# PCFGs: Parsing & Evaluation

Deep Processing Techniques for NLP Ling 571 January 23, 2017

#### Roadmap

• PCFGs:

• Review: Definitions and Disambiguation

- PCKY parsing
  - Algorithm and Example
- Evaluation
  - Methods & Issues
- Issues with PCFGs

## PCFGs

- Probabilistic Context-free Grammars
  - Augmentation of CFGs
  - *N* a set of **non-terminal symbols** (or **variables**)
  - $\Sigma$  a set of **terminal symbols** (disjoint from *N*)
  - *R* a set of **rules** or productions, each of the form  $A \rightarrow \beta$  [*p*], where *A* is a non-terminal,

 $\beta$  is a string of symbols from the infinite set of strings  $(\Sigma \cup N)*$ ,

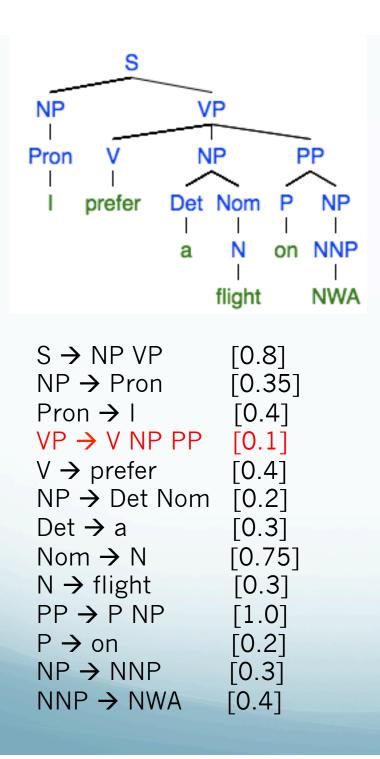
and p is a number between 0 and 1 expressing  $P(\beta|A)$ 

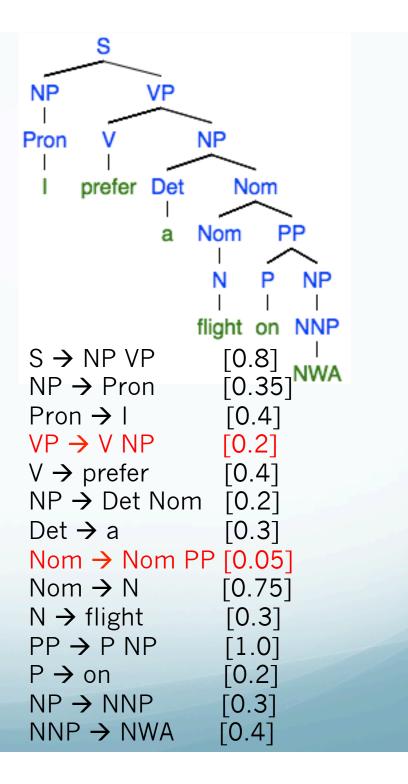
*S* a designated **start symbol** 

### Disambiguation

- A PCFG assigns probability to each parse tree T for input S.
  - Probability of T: product of all rules to derive T

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





#### Parsing Problem for PCFGs

• Select T such that:

$$\hat{T}(S) = \underset{Ts.t,S=yield(T)}{\operatorname{argmax}} P(T)$$

- String of words S is *yield* of parse tree over S
- Select tree that maximizes probability of parse
- Extend existing algorithms: e.g., CKY
  - Most modern PCFG parsers based on CKY
    - Augmented with probabilities

#### Probabilistic CKY

- Like regular CKY
  - Assume grammar in Chomsky Normal Form (CNF)
    - Productions:
      - $A \rightarrow B C \text{ or } A \rightarrow w$
  - Represent input with indices b/t words
    - E.g., 0 Book 1 that 2 flight 3 through 4 Houston 5
- For input string length n and non-terminals V
  - Cell[i,j,A] in (n+1)x(n+1)xV matrix contains
    - Probability that constituent A spans [i,j]

### Probabilistic CKY Algorithm

```
tion PROBABILISTIC-CKY(words,grammar) returns most probable parse
and its probability
j \leftarrow from 1 to LENGTH(words) do
for all { A \mid 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 \mid A \rightarrow BC \in grammar,
and table[i,k,B] > 0 and table[k, j, C] > 0 }
if (table[i,j,A] < P(A \rightarrow BC) \times table[i,k,B] \times table[k,j,C]) then
table[i,j,A] \leftarrow P(A \rightarrow BC) \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]
```

#### PCKY Grammar Segment

- S → NP VP [0.80]
- NP → Det N [0.30]
- VP → V NP [0.20]
- $V \rightarrow$  includes [0.05]

- Det  $\rightarrow$  the [0.40]
- Det → a [0.40]
- N → meal [0.01]
- N  $\rightarrow$  flight [0.02]

# PCKY Matrix: The flight includes a meal

Det: 0.4 [0,1]	NP: 0.3*0.4*0.02 =.0024 [0,2]	[0,3]	[0,4]	S: 0.8* 0.000012* 0.0024 [0,5]
	N: 0.02 [1,2]	[1,3]	[1,4]	[1,5]
		V: 0.05 [2,3]	[2,4]	VP: 0.2*0.05* 0.0012=0.0 00012 [2,5]
			Det: 0.4 [3,4]	NP: 0.3*0.4*0.01 =0.0012 [3,5]
				N: 0.01 [4,5]

#### Learning Probabilities

- Simplest way:
  - Treebank of parsed sentences
  - To compute probability of a rule, count:
    - Number of times non-terminal is expanded
    - Number of times non-terminal is expanded by given rule

$$P(\alpha \to \beta \mid \alpha) = \frac{Count(\alpha \to \beta)}{\sum_{\gamma} Count(\alpha \to \gamma)} = \frac{Count(\alpha \to \beta)}{Count(\alpha)}$$

Alternative: Learn probabilities by re-estimating
(Later)

# Probabilistic Parser Development Paradigm

- Training:
  - (Large) Set of sentences with associated parses (Treebank)
    - E.g., Wall Street Journal section of Penn Treebank, sec 2-21
      - 39,830 sentences
    - Used to estimate rule probabilities
- Development (dev):
  - (Small) Set of sentences with associated parses (WSJ, 22)
    - Used to tune/verify parser; check for overfitting, etc.
- Test:
  - (Small-med) Set of sentences w/parses (WSJ, 23)
    - 2416 sentences
  - Held out, used for final evaluation

#### Parser Evaluation

- Assume a 'gold standard' set of parses for test set
- How can we tell how good the parser is?
- How can we tell how good a parse is?
  - Maximally strict: identical to 'gold standard'
  - Partial credit:
    - Constituents in output match those in reference
      - Same start point, end point, non-terminal symbol

#### Parseval

- How can we compute parse score from constituents?
- Multiple measures:
  - Labeled recall (LR):
    - # of correct constituents in hyp. parse
    - # of constituents in reference parse
  - Labeled precision (LP):
    - # of correct constituents in hyp. parse
    - # of total constituents in hyp. parse

#### Parseval (cont'd)

#### • F-measure:

• Combines precision and recall

$$F_{\beta} = \frac{(\beta^2 + 1)PR}{\beta^2(P+R)}$$

• F1-measure: 
$$\beta = 1$$
  $F_1 = \frac{2PR}{(P+R)}$ 

- Crossing-brackets:
  - # of constituents where reference parse has bracketing ((A B) C) and hyp. has (A (B C))

#### **Precision and Recall**

- Gold standard
  - (S (NP (A a) ) (VP (B b) (NP (C c)) (PP (D d))))
- Hypothesis
  - (S (NP (A a)) (VP (B b) (NP (C c) (PP (D d)))))
- G: S(0,4) NP(0,1) VP (1,4) NP (2,3) PP(3,4)
- H: S(0,4) NP(0,1) VP (1,4) NP (2,4) PP(3,4)
- LP: 4/5
- LR: 4/5
- F1: 4/5

#### State-of-the-Art Parsing

- Parsers trained/tested on *Wall Street Journal* PTB
  - LR: 90%+;
  - LP: 90%+;
  - Crossing brackets: 1%
- Standard implementation of Parseval: evalb

#### **Evaluation Issues**

- Constituents?
  - Other grammar formalisms
    - LFG, Dependency structure, ...
    - Require conversion to PTB format
  - Extrinsic evaluation
    - How well does this match semantics, etc?