PCFGs

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Today's lecture

1. Uncertainty
2. Probabilistic Context-Free Grammars
   - Uses of PCFGs: Disambiguation
   - Benefits of PCFGs
   - Issues
3. Probabilistic parsing
   - Probabilistic CKY
4. PCKY Example
5. Homework 3

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Uncertain language

CFGs are fine when the input is 100% predictable. But what about when the input data have never been seen?

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- the weather
- the stock market
- what someone will say next to a speech recognition system

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Uncertain but regular

Strategy for leveraging probability theory for NLP: exploit regularities in known data to predict the structure of unseen data.

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What is a PCFG?

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It can be used to assign a probability to every string in the language (language model) and to every structure in the language.

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$\mathbf{S}$ = *To get out of recession, we must obamafy the economy.*
$P(\mathbf{S}) = 0.000000004538$

Formal definition of a PCFG

Definition

A CFG grammar is formally defined as $G = \langle N, \Sigma, P, S \rangle$ where:

- N is a set of non-terminal symbols, typically $S, A, B, \ldots$
- S is the starting or goal symbol from N, i.e., $S \in N$
- Σ is a set of terminal symbols, typically $x, y, z, \ldots$ disjoint from N
- P is a set of production rules with attached probabilities.

Formal definition of a PCFG (cont)

Definition

The productions P are of the form: $A \rightarrow \beta \;\; [p]$, where:

- A is a non-terminal $A \in N$
- β is a string of symbols from $(\Sigma \cup N)$
- $[p]$ is the probability (from 0 to 1) that A will have β as its constituent.

Conditional probability

- Thus, p is a **conditional probability**: the probability of some event e_1 given the occurrence of some other event e_2: $P(e_1|e_2)$, e.g., $P(raining|wetroads)$.

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PCFGs are defined according to a generative perspective: top-down

It turns out that the non-generative approach, i.e., $P(LHS|RHS)$, gives a poor parsing model.

Calculating probabilities

Treebank as grammar

A rule probability is calculated by summing the occurrences of rules in a labeled, bracketed treebank. That is, the treebank acts a kind of implicit grammar, and the explicit grammar can be "induced" from labeled and bracketed trees.

$$P(A \rightarrow \beta | A) = \frac{Count(A \rightarrow \beta)}{\sum_{\gamma} Count(A \rightarrow \gamma)} = \frac{Count(A \rightarrow \beta)}{Count(A)}$$

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Probability Distribution

The total probability for a given Nonterminal must sum to one:

$$\sum_{\beta} P(A \rightarrow \beta) = 1$$

In a given corpus:

$S \rightarrow \beta$	occurs 212 times
$S \rightarrow NP\ VP$	occurs 97 times
$S \rightarrow AUX\ NP\ VP$	occurs 43
$S \rightarrow VP$	occurs 58
$S \rightarrow ADJP$	occurs 14 times

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$S \rightarrow ADJP$	occurs 14 times	P=0.0660
		$0.9999 \approx 1$

Using PCFGs for disambiguation

Probability of a particular parse tree (its derivation) is defined as:

$$P(T) = \prod_{i=1}^{n} P(RHS_i | LHS_i)$$

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That is, we multiply together all rule expansion probabilities to obtain the probability of the tree.

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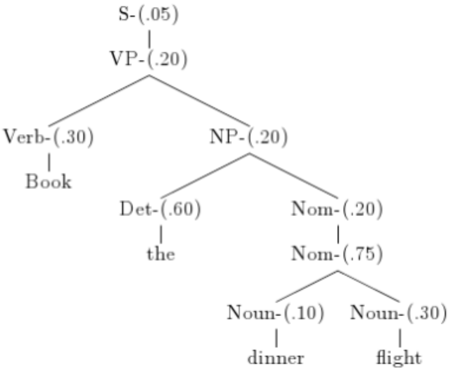
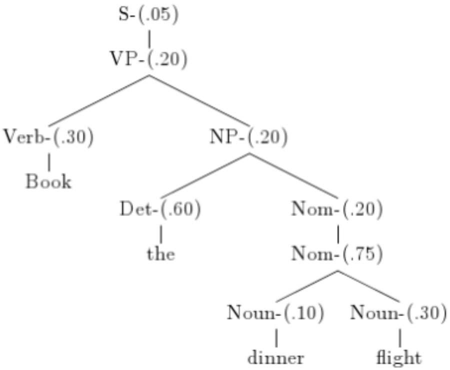
Probability of a parse tree 1

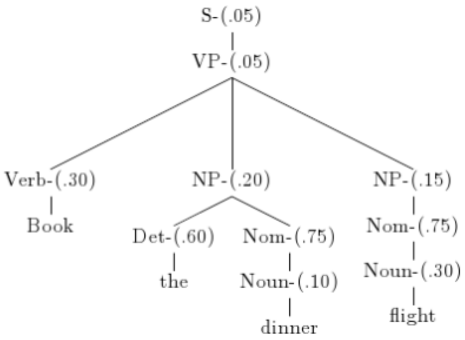


Probability of a parse tree 1



$$.05 \times .20 \times .30 \times .20 \times .60 \times .20 \times .75 \times .10 \times .30 = 1.62 \times 10^{-6}$$

Probability of a parse tree 2



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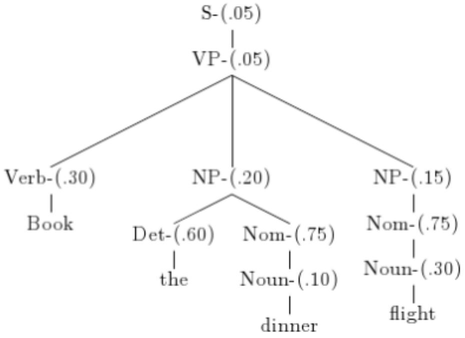
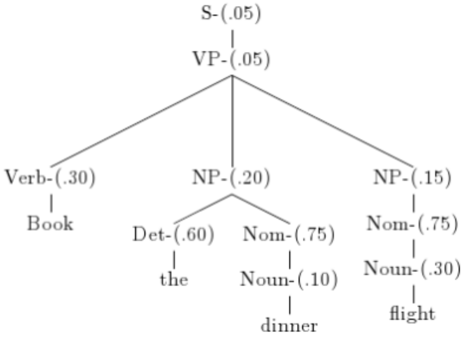


$$.05 * .05 * .30 * .20 * .60 * .75 * .10 * .15 * .75 * .30 = 2.28 \times 10^{-7}$$

Probability of a parse tree 2



$.05 * .05 * .30 * .20 * .60 * .75 * .10 * .15 * .75 * .30 = 2.28 \times 10^{-7}$

Parse tree 1 was greater: $1.62 \times 10^{-6} > 2.28 \times 10^{-7}$

Disambiguation strategy

A disambiguation strategy is to choose the parse with the highest probability:

$$\hat{T}(S) = \arg \max_{yield(T)}$$

- Choose the most likely parse $\hat{T}$ given the $yield(T)$, or the string sequence S
- What exactly is being maximized?
- The probability of the parse tree T given input sentence S.

Benefits of using PCFGs

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- PCFGs help smooth out disfluencies and other errors in the training set.

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- As the number of possible trees for a given input grows, a PCFG gives some idea of the plausibility of a particular parse.
- PCFGs help smooth out disfluencies and other errors in the training set.
- PCFGs are good for inducing grammars from positive data (from parsed treebanks).

Issues

Place invariance

probability of a subtree does not depend on the position of its terminals

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Recall example tree:

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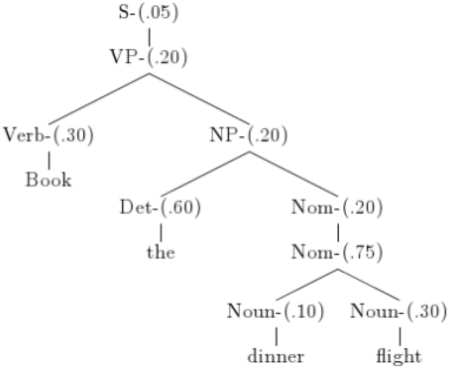
Probability of a parse tree



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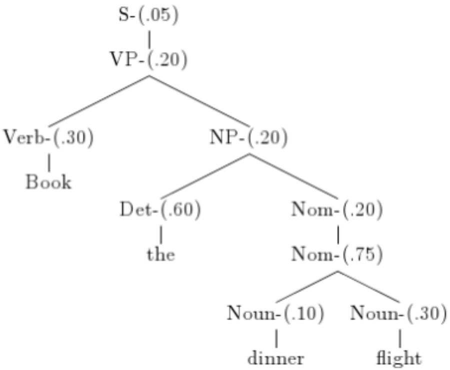

$$P(NP) = .20 \times .60 \times .20 \times .75 \times .10 \times .30 = 0.00054$$

Some assumptions with PCFGs

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- **place invariance**: probability of a subtree does not depend on the position of its terminals
  P(*the dog bit the boy*) = P(*the boy bit the dog*)
- **context-free**: probability of a subtree does not depend on words not dominated by the subtree
  (the bird) swims ..., (the bird) flies ...

Context sensitivity of certain rules

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Subject	91%	9%
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Example

He saw the accident involving the red car.

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should be more likely than:

Example

The man in the street near the bank saw it

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Deterministic parsing

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Strategy: prune search space by eliminating suboptimal or improbable ones

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Strategy: prune search space by eliminating suboptimal or improbable ones

Use a PCFG to guide the pruning process; chose the best parse, or *n* best parses.

CKY vs. Prob-CKY

- In the non-probabilistic version, what's contained in a CKY cell?

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CKY vs. Prob-CKY

- In the non-probabilistic version, what's contained in a CKY cell?
- All possible structures for a given span of input; in other words, all possible syntactic interpretations for a given substring.
  ...(time flies)... can be a VP, S, NP, ...

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CKY vs. Prob-CKY

- In the non-probabilistic version, what's contained in a CKY cell?
- All possible structures for a given span of input; in other words, all possible syntactic interpretations for a given substring.
  ...(time flies)... can be a VP, S, NP, ...
- What if we only need the most likely parse (or top 10 most likely parses) ?

Probabilistic-CKY

function PROBABILISTIC-CKY(*words*, *grammar*) **returns** most probable *parse*, 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 $\{A | A \rightarrow B \ \ C \in grammar,$
and $table[i,k,B] > 0$ and $table[k,j,C] > 0\}$
if $table[i,j,A] < P(A \rightarrow B \ \ C) \times table[i,k,B] \times table[k,j,C])$
$table[i,j,A] \leftarrow P(A \rightarrow B \ \ C) \times table[i,k,B] \times table[k,j,C])$
$back[i,j,A] \leftarrow \{k, B, C\}$
return BUILD_TREE(*back*[1,LENGTH(*words*), *S*]), *table*[1,LENGTH(*words*), *S*]

See pcky_eg.pdf.

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CKY example

a 1	pilot 2	likes 3	flying 4	planes 5

$S \longrightarrow NP\ VP$
$VP \longrightarrow VBG\ NNS$
$VP \longrightarrow VBZ\ VP$
$VP \longrightarrow VBZ\ NP$
$NP \longrightarrow DT\ NN$
$NP \longrightarrow JJ\ NNS$
$DT \longrightarrow a$
$NN \longrightarrow pilot$
$VBZ \longrightarrow likes$
$VBG \longrightarrow flying$
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CKY example

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1	2	3	4	5
DT				

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$NP \longrightarrow JJ\ NNS$
$DT \longrightarrow a$
$NN \longrightarrow pilot$
$VBZ \longrightarrow likes$
$VBG \longrightarrow flying$
$JJ \longrightarrow flying$
$NNS \longrightarrow planes$

CKY example

a 1	pilot 2	likes 3	flying 4	planes 5
DT	NP	-	-	
	NN	-	-	
		VBZ	-	
			JJ VBG	
				NNS

S → *NP VP*
VP → *VBG NNS*
VP → *VBZ VP*
VP → *VBZ NP*
NP → *DT NN*
NP → *JJ NNS*
DT → *a*
NN → *pilot*
VBZ → *likes*
VBG → *flying*
JJ → *flying*
NNS → *planes*

CKY example

a 1	pilot 2	likes 3	flying 4	planes 5
DT	NP	-	-	
	NN	-	-	
		VBZ	-	
			JJ VBG	NP
				NNS

#

$S \longrightarrow NP\ VP$
$VP \longrightarrow VBG\ NNS$
$VP \longrightarrow VBZ\ VP$
$VP \longrightarrow VBZ\ NP$
$NP \longrightarrow DT\ NN$
$NP \longrightarrow JJ\ NNS$
$DT \longrightarrow a$
$NN \longrightarrow pilot$
$VBZ \longrightarrow likes$
$VBG \longrightarrow flying$
$JJ \longrightarrow flying$
$NNS \longrightarrow planes$

CKY example

a 1	pilot 2	likes 3	flying 4	planes 5
DT	NP	-	-	
	NN	-	-	
		VBZ	-	
			JJ VBG	NP VP
				NNS

- $S \longrightarrow NP\ VP$
- \# $VP \longrightarrow VBG\ NNS$
- $VP \longrightarrow VBZ\ VP$
- $VP \longrightarrow VBZ\ NP$
- $NP \longrightarrow DT\ NN$
- $NP \longrightarrow JJ\ NNS$
- $DT \longrightarrow a$
- $NN \longrightarrow pilot$
- $VBZ \longrightarrow likes$
- $VBG \longrightarrow flying$
- $JJ \longrightarrow flying$
- $NNS \longrightarrow planes$

CKY example

a 1	pilot 2	likes 3	flying 4	planes 5
DT	NP	-	-	
	NN	-	-	
		VBZ	-	VP
			JJ VBG	NP VP
				NNS

#

$S \longrightarrow NP\ VP$
$VP \longrightarrow VBG\ NNS$
$VP \longrightarrow VBZ\ VP$
$VP \longrightarrow VBZ\ NP$
$NP \longrightarrow DT\ NN$
$NP \longrightarrow JJ\ NNS$
$DT \longrightarrow a$
$NN \longrightarrow pilot$
$VBZ \longrightarrow likes$
$VBG \longrightarrow flying$
$JJ \longrightarrow flying$
$NNS \longrightarrow planes$

CKY example

a 1	pilot 2	likes 3	flying 4	planes 5
DT	NP	-	-	
	NN	-	-	
		VBZ	-	VP VP
			JJ VBG	NP VP
				NNS

#

$S \longrightarrow NP\ VP$
$VP \longrightarrow VBG\ NNS$
$VP \longrightarrow VBZ\ VP$
$VP \longrightarrow VBZ\ NP$
$NP \longrightarrow DT\ NN$
$NP \longrightarrow JJ\ NNS$
$DT \longrightarrow a$
$NN \longrightarrow pilot$
$VBZ \longrightarrow likes$
$VBG \longrightarrow flying$
$JJ \longrightarrow flying$
$NNS \longrightarrow planes$

CKY example

a 1	pilot 2	likes 3	flying 4	planes 5
DT	NP	-	-	
	NN	-	-	-
		VBZ	-	VP VP
			JJ VBG	NP VP
				NNS

$S \longrightarrow NP\ VP$
$VP \longrightarrow VBG\ NNS$
$VP \longrightarrow VBZ\ VP$
$VP \longrightarrow VBZ\ NP$
$NP \longrightarrow DT\ NN$
$NP \longrightarrow JJ\ NNS$
$DT \longrightarrow a$
$NN \longrightarrow pilot$
$VBZ \longrightarrow likes$
$VBG \longrightarrow flying$
$JJ \longrightarrow flying$
$NNS \longrightarrow planes$

CKY example

a 1	pilot 2	likes 3	flying 4	planes 5
DT	NP	-	-	S
	NN	-	-	-
		VBZ	-	VP VP
			JJ VBG	NP VP
				NNS

\# $S \longrightarrow NP\ VP$
$VP \longrightarrow VBG\ NNS$
$VP \longrightarrow VBZ\ VP$
$VP \longrightarrow VBZ\ NP$
$NP \longrightarrow DT\ NN$
$NP \longrightarrow JJ\ NNS$
$DT \longrightarrow a$
$NN \longrightarrow pilot$
$VBZ \longrightarrow likes$
$VBG \longrightarrow flying$
$JJ \longrightarrow flying$
$NNS \longrightarrow planes$

CKY example

a 1	pilot 2	likes 3	flying 4	planes 5
DT	NP	-	-	S S
	NN	-	-	-
		VBZ	-	VP VP
			JJ VBG	NP VP
				NNS

$S \longrightarrow NP\ VP$
$VP \longrightarrow VBG\ NNS$
$VP \longrightarrow VBZ\ VP$
$VP \longrightarrow VBZ\ NP$
$NP \longrightarrow DT\ NN$
$NP \longrightarrow JJ\ NNS$
$DT \longrightarrow a$
$NN \longrightarrow pilot$
$VBZ \longrightarrow likes$
$VBG \longrightarrow flying$
$JJ \longrightarrow flying$
$NNS \longrightarrow planes$

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]				

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
#	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	**pilot** 2	likes 3	flying 4	planes 5
DT [0.3]				
	NN [0.1]			

	$S \longrightarrow NP\ VP$		[1.0]
	$VP \longrightarrow VBG\ NNS$		[0.1]
	$VP \longrightarrow VBZ\ VP$		[0.1]
	$VP \longrightarrow VBZ\ NP$		[0.3]
	$NP \longrightarrow DT\ NN$		[0.3]
	$NP \longrightarrow JJ\ NNS$		[0.4]
	$DT \longrightarrow a$		[0.3]
#	$NN \longrightarrow pilot$		[0.1]
	$VBZ \longrightarrow likes$		[0.4]
	$VBG \longrightarrow flying$		[0.5]
	$JJ \longrightarrow flying$		[0.1]
	$NNS \longrightarrow planes$		[.34]

Probabilistic CKY: all parses

a 1	**pilot** 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]			
	NN [0.1]			

	Rule	Prob
	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
#	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

0.3 x 0.1 x 0.3 = 0.009

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]			
	NN [0.1]			
		VBZ [0.4]		

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
#	$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]			
	NN [0.1]	-		
		VBZ [0.4]		

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-		
		VBZ [0.4]		

S	$\longrightarrow NP\ VP$	[1.0]
VP	$\longrightarrow VBG\ NNS$	[0.1]
VP	$\longrightarrow VBZ\ VP$	[0.1]
VP	$\longrightarrow VBZ\ NP$	[0.3]
NP	$\longrightarrow DT\ NN$	[0.3]
NP	$\longrightarrow JJ\ NNS$	[0.4]
DT	$\longrightarrow a$	[0.3]
NN	$\longrightarrow pilot$	[0.1]
VBZ	$\longrightarrow likes$	[0.4]
VBG	$\longrightarrow flying$	[0.5]
JJ	$\longrightarrow flying$	[0.1]
NNS	$\longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-		
		VBZ [0.4]		
			JJ [0.1]	

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
#	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-		
		VBZ [0.4]		
			JJ [0.1] VBG [0.5]	

	$S \longrightarrow NP\ VP$		[1.0]
	$VP \longrightarrow VBG\ NNS$		[0.1]
	$VP \longrightarrow VBZ\ VP$		[0.1]
	$VP \longrightarrow VBZ\ NP$		[0.3]
	$NP \longrightarrow DT\ NN$		[0.3]
	$NP \longrightarrow JJ\ NNS$		[0.4]
	$DT \longrightarrow a$		[0.3]
	$NN \longrightarrow pilot$		[0.1]
	$VBZ \longrightarrow likes$		[0.4]
#	$VBG \longrightarrow flying$		[0.5]
	$JJ \longrightarrow flying$		[0.1]
	$NNS \longrightarrow planes$		[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-		
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	

$S \longrightarrow NP\ VP$		[1.0]
$VP \longrightarrow VBG\ NNS$		[0.1]
$VP \longrightarrow VBZ\ VP$		[0.1]
$VP \longrightarrow VBZ\ NP$		[0.3]
$NP \longrightarrow DT\ NN$		[0.3]
$NP \longrightarrow JJ\ NNS$		[0.4]
$DT \longrightarrow a$		[0.3]
$NN \longrightarrow pilot$		[0.1]
$VBZ \longrightarrow likes$		[0.4]
$VBG \longrightarrow flying$		[0.5]
$JJ \longrightarrow flying$		[0.1]
$NNS \longrightarrow planes$		[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	

S → *NP VP*	[1.0]
VP → *VBG NNS*	[0.1]
VP → *VBZ VP*	[0.1]
VP → *VBZ NP*	[0.3]
NP → *DT NN*	[0.3]
NP → *JJ NNS*	[0.4]
DT → *a*	[0.3]
NN → *pilot*	[0.1]
VBZ → *likes*	[0.4]
VBG → *flying*	[0.5]
JJ → *flying*	[0.1]
NNS → *planes*	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	
				NNS [.34]

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
#	$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	NP [.0136]
				NNS [.34]

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
#	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

$0.1 \times 0.34 \times 0.4 =$
0.0136

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

	$S \longrightarrow NP\ VP$	[1.0]
#	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

$0.5 \times 0.34 \times 0.1 = 0.017$

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	VP [.001632]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
#	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

$0.4 \times 0.0136 \times 0.3 =$
0.001632

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	VP [.001632] VP [.00068]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

	Rule	Prob.
	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
#	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

$0.4 \times 0.017 \times 0.1 =$
0.00068

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	-
		VBZ [0.4]	-	VP [.001632] VP [.00068]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	S [$1.4688x10^{-5}$]
	NN [0.1]	-	-	-
		VBZ [0.4]	-	VP [.001632] VP [.00068]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

#	Rule	Prob
	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

$0.009 \times 0.001632 \times 1.0 = 1.4688x10^{-5}$

Probabilistic CKY: all parses

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	S [$1.4688x10^{-5}$] S [$6.12x10^{-6}$]
	NN [0.1]	-	-	-
		VBZ [0.4]	-	VP [.001632] VP [.00068]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

$0.009 \times 0.00068 \times 1.0 = 6.12x10^{-6}$

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5

$S \longrightarrow NP\ VP$		[1.0]
$VP \longrightarrow VBG\ NNS$		[0.1]
$VP \longrightarrow VBZ\ VP$		[0.1]
$VP \longrightarrow VBZ\ NP$		[0.3]
$NP \longrightarrow DT\ NN$		[0.3]
$NP \longrightarrow JJ\ NNS$		[0.4]
$DT \longrightarrow a$		[0.3]
$NN \longrightarrow pilot$		[0.1]
$VBZ \longrightarrow likes$		[0.4]
$VBG \longrightarrow flying$		[0.5]
$JJ \longrightarrow flying$		[0.1]
$NNS \longrightarrow planes$		[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]				

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
#	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	**pilot** 2	likes 3	flying 4	planes 5
DT [0.3]				
	NN [0.1]			

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
#	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	**pilot** 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]			
	NN [0.1]			

	S → *NP VP*	[1.0]
	VP → *VBG NNS*	[0.1]
	VP → *VBZ VP*	[0.1]
	VP → *VBZ NP*	[0.3]
#	*NP* → *DT NN*	[0.3]
	NP → *JJ NNS*	[0.4]
	DT → *a*	[0.3]
	NN → *pilot*	[0.1]
	VBZ → *likes*	[0.4]
	VBG → *flying*	[0.5]
	JJ → *flying*	[0.1]
	NNS → *planes*	[.34]

$0.3 \times 0.1 \times 0.3 =$
0.009

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]			
	NN [0.1]			
		VBZ [0.4]		

#

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]			
	NN [0.1]	-		
		VBZ [0.4]		

S	$\longrightarrow$ NP VP	[1.0]
VP	$\longrightarrow$ VBG NNS	[0.1]
VP	$\longrightarrow$ VBZ VP	[0.1]
VP	$\longrightarrow$ VBZ NP	[0.3]
NP	$\longrightarrow$ DT NN	[0.3]
NP	$\longrightarrow$ JJ NNS	[0.4]
DT	$\longrightarrow$ a	[0.3]
NN	$\longrightarrow$ $pilot$	[0.1]
VBZ	$\longrightarrow$ $likes$	[0.4]
VBG	$\longrightarrow$ $flying$	[0.5]
JJ	$\longrightarrow$ $flying$	[0.1]
NNS	$\longrightarrow$ $planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-		
		VBZ [0.4]		

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-		
		VBZ [0.4]		
			JJ [0.1]	

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
#	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-		
		VBZ [0.4]		
			JJ [0.1] VBG [0.5]	

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
#	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-		
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-		
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	

$S \longrightarrow NP\ VP$	[1.0]
$VP \longrightarrow VBG\ NNS$	[0.1]
$VP \longrightarrow VBZ\ VP$	[0.1]
$VP \longrightarrow VBZ\ NP$	[0.3]
$NP \longrightarrow DT\ NN$	[0.3]
$NP \longrightarrow JJ\ NNS$	[0.4]
$DT \longrightarrow a$	[0.3]
$NN \longrightarrow pilot$	[0.1]
$VBZ \longrightarrow likes$	[0.4]
$VBG \longrightarrow flying$	[0.5]
$JJ \longrightarrow flying$	[0.1]
$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	
				NNS [.34]

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
#	$NNS \longrightarrow planes$	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	NP [.0136]
				NNS [.34]

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
#	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

$0.1 \times 0.34 \times 0.4 =$
0.0136

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

	Rule	Prob.
	$S \longrightarrow NP\ VP$	[1.0]
#	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

$0.5 \times 0.34 \times 0.1 =$
0.017

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	VP [.001632]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

	Rule	Prob
	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
	$VP \longrightarrow VBZ\ VP$	[0.1]
#	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

$0.4 \times 0.0136 \times 0.3 = 0.001632$

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	VP [.001632]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

	$S \longrightarrow NP\ VP$	[1.0]
	$VP \longrightarrow VBG\ NNS$	[0.1]
#	$VP \longrightarrow VBZ\ VP$	[0.1]
	$VP \longrightarrow VBZ\ NP$	[0.3]
	$NP \longrightarrow DT\ NN$	[0.3]
	$NP \longrightarrow JJ\ NNS$	[0.4]
	$DT \longrightarrow a$	[0.3]
	$NN \longrightarrow pilot$	[0.1]
	$VBZ \longrightarrow likes$	[0.4]
	$VBG \longrightarrow flying$	[0.5]
	$JJ \longrightarrow flying$	[0.1]
	$NNS \longrightarrow planes$	[.34]

Move second VP to chart?
0.4 x 0.017 x 0.1 = 0.00068

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	
		VBZ [0.4]	-	VP [.001632]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

$S \longrightarrow NP\ VP$		[1.0]
$VP \longrightarrow VBG\ NNS$		[0.1]
$VP \longrightarrow VBZ\ VP$		[0.1]
$VP \longrightarrow VBZ\ NP$		[0.3]
$NP \longrightarrow DT\ NN$		[0.3]
$NP \longrightarrow JJ\ NNS$		[0.4]
$DT \longrightarrow a$		[0.3]
$NN \longrightarrow pilot$		[0.1]
$VBZ \longrightarrow likes$		[0.4]
$VBG \longrightarrow flying$		[0.5]
$JJ \longrightarrow flying$		[0.1]
$NNS \longrightarrow planes$		[.34]

Is 0.001632
less than 0.00068 ?

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	
	NN [0.1]	-	-	-
		VBZ [0.4]	-	VP [.001632]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

S	→ *NP VP*	[1.0]
VP	→ *VBG NNS*	[0.1]
VP	→ *VBZ VP*	[0.1]
VP	→ *VBZ NP*	[0.3]
NP	→ *DT NN*	[0.3]
NP	→ *JJ NNS*	[0.4]
DT	→ *a*	[0.3]
NN	→ *pilot*	[0.1]
VBZ	→ *likes*	[0.4]
VBG	→ *flying*	[0.5]
JJ	→ *flying*	[0.1]
NNS	→ *planes*	[.34]

Probabilistic CKY: best parse

a 1	pilot 2	likes 3	flying 4	planes 5
DT [0.3]	NP [.009]	-	-	S [$1.4688x10^{-5}$]
	NN [0.1]	-	-	-
		VBZ [0.4]	-	VP [.001632]
			JJ [0.1] VBG [0.5]	NP [.0136] VP [.017]
				NNS [.34]

#		
	S → *NP VP*	[1.0]
	VP → *VBG NNS*	[0.1]
	VP → *VBZ VP*	[0.1]
	VP → *VBZ NP*	[0.3]
	NP → *DT NN*	[0.3]
	NP → *JJ NNS*	[0.4]
	DT → *a*	[0.3]
	NN → *pilot*	[0.1]
	VBZ → *likes*	[0.4]
	VBG → *flying*	[0.5]
	JJ → *flying*	[0.1]
	NNS → *planes*	[.34]

$0.009 \times 0.001632 \times 1.0 = 1.4688x10^{-5}$

Today's lecture

1. Uncertainty
2. Probabilistic Context-Free Grammars
   - Uses of PCFGs: Disambiguation
   - Benefits of PCFGs
   - Issues
3. Probabilistic parsing
   - Probabilistic CKY
4. PCKY Example
5. Homework 3

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Homework 3

1. work with a real PCFG
2. build a probabistic parser (CKY)
3. evaluate the results

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$$P(\textit{Hw3 is easy.}) = 0.0000001$$
$$P(\textit{Hw3 is hard.}) = 0.004$$

Parsing: dev/train/test paradigm

The Wall Street Journal (WSJ) section of the Penn Treebank (PTB), for all its faults, provides a very useful resource for comparing parser performance.

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Parsing: dev/train/test paradigm

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In building a probabilistic parser, there are four kinds of resources that are commonly used esp. in the ACL related literature:

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1. **training data**: large number of annotated sentences (sec. 2–21 of PTB has 39,830 sentences)

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2. **development data**: small number of annotated sentences used to "tweak" parser (sec. 22, of PTB)

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3. **test data**: small-medium number of un-annotated sentences used as input to parser (sec. 23 of PTB has 2416 sentences, $\sim$ 6% of training set)

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1. **training data**: large number of annotated sentences (sec. 2–21 of PTB has 39,830 sentences)
2. **development data**: small number of annotated sentences used to "tweak" parser (sec. 22, of PTB)
3. **test data**: small-medium number of un-annotated sentences used as input to parser (sec. 23 of PTB has 2416 sentences, $\sim 6\%$ of training set)
4. **gold standard**: annotated version of test data, with no errors (hidden till parser is developed)

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