

CS498JH: Introduction to NLP (Fall 2012)

<http://cs.illinois.edu/class/cs498jh>

Lecture 12:

The CKY parsing algorithm

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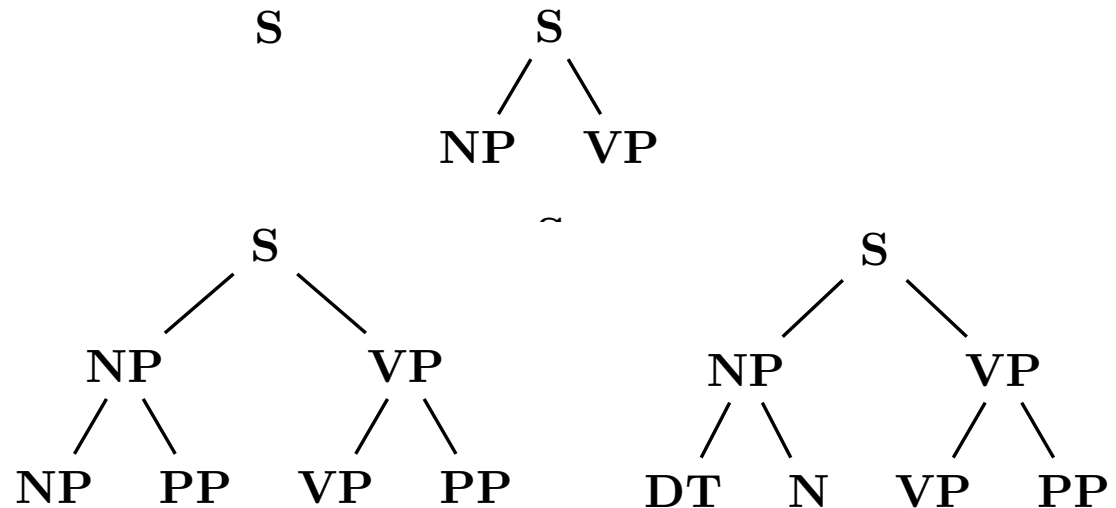
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Naive top-down parsing

S → NP VP
NP → NP PP
NP → Noun
VP → VP PP
VP → Verb NP

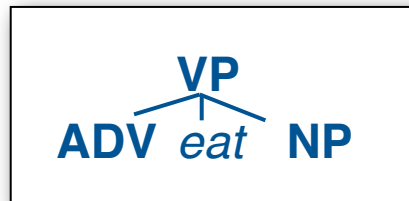


The number of trees is exponential!
Many subtrees are the same.

Chomsky Normal Form

The right-hand side of a standard CFG can have an **arbitrary number of symbols** (terminals and nonterminals):

$VP \rightarrow ADV \text{ eat } NP$



A CFG in **Chomsky Normal Form** (CNF) allows only two kinds of right-hand sides:

- **Two nonterminals:** $VP \rightarrow ADV VP$
- **One terminal:** $VP \rightarrow eat$

Any CFG can be transformed into an equivalent CNF:

$VP \rightarrow ADV VP_1$

$VP_1 \rightarrow VP_2 NP$

$VP_2 \rightarrow eat$



A note about ϵ -productions

Formally, context-free grammars are allowed to have **empty productions** (ϵ = the empty string):

$VP \rightarrow V \text{ NP}$ $NP \rightarrow \text{DT Noun}$ $NP \rightarrow \epsilon$

These can always be **eliminated** without changing the language generated by the grammar:

$VP \rightarrow V \text{ NP}$ $NP \rightarrow \text{DT Noun}$ $NP \rightarrow \epsilon$

becomes

$VP \rightarrow V \text{ NP}$ $VP \rightarrow V \epsilon$ $NP \rightarrow \text{DT Noun}$

which in turn becomes

$VP \rightarrow V \text{ NP}$ $VP \rightarrow V$ $NP \rightarrow \text{DT Noun}$

We will assume that our grammars don't have ϵ -productions

CKY chart parsing algorithm

Bottom-up parsing:

- start with the words

Dynamic programming:

- save the results in a table/chart

- re-use these results in finding larger constituents

Complexity: $O(n^3|G|)$

- n : length of string, $|G|$: size of grammar)

Presumes a CFG in **Chomsky Normal Form**:

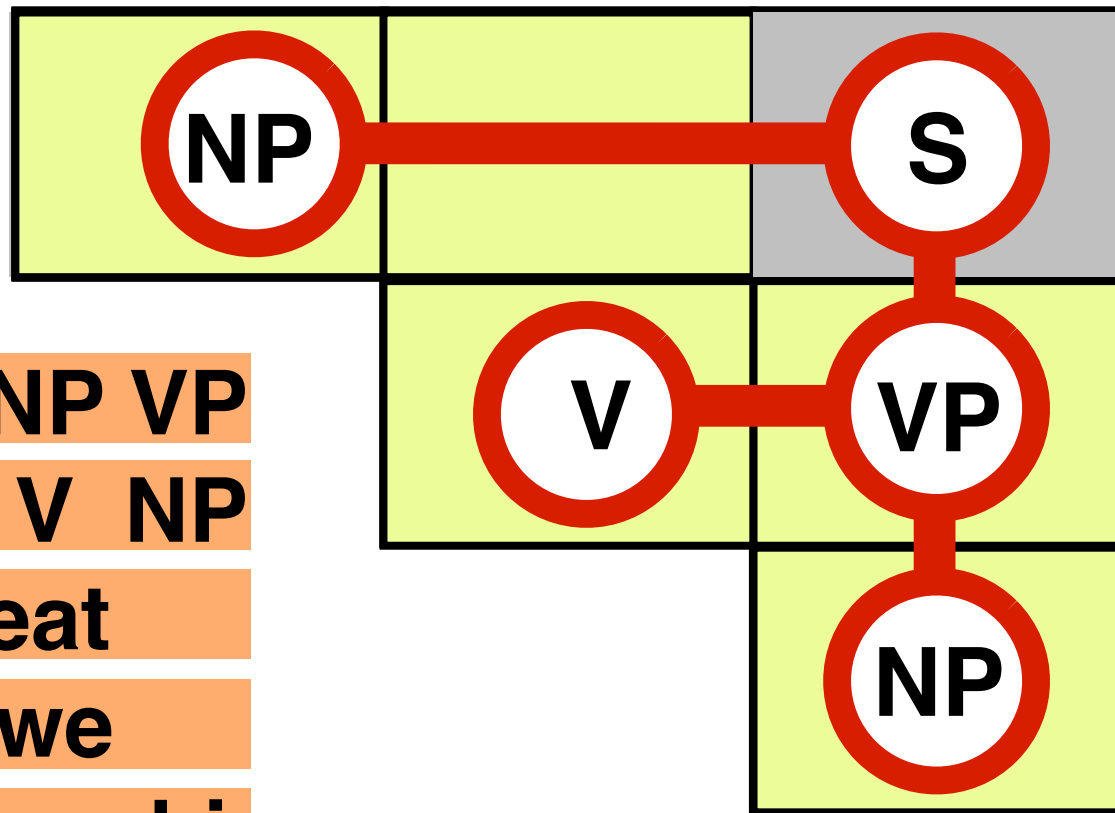
- Rules are all either $A \rightarrow B C$ or $A \rightarrow a$

- (with A, B, C nonterminals and a a terminal)

The CKY parsing algorithm

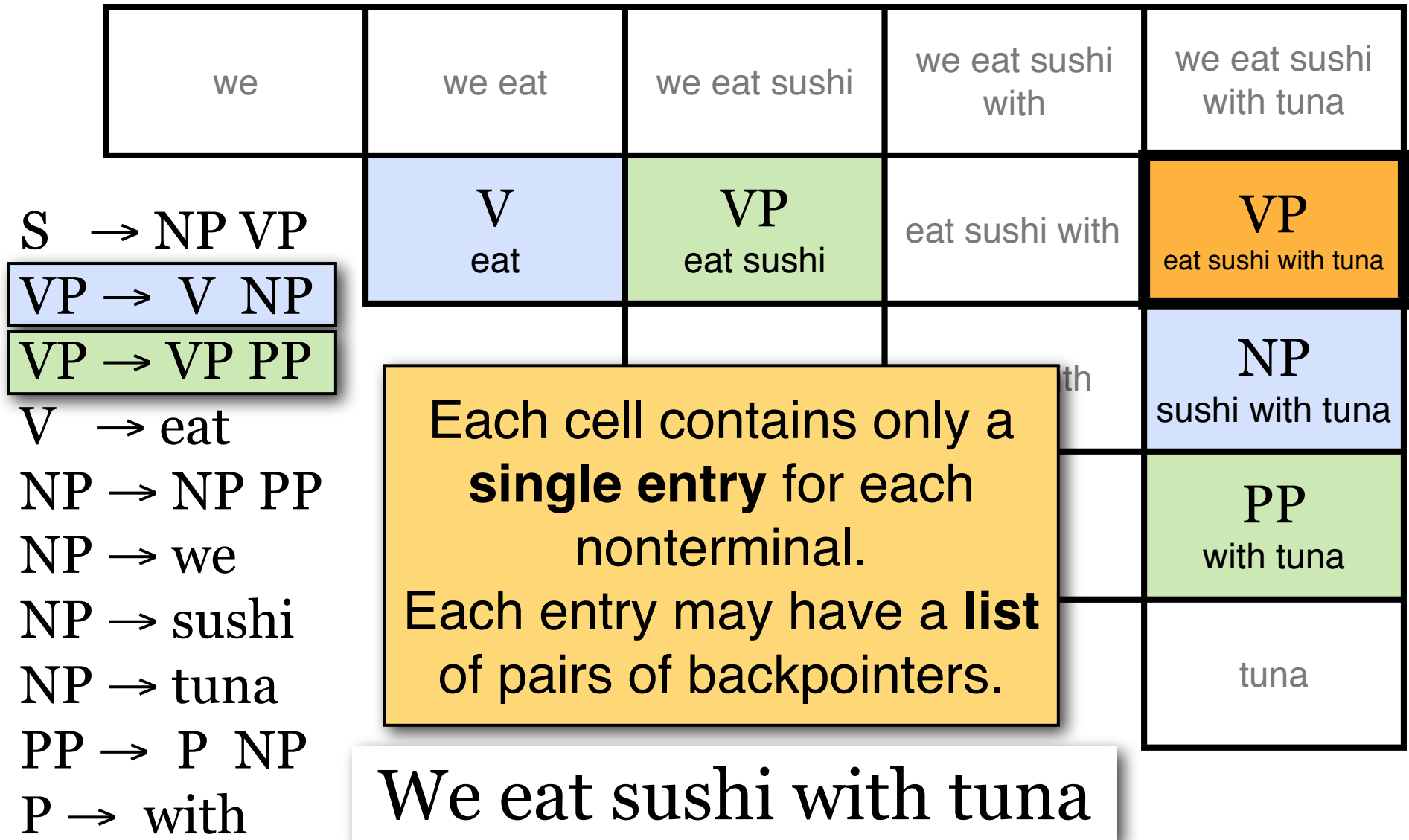
To recover the parse tree, each entry needs **pairs** of backpointers.

S → NP VP
VP → V NP
V → eat
NP → we
NP → sushi



We eat sushi

The CKY parsing algorithm



How do you count the **number of parse trees** for a sentence?

1. For each **pair of backpointers**
(e.g. $VP \rightarrow V \ NP$): **multiply** #trees of children
$$\text{trees}(VP_{VP \rightarrow V \ NP}) = \text{trees}(V) \times \text{trees}(NP)$$

2. For each **list of pairs of backpointers**
(e.g. $VP \rightarrow V \ NP$ and $VP \rightarrow VP \ PP$): **sum** #trees
$$\text{trees}(VP) = \text{trees}(VP_{VP \rightarrow V \ NP}) + \text{trees}(VP_{VP \rightarrow VP \ PP})$$

The CKY parsing algorithm

$S \rightarrow NP VP$

$VP \rightarrow V NP$

$VP \rightarrow VP PP$

$V \rightarrow \text{drinks}$

$NP \rightarrow NP PP$

$NP \rightarrow \text{we}$

$NP \rightarrow \text{drinks}$

$NP \rightarrow \text{milk}$

$PP \rightarrow P NP$

$P \rightarrow \text{with}$

V buy	VP buy drinks	buy drinks with	VP buy drinks with milk
	V, NP drinks	drinks with	VP, NP drinks with milk
		P	PP

Each cell may have **one entry**
for each nonterminal

We buy drinks with milk

CKY: filling the chart

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

CKY: filling one cell

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

chart[2][6]:

w_1 **w_2** **w_3** **w_4** **w_5** **w_6** w_7

chart[2][6]:

w_1 **w_2** **w_3** **w_4** **w_5** **w_6** w_7

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

chart[2][6]:

w_1 **w_2** **w_3** **w_4** **w_5** **w_6** w_7

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

chart[2][6]:

w_1 **w_2** **w_3** **w_4** **w_5** **w_6** w_7

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

chart[2][6]:

w_1 **w_2** **w_3** **w_4** **w_5** **w_6** w_7

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

Cocke Kasami Younger (1)

```
ckyParse(n):
    initChart(n)
    fillChart(n)
```

```
initChart(n):
  for  $i = 1 \dots n$ :
    initCell(i,i)
```

```

initCell(i,i):
  for c in lex(word[i]):
    addToCell(cell[i][i], c, null, null)
addToCell(Parent,cell,Left, Right)
  if (cell.hasEntry(Parent)):
    P = cell.getEntry(Parent)
    P.addBackpointers(Left, Right)
  else cell.addEntry(Parent, Left, Right)

```

w_1	w_i	...	w_n	
							w_1
							...
							...
							w_i
							...
							w_n

```
fillChart(n):
  for span = 1...n-1:
    for i = 1...n-span:
      fillCell(i,i+span)
```

```

fillCell(i,j):
  for  $k = i..j-1$ :
    combineCells( $i, k, j$ )

```

```

combineCells(i,k,j):
  for Y in cell[i][k]:
    for Z in cell[k + 1][j]:
      for X in Nonterminals:
        if  $X \rightarrow YZ$  in Rules:
          addToCell(cell[i][j], X, Y, Z)

```

[illegible]

Exercise: CKY parser

S \rightarrow **NP VP**

NP \rightarrow **NP PP**

NP \rightarrow **Noun**

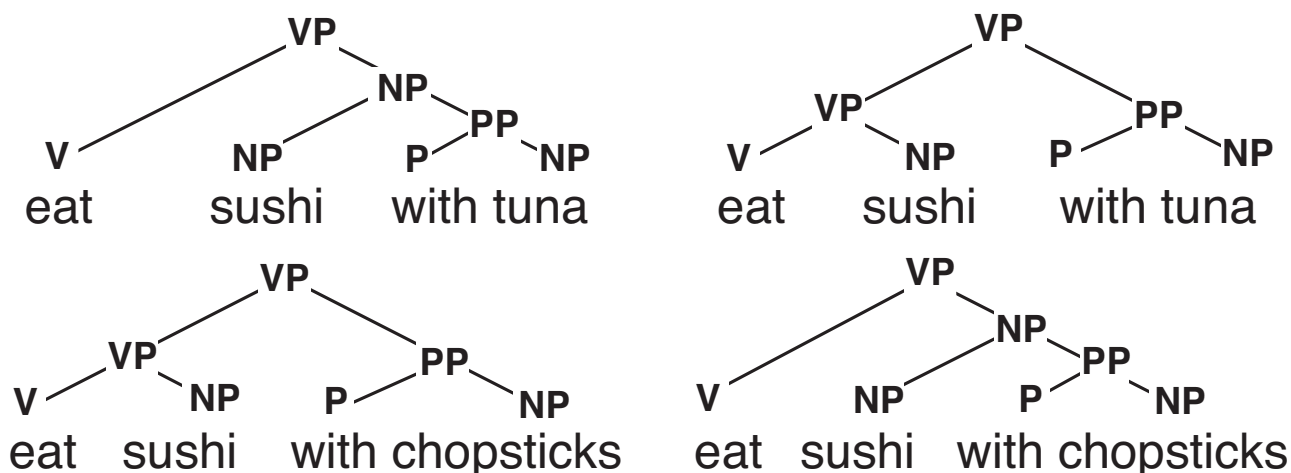
VP \rightarrow **VP PP**

VP \rightarrow **Verb NP**

I eat sushi with chopsticks

Grammars are ambiguous

A grammar might generate multiple trees for a sentence:



What's the most likely parse τ for sentence S ?

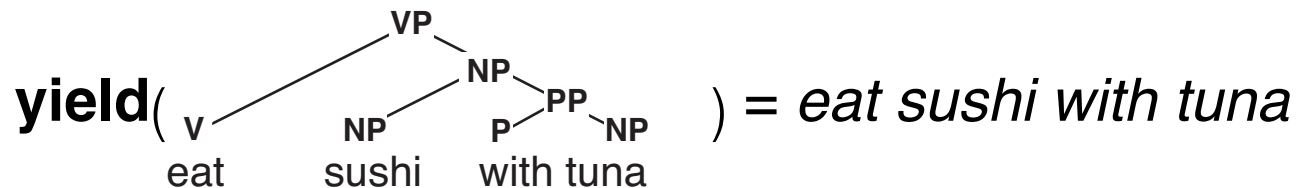
We need a model of $P(\tau \mid S)$

Computing $P(\tau \mid S)$

Using Bayes' Rule:

$$\begin{aligned}\arg \max_{\tau} P(\tau \mid S) &= \arg \max_{\tau} \frac{P(\tau, S)}{P(S)} \\ &= \arg \max_{\tau} P(\tau, S) \\ &= \arg \max_{\tau} P(\tau) \quad \text{if } S = \text{yield}(\tau)\end{aligned}$$

The **yield of a tree** is the string of terminal symbols that can be read off the leaf nodes



Computing $P(\tau)$

T is the (infinite) set of all trees in the language:

$$L = \{s \in \Sigma^* \mid \exists \tau \in T : \text{yield}(\tau) = s\}$$

We need to define $P(\tau)$ such that:

$$\forall \tau \in T : 0 \leq P(\tau) \leq 1$$

$$\sum_{\tau \in T} P(\tau) = 1$$

The set T is generated by a context-free grammar

$S \rightarrow NP VP$	$VP \rightarrow Verb NP$	$NP \rightarrow Det Noun$
$S \rightarrow S conj S$	$VP \rightarrow VP PP$	$NP \rightarrow NP PP$
$S \rightarrow \dots\dots$	$VP \rightarrow \dots\dots$	$NP \rightarrow \dots\dots$

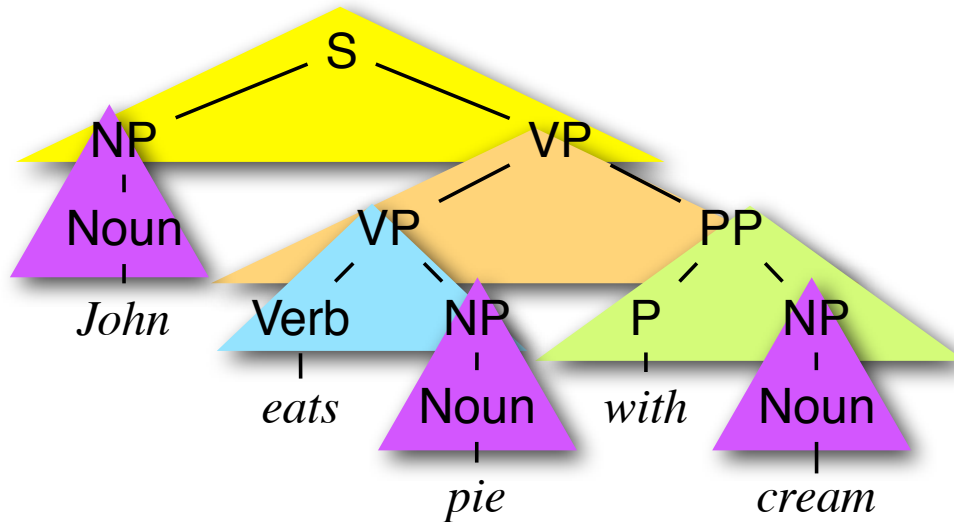
Probabilistic Context-Free Grammars

For every nonterminal X , define a probability distribution $P(X \rightarrow \alpha \mid X)$ over all rules with the same LHS symbol X :

S	\rightarrow	$NP \ VP$	0.8
S	\rightarrow	$S \ conj \ S$	0.2
NP	\rightarrow	$Noun$	0.2
NP	\rightarrow	$Det \ Noun$	0.4
NP	\rightarrow	$NP \ PP$	0.2
NP	\rightarrow	$NP \ conj \ NP$	0.2
VP	\rightarrow	$Verb$	0.4
VP	\rightarrow	$Verb \ NP$	0.3
VP	\rightarrow	$Verb \ NP \ NP$	0.1
VP	\rightarrow	$VP \ PP$	0.2
PP	\rightarrow	$P \ NP$	1.0

Computing $P(\tau)$ with a PCFG

The probability of a tree τ is the product of the probabilities of all its rules:



$$P(\tau) = 0.8 \times 0.3 \times 0.2 \times 1.0 \times 0.2^3 = 0.00384$$

S	→	NP VP	0.8
S	→	S conj S	0.2
NP	→	Noun	0.2
NP	→	Det Noun	0.4
NP	→	NP PP	0.2
NP	→	NP conj NP	0.2
VP	→	Verb	0.4
VP	→	Verb NP	0.3
VP	→	Verb NP NP	0.1
VP	→	VP PP	0.2
PP	→	P NP	1.0

The three basic problems for PCFGs

We observe an **output sequence** $w = w_1 \dots w_N$:

$w = \text{"she promised to back the bill"}$

Problem I (Likelihood): find $P(w \mid \lambda)$

Given a PCFG with parameters λ , compute **the likelihood of the observed output**, $P(w \mid \lambda)$

Problem II (Decoding): find $\tau^* = \operatorname{argmax}_{\tau} P(\tau, w \mid \lambda)$

Given a PCFG with parameters λ , what is **the most likely tree** τ to generate w ?

Problem III (Estimation): find $\operatorname{argmax}_{\lambda} P(w \mid \lambda)$

Find the parameters λ which maximize $P(w \mid \lambda)$

PCFG parsing (decoding): Probabilistic CKY

Probabilistic CKY

Like standard CKY, but with probabilities.

Terminals have probability $p = 1$

Non-terminals: associate $P(X \rightarrow YZ \mid X)$ with every pair of backpointers from x in `cell[i][j]` to y in `cell[i][k]` and z in `cell[k+1][j]`

Finding the most likely parse

Local greedy (Viterbi) search is guaranteed to be optimal:

For every non-terminal x in `cell[i][j]`, keep only the highest-scoring pair of backpointers to any pair of children (y in `cell[i][k]` and z in `cell[k+1][j]`):

$$P_{VIT}(X) = \mathbf{argmax}_{Y,Z} P_{VIT}(Y) \times P_{VIT}(Z) \times P(X \rightarrow YZ \mid X)$$

Probabilistic CKY

Input: POS-tagged sentence

John_N eats_V pie_N with_P cream_N

John	eats	pie	with	cream	
N NP 0.2	S $0.8 \cdot 0.2 \cdot 0.4$	S $0.8 \cdot 0.2 \cdot 0.08$		S $0.2 \cdot 0.0024 \cdot 0.8$	John
	V VP 0.4	VP $0.3 \cdot 0.2$		VP $\max(0.008 \cdot 0.2, 0.06 \cdot 0.2 \cdot 0.2)$	eats
		N NP 0.2		NP $0.2 \cdot 0.2 \cdot 0.2$	pie
			P	PP $1 \cdot 0.2$	with
				N NP 0.2	cream

S	→ NP VP	0.8
S	→ S conj S	0.2
NP	→ Noun	0.2
NP	→ Det Noun	0.4
NP	→ NP PP	0.2
NP	→ NP conj NP	0.2
VP	→ Verb	0.4
VP	→ Verb NP	0.3
VP	→ Verb NP NP	0.1
VP	→ VP PP	0.2
PP	→ P NP	1.0