Phrase-Based Translation

Machine Translation

$$p(English|Chinese) \sim$$

$$p(English) \times p(Chinese|English)$$

language model

translation model

Machine Translation

$$p(English|Chinese) \sim$$

$$\underbrace{p(English)}_{\text{language model}} \times \underbrace{\boxed{p(Chinese|English)}}_{\text{translation model}}$$

The IBM Models

The IBM Models

- Fertility probabilities.

The IBM Models

- Fertility probabilities.
- Word translation probabilities.

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- Fertility probabilities.
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- Distortion probabilities.

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The IBM Models

- Fertility probabilities.
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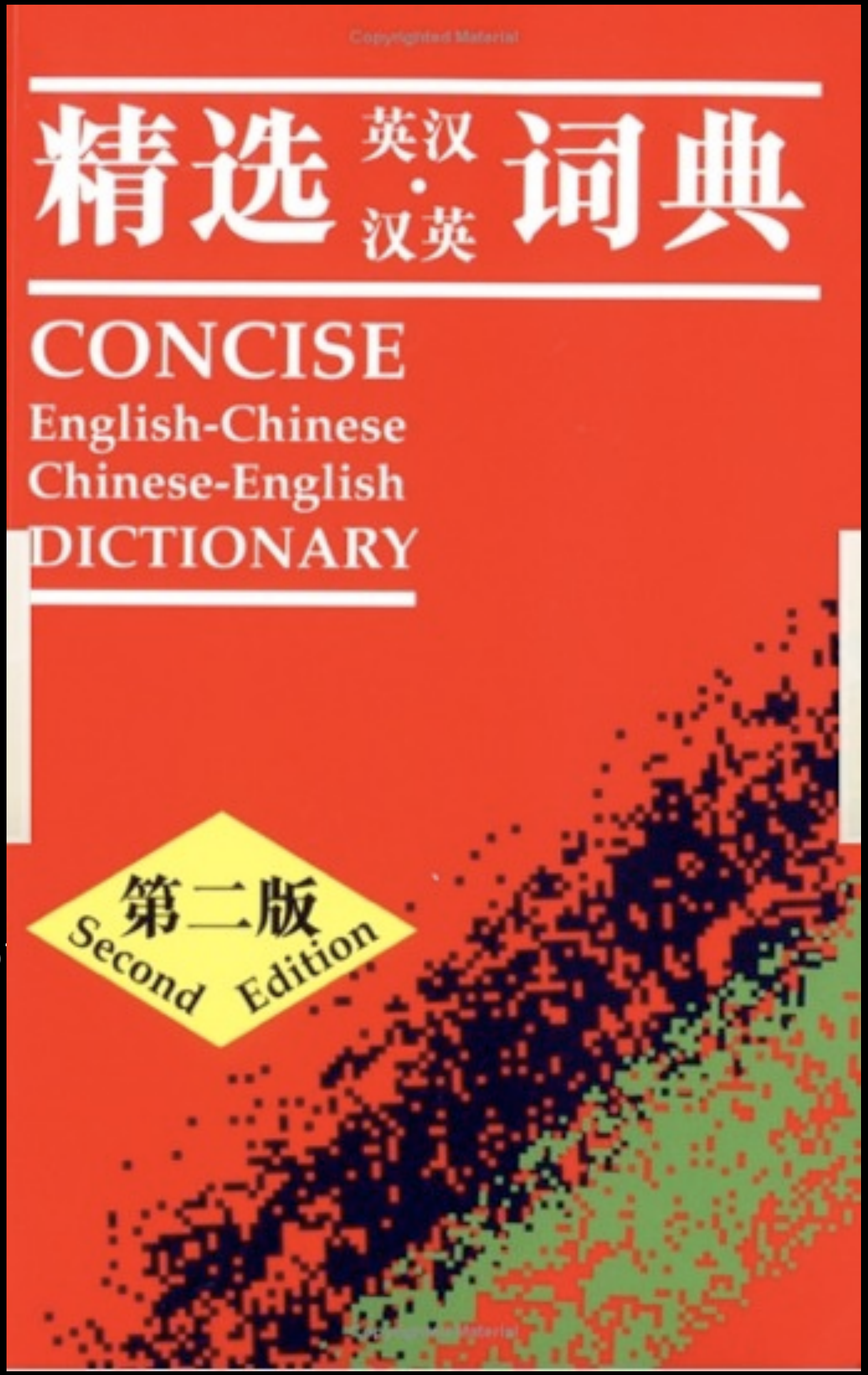
- Some problems:
  - Weak reordering model -- outp
  - Many decisions -- many things



The IBM Models

- Fertility probabilities.
- Word translation probabilities.
- Distortion probabilities.
- Some problems:
  - Weak reordering model -- output is not fluent.
  - Many decisions -- many things can go wrong.

IBM Model 4

Although north wind howls , but sky still very clear .

虽然 北 风 呼啸 ，但 天空 依然 十分 清澈 。

IBM Model 4

Although north wind howls , but sky still very clear .

虽然 北 风 呼啸 ，但 天空 依然 十分 清澈 。

↓

虽然

IBM Model 4

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虽然 北 风 呼啸 ，但 天空 依然 十分 清澈 。

$\downarrow$

虽然

$$p_f(1|\text{虽然})$$

IBM Model 4

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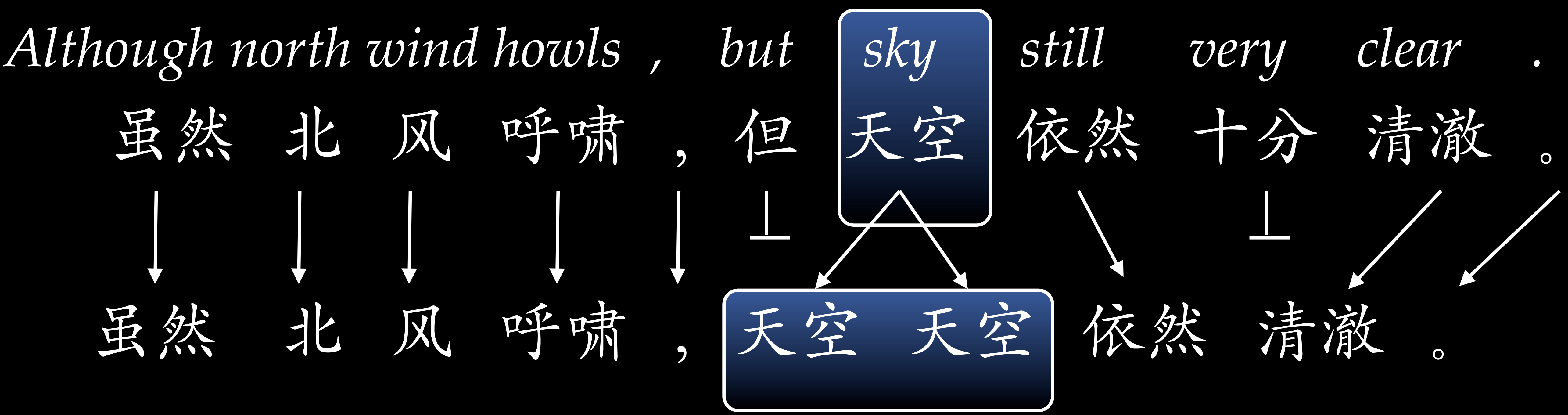
IBM Model 4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⊥ ⊥
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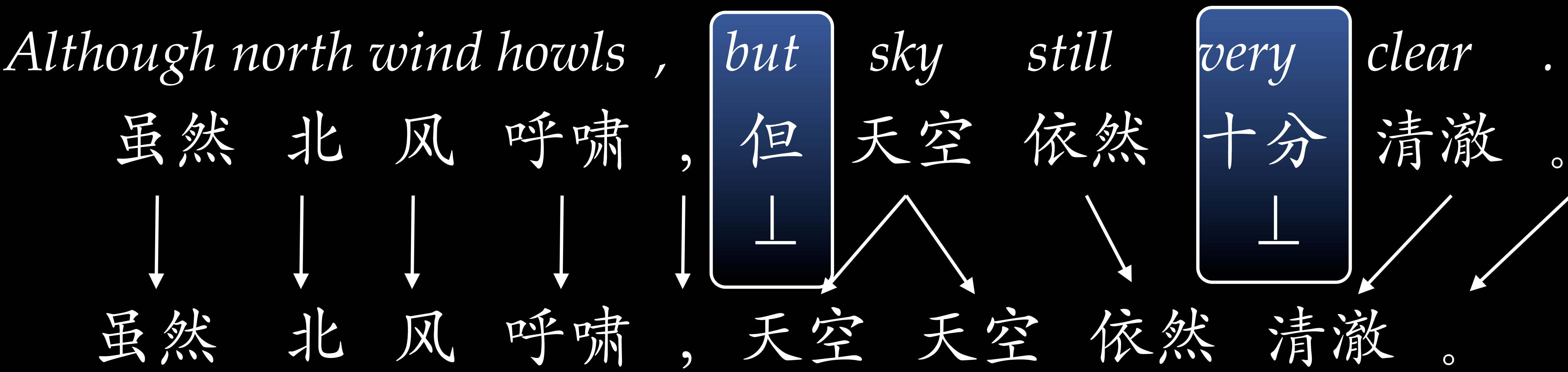
IBM Model 4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Although north wind howls , but sky still very clear .

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$\perp$ $\perp$

虽然 北 风 呼啸 ，天空 天空 依然 清澈 。 ε ε

IBM Model 4

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虽然 北 风 呼啸 ，但 天空 依然 十分 清澈 。ε

$\perp$ $\perp$

虽然 北 风 呼啸 ，天空 天空 依然 清澈 。 ε ε

However

IBM Model 4

Although north wind howls , but sky still very clear .

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$\perp$ $\perp$

虽然 北 风 呼啸 ，天空 天空 依然 清澈 。 ε ε

However

$$p_t(However|\text{虽然})$$

IBM Model 4


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⊥
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虽然 北 风 呼啸 ， 天空 天空 依然 清澈 。 ε ε
However north wind strong , the sky remained clear . under the

IBM Model 4

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___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___

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$\perp$ $\perp$

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However north wind strong , the sky remained clear . under the

___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___ ___

$$p_d(0|However)$$

IBM Model 4

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虽然 北 风 呼啸 ， 天空 天空 依然 清澈 。 ε ε
However north wind strong , the sky remained clear . under the

IBM Model 4

$$p_d(8|north)$$

IBM Model 4


Although north wind howls , but sky still very clear .
虽然 北 风 呼啸 ，但 天空 依然 十分 清澈 。ε
⊥
⊥
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⊥
⊥
虽然 北 风 呼啸 ， 天空 天空 依然 清澈 。 ε ε
However north wind strong , the sky remained clear . under the
However , the sky remained clear under the strong north wind .

IBM Model 4

However , the sky remained clear under the strong north wind .

$$p(English, alignment|Chinese) = \prod_{p_f} \prod_{p_t} \prod_{p_d}$$

IBM Model 4

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IBM Model 4

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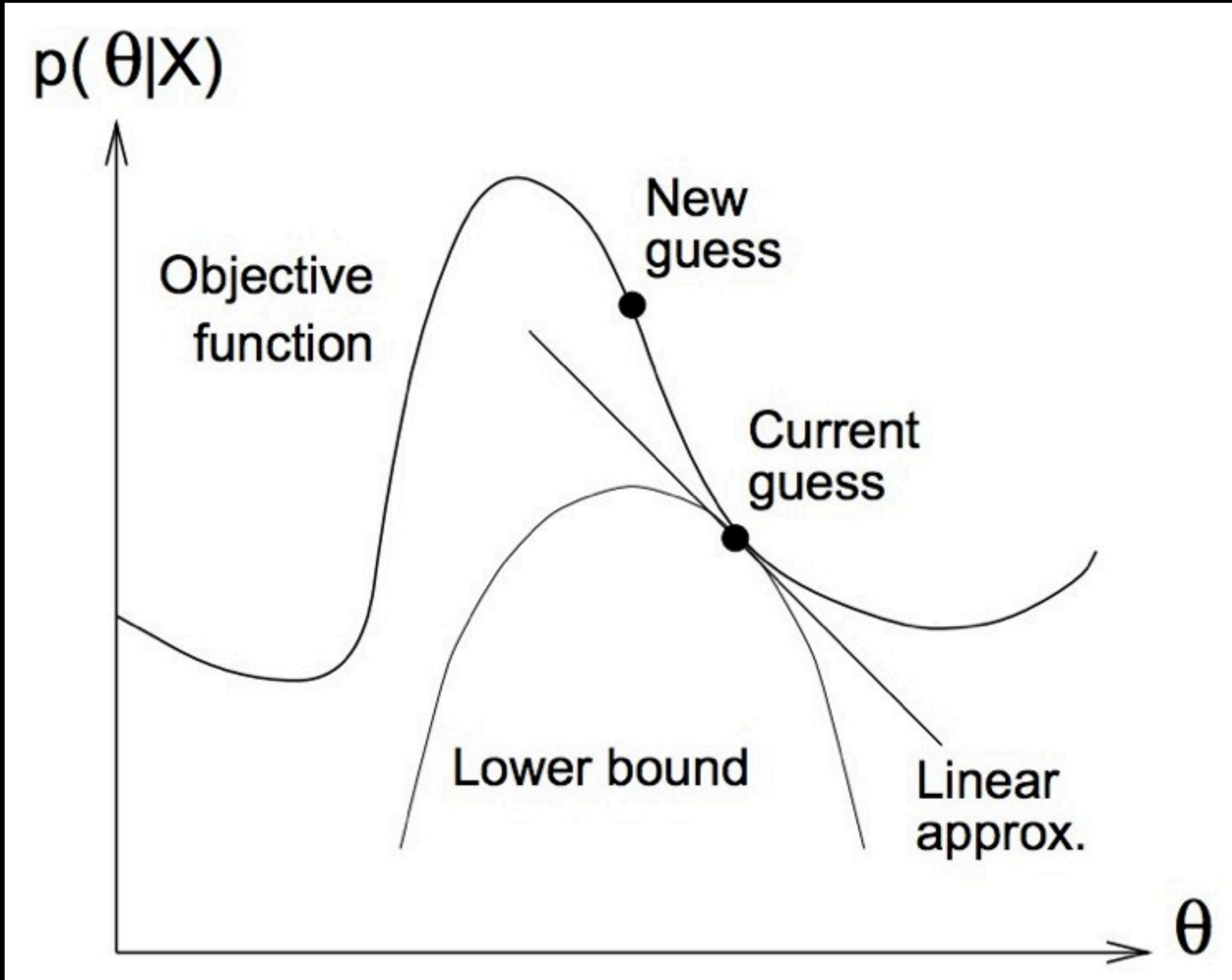
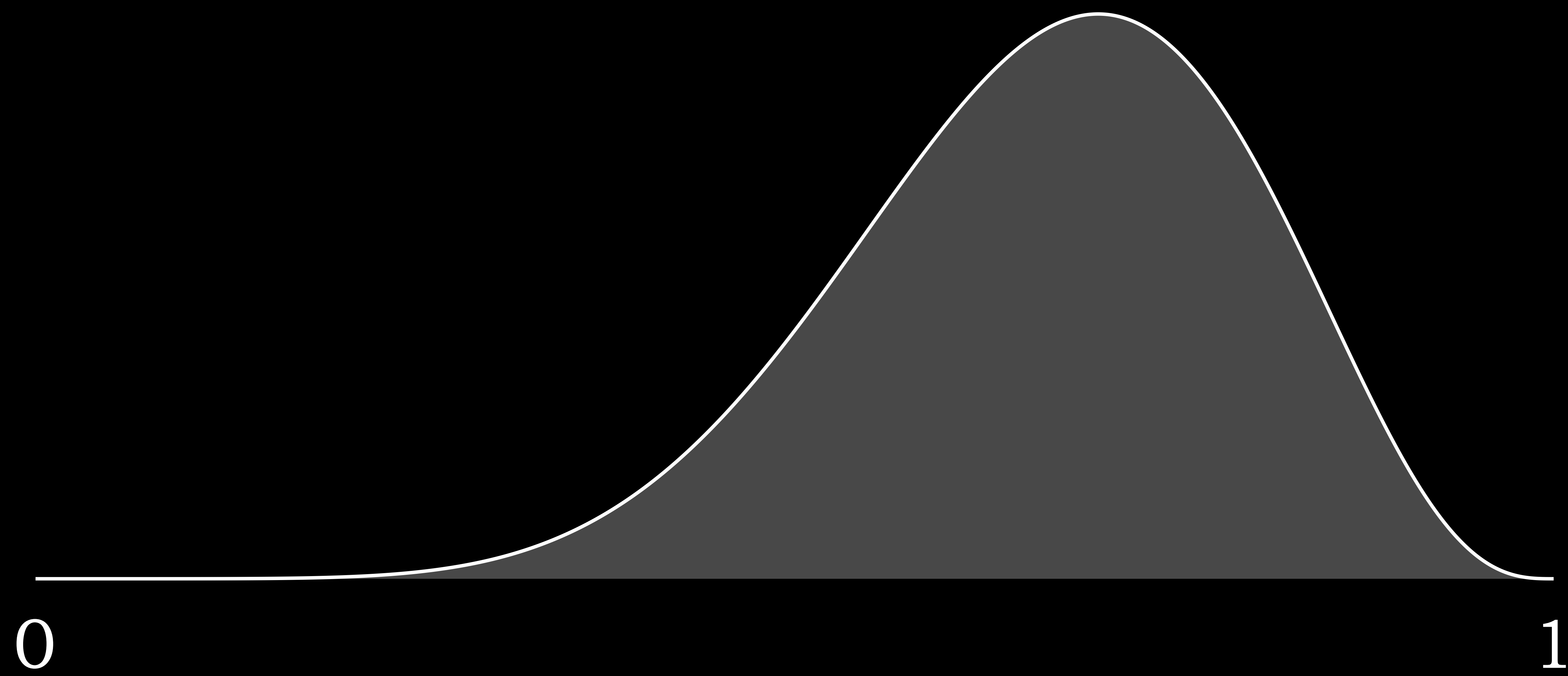
However , the sky remained clear under the strong north wind .

$$p(English|Chinese) = \sum_{alignments} \prod_{p_f} \prod_{p_t} \prod_{p_d}$$



(from Minka '98)

... and, likelihood is ***convex*** for IBM Model 1:



But not IBM Models 3-5!

Tradeoffs: Modeling v. Learning

	Lexical Translation	Local ordering dependency	Fertility	Convex	Tractable Exact Algorithms
IBM Model 1	✔	✘	✘	✔	✔
HMM	✔	✔	✘	✘	✔
IBM Model 4	✔	✔	✔	✘	✘

Tradeoffs: Modeling v. Learning

Lesson:
Trade exactness
for expressivity

	Lexical Translation	Local ordering dependency	Fertility	Convex	Tractable Exact Algorithms
IBM Model 1	✔	✘	✘	✔	✔
HMM	✔	✔	✘	✘	✔
IBM Model 4	✔	✔	✔	✘	✘

IBM Model 4

However , the sky remained clear under the strong north wind .

What are some things this model doesn’t account for?

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Phrase-based Models

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However

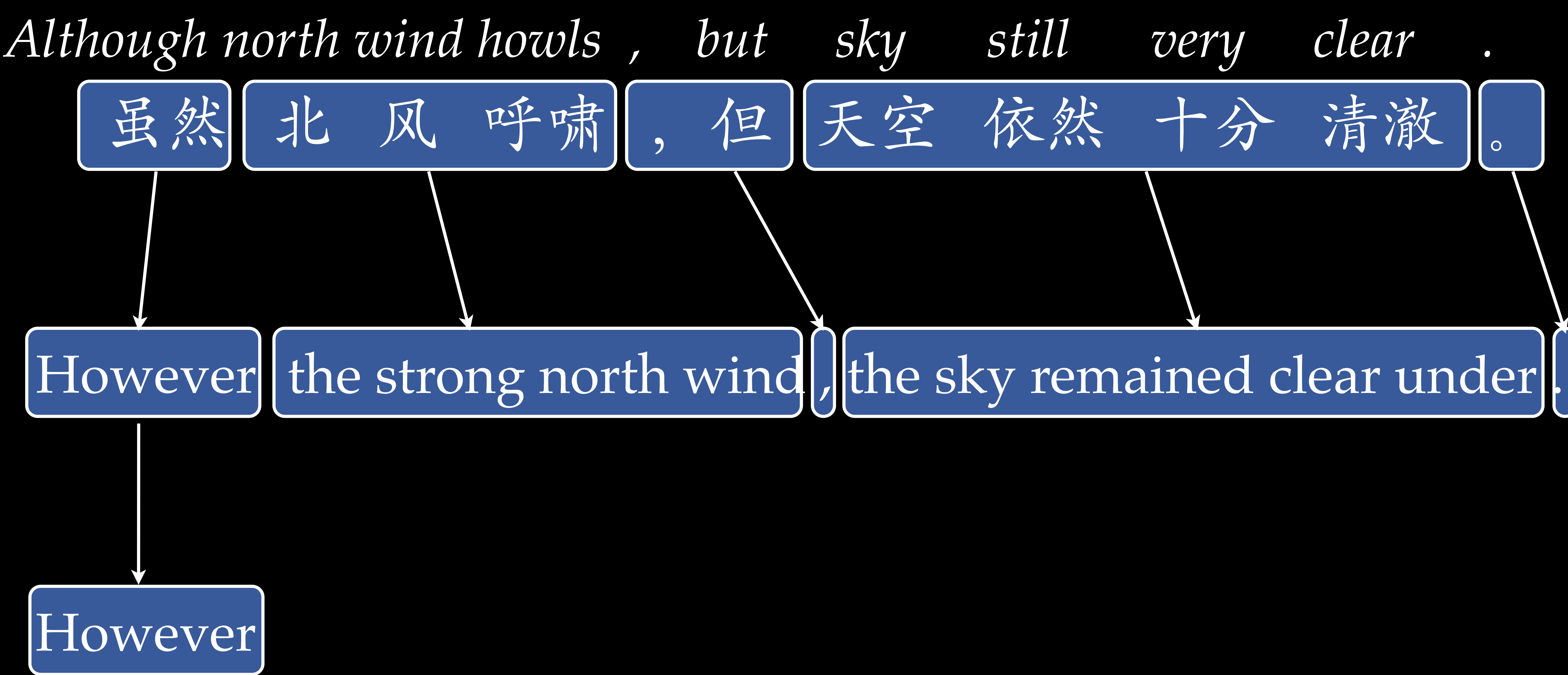
Phrase-based Models

Although north wind howls , but sky still very clear .

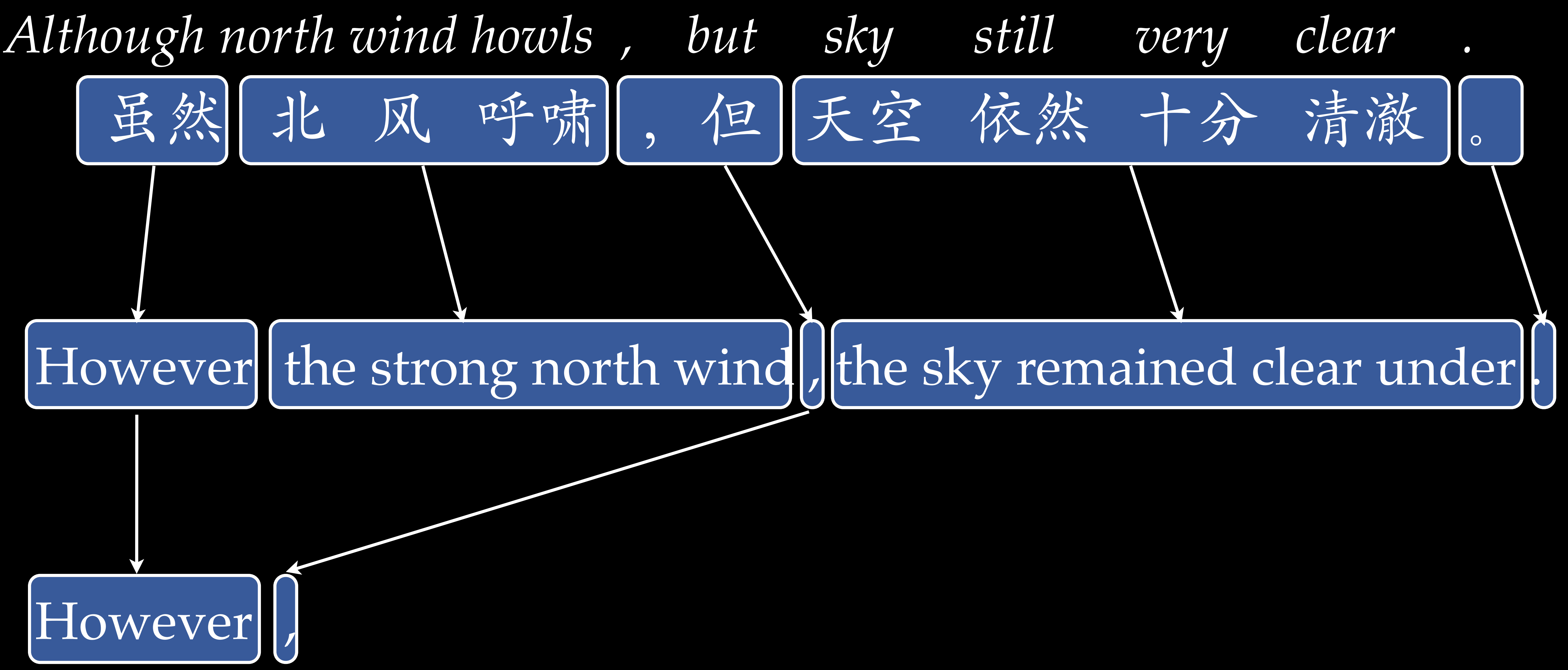
虽然 | 北 风 呼啸 | ，但 | 天空 依然 十分 清澈 | 。

However | the strong north wind | , | the sky remained clear under | .

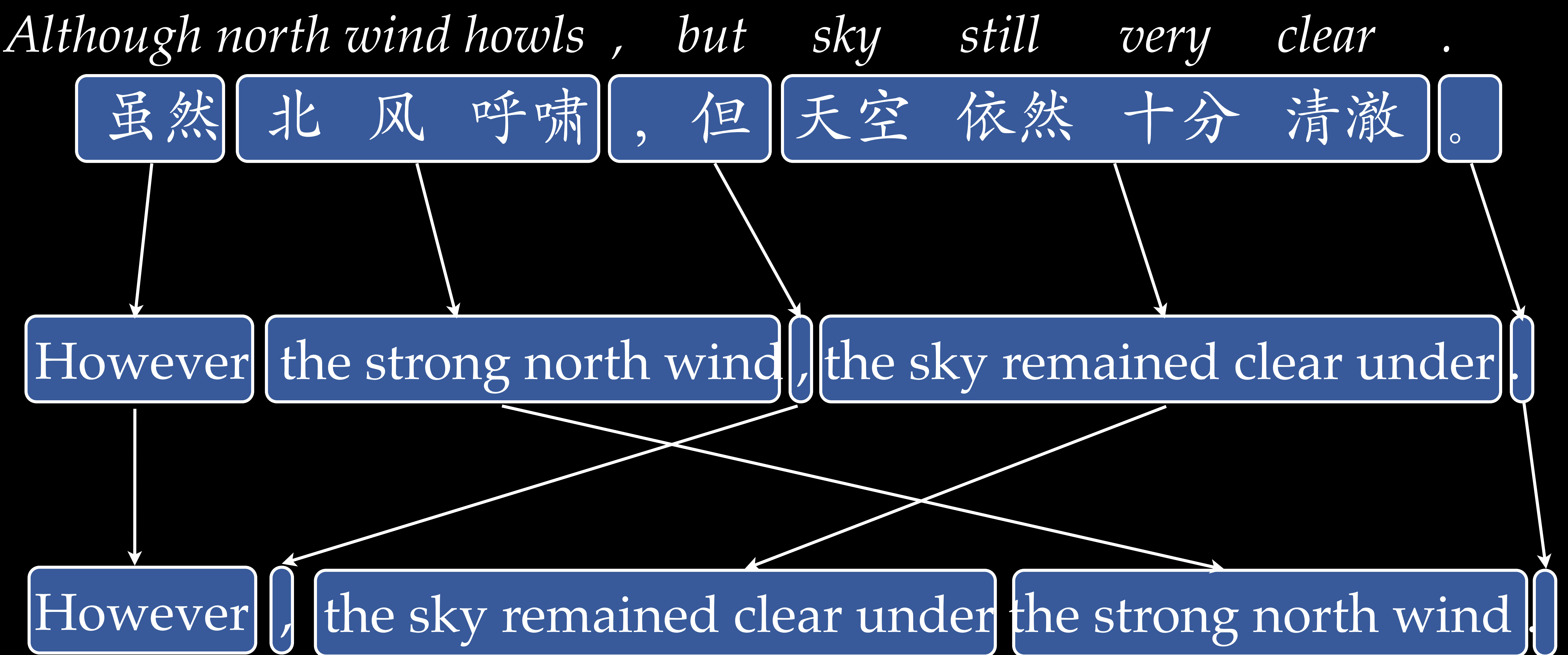
Phrase-based Models



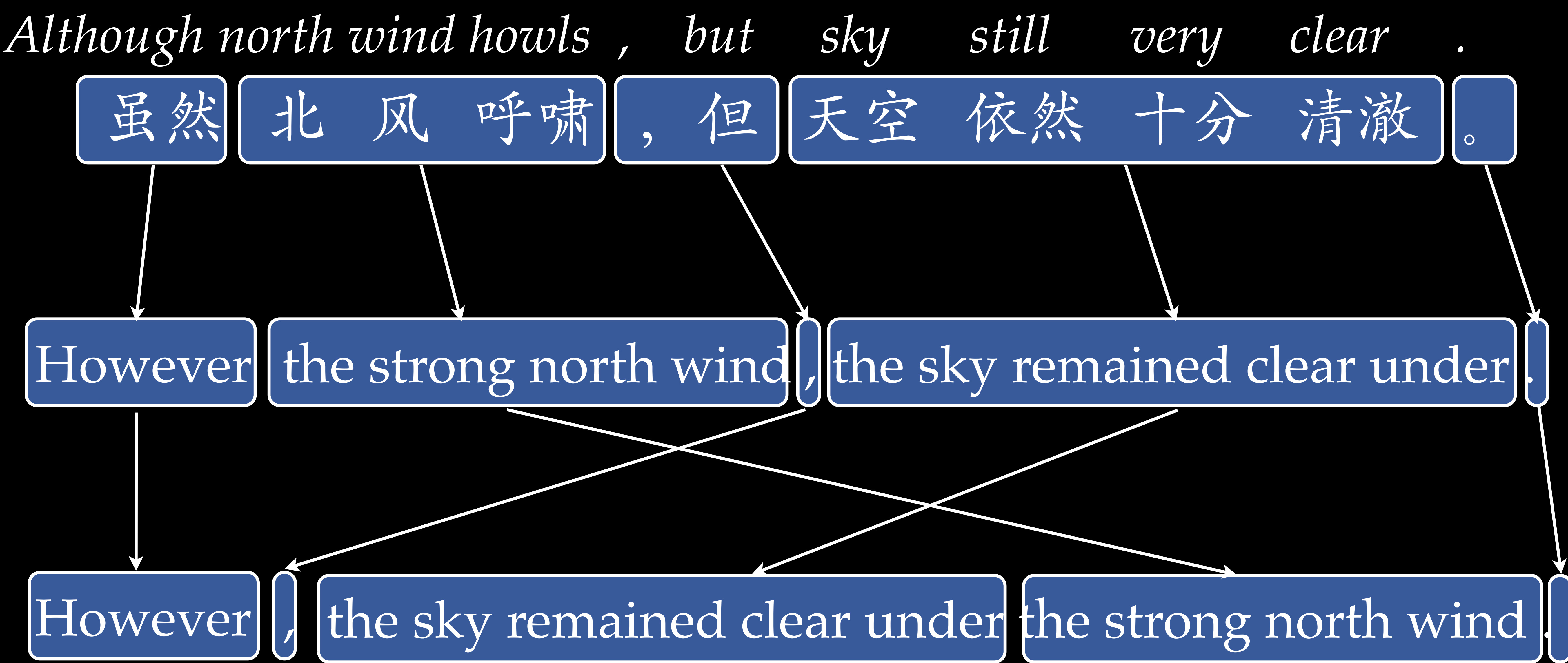
Phrase-based Models



Phrase-based Models



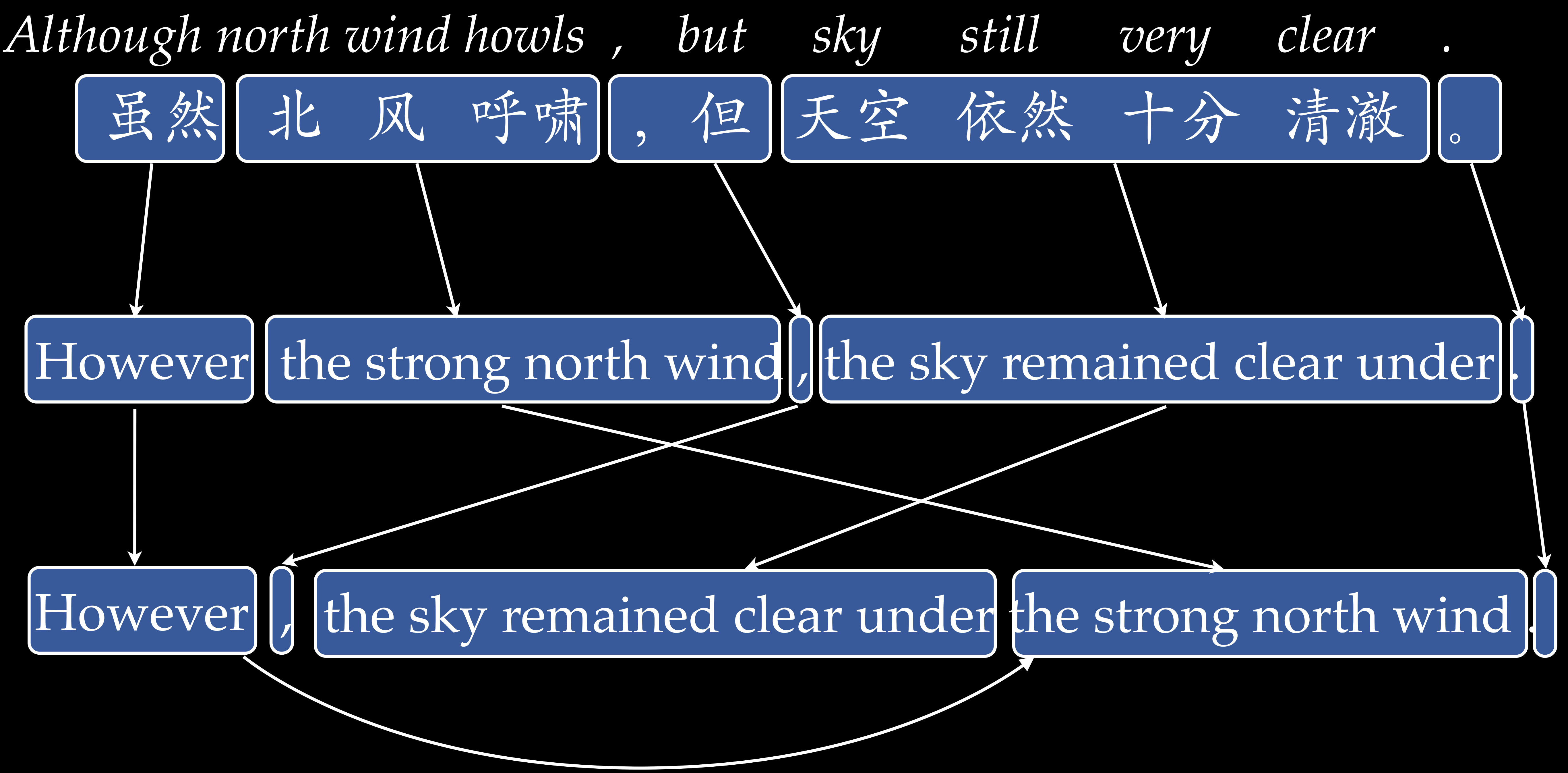
Phrase-based Models



$$p(English, alignment|Chinese) =$$

$$p(segmentation) \cdot p(translations) \cdot p(reorderings)$$

Phrase-based Models



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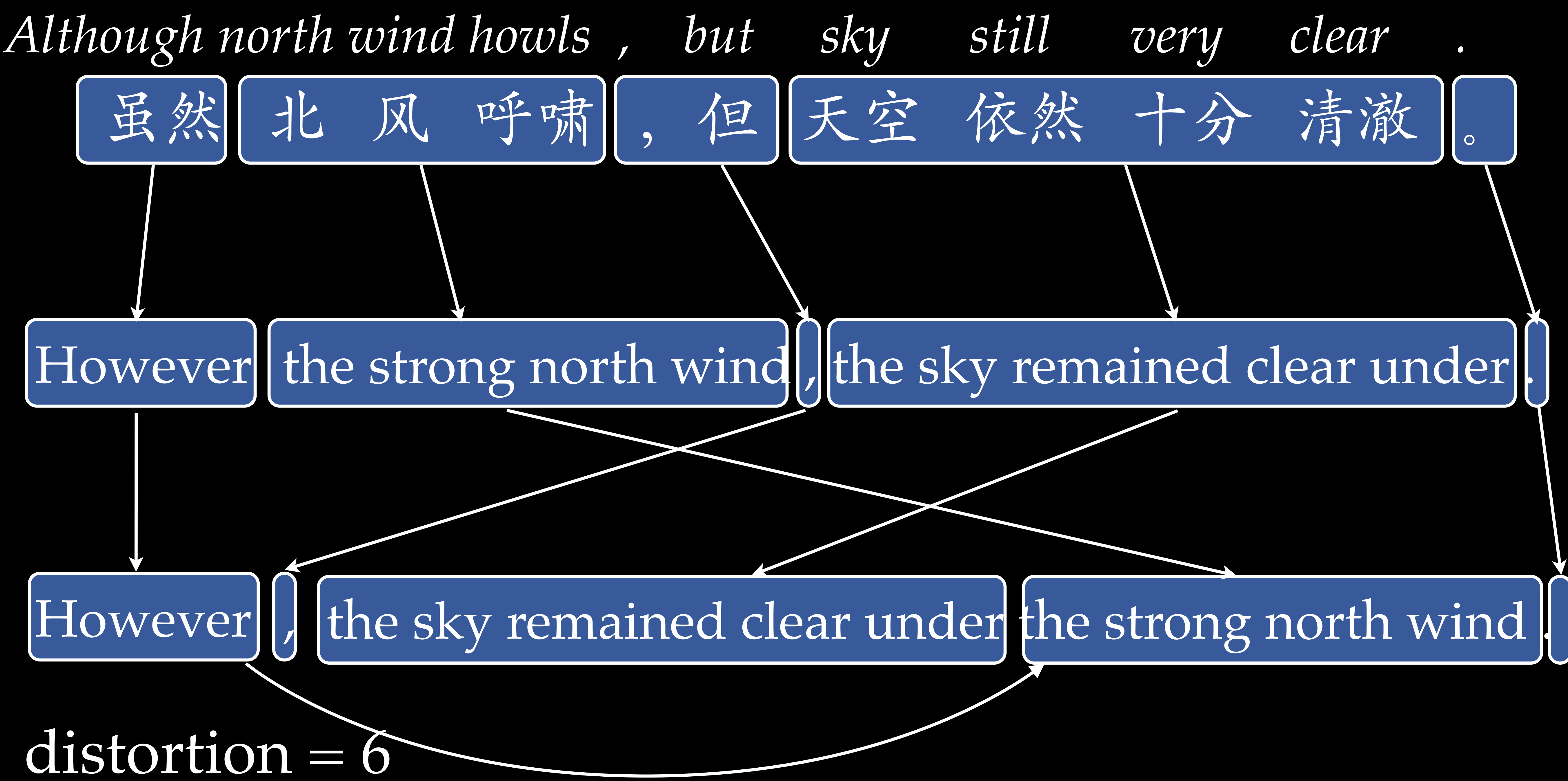
Phrase-based Models



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Phrase-based Models

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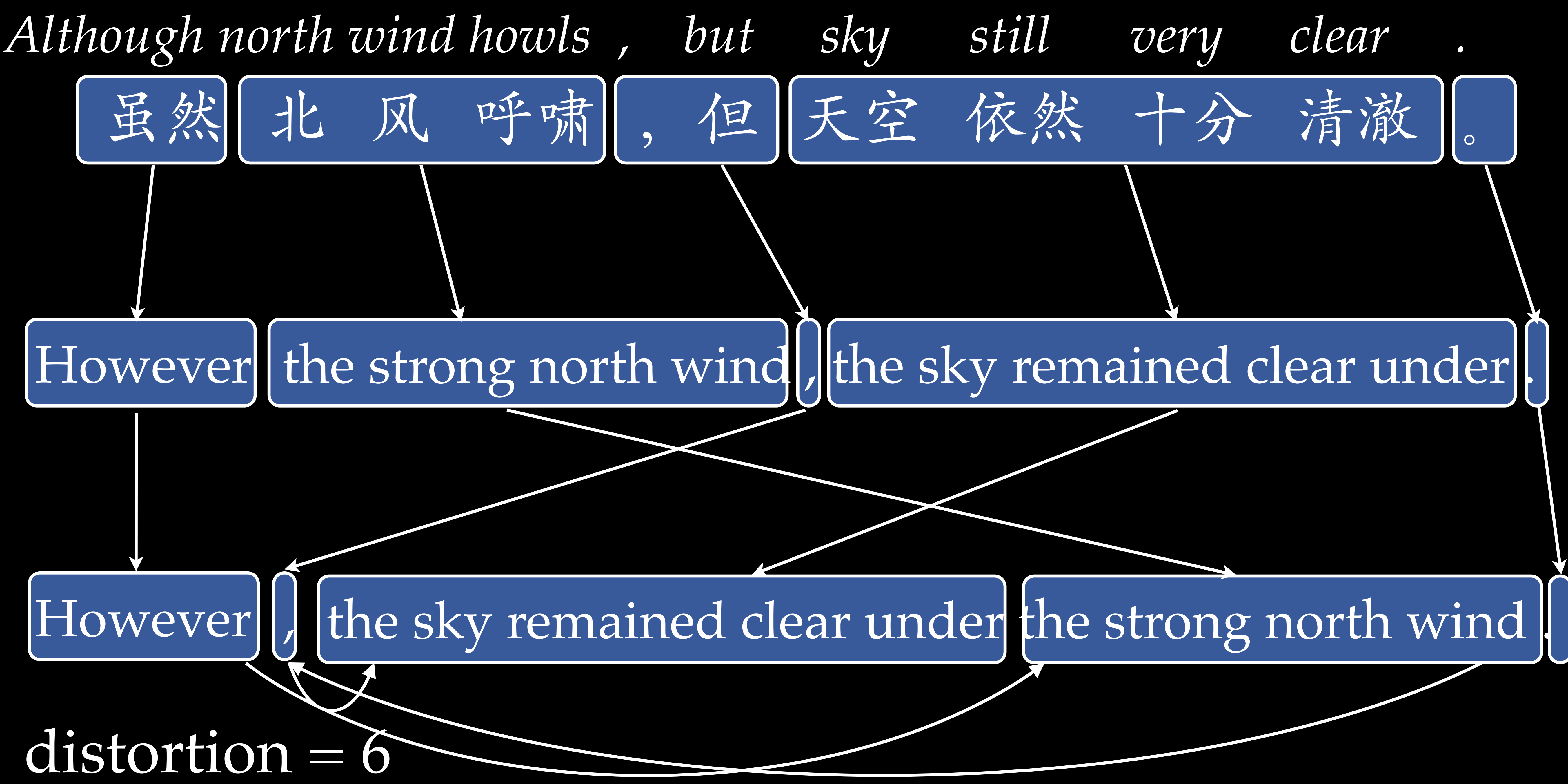

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Phrase-based Models

distortion = 6

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Phrase-based Models

Phrase-based Models

- Segmentation probabilities.

Phrase-based Models

- Segmentation probabilities.
- Phrase translation probabilities.

Phrase-based Models

- Segmentation probabilities.
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Phrase-based Models

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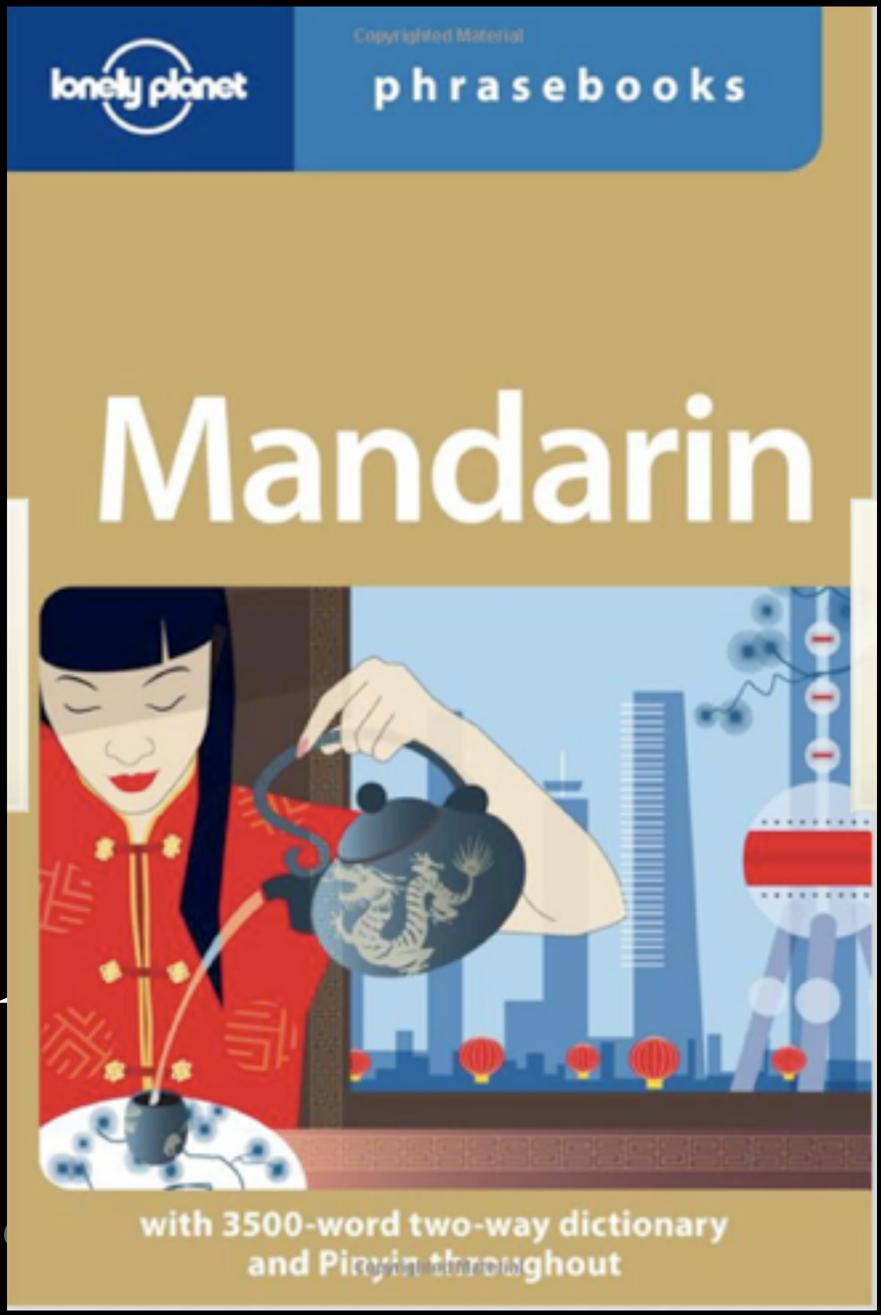

Phrase-based Models

- Segmentation probabilities.
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Phrase-based Models

- Segmentation probabilities: fixed (uniform)
- **Phrase translation probabilities.**
- Distortion probabilities: fixed (decaying)

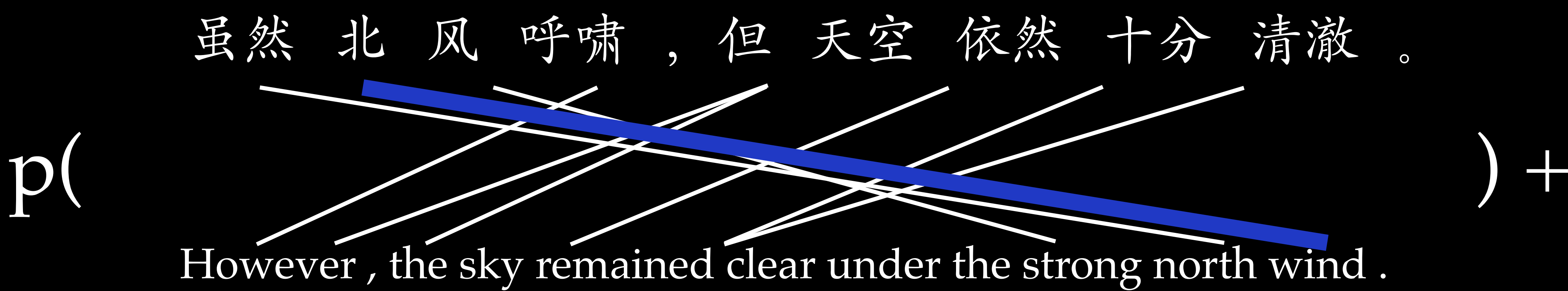
Learning $p(Chinese \mid English)$

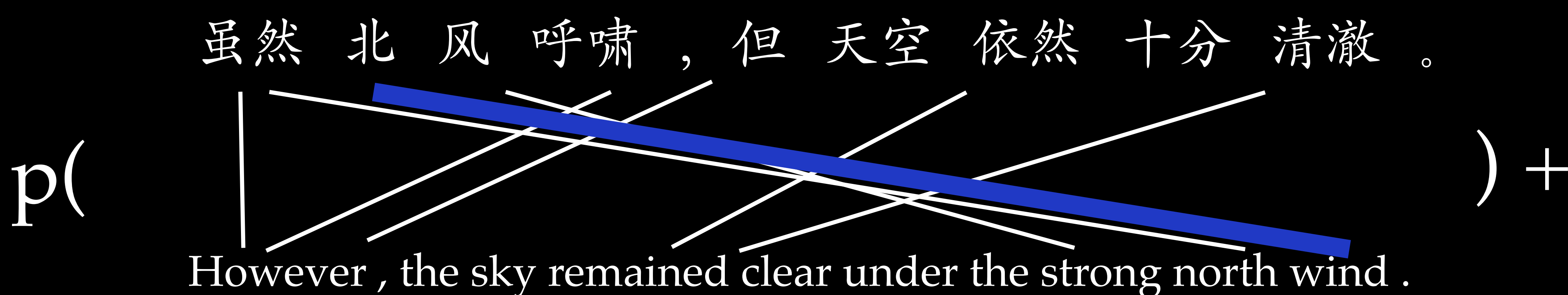
- Reminder: (nearly) every problem comes down to computing either:
  - Sums: MLE or EM (learning)
  - Maximum: most probable (decoding)

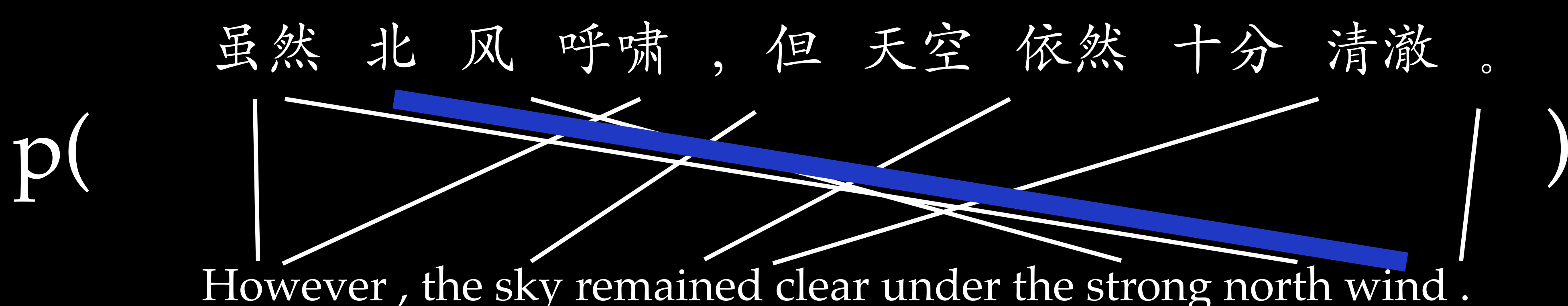
Recap: Expectation Maximization

- Arbitrarily select a set of parameters (say, uniform).
- Calculate ***expected counts*** of the unseen events.
- Choose new parameters to maximize likelihood, using expected counts as proxy for observed counts.
- Iterate.
- Guaranteed that likelihood is monotonically nondecreasing.

Marginalize: sum all alignments containing the link







Divide by sum of all *possible* alignments

p(虽然 北 风 呼啸 ， 但 天空 依然 十分 清澈 。

However , the sky remained clear under the strong north wind .) +

p(虽然 北 风 呼啸 ， 但 天空 依然 十分 清澈 。

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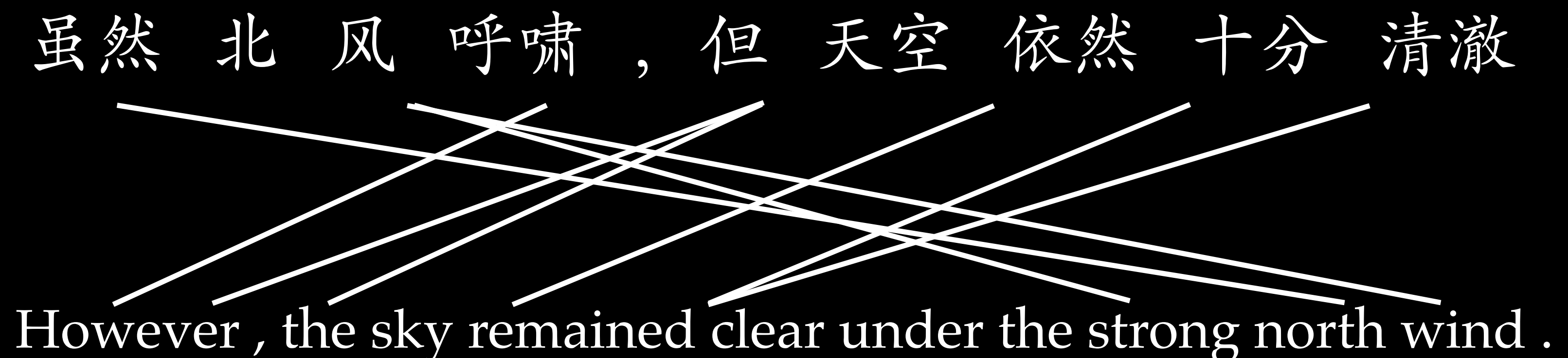
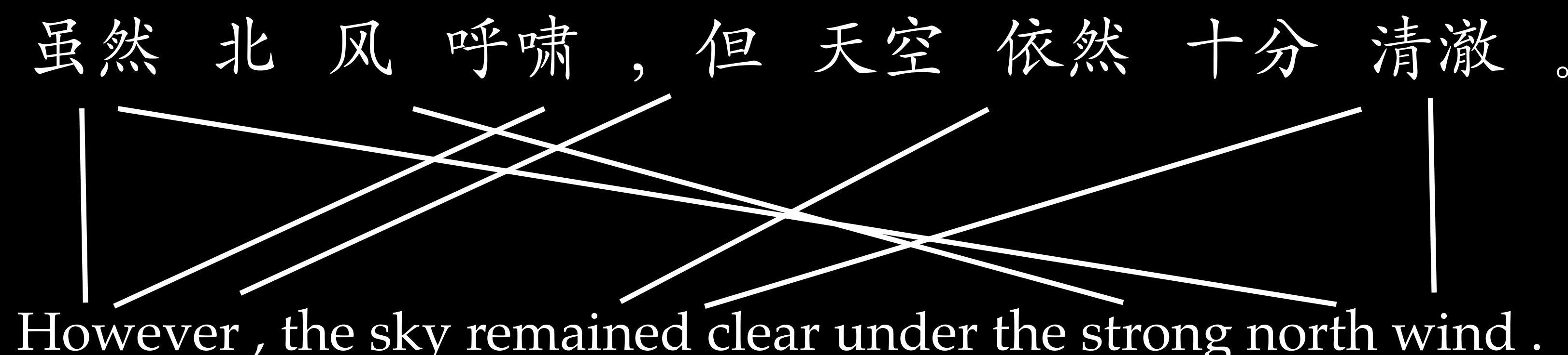
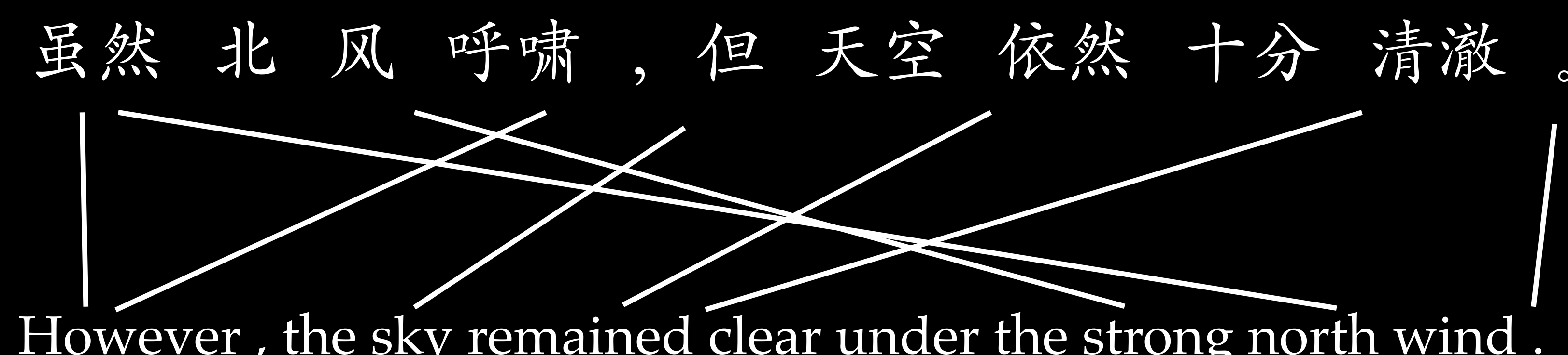
p(


) +

p(


) +

p(


)

We have to sum over exponentially many alignments!

EM for Model 1

probability of an alignment.

$$p(F, A|E) = p(I|J) \prod_{a_i} p(a_i = j) p(f_i|e_j)$$

EM for Model 1

probability of an alignment.

$$p(F, A|E) = \underbrace{p(I|J)}_{\text{observed}} \prod_{a_i} \underbrace{p(a_i = j)}_{\text{uniform}} p(f_i|e_j)$$

EM for Model 1

probability of an alignment.

factors across words.

$$p(F, A|E) = p(I|J) \prod_{a_i} p(a_i = j) \boxed{p(f_i|e_j)}$$

observed

uniform

EM for Model 1

$$p(a_i = j|F, E) = \frac{p(a_i = j, F|E)}{p(F, E)} =$$

EM for Model 1

$$p(a_i = j|F, E) = \frac{p(a_i = j, F|E)}{p(F, E)} =$$

$$\sum_{a \in A: 北 \leftrightarrow north} p(north|北\ ) \cdot p(rest\ of\ a)$$

EM for Model 1

$$p(a_i = j|F, E) = \frac{p(a_i = j, F|E)}{p(F, E)} =$$

$$\sum_{a \in A: 北 \leftrightarrow north} p(north|北\ ) \cdot p(rest\ of\ a)$$

marginal probability of
alignments containing link

EM for Model 1

marginal probability of
alignments containing link

$$p(north|北\,) \sum_{a \in A:北 \leftrightarrow north} p(rest\ of\ a)$$

EM for Model 1

marginal probability of
alignments containing link

$$\frac{p(north|北\ ) \displaystyle\sum_{a \in A: 北 \leftrightarrow north} p(rest\ of\ a)}{\displaystyle\sum_{c \in Chinese\ words} p(north|c) \sum_{a \in A: \quad \leftrightarrow north} p(rest\ of\ a)}$$

marginal probability of all
alignments

EM for Model 1

marginal probability of
alignments containing link

$$\frac{p(north|北) \sum_{a \in A: 北 \leftrightarrow north} p(rest\ of\ a)}{\sum_{c \in Chinese\ words} p(north|c) \sum_{a \in A: c \leftrightarrow north} p(rest\ of\ a)}$$

marginal probability of all
alignments

EM for Model 1

marginal probability of
alignments containing link

$$\frac{p(north|北) \displaystyle\sum_{a \in A: 北 \leftrightarrow north} p(rest\ of\ a)}{\displaystyle\sum_{c \in Chinese\ words} p(north|c) \sum_{a \in A:\, c \leftrightarrow north} p(rest\ of\ a)}$$

identical!

marginal probability of all
alignments

EM for Model 1

$$\frac{p(north|\text{北})}{\sum_{c \in Chinese\ words} p(north|c)}$$

EM for Phrase-Based

- Model parameters: *p(E phrase | F phrase)*
- All we need to do is compute expectations:

$$p(a_{i,i'} = \langle j, j' \rangle | F, E) = \frac{p(a_{i,i'} = \langle j, j' \rangle, F | E)}{p(F, E)}$$

EM for Phrase-Based

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p(F,E) sums over all possible phrase alignments

EM for Phrase-Based

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$$p(a_{i,i'} = \langle j, j' \rangle | F, E) = \frac{p(a_{i,i'} = \langle j, j' \rangle, F | E)}{p(F, E)}$$

p(F,E) sums over all possible phrase alignments

...which are one-to-one by definition.

EM for Phrase-Based

Although north wind howls , but sky still very clear .

虽然 北 风 呼啸 ，但 天空 依然 十分 清澈 。

However , the sky remained clear under the strong north wind .

$$p(a_{i,i'} = \langle j, j' \rangle | F, E) = \frac{p(a_{i,i'} = \langle j, j' \rangle, F | E)}{p(F, E)}$$

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$$p(a_{i,i'} = \langle j, j' \rangle | F, E) = \frac{p(a_{i,i'} = \langle j, j' \rangle, F | E)}{p(F, E)}$$

Can we compute this quantity?

EM for Phrase-Based

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$$p(a_{i,i'} = \langle j, j' \rangle | F, E) = \frac{p(a_{i,i'} = \langle j, j' \rangle, F | E)}{p(F, E)}$$

Can we compute this quantity?

How many 1-to-1 alignments are there of the remaing 8 Chinese and 8 English words?

Recap: Expectation Maximization

- Arbitrarily select a set of parameters (say, uniform).
- Calculate ***expected counts*** of the unseen events.
- Choose new parameters to maximize likelihood, using expected counts as proxy for observed counts.
- Iterate.
- Guaranteed that likelihood is monotonically nondecreasing.

Recap: Expectation Maximization

- Arbitrarily select a set of parameters (say, uniform).
- Calculate ***expected counts*** of the unseen events.
- Choose new parameters to maximize likelihood, us… …nts.
- It…
- G… n…

Computing expectations from a phrase-based model, given a sentence pair, is #P-Complete (by reduction to counting perfect matchings; DeNero & Klein, 2008)

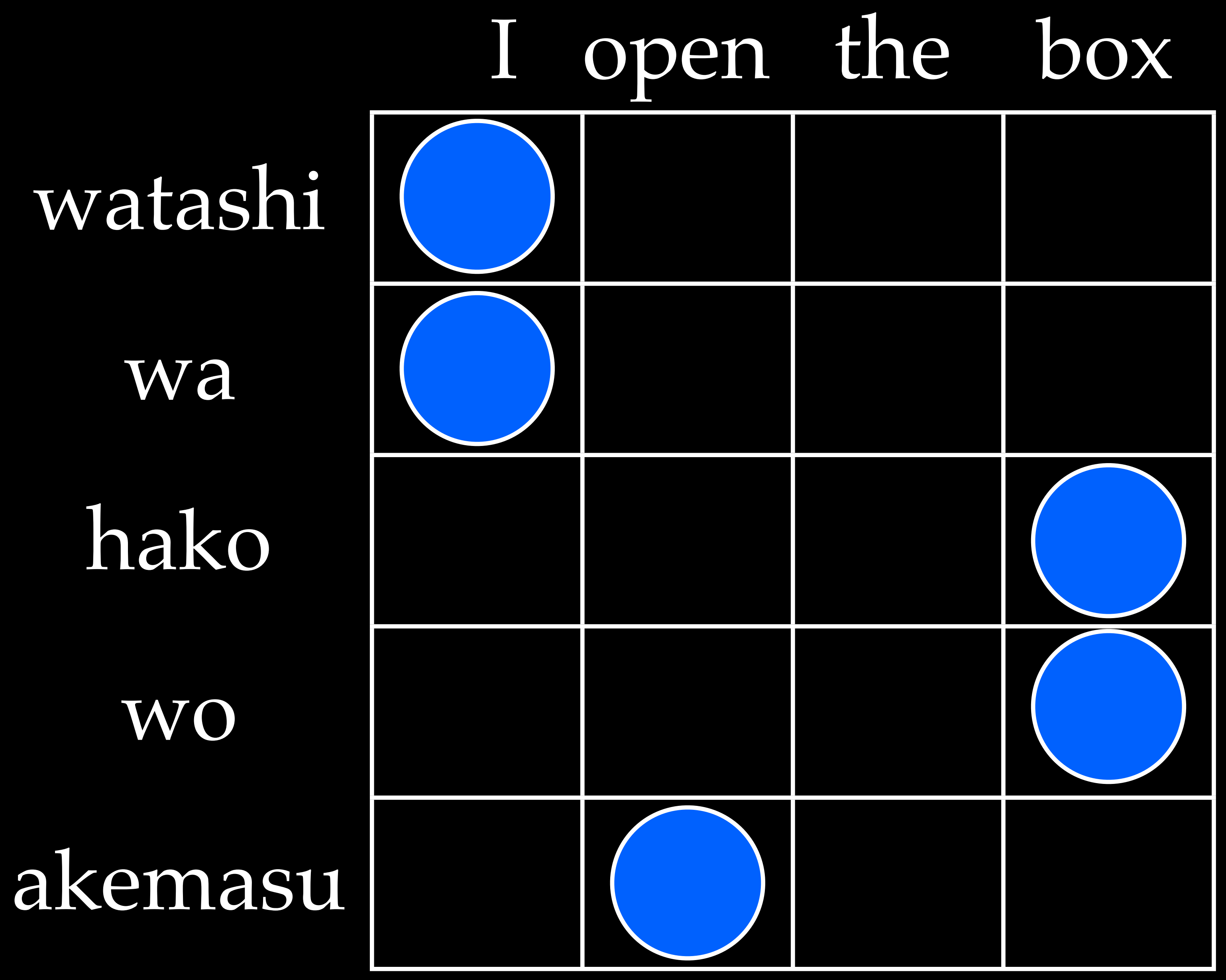
Now What?

- Option #1: approximate expectations
  - Restrict computation to some tractable subset of the alignment space (arbitrarily biased).
  - Markov chain Monte Carlo (very slow).

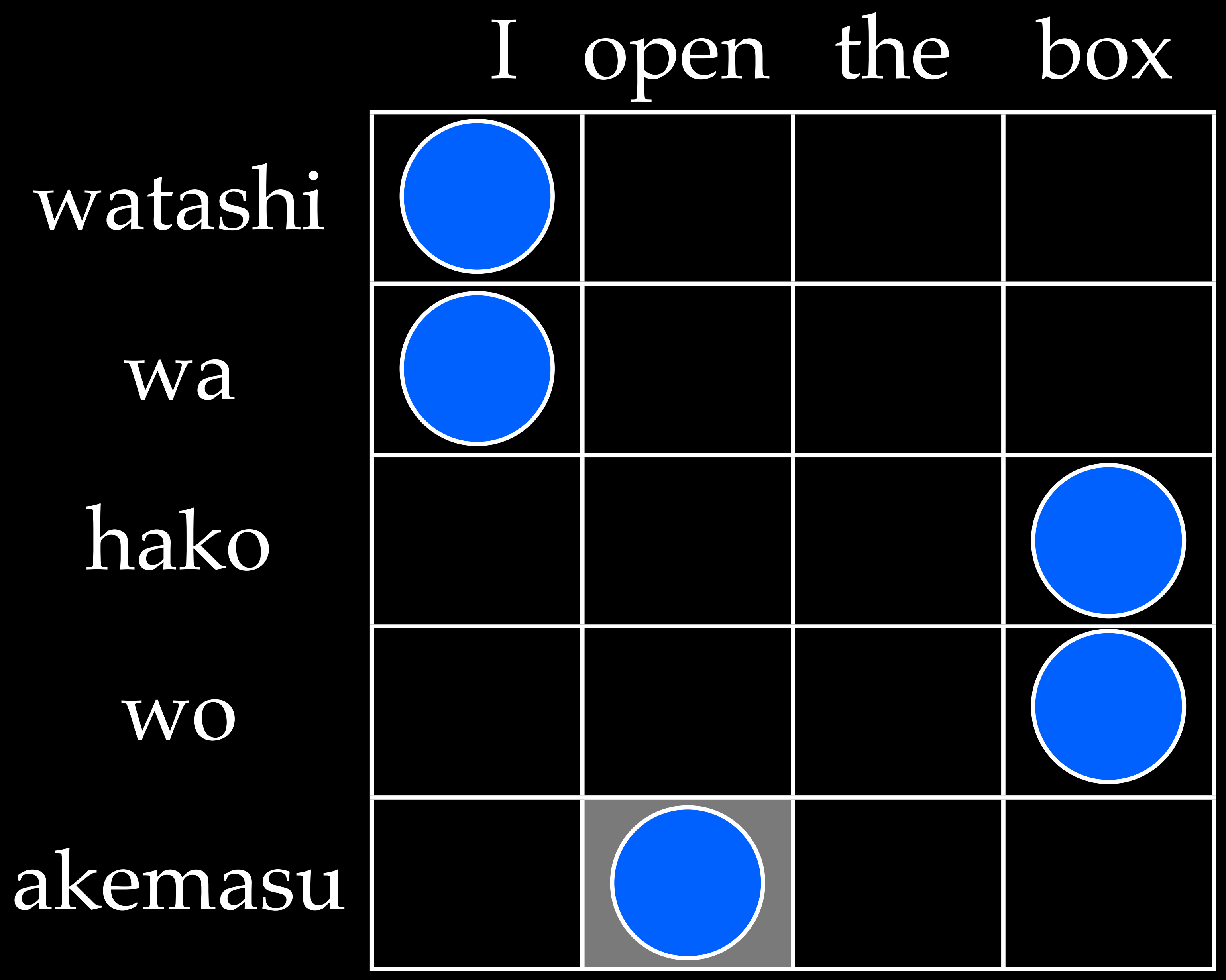
Now What?

- Change the problem definition
  - We already know how to learn word-to-word translation models efficiently.
  - Idea: learn word-to-word alignments, extract most probable alignment, then treat it as observed.
  - Learn phrase translations consistent with word alignments.
  - Decouples alignment from model learning -- is this a good thing?

Phrase Extraction

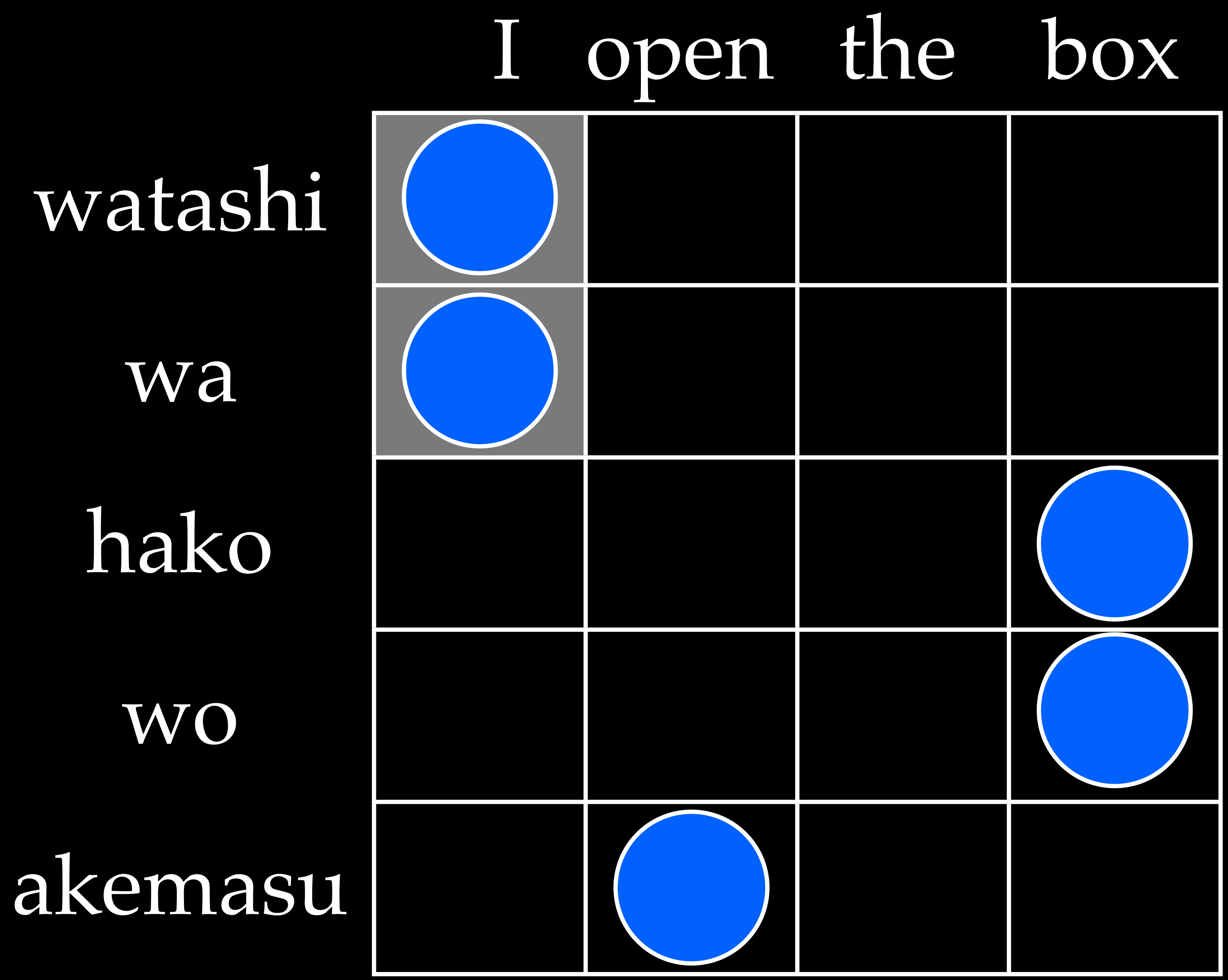


Phrase Extraction



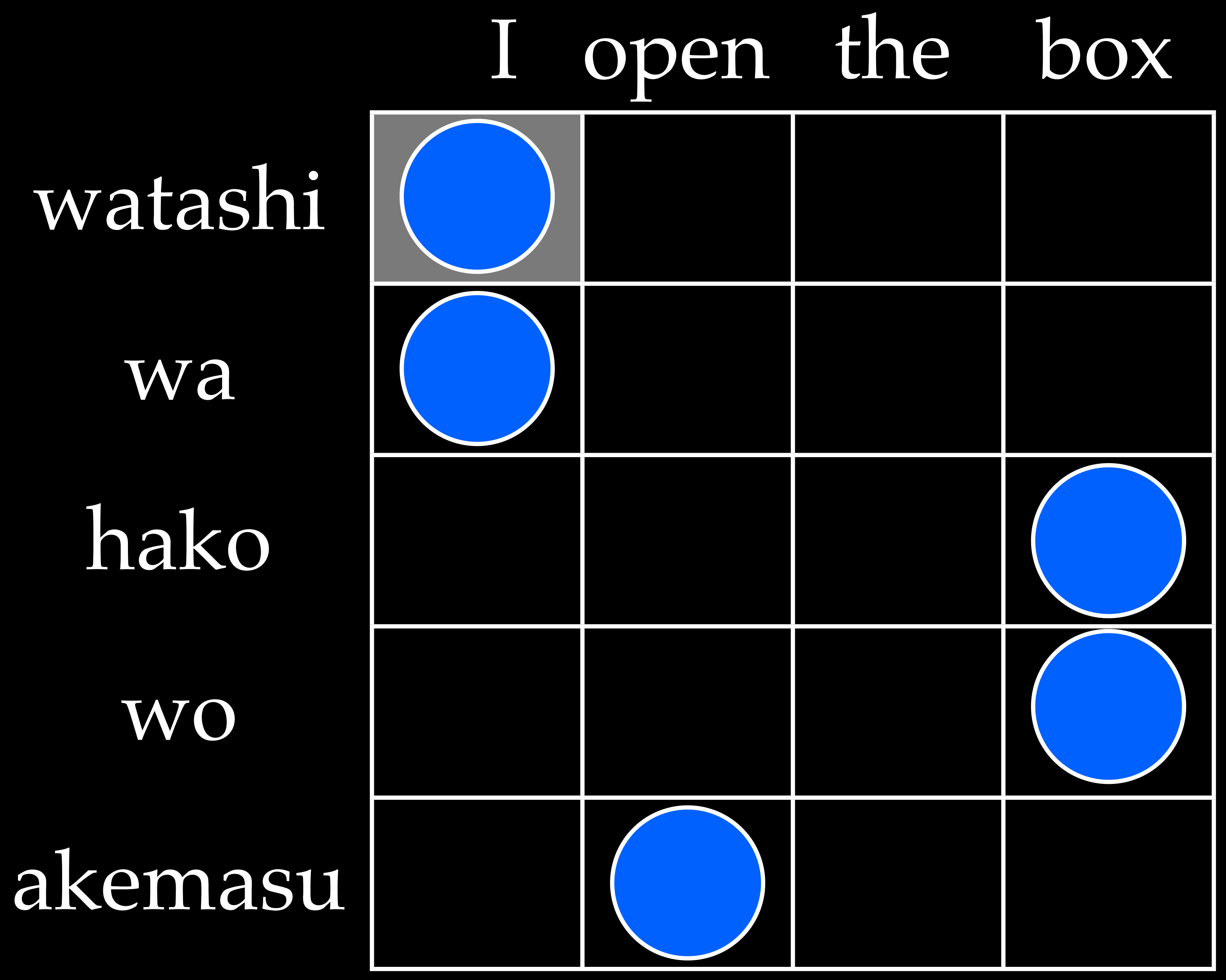
akemasu / open

Phrase Extraction



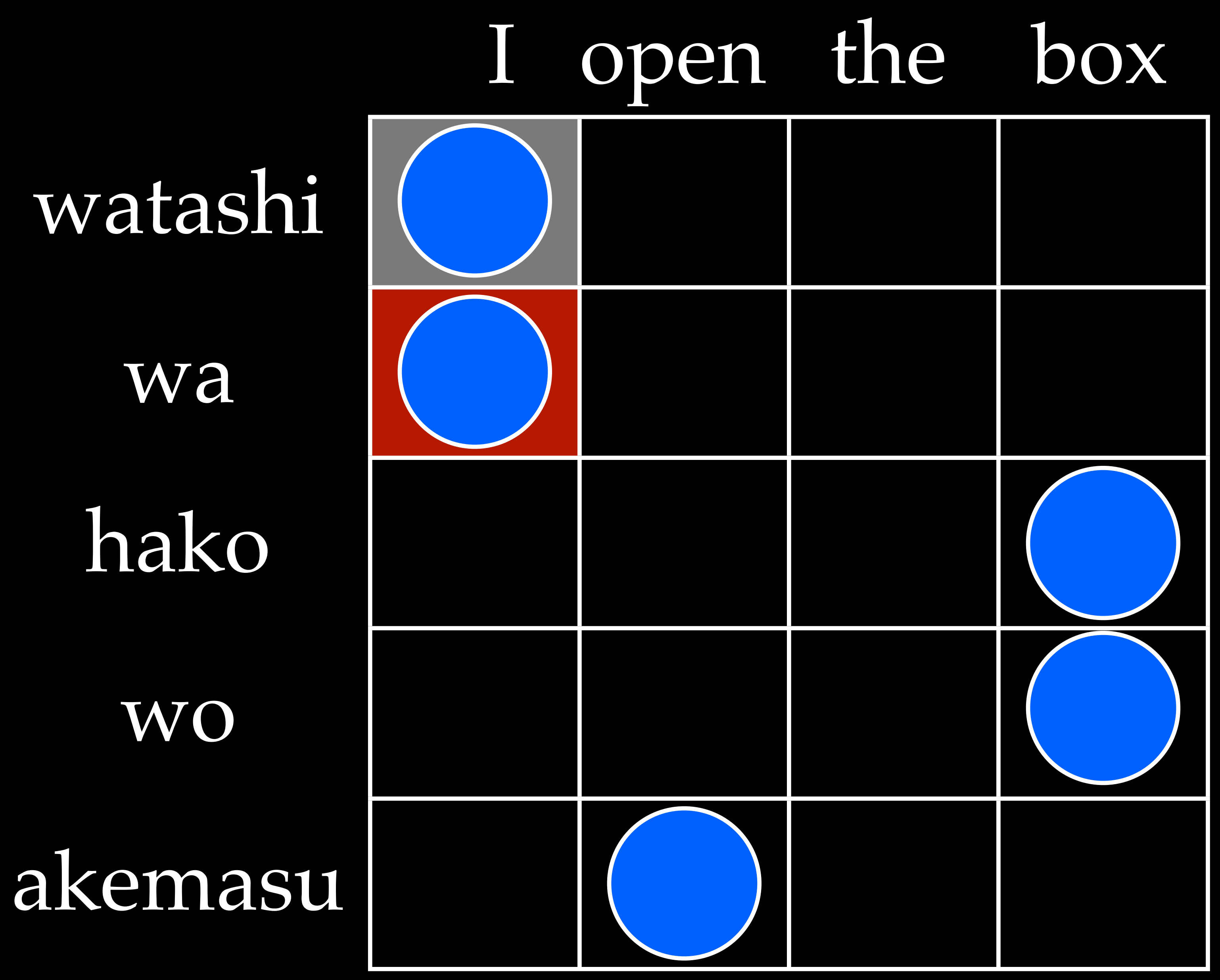
watashi wa / I

Phrase Extraction



watashi / I

Phrase Extraction



watashi wa / I

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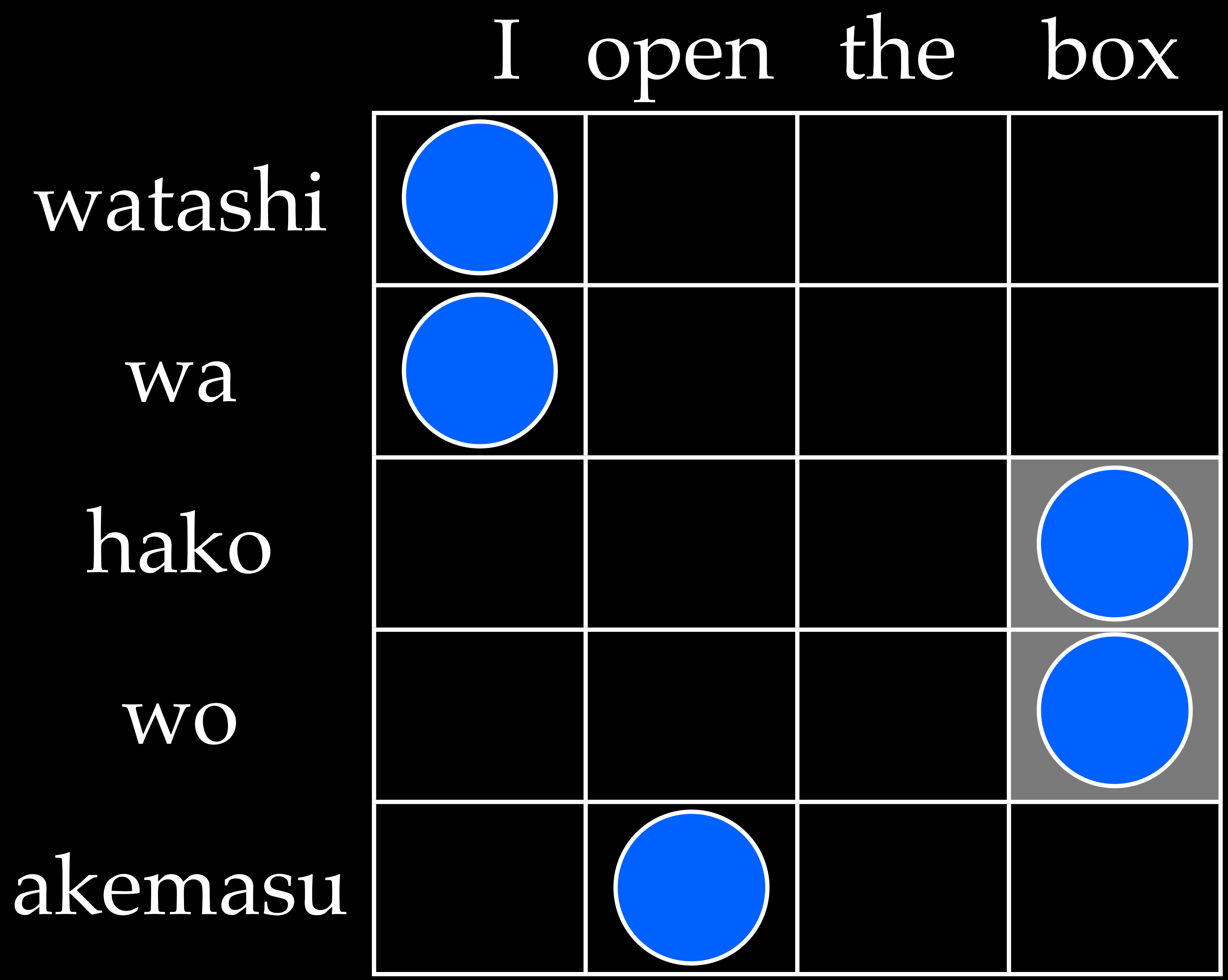
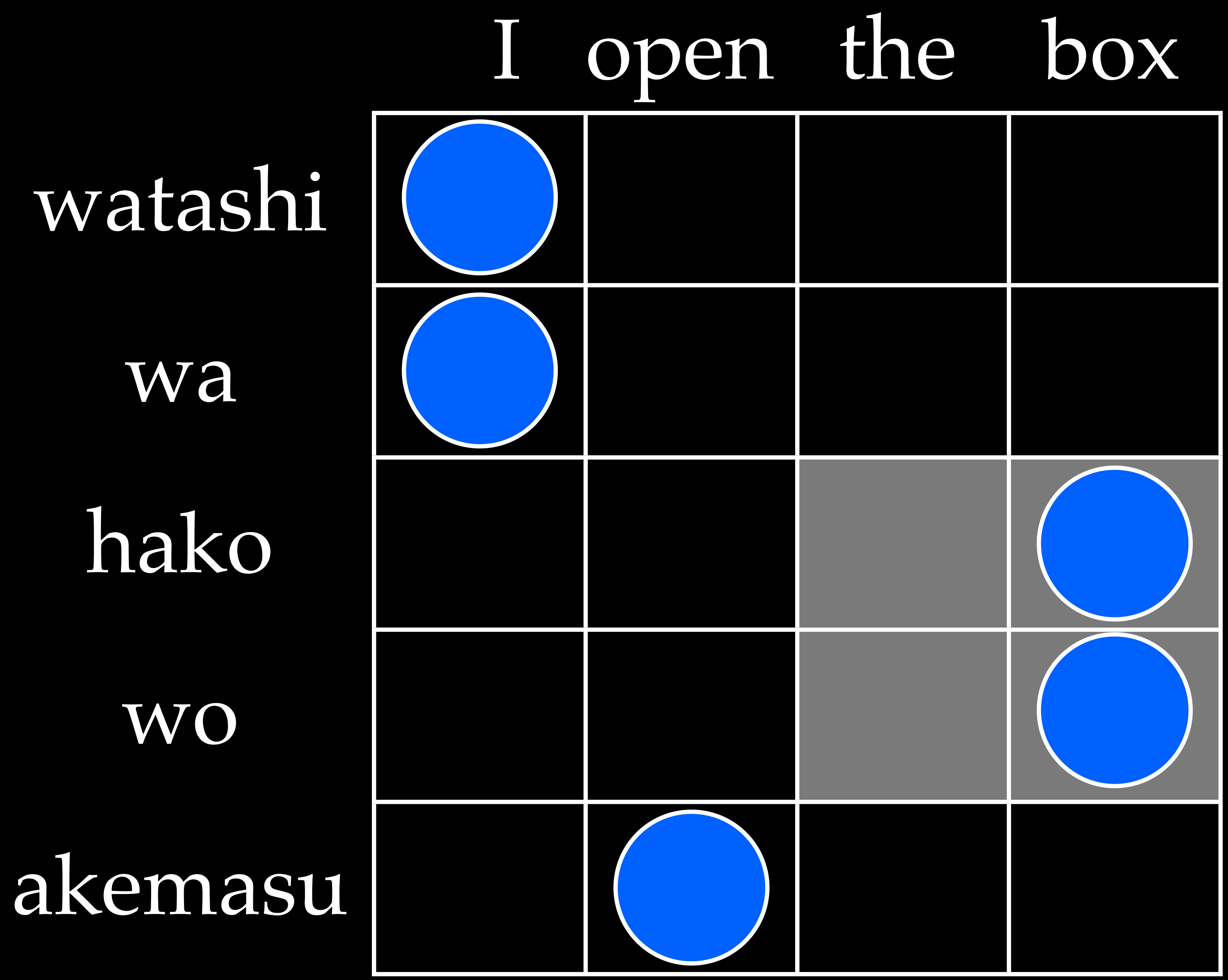


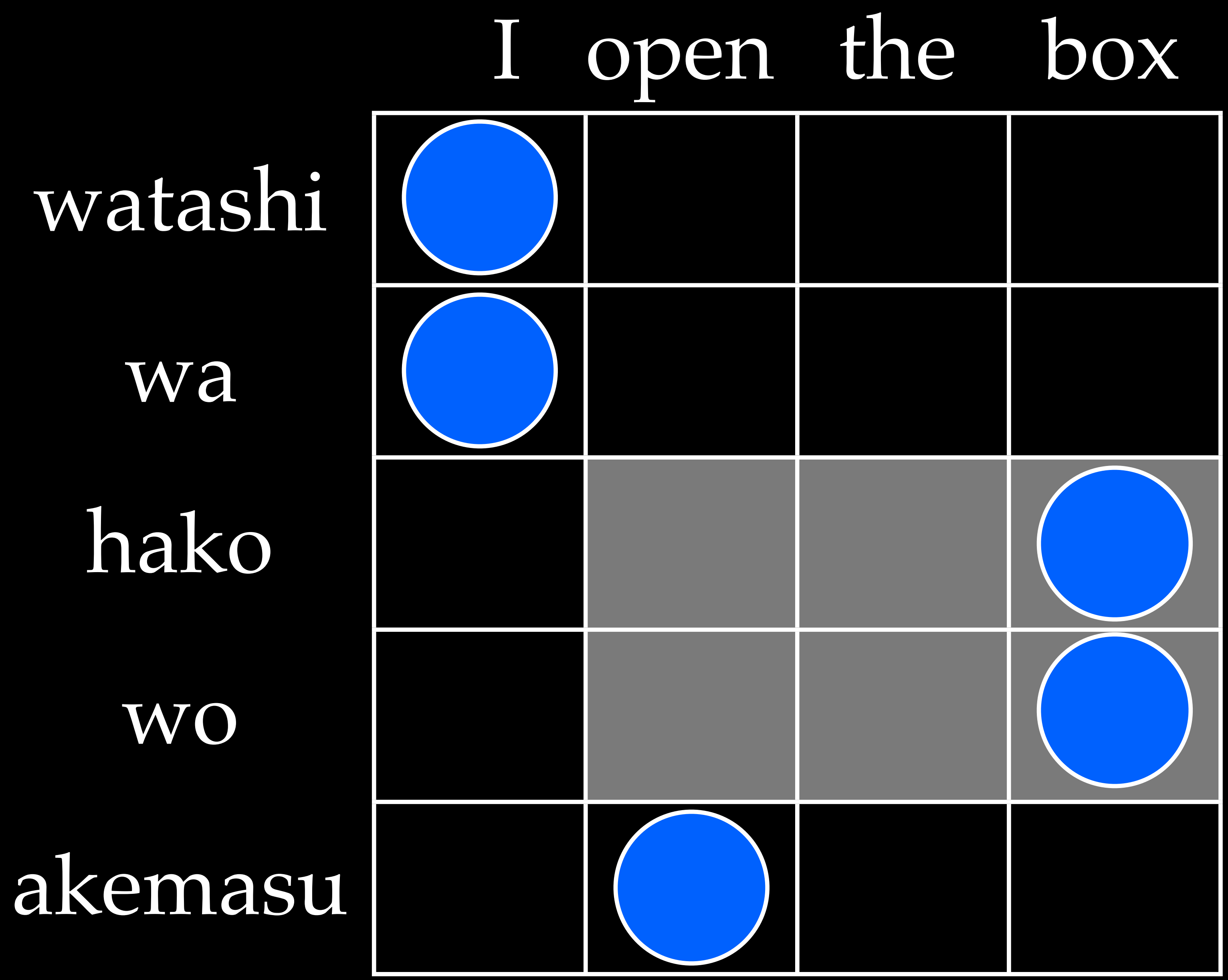
hako wo / box

Phrase Extraction



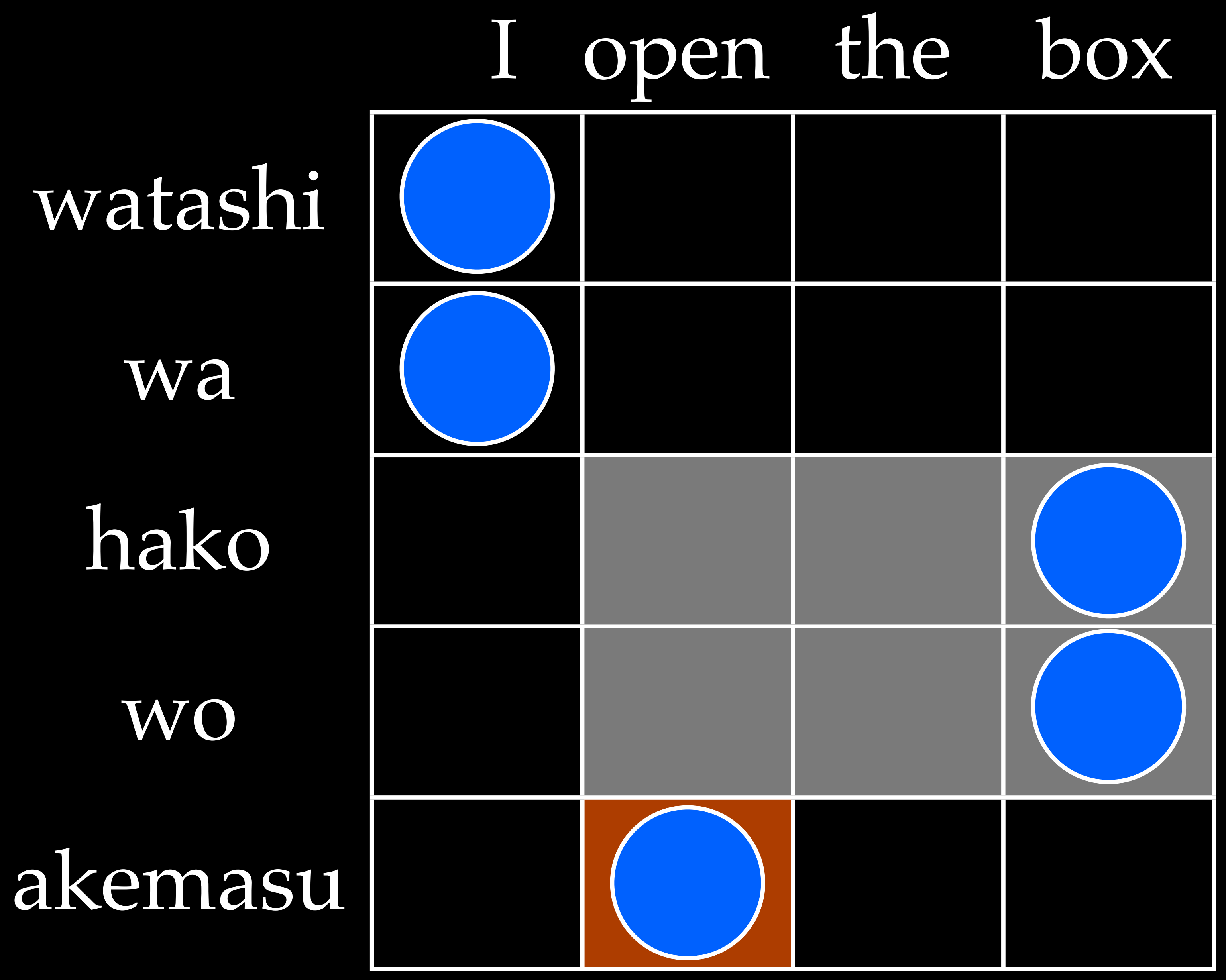
hako wo / the box

Phrase Extraction



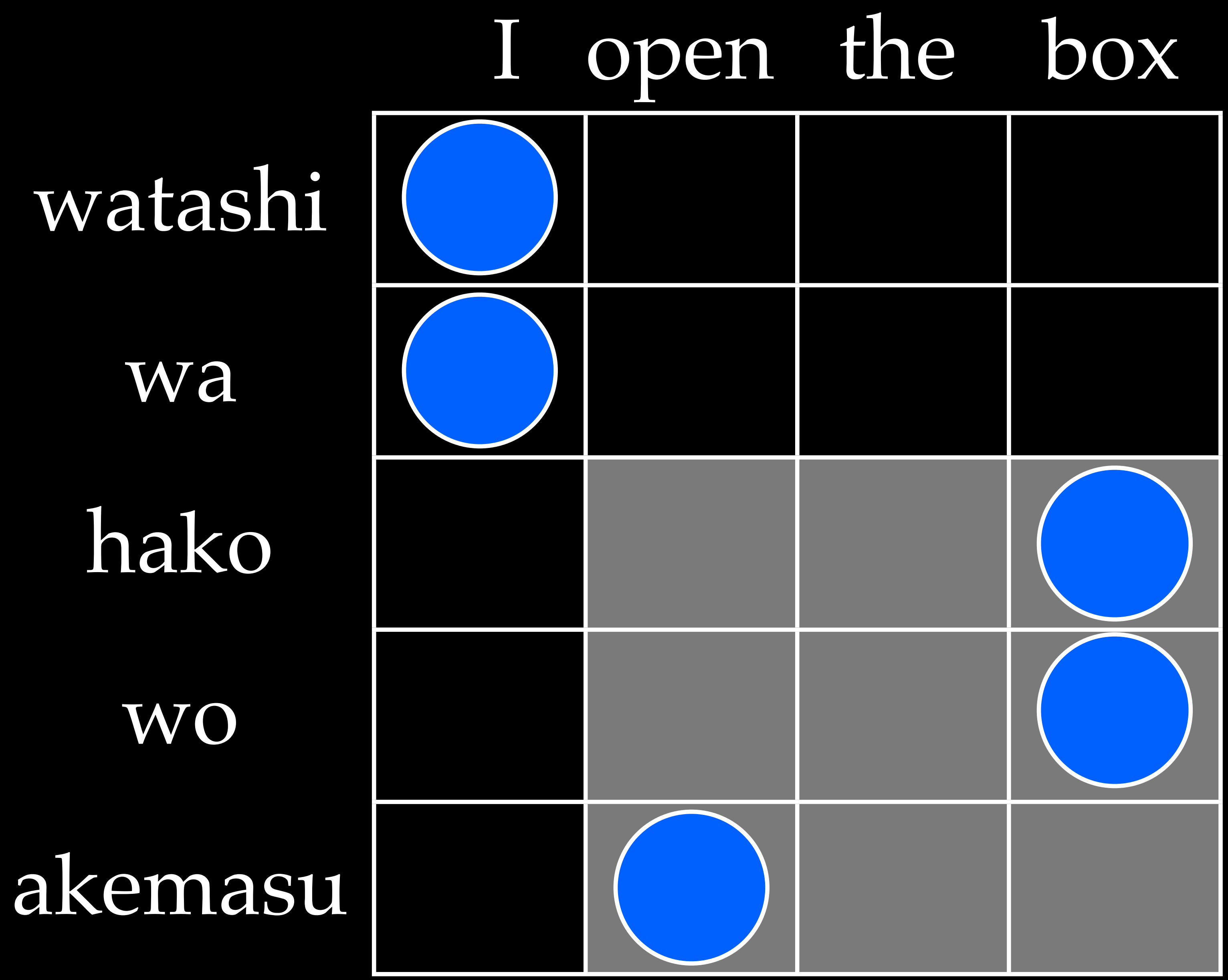
hako wo / open the box

Phrase Extraction



hako wo / open the box

Phrase Extraction



hako wo akemasu / open the box

Phrasal Translation Estimation

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- Approximation #1 (EM over restricted space)
  - Align with a word-based model.
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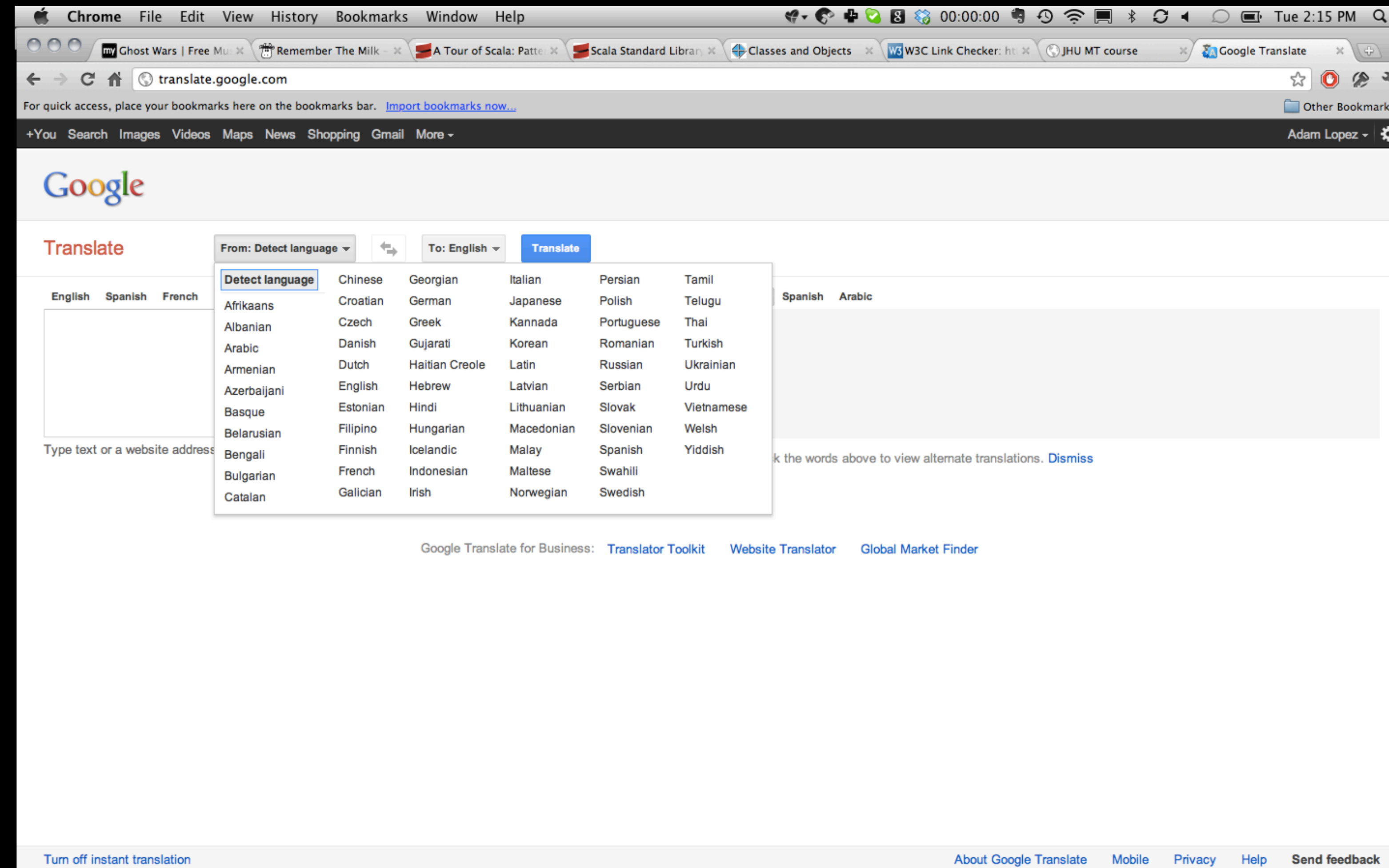
- Many other possible approximations!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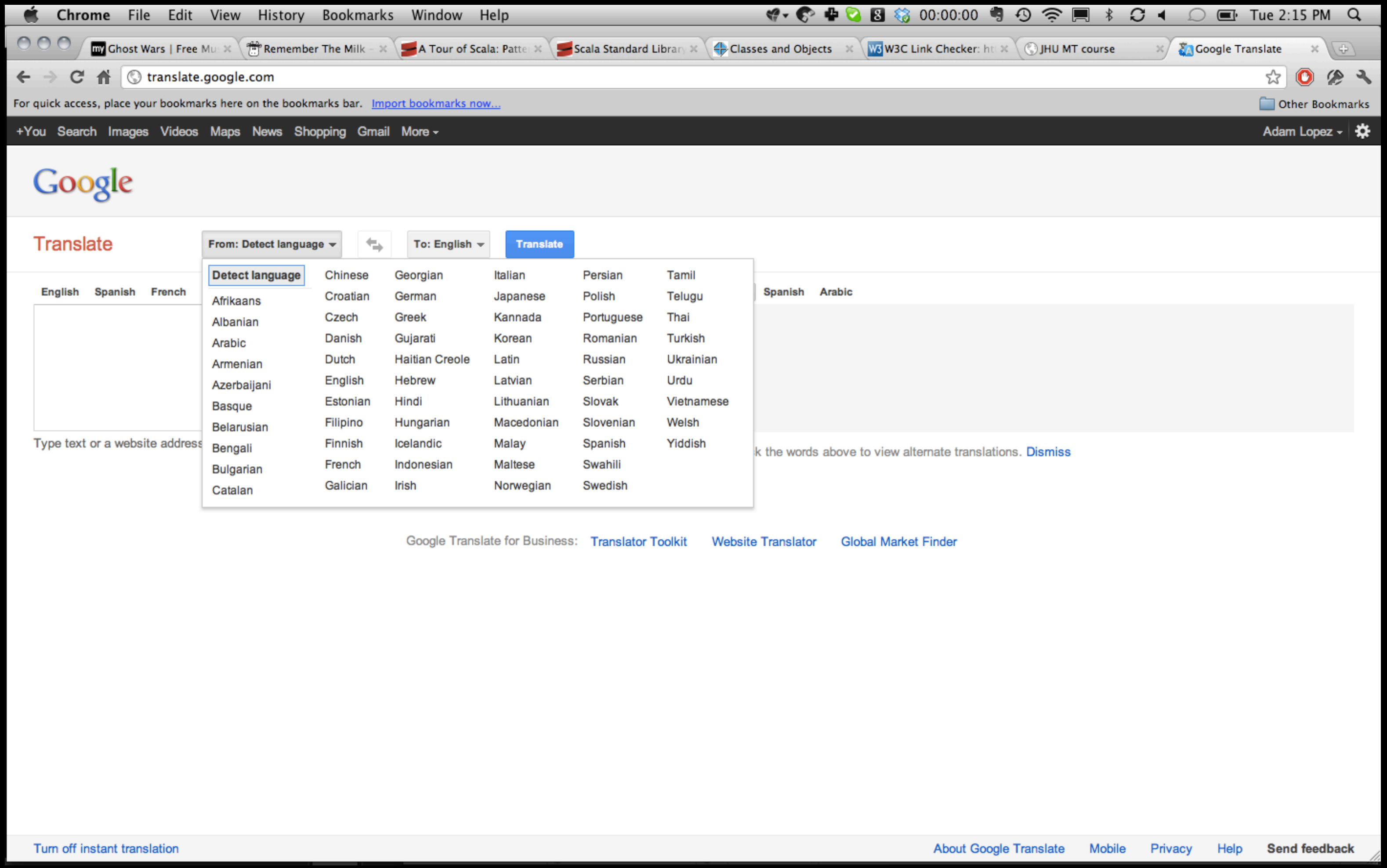
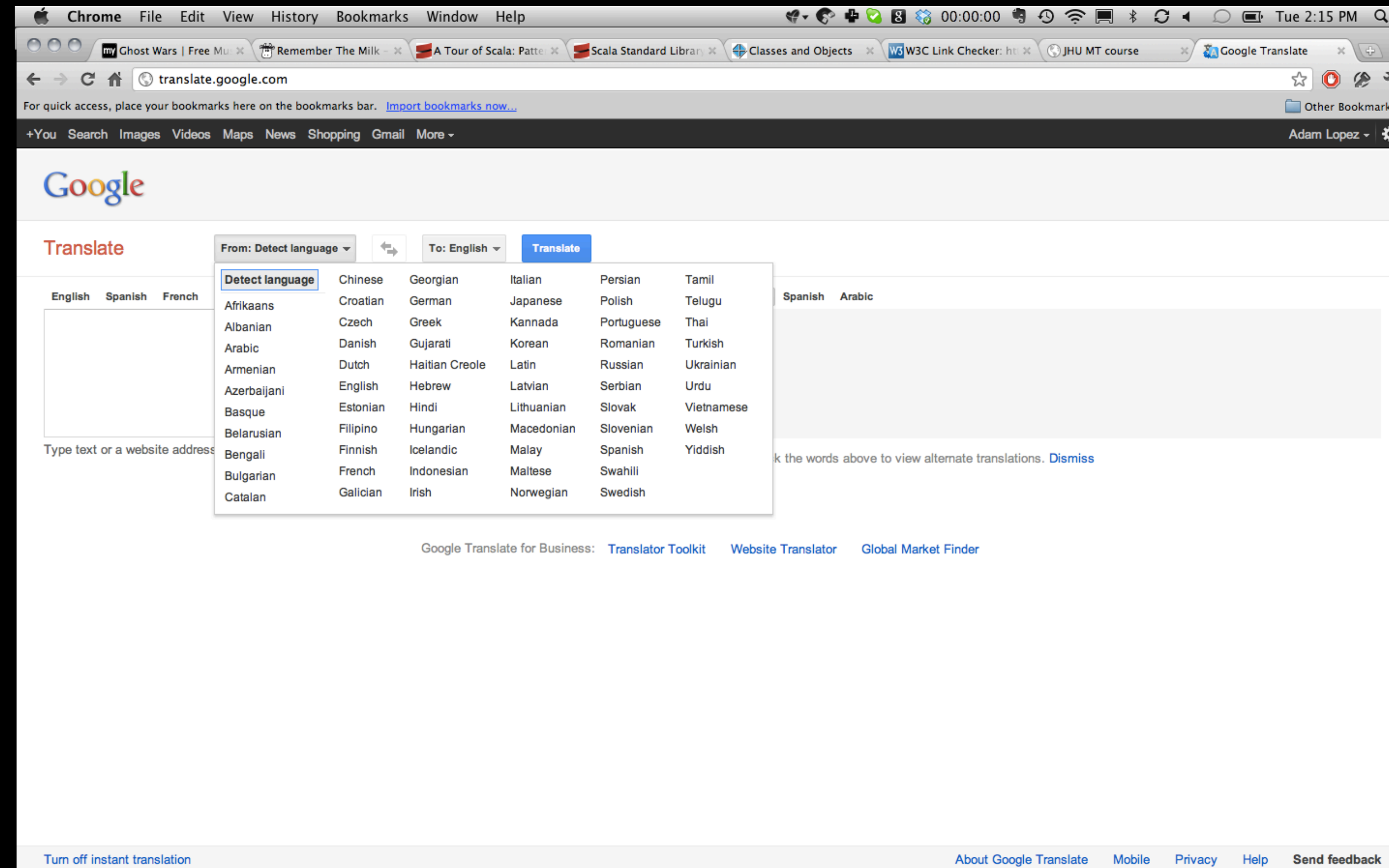


- Some key ingredients in Moses / Google Translate:



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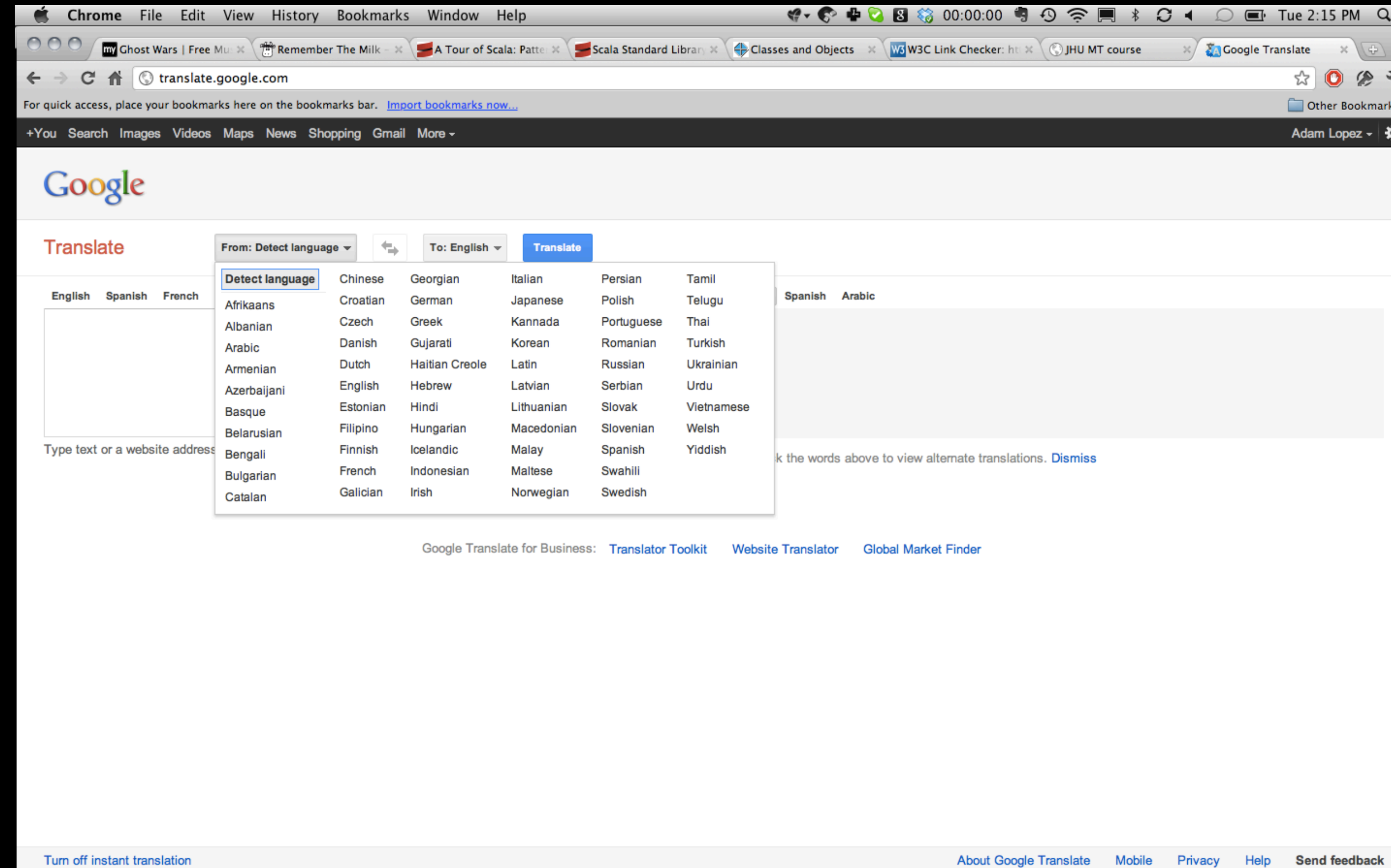

- Some key ingredients in Moses / Google Translate:
  - Phrase-based translation models
  - … Learned heuristically from word alignments