

Class Tutorial 4

1. Markov Chains

Definition: the hitting time T_{ij} is a random variable that corresponds to the first time of visiting state j when starting from state i . The probability function of T_{ij} is given by

$$P(T_{ij} = k) = P(X_k = j, X_{k-1} \neq j, \dots, X_1 \neq j | X_0 = i) \quad k = 1, 2, \dots$$

Also, let $\mu_{ij} = \mathbb{E}[T_{ij}]$.

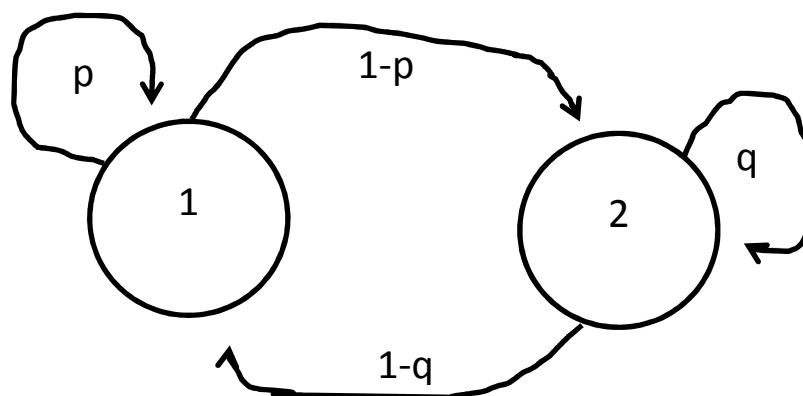
Consider the two state Markov chain with transition matrix

$$\begin{pmatrix} p & 1-p \\ 1-q & q \end{pmatrix}$$

- Draw the transition diagram for this Markov chain.
- Calculate μ_{ij} directly, using the probability function.
- Calculate μ_{ij} by conditioning, using the smoothing theorem.

Solution

a.



b. We will calculate μ_{12} . The calculation is similar for the other terms.

By definition:

$$P(T_{12} = k) = P(X_k = 2, X_{k-1} = 1, \dots, X_1 = 1 | X_0 = 1) \\ = p^{k-1}(1-p)$$

And

$$\mu_{12} = \sum_{k=1}^{\infty} k p^{k-1} (1-p) = (1-p) \sum_{k=0}^{\infty} k p^{k-1} \\ = (1-p) \sum_{k=0}^{\infty} \frac{\partial}{\partial p} p^k = (1-p) \frac{\partial}{\partial p} \left(\frac{1}{1-p} \right) \\ = \frac{(1-p)}{(1-p)^2} = \frac{1}{1-p}$$

c. Note that by smoothing we have $\mathbb{E}[T_{12}] = \mathbb{E}[\mathbb{E}[T_{12} | X_1]]$,

but, observe that by definition we have that

$$\mathbb{E}[T_{12} | X_1 = 1] = \mathbb{E}[T_{12}] + 1,$$

And

$$\mathbb{E}[T_{12} | X_1 = 2] = 1,$$

Therefore

$$\mathbb{E}[T_{12}] = \mu_{12} = p(\mu_{12} + 1) + (1-p) \cdot 1.$$

Solving for μ_{12} gives

$$\mu_{12} = \frac{1}{1-p}.$$

2. Viterbi Algorithm

Consider the following Hidden Markov Model definition. A sequence of T states

$X_1, \dots, X_T \in \mathcal{X}$ are generated by a Markov chain with transition probabilities

$P(X_{k+1} = j | X_k = i) = p_{ij}$ and initial state distribution $P(X_1 = i) = \rho_i$. For each state

X_k , an observation $Y_k \in \mathcal{Y}$ is generated according to a distribution $P(Y = j | X = i) = q_{ij}$,

and independently of other states or observations.

The HMM decoding problem is as follows. Given an *observation* sequence Y_1, \dots, Y_T , and the HMM parameters p_{ij}, ρ_i , and q_{ij} , find the most likely state sequence X_1, \dots, X_T that generated them, i.e., find

$$\max_{X_1, \dots, X_T} P(X_1, \dots, X_T | Y_1, \dots, Y_T)$$

Using Bayes rule, we have

$$\begin{aligned} \max_{X_1, \dots, X_T} P(X_1, \dots, X_T | Y_1, \dots, Y_T) &= \max_{X_1, \dots, X_T} \frac{P(X_1, \dots, X_T, Y_1, \dots, Y_T)}{P(Y_1, \dots, Y_T)} \\ &= \max_{X_1, \dots, X_T} P(X_1, \dots, X_T, Y_1, \dots, Y_T) \end{aligned}$$

The Viterbi algorithm uses dynamic programming to solve the HMM decoding problem.

a. Write $P(X_1, \dots, X_T, Y_1, \dots, Y_T)$ explicitly using p_{ij}, ρ_i , and q_{ij} .

Let $V_t(i)$ denote the likelihood of the most likely sequence that generated Y_1, \dots, Y_t and ends in state $X_t = i$, i.e.,

$$V_t(i) = \max_{X_1, \dots, X_{t-1}} P(X_1, \dots, X_{t-1}, Y_1, \dots, Y_t, X_t = i)$$

b. Write an expression for $V_1(i)$.

c. Write a recursive formula for $V_{t+1}(i)$.

d. What is the complexity of the resulting recursive algorithm?

Solution:

a. $P(X_1, \dots, X_T, Y_1, \dots, Y_T) = \rho_{X_1} q_{X_1, Y_1} p_{X_1, X_2} \cdots p_{X_{T-1}, X_T} q_{X_T, Y_T}$

b.

$$V_1(i) = P(Y_1, X_1 = i) = \rho_i q_{i, Y_1}$$

c.

$$\begin{aligned}
V_{t+1}(i) &= \max_{X_1, \dots, X_t} P(X_1, \dots, X_t, Y_1, \dots, Y_{t+1}, X_{t+1} = i) \\
&= \max_{X_1, \dots, X_t} P(X_{t+1} = i, Y_{t+1} | X_t) P(X_1, \dots, X_t, Y_1, \dots, Y_t) \\
&= \max_{X_t} \max_{X_1, \dots, X_{t-1}} P(X_{t+1} = i, Y_{t+1} | X_t) P(X_1, \dots, X_t, Y_1, \dots, Y_t) \\
&= \max_{X_t} P(X_{t+1} = i, Y_{t+1} | X_t) \max_{X_1, \dots, X_{t-1}} P(X_1, \dots, X_t, Y_1, \dots, Y_t) \\
&= \max_{X_t} P(X_{t+1} = i, Y_{t+1} | X_t) V_t(X_t) \\
&= \max_{X_t} p_{X_t, i} q_{i, Y_{t+1}} V_t(X_t) \\
&= q_{i, Y_{t+1}} \max_{X_t} p_{X_t, i} V_t(X_t)
\end{aligned}$$

d. The complexity is $\mathcal{O}(T|\mathcal{X}|^2)$.