

EE 513: Stochastic Systems Theory
Fall 2022 Schmid

Final (take home)

Distributed on December 15, 2022 (at 9 am)
Due is on December 16, 2022 (at 9 am)

Do your own work. The test is take home and thus open book and notes.

Name: Ali Zafari

Pledge: "I have neither given nor received unauthorized aid on this examination."

Signed: 

Problem	Points	Points received
1	13	
2	15	
3	12	
4	15	
5	15	
6	15	
7	15	
Bonus	10	
Total		

$$(1) a \quad X_i \sim \text{Pois}(\lambda) \Rightarrow p(x_i) = \frac{\lambda^{x_i} e^{-\lambda}}{x_i!}$$

$$L = p(x_1) p(x_2) \dots p(x_n) = \prod_{i=1}^n p(x_i) = \frac{\lambda^{\sum x_i} e^{-n\lambda}}{x_1! x_2! \dots x_n!}$$

$$\frac{\partial L}{\partial \lambda} = 0 \Rightarrow \sum x_i \lambda^{\sum x_i - 1} e^{-n\lambda} - n e^{-n\lambda} \lambda^{\sum x_i} = 0$$

$$\lambda^{\sum x_i} e^{-n\lambda} \left(\frac{\sum x_i}{\lambda} - n \right) = 0$$

$$\Rightarrow \boxed{\lambda_{MLE} = \frac{\sum x_i}{n}}$$

(1) b

$$\text{bias} \triangleq E[\lambda_{MLE}] - \lambda = E\left[\frac{\sum x_i}{n}\right] - \lambda = \frac{n\lambda}{n} - \lambda = 0$$

$$\text{Variance: } \text{Var}(\lambda_{MLE}) = \text{Var}\left(\frac{\sum x_i}{n}\right) = \frac{1}{n^2} n \times \overbrace{\text{Var}(x_i)}^{\lambda} = \frac{\lambda}{n}$$

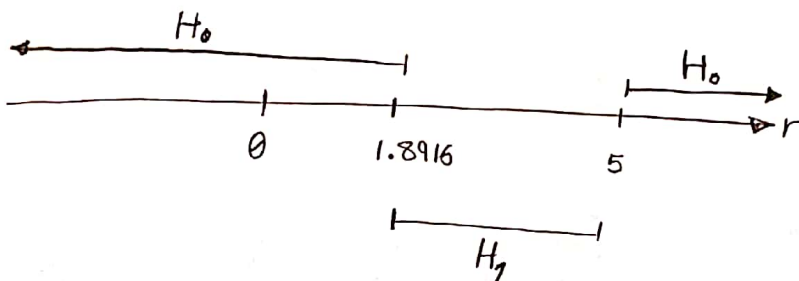
② Bayesian decision rule:
(assuming $r \in [0, 5]$)

$$\ln \frac{P(R=r | H_1)}{P(R=r | H_0)} \gtrless_{H_0}^{H_1} \ln \frac{\pi_0}{\pi_1}$$

$$\ln \frac{\sqrt{2\pi}}{5} + \frac{r^2}{2} \gtrless_{H_0}^{H_1} \ln 3$$

$$0 \leq r \leq 5 \begin{cases} r^2 \gtrless_{H_0}^{H_1} 3.5782 \\ r \gtrless_{H_0}^{H_1} 1.8916 \end{cases}$$

Decision boundaries:



$$P_{FA} = P(H_1 | H_0) = \int_{1.8916}^5 P(r | H_0) dr = \int_{1.8916}^5 \frac{1}{\sqrt{2\pi}} e^{-\frac{r^2}{2}} dr = Q(1.8916) - Q(5) = 0.0293$$

$$P_{miss} = P(H_0 | H_1) = \int_{-\infty}^{1.8916} P(r | H_1) dr + \int_5^{\infty} P(r | H_1) dr = \frac{1}{5} \times (1.8916 - 0) + 0 = 0.3632$$

$$P_{error} = \pi_0 P_{FA} + \pi_1 P_{miss} = \frac{3}{4} \times 0.0293 + \frac{1}{4} \times 0.3632 = 0.1128$$

③

$$m_x = \frac{1}{3} + 0 - \frac{1}{3} = 0$$

$$\sigma_x^2 = E[x^2] - \overset{0}{E[x]^2} = \frac{1}{3} + 0 + \frac{1}{3} = \frac{2}{3}$$

$$E[M_n] = \frac{n E[x]}{n} = 0$$

$$\text{Var}[M_n] = \frac{1}{n^2} n \sigma_x^2 = \frac{\sigma_x^2}{n} = \frac{2}{3n}$$

to prove WLLN, we start by Chebyshev's inequality:

$$P(|M_n - E[M_n]| > \epsilon) \leq \frac{\text{Var}[M_n]}{\epsilon^2}$$

$$P(|M_n - 0| > \epsilon) \leq \frac{2}{3n\epsilon^2}$$

it can be seen from equation above that as $n \rightarrow \infty$, the sample mean (M_n) will converge to $m_x = 0$ in probability.

$$M_n \xrightarrow[\text{as } n \rightarrow \infty]{\text{in Prob.}} 0$$

4

$$\lambda = 15 \frac{\text{message}}{\text{second}} \times 60 = 900 \frac{\text{message}}{\text{minute}}$$

$$K \sim \text{Pois}(900)$$

$$K_n \triangleq K_1 + K_2 + \dots + K_{900}$$

$$, K_i \sim \text{Pois}(1)$$

$$\Rightarrow K_n \sim \text{Pois}(900)$$

from CLT:

$$\frac{K_n - E[K_n]}{\sigma_{K_n}} \sim \mathcal{N}(0, 1)$$

$$E[K_n] = \sum_1^{900} E[K_i] = 900 \times 1$$

$$\sigma_{K_n}^2 = \sum_1^{900} \sigma_{K_i}^2 = 900 \Rightarrow \sigma_{K_n} = 30$$

$$\Rightarrow \frac{K_n - 900}{30} \sim \mathcal{N}(0, 1)$$

$$\Rightarrow P(K_n > 950) = P\left(\frac{K_n - 900}{30} > \frac{950 - 900}{30}\right) \stackrel{\text{CLT}}{=} Q\left(\frac{5}{3}\right) = 0.0478$$

aside

Sum of independent Poisson random variables is a Poisson random variable.

proof:

$$X_1 \sim \text{Pois}(\lambda_1)$$

$$X_2 \sim \text{Pois}(\lambda_2) \quad X_1 \perp\!\!\!\perp X_2$$

$$Y \triangleq X_1 + X_2$$

$$\begin{aligned} \Phi_Y(j\nu) &= \Phi_{X_1}(j\nu) \cdot \Phi_{X_2}(j\nu) \\ &= e^{\lambda_1(e^{j\nu}-1)} \cdot e^{\lambda_2(e^{j\nu}-1)} \\ &= e^{(\lambda_1+\lambda_2)(e^{j\nu}-1)} \end{aligned}$$

$$\Rightarrow Y \sim \text{Pois}(\lambda_1 + \lambda_2)$$

5a

$$E[X(t)] \stackrel{A \perp \theta}{=} E_A[A] E_\theta[\cos(2\pi f_c t + \theta)] = 2 \times 0 = 0$$

$$\begin{aligned} R_{XX}(t, u) &= E_{A, \theta} [A \cos(2\pi f_c t + \theta) \times A \cos(2\pi f_c u + \theta)] \\ &= E_A[A^2] \left\{ E_\theta \left[\frac{1}{2} \cos(2\pi f_c (t+u) + 2\theta) \right] + E_\theta \left[\frac{1}{2} \cos(2\pi f_c (t-u)) \right] \right\} \\ &= \left(\frac{1}{2} \times 16 + \frac{1}{2} \times 0 \right) \left(\frac{1}{2} \cos(2\pi f_c (t-u)) \right) \\ &= 4 \cos(2\pi f_c (t-u)) \end{aligned}$$

$$\tau \triangleq t-u \rightarrow R_{XX}(\tau) = 4 \cos 2\pi f_c \tau$$

5b

I. $E[X(t)] = 0$ is constant and bounded ($< \infty$)

II. $R_{XX}(t, u)$ is a function of $t-u$ ($\triangleq \tau$)

\Rightarrow Therefore $X(t)$ is WSS random process.

5)c

Frequency response of whole LTI system is:

$$G(f) = \frac{Z(f)}{X(f)} = \frac{X(f) - H(f)X(f)}{X(f)} = 1 - H(f) = \frac{f^2}{1+f^2}$$

PSD of the output will be:

$$S_Z(f) = S_X(f) |G(f)|^2$$

PSD of the input is the Fourier Transform of autocorrelation function of it:

$$\begin{aligned} S_X(f) &= \mathcal{F}\{R_{XX}(\tau)\} = \mathcal{F}\left\{4 \frac{e^{j2\pi f_c \tau} + e^{-j2\pi f_c \tau}}{2}\right\} \\ &= 2\delta(f-f_c) + 2\delta(f+f_c) \end{aligned}$$

$$\begin{aligned} \xrightarrow{f_c=1} S_Z(f) &= \left[2\delta(f-1) + 2\delta(f+1)\right] \left|\frac{f^2}{1+f^2}\right|^2 \\ &= 2\left(\frac{(1)^2}{1+1^2}\right)^2 \delta(f-1) + 2\left(\frac{(-1)^2}{1+(-1)^2}\right)^2 \delta(f+1) \\ &= \frac{1}{2}\delta(f-1) + \frac{1}{2}\delta(f+1) \end{aligned}$$

5)d

$$\underbrace{E[|Z(t)|^2]}_{\text{average power}} = R_{ZZ}(\theta) = \mathcal{F}^{-1}\left\{\frac{1}{2}\delta(f-1) + \frac{1}{2}\delta(f+1)\right\} \bigg|_{\tau=\theta} = \cos 2\pi\tau \bigg|_{\tau=\theta} = 1$$

6a

$$Z = X + 2Y$$

$$P(Z \leq z) = F_Z(z) = \iint_{D_z} f_{XY}(x, y) dy dx$$

$$= \int_{-\infty}^{+\infty} \int_{-\infty}^{\frac{z-x}{2}} f_{XY}(x, y) dy dx$$

$$f_Z(z) = \frac{d F_Z(z)}{dz} = \int_{-\infty}^{+\infty} \frac{1}{2} f_{XY}(x, \frac{z-x}{2}) dx$$

6b

$$f_{ZW}(z, w) = f_{XY}\left(\overbrace{\frac{2w+z}{5}}^x, \overbrace{\frac{2z-w}{5}}^y\right) \times \frac{1}{|J(x, y)|}$$

$$|J(x, y)| = \left| \det \begin{bmatrix} \partial z / \partial x & \partial z / \partial y \\ \partial w / \partial x & \partial w / \partial y \end{bmatrix} \right| = \left| \det \begin{bmatrix} 1 & 2 \\ 2 & -1 \end{bmatrix} \right| = |-5| = 5$$

7a

I. X is Gaussian.

II. Since X and Y are jointly Gaussian, any linear combination of them is also Gaussian. As a result $X + aY$ is Gaussian.

III. linear combination of X and $X + aY$, i.e. $AX + B(X + aY)$, can be written as linear combination of X and Y , i.e. $(A+B)X + (Ba)Y$. Therefore X and $X + aY$ are Jointly Gaussian.

As a result, uncorrelatedness is same as independence for X and $X + aY$.

$$\begin{aligned}\text{Cov}(X, X + aY) &= E[(X - E[X])(X + aY - E[X + aY])] \\ &= E[X^2] + a E[XY]\end{aligned}$$

We need to find $E[X^2]$ and $E[XY]$:

$$\rightarrow \sigma_x^2 = E[X^2] - E[X]^2 \Rightarrow E[X^2] = 16$$

$$\rightarrow \rho = \frac{\text{Cov}(X, Y)}{\sqrt{\sigma_x^2 \sigma_y^2}} = \frac{E[XY] - E[X]E[Y]}{4 \times 3} \Rightarrow E[XY] = 12\rho$$

$$\Rightarrow \text{Cov}(X, X + aY) = 0 \Rightarrow 16 + 12a\rho = 0 \Rightarrow \boxed{\rho = -\frac{4}{3a}}$$

7b

I. To have $2X+dY$ and $(X-dY)^2$ independent, we know that $g(2X+dY)$ and $f((X-dY)^2)$ must also be independent for any choice of g and f .

II. Therefore $2X+dY$ and $X-dY$ must be independent.

III. linear combination of $2X+dY$ and $X-dY$, i.e.

$A(2X+dY) + B(X-dY)$, can be written as $(2A+B)X + (Ad-Bd)Y$ which is a linear combination of X and Y , and hence Jointly Gaussian.

As a result, uncorrelatedness is same as independence for $2X+dY$ and $X-dY$.

$$\text{Cov}(2X+dY, X-dY) = E[(2X+dY - E[2X+dY])(X-dY - E[X-dY])] = 0$$

from part (a)

$$\begin{aligned} &= E[2X^2 - dXY - d^2Y^2] \\ &= 2 \times 16 - d(12\rho) - d^2 \times 9 = 0 \end{aligned}$$

$$\Rightarrow 9d^2 + 12\rho d - 32 = 0$$

$$\Rightarrow d = \frac{-12\rho \pm \sqrt{144\rho^2 + 1152}}{18}$$

a few examples of d

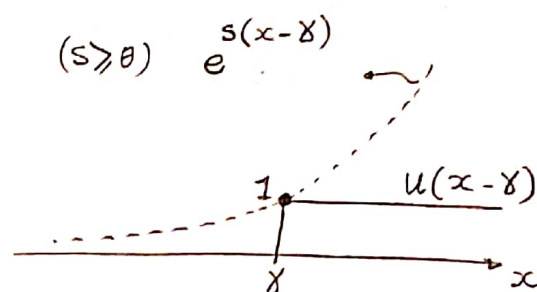
$$\begin{cases} \text{if } \rho = 0 \rightarrow d = \pm 1.8856 \\ \text{if } \rho = 0.5 \rightarrow d = 1.58, d = -2.24 \\ \text{if } \rho = 1 \rightarrow d = 1.33, d = -2.67 \end{cases}$$

Bonus Problem a

$$P(X > \overbrace{E[X] + \epsilon}^{\triangleq \gamma}) = P(X > \gamma) = \int_{\gamma}^{+\infty} f_X(x) dx = \int_{-\infty}^{+\infty} u(x - \gamma) f_X(x) dx$$

$(\epsilon > 0)$ $(\gamma > E[X])$

replacing step function by an exponential, we will find an upperbound for the probability:



$$P(X > \gamma) \leq \int_{-\infty}^{+\infty} e^{s(x - \gamma)} f_X(x) dx = \boxed{\int_{-\infty}^{+\infty} e^{sx} f_X(x) dx} e^{-s\gamma}$$

$\Phi_X(s)$
 ↓
 Moment Generating Function (MGF)

we already know MGF is defined as:

$$\Phi_X(s) = E[e^{sX}] = \int_{-\infty}^{+\infty} e^{sx} f_X(x) dx$$

we now define log-MGF:

$$\varphi_X(s) \triangleq \ln \Phi_X(s)$$

$$\Rightarrow P(X > \gamma) \leq e^{\varphi_X(s)} \cdot e^{-s\gamma} \quad (s \geq 0, \gamma > E[X])$$

$e^{-s\gamma + \varphi_X(s)}$ is the Chernoff Bound.

Now we try to find the tightest Chernoff Bound:

$$\Rightarrow s^* = \arg \min_{s \geq 0} e^{-s\gamma + \varphi_X(s)} = \arg \min_{s \geq 0} -s\gamma + \varphi_X(s) = \arg \max_{s \geq 0} s\gamma - \varphi_X(s)$$

Bonus Problem b

$$X \sim N(5, 4) \Rightarrow \Phi_X(s) = e^{5s + 2s^2}$$

$$\Rightarrow \varphi_X(s) = 5s + 2s^2$$

to find s^* which maximizes $s\gamma - \varphi_X(s)$, we take derivate of it:

$$\frac{d}{ds} \{s\gamma - 5s - 2s^2\} = 0 \Rightarrow \gamma - 5 - 4s = 0 \Rightarrow s^* = \frac{\gamma - 5}{4}$$

So the Chernoff Bound will be:

$$P(X > \gamma) \leq e^{-\gamma(-\frac{5+\gamma}{4}) + 5(-\frac{5+\gamma}{4}) + 2(-\frac{5+\gamma}{4})^2} = e^{-\frac{(\gamma-5)^2}{8}}$$

For Gaussian we have access to the actual value of probabilities:

$$P(X > \gamma) = P(X - E[X] > \epsilon) = P(X - 5 > \epsilon) = P\left(\frac{X-5}{2} > \frac{\epsilon}{2}\right) = Q\left(\frac{\epsilon}{2}\right)$$

So to compare, we need to check values of $Q(\frac{\epsilon}{2})$

and $e^{(8-5)^2/8} = e^{\epsilon^2/8}$.

Chernoff Bound : $P(X-5 > \epsilon) \leq e^{-\epsilon^2/8}$
 $(X = 5 + \epsilon)$

Actual Value : $P(X-5 > \epsilon) = Q(\frac{\epsilon}{2})$

Bonus Problem C

