Refining Generative Grammars

Parser Evaluation

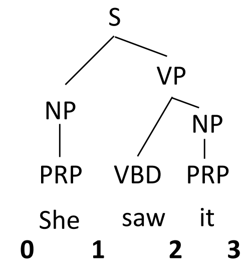
- View a parse as a set of labeled *brackets* / constituents

S(0,3)

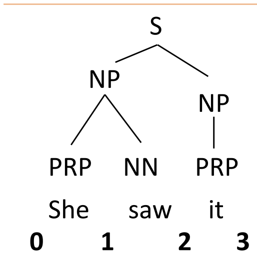
NP(0,1)

PRP(0,1) (but standard evaluation *does not count POS tags*)

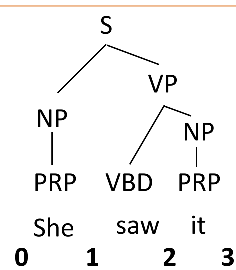
VP(1,3), VBD(1,2), NP(2,3), PRP(2,3)



Parser Evaluation



S(0,3),
NP(0,2),
NP(2,3),
~~PRP(0,1),~~
~~NN(1,2),~~
~~PRP(2,3)~~



S(0,3),
NP(0,1),
VP(1,3),
NP(2,3),
~~PRP(0,1),~~
~~VBD(1,2),~~
~~PRP(2,3)~~

- Precision: number of correct predictions / number of predictions = 2/3
- Recall: number of correct predictions / number of golds = 2/4
- F1: harmonic mean of precision and recall = $(1/2 * ((2/4)^{-1} + (2/3)^{-1}))^{-1}$

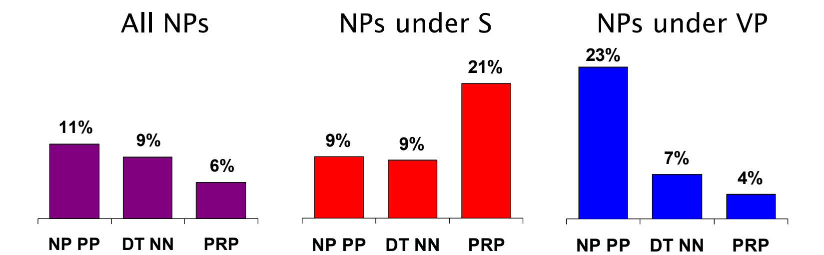
= 0.57 (closer to min)

Results

- Standard dataset for English: Penn Treebank (Marcus et al., 1993)
- "Vanilla" PCFG: ~75 F1
- Best PCFGs for English: ~90 F1
- State-of-the-art discriminative models (using unlabeled data): 95 F1
- Other languages: results vary widely depending on annotation + complexity of the grammar

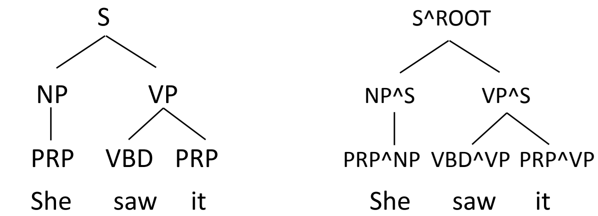
Klein and Manning (2003)

PCFG Independence Assumptions



- Language is not context-free: NPs in different contexts rewrite differently
- [They]$_{NP}$ received [the package of books]$_{NP}$

Vertical Markovization

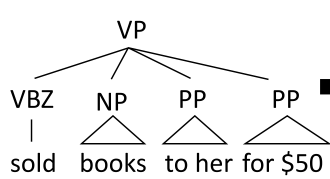


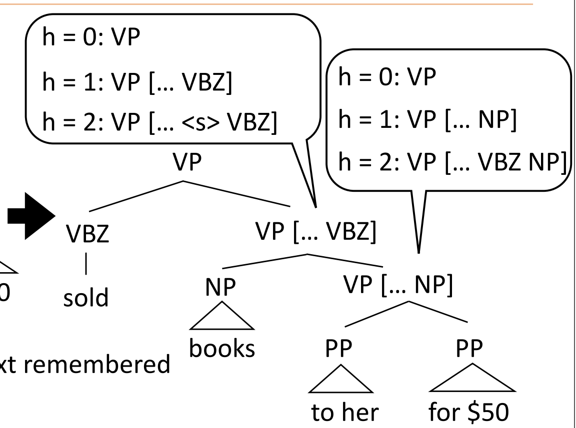
Basic tree (v = 0)

v = 1 Markovization

- Why is this a good idea?

Horizontal Markovization

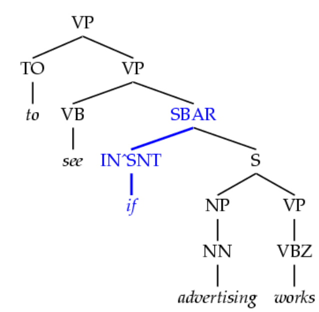




- Changes amount of context remembered in binarization process

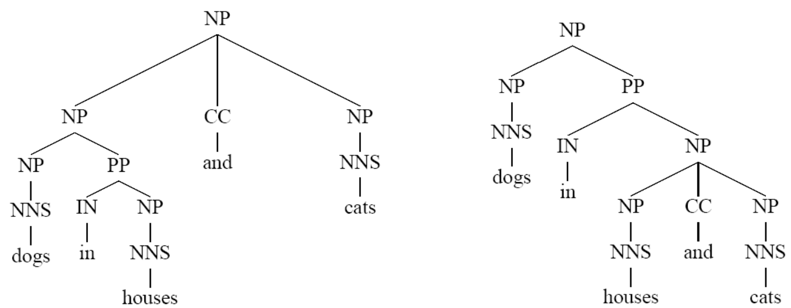
Tag Splits

- Can do some other ad hoc tag splits
- Sentential prepositions behave differently from other prepositions
- 75 F1 with basic PCFG => 86.3 F1 with a highly customized PCFG (v = 2, h = 2, other hacks like this)



Klein and Manning (2003)

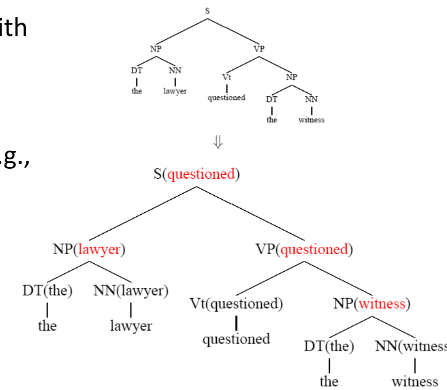
Lexicalized Parsers



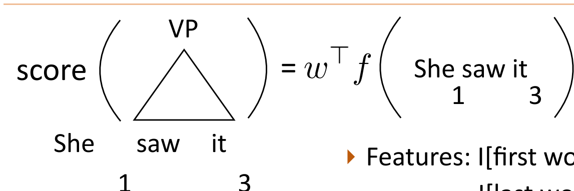
- Even with parent annotation, these trees have the same rules. Need to use the words

Lexicalized Parsers

- Annotate each grammar symbol with its "head word": most important word of that constituent
- Rules for identifying headwords (e.g., the last word of an NP before a preposition is typically the head)
- Collins and Charniak (late 90s): ~89 F1 with these



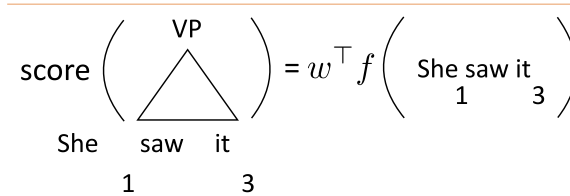
Discriminative Parsers



Taskar et al. (2004), Hall et al. (2014), Stern et al. (2017), Kitaev et al. (2018)

- Features: I[first word = saw & VP]
  I[last word = it & VP]
  I[word before span = She & VP]
- ...or use neural networks
- Score *constituents* with a feature-based model
- Simple version of this model: Train a span classifier to predict type of span or NONE if it's not in the tree

Discriminative Parsers



Taskar et al. (2004), Hall et al. (2014), Stern et al. (2017), Kitaev et al. (2018)

- CKY: instead of rule probabilities, maximize sum of scores of the spans included in a tree
  - Why is CKY still necessary? Why can't we just independently label spans with our classifier?
- Neural net models get 91-93 F1, 95 F1 with other tricks we'll see later. Works well for other languages too!