# Inducing Sentence Structure from Parallel Corpora for Reordering

John DeNero and Jakob Uszkoreit

Google research

# Overview

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# Syntax Matters for Hierarchical Reordering

English-to-Japanese Web Translation

Tune Test

Single-Reference BLEU

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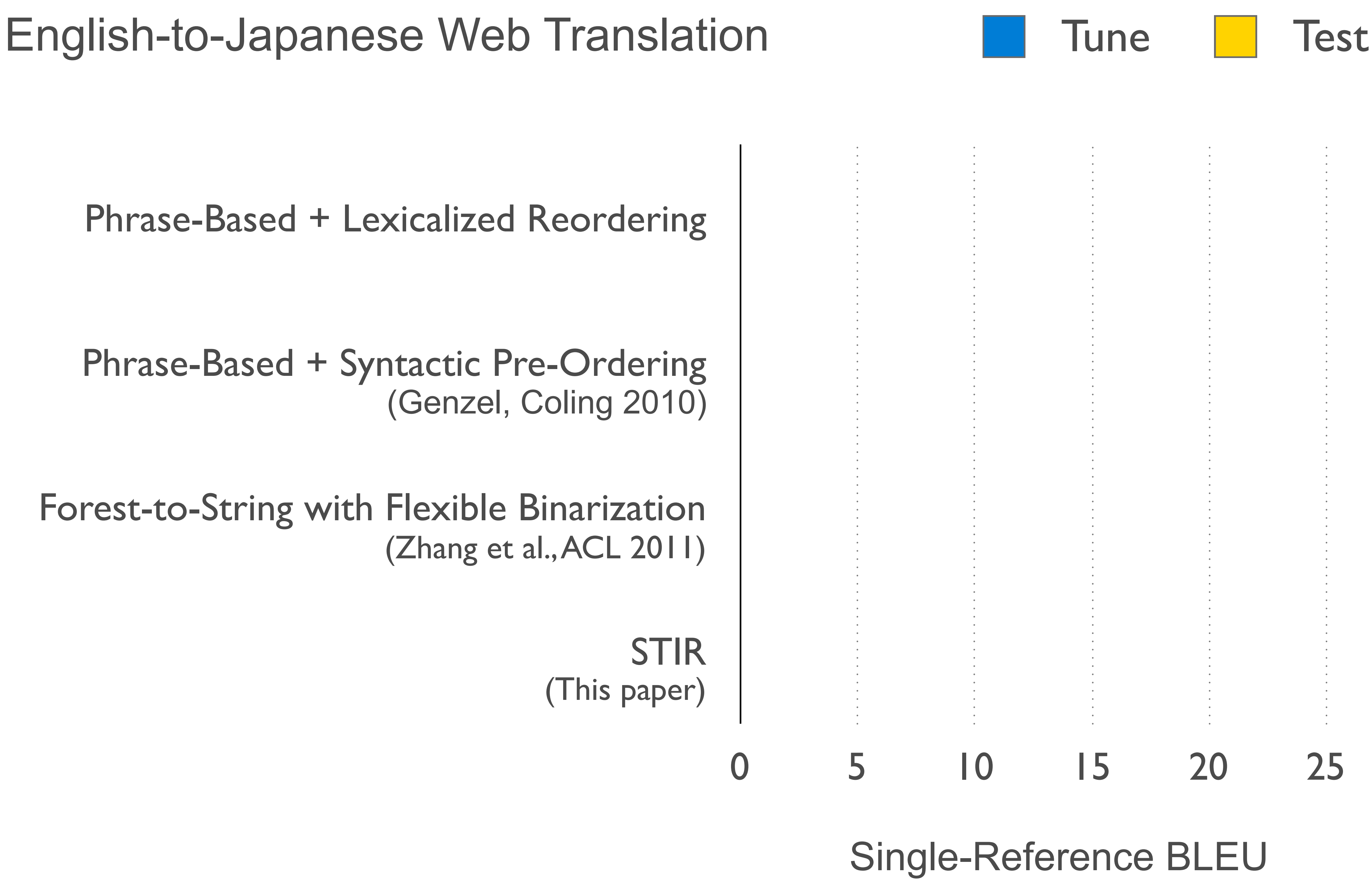

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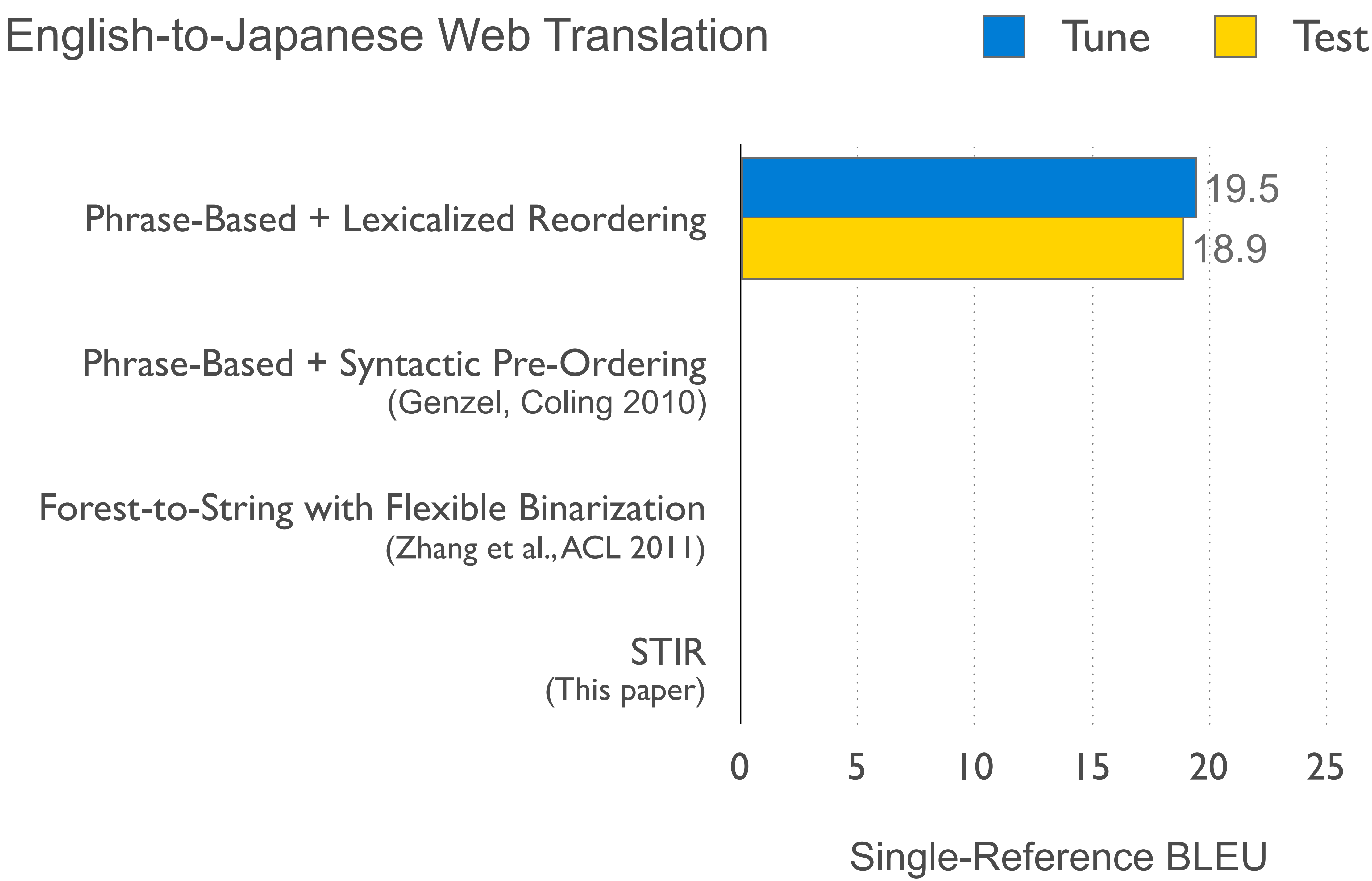

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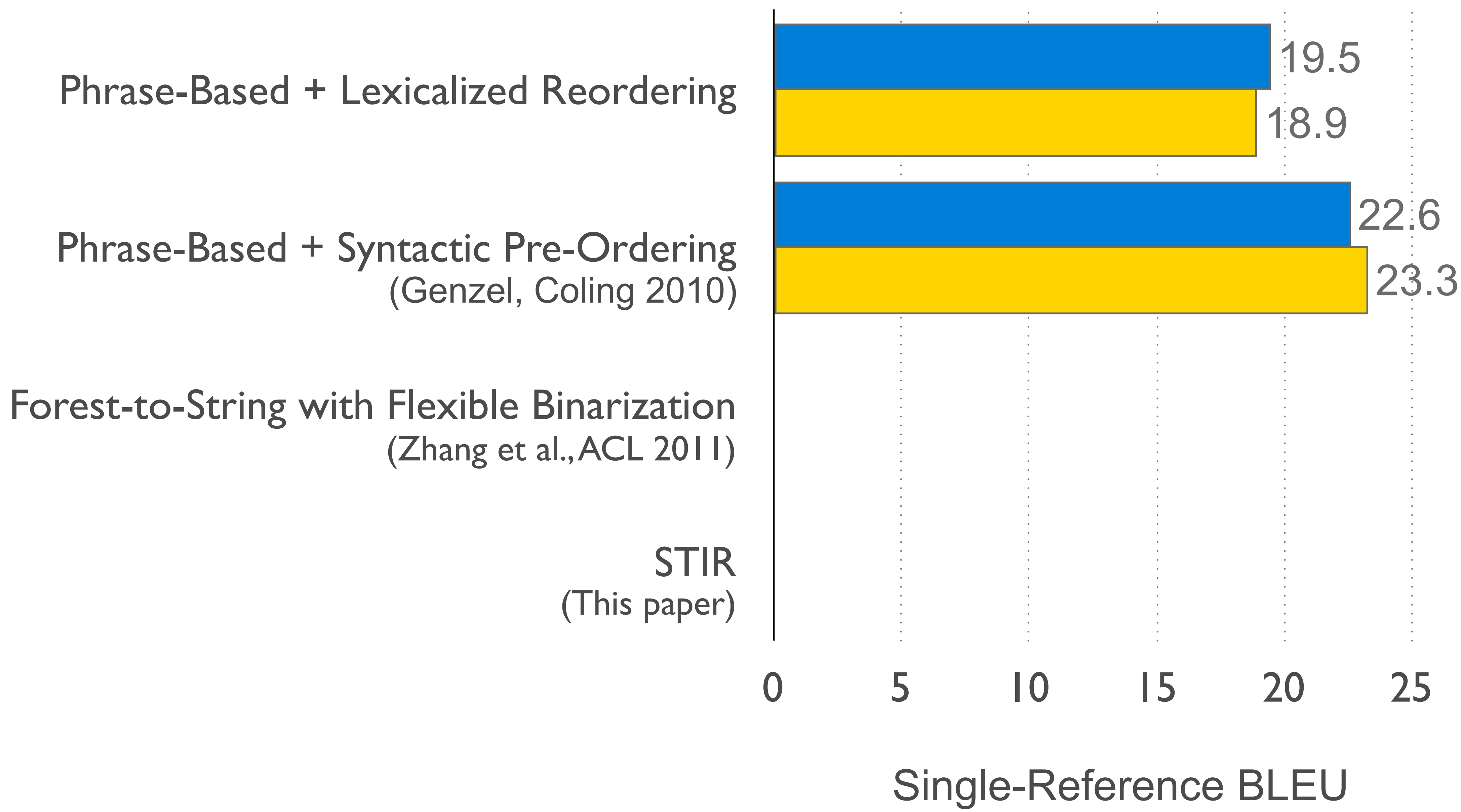

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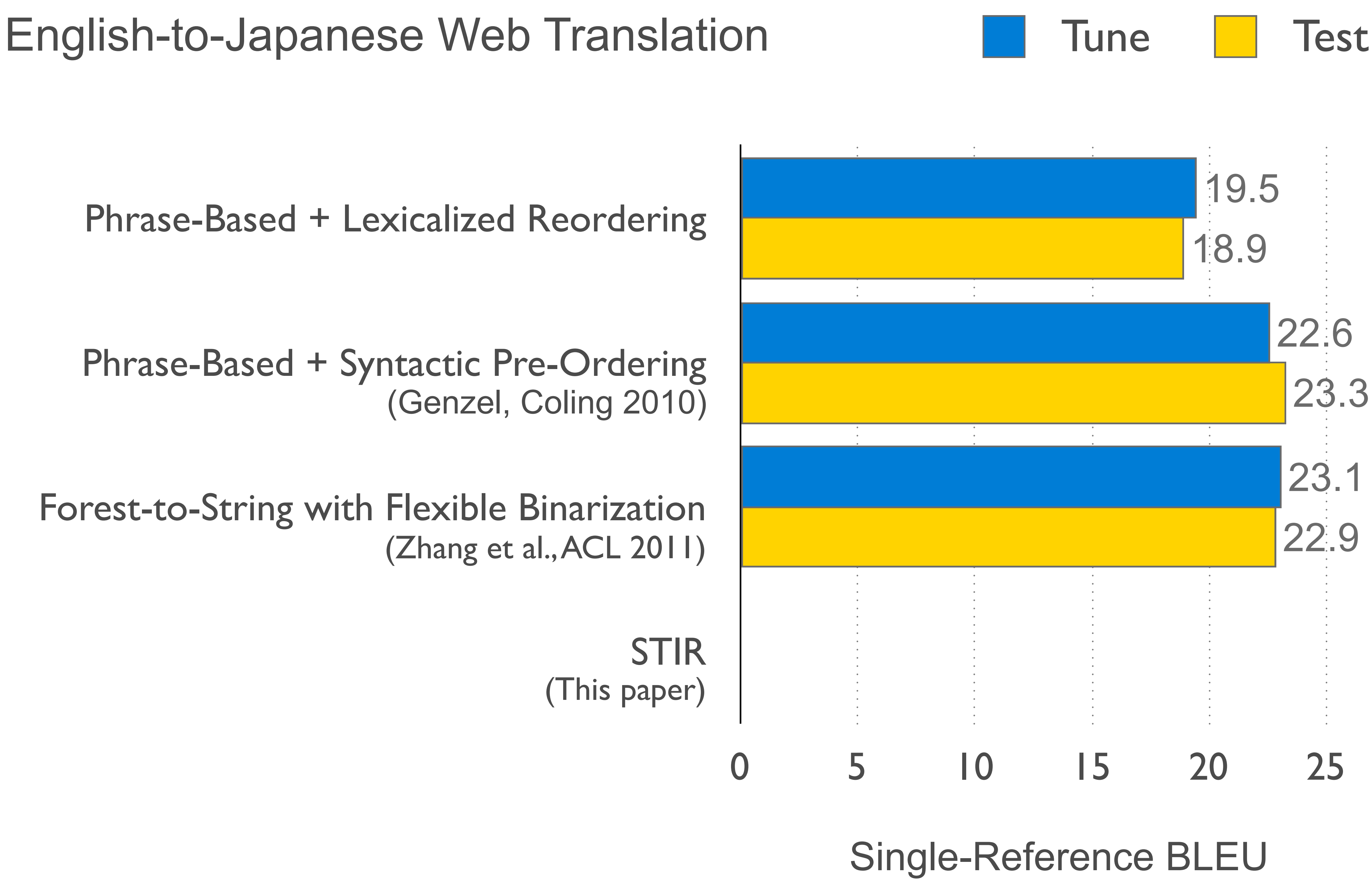

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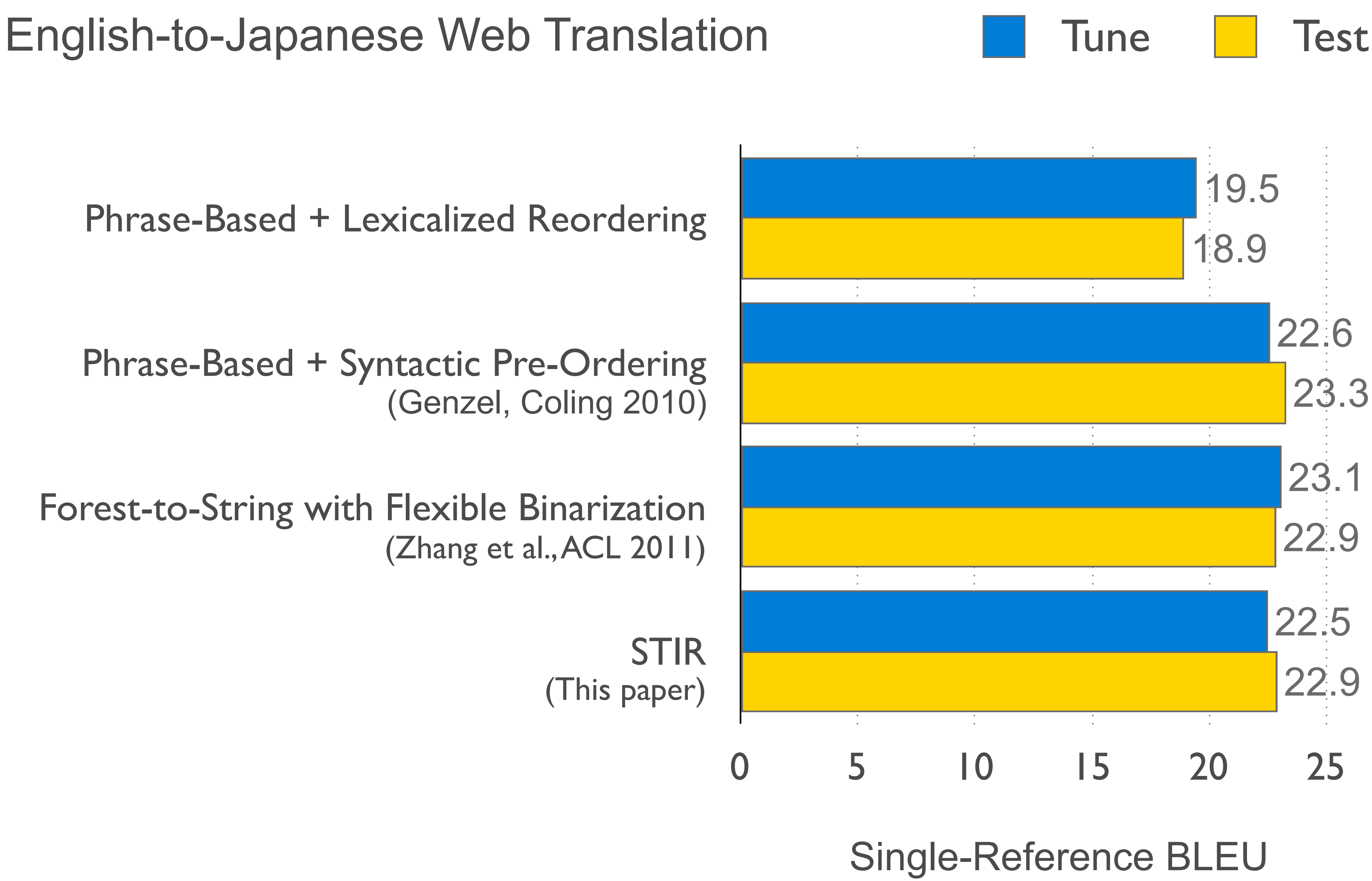

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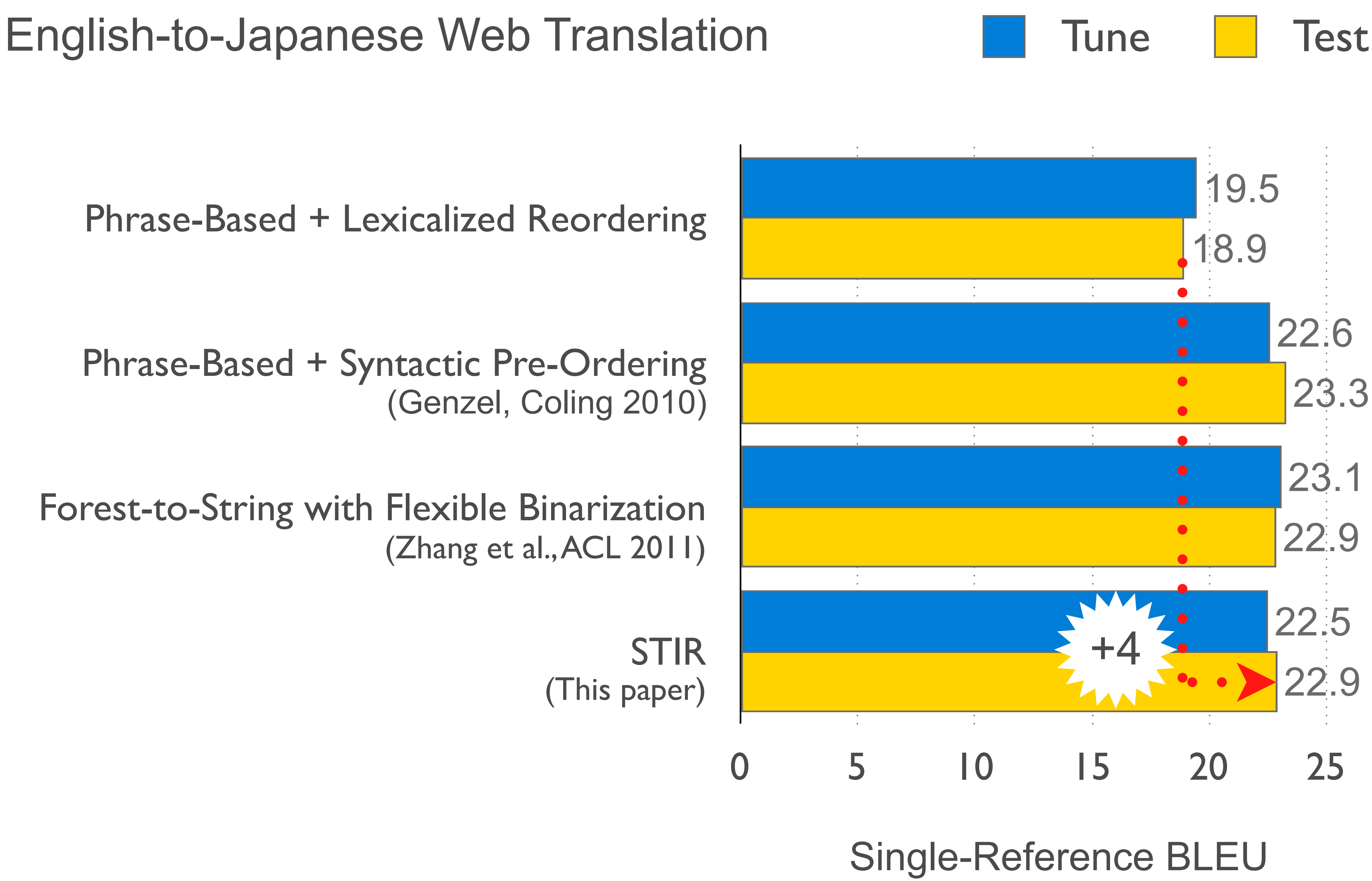

# Syntactic Pre-Ordering in Phrase-Based Systems

**Pre-Ordering Pipeline**

**Translation Pipeline**

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S V O

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Monolingual parsing model

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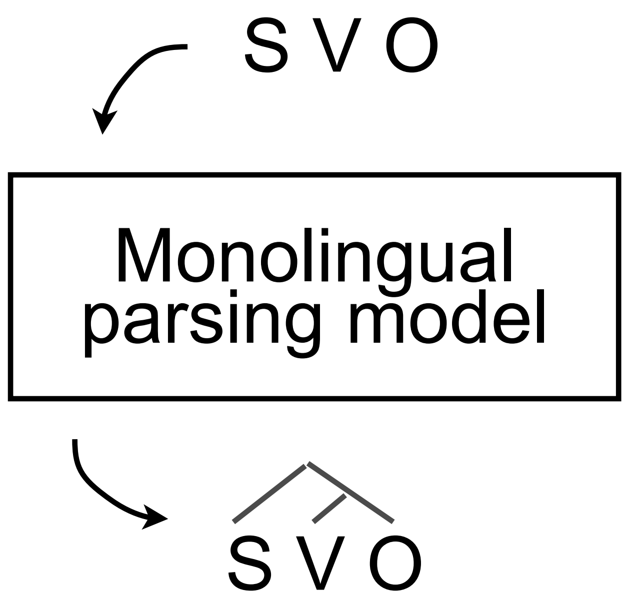

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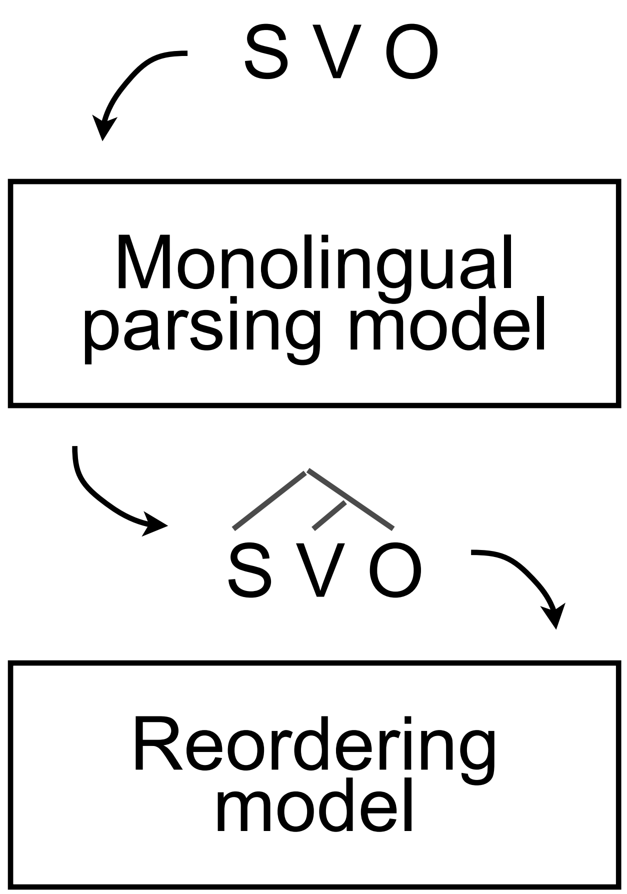

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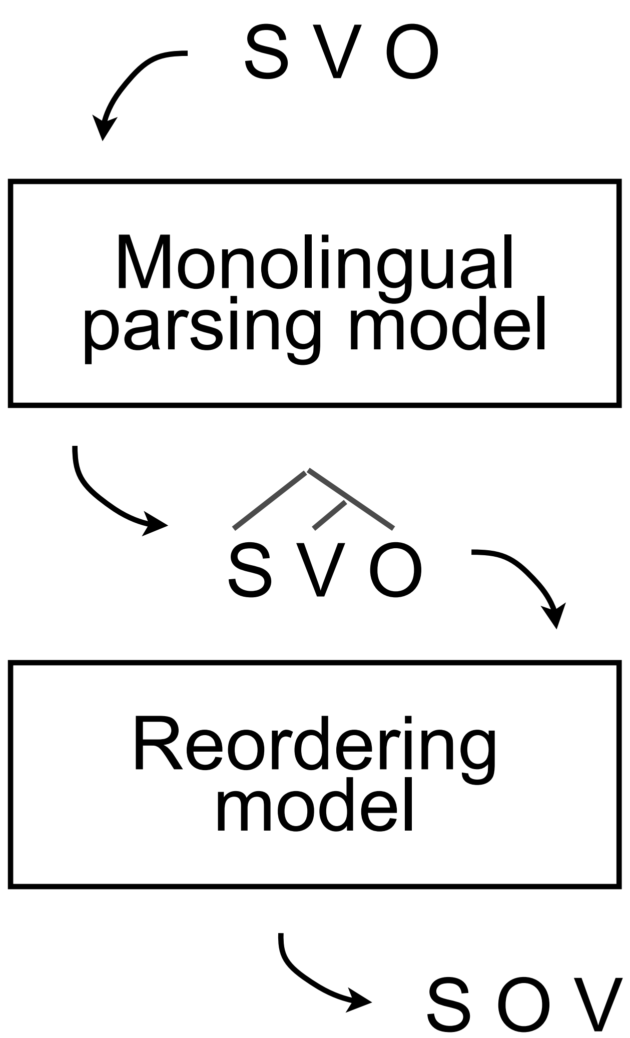

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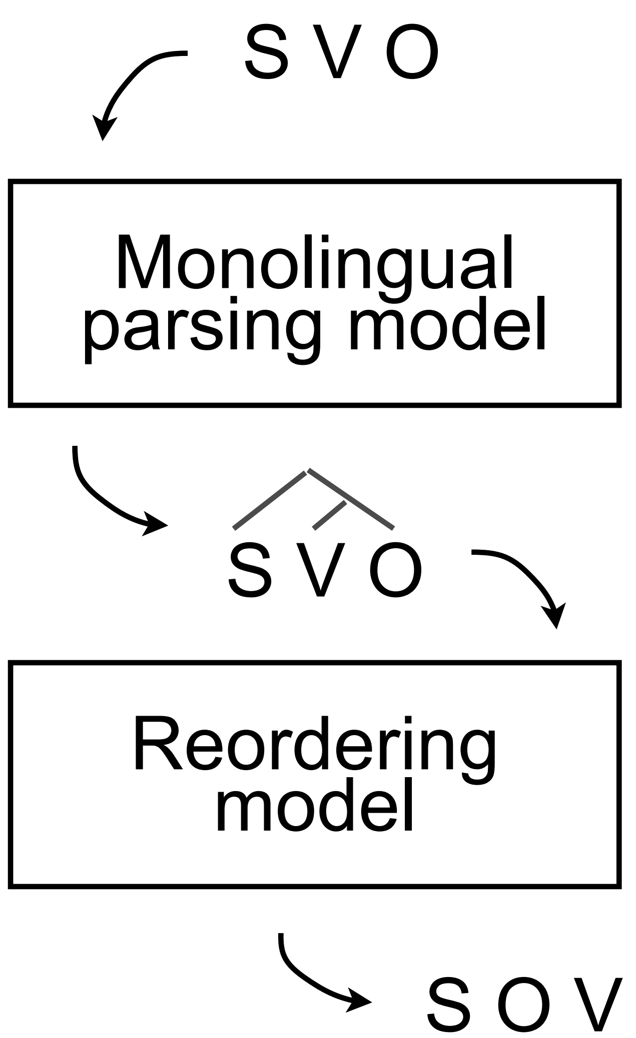


**Translation Pipeline**

Source training

Target training

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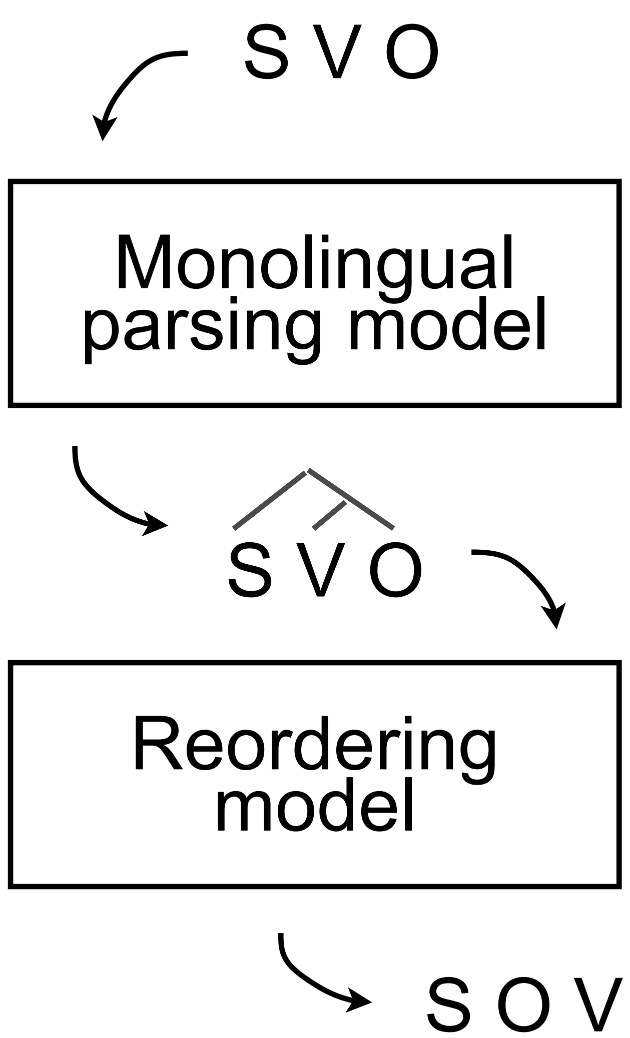


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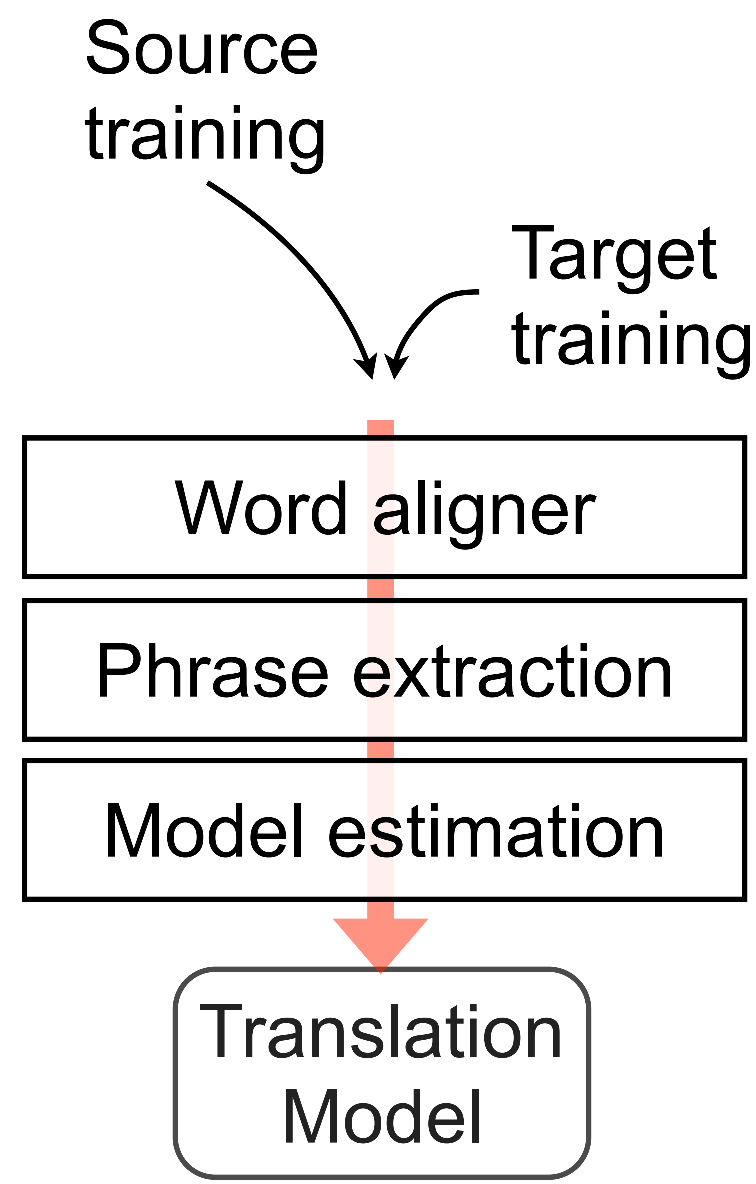

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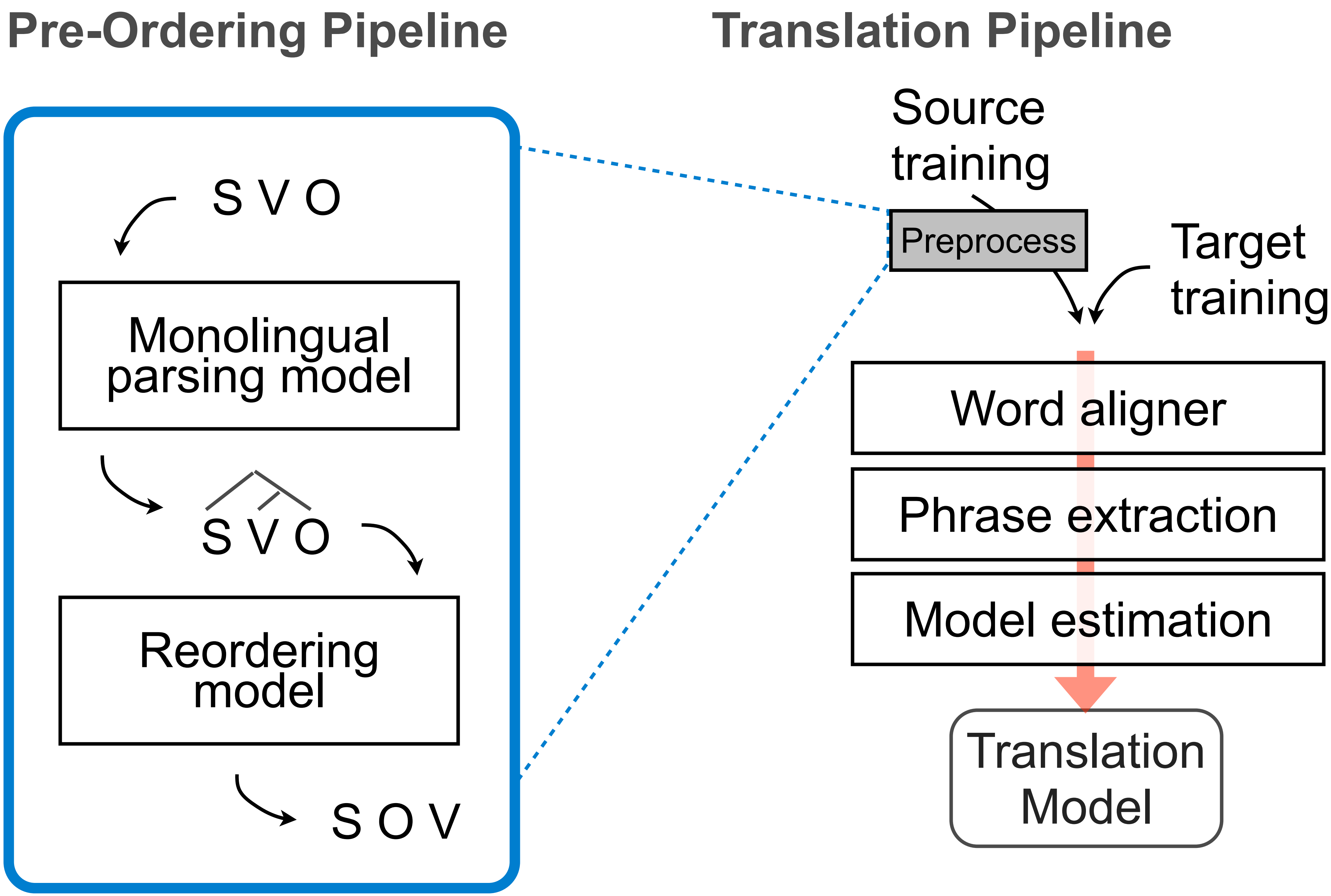

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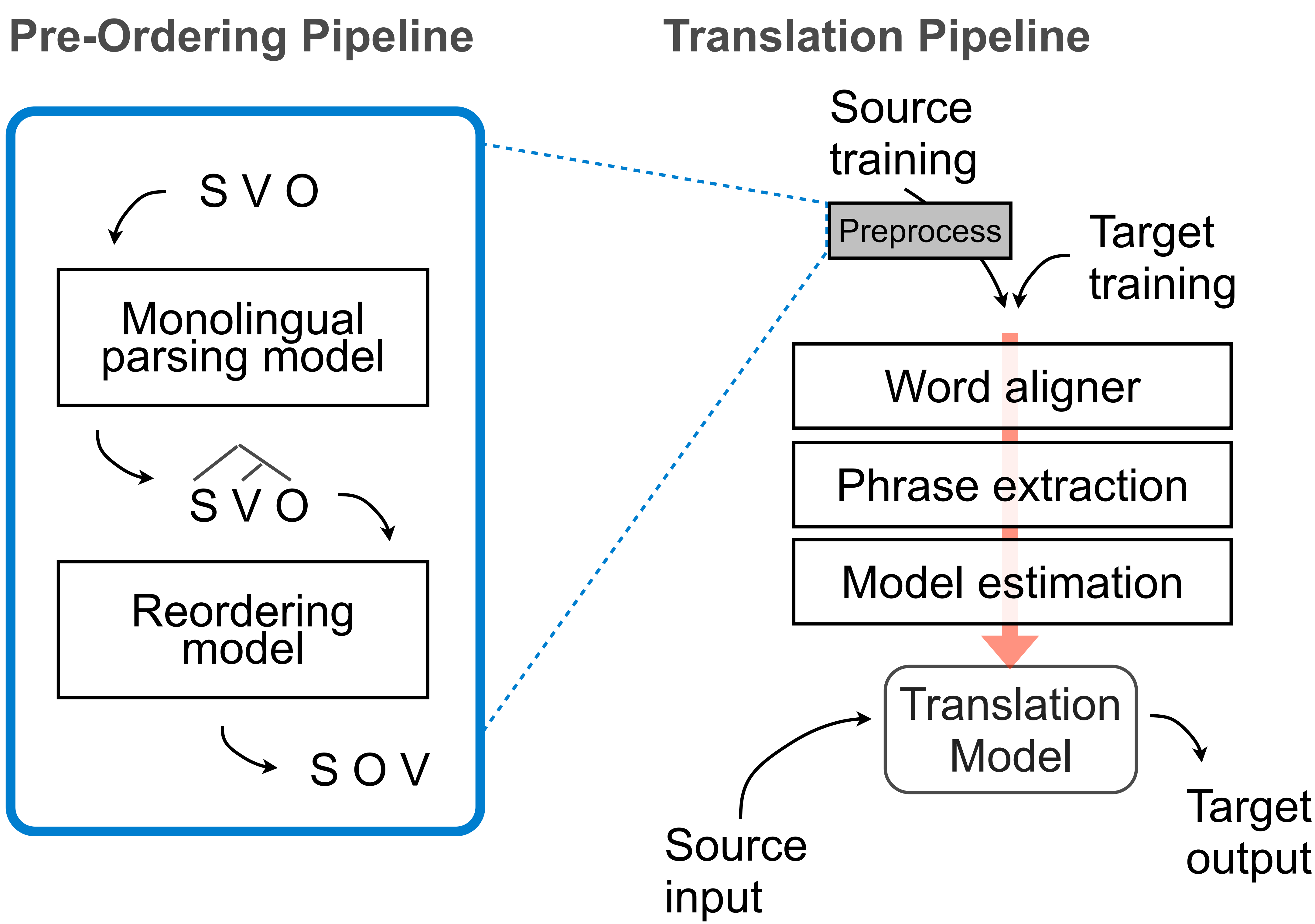

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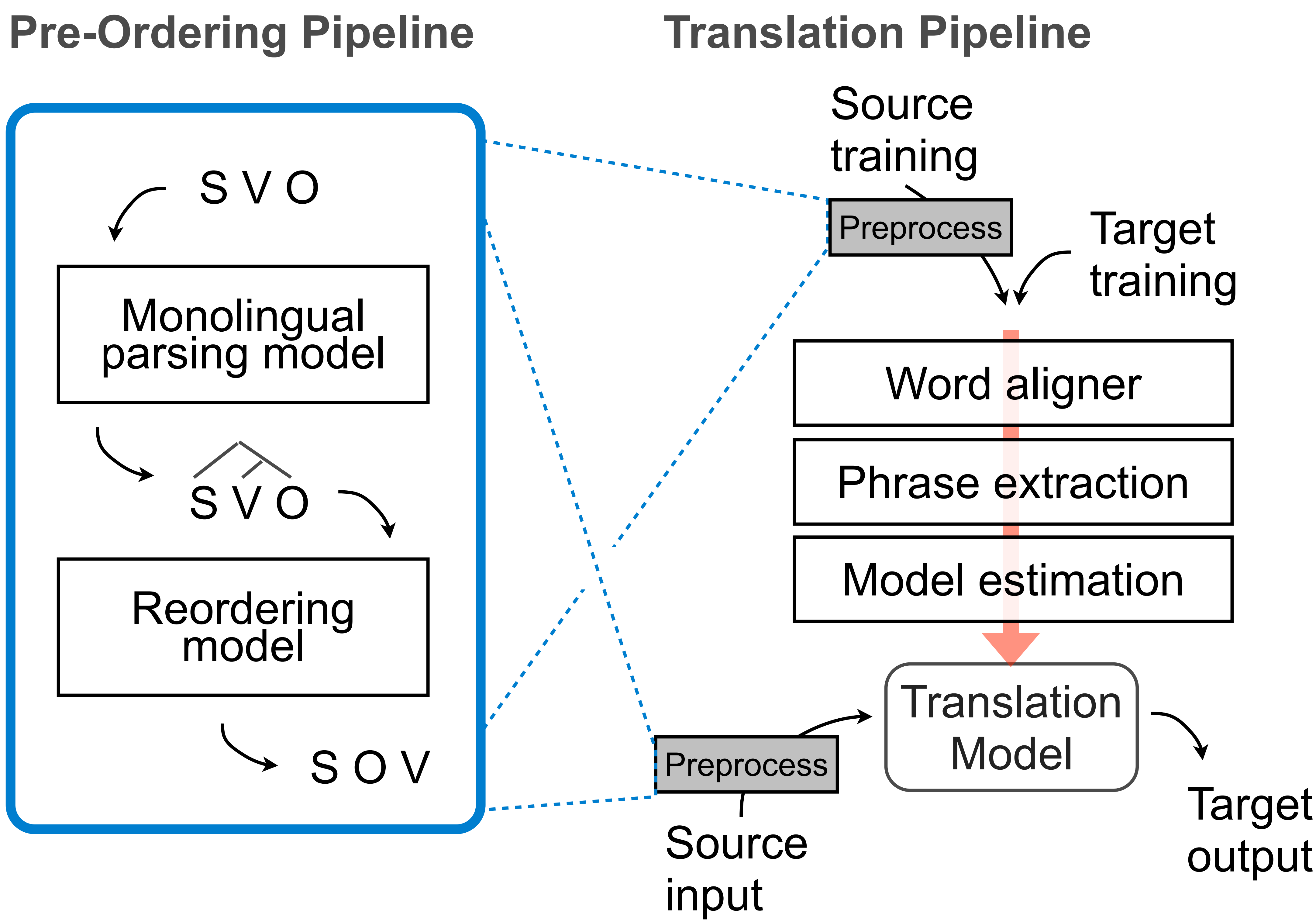

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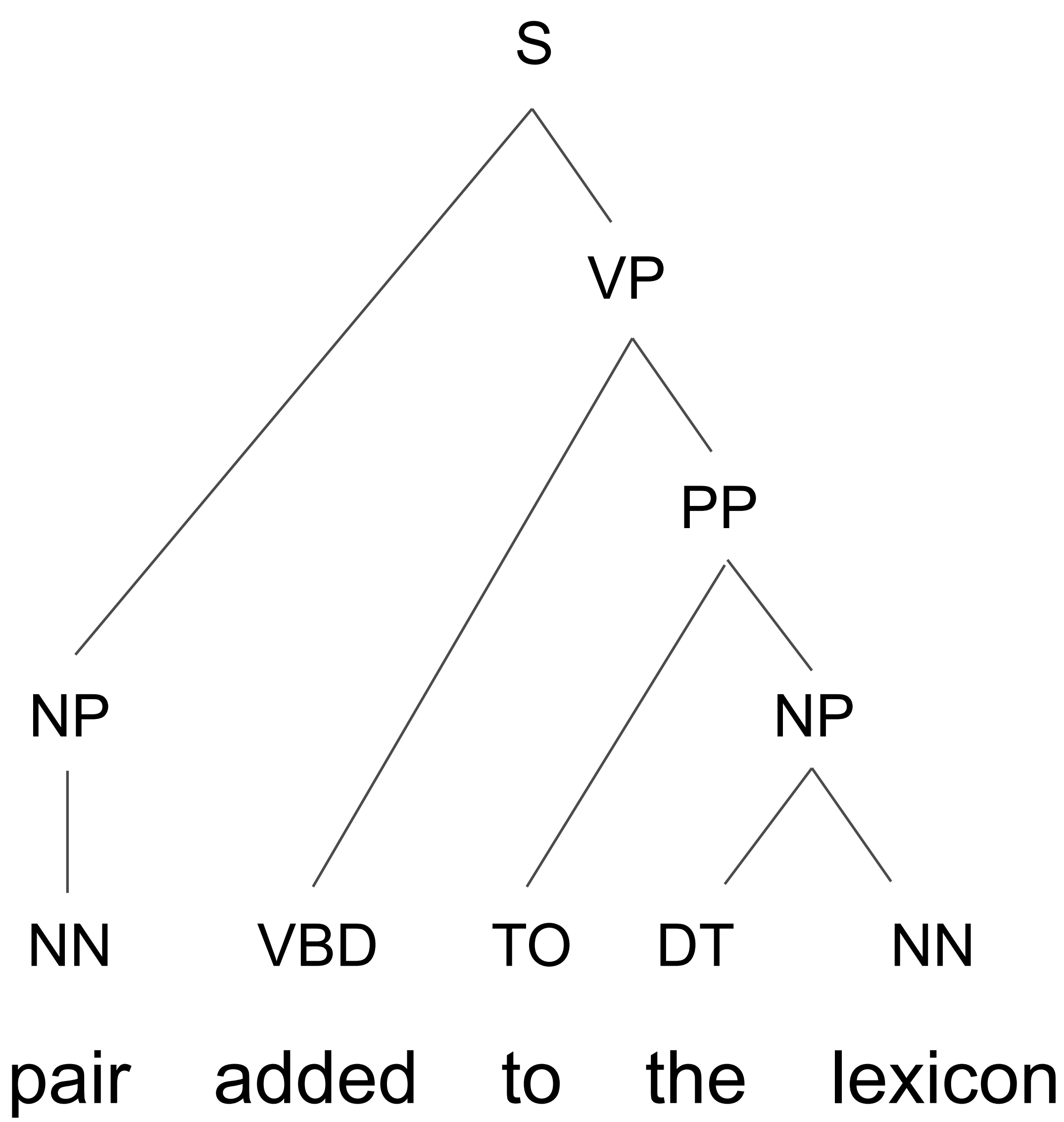

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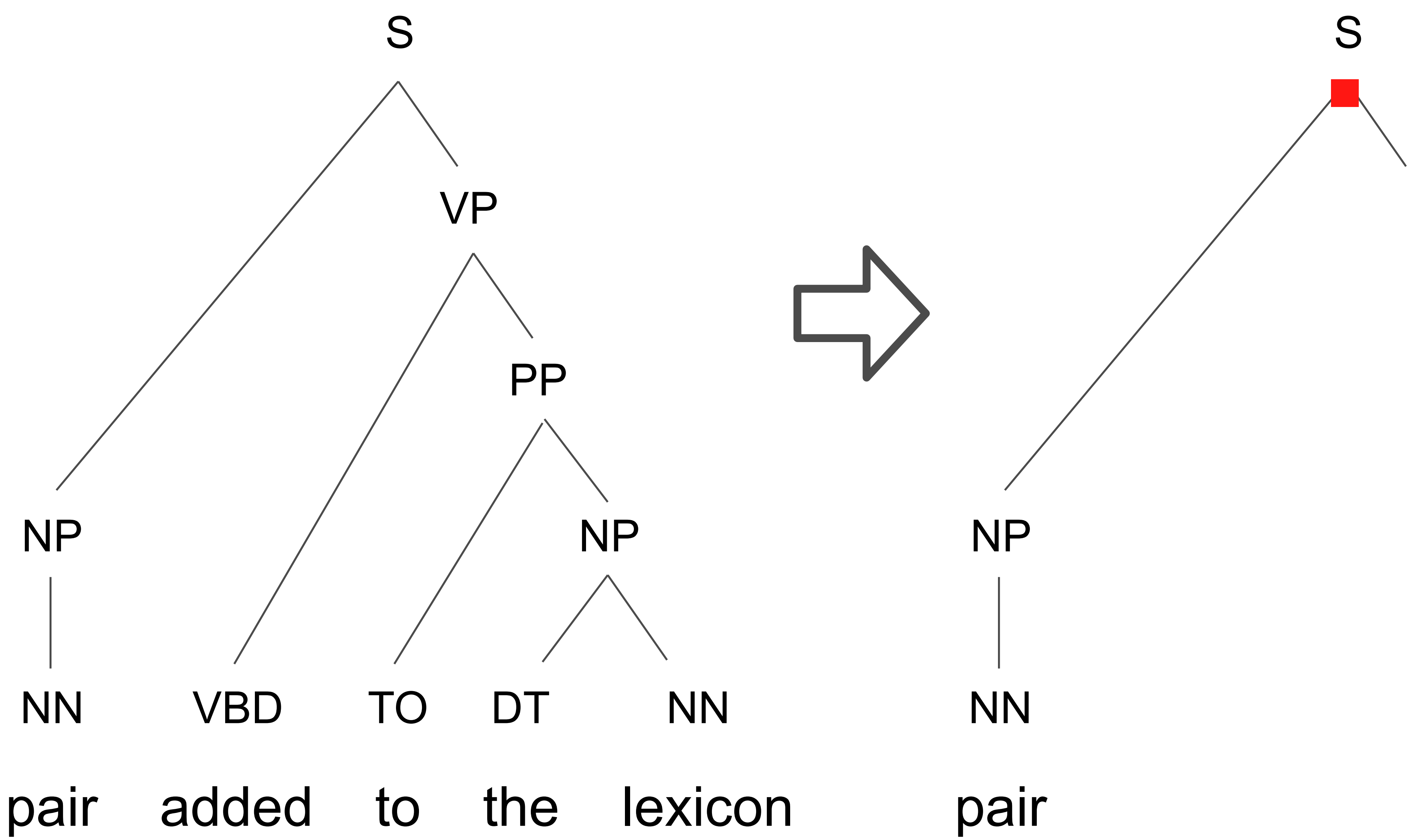

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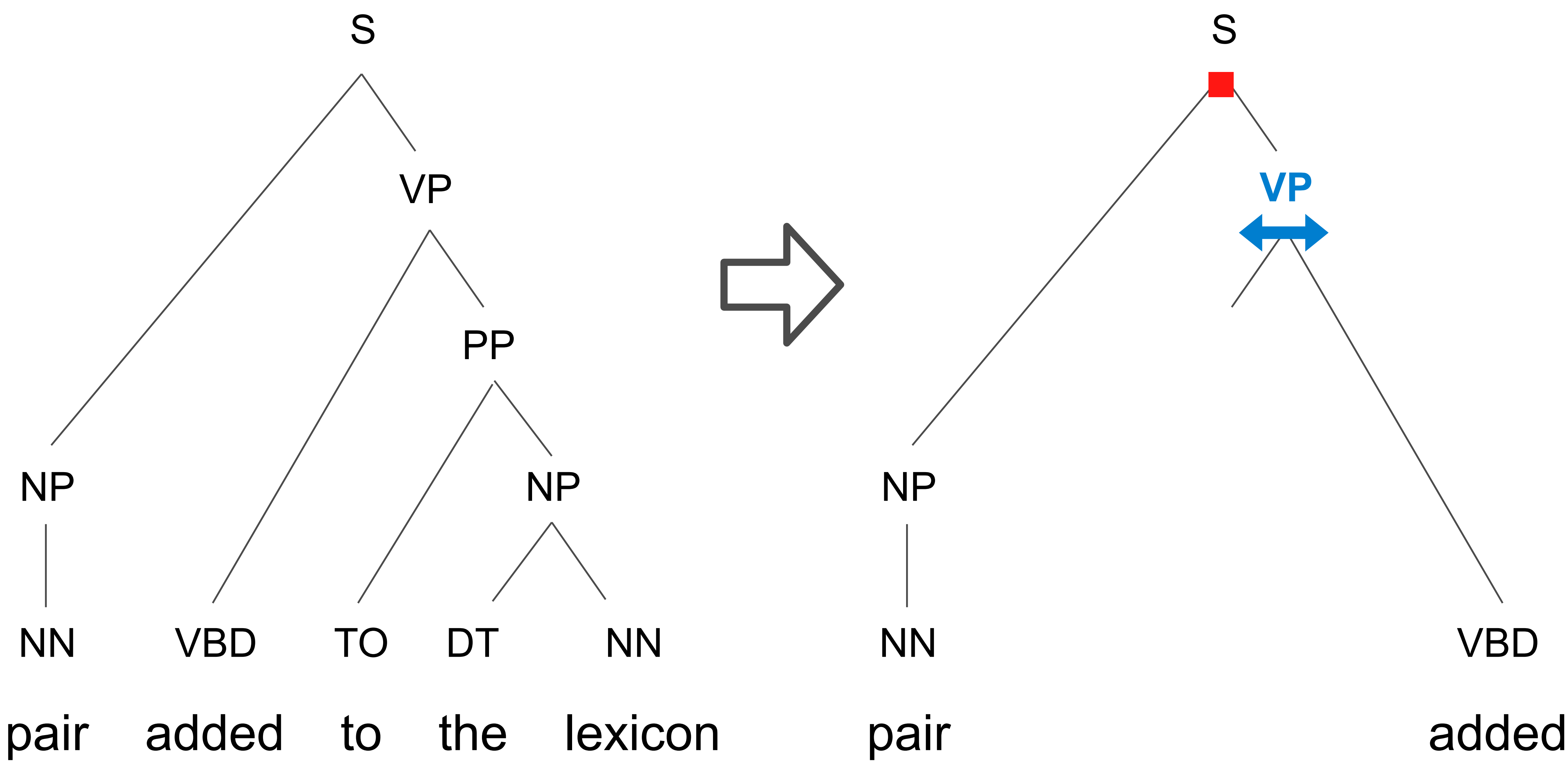

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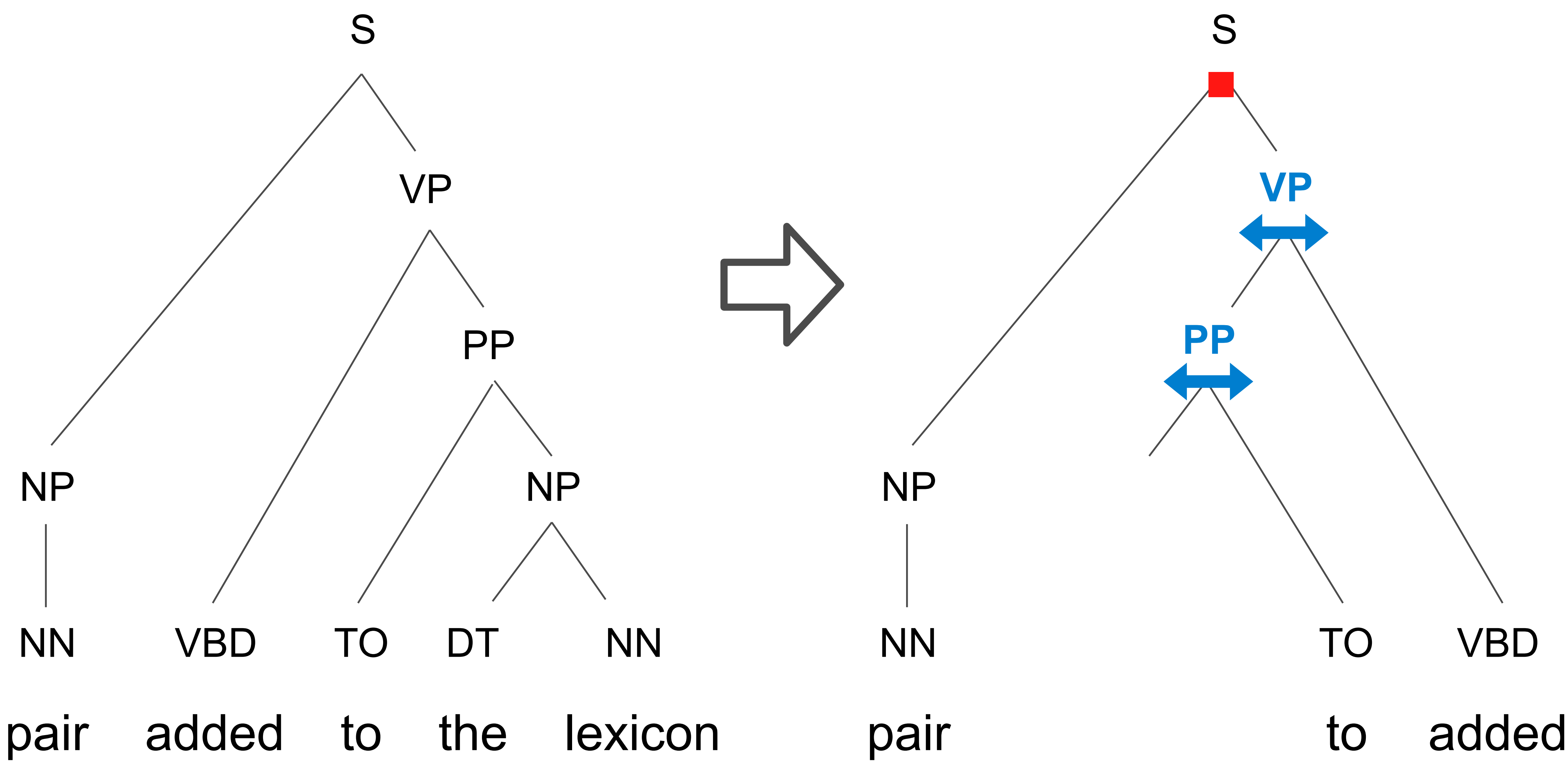

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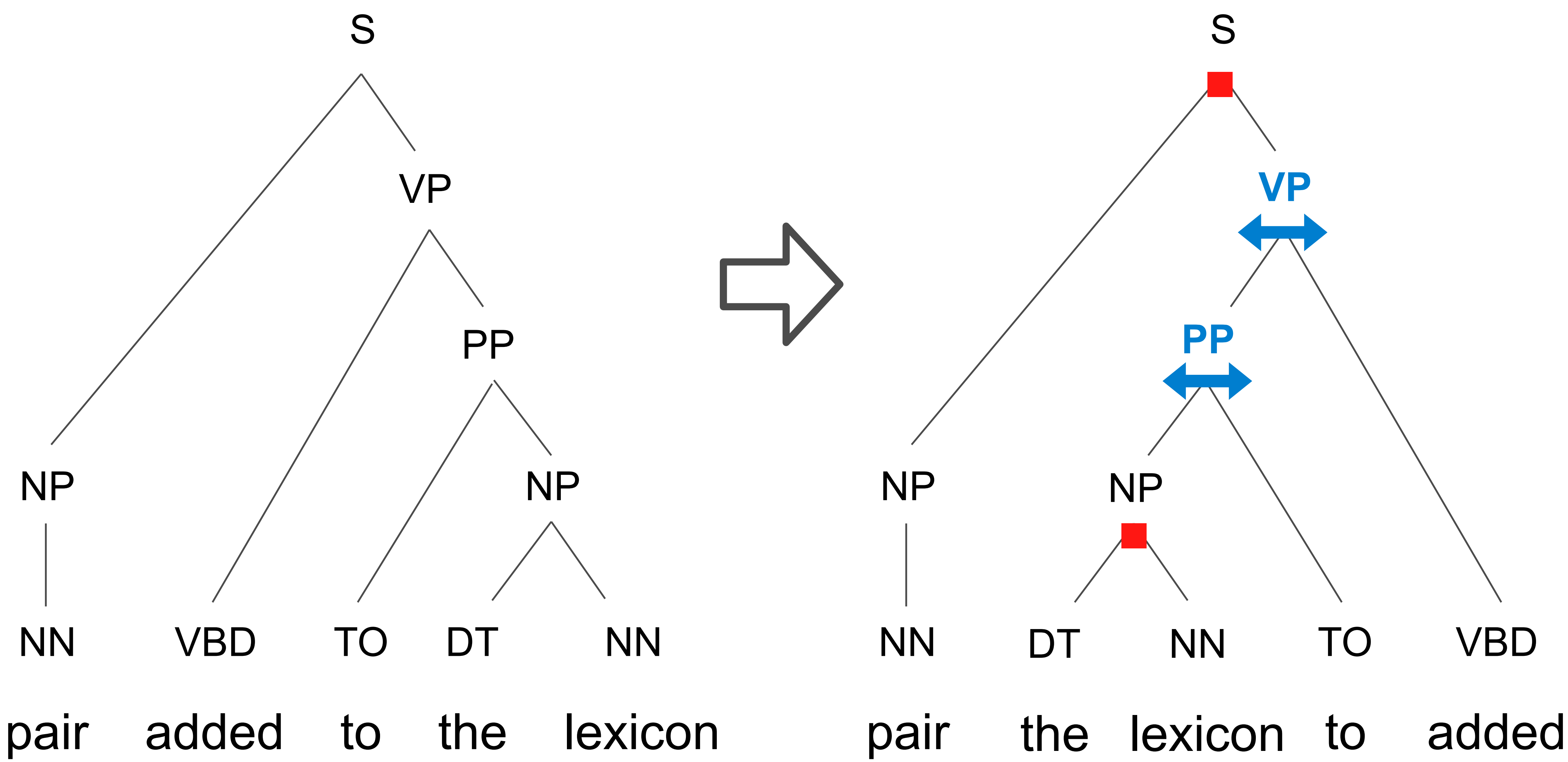

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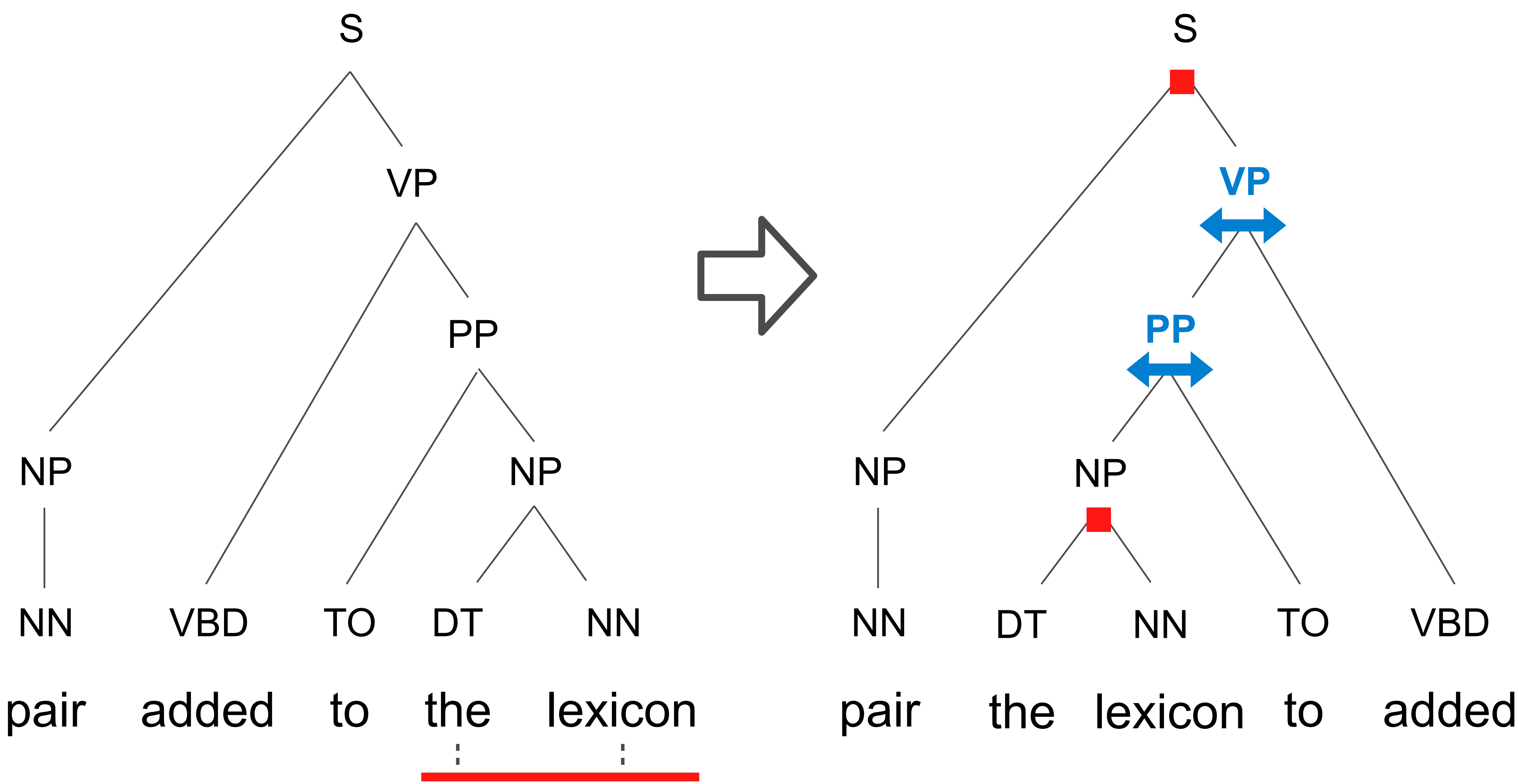

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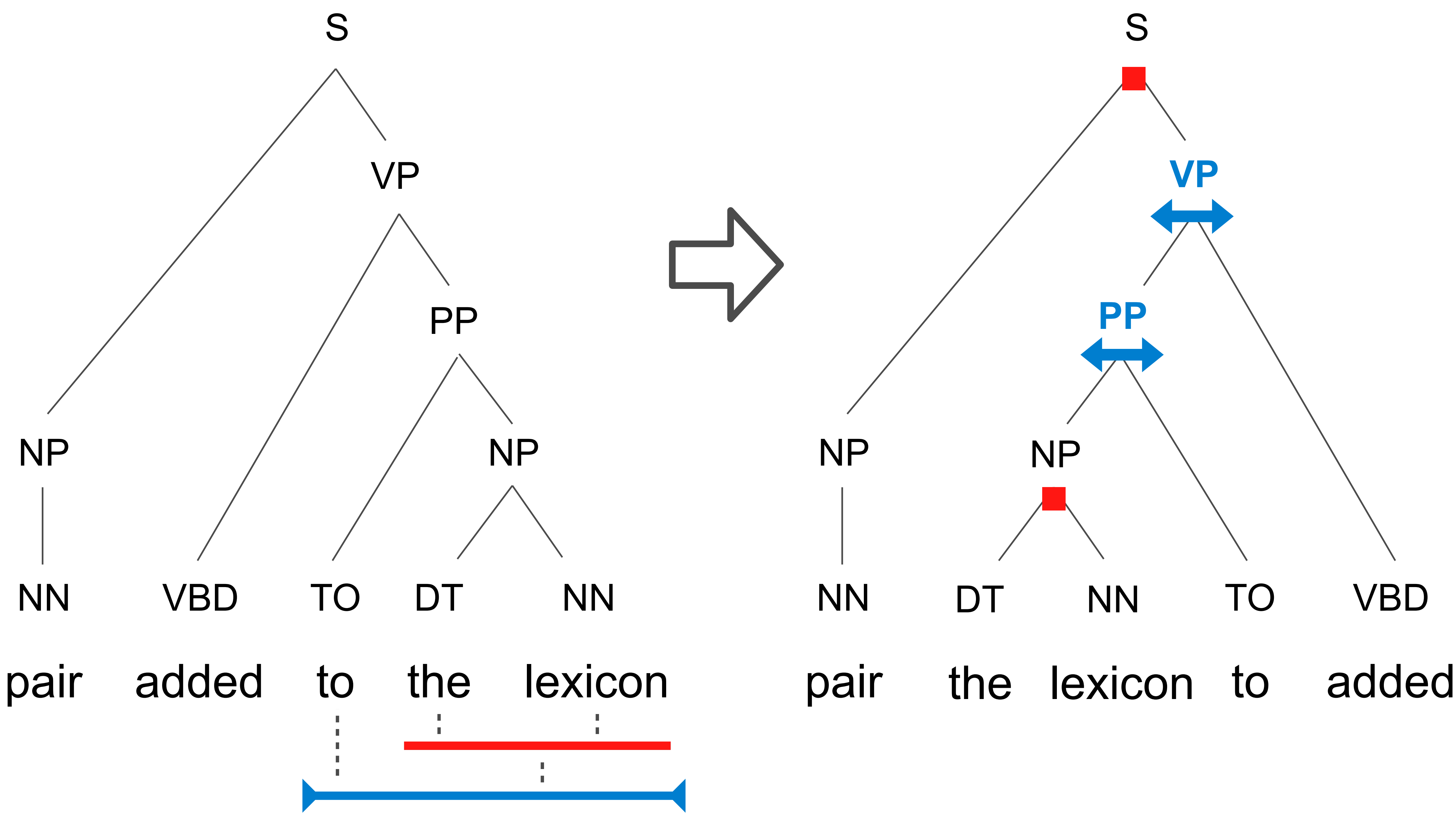

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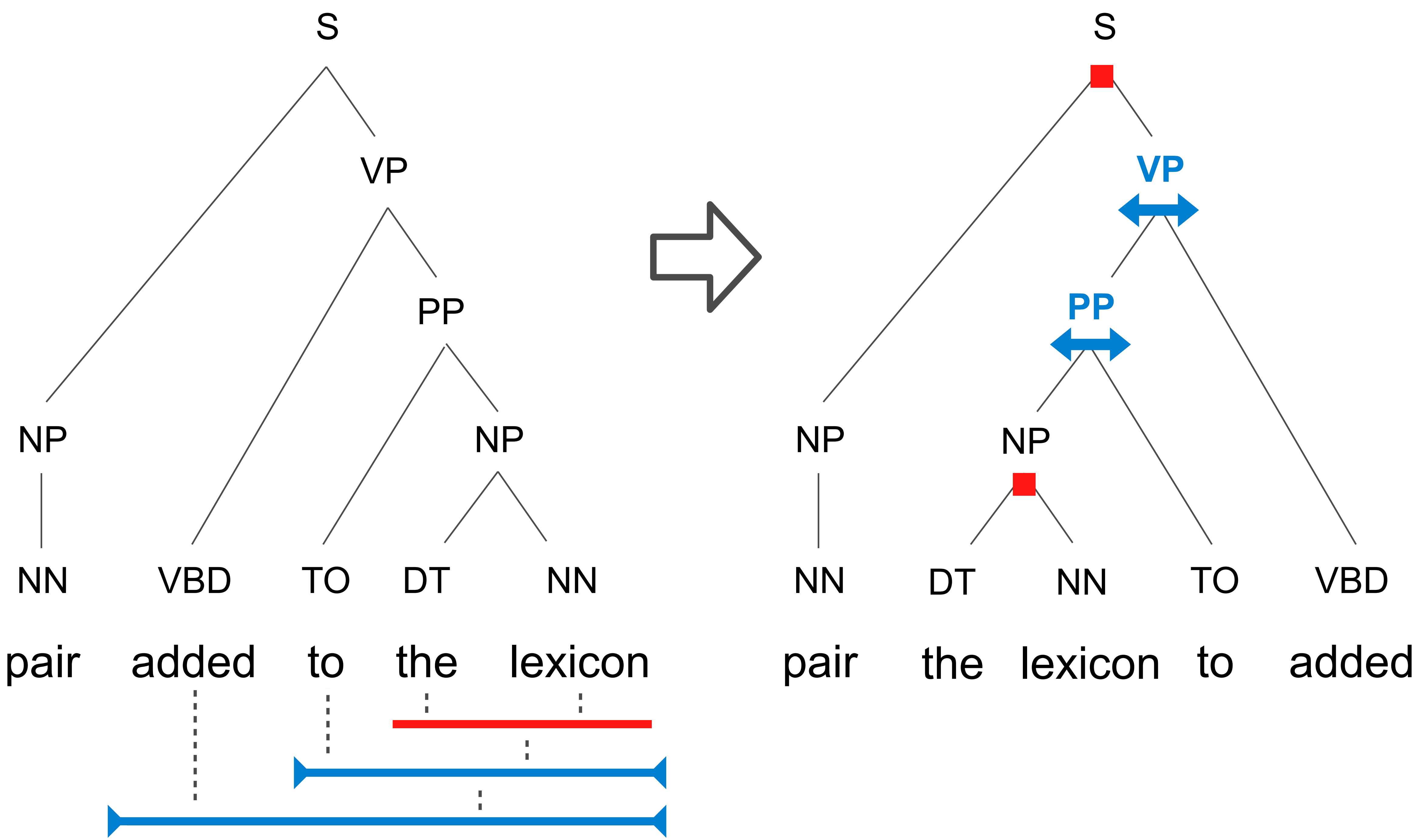

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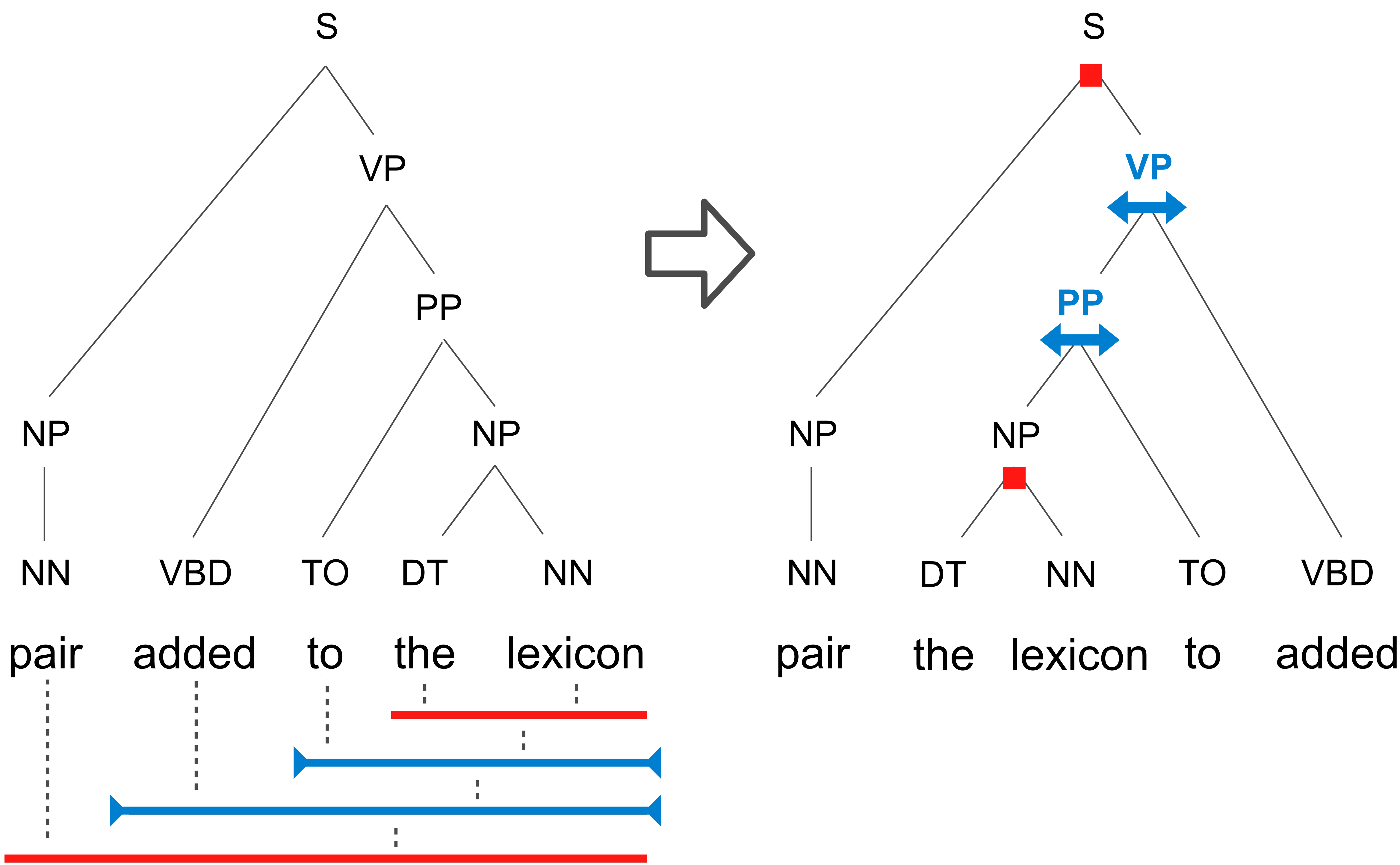

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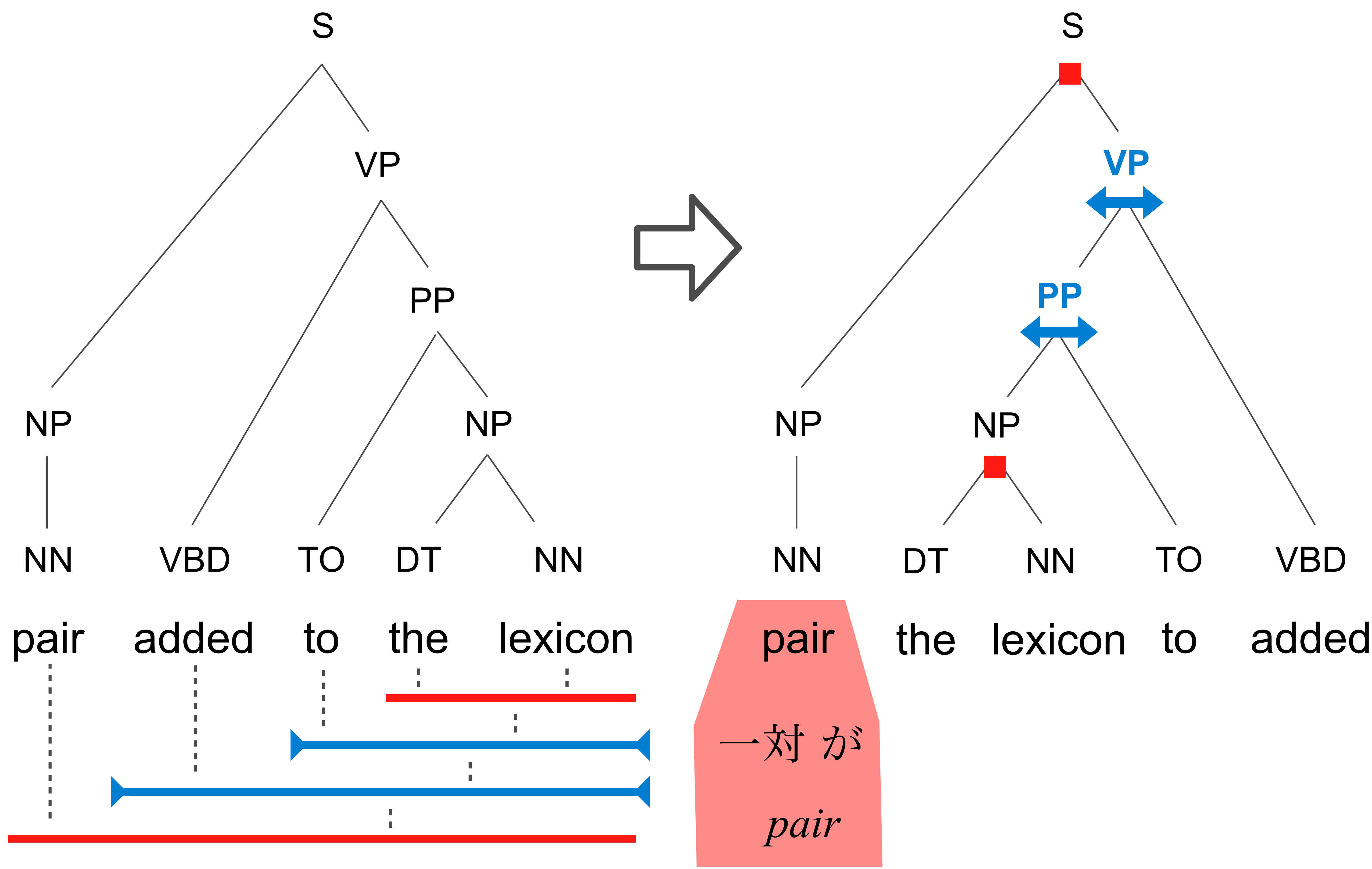

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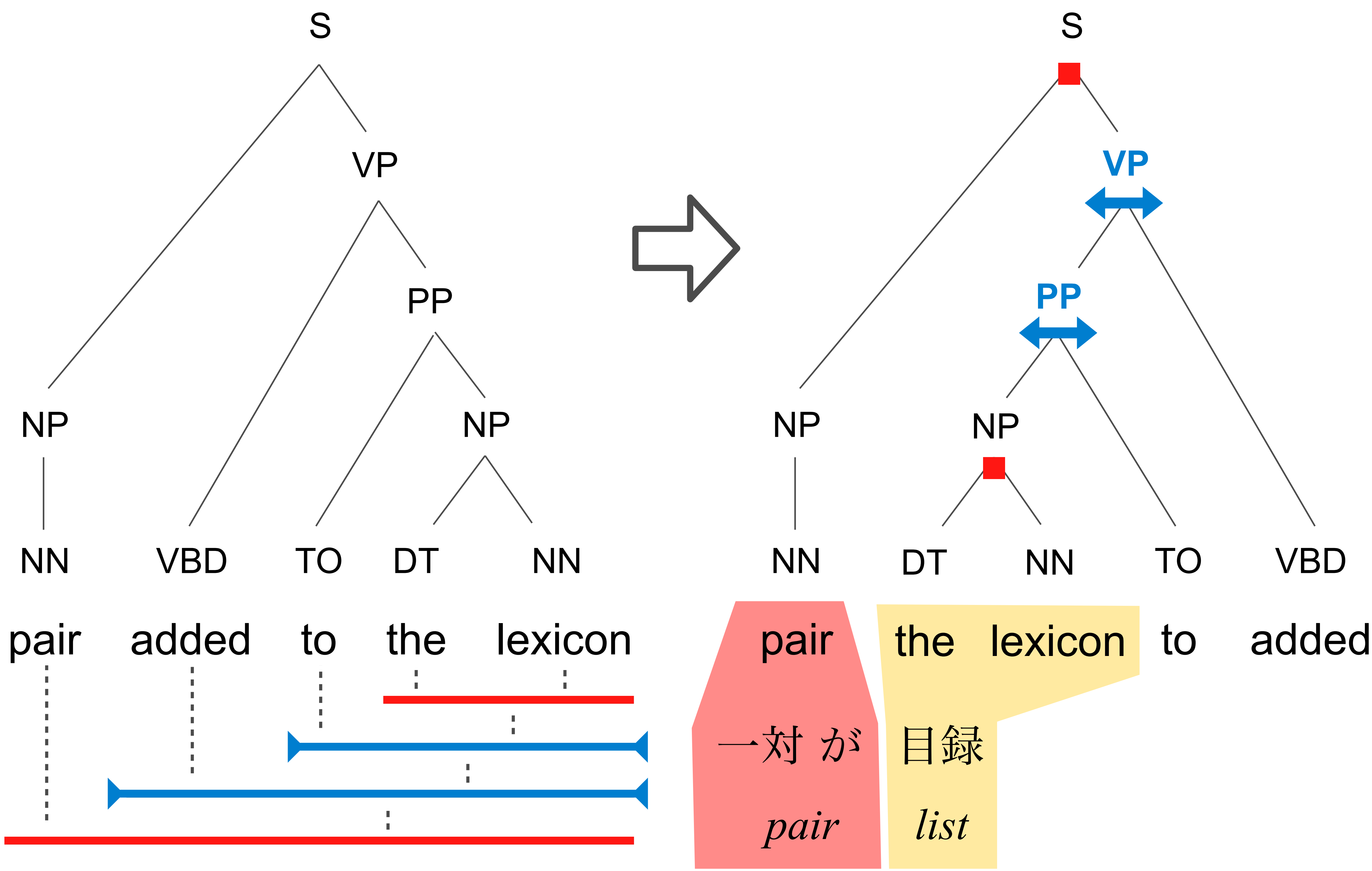

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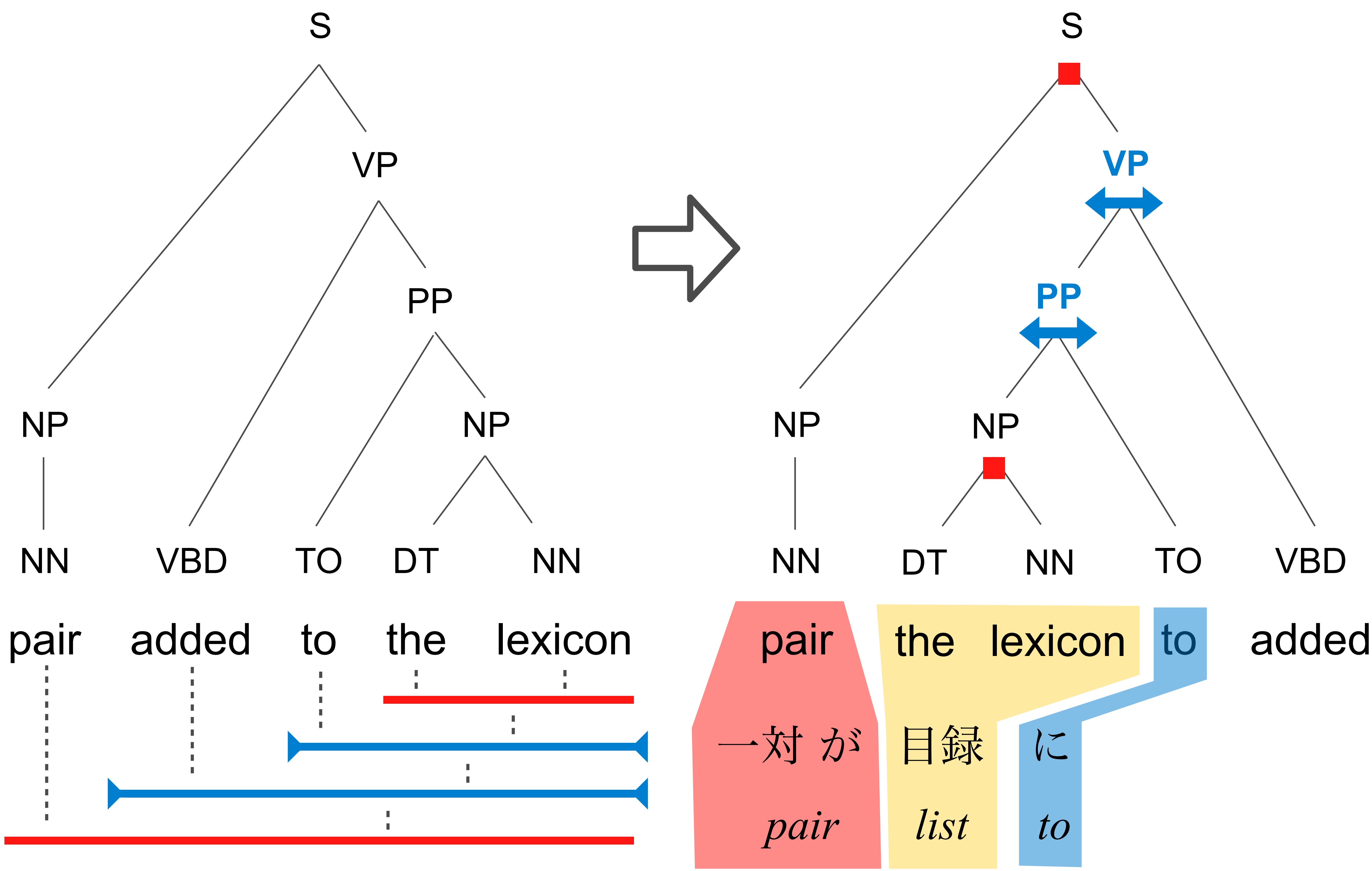

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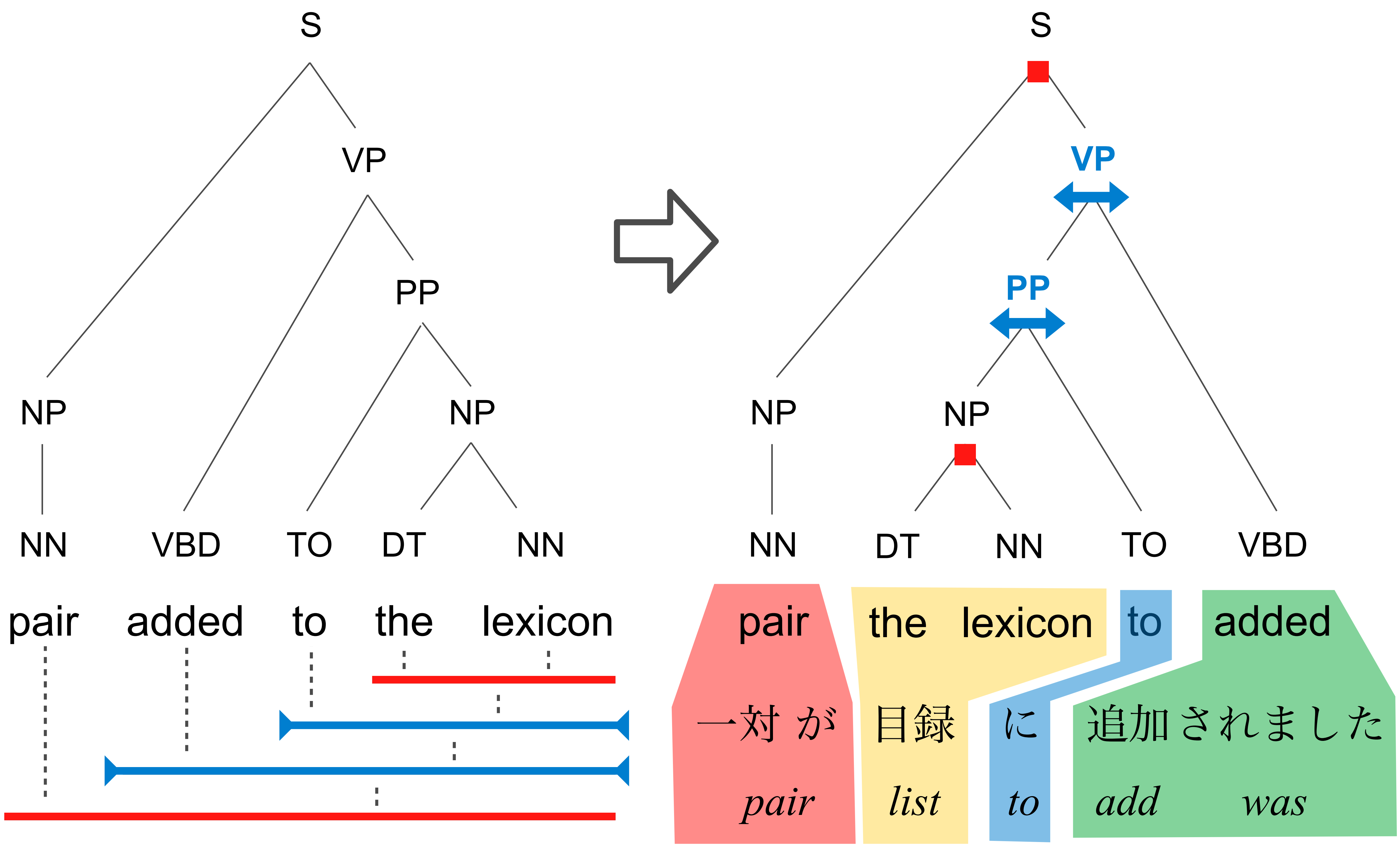

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**Decisions** **Methods**

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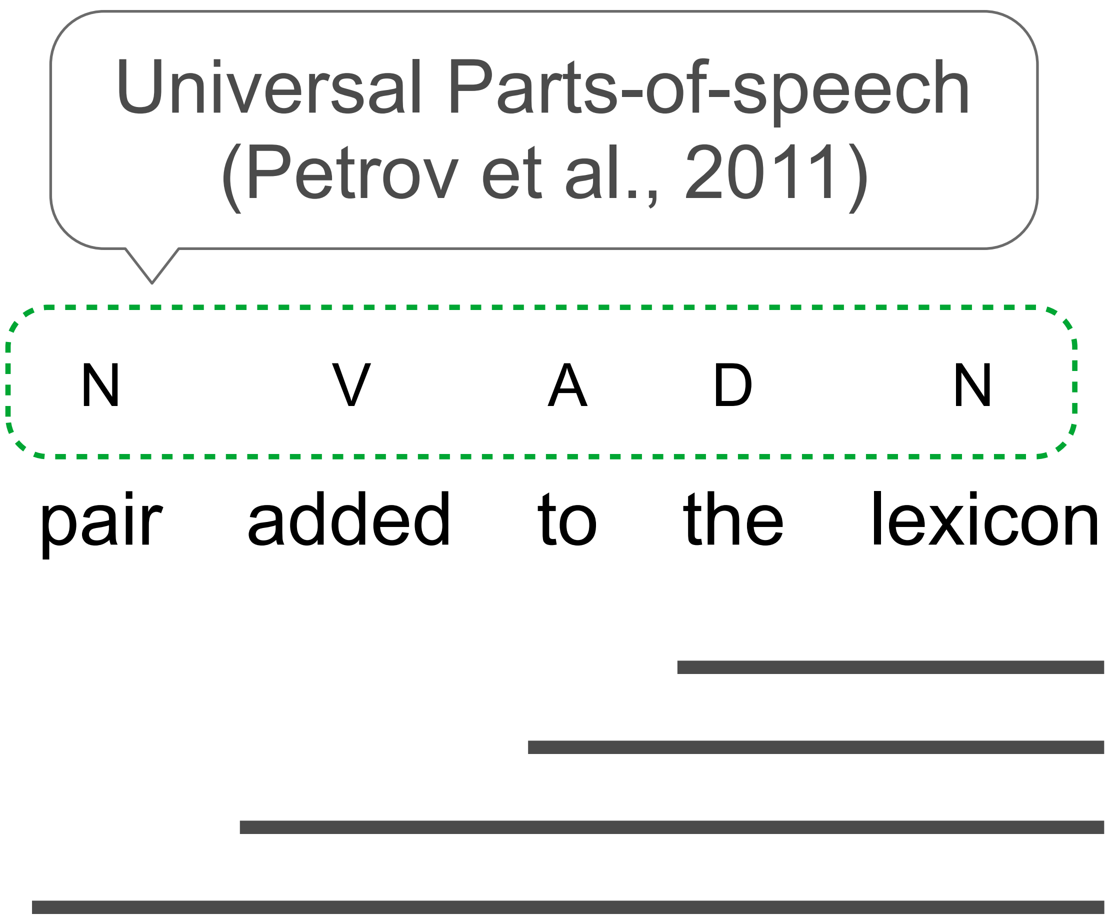


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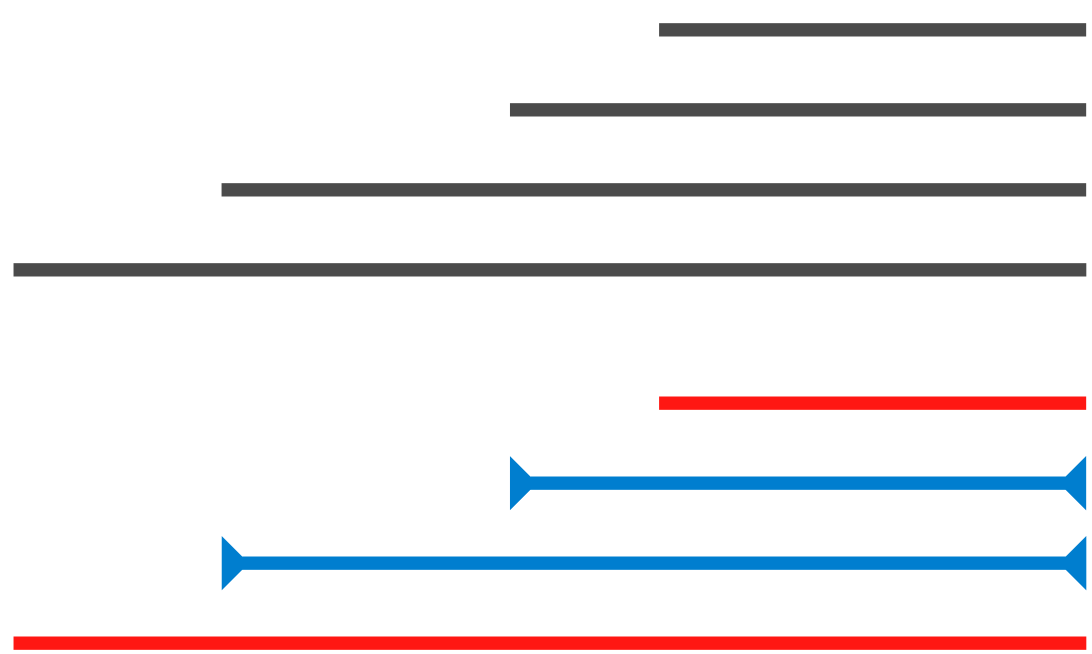

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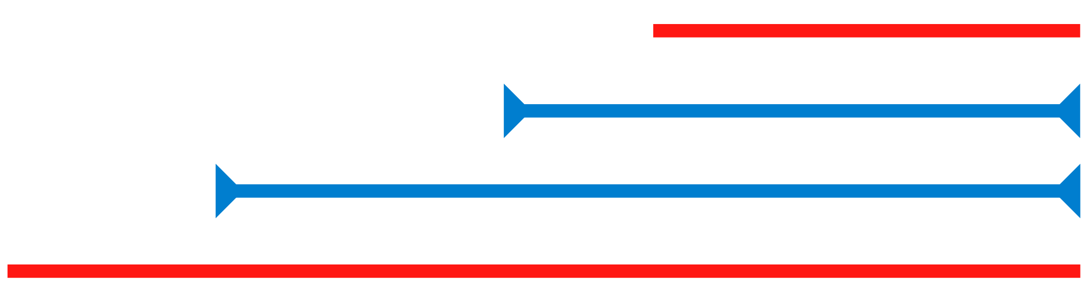

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- Alignments gives reordering
- Reordering classifier

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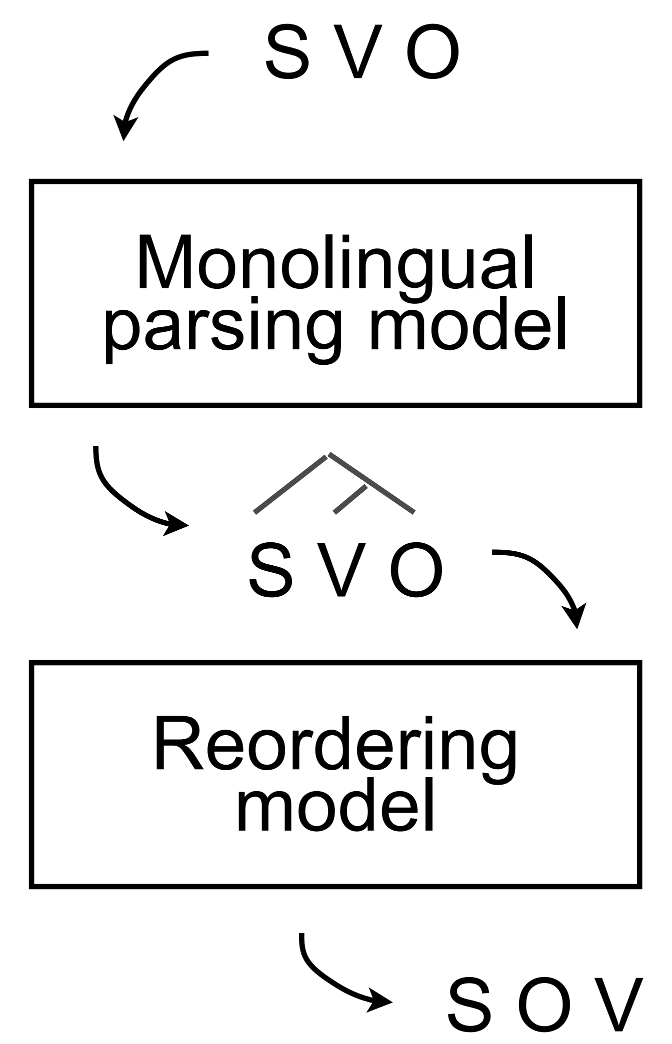
**Analyze Aligned Parallel Corpus**

**Pre-Ordering Pipeline**



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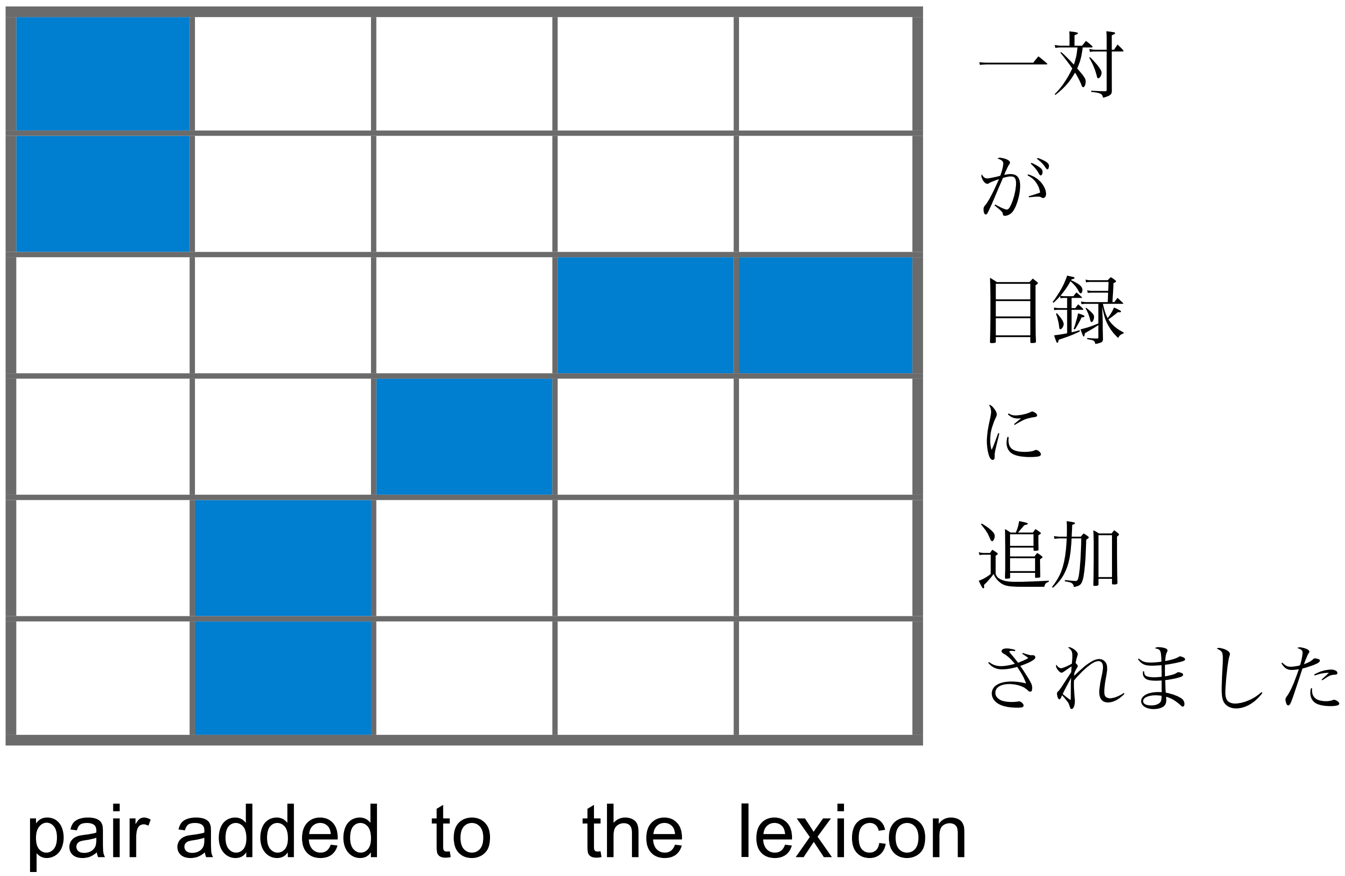


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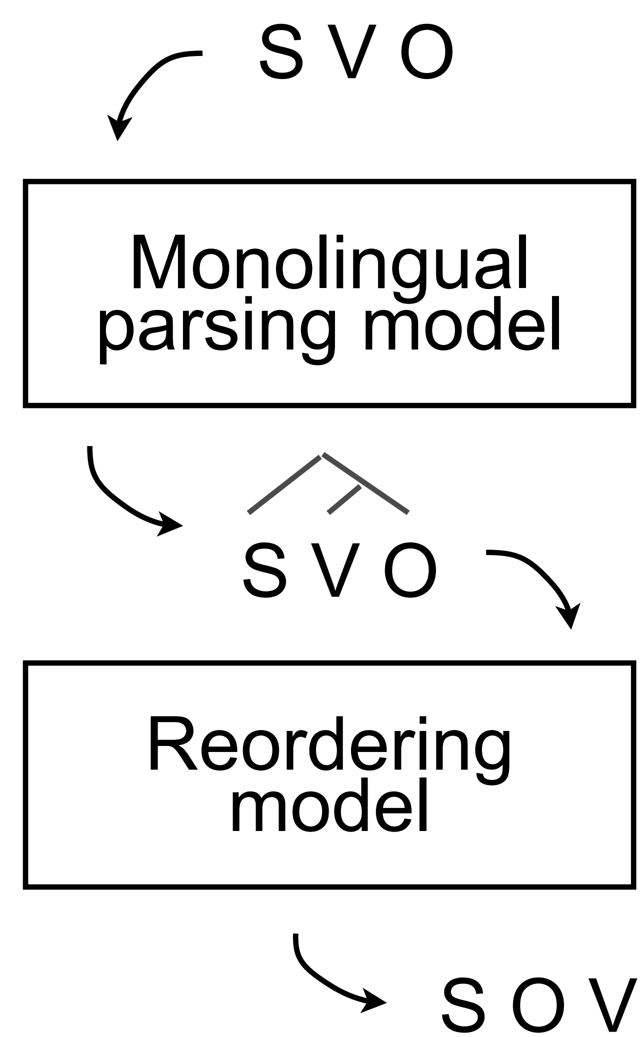

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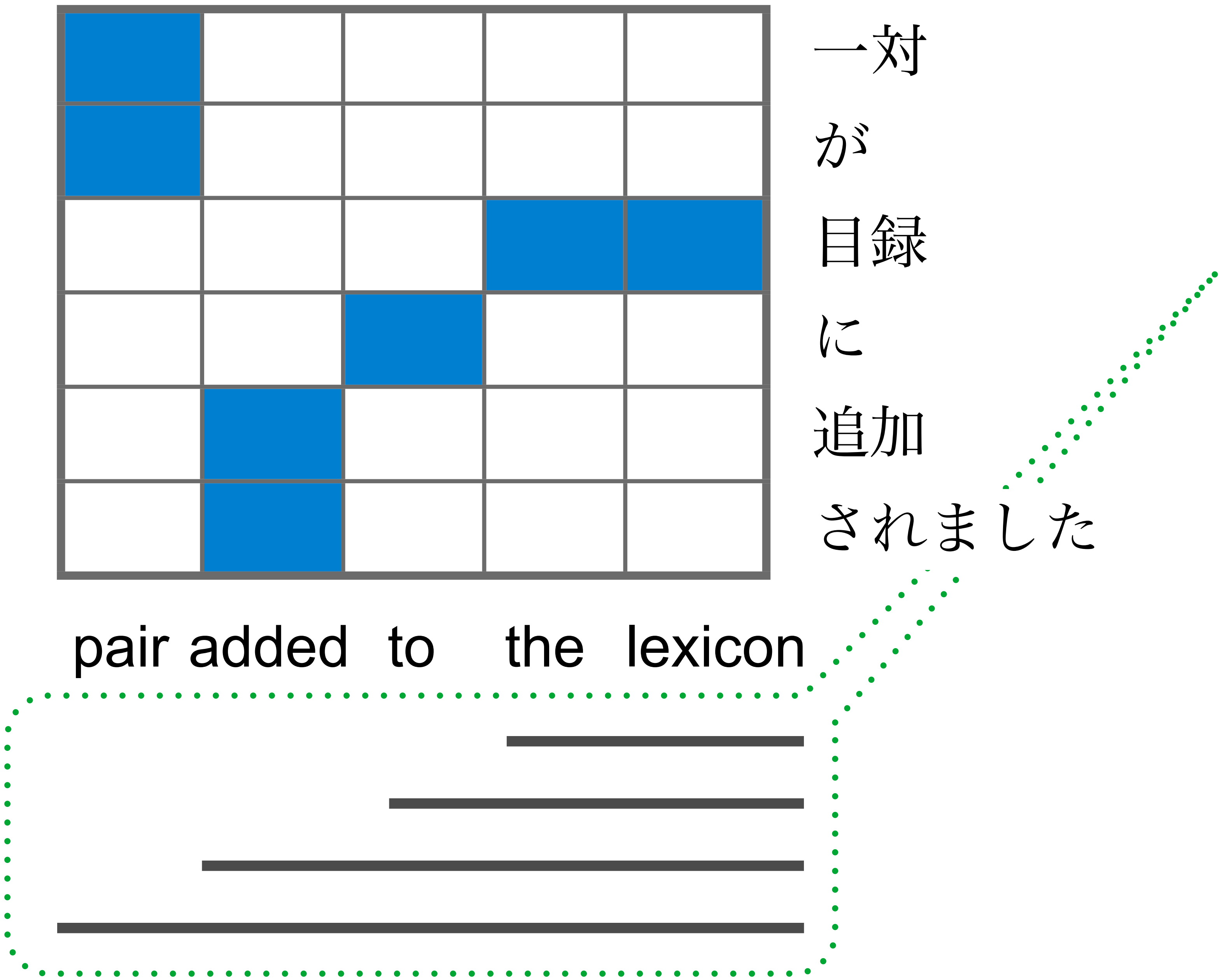


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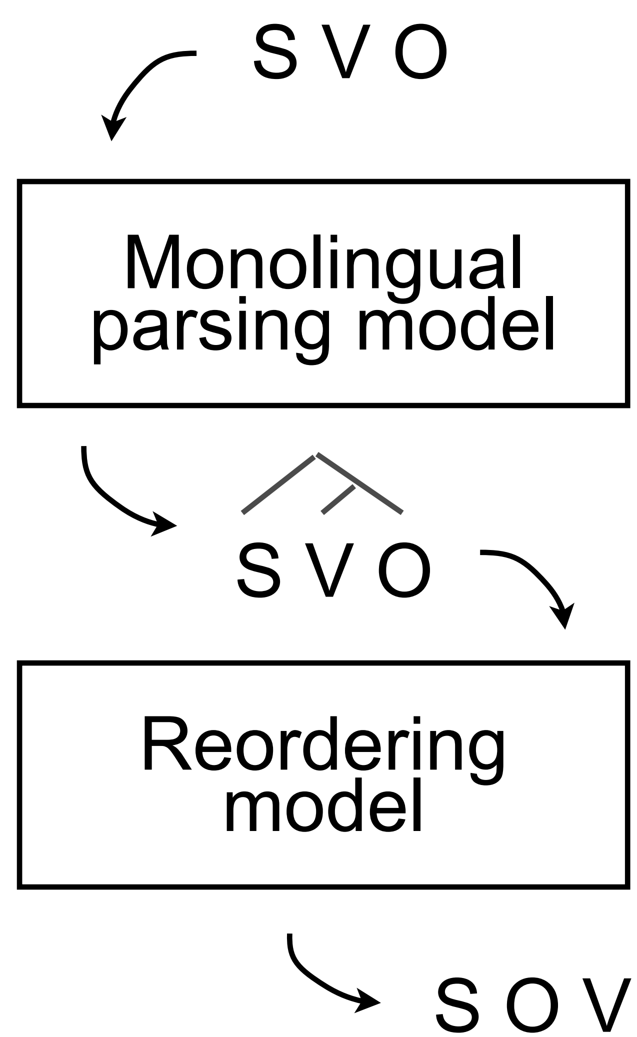

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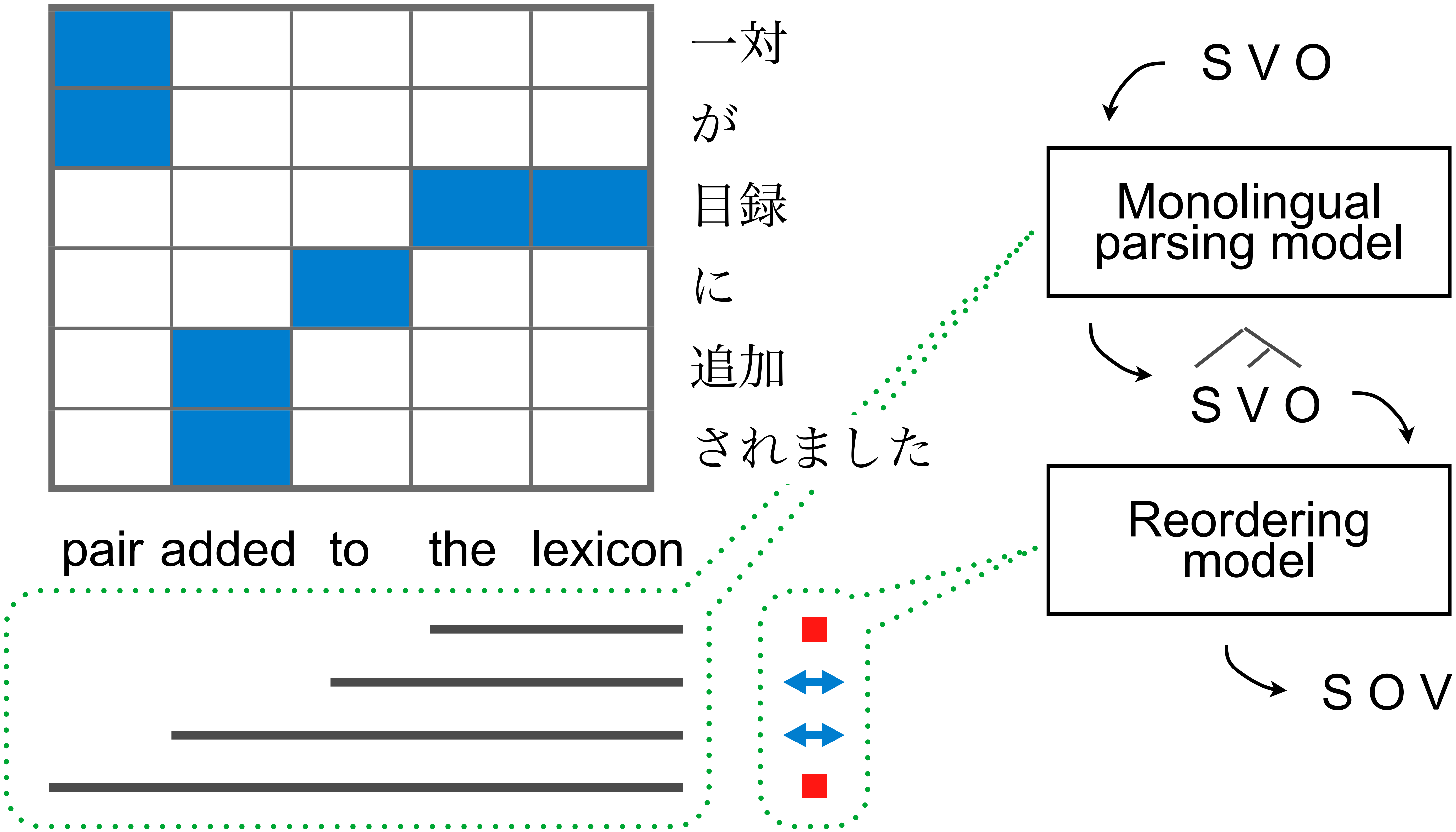

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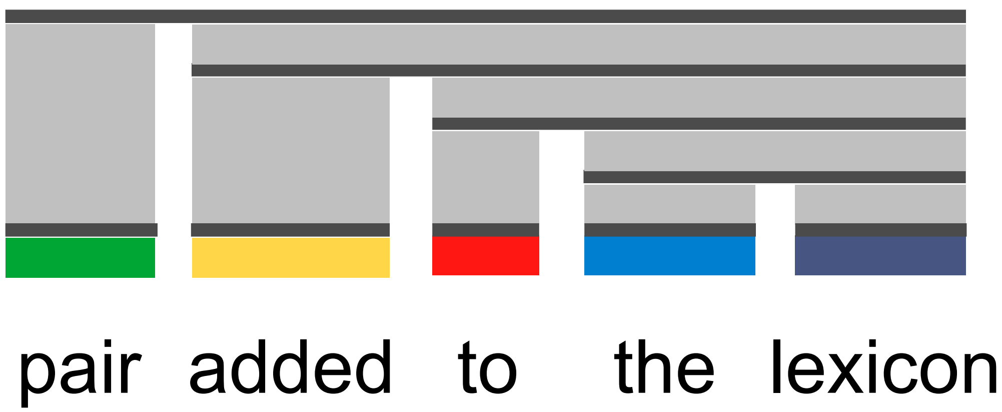


A tree is defined by the set of spans it contains

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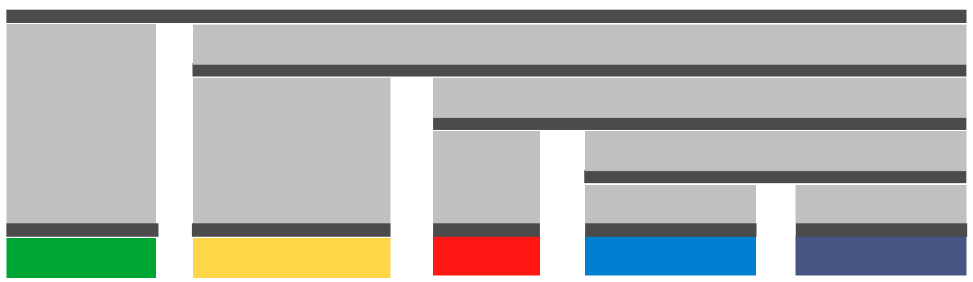

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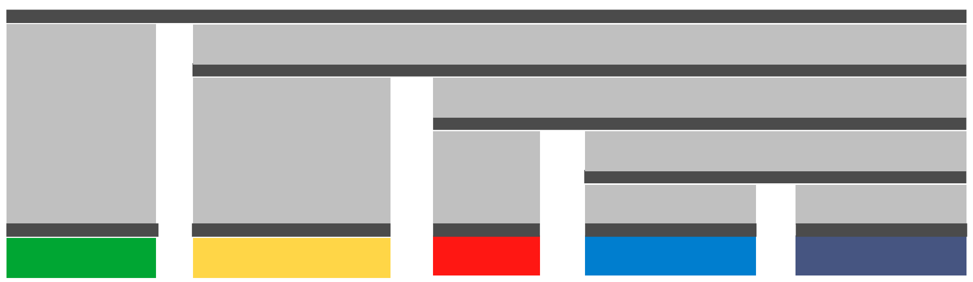

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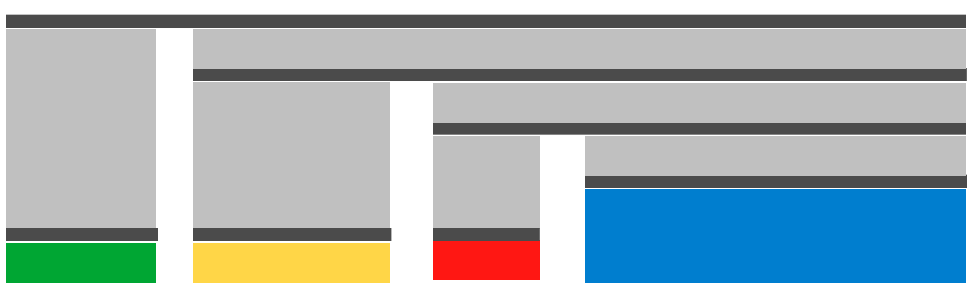

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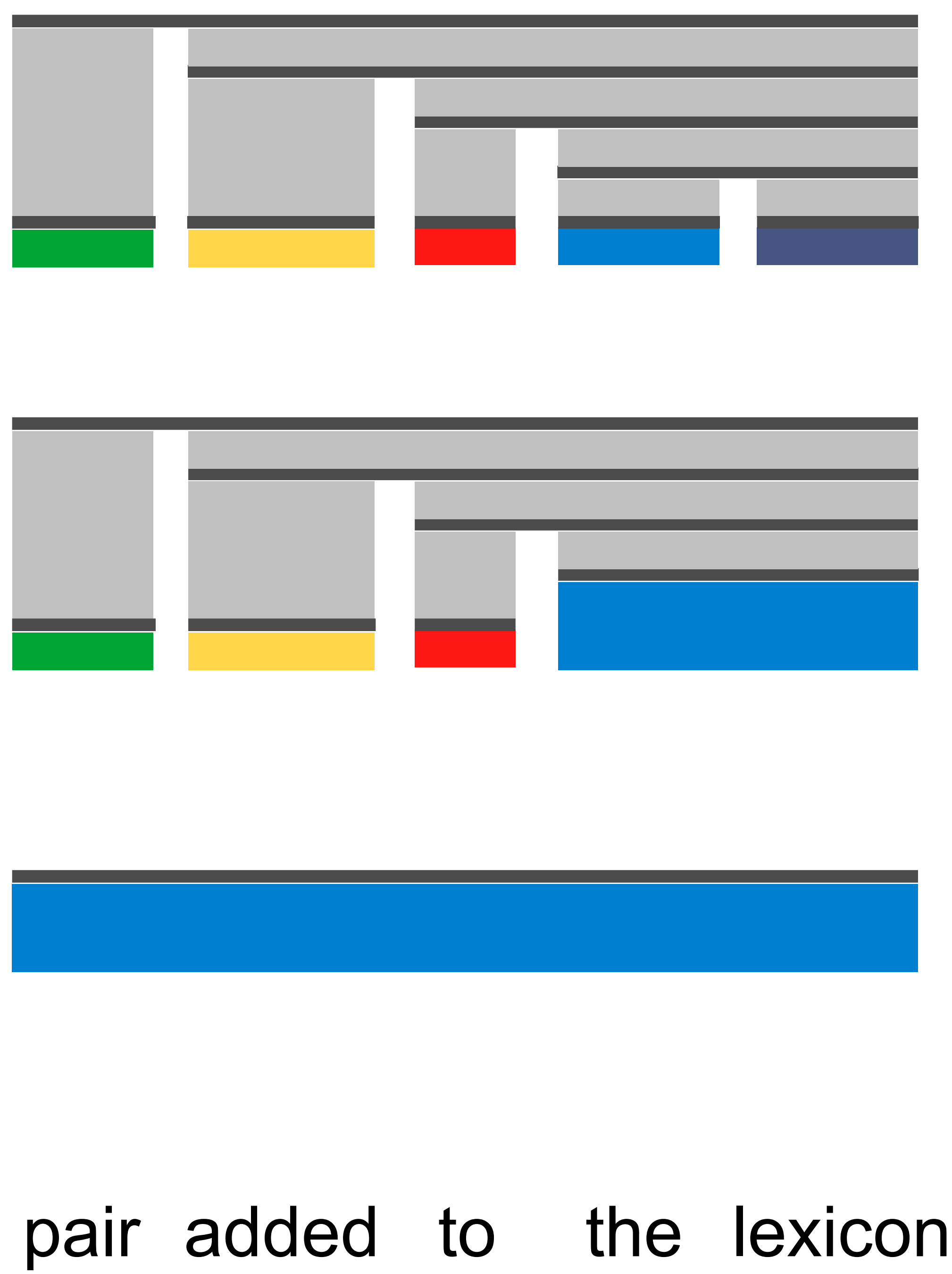
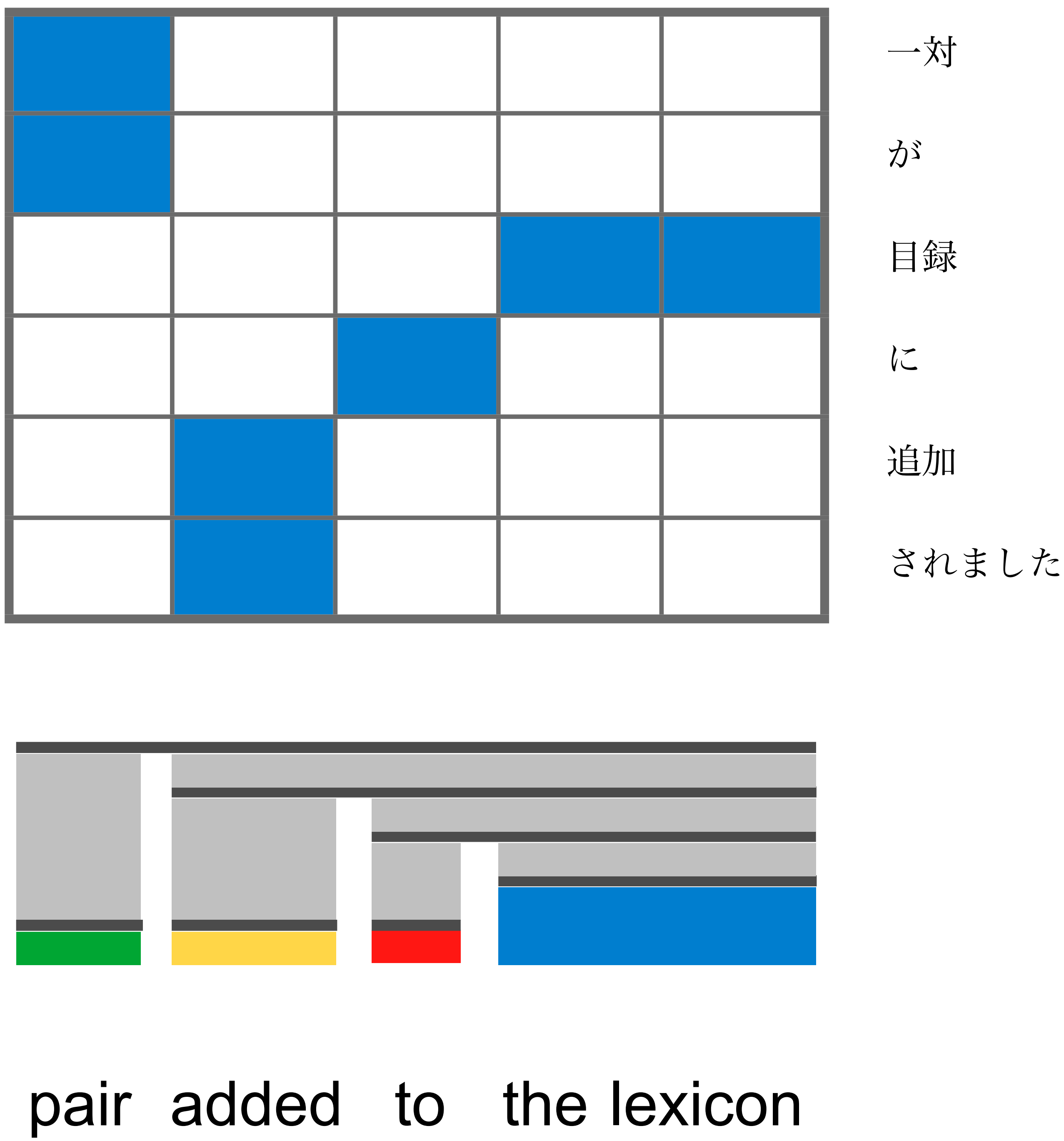



A tree is defined by the set of spans it contains

Not every word will correspond to a span

A tree can be composed of only a single span

# Parallel Parsing Model Constraint



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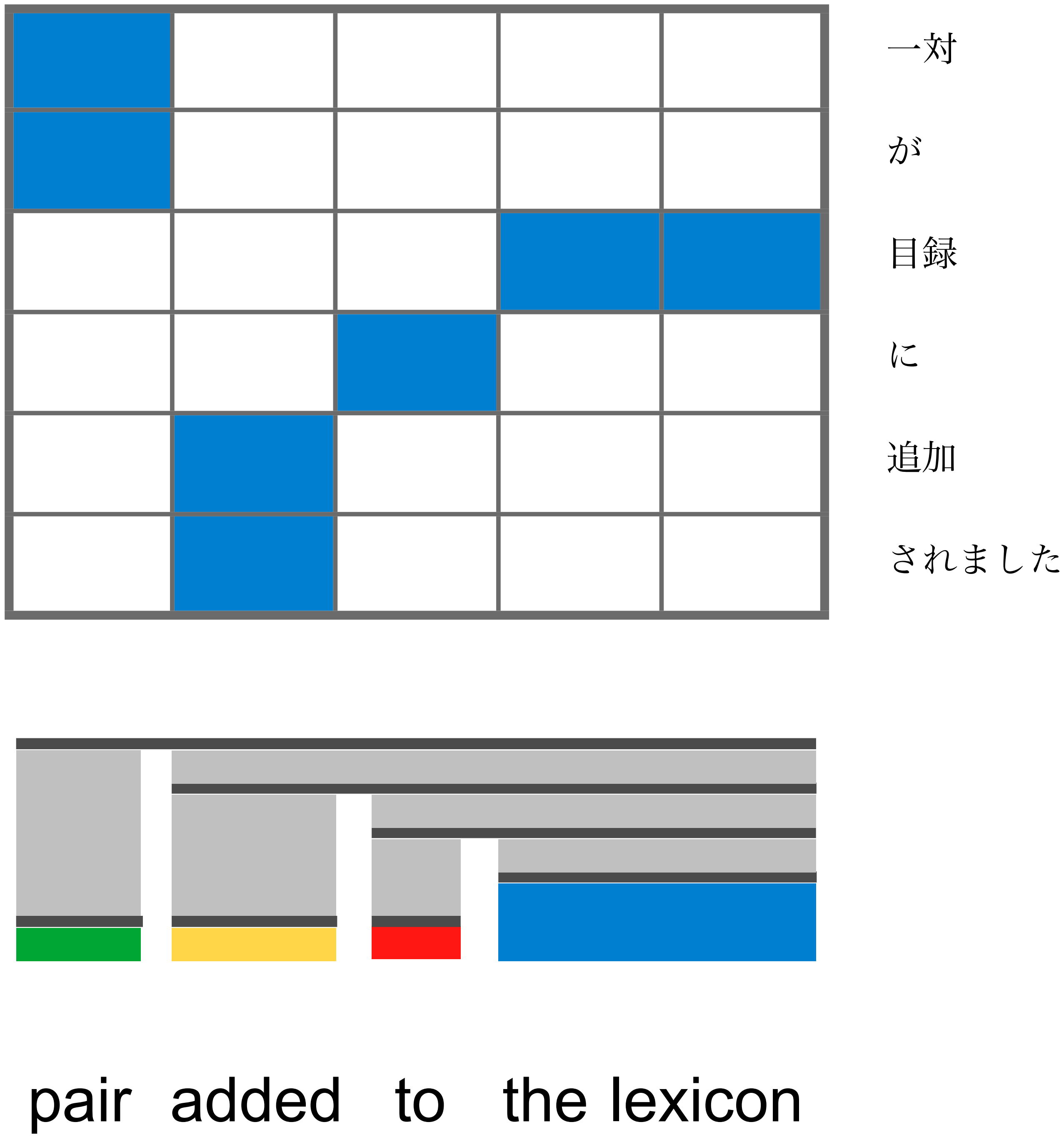


An alignment licenses a tree if every tree span is *aligned contiguously*

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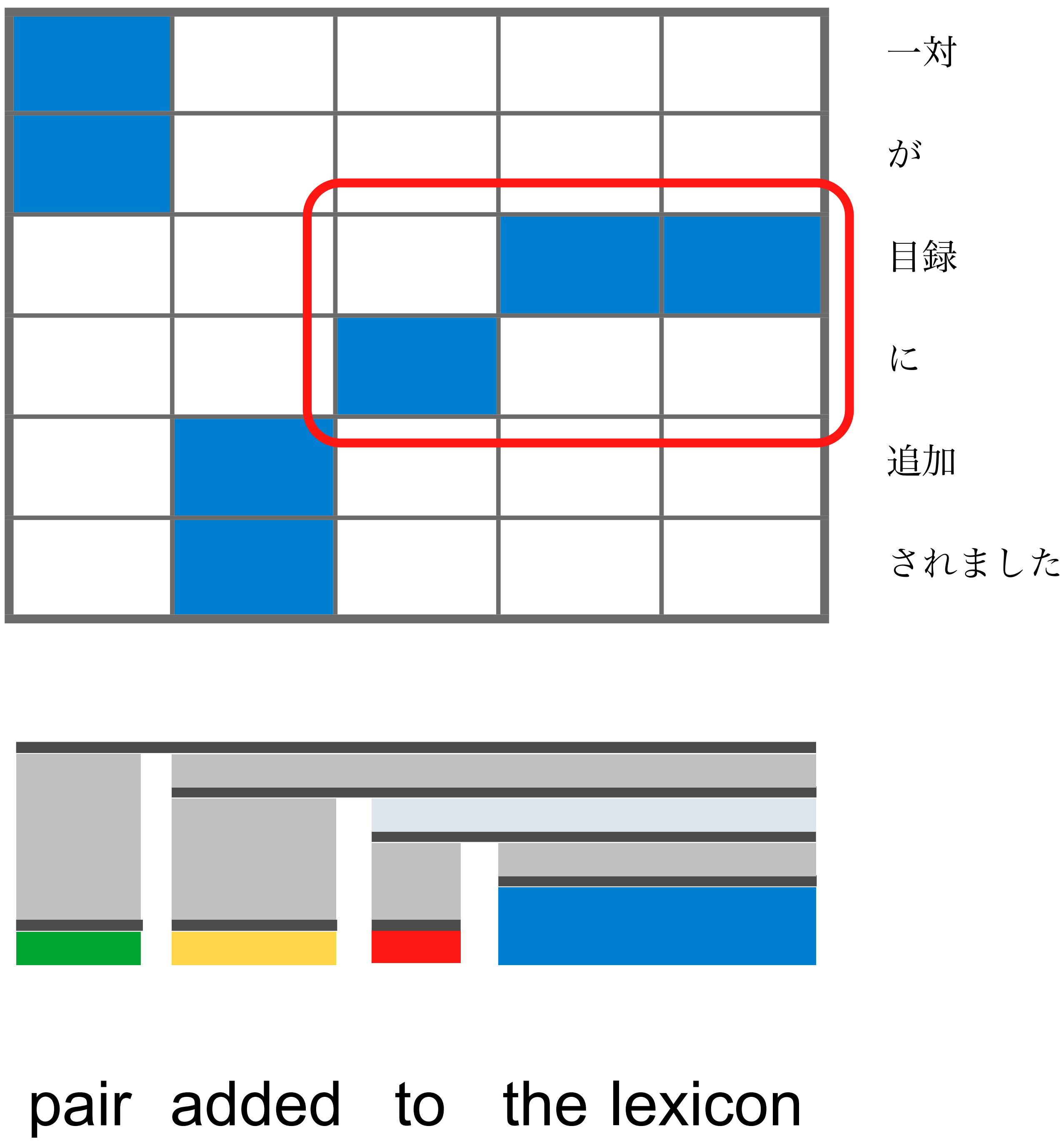


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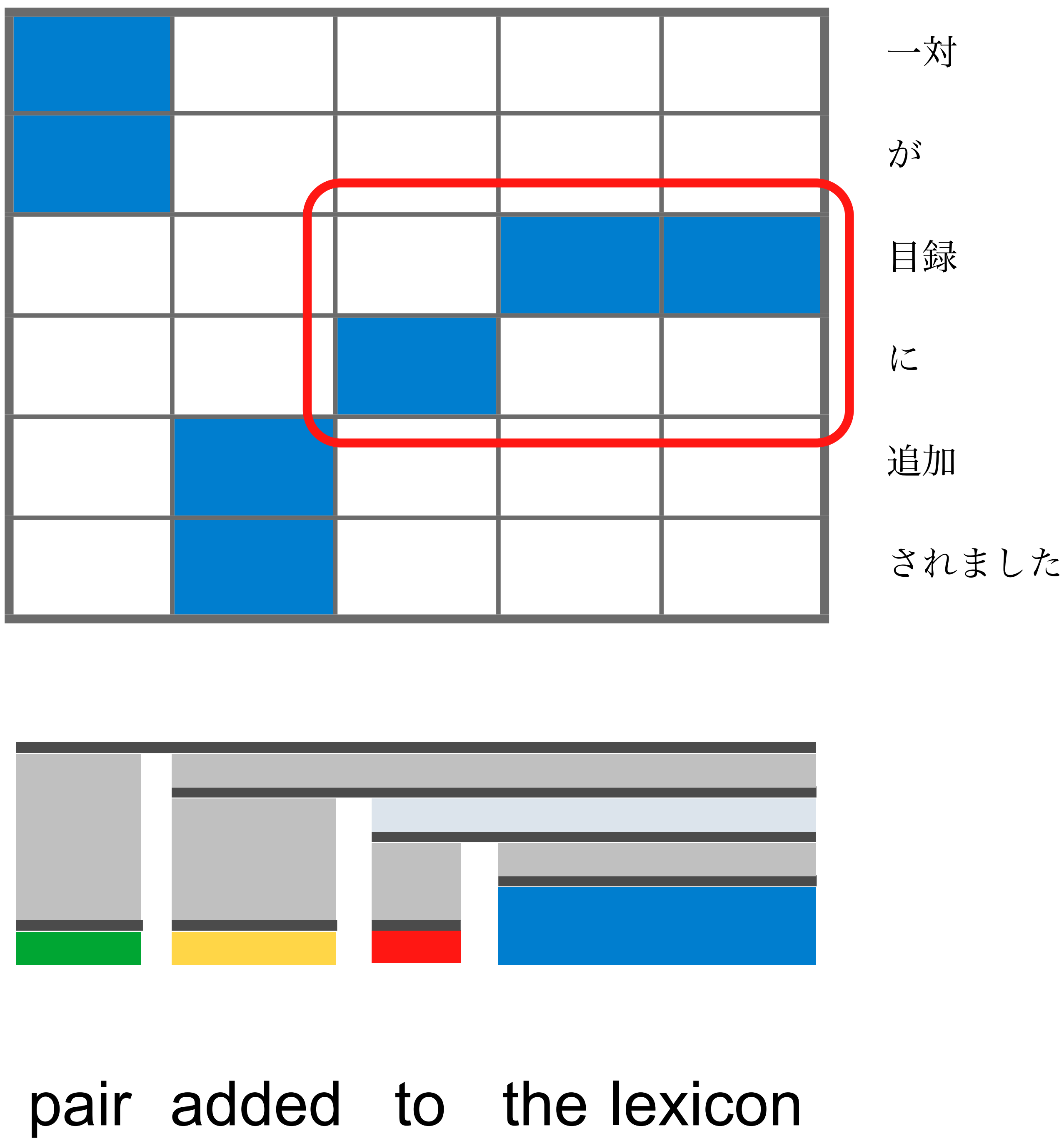


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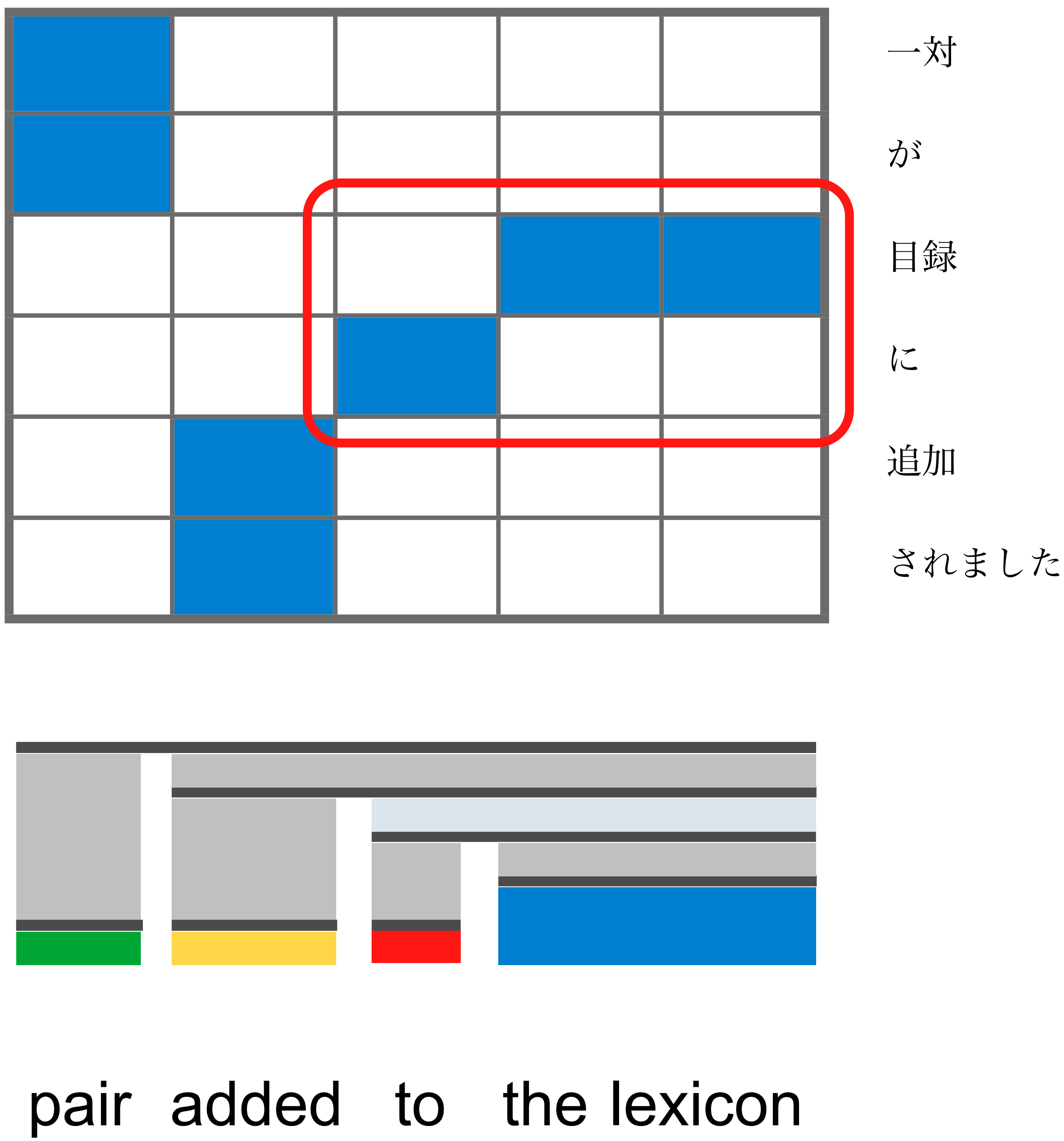


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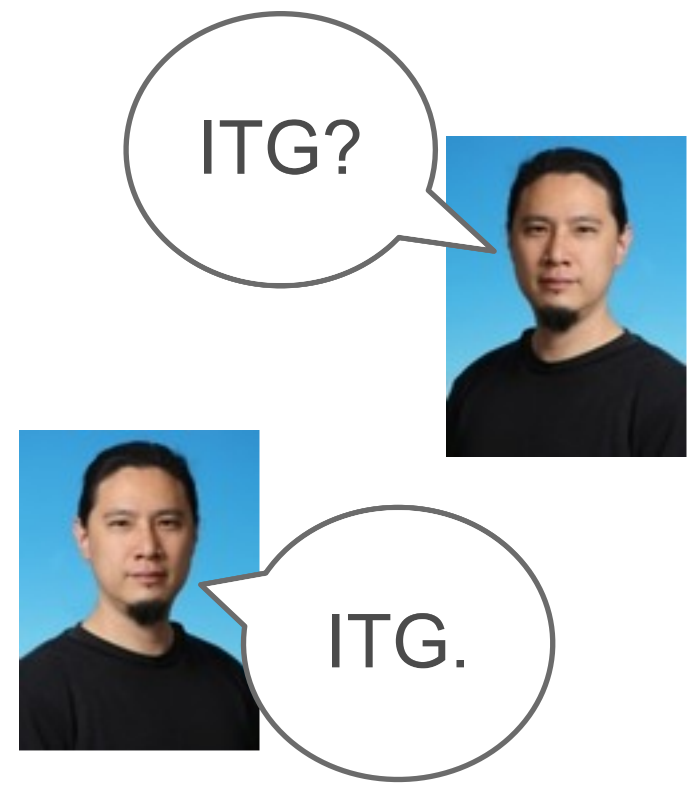

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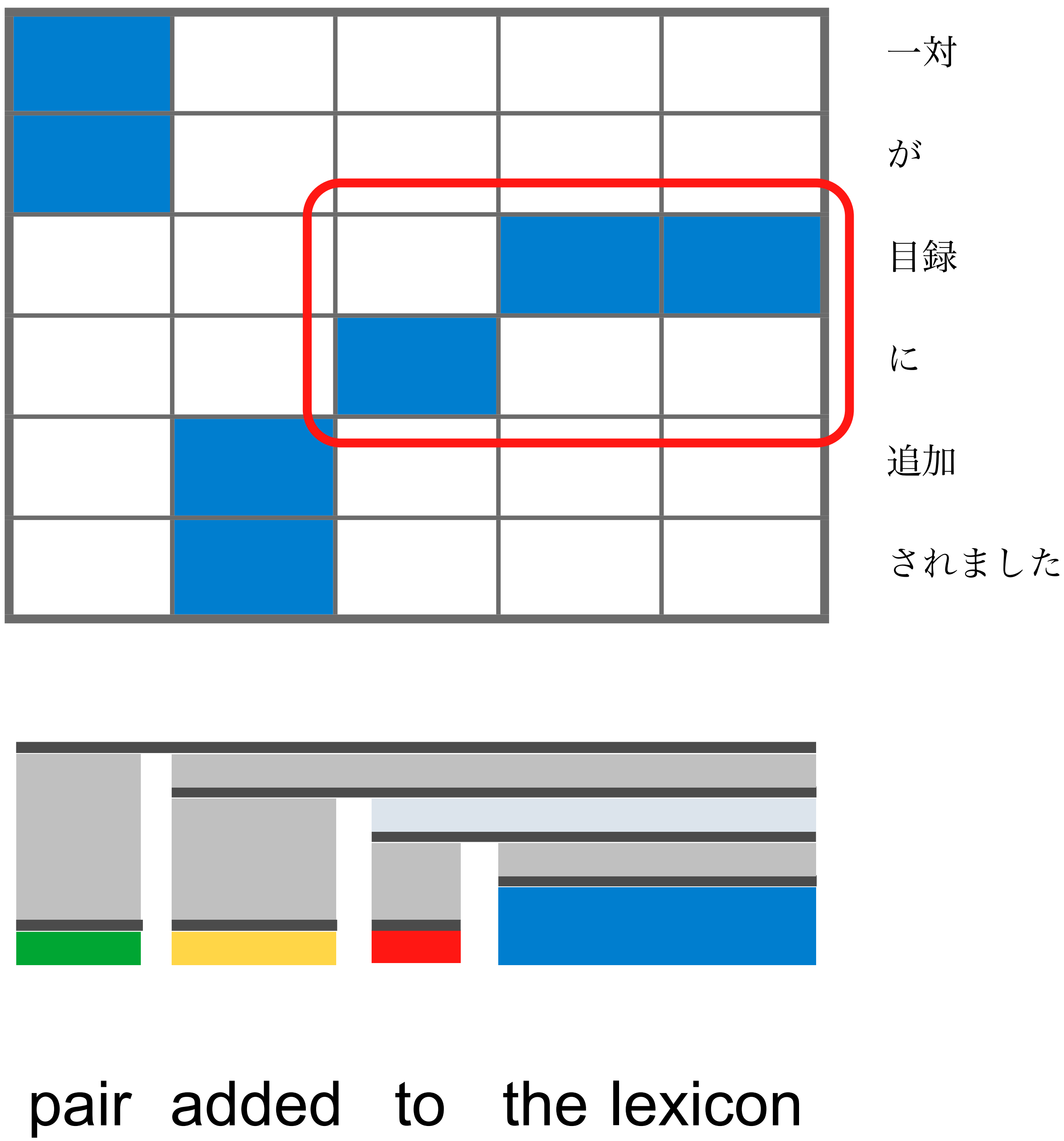


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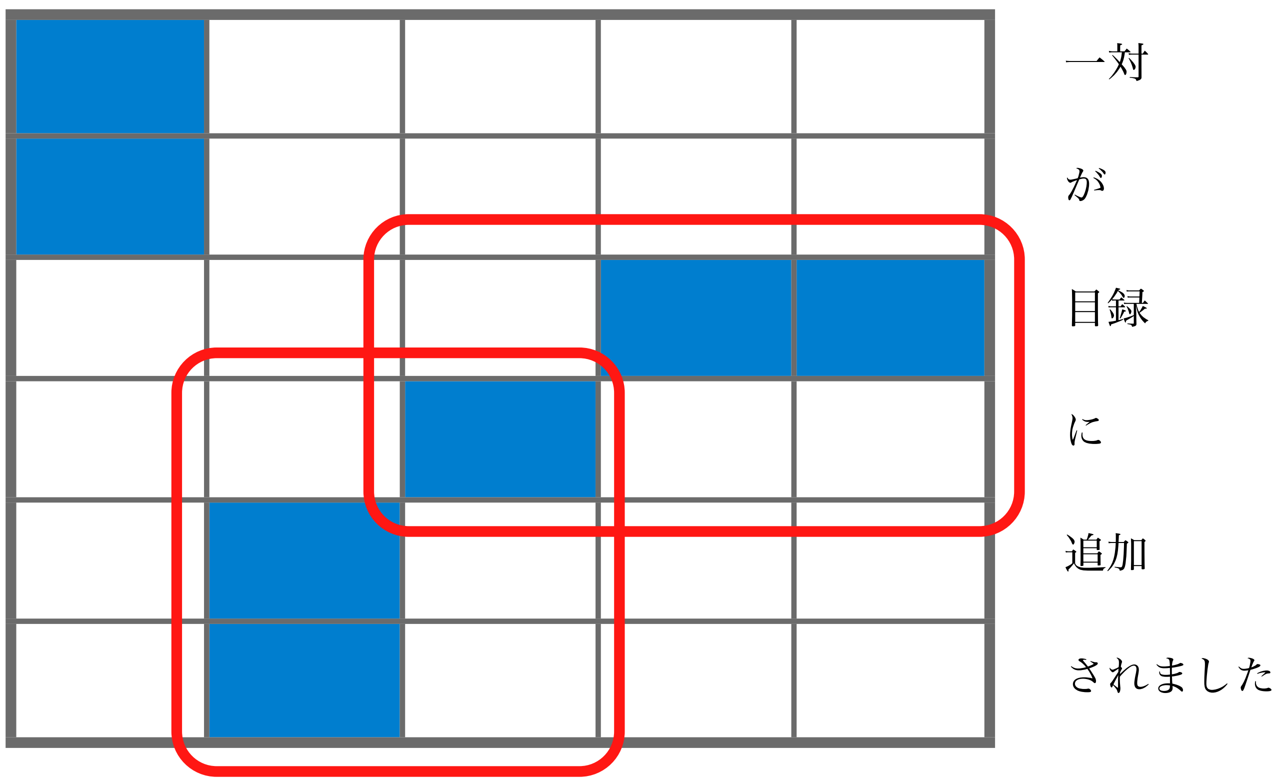


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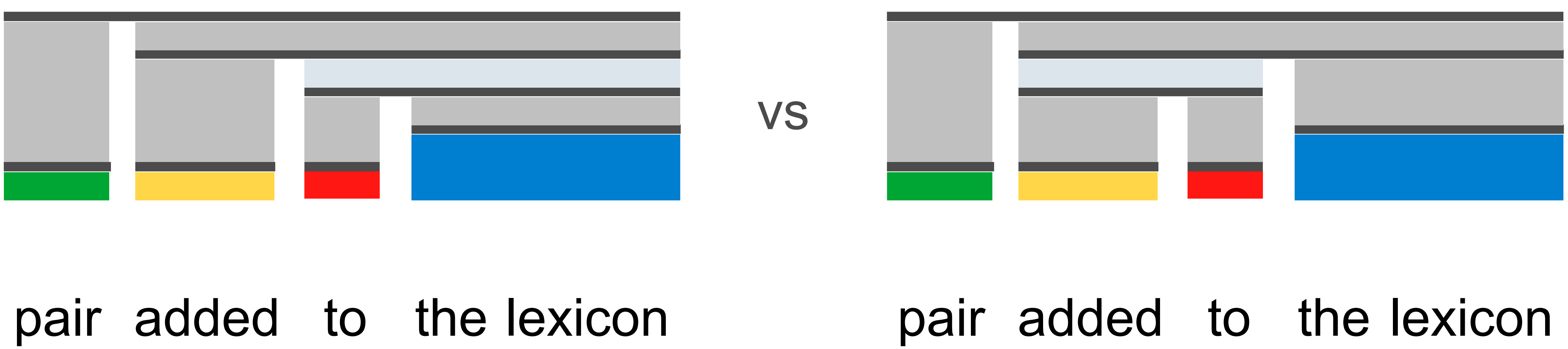

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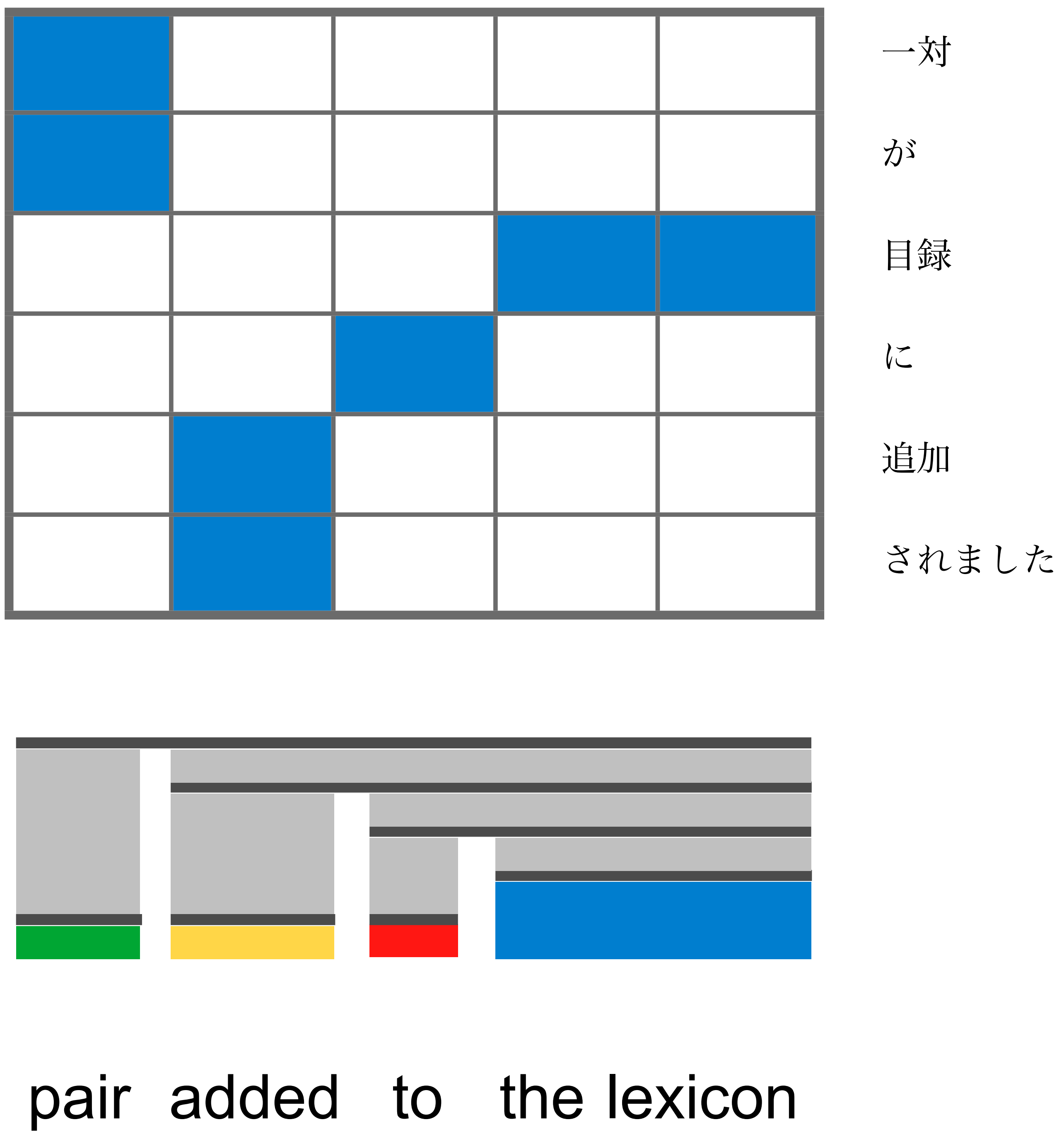


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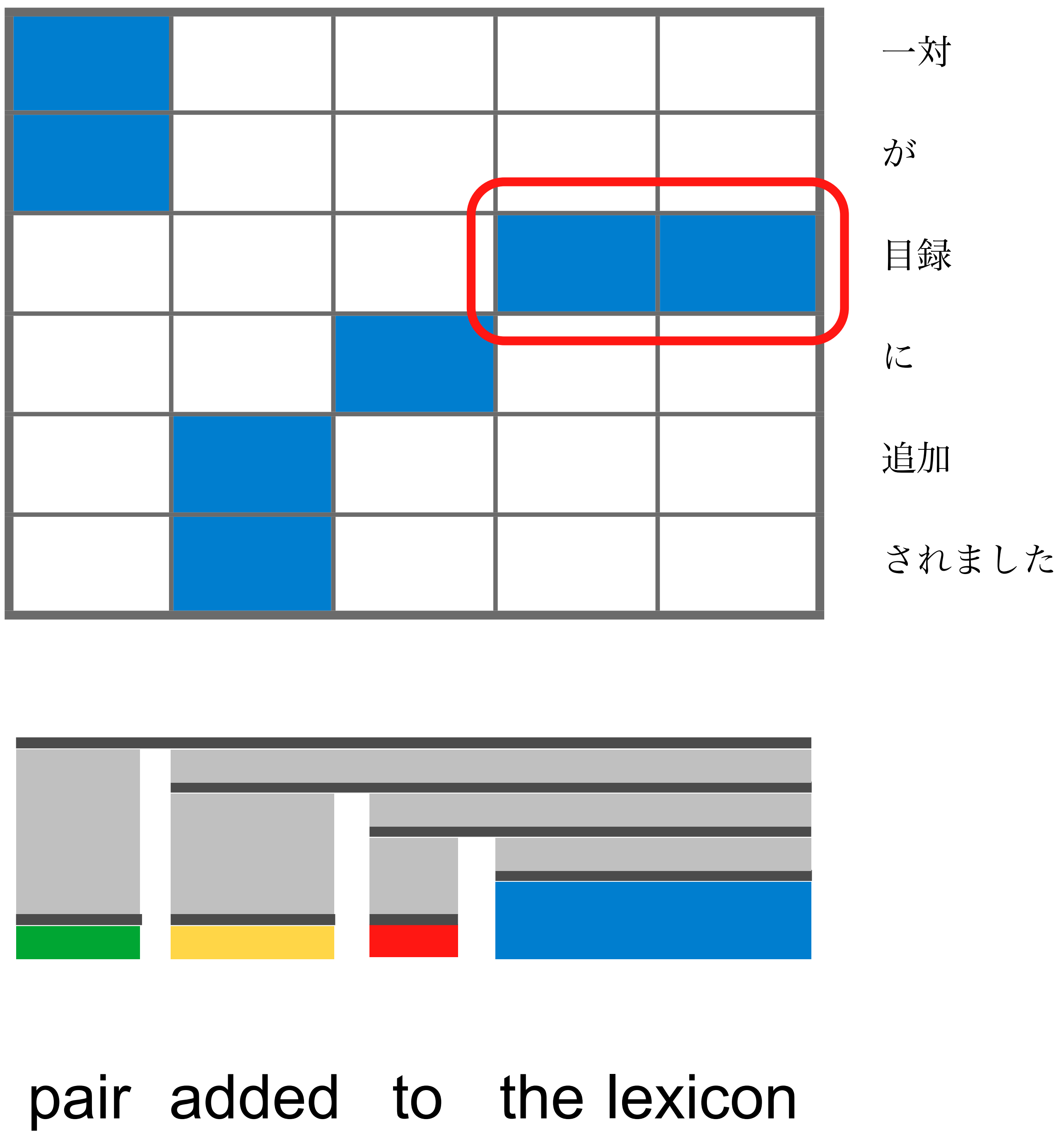


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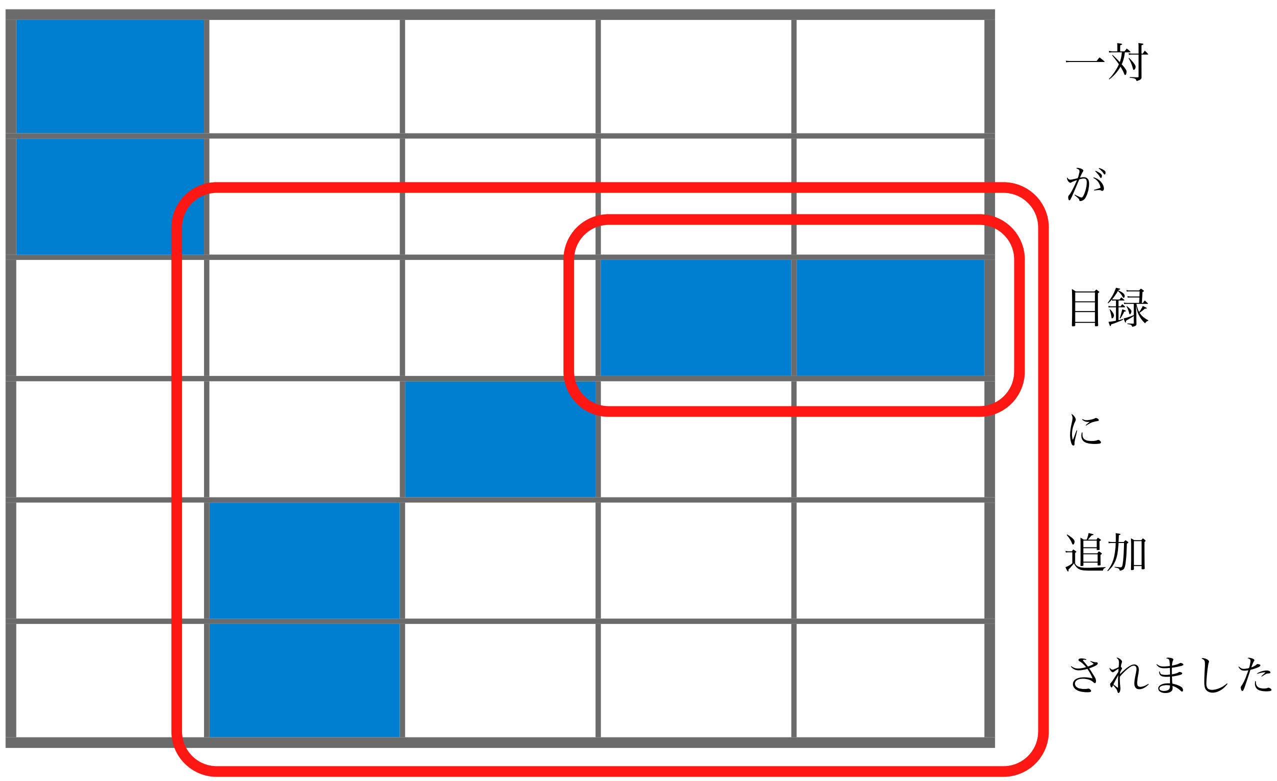


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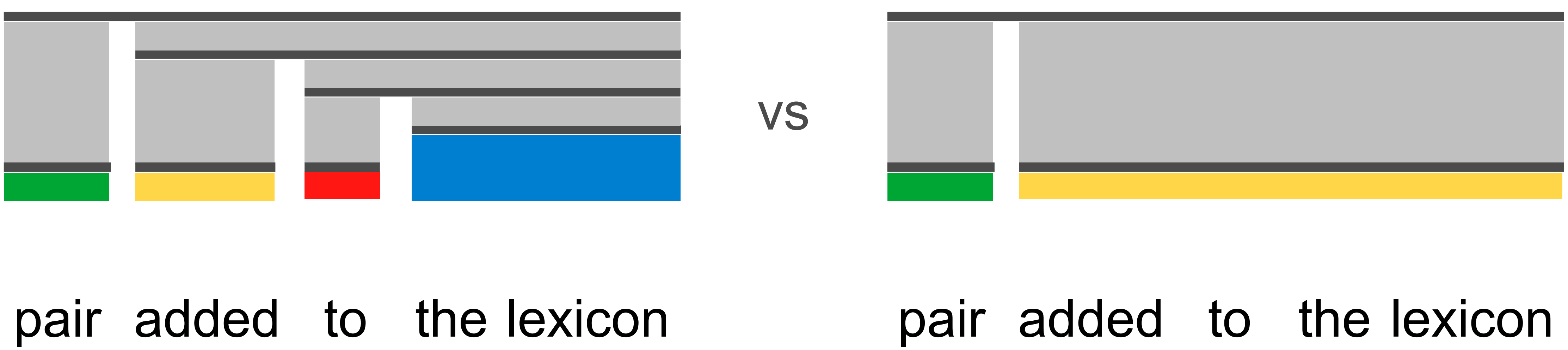

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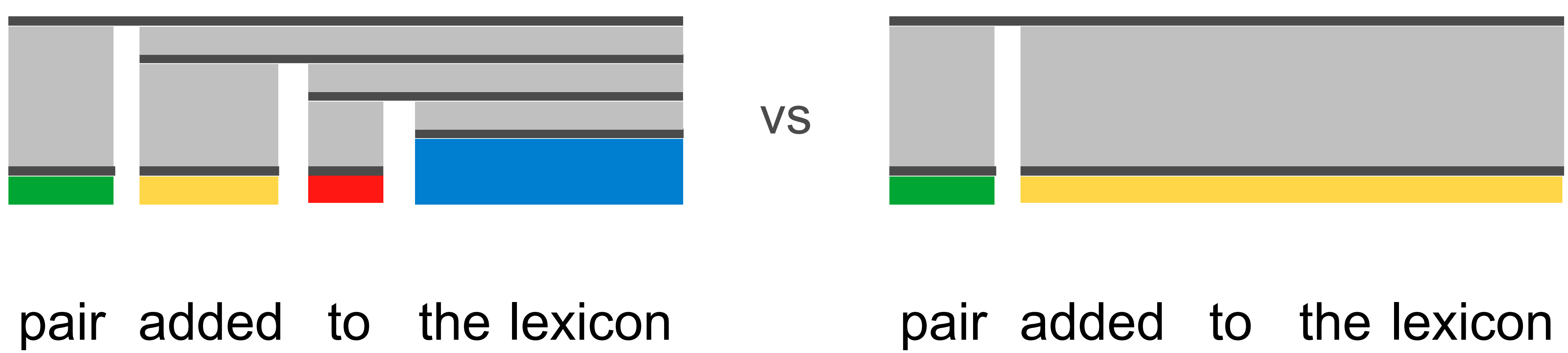

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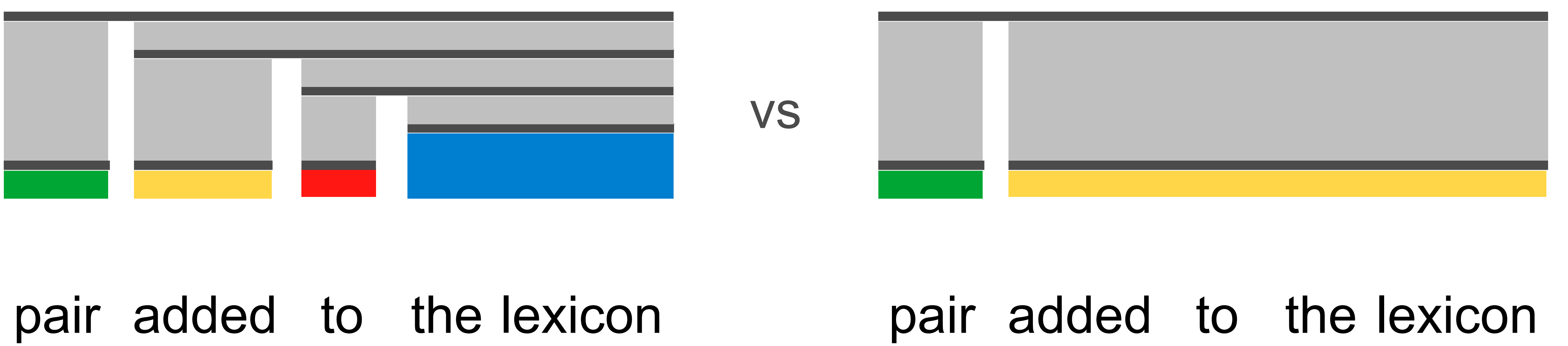

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English-Japanese

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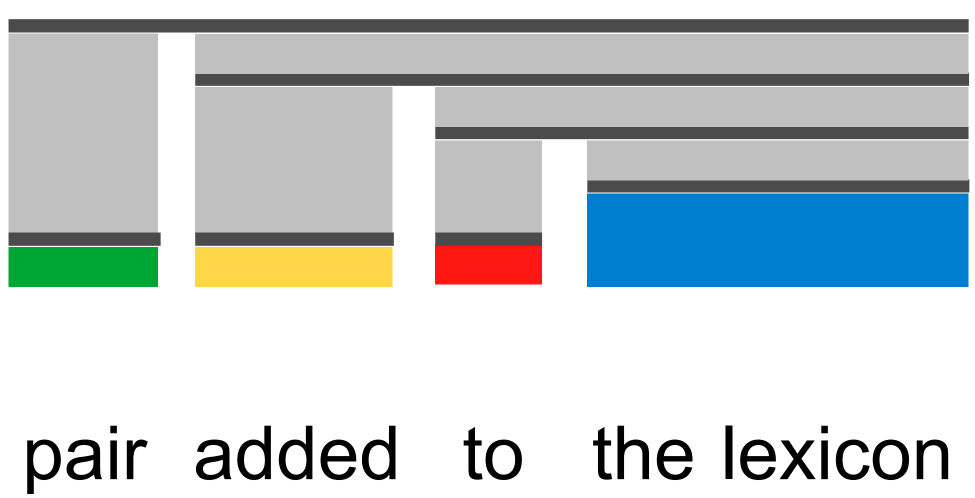

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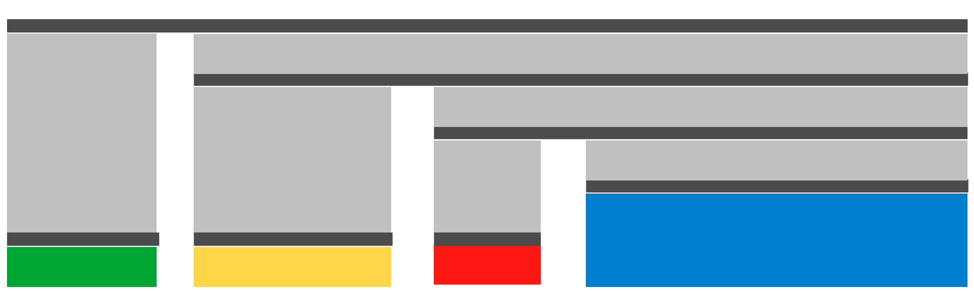

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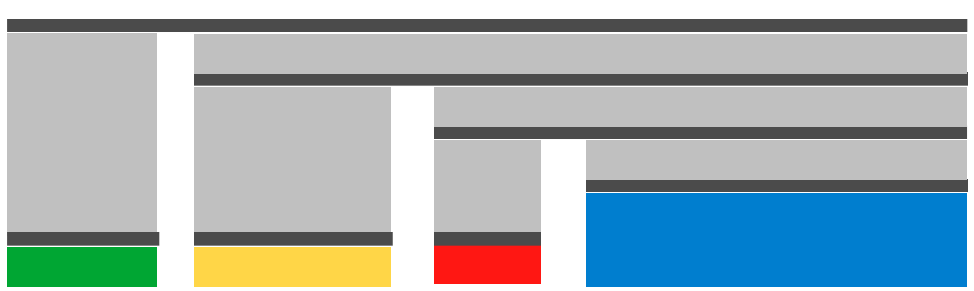

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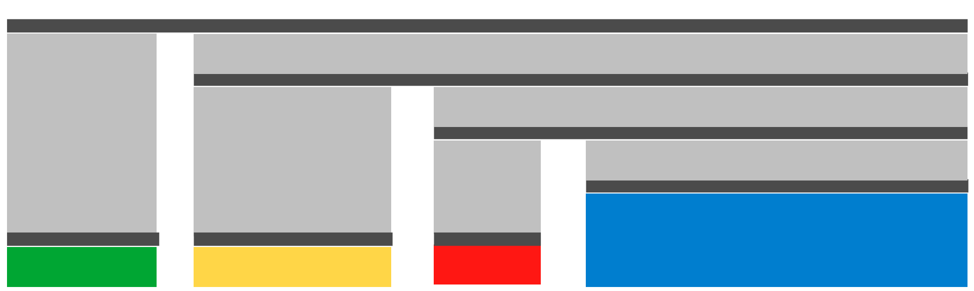

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$\prod_e \phi(e)$, constituents, contexts, span length, common words, ...

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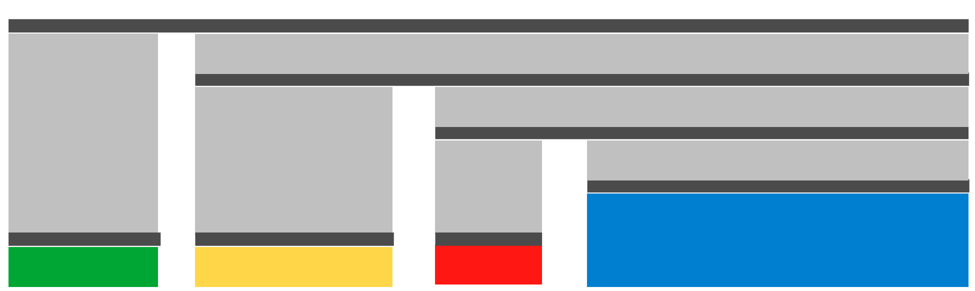

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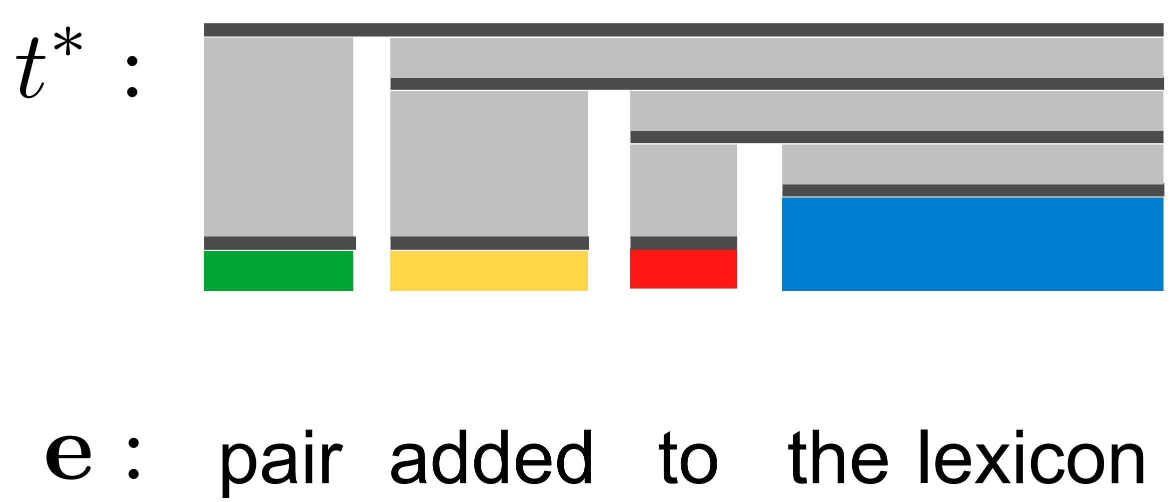

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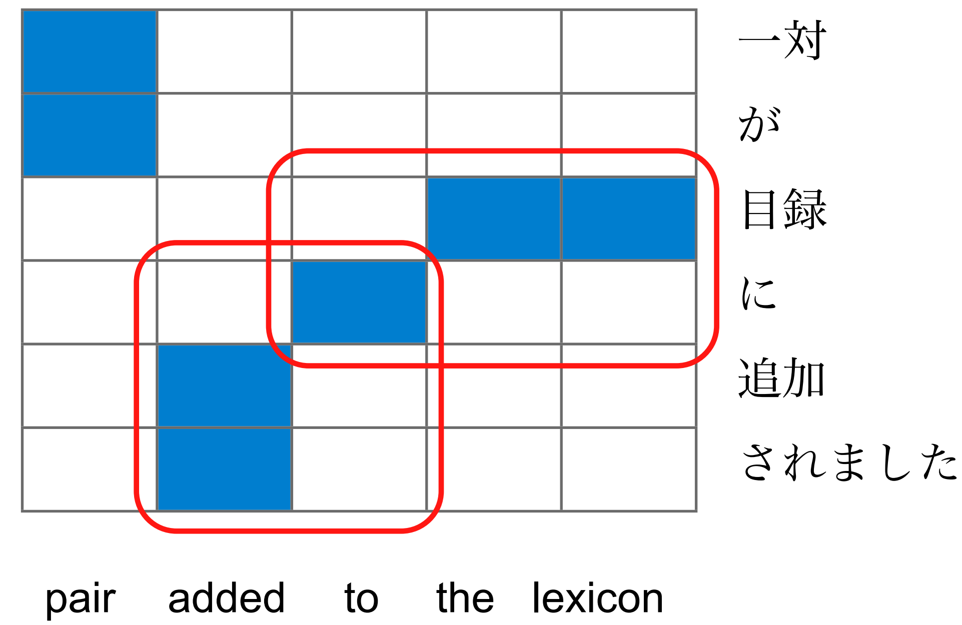


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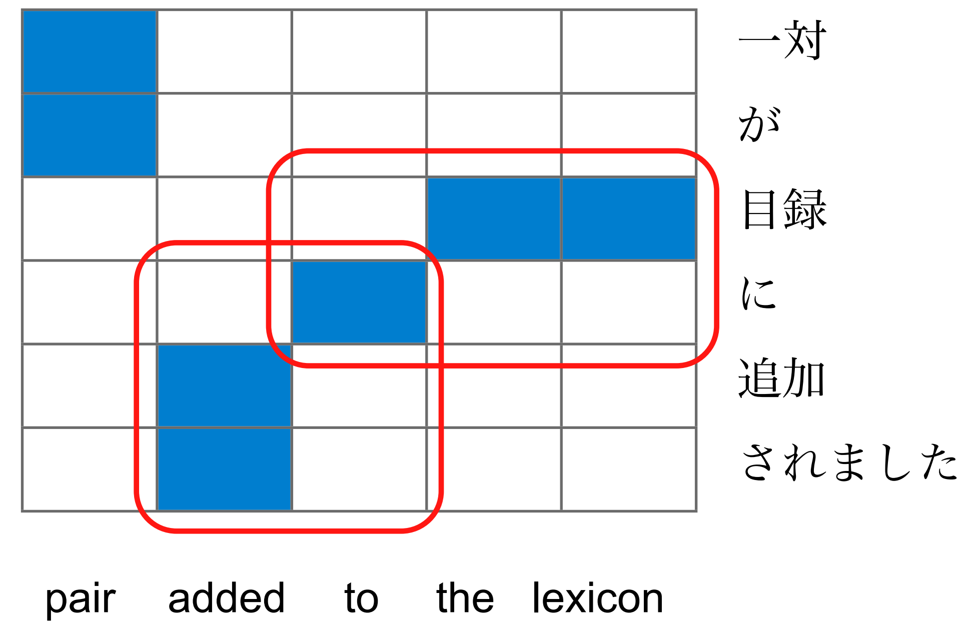


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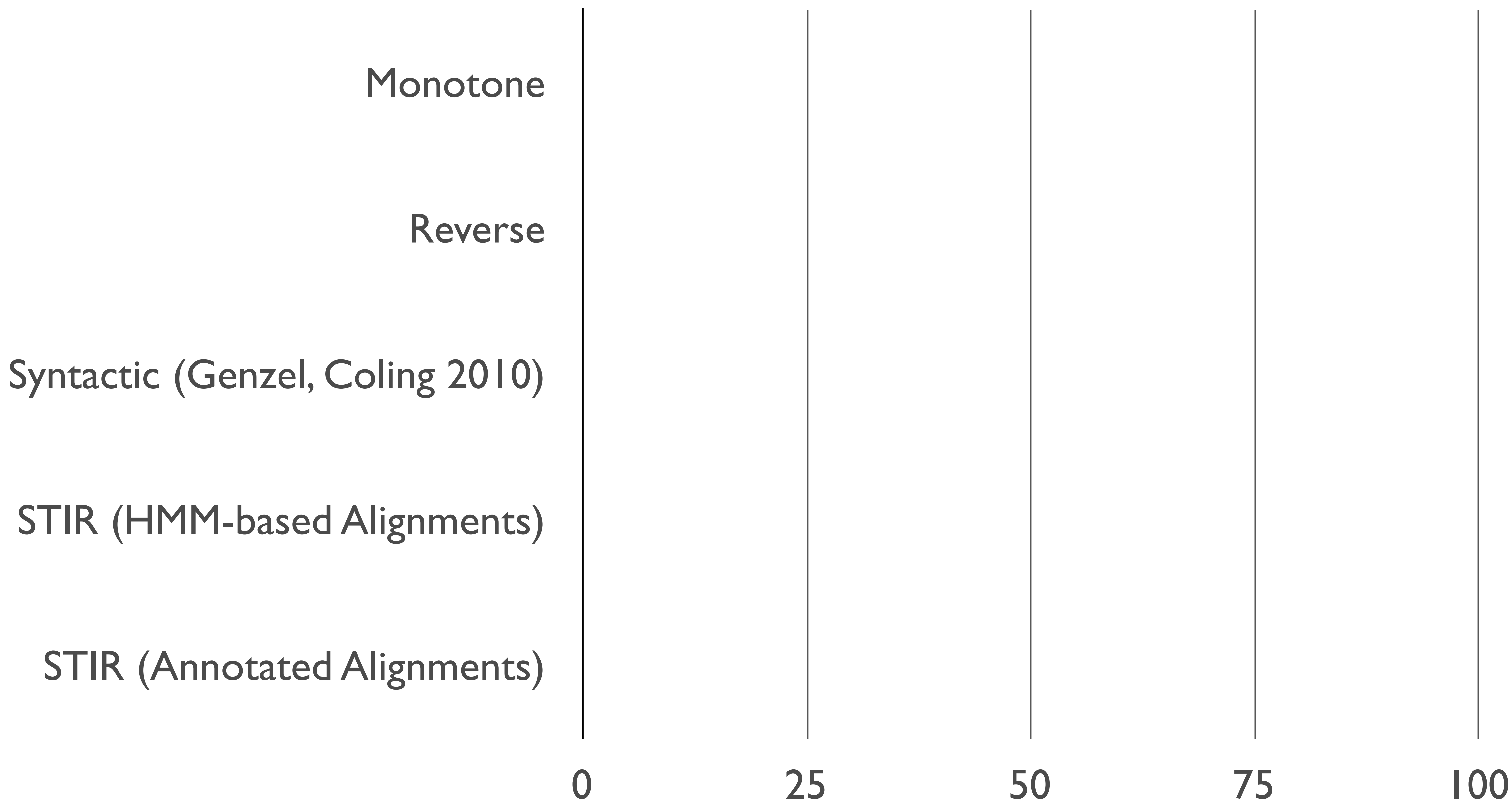

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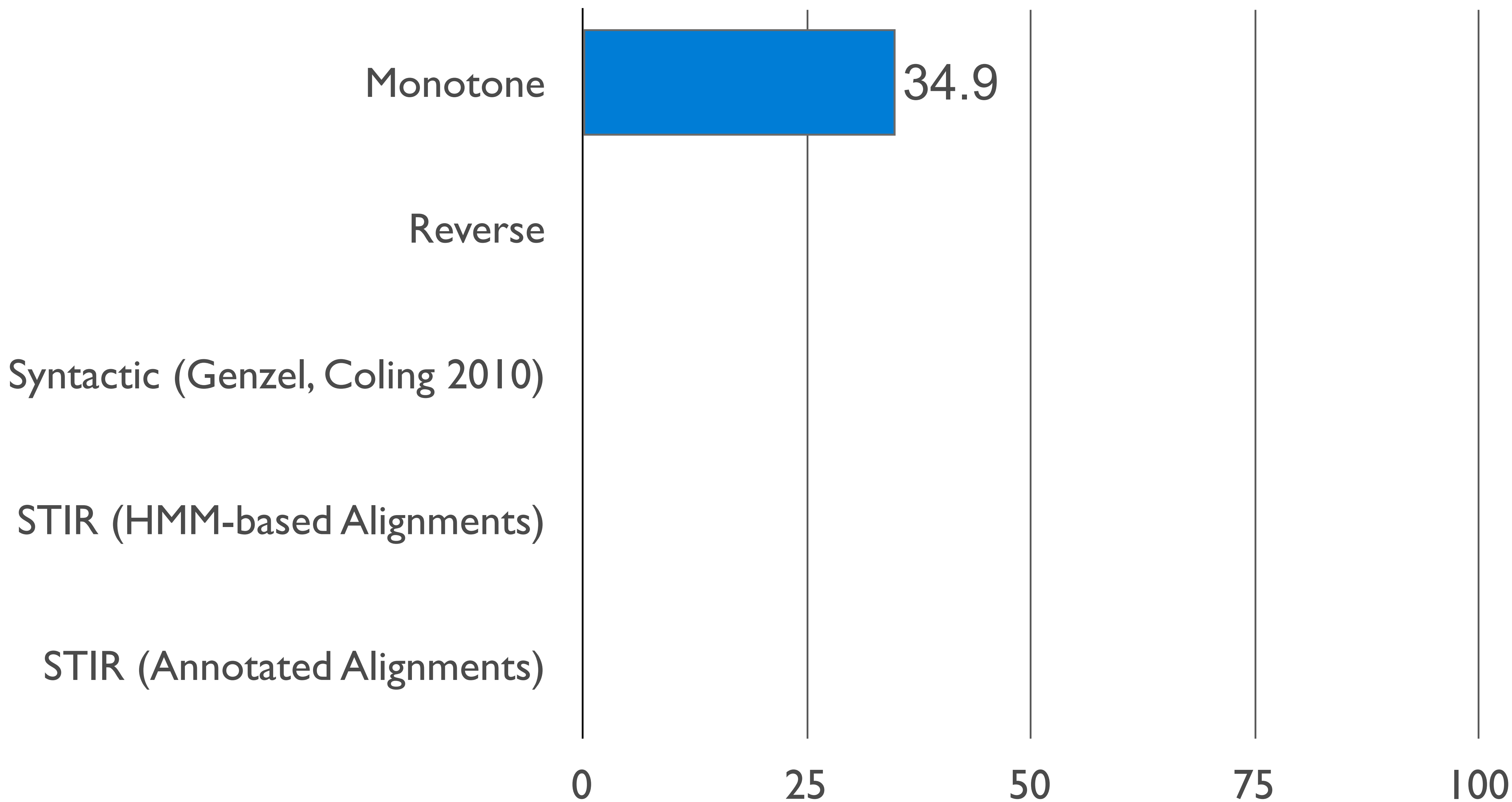

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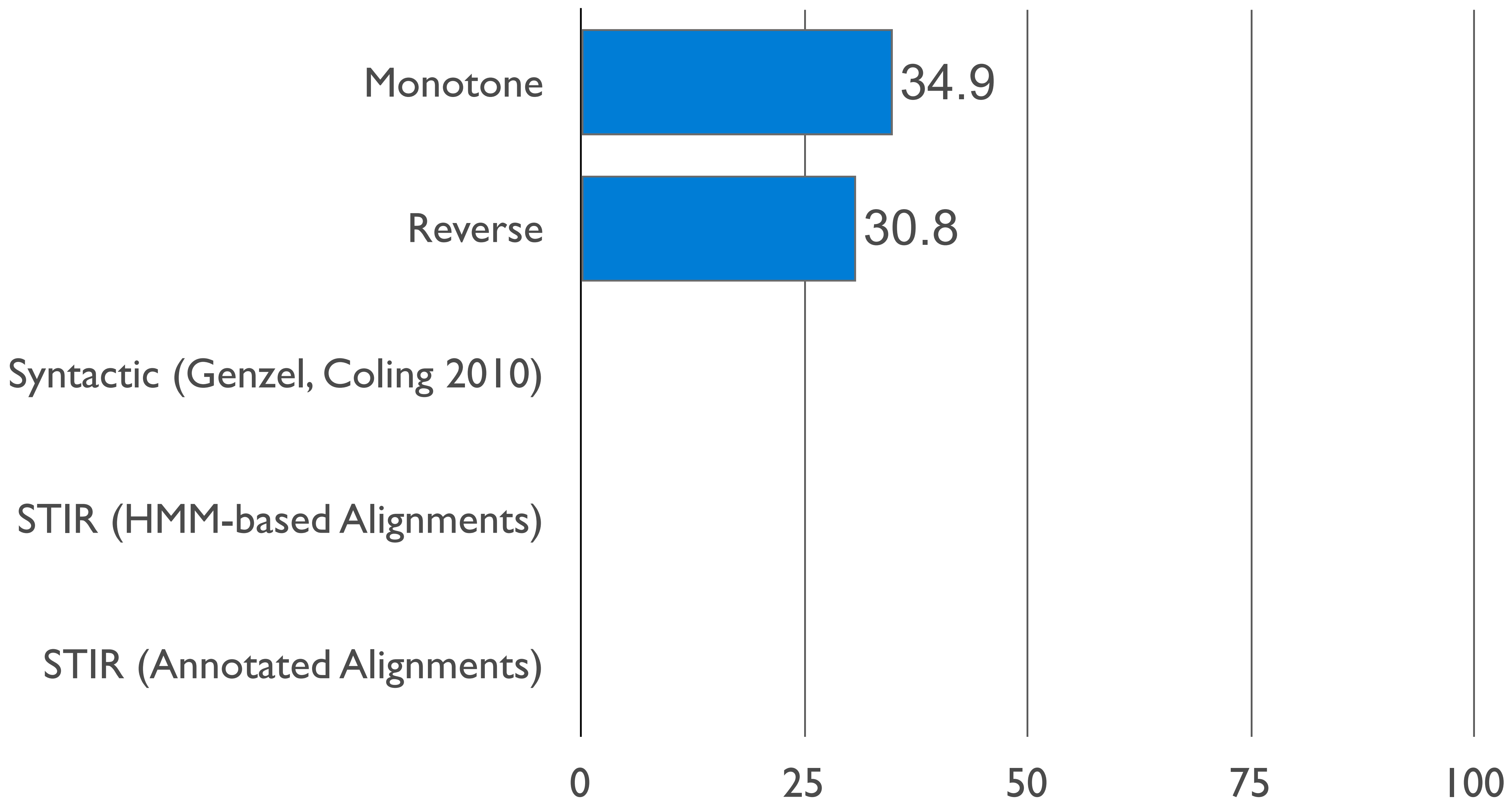

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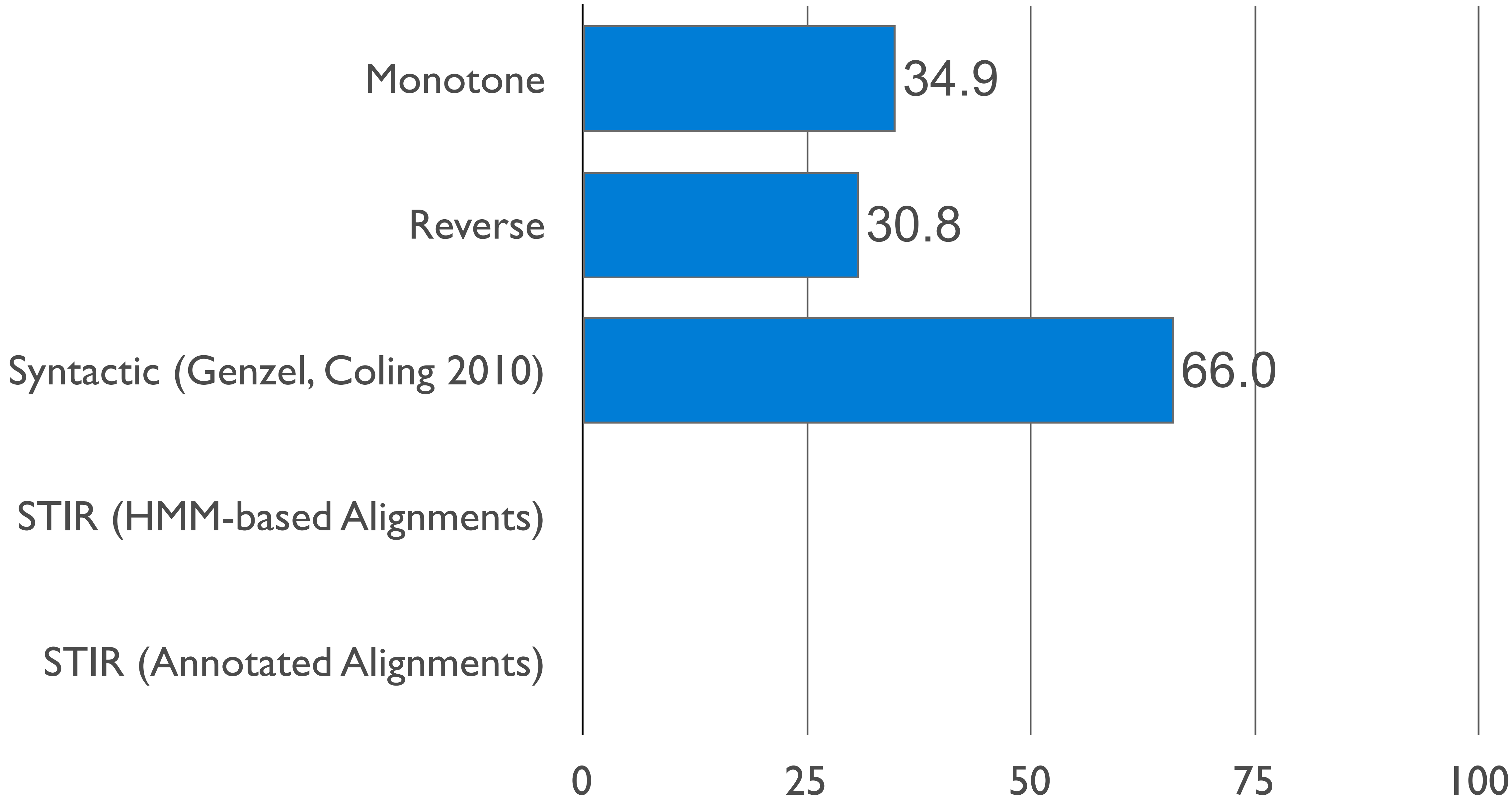

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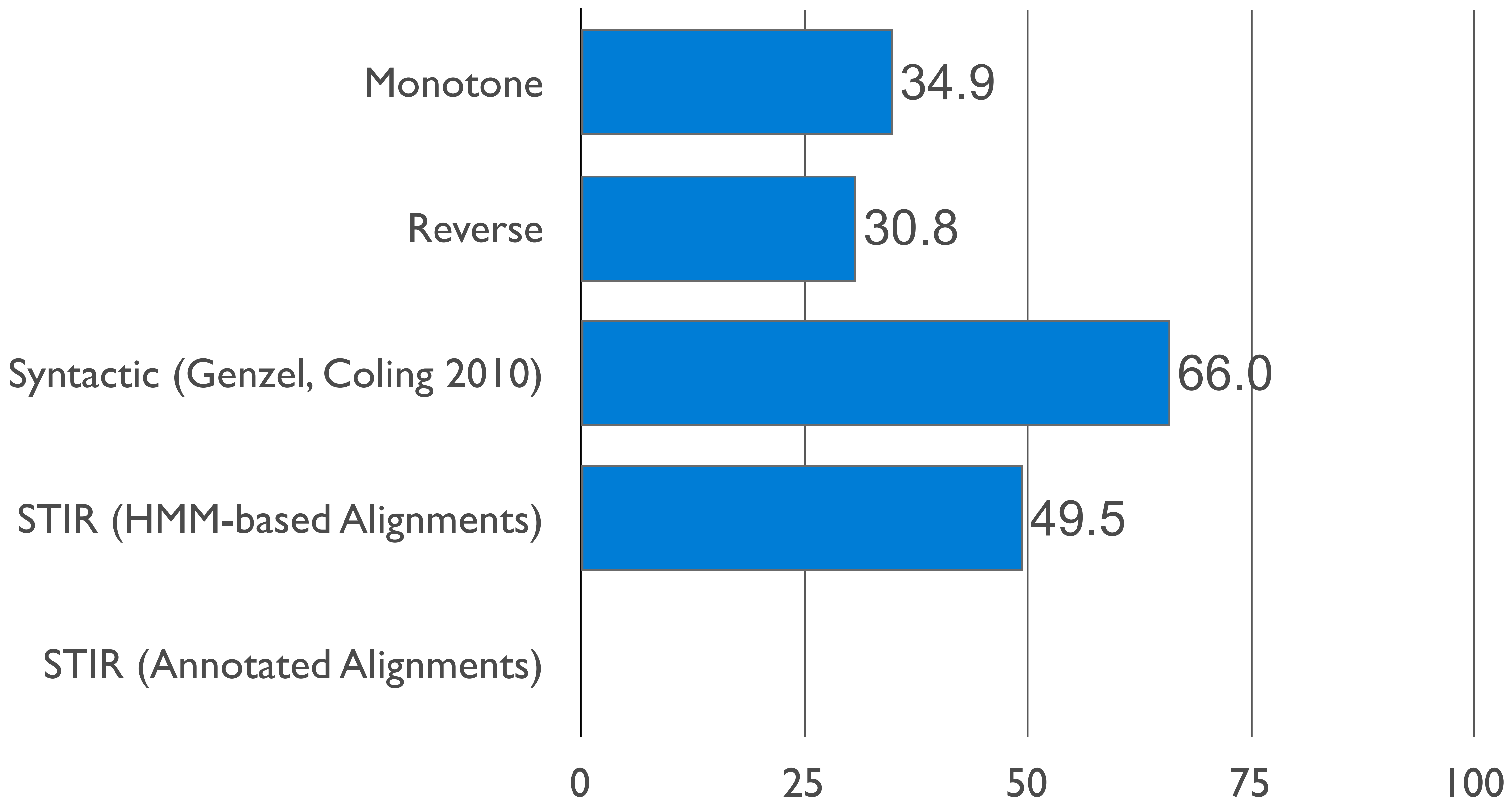

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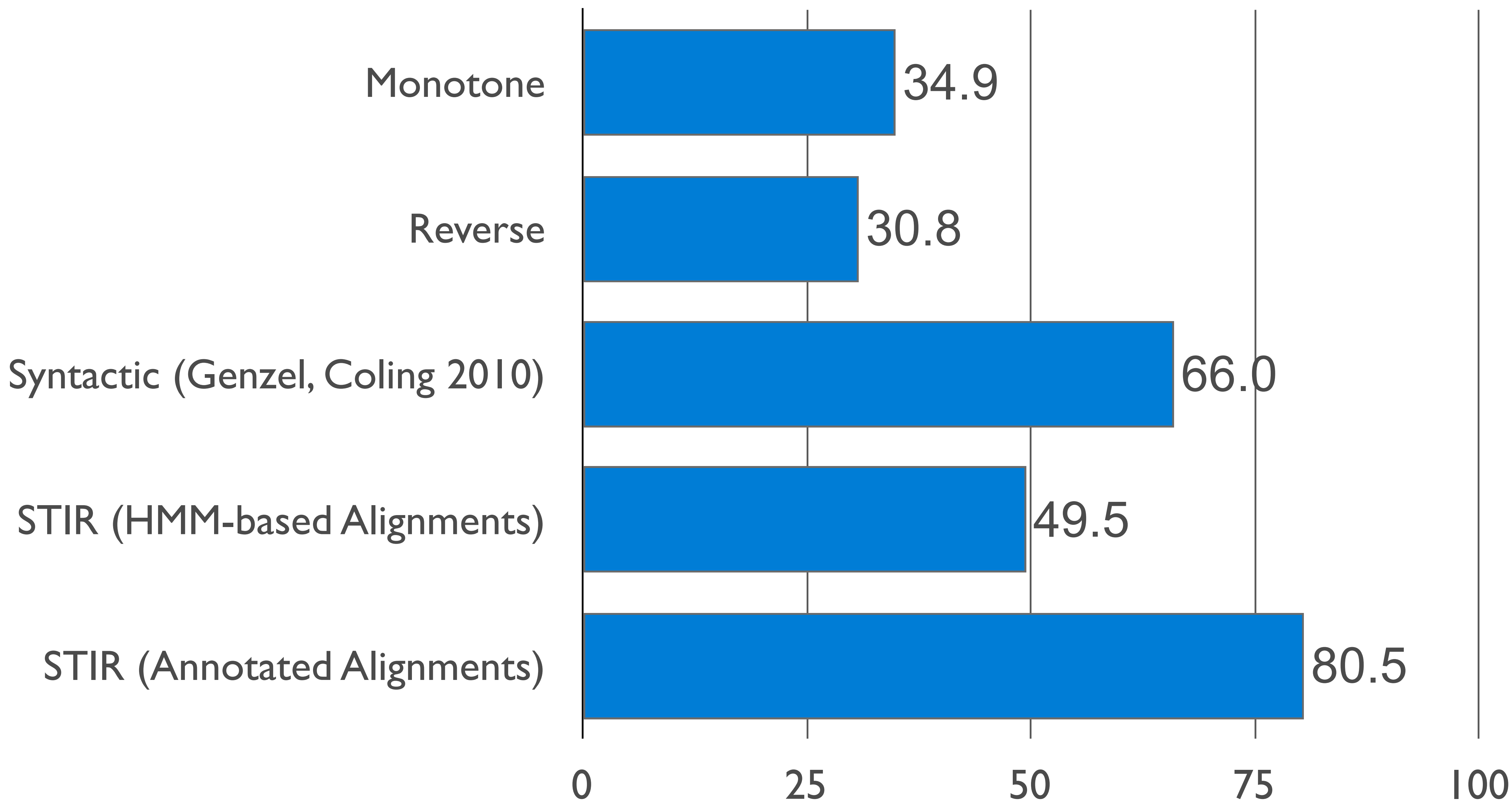
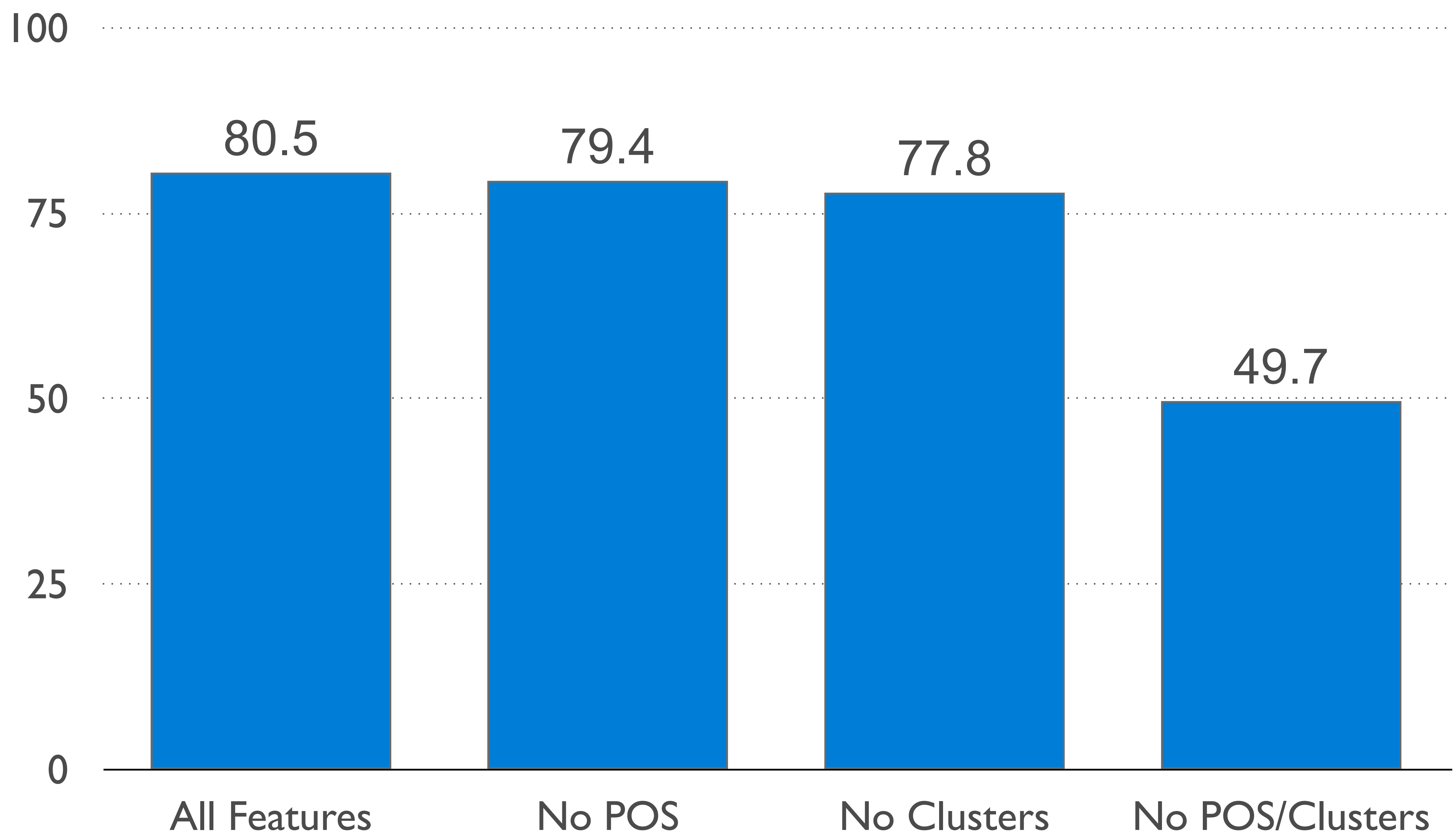


# Results: Supervised & Induced Parts-of-Speech



# End-to-End Translation Experiments

- Translation model trained on ~700 million tokens of parallel text
- Primarily extracted from the web (Uszkoreit et al., Coling 2010)
- Alignments: 2 iterations IBM Model 1; 2 iterations HMM-based model
- Tune and test: 3100 and 1000 sentences sampled from the web

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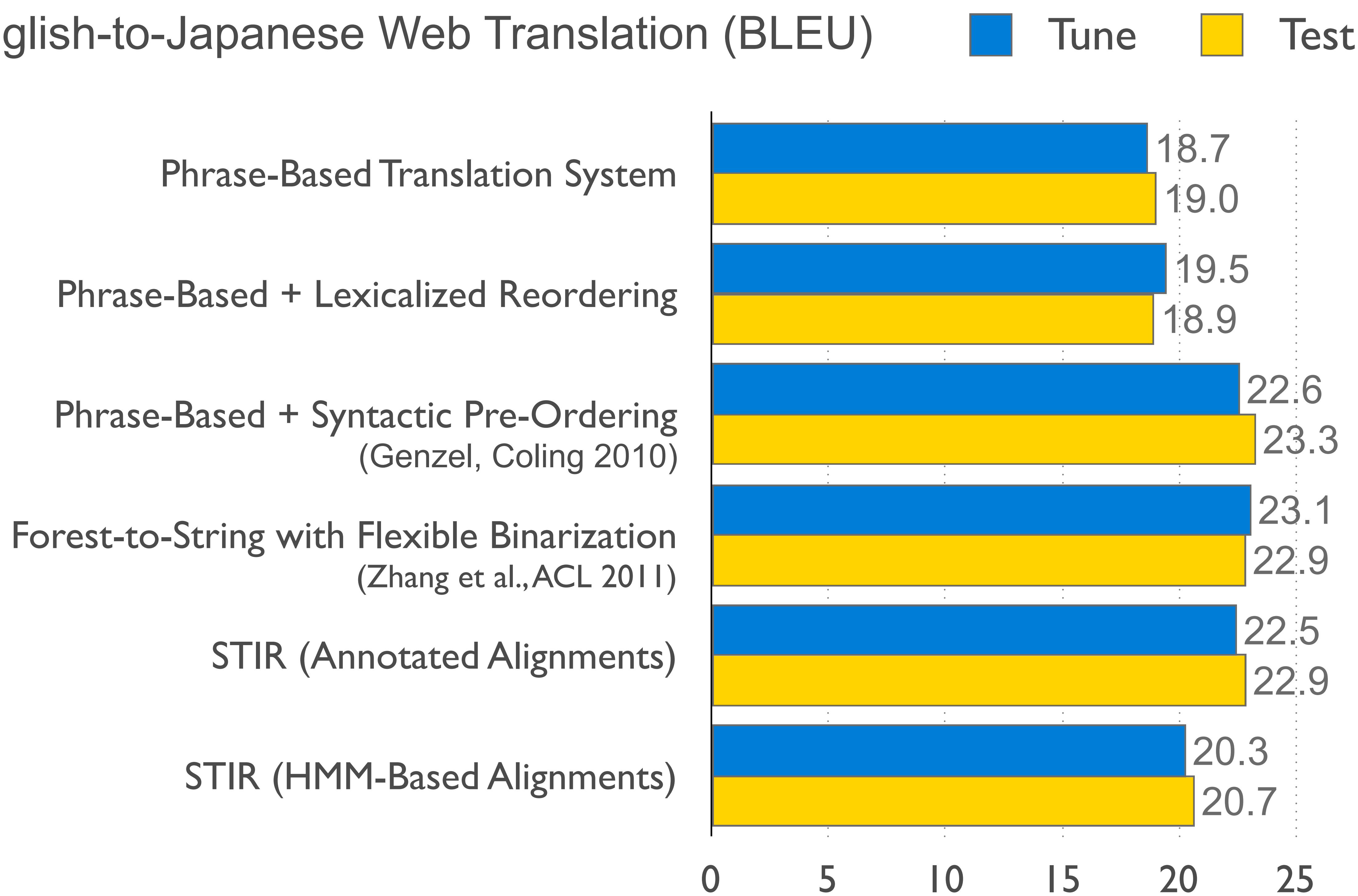
English-to-Japanese Web Translation (BLEU)



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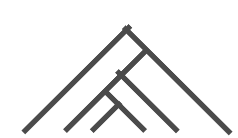

snahkT! snahkT! Thanks!