Parameter Estimation and Lexicalization for PCFGs

Informatics 2A: Lecture 21

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1. Standard PCFGs
   - Parameter Estimation
   - Problem 1: Assuming Independence
   - Problem 2: Ignoring Lexical Information

2. Lexicalized PCFGs
   - Lexicalization
   - Head Lexicalization

Reading:

J&M 2nd edition, ch. 14.2–14.6,
NLTK Book, Chapter 8, final section on Weighted Grammar.

Clicker Question

$S \longrightarrow NP\ VP$	(1.0)		$NPR \longrightarrow John$	(0.5)
$NP \longrightarrow DET\ N$	(0.7)		$NPR \longrightarrow Mary$	(0.5)
$NP \longrightarrow NPR$	(0.3)		$V \longrightarrow saw$	(0.4)
$VP \longrightarrow V\ PP$	(0.7)		$V \longrightarrow loves$	(0.6)
$VP \longrightarrow V\ NP$	(0.3)		$DET \longrightarrow a$	(1.0)
$PP \longrightarrow Prep\ NP$	(1.0)		$N \longrightarrow cat$	(0.6)
			$N \longrightarrow saw$	(0.4)

What is the probability of the sentence *John saw a saw*?

1. 0.02
2. 0.00016
3. 0.00504
4. 0.0002

Parameter Estimation

In a PCFG every rule is associated with a probability.
But where do these rule probabilities come from?

Use a large parsed corpus such as the Penn Treebank.

```
( (S
    (NP-SBJ (DT That) (JJ cold)
      (, ,)
      (JJ empty) (NN sky) )
    (VP (VBD was)
      (ADJP-PRD (JJ full)
        (PP (IN of)
          (NP (NN fire)
            (CC and)
            (NN light) ))))
    (. .) ))
```

$S \rightarrow NP\text{-}SBJ\ VP$
$VP \rightarrow VBD\ ADJP\text{-}PRD$
$PP \rightarrow IN\ NP$
$NP \rightarrow NN\ CC\ NN$
etc.

Parameter Estimation

In a PCFG every rule is associated with a probability.
But where do these rule probabilities come from?

Use a large parsed corpus such as the Penn Treebank.

- Obtain grammar rules by reading them off the trees.
- Calculate number of times LHS → RHS occurs over number of times LHS occurs.

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

Parameter Estimation

Corpus of parsed sentences:

'S1: [S [NP grass] [VP grows]]'
'S2: [S [NP grass] [VP grows] [AP slowly]]'
'S3: [S [NP grass] [VP grows] [AP fast]]'
'S4: [S [NP bananas] [VP grow]]'

Compute PCFG probabilities:

r	Rule	α	$P(r\|\alpha)$
$r1$	S $\rightarrow$ NP VP	S	$2/4$
$r2$	S $\rightarrow$ NP VP AP	S	$2/4$

Parameter Estimation

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$r4$	NP $\rightarrow$ bananas	NP	$1/4$
$r5$	VP $\rightarrow$ grows	VP	$3/4$
$r6$	VP $\rightarrow$ grow	VP	$1/4$
$r7$	AP $\rightarrow$ fast	AP	$1/2$

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$r4$	NP $\rightarrow$ bananas	NP	1/4
$r5$	VP $\rightarrow$ grows	VP	3/4
$r6$	VP $\rightarrow$ grow	VP	1/4
$r7$	AP $\rightarrow$ fast	AP	1/2
$r8$	AP $\rightarrow$ slowly	AP	1/2

Parameter Estimation

With these parameters (rule probabilities), we can now compute the probabilities of the four sentences S1–S4:

$$\begin{aligned} P(S1) &= P(r1|S)P(r3|NP)P(r5|VP) \\ &= 2/4 \cdot 3/4 \cdot 3/4 = 0.28125 \end{aligned}$$

$$\begin{aligned} P(S2) &= P(r2|S)P(r3|NP)P(r5|VP)P(r7|AP) \\ &= 2/4 \cdot 3/4 \cdot 3/4 \cdot 1/2 = 0.140625 \end{aligned}$$

$$\begin{aligned} P(S3) &= P(r2|S)P(r3|NP)P(r5|VP)P(r7|AP) \\ &= 2/4 \cdot 3/4 \cdot 3/4 \cdot 1/2 = 0.140625 \end{aligned}$$

$$\begin{aligned} P(S4) &= P(r1|S)P(r4|NP)P(r6|VP) \\ &= 2/4 \cdot 1/4 \cdot 1/4 = 0.03125 \end{aligned}$$

Parameter Estimation

What if we don't have a treebank, but we do have an unparsed corpus and (non-probabilistic) parser?

1. Take a CFG and set all rules to have equal probability.
2. Parse the (flat) corpus with the CFG.
3. Adjust the probabilities.
4. Repeat steps two and three until probabilities converge.

This is the **inside-outside algorithm** (Baker, 1979), a type of Expectation Maximisation algorithm. It can also be used to induce a grammar, but only with limited success.

Problems with Standard PCFGs

While standard PCFGs are already useful for some purposes, they can produce poor result when used for disambiguation.

Why is that?

1. They assume the rule choices are independent of one another.
2. They ignore lexical information until the very end of the analysis, when word classes are rewritten to word tokens.

How can this lead to bad choices among possible parses?

Problem 1: Assuming Independence

By definition, a CFG assumes that the expansion of non-terminals is completely independent. It doesn't matter:

- where a non-terminal is in the analysis;
- what else is (or isn't) in the analysis.

The same assumption holds for standard PCFGs: The probability of a rule is the same, no matter

- where it is applied in the analysis;
- what else is (or isn't) in the analysis.

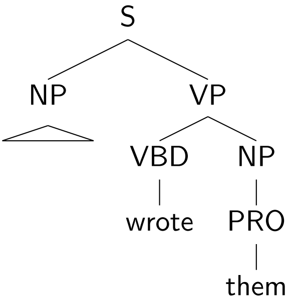
But this assumption is too simple!

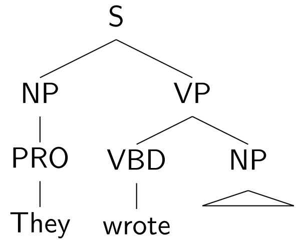
Problem 1: Assuming Independence

$S \rightarrow NP\ VP$ $\quad$ $NP \rightarrow PRO$

$VP \rightarrow VBD\ NP$ $\quad$ $NP \rightarrow DT\ NOM$

The above rules assign the same probability to both these trees, because they use the same re-write rules, and probability calculations do not depend on where rules are used.





Problem 1: Assuming independence

But in speech corpora, 91% of 31021 subject NPs are pronouns:

(1) a. She's able to take her baby to work with her.
b. My wife worked until we had a family.

while only 34% of 7489 object NPs are pronouns:

(2) a. Some laws absolutely prohibit it.
b. It wasn't clear how NL and Mr. Simmons would respond if Georgia Gulf spurns them again.

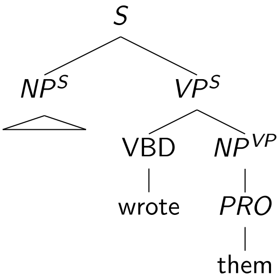
So the probability of NP $\rightarrow$ PRO should depend on where in the analysis it applies (e.g., subject or object position).

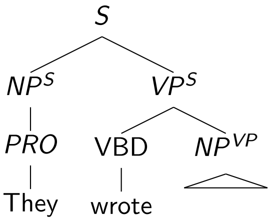
Addressing the independence problem

One way of introducing greater sensitivity into PCFGs is via parent annotation: subdivide (all or some) non-terminal categories according to the non-terminal that appears as the node's immediate parent. E.g. NP subdivides into NP^S, NP^{VP}, …

$S \rightarrow NP^S \; VP^S$
$VP^S \rightarrow VBD^{VP} \; NP^{VP}$

$NP^S \rightarrow PRO$
$NP^{VP} \rightarrow PRO$, etc.





Addressing the independence problem

Node-splitting via parent annotation allows different probabilities to be assigned e.g. to the rules

$$NP^{S} \rightarrow PRO, \qquad NP^{VP} \rightarrow PRO$$

medskip However, too much node-splitting can mean not enough data to obtain realistic rule probabilities, unless we have an enormous training corpus.

There are even algorithms that try to identify the optimal amount of node-splitting for a given training set!

Problem 2: Ignoring Lexical Information

$S \longrightarrow NP\ VP$	$N \longrightarrow sack \mid bin \mid \cdots$
$NP \longrightarrow NNS \mid NN$	$NNS \longrightarrow students$
$VP \longrightarrow VBD\ NP \mid VBD\ NP\ PP$	$V \longrightarrow dumped \mid spotted$
$PP \longrightarrow P\ NP$	$DT \longrightarrow a \mid the$
$NP \longrightarrow DT\ NN$	$\mathrm{P} \longrightarrow in$

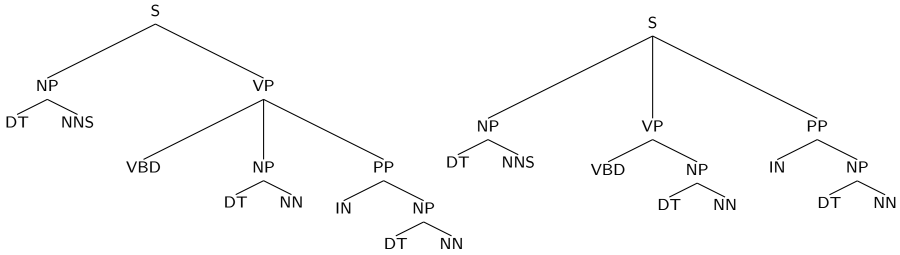
Consider the sentences:

(3) a. The students dumped the sack in the bin.
b. The students spotted the flaw in the plan.

Because rules for rewriting non-terminals ignore word tokens until the very end, let's consider these simply as strings of POS tags:

(4) DT NNS VBD DT NN IN DT NN

Problem 2: Ignoring Lexical Information



Which do we want for *The students dumped the sack in the bin*?
Which for *The students spotted the flaw in the plan*?

The most appropriate analysis depends in part on the actual words occurring. The word *dumped*, implying motion, is more likely to have an associated prepositional phrase than *spotted*.

Lexicalized PCFGs

A PCFG can be lexicalised by associating a word with every non-terminal in the grammar.

It is head-lexicalised if the word is the head of the constituent described by the non-terminal.

Each non-terminal has a head that determines syntactic properties of phrase (e.g., which other phrases it can combine with).

Example

Noun Phrase (NP): Noun
Adjective Phrase (AP): Adjective
Verb Phrase (VP): Verb
Prepositional Phrase (PP): Preposition

Lexicalization

We can lexicalize a PCFG by annotating each non-terminal with its head word, starting with the terminals – replacing

VP	$\rightarrow$	VBD NP PP
VP	$\rightarrow$	VBD NP
NP	$\rightarrow$	DT NN
NP	$\rightarrow$	NNS
PP	$\rightarrow$	P NP

with rules such as

VP(dumped)	$\rightarrow$	V(dumped) NP(sack) PP(in)
VP(spotted)	$\rightarrow$	V(spotted) NP(flaw) PP(in)
VP(dumped)	$\rightarrow$	V(dumped) NP(sack)
VP(spotted)	$\rightarrow$	V(spotted) NP(flaw)
NP(flaw)	$\rightarrow$	DT(the) NN(flaw)
PP(in)	$\rightarrow$	P(in) NP(bin)
PP(in)	$\rightarrow$	P(in) NP(plan)

Head Lexicalization

In principle, each of these rules can now have its own probability. But that would mean a ridiculous expansion in the set of grammar rules, with no parsed corpus large enough to estimate their probabilities accurately.

Instead we just lexicalize the head of phrase:

VP(dumped)	$\rightarrow$	V(dumped) NP PP
VP(spotted)	$\rightarrow$	V(spotted) NP PP
VP(dumped)	$\rightarrow$	V(dumped) NP
VP(spotted)	$\rightarrow$	V(spotted) NP
NP(flaw)	$\rightarrow$	DT NN(flaw)
PP(in)	$\rightarrow$	P(in) NP

Such grammars are called lexicalized PCFGs or, alternatively, probabilistic lexicalized CFGs.

Head Lexicalization

For lexicalized PCFGs, rule probabilities can be reasonably estimated from a corpus.

In the simplest version, the lexicalized rules are supplemented by head selection rules, whose probabilities can also be estimated from a corpus:

$$\begin{array}{lcl} \text{VP} & \rightarrow & \text{VP(dumped)} \\ \text{VP} & \rightarrow & \text{VP(spotted)} \\ \text{NP} & \rightarrow & \text{NP(sack)} \\ \text{NP} & \rightarrow & \text{NP(flaw)} \\ \text{PP} & \rightarrow & \text{PP(in)} \end{array}$$

Combining approaches

We can also combine the ideas of head lexicalization with parent annotation, leading to rules like

$$
\begin{aligned}
NP^{VP(dumped)} &\rightarrow NP(sack)^{VP(dumped)} \\
NP^{VP(spotted)} &\rightarrow NP(flaw)^{VP(spotted)} \\
PP^{VP(dumped)} &\rightarrow PP(in)^{VP(dumped)}
\end{aligned}
$$

The probabilities for such rules can be used to take account of commonly occurring word combinations, e.g. of verb-object or verb-preposition. These include long-distance correlations invisible to N-gram technology.

Grammars with these doubly-lexicalized rules are still feasible, given enough training data. This is roughly the idea behind the Collins parser (not covered here).