CMPT-413
Computational Linguistics

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Probabilistic CFG (PCFG)

$$
\begin{array}{lclc}
S & \rightarrow & NP\ VP & 1 \\
VP & \rightarrow & V\ NP & 0.9 \\
VP & \rightarrow & VP\ PP & 0.1 \\
PP & \rightarrow & P\ NP & 1 \\
NP & \rightarrow & NP\ PP & 0.25 \\
NP & \rightarrow & Calvin & 0.25 \\
NP & \rightarrow & monsters & 0.25 \\
NP & \rightarrow & school & 0.25 \\
V & \rightarrow & imagined & 1 \\
P & \rightarrow & in & 1
\end{array}
$$

$$P(input) = \sum_{tree} P(tree \mid input)$$

$$P(Calvin\ imagined\ monsters\ in\ school) = ?$$

Notice that $P(VP \rightarrow V\ NP) + P(VP \rightarrow VP\ PP) = 1.0$

Probabilistic CFG (PCFG)

$$P(\textit{Calvin imagined monsters in school}) = ?$$

```
(S (NP Calvin)
   (VP (V imagined)
       (NP (NP monsters)
           (PP (P in)
               (NP school)))))

(S (NP Calvin)
   (VP (VP (V imagined)
           (NP monsters))
       (PP (P in)
           (NP school))))
```


Probabilistic CFG (PCFG)

```
(S (NP Calvin)
   (VP (V imagined)
       (NP (NP monsters)
           (PP (P in)
               (NP school)))))
```

$$\begin{aligned} P(tree_1) &= P(S \to NP\ VP) \times P(NP \to Calvin) \times P(VP \to V\ NP) \times \\ &\quad P(V \to imagined) \times P(NP \to NP\ PP) \times P(NP \to monsters) \times \\ &\quad P(PP \to P\ NP) \times P(P \to in) \times P(NP \to school) \\ &= 1 \times 0.25 \times 0.9 \times 1 \times 0.25 \times 0.25 \times 1 \times 1 \times 0.25 = .003515625 \end{aligned}$$

Probabilistic CFG (PCFG)

```
(S (NP Calvin)
   (VP (VP (V imagined)
           (NP monsters))
       (PP (P in)
           (NP school))))
```

$$\begin{aligned} P(\mathit{tree}_2) &= P(S \rightarrow NP\ VP) \times P(NP \rightarrow \mathit{Calvin}) \times P(VP \rightarrow VP\ PP) \times \\ &\quad P(VP \rightarrow V\ NP) \times P(V \rightarrow \mathit{imagined}) \times P(NP \rightarrow \mathit{monsters}) \times \\ &\quad P(PP \rightarrow P\ NP) \times P(P \rightarrow \mathit{in}) \times P(NP \rightarrow \mathit{school}) \\ &= 1 \times 0.25 \times 0.1 \times 0.9 \times 1 \times 0.25 \times 1 \times 1 \times 0.25 = .00140625 \end{aligned}$$

Probabilistic CFG (PCFG)

$$\begin{aligned} P(\mathit{Calvin\ imagined\ monsters\ in\ school}) &= P(\mathit{tree}_1) + P(\mathit{tree}_2) \\ &= .003515625 + .00140625 \\ &= .004921875 \\ \text{Most likely tree is } \mathit{tree}_1 &= \arg\max_{\mathit{tree}} P(\mathit{tree} \mid \mathit{input}) \end{aligned}$$

```
(S (NP Calvin)
   (VP (V imagined)
       (NP (NP monsters)
           (PP (P in)
               (NP school)))))
```

```
(S (NP Calvin)
   (VP (VP (V imagined)
           (NP monsters))
       (PP (P in)
           (NP school))))
```

PCFG

- Central condition: $\sum_\alpha P(A \to \alpha) = 1$
- Called a *proper* PCFG if this condition holds
- Note that this means $P(A \to \alpha) = P(\alpha \mid A) = \frac{f(A,\alpha)}{f(A)}$
- $P(T \mid S) = \frac{P(T,S)}{P(S)} = P(T,S) = \prod_i P(RHS_i \mid LHS_i)$

PCFG

- What is the PCFG that can be extracted from this single tree:

```
(S   (NP (Det the) (NP man))
     (VP  (VP  (V played)
                (NP (Det a) (NP game)))
          (PP  (P with)
                (NP (Det the) (NP dog)))))
```

- How many different rhs α exist for $A \to \alpha$ where A can be *S, NP, VP, PP, Det, N, V, P*

PCFG

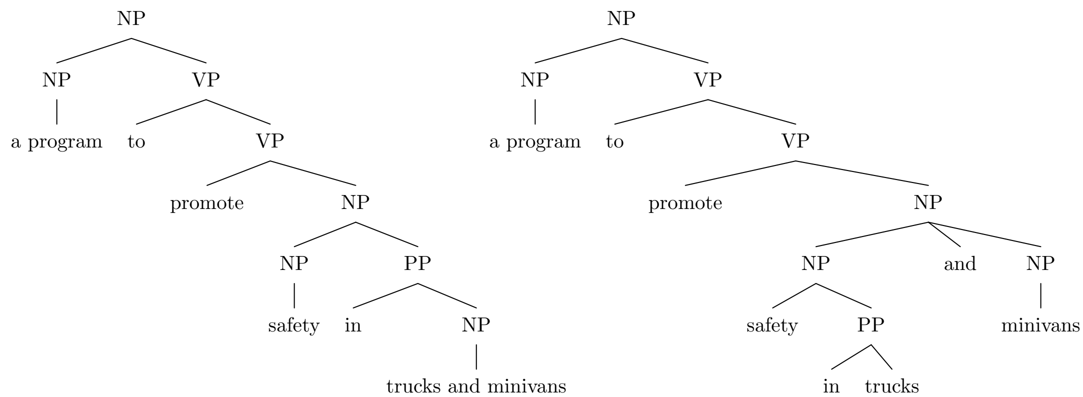
S	$\rightarrow$	$NP\ VP$	$c = 1$	$p = 1/1$	$= 1.0$
NP	$\rightarrow$	$Det\ NP$	$c = 3$	$p = 3/6$	$= 0.5$
NP	$\rightarrow$	man	$c = 1$	$p = 1/6$	$= 0.1667$
NP	$\rightarrow$	$game$	$c = 1$	$p = 1/6$	$= 0.1667$
NP	$\rightarrow$	dog	$c = 1$	$p = 1/6$	$= 0.1667$
VP	$\rightarrow$	$VP\ PP$	$c = 1$	$p = 1/2$	$= 0.5$
VP	$\rightarrow$	$V\ NP$	$c = 1$	$p = 1/2$	$= 0.5$
PP	$\rightarrow$	$P\ NP$	$c = 1$	$p = 1/1$	$= 1.0$
Det	$\rightarrow$	the	$c = 2$	$p = 2/3$	$= 0.67$
Det	$\rightarrow$	a	$c = 1$	$p = 1/3$	$= 0.33$
V	$\rightarrow$	$played$	$c = 1$	$p = 1/1$	$= 1.0$
P	$\rightarrow$	$with$	$c = 1$	$p = 1/1$	$= 1.0$

- We can do this with multiple trees. Simply count occurrences of CFG rules over all the trees.
- A repository of such trees labelled by a human is called a TreeBank.

Ambiguity

- Part of Speech ambiguity
  `saw` → noun
  `saw` → verb
- Structural ambiguity: Prepositional Phrases
  `I saw (the man) with the telescope`
  `I saw (the man with the telescope)`
- Structural ambiguity: Coordination
  `a program to promote safety in ((trucks) and (minivans))`
  `a program to promote ((safety in trucks) and (minivans))`
  `((a program to promote safety in trucks) and (minivans))`

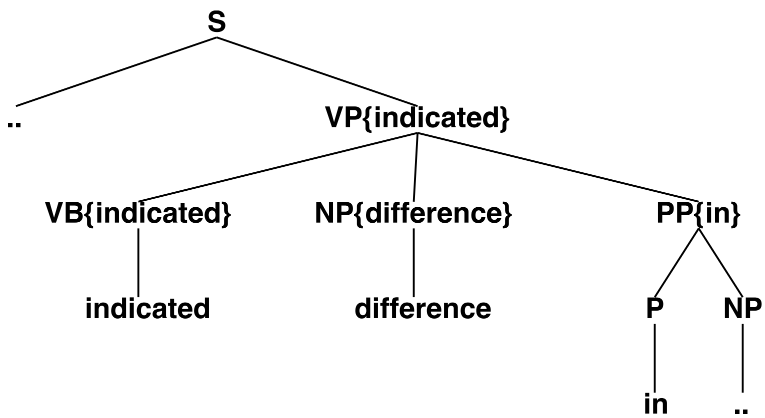
Ambiguity ← attachment choice in alternative parses



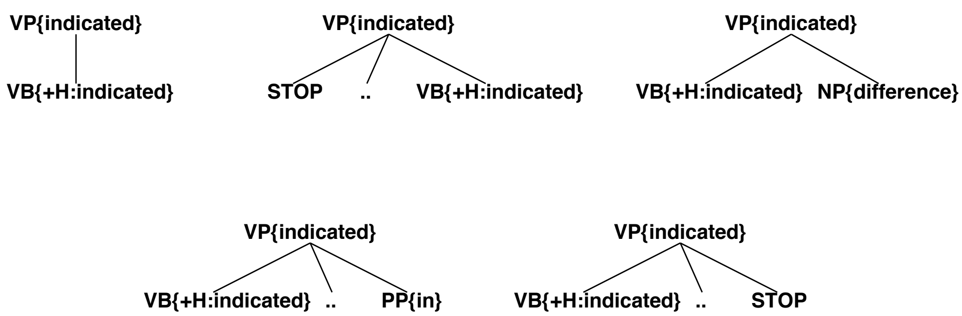
Parsing as a machine learning problem

- S = a sentence
  T = a parse tree
  A statistical parsing model defines $P(T \mid S)$
- Find best parse: $\underset{T}{\arg\max}\ P(T \mid S)$
- $P(T \mid S) = \frac{P(T,S)}{P(S)} = P(T, S)$
- Best parse: $\underset{T}{\arg\max}\ P(T, S)$
- e.g. for PCFGs: $P(T, S) = \prod_{i=1\ldots n} P(\mathrm{RHS}_i \mid \mathrm{LHS}_i)$

Adding Lexical Information to PCFG



Adding Lexical Information to PCFG (Collins 99, Charniak 00)



$$
\begin{aligned}
&P_h(\mathtt{VB} \mid \mathtt{VP}, \mathtt{indicated}) \times P_l(\mathtt{STOP} \mid \mathtt{VP}, \mathtt{VB}, \mathtt{indicated}) \times \\
&P_r(\mathtt{NP(difference)} \mid \mathtt{VP}, \mathtt{VB}, \mathtt{indicated}) \times \\
&P_r(\mathtt{PP(in)} \mid \mathtt{VP}, \mathtt{VB}, \mathtt{indicated}) \times \\
&P_r(\mathtt{STOP} \mid \mathtt{VP}, \mathtt{VB}, \mathtt{indicated})
\end{aligned}
$$

Evaluation of Parsing

- Consider a candidate parse to be evaluated against the truth (or gold-standard parse):

```
candidate: (S (A (P this) (Q is)) (A (R a) (T test)))
gold:      (S (A (P this)) (B (Q is) (A (R a) (T test))))
```

- In order to evaluate this, we list all the constituents

Candidate	Gold
(0,4,S)	(0,4,S)
(0,2,A)	(0,1,A)
(2,4,A)	(1,4,B)
	(2,4,A)

- Skip spans of length 1 which would be equivalent to part of speech tagging accuracy.
- Precision is defined as $\frac{\#correct}{\#proposed} = \frac{2}{3}$ and recall as $\frac{\#correct}{\#in\ gold} = \frac{2}{4}$.
- Another measure: crossing brackets,

```
candidate: [ an [incredibly expensive] coat ] (1 CB)
gold:      [ an [incredibly [expensive coat]]
```


Evaluation of Parsing

$$\text{Bracketing recall } R = \frac{\text{num of correct constituents}}{\text{num of constituents in the goldfile}}$$

$$\text{Bracketing precision } P = \frac{\text{num of correct constituents}}{\text{num of constituents in the parsed file}}$$

Complete match = % of sents where recall & precision are both 100%

$$\text{Average crossing} = \frac{\text{num of constituents crossing a goldfile constituent}}{\text{num of sents}}$$

No crossing = % of sents which have 0 crossing brackets

2 or less crossing = % of sents which have $\leq$ 2 crossing brackets

Statistical Parsing Results

$$\text{F1-score} = 2\frac{\textit{precision} \cdot \textit{recall}}{\textit{precision} + \textit{recall}}$$

System	$\leq 100wds$ F1-score
Shift-Reduce (Magerman, 1995)	84.14
PCFG with Lexical Features (Collins, 1999)	88.19
PCFG with Lexical Features (Charniak, 1999)	89.54
n-best Re-ranking (Collins, 2000)	89.74
Unlexicalized Berkeley parser (Petrov et al, 2007)	90.10
n-best Re-ranking (Charniak and Johnson, 2005)	91.02
Tree-insertion grammars (Carreras, Collins, Koo, 2008)	91.10
Ensemble *n*-best Re-ranking (Johnson and Ural, 2010)	91.49
Forest Re-ranking (Huang, 2010)	91.70
Unlabeled Data with Self-Training (McCloskey et al, 2006)	92.10

Practical Issues: Beam Thresholding and Priors

- Probability of nonterminal X spanning $j \dots k$: $N[X, j, k]$
- Beam Thresholding compares $N[X, j, k]$ with every other Y where $N[Y, j, k]$
- But what should be compared?
- Just the *inside probability*: $P(X \stackrel{*}{\Rightarrow} t_j \dots t_k)$? written as $\beta(X, j, k)$
- Perhaps $\beta(\mathtt{FRAG}, 0, 3) > \beta(\mathtt{NP}, 0, 3)$, but NPs are much more likely than FRAGs in general

Practical Issues: Beam Thresholding and Priors

- The correct estimate is the *outside probability*:

$$P(S \overset{*}{\Rightarrow} t_1 \ldots t_{j-1}\ X\ t_{k+1} \ldots t_n)$$

  written as $\alpha(X, j, k)$
- Unfortunately, you can only compute $\alpha(X, j, k)$ efficiently after you finish parsing and reach $(S, 0, n)$

Practical Issues: Beam Thresholding and Priors

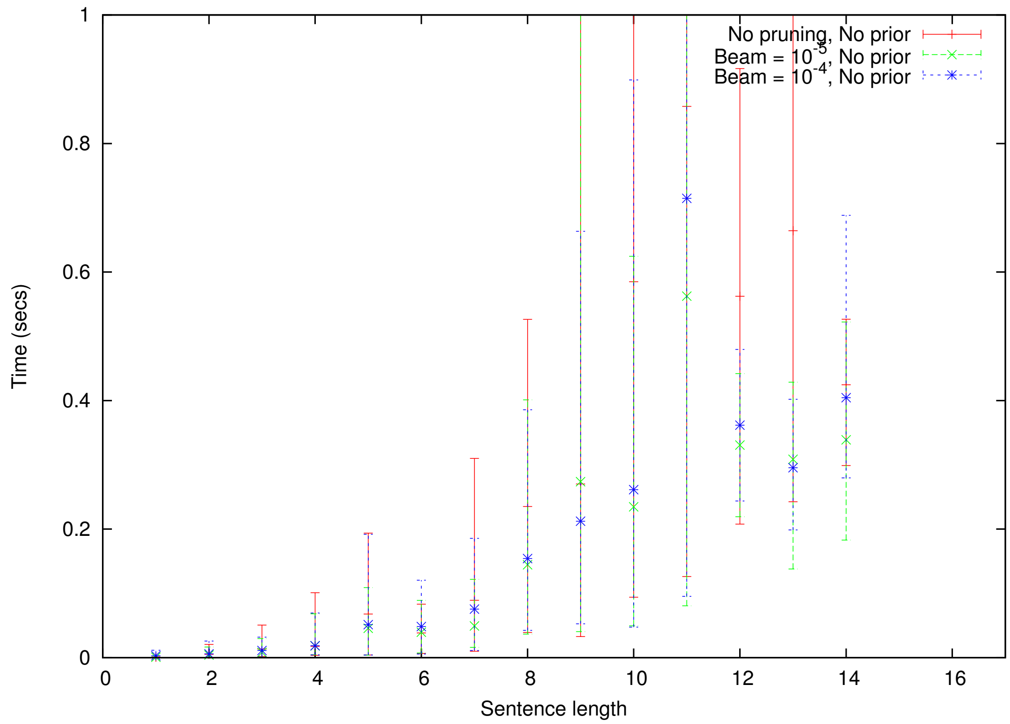
- To make things easier we multiply the prior probability $P(X)$ with the inside probability
- In beam Thresholding we compare every new insertion of X for span j, k as follows:
  Compare $P(X) \cdot \beta(X, j, k)$ with the most probable Y $P(Y) \cdot \beta(Y, j, k)$
- Assume Y is the most probable entry in j, k, then we compare

$$\text{beam} \cdot P(Y) \cdot \beta(Y, j, k) \quad (1)$$

$$P(X) \cdot \beta(X, j, k) \quad (2)$$

- If $(2) < (1)$ then we prune X for this span j, k
- beam is set to a small value, say 0.001 or even 0.01.
- As the beam value increases, the parser speed increases (since more entries are pruned).
- A simpler (but not as effective) alternative to using the beam is to keep only the top K entries for each span j, k

Experiments with Beam Thresholding



Experiments with Beam Thresholding