

Decoding continued +
Phrase-based
translation

The IBM Models

The IBM Models

- Fertility probabilities.

The IBM Models

- Fertility probabilities.
- Word translation probabilities.

The IBM Models

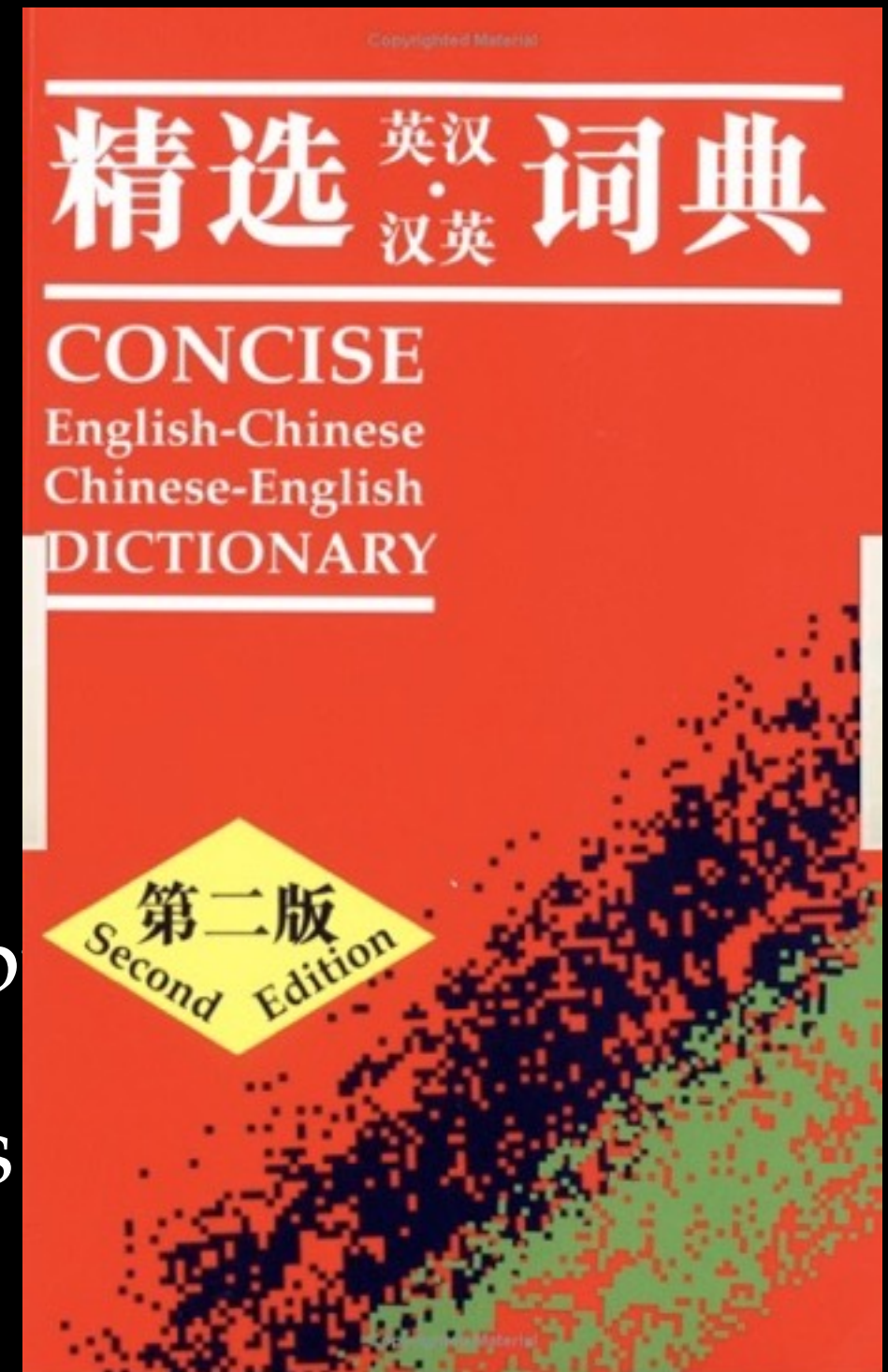
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 - Weak reordering model -- output is not fluent.
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IBM Model 4

Although north wind howls , but sky still very clear .

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

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
Fertility
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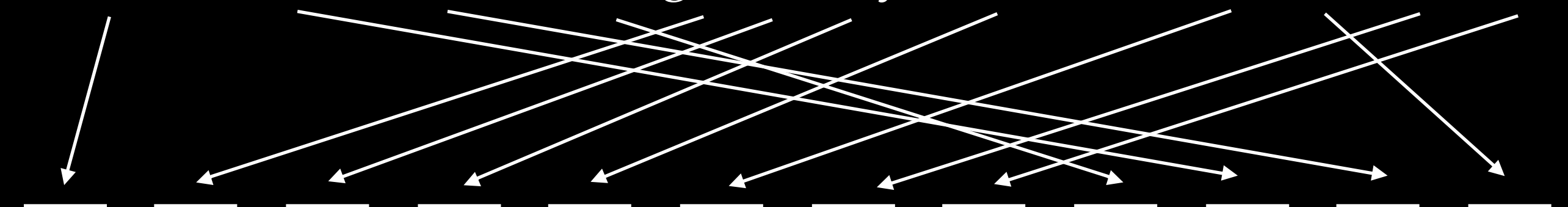
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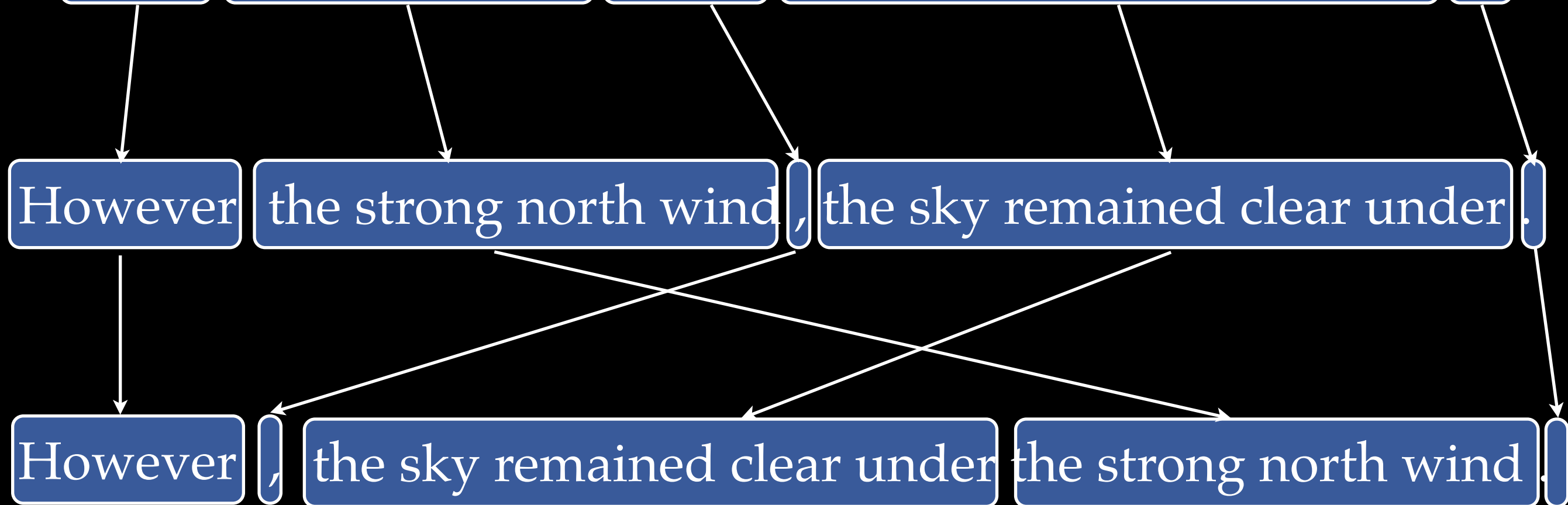
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Phrase-based Models

- 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.

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:

$$p(a_{i,i'}, j, j' = 1 \mid F, E) = \frac{p(a_{i,i'}, j, j' = 1, F \mid E)}{p(F \mid E)}$$

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

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Can we compute this quantity?

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

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

$v_1 \vee v_2 \vee v_3$ ----->
 $\bar{v}_1 \vee v_2 \vee \bar{v}_3$ ----->
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assign(v_1)
 assign(v_2)
 assign(v_3)

v_1	\bar{v}_1	\bar{v}_1	\bar{v}_1	v_2	v_2	\bar{v}_2	\bar{v}_2	v_3	v_3	\bar{v}_3	\bar{v}_3
											
											
											
											
   	   	   	   								
				  	   	   	   				
								   	    	    	    

$$\bar{v}_1 \vee \bar{v}_2 \vee v_3 \quad \text{----->}$$

$$\text{assign}(v_3)$$

v_1	\bar{v}_1	v_1	\bar{v}_1	v_2	v_2	\bar{v}_2	\bar{v}_2	v_3	v_3	\bar{v}_3	\bar{v}_3

v_1	\bar{v}_1	v_1	\bar{v}_1	v_2	v_2	\bar{v}_2	\bar{v}_2	v_3	v_3	\bar{v}_3	\bar{v}_3

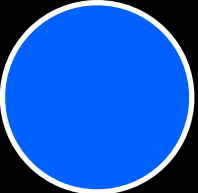
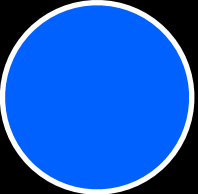
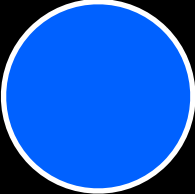
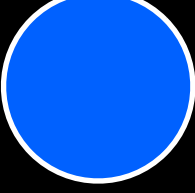
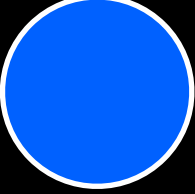
Now What?

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

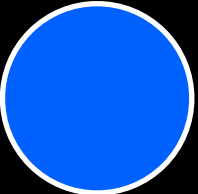
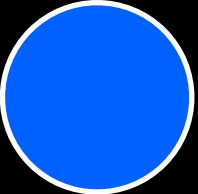
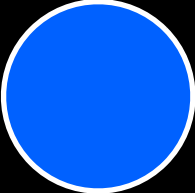
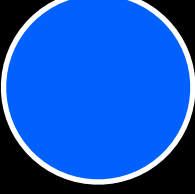

Now What?

- 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?



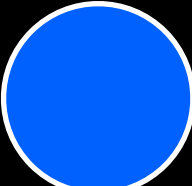
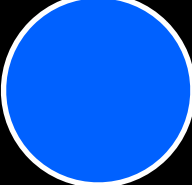
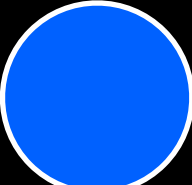
Phrase Extraction

	I	open	the	box
watashi				
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Phrase Extraction


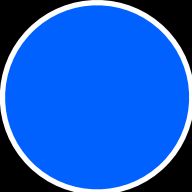
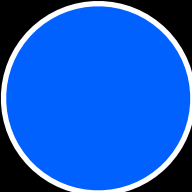
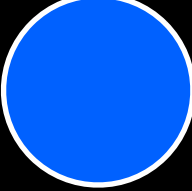
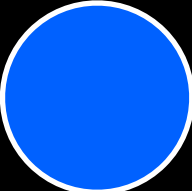
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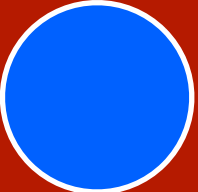
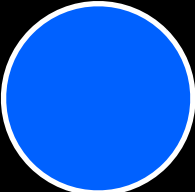
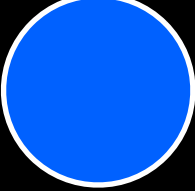
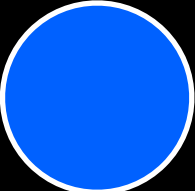
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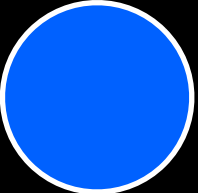
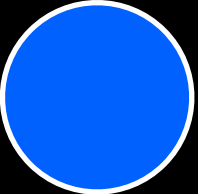


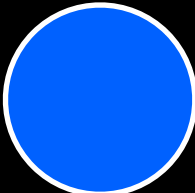
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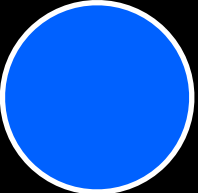
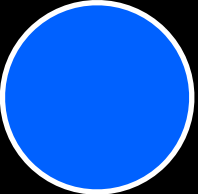


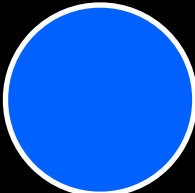
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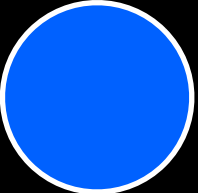
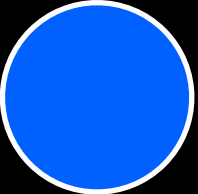

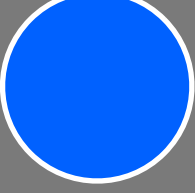
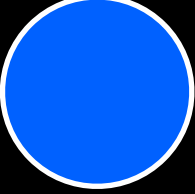
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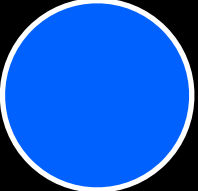
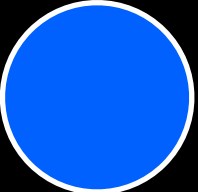


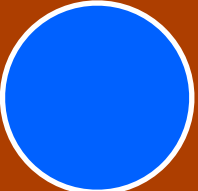
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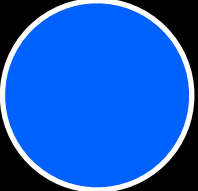
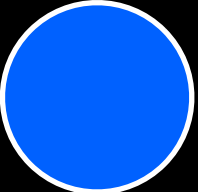



hako wo / open the box

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.

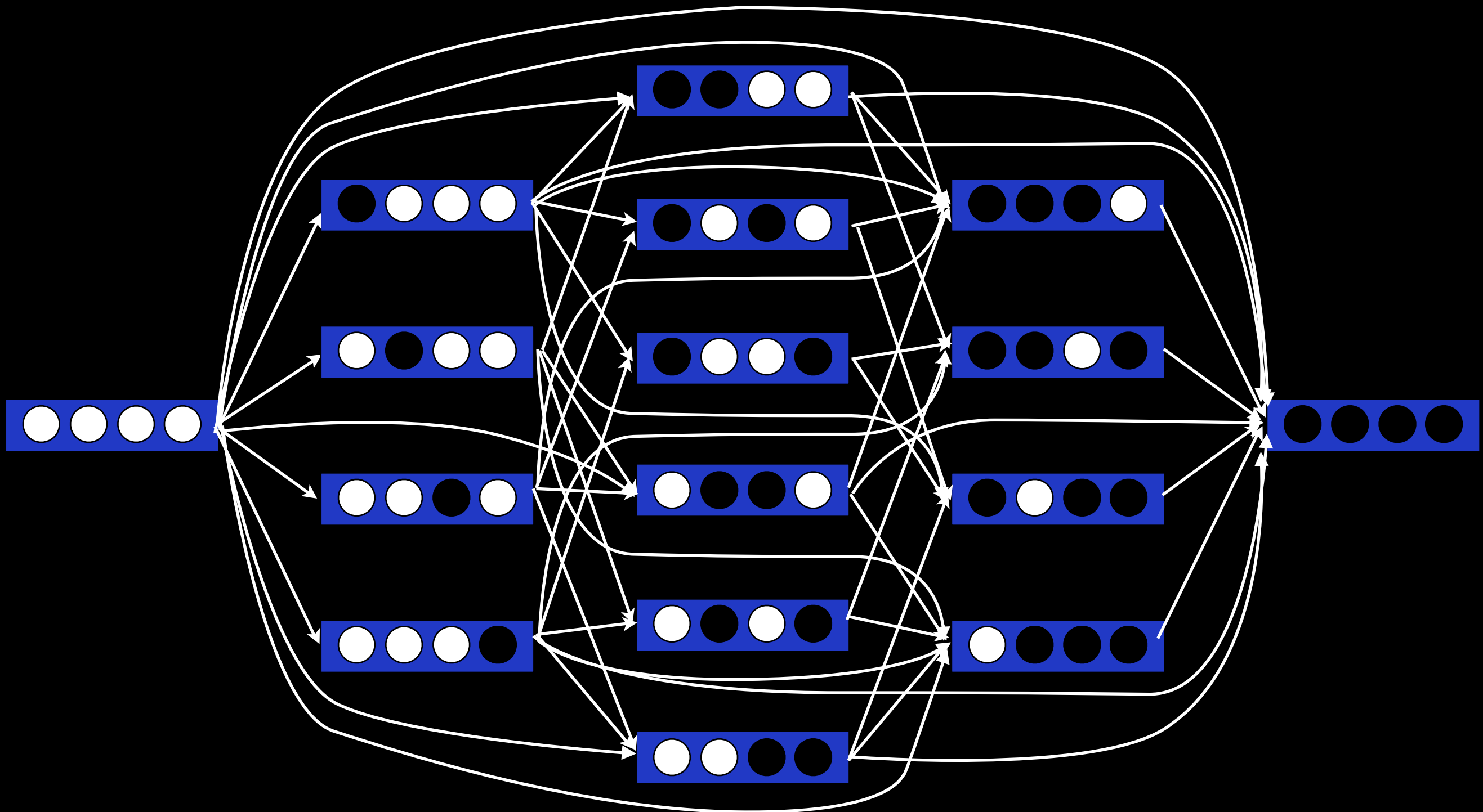
Decoding

We want to solve this problem:

$$e^* = \arg \max_e p(\mathbf{e}|\mathbf{f})$$

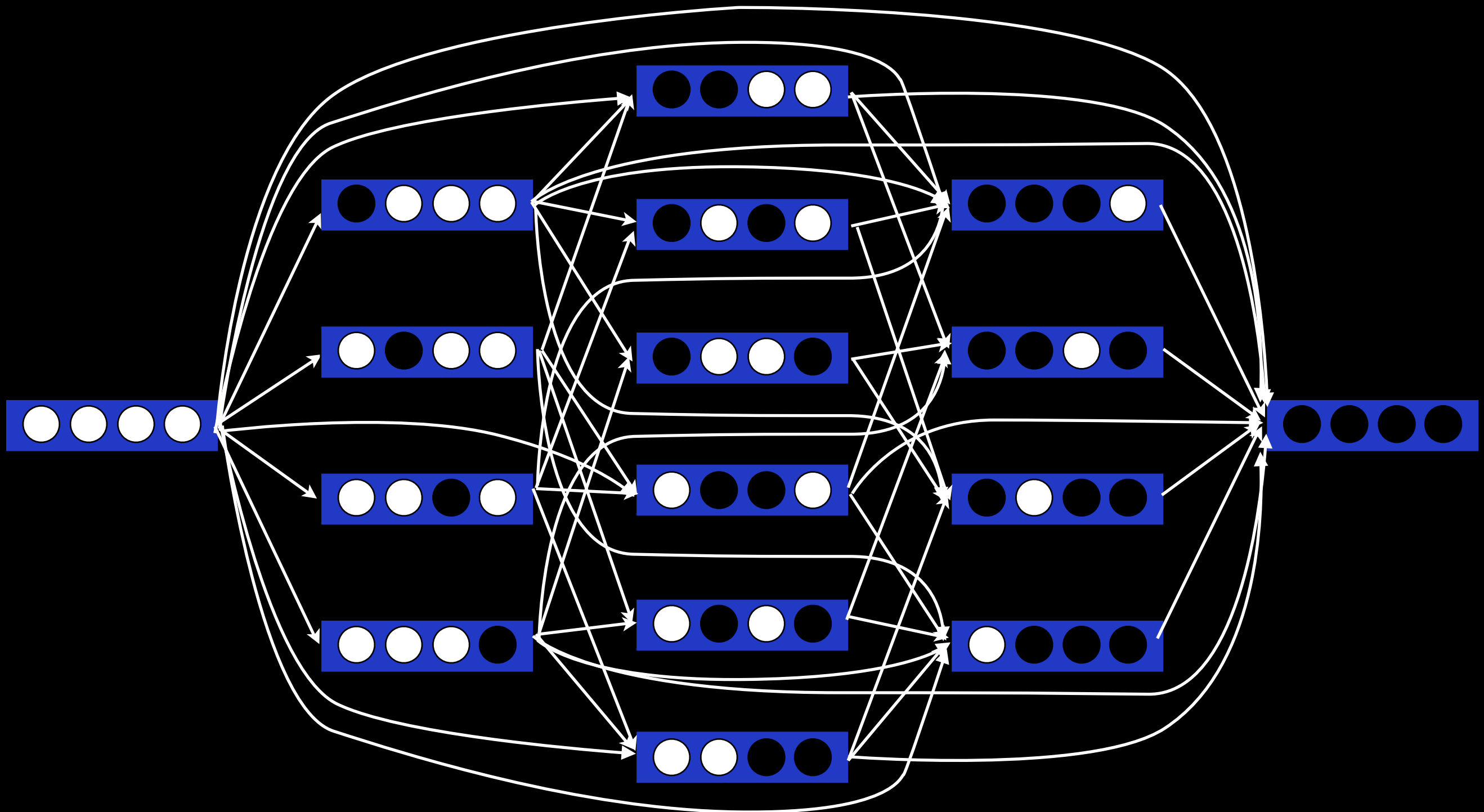
Does this problem look familiar?

Decoding similar to IBM4



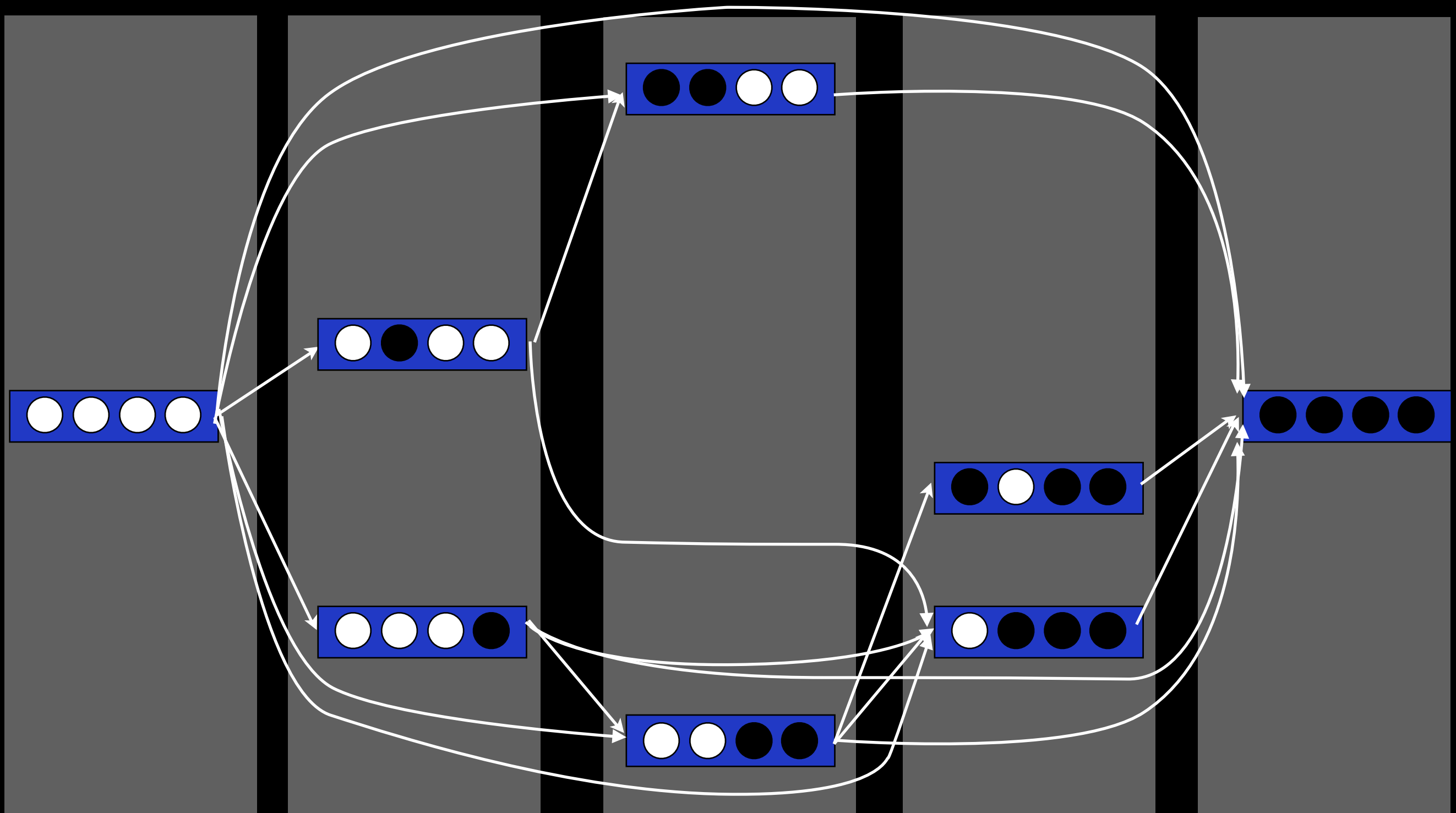
Dynamic Programming

Decoding similar to IBM4



Dynamic Programming

Approximation: Pruning



Similar approximations applicable

ChromeFileEditViewHistoryBookmarksWindowHelp

my Ghost Wars | Free Mu...Remember The Milk...A Tour of Scala: Patte...Scala Standard Libran...Classes and Objects...W3C Link Checker: ht...JHU MT courseGoogle Translate

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Adam Lopez

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To: English

Translate

Detect language

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Belarusian

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Bulgarian

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Czech

Danish

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English

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Finnish

French

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Georgian

German

Greek

Gujarati

Haitian Creole

Hebrew

Hindi

Hungarian

Indonesian

Irish

Italian

Japanese

Kannada

Korean

Latin

Latvian

Lithuanian

Macedonian

Malay

Maltese

Norwegian

Persian

Polish

Portuguese

Romanian

Russian

Serbian

Slovak

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Swahili

Swedish

Tamil

Telugu

Thai

Turkish

Ukrainian

Urdu

Vietnamese

Welsh

Yiddish

Spanish

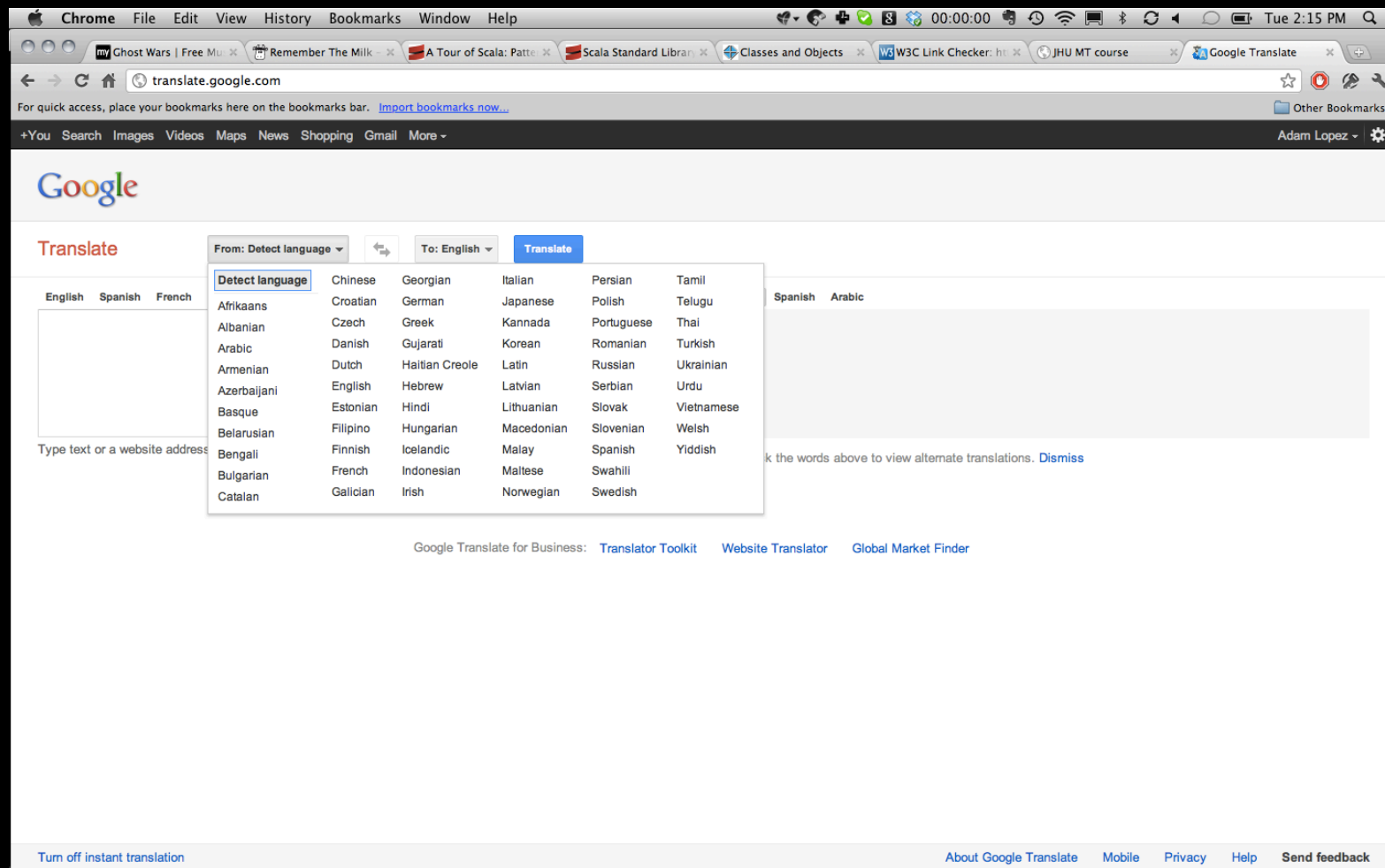
Arabic

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

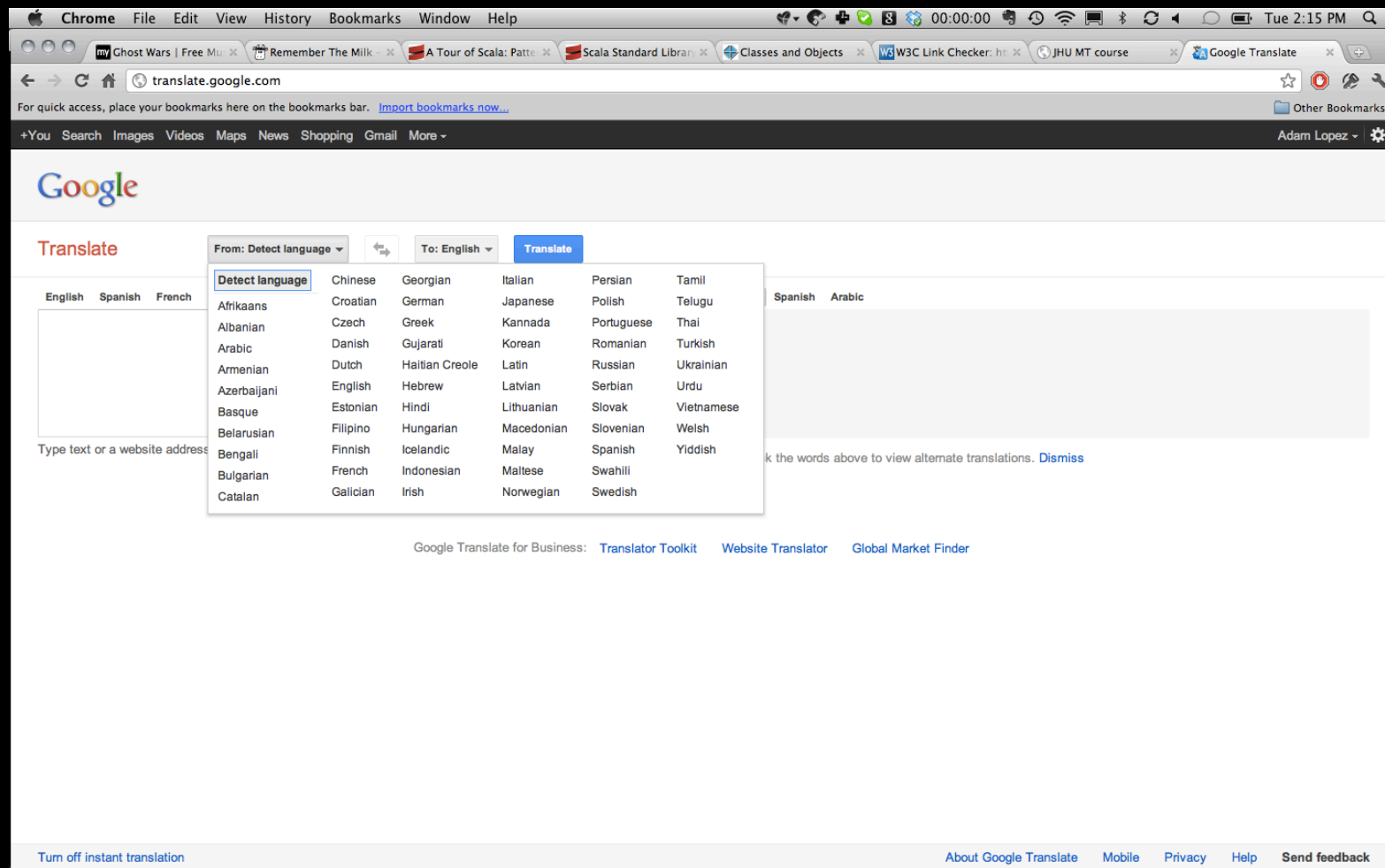
Google Translate for Business: [Translator Toolkit](#) [Website Translator](#) [Global Market Finder](#)

Turn off instant translation

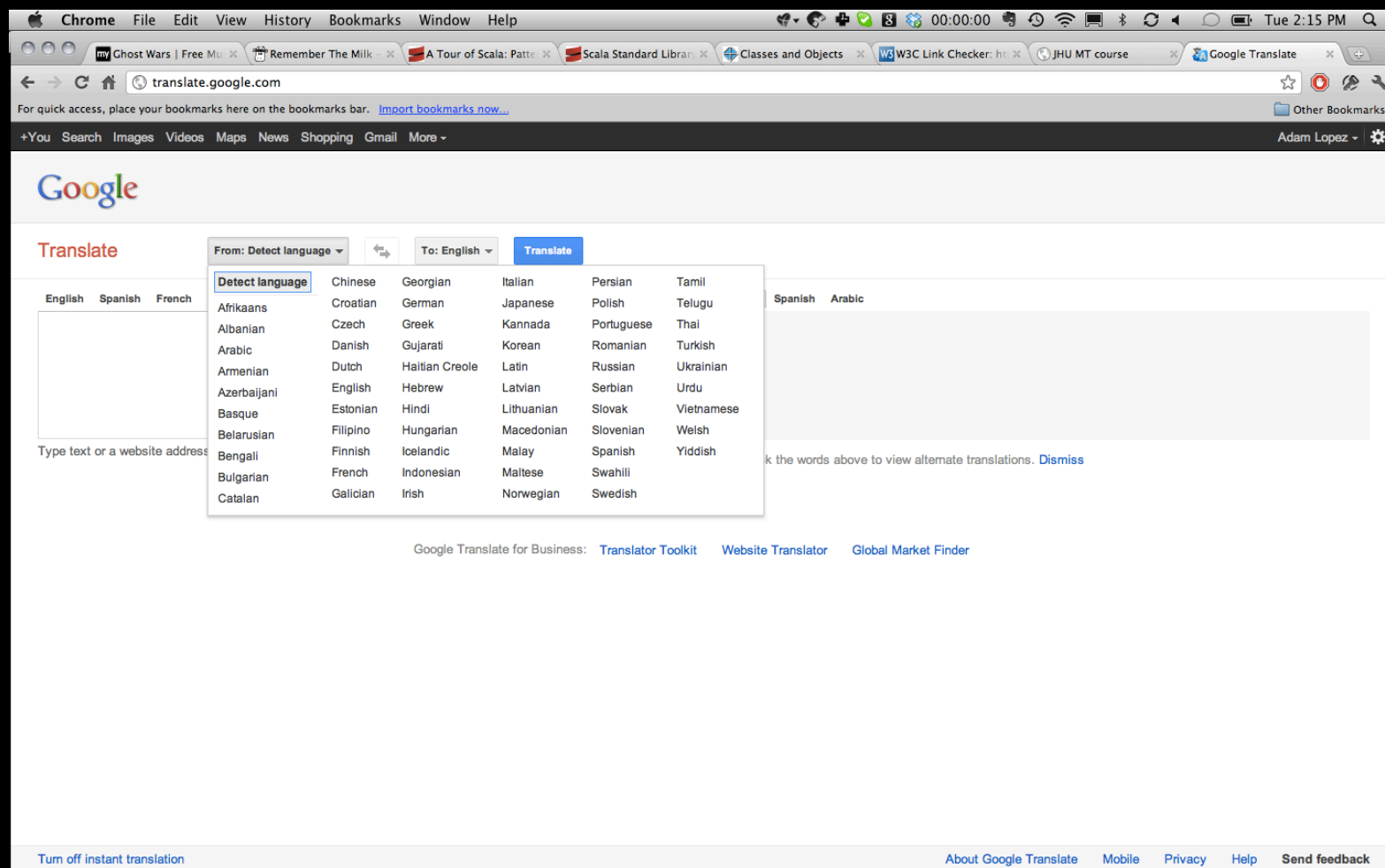
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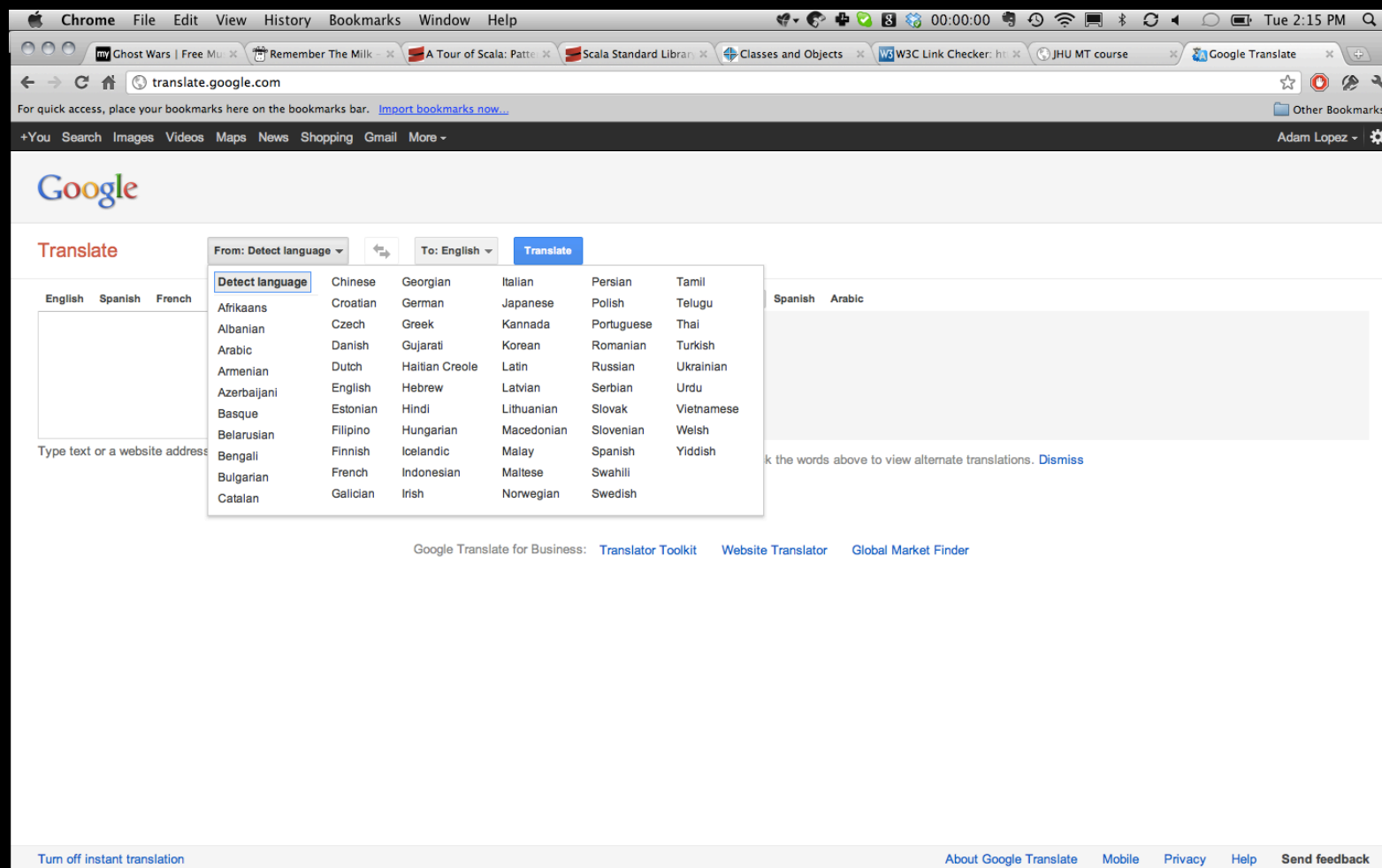
● Key ingredients in Google Translate (2006-2017):



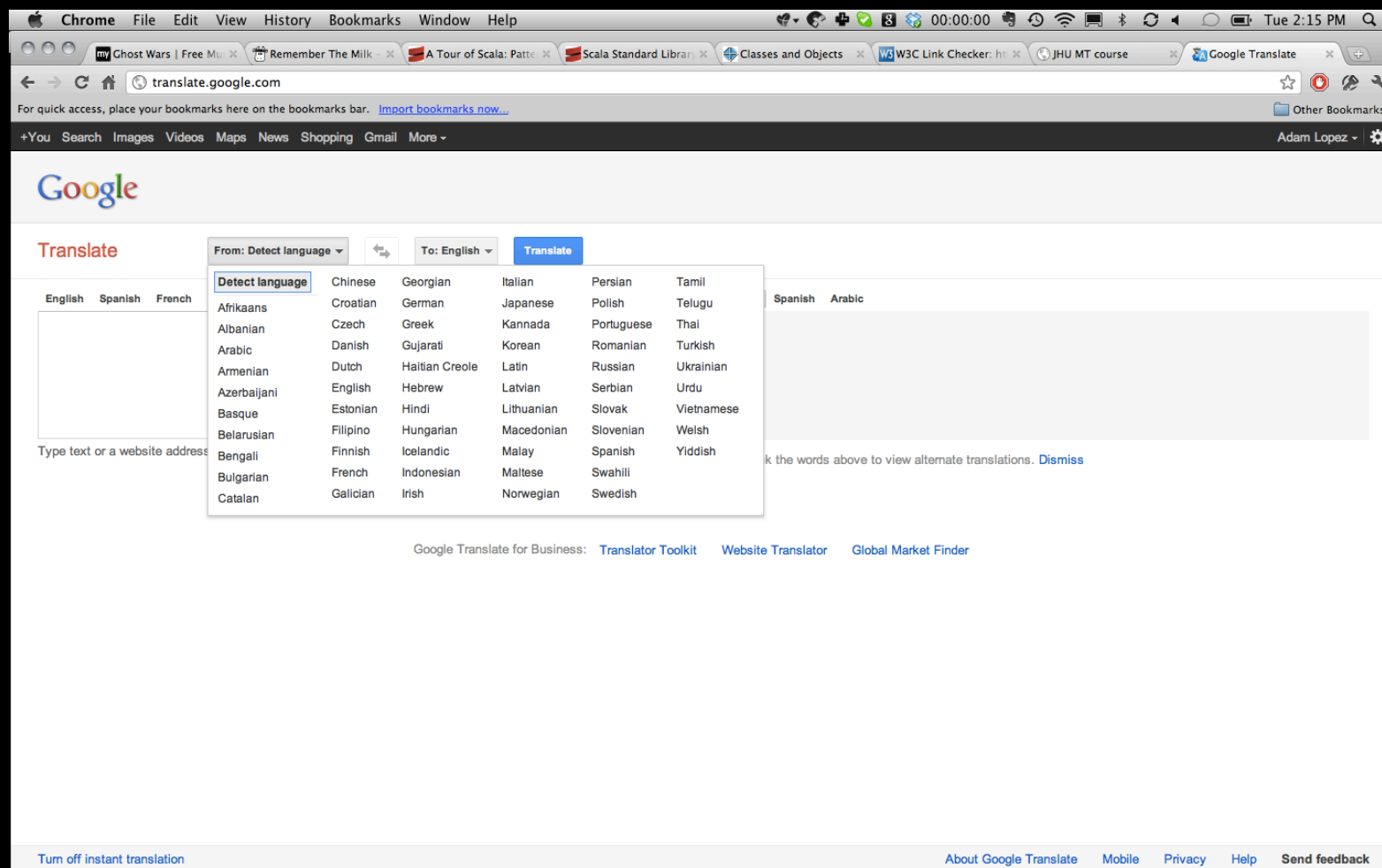
- Key ingredients in Google Translate (2006-2017):
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- Key ingredients in Google Translate (2006-2017):
 - Phrase-based translation models
 - ... Learned heuristically from word alignments
 - ... Coupled with a huge language model
 - ... And decoding with severe pruning heuristics

Dynamic programming

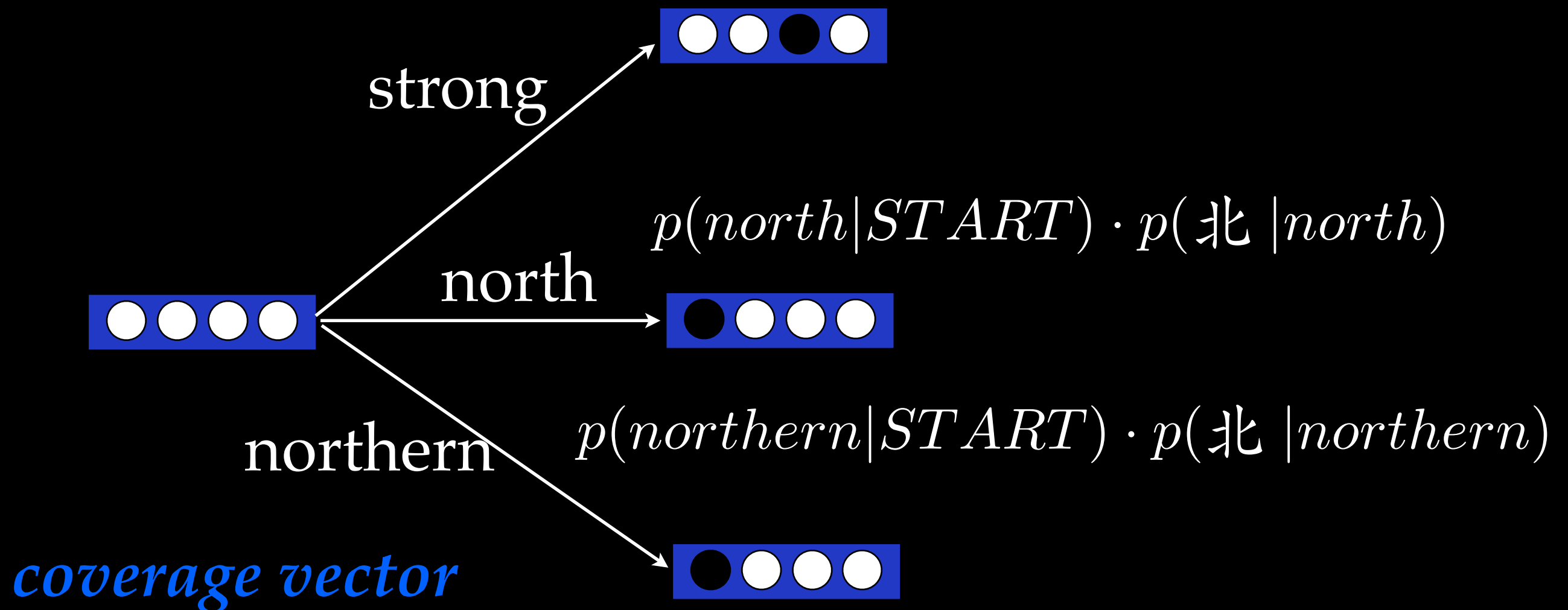
北 风 呼 啸 。

There are $5^n n!$ target sentences.

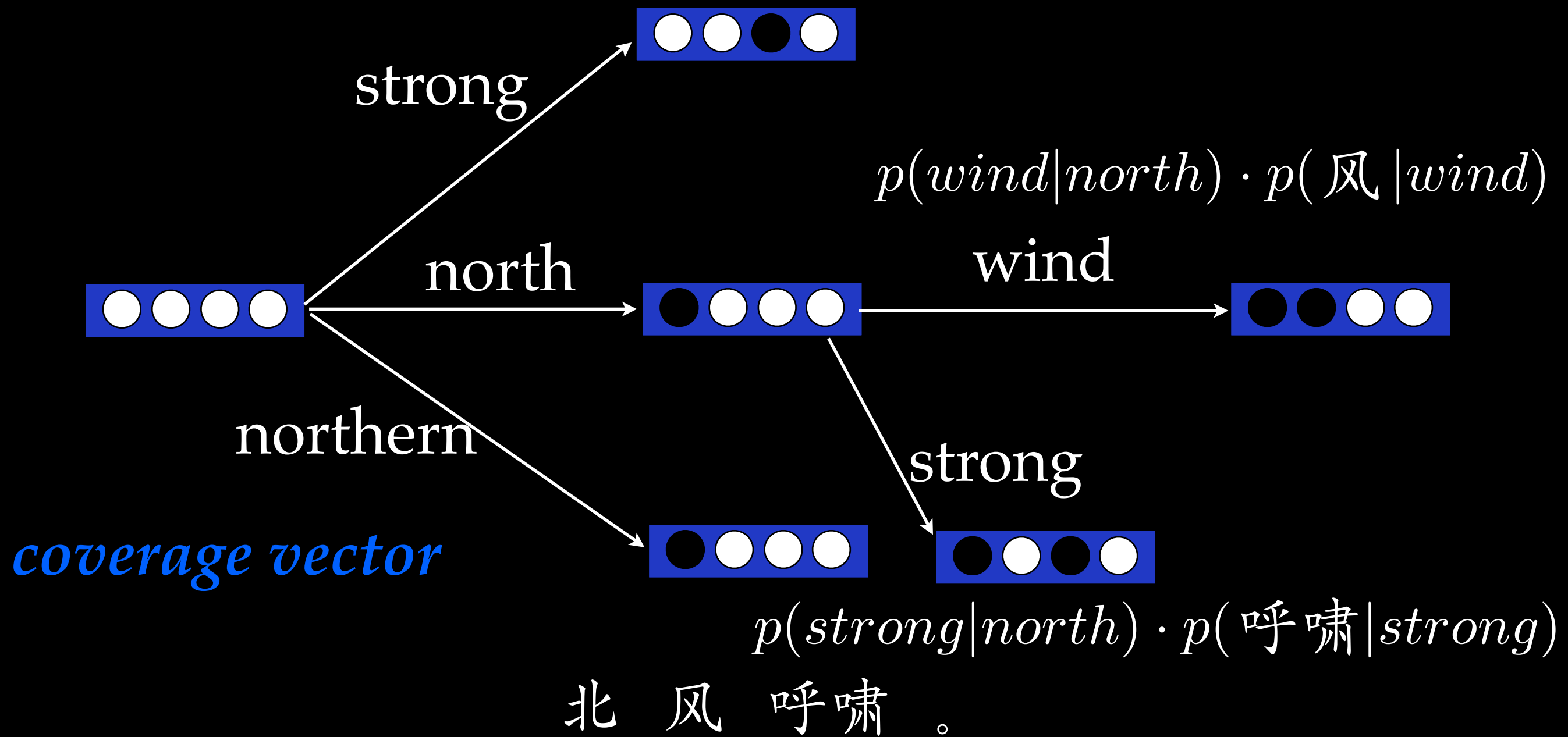
But there are only $O(5n)$ ways to start them.

Dynamic programming

$$p(\textit{strong}|\textit{START}) \cdot p(\text{呼啸}|\textit{strong})$$

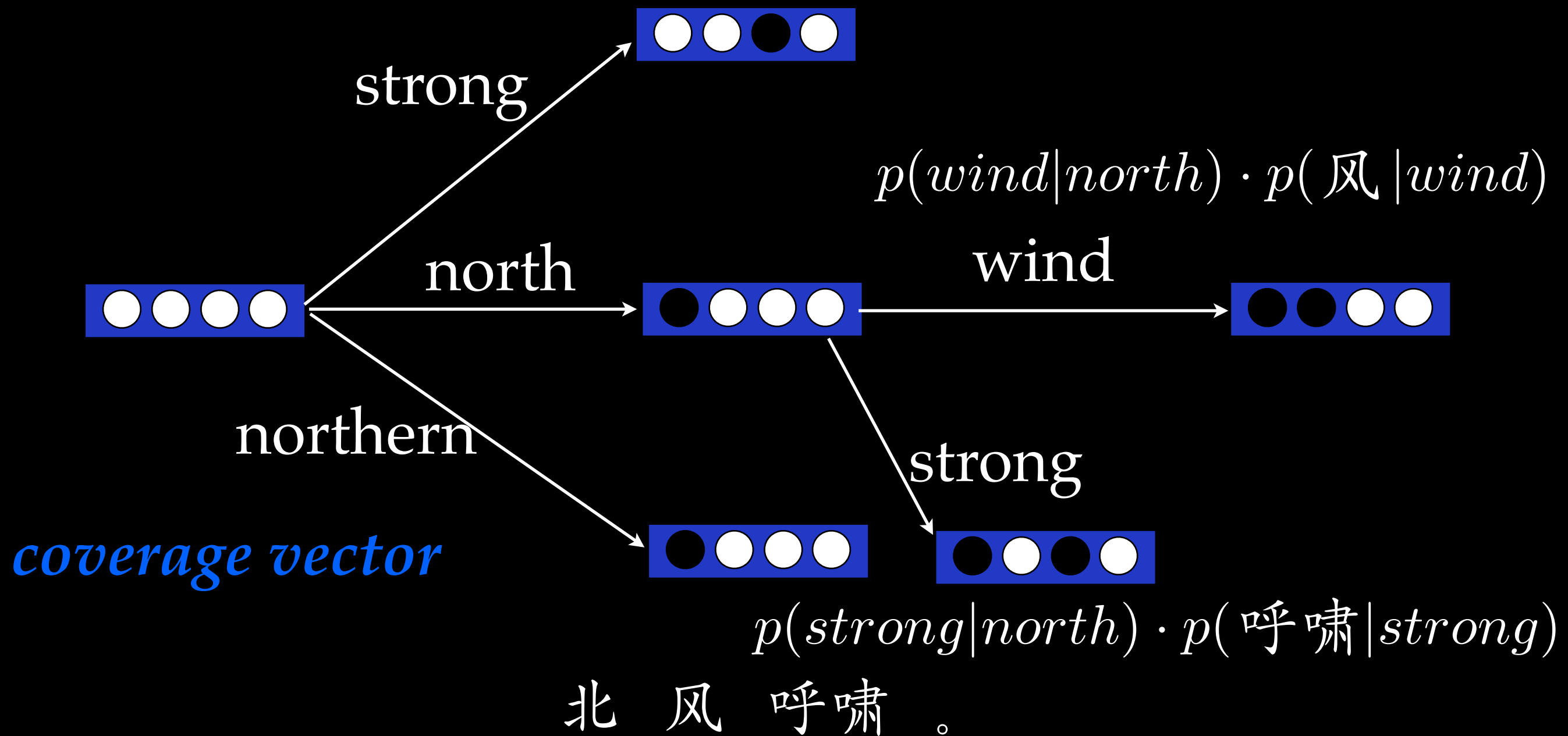


Dynamic programming



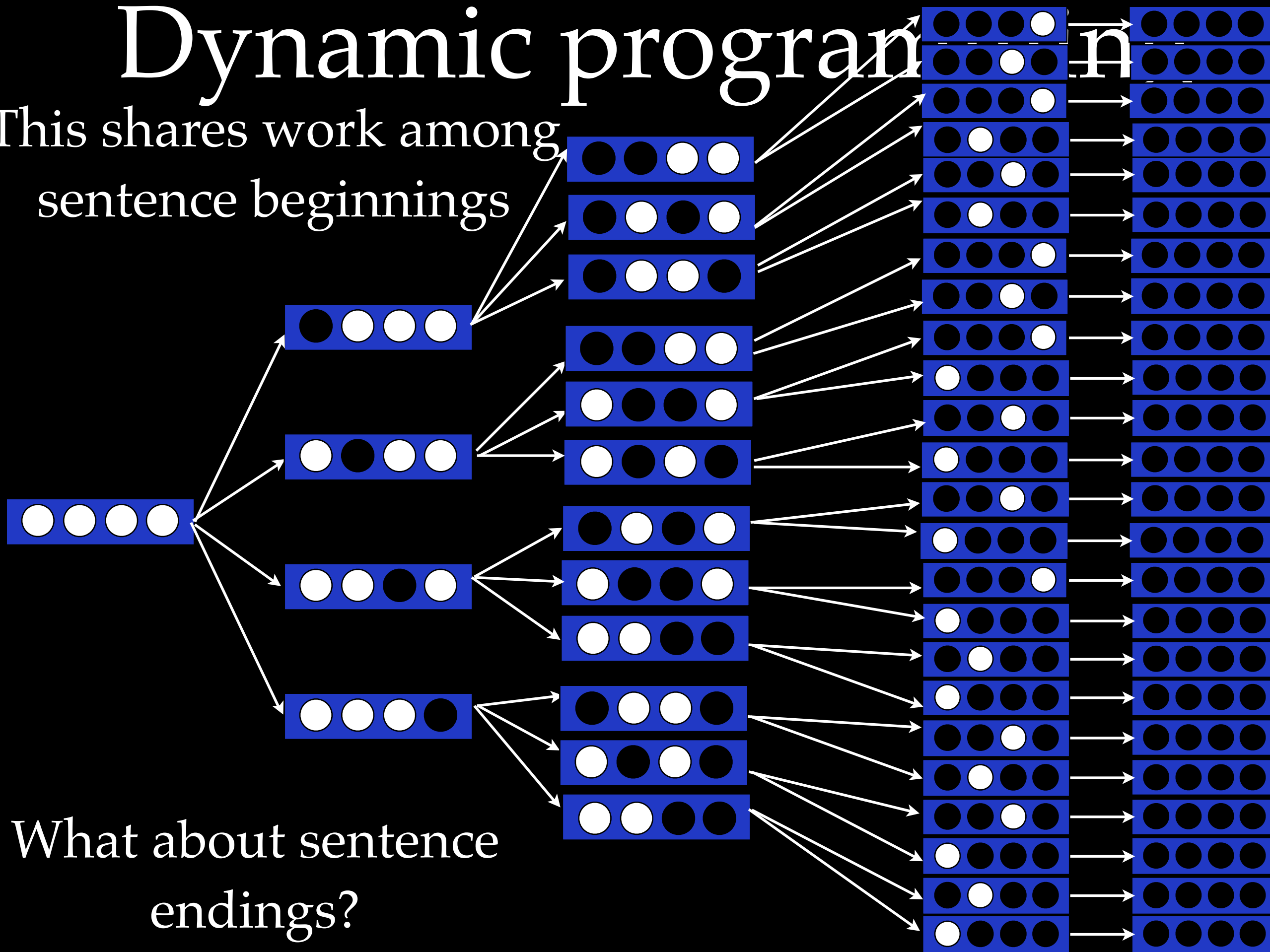
Dynamic programming

This shares work among
sentence beginnings

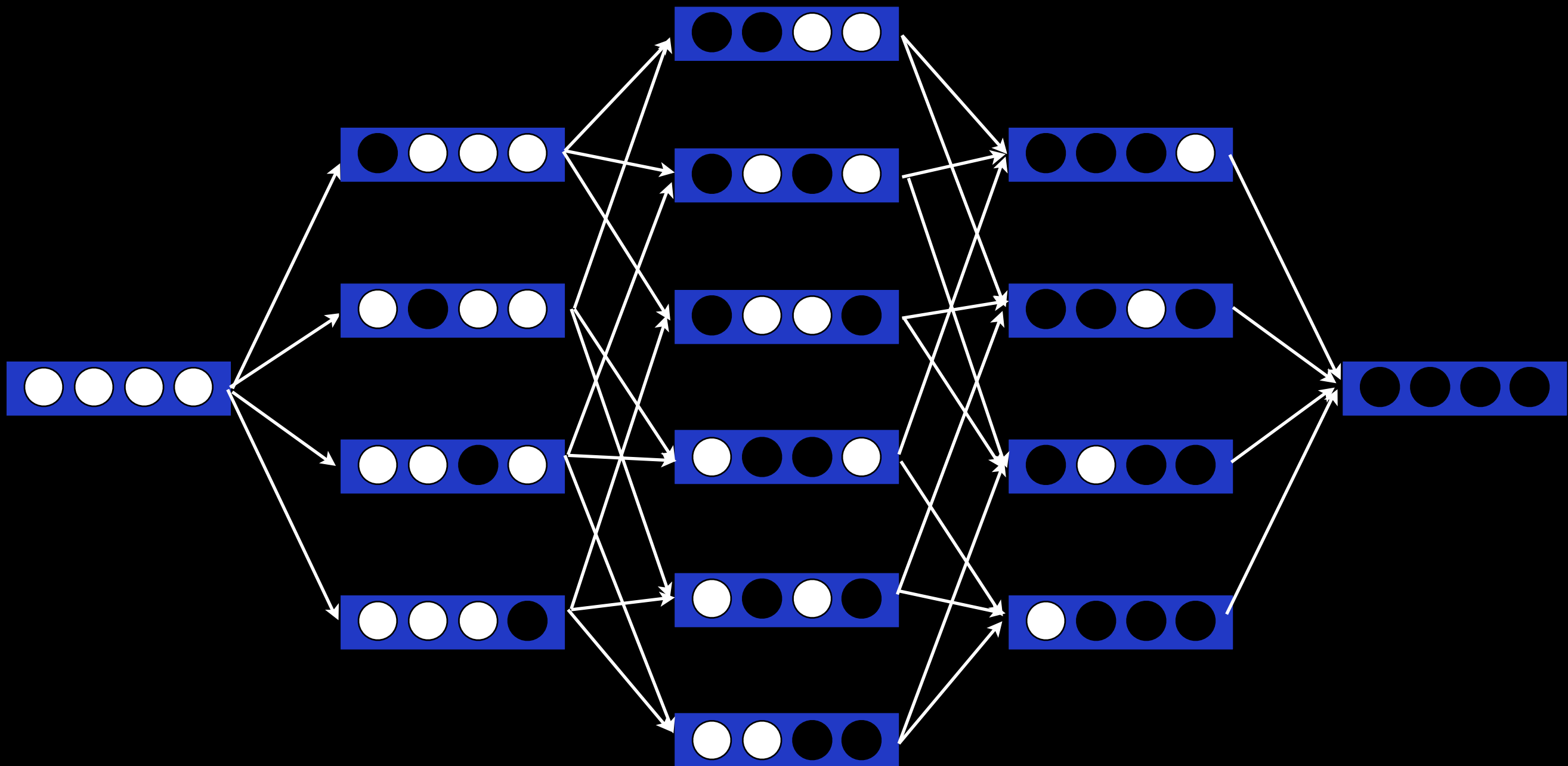


Dynamic programming

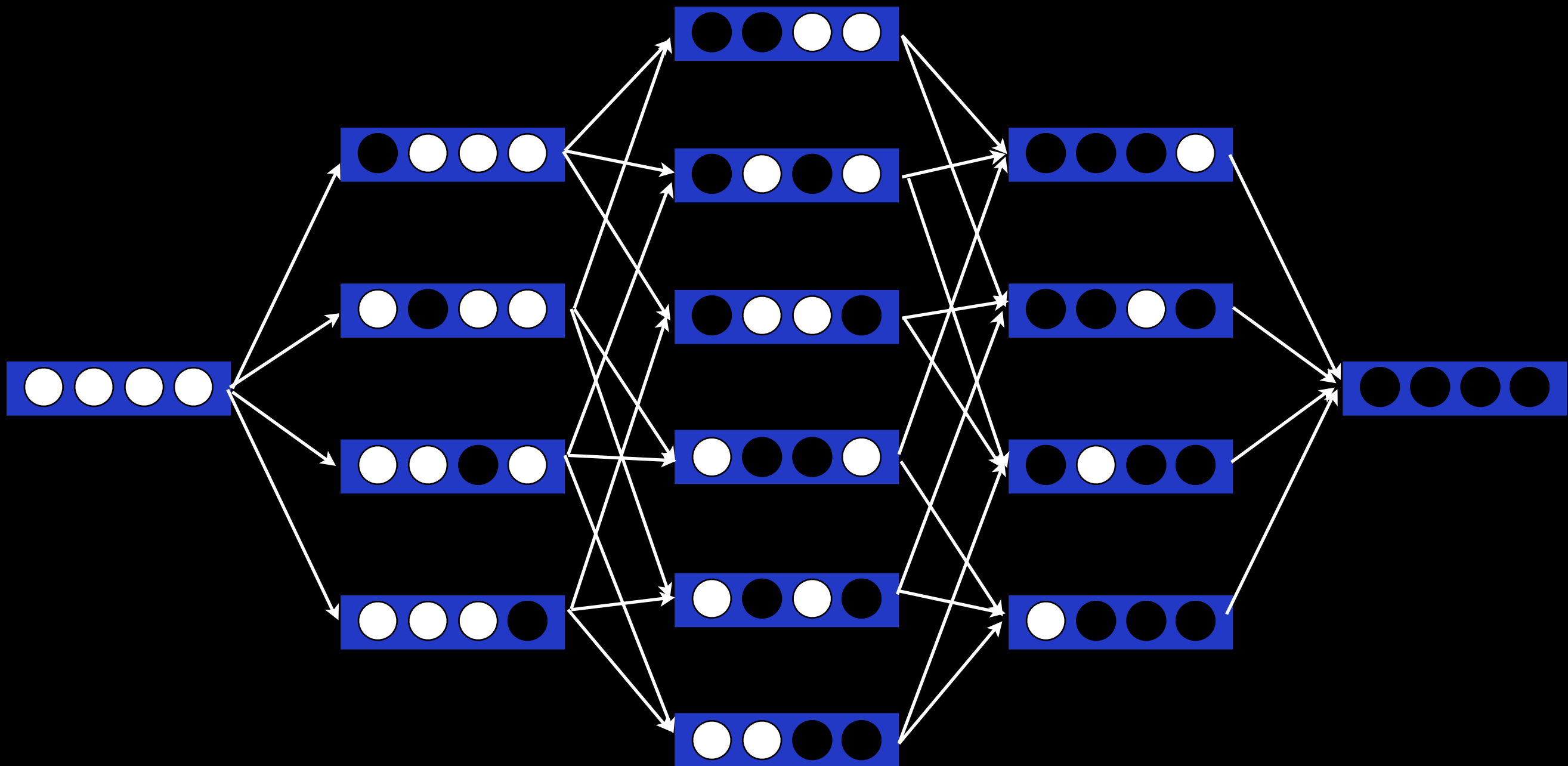
This shares work among
sentence beginnings



Approximation: Pruning

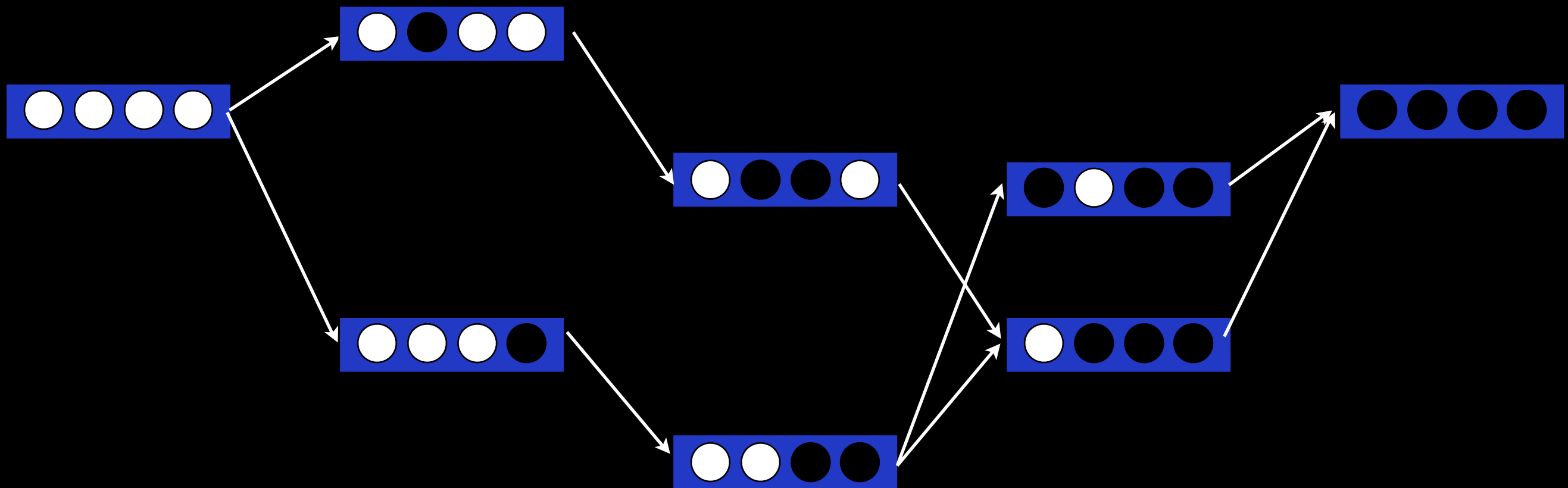


Approximation: Pruning



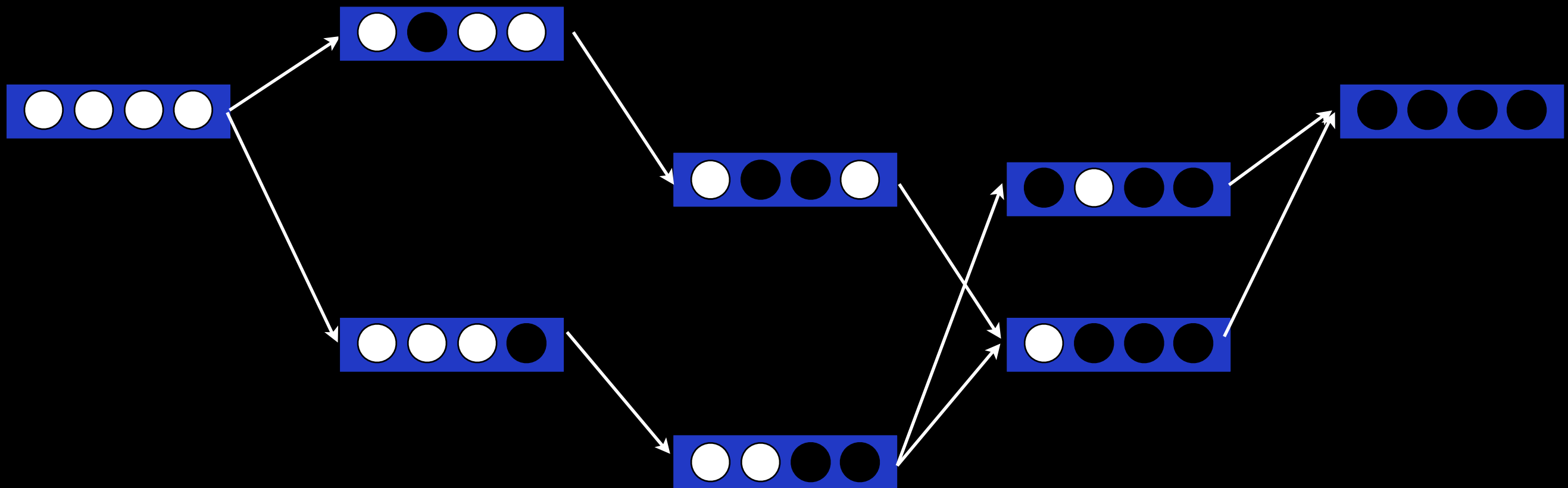
Idea: prune states by cost of shortest path to them

Approximation: Pruning



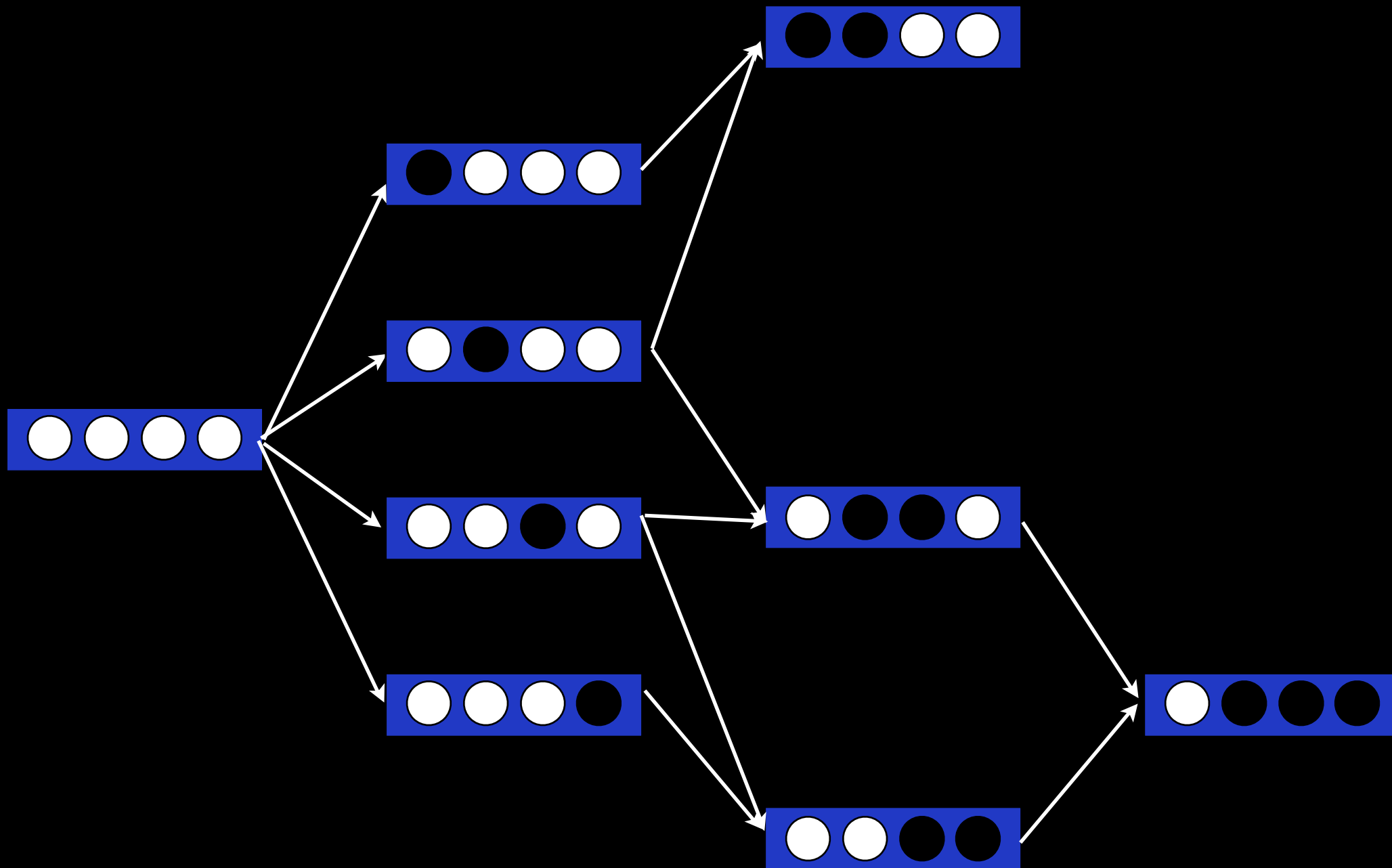
Idea: prune states by accumulated path length

Approximation: Pruning



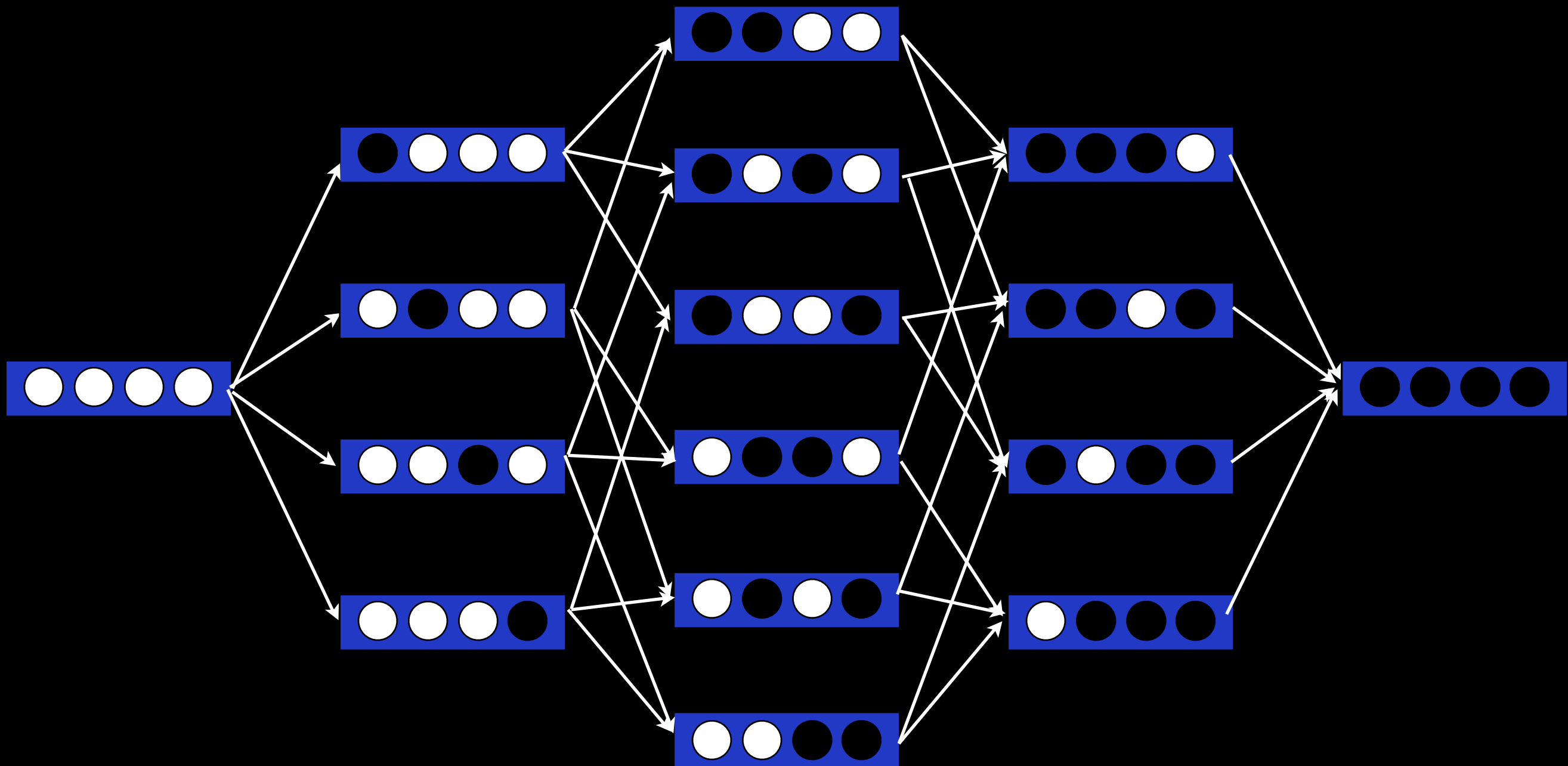
Ideal result: only high-probability paths enumerated

Approximation: Pruning

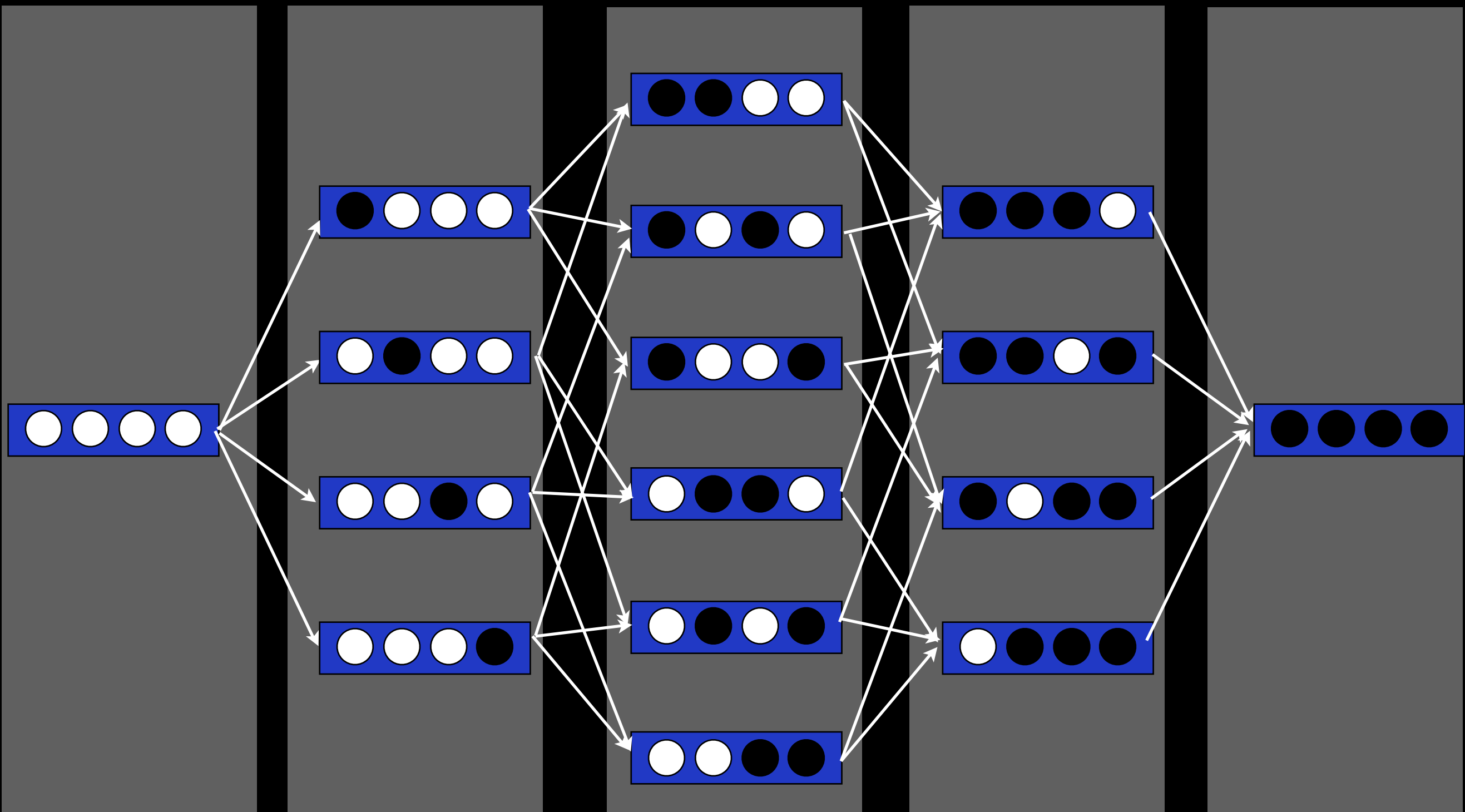


Actual result: longer paths have lower probability!

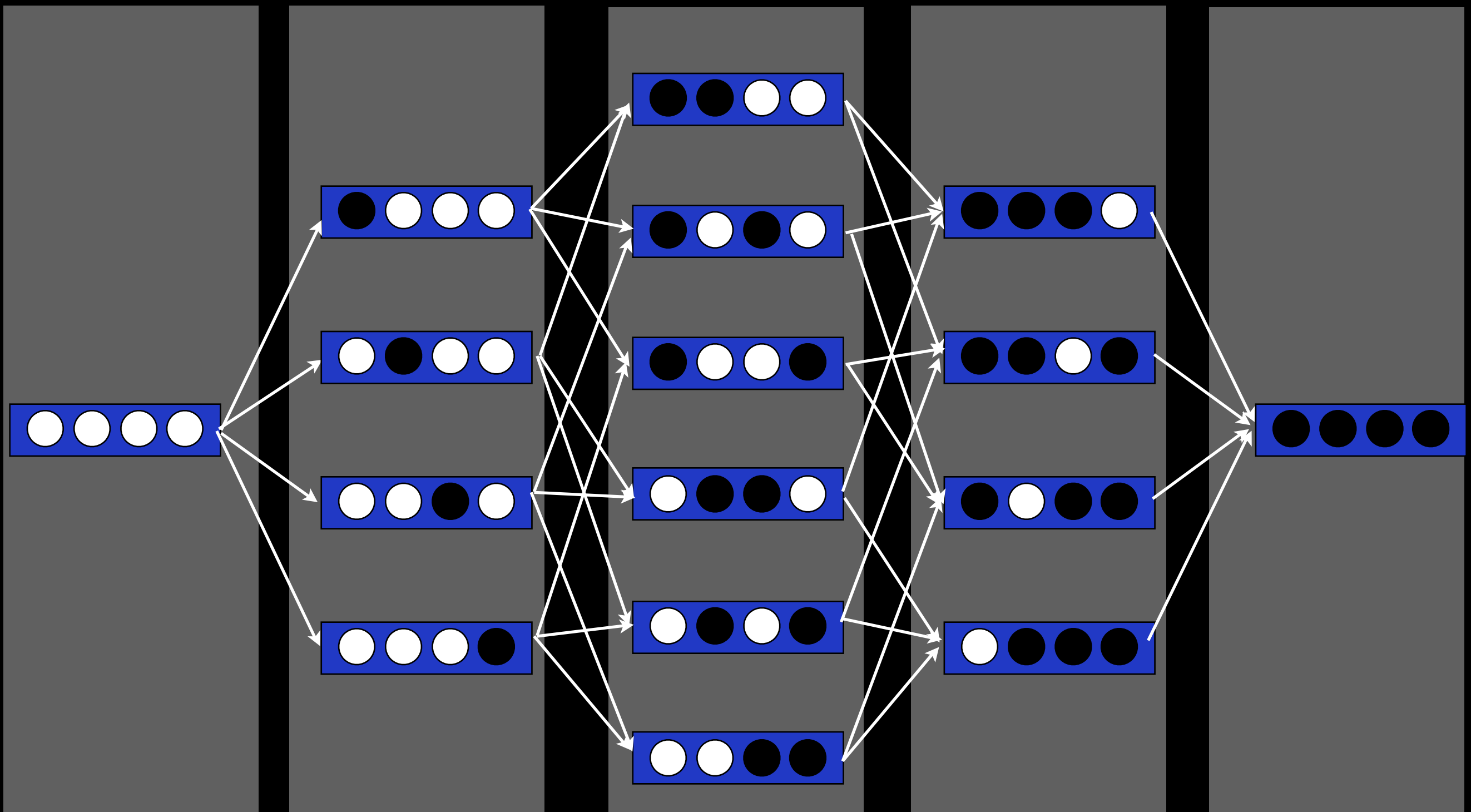
Approximation: Pruning



Approximation: Pruning

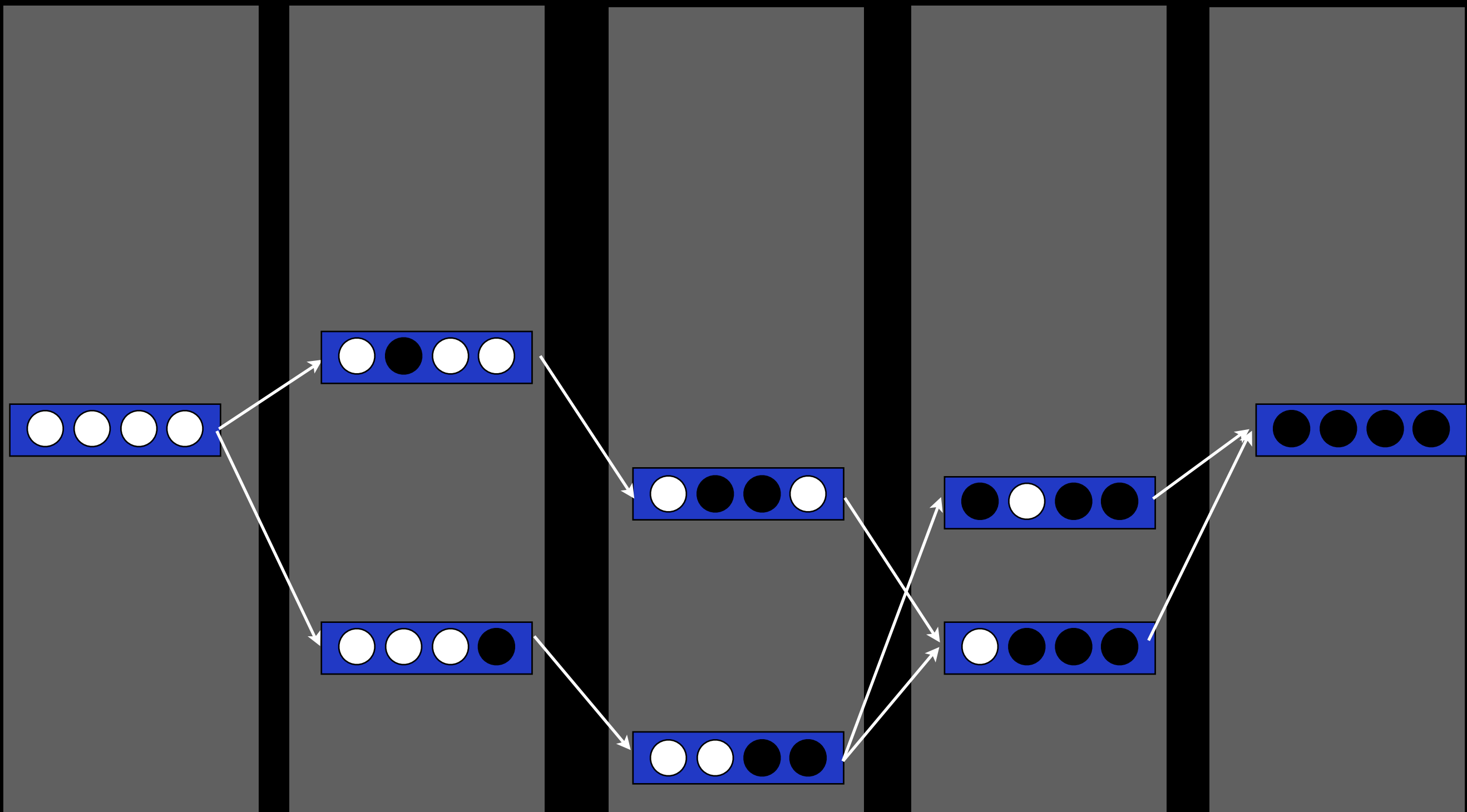


Approximation: Pruning



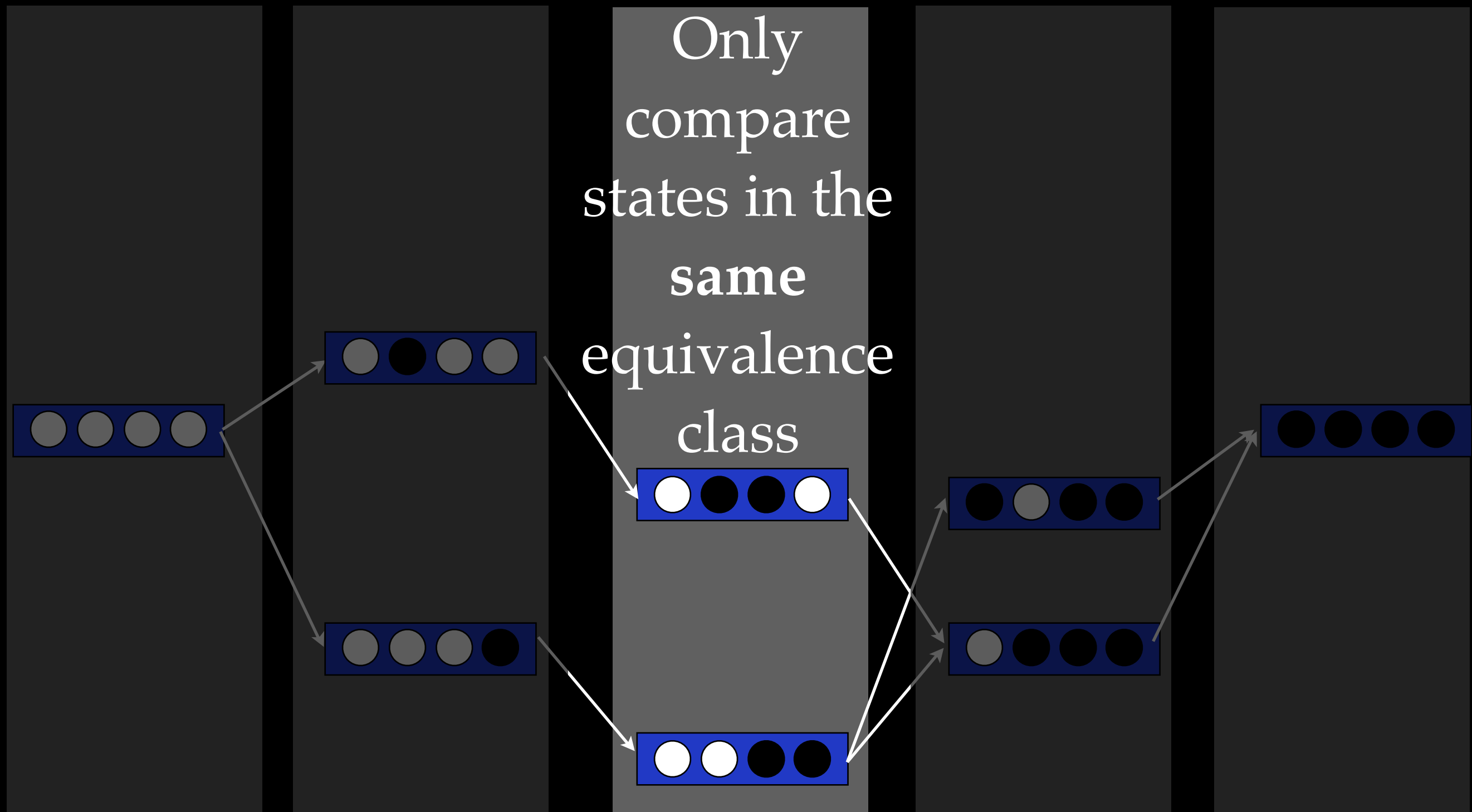
Solution: Group states by number of covered words.

Approximation: Pruning



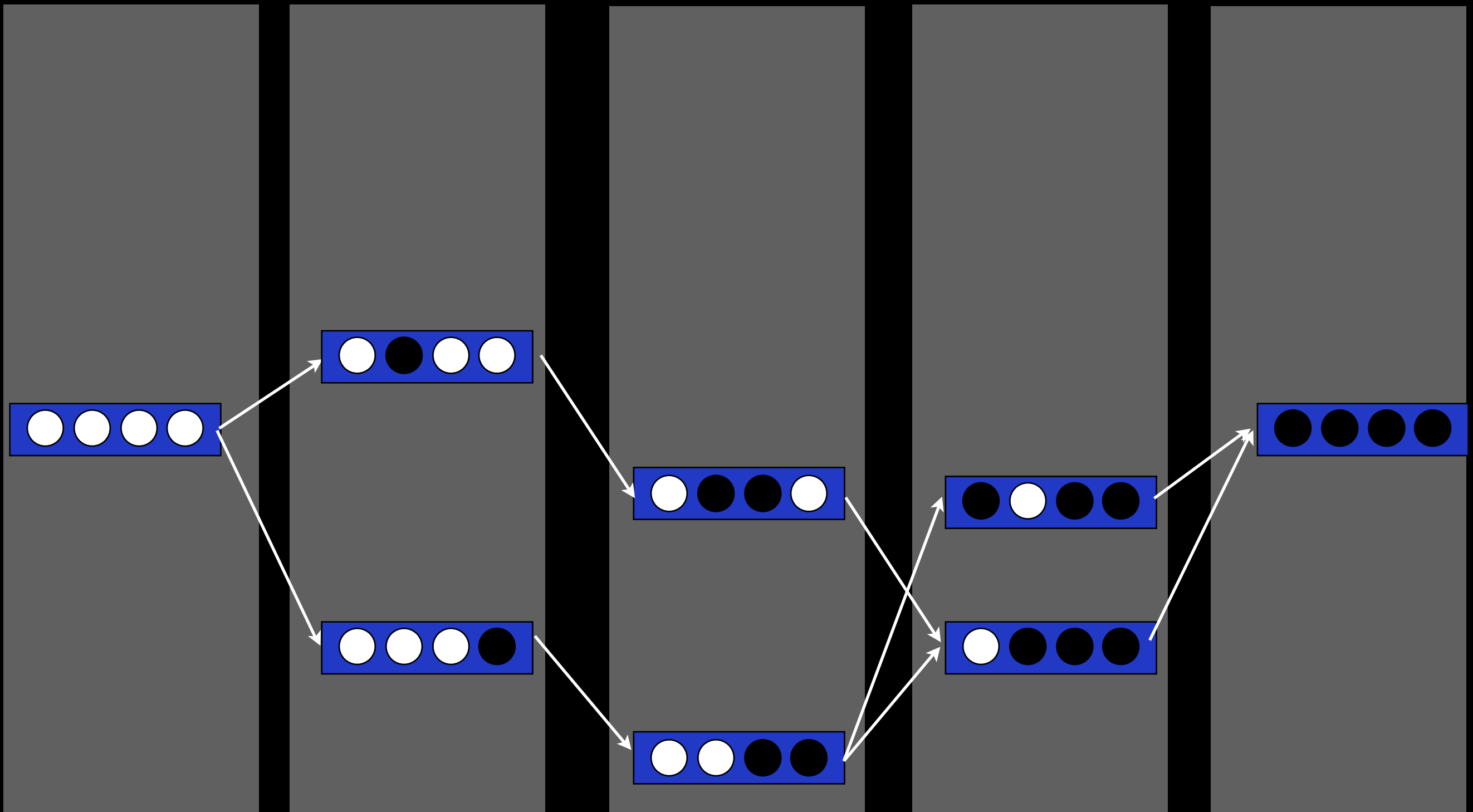
Solution: Group states by number of covered words.

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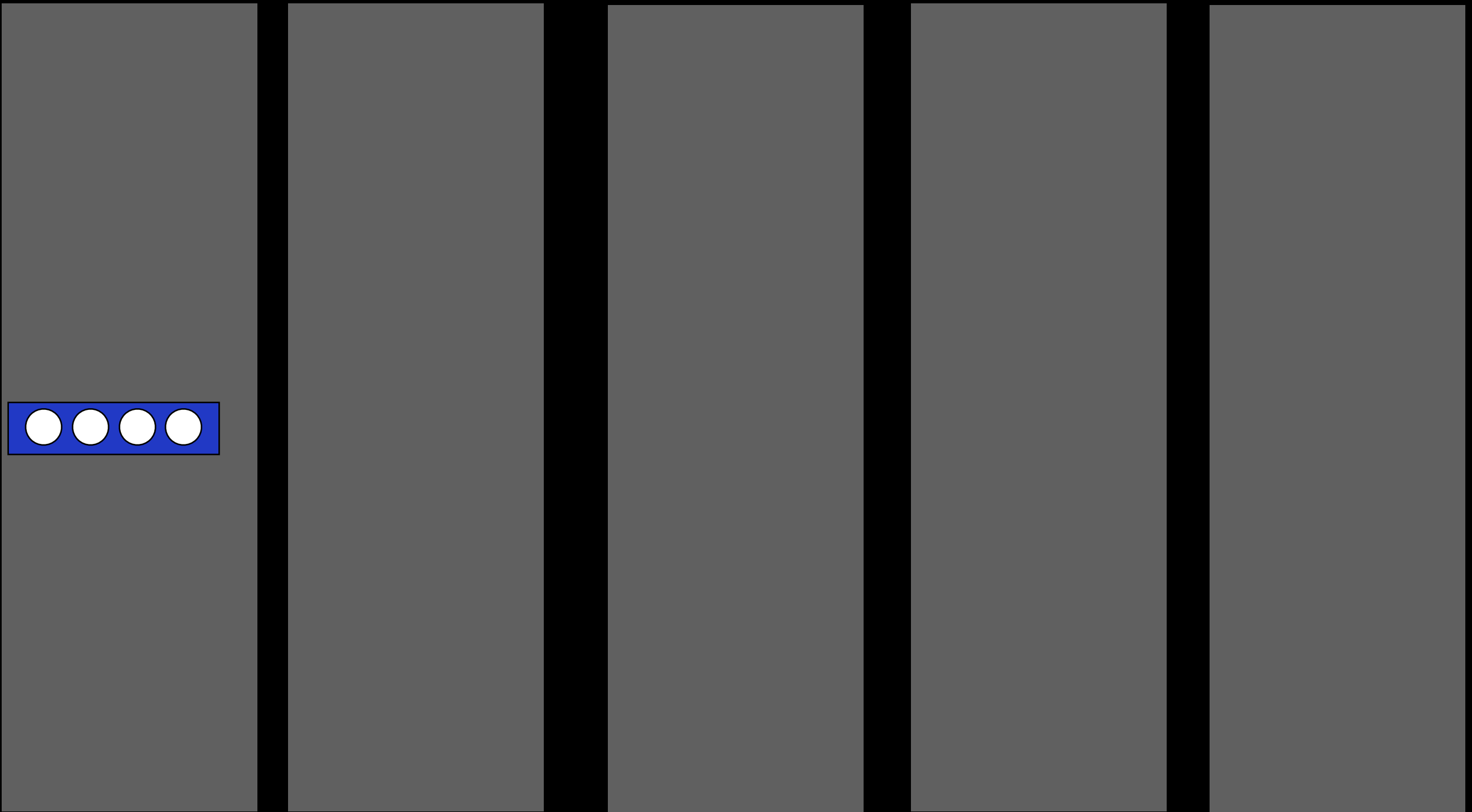
Solution: Group states by number of covered words.

Approximation: Pruning



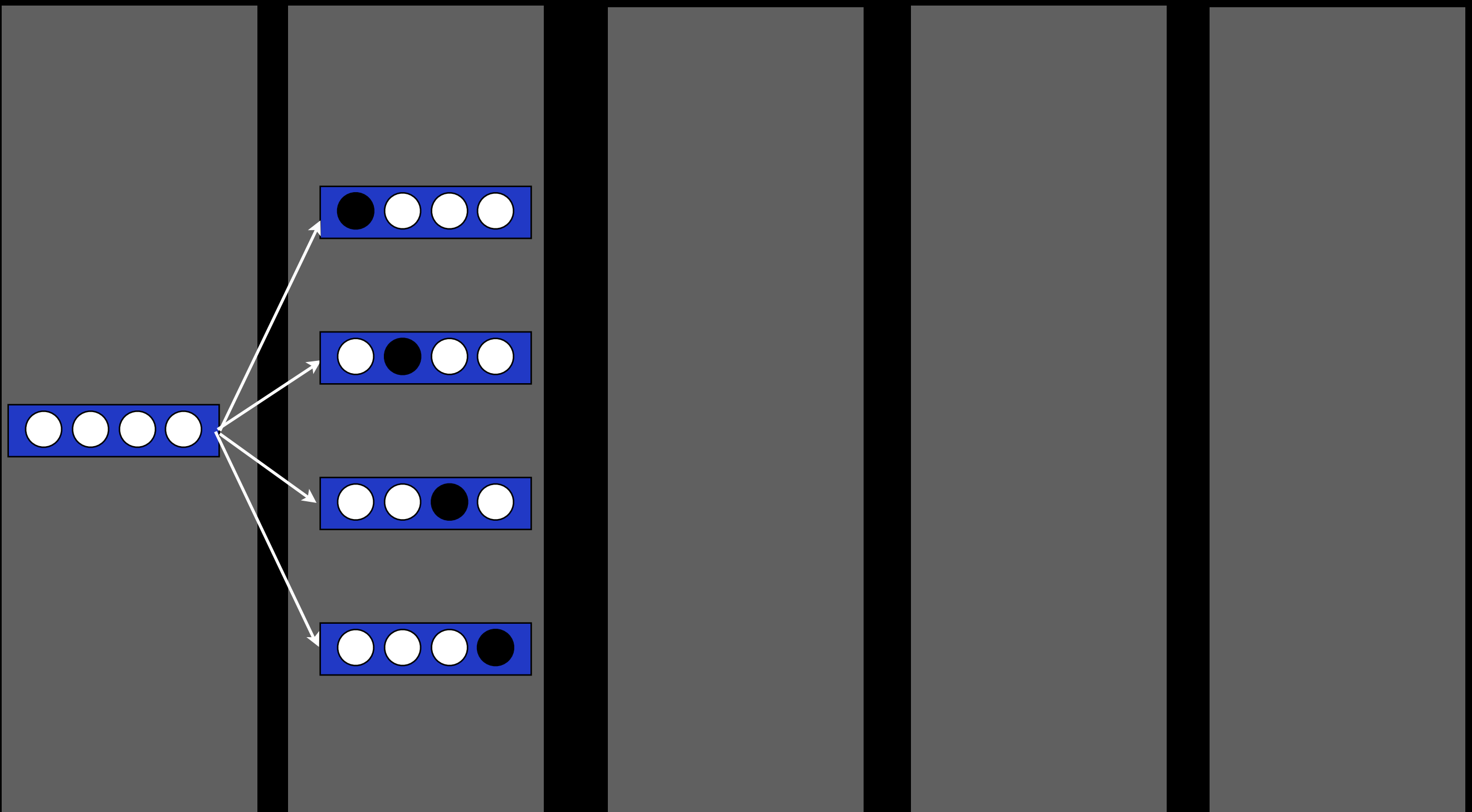
“Stack” decoding: a linear-time approximation

Approximation: Pruning



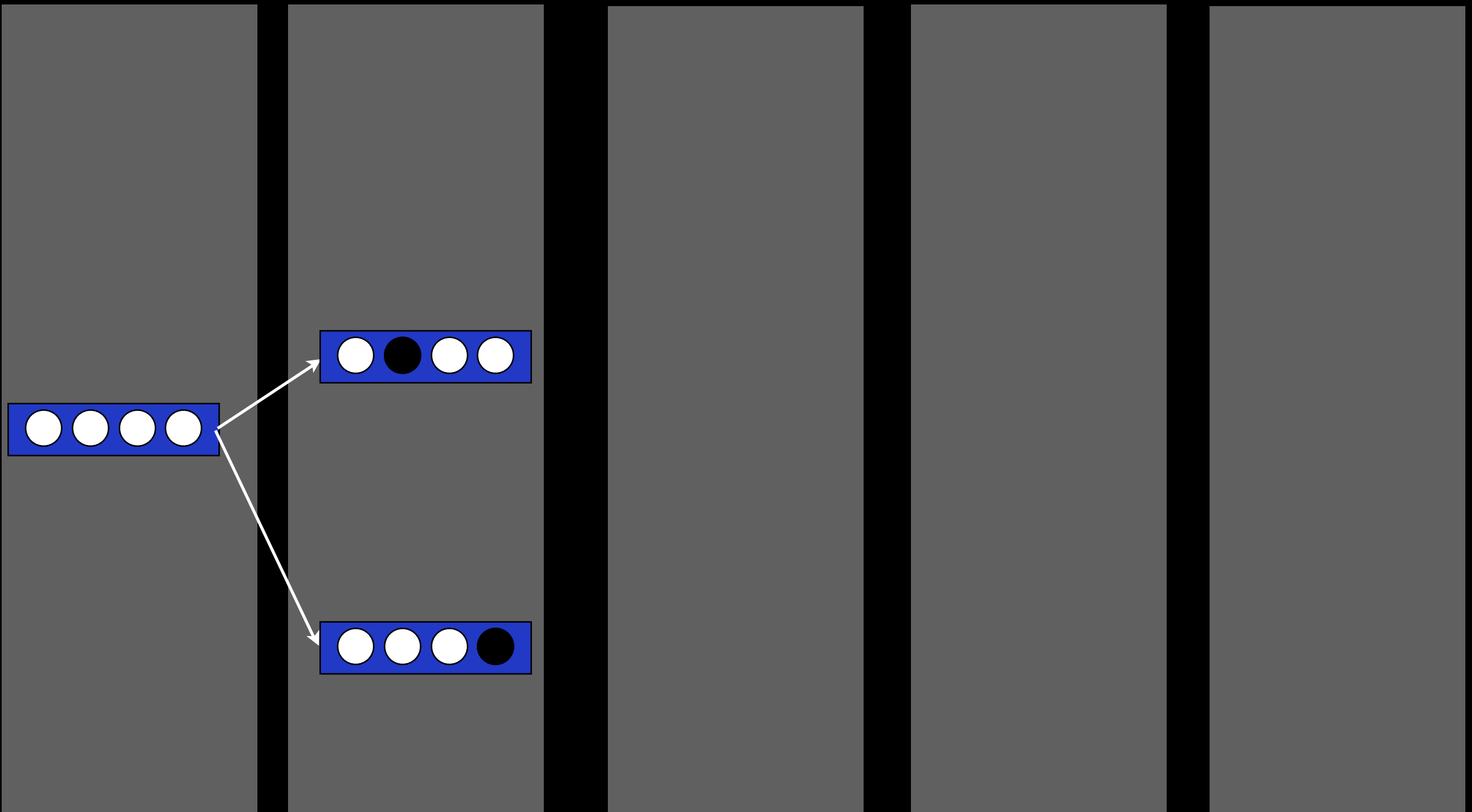
“Stack” decoding: a linear-time approximation

Approximation: Pruning



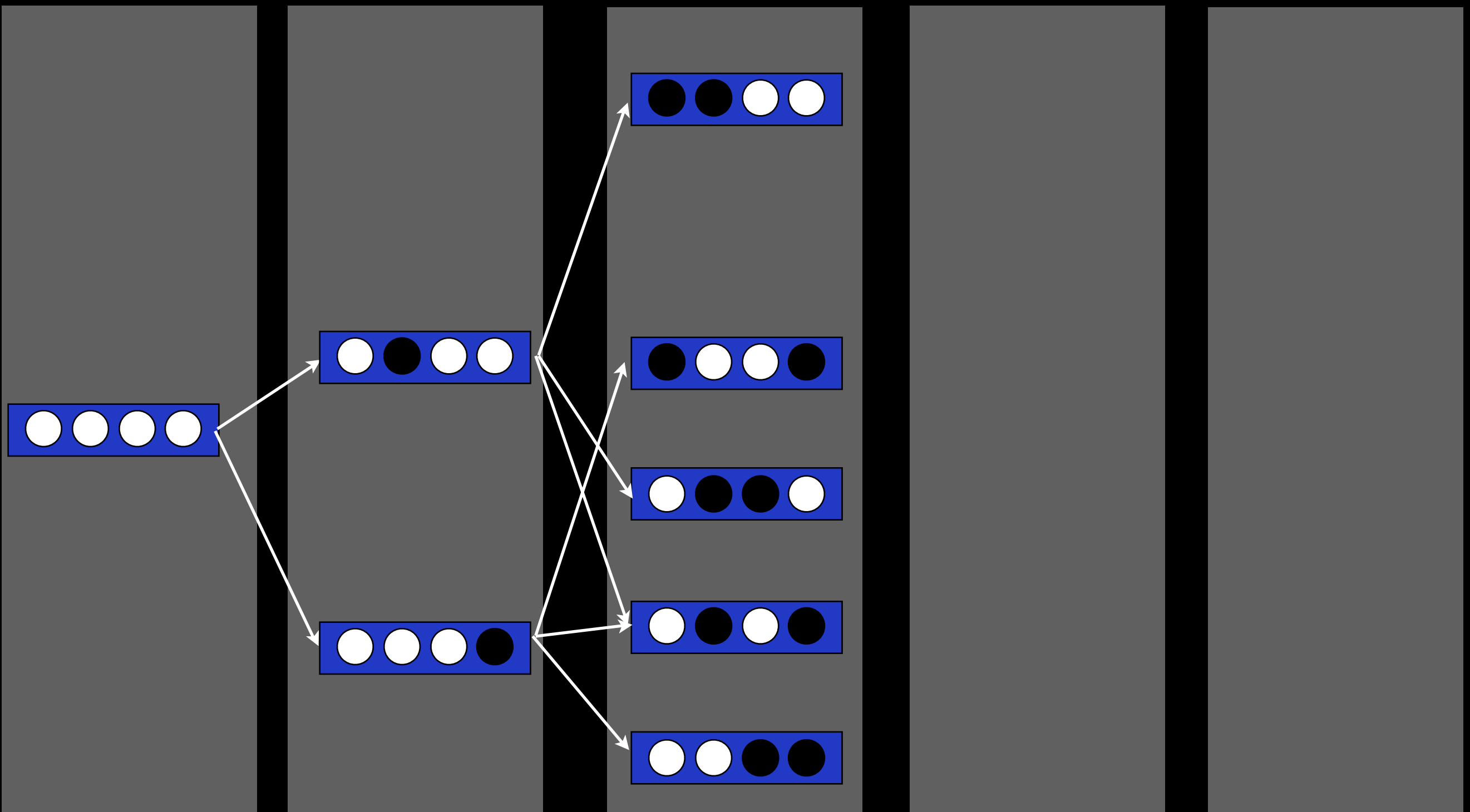
“Stack” decoding: a linear-time approximation

Approximation: Pruning



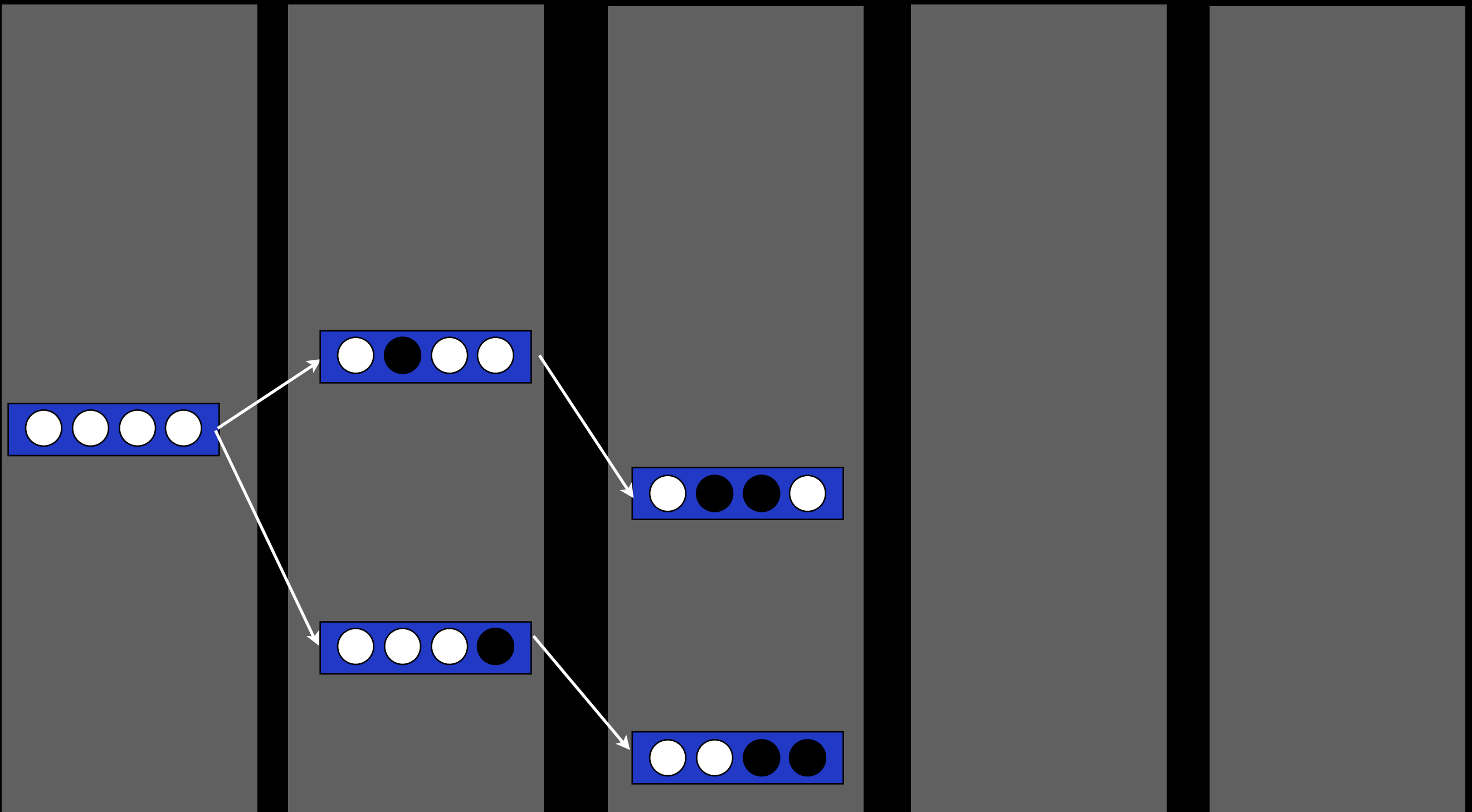
“Stack” decoding: a linear-time approximation

Approximation: Pruning



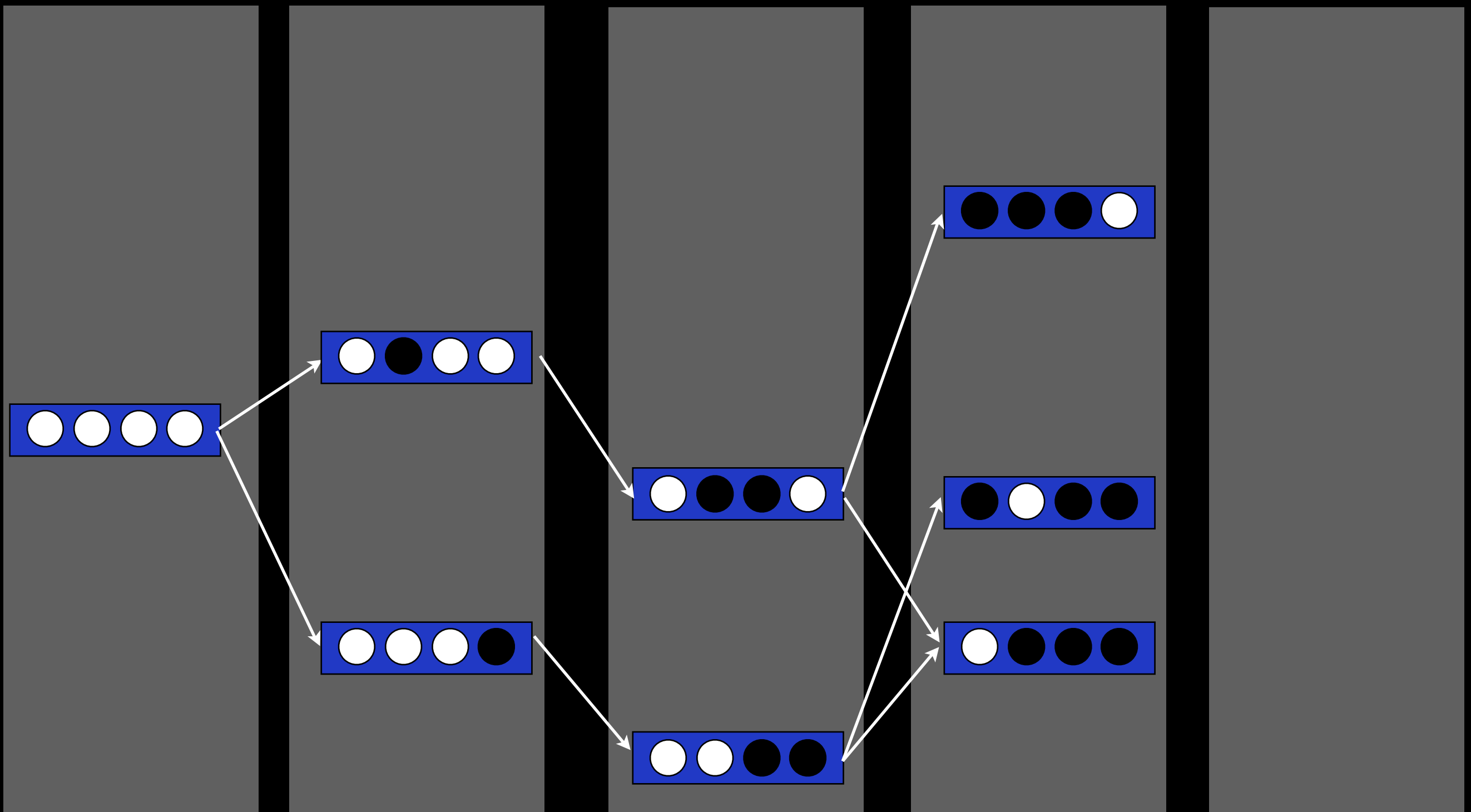
“Stack” decoding: a linear-time approximation

Approximation: Pruning



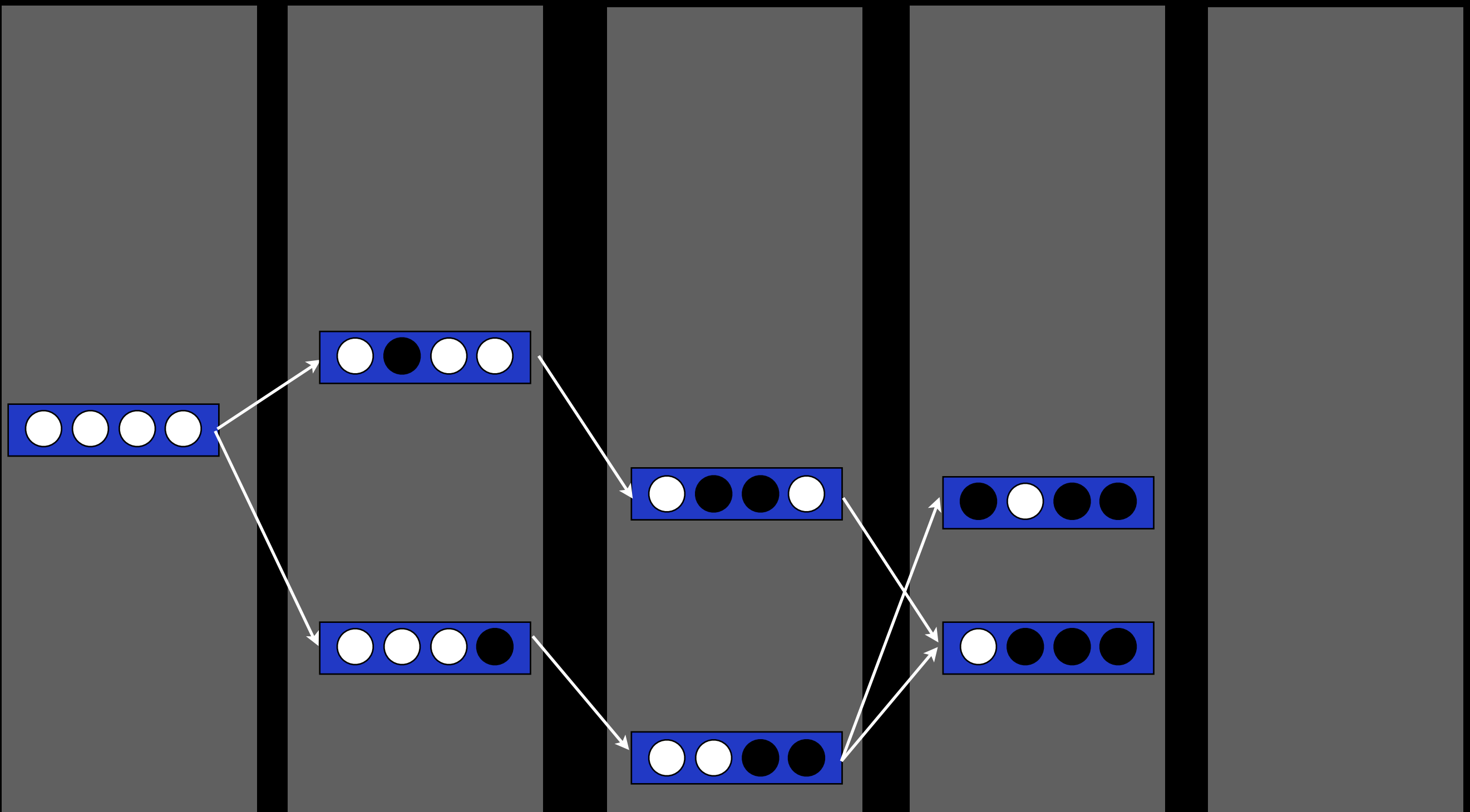
“Stack” decoding: a linear-time approximation

Approximation: Pruning



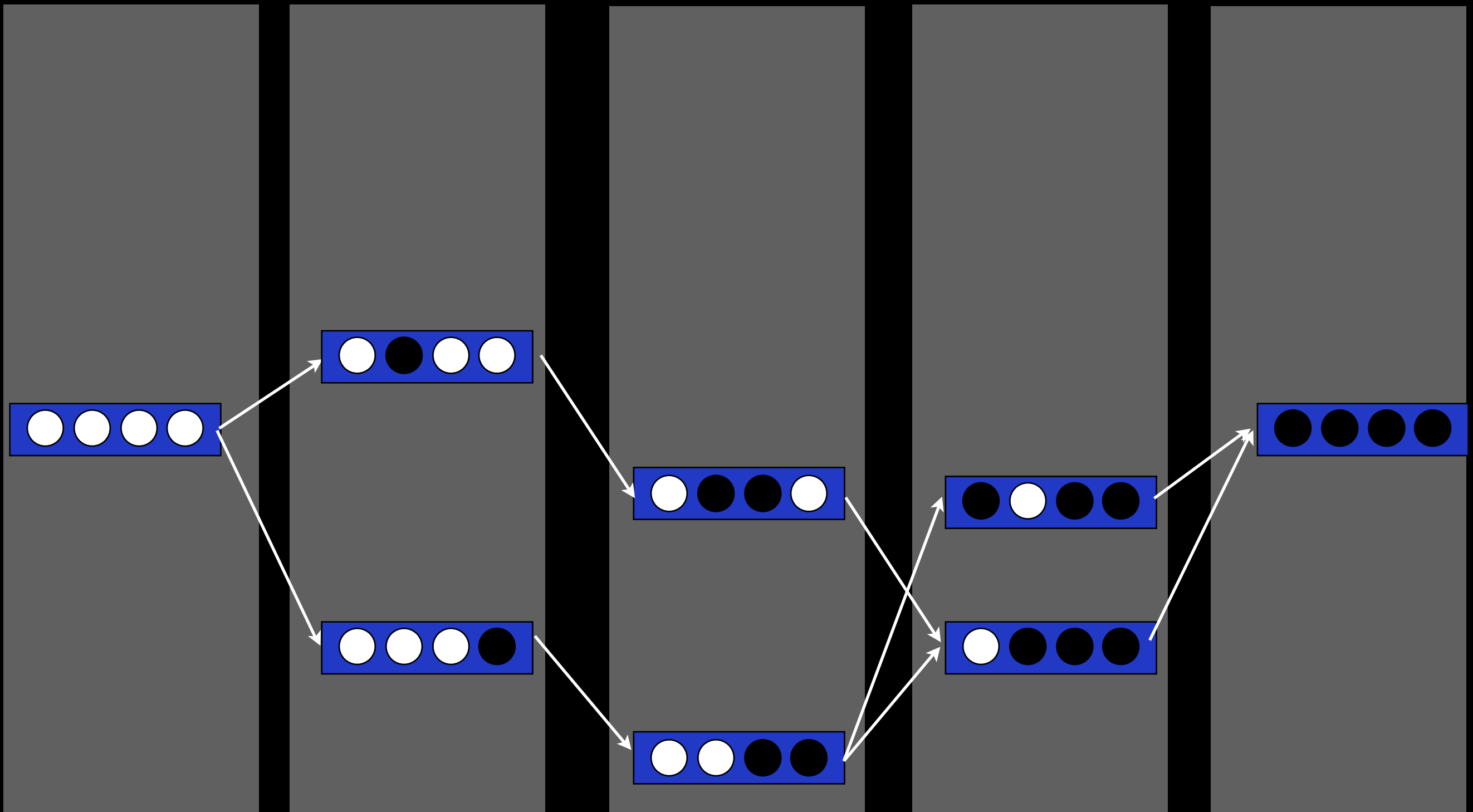
“Stack” decoding: a linear-time approximation

Approximation: Pruning



“Stack” decoding: a linear-time approximation

Approximation: Pruning



“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: $O(2^n)$

the sky

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

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虽然北风呼啸, 但天空依然十分清澈。

$$d = 4$$

window

Approximation: distortion limits

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

Approximation: distortion limits

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

the sky

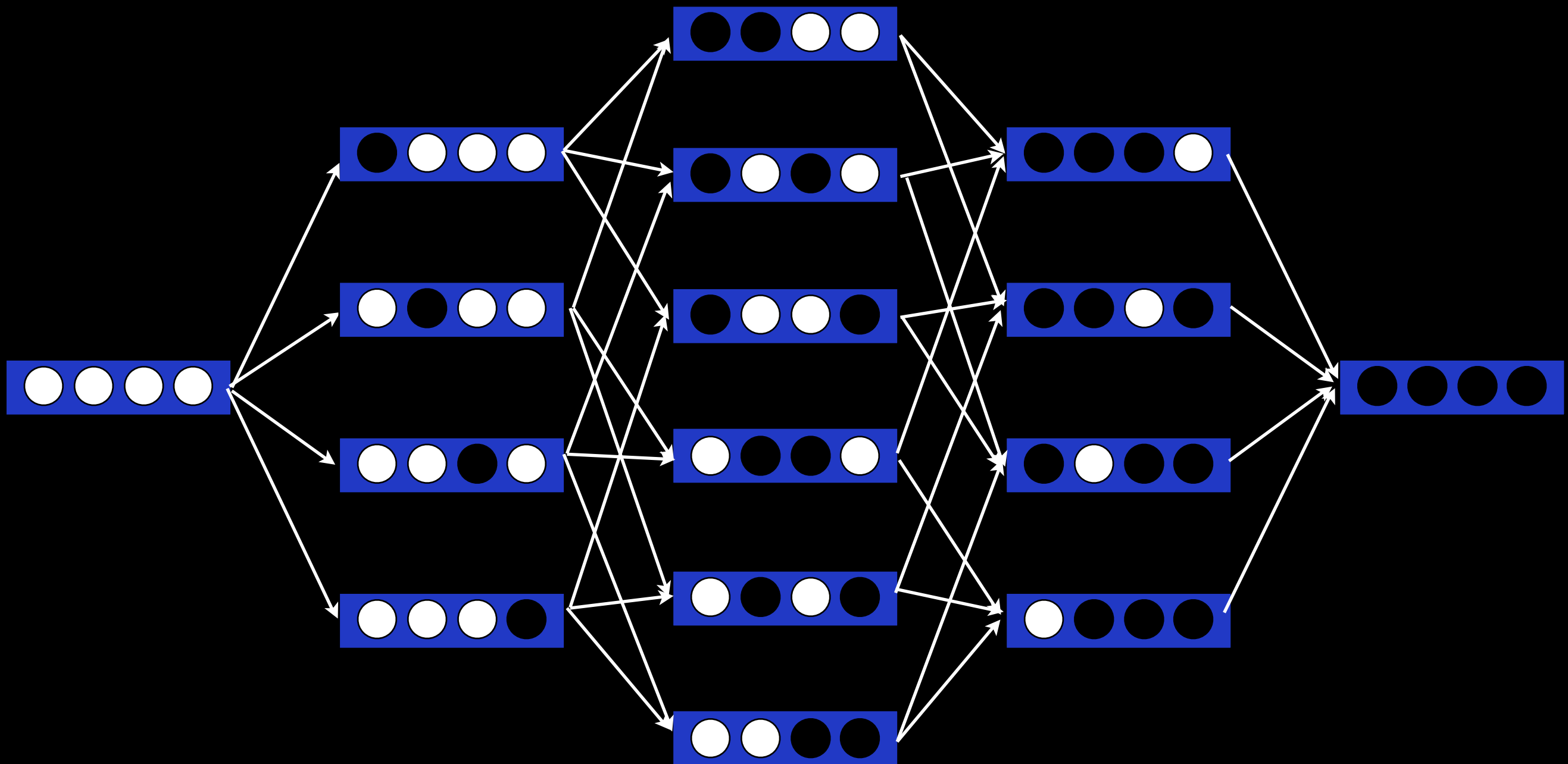
虽然北风呼啸, 但天空依然十分清澈。

outside window
to left: covered

$d = 4$
window

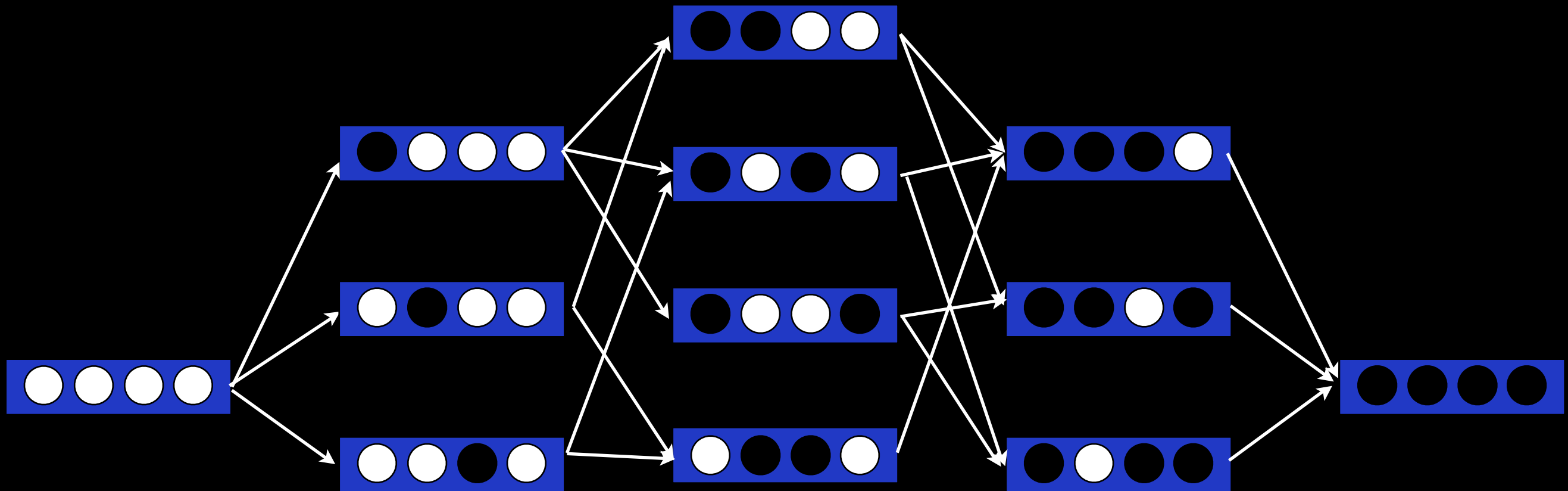
outside window
to right: uncovered

Approximation: distortion limits



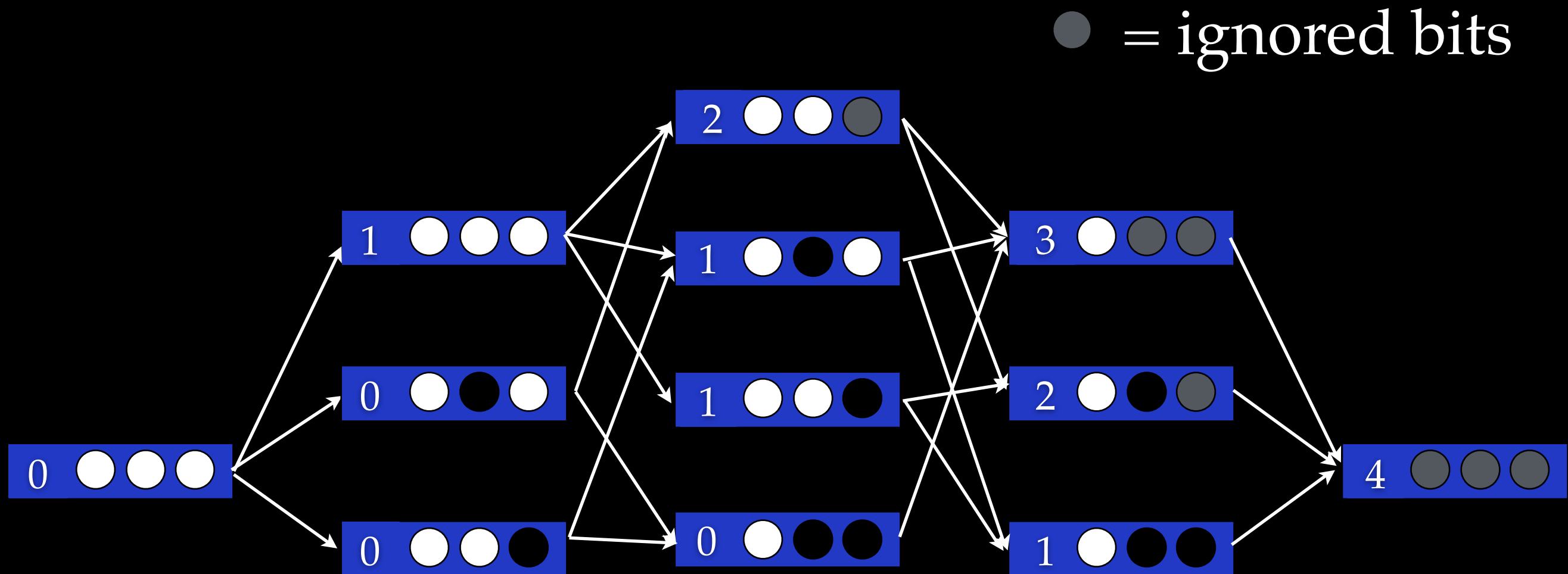
no distortion limit

Approximation: distortion limits



distortion limit = 3

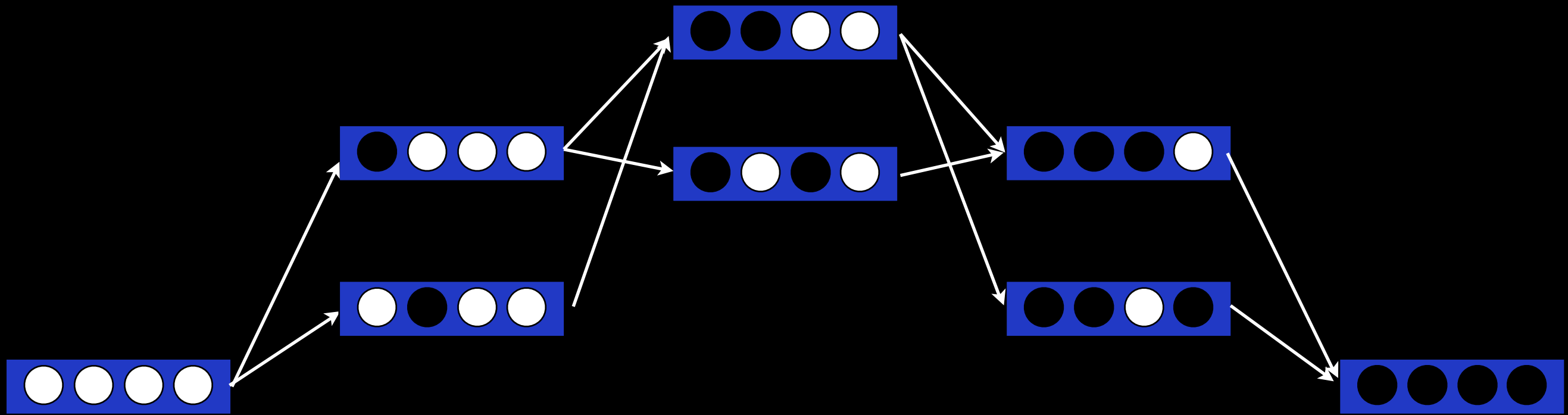
Approximation: distortion limits



alternative representation with length of covered
section + bitmap of window

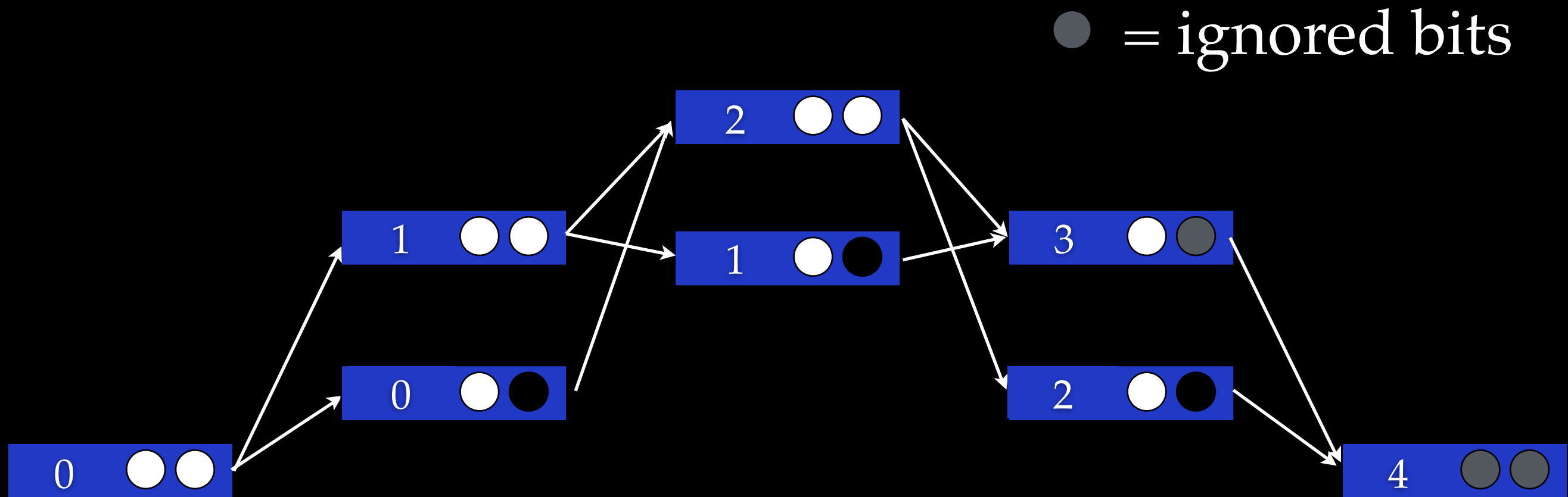
distortion limit = 3

Approximation: distortion limits



distortion limit = 2

Approximation: distortion limits

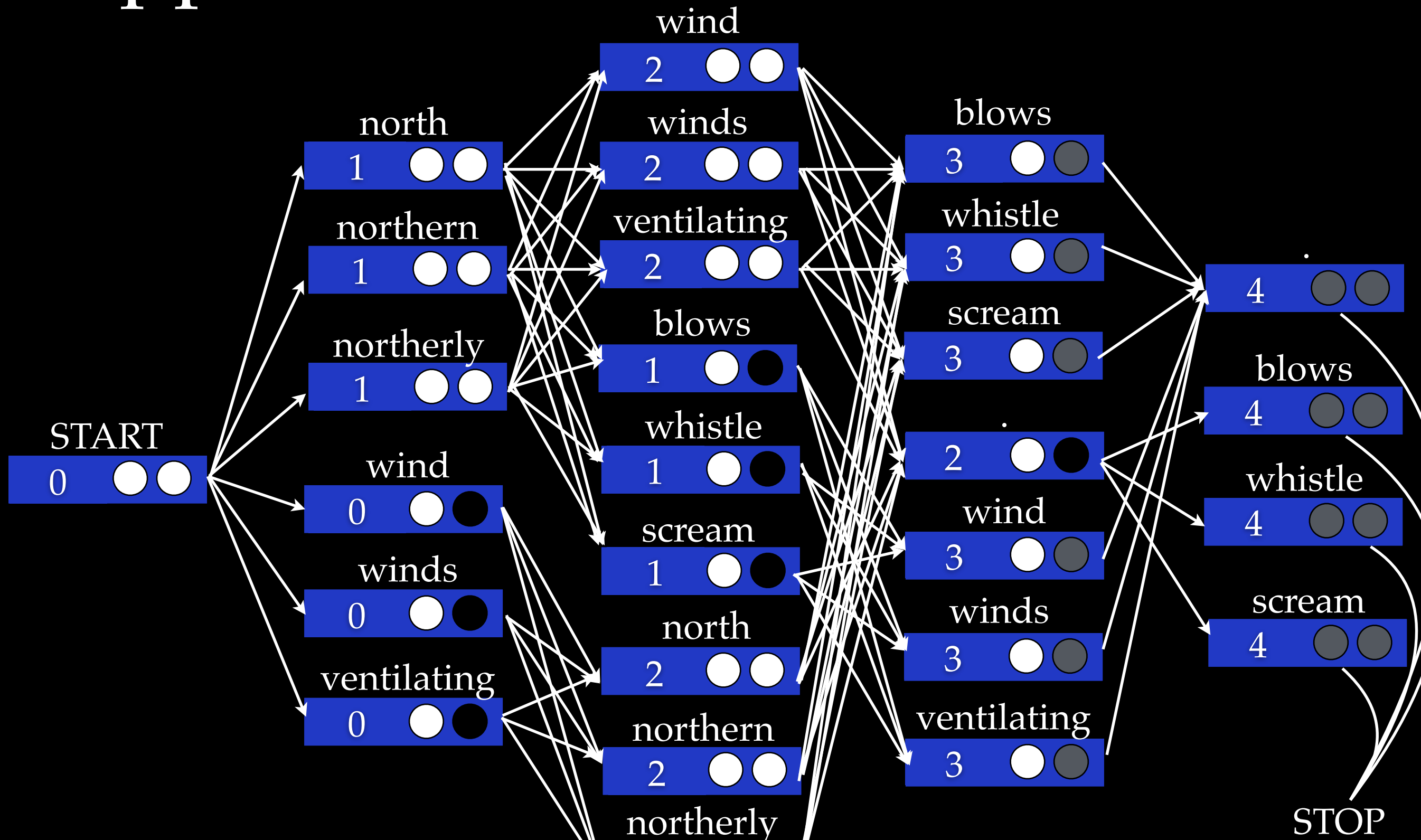


What is this representation missing?

alternative representation with length of covered
section + bitmap of window

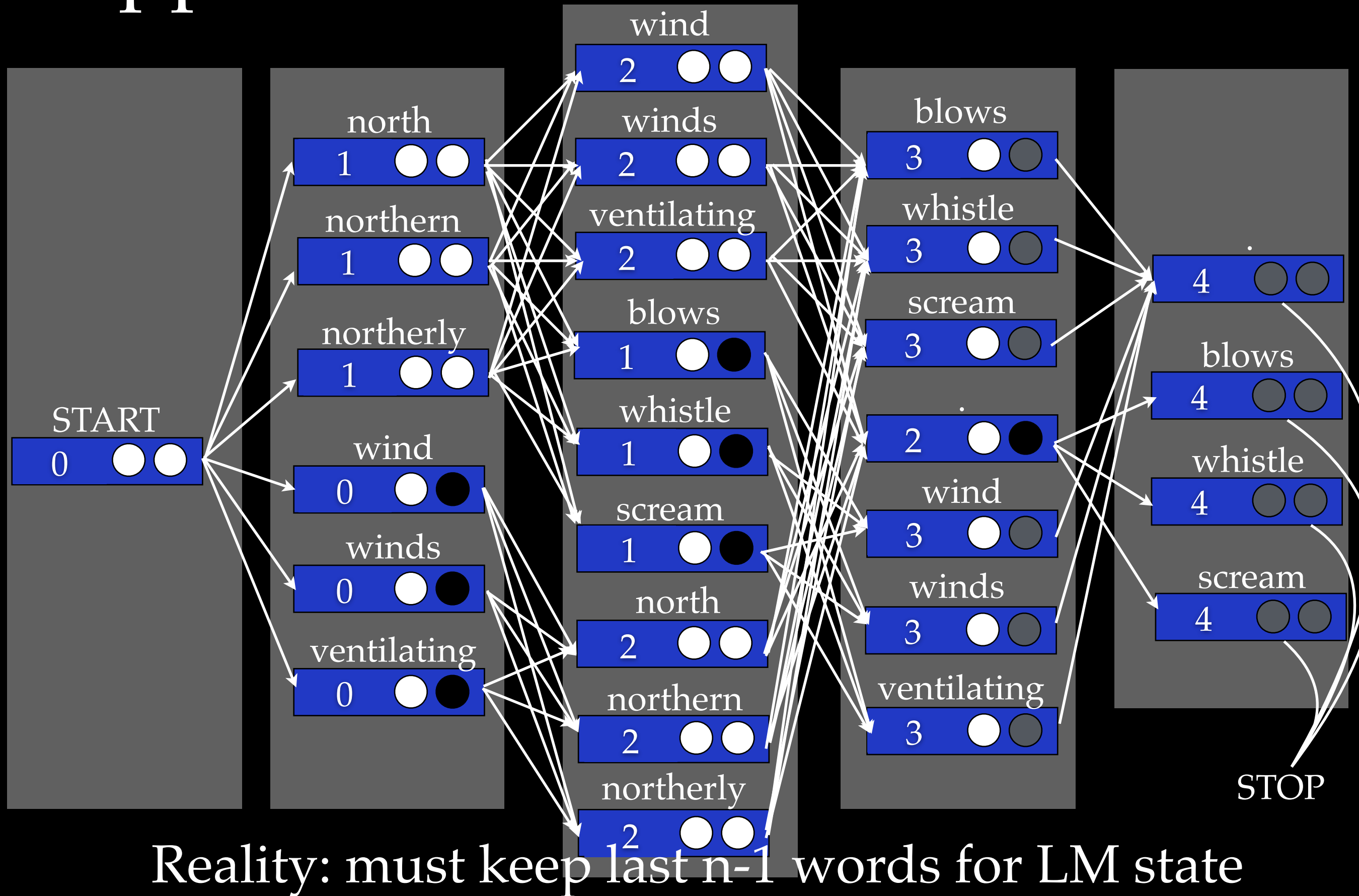
distortion limit = 2

Approximation: distortion limits

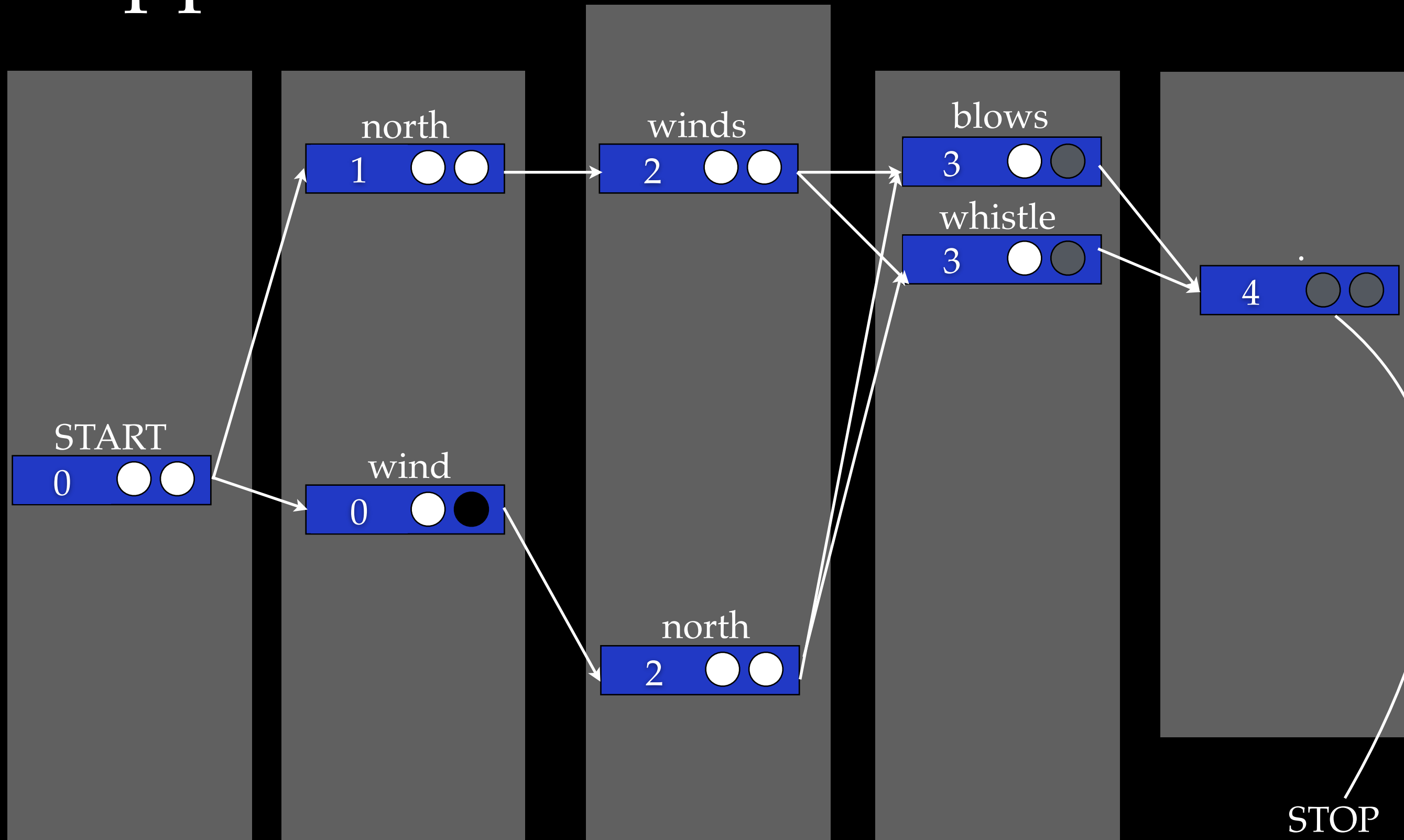


Reality: must keep last $n-1$ words for LM state

Approximation: distortion limits



Approximation: distortion limits



So, stack pruning is still useful

Putting it all together

```
1: place empty hypothesis into stack 0
2: for all stacks  $0 \dots n-1$  do
3:   for all hypotheses in stack do
4:     for all translation options do
5:       if applicable then
6:         create new hypothesis
7:         place in stack
8:         recombine with existing hypothesis if possible
9:         prune stack if too big
10:      end if
11:    end for
12:  end for
13: end for
```

Things you need to determine:

What does a hypothesis (partial translation) look like?

What are all possible extensions of a hypothesis?

What is a reasonable equivalence class (stack)?