

Natural Language Processing

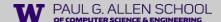
Syntactic parsing

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Announcements

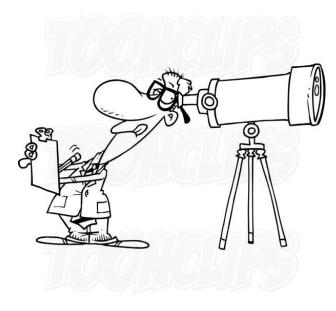
- HW2 is due Monday
 - Note that TAs are not required to provide fast responses over weekends
 - Use TAs office hours this week
 - No extensions beyond "standard" late days due to Thanksgiving

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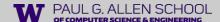
Ambiguity

I saw a girl with a telescope



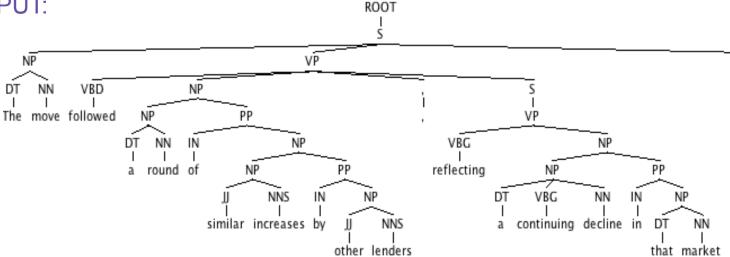




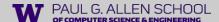


Syntactic Parsing

- INPUT:
 - The move followed a round of similar increases by other lenders, reflecting a continuing decline in that market
- OUTPUT:

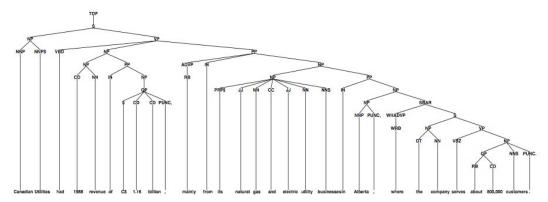


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A Supervised ML Problem

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



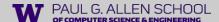
Canadian Utilities had 1988 revenue of \$ 1.16 billion, mainly from its natural gas and

electric utility businesses in Alberta, where the company serves about 800,000 customers [from Michael Collins slides]

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Syntax



Syntax

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

my dogPron N

the dogDet N

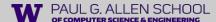
the catDet N

o and Conj

the large catDet Adj N

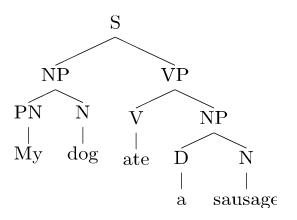
the black catDet Adj N

ate a sausageV Det N



Parsing

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

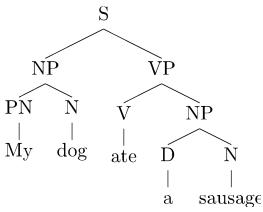


Constituent (a.k.a. phrase-structure) tree

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Constituent trees

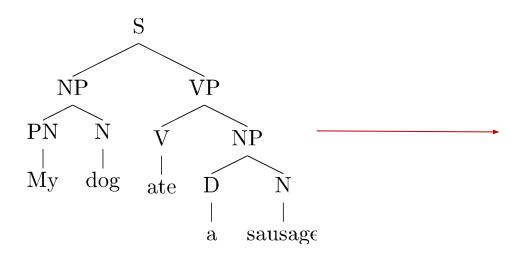
- Internal nodes correspond to phrases
 - S a sentence
 - NP Noun Phrase: My dog, a sandwich, lakes,...
 - VP Verb Phrase: ate a sausage, barked, ...
 - PP Prepositional phrases: with a friend, in a car, ...

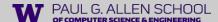


- Nodes immediately above words are PoS tags (aka preterminals)
 - PN pronoun
 - D determiner
 - V verb
 - N noun
 - P preposition

Bracketing notation

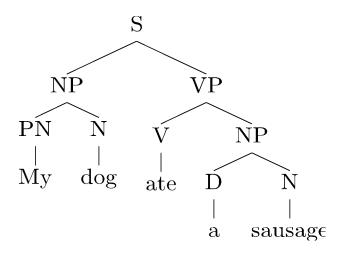
• It is often convenient to represent a tree as a bracketed sequence

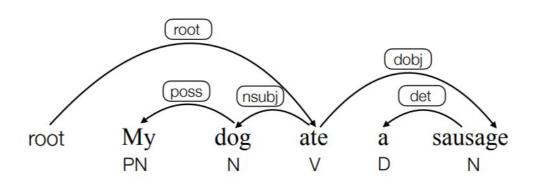




Parsing

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





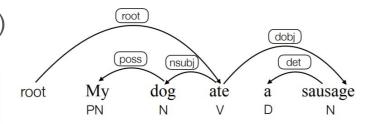
Constituent (a.k.a. phrase-structure) tree

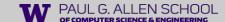
Dependency tree

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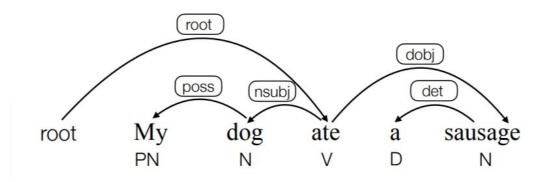
Dependency trees

- Nodes are words (along with part-of-speech tags)
- Directed arcs encode syntactic dependencies between them
- Labels are types of relations between the words
 - poss possessive
 - dobj direct object
 - o nsub subject
 - det determiner





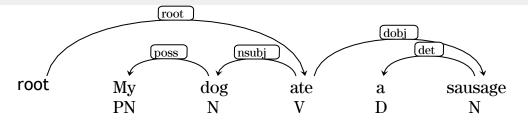
Recovering shallow semantics



- Some semantic information can be (approximately) derived from syntactic information
 - Subjects (nsubj) are (often) agents ("initiator / doers for an action")
 - Direct objects (dobj) are (often) patients ("affected entities")

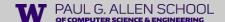
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Recovering shallow semantics



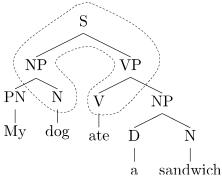
- Some semantic information can be (approximately) derived from syntactic information
 - Subjects (nsubj) are (often) agents ("initiator / doers for an action")
 - Direct objects (dobj) are (often) patients ("affected entities")
- But even for agents and patients consider:
 - Mary is baking a cake in the oven
 - A cake is baking in the oven
- In general it is not trivial even for the most shallow forms of semantics
 - o E.g., consider prepositions: in can encode direction, position, temporal information, ...

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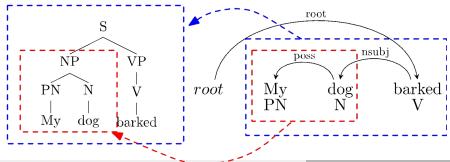


Constituent and dependency representations

Constituent trees can (potentially) be converted to dependency trees

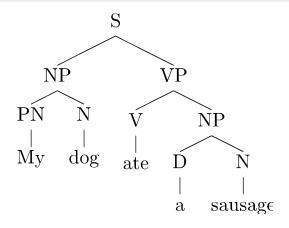


Dependency trees can (potentially) be converted to constituent trees



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Constituent trees



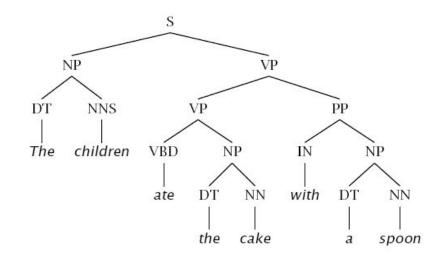
- Internal nodes correspond to phrases
 - S a sentence
 - NP (Noun Phrase): My dog, a sandwich, lakes,..
 - VP (Verb Phrase): ate a sausage, barked, ...
 - PP (Prepositional phrases): with a friend, in a car,

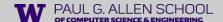
. . .

- Nodes immediately above words are PoS tags (aka preterminals)
 - PN pronoun
 - D determiner
 - V verb
 - 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





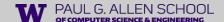
Morphology/Syntax/Semantics

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

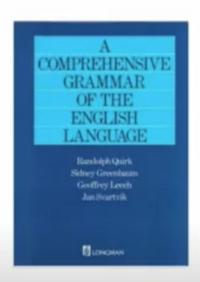
Afyonkarahisarlılaştırabildiklerimizdenmişsinizcesinee

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

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English grammar



Product Details (from Amazon)

Hardcover: 1779 pages

Publisher: Longman; 2nd Revised edition

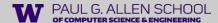
Language: English

ISBN-10: 0582517346

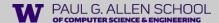
ISBN-13: 978-0582517349

Product Dimensions: 8.4 x 2.4 x 10 inches

Shipping Weight: 4.6 pounds



Context Free Grammar (CFG)



Context Free Grammar (CFG)

Grammar (CFG)

 $ROOT \rightarrow S$

 $S \rightarrow NP VP$

NP → DT NN

 $NP \rightarrow NN NNS$

 $NP \rightarrow NP PP$

 $VP \rightarrow VBP NP$

VP → VBP NP PP

PP → IN NP

Lexicon

 $NN \rightarrow interest$

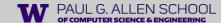
NNS → raises

VBP → interest

VBZ → raises

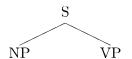
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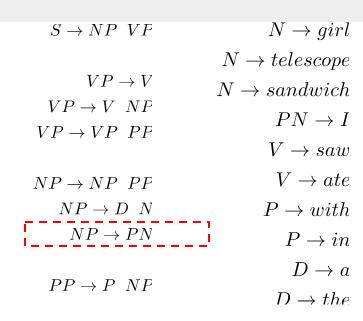
Other grammar formalisms: LFG, HPSG, TAG, CCG...

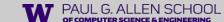


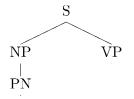
 \mathbf{S}

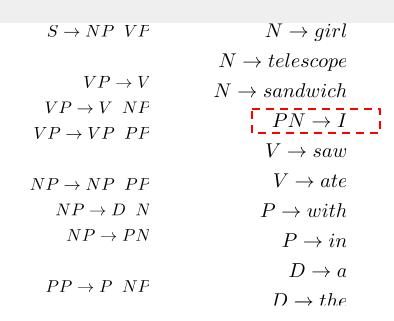
$S \rightarrow NP \ VP$	N o girl
'	$N \to telescope$
VP o V	$N \rightarrow sandwich$
$VP \rightarrow V NP$	PN o I
$VP \rightarrow VP PP$	$V \to saw$
$NP \rightarrow NP PP$	$V \to ate$
NP o D N	$P \rightarrow with$
$NP \to PN$	P o in
	$D \to a$
$PP \rightarrow P \ NP$	$D \rightarrow the$

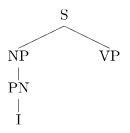


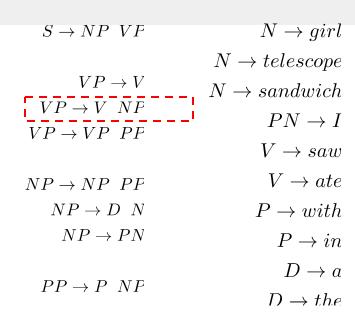


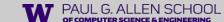


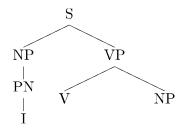


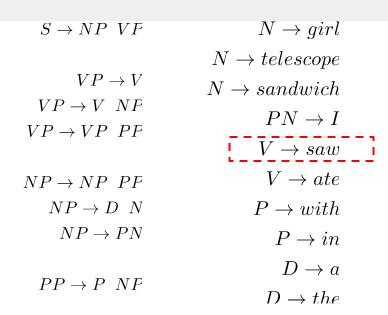


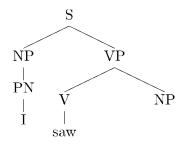


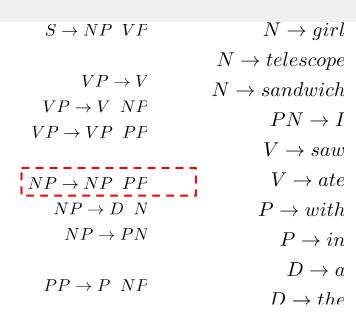


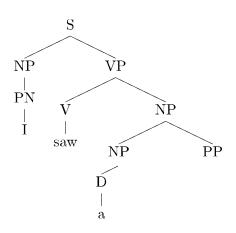


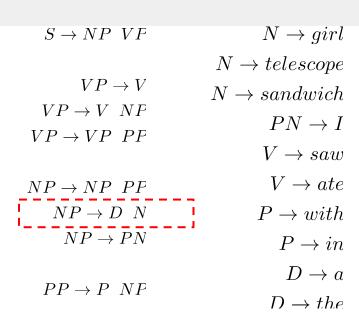


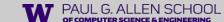


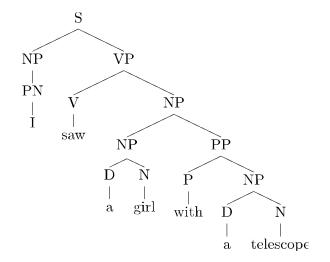


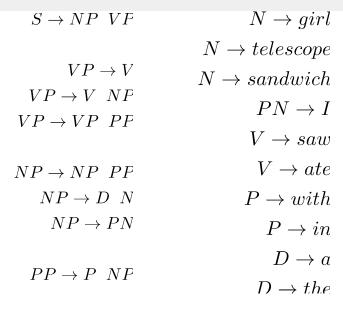














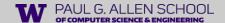


Treebank Sentences

```
( (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 $X \to Y_1 Y_2 \dots Y_k$, with $X, Y_i \in \mathbb{N}$
 - Examples: $S \rightarrow NP VP$, $VP \rightarrow VP CC VP$
 - Also called rewrites, productions, or local trees



An example grammar

 $N = \{S, VP, NP, PP, N, V, PN, P\}$

 $T = \{girl, telescope, sandwich, I, saw, ate, with, in, a, the\}$

 $S = \{S\}$

R:

Called Inner rules

$$S \rightarrow NP VP$$

(NP A girl) (VP ate a sandwich)

$$VP \rightarrow V$$

$$VP \rightarrow V NP$$

 $VP \rightarrow VP \ PP$

(V ate) (NP a sandwich)

(VP saw a girl) (PP with a telescope)

$NP \rightarrow NP \ PP$

$$NP \rightarrow D \ N$$

 $NP \to PN$

(NP a girl) (PP with a sandwich)

(D a) (N sandwich)

$PP \rightarrow P NP$ (P with) (NP with a sandwich)

Preterminal rules

 $N \rightarrow qirl$

 $N \rightarrow telescope$

 $N \rightarrow sandwich$

 $PN \to I$

 $V \rightarrow saw$

 $V \rightarrow ate$

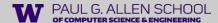
 $P \rightarrow with$

 $P \rightarrow in$

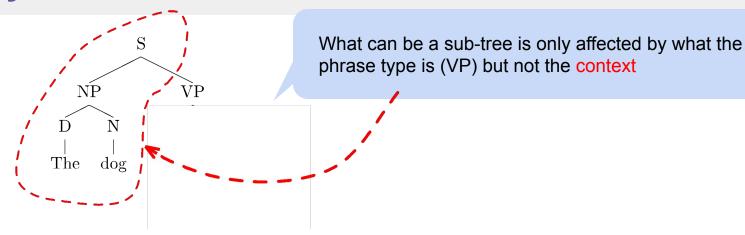
 $D \to a$

 $D \rightarrow the$

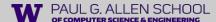
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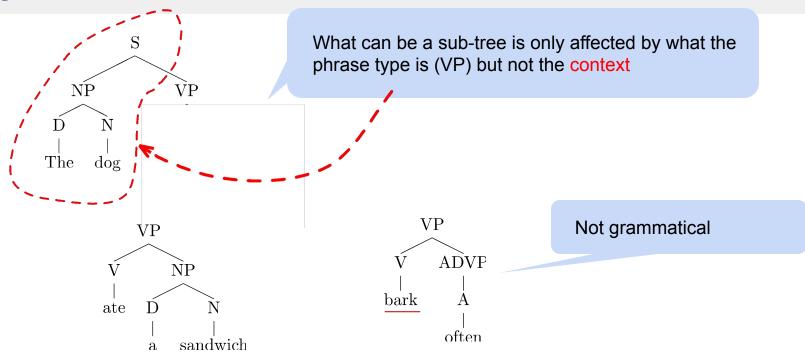
Why context-free?



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Why context-free?



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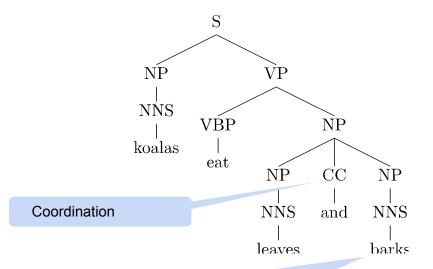


Ambiguities

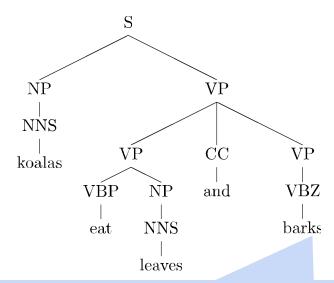


Coordination ambiguity

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

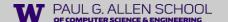


"Bark" can refer both to a noun or a verb



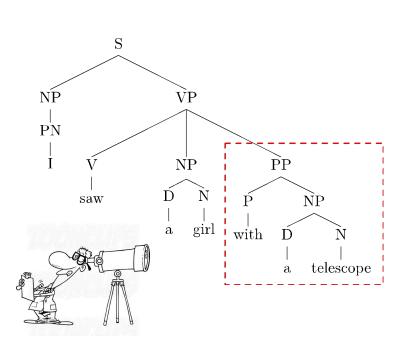
This tree would be ruled out if the context would be somehow captured (subject-verb agreement)

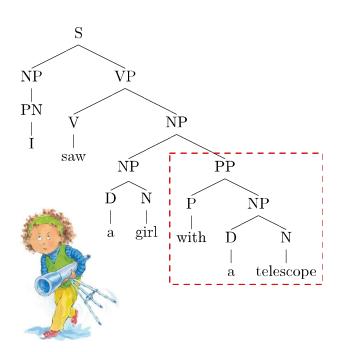
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Why parsing is hard? Ambiguity

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)
- Put the block (in the box (on the table in the kitchen))
- Put ((the block in the box) on the table) in the kitchen.
- Put (the block (in the box on the table)) in the kitchen.
- Put (the block in the box) (on the table in the kitchen)

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

A general case:

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

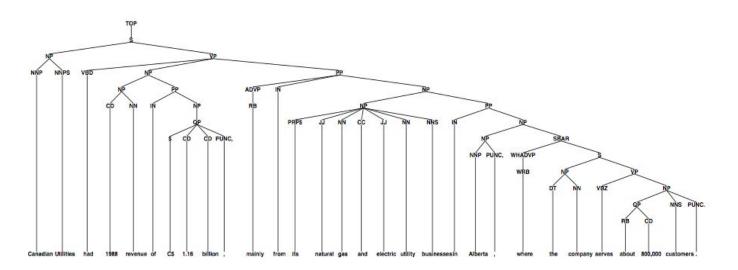
$$Cat_n = \binom{2n}{n} - \binom{2n}{n-1} \sim \frac{4^n}{n^{3/2}\sqrt{\pi}}$$

Catalan numbers

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



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]

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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

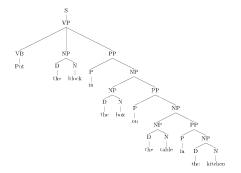
- Modifier scope within NPs
 - impractical design requirements
 plastic cup holder

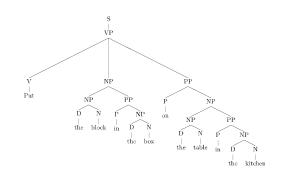
- Multiple gap constructions
 - The chicken is ready to eat.
 The contractors are rich enough to sue.
- Coordination scope:
 - Small rats and mice can squeeze into holes or cracks in the wall.

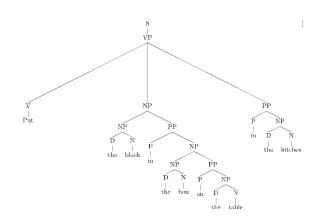
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How to Deal with Ambiguity?

• 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

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Probabilistic Context Free Grammar (PCFG)

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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
 - R: the set of rules
 - Of the form $X \to Y_1 Y_2 \dots Y_k$, with $X, Y_i \in \mathbb{N}$
 - Examples: $S \rightarrow NP VP$, $VP \rightarrow VP CC VP$
 - Also called rewrites, productions, or local trees
- A PCFG adds:
 - A top-down production probability per rule $P(Y_1 Y_2 ... Y_k \mid X)$

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Associate probabilities with the rules : p(X ightarrow lpha)

$$\forall X \to \alpha \in R: \quad 0 \le p(X \to \alpha) \le 1$$

 $\forall X \in N: \quad \sum p(X \to \alpha) = 1$

 $\alpha: X \to \alpha \in R$

$$S oup NP \ VP$$
 1.0 (NP A girl) (VP ate a sandwich) $VP oup V$ 0.2 $VP oup V \ NP$ 0.4 (VP ate) (NP a sandwich) $VP oup VP \ PP$ 0.4 (VP saw a girl) (PP with ...) $NP oup NP \ PP$ 0.3 (NP a girl) (PP with) $NP oup D \ N$ 0.5 (D a) (N sandwich) $NP oup PN$ 0.2 (P with) (NP with a sandwich) $PP oup PNP \ Vulia Tsvetkov$

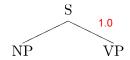
Now we can score a tree as a product of probabilities corresponding to the used rules

N o girl	0.2
$N \rightarrow telescope$	0.7
$N \rightarrow sandwich$	0.1
PN o I	1.0
$V \to saw$	0.5
$V \rightarrow ate$	0.5
$P \rightarrow with$	0.6
$P \rightarrow in$	0.4
D o a	0.3

S

$$S
ightarrow NP \ VP \ 1.0$$
 $VP
ightarrow V \ 0.2$ $VP
ightarrow V \ NP \ 0.4$ $VP
ightarrow VP \ PP \ 0.4$ $NP
ightarrow NP \ PP \ 0.3$ $NP
ightarrow D \ N \ 0.5$ $NP
ightarrow PN \ 0.2$ $PP
ightarrow P \ NP \ 1.0$

$$N
ightarrow girl$$
 0.2 $N
ightarrow telescope$ 0.7 $N
ightarrow sandwich$ 0.1 $PN
ightarrow I$ 1.0 $V
ightarrow saw$ 0.5 $V
ightarrow ate$ 0.5 $P
ightarrow with$ 0.6 $P
ightarrow in$ 0.4 $D
ightarrow a$ 0.3 $D
ightarrow the$ 0.7





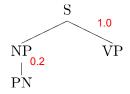
$$VP
ightarrow V$$
 0.2 $VP
ightarrow V$ NP 0.4 $VP
ightarrow VP$ PP 0.4

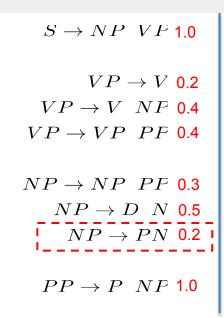
$$NP
ightarrow NP \ PP \ 0.3$$
 $NP
ightarrow D \ N \ 0.5$ $NP
ightarrow PN \ 0.2$

$$PP \rightarrow P \ NP \ \text{1.0}$$

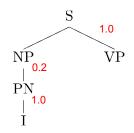
$$N
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 0.2
 $N
ightarrow telescope$ 0.7
 $N
ightarrow sandwich$ 0.1
 $PN
ightarrow I$ 1.0
 $V
ightarrow saw$ 0.5
 $V
ightarrow ate$ 0.5
 $P
ightarrow with$ 0.6
 $P
ightarrow in$ 0.4
 $D
ightarrow a$ 0.3
 $D
ightarrow the$ 0.7

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





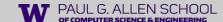
$$N
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 0.2
 $N
ightarrow telescope$ 0.7
 $N
ightarrow sandwich$ 0.1
 $PN
ightarrow I$ 1.0
 $V
ightarrow saw$ 0.5
 $V
ightarrow ate$ 0.5
 $P
ightarrow with$ 0.6
 $P
ightarrow in$ 0.4
 $D
ightarrow a$ 0.3
 $D
ightarrow the$ 0.7

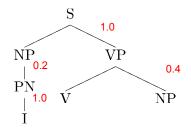


$$S
ightarrow NP \ VP \ 1.0$$
 $VP
ightarrow V \ 0.2$ $VP
ightarrow V \ NP \ 0.4$ $VP
ightarrow VP \ PP \ 0.4$ $NP
ightarrow NP \ PP \ 0.3$ $NP
ightarrow D \ N \ 0.5$ $NP
ightarrow PN \ 0.2$ $PP
ightarrow P \ NP \ 1.0$

$$N
ightarrow girl$$
 0.2
 $N
ightarrow telescope$ 0.7
 $N
ightarrow sandwich$ 0.1
 $PN
ightarrow I$ 1.0
 $V
ightarrow saw$ 0.5
 $V
ightarrow ate$ 0.5
 $P
ightarrow with$ 0.6
 $P
ightarrow in$ 0.4
 $D
ightarrow a$ 0.3
 $D
ightarrow the$ 0.7

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

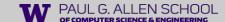


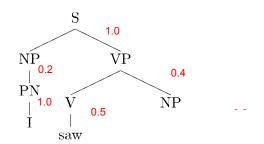


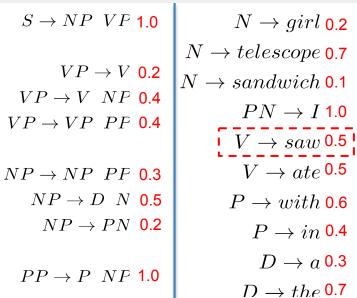
$$S
ightarrow NP \ VP \ 1.0$$
 $VP
ightarrow V \ 0.2$ $VP
ightarrow V \ NP \ 0.4$ $VP
ightarrow VP \ PP \ 0.4$ $NP
ightarrow NP \ PP \ 0.3$ $NP
ightarrow D \ N \ 0.5$ $NP
ightarrow PN \ 0.2$ $PP
ightarrow P \ NP \ 1.0$

$$S
ightarrow NP VP$$
 1.0 $N
ightarrow girl 0.2$ $N
ightarrow girl 0.2$ $N
ightarrow telescope 0.7$ $N
ightarrow sandwich 0.1$ $PN
ightarrow I$ 1.0 $V
ightarrow saw 0.5$ $VP
ightarrow NP PP 0.3$ $V
ightarrow ate 0.5$ V

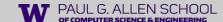
$$p(T) = 1.0 \times 0.2 \times 1.0 \times 0.4 \times$$

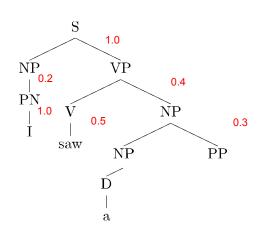


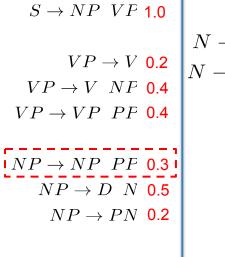




$$p(T) = 1.0 \times 0.2 \times 1.0 \times 0.4 \times 0.5 \times$$



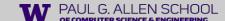


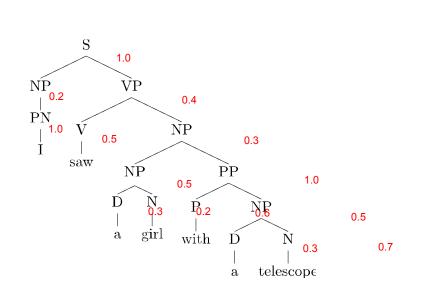


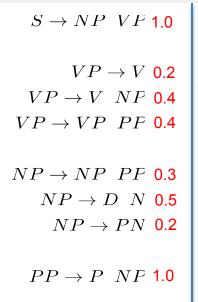
 $PP \rightarrow P NP 1.0$

$$N
ightarrow girl$$
 0.2 $N
ightarrow telescope$ 0.7 $N
ightarrow sandwich$ 0.1 $PN
ightarrow I$ 1.0 $V
ightarrow saw$ 0.5 $V
ightarrow ate$ 0.5 $P
ightarrow with$ 0.6 $P
ightarrow in$ 0.4 $D
ightarrow a$ 0.3 $D
ightarrow the$ 0.7

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





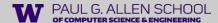


$$N
ightarrow telescope$$
 0.7 $N
ightarrow sandwich$ 0.1 $PN
ightarrow I$ 1.0 $V
ightarrow saw$ 0.5 $V
ightarrow ate$ 0.5 $P
ightarrow with$ 0.6 $P
ightarrow in$ 0.4 $D
ightarrow a$ 0.3 $D
ightarrow the$ 0.7

 $N \rightarrow girl$ 0.2



 $p(T) = 1.0 \times 0.2 \times 1.0 \times 0.4 \times 0.5 \times 0.3 \times \\ 0.5 \times 0.3 \times 0.2 \times 1.0 \times 0.6 \times 0.5 \times 0.3 \times 0.7 = 2.26 \times 10^{-1}$ Yulia Tsvetkov

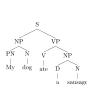


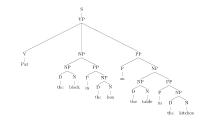
PCFG Estimation

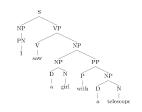
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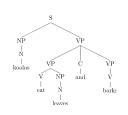
ML estimation

A treebank: a collection sentences annotated with constituent trees.









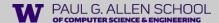
An estimated probability of a rule (maximum likelihood estimates)

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

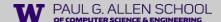
The number of times the rule used in the corpus

The number of times the nonterminal X appears in the treebank

- Smoothing is helpful
 - Especially important for preterminal rules



Parsing evaluation

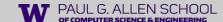


Parsing evaluation

- 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.

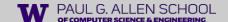
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Standard evaluation setting in parsing

- 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

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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

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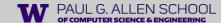
Brackets scores

Subtree signatures for CKY

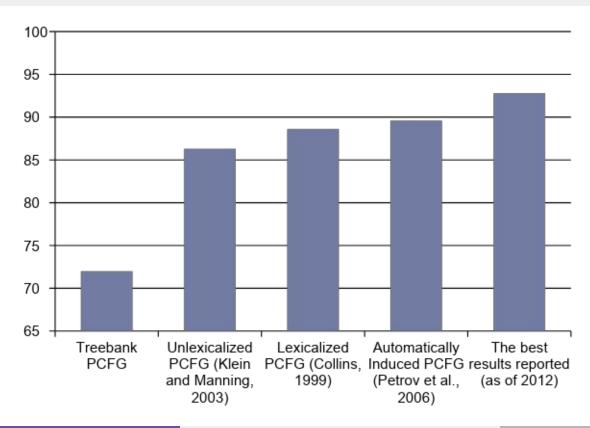
- The most standard score is bracket score
- It regards a tree as a collection of brackets:

[min, max, C]

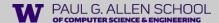
- The set of brackets predicted by a parser is compared against the set of brackets in the tree annotated by a linguist
- Precision, recall and F1 are used as scores



Preview: F1 bracket score



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CKY Parsing

Parsing

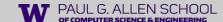
- Parsing is search through the space of all possible parses
 - o e.g., we may want either any parse, all parses or the highest scoring parse (if PCFG):

arg max P(T)

 $T \in G(x)$

- Bottom-up:
 - 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
 - o can be used both for the recognition and parsing problems
 - Very important in NLP (and beyond)

We will start with the non-probabilistic version

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Constraints on the grammar

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

$$C \to x$$

$$C \to x^{-1}$$

$$C \to C_1 C_2$$

Unary preterminal rules (generation of words given PoS tags)

$$N \to telescop\epsilon$$
 $D \to th\epsilon$

Binary inner rules
$$S \rightarrow NPVP$$
 $NP \rightarrow D$ N

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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

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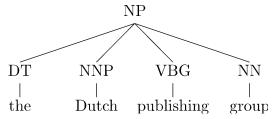
Transformation to CNF form

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: $C \rightarrow C_1$
- Get rid of N-ary rules: $C \to C_1 \ C_2 \dots C_n \ (n > 2)$

Crucial to process them, as required for efficient parsing

• Consider $NP \rightarrow DT \ NNP \ VBG \ NN$



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

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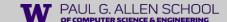
Consider



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

 $NP \rightarrow DT NNP VBG NN$

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



• Consider $NP \rightarrow DT \ NNP \ VBG \ NN$



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

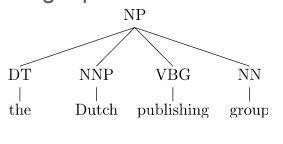
$$NP \rightarrow DT X$$
 $X \rightarrow NNP Y$
 $Y \rightarrow VBG NN$

A more systematic way to refer to new non-terminals

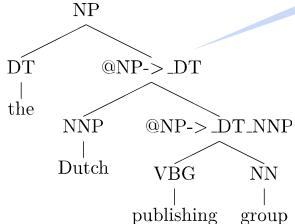
$$NP \rightarrow DT$$
 @ $NP|DT$ @ $NP|DT_NNP$ @ $NP|DT_NNP \rightarrow VBG$ NN



Instead of binarizing tuples we can binarize trees on preprocessing:



Also known as **lossless Markovization** in the context of PCFGs



Can be easily reversed on postprocessing

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CKY: Parsing task

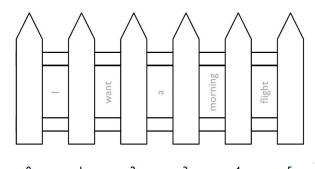
- We are given
 - a grammar <N, T, S, R>

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

Our goal is to produce a parse tree for w

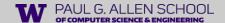
CKY: Parsing task

- We a given
 - o a grammar <N, T, S, R>
 - \circ a sequence of words $\boldsymbol{w}=(w_1,w_2,\ldots,w_n)$
- Our goal is to produce a parse tree for w
- We need an easy way to refer to substrings of w



indices refer to fenceposts

span (i, j) refers to words between fenceposts i and j



Parsing one word

$$C \to w_i$$





Parsing one word



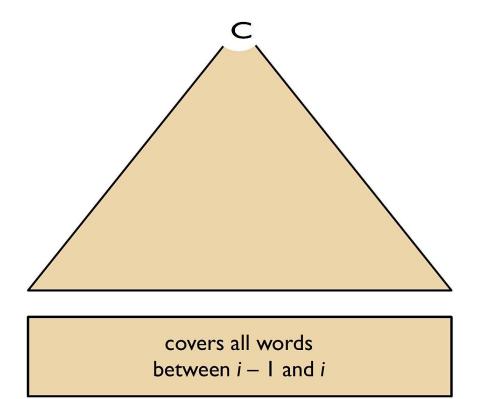
$$C \to w_i$$

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Parsing one word



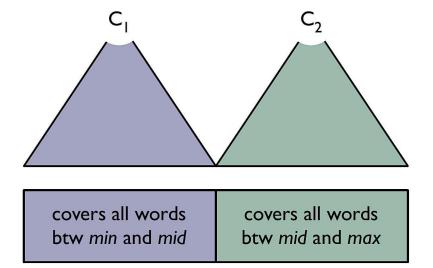


 $C \to w_i$



Parsing longer spans

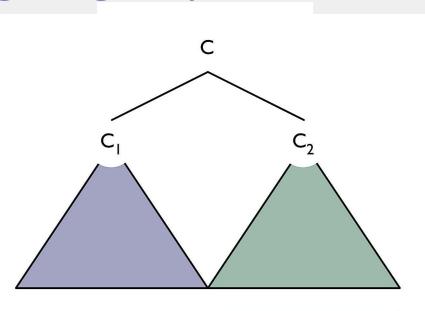




Check through all C1, C2, mid



Parsing longer spans

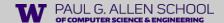


covers all words btw min and mid

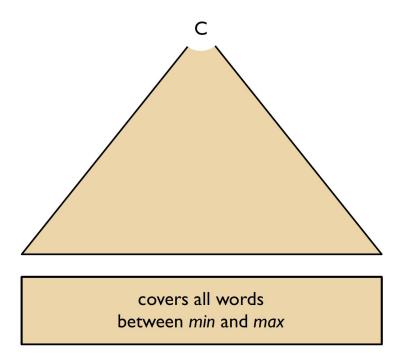
covers all words btw mid and max



Check through all C1, C2, mid



Parsing longer spans



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$$\begin{vmatrix} | lead | can | poison \\ 0 & 1 & 2 & 3 \end{vmatrix}$$

max = 1max = 2max = 3

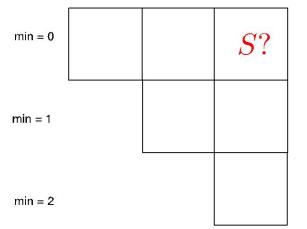


Chart (aka parsing triangle)

$$VP \rightarrow M V$$
 $VP \rightarrow V$

$$NP \to N$$

$$NP \to N \ NP$$

$$N \to can$$
$$N \to lead$$

$$N \rightarrow ieaa$$
 $N \rightarrow noisean$

$$N \to poison$$

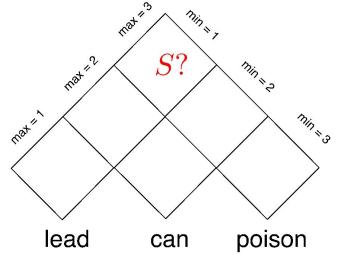
$$M \to can$$

$$M \to must$$

$$V \to poison$$

 $V \to lead$

0



$$VP \to M V$$

 $VP \to V$

$$NP \to N$$

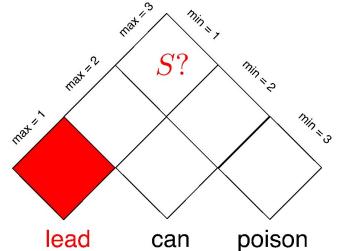
$$NP \to N \ NP$$

$$N \rightarrow can$$
 $N \rightarrow lead$ $N \rightarrow poison$

$$M \to can$$
 $M \to must$

$$V o poison$$
 $V o lead$

	lead	can	pois	son
0	-	1	2	3



$$VP \rightarrow M V$$
 $VP \rightarrow V$

$$NP \to N$$

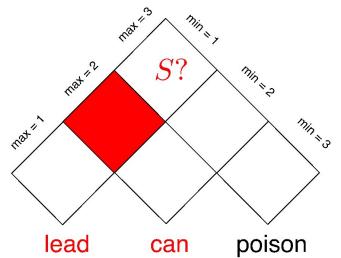
$$NP \to N \ NP$$

$$N \to can$$
$$N \to lead$$

$$N \to poison$$

$$M \to can$$
 $M \to must$

$$V o poison$$
 $V o lead$



$$VP \rightarrow M V$$
 $VP \rightarrow V$

$$NP \to N$$

$$NP \to N \ NP$$

$$N \to can$$
$$N \to lead$$

$$N \to poison$$

$$M \to can$$

$$M \to must$$

$$V \rightarrow poison$$

 $V \rightarrow lead$

min = 0		S?
min = 1		
min = 2		

max = 2

max = 3

max = 1

$$VP \to M V$$

 $VP \to V$

$$NP \to N$$

$$NP \to N \ NP$$

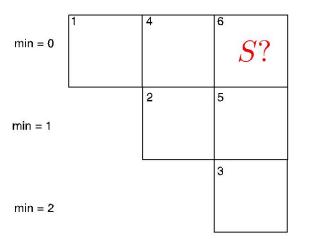
$$N o can$$
 $N o lead$ $N o poison$

$$M \to can$$

$$M \to must$$

$$V \rightarrow poison$$
 $V \rightarrow lead$

max = 1	max = 2	max = 3



$$VP \rightarrow M \ V$$

 $VP \rightarrow V$

$$NP \to N$$

$$NP \to N \ NP$$

$$N o can$$
 $N o lead$ $N o poison$

$$M \to can$$

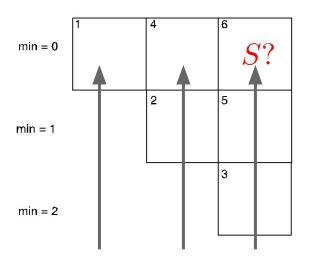
$$M \to must$$

$$V \rightarrow poison$$
 $V \rightarrow lead$

max	=	1
	_	•

$$max = 2$$

$$max = 3$$



$$VP \to M V$$
 $VP \to V$

$$NP \to N$$

$$NP \to N \ NP$$

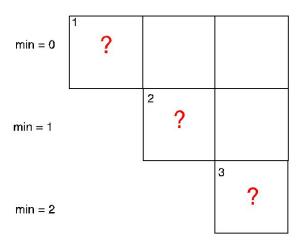
$$N o can$$
 $N o lead$ $N o poison$

$$M \to can$$

$$M \to must$$

$$V \rightarrow poison$$
 $V \rightarrow lead$

$$max = 1$$
 $max = 2$ $max = 3$



$$VP \to M V$$
 $VP \to V$

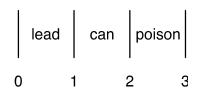
$$NP \to N$$

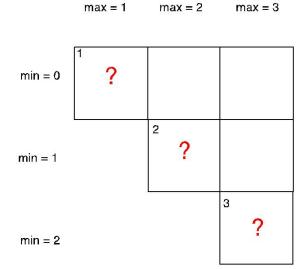
$$NP \to N \ NP$$

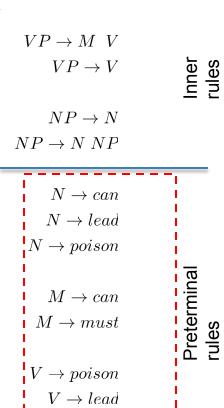
$$N o can$$
 $N o lead$ $N o poison$

$$M \to can$$
 $M \to must$

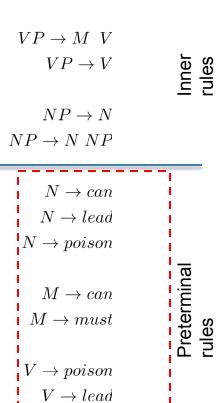
$$V o poison$$
 $V o lead$







max = 1	max = 2	max = 3



$$max = 1$$
 $max = 2$ $max = 3$

$$\min = 0 \quad \begin{bmatrix} 1 & N, V & 4 & \\ NP, VP & ? & \\ \end{bmatrix}$$

$$\min = 1 \quad \begin{bmatrix} 2 & N, M & \\ NP & \\ \end{bmatrix}$$

$$NP \quad \begin{bmatrix} 3 & N, V & \\ NP, VP & \\ \end{bmatrix}$$

$$NP, VP \quad \end{bmatrix}$$

$$VP \to M V$$
 $VP \to V$

$$NP \to N$$

$$NP \to N \ NP$$

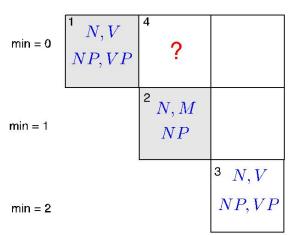
$$N \rightarrow can$$
 $N \rightarrow lead$
 $N \rightarrow poison$

$$M \to can$$

$$M \to must$$

$$V \rightarrow poison$$
 $V \rightarrow lead$

> max = 1max = 2max = 3



 $VP \rightarrow M V$

 $M \to can$ $M \to must$

 $N \rightarrow poison$

$$V \rightarrow poison$$
 $V \rightarrow lead$

$$\min = 0 \quad \begin{bmatrix} 1 & N, V & 4 & NP & \\ NP, VP & & & \\ \end{bmatrix}$$

$$\min = 1 \quad \begin{bmatrix} 2 & N, M & \\ & NP & \\ & & \\ \end{bmatrix}$$

$$\min = 2 \quad \begin{bmatrix} 3 & N, V & \\ & NP, VP & \\ \end{bmatrix}$$

max = 2

max = 3

max = 1

 $VP \rightarrow M V$ $VP \rightarrow V$

 $NP \to N$ $NP \rightarrow N NP$

$$N \to can$$

$$N \to lead$$

$$N \to poison$$

$$M \to can$$

$$M \to must$$

$$V \rightarrow poison$$
 $V \rightarrow lead$

$$max = 1$$
 $max = 2$ $max = 3$

$$\min = 0 \quad \begin{bmatrix} 1 & N, V & 4 & NP \\ NP, VP & & & \\ \end{bmatrix}$$

$$\min = 1 \quad \begin{bmatrix} 2 & N, M & 5 \\ & NP & & \\ \end{bmatrix}$$

$$NP \quad \begin{bmatrix} 3 & N, V \\ & NP, VP \\ \end{bmatrix}$$

$$NP, VP \quad \begin{bmatrix} 3 & N, V \\ & & \\ \end{bmatrix}$$

$$VP \to M V$$
 $VP \to V$

$$NP \to N$$

$$NP \to N \ NP$$

$$N o can$$
 $N o lead$ $N o poison$

$$M \to can$$

$$M \to must$$

$$V \rightarrow poison$$
 $V \rightarrow lead$

2

3

0

max = 1max = 2max = 3

$$\min = 0 \quad \begin{bmatrix} 1 & N, V & 4 & NP \\ NP, VP & & & \\ \end{bmatrix}$$

$$\min = 1 \quad \begin{bmatrix} 2 & N, M & 5S, VP, \\ NP & & NP \\ \end{bmatrix}$$

$$\min = 2 \quad \begin{bmatrix} 3 & N, V \\ NP, VP \\ \end{bmatrix}$$

$$NP \to N$$

$$NP \to N NP$$

$$N o can$$
 $N o lead$ $N o poison$

$$M \to can$$
 $M \to must$

$$V o poison \ V o lead$$

max = 1max = 2max = 3

$$\min = 0 \quad \begin{bmatrix} 1 & N, V & 4 & NP & 6 \\ NP, VP & & & ? \\ \end{bmatrix}$$

$$\min = 1 \quad \begin{bmatrix} 2 & N, M & 5S, VP, \\ NP & & NP \\ \end{bmatrix}$$

$$\min = 2 \quad \begin{bmatrix} 3 & N, V \\ NP, VP \\ \end{bmatrix}$$

 $VP \rightarrow M V$ $VP \rightarrow V$

$$NP \to N$$

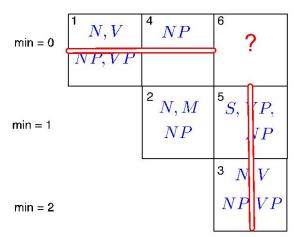
$$NP \to N \ NP$$

$$N
ightarrow can$$
 $N
ightarrow lead$ $N
ightarrow poison$

$$M \to can$$
 $M \to must$

$$V \rightarrow poison$$
 $V \rightarrow lead$

$$max = 1$$
 $max = 2$ $max = 3$



$$VP \to M V$$

$$VP \to V$$

$$NP \to N$$

$$NP \to N \ NP$$

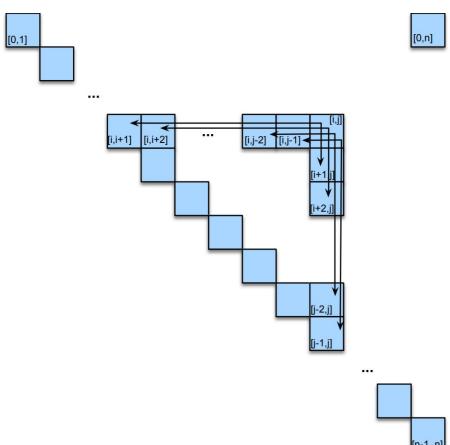
$$N o can$$
 $N o lead$ $N o poison$

$$M \to can$$

$$M \to must$$

$$V o poison$$
 $V o lead$





	lead	can	poisor	ו
0	1	1	2	3

max = 1max = 2max = 3

 ^{6}S , NPNPmin = 0NP, VPmid=1 $^{5}S, VP,$ N, Mmin = 1NPNP|3|N,VNP, VPmin = 2

 $VP \rightarrow M V$ $VP \rightarrow V$

 $NP \to N$ $NP \rightarrow N NP$

> $N \to can$ $N \rightarrow lead$

 $N \rightarrow poison$

 $M \to can$ $M \to must$

 $V \rightarrow poison$ $V \rightarrow lead$

$$max = 1$$
 $max = 2$ $max = 3$

mid=2

$$\min = 0 \quad \begin{bmatrix} 1 & N, V & 4 & NP & 6 & S, NP \\ NP, VP & & & S(?!) \end{bmatrix}$$

$$\min = 1 \quad \begin{bmatrix} 2 & N, M & 5 \\ NP & & NP \end{bmatrix}$$

$$\min = 2 \quad \begin{bmatrix} 3 & N, V \\ NP, VP \end{bmatrix}$$

$$VP \to M V$$
 $VP \to V$

$$NP \to N$$

$$NP \to N \ NP$$

$$N o can$$
 $N o lead$ $N o poison$

$$M \to can$$
 $M \to must$

$$V \rightarrow poison$$
 $V \rightarrow lead$

$$max = 1$$
 $max = 2$ $max = 3$

$$\min = 0 \quad \begin{bmatrix} 1 & N, V & 4 & NP & 6 & S, NP \\ NP, VP & & & S(?!) \end{bmatrix}$$

$$\min = 1 \quad \begin{bmatrix} 2 & N, M & 5 & S, VP, \\ NP & & NP \end{bmatrix}$$

$$\min = 2 \quad \begin{bmatrix} 3 & N, V & \\ NP, VP & \\ NP, VP & \end{bmatrix}$$

Apparently the sentence is ambiguous for the grammar: (as the grammar overgenerates)

$$\begin{array}{c} VP \rightarrow M \ V \\ VP \rightarrow V \end{array}$$

$$NP \to N$$

$$NP \to N \ NP$$

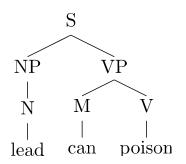
$$N o can$$
 $N o lead$ $N o poison$

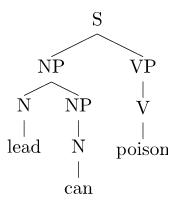
$$M \to can$$
 $M \to must$

$$V \rightarrow poison$$

 $V \rightarrow lead$

Ambiguity





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

Yulia Tsvetkov 102 Undergrad NLP 2022