CS371N: Natural Language Processing
Lecture 17: Parsing II

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Announcements

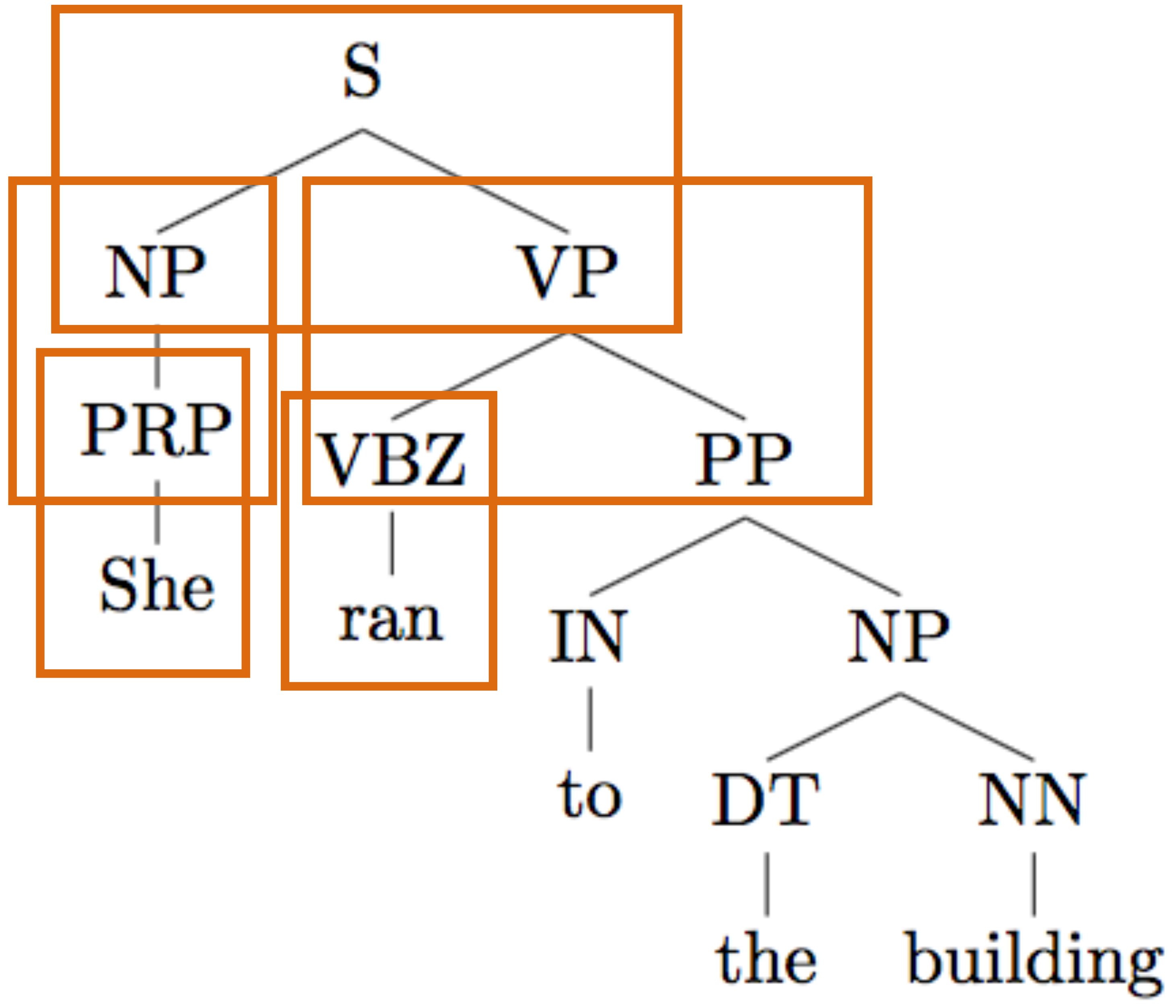
- A4 due today
- Midterm Thursday:
  - One 8.5”x11” notesheet
  - No calculators
  - Multiple choice, short-answer, and long-answer

Recap: PCFGs

Grammar (CFG)				Lexicon	
ROOT → S	1.0	NP → NP PP	0.3	NN → interest	1.0
S → NP VP	1.0	VP → VBP NP	0.7	NNS → raises	1.0
NP → DT NN	0.2	VP → VBP NP PP	0.3	VBP → interest	1.0
NP → NN NNS	0.5	PP → IN NP	1.0	VBZ → raises	1.0

- Context-free grammar: symbols which rewrite as one or more symbols
- Lexicon consists of "preterminals" (POS tags) rewriting as terminals (words)
- CFG is a tuple (N, T, S, R): N = nonterminals, T = terminals, S = start symbol (generally a special ROOT symbol), R = rules
- PCFG: probabilities associated with rewrites, normalize by source symbol

Recap: Learning PCFGs



$S \rightarrow NP\ VP$ 1.0

$NP \rightarrow PRP$ 0.5

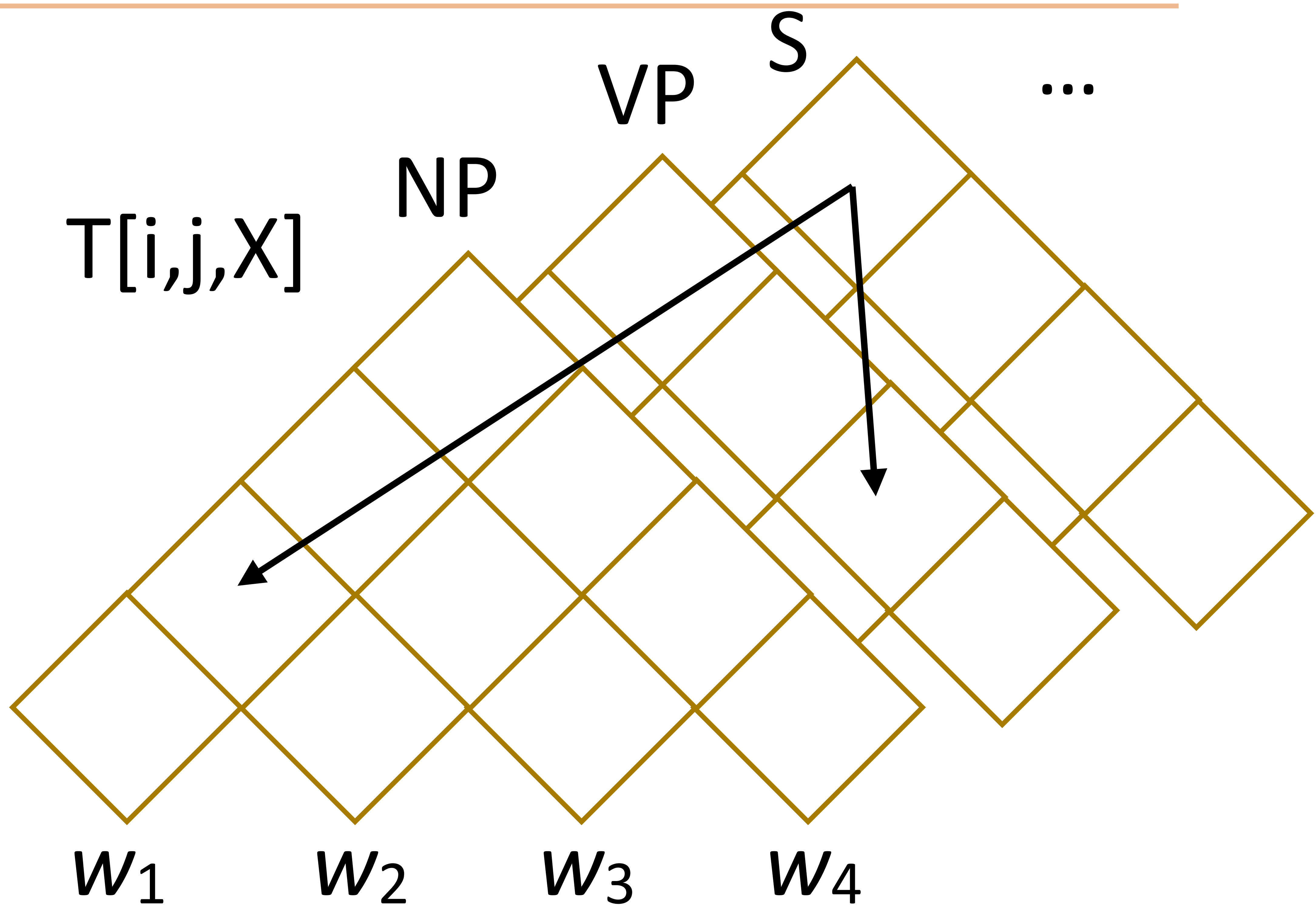
$NP \rightarrow DT\ NN$ 0.5

…

- Maximum likelihood PCFG for a set of labeled trees: count and normalize! Same as HMMs / Naive Bayes

Recap: CKY

- Chart: T[i,j,X] = best score for X over (i, j)
- Base: T[i,i+1,X] = log P(X $\rightarrow$ w_i)
- Loop over all split points k, apply rules X -> Y Z to build X in every possible way



S[0,4] => NP[0,2] VP[2,4]

- Recurrence:

$$T[i,j,X] = \max_{k} \max_{r:\, X \rightarrow X1\ X2} T[i,k,X1] + T[k,j,X2] + \log P(X \rightarrow X1\ X2)$$

- Runtime: O(n^3G) G = grammar constant

Parser Evaluation

Parser Evaluation

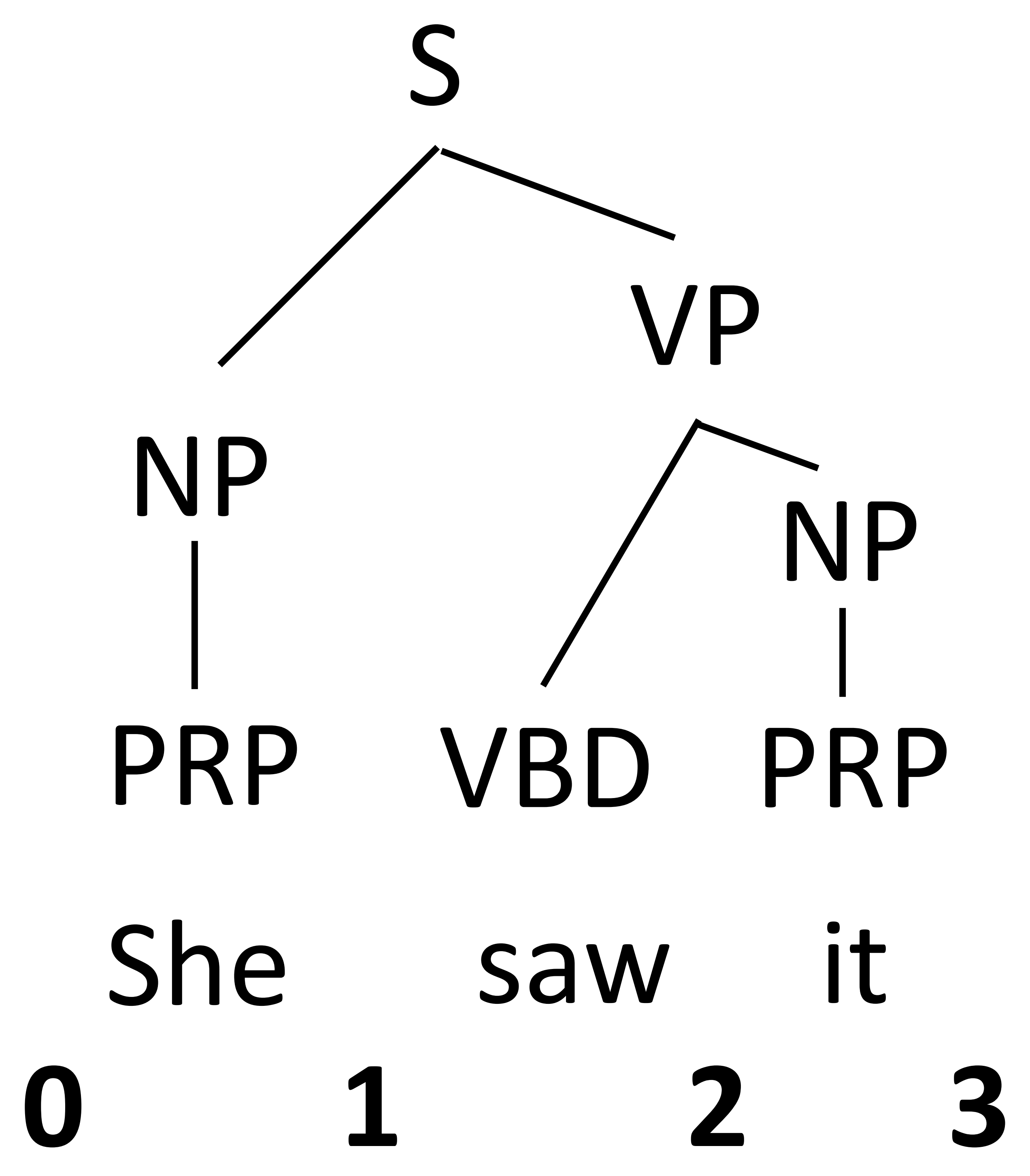
- View a parse as a set of labeled *brackets* / constituents

S(0,3)

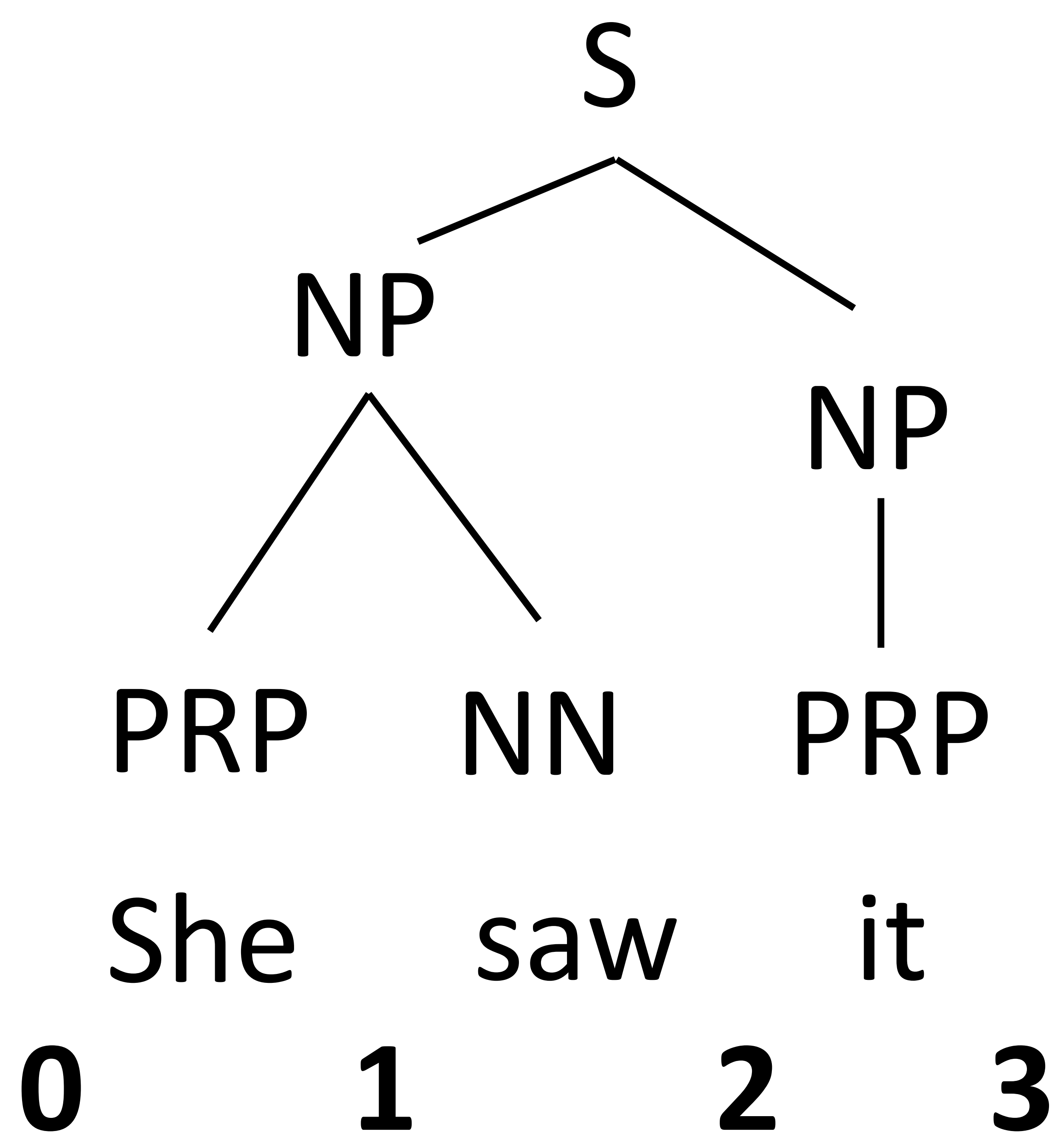
NP(0,1)

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

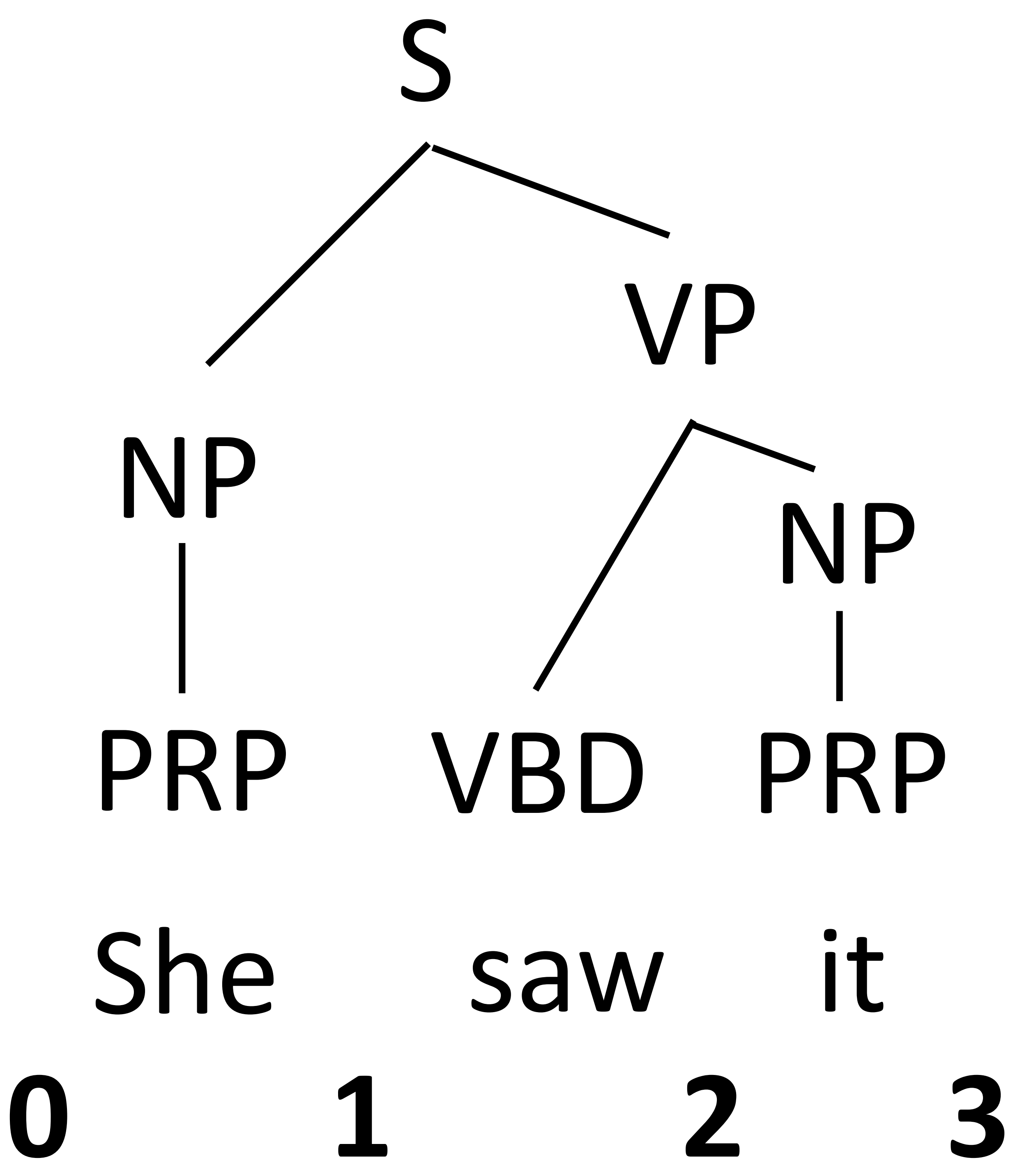
VP(1,3), VBD(1,2), NP(2,3), PRP(2,3)



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)

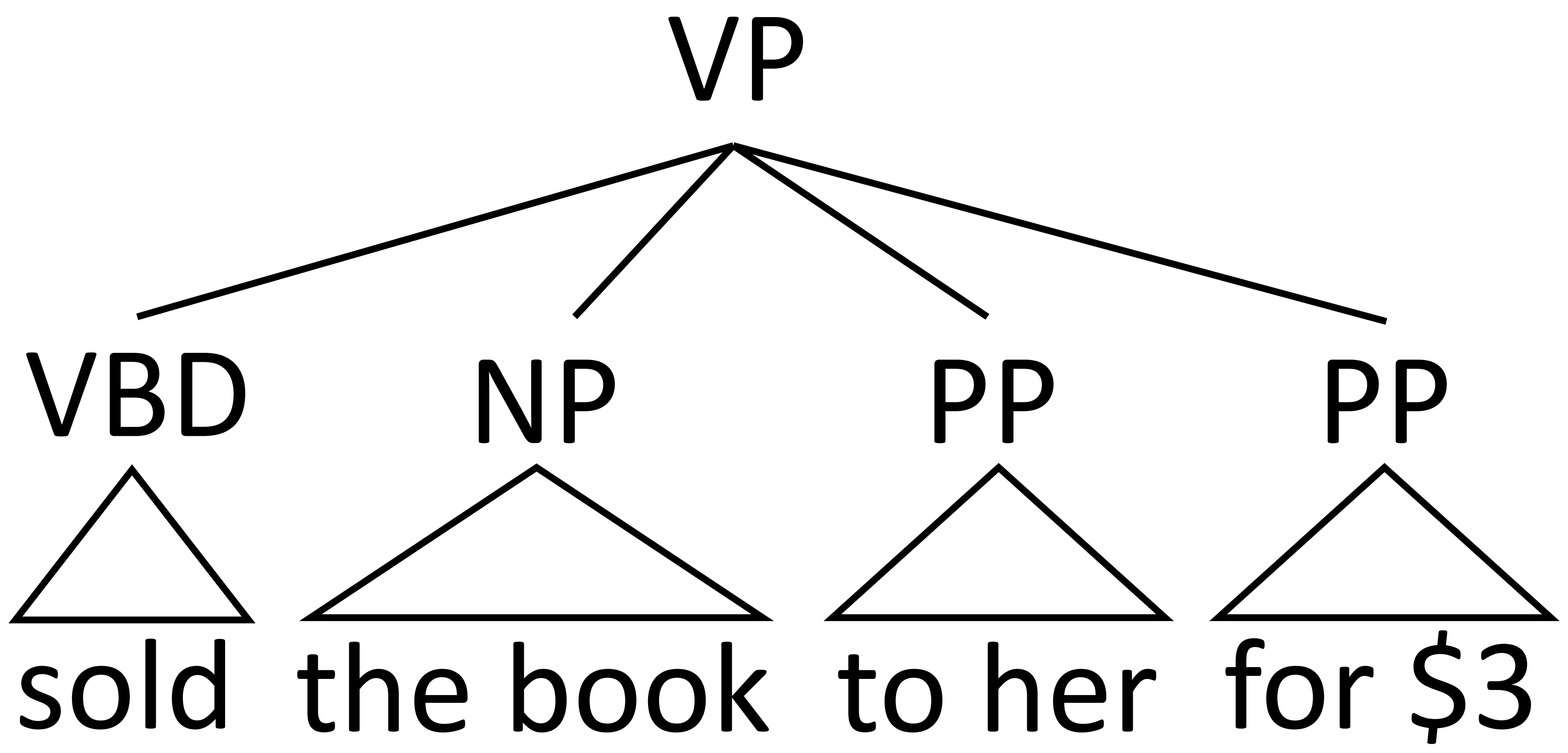
Results

- Standard dataset for English: Penn Treebank (Marcus et al., 1993)
- "Vanilla" PCFG: ~71 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

Grammar Preprocessing

Binarization

- To parse efficiently, we need our PCFGs to be at most binary (not CNF)

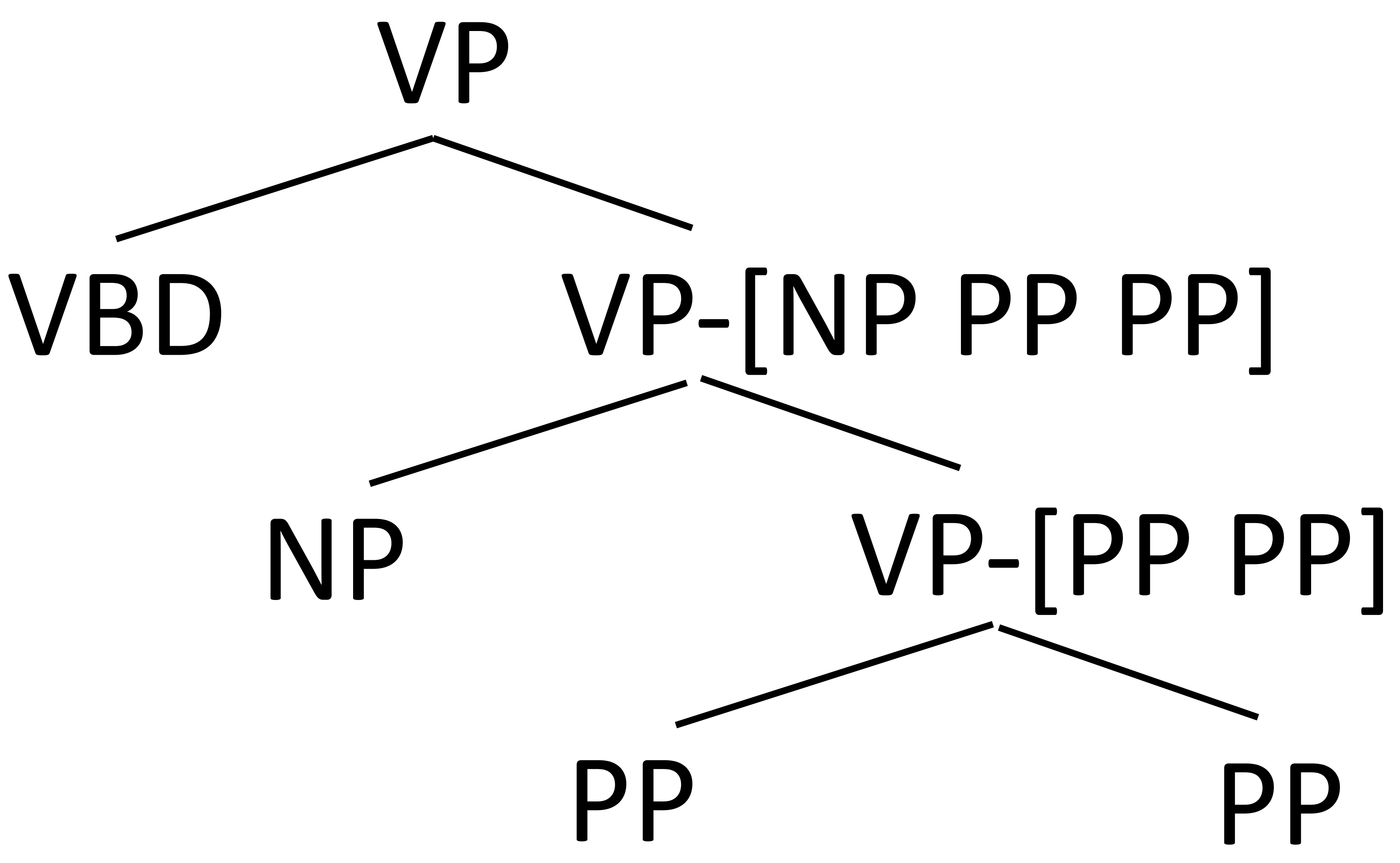


$P(VP \rightarrow VBD\ NP\ PP\ PP) = 0.2$

$P(VP \rightarrow VBZ\ PP) = 0.1$

…

- Solution: transform the trees. Introduce intermediate special symbols that rewrite deterministically

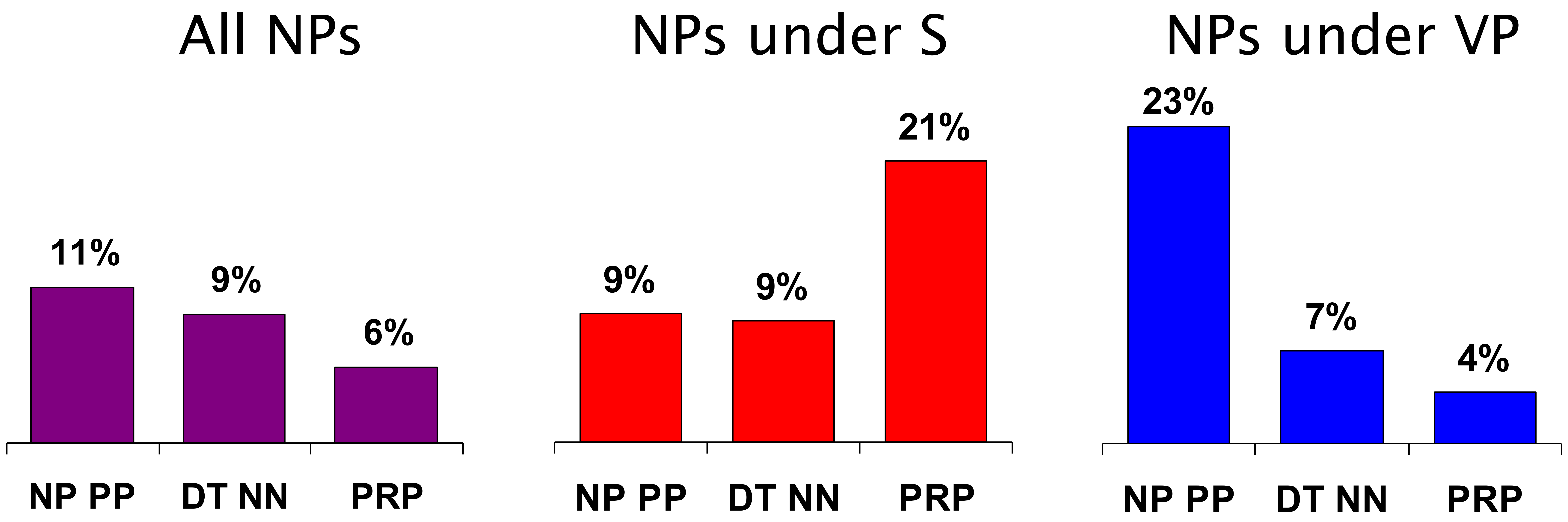


$P(VP \rightarrow VBD\ VP\text{-}[NP\ PP\ PP]) = 0.2$

$P(VP\text{-}[NP\ PP\ PP] \rightarrow NP\ VP\text{-}[PP\ PP]) = 1.0$

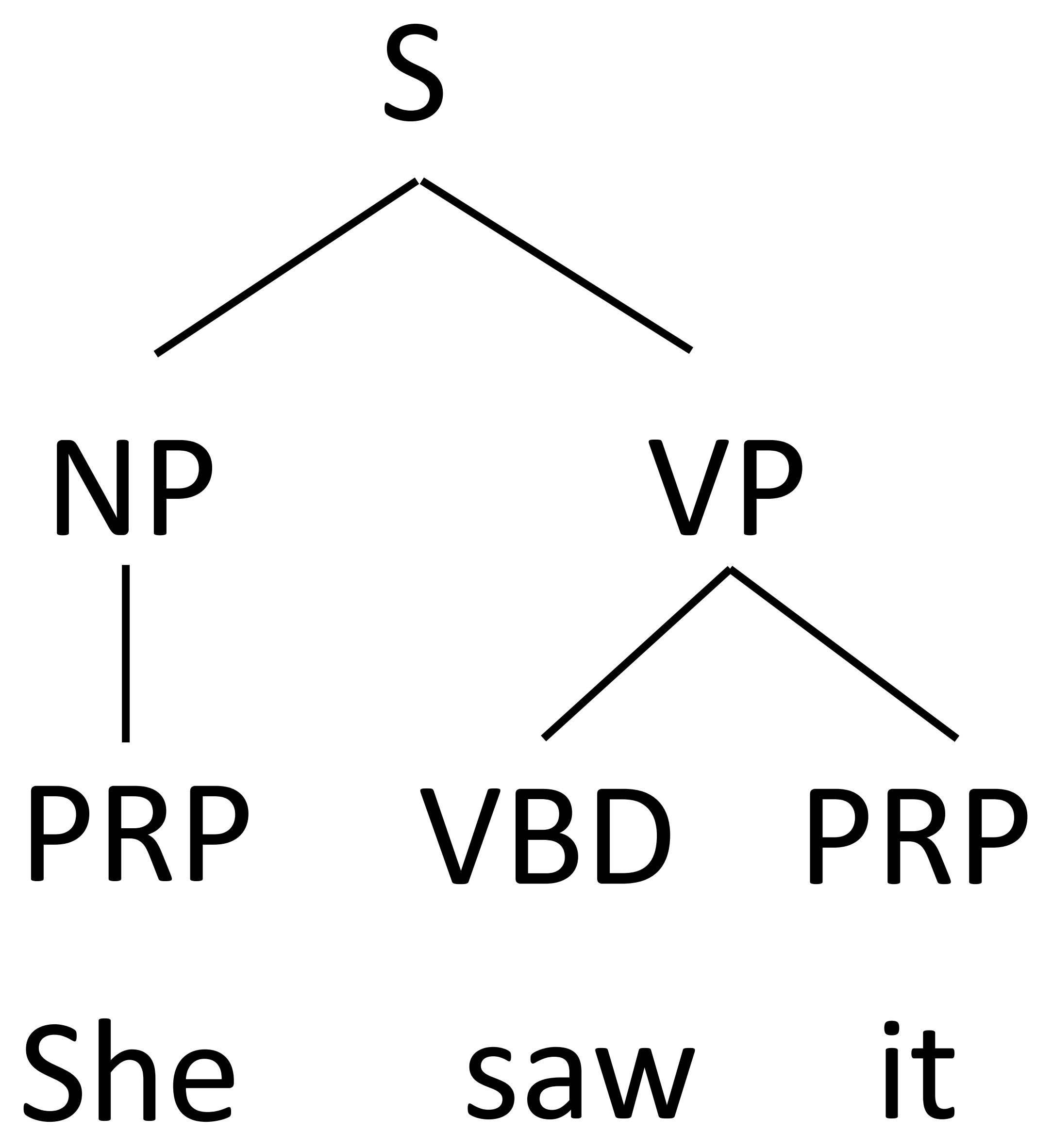
$P(VP\text{-}[PP\ PP] \rightarrow PP\ PP) = 1.0$

PCFG Independence Assumptions

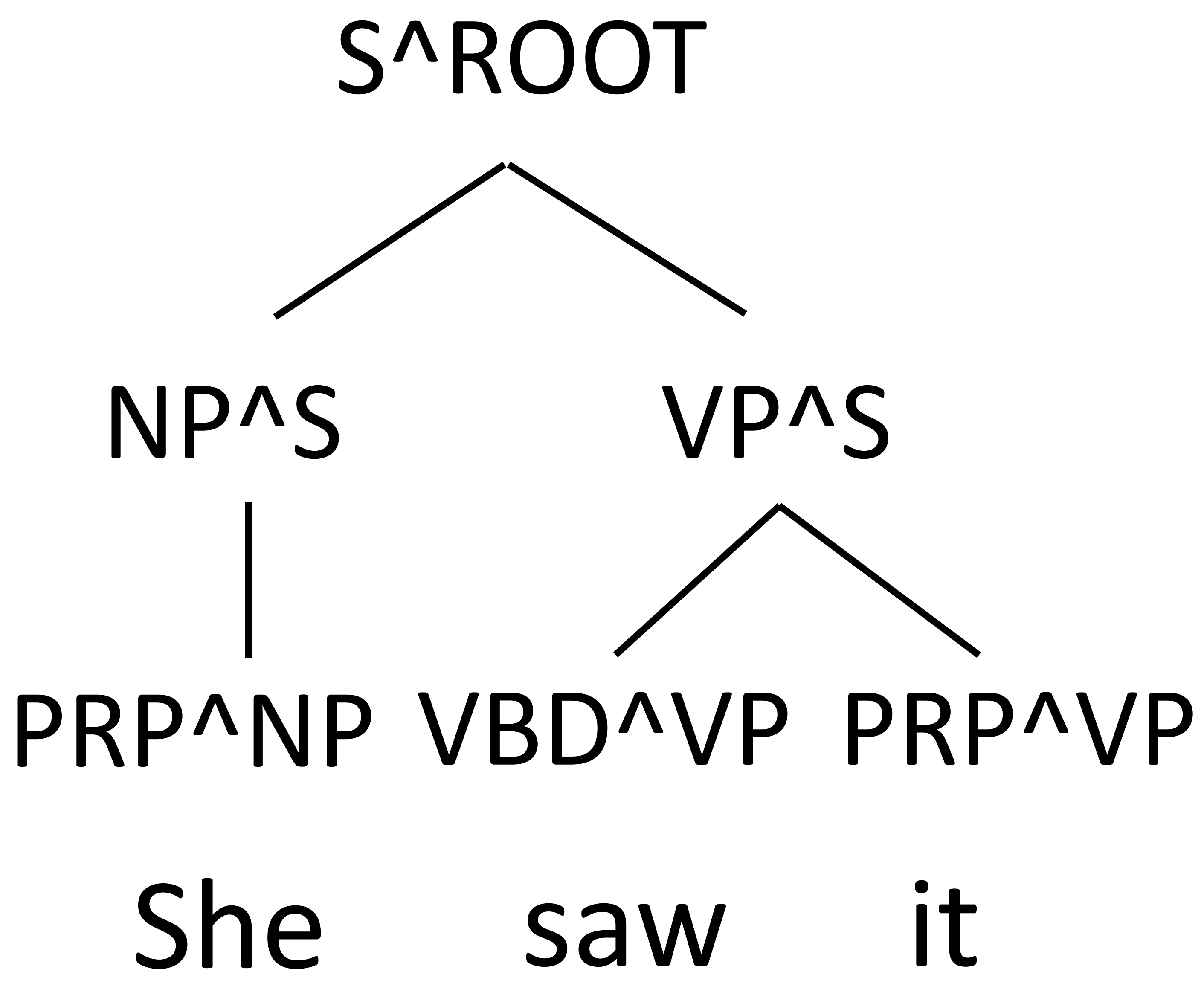


- Language is not context-free: NPs in different contexts rewrite differently
- $[\text{They}]_{NP}$ received $[\text{the package of books}]_{NP}$

Vertical Markovization



Basic tree (v = 1)

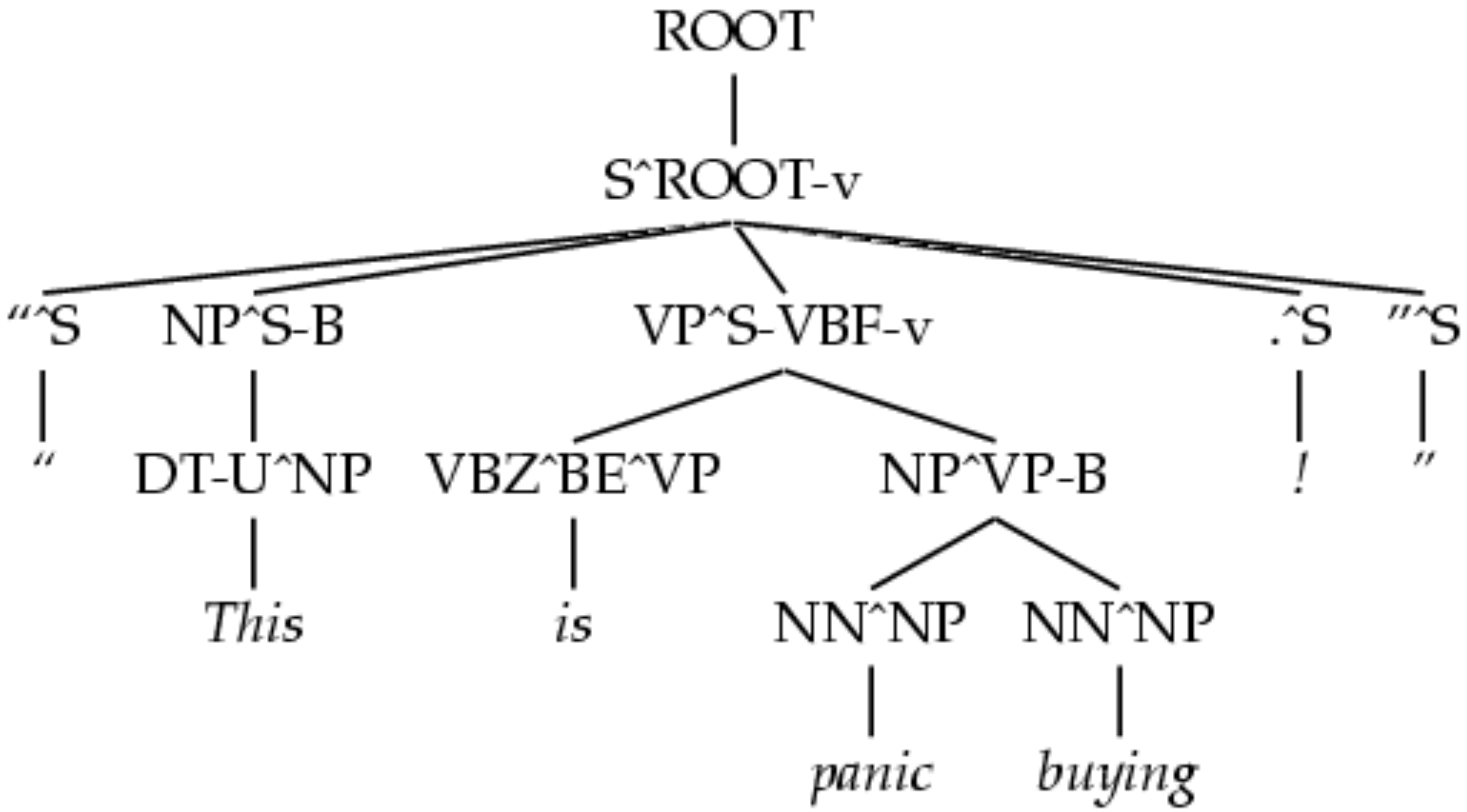


v = 2 Markovization

- Why is this a good idea?

Annotated Tree

- Augment the grammar: deterministically transform symbols to be "less context free" (binarization not shown here)



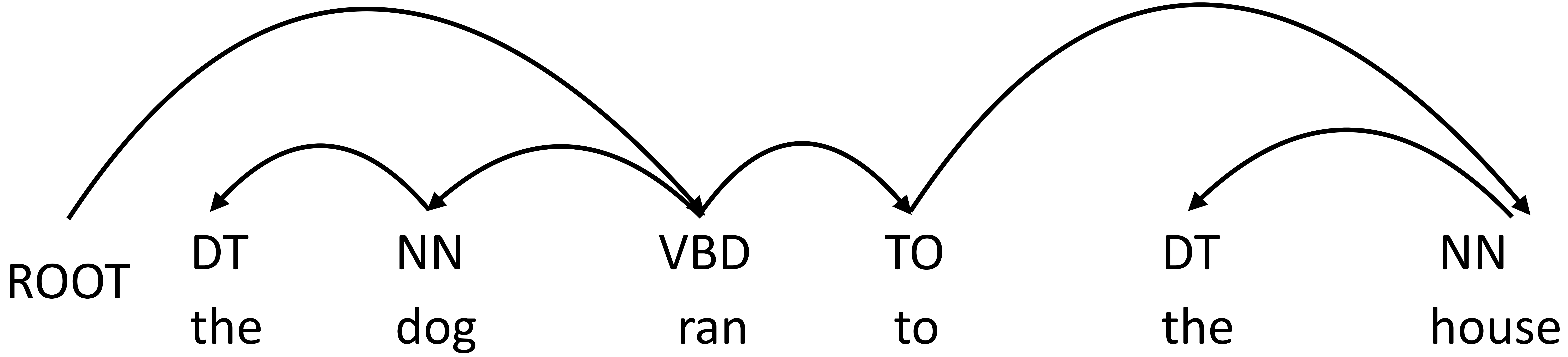
- 75 F1 with basic PCFG => 86.3 F1 with this highly customized PCFG (SOTA was 90 F1 at the time, but with more complex methods)

Klein and Manning (2003)

Dependency Parsing

Dependency Parsing

- Dependencies: syntactic structure is defined by relations between words
  - Head (parent, governor) connected to dependent (child, modifier)
  - Each word has exactly one parent except for the ROOT symbol, dependencies must form a directed acyclic graph



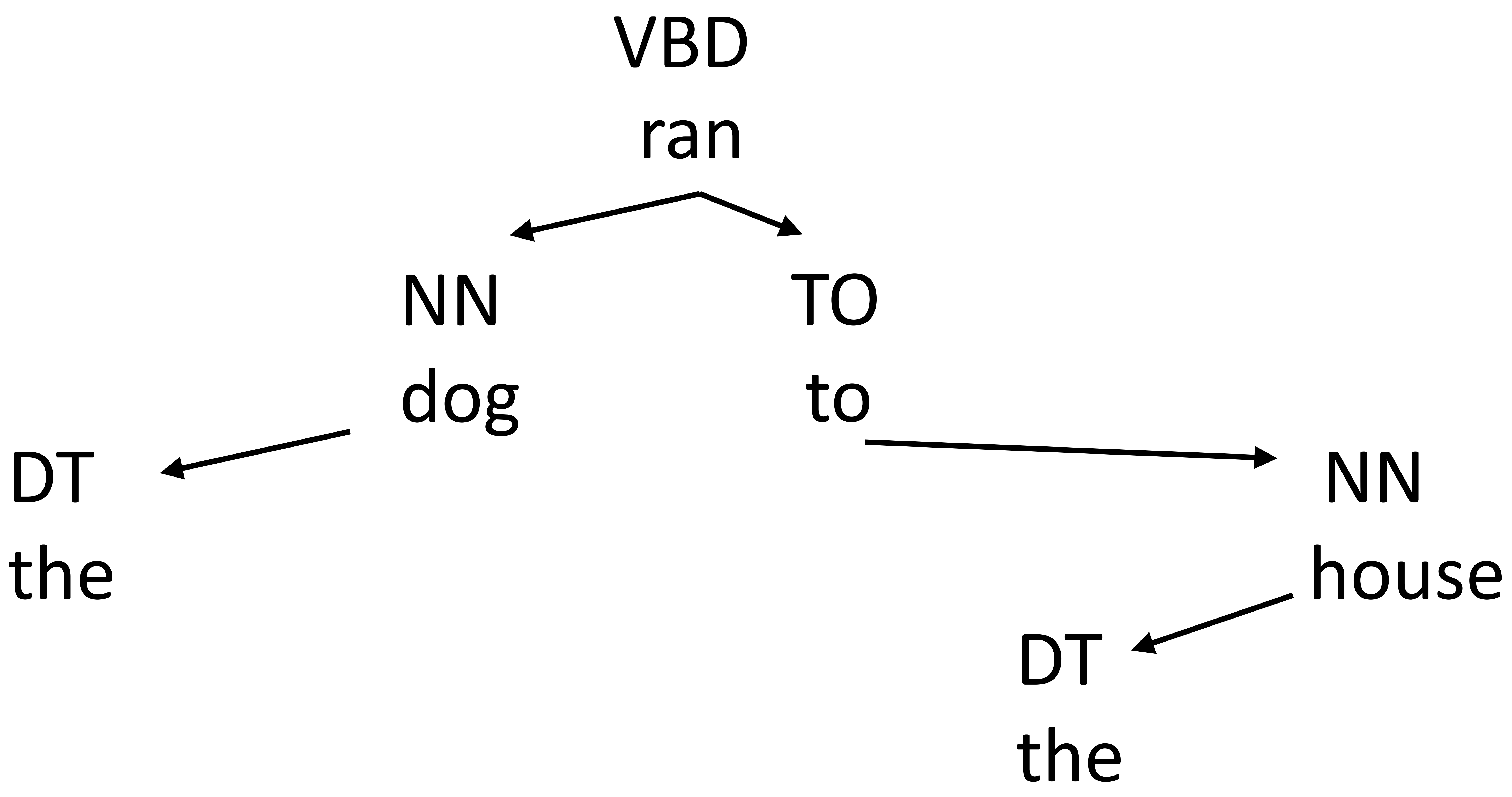
- POS tags same as before, usually run a tagger first as preprocessing

Why are they defined this way?

- Constituency tests:
  - Substitution by *proform*: the dog *did so [ran to the house]*, *he [the dog]* ran to the house
  - Clefting (*It was [to the house] that the dog ran*…)
- Dependency: verb is the root of the clause, everything else follows from that
  - No notion of a VP!

Dependency Parsing

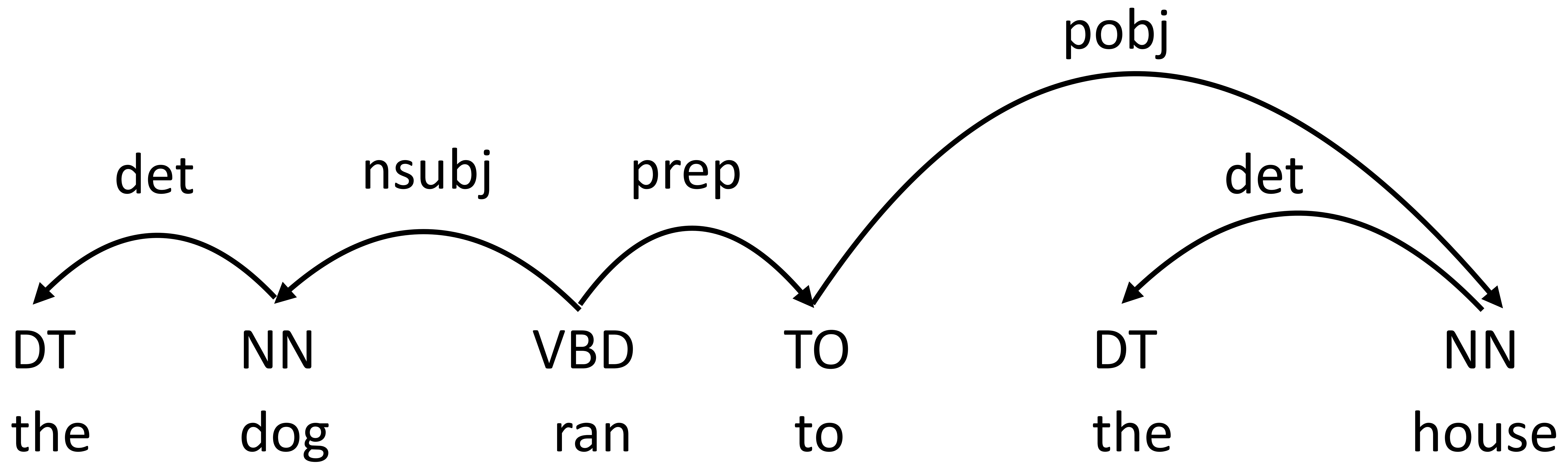
- Still a notion of hierarchy! Subtrees often align with constituents



Dependency Parsing

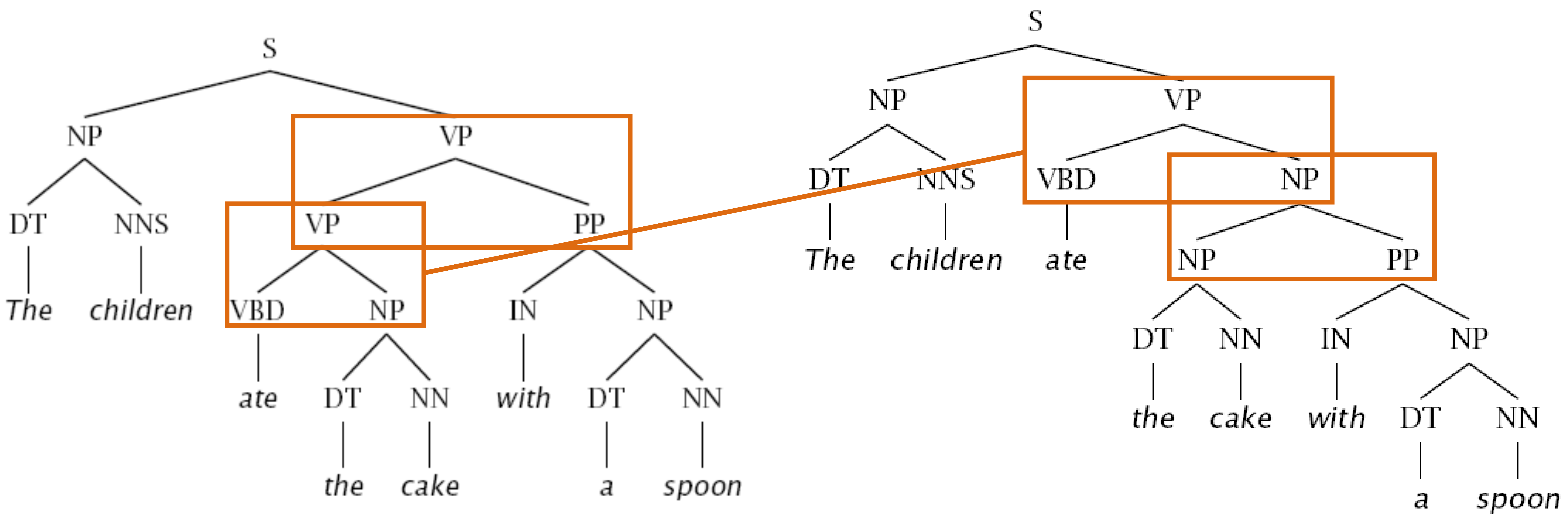
- Can label dependencies according to syntactic function

- Major source of ambiguity is in the structure, so we focus on that more (labeling separately with a classifier works pretty well)



Dependency vs. Constituency: PP Attachment

- Constituency: several rule productions need to change



Dependency vs. Constituency: PP Attachment

- Dependency: one word (with) assigned a different parent

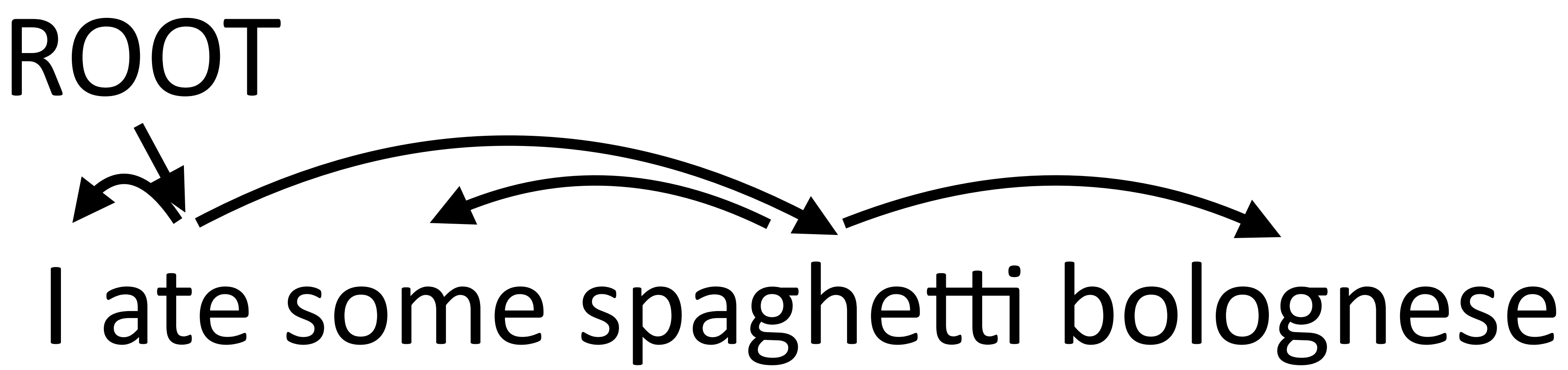
the children ate the cake with a spoon

- corenlp.run: *spoon* is child instead of *with*. This is just a different formalism
- More predicate-argument focused view of syntax
- "What's the main verb of the sentence? What is its subject and object?"
  — easier to answer under dependency parsing

Parsers Today

Modern Parsers

- Shift-reduce parsers: parsers that construct a tree from a sentence via a greedy sequence of operations. similar to parsing algorithms for compilers:



Shift, Shift, Left-arc, Shift, Shift, Left-arc, Shift, Right-arc, Right-arc, Right-arc

I <- ate

some <- spaghetti

spaghetti -> bolognese

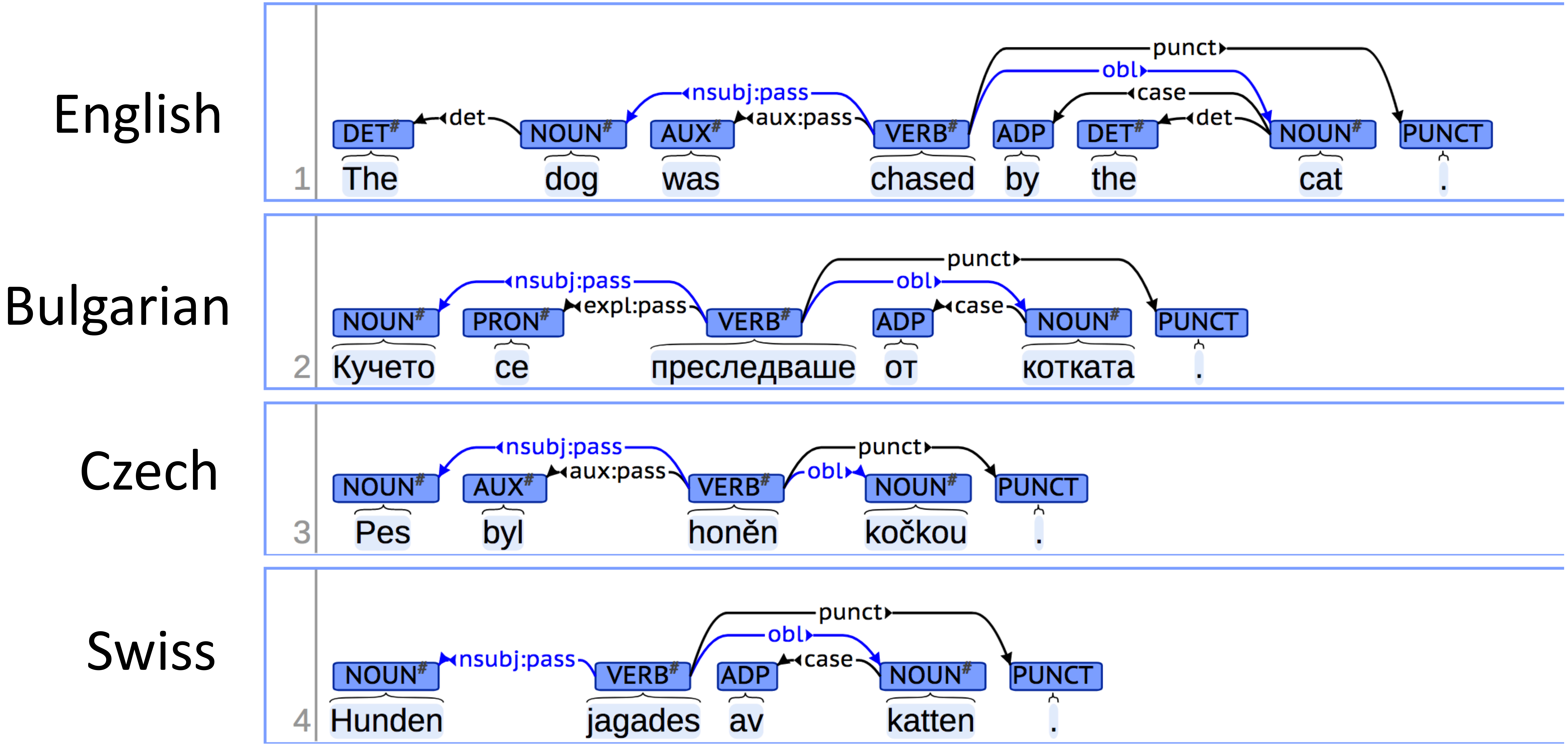
ate -> spaghetti

ROOT -> ate

- These parsers historically worked less well. But with neural networks, they're pretty good and **very** fast!

Universal Dependencies

- Annotate dependencies with the same representation in many languages



http://universaldependencies.org/

Reflections on Structure

- What is the role of it now?

- Systems still make these kinds of judgments, just not explicitly

- To improve systems, do we need to understand what they do?