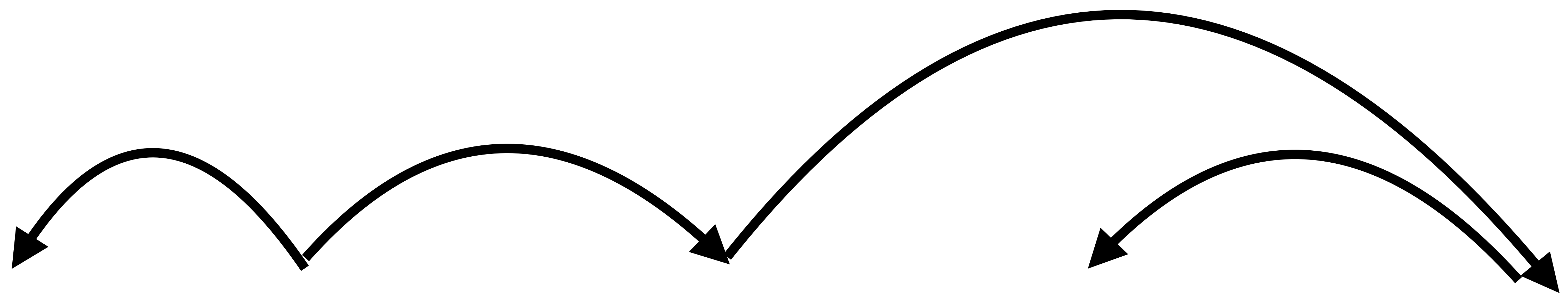
# CS388: Natural Language Processing

## Lecture 12: Dependency Parsing



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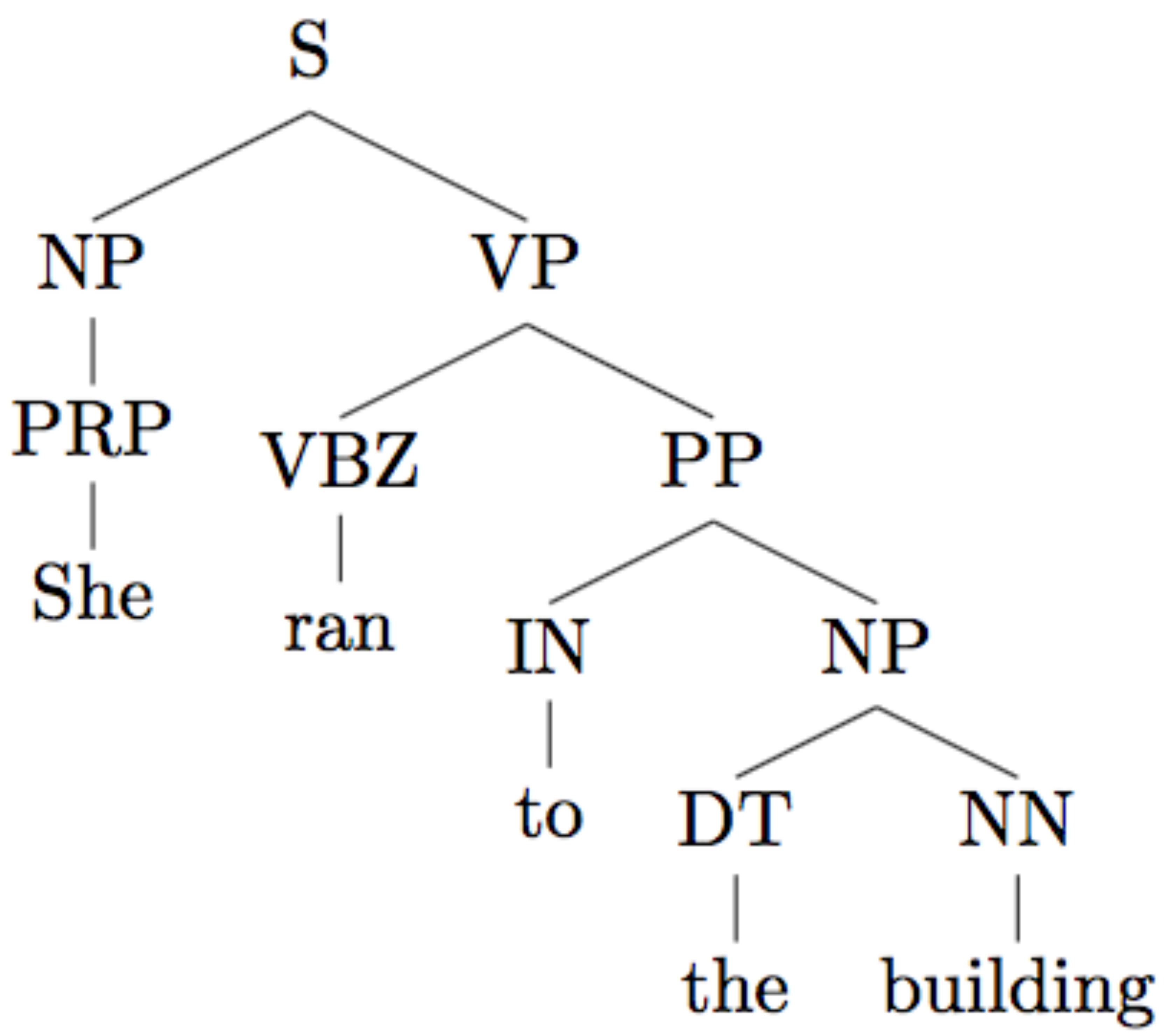
# Administrivia

- Project 1 graded
- Submission on Gradescope
- Final project proposals due next Thursday

# Recall: Constituency

- Tree-structured syntactic analyses of sentences
- Nonterminals (NP, VP, etc.) as well as POS tags (bottom layer)
- Structured is defined by a CFG



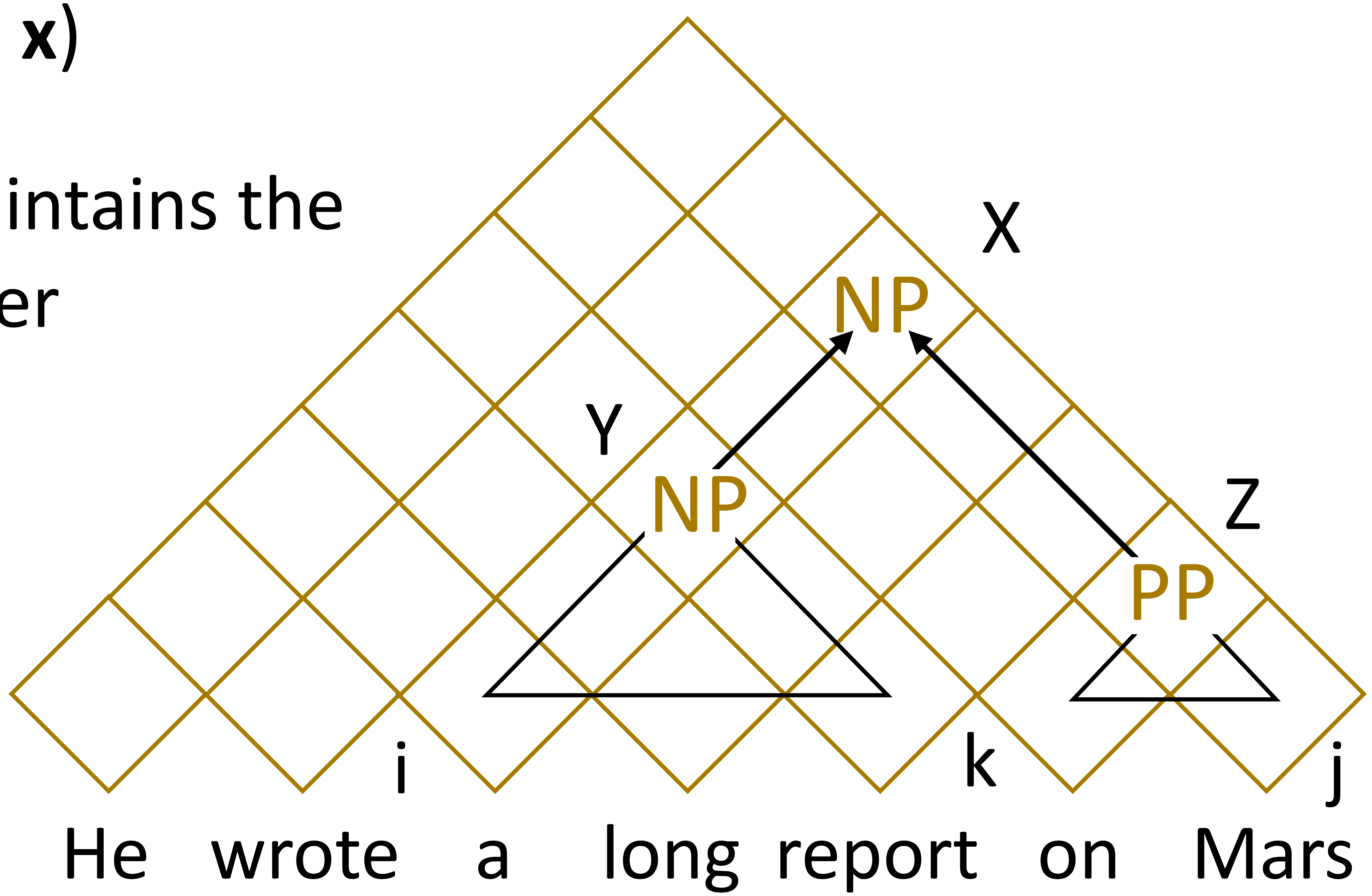
# Recall: PCFGs

| 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

# Recall: CKY

- Find argmax P(T|**x**) = argmax P(T, **x**)
- Dynamic programming: chart maintains the best way of building symbol X over span (i, j)
- Loop over all split points k, apply rules X -> Y Z to build X in every possible way




Cocke-Kasami-Younger

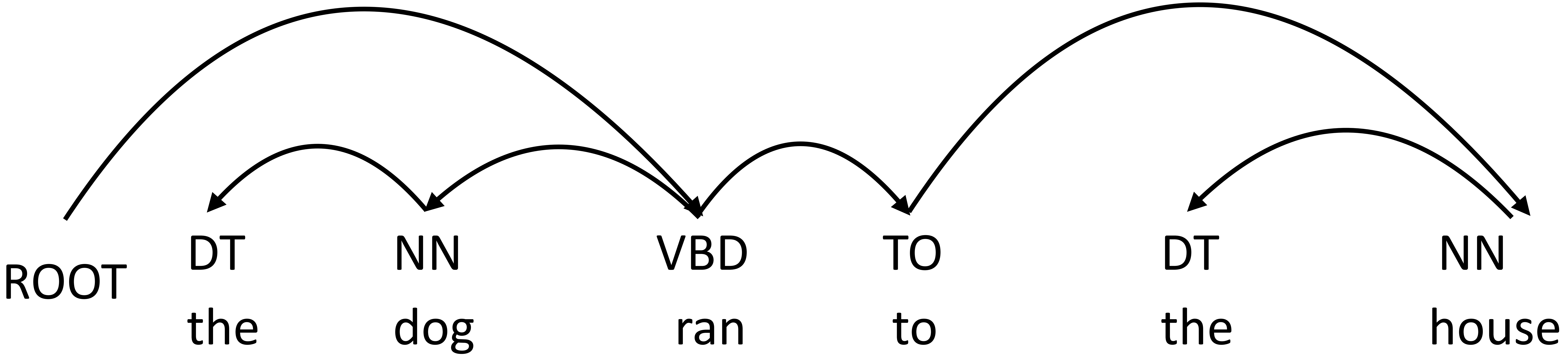
# Outline

- Dependency representation, contrast with constituency
- Graph-based dependency parsers
- Transition-based (shift-reduce) dependency parsers
- State-of-the-art parsers

# Dependency Representation

# Dependency Parsing

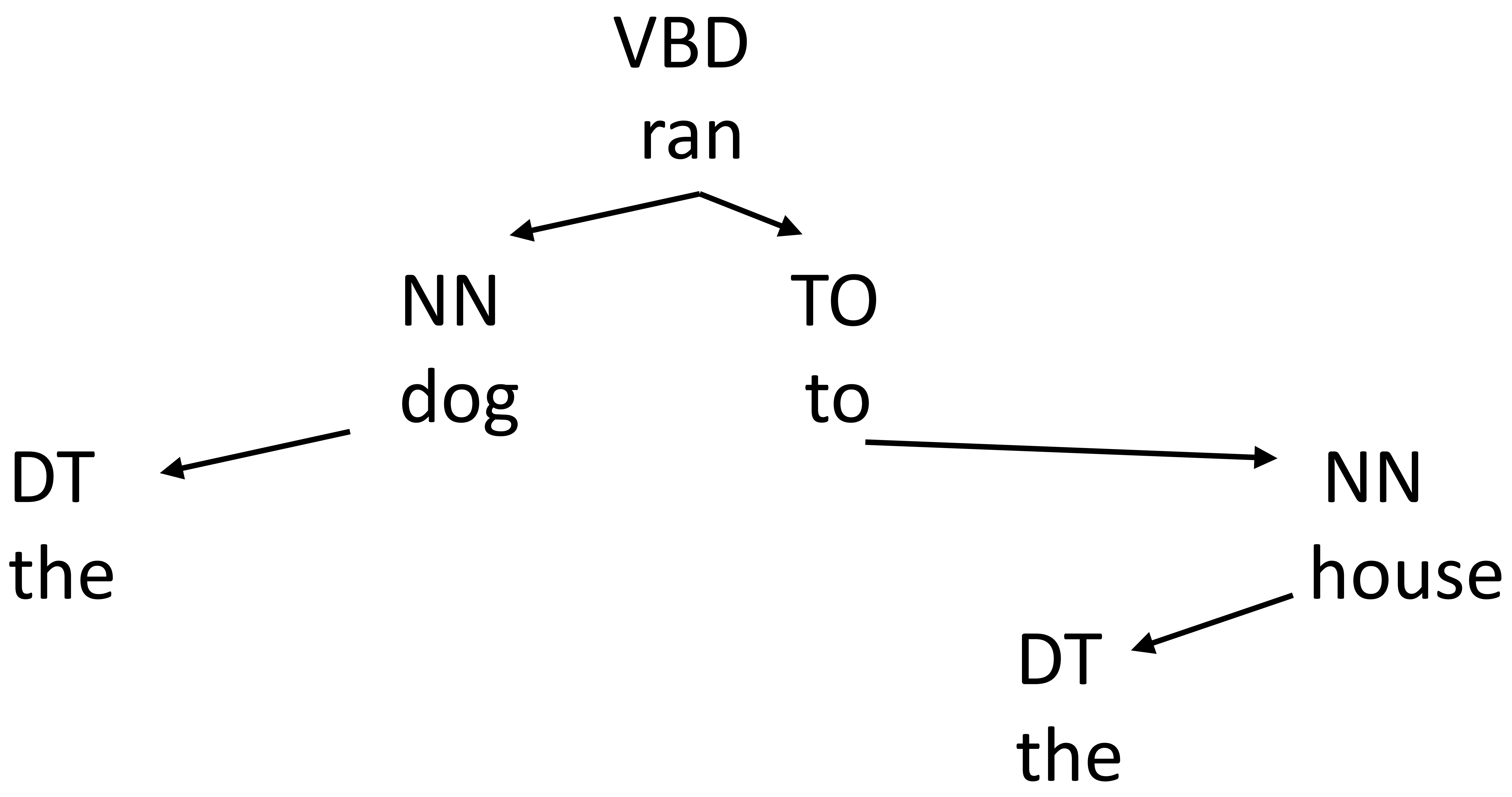
- Dependency syntax: syntactic structure is defined by these arcs
  - Head (parent, governor) connected to dependent (child, modifier)
  - Each word has exactly one parent except for the ROOT symbol, dependencies must form a directed acyclic graph




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

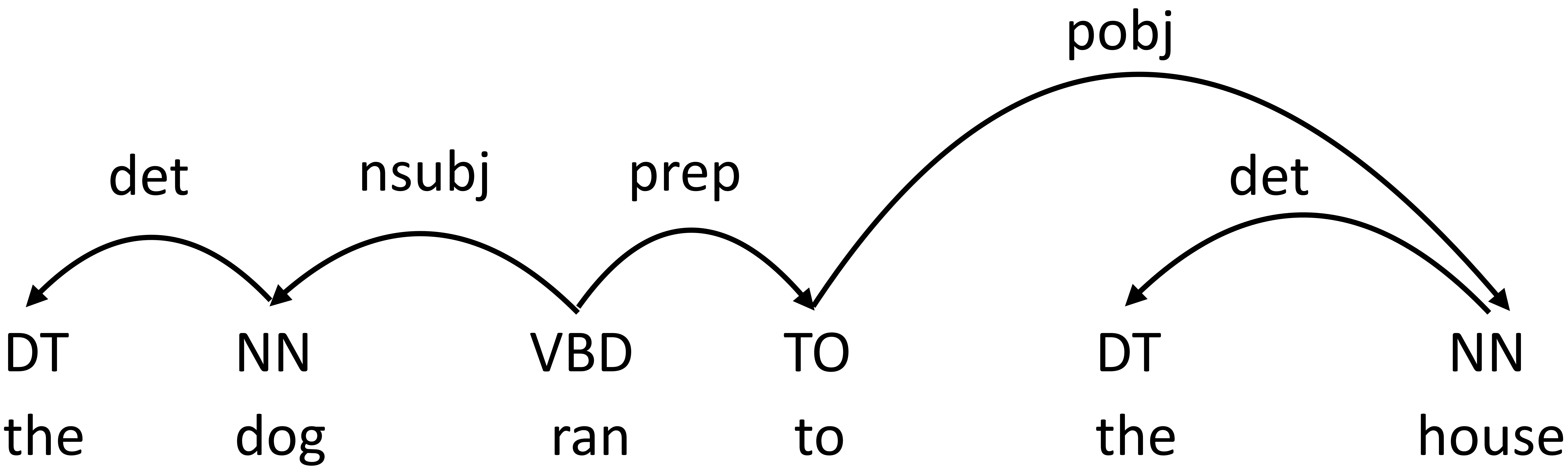
# Dependency Parsing

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



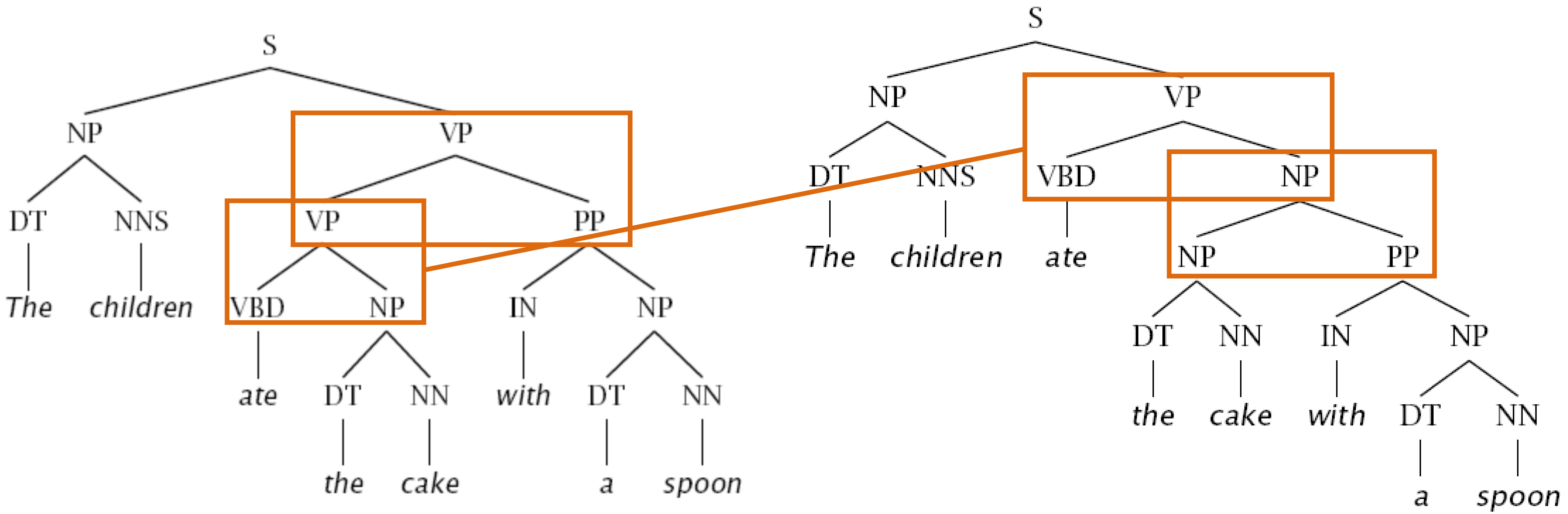
# Dependency Parsing

- 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

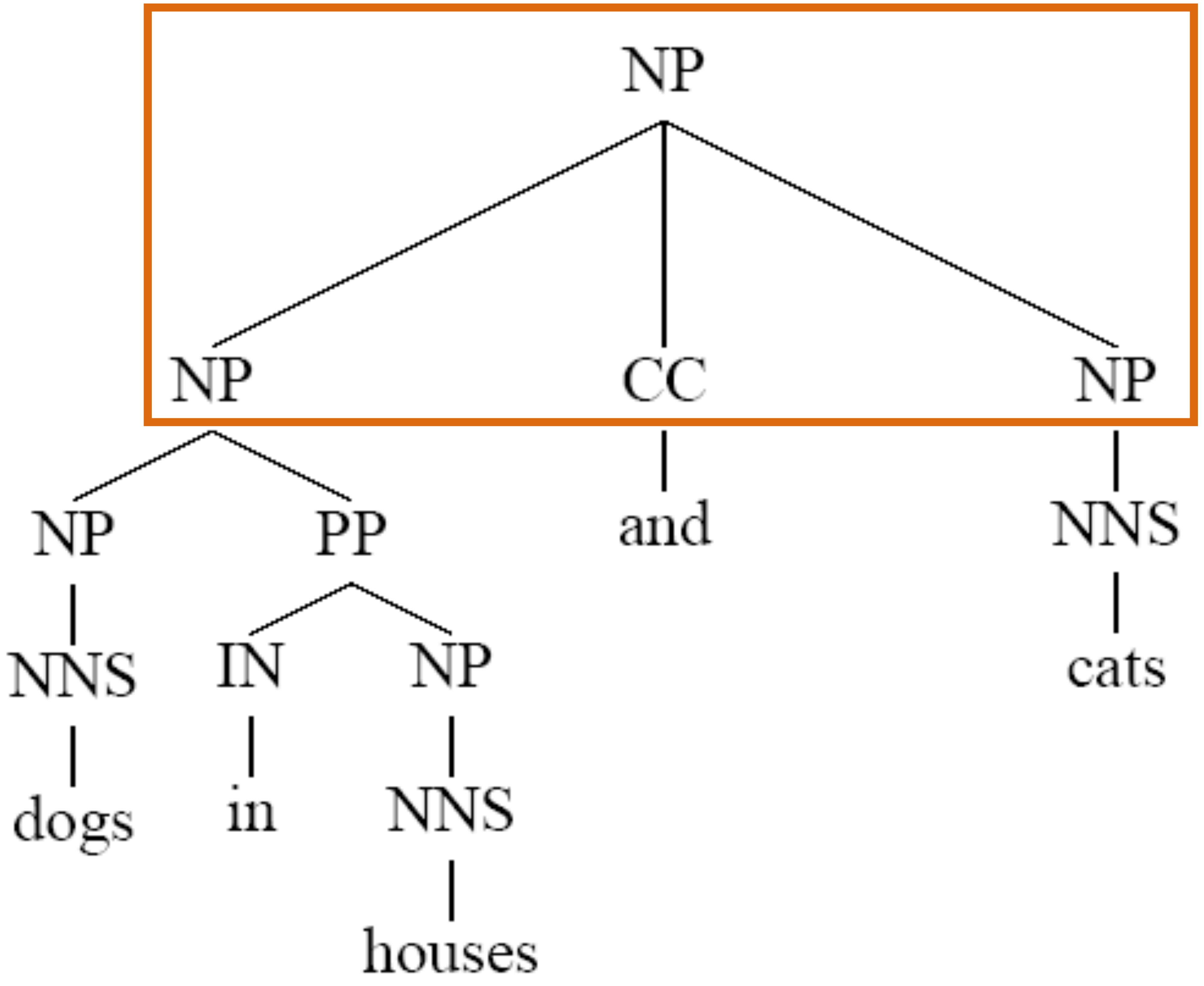
- Dependency: one word (with) assigned a different parent

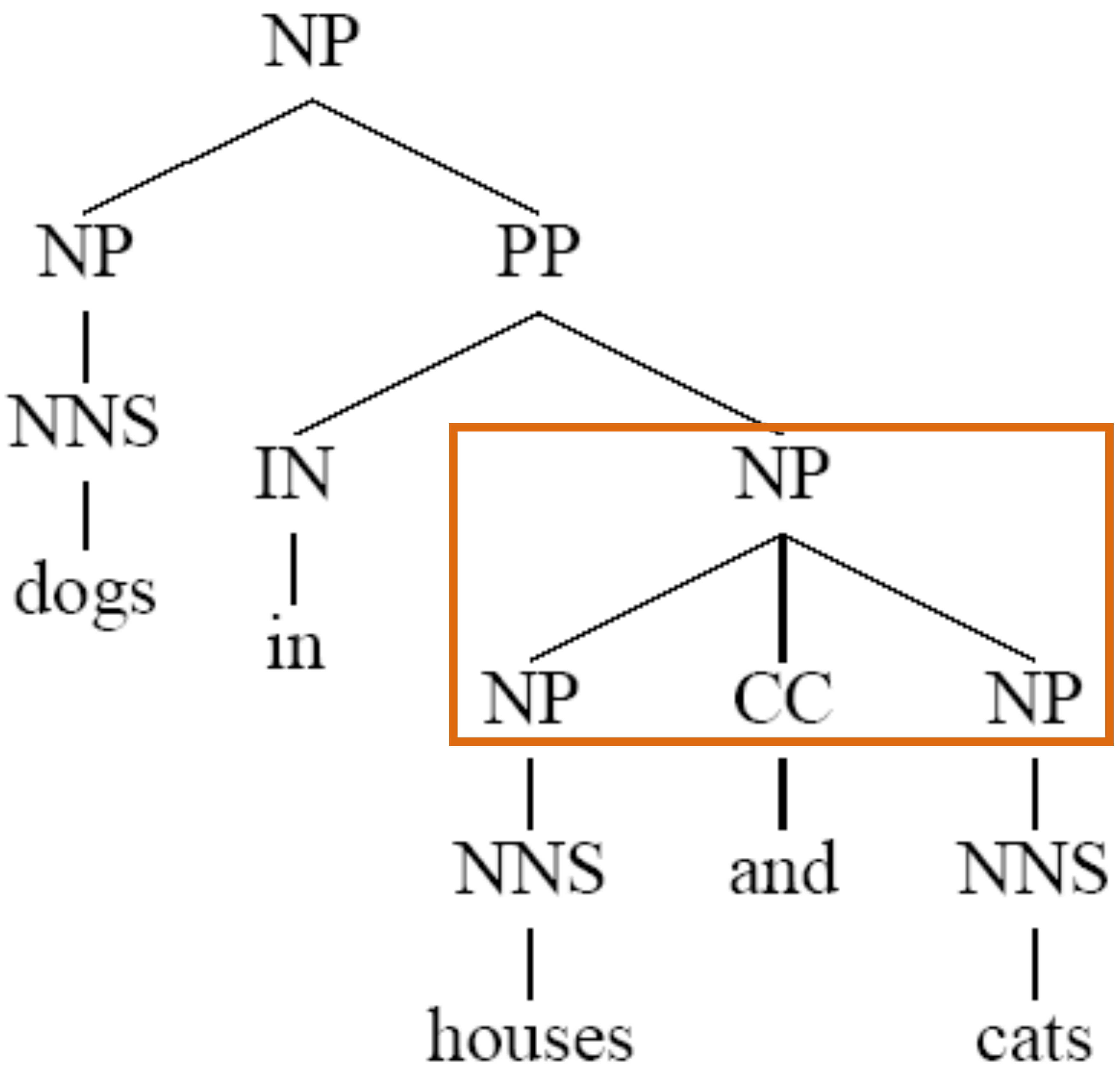
the children ate the cake with a spoon

- 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

# Dependency vs. Constituency: Coordination

- Constituency: ternary rule NP -> NP CC NP



# Dependency vs. Constituency: Coordination

- Dependency: first item is the head

**dogs** in houses **and cats** dogs in **houses and cats**

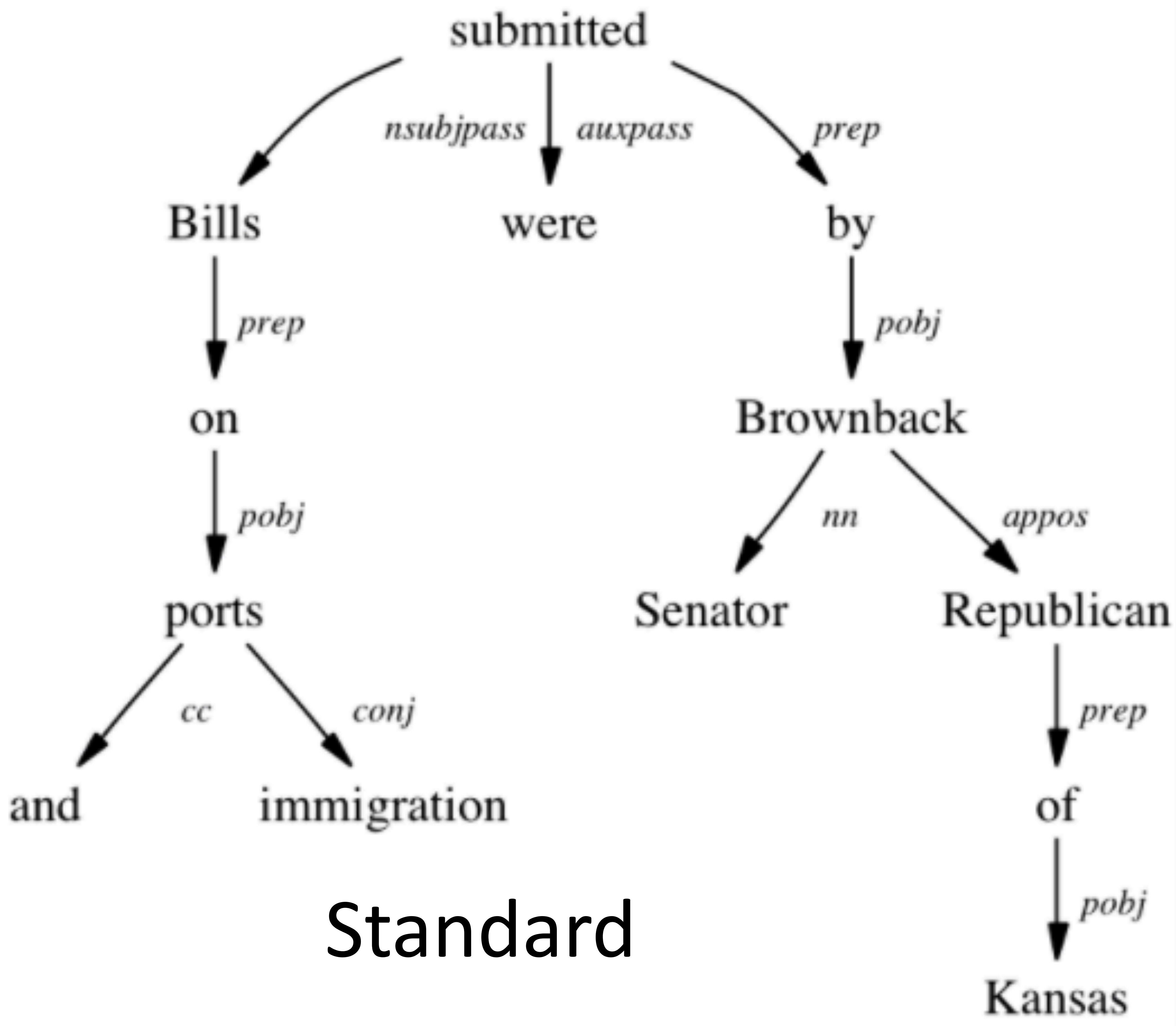
[dogs in houses] and cats dogs in [houses and cats]

- Coordination is decomposed across a few arcs as opposed to being a single rule production as in constituency
- Can also choose *and* to be the head
- In both cases, headword doesn't really represent the phrase — constituency representation makes more sense

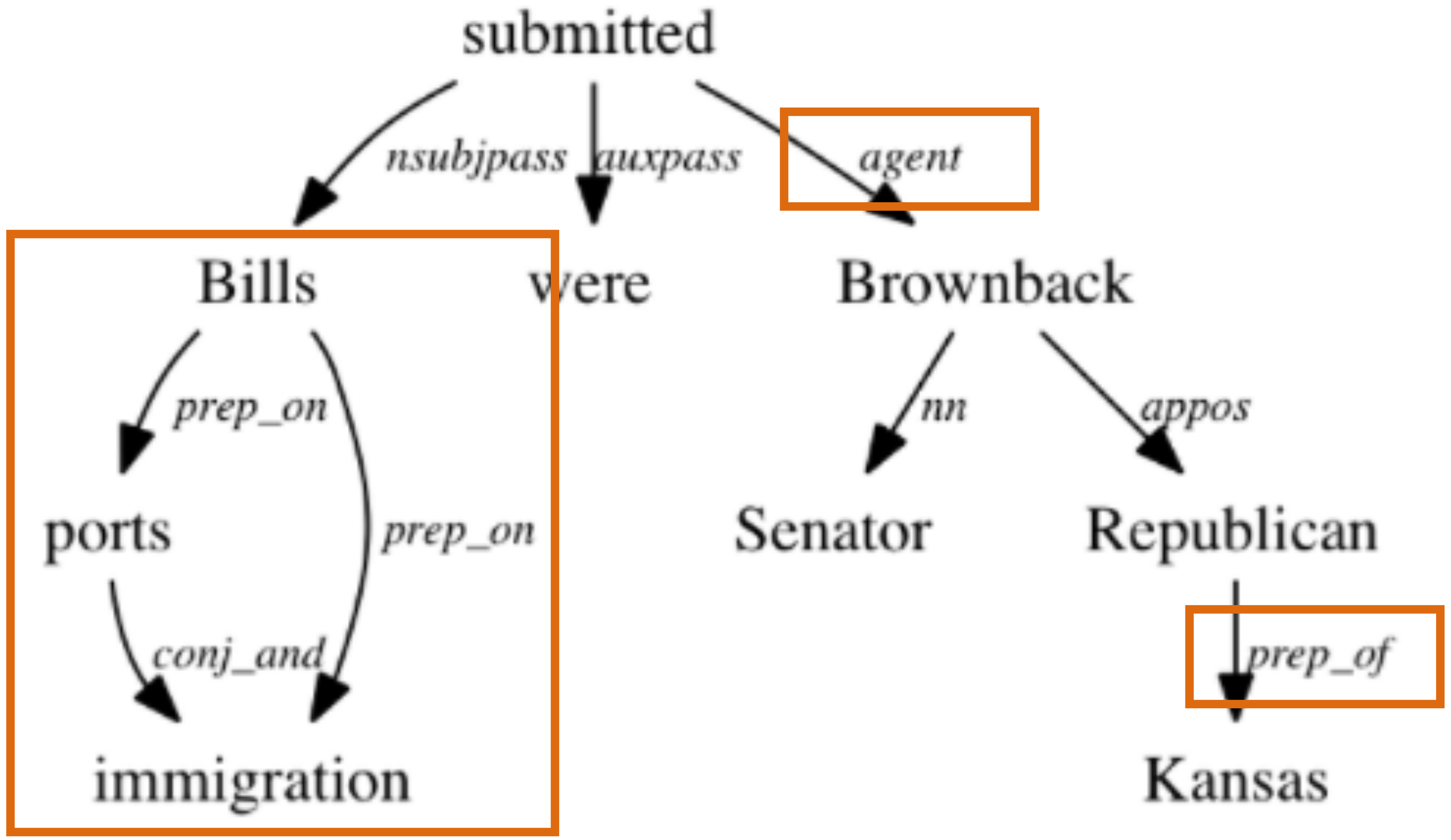
# Stanford Dependencies

- Designed to be practically useful for relation extraction

Bills on ports and immigration were submitted by Senator Brownback, Republican of Kansas




Standard



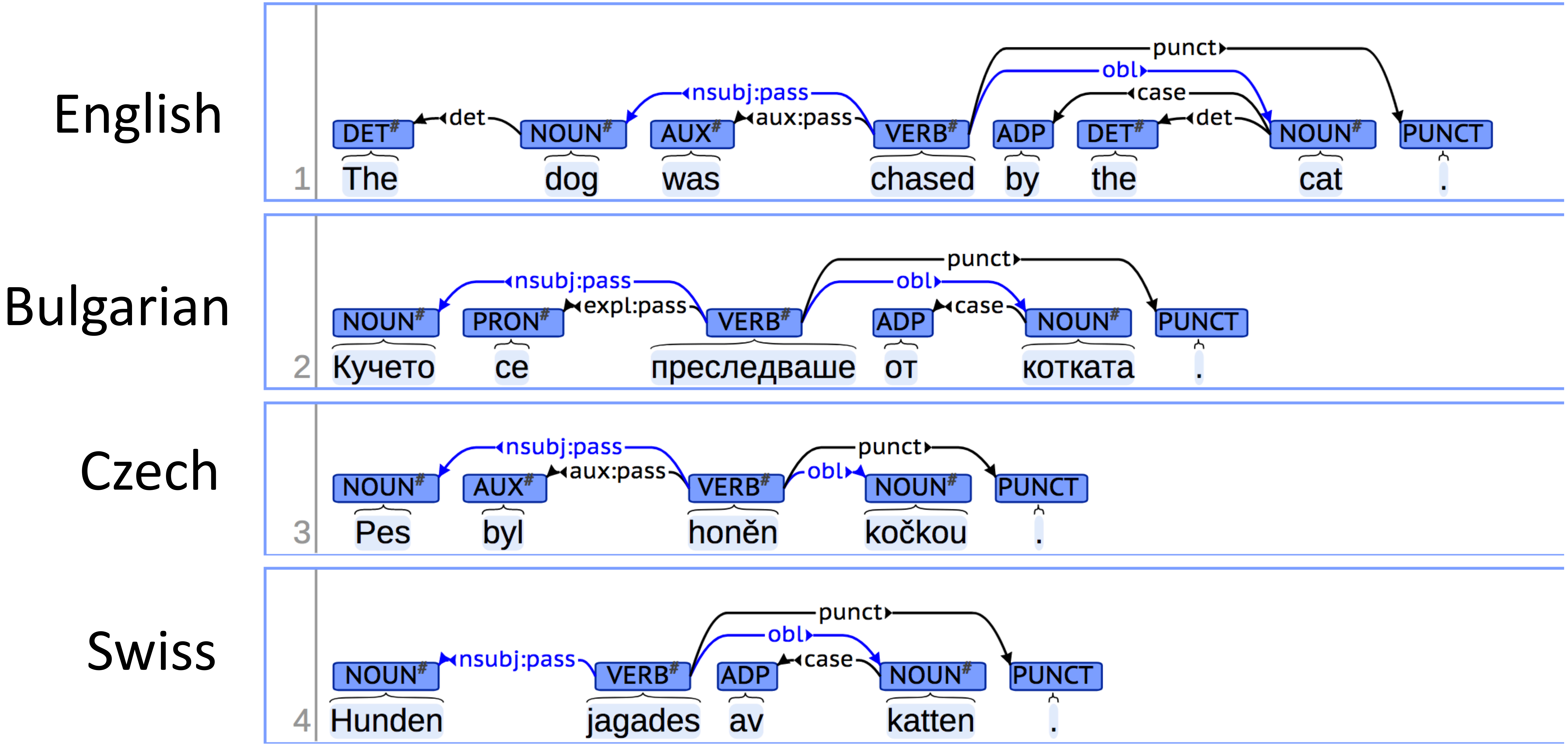

Collapsed

# Dependency vs. Constituency

- Dependency is often more useful in practice (models predicate argument structure)
- Slightly different representational choices:
  - PP attachment is better modeled under dependency
  - Coordination is better modeled under constituency
- Dependency parsers are easier to build: no "grammar engineering", no unaries, easier to get structured discriminative models working well
- Dependency parsers are usually faster
- Dependencies are more universal cross-lingually

# Universal Dependencies

- Annotate dependencies with the same representation in many languages




http://universaldependencies.org/

# Graph-Based Parsing

# Defining Dependency Graphs

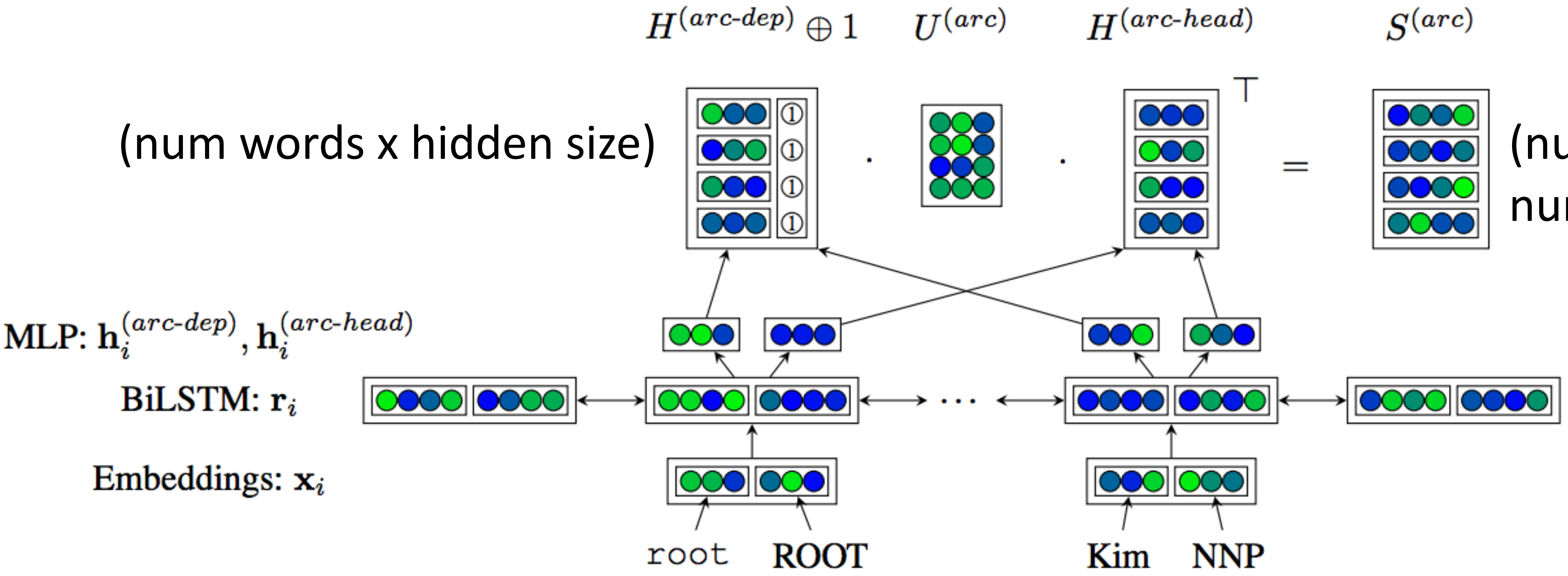
- Words in sentence **x**, tree T is a collection of directed edges (parent(i), i) for each word i
  - Parsing = identify parent(i) for each word
  - Each word has exactly one parent. Edges must form a projective tree
- Log-linear CRF (discriminative): $P(T|\mathbf{x}) = \exp\left(\sum_i w^\top f(i, \mathrm{parent}(i), \mathbf{x})\right)$
- Example of a feature = I[head=*to* & modifier=*house*]

ROOT the dog ran $\boxed{\text{to}}$ the $\boxed{\text{house}}$

# Biaffine Neural Parsing

- Neural CRFs for dependency parsing: let $c$ = LSTM embedding of $i$, $p$ = LSTM embedding of parent($i$). $score(i, \text{parent}(i), \mathbf{x}) = p^{\top}Uc$

(num words x hidden size)



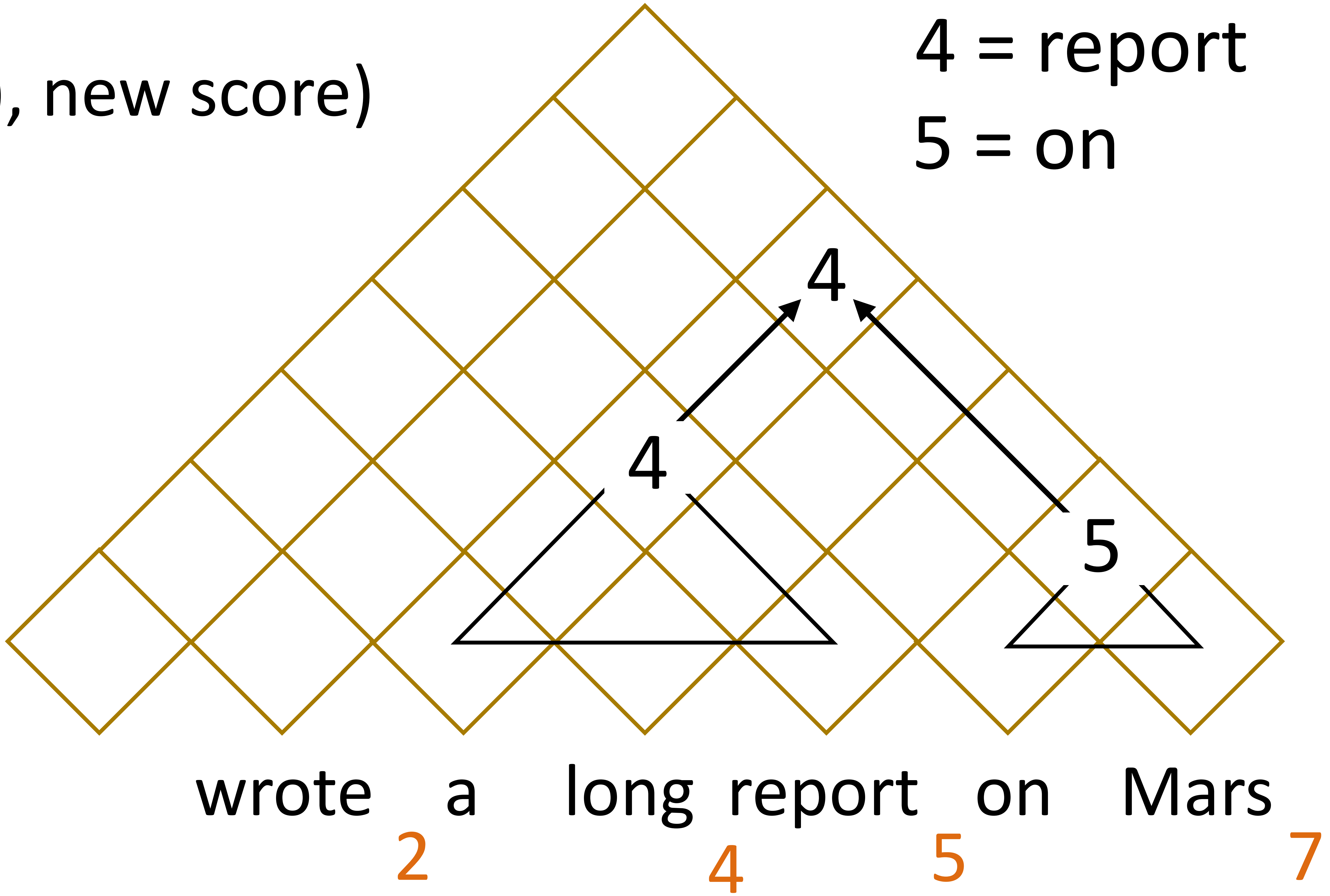

(num words x num words)

LSTM looks at words and POS

Dozat and Manning (2017)

# Generalizing CKY

- DP chart with three dimensions: start, end, and head, start <= head < end
- new score = chart(2, 5, 4) + chart(5, 7, 5) + edge score(4 -> 5)
- score(2, 7, 4) = max(score(2, 7, 4), new score)
- Many *spurious derivations*: can build the same tree in many ways…need a better algorithm
- Eisner's algorithm is cubic time



# Evaluating Dependency Parsing

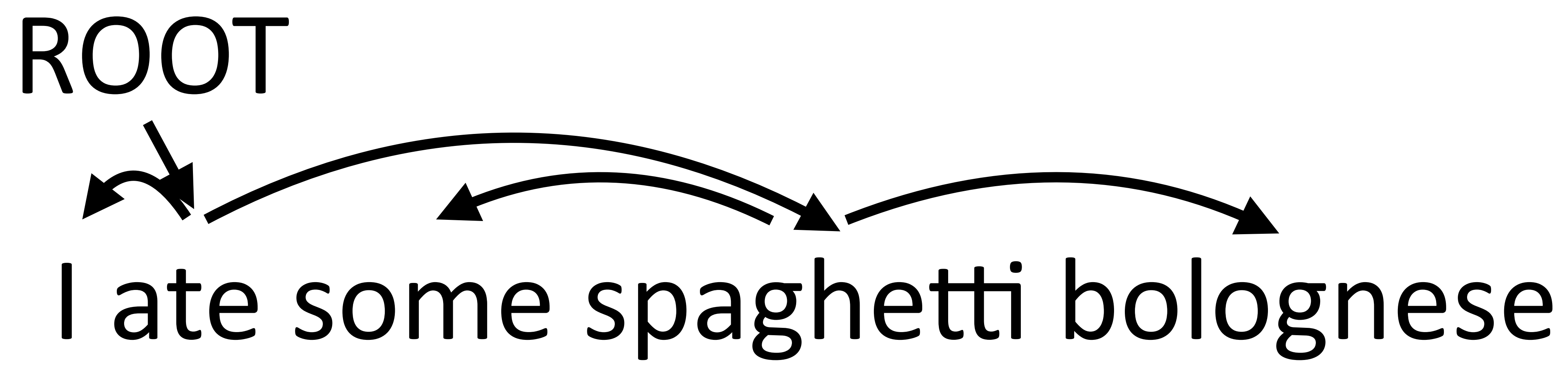
- UAS: unlabeled attachment score. Accuracy of choosing each word's parent (*n* decisions per sentence)
- LAS: additionally consider label for each edge
- Log-linear CRF parser, decoding with Eisner algorithm: 91 UAS
- Higher-order features from Koo parser: 93 UAS
- Best English results with neural CRFs (Dozat and Manning): 95-96 UAS

# Shift-Reduce Parsing

# Shift-Reduce Parsing

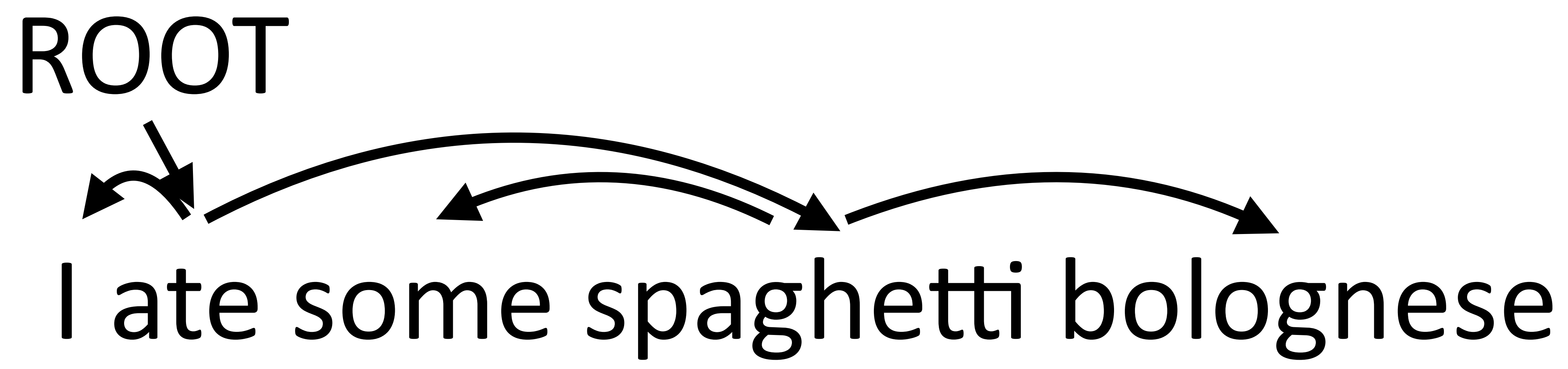
- Similar to deterministic parsers for compilers
  - Also called transition-based parsing
- A tree is built from a sequence of incremental decisions moving left to right through the sentence
- Stack containing partially-built tree, buffer containing rest of sentence
- Shifts consume the buffer, reduces build a tree on the stack

# Shift-Reduce Parsing




- Initial state: Stack: [ROOT] Buffer: [I ate some spaghetti bolognese]
- Shift: top of buffer -> top of stack
  - Shift 1: Stack: [ROOT I] Buffer: [ate some spaghetti bolognese]
  - Shift 2: Stack: [ROOT I ate] Buffer: [some spaghetti bolognese]

# Shift-Reduce Parsing




- State: Stack: [ROOT I ate] Buffer: [some spaghetti bolognese]

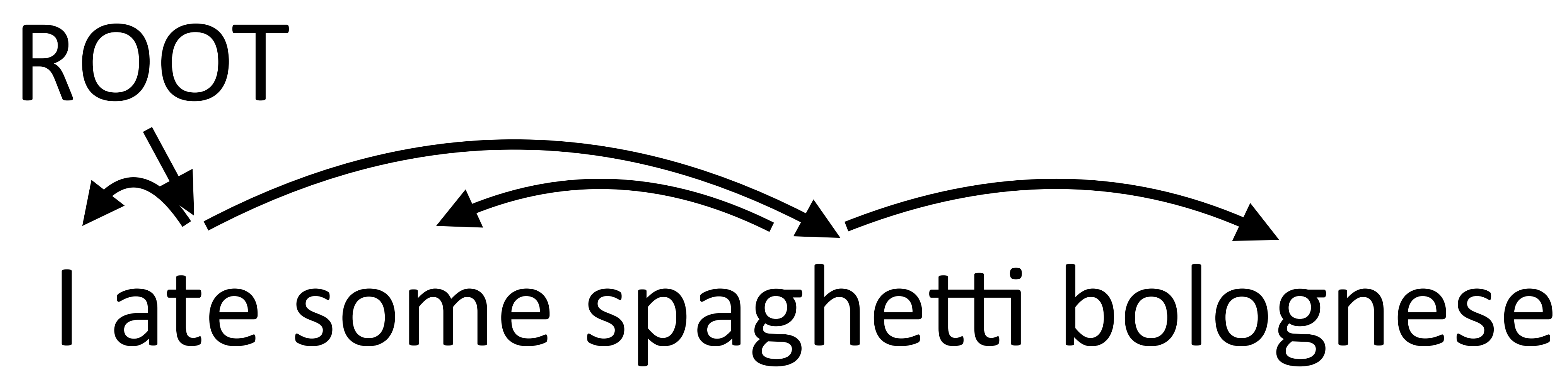
- Left-arc (reduce): Let $\sigma$ denote the stack, $\sigma|w_{-1}$ = stack ending in $w_{-1}$
  - "Pop two elements, add an arc, put them back on the stack"

$$\boxed{\sigma|w_{-2}, w_{-1}} \rightarrow \boxed{\sigma|w_{-1}}$$ $w_{-2}$ is now a child of $w_{-1}$

- State: Stack: [ROOT ate] Buffer: [some spaghetti bolognese]

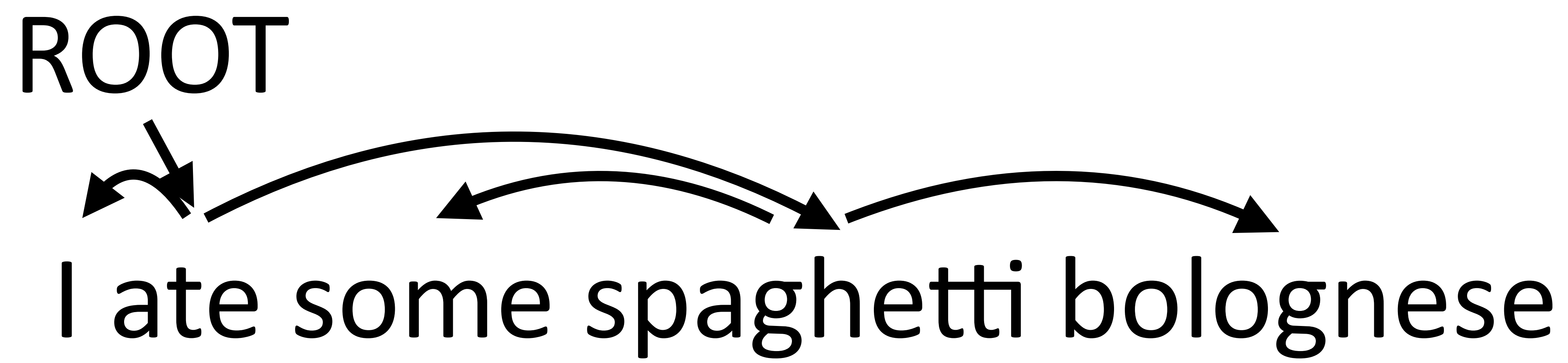
I

# Arc-Standard Parsing




- Start: stack contains [ROOT], buffer contains [I ate some spaghetti bolognese]
- Arc-standard system: three operations
  - Shift: top of buffer -> top of stack
  - Left-Arc: $\boxed{\sigma|w_{-2}, w_{-1}} \rightarrow \boxed{\sigma|w_{-1}}$, $w_{-2}$ is now a child of $w_{-1}$
  - Right-Arc $\boxed{\sigma|w_{-2}, w_{-1}} \rightarrow \boxed{\sigma|w_{-2}}$ , $w_{-1}$ is now a child of $w_{-2}$
- End: stack contains [ROOT], buffer is empty []
- How many transitions do we need if we have n words in a sentence?

# Arc-Standard Parsing



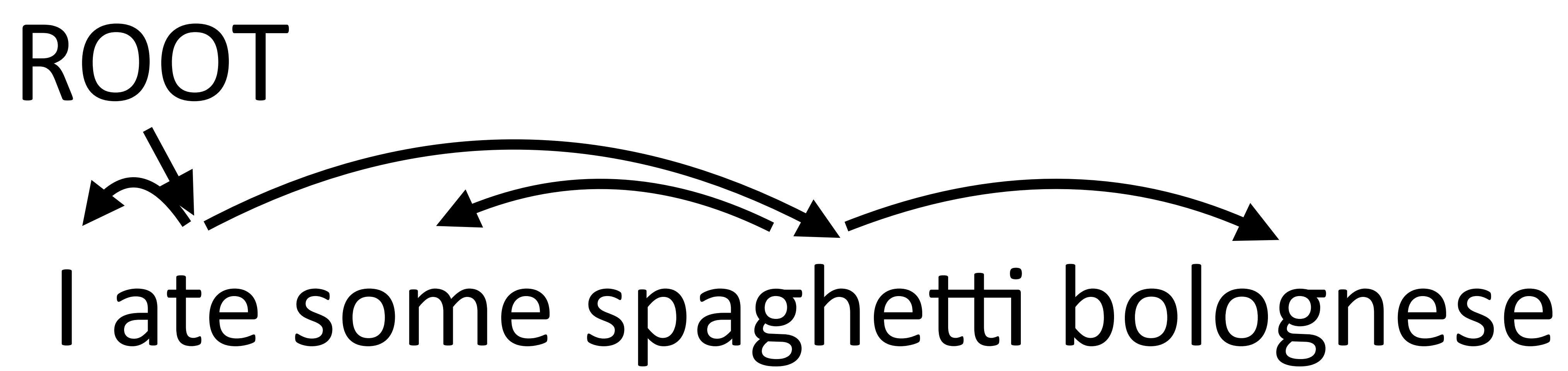

| | |
|---|---|
| S | top of buffer -> top of stack |
| LA | pop two, left arc between them |
| RA | pop two, right arc between them |

| Stack | Action | Buffer |
|---|---|---|
| [ROOT] | S | [I ate some spaghetti bolognese] |
| [ROOT I] | S | [ate some spaghetti bolognese] |
| [ROOT I ate] | L | [some spaghetti bolognese] |
| [ROOT ate] | | [some spaghetti bolognese] |

I

- Could do the left arc later! But no reason to wait
- Can’t attach ROOT <- ate yet even though this is a correct dependency!

# Arc-Standard Parsing




| | |
|---|---|
| S | top of buffer -> top of stack |
| LA | pop two, left arc between them |
| RA | pop two, right arc between them |

[ROOT ate] [some spaghetti bolognese]

I

$\boxed{S}$

$\boxed{S}$

[ROOT ate some spaghetti] [bolognese]

I

$\boxed{L}$

[ROOT ate spaghetti] [bolognese]

I some

$\boxed{S}$

# Arc-Standard Parsing

ROOT

I ate some spaghetti bolognese

| | |
|---|---|
| S | top of buffer -> top of stack |
| LA | pop two, left arc between them |
| RA | pop two, right arc between them |

[ROOT ate spaghetti bolognese] []

I some

R

[ROOT ate spaghetti] []

I some bolognese

R

[ROOT ate] []

spaghetti

I

some bolognese

- Stack consists of all words that are still waiting for right children, end with a bunch of right-arc ops

Final state:

[ROOT] []

ate

spaghetti

I

some bolognese

# Building Shift-Reduce Parsers

[ROOT]　　　　　　　　　　[I ate some spaghetti bolognese]

- How do we make the right decision in this case?
- Only one legal move (shift)

[ROOT ate some spaghetti]　　　　[bolognese]

I

- How do we make the right decision in this case? (all three actions legal)
- Multi-way classification problem: shift, left-arc, or right-arc?

$$\text{argmax}_{a \in \{\text{S},\text{LA},\text{RA}\}} w^\top f(\text{stack}, \text{buffer}, a)$$

# Features for Shift-Reduce Parsing

[ROOT ate some spaghetti]        [bolognese]

↓

I

- Features to know this should left-arc?
- One of the harder feature design tasks!
- In this case: the stack tag sequence VBD - DT - NN is pretty informative — looks like a verb taking a direct object which has a determiner in it
- Things to look at: top words/POS of buffer, top words/POS of stack, leftmost and rightmost children of top items on the stack

# Training a Greedy Model

[ROOT ate some spaghetti] [bologness]

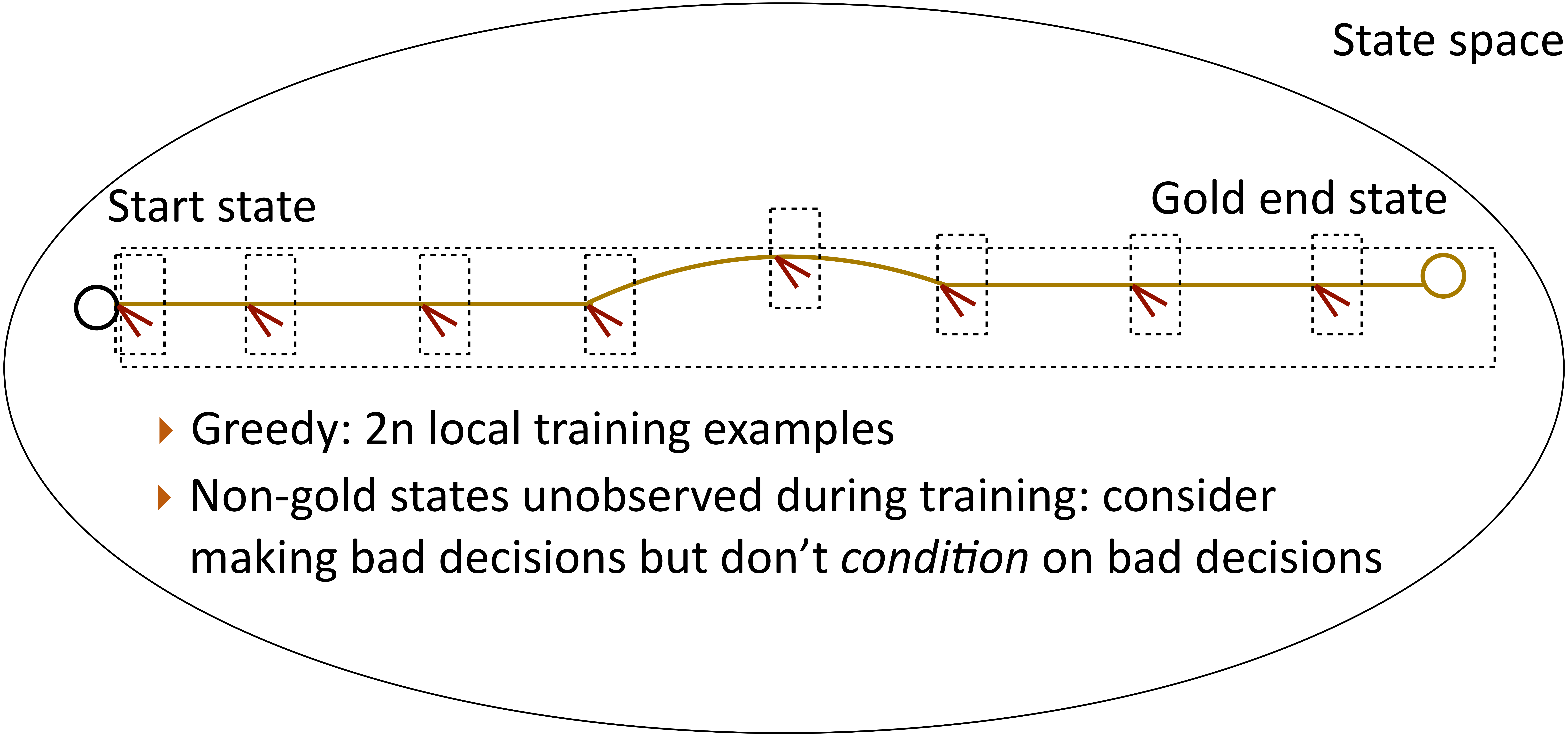
↓

I

$$\mathrm{argmax}_{a \in \{\mathrm{S},\mathrm{LA},\mathrm{RA}\}} w^\top f(\mathrm{stack}, \mathrm{buffer}, a)$$

- Can turn a tree into a decision sequence ***a*** by building an *oracle*
- Train a classifier to predict the right decision using these as training data
- Training data assumes you made correct decisions up to this point and teaches you to make the correct decision, but what if you screwed up…

# Greedy training




- Greedy: 2n local training examples
- Non-gold states unobserved during training: consider making bad decisions but don't *condition* on bad decisions

# Speed Tradeoffs

| | Parser | Dev UAS | Dev LAS | Test UAS | Test LAS | Speed (sent/s) |
|---|---|---|---|---|---|---|
| Unoptimized S-R | standard | 89.9 | 88.7 | 89.7 | 88.3 | 51 |
| | eager | 90.3 | 89.2 | 89.9 | 88.6 | 63 |
| Optimized S-R | Malt:sp | 90.0 | 88.8 | 89.9 | 88.5 | 560 |
| | Malt:eager | 90.1 | 88.9 | 90.1 | 88.7 | 535 |
| Graph-based | MSTParser | 92.1 | 90.8 | **92.0** | 90.5 | 12 |
| Neural S-R | Our parser | **92.2** | **91.0** | **92.0** | **90.7** | **1013** |

- Many early-2000s constituency parsers were ~5 sentences/sec
- Using S-R used to mean taking a performance hit compared to graph-based, that's no longer (quite as) true

Chen and Manning (2014)

# State-of-the-art Dependency Parsers

# Dependency Parsers

- 2005: Eisner algorithm graph-based parser was SOTA (~91 UAS)
- 2010: Koo's 3rd-order parser was SOTA for graph-based (~93 UAS)
- 2012: Maltparser was SOTA was for transition-based (~90 UAS)
- 2014: Chen and Manning got 92 UAS with transition-based neural model
- 2016: Improvements to Chen and Manning

# Shift-Reduce with FFNNs

**Softmax layer:**

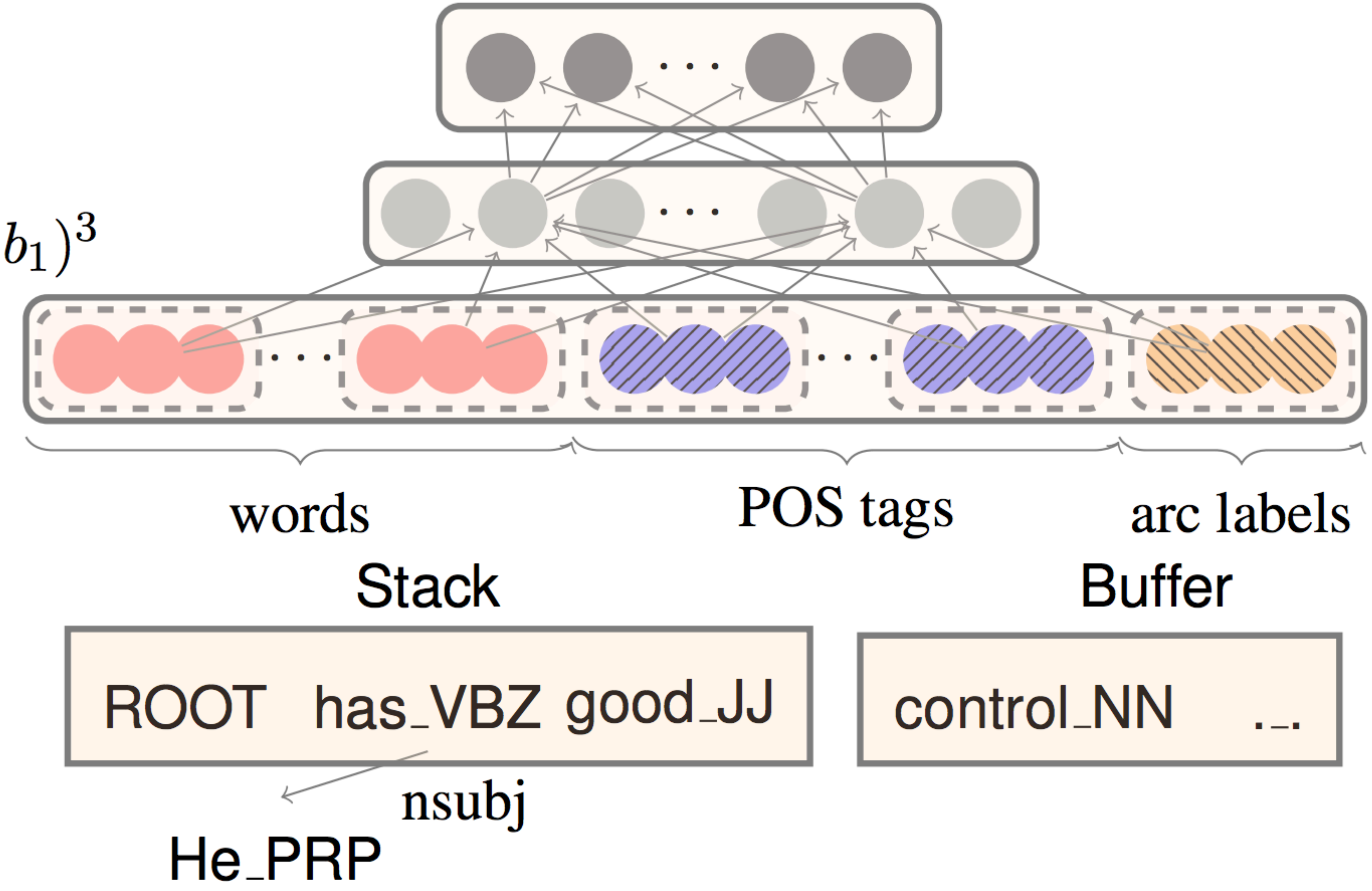
$$p = \mathtt{softmax}(W_2 h)$$

**Hidden layer:**

$$h = (W_1^w x^w + W_1^t x^t + W_1^l x^l + b_1)^3$$

**Input layer:** $[x^w, x^t, x^l]$

**Configuration**



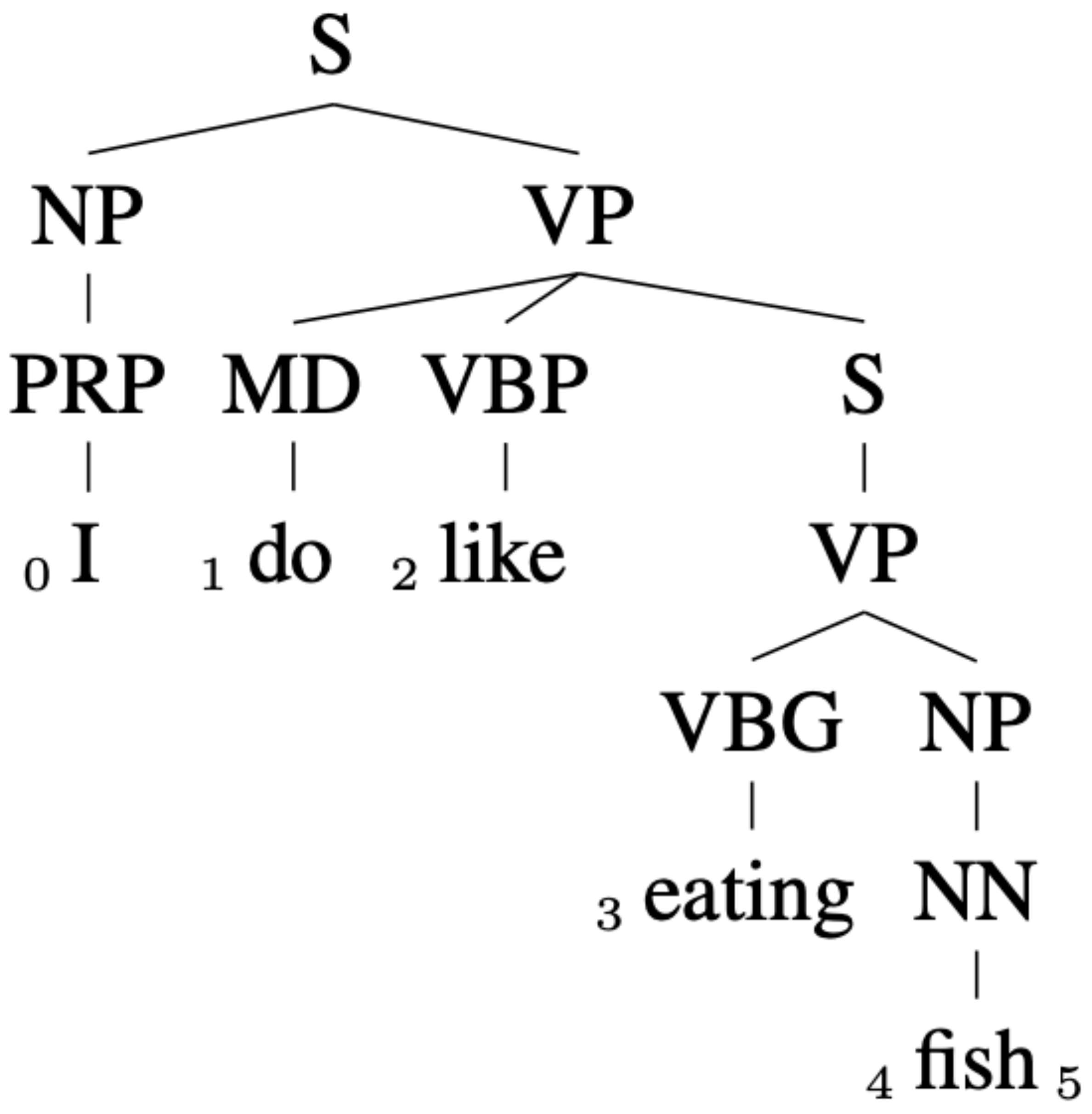

Chen and Manning (2014)

# Parsey McParseFace (a.k.a. SyntaxNet)

- 94.61 UAS on the Penn Treebank using a global transition-based system with early updating (compared to 95.8 for Dozat, 93.7 for Koo in 2009)
  - Additional data harvested via “tri-training”, form of self-training
- Feedforward neural nets looking at words and POS associated with words in the stack / those words’ children / words in the buffer
- Feature set pioneered by Chen and Manning (2014), Google fine-tuned it

Andor et al. (2016)

# Shift-Reduce Constituency




(a) gold parse tree

| steps | structural action | label action | stack after | bracket |
|---|---|---|---|---|
| 1–2 | sh(I/PRP) | label-NP | $_0\triangle_1$ | $_0NP_1$ |
| 3–4 | sh(do/MD) | nolabel | $_0\triangle_1\triangle_2$ | |
| 5–6 | sh(like/VBP) | nolabel | $_0\triangle_1\triangle_2\triangle_3$ | |
| 7–8 | comb | nolabel | $_0\triangle_1\triangle_3$ | |
| 9–10 | sh(eating/VBG) | nolabel | $_0\triangle_1\triangle_3\triangle_4$ | |
| 11–12 | sh(fish/NN) | label-NP | $_0\triangle_1\triangle_3\triangle_4\triangle_5$ | $_4NP_5$ |
| 13–14 | comb | label-S-VP | $_0\triangle_1\triangle_3\triangle_5$ | $_3S_5$, $_3VP_5$ |
| 15–16 | comb | label-VP | $_0\triangle_1\triangle_5$ | $_1VP_5$ |
| 17–18 | comb | label-S | $_0\triangle_5$ | $_0S_5$ |

(b) static oracle actions

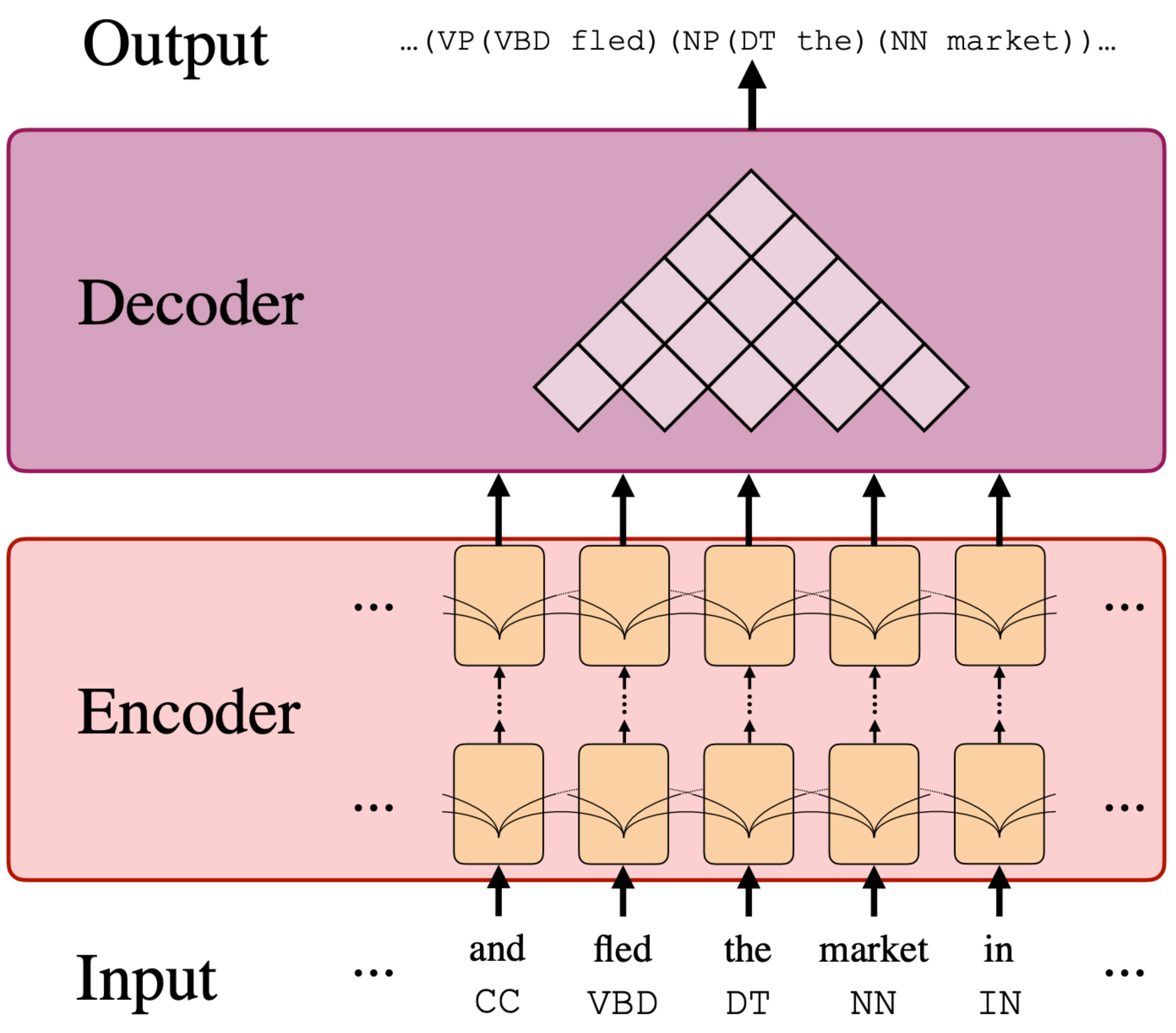
combine with no label for ternary rules

- Can do shift-reduce for constituency as well, reduce operation builds constituents

Cross and Huang (2016)

# Pre-trained Models

- Improves the neural CRF by using a transformer layer (self-attentive), character-level modeling, and ELMo
- 95.21 on Penn Treebank dev set — much better than past parsers! (~92-93)
- This constituency parser with BERT is one of the strongest today, or use a transition-based version due to Kitaev and Klein (2020)




Kitaev and Klein (2018)

# Recap

- Shift-reduce parsing can work nearly as well as graph-based
- Arc-standard system for transition-based parsing
- Purely greedy or more "global" approaches
- Next time: semantic parsing