Statistical Constituency Parsing

Chapter 13
(selected sections)

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Statistical Parsing

The rise of data and statistics

Pre 1990 (“Classical”) NLP Parsing

- Wrote symbolic grammar (CFG or often richer) and lexicon
- This scaled badly and didn’t give coverage.

  Fed raises interest rates 0.5% in effort to control inflation

– Minimal grammar:	36 parses
– Simple 10 rule grammar:	592 parses
– Real-size broad-coverage grammar:	millions of parses

Classical NLP Parsing: The problem and its solution

- Constraints can be added to grammars to limit unlikely/weird parses for sentences
  - But the attempt makes the grammars not robust
    - Commonly 30% of sentences in even an edited text would have *no* parse.
- A less constrained grammar can parse more sentences
  - But simple sentences end up with ever more parses with no way to choose between them
- We need mechanisms that allow us to find the most likely parse(s) for a sentence
  - Statistical parsing lets us work with very loose grammars that admit millions of parses for sentences but still quickly find the best parse(s)

The rise of annotated data: The Penn Treebank

[Marcus et al. 1993, *Computational Linguistics*]

```
( (S
   (NP-SBJ (DT The) (NN move))
   (VP (VBD followed)
    (NP
     (NP (DT a) (NN round))
     (PP (IN of)
      (NP
       (NP (JJ similar) (NNS increases))
       (PP (IN by)
        (NP (JJ other) (NNS lenders)))
       (PP (IN against)
        (NP (NNP Arizona) (JJ real) (NN estate) (NNS loans))))))
    (, ,)
    (S-ADV
     (NP-SBJ (-NONE- *))
     (VP (VBG reflecting)
      (NP
       (NP (DT a) (VBG continuing) (NN decline))
       (PP-LOC (IN in)
        (NP (DT that) (NN market)))))))
   (. .)))
```

The rise of annotated data

- Starting off, building a treebank seems a lot slower and less useful than building a grammar

- But a treebank gives us many things
  - Reusability of the labor
    - Many parsers, POS taggers, etc.
    - Valuable resource for linguistics
  - Broad coverage
  - Frequencies and distributional information
  - A way to evaluate systems

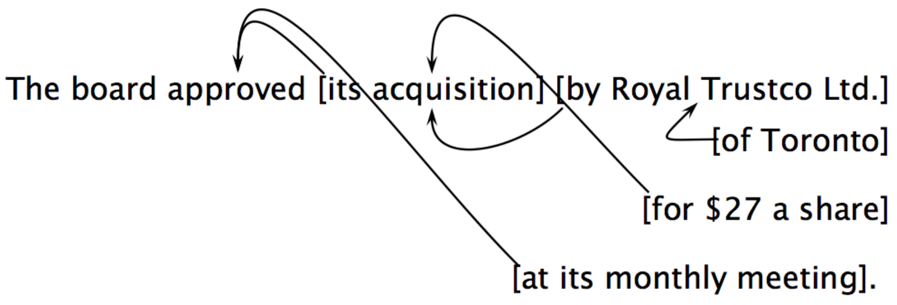
Statistical parsing applications

Statistical parsers are robust and widely used in applications:

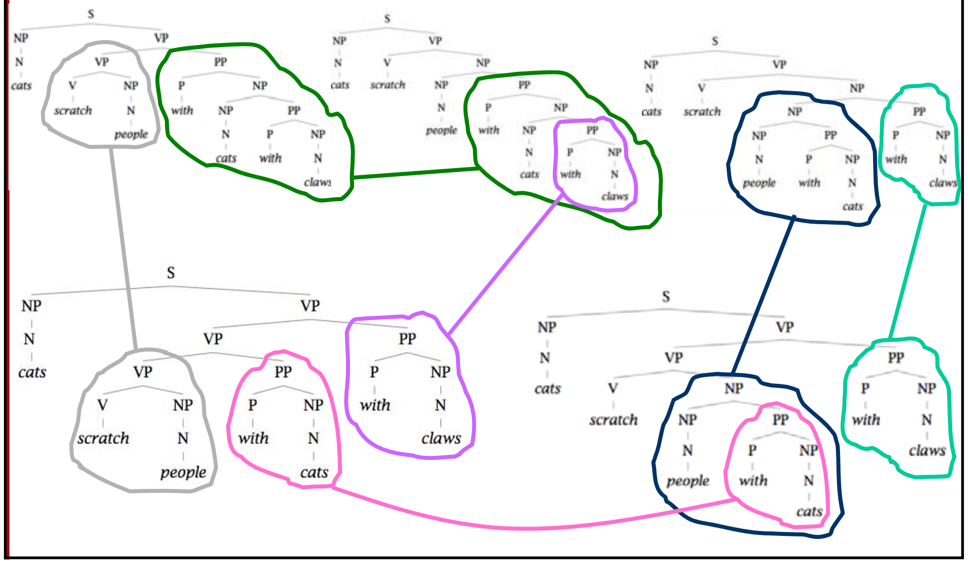
- High precision question answering [Pasca and Harabagiu SIGIR 2001]
- Improving biological named entity finding [Finkel et al. JNLPBA 2004]
- Syntactically based sentence compression [Lin and Wilbur 2007]
- Extracting opinions about products [Bloom et al. NAACL 2007]
- Improved interaction in computer games [Gorniak and Roy 2005]
- Helping linguists find data [Resnik et al. BLS 2005]
- Source sentence analysis for machine translation [Xu et al. 2009]
- Relation extraction systems [Fundel et al. *Bioinformatics* 2006]

Attachment ambiguities

- Recall that a key parsing decision is how we 'attach' various constituents


The board approved [its acquisition] [by Royal Trustco Ltd.]
[of Toronto]
[for $27 a share]
[at its monthly meeting].

Two problems to solve: 1. Repeated work (last chapter)



Two problems to solve: 2. Choosing the correct parse (today's class)

- How do we work out the correct attachment?
- Words are good predictors of attachment
  - Even absent full understanding
- Our statistical parsers will try to exploit such statistics.

Statistical Parsing

- Statistical parsing uses a probabilistic model of syntax in order to assign probabilities to each parse tree.
- Provides principled approach to resolving syntactic ambiguity.
- Allows supervised learning of parsers from tree-banks of parse trees provided by human linguists.

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Probabilistic Context Free Grammar (PCFG)

- A PCFG is a probabilistic version of a CFG where each production has a probability.
- Probabilities of all productions rewriting a given non-terminal must add to 1, defining a distribution for each non-terminal.
- String generation is now probabilistic where production probabilities are used to non-deterministically select a production for rewriting a given non-terminal.

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Simple PCFG for ATIS English

Grammar	Prob	
S → NP VP	0.8	
S → Aux NP VP	0.1	+ 1.0
S → VP	0.1	
NP → Pronoun	0.2	
NP → Proper-Noun	0.2	+ 1.0
NP → Det Nominal	0.6	
Nominal → Noun	0.3	
Nominal → Nominal Noun	0.2	+ 1.0
Nominal → Nominal PP	0.5	
VP → Verb	0.2	
VP → Verb NP	0.5	+ 1.0
VP → VP PP	0.3	
PP → Prep NP	1.0	

Lexicon

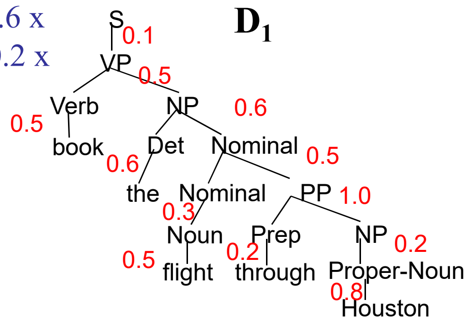
Det → the | a | that | this
0.6 0.2 0.1 0.1
Noun → book | flight | meal | money
0.1 0.5 0.2 0.2
Verb → book | include | prefer
0.5 0.2 0.3
Pronoun → I | he | she | me
0.5 0.1 0.1 0.3
Proper-Noun → Houston | NWA
0.8 0.2
Aux → does
1.0
Prep → from | to | on | near | through
0.25 0.25 0.1 0.2 0.2

Sentence Probability

- Assume productions for each node are chosen independently.
- Probability of derivation is the product of the probabilities of its productions.

$P(D_1) = 0.1 \times 0.5 \times 0.5 \times 0.6 \times 0.6 \times 0.5 \times 0.3 \times 1.0 \times 0.2 \times 0.2 \times 0.5 \times 0.8$
$= 0.0000216$

D_1



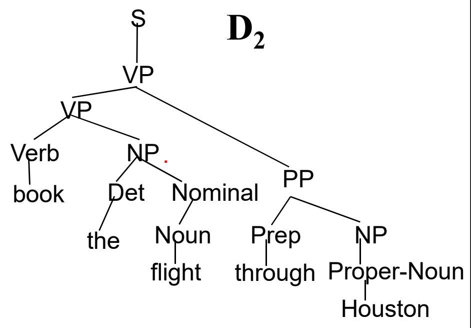
Other Parses?

- book the flight through Houston

Syntactic Disambiguation

- Resolve ambiguity by picking most probable parse tree.

$P(D_2) =$

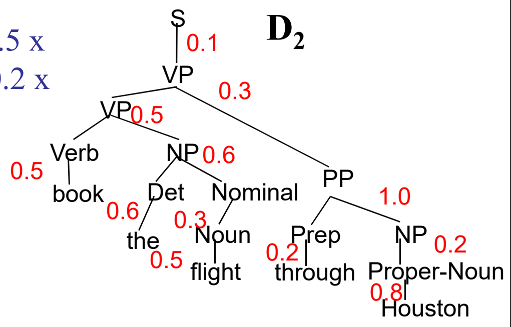


D_2

Syntactic Disambiguation

- Resolve ambiguity by picking most probable parse tree.

$P(D_2) = 0.1 \times 0.3 \times 0.5 \times 0.6 \times 0.5 \times$
$0.6 \times 0.3 \times 1.0 \times 0.5 \times 0.2 \times$
0.2×0.8
$= 0.00001296$



D_2

Syntactic Disambiguation

- Resolve ambiguity by picking most probable parse tree.

$P(D_2) = 0.1 \times 0.3 \times 0.5 \times 0.6 \times 0.5 \times$
$0.6 \times 0.3 \times 1.0 \times 0.5 \times 0.2 \times$
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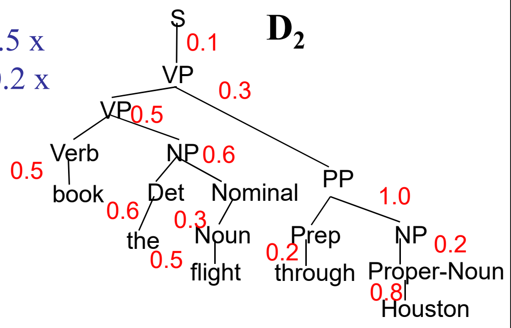
$= 0.00001296$



D_2

Disambiguation Result?

Sentence Probability

- Probability of a sentence is the sum of the probabilities of all of its derivations.

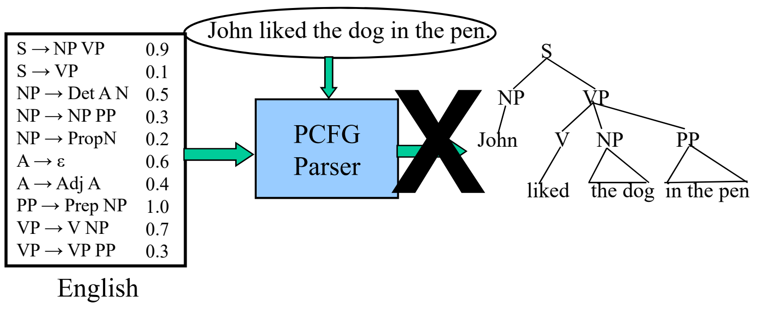
P("book the flight through Houston") =
$P(D_1) + P(D_2) = 0.0000216 + 0.00001296$
$= 0.00003456$

Three Useful PCFG Tasks

- Observation likelihood: To classify and order sentences.
- Most likely derivation: To determine the most likely parse tree for a sentence.
- Maximum likelihood training: To train a PCFG to fit empirical training data.

PCFG: Most Likely Derivation

- There is an analog to the Viterbi algorithm to efficiently determine the most probable derivation (parse tree) for a sentence.



S → NP VP	0.9
S → VP	0.1
NP → Det A N	0.5
NP → NP PP	0.3
NP → PropN	0.2
A → ε	0.6
A → Adj A	0.4
PP → Prep NP	1.0
VP → V NP	0.7
VP → VP PP	0.3

PCFG: Most Likely Derivation

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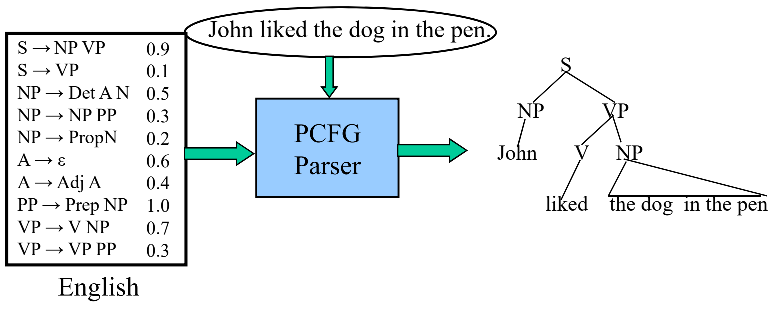

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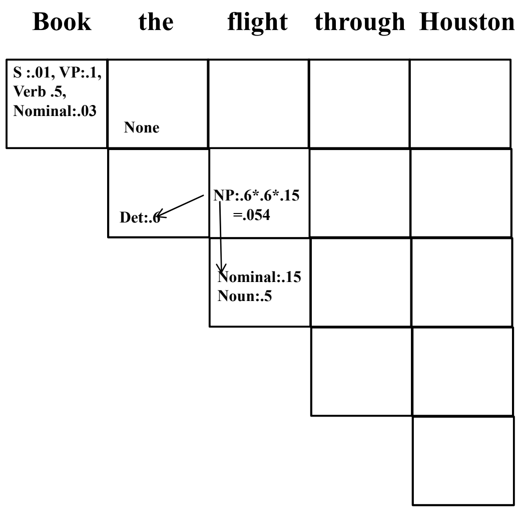
Probabilistic CKY

- CKY can be modified for PCFG parsing by including in each cell a probability for each non-terminal.
- Cell[*i*,*j*] must retain the *most probable* derivation of each constituent (non-terminal) covering words *i* +1 through *j* together with its associated probability.
- When transforming the grammar to CNF, must set production probabilities to preserve the probability of derivations.

(Incomplete) Probabilistic CNF Grammar

S → NP VP	
S → X1 VP	
X1 → Aux NP	
S → book	0.01
S → Verb NP	0.05
S → VP PP	
NP → I | he | she | me	
NP → Houston | NWA	
NP → Det Nominal	0.6
Nominal → book	0.03
Nominal → flight	0.15
Nominal → Nominal Noun	
Nominal → Nominal PP	0.01
VP → book	0.1
Verb → book	0.5
VP → Verb NP	0.5
VP → VP PP	
PP → Prep NP	

Probabilistic CKY Parser



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Probabilistic CKY Parser

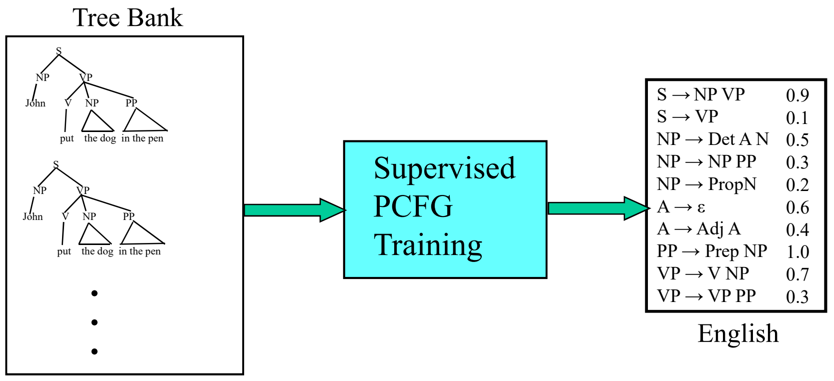
Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03	None	VP:.5*.5*.054 =.0135		
	Det:.6	NP:.6*.6*.15 =.054		
		Nominal:.15 Noun:.5		

Probabilistic CKY Parser

Book	the	flight	through	Houston
S :.01, VP:.1, Verb:.5 Nominal:.03 Noun:.1	None	S:.05*.5*.054 =.00135 VP:.5*.5*.054 =.0135		
	Det:.6	NP:.6*.6*.15 =.054		
		Nominal:.15 Noun:.5		

PCFG: Supervised Training

- If parse trees are provided for training sentences, a grammar and its parameters can be can all be estimated directly from counts accumulated from the tree-bank (with appropriate smoothing).



S → NP VP	0.9
S → VP	0.1
NP → Det A N	0.5
NP → NP PP	0.3
NP → PropN	0.2
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PP → Prep NP	1.0
VP → V NP	0.7
VP → VP PP	0.3

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Estimating Production Probabilities

- Set of production rules can be taken directly from the set of rewrites in the treebank.
- Parameters can be directly estimated from frequency counts in the treebank.

$$P(\alpha \to \beta \mid \alpha) = \frac{\text{count}(\alpha \to \beta)}{\sum_{\gamma} \text{count}(\alpha \to \gamma)} = \frac{\text{count}(\alpha \to \beta)}{\text{count}(\alpha)}$$

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Parsing Evaluation Metrics

- PARSEVAL metrics measure the fraction of the constituents that match between the computed and human parse trees. If *P* is the system's parse tree and *T* is the human parse tree (the "gold standard"):
  - ***Recall*** = (# correct constituents in *P*) / (# constituents in *T*)
  - ***Precision*** = (# correct constituents in *P*) / (# constituents in *P*)
- ***Labeled Precision*** and ***labeled recall*** require getting the non-terminal label on the constituent node correct to count as correct.
- F_1 is the harmonic mean of precision and recall.

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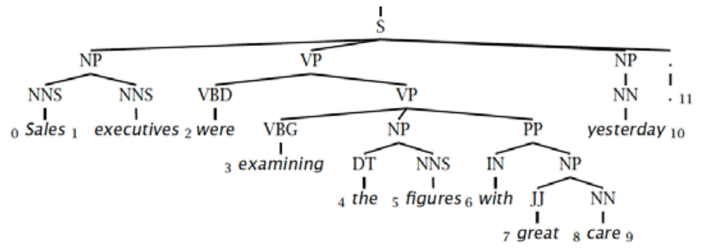
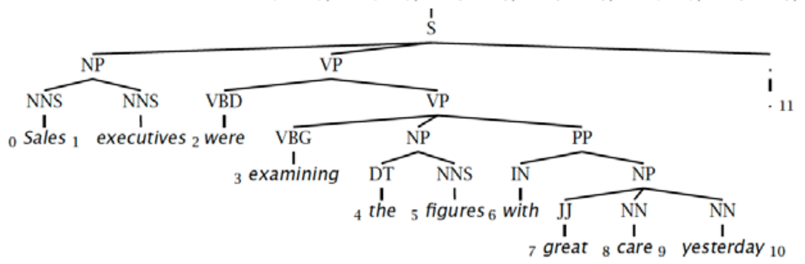
Evaluating constituency parsing

Gold standard brackets: **S-(0:11)**, **NP-(0:2)**, VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), NP-(9:10)



Candidate brackets: **S-(0:11)**, **NP-(0:2)**, VP-(2:10), VP-(3:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)



Evaluating constituency parsing

Gold standard brackets:

S-(0:11), NP-(0:2), VP-(2:9), VP-(3:9), **NP-(4:6)**, PP-(6-9), NP-(7,9), NP-(9:10)

Candidate brackets:

S-(0:11), **NP-(0:2)**, VP-(2:10), VP-(3:10), **NP-(4:6)**, PP-(6-10), NP-(7,10)

Labeled Precision	3/7 = 42.9%
Labeled Recall	3/8 = 37.5%
Tagging Accuracy	11/11 = 100.0%

How good are PCFGs?

- Penn WSJ parsing accuracy is high
- Robust
  - Usually admit everything, but with low probability
- Partial solution for grammar ambiguity
  - A PCFG gives some idea of the plausibility of a parse
  - But not so good because the independence assumptions are too strong
- Give a probabilistic language model
  - But in the simple case it performs worse than a trigram model
- The problem seems to be that PCFGs lack the lexicalization of a trigram model

Vanilla PCFG Limitations

- Since probabilities of productions do not rely on specific words or concepts, only general structural disambiguation is possible (e.g. prefer to attach PPs to Nominals).
- Consequently, vanilla PCFGs cannot resolve syntactic ambiguities that require semantics to resolve, e.g. ate with fork vs. meatballs.
- In order to work well, PCFGs must be lexicalized, i.e. productions must be specialized to specific words by including their head-word in their LHS non-terminals (e.g. VP-ate).

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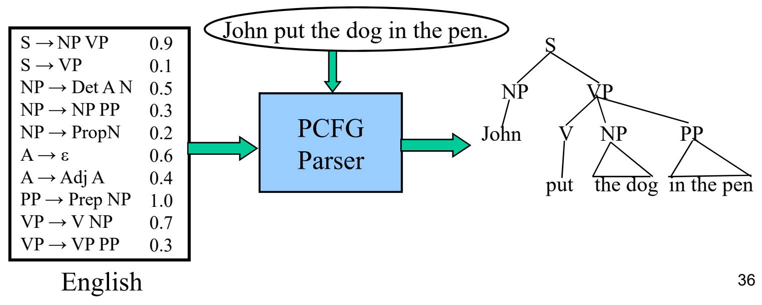
Example of Importance of Lexicalization

- A general preference for attaching PPs to NPs rather than VPs can be learned by a vanilla PCFG.
- But the desired preference can depend on specific words.



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$S \rightarrow VP$	0.1
$NP \rightarrow Det\ A\ N$	0.5
$NP \rightarrow NP\ PP$	0.3
$NP \rightarrow PropN$	0.2
$A \rightarrow \varepsilon$	0.6
$A \rightarrow Adj\ A$	0.4
$PP \rightarrow Prep\ NP$	1.0
$VP \rightarrow V\ NP$	0.7
$VP \rightarrow VP\ PP$	0.3

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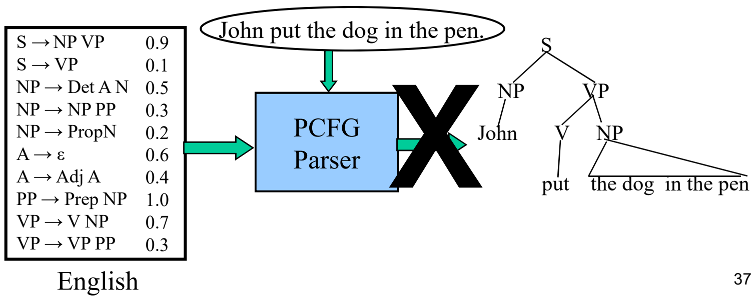

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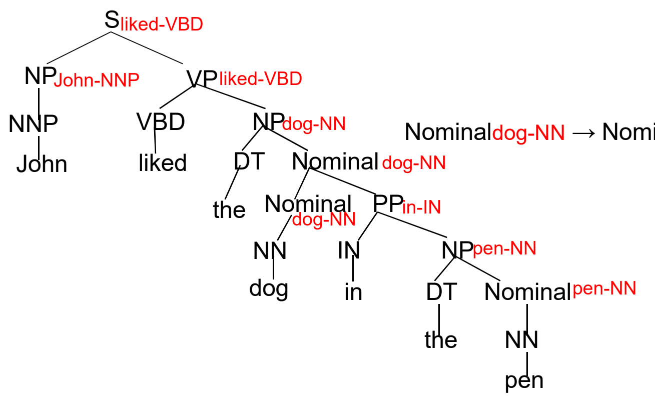
Head Words

- Syntactic phrases usually have a word in them that is most “central” to the phrase.
- Linguists have defined the concept of a lexical **head** of a phrase.
- Simple rules can identify the head of any phrase by percolating head words up the parse tree.
  - Head of a VP is the main verb
  - Head of an NP is the main noun
  - Head of a PP is the preposition
  - Head of a sentence is the head of its VP

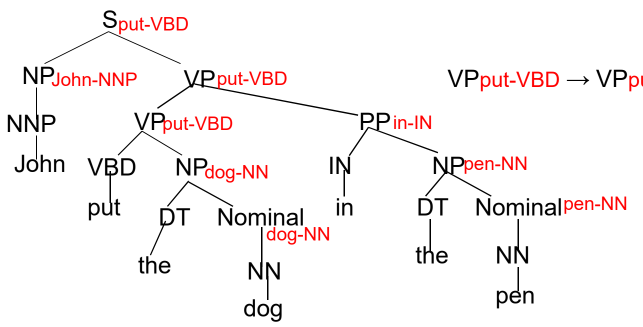
Lexicalized Productions

- Specialized productions can be generated by including the head word and its POS of each non-terminal as part of that non-terminal’s symbol.



$\text{Nominal}_{\text{dog-NN}} \rightarrow \text{Nominal}_{\text{dog-NN}}\ \text{PP}_{\text{in-IN}}$

Lexicalized Productions



$\text{VP}_{\text{put-VBD}} \rightarrow \text{VP}_{\text{put-VBD}}\ \text{PP}_{\text{in-IN}}$

Parameterizing Lexicalized Productions

- Accurately estimating parameters on such a large number of very specialized productions could require enormous amounts of treebank data.
- Need some way of estimating parameters for lexicalized productions that makes reasonable independence assumptions so that accurate probabilities for very specific rules can be learned.

Collins' Parser

- Collins' (1999) parser assumes a simple generative model of lexicalized productions.

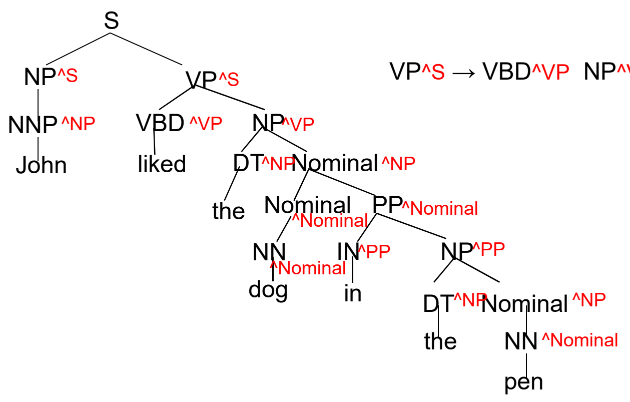
Missed Context Dependence

- Another problem with CFGs is that which production is used to expand a non-terminal is independent of its context.
- However, this independence is frequently violated for normal grammars.
  - NPs that are subjects are more likely to be pronouns than NPs that are objects.

Splitting Non-Terminals

- To provide more contextual information, non-terminals can be split into multiple new non-terminals based on their parent in the parse tree using parent annotation.
  - A subject NP becomes NP^S since its parent node is an S.
  - An object NP becomes NP^VP since its parent node is a VP

Parent Annotation Example



VP^S → VBD^VP NP^VP

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Split and Merge

- Non-terminal splitting greatly increases the size of the grammar and the number of parameters that need to be learned from limited training data.
- Best approach is to only split non-terminals when it improves the accuracy of the grammar.
- May also help to merge some non-terminals to remove some un-helpful distinctions and learn more accurate parameters for the merged productions.
- Method: Heuristically search for a combination of splits and merges that produces a grammar that maximizes the likelihood of the training treebank.

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Human Parsing

- Computational parsers can be used to predict human reading time as measured by tracking the time taken to read each word in a sentence.
- Psycholinguistic studies show that words that are more probable given the preceding lexical and syntactic context are read faster.

Garden Path Sentences

- People are confused by sentences that seem to have a particular syntactic structure but then suddenly violate this structure, so the listener is "lead down the garden path".
  - The horse raced past the barn fell.
    - vs. The horse raced past the barn broke his leg.
  - The complex houses married students.
  - The old man the sea.
  - While Anna dressed the baby spit up on the bed.

Statistical Parsing Conclusions

- Statistical models such as PCFGs allow for probabilistic resolution of ambiguities.
- PCFGs can be easily learned from treebanks.
- Lexicalization and non-terminal splitting are required to effectively resolve many ambiguities.
- Current statistical parsers are quite accurate but not yet at the level of human-expert agreement.

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Try at Home

- http://nlp.cs.berkeley.edu/software.shtml
  - http://tomato.banatao.berkeley.edu:8080/parser/parser.html
- https://nlp.stanford.edu/software/lex-parser.shtml
  - http://nlp.stanford.edu:8080/parser/

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