Optimal Shift-Reduce Constituent Parsing with Structured Perceptron

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Hanoi University of Science and Technology

Vietnam

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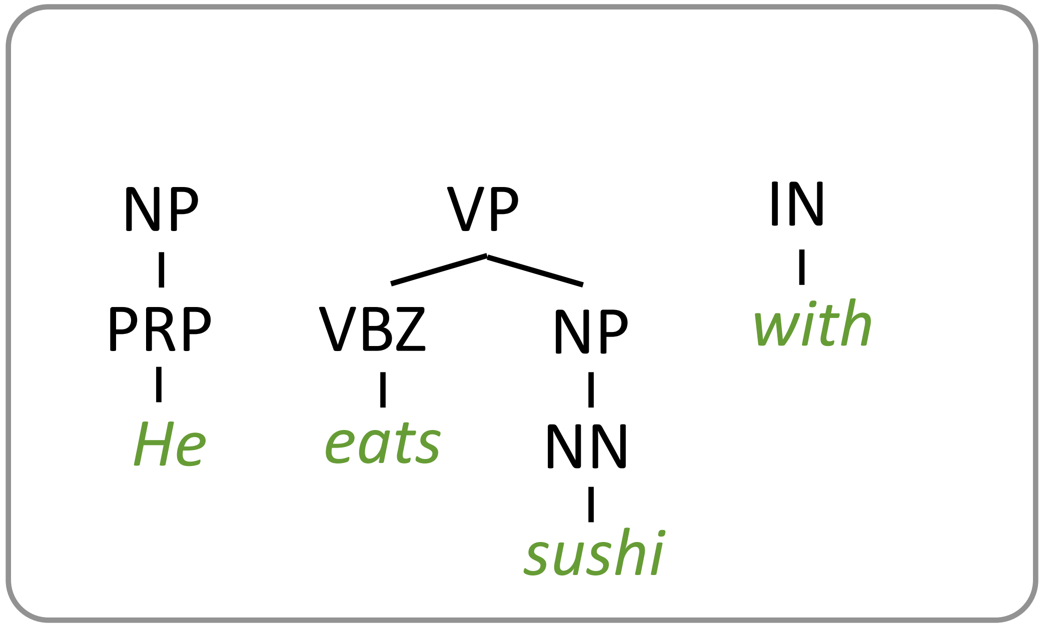
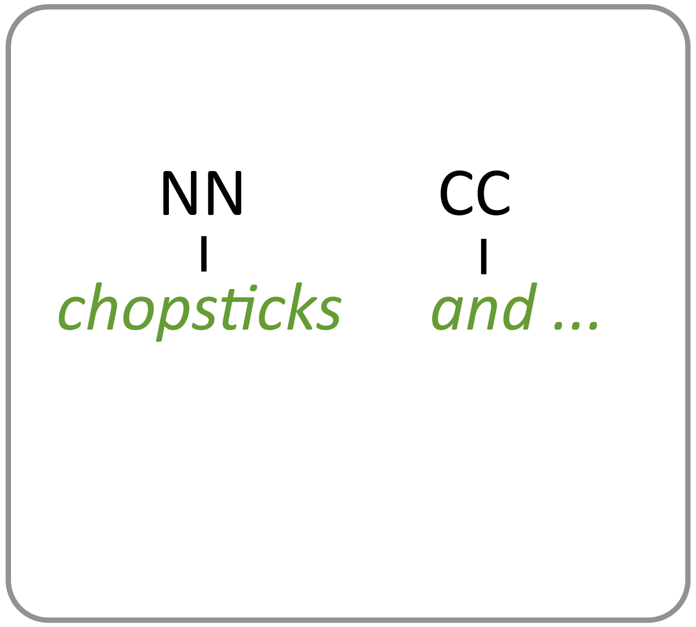
National Institute of Informatics

Japan

Advantages of Shift-reduce Parsing ?





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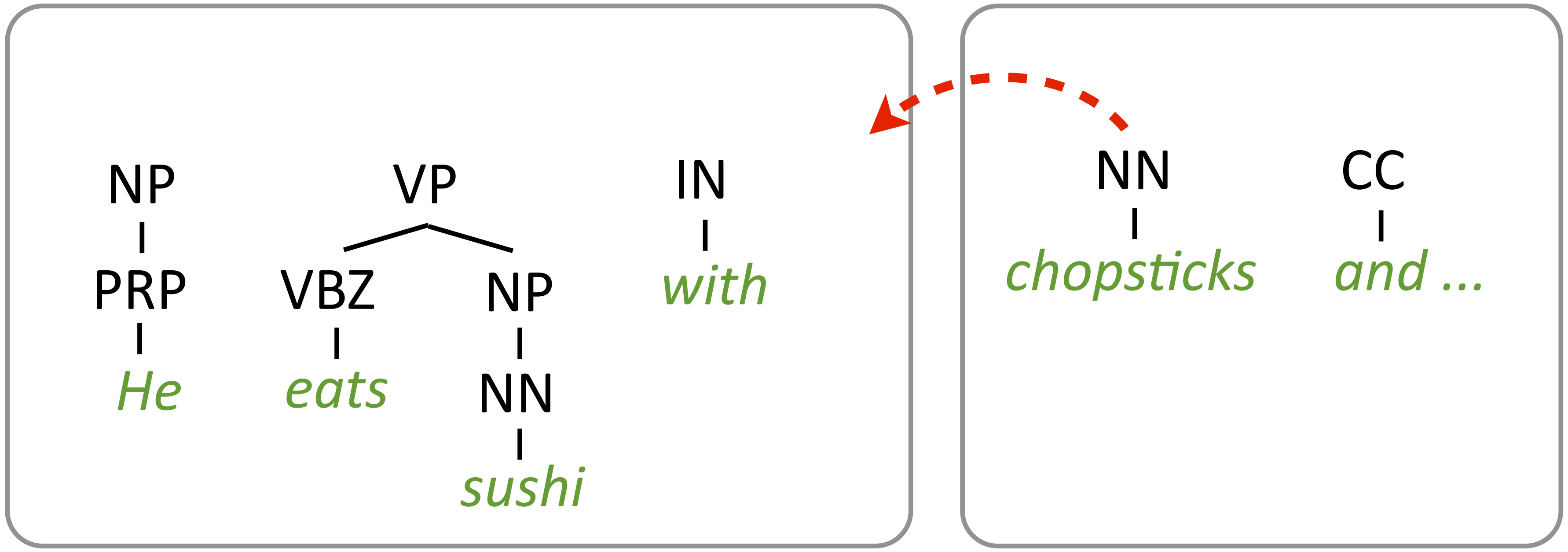

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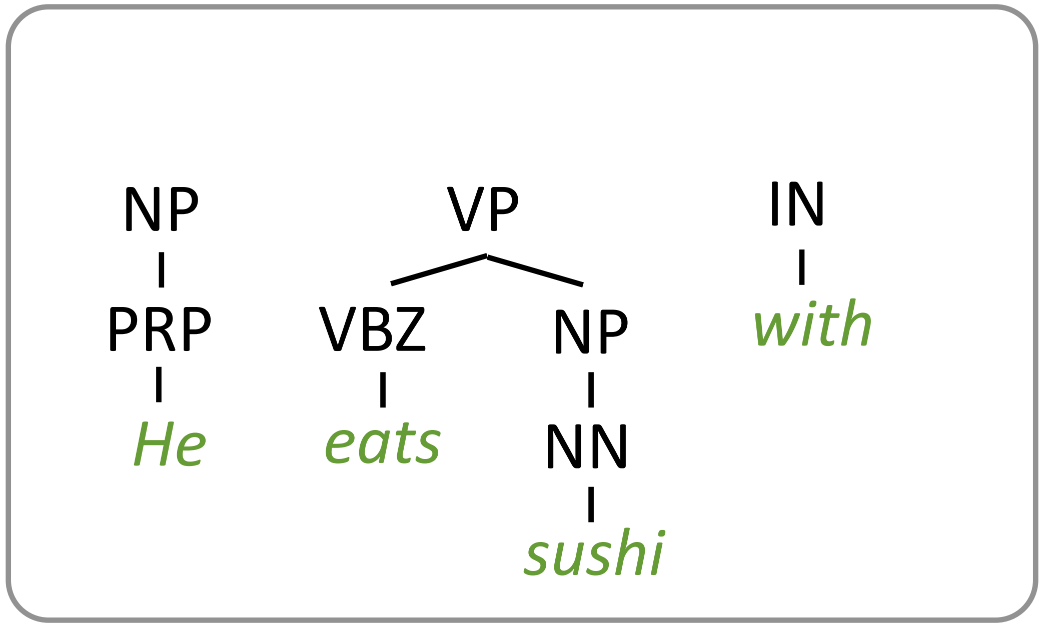

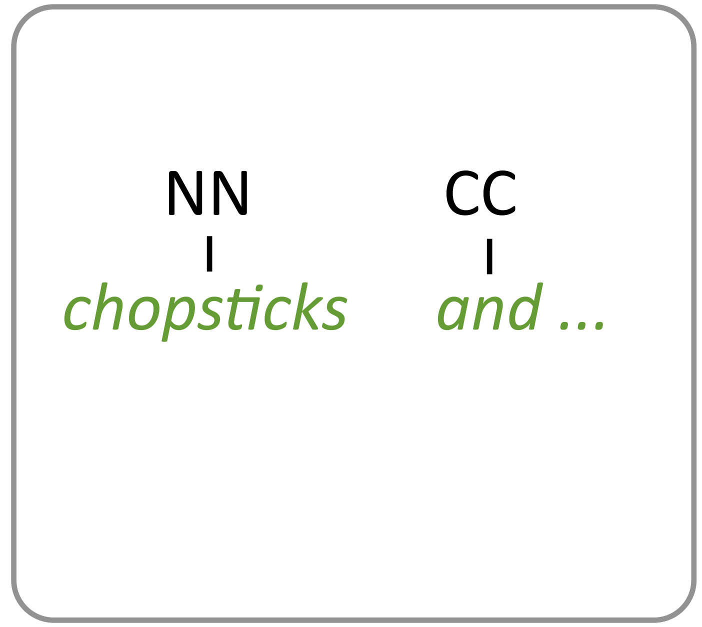

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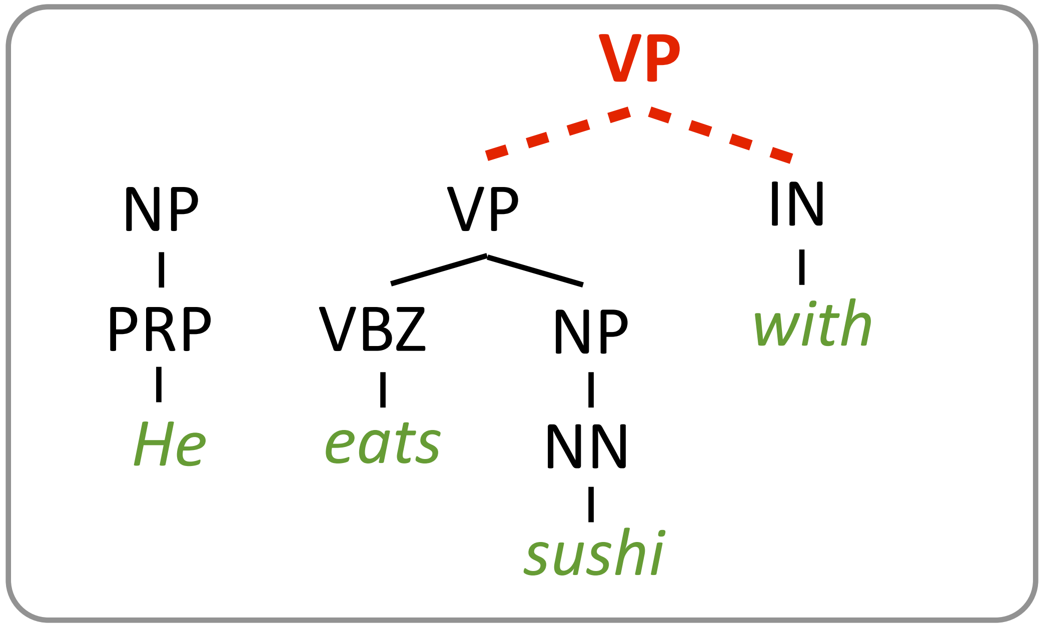

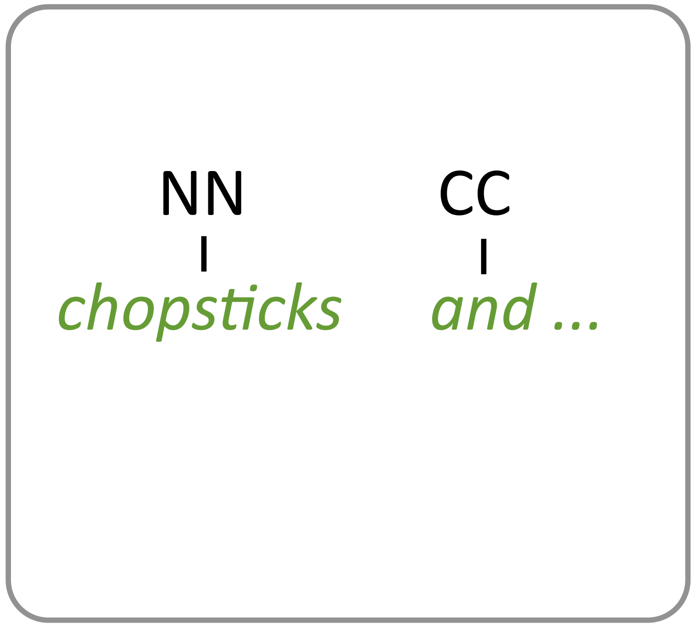

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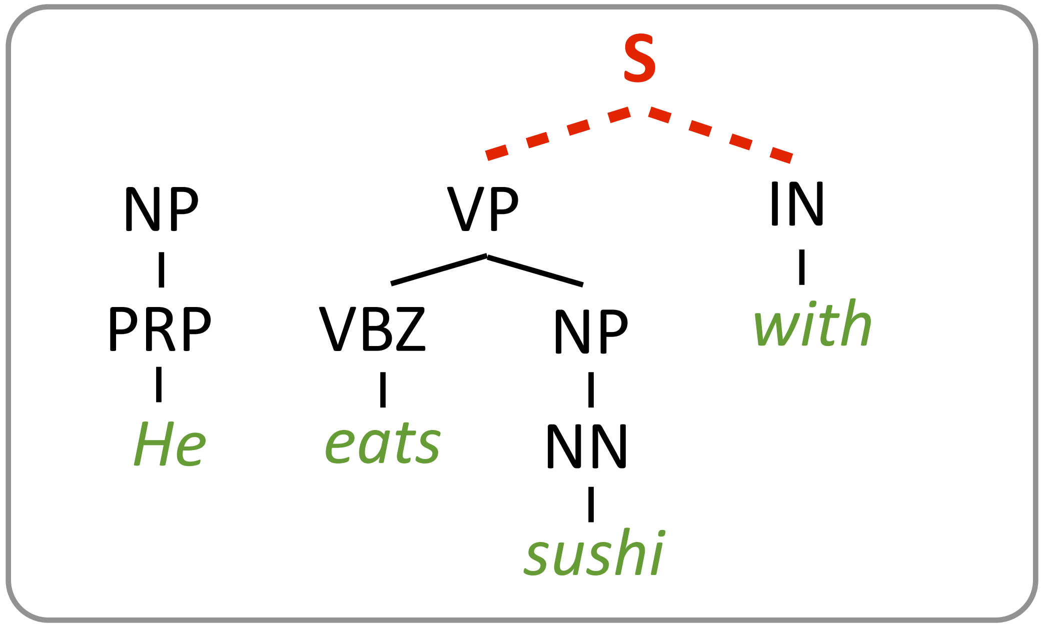

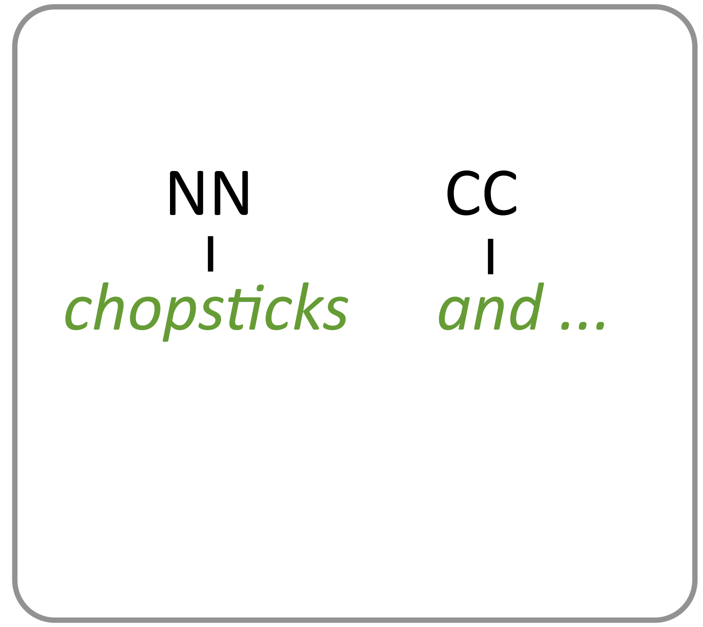

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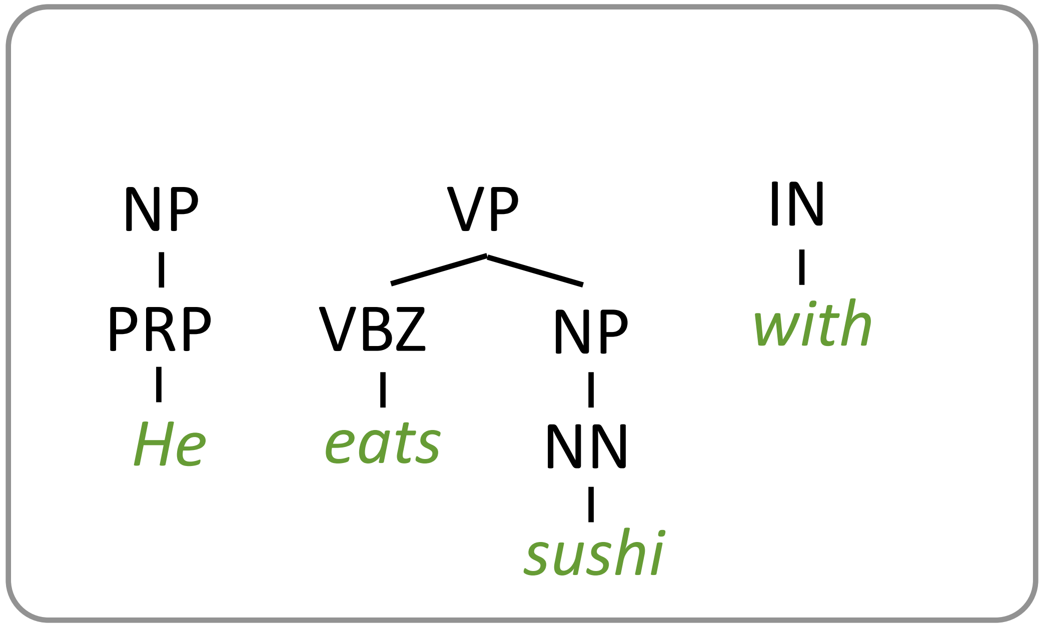

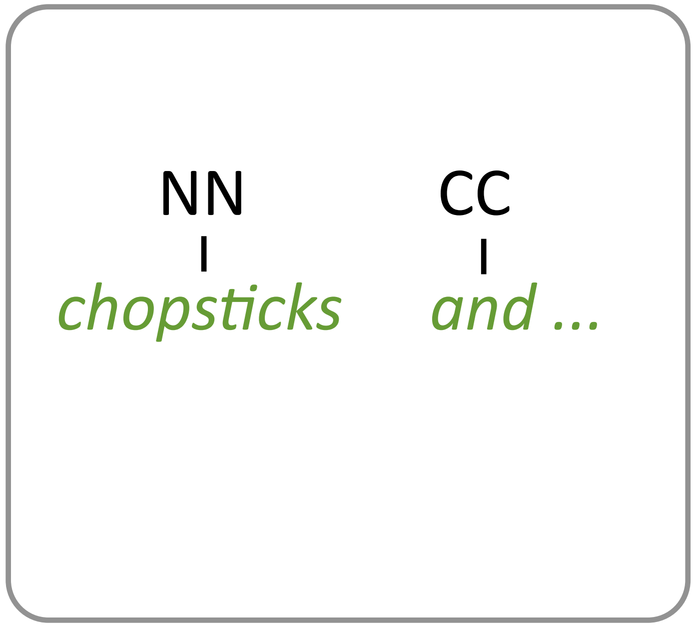

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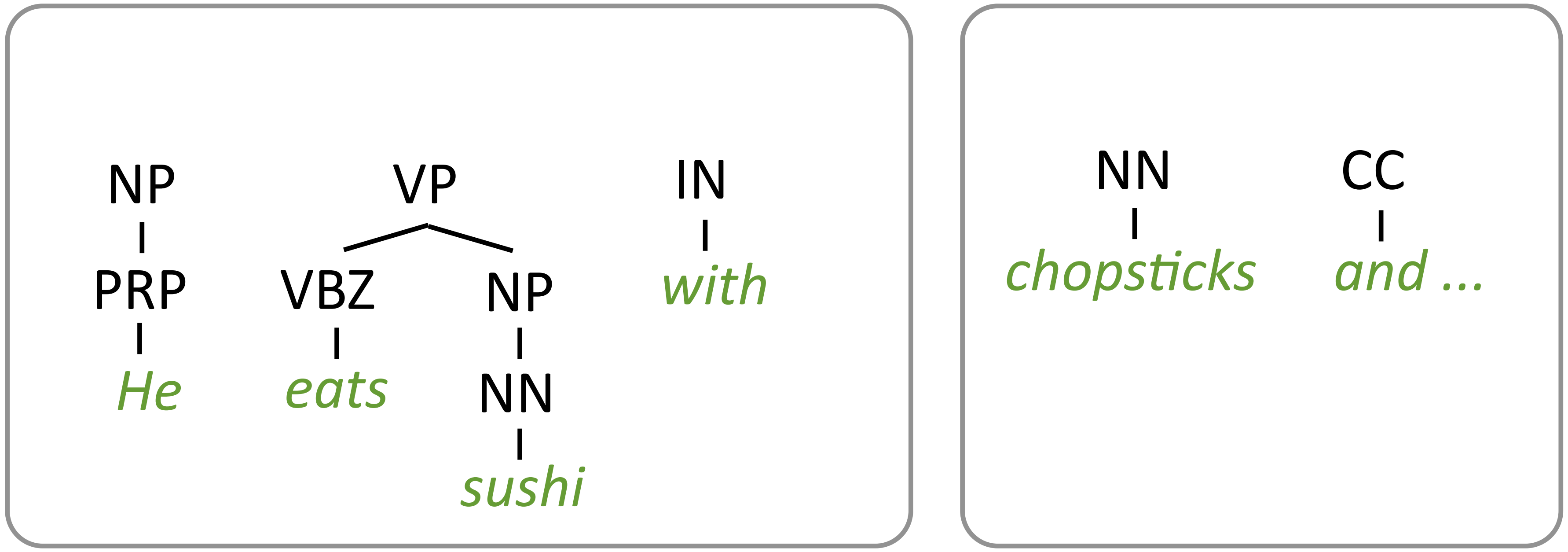

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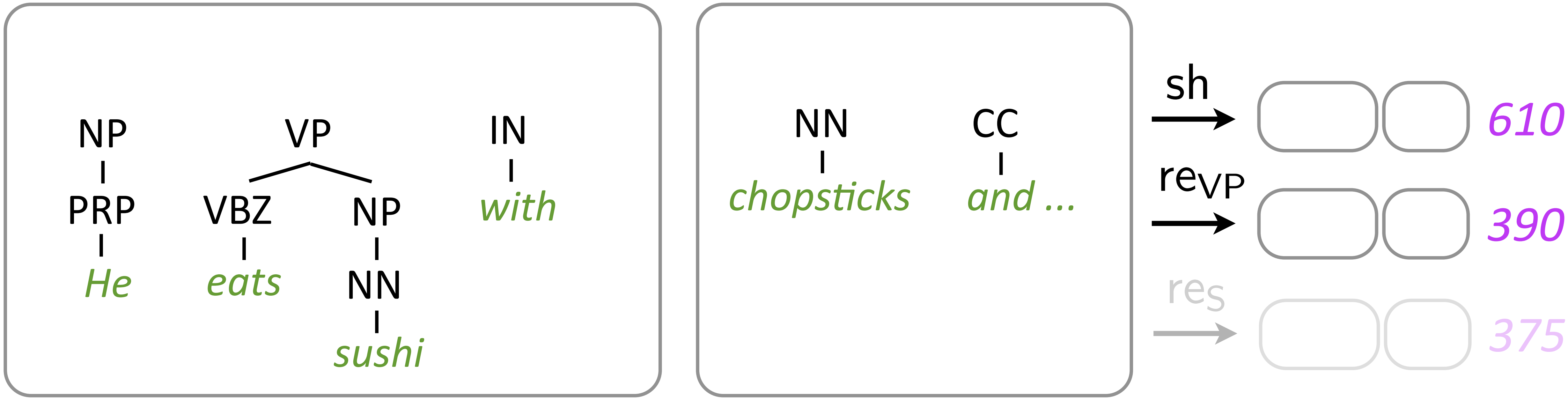

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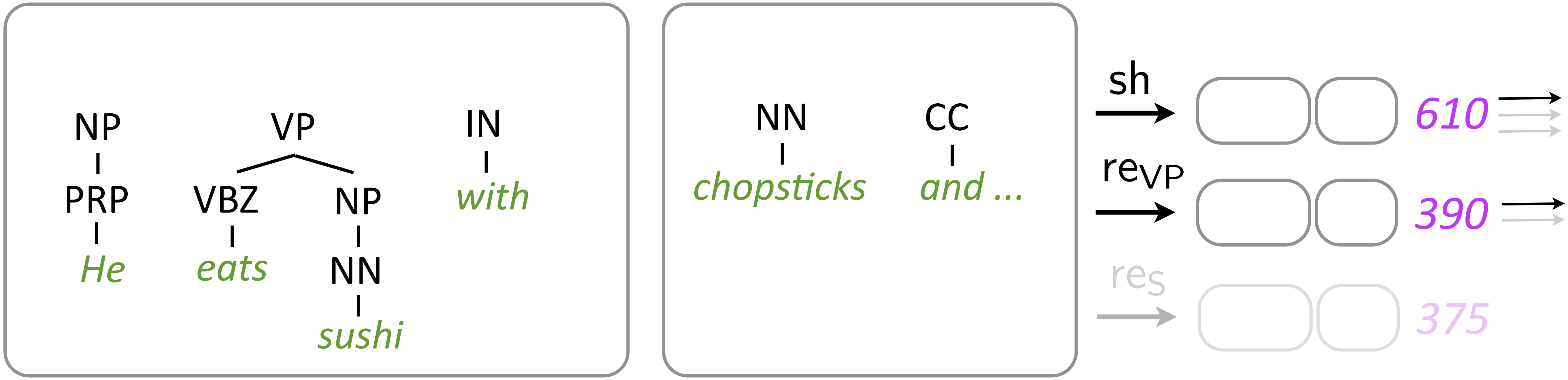

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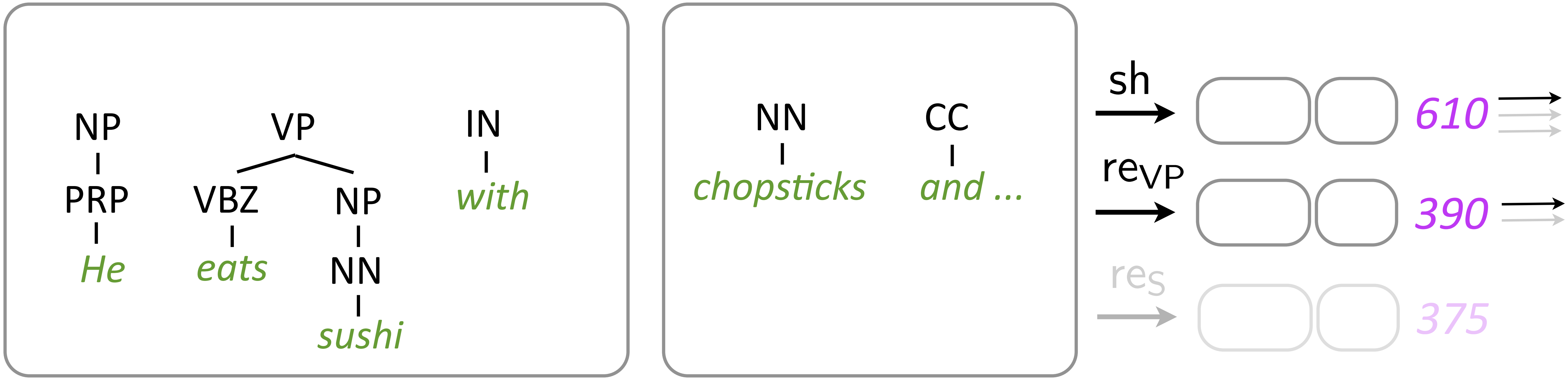

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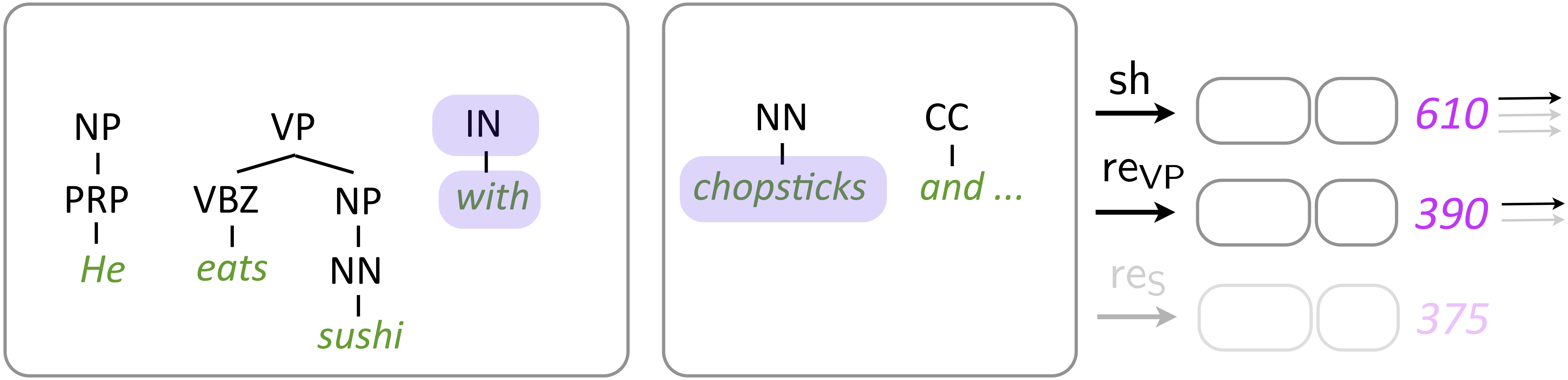

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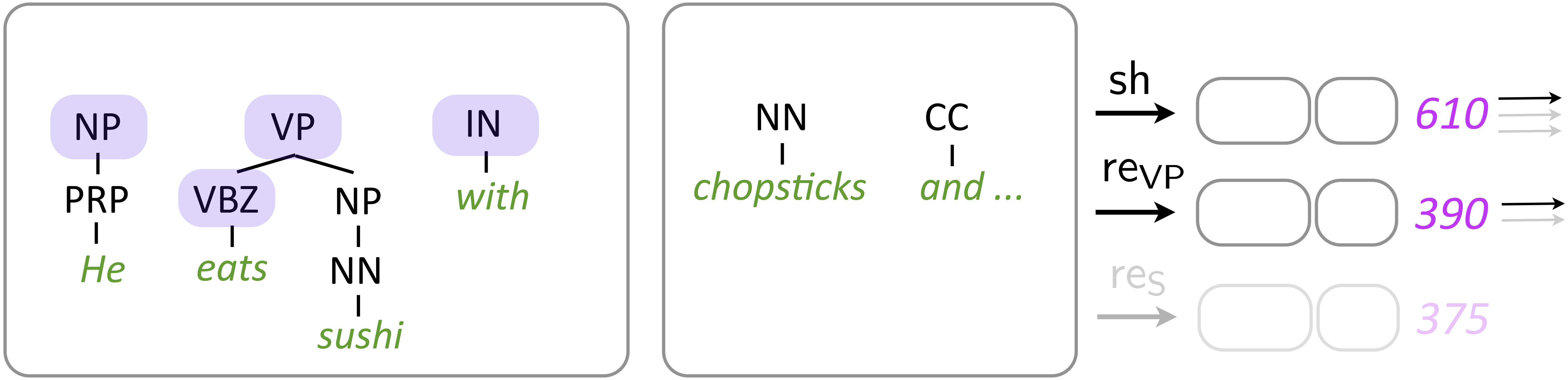

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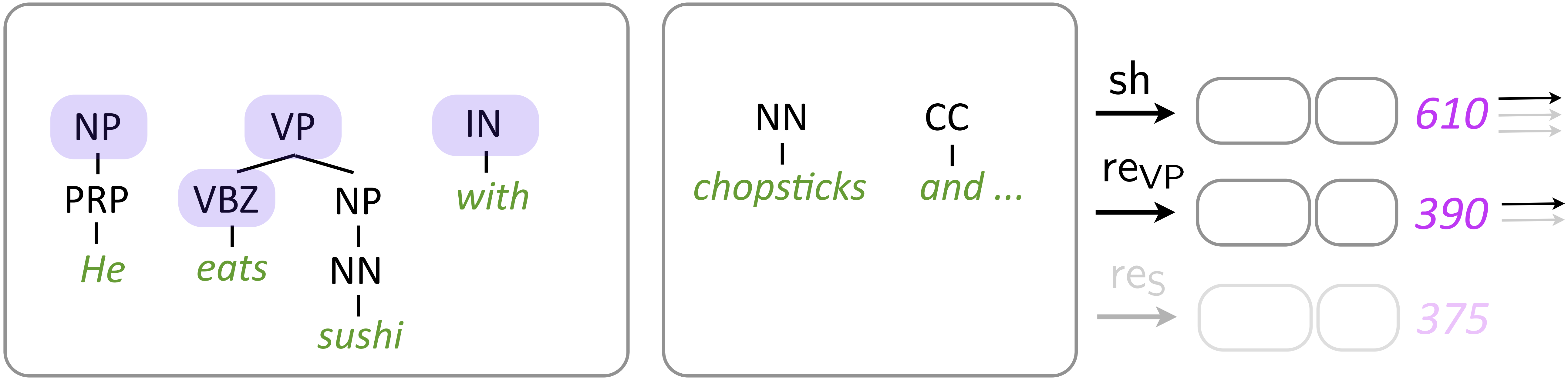

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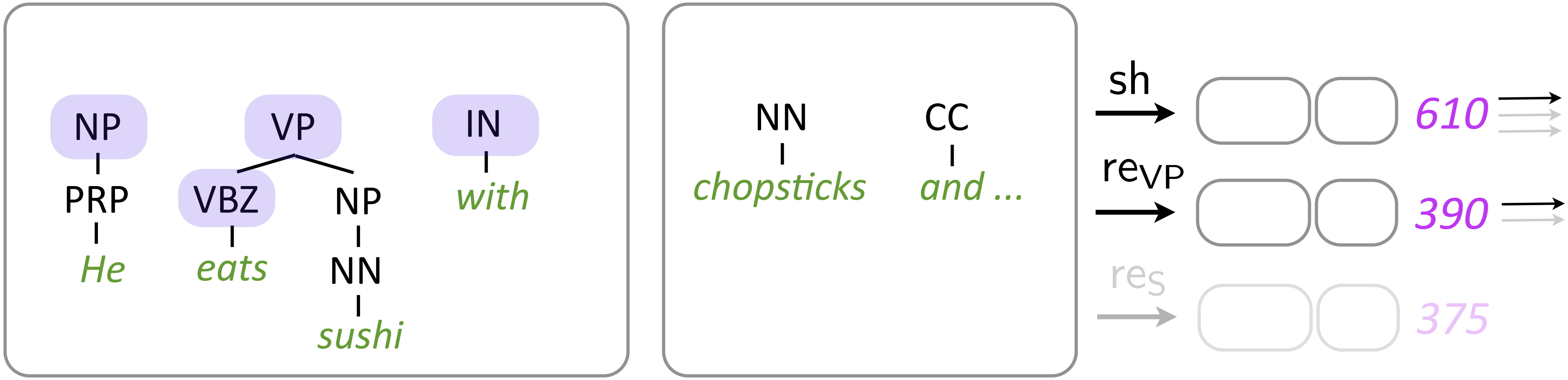

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Constituency: [Zhang & Clark, 2009; Zhu et al., 2013; Wang & Xue, 2014, Mi et al., 2015]

Dependency: [Huang & Sagae 2010; Zhang & Nivre, 2011; Bohnet et al., 2013]

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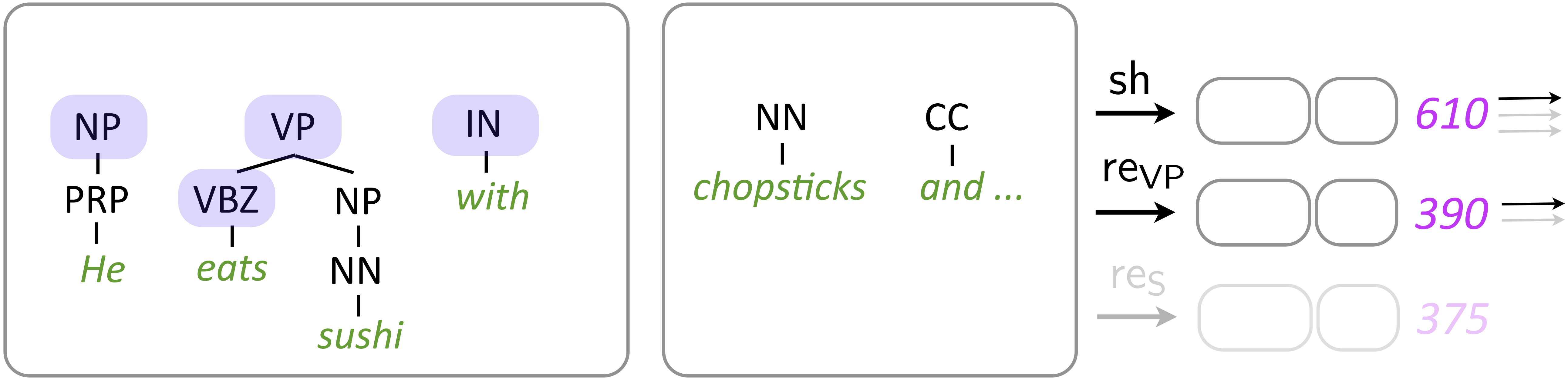

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Question: Is this current design ... really the best?

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Shift-reduce constituent parser **with exact search**

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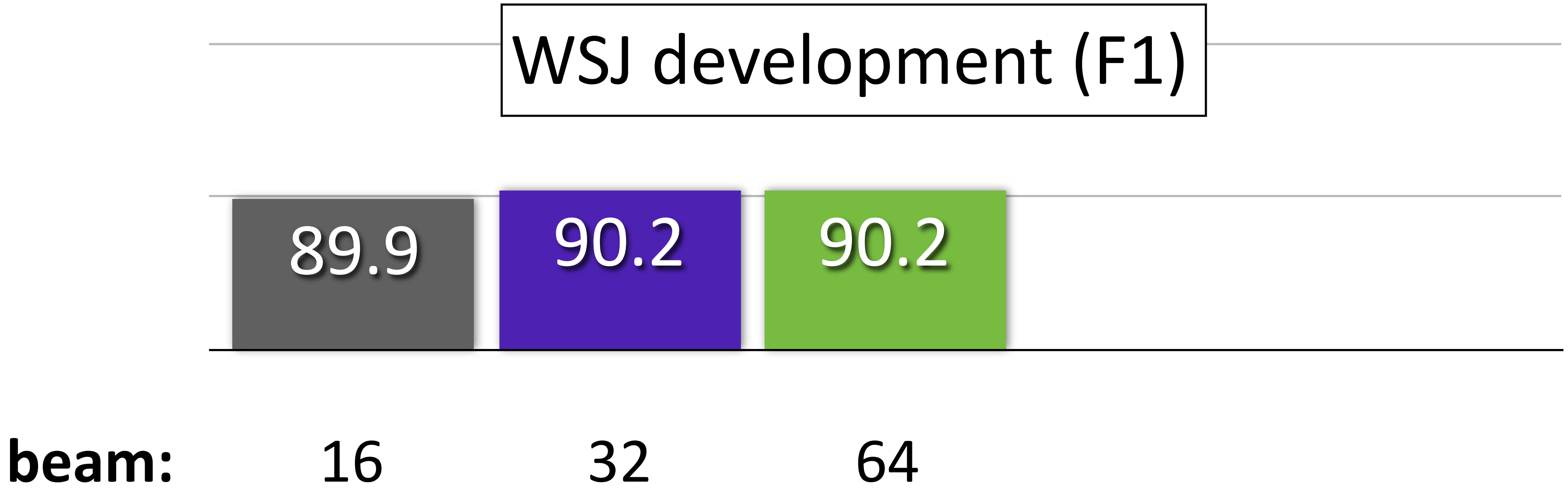

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Shift-reduce constituent parser **with exact search**

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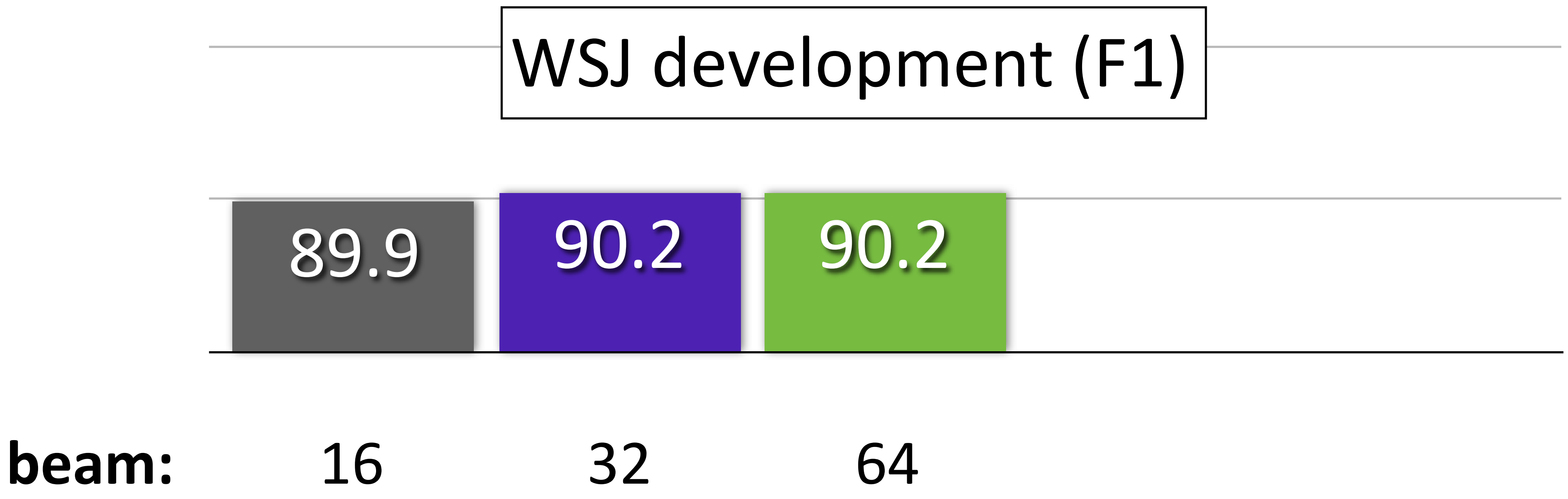

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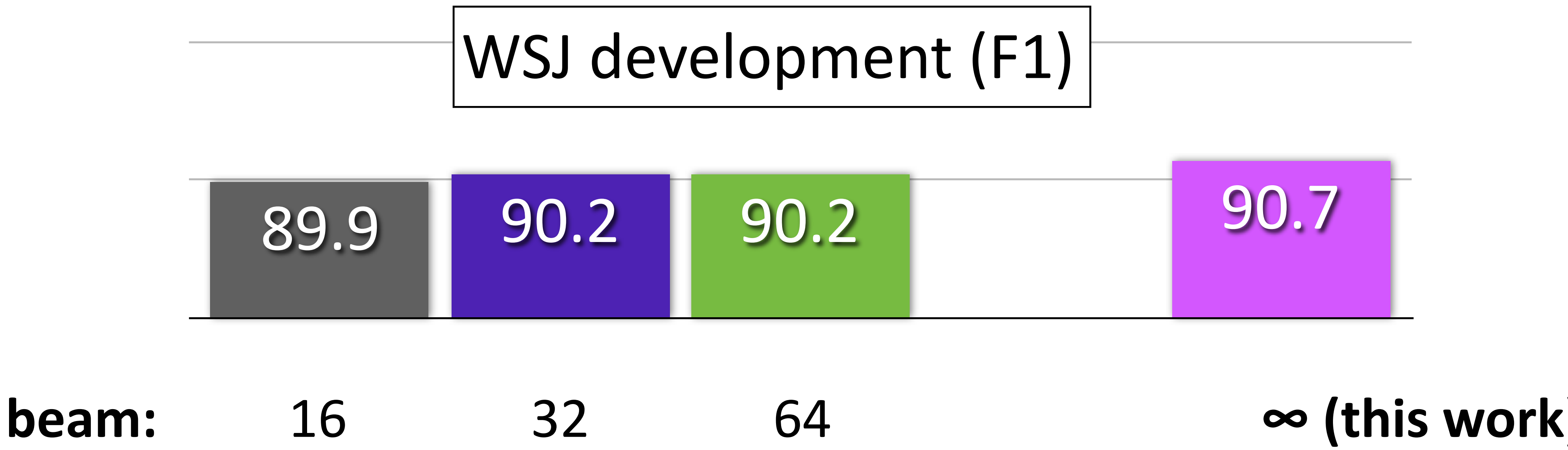

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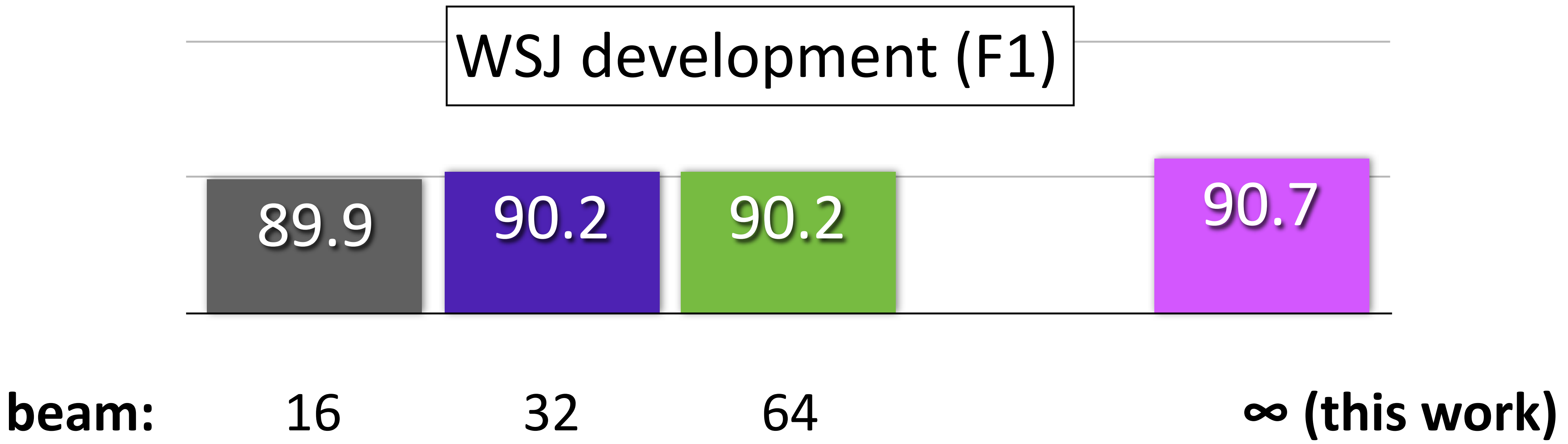

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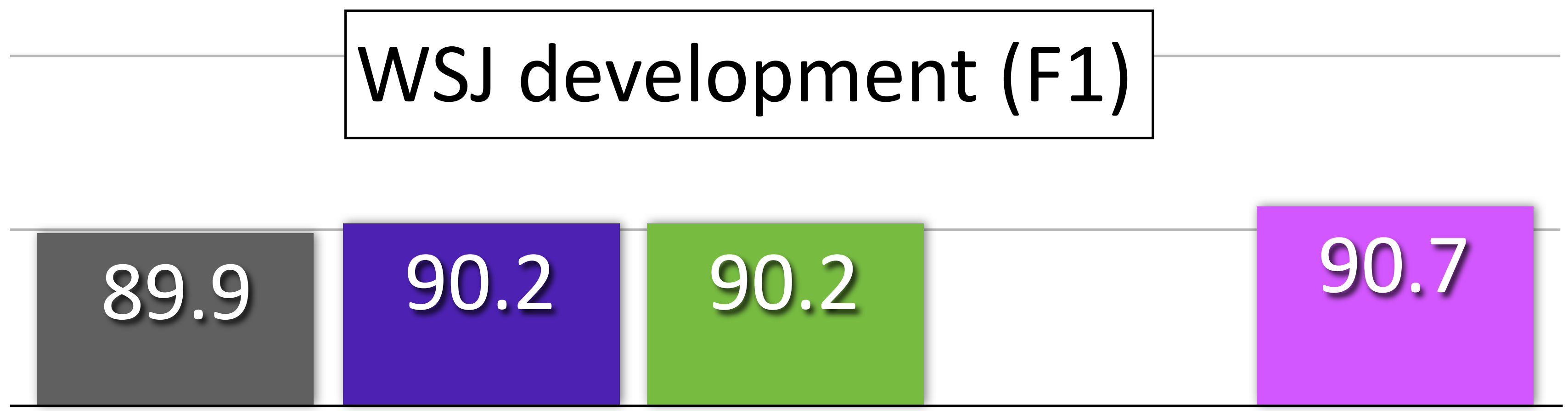

beam:	16	32	64	**∞ (this work)**
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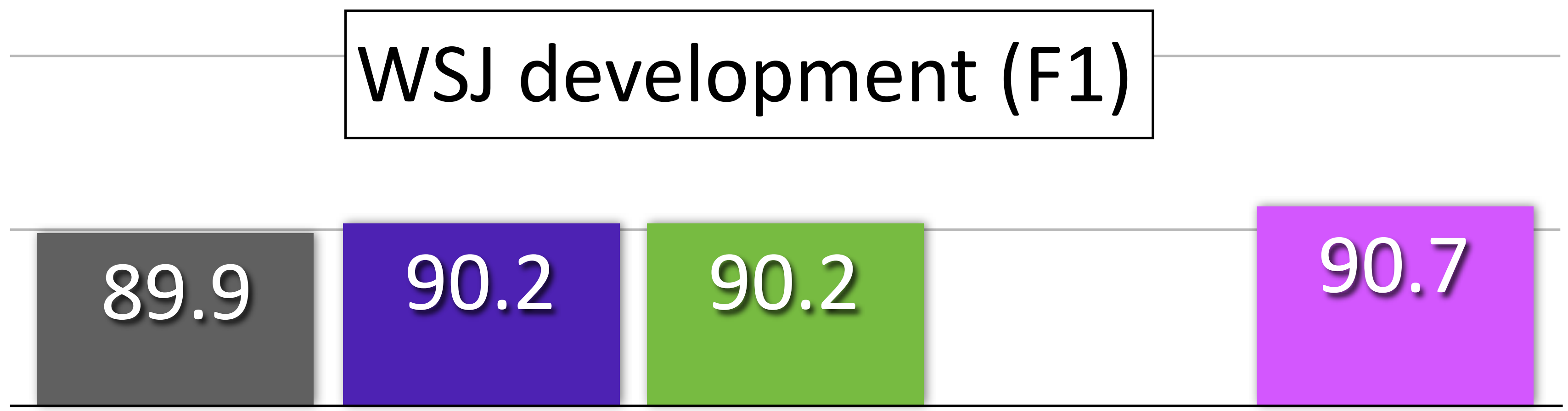

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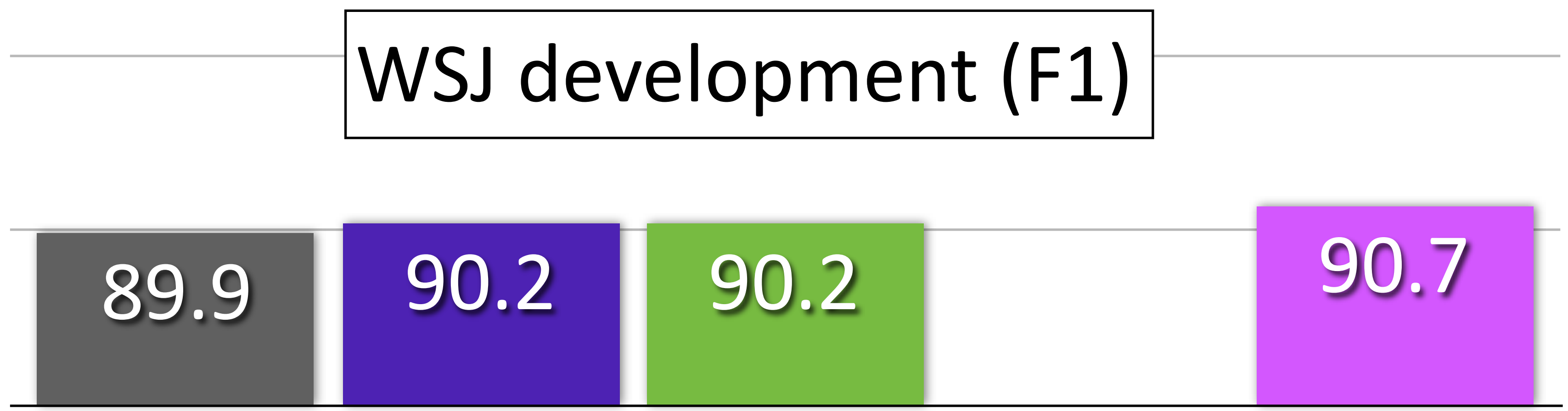

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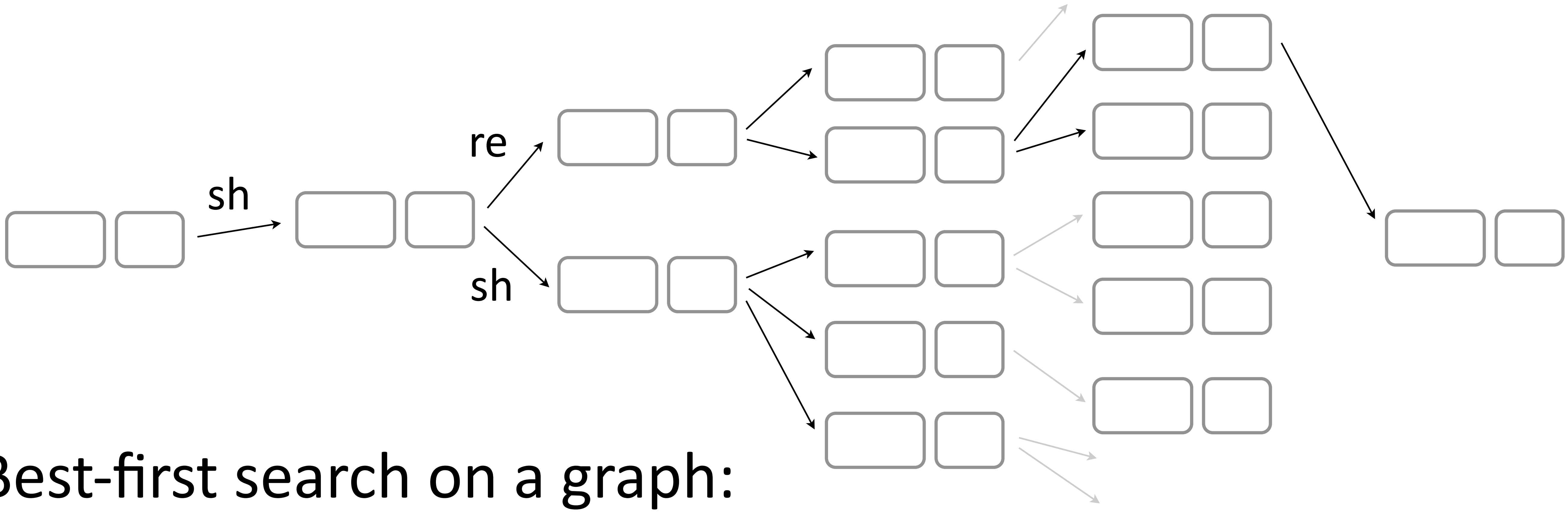
Technical contributions:

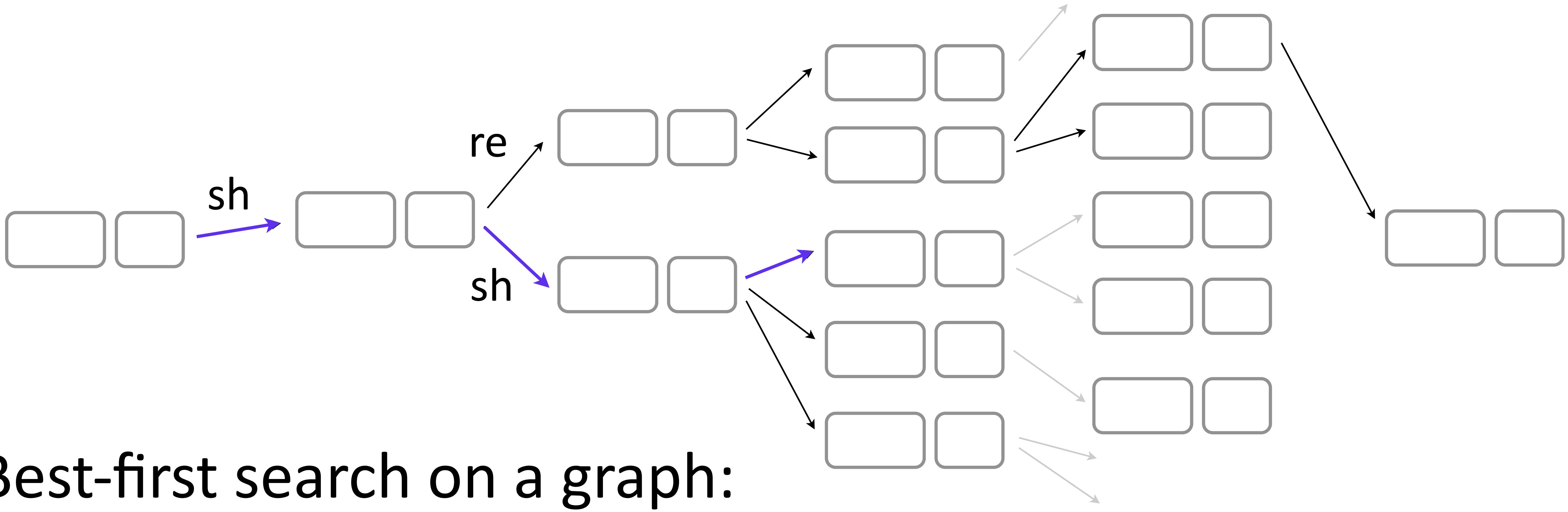
- New feature templates that facilitate search
- New A* heuristics to further speed up search

Framework



Best-first search on a graph:

Framework



Best-first search on a graph:

Goal: Finding the lowest cost path

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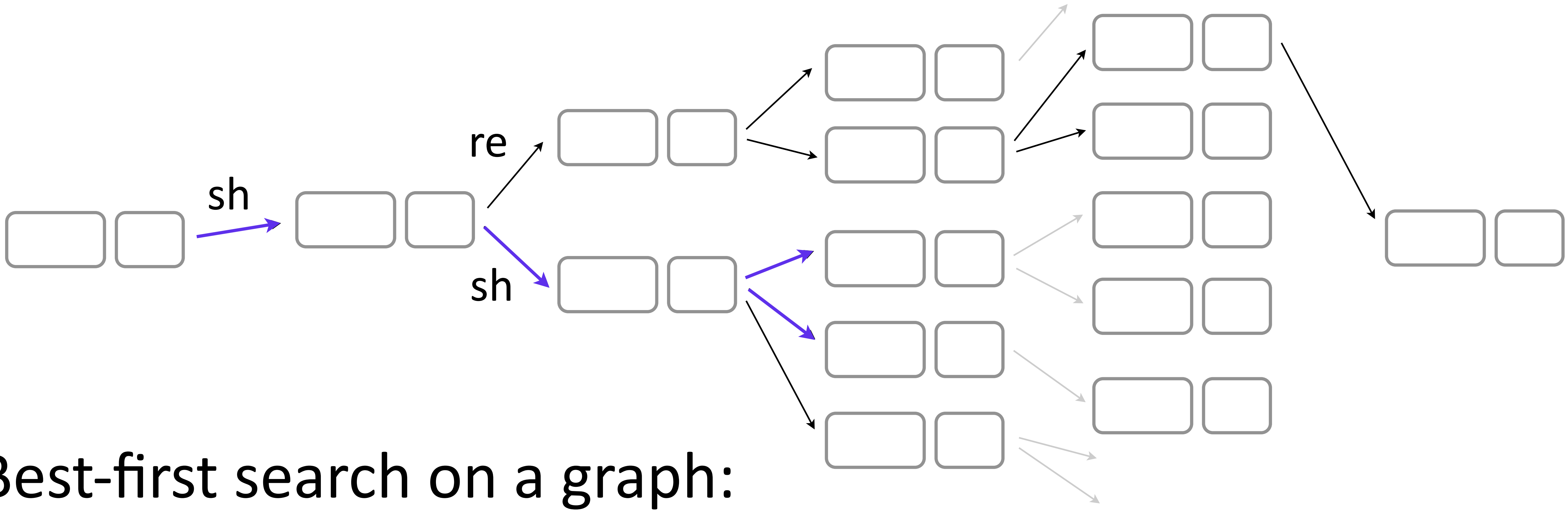

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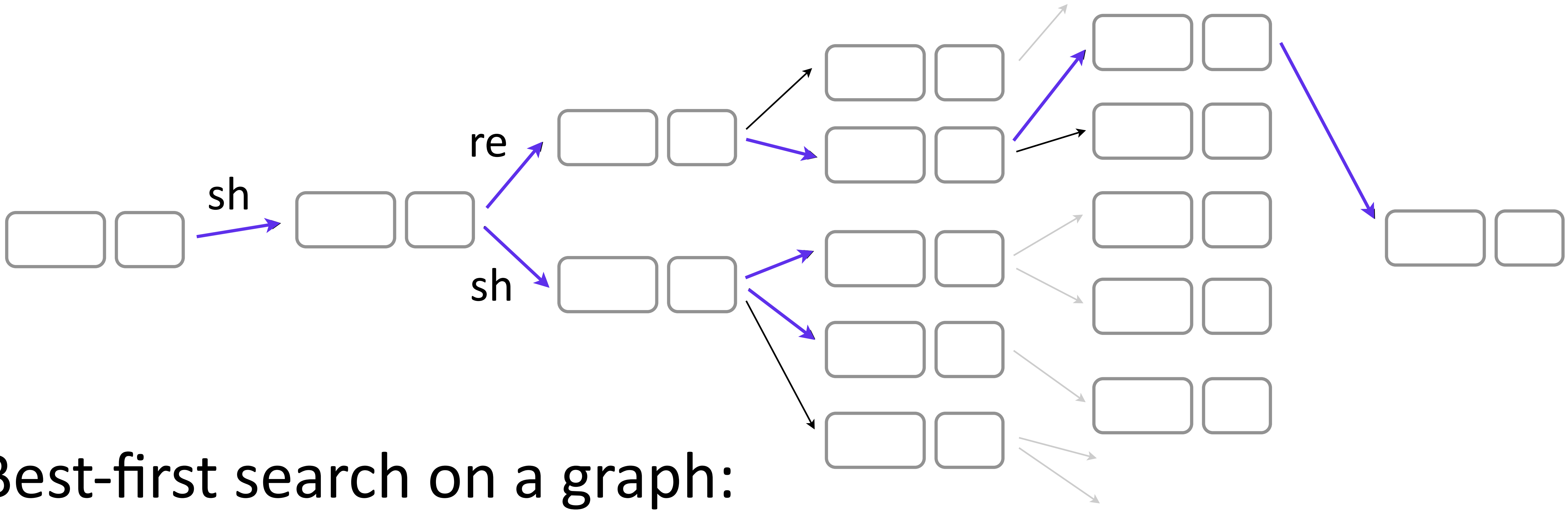

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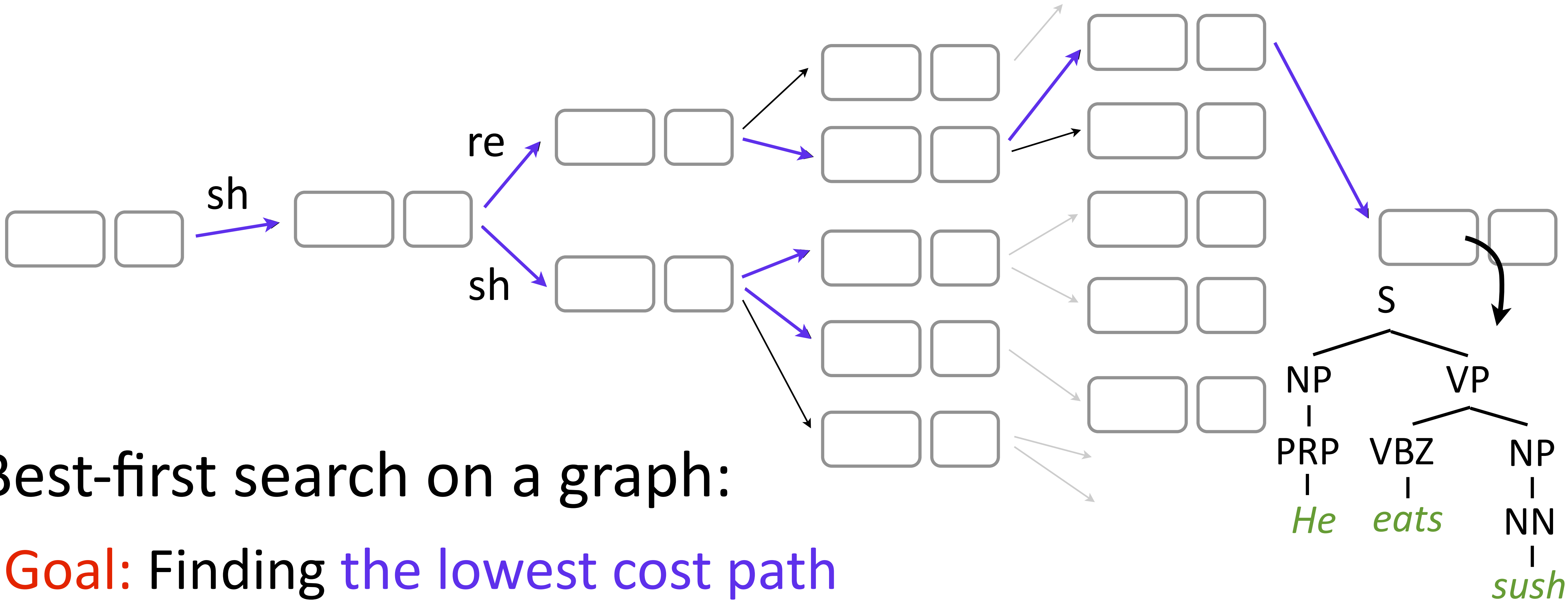

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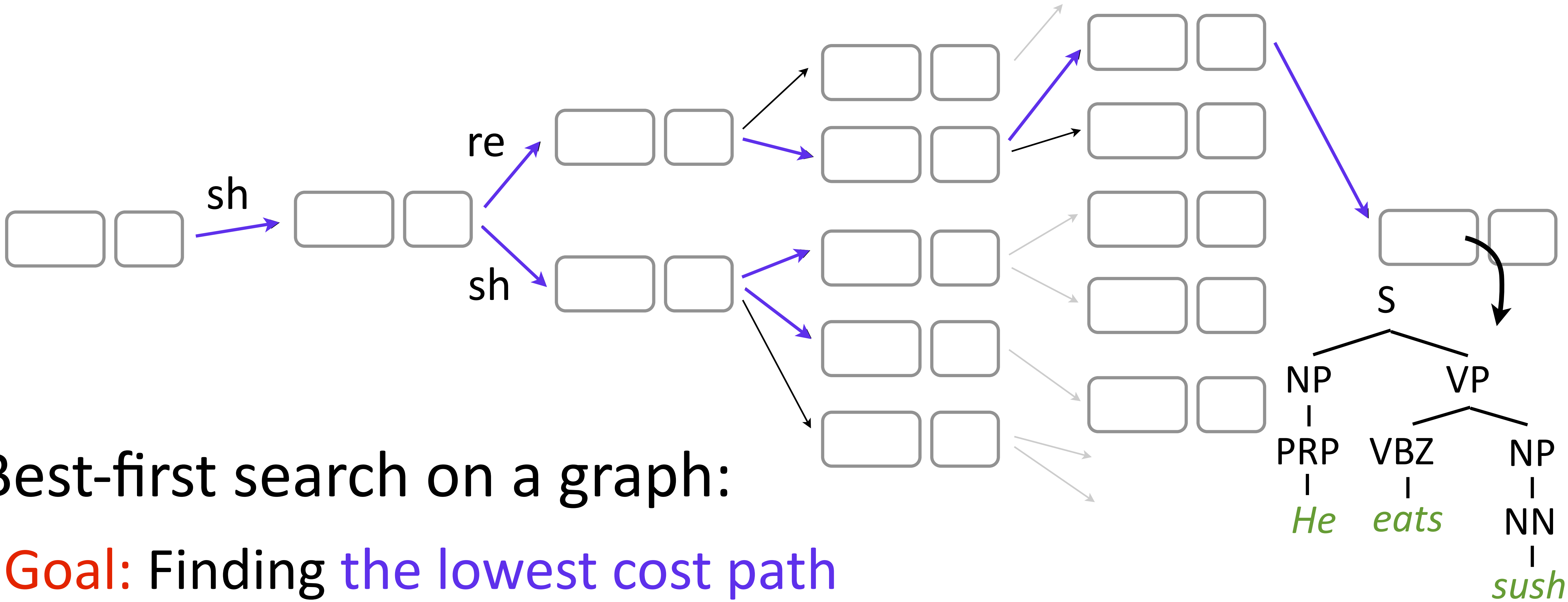

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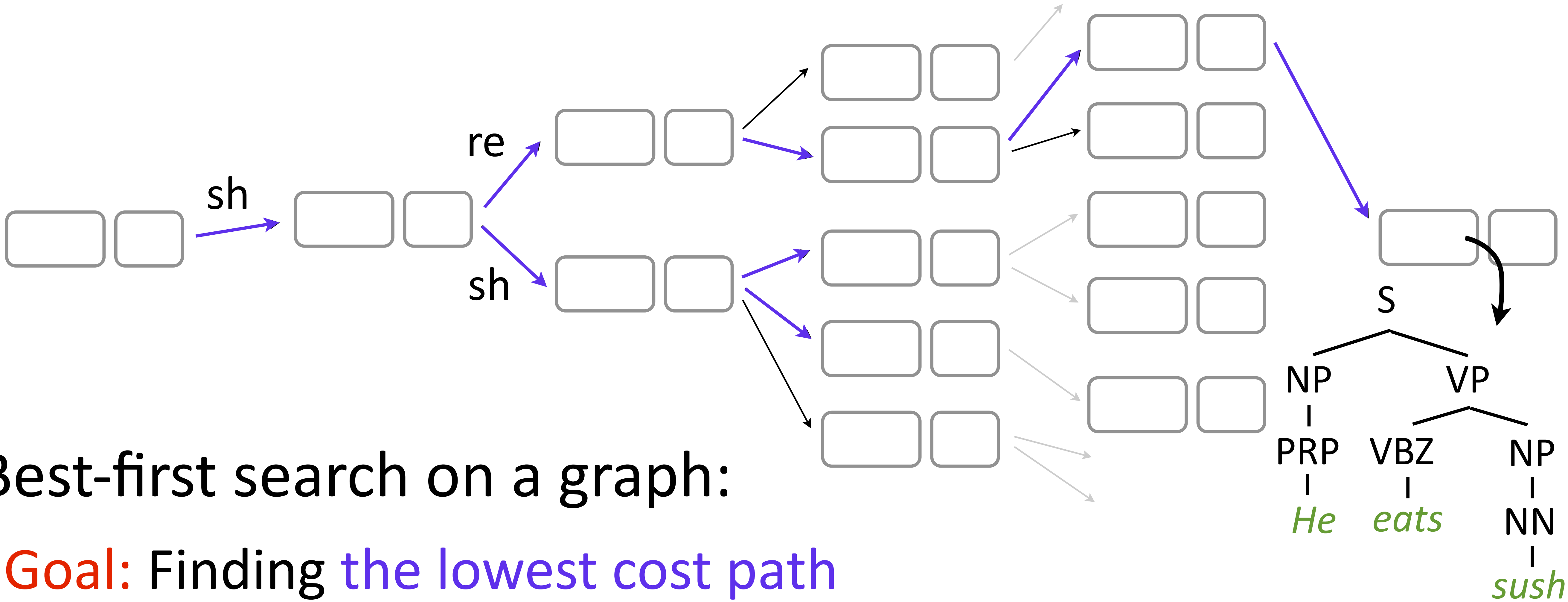

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Model: Structured perceptron

- State-of-the-art model for shift-reduce parsing [Zhu et al., 2013; Wang & Xue, 2014; Mi et al., 2015]

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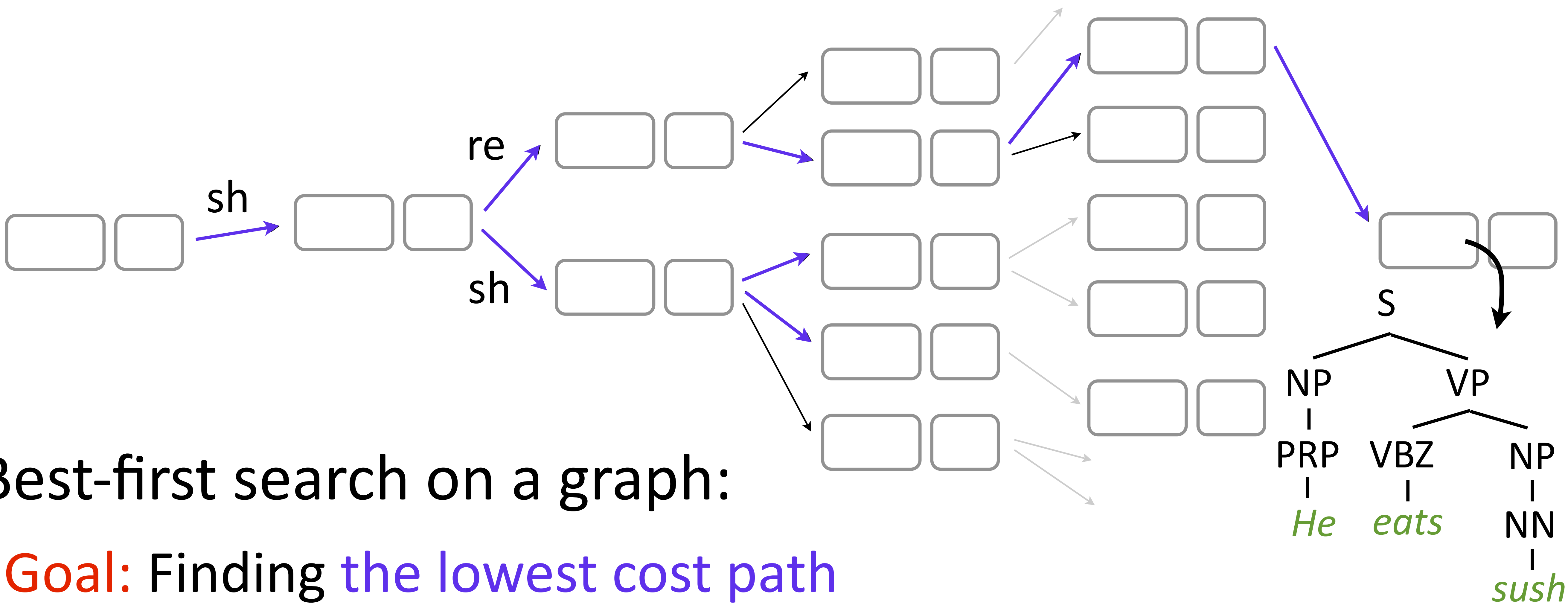

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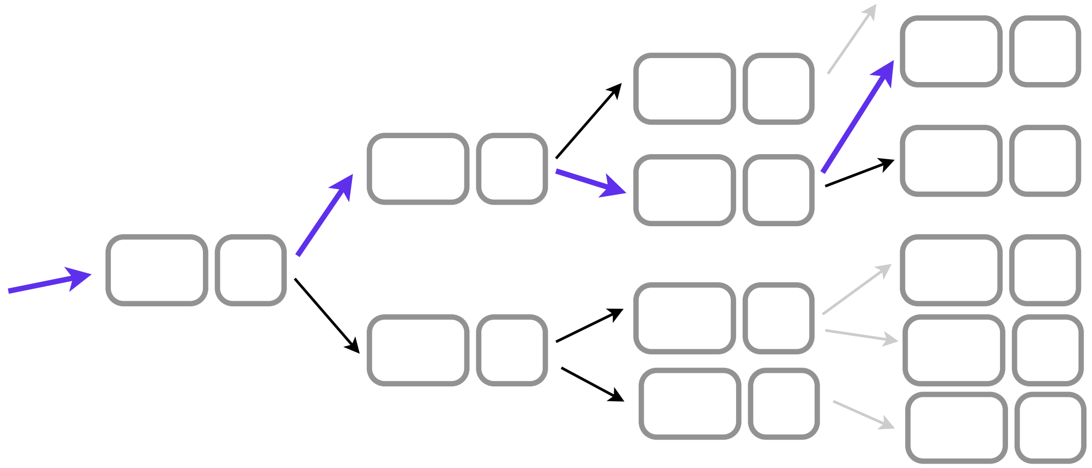
Previous best-first shift-reduce parsing

- Initial work [Sagae & Lavie, 2006]

  Search on exponentially large graph



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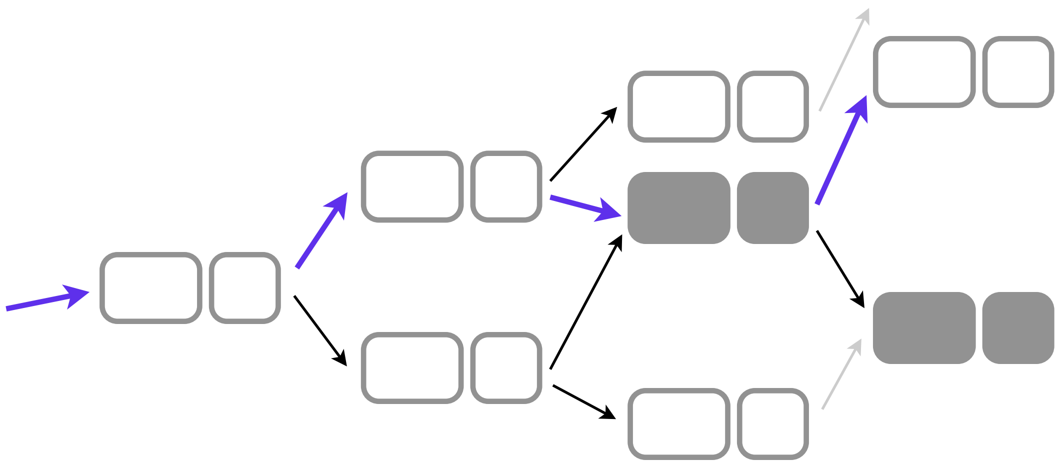

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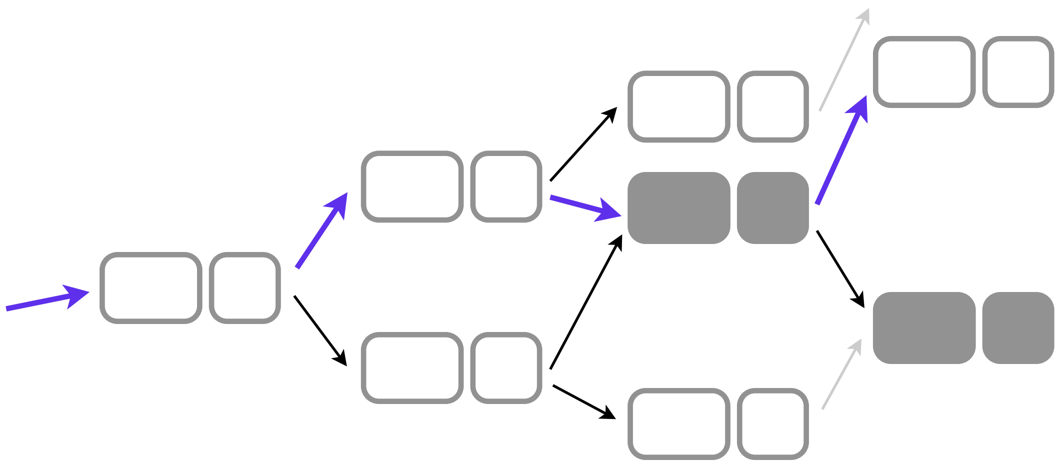

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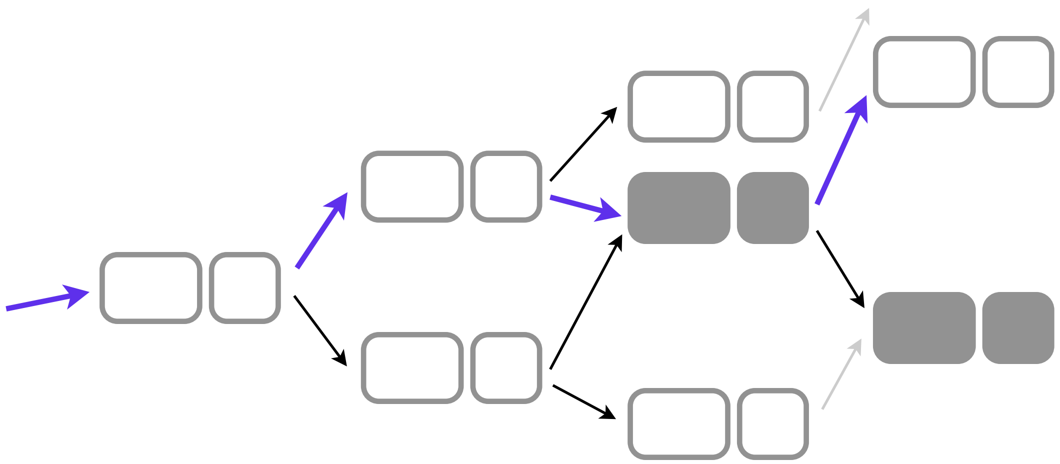

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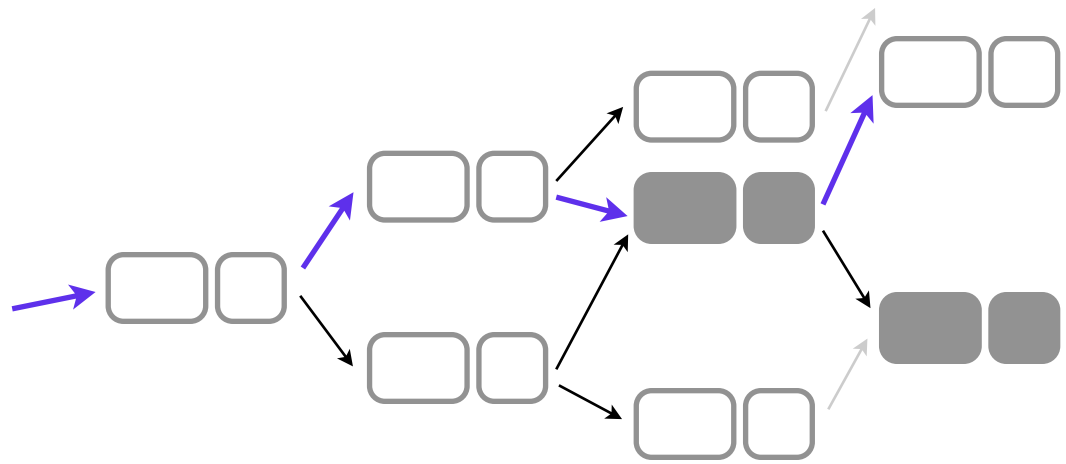

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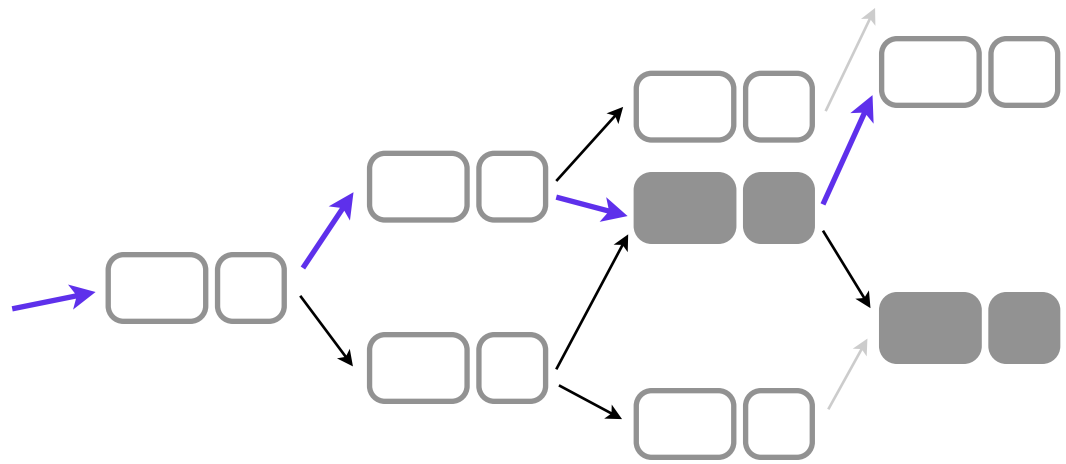

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Challenge: Search gets much harder with structured perceptron

Outline

DP best-first shift-reduce parsing

- for **constituency**
- with **structured perceptron**

MaxEnt vs. Structured perceptron

- Structured perceptron is strong
- but its search is much harder

Improving search efficiency of structured perceptron

- New feature templates
- A* search

Final experiment

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Basic algorithm: Zhao et al (2013)'s DP best-first search

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How to apply for constituent parsing?

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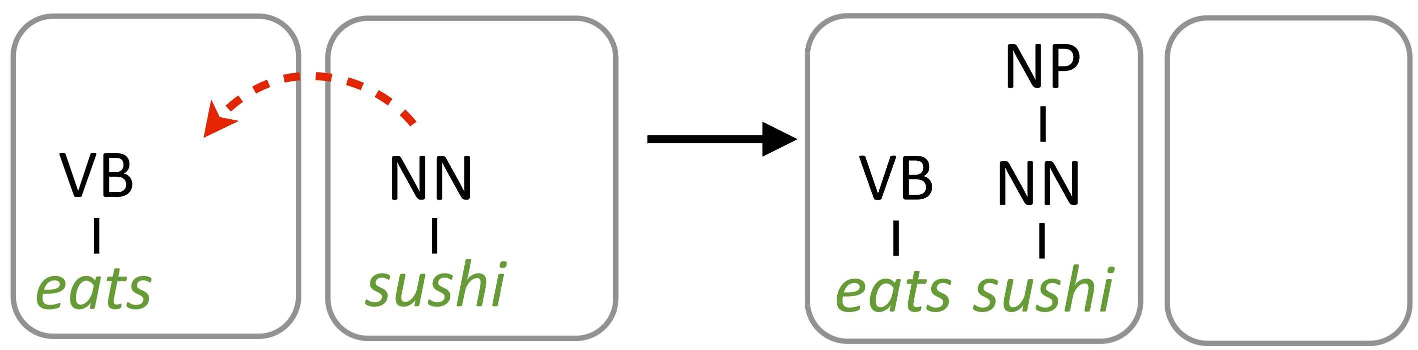

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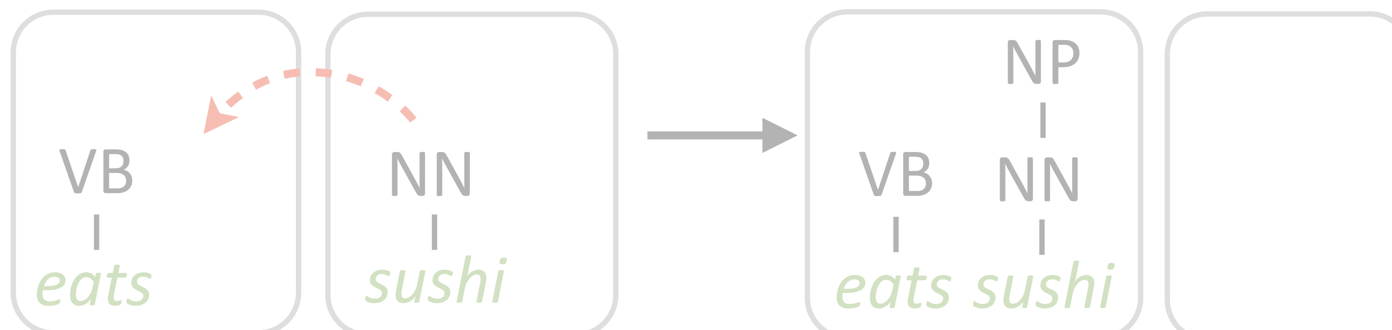
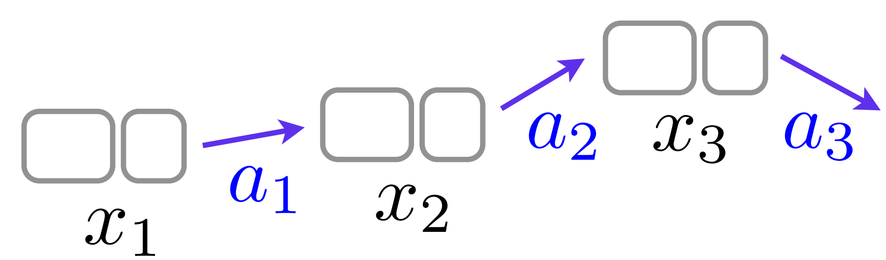


What is edge cost in structured perceptron?



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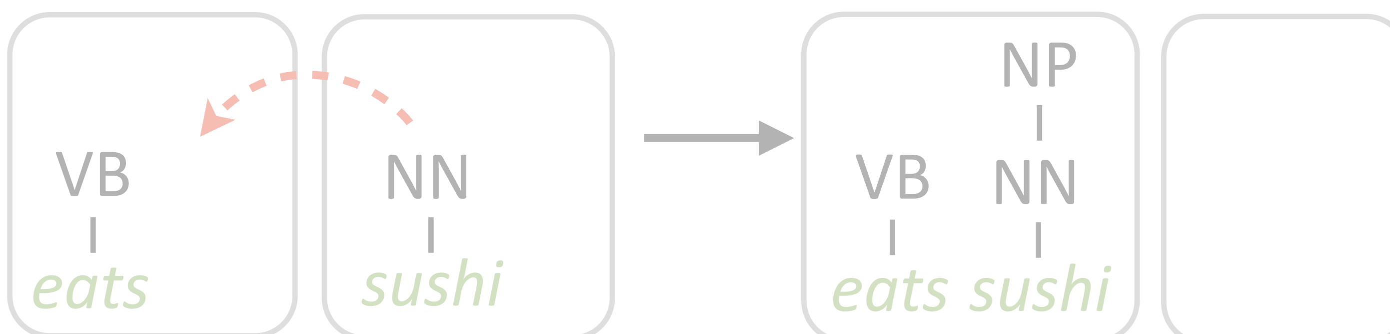

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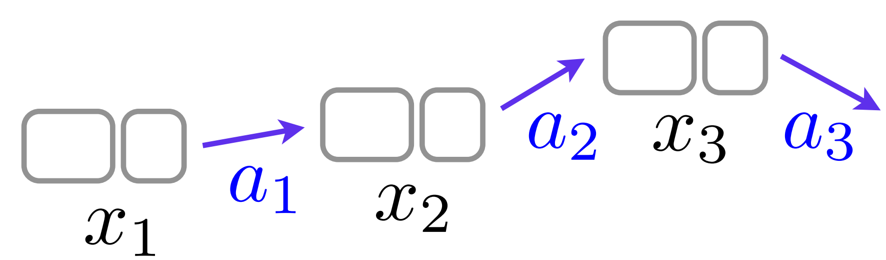

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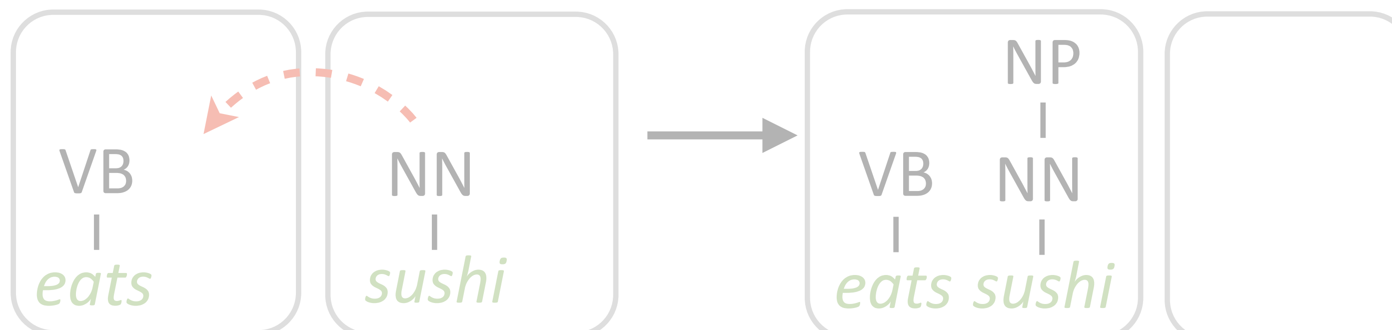

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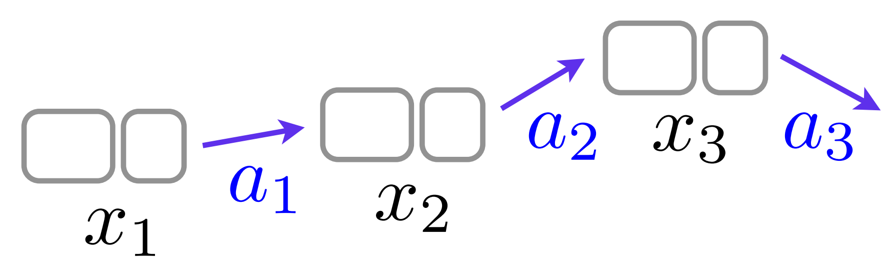

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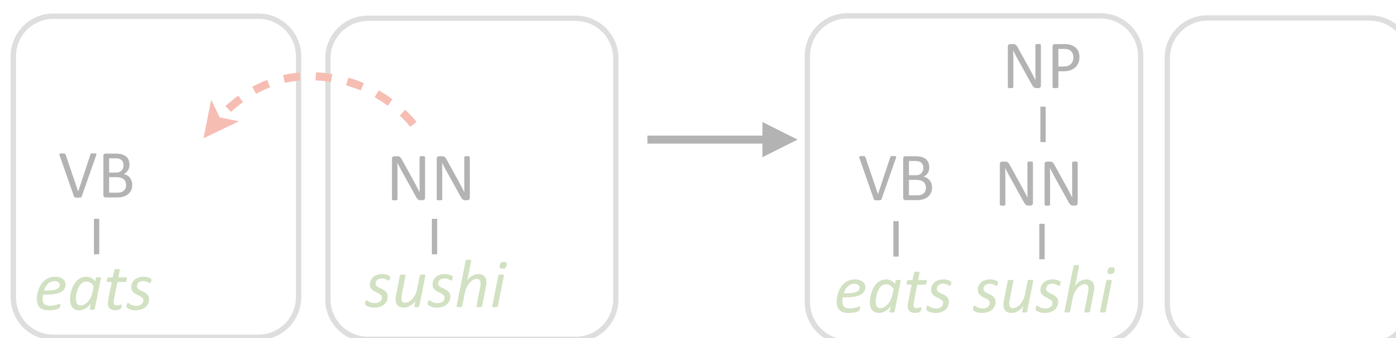

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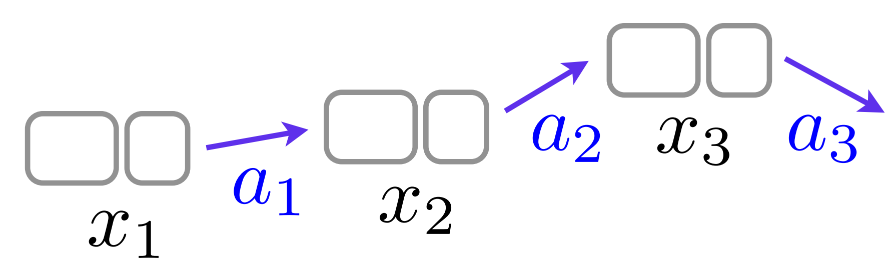
Score to a derivation: $\sum_{i=1}^{2n} \theta^{\mathsf{T}} f(a_i, x_i)$

Our edge cost: $\theta^{\mathsf{T}} f(a, x) + \delta$



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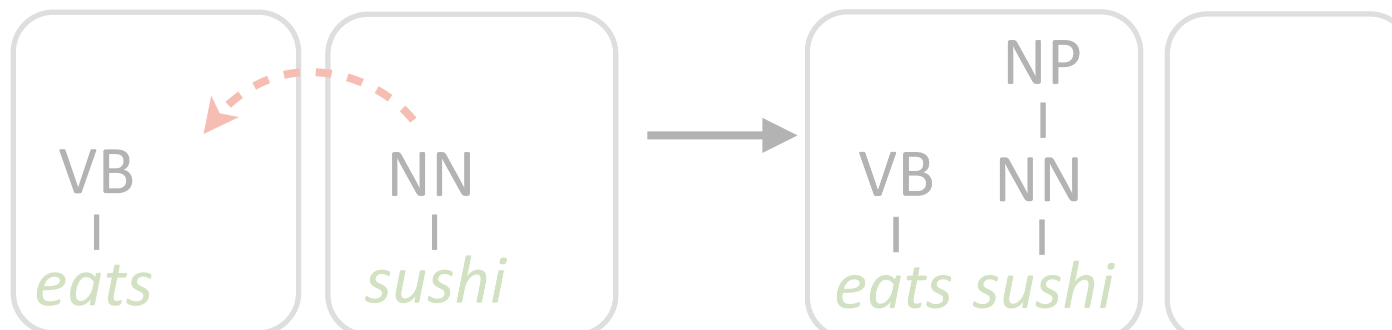

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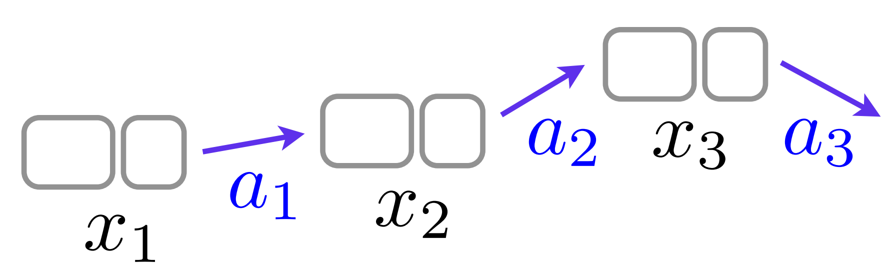

Our edge cost: $\theta^{\intercal} f(a, x) + \delta$

could be negative

DP best-first parsing for constituency

Basic algorithm: Zhao et al (2013)'s DP best-first search

How to apply for constituent parsing?

- The main difficulty with constituent parsing is unary rule
- We develop a transition system without unary rules

What is edge cost in structured perceptron?

Constraint for optimality: Every cost must be positive

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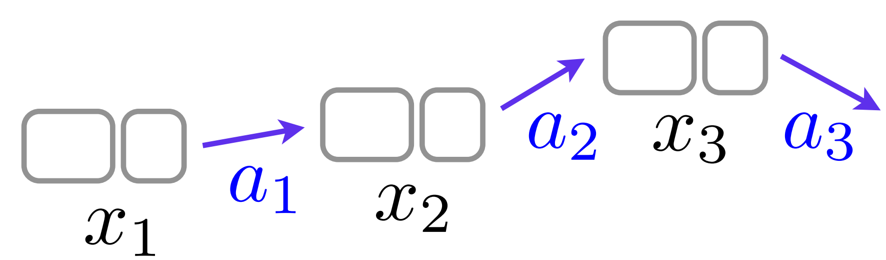

Our edge cost: $\theta^\intercal f(a, x) + \delta$

could be negative

Constant offset to prevent negative

Outline

DP best-first shift-reduce parsing

- for **constituency**
- with **structured perceptron**

MaxEnt vs. Structured perceptron

- Structured perceptron is strong
- but its search is much harder

Improving search efficiency of structured perceptron

- New feature templates
- A* search

Final experiment

MaxEnt. vs. Structured Perceptron

- Data: WSJ Section 22
- Relatively simple features

F1 score **Search efficiency**

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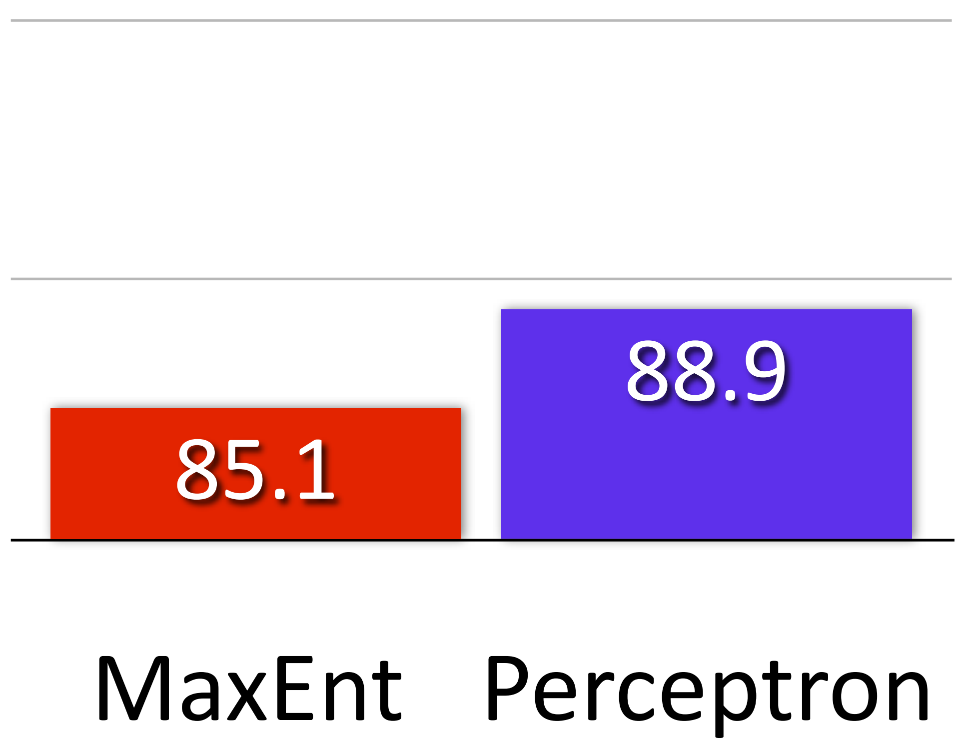

Search efficiency

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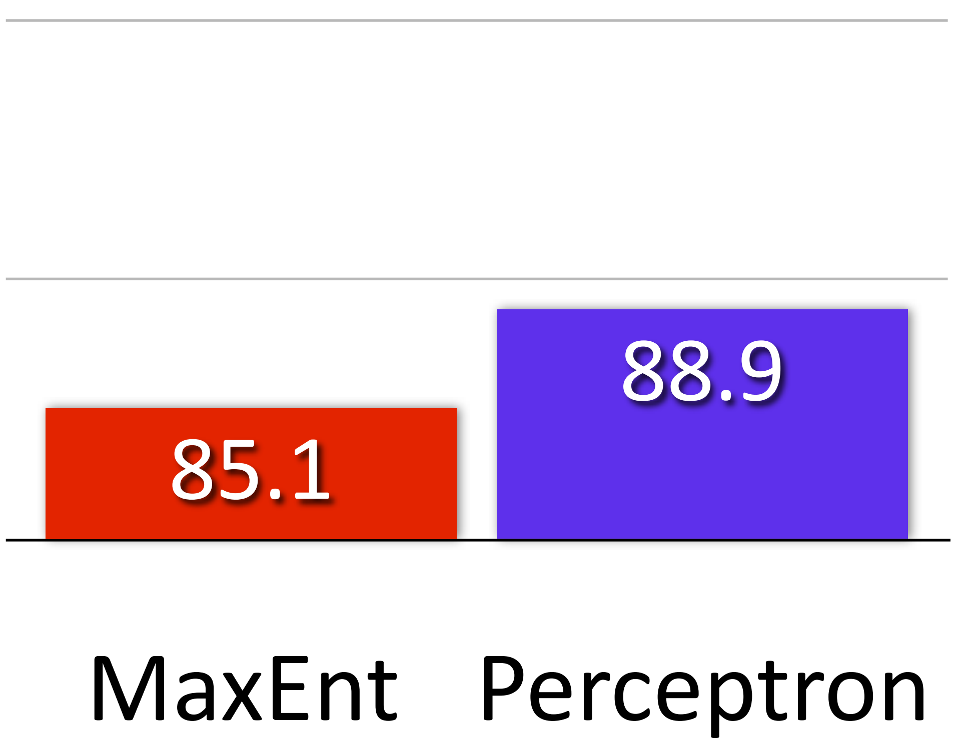

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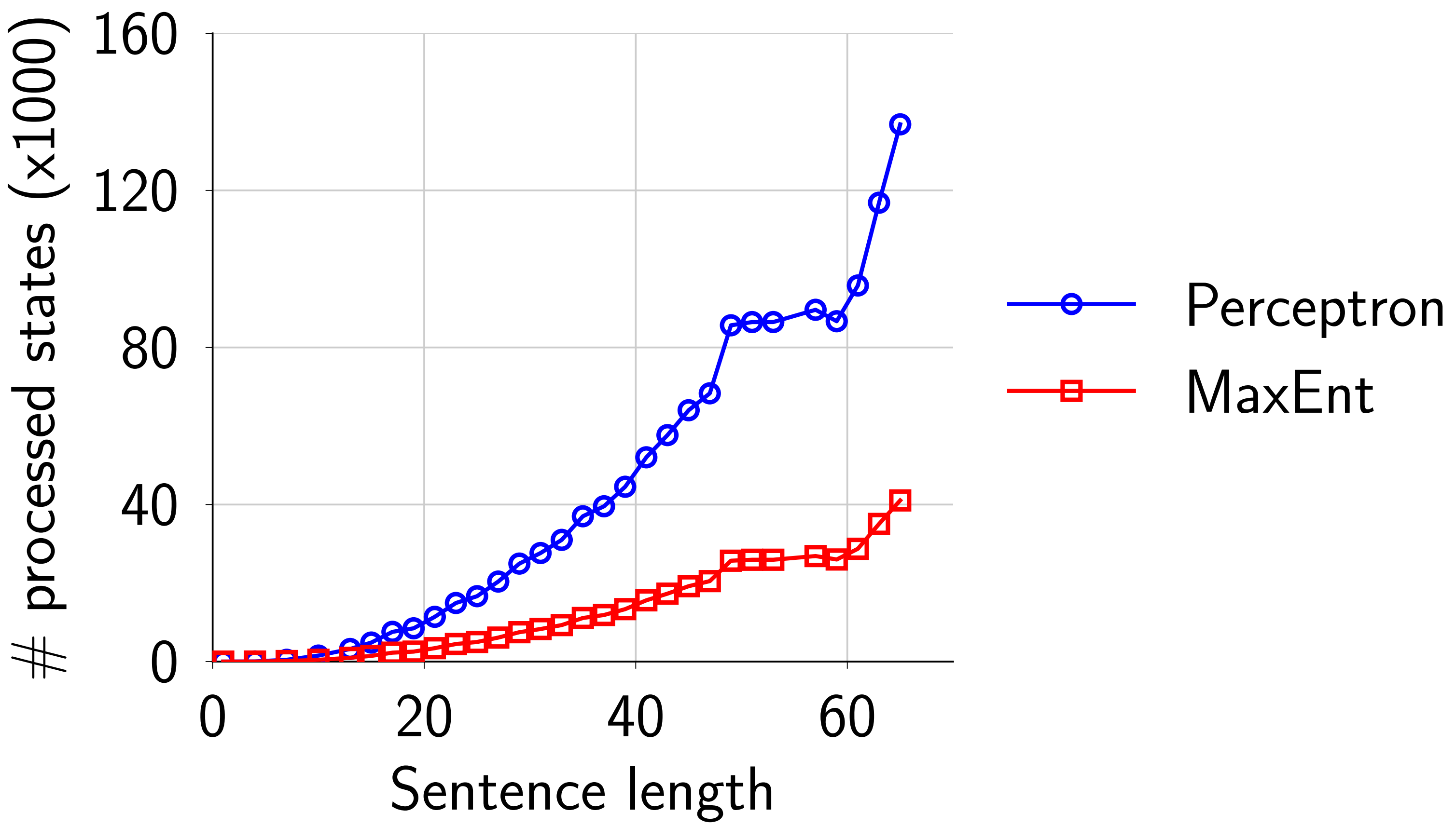
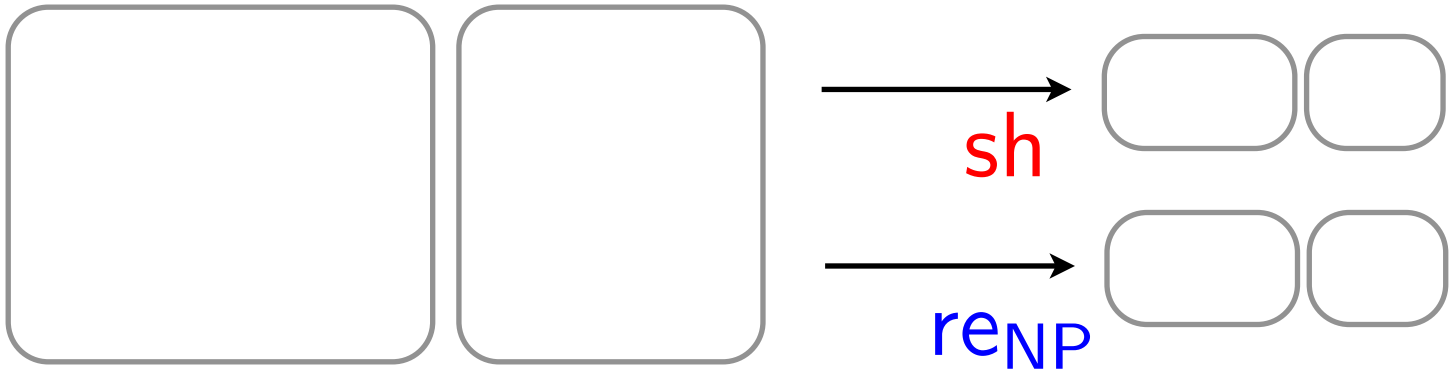


- Structured perceptron is strong
- but its search is much harder ⇒ Why?

Why is search of structured perceptron so hard?



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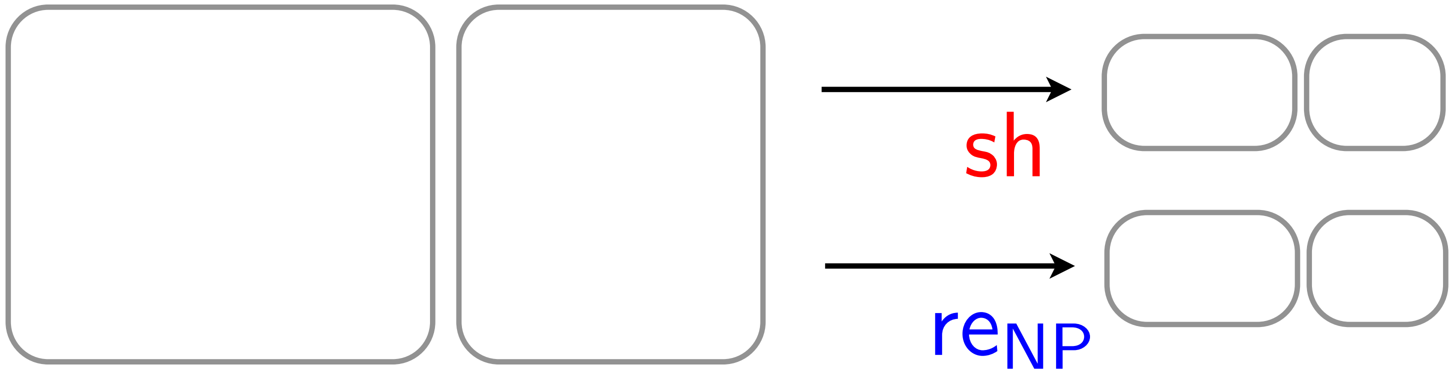

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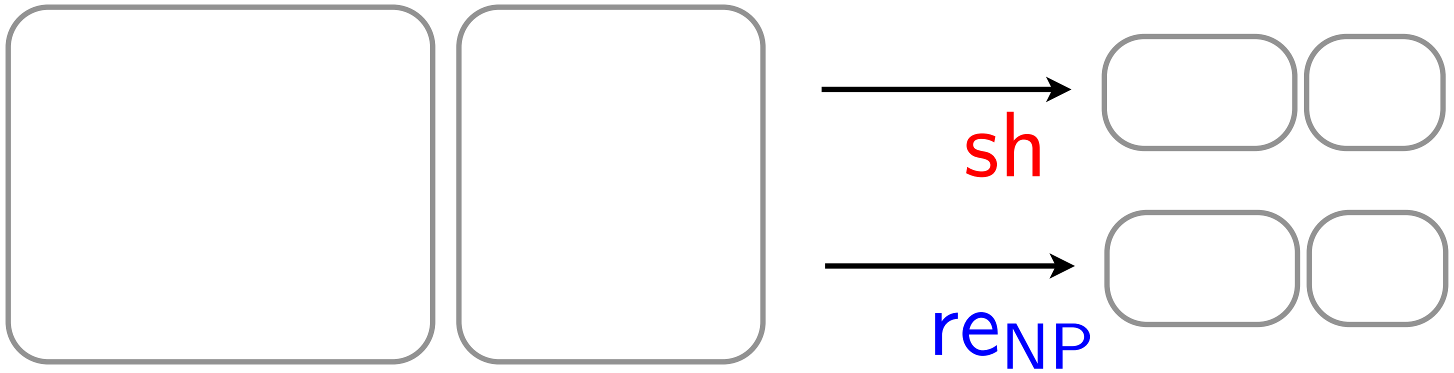

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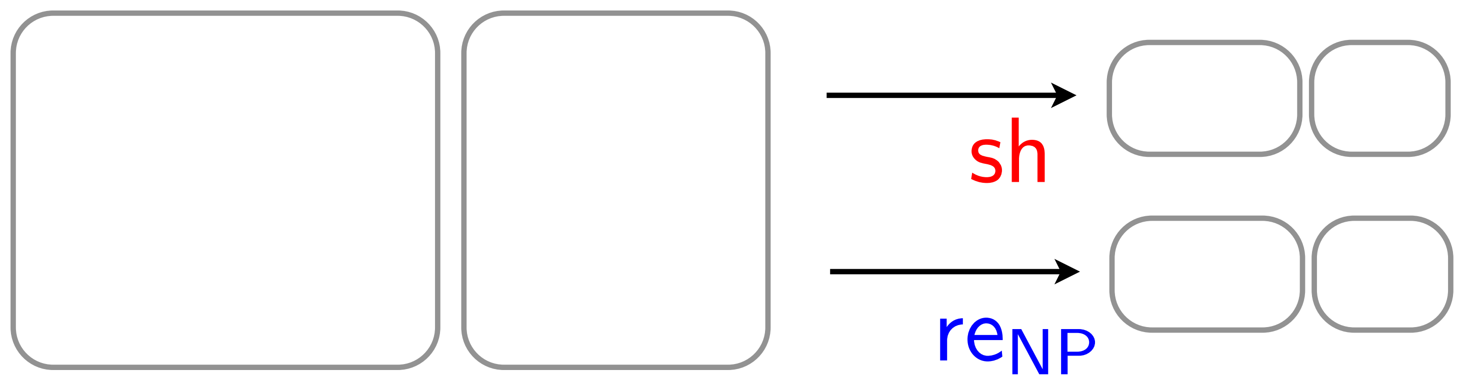

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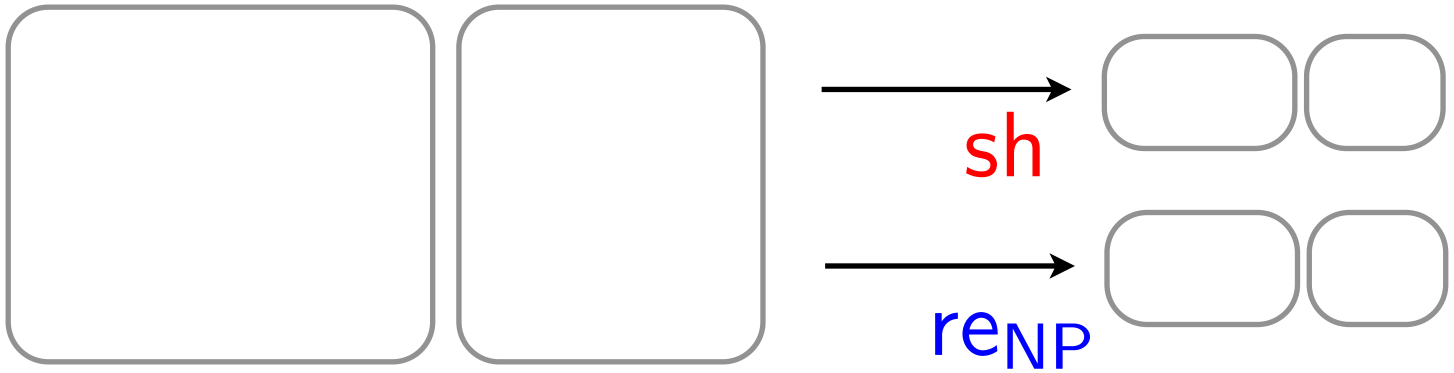

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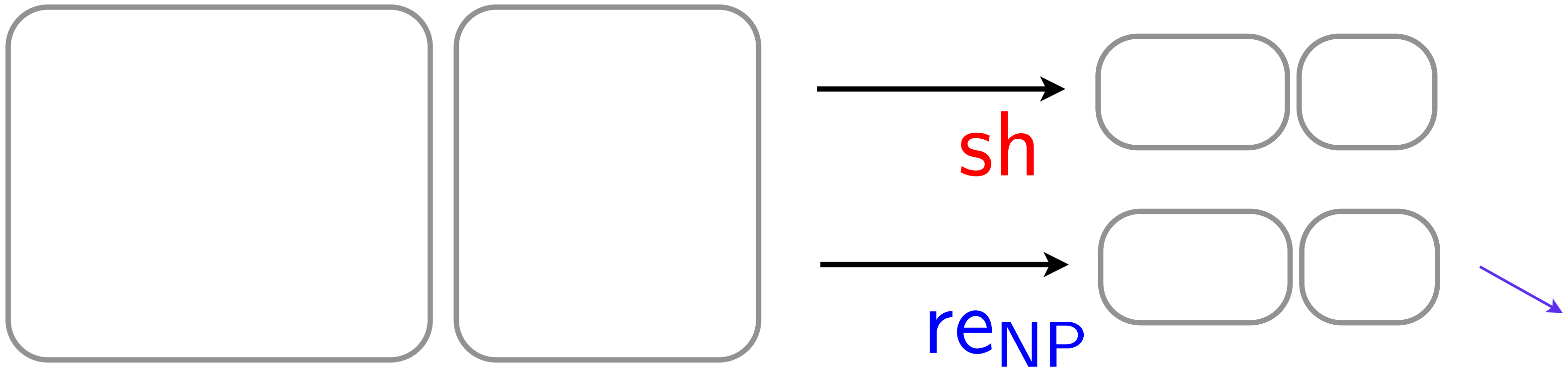

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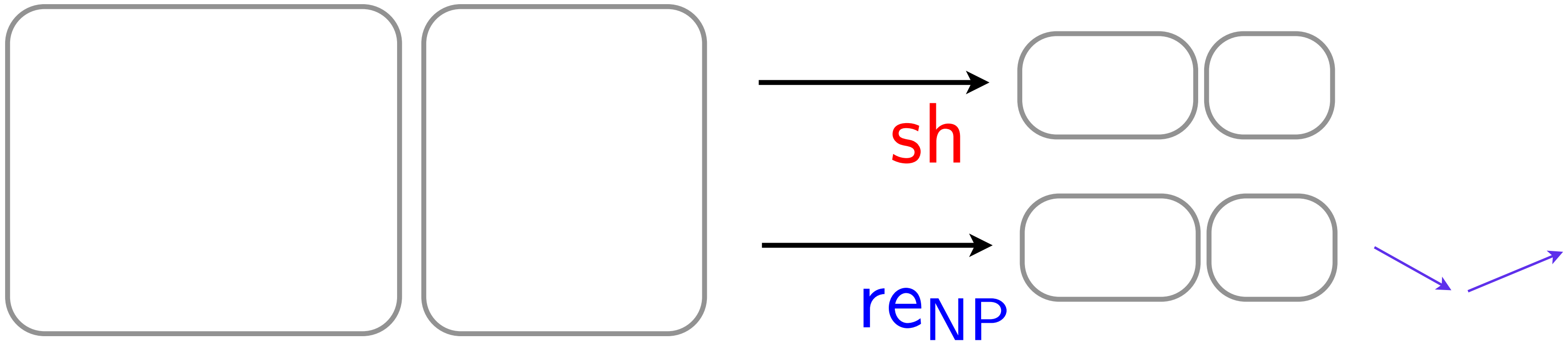

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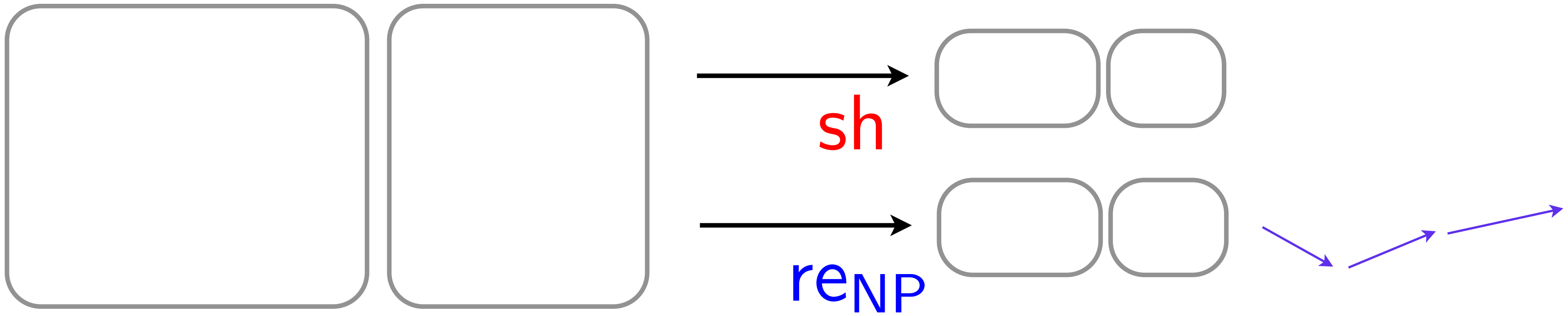

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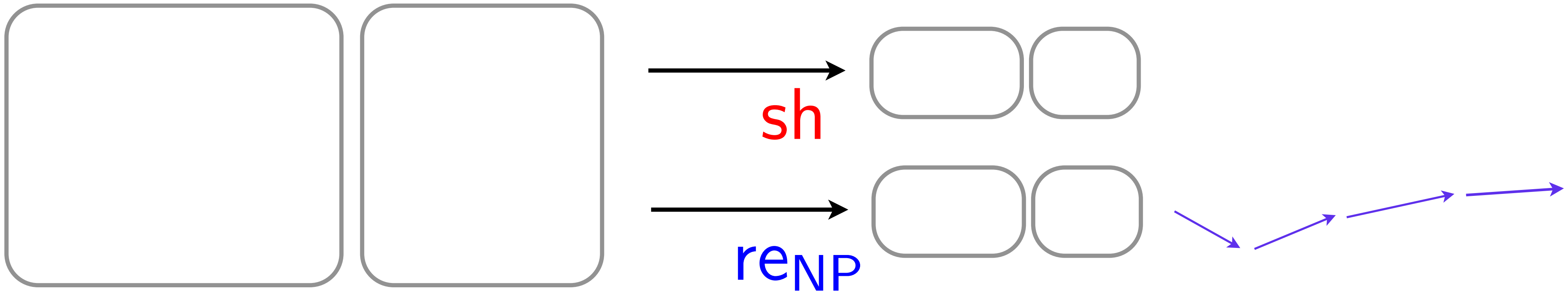

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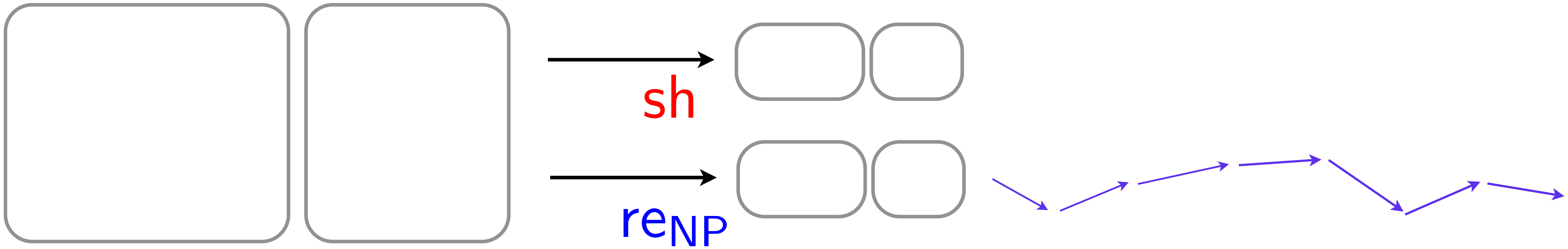

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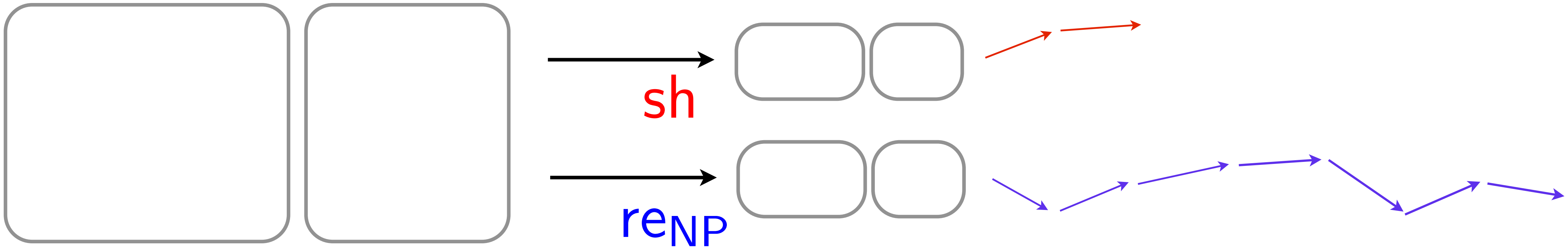

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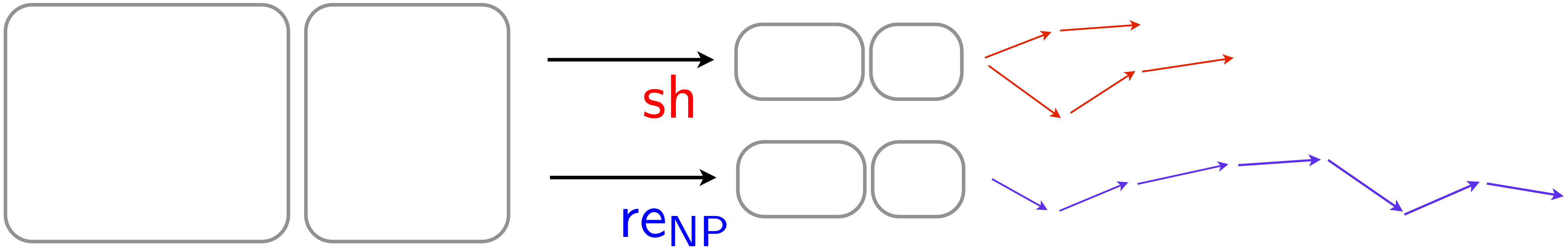

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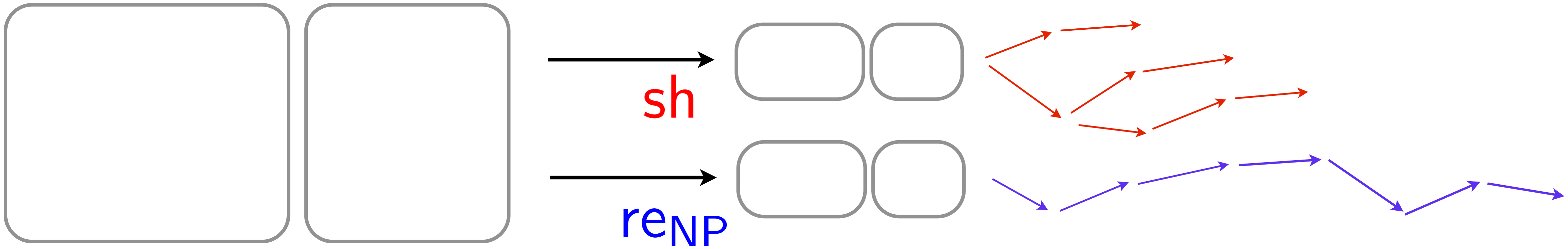

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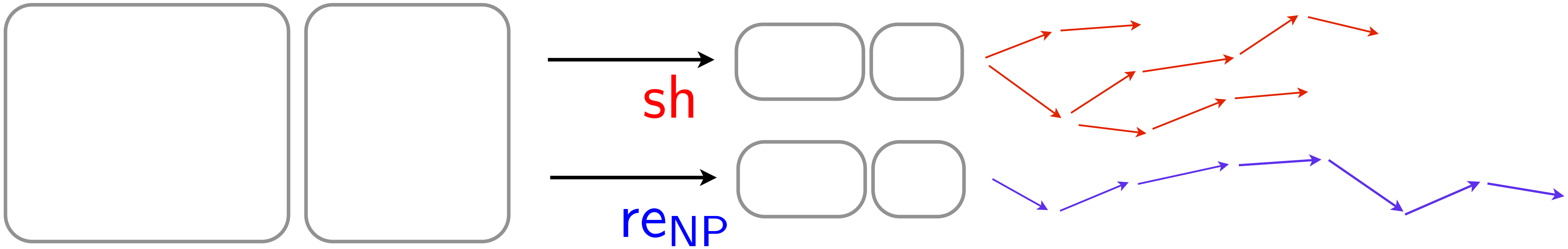

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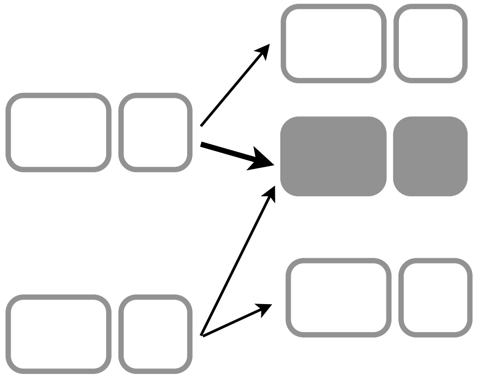
Feature design determines the worst time complexity of DP



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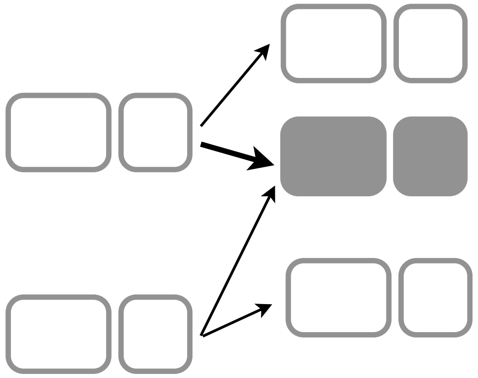
⇒ Two states are merged if their features look the same



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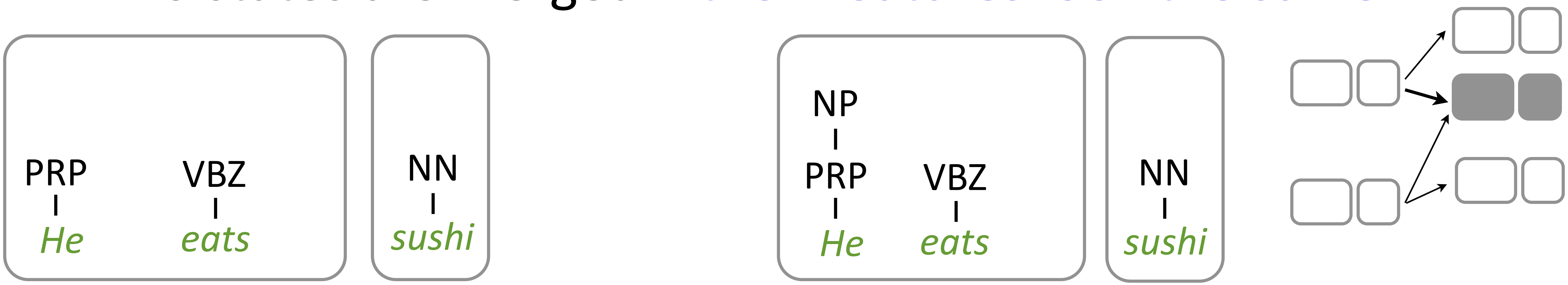

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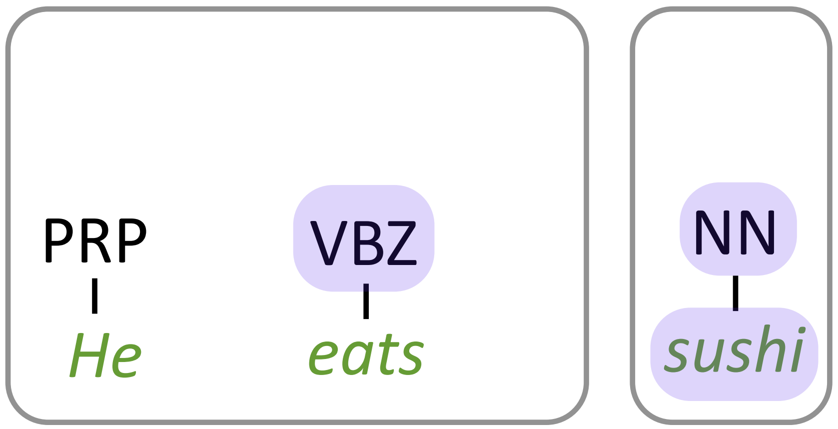

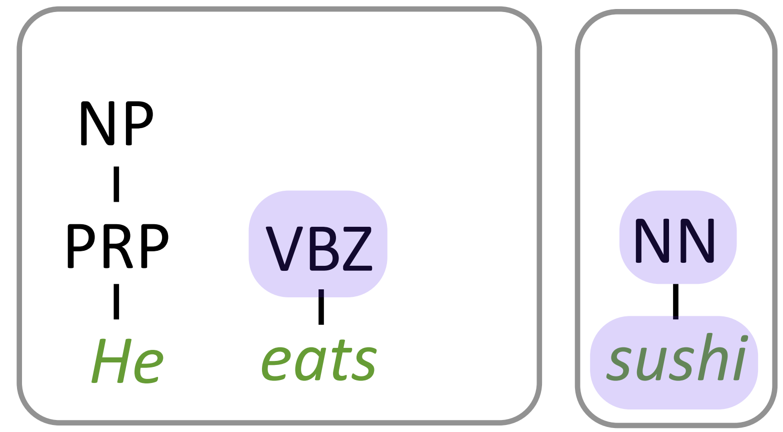

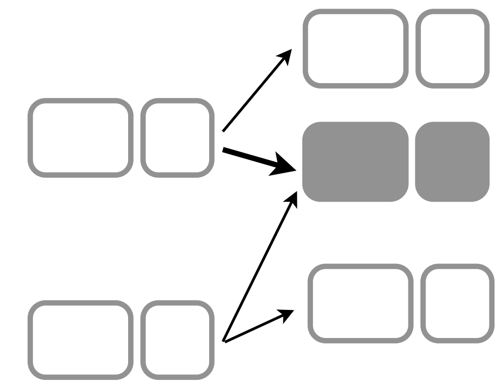

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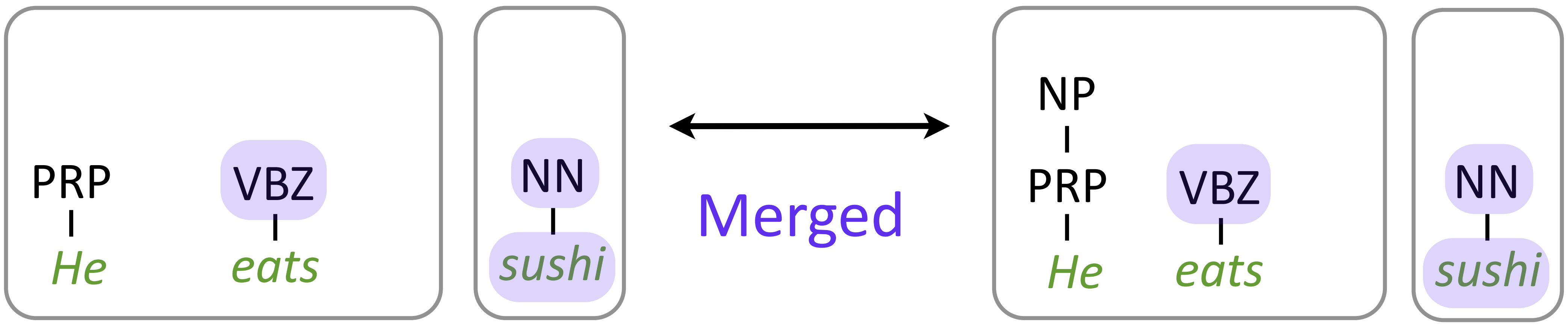

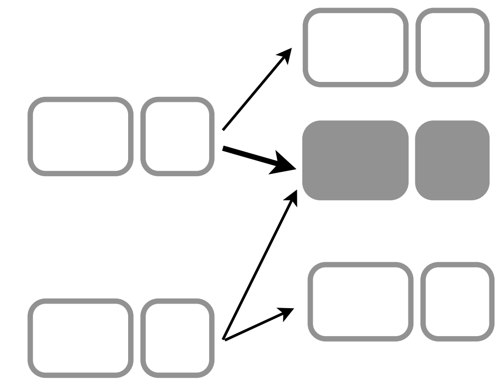

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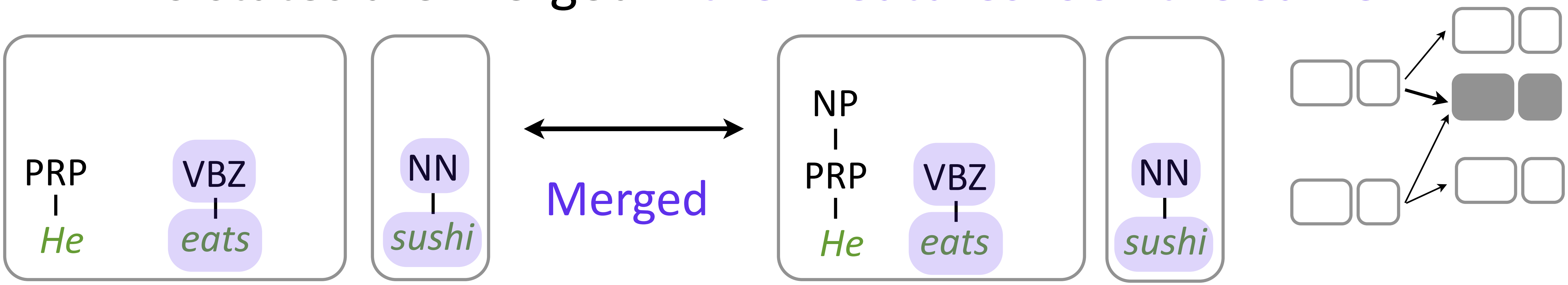

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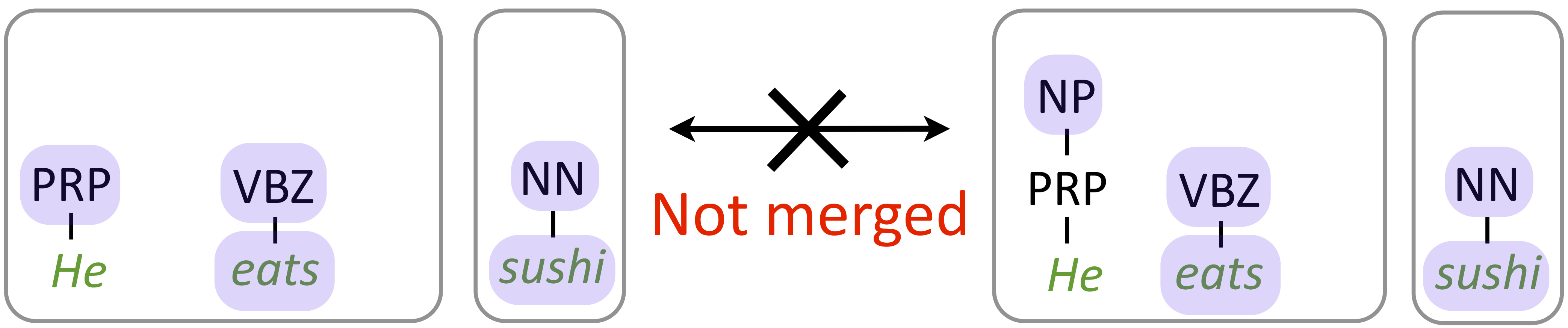

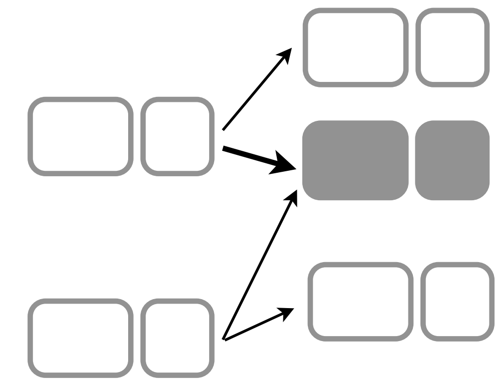

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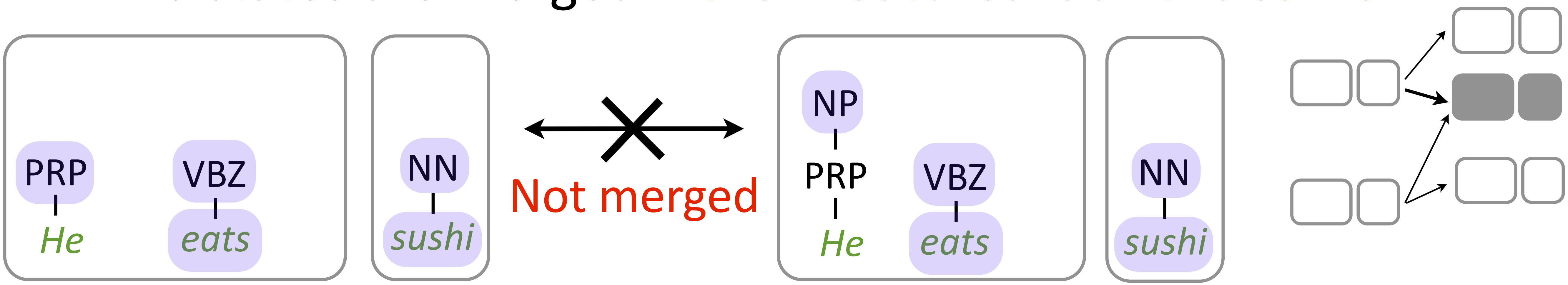

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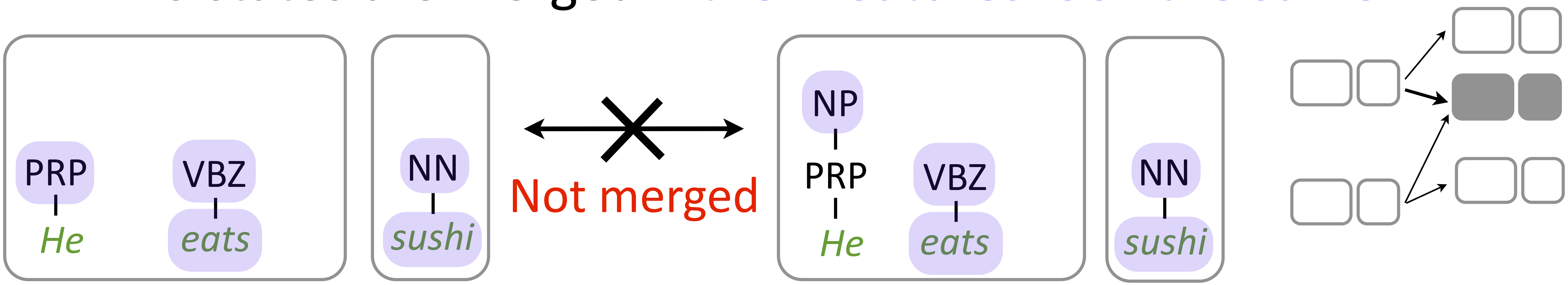

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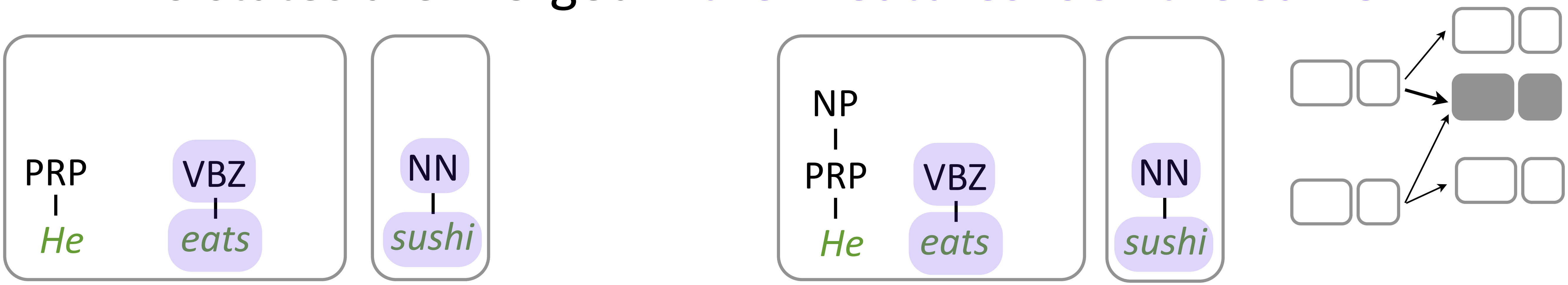

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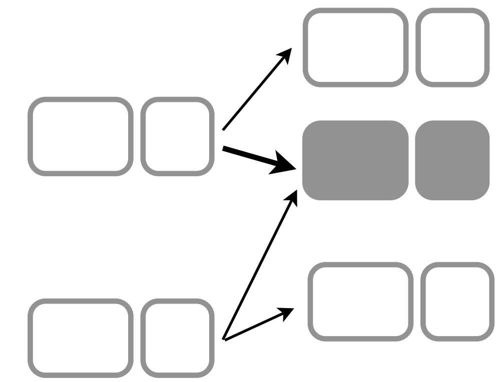

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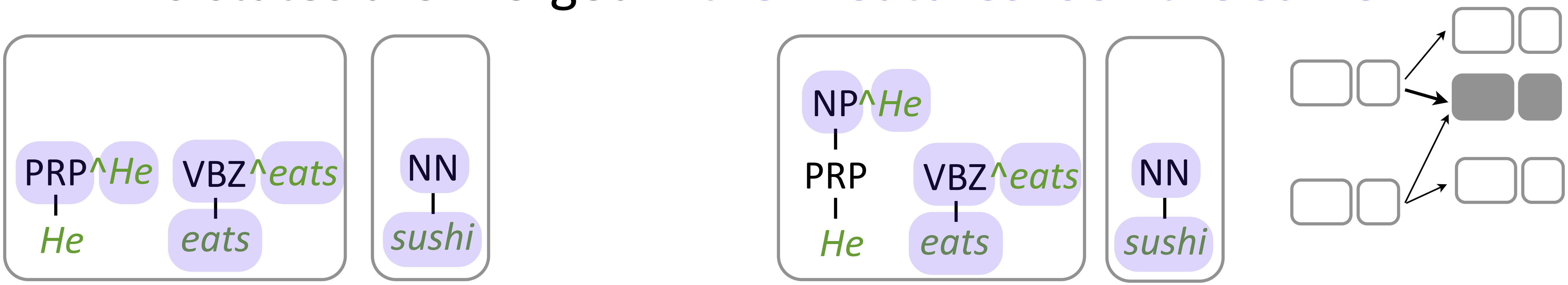

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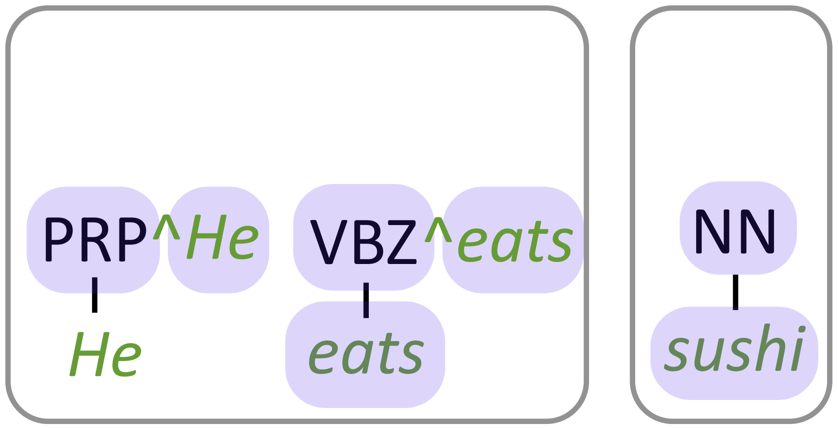

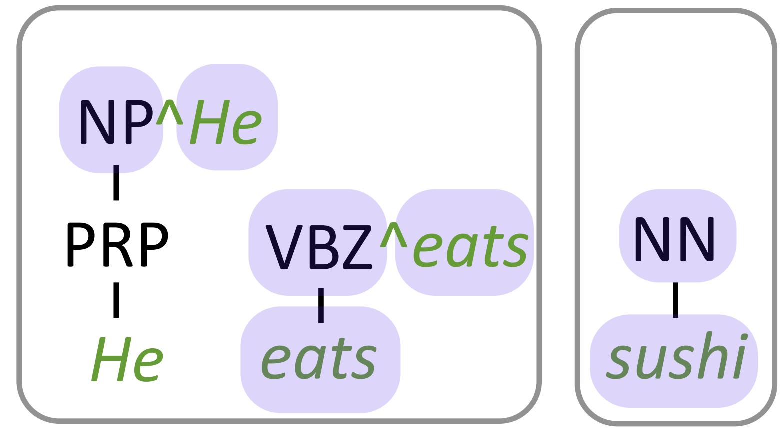

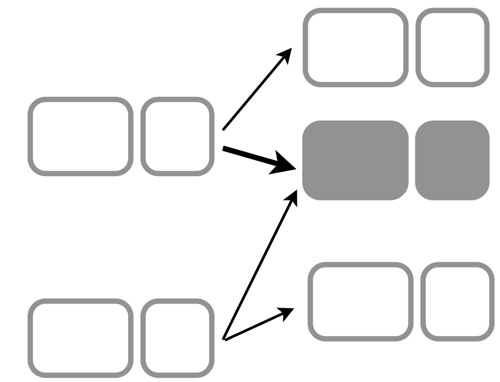

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State-of-the-art features [Zhu et al., 2013] (with beam-search)

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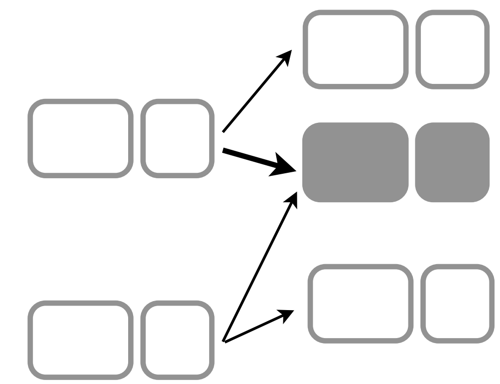

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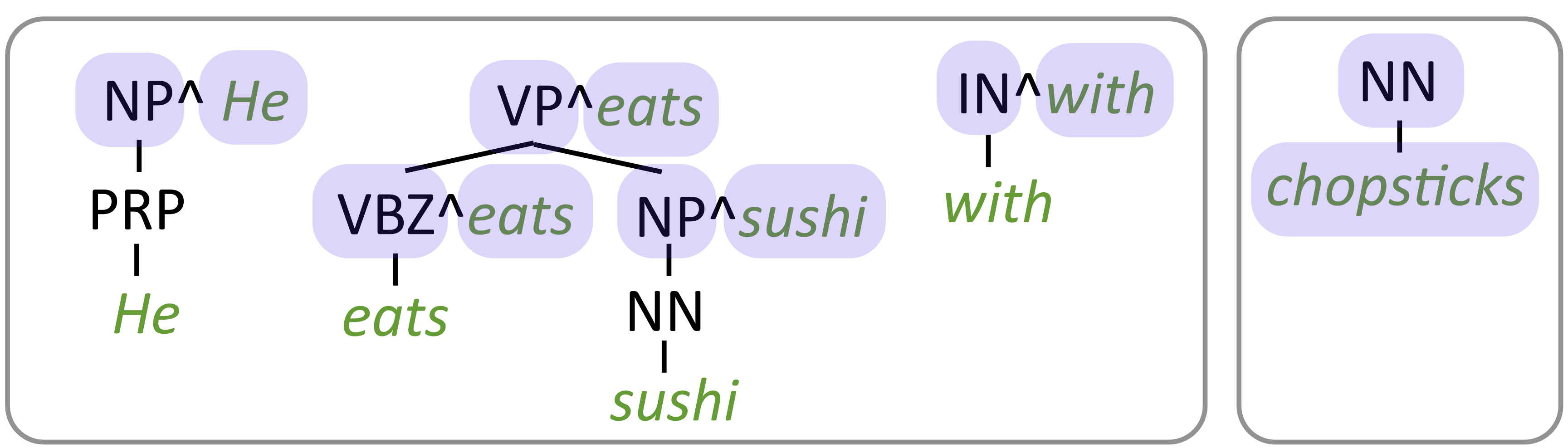

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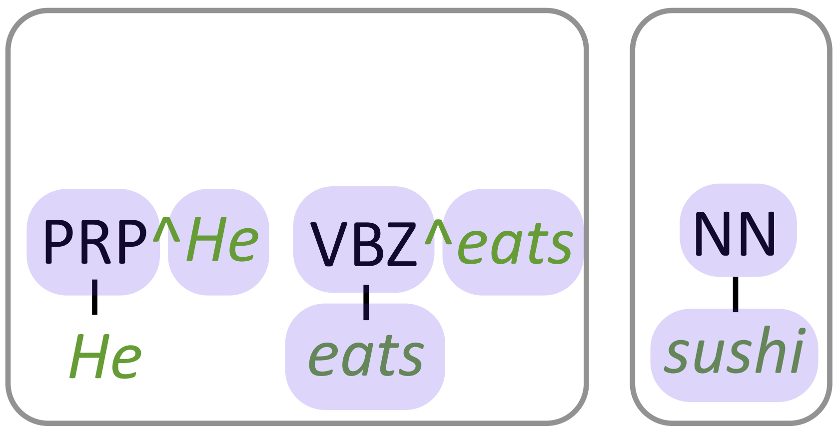

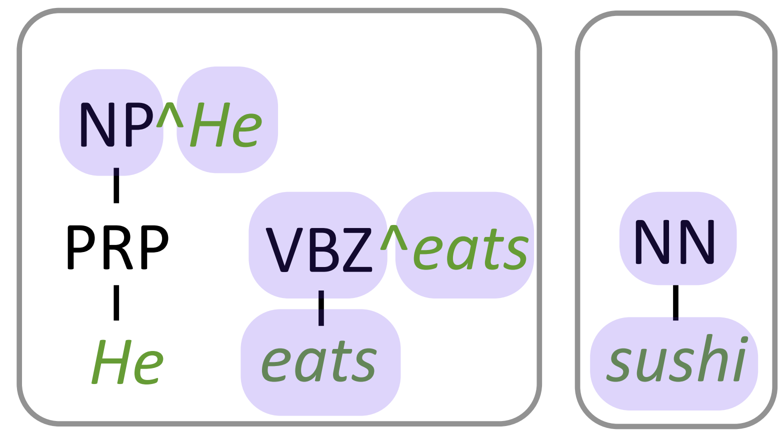

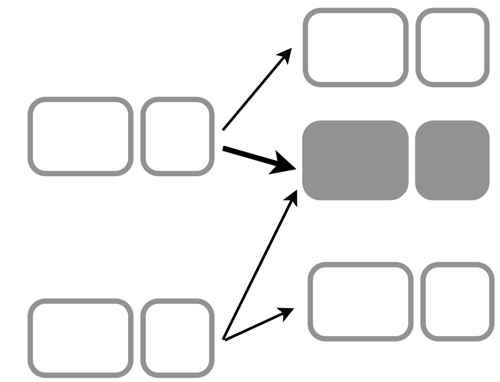

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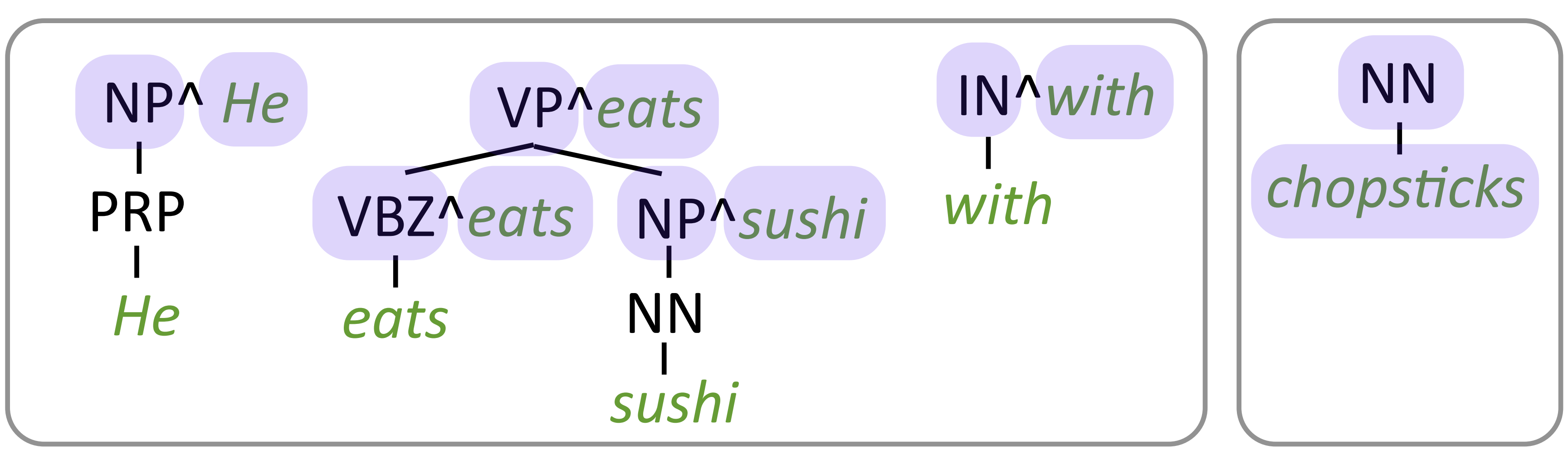

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- at least $O(n^{10})$?

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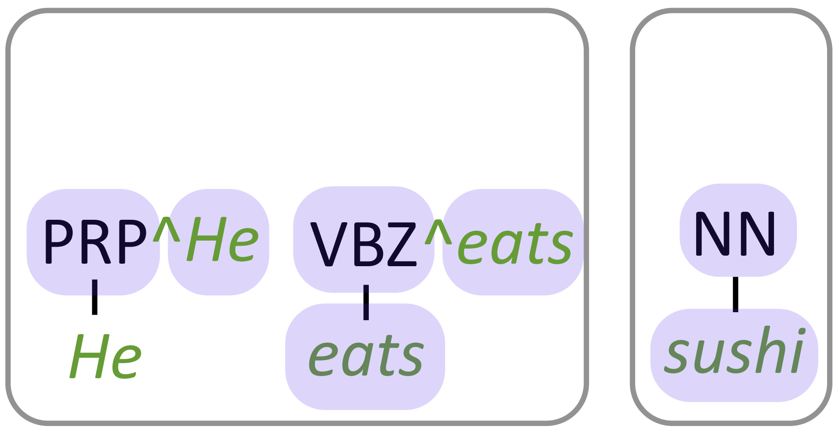

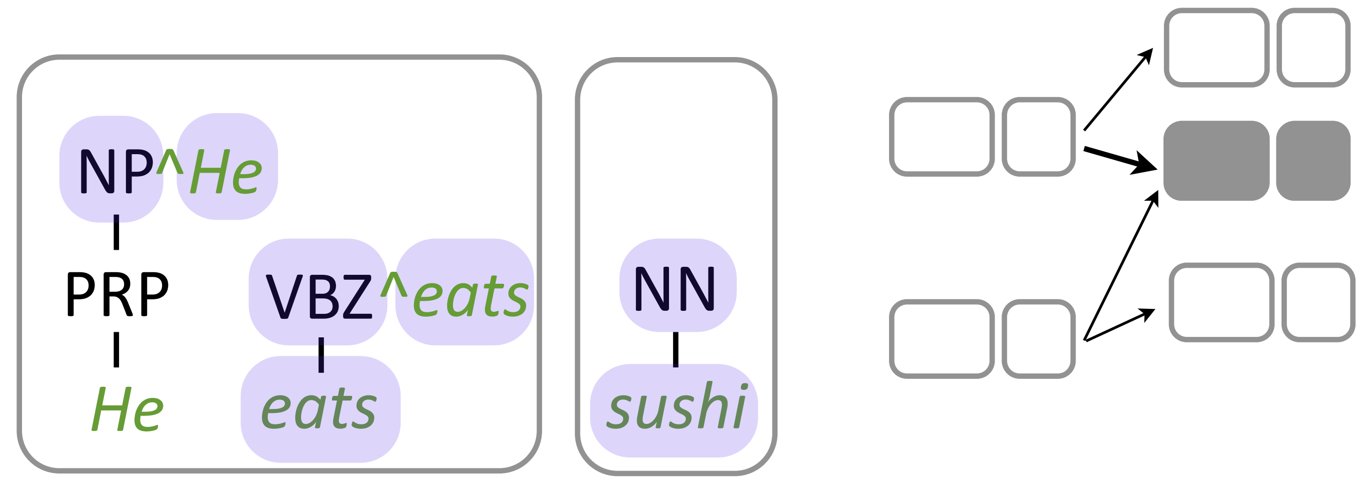

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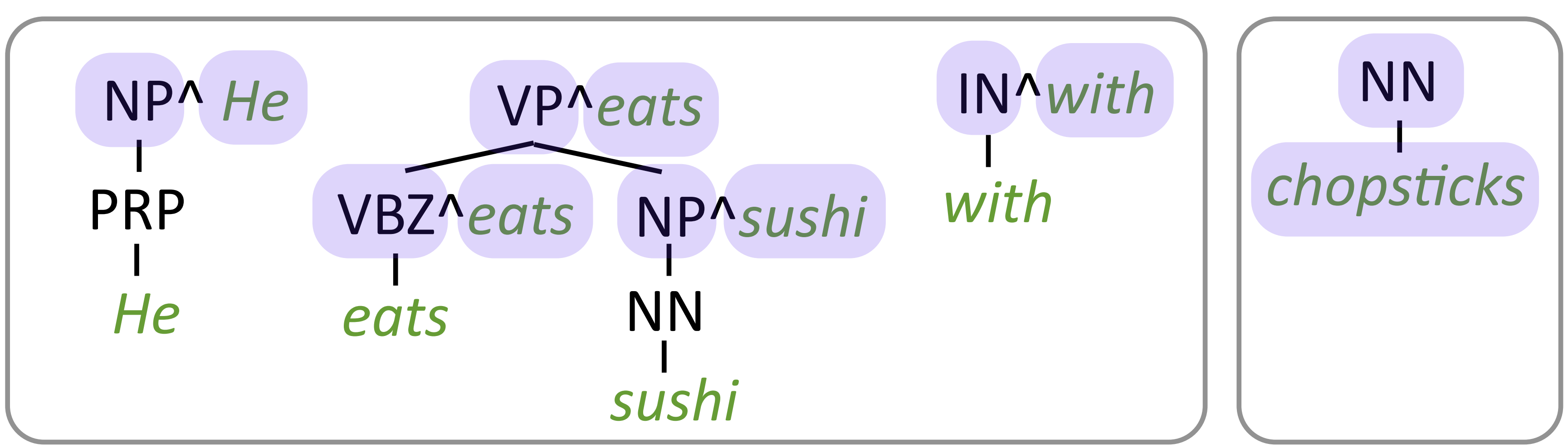

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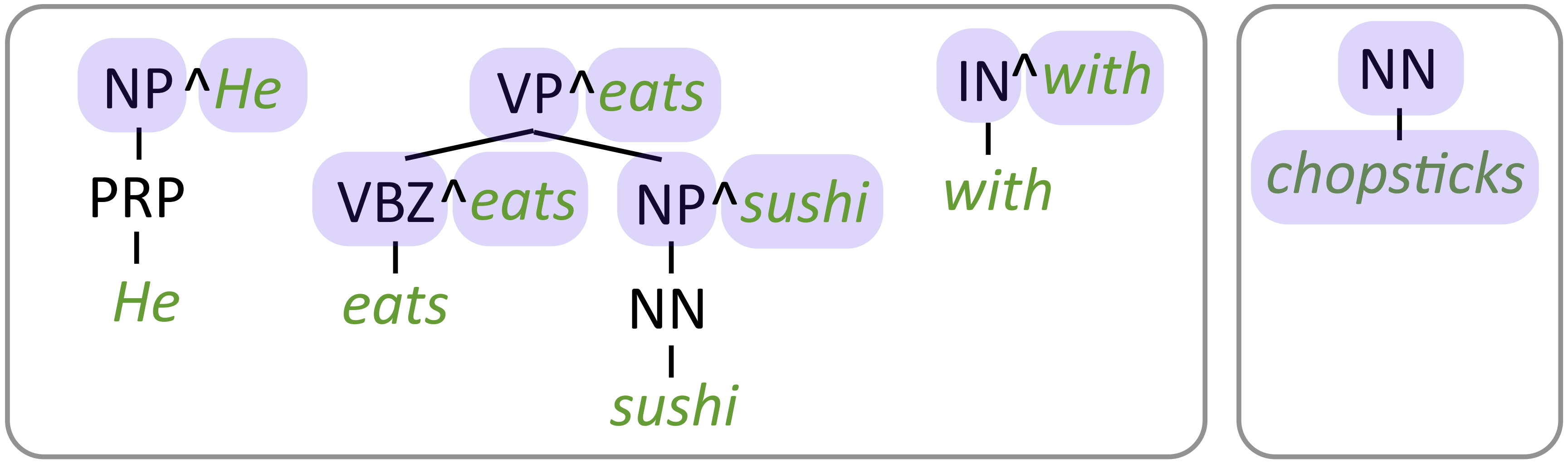
How to solve this?

Recipe 1: Utilizing cheap features



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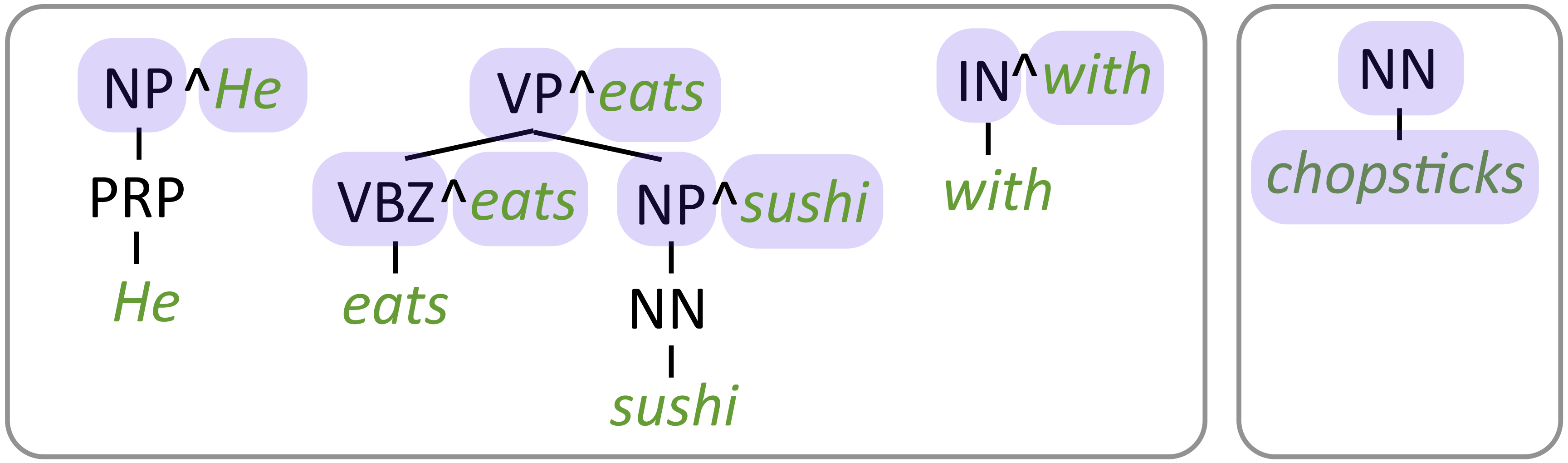

- Remembering head is expensive

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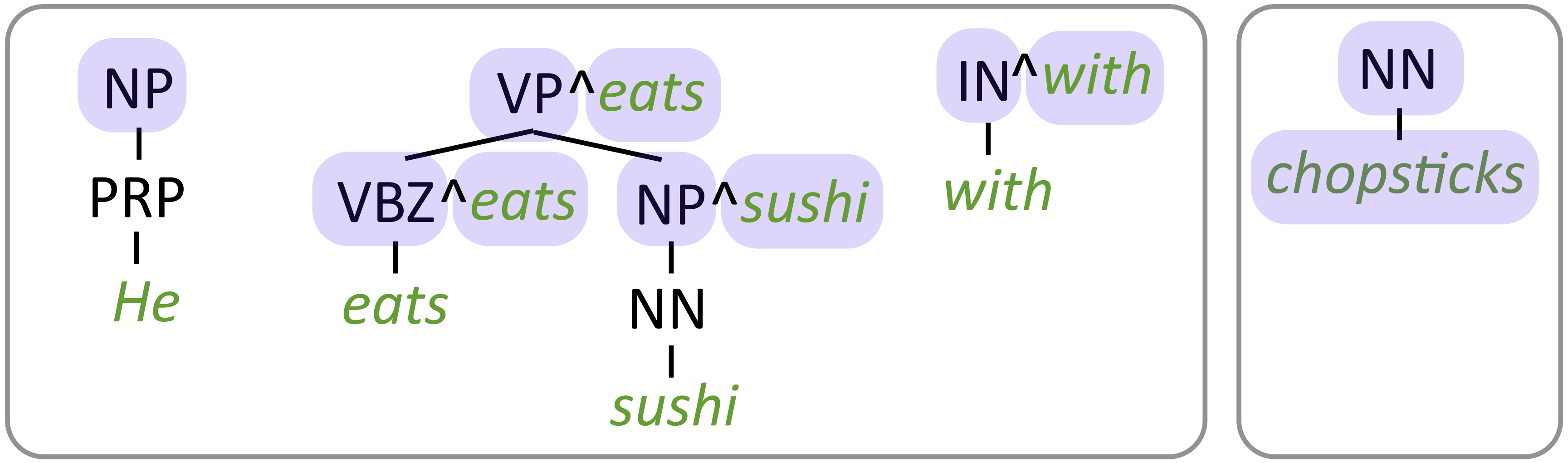

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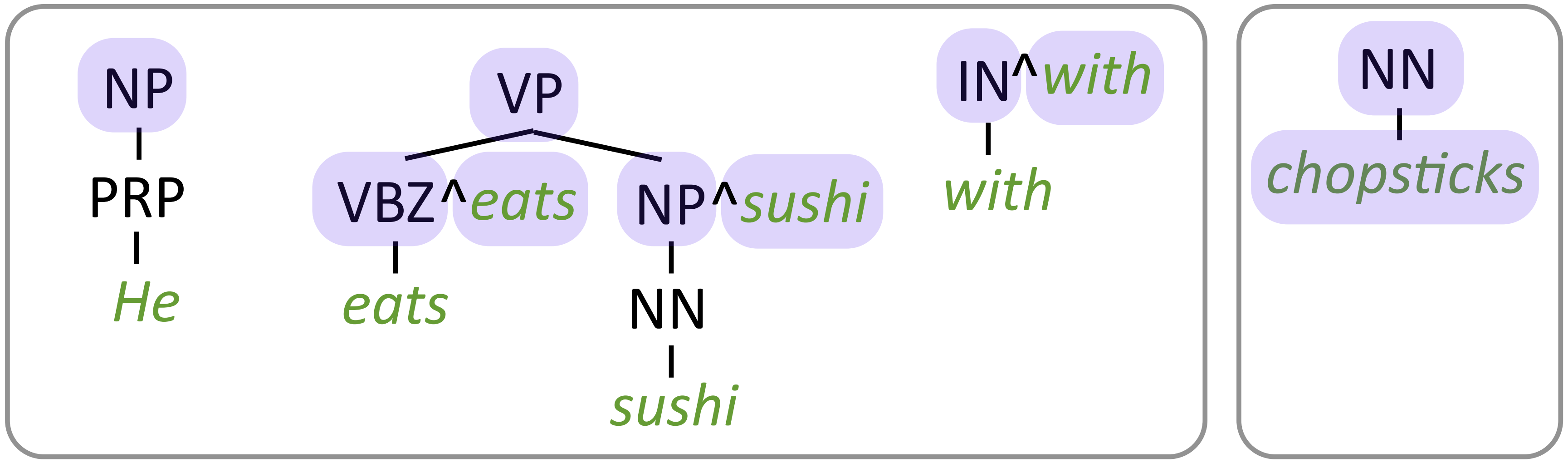

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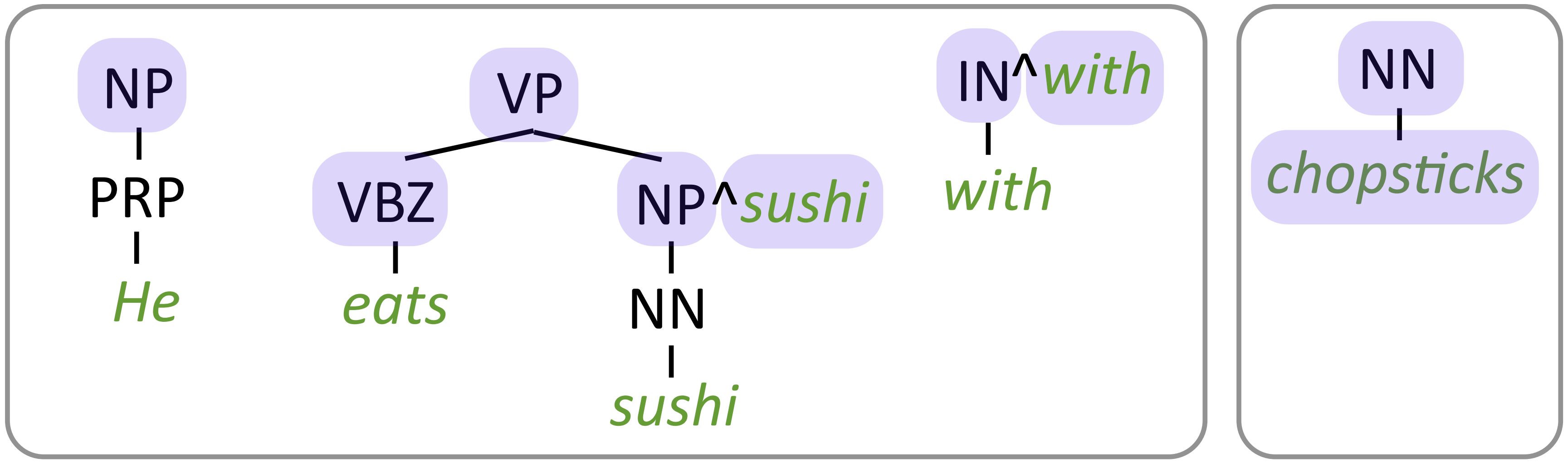

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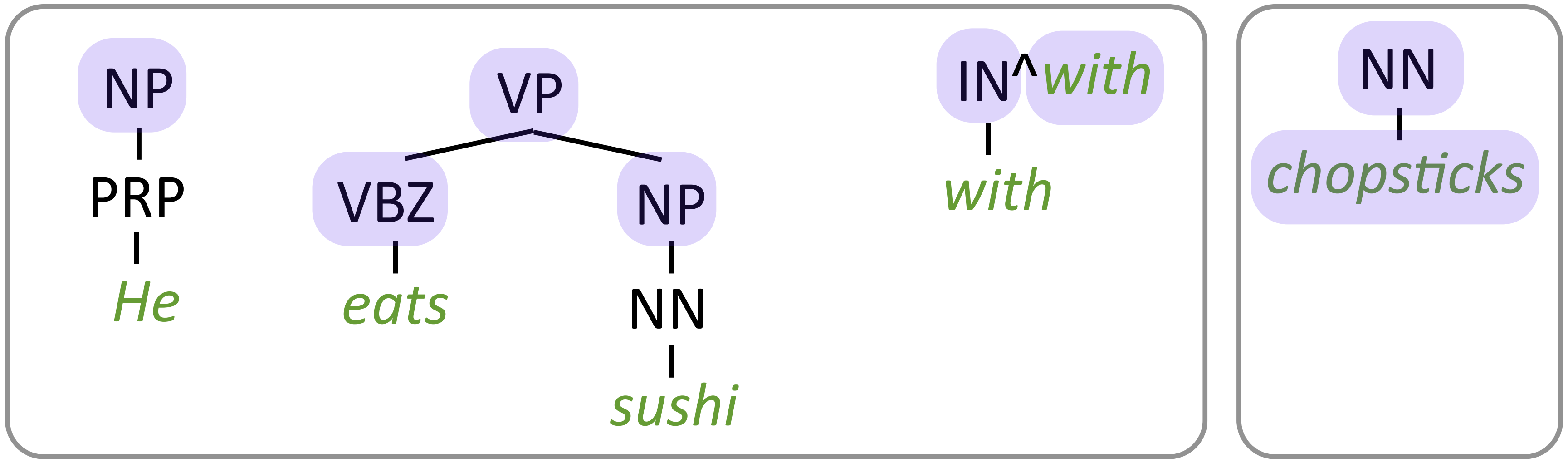

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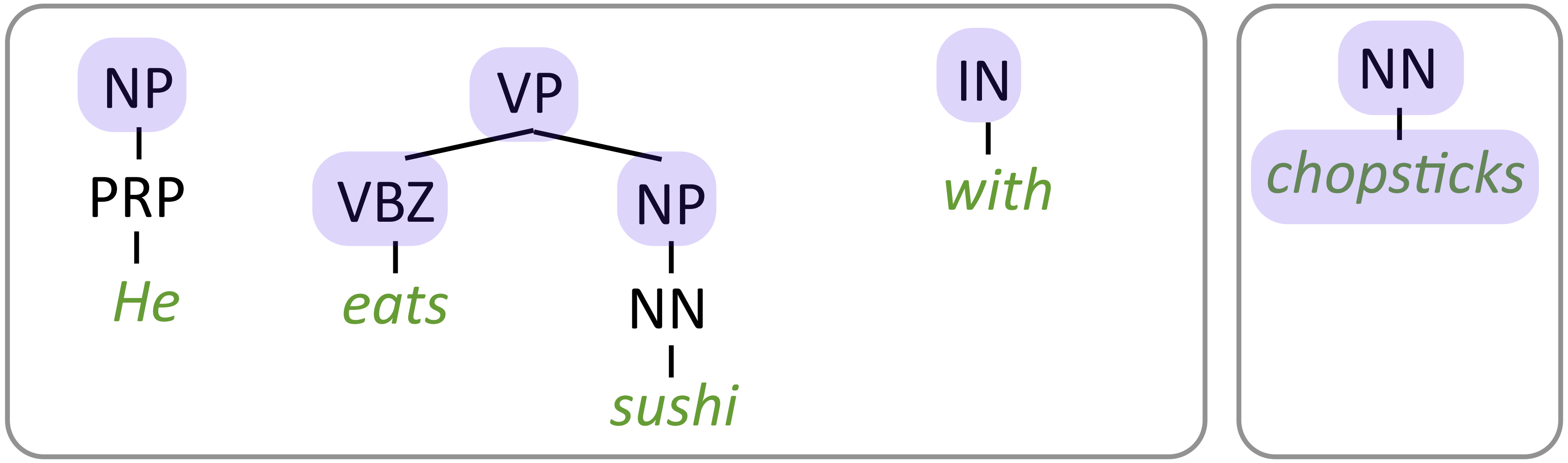

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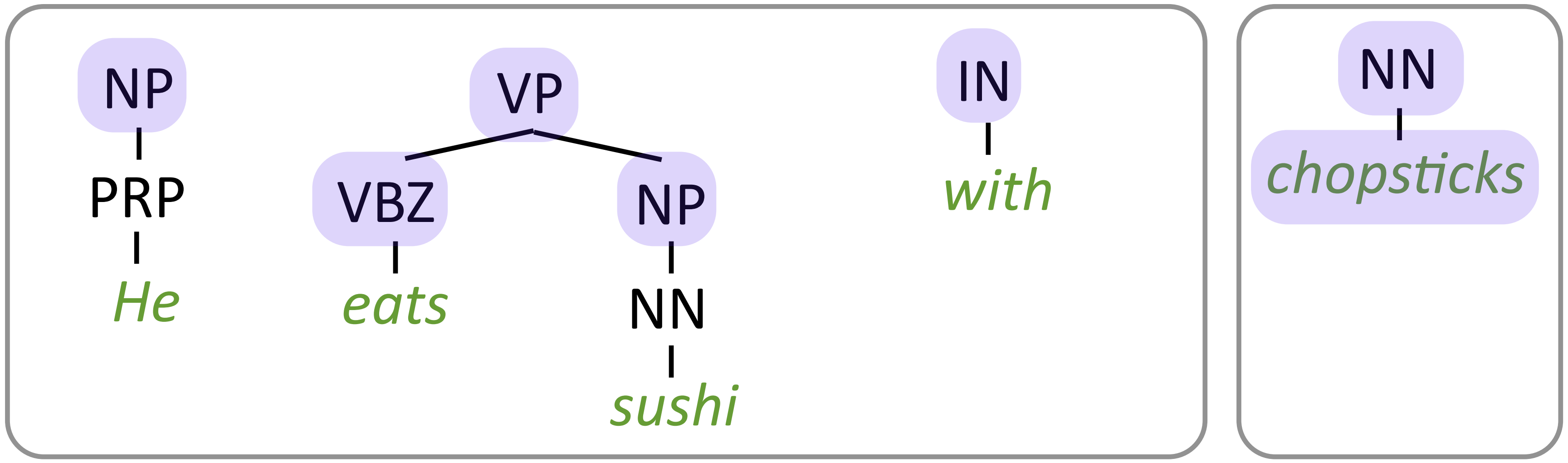

- Remembering head is expensive
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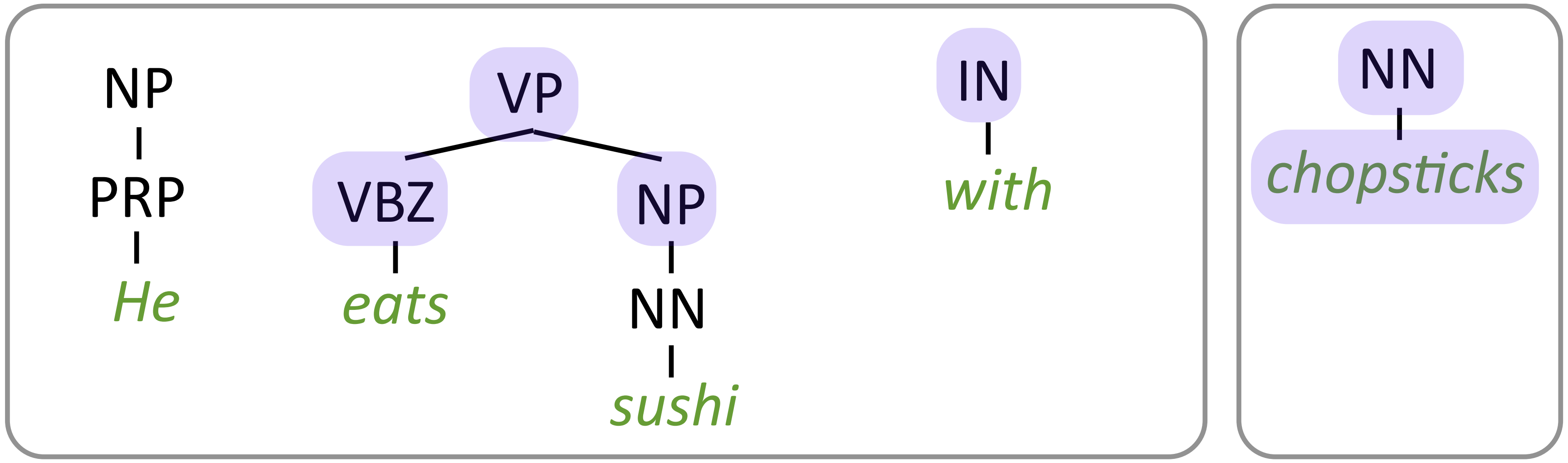

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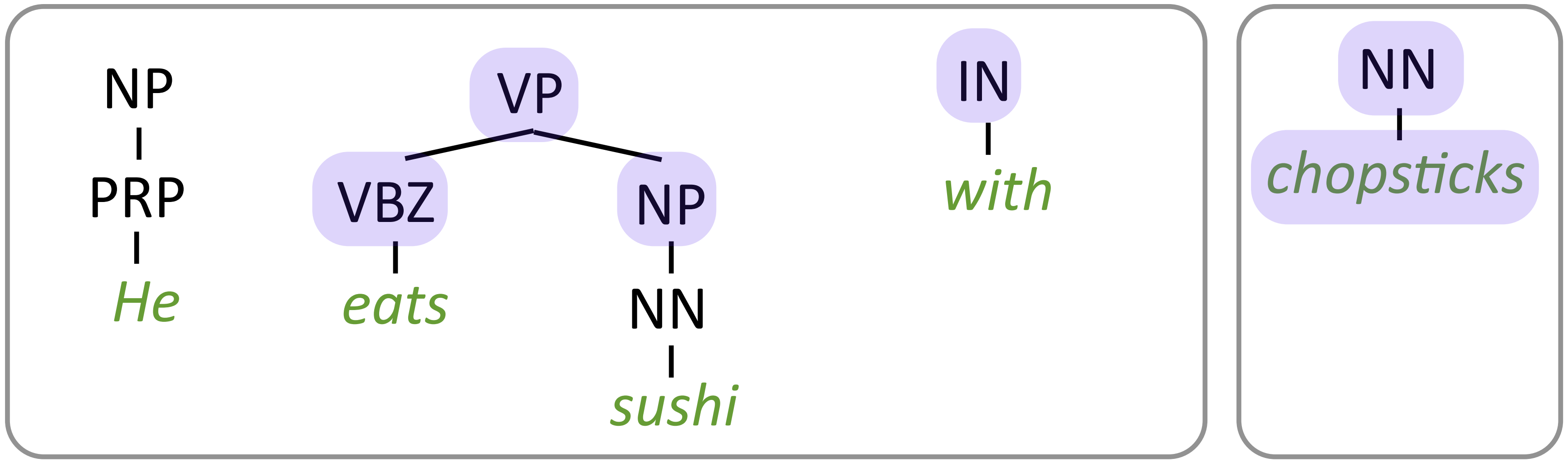

- Remembering head is expensive
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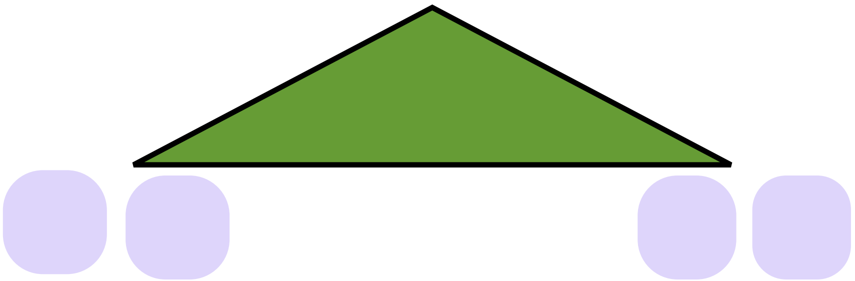
- The span around a subtree is cheap



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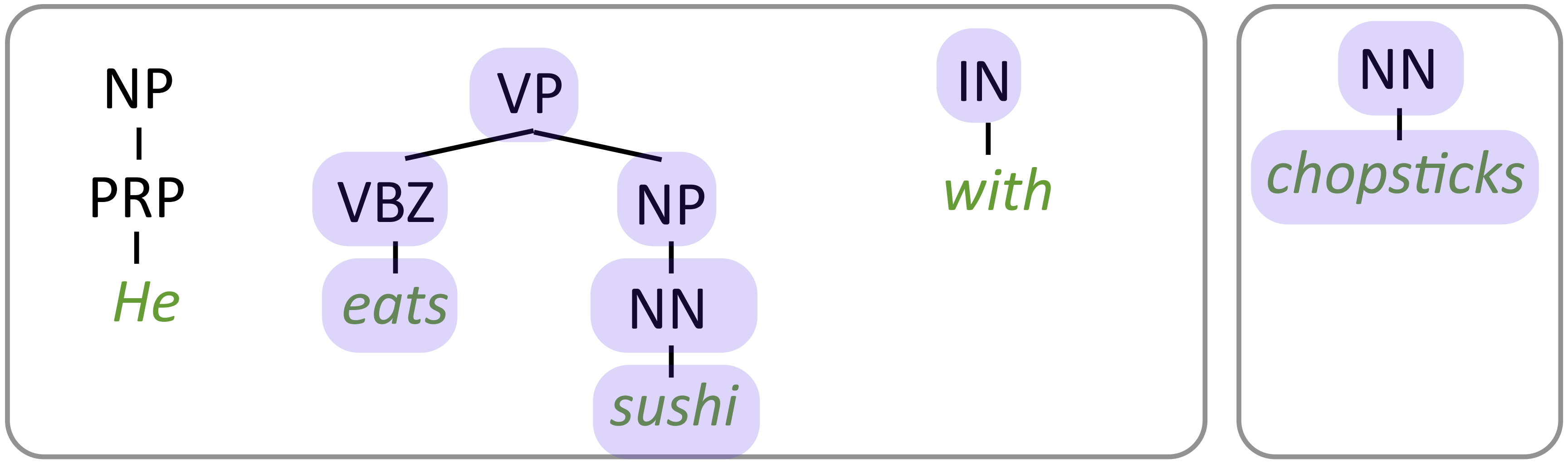

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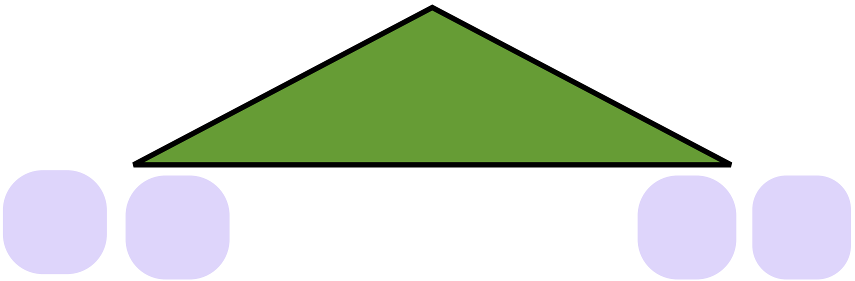

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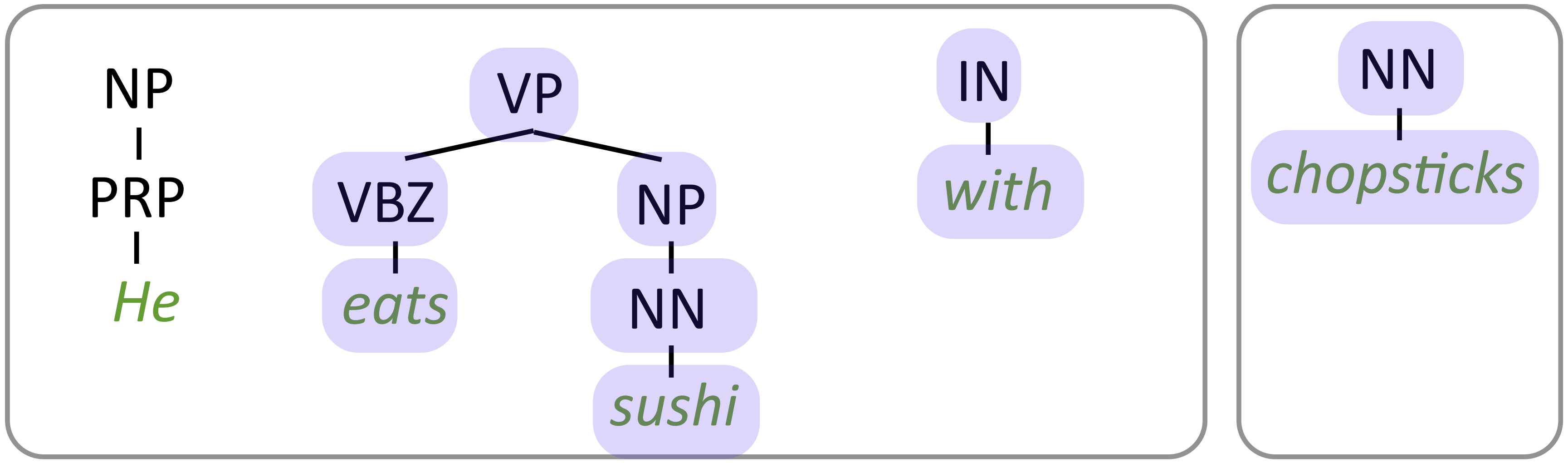

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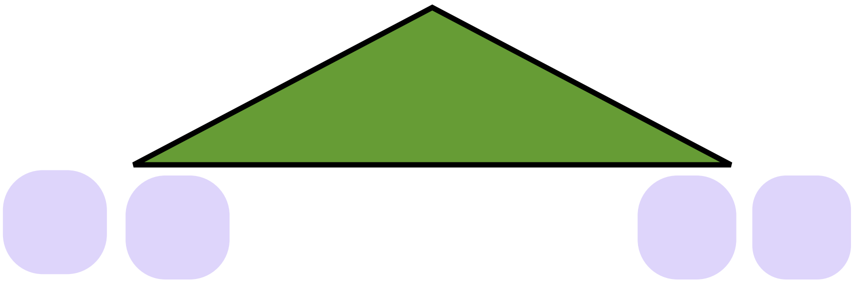

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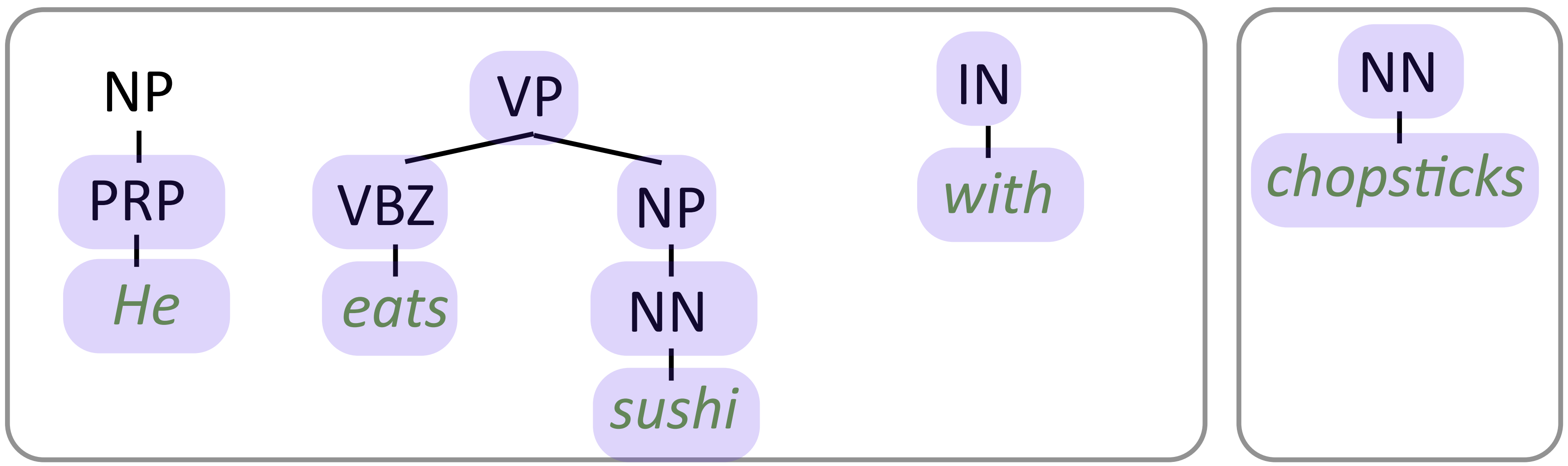

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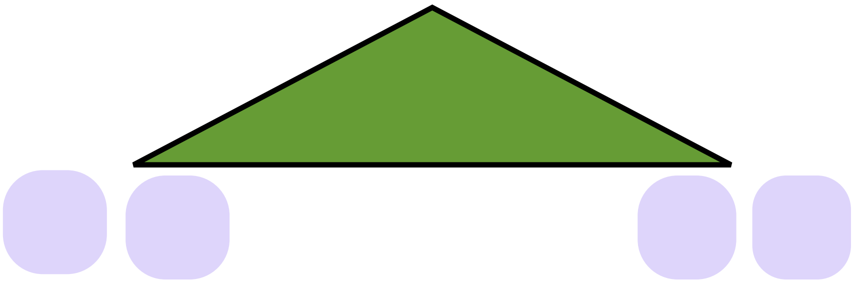

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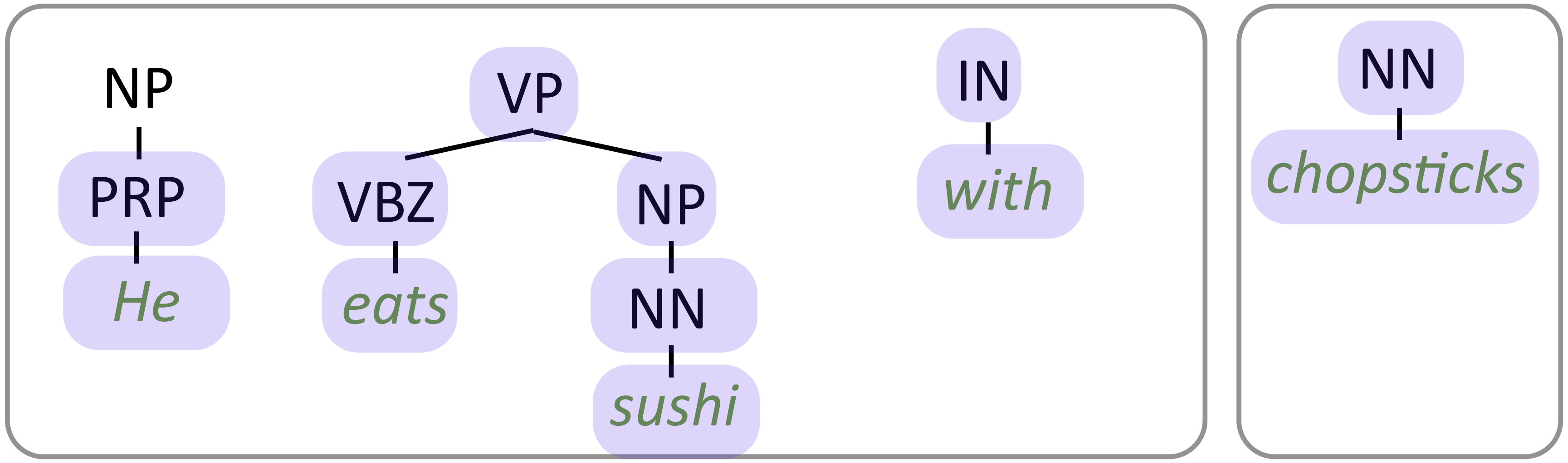

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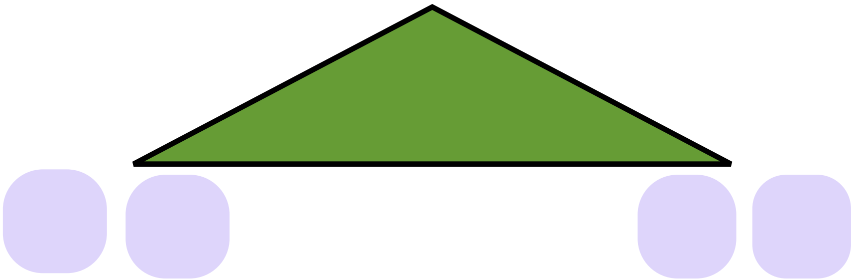

⇒ Inspired by the recent CRF parser with span features

[Hall et al., 2014]

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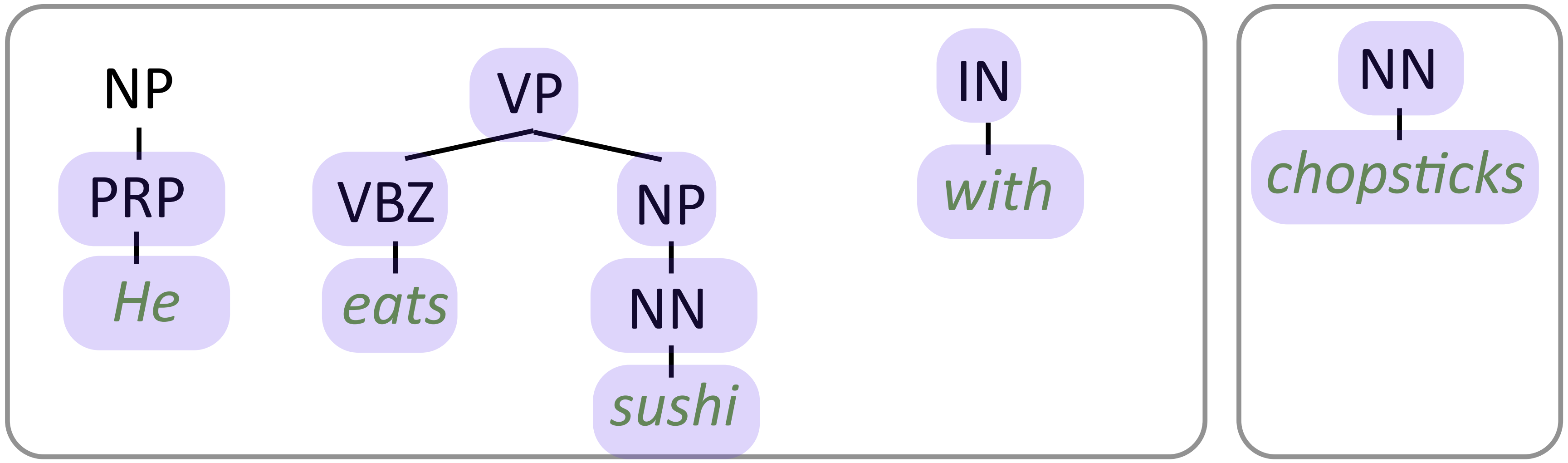

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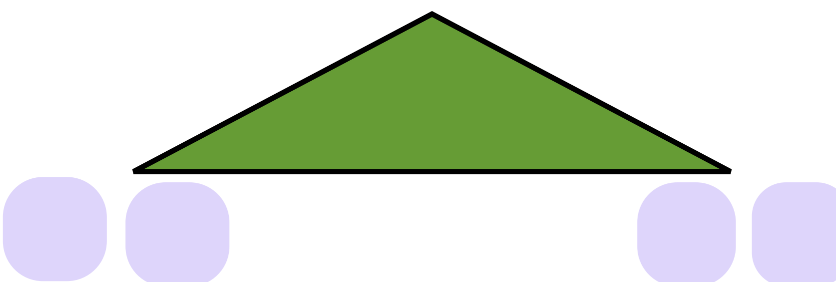

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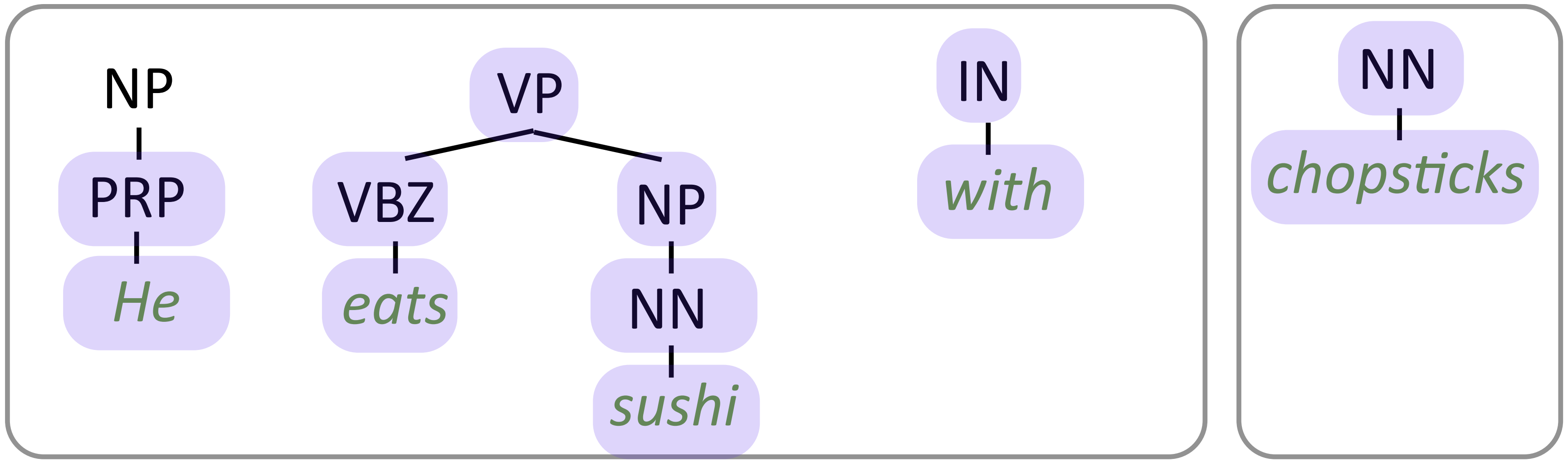

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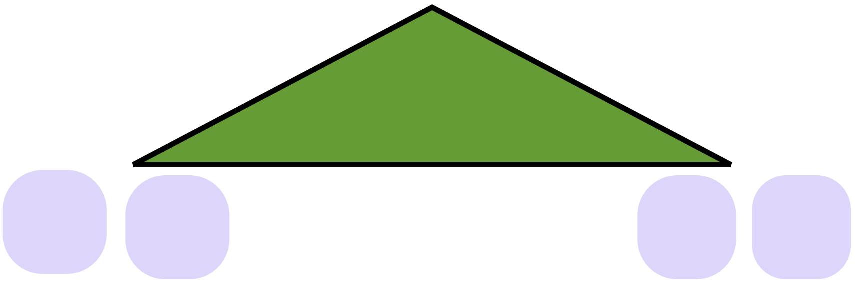

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  ⇒ Inspired by the recent CRF parser with span features

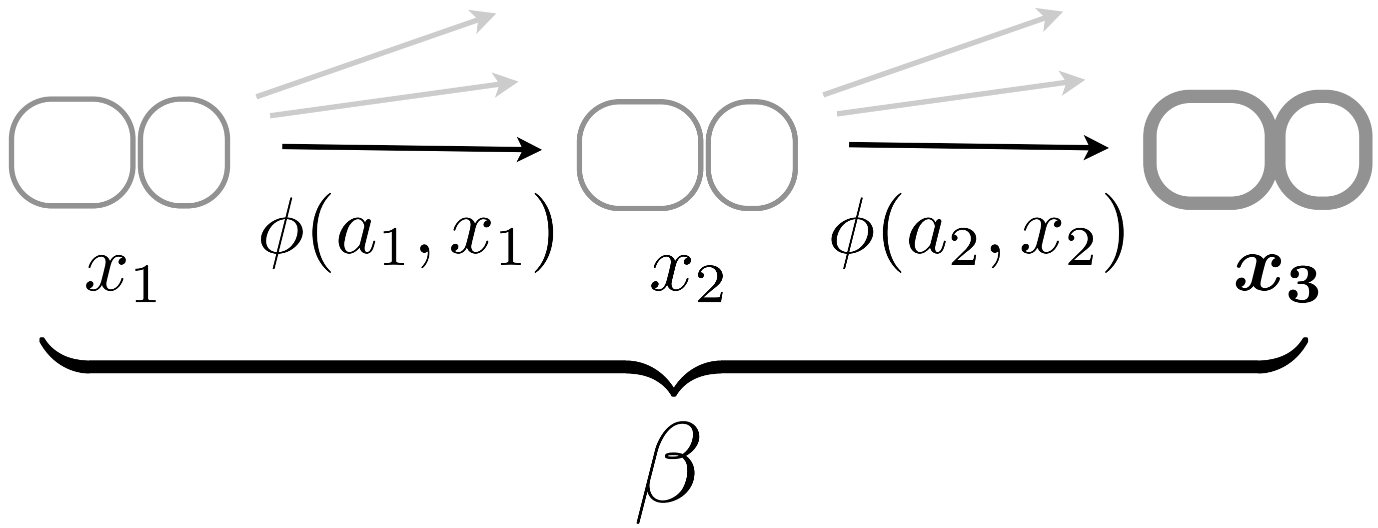
  [Hall et al., 2014]

- Worst time complexity: $O(n^4|G|^3|N|)$

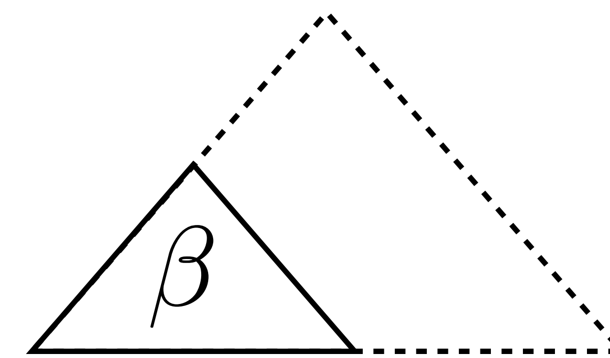
  ⇒ Improved but is still expensive...

Recipe 2: A* search

$\phi(a, x)$: edge cost



- Modify the state cost: β



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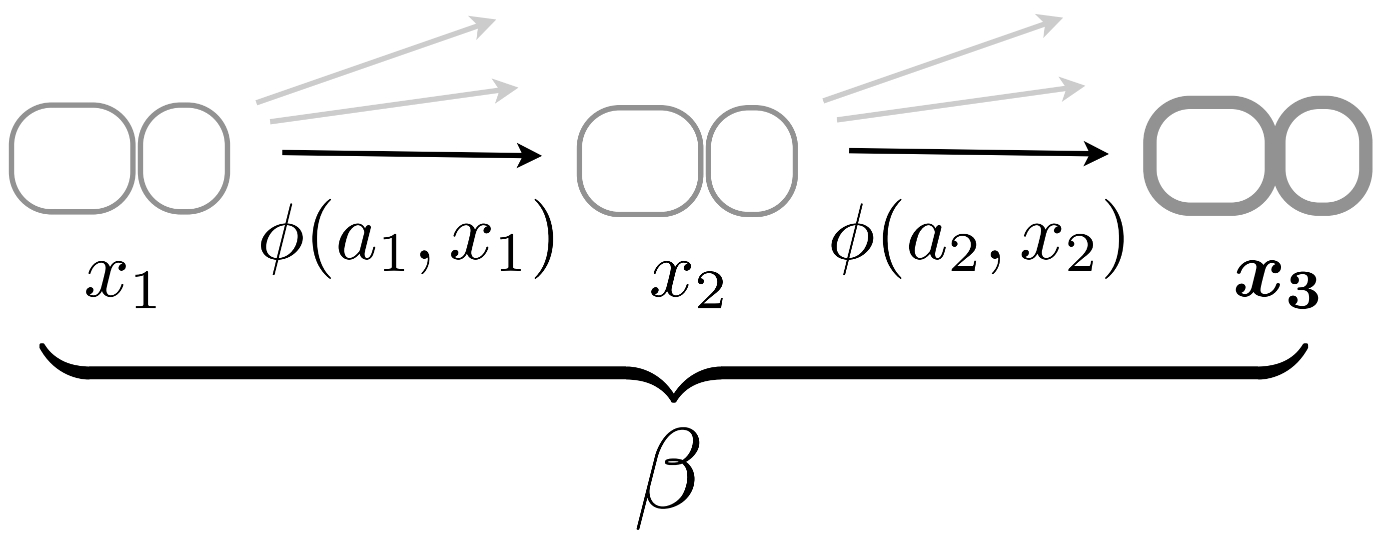

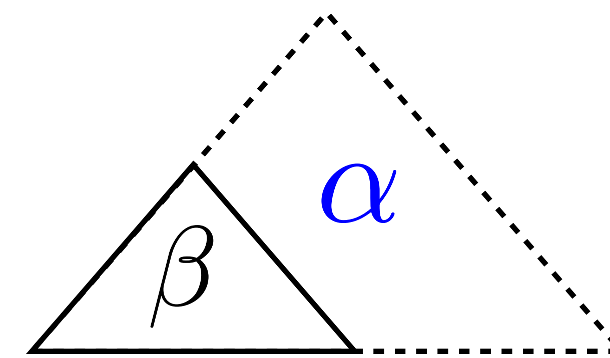

- Modify the state cost: $\beta + \alpha$
- α: approximation of the cost outside the current parse

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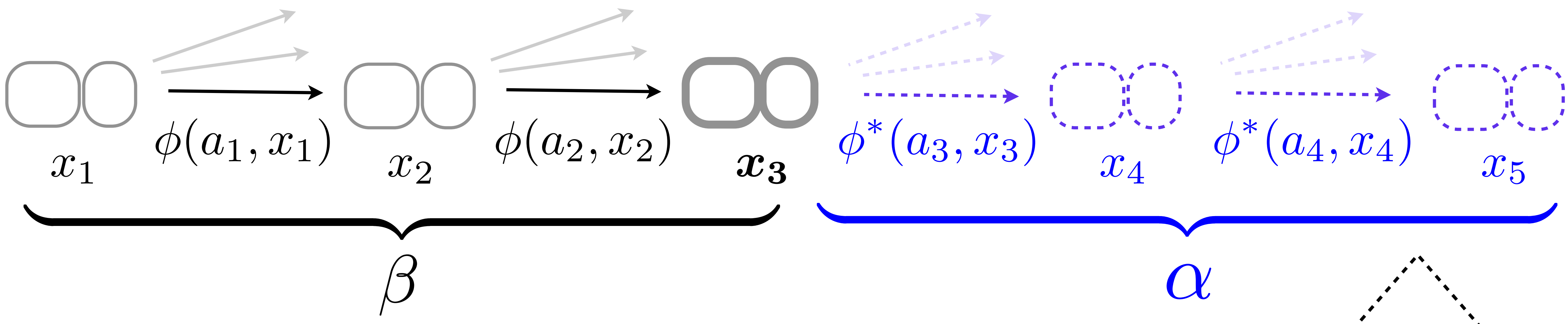

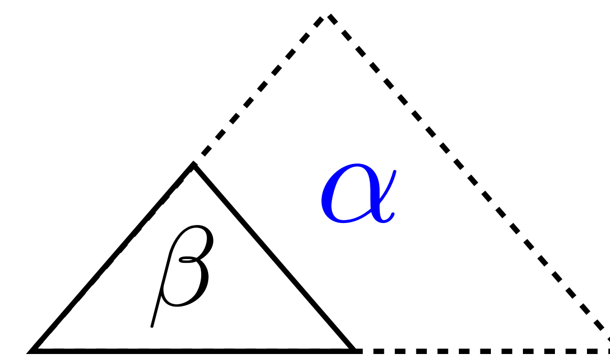

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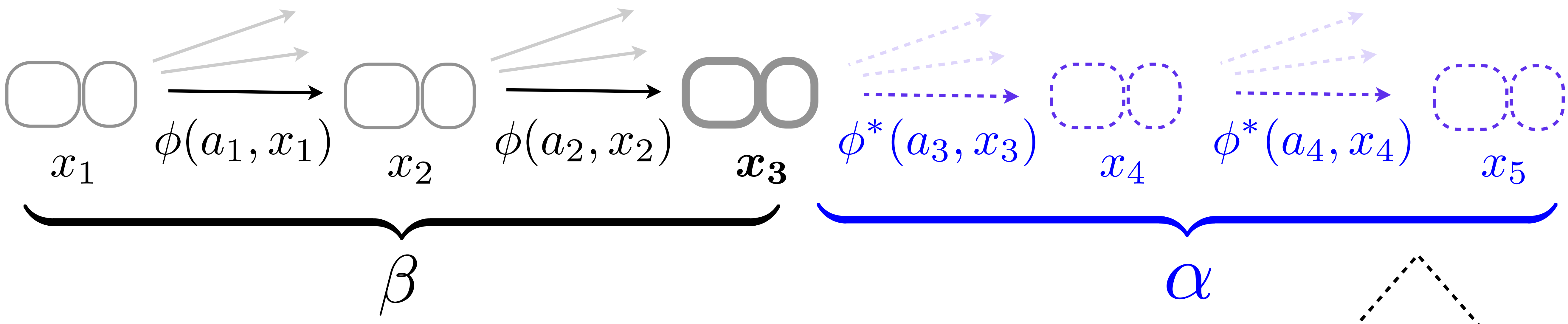

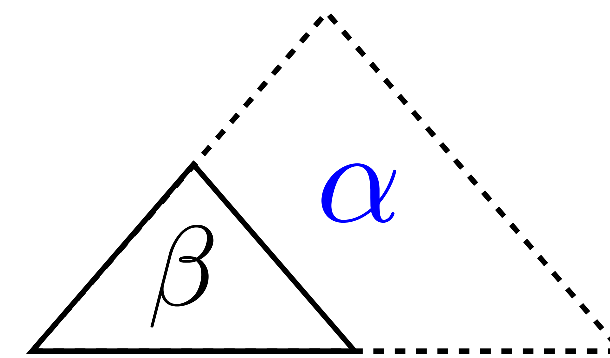

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  - $\Rightarrow$ If approximation is good, search is accelerated

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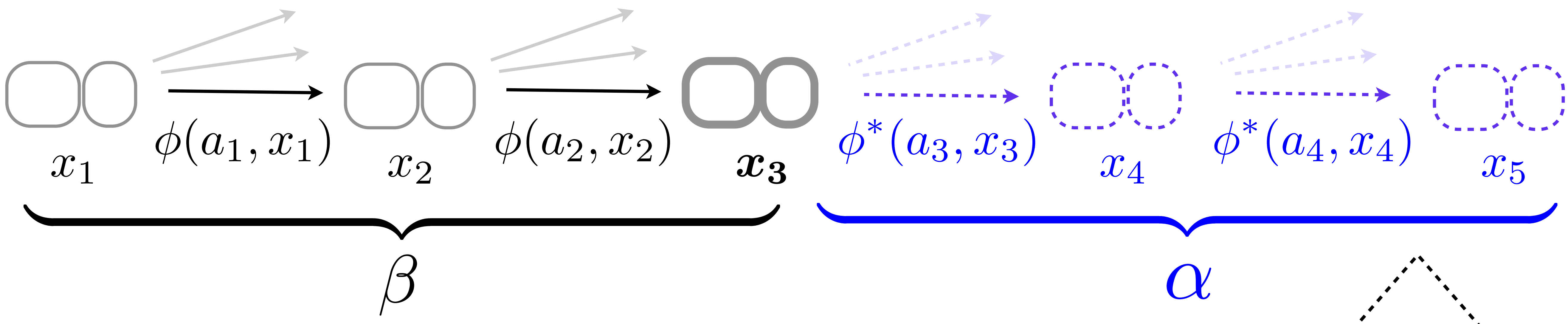
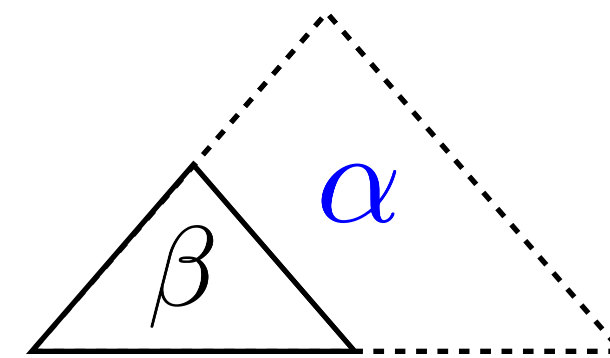




- Modify the state cost: $\beta + \alpha$
- α: approximation of the cost outside the current parse

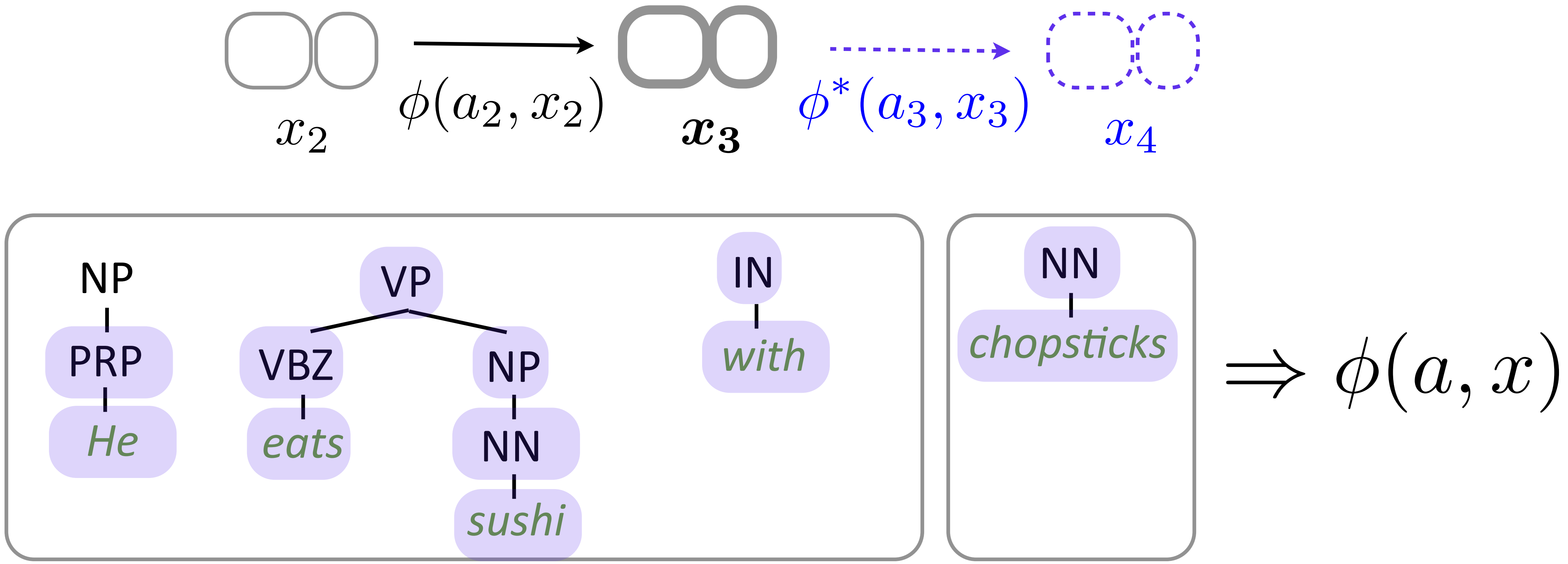
  ⇒ If approximation is good, search is accelerated

Constraint for optimality:

α must be a lower bound of actual outside cost

$$\phi(a, x) \geq \phi^*(a, x)$$

Idea: Parsing with simpler features



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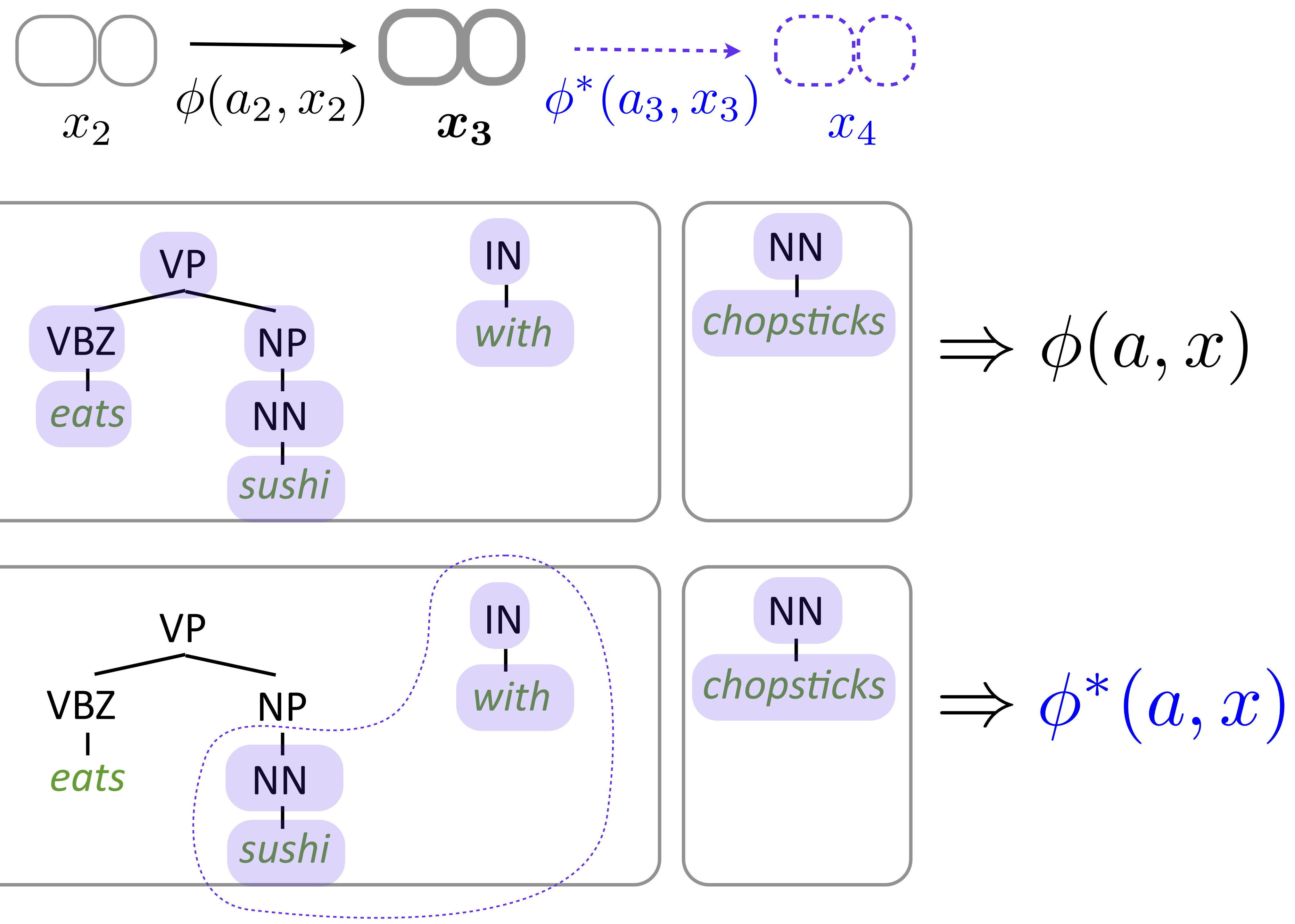

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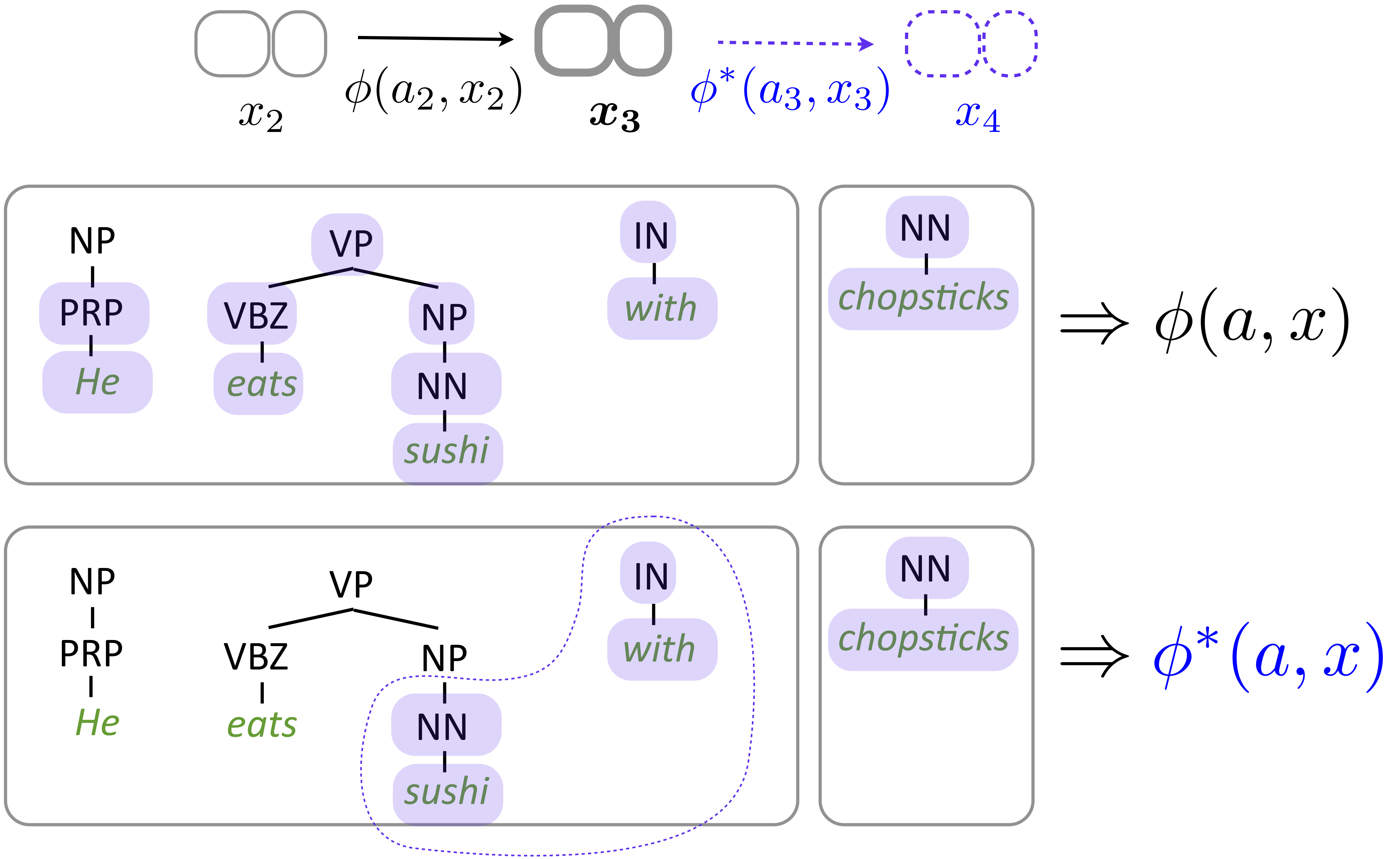

- Time complexity to calculate heuristic cost: $O(n^3|G|)$

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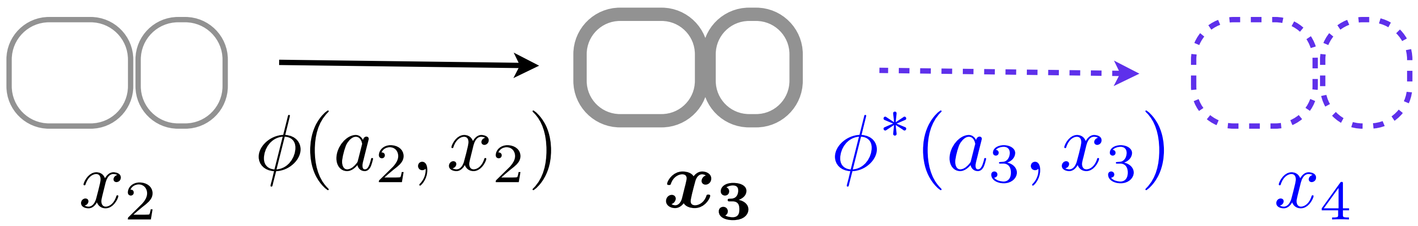
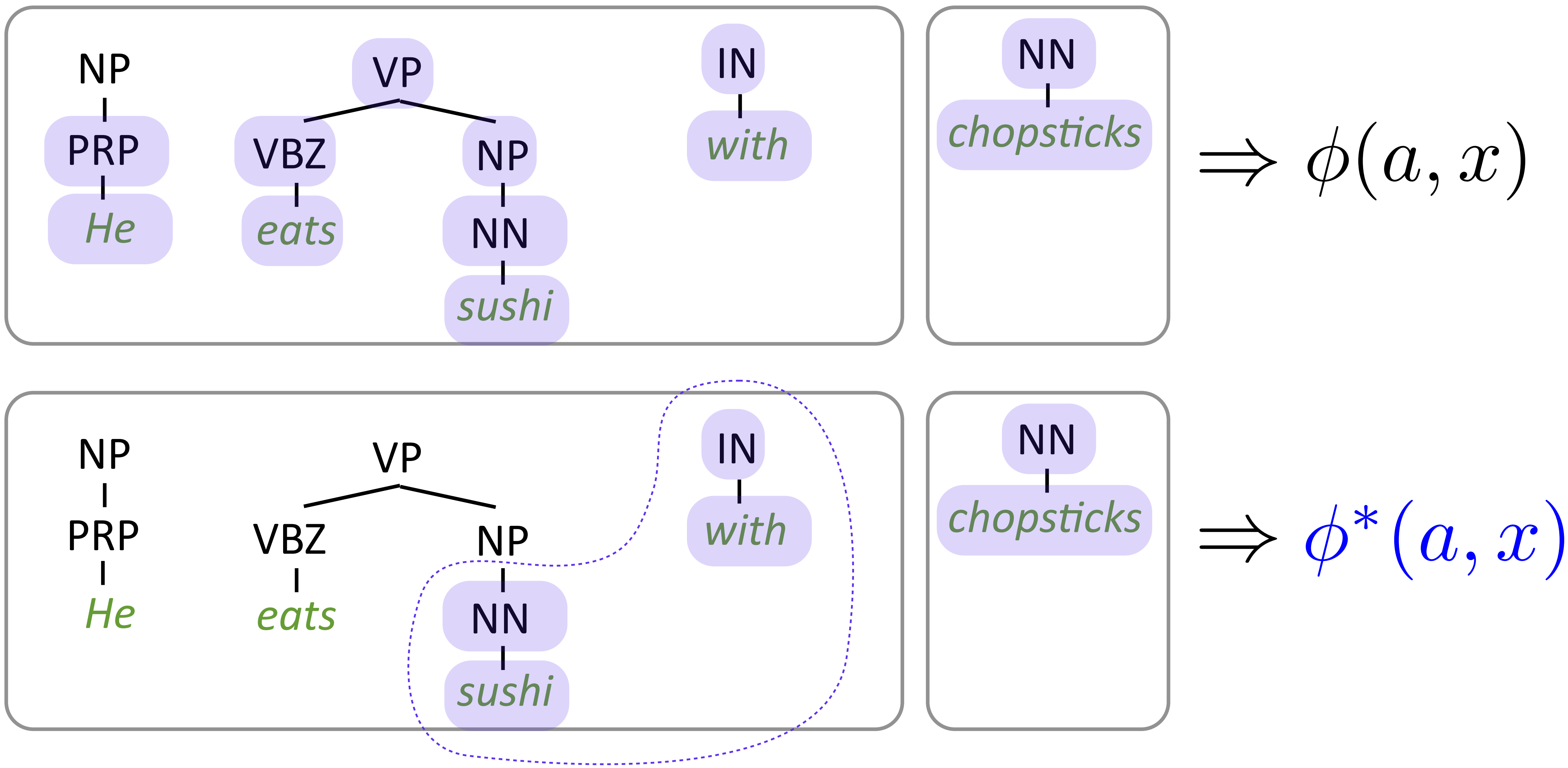
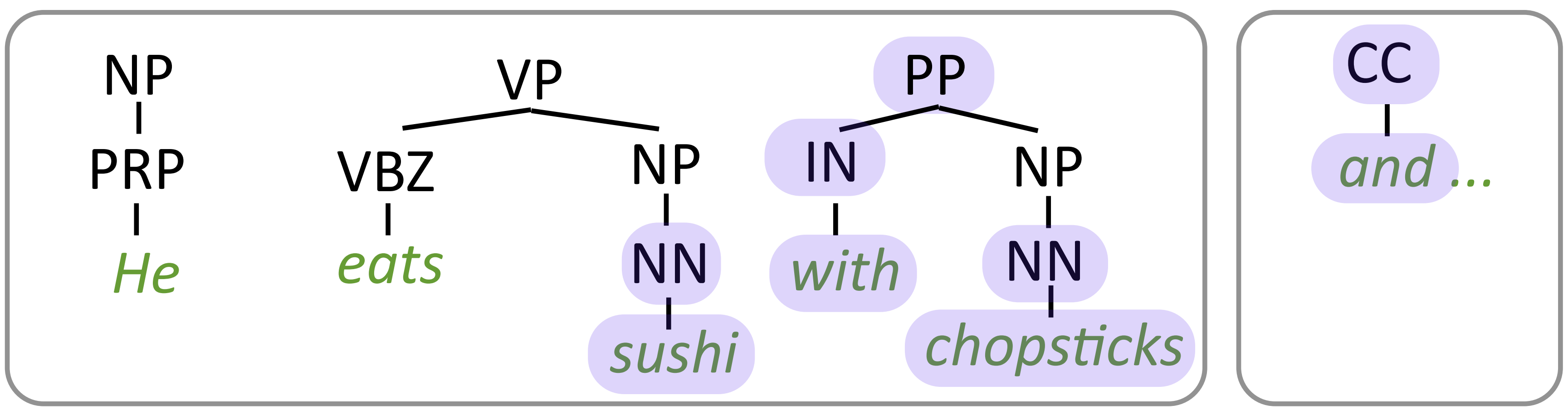




- Time complexity to calculate heuristic cost: $O(n^3|G|)$
- We can calculate $\phi^*(a|x)$ to always underestimate the true cost

Applying hierarchical A*

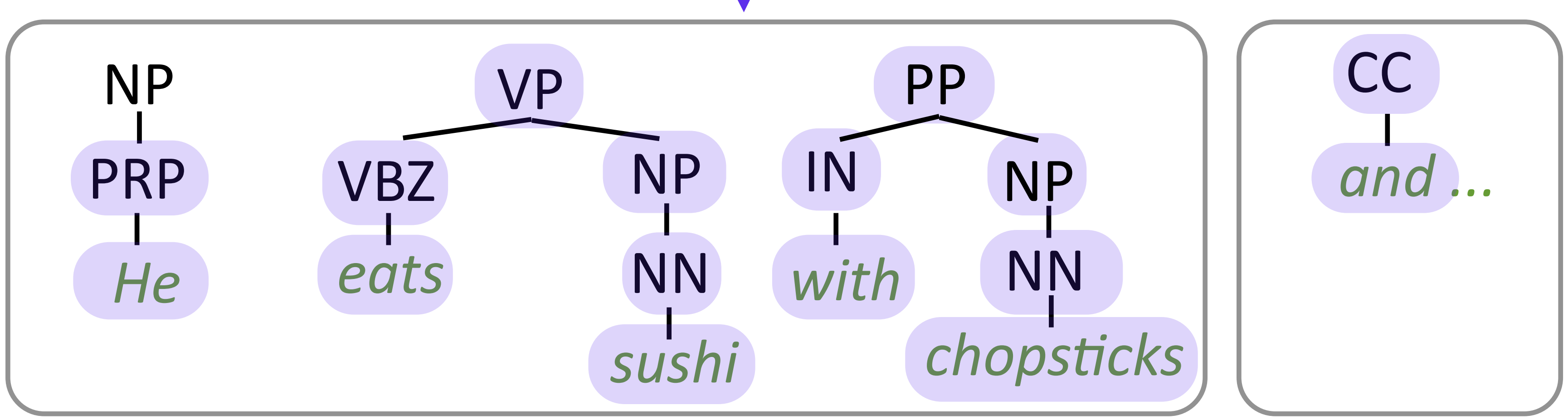
[Pauls & Klein, 2009]



$O(n^3|G|)$

still a bit expensive

Simplify features



$O(n^4|G|^3|N|)$

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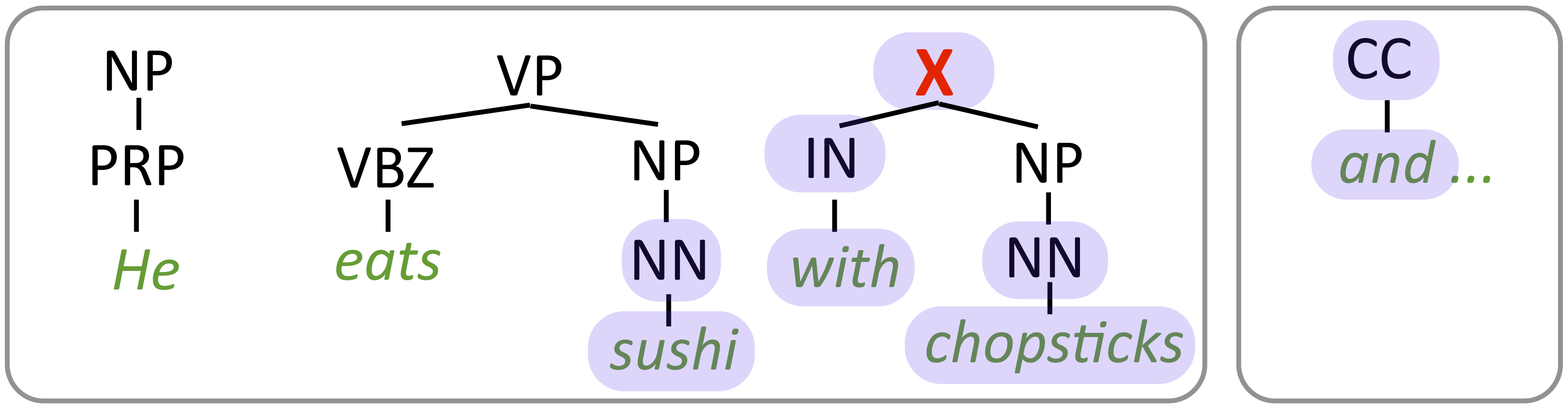
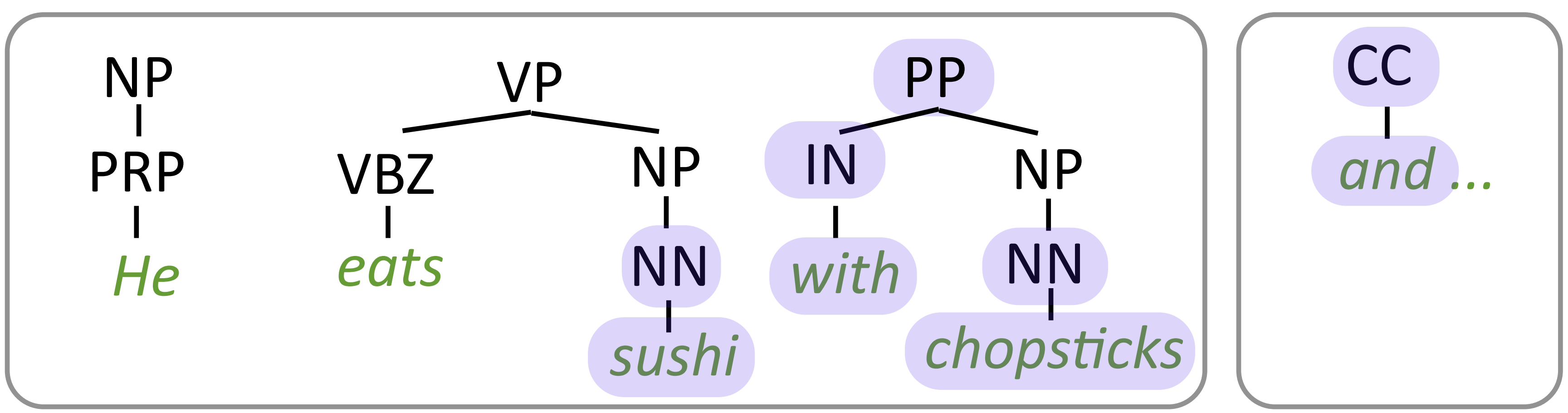


$O(n^3)$

Simplify grammar [Klein & Manning, 2003]



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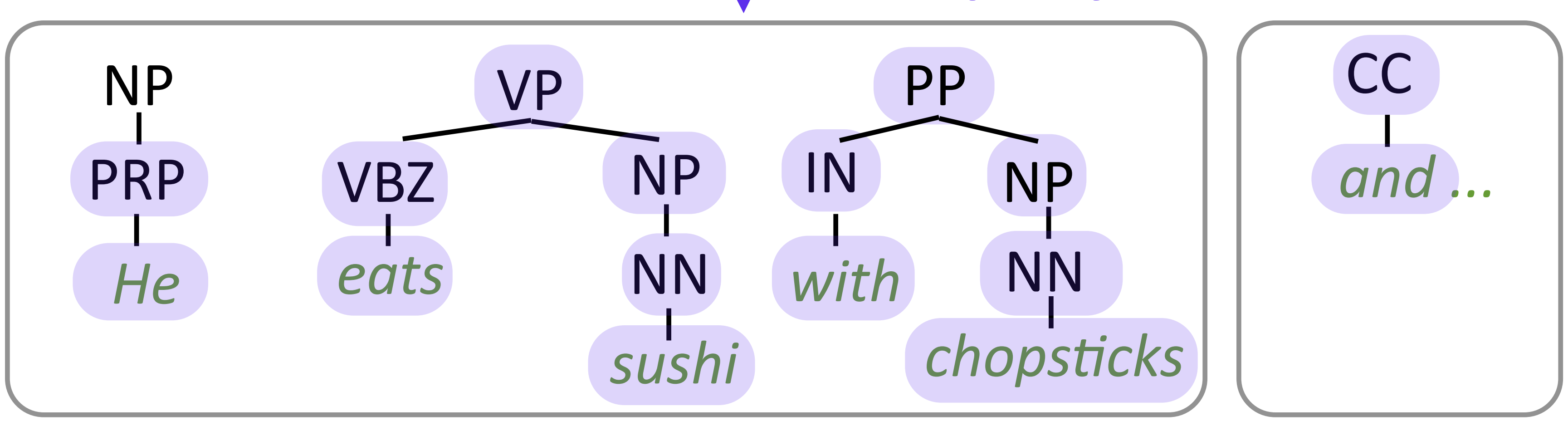


$O(n^4|G|^3|N|)$

Outline

DP best-first shift-reduce parsing

- for **constituency**
- with **structured perceptron**

MaxEnt vs. Structured perceptron

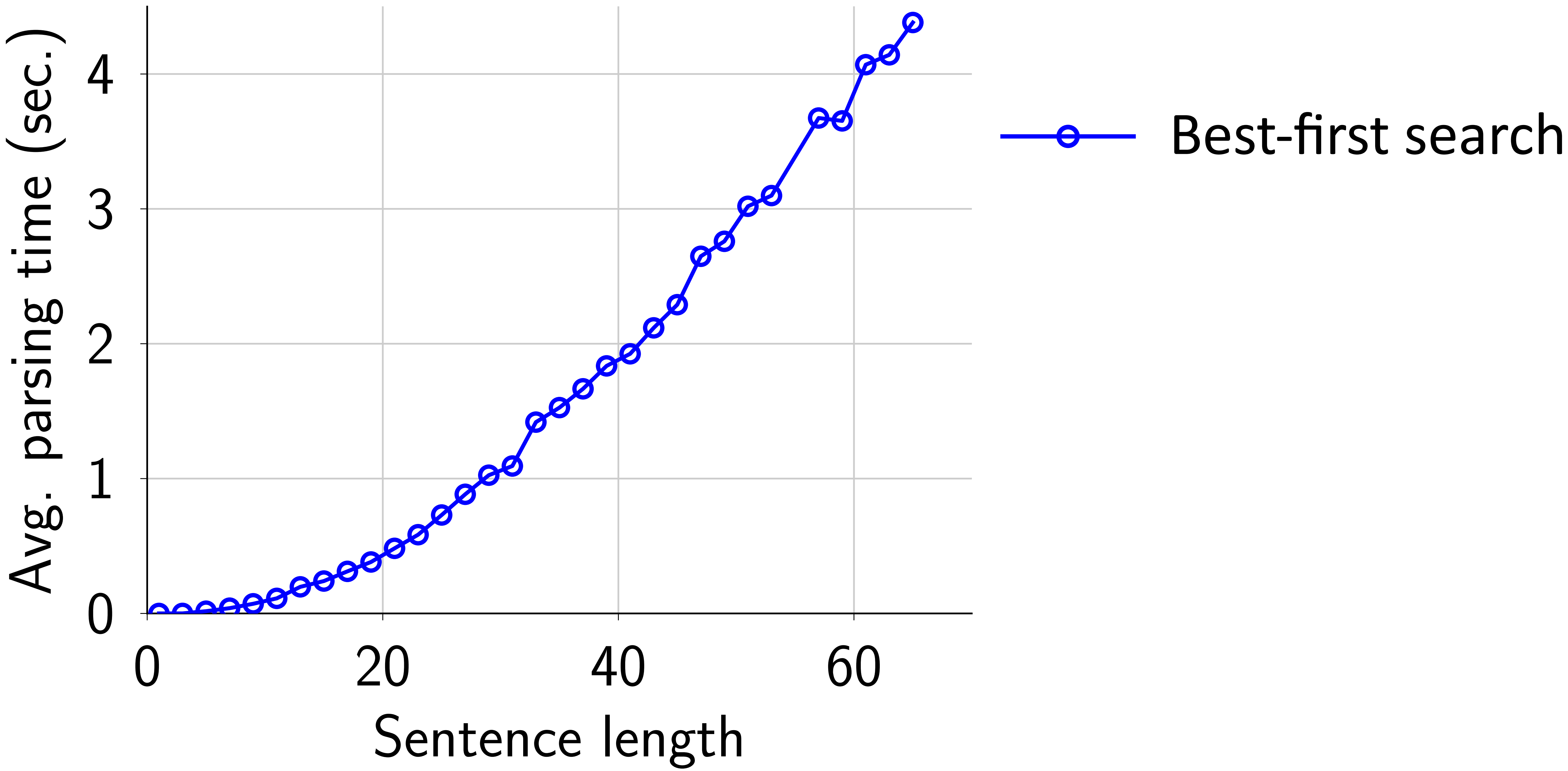
- Structured perceptron is strong
- but its search is much harder

Improving search efficiency of structured perceptron

- New feature templates
- A* search

Final experiment

Hierarchical A* works quite well



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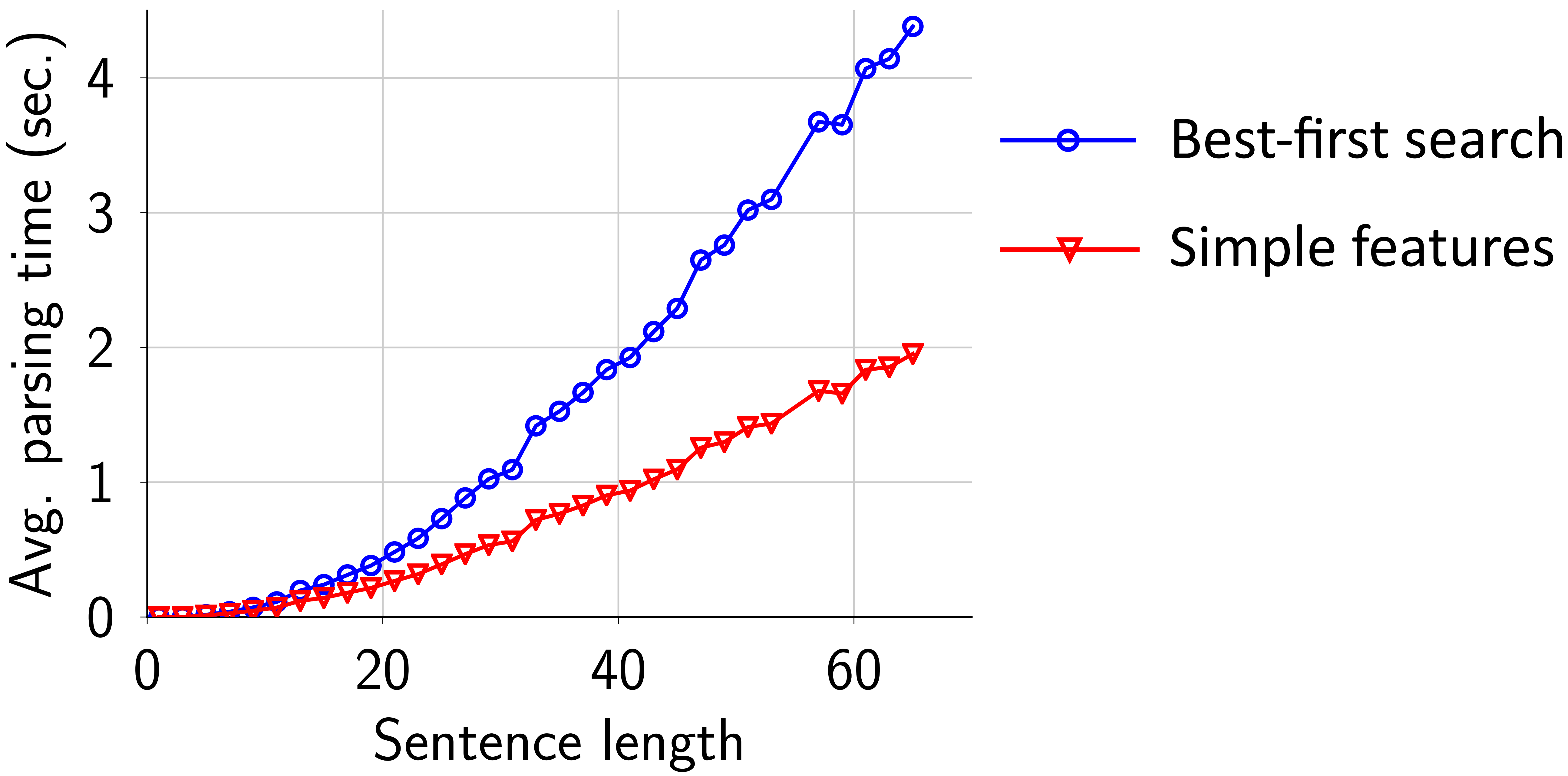

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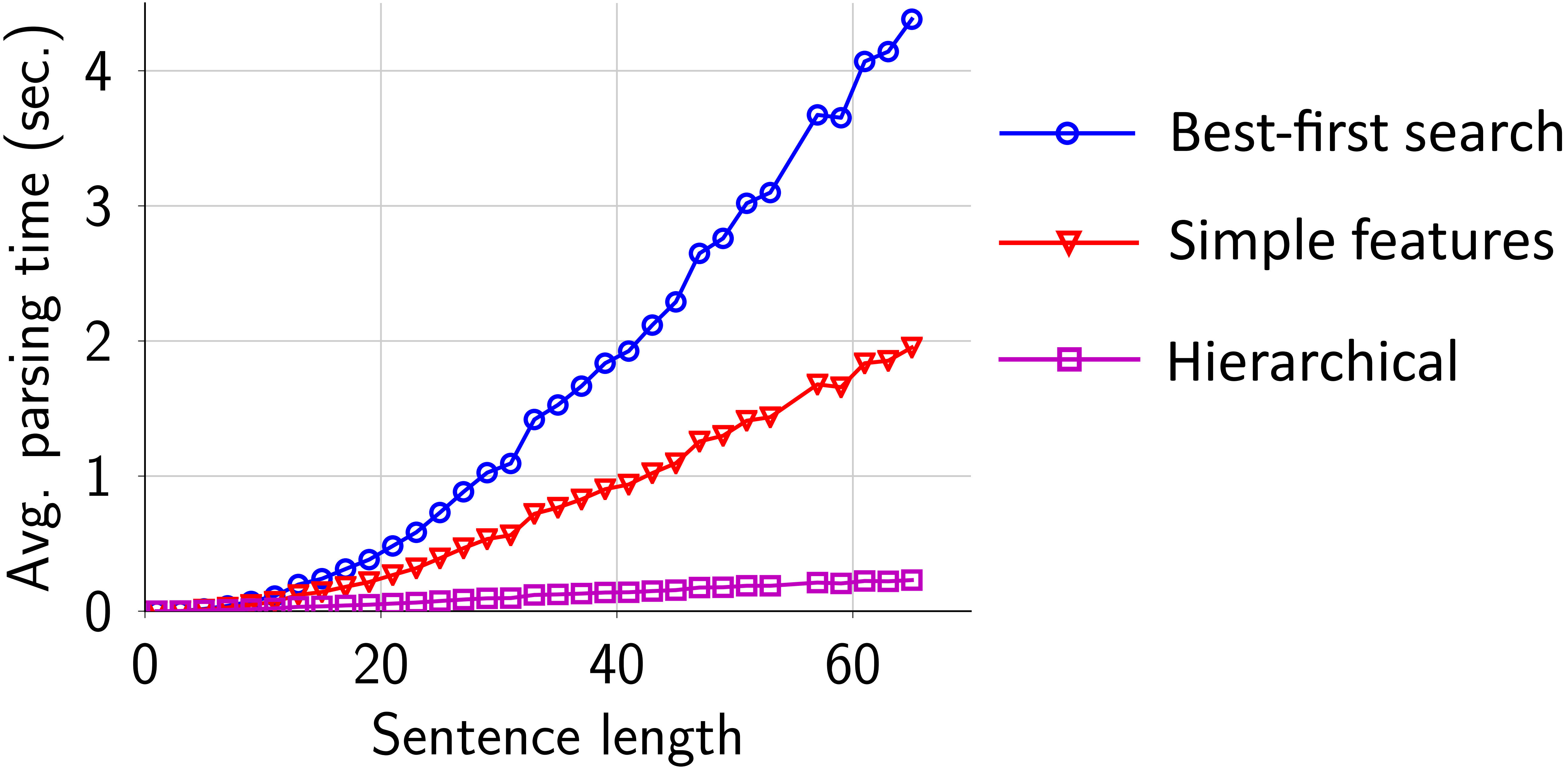


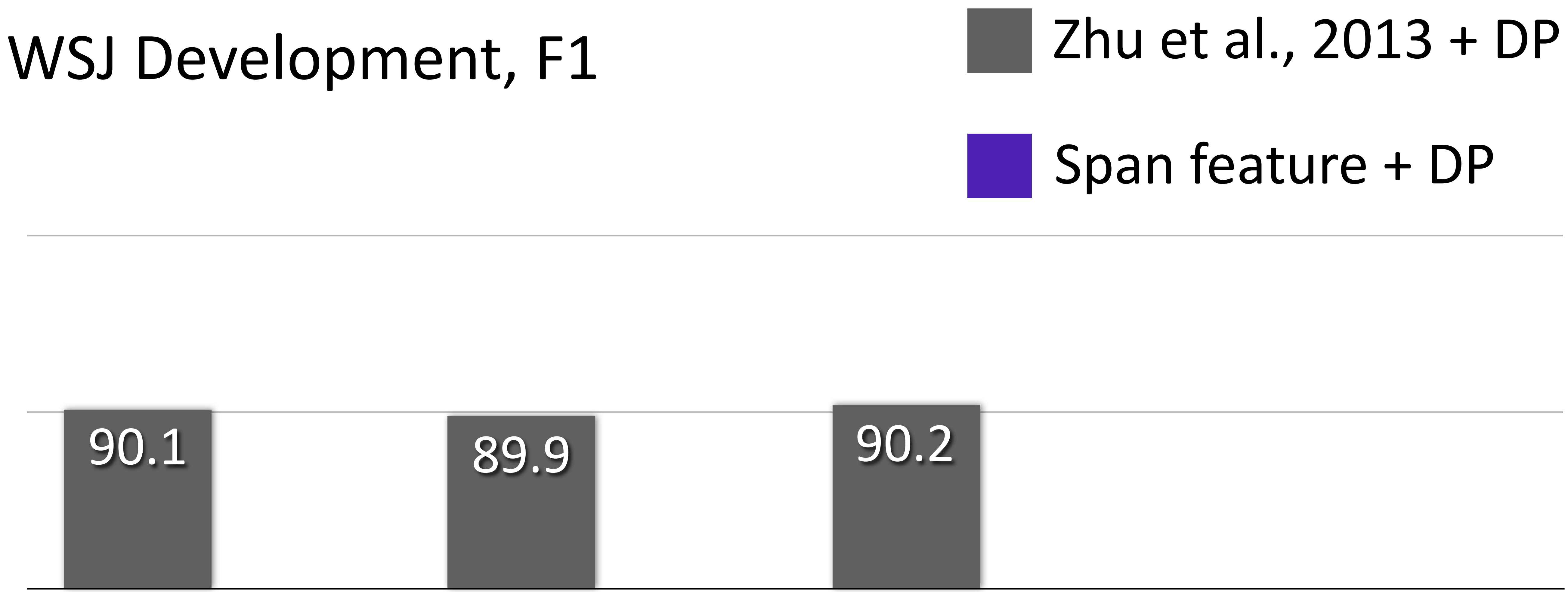
Effect of span features

WSJ Development, F1

Zhu et al., 2013 + DP

Span feature + DP

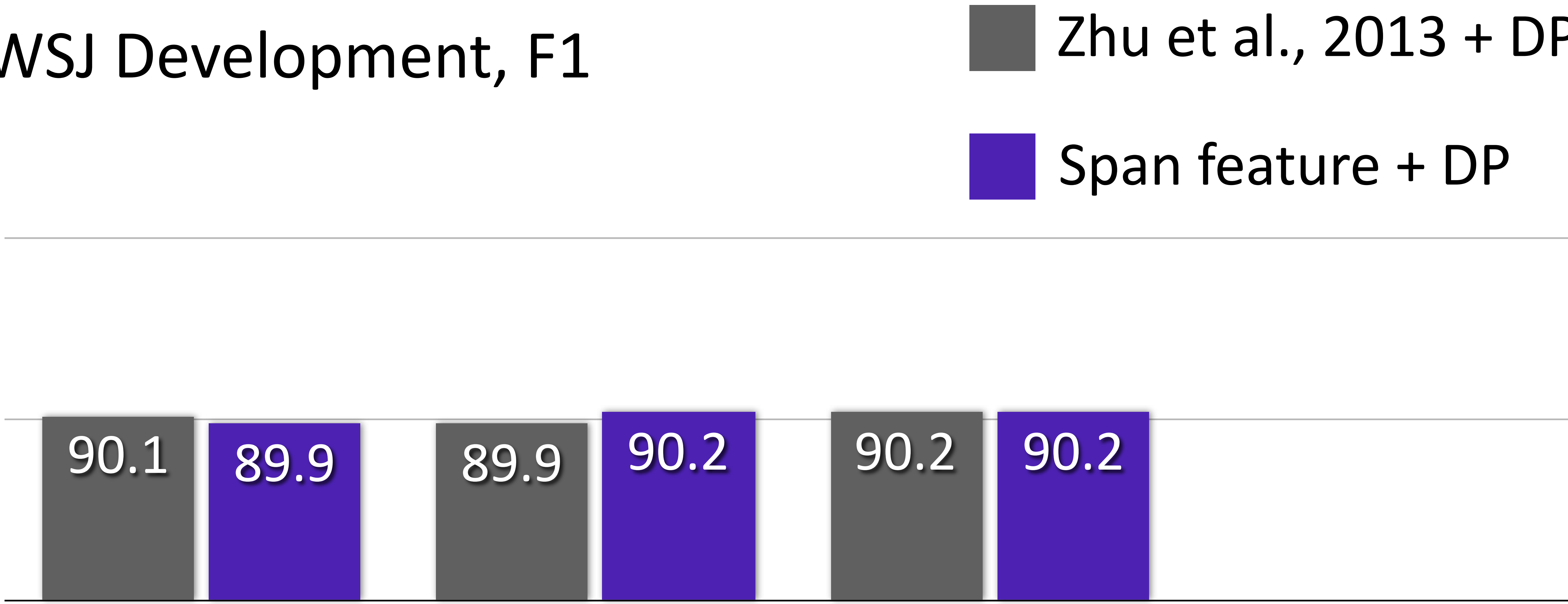
Effect of span features



beam:	16	32	64
Sent./s.:	31.9	17.0	9.1

Effect of span features

WSJ Development, F1



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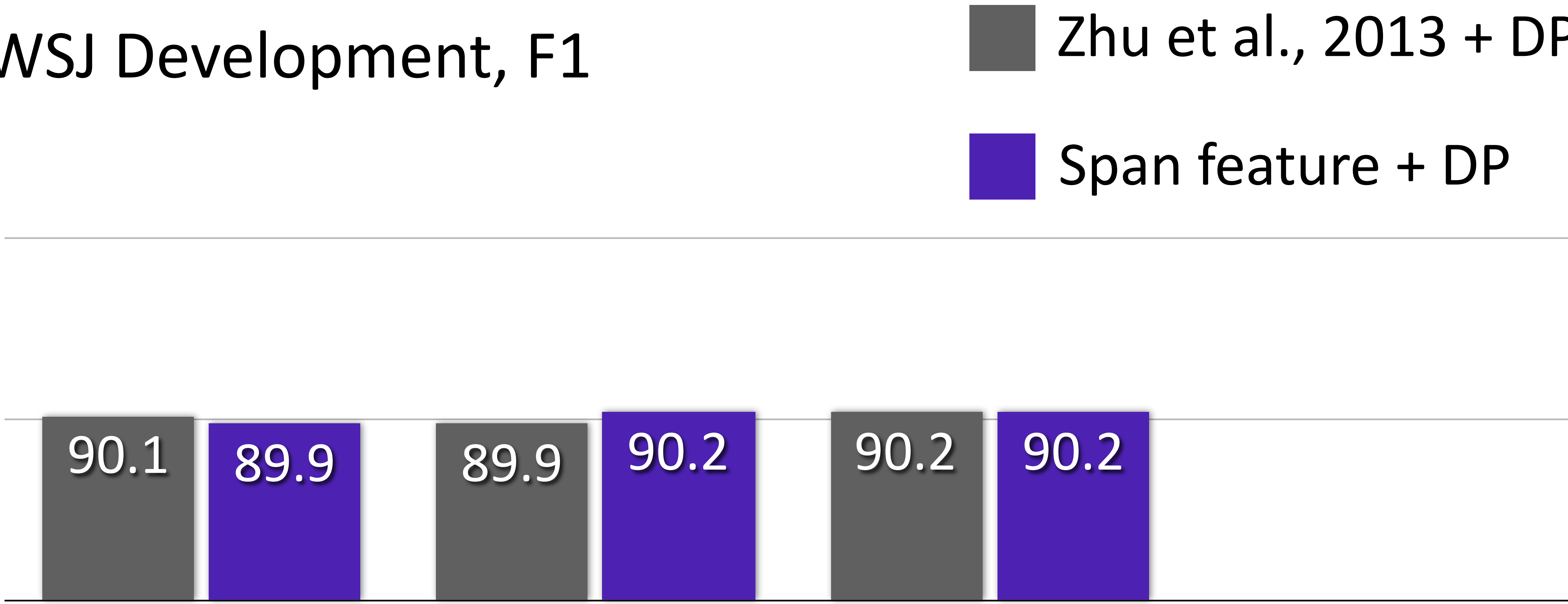
Effect of span features

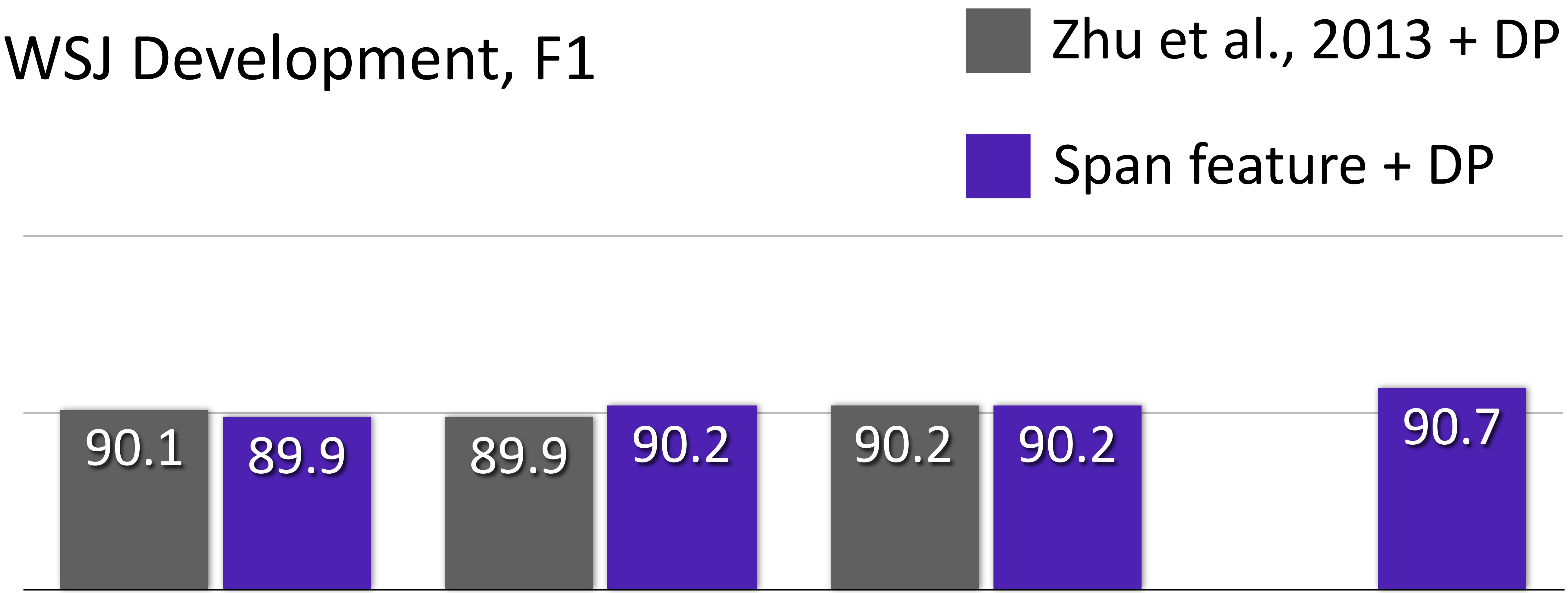
WSJ Development, F1



beam:	16	32	64
Sent./s.:	31.9	17.0	9.1

- Span feature is competitive to the current state-of-the-art

Effect of span features



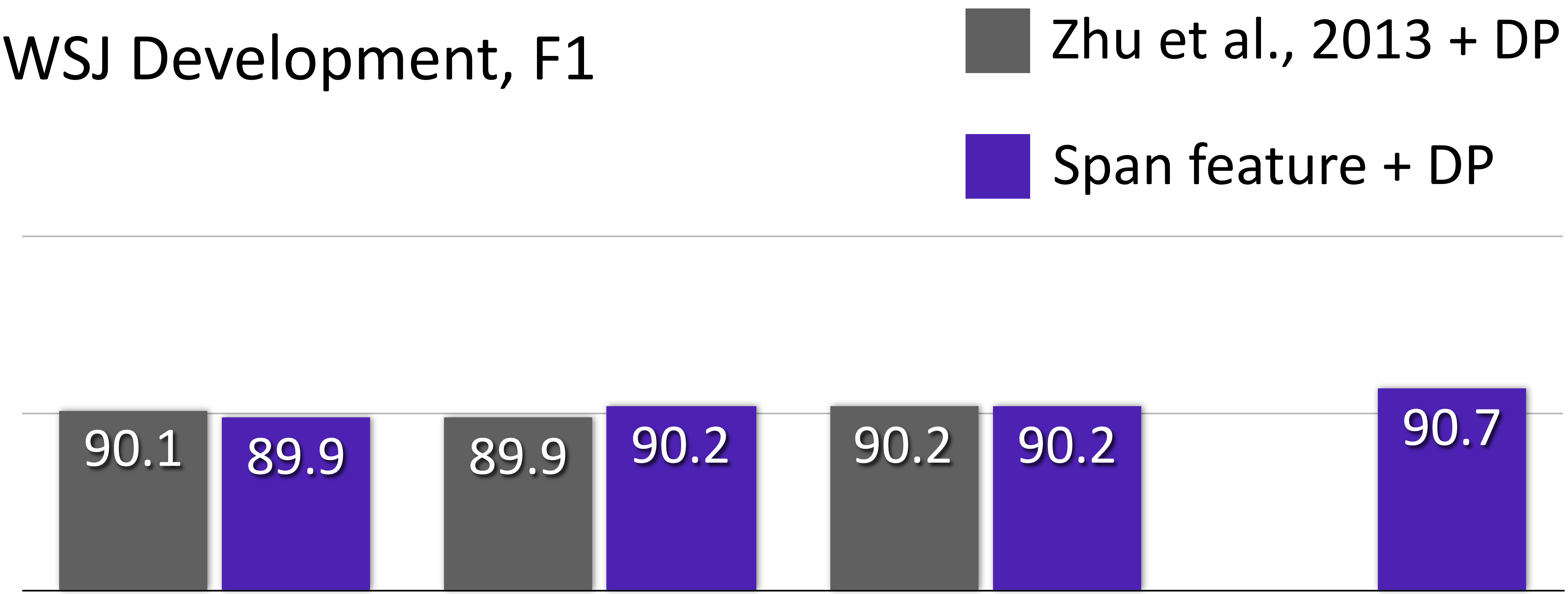
beam: 16 32 64 ∞

Sent./s.: 31.9 17.0 9.1 13.6

- Span feature is competitive to the current state-of-the-art

Effect of span features

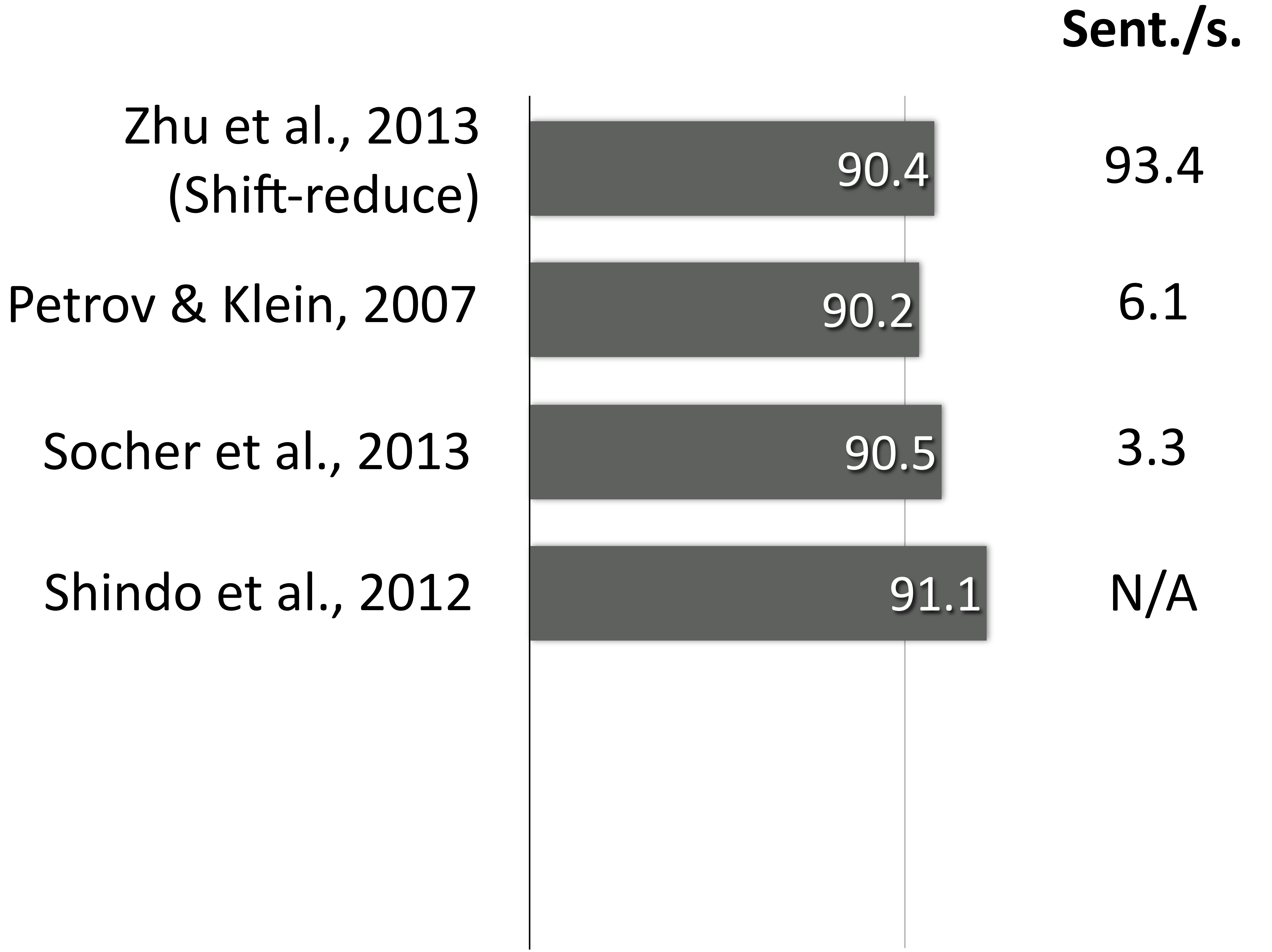
WSJ Development, F1



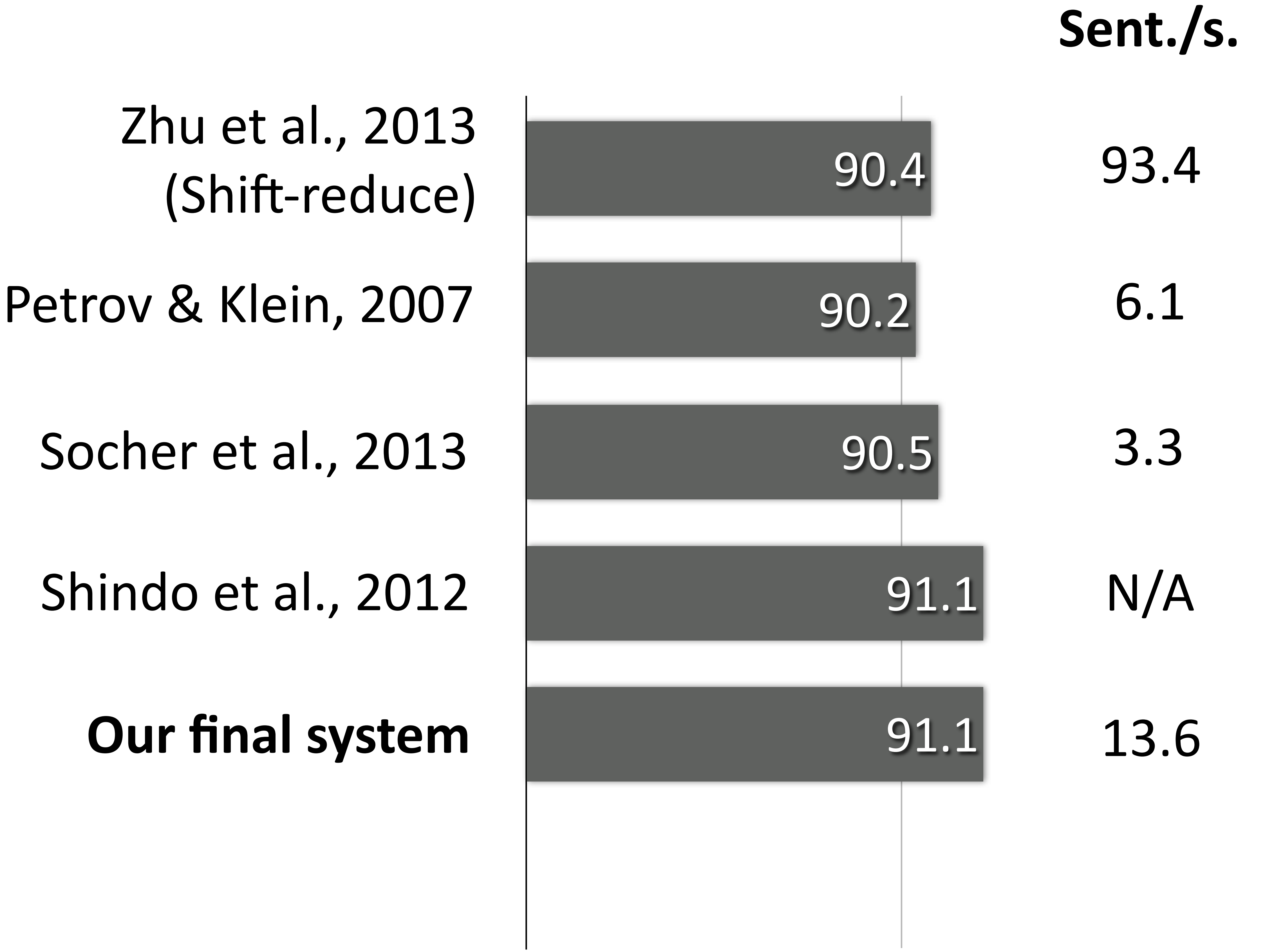
beam:	16	32	64	∞
Sent./s.:	31.9	17.0	9.1	13.6

- Span feature is competitive to the current state-of-the-art
- A* search gives the best score (faster than beam = 64)

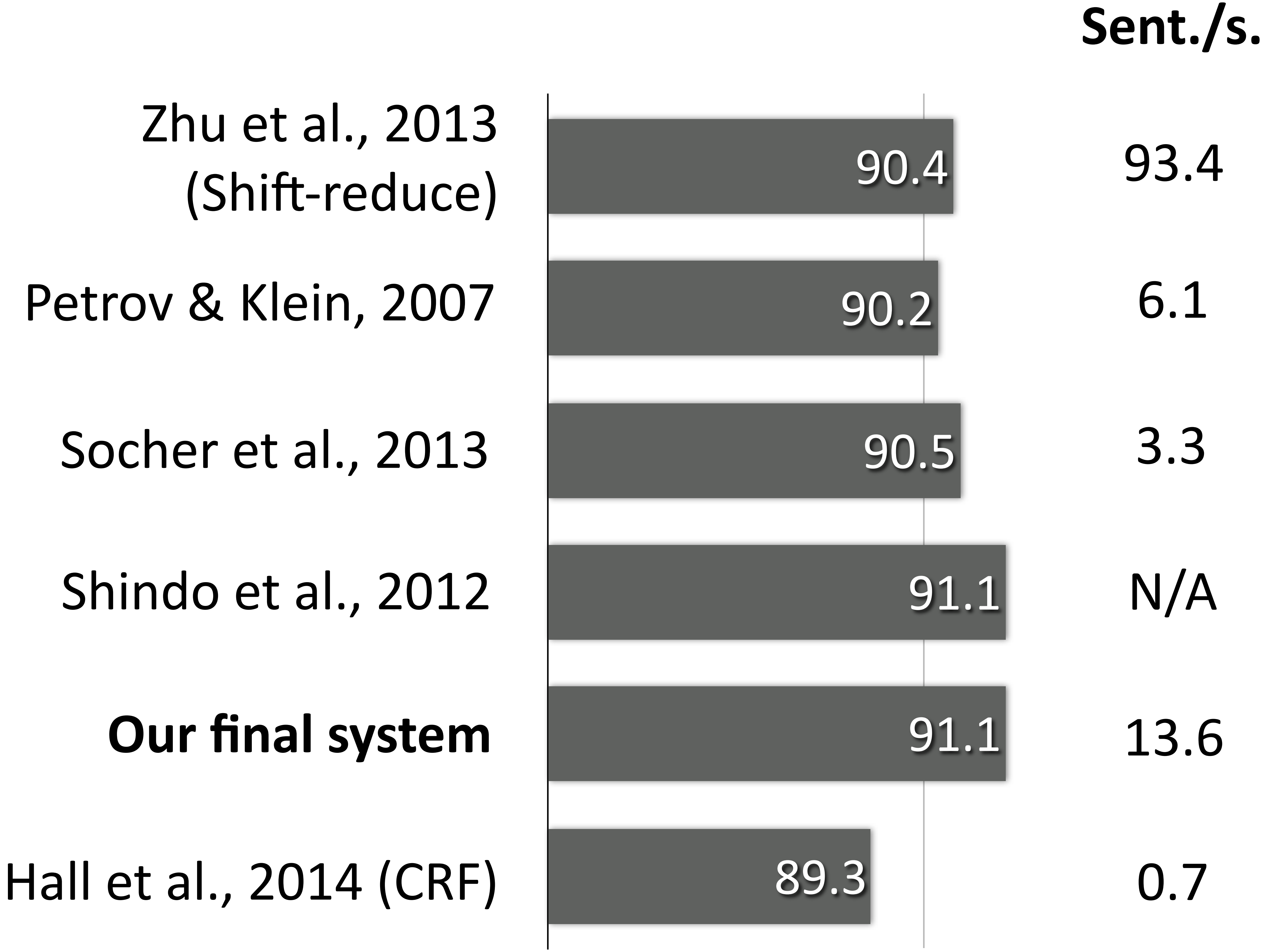
Comparison on WSJ test set



Comparison on WSJ test set

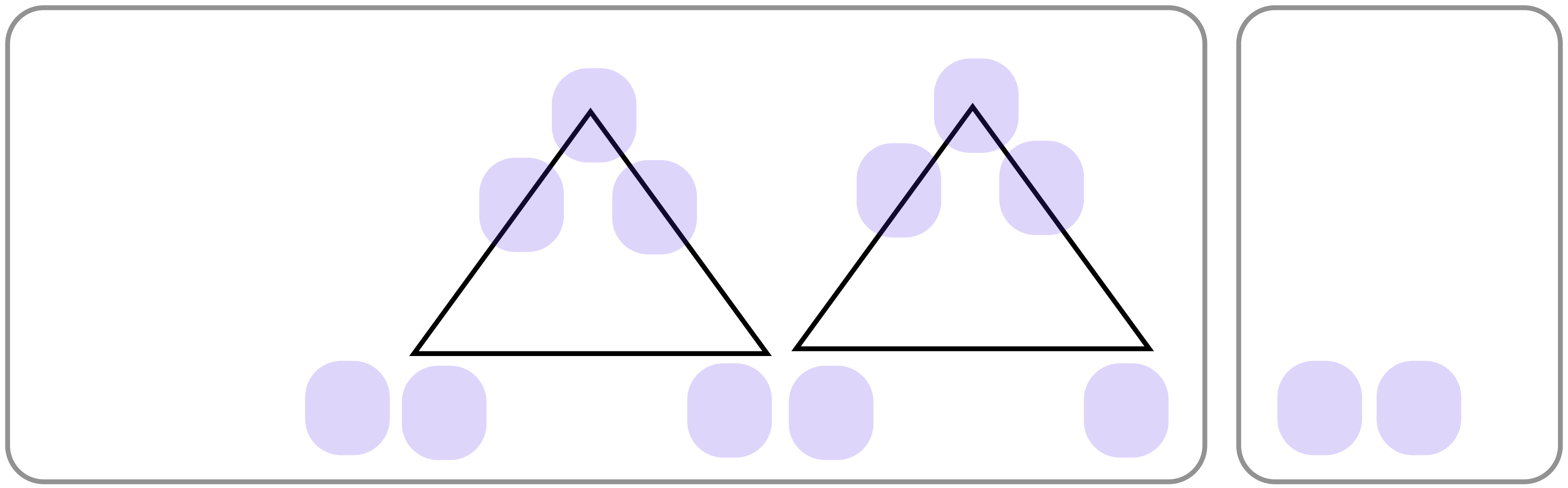


Comparison on WSJ test set



[Hall et al., 2014]

What's the difference with CRF parsing?



Our parser looks similar to the discriminative CKY (CRF):

- Features come from the top two subtrees
- but our parser outperforms the CRF parser (91.1 vs. 89.3)

What's the source of this difference?

- Scoring for shift actions?
- Or just because our parser utilizes more features?

Conclusion

Question:

Are beam-search & complex features the best strategy for shift-reduce parsing?

Our findings:

- It is not always the best in constituent parsing
- Practical shift-reduce parsing with exact search is possible

Our system is available at:

https://github.com/mynlp/optsr

The trained model is still unavailable (coming soon)