

# Hidden Markov Models

CISC 5800  
Professor Daniel Leeds

## Representing sequence data

- Spoken language
- DNA sequences
- Daily stock values



Example: spoken language

F?r plu? fi?e is nine

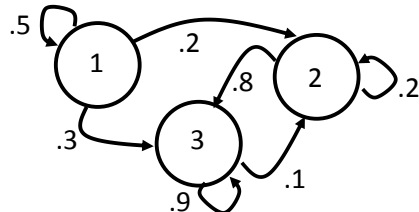
- Between F and r expect a vowel: "aw", "ee", "ah"; NOT "oh", "uh"
- At end of "plu" expect consonant: "g", "m", "s"; NOT "d", "p"

2

## Markov Models

Start with:

- $n$  states:  $s_1, \dots, s_n$
- Probability of initial start states:  $\Pi_1, \dots, \Pi_n$
- Probability of transition between states:  $A_{i,j} = P(q_t=s_i | q_{t-1}=s_j)$

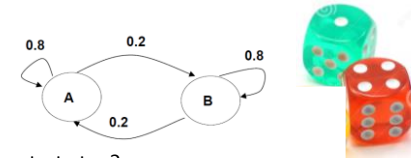


3

## A dice-y example

$$\Pi_A = 0.3, \Pi_B = 0.7$$

- Two colored die

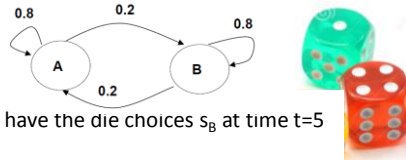


- What is the probability we start at  $s_A$ ?
- What is the probability we have the sequence of die choices:  
 $s_A, s_A$ ?

- What is the probability we have the sequence of die choices:  
 $s_B, s_A, s_B, s_A$ ?

4

## A dice-y example



- What is the probability we have the die choices  $s_B$  at time  $t=5$

$$\Pi_A = 0.3, \Pi_B = 0.7$$

- Dynamic programming: find answer for  $q_t$ , then compute  $q_{t+1}$

State \ Time	$t_1$	$t_2$	$t_3$
$s_A$	0.3		
$s_B$	0.7		

$$p_t(i) = \sum_j p(q_t = s_i | q_{t-1} = s_j) p_{t-1}(j)$$

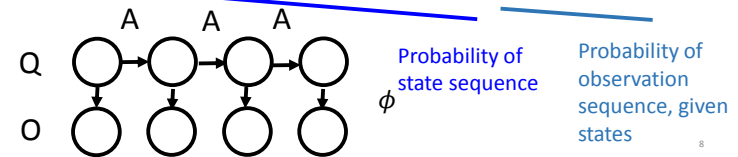
$p_t(i) = P(q_t = s_i)$  -- Probability state  $i$  at time  $t$

6

## Hidden Markov Models

- Actual state  $q$  "hidden"
- State produces visible data  $o$ :  $\phi_{i,j} = P(o_t = x_i | q_t = s_j)$
- Compute

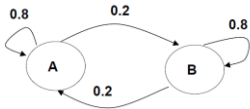
$$P(O, Q | \theta) = p(q_1 | \pi) \left( \prod_{t=2}^T p(q_t | q_{t-1}, A) \right) \left( \prod_{t=1}^T p(o_t | q_t, \phi) \right)$$



8

## Deducing die based on observed "emissions"

Each color is biased



$o$	$P(o   s_A)$	$P(o   s_B)$
1	.3	.1
2	.2	.1
3	.2	.1
4	.1	.2
5	.1	.2
6	.1	.3



Intuition – balance transition and emission probabilities

Observed numbers: 554565254556 – the 2 is probably from  $s_B$

Observed numbers: 554565213321 – the 2 is probably from  $s_A$

9

## Deducing die based on observed "emissions"

Each color is biased



$o$	$P(o   s_R)$	$P(o   s_B)$
1	.3	.1
2	.2	.1
3	.2	.1
4	.1	.2
5	.1	.2
6	.1	.3



- We see: 5      What is probability of  $o=5$ ,  $q=B$  (blue)

- We see: 5, 3      What is probability of  $o=5,3$  |  $q=B$ ,  $B$ ?

10

Goal: calculate most likely states given observable data

$$\arg \max_Q P(Q|O) = \arg \max_Q \frac{P(O|Q)P(Q)}{P(O)}$$

Define and use  $\delta_t(i)$

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

$\delta_t(i)$  : max possible value of  $P(q_1, \dots, q_t, o_1, \dots, o_t)$  given we insist  $q_t = s_i$

Find the most likely path from  $q_1$  to  $q_t$  that

- $q_t = s_i$
- Outputs are  $o_1, \dots, o_t$

12

Viterbi algorithm:  $\delta_t(i)$

$$\delta_1(i) = \Pi_i P(o_1 | q_1 = s_i) = \Pi_i \phi_{o_1, i}$$

$$\delta_t(i) = P(o_t | q_t = s_i) \max_j \delta_{t-1}(j) P(q_t = s_i | q_{t-1} = s_j) = \phi_{o_t, i} \max_j \delta_{t-1}(j) A_{i,j}$$

$$P(Q^* | O) = \arg \max_Q P(Q | O) = \arg \max_i \delta_t(i)$$

13

Viterbi algorithm: bigger picture

Compute all  $\delta_t(i)$ 's

- At time  $t=1$  compute  $\delta_1(i)$  for every state  $i$
- At time  $t=2$  compute  $\delta_2(i)$  for every state  $i$  (based on  $\delta_1(i)$  values)
- ...
- At time  $t=T$  compute  $\delta_T(i)$  for every state  $i$  (based on  $\delta_{T-1}(i)$  values)

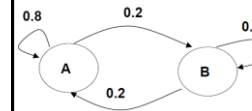
Find states going from  $t=T$  back to  $t=1$  to lead to max  $\delta_T(i)$

- Now find state  $j$  that gives maximum value for  $\delta_T(j)$
- Find state  $k$  at time  $T-1$  used to maximize  $\delta_T(j)$
- ...
- Find state  $z$  at time 1 used to maximize  $\delta_2(y)$

14

Viterbi in action: observe "5, 1"

$$\Pi_A = 0.3, \Pi_B = 0.7$$



o	P(o s <sub>A</sub> )	P(o s <sub>B</sub> )
1	.3	.1
2	.2	.1
3	.2	.1
4	.1	.2
5	.1	.2
6	.1	.3



$\delta_2(A)$ :

$\delta_2(B)$ :

	t=1 (o <sub>1</sub> =5)	t=2 (o <sub>2</sub> =1)
q <sub>t</sub> =s <sub>A</sub>	.3x.1 = .03	
q <sub>t</sub> =s <sub>B</sub>	.7x.2 = .14	

15

## Parameters in HMM

Initial probabilities:  $\pi_i$

Transition probabilities  $A_{i,j}$

Emission probabilities  $\phi_{i,j}$

**How do we learn  
these values?**

20