CMPT-413: Computational Linguistics

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Probabilistic CFG (PCFG)

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

$$P_G(I) = \sum_T P_G(T \mid I)$$

P_G(*imagined monsters in school*) $=?$

PCFG

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

PCFG

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

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

- How many different rhs α exist for $A \rightarrow \alpha$

Parsing PCFGs: CYK algorithm + the Viterbi algorithm

$\{ \; p\texttt{:} \quad \texttt{S} \rightarrow \texttt{S S} \, , 1 - p\texttt{:} \quad \texttt{S} \rightarrow \texttt{a} \, \}$

a	a	a	a
$1 - p$: $S_{0,1} \rightarrow$ a	$1 - p$: $S_{1,2} \rightarrow$ a	$1 - p$: $S_{2,3} \rightarrow$ a	$1 - p$: $S_{3,4} \rightarrow$ a
$S_{0,1} \times S_{1,2}$ $= S_{0,2} \rightarrow$ S S $p(1 - p)^2$	$S_{1,2} \times S_{2,3}$ $= S_{1,3} \rightarrow$ S S $p(1 - p)^2$	$S_{2,3} \times S_{3,4}$ $= S_{2,4} \rightarrow$ S S $p(1 - p)^2$	
$S_{0,1} + S_{1,3}$ OR $S_{0,2} + S_{2,3}$ $= S_{0,3} \rightarrow$ S S $\max(p(1 - p)^3,$ $p(1 - p)^3)$	$S_{1,2} + S_{2,4}$ OR $S_{1,3} + S_{3,4}$ $= S_{1,4} \rightarrow$ S S $\max(p(1 - p)^3,$ $p(1 - p)^3)$		
What goes in this cell? ?? $= S_{0,4}$			

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

Calvin	imagined	monsters	in	school
$\text{NP}_{0,1}$ 0.25	$\text{V}_{1,2}$ 1	$\text{NP}_{2,3}$ 0.25	$\text{P}_{3,4}$ 1	$\text{NP}_{3,4}$ 0.25
	$\text{V}_{1,2} \times \text{NP}_{2,3}$ $= \text{VP}_{1,3} \rightarrow \text{V NP}$ $1 \times 0.25 \times 0.9$		$\text{P}_{3,4} \times \text{NP}_{4,5}$ $= \text{PP}_{3,5} \rightarrow \text{P NP}$ $1^2 \times 0.25$	
	$\text{VP}_{1,3} \times \text{PP}_{3,5}$ OR $\text{V}_{1,2} \times \text{NP}_{2,5}$ $= \text{VP}_{1,5}$ x	$\text{NP}_{2,3} \times \text{PP}_{3,5}$ $= \text{NP}_{2,5} \rightarrow \text{NP PP}$ 0.25^3		
$= \text{S}_{0,4}$ $x \times 0.25$				

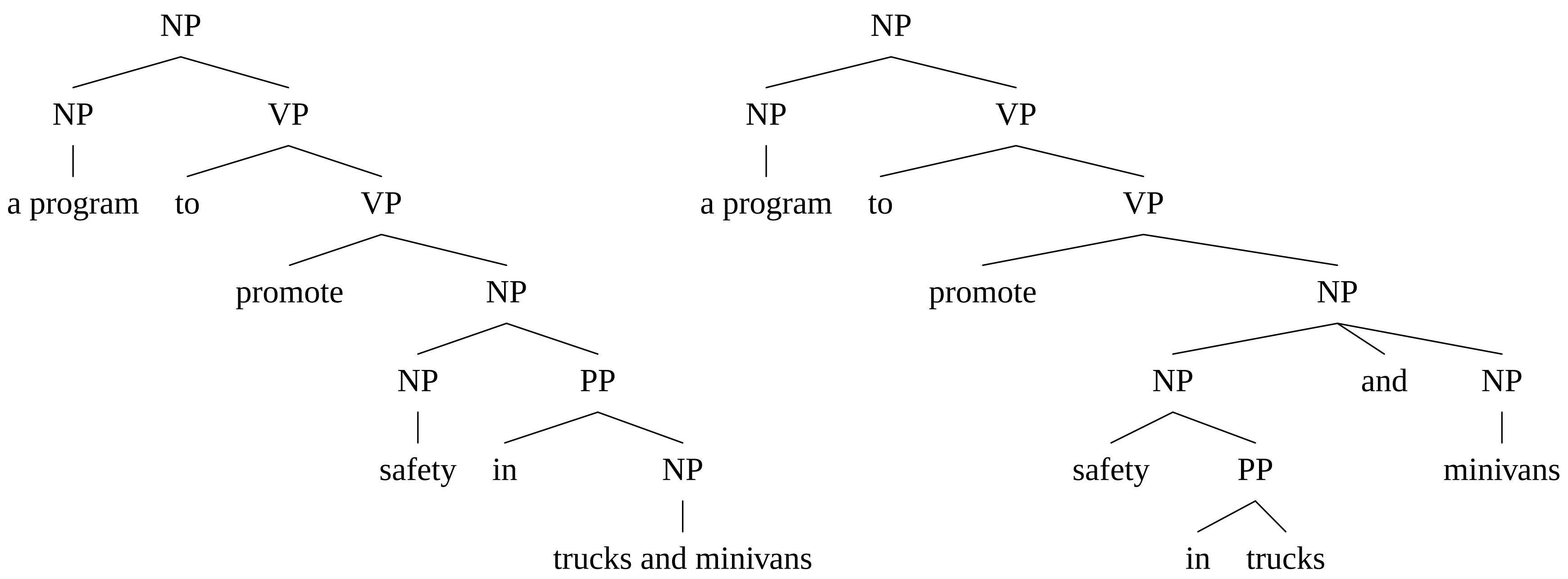
A Key Problem in Processing Language: Ambiguity: (Church and Patil 1982; Collins 1999)

- Part of Speech ambiguity
  `saw` $\longrightarrow$ noun
  `saw` $\longrightarrow$ 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: $\arg\max_{T} P(T \mid S)$
- $P(T \mid S) = \frac{P(T,S)}{P(S)} = P(T,S)$
- Best parse: $\arg\max_{T} P(T,S)$
- e.g. for PCFGs: $P(T,S) = \prod_{i=1\ldots n} P(\mathrm{RHS}_i \mid \mathrm{LHS}_i)$

Prepositional Phrases

- noun attach: *I bought the shirt with pockets*
- verb attach: *I washed the shirt with soap*
- As in the case of other attachment decisions in parsing: it depends on the meaning of the entire sentence – the so-called AI complete problem
- First we give a precise characterization of the problem and then we try to solve it using statistical associations between words

Structure Based Ambiguity Resolution

- Right association: a constituent (NP or PP) tends to attach to another constituent immediately to its right (Kimball 1973)

- Minimal attachment: a constituent tends to attach to an existing non-terminal using the fewest additional syntactic nodes (Frazier 1978)

- These two principles make opposite predictions for prepositional phrase attachment:
  e.g. in I $[_{VP}$ saw $[_{NP}$ the man $\ldots$ $[_{PP}$ with the telescope],
  RA predicts that the PP attaches to the NP,
  and MA predicts VP attachment

Structure Based Ambiguity Resolution

- Garden-paths look structural:
  The horse raced past the barn fell

- Neither MA or RA account for more than 55% of the cases in real text

- Psycholinguistic experiments using eyetracking show that humans resolve ambiguities as soon as possible in the left to right sequence using the words to disambiguate

- Garden-paths are lexical and not structural:
  The flowers delivered for the patient arrived

Ambiguity Resolution: Prepositional Phrases in English

- Learning Prepositional Phrase Attachment: Annotated Data

v	n1	p	n2	Attachment
join	board	as	director	V
is	chairman	of	N.V.	N
using	crocidolite	in	filters	V
bring	attention	to	problem	V
is	asbestos	in	products	N
making	paper	for	filters	N
including	three	with	cancer	N
⋮	⋮	⋮	⋮	⋮

Prepositional Phrase Attachment

Method	Accuracy
Always noun attachment	59.0
Most likely for each preposition	72.2
Average Human (4 head words only)	88.2
Average Human (whole sentence)	93.2

Katz Back-off Smoothing

1. If $f(v, n1, p, n2) > 0$ and $\hat{p} \neq 0.5$

$$\hat{p}(1 \mid v, n1, p, n2) = \frac{f(1, v, n1, p, n2)}{f(v, n1, p, n2)}$$

2. Else if $f(v, n1, p) + f(v, p, n2) + f(n1, p, n2) > 0$ and $\hat{p} \neq 0.5$

$$\hat{p}(1 \mid v, n1, p, n2) = \frac{f(1, v, n1, p) + f(1, v, p, n2) + f(1, n1, p, n2)}{f(v, n1, p) + f(v, p, n2) + f(n1, p, n2)}$$

3. Else if $f(v,p) + f(n1,p) + f(p,n2) > 0$

$$\hat{p}(1 \mid v, n1, p, n2) = \frac{f(1,v,p) + f(1,n1,p) + f(1,p,n2)}{f(v,p) + f(n1,p) + f(p,n2)}$$

4. Else if $f(p) > 0$

$$\hat{p}(1 \mid v, n1, p, n2) = \frac{f(1,p)}{f(p)}$$

5. Else $\hat{p}(1 \mid v, n1, p, n2) = 1.0$

Prepositional Phrase Attachment: (Collins and Brooks 1995)

- **Results**: 84.5% accuracy
  with the use of some limited word classes for dates, numbers, etc.

- Using complex word classes taken from `WordNet` (which we shall be looking at later in this course) increases accuracy to 88%
  (Stetina and Nagao 1998)

- Can we improve on parsing performance using Probabilistic CFGs by using the insights detailed above

Two other studies

- **Brill and Resnik 1994**:
  use transformation based learning for PP attachment
  80.8% with words; with Wordnet classes: 81.8%
  only 266 transformations learned
  automatically learned importance of preposition (assumed in CB95)

- **Merlo, Crocker and Berthouzoz 1997**:
  test on multiple PPs, generalize the 2 PP case
  14 structures possible for 3PPs assuming a single verb: all 14 are attested in the Treebank
  same model as CB95; but generalized to dealing with upto 3PPs
  1PP: 84.3%   2PP: 69.6%   3PP: 43.6%
  this is still not the real problem faced in parsing natural language