

## PCFG algorithms

### A. Overview

- (1)
  - a. PCFGs
  - b. CNF
  - c. Chart parsing
  - d. Forward probabilities
  - e. Backward probabilities
  - f. Inside-outside algorithm

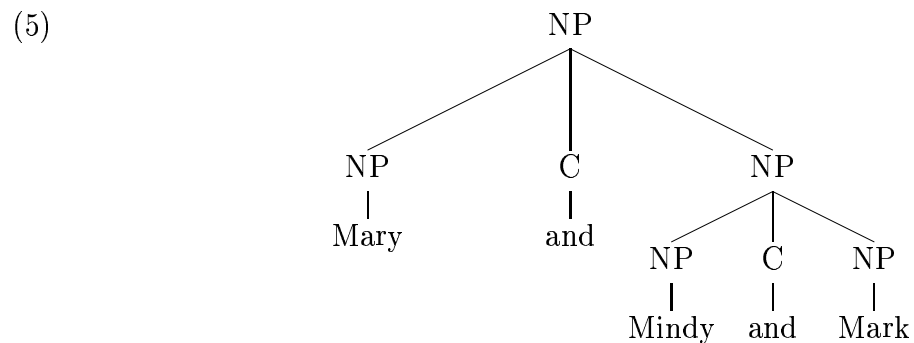
### B. What is a PCFG?

- (2) Sentence probability:  $p(s) = \sum_j p(t_j)p(s|t_j)$

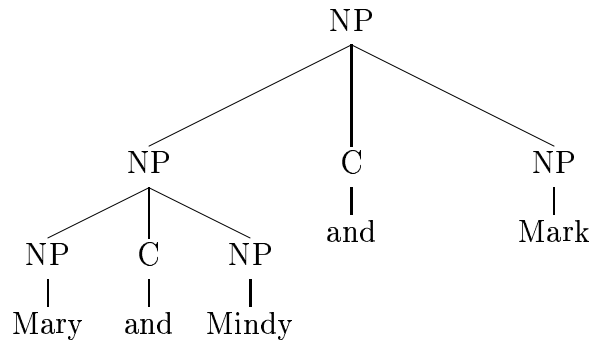
- (3)

NP	→	NP C NP	.4
NP	→	Mary	.3
NP	→	Mindy	.2
NP	→	Mark	.1
C	→	and	1

- (4) The probability of each parse is:  $.3 \times .2 \times .1 \times 1 \times 1 \times .4 \times .4 = .00096$ . The overall probability of the string is  $.00096 + .00096 = .00192$ .



(6)

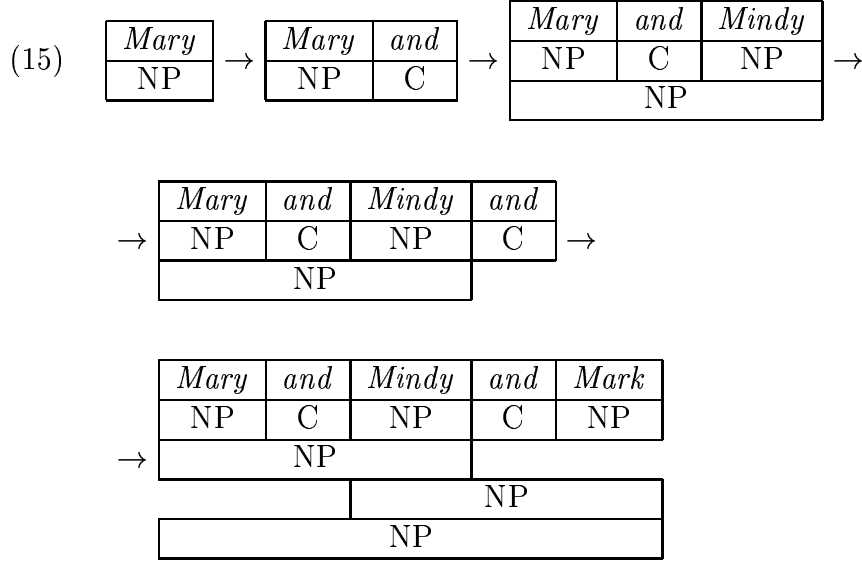


### C. Chomsky-normal form

- (7) Any context-free grammar can be expressed as in Chomsky-normal form (CNF) without any change in expressive power.
- (8) Chomsky-Normal Form
  - a.  $A \rightarrow BC$ , where  $A$ ,  $B$ , and  $C$  are non-terminal symbols.
  - b.  $A \rightarrow a$ , where  $A$  is a non-terminal and  $a$  is a single terminal.
- (9) Demonstrating the inside-outside algorithm is much easier with a CFG in CNF.

### D. Chart parsing

- (10) How do we find whether a sentence is legal with respect to some CFG?
- (11) This is a hard problem because, in principle, we must keep track of every possible application of every rewrite rule as we proceed from left to right.
- (12) *The horse raced past the barn fell.*
- (13) Chart parsing (dynamic programming) is an efficient way to do this.
- (14) Chart parsing  
Keep track of *all* successful rewrite rule applications in a chart as you parse left to right.



- (16) Why is this efficient?:
- We do *not* keep track of all complete parses.
  - Once we know a rule can succeed, we record that success for all future parses.

### E. Inside and outside probabilities

- (17) Backward probability = “inside” probability  
 $\beta_j(k, l) \stackrel{\text{def}}{=} p(w_{k,l} | N_{k,l}^j)$
- (18) Base case for inside probability for PCFG in CNF  
 $\beta_j(k, k) = p(w_k | N_{k,k}^j) = p(N^j \rightarrow w_k)$
- (19) Recursive case for inside probability for PCFG in CNF  
 $\beta_j(k, l) \stackrel{\text{def}}{=} \sum_{p,q,m} p(N^j \rightarrow N^p N^q) \beta_p(k, m) \beta_q(m+1, l)$
- (20) Forward probability = “outside” probability  
 $\alpha_j(k, l) \stackrel{\text{def}}{=} p(w_{1,k-1}, N_{k,l}^j, w_{l+1,n})$
- (21) Base case for outside probability for PCFG in CNF  
 $\alpha_1(1, n) = p(N_{1,n}^1) = 1$
- (22) Recursive case for outside probability for PCFG in CNF  

$$\alpha_j(k, l) \stackrel{\text{def}}{=} \sum_{h,p,q} \alpha_p(h, l) p(N^p \rightarrow N^q N^j) \beta_q(h, k-1) + \sum_{m,p,q} \alpha_p(k, m) p(N^p \rightarrow N^j N^q) \beta_q(l+1, m)$$

## F. Training a PCFG

$$(23) \quad |N^j \rightarrow N^p N^q| \stackrel{\text{def}}{=} \frac{1}{p(w_{1,n})} \sum_{k,l,m} \alpha_j(k, l) p(N^j \rightarrow N^p N^q) \beta_p(k, m) \beta_q(m + 1, l)$$

## References

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