



Advanced PCFG Models

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Syntactic Parsing
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Slides partly from Joakim Nivre



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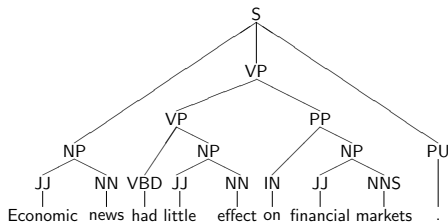
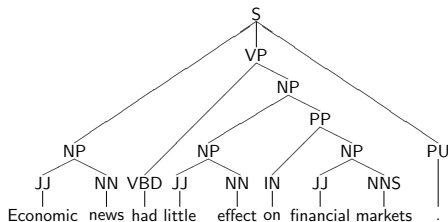
Lack of Sensitivity to Structural Context

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

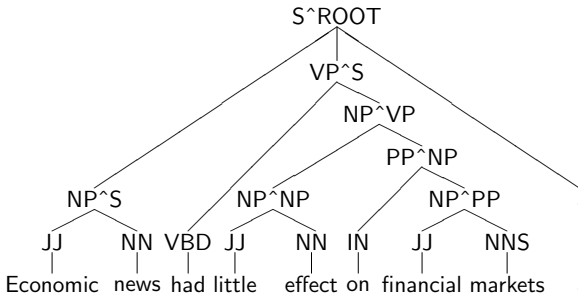
S	→	NP VP PU	1.00
VP	→	VP PP	0.33
VP	→	VBD NP	0.67
NP	→	NP PP	0.14
NP	→	JJ NN	0.57
NP	→	JJ NNS	0.29
PP	→	IN NP	1.00
PU	→	.	1.00
JJ	→	Economic	0.33
JJ	→	little	0.33
JJ	→	financial	0.33
NN	→	news	0.50
NN	→	effect	0.50
NNS	→	markets	1.00
VBD	→	had	1.00
IN	→	on	1.00





Parent Annotation

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



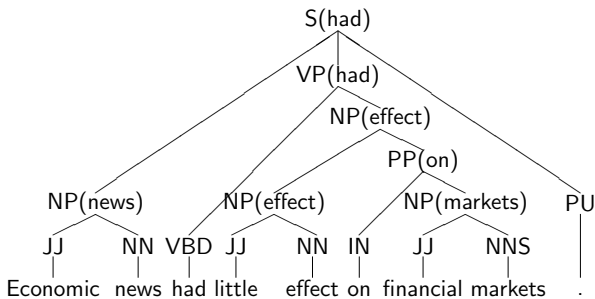


Lexicalization

Nonterminals: $N_{|ex} = \{A(a) \mid A \in N, a \in \Sigma\}$

Rules: $A(a) \rightarrow \dots B(a) \dots$

$A(a) \rightarrow a$





Smoothing of the Lexicalized PCFG

$$\begin{aligned}q &= Q(A(a) \rightarrow B(b) C(a)) \\ &= P(A \rightarrow_2 B C, b | A, a) \\ &= P(A \rightarrow_2 B C | A, a) \cdot P(b | A \rightarrow_2 B C, a)\end{aligned}$$

$$\begin{aligned}q_1 &= P(A \rightarrow_2 B C | A, a) \\ &\approx \lambda \frac{\text{COUNT}(A \rightarrow_2 B C, a)}{\text{COUNT}(A, a)} + (1 - \lambda) \frac{\text{COUNT}(A \rightarrow_2 B C)}{\text{COUNT}(A)}\end{aligned}$$

$$\begin{aligned}q_2 &= P(b | A \rightarrow_2 B C, a) \\ &\approx \lambda \frac{\text{COUNT}(b, A \rightarrow_2 B C, a)}{\text{COUNT}(A \rightarrow_2 B C, a)} + (1 - \lambda) \frac{\text{COUNT}(b, A \rightarrow_2 B C)}{\text{COUNT}(A \rightarrow_2 B C)}\end{aligned}$$



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 $C[k, j, C] > 0$

 if ($C[i, j, A] < Q(A \rightarrow B C) \cdot C[i, k, B] \cdot C[k, j, C]$) then

$C[i, j, A] := Q(A \rightarrow B C) \cdot C[i, k, B] \cdot C[k, j, C]$

$\mathcal{B}[i, j, A] := (k, B, C)$

return BUILD-TREE($\mathcal{B}[0, n, S]$)



Lexicalized CKY Parsing

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



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



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- ▶ The first seminar will cover a transition-based neural model



- ▶ Now: supervision with Paloma
 - ▶ Chomsky
 - ▶ Zoom (other Zoom link!)