Language and Statistics II

Lecture 11: Modern Parsers

Noah Smith

Last Time

- Vanilla PCFGs
- Treebanks
- Parsing Algorithms for PCFGs

Today

- Some useful transformations on trees
- Modern parsing models:
 - Collins (1997; 2003)
 - Charniak (1997; 2000)





 $NP^{VP} \rightarrow^{p} NP^{NP} PP^{NP}$

$$NP^{NP} \rightarrow^{r} NP^{NP} PP^{NP}$$

 $NP^{VP} \rightarrow q NP^{NP} PP^{NP} PP^{NP}$



• Another way to think about it ...

Before:
$$p(\text{tree}) = \prod_{n \in \text{tree's nonterminal tokens}} \rho(n' \text{s children}|n)$$

Now: $p(\text{tree}) = \prod_{n \in \text{tree's nonterminal tokens}} \rho(n' \text{s children}|n, n' \text{s parent})$

- This could conceivably help performance (weaker independence assumptions)
- This could conceivably hurt performance (data sparseness)

• From Johnson (1998):

PCFG from WSJ Treebank: 14,962 rules

• Of those, 1,327 would **always** be subsumed!

After parent annotation: 22,773 rules

• Only 965 would always be subsumed!

Recall 69.7% → 79.2%; precision 73.5% → 80.0%

 Trick: check for subsumed rules, remove them from the grammar → faster parsing.

Head Annotation

"I love all my children, but one of them is **special**."

$$S \rightarrow NP \underline{VP}$$

$$VP \rightarrow \underline{VBD} NP$$

$$NP \rightarrow DT \underline{NNS} PP$$

Heads not in the Treebank.

Usually people use **deterministic head rules** (Magerman, 1995).

Head Annotation



Lexicalization

 Every nonterminal node is annotated with a word from its yield; such that lex(n) = lex(head(n))

Lexical Head Annotation



Lexicalization

- Every nonterminal node is annotated with a word from its yield; such that
 lex(n) = lex(head(n))
- What might this allow?
- What might we worry about?

Currently, this is controversial (we'll see why)!

• Take away the nonlexical parts.



• Take away the nonlexical parts.



• Merge redundant nodes upward.



Crucial Point

- By "decorating" the treebank, we have been carrying additional information around the trees.
- The **hope** is to improve the ability of a PCFG to predict syntactic structure correctly.
- The **worry** is that our grammar will get really big and the probabilities too hard to estimate.
 - Also, speed. More rules \rightarrow bigger grammar \rightarrow slower parsing.

• Can represent some things that are hard for CFGs (but then it's not a PCFG anymore):



- Don't have to be lexicalized
- Often faster to parse
- Closer to semantics?
- We'll come back to this representation.

- Trees are headed & lexicalized.
- Many, many rules!

$$VP_{saw} \rightarrow \underline{V}_{saw} NP_{man} PP_{through}$$

$$VP_{saw} \rightarrow \underline{V}_{saw} NP_{man} PP_{with}$$

$$VP_{saw} \rightarrow \underline{V}_{saw} NP_{woman} PP_{through}$$

$$VP_{saw} \rightarrow \underline{V}_{saw} NP_{man}$$

• We are given the parent and its lexeme.



- We are given the parent and its lexeme.
- Randomly generate the head nonterminal.



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- Generate a sequence of right children.



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- Wanted to model **distance**. How?
- Assume depth-first recursion.



- Wanted to model **distance**. How?
- Assume depth-first recursion.
- Can then condition the next child on (features of) the yield between it and the head:

 $p(PP_{with} | VP_{saw}, right, "the cat who liked milk") \approx p(PP_{with} | VP_{saw}, right, length>0, +verb)$

 1997 version looked for commas, too; later this was removed.

$$p(\langle L, u \rangle_{1}^{n}, \langle H, w \rangle, \langle R, v \rangle_{1}^{m} | \langle P, w \rangle) =$$

$$p(H|\langle P, w \rangle) \cdot \left(\prod_{i=1}^{n} p(\langle L, u \rangle_{i} | \langle P, w \rangle, H, \text{left}, \Delta_{i})\right) p(\text{stop}|\langle P, w \rangle, H, \text{left}, \Delta_{n+1})$$

$$\cdot \left(\prod_{i=1}^{m} p(\langle R, v \rangle_{i} | \langle P, w \rangle, H, \text{right}, \Delta_{i})\right) p(\text{stop}|\langle P, w \rangle, H, \text{right}, \Delta_{m+1})$$

Collins Models 2 & 3 (1997)

(blackboard)



Other Details

- Smoothing: deleted interpolation.
- Unknown words: every type with count ≤ 5 became UNK
- Tagging is not a separate stage; it is just part of the parse.

Further Refinements

- Base noun phrases
 - Labeled "NPB"
 - First-order Markov model for children of head!
- Coordinators ("and") predicted **together** with the later argument.
- Punctuation treated similarly (see the 2003 paper)

Charniak (1997)

- Similar setup.
 - Lexicalized PCFG, factored model for rules
 - Tags don't travel up the tree as in Collins
 - Tagging part of parsing
 - Deleted interpolation for smoothing
- Used an additional 30 million words of unannotated data.

Charniak (1997)



Charniak (2000)

- The 2000 parser is "maximum entropy inspired."
- It is closer to Collins' model (Markovized children), but the estimation is bizarre.
 - Smoothed, backed-off probabilities are multiplied together - almost like a product of experts.

Comparison

		labeled recall	labeled precision	average crossing brackets
Collins	Model 1	87.5	87.7	1.09
	Model 2	88.1	88.3	1.06
	Model 3	88.0	88.3	1.05
Charniak	1997	86.7	86.6	1.20
	2000	89.6	89.5	0.88