## Genome 540 Discussion

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## Assignment 7 Questions?

- Part 1: Use your predicted D-segments from hw6 to
- Generate a new scoring scheme
- Simulate background sequence
- Part 2: Run your D-segment program on the background and compare to the real data
- Part 3: Answer some questions

Assignment 8

## HMM Tasks

## Rabiner 1989:

Likelihood: Given an $\mathrm{HMM} \lambda=(\mathrm{A}, \mathrm{B})$ and an observation sequence O , determine the likelihood $\mathrm{P}(\mathrm{O} \mid \lambda$ ).
Decoding: Given an observation sequence $O$ and an $H M M \lambda=$ (A, B), discover the best hidden state sequence Q .
Learning: Given an observation sequence $O$ and the set of states in the HMM, learn the HMM parameters $A$ and $B$.

## Example

Your dog is very moody and you want to know when they like or hate you so you start recording what they are doing when you get home everyday...

Waiting


Lounging


Sleeping


## Model



## Graphical representation with data



## Graphical representation with data



## Graphical representation with data

State 1


## Graphical representation with data

Emission


## Graphical representation with data

Transition


## Baum Welch (Forward/Backward) - "Training" an HMM

## 1. Step 1: Expectation

a. Compute the forward probabilities
b. Compute the backward probabilities
2. Step 3: Maximization
a. Update the transition and emission probabilities

## Forward Algorithm - Likelihood of an observed sequence

3 steps:

1. Initialization
2. Recursion
3. Termination

## Forward Algorithm - Likelihood of an observed sequence



## Computing the backward probabilities

Backward probabilities: probability of seeing the observations from time $\dagger+1$ to the end


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## Computing the backward probabilities

 ?

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$$
b_{t}(i)=b_{t+1}(L)^{*} a_{L L}{ }^{*} e(L \mid L)+b_{t+1}(H)^{*} a_{L H}{ }^{*} e(L \mid H)^{* *} \text { Initialize assuming } b_{T}(i)=1
$$



## Calculating the transition probabilities



## Calculating the transition probabilities

$$
P_{\dagger}(i, j)=\frac{f_{t}(i) * a_{i j}{ }^{*} e_{j}\left(o_{t+1}\right) * b_{t+1}(j) \longleftarrow \begin{array}{l}
\text { Probability of observations } \\
\text { constrained on a specific } \\
\text { transition }
\end{array}}{\sum^{N}{ }_{j=1} f_{t}(j) b_{t}(j)} \quad \begin{aligned}
& \text { Probability of observations } \\
& \text { given the model }
\end{aligned}
$$

$$
\underline{a}(i, j)=\frac{\sum_{t=1}^{T-1} P_{t}(i, j)}{\sum_{t=1}^{T-1} \sum_{k=1}^{N} P_{t}(i, k)}
$$

## Calculating the emission probabilities

$$
\begin{aligned}
& V_{t}(j)=\frac{f_{t}(j) b_{t}(j)}{P(O \mid \lambda)}=\frac{f_{t}(j) b_{t}(j)}{\sum_{j=1}^{N} f_{t}(j) b_{t}(j)} \quad \begin{array}{l}
\text { Probability of being in state } j \text { at } \\
\text { observation sequence } O \text { and the }
\end{array} \\
& e_{t}\left(v_{k}(j)=\frac{\text { expected number of times in state } j \text { and observing symbol } v_{k}}{\text { expected number of times in state } j}\right. \\
& e_{t}\left(v_{k} \mid j\right)=e_{j}\left(v_{k}\right)=\frac{\sum_{t=1, O t=v}{ }^{\top} v_{t}(j) \longleftarrow}{\sum_{t=1}^{\top} y_{t}(j)} \quad \text { Sum of all } v_{t}(j) \text { where the observed symbol = } v_{k}
\end{aligned}
$$

## Avoiding vanishing probabilities

- Scaling
- Good tutorial
- Work in log space
- Mann 2006


## Scaling

- When computing forward probabilities, also compute a scaling factor $c_{\dagger}$

$$
c_{\dagger}=\frac{1}{\sum_{i=1}^{N} f_{t}(i)}
$$

- New forward probabilities at time $\dagger$ are multiplied by $c_{\dagger}$
- Use c for scaling backward probabilities as well
- To get back true forward/backward probabilities

$$
f_{t}^{*}(i)=\left(\prod_{t=1}^{\dagger} c_{t}\right) f_{t}(i)
$$

## Reminders

- HW7 due this Sunday, 11:59pm
- Please have your name in the filename of your homework assignment and match the template

