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Hidden Markov Models

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Slide 1

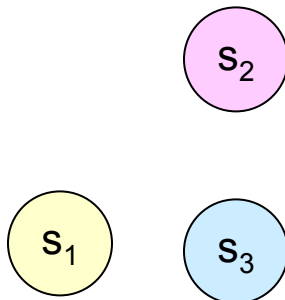
A Markov System

Has N states, called $s_1, s_2 \dots s_N$

There are discrete timesteps,
 $t=0, t=1, \dots$

$N = 3$

$t=0$



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Slide 2

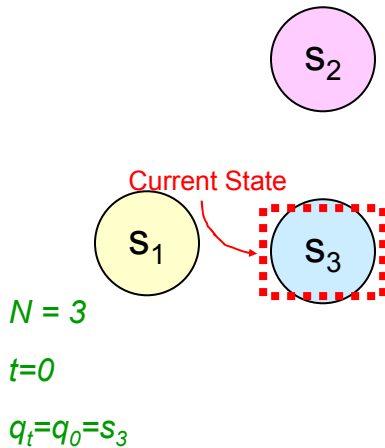
A Markov System

Has N states, called $s_1, s_2 \dots s_N$

There are discrete timesteps,
 $t=0, t=1, \dots$

On the t 'th timestep the system is
in exactly one of the available
states. Call it q_t

Note: $q_t \in \{s_1, s_2 \dots s_N\}$



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Slide 3

A Markov System

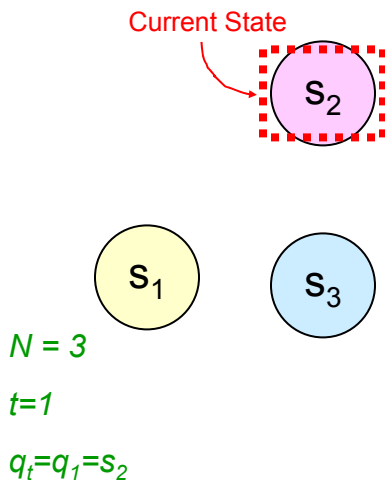
Has N states, called $s_1, s_2 \dots s_N$

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in exactly one of the available
states. Call it q_t

Note: $q_t \in \{s_1, s_2 \dots s_N\}$

Between each timestep, the next
state is chosen randomly.



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Slide 4

A Markov System

Has N states, called $s_1, s_2 \dots s_N$

There are discrete timesteps, $t=0, t=1, \dots$

On the t 'th timestep the system is in exactly one of the available states. Call it q_t

Note: $q_t \in \{s_1, s_2 \dots s_N\}$

Between each timestep, the next state is chosen randomly.

The current state determines the probability distribution for the next state.

$P(q_{t+1}=s_1|q_t=s_1) = 0$
 $P(q_{t+1}=s_2|q_t=s_1) = 0$
 $P(q_{t+1}=s_3|q_t=s_1) = 1$

s_2

s_1

s_3

$N = 3$

$t = 1$

$q_t = q_1 = s_2$

$P(q_{t+1}=s_1|q_t=s_3) = 1/3$
 $P(q_{t+1}=s_2|q_t=s_3) = 2/3$
 $P(q_{t+1}=s_3|q_t=s_3) = 0$

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Slide 5

A Markov System

Has N states, called $s_1, s_2 \dots s_N$

There are discrete timesteps, $t=0, t=1, \dots$

On the t 'th timestep the system is in exactly one of the available states. Call it q_t

Note: $q_t \in \{s_1, s_2 \dots s_N\}$

Between each timestep, the next state is chosen randomly.

The current state determines the probability distribution for the next state.

$P(q_{t+1}=s_1|q_t=s_1) = 0$
 $P(q_{t+1}=s_2|q_t=s_1) = 0$
 $P(q_{t+1}=s_3|q_t=s_1) = 1$

s_2

s_1

s_3

$N = 3$

$t = 1$

$q_t = q_1 = s_2$

$P(q_{t+1}=s_1|q_t=s_3) = 1/3$
 $P(q_{t+1}=s_2|q_t=s_3) = 2/3$
 $P(q_{t+1}=s_3|q_t=s_3) = 0$

Often notated with arcs between states

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Slide 6

Markov Property

q_{t+1} is conditionally independent of $\{q_{t-1}, q_{t-2}, \dots, q_1, q_0\}$ given q_t .

In other words:

$P(q_{t+1} = s_j | q_t = s_i) =$
 $P(q_{t+1} = s_j | q_t = s_i, \text{any earlier history})$

Question: what would be the best Bayes Net structure to represent the Joint Distribution of $(q_0, q_1, \dots, q_3, q_4)$?

Transition Probabilities:

From S_1 :

- $P(q_{t+1}=s_1|q_t=s_1) = 0$
- $P(q_{t+1}=s_2|q_t=s_1) = 0$
- $P(q_{t+1}=s_3|q_t=s_1) = 1$

From S_2 :

- $P(q_{t+1}=s_1|q_t=s_2) = 1/2$
- $P(q_{t+1}=s_2|q_t=s_2) = 1/2$
- $P(q_{t+1}=s_3|q_t=s_2) = 0$

From S_3 :

- $P(q_{t+1}=s_1|q_t=s_3) = 1/3$
- $P(q_{t+1}=s_2|q_t=s_3) = 2/3$
- $P(q_{t+1}=s_3|q_t=s_3) = 0$

$N = 3$

$t = 1$

$q_t = q_1 = s_2$

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Slide 7

Markov Property

q_{t+1} is conditionally independent of $\{q_{t-1}, q_{t-2}, \dots, q_1, q_0\}$ given q_t .

In other words:

$P(q_{t+1} = s_j | q_t = s_i) =$
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Question: what would be the best Bayes Net structure to represent the Joint Distribution of $(q_0, q_1, q_2, q_3, q_4)$?

Transition Probabilities:

From q_0 :

- $P(q_{t+1}=s_1|q_t=s_2) = 1/2$
- $P(q_{t+1}=s_2|q_t=s_2) = 1/2$
- $P(q_{t+1}=s_3|q_t=s_2) = 0$

From q_2 :

- $P(q_{t+1}=s_1|q_t=s_3) = 1/3$
- $P(q_{t+1}=s_2|q_t=s_3) = 2/3$
- $P(q_{t+1}=s_3|q_t=s_3) = 0$

Answer:

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Markov Property

q_{t+1} is conditionally independent

Answer: $P(q_{t+1}=s_1|q_t=s_2) = 1/2$

Each of these probability tables is identical

Notation: $a_{ij} = P(q_{t+1} = s_j | q_t = s_i)$

the Joint Distribution of $(q_0, q_1, q_2, q_3, q_4)$?

i	$P(q_{t+1}=s_1 q_t=s_i)$	$P(q_{t+1}=s_2 q_t=s_i)$...	$P(q_{t+1}=s_j q_t=s_i)$...	$P(q_{t+1}=s_N q_t=s_i)$
1	a_{11}	a_{12}	...	a_{1j}	...	a_{1N}
2	a_{21}	a_{22}	...	a_{2j}	...	a_{2N}
3	a_{31}	a_{32}	...	a_{3j}	...	a_{3N}
...
i	a_{i1}	a_{i2}	...	a_{ij}	...	a_{iN}
...
N	a_{N1}	a_{N2}	...	a_{Nj}	...	a_{NN}

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Slide 9

A Blind Robot

A human and a robot wander around randomly on a grid...

STATE $q = \langle \text{Location of Robot, Location of Human} \rangle$

Note: N (num. states) = $18 * 18 = 324$

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Slide 10

Dynamics of System

$q_0 =$

					R
H					

Each timestep the human moves randomly to an adjacent cell. And Robot also moves randomly to an adjacent cell.

Typical Questions:

- “What’s the expected time until the human is crushed like a bug?”
- “What’s the probability that the robot will hit the left wall before it hits the human?”
- “What’s the probability Robot crushes human on next time step?”

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Slide 11

Example Question

“It’s currently time t , and human remains uncrushed. What’s the probability of crushing occurring at time $t + 1$?”

If robot is blind:

We can compute this in advance.

← We’ll do this first

If robot is omnipotent:

(I.E. If robot knows state at time t),
can compute directly.

← Too Easy. We won’t do this

If robot has some sensors, but
incomplete state information ...

Hidden Markov Models are
applicable!

← Main Body
of Lecture

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Slide 12

What is $P(q_t = s)$? slow, stupid answer

Step 1: Work out how to compute $P(Q)$ for any path Q

$$= q_1 q_2 q_3 \dots q_t$$

Given we know the start state q_1 (i.e. $P(q_1)=1$)

$$\begin{aligned} P(q_1 q_2 \dots q_t) &= P(q_1 q_2 \dots q_{t-1}) P(q_t | q_1 q_2 \dots q_{t-1}) \\ &= P(q_1 q_2 \dots q_{t-1}) P(q_t | q_{t-1}) \quad \text{WHY?} \\ &= P(q_2 | q_1) P(q_3 | q_2) \dots P(q_t | q_{t-1}) \end{aligned}$$

Step 2: Use this knowledge to get $P(q_t = s)$

$$P(q_t = s) = \sum_{Q \in \text{Paths of length } t \text{ that end in } s} P(Q)$$

Computation is exponential in t

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Slide 13

What is $P(q_t = s)$? Clever answer

- For each state s_j , define
 $p_t(i) = \text{Prob. state is } s_j \text{ at time } t$
 $= P(q_t = s_j)$
- Easy to do inductive definition

$$\forall i \quad p_0(i) =$$

$$\forall j \quad p_{t+1}(j) = P(q_{t+1} = s_j) =$$

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Slide 14

What is $P(q_t = s)$? Clever answer

- For each state s_i , define

$$p_t(i) = \text{Prob. state is } s_i \text{ at time } t$$

$$= P(q_t = s_i)$$

- Easy to do inductive definition

$$\forall i \quad p_0(i) = \begin{cases} 1 & \text{if } s_i \text{ is the start state} \\ 0 & \text{otherwise} \end{cases}$$

$$\forall j \quad p_{t+1}(j) = P(q_{t+1} = s_j) =$$

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Slide 15

What is $P(q_t = s)$? Clever answer

- For each state s_i , define

$$p_t(i) = \text{Prob. state is } s_i \text{ at time } t$$

$$= P(q_t = s_i)$$

- Easy to do inductive definition

$$\forall i \quad p_0(i) = \begin{cases} 1 & \text{if } s_i \text{ is the start state} \\ 0 & \text{otherwise} \end{cases}$$

$$\forall j \quad p_{t+1}(j) = P(q_{t+1} = s_j) =$$

$$\sum_{i=1}^N P(q_{t+1} = s_j \wedge q_t = s_i) =$$

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Slide 16

What is $P(q_t = s)$? Clever answer

- For each state s_j , define
 $p_t(i) = \text{Prob. state is } s_i \text{ at time } t$
 $= P(q_t = s_i)$

- Easy to do inductive definition

$$\forall i \quad p_0(i) = \begin{cases} 1 & \text{if } s_i \text{ is the start state} \\ 0 & \text{otherwise} \end{cases}$$

$$\forall j \quad p_{t+1}(j) = P(q_{t+1} = s_j) =$$

$$\sum_{i=1}^N P(q_{t+1} = s_j \wedge q_t = s_i) =$$

$$\sum_{i=1}^N P(q_{t+1} = s_j | q_t = s_i) P(q_t = s_i) = \sum_{i=1}^N a_{ij} p_t(i)$$

Remember,

$$a_{ij} = P(q_{t+1} = s_j | q_t = s_i)$$

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Slide 17

What is $P(q_t = s)$? Clever answer

- For each state s_j , define
 $p_t(i) = \text{Prob. state is } s_i \text{ at time } t$
 $= P(q_t = s_i)$

- Easy to do inductive definition

$$\forall i \quad p_0(i) = \begin{cases} 1 & \text{if } s_i \text{ is the start state} \\ 0 & \text{otherwise} \end{cases}$$

$$\forall j \quad p_{t+1}(j) = P(q_{t+1} = s_j) =$$

$$\sum_{i=1}^N P(q_{t+1} = s_j \wedge q_t = s_i) =$$

$$\sum_{i=1}^N P(q_{t+1} = s_j | q_t = s_i) P(q_t = s_i) = \sum_{i=1}^N a_{ij} p_t(i)$$

- Computation is simple.
- Just fill in **this** table in **this** order:

t	$p_t(1)$	$p_t(2)$...	$p_t(N)$
0	0	1		0
1				
:				
t_{final}				

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Slide 18

What is $P(q_t = s)$? Clever answer

- For each state s_i , define

$$p_t(i) = \text{Prob. state is } s_i \text{ at time } t \\ = P(q_t = s_i)$$

- Easy to do inductive definition

$$\forall i \quad p_0(i) = \begin{cases} 1 & \text{if } s_i \text{ is the start state} \\ 0 & \text{otherwise} \end{cases}$$

$$\forall j \quad p_{t+1}(j) = P(q_{t+1} = s_j) =$$

$$\sum_{i=1}^N P(q_{t+1} = s_j \wedge q_t = s_i) =$$

$$\sum_{i=1}^N P(q_{t+1} = s_j | q_t = s_i) P(q_t = s_i) = \sum_{i=1}^N a_{ij} p_t(i)$$

- Cost of computing $P_t(i)$ for all states S_i is now $O(t N^2)$
- The stupid way was $O(N^t)$
- This was a simple example
- It was meant to warm you up to this trick, called **Dynamic Programming**, because HMMs do many tricks like this.

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Slide 19

Hidden State

“It’s currently time t , and human remains uncrushed. What’s the probability of crushing occurring at time $t + 1$?”

If robot is blind:

We can compute this in advance.

← We'll do this first

If robot is omnipotent:

(I.E. If robot knows state at time t),
can compute directly.

← Too Easy. We won't do this

If robot has some sensors, but incomplete state information ...

Hidden Markov Models are applicable!

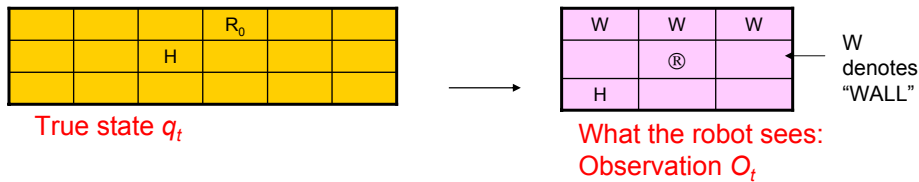
← Main Body of Lecture

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Slide 20

Hidden State

- The previous example tried to estimate $P(q_t = s_i)$ unconditionally (using no observed evidence).
- Suppose we can observe something that's affected by the true state.
- Example: Proximity sensors. (tell us the contents of the 8 adjacent squares)

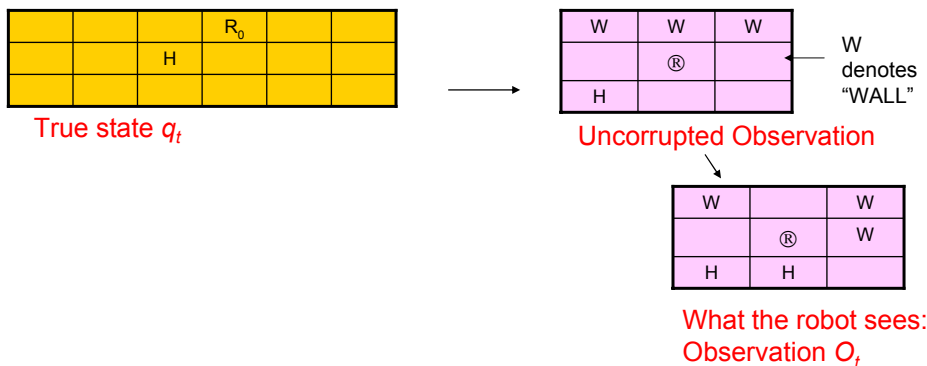


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Noisy Hidden State

- Example: Noisy Proximity sensors. (unreliably tell us the contents of the 8 adjacent squares)



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Noisy Hidden State

- Example: Noisy Proximity sensors. (unreliably tell us the contents of the 8 adjacent squares)

			R_0		2
		H			

True state q_t

O_t is noisily determined depending on the current state.

Assume that O_t is conditionally independent of $\{q_{t-1}, q_{t-2}, \dots, q_1, q_0, O_{t-1}, O_{t-2}, \dots, O_1, O_0\}$ given q_t .

In other words:

$$P(O_t = X | q_t = s_i) =$$

$$P(O_t = X | q_t = s_i, \text{any earlier history})$$

W	W	W
	Ⓡ	
H		

W denotes "WALL"

Uncorrupted Observation

W		W
	Ⓡ	W
H	H	

What the robot sees:
Observation O_t

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Slide 23

Noisy Hidden State

- Example: Noisy Proximity sensors. (unreliably tell us the contents of the 8 adjacent squares)

			R_0		2
		H			

True state q_t

O_t is noisily determined depending on the current state.

Assume that O_t is conditionally independent of $\{q_{t-1}, q_{t-2}, \dots, q_1, q_0, O_{t-1}, O_{t-2}, \dots, O_1, O_0\}$ given q_t .

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W	W	W
	Ⓡ	
H		

W denotes "WALL"

Uncorrupted Observation

W		W
	Ⓡ	W
H	H	

What the robot sees:
Observation O_t

Question: what'd be the best Bayes Net structure to represent the Joint Distribution of $(q_0, q_1, q_2, q_3, q_4, O_0, O_1, O_2, O_3, O_4)$?

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Answer:

Hidden State

Proximity sensors. (unreliably tell us adjacent squares)

Depending on O_{t-1} ,

Uncorrupted Observation

What the robot sees: Observation O_t

Question: what'd be the best Bayes Net structure to represent the Joint Distribution of $(q_0, q_1, q_2, q_3, q_4, O_0, O_1, O_2, O_3, O_4)$?

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Answer:

Hidden State

Proximity sensors. (unreliably tell us adjacent squares)

Notation:

$$b_i(k) = P(O_t = k | q_t = s_i)$$

	$P(O_t=1 q_t=s_1)$	$P(O_t=2 q_t=s_1)$	$P(O_t=k q_t=s_1)$	$P(O_t=M q_t=s_1)$
1	$b_1(1)$	$b_1(2)$	$b_1(k)$	$b_1(M)$
2	$b_2(1)$	$b_2(2)$	$b_2(k)$	$b_2(M)$
3	$b_3(1)$	$b_3(2)$	$b_3(k)$	$b_3(M)$
\vdots	\vdots	\vdots	\vdots	\vdots
i	$b_i(1)$	$b_i(2)$	$b_i(k)$	$b_i(M)$
\vdots	\vdots	\vdots	\vdots	\vdots
N	$b_N(1)$	$b_N(2)$	$b_N(k)$	$b_N(M)$

What the robot sees: Observation O_t

Question: what'd be the best Bayes Net structure to represent the Joint Distribution of $(q_0, q_1, q_2, q_3, q_4, O_0, O_1, O_2, O_3, O_4)$?

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Hidden Markov Models

Our robot with noisy sensors is a good example of an HMM

- Question 1: State Estimation

What is $P(q_T = S_i \mid O_1 O_2 \dots O_T)$

It will turn out that a new cute D.P. trick will get this for us.

- Question 2: Most Probable Path

Given $O_1 O_2 \dots O_T$, what is the most probable path that I took?

And what is that probability?

Yet another famous D.P. trick, the VITERBI algorithm, gets this.

- Question 3: Learning HMMs:

Given $O_1 O_2 \dots O_T$, what is the maximum likelihood HMM that could have produced this string of observations?

Very very useful. Uses the E.M. Algorithm

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Are H.M.M.s Useful?

You bet !!

- Robot planning + sensing when there's uncertainty (e.g. Reid Simmons / Sebastian Thrun / Sven Koenig)
- Speech Recognition/Understanding
Phones → Words, Signal → phones
- Human Genome Project
Complicated stuff your lecturer knows nothing about.
- Consumer decision modeling
- Economics & Finance.

Plus at least 5 other things I haven't thought of.

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Some Famous HMM Tasks

Question 1: State Estimation

What is $P(q_T = S_i \mid O_1 O_2 \dots O_T)$

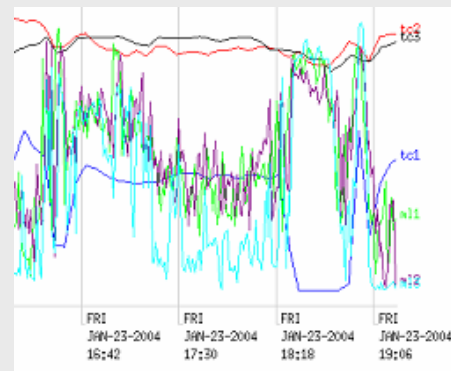
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Some Famous HMM Tasks

Question 1: State Estimation

What is $P(q_T = S_i \mid O_1 O_2 \dots O_T)$



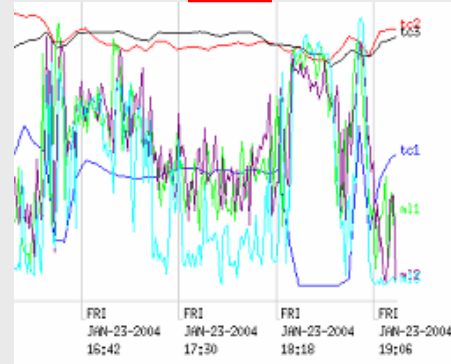
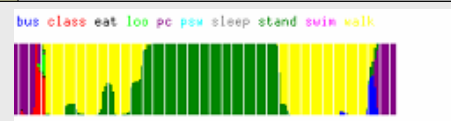
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Some Famous HMM Tasks

Question 1: State Estimation

What is $P(q_T = s_i | O_1 O_2 \dots O_T)$?



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Some Famous HMM Tasks

Question 1: State Estimation

What is $P(q_T = s_i | O_1 O_2 \dots O_T)$?

Question 2: Most Probable Path

Given $O_1 O_2 \dots O_T$, what is the most probable path that I took?

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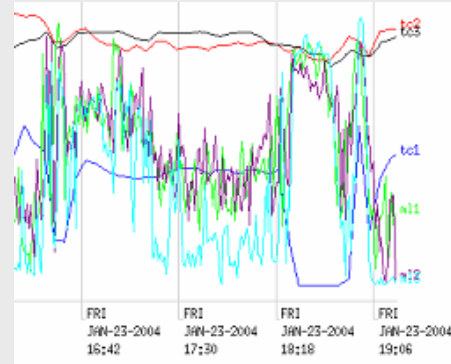
Some Famous HMM Tasks

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Some Famous HMM Tasks

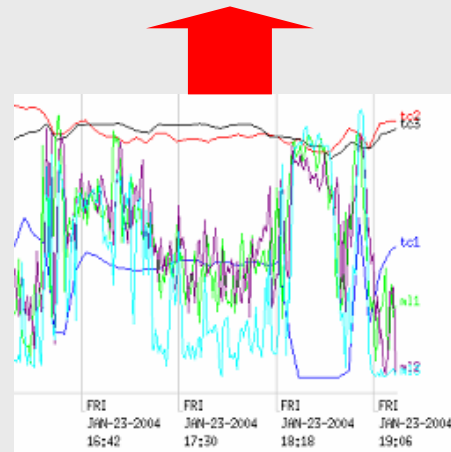
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Question 2: Most Probable Path

Given $O_1 O_2 \dots O_T$, what is the most probable path that I took?

Woke up at 8.35, Got on Bus at 9.46,
Sat in lecture 10.05-11.22...



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Some Famous HMM Tasks

Question 1: State Estimation

What is $P(q_T = S_i \mid O_1 O_2 \dots O_T)$

Question 2: Most Probable Path

Given $O_1 O_2 \dots O_T$, what is the most probable path that I took?

Question 3: Learning HMMs:

Given $O_1 O_2 \dots O_T$, what is the maximum likelihood HMM that could have produced this string of observations?

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Some Famous HMM Tasks

Question 1: State Estimation

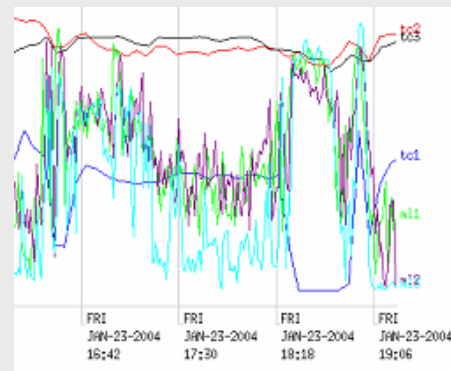
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Some Famous

Question 1: State Estimation

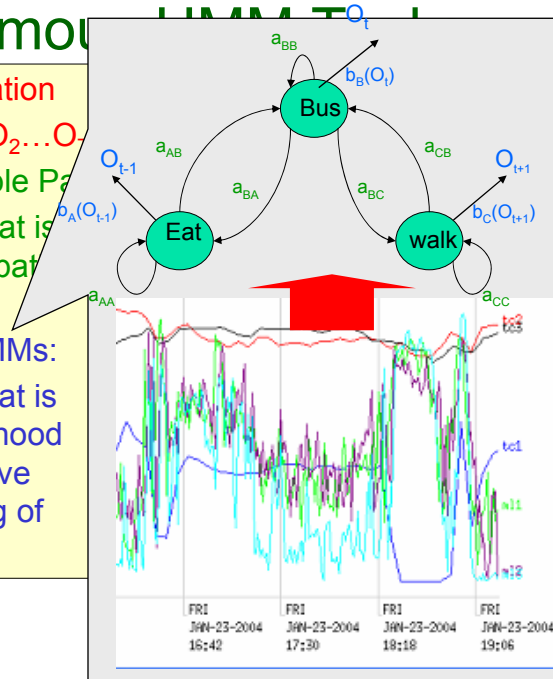
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Given $O_1 O_2 \dots O_T$, what is the most probable path that I took?

Question 3: Learning HMMs:

Given $O_1 O_2 \dots O_T$, what is the maximum likelihood HMM that could have produced this string of observations?



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Slide 37

Basic Operations in HMMs

For an observation sequence $O = O_1 \dots O_T$, the three basic HMM operations are:

Problem	Algorithm	Complexity
Evaluation: Calculating $P(q_i = S_i \mid O_1 O_2 \dots O_i)$	Forward-Backward	$O(TN^2)$
Inference: Computing $Q^* = \operatorname{argmax}_Q P(Q O)$	Viterbi Decoding	$O(TN^2)$
Learning: Computing $\lambda^* = \operatorname{argmax}_\lambda P(O \lambda)$	Baum-Welch (EM)	$O(TN^2)$

$T = \#$ timesteps, $N = \#$ states

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Slide 38

HMM Notation (from Rabiner's Survey)

The states are labeled $S_1 S_2 \dots S_N$

For a particular trial....

Let T be the number of observations

T is also the number of states passed through

$O = O_1 O_2 \dots O_T$ is the sequence of observations

$Q = q_1 q_2 \dots q_T$ is the notation for a path of states

$\lambda = \langle N, M, \{\pi_i\}, \{a_{ij}\}, \{b_i(j)\} \rangle$ is the specification of an HMM

*L. R. Rabiner, "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," Proc. of the IEEE, Vol.77, No.2, pp.257--286, 1989.

Available from

<http://ieeexplore.ieee.org/iel5/5/698/00018626.pdf?arnumber=18626>

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Slide 39

HMM Formal Definition

An HMM, λ , is a 5-tuple consisting of

- N the number of states
- M the number of possible observations
- $\{\pi_1, \pi_2, \dots, \pi_N\}$ The starting state probabilities

$$P(q_0 = S_i) = \pi_i$$

This is new. In our previous example, start state was deterministic

- | | | | |
|----------|----------|-----|----------|
| a_{11} | a_{22} | ... | a_{1N} |
| a_{21} | a_{22} | ... | a_{2N} |
| \vdots | \vdots | | \vdots |
| a_{N1} | a_{N2} | ... | a_{NN} |

The state transition probabilities
 $P(q_{t+1}=S_j | q_t=S_i)=a_{ij}$
- | | | | |
|----------|----------|-----|----------|
| $b_1(1)$ | $b_1(2)$ | ... | $b_1(M)$ |
| $b_2(1)$ | $b_2(2)$ | ... | $b_2(M)$ |
| \vdots | \vdots | | \vdots |
| $b_N(1)$ | $b_N(2)$ | ... | $b_N(M)$ |

The observation probabilities
 $P(O_i=k | q_i=S_i)=b_i(k)$

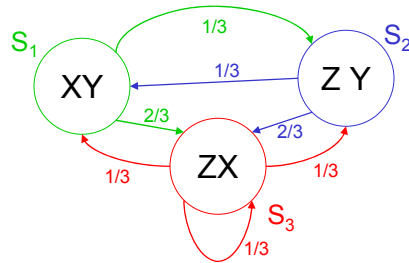
Copyright © Andrew W. Moore

Slide 40

Here's an HMM

Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.



$$N = 3$$

$$M = 3$$

$$\pi_1 = 1/2$$

$$\pi_2 = 1/2$$

$$\pi_3 = 0$$

$$a_{11} = 0$$

$$a_{12} = 1/3$$

$$a_{13} = 2/3$$

$$a_{12} = 1/3$$

$$a_{22} = 0$$

$$a_{13} = 2/3$$

$$a_{13} = 1/3$$

$$a_{32} = 1/3$$

$$a_{13} = 1/3$$

$$b_1(X) = 1/2$$

$$b_1(Y) = 1/2$$

$$b_1(Z) = 0$$

$$b_2(X) = 0$$

$$b_2(Y) = 1/2$$

$$b_2(Z) = 1/2$$

$$b_3(X) = 1/2$$

$$b_3(Y) = 0$$

$$b_3(Z) = 1/2$$

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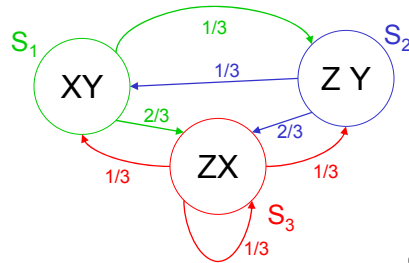
Slide 41

Here's an HMM

Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.

Let's generate a sequence of observations:



$$N = 3$$

$$M = 3$$

$$\pi_1 = 1/2$$

$$\pi_2 = 1/2$$

$$\pi_3 = 0$$

$$a_{11} = 0$$

$$a_{12} = 1/3$$

$$a_{13} = 2/3$$

$$a_{12} = 1/3$$

$$a_{22} = 0$$

$$a_{13} = 2/3$$

$$a_{13} = 1/3$$

$$a_{32} = 1/3$$

$$a_{13} = 1/3$$

$$b_1(X) = 1/2$$

$$b_1(Y) = 1/2$$

$$b_1(Z) = 0$$

$$b_2(X) = 0$$

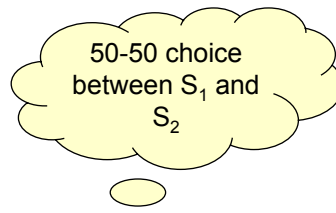
$$b_2(Y) = 1/2$$

$$b_2(Z) = 1/2$$

$$b_3(X) = 1/2$$

$$b_3(Y) = 0$$

$$b_3(Z) = 1/2$$

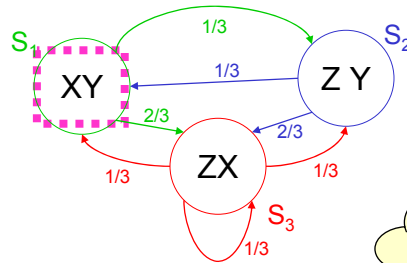


$q_0 =$	<u> </u>	$O_0 =$	<u> </u>
$q_1 =$	<u> </u>	$O_1 =$	<u> </u>
$q_2 =$	<u> </u>	$O_2 =$	<u> </u>

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Slide 42

Here's an HMM



$$N = 3$$

$$M = 3$$

$$\pi_1 = \frac{1}{2}$$

$$\pi_2 = \frac{1}{2}$$

$$\pi_3 = 0$$

$$a_{11} = 0$$

$$a_{12} = \frac{1}{3}$$

$$a_{13} = \frac{1}{3}$$

$$a_{22} = 0$$

$$a_{32} = \frac{1}{3}$$

$$a_{13} = \frac{2}{3}$$

$$a_{23} = \frac{2}{3}$$

$$a_{33} = \frac{1}{3}$$

$$b_1(X) = \frac{1}{2}$$

$$b_2(X) = 0$$

$$b_3(X) = \frac{1}{2}$$

$$b_1(Y) = \frac{1}{2}$$

$$b_2(Y) = \frac{1}{2}$$

$$b_3(Y) = 0$$

$$b_1(Z) = 0$$

$$b_2(Z) = \frac{1}{2}$$

$$b_3(Z) = \frac{1}{2}$$

Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.

Let's generate a sequence of observations:

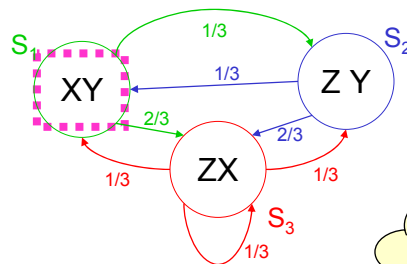
50-50 choice between X and Y

$q_0 =$	S_1	$O_0 =$	—
$q_1 =$	—	$O_1 =$	—
$q_2 =$	—	$O_2 =$	—

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Slide 43

Here's an HMM



$$N = 3$$

$$M = 3$$

$$\pi_1 = \frac{1}{2}$$

$$\pi_2 = \frac{1}{2}$$

$$\pi_3 = 0$$

$$a_{11} = 0$$

$$a_{12} = \frac{1}{3}$$

$$a_{13} = \frac{1}{3}$$

$$a_{22} = 0$$

$$a_{32} = \frac{1}{3}$$

$$a_{13} = \frac{2}{3}$$

$$a_{23} = \frac{2}{3}$$

$$a_{33} = \frac{1}{3}$$

$$b_1(X) = \frac{1}{2}$$

$$b_2(X) = 0$$

$$b_3(X) = \frac{1}{2}$$

$$b_1(Y) = \frac{1}{2}$$

$$b_2(Y) = \frac{1}{2}$$

$$b_3(Y) = 0$$

$$b_1(Z) = 0$$

$$b_2(Z) = \frac{1}{2}$$

$$b_3(Z) = \frac{1}{2}$$

Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.

Let's generate a sequence of observations:

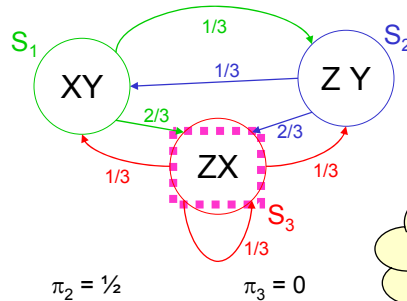
Goto S_3 with probability $\frac{2}{3}$ or S_2 with prob. $\frac{1}{3}$

$q_0 =$	S_1	$O_0 =$	X
$q_1 =$	—	$O_1 =$	—
$q_2 =$	—	$O_2 =$	—

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Slide 44

Here's an HMM



$N = 3$
 $M = 3$
 $\pi_1 = \frac{1}{2}$

$\pi_2 = \frac{1}{2}$

$\pi_3 = 0$

$a_{11} = 0$
 $a_{12} = \frac{1}{3}$
 $a_{13} = \frac{1}{3}$

$a_{21} = \frac{2}{3}$
 $a_{22} = 0$
 $a_{23} = \frac{1}{3}$

$a_{31} = \frac{1}{3}$
 $a_{32} = \frac{2}{3}$
 $a_{33} = \frac{1}{3}$

$b_1(X) = \frac{1}{2}$
 $b_2(X) = 0$
 $b_3(X) = \frac{1}{2}$

$b_1(Y) = \frac{1}{2}$
 $b_2(Y) = \frac{1}{2}$
 $b_3(Y) = 0$

$b_1(Z) = 0$
 $b_2(Z) = \frac{1}{2}$
 $b_3(Z) = \frac{1}{2}$

Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.

Let's generate a sequence of observations:

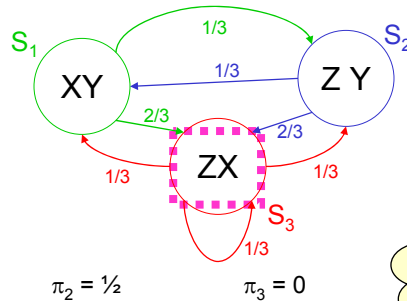
50-50 choice between Z and X

$q_0 =$	S_1	$O_0 =$	X
$q_1 =$	S_3	$O_1 =$	—
$q_2 =$	—	$O_2 =$	—

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Here's an HMM



$N = 3$
 $M = 3$
 $\pi_1 = \frac{1}{2}$

$\pi_2 = \frac{1}{2}$

$\pi_3 = 0$

$a_{11} = 0$
 $a_{12} = \frac{1}{3}$
 $a_{13} = \frac{1}{3}$

$a_{21} = \frac{2}{3}$
 $a_{22} = 0$
 $a_{23} = \frac{1}{3}$

$a_{31} = \frac{1}{3}$
 $a_{32} = \frac{2}{3}$
 $a_{33} = \frac{1}{3}$

$b_1(X) = \frac{1}{2}$
 $b_2(X) = 0$
 $b_3(X) = \frac{1}{2}$

$b_1(Y) = \frac{1}{2}$
 $b_2(Y) = \frac{1}{2}$
 $b_3(Y) = 0$

$b_1(Z) = 0$
 $b_2(Z) = \frac{1}{2}$
 $b_3(Z) = \frac{1}{2}$

Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.

Let's generate a sequence of observations:

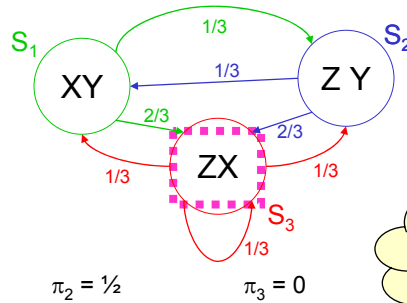
Each of the three next states is equally likely

$q_0 =$	S_1	$O_0 =$	X
$q_1 =$	S_3	$O_1 =$	X
$q_2 =$	—	$O_2 =$	—

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Slide 46

Here's an HMM



$$N = 3$$

$$M = 3$$

$$\pi_1 = \frac{1}{2}$$

$$\pi_2 = \frac{1}{2}$$

$$\pi_3 = 0$$

$$a_{11} = 0$$

$$a_{12} = \frac{1}{3}$$

$$a_{13} = \frac{1}{3}$$

$$a_{22} = 0$$

$$a_{32} = \frac{1}{3}$$

$$a_{13} = \frac{2}{3}$$

$$a_{23} = \frac{2}{3}$$

$$a_{33} = \frac{1}{3}$$

$$b_1(X) = \frac{1}{2}$$

$$b_2(X) = 0$$

$$b_3(X) = \frac{1}{2}$$

$$b_1(Y) = \frac{1}{2}$$

$$b_2(Y) = \frac{1}{2}$$

$$b_3(Y) = 0$$

$$b_1(Z) = 0$$

$$b_2(Z) = \frac{1}{2}$$

$$b_3(Z) = \frac{1}{2}$$

Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.

Let's generate a sequence of observations:

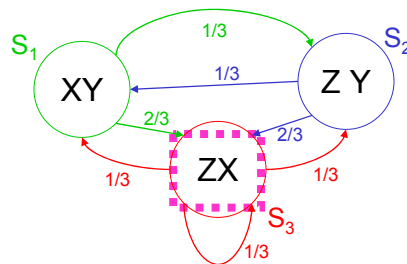
50-50 choice between Z and X

$q_0 =$	S_1	$O_0 =$	X
$q_1 =$	S_3	$O_1 =$	X
$q_2 =$	S_3	$O_2 =$	—

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Slide 47

Here's an HMM



$$N = 3$$

$$M = 3$$

$$\pi_1 = \frac{1}{2}$$

$$\pi_2 = \frac{1}{2}$$

$$\pi_3 = 0$$

$$a_{11} = 0$$

$$a_{12} = \frac{1}{3}$$

$$a_{13} = \frac{1}{3}$$

$$a_{22} = 0$$

$$a_{32} = \frac{1}{3}$$

$$a_{13} = \frac{2}{3}$$

$$a_{23} = \frac{2}{3}$$

$$a_{33} = \frac{1}{3}$$

$$b_1(X) = \frac{1}{2}$$

$$b_2(X) = 0$$

$$b_3(X) = \frac{1}{2}$$

$$b_1(Y) = \frac{1}{2}$$

$$b_2(Y) = \frac{1}{2}$$

$$b_3(Y) = 0$$

$$b_1(Z) = 0$$

$$b_2(Z) = \frac{1}{2}$$

$$b_3(Z) = \frac{1}{2}$$

Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.

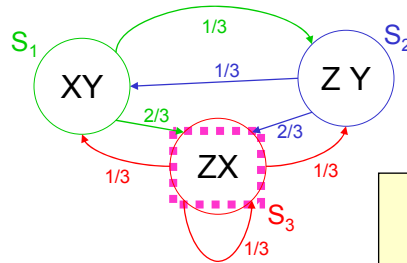
Let's generate a sequence of observations:

$q_0 =$	S_1	$O_0 =$	X
$q_1 =$	S_3	$O_1 =$	X
$q_2 =$	S_3	$O_2 =$	Z

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Slide 48

State Estimation



Start randomly in state 1 or 2

Choose one of the output symbols in each state at random.

Let's generate a sequence of observations:

This is what the observer has to work with...

$q_0 =$?	$O_0 =$	X
$q_1 =$?	$O_1 =$	X
$q_2 =$?	$O_2 =$	Z

$N = 3$
 $M = 3$
 $\pi_1 = 1/2$

$\pi_2 = 1/2$

$\pi_3 = 0$

$a_{11} = 0$
 $a_{12} = 1/3$
 $a_{13} = 1/3$

$a_{21} = 1/3$
 $a_{22} = 0$
 $a_{23} = 1/3$

$a_{31} = 2/3$
 $a_{32} = 2/3$
 $a_{33} = 1/3$

$b_1(X) = 1/2$
 $b_2(X) = 0$
 $b_3(X) = 1/2$

$b_1(Y) = 1/2$
 $b_2(Y) = 1/2$
 $b_3(Y) = 0$

$b_1(Z) = 0$
 $b_2(Z) = 1/2$
 $b_3(Z) = 1/2$

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Slide 49

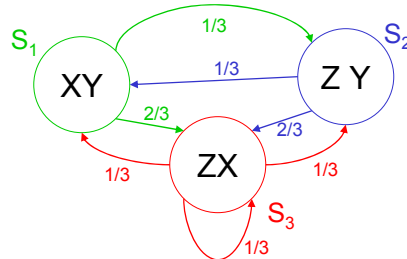
Prob. of a series of observations

What is $P(\mathbf{O}) = P(O_1 O_2 O_3) = P(O_1 = X \wedge O_2 = X \wedge O_3 = Z)$?

Slow, stupid way:

$$P(\mathbf{O}) = \sum_{Q \in \text{Paths of length 3}} P(\mathbf{O} \wedge Q)$$

$$= \sum_{Q \in \text{Paths of length 3}} P(\mathbf{O} | Q) P(Q)$$



How do we compute $P(Q)$ for an arbitrary path Q ?

How do we compute $P(\mathbf{O} | Q)$ for an arbitrary path Q ?

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Slide 50

Prob. of a series of observations

What is $P(\mathbf{O}) = P(O_1 O_2 O_3) =$
 $P(O_1 = X \wedge O_2 = X \wedge O_3 = Z)$?

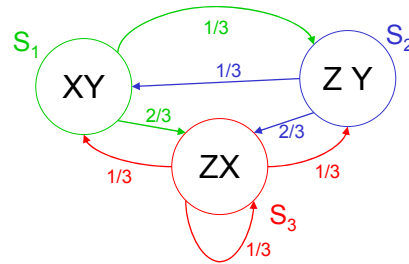
Slow, stupid way:

$$P(\mathbf{O}) = \sum_{Q \in \text{Paths of length 3}} P(\mathbf{O} \wedge Q)$$

$$= \sum_{Q \in \text{Paths of length 3}} P(\mathbf{O} | Q) P(Q)$$

How do we compute $P(Q)$ for an arbitrary path Q ?

How do we compute $P(\mathbf{O} | Q)$ for an arbitrary path Q ?



$$P(Q) = P(q_1, q_2, q_3)$$

$$= P(q_1) P(q_2, q_3 | q_1) \text{ (chain rule)}$$

$$= P(q_1) P(q_2 | q_1) P(q_3 | q_2, q_1) \text{ (chain)}$$

$$= P(q_1) P(q_2 | q_1) P(q_3 | q_2) \text{ (why?)}$$

Example in the case $Q = S_1 S_3 S_3$:

$$= 1/2 * 2/3 * 1/3 = 1/9$$

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Slide 51

Prob. of a series of observations

What is $P(\mathbf{O}) = P(O_1 O_2 O_3) =$
 $P(O_1 = X \wedge O_2 = X \wedge O_3 = Z)$?

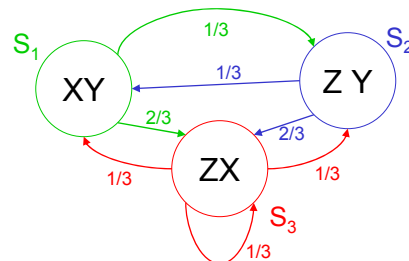
Slow, stupid way:

$$P(\mathbf{O}) = \sum_{Q \in \text{Paths of length 3}} P(\mathbf{O} \wedge Q)$$

$$= \sum_{Q \in \text{Paths of length 3}} P(\mathbf{O} | Q) P(Q)$$

How do we compute $P(Q)$ for an arbitrary path Q ?

How do we compute $P(\mathbf{O} | Q)$ for an arbitrary path Q ?



$$P(\mathbf{O} | Q)$$

$$= P(O_1 O_2 O_3 | q_1 q_2 q_3)$$

$$= P(O_1 | q_1) P(O_2 | q_2) P(O_3 | q_3) \text{ (why?)}$$

Example in the case $Q = S_1 S_3 S_3$:

$$= P(X | S_1) P(X | S_3) P(Z | S_3) =$$

$$= 1/2 * 1/2 * 1/2 = 1/8$$

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Slide 52

Prob. of a series of observations

What is $P(\mathbf{O}) = P(O_1 O_2 O_3) =$
 $P(O_1 = X \wedge O_2 = X \wedge O_3 = Z)$?

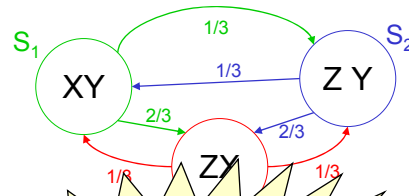
Slow, stupid way:

$$P(\mathbf{O}) = \sum_{Q \in \text{Paths of length 3}} P(\mathbf{O} \wedge Q)$$

$$= \sum_{Q \in \text{Paths of length 3}} P(\mathbf{O} | Q) P(Q)$$

How do we compute $P(Q)$ for an arbitrary path Q ?

How do we compute $P(\mathbf{O} | Q)$ for an arbitrary path Q ?



$P(\mathbf{O})$ would need 27 $P(Q)$ computations and 27 $P(\mathbf{O} | Q)$ computations

A sequence of 20 observations would need $3^{20} =$ 3.5 billion computations and 3.5 billion $P(\mathbf{O} | Q)$ computations

So let's be smarter...

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Slide 53

The Prob. of a given series of observations, non-exponential-cost-style

Given observations $O_1 O_2 \dots O_T$

Define

$$\alpha_t(i) = P(O_1 O_2 \dots O_t \wedge q_t = S_i | \lambda) \quad \text{where } 1 \leq t \leq T$$

$\alpha_t(i)$ = Probability that, in a random trial,

- We'd have seen the first t observations
- We'd have ended up in S_i as the t 'th state visited.

In our example, what is $\alpha_2(3)$?

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Slide 54

$\alpha_t(i)$: easy to define recursively

$\alpha_t(i) = P(O_1 O_2 \dots O_T \wedge q_t = S_i \mid \lambda)$ ($\alpha_t(i)$ can be defined stupidly by considering all paths length " t ". How?)

$$\begin{aligned}\alpha_1(i) &= P(O_1 \wedge q_1 = S_i) \\ &= P(q_1 = S_i)P(O_1 | q_1 = S_i) \\ &= \text{what?} \\ \alpha_{t+1}(j) &= P(O_1 O_2 \dots O_t O_{t+1} \wedge q_{t+1} = S_j) \\ &= \end{aligned}$$

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Slide 55

$\alpha_t(i)$: easy to define recursively

$\alpha_t(i) = P(O_1 O_2 \dots O_T \wedge q_t = S_i \mid \lambda)$ ($\alpha_t(i)$ can be defined stupidly by considering all paths length " t ". How?)

$$\begin{aligned}\alpha_1(i) &= P(O_1 \wedge q_1 = S_i) \\ &= P(q_1 = S_i)P(O_1 | q_1 = S_i) \\ &= \text{what?} \\ \alpha_{t+1}(j) &= P(O_1 O_2 \dots O_t O_{t+1} \wedge q_{t+1} = S_j) \\ &= \sum_{i=1}^N P(O_1 O_2 \dots O_t \wedge q_t = S_i \wedge O_{t+1} \wedge q_{t+1} = S_j) \\ &= \sum_{i=1}^N P(O_{t+1}, q_{t+1} = S_j | O_1 O_2 \dots O_t \wedge q_t = S_i) P(O_1 O_2 \dots O_t \wedge q_t = S_i) \\ &= \sum_i P(O_{t+1}, q_{t+1} = S_j | q_t = S_i) \alpha_t(i) \\ &= \sum_i P(q_{t+1} = S_j | q_t = S_i) P(O_{t+1} | q_{t+1} = S_j) \alpha_t(i) \\ &= \sum_i a_{ij} b_j(O_{t+1}) \alpha_t(i)\end{aligned}$$

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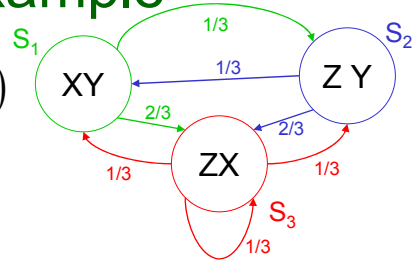
Slide 56

in our example

$$\alpha_t(i) = P(O_1 O_2 \dots O_t \wedge q_t = S_i | \lambda)$$

$$\alpha_1(i) = b_i(O_1) \pi_i$$

$$\alpha_{t+1}(j) = \sum_i a_{ij} b_j(O_{t+1}) \alpha_t(i)$$



WE SAW $O_1 O_2 O_3 = X X Z$

$$\alpha_1(1) = \frac{1}{4}$$

$$\alpha_1(2) = 0$$

$$\alpha_1(3) = 0$$

$$\alpha_2(1) = 0$$

$$\alpha_2(2) = 0$$

$$\alpha_2(3) = \frac{1}{12}$$

$$\alpha_3(1) = 0$$

$$\alpha_3(2) = \frac{1}{72}$$

$$\alpha_3(3) = \frac{1}{72}$$

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Slide 57

Easy Question

We can cheaply compute

$$\alpha_t(i) = P(O_1 O_2 \dots O_t \wedge q_t = S_i)$$

(How) can we cheaply compute

$$P(O_1 O_2 \dots O_t) \quad ?$$

(How) can we cheaply compute

$$P(q_t = S_i | O_1 O_2 \dots O_t)$$

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Slide 58

Easy Question

We can cheaply compute

$$\alpha_t(i) = P(O_1 O_2 \dots O_t \wedge q_t = S_i)$$

(How) can we cheaply compute

$$P(O_1 O_2 \dots O_t) \quad ? \quad \sum_{i=1}^N \alpha_t(i)$$

(How) can we cheaply compute

$$P(q_t = S_i | O_1 O_2 \dots O_t) \quad \frac{\alpha_t(i)}{\sum_{j=1}^N \alpha_t(j)}$$

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Slide 59

Most probable path given observations

What's most probable path given $O_1 O_2 \dots O_T$, i.e.

What is $\underset{Q}{\operatorname{argmax}} P(Q | O_1 O_2 \dots O_T)$?

Slow, stupid answer :

$$\begin{aligned} & \underset{Q}{\operatorname{argmax}} P(Q | O_1 O_2 \dots O_T) \\ &= \underset{Q}{\operatorname{argmax}} \frac{P(O_1 O_2 \dots O_T | Q) P(Q)}{P(O_1 O_2 \dots O_T)} \\ &= \underset{Q}{\operatorname{argmax}} P(O_1 O_2 \dots O_T | Q) P(Q) \end{aligned}$$

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Efficient MPP computation

We're going to compute the following variables:

$$\delta_t(i) = \max_{q_1 q_2 \dots q_{t-1}} P(q_1 q_2 \dots q_{t-1} \wedge q_t = S_i \wedge O_1 \dots O_t)$$

= The Probability of the path of Length t-1 with the maximum chance of doing all these things:

...OCCURRING

and

...ENDING UP IN STATE S_i

and

...PRODUCING OUTPUT $O_1 \dots O_t$

DEFINE: $mpp_t(i)$ = that path

So: $\delta_t(i) = \text{Prob}(mpp_t(i))$

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The Viterbi Algorithm

$$\delta_t(i) = \max_{q_1 q_2 \dots q_{t-1}} P(q_1 q_2 \dots q_{t-1} \wedge q_t = S_i \wedge O_1 O_2 \dots O_t)$$

$$mpp_t(i) = \underset{\text{argmax}}{q_1 q_2 \dots q_{t-1}} P(q_1 q_2 \dots q_{t-1} \wedge q_t = S_i \wedge O_1 O_2 \dots O_t)$$

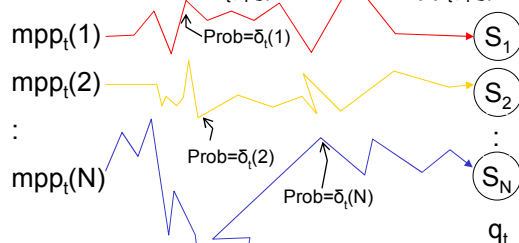
$$\delta_1(i) = \max_{q_1} P(q_1 = S_i \wedge O_1)$$

$$= P(q_1 = S_i) P(O_1 | q_1 = S_i)$$

$$= \pi_i b_i(O_1)$$

Now, suppose we have all the $\delta_t(i)$'s and $mpp_t(i)$'s for all i .

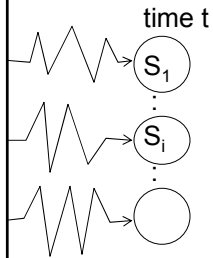
HOW TO GET $\delta_{t+1}(j)$ and $mpp_{t+1}(j)$?



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Slide 62

The Viterbi Algorithm



time t+1

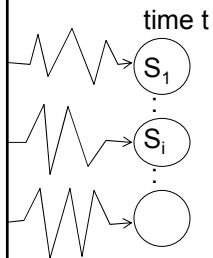


The most prob path with last two states $S_i S_j$ is the most prob path to S_i , followed by transition $S_i \rightarrow S_j$

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Slide 63

The Viterbi Algorithm



time t+1



The most prob path with last two states $S_i S_j$ is the most prob path to S_i , followed by transition $S_i \rightarrow S_j$

What is the prob of that path?

$$\delta_t(i) \times P(S_i \rightarrow S_j \wedge O_{t+1} | \lambda) = \delta_t(i) a_{ij} b_j(O_{t+1})$$

SO The most probable path to S_j has

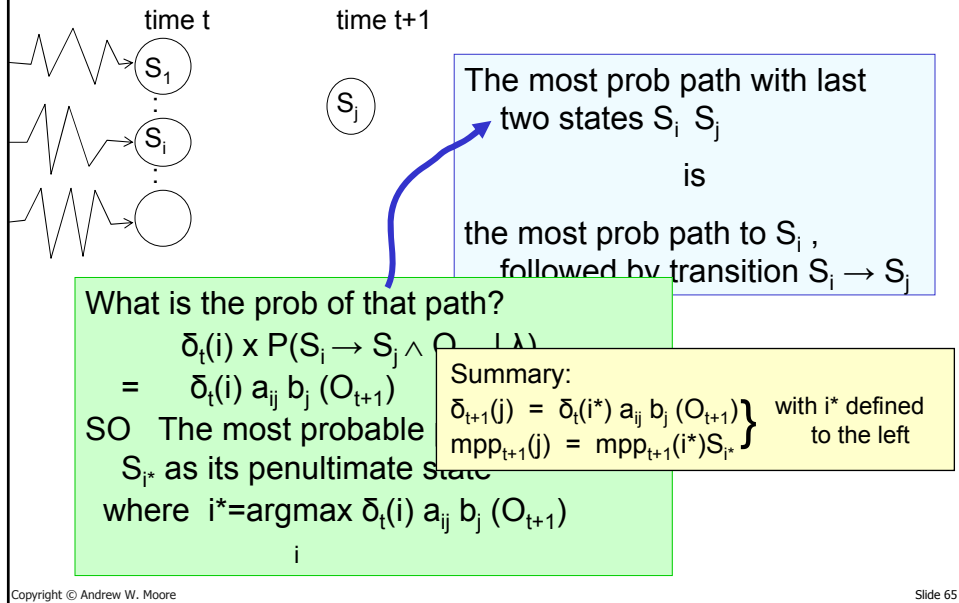
S_{i^*} as its penultimate state

where $i^* = \underset{i}{\operatorname{argmax}} \delta_t(i) a_{ij} b_j(O_{t+1})$

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The Viterbi Algorithm



What's Viterbi used for?

Classic Example

Speech recognition:

Signal \rightarrow words

HMM \rightarrow observable is signal

\rightarrow Hidden state is part of word formation

What is the most probable word given this signal?

UTTERLY GROSS SIMPLIFICATION

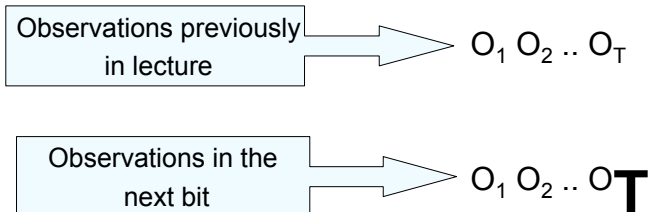
In practice: many levels of inference; not one big jump.

HMMs are used and useful

But how do you design an HMM?

Occasionally, (e.g. in our robot example) it is reasonable to deduce the HMM from first principles.

But usually, especially in Speech or Genetics, it is better to infer it from large amounts of data. $O_1 O_2 \dots O_T$ with a big “T”.



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Inferring an HMM

Remember, we've been doing things like

$$P(O_1 O_2 \dots O_T | \lambda)$$

That “ λ ” is the notation for our HMM parameters.

Now We have some observations and we want to estimate λ from them.

AS USUAL: We could use

(i) MAX LIKELIHOOD $\lambda = \underset{\lambda}{\operatorname{argmax}} P(O_1 \dots O_T | \lambda)$

(ii) BAYES

Work out $P(\lambda | O_1 \dots O_T)$

and then take $E[\lambda]$ or $\underset{\lambda}{\operatorname{max}} P(\lambda | O_1 \dots O_T)$

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Max likelihood HMM estimation

Define

$$\gamma_t(i) = P(q_t = S_i \mid O_1 O_2 \dots O_T, \lambda)$$

$$\varepsilon_t(i, j) = P(q_t = S_i \wedge q_{t+1} = S_j \mid O_1 O_2 \dots O_T, \lambda)$$

$\gamma_t(i)$ and $\varepsilon_t(i, j)$ can be computed efficiently $\forall i, j, t$
(Details in Rabiner paper)

$$\sum_{t=1}^{T-1} \gamma_t(i) = \text{Expected number of transitions out of state } i \text{ during the path}$$

$$\sum_{t=1}^{T-1} \varepsilon_t(i, j) = \text{Expected number of transitions from state } i \text{ to state } j \text{ during the path}$$

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$$\gamma_t(i) = P(q_t = S_i \mid O_1 O_2 \dots O_T, \lambda)$$

$$\varepsilon_t(i, j) = P(q_t = S_i \wedge q_{t+1} = S_j \mid O_1 O_2 \dots O_T, \lambda)$$

$$\sum_{t=1}^{T-1} \gamma_t(i) = \text{expected number of transitions out of state } i \text{ during path}$$

$$\sum_{t=1}^{T-1} \varepsilon_t(i, j) = \text{expected number of transitions out of } i \text{ and into } j \text{ during path}$$

HMM estimation

$$\text{Notice } \frac{\sum_{t=1}^{T-1} \varepsilon_t(i, j)}{\sum_{t=1}^{T-1} \gamma_t(i)} = \frac{\left(\begin{array}{c} \text{expected frequency} \\ i \rightarrow j \end{array} \right)}{\left(\begin{array}{c} \text{expected frequency} \\ i \end{array} \right)}$$

= Estimate of Prob(Next state S_j | This state S_i)

We can re - estimate

$$a_{ij} \leftarrow \frac{\sum_{t=1}^{T-1} \varepsilon_t(i, j)}{\sum_{t=1}^{T-1} \gamma_t(i)}$$

We can also re - estimate

$$b_j(O_k) \leftarrow \dots \quad (\text{See Rabiner})$$

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We want a_{ij}^{new} = new estimate of $P(q_{t+1} = s_j \mid q_t = s_i)$

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We want a_{ij}^{new} = new estimate of $P(q_{t+1} = s_j \mid q_t = s_i)$

$$= \frac{\text{Expected \# transitions } i \rightarrow j \mid \lambda^{\text{old}}, O_1, O_2, \dots, O_T}{\sum_{k=1}^N \text{Expected \# transitions } i \rightarrow k \mid \lambda^{\text{old}}, O_1, O_2, \dots, O_T}$$

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We want a_{ij}^{new} = new estimate of $P(q_{t+1} = s_j | q_t = s_i)$

$$= \frac{\text{Expected \# transitions } i \rightarrow j | \lambda^{\text{old}}, O_1, O_2, \dots, O_T}{\sum_{k=1}^N \text{Expected \# transitions } i \rightarrow k | \lambda^{\text{old}}, O_1, O_2, \dots, O_T}$$

$$= \frac{\sum_{t=1}^T P(q_{t+1} = s_j, q_t = s_i | \lambda^{\text{old}}, O_1, O_2, \dots, O_T)}{\sum_{k=1}^N \sum_{t=1}^T P(q_{t+1} = s_k, q_t = s_i | \lambda^{\text{old}}, O_1, O_2, \dots, O_T)}$$

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We want a_{ij}^{new} = new estimate of $P(q_{t+1} = s_j | q_t = s_i)$

$$= \frac{\text{Expected \# transitions } i \rightarrow j | \lambda^{\text{old}}, O_1, O_2, \dots, O_T}{\sum_{k=1}^N \text{Expected \# transitions } i \rightarrow k | \lambda^{\text{old}}, O_1, O_2, \dots, O_T}$$

$$= \frac{\sum_{t=1}^T P(q_{t+1} = s_j, q_t = s_i | \lambda^{\text{old}}, O_1, O_2, \dots, O_T)}{\sum_{k=1}^N \sum_{t=1}^T P(q_{t+1} = s_k, q_t = s_i | \lambda^{\text{old}}, O_1, O_2, \dots, O_T)}$$

$$= \frac{S_{ij}}{\sum_{k=1}^N S_{ik}} \text{ where } S_{ij} = \sum_{t=1}^T P(q_{t+1} = s_j, q_t = s_i, O_1, \dots, O_T | \lambda^{\text{old}})$$

= What?

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We want a_{ij}^{new} = new estimate of $P(q_{t+1} = s_j \mid q_t = s_i)$

$$\begin{aligned}
 &= \frac{\text{Expected \# transitions } i \rightarrow j \mid \lambda^{\text{old}}, O_1, O_2, \dots, O_T}{\sum_{k=1}^N \text{Expected \# transitions } i \rightarrow k \mid \lambda^{\text{old}}, O_1, O_2, \dots, O_T} \\
 &= \frac{\sum_{t=1}^T P(q_{t+1} = s_j, q_t = s_i \mid \lambda^{\text{old}}, O_1, O_2, \dots, O_T)}{\sum_{k=1}^N \sum_{t=1}^T P(q_{t+1} = s_k, q_t = s_i \mid \lambda^{\text{old}}, O_1, O_2, \dots, O_T)}
 \end{aligned}$$

$$\begin{aligned}
 &= \frac{S_{ij}}{\sum_{k=1}^N S_{ik}} \text{ where } S_{ij} = \sum_{t=1}^T P(q_{t+1} = s_j, q_t = s_i, O_1, \dots, O_T \mid \lambda^{\text{old}}) \\
 &= a_{ij} \sum_{t=1}^T \alpha_t(i) \beta_{t+1}(j) b_j(O_{t+1})
 \end{aligned}$$

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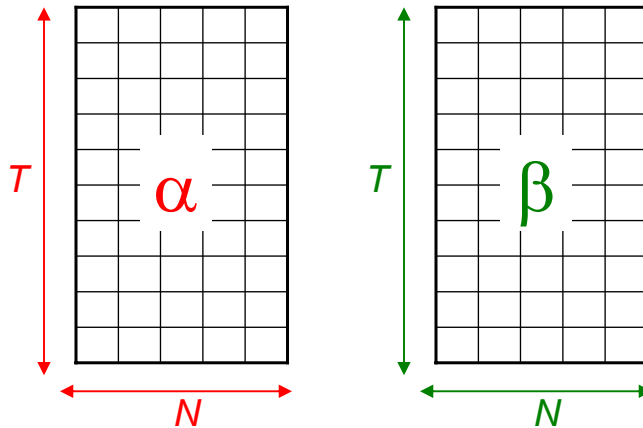
Slide 75

$$\text{We want } a_{ij}^{\text{new}} = S_{ij} / \sum_{k=1}^N S_{ik} \text{ where } S_{ij} = a_{ij} \sum_{t=1}^T \alpha_t(i) \beta_{t+1}(j) b_j(O_{t+1})$$

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We want $a_{ij}^{\text{new}} = S_{ij} / \sum_{k=1}^N S_{ik}$ where $S_{ij} = a_{ij} \sum_{t=1}^T \alpha_t(i) \beta_{t+1}(j) b_j(O_{t+1})$



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Slide 77

EM for HMMs

If we knew λ we could estimate EXPECTATIONS of quantities such as

Expected number of times in state i

Expected number of transitions $i \rightarrow j$

If we knew the quantities such as

Expected number of times in state i

Expected number of transitions $i \rightarrow j$

We could compute the MAX LIKELIHOOD estimate of

$$\lambda = \langle \{a_{ij}\}, \{b_i(j)\}, \pi_i \rangle$$

Roll on the EM Algorithm...

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Slide 78

EM 4 HMMs

1. Get your observations $O_1 \dots O_T$
 2. Guess your first λ estimate $\lambda(0)$, $k=0$
 3. $k = k+1$
 4. Given $O_1 \dots O_T$, $\lambda(k)$ compute
 $\gamma_t(i)$, $\xi_t(i,j)$ $\forall 1 \leq t \leq T$, $\forall 1 \leq i \leq N$, $\forall 1 \leq j \leq N$
 5. Compute expected freq. of state i , and expected freq. $i \rightarrow j$
 6. Compute new estimates of a_{ij} , $b_j(k)$, π_i accordingly. Call them $\lambda(k+1)$
 7. Goto 3, unless converged.
- **Also known (for the HMM case) as the BAUM-WELCH algorithm.**

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Bad News

- There are lots of local minima

Good News

- The local minima are usually adequate models of the data.

Notice

- EM does not estimate the number of states. That must be given.
- Often, HMMs are forced to have some links with zero probability. This is done by setting $a_{ij}=0$ in initial estimate $\lambda(0)$
- Easy extension of everything seen today: HMMs with real valued outputs

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Bad News

Trade-off between too few states (inadequately modeling the structure in the data) and too many (fitting the noise).

Thus #states is a regularization parameter.

Blah blah blah... bias variance tradeoff...blah
blah...cross-validation...blah blah....AIC,
BIC....blah blah (same ol' same ol')

- There are lots of
- The local minimum

Notice

- EM does not estimate the number of states. That must be given.
- Often, HMMs are forced to have some links with zero probability. This is done by setting $a_{ij}=0$ in initial estimate $\lambda(0)$
- Easy extension of everything seen today: HMMs with real valued outputs

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What You Should Know

- What is an HMM ?
- Computing (and defining) $\alpha_t(i)$
- The Viterbi algorithm
- Outline of the EM algorithm
- To be very happy with the kind of maths and analysis needed for HMMs
- Fairly thorough reading of Rabiner* up to page 266* [Up to but not including "IV. Types of HMMs"].

DON'T PANIC:
starts on p. 257.

*L. R. Rabiner, "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition," Proc. of the IEEE, Vol.77, No.2, pp.257--286, 1989.

<http://ieeexplore.ieee.org/iel5/5/698/00018626.pdf?arnumber=18626>

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