Problems with CFG parsing

Ambiguity is a serious problem in parsing since sentences have multiple parses. Common causes are:

Attachment ambiguity. A constituent can be attached at different points in the parse tree.

Example: (Show N|V) (the Det) (menu N) (on Prep) (the Det) (Shatabdi PropN) (from Prep) (Kanpur PropN) (to Prep) (Delhi PropN).

 $S \rightarrow VP \rightarrow V NP$ $S \rightarrow V NP PP$

NP and PP can be broken down in multiple ways.

- Coordination ambiguity. Conjuncts are ambiguous.
 Young boys and girls will enjoy Techkriti.
 Young (boys and girls)... or (Young boys) and girls...
- Coordination and attachment ambiguities can interact to produce large number of parses.



Probabilistic CFGs

- Standard CFL parsers return all parses. There is no way for a parser to decide which parse is more likely.
- One solution is to use Probabilistic CFGs where each rule has an associated probability. Consequently, each parse can be given a probability and the parse with the highest probability can be returned.

PCFGs

Definition 1 (PCFG)

A PCFG G is a 5-tuple (N, Σ, R, S, P) where the first four elements of the tuple are the same as a CFG and $P: R \to [0,1]$ is a mapping that assigns a value between 0 and 1 to each rule in R. A rule in a PCFG has the following structure:

 $A \to \alpha_i$, p_i with $\sum_{(A \to \alpha_i, p_i \in R)} p_i = 1$ (that is probablities of all rules with non-terminal A add upto 1) - such a grammar is called a proper PCFG.

Let $w = w_1, \ldots, w_n$ be the input sentence, let w_{ij} stand for the sequence $w_i, \ldots, w_j, A_{(ij)}$ denote that non-terminal A derives the string/sequence w_i, \ldots, w_j . The probability of the sentence $w = w_{1n}$ w.r.t. to grammar G is:

$$P(w) = P(w_{1n}) = \sum_{t} P(w_{1n}, t) = \sum_{(t|y \text{ield}(t) = w_{1n})} P(t)$$

t is a parse tree of w using G and P(t) is the product of probabilities of all rules used in the tree.

Assumptions

- Place invariance: probability of a sub-tree t generated by A does not depend on where in w, $A_{(ij)}$ occurs.
- Context freeness: probability of a sub-tree *t* does not depend on words or terminals not generated by *t* (leaves).
- Ancestor free: probability of tree t does not depend on other nodes that are ancestors of the non-terminal generating t.

Example

$$S
ightarrow NP \ VP, \ 1.0$$
 $PP
ightarrow P \ NP, \ 1.0$ $VP
ightarrow V \ NP, \ 0.7 \ | \ VP \ PP, \ 0.3$ $P
ightarrow \ ext{with}, \ 1.0$ $V
ightarrow \ ext{saw}, \ 1.0$

contd.

Astronomers saw stars with binoculars.

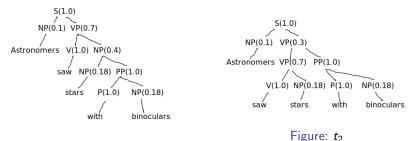


Figure: t₁

$$\begin{array}{l} P(t_1) = 1 \times 0.1 \times 0.7 \times 0.4 \times 0.18 \times 0.18 = 0.0009072 \\ P(t_2) = 1 \times 0.1 \times 0.3 \times 0.7 \times 0.18 \times 0.18 = 0.0006804 \\ \text{A PCFG is } \underline{\text{consistent}} \text{ if } \sum_{t \in \text{ All parses of } w_{1n}} = 1 \\ \text{Consistency in set } \underline{\text{consistency } \underline{\text{co$$

Consistency is not guaranteed by properness.



Features of PCFG

- PCFGs give some idea of the plausibility of parses. But this is based on purely structural constraints and lexical influences are not present.
- PCFGs can be used for grammar induction from bracketed labelled corpora.
- PCFGs are robust and can handle grammatical errors/disfluencies by giving lower probabilities to such sentences.

Limitations of PCFGs

- Do not always give information on plausibility of parse.
- The implied independence assumptions do not hold. For example, in the Switchboard corpus:

Insensitive to lexical dependencies. Example:

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[workers [dumped sacks [into a bin]]], VP \rightarrow VBD \ NP \ PP [workers [dumped [sacks [into [a bin]]]]], VP \rightarrow VBD \ PP, \ PP \rightarrow P \ NP
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Contrast with: fishermen caught tons of fish.

■ Tend to favour shallow trees.



Inducing a PCFG from a training corpus

- The training corpus \mathcal{L} is a set of parse trees t_1, \ldots, t_m . For example the Penn treebank.
- $oldsymbol{S}$ is the common start symbol for all the trees in \mathcal{L} . The set N of non-terminals is the set of all non-terminals in the trees in \mathcal{L} . Σ is the set of all terminals in the set of trees in \mathcal{L} . R is the set of all rules in all the trees in \mathcal{L} .
- The probability estimate for a rule $A \to \alpha$ is the ML estimate given by $P(A \to \alpha) = \frac{\mathsf{count}(A \to \alpha)}{\mathsf{count}(A)}$, where counting is over all trees in \mathcal{L} .
- The training set \mathcal{L} is normally contructed manually or using a standard CFG parser with manual curation of the parses output by the parser.
- Sequence to sequence methods are not as successful in constituent parse generation compared to their success in tagging problems.



¹Derivations are assumed to be left-most.

Finding the max probability parse

Problem statement and Notation:

Let T(w) be the set of all possible left-most parses for w. For $t \in T(w)$, P(t) is the probability of the parse tree t.

The problem is to find $t_{max} = \underset{t \in T(w)}{\operatorname{argmax}} P(t)$.

Let G be a PCFG in CNF, $w = w_{1n}$ the input string to be parsed, w_{ij} a substring of w,

 $\pi[i,j,A]$: table entry containing the NT A that has the max probability for substring w_{ij} .

A bottom-up recursive method (based on CYK) is able to find t_{max} . Now table entries contain both the non-terminals the can generate w_{ij} but also the probability of the corresponding sub-tree. Only the max probability is retained.

The table entries are filled by induction. Choose max among all possibilities:

- Base case: $\pi(i, i, A) = P(A \rightarrow w_i)$ or 0 if $A \rightarrow w_i \notin R$.
- Recursive case: Strings of length > 1. $A \stackrel{\star}{\Rightarrow} w_{ij}$ iff \exists a rule $A \rightarrow BC$ such that $B \stackrel{\star}{\Rightarrow} w_{ik}$ and $C \stackrel{\star}{\Rightarrow} w_{k+1j}$.
- Compute the probability by multiplying the probabilities of these two parts (they have been already calculated in the recursion).

$$\pi[i,j,A] = \max_{\substack{A \to BC \in R \\ k \in \{i...(j-1)\}}} (P(A \to BC) \times \pi[i,k,B] \times \pi[k+1,j,C])$$

The CYK PCFG algorithm²

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Algorithm 0.1: CYK(w = w_{1n}, G)
  for each (i \in 1 \dots n), for each (A \in N)

do \begin{cases}
if (A \to w_i \in R) \\
then \pi[i, i, A] = P(A \to w_i) \\
else \pi[i, i, A] \leftarrow 0
\end{cases}

  for l = 1 ... (n-1)
       do for i = 1 ... (n - l)
  \mathbf{do} \ \begin{cases} j \leftarrow i+1 \\ \text{for each } (A \in N) \\ \\ \mathbf{do} \ \begin{cases} \pi[i,j,A] = \max\limits_{\substack{A \rightarrow BC \\ k \in i...j-1}} (P(A \rightarrow BC) \times \pi[i,k,B] \times \pi[k+1,j,C]) \\ \\ bkptr[i,j,A] = \operatorname*{argmax}_{\substack{A \rightarrow BC \\ k \in i...j-1}} (P(A \rightarrow BC) \times \pi[i,k,B] \times \pi[k+1,j,C]) \end{cases}
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²From Collins

Handling violation of indp. assumptions

- All violations have to be handled structurally.
- Split NTs. For example, instead of NP have NP_{sub} and NP_{obj} then $NP_{sub} \rightarrow Pro$ and $NP_{obj} \rightarrow Pro$ can have different probabilities. This will lead to a change in rules: $S \rightarrow NP_{sub} \ VP, \ VP \rightarrow V \ NP_{obj}$.
- This is a general approach to indp. problems. For example, adverbs also occur in different positions more commonly. RB_{adv} also, now; RB_{VP} n't, not; RB_{NP} only, just.

Lexical conditioning

- Dependence on context words can be handled by lexicalized rules. Example: VP[dumped] → VBD[dumped] NP[sacks] PP[into]. Often PoS tags are included.
- This leads to sparsity problems while estimating probabilities. Usually solved by using multiple smaller rules to generalize one complex rule which most often will not suffer from sparsity.