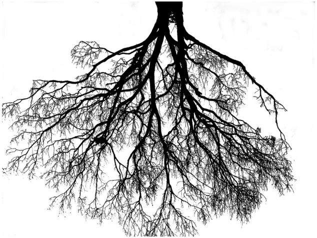
Probabilistic Context-free Grammars and Other Syntactic Language Models



Jon Dehdari

January 4, 2016

Kelsey and other Grammers

- A **grammar** here is another word for a language model
- They consist of four sets $G = \langle \Sigma, N, S, P \rangle$

terminals – word types; lowest nodes in syntax trees
Examples: *dog, the, eats*

non-terminals – phrasal types; middle nodes in syntax trees
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start symbol – "S"; the top node in syntax trees

production rules – recursive symbol substitutions

Examples:

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N &\rightarrow dog \\
N &\rightarrow cat \\
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Visualization

- Sentences are often visualized using **derivation trees**, also known as **parse trees** or **syntax trees**
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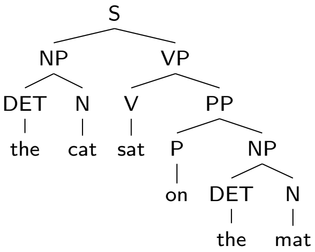

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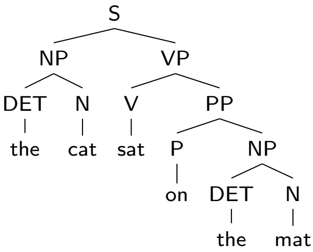

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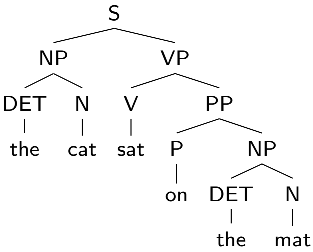

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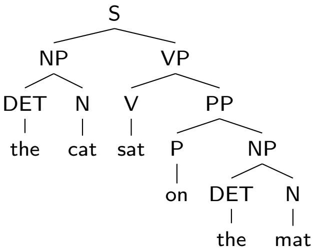

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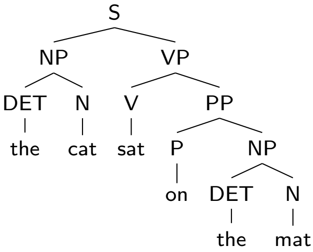

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- Originally these trees were **mere visualizations** of how you could generate a grammatical sentence, given a grammar
- Then people started to think of these trees as the actual **structure** of a sentence
- Confusion ensued

Context-free Grammars

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- CFGs can generate and recognize **center embedding**, but not more complex word order phenomena, so effectively CFG parse trees have **no crossing lines**
- Non-projective dependency grammars are more or less equivalent to CFGs (they have the same weak generative capacity)

Treebanks

- It's a lot of work to define a language model by hand (including context-free grammars), so another way is to annotate treebanks
- Example: (S (NP (DET the) (N cat))(VP (V sat)(PP (P on)(NP (DET the) (N mat)))))

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- Here is a link to a list of syntactic treebanks

PCFGs

- We can induce a **probabilistic context-free grammar** (PCFG) from the treebank
- With multiple annotated sentences, we can get probabilities for production rules. Example:

1.0	S	$\rightarrow NP\ VP$
0.6	NP	$\rightarrow DET\ N$
0.4	NP	$\rightarrow ADJ\ N$
0.7	VP	$\rightarrow V\ NP$
0.3	VP	$\rightarrow V$
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1.0	DET	$\rightarrow$ *the*

- Notice that the probabilities for each left-hand side must sum to one (unity)

Parameter Estimation

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- If we have a treebank, we can start with just counting how often productions occur (maximum likelihood estimation)
- If we don't have a treebank, we can still use unannotated text, and apply the **inside-outside algorithm**
- The inside–outside algorithm is just the expectation–maximization (EM) algorithm applied to trees
- We start by randomly initializing probabilities to all possible rule productions, then use EM to search for good rule probabilities that maximize the likelihood of the training set

Inside-Outside Algorithm

- The inside–outside algorithm uses inside- and outside-probabilities:
  - Inside probability: $\beta_j(p,q) = P(w_{pq} | N^j_{pq}, G)$
  - Outside probability: $\alpha_j(p,q) = P(w_{1(p-1)}, N^j_{pq}, w_{(q+1)m} | G)$

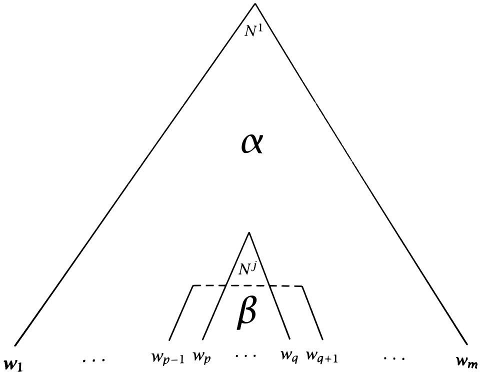

Image courtesy of Manning & Schütze (1999), figure 11.3.

String Probabilities

- We use the inside probability of the entire sentence to get the probability of that sentence:

$$P(w_{1\,m}|G) = P(N^1 \overset{*}{\Rightarrow} w_{1\,m}|G) = \beta(1, m)$$

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- Probabilities of ambiguous parses at a given non-terminal are summed, since either parse could have produced the final substring

PCFGs *vs.* *n*-gram Language Models (Lexicalized Probabilistic Regular Grammars)

- PCFGs can better handle long-distance dependencies like subject-verb agreement and filler-gap dependencies
- PCFGs usually give worse perplexity than *n*-gram LMs. Why?

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- PCFGs take longer to train
- PCFGs need manually-annotated treebanks to give decent results
- PCFG parsers (eg. CKY) are usually not incremental