

# Probability and Random Processes — Monsoon 2023

## Assignment 4 Solutions

PRP TAs

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### Problem 1

Consider a random variable  $X$  with the following two-sided exponential PDF

$$f_X(x) = \begin{cases} p\lambda e^{-\lambda x}, & \text{if } x \geq 0, \\ (1-p)\lambda e^{\lambda x}, & \text{if } x < 0, \end{cases}$$

where  $\lambda$  and  $p$  are scalars with  $\lambda > 0$  and  $p \in [0, 1]$ .

To find the expectation value we use the formula:

$$E[X] = \int_0^\infty x f_X(x) dx$$

t For given PDF we split it into two halves:

$$\begin{aligned} E[X] &= \int_0^\infty x p \lambda e^{-\lambda x} dx + \int_{-\infty}^0 x (1-p) \lambda e^{\lambda x} dx \\ &= p \int_0^\infty x \lambda e^{-\lambda x} dx + (1-p) \int_{-\infty}^0 x \lambda e^{\lambda x} dx \\ &= p \left( x \int_0^\infty \lambda e^{-\lambda x} dx - \int_0^\infty 1 \cdot \int_0^\infty \lambda e^{-\lambda x} dx \right) + (1-p) \left( x \cdot \int_{-\infty}^0 \lambda e^{\lambda x} dx - \int_{-\infty}^0 \int_{-\infty}^0 1 \cdot \lambda e^{\lambda x} dx \right) \end{aligned}$$

On simplification you get mean  $E[X] = \frac{(2p-1)}{\lambda}$

To find the variance we need  $E[X^2] = \int_{-\infty}^\infty x^2 f_X(x) dx$

$$\Rightarrow p \left( \int_0^\infty x^2 \lambda e^{-\lambda x} dx \right) + (1-p) \left( \int_{-\infty}^0 x^2 \lambda e^{\lambda x} dx \right)$$

By using integration by parts and after simplification you get  $E[X^2] = \frac{2}{\lambda^2}$

Thus Variance of  $x$  if given by  $Var(X) = E[X^2] - E[X]^2$

$$\Rightarrow Var(X) = \frac{2}{\lambda^2} - \left( \frac{(2p-1)}{\lambda} \right)^2$$

$$Var(X) = \frac{1 + 4p - 4p^2}{\lambda^2}$$

## Problem 2

We are given a gaussian random variable with pdf,

$$f_X(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

(a)

We need to prove that the gaussian pdf given is valid, i.e.,

$$\int_{-\infty}^{\infty} f_X(x) dx = 1$$

*Proof.* Let  $I := \int_{-\infty}^{\infty} f_X(x) dx$ . Then, taking the transformation of variables  $z = \frac{x-\mu}{\sigma}$ ,  $dz = \frac{dx}{\sigma}$ .

$$\begin{aligned} I &= \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx \\ &= \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{z^2}{2}} dz \end{aligned}$$

Then, if we square both sides of the above equation, we get,

$$\begin{aligned} I^2 &= \frac{1}{2\pi} \left( \int_{-\infty}^{\infty} e^{-\frac{z^2}{2}} \right)^2 \\ &= \frac{1}{2\pi} \left[ \int_{-\infty}^{\infty} e^{-\frac{z^2}{2}} \right] \left[ \int_{-\infty}^{\infty} e^{-\frac{w^2}{2}} \right] && \text{(Change in variables)} \\ &= \frac{1}{2\pi} \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} e^{-\frac{z^2+w^2}{2}} dz dw \end{aligned}$$

Now, we transform the problem into polar coordinates by applying the transformation,  $x = r\cos\theta$ ,  $y = r\sin\theta$ ,  $dx dy = r dr d\theta$ .

$$\begin{aligned} I^2 &= \frac{1}{2\pi} \int_0^{2\pi} \int_0^{\infty} r e^{-\frac{r^2}{2}} dr d\theta \\ &= \frac{1}{2\pi} (-2\pi) e^{-\frac{r^2}{2}} \Big|_0^{\infty} \\ &= 1 \end{aligned}$$

Therefore,  $I^2 = 1 \Rightarrow I = 1$  ( $\because I > 0$ ).  
Q.E.D.

□

(b)

Now we prove that the mean of the gaussian r.v. is  $\mu$ .

*Proof.* We use the definition of expectation as follows,

$$\begin{aligned}\mathbb{E}[X] &= \int_{-\infty}^{\infty} x f_X(x) dx \\ &= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} x e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx\end{aligned}$$

Applying the same transformation of equations as in (a),

$$\begin{aligned}\mathbb{E}[X] &= \frac{1}{\sqrt{2\pi}} \left( \sigma \int_{-\infty}^{\infty} z e^{-\frac{z^2}{2}} dz + \mu \int_{-\infty}^{\infty} e^{-\frac{z^2}{2}} dz \right) \\ &= \mu\end{aligned}$$

Hence,  $\mathbb{E}[x] = \mu$ .

Q.E.D.

□

(c)

Finally, we need to prove that  $\text{var}(X) = \sigma^2$ .

*Proof.*

$$\begin{aligned}\text{var}(X) &= \mathbb{E}[(X - \mu)^2] \\ &= \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} (x - \mu)^2 e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx\end{aligned}$$

Applying the same transformation as in part (b), we get,

$$\begin{aligned}\text{var}(X) &= \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} z^2 e^{-\frac{z^2}{2}} dz \\ &= \frac{\sigma^2}{\sqrt{2\pi}} \left[ -z e^{-\frac{z^2}{2}} \Big|_{-\infty}^{\infty} + \int_{-\infty}^{\infty} e^{-\frac{z^2}{2}} dz \right] \\ &= \frac{\sigma^2}{\sqrt{2\pi}} \int_{-\infty}^{\infty} e^{-\frac{z^2}{2}} dz \\ &= \sigma^2\end{aligned}$$

Therefore,  $\text{var}(X) = \sigma^2$ .

Q.E.D.

□

### Problem 3

Let  $x$  be the point where the stick gets split. We know that  $X \sim U[0,1]$ . Thus  $f_X(x) = 1$ . If  $x < p$ , then point  $p$  is contained in the right substick which has length  $1 - x$ . Whereas if  $x \geq p$ , the point  $p$  is contained in the left substick having length  $x$ .

Let  $l(x)$  be a function denoting the length of the substick given the splitting point  $x$ .

$$\begin{aligned}
 l(x) &= \begin{cases} 1 - x & \text{if } x < p \\ x & \text{if } x \geq p \end{cases} \\
 E_X[l(x)] &= \int_0^1 f_X(x) \cdot l(x) \, dx \\
 &= \int_0^p f_X(x) \cdot (1 - x) \, dx + \int_p^1 f_X(x) \cdot x \, dx \\
 &= \int_0^p (1 - x) \, dx + \int_p^1 x \, dx \\
 &= \left[ x - \frac{x^2}{2} \right]_0^p + \left[ \frac{x^2}{2} \right]_p^1 \\
 &= \left[ p - \frac{p^2}{2} - 0 + 0 \right] + \left[ \frac{1}{2} - \frac{p^2}{2} \right] \\
 &= p - p^2 + \frac{1}{2}
 \end{aligned}$$

To find the value of  $p$  which maximizes the expected length of substick containing  $p$  i.e.  $L = E_X[l(x)]$ . We differentiate the expression for  $L$  wrt.  $x$  and equate that to 0.

$$\frac{dL}{dp} = 1 - 2p = 0. \implies p = \frac{1}{2}$$

Since the equation for  $L$  is a downward parabola, the derivative is zero only at a maxima.

### Problem 4

Firstly, we try to find  $E[X]$  in terms of  $P(X > x)$ .

$$\begin{aligned}
 E[X] &= \int_0^\infty x \cdot f_X(x) \, dx \\
 &= \int_0^\infty \left( \int_0^x dy \right) f_X(x) \, dx \\
 &= \int_0^\infty \left( \int_y^\infty f_X(x) \, dx \right) dy \\
 &= \int_0^\infty P(X > y) \, dy \\
 &= \int_0^\infty P(X > x) \, dx
 \end{aligned}$$

Now, use this to calculate  $E[X^n]$ .

$$\begin{aligned} E[X^n] &= \int_0^\infty P(X^n > x) dx \\ &= \int_0^\infty P(X > x^{\frac{1}{n}}) dx \end{aligned}$$

Changing the variable from  $x$  to  $t$  such that  $t = x^{\frac{1}{n}}$  and thus,  $dx = n.t^{n-1}dt$ .

$$\begin{aligned} E[X^n] &= \int_0^\infty n.t^{n-1}.P(X > t) dt \\ &= \int_0^\infty n.x^{n-1}.P(X > x) dx \end{aligned}$$

Hence, proved.

## Problem 5

(a)

$$F_Y(y) = P(Y \leq y) \tag{1}$$

$$= P(F_X(X) \leq y) \tag{2}$$

$$= P(X \leq F_X^{-1}(y)) \tag{3}$$

$$= F_X(F_X^{-1}(y)) = y \tag{4}$$

Note that the range of  $Y$  is  $[0, 1]$  by definition of CDF. Equivalence between eqn. (2) and (3) holds due to the fact that  $F_X$  is strictly increasing in  $(0, 1)$  and inverse of a monotonic function is well defined.

(b)

$$F_Z(z) = P(Z \leq z) \tag{1}$$

$$= P(-\log F_X(x) \leq z) \tag{2}$$

$$= P(\log F_X(x) \geq -z) \tag{3}$$

$$= P(e^{\log F_X(x)} \geq e^{-z}) \tag{4}$$

$$= P(F_X(X) \geq e^{-z}) \tag{5}$$

$$= P(X \geq F_X^{-1}(e^{-z})) \tag{6}$$

$$= 1 - P(X < F_X^{-1}(e^{-z})) \tag{7}$$

$$= 1 - F_X(F_X^{-1}(e^{-z})) \tag{8}$$

$$= 1 - e^{-z} \tag{9}$$

$$\Rightarrow f_Z(z) = \frac{dF_Z}{dz}(z) = e^{-z} \tag{10}$$

Note that equivalence between eqn. (3) and (4) holds as  $e^t$  is an increasing function in  $(-\infty, \infty)$  and thus, there is a bijective mapping between events in (3) and (4).

## Problem 6

$$\begin{aligned}
 P_Y(y) &= P(Y = y) \\
 &= P(\lfloor X \rfloor = y) \\
 &= P(y \leq X < y + 1) \\
 &= \int_y^{y+1} f_X(t) dt \\
 &= \int_y^{y+1} \lambda e^{-\lambda t} dt \\
 &= \lambda \left[ \frac{e^{-\lambda t}}{-\lambda} \right]_y^{y+1} \\
 &= - \left[ e^{-\lambda t} \right]_y^{y+1} \\
 &= -[e^{-\lambda(y+1)} - e^{-\lambda y}] \\
 &= e^{-\lambda y}(1 - e^{-\lambda})
 \end{aligned}$$

$$\begin{aligned}
 F_R(r) &= P(R \leq r) \\
 &= P(X - \lfloor X \rfloor \leq r) \\
 &= P\left(\bigcup_{i=0}^{\infty} \{\omega \in \Omega : X(\omega) \in [i, i+r]\}\right) \\
 &= \sum_{i=0}^{\infty} P(\{\omega \in \Omega : X(\omega) \in [i, i+r]\}) \\
 &= \sum_{i=0}^{\infty} \int_i^{i+r} f_X(t) dt \\
 \Rightarrow f_R(r) &= \frac{dF_R}{dr}(r) = \sum_{i=0}^{\infty} \frac{d}{dr} \int_i^{i+r} f_X(t) dt = \sum_{i=0}^{\infty} f_X(i+r) \\
 &= \sum_{i=0}^{\infty} \lambda e^{-\lambda(i+r)} \\
 &= \lambda e^{-\lambda r} \sum_{i=0}^{\infty} e^{-\lambda i} \\
 &= \frac{\lambda e^{-\lambda r}}{1 - e^{-\lambda}}
 \end{aligned}$$