Inducing Sentence Structure from Parallel Corpora for Reordering

John DeNero and Jakob Uszkoreit

Google research

Overview

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- Translation is an end-task application for syntactic parsing

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  - Lexical disambiguation

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  - Learning signal comes from aligned parallel corpora

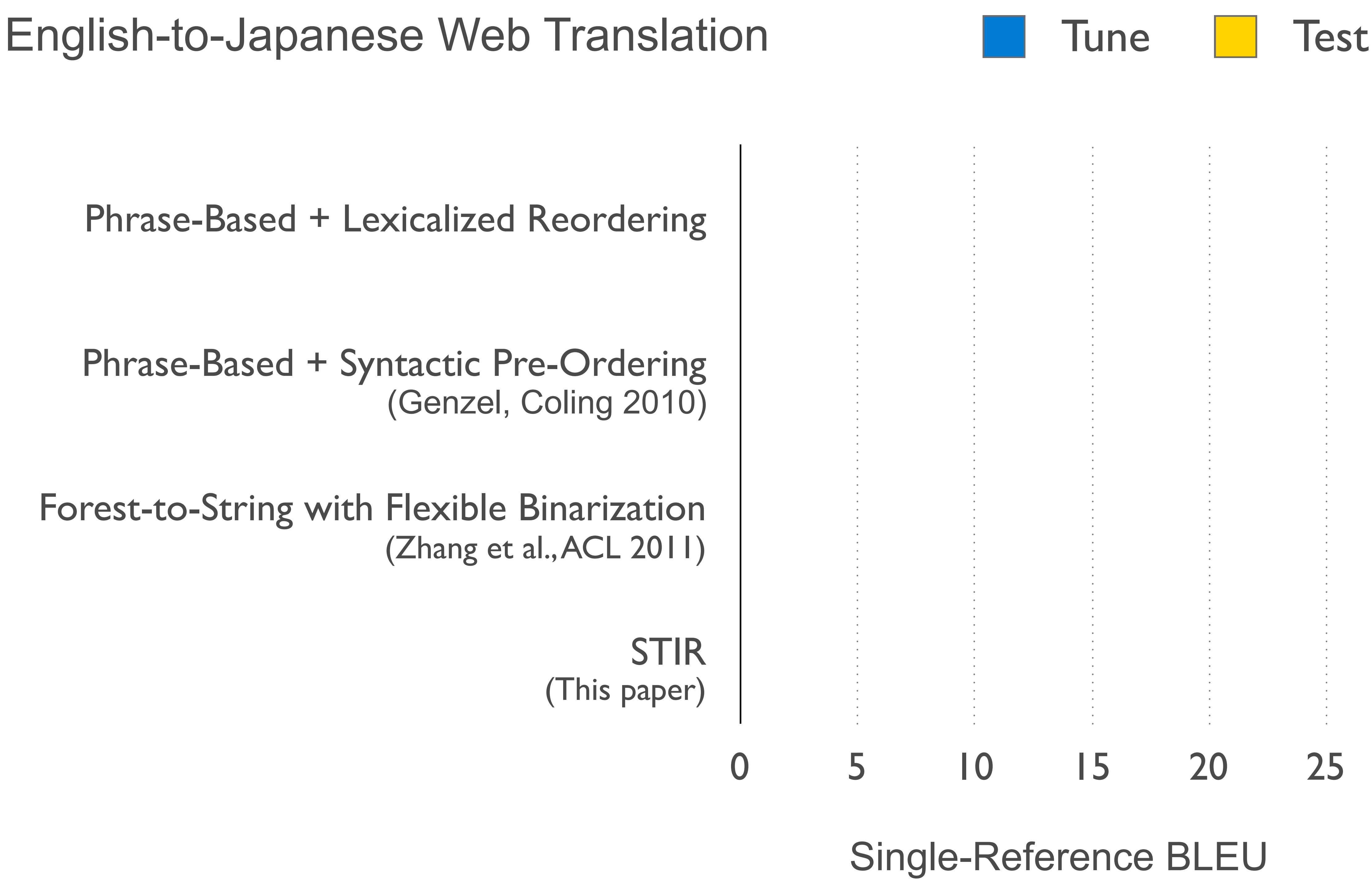
Syntax Matters for Hierarchical Reordering

English-to-Japanese Web Translation

Tune Test

Single-Reference BLEU

Syntax Matters for Hierarchical Reordering



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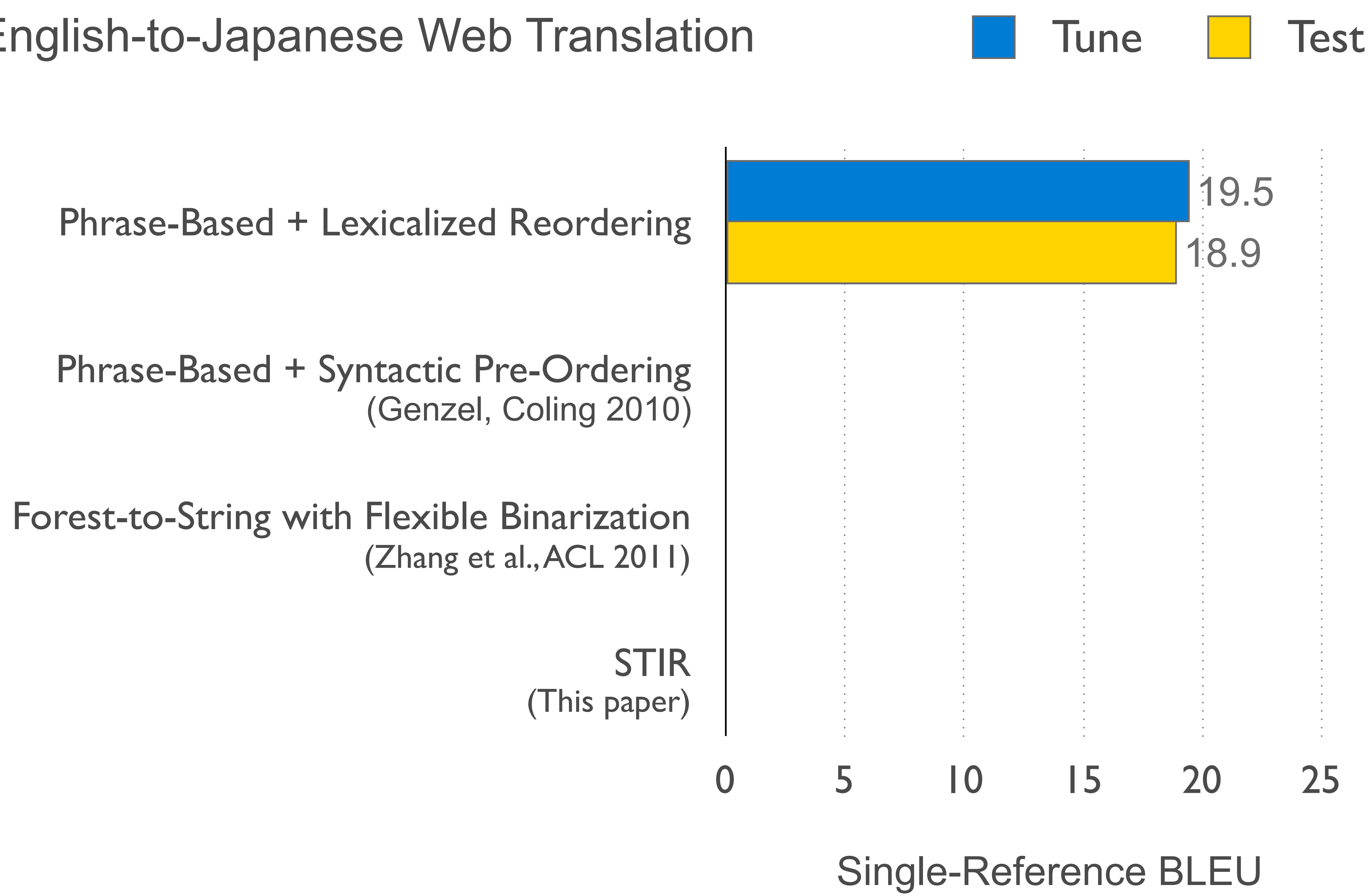

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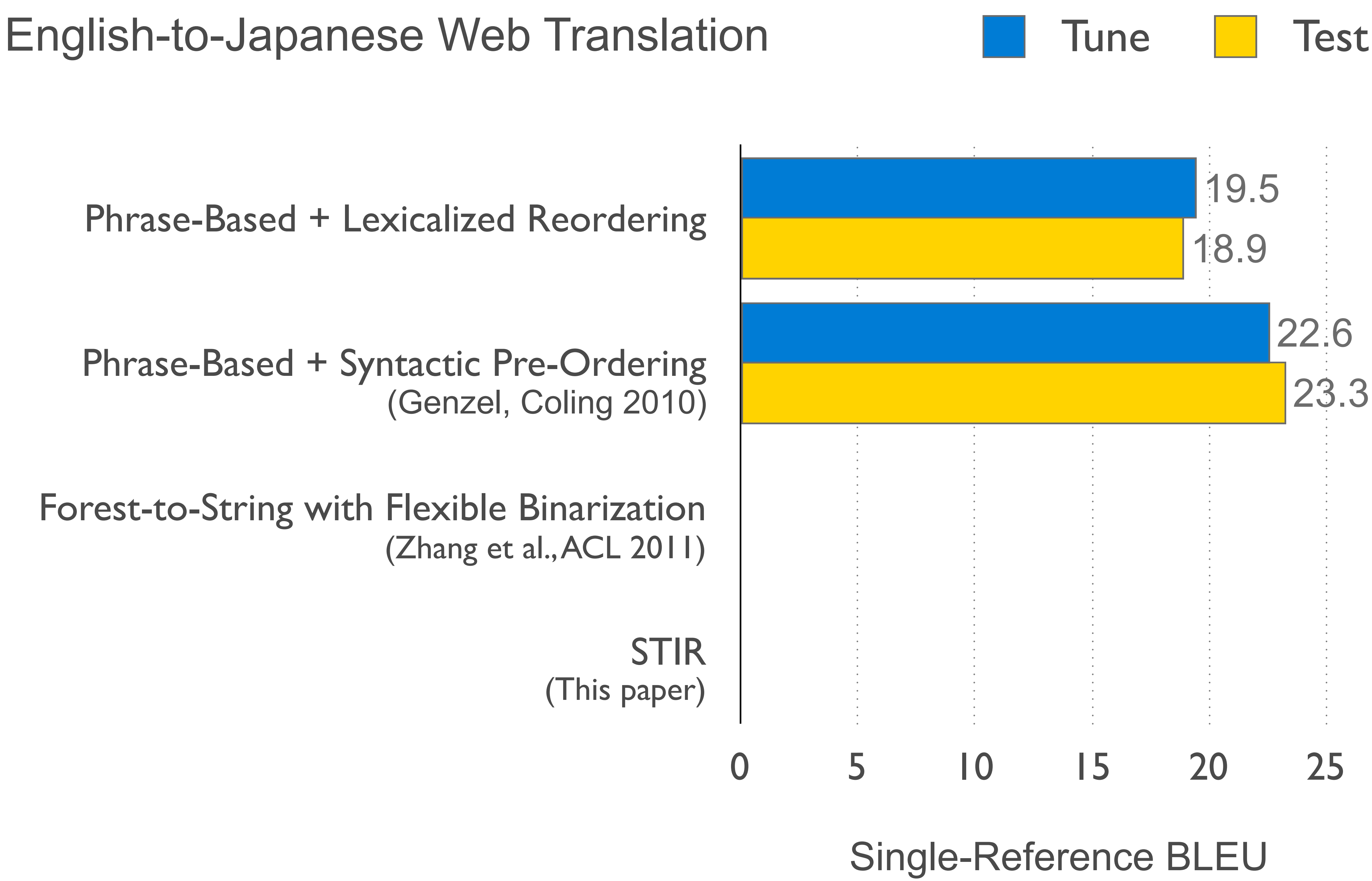

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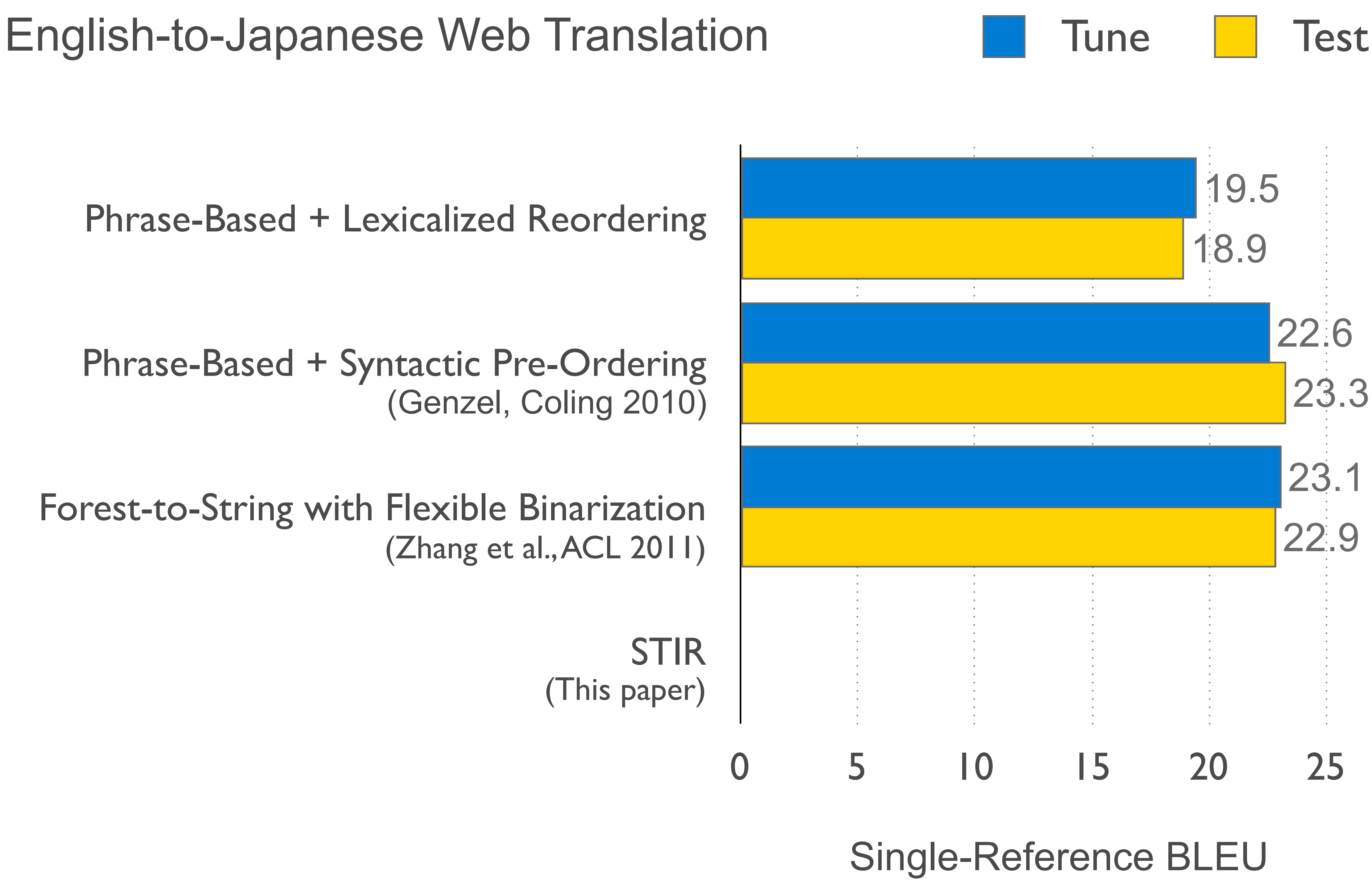

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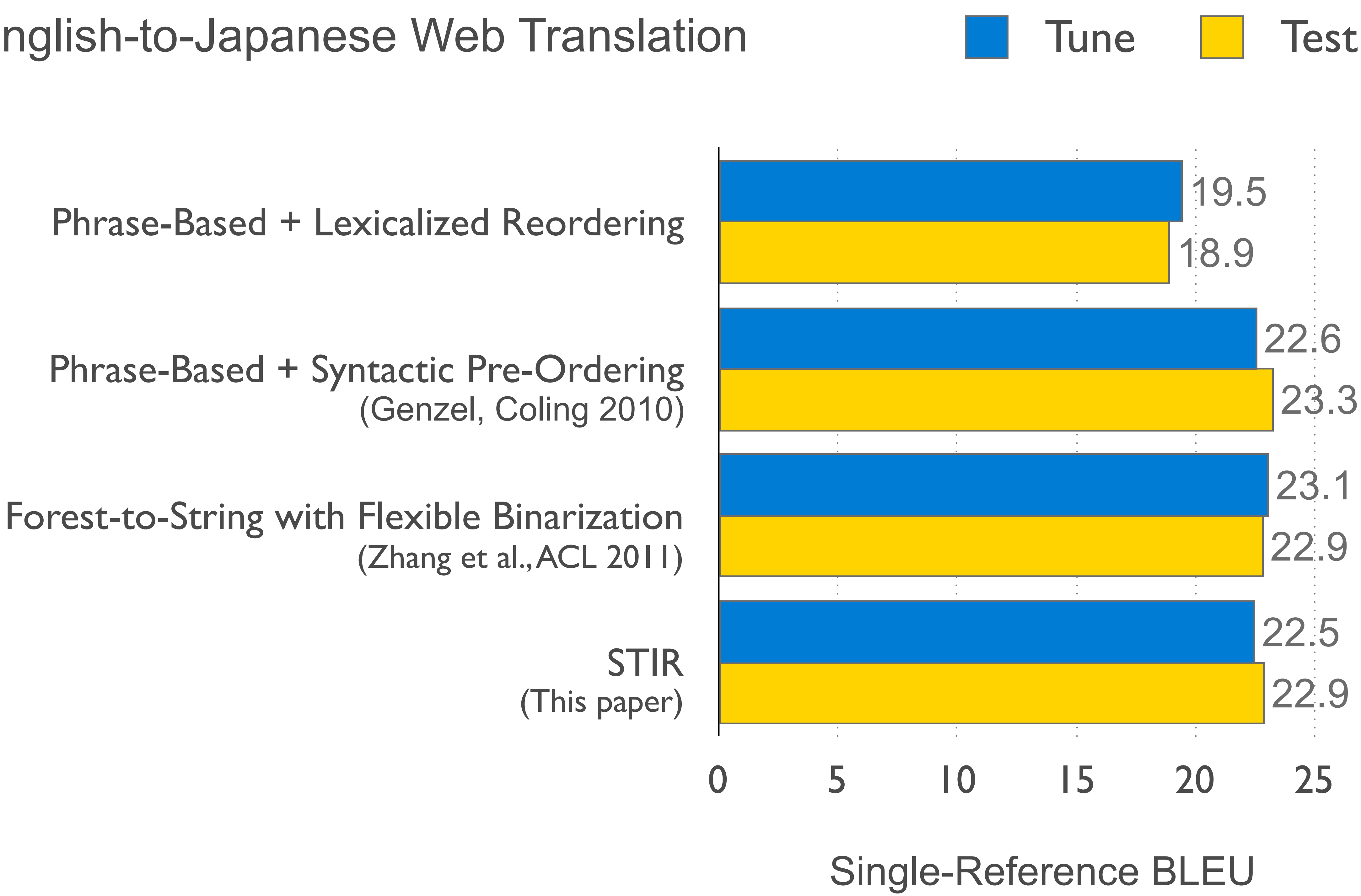

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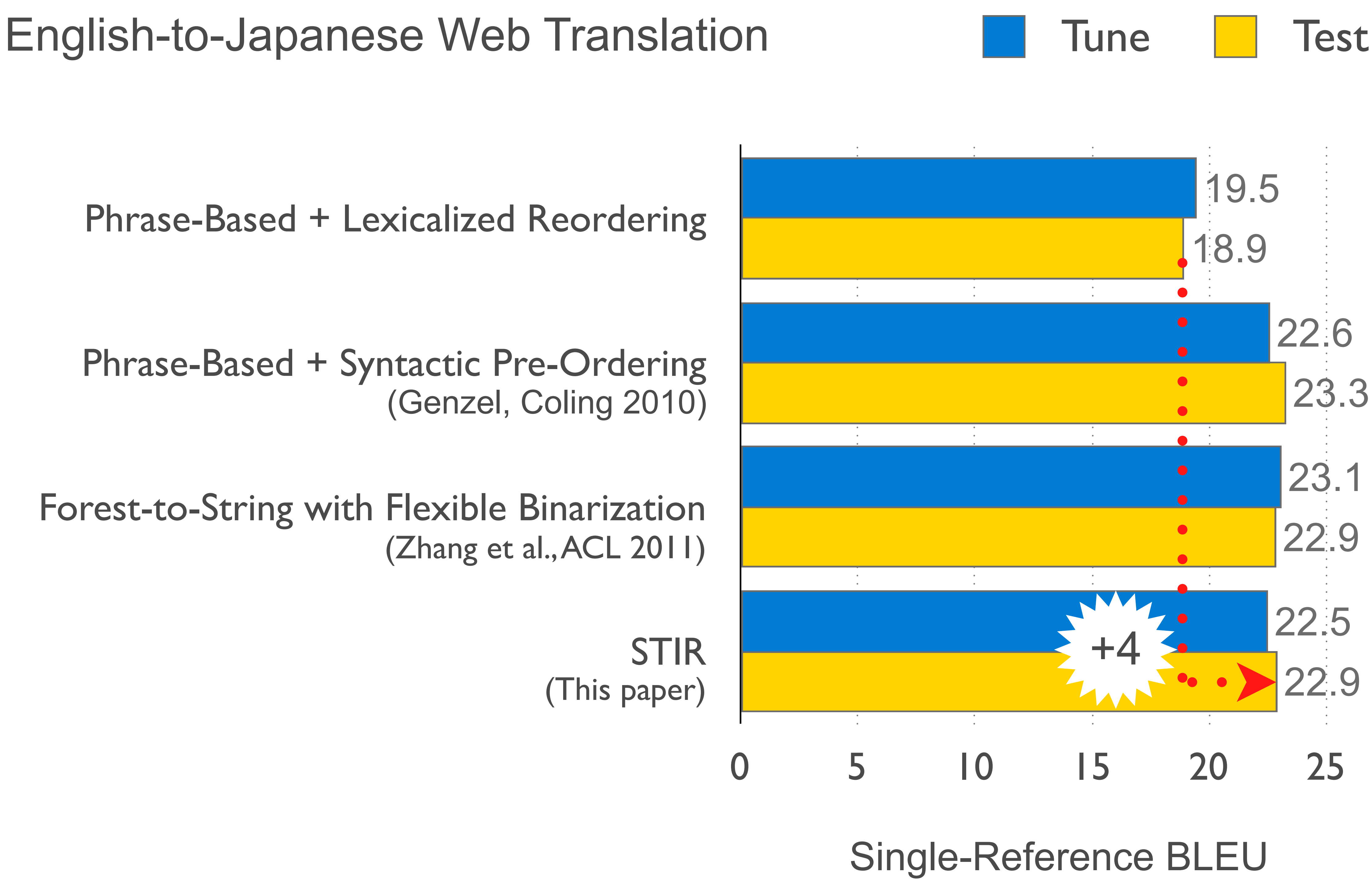

Syntactic Pre-Ordering in Phrase-Based Systems

Pre-Ordering Pipeline

Translation Pipeline

Syntactic Pre-Ordering in Phrase-Based Systems

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S V O

Syntactic Pre-Ordering in Phrase-Based Systems

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Monolingual parsing model

Syntactic Pre-Ordering in Phrase-Based Systems

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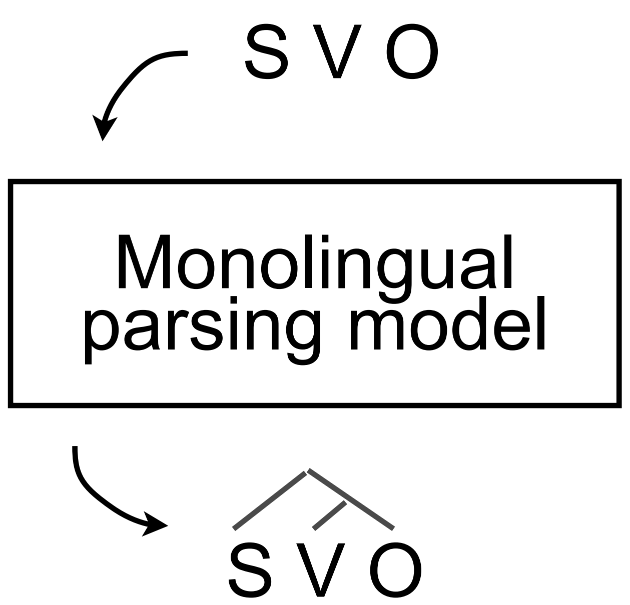
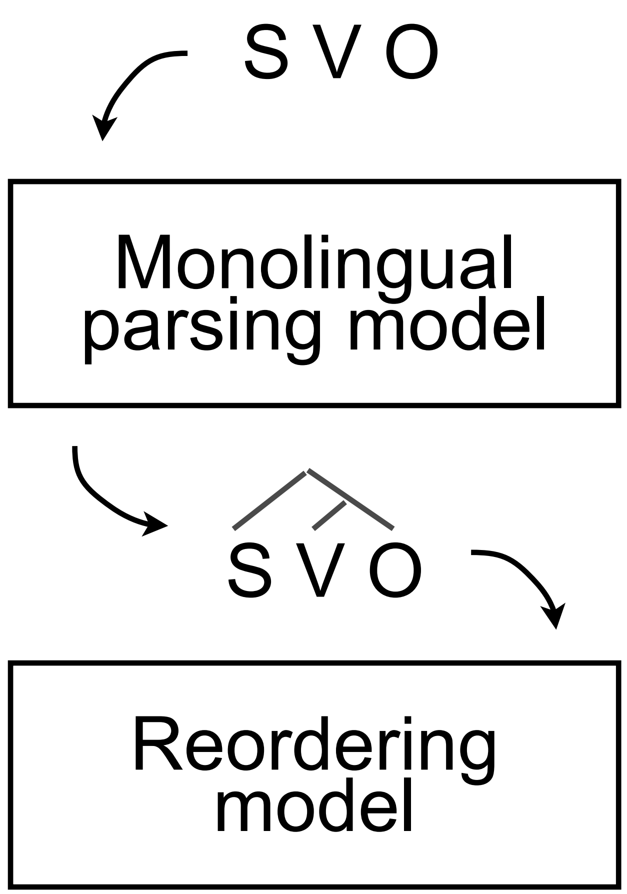


Syntactic Pre-Ordering in Phrase-Based Systems

Pre-Ordering Pipeline | **Translation Pipeline**



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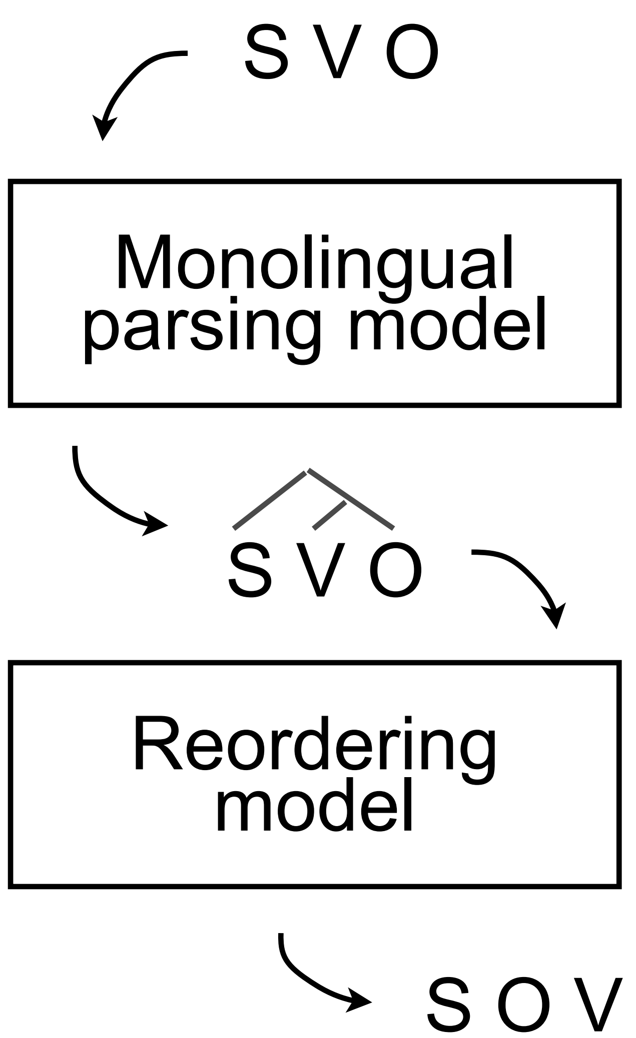

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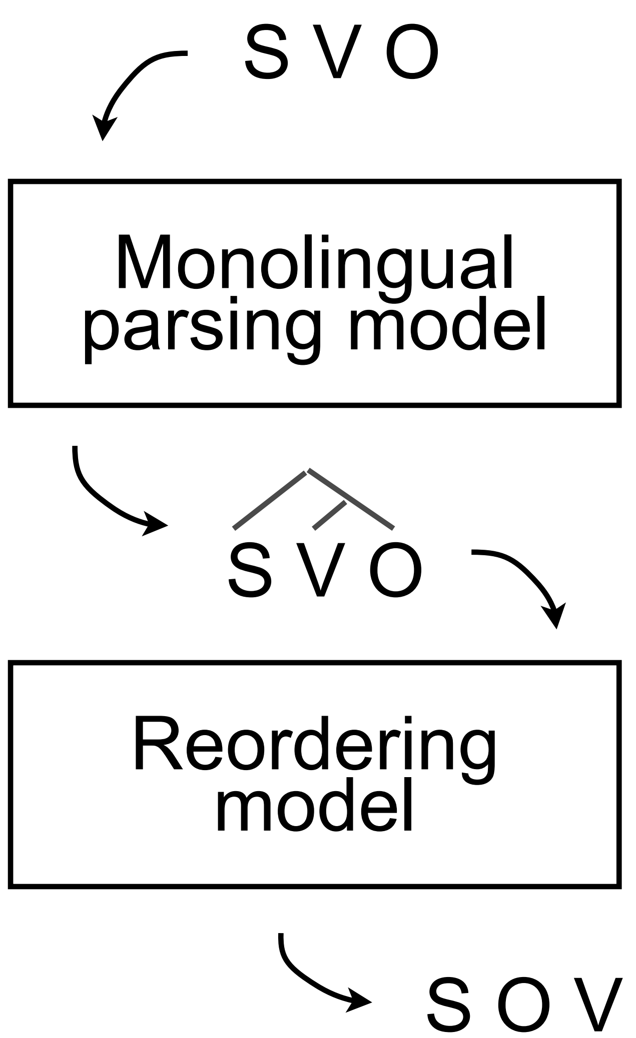

Translation Pipeline

Source training

Target training

Syntactic Pre-Ordering in Phrase-Based Systems

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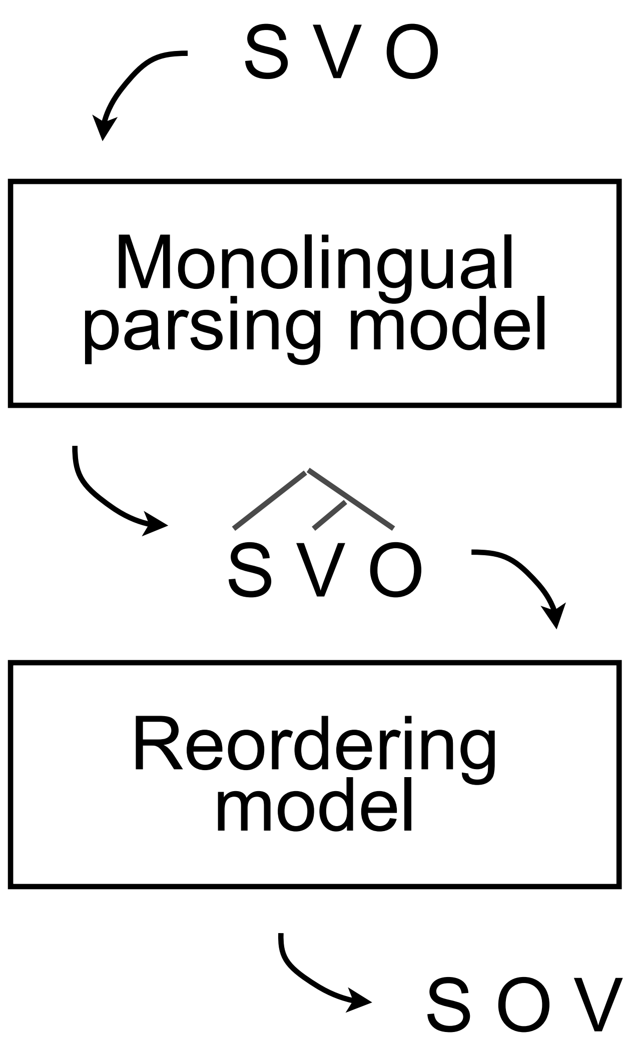

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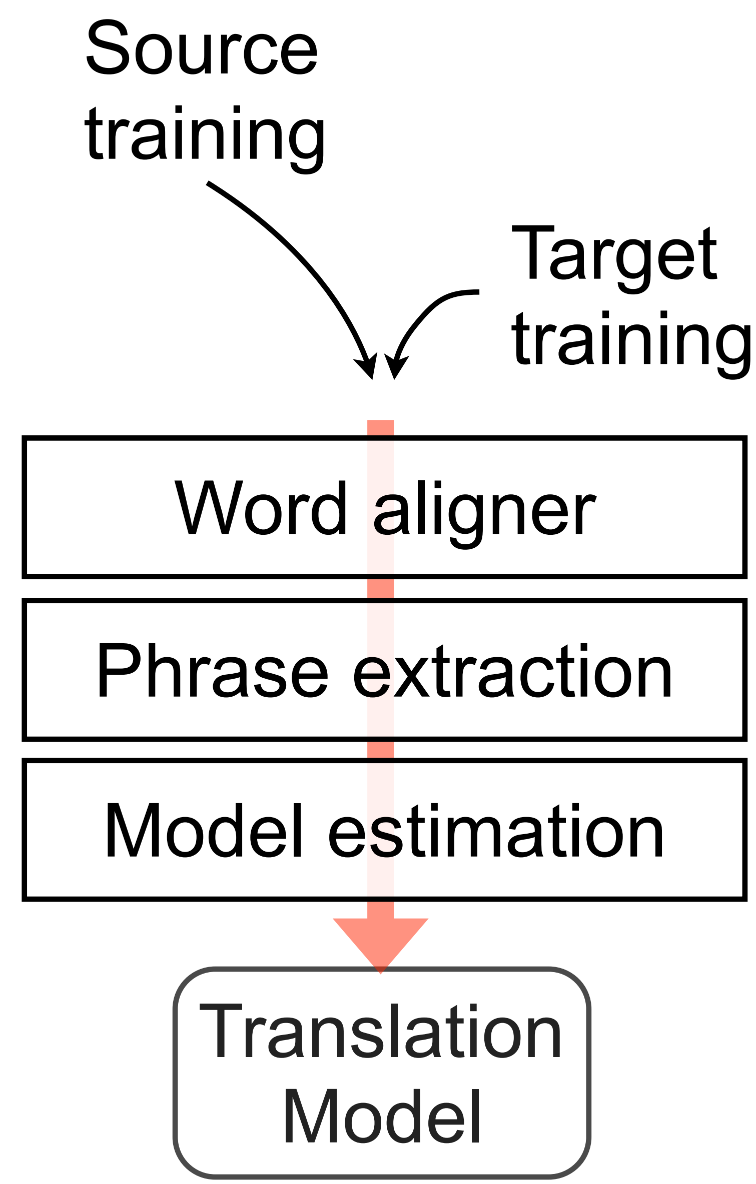

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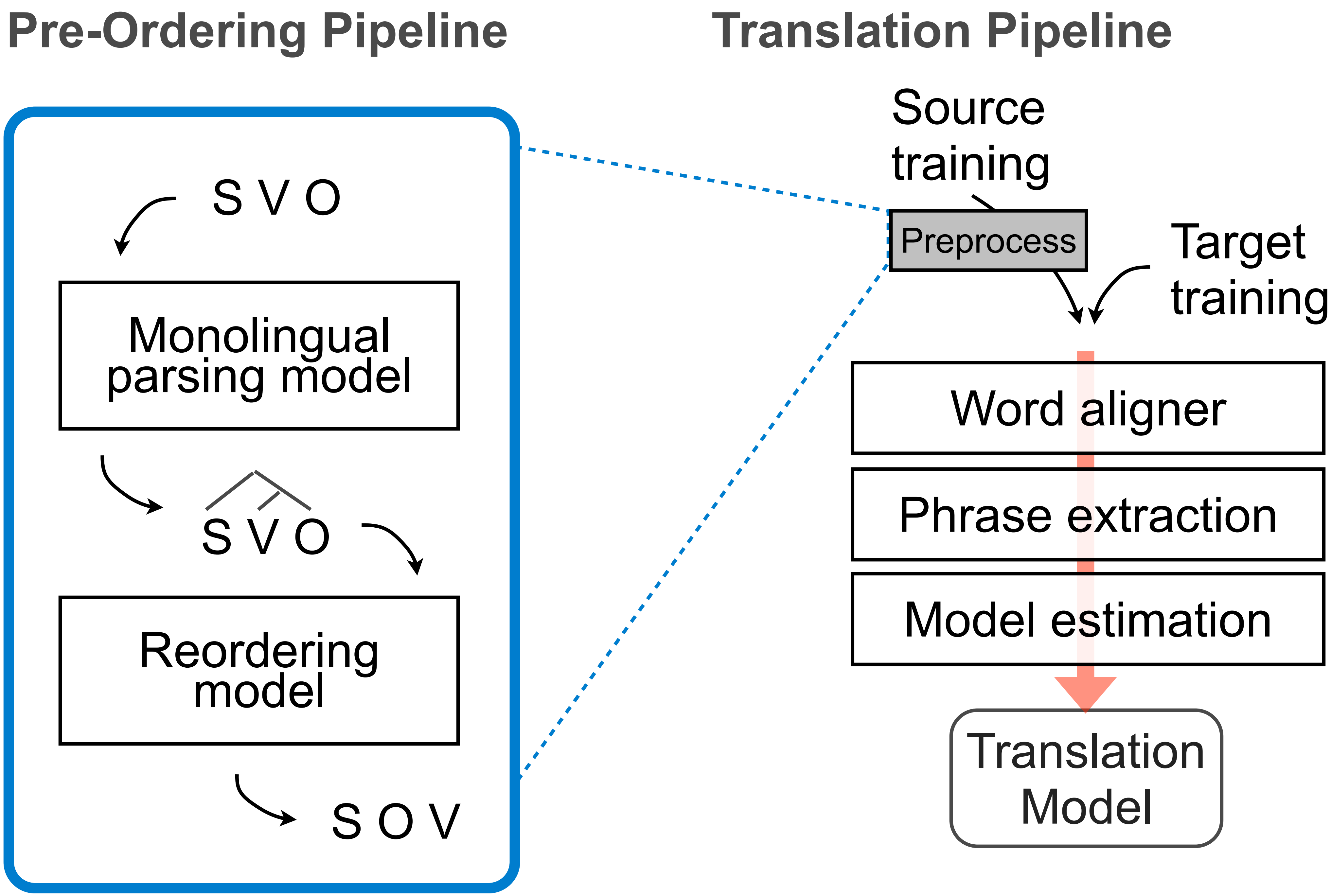

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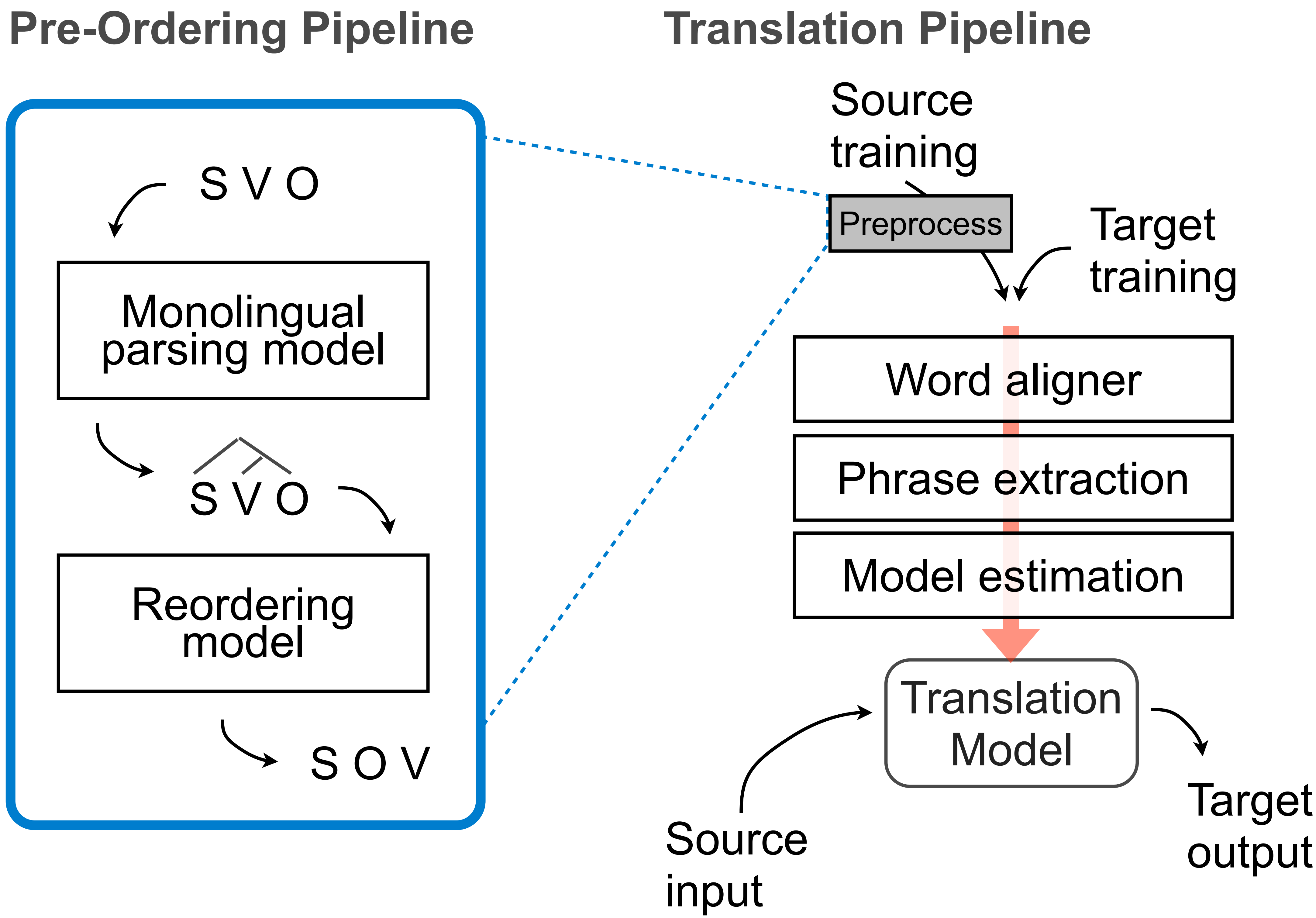

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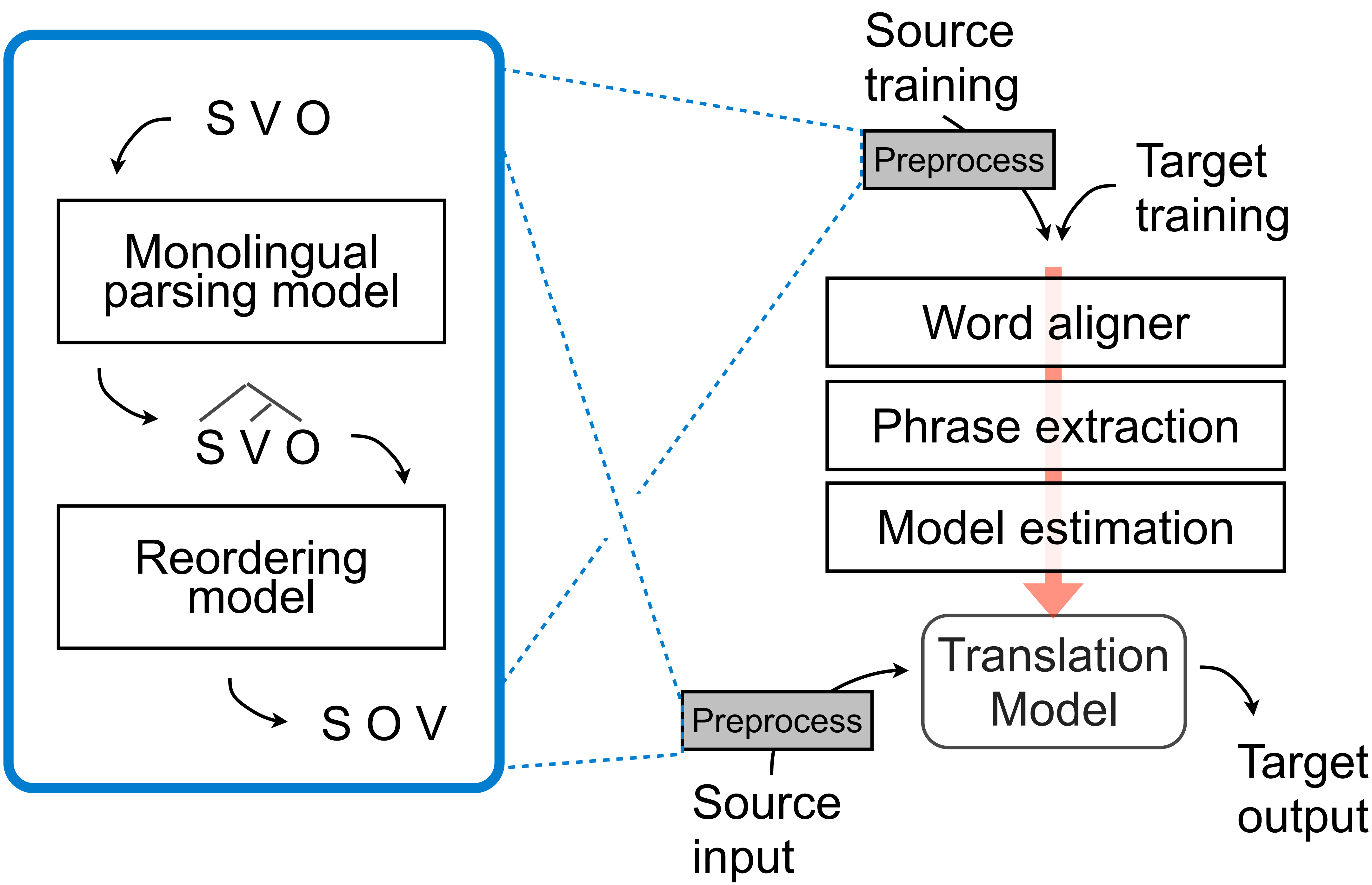

Syntactic Pre-Ordering Example

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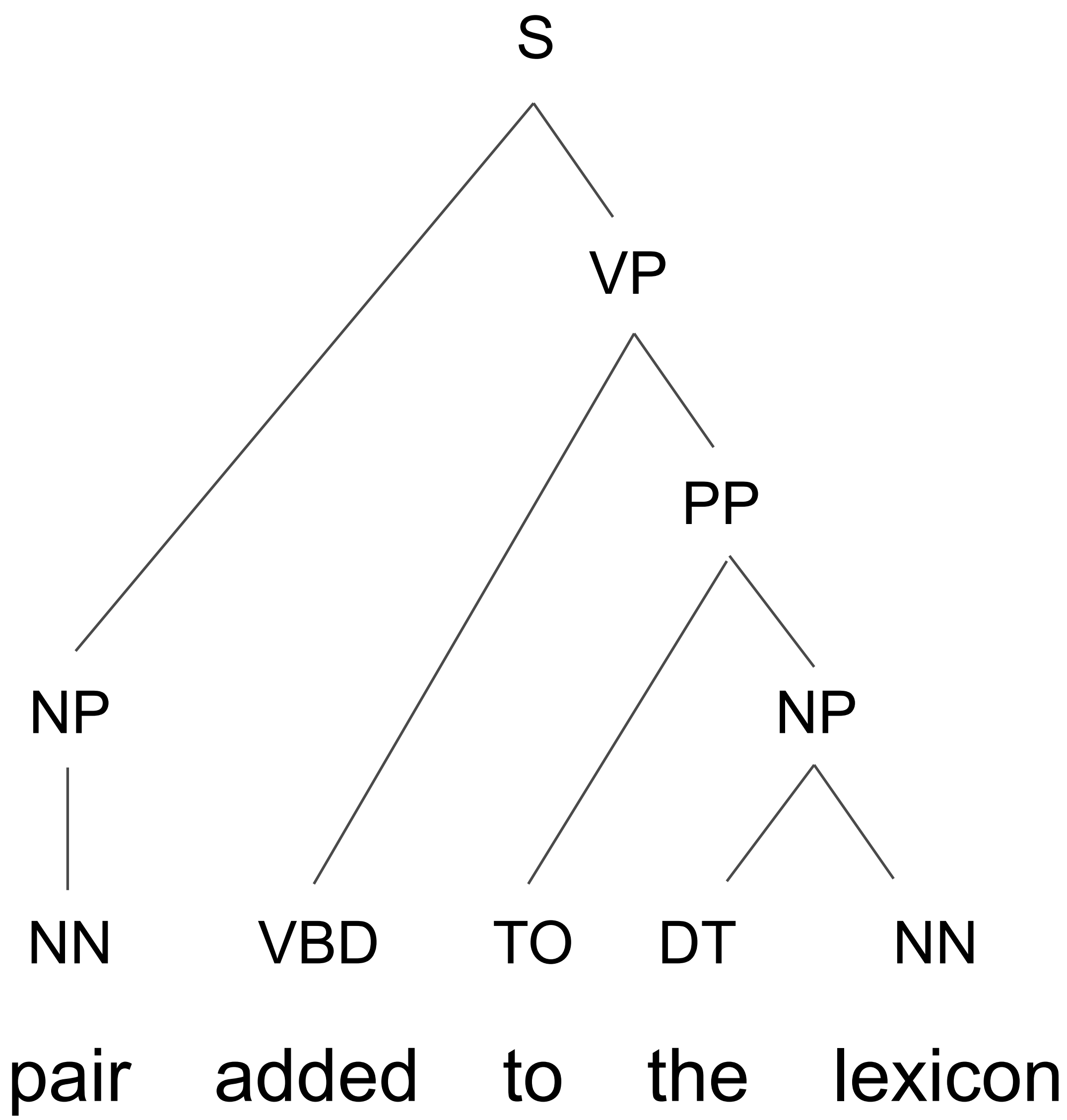

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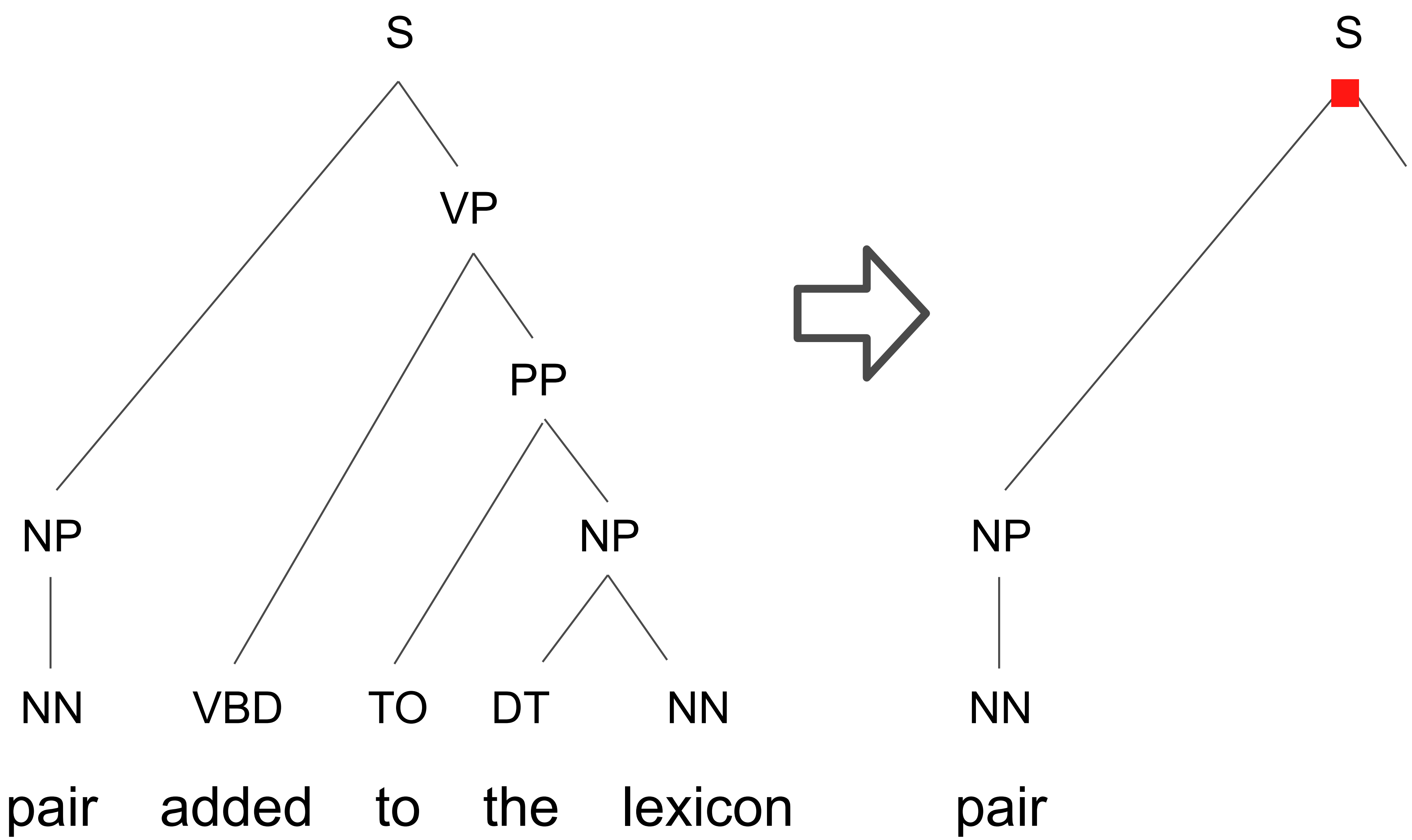

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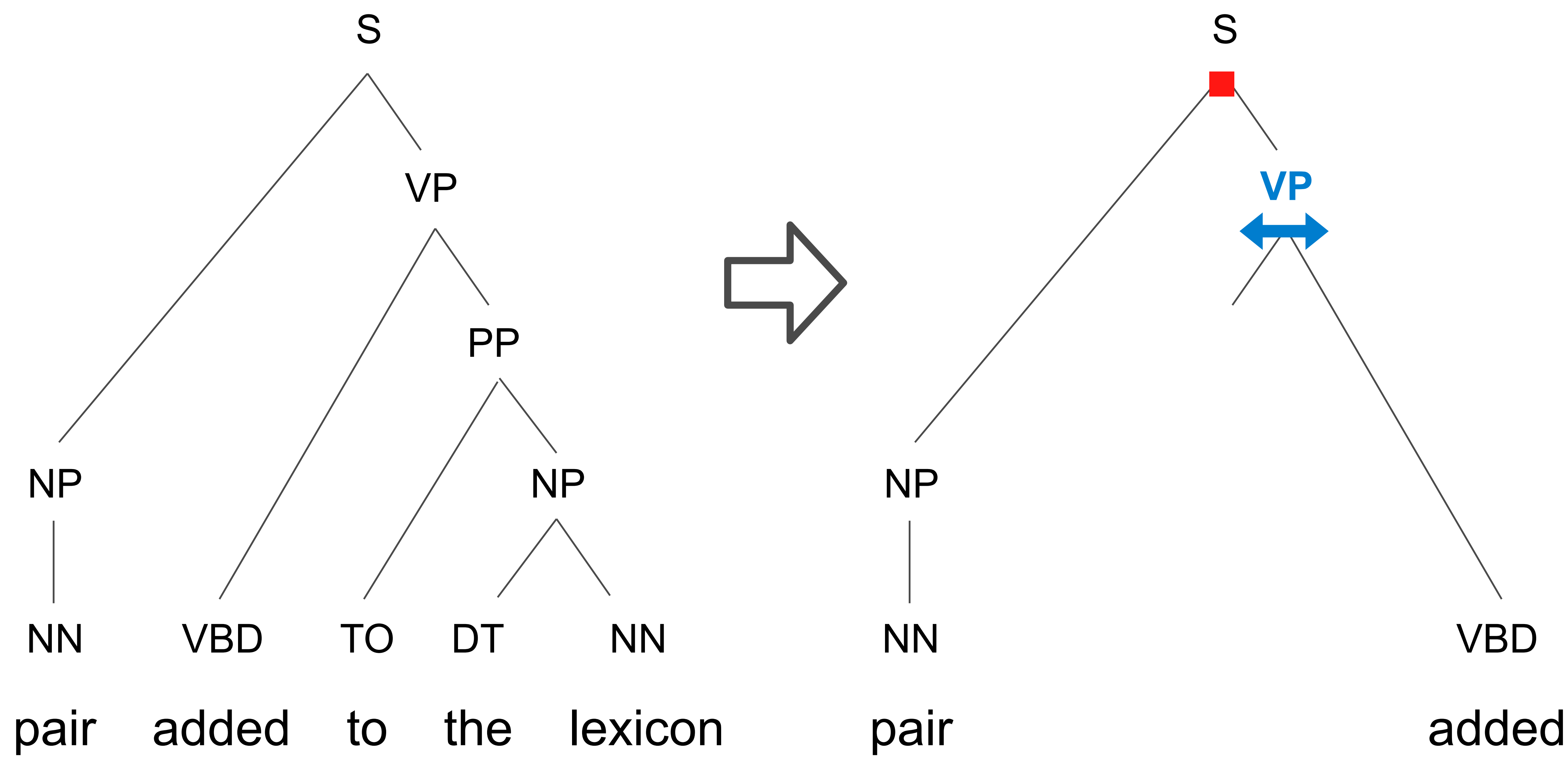

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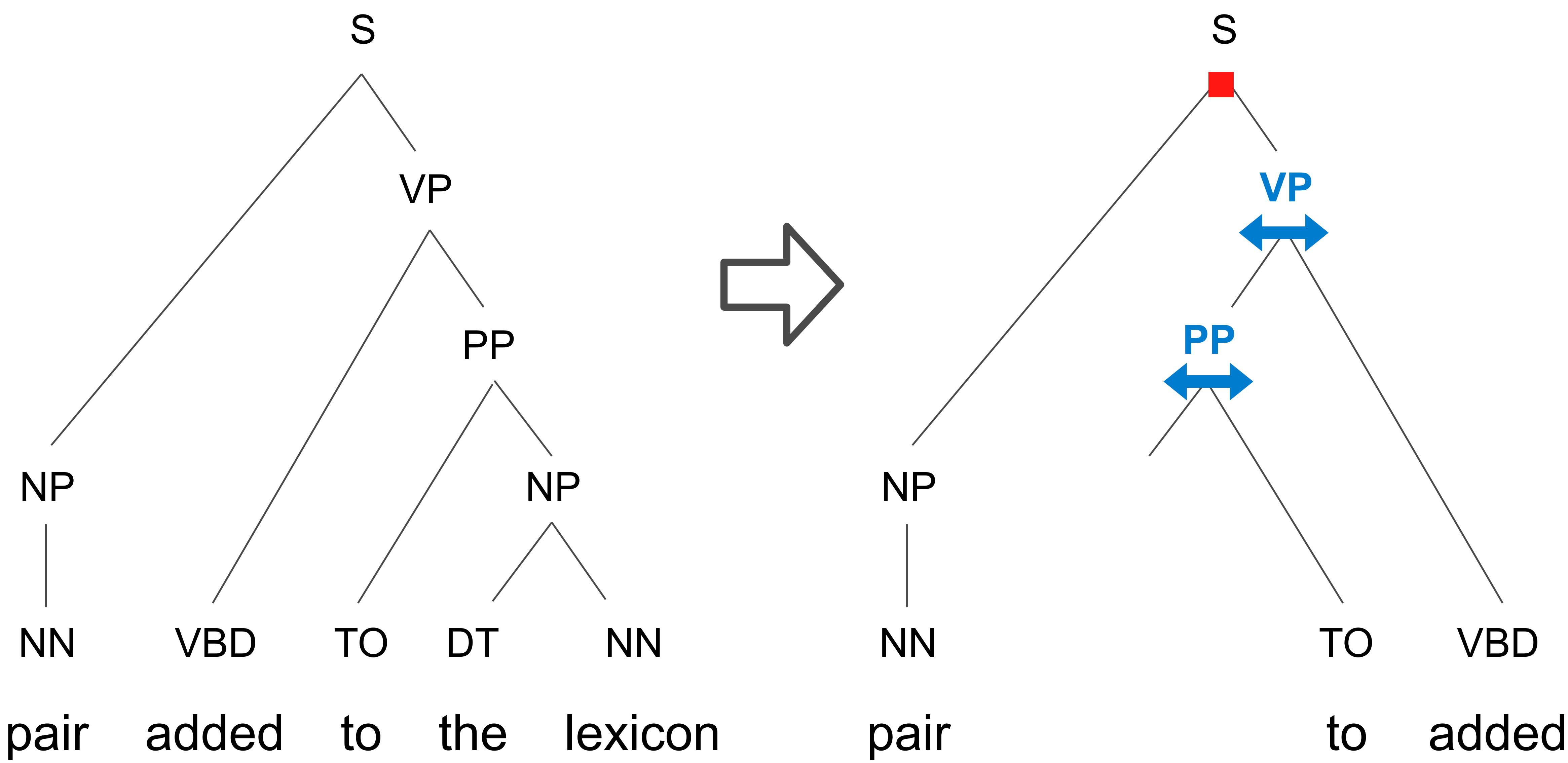

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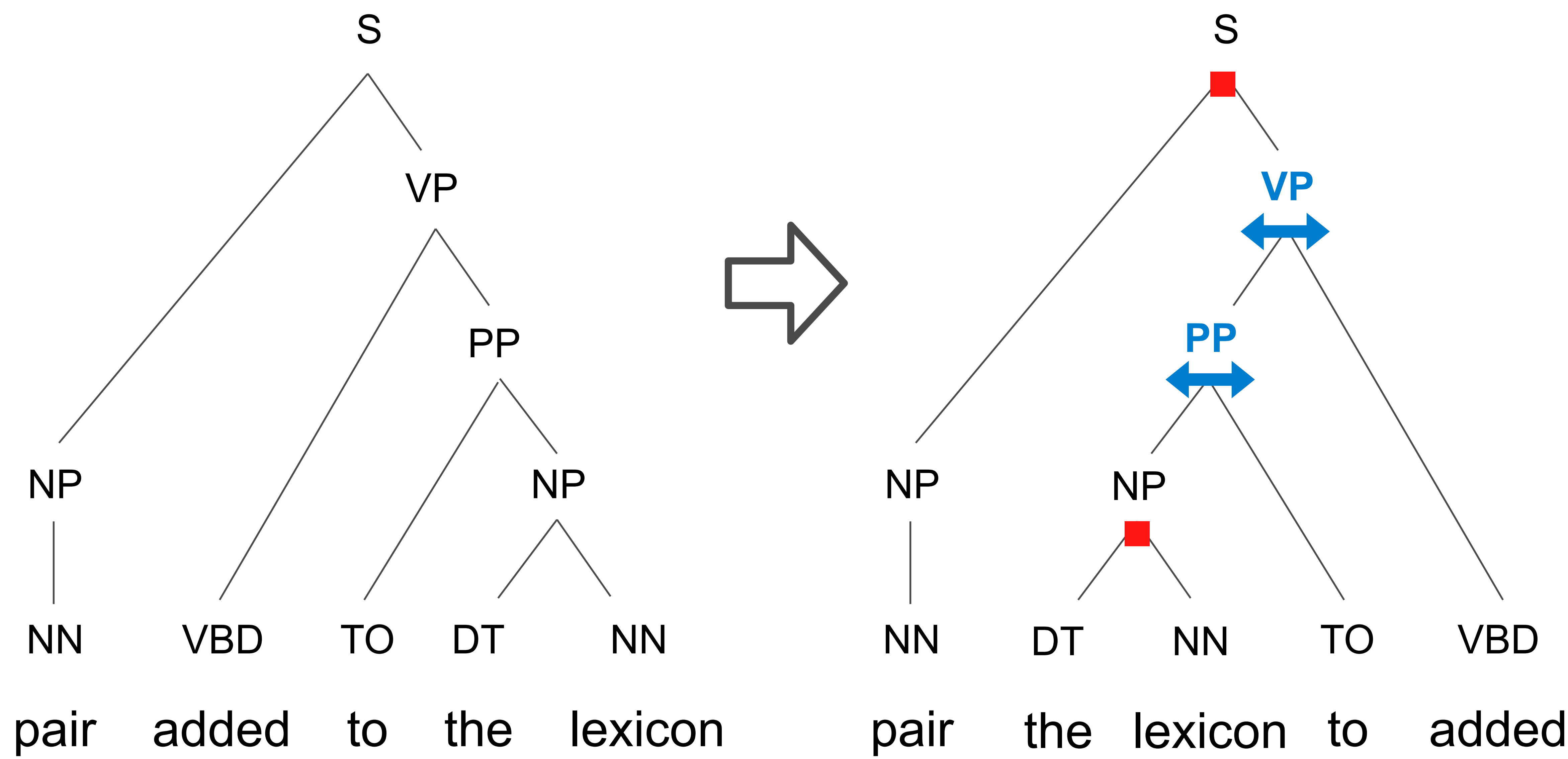

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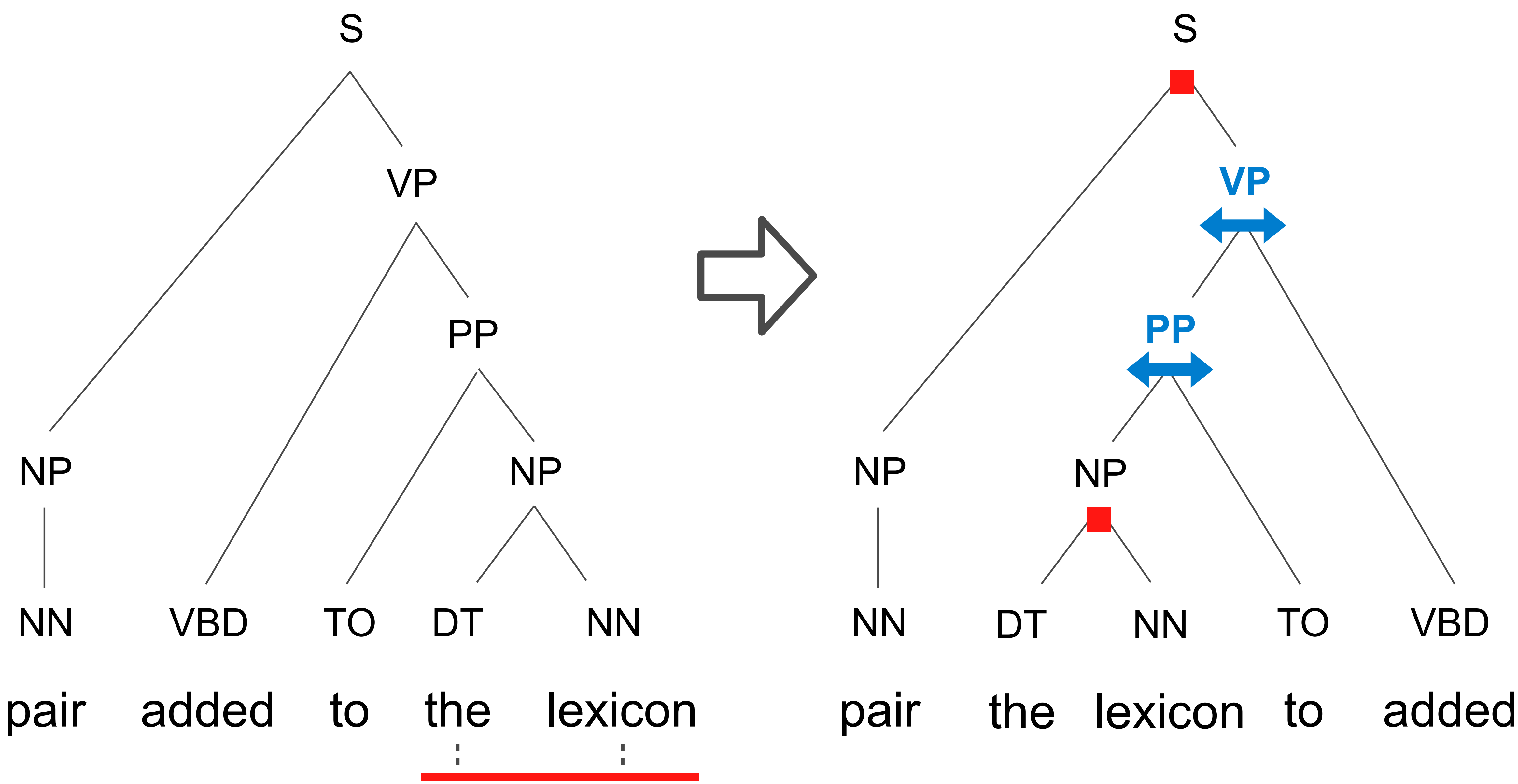

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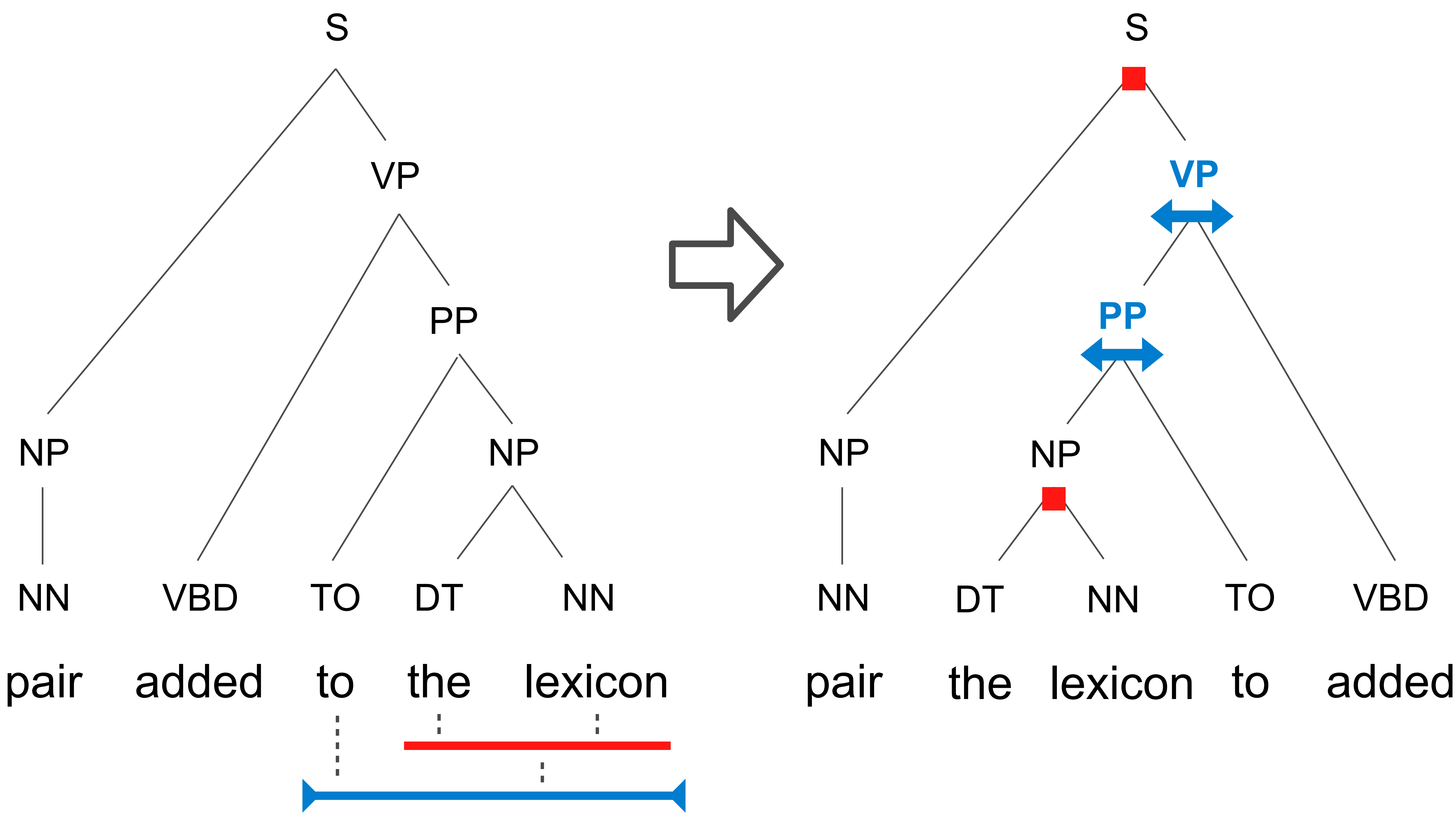

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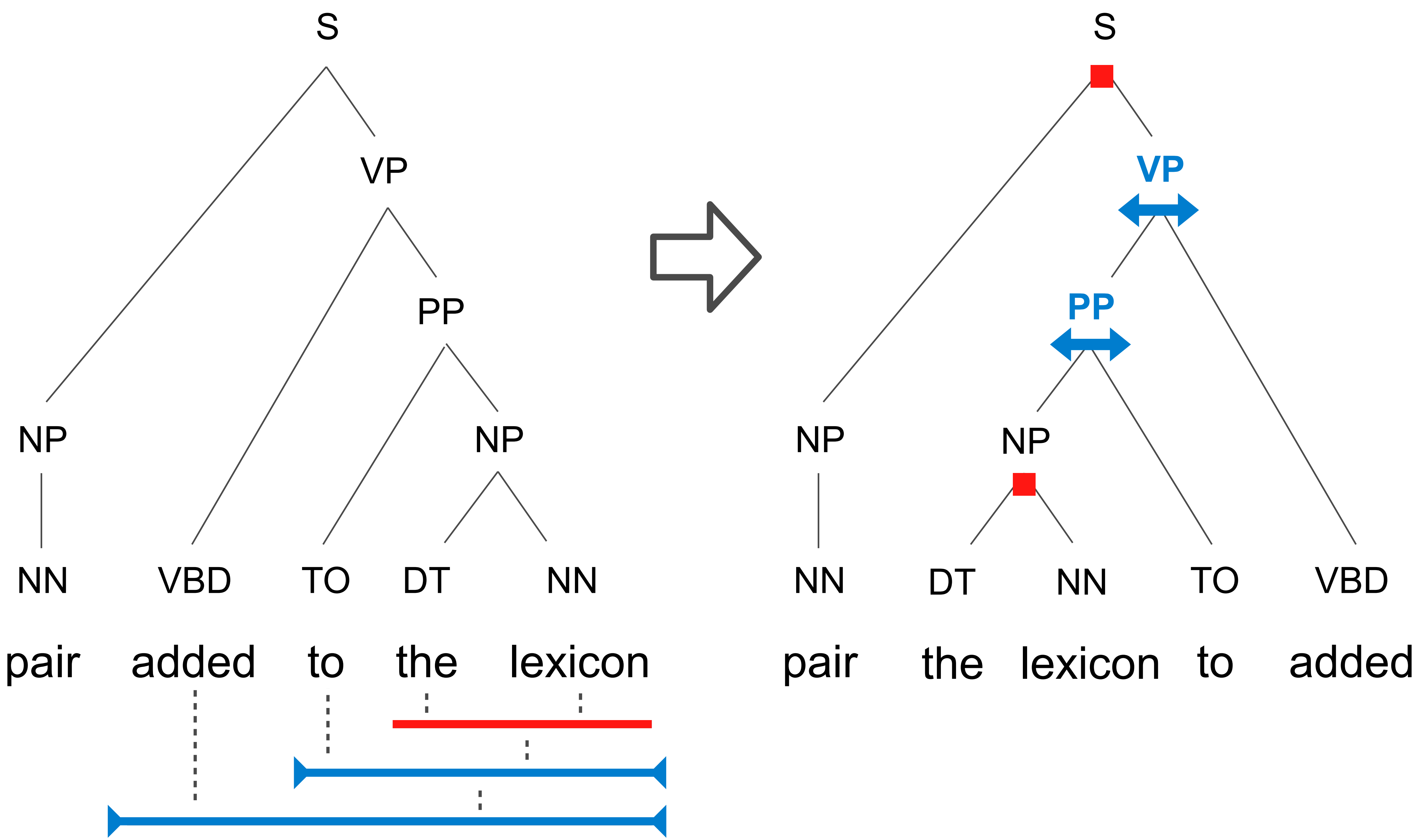

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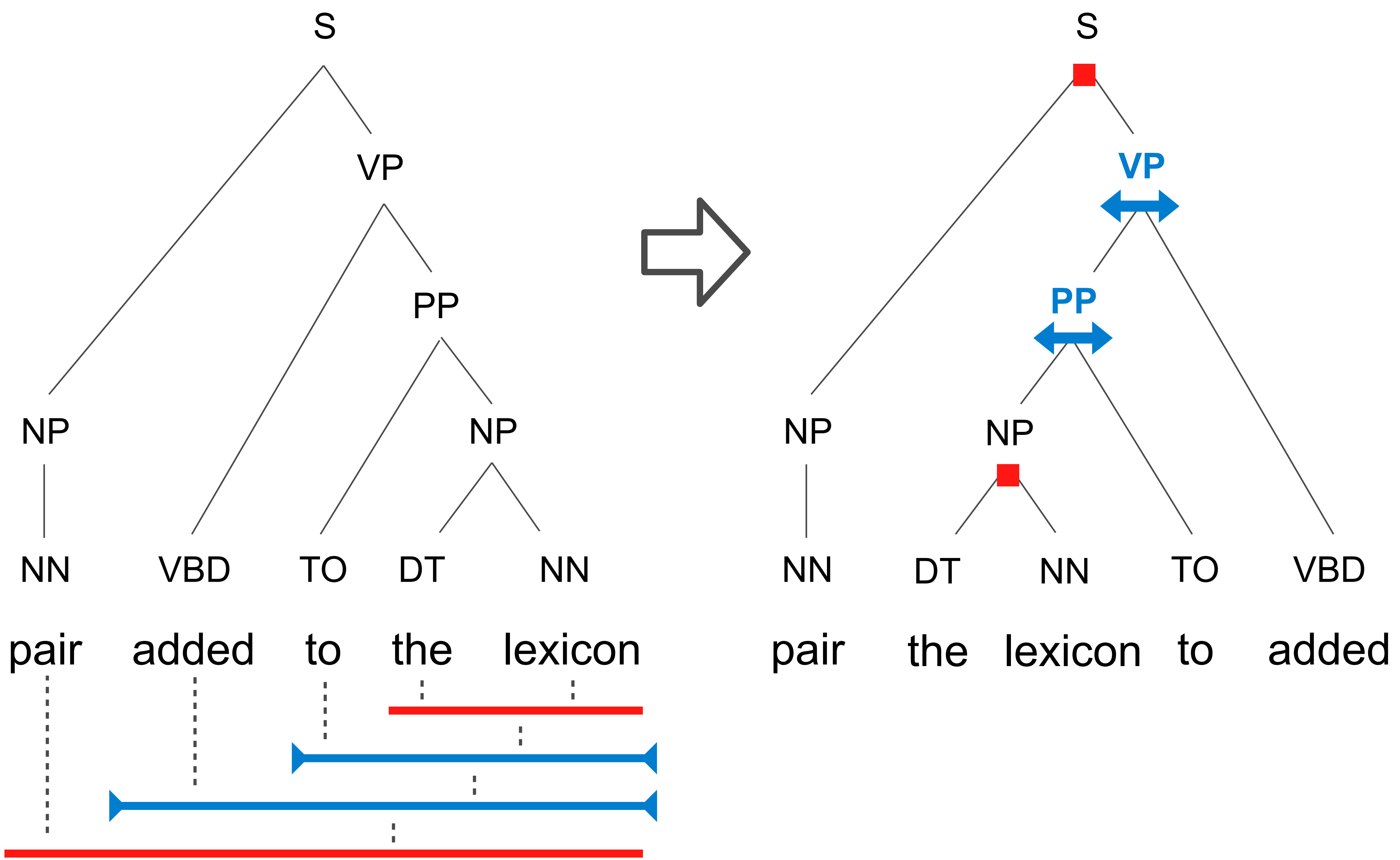

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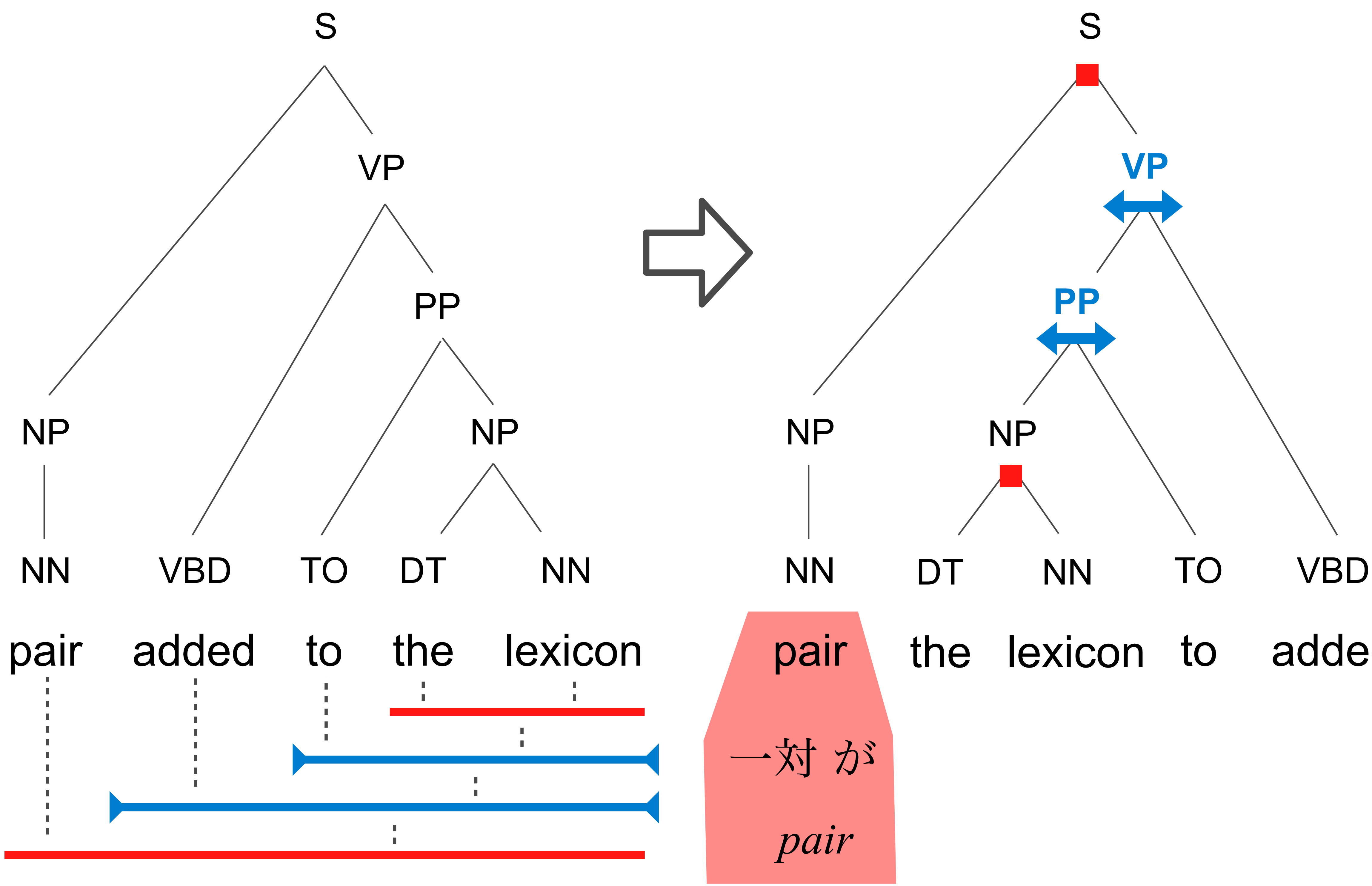

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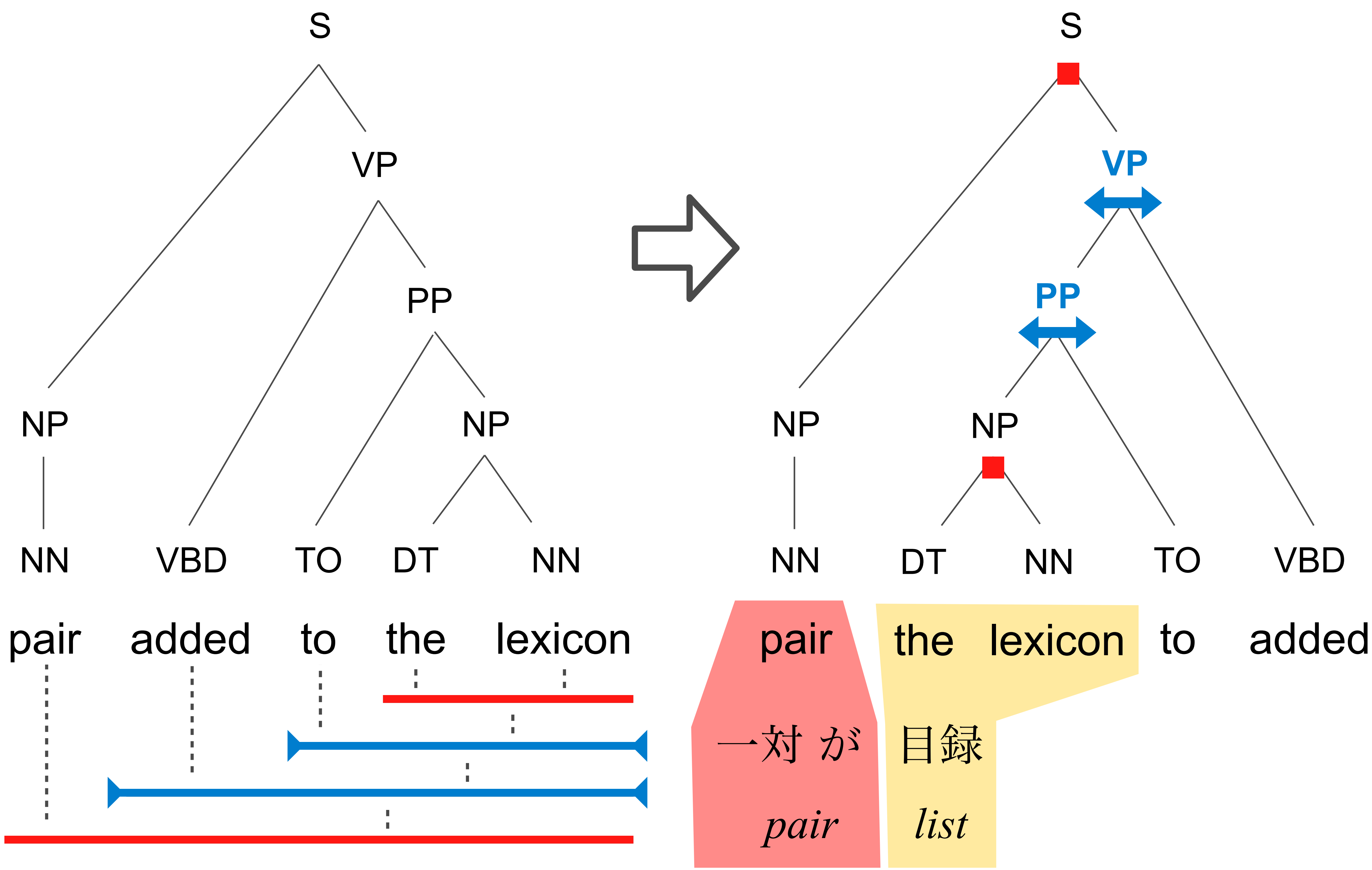

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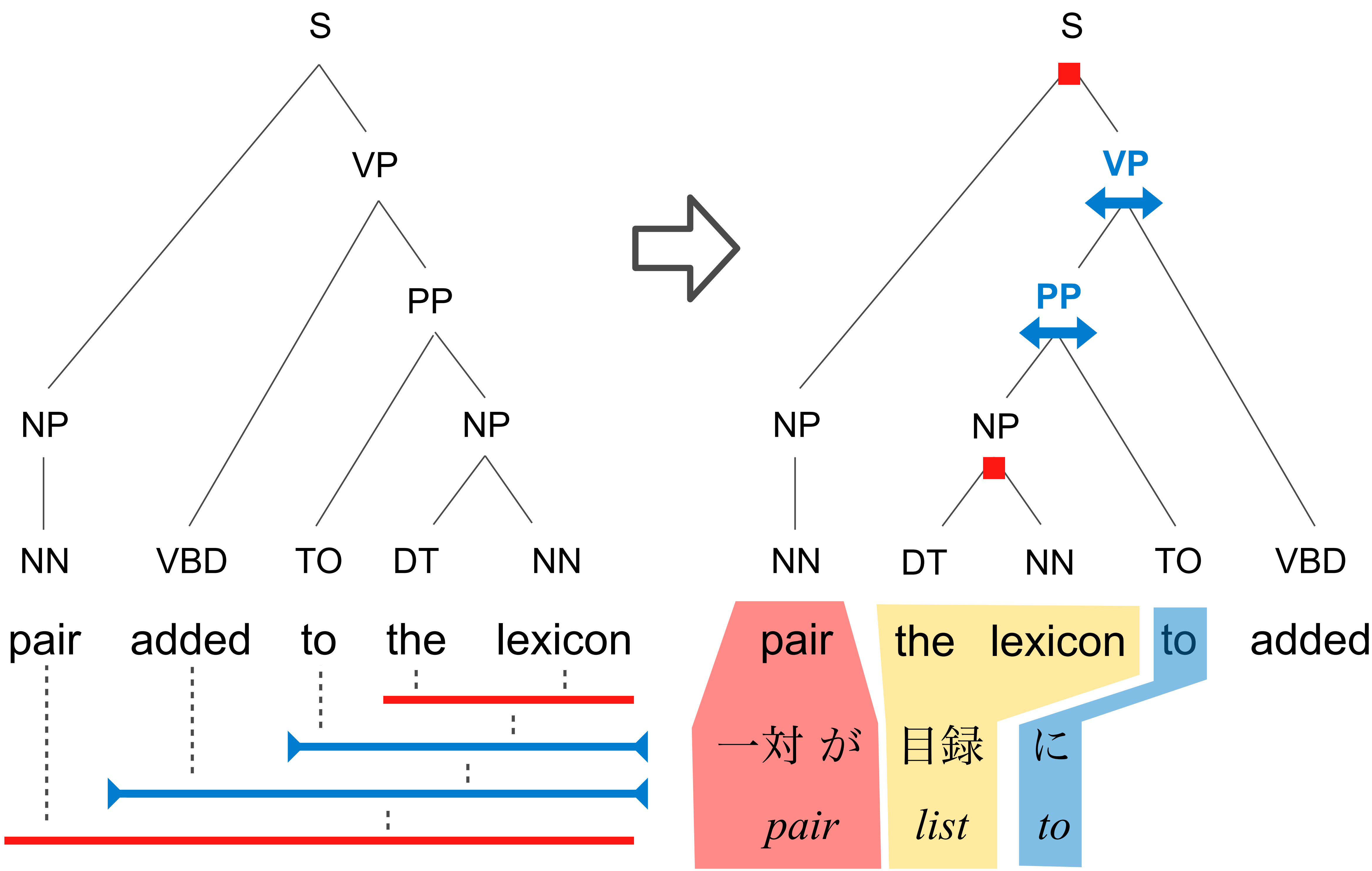

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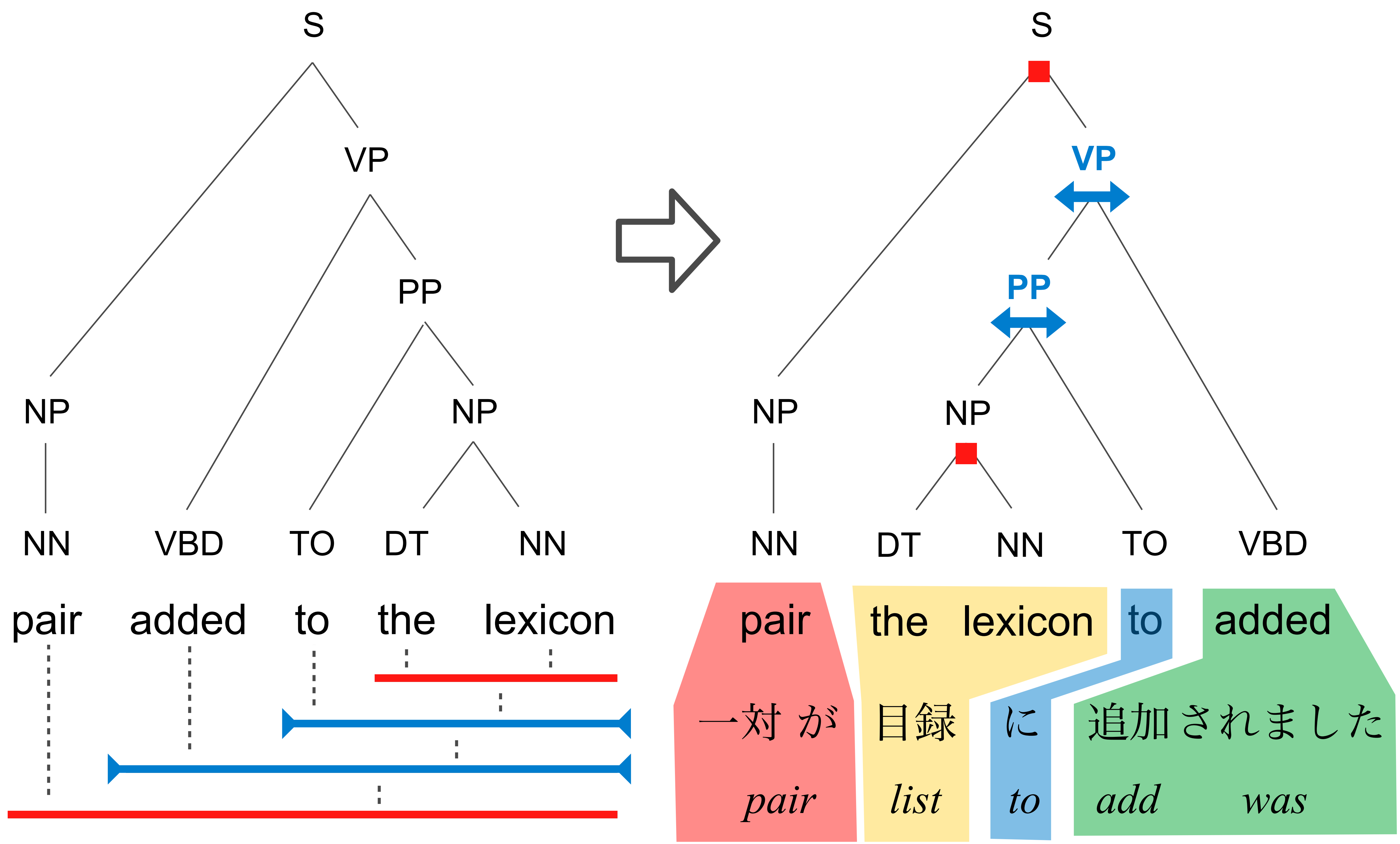

Bracketing and Word Classes are Often Sufficient

Decisions | **Methods**

pair added to the lexicon

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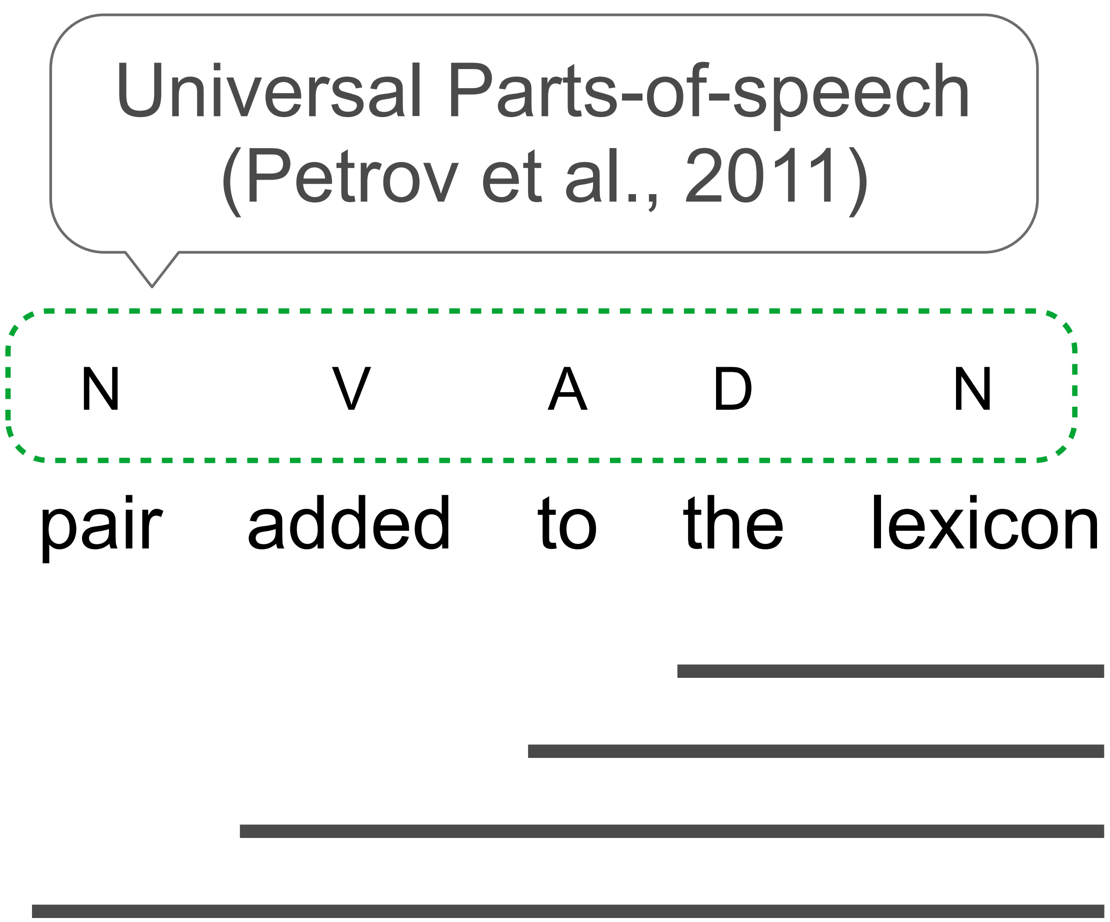

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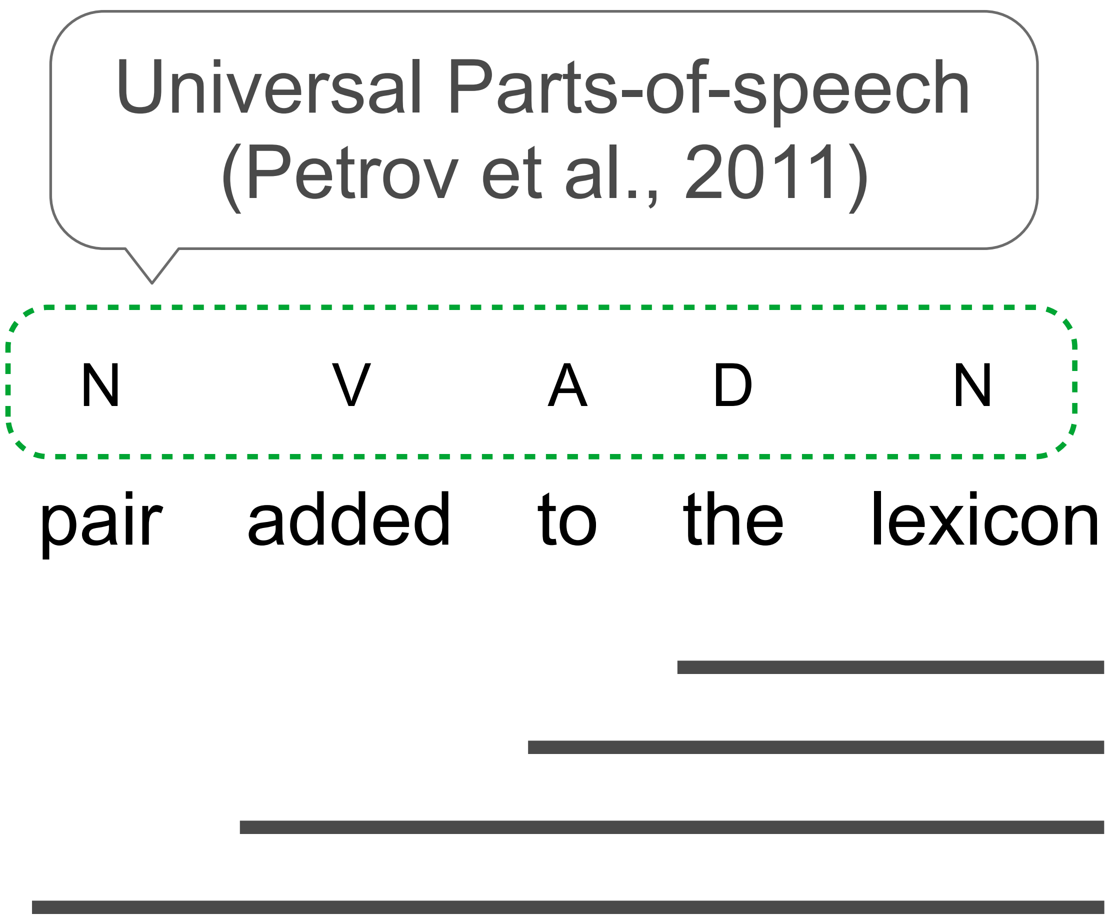

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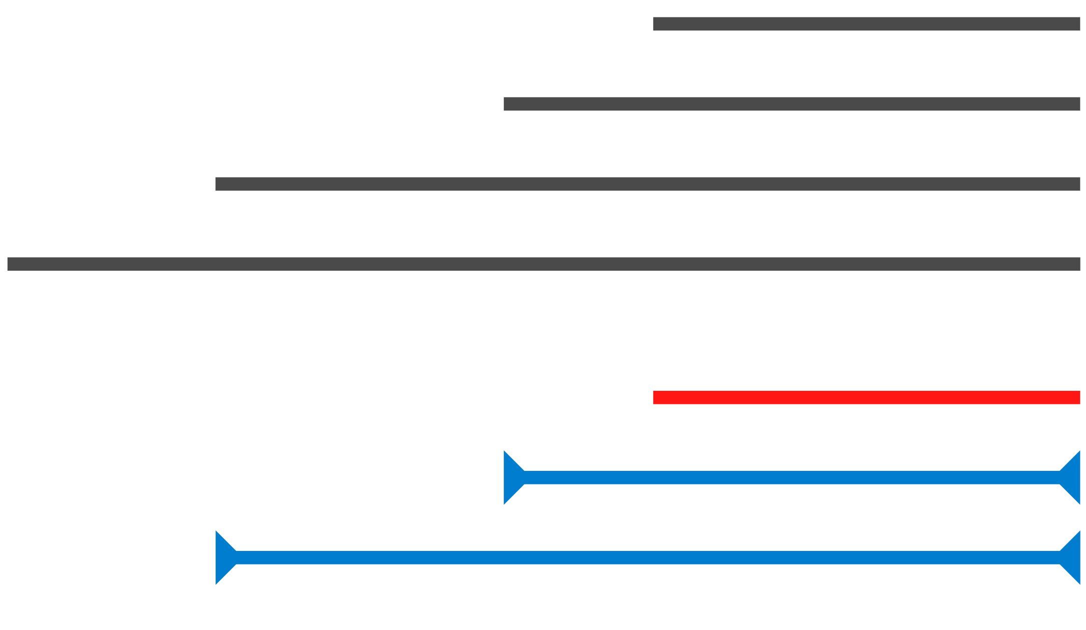

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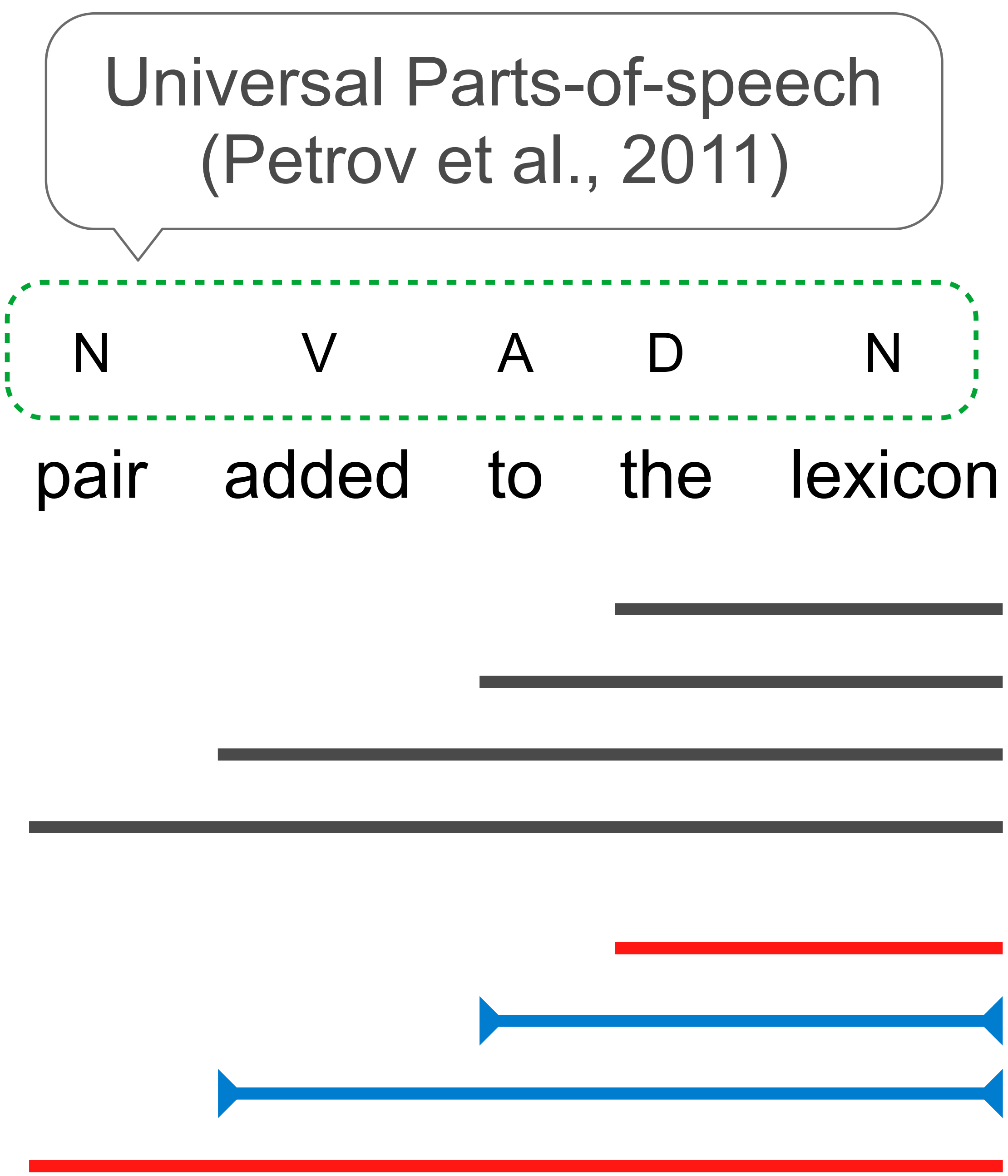

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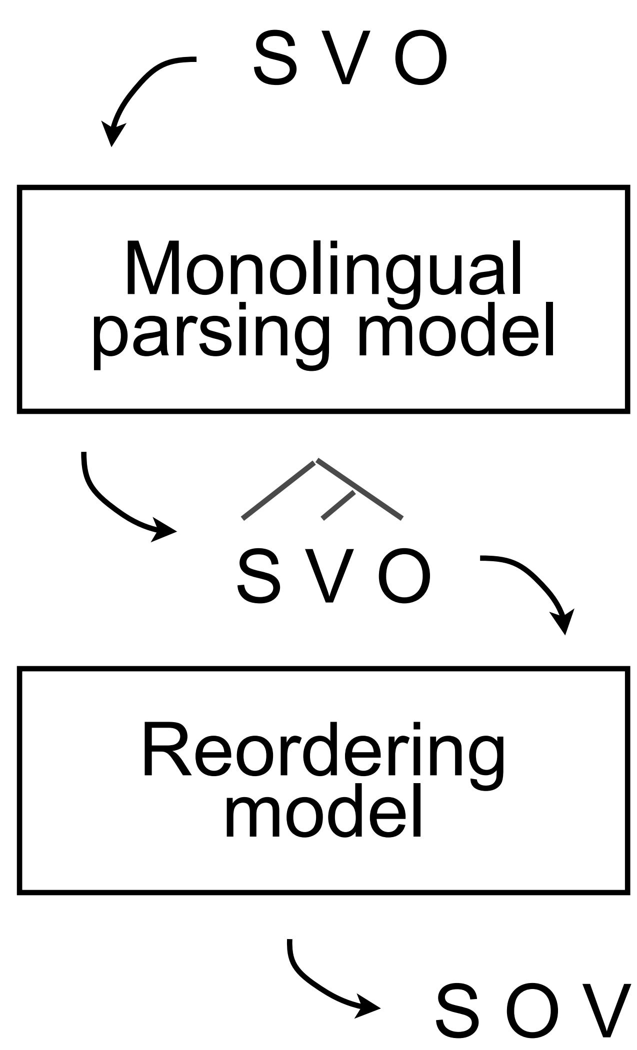
- Alignments gives reordering
- Reordering classifier

Pre-Ordering from a Parallel Corpus

Analyze Aligned Parallel Corpus

Pre-Ordering Pipeline



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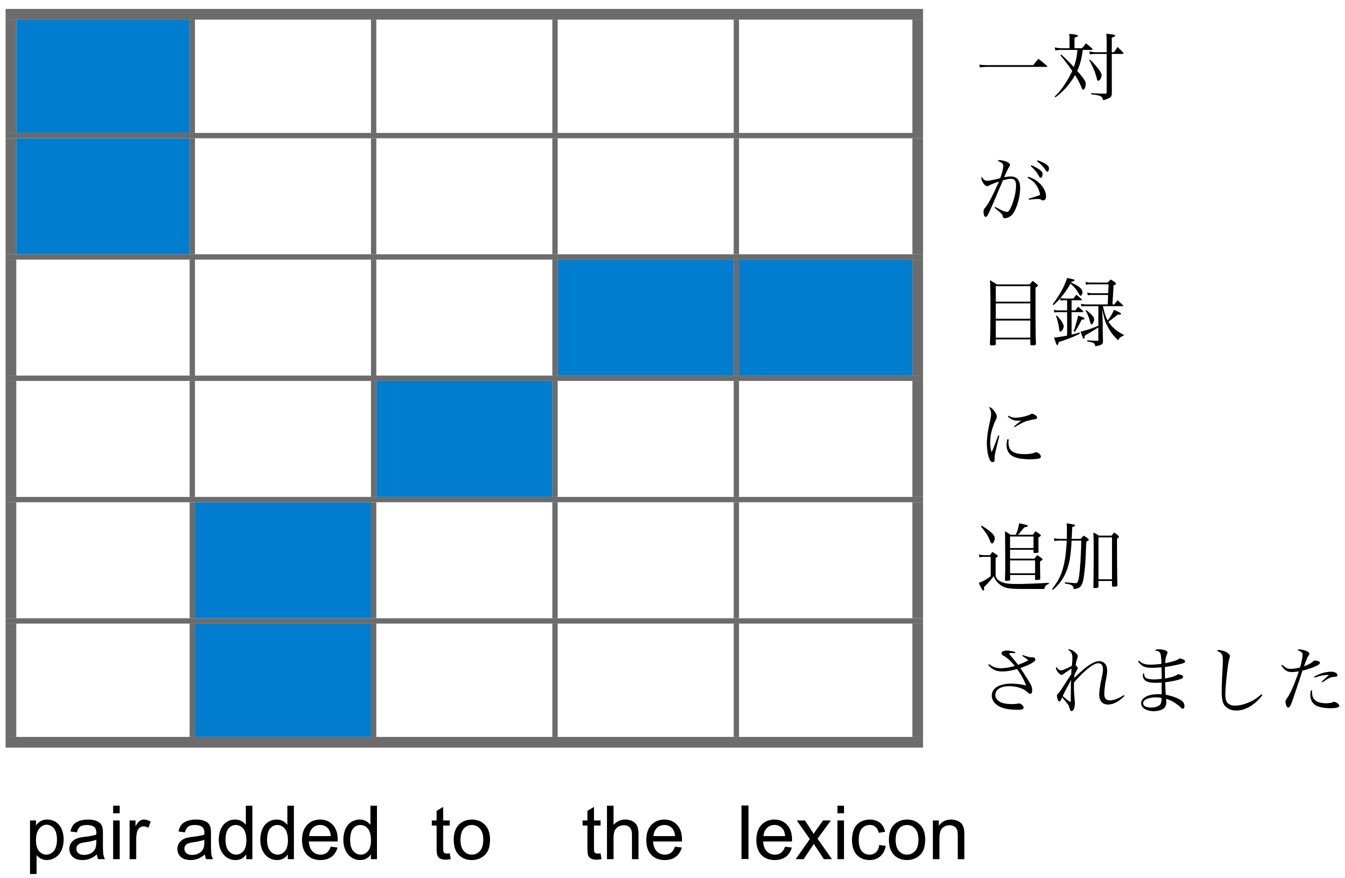

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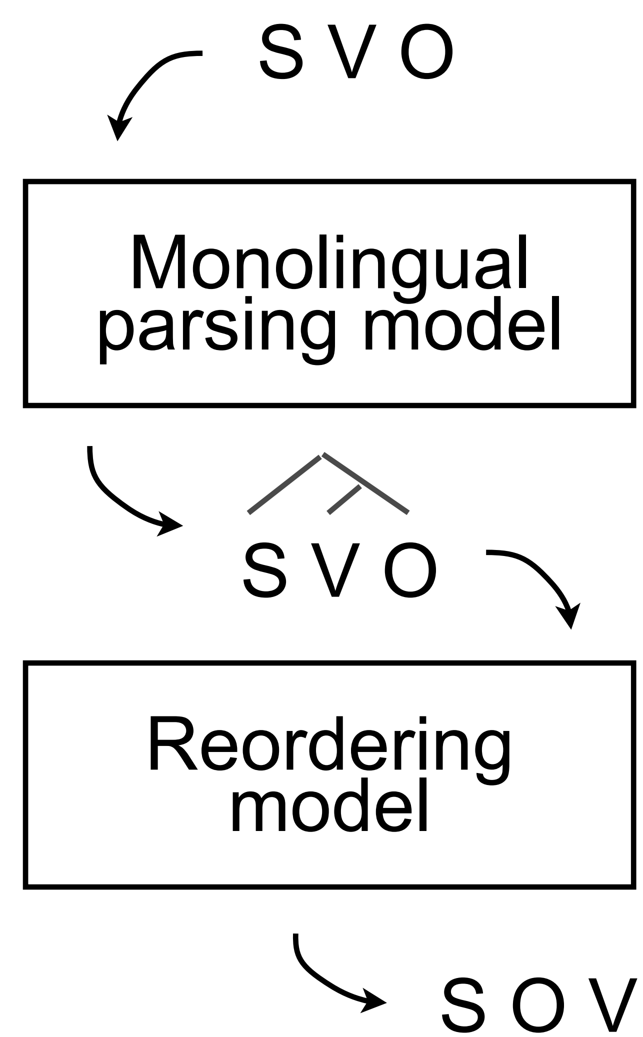

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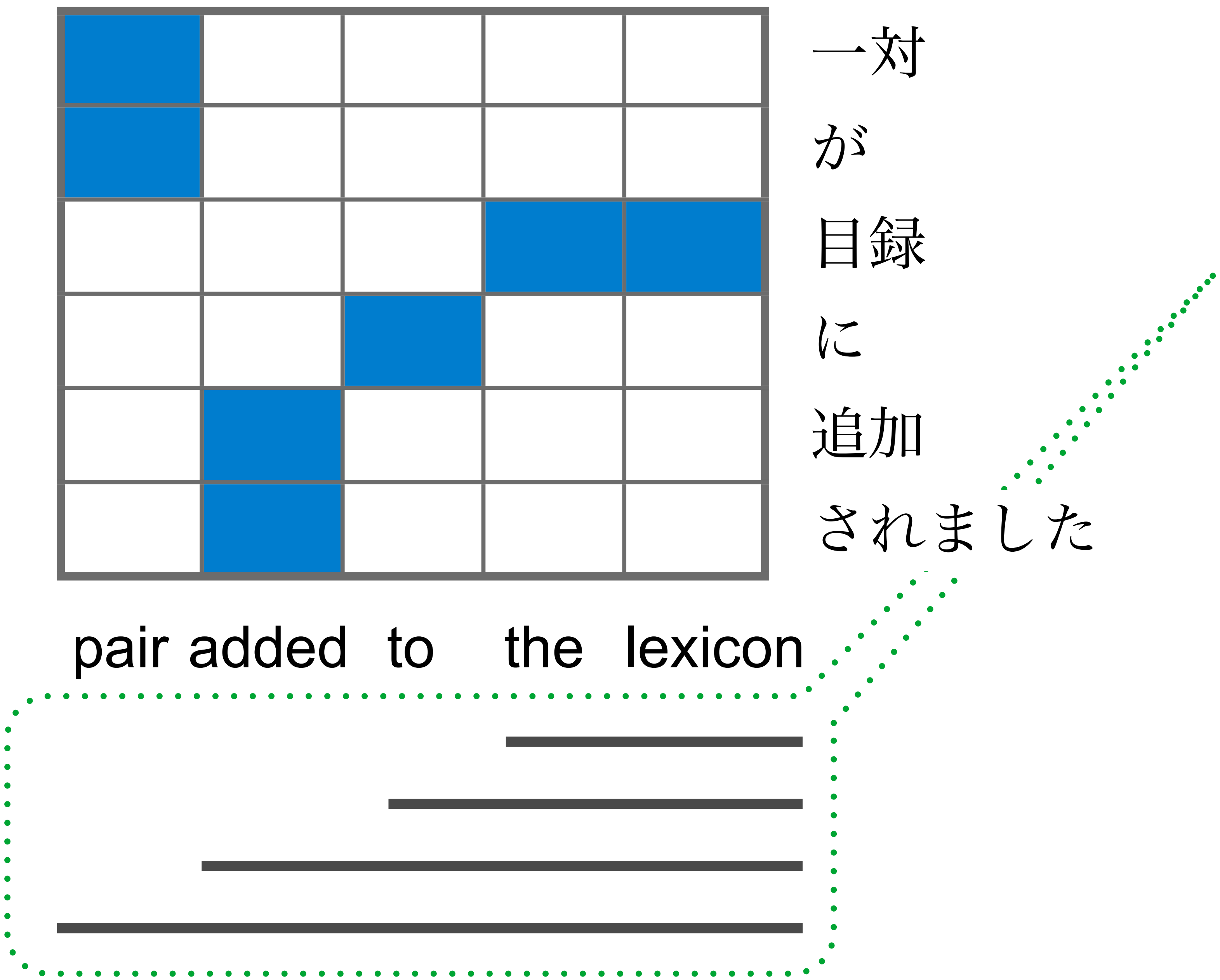

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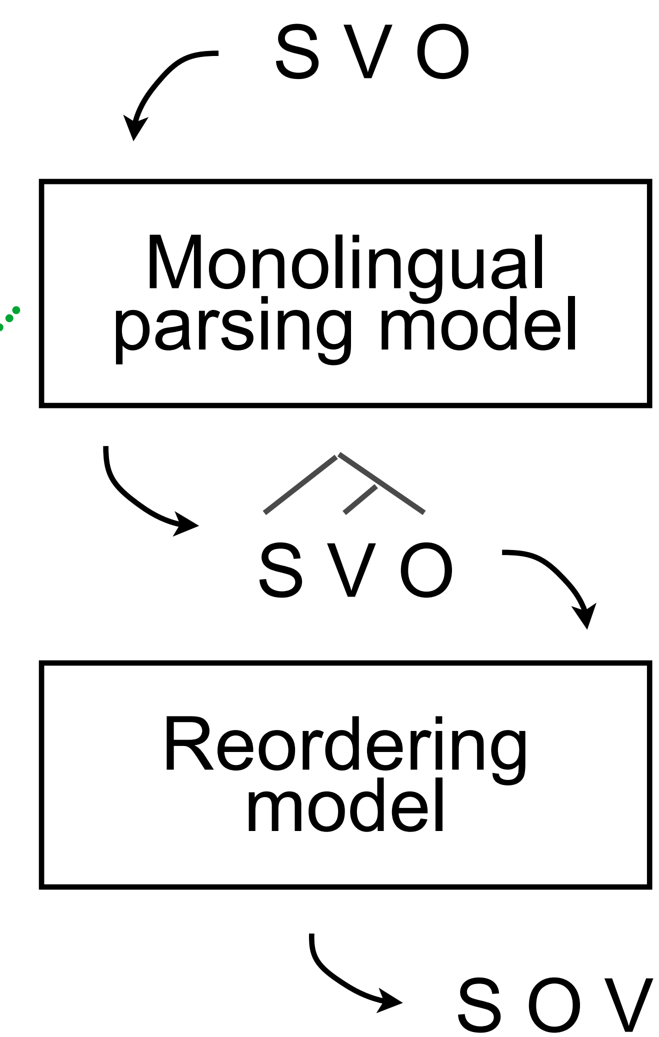

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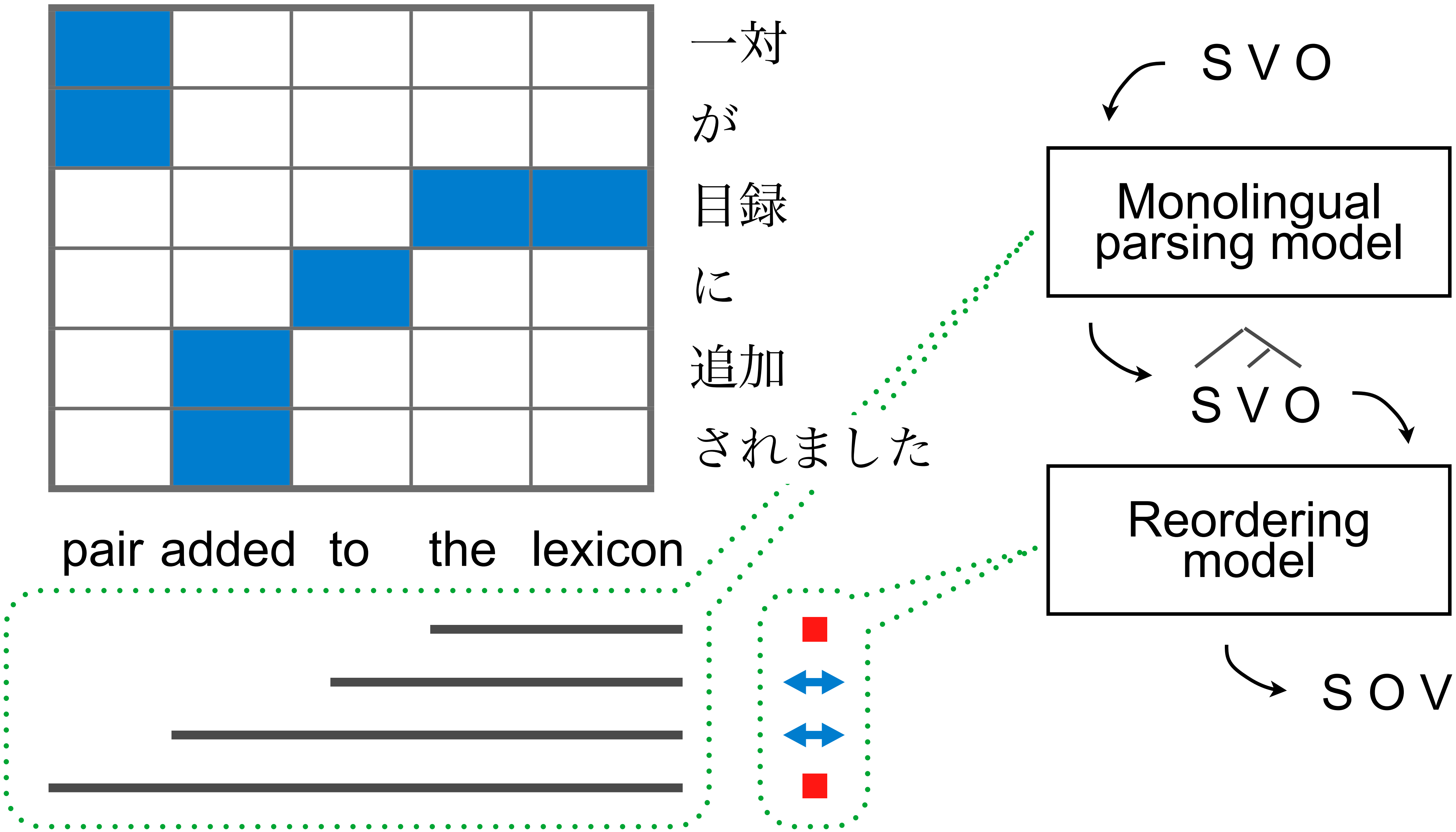
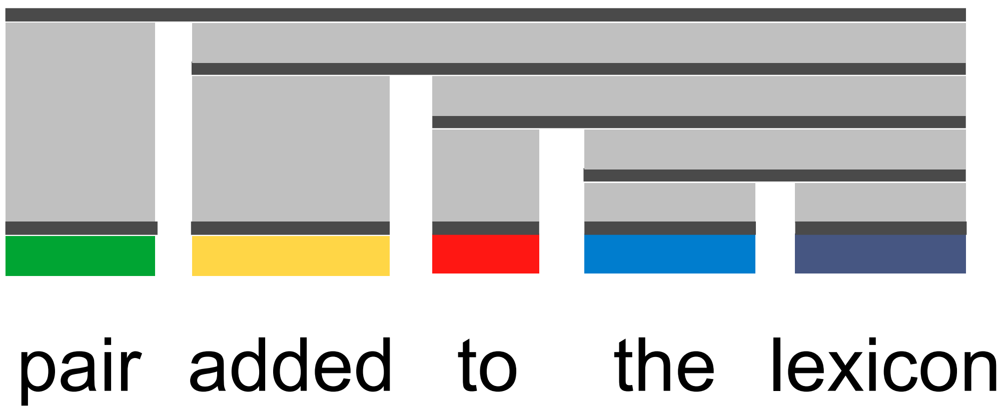


Binary Bracketing Trees with Phrasal Terminals



A tree is defined by the set of spans it contains

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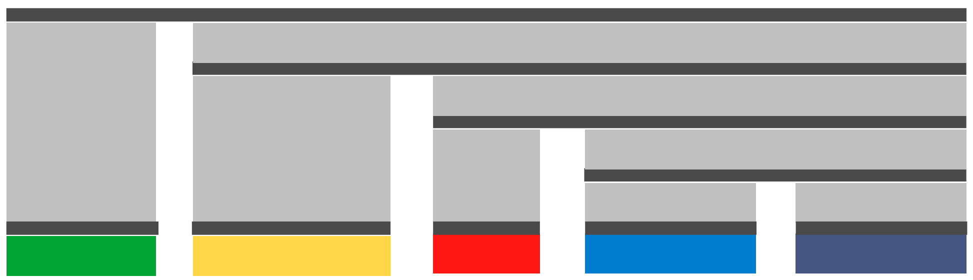

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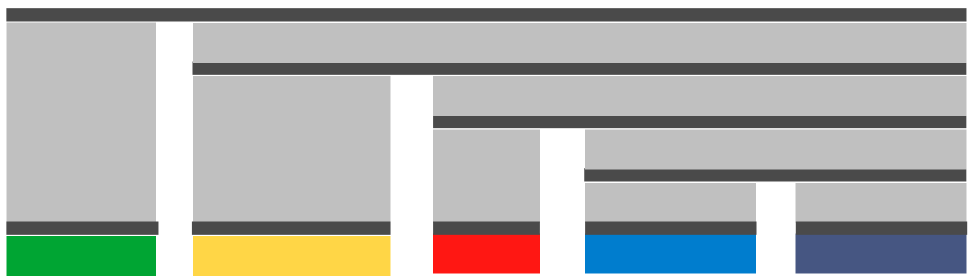

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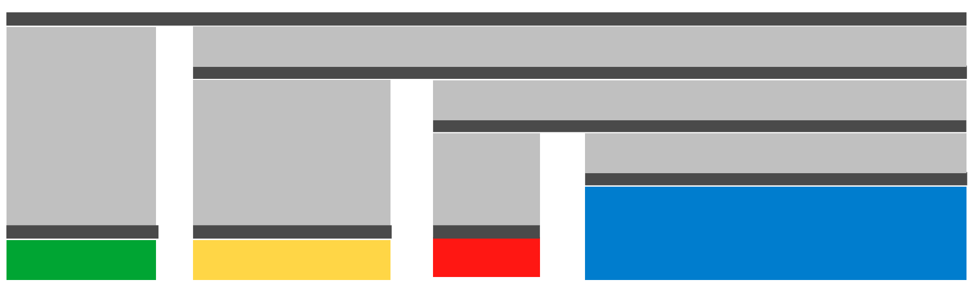

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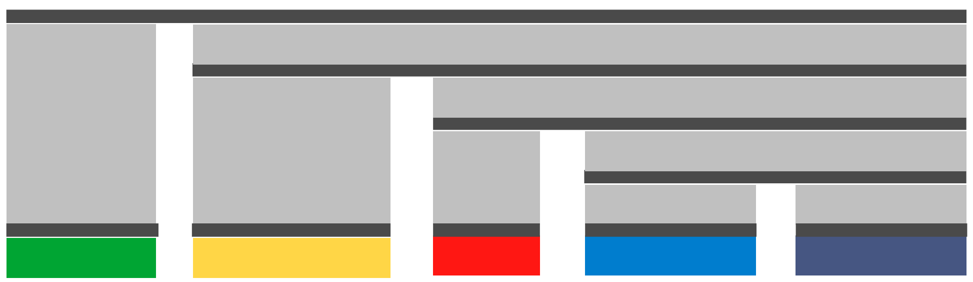

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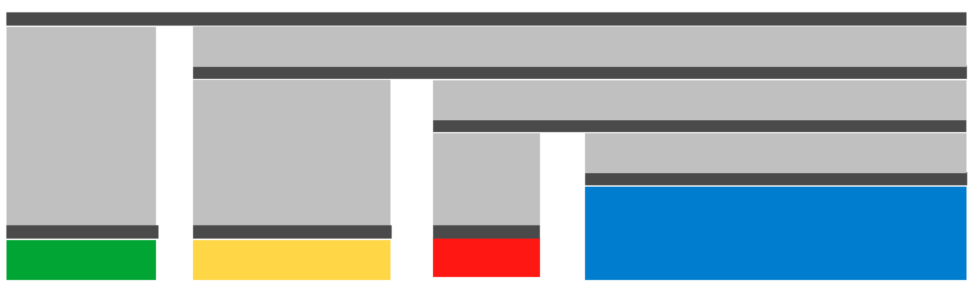

Not every word will correspond to a span

A tree can be composed of only a single span

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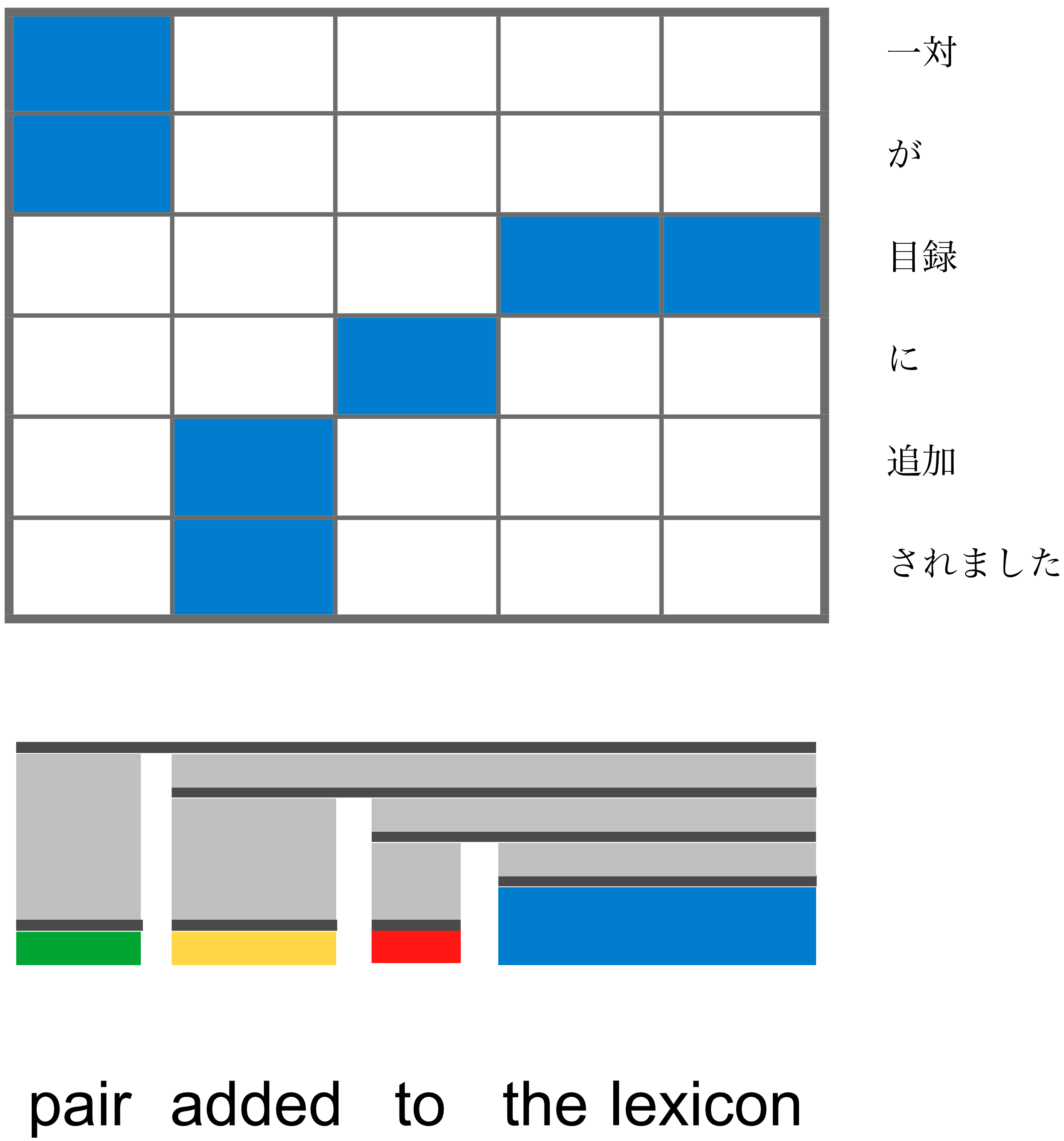
Parallel Parsing Model Constraint



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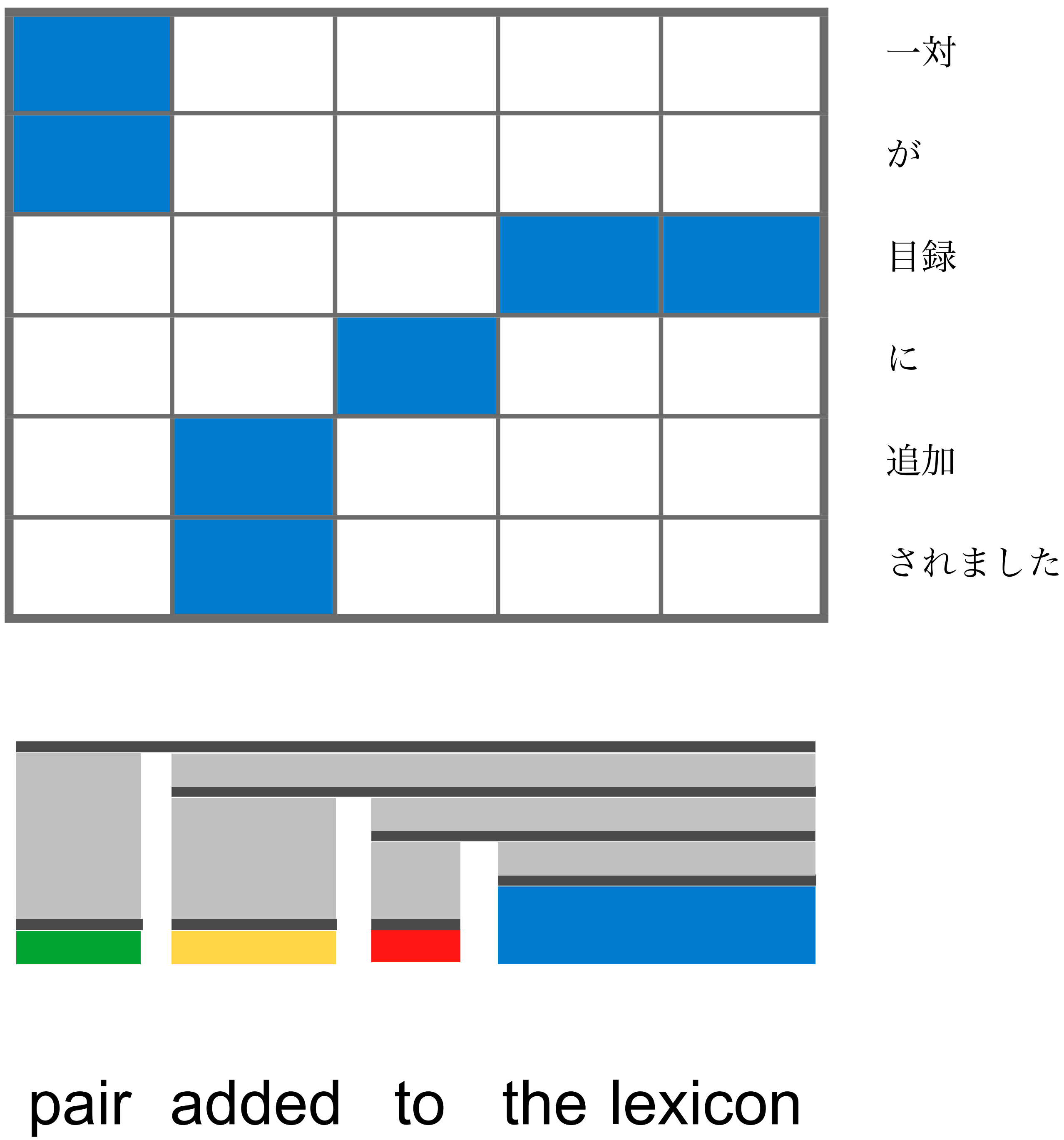

An alignment licenses a tree if every tree span is *aligned contiguously*

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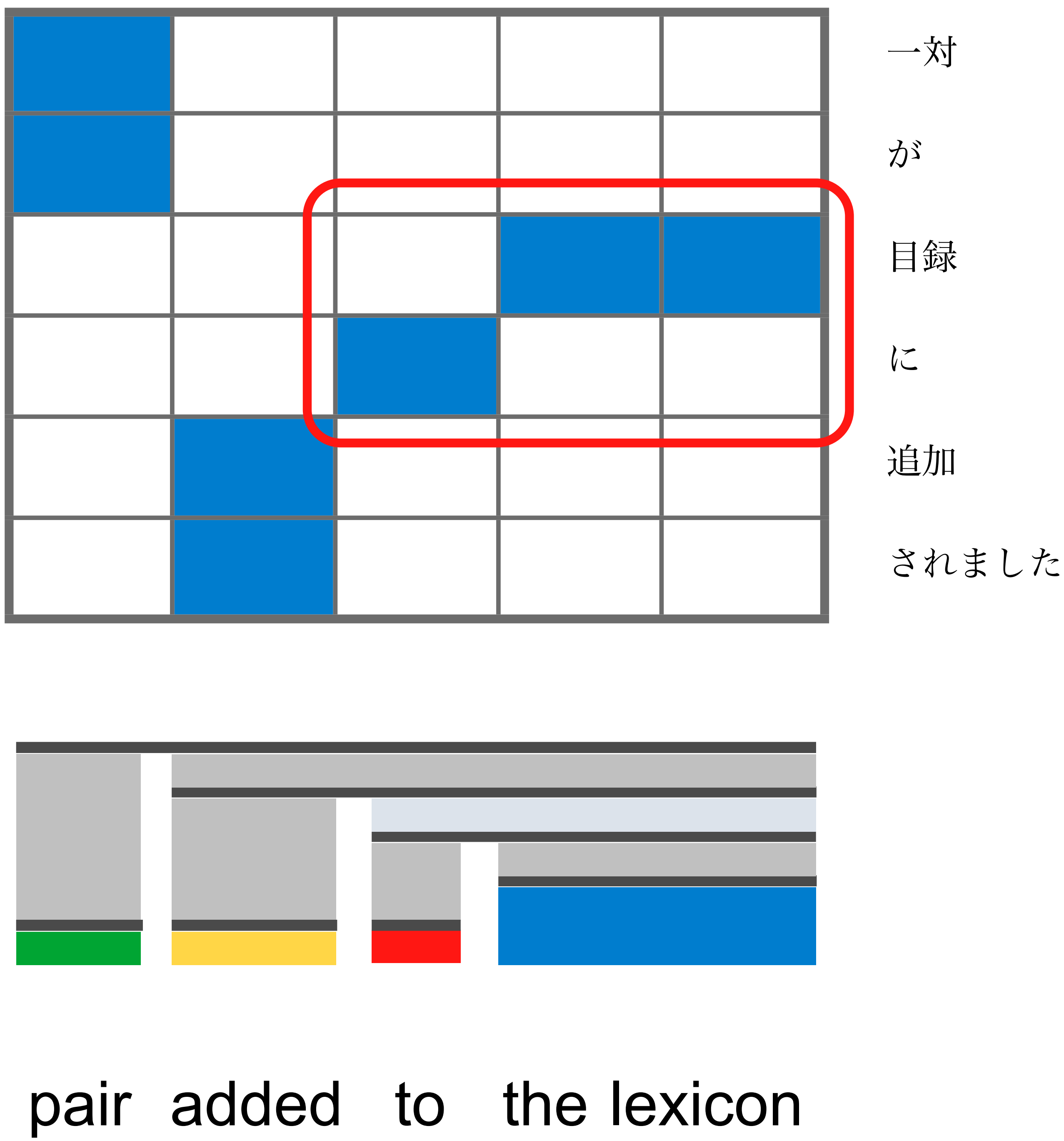

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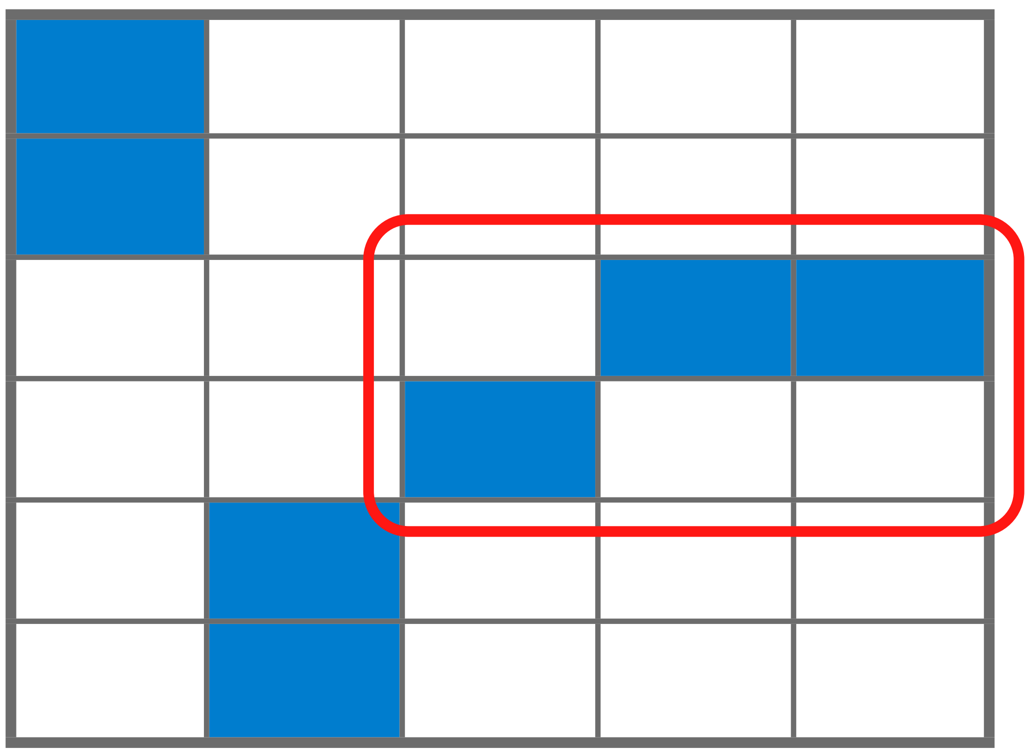

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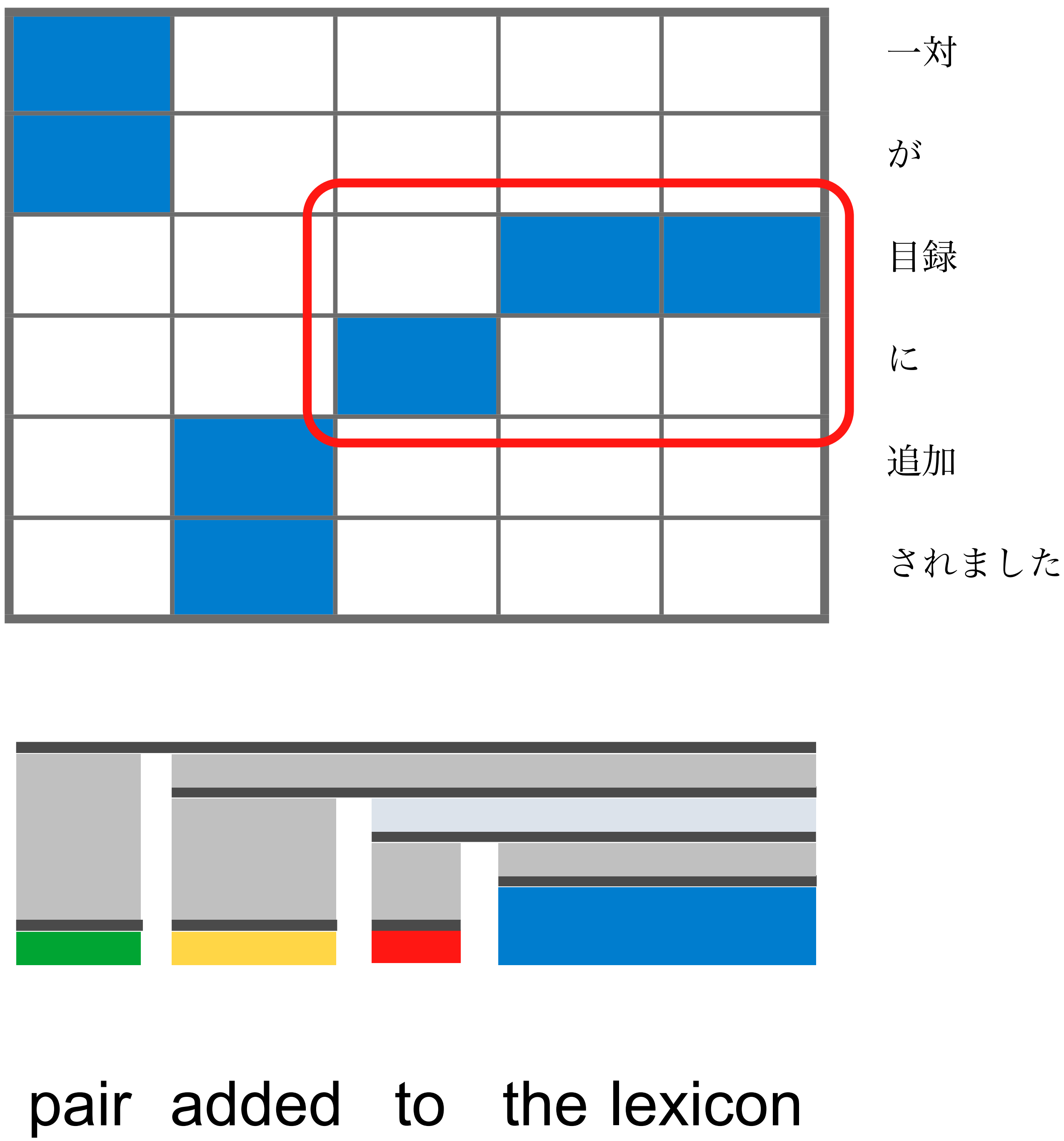

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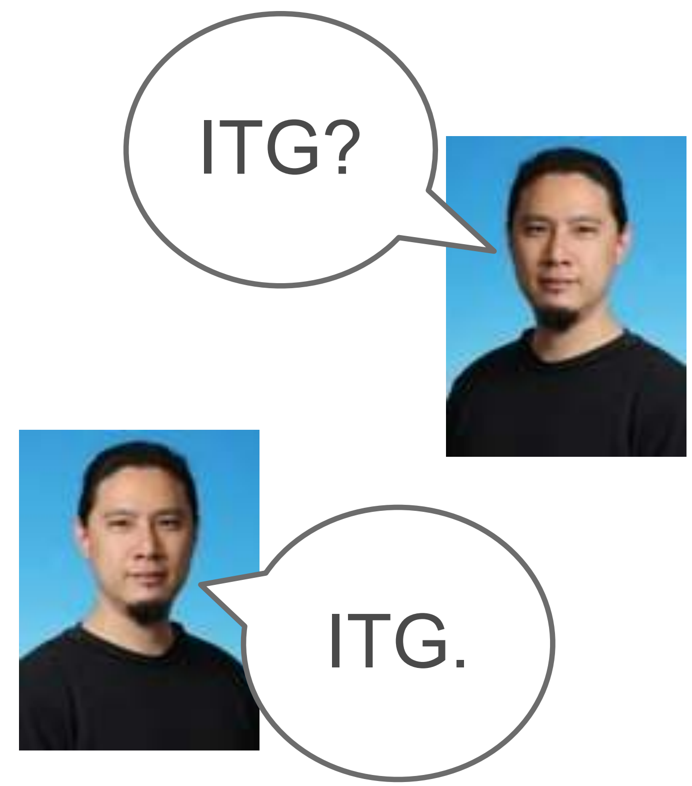

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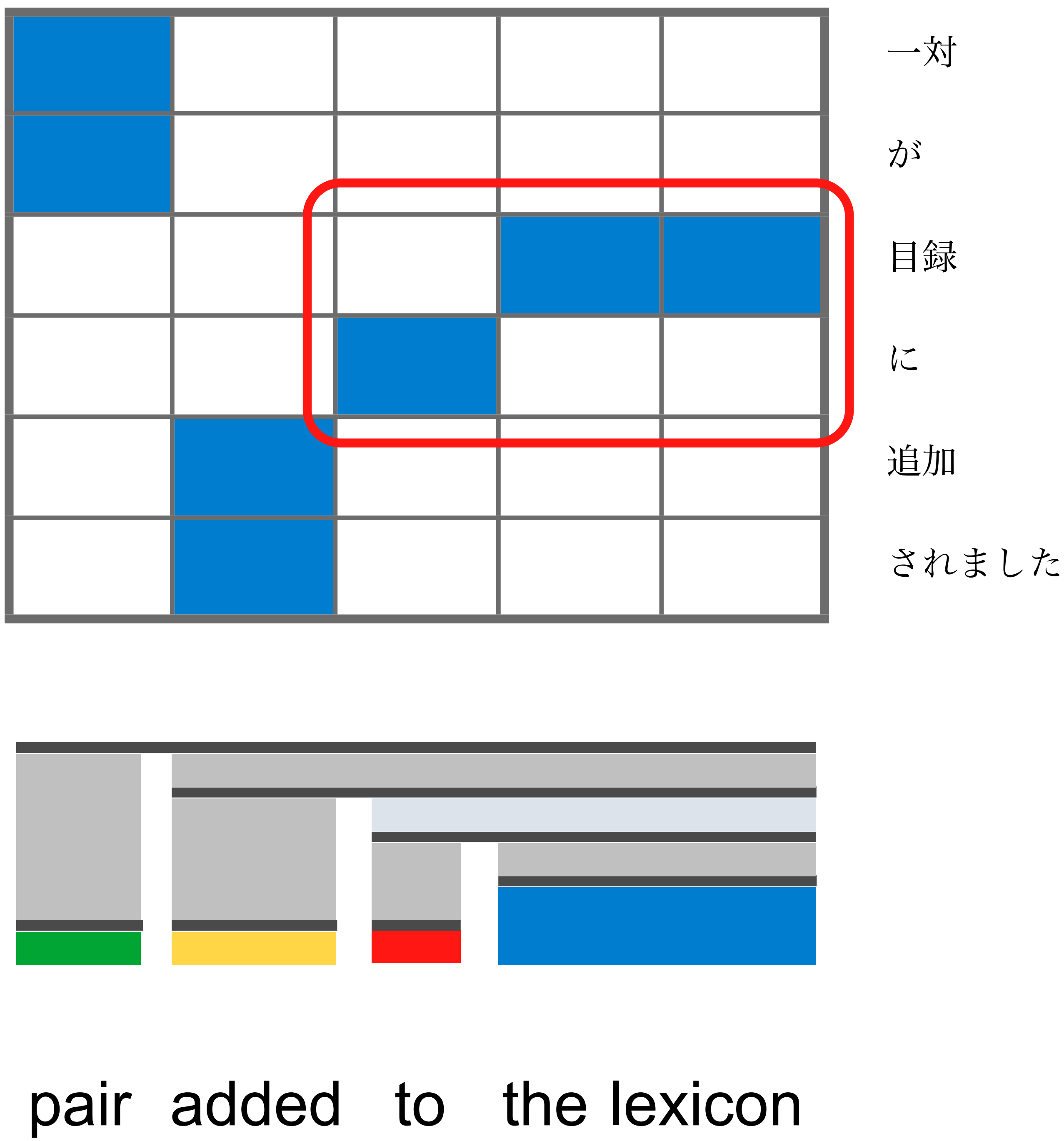

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Remaining ambiguity:

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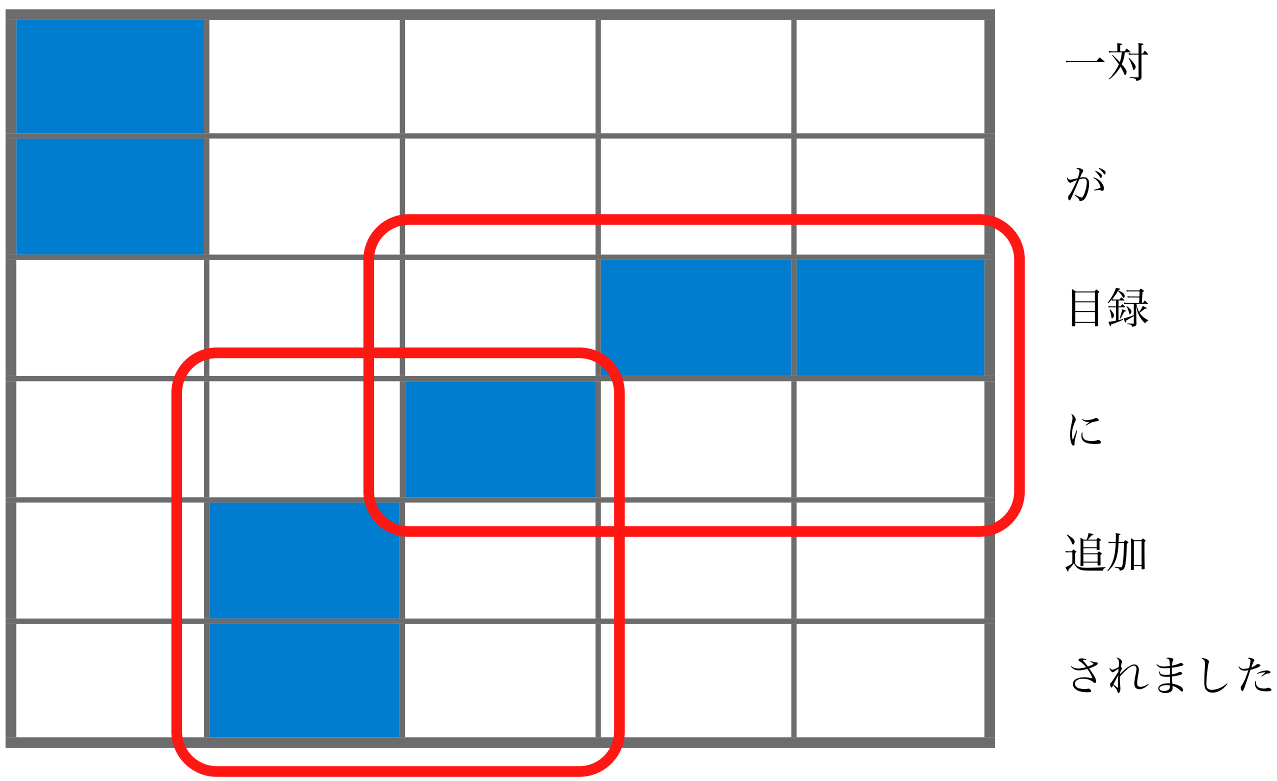

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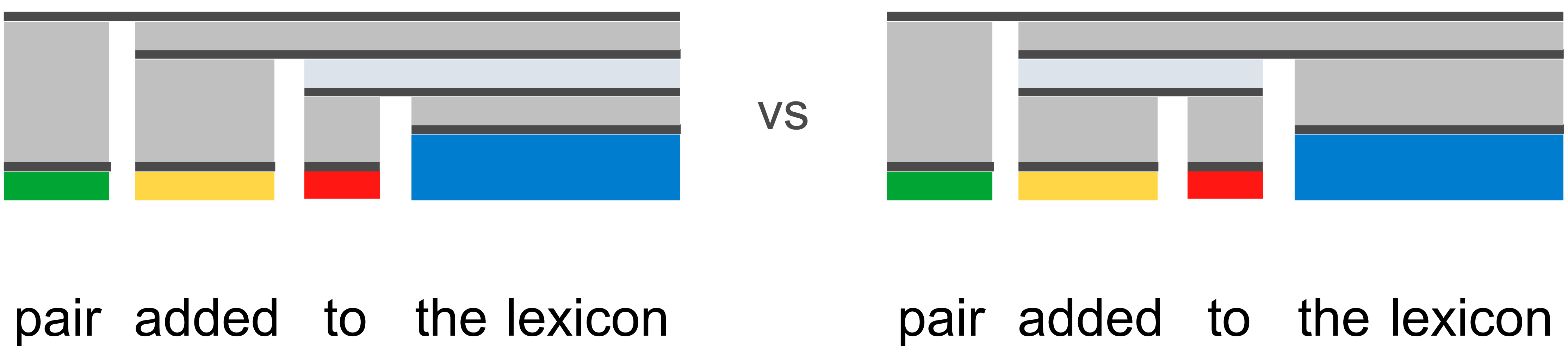

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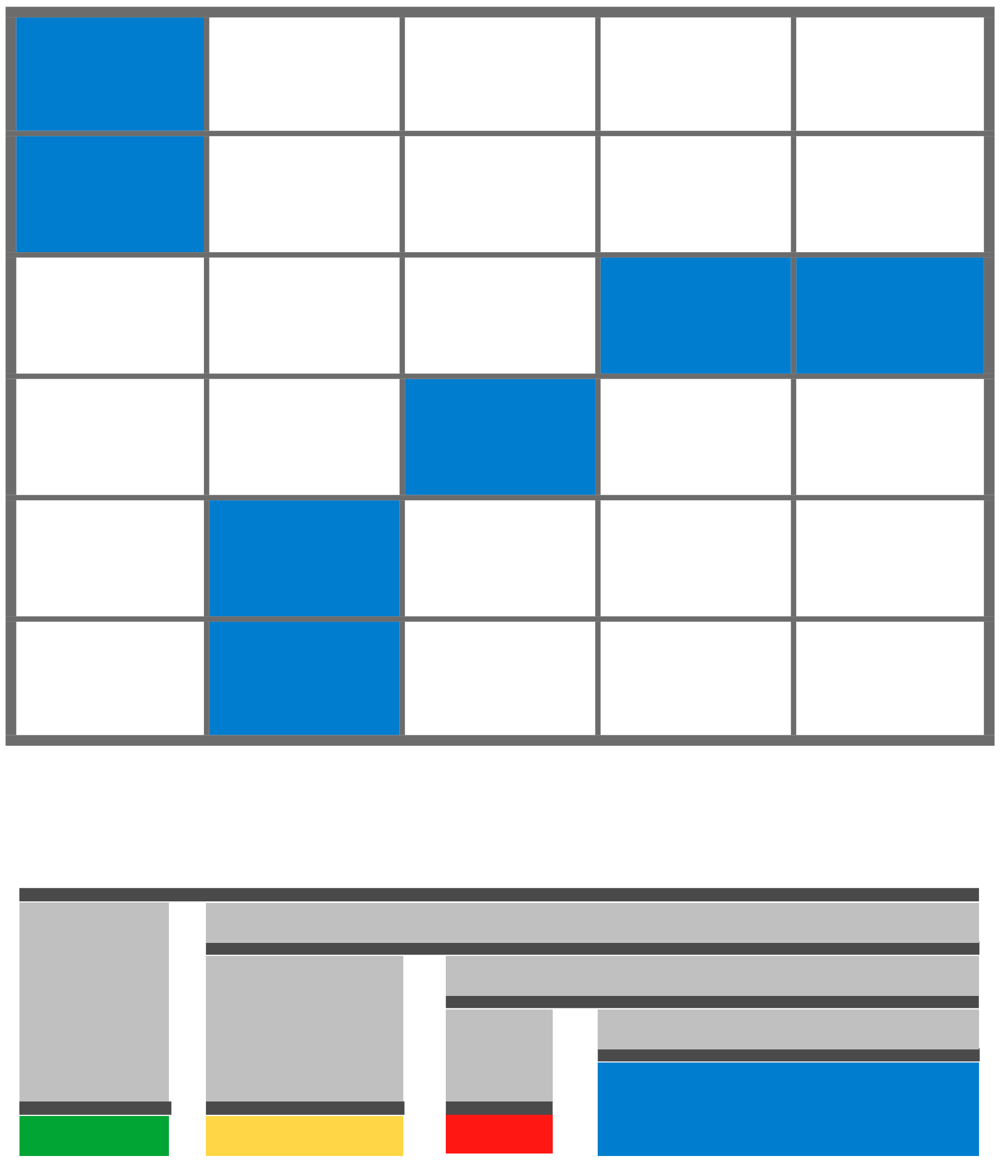

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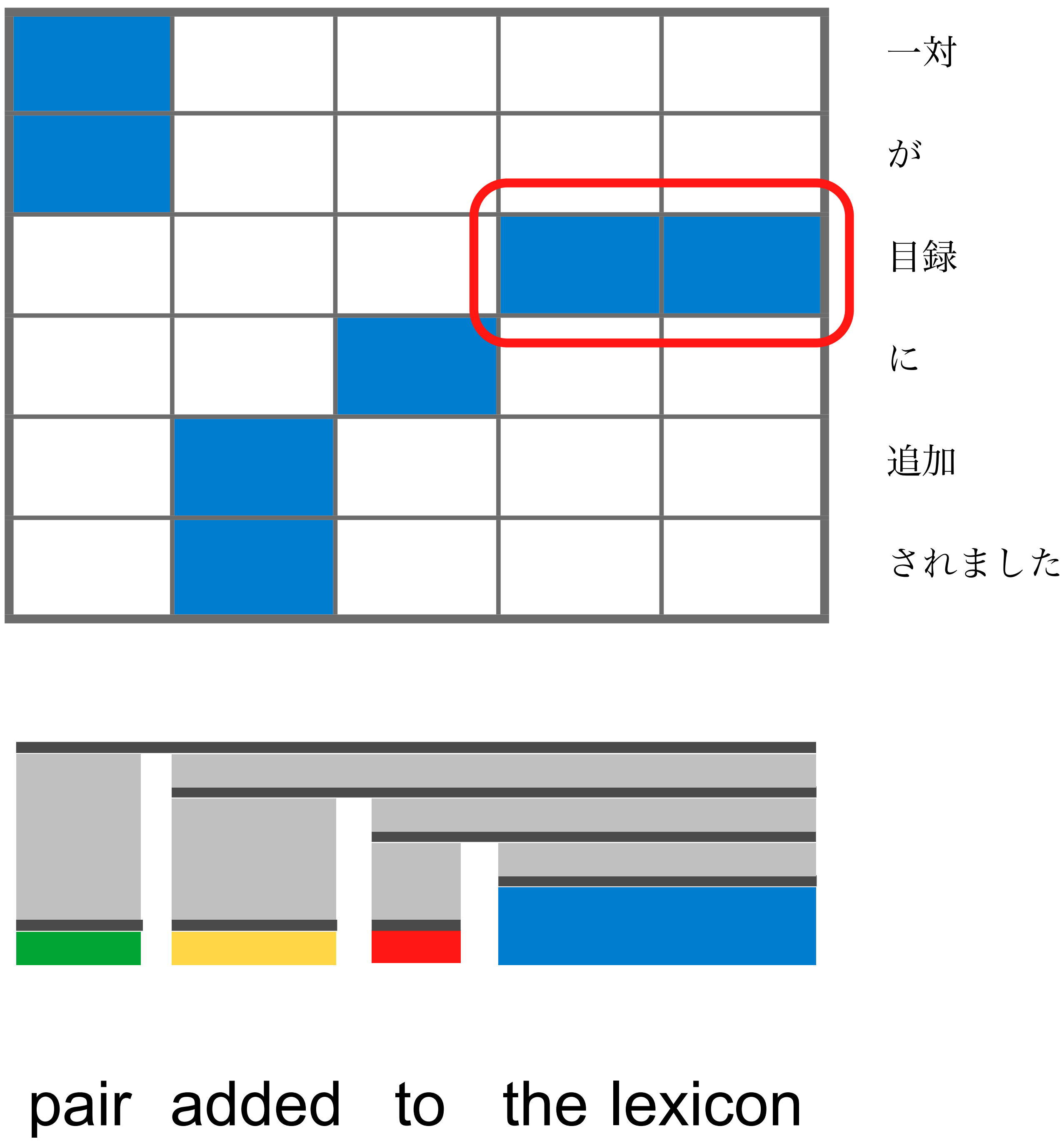

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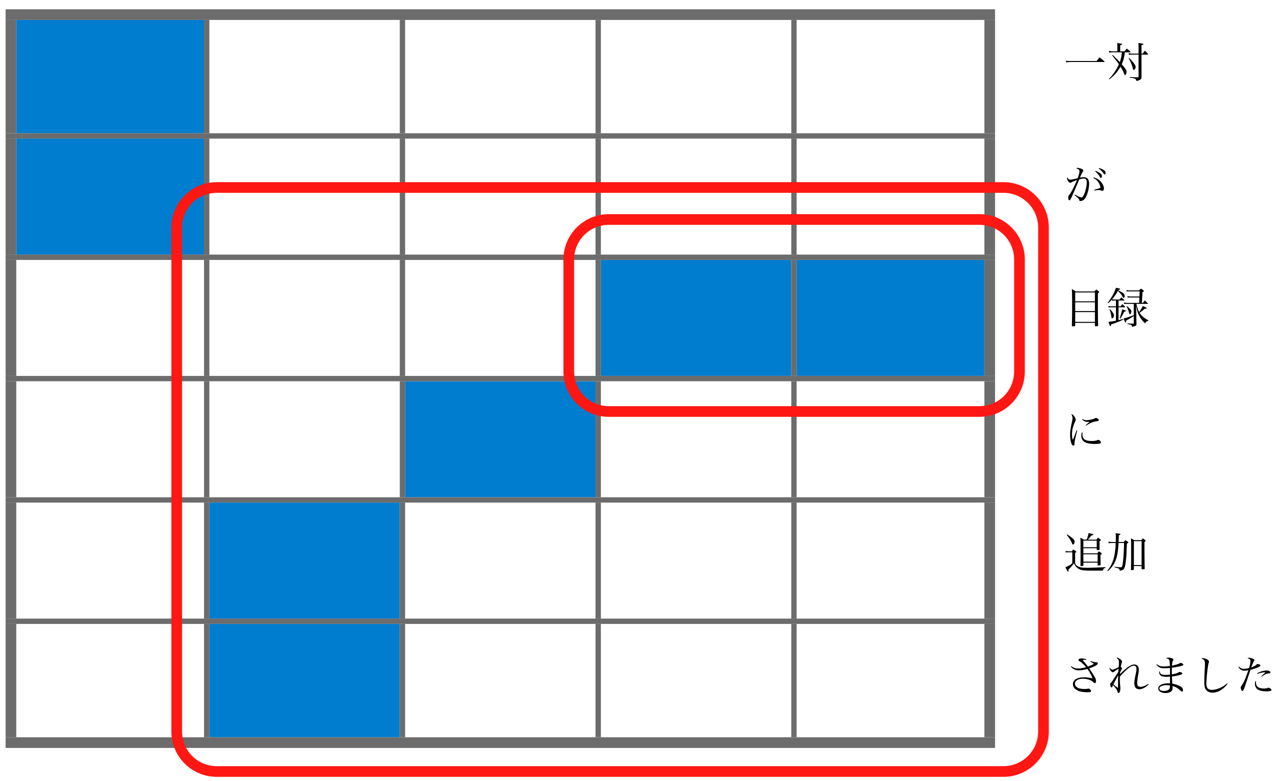

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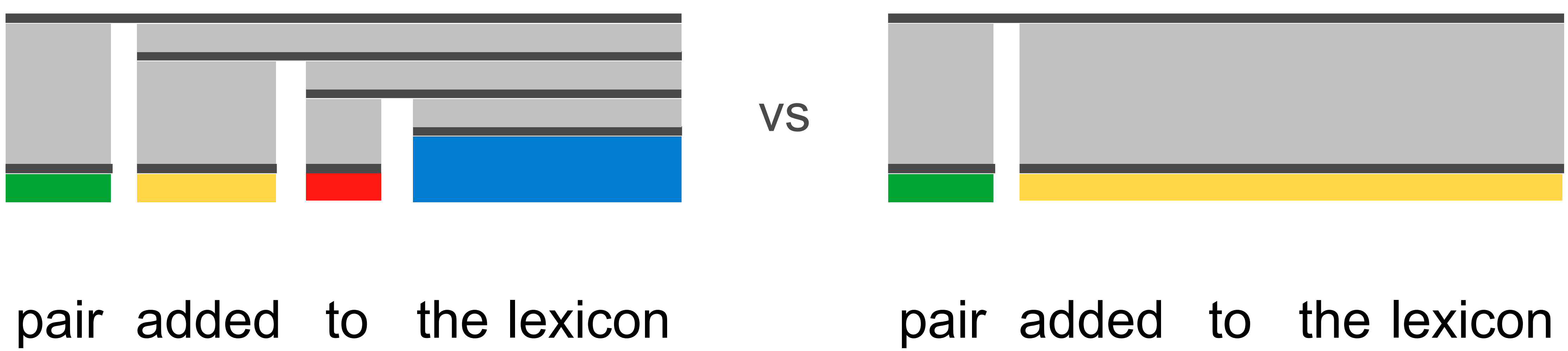
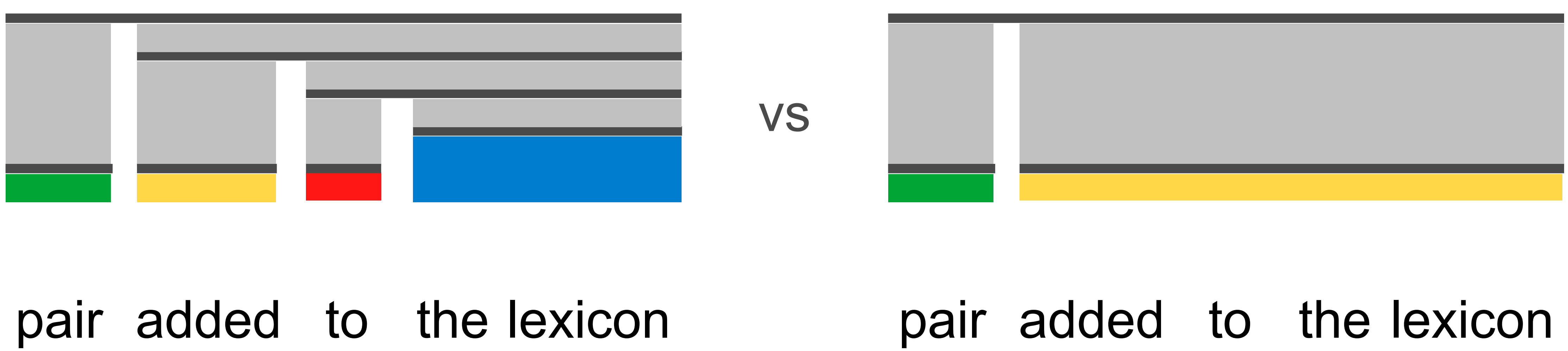


Parallel Parsing Model



Parallel Parsing Model

$$\phi(\text{pair}) \cdot \phi(\text{added})$$
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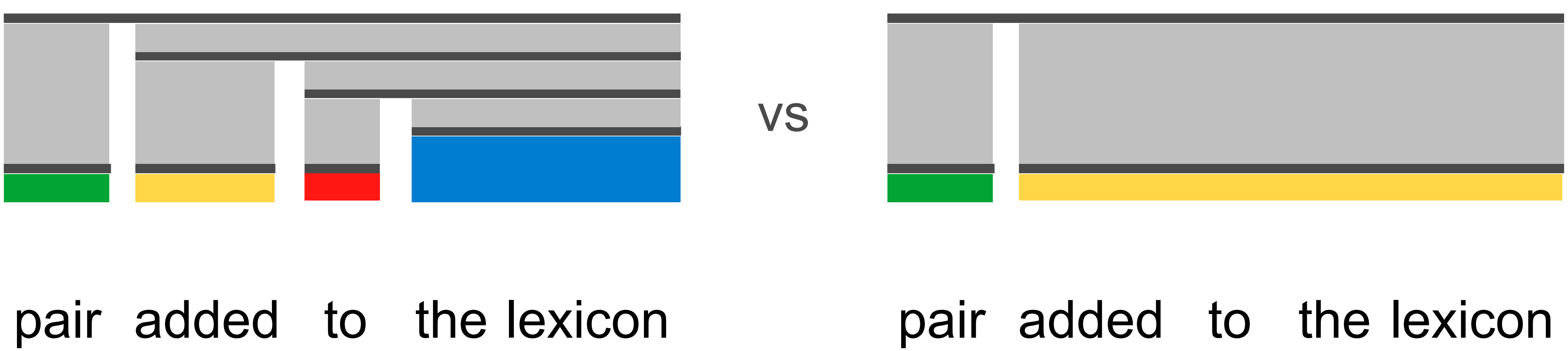

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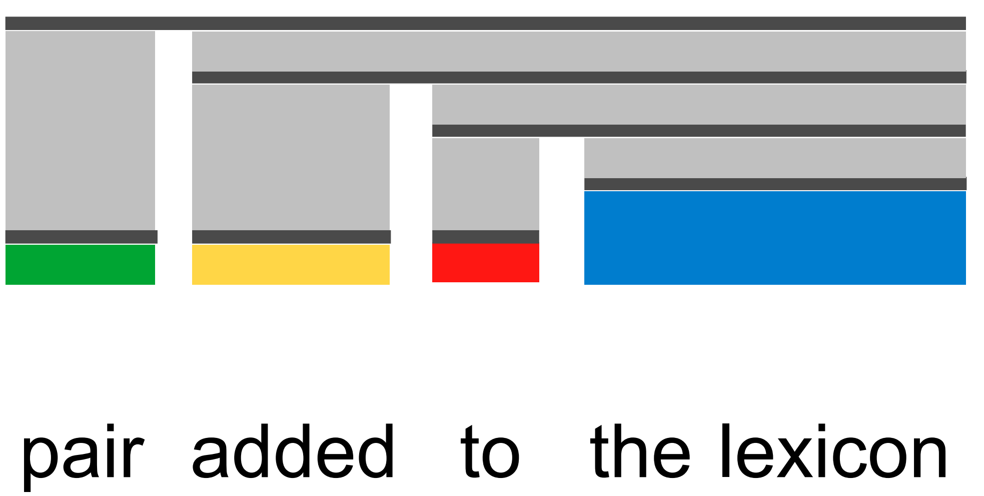

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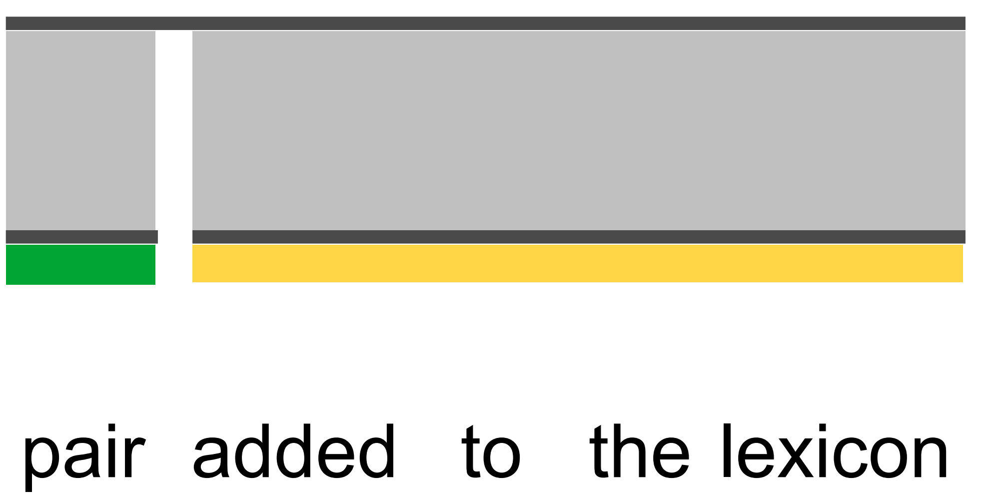

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English-Japanese

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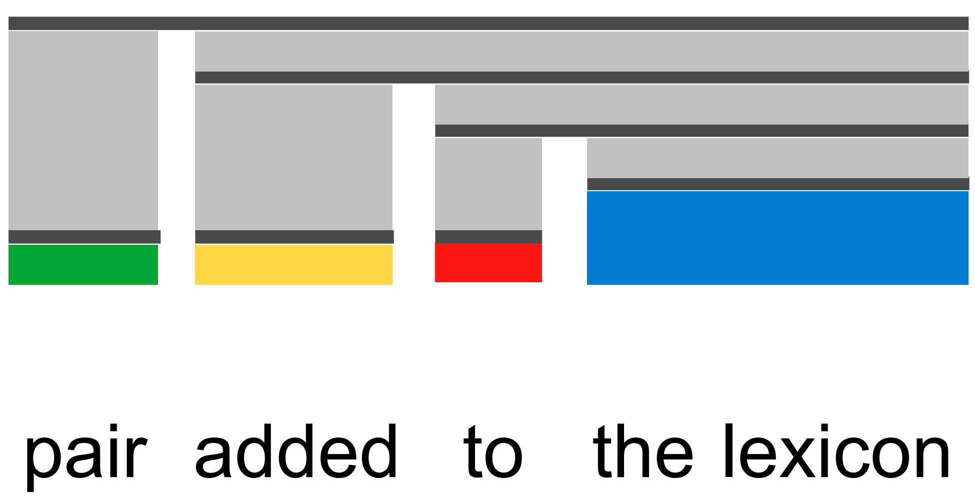

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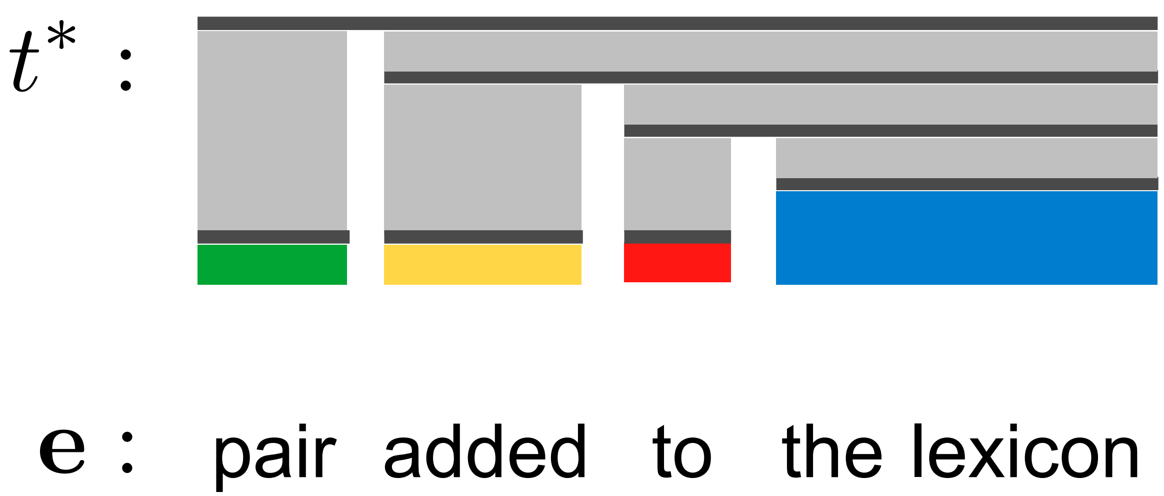

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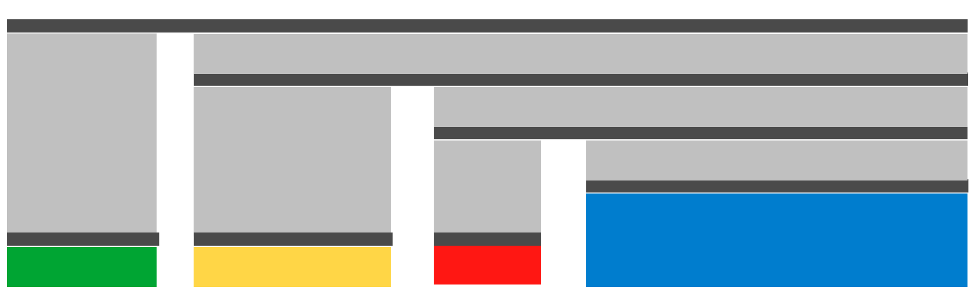

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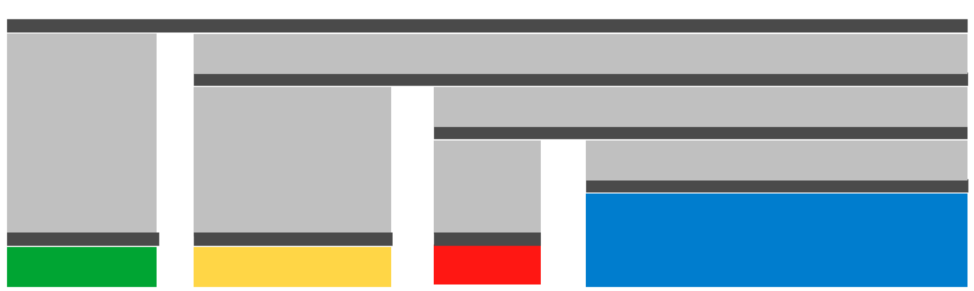

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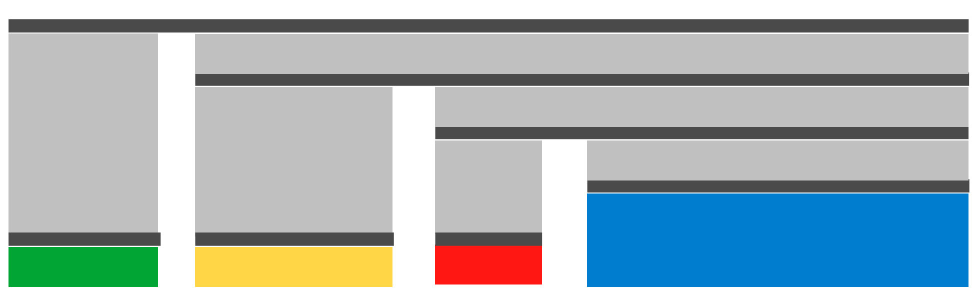

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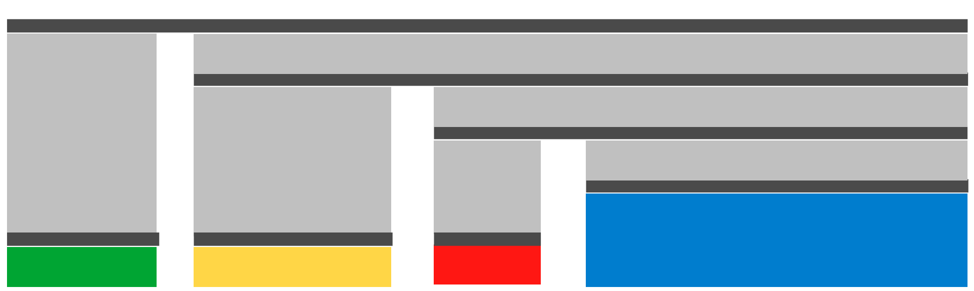

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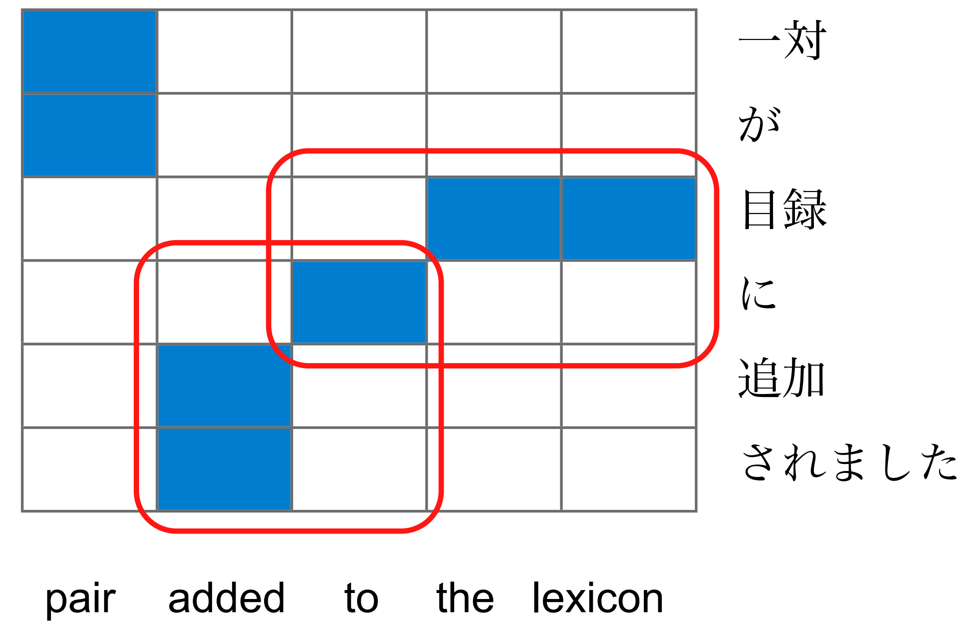

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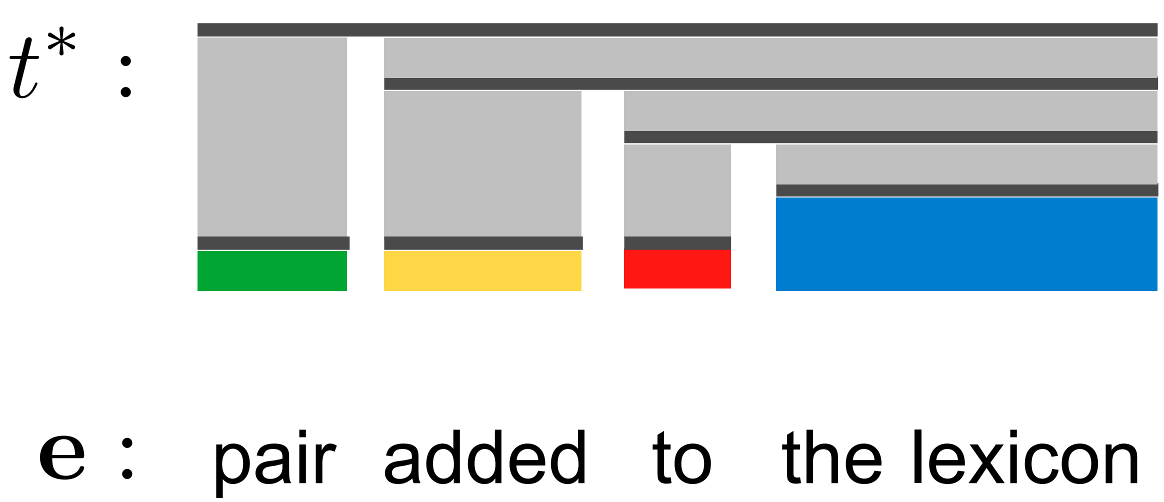

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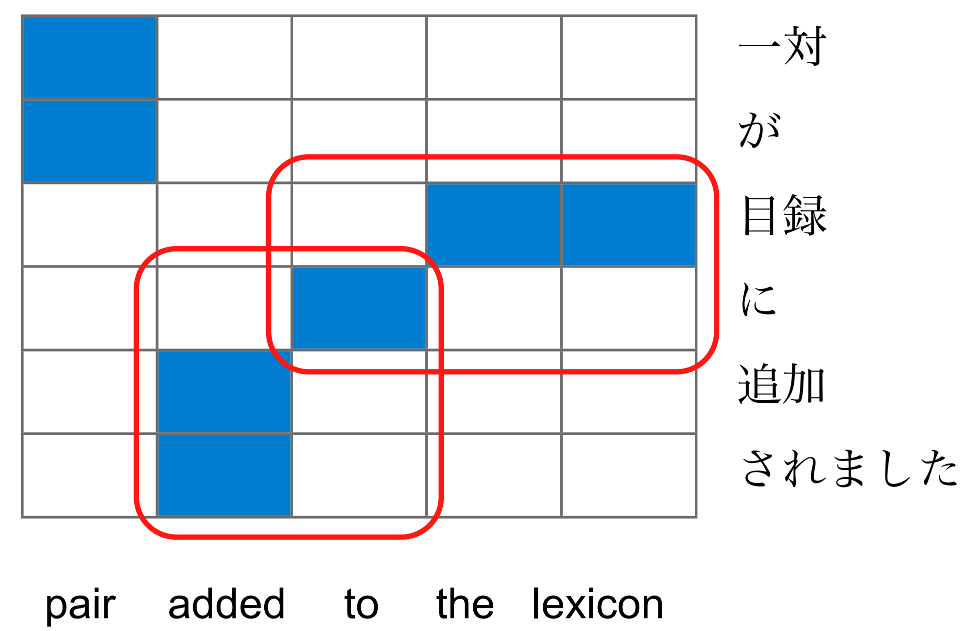

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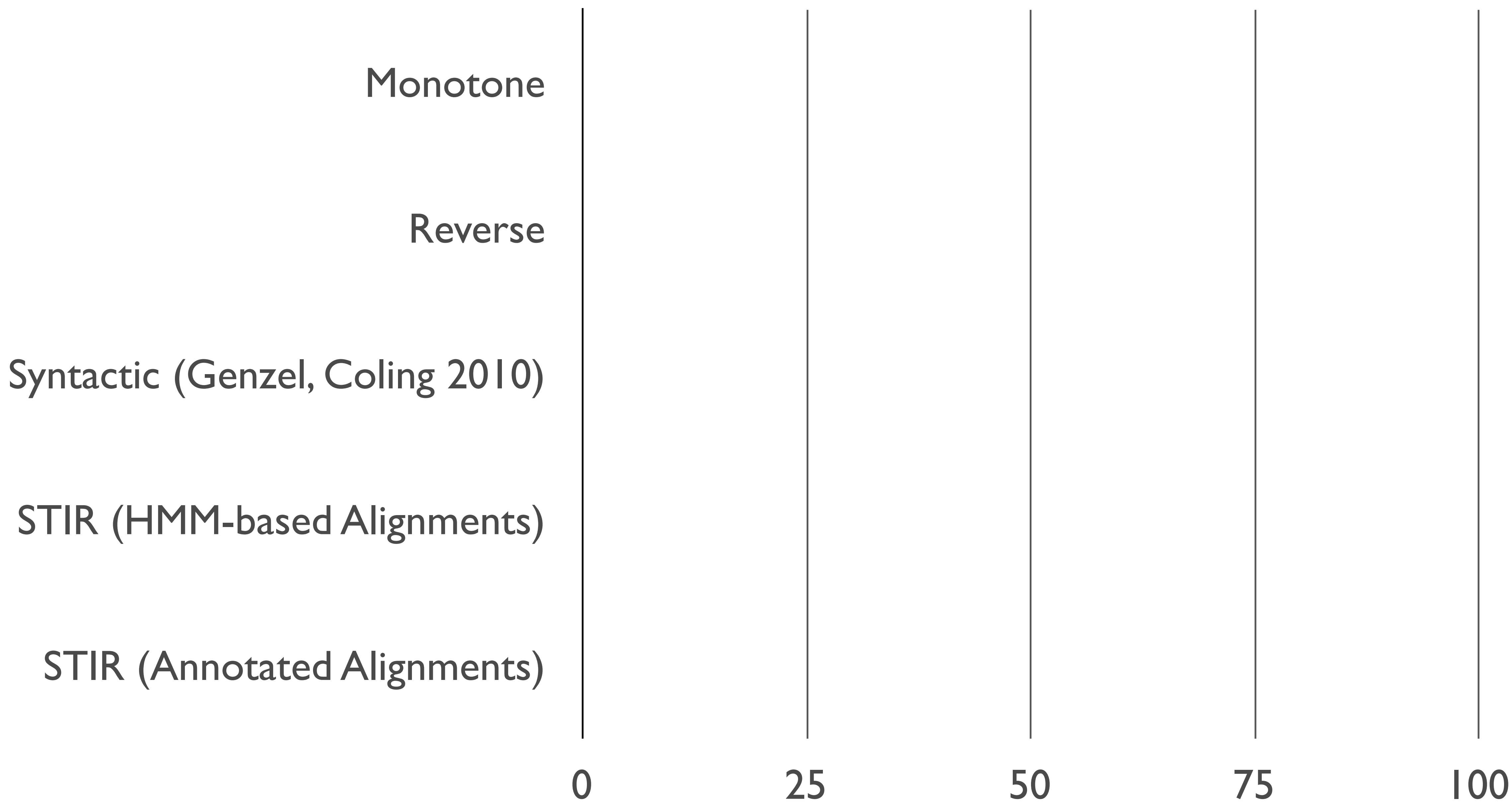

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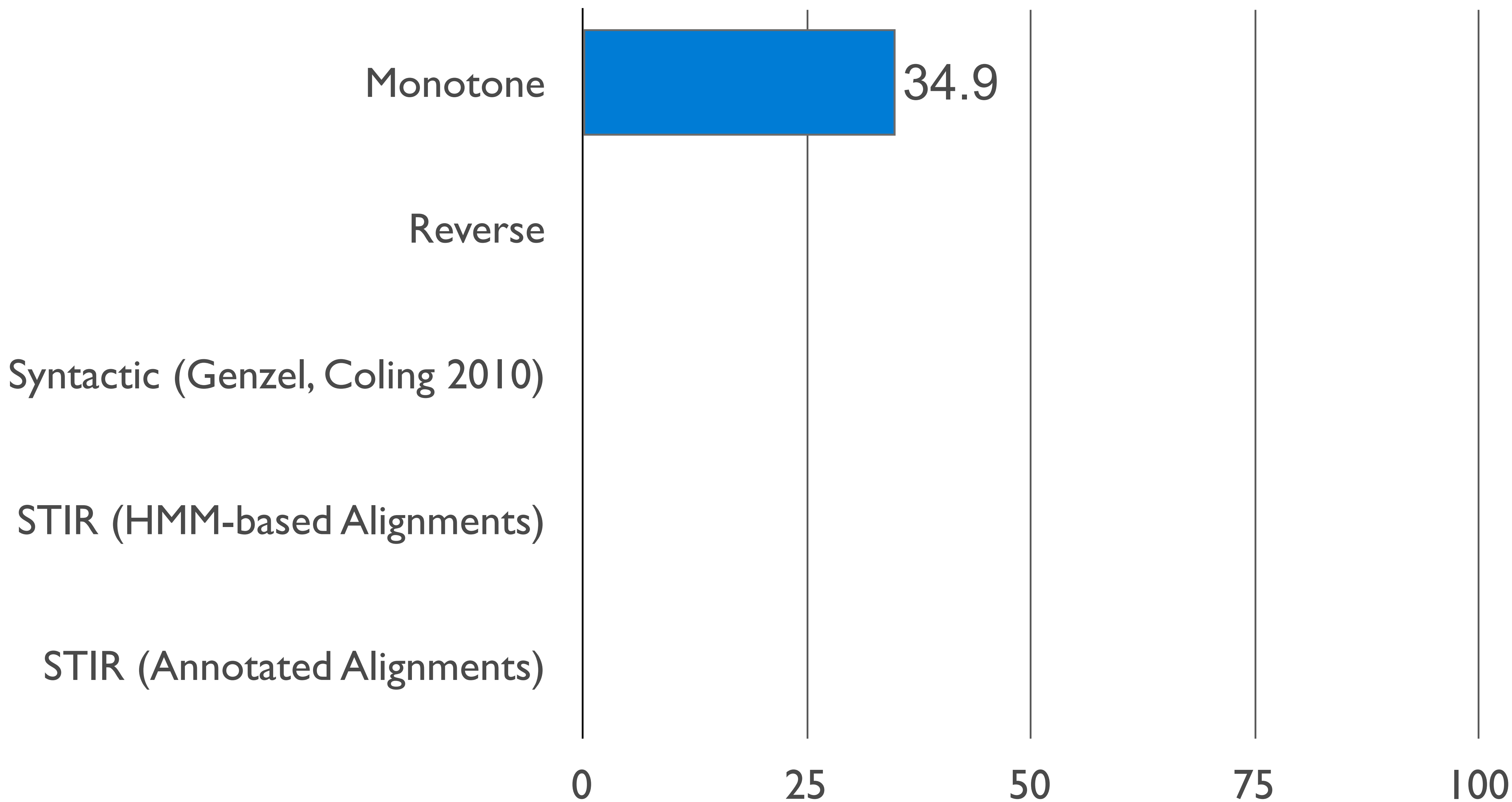

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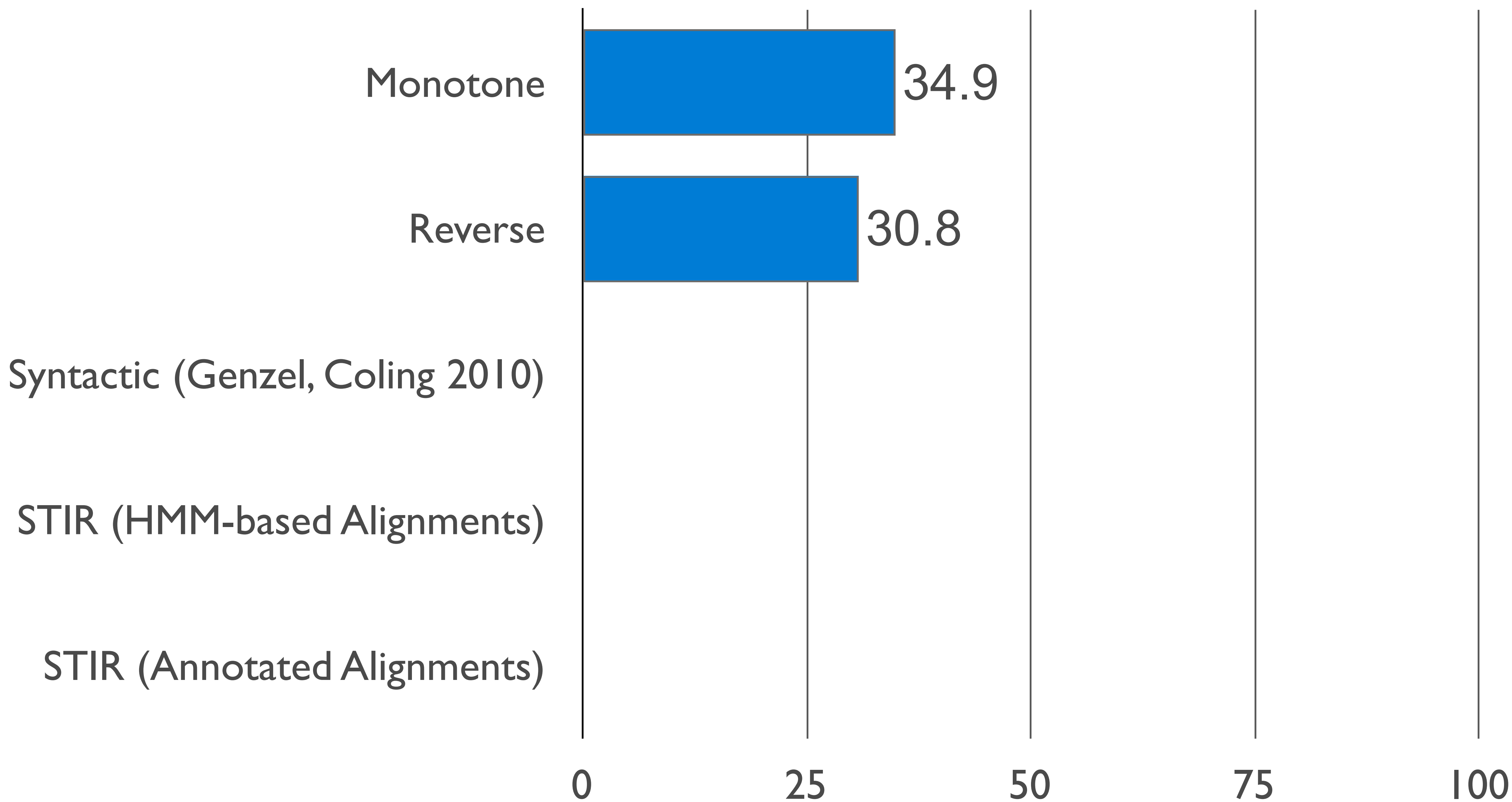

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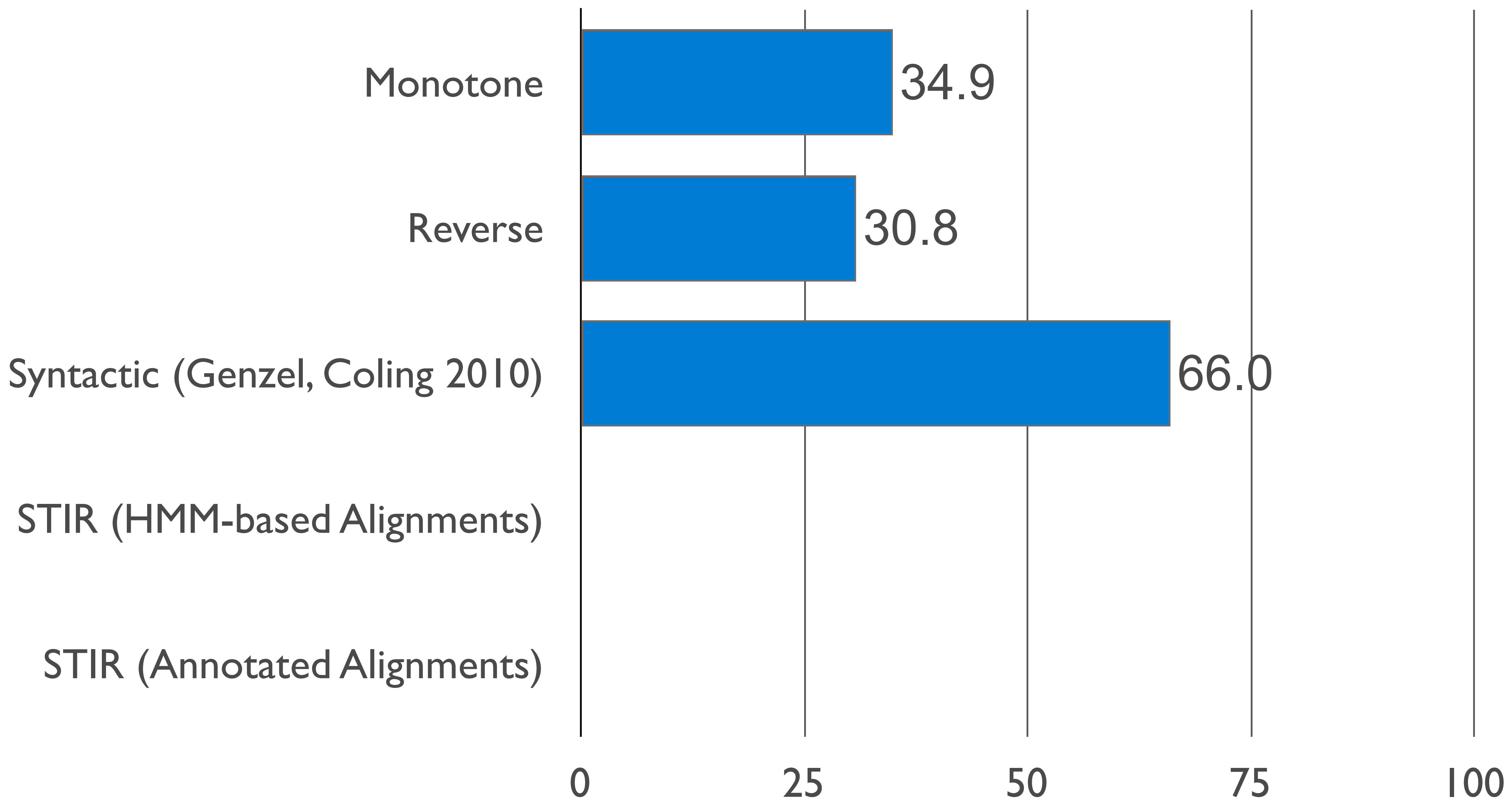

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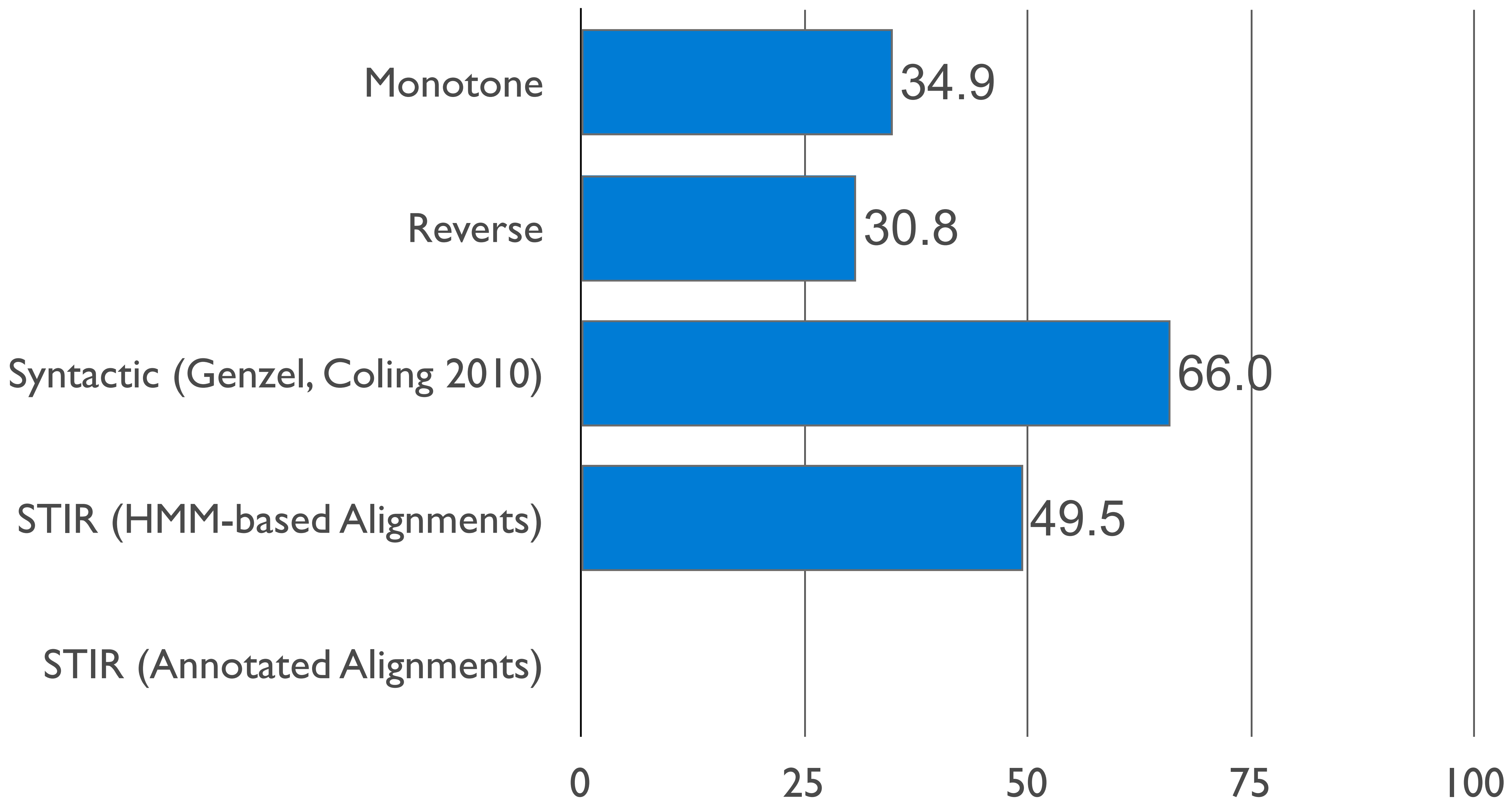

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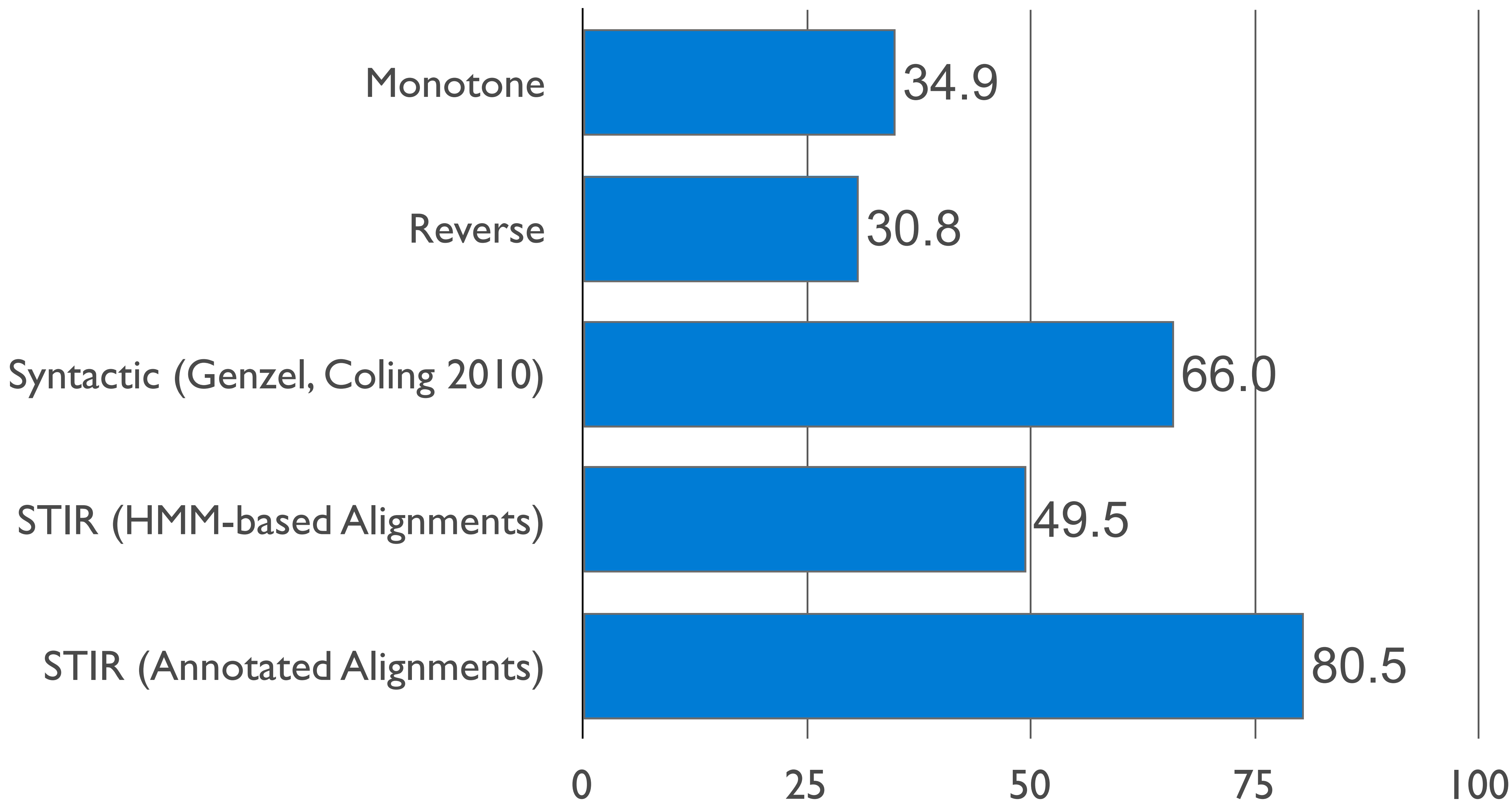
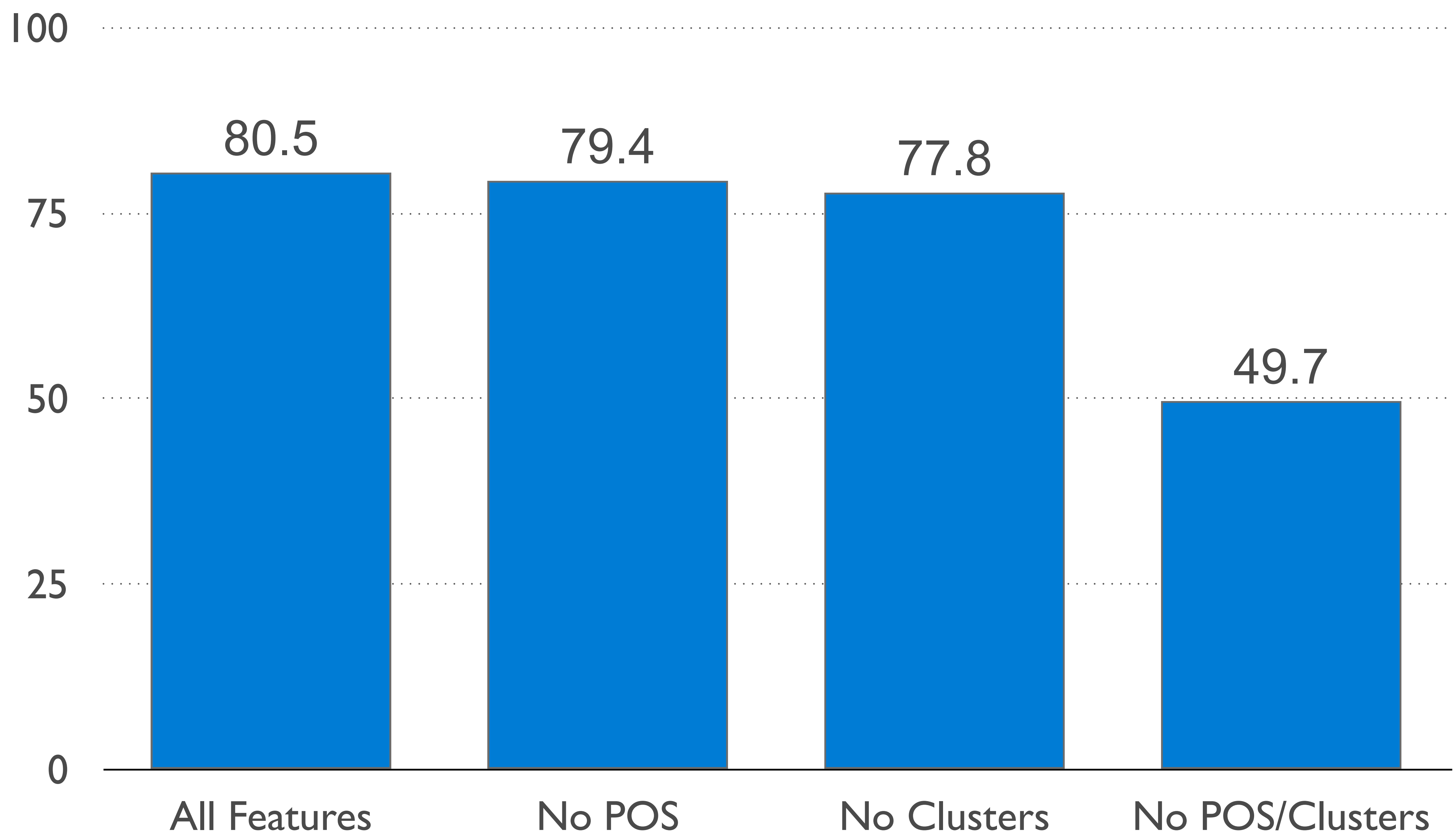


Results: Supervised & Induced Parts-of-Speech



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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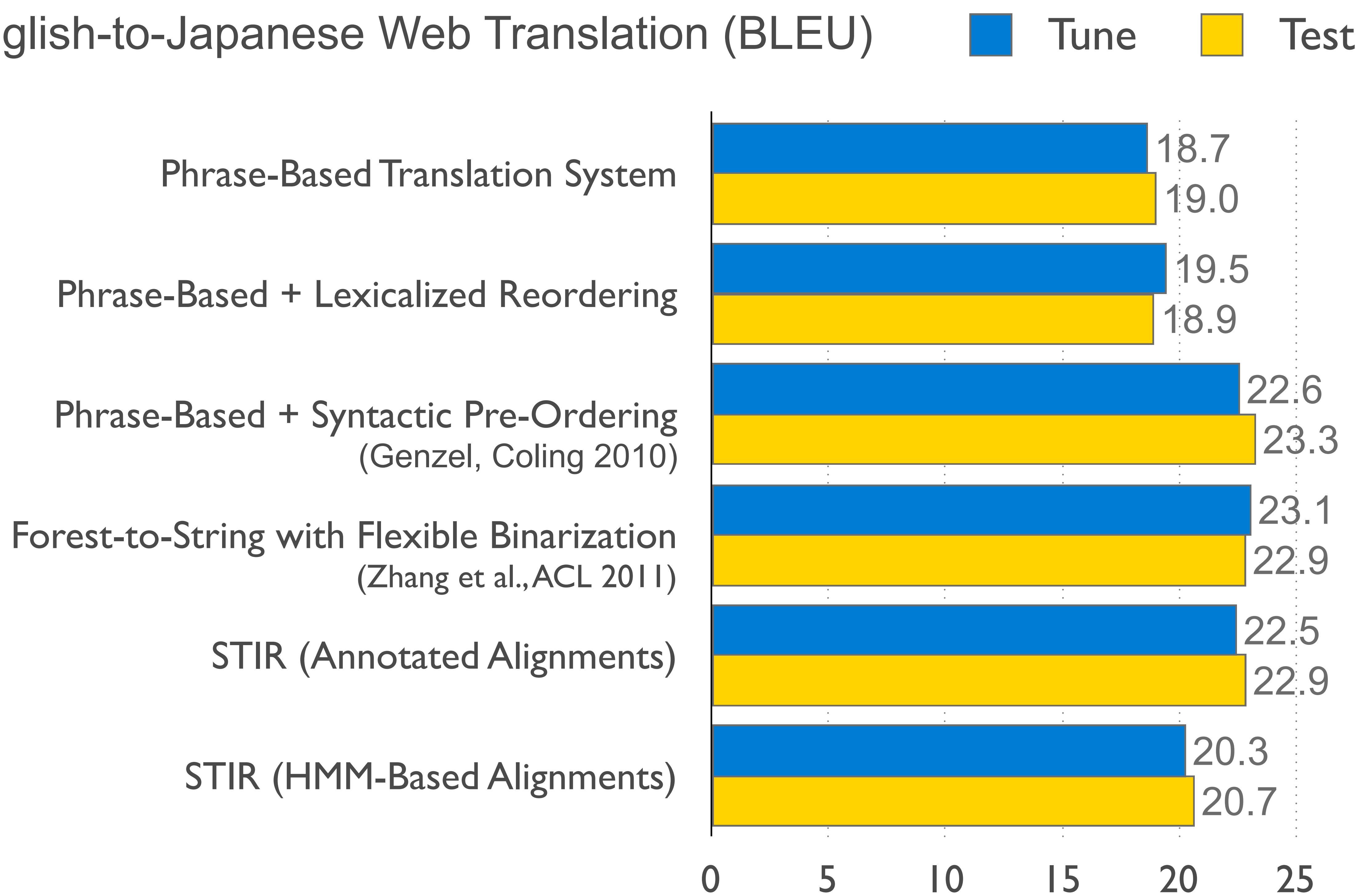
English-to-Japanese Web Translation (BLEU)



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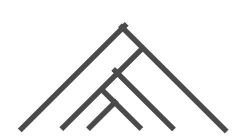

snahkT! snahkT! Thanks!