Advanced PCFG Models

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Syntactic Parsing
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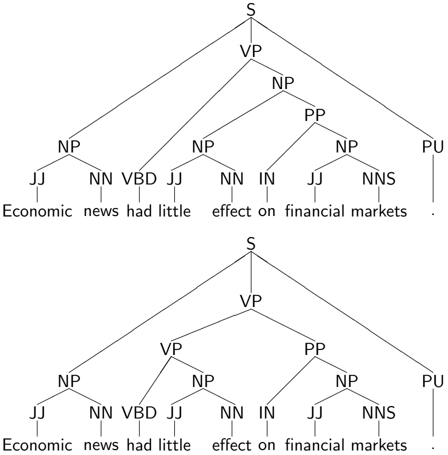
Slides partly from Joakim Nivre

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%

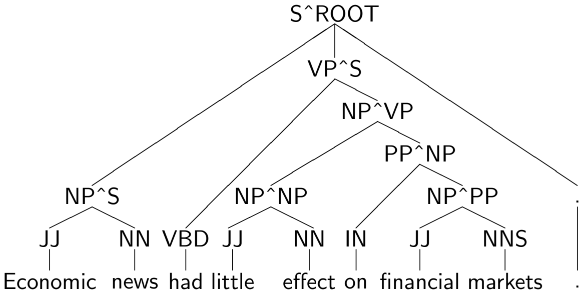
Lack of Sensitivity to Lexical Information

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



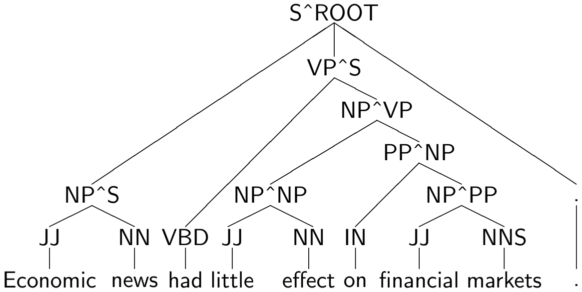
Parent Annotation

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



Parent Annotation

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



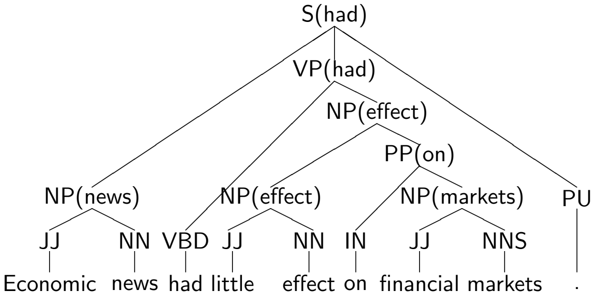
Also referred to as vertical markovization

Lexicalization

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

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

$A(a) \rightarrow a$



Smoothing of the Lexicalized PCFG

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

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

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

Non-lexicalized CKY Parsing

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

Lexicalized CKY Parsing

PARSE(G, x)

for j from 1 to n do

  for all $A : A(x_j) \to x_j \in R$

    $\mathcal{C}[j-1, j, j, A] := Q(A(x_j) \to x_j)$

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 $A : A(x_h) \to B(x_h)C(x_m) \in R$ and $\mathcal{C}[i, k, h, B] > 0$ and $\mathcal{C}[k, j, m, C] > 0$

            if $(\mathcal{C}[i, j, h, A] < Q(A(x_h) \to B(x_h)C(x_m)) \cdot \mathcal{C}[i, k, h, B] \cdot \mathcal{C}[k, j, m, C])$ then

              $\mathcal{C}[i, j, h, A] := Q(A(x_h) \to B(x_h)C(x_m)) \cdot \mathcal{C}[i, k, h, B] \cdot \mathcal{C}[k, j, m, C]$

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

      for h from $k+1$ to j do

        for m from $i+1$ to k do

          for all $A : A(x_h) \to B(x_m)C(x_h) \in R$ and $\mathcal{C}[i, k, m, B] > 0$ and $\mathcal{C}[k, j, h, C] > 0$

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              $\mathcal{C}[i, j, h, A] := Q(A(x_h) \to B(x_m)C(x_h)) \cdot \mathcal{C}[i, k, m, B] \cdot \mathcal{C}[k, j, h, C]$

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

return $\max_h \mathcal{C}[0, n, h, S]$, BUILD-TREE($\mathcal{B}[0, n, \mathrm{argmax}_h\, \mathcal{C}[0, n, h, S], S]$)

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

Horisontal Markovization

N-ary rule:

$$\text{VP} \rightarrow \text{VB NP PP PP}$$

No limit ($h = \infty$):

$$\begin{array}{rcl} \text{VP} & \rightarrow & \langle\text{VP:[VB] NP PP PP}\rangle \\ \langle\text{VP:[VB] NP PP PP}\rangle & \rightarrow & \langle\text{VP:[VB] NP PP}\rangle\ \text{PP} \\ \langle\text{VP:[VB] NP PP}\rangle & \rightarrow & \langle\text{VP:[VB] NP}\rangle\ \text{PP} \\ \langle\text{VP:[VB] NP}\rangle & \rightarrow & \langle\text{VP:[VB]}\rangle\ \text{NP} \\ \langle\text{VP:[VB]}\rangle & \rightarrow & \text{VB} \end{array}$$

First-order markovization ($h = 1$):

$$\begin{array}{rcl} \text{VP} & \rightarrow & \langle\text{VP:[VB]} \ldots \text{PP}\rangle \\ \langle\text{VP:[VB]} \ldots \text{PP}\rangle & \rightarrow & \langle\text{VP:[VB]} \ldots \text{PP}\rangle\ \text{PP} \\ \langle\text{VP:[VB]} \ldots \text{PP}\rangle & \rightarrow & \langle\text{VP:[VB]} \ldots \text{NP}\rangle\ \text{PP} \\ \langle\text{VP:[VB]} \ldots \text{NP}\rangle & \rightarrow & \langle\text{VP:[VB]}\rangle\ \text{NP} \\ \langle\text{VP:[VB]}\rangle & \rightarrow & \text{VB} \end{array}$$

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 (Pre-neural) 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
  - Often not grammar-based, but letting the neural networks score all possible phrases (e.g. span-based parsing)
  - Typically gives better results

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- The first seminar covered a transition-based neural model