

Phrase-Based Translation

Machine Translation

$$p(\textit{English}|\textit{Chinese}) \sim$$

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

language model



The diagram illustrates the relationship between machine translation models and the joint probability formula. It features a central equation $p(\textit{English}) \times p(\textit{Chinese}|\textit{English})$ which is equated to $p(\textit{English}|\textit{Chinese})$. Below the first term of the product, $p(\textit{English})$, is the text 'language model' with an arrow pointing up to it. Below the second term, $p(\textit{Chinese}|\textit{English})$, is the text 'translation model' with an arrow pointing up to it.

translation model

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translation model

The IBM Models

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- Fertility probabilities.

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- Fertility probabilities.
- Word translation probabilities.

The IBM Models

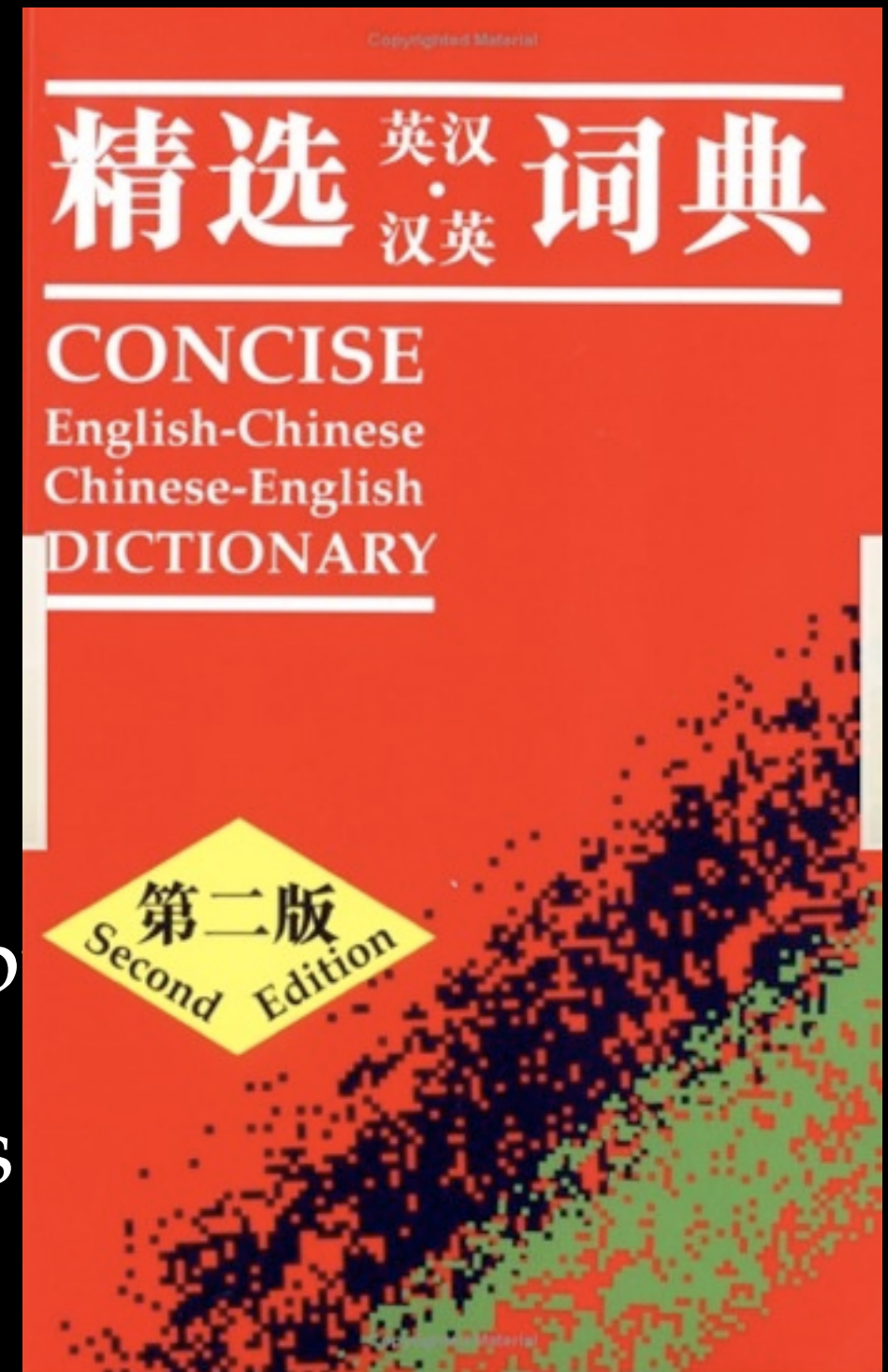
- Fertility probabilities.
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- Some problems:
 - Weak reordering model -- output is not fluent.
 - Many decisions -- many things can go wrong.

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IBM Model 4

Although north wind howls , but sky still very clear .

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Tradeoffs: Modeling v. Learning

Lexical Translation
Local ordering dependency
Fertility
Convex
Tractable Exact
Inference

IBM Model 1	✓	✗	✗	✓	✓
HMM	✓	✓	✗	✗	✓
IBM Model 4	✓	✓	✓	✗	✗

Tradeoffs: Modeling v. Learning

Lesson:
Trade exactness
for expressivity

Lexical Translation
Local ordering
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	Lexical Translation	Local ordering	Fertility	Convex	Tractable Exact Inference
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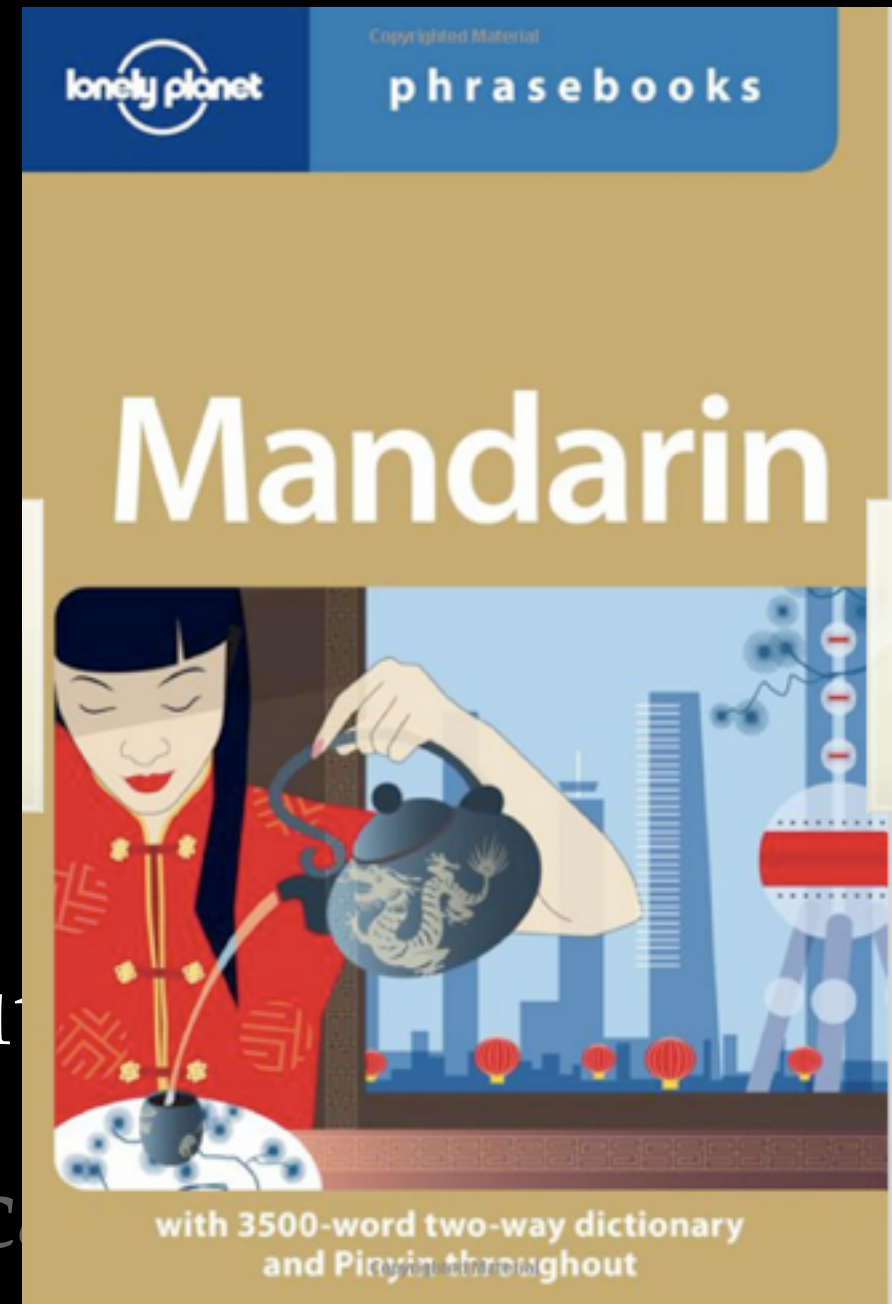
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Phrase-based Models

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

Learning $p(\text{Chinese} \mid \text{English})$

- 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

$p(\text{虽然 北 风 呼 啸 , 但 天 空 依 然 十 分 清 澈 。} \text{)} +$

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Divide by sum of all *possible* alignments

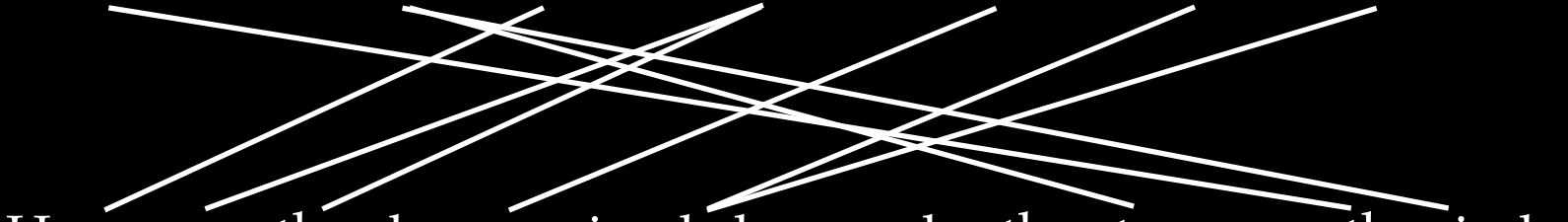
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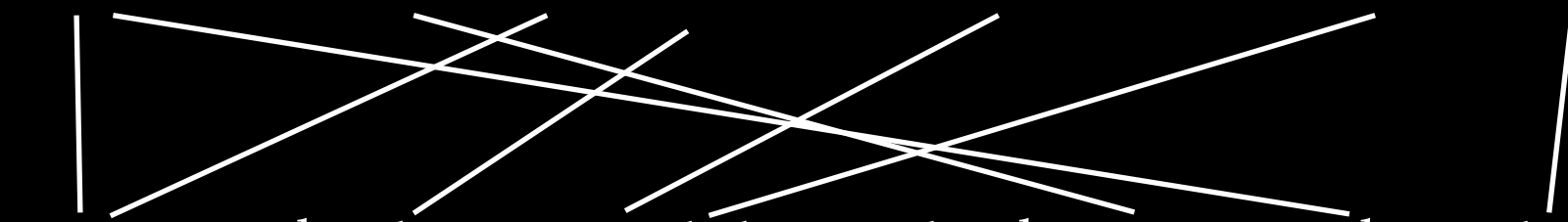
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We have to sum over exponentially many alignments!

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.

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

observed

uniform

EM for Model 1

probability of an alignment.

factors across words.

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

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EM for Model 1

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

EM for Model 1

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

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

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marginal probability of
alignments containing link

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EM for Model 1

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

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

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

identical!



marginal probability of all
alignments

EM for Model 1

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

EM for Phrase-Based

- Model parameters: $p(E \text{ phrase} \mid F \text{ phrase})$
- All we need to do is compute expectations:

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

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...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** .

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

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Can we compute this quantity?

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Can we compute this quantity?

How many 1-to-1 alignments are there of the remaining 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, using the expected counts.

- It is #P-Complete to compute the expected counts from a phrase-based model, given a sentence pair, is #P-Complete (by reduction to counting perfect matchings; DeNero & Klein, 2008)
- Counting perfect matchings is #P-Complete

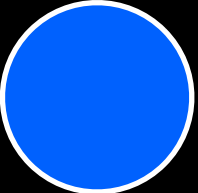
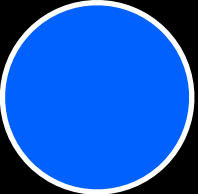
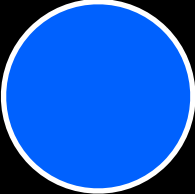
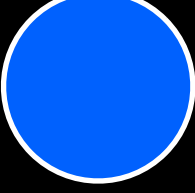
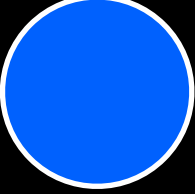
Now What?

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

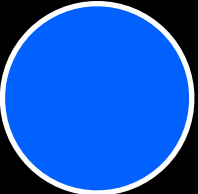
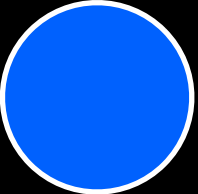
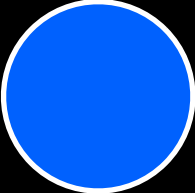
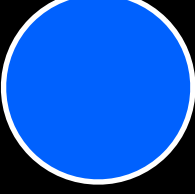

Now What?

- 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?



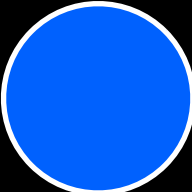
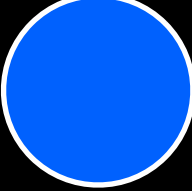
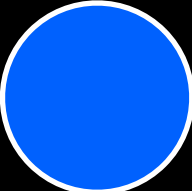
Phrase Extraction

	I open the box			
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wa				
hako				
wo				
akemasu				

Phrase Extraction


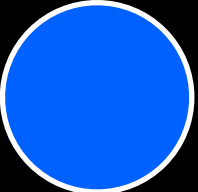
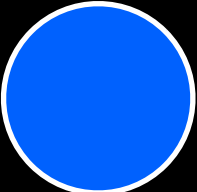
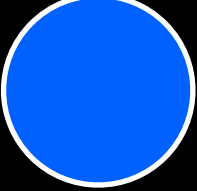
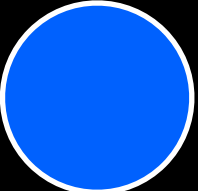
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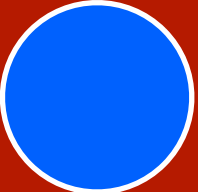
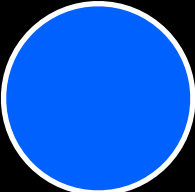
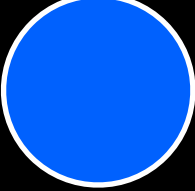
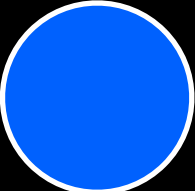
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wo				
akemasu				

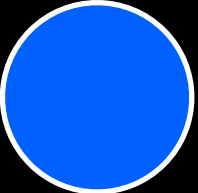
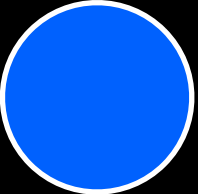


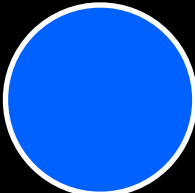
watashi / I

Phrase Extraction

	I open the box			
watashi				
wa				
hako				
wo				
akemasu				

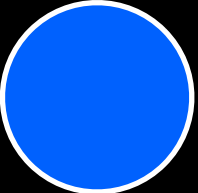
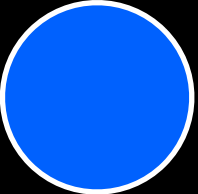


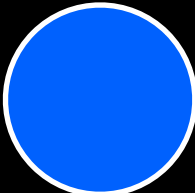
watashi~~wa~~ / I

Phrase Extraction

	I open the box			
watashi				
wa				
hako				
wo				
akemasu				

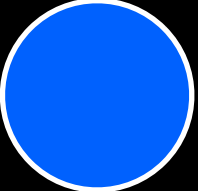
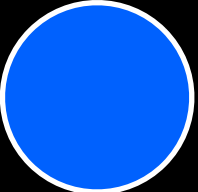


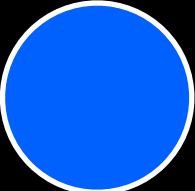
hako wo / box

Phrase Extraction

	I open the box			
watashi				
wa				
hako				
wo				
akemasu				

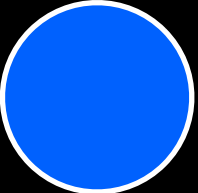
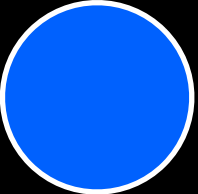



hako wo / the box

Phrase Extraction

	I open the box			
watashi				
wa				
hako				
wo				
akemasu				

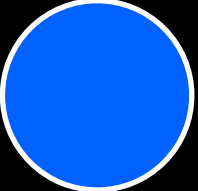
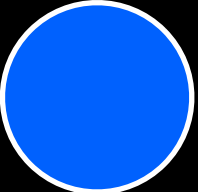



hako wo / open the box

Phrase Extraction

	I open the box			
watashi				
wa				
hako				
wo				
akemasu				

hako wo /  open the box

Phrase Extraction

	I open the box			
watashi				
wa				
hako				
wo				
akemasu				

hako wo akemasu / open the box

Phrasal Translation Estimation

Phrasal Translation Estimation

- Option #1 (EM over restricted space)
 - Align with a word-based model.
 - Compute expectations only over alignments consistent with the alignment grid.

Phrasal Translation Estimation

- Option #1 (EM over restricted space)
 - Align with a word-based model.
 - 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.

北 风 呼 啸 。

北 风 呼 啸 。

segmentations

substitutions

permutations

北 风 呼 啸 。

segmentations $O(2^n)$

substitutions

permutations

北 风 呼 啸 。

segmentations $O(2^n)$

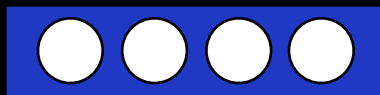
substitutions $O(5^n)$

permutations

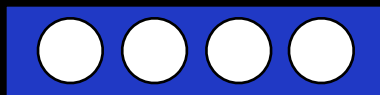
北 风 呼 啸 。

segmentations	$O(2^n)$
substitutions	$O(5^n)$
permutations	$O(n!)$

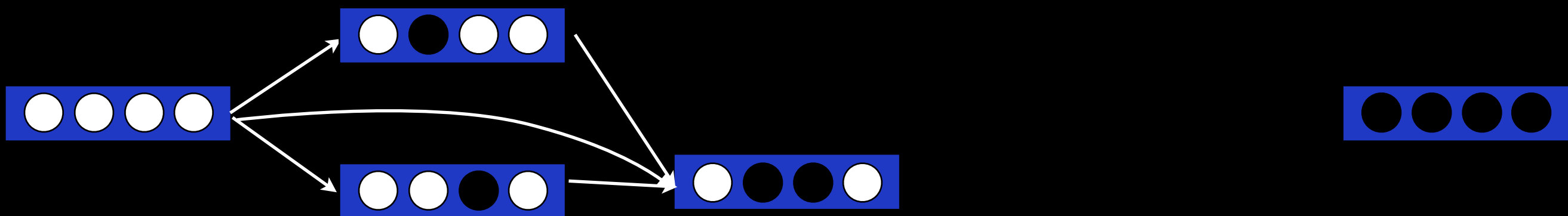
Key Idea



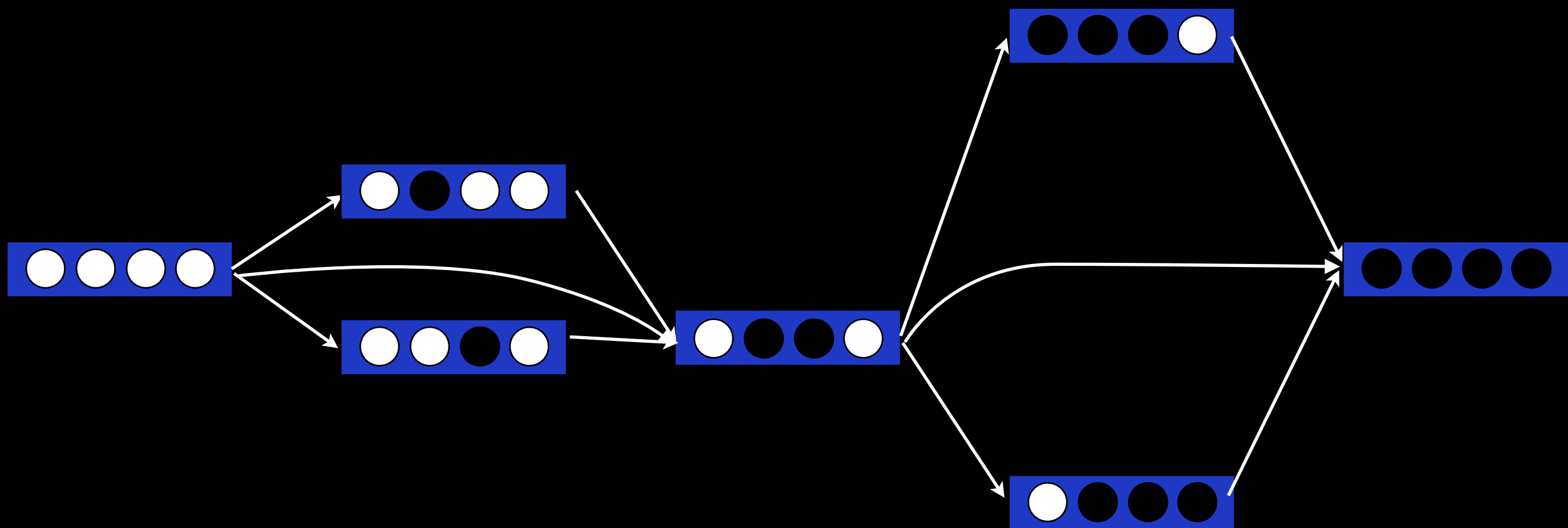
Key Idea



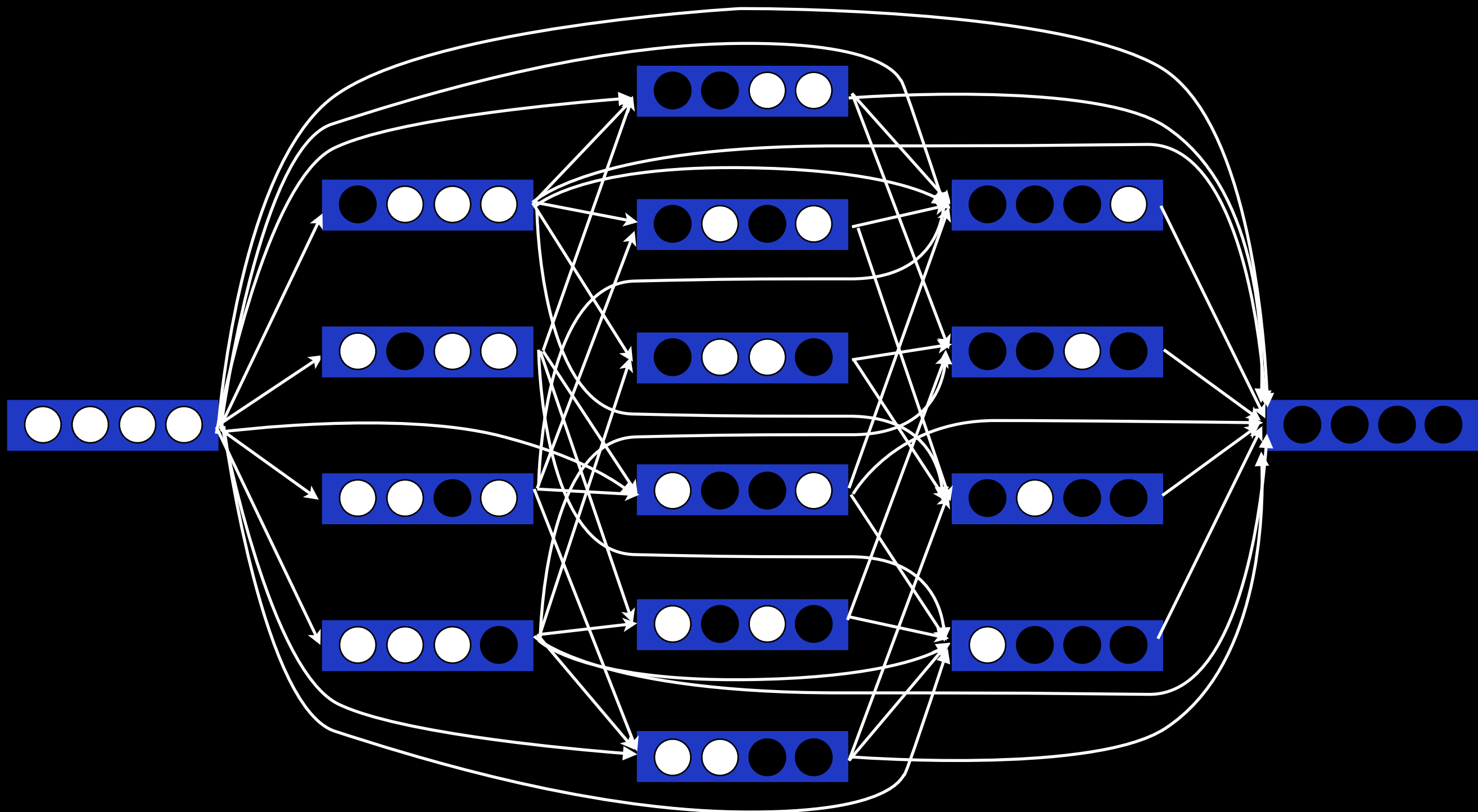
Key Idea



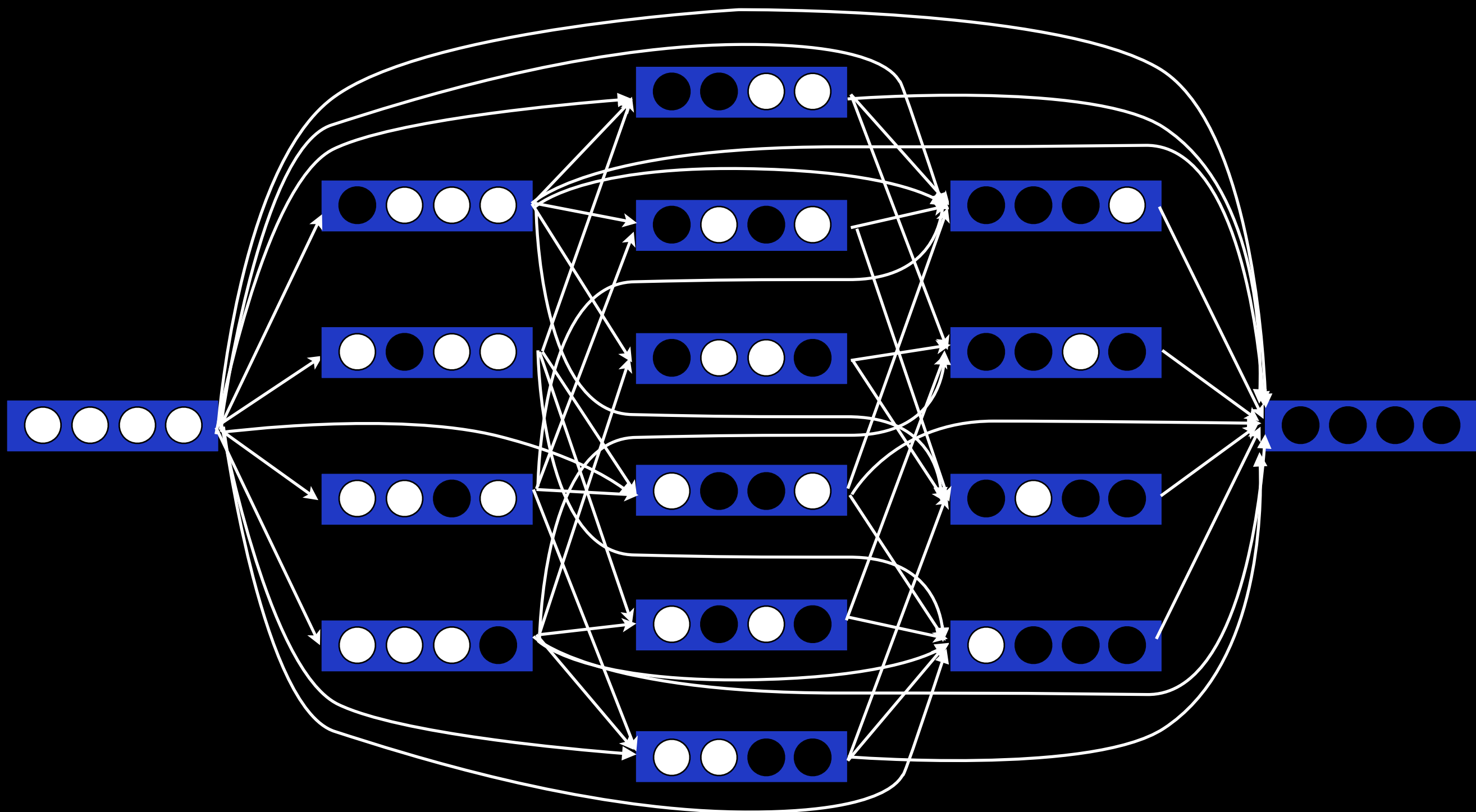
Key Idea



Key Idea



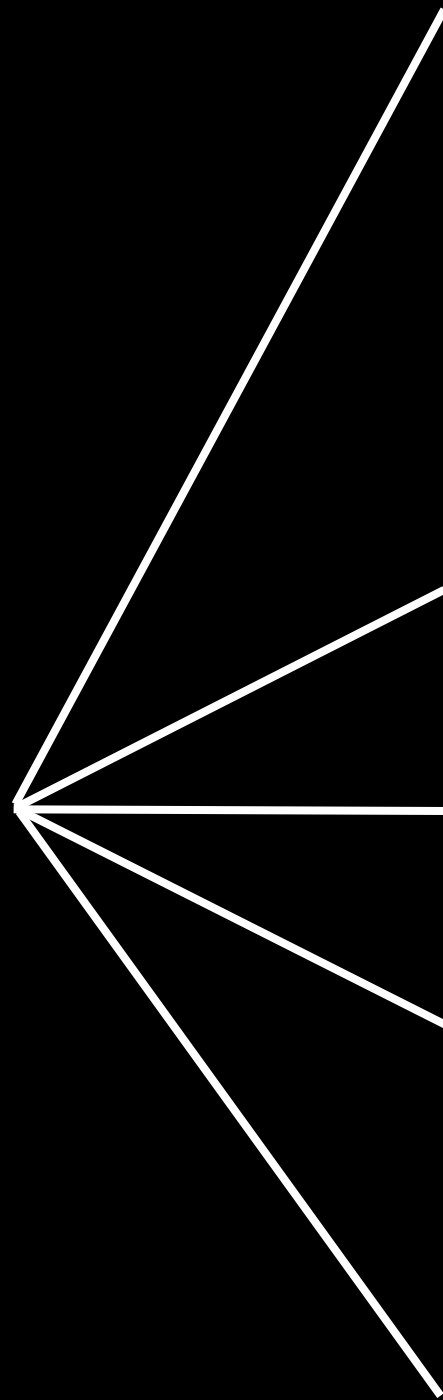
Key Idea



Dynamic Programming

虽然北 风 呼 啸，但 天 空 依 然 十 分 清 澈。

虽然北 风 呼 啸 ， 但 天 空 依 然 十 分 清 澈 。



START However

虽然 北 风 呼 啸 ， 但 天 空 依 然 十 分 清 澈 。

START Although

虽然 北 风 呼 啸 ， 但 天 空 依 然 十 分 清 澈 。

crystal clear

虽然 北 风 呼 啸 ， 但 天 空 依 然 十 分 清 澈 。

START However

虽然北风呼啸，但天空依然十分清澈。

START Although

虽然北风呼啸，但天空依然十分清澈。

crystal clear

虽然北风呼啸，但天空依然十分清澈。

wind screamed

虽然北 风呼啸，但天空依然十分清澈。

wind shrieked

虽然北 风呼啸，但天空依然十分清澈。

north wind

虽然北 风呼啸，但天空依然十分清澈。

wind screamed

虽然北 风呼啸，但天空依然十分清澈。

wind shrieked

虽然北 风呼啸，但天空依然十分清澈。

north wind

虽然北 风呼啸，但天空依然十分清澈。



shrieked ,

虽然 北 风 呼 啸 , 但 天 空 依 然 十 分 清 澈 。

the sky

虽然 北 风 呼 啸 , 但 天 空 依 然 十 分 清 澈 。

, yet

虽然 北 风 呼 啸 , 但 天 空 依 然 十 分 清 澈 。



shrieked ,

虽然北 风呼啸，但天空依然十分清澈。

the sky



虽然北 风呼啸，但天空依然十分清澈。

, yet



虽然北 风呼啸，但天空依然十分清澈。

sky ,



虽然北 风 呼 啸 ， 但 天 空 依 然 十 分 清 澈 。

sky ,

虽然北 风 呼啸 , 但 天空 依然 十分 清澈 。

still quite

虽然北 风呼啸，但天空依然十分清澈。

clear .

虽然北 风呼啸，但天空依然十分清澈。

blue .

虽然北 风呼啸，但天空依然十分清澈。

still quite

虽然北 风呼啸，但天空依然十分清澈。

clear .

虽然北 风呼啸，但天空依然十分清澈。

blue .

虽然北 风呼啸，但天空依然十分清澈。

Although the northern wind shrieked
across the sky, but was still very clear.

虽然北 风 呼 啸 ， 但 天 空 依 然 十 分 清 澈 。

Wait a second.

Wait a second.

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

Wait a second.

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

Can we do better?

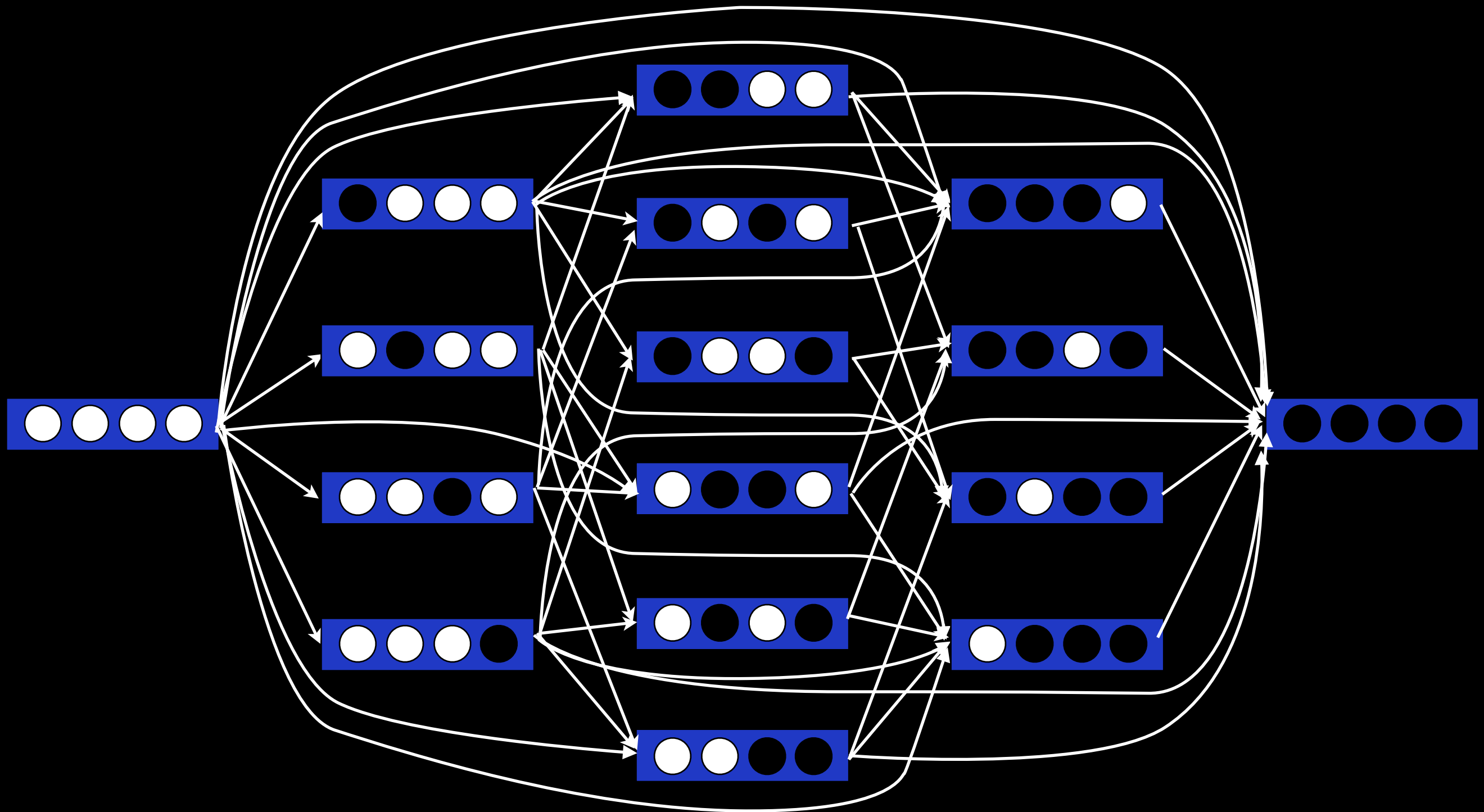
Wait a second.

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

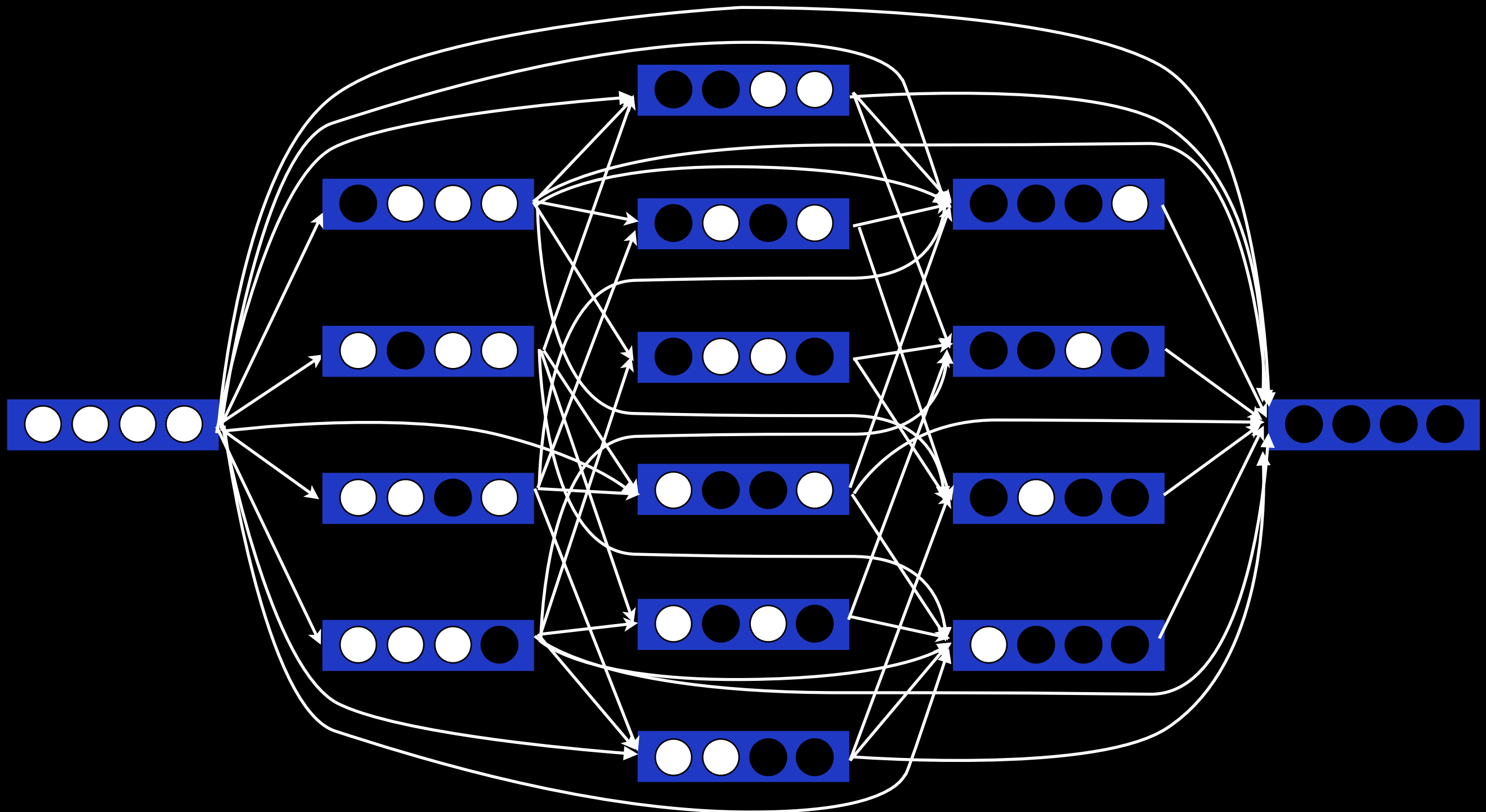
Can we do better?

NO! Knight (1999) shows that this is NP-Complete,
by reduction to Hamiltonian Circuit.

Approximation: Pruning

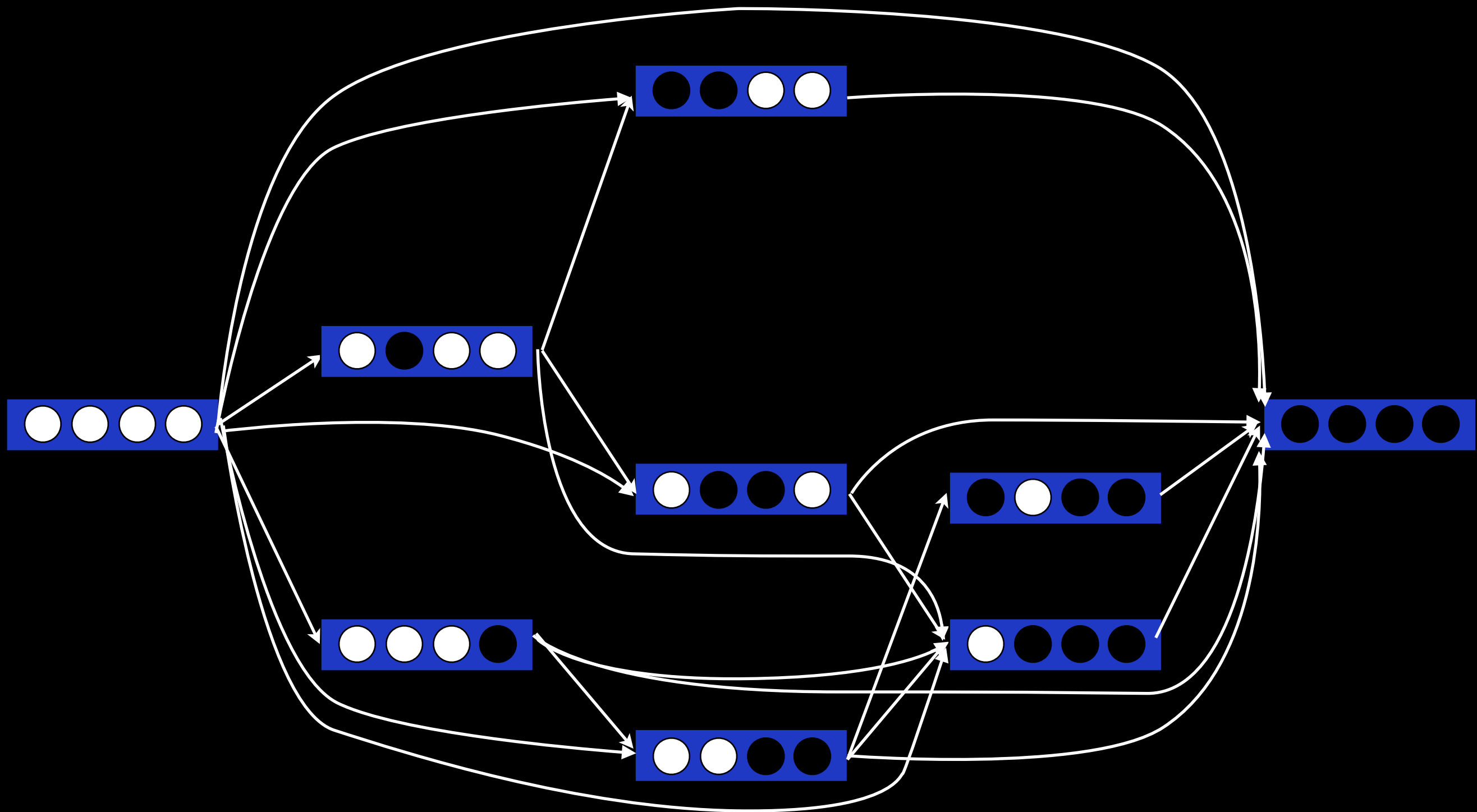


Approximation: Pruning

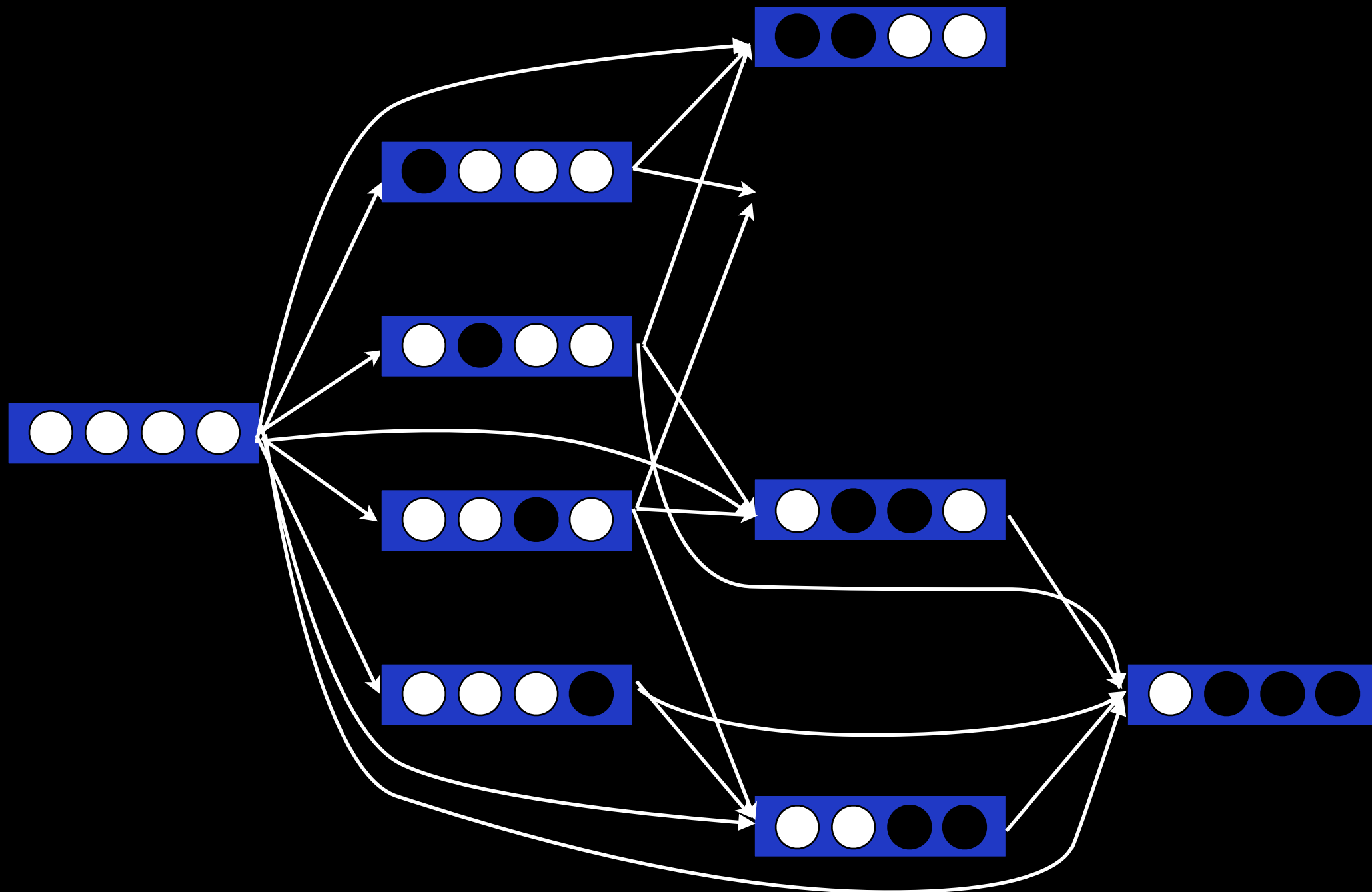


Idea: prune states by accumulated path length

Approximation: Pruning

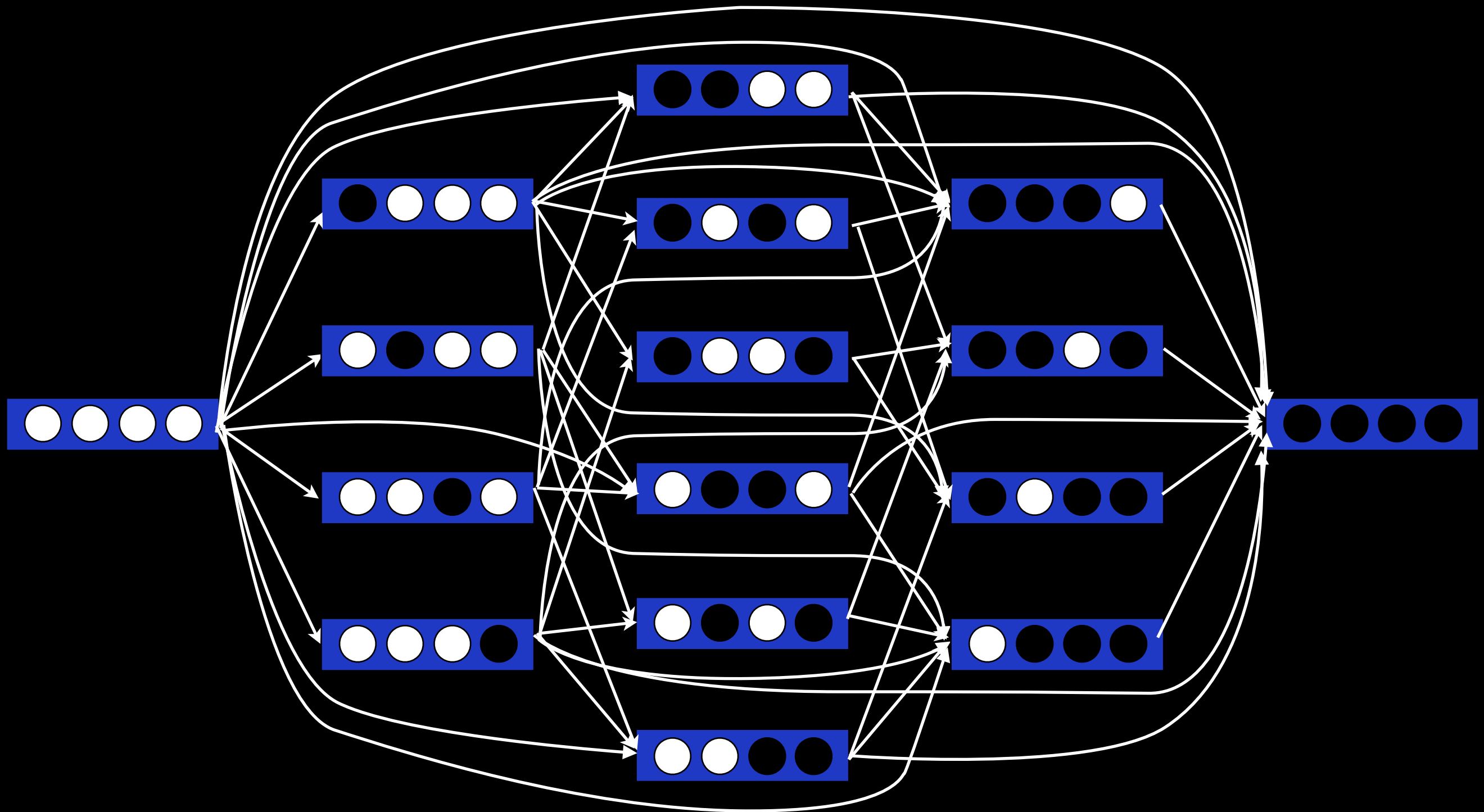


Approximation: Pruning

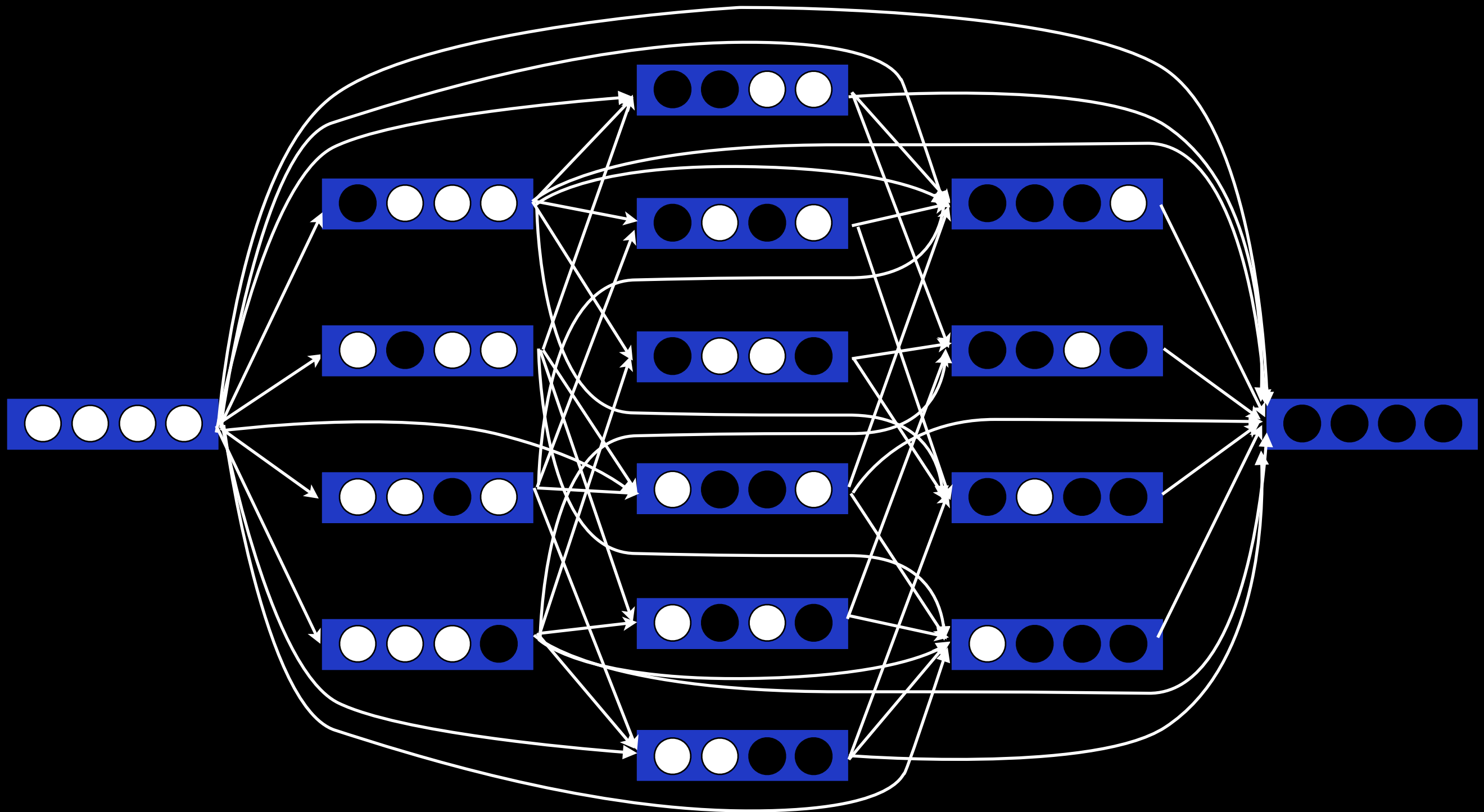


reality: longer paths have lower probability!

Approximation: Pruning

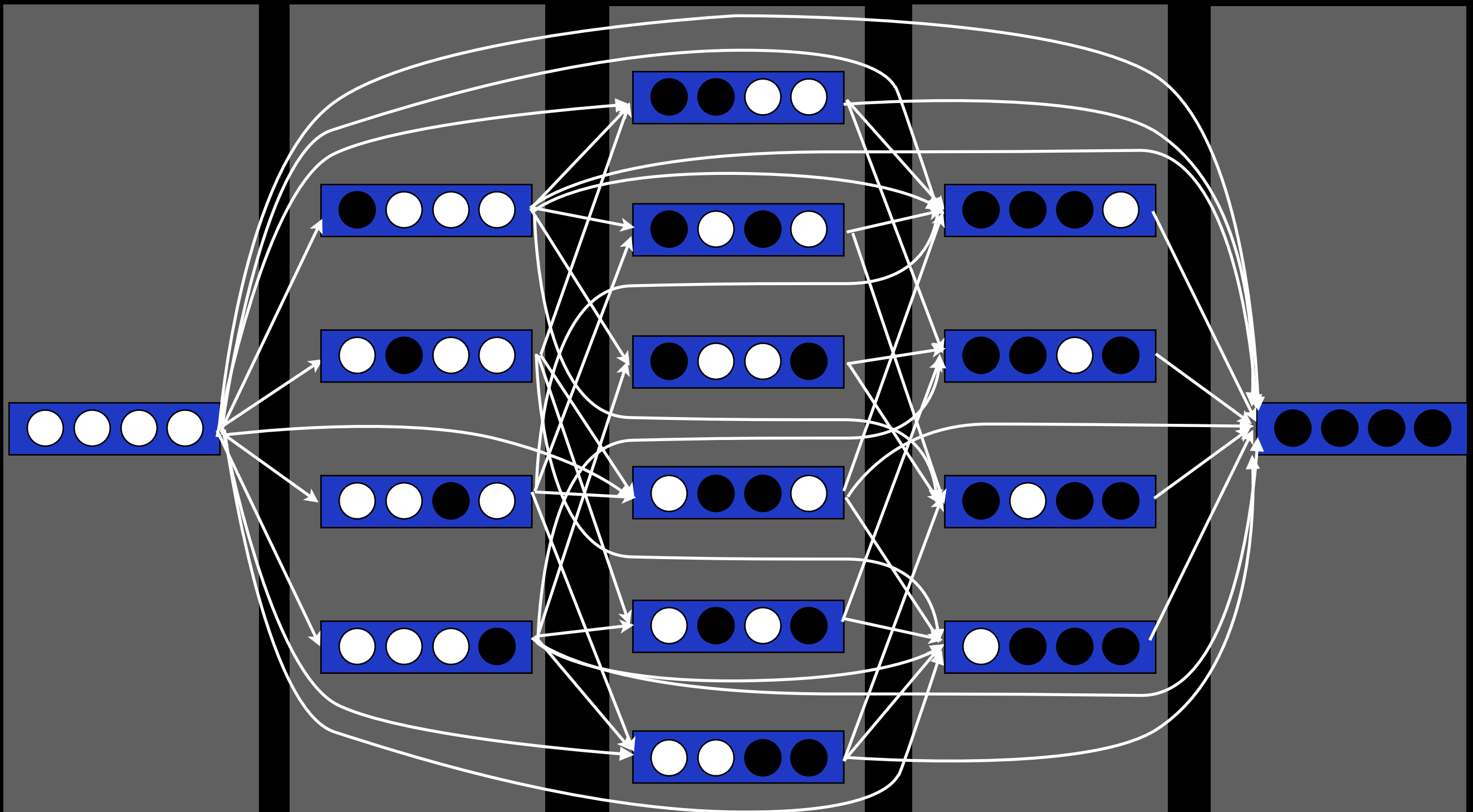


Approximation: Pruning



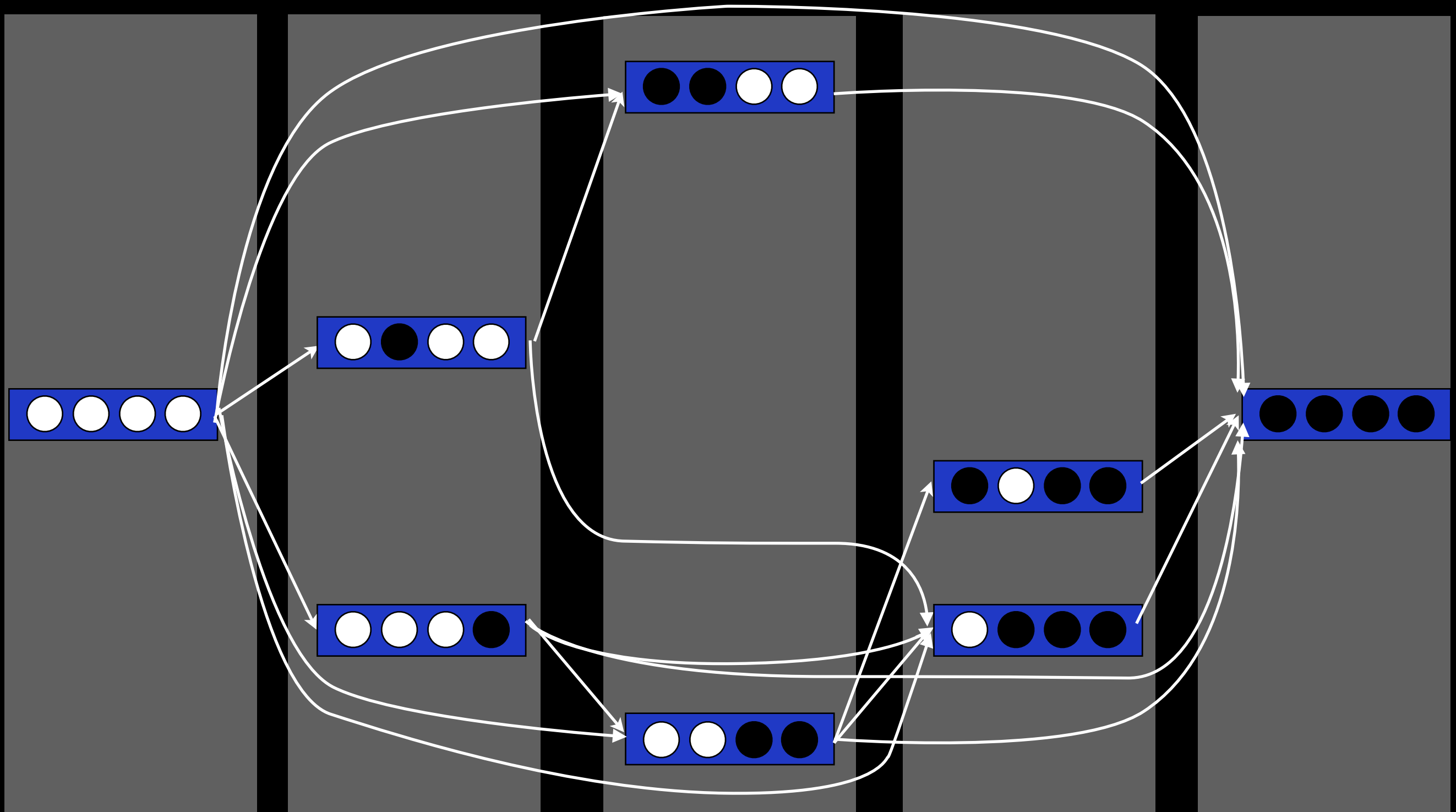
Solution: Group states by number of covered words.

Approximation: Pruning



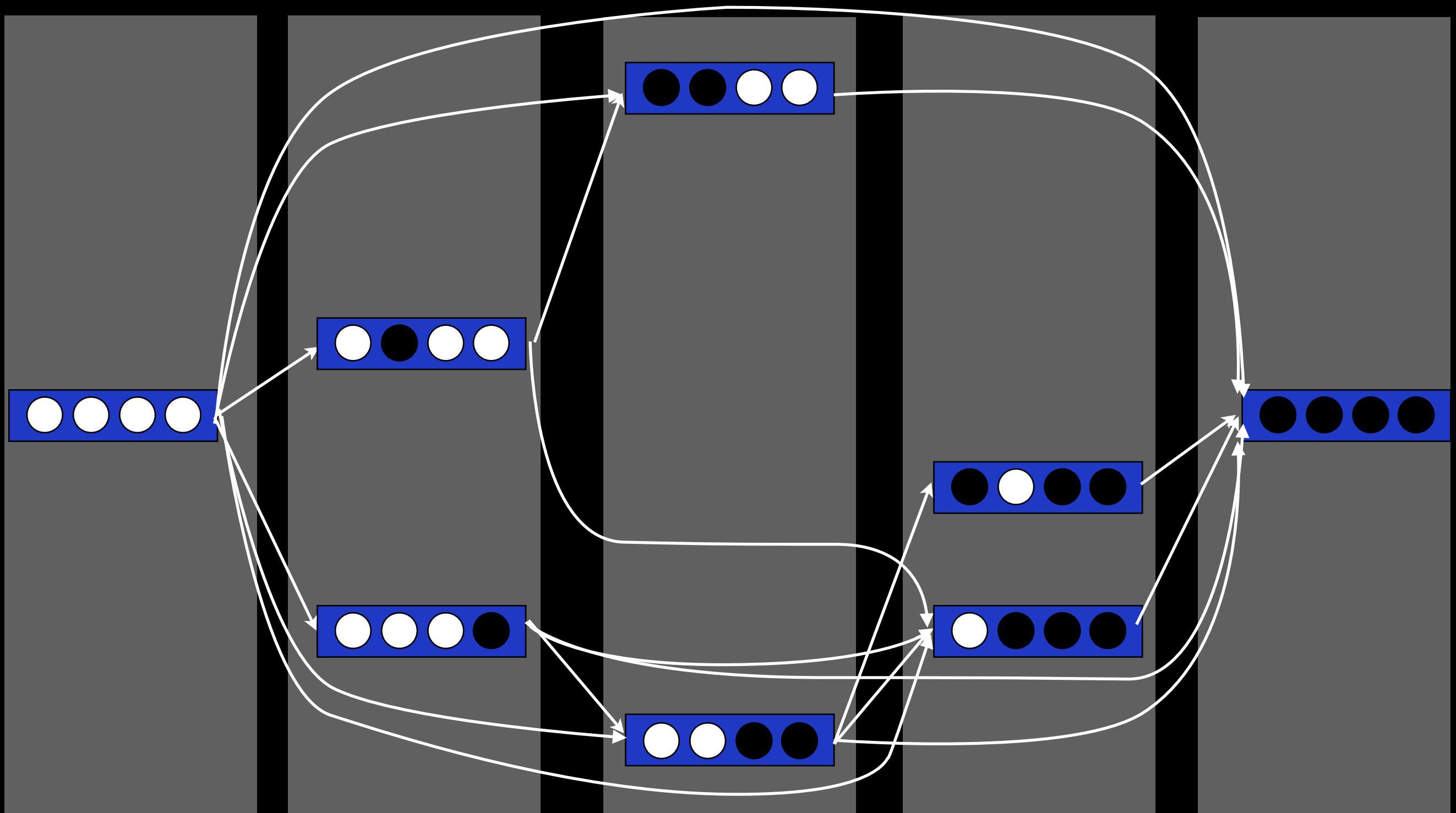
Solution: Group states by number of covered words.

Approximation: Pruning



Solution: Group states by number of covered words.

Approximation: Pruning



“Stack” decoding: a linear-time approximation

the sky

虽然北风呼啸，但天空依然十分清澈。

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

the sky

虽然北风呼啸，但天空依然十分清澈。

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

the sky

虽然北风呼啸，但天空依然十分清澈。

$$d = 4$$

window

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

the sky

虽然北风呼啸，但天空依然十分清澈。

outside window
to left: covered

$d = 4$
window

outside window
to right: uncovered

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

the sky

虽然北风呼啸，但天空依然十分清澈。

outside window
to left: covered

$d = 4$
window

outside window
to right: uncovered

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Adam Lopez

Translate

EnglishSpanishFrench

Type text or a website address

From: Detect language

To: English

Translate

Detect language

ChineseGeorgianItalianPersianTamil

AfrikaansCroatianGermanJapanesePolishTelugu

AlbanianCzechGreekKannadaPortugueseThai

ArabicDanishGujaratiKoreanRomanianTurkish

ArmenianDutchHaitian CreoleLatinRussianUkrainian

AzerbaijaniEnglishHebrewLatvianSerbianUrdu

BasqueEstonianHindiLithuanianSlovakVietnamese

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CatalanGalicianIrishNorwegianSwedish

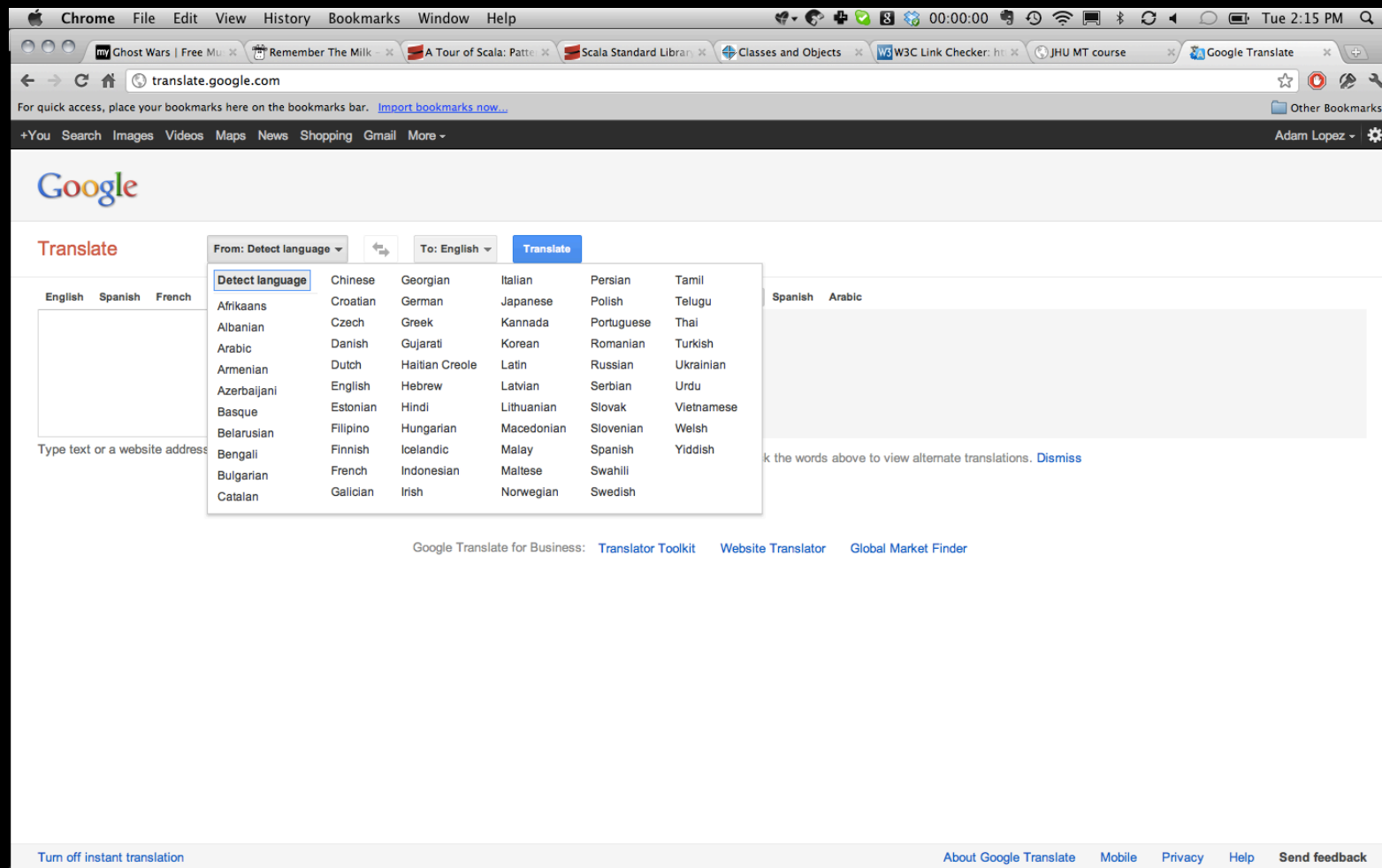
SpanishArabic

Click the words above to view alternate translations. [Dismiss](#)

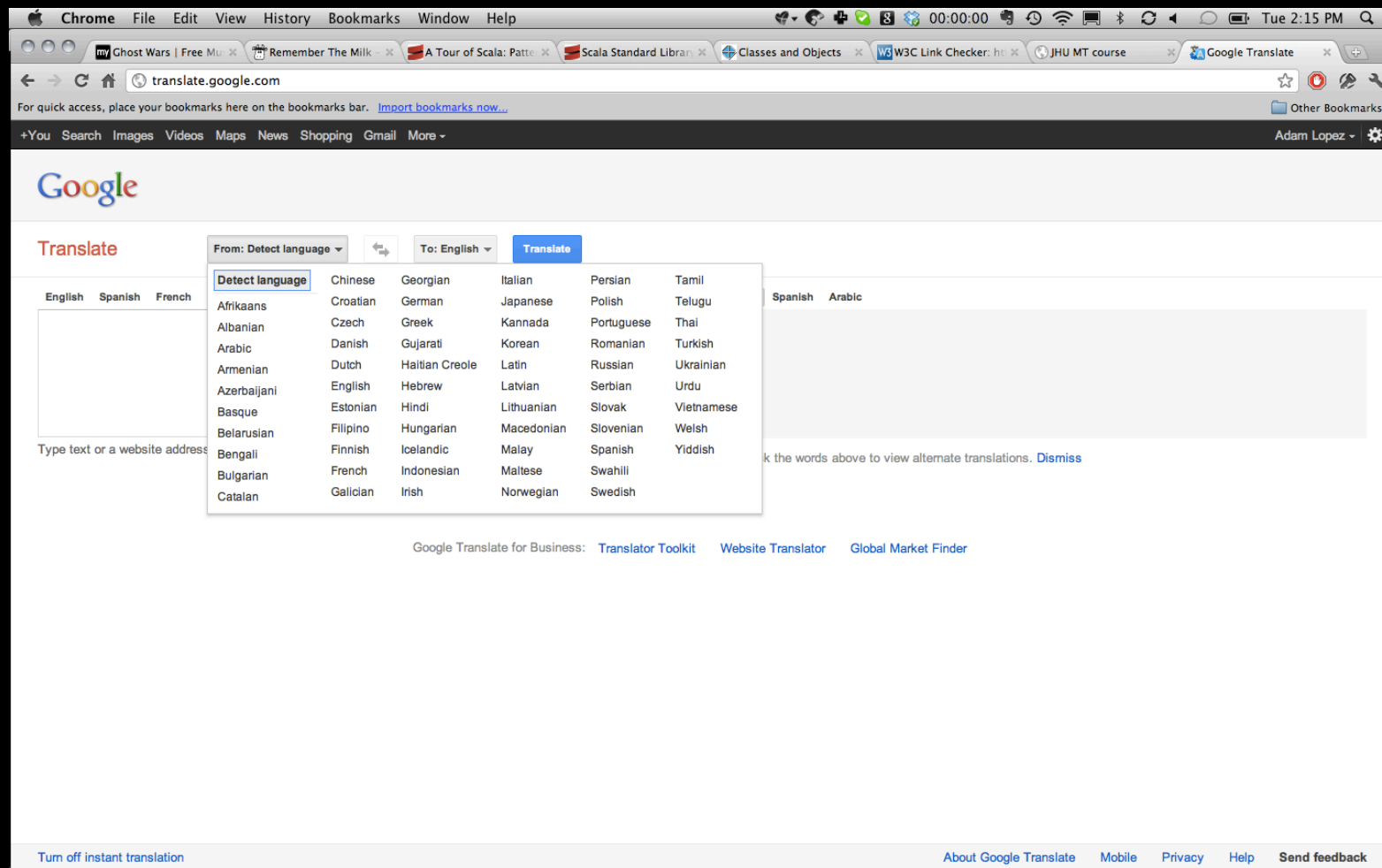
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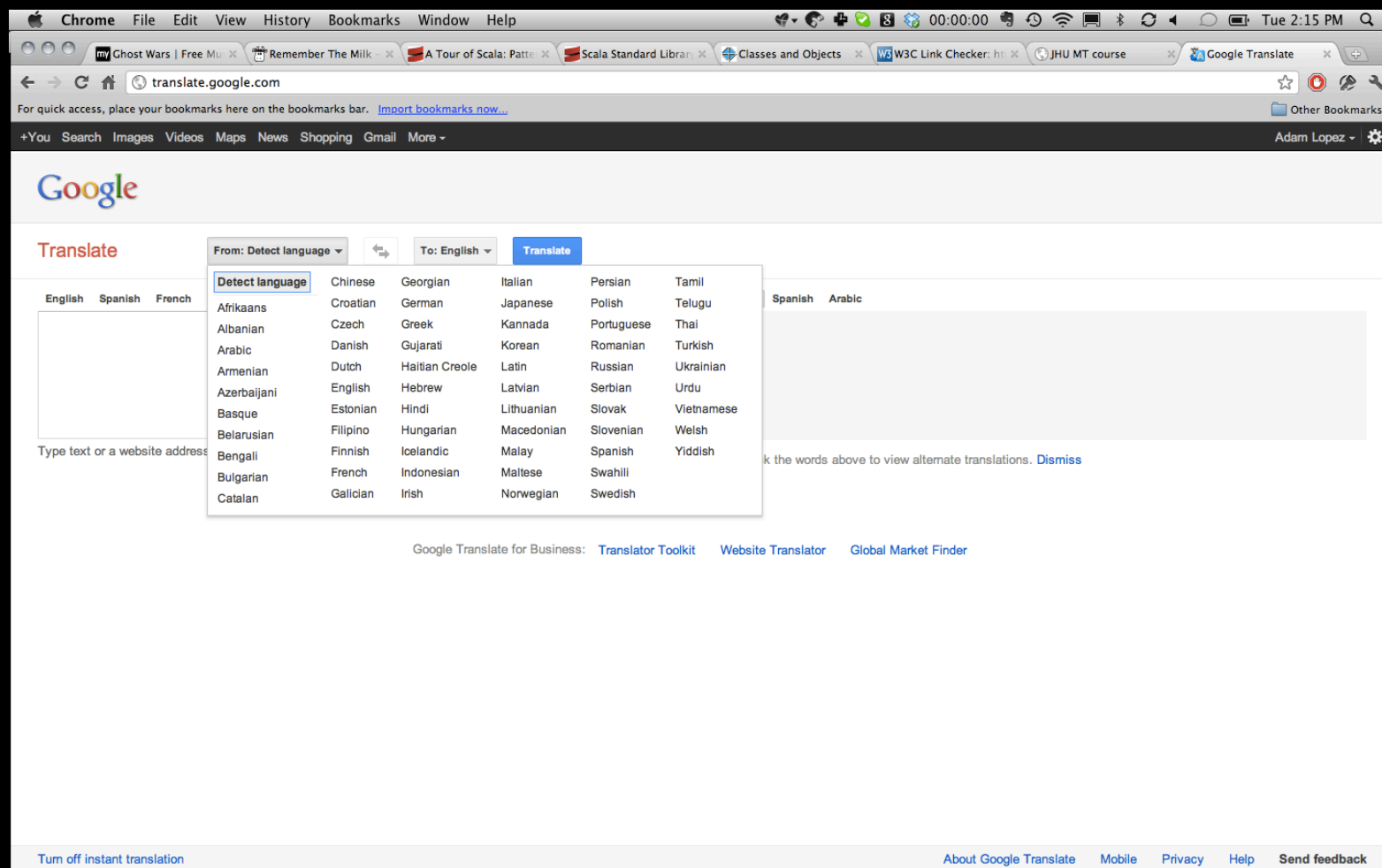
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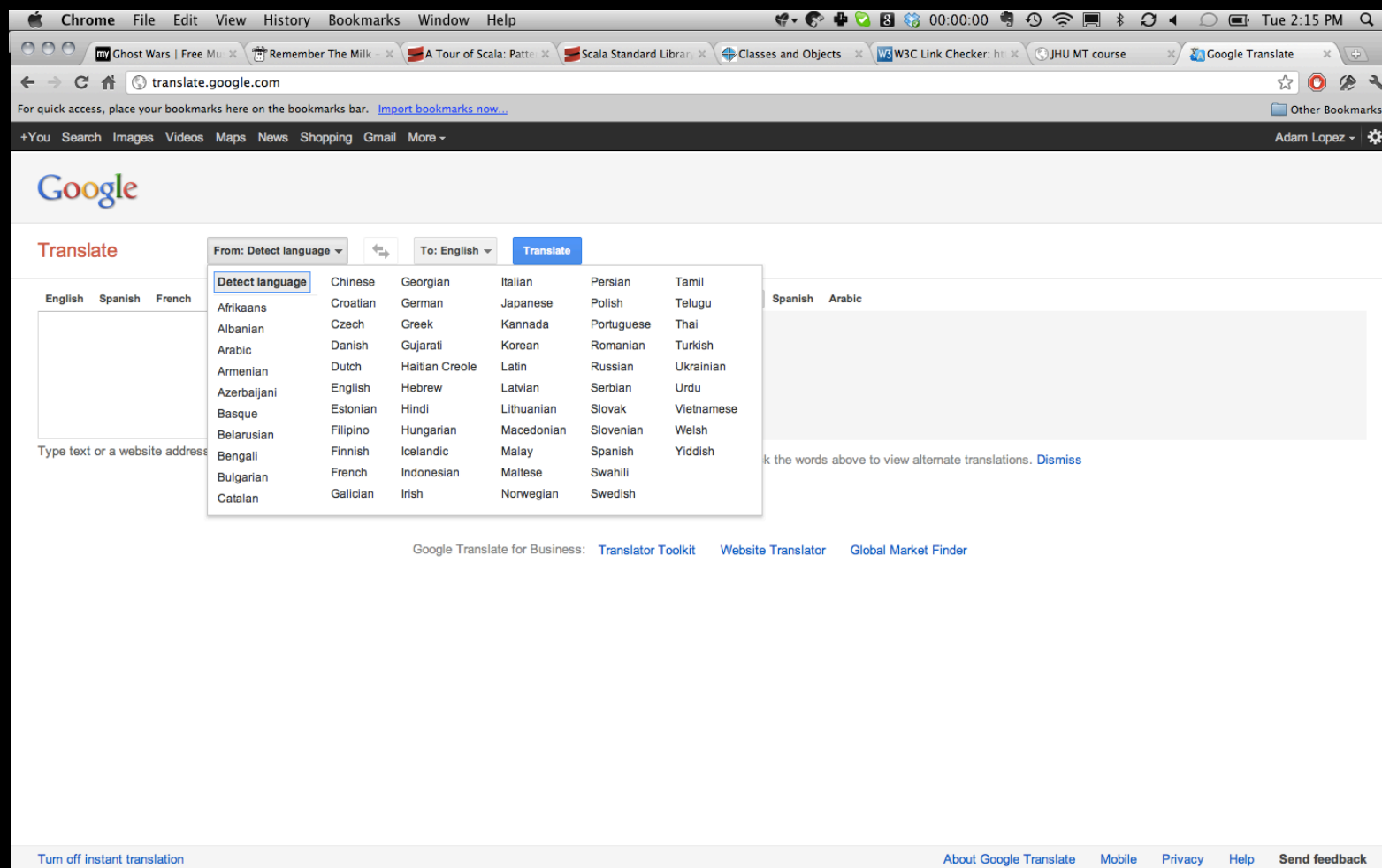
● Some (not all) key ingredients in Google Translate:



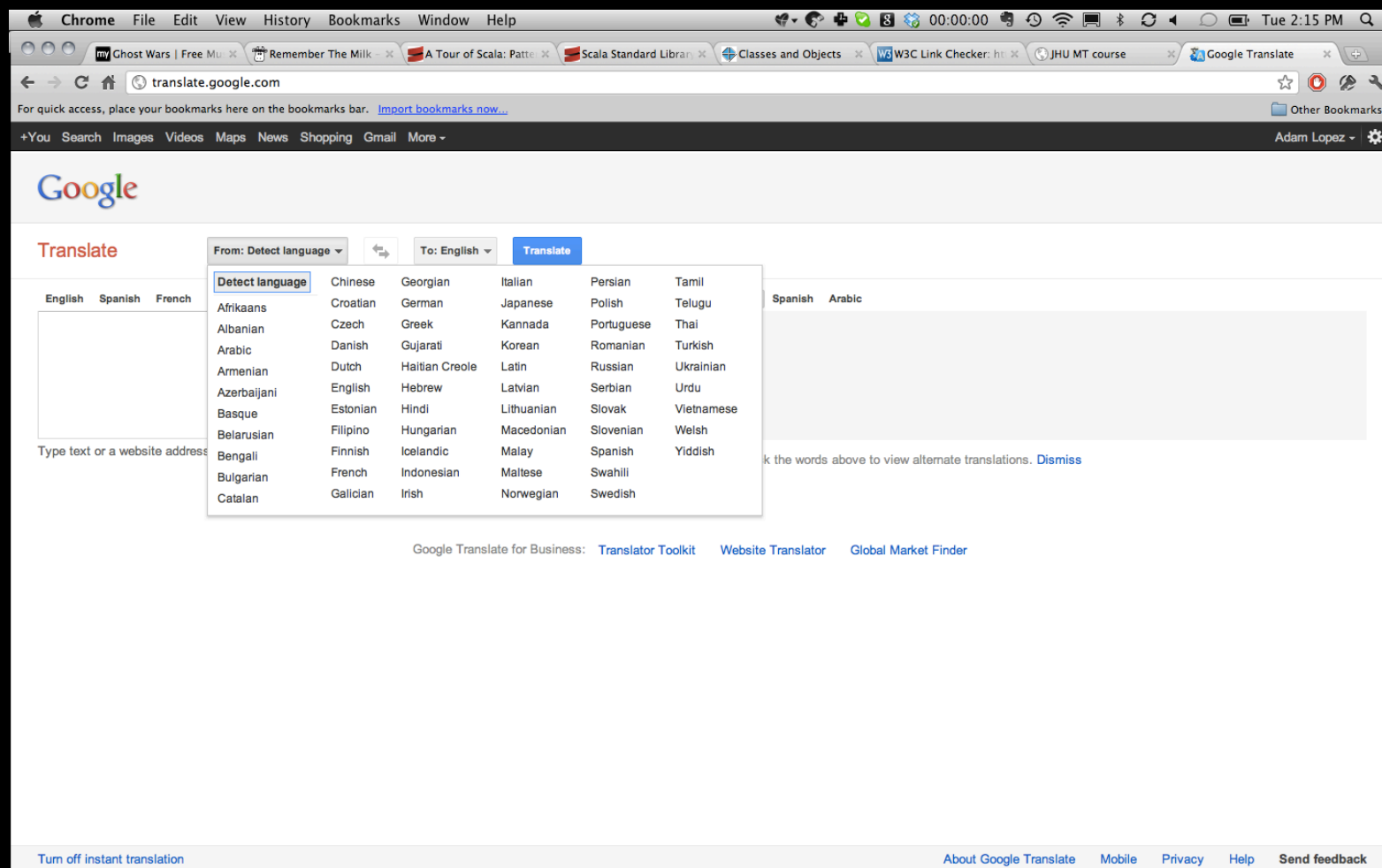
- Some (not all) key ingredients in Google Translate:
- Phrase-based translation models



- Some (not all) key ingredients in Google Translate:
 - Phrase-based translation models
 - ... Learned heuristically from word alignments



- Some (not all) key ingredients in Google Translate:
 - Phrase-based translation models
 - ... Learned heuristically from word alignments
 - ... Coupled with a huge language model



- Some (not all) key ingredients in Google Translate:
 - Phrase-based translation models
 - ... Learned heuristically from word alignments
 - ... Coupled with a huge language model
 - ... And very tight pruning heuristics