

# Hidden Markov Models (Part 1)

BMI/CS 576

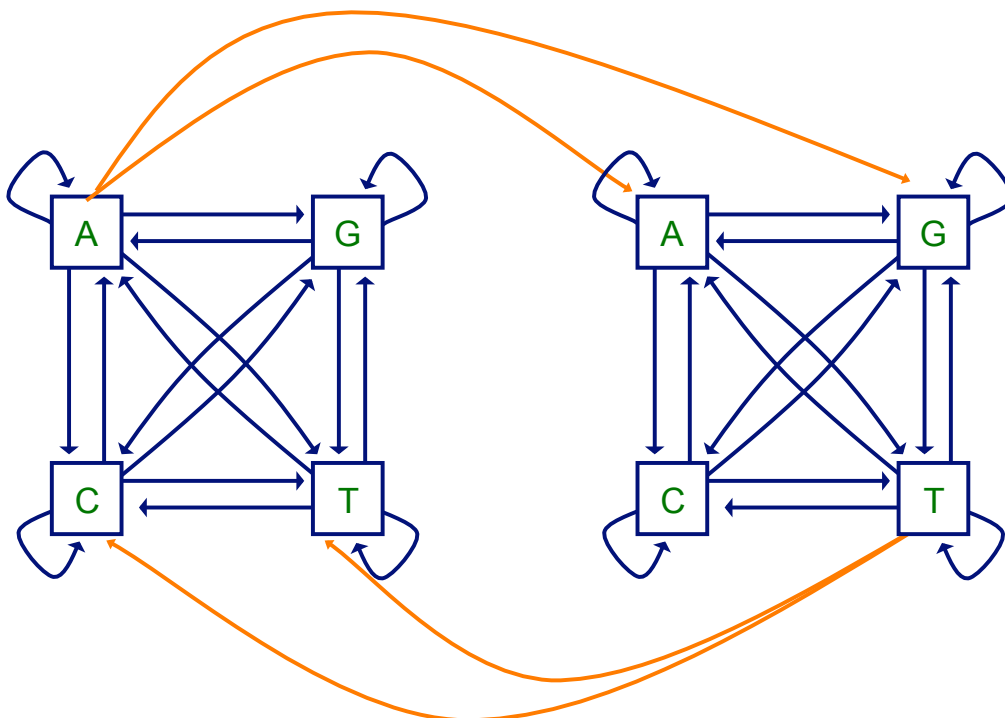
[www.biostat.wisc.edu/bmi576.html](http://www.biostat.wisc.edu/bmi576.html)

Mark Craven

[craven@biostat.wisc.edu](mailto:craven@biostat.wisc.edu)

Fall 2011

## A simple HMM



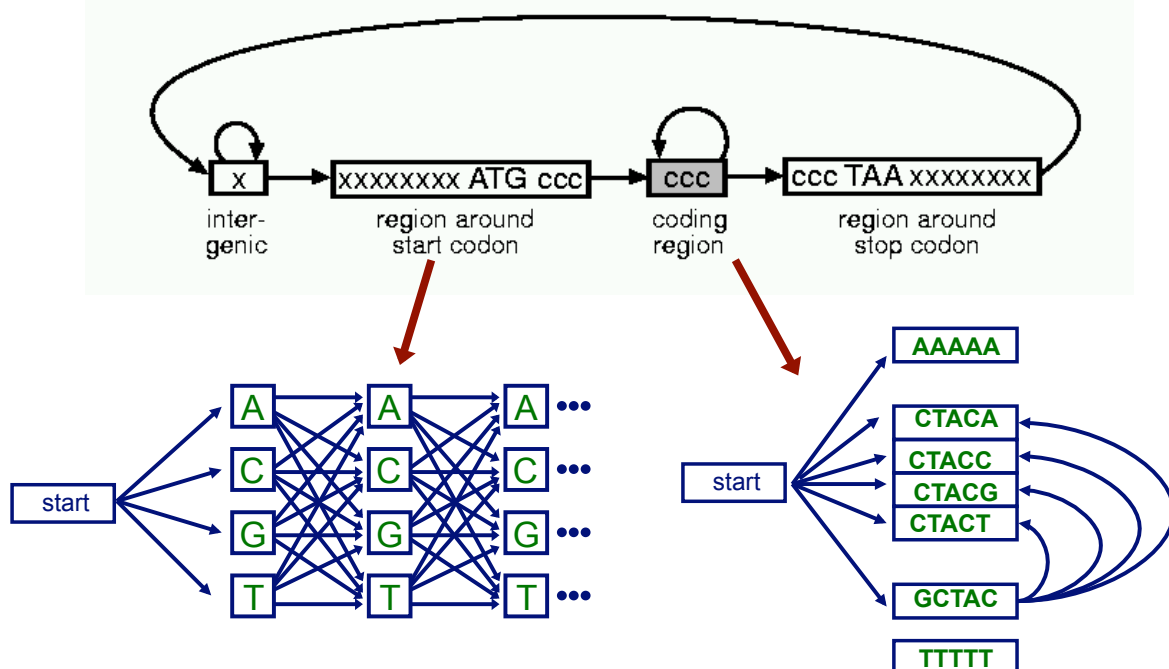
- given say a **T** in our input sequence, which state emitted it?

# The hidden part of the problem

- we'll distinguish between the *observed* parts of a problem and the *hidden* parts
- in the Markov models we've considered previously, it is clear which state accounts for each part of the observed sequence
- in the model above, there are multiple states that could account for each part of the observed sequence – this is the hidden part of the problem

# Simple HMM for gene finding

Figure from A. Krogh, An Introduction to Hidden Markov Models for Biological Sequences



## The parameters of an HMM

- as in Markov chain models, we have transition probabilities

$$a_{kl} = P(\pi_i = l \mid \pi_{i-1} = k)$$

probability of a transition from state  $k$  to  $l$

$\pi$  represents a path (sequence of states) through the model

- since we've decoupled states and characters, we might also have emission probabilities

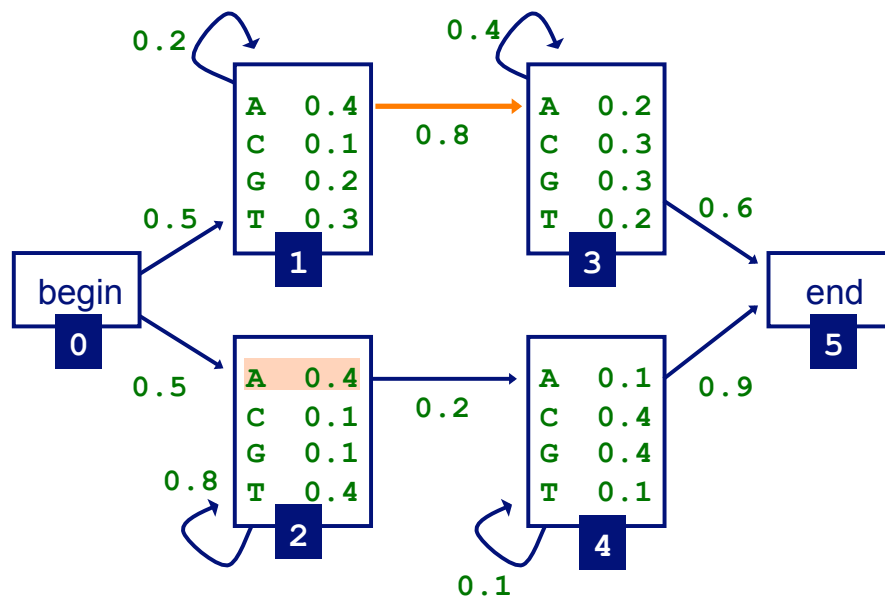
$$e_k(b) = P(x_i = b \mid \pi_i = k)$$

probability of emitting character  $b$  in state  $k$

## A simple HMM with emission parameters

$a_{13}$  probability of a transition from state 1 to state 3

$e_2(A)$  probability of emitting character A in state 2

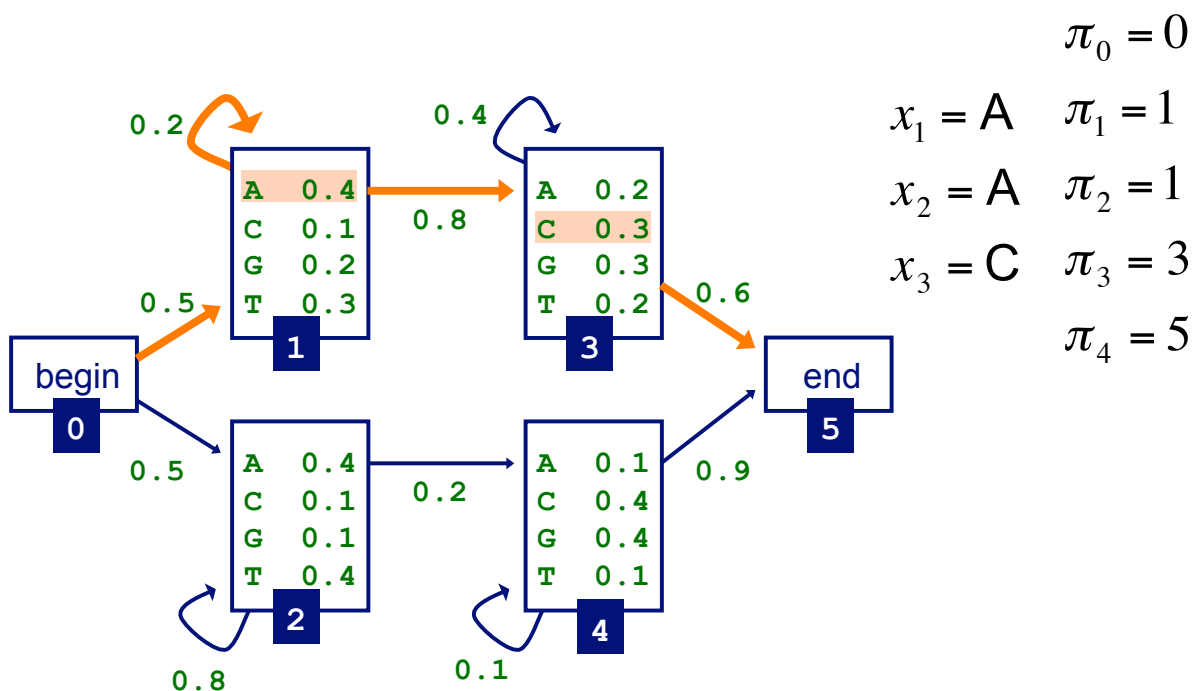


## Three important questions

- How likely is a given sequence?  
the Forward algorithm
- What is the most probable “path” for generating a given sequence?  
the Viterbi algorithm
- How can we learn the HMM parameters given a set of sequences?  
the Forward-Backward (Baum-Welch) algorithm

## Path notation

- let  $\pi$  be a vector representing a path through the HMM



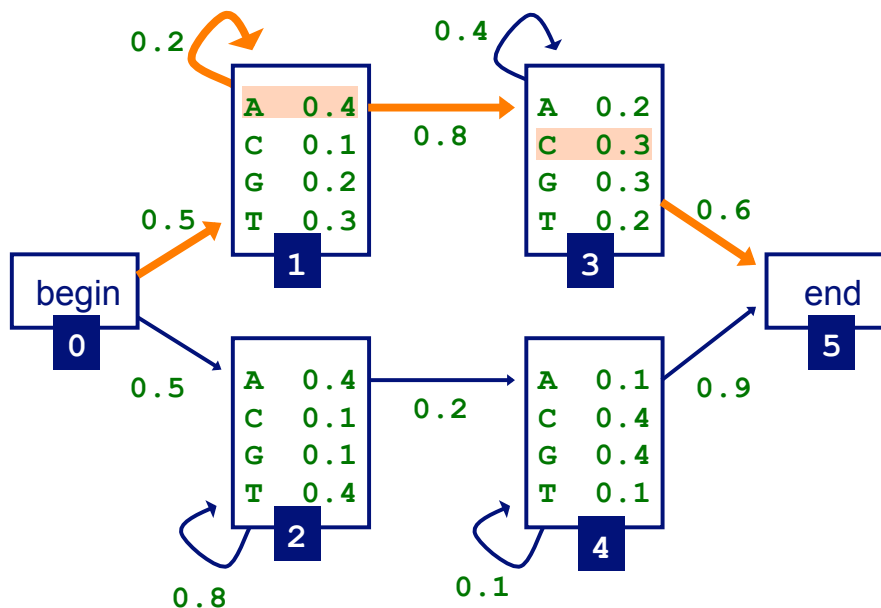
## How likely is a given sequence?

- the probability that the path  $\pi_0 \dots \pi_N$  is taken and the sequence  $x_1 \dots x_L$  is generated:

$$P(x_1 \dots x_L, \pi_0 \dots \pi_N) = a_{0\pi_1} \prod_{i=1}^L e_{\pi_i}(x_i) a_{\pi_i \pi_{i+1}}$$

(assuming begin/end are the only silent states on path)

## How likely is a given sequence?



$$P(\text{AAC}, \pi) = a_{01} \times e_1(\text{A}) \times a_{11} \times e_1(\text{A}) \times a_{13} \times e_3(\text{C}) \times a_{35}$$

$$= 0.5 \times 0.4 \times 0.2 \times 0.4 \times 0.8 \times 0.3 \times 0.6$$

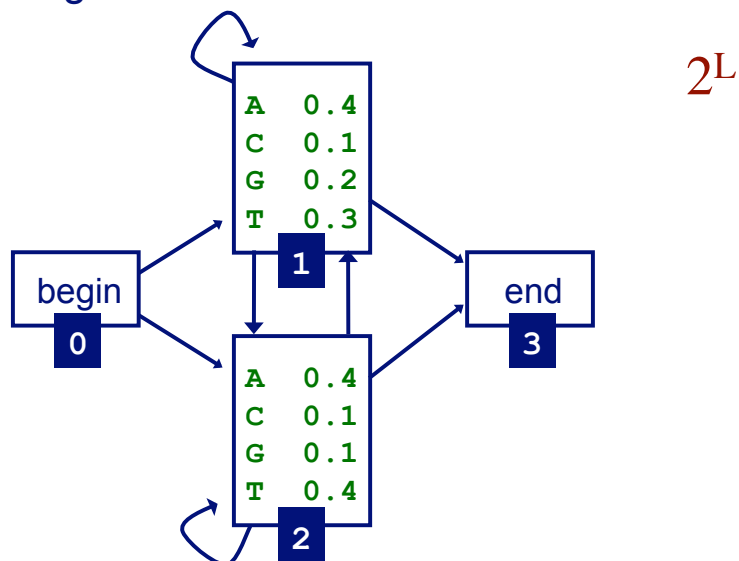
## How likely is a given sequence?

- the probability over *all* paths is:

$$P(x_1 \dots x_L) = \sum_{\pi} P(x_1 \dots x_L, \underbrace{\pi_0 \dots \pi_N}_{\pi})$$

## Number of paths

- for a sequence of length  $L$ , how many possible paths through this HMM are there?



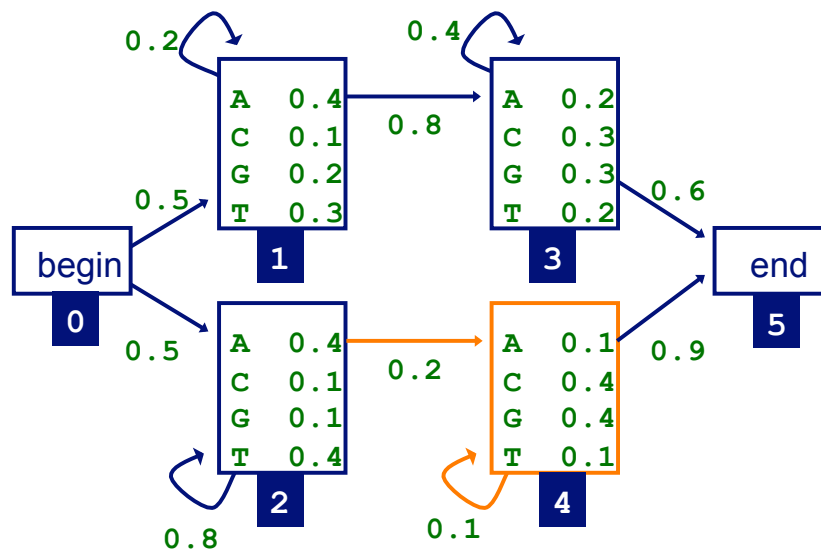
- the Forward algorithm enables us to compute  $P(x_1 \dots x_L)$  efficiently

# How likely is a given sequence: the Forward algorithm

- define  $f_k(i)$  to be the probability of being in state  $k$  having observed the first  $i$  characters of  $x$
- we want to compute  $f_N(L)$ , the probability of being in the end state having observed all of  $x$
- can define this recursively

## The Forward algorithm

- because of the Markov property, don't have to explicitly enumerate every path – use dynamic programming instead



- e.g. compute  $f_4(i)$  using  $f_2(i-1)$ ,  $f_4(i-1)$

# The Forward algorithm

initialization:

$$f_0(0) = 1$$

probability that we're in start state and have observed 0 characters from the sequence

$$f_k(0) = 0, \quad \text{for } k \text{ that are not silent states}$$

# The Forward algorithm

recursion for emitting states ( $i=1\dots L$ ):

$$f_l(i) = e_l(i) \sum_k f_k(i-1) a_{kl}$$

recursion for silent states:

$$f_l(i) = \sum_k f_k(i) a_{kl}$$



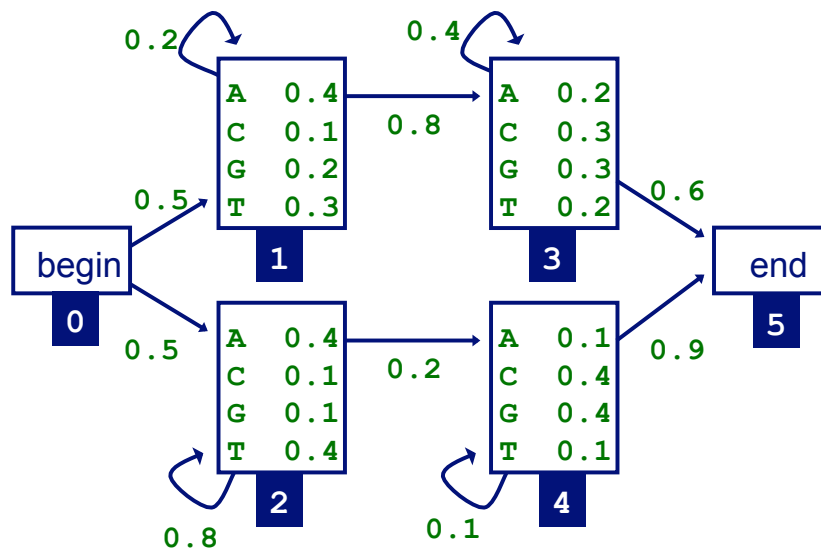
# The Forward algorithm

termination:

$$P(x) = P(x_1 \dots x_L) = f_N(L) = \sum_k f_k(L) a_{kN}$$

probability that we're in the end state and have observed the entire sequence

## Forward algorithm example



- given the sequence  $x = \text{TAGA}$

## Forward algorithm example

- given the sequence  $x = \text{TAGA}$
- initialization

$$f_0(0) = 1 \quad f_1(0) = 0 \quad \dots \quad f_5(0) = 0$$

- computing other values

$$f_1(1) = e_1(T) \times (f_0(0)a_{01} + f_1(0)a_{11}) = \\ 0.3 \times (1 \times 0.5 + 0 \times 0.2) = 0.15$$

$$f_2(1) = 0.4 \times (1 \times 0.5 + 0 \times 0.8)$$

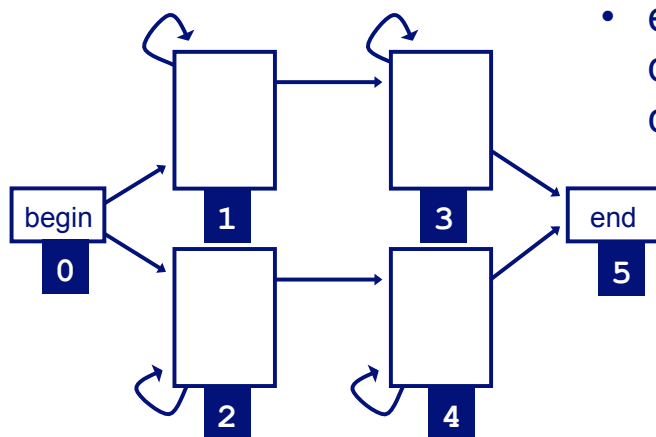
$$f_1(2) = e_1(A) \times (f_0(1)a_{01} + f_1(1)a_{11}) = \\ 0.4 \times (0 \times 0.5 + 0.15 \times 0.2)$$

...

$$P(\text{TAGA}) = f_5(4) = (f_3(4)a_{35} + f_4(4)a_{45})$$

## Forward algorithm note

- in some cases, we can make the algorithm more efficient by taking into account the minimum number of steps that must be taken to reach a state



- e.g. for this HMM, we don't need to initialize or compute the values

$$f_3(0), f_4(0), \\ f_5(0), f_5(1)$$

## Three important questions

- How likely is a given sequence?
- What is the most probable “path” for generating a given sequence?
- How can we learn the HMM parameters given a set of sequences?

## Finding the most probable path: the Viterbi algorithm

- define  $v_k(i)$  to be the probability of the most probable path accounting for the first  $i$  characters of  $x$  and ending in state  $k$
- we want to compute  $v_N(L)$ , the probability of the most probable path accounting for all of the sequence and ending in the end state
- can define recursively, use DP to find  $v_N(L)$  efficiently

## Finding the most probable path: the Viterbi algorithm

- initialization:

$$v_0(0) = 1$$

$$v_k(0) = 0, \quad \text{for } k \text{ that are not silent states}$$

## The Viterbi algorithm

- recursion for emitting states ( $i = 1 \dots L$ ):

$$v_l(i) = e_l(x_i) \max_k [v_k(i-1)a_{kl}]$$

$$\text{ptr}_l(i) = \arg \max_k [v_k(i-1)a_{kl}] \quad \text{keep track of most probable path}$$

- recursion for silent states:

$$v_l(i) = \max_k [v_k(i)a_{kl}]$$

$$\text{ptr}_l(i) = \arg \max_k [v_k(i)a_{kl}]$$

## The Viterbi algorithm

- termination:

$$P(x, \pi) = \max_k (v_k(L) a_{kN})$$

$$\pi_L = \arg \max_k (v_k(L) a_{kN})$$

- traceback: follow pointers back starting at  $\pi_L$

## Three important questions

- How likely is a given sequence?
- What is the most probable “path” for generating a given sequence?
- How can we learn the HMM parameters given a set of sequences?