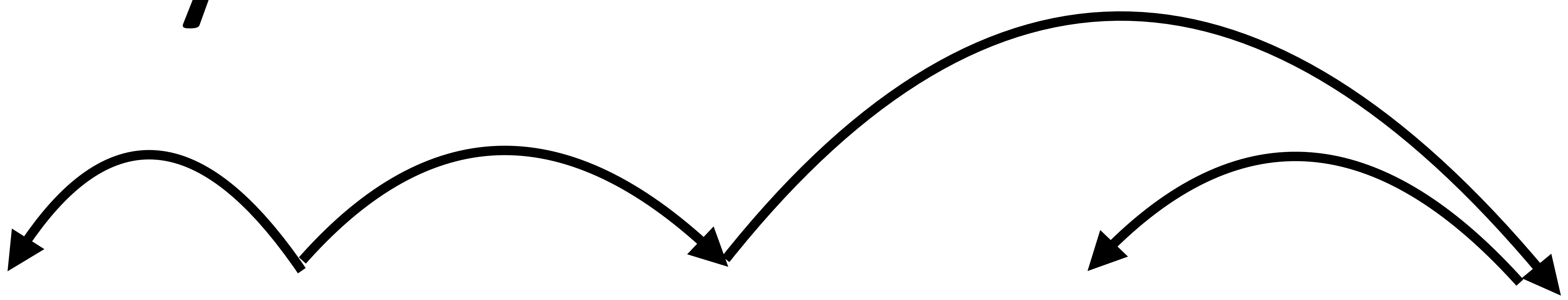
CS388: Natural Language Processing

Lecture 17: Syntax II: Dependency Parsing



Greg Durrett

TEXAS

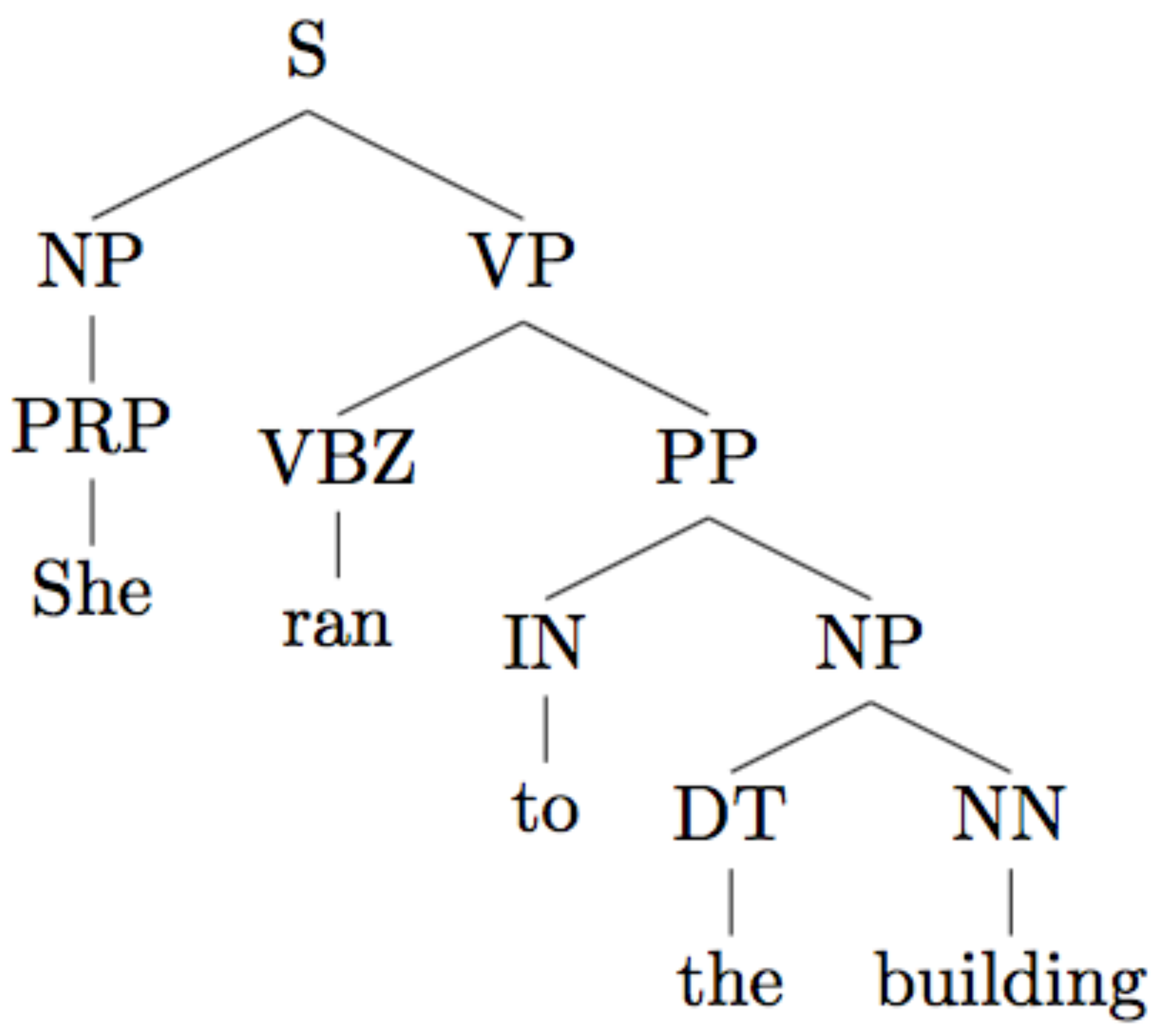
The University of Texas at Austin

Administrivia

- Project 3 graded soon

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

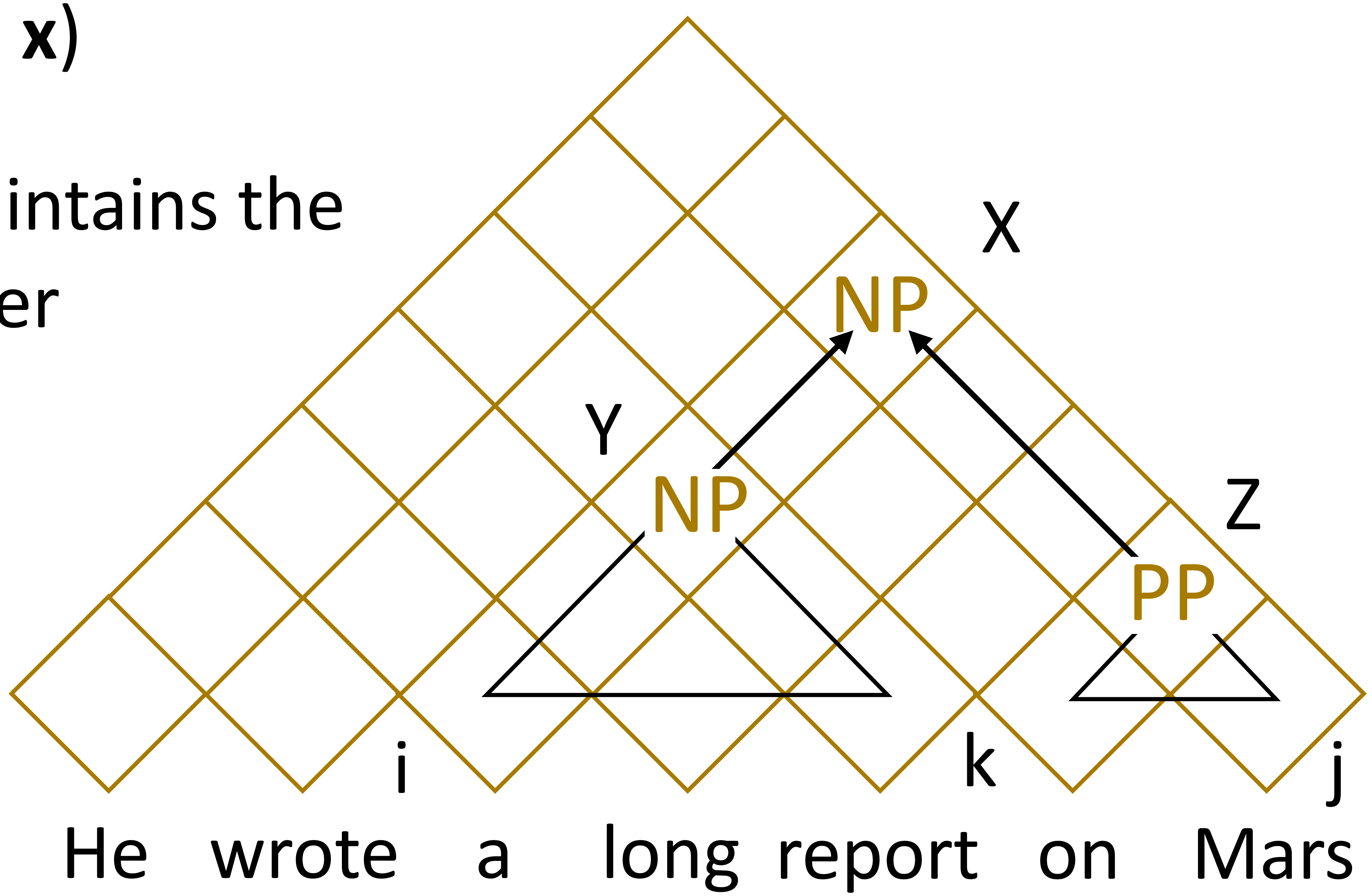
- Context-free grammar: symbols which rewrite as one or more symbols
- Lexicon consists of "preterminals" (POS tags) rewriting as terminals (words)
- CFG is a tuple (N, T, S, R): N = nonterminals, T = terminals, S = start symbol (generally a special ROOT symbol), R = rules
- PCFG: probabilities associated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

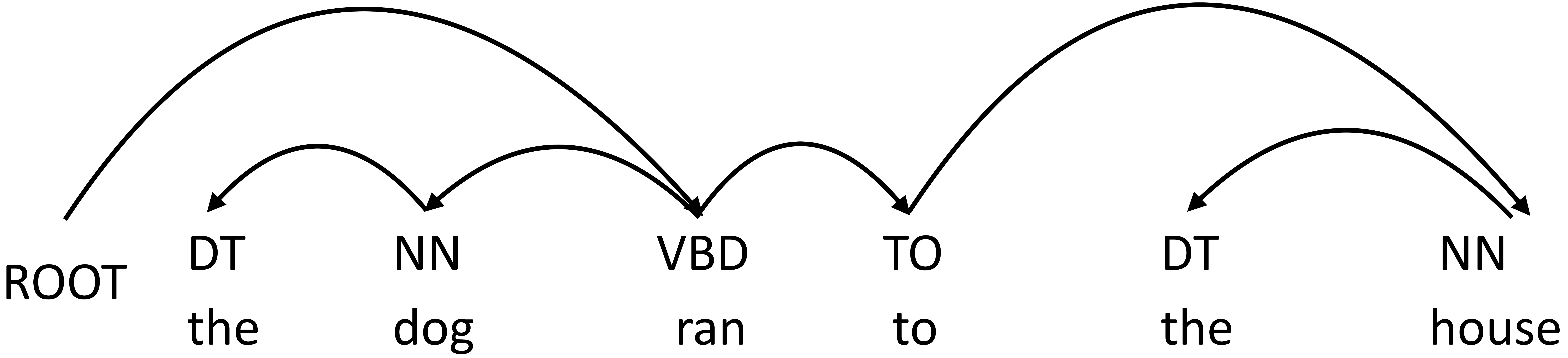
Outline

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

Dependency Representation

Dependency Parsing

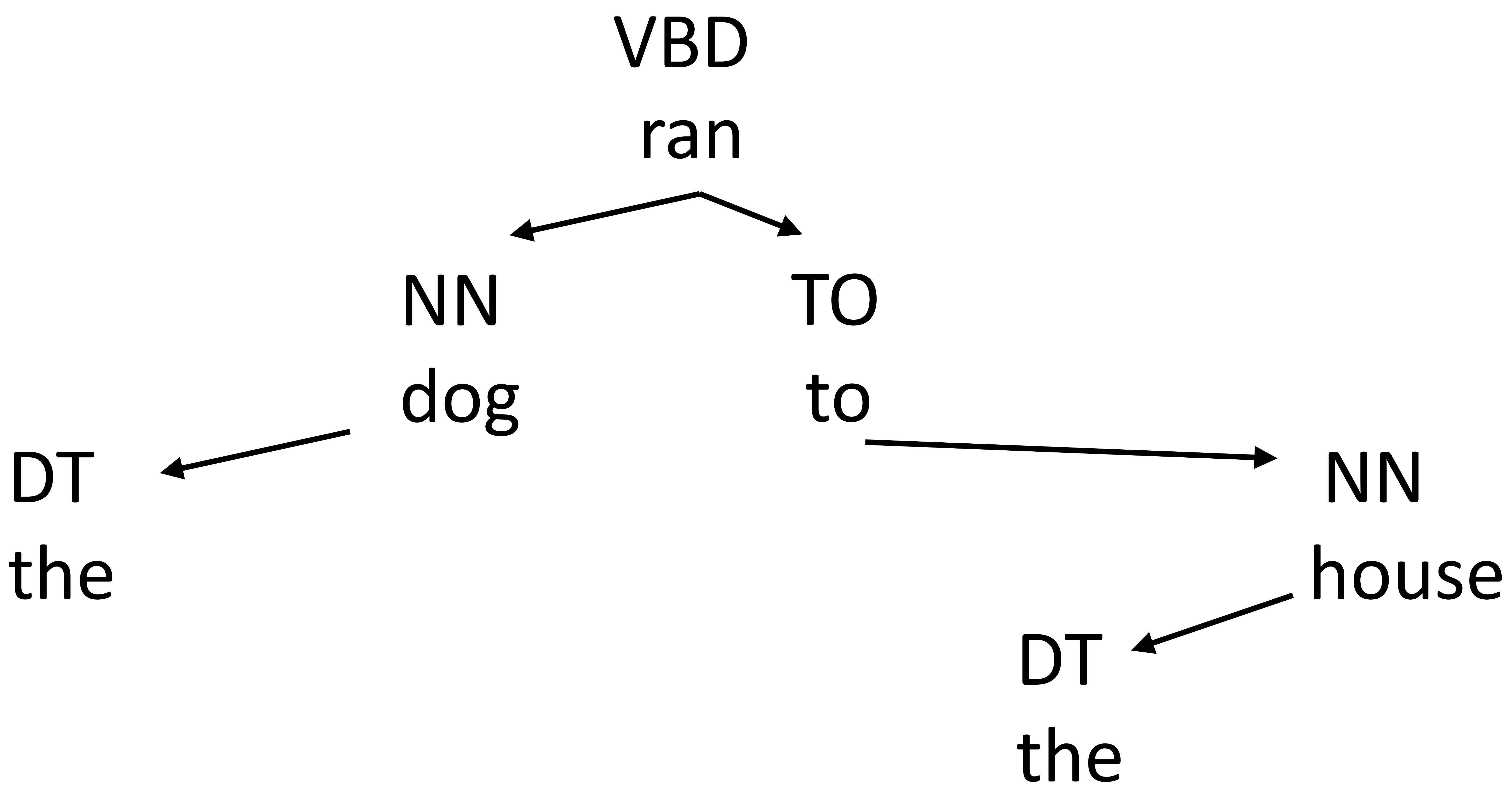
- Dependency syntax: syntactic structure is defined by these arcs
  - Head (parent, governor) connected to dependent (child, modifier)
  - Each word has exactly one parent except for the ROOT symbol, dependencies must form a directed acyclic graph



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

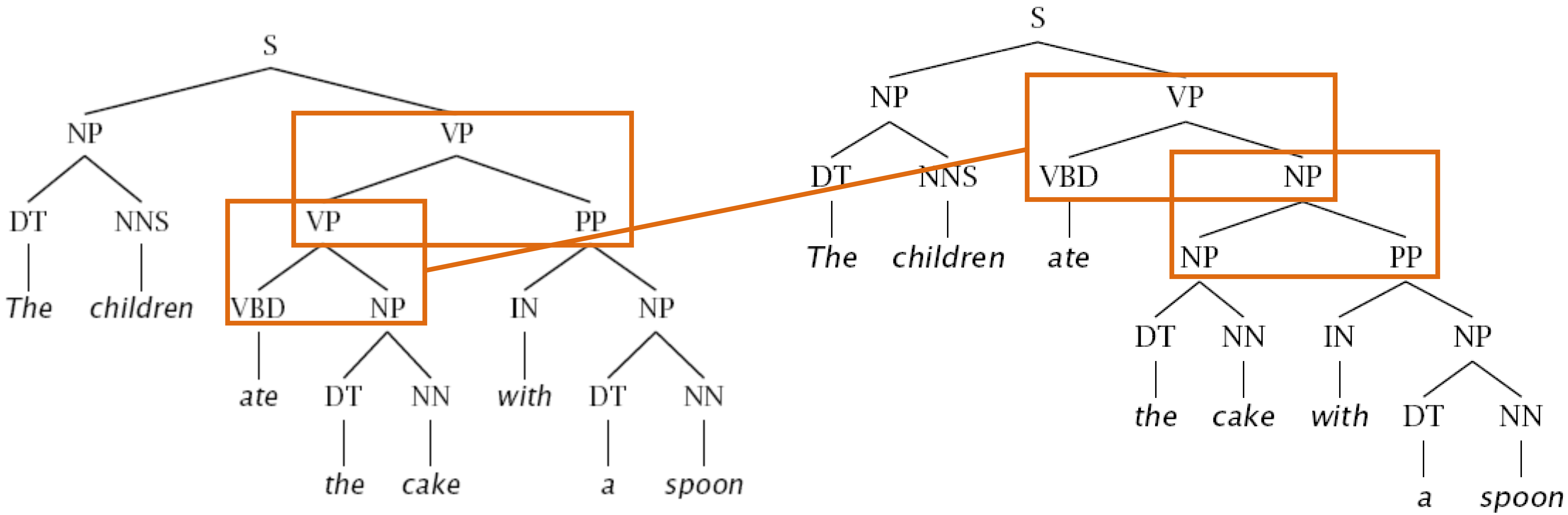
Dependency Parsing

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



Dependency vs. Constituency: PP Attachment

- Constituency: several rule productions need to change



Dependency vs. Constituency: PP Attachment

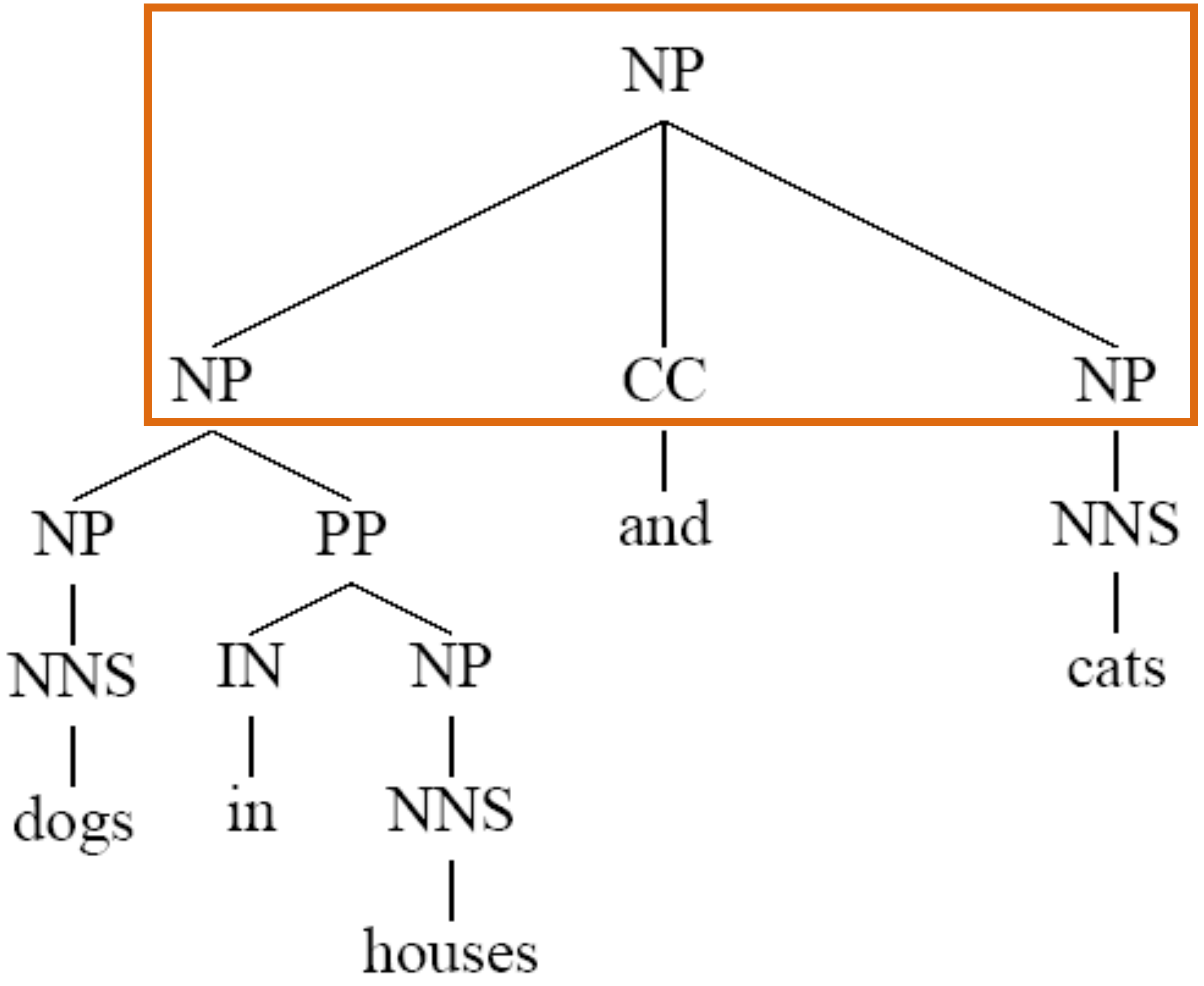
- Dependency: one word (with) assigned a different parent

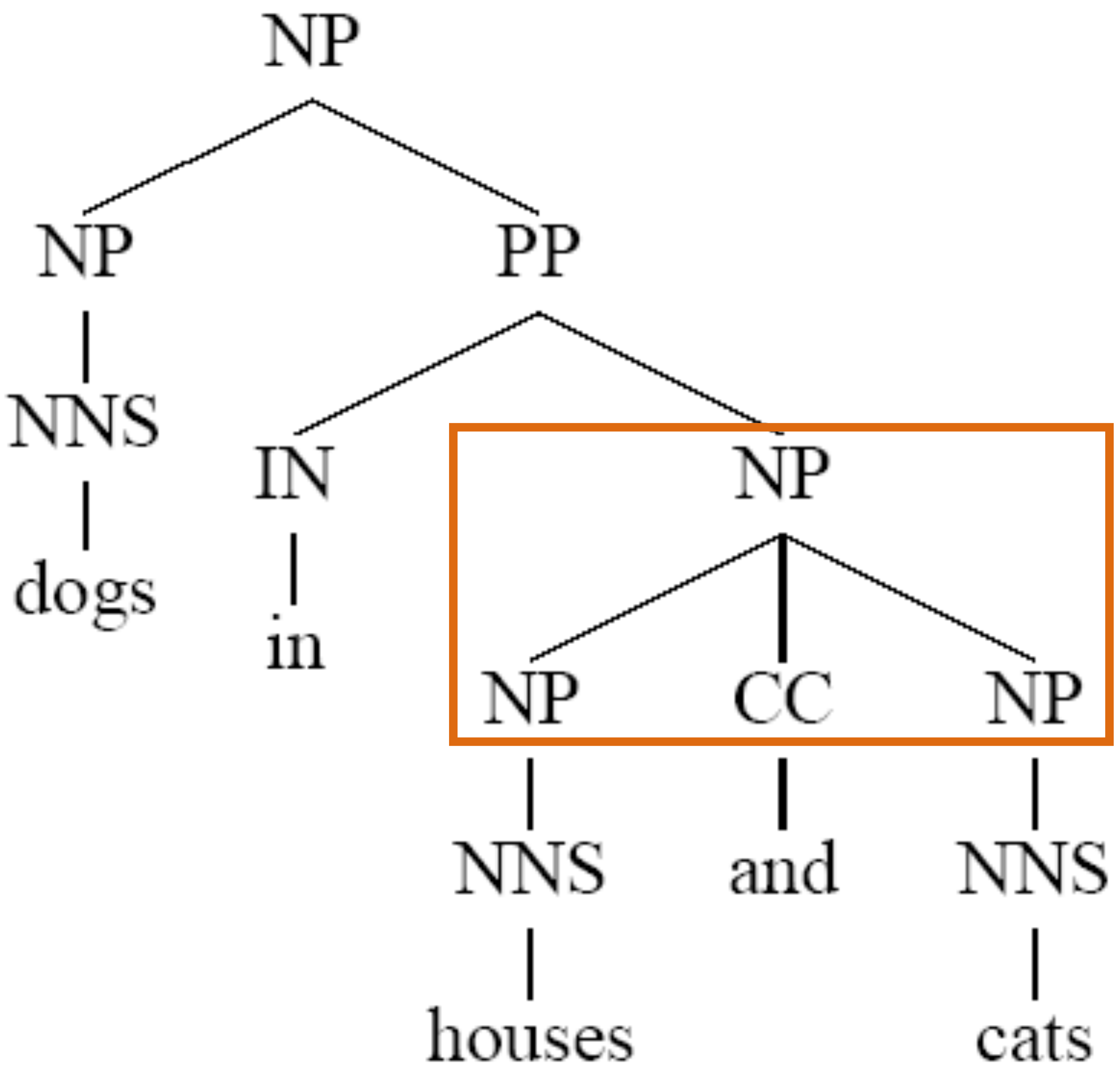
the children ate the cake with a spoon

- 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**

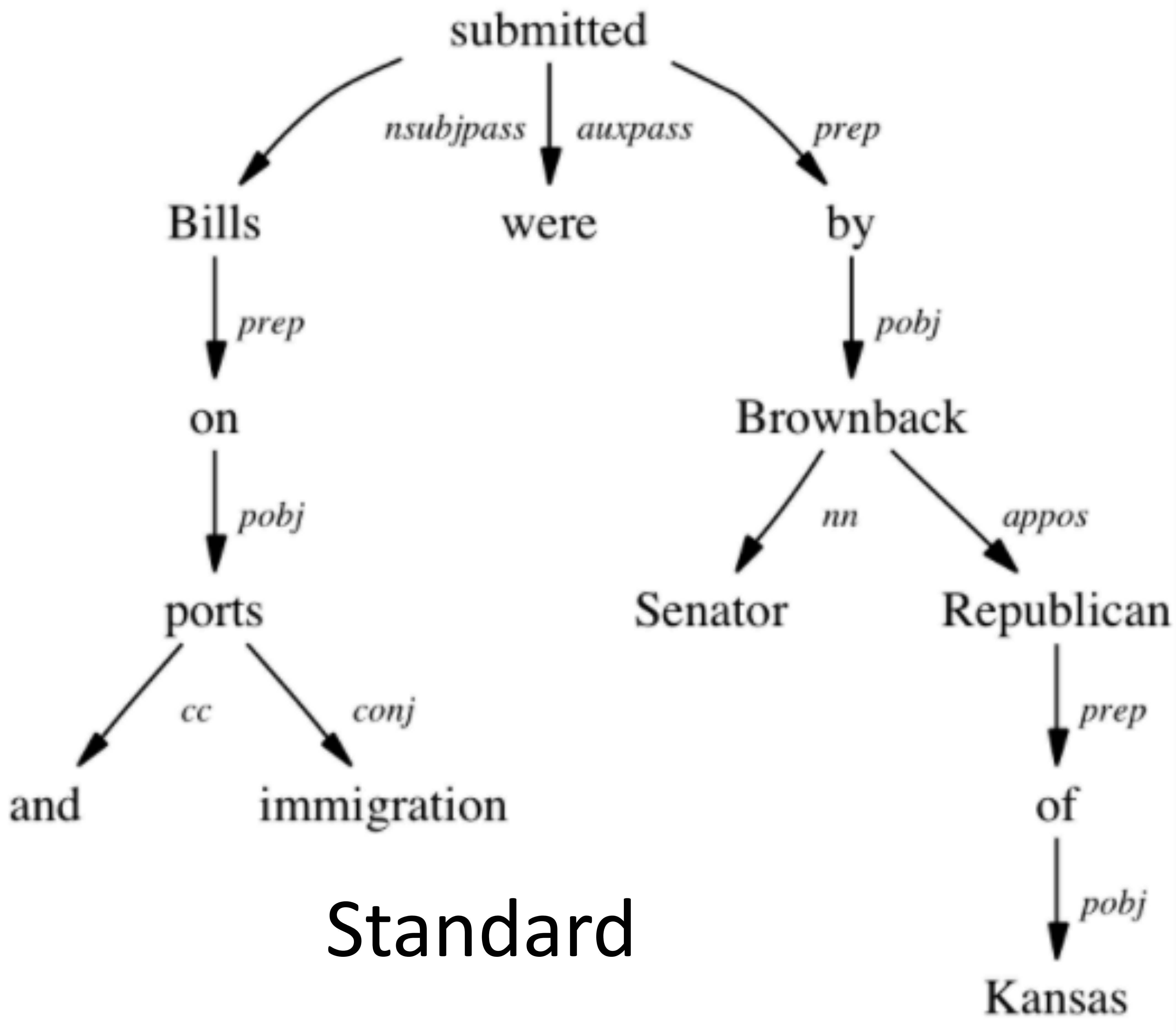
[dogs in houses] and cats dogs in [houses and cats]

- 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

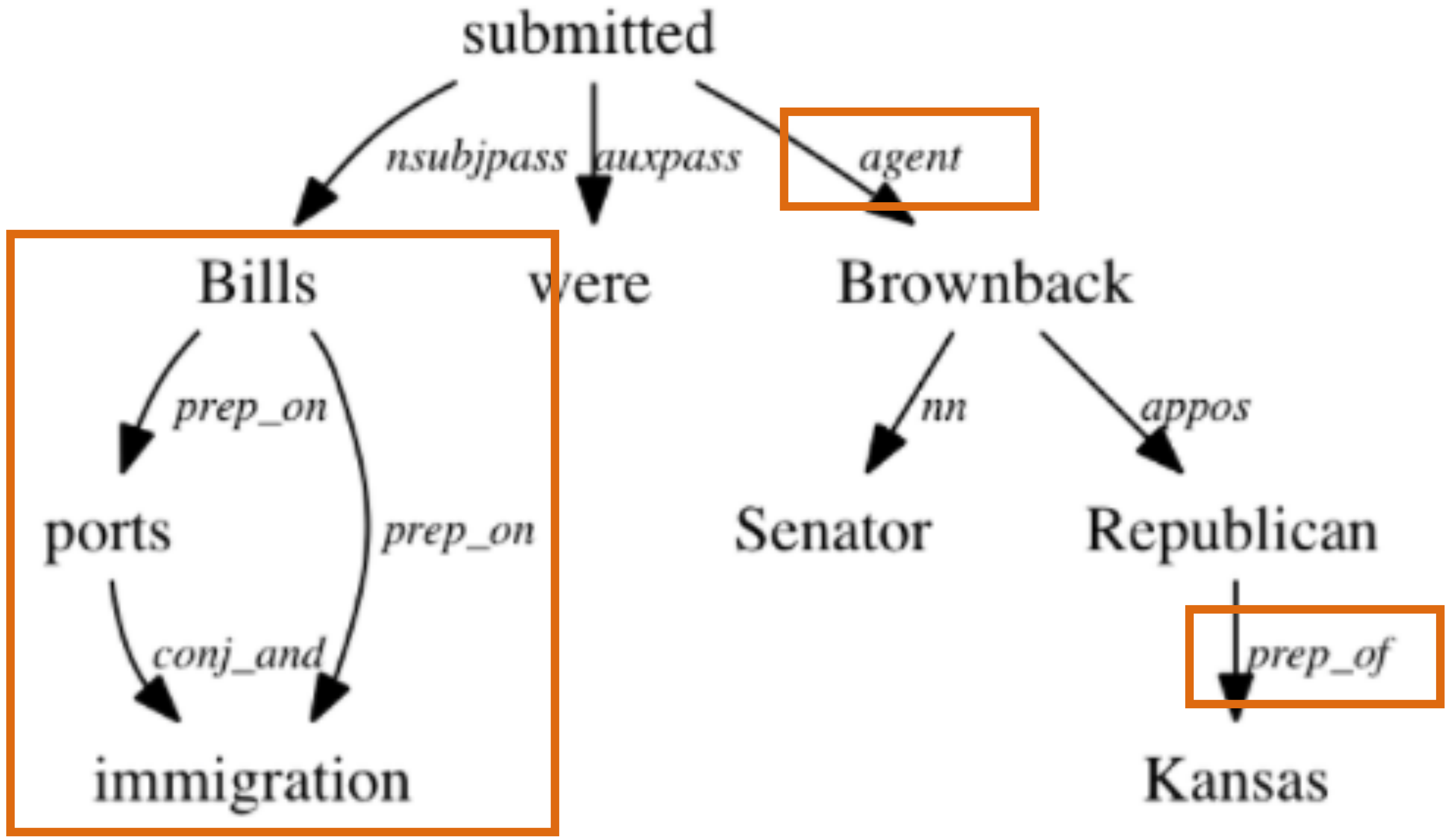
Stanford Dependencies

- 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: Czech was one of the first languages for dep parsing in NLP due to its free word order

Universal Dependencies

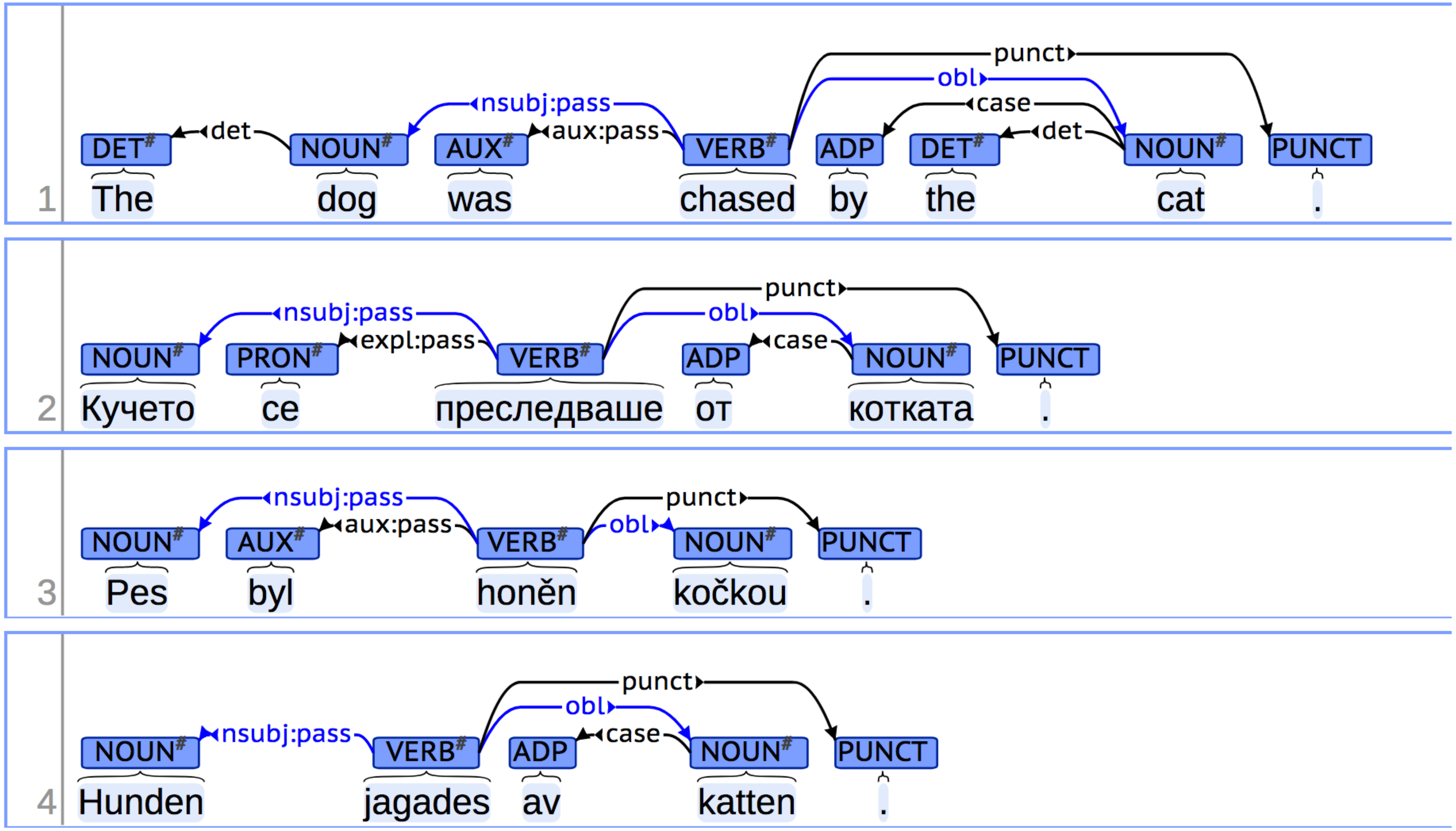
- Annotate dependencies with the same representation in many languages

English

Bulgarian

Czech

Swiss



http://universaldependencies.org/

Graph-Based Parsing

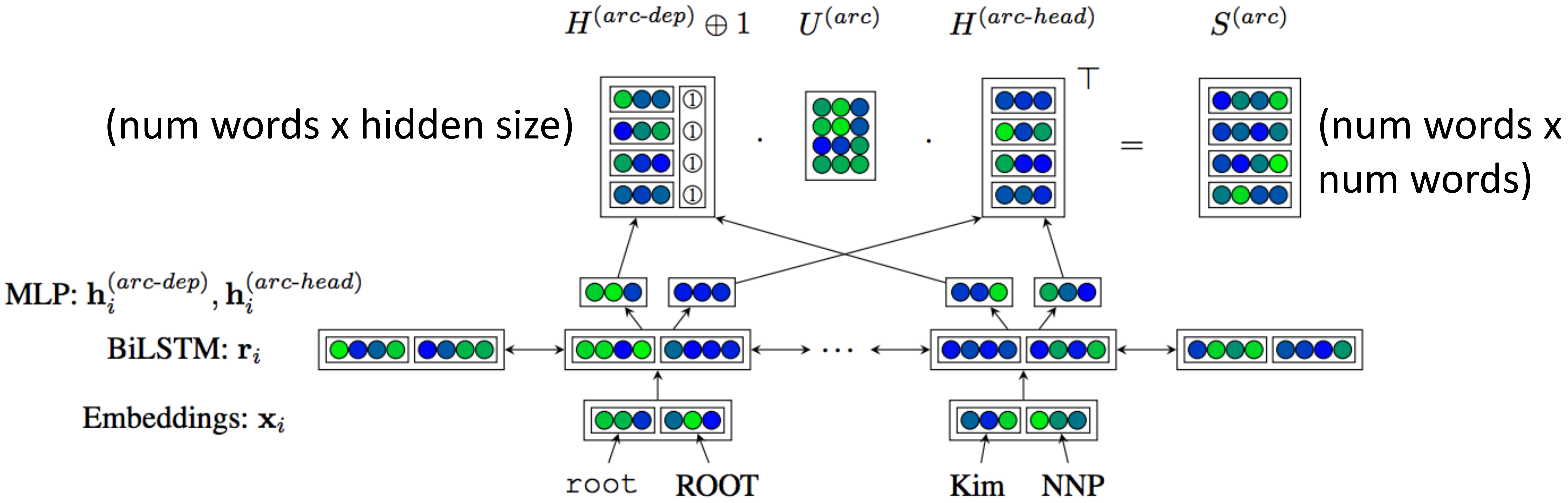
Defining Dependency Graphs

- 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*, parent(*i*), **x**) = $p^{\mathsf{T}}Uc$

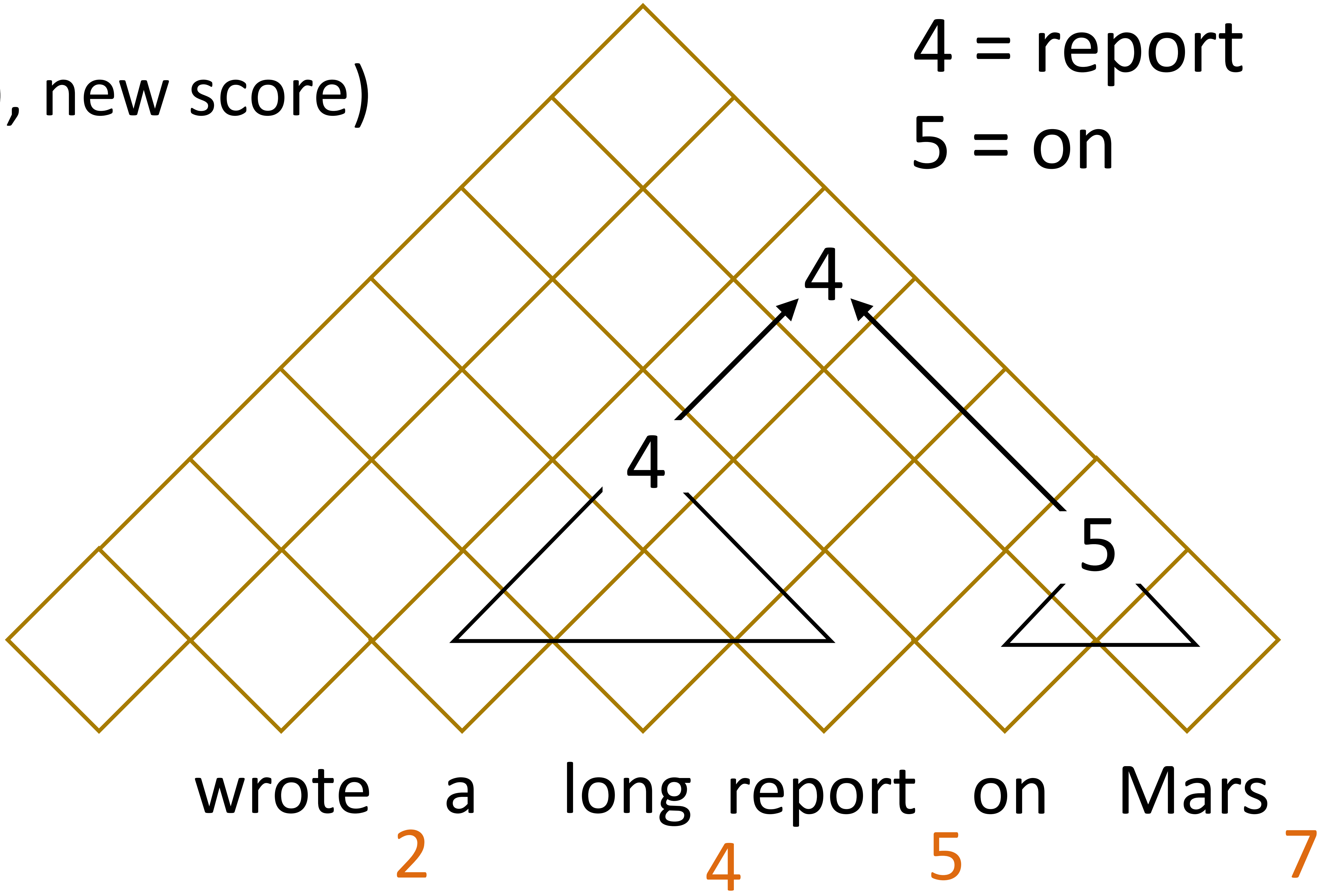


LSTM looks at words and POS

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

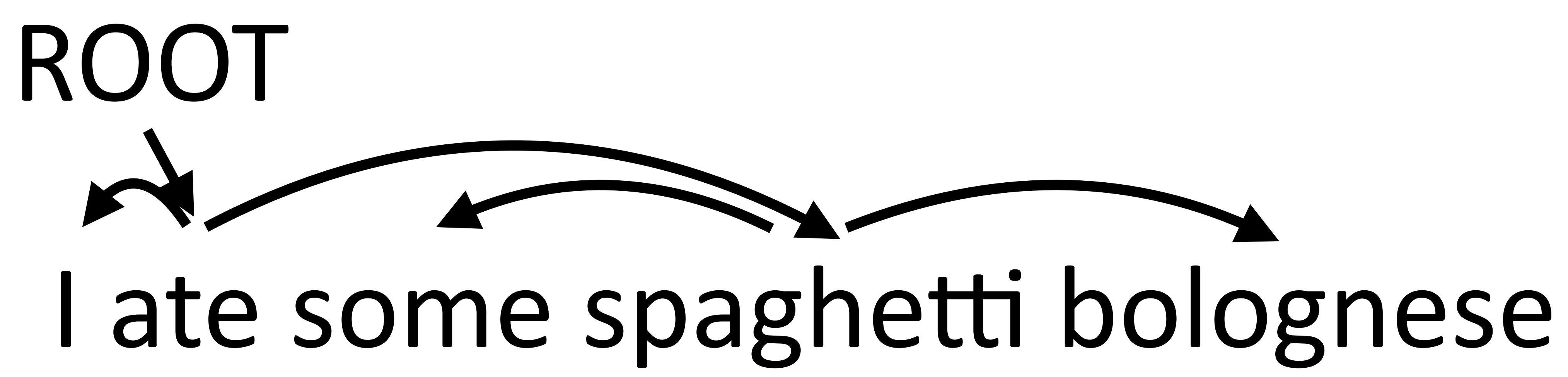
- UAS: unlabeled attachment score. Accuracy of choosing each word's parent (*n* decisions per sentence)
- LAS: additionally consider label for each edge
- Log-linear CRF parser, decoding with Eisner algorithm: 91 UAS
- Higher-order features from Koo parser: 93 UAS
- Best English results with neural CRFs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

Shift-Reduce Parsing

Shift-Reduce Parsing

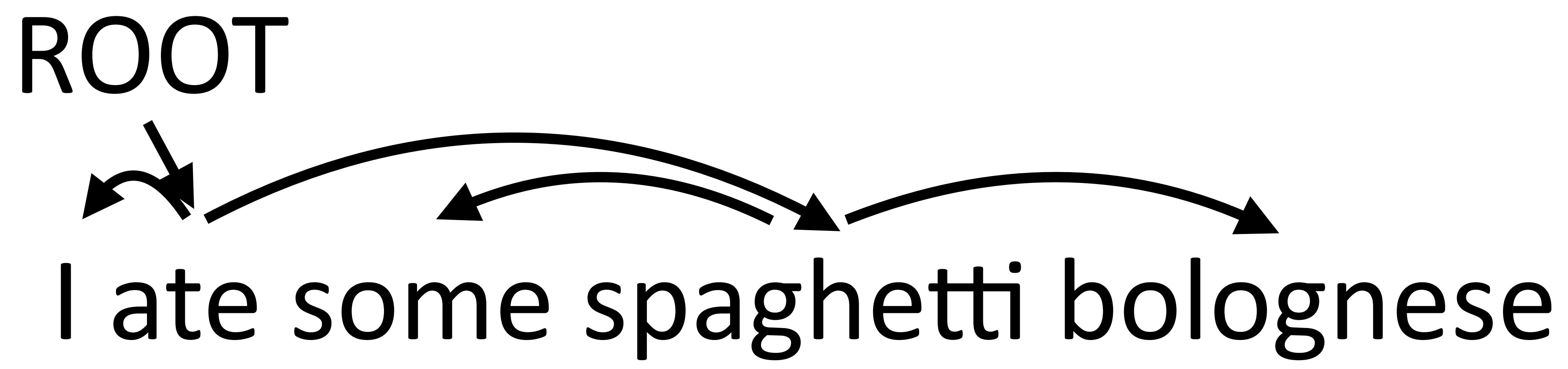
- Similar to deterministic parsers for compilers
  - Also called transition-based parsing
- A tree is built from a sequence of incremental decisions moving left to right through the sentence
- Stack containing partially-built tree, buffer containing rest of sentence
- Shifts consume the buffer, reduces 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 σ denote the stack, $\sigma | w_{-1}$ = stack ending in w_{-1}
  - "Pop two elements, add an arc, put them back on the stack"

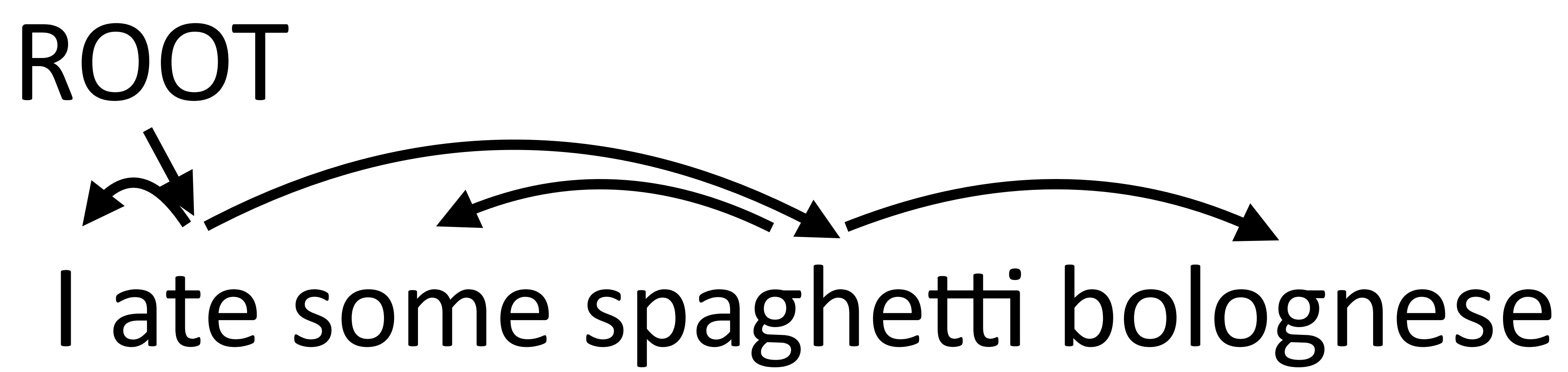
$$\boxed{\sigma | w_{-2}, w_{-1}} \rightarrow \boxed{\sigma | w_{-1}}$$ w_{-2} is now a child of w_{-1}

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

$\downarrow$

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

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] [I ate some spaghetti bolognese]

$\boxed{S}$

[ROOT I] [ate some spaghetti bolognese]

$\boxed{S}$

[ROOT I ate] [some spaghetti bolognese]

$\boxed{L}$

[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

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] — I

S

[some spaghetti bolognese]

S

[ROOT ate some spaghetti] — I

[bolognese]

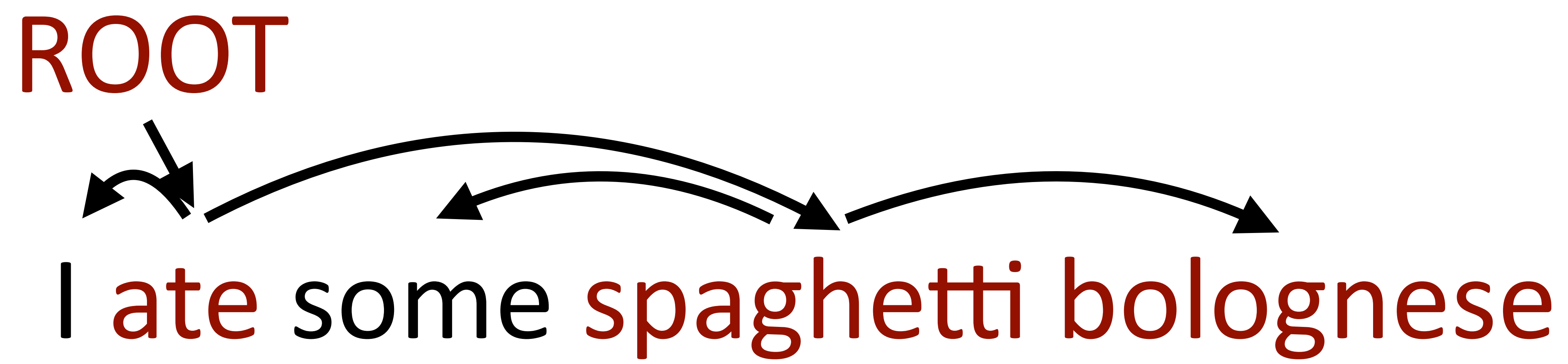
L

[ROOT ate spaghetti] — I, some

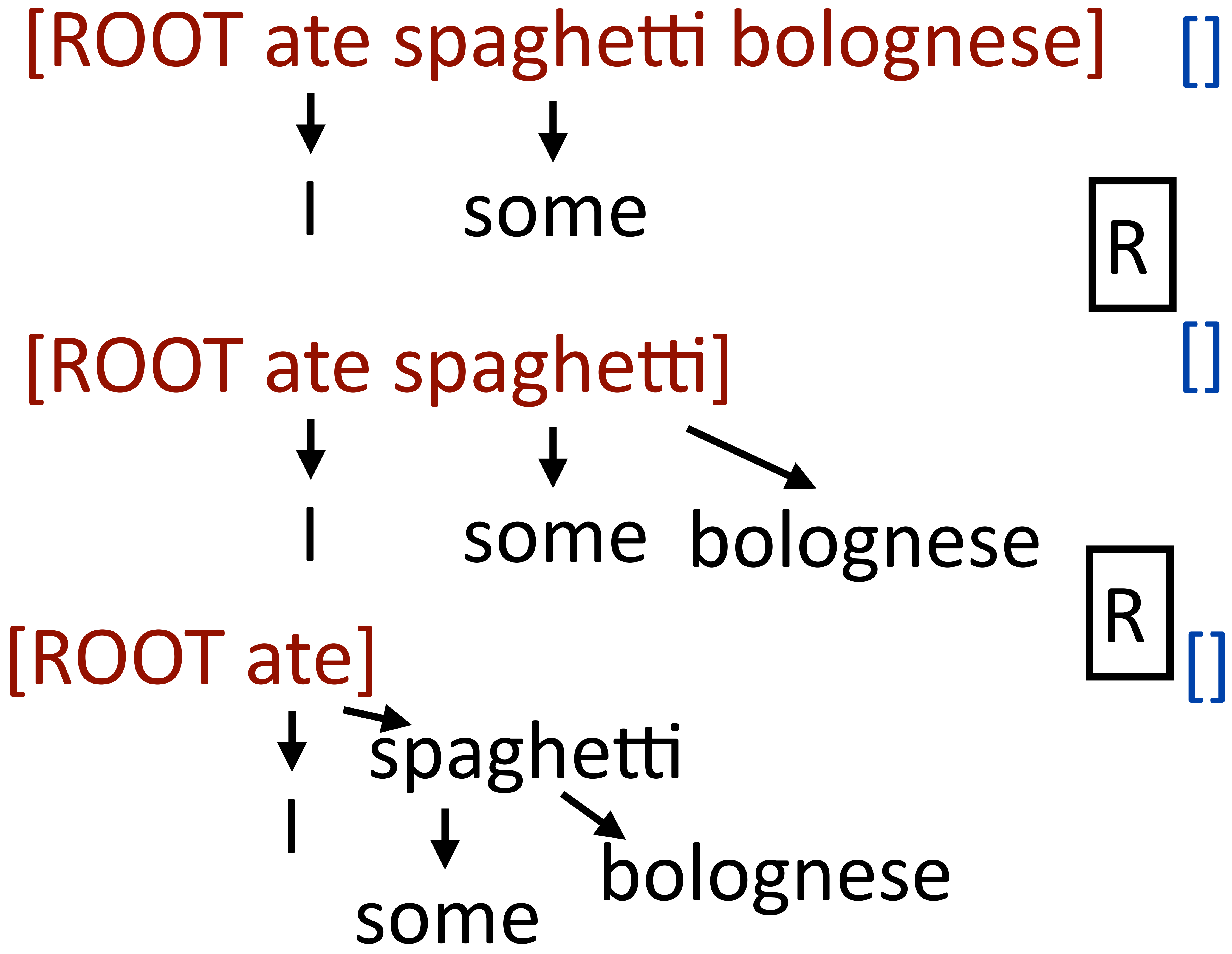
[bolognese]

S

Arc-Standard Parsing

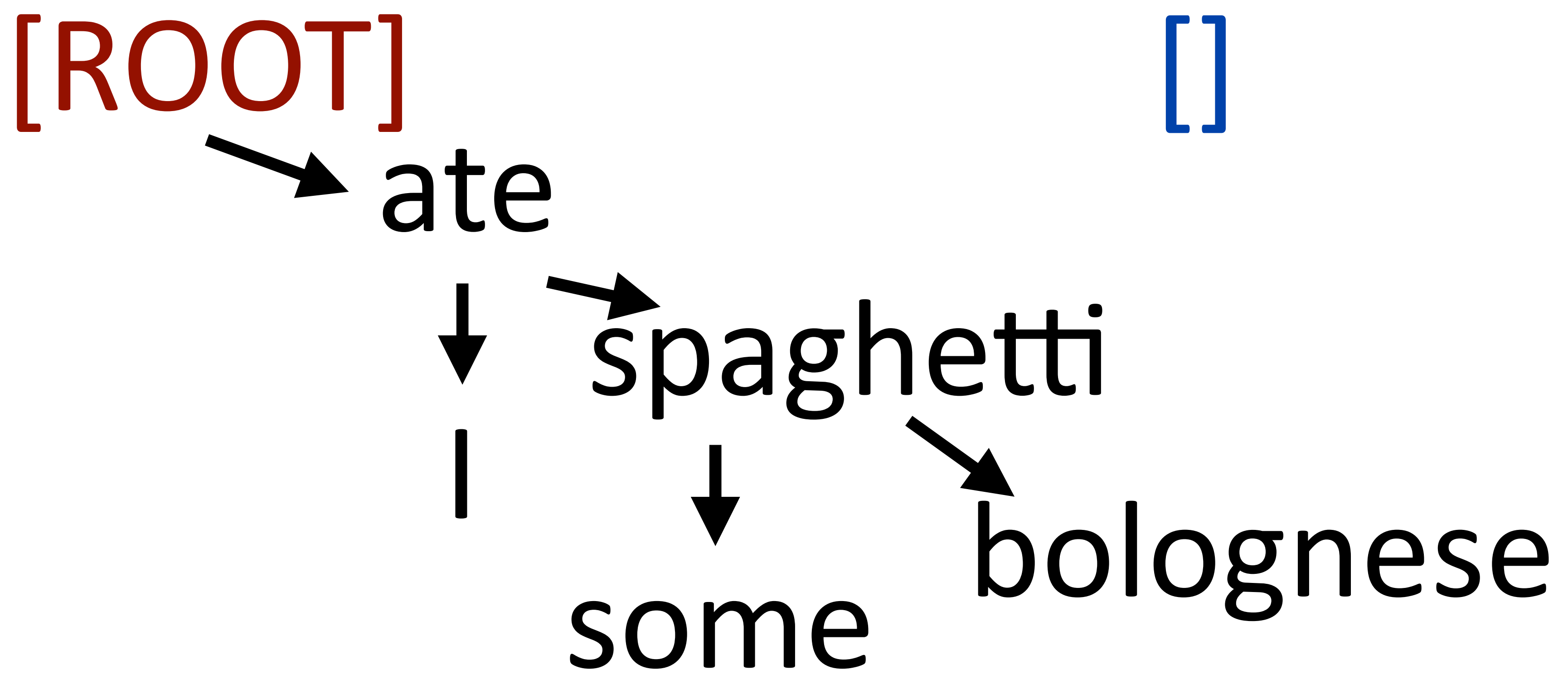


S	top of buffer -> top of stack
LA	pop two, left arc between them
RA	pop two, right arc between them



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

Final state:



Building Shift-Reduce Parsers

[ROOT] [I ate some spaghetti bologenese]

- 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?

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

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]　　　[bolognese]

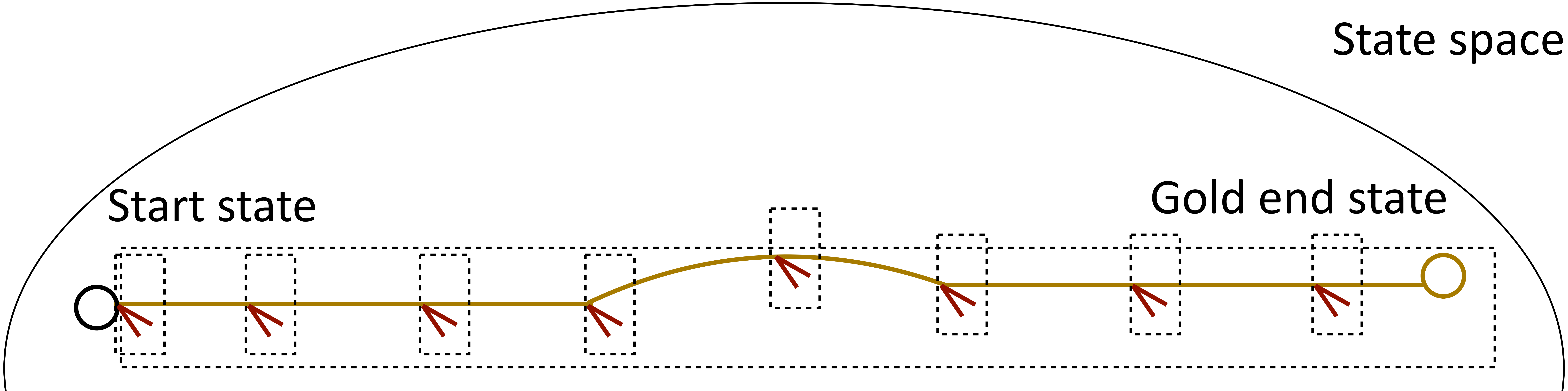
↓

I

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

- 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

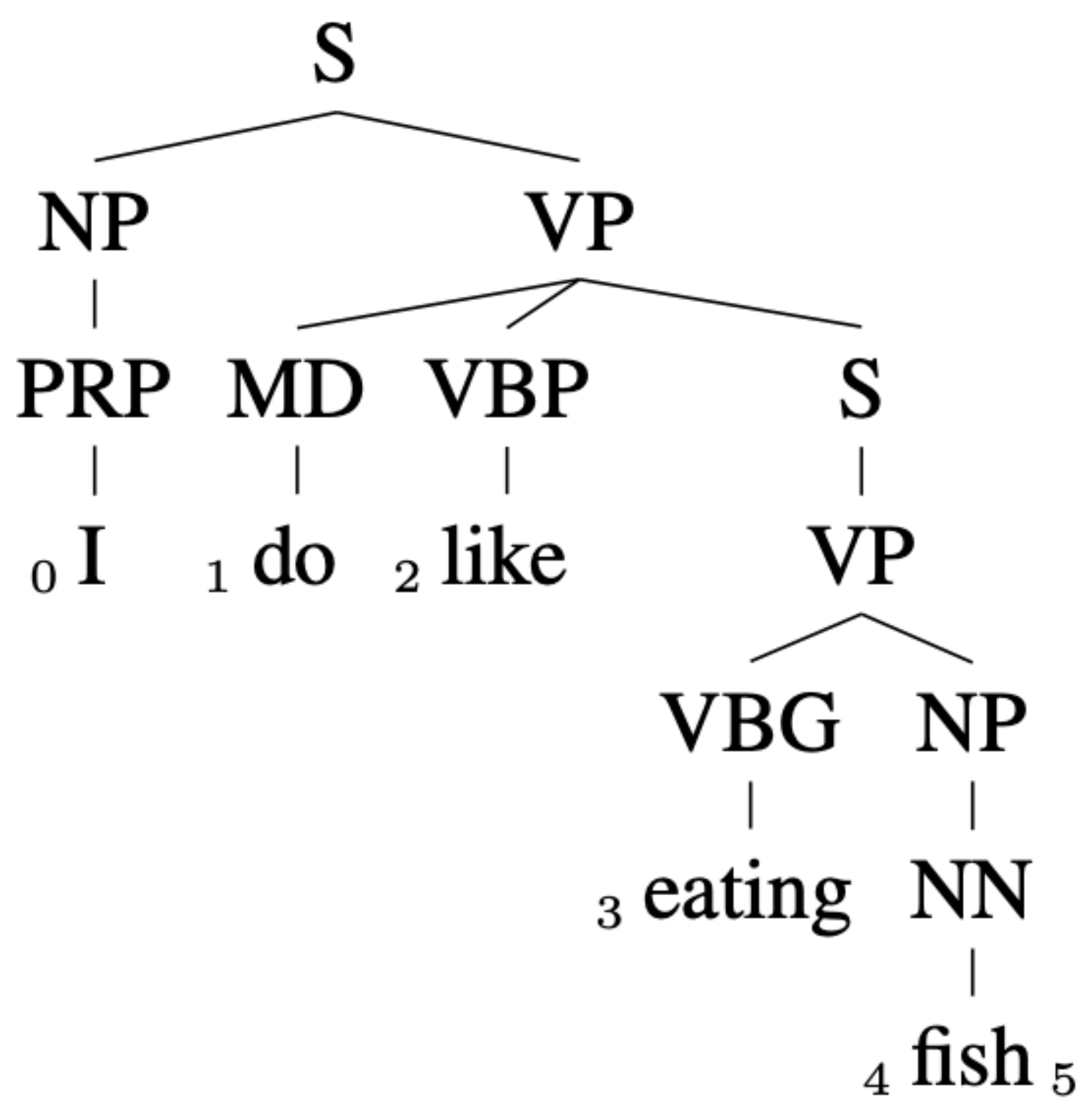
Speed Tradeoffs

	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)

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

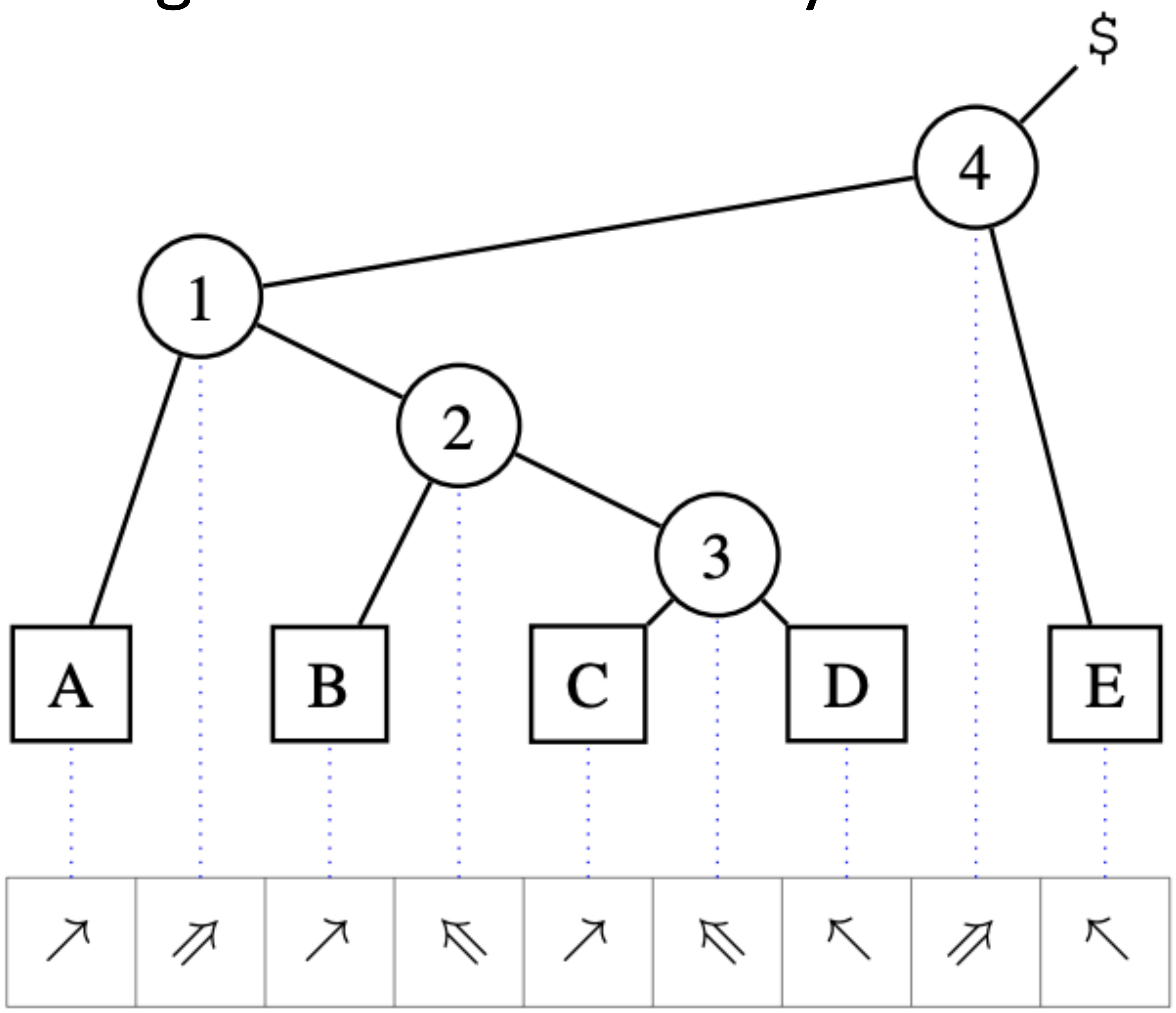
combine with no label for ternary rules

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

Cross and Huang (2016)

Shift-Reduce Constituency

- "Tetra tagging": four possible tags to get unlabeled binary trees



- "↗": This terminal node is a left-child.
- "↖": This terminal node is a right-child.
- "⇗": The shortest span crossing this fence-post is a left-child.
- "⇖": The shortest span crossing this fence-post is a right-child.

	Sents/s	Hardware	F1
Vilares et al. (2019)	942	1x GPU	91.13
Kitaev et al. (2019)*	39	1x GPU	95.59
Zhou and Zhao (2019)*	–	–	95.84
This work*	1200	1x TPU v3-8	95.44

Kitaev and Klein (2020)

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:

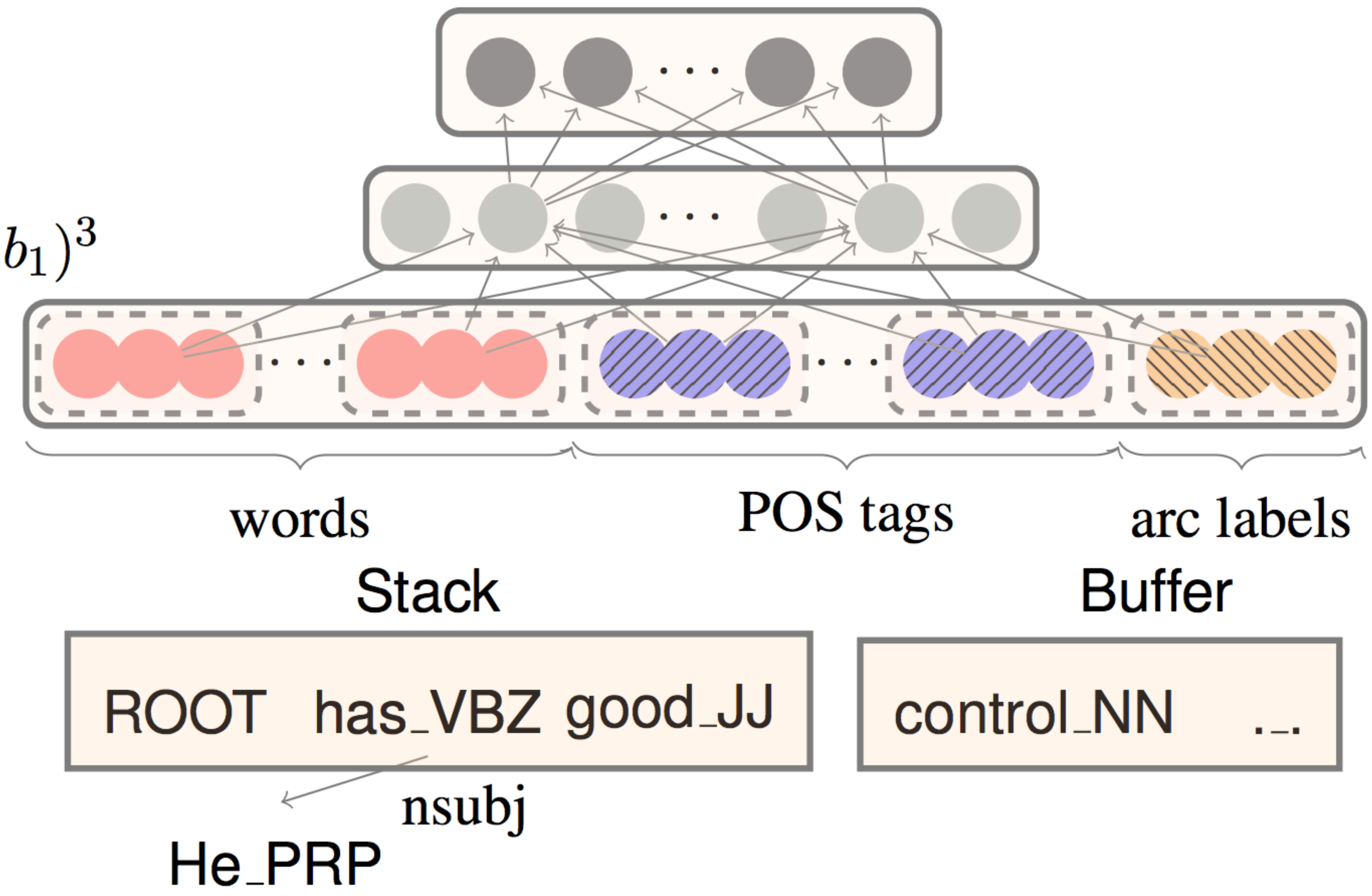
$$p = \mathtt{softmax}(W_2 h)$$

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



Danqi Chen and Manning (2014)

Parsey McParseFace (a.k.a. SyntaxNet)

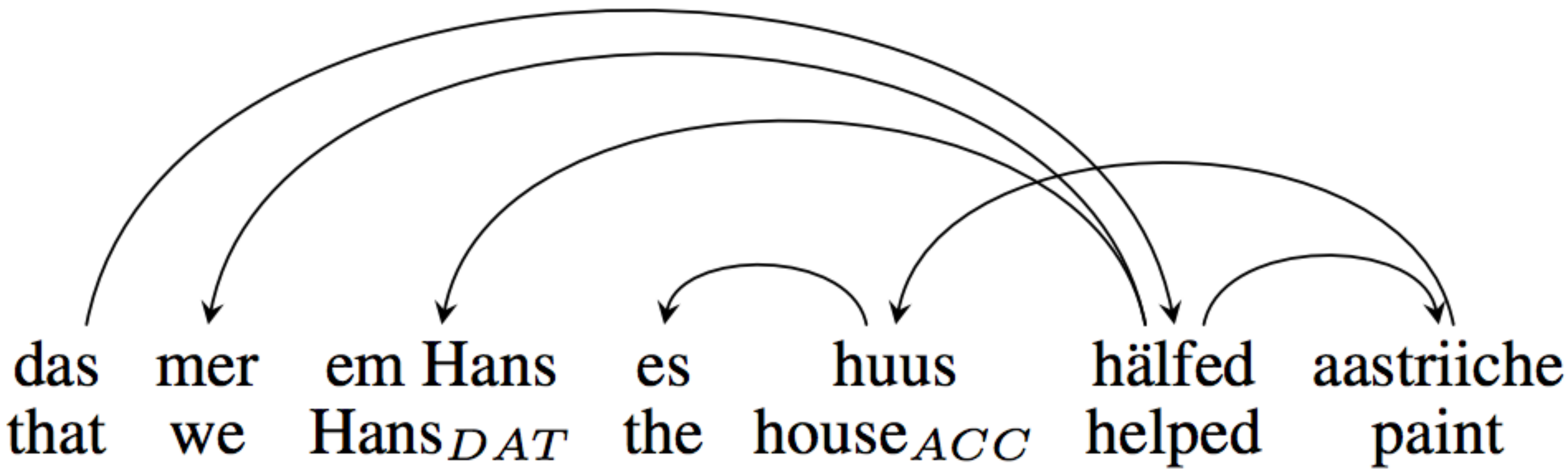
- 94.61 UAS on the Penn Treebank using a global transition-based system with early updating (compared to 95.8 for Dozat, 93.7 for Koo in 2009)
  - Additional data harvested via "tri-training", form of self-training

- 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)

Challenges in other languages

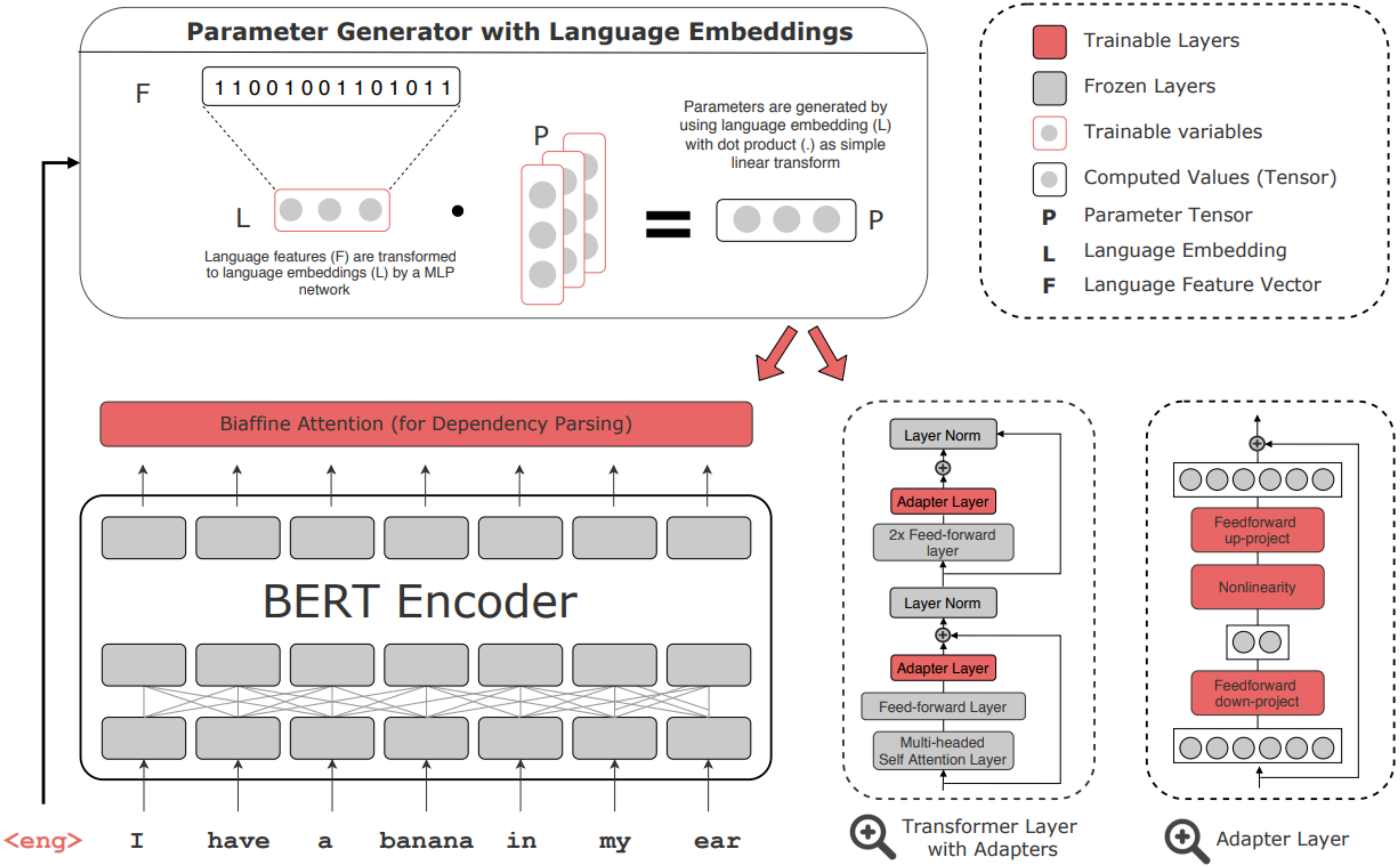


- Swiss German example: note that the arcs cross, unlike in our English examples, which were almost entirely projective
- (Swiss German also has famous non-context-free constructions)
- As a result: some different transition-based algorithms are needed

credit: Pitler et al. (2013)

Multilingual Parsing

- Interest in multilingual dependency parsing as far back as CoNLL 2006 shared task
- Now: can parse many languages with one pre-trained model



Üstün et al. (2020)

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?

Recap

- Shift-reduce parsing can work nearly as well as graph-based
- Arc-standard system for transition-based parsing
- Strong learning-based parsers, including multilingual parsers