



<http://www.youtube.com/watch?v=jPGgl5VH5go>

Hidden Markov Models

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Admin

- ▶ **Final project**
 - ▶ Experimentally evaluate some idea/method we've discussed (or will discuss) in class
 - ▶ Must work in pairs (come talk to me if this causes a problem)
- ▶ **Schedule:**
 - ▶ Literature review (this week)
 - ▶ Proposal
 - ▶ Status report(s)
 - ▶ Paper draft
 - ▶ Peer reviews
 - ▶ Final paper
 - ▶ Presentations
- ▶ **Homework 6 out soon**
- ▶ **Last assignment next week on HMMs**
- ▶ **Midterm**
 - ▶ average: 45
 - ▶ high: 56.5 (2nd highest 51)

Bayes rule: a refresher

$$P(A|B) = \frac{P(B|A)P(A)}{P(B)}$$

$$P(A|B,C) = \frac{P(B,C|A)P(A)}{P(B,C)} = \frac{P(B|A,C)P(A|C)}{P(B|C)} = \frac{P(C|A,B)P(A|B)}{P(C|B)}$$

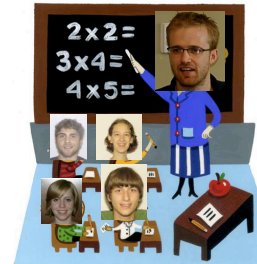
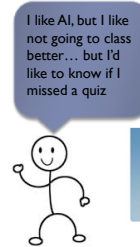
We'll see this version a lot today

Predicting the Quiz



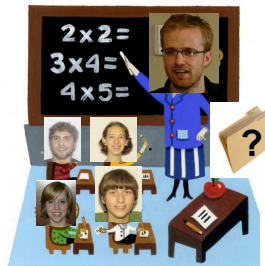
- ▶ I give quizzes in CS51 on written problems
- ▶ Often, I print out the problem and hand out the quiz at the beginning
 - ▶ One class, I gave a quiz, but had the students use their own paper
 - ▶ Sometimes I bring graded quizzes or exams to hand back
- ▶ In both situations, students have mispredicted quizzes

The setup



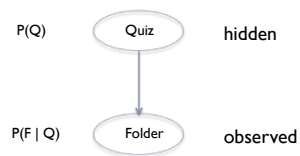
The setup

Every day the student walks by the classroom window and looks to see if there is a folder



Bayesian model for this process?

- ▶ What are the variables?
 - ▶ Folder/no-folder
 - ▶ Quiz/no-quiz
- ▶ How are they related?



Bayesian model for this process?

hidden: Quiz
observed: Folder

$P(Q)$
 $P(F|Q)$

Any other information?
What about from day to day?

Sequential process!

hidden/state: $Q_1 \rightarrow Q_2 \rightarrow Q_3 \rightarrow \dots$
observed: F_1, F_2, F_3

What would these conditional probability distributions look like?

$P(Q_1) P(F_1 | Q_1)$
 $P(Q_2 | Q_1) P(F_2 | Q_2)$
 $P(Q_3 | Q_1, Q_2) P(F_3 | Q_3)$
 $P(Q_i | Q_1, Q_2, \dots, Q_{i-1}) P(F_i | Q_i)$

Any assumption that could reduce the parameter space?

Markov assumption

hidden/state: $Q_1 \rightarrow Q_2 \rightarrow Q_3 \rightarrow \dots$
observed: F_1, F_2, F_3

Markov assumption: the current state (Q) only depends on a fixed number of previous states

first-order Markov assumption: only the previous state

Hidden Markov Model

hidden/state: $Q_1 \rightarrow Q_2 \rightarrow Q_3 \rightarrow \dots$
observed: F_1, F_2, F_3

Called a Hidden Markov Model (or Dynamic Bayes Net)*
*these two are different, we'll differentiate later

Hidden Markov Models

hidden/
state

observed

What are the CPDs?

$P(Q_1)$ $P(F_1 | Q_1)$
 $P(Q_2 | Q_1)$ $P(F_2 | Q_2)$
 $P(Q_3 | Q_2)$ $P(F_3 | Q_3)$
 $P(Q_i | Q_{i-1})$ $P(F_i | Q_i)$

This is still a lot of parameters! Can we tie any parameters, like we did for multinomial NB?

Hidden Markov Models

hidden/
state

observed

$P(Q_2 | Q_1) = P(Q_3 | Q_2) = P(Q_4 | Q_3) = P(Q_i | Q_{i-1})$
 $P(F_1 | Q_1) = P(F_2 | Q_2) = P(F_3 | Q_3) = P(F_i | Q_i)$

Stationary process: value of the state may change but not the underlying distribution

Hidden Markov Models

hidden/
state

observed

What are some of the independences/conditional independences?

What questions could we ask?

- Filtering: What is the distribution over Q today?
 - $P(Q_t | F_{1:t})$
- Prediction: What is the distribution Q in the future?
 - $P(Q_{t+k} | F_{1:t})$ - k days from now
- Smoothing: What is the distribution over Q in the past?
 - $P(Q_k | F_{1:t})$ - for $k < t$
- Most likely explanation: What states have we been in?
 - $\text{argmax}_{Q_{1:t}} P(Q_{1:t} | F_{1:t})$
- Learning
 - Learn CPD tables given observations

hidden/
state

observed

Filtering

Given my observations up to and including today, what is the probability of a Quiz?
 $P(Q_t | F_{1:t})$

Like to get this defined recursively with respect to $P(Q_{t-1} | F_{1:t-1})$

hidden/
state

observed

Filtering

Given my observations up to and including today, what is the probability of a Quiz?

$$P(Q_t | F_{1:t}) = P(Q_t | F_{1:t-1}, F_t)$$

Bayes' rule

$$= \alpha P(F_t | Q_t, F_{1:t-1}) P(Q_t | F_{1:t-1})$$

Markov model

$$= \alpha P(F_t | Q_t) P(Q_t | F_{1:t-1})$$

$$= \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | F_{1:t-1}, q_{t-1}) P(q_{t-1} | F_{1:t-1})$$

Markov model

$$= \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) P(q_{t-1} | F_{1:t-1})$$

hidden/
state

observed

Filtering

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) P(q_{t-1} | F_{1:t-1})$$

What is this?

probability of folder given quiz probability of quiz given quiz yesterday

Can be read from our CPTs

hidden/
state

observed

Filtering

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) P(q_{t-1} | F_{1:t-1})$$

recursive definition (aka forward message)

probability of folder given quiz probability of quiz given quiz yesterday

Can be read from our CPTs

hidden/
state

observed

Filtering:
What is the probability of a quiz today given no folder for the past two days?

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) \cdot message(q_{t-1})$$

Q_{t-1}	Q_t
T	0.1
F	0.5

$P(Q_0) = 0.25$

- Start from the beginning and work your way forward
- Each previous answer passes a "message" forward

Q_t	F_t
T	0.8
F	0.3

hidden/
state

observed

Filtering:
What is the probability of a quiz today given no folder for the past two days?

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) \cdot message(q_{t-1})$$

Q_{t-1}	Q_t
T	0.1
F	0.5

$P(Q_0) = 0.25$

$$P(Q_0) = \begin{bmatrix} 0.25 \\ 0.75 \end{bmatrix}$$

Q_t	F_t
T	0.8
F	0.3

hidden/
state

observed

Filtering:
What is the probability of a quiz today given no folder for the past two days?

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) \cdot message(q_{t-1})$$

$$P(Q_t | F_t) = \alpha P(-f_t | Q_t) (P(Q_t | True) \cdot message(True)) + P(Q_t | False) \cdot message(False)$$

Q_{t-1}	Q_t
T	0.1
F	0.5

Q_t	F_t
T	0.8
F	0.3

hidden/
state

observed

Filtering:
What is the probability of a quiz today given no folder for the past two days?

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) \cdot message(q_{t-1})$$

$$P(Q_t | F_t) = \alpha P(-f_t | Q_t) (P(Q_t | True) \cdot message(True)) + P(Q_t | False) \cdot message(False)$$

Q_{t-1}	Q_t
T	0.1
F	0.5

$$= \alpha \begin{bmatrix} 0.2 \\ 0.7 \end{bmatrix} \begin{bmatrix} 0.1 & 0.25 \\ 0.9 & 0.75 \end{bmatrix} \begin{bmatrix} 0.5 \\ 0.75 \end{bmatrix}$$

$$= \alpha \begin{bmatrix} 0.125 \\ 0.42 \end{bmatrix} = \begin{bmatrix} 0.23 \\ 0.77 \end{bmatrix}$$

Q_t	F_t
T	0.8
F	0.3

hidden/
state

observed

Filtering:
 What is the probability of a quiz today given no folder for the past two days?

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) \cdot message(q_{t-1})$$

$$P(Q_2 | F_{1:2}) = \alpha P(F_2 | Q_2) (P(Q_2 | True) \cdot message(True) + P(Q_2 | False) \cdot message(False))$$

$$= \alpha \begin{bmatrix} 0.2 \\ 0.7 \end{bmatrix} \begin{bmatrix} 0.1 \\ 0.9 \end{bmatrix} \begin{bmatrix} 0.5 \\ 0.77 \end{bmatrix}$$

$$= \alpha \begin{bmatrix} 0.0816 \\ 0.414 \end{bmatrix} = \begin{bmatrix} 0.165 \\ 0.835 \end{bmatrix}$$

Q _{t-1}	Q _t
T	0.1
F	0.5

Q _t	F _t
T	0.8
F	0.3

hidden/
state

observed

Filtering:
 What is the probability of a quiz today given no folder for the past two days?

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) \cdot message(q_{t-1})$$

$$P(Q_3 | F_{1:3}) = \alpha P(F_3 | Q_3) (P(Q_3 | True) \cdot message(True) + P(Q_3 | False) \cdot message(False))$$

We could keep going with more evidence..

Q _{t-1}	Q _t
T	0.1
F	0.5

Q _t	F _t
T	0.8
F	0.3

hidden/
state

observed

Forward message

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) \cdot message(q_{t-1})$$

$$P(Q_3 | F_{1:3}) = \alpha P(F_3 | Q_3) (P(Q_3 | True) \cdot message(True) + P(Q_3 | False) \cdot message(False))$$

This message is called the “forward” message. Why?

Prediction

- Given our equation for filtering, how can we predict what will happen in the future?
- $P(Q_{t+k} | F_{1:t})$ – k days from now

$$P(Q_t | F_{1:t}) = \alpha P(F_t | Q_t) \sum_{q_{t-1}} P(Q_t | q_{t-1}) P(q_{t-1} | F_{1:t-1})$$

probability of folder given quiz probability of quiz given quiz yesterday

Can be read from our CPTs

recursive (message)



Prediction

- ▶ We no longer have evidence, so we only take into account the state probabilities

$$P(Q_{t+k} | F_{t'}) = \alpha \sum_{q_{t+k-1}} \underbrace{P(Q_{t+k} | q_{t+k-1})}_{\text{probability of quiz given quiz the previous day}} P(q_{t+k-1} | F_{t'-1})$$

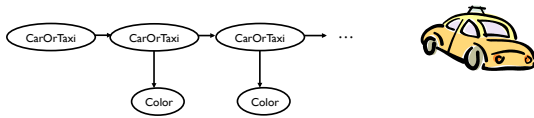
↖ recursive (message)

Your turn

- You live on the top floor of a building, giving you a good view of the street from your kitchen window 
 - Its really cold outside, so you'd rather maximize your time inside and watch for a taxi out the window 
 - There is a constant stream of vehicles coming in, but you can only make out the color
 - You'd like to predict whether or not it's a taxi
 - Formulate this problem as an HMM problem
- ▶ Step 1: what does the HMM look like?

Your turn

- ▶ Problem: Identify the taxi



CT _{t-1}	CT _t	P(CT _t CT _{t-1})
C	C	0.5
C	T	0.5
T	C	0.75
T	T	0.25

CT	Col	P(Col CT)
C	Y	0.1
C	NY	0.9
T	Y	0.75
T	NY	0.25

Your Turn

- ▶ You just saw a red vehicle, and now you see a yellow vehicle. What is the probability that the vehicle you see is a taxi? (Assume taxis and cars are equally likely when you start looking)
- ▶ What is the probability that the next vehicle will be a taxi?

CT _{t-1}	CT _t	P(CT _t CT _{t-1})	CT	Col	P(Col CT)
C	C	0.5	C	Y	0.1
C	T	0.5	C	NY	0.9
T	C	0.75	T	Y	0.75
T	T	0.25	T	NY	0.25

$$P(X_t | E_{t'}) = \alpha P(E_t | X_t) \sum_{x_{t-1}} P(X_t | x_{t-1}) P(x_{t-1} | E_{t'-1})$$

Filtering: red then yellow, equal prior

CT _{i-1}	CT _i	P(CT _i CT _{i-1})	CT	Col	P(Col CT _i)
C	C	0.5	C	Y	0.1
C	T	0.5	C	NY	0.9
T	C	0.75	T	Y	0.75
T	T	0.25	T	NY	0.25

$$P(X_i | E_i) = \alpha P(f_i | X_i) (P(X_i | C) \cdot \text{message}(C) + P(X_i | T) \cdot \text{message}(T))$$

$$= \alpha P(f_i | X_i) \left(\begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} \text{message}(C) + \begin{bmatrix} 0.75 \\ 0.25 \end{bmatrix} \text{message}(T) \right)$$

First message: [0.50, 0.50] (equal prior)

Filtering: red with equal prior

CT _{i-1}	CT _i	P(CT _i CT _{i-1})	CT	Col	P(Col CT _i)
C	C	0.5	C	Y	0.1
C	T	0.5	C	NY	0.9
T	C	0.75	T	Y	0.75
T	T	0.25	T	NY	0.25

$$P(X_i | E_i) = \alpha P(NY | X_i) (P(X_i | C) \cdot \text{message}(C) + P(X_i | T) \cdot \text{message}(T))$$

$$= \alpha \begin{bmatrix} 0.9 \\ 0.25 \end{bmatrix} \left(\begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} 0.5 + \begin{bmatrix} 0.75 \\ 0.25 \end{bmatrix} 0.5 \right)$$

$$= \alpha \begin{bmatrix} 0.5625 \\ 0.09375 \end{bmatrix} = \begin{bmatrix} 0.857 \\ 0.143 \end{bmatrix} \begin{matrix} car \\ taxi \end{matrix} \quad \begin{matrix} \text{became more} \\ \text{probable that it's a car} \end{matrix}$$

Filtering: now yellow

CT _{i-1}	CT _i	P(CT _i CT _{i-1})	CT	Col	P(Col CT _i)
C	C	0.5	C	Y	0.1
C	T	0.5	C	NY	0.9
T	C	0.75	T	Y	0.75
T	T	0.25	T	NY	0.25

$$P(X_i | E_i) = \alpha P(Y | X_i) (P(X_i | C) \cdot \text{message}(C) + P(X_i | T) \cdot \text{message}(T))$$

$$= \alpha \begin{bmatrix} 0.1 \\ 0.75 \end{bmatrix} \left(\begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} 0.857 + \begin{bmatrix} 0.75 \\ 0.25 \end{bmatrix} 0.143 \right)$$

$$= \alpha \begin{bmatrix} 0.0536 \\ 0.348 \end{bmatrix} = \begin{bmatrix} 0.133 \\ 0.867 \end{bmatrix} \begin{matrix} car \\ taxi \end{matrix} \quad \begin{matrix} \text{much more likely that} \\ \text{it's a taxi} \end{matrix}$$

Prediction: a cab next?

CT _{i-1}	CT _i	P(CT _i CT _{i-1})	CT	Col	P(Col CT _i)
C	C	0.5	C	Y	0.1
C	T	0.5	C	NY	0.9
T	C	0.75	T	Y	0.75
T	T	0.25	T	NY	0.25

$$P(X_i | E_i) = \alpha (P(X_i | C) \cdot \text{message}(C) + P(X_i | T) \cdot \text{message}(T))$$

$$= \alpha \left(\begin{bmatrix} 0.5 \\ 0.5 \end{bmatrix} 0.252 + \begin{bmatrix} 0.75 \\ 0.25 \end{bmatrix} 0.748 \right)$$

$$= \begin{bmatrix} 0.687 \\ 0.421 \end{bmatrix} \begin{matrix} car \\ taxi \end{matrix} \quad \begin{matrix} \text{will slowly move} \\ \text{towards a stationary} \\ \text{prediction as we look} \\ \text{further and further out} \end{matrix}$$

Stationary distribution

cars from now	P(car)	P(taxi)
2	0.687	0.313
3	0.57825	0.42175
4	0.6054375	0.3945625
5	0.598640625	0.401359375
6	0.60033984375	0.39966015625
7	0.599915039063	0.400084960938
8	0.600021240234	0.399978759766
9	0.599994689941	0.400005310059
10	0.600001327515	0.399998672485
11	0.599999668121	0.400000331879
12	0.60000008297	0.39999991703
...	0.599999979258	0.400000020742
	0.600000005186	0.399999994814
	0.599999998704	0.400000001296
	0.600000000324	0.399999999676
	0.599999999919	0.400000000081

CT _{t-1}	CT _t	P(CT _t CT _{t-1})
C	C	0.5
C	T	0.5
T	C	0.75
T	T	0.25

CT	Col	P(Col CT)
C	Y	0.1
C	NY	0.9
T	Y	0.75
T	NY	0.25