

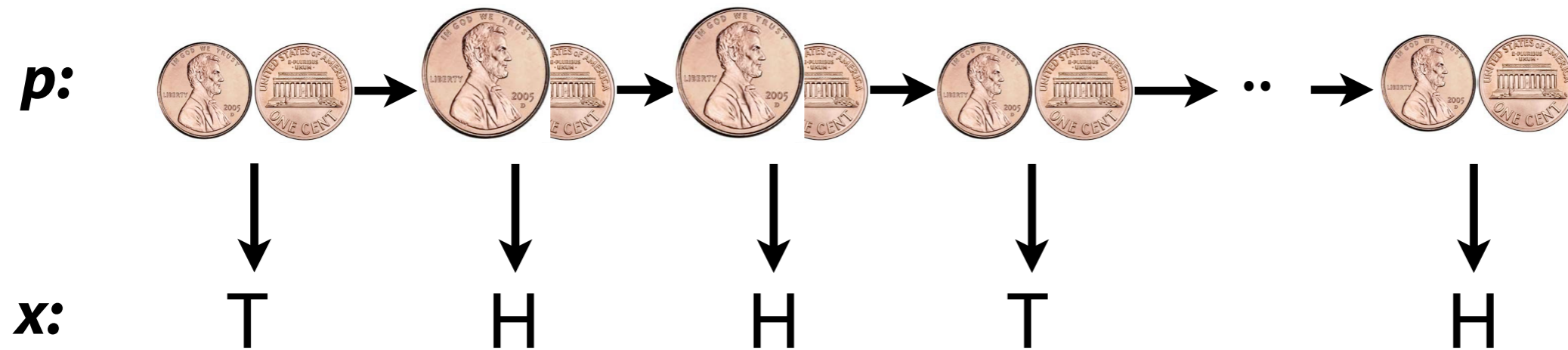
HMMs part 2: decoding with Viterbi

Ben Langmead



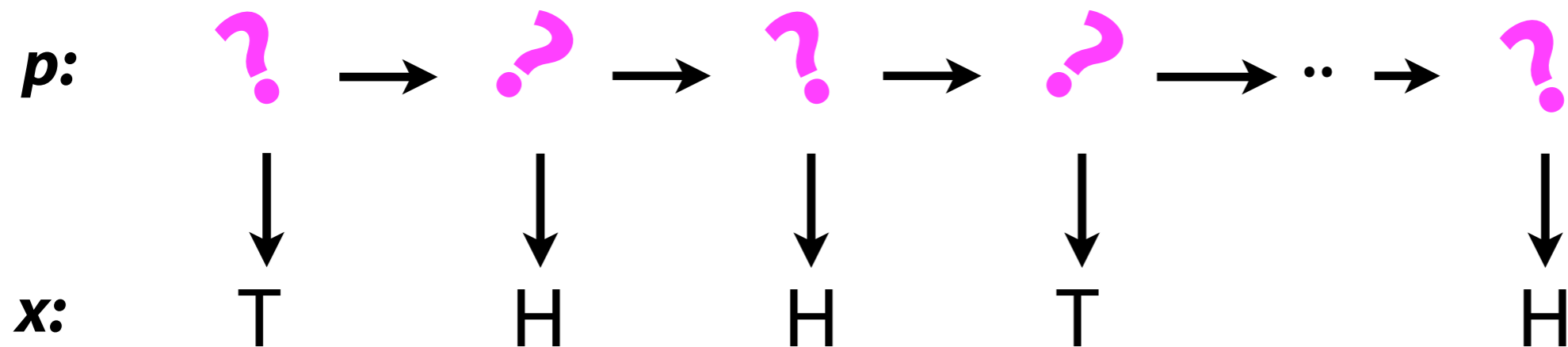
For original Keynote files, email me (ben.langmead@gmail.com)

Hidden Markov Model



Hidden Markov Model

When was the dealer using the loaded coin?



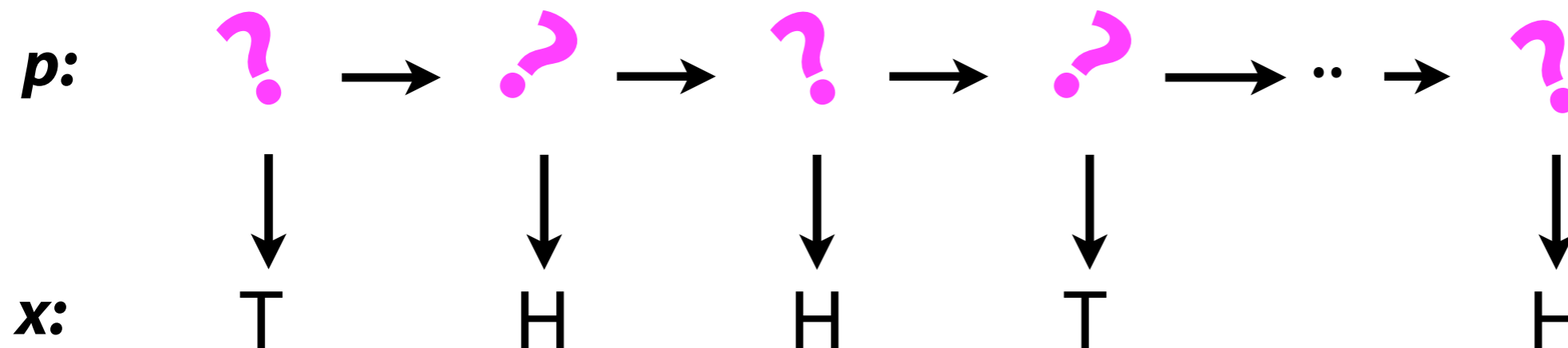
Many possible *paths* p ; fair-or-loaded sequences

p^* denotes the *most likely* given the emission sequence x

$$p^* = \operatorname{argmax}_p P(p | x) = \operatorname{argmax}_p$$

Hidden Markov Model

When was the dealer using the loaded coin?



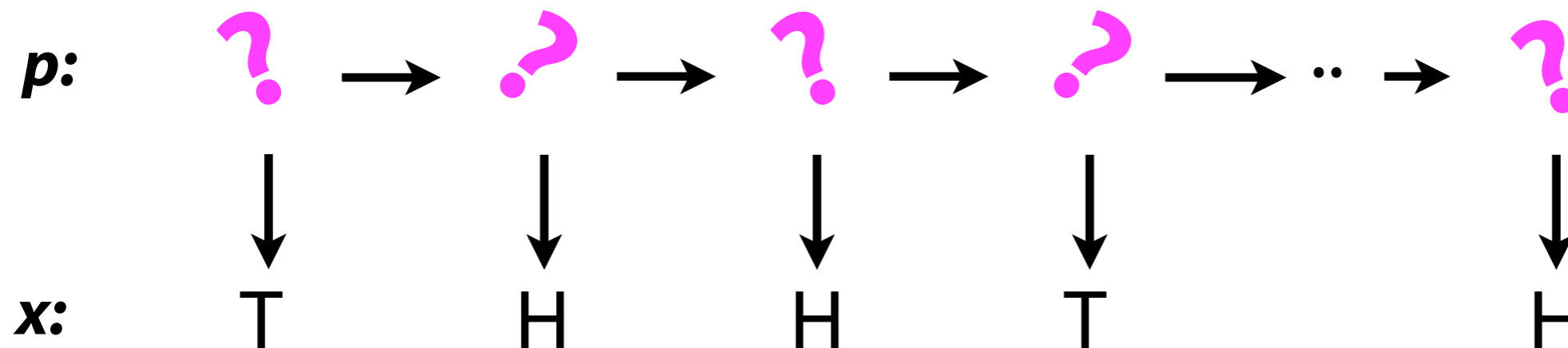
Many possible *paths* p ; fair-or-loaded sequences

p^* denotes the *most likely* given the emission sequence x

$$p^* = \operatorname{argmax}_p P(p | x) = \operatorname{argmax}_p \frac{P(p, x)}{P(x)}$$

Hidden Markov Model

When was the dealer using the loaded coin?



Many possible **paths** p ; fair-or-loaded sequences

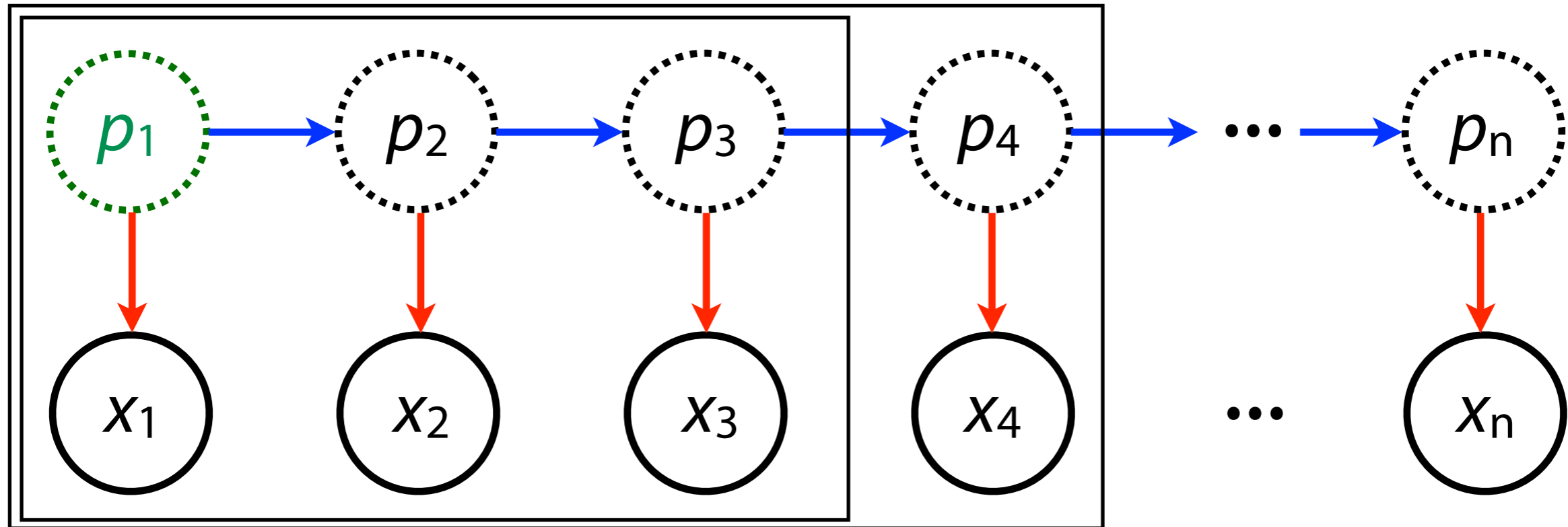
p^* denotes the *most likely* given the emission sequence x

$$p^* = \operatorname{argmax}_p P(p | x) = \operatorname{argmax}_p P(p, x)$$

↘ $P(x)$ denominator
doesn't affect argmax

Finding p^* given x is *decoding*

Hidden Markov Model



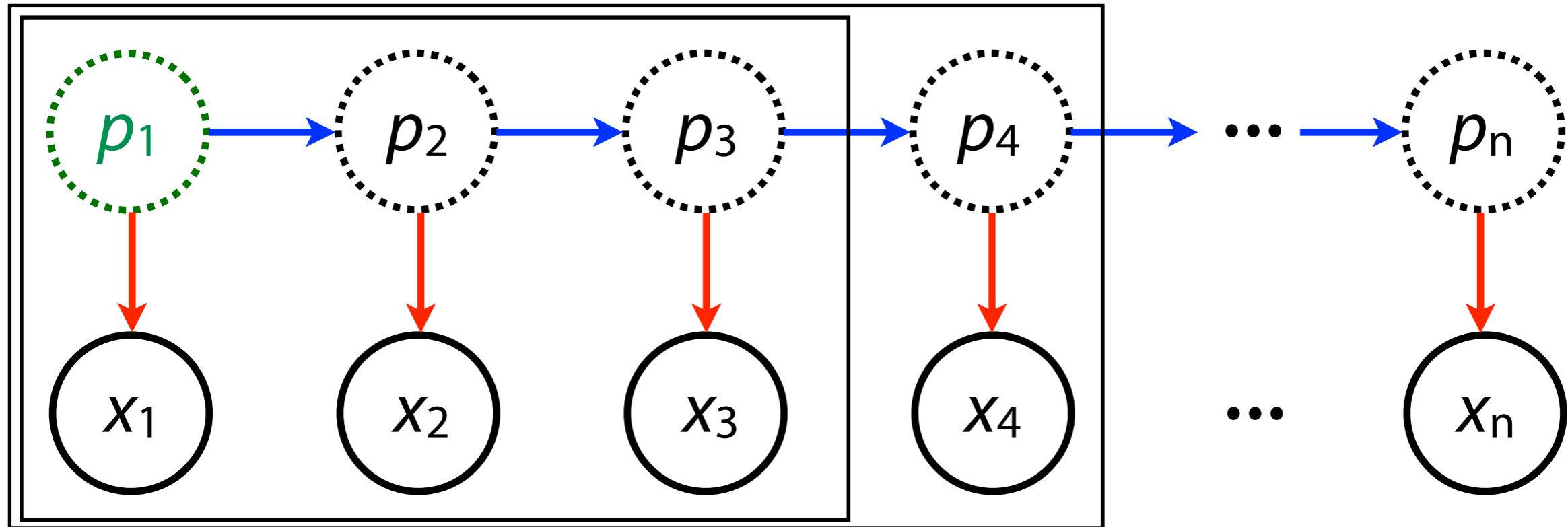
$$P(p_1, p_2, \dots, p_n, x_1, x_2, \dots, x_n) = \prod_{k=1}^n P(x_k | p_k) \cdot \prod_{k=2}^n P(p_k | p_{k-1}) \cdot P(p_1)$$

Say we know $P(p_1, p_2, p_3, x_1, x_2, x_3)$,

Computing $P(p_1, p_2, p_3, p_4, x_1, x_2, x_3, x_4)$ is easy...

...just multiply in $P(x_4 | p_4)$ and $P(p_4 | p_3)$

Hidden Markov Model



$$P(p_1, p_2, \dots, p_n, x_1, x_2, \dots, x_n) = \prod_{k=1}^n P(x_k | p_k) \cdot \prod_{k=2}^n P(p_k | p_{k-1}) \cdot P(p_1)$$

Say we know $\operatorname{argmax}_{p_1, p_2, p_3} P(p_1, p_2, p_3, x_1, x_2, x_3)$,

Is computing $\operatorname{argmax}_{p_1, p_2, p_3, p_4} P(p_1, p_2, p_3, p_4, x_1, x_2, x_3, x_4)$ easy?

Sort of!

Decoding example

Dealer repeatedly flips a coin. Coin is sometimes *fair*, $P(\text{heads}) = 0.5$, sometimes *loaded*, $P(\text{heads}) = 0.8$. Between flips, dealer switches coins with prob. 0.2.

A	F	L
F	0.8	0.2
L	0.2	0.8

E	H	T
F	0.5	0.5
L	0.8	0.2

50/50 prob of starting with fair/loaded

	F	L
I	0.5	0.5

For $X = \text{HTTTHH}$, $\text{argmax}_p = \text{FFFFFF}$

For $X = \text{HTTTHH}$ **H**, $\text{argmax}_p = \text{LLLLLLL}$

Decoding example

A	F	L
F	0.8	0.2
L	0.2	0.8

E	H	T
F	0.5	0.5
L	0.8	0.2

	F	L
I	0.5	0.5

For $X = \text{HTTTHH}$

$\text{argmax} = \text{FFFFF}$

$p_1, p_2, p_3, p_4, p_5 = \text{F}$

$\text{argmax} = \text{LLLLL}$

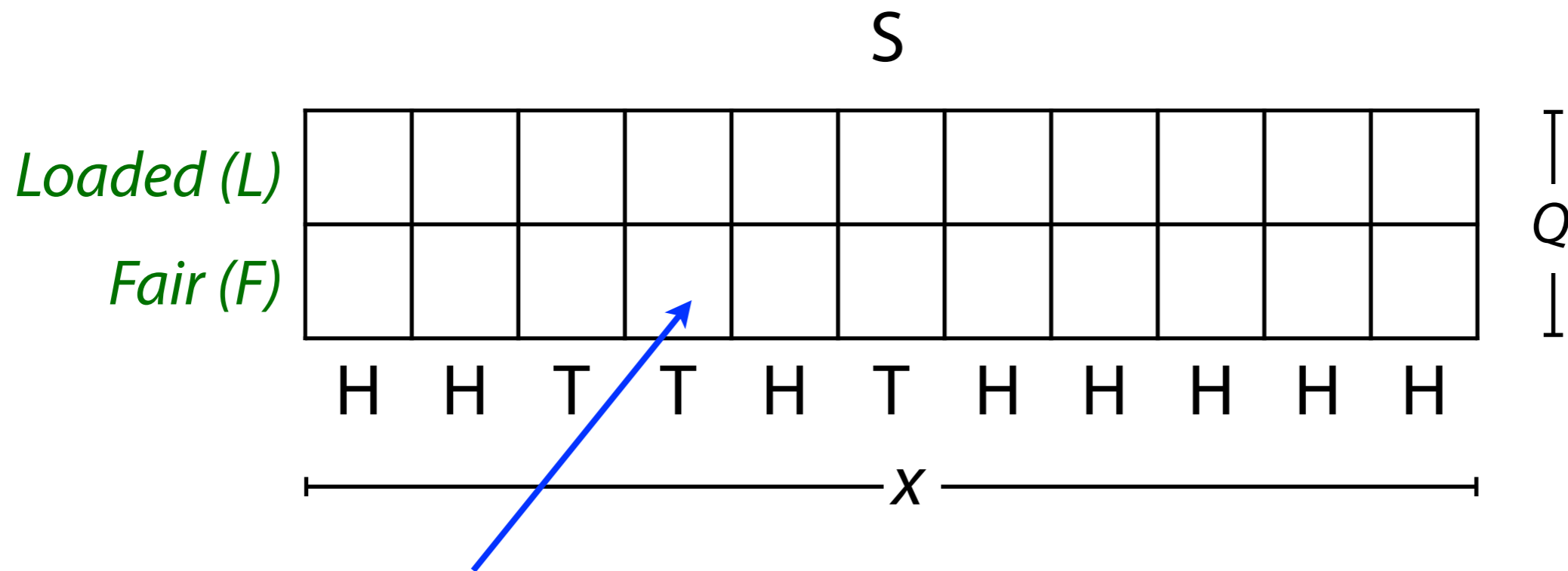
$p_1, p_2, p_3, p_4, p_5 = \text{L}$

For $X = \text{HTTTHH}$ **H**

Answer will be
an extension of
one of these

Hidden Markov Model: Viterbi algorithm

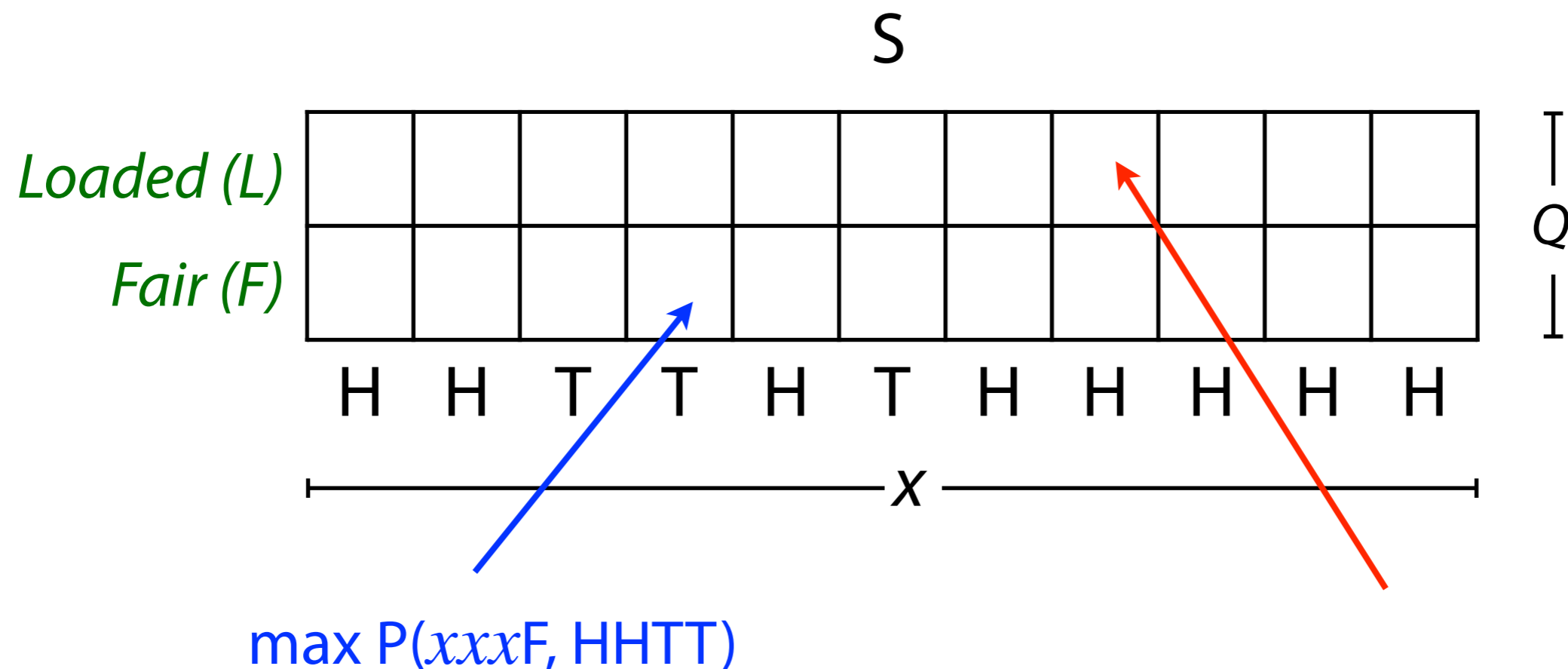
Fill in a **dynamic programming** matrix S



$S_{k,i}$ is the *max joint probability* of observing the length- $i+1$ prefix of x and any sequence of states **ending in state k**

Hidden Markov Model: Viterbi algorithm

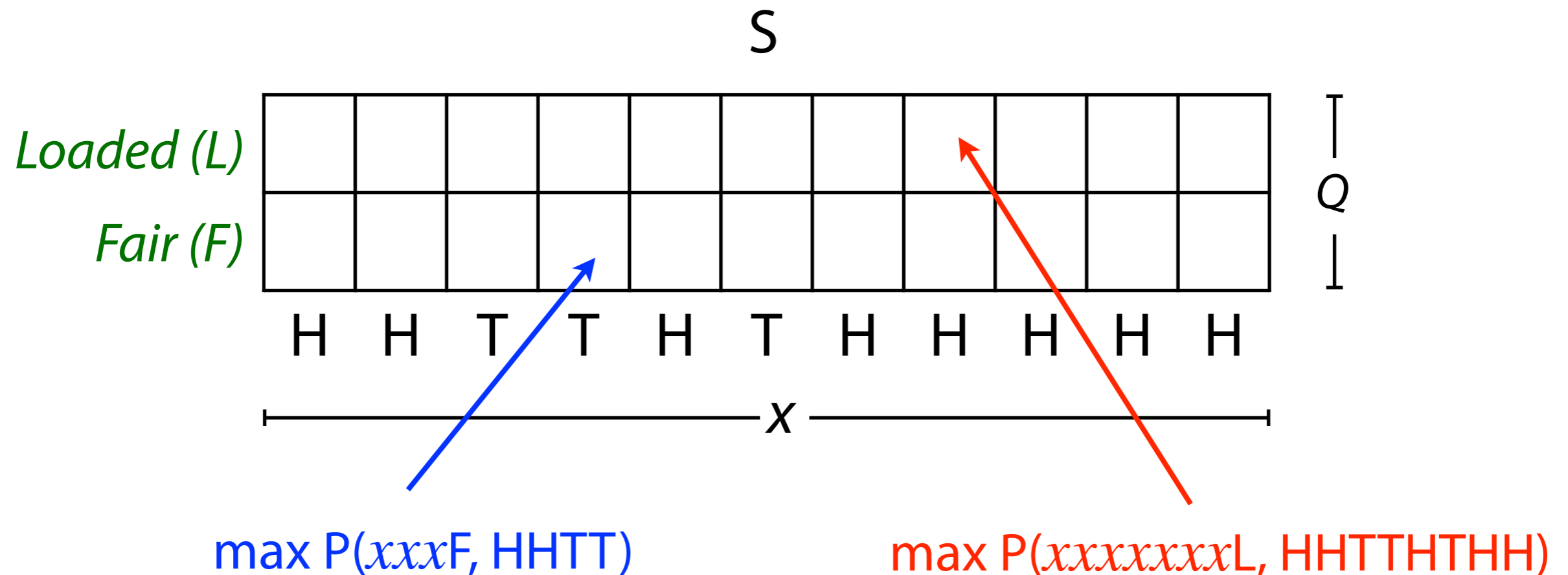
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Hidden Markov Model: Viterbi algorithm

Fill in a **dynamic programming** matrix S



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Hidden Markov Model: Viterbi algorithm

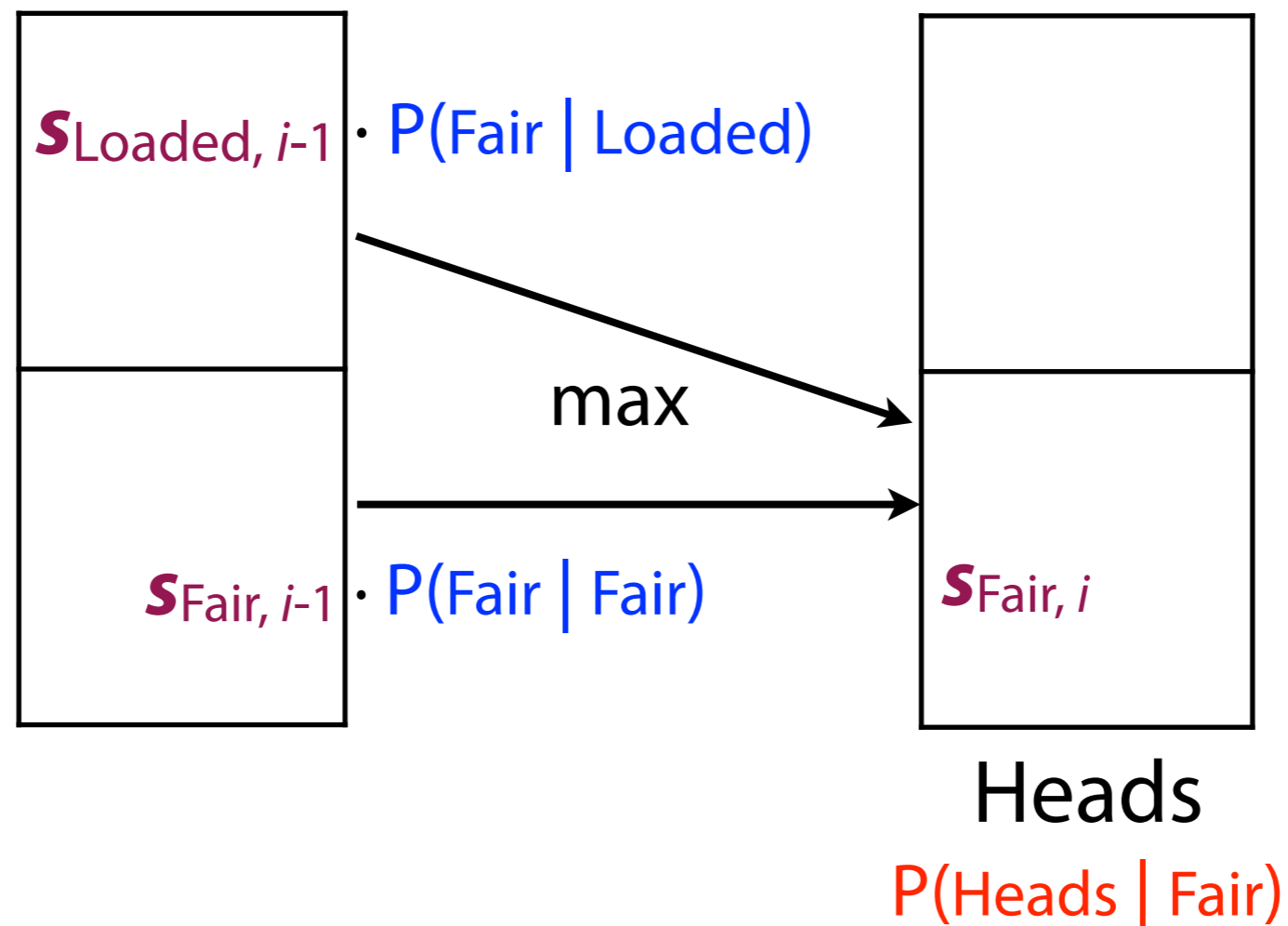
Say x_i is Heads

$$s_{\text{Loaded}, i} =$$

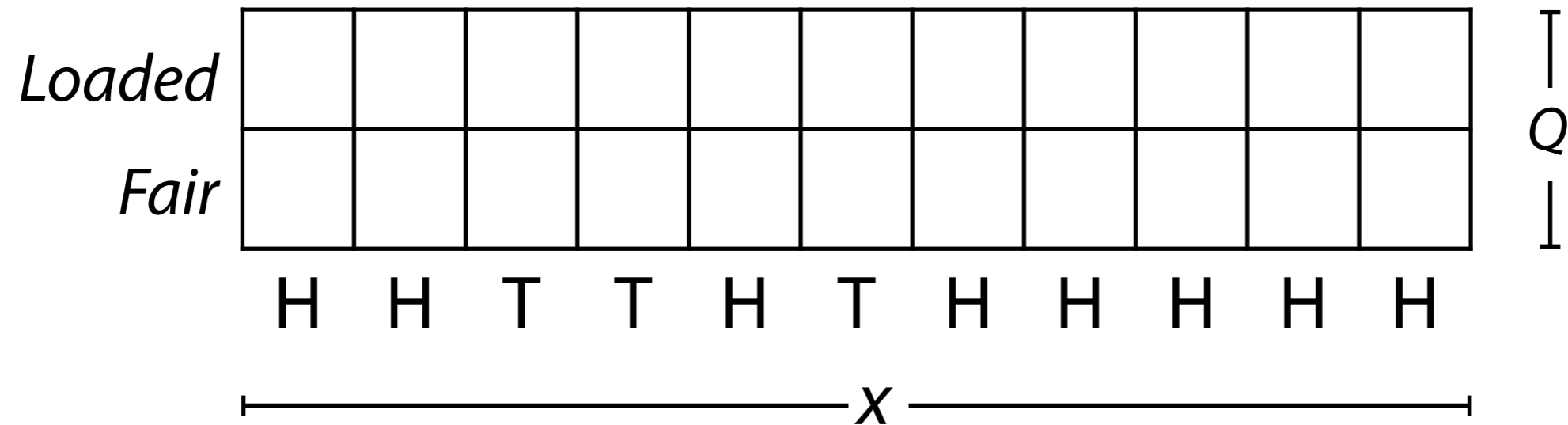
Hidden Markov Model: Viterbi algorithm

Say x_i is Heads

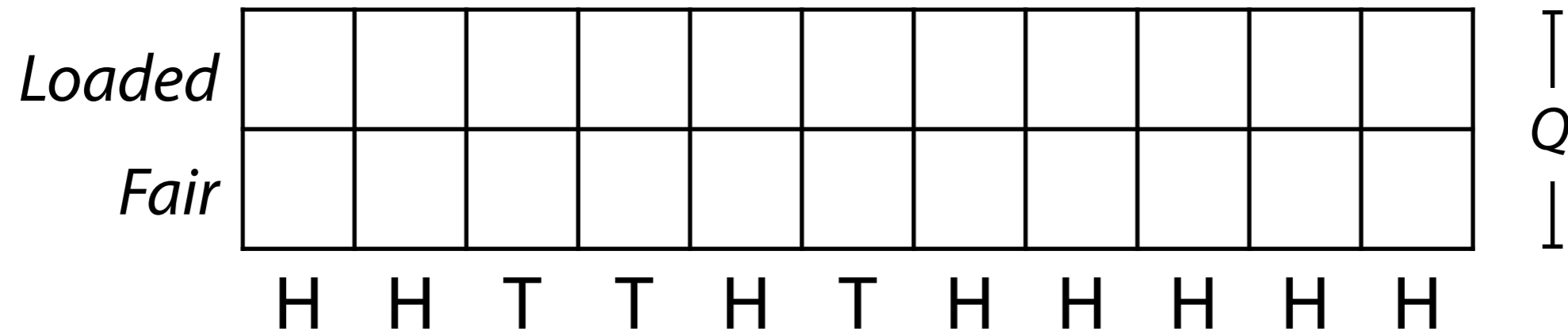
$$\boxed{s_{\text{Fair}, i}} = \underset{\text{Emission prob}}{\text{P(Heads | Fair)}} \cdot \max_{k \in \{\text{Fair, Loaded}\}} \{ \underset{\text{Transition prob}}{s_{k, i-1} \cdot \text{P(Fair | k)}} \}$$



Hidden Markov Model: Viterbi algorithm



Hidden Markov Model: Viterbi algorithm



Dealer repeatedly flips a coin. Coin is sometimes *fair*, $P(\text{heads}) = 0.5$, sometimes *loaded*, $P(\text{heads}) = 0.8$. Between flips, dealer switches coins with prob. 0.4.

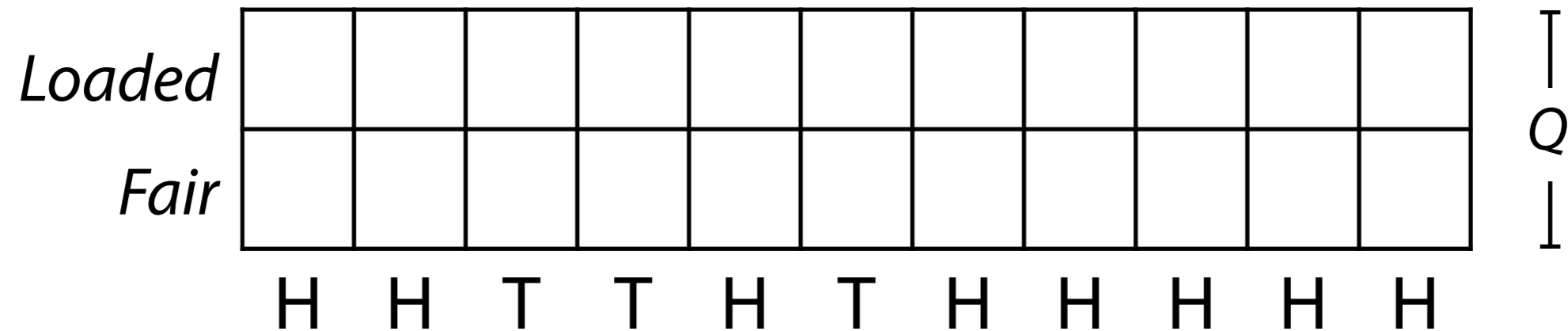
A	F	L
F	0.6	0.4
L	0.4	0.6

E	H	T
F	0.5	0.5
L	0.8	0.2

50/50 prob of starting with fair/loaded

	F	L
I	0.5	0.5

Hidden Markov Model: Viterbi algorithm



$S_{L,0} =$

A	F	L
F	0.6	0.4
L	0.4	0.6

E	H	T
F	0.5	0.5
L	0.8	0.2

$S_{F,0} =$

	F	L
I	0.5	0.5

Hidden Markov Model: Viterbi algorithm

<i>Loaded</i>	0.4											Q
<i>Fair</i>	0.25											
		H	H	T	T	H	T	H	H	H	H	

$$S_{L,0} = P(L) \cdot P(H | L)$$

$$= 0.5 \cdot 0.8$$

$$S_{F,0} = P(H) \cdot P(H | F)$$

$$= 0.5 \cdot 0.5$$

A	F	L
F	0.6	0.4
L	0.4	0.6

E	H	T
F	0.5	0.5
L	0.8	0.2

	F	L
I	0.5	0.5

Hidden Markov Model: Viterbi algorithm

<i>Loaded</i>	0.4											 Q
<i>Fair</i>	0.25											
	H	H	T	T	H	T	H	H	H	H	H	

$S_{L,1} =$

A	F	L
F	0.6	0.4
L	0.4	0.6

E	H	T
F	0.5	0.5
L	0.8	0.2

Hidden Markov Model: Viterbi algorithm

<i>Loaded</i>	0.4											$\begin{array}{ l} \hline Q \\ \hline \end{array}$
<i>Fair</i>	0.25											
		H	H	T	T	H	T	H	H	H	H	

$$S_{L,1} = P(H | L) \cdot$$

$$\max \begin{cases} 0.4 \cdot P(L | L) \\ 0.25 \cdot P(L | F) \end{cases}$$

A	F	L
F	0.6	0.4
L	0.4	0.6

E	H	T
F	0.5	0.5
L	0.8	0.2

Hidden Markov Model: Viterbi algorithm

<i>Loaded</i>	0.4	0.19										Q
<i>Fair</i>	0.25											
	H	H	T	T	H	T	H	H	H	H	H	

$$S_{L,1} = 0.8 \cdot$$

$$\max \begin{cases} 0.4 \cdot 0.6 \\ 0.25 \cdot 0.4 \end{cases}$$

$$= 0.8 \cdot 0.4 \cdot 0.6 \approx 0.19$$

A	F	L
F	0.6	0.4
L	0.4	0.6

E	H	T
F	0.5	0.5
L	0.8	0.2

Hidden Markov Model: Viterbi algorithm

<i>Loaded</i>	0.4	0.19										Q
<i>Fair</i>	0.25											
	H	H	T	T	H	T	H	H	H	H	H	

$$S_{F,1} = P(H | F) \cdot$$

$$\max \begin{cases} 0.4 \cdot P(F | L) \\ 0.25 \cdot P(F | F) \end{cases}$$

A	F	L
F	0.6	0.4
L	0.4	0.6

E	H	T
F	0.5	0.5
L	0.8	0.2

Hidden Markov Model: Viterbi algorithm

<i>Loaded</i>	0.4	0.19										Q
<i>Fair</i>	0.25	0.08										
	H	H	T	T	H	T	H	H	H	H	H	

$$S_{F,1} = 0.5 \cdot$$

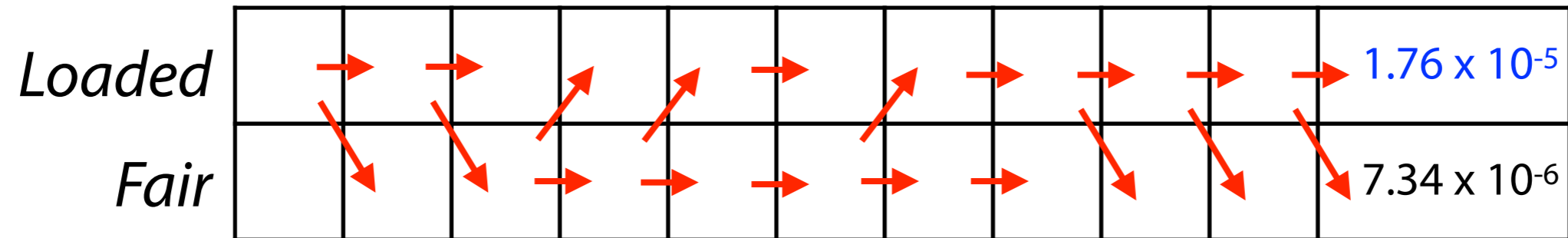
$$\max \begin{cases} 0.4 \cdot 0.4 \\ 0.25 \cdot 0.6 \end{cases}$$

$$= 0.5 \cdot 0.4 \cdot 0.4 = 0.08$$

A	F	L
F	0.6	0.4
L	0.4	0.6

E	H	T
F	0.5	0.5
L	0.8	0.2

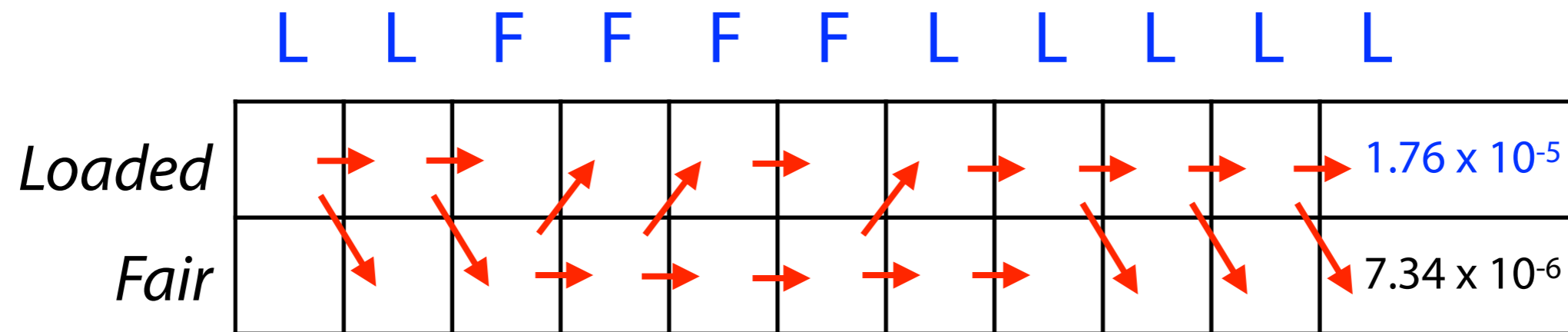
Hidden Markov Model: Viterbi algorithm



Traceback **arrows** track which term “wins” the maximum

Traceback procedure:

Hidden Markov Model: Viterbi algorithm



Traceback **arrows** track which term "wins" the maximum

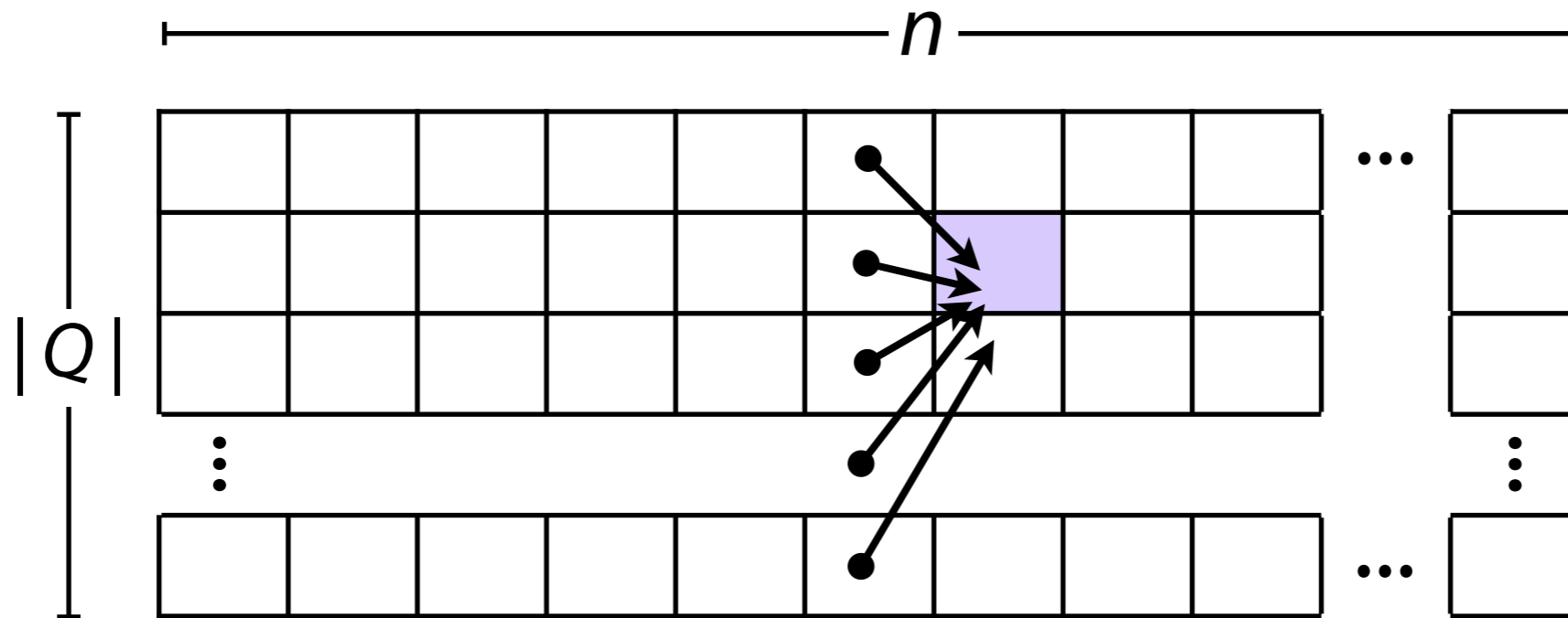
Traceback procedure:

Start from **greatest** score in final column

Keep asking "how did I get here?" (which predecessor "won" the maximum) until we reach 1st column

Hidden Markov Model: Viterbi algorithm

How much work is this? Q = set of states, n = length of emission string



$S_{k,i}$ values to calculate = $n \cdot |Q|$, each involves max over $|Q|$ products

Time:

$$O(n \cdot |Q|^2)$$

Space: Matrix A has $|Q|^2$ elements, E has $|Q| \cdot |\Sigma|$ elements, I has $|Q|$ elements