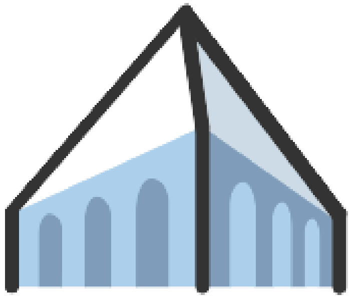
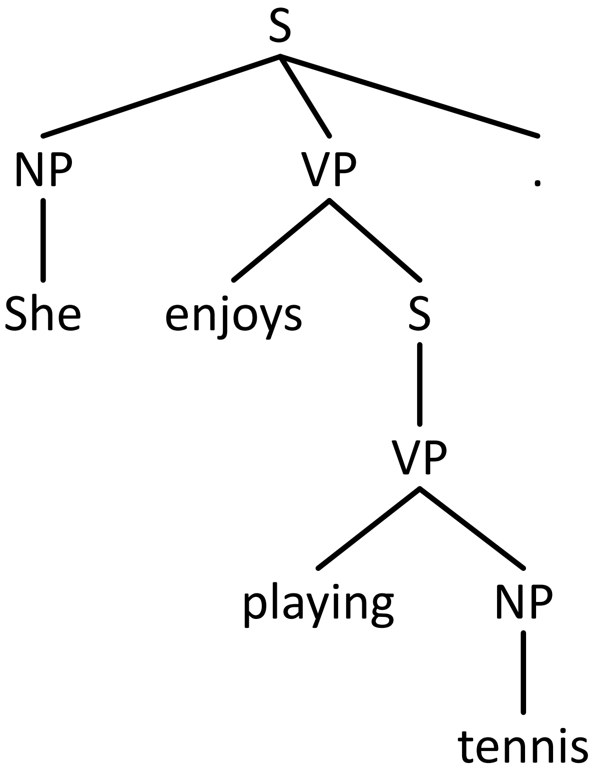
A Minimal Span-Based Neural Constituency Parser



Mitchell Stern, Jacob Andreas, Dan Klein
UC Berkeley

Parsing as Span Classification



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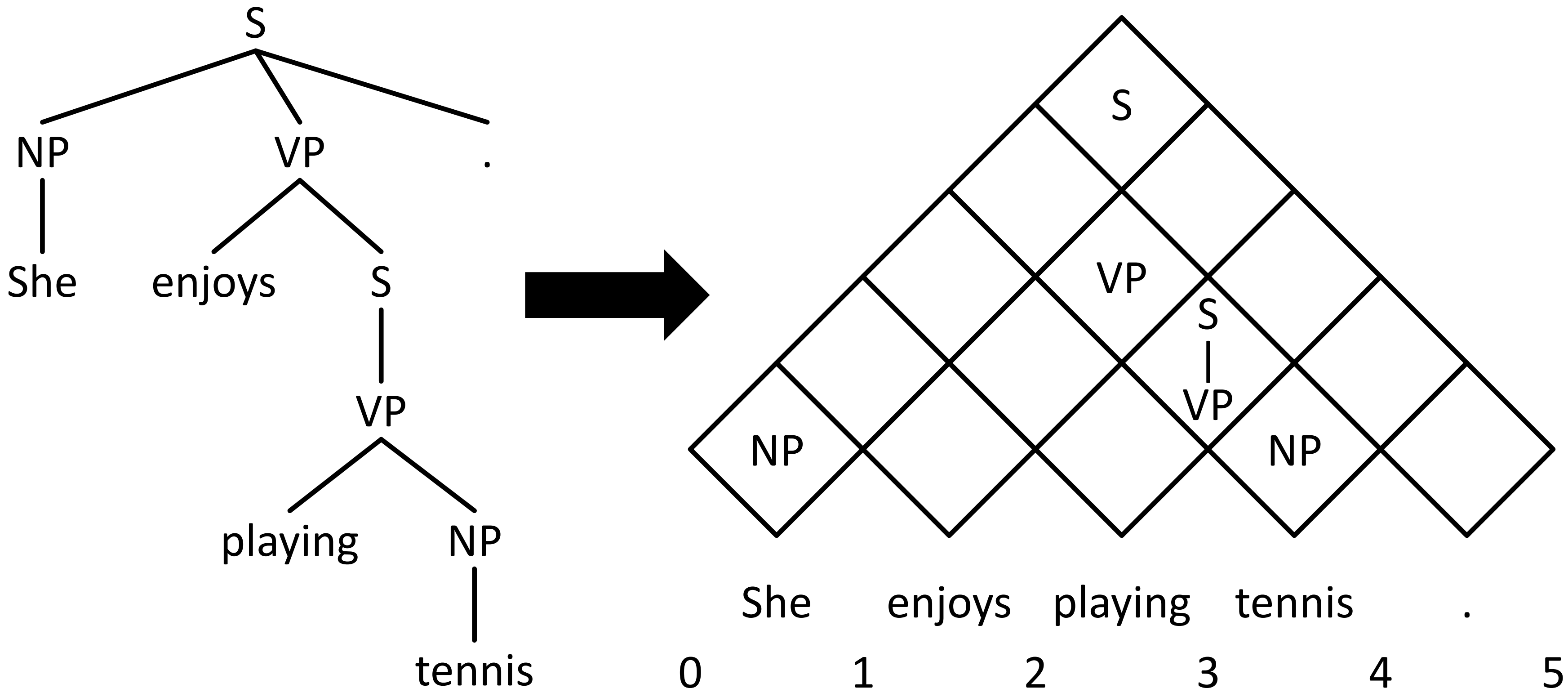

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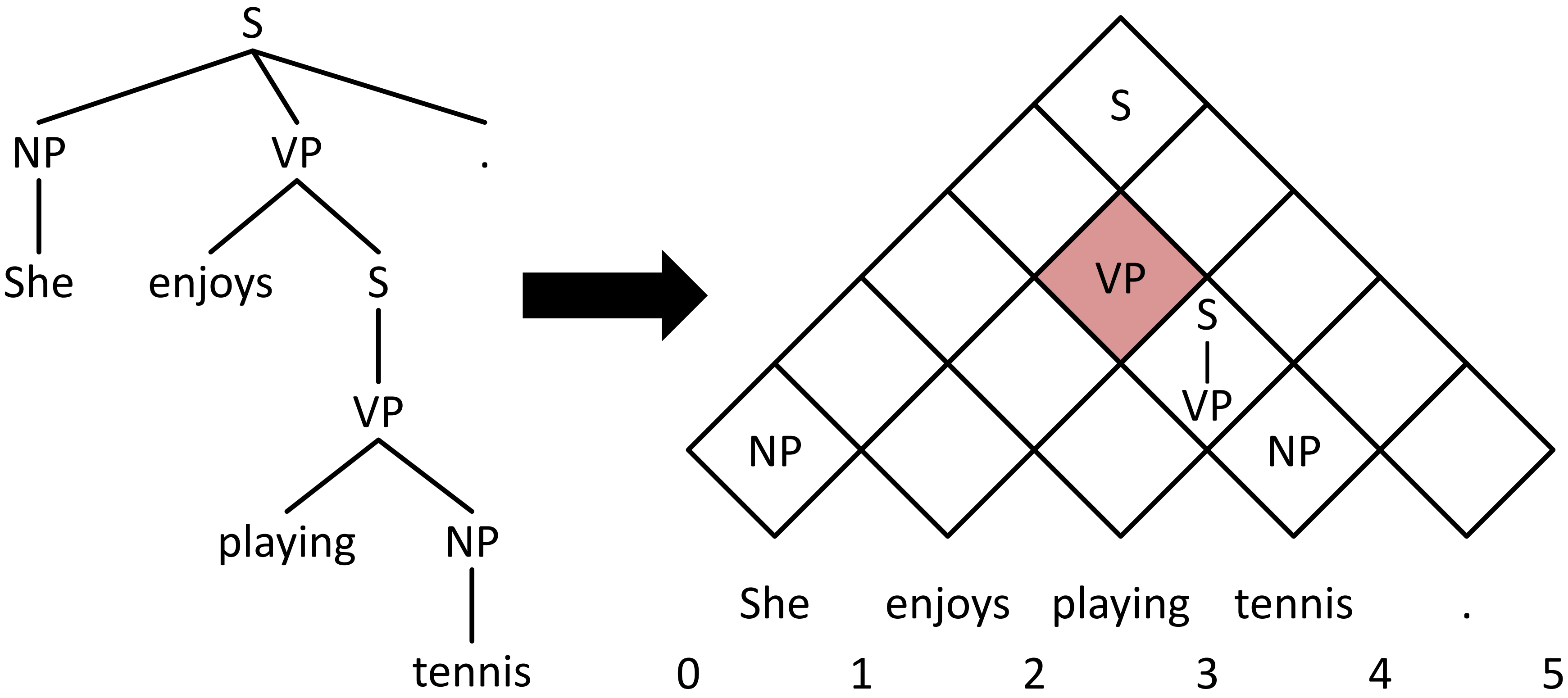

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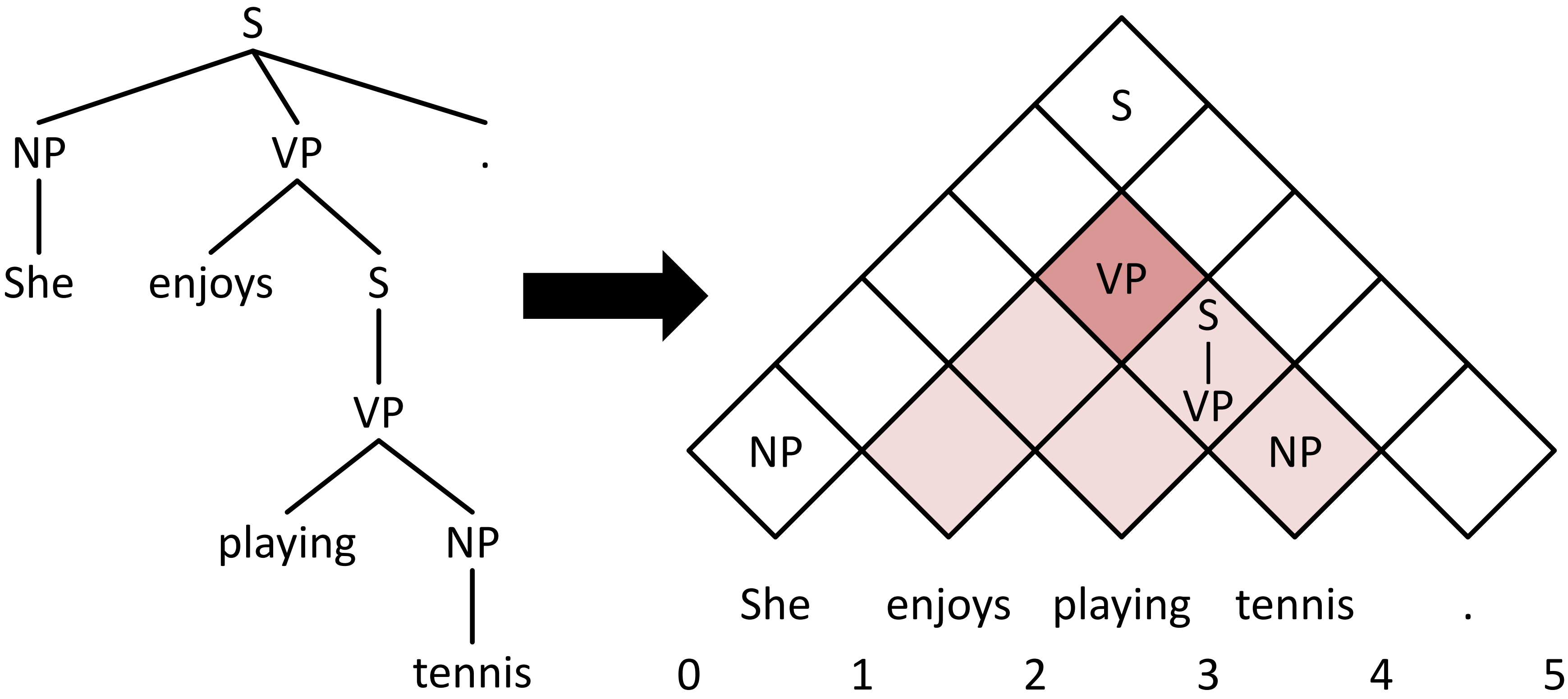

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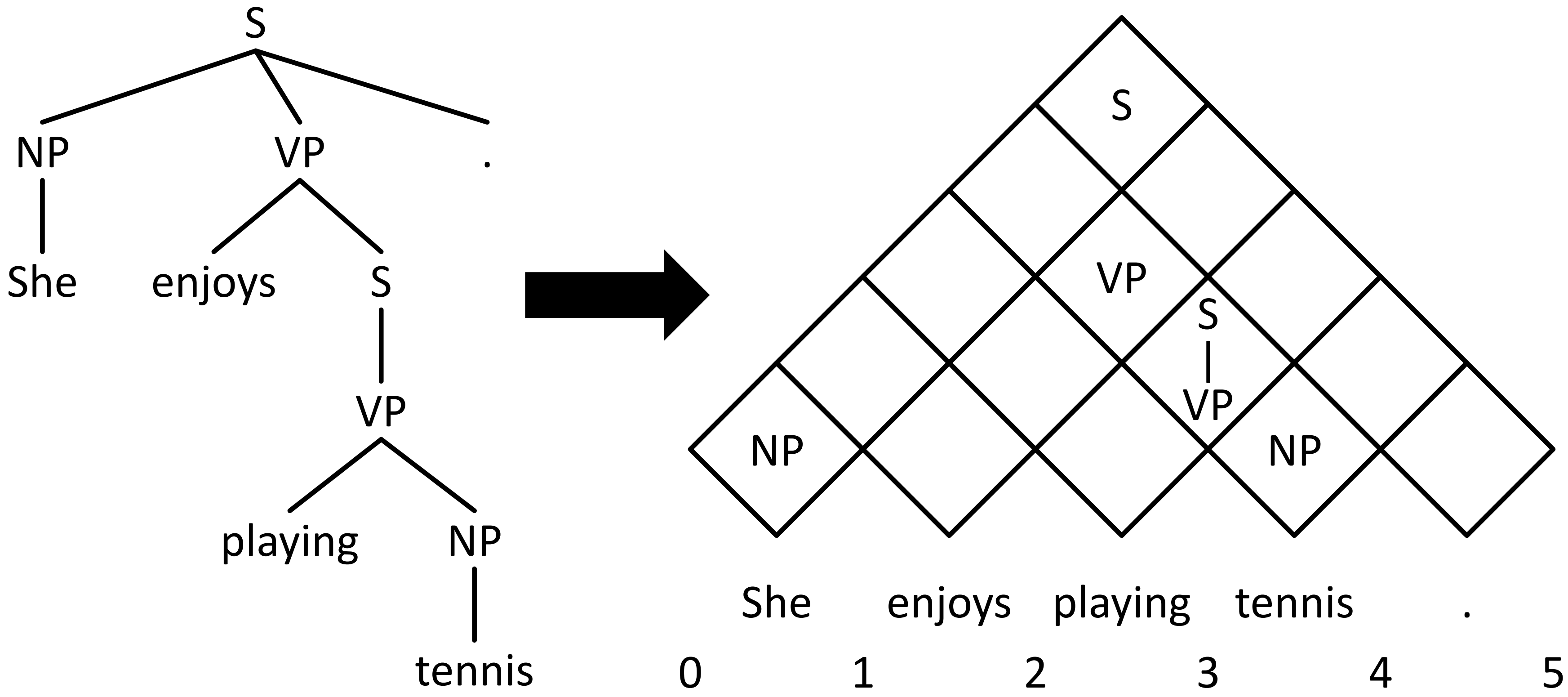

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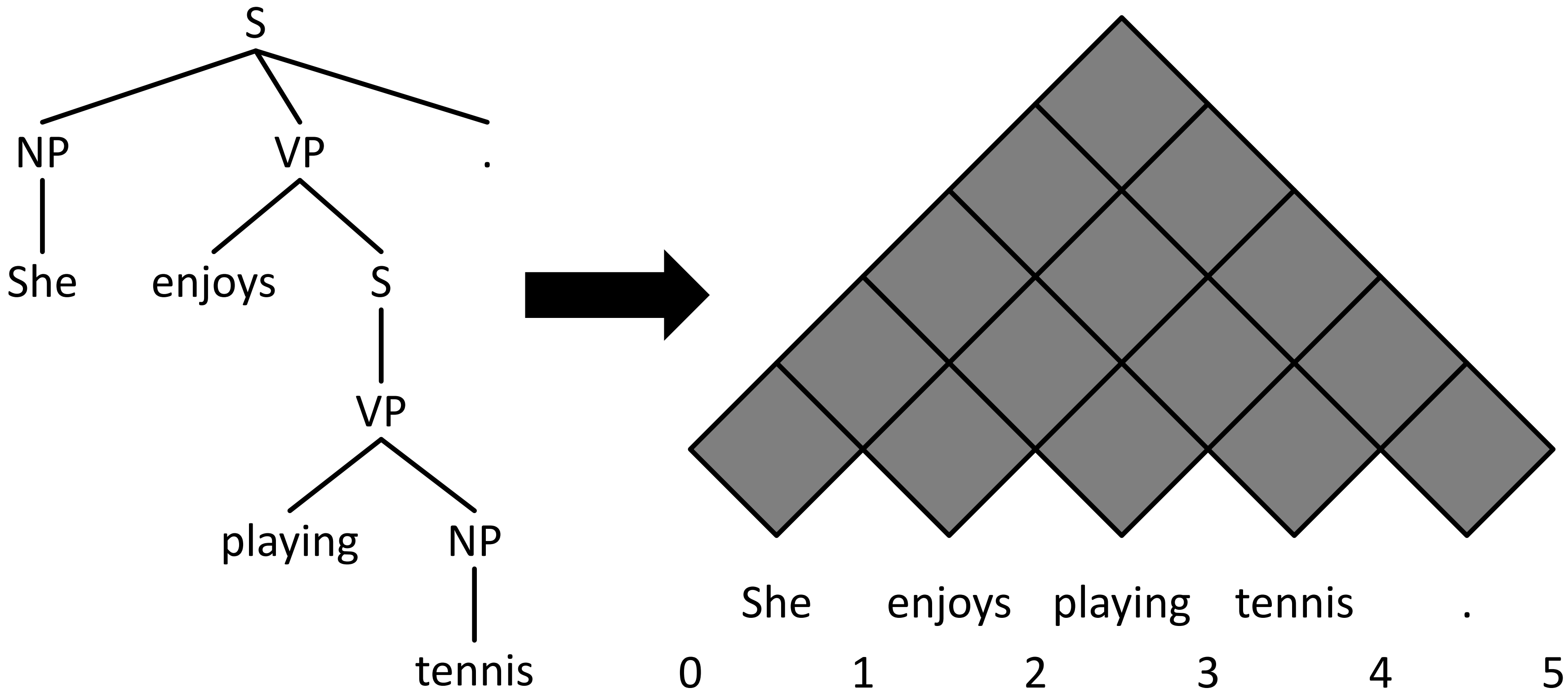

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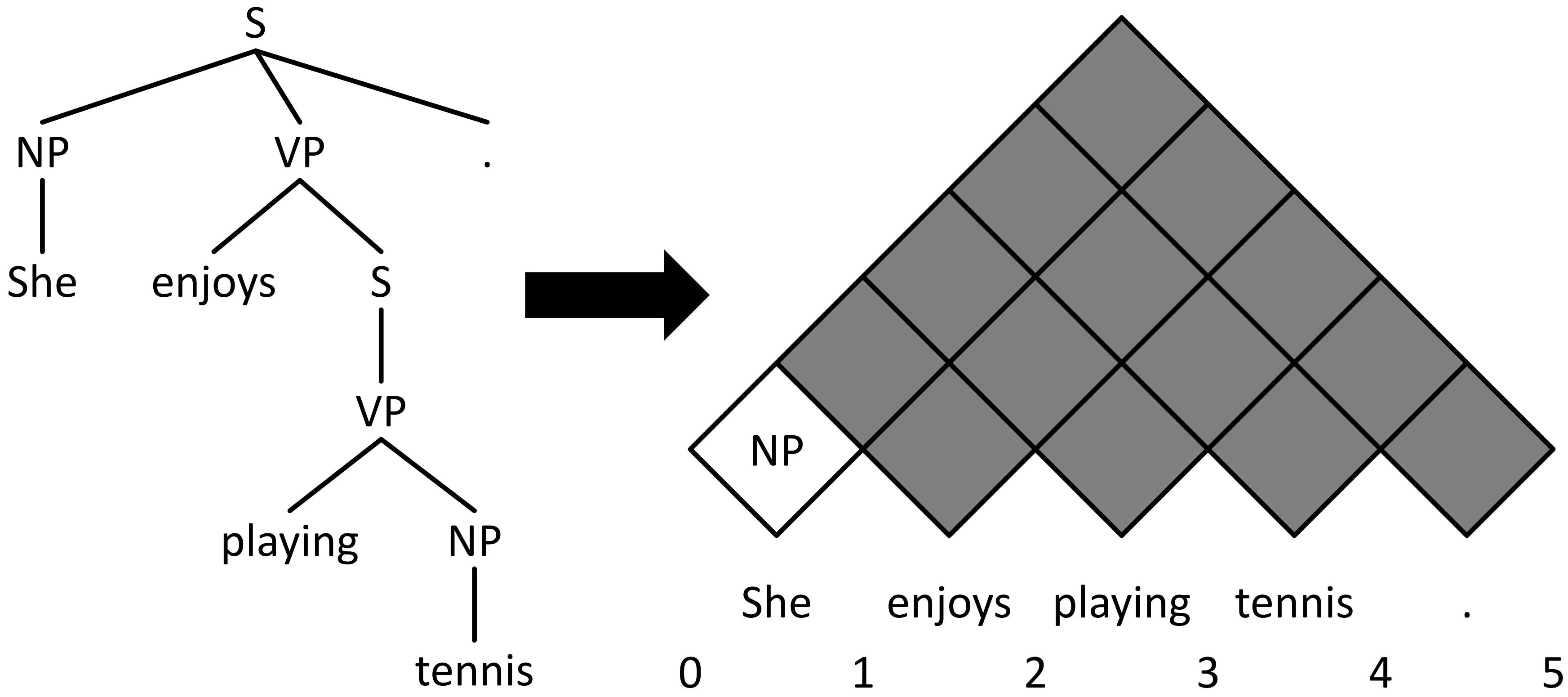

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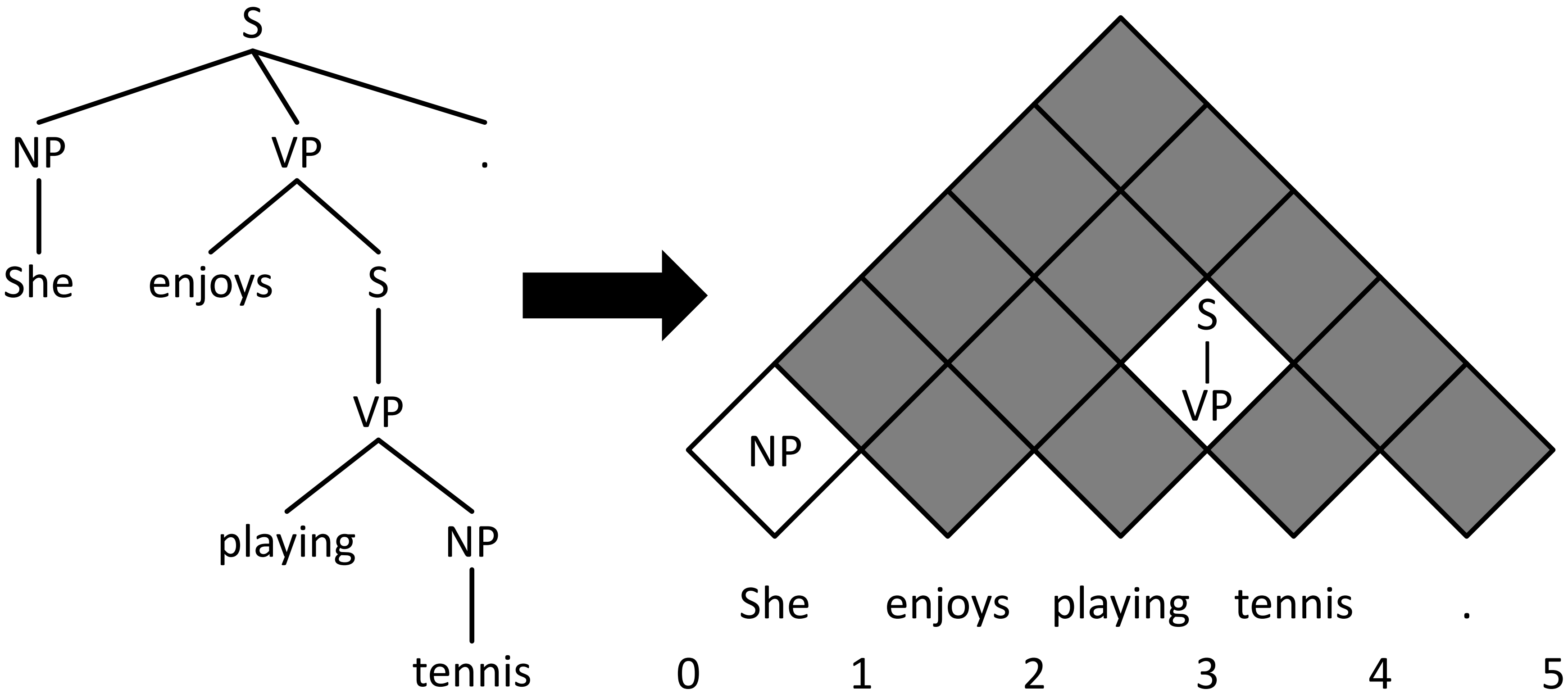

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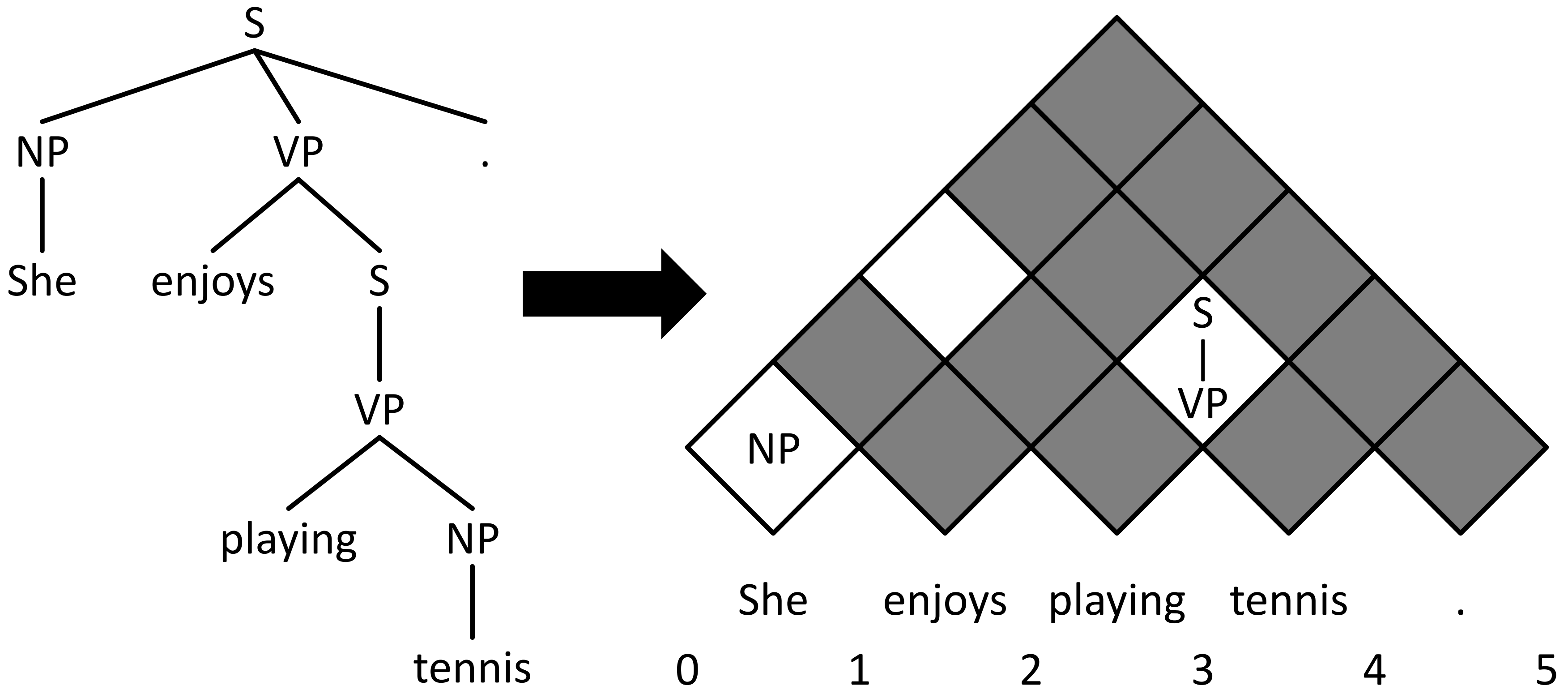

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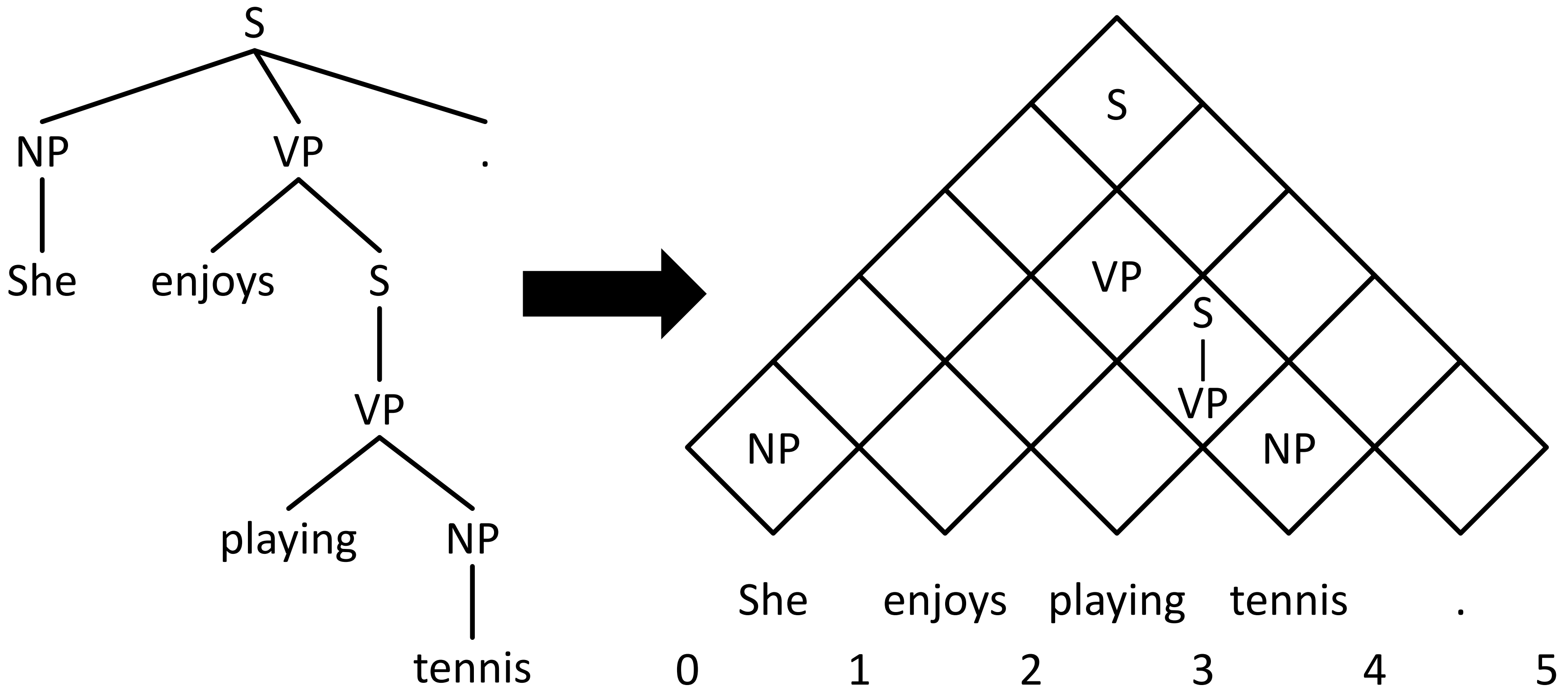

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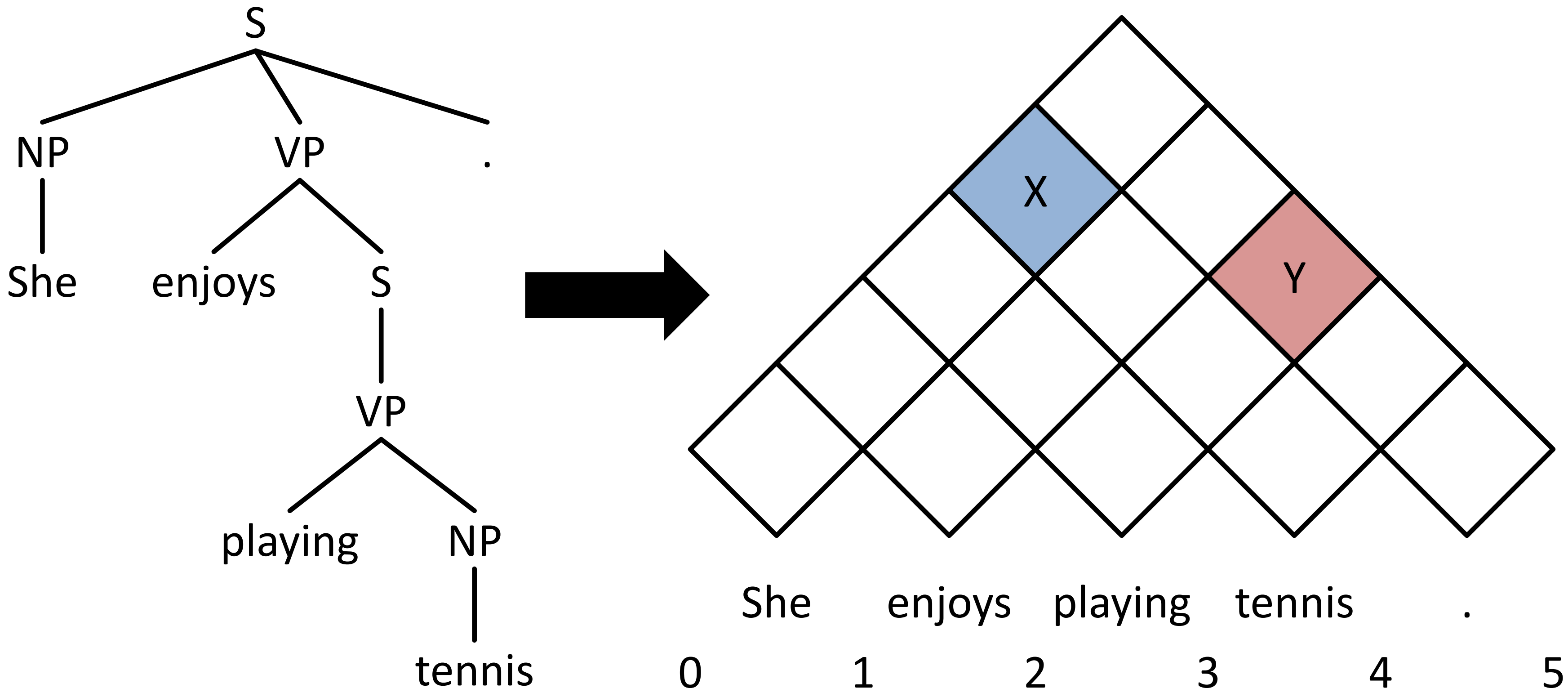

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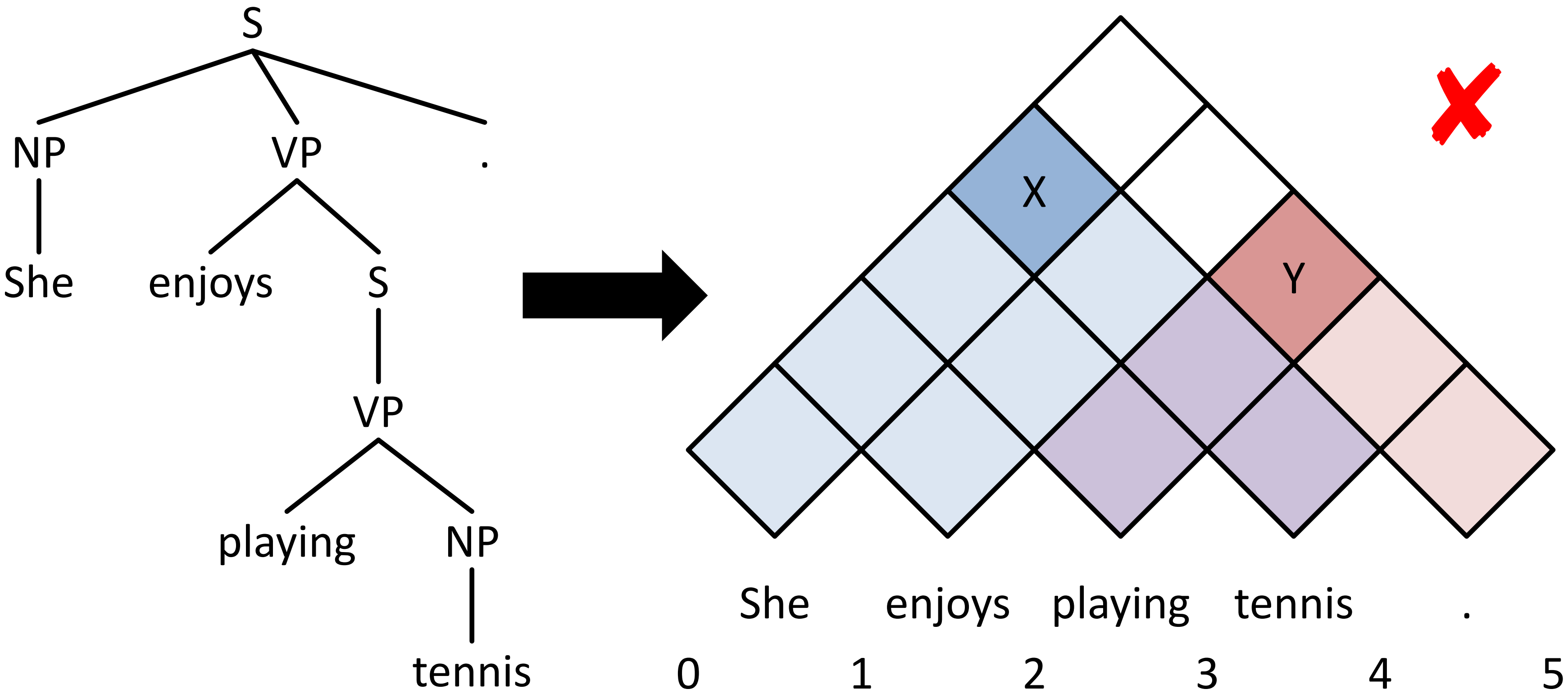

Minimality in Parsing

Grammar:

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S(decided) $\longrightarrow$ NP(workers) VP(decided) [Collins (1999)]

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S $\rightarrow$ NP^S VP^S [Klein and Manning (2003)]

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S(decided)	$\rightarrow$	NP(workers)	VP(decided)	[Collins (1999)]
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S	$\rightarrow$	NP	VP	[Hall et al. (2014)]

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S				[Vinyals et al. (2015)]

Minimality in Parsing

Scoring:

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score(S $\longrightarrow$ NP^S VP^S)

[Klein and Manning (2003)]

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score(i, j, S) [This work]

Minimality in Parsing

Decoding:

Minimality in Parsing

Decoding:

Chart-based

Globally optimal, $O(n^3)$ time complexity

Minimality in Parsing

Decoding:

Chart-based

Globally optimal, $O(n^3)$ time complexity

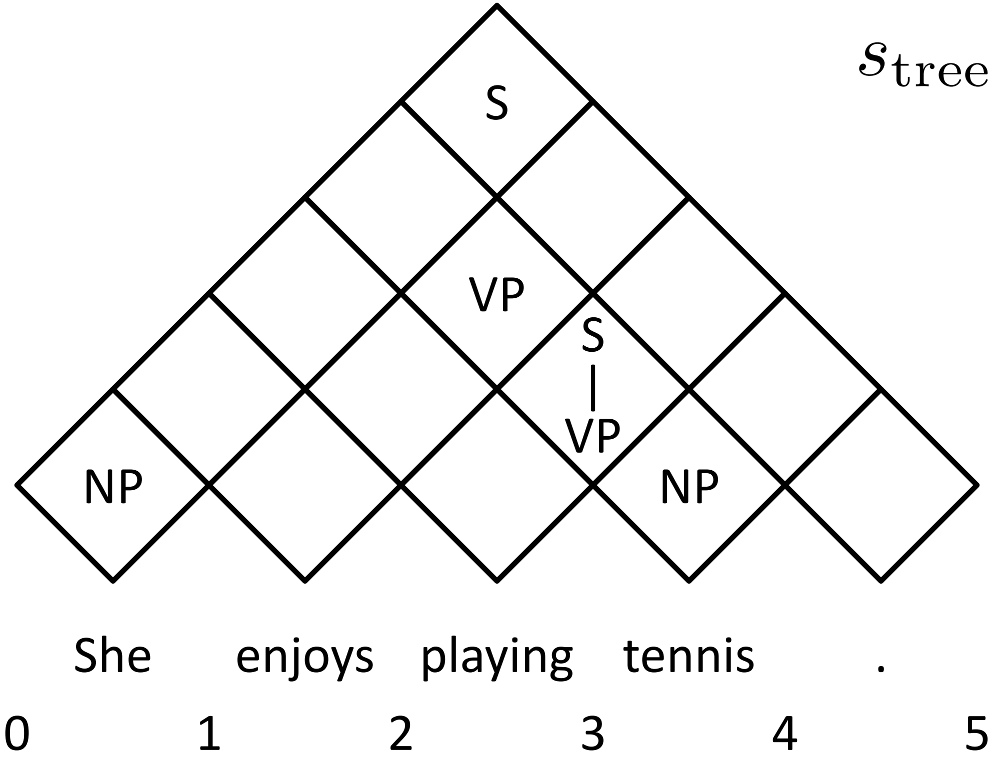
Transition-based

Greedy, $O(n)$ or $O(n^2)$ time complexity

Tree Scoring Function

$$s_{\text{tree}}(T) = \sum_{(\ell,(i,j))\in T} s(i,j,\ell)$$

Tree Scoring Function



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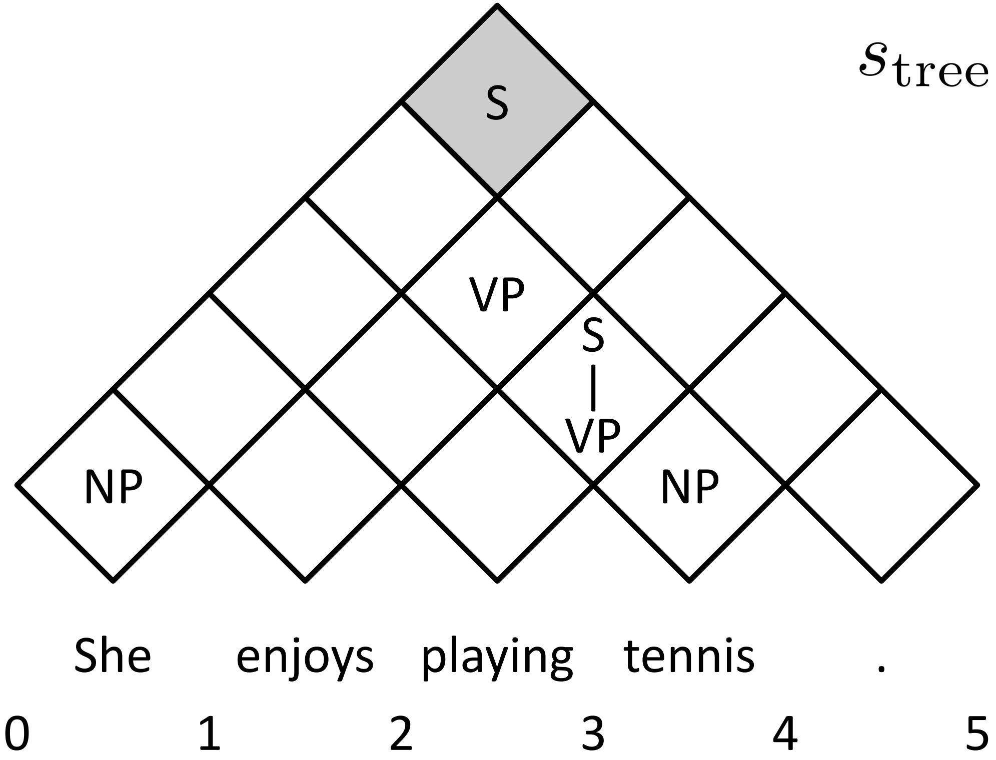

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$$= s(0,5,\mathrm{S})$$

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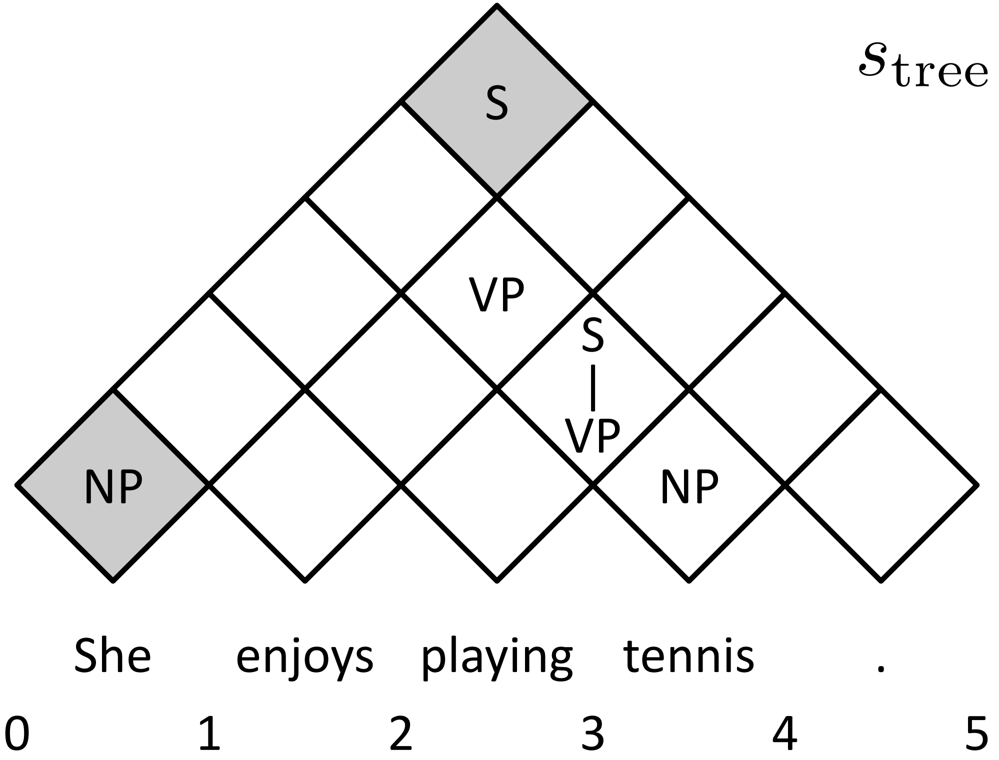
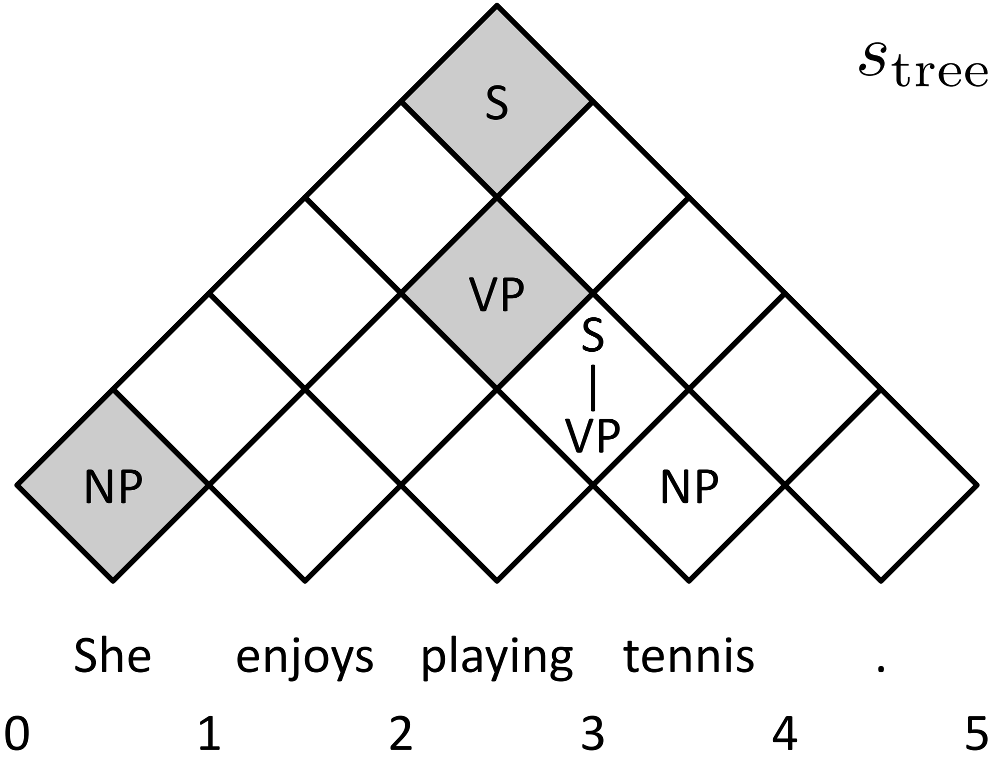


$$s_{\text{tree}}(T) = \sum_{(\ell,(i,j)) \in T} s(i,j,\ell)$$

$$= s(0,5,\mathrm{S})$$

$$+ s(0,1,\mathrm{NP})$$

Tree Scoring Function



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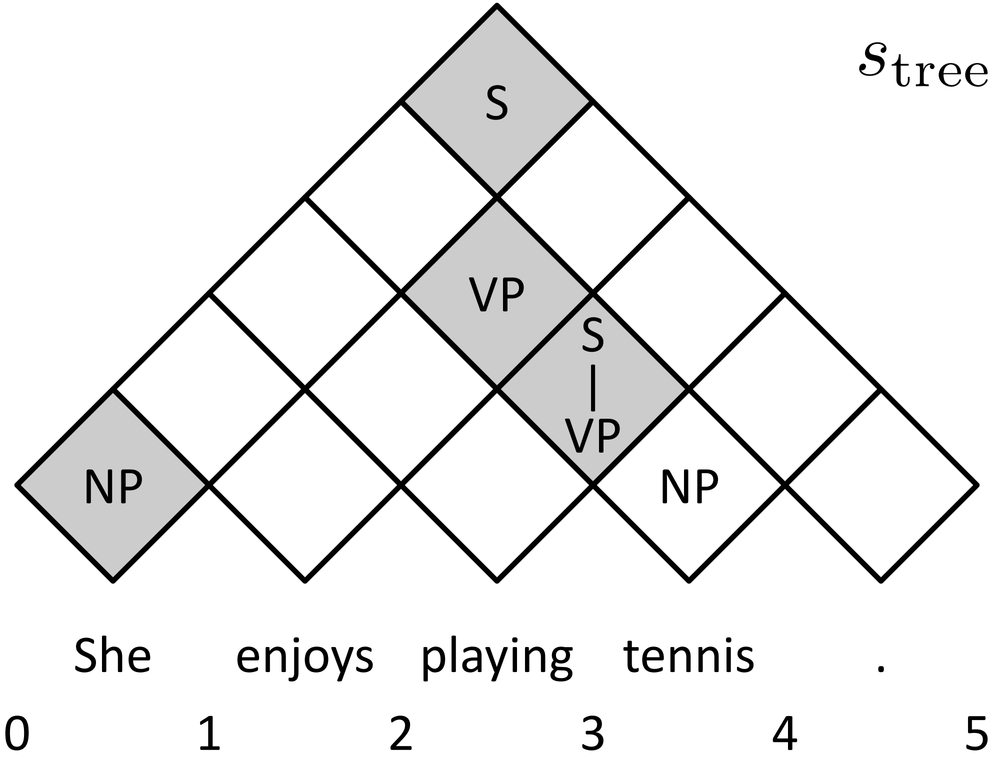
Tree Scoring Function



$$s_{\text{tree}}(T) = \sum_{(\ell,(i,j))\in T} s(i,j,\ell)$$

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$$+\ s(2,4,\mathrm{S\text{–}VP})$$

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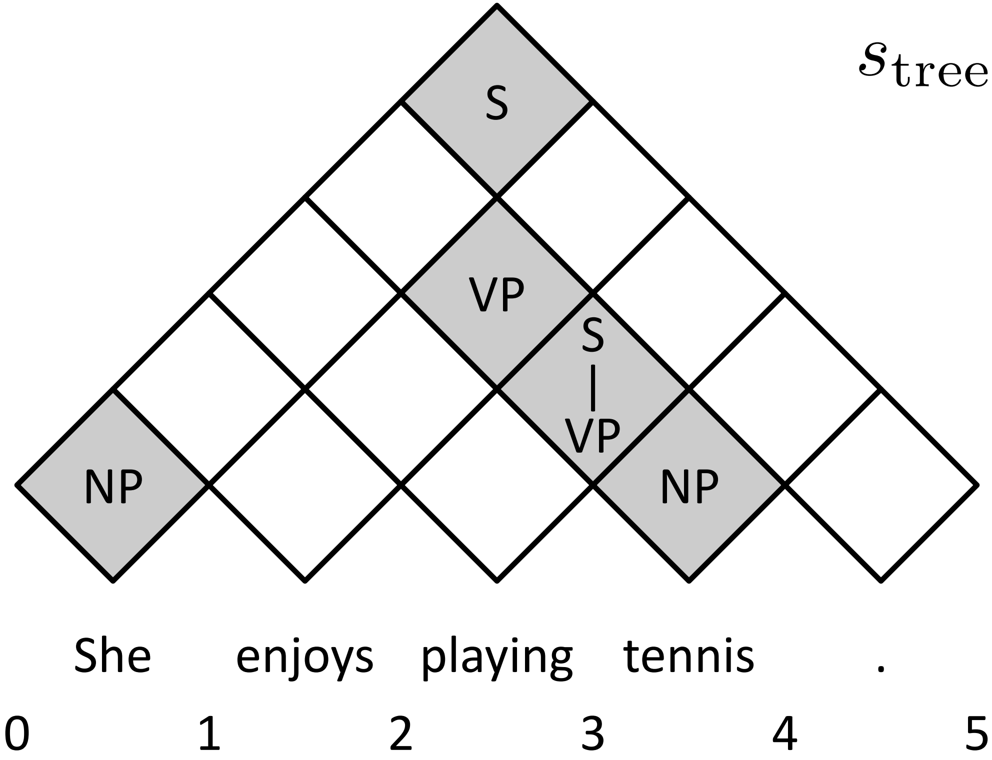

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$$+ \; s(0,1,\mathrm{NP})$$
$$+ \; s(1,4,\mathrm{VP})$$
$$+ \; s(2,4,\mathrm{S–VP})$$
$$+ \; s(3,4,\mathrm{NP})$$

Dynamic Program: Base Case

$$s_{\text{best}}(i, i+1) = \max_{\ell}[s(i, i+1, \ell)]$$

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$$s_{\text{best}}(i, i+1) = \overbrace{\max_{\ell}[s(i, i+1, \ell)]}^{\text{Pick best label}}$$

Dynamic Program: General Case

$$s_{\text{best}}(i,j) = \max_{\ell}[s(i,j,\ell)] + \max_{k}[s_{\text{best}}(i,k) + s_{\text{best}}(k,j)]$$

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Scoring Function Implementation

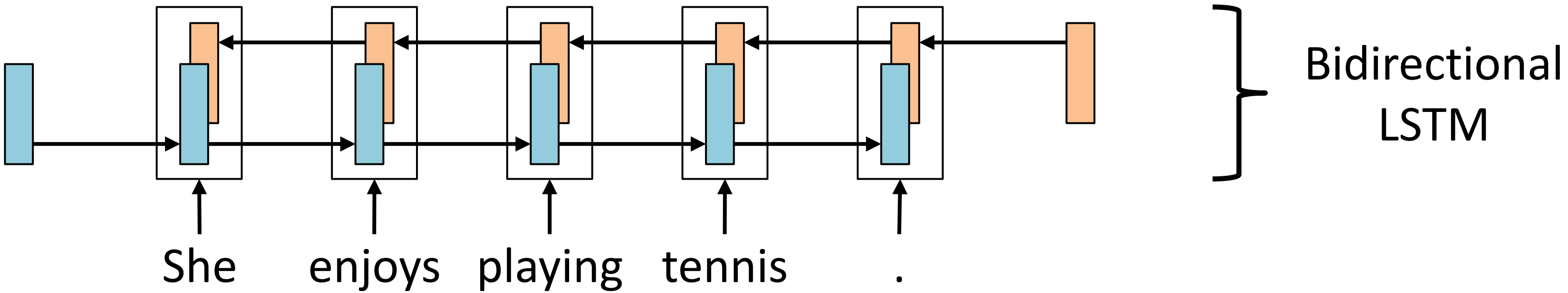
[Inspired by Cross and Huang (2016)]

Scoring Function Implementation

She enjoys playing tennis .

[Inspired by Cross and Huang (2016)]

Scoring Function Implementation



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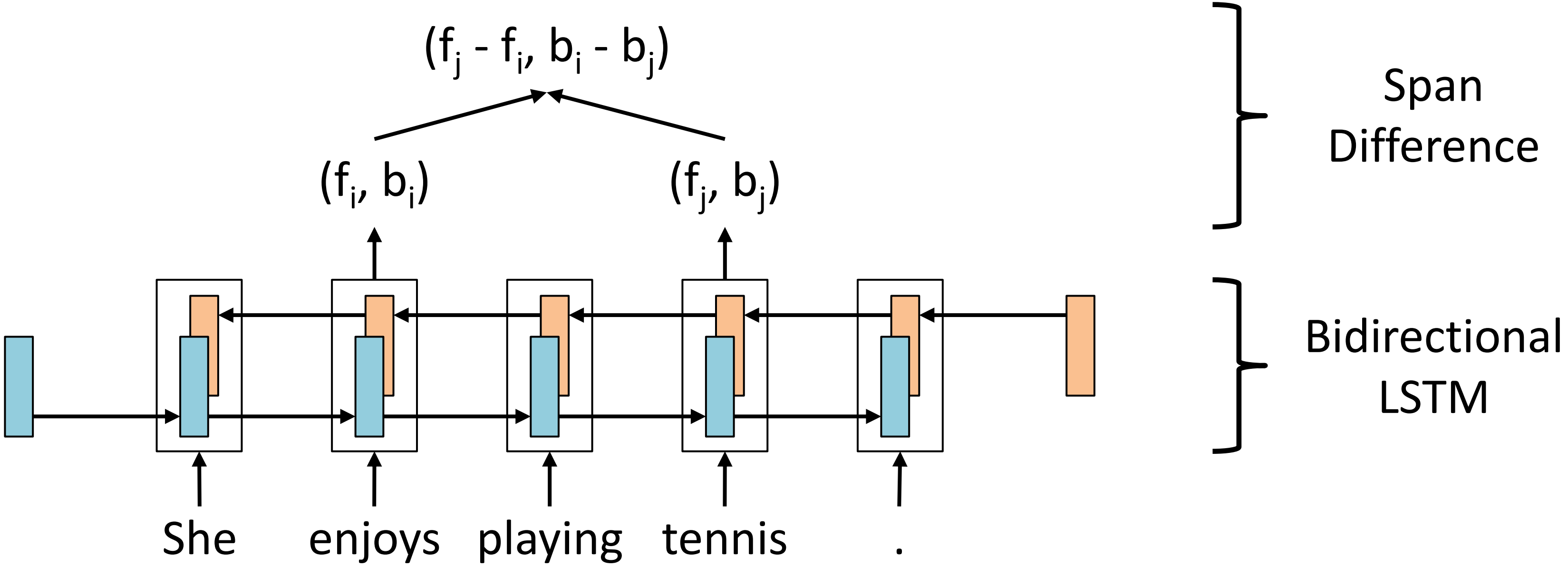

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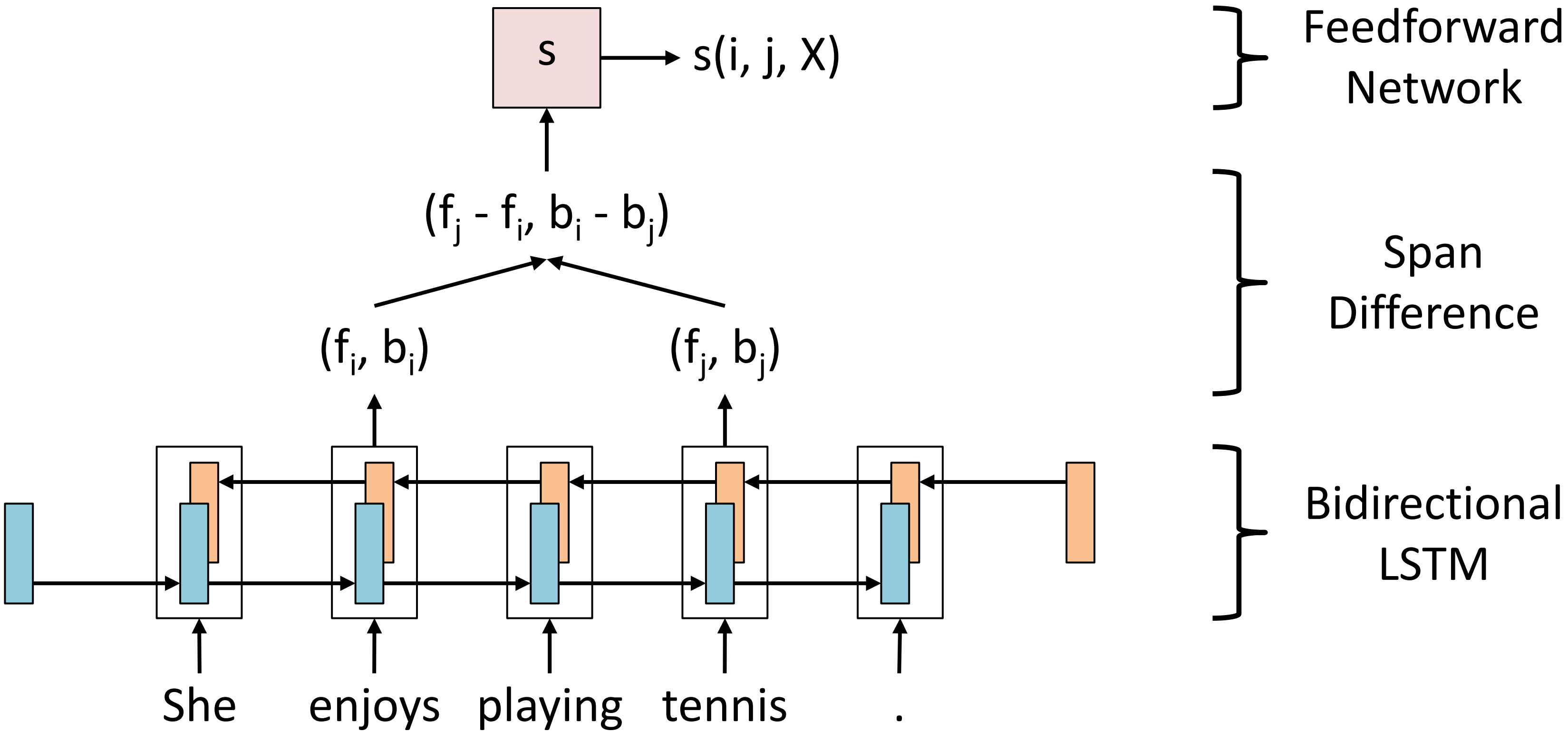

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Training

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Want $s_{\mathrm{tree}}(T^*) > s_{\mathrm{tree}}(T)$ for all $T \neq T^*$

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Require larger margin for higher loss:

$$s_{\text{tree}}(T^*) \geq \Delta(T, T^*) + s_{\text{tree}}(T)$$

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Require larger margin for higher loss:

$$s_{\text{tree}}(T^*) \geq \Delta(T, T^*) + s_{\text{tree}}(T)$$

Use hinge penalty function:

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

Training

Use loss-augmented decoding during training:

$$\hat{T} = \max_{T} [\Delta(T, T^*) + s_{\text{tree}}(T)]$$

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Loss-augmented decoding for Hamming loss:

Replace $s(i, j, \ell)$ with $s(i, j, \ell) + \mathbf{1}(\ell \neq \ell^*_{ij})$

Initial Results

Parser	F1 Score
Hall et al. (2014)	89.2
Vinyals et al. (2015)	88.3
Cross and Huang (2016)	91.3
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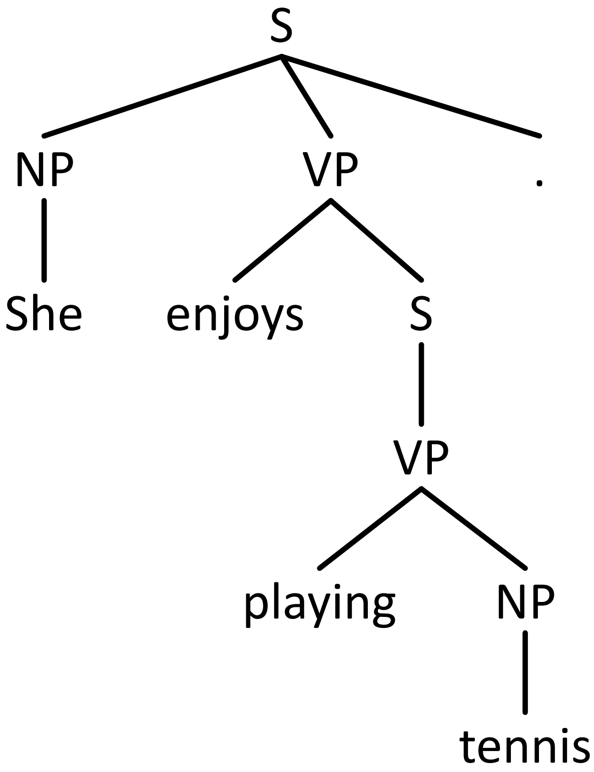
Our Chart Parser	91.7

Top-Down Parsing



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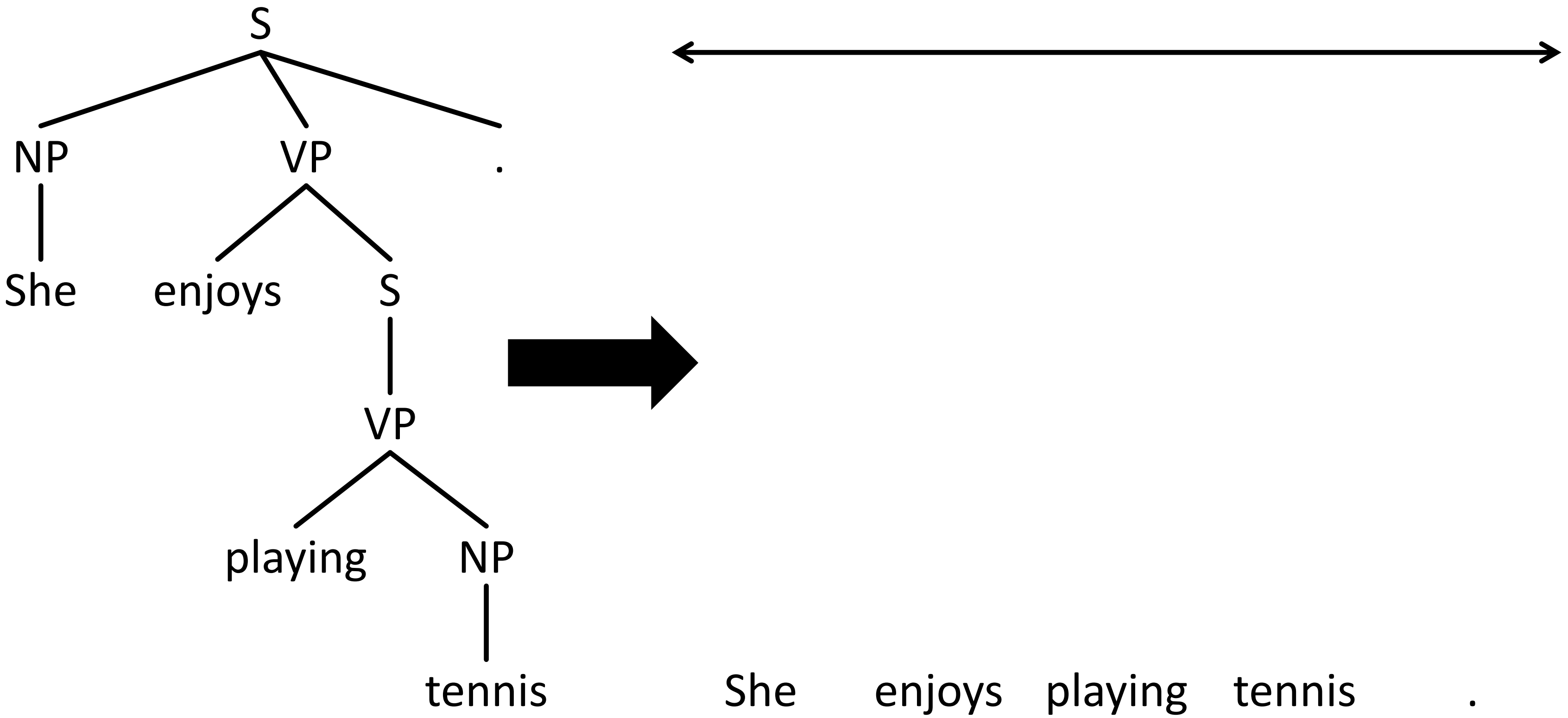

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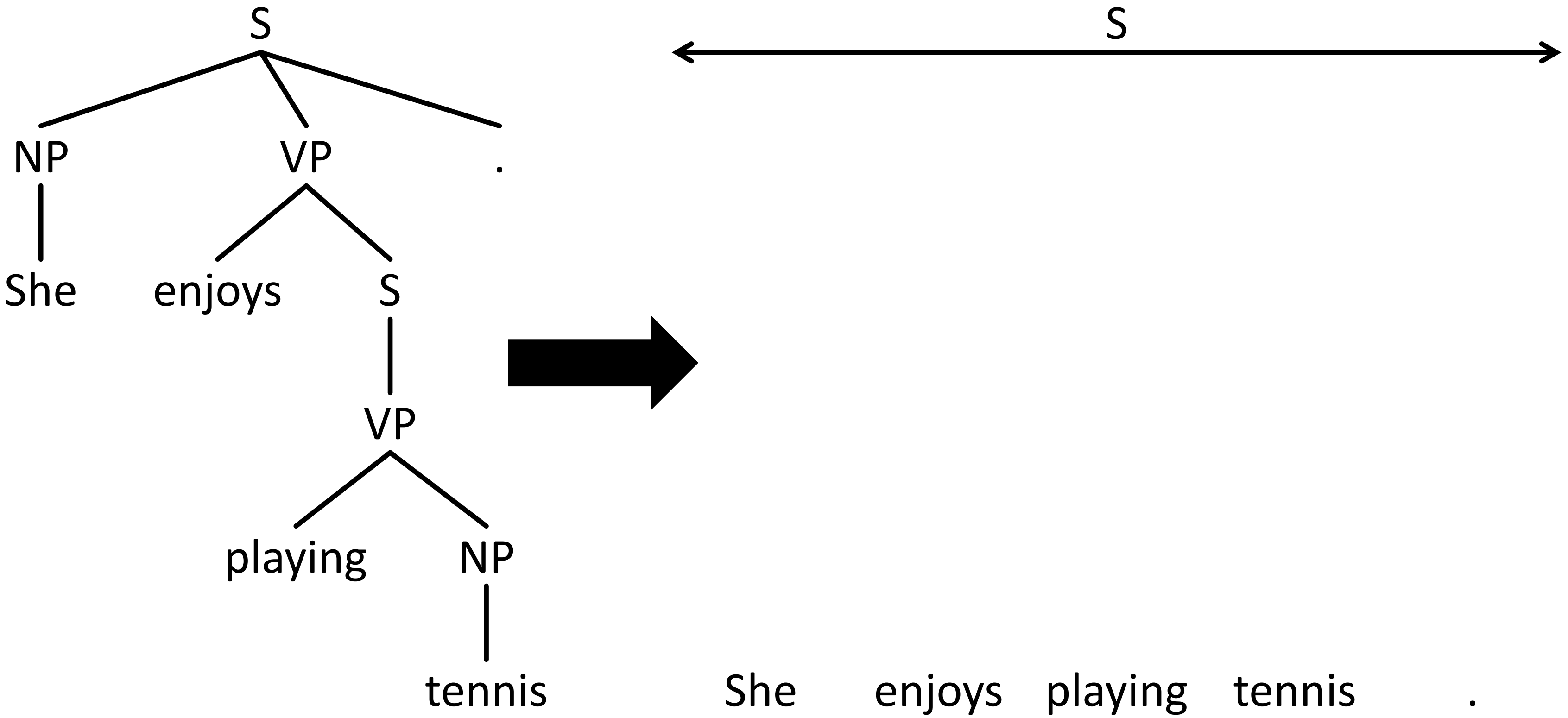

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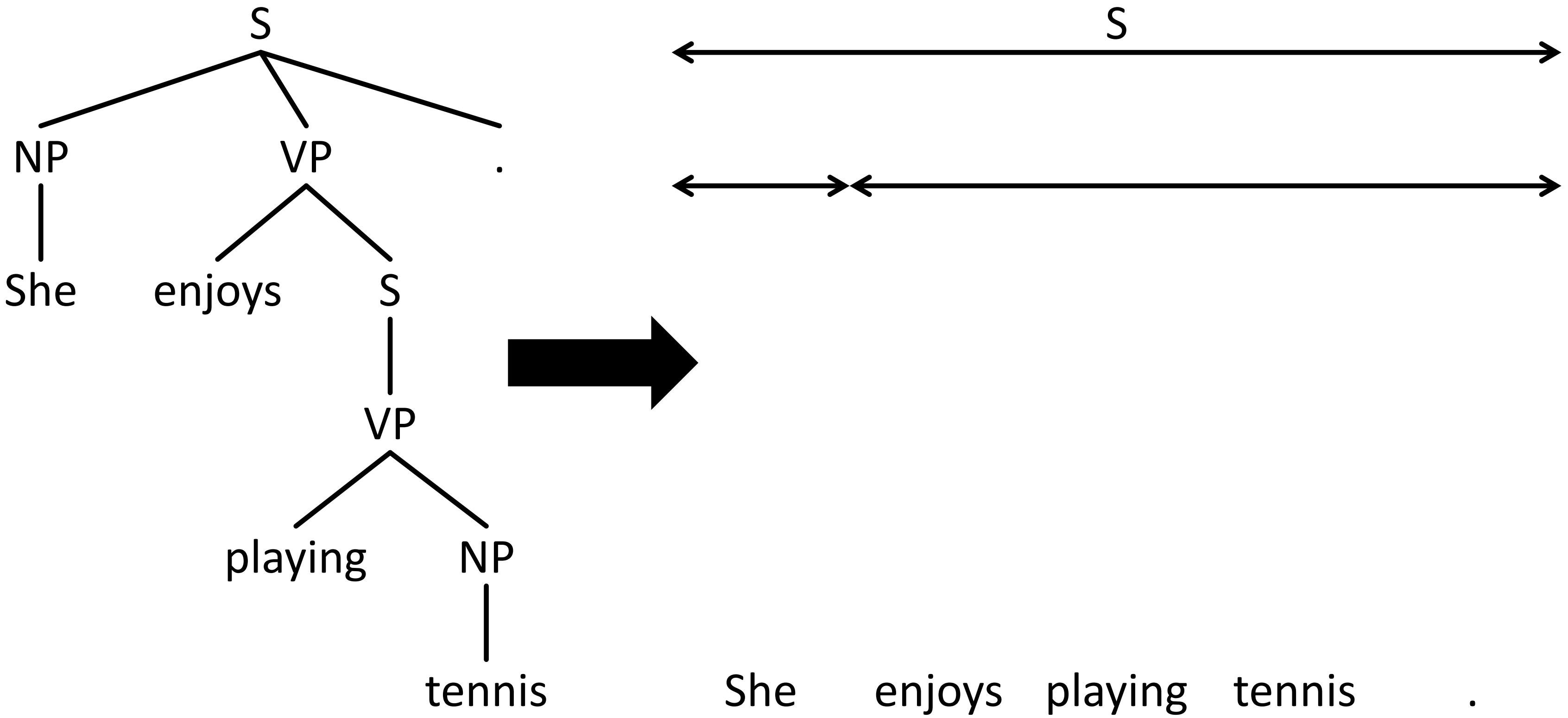

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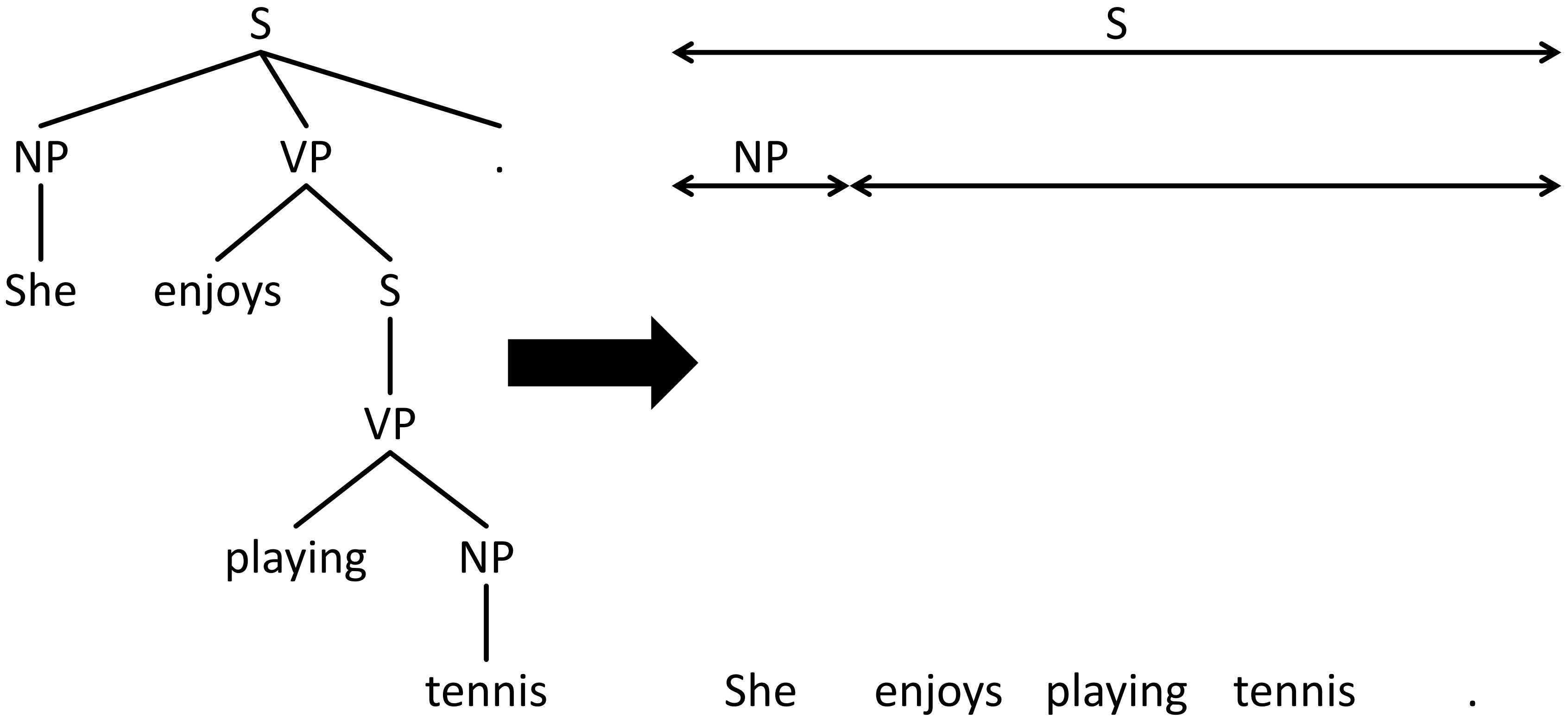

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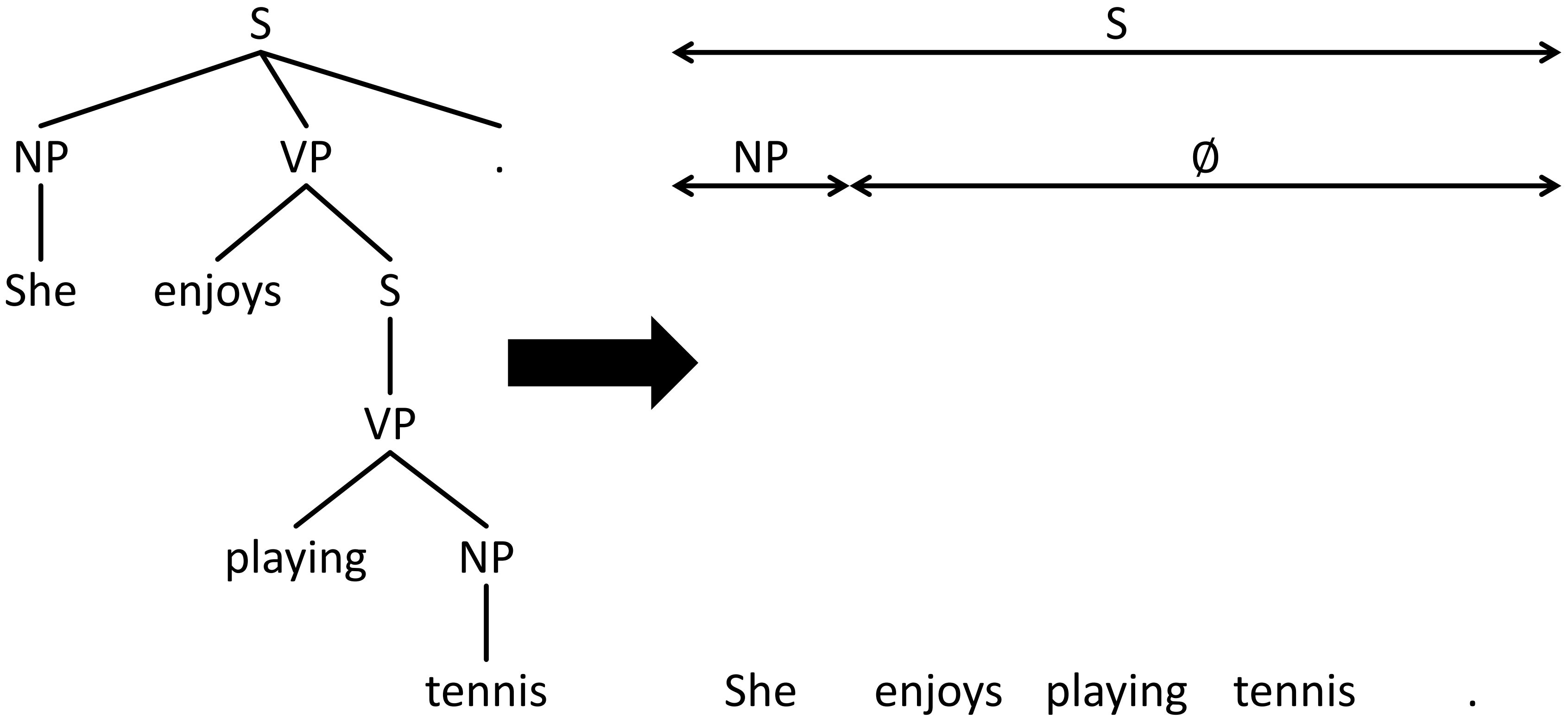

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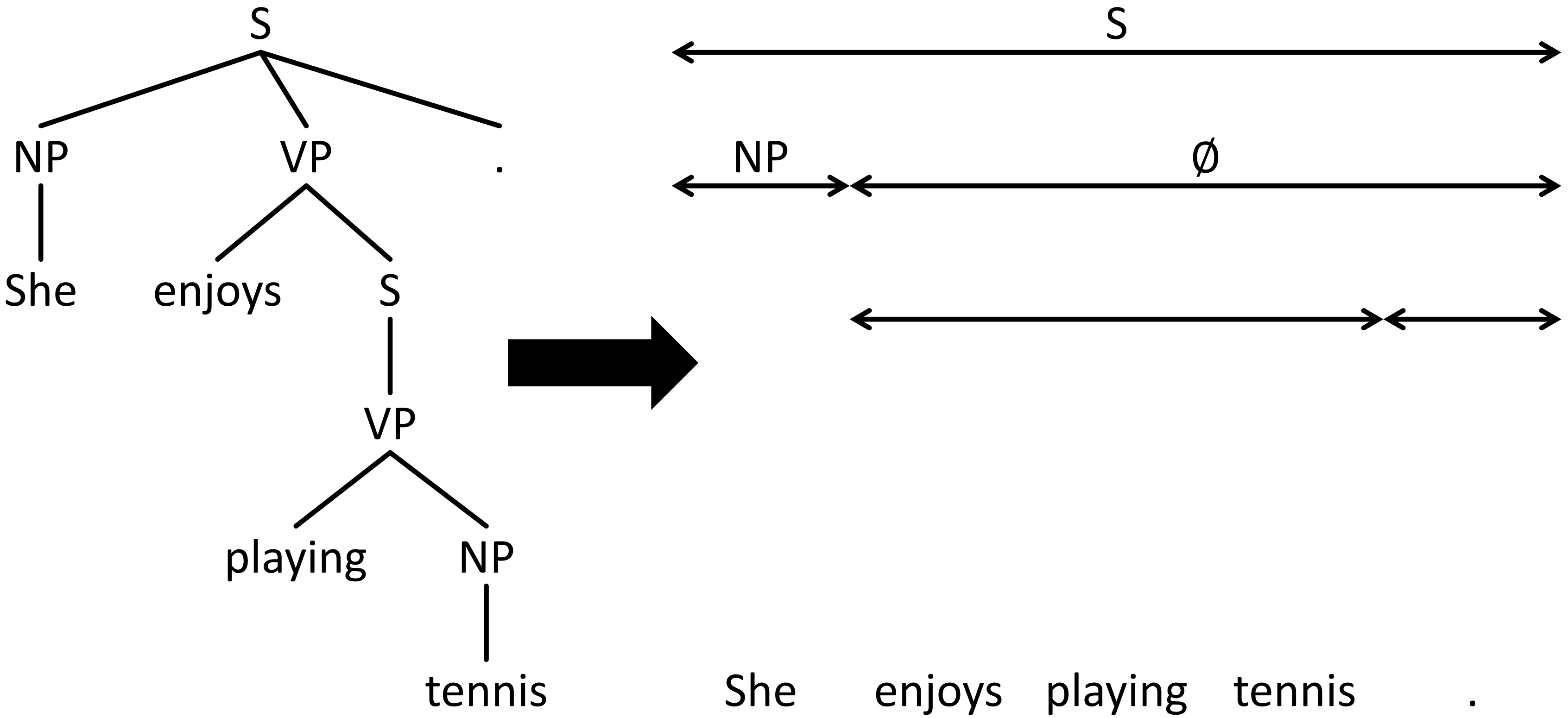

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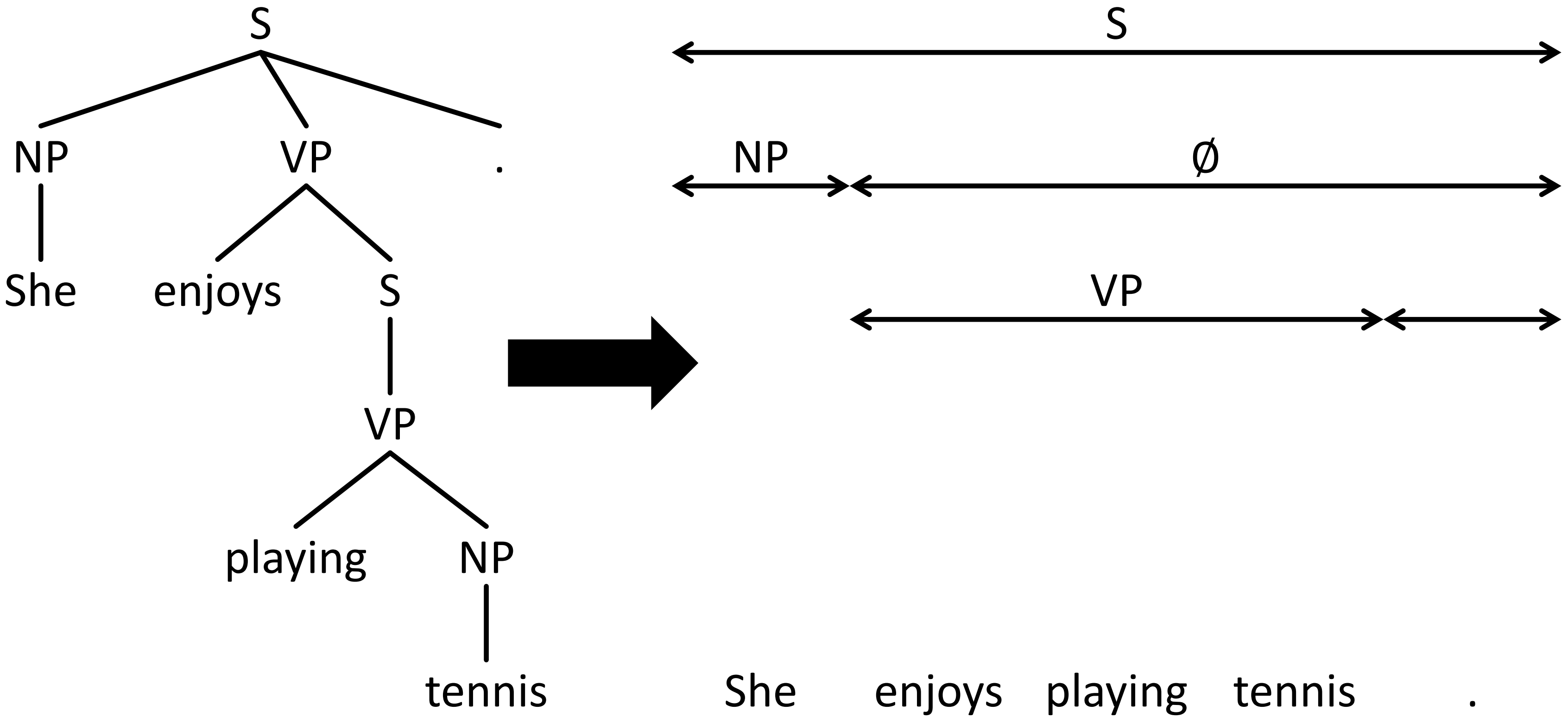

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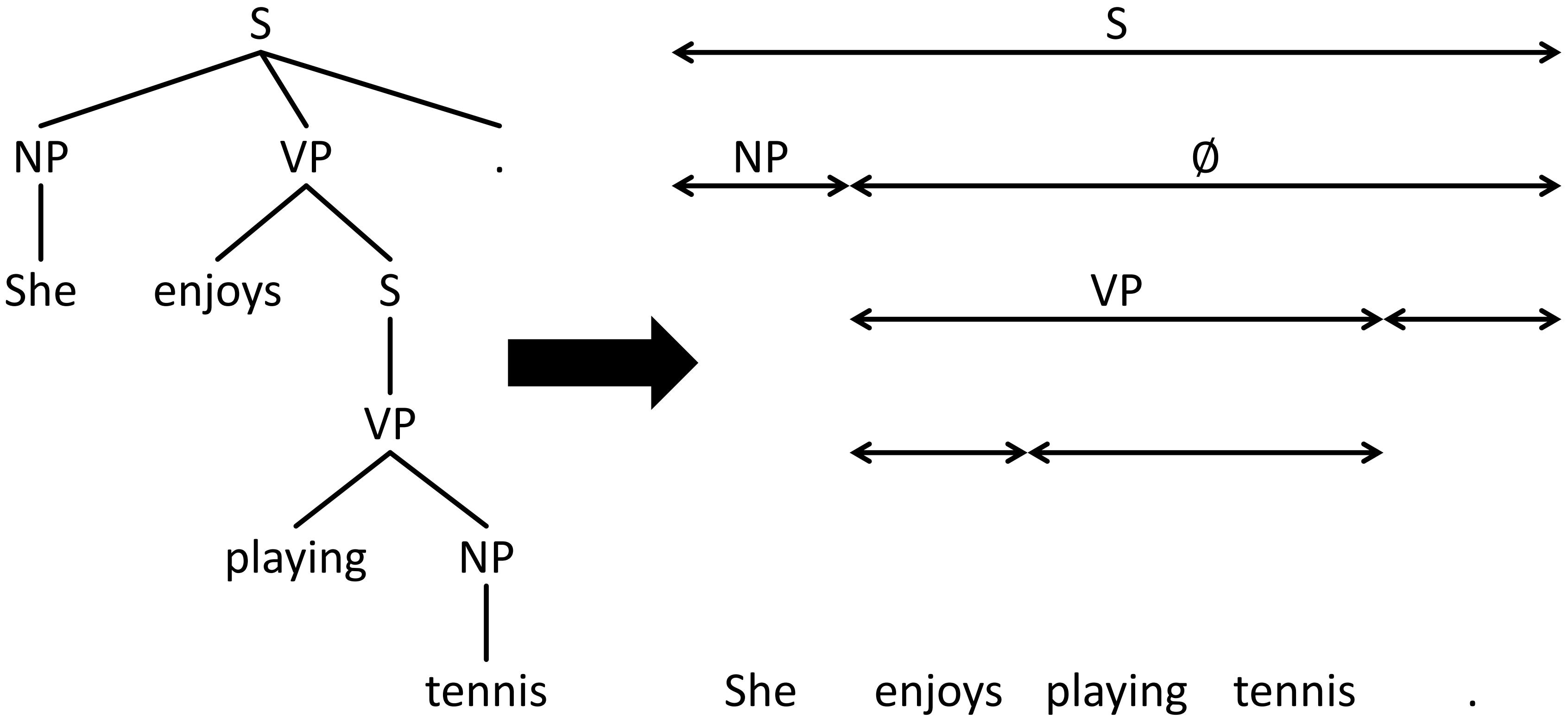

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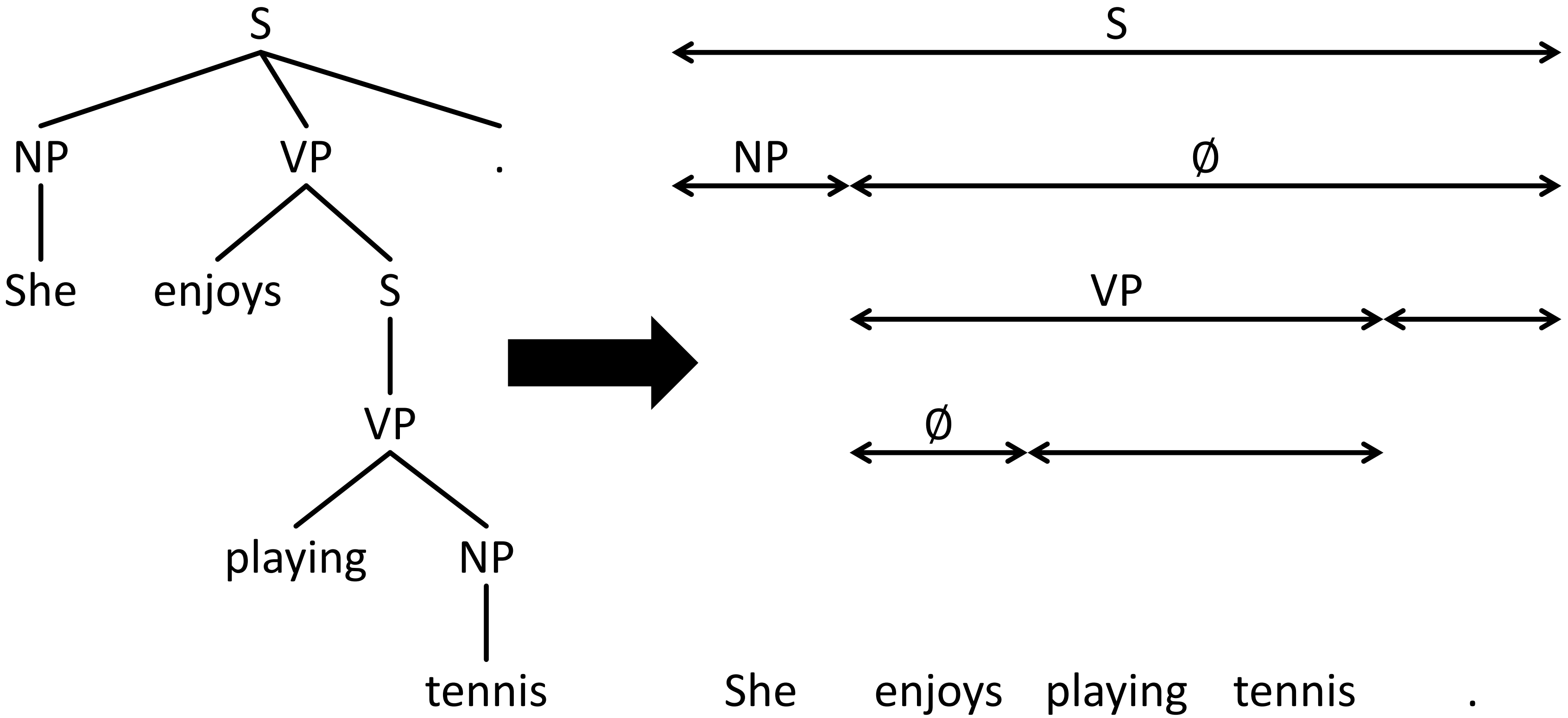

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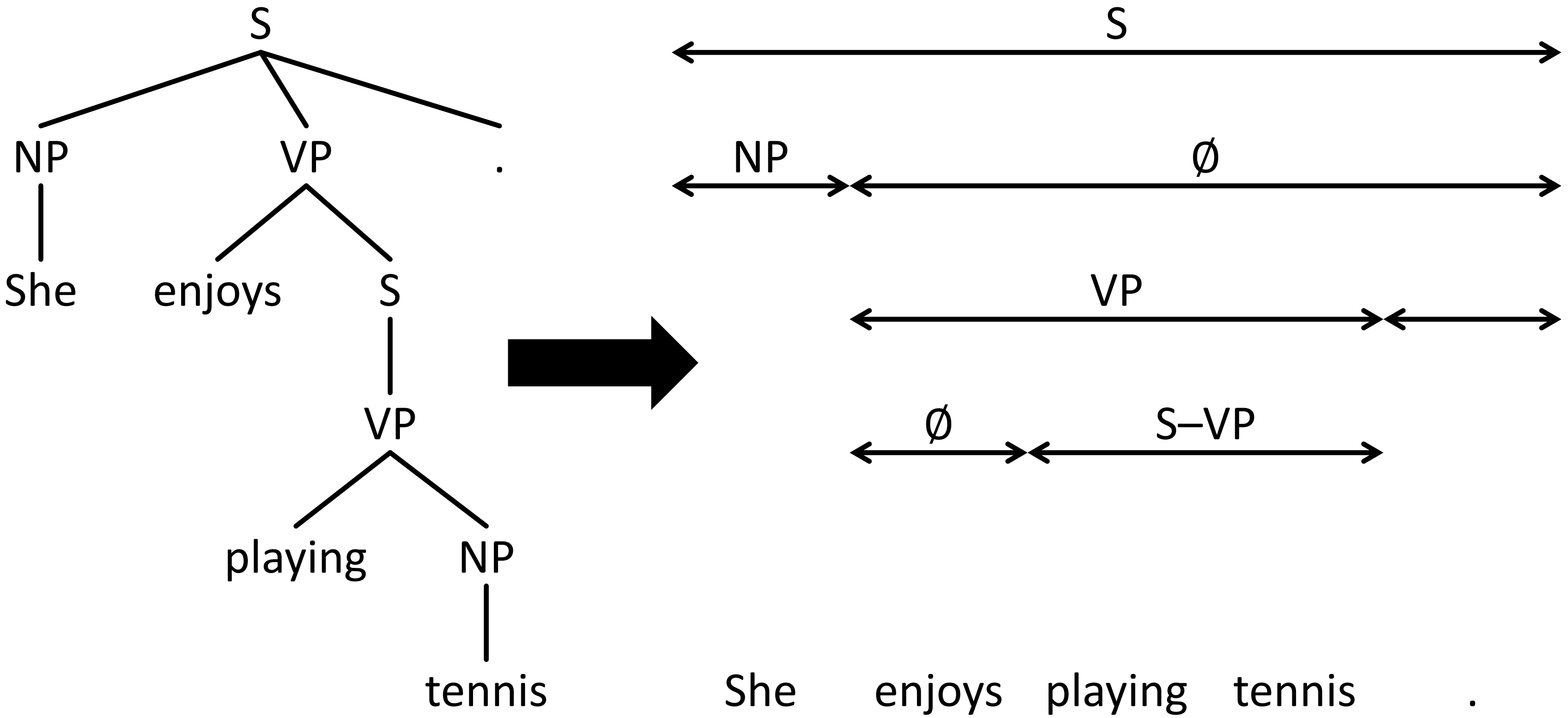

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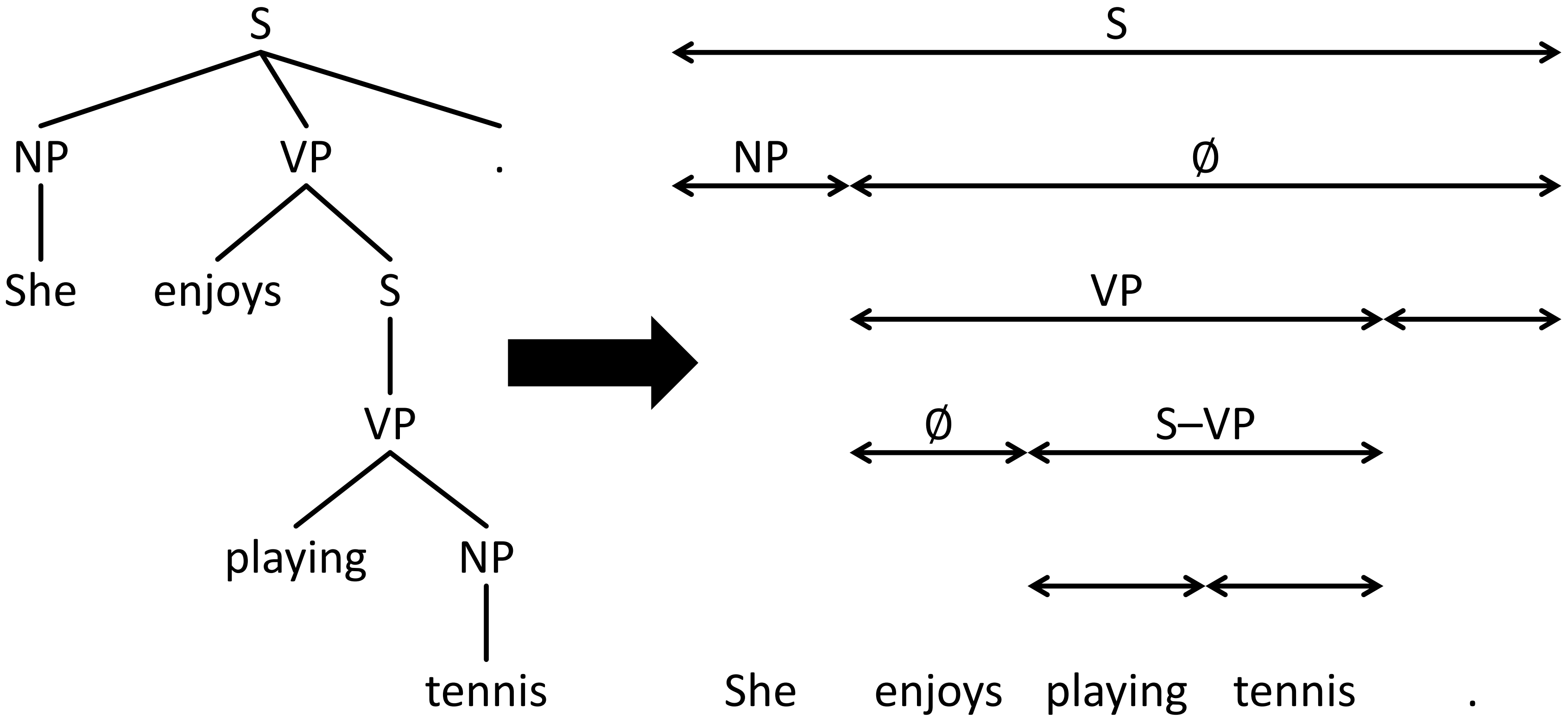

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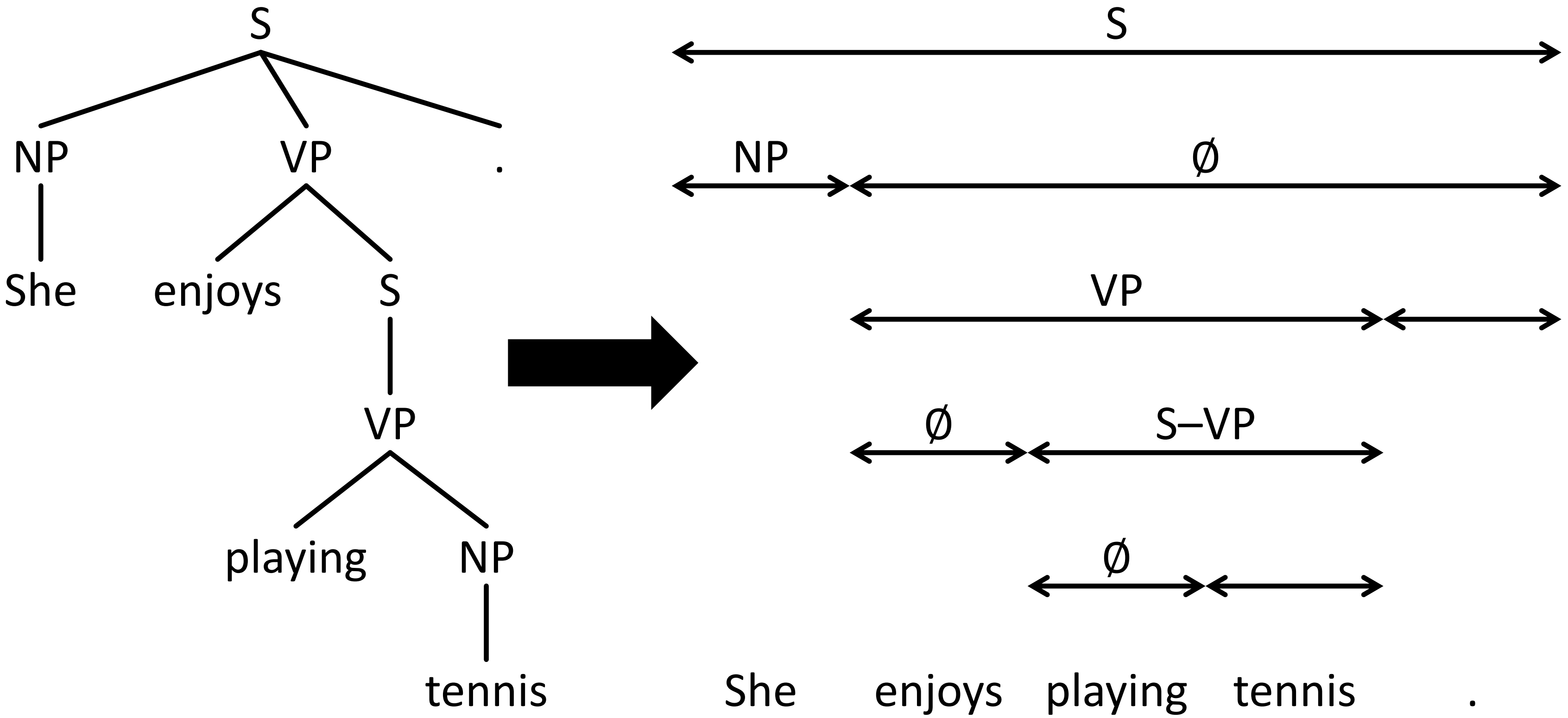

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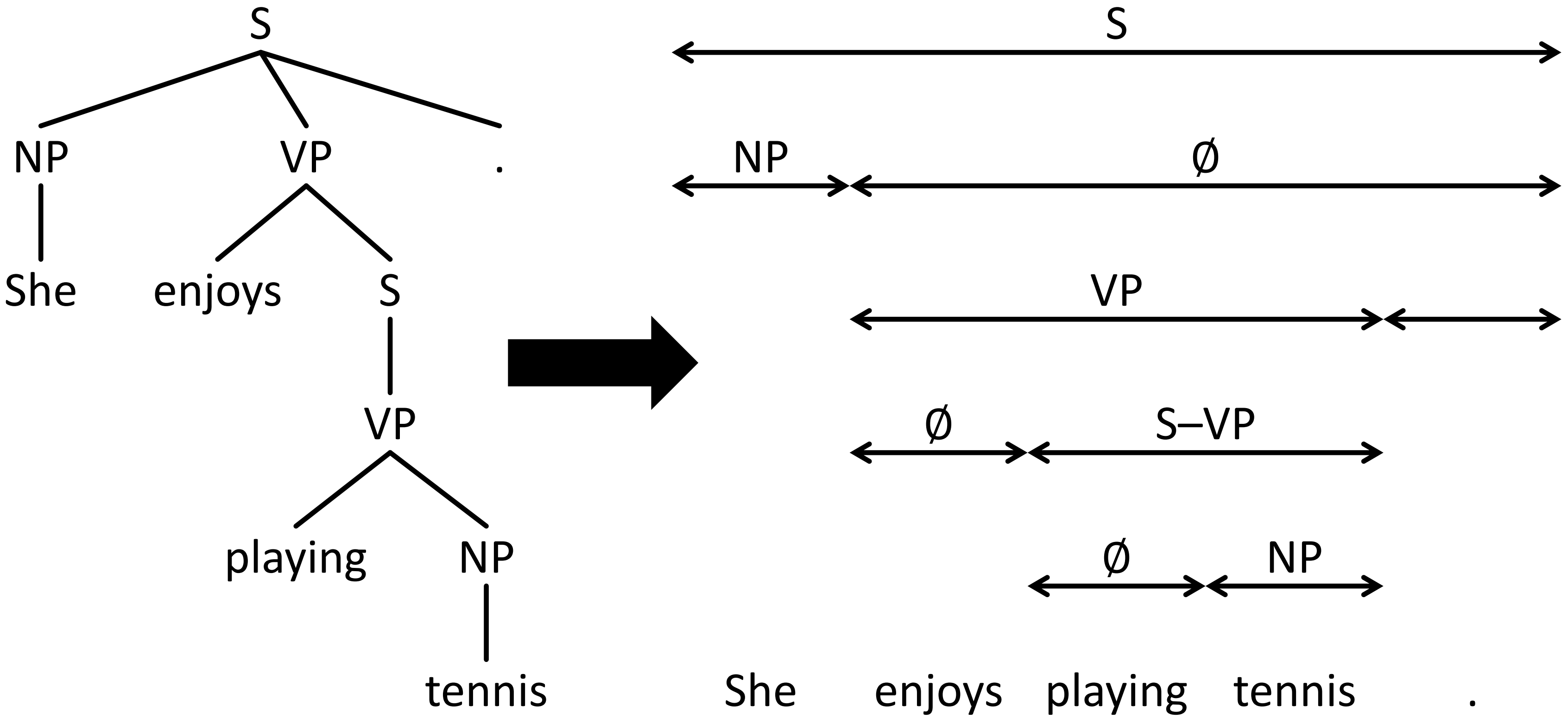

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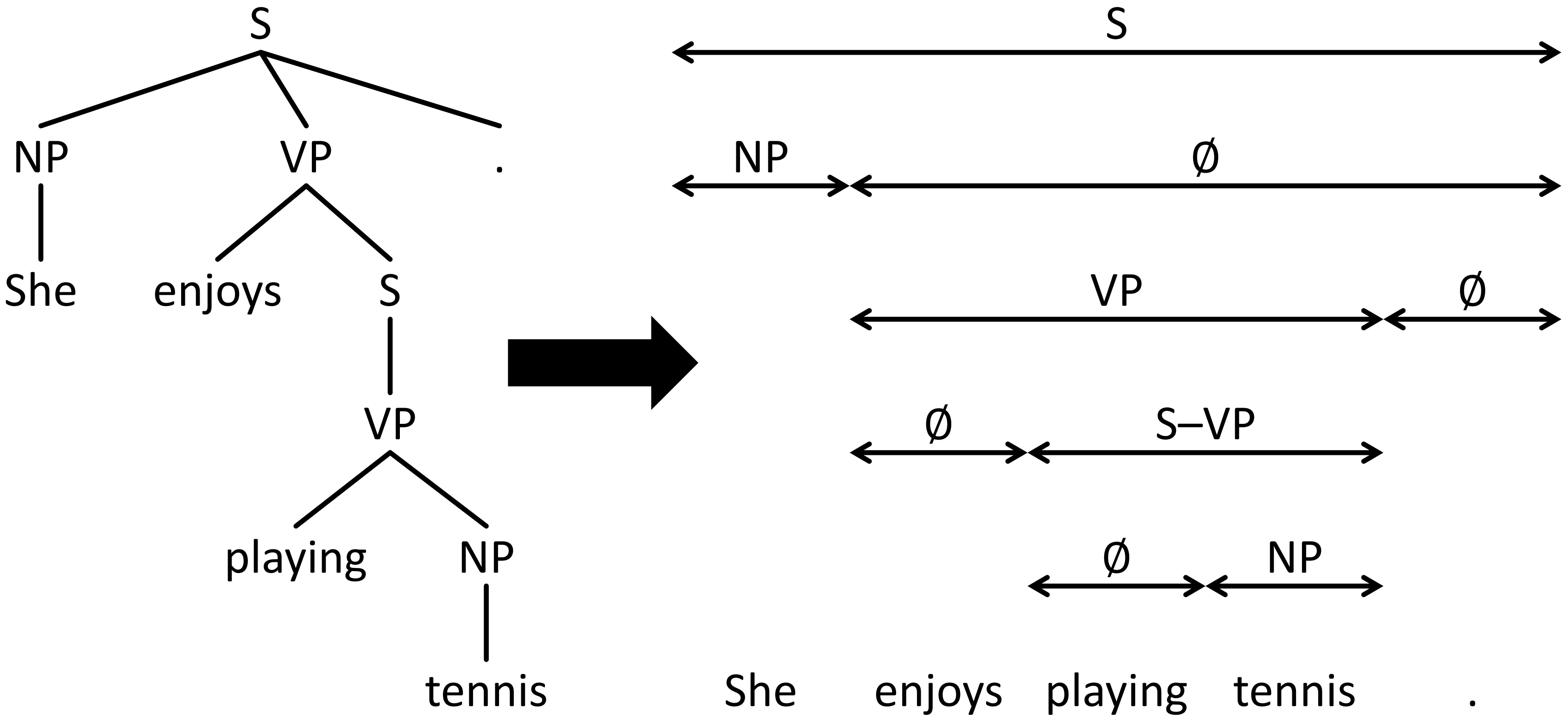

Greedily Label and Split

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$$\hat{\ell} = \underset{\ell}{\operatorname{argmax}}[s_{\text{label}}(i, j, \ell)]$$

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$$\hat{\ell} = \underset{\ell}{\operatorname{argmax}}[s_{\text{label}}(i, j, \ell)]$$

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Top-Down Training

Margin constraint for each decision:

$$\text{score(gold)} \geq 1 + \text{score(other)}$$

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Margin constraint for each decision:

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Train with exploration using a dynamic oracle

[Goldberg and Nivre (2012), Cross and Huang (2016)]

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Extensions

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Label scoring for unary chains:

- Split unary chains into top-middle-bottom

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Structured label loss for unary chains:

- Hamming distance on labels (vs. 0-1 loss)

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Label scoring for unary chains:

- Split unary chains into top-middle-bottom

Structured label loss for unary chains:

- Hamming distance on labels (vs. 0-1 loss)

Split-based (vs. span-based) scoring:

- Left-right, concatenate, deep biaffine

[Cross and Huang (2016)] [Dozat and Manning (2016)]

Final Results

Parser	F1 Score
Hall et al. (2014)	89.2
Vinyals et al. (2015)	88.3
Cross and Huang (2016)	91.3
Dyer et al. (2016)	91.7
Liu and Zhang (2016)	91.7
Our Best Chart Parser	91.8
Our Best Top-Down Parser	91.8

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Various extensions yield only minimal gains beyond the core system.

Thanks!