

SI 140A-02 Probability & Statistics for EECS, Fall 2024

Homework 11

Name:

Student ID:

Due on Dec. 24, 2024, 11:59 UTC+8

Read all the instructions below carefully before you start working on the assignment, and before you make a submission.

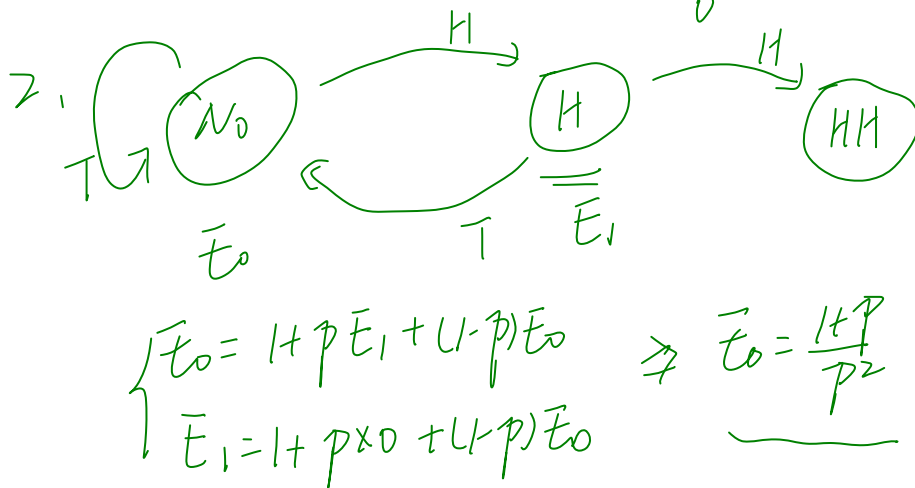
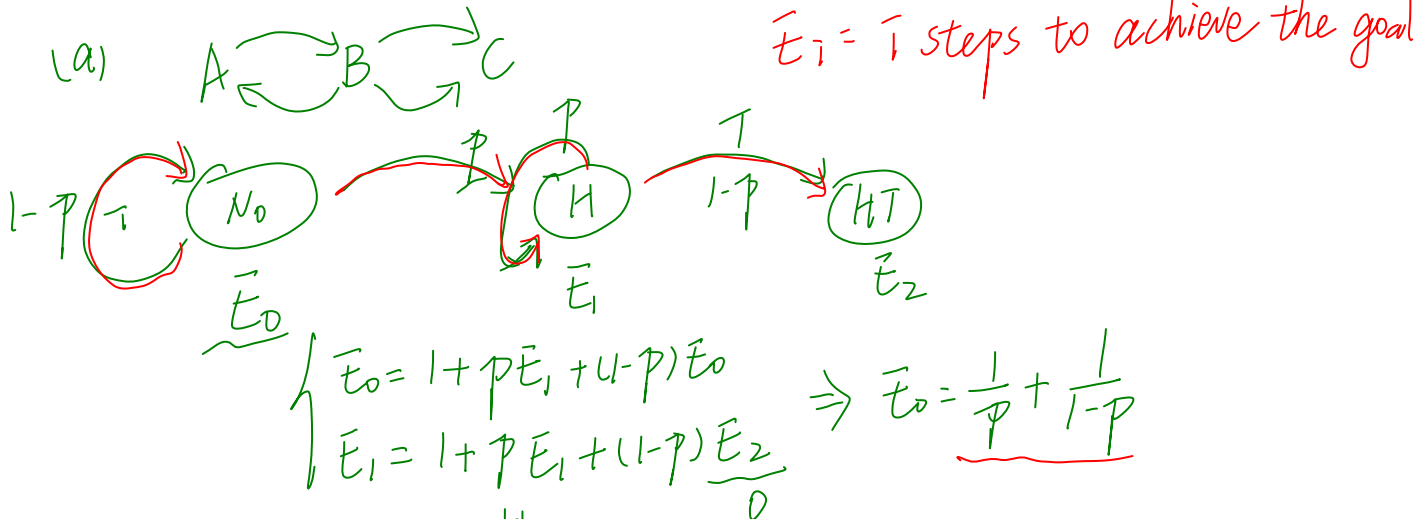
- You are required to write down all the major steps towards making your conclusions; otherwise you may obtain limited points of the problem.
- Write your homework in English; otherwise you will get no points of this homework.
- Any form of plagiarism will lead to 0 point of this homework.

Problem 1

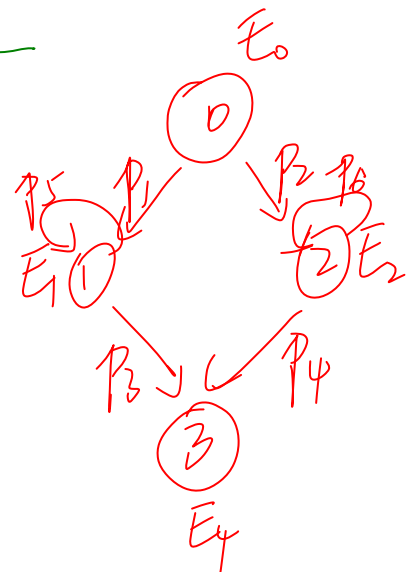
A coin with probability p of Heads is flipped repeatedly, where p is a known constant, with $0 < p < 1$.

(a) What is the expected number of flips until the pattern HT is observed?

(b) What is the expected number of flips until the pattern HH is observed?



$$\begin{cases} \bar{E}_0 = 1 + p_1\bar{E}_1 + p_2\bar{E}_2 \\ \bar{E}_1 = 1 + p_3\bar{E}_4 + p_5\bar{E}_1 \\ \bar{E}_2 = 1 + p_4\bar{E}_4 + p_6\bar{E}_2 \end{cases}$$



Problem 2

Given two random variables X and Y , the corresponding joint PDF is

$$f_{X,Y}(x,y) = \begin{cases} x+y & \text{if } 0 \leq x \leq 1, 0 \leq y \leq 1 \\ 0 & \text{Otherwise} \end{cases}$$

Find $\underline{E[Y | X]}$ and $\underline{L[Y | X]}$.

$$(1) f_X(x) = \int_0^1 f_{X,Y}(x,y) dy = x + \frac{1}{2}$$

$$f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{x+y}{x+\frac{1}{2}}, \quad (x,y)$$

$$\underline{E[Y | X=x]} = \int_0^1 y \cdot \frac{x+y}{x+\frac{1}{2}} dy = \frac{3x+2}{6x+3}$$

$$(2) \underline{L[Y | X]} = \underline{E[Y]} + \frac{\text{Cov}(X,Y)}{\text{Var}(X)} (X - \underline{E}(X))$$

$$\underline{E[Y]} = \int_0^1 y f_Y(y) dy = \int_0^1 y \left[\int_{-\infty}^{\infty} f_{X,Y}(x,y) dx \right] dy = \frac{7}{12}$$

$$\text{Var}(X) = \underline{E[X^2]} - \underline{E[X]}^2 \Rightarrow \frac{11}{144}$$

$$\int_0^1 x^2 \left(\frac{1}{2} + x \right) dx = \frac{5}{12} \quad \rightarrow \quad \underline{E[X]} = \int_0^1 x \left(\frac{1}{2} + x \right) dx = \frac{7}{12}$$

$$\text{Cov}(X,Y) = \underline{E[XY]} - \underline{E[X]} \underline{E[Y]}$$

$$= \int_0^1 \int_0^1 xy f_{X,Y}(x,y) dx dy - \underline{E[X]} \underline{E[Y]} = \frac{7}{12} \cdot \frac{7}{12}$$

$$= -\frac{1}{144}$$

$$\underline{L} = \frac{7}{12} - \frac{1}{12} X$$

Problem 3

Let X be the height of a randomly chosen adult man, and Y be his father's height, where X and Y have been standardized to have mean 0 and standard deviation 1. Suppose that (X, Y) is Bivariate Normal, with $X, Y \sim \mathcal{N}(0, 1)$ and $\text{Corr}(X, Y) = \rho$.

- Let $y = ax + b$ be the equation of the best line for predicting Y from X (in the sense of minimizing the mean squared error), e.g., if we were to observe $X = 1.3$ then we would predict that Y is $1.3a + b$. Now suppose that we want to use Y to predict X , rather than using X to predict Y . Give and explain an intuitive guess for what the slope is of the best line for predicting X from Y .
- Find a constant c (in terms of ρ) and an r.v. V such that $Y = cX + V$, with V independent of X .
Hint: Start by finding c such that $\text{Cov}(X, Y - cX) = 0$.
- Find a constant d (in terms of ρ) and an r.v. W such that $X = dY + W$, with W independent of Y .
- Find $E(Y | X)$ and $E(X | Y)$.
- Reconcile (a) and (d), giving a clear and correct intuitive explanation.

$$(a) \quad Y = aX + b \Rightarrow X = \frac{1}{a}Y + \frac{b}{a}$$

$$a = \rho \cdot \frac{\sigma_Y}{\sigma_X} \Rightarrow a = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sum (x_i - \bar{x})^2}$$

$$\rho = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2} \cdot \sqrt{\sum (y_i - \bar{y})^2}} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sigma_X \sigma_Y}$$

$$a = \rho \cdot \frac{\sigma_Y}{\sigma_X} = \rho$$

$$\frac{1}{a} = \frac{1}{\rho}$$

$$(b) \quad \text{Independent, } \text{Cov}(X, V) = 0 = \text{Cov}(X, Y - cX)$$

$$\Rightarrow c = \rho$$

$$(c) \quad \text{Independent } \text{Cov}(Y, W) = 0$$

$$= \text{Cov}(Y, X - dY) \Rightarrow d = \rho$$

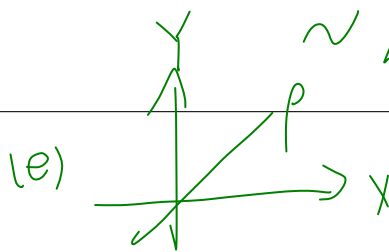
$$(d) \quad f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)}$$

$$= \frac{1}{\sqrt{2\pi(1-\rho^2)}} \exp\left(-\frac{(y-\rho x)^2}{2(1-\rho^2)}\right)$$

$$\sim \mathcal{N}(\rho x, 1-\rho^2)$$

$$\begin{cases} X \sim \mathcal{N}(\mu_X, \sigma_X^2) \\ Y \sim \mathcal{N}(\mu_Y, \sigma_Y^2) \\ \text{Corr} = \rho \end{cases}$$

$$\begin{cases} E[Y|X] = \rho X \\ E[X|Y] = \rho Y \end{cases}$$



Problem 4

Show the following orthogonality properties of MMSE:

(a) For any function $\phi(\cdot)$, one has

$$E[(Y - E[Y | X])\phi(X)] = 0$$

(b) If the function $g(X)$ satisfied

$$E[(Y - g(X))\phi(X)] = 0, \forall \phi(\cdot)$$

then $g(X) = E(Y | X)$.

$$\begin{aligned} (a) \quad E[(Y - E[Y|X])\phi(X)] &= E[Y\phi(X)] - E[E(Y|X)\phi(X)] \\ &= E[Y\phi(X)] - E[E(Y\phi(X)|X)] \\ &= E[Y\phi(X)] - E[Y\phi(X)] \\ &= 0 \end{aligned}$$

$$\begin{aligned} (b) \quad g(X) &= E[Y|X] + f(X) \quad \leftarrow \\ E[(Y - E[Y|X] - f(X))\phi(X)] &= \\ = E[Y\phi(X)] - E[E(Y|X)\phi(X)] - E[f(X)\phi(X)] &= 0 \\ \underbrace{E[Y\phi(X)] - E[E(Y|X)\phi(X)]}_0 - E[f(X)\phi(X)] &= 0 \\ E[f(X)\phi(X)] = 0 &\Rightarrow f(X) = 0 \\ g(X) &= E[Y|X] \end{aligned}$$

Problem 5

Given a coin with the probability p of landing heads. p is unknown and we need to estimate its value through data. In our data collection model, we have n independent tosses, result of each toss is either Head or Tail. Let X denote the number of heads in the total n tosses. Now we conduct experiments to collect data and find $X = k$. Then we need to find \hat{p} , the estimation of p .

- Assume p is an unknown constant. Find \hat{p} through the MLE (Maximum Likelihood Estimation) rule.
- Assume p is a random variable with a prior distribution $p \sim \text{Beta}(a, b)$, where a and b are known constants. Find \hat{p} through the MAP (Maximum a Posterior Probability) rule.
- Assume p is a random variable with a prior distribution $p \sim \text{Beta}(a, b)$, where a and b are known constants. Find \hat{p} through the MMSE (Minimal Mean Squared Error) rule.

$$1a) L(p|k) = \binom{n}{k} p^k (1-p)^{n-k} \Rightarrow \ell(p|k) = \log L = \log \binom{n}{k} + k \log p + (n-k) \log (1-p)$$

$$\frac{\partial \ell}{\partial p} = \frac{k}{p} - \frac{n-k}{1-p} = 0 \Rightarrow \hat{p} = \frac{k}{n}$$

$$1b) f(p) = \frac{p^{a-1} (1-p)^{b-1}}{\beta(a, b)} \propto p^{a-1} (1-p)^{b-1} \quad P(p|X=k) \propto \frac{P(X=k|p) P(p)}{p^k (1-p)^{n-k}}$$

$$f(p|X=k) \propto p^{a+k-1} (1-p)^{b+n-k-1}$$

$$p^* = \underset{p}{\operatorname{argmax}} f(p|X) \Rightarrow \log f(p|X) = (a+k-1) \log p + (b+n-k-1) \log (1-p) = g(p)$$

$$g'(p) = -\frac{a+k-1}{p} - \frac{b+n-k-1}{1-p} \quad g''(p) = -\frac{a+k-1}{p^2} - \frac{b+n-k-1}{(1-p)^2} < 0$$

$$g'(p) = 0 \Rightarrow p^* = \frac{a+k-1}{a+b+n-2}$$

1c) Beta - Binomial conjugacy

$$E = \frac{a+k}{a+b+n}$$

Problem 6

(Optional Challenging Problem) Use two different methods to show that if X and Y are jointly Normal random variables, then

$$E[Y | X] = L[Y | X] = E(Y) + \frac{\text{Cov}(X, Y)}{\text{Var}(X)}(X - E(X))$$

$$E[Y | X] = \alpha X + \beta = L[Y | X]$$

$$\text{Cov}(X, Y) = \text{Cov}(X, \alpha X + \beta) = \alpha \text{Var}(X)$$

$$\Rightarrow \alpha = \frac{\text{Cov}(X, Y)}{\text{Var}(X)} \quad \beta = \frac{E[Y] - \alpha E[X]}{E[Y | X] - \alpha E[X]}$$

$$E[Y | X] = \frac{\text{Cov}(X, Y)}{\text{Var}(X)}(X - E(X)) + E(Y)$$