# Probabilistic Context Free Grammars Lecture \#14 

Computational Linguistics CMPSCI 591N, Spring 2006



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(including slides from Jason Eisner)

## Ambiguity in Parsing

- Time flies like an arrow.
- Fruit flies like a banana.
- I saw the man with the telescope.


## How to solve this combinatorial explosion of ambiguity?

1. First try parsing without any weird rules, throwing them in only if needed.
2. Better: every rule has a weight. A tree's weight is total weight of all its rules.
Pick the overall "lightest" parse of sentence.
3. Can we pick the weights automatically? We'll get to this later ...

## CYK Parser

Input: A string of words, grammar in CNF
Output: yes/no
Data structure: $\mathrm{n} \times \mathrm{n}$ table rows labeled 0 to $n-1$, columns 1 to $n$ cell ( $\mathrm{i}, \mathrm{j}$ ) lists constituents spanning $\mathrm{i}, \mathrm{j}$

For each i from 1 to n
Add to ( $\mathrm{i}-1, \mathrm{i}$ ) all Nonterminals that could produce the word at ( $\mathrm{i}-1, \mathrm{i}$ )

|  | me 1 | 2 lik | 3 | 4 arr |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  | $\begin{array}{\|ll} \hline \text { NP } & 3 \\ \text { Vst } & 3 \end{array}$ |  |  |  |  |  |  |
|  |  |  |  |  |  |  |  |
| 1 |  | $\begin{array}{ll}\text { NP } & 4 \\ \text { VP } & 4\end{array}$ |  |  |  |  | $\begin{aligned} & 1 \mathrm{VP} \rightarrow \mathrm{~V} \mathrm{NP} \\ & 2 \mathrm{VP} \rightarrow \mathrm{VP} \mathrm{PP} \\ & 1 \mathrm{NP} \rightarrow \operatorname{Det} \mathrm{~N} \end{aligned}$ |
| 2 |  |  | $\begin{array}{ll}\text { P } & 2 \\ \mathrm{~V} & 5\end{array}$ |  |  |  | $\begin{aligned} & 1 \mathrm{NP} \rightarrow \operatorname{Det} \mathrm{~N} \\ & 2 \mathrm{NP} \rightarrow \mathrm{NP} \mathrm{PP} \end{aligned}$ |
| 3 |  |  |  | Det 1 |  |  | $3 N P \rightarrow N P N P$ |
| 4 |  |  |  |  |  |  | $0 \mathrm{PP} \rightarrow \mathrm{P}$ NP |

## CYK Parser

For width from 2 to n
For start from 0 to n -width
Define end to be start+width
For mid from start+1 to end-1
For every constituent in (start, mid)
For every constituent in (mid,end)
For all ways of combining them (if any)
Add the resulting constituent to (start,end).























## Follow backpointers ...



```
time 1 flies 2 like 3 an 4 arrow 5
```

| NP | 3 | NP | 10 |  |  |  |  |
| :--- | :--- | :--- | :--- | :--- | :--- | :--- | :--- |
| Vst | 3 | S | 8 |  |  |  |  |
| 0 |  |  |  |  |  |  | NP |

$1 \mathrm{~S} \rightarrow \mathrm{NP}$ VP
$6 \mathrm{~S} \rightarrow \mathrm{Vst} N P$
$2 \mathrm{~S} \rightarrow \mathrm{SPP}$
$1 \mathrm{VP} \rightarrow \mathrm{V}$ NP
$2 \mathrm{VP} \rightarrow \mathrm{VP} \mathrm{PP}$
$1 \mathrm{NP} \rightarrow \operatorname{Det} \mathrm{N}$
$2 \mathrm{NP} \rightarrow \mathrm{NP} \mathrm{PP}$
$3 \mathrm{NP} \rightarrow \mathrm{NPNP}$
$0 \mathrm{PP} \rightarrow \mathrm{PNP}$




$$
\begin{aligned}
& \overbrace{N P}^{S} \\
& 1 S \rightarrow N P V P \\
& 6 \mathrm{~S} \rightarrow \text { Vst NP } \\
& 2 S \rightarrow \text { SPP } \\
& 1 \mathrm{VP} \rightarrow \mathrm{VNP} \\
& 2 \text { VP } \rightarrow \text { VP PP } \\
& 1 \mathrm{NP} \rightarrow \text { Det } N \\
& 2 \mathrm{NP} \rightarrow \mathrm{NP} \text { PP } \\
& 3 \mathrm{NP} \rightarrow \mathrm{NP} \text { NP } \\
& 0 \text { PP } \rightarrow \text { P NP }
\end{aligned}
$$

## Which entries do we need?



## Which entries do we need?



## Not worth keeping ...

time 1 flies 2 like 3 an 4 arrow 5

$1 S \rightarrow N P$ VP
$6 \mathrm{~S} \rightarrow$ Vst NP
$2 S \rightarrow S$ PP
$1 \mathrm{VP} \rightarrow \mathrm{VNP}$
$2 \mathrm{VP} \rightarrow \mathrm{VP}$ PP
$1 \mathrm{NP} \rightarrow \operatorname{Det} \mathrm{N}$
$2 N P \rightarrow N P$ PP
$3 \mathrm{NP} \rightarrow \mathrm{NP}$ NP
$0 \mathrm{PP} \rightarrow \mathrm{PNP}$

## ... since it just breeds worse options



## Keep only best-in-class!



## Keep only best-in-class!

 (and backpointers so you can recover parse)

## Probabilistic Trees

- Instead of lightest weight tree, take highest probability tree
- Given any tree, your assignment generator would have some probability of producing it!
- Just like using n-grams to choose among strings ...
- What is the probability of this tree?



## Probabilistic Trees

- Instead of lightest weight tree, take highest probability tree
- Given any tree, your assignment generator would have some probability of producing it!
- Just like using n-grams to choose among strings ...
- What is the probability of this tree?
- You rolled a lot of independent dice...



## Chain rule: One word at a time

p (time flies like an arrow)
$=p$ (time)

* $p$ (flies | time)
* p(like | time flies)
* p(an | time flies like)
* p(arrow | time flies like an)


## Chain rule + backoff (to get trigram model)

p (time flies like an arrow)
$=p$ (time)

* $p$ (flies | time)
* p(like | time flies)
* p(an | time flies like)
* p(arrow | time flies like an)


## Chain rule - written differently

p (time flies like an arrow)
$=p$ (time)

* $p$ (time flies | time)
* p(time flies like | time flies)
* p(time flies like an | time flies like)
* p(time flies like an arrow | time flies like an)

Proof: $p(x, y \mid x)=p(x \mid x) * p(y \mid x, x)=1 * p(y \mid x)$

## Chain rule + backoff

$p$ (time flies like an arrow)
$=p($ time $)$

* p(time flies I time)
* p(time flies like I time flies)
* p(time flies like an I time flies like)
* p(time flies like an arrow I time flies like an)

Proof: $p(x, y \mid x)=p(x \mid x)^{*} p(y \mid x, x)=1^{*} p(y \mid x)$

## Chain rule: One node at a time



## Chain rule + backoff



## Simplified notation



## Already have a CKY alg for weights ...



Just let w( $x \rightarrow y z)=-\log \mathbf{p}(x \rightarrow y z \mid x)$ Then lightest tree has highest prob ${ }^{49}$


## Need only best-in-class to get best parse



## Why probabilities not weights?

- We just saw probabilities are really just a special case of weights ...
- ... but we can estimate them from training data by counting and smoothing! Use all of our lovely probability theory machinery!


## Probabilistic Context Free Grammars

A PCFG $G$ consists of the usual parts of a CFG

- A set of terminals, $\left\{w^{k}\right\}, k=1, \ldots, V$
- A set of nonterminals, $\left\{N^{i}\right\}, i=1, \ldots, n$
- A designated start symbol, $N^{1}$
- A set of rules, $\left\{N^{i} \rightarrow \zeta^{j}\right\}$, (where $\zeta^{j}$ is a sequence of terminals and nonterminals)
and
- A corresponding set of probabilities on rules such that:

$$
\forall i \quad \sum_{j} P\left(N^{i} \rightarrow \zeta^{j}\right)=1
$$

## A simple PCFG (in CNF)

| $\mathrm{S} \rightarrow \mathrm{NP} \mathrm{VP}$ | 1.0 | $\mathrm{NP} \rightarrow$ NP PP | 0.4 |
| :--- | :--- | :--- | :--- |
| $\mathrm{PP} \rightarrow \mathrm{P} \mathrm{NP}$ | 1.0 | $\mathrm{NP} \rightarrow$ astronomers | 0.1 |
| $\mathrm{VP} \rightarrow \mathrm{V} \mathrm{NP}$ | 0.7 | $\mathrm{NP} \rightarrow$ ears | 0.18 |
| $\mathrm{VP} \rightarrow \mathrm{VP} P \mathrm{PP}$ | 0.3 | $\mathrm{NP} \rightarrow$ saw | 0.04 |
| $\mathrm{P} \rightarrow$ with | 1.0 | $\mathrm{NP} \rightarrow$ stars | 0.18 |
| $\mathrm{~V} \rightarrow$ saw | 1.0 | $\mathrm{NP} \rightarrow$ telescopes | 0.1 |



$$
\overbrace{\text { astronomers }}^{t_{2}:}
$$

## The two parse trees' probabilities and the sentence probability

$$
\begin{aligned}
P\left(t_{1}\right)= & 1.0 \times 0.1 \times 0.7 \times 1.0 \times 0.4 \\
& \times 0.18 \times 1.0 \times 1.0 \times 0.18 \\
= & 0.0009072 \\
P\left(t_{2}\right)= & 1.0 \times 0.1 \times 0.3 \times 0.7 \times 1.0 \\
& \times 0.18 \times 1.0 \times 1.0 \times 0.18 \\
= & 0.0006804 \\
P\left(w_{15}\right)= & P\left(t_{1}\right)+P\left(t_{2}\right)=0.0015876
\end{aligned}
$$

## Assumptions of PCFGs

1. Place invariance (like time invariance in HMM):

$$
\forall k \quad P\left(N_{k(k+c)}^{j} \rightarrow \zeta\right) \text { is the same }
$$

2. Context-free:

$$
P\left(N_{k l}^{j} \rightarrow \zeta \mid \text { words outside } w_{k} \ldots w_{l}\right)=P\left(N_{k l}^{j} \rightarrow \zeta\right)
$$

3. Ancestor-free:

$$
P\left(N_{k l}^{j} \rightarrow \zeta \mid \text { ancestor nodes of } N_{k l}^{j}\right)=P\left(N_{k l}^{j} \rightarrow \zeta\right)
$$

The sufficient statistics of a PCFG are thus simply counts of how often different local tree configurations occurred (= counts of which grammar rules were applied).

## Some features of PCFGs

Reasons to use a PCFG, and some idea of their limitations:

- Partial solution for grammar ambiguity: a PCFG gives some idea of the plausibility of a sentence.
■ But, in the simple case, not a very good idea, as independence assumptions are two strong (e.g., not lexicalized).
- Gives a probabilistic language model for English.

■ In the simple case, a PCFG is a worse language model for English than a trigram model.

■ Better for grammar induction (Gold 1967 vs. Horning 1969)

■ Robustness. (Admit everything with low probability.)

## Some features of PCFGs

- A PCFG encodes certain biases, e.g., that smaller trees are normally more probable.
- One can hope to combine the strengths of a PCFG and a trigram model.
We'll look at simple PCFGs first. They have certain inadequacies, but we'll see that most of the state-of-the-art probabilistic parsers are fundamentally PCFG models, just with various enrichments to the grammar

