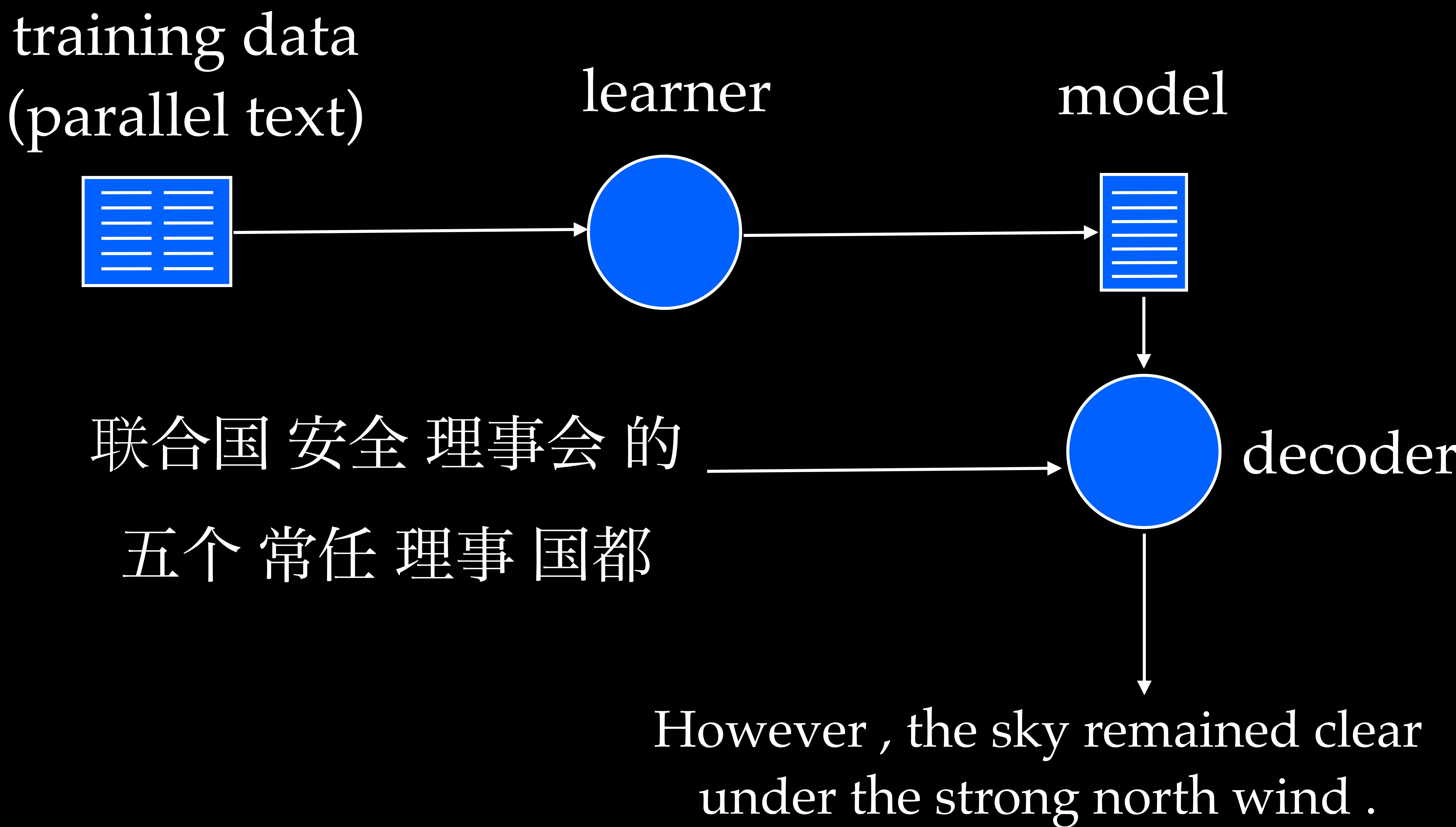
Learning (continued), Prediction, and Phrase Modeling

Adam Lopez
Johns Hopkins

Quick Recap


training data
(parallel text)
learner
model
decoder
联合国 安全 理事会 的
五个 常任 理事 国都
However , the sky remained clear
under the strong north wind .

IBM Model 1

Although north wind howls , but sky still very clear .

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

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$$p(Chinese\ word\ position)$$

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

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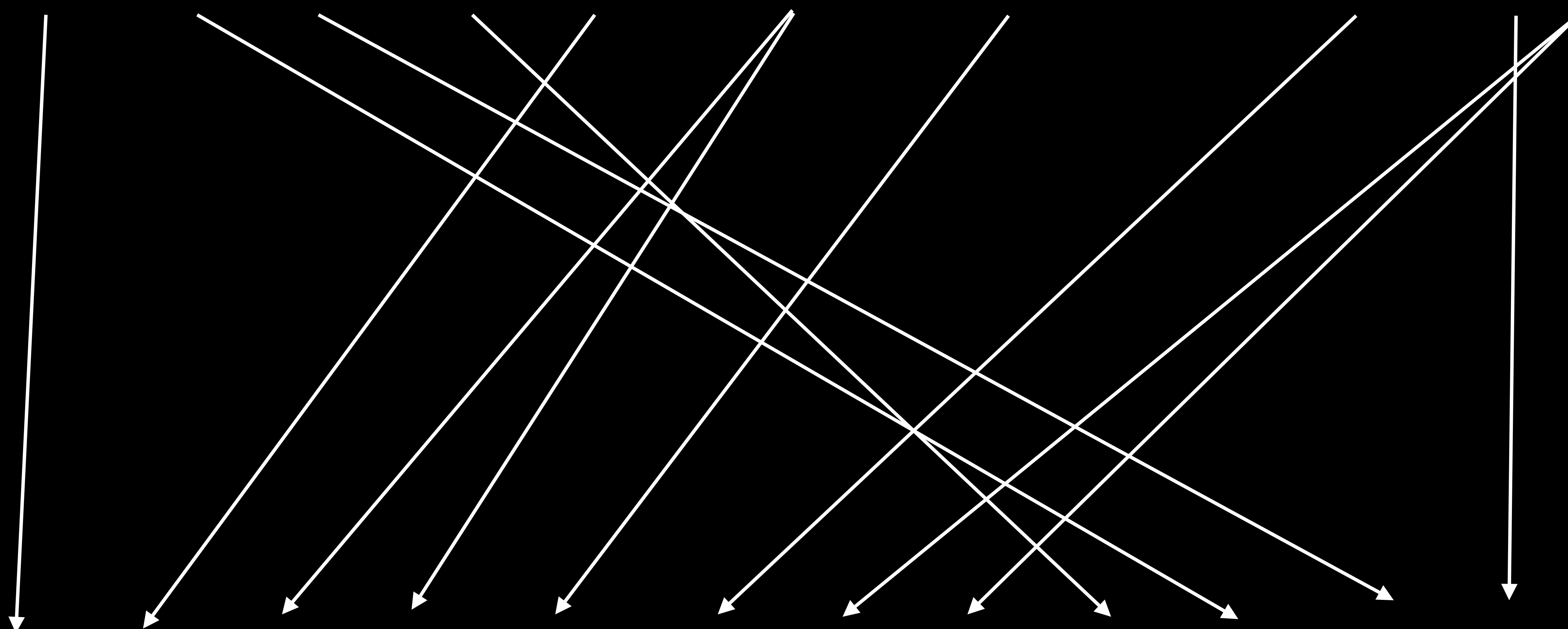

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IBM Model 1

$$p(despite|\text{虽然})$$

$$p(however|\text{虽然})$$

$$p(although|\text{虽然})$$

$$p(northern|\text{北})$$

$$p(north|\text{北})$$

IBM Model 1

$p(despite|\text{虽然})$???

$p(however|\text{虽然})$???

$p(although|\text{虽然})$???

$p(northern|\text{北})$???

$p(north|\text{北})$???

IBM Model 1

$$\theta \left\{ \begin{array}{ll} p(despite|\text{虽然}) & ??? \\ p(however|\text{虽然}) & ??? \\ p(although|\text{虽然}) & ??? \\ & \\ p(northern|\text{北}) & ??? \\ p(north|\text{北}) & ??? \end{array} \right.$$

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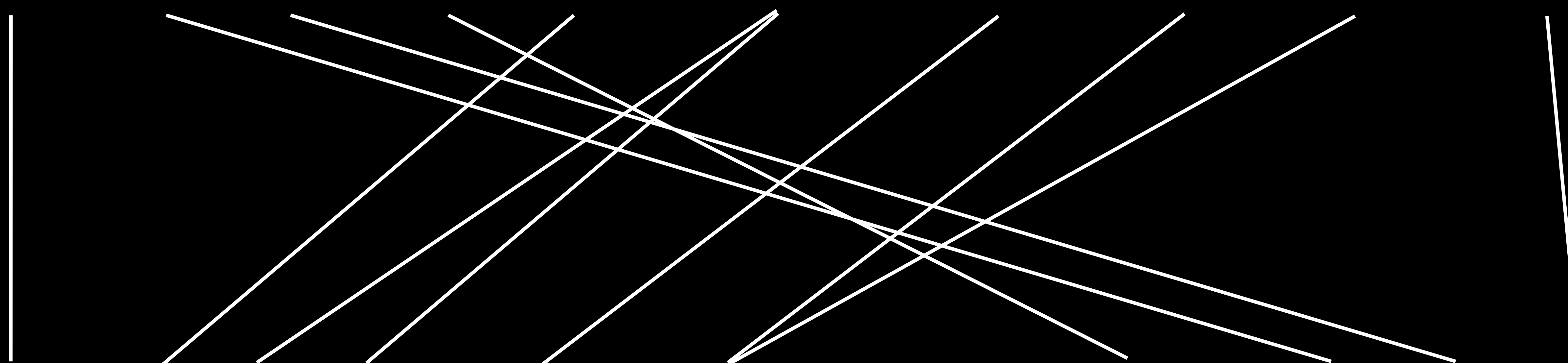

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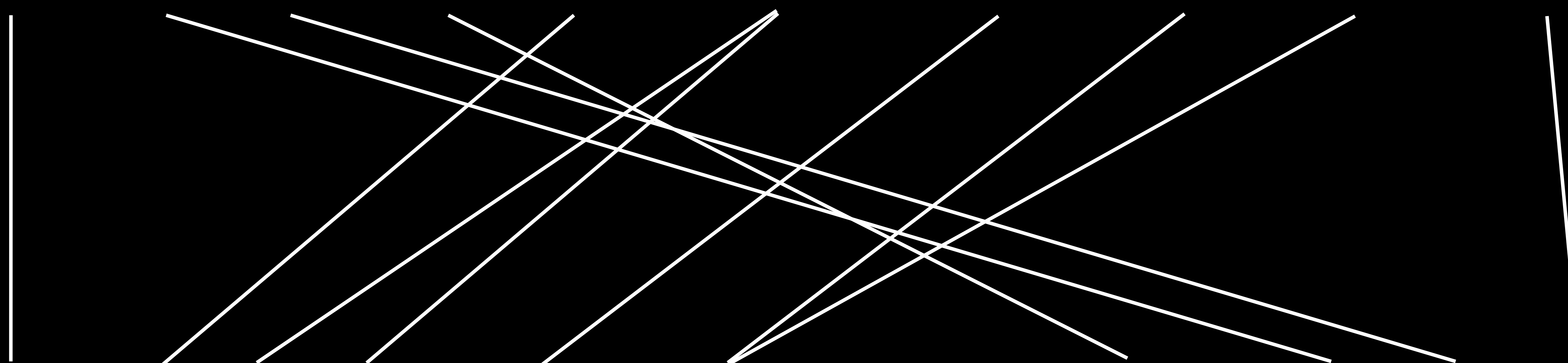

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- Optimization

MLE for IBM Model 1 (observed)

$$\hat{\theta} = \arg\max_{\theta} \prod_{n=1}^{N} \left(p(I^{(n)}|J^{(n)}) \prod_{i=1}^{I^{(n)}} p(a_i^{(n)}|J^{(n)}) \cdot p(f_i^{(n)}|e_{a_i}^{(n)}) \right)$$

MLE for IBM Model 1 (observed)

number of sentences

alignment of French word at position *i*

$$\hat{\theta} = \arg\max_{\theta} \prod_{n=1}^{N} \left(p(I^{(n)} | J^{(n)}) \prod_{i=1}^{I^{(n)}} p(a_i^{(n)} | J^{(n)}) \cdot p(f_i^{(n)} | e_{a_i}^{(n)}) \right)$$

French, English sentence lengths

French, English word pair

MLE for IBM Model 1 (observed)

$$\hat{\theta} = \arg\max_{\theta} \prod_{n=1}^{N} \left(\underbrace{p(I^{(n)}|J^{(n)}) \prod_{i=1}^{I^{(n)}} p(a_i^{(n)}|J^{(n)})}_{\text{constant!}} \cdot p(f_i^{(n)}|e_{a_i}^{(n)}) \right)$$

MLE for IBM Model 1 (observed)

$$\hat{\theta} = \arg\max_{\theta} C \prod_{n=1}^{N} \prod_{i=1}^{I^{(n)}} p(f_i^{(n)} | e_{a_i}^{(n)})$$

MLE for IBM Model 1 (observed)

$$\hat{\theta} = \arg\max_{\theta} \log \left(C \prod_{n=1}^{N} \prod_{i=1}^{I^{(n)}} p(f_i^{(n)} | e_{a_i}^{(n)}) \right)$$

$$\log(a) < \log(b) \iff a < b$$

MLE for IBM Model 1 (observed)

$$\hat{\theta} = \arg\max_{\theta} \log \left(C \cdot \prod_{f,e} p(f|e)^{count(\langle f,e \rangle)} \right)$$

MLE for IBM Model 1 (observed)

$$\hat{\theta} = \arg\max_{\theta} \log C + \sum_{f,e} count(\langle f, e \rangle) \log p(f|e)$$

log of product = sum of logs

MLE for IBM Model 1 (observed)

$$\Lambda(\theta, \lambda) = \log C + \sum_{f,e} count(\langle f, e \rangle) \log p(f|e)$$

$$\underbrace{- \sum_{e} \lambda_e \left(\sum_{f} p(f|e) - 1 \right)}_{\text{Lagrange multiplier expresses normalization constraint}}$$

MLE for IBM Model 1 (observed)

$$\Lambda(\theta, \lambda) = \log C + \sum_{f,e} count(\langle f, e \rangle) \log p(f|e) - \sum_{e} \lambda_e \left(\sum_{f} p(f|e) - 1 \right)$$

derivative $$\frac{\partial \Lambda(\theta, \lambda)}{\partial p(f|e)} = \frac{count(\langle f, e \rangle)}{p(f|e)} - \lambda_e$$

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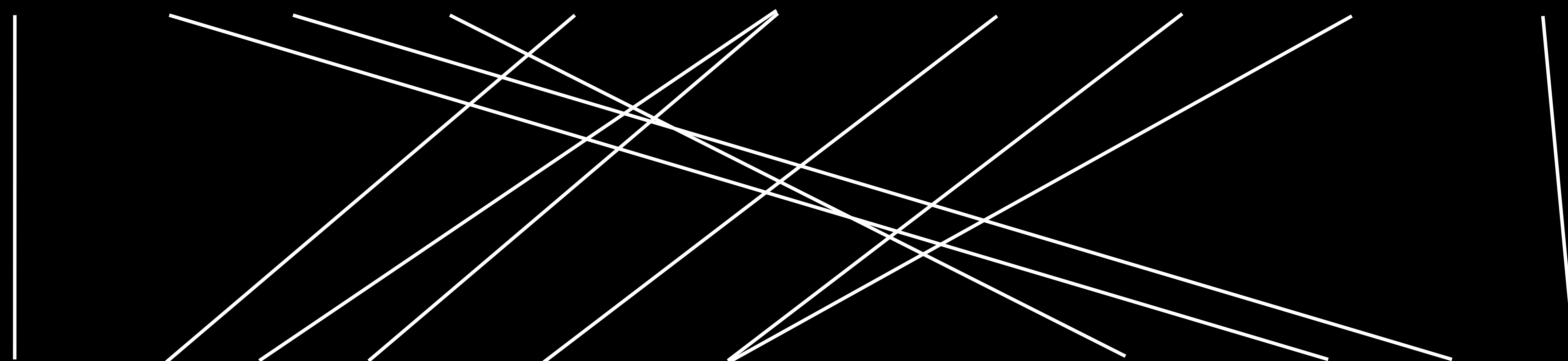

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MLE for IBM Model 1 (unobserved)

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$p(however|\text{虽然}) = ???$

MLE for IBM Model 1 (observed)

$$\hat{\theta} = \arg\max_{\theta} \log \left(C \prod_{n=1}^{N} \prod_{i=1}^{I^{(n)}} p(f_i^{(n)} | e_{a_i}^{(n)}) \right)$$

MLE for IBM Model 1 (unobserved)

$$\hat{\theta} = \arg\max_{\theta} \log \left(C \prod_{n=1}^{N} \sum_{a} \prod_{i=1}^{I^{(n)}} p(f_i^{(n)} | e_{a_i}^{(n)}) \right)$$

marginalize over alignments:

$$p(f|e) = \sum_{a} p(f, a|e)$$

MLE for IBM Model 1 (unobserved)

$$\hat{\theta} = \arg\max_{\theta} \log \left(C \cdot \prod_{f,e} p(f|e)^{\mathbb{E}[count(\langle f,e \rangle)]} \right)$$

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$$\hat{\theta} = \arg\max_{\theta} \log \left(C \cdot \prod_{f,e} p(f|e)^{\mathbb{E}[count(\langle f,e \rangle)]} \right)$$

Not constant! Depends on parameters,
no analytic solution.

MLE for IBM Model 1 (unobserved)

$$\hat{\theta} = \arg\max_{\theta} \log \left(C \cdot \prod_{f,e} p(f|e)^{\mathbb{E}[count(\langle f,e \rangle)]} \right)$$

Not constant! Depends on parameters, no analytic solution.

But it does strongly imply an iterative solution.

Likelihood Estimation for Model 1

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Parameters and alignments are both unknown.

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

$p(English\ word|Chinese\ word)$ unobserved!

Likelihood Estimation for Model 1

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If we knew the alignments, we could calculate the values of the parameters.

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$p(English\ word|Chinese\ word)$ unobserved!

The Plan: Bootstrapping

- 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.
- Guarantee: likelihood will be monotonically nondecreasing.

The Plan: Bootstrapping

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if we had observed the alignment, this line would either be here (count 1) or it wouldn't (count 0).

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The Plan: Bootstrapping

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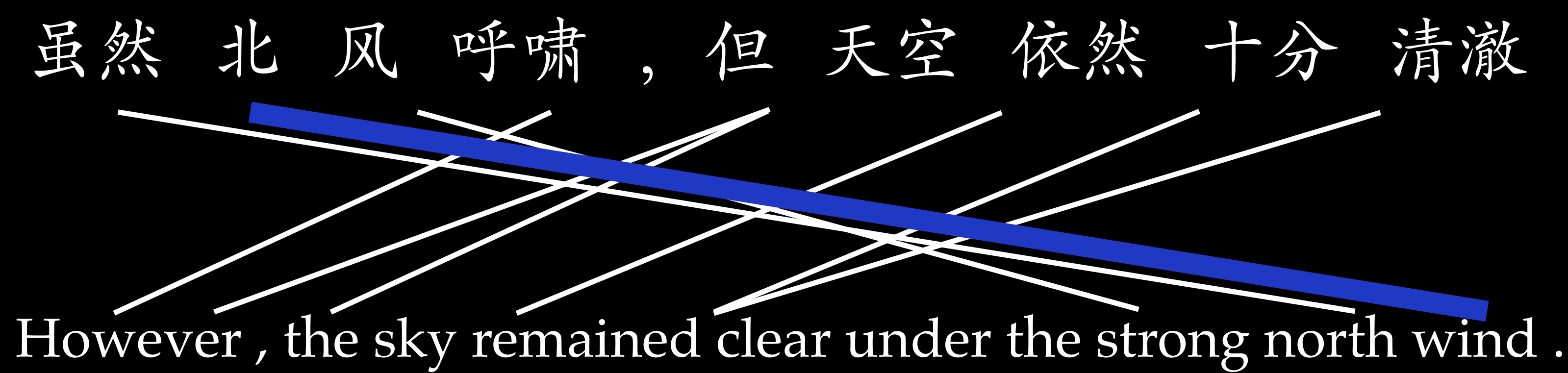
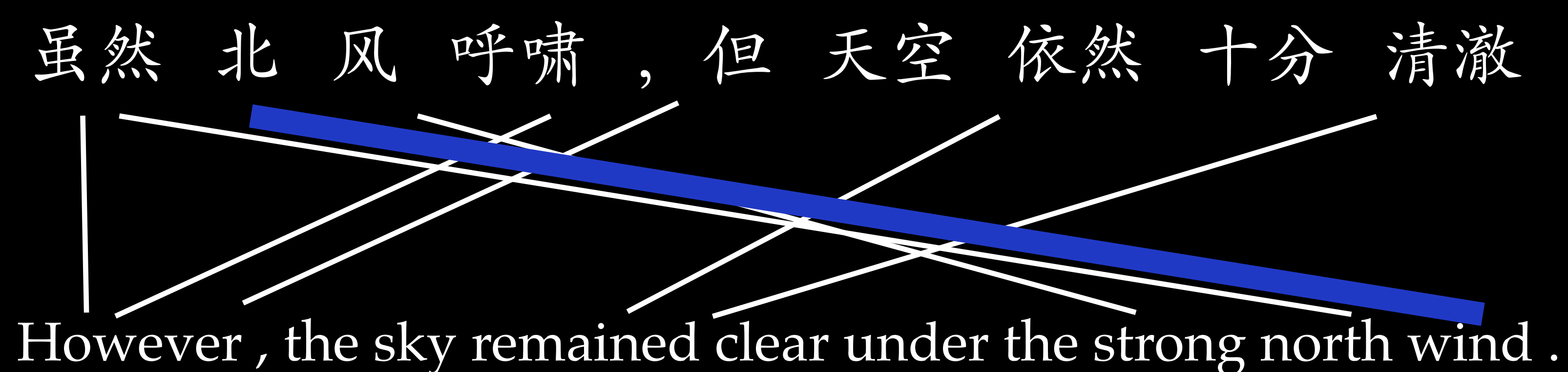
if we had observed the alignment, this line would either be here (count 1) or it wouldn't (count 0).

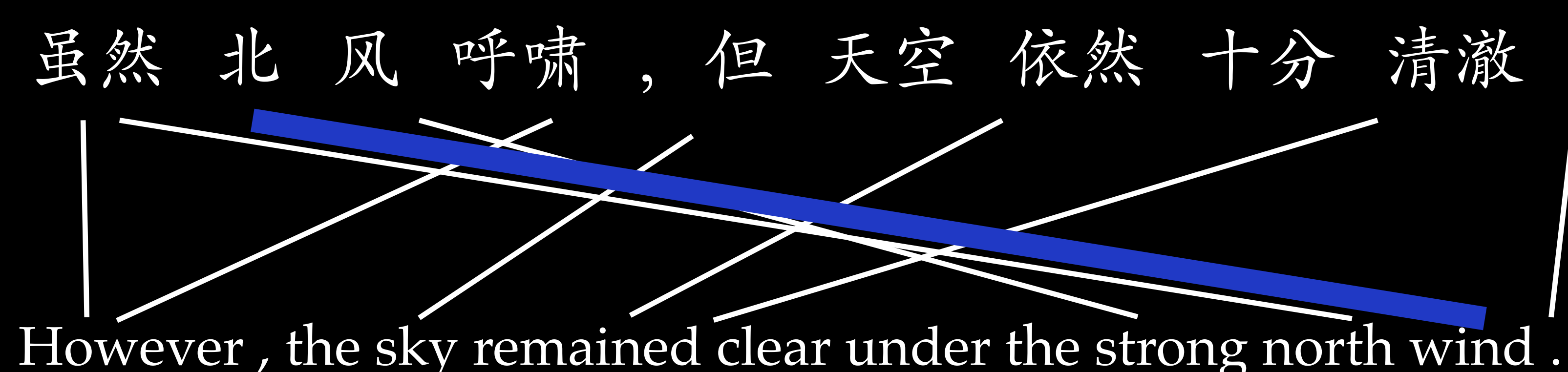
since we didn't observe the alignment, we calculate the probability that it's there.

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

Marginalize: sum all alignments containing the link

p() +

p() +

p()

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 .) +

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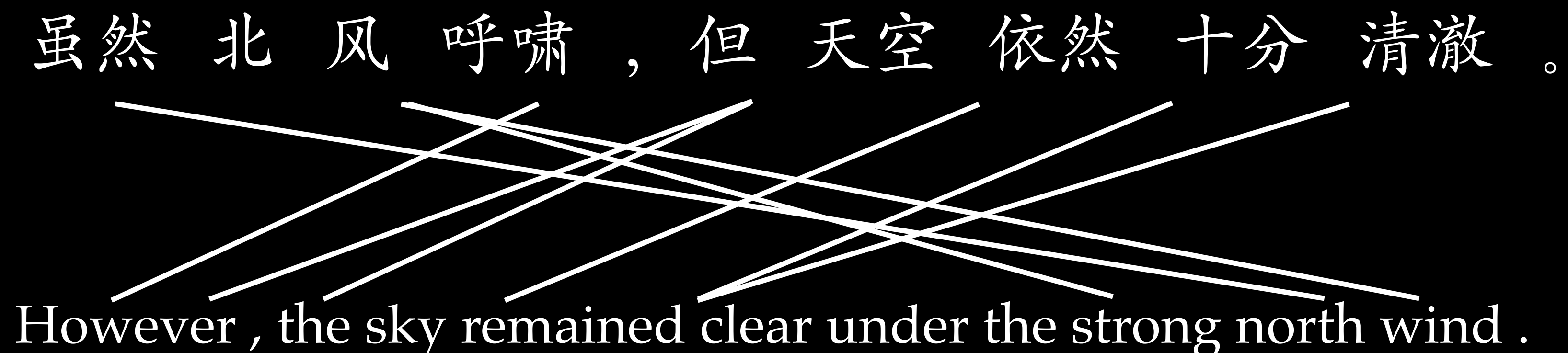
p(

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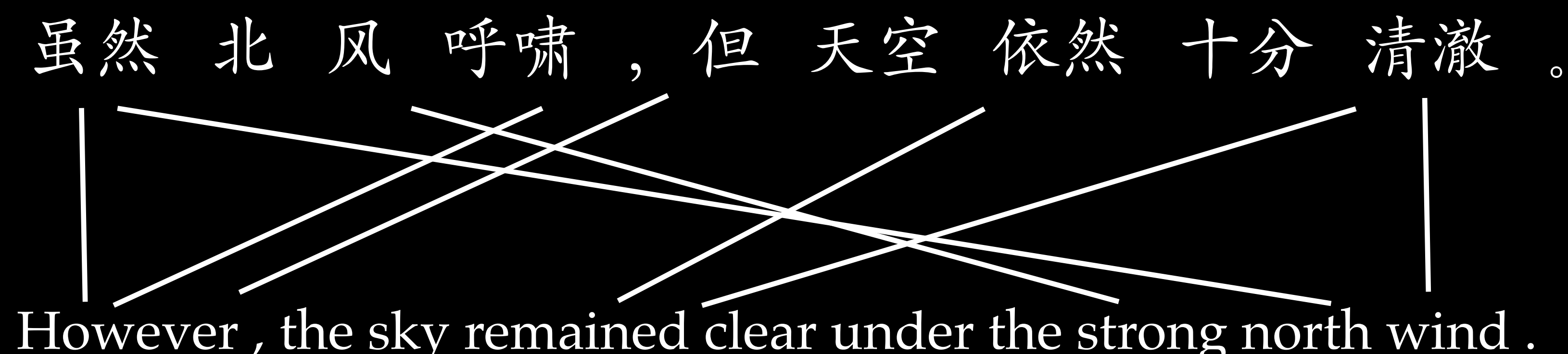
p(

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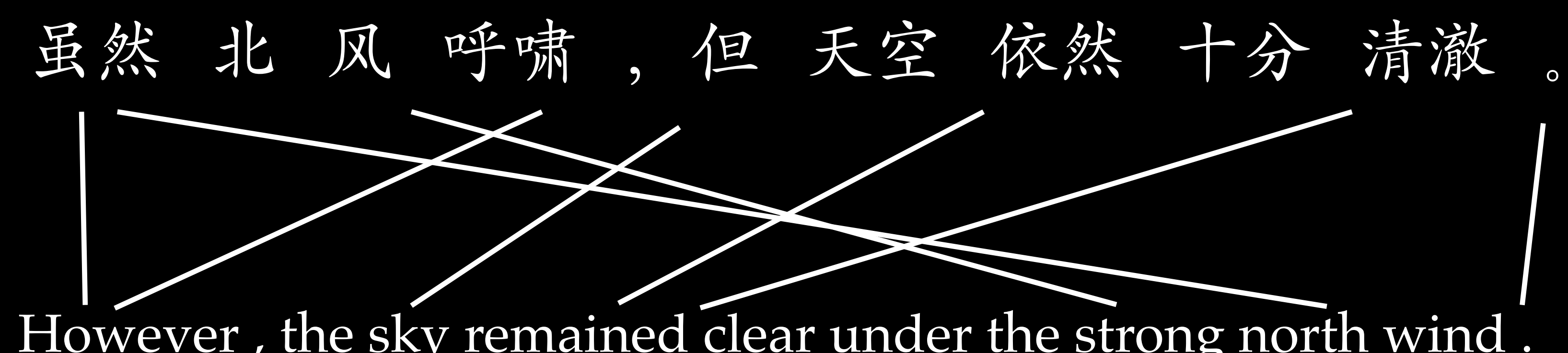
p(

)

Is this hard? How many alignments are there?

Expectation Maximization

probability of an alignment.

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

Expectation Maximization

probability of an alignment.

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

observed

uniform

Expectation Maximization

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

Expectation Maximization

marginal probability of
alignments containing link

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

Expectation Maximization

marginal probability of
alignments containing link

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

Expectation Maximization

marginal probability of
alignments containing link

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

marginal probability of all
alignments

Expectation Maximization

marginal probability of
alignments containing link

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

marginal probability of all
alignments

Expectation Maximization

marginal probability of
alignments containing link

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

identical!

marginal probability of all
alignments

Expectation Maximization

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

Expectation Maximization

marginal probability (expected count) of an alignment containing the link

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

Expectation Maximization

marginal probability (expected count) of an alignment containing the link

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

For each sentence, use this quantity instead of 0 or 1

Translation Models

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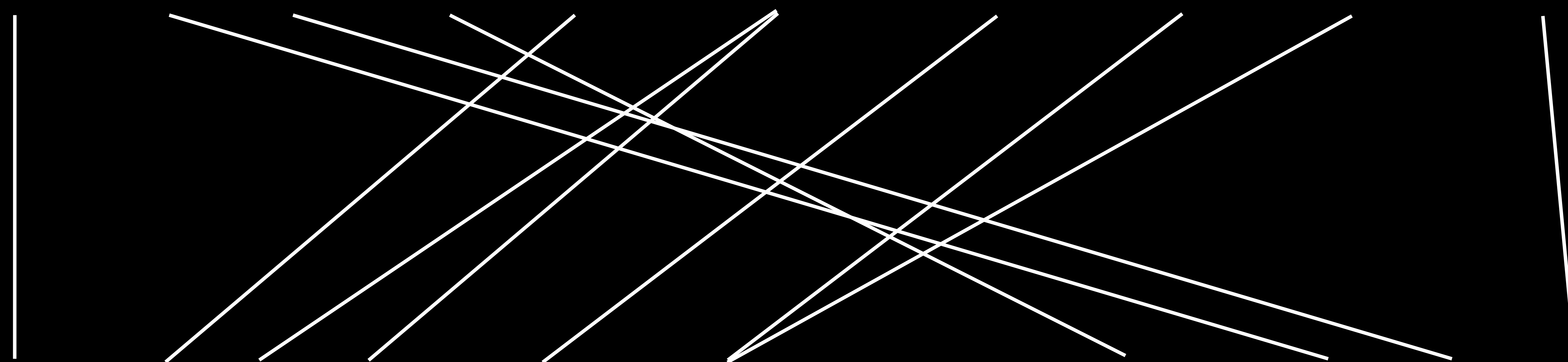

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$$p(however \mid \text{虽然}) = \frac{\textit{Expected}\ \text{\# of times 虽然 aligns to However}}{\text{\# of times 虽然 occurs}}$$

Expectation Maximization

Why does this even work?

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

Expectation Maximization

Observation 1: We are still solving a maximum likelihood estimation problem.

Expectation Maximization

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$$p(Chinese|English) = \sum_{alignments} p(Chinese, alignment|English)$$

Expectation Maximization

Observation 1: We are still solving a maximum likelihood estimation problem.

$$p(Chinese|English) = \sum_{alignments} p(Chinese, alignment|English)$$

MLE: choose parameters that maximize this expression.

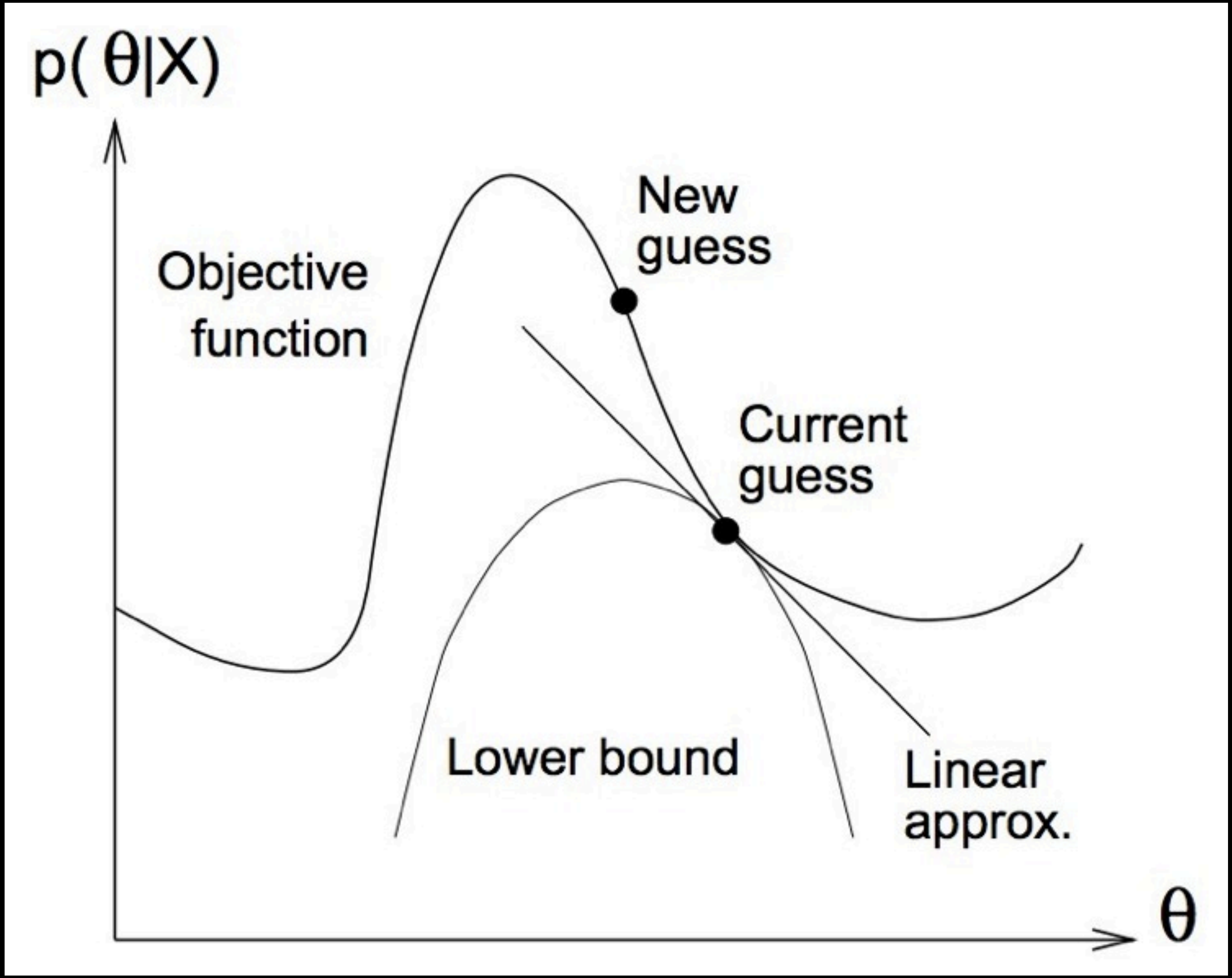
Expectation Maximization

Observation 1: We are still solving a maximum likelihood estimation problem.

$$p(Chinese|English) = \sum_{alignments} p(Chinese, alignment|English)$$

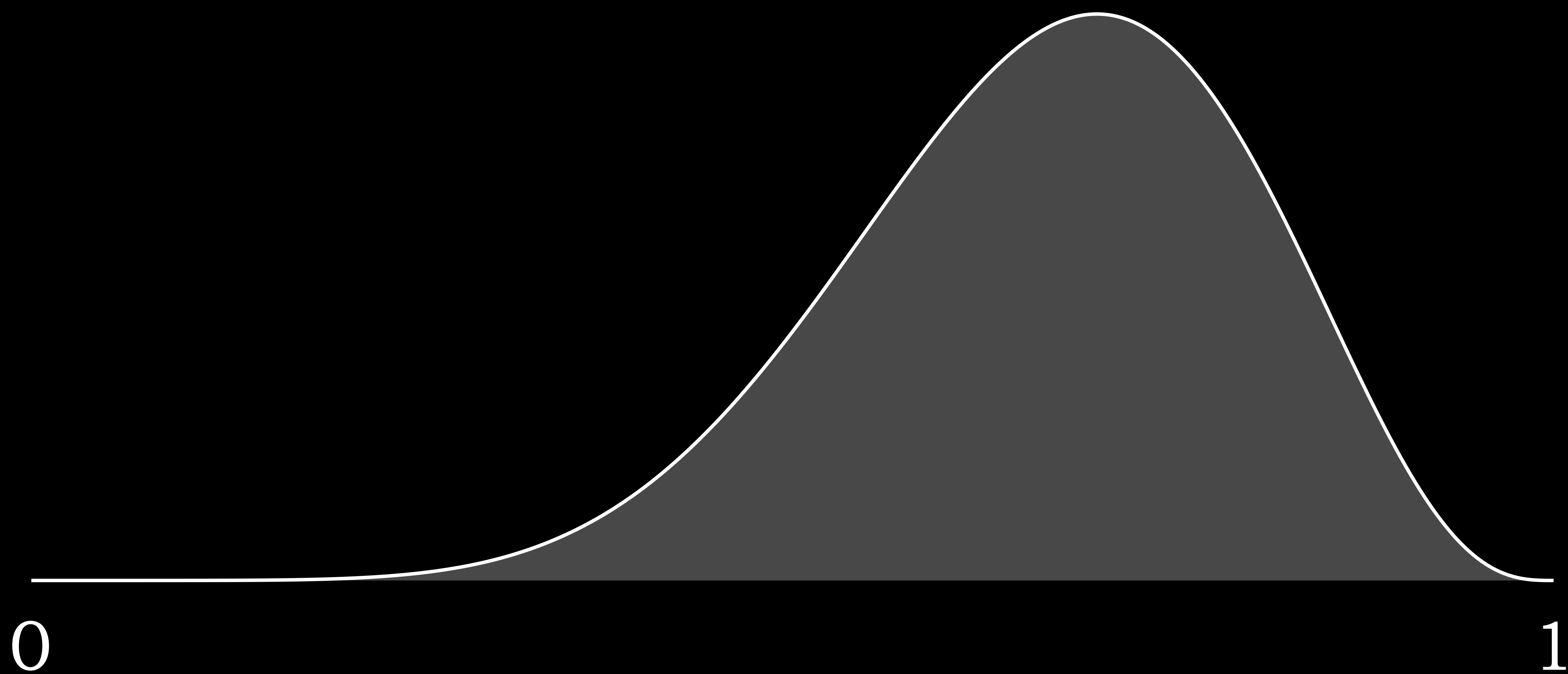
MLE: choose parameters that maximize this expression.

Minor problem: there is no analytic solution.



(from Minka ’98)

... and, likelihood is ***convex*** for this model:



Exercises!

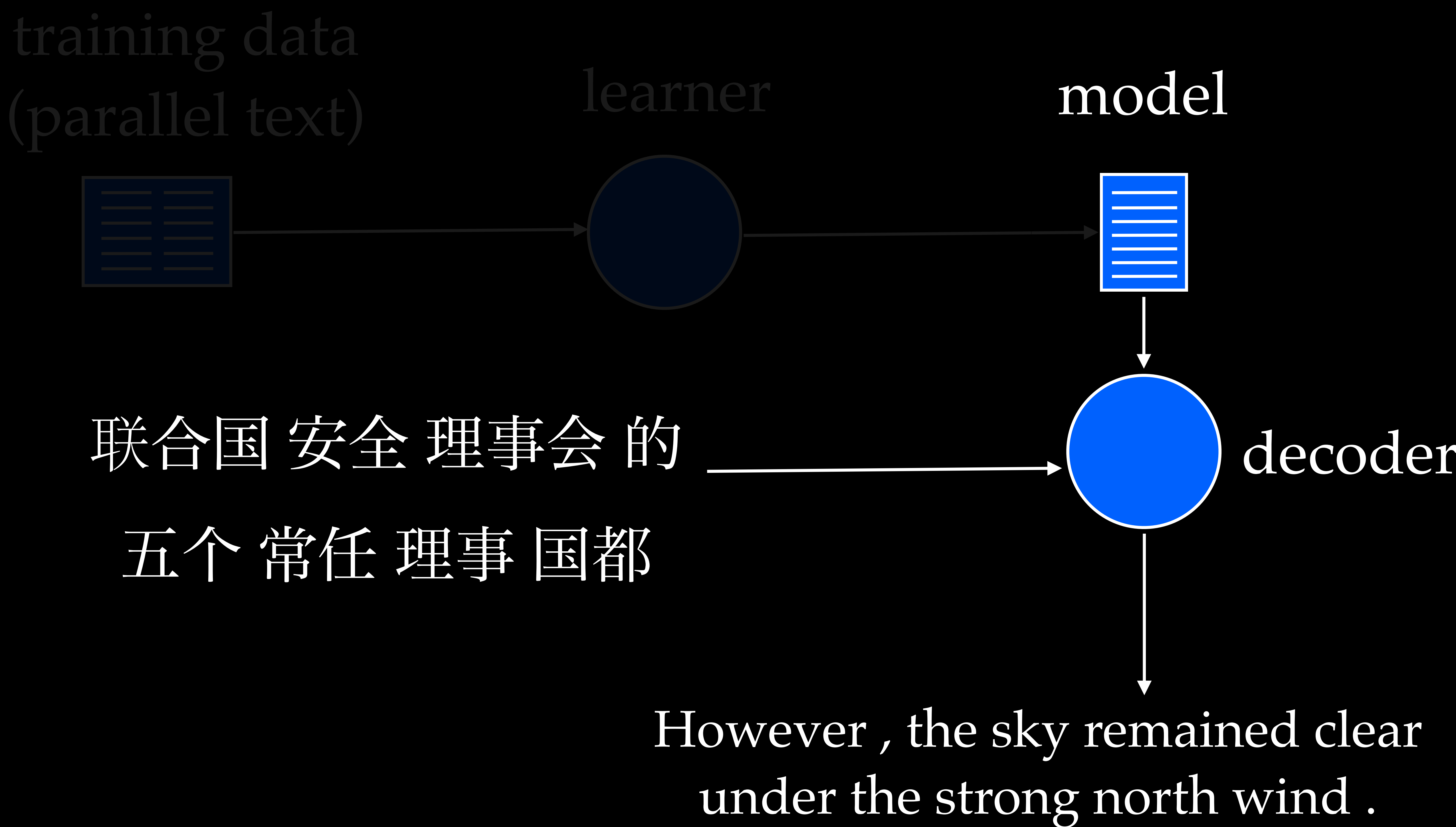
- Totally optional.
- Most effective way to understand concepts is to apply them!
- I'm happy to answer questions.

http://www.cs.jhu.edu/~alopez/nasslli2012/exercise1.html

Summary

- ***Learning is optimization***: choose parameters that optimize some function, such as likelihood.
- Supervised: maximum likelihood.
  - Beware of overfitting.
- Unsupervised: expectation maximization.
- Many, many, many other algorithms.
- Next up: prediction, better models.

Overview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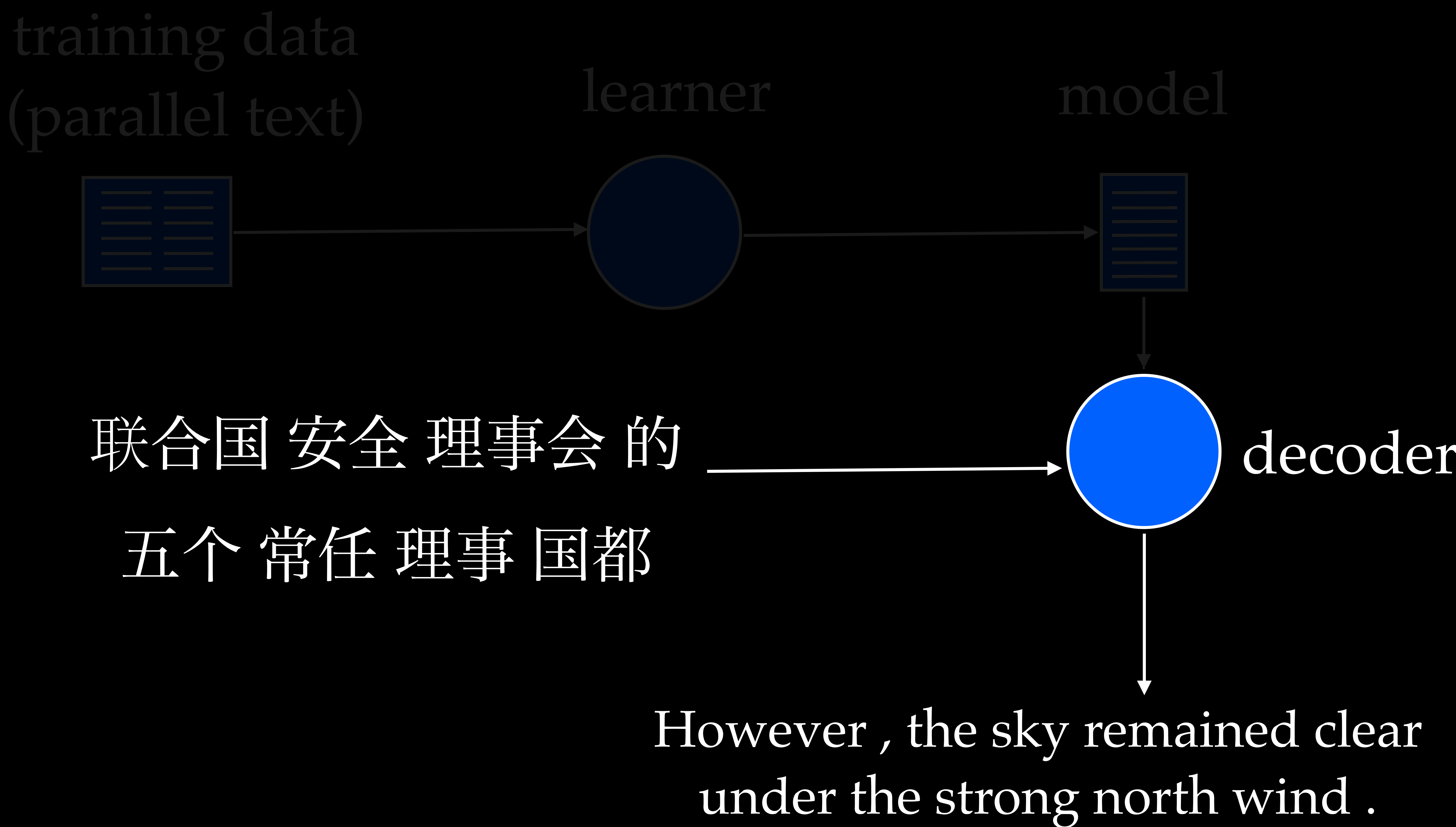
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Quick Recap

$$p(English|Chinese) =$$

$$\frac{p(English) \times p(Chinese|English)}{p(Chinese)}$$

language model

translation model

normalization term (ensures we're working with valid probabilities).

Quick Recap

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

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

language model

translation model

Decoding

Probability models enable us to ***make predictions***: Given a particular Chinese sentence, what is the most probable English sentence corresponding to it?

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In math, we want to solve:

$$\text{argmax}_{English}\, p(English|Chinese)$$

Decoding

Probability models enable us to ***make predictions***:
Given a particular Chinese sentence, what is the most probable English sentence corresponding to it?

In math, we want to solve:

$$\mathrm{argmax}_{English}\, p(English|Chinese)$$

problem: there are a lot of English sentences to choose from!


THE WØRD

- Optimization

北 风 呼啸 。

北 风 呼啸 。

substitutions

permutations

北 风 呼啸 。

substitutions $O(5^n)$

permutations

北 风 呼啸 。

substitutions	$O(5^n)$
permutations	$O(n!)$

北 风 呼啸 。

substitutions $O(5^n)$

permutations $O(n!)$

15,000 possibilities!

北 风 呼啸 。

Can we do this without enumerating $O(5^n n!)$ pairs?

北 风 呼啸 。

the strong north wind .

Can we do this without enumerating $O(5^n n!)$ pairs?

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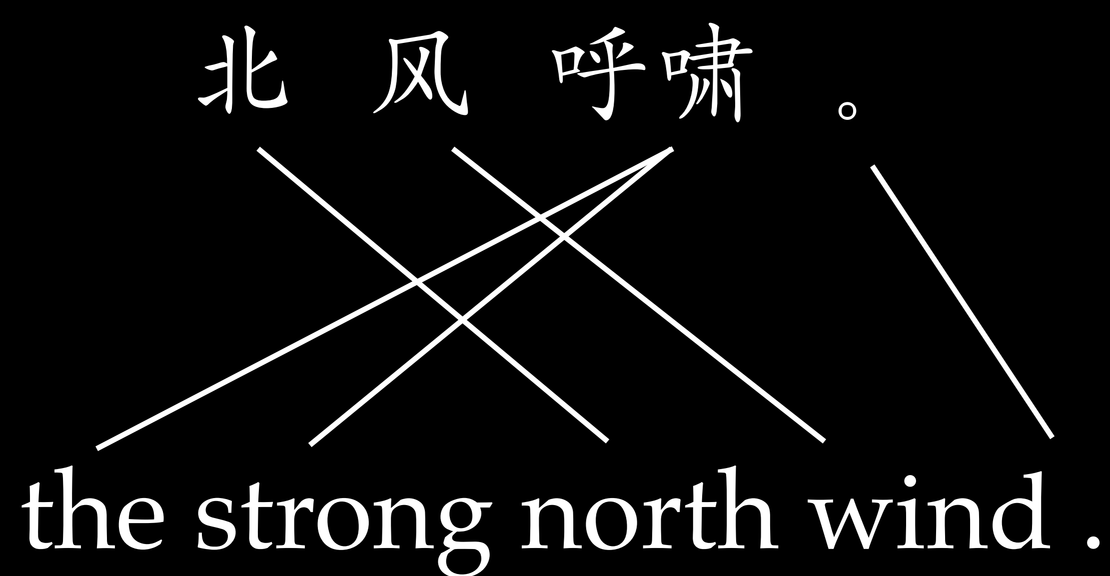
Can we do this without enumerating $O(5^n n!)$ pairs?

Given a sentence pair and an alignment, we can easily calculate

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

Can we do this without enumerating $O(5^n n!)$ pairs?

Key Idea



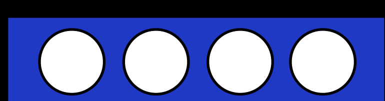
There are $O(5^n n!)$ target sentences.

But there are only $O(5^n)$ ways to start them.

Key Idea

北 风 呼啸 。

Key Idea



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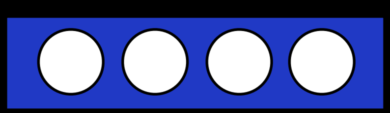


coverage vector

北 风 呼啸 。

Key Idea

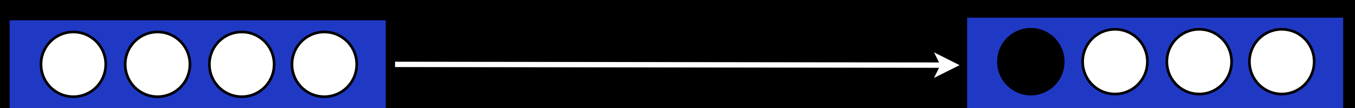
coverage vector

北 风 呼啸 。

Key Idea

$$p(north|START) \cdot p(北\,|north)$$

north



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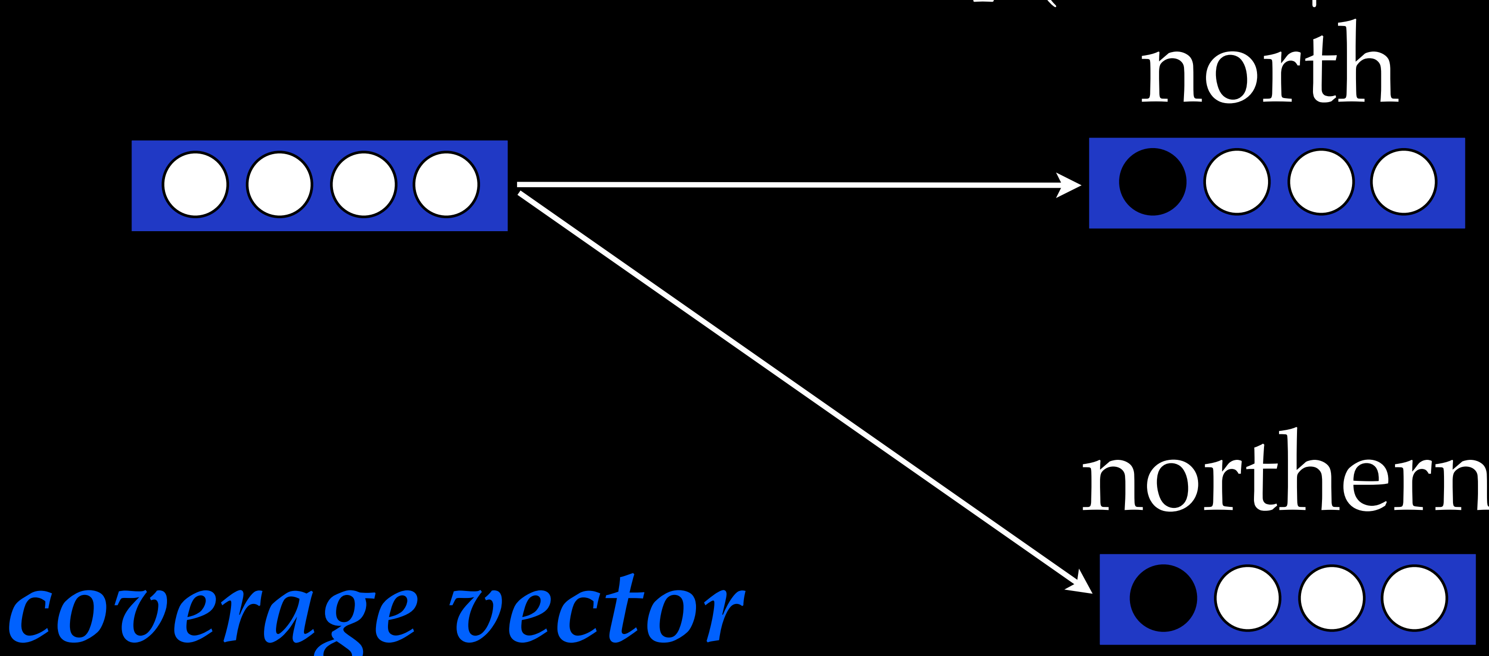

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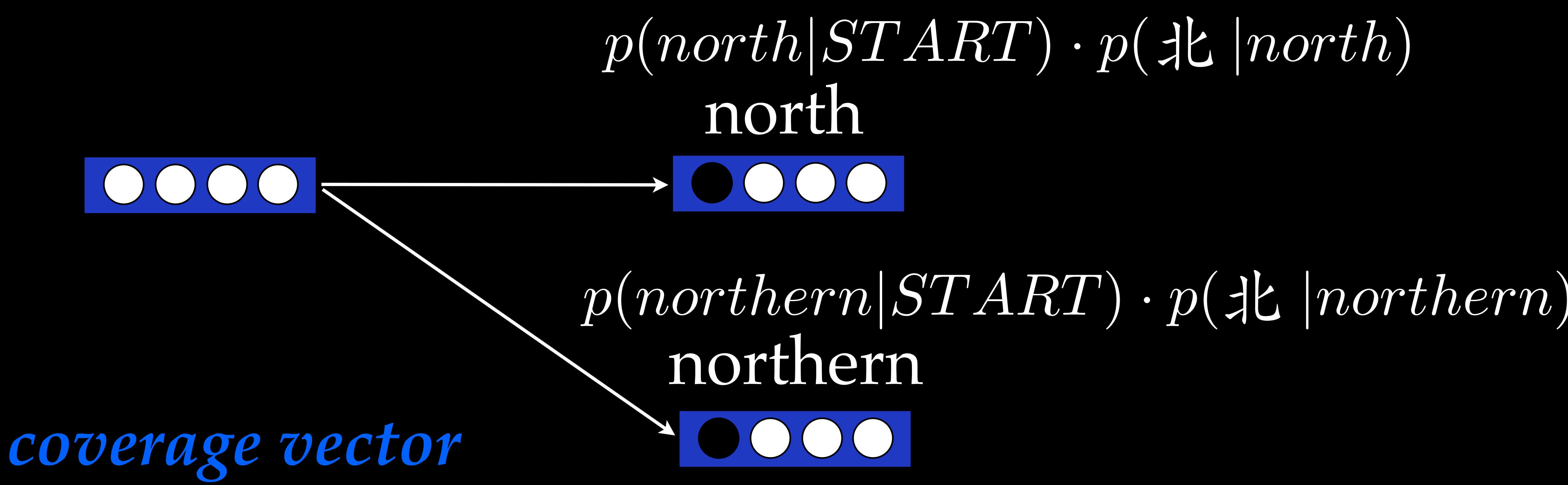

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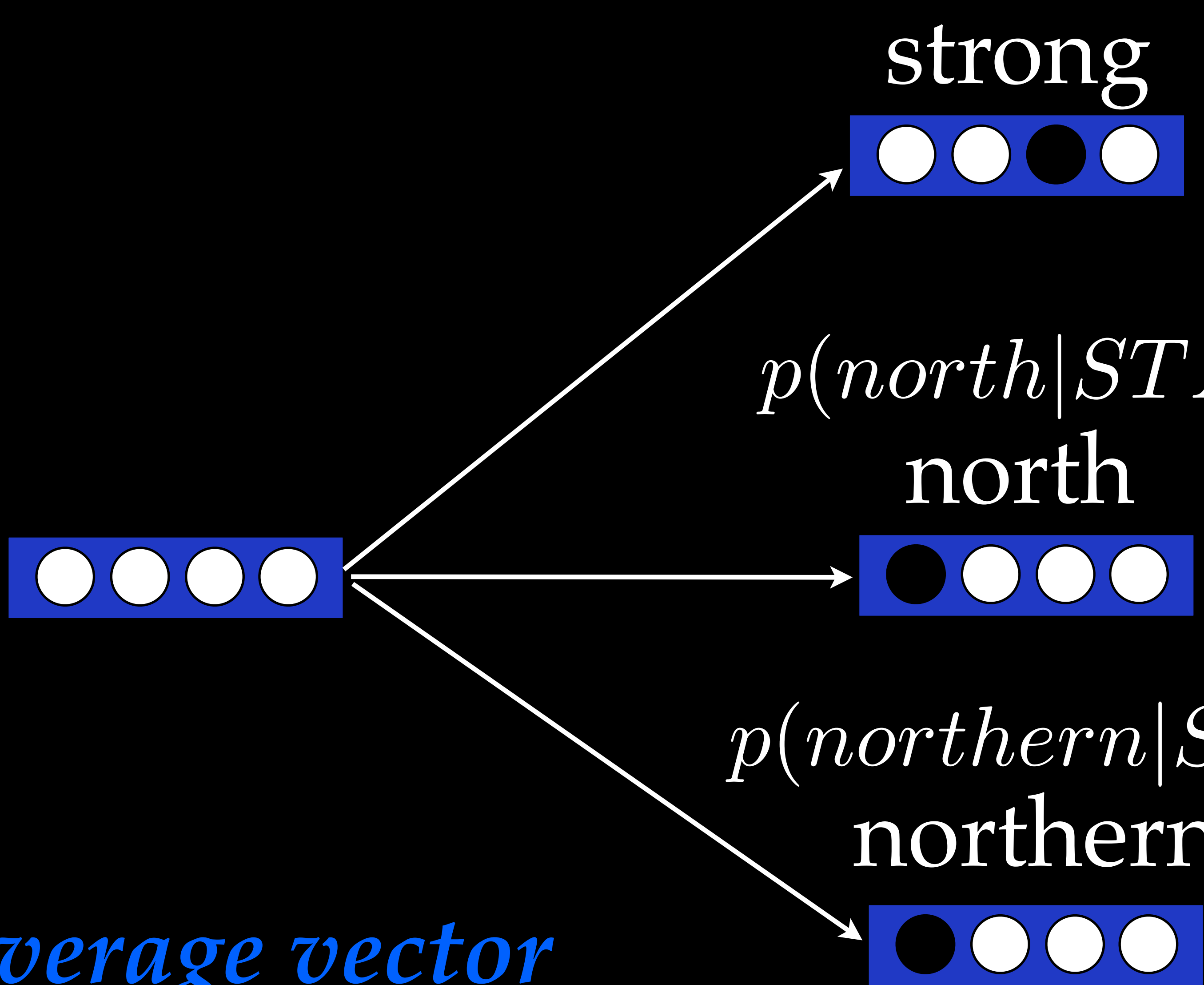

$$p(north|START) \cdot p(北|north)$$

$$p(northern|START) \cdot p(北|northern)$$

coverage vector

北 风 呼啸 。

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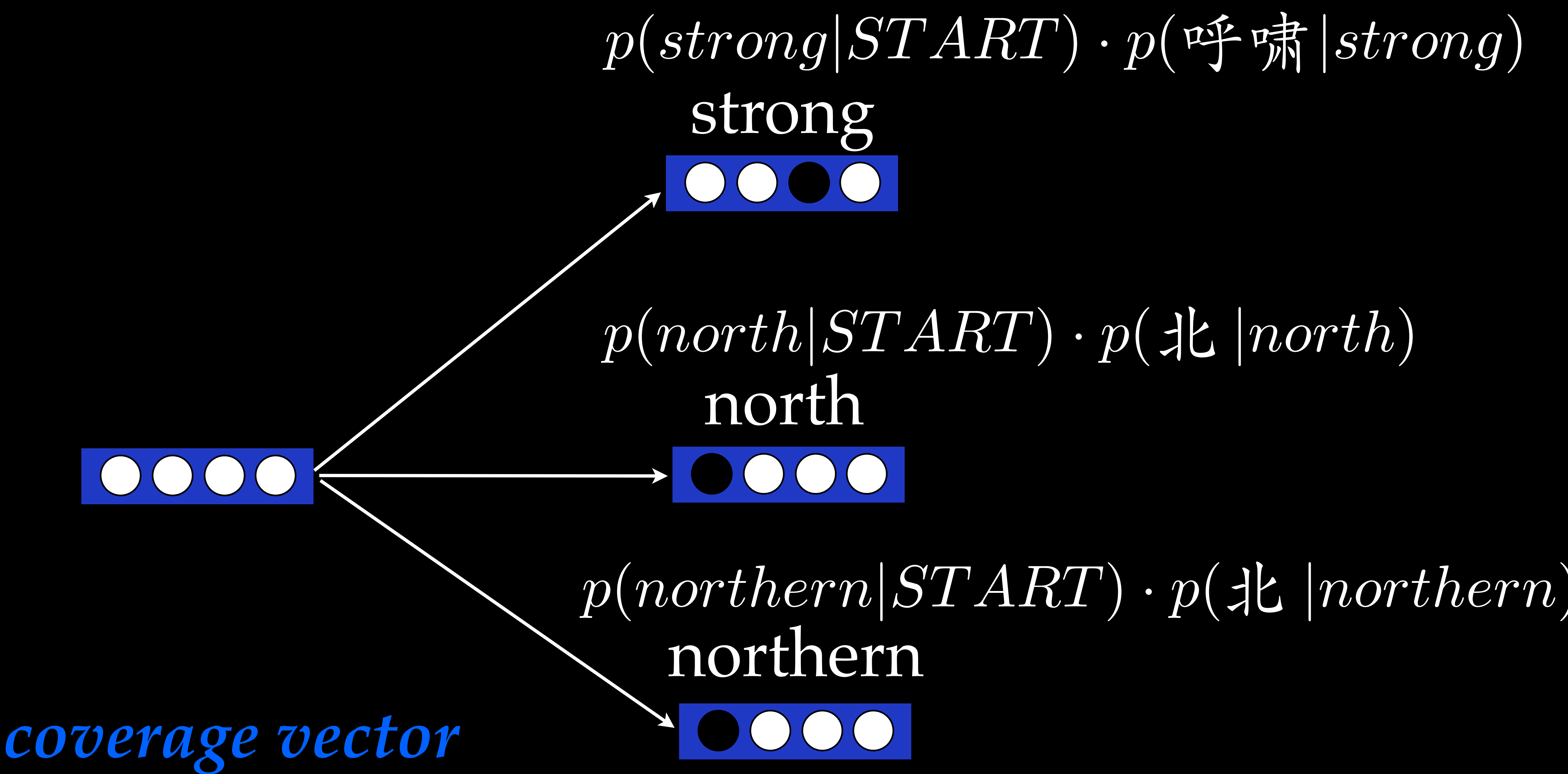

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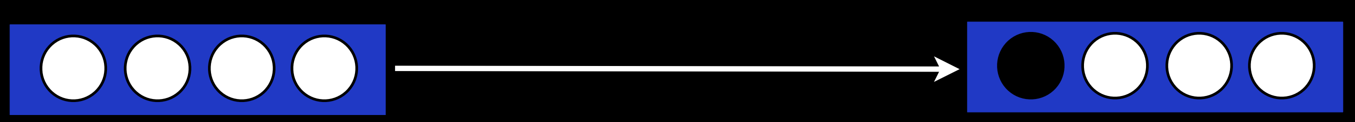
$$p(north|START) \cdot p(\text{北}|north)$$

north



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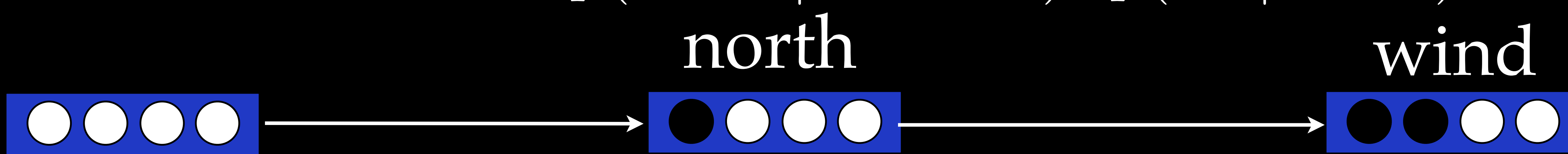

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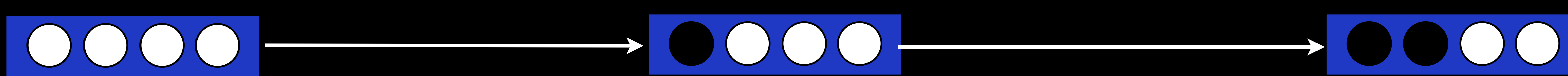
Key Idea

$p(north|START) \cdot p(北|north)$

north

wind

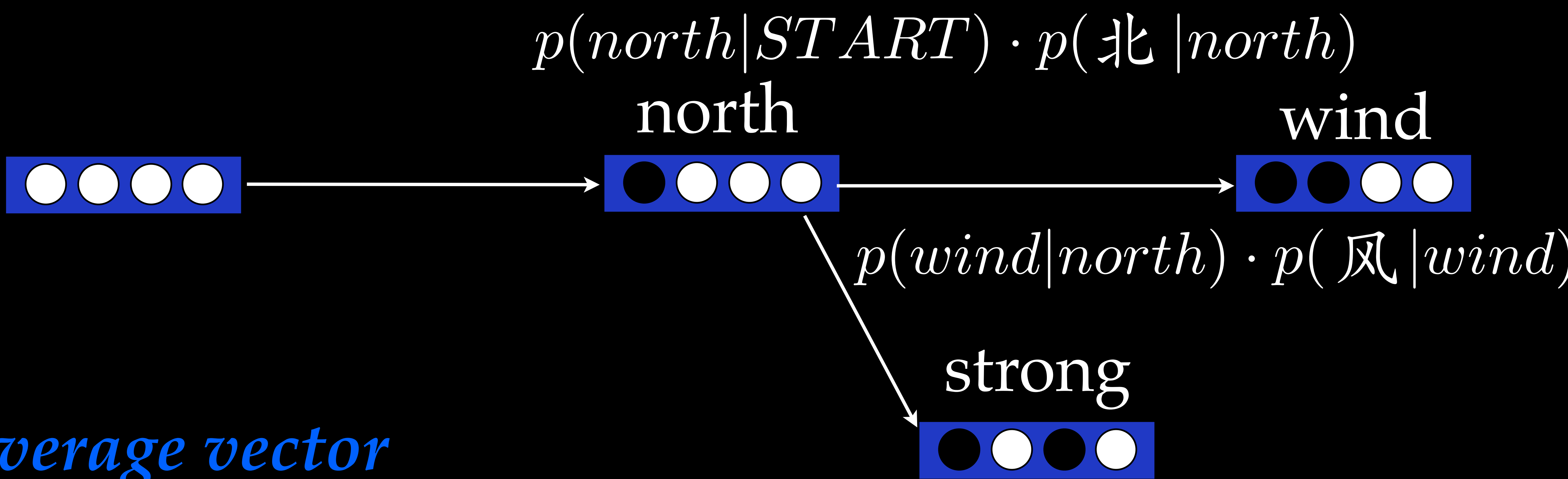


$p(wind|north) \cdot p(风|wind)$

coverage vector

北 风 呼啸 。

Key Idea



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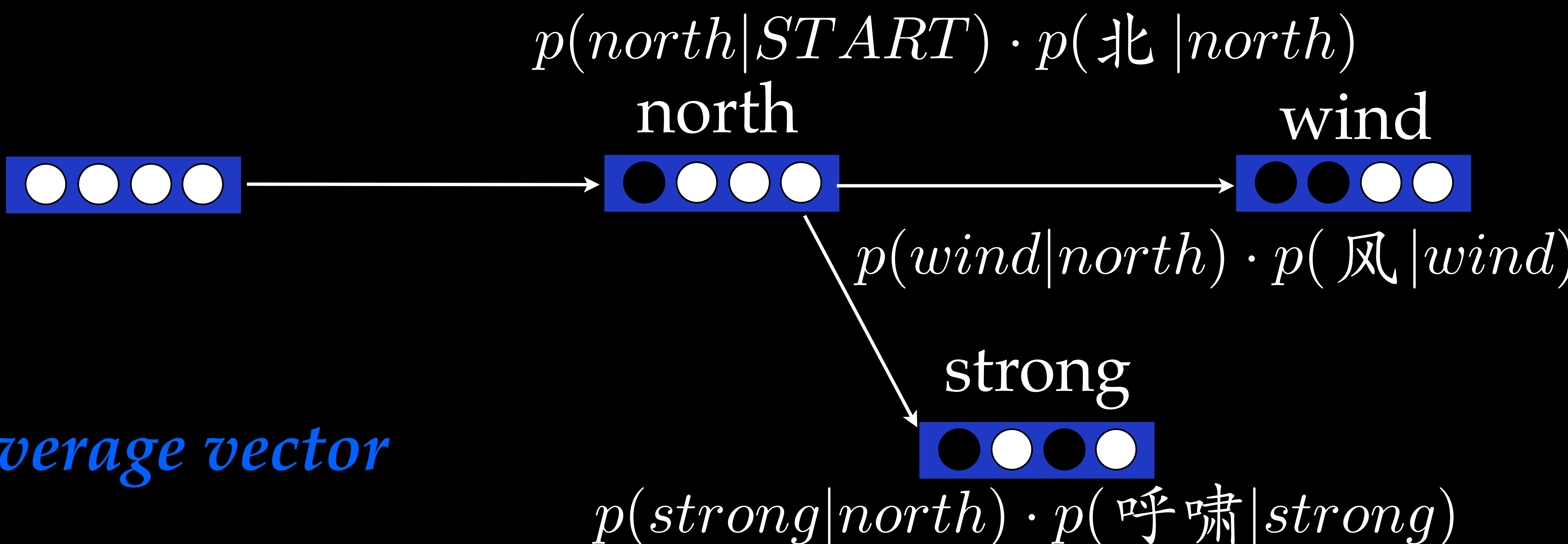

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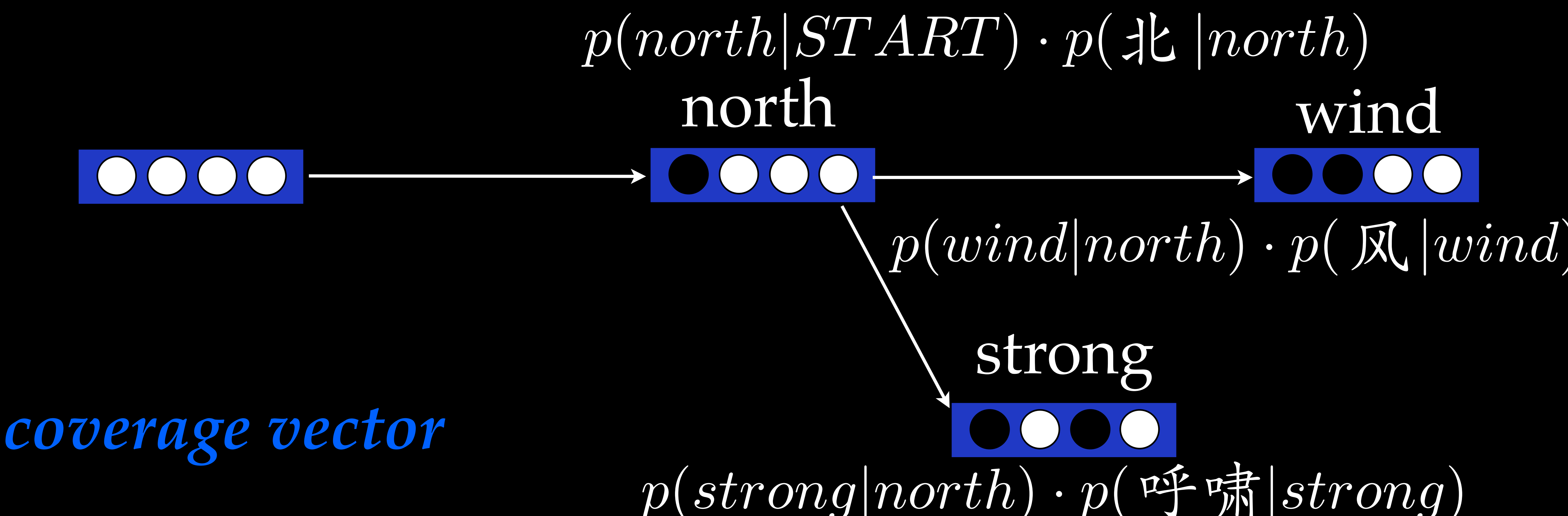
Key Idea

Work done at sentence beginnings is shared across many possible output sentences!



北　风　呼啸　。

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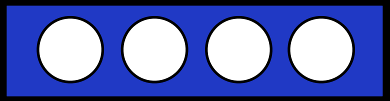

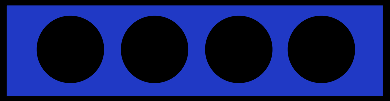

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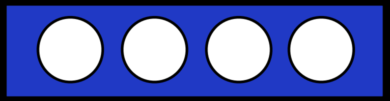

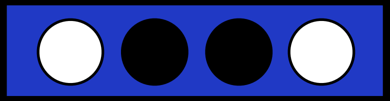

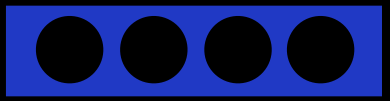

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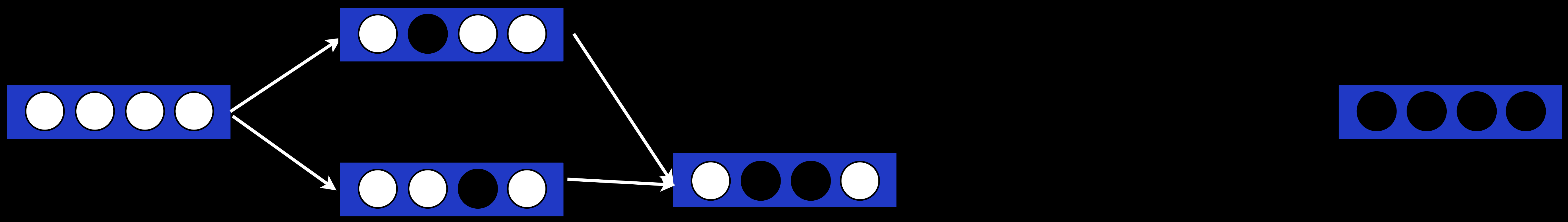

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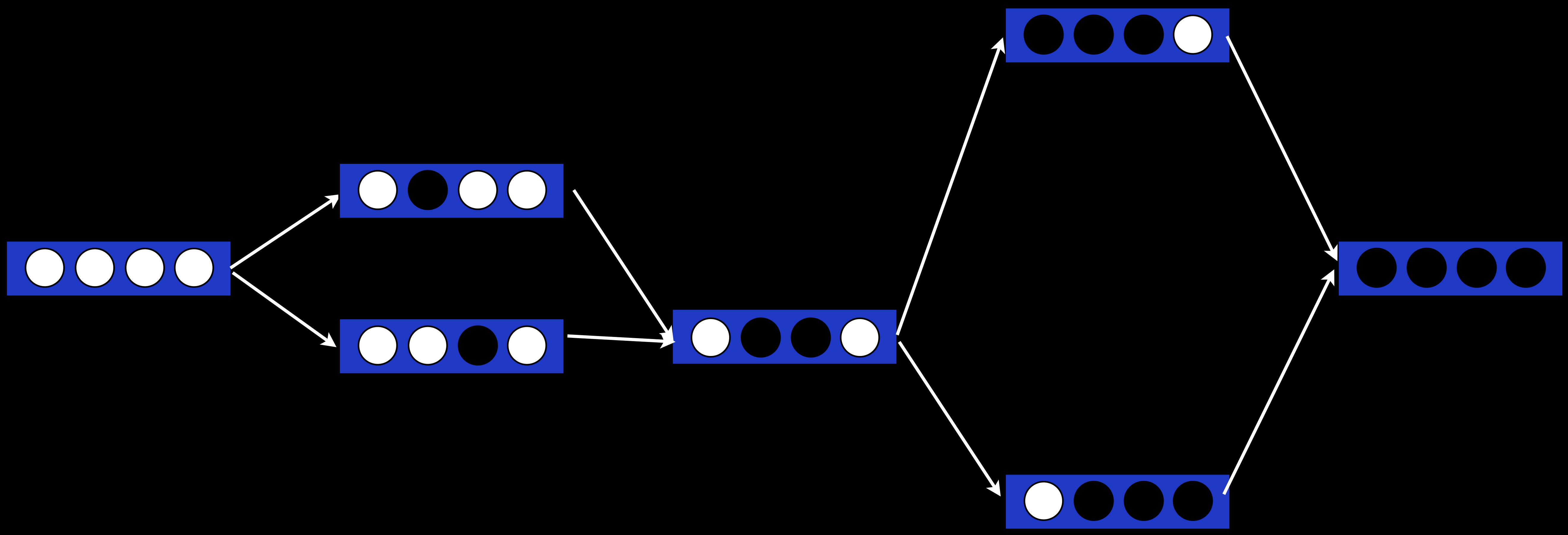

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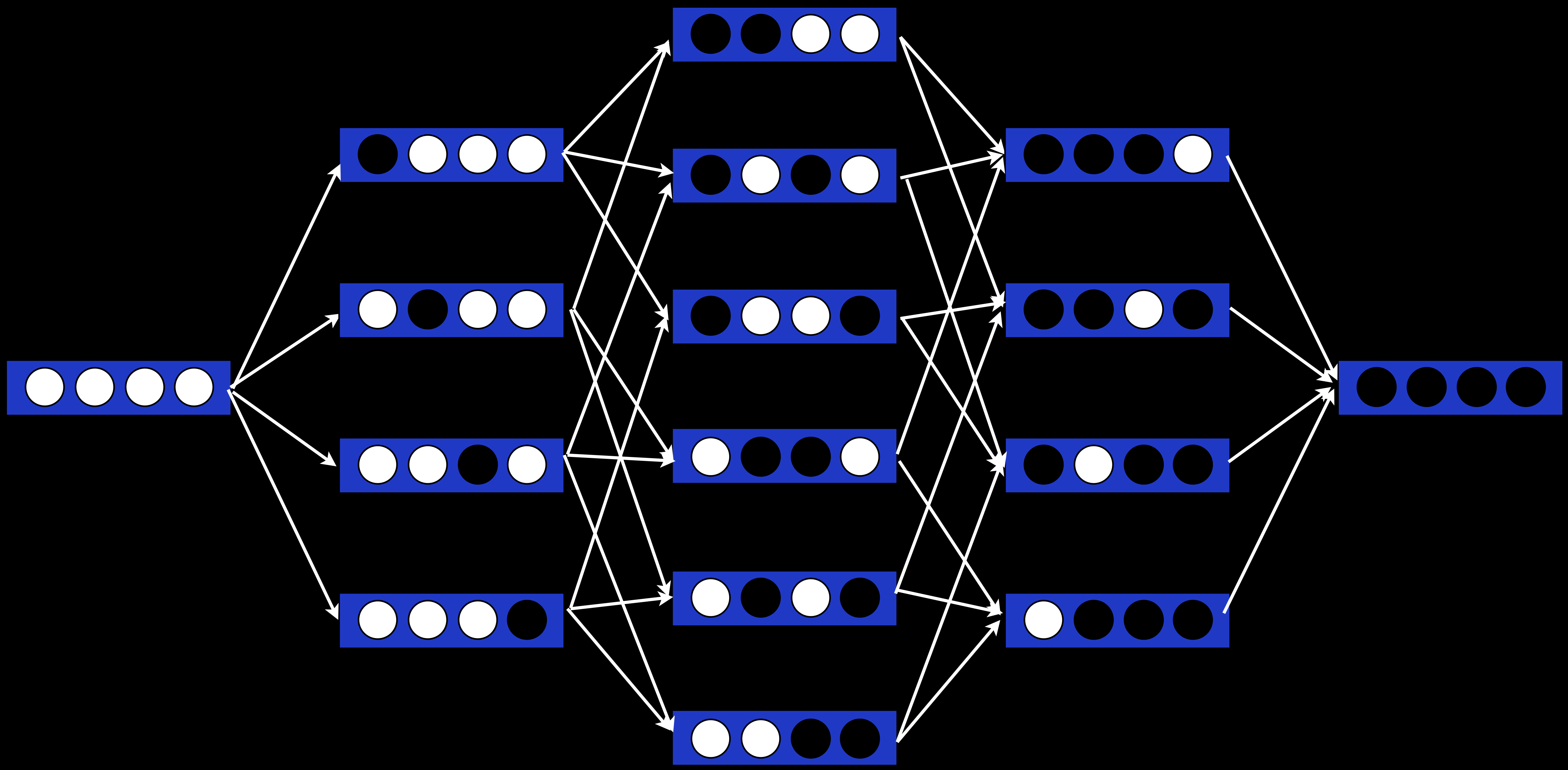

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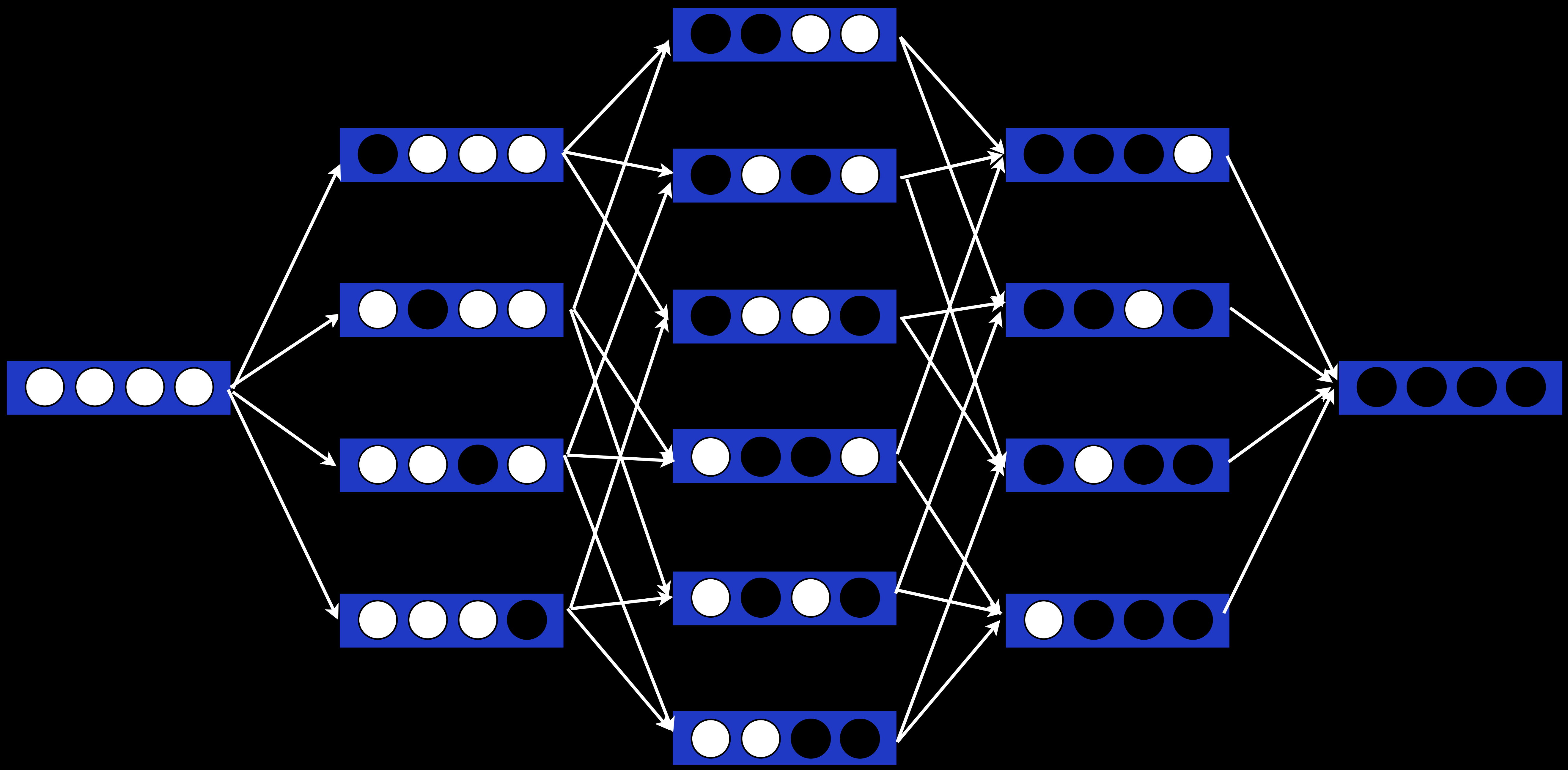
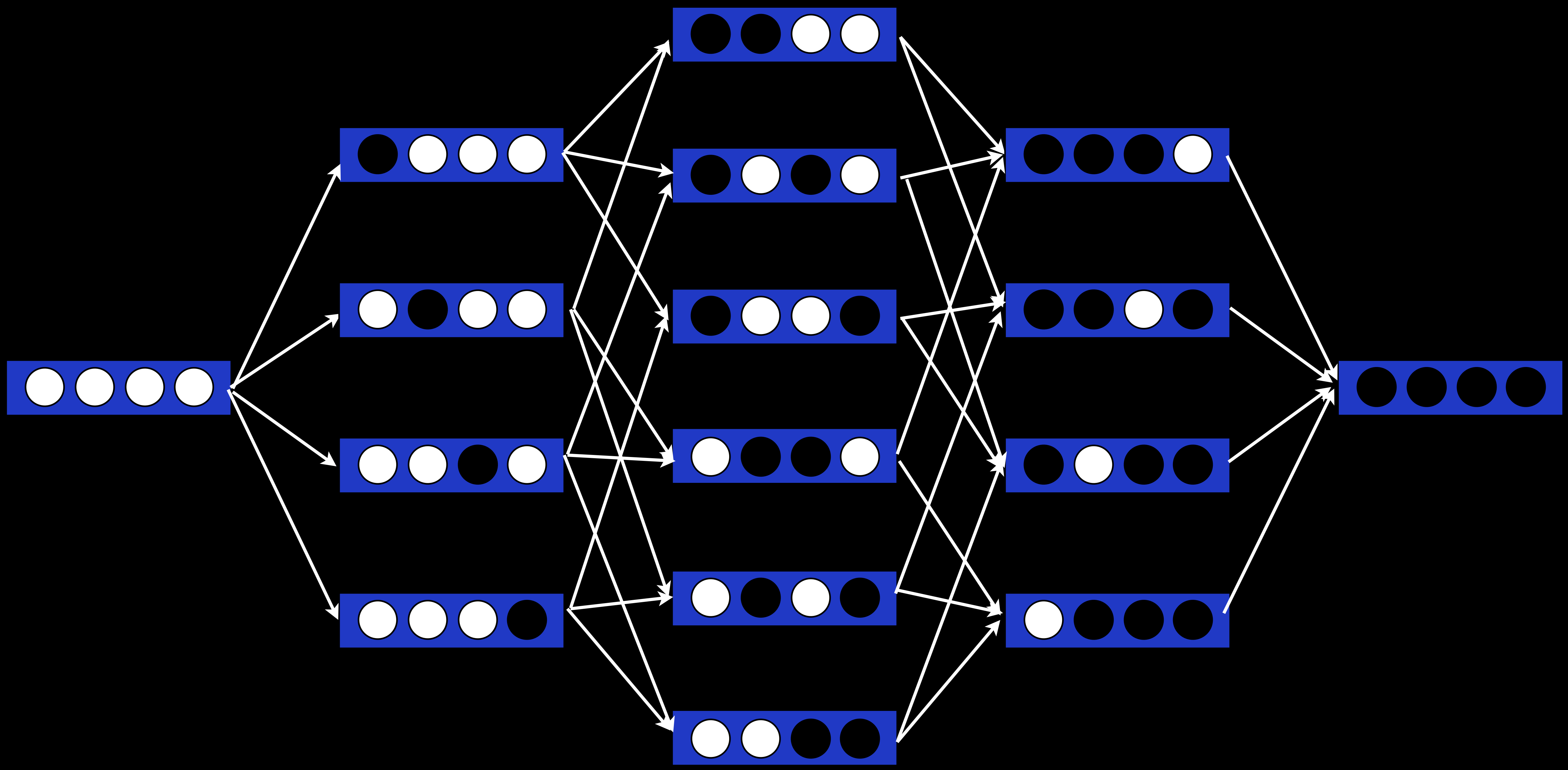


Dynamic Programming

Key Idea

amount of work:

$$O(5^n 2^n)$$



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amount of work:

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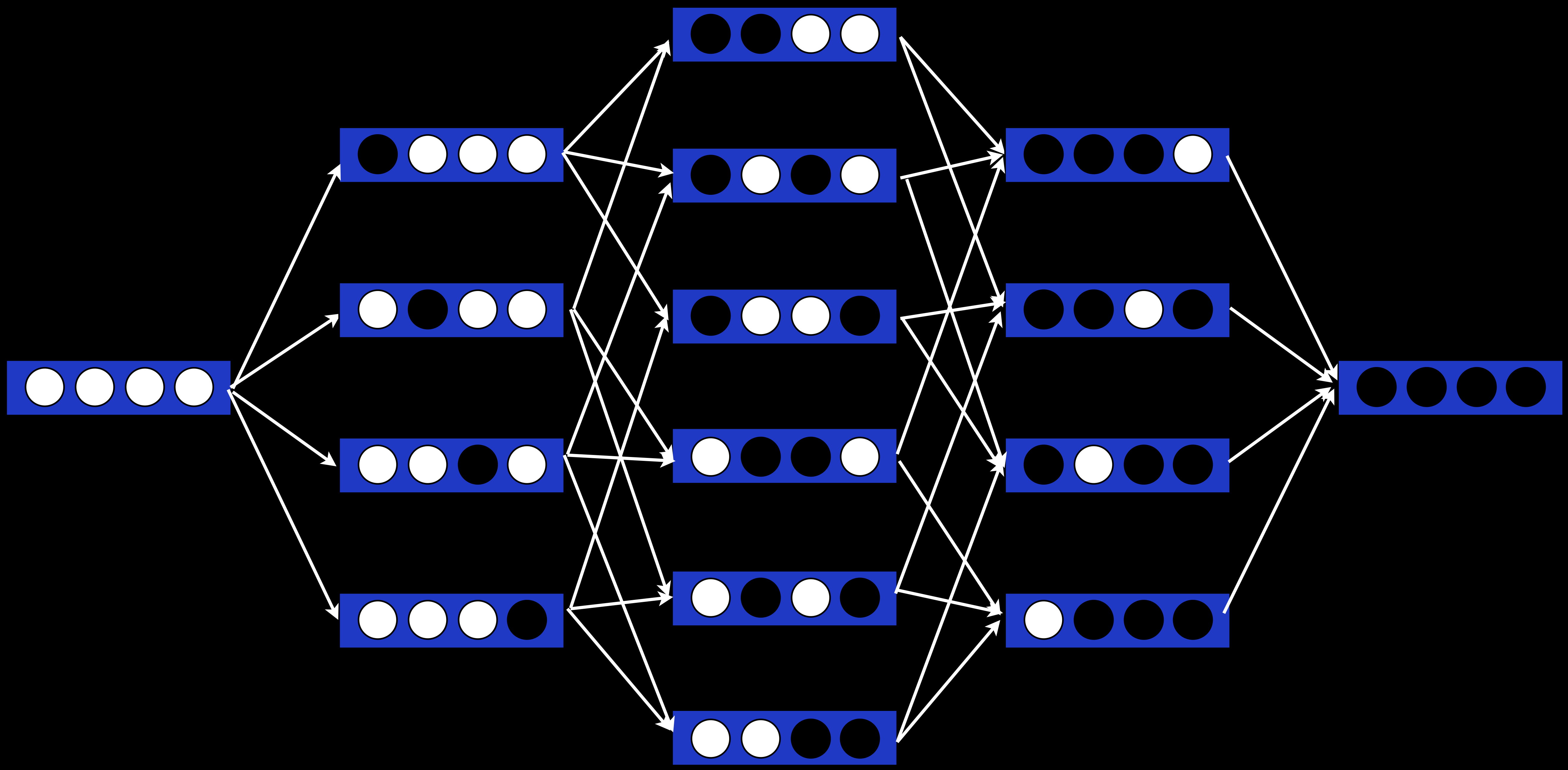
bad, but much better than $O(5^n n!)$



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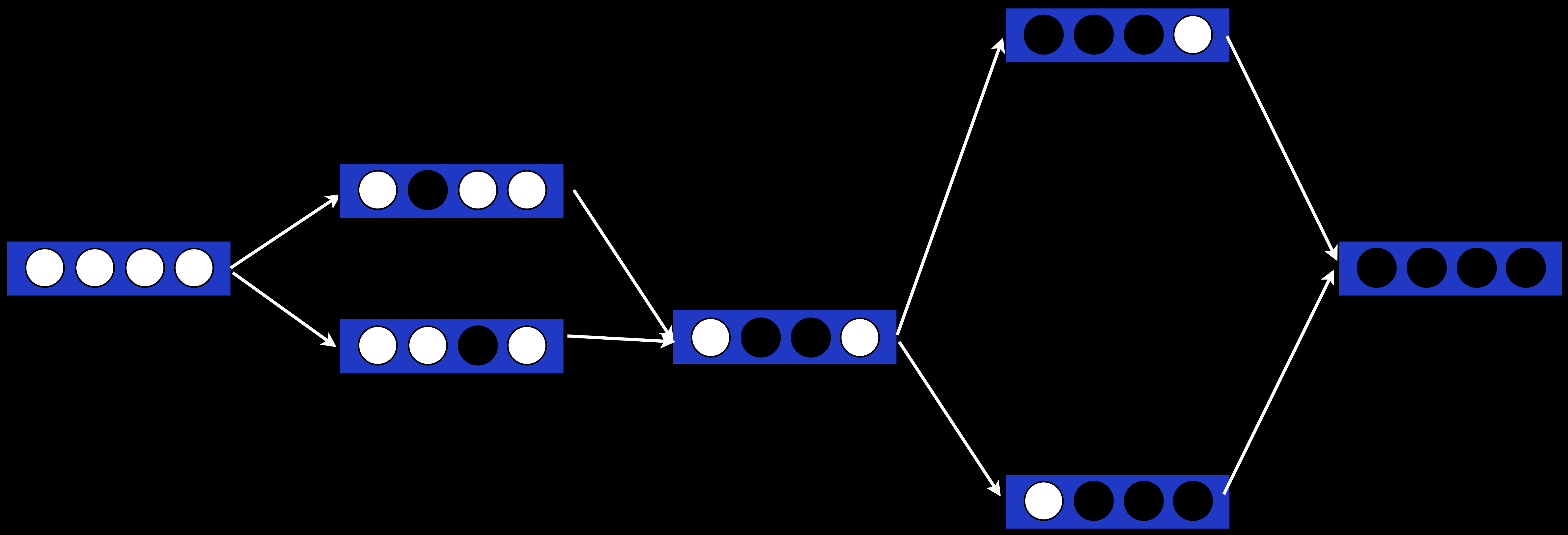

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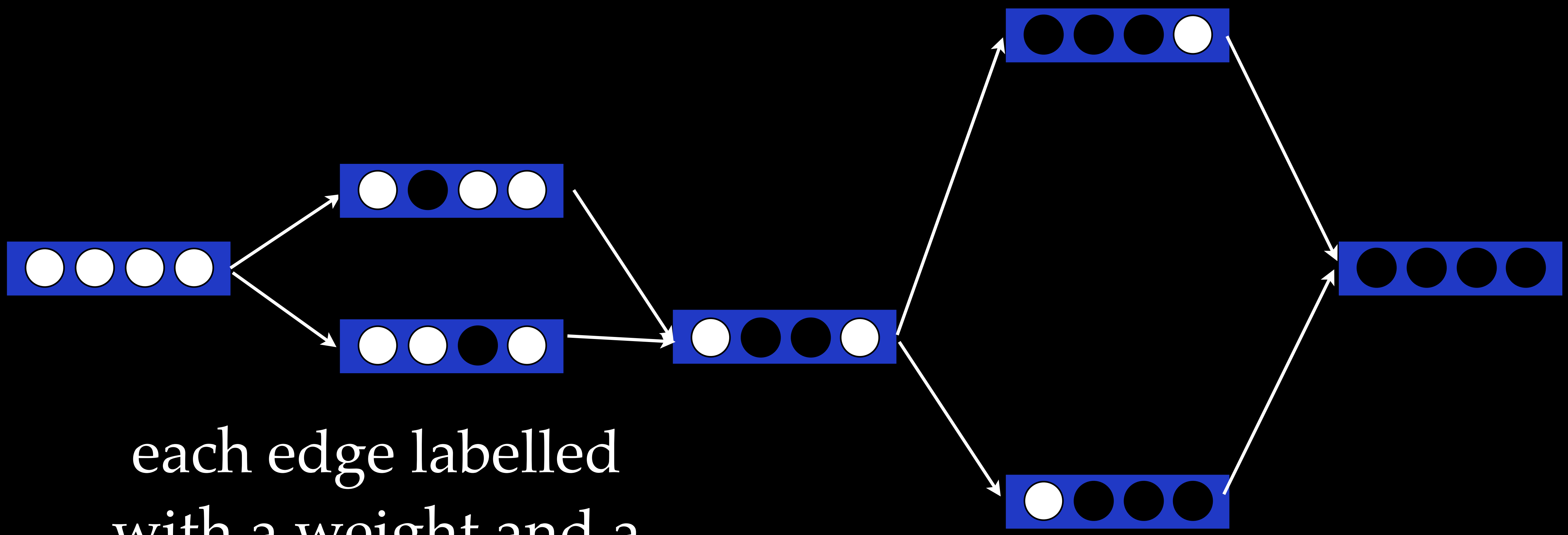

each edge labelled with a weight and a word (or words)

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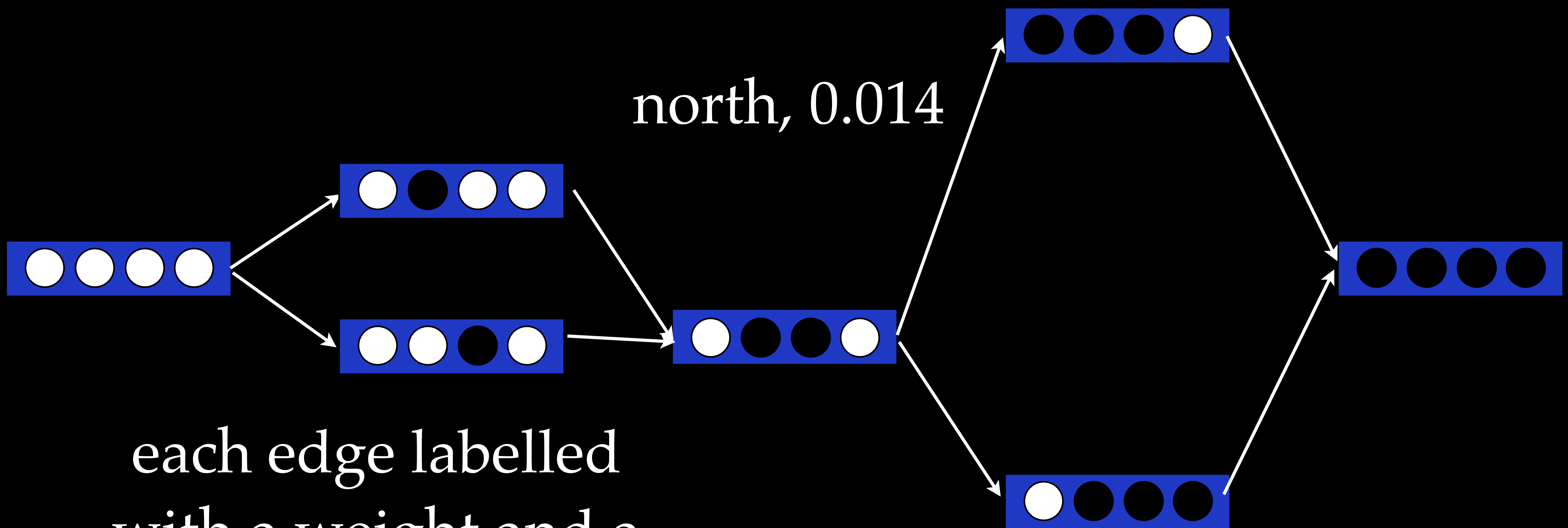

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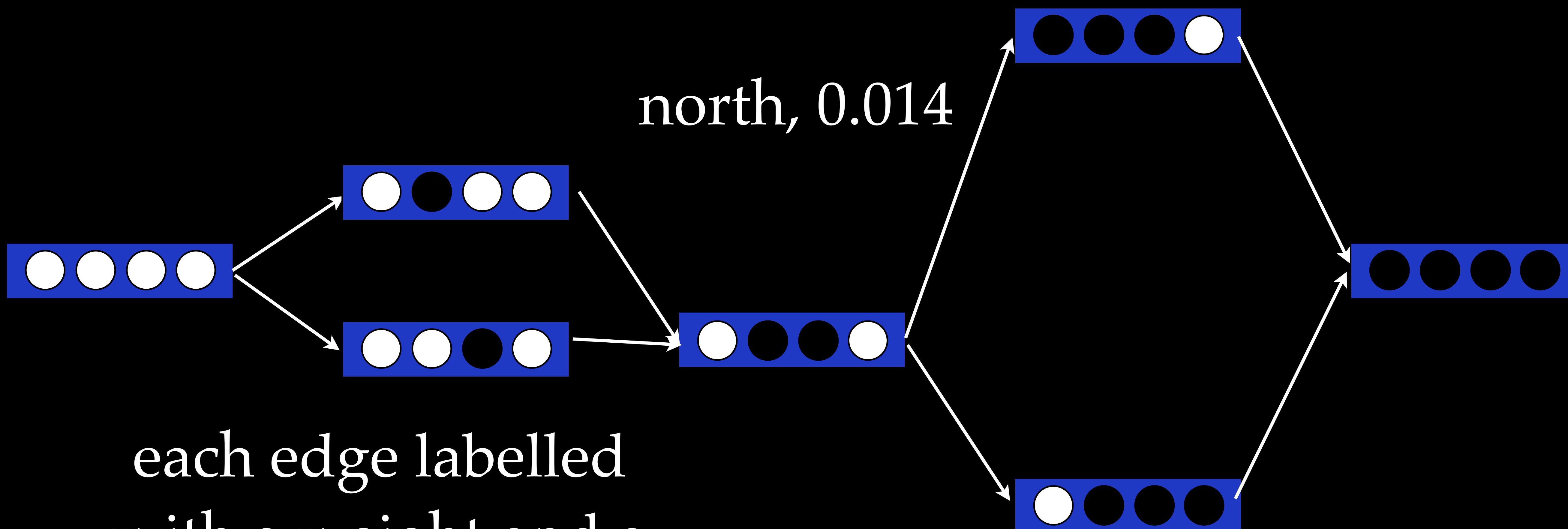
weighted finite-state automata



each edge labelled with a weight and a word (or words)

Dynamic Programming

Weighted languages

- The lattice describing the set of all possible translations is a ***weighted finite state automaton***.
- So is the language model.
- Since regular languages are closed under intersection, we can intersect the devices and run shortest path graph algorithms.
- Taking their intersection is equivalent to computing the probability under Bayes' rule.

Practical Issues

$O(5^n 2^n)$ is still far too much work.

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Can we do better?

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北 风 呼啸 。

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north wind the strong .

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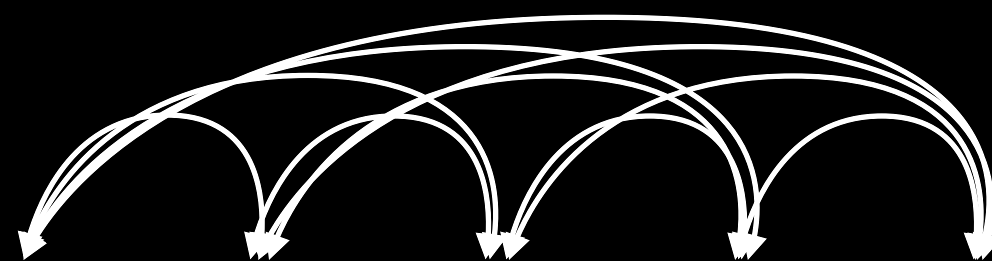

north wind the strong .

Each arc weighted by
translation probability +
bigram probability

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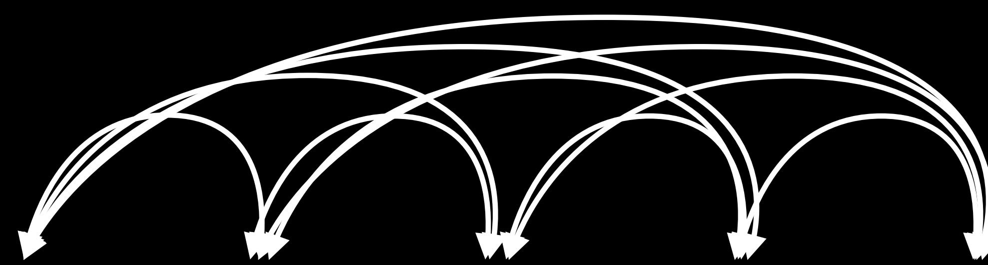

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Objective: find shortest path that visits each word once.

Can we do better?

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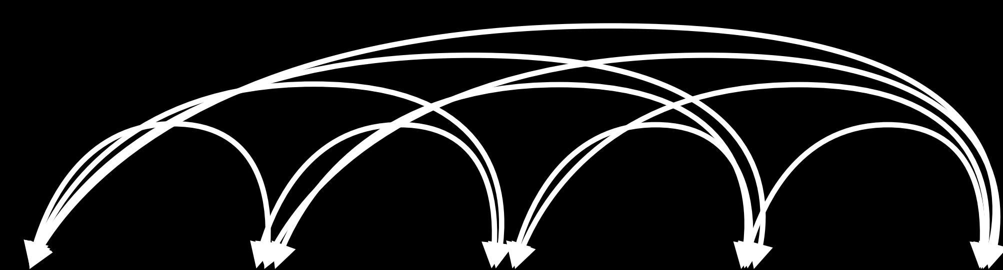


London Paris NY Tokyo .

Each arc weighted by
translation probability +
bigram probability

Objective: find shortest path that visits each word once.

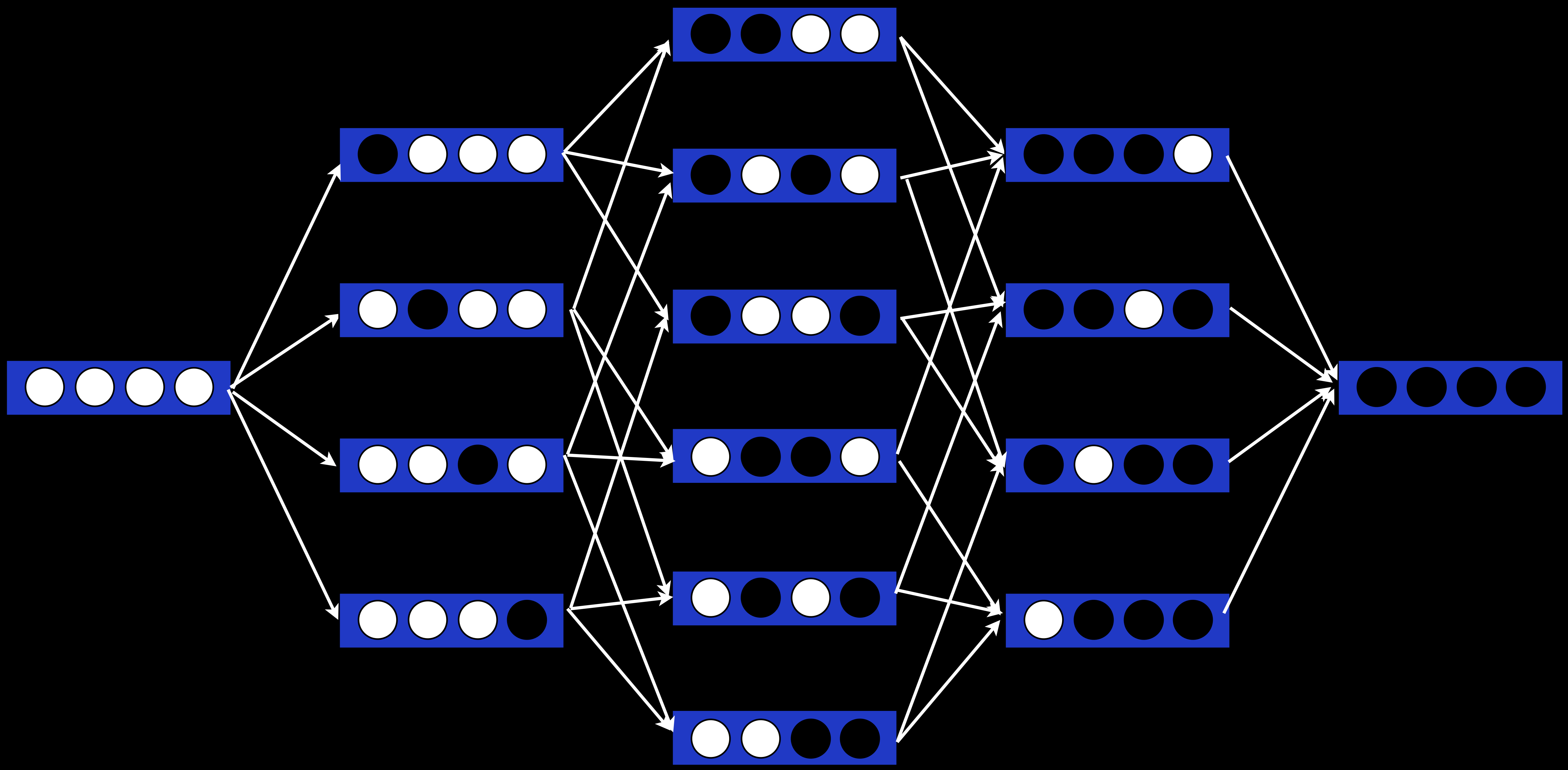
Can we do better?

Probably not: this is the traveling salesman problem.

Each arc weighted by
translation probability +
bigram probability

Objective: find shortest path that visits each word once.

Approximation: Pruning



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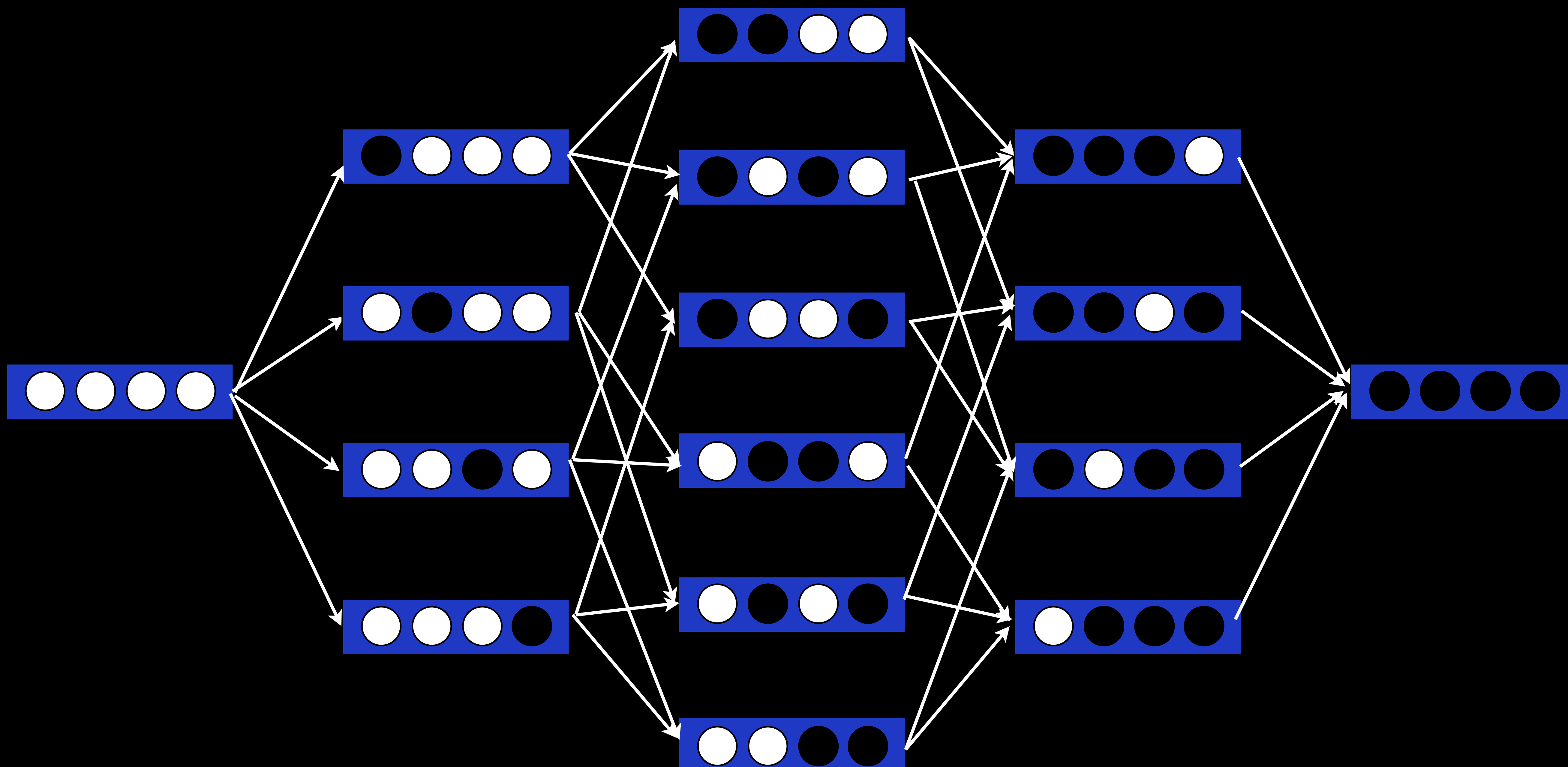
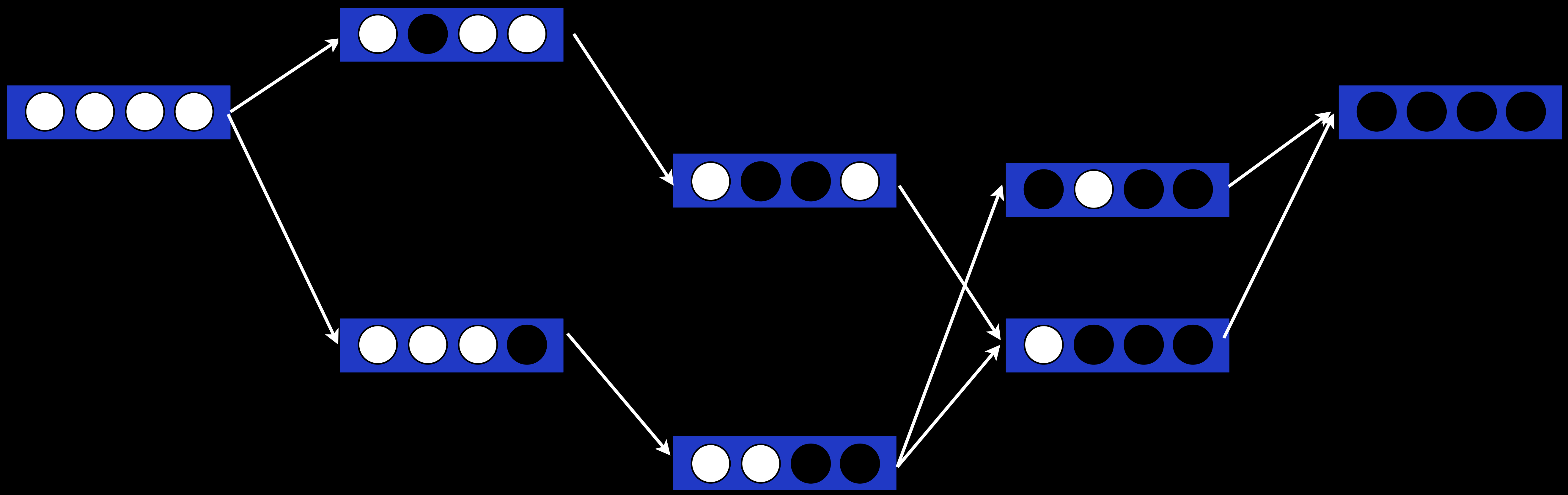


Idea: prune states by accumulated path length

Approximation: Pruning



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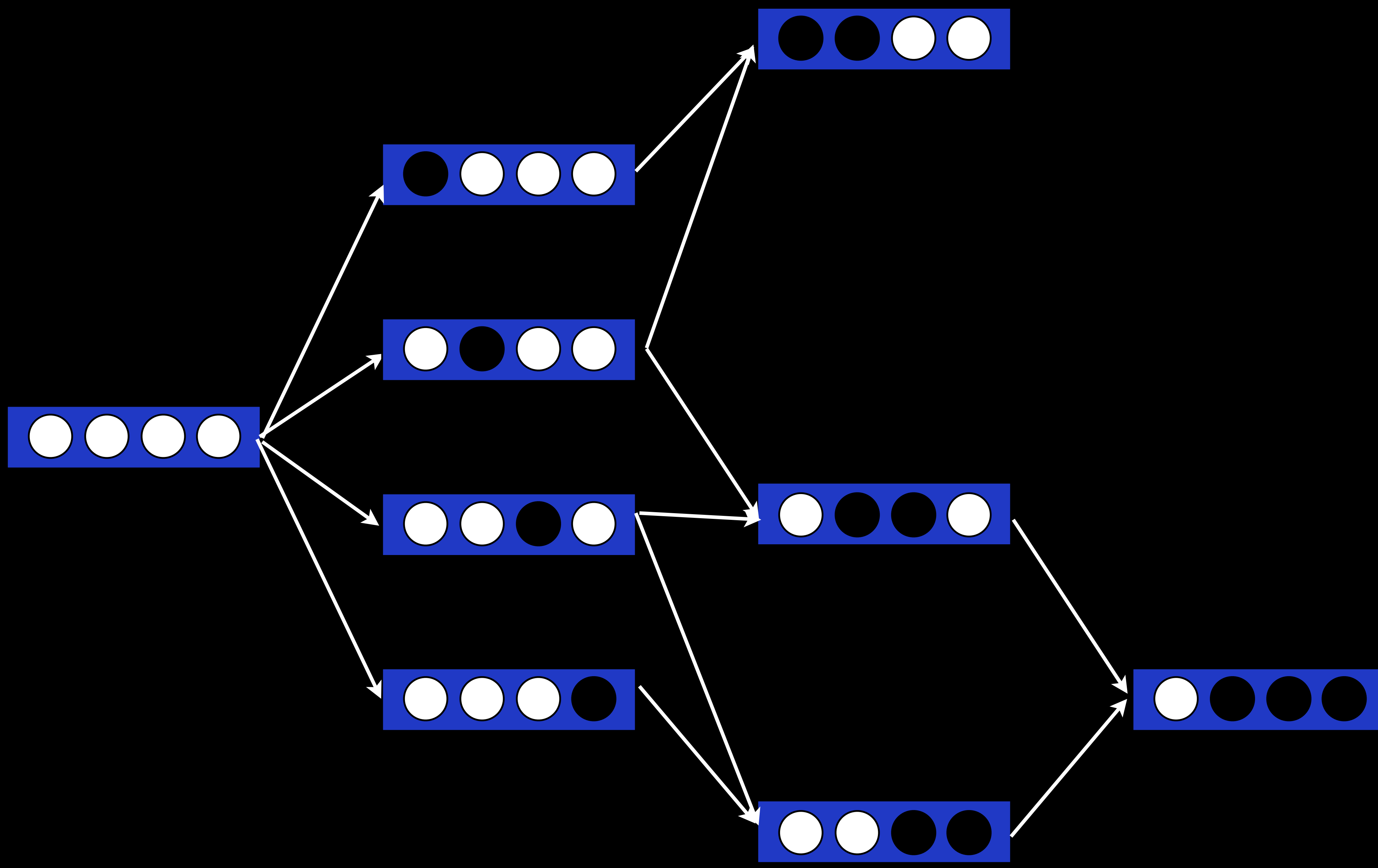

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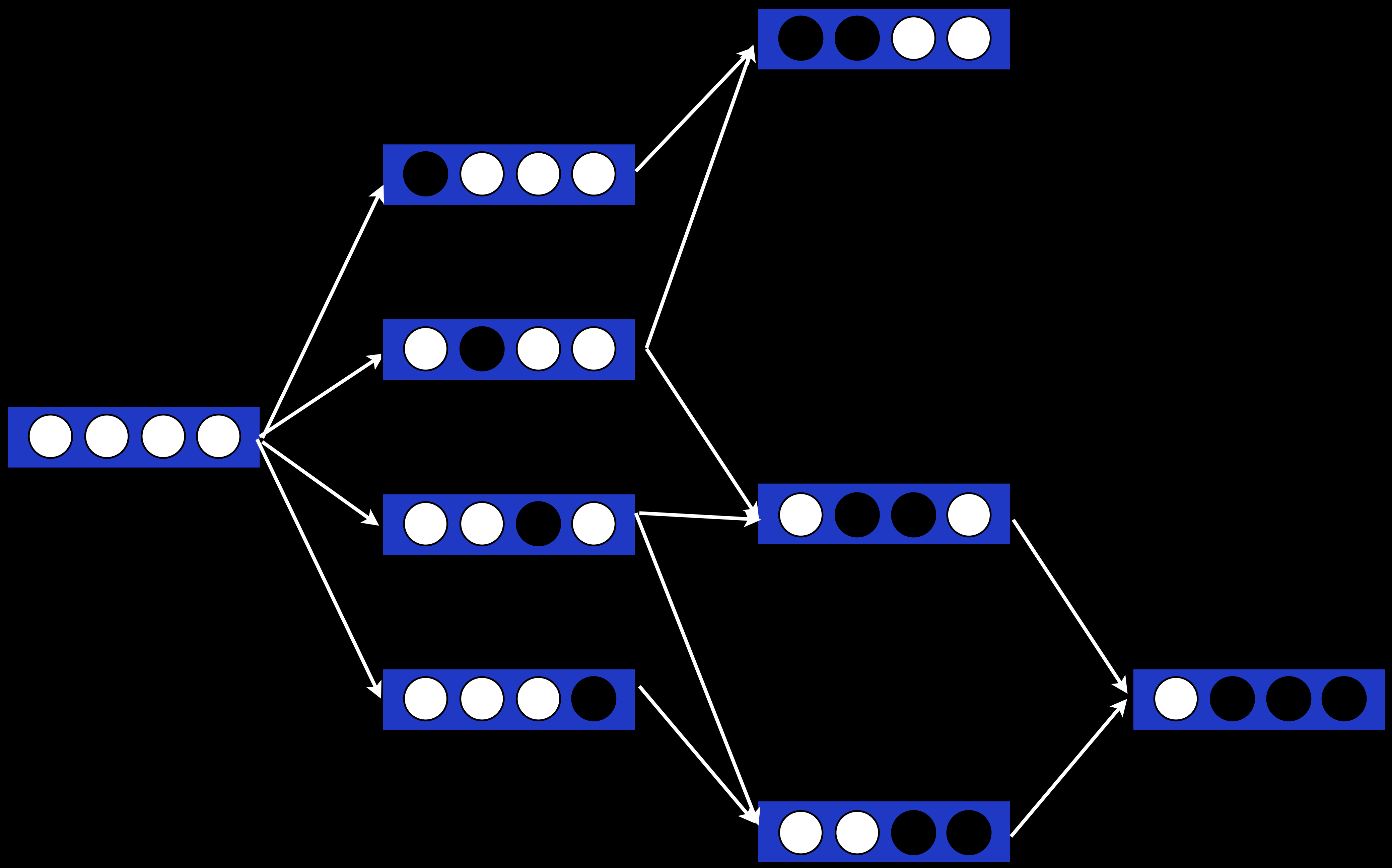
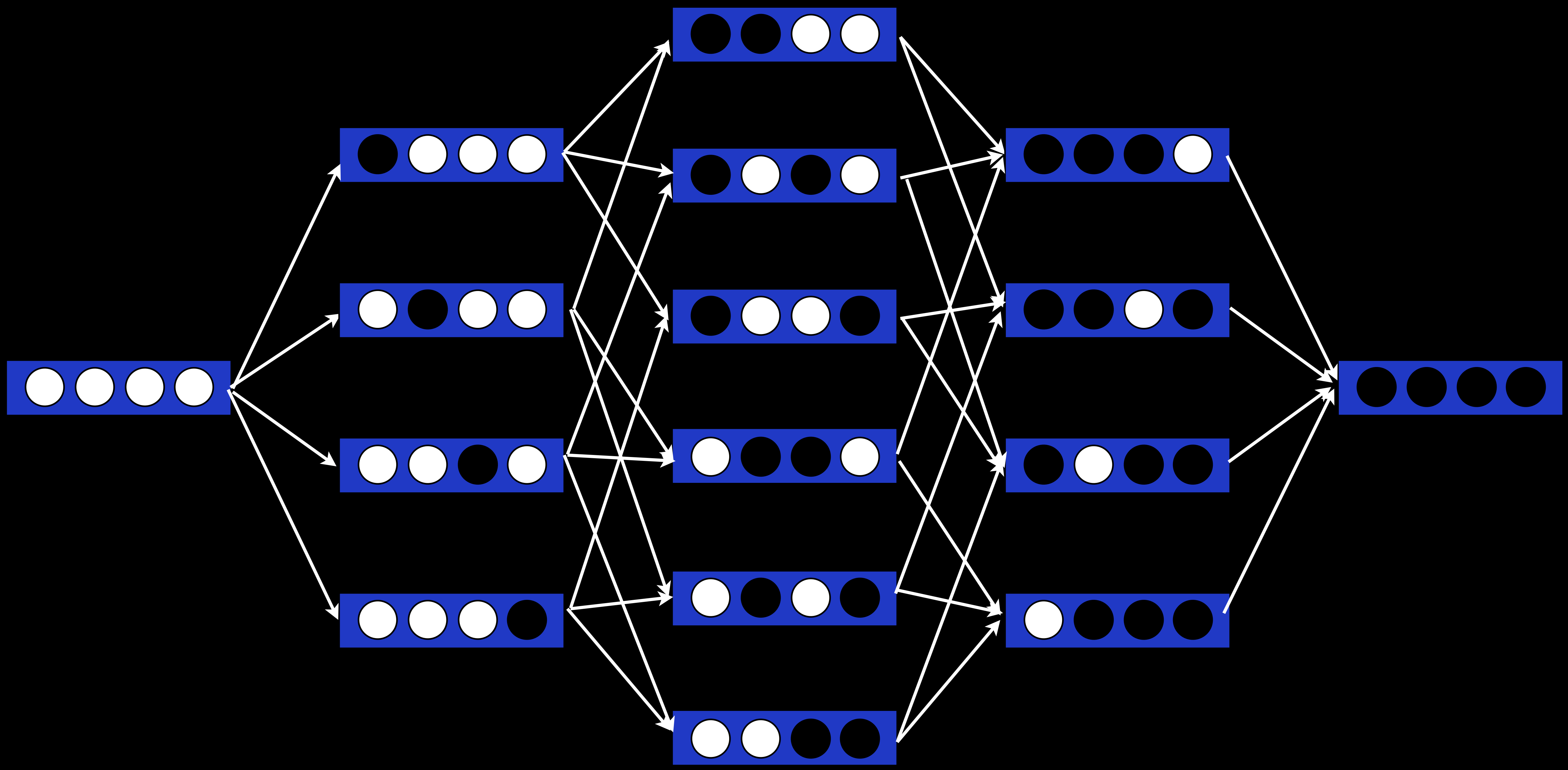


Reality: longer paths have lower probability!

Approximation: Pruning



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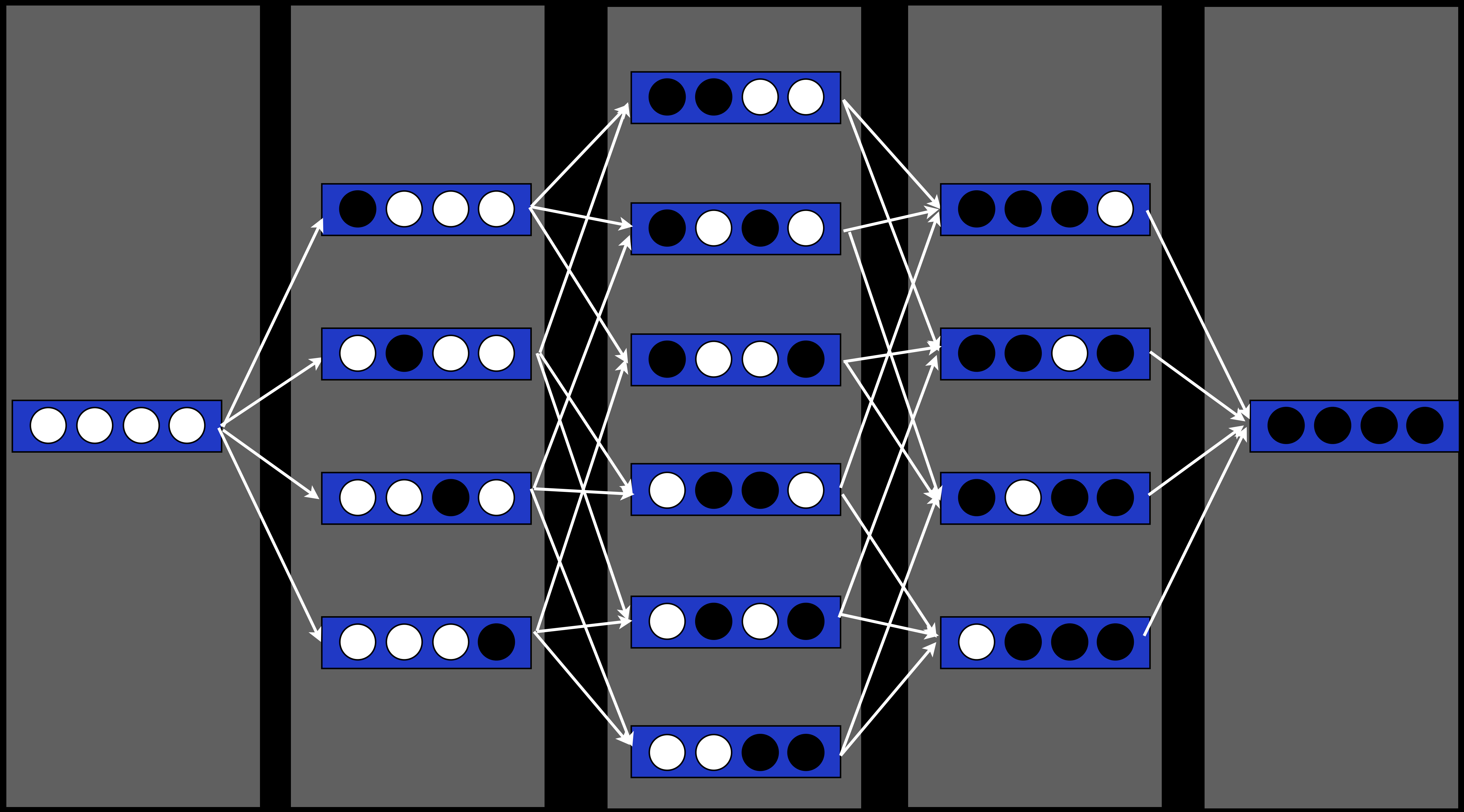

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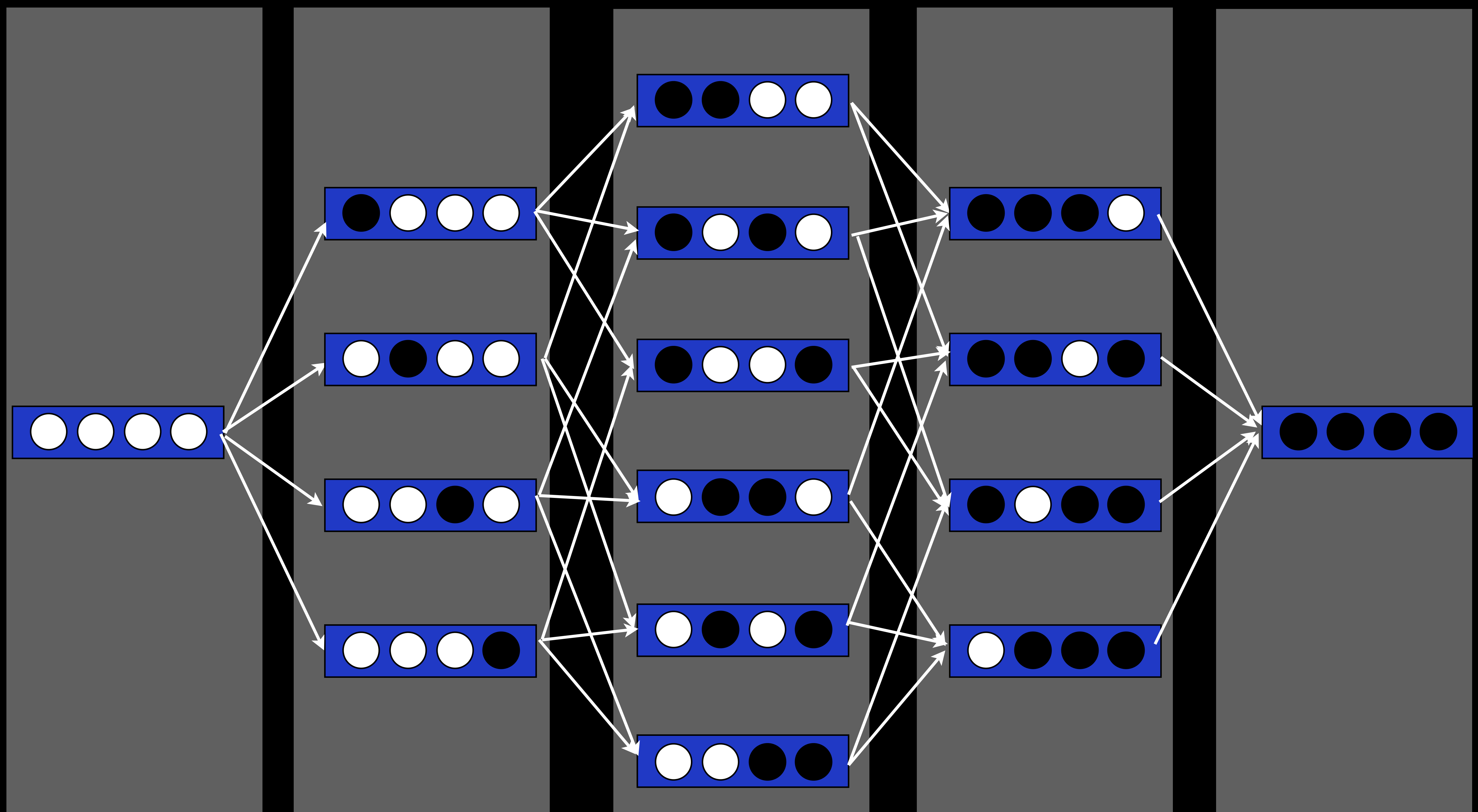
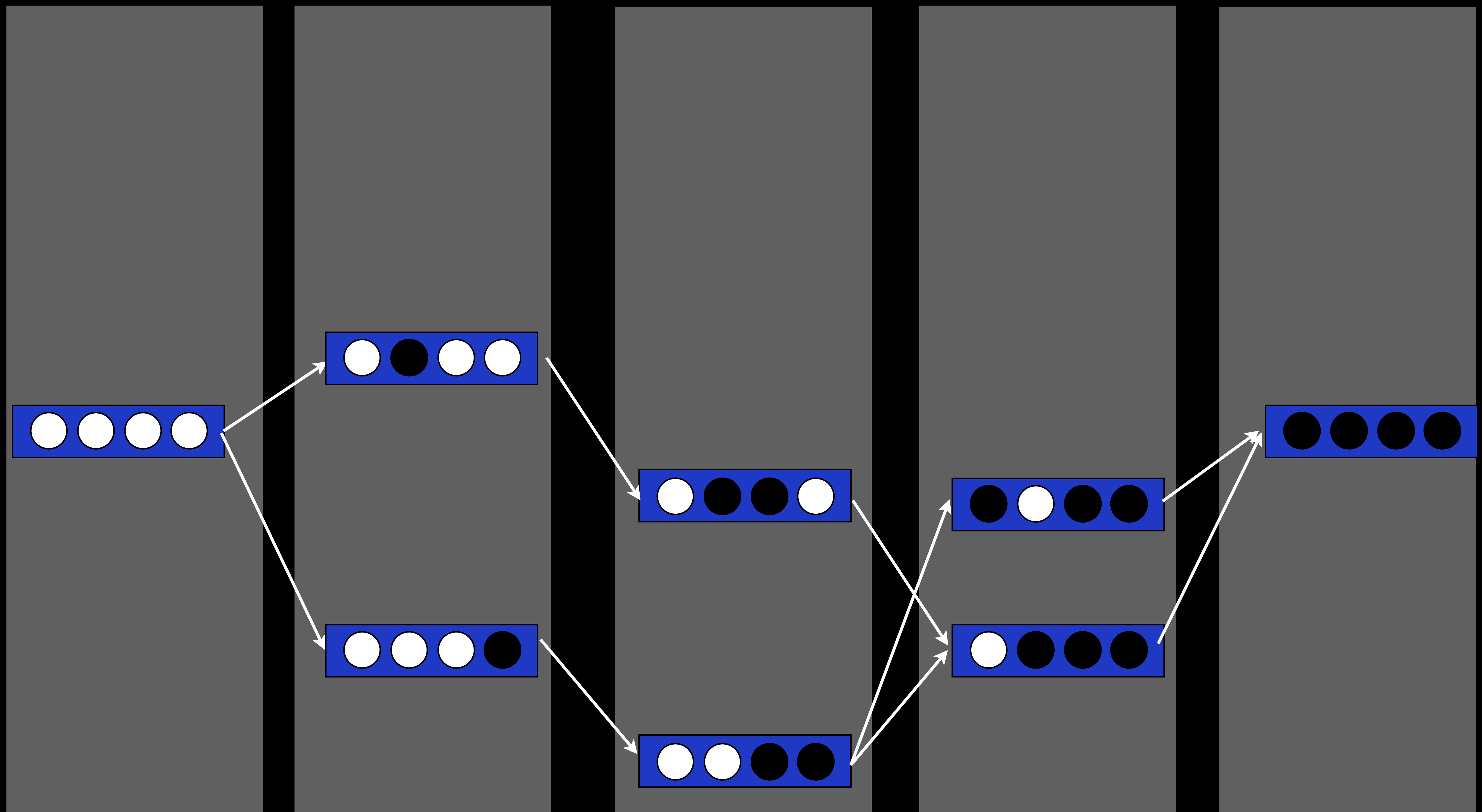


Solution: Group states by number of covered words.

Approximation: Pruning



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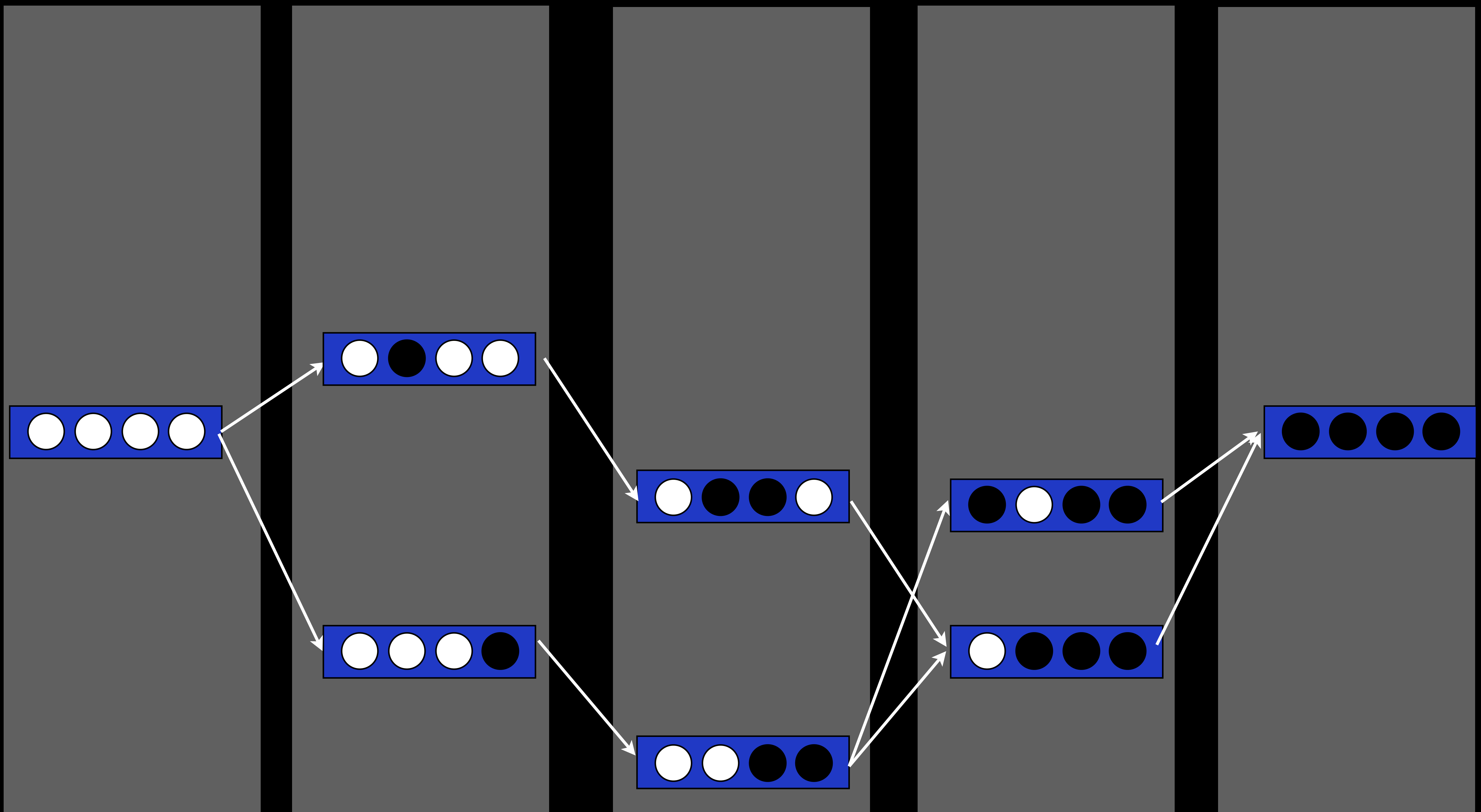

“Stack” decoding: a linear-time approximation

Approximation: Distortion Limits

the sky

虽然 北 风 呼啸 , 但 天空 依然 十分 清澈 。

Approximation: Distortion Limits

number of vertices: $O(2^n)$

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$d = 4$

window

Approximation: Distortion Limits

number of vertices: $O(2^n)$

the sky

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outside window
to left: covered

$d = 4$

window

outside window
to right: uncovered

Approximation: Distortion Limits

number of vertices: $O(n2^d)$

the sky

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- We need every possible trick to make decoding fast.
- Dynamic programming: greatly reduces complexity of exact search, but still too slow.
- NP-Completeness means exact solutions unlikely.
- Common approximations: stack decoding, distortion limits
- But, these approximations have a cost: we may not find the true argmax.

Modeling Translation

- Write down your model formally, e.g.

- Choose model parameters to optimize some objective, e.g.:

$$\hat{\theta} = \arg\ \max p_\theta(data)$$

- Search for translations that optimize some decision function, e.g.:

$$\mathrm{argmax}_{English}\, p(English|Chinese)$$

la empresa tiene enemigos fuertes en Europa .

Garcia and associates .
Garcia y asociados .

Carlos Garcia has three associates .
Carlos Garcia tiene tres asociados .

his associates are not strong .
sus asociados no son fuertes .

Garcia has a company also .
Garcia tambien tiene una empresa .

its clients are angry .
sus clientes estan enfadados .

the associates are also angry .
los asociados tambien estan enfadados .

the clients and the associates are enemies .
los clientes y los asociados son enemigos .

the company has three groups .
la empresa tiene tres grupos .

its groups are in Europe .
sus grupos estan en Europa .

the modern groups sell strong pharmaceuticals .
los grupos modernos venden medicinas fuertes .

the groups do not sell zanzanine .
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Restriction to linguistic phrases seems to hurt (Koehn et al. 2003)

Phrase-based Models

Although north wind howls , but sky still very clear .

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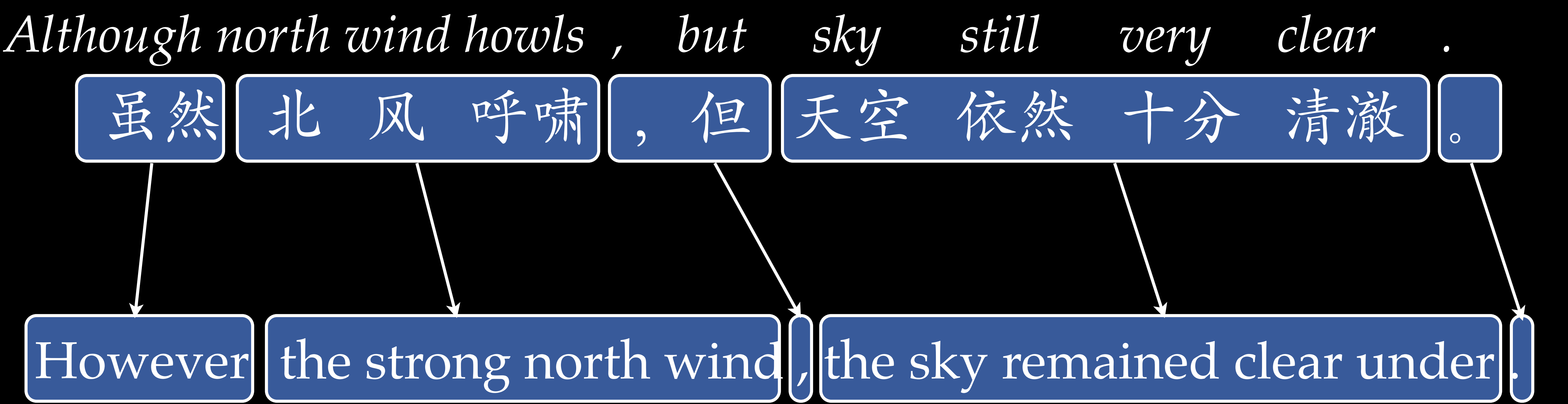
Phrase-based Models

Although north wind howls , but sky still very clear .

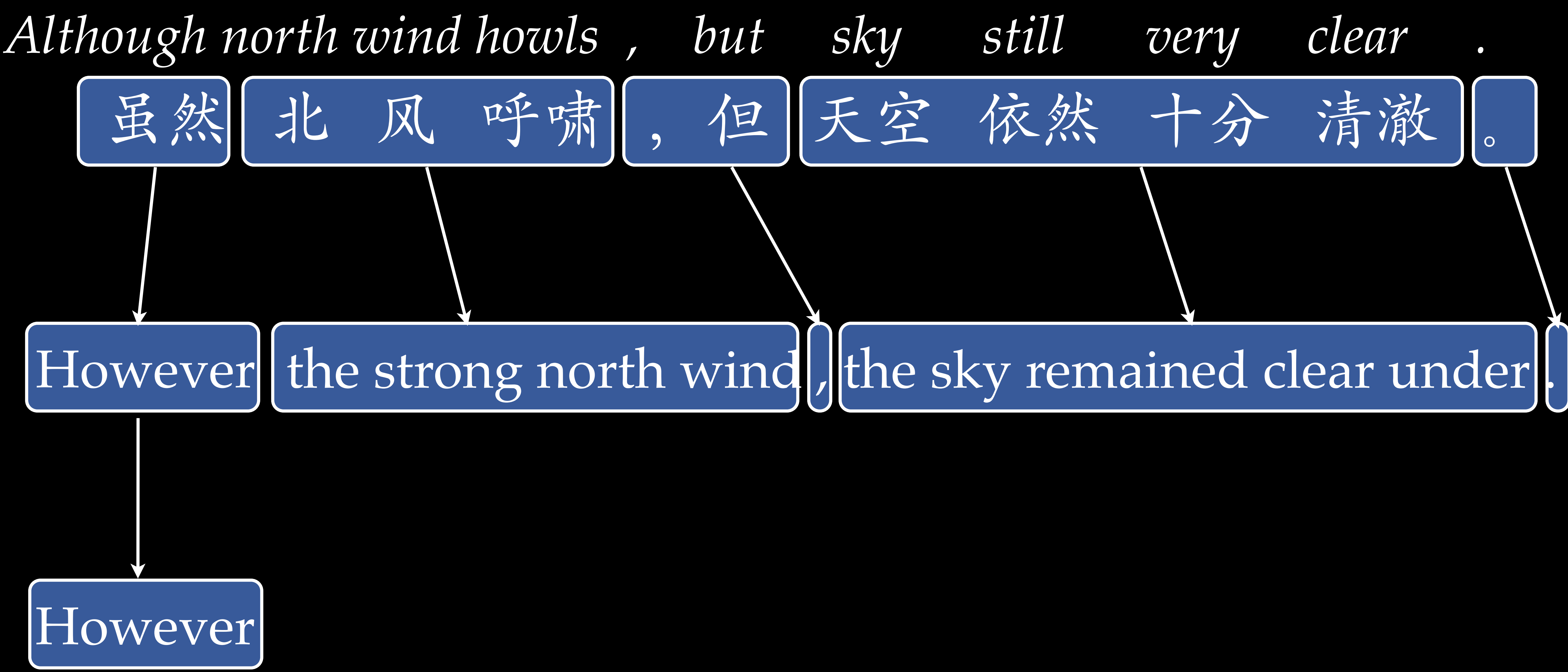
虽然 | 北 风 呼啸 | ，但 | 天空 依然 十分 清澈 | 。

However

Phrase-based Models



Phrase-based Models



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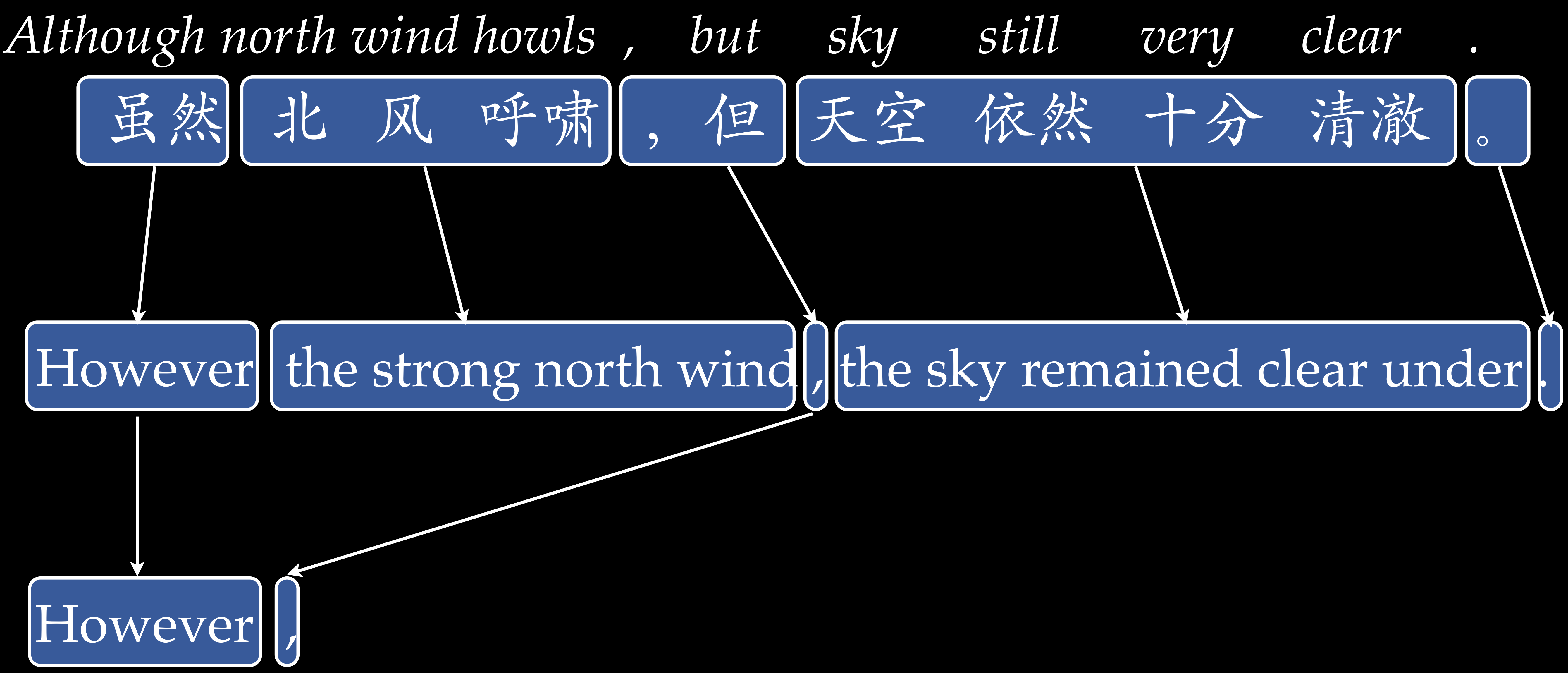

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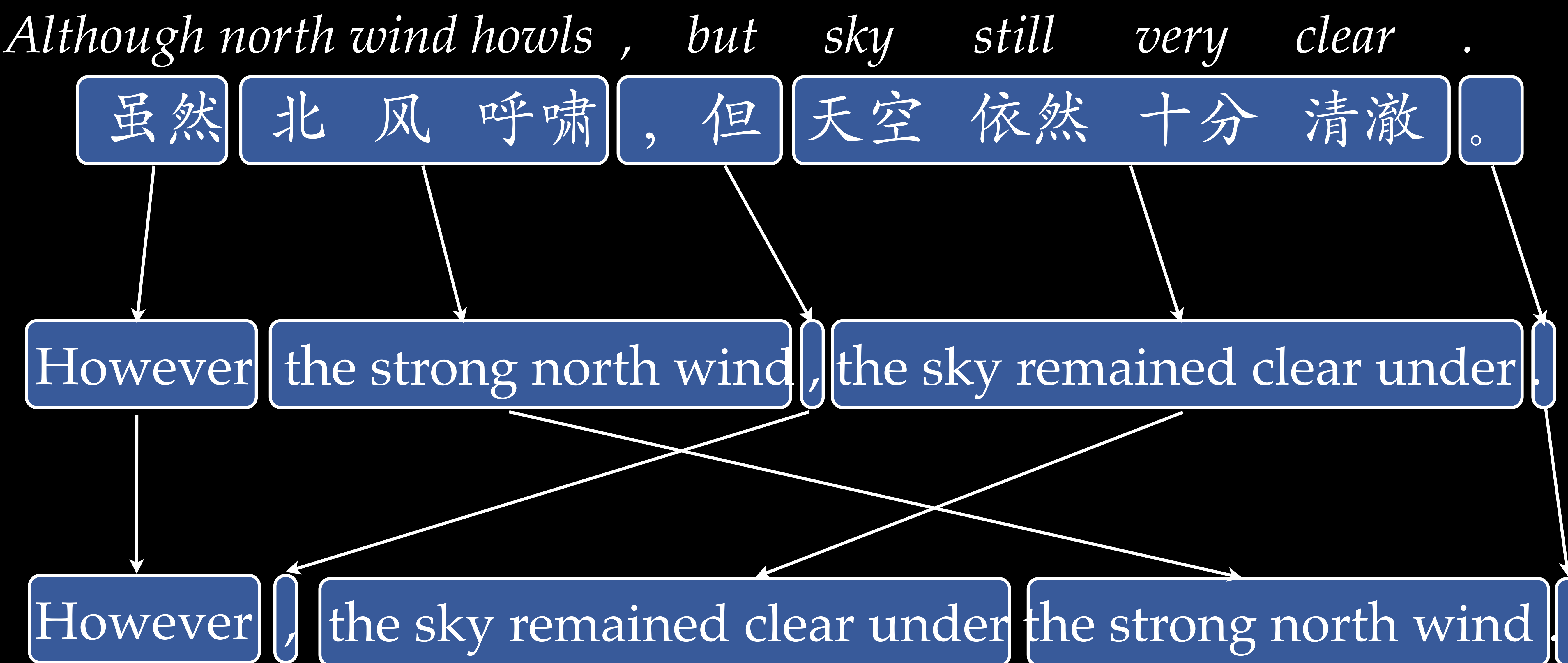

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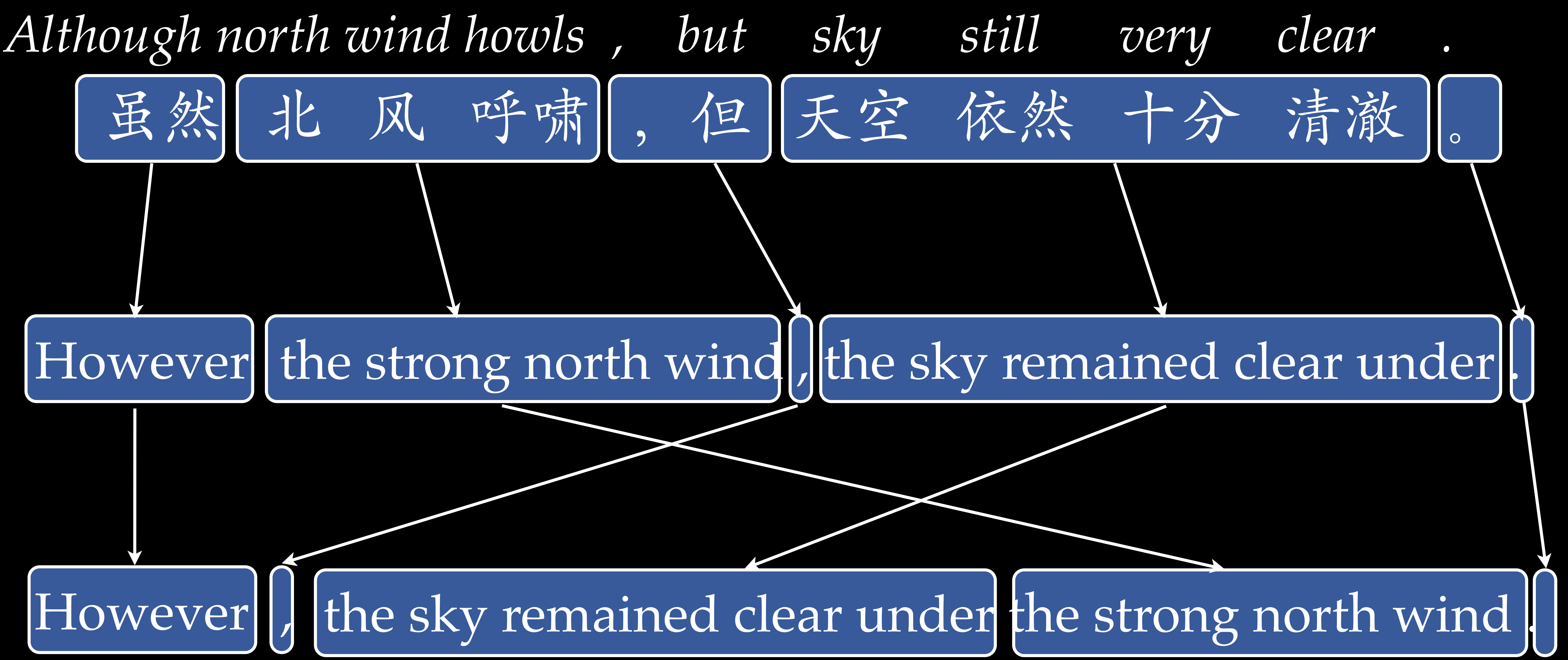

$$p(English, alignment|Chinese) =$$

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

Phrase-based Models

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- Segmentation probabilities.

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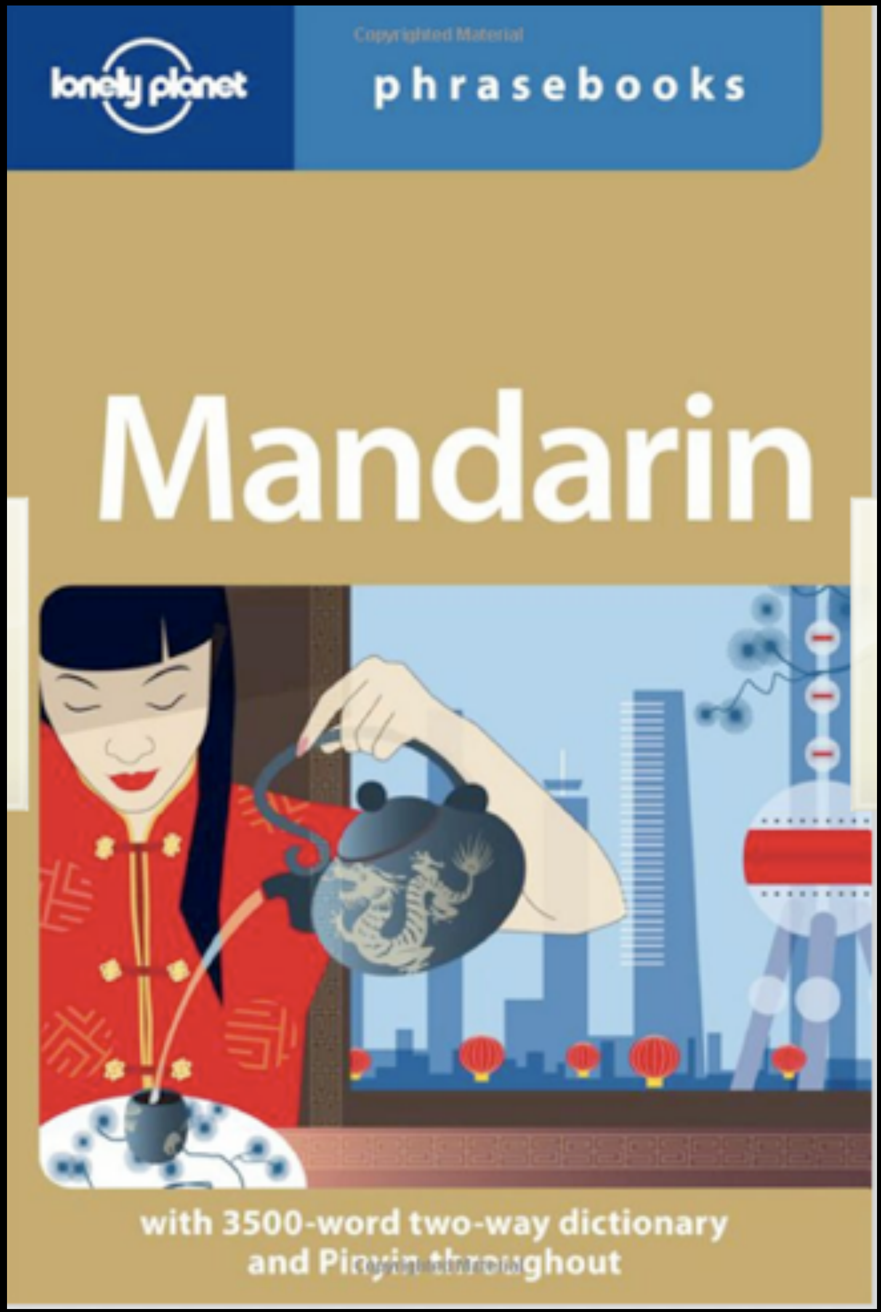

Phrase-based Models

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

Learning

- 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.

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- 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)

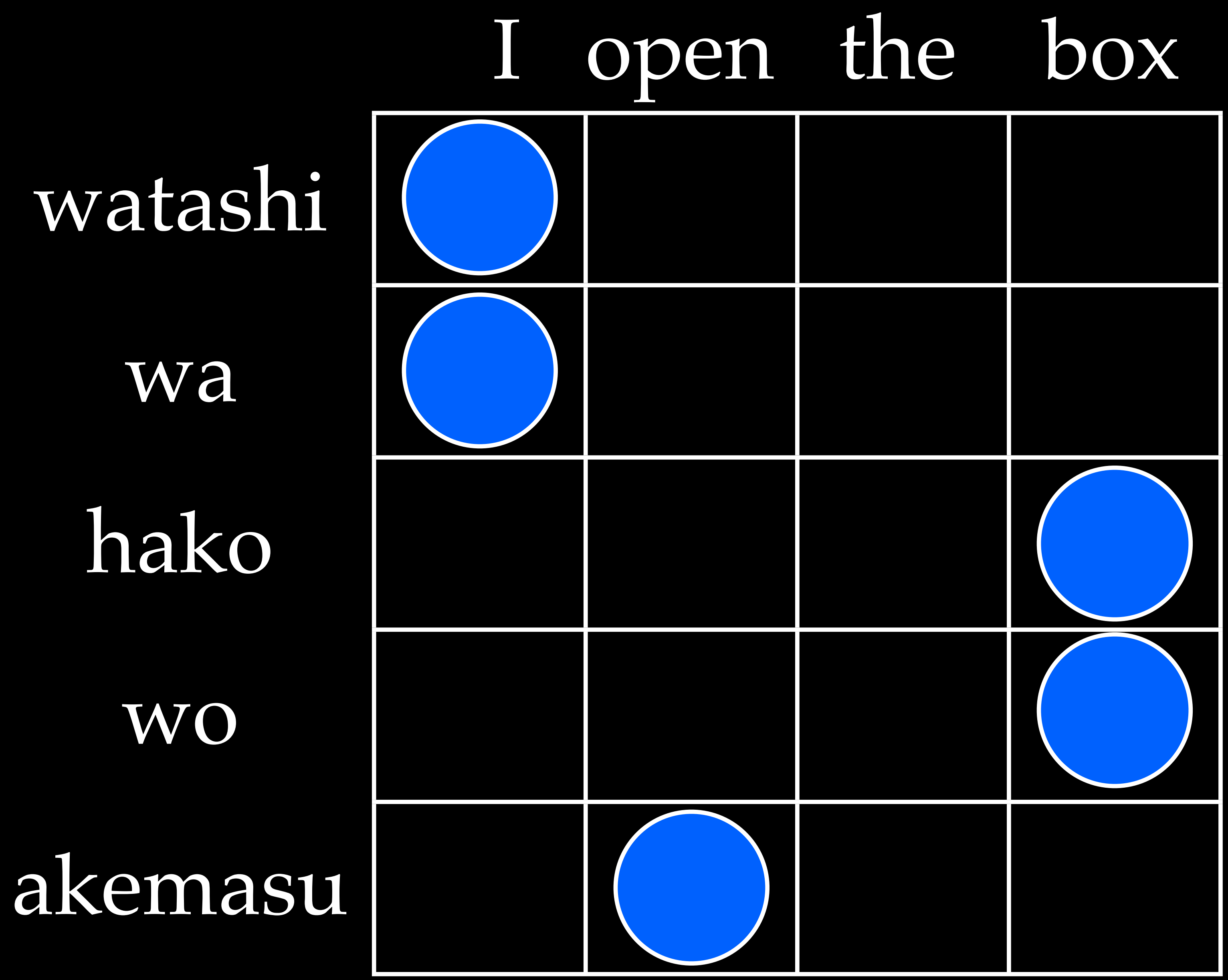
Now What?

- 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



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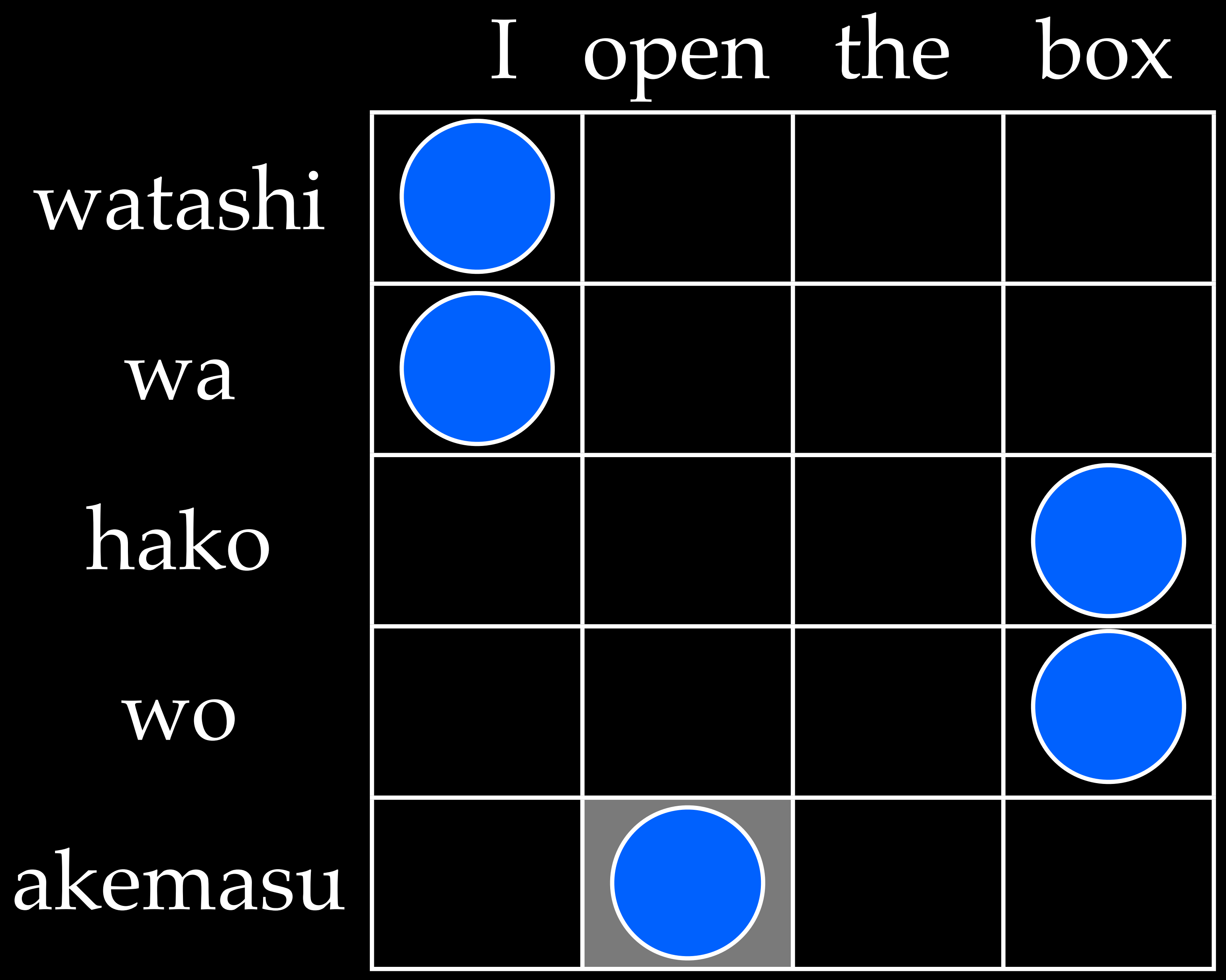
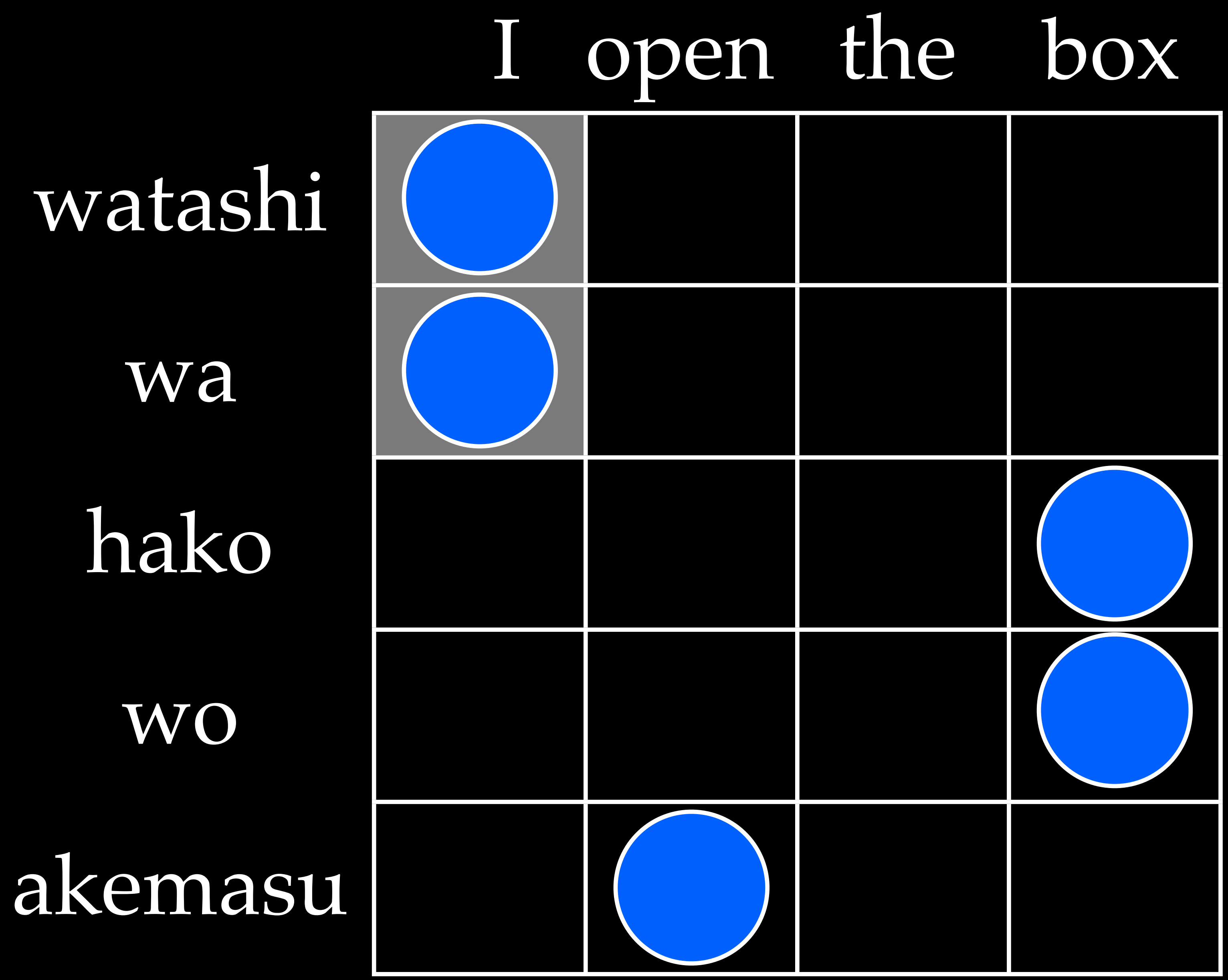


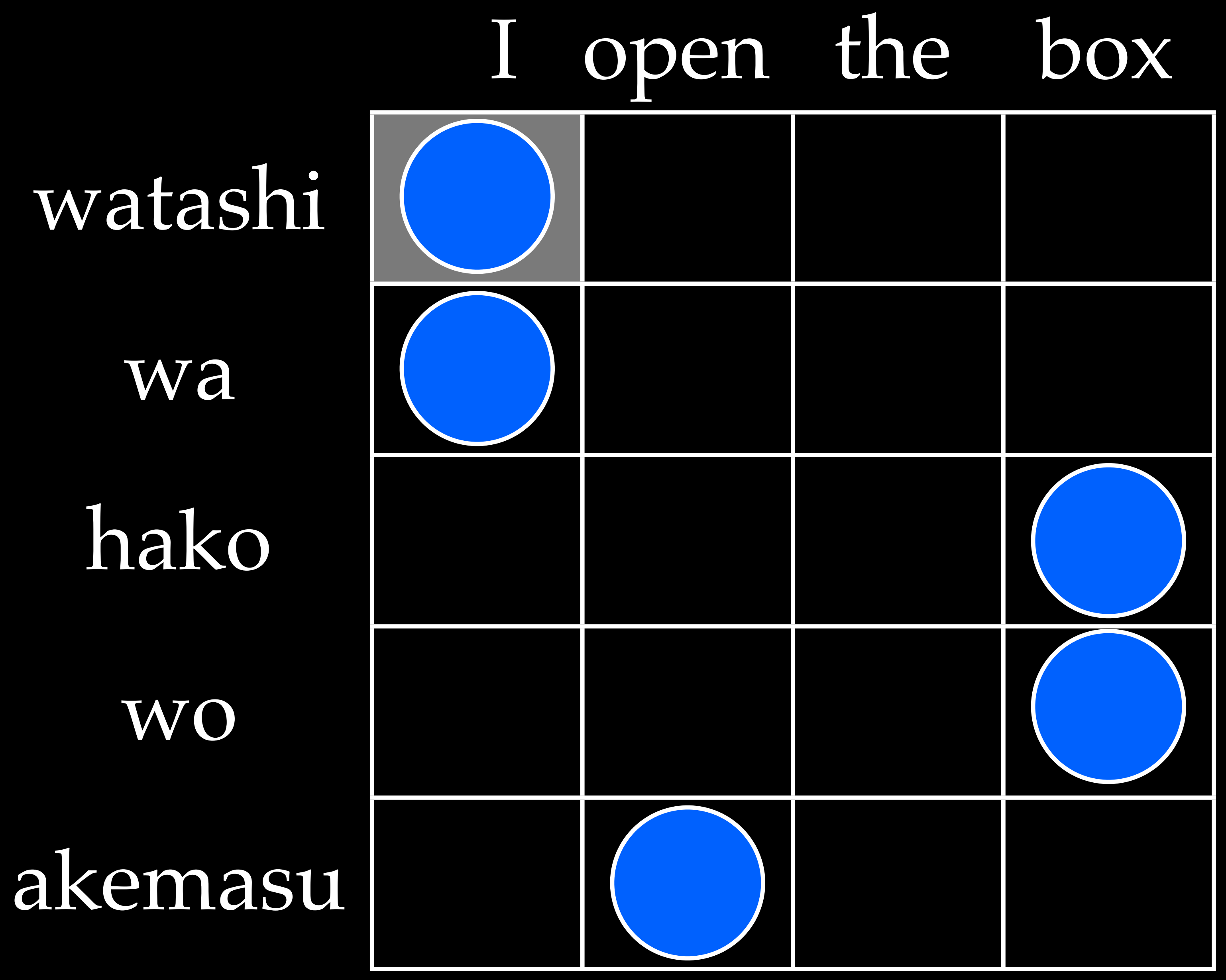
akemasu / open

Phrase Extraction



watashi wa / I

Phrase Extraction



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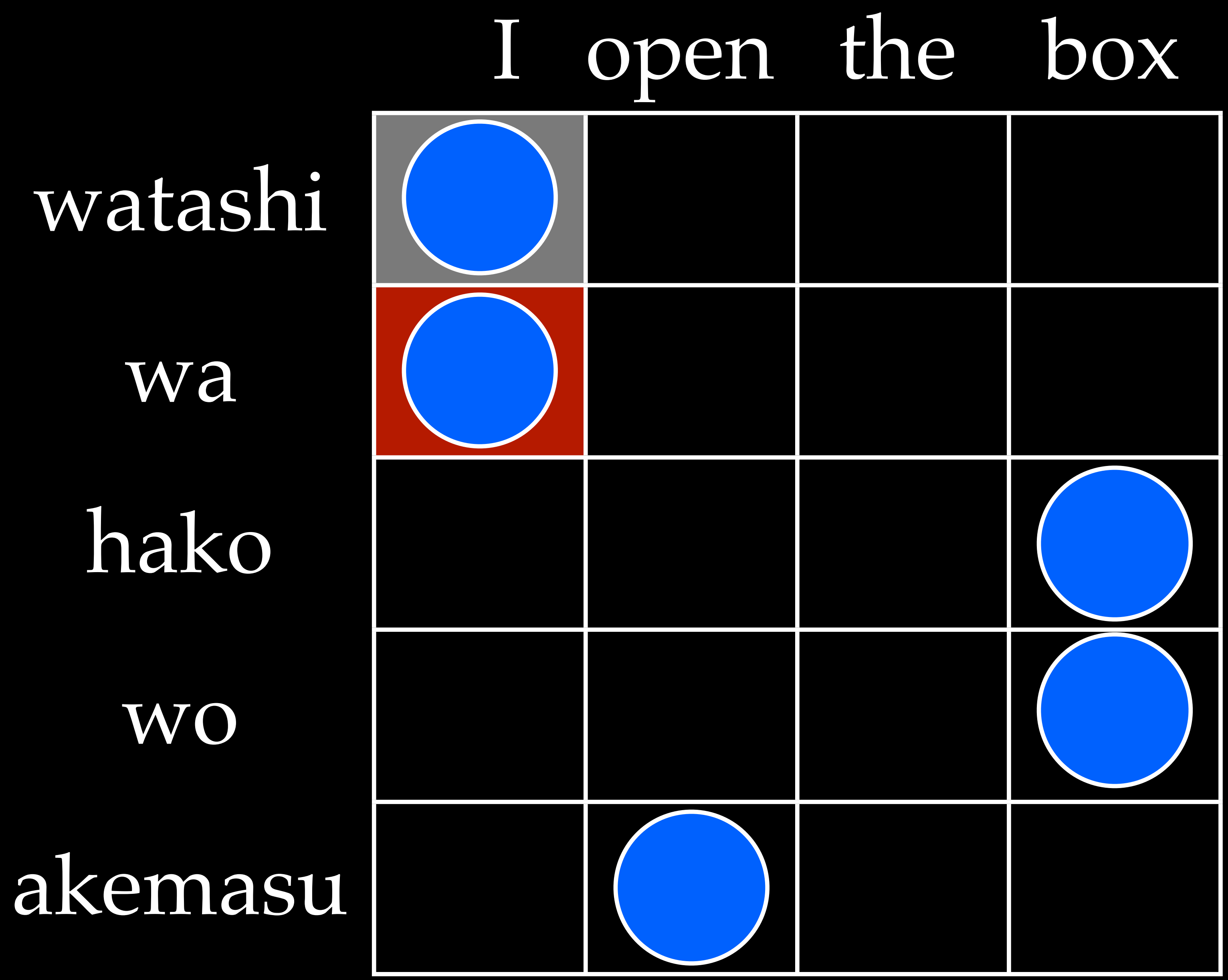

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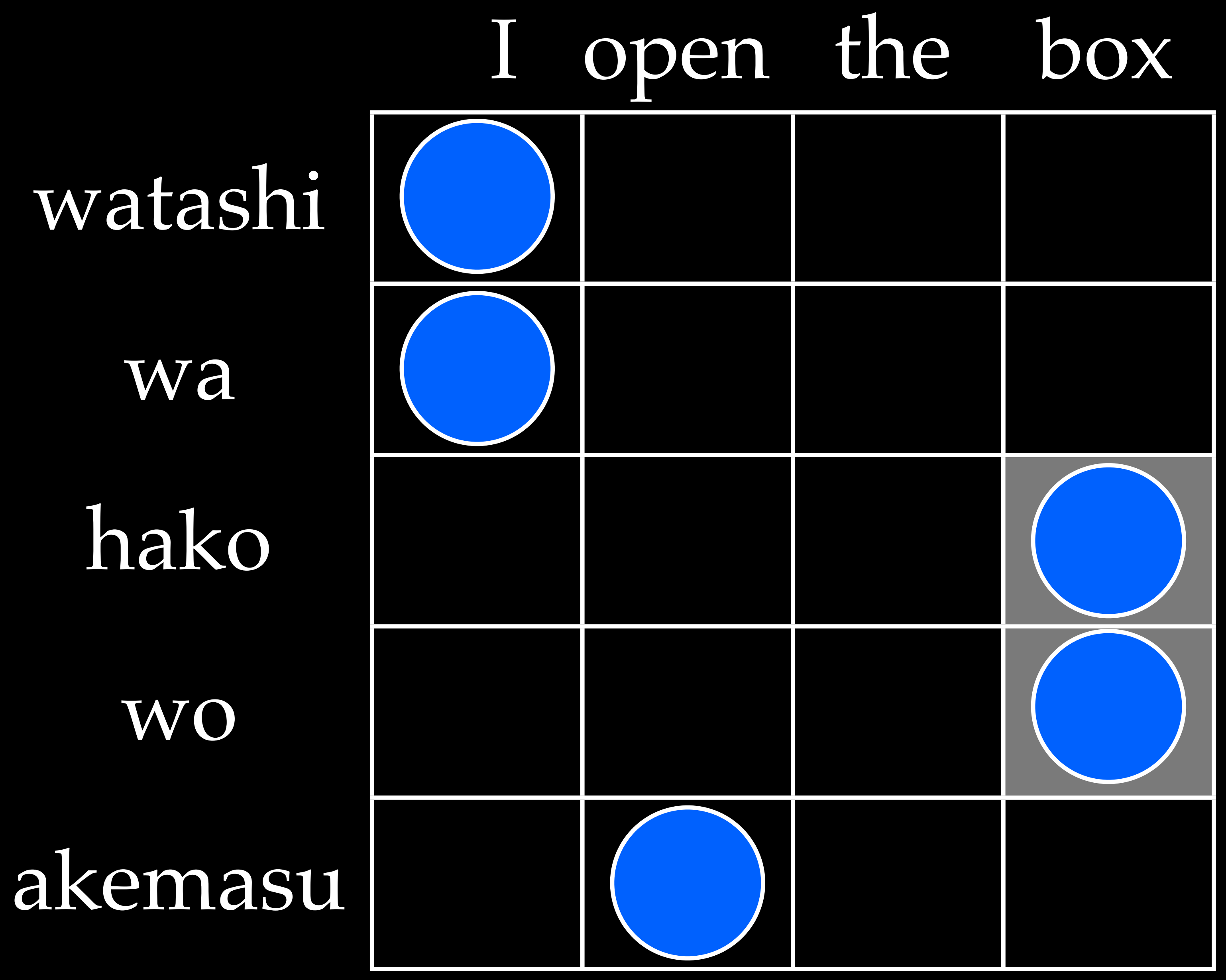

hako wo / box

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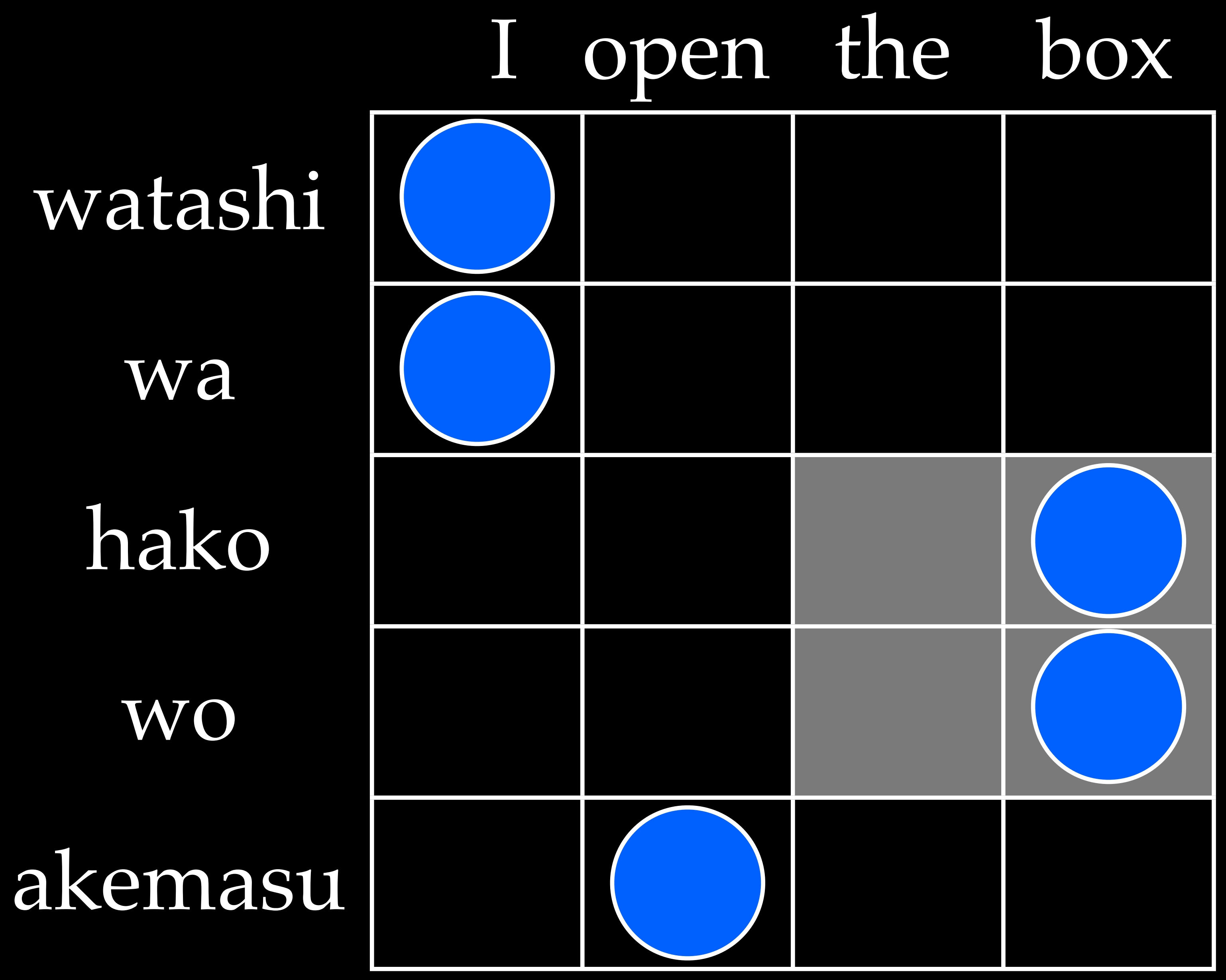

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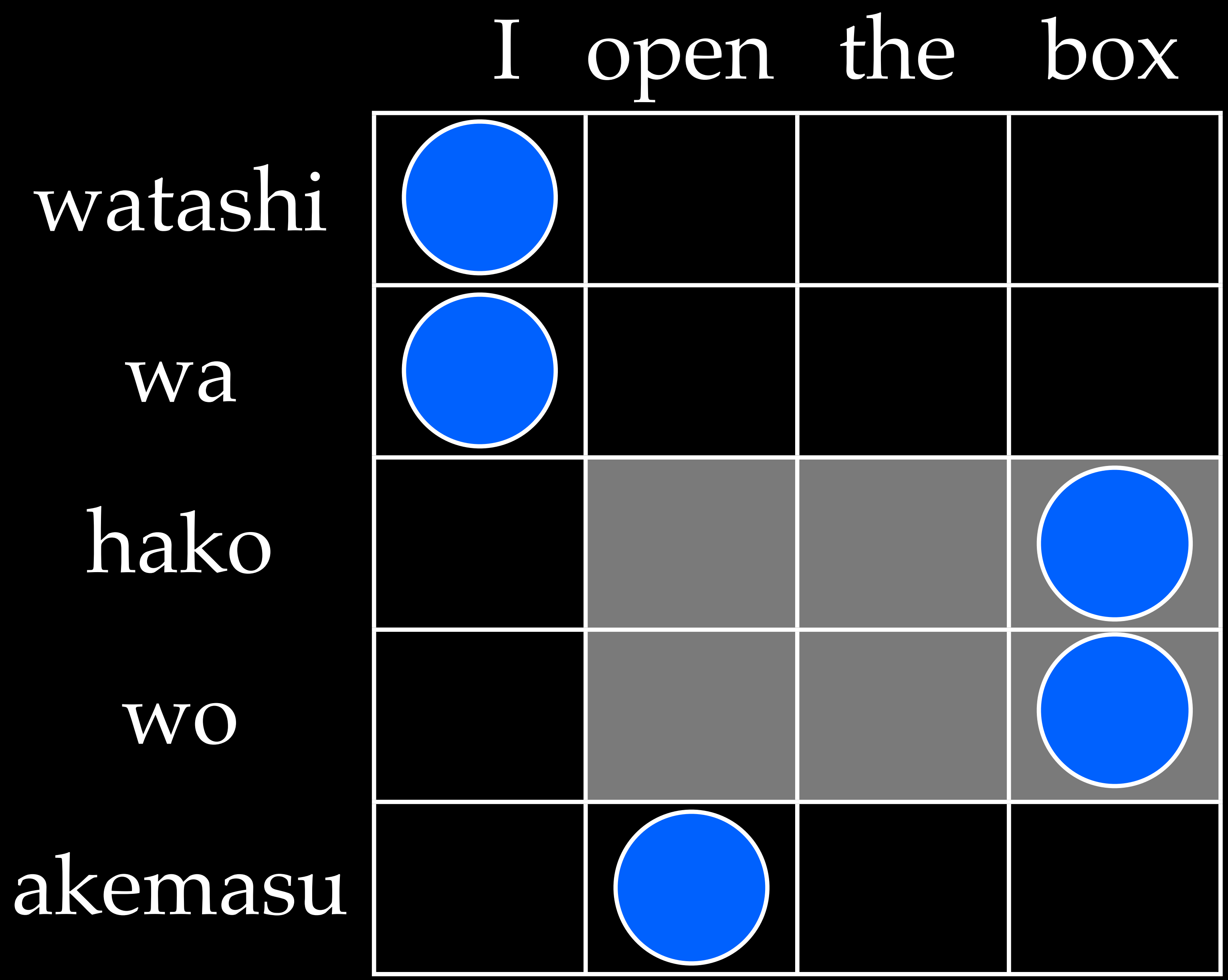

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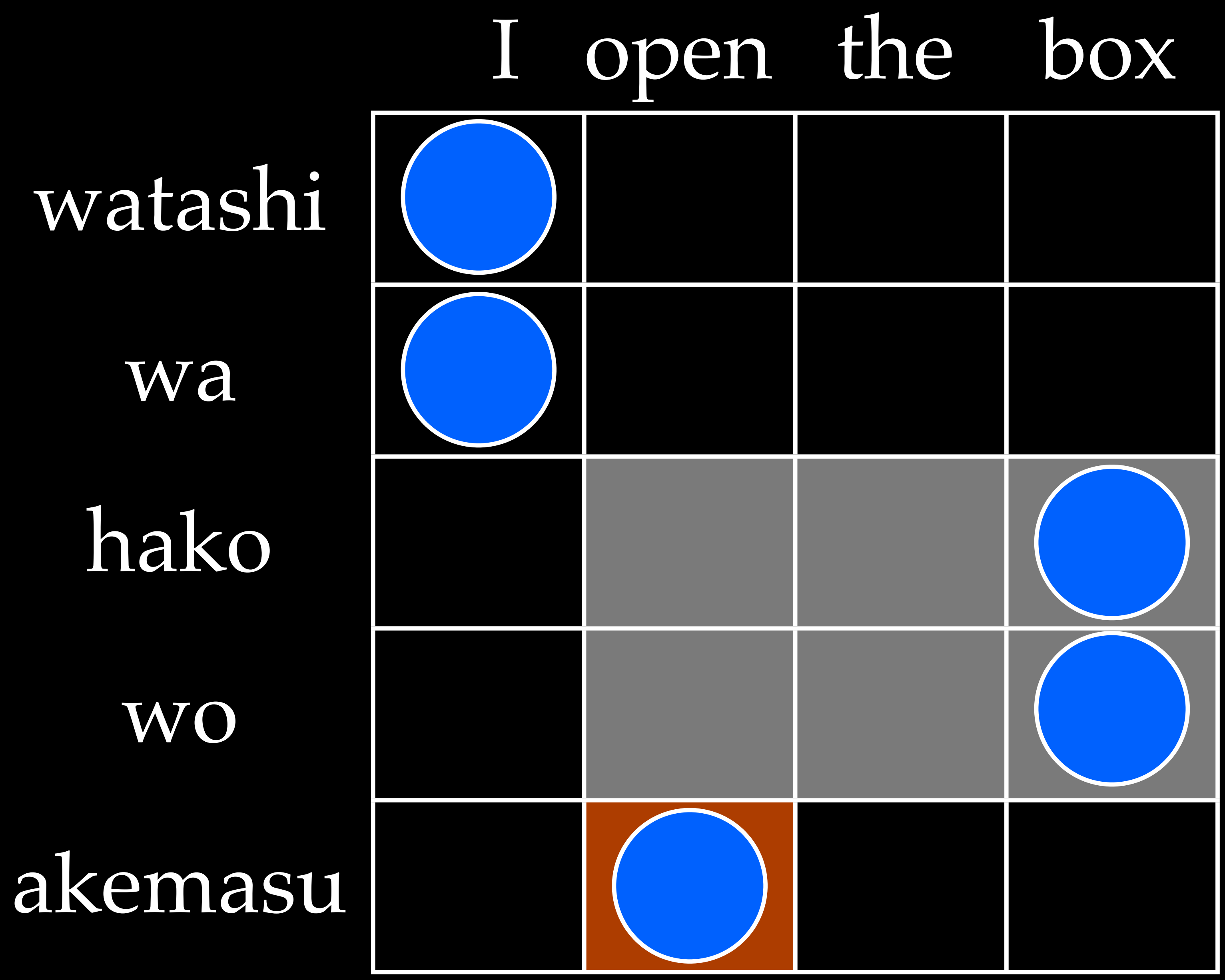

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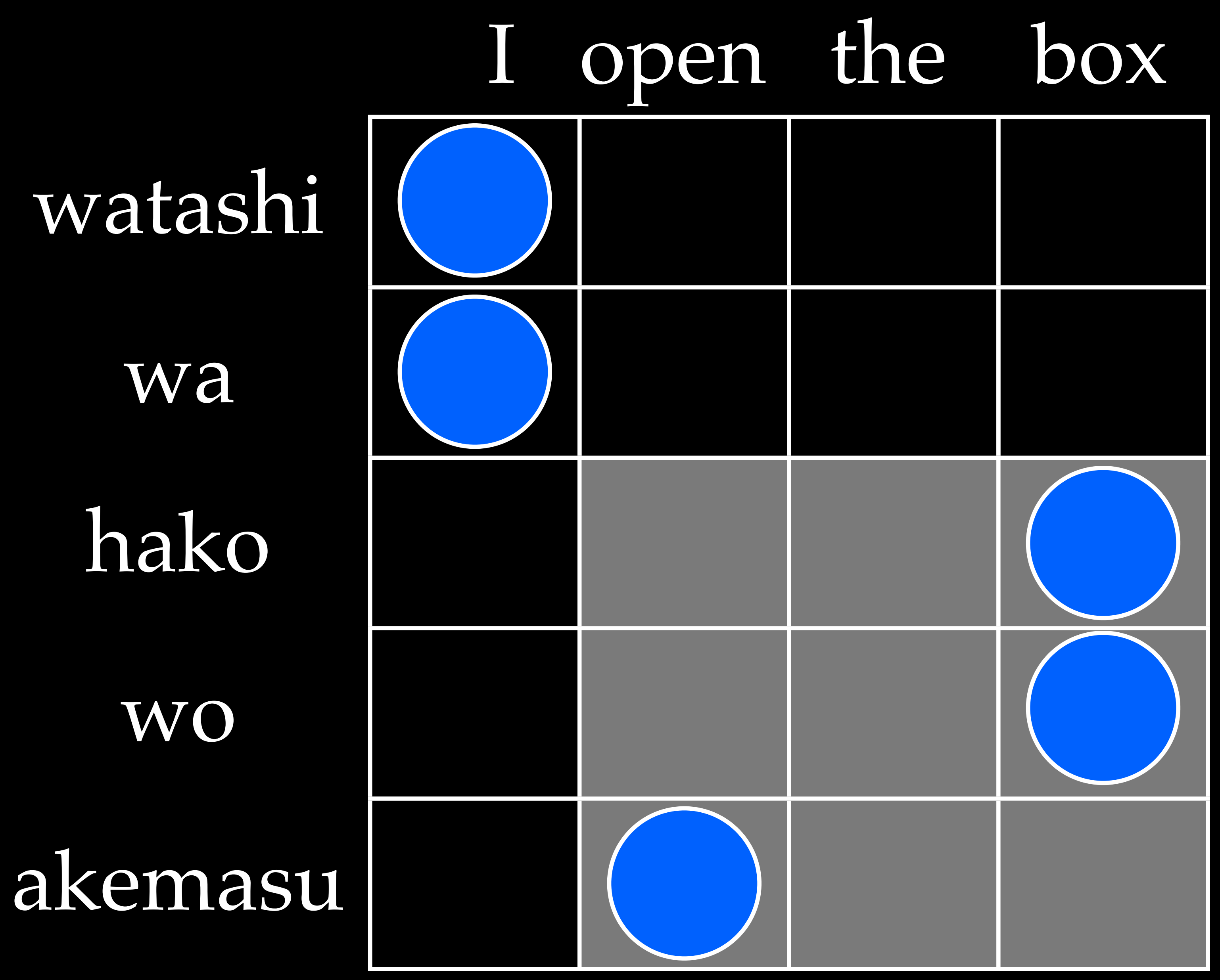

hako wo akemasu / open the box

Phrasal Translation Estimation

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- Option #1 (EM over restricted space)
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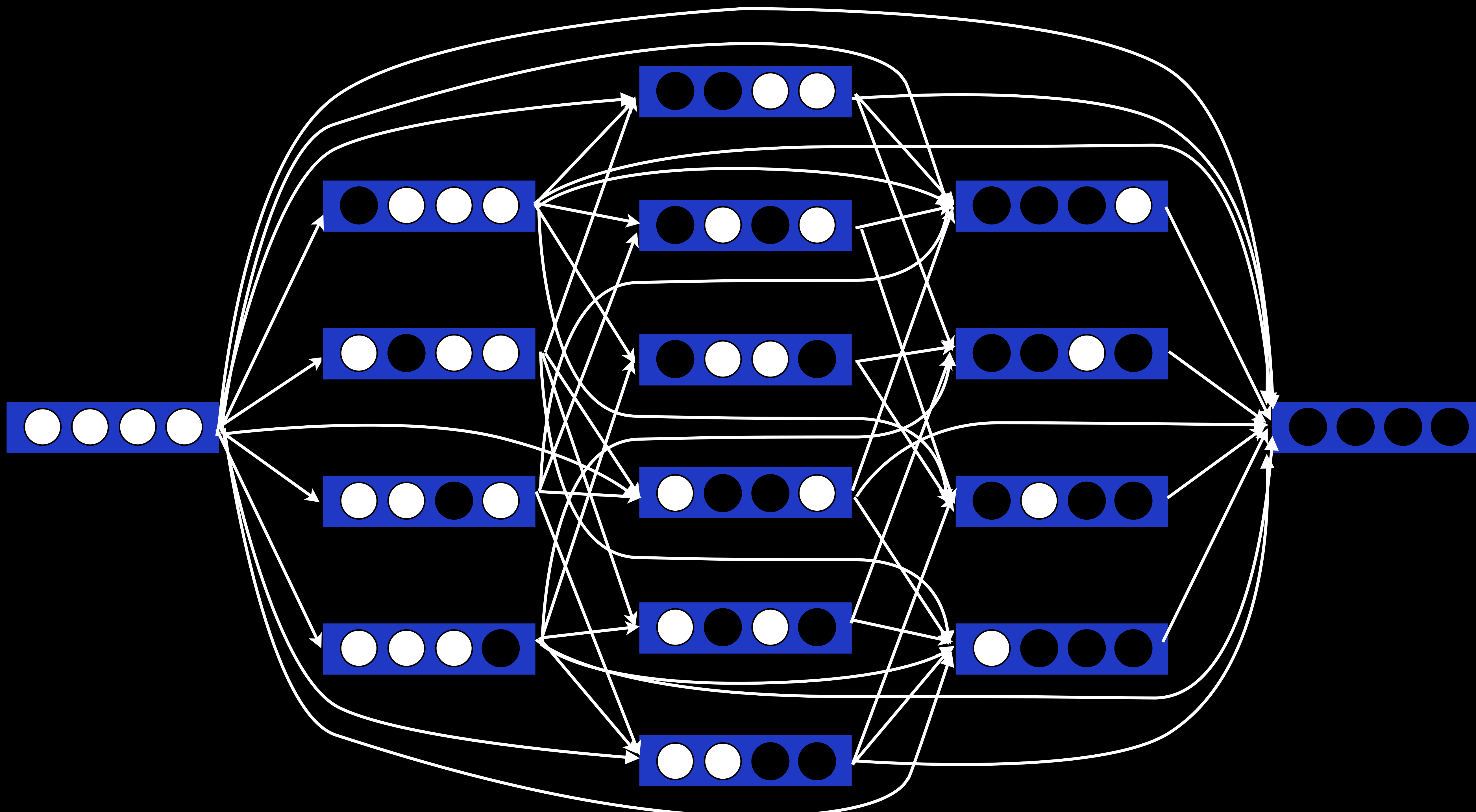
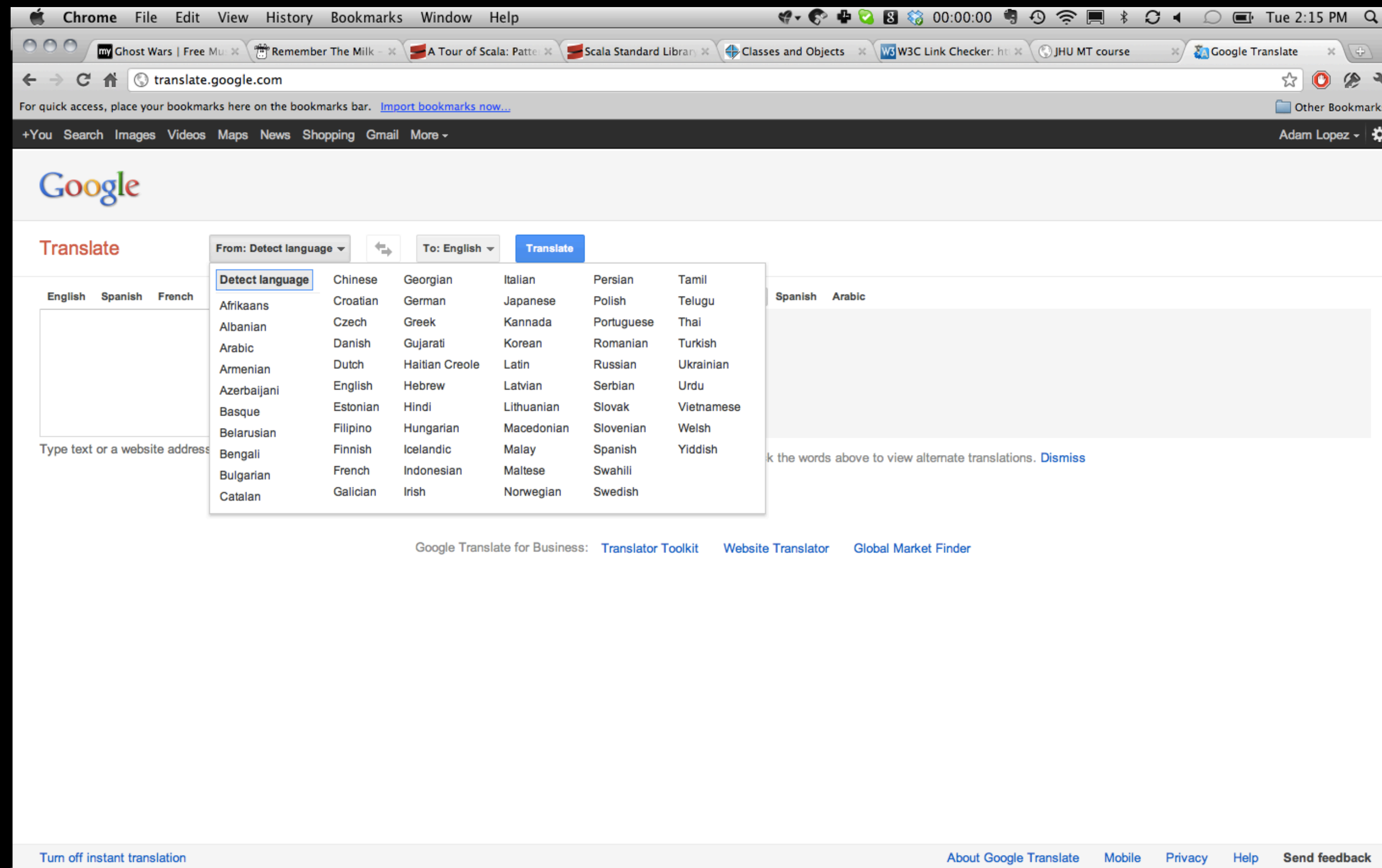
  - Compute expectations only over alignments consistent with the alignment grid.
- Option #2 (Non-global estimation)
  - View phrase pairs as observed, irrespective of context or overlap.

Search




Chrome File Edit View History Bookmarks Window Help
Tue 2:15 PM
Ghost Wars | Free Mu
Remember The Milk
A Tour of Scala: Patte
Scala Standard Librar
Classes and Objects
W3C Link Checker: ht
JHU MT course
Google Translate
translate.google.com
For quick access, place your bookmarks here on the bookmarks bar. Import bookmarks now...
Other Bookmarks
+You Search Images Videos Maps News Shopping Gmail More
Adam Lopez
Google
Translate
From: Detect language
To: English
Translate
English Spanish French
Spanish Arabic
Detect language
Afrikaans
Albanian
Arabic
Armenian
Azerbaijani
Basque
Belarusian
Bengali
Bulgarian
Catalan
Chinese
Croatian
Czech
Danish
Dutch
English
Estonian
Filipino
Finnish
French
Galician
Georgian
German
Greek
Gujarati
Haitian Creole
Hebrew
Hindi
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Icelandic
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Spanish
Swahili
Swedish
Tamil
Telugu
Thai
Turkish
Ukrainian
Urdu
Vietnamese
Welsh
Yiddish
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k the words above to view alternate translations. Dismiss
Google Translate for Business: Translator Toolkit Website Translator Global Market Finder
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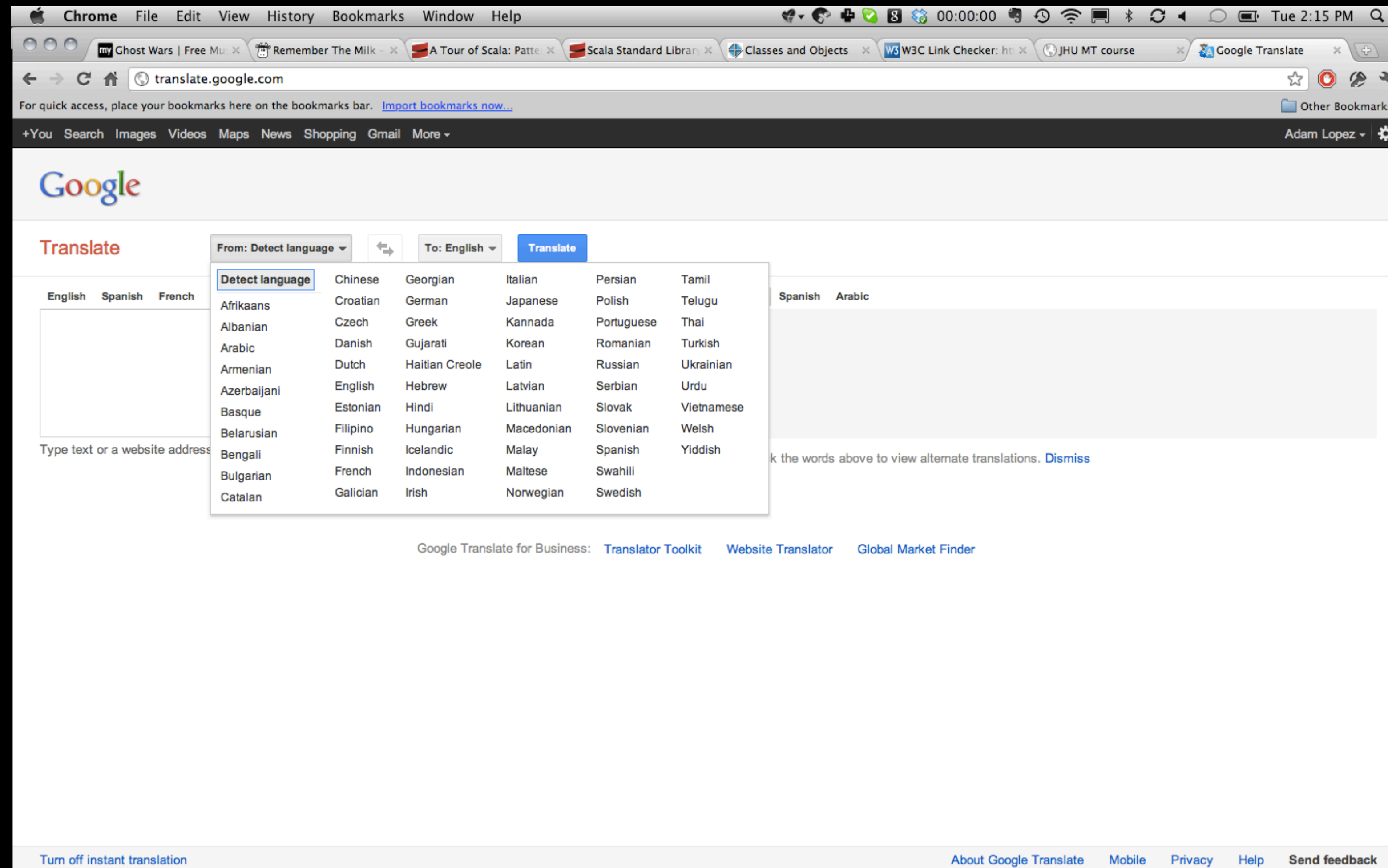
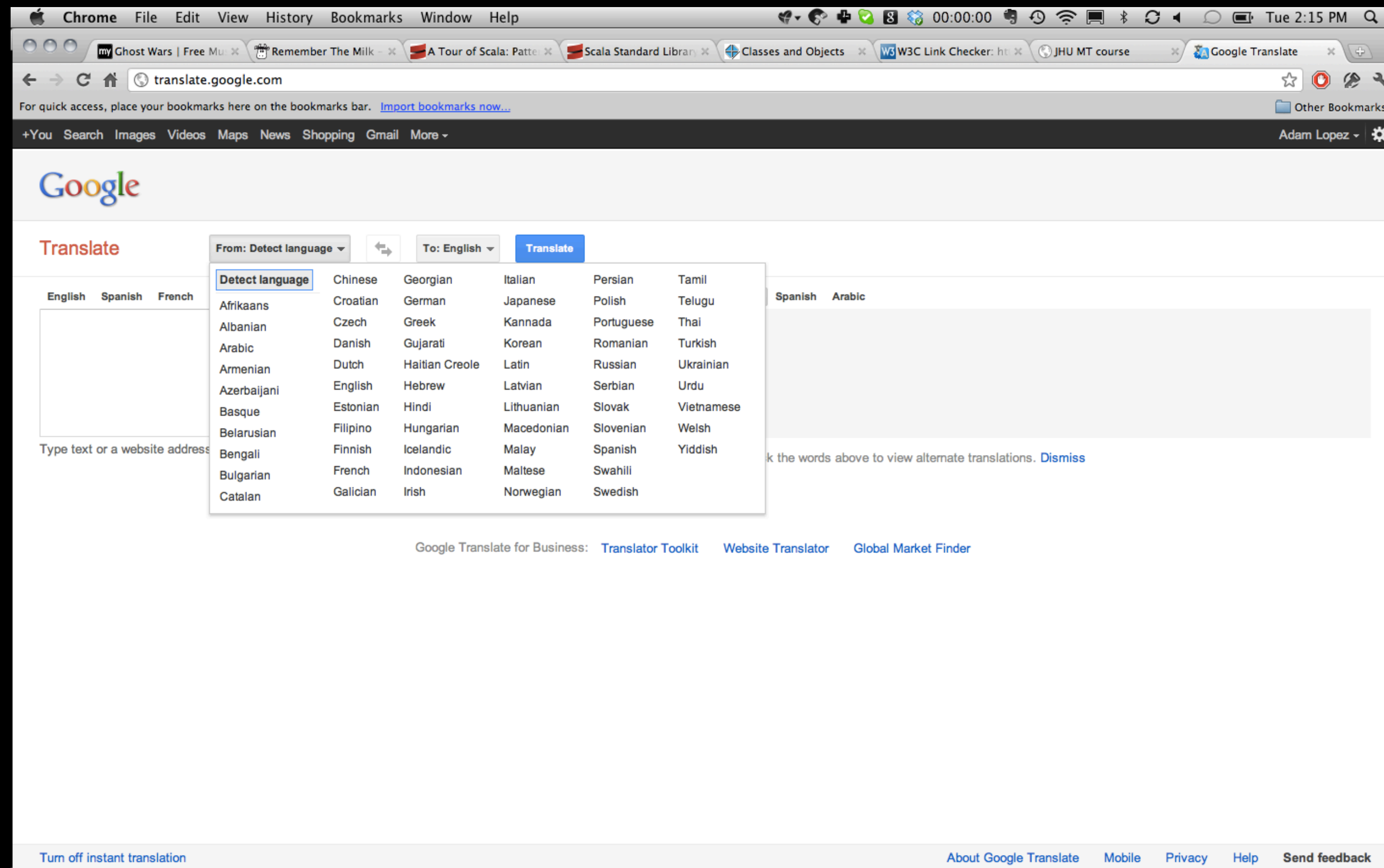


- Some (not all) key ingredients in Google Translate:



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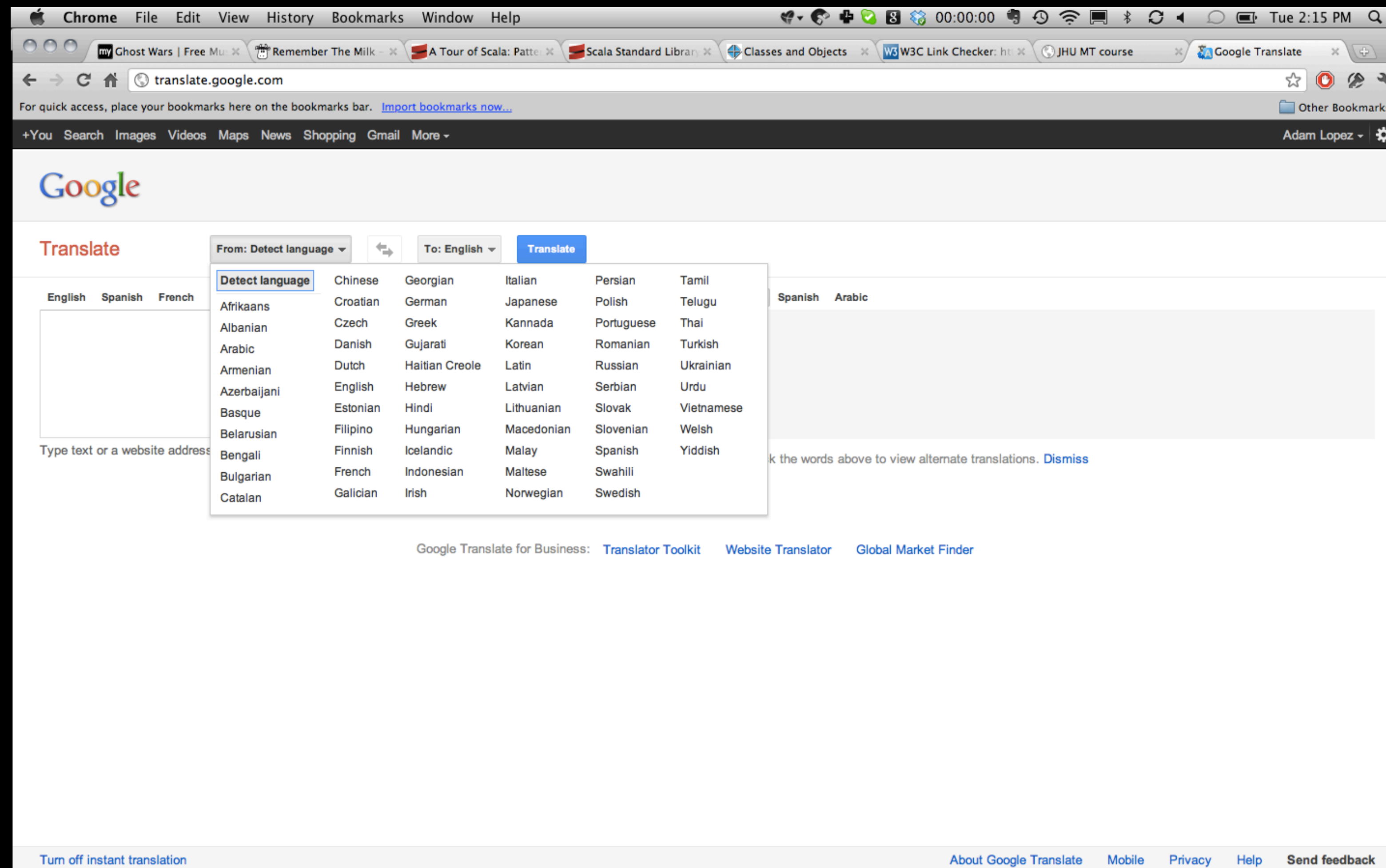

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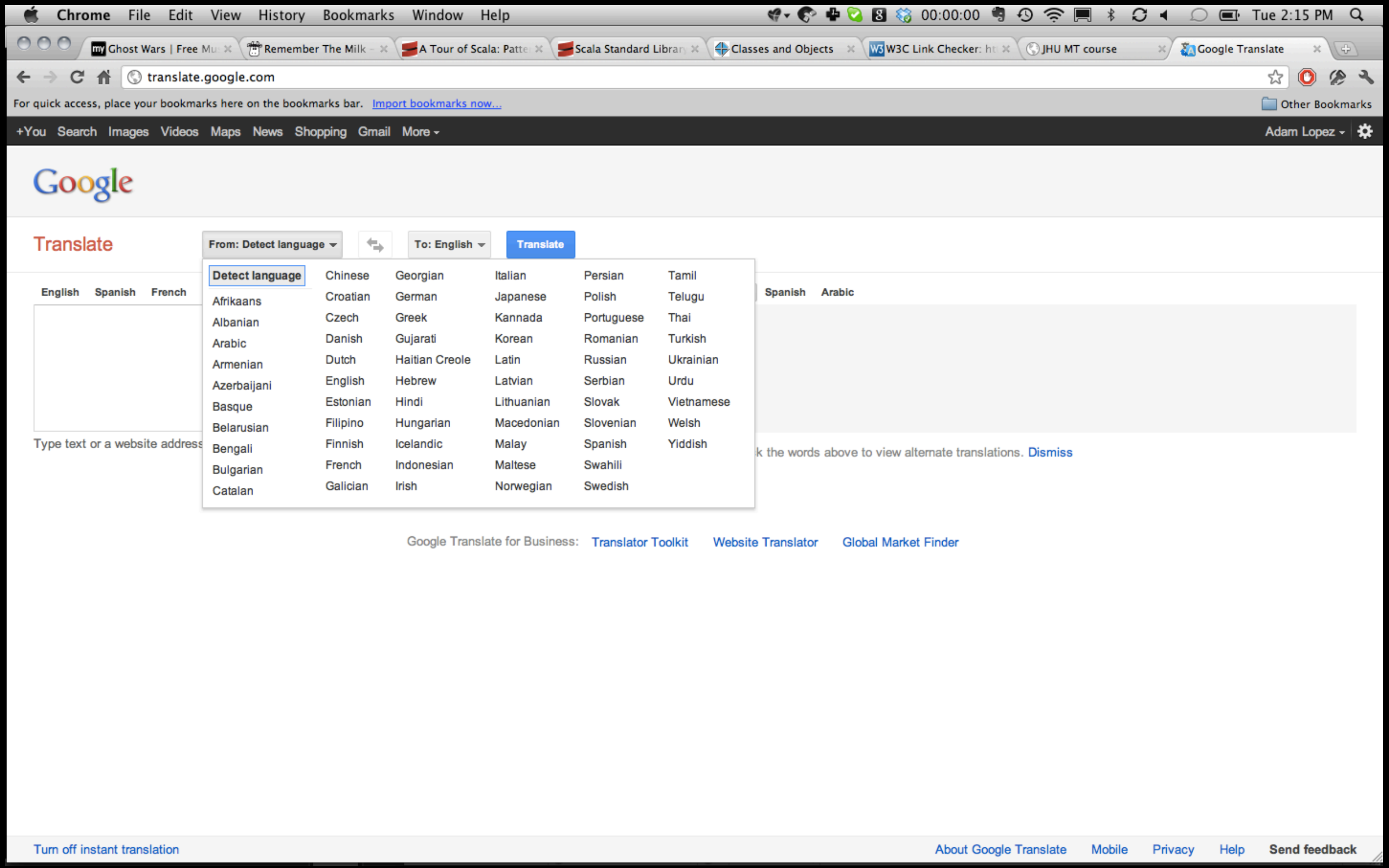

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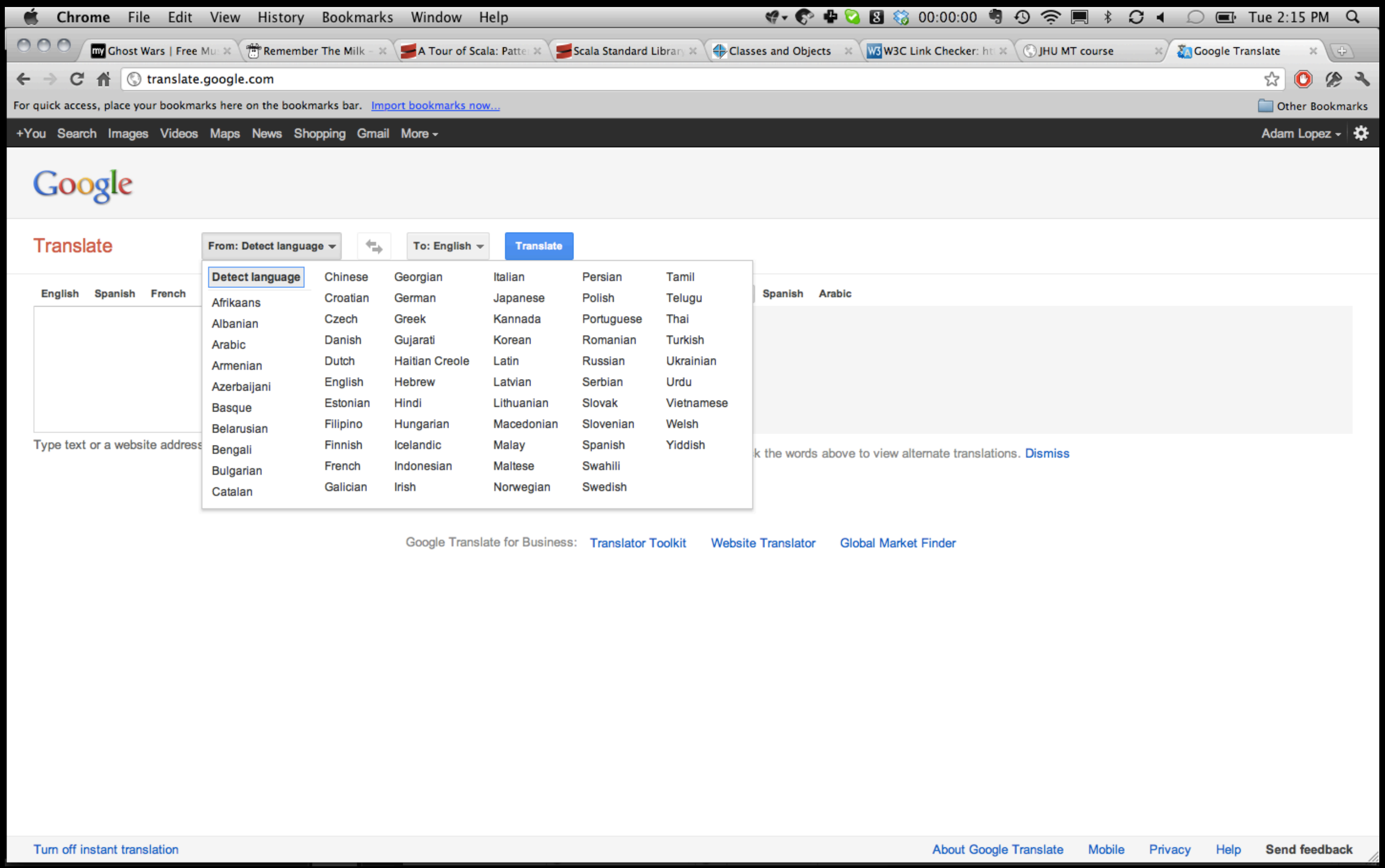

- Some (not all) key ingredients in Google Translate:
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  - ... Coupled with a huge language model
  - ... And very tight pruning heuristics

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- But they are widely regarded as state-of-the-art.
- Why? Simple models are easier to learn and deploy.
- Need proof? Google uses a phrase-based model.

Implementations

- Phrase-based Translation
  - Moses -- www.statmt.org/moses/
  - cdec -- www.cdec-decoder.org
- Language models
  - KenLM -- http://kheafield.com/code/kenlm/
  - SRI-LM -- www.speech.sri.com/projects/srilm/

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- Need dynamic programming with approximations.
- Is this the best we can do?