

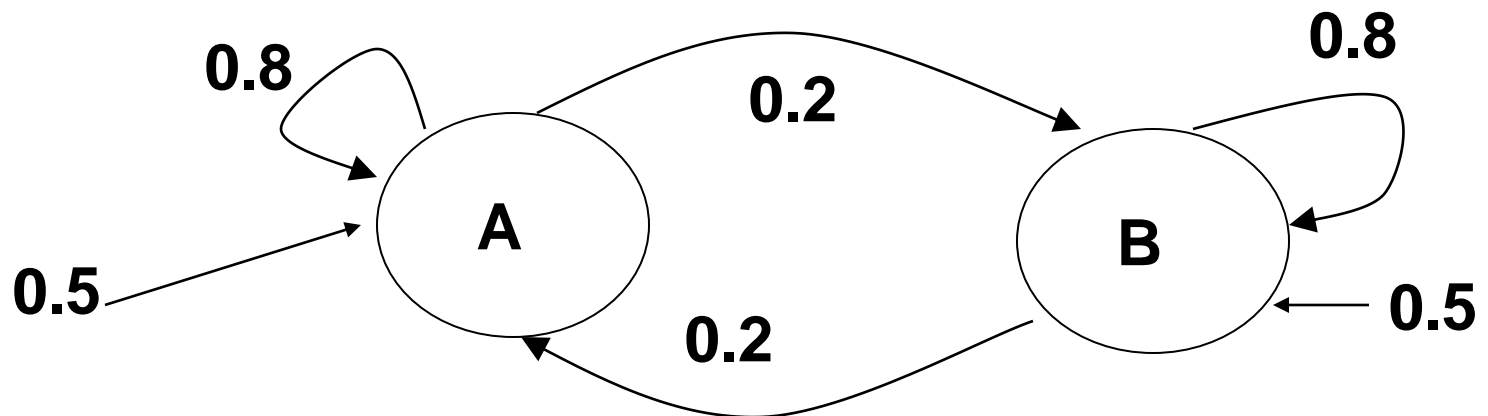
10-601

Machine Learning

Learning in HMMs

A Hidden Markov model

- A set of states $\{s_1 \dots s_n\}$
 - In each time point we are in exactly one of these states denoted by q_t
- Π_i , the probability that we *start* at state s_i
- A transition probability model, $P(q_t = s_i \mid q_{t-1} = s_j)$
- A set of possible outputs Σ
 - At time t we emit a symbol $\sigma \in \Sigma$
- An emission probability model, $p(o_t = \sigma \mid s_i)$



Inference in HMMs

- Computing $P(Q)$ and $P(q_t = s_i)$ ✓
- Computing $P(Q | O)$ and $P(q_t = s_i | O)$ ✓
- Computing $\operatorname{argmax}_Q P(Q)$ ✓

Learning HMMs

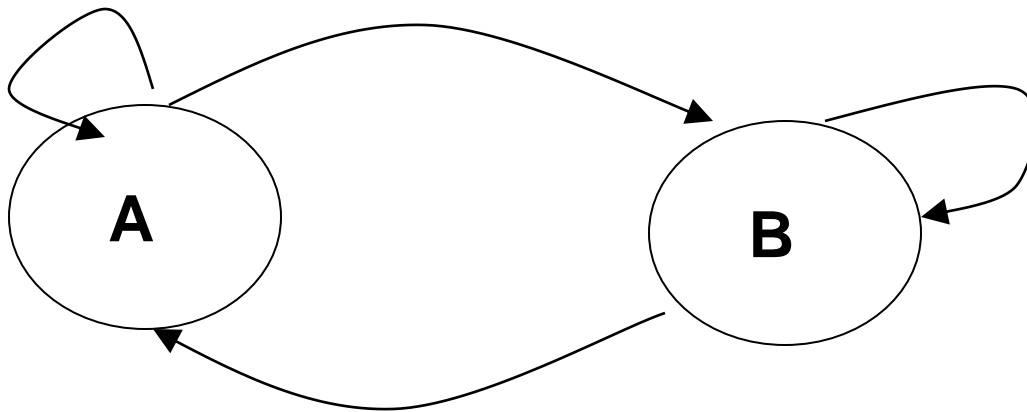
- Until now we assumed that the emission and transition probabilities are known
- This is usually not the case
 - How is “AI” pronounced by different individuals?
 - What is the probability of hearing “class” after “AI”?

While we will discuss learning the transition and emission models, we will not discuss selecting the states.

This is usually a function of domain knowledge.

Example

- Assume the model below
- We also observe the following sequence:
1,2,2,5,6,5,1,2,3,3,5,3,3,2
- How can we determine the initial, transition and emission probabilities?



Initial probabilities

Q: assume we can observe the following sets of states:

A A A B B A A
A A B B B B B
B A A B B A B

how can we learn the initial probabilities?

A: Maximum likelihood estimation

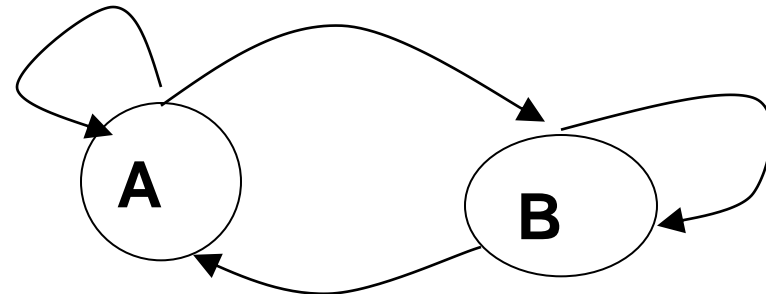
Find the initial probabilities π such that

$$\pi^* = \arg \max_{\pi} \prod_k \pi(q_1) \prod_{t=2}^T p(q_t | q_{t-1}) \Rightarrow$$

$$\pi^* = \arg \max_{\pi} \prod_k \pi(q_1)$$

$$\pi_A = \#A / (\#A + \#B)$$

k is the number of
sequences available for
training



Transition probabilities

Q: assume we can observe the set of states:

AAABBAABBBBBAABBBB

how can we learn the transition probabilities?

A: Maximum likelihood estimation

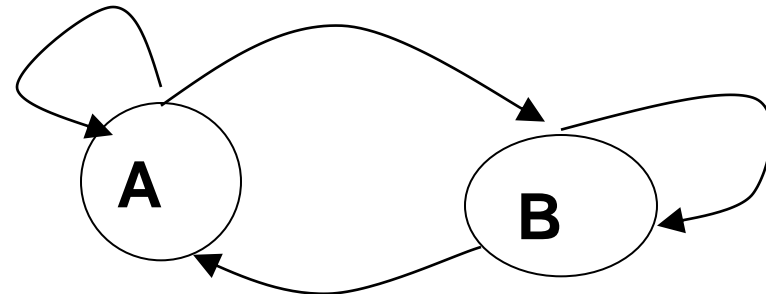
Find a transition matrix a such that

remember that we
defined $a_{i,j} = p(q_t = s_j | q_{t-1} = s_i)$

$$a^* = \arg \max_a \prod_k \pi(q_1) \prod_{t=2}^T p(q_t | q_{t-1}) \Rightarrow$$

$$a^* = \arg \max_a \prod_{t=2}^T p(q_t | q_{t-1})$$

$$a_{A,B} = \#AB / (\#AB + \#AA)$$



Emission probabilities

Q: assume we can observe the set of states:

A A A B B A A A B B B B B A A

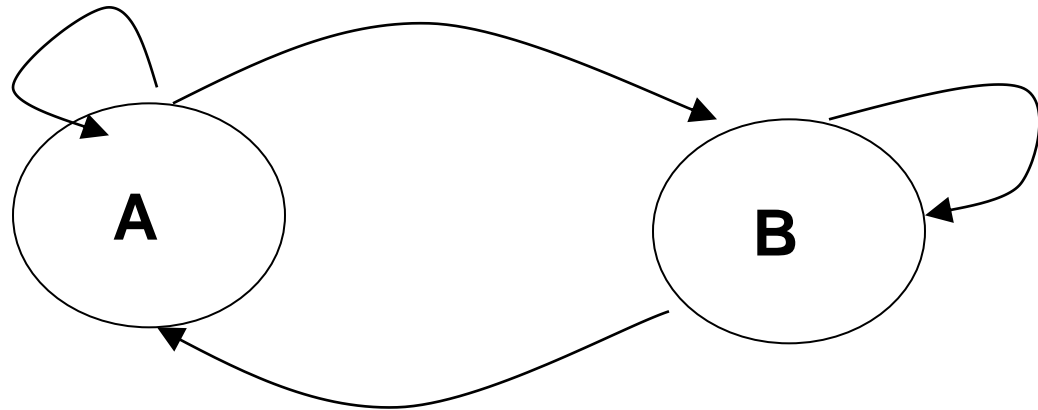
and the set of dice values

1 2 3 5 6 3 2 1 1 3 4 5 6 5 2 3

how can we learn the emission probabilities?

A: Maximum likelihood estimation

$$b_A(5) = \#A5 / (\#A1 + \#A2 + \dots + \#A6)$$



Learning HMMs

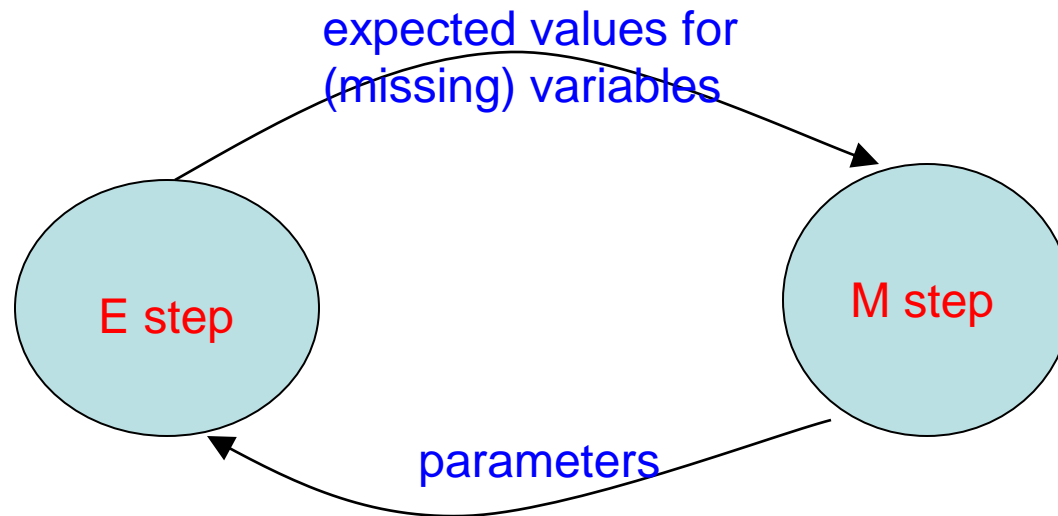
- In most case we do not know what states generated each of the outputs (fully unsupervised)
- ... but had we known, it would be very easy to determine an emission and transition model!
- On the other hand, if we had such a model we could determine the set of states using the inference methods we discussed

Expectation Maximization (EM)

- Appropriate for problems with 'missing values' for the variables.
- For example, in HMMs we usually do not observe the states

Expectation Maximization (EM): Quick reminder

- Two steps
- E step: Fill in the expected values for the missing variables
- M step: Regular maximum likelihood estimation (MLE) using the values computed in the E step and the values of the other variables
- Guaranteed to converge (though only to a local minima).



Forward-Backward

- We already defined a *forward* looking variable

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

- We also need to define a *backward* looking variable

$$\beta_t(i) = P(O_{t+1}, \dots, O_T \mid s_t = i)$$

Forward-Backward

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

- We also need to define a *backward* looking variable

$$\beta_t(i) = P(O_{t+1}, \dots, O_T \mid q_t = s_i) = \sum_j a_{i,j} b_j(O_{t+1}) \beta_{t+1}(j)$$

Forward-Backward

- We already defined a *forward* looking variable

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

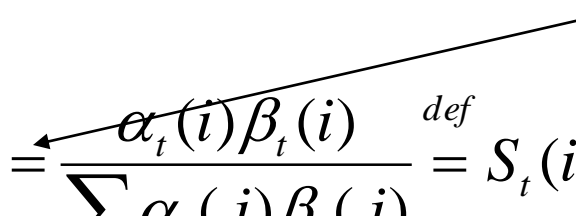
- We also need to define a *backward* looking variable

$$\beta_t(i) = P(O_{t+1}, \dots, O_T \mid q_t = s_i)$$

- Using these two definitions we can show

$$P(q_t = s_i \mid O_1, \dots, O_T) = \frac{\alpha_t(i) \beta_t(i)}{\sum_j \alpha_t(j) \beta_t(j)} \stackrel{\text{def}}{=} S_t(i)$$

P(A|B)=P(A,B)/P(B)



State and transition probabilities

- Probability of a state

$$P(q_t = s_i \mid O_1, \dots, O_T) = \frac{\alpha_t(i)\beta_t(i)}{\sum_j \alpha_t(j)\beta_t(j)} \stackrel{\text{def}}{=} S_t(i)$$

- We can also derive a transition probability

$$P(q_t = s_i, q_{t+1} = s_j \mid o_1, \dots, o_T) = S_t(i, j)$$

$$\begin{aligned} P(q_t = s_i, q_{t+1} = s_j \mid o_1, \dots, o_n) &= \\ &= \frac{\alpha_t(i)P(q_{t+1} = s_j \mid q_t = s_i)P(o_{t+1} \mid q_{t+1} = s_j)\beta_{t+1}(j)}{\sum_j \alpha_t(j)\beta_t(j)} \stackrel{\text{def}}{=} S_t(i, j) \end{aligned}$$

E step

- Compute $S_t(i)$ and $S_t(i,j)$ for all t, i , and j ($1 \leq t \leq n$, $1 \leq i \leq k$, $2 \leq j \leq k$)

$$P(q_t = s_i \mid O_1, \dots, O_T) = S_t(i)$$

$$P(q_t = s_i, q_{t+1} = s_j \mid o_1, \dots, o_T) = S_t(i, j)$$

M step (1)

Compute transition probabilities:

$$a_{i,j} = \frac{\hat{n}(i, j)}{\sum_k \hat{n}(i, k)}$$

where

$$\hat{n}(i, j) = \sum_t S_t(i, j)$$

M step (2)

Compute emission probabilities (here we assume a multinomial distribution):

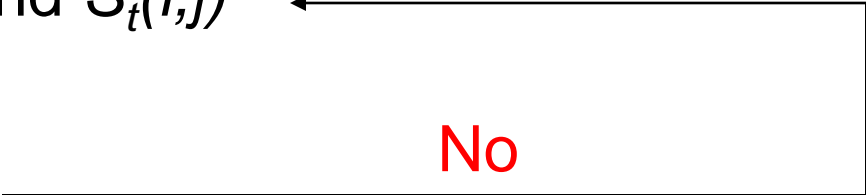
define:

$$B_k(j) = \sum_{t|o_t=j} S_t(k)$$

then

$$b_k(j) = \frac{B_k(j)}{\sum_i B_k(i)}$$

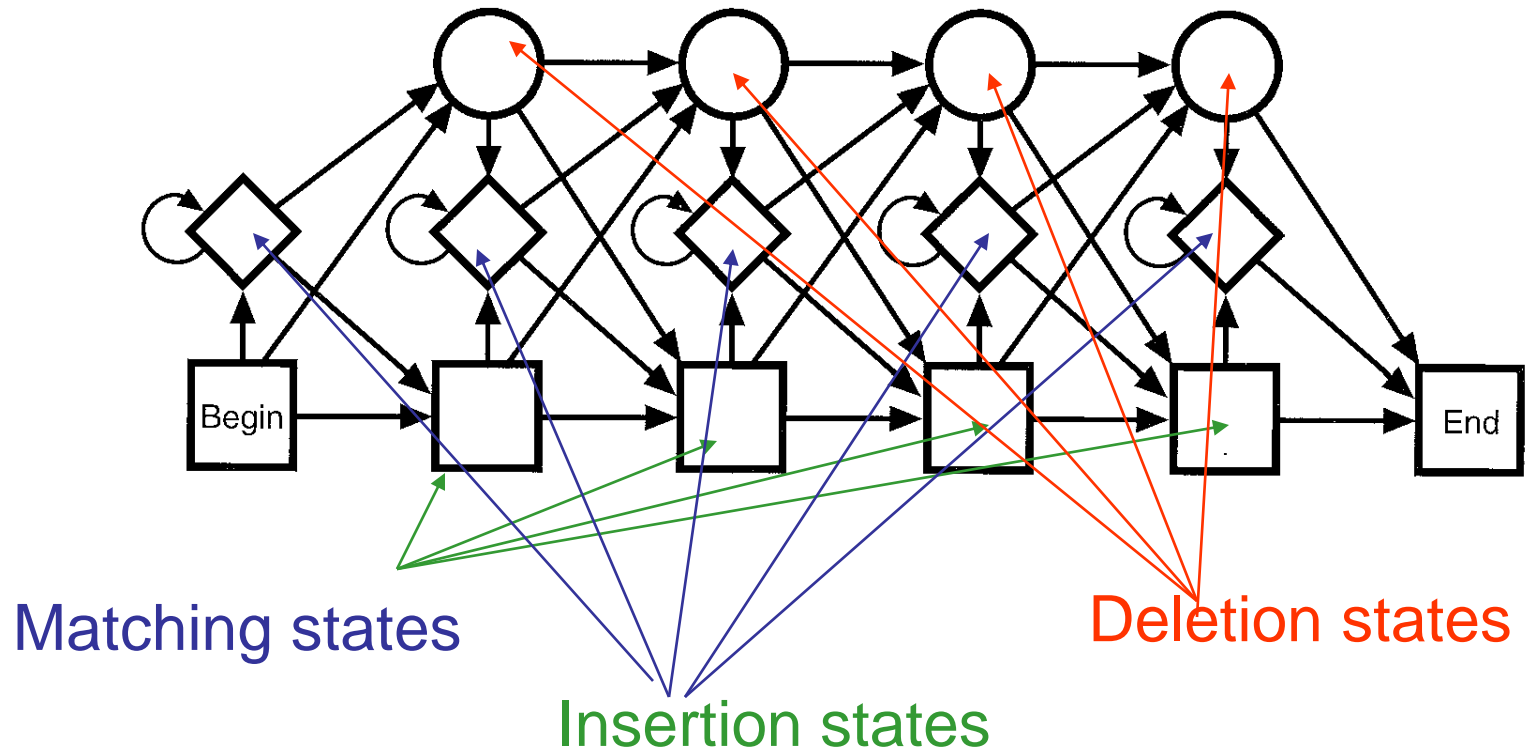
Complete EM algorithm for learning the parameters of HMMs (Baum-Welch)

- Inputs: 1. Observations $O_1 \dots O_T$
2. Number of states, model
1. Guess initial transition and emission parameters
 2. Compute E step: $S_t(i)$ and $S_t(i,j)$
 3. Compute M step
 4. Convergence? 

```
graph LR; 4[4. Convergence?] -- No --> 2[2. Compute E step];
```
 5. Output complete model

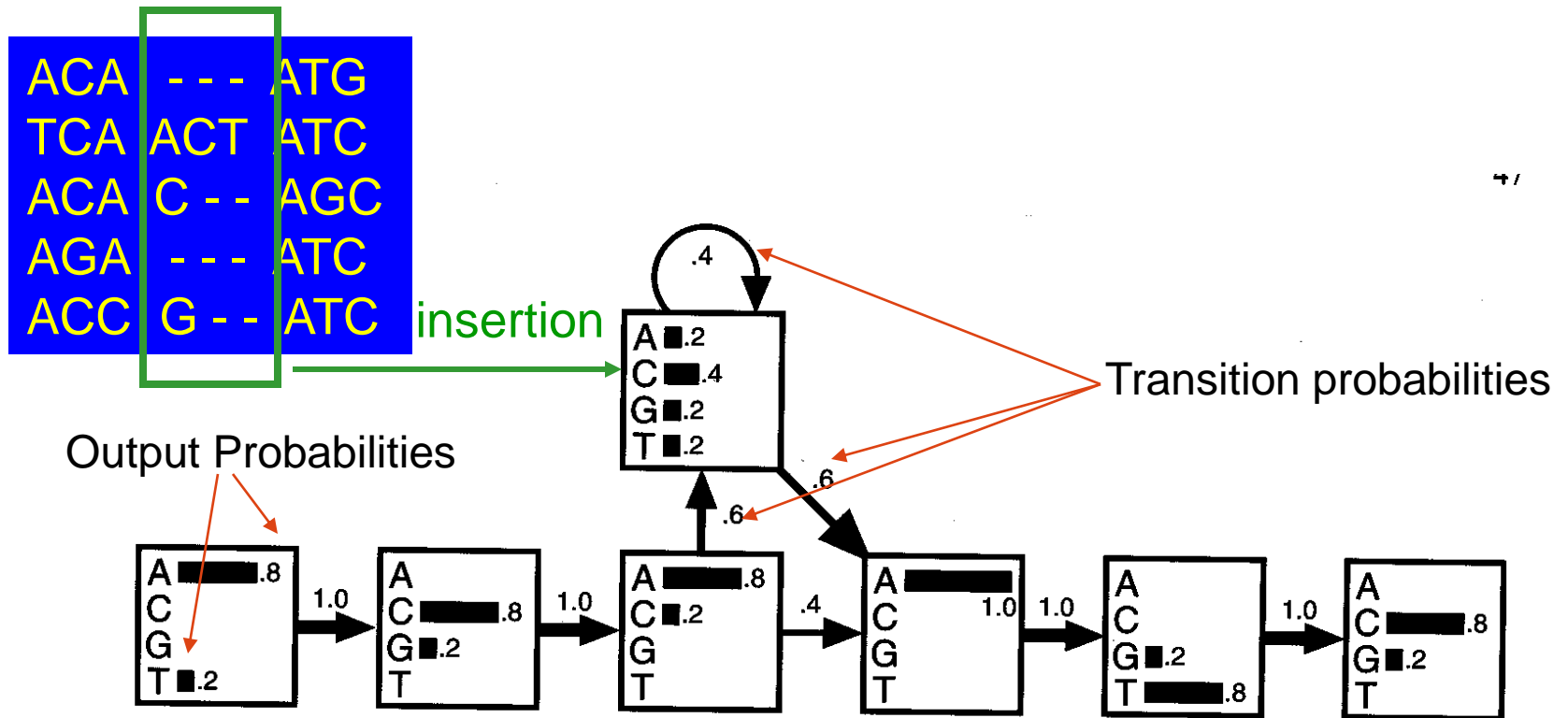
We did not discuss initial probability estimation. These can be deduced from multiple sets of observation (for example, several recorded customers for speech processing)

Building HMMs—*Topology*



No of matching states = average sequence length in the family
PFAM Database - of Protein families
(<http://pfam.wustl.edu>)

Building – *from an existing alignment*



A **HMM model** for a DNA motif alignments, The **transitions** are shown with arrows whose thickness indicate their probability. In each state, the **histogram** shows the probabilities of the four bases.