

**6.864: Lecture 2, Fall 2007**  
**Parsing and Syntax I**

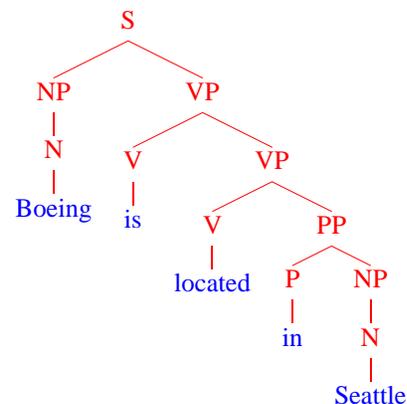
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**Parsing (Syntactic Structure)**

INPUT:

Boeing is located in Seattle.

OUTPUT:



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**Overview**

- An introduction to the parsing problem
- Context free grammars
- A brief(!) sketch of the syntax of English
- Examples of ambiguous structures
- PCFGs, their formal properties, and useful algorithms
- Weaknesses of PCFGs

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**Syntactic Formalisms**

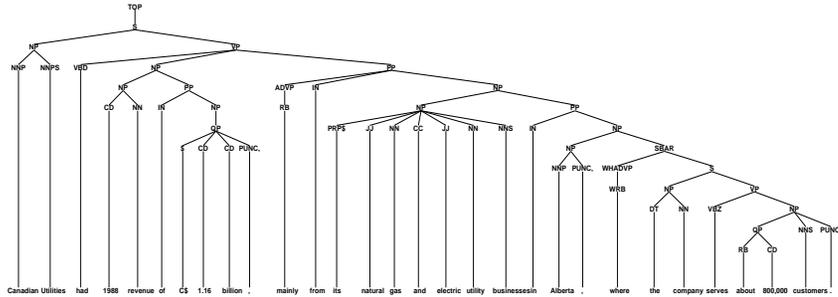
- Work in formal syntax goes back to Chomsky's PhD thesis in the 1950s
- Examples of current formalisms: minimalism, lexical functional grammar (LFG), head-driven phrase-structure grammar (HPSG), tree adjoining grammars (TAG), categorial grammars

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## Data for Parsing Experiments

- Penn WSJ Treebank = 50,000 sentences with associated trees
- Usual set-up: 40,000 training sentences, 2400 test sentences

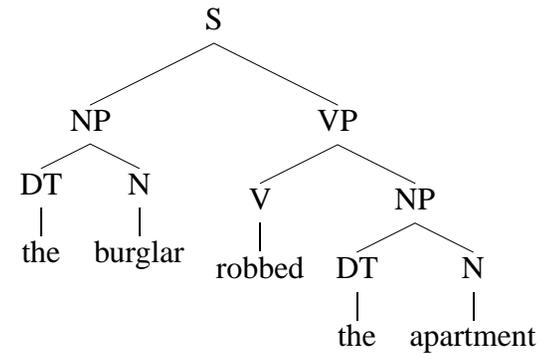
### An example tree:



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

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### 2) Phrases



Noun Phrases (NP): “the burglar”, “the apartment”

Verb Phrases (VP): “robbed the apartment”

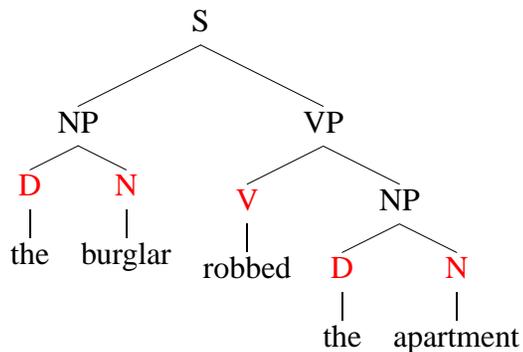
Sentences (S): “the burglar robbed the apartment”

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## The Information Conveyed by Parse Trees

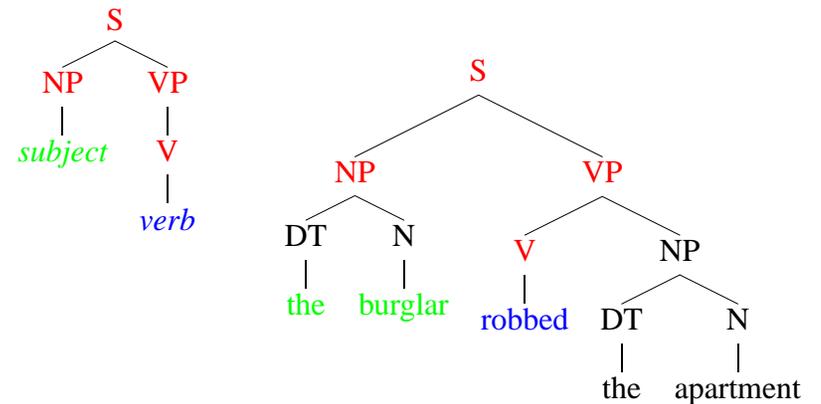
### 1) Part of speech for each word

(N = noun, V = verb, D = determiner)



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### 3) Useful Relationships



⇒ “the burglar” is the subject of “robbed”

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## An Example Application: Machine Translation

- English word order is *subject – verb – object*
- Japanese word order is *subject – object – verb*

English: IBM bought Lotus  
Japanese: *IBM Lotus bought*

English: Sources said that IBM bought Lotus yesterday  
Japanese: *Sources yesterday IBM Lotus bought that said*

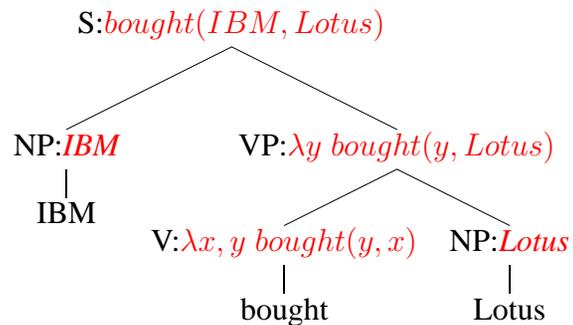
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## Overview

- An introduction to the parsing problem
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## Syntax and Compositional Semantics



- Each syntactic non-terminal now has an associated **semantic expression**

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## Context-Free Grammars

[Hopcroft and Ullman 1979]

A context free grammar  $G = (N, \Sigma, R, S)$  where:

- $N$  is a set of non-terminal symbols
- $\Sigma$  is a set of terminal symbols
- $R$  is a set of rules of the form  $X \rightarrow Y_1 Y_2 \dots Y_n$  for  $n \geq 0$ ,  $X \in N$ ,  $Y_i \in (N \cup \Sigma)$
- $S \in N$  is a distinguished start symbol

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## A Context-Free Grammar for English

$N = \{S, NP, VP, PP, DT, Vi, Vt, NN, IN\}$

$S = S$

$\Sigma = \{\text{sleeps, saw, man, woman, telescope, the, with, in}\}$

$R =$

S	$\Rightarrow$	NP	VP
VP	$\Rightarrow$	Vi	
VP	$\Rightarrow$	Vt	NP
VP	$\Rightarrow$	VP	PP
NP	$\Rightarrow$	DT	NN
NP	$\Rightarrow$	NP	PP
PP	$\Rightarrow$	IN	NP

Vi	$\Rightarrow$	sleeps
Vt	$\Rightarrow$	saw
NN	$\Rightarrow$	man
NN	$\Rightarrow$	woman
NN	$\Rightarrow$	telescope
DT	$\Rightarrow$	the
IN	$\Rightarrow$	with
IN	$\Rightarrow$	in

Note: S=sentence, VP=verb phrase, NP=noun phrase, PP=prepositional phrase, DT=determiner, Vi=intransitive verb, Vt=transitive verb, NN=noun, IN=preposition

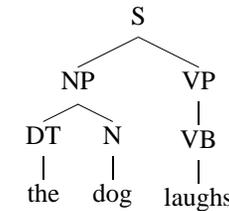
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## DERIVATION

S  
NP VP  
DT N VP  
the N VP  
the dog VP  
the dog VB  
the dog laughs

## RULES USED

$S \rightarrow NP VP$   
 $NP \rightarrow DT N$   
 $DT \rightarrow \text{the}$   
 $N \rightarrow \text{dog}$   
 $VP \rightarrow VB$   
 $VB \rightarrow \text{laughs}$



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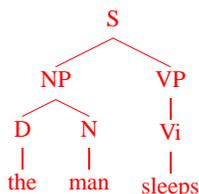
## Left-Most Derivations

A left-most derivation is a sequence of strings  $s_1 \dots s_n$ , where

- $s_1 = S$ , the start symbol
- $s_n \in \Sigma^*$ , i.e.  $s_n$  is made up of terminal symbols only
- Each  $s_i$  for  $i = 2 \dots n$  is derived from  $s_{i-1}$  by picking the left-most non-terminal  $X$  in  $s_{i-1}$  and replacing it by some  $\beta$  where  $X \rightarrow \beta$  is a rule in  $R$

For example: [S], [NP VP], [D N VP], [the N VP], [the man VP], [the man Vi], [the man sleeps]

Representation of a derivation as a tree:



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## Properties of CFGs

- A CFG defines a set of possible derivations
- A string  $s \in \Sigma^*$  is in the *language* defined by the CFG if there is at least one derivation which yields  $s$
- Each string in the language generated by the CFG may have more than one derivation (“ambiguity”)

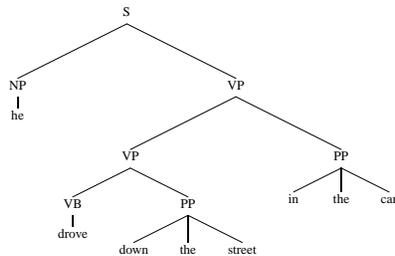
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## DERIVATION

S  
 NP VP  
 he VP  
 he VP PP  
 he VB PP PP  
 he drove PP PP  
 he drove down the street PP  
 he drove down the street in the car

## RULES USED

$S \rightarrow NP VP$   
 $NP \rightarrow he$   
 $VP \rightarrow VP PP$   
 $VP \rightarrow VB PP$   
 $VB \rightarrow drove$   
 $PP \rightarrow down\ the\ street$   
 $PP \rightarrow in\ the\ car$



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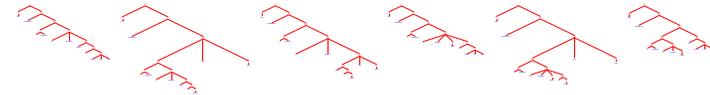
## The Problem with Parsing: **Ambiguity**

INPUT:

She announced a program to promote safety in trucks and vans



POSSIBLE OUTPUTS:



And there are more...

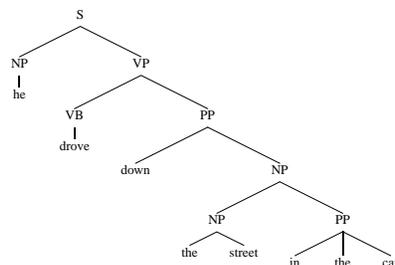
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## DERIVATION

S  
 NP VP  
 he VP  
 he VB PP  
 he drove PP  
 he drove down NP  
 he drove down NP PP  
 he drove down the street PP  
 he drove down the street in the car

## RULES USED

$S \rightarrow NP VP$   
 $NP \rightarrow he$   
 $VP \rightarrow VB PP$   
 $VB \rightarrow drove$   
 $PP \rightarrow down\ NP$   
 $NP \rightarrow NP PP$   
 $NP \rightarrow the\ street$   
 $PP \rightarrow in\ the\ car$



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- **A brief(!) sketch of the syntax of English**
- Examples of ambiguous structures
- PCFGs, their formal properties, and useful algorithms
- Weaknesses of PCFGs

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The screenshot shows the Amazon.com product page for the book 'A Comprehensive Grammar of the English Language'. At the top, there's a navigation bar with 'amazon.com', 'WELCOME', 'YOUR ACCOUNT', 'VIEW CART', 'WISHLIST', and 'HELP'. Below this is a promotional banner for 'Fiestaware' with a 'Shop Fiestaware' button. The main product section includes a search bar with 'Books' entered, a 'READY TO BUY?' section with 'Add to Shopping Cart' and 'Sign in to turn on 1-Click ordering' buttons, and a 'WEB SEARCH' section. The 'BOOK INFORMATION' section shows the book title, authors (Rodney D. Huddleston, Geoffrey Leech, Sidney Greenbaum), a star rating of 4.5, and a 'Submit' button. There's also a 'Rate This Item' section with a 5-point scale. Below the book details, there are sections for 'Favorite Magazines!', 'Calphalon Sale' (Save 20% on cookware), and 'Better Together' recommendations.

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## A Brief Overview of English Syntax

### Parts of Speech (tags from the Brown corpus):

- Nouns
  - NN = singular noun e.g., man, dog, park
  - NNS = plural noun e.g., telescopes, houses, buildings
  - NNP = proper noun e.g., Smith, Gates, IBM
- Determiners
  - DT = determiner e.g., the, a, some, every
- Adjectives
  - JJ = adjective e.g., red, green, large, idealistic

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This screenshot shows the 'Customers who bought this book also bought' and 'Customers interested in this title may also be interested in' sections of the Amazon product page. The 'Customers who bought this book also bought' section lists several related books, including 'The Cambridge Grammar of the English Language' by Rodney D. Huddleston, 'The Oxford Dictionary of English Grammar' by Sylvia Chalker, and 'The Oxford English Grammar' by Sidney Greenbaum. The 'Customers interested in this title may also be interested in' section features 'English Grammar Software' and 'Advanced English' learning materials. Below these sections, there are 'Product Details' (Hardcover, 1779 pages, published by Addison-Wesley in 1989), 'Shipping' information, and a 'What's Your Advice?' section with a star rating and a 'Submit' button. At the bottom, there are 'Spotlight Reviews' and a section for '16 of 16 people found the following review helpful:'.

## A Fragment of a Noun Phrase Grammar

- NN ⇒ box
- NN ⇒ car
- NN ⇒ mechanic
- NN ⇒ pigeon
- DT ⇒ the
- DT ⇒ a
- JJ ⇒ fast
- JJ ⇒ metal
- JJ ⇒ idealistic
- JJ ⇒ clay

- $\bar{N}$  ⇒ NN
- $\bar{N}$  ⇒ NN  $\bar{N}$
- $\bar{N}$  ⇒ JJ  $\bar{N}$
- $\bar{N}$  ⇒  $\bar{N}$   $\bar{N}$
- NP ⇒ DT  $\bar{N}$

### Generates:

a box, the box, the metal box, the fast car mechanic, . . .

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## Prepositions, and Prepositional Phrases

- Prepositions

IN = preposition e.g., of, in, out, beside, as

## Verbs, Verb Phrases, and Sentences

- Basic Verb Types

Vi = Intransitive verb e.g., sleeps, walks, laughs

Vt = Transitive verb e.g., sees, saw, likes

Vd = Ditransitive verb e.g., gave

- Basic VP Rules

VP → Vi

VP → Vt NP

VP → Vd NP NP

- Basic S Rule

S → NP VP

### Examples of VP:

sleeps, walks, likes the mechanic, gave the mechanic the fast car,  
gave the fast car mechanic the pigeon in the box, . . .

## An Extended Grammar

$\bar{N}$ ⇒ NN $\bar{N}$ ⇒ NN $\bar{N}$ $\bar{N}$ ⇒ JJ $\bar{N}$ $\bar{N}$ ⇒ $\bar{N}$ $\bar{N}$ NP ⇒ DT $\bar{N}$	NN ⇒ box NN ⇒ car NN ⇒ mechanic NN ⇒ pigeon  DT ⇒ the DT ⇒ a	JJ ⇒ fast JJ ⇒ metal JJ ⇒ idealistic  IN ⇒ in IN ⇒ under IN ⇒ of IN ⇒ on IN ⇒ with IN ⇒ as
PP ⇒ IN NP $\bar{N}$ ⇒ $\bar{N}$ PP		

### Generates:

in a box, under the box, the fast car mechanic under the pigeon in the box, . . .

### Examples of S:

the man sleeps, the dog walks, the dog likes the mechanic, the dog  
in the box gave the mechanic the fast car, . . .

## PPs Modifying Verb Phrases

### A new rule:

VP → VP PP

### New examples of VP:

sleeps in the car, walks like the mechanic, gave the mechanic the fast car on Tuesday, . . .

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## More Verbs

- New Verb Types

V[5] e.g., said, reported

V[6] e.g., told, informed

V[7] e.g., bet

- New VP Rules

VP → V[5] SBAR

VP → V[6] NP SBAR

VP → V[7] NP NP SBAR

### Examples of New VPs:

said that the man sleeps

told the dog that the mechanic likes the pigeon

bet the pigeon \$50 that the mechanic owns a fast car

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## Complementizers, and SBARs

- Complementizers

COMP = complementizer e.g., that

- SBAR

SBAR → COMP S

### Examples:

that the man sleeps, that the mechanic saw the dog . . .

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## Coordination

- A New Part-of-Speech:

CC = Coordinator e.g., and, or, but

- New Rules

NP → NP CC NP

$\bar{N}$  →  $\bar{N}$  CC  $\bar{N}$

VP → VP CC VP

S → S CC S

SBAR → SBAR CC SBAR

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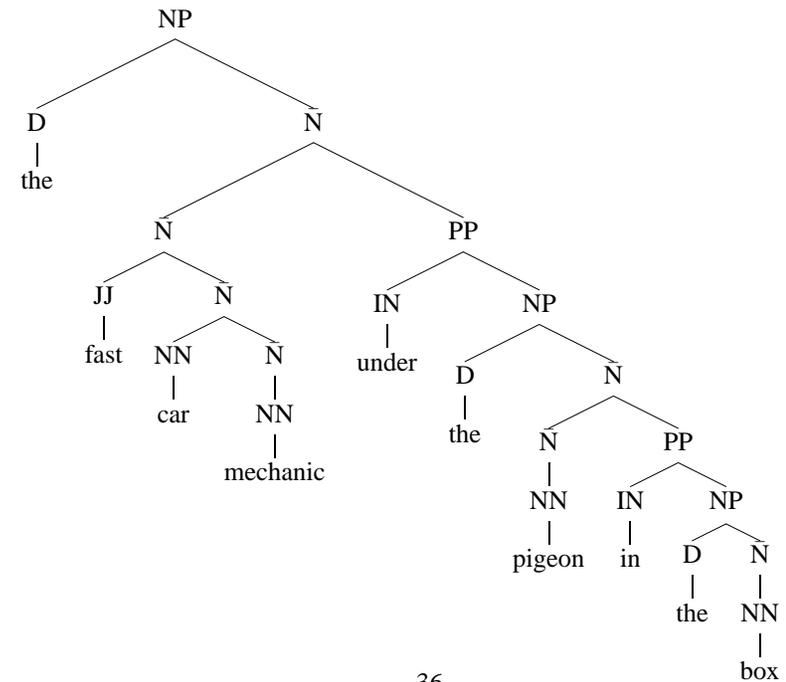
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## Sources of Ambiguity

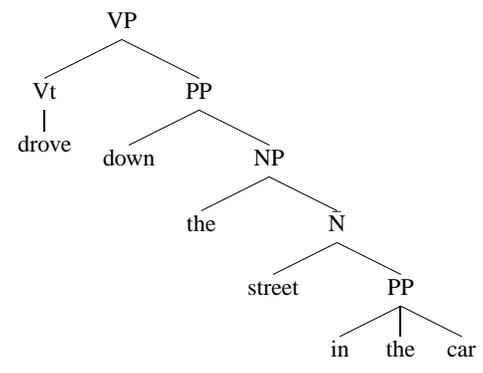
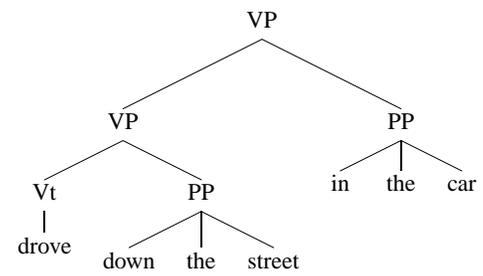
- Part-of-Speech ambiguity  
NNS → walks  
Vi → walks
- Prepositional Phrase Attachment  
the fast car mechanic under the pigeon in the box

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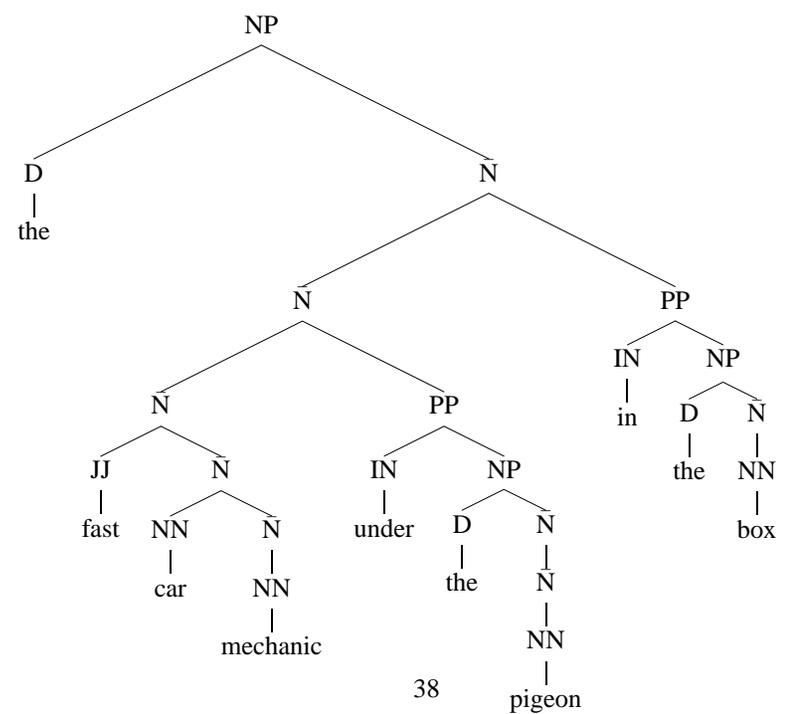


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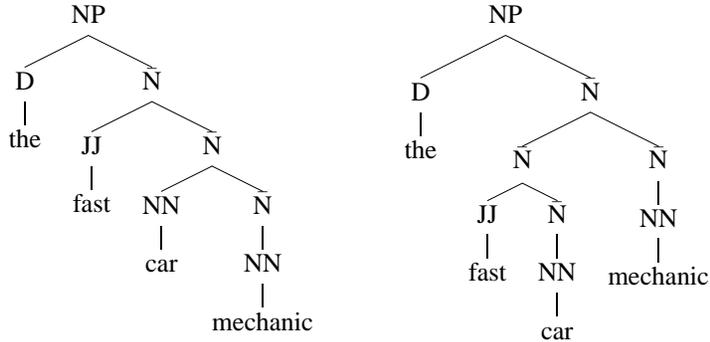
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Two analyses for: [John was believed to have been shot by Bill](#)

## Sources of Ambiguity: Noun Premodifiers

- Noun premodifiers:



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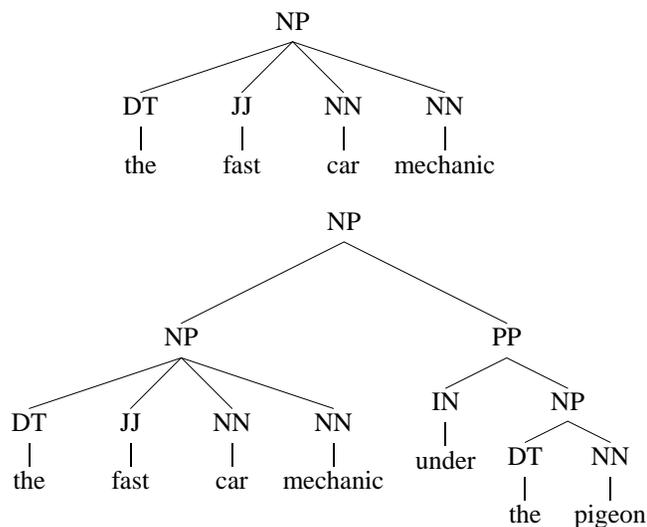
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## A Funny Thing about the Penn Treebank

Leaves NP premodifier structure flat, or underspecified:



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## A Probabilistic Context-Free Grammar (PCFG)

S	⇒	NP VP	1.0
VP	⇒	Vi	0.4
VP	⇒	Vt NP	0.4
VP	⇒	VP PP	0.2
NP	⇒	DT NN	0.3
NP	⇒	NP PP	0.7
PP	⇒	P NP	1.0

Vi	⇒	sleeps	1.0
Vt	⇒	saw	1.0
NN	⇒	man	0.7
NN	⇒	woman	0.2
NN	⇒	telescope	0.1
DT	⇒	the	1.0
IN	⇒	with	0.5
IN	⇒	in	0.5

- Probability of a tree with rules  $\alpha_i \rightarrow \beta_i$  is  $\prod_i P(\alpha_i \rightarrow \beta_i | \alpha_i)$

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### DERIVATION

S  
 NP VP  
 DT N VP  
 the N VP  
 the dog VP  
 the dog VB  
 the dog laughs

### RULES USED

$S \rightarrow NP VP$   
 $NP \rightarrow DT N$   
 $DT \rightarrow the$   
 $N \rightarrow dog$   
 $VP \rightarrow VB$   
 $VB \rightarrow laughs$

### PROBABILITY

1.0  
 0.3  
 1.0  
 0.1  
 0.4  
 0.5

TOTAL PROBABILITY =  $1.0 \times 0.3 \times 1.0 \times 0.1 \times 0.4 \times 0.5$

## Properties of PCFGs

- Assigns a probability to each *left-most derivation*, or parse-tree, allowed by the underlying CFG
- Say we have a sentence  $S$ , set of derivations for that sentence is  $\mathcal{T}(S)$ . Then a PCFG assigns a probability to each member of  $\mathcal{T}(S)$ . i.e., *we now have a ranking in order of probability*.
- The probability of a string  $S$  is

$$\sum_{T \in \mathcal{T}(S)} P(T, S)$$

## Deriving a PCFG from a Corpus

- Given a set of example trees, the underlying CFG can simply be **all rules seen in the corpus**
- Maximum Likelihood estimates:

$$P_{ML}(\alpha \rightarrow \beta | \alpha) = \frac{\text{Count}(\alpha \rightarrow \beta)}{\text{Count}(\alpha)}$$

where the counts are taken from a training set of example trees.

- **If the training data is generated by a PCFG**, then as the training data size goes to infinity, the maximum-likelihood PCFG will converge to the same distribution as the ‘true’ PCFG.

## PCFGs

[Booth and Thompson 73] showed that a CFG with rule probabilities correctly defines a distribution over the set of derivations provided that:

1. The rule probabilities define conditional distributions over the different ways of rewriting each non-terminal.
2. A technical condition on the rule probabilities ensuring that the probability of the derivation terminating in a finite number of steps is 1. (This condition is not really a practical concern.)

## Algorithms for PCFGs

- Given a PCFG and a sentence  $S$ , define  $\mathcal{T}(S)$  to be the set of trees with  $S$  as the yield.

- Given a PCFG and a sentence  $S$ , how do we find

$$\arg \max_{T \in \mathcal{T}(S)} P(T, S)$$

- Given a PCFG and a sentence  $S$ , how do we find

$$P(S) = \sum_{T \in \mathcal{T}(S)} P(T, S)$$

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## A Dynamic Programming Algorithm

- Given a PCFG and a sentence  $S$ , how do we find

$$\max_{T \in \mathcal{T}(S)} P(T, S)$$

- Notation:

$n$  = number of words in the sentence

$N_k$  for  $k = 1 \dots K$  is  $k$ 'th non-terminal

$N_1 = S$  (the start symbol)

- Define a dynamic programming table

$\pi[i, j, k]$  = maximum probability of a constituent with non-terminal  $N_k$  spanning words  $i \dots j$  inclusive

- Our goal is to calculate  $\max_{T \in \mathcal{T}(S)} P(T, S) = \pi[1, n, 1]$

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## Chomsky Normal Form

A context free grammar  $G = (N, \Sigma, R, S)$  in Chomsky Normal Form is as follows

- $N$  is a set of non-terminal symbols
- $\Sigma$  is a set of terminal symbols
- $R$  is a set of rules which take one of two forms:
  - $X \rightarrow Y_1 Y_2$  for  $X \in N$ , and  $Y_1, Y_2 \in N$
  - $X \rightarrow Y$  for  $X \in N$ , and  $Y \in \Sigma$
- $S \in N$  is a distinguished start symbol

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## A Dynamic Programming Algorithm

- Base case definition: for all  $i = 1 \dots n$ , for  $k = 1 \dots K$

$$\pi[i, i, k] = P(N_k \rightarrow w_i \mid N_k)$$

(note: define  $P(N_k \rightarrow w_i \mid N_k) = 0$  if  $N_k \rightarrow w_i$  is not in the grammar)

- Recursive definition: for all  $i = 1 \dots n$ ,  $j = (i + 1) \dots n$ ,  $k = 1 \dots K$ ,

$$\pi[i, j, k] = \max_{\substack{i \leq s < j \\ 1 \leq l \leq K \\ 1 \leq m \leq K}} \{P(N_k \rightarrow N_l N_m \mid N_k) \times \pi[i, s, l] \times \pi[s + 1, j, m]\}$$

(note: define  $P(N_k \rightarrow N_l N_m \mid N_k) = 0$  if  $N_k \rightarrow N_l N_m$  is not in the grammar)

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### Initialization:

For  $i = 1 \dots n, k = 1 \dots K$   
 $\pi[i, i, k] = P(N_k \rightarrow w_i | N_k)$

### Main Loop:

For  $length = 1 \dots (n - 1), i = 1 \dots (n - length), k = 1 \dots K$   
 $j \leftarrow i + length$   
 $max \leftarrow 0$   
 For  $s = i \dots (j - 1),$   
 For  $N_l, N_m$  such that  $N_k \rightarrow N_l N_m$  is in the grammar  
 $prob \leftarrow P(N_k \rightarrow N_l N_m) \times \pi[i, s, l] \times \pi[s + 1, j, m]$   
 If  $prob > max$   
 $max \leftarrow prob$   
 //Store backpointers which imply the best parse  
 $Split(i, j, k) = \{s, l, m\}$   
 $\pi[i, j, k] = max$

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## A Dynamic Programming Algorithm for the Sum

- Base case definition: for all  $i = 1 \dots n, \text{ for } k = 1 \dots K$

$$\pi[i, i, k] = P(N_k \rightarrow w_i | N_k)$$

(note: define  $P(N_k \rightarrow w_i | N_k) = 0$  if  $N_k \rightarrow w_i$  is not in the grammar)

- Recursive definition: for all  $i = 1 \dots n, j = (i + 1) \dots n, k = 1 \dots K,$

$$\pi[i, j, k] = \sum_{\substack{i \leq s < j \\ 1 \leq l \leq K \\ 1 \leq m \leq K}} \{P(N_k \rightarrow N_l N_m | N_k) \times \pi[i, s, l] \times \pi[s + 1, j, m]\}$$

(note: define  $P(N_k \rightarrow N_l N_m | N_k) = 0$  if  $N_k \rightarrow N_l N_m$  is not in the grammar)

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## A Dynamic Programming Algorithm for the Sum

- Given a PCFG and a sentence  $S$ , how do we find

$$\sum_{T \in \mathcal{T}(S)} P(T, S)$$

- Notation:

$n$  = number of words in the sentence  
 $N_k$  for  $k = 1 \dots K$  is  $k$ 'th non-terminal  
 $N_1 = S$  (the start symbol)

- Define a dynamic programming table

$\pi[i, j, k] =$  sum of probability of parses with root label  $N_k$   
 spanning words  $i \dots j$  inclusive

- Our goal is to calculate  $\sum_{T \in \mathcal{T}(S)} P(T, S) = \pi[1, n, 1]$

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### Initialization:

For  $i = 1 \dots n, k = 1 \dots K$   
 $\pi[i, i, k] = P(N_k \rightarrow w_i | N_k)$

### Main Loop:

For  $length = 1 \dots (n - 1), i = 1 \dots (n - length), k = 1 \dots K$   
 $j \leftarrow i + length$   
 $sum \leftarrow 0$   
 For  $s = i \dots (j - 1),$   
 For  $N_l, N_m$  such that  $N_k \rightarrow N_l N_m$  is in the grammar  
 $prob \leftarrow P(N_k \rightarrow N_l N_m) \times \pi[i, s, l] \times \pi[s + 1, j, m]$   
 $sum \leftarrow sum + prob$   
 $\pi[i, j, k] = sum$

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## Weaknesses of PCFGs

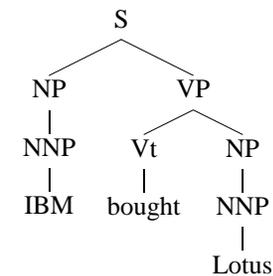
- Lack of sensitivity to lexical information
- Lack of sensitivity to structural frequencies

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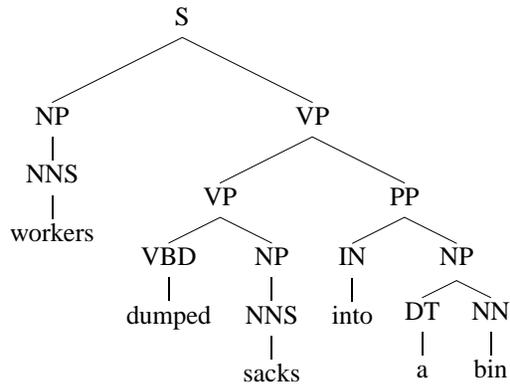


$$\begin{aligned} \text{PROB} = & P(S \rightarrow NP VP \mid S) && \times P(\text{NNP} \rightarrow \text{IBM} \mid \text{NNP}) \\ & \times P(\text{VP} \rightarrow V \text{ NP} \mid \text{VP}) && \times P(\text{Vt} \rightarrow \text{bought} \mid \text{Vt}) \\ & \times P(\text{NP} \rightarrow \text{NNP} \mid \text{NP}) && \times P(\text{NNP} \rightarrow \text{Lotus} \mid \text{NNP}) \\ & \times P(\text{NP} \rightarrow \text{NNP} \mid \text{NP}) \end{aligned}$$

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## Another Case of PP Attachment Ambiguity

(a)



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Rules
$S \rightarrow NP VP$
$NP \rightarrow NNS$
<b><math>VP \rightarrow VP PP</math></b>
$VP \rightarrow VBD NP$
$NP \rightarrow NNS$
$PP \rightarrow IN NP$
$NP \rightarrow DT NN$
$NNS \rightarrow workers$
$VBD \rightarrow dumped$
$NNS \rightarrow sacks$
$IN \rightarrow into$
$DT \rightarrow a$
$NN \rightarrow bin$

(a)

Rules
$S \rightarrow NP VP$
$NP \rightarrow NNS$
<b><math>NP \rightarrow NP PP</math></b>
$VP \rightarrow VBD NP$
$NP \rightarrow NNS$
$PP \rightarrow IN NP$
$NP \rightarrow DT NN$
$NNS \rightarrow workers$
$VBD \rightarrow dumped$
$NNS \rightarrow sacks$
$IN \rightarrow into$
$DT \rightarrow a$
$NN \rightarrow bin$

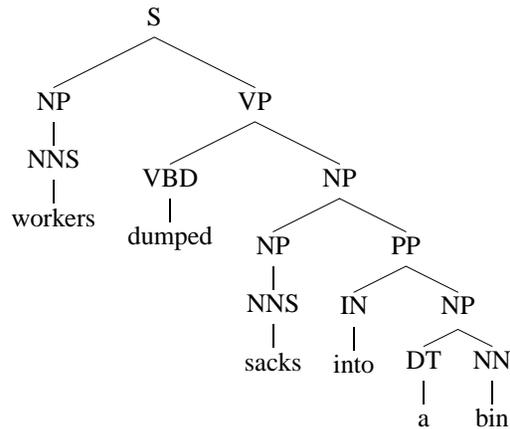
(b)

If  $P(NP \rightarrow NP PP \mid NP) > P(VP \rightarrow VP PP \mid VP)$  then (b) is more probable, else (a) is more probable.

**Attachment decision is completely independent of the words**

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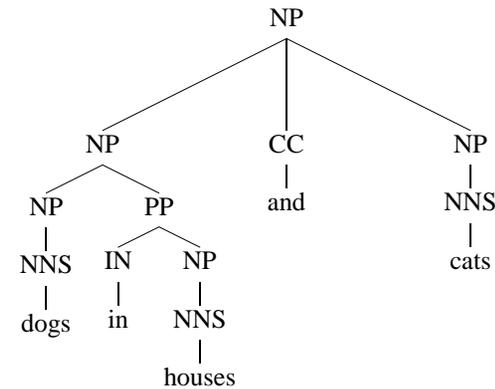
(b)



62

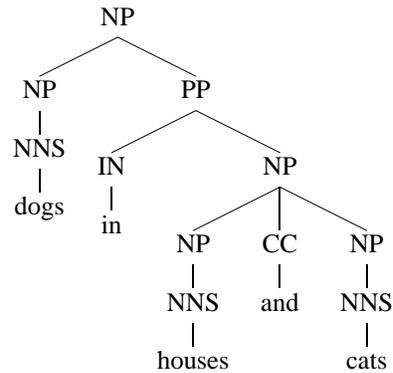
## A Case of Coordination Ambiguity

(a)



64

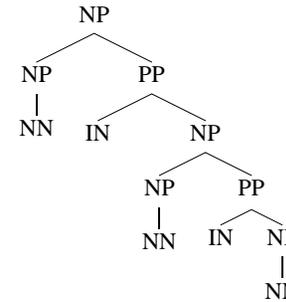
(b)



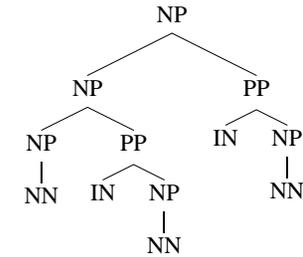
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## Structural Preferences: Close Attachment

(a)



(b)



- Example: [president of a company in Africa](#)
- Both parses have the same rules, therefore receive same probability under a PCFG
- “Close attachment” (structure (a)) is twice as likely in Wall Street Journal text.

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(a)

Rules
NP → NP CC NP
NP → NP PP
NP → NNS
PP → IN NP
NP → NNS
NP → NNS
NNS → dogs
IN → in
NNS → houses
CC → and
NNS → cats

(b)

Rules
NP → NP CC NP
NP → NP PP
NP → NNS
PP → IN NP
NP → NNS
NP → NNS
NNS → dogs
IN → in
NNS → houses
CC → and
NNS → cats

**Here the two parses have identical rules, and therefore have identical probability under any assignment of PCFG rule probabilities**

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## Structural Preferences: Close Attachment

**Previous example:** [John was believed to have been shot by Bill](#)

Here the low attachment analysis (Bill does the *shooting*) contains same rules as the high attachment analysis (Bill does the *believing*), so the two analyses receive same probability.

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## References

- [Booth and Thompson 73] Booth, T., and Thompson, R. 1973. Applying probability measures to abstract languages. *IEEE Transactions on Computers*, C-22(5), pages 442–450.
- [Hopcroft and Ullman 1979] Hopcroft, J. E., and Ullman, J. D. 1979. *Introduction to automata theory, languages, and computation*. Reading, Mass.: Addison–Wesley.