

**Midterm Exam #3**

**Group 1**

Session 25

November 17, 2020

75 minutes

**Solutions**

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1. (25 pts.) Let  $\mathbf{X}$  and  $\mathbf{Y}$  be two jointly distributed random variables with joint pdf

$$f_{\mathbf{XY}}(x, y) = kx^2y \cdot 1_{[0, y]}(x)1_{[0, 1]}(y).$$

- Find the constant  $k$  that makes  $f_{\mathbf{XY}}(x, y)$  a valid joint pdf.
- Find the marginal pdf  $f_{\mathbf{Y}}(y)$ .
- Find the conditional pdf  $f_{\mathbf{X}}(x|\{\mathbf{Y} = y\})$ .
- Find the *minimum mean-square error* (MMS) estimator  $\hat{x}_{MMS}(y)$  of  $\mathbf{X}$  given  $\{\mathbf{Y} = y\}$ .
- Find the *maximum a posteriori probability* (MAP) estimator  $\hat{x}_{MMS}(y)$  of  $\mathbf{X}$  given  $\{\mathbf{Y} = y\}$ .

$$\begin{aligned}
 (a) \quad 1 &= \iint_{\mathbb{R}^2} f_{\mathbf{XY}}(x, y) dx dy = \int_0^1 \int_0^y kx^2y dx dy = k \int_0^1 y \int_0^y x^2 dx dy \\
 &= k \int_0^1 y \left[ \frac{x^3}{3} \Big|_0^y \right] dy = \frac{k}{3} \int_0^1 y^4 dy = \frac{k}{15} \cdot y^5 \Big|_0^1 \\
 &= \frac{k}{15}. \quad \therefore \boxed{k = 15}
 \end{aligned}$$

$$\begin{aligned}
 (b) \quad f_{\mathbf{Y}}(y) &= \int_{-\infty}^{\infty} f_{\mathbf{XY}}(x, y) dx = \int_0^y 15x^2y dx = \frac{15}{3} \cdot y \cdot x^3 \Big|_0^y \\
 &= \frac{15}{3} y^4 \cdot 1_{[0, 1]}(y) = \boxed{5y^4 \cdot 1_{[0, 1]}(y)}
 \end{aligned}$$

$$\begin{aligned}
 (c) \quad f_{\mathbf{X}}(x|\{\mathbf{Y} = y\}) &= \frac{f_{\mathbf{XY}}(x, y)}{f_{\mathbf{Y}}(y)} = \frac{15x^2y \cdot 1_{[0, y]}(x) \cdot 1_{[0, 1]}(y)}{5y^4 \cdot 1_{[0, 1]}(y)} \\
 &= \boxed{\frac{3x^2}{y^3} \cdot 1_{[0, y]}(x)}
 \end{aligned}$$

(Problem 1 Solution Continued)

$$\begin{aligned} (d) \hat{x}_{MMSE}(y) &= E[X | \xi \Psi = y^3] = \int_{-\infty}^{\infty} x f_*(x | \xi \Psi = y^3) dx \\ &= \int_0^y x \frac{3x^2}{y^3} dx = \int_0^y \frac{3x^3}{y^3} dx = \frac{3}{4y^3} \cdot x^4 \Big|_0^y \\ &= \frac{3}{4y^3} (y^4 - 0) = \boxed{\frac{3y}{4}} \end{aligned}$$

$$(e) \hat{x}_{MAP} = \arg \max_{x \in [0, y]} \left\{ \frac{3x^2}{y^3} \right\} = \boxed{y} \quad (\text{the endpoint})$$

2. (25 pts.) Let  $\mathbf{X}$  and  $\mathbf{Y}$  be two jointly distributed random variables with joint characteristic function

$$\Phi_{\mathbf{XY}}(\omega_1, \omega_2) = \frac{1}{(1 - i\omega_1)(1 - i2\omega_2)}.$$

- Calculate the value of  $E[\mathbf{X}]$ .
- Calculate the value of  $E[\mathbf{Y}]$ .
- Calculate the value of  $E[\mathbf{XY}]$ .
- Calculate the value of  $E[\mathbf{X}^j \mathbf{Y}^k]$  if  $j$  and  $k$  are positive integers.
- Calculate the correlation coefficient between  $\mathbf{X}$  and  $\mathbf{Y}$ .

We have  $\phi_{\mathbf{XY}}(s_1, s_2) = \frac{1}{(1 - s_1)(1 - 2s_2)}$

$$\phi_{\mathbf{X}}(s) = \phi_{\mathbf{XY}}(s, 0) = \frac{1}{1 - s}$$

$$\phi_{\mathbf{Y}}(s) = \phi_{\mathbf{XY}}(0, s) = \frac{1}{1 - 2s^2}$$

$$\begin{aligned} (a) E[\mathbf{X}] &= \left. \frac{d\phi_{\mathbf{X}}(s)}{ds} \right|_{s=0} = \left. \frac{d}{ds} (1-s)^{-1} \right|_{s=0} = -1(1-s)^{-2}(-1) \Big|_{s=0} \\ &= \boxed{1} \end{aligned}$$

$$\begin{aligned} (b) E[\mathbf{Y}] &= \left. \frac{d\phi_{\mathbf{Y}}(s)}{ds} \right|_{s=0} = \left. \frac{d}{ds} (1-2s)^{-1} \right|_{s=0} = -1(1-2s)^{-2}(-2) \Big|_{s=0} \\ &= \boxed{2} \end{aligned}$$

$$\begin{aligned} (c) E[\mathbf{XY}] &= \left. \frac{\partial^2 \phi_{\mathbf{XY}}(s_1, s_2)}{\partial s_1 \partial s_2} \right|_{s_1=0, s_2=0} = \left. \frac{\partial^2}{\partial s_1 \partial s_2} (1-s_1)^{-1} (1-2s_2)^{-1} \right|_{s_1=0, s_2=0} \\ &= -1(1-s_1)^{-2}(-1)(-1)(1-2s_2)^{-2}(-2) \Big|_{s_1=0, s_2=0} \\ &= (-1)(1)(-1)(-1)(1)(-2) \\ &= \boxed{2} \end{aligned}$$

(Problem 2 Solution Continued)

$$\begin{aligned}
 (d) \quad E[X^j Y^k] &= \frac{\partial^{j+k} \phi_{XY}(s_1, s_2)}{\partial s_1^j \partial s_2^k} \\
 &= \frac{\partial^{j+k}}{\partial s_1^j \partial s_2^k} \{ (1-s_1)^{-1} (1-2s_2)^{-1} \} \\
 &= (-1)(-2)\dots(-j) (1-s_1)^{-(j+1)} \cdot (-1)^j \cdot (-1)(-2)\dots(-k) (1-2s_2)^{-(k+1)} (-2)^k \\
 &= (j!)(k!)(2^k) = \boxed{j! k! 2^k}
 \end{aligned}$$

$$\begin{aligned}
 (e) \quad r_{XY} &= \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y} = \frac{E[XY] - E[X] \cdot E[Y]}{\sigma_X \sigma_Y} = \frac{2 - (1)(2)}{\sigma_X \sigma_Y} \\
 &= \frac{0}{\sigma_X \sigma_Y} = \boxed{0}
 \end{aligned}$$

3. (25 pts.) The number of cars  $N$  that pass a point on a highway in one hour is a Poisson random variable with mean  $\lambda$ . The probability that any car is exceeding the speed limit is  $p$ , independent of the other cars. Let  $M$  be the number of cars exceeding the speed limit during this one hour period. In this problem, you will find the pmf of  $M$  using characteristic functions and iterated expectation, using the following procedure:

- Compute the characteristic function of the Poisson random variable  $N$ .
- Using iterated expectation, compute the characteristic function of  $M$ , using the fact that

$$\Phi_M(\omega) = E[e^{i\omega M}] = E_N[E_M[e^{i\omega M}|N]] = \sum_{n=0}^{\infty} p_N(n) \cdot E_M[e^{i\omega M}|N=n].$$

- Based on your answer in part (b), write down the pmf of the random variable  $M$ .
- What are the mean and variance of  $M$ ?

$$\begin{aligned} (a) \quad \Phi_N(\omega) &= E[e^{i\omega N}] = \sum_{n=0}^{\infty} P_N(n) e^{i\omega n} = \sum_{n=0}^{\infty} e^{i\omega n} \cdot \frac{\lambda^n e^{-\lambda}}{n!} \\ &= e^{-\lambda} \sum_{n=0}^{\infty} \frac{(\lambda e^{i\omega})^n}{n!} = e^{-\lambda} \cdot e^{\lambda e^{i\omega}} \\ &= \boxed{e^{\lambda(e^{i\omega}-1)}} \quad (\text{The characteristic function of a Poisson RV with mean } \lambda.) \end{aligned}$$

$$\begin{aligned} (b) \quad \Phi_M(\omega) &= E[e^{i\omega M}] = E_N[E_M[e^{i\omega M}|N]] \\ &= \sum_{n=0}^{\infty} P_N(n) \cdot E[e^{i\omega M}|N=n] \quad \dots (*) \end{aligned}$$

Now given that  $N=n$ ,  $M$  is a binomial RV corresponding to  $n$  trials with probability  $p$  of success (speeding in this case.) Thus we have

$$\begin{aligned} E[e^{i\omega M}|N=n] &= \sum_{m=0}^n e^{i\omega m} \binom{n}{m} p^m (1-p)^{n-m} \\ &= \sum_{m=0}^n \binom{n}{m} (pe^{i\omega})^m (1-p)^{n-m} \stackrel{\text{binomial theorem}}{=} (pe^{i\omega} + 1-p)^n \\ &= (1 + p(e^{i\omega} - 1))^n \end{aligned}$$

(Problem 3 Solution Continued)

$$\begin{aligned}
 \text{So } \Phi_M(\omega) &= \sum_{n=0}^{\infty} p_M(n) (1 + p(e^{i\omega} - 1))^n \\
 &= \sum_{n=0}^{\infty} \frac{\lambda^n e^{-\lambda}}{n!} (1 + p(e^{i\omega} - 1))^n \\
 &= e^{-\lambda} \sum_{n=0}^{\infty} \frac{[\lambda(1 + p(e^{i\omega} - 1))]^n}{n!} = e^{-\lambda} e^{\lambda(1 + p(e^{i\omega} - 1))} \\
 &= \boxed{e^{\lambda p(e^{i\omega} - 1)}} \quad (\text{This is the char. fcn. of a Poisson RV with mean } \lambda p.)
 \end{aligned}$$

(c) From the char. fcn. in part (b), we have that  $M$  is a Poisson RV with mean  $\lambda p$ . Thus

$$\boxed{P_M(m) = \frac{(\lambda p)^m e^{-\lambda p}}{m!}, \quad m = 0, 1, 2, \dots}$$

(d) For a Poisson RV, the mean is equal to the variance. Thus we have

$$\boxed{\text{var}(M) = E[M] = \lambda p.}$$

4. (25 pts.) Let  $X_1, X_2, \dots, X_n, \dots$  be a sequence of independent, identically distributed, exponential random variables, each having mean  $\mu$ . Define a new random sequence  $Y_1, Y_2, \dots, Y_n, \dots$ , where

$$Y_n = \min \{X_1, X_2, \dots, X_n\}, \quad n = 1, 2, 3, \dots$$

(i.e.,  $Y_n$  takes on the minimum value of the first  $n$  random variables  $X_1, X_2, \dots, X_n$  in the initial random sequence.)

- Find the probability density function of  $Y_n$ .
- Does the random sequence  $\{Y_n\}$  converge in probability as  $n \rightarrow \infty$ ? Justify your answer.
- Does the random sequence  $\{Y_n\}$  converge in the mean-square sense as  $n \rightarrow \infty$ ? Justify your answer.

(a) We will start by finding the cdf of  $Y_n$ .

$$\begin{aligned} F_{Y_n}(y) &= P(\{Y_n \leq y\}) = 1 - P(\{Y_n > y\}) \\ &= 1 - P(\{X_1 > y\} \cap \{X_2 > y\} \cap \dots \cap \{X_n > y\}) \\ &= 1 - P(\{X_1 > y\}) \cdot P(\{X_2 > y\}) \cdot \dots \cdot P(\{X_n > y\}) \end{aligned}$$

Now  $P(\{X_j > y\}) = 1 - F_{X_j}(y)$ , where

$$F_{X_j}(y) = \int_{-\infty}^y \frac{1}{\mu} e^{-x/\mu} \cdot 1_{[0, \infty)}(x) dx = \begin{cases} 1 - e^{-y/\mu}, & y \geq 0 \\ 0, & y < 0 \end{cases}$$

$$\therefore F_{Y_n}(y) = 1 - (1 - F_{X_j}(y))^n = \begin{cases} (e^{-y/\mu})^n, & y \geq 0 \\ 0, & y < 0 \end{cases}$$

Thus it follows that

$$\begin{aligned} f_{Y_n}(y) &= \frac{dF_{Y_n}(y)}{dy} = \frac{d}{dy} \left( \exp\left(\frac{-y}{\mu/n}\right) 1_{[0, \infty)}(y) \right) \\ &= \boxed{\frac{1}{\mu/n} \exp\left(\frac{-y}{\mu/n}\right) 1_{[0, \infty)}(y)} \end{aligned}$$

which is an exponential pdf with mean  $\frac{\mu}{n}$ .



(Problem 4 Solution Continued)

(b) Because  $Y_n$  is exponential with mean  $\mu/n$ , I suspect it is converging to 0 in some sense. Let's check to see if it is converging to 0 in probability.

The sequence  $\{Y_n\}$  converges to 0 in probability if

$$P(\{|Y_n - 0| > \varepsilon\}) \rightarrow 0 \text{ as } n \rightarrow \infty \text{ for all } \varepsilon > 0.$$

Note that

$$\begin{aligned} P(\{|Y_n - 0| > \varepsilon\}) &= P(\{Y_n > \varepsilon\}) = 1 - F_{Y_n}(\varepsilon) \\ &= 1 - (1 - \exp[-\frac{\varepsilon}{\mu/n}]) , \varepsilon > 0 \\ &= \exp(-\frac{\varepsilon n}{\mu}) \xrightarrow{n \rightarrow \infty} 0 \text{ for all } \varepsilon > 0 \text{ and } \mu > 0. \end{aligned}$$

$$\therefore P(\{|Y_n - 0| > \varepsilon\}) \rightarrow 0 \text{ as } n \rightarrow \infty \text{ for } \forall \varepsilon > 0.$$

$$\Rightarrow Y_n \xrightarrow{(p)} 0 \text{ as } n \rightarrow \infty \therefore \boxed{\{Y_n\} \text{ converges to 0 in probability}}$$

(c) We now check to see if  $\{Y_n\}$  converges to 0 in the mean-square sense.

$$E[|Y_n - 0|^2] = E[Y_n^2]$$

Now from part (a), we know that  $Y_n$  is exponentially distributed with mean  $\mu_n \triangleq E[Y_n] = \frac{\mu}{n}$ .

(Problem 4 Solution Continued)

Thus it follows that  $\Psi_n$  has characteristic function

$$\Phi_{\Psi_n}(\omega) = \frac{1}{(1 - i\omega\mu_n)}$$

and by the moment theorem, it follows that

$$\begin{aligned} E[\Psi_n^2] &= \frac{\partial^2}{\partial(i\omega)^2} (1 - i\omega\mu_n)^{-1} \Big|_{i\omega=0} = \frac{\partial}{\partial(i\omega)} \left\{ \mu_n (1 - i\omega\mu_n)^{-2} \right\} \Big|_{i\omega=0} \\ &= 2\mu_n^2 (1 - i\omega\mu_n)^{-3} \Big|_{i\omega=0} = 2\mu_n^2 = \underline{\underline{\frac{2\mu}{n^2}}} \end{aligned}$$

Thus it follows that

$$E[|\Psi_n - 0|^2] = \frac{2\mu}{n^2} \rightarrow 0 \text{ as } n \rightarrow \infty.$$

$$\therefore \Psi_n \xrightarrow{\text{(m.s)}} 0 \text{ as } n \rightarrow \infty$$

Yes,  $\{\Psi_n\}$  converges to 0 in mean-square