CS 4248 Natural Language Processing

Professor NG Hwee Tou

Department of Computer Science
School of Computing
National University of Singapore
nght@comp.nus.edu.sg

Syntactic Parsing

- Syntactic parsing: The task of recognizing a sentence and assigning a syntactic structure to it
- Useful for information extraction, semantic analysis, etc.

A Sample CFG

 $S \rightarrow NP VP$

 $S \rightarrow Aux NP VP$

 $S \rightarrow VP$

NP → Pronoun

NP → Proper-Noun

NP → Det Nominal

Nominal → Noun

Nominal → Nominal Noun

Nominal → Nominal PP

 $VP \rightarrow Verb$

VP → Verb NP

VP → Verb NP PP

 $VP \rightarrow Verb PP$

 $VP \rightarrow VP PP$

PP → Prep NP

A Sample Lexicon

```
Det → that | this | a

Noun → book | flight | meal | money

Verb → book | include | prefer

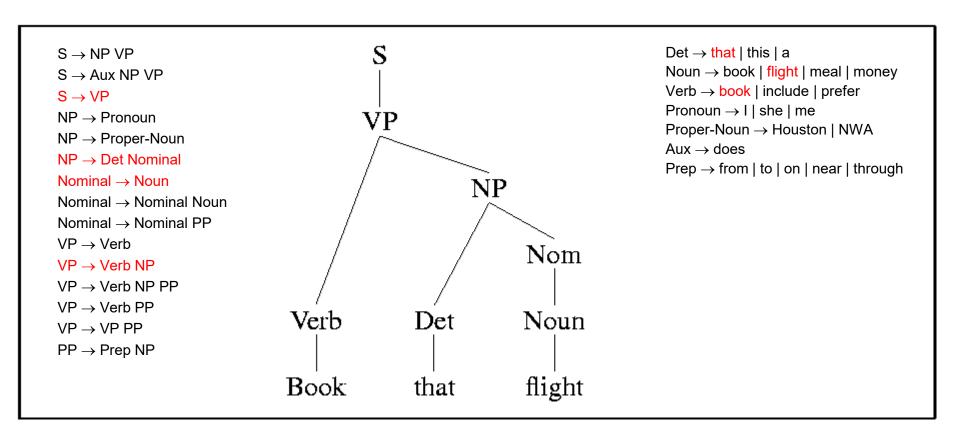
Pronoun → I | she | me

Proper-Noun → Houston | NWA

Aux → does

Prep → from | to | on | near | through
```

Parse Tree



 $S \rightarrow NP VP$

 $S \rightarrow Aux NP VP$

 $S \rightarrow VP$

NP → Pronoun

NP → Proper-Noun

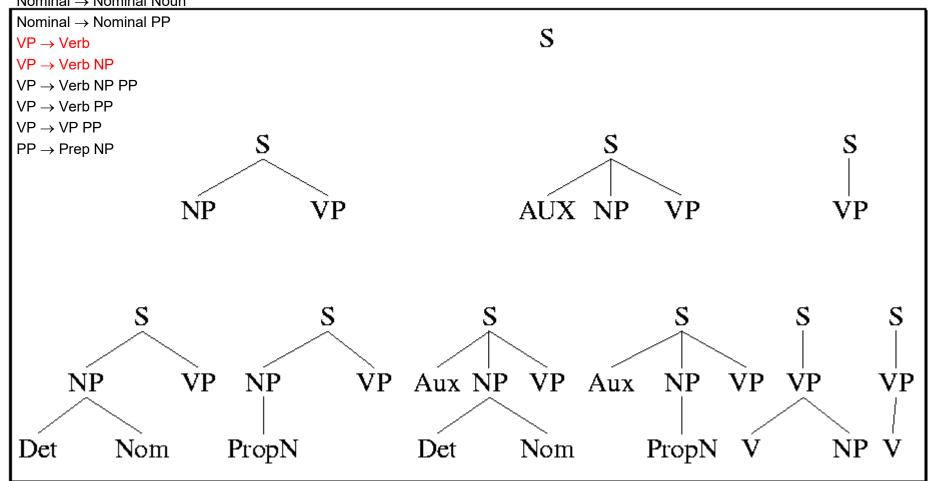
NP → Det Nominal

Nominal → Noun

Top-Down Parsing

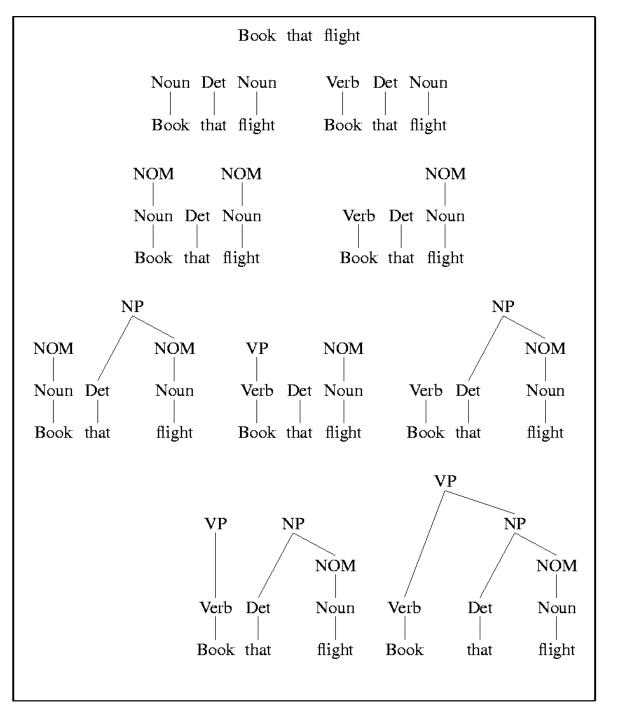
Det \rightarrow that | this | a Noun → book | flight | meal | money Verb → book | include | prefer Pronoun \rightarrow I | she | me Proper-Noun → Houston | NWA $Aux \rightarrow does$ Prep → from | to | on | near | through

Nominal → Nominal Noun



Bottom-Up Parsing

```
S \rightarrow NP VP
S \rightarrow Aux NP VP
S \rightarrow VP
NP → Pronoun
NP → Proper-Noun
NP → Det Nominal
Nominal → Noun
Nominal → Nominal Noun
Nominal → Nominal PP
VP → Verb
VP → Verb NP
VP → Verb NP PP
VP \rightarrow Verb PP
VP \rightarrow VP PP
PP → Prep NP
Det \rightarrow that | this | a
Noun → book | flight | meal | money
Verb → book | include | prefer
Pronoun \rightarrow I | she | me
Proper-Noun → Houston | NWA
Aux \rightarrow does
Prep → from | to | on | near | through
```



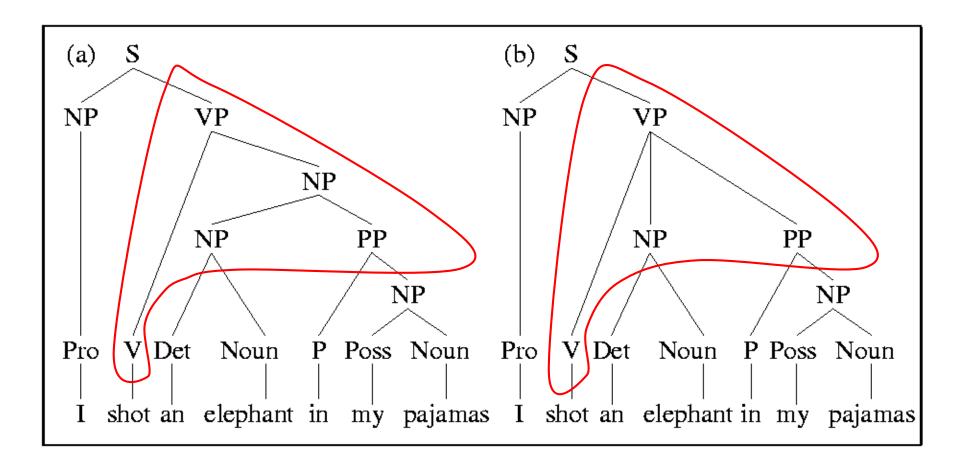
Top-Down vs. Bottom-Up Parsing

- Top-down parsing
 - goal-directed search
 - Never wastes time exploring trees that cannot result in an S
- Bottom-up parsing
 - data-directed search
 - Never suggests trees that are not grounded in the actual input sentence
- Need to incorporate features of both

Structural Ambiguity

- Attachment ambiguity
- Noun-phrase bracketing ambiguity
- Coordination ambiguity

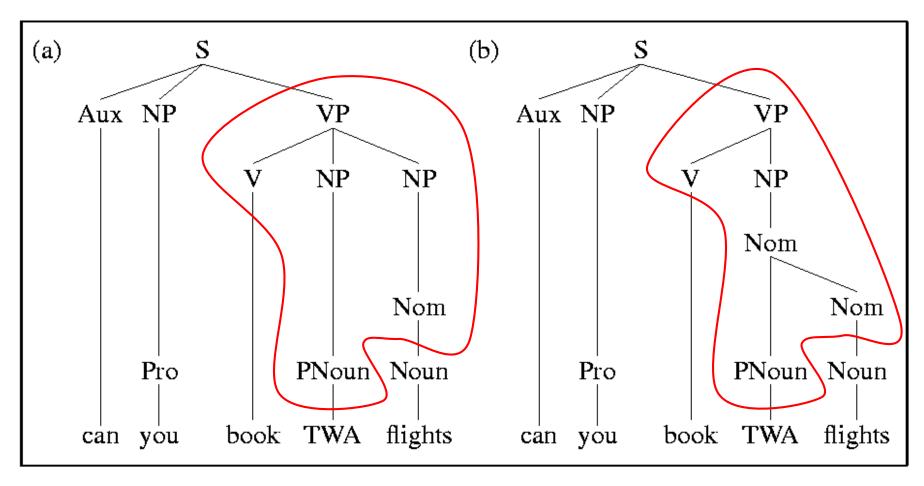
Attachment Ambiguity



Attachment Ambiguity

```
We [saw [[the Eiffel Tower] [flying into Paris]]]
We [saw ] [the Eiffel Tower] [flying into Paris]]
```

Noun-Phrase Bracketing Ambiguity



Coordination Ambiguity

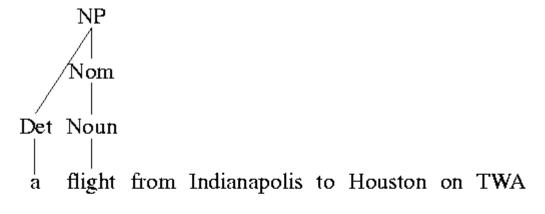
old [men and women]

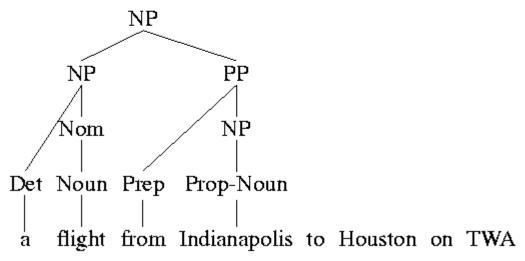
[old men] and [women]

Parsing as Search

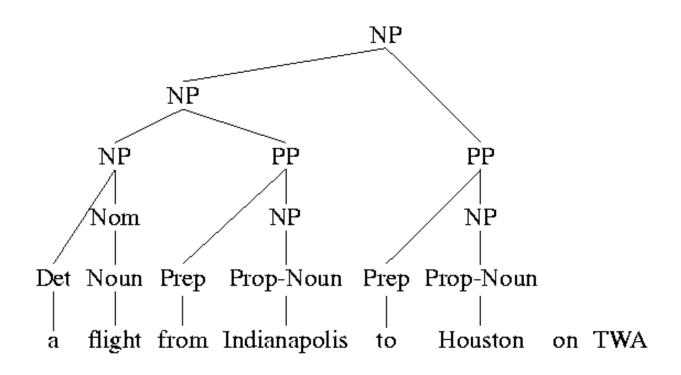
- Parsing involves searching the space of parse trees
- Agenda-based backtracking search leads to reduplication of work (repeated parsing of subtrees)

Repeated Parsing of Subtrees

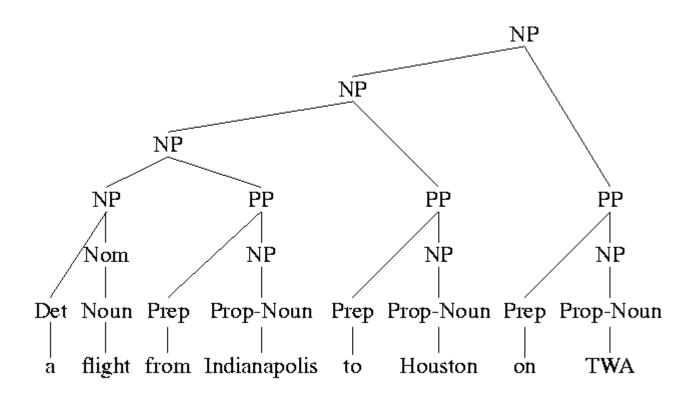




Repeated Parsing of Subtrees



Repeated Parsing of Subtrees



The CKY Algorithm

- CKY (Cocke-Kasami-Younger)
- Bottom-up dynamic programming algorithm
- Requires the CFG to be in Chomsky Normal Form (CNF)
 - The grammar is ε -free
 - Each production of the grammar is either of the form A → B C or A → a (i.e., either 2 non-terminal symbols or 1 terminal symbol on RHS)
- Any CFG can be converted into a weakly equivalent CFG in Chomsky Normal Form

A Sample CFG in CNF

```
S \rightarrow NP VP
S \rightarrow X1 VP
```

 $X1 \rightarrow Aux NP$

S → book | include | prefer

 $S \rightarrow Verb NP$

 $S \rightarrow X2 PP$

S → Verb PP

 $S \rightarrow VP PP$

 $NP \rightarrow I \mid she \mid me$

NP → Houston | NWA

NP → Det Nominal

```
Nominal → book | flight | meal 
| money
```

Nominal → Nominal Noun

Nominal → Nominal PP

VP → book | include | prefer

VP → Verb NP

 $VP \rightarrow X2 PP$

 $X2 \rightarrow Verb NP$

VP → Verb PP

 $VP \rightarrow VP PP$

PP → Prep NP

A Sample Lexicon

```
Det → that | this | a

Noun → book | flight | meal | money

Verb → book | include | prefer

Pronoun → I | she | me

Proper-Noun → Houston | NWA

Aux → does

Prep → from | to | on | near | through
```

The CKY Algorithm

	book o	a	flight	through	Houston 5
$S \rightarrow NP VP$	S, VP, Verb, Nominal, Noun		S, VP, X2		S, VP
$S \rightarrow X1 VP$	[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
$X1 \rightarrow Aux NP$ $S \rightarrow book \mid include$ $S \rightarrow Verb NP$	prefer	Det	NP		NP
$S \rightarrow X2 PP$ $S \rightarrow Verb PP$		[1,2]	[1,3]	[1,4]	[1,5]
$S \rightarrow VP PP$ $NP \rightarrow I \mid she \mid me$ $NP \rightarrow Houston \mid NV$			Nominal, Noun		Nominal
NP → Det Nominal Nominal → book I f	light meal money		[2,3]	[2,4]	[2,5]
Nominal → Nominal Nominal → Nominal	al Noun al PP	'		Prep	PP
VP → book includ VP → Verb NP	Det → that	this <mark>a</mark> <mark>ok flight</mark> meal mon	ney	[3,4]	[3,5]
$VP \rightarrow X2 PP$ $X2 \rightarrow Verb NP$ $VP \rightarrow Verb PP$	Pronoun $ ightarrow$	ok include prefer I she me In → Houston NWA	-		NP, PN
$VP \rightarrow VP PP$ $PP \rightarrow Prep NP$	$Aux \rightarrow doe$	·	ugh		[4,5]

The CKY Algorithm: Filling the Cell [1,5]

	book o	a	flight	through	Houston 5
$S \rightarrow NP VP$	S, VP, Verb, Nominal, Noun	ro 01	S, VP, X2	FO 41	S, VP
$S \rightarrow X1 VP$ $X1 \rightarrow Aux NP$	[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
$S \rightarrow book \mid include$ $S \rightarrow Verb NP$ $S \rightarrow X2 PP$	prefer	Det L	NP		NP •
$S \rightarrow Verb PP$ $S \rightarrow VP PP$		[1,2]	[1,3]	[1,4]	[1,5]
NP → I she me NP → Houston NWA			Nominal, Noun		Nominal R
NP → Det Nominal Nominal → book flight meal money			[2,3]	[2,4]	[2,5]
Nominal → Nomina Nominal → Nomina	al PP			Prep	PP
VP → book include prefer VP → Verb NP Noun → book flight meal			ney	[3,4]	[3,5]
$VP \rightarrow X2 PP$ $X2 \rightarrow Verb NP$ $VP \rightarrow Verb PP$	Verb → <mark>boo</mark> Pronoun →	ok include prefer · I she me ın → Houston NWA	-		NP, PN
$VP \rightarrow VP PP$ $PP \rightarrow Prep NP$	$Aux \rightarrow doe$	·	[4.5]		

The CKY Algorithm: Filling the Cell [1,5]

	book o	a	flight	through	Houston 5
$S \rightarrow NP VP$	S, VP, Verb, Nominal, Noun		S, VP, X2		S, VP
$S \rightarrow X1 VP$	[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
$X1 \rightarrow Aux NP$ $S \rightarrow book \mid include$ $S \rightarrow Verb NP$	prefer	Det	NP L		NP
$S \rightarrow X2 PP$ $S \rightarrow Verb PP$		[1,2]	[1,3]	[1,4]	[1,5]
$S \rightarrow VP PP$ $NP \rightarrow I \mid she \mid me$ $NP \rightarrow Houston \mid NWA$			Nominal, Noun		Nominal
NP → Det Nominal	light meal money		[2,3]	[2,4]	[2,5]
Nominal → Nominal Nominal → Nominal	al Noun			Prep	PP
VP → book includ VP → Verb NP	Det → that	this a this a o <mark>ck flight</mark> meal mon	ney	[3,4]	R [3,5]
$VP \rightarrow X2 PP$ $X2 \rightarrow Verb NP$ $VP \rightarrow Verb PP$	Pronoun $ ightarrow$	ok include prefer I she me ın → Houston NWA		NP, PN	
$VP \rightarrow VP \ PP$ Aux \rightarrow does $PP \rightarrow Prep \ NP$ Prep $\rightarrow from \ to \ on \ near \ th$			ugh		[4,5]

The CKY Algorithm: Filling the Cell [1,5]

	book o	a	flight	through	Houston 5
$S \rightarrow NP VP$	S, VP, Verb, Nominal, Noun		S, VP, X2		S, VP
$S \rightarrow X1 VP$	[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
$X1 \rightarrow Aux NP$ $S \rightarrow book \mid include$	prefer	Det	NP		NP
$S \rightarrow Verb NP$ $S \rightarrow X2 PP$ $S \rightarrow Verb PP$		[1,2]	[1,3]	L [1,4]	[1,5]
$S \rightarrow VP PP$ $NP \rightarrow I \mid she \mid me$ $NP \rightarrow Houston \mid NWA$			Nominal, Noun		Nominal
NP → Det Nominal Nominal → book 1	flight meal money		[2,3]	[2,4]	[2,5]
Nominal → Nominal Nominal → Nominal	al Noun al PP			Prep	PP
$VP \rightarrow \frac{book}{VP} \mid includ$ $VP \rightarrow Verb NP$ $VP \rightarrow X2 PP$	Det → that	this <mark>a</mark> ook flight meal mor	ney	[3,4]	[3,5]
$X2 \rightarrow Verb NP$		ok include prefer · I she me		NP, PN	
$VP \rightarrow Verb PP$ $VP \rightarrow VP PP$ $PP \rightarrow Prep NP$	Proper-Nou Aux \rightarrow doe	ın → <mark>Houston</mark> NWA	ough		[4,5] R

The CKY Algorithm

function CKY-Parse(words, grammar) returns table

```
for j ← from 1 to Length(words) do table[j-1,j] \leftarrow \{A \mid A \rightarrow words[j] \in grammar \} for i ← from j – 2 downto 0 do for k \leftarrow i+1 \ to \ j-1 \ do table[i,j] \leftarrow table[i,j] \cup \{A \mid A \rightarrow BC \in grammar, B \in table[i,k], C \in table[k,j] \}
```

CKY Parsing

- To return all possible parses:
 - Augment each entry such that each non-terminal is paired with pointers to the entries from which it was derived
 - Permit multiple versions of the same non-terminal to be entered in an entry

Statistical Parsing

Resolving structural ambiguity: choose the most probable parse

Probabilistic Context-Free Grammars

- PCFG
- $G = (N, \Sigma, P, S, D)$
 - A set of non-terminal symbols (or variables) N
 - A set of terminal symbols Σ (N \cap Σ = \emptyset)
 - A set of productions P, each of the form $A \rightarrow \alpha$, where $A \in N$ and $\alpha \in (\Sigma \cup N)^*$
 - A designated start symbol S ∈ N
 - A function D that assigns a probability to each rule in P
- $P(A \rightarrow \alpha)$ or $P(A \rightarrow \alpha \mid A)$

Probabilistic Context-Free Grammars

$S \rightarrow NP VP$	[.80]	$Det \rightarrow that [.05] \mid the [.80] \mid a$	[.15]
$S \rightarrow Aux NP VP$	[.15]	Noun → book	[.10]
$S \rightarrow VP$	[.05]	Noun \rightarrow flights	[.50]
$NP \rightarrow Det Nom$	[.20]	$Noun \rightarrow meal$	[.40]
NP → Proper-Noun	[.35]	$Verb \rightarrow book$	[.30]
$NP \rightarrow Nom$	[.05]	Verb ightarrow include	[.30]
$NP \rightarrow Pronoun$	[.40]	Verb → want	[.40]
Nom → Noun	[.75]	$Aux \rightarrow can$	[.40]
Nom → Noun Nom	[.20]	$Aux \rightarrow does$	[.30]
Nom → Proper-Noun Nom	[.05]	$Aux \rightarrow do$	[.30]
$VP \rightarrow Verb$	[.55]	Proper-Noun → TWA	[.40]
$VP \rightarrow Verb NP$	[.40]	Proper-Noun $ o$ Denver	[.40].60
$VP \rightarrow Verb NP NP$	[.05]	$ Pronoun \rightarrow you[.40] I[.60]$	

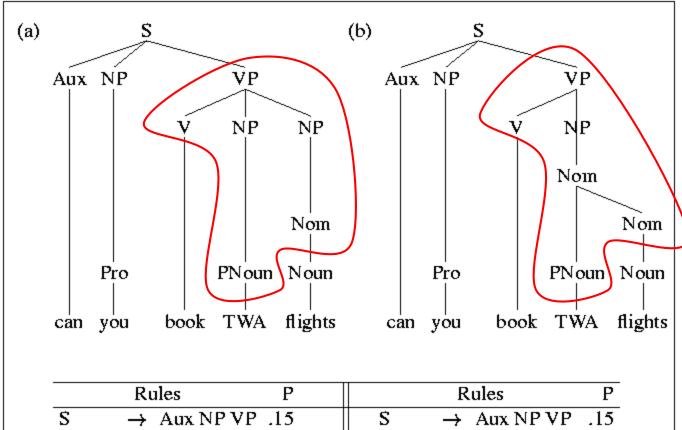
PCFG

$$P(T,S) = \prod_{n \in T} p(r(n))$$

$$P(T_l) = .15 \times .40 \times .05 \times .05 \times .35 \times .75 \times .40 \times .40 \times .30 \times .40 \times .50 = 3.78 \times 10^{-7}$$

$$P(T_r) = .15 \times .40 \times .40 \times .05 \times .05 \times .75 \times .40 \times .40 \times .30 \times .40 \times .50 = 4.32 \times 10^{-7}$$

$$\hat{T}(S) = \underset{T \text{ s.t.} S = yield(T)}{\operatorname{arg max}} P(T \mid S) = \underset{T \text{ s.t.} S = yield(T)}{\operatorname{arg max}} \frac{P(T, S)}{P(S)}$$
$$= \underset{T \text{ s.t.} S = yield(T)}{\operatorname{arg max}} P(T, S) = \underset{T \text{ s.t.} S = yield(T)}{\operatorname{arg max}} P(T)$$



PCFG

	Rι	ıles	Р		R	ules	Р
S	\rightarrow	Aux NP VP	.15	S	\rightarrow	Aux NP VP	.15
NP	\rightarrow	Pro	.40	NP	\rightarrow	Pro	.40
VP	\rightarrow	VNPNP	.05	VP	\rightarrow	VNP	.40
NP	\rightarrow	Nom	.05	NP	\rightarrow	Nom	.05
NP	\rightarrow	PNoun	ر 35.	Nom	\rightarrow	PNoun Nom	.05
Nom	\rightarrow	Noun	.75	Nom	\rightarrow	Noun	.75
Aux	\rightarrow	Can	.40	Aux	\rightarrow	Can	.40
NP	\rightarrow	Fio	.40	NP	\rightarrow	Fro	.40
Pro	\rightarrow	you	.40	Pro	\rightarrow	you	.40
Verb	\rightarrow	book	.30	Verb	\rightarrow	book	.30
PNoun	\rightarrow	TWA	.40	Pnoun	\rightarrow	TWA	.40
Noun	\rightarrow	flights	.50	Noun	\rightarrow	flights	.50

Probabilistic CKY Parsing

- Probabilistic CKY (Cocke-Kasami-Younger) algorithm for parsing PCFG
- Bottom-up dynamic programming algorithm
- Assume PCFG is in Chomsky Normal Form (production is either A → B C or A → a)
- table[i, j, A] stores the max probability for a constituent A spanning word positions i to j
- Probability of the most probably parse is table[0, n, S]

The Probabilistic CKY Algorithm

book o	а	flight 2		Houston
S, VP, Verb, Nominal, Noun		S, VP, X2		S, VP
[0,1]	[0,2]	[0,3]	[0,4]	[0,5]
	Det	NP		NP
	[1,2]	[1,3]	[1,4]	[1,5]
		Nominal, Noun		Nominal
		[2,3]	[2,4]	[2,5]
			Prep	PP
			[3,4]	[3,5]
				NP, PN
				[4,5]

The Probabilistic CKY Algorithm

function Probabilistic-CKY(words, grammar) **returns** most probable parse and its probability

```
for j \leftarrow from 1 to Length(words) do for all { A | A \rightarrow words[j] \in grammar } table[j - 1, j, A] \leftarrow P(A \rightarrow words[j]) 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 table[i, k, B] > 0 and table[k, j, C] > 0 } if (table[i, j, A] < P(A \rightarrow BC) \times table[i, k, B] \times table[k, j, C] then table[i, j, A] \leftarrow P(A \rightarrow BC) \times table[i, k, B] \times table[k, j, C] back[i, j, A] \leftarrow { k, B, C } return Build-Tree(back[0, Length(words), S]), table[0, Length(words), S]
```

Learning PCFG Rule Probabilities

Estimate from parsed sentences (treebank)

$$P(\alpha \to \beta \mid \alpha) = \frac{\text{Count}(\alpha \to \beta)}{\sum_{\gamma} \text{Count}(\alpha \to \gamma)} = \frac{\text{Count}(\alpha \to \beta)}{\text{Count}(\alpha)}$$

Problems with PCFGs

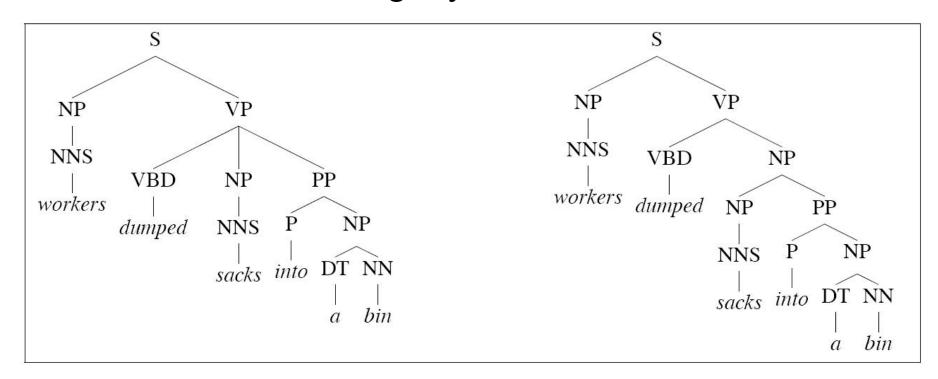
- Poor independence assumptions
- Lack of sensitivity to words

Poor Independence Assumptions

- The expansion of a non-terminal actually depends on its context
- Example:
 - An NP can be a pronoun or non-pronoun (e.g., proper noun or determiner noun sequence)
 - NP → PRP
 - NP → DT NN
 - Subject NP: 91% pronoun, 9% non-pronoun
 - Object NP: 34% pronoun, 66% non-pronoun

Lack of Sensitivity to Words

Attachment ambiguity

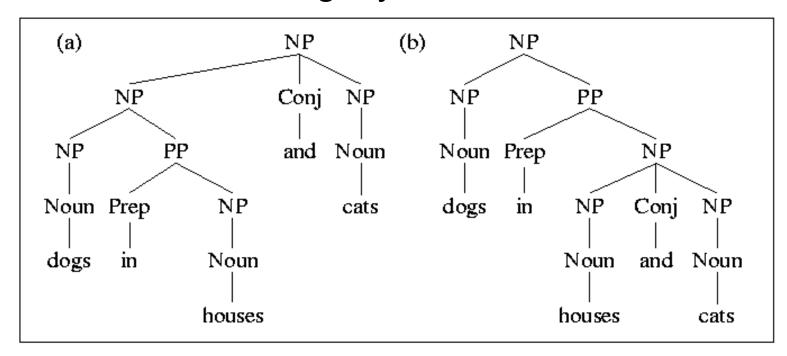


Lack of Sensitivity to Words

- Attachment ambiguity
 - VP attachment: Workers dumped sacks into a bin
 - NP attachment: Workers sold sacks of a chemical
 - Knowing the particular words (dumped, sacks, into, sold, sacks, of) helps in disambiguation

Lack of Sensitivity to Words

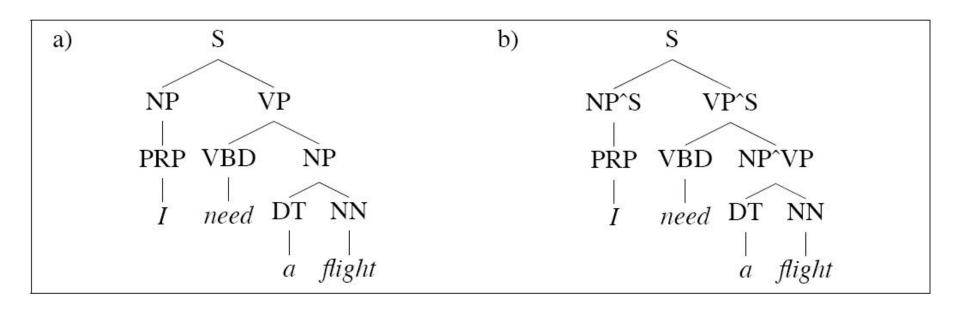
Coordination ambiguity



Same set of rules used and hence the same probability

Splitting Non-terminals

Parent annotation



- Each non-terminal in a parse tree is annotated with a word (lexical head)
- Identify one RHS constituent of a PCFG rule as the head child of that rule
- Lexical head of the parent (LHS of a PCFG rule) is the lexical head of the head child

Head child (underlined):

 $S \rightarrow NP \underline{VP}$

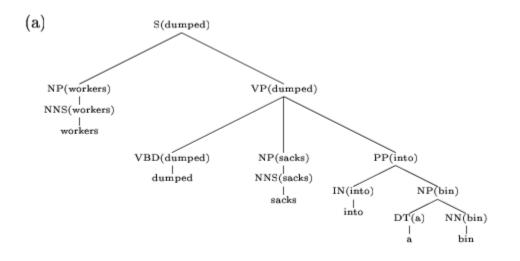
 $NP \rightarrow \underline{NNS}$

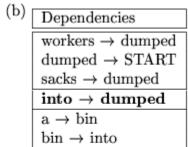
VP → VBD NP PP

 $PP \rightarrow IN NP$

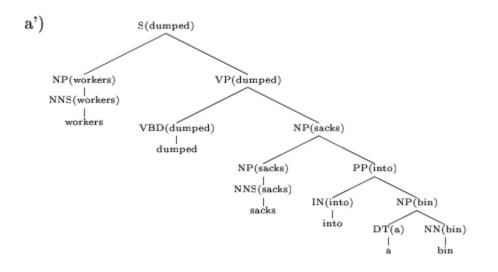
 $NP \rightarrow DT NN$

 $NP \rightarrow \underline{NP} PP$





modifier → head



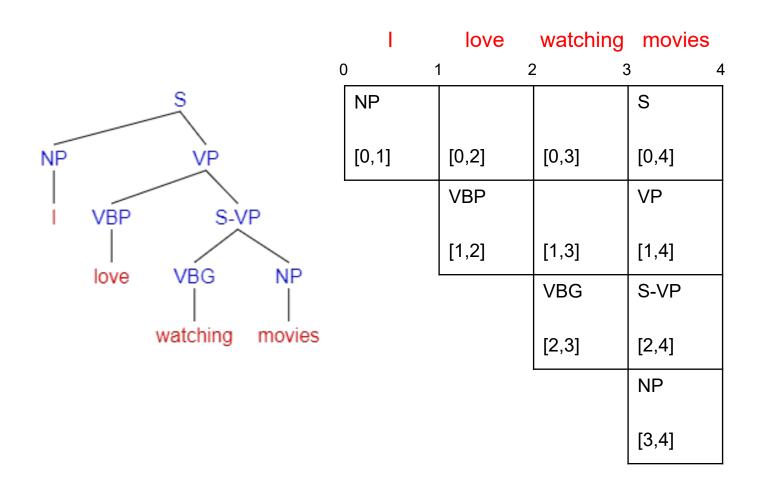
1. 2)	*\					
b')	Dependencies					
	$workers \rightarrow dumped$					
	$dumped \rightarrow START$					
	$sacks \rightarrow dumped$					
	into \rightarrow sacks					
	$a \rightarrow bin$					
	$bin \rightarrow into$					

modifier → head

Neural Constituency Parsing

 Materials from "A minimal span-based neural constituency parser", Mitchell Stern, Jacob Andreas, Dan Klein, ACL 2017

Parsing as Span Classification



Parse Tree Scoring Function

$$s_{\text{tree}}(T) = \sum_{(i,j,l) \in T} s(i,j,l)$$

$$= s(0,1,NP)$$

$$+ s(1,2,VBP)$$

$$+ s(2,3,VBG)$$

$$+ s(3,4,NP)$$

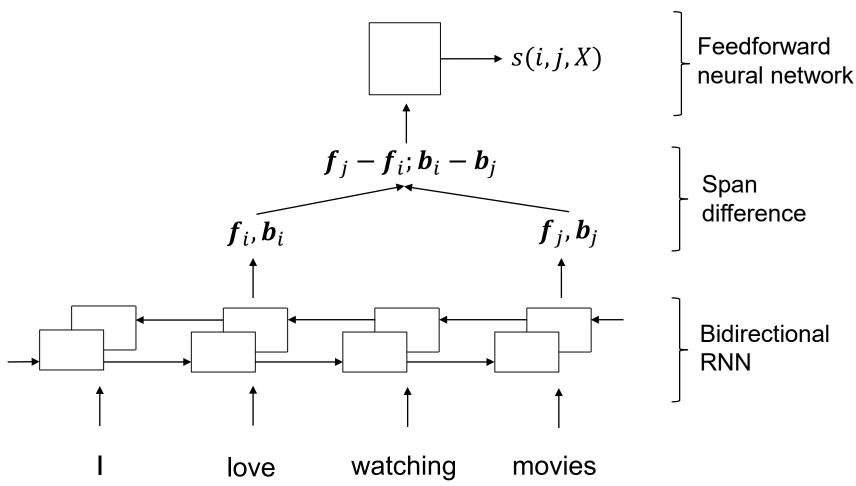
$$+ s(2,4,S-VP)$$

$$+ s(1,4,VP)$$

$$+ s(0,4,S)$$

	1	love	watching	movies
0	1	2	2 3	3 4
	NP			S
	[0,1]	[0,2]	[0,3]	[0,4]
		VBP		VP
		[1,2]	[1,3]	[1,4]
	·		VBG	S-VP
			[2,3]	[2,4]
		·		NP
				[3,4]

NN Implementation of Scoring Function



Dynamic Programming Algorithm

$$\begin{split} s_{\text{best}}(i,j) &= \max_{l} [s(i,j,l)] & \text{if } j-i=1 \\ s_{\text{best}}(i,j) &= \max_{l} [s(i,j,l)] \\ &+ \max_{k} [s_{\text{best}}(i,k) + s_{\text{best}}(k,j)] & \text{if } j-i>1 \end{split}$$

- Grammar rules are not used
- Label (non-terminal symbol) and break point selected independently

Training

- Margin-based training
- Let T^* be the gold parse tree
- Objective: $s_{\text{tree}}(T^*) > s_{\text{tree}}(T)$ for all $T \neq T^*$
- Compute the best predicted tree \hat{T} under the current model using dynamic programming

$$\widehat{T} = \underset{T}{\operatorname{argmax}}[s_{\operatorname{tree}}(T)]$$

Hinge loss:

$$\sum_{\substack{(T^*, \hat{T}) \in D_{\text{train}} \\ \hat{T} \neq T^*}} \max(0, 1 - (s_{\text{tree}}(T^*) - s_{\text{tree}}(\hat{T})))$$

Evaluating Parsers

- Benchmark corpus: Penn Treebank
- PARSEVAL measures:

labeled recall
$$R = \frac{\text{\#correct constituents in parser's parse of } s}{\text{\# constituents in treebank's parse of } s}$$
labeled precision $P = \frac{\text{\#correct constituents in parser's parse of } s}{\text{\# constituents in parser's parse of } s}$
labeled $F1 = \frac{2RP}{R+P}$

 A constituent is correct if there is a constituent in the treebank's parse that spans the same words with the same non-terminal symbol

Parser Accuracy

Parser	F1 Score (%)
PCFG	73.0
Lexicalized PCFG	87.2
Span-based RNN	91.7
Span-based transformer + Pretrained LM	96.0