CS769 Advanced NLP

Syntactic Parsing I: Constituency Grammar

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Slides adapted from Bob, Hao, Dan

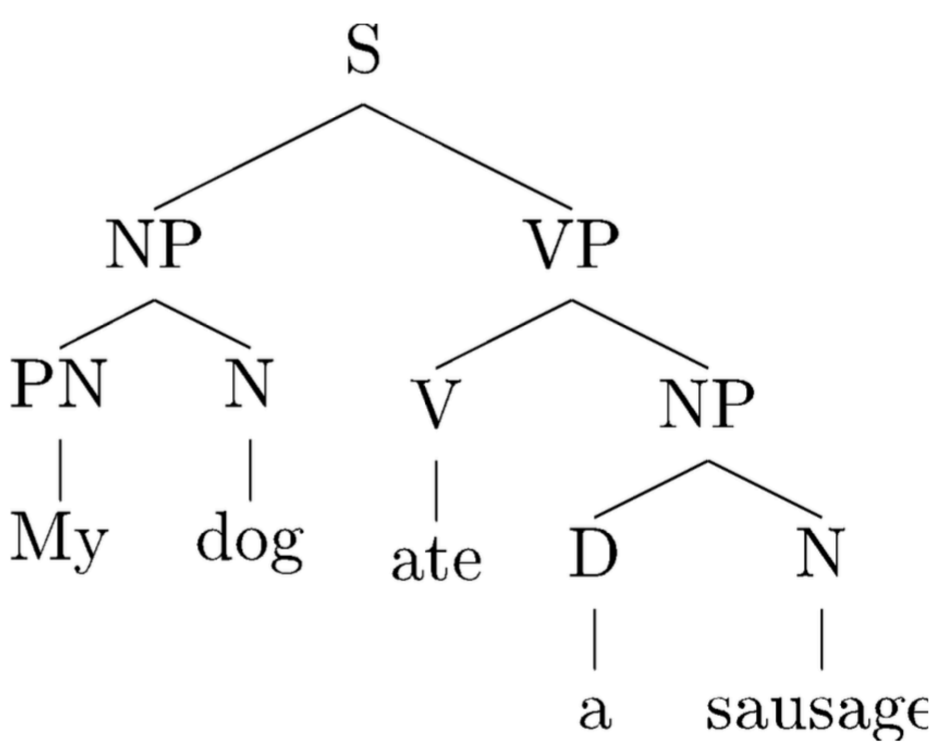
https://junjiehu.github.io/cs769-spring23/

Goals for Today

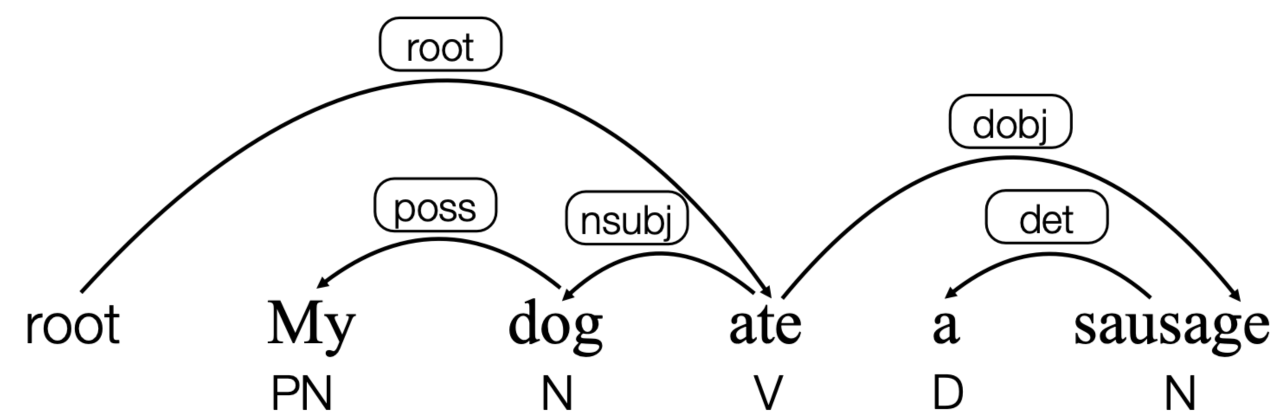
- Syntactic Parsing
- Probabilistic Context-Free Grammar (PCFG)
- **Supervised PCFG** (**Generative**)
- **CYK Decoding Algorithm**
- **Supervised Span-based Neural Models** (**Discriminative**)
- **Unsupervised** Parsing (Grammar Induction)

Syntactic Parsing

- The process of predicting **syntactic representations**
- Two types of linguistic structures:



Constituency (aka phrase structure) tree:
Focus on the structure of the sentence

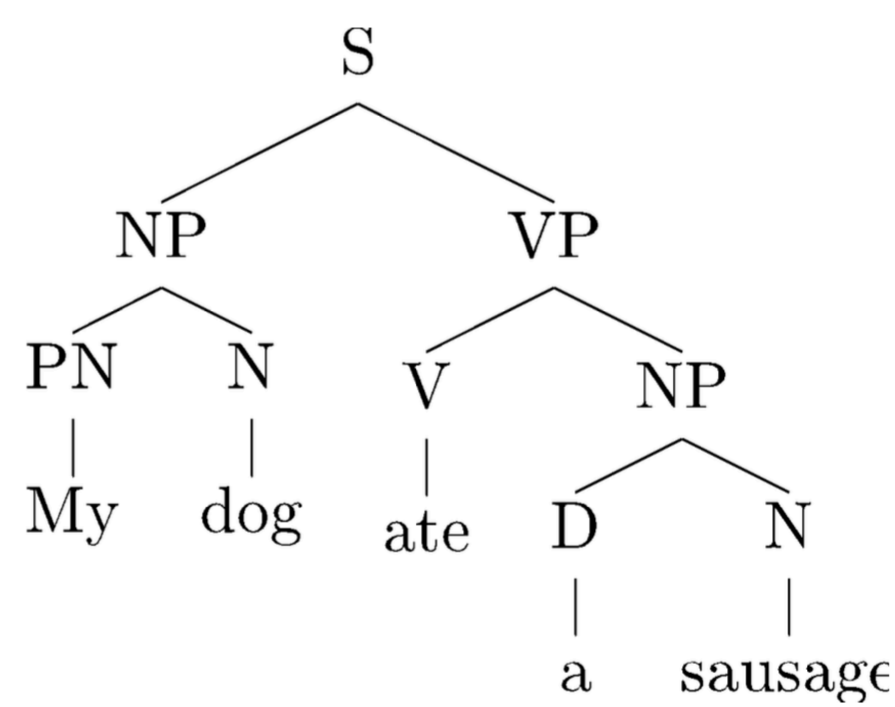


Dependency tree:
Focus on relations between words

Constituency Trees

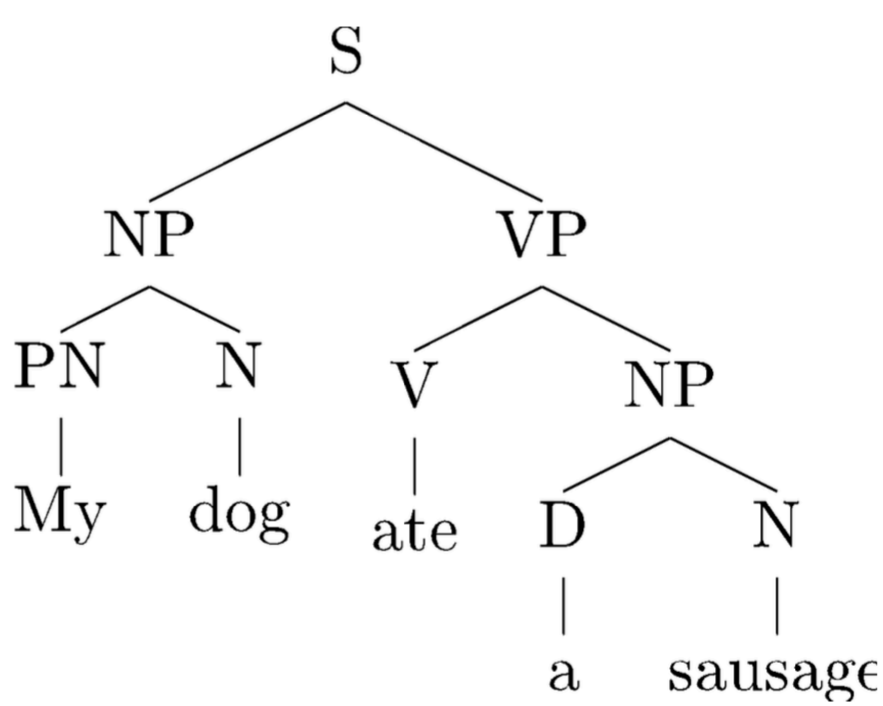
- Internal nodes (or non-terminals) correspond to phrases
  - S: a sentence
  - NP (noun phrase): My dog, a sandwich, …
  - VP (verb phrase): ate a sausage, …
  - PP (prepositional phrases): with a friend, in a car, …

- Nodes immediately above words are part-of-speech tags (or preterminals).
  - PN: pronoun
  - D: determiner
  - V: verb
  - N: noun
  - P: preposition



Bracketing notation

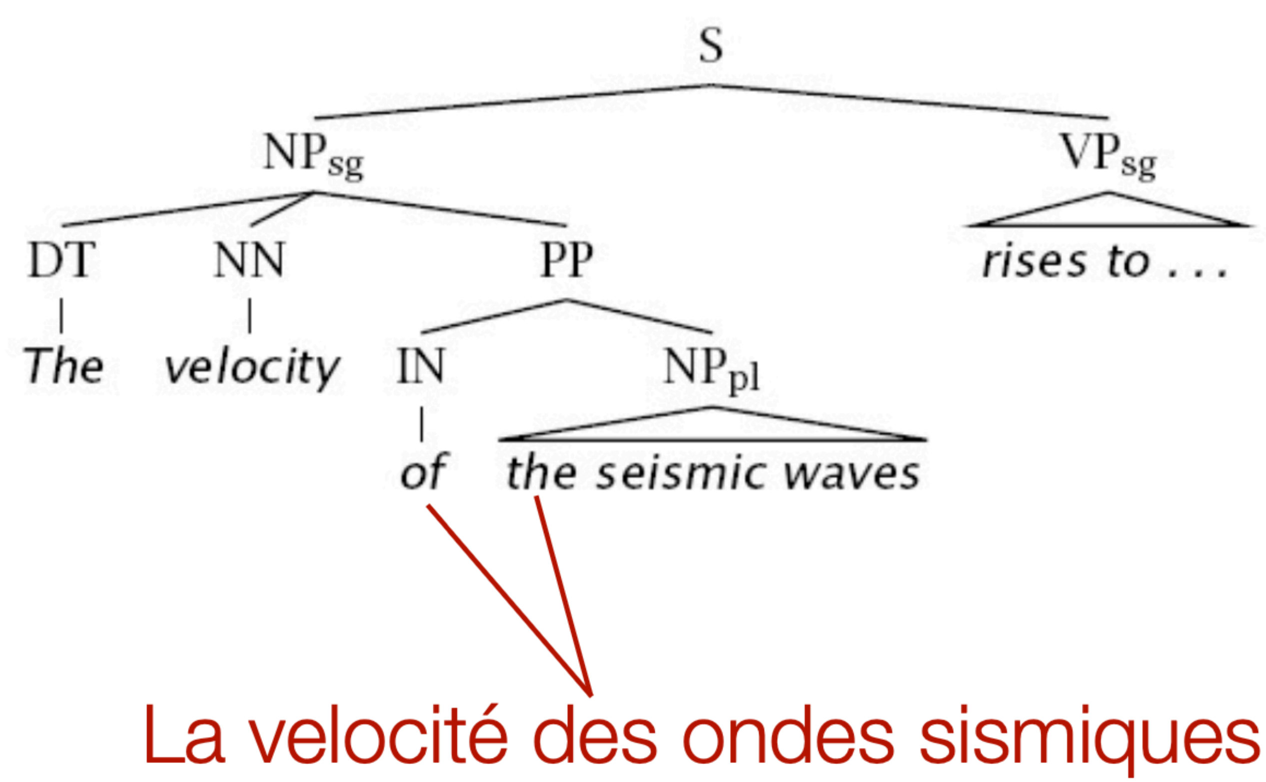
- Often convenient to represent a tree as **a bracketed sequence**:
- In principle, constituency tree can be an n-nary tree, however, it is easy to convert it to a binary tree (by adding a null non-terminal Ø). By convention, we often just represent the structure as a binary tree.




```
(S
   (NP (PN My) (N dog) )
   (VP (V ate)
      (NP (D a) (N sausage) )
   )
)
```

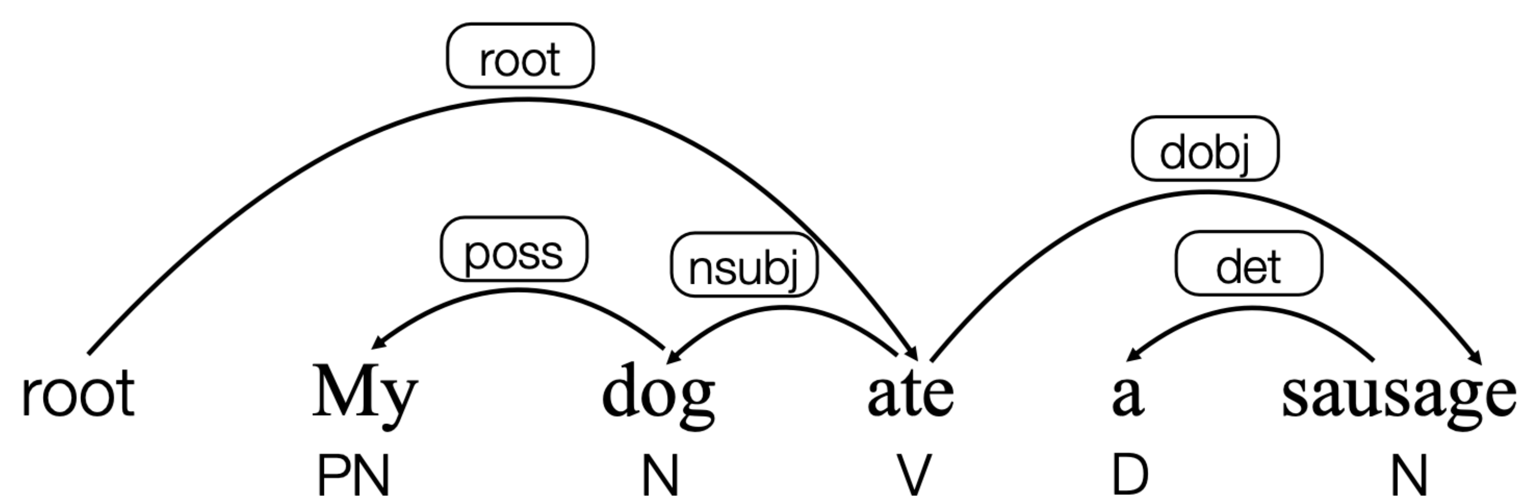
Constituency is not always clear

- Coordination:
  - Example: He went to and came from the store.
- Phonological reduction:
  - I will go → I'll go
  - I want to go → I wanna go
  - A le centre → au centre



Dependency Trees

- Nodes are words (along with part-of-speech tags)
- Directed arcs encode syntactic dependencies between words
- Labels are types of relations between words:
    - **root**: root of the tree, usually points to a verb
    - **poss**: possessive
    - **dobj**: direct object
    - **nsub**: (noun) subject
    - **det**: determiner

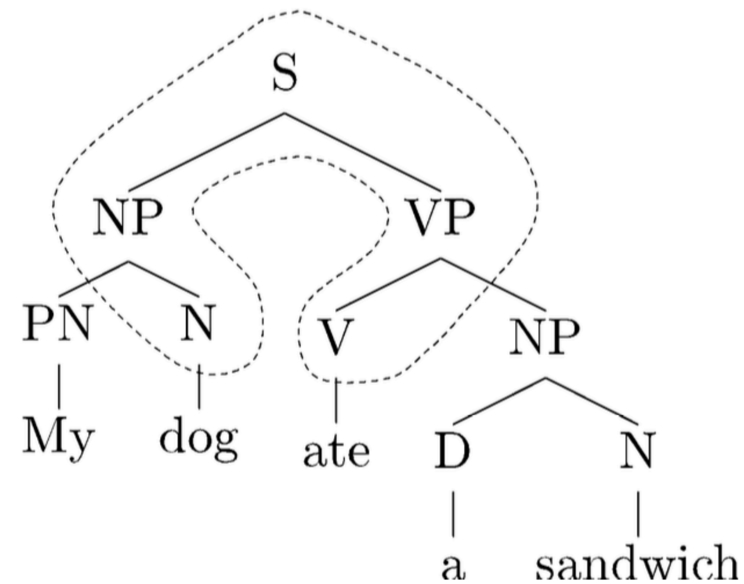


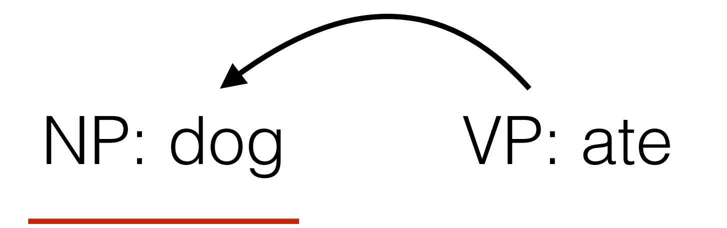
Dependency parsing

- Recover shallow semantics
- Shallow semantic information can be (approximately) derived from syntactic information
  - Subjects (nsubj) are often **agents**: *initiators / doers of an action*
  - Direct objects (dobj) are often **patients**: *affected entities*
- But not always true. Even for agents and patients, consider:
  - Mary is baking a cake in the oven
  - A cake is baking in the oven
- In general, it is not trivial even for the most shallow forms of semantics
  - e.g., prepositions: ***in*** can encode direction, position, temporal information, …

Constituency ↔ Dependency

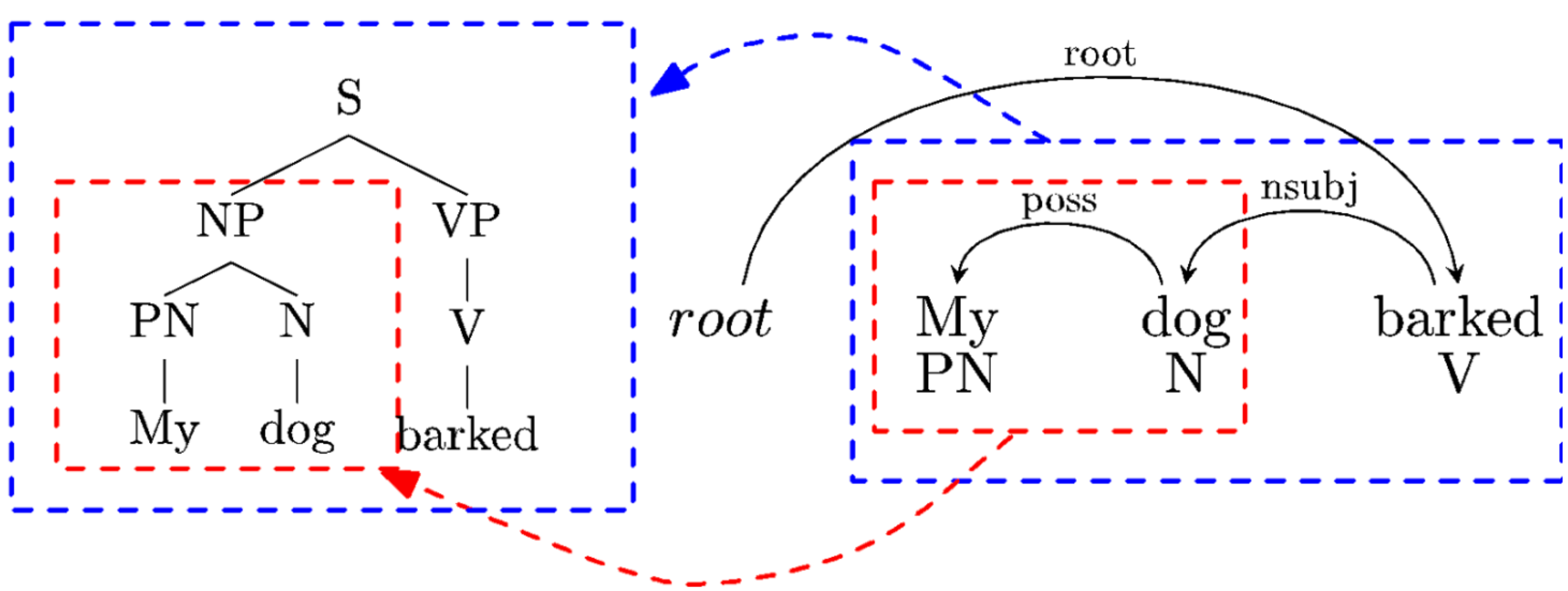
- Constituency trees can (potentially) → dependency trees





Lexicalized non-terminal
w/ head word

- Dependency trees can (potentially) → constituency trees



Context Free Grammar (CFG) & Probabilistic CFG

Context-free grammars (CFG)

- Context-free grammars (CFG): a formalism for parsing.

Grammar (CFG)

ROOT → S

S → NP VP

NP → DT NN

NP → NN NNS

NP → NP PP

VP → VBP NP

VP → VBP NP PP

PP → IN NP

Lexicon

NN → interest

NNS → raises

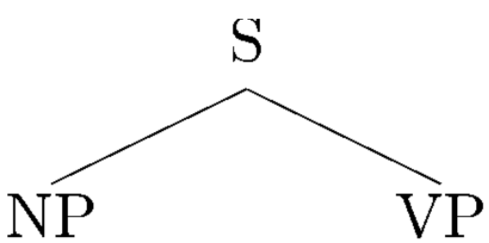
VBP → interest

VBP → raises

…

- Other (non-CF) grammar formalism: LFG, HPSG, TAG, CCG, …

CFG for Syntactic Parsing



Grammar (CFG)

$\boxed{S \rightarrow NP\ VP}$

VP → V
VP → V NP
VP → VP PP

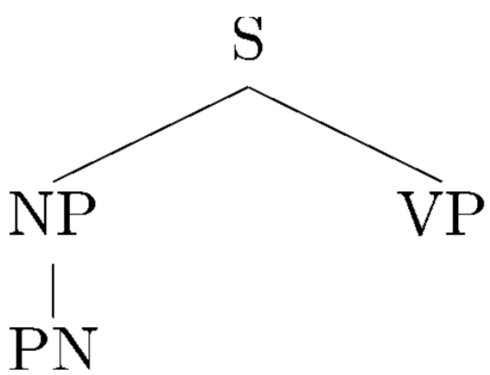
NP → NP PP
NP → D N
NP → PN

PP → P NP

Lexicon

N → girl
N → telescope
N → sandwich
PN → I
V → saw
V → ate
P → with
P → in
D → a
D → the

CFG for Syntactic Parsing



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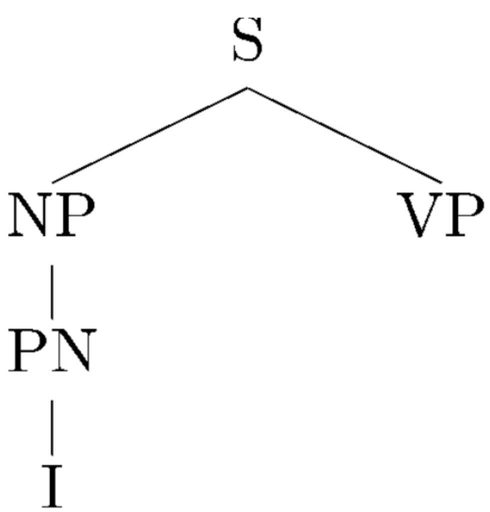

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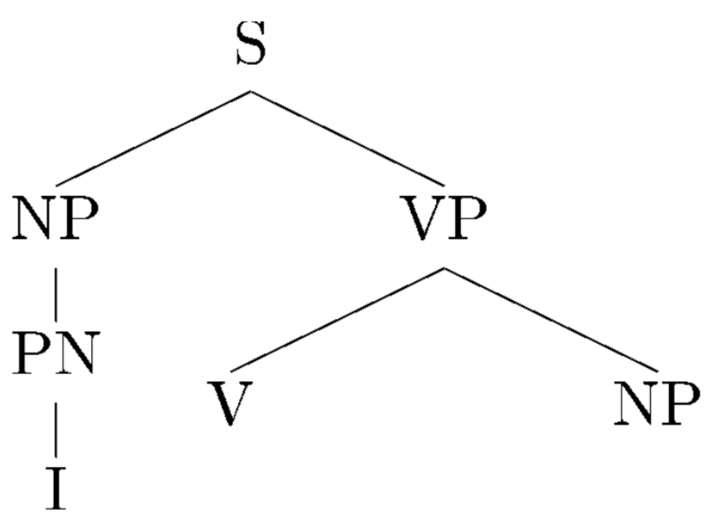

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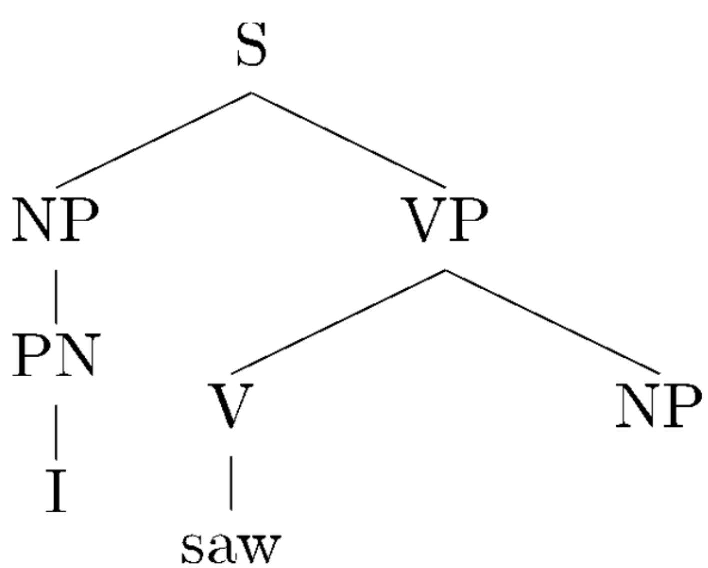

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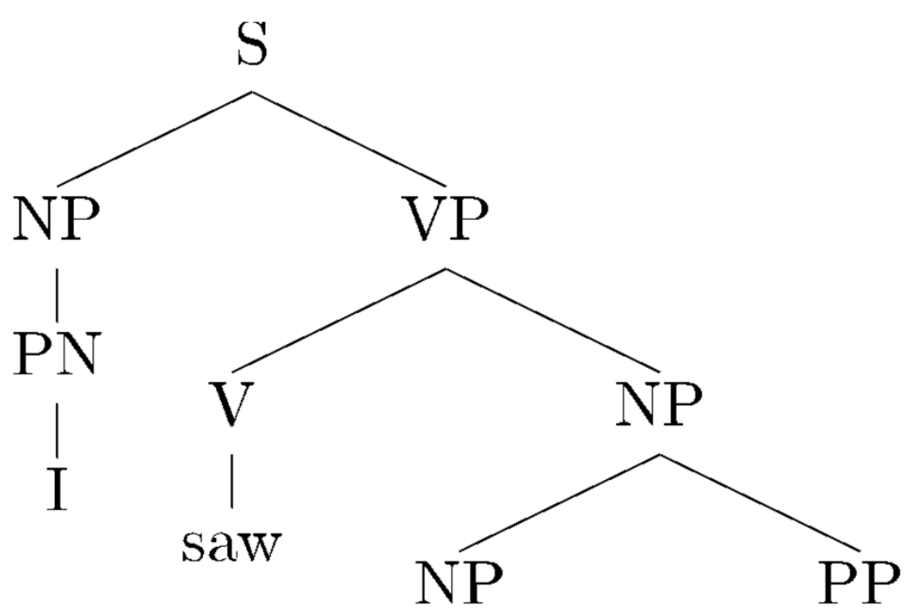

Grammar (CFG)

$S \to NP\ VP$

$VP \to V$
$VP \to V\ NP$
$VP \to VP\ PP$

$\boxed{NP \to NP\ PP}$
$NP \to D\ N$
$NP \to PN$

$PP \to P\ NP$

Lexicon

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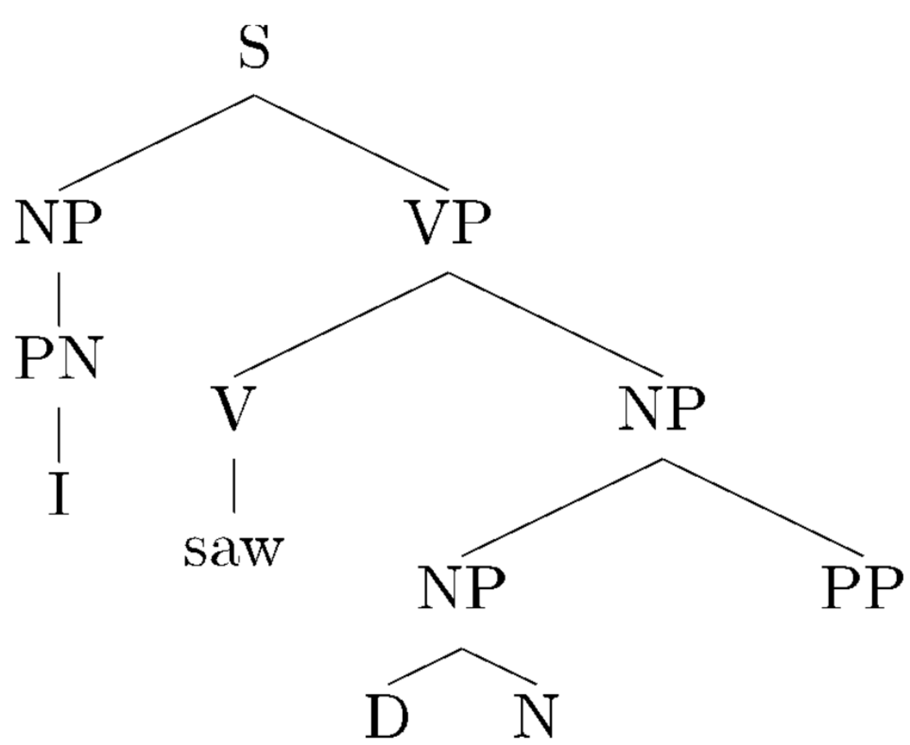

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$\boxed{\text{NP} \rightarrow \text{D N}}$
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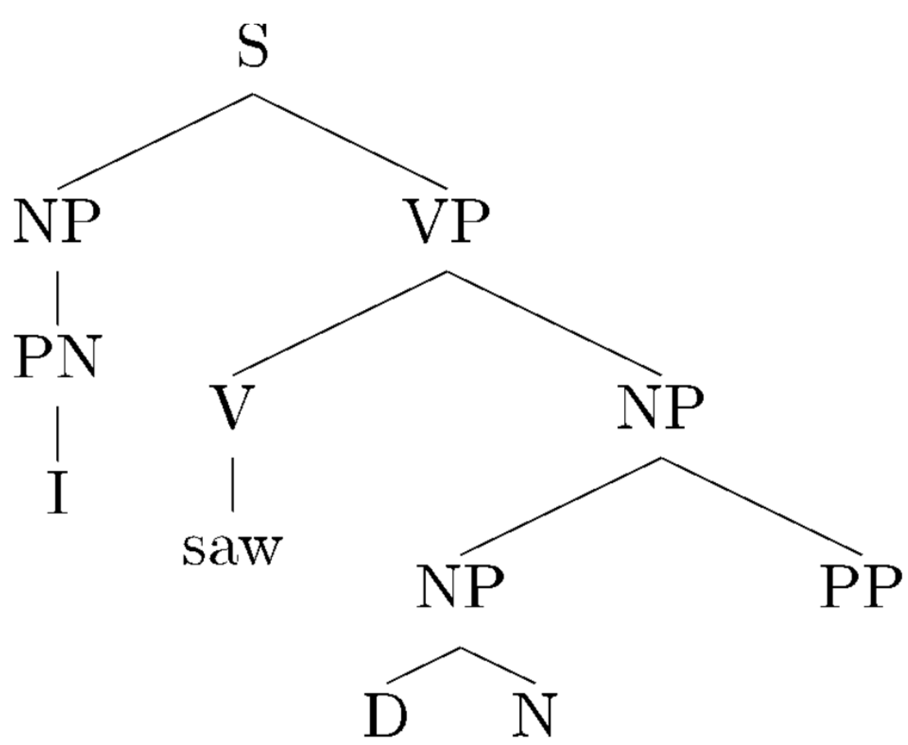

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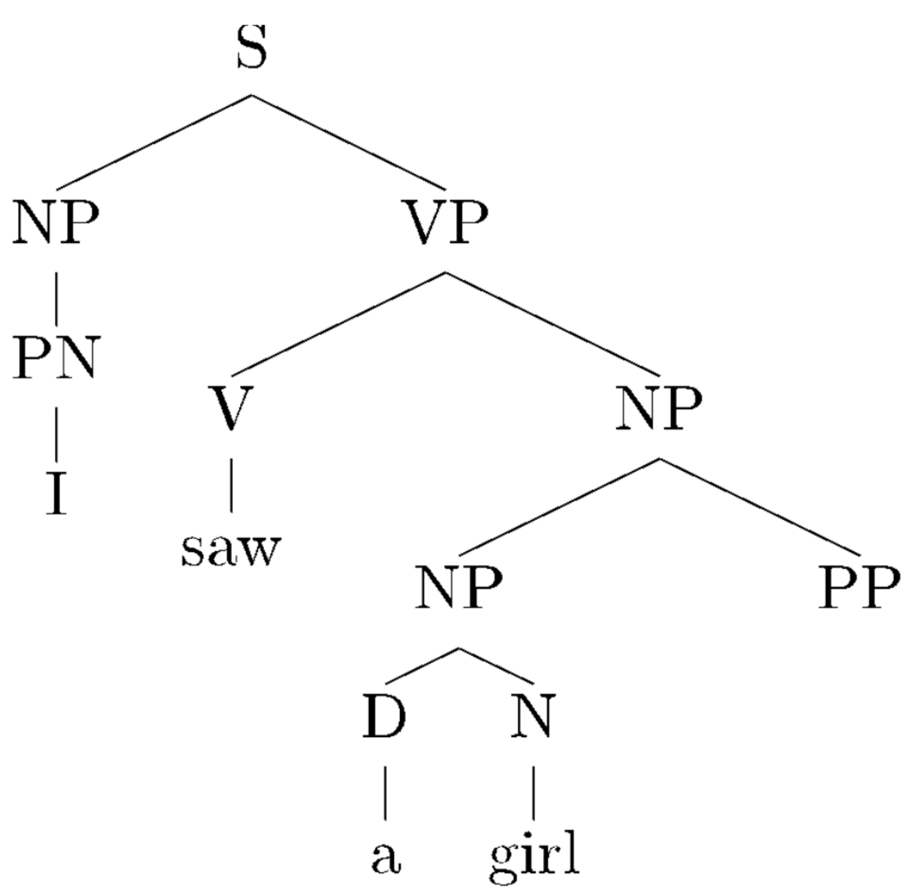

Grammar (CFG)

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$VP \rightarrow V$

$VP \rightarrow V\ NP$

$VP \rightarrow VP\ PP$

$NP \rightarrow NP\ PP$

$NP \rightarrow D\ N$

$NP \rightarrow PN$

$PP \rightarrow P\ NP$

Lexicon

$\boxed{N \rightarrow \text{girl}}$

$N \rightarrow \text{telescope}$

$N \rightarrow \text{sandwich}$

$PN \rightarrow \text{I}$

$V \rightarrow \text{saw}$

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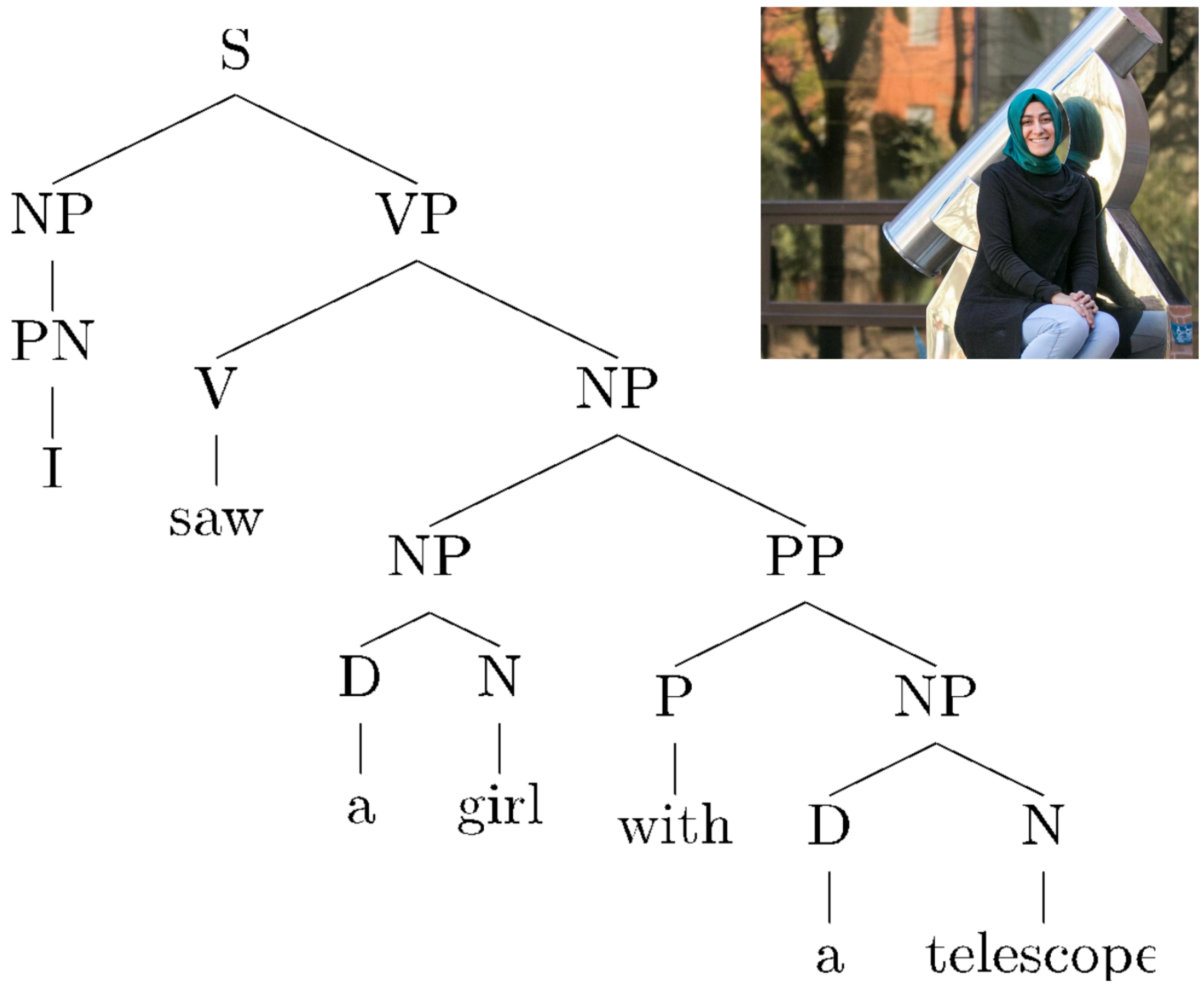
$P \rightarrow \text{in}$

$\boxed{D \rightarrow \text{a}}$

$D \rightarrow \text{the}$

CFG for Syntactic Parsing



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Probabilistic context-free grammars (PCFG)

- **CFG**: A 4-tupe (N, Σ, R, S):
  - N: a set of non-terminal symbols
  - Σ: a set of terminal symbols (disjoint from N)
  - S: a designated start symbol and a member of N
  - R: a set of rules, each of the form $\boxed{A \rightarrow s,}$ where A is a non-terminal, s is a string of symbols, $A \in N, s \in (\Sigma \cup N)*$

$$\boxed{\begin{aligned} S &\rightarrow A, \\ A &\rightarrow BC, \\ A &\rightarrow \alpha, \end{aligned}} \quad \begin{aligned} & A \in N \\ & A \in N, B, C \in N \cup \Sigma \\ & \alpha \in \Sigma \end{aligned} \longleftarrow$$

Without loss of generality, only consider binary branching; Chomsky Normal Form

- **PCFG** adds a top-down production probability per rule.
  - Model the probability of each rule: $P(A \rightarrow s)$

$$\forall A \rightarrow s \in R : 0 \leq P(A \rightarrow s) \leq 1$$

$$\forall A \in N : \sum_{s \text{ where } A \rightarrow s \in R} P(A \rightarrow s) = 1$$

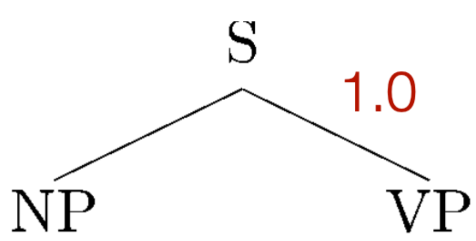
PCFG (Example)

S → NP VP	1.0	(NP a girl) (VP ate a sandwich)
VP → V	0.2	
VP → V NP	0.4	(V ate) (NP a sandwich)
VP → VP PP	0.4	(VP saw a girl) (PP with a telescope)
NP → NP PP	0.3	(NP a girl) (PP with a sandwich)
NP → D N	0.5	(D a) (N sandwich)
NP → PN	0.2	
PP → P NP	1.0	(P with) (NP a sandwich)

N → *girl*	0.2
N → *telescope*	0.7
N → *sandwich*	0.1
PN → *I*	1.0
V → *saw*	0.5
V → *ate*	0.5
P → *with*	0.6
P → *in*	0.4
D → *a*	0.3
D → *the*	0.7

Now we can score a tree as a product of probabilities corresponding to the used rules!

PCFG (Example)



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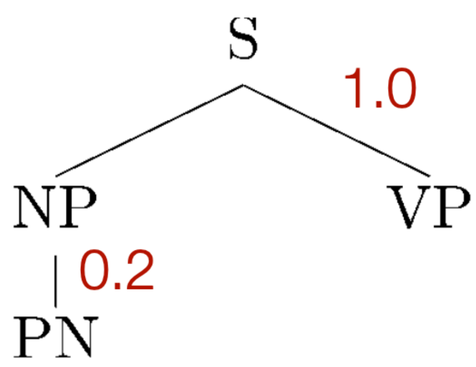
PP → P NP	1.0	D → *the*	0.7

$P(T) = 1.0\ *$

PCFG (Example)



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$P(T)$ = 1.0 * 0.2 *

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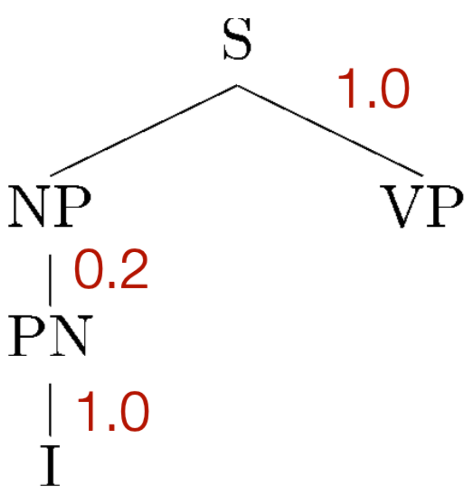

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$P(T)$ = 1.0 * 0.2 * 1.0 *

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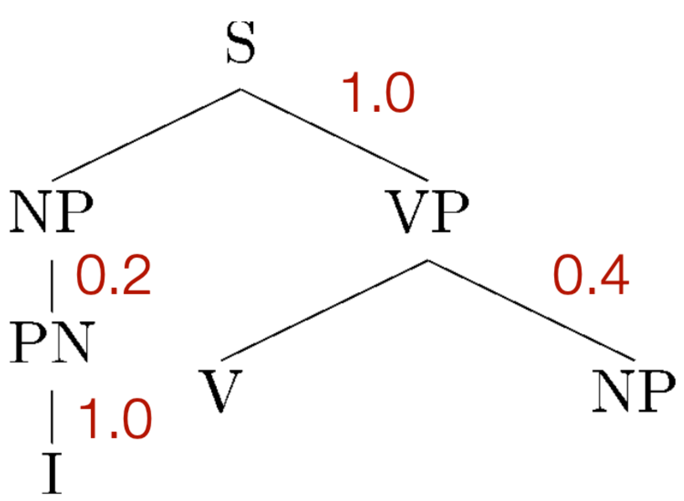

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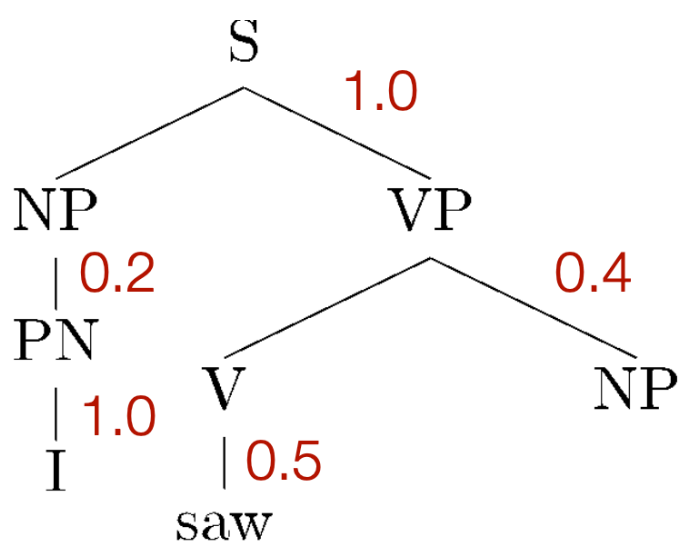
P(*T*) = 1.0 * 0.2 * 1.0 * 0.4 *

PCFG (Example)



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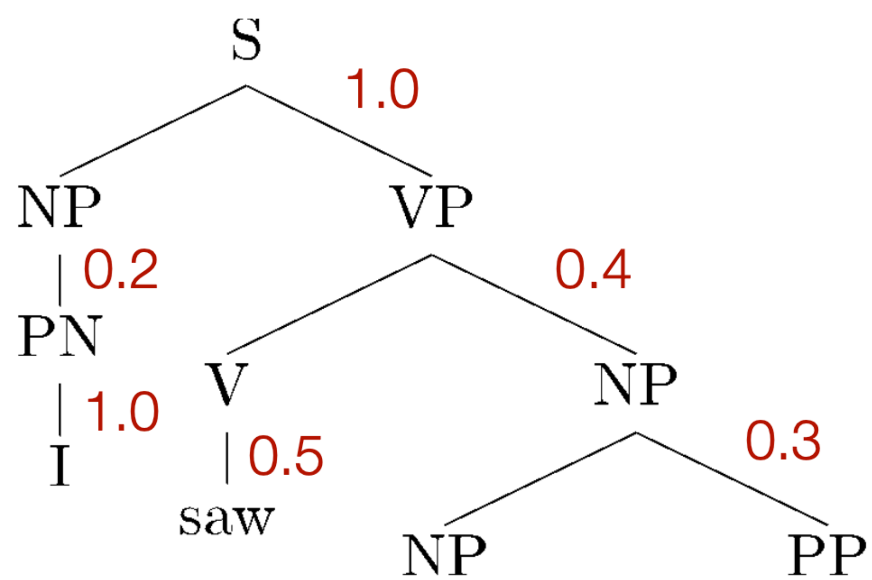

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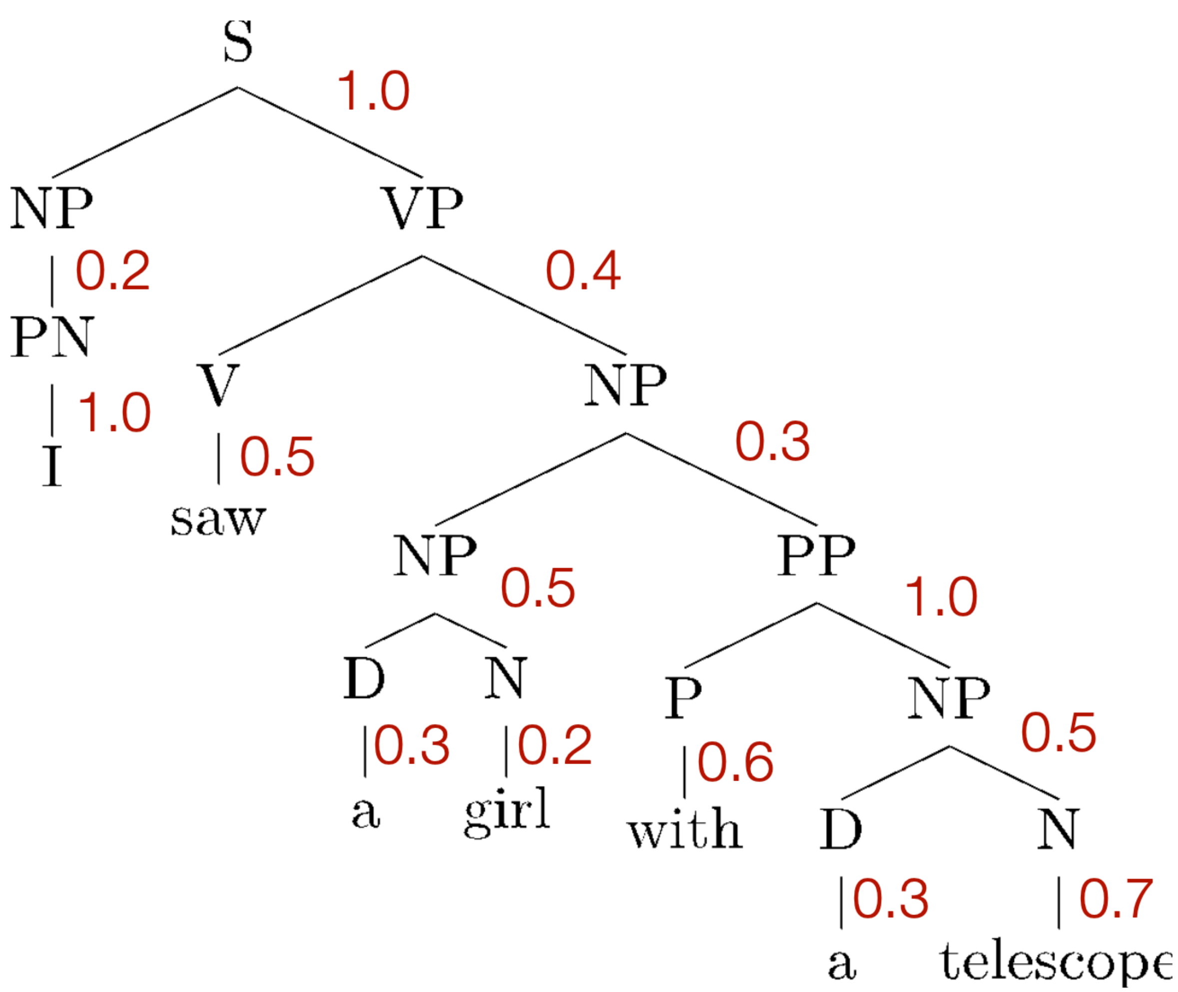

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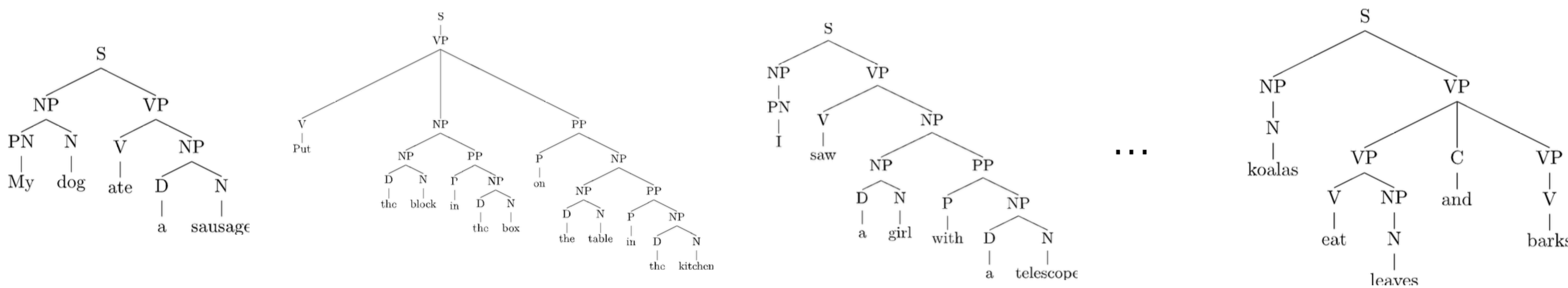
P(*T*) = 1.0 * 0.2 * 1.0 * 0.4 * 0.5 * 0.3 * 0.5 * 0.3 * 0.2 * 1.0 * 0.6 * 0.5 * 0.3 * 0.7 = 2.26e-5

PCFG Supervised Learning & Decoding

PCFG Supervised Learning

- A treebank: a collection of sentences annotated with constituency trees
  - Penn Treebank: (X, T) pairs



- PCFG: a generative model, maximizing the joint probability of a sentence given a tree.
  - If we constraint the search space to be all valid trees that can generate the sentence, this becomes:

$$\max P(X, T) = \max P(X|T)P(T) = \max_{T \in \mathrm{GEN}(X)} P(X|T)P(T)$$

PCFG Supervised Learning

- Estimate probability of each rule by maximum likelihood estimation:

$$P(T) = \sum_{A \to s \in R} P(A \to s), \quad T \in \mathrm{GEN}(X)$$

$$P(A \to s) = \frac{Count(A \to s)}{Count(A)}$$

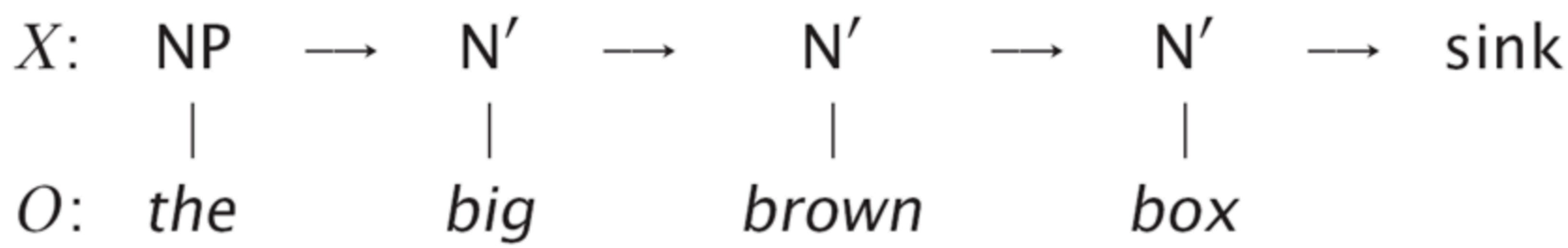
times the rule was used in the data

times the nonterminal was used in the data

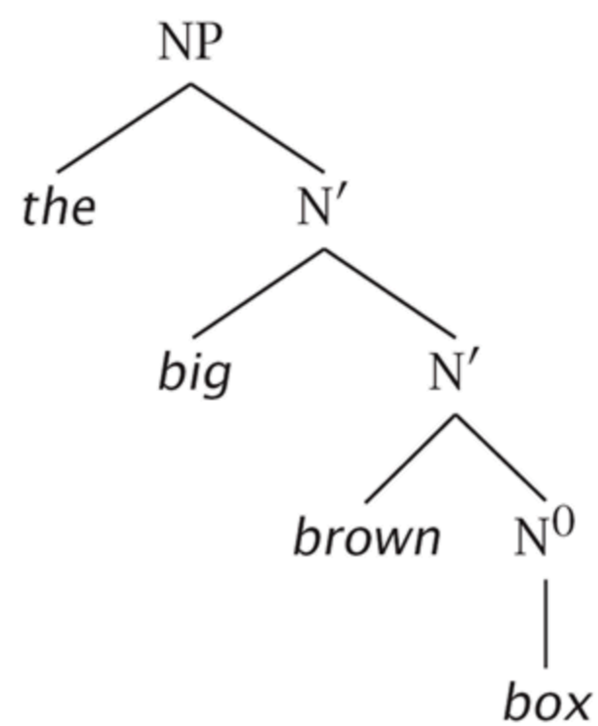
- Smoothing is helpful (esp. for rules that produce one word)
- If we don't have training data, use EM algorithm to estimate the probability

HMM vs PCFG

HMM: Linear Markov Chain

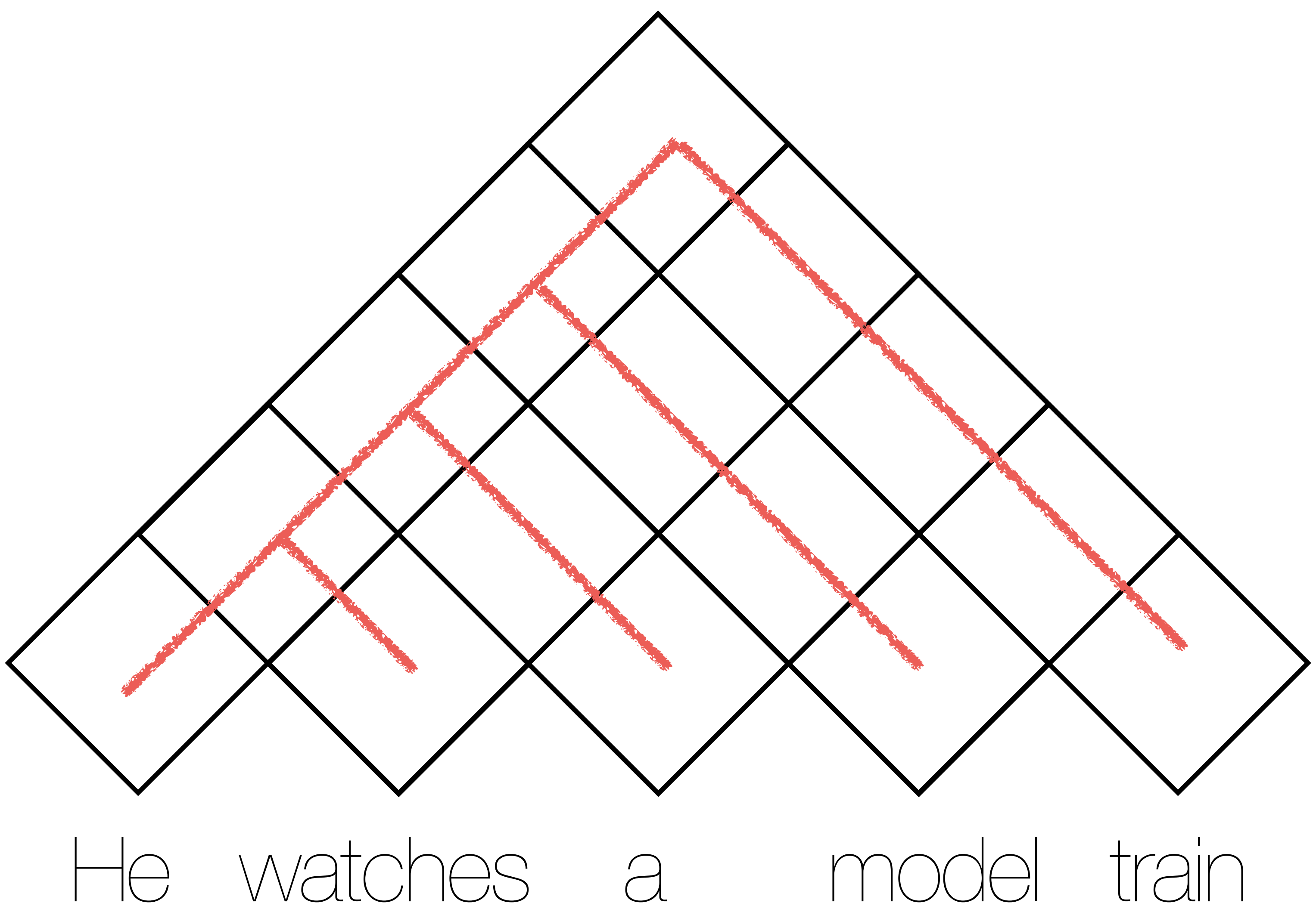


PCFG: tree



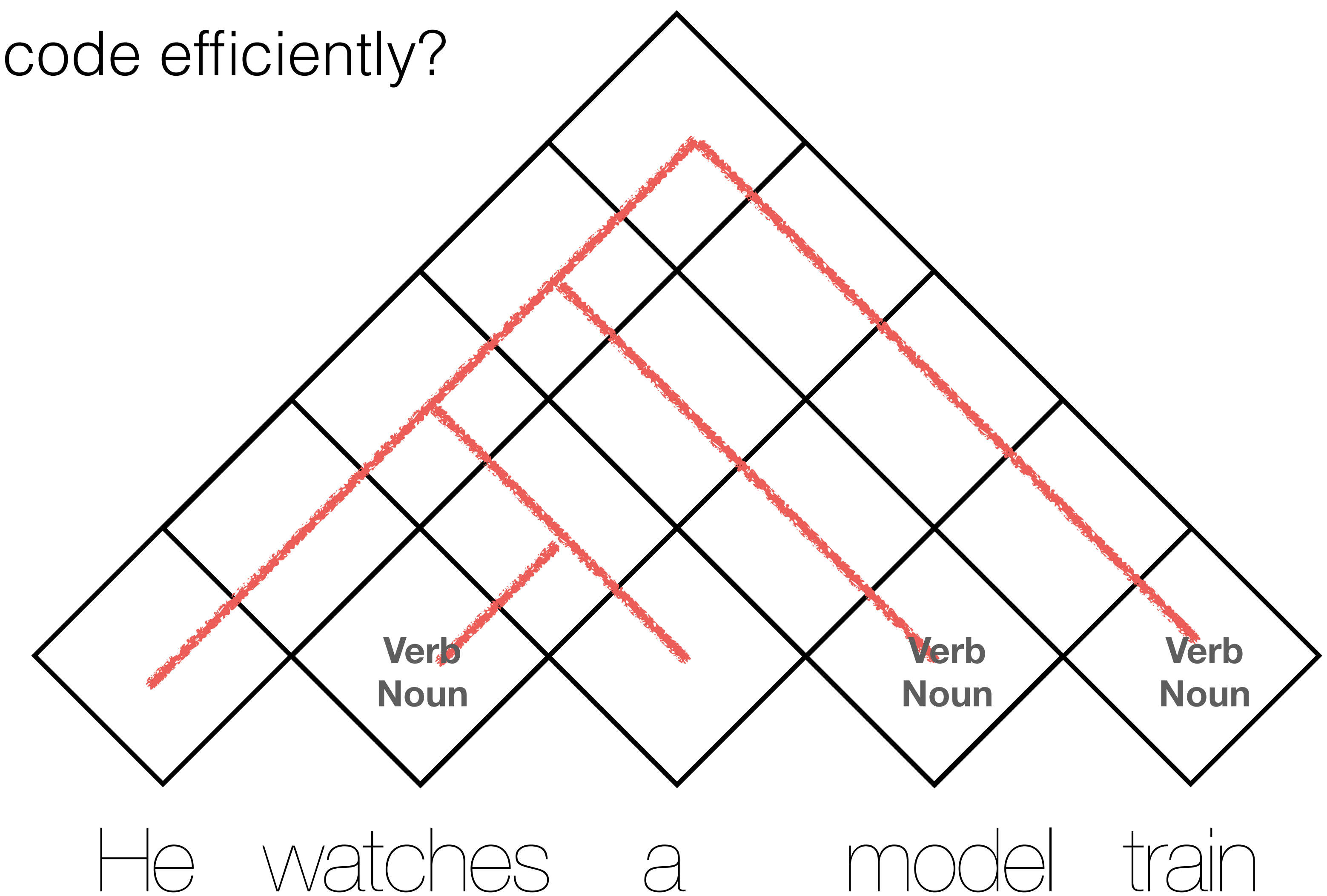
PCFG Decoding

- Brute force solution: enumerate all possible binary trees, score them, find the tree with maximum score



PCFG Decoding

- Brute force solution: enumerate all possible binary trees, score them, find the tree with maximum score
- For a sentence of n words, there are (n-1)! possible binary trees. Each word may have more than 1 possible POS tags
- How to decode efficiently?



PCFG Decoding: CYK Algorithm

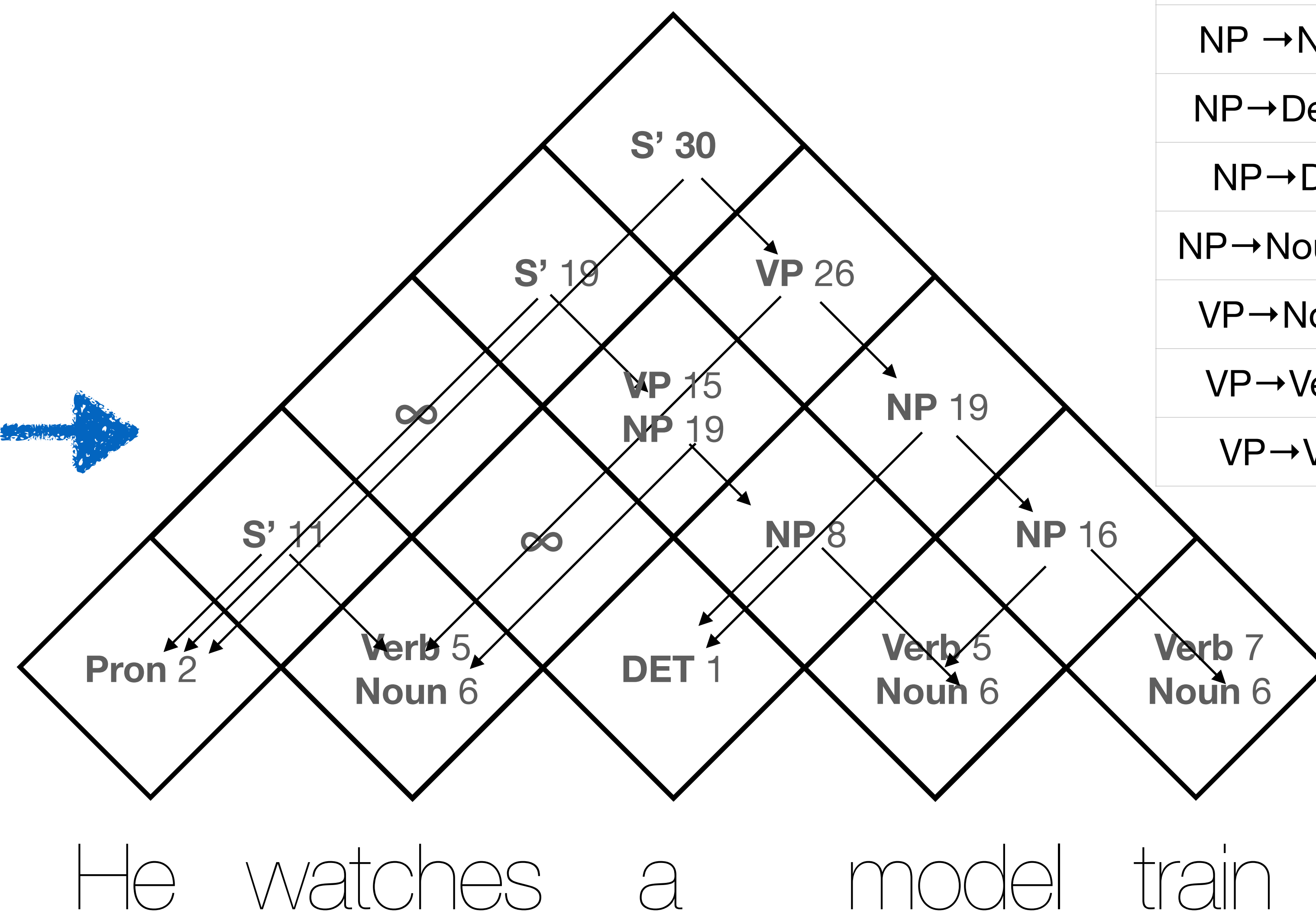
Bottom-up Dynamic Programming

Remember to store back-pointer!

Binary Rule	-log prob
S' →Pron Verb	4
S' →Pron VP	2
S' →NP VP	2
NP →NP Verb	5
NP→Det Noun	2
NP→Det NP	2
NP→Noun Noun	4
VP→Noun NP	5
VP→Verb NP	2
VP→VP NP	2

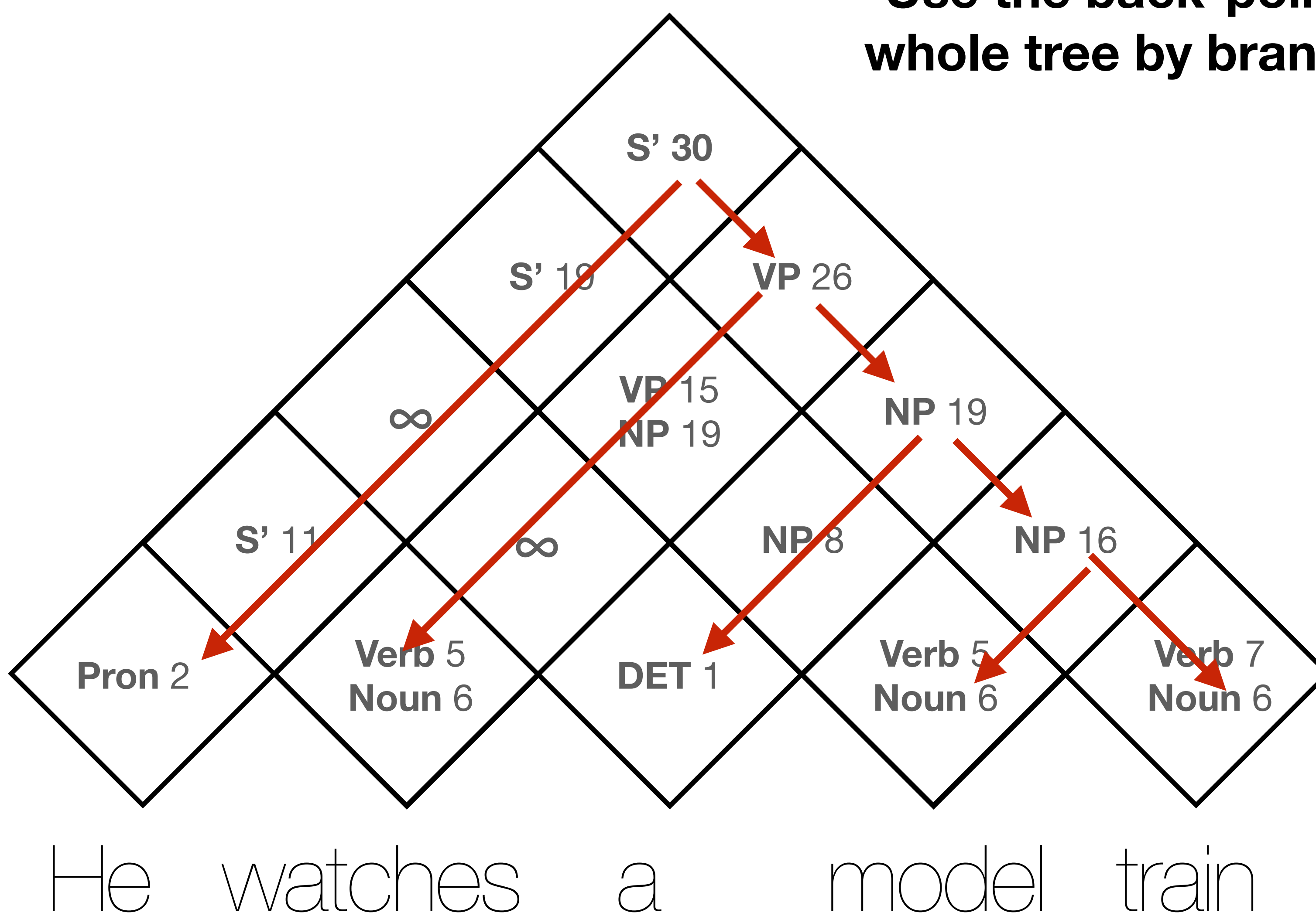
Binary rule
$A \rightarrow BC$

Lexical rule
(Unary rule)
$A \rightarrow \alpha, \alpha \in \Sigma$



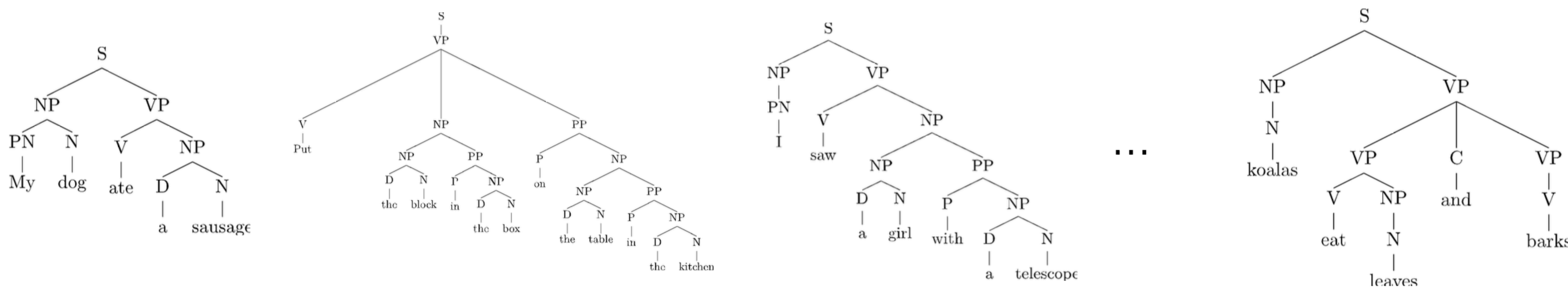
PCFG Decoding: CYK Algorithm

Use the back-pointer to build the whole tree by branching from root.



PCFG CYK Decoding

- A treebank: a collection of sentences annotated with constituency trees
  - Penn Treebank



- Estimate probability of each rule by maximum likelihood estimation:

$$P(A \to s) = \frac{Count(A \to s)}{Count(A)}$$

times the rule was used in the data

times the nonterminal was used in the data

- Smoothing is helpful (esp. for rules that produce one word)

PCFG Decoding: CYK Algorithm

- The score (or unnormalized probability) of a constituent with a non-terminal is often called inside probability
  - Computed by dynamic programming

$$s_{\text{label}}(i, j, A) = \max_{k,B,C} P(A \to BC) \times s_{\text{label}}(i, k, B) \times s_{\text{label}}(k+1, j, C)$$

Semiring Conversion

- The score (or unnormalized probability) of a constituent with a non-terminal is often called inside probability
  - Computed by dynamic programming
  - Numerically unstable

$$s_{\mathrm{label}}(i,j,A) = \max_{k,B,C} P(A \to BC) \times s_{\mathrm{label}}(i,k,B) \times s_{\mathrm{label}}(k+1,j,C)$$

  - Define the minimum cost score, and rewrite the scores

$$s'_{\mathrm{label}}(i,j,A) = -\log s_{\mathrm{label}}(i,j,A)$$

$$s'_{\mathrm{label}}(i,j,A) = \min_{k,B,C} \left(-\log P(A \to BC) + s'_{\mathrm{label}}(i,k,B) + s'_{\mathrm{label}}(k+1,j,C)\right)$$

Semiring Parsing

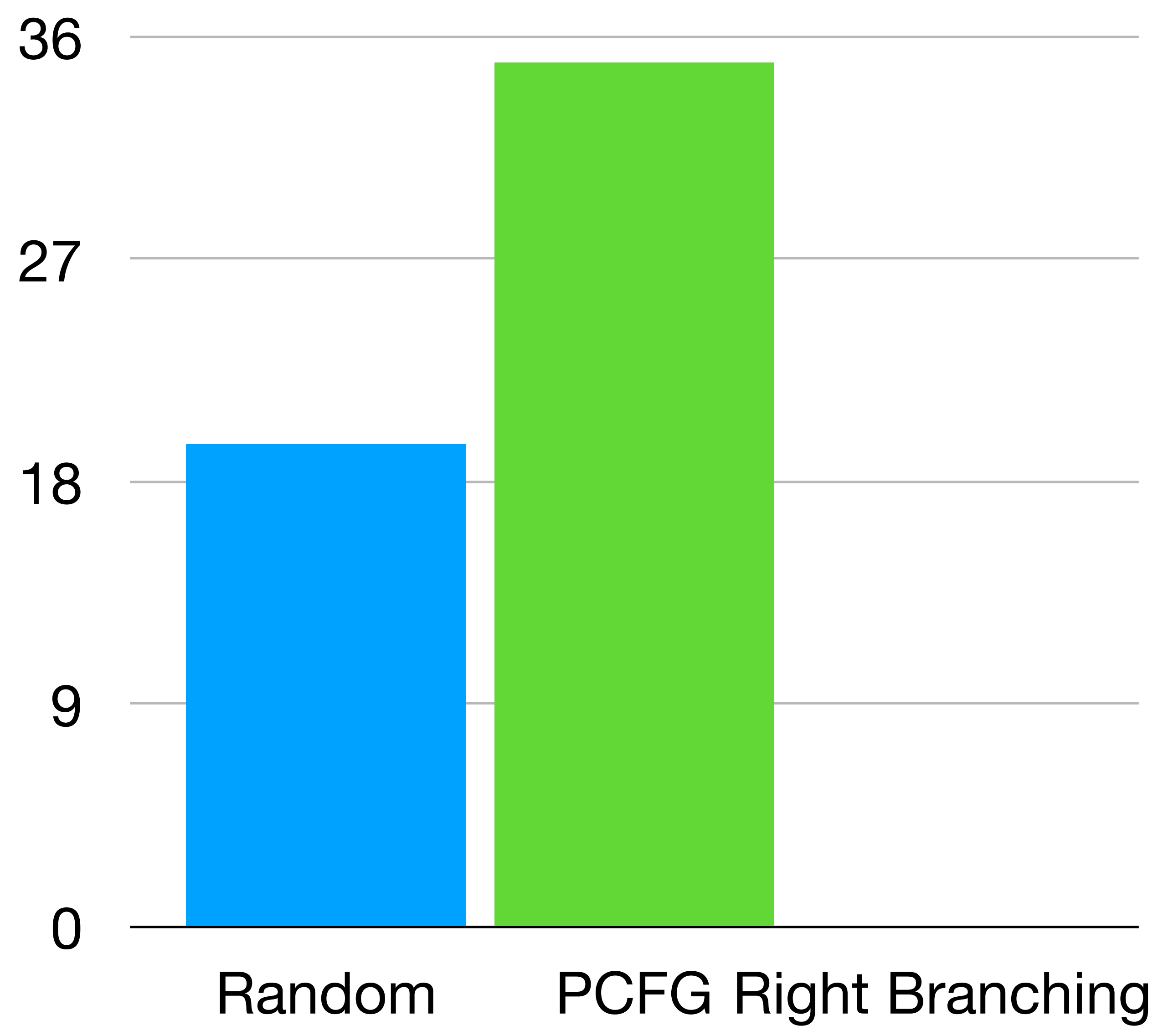
“Add” $\oplus$ “Multiply” $\otimes$

$$s_{\text{label}}(i,j,A) = \boxed{\max_{k,B,C}} P(A \rightarrow BC) \boxed{\times} s_{\text{label}}(i,k,B) \boxed{\times} s_{\text{label}}(k+1,j,C)$$

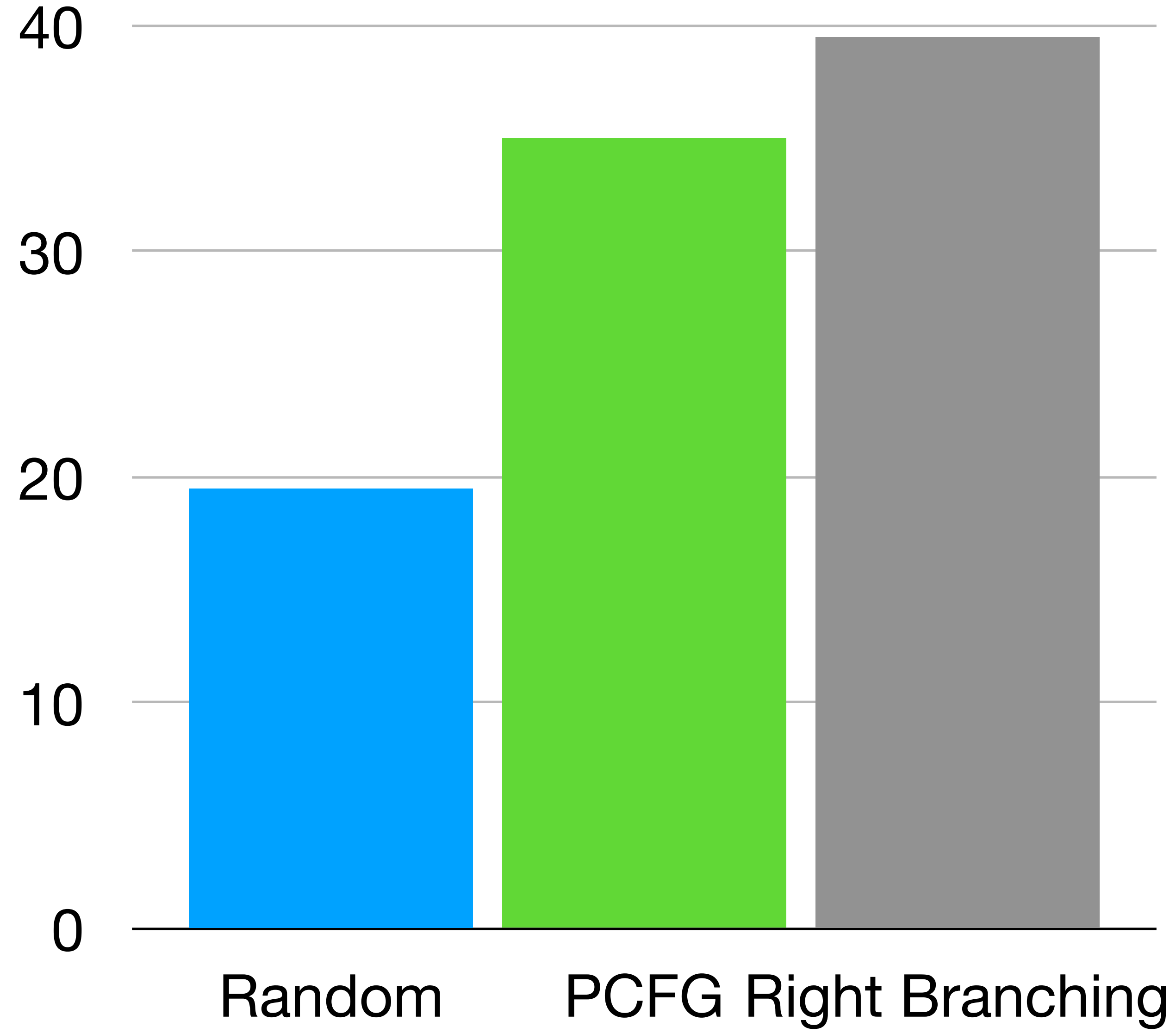
$$s'_{\text{label}}(i,j,A) = \boxed{\min_{k,B,C}} (-\log P(A \rightarrow BC) \boxed{+} s'_{\text{label}}(i,k,B) \boxed{+} s'_{\text{label}}(k+1,j,C))$$

	weights	$\oplus$	$\otimes$	⓪	①
total prob	[0, 1]	+	x	0	1
max prob	[0, 1]	max	x	0	1
min -logp	[0, ∞]	min	+	∞	0
log prob	[-∞, 0]	logsumexp	+	-∞	0
recognizer	T/F	or	and	F	T

Semiring is an algebraic structure in ring theory: https://en.wikipedia.org/wiki/Semiring



Great News: It works (better than random)

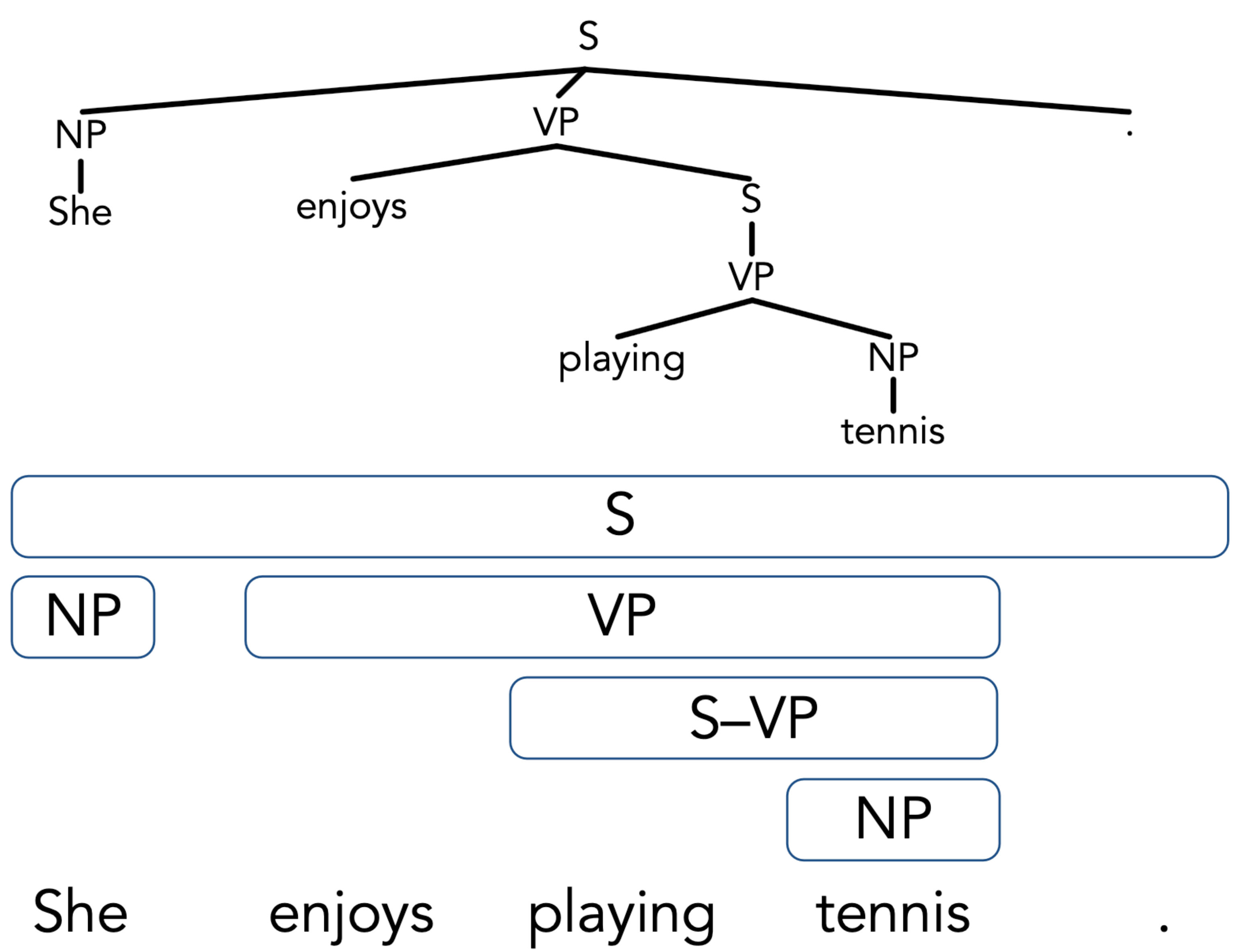


Bad News: It is even worse than right branching. Why?

Supervised Parsing: Span-based Neural Models

Span-Based Parsing

$$P(Y_{i:j} = c | X_{i:j}) = w_c \cdot F_c(X_{i:j})$$



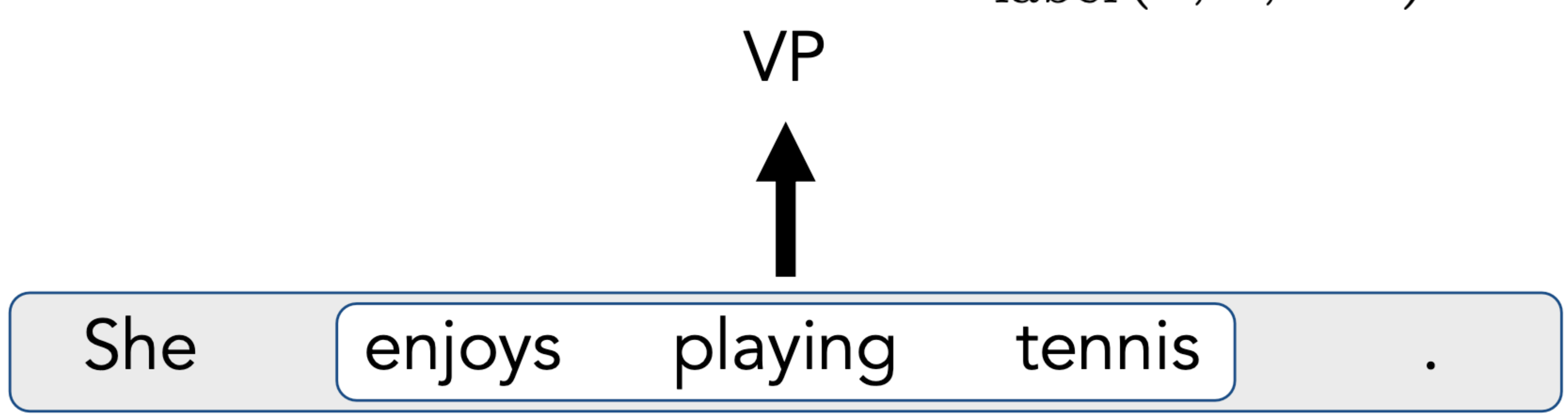
Stern et. al 2016. A Minimal Span-Based Neural Constituency Parser

Span-Based Parsing

$$s_{\text{label}}(i, j, \ell)$$

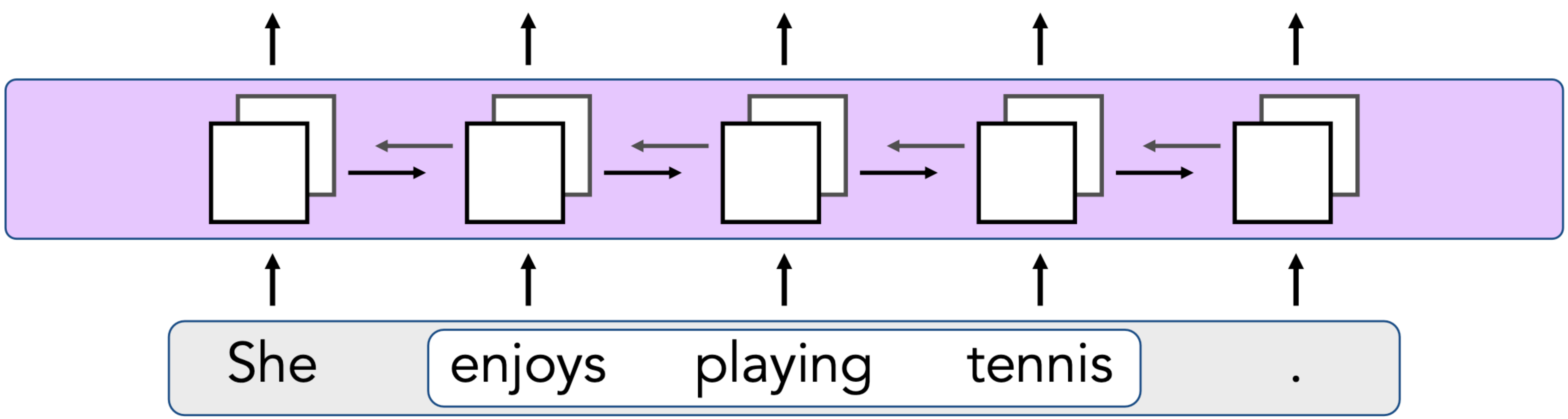
Scoring a span from the i-th word to j-th word being the label of ℓ

$$s_{\text{label}}(1, 3, \text{VP})$$

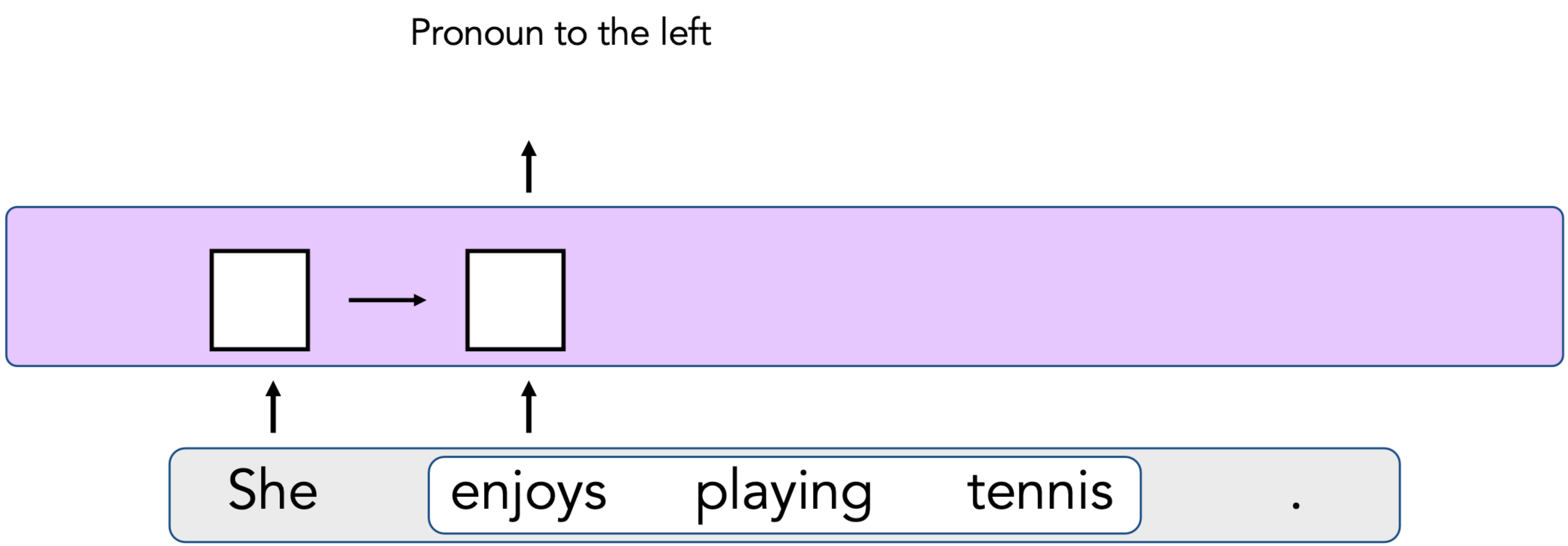


Word index: 0 1 2 3 4

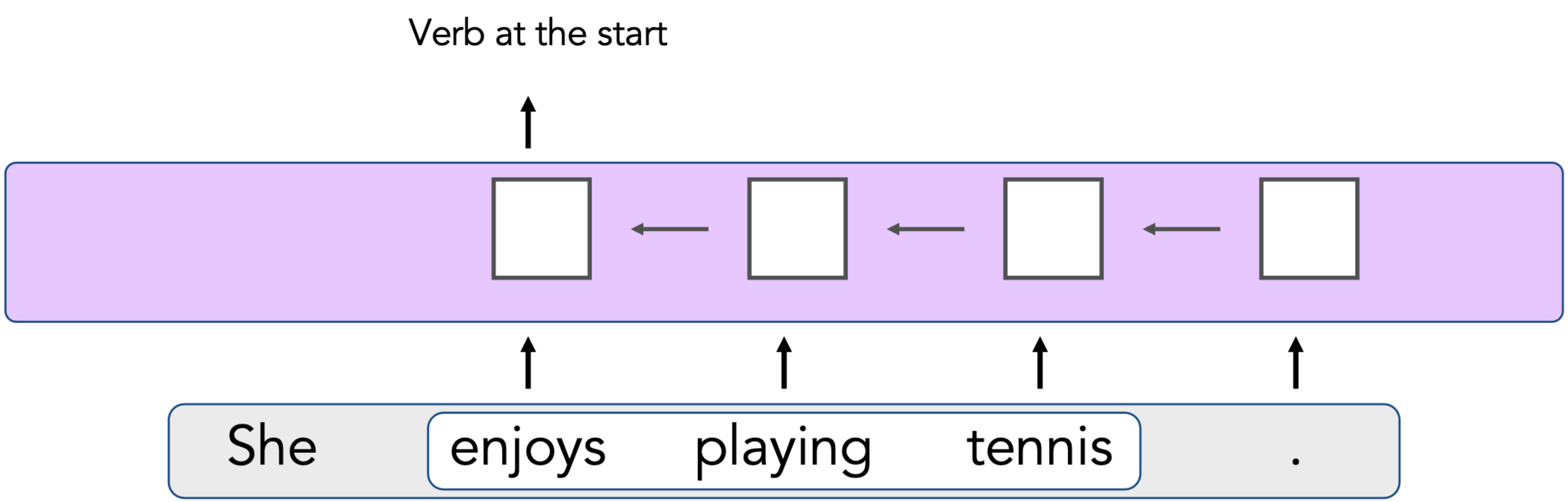
Span-Based Parsing



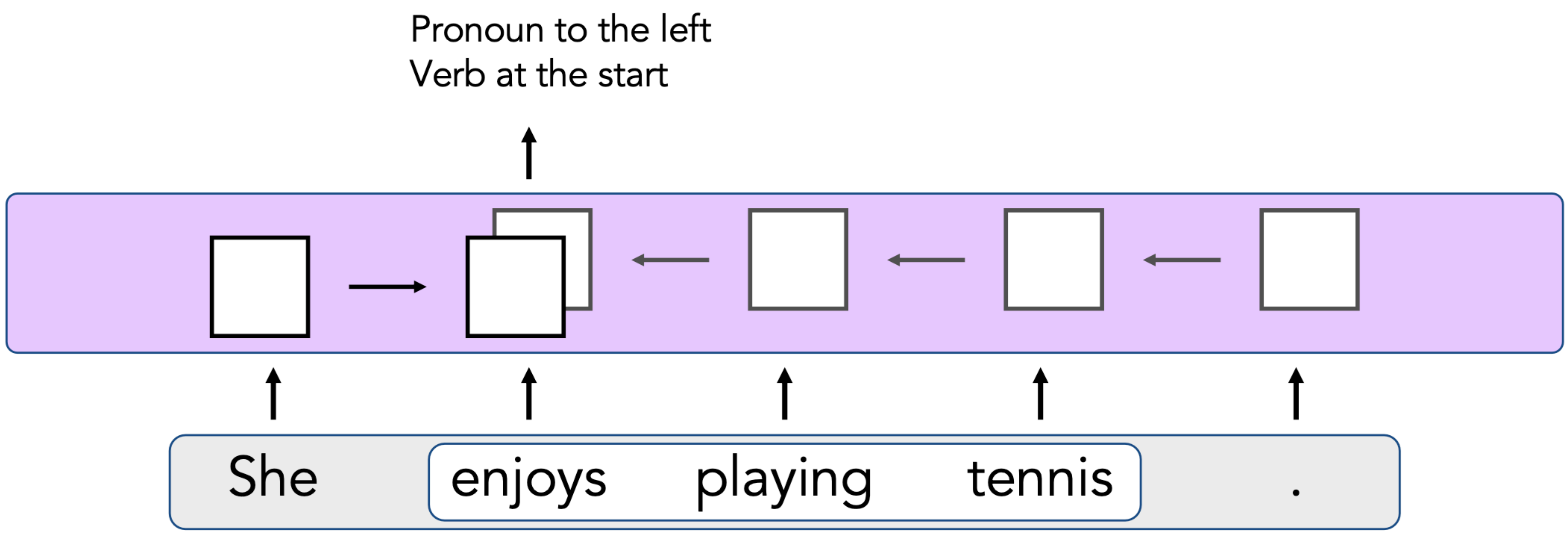
Span-Based Parsing



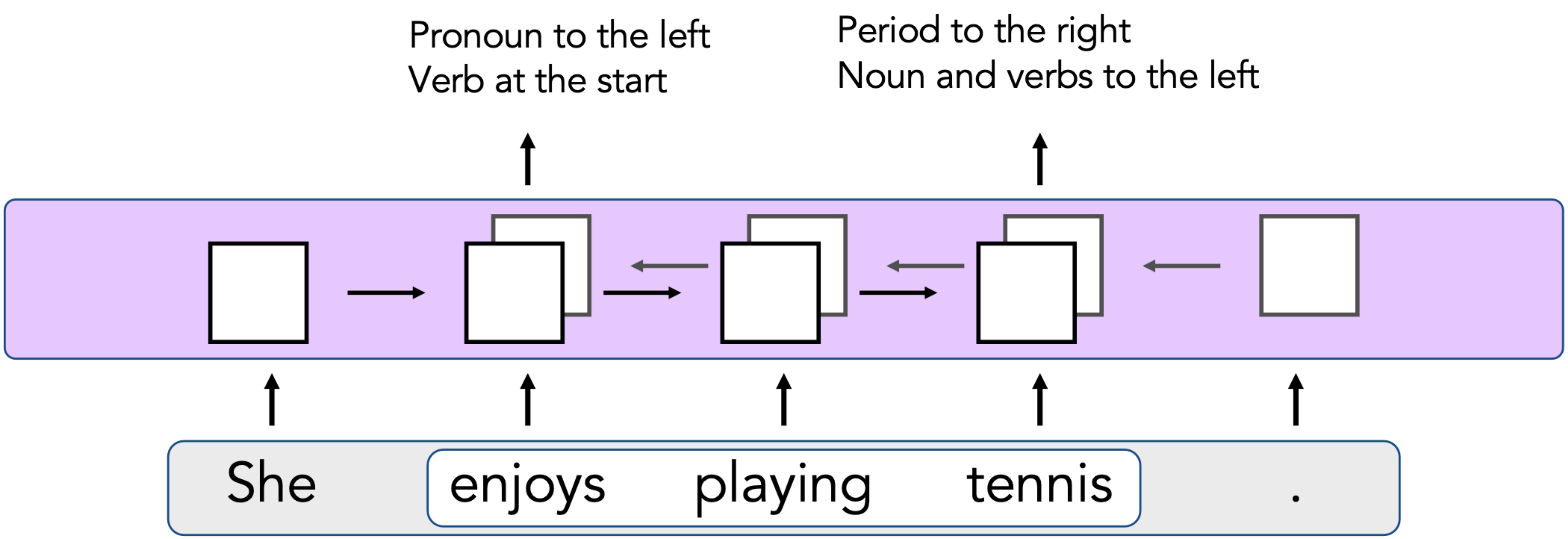
Span-Based Parsing



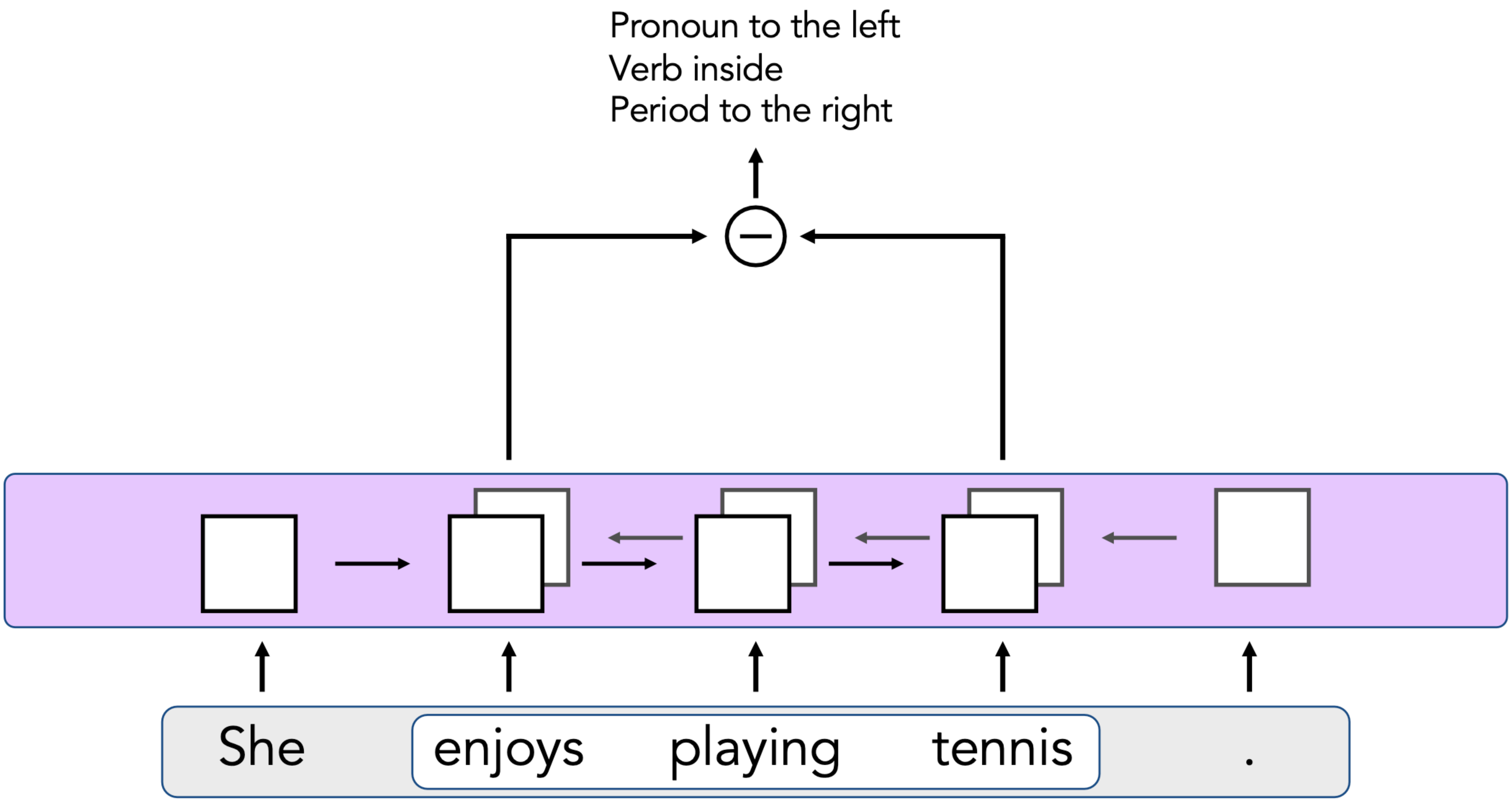
Span-Based Parsing



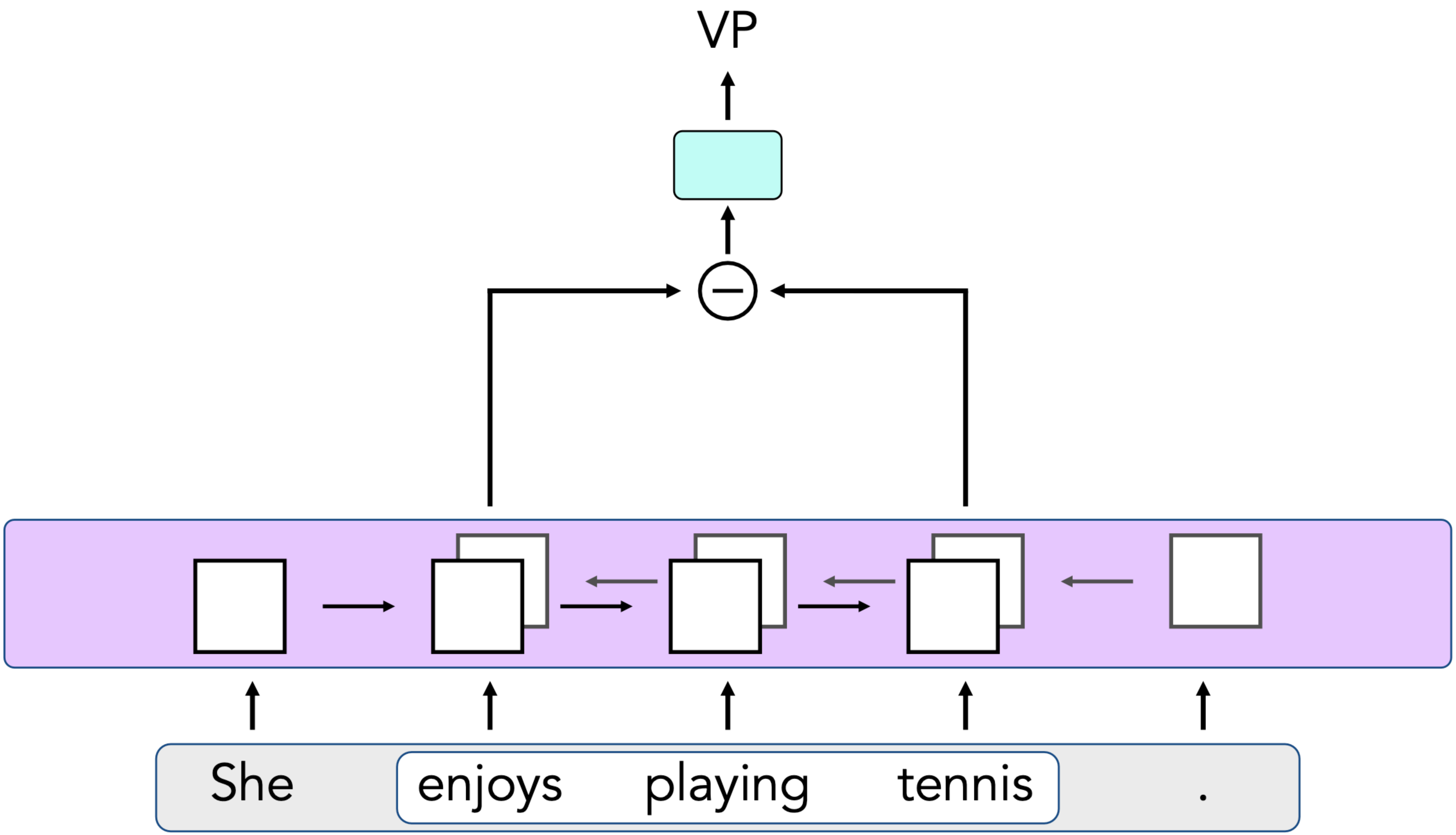
Span-Based Parsing



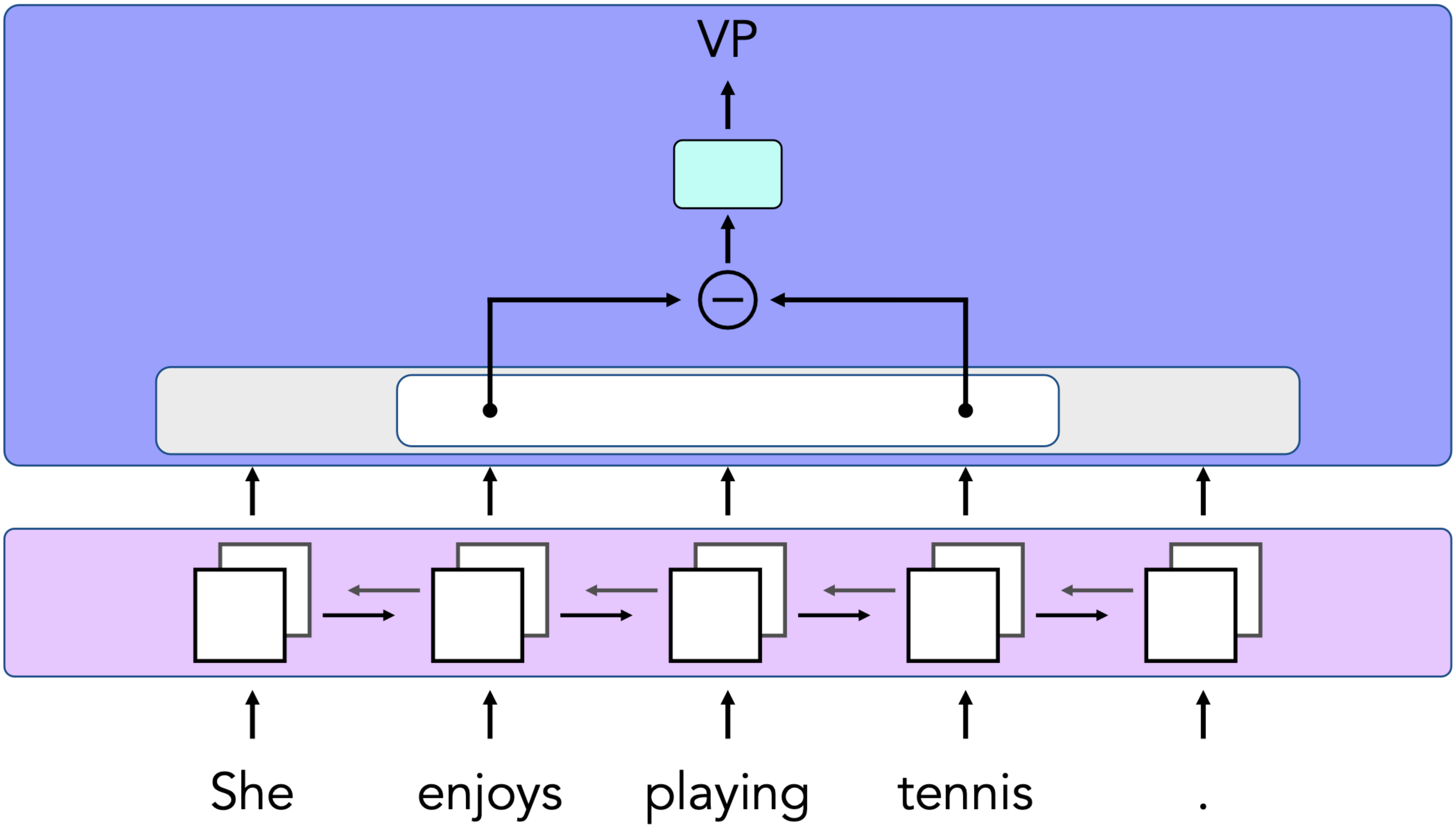
Span-Based Parsing



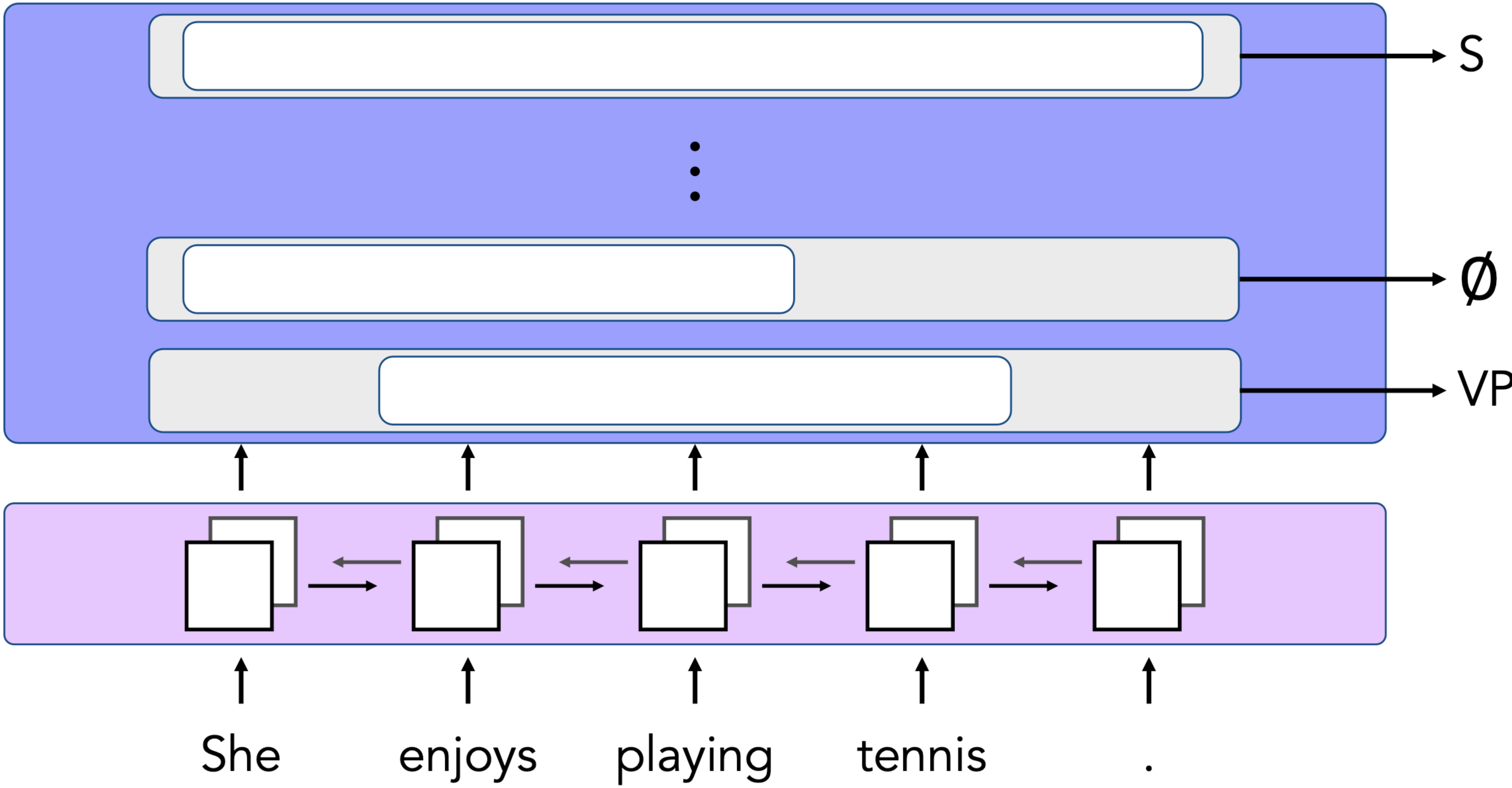
Span-Based Parsing



Span-Based Parsing

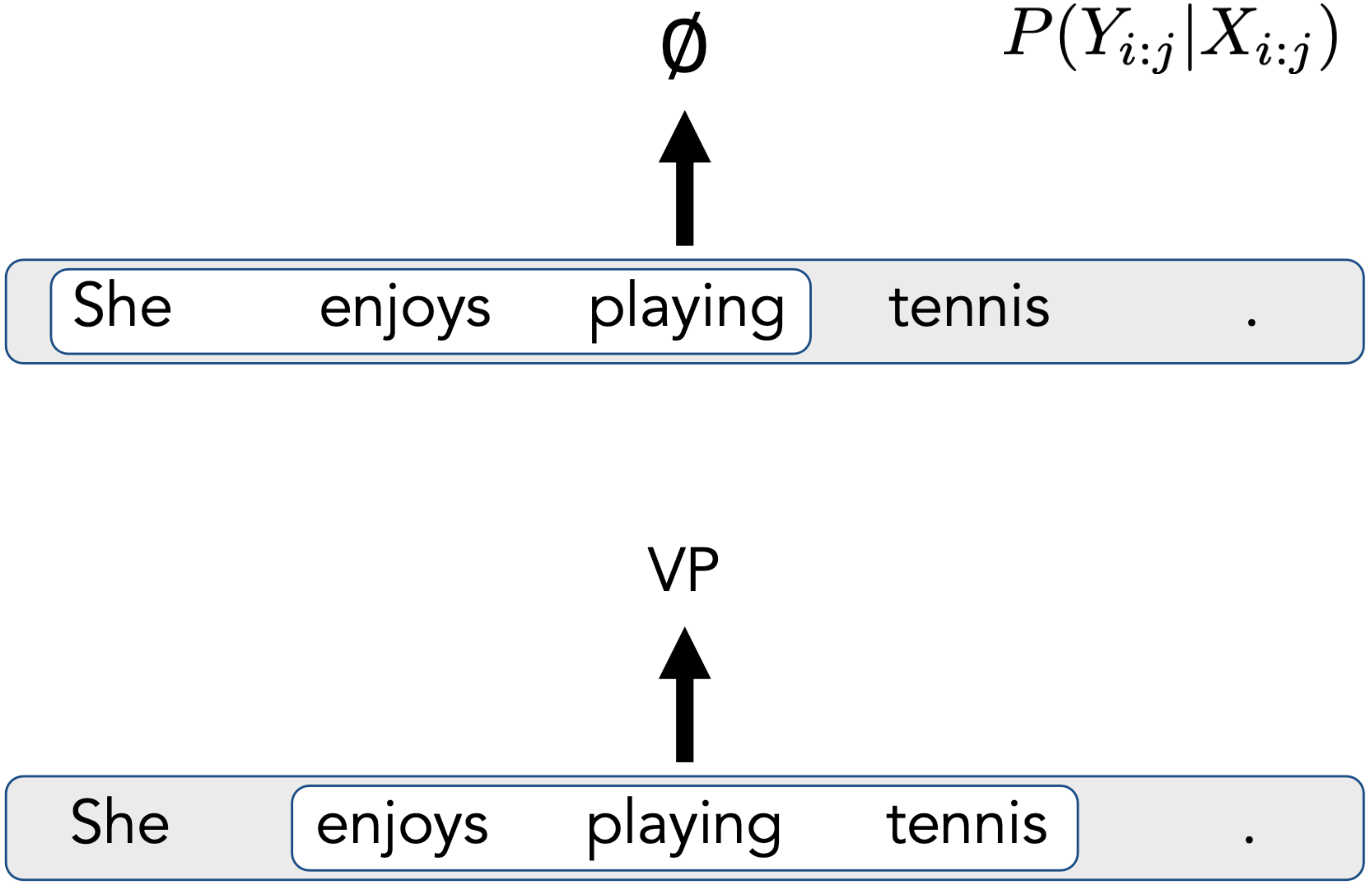


Span-Based Parsing



Span-Based Parsing

$$P(Y_{i:j}|X_{i:j})$$



Training: Margin Loss

- Find the best tree using the current model

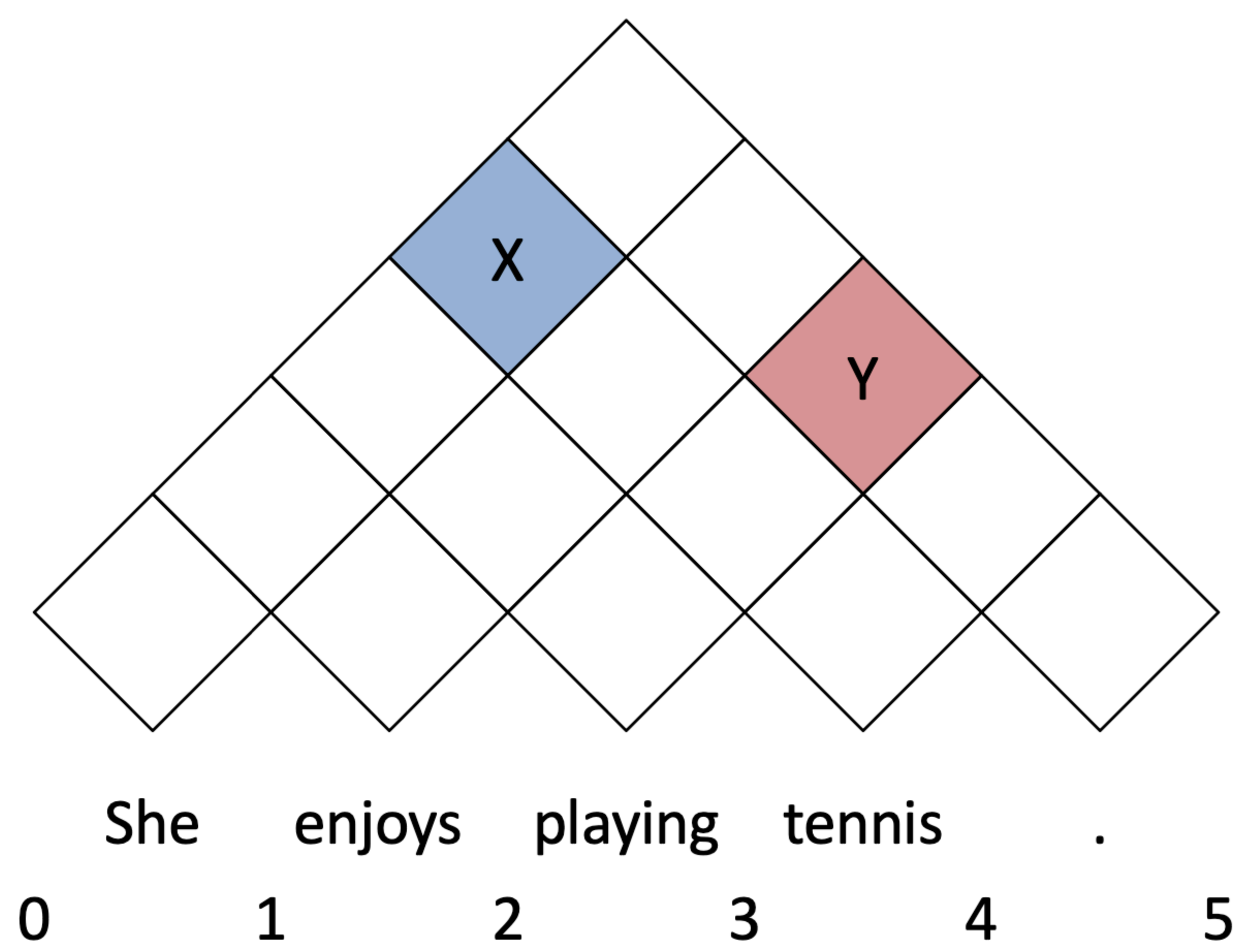
$$\widehat{T} = \underset{T}{\operatorname{argmax}} \left[s_{\text{tree}}(T) \right].$$

- Margin loss:

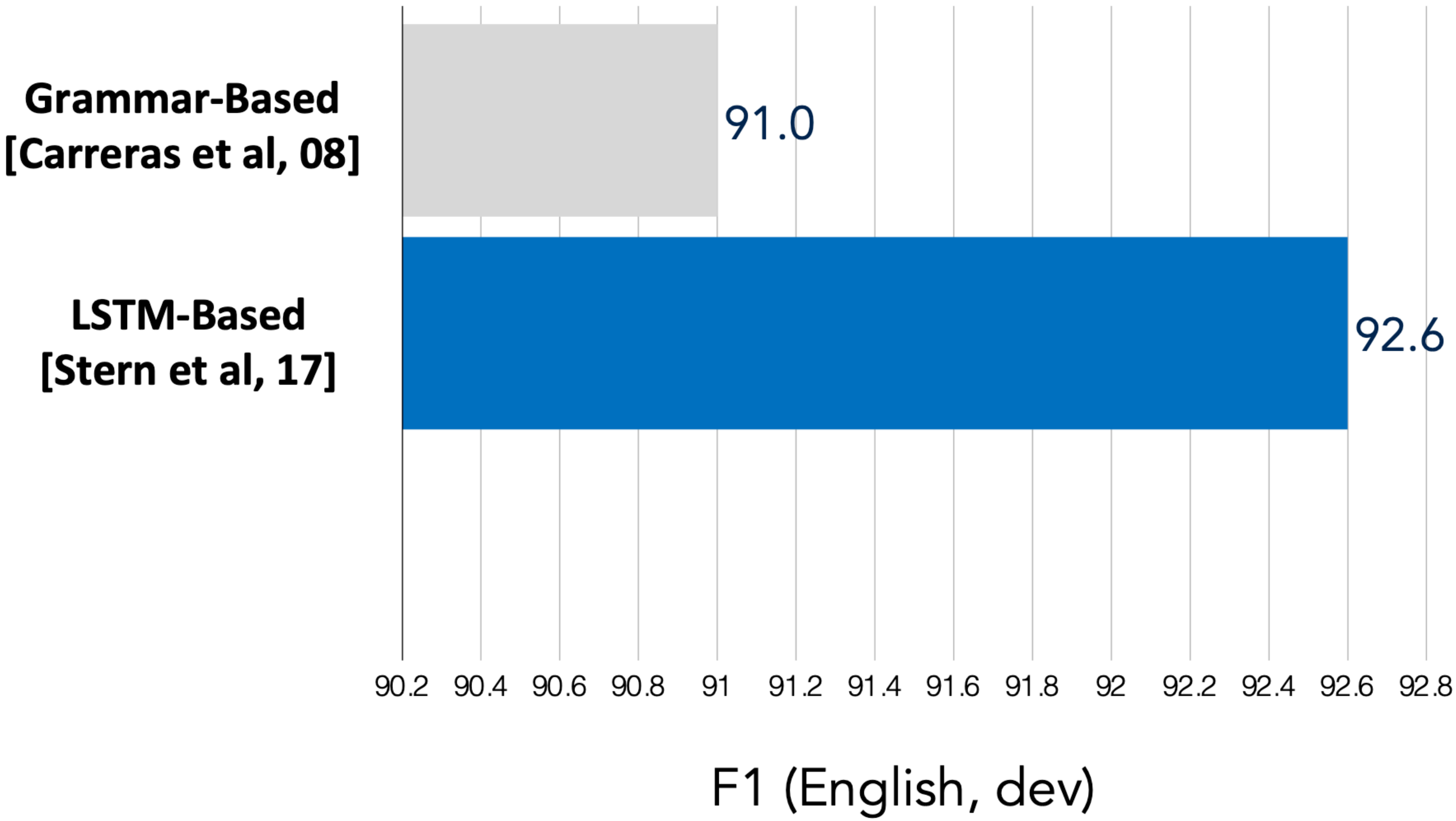
$$\max\left(0,\ 1 - s_{\text{tree}}(T^*) + s_{\text{tree}}(\widehat{T})\right)$$

Decoding: CYK

- Same as counting-based PCFG
- Use the learned scores for possible spans in the following chart

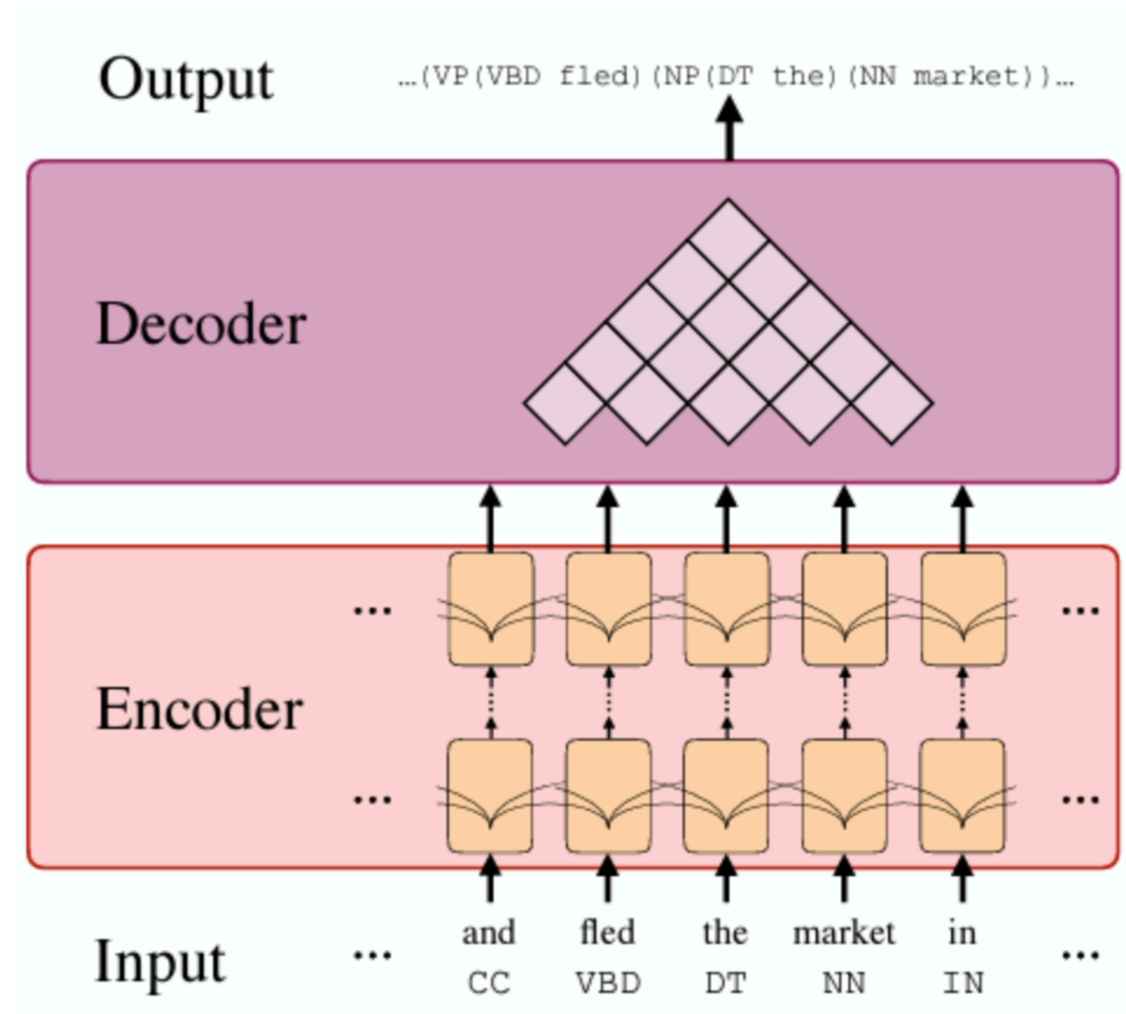


Improves over non-neural methods



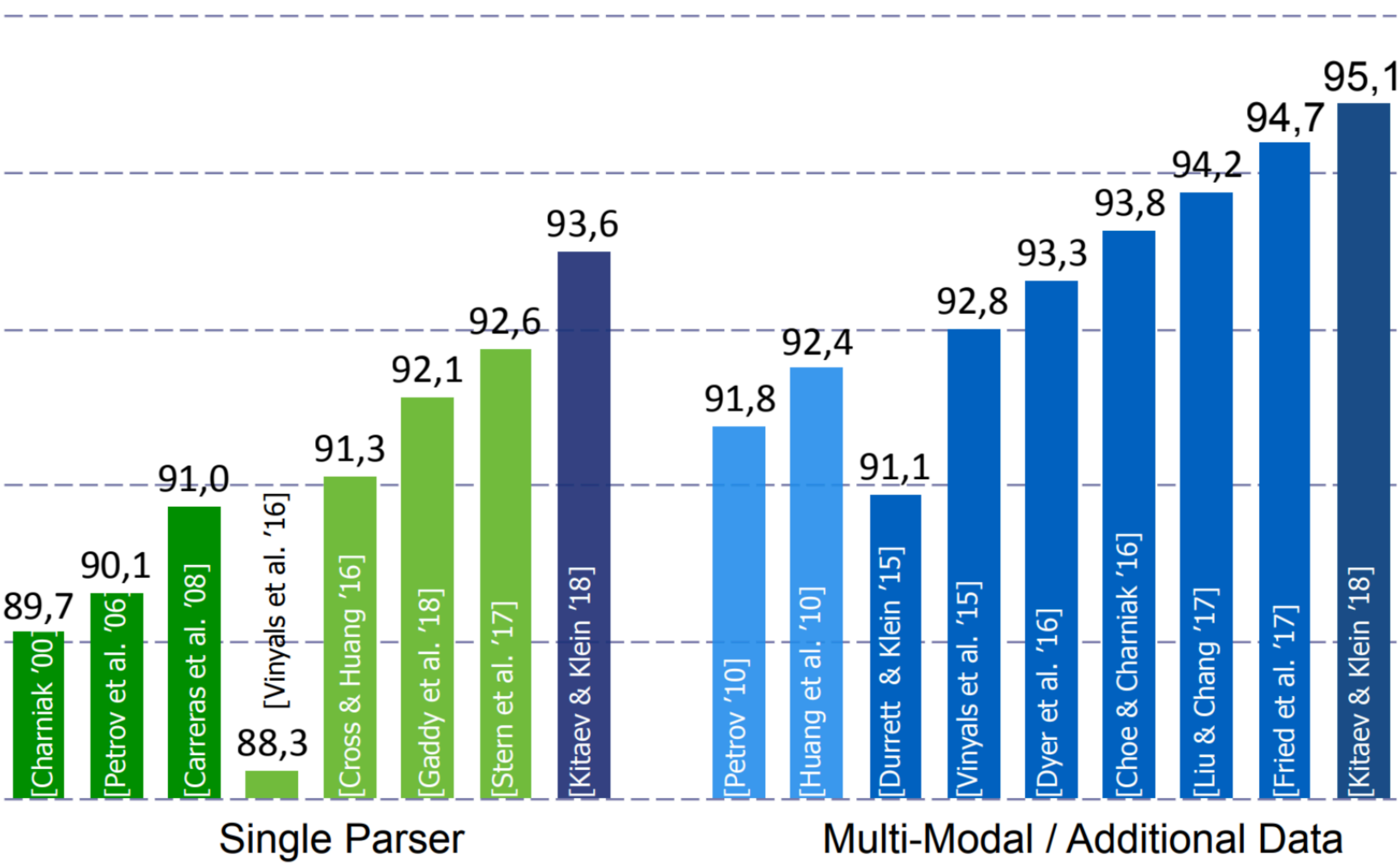
SoTA Self-attention-based Parser

- Use the Transformer encoder instead of Bi-LSTM
  - Split the word hidden vector from Transformer into two half vectors $h_i = [\overrightarrow{h_i}; \overleftarrow{h_i}]$
  - Replace the forward and backward hidden vectors of Bi-LSTM by the new vectors



Kitaev et al. 2018. Constituency Parsing with a Self-Attentive Encoder

Historical Trends on Penn Treebank



Unsupervised Parsing (Grammar Induction)

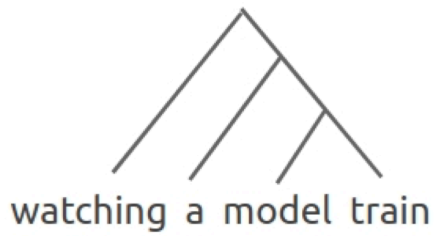
Grammar Induction (Unsupervised Parsing)

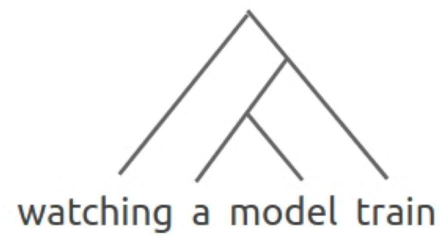
Learning a set of (probabilistic) grammar rules

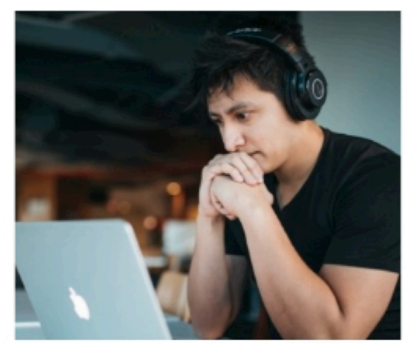
Typical grammar induction methods

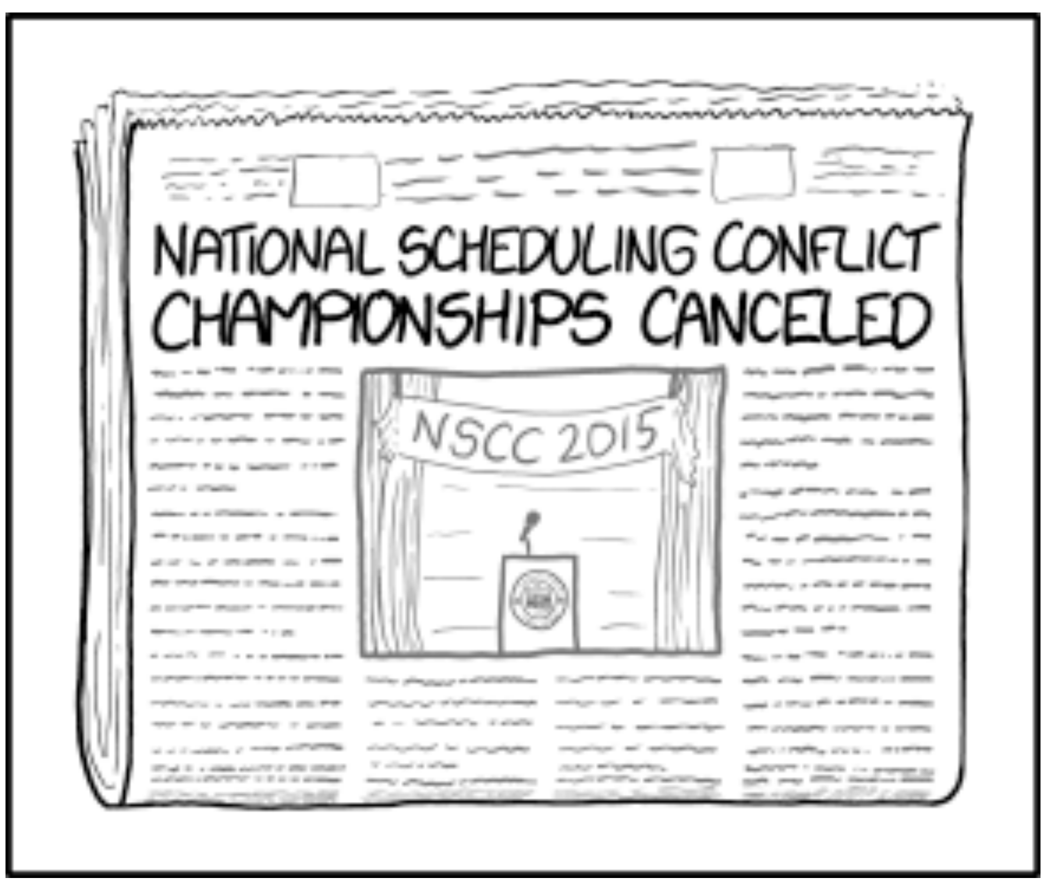
unsupervised constituency and dependency parsing

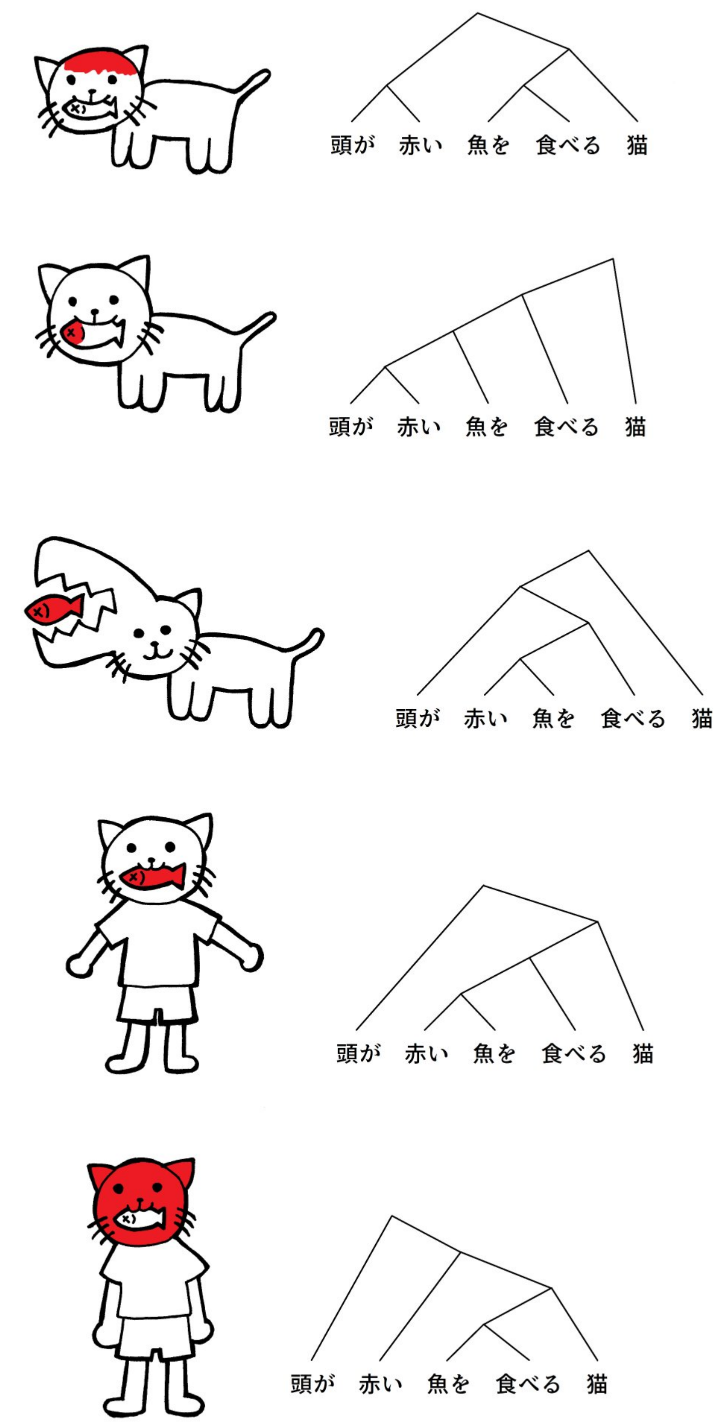
Explosion of ambiguity

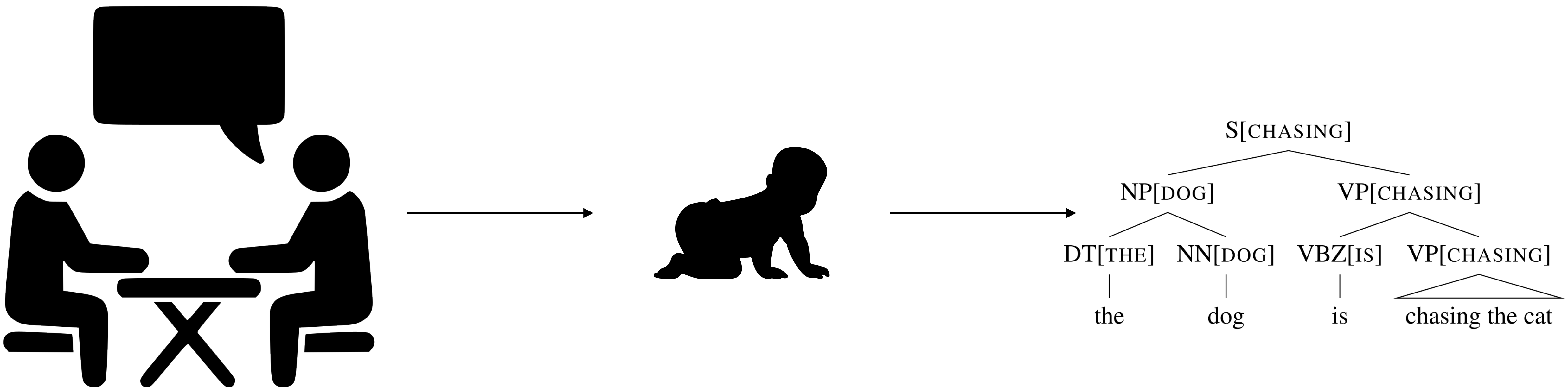




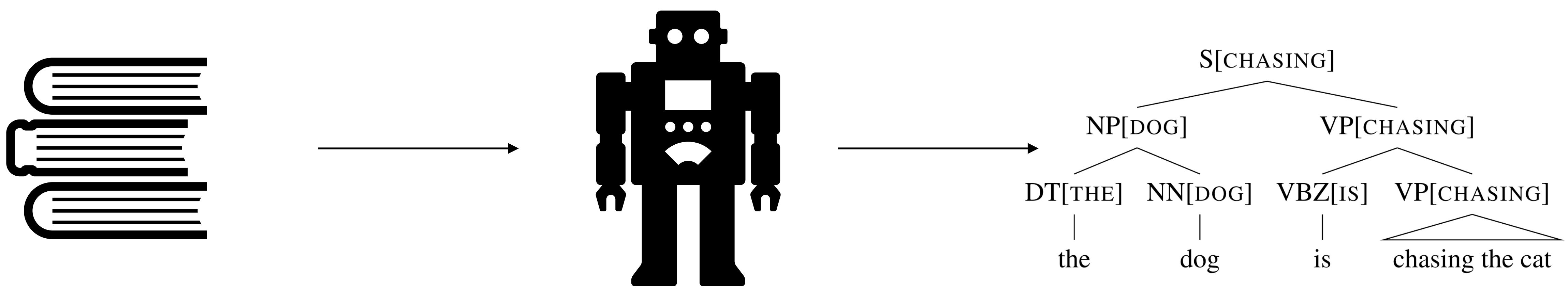








Mystery: humans learn to parse without learning to parse (from labels)



Grammar Induction

Neural PCFGs

- Neural parameterization for PCFGs

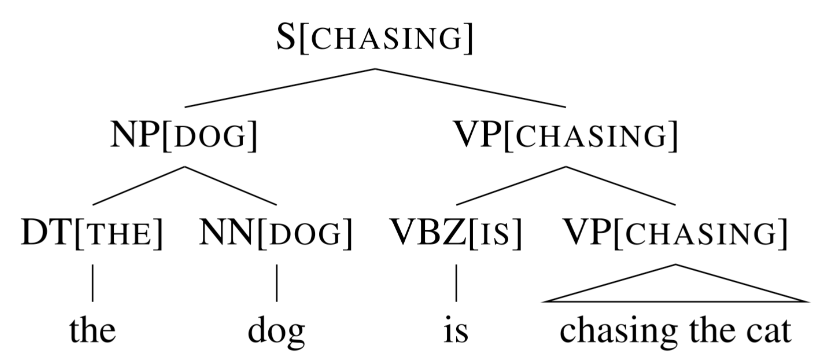
$$\pi_{T \to w} = \textsc{NeuralNet}(\mathbf{w}_T) = \frac{\exp(\mathbf{u}_w^\top f(\mathbf{w}_T))}{\sum_{w' \in \Sigma} \exp(\mathbf{u}_{w'}^\top f(\mathbf{w}_T))}$$

$$\pi_{T \to w} \propto \exp\left(\underbrace{\mathbf{u}_w^\top}_{\text{output emb.}} \overbrace{f(\underbrace{\mathbf{w}_T}_{\text{input emb.}})}^{\text{shared neural net}} \right)$$

  - same training method: MLE
  - Where's the magic?
    - Expectation-Maximization (EM) algorithm

Neural L-PCFGs

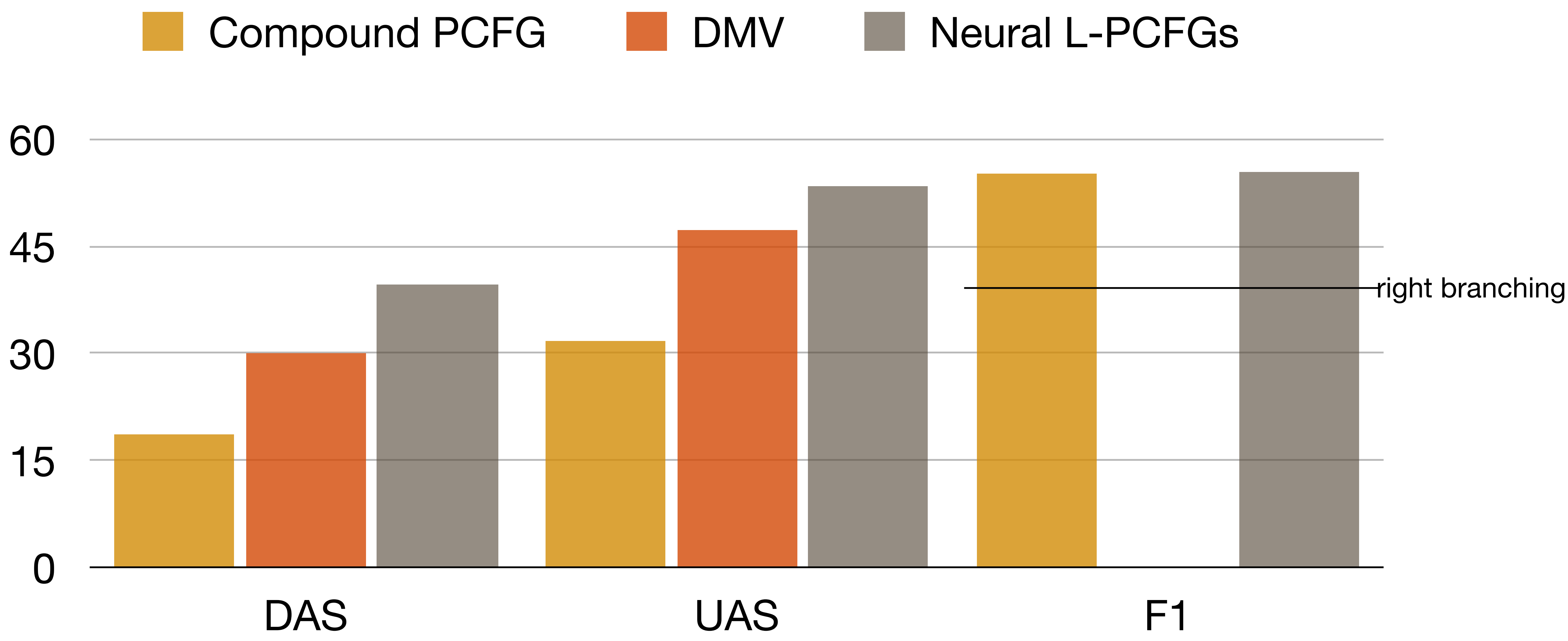
- You can further improve Neural PCFGs by adding head annotations



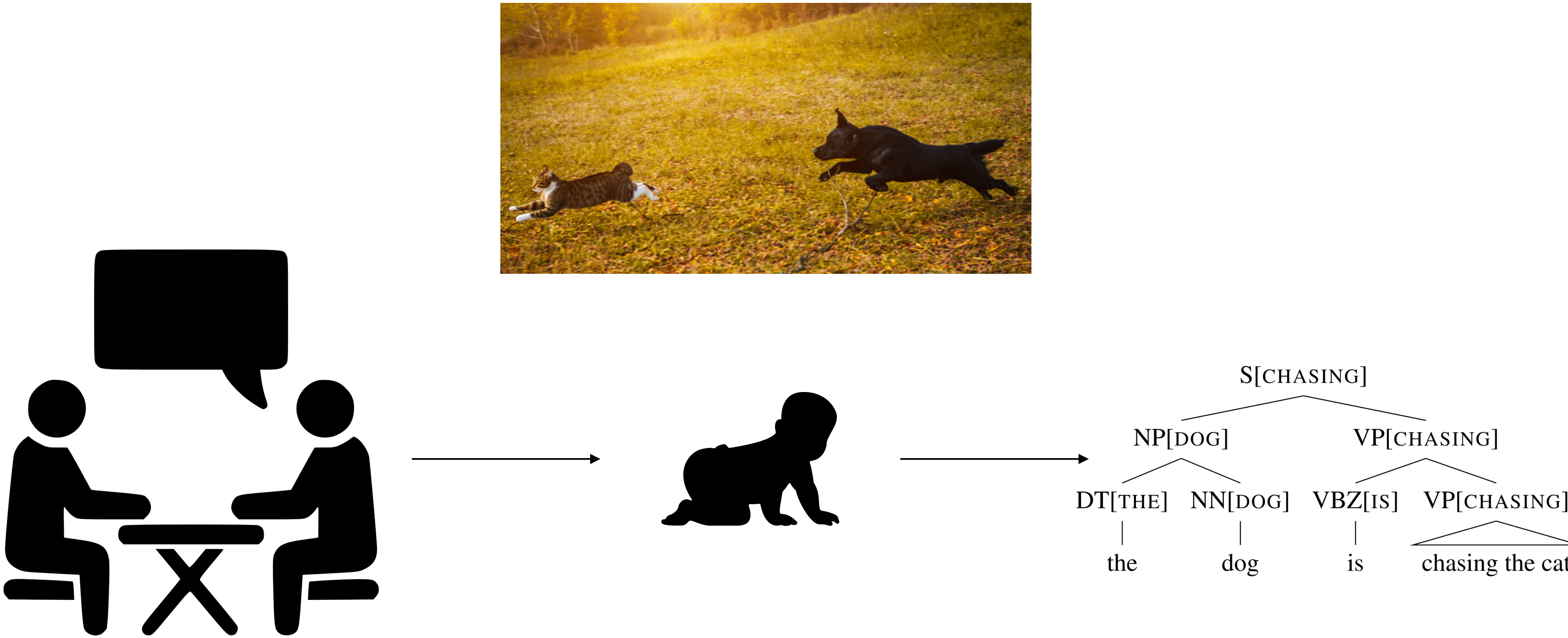
$$
\begin{aligned}
S &\to A, && A \in \mathcal{N} \\
A &\to BC, && A \in \mathcal{N}, B, C \in \mathcal{N} \cup \mathcal{P} \\
T &\to \alpha, && T \in \mathcal{P}
\end{aligned}
$$

$$
\begin{array}{lll}
1 & S \to A[\alpha], & A \in \mathcal{N} \\
2l & A[\alpha] \to B[\alpha]C[\beta], & A \in \mathcal{N}, B, C \in \mathcal{N} \cup \mathcal{P} \\
2r & A[\alpha] \to B[\beta]C[\alpha], & A \in \mathcal{N}, B, C \in \mathcal{N} \cup \mathcal{P} \\
3 & T[\alpha] \to \alpha, & T \in \mathcal{P}
\end{array}
$$

Results



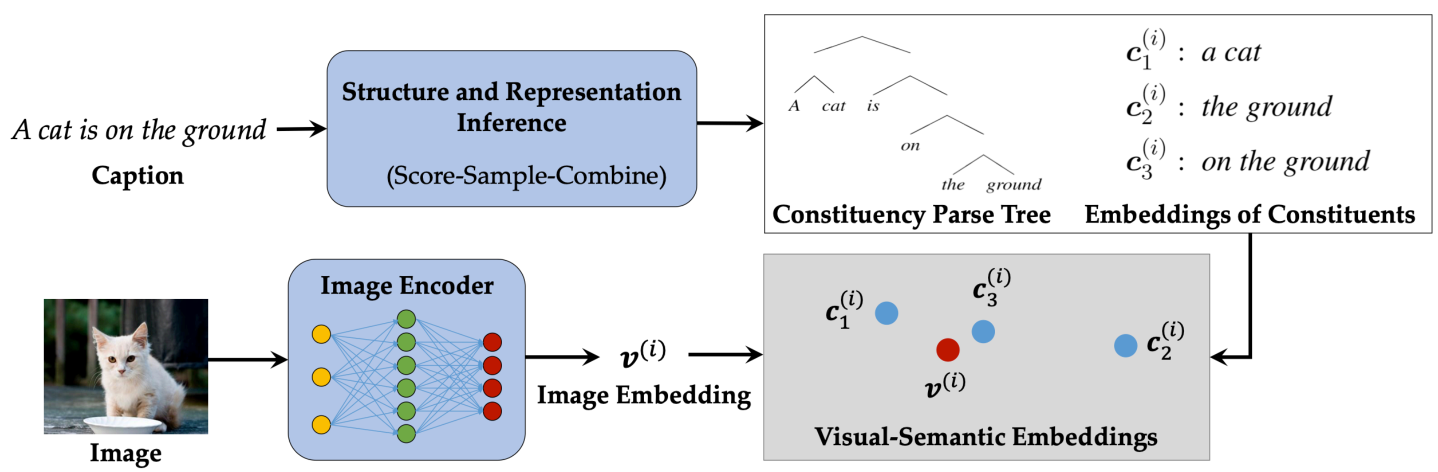
Compound PCFG
DMV
Neural L-PCFGs
60
45
30
15
0
right branching
DAS
UAS
F1

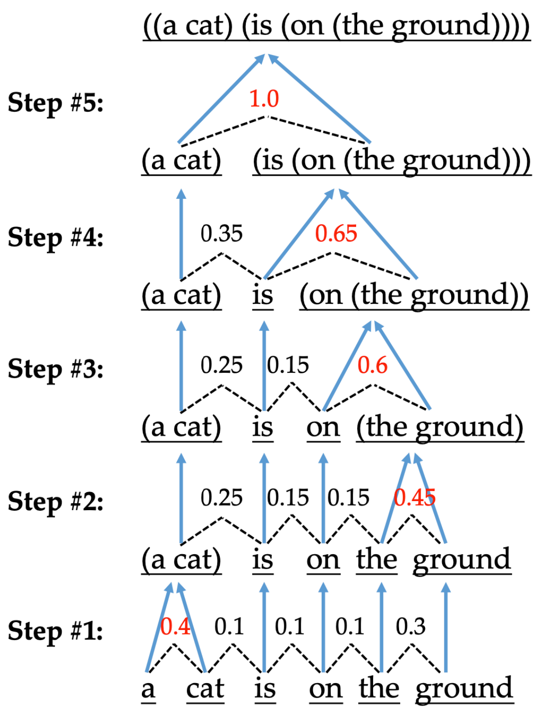


Key to the mystery: visual prior?

Visual Prior Grammar Induction

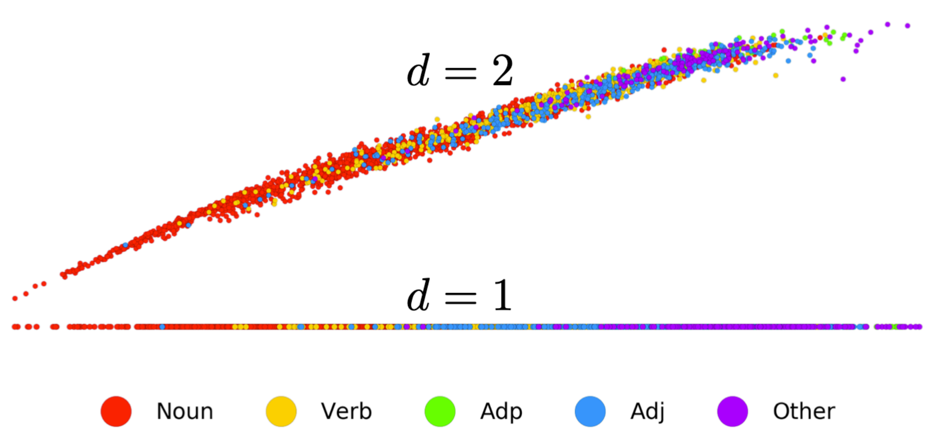
- Visual grounded neural syntax acquisition





Visual Prior Grammar Induction

- Visual grounded neural syntax acquisition
  - Similar results even if the dimension of embeddings get shrunk to 1 or 2.
  - embedding
    tags
  - concretene



Model	NP	VP	PP	ADJP	Avg. F_1
Shi2019	79.6	26.2	42.0	22.0	50.4 ± 0.3
Shi2019*	80.5	26.9	45.0	21.3	51.4 ± 1.1
$1, s_{\text{WS}}, c_{\text{ME}}$	77.2	17.0	53.4	18.2	49.7 ± 5.9
$2, s_{\text{WS}}, c_{\text{ME}}$	**80.8**	19.1	52.3	17.1	51.6 ± 0.6
+HI					
Shi2019	74.6	32.5	66.5	21.7	53.3 ± 0.2
Shi2019*	73.1	33.9	64.5	22.5	51.8 ± 0.3
$1, s_{\text{WS}}, c_{\text{ME}}$	74.0	35.2	62.0	24.2	51.8 ± 0.4
$2, s_{\text{WS}}, c_{\text{ME}}$	73.8	30.2	63.7	21.9	51.3 ± 0.1
+HI+FastText					
Shi2019	78.8	24.4	65.6	22.0	54.4 ± 0.3
Shi2019*	77.3	23.9	64.3	21.9	53.3 ± 0.1
$1, s_{\text{WS}}, c_{\text{ME}}$	76.6	21.9	68.7	20.6	53.5 ± 1.4
$2, s_{\text{WS}}, c_{\text{ME}}$	77.5	22.8	66.3	19.3	53.6 ± 0.2
+HI+FastText-IN					
Shi2019*	78.3	26.6	67.5	22.1	54.9 ± 0.1
$1, s_{\text{M}}, c_{\text{MX}}$	79.6	29.0	38.3	23.5	49.7 ± 0.2
$1, s_{\text{MHI}}, c_{\text{MX}}$	77.6	**45.0**	72.3	**24.3**	$\mathbf{57.5 \pm 0.1}$
$1, s_{\text{M}}, c_{\text{ME}}$	80.0	26.9	62.2	23.2	54.3 ± 0.2
$1, s_{\text{MHI}}, c_{\text{ME}}$	76.5	20.5	63.6	22.7	52.2 ± 0.3
$1, s_{\text{WS}}, c_{\text{ME}}$	77.7	26.3	**72.5**	22.0	55.5 ± 0.1
$2, s_{\text{WS}}, c_{\text{ME}}$	78.5	26.3	69.5	21.1	55.2 ± 0.1

Visual Prior Grammar Induction

- Recommend readings
  - *Visually Grounded Compound PCFGs.*
  - *Dependency Induction Through the Lens of Visual Perception*

Questions?