

LING5702: Lecture Notes 19

A Model of Grammar Acquisition

So far we've seen how babies can discover words in a language.

Today we'll see how (probabilistic) syntactic grammars and lexicons can be learned.

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19.1 A model of grammar acquisition [Jin et al., 2021]

As a baby, you would be exposed to lots of sentences in your caregivers' language.

Imagine you could generate **random grammars** and then assign probabilities to these sentences.

The grammar that best predicts the sentences has the highest probability given the sentences:

$$\begin{aligned} P(\text{grammar} \mid \text{sentences}) &= \frac{P(\text{sentences, grammar})}{P(\text{sentences})} \\ &= \frac{P(\text{grammar}) \cdot \frac{P(\text{sentences, grammar})}{P(\text{grammar})}}{P(\text{sentences})} \\ &= \frac{P(\text{grammar}) \cdot P(\text{sentences} \mid \text{grammar})}{P(\text{sentences})} \\ &= \frac{P(\text{grammar}) \cdot \sum_{\text{trees}} P(\text{trees} \mid \text{grammar}) \cdot P(\text{sentences} \mid \text{trees})}{P(\text{sentences})} \end{aligned}$$

This is called **Bayes' law**.

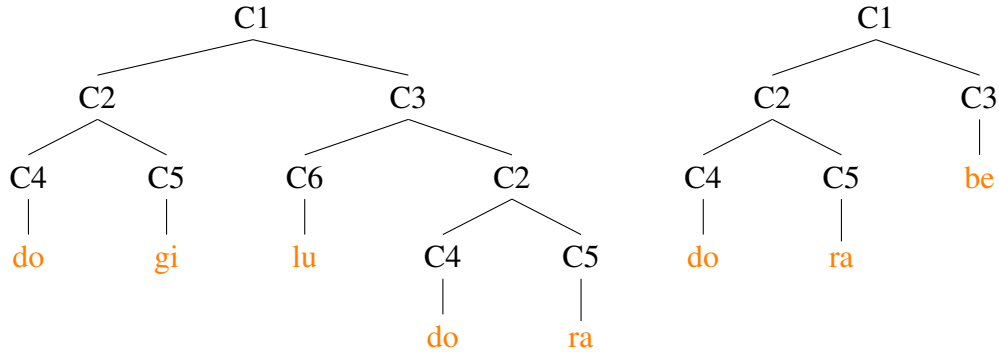
Since the probability of grammars is uniform and of sentences given trees is deterministic (based on matching tree terminals), then the tree probabilities determine which grammar is preferred.

19.2 Example: choosing among grammars

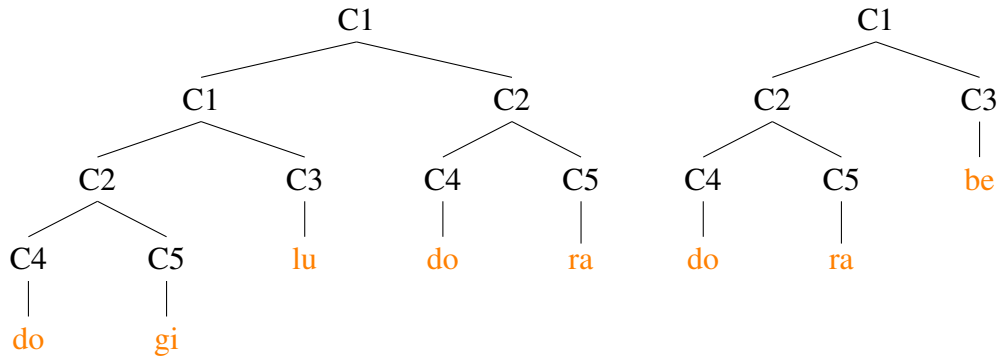
Suppose we encounter the following utterances:

- (1) do gi lu do ra
- (2) do ra be

We could assign them this analysis (Analysis A):



or we could assign them this analysis (Analysis B):



We can distinguish these based on their probability, according to a probabilistic grammar.

We estimate the rule probabilities using relative frequency estimation:

$$P(a \rightarrow b c \mid a) = \frac{\text{number of times } a \rightarrow b c \text{ occurs}}{\text{number of times } a \text{ occurs}}.$$

This gives us the following probabilistic grammar for Analysis A:

$$P(C1 \rightarrow C2 C3 \mid C1) = \frac{2}{2} = 1$$

$$P(C2 \rightarrow C4 C5 \mid C2) = \frac{3}{3} = 1$$

$$P(C3 \rightarrow C6 C2 \mid C3) = \frac{1}{2} = .5$$

$$P(C3 \rightarrow be \mid C3) = \frac{1}{2} = .5$$

$$P(C4 \rightarrow do \mid C4) = \frac{3}{3} = 1$$

$$P(C5 \rightarrow gi \mid C5) = \frac{1}{3} = .333$$

$$P(C5 \rightarrow ra \mid C5) = \frac{2}{3} = .667$$

$$P(C6 \rightarrow lu \mid C6) = \frac{1}{1} = 1$$

so the total ('joint') probability of all the trees in Analysis A is:

$$\overbrace{1 \cdot 1 \cdot 1 \cdot 1 \cdot 1 \cdot .5}^{\text{grammatical rules}} \cdot \overbrace{.5 \cdot 1 \cdot 1 \cdot 1 \cdot .333 \cdot .667 \cdot .667 \cdot 1}^{\text{lexical rules}} = 0.03703$$

(NOTE: probabilities for branches that occur multiple times must be multiplied in multiple times!)

On the other hand, we get the following probabilistic grammar for Analysis B:

$$P(C1 \rightarrow C2 C3 \mid C1) = \frac{1}{3} = .333$$

$$P(C1 \rightarrow C1 C2 \mid C1) = \frac{2}{3} = .667$$

$$P(C2 \rightarrow C4 C5 \mid C2) = \frac{3}{3} = 1$$

$$P(C3 \rightarrow lu \mid C3) = \frac{1}{2} = .5$$

$$P(C3 \rightarrow be \mid C3) = \frac{1}{2} = .5$$

$$P(C4 \rightarrow do \mid C4) = \frac{3}{3} = 1$$

$$P(C5 \rightarrow gi \mid C5) = \frac{1}{3} = .333$$

$$P(C5 \rightarrow ra \mid C5) = \frac{2}{3} = .667$$

so the total ('joint') probability of all the trees in Analysis B is:

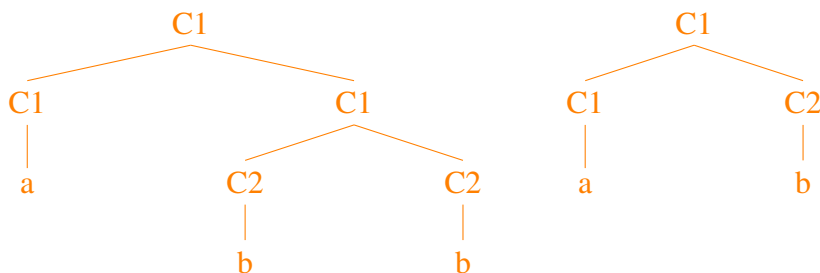
$$\overbrace{.333 \cdot .667 \cdot .667 \cdot 1 \cdot 1 \cdot 1}^{\text{grammatical rules}} \cdot \overbrace{.5 \cdot .5 \cdot 1 \cdot 1 \cdot 1 \cdot .333 \cdot .667 \cdot .667}^{\text{lexical rules}} = 0.005388$$

(NOTE: probabilities for branches that occur multiple times must be multiplied in multiple times!)

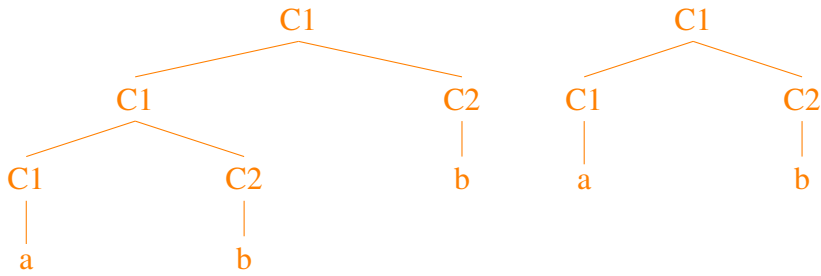
The first analysis is about 7 times more likely!

19.3 Practice

1. Calculate a probabilistic grammar based on the below evidence:



2. Calculate a probabilistic grammar based on the below evidence:



19.4 Practice

Which of the tree sets in the above problem has a lower probability?

References

[Jin et al., 2021] Jin, L., Schwartz, L., Doshi-Velez, F., Miller, T., and Schuler, W. (2021). Depth-Bounded Statistical PCFG Induction as a Model of Human Grammar Acquisition. *Computational Linguistics*, 47(1):181–216.