

Advanced PCFG Models

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Slides partly from Joakim Nivre



- 1. Problems with Treebank PCFGs
- 2. Parent Annotation
- 3. Lexicalization
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Lack of Sensitivity to Structural Context

Tree Context	NP PP	DT NN	PRP
Anywhere	11%	9%	6%
NP under S	9%	9%	21%
NP under VP	23%	7%	4%



Lack of Sensitivity to Lexical Information

S	\rightarrow	NP VP PU	1.00
VP	\rightarrow	VP PP	0.33
VP	\rightarrow	VBD NP	0.67
NP	\rightarrow	NP PP	0.14
NΡ	\rightarrow	JJ NN	0.57
NΡ	\rightarrow	JJ NNS	0.29
PP	\rightarrow	IN NP	1.00
ΡU	\rightarrow	•	1.00
JJ	\rightarrow	Economic	0.33
JJ	\rightarrow	little	0.33
JJ	\rightarrow	financial	0.33
NN	\rightarrow	news	0.50
NN	\rightarrow	effect	0.50
NNS	\rightarrow	markets	1.00
/BD	\rightarrow	had	1.00
IN	\rightarrow	on	1.00





Parent Annotation

Replace nonterminal A with A^{B} when A is child of B.





Parent Annotation

Replace nonterminal A with A^{B} when A is child of B.



Described in the first seminar article



Lexicalization





Smoothing of the Lexicalized PCFG

$$q = Q(A(a) \rightarrow B(b) C(a))$$

= $P(A \rightarrow_2 B C, b \mid A, a)$
= $P(A \rightarrow_2 B C \mid A, a) \cdot P(b \mid A \rightarrow_2 B C, a)$
$$q_1 = P(A \rightarrow_2 B C \mid A, a)$$

 $\approx \lambda \frac{\text{count}(A \rightarrow_2 B C, a)}{\text{count}(A, a)} + (1 - \lambda) \frac{\text{count}(A \rightarrow_2 B C)}{\text{count}(A)}$

$$\begin{array}{rcl} q_2 &=& P(b \mid A \rightarrow_2 B \ C, a) \\ &\approx& \lambda \frac{\text{count}(b, A \rightarrow_2 B \ C, a)}{\text{count}(A \rightarrow_2 B \ C, a)} + (1 - \lambda) \frac{\text{count}(b, A \rightarrow_2 B \ C)}{\text{count}(A \rightarrow_2 B \ C)} \end{array}$$



Non-lexicalized CKY Parsing

PARSE(G, x) for j from 1 to n do for all $A : A \rightarrow x_j \in R$ $C[j - 1, j, A] := Q(A \rightarrow x_j)$ for j from 2 to n do for i from j - 2 downto 0 do for k from i + 1 to j - 1 do for all $A \rightarrow BC \in R$ and C[i, k, B] > 0 and C[k, j, C] > 0if $(C[i, j, A] < Q(A \rightarrow B C) \cdot C[i, k, B] \cdot C[k, j, C]$ then $C[i, j, A] := Q(A \rightarrow B C) \cdot C[i, k, B] \cdot C[k, j, C]$ B[i, j, A] := (k, B, C)return BUILD-TREE(B[0, n, S])





Lexicalized CKY Parsing

PARSE(G, x) for *j* from 1 to *n* do for all $A : A(x_i) \to x_i \in R$ $C[i-1, j, j, A] := Q(A(x_i) \rightarrow x_i)$ for *j* from 2 to *n* do for *i* from i - 2 downto 0 do for k from i + 1 to i - 1 do for h from i + 1 to k do for m from k + 1 to i do for all $A: A(x_h) \to B(x_h)C(x_m) \in R$ and C[i, k, h, B] > 0 and C[k, j, m, C] > 0if $(C[i, i, h, A] < Q(A(x_h) \rightarrow B(x_h)C(x_m)) \cdot C[i, k, h, B] \cdot C[k, i, m, C])$ then $C[i, i, h, A] := Q(A(x_h) \rightarrow B(x_h)C(x_m)) \cdot C[i, k, h, B] \cdot C[k, i, m, C]$ $\mathcal{B}[i, i, h, A] := (k, B, h, C, m)$ for h from k + 1 to i do for m from i + 1 to k do for all $A: A(x_b) \rightarrow B(x_m)C(x_b) \in R$ and C[i, k, m, B] > 0 and C[k, i, h, C] > 0if $(\mathcal{C}[i, j, m, A] < Q(A(x_h) \rightarrow B(x_m)\mathcal{C}(x_h)) \cdot \mathcal{C}[i, k, m, B] \cdot \mathcal{C}[k, j, h, C])$ then $C[i, j, h, A] := Q(A(x_h) \rightarrow B(x_m)C(x_h)) \cdot C[i, k, m, B] \cdot C[k, j, h, C]$ $\mathcal{B}[i, i, h, A] := (k, B, m, C, h)$ return max_h C[0, n, h, S], BUILD-TREE($\mathcal{B}[0, n, \operatorname{argmax}_{h} C[0, n, h, S], S]$)



Complexity

- Two extra loops in the algorithm, for the head of left and right trees
- Complexity is thus $O(n^5)$ instead of $O(n^3)$
- Too slow for many practical applications
- Pruning techniques often used
 - Means that we do not necessarily find the best tree, even given our model



Latent Variables

- Extract treebank PCFG
- Repeat k times:
 - 1. Split every nonterminal A into A_1 and A_2 (and duplicate rules)
 - 2. Train a new PCFG with the split nonterminals using EM
 - 3. Merge back splits that do not increase likelihood



Some Famous Parsers

	Par	Lex	Mark	Lat
Collins	+	+	+	—
Charniak	+	+	+	_
Stanford	+	_	+	_
Berkeley	+	—	+	+



Other Parsing Frameworks

- Shift-reduce parsing (transition-based)
 - Does not need a chart
 - Greedy
 - Linear time complexity
- Neural networks in parsing
 - Can reduce independence assumptions
 - Typically gives better results
 - Example: Recurrent neural network grammars (RNNG)



CNF conversion 1

Probably easiest to solve by a recursive function XXX represent either a list or string

```
List contains two strings
e.g.: ["IN", "as"]
    Do nothing
List contains two items, string and list
e.g. : ["NP" ["PRP", XXX]]
    Contract the two grammar symbols, and remove one list
    Apply cnf-method to the resulting tree
      cnf(["NP+PRP", XXX])
List contains three symbols, string, list, list
e.g. ["NP", ["DT", XXX], ["NNS", XXX]]
    Keep as it is, and apply cnf-method to the two lists
       cnf(["DT", XXX]), cnf(["NNS", XXX])
```



CNF conversion 2

Probably easiest to solve by a recursive function XXX represent either a list or string

List contains more than three symbols, string, list, list, list, ...
e.g. ["S", ["NP", XXX], ["VP", XXX], [".", XXX]]
Keep first two items, create an extra list with new label to which
you give a "new" label. Apply cnf to the resulting tree

think about the naming and markovization!

List contains something else: Something has gone wrong!



Backtrace

```
Assume that backpointers are lists:\\
(lh, rh1, rh2, min, mid, max) if binary rule\\
(pos, word) if preterminal rule \\
```

```
BACKTRACE(bp, bpchart)
if not defined(bp) then
    return NONE
    # should not happen!
else if length(bp) == 2 then
    return makeList(pos, word)
else    # length(bp) == 6
    return makeList(lh, BACKTRACE(bpchart(min, mid, rh1),bpchart)
                             BACKTRACE(bpchart(mid, max, rh2),bpchart)))
```