

Sampling Alignment Structure under a Bayesian Translation Model



John DeNero
Alexandre Bouchard-Côté
Dan Klein

Training a Machine Translation System

Input:

Gracias , lo haré de muy buen grado .
Thank you , I shall do so gladly .

Training a Machine Translation System

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Gracias , lo haré de muy buen grado .
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*First, we learn
word alignments,*

Thank you , I shall do so gladly .

Gracias

,

lo

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de

muy

buen

grado

.

Gloss

Thanks

,

that

do [first; future]

of

very

good

degree

.

Training a Machine Translation System

Input:

Gracias , lo haré de muy buen grado .
Thank you , I shall do so gladly .

*First, we learn
word alignments,*

*then we infer
aligned phrases.*

											<u>Gloss</u>
										Gracias	<i>Thanks</i>
										,	<i>,</i>
										lo	<i>that</i>
										haré	<i>do [first; future]</i>
										de	<i>of</i>
										muy	<i>very</i>
										buen	<i>good</i>
										grado	<i>degree</i>
										.	<i>.</i>
Thank you	,	I	shall	do	so	gladly	.				

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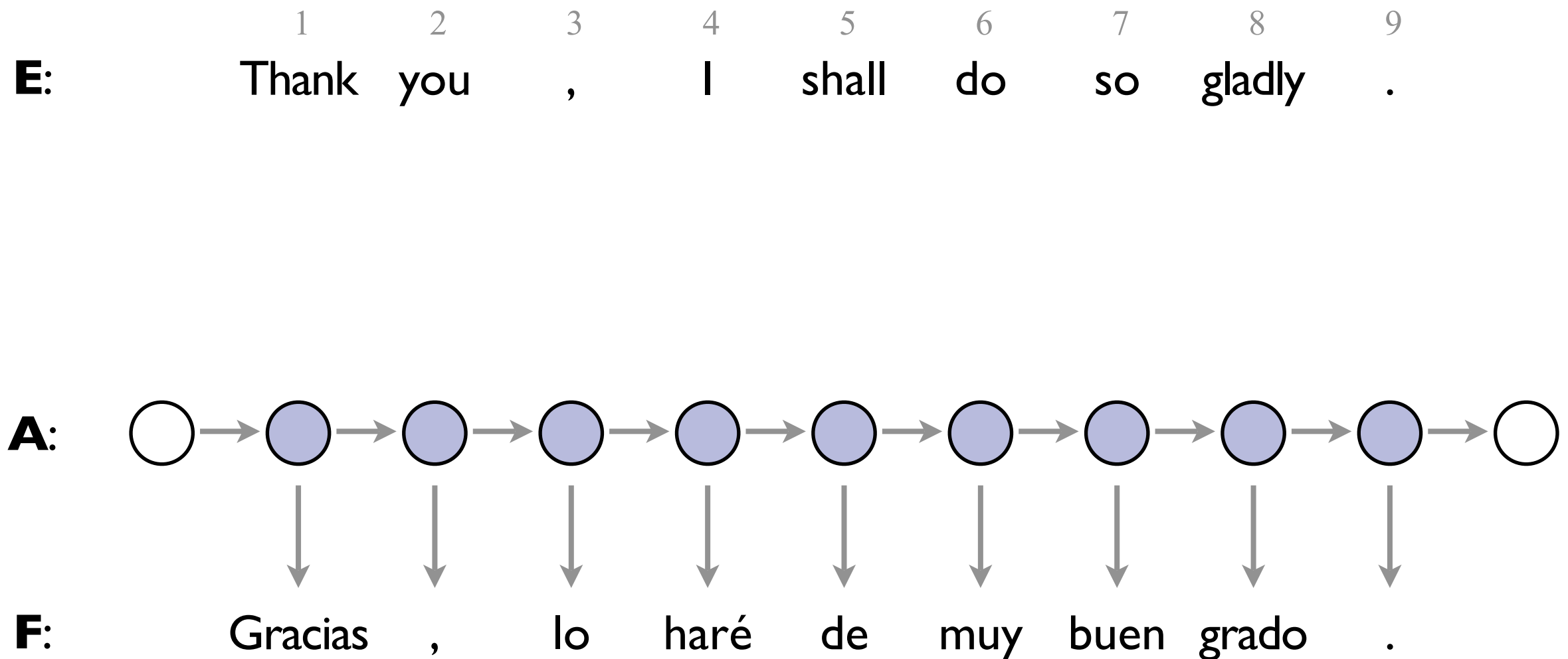
.

Statistical Word Alignment

E: Thank you , I shall do so gladly .

F: Gracias , lo haré de muy buen grado .

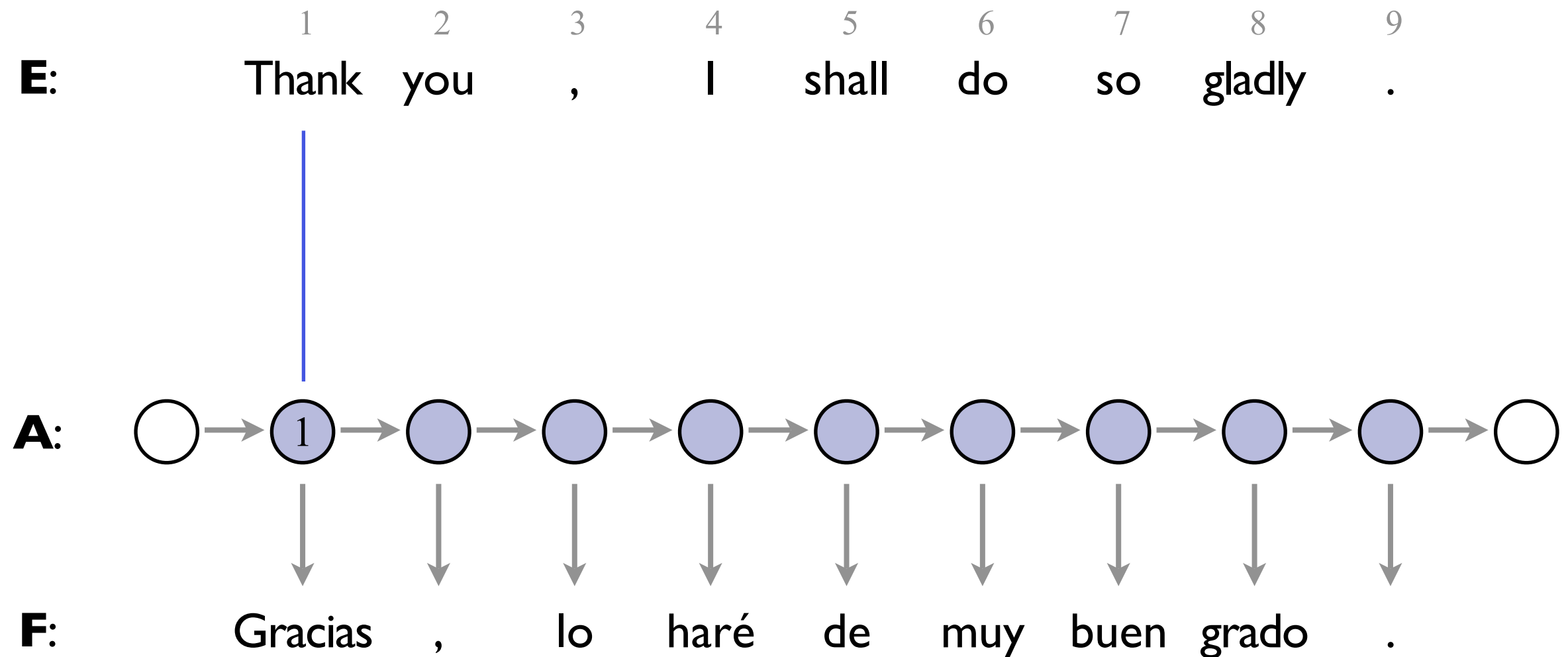
Statistical Word Alignment



Model Parameters

Emissions: $P(F_1 = \text{Gracias} \mid E_{A_1} = \text{Thank})$ *Transitions:* $P(A_2 = 3 \mid A_1 = 1)$

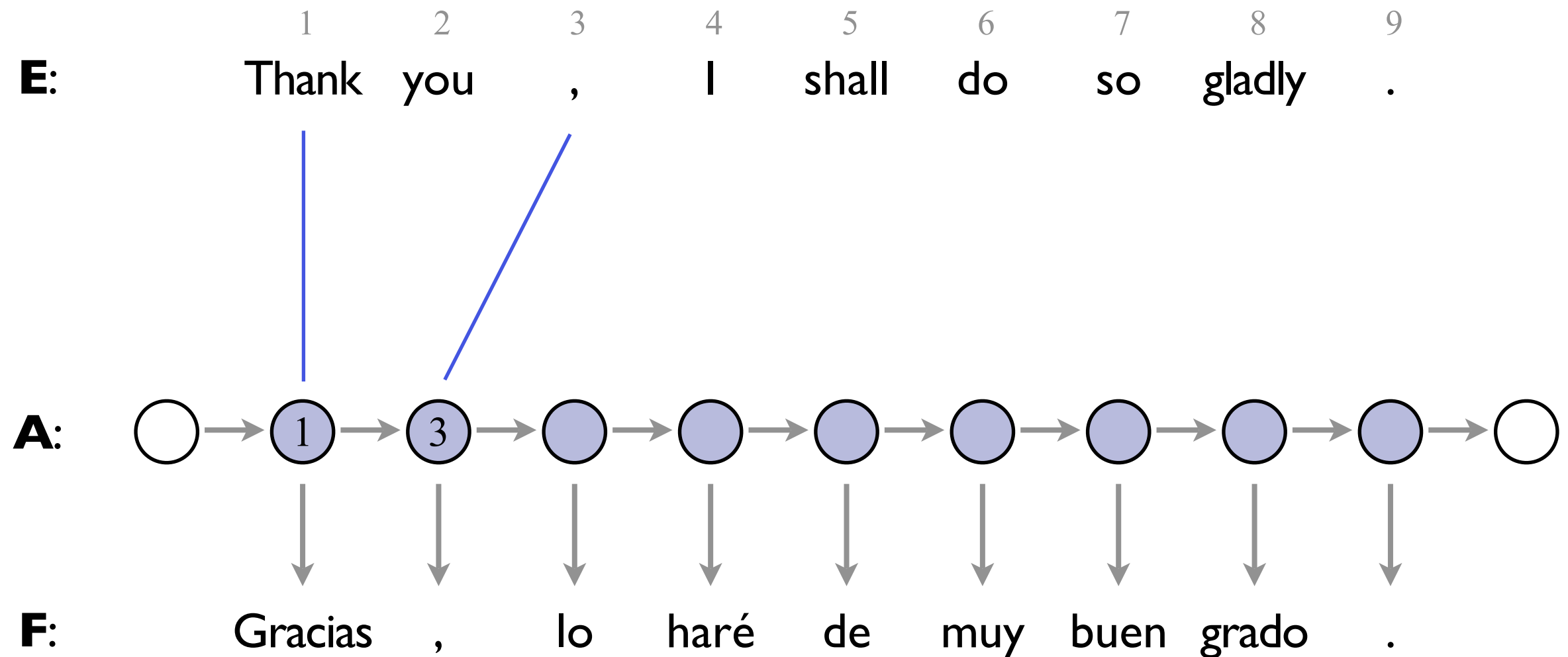
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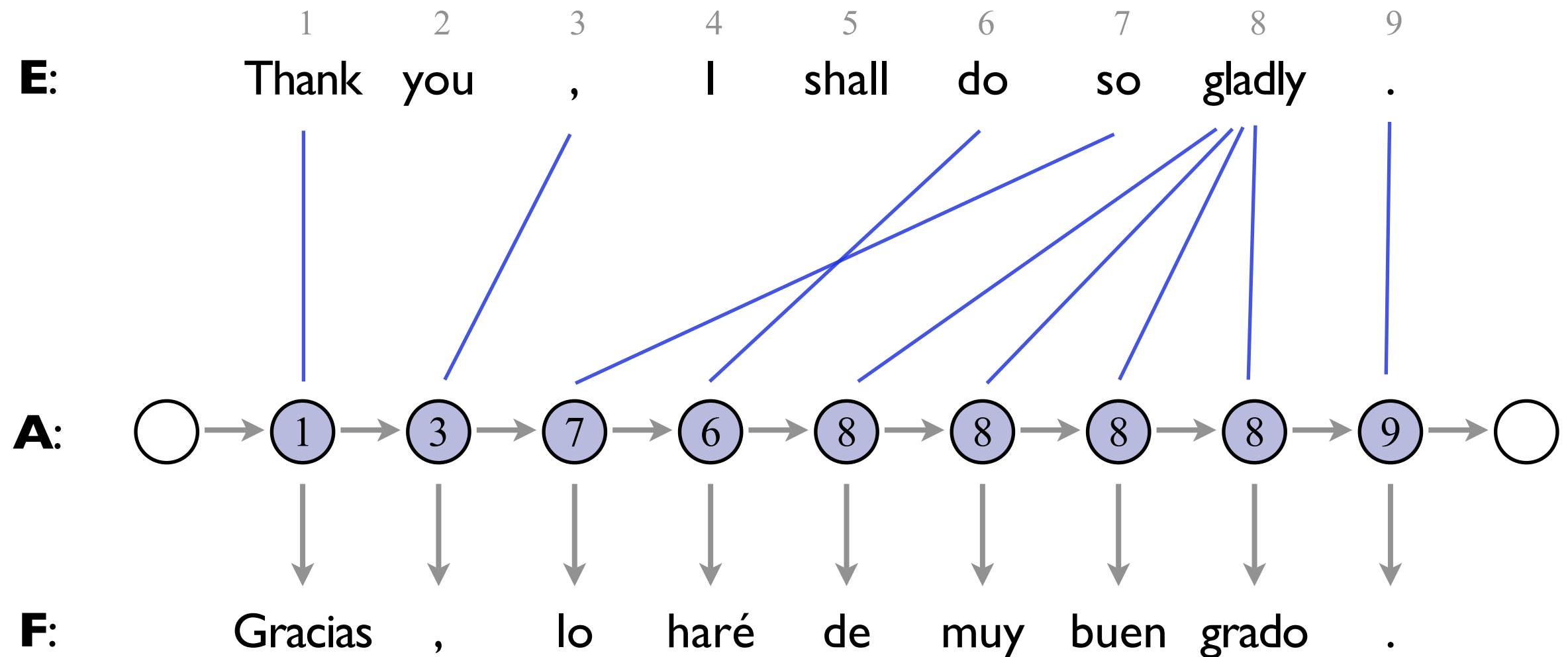
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What Happens in Practice

A real word alignment
(GIZA++ Model 4 with
grow-diag-final combination)

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Thank you , I shall do so gladly .

A sampled phrase alignment
(our system)

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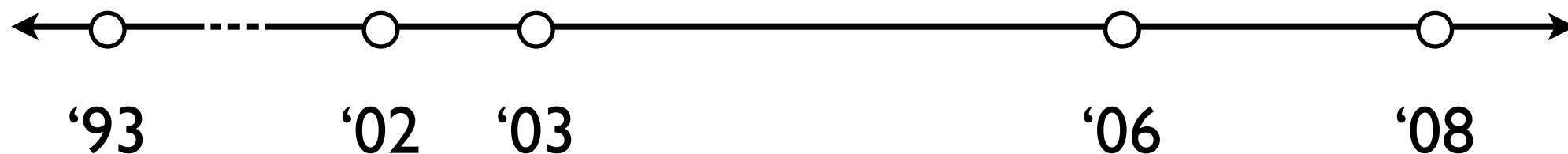
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A Brief History of Phrase Alignment

The Challenge:

Train models that explicitly align phrases, not just words



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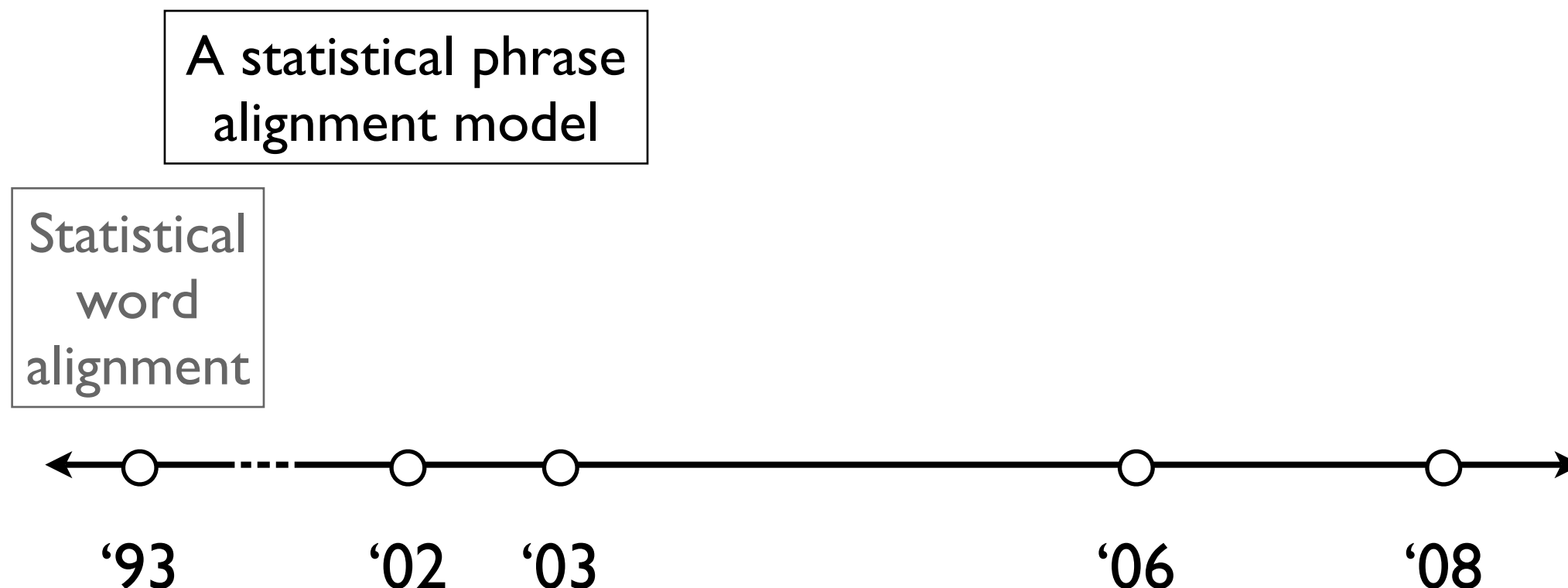
Train models that explicitly align phrases, not just words



A Brief History of Phrase Alignment

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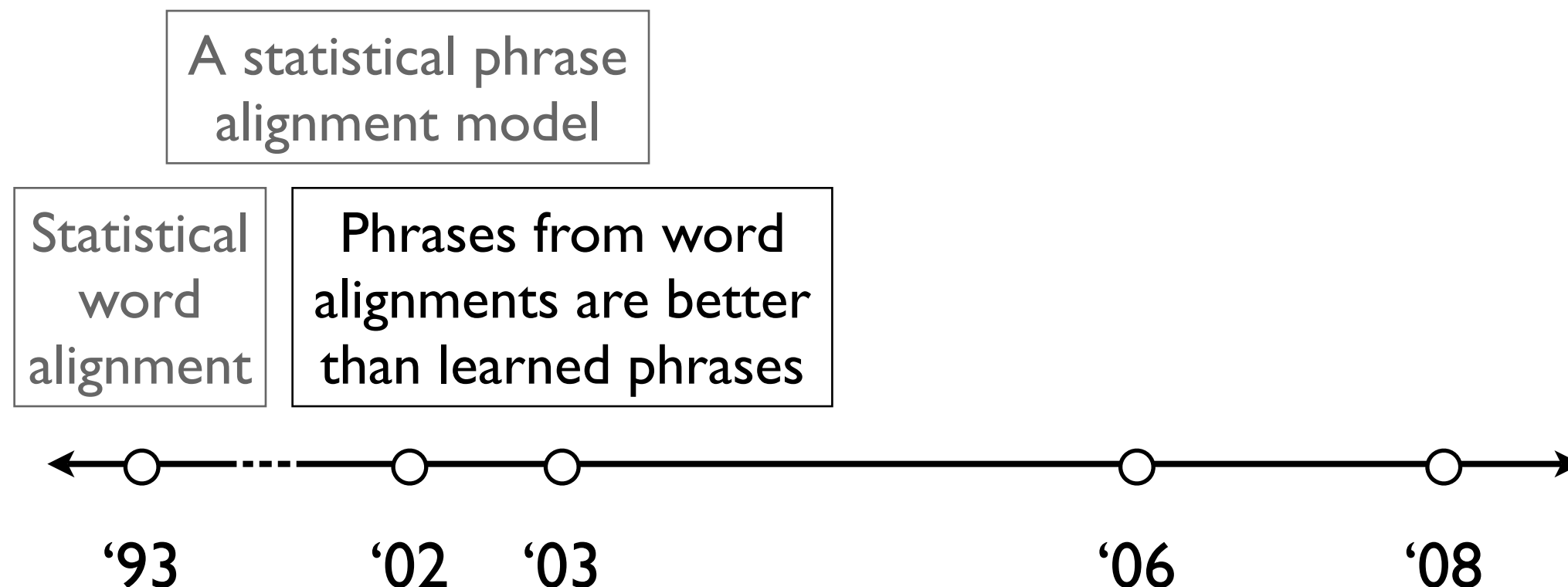
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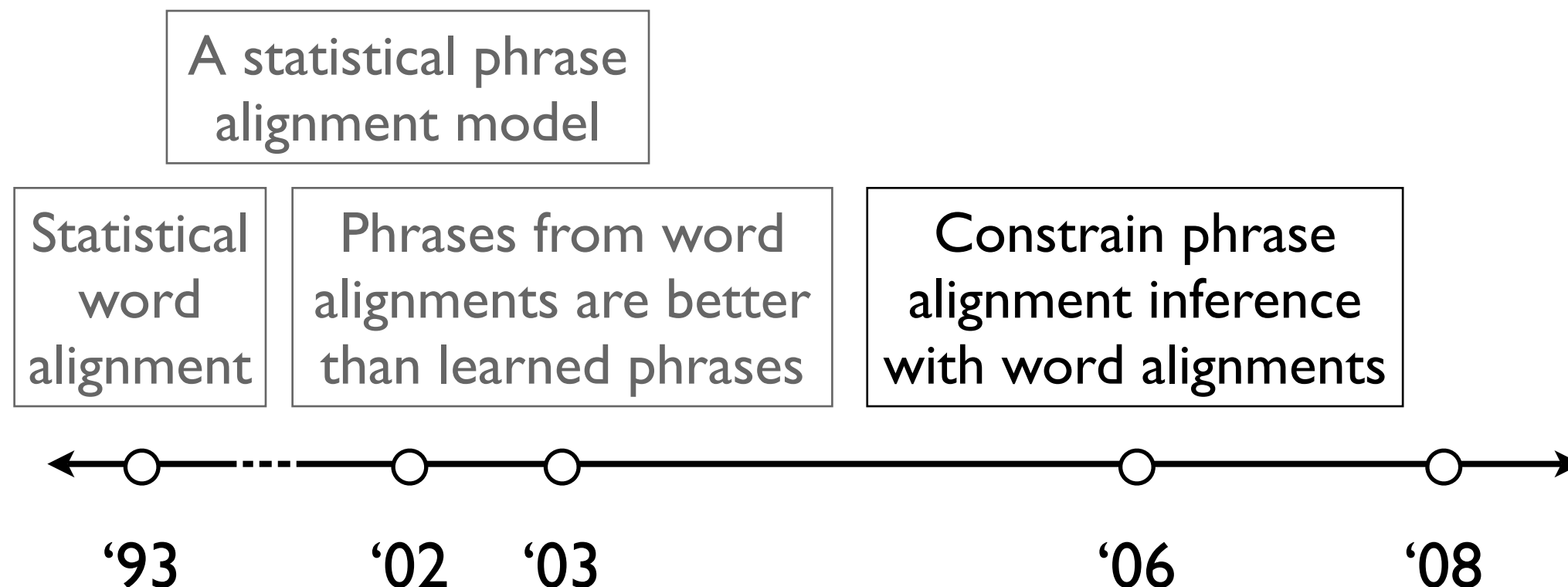
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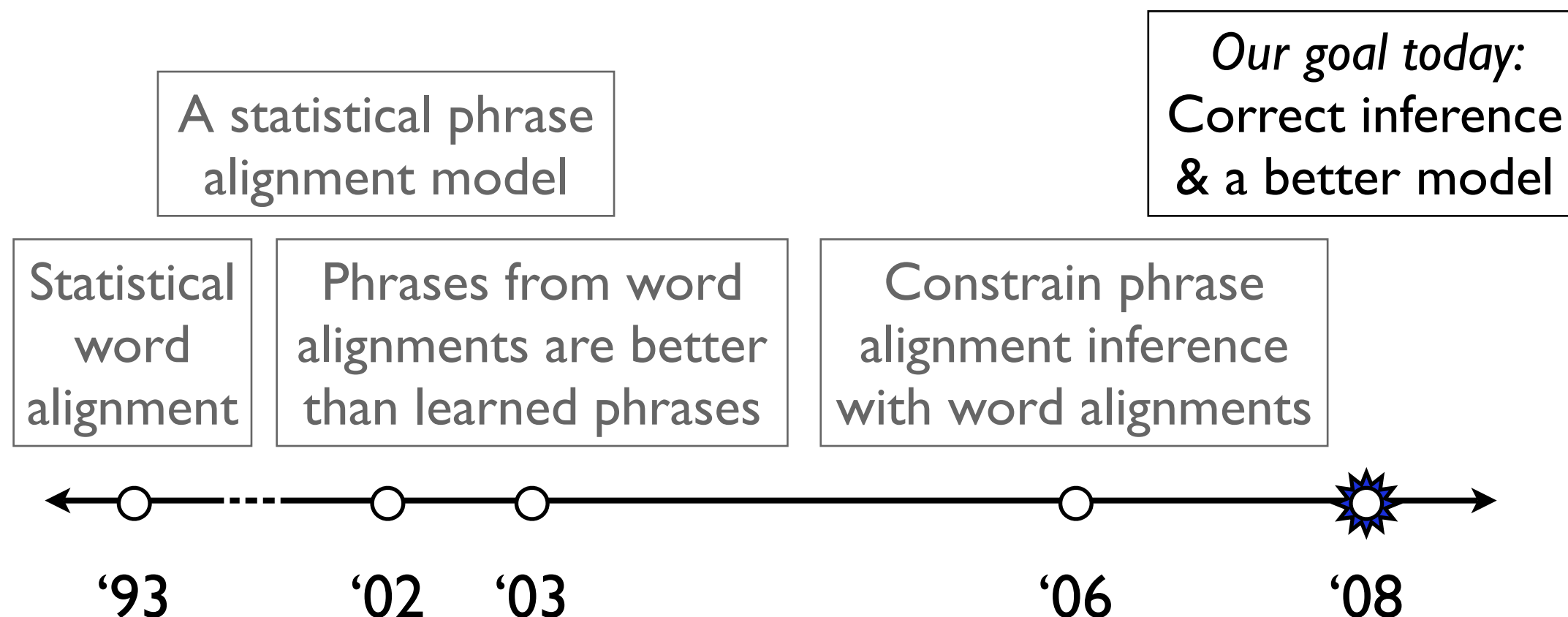
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A Brief History of Phrase Alignment

The Challenge:

Train models that explicitly align phrases, not just words



A Generative Phrase Alignment Model

**Process for
generating a
sentence pair:**

A Generative Phrase Alignment Model

**Process for
generating a
sentence pair:**

*Choose number
of phrase pairs*



A Generative Phrase Alignment Model

Process for generating a sentence pair:

*Choose number
of phrase pairs*

*Generate each
phrase pair*

日本 冻结
Japan to freeze

提供 援助
aid

向 俄
to Russia

A Generative Phrase Alignment Model

Process for generating a sentence pair:

*Choose number
of phrase pairs*

*Generate each
phrase pair*

*Keep the
English order*

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A Generative Phrase Alignment Model

Process for generating a sentence pair:

*Choose number
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*Reorder the
Chinese phrases*

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A Generative Phrase Alignment Model

Process for generating a sentence pair:

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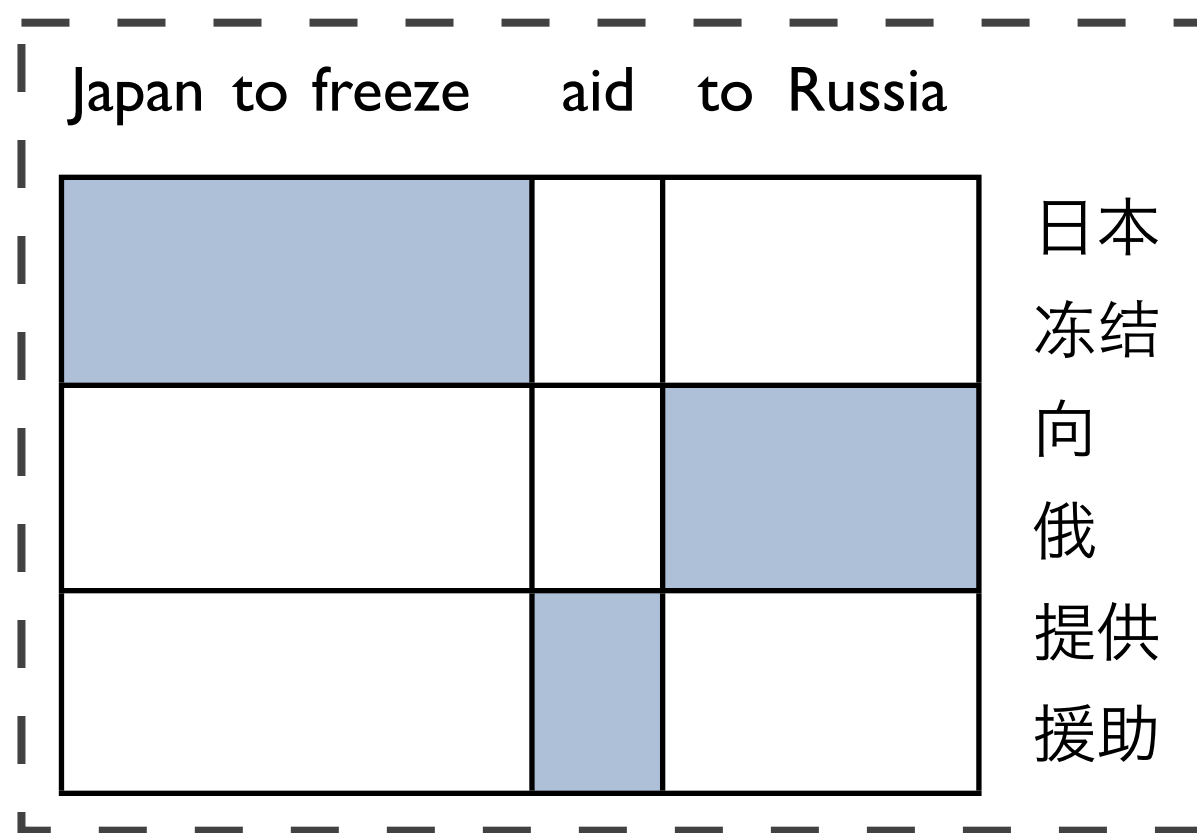
*Generate each
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*Keep the
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*Reorder the
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日本 冻结 向 俄 提供 援助



*A phrase-aligned sentence pair
(a list of phrase pairs and a permutation)*

Estimating Model Parameters

*A phrase-aligned sentence pair a is
a list of phrase pairs $\langle e, f \rangle$ and a permutation σ_a .*

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$$P(a) = \prod_{\langle e, f \rangle \in a} \phi(\langle e, f \rangle) \cdot \delta(\sigma_a)$$

Estimating Model Parameters

*A phrase-aligned sentence pair a is
a list of phrase pairs $\langle e, f \rangle$ and a permutation σ_a .*

$$P(a) = \prod_{\langle e, f \rangle \in a} \phi(\langle e, f \rangle) \cdot \delta(\sigma_a)$$

Maximum likelihood:
choose ϕ to maximize the probability of the training corpus:

$$\max_{\phi} \prod_{(\mathbf{e}, \mathbf{f})} \left[\sum_{a \text{ for } (\mathbf{e}, \mathbf{f})} \prod_{\langle e, f \rangle \in a} \phi(\langle e, f \rangle) \cdot \delta(\sigma_a) \right]$$

We Need a Prior over Phrase Pairs

Japan to freeze aid to Russia .

日本

冻结

向

俄

提供

援助

。

Gloss

Japan

freeze

to

Russia

supply

assistance

。

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冻结	<i>freeze</i>
向	<i>to</i>
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$$\max_{\phi} \prod_{(\mathbf{e}, \mathbf{f})} \left[\sum_{a \text{ for } (\mathbf{e}, \mathbf{f})} \prod_{\langle e, f \rangle \in a} \phi(\langle e, f \rangle) \cdot \delta(\sigma_a) \right]$$

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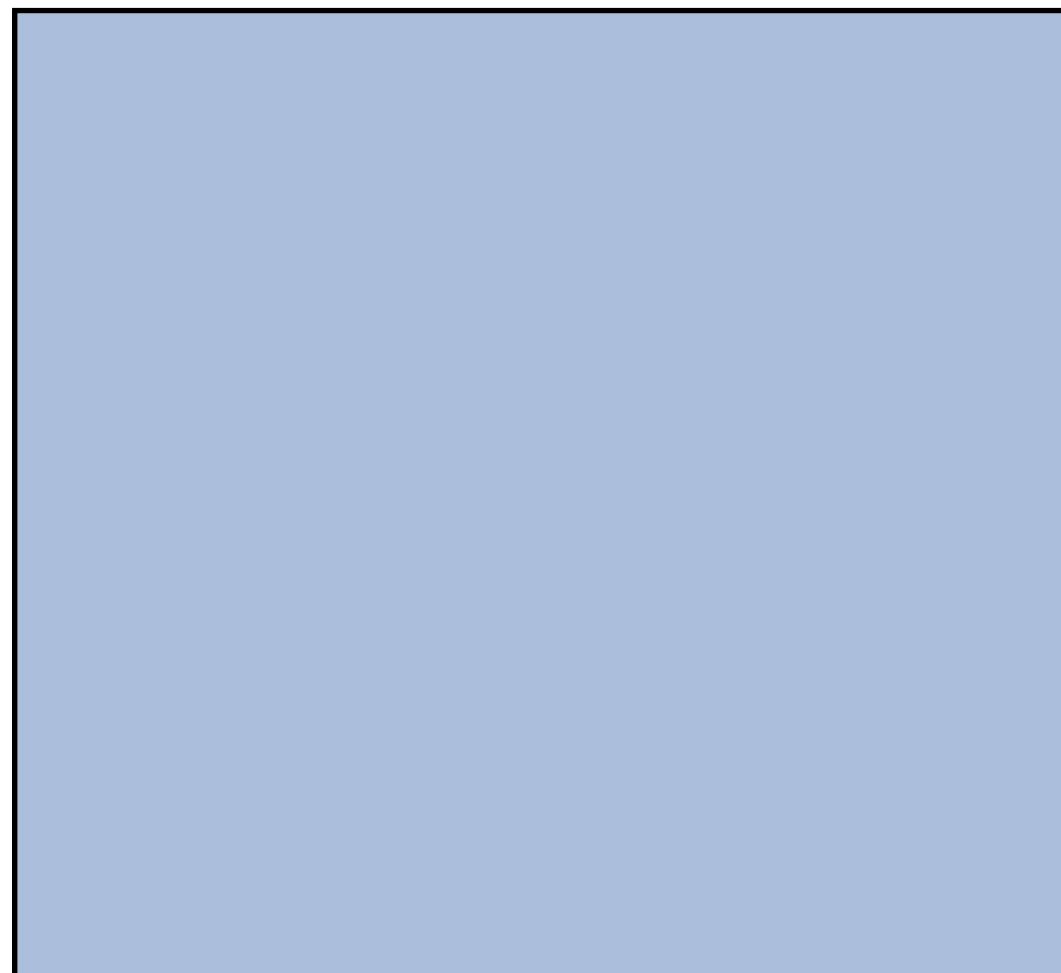
日本	<i>Japan</i>
冻结	<i>freeze</i>
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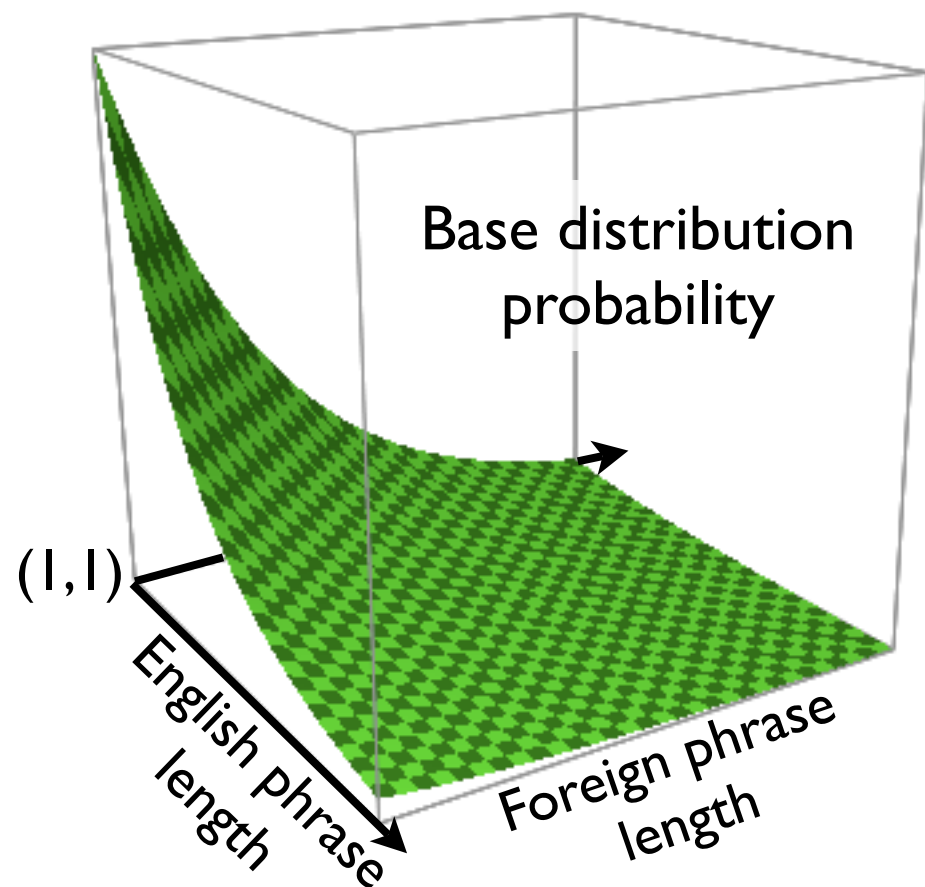
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$$\max_{\phi} P(\phi) \cdot \prod_{(\mathbf{e}, \mathbf{f})} \left[\sum_{a \text{ for } (\mathbf{e}, \mathbf{f})} \prod_{\langle e, f \rangle \in a} \phi(\langle e, f \rangle) \cdot \delta(\sigma_a) \right]$$

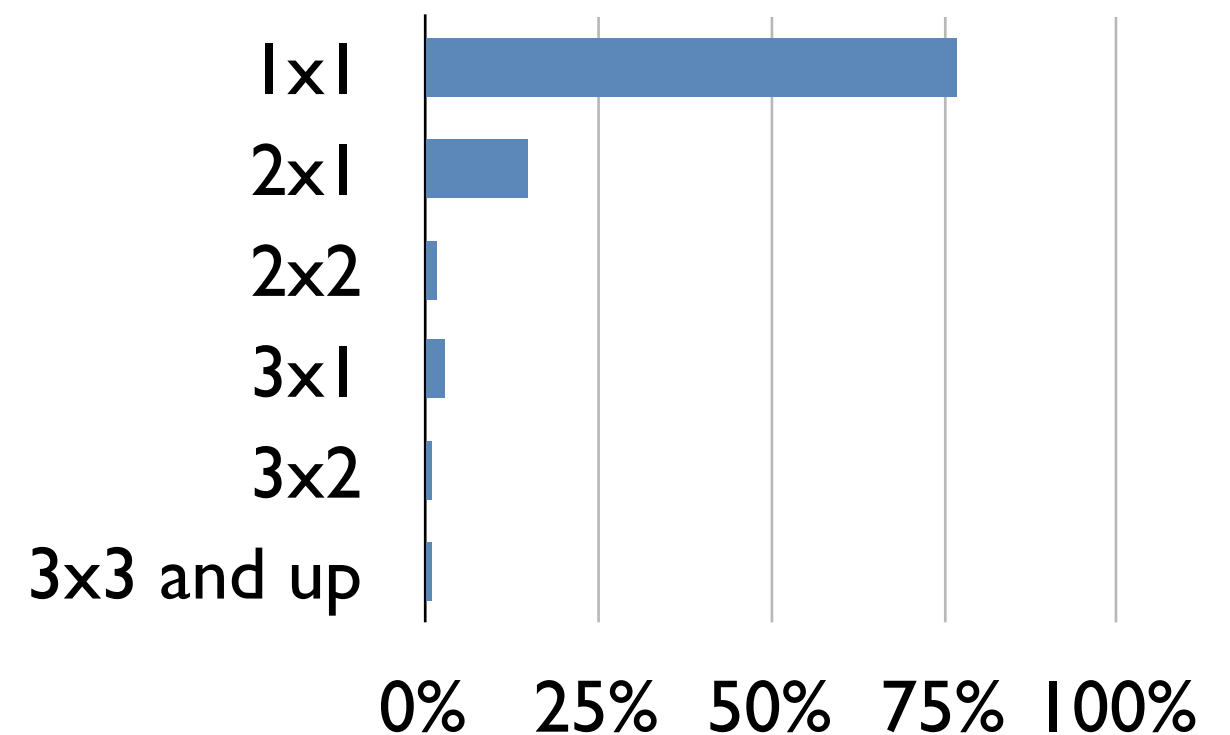
Our Prior, in Brief

A Dirichlet Process Prior that

- Strongly prefers shorter phrases (base distribution)
- Strongly prefers to reuse phrases (concentration)
- Plays nicely with our sampler (collapsed Gibbs)



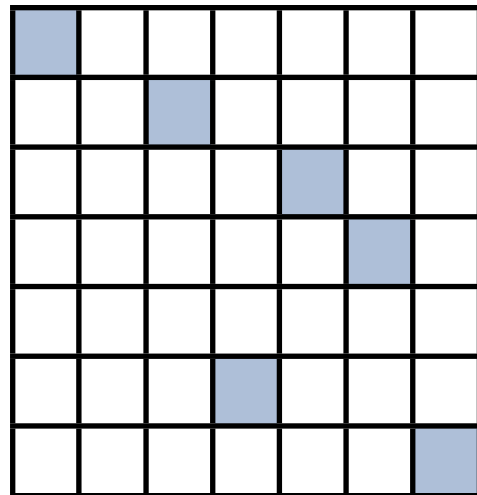
Observed phrase pair sizes



Sampling Phrase Alignments

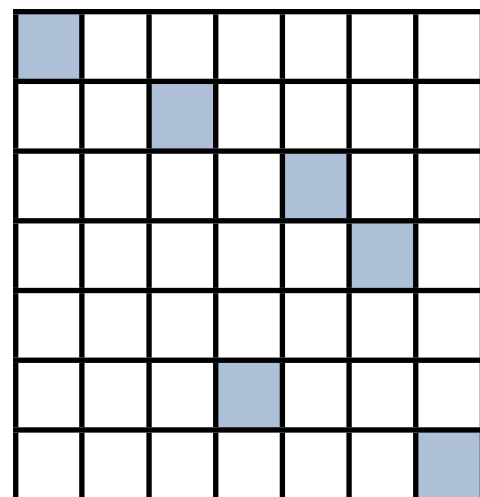
Sampling Phrase Alignments

Initial phrase
alignment

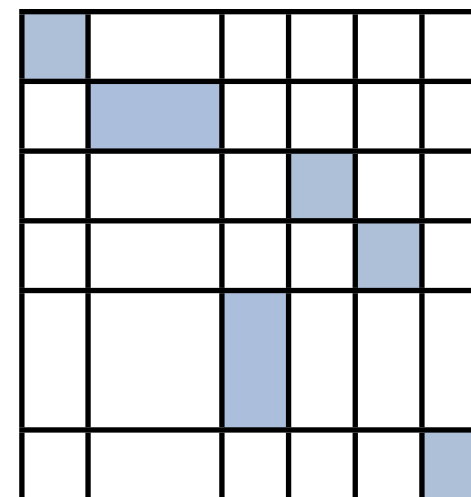
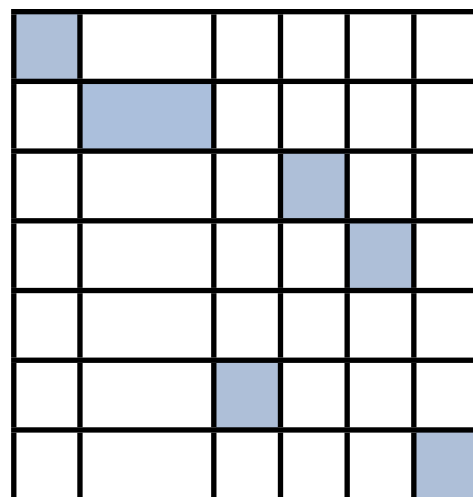


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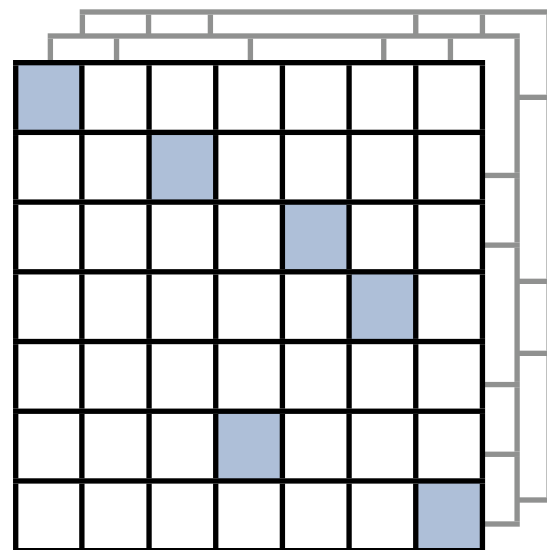


Stochastically apply local edit operators

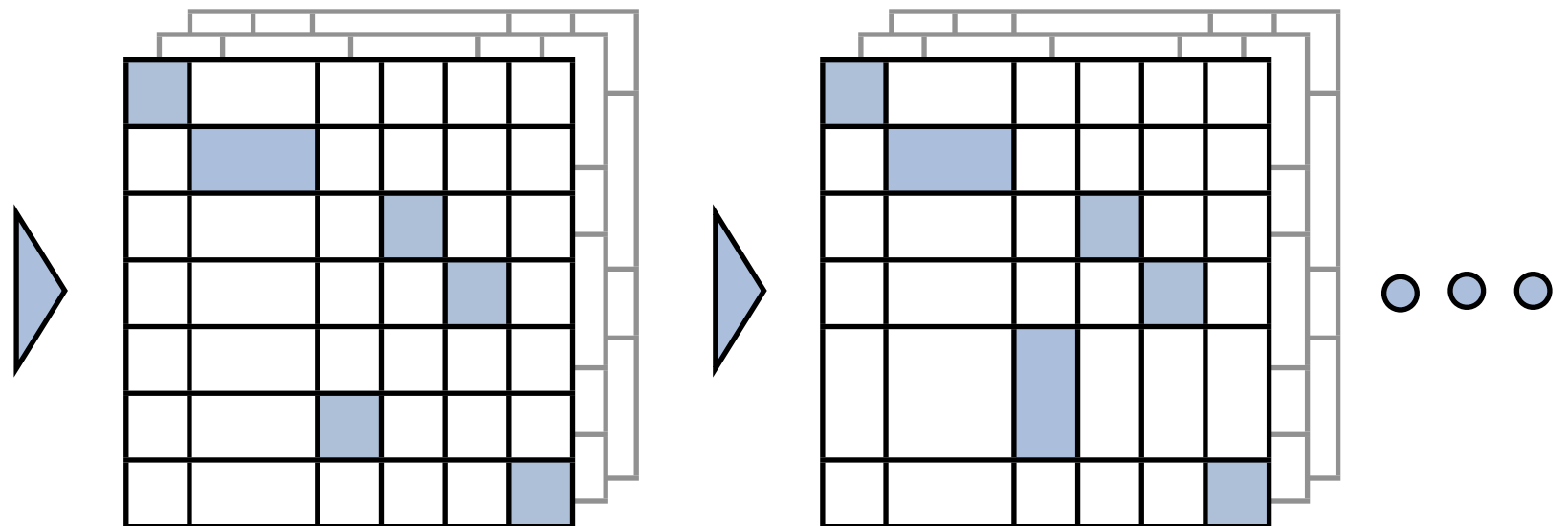


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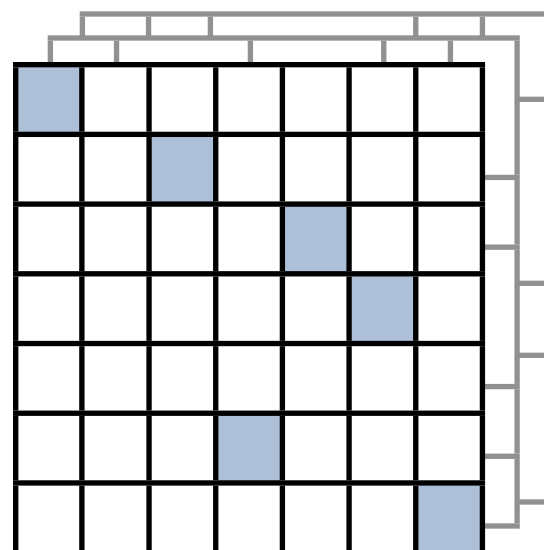


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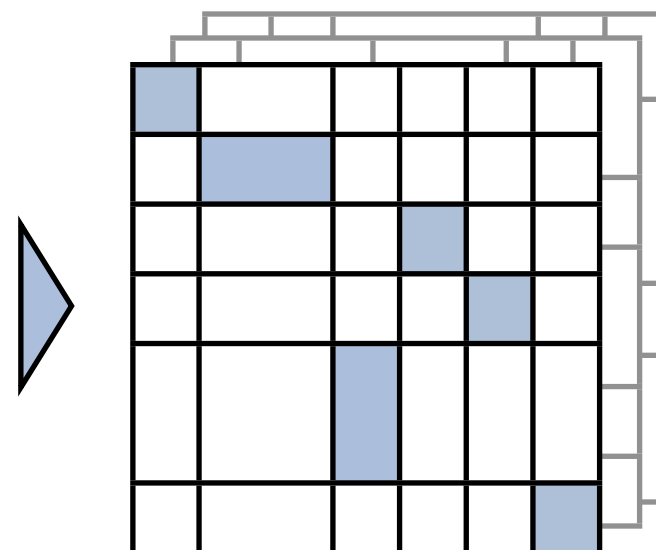
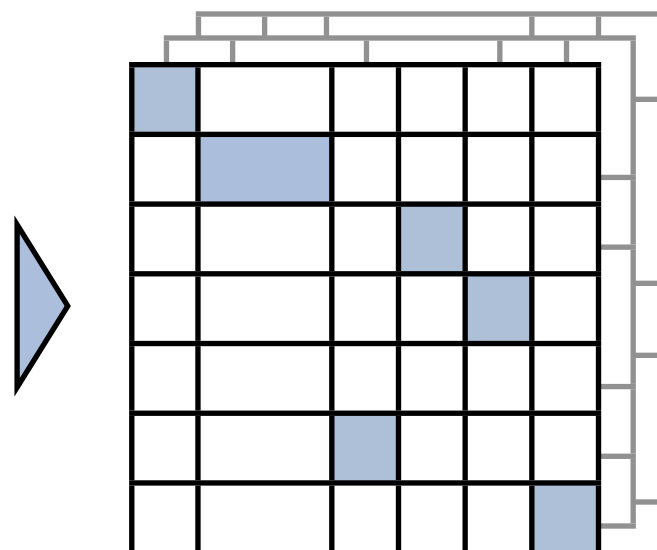


Sampling Phrase Alignments

Initial phrase
alignment



Stochastically apply local edit operators



...

As samples are generated:

- Track phrase pair counts for current sample
- Average phrase alignment counts over all samples

Gibbs Sampling Example: Flip Operator

The boys are eating



Ellos



comen

Gibbs Sampling Example: Flip Operator

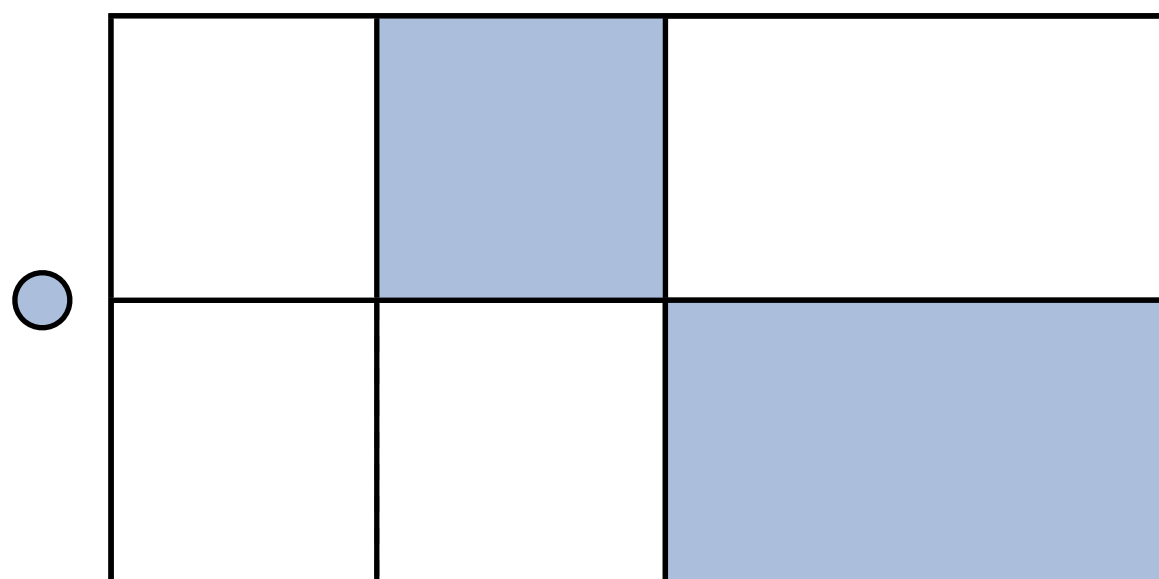
Procedure:

The boys are eating



Ellos

comen



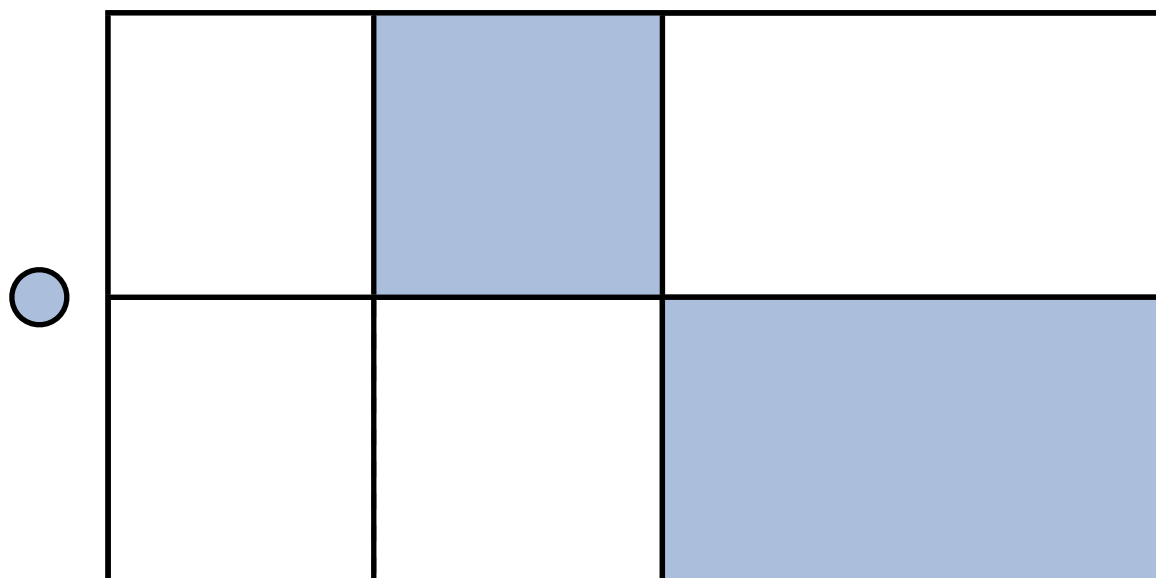
Gibbs Sampling Example: Flip Operator

The  boys are eating

Ellos

comen



Procedure:

- Choose a position


Gibbs Sampling Example: Flip Operator

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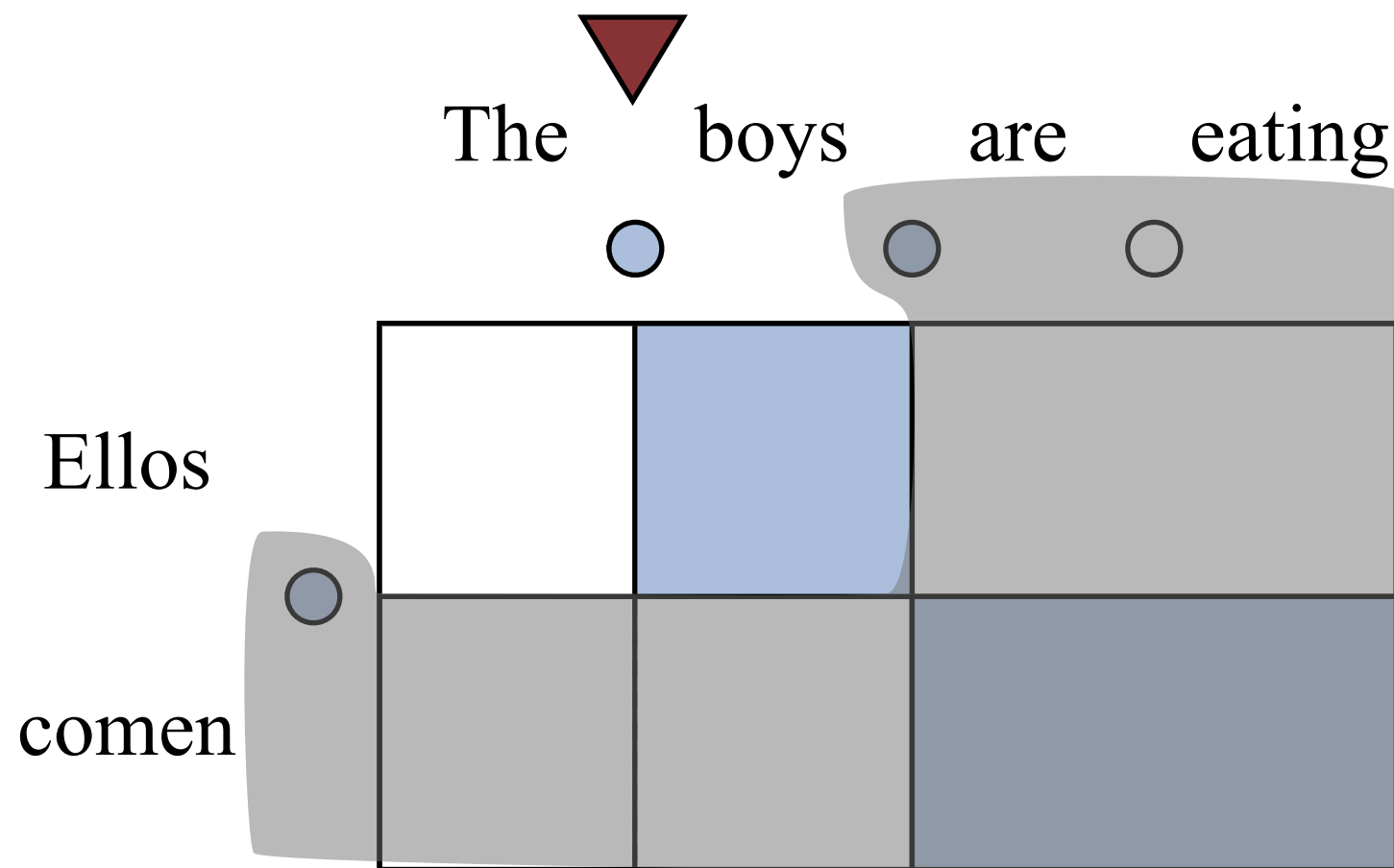
comen



Procedure:

- Choose a position
- List all outcomes

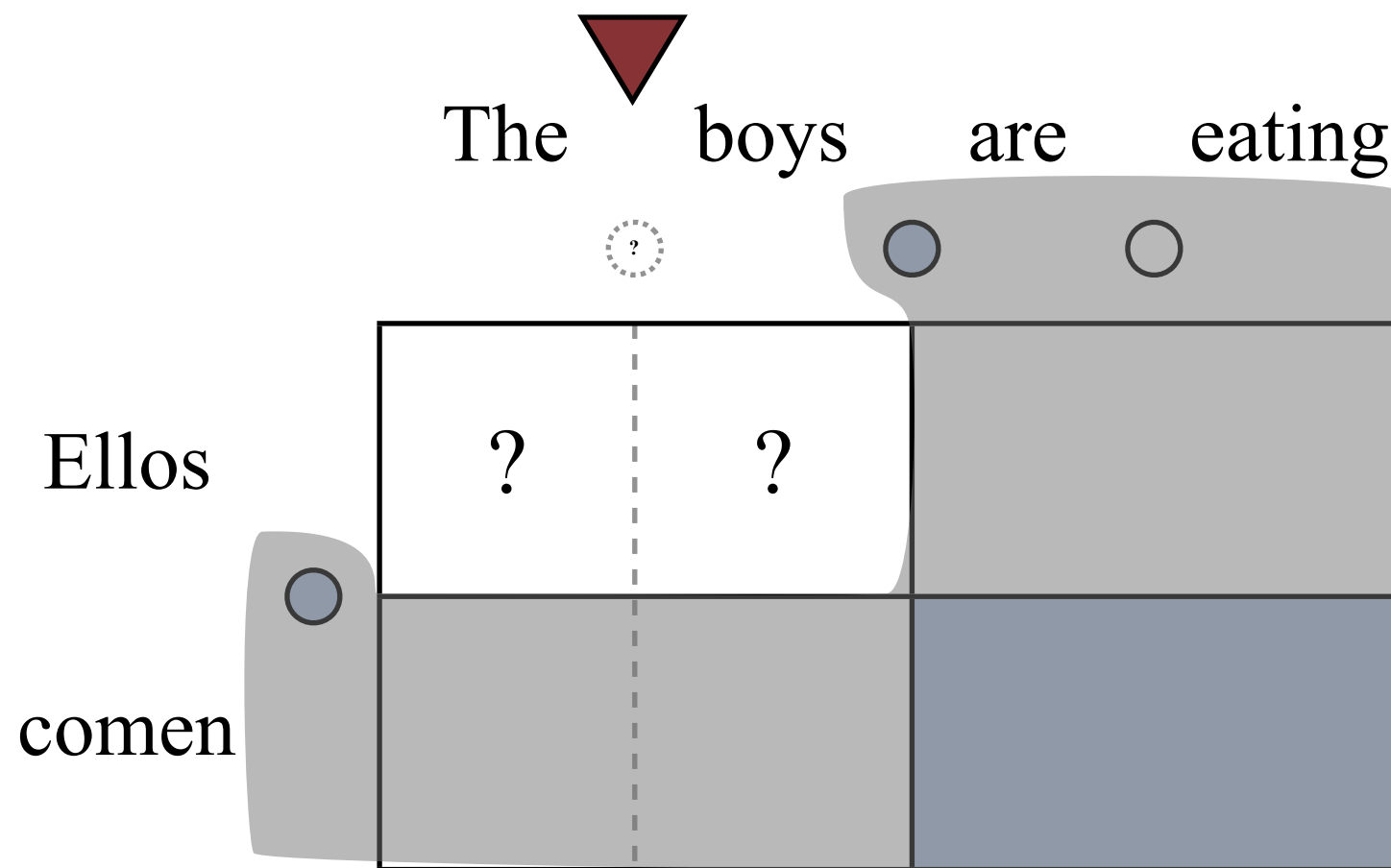
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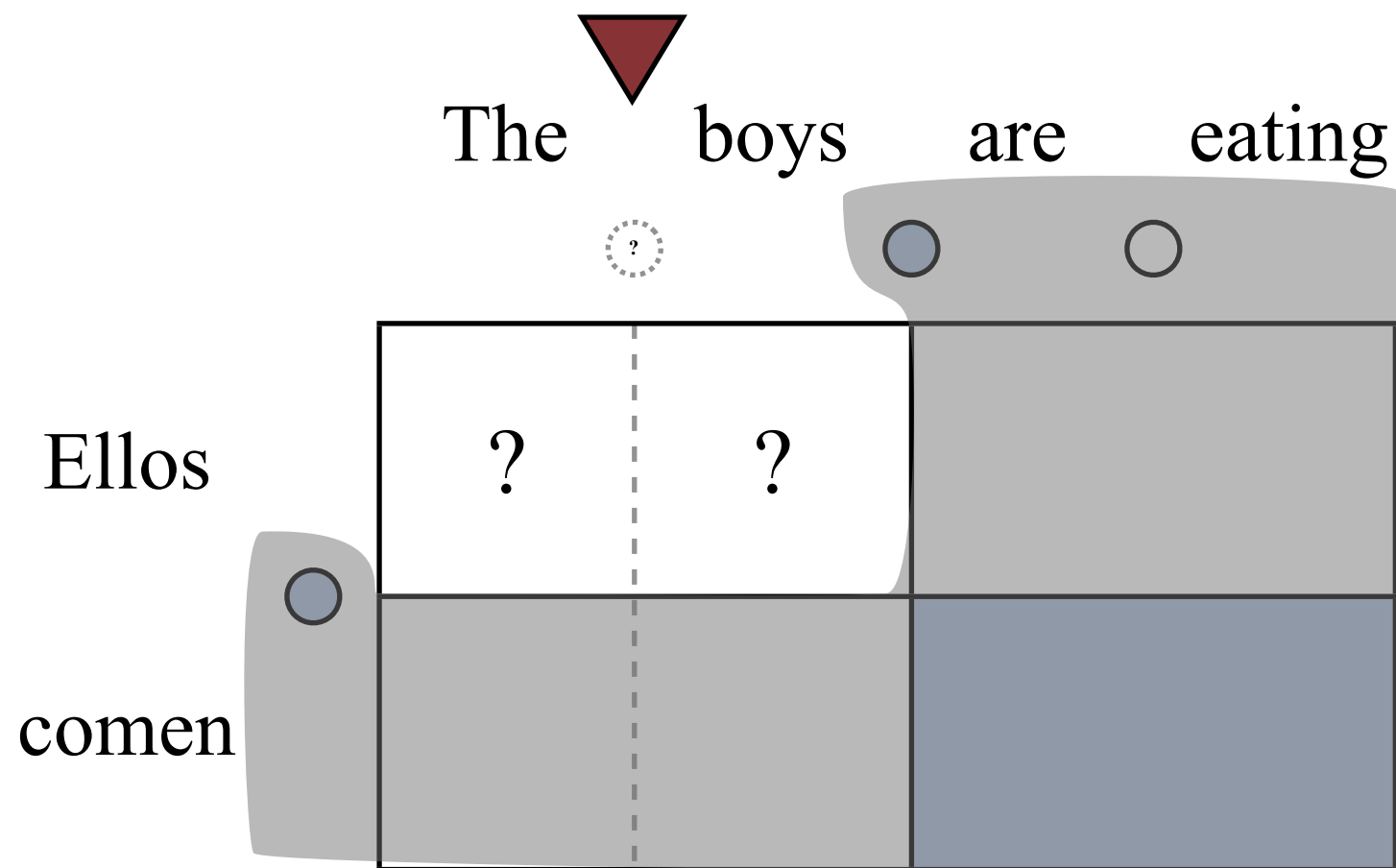
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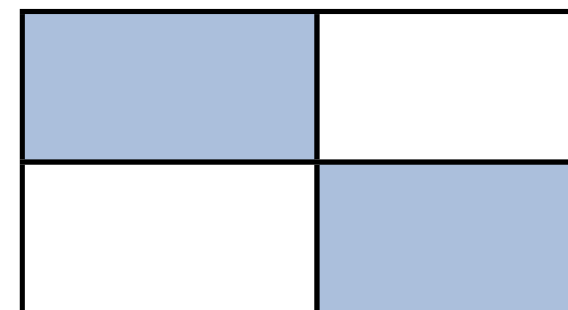
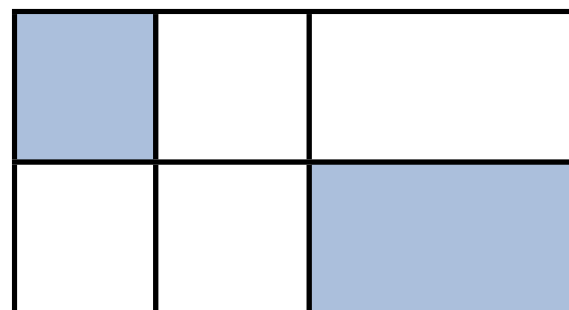
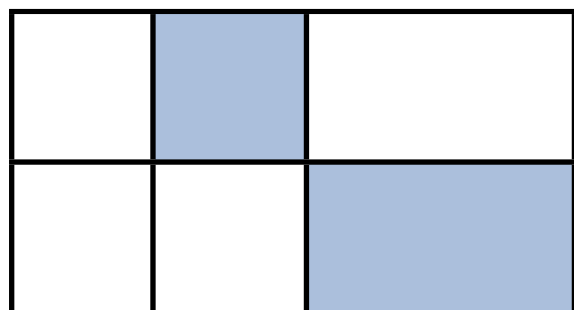
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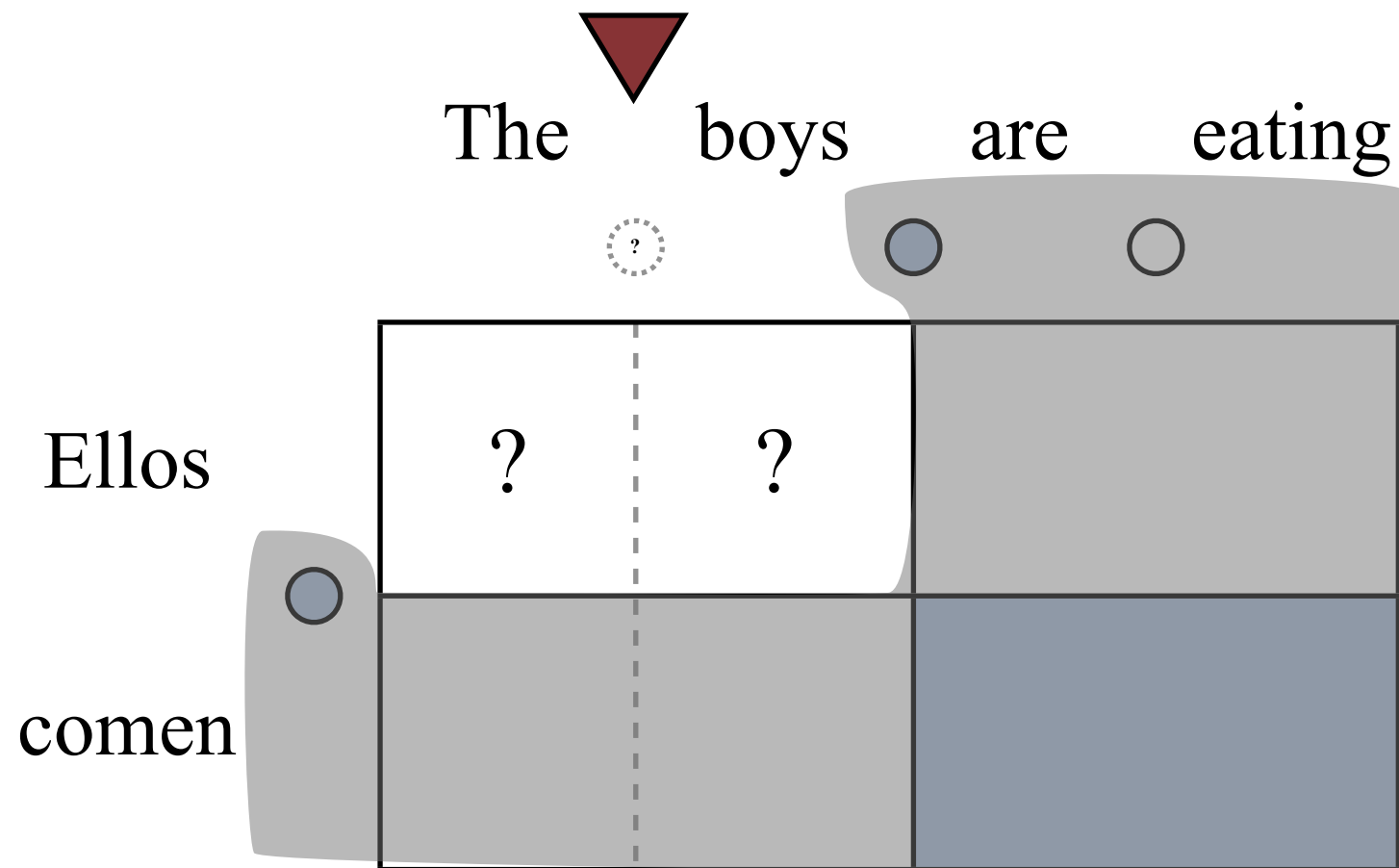


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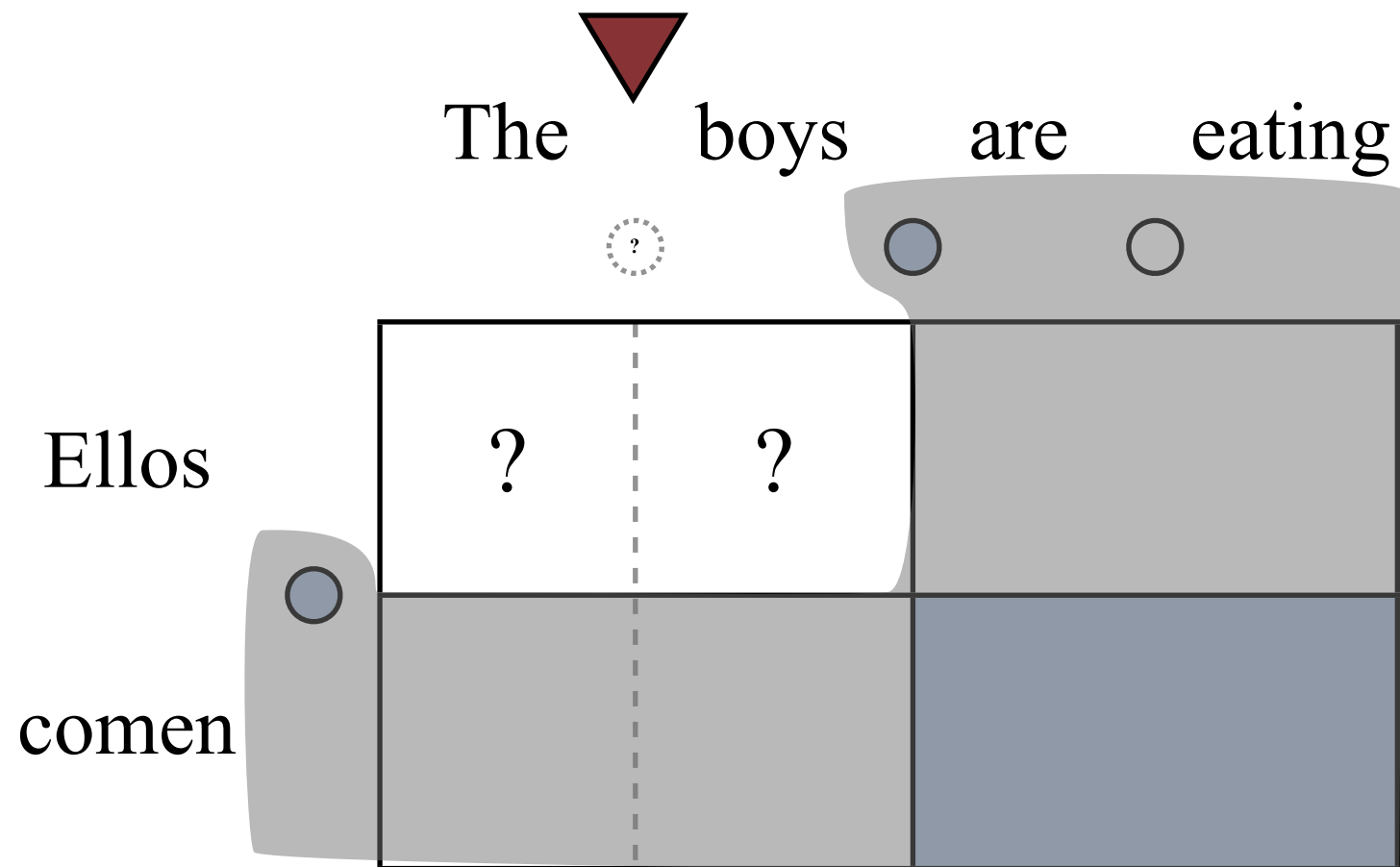
- Choose a position
- List all outcomes
- Compute posteriors

$$P(\cdot | state) \propto \frac{P(boys, ellos) \cdot P(the, -)}{P(the, -)}$$

$$\frac{P(boys, -) \cdot P(the, ellos)}{P(the, ellos)}$$

$$P(the\ boys, ellos)$$

Gibbs Sampling Example: Flip Operator



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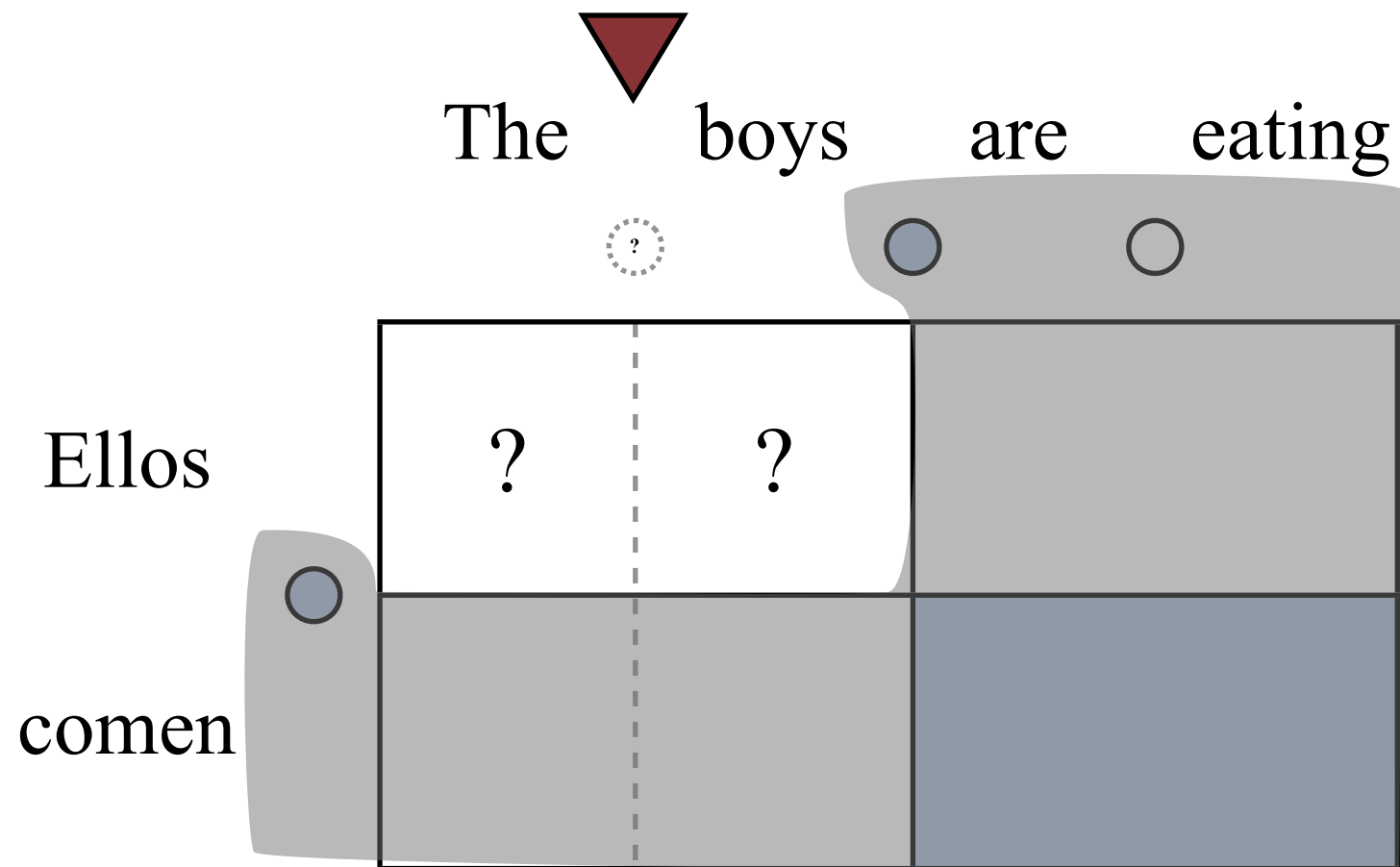
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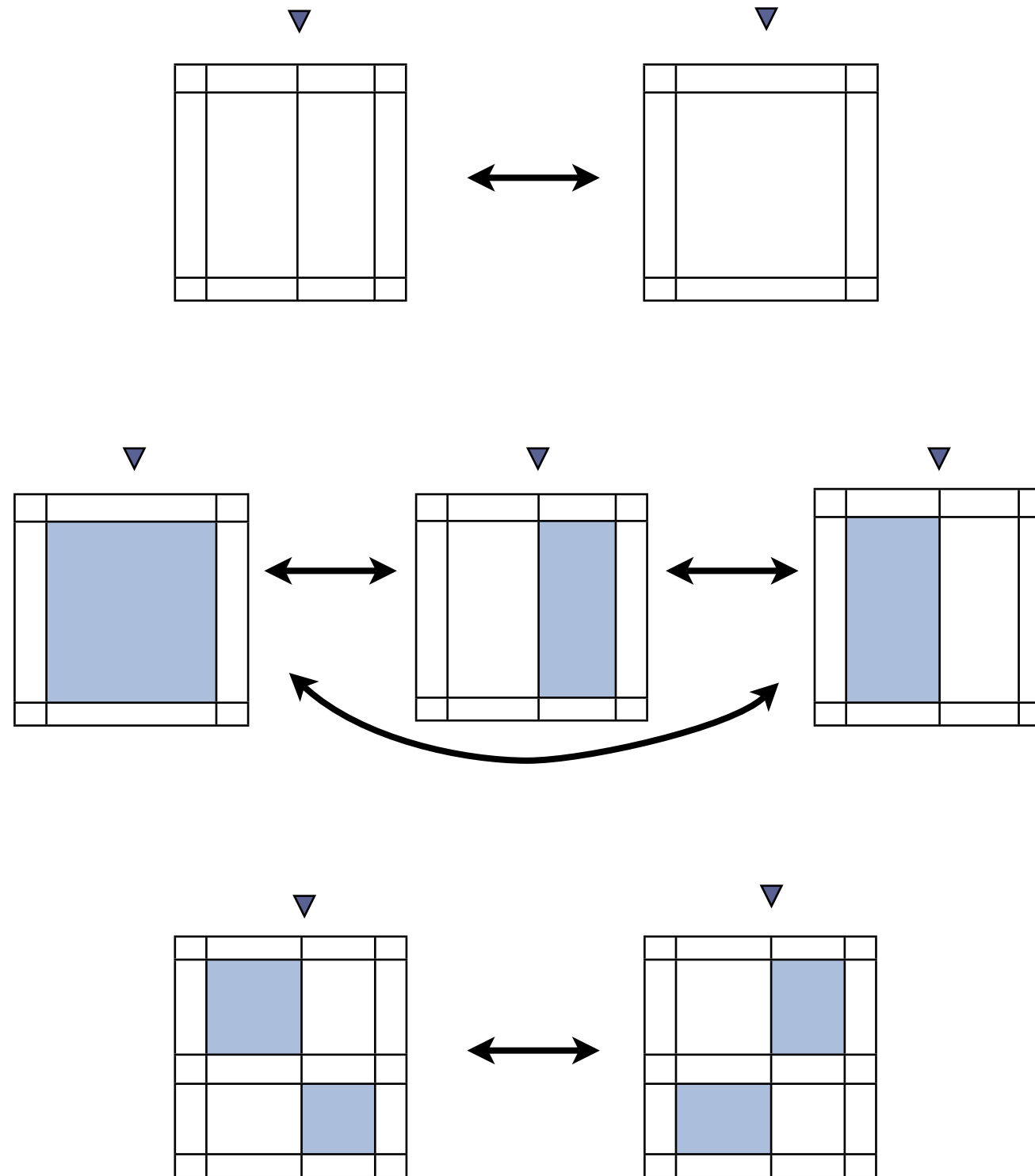
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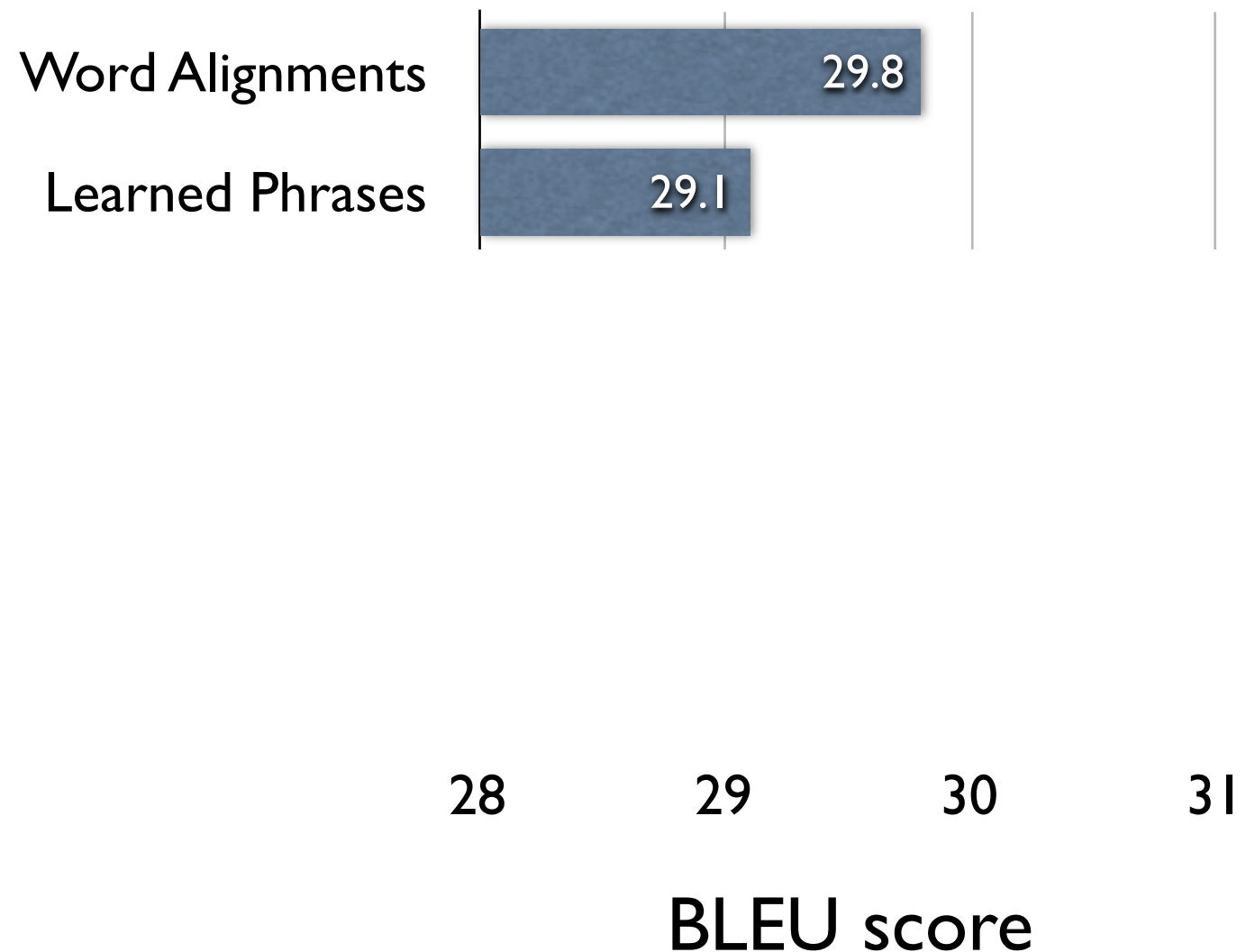
$$P(the\ boys, ellos)$$

The Flip Operator Configurations



Performance Results

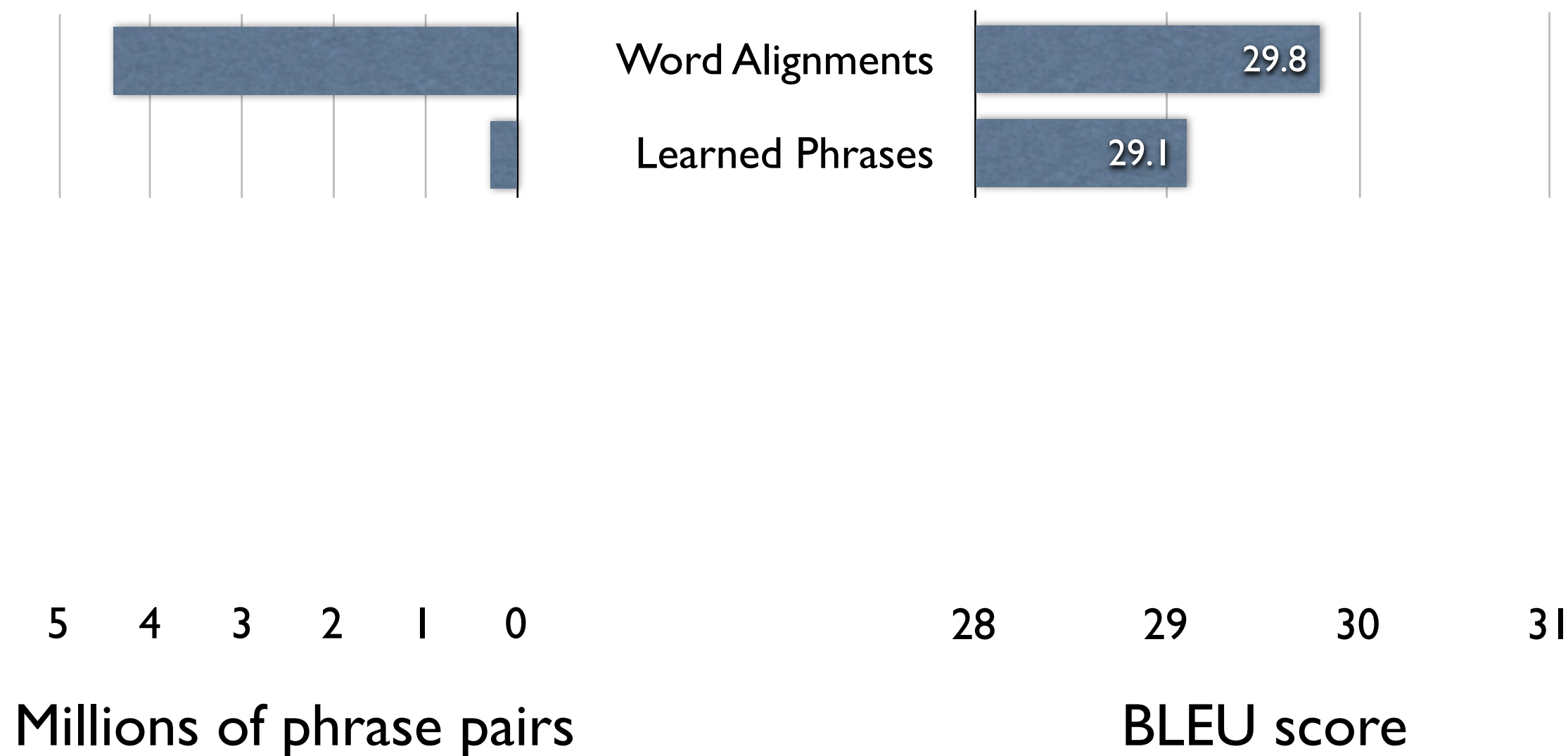
Translation performance in a phrase-based system (Moses)
for English-Spanish parliamentary proceedings (Europarl)



* Includes additional lexical features to discourage undesirable phrase pairs

Performance Results

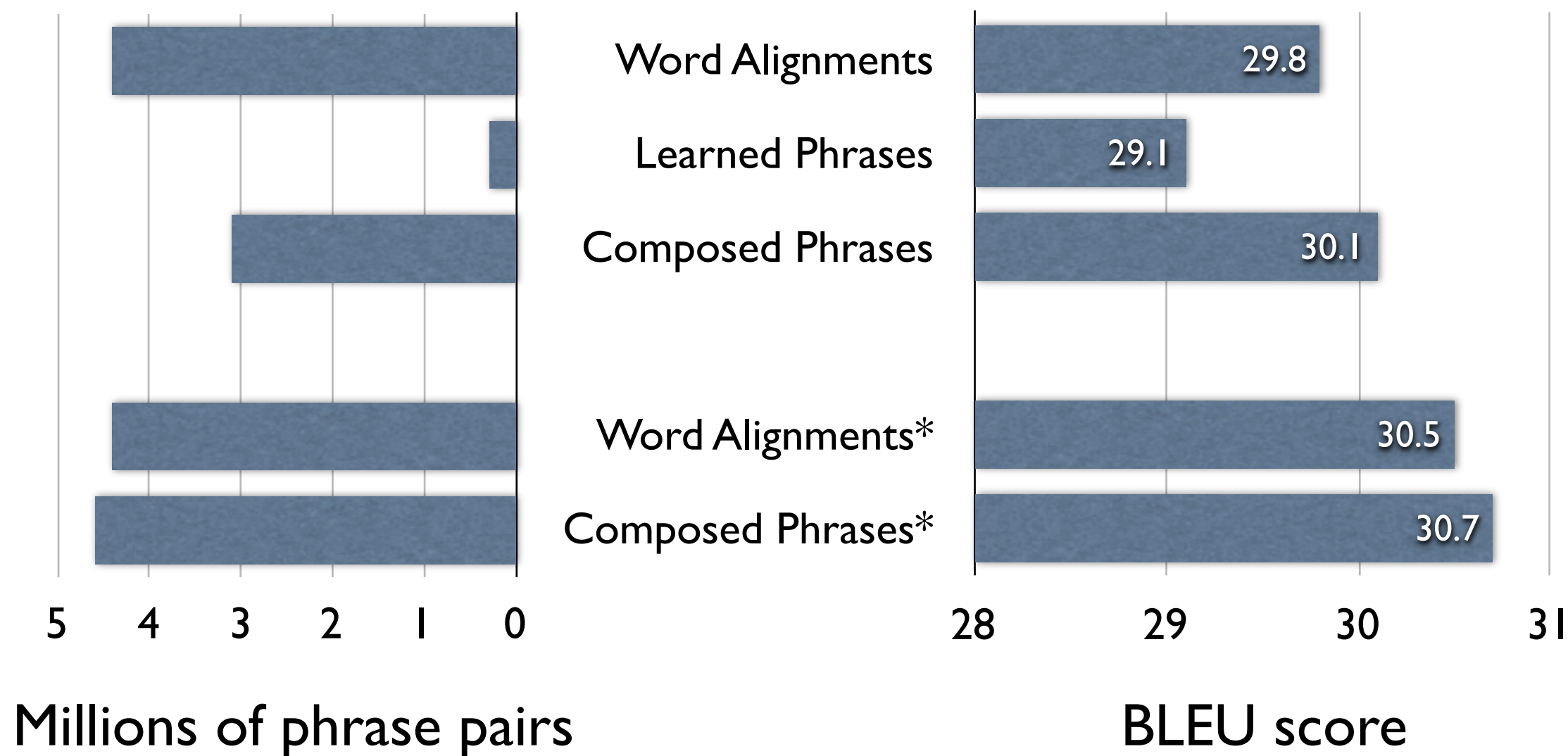
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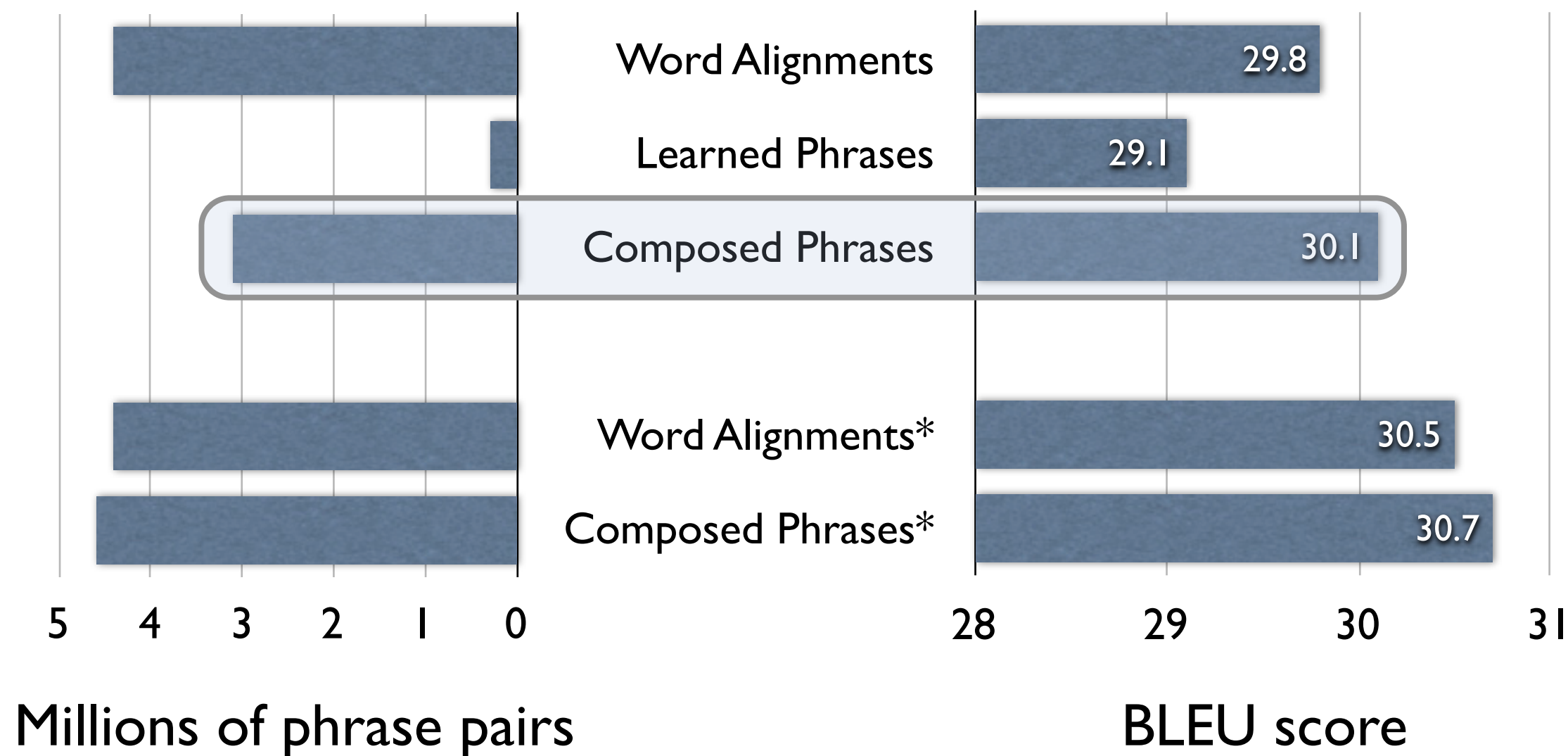
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