, DT, VB
 - T: the set of terminals (the words)
 - S: the start symbol
 - Often written as ROOT or TOP
 - Not usually the sentence non-terminal S
 - \circ R: the set of rules
 - Of the form $X \rightarrow Y_1 Y_2 \dots Y_k$, with $X, Y_i \in N$
 - Examples: $S \rightarrow NPVP$, $VP \rightarrow VPCCVP$
 - Also called rewrites, productions, or local trees
- A PCFG adds:
 - A top-down production probability per rule $P(Y_1 Y_2 ... Y_k | X)$

Associate prob ∀ √	abilities with th $X \to \alpha \in F$ $\forall X \in N :$	the rules : $p(X \to \alpha)$ $R: 0 \le p(X \to \alpha) \le 1$ $\sum_{\alpha: X \to \alpha \in R} p(X \to \alpha) = 1$		Now we can score a tree a product of probabilities corresponding to the used	as a I rules
$S \rightarrow NP VP$	$\rightarrow NP VP$ 1.0 (NP A girl) (VP ate a sandwich)	1	N o girl	0.2	
			$N \rightarrow telescope$	0.7	
$VP \rightarrow V$	0.2			$N \rightarrow sandwich$	0.1
$VP \rightarrow V NP$	0.4	(VP ate) (NP a sandwich)		$PN \rightarrow I$	1.0
$VP \rightarrow VP PP$	0.4	(VP saw a girl) (PP with)		$V \rightarrow saw$	0.5
				$V \rightarrow ate$	0.5
$NP \rightarrow NP PP$	0.3	(NP a giri) (PP with)		$P \rightarrow with$	0.6
$NP \rightarrow D N$	0.5	(D a) (N sandwich)			0.0
$NP \rightarrow PN$	0.2			P ightarrow in	0.4
				D ightarrow a	0.3
$PP \rightarrow P \ NP$	1.0	(P with) (NP with a sandwich) $_{a}$		$D \rightarrow the$	0.7

 $S \rightarrow NP VP$ 1.0 $N \rightarrow girl 0.2$ $N \rightarrow telescope 0.7$ $VP \rightarrow V$ 0.2 $N \rightarrow sandwich 0.1$ $VP \rightarrow V NP$ 0.4 $PN \rightarrow I$ 1.0 $VP \rightarrow VP PP 0.4$ $V \rightarrow saw$ 0.5 $V \rightarrow ate^{0.5}$ $NP \rightarrow NP PP 0.3$ $NP \rightarrow D N 0.5$ $P \rightarrow with 0.6$ $NP \rightarrow PN$ 0.2 $P \rightarrow in$ 0.4 $D \rightarrow a \, 0.3$ $PP \rightarrow P NP$ **1.0** $D \rightarrow the 0.7$

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 \mathbf{S} 1.0 ΝŶ ŴΡ

$$\begin{array}{c} S \rightarrow NP \ VF 1.0 \\ VP \rightarrow V \ 0.2 \\ VP \rightarrow V \ NF \ 0.4 \\ VP \rightarrow VP \ PF \ 0.4 \\ NP \rightarrow VP \ PF \ 0.4 \\ NP \rightarrow NP \ PF \ 0.3 \\ NP \rightarrow D \ N \ 0.5 \\ NP \rightarrow PN \ 0.2 \\ PP \rightarrow P \ NF \ 1.0 \end{array} \begin{array}{c} N \rightarrow girl \ 0.2 \\ N \rightarrow telescope \ 0.7 \\ N \rightarrow sandwich \ 0.1 \\ PN \rightarrow I \ 1.0 \\ V \rightarrow saw \ 0.5 \\ V \rightarrow ate \ 0.5 \\ P \rightarrow with \ 0.6 \\ P \rightarrow in \ 0.4 \\ D \rightarrow a \ 0.3 \\ D \rightarrow the \ 0.7 \end{array}$$

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with 0.6

$$p(T) = 1.0 \times$$

 $S \rightarrow NP VP$ 1.0 $N \rightarrow girl 0.2$ $N \rightarrow telescope 0.7$ $VP \rightarrow V$ 0.2 $N \rightarrow sandwich \, 0.1$ $VP \rightarrow V NP 0.4$ $PN \rightarrow I$ 1.0 $VP \rightarrow VP PP 0.4$ $V \rightarrow saw$ 0.5 $V \rightarrow ate^{0.5}$ $NP \rightarrow NP PP 0.3$ $NP \rightarrow D N 0.5$ $P \rightarrow with 0.6$ NP
ightarrow PN 0.2 I $P \rightarrow in$ 0.4 $D \rightarrow a \, \mathbf{0.3}$ $PP \rightarrow P NP$ **1.0** $D \rightarrow the 0.7$



$$p(T) = 1.0 \times 0.2 \times$$

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 $S \rightarrow NP VP$ 1.0 $N \rightarrow girl 0.2$ $N \rightarrow telescope 0.7$ $VP \rightarrow V$ 0.2 $N \rightarrow sandwich 0.1$ $VP \rightarrow V NP$ 0.4 $PN \rightarrow I$ 1.0 $VP \rightarrow VP PP 0.4$ $V \rightarrow saw$ 0.5 $V \rightarrow ate^{0.5}$ $NP \rightarrow NP PP 0.3$ $NP \rightarrow D N 0.5$ $P \rightarrow with 0.6$ $NP \rightarrow PN$ 0.2 $P \rightarrow in \, 0.4$ $D \rightarrow a 0.3$ $PP \rightarrow P NP$ **1.0** $D \rightarrow the 0.7$



 $p(T) = 1.0 \times 0.2 \times 1.0 \times$

 $S \rightarrow NP VP$ 1.0 $N \rightarrow girl$ 0.2 $N \rightarrow telescope 0.7$ $VP \rightarrow V \ 0.2$ $VP \rightarrow V \ NP \ 0.4$ $N \rightarrow sandwich \ 0.1$ $PN \rightarrow L10$ $PN \rightarrow I$ 1.0 $VP \rightarrow VP PP 0.4$ $V \rightarrow saw$ 0.5 $V \rightarrow ate^{0.5}$ $NP \rightarrow NP PP 0.3$ $NP \rightarrow D N 0.5$ $P \rightarrow with 0.6$ $NP \rightarrow PN$ 0.2 $P \rightarrow in$ 0.4 $D \rightarrow a 0.3$ $PP \rightarrow P NP$ 1.0 $D \rightarrow the 0.7$



 $p(T) = 1.0 \times 0.2 \times 1.0 \times 0.4 \times$

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$$S \rightarrow NP \ VF \ 1.0$$

$$VP \rightarrow V \ 0.2$$

$$VP \rightarrow V \ NP \ 0.4$$

$$VP \rightarrow VP \ PF \ 0.4$$

$$N \rightarrow telescope \ 0.7$$

$$N \rightarrow sandwich \ 0.1$$

$$PN \rightarrow I \ 1.0$$

$$V \rightarrow saw \ 0.5$$

$$V \rightarrow ate \ 0.5$$

$$V \rightarrow ate \ 0.5$$

$$P \rightarrow with \ 0.6$$

$$P \rightarrow in \ 0.4$$

$$D \rightarrow a \ 0.3$$

$$D \rightarrow the \ 0.7$$



 $p(T) = 1.0 \times 0.2 \times 1.0 \times 0.4 \times 0.5 \times$



 $p(T) = 1.0 \times 0.2 \times 1.0 \times 0.4 \times 0.5 \times 0.3 \times$

$S \rightarrow NP \ VP$ 1.0	N ightarrow girl 0.2
	$N \rightarrow telescope$ 0.7
$VP \rightarrow V$ 0.2	$N \rightarrow sandwich $ 0.1
$VP \rightarrow V NP 0.4$ $VP \rightarrow VP PP 0.4$	PN ightarrow I 1.0
	V ightarrow saw 0.5
$NP \rightarrow NP PP$ 0.3	V ightarrow ate 0.5
$NP \rightarrow D \ N \ 0.5$	$P \rightarrow with {\rm 0.6}$
$NP \rightarrow PN$ 0.2	P ightarrow in 0.4
	D ightarrow a 0.3
$PP \rightarrow P NP 1.0$	$D \rightarrow the 0.7$





PCFG Estimation

Maximum likelihood estimation

• A treebank: a collection sentences annotated with constituent trees



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• An estimated probability of a rule (maximum likelihood estimates)

$$p(X \to \alpha) = \frac{C(X \to \alpha)}{C(X)}$$

- Smoothing is helpful
 - Especially important for preterminal rules

The number of times the rule used in the corpus

The number of times the nonterminal X appears in the treebank

Parsing evaluation

Parsing evaluation

- Intrinsic evaluation:
 - Automatic: evaluate against annotation provided by human experts (gold standard) according to some predefined measure
 - Manual: ... according to human judgment

- Extrinsic evaluation: score syntactic representation by comparing how well a system using this representation performs on some task
 - E.g., use syntactic representation as input for a semantic analyzer and compare results of the analyzer using syntax predicted by different parsers.

Standard evaluation setting in parsing

- Automatic intrinsic evaluation is used: parsers are evaluated against gold standard by provided by linguists
 - There is a standard split into the parts:
 - training set: used for estimation of model parameters
 - development set: used for tuning the model (initial experiments)
 - test set: final experiments to compare against previous work

Automatic evaluation of constituent parsers

- Exact match: percentage of trees predicted correctly
- Bracket score: scores how well individual phrases (and their boundaries) are identified

The most standard measure; we will focus on it

Brackets scores

- The most standard score is bracket score
- It regards a tree as a collection of brackets:
- The set of brackets predicted by a parser is compared against the set of brackets in the tree annotated by a linguist
- Precision, recall and F1 are used as scores

Subtree signatures for CKY

[min, max, C]

Preview: F1 bracket score



CKY Parsing

Parsing

- Parsing is search through the space of all possible parses
 - e.g., we may want either any parse, all parses or the highest scoring parse (if PCFG):

$\underset{T \in G(x)}{\operatorname{arg max}} P(T)$

- Bottom-up:
 - \circ $\,$ One starts from words and attempt to construct the full tree $\,$

- Top-down
 - Start from the start symbol and attempt to expand to get the sentence

CKY algorithm (aka CYK)

- Cocke-Kasami-Younger algorithm
 - Independently discovered in late 60s / early 70s

- An efficient bottom up parsing algorithm for (P)CFGs
 - can be used both for the recognition and parsing problems
 - Very important in NLP (and beyond)

• We will start with the non-probabilistic version

Constraints on the grammar

• The basic CKY algorithm supports only rules in the Chomsky Normal Form (CNF):

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Constraints on the grammar

• The basic CKY algorithm supports only rules in the Chomsky Normal Form (CNF):

 $C \to x$ $C \to C_1 C_2$

- Any CFG can be converted to an equivalent CNF
 - Equivalent means that they define the same language
 - However (syntactic) trees will look differently
 - It is possible to address it by defining such transformations that allows for easy reverse transformation

Transformation to CNF form

• What one need to do to convert to CNF form

- Get rid of rules that mix terminals and non-terminals
- Get rid of unary rules:
- Get rid of N-ary rules:

 $C \to C_1$

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 $C \to C_1 \ C_2 \dots C_n \ (n > 2)$

Crucial to process them, as required for efficient parsing

Transformation to CNF form: binarization



• How do we get a set of binary rules which are equivalent?

Transformation to CNF form: binarization



 How do we get a set of binary rules which are equivalent? *NP* → *DT X X* → *NNP Y Y* → *VBG NN*

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Transformation to CNF form: binarization



• How do we get a set of binary rules which are equivalent?

 $NP \to DT \ X$ $X \to NNP \ Y$ $Y \to VBG \ NN$

 A more systematic way to refer to new non-terminals NP → DT @NP|DT
 @NP|DT → NNP @NP|DT_NNP
 @NP|DT_NNP → VBG NN

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Transformation to CNF form: binarization

• Instead of binarizing tuples we can binarize trees on preprocessing:



CKY: Parsing task

- We are given
 - \circ a grammar <N, T, S, R>
 - \circ a sequence of words

$$\boldsymbol{w} = (w_1, w_2, \dots, w_n)$$

• Our goal is to produce a parse tree for w

CKY: Parsing task

- We a given
 - \circ a grammar < N, T, S, R>

$$\circ$$
 a sequence of words $oldsymbol{w} = (w_1, w_2, \dots, w_n)$

- Our goal is to produce a parse tree for w
- We need an easy way to refer to substrings of w



Parsing one word



Wi

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Parsing one word



Parsing one word



covers all words between *i* – 1 and *i*

 $C \to w_i$

Parsing longer spans

$C \rightarrow C_1 \ C_2$

Check through all C1, C2, mid



covers all words co	overs all words
btw <i>min</i> and <i>mid</i> bt	w <i>mid</i> and <i>max</i>

Parsing longer spans

$C \rightarrow C_1 \ C_2$



btw min and mid btw	vers all words v mid and max
---------------------	---------------------------------

Check through all C1, C2, mid

Parsing longer spans



covers all words between *min* and *max*

lead can poison					$VP \to M \ V$ $VP \to V$	nner ules
0 1 2 0	max = 1	max = 2	max = 3		$NP \to N$ $NP \to N NP$	
min = 0			S?		N ightarrow can N ightarrow lead N ightarrow poison	
min = 1					$\begin{array}{c} M \rightarrow can \\ M \rightarrow must \end{array}$	eterminal
min = 2				Chart (aka parsing triangle)	V o poison V o lead	E E







lead can poison			$\begin{array}{ccc} VP \rightarrow M & V \\ VP \rightarrow V \end{array}$	iner Iles
0 1 2 3	max = 1 max = 2	max = 3	$NP \to N$ $NP \to N NP$	<u> </u>
min = 0		S?	$\begin{bmatrix} N \to can \\ N \to lead \\ N \to poison \end{bmatrix}$	
min = 1			$\begin{array}{c} M \to can \\ M \to must \end{array}$	eterminal
min = 2			$ \begin{bmatrix} V \to poison \\ V \to lead \end{bmatrix} $	ē e

lead	can	poison				$VP \rightarrow M V$	
0 1	2	3				$VP \rightarrow V$	nner ules
0 1	L	G	max = 1	max = 2	max = 3	NP o N NP o N NP	
		min = 0	1	4	⁶ S?	$\begin{bmatrix} N \to can \\ N \to lead \\ N \to poison \end{bmatrix}$	
		min = 1		2	5	$\begin{array}{c} M \rightarrow can \\ M \rightarrow must \end{array}$	reterminal Jes
		min = 2				$\begin{bmatrix} V \to poison \\ V \to lead \end{bmatrix}$	σ Ξ

lea	ad c	an po	bison				$VP \rightarrow M V$	5.0
0	1	2	3				$V P \rightarrow V$	Inne rules
							$NP \rightarrow N$	
				max = 1	max =	2 max = 3	$NP \rightarrow N \ NP$	
				1	4	6	$N \rightarrow can$	
			min = 0			S?	$N \rightarrow lead$	
							$N \rightarrow poison$	
					2	5		a
			min = 1				$M \to can$	ш.
							$M \rightarrow must$	es
						3		Pre
			min = 2				$V \rightarrow poison$	
							\Box $V \rightarrow lead$	

lead	can	poison				$VP \to M V$ $VP \to V$	re S
0	2	2 3					Inn rule
						$NP \rightarrow N$	
			max = 1	max = 2	max = 3	$NP \rightarrow N \ NP$	
			1			\rceil $N \rightarrow can$	
		min = 0	?			$N \rightarrow lead$	
						$ \qquad \qquad$	
		min - 1		2		$M \rightarrow can$	linal
		mm = 1				$M \rightarrow can$	erm
				L	3		rete
		min = 2			?	$V \rightarrow poison$	C 2
					~		





	$VP \rightarrow M V$				poison	can	lead	
Inner rules	$VP \rightarrow V$				 2 3		1	 0
	$NP \to N$ $NP \to N NP$	max = 3	max = 2	max = 1				
	N ightarrow can N ightarrow lead N ightarrow poison		4 ?	$\begin{bmatrix} 1 & N, V \\ NP, VP \end{bmatrix}$	min = 0			
eterminal les	$M \to can$ $M \to must$	3 37 17	² N, M NP		m in = 1			
P L	$V ightarrow poison \ V ightarrow lead$	NP,VP			min = 2			





	$VP \rightarrow M V$				poison	can	lead	
lnner rules	$VP \rightarrow V$			3	2 3		1	 0
	$NP \to N$ $NP \to N NP$	max = 3	l max = 2	max =				
	$N ightarrow can \ N ightarrow lead \ N ightarrow poison$		$\begin{array}{c} & & \\$	$n = 0 \begin{bmatrix} 1 & N, V \\ NP, V \end{bmatrix}$	min =			
eterminal es	$\begin{array}{c} M \rightarrow can \\ M \rightarrow must \end{array}$	5 ?	² N, M NP	n = 1	m in = 7			
P	$V ightarrow poison \ V ightarrow lead$	3 N,V NP,VP		n = 2	min = 2			



leac	can	poison				$\begin{array}{ccc} VP \rightarrow M & V \\ VP \rightarrow V \end{array}$	ler
0	1	2 3	max = 1	max = 2	max = 3	$NP \to N$ $NP \to N NP$	Inn
		min = 0	$\begin{bmatrix} 1 & N, V \\ NP, VP \end{bmatrix}$	⁴ NP	⁶ ?	$\begin{bmatrix} N \to can \\ N \to lead \\ N \to poison \end{bmatrix}$	
		m in = 1		² N, M NP	5S, VP, NP	$\begin{array}{c} M \rightarrow can \\ M \rightarrow must \end{array}$	eterminal
		min = 2			3 N, V NP, VP	$\begin{bmatrix} V \to poison \\ V \to lead \end{bmatrix}$	E E E E E E E

lead	can poison		$\begin{array}{ccc} VP \rightarrow M & V \\ VP \rightarrow V \end{array}$	ler es
0 1	23	max = 1 max = 2 ma	$NP \rightarrow N$	Inn rul
	min = 0	$\begin{bmatrix} 1 & N, V & 4 & NP \\ \hline NP, VP & & & \\ \hline \end{bmatrix} \begin{bmatrix} 6 & & & \\ \hline \end{array} $? $N \rightarrow can$ $N \rightarrow lead$ $N \rightarrow poison$	
	min = 1	$\begin{bmatrix} 2 & N, M \\ NP \end{bmatrix} \stackrel{5}{}_{S,}$	$ \begin{array}{c} M \to can \\ M \to must \end{array} $	eterminal les
	min = 2	NH NH	$\begin{array}{c} V \\ ead \end{array}$	£ 5

















lead ca	in poison				$VP \to M \ V$ $VP \to V$	nner Mes
0 1	2 3	max = 1	max = 2	max = 3	$NP \to N$ $NP \to N NP$	
mid=2	min = 0	$\begin{bmatrix} 1 & N, V \\ NP, VP \end{bmatrix}$	⁴ NP	⁶ S, NP S(?!)	$\begin{bmatrix} N \to can \\ N \to lead \\ N \to poison \end{bmatrix}$	
	min = 1		² N, M NP	⁵ <i>S</i> , <i>VP</i> , <i>NP</i>	$\begin{array}{c} M \rightarrow can \\ M \rightarrow must \end{array}$	eterminal
	min = 2			³ N, V NP, VP	$\left \begin{array}{c} V \to poison \\ V \to lead \end{array} \right $	A D





Ambiguity





No subject-verb agreement, and *poison* used as an intransitive verb