

# Grammars and Constituency Parsing

JURAFSKY AND MARTIN CHAPTERS 12 AND 13

# Reminders



QUIZ IS DUE TONIGHT BY  
11:59PM



HOMEWORK 7 DUE DATE IS  
POSTPONED TO 3/18

# Formal Definition of a CFG

A context-free grammar  $G$  is defined by four parameters:  $N$ ,  $\Sigma$ ,  $R$ ,  $S$

**$N$**  is a set of **non-terminal symbols** (or variables)

- In NLP, we often use the Penn Treebank tag set

**$\Sigma$**  is set of **terminal symbols**

- These are the words (also sometimes called the leaf nodes of the parse tree)

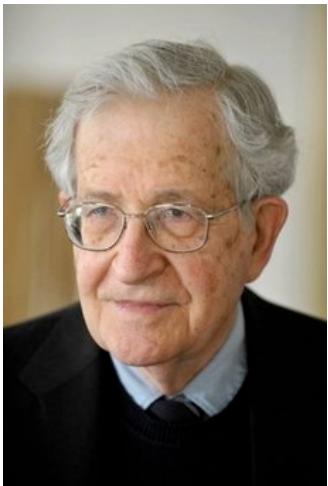
**$R$**  is a set of production rules, each of the form  $A \rightarrow \beta$

- $S \rightarrow Aux\ NP\ VP$
- $Nominal \rightarrow Nominal\ Gerund\ VP$  (recursive)

**$S$**  is the start symbol (a non-terminal)

# Where do grammars come from?

Linguists



Noam Chomsky

Write symbolic grammar (CFG or often richer) and lexicon

$S \rightarrow NP\ VP$

$NN \rightarrow interest$

$NP \rightarrow (DT)\ NN$

$NNS \rightarrow rates$

$NP \rightarrow NN\ NNS$

$NNS \rightarrow raises$

$NP \rightarrow NNP$

$VBP \rightarrow interest$

$VP \rightarrow V\ NP$

$VBZ \rightarrow rates$



Ivan Sag



Joan Bresnan

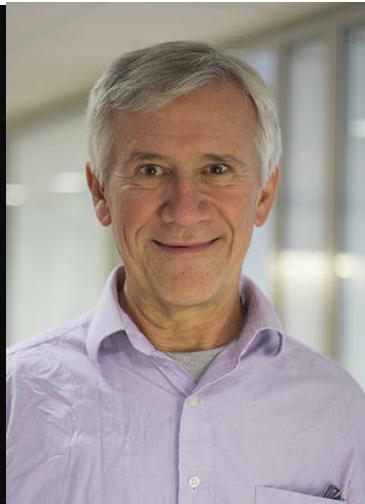
# Coverage of grammars

Manually written grammars have two problems.

1. **Coverage** – they tend to only cover a subset of a language, since actual language use is widely varied and hugely complex. Therefore writing a broad coverage grammar by hand takes an entire career.
2. **Overgeneration** – writing rules that will only generate grammatical sentences is hard. Broad coverage tends to come at the expense of overgeneration.



Ann Copestake



Dan Flickinger



Mark Steedman

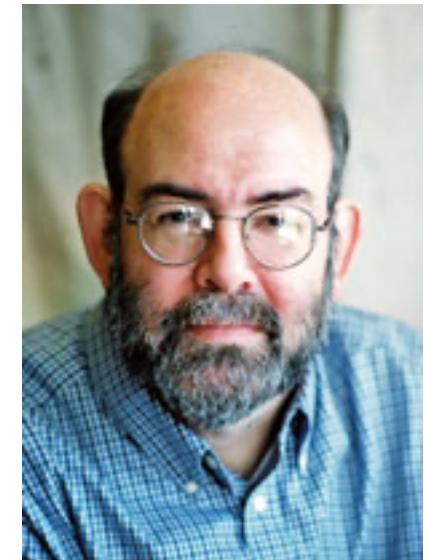


Arvind Joshi

# Treebanks as grammar

Treebanks == data

Initially, building a treebank might seem like it would be a lot slower and less useful than building a grammar.



Mitch Marcus

However, a treebank gives us many things

- Reusability of the labor
  - Many parsers, POS taggers, etc.
  - Valuable resource for linguistics
- Broad coverage
- Frequencies and distributional information
- A way to evaluate systems



Scholar About 24,900 results (0.07 sec)

## Building a large annotated corpus of English: The Penn Treebank

M Marcus, B Santorini, MA Marcinkiewicz - 1993 - repository.upenn.edu

In this paper, we review our experience with constructing one such large annotated corpus--the **Penn Treebank**, a corpus consisting of over 4.5 million words of American English.

During the first three-year phase of the **Penn Treebank** Project (1989-1992), this corpus has ...

☆ 99 Cited by 7990 Related articles All 30 versions >>



Semantic Scholar

5,604 Citations

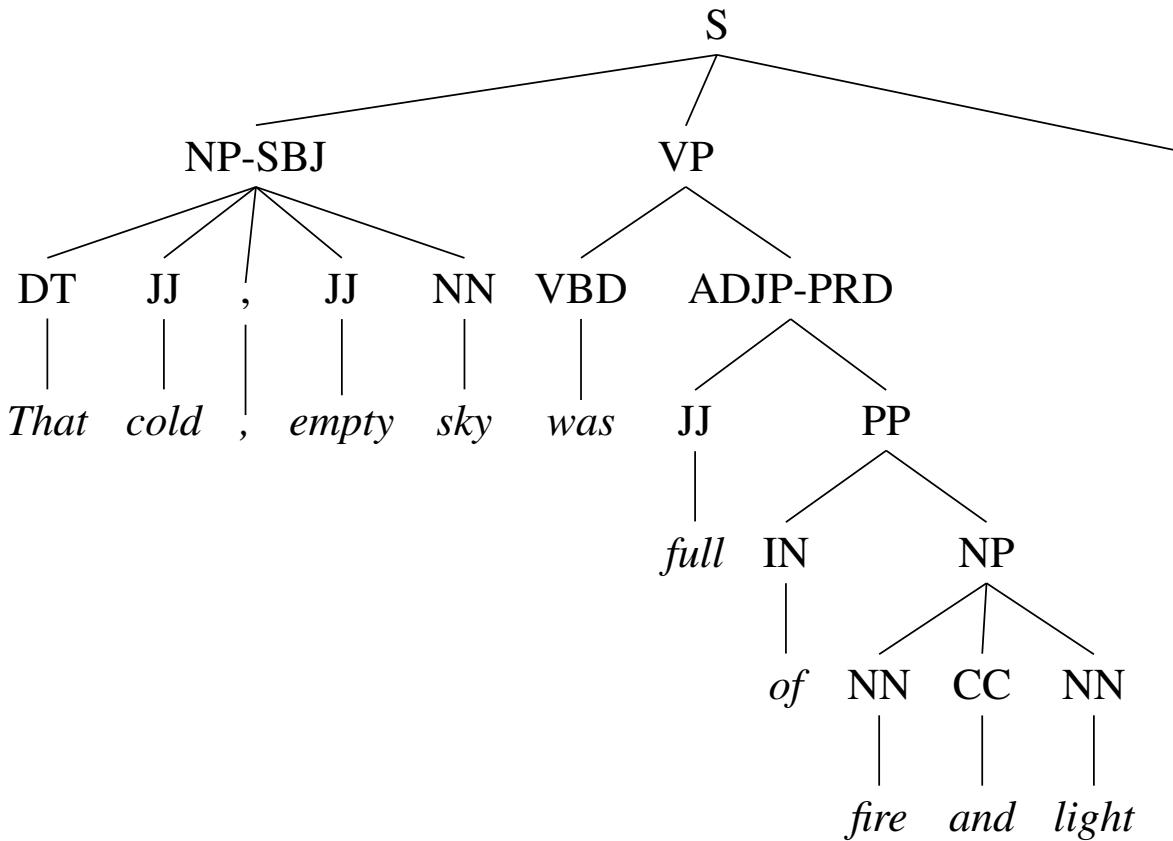
1,253 Highly Influenced Papers

3,033 Cite Methods

1,658 Cite Background

50 Cite Results

i



Extracted rules		
$S \rightarrow NP\ VP\ .$	$DT \rightarrow That$	$JJ \rightarrow full$
$NP \rightarrow DT\ JJ\ ,\ JJ\ NN$	$JJ \rightarrow cold$	$IN \rightarrow of$
$VP \rightarrow VBD\ ADJP$	$, \rightarrow ,$	$NN \rightarrow fire$
$ADJP \rightarrow JJ\ PP$	$JJ \rightarrow empty$	$CC \rightarrow and$
$PP \rightarrow IN\ NP$	$NN \rightarrow sky$	$NN \rightarrow light$
$NP \rightarrow NN\ CC\ NN$	$VBD \rightarrow was$	

# Some of the rules, with counts

40717 PP → IN NP	100 VP → VBD PP-PRD
33803 S → NP-SBJ VP	100 PRN → : NP :
22513 NP-SBJ → -NONE-	100 NP → DT JJS
21877 NP → NP PP	100 NP-CLR → NN
20740 NP → DT NN	99 NP-SBJ-1 → DT NNP
14153 S → NP-SBJ VP .	98 VP → VBN NP PP-DIR
12922 VP → TO VP	98 VP → VBD PP-TMP
11881 PP-LOC → IN NP	98 PP-TMP → VBG NP
11467 NP-SBJ → PRP	97 VP → VBD ADVP-TMP VP
11378 NP → -NONE-	...
11291 NP → NN	10 WHNP-1 → WRB JJ
...	10 VP → VP CC VP PP-TMP
989 VP → VBG S	10 VP → VP CC VP ADVP-MNR
985 NP-SBJ → NN	10 VP → VBZ S , SBAR-ADV
983 PP-MNR → IN NP	10 VP → VBZ S ADVP-TMP
983 NP-SBJ → DT	
969 VP → VBN VP	

4500 rules  
for VP!

# Redundant rules?

The Penn Treebank by this series of rules:

$$\begin{aligned} \text{VP} &\rightarrow \text{VBD } \text{NP } \text{PP} \\ \text{VP} &\rightarrow \text{VBD } \text{NP } \text{PP } \text{PP} \\ \text{VP} &\rightarrow \text{VBD } \text{NP } \text{PP } \text{PP } \text{PP} \\ \text{VP} &\rightarrow \text{VBD } \text{NP } \text{PP } \text{PP } \text{PP } \text{PP} \end{aligned}$$

We can also represent that with a two-rule grammar as

$$\begin{aligned} \text{VP} &\rightarrow \text{VBD } \text{NP } \text{PP} \\ \text{VP} &\rightarrow \text{VP } \text{PP} \end{aligned}$$

# NP rules

NP → DT JJ NN  
NP → DT JJ NNS  
NP → DT JJ NN NN  
NP → DT JJ JJ NN  
NP → DT JJ CD NNS  
NP → RB DT JJ NN NN  
NP → RB DT JJ JJ NNS  
NP → DT JJ JJ NNP NNS  
NP → DT NNP NNP NNP NNP JJ NN  
NP → DT JJ NNP CC JJ JJ NN NNS  
NP → RB DT JJS NN NN SBAR  
NP → DT VBG JJ NNP NNP CC NNP  
NP → DT JJ NNS , NNS CC NN NNS NN  
NP → DT JJ JJ VBG NN NNP NNP FW NNP  
NP → NP JJ , JJ " SBAR " NNS

[DT The] [JJ state-owned] [JJ industrial]  
[VBG holding] [NN company] [NNP  
Instituto] [NNP Nacional] [FW de]  
[NNP Industria]

[NP Shearson's] [JJ easy-to-film], [JJ black-and-white]  
"[SBAR Where We Stand]" [NNS commercials]

# Chomsky normal form

Real rules extracted from the Penn Treebank can get crazy. We can derive an equivalent grammar by converting the rules into binary branching rules.

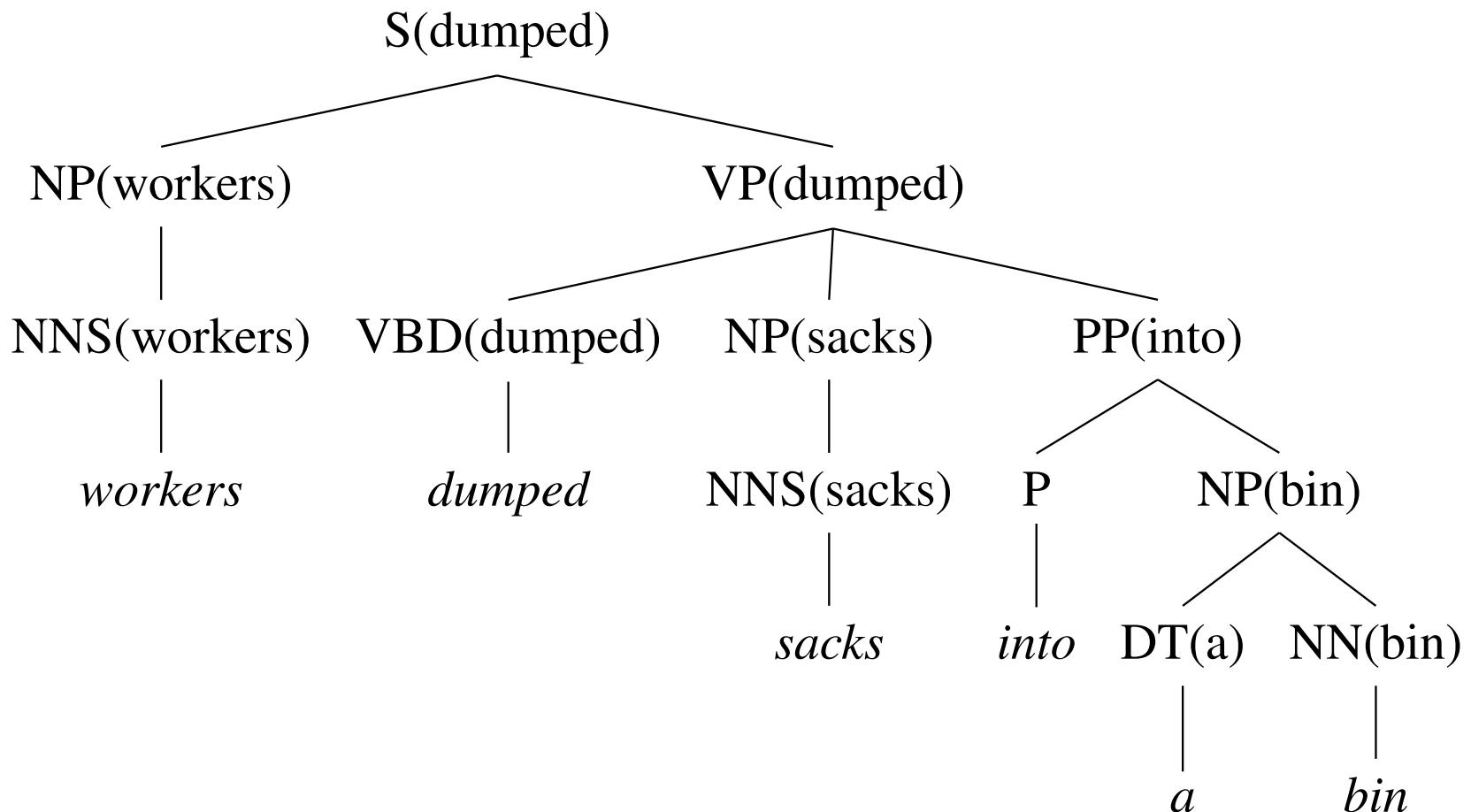
$$A \rightarrow B C D$$

can be converted to two rules:

$$\begin{aligned} A &\rightarrow B X \\ X &\rightarrow C D \end{aligned}$$

These are called Chomsky Normal Form rules. The resulting binary branching grammar is **weakly equivalent** because it generates the same set of strings but assigns different phrase structures to sentences.

# Lexical Heads



# Lexicalized Grammars

Unlike rules derived from the Penn Treebank, which tends to emphasize **phrase structure rules**, many modern syntactic theories emphasize the role of the **lexicon**. The lexicon can encode information like subcategorization frames.

1. HPSG – Head-driven phrase structure grammars
2. LFG – Lexical functional grammars
3. TAG – Tree adjoining Grammar
4. CCG – Combinatory Categorial Grammar

# Combinatory Categorial Grammar (CCG)

A set of categories, a **lexicon** that associates words with categories, and a set of rules that govern how categories combine in context.

word	category	
flight	N	atomic
Miami	NP	atomic
cancel	(S\NP)/NP	complex category / function

# Parsing in CCG

*United*      *serves*      *Miami*

Rules are simple:

$$X/Y \ Y \Rightarrow X$$

$$Y \ X\backslash Y \Rightarrow X$$

*forward function application*

*backward function application*

# Parsing in CCG

<i>We</i>	<i>flew</i>	<i>to</i>	<i>Geneva</i>	<i>and</i>	<i>drove</i>	<i>to</i>	<i>Chamonix</i>
$\overline{\text{NP}}$	$\overline{(\text{S} \setminus \text{NP})/\text{PP}}$	$\overline{\text{PP}/\text{NP}}$	$\overline{\text{NP}}$	$\overline{\text{CONJ}}$	$\overline{(\text{S} \setminus \text{NP})/\text{PP}}$	$\overline{\text{PP}/\text{NP}}$	$\overline{\text{NP}}$

Rules are simple:

$$X/Y \ Y \Rightarrow X$$

$$Y \ X \setminus Y \Rightarrow X$$

*forward function application*

*backward function application*

$$X \text{ CONJ } X \Rightarrow X$$

**Conjunction**

# CCG Bank

Julia Hockenmaier created a treebank for CCG.

It was created by translating phrase-structure trees from the Penn Treebank.

It resulted in 48,934 sentences paired with CCG derivations, and a lexicon with 44,000 words and 1200 categories.



Julia Hockenmaier

# Constituency Parsing

JURAFSKY AND MARTIN CHAPTER 13

# Headlines

Iraqi Head Seeks Arms

Juvenile Court to Try Shooting Defendant

Teacher Strikes Idle Kids

Stolen Painting Found by Tree

Kids Make Nutritious Snacks

Local High School Dropouts Cut in Half

British Left Waffles on Falkland Islands

Red Tape Holds Up New Bridges

Ban on Nude Dancing on Governor's Desk

Trump Wins on Economy, but More Lies Ahead

# Ambiguity

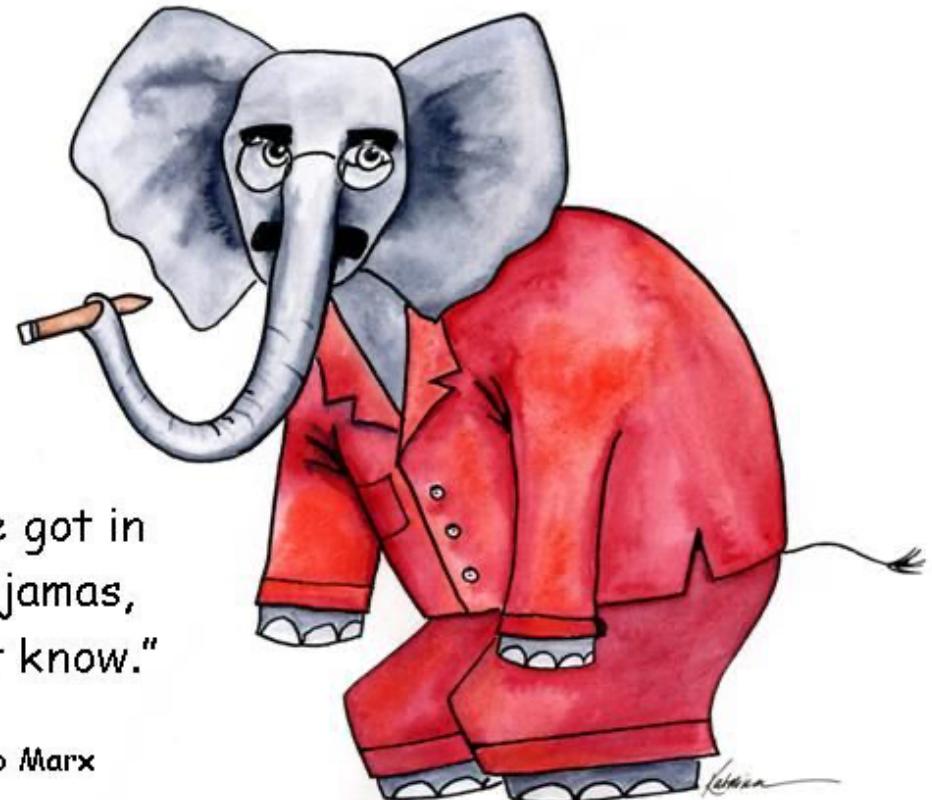
**Ambiguity** can arise because of words with **multiple senses** or **POS tags**.  
Many kinds of ambiguity are also structural.

"One morning I shot an elephant in my pajamas.

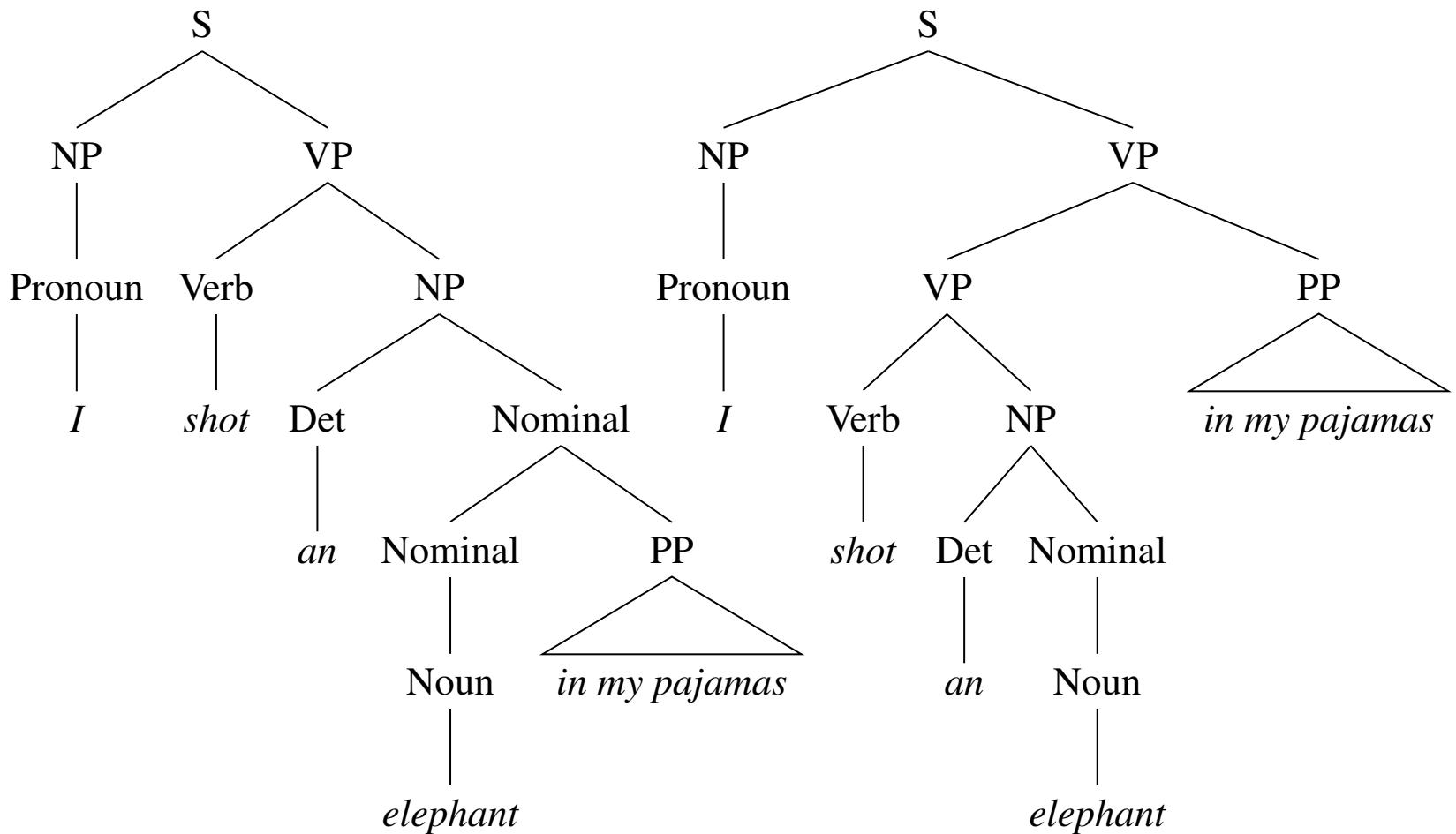


How he got in  
my pajamas,  
I don't know."

Groucho Marx



# Attachment Ambiguity



# Parsing Algorithms

NLP systems need to choose a single correct parse from many, many possible parses. They need to perform **syntactic disambiguation**.

Effective disambiguation algorithms require a variety of information to be integrated into parsing algorithms. Such information includes:

1. statistical information
2. semantic understanding
3. contextual knowledge

We'll start by looking at an efficient dynamic programming algorithm, and then see how to add statistics to it.

# The Parsing Problem

Given sentence  $x$  and grammar  $G$ ,

Recognition

Is sentence  $x$  in the grammar? If so, prove it.  
“Proof” is a deduction, valid parse tree.

Parsing

Show one or more derivations for  $x$  in  $G$ .

Even with small grammars, brute force grows exponentially!

“Book that flight”

# Left to Right?

The old man the boat.

The complex houses married and single soldiers and their families.

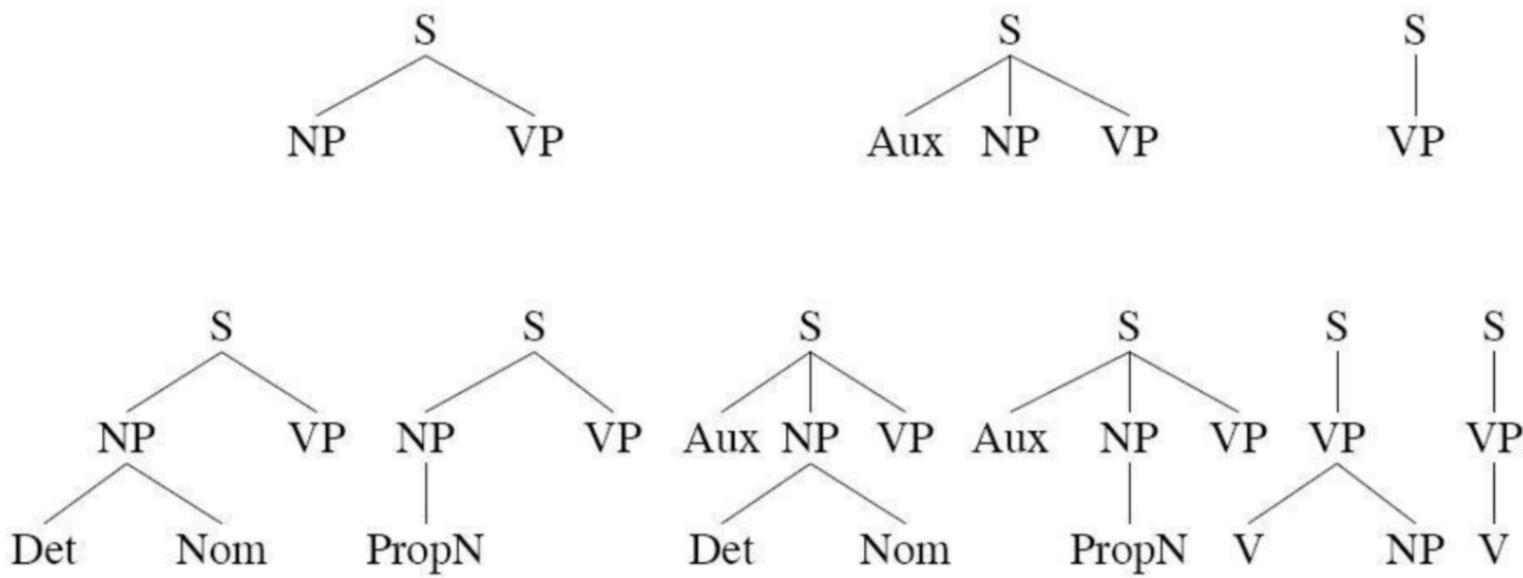
Garden Path Sentences

# Top Down Parsing

Considers only valid trees  
But are inconsistent with the words!

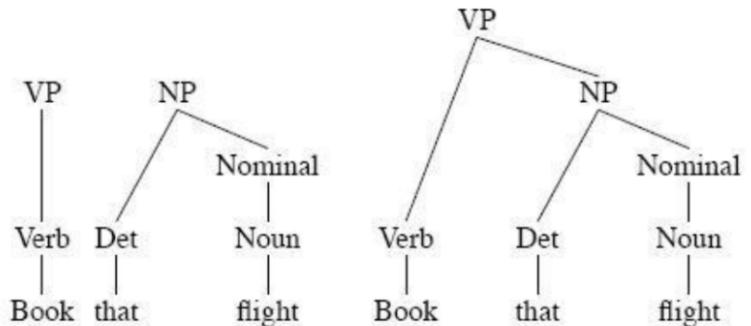
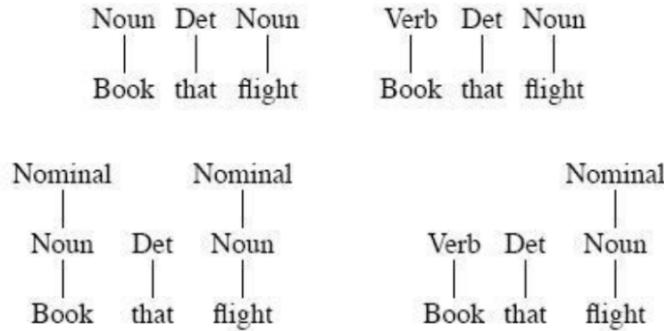
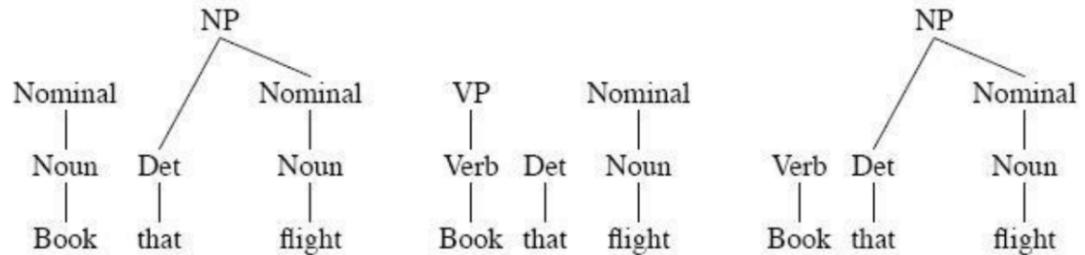
“Book that flight”

S



# Bottom-up Parsing

“Book that flight”



Builds only consistent trees  
But most of them are invalid (don't go anywhere)!

# Chomsky Normal Form

Context free grammar where all non-terminals to go:

- 2 non-terminals, or
- A single terminal

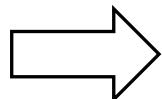
$$A \rightarrow B C$$

$$D \rightarrow w$$

Converting to CNF

Case 1

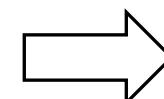
$$\begin{array}{l} A \rightarrow B \\ B \rightarrow C D \\ B \rightarrow w \end{array}$$



$$\begin{array}{l} A \rightarrow C D \\ A \rightarrow w \end{array}$$

Case 2

$$A \rightarrow B C D E$$



$$\begin{array}{l} A \rightarrow X E \\ X \rightarrow Y D \\ Y \rightarrow B C \end{array}$$

## Original Grammar

$S \rightarrow NP VP$

$S \rightarrow Aux NP VP$

$S \rightarrow VP$

$NP \rightarrow Pronoun$

$NP \rightarrow Proper-Noun$

$NP \rightarrow Det Nominal$

$Nominal \rightarrow Noun$

$Nominal \rightarrow Nominal Noun$

$Nominal \rightarrow Nominal PP$

$VP \rightarrow Verb$

$VP \rightarrow Verb NP$

$VP \rightarrow Verb NP PP$

$VP \rightarrow Verb PP$

$VP \rightarrow VP PP$

$PP \rightarrow Preposition NP$

## Chomsky Normal Form

$S \rightarrow NP VP$

$S \rightarrow X1 VP$

$X1 \rightarrow Aux NP$

$S \rightarrow book | include | prefer$

$S \rightarrow Verb NP$

$S \rightarrow X2 PP$

$S \rightarrow Verb PP$

$S \rightarrow VP PP$

$NP \rightarrow I | she | me$

$NP \rightarrow TWA | Houston$

$NP \rightarrow Det Nominal$

$Nominal \rightarrow book | flight | meal | money$

$Nominal \rightarrow Nominal Noun$

$Nominal \rightarrow Nominal PP$

$VP \rightarrow book | include | prefer$

$VP \rightarrow Verb NP$

$VP \rightarrow X2 PP$

$X2 \rightarrow Verb NP$

$VP \rightarrow Verb PP$

$VP \rightarrow VP PP$

$PP \rightarrow Preposition NP$

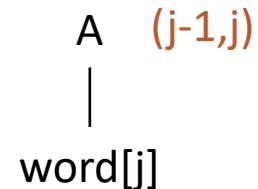
# Dynamic Programming

$\text{table}[i,j]$  = Set of all valid non-terminals for the constituent span  $(i,j)$

Base case

Rule:  $A \rightarrow \text{word}[j]$

A should be in  $\text{table}[j-1,j]$



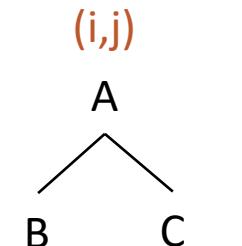
Recursion

Rule:  $A \rightarrow B C$

If you find a k such that

B is in  $\text{table}[i,k]$ , and

C is in  $\text{table}[k,j]$ , then A should be in  $\text{table}[i,j]$



# Dynamic Programming

$$S \in \text{table}[0, n]$$

table[i,j] = Set of all valid non-terminals for the constituent span (i,j)

Base case

Rule:  $A \rightarrow \text{word}[j] \leftarrow A \in \text{table}[\underline{j-1}, \underline{j}]$

A should be in  $\text{table}[\underline{j-1}, \underline{j}]$

$\begin{array}{c} A \\ \text{---} \\ \text{word}[j] \end{array}$

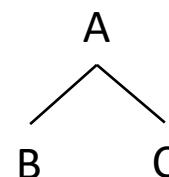
Recursion

Rule:  $A \rightarrow B C$

If you find a k such that

B is in  $\text{table}[i,k]$ , and

C is in  $\text{table}[k,j]$ , then A should be in  $\text{table}[i,j]$



(i,j)  
A  
|  
B C  
(i,k) (k,j)

# CKY Algorithm

```
function CKY-PARSE(words, grammar) returns table
    for j  $\leftarrow$  from 1 to LENGTH(words) do
        for all {A | A  $\rightarrow$  words[j]  $\in$  grammar}
            table[j - 1, j]  $\leftarrow$  table[j - 1, j]  $\cup$  A
    for i  $\leftarrow$  from j - 2 downto 0 do
        for k  $\leftarrow$  i + 1 to j - 1 do
            for all {A | A  $\rightarrow$  BC  $\in$  grammar and B  $\in$  table[i, k] and C  $\in$  table[k, j]}
                table[i, j]  $\leftarrow$  table[i, j]  $\cup$  A
```

# CKY Algorithm

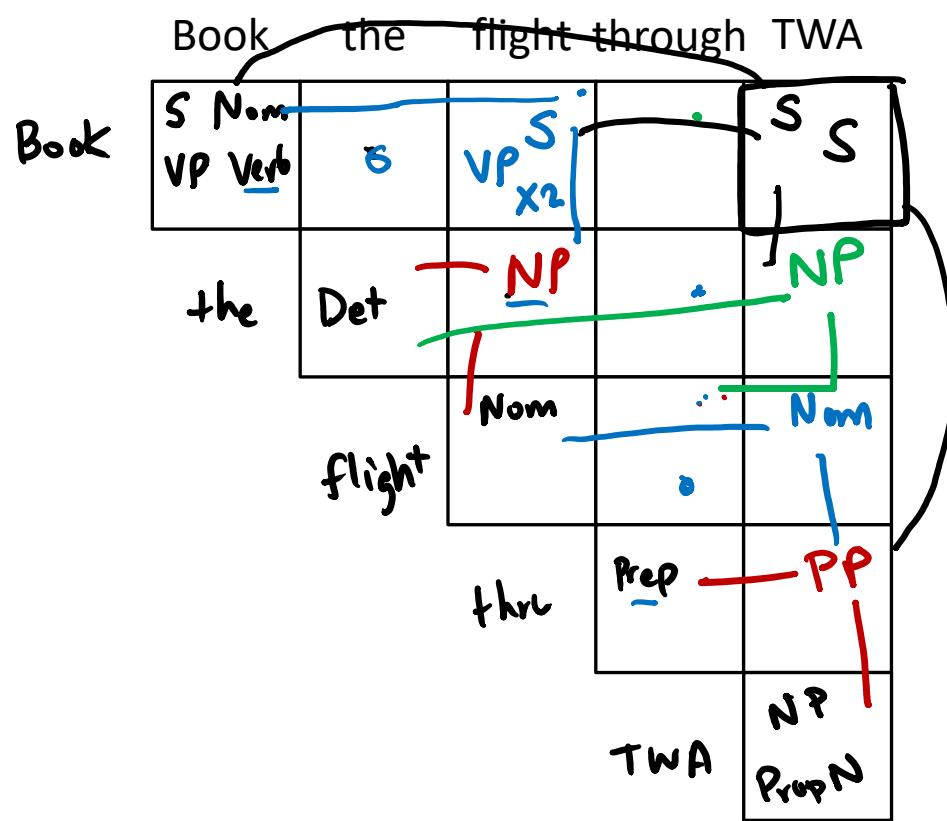
$S \rightarrow NP VP$   
 $S \rightarrow X1 VP$   
 $X1 \rightarrow Aux NP$   
 $S \rightarrow book | include | prefer$   
 $S \rightarrow Verb NP$   
 $S \rightarrow X2 PP$   
 $S \rightarrow Verb PP$   
 $S \rightarrow VP PP$   
 $NP \rightarrow I | she | me$   
 $NP \rightarrow TWA | Houston$   
 $NP \rightarrow Det Nominal$   
 $Nominal \rightarrow book | flight | meal | money$   
 $Nominal \rightarrow Nominal Noun$   
 $Nominal \rightarrow Nominal PP$   
 $VP \rightarrow book | include | prefer$   
 $VP \rightarrow Verb NP$   
 $VP \rightarrow X2 PP$   
 $X2 \rightarrow Verb NP$   
 $VP \rightarrow Verb PP$   
 $VP \rightarrow VP PP$   
 $PP \rightarrow Preposition NP$

Book    the    flight    through    TWA

[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	[1,2]	[1,3]	[1,4]	[1,5]
		[2,3]	[2,4]	[2,5]
			[3,4]	[3,5]
				[4,5]

# CKY Algorithm

$S \rightarrow NP VP$   
 $S \rightarrow X1 VP$   
 $X1 \rightarrow Aux NP$   
 $S \rightarrow book | include | prefer -$   
 $S \rightarrow Verb NP$  underline  
 $S \rightarrow X2 PP$  ←  
 $S \rightarrow Verb PP$  ←  
 $S \rightarrow VP PP$   
 $NP \rightarrow I | she | me$   
 $NP \rightarrow TWA | Houston -$   
 $NP \rightarrow Det Nominal$  ←  
 $Nominal \rightarrow book | flight | meal | money$   
 $Nominal \rightarrow Nominal Noun$   
 $Nominal \rightarrow Nominal PP$  underline  
 $VP \rightarrow book | include | prefer -$   
 $VP \rightarrow Verb NP$  underline  
 $VP \rightarrow X2 PP$   
 $X2 \rightarrow Verb NP$  underline  
 $VP \rightarrow Verb PP$   
 $VP \rightarrow VP PP$   
 $PP \rightarrow Preposition NP$  ←

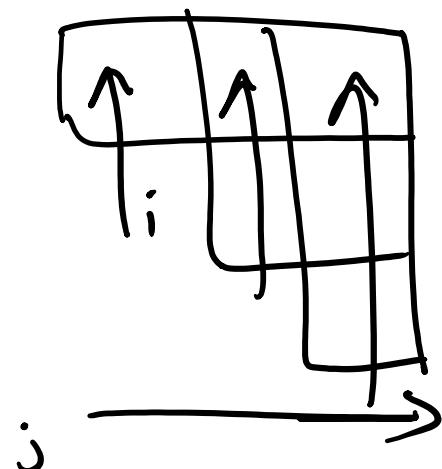


# CKY Algorithm

**function** CKY-PARSE(*words*, *grammar*) **returns** *table*

```
    for j from 1 to LENGTH(words) do
        for all {A | A  $\rightarrow$  words[j]  $\in$  grammar} do
            table[j - 1, j]  $\leftarrow$  table[j - 1, j]  $\cup$  A
    for i from j - 2 downto 0 do
        for k from i + 1 to j - 1 do
            for all {A | A  $\rightarrow$  BC  $\in$  grammar and B  $\in$  table[i, k] and C  $\in$  table[k, j] } do
                table[i, j]  $\leftarrow$  table[i, j]  $\cup$  A
```

*|R|*



# CKY Algorithm: Complexity

$|N|$ : Number of non-terminals

$|R|$ : Number of rules

$n$ : Number of tokens in the sentence

Memory

Time

# CKY Algorithm: Complexity

$|N|$ : Number of non-terminals

$|R|$ : Number of rules

$n$ : Number of tokens in the sentence

Memory

$$O(n^2 |N|)$$

Time

$$O(n^3 |R|)$$

# Outline

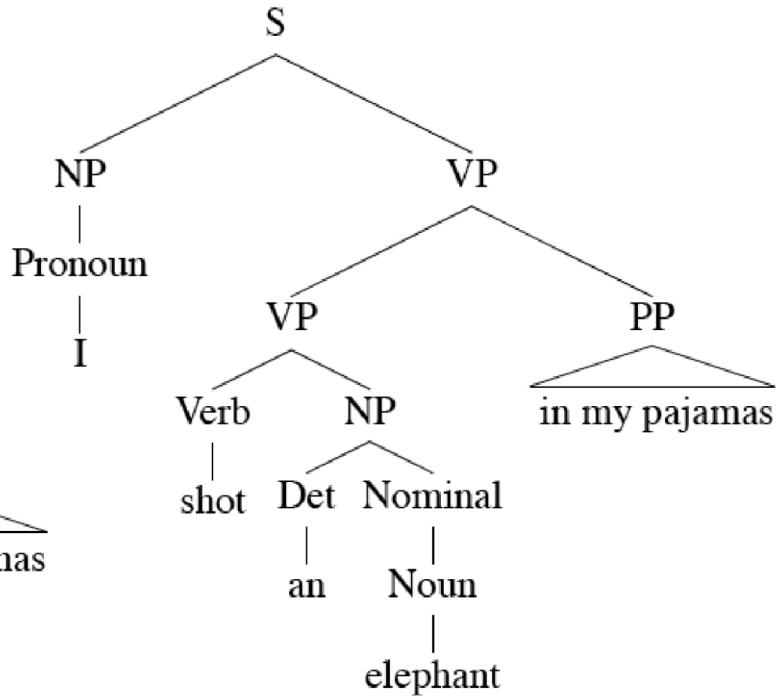
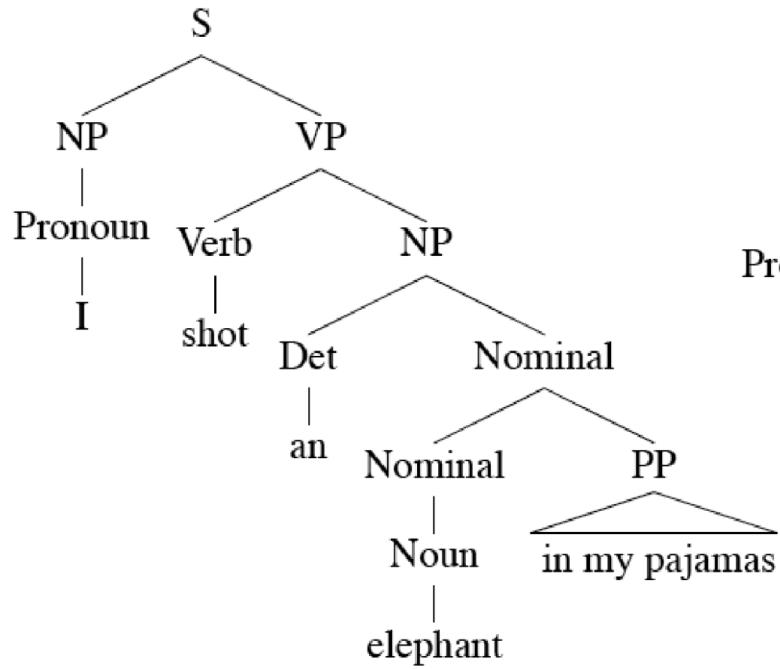
Parsing: CKY Algorithm

Extensions: Probabilistic and Lexicalized

Dependency Parsing

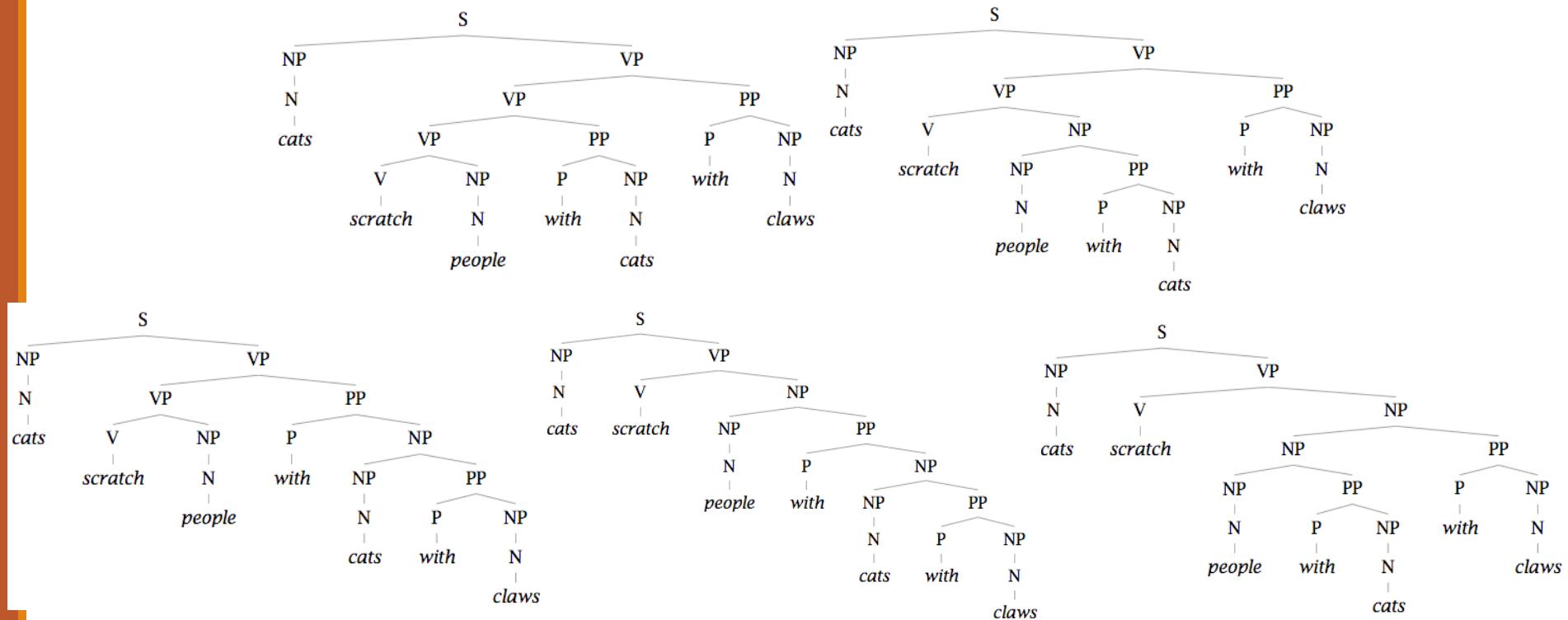
# Ambiguity: Which parse?

I shot an elephant in my pajamas.



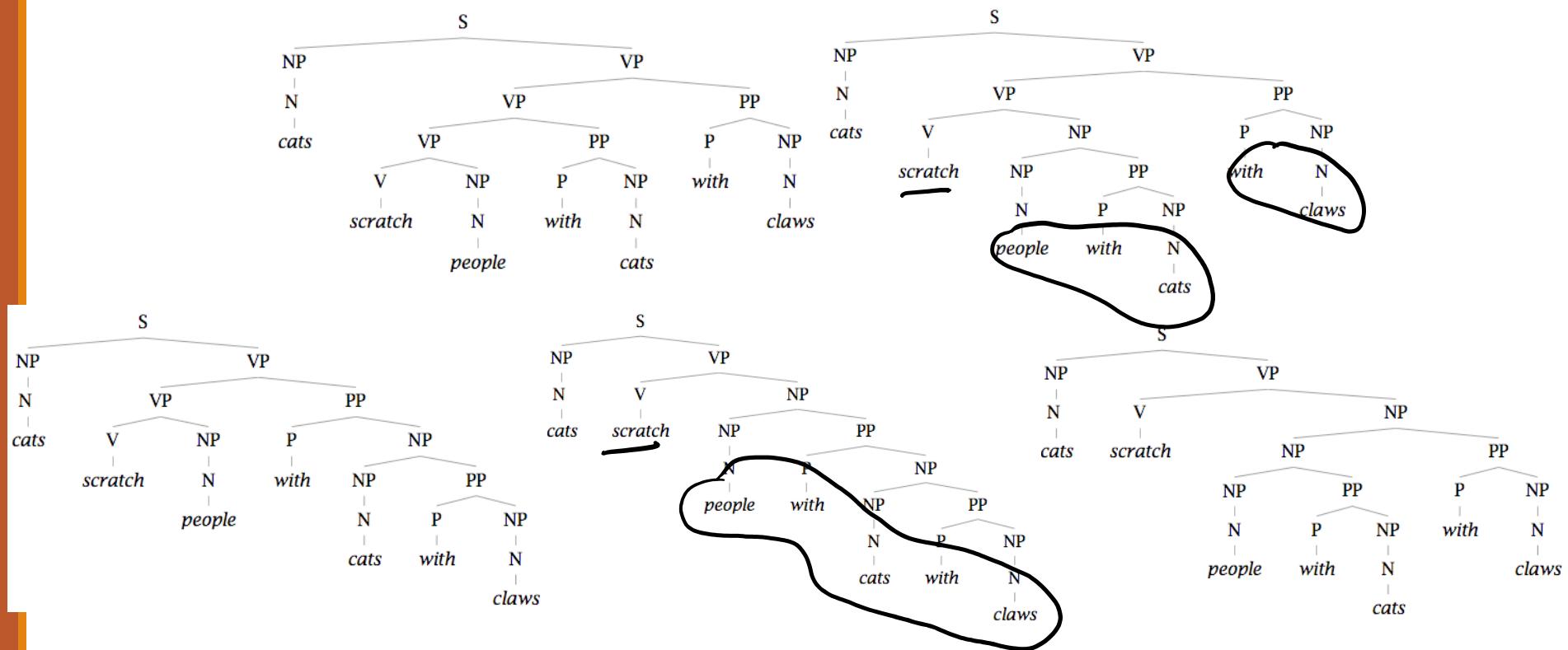
# Finding the Best Parse Tree

Cats scratch people with cats with claws.



# Finding the Best Parse Tree

Cats scratch people with cats with claws.



# Probabilistic CFGs

Same as a regular context-free grammar:

- Terminal, non-terminals, and rules
- Additionally, attach a probability to each rule!

Rule:  $A \rightarrow B C$

Probability:  $P(A \rightarrow B C | A)$

Compute the probability of a parse tree:

# Probabilistic CFGs

Same as a regular context-free grammar:

- Terminal, non-terminals, and rules
- Additionally, attach a probability to each rule!

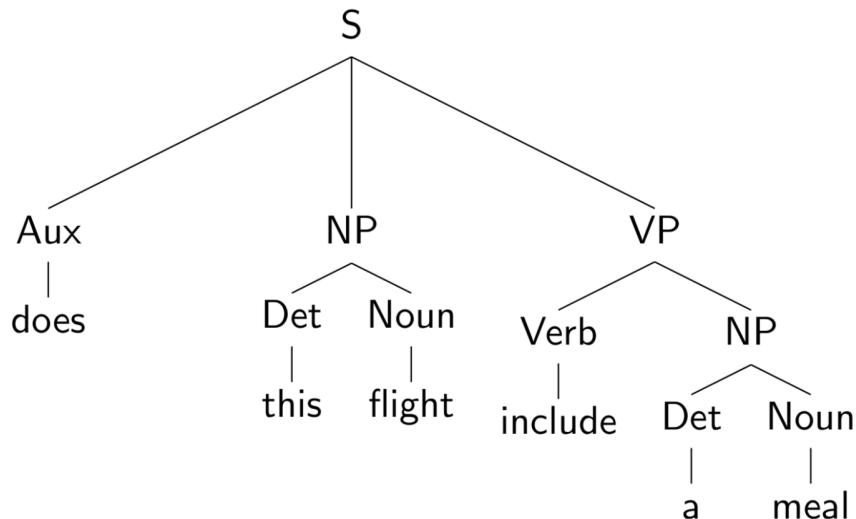
Rule:  $A \rightarrow B C$

Probability:  $P(A \rightarrow B C | A)$

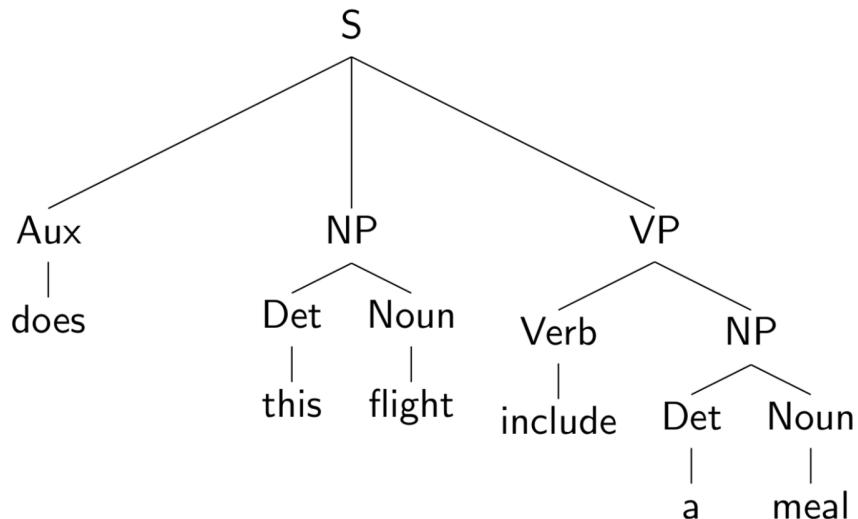
Compute the probability of a parse tree:

$$\prod_{A \rightarrow BC \in T} P(A \rightarrow BC | A)$$

# Example of a PCFG



# Example of a PCFG



$P(Aux \mid NP \mid VP \mid S)$

$P(\text{does} \mid AUX)$

$P(\text{Det} \mid \text{Noun} \mid NP)$

$P(\text{this} \mid \text{DET}) \quad P(\text{flight} \mid \text{Noun})$

⋮

# Estimating the probabilities

# Estimating the probabilities

$$P(\alpha \rightarrow \beta | \alpha) = \frac{\# \alpha \rightarrow \beta}{\# \alpha}$$

# The Parsing Problem

Given sentence  $x$  and grammar  $G$ ,

Recognition

Is sentence  $x$  in the grammar? If so, prove it.  
“Proof” is a deduction, valid parse tree.

Parsing

Show one or more derivations for  $x$  in  $G$ .

$$\underset{t \in T_x}{\operatorname{argmax}} p(t \mid x)$$

Even with small grammars, grows exponentially!

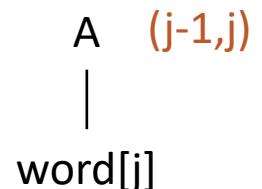
# Probabilistic CKY Algorithm

$T[i,j,A]$  = Probability of the best parse with root A for the span  $(i,j)$

Base case

Rule:  $P(A \rightarrow word[j])$

$$T[j-1,j,A] = P(word[j] \mid A)$$

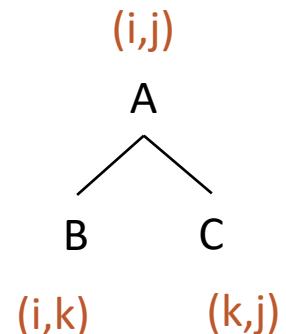


Recursion

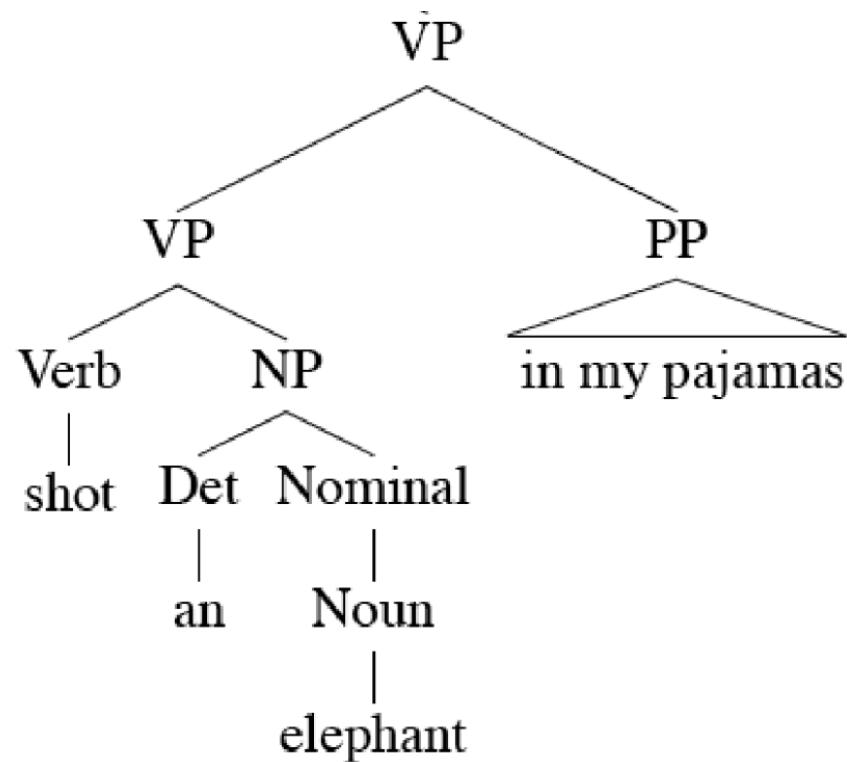
Rule:  $P(A \rightarrow B C)$

Try every position k, and every non-terminal pair:

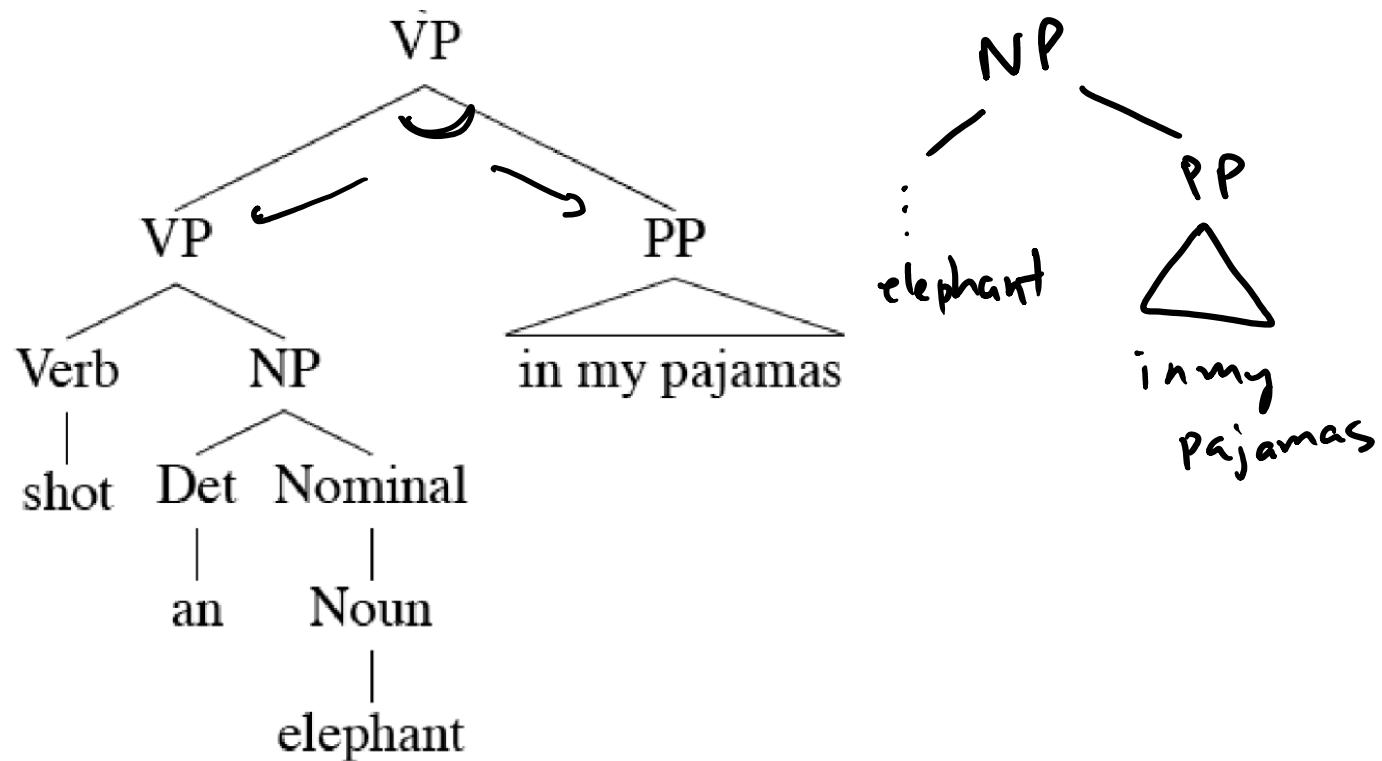
$$T[i,j,A] = \max_k P(B C \mid A) T[i,k,B] T[k,j,C]$$



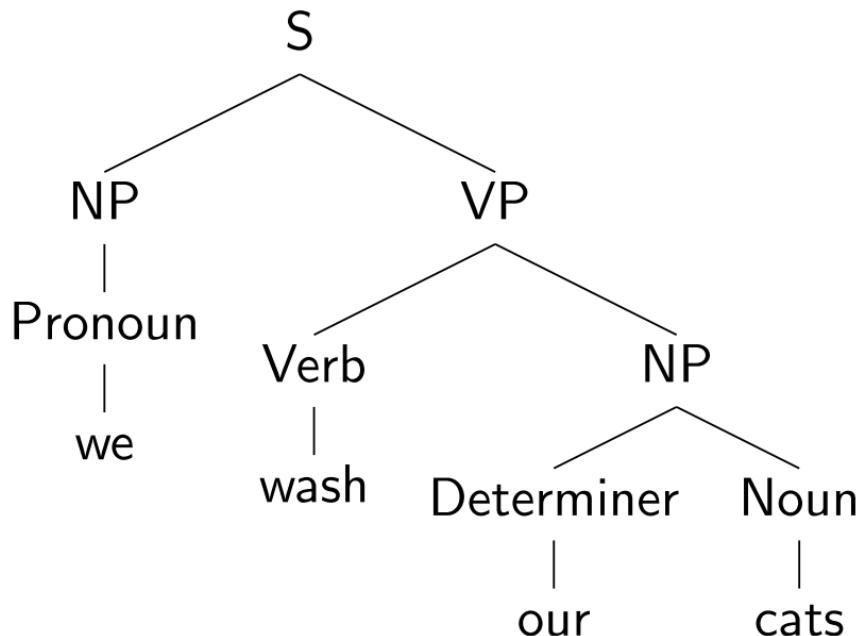
# Lexicalized PCFGs



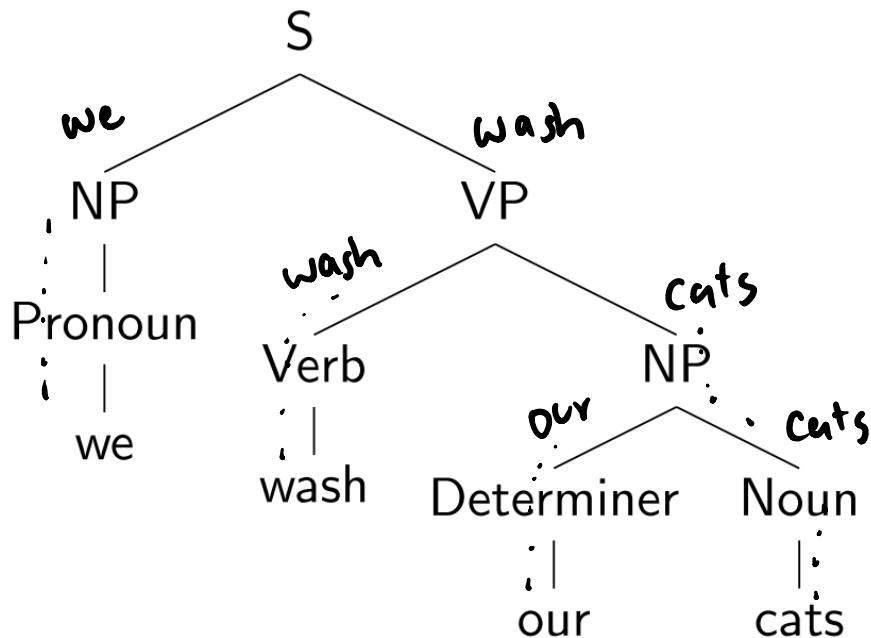
# Lexicalized PCFGs



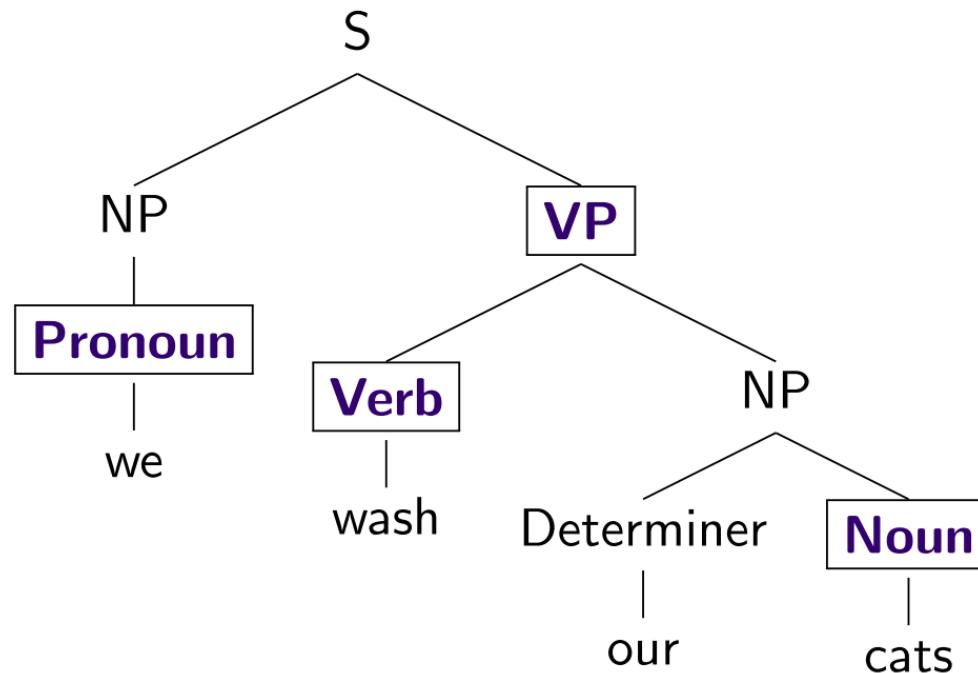
# Lexicalizing a CFG



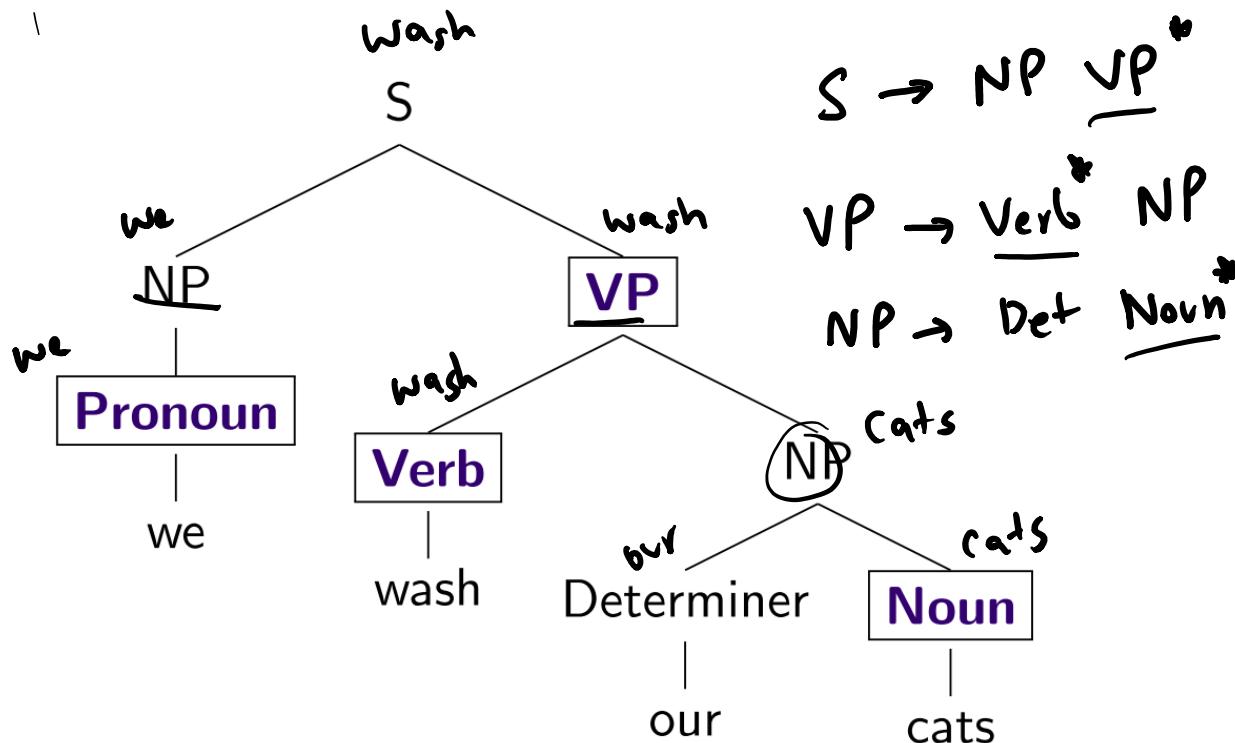
# Lexicalizing a CFG



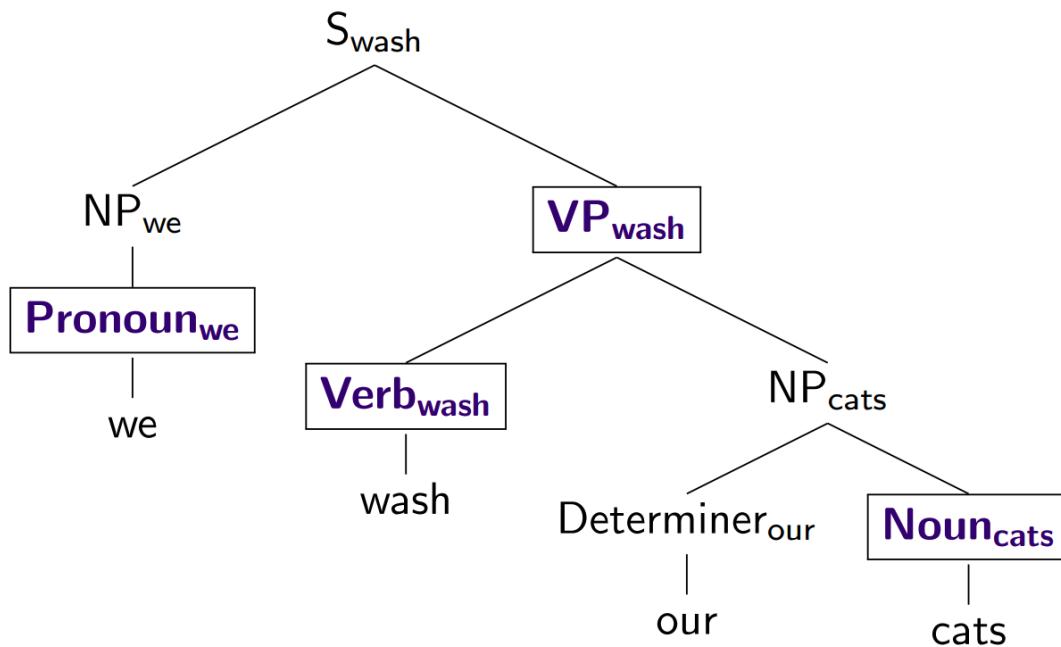
# Lexicalizing a CFG



# Lexicalizing a CFG



# Lexicalizing a CFG



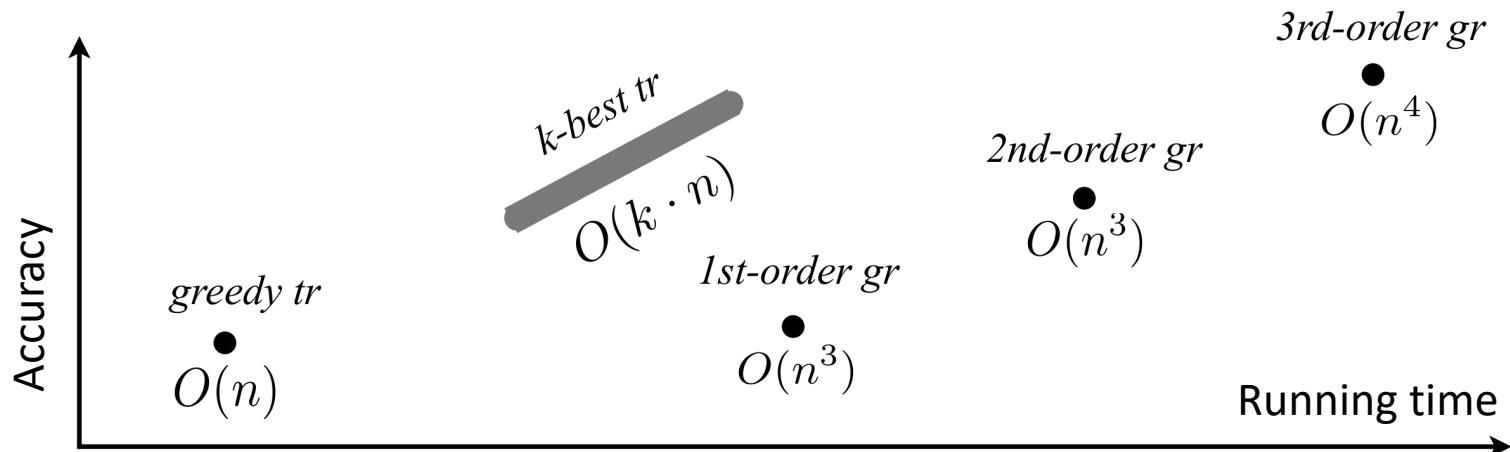
# Parsing Algorithms

## Transition-based

- Fast, greedy, linear-time
- Trained for greedy search
- Features decide what to do next
- Beam search, i.e.  $k$ -best

## Graph-based

- Slower, exhaustive algorithms
- Dynamic programming, inference
- Features used to score whole trees



# Graph-based Parsing

$$\operatorname{argmax}_{t \in T} \text{score}(t, \theta)$$

(  
1<sup>st</sup> order / fully factored  
 $\sum_i \theta_i \phi(e_i | c_i, p_i, l_i)$   
;

2<sup>nd</sup> order  $\phi(e_i, e_j)$

3<sup>rd</sup> order  $\phi(e_i, e_j, e_k)$

Proj: Dynamic Programming  
NonProj: Maximum Spanning Tree