

EE306 : Signals and Systems II

Lecture 4

* Functions of random variables

→ CDFs and PDFs of functions of RVs $Y = g(X)$:

- Find the CDF

$F_Y(y) = P(Y \leq y) = P(g(X) \leq y)$. If g^{-1} is unique:

$$F_Y(y) = P(X \leq g^{-1}(y)) = F_X(g^{-1}(y)).$$

- Find $g^{-1}(y)$ and continue to get $F_Y(y)$.

- Differentiate the CDF to get the PDF.

→ You can also directly write (cont., what

$$f_Y(y) = \sum_k F_X(x_k) \left| \frac{dx}{dy} \right|_{x=x_k}, \quad \text{if discrete?}$$

where each x_k is a possible $g^{-1}(y)$.

Ex 1 Let the random variable Y be defined as $Y = X^2$, where X is a continuous RV with a known distribution. Find $F_Y(y)$ and $f_Y(y)$.

Sol. $F_Y(y) = P(Y \leq y) = P(X^2 \leq y)$

$$= P(-\sqrt{y} \leq X \leq \sqrt{y})$$

$$= F_X(\sqrt{y}) - F_X(-\sqrt{y}), \quad y \geq 0.$$

For $y < 0$, $F_Y(y) = 0$ since $Y = X^2 \geq 0$.

Next, $f_y(y) = \frac{df_y(y)}{dy}$. Thus $f_y(y) = 0$, $y \leq 0$,

$$\text{and } f_y(y) = \frac{1}{2\sqrt{y}} f_x(\sqrt{y}) + \frac{1}{2\sqrt{y}} f_x(-\sqrt{y}) \\ = \frac{1}{2\sqrt{y}} (f_x(\sqrt{y}) + f_x(-\sqrt{y})).$$

→ Direct method: $y = x^2 \Rightarrow y = x^2$. Thus,
 $y = (g^{-1}(y))^2 \Rightarrow g_1^{-1}(y) = x_1 = \sqrt{y} \rightarrow y = g(x) = x^2$.
and $g_2^{-1}(y) = x_2 = -\sqrt{y}$.

$$\text{Then, } f_y(y) = \sum_{k=1}^2 f_x(x_k) \left| \frac{dx}{dy} \right|_{x=x_k} \\ = \frac{1}{2\sqrt{y}} (f_x(\sqrt{y}) + f_x(-\sqrt{y})).$$

EX 2 Computer generation of random variables.

→ Suppose you have RV U that is uniform in the interval $[0, 1)$. Find $g(U)$ that gives X , an RV that is exponential with λ .

Sol. In general, let $U = h(X) = F_X(X)$.

$$\text{Then, } F_U(u) = P(U \leq u) = P(F_X(X) \leq u) \\ = P(X \leq F_X^{-1}(u)) = F_X(F_X^{-1}(u)).$$

This means $F_U(u) = u$, $0 \leq u \leq 1$.

Thus, $U = F_X(X)$ is a uniform RV in $[0,1]$

for any continuous RV X ! (Meaning?)

since $U = F_X(X) \Rightarrow X = F_X^{-1}(U) = g(U)$.

We know that $F_X(x) = 1 - e^{-\lambda x}$, $x \geq 0$, $\lambda > 0$.

Thus, $y = 1 - e^{-\lambda g(y)} \Rightarrow -\lambda g(y) = \ln(1-y)$.

$$\Rightarrow g(y) = \frac{-1}{\lambda} \ln(1-y) = F_X^{-1}(y).$$

$$\text{Finally, } X = \frac{-1}{\lambda} \ln(1-U) = F_X^{-1}(U).$$

* Transform methods $E(g(X)) = \int_X g(x) f_X(x) dx$ (cont.)

→ characteristic function

$$\phi_X(\omega) = E(e^{j\omega X}) = \int_{-\infty}^{\infty} e^{j\omega x} f_X(x) dx \text{ (cont. RVs).}$$

$$\text{Generating moments } E(X^n) = \frac{1}{j^n} \left. \frac{d^n}{d\omega^n} \phi_X(\omega) \right|_{\omega=0}.$$

Q How can we show this is true?

→ Probability generating function

$$G_X(z) = E(z^X) = \sum_{x=0}^{\infty} P_X(x) z^x \text{ (non-neg. discr. RVs).}$$

Generating probabilities

$$P_X(x) = \frac{1}{x!} \left. \frac{d^x}{dz^x} G_X(z) \right|_{z=0}.$$

It can also be used to generate moments.

EX3 Let $Y = aX + b$, where X is Gaussian with m, σ^2 . Find the characteristic fn of Y .

Sol. $\phi_Y(\omega) = E(e^{j\omega Y}) = E(e^{j\omega(aX+b)})$
 $= e^{j\omega b} E(e^{j\omega a X})$.

$$E(e^{j\omega a X}) = \int_{-\infty}^{\infty} e^{j\omega a x} \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(x-m)^2}{2\sigma^2}} dx.$$

$$\text{Exponent} = \frac{-1}{2\sigma^2} [x^2 - 2mx + m^2 - 2\sigma^2 j\omega a x]$$

$$= \frac{-1}{2\sigma^2} [x - (m + j\sigma^2 \omega a)]^2 + \frac{1}{2\sigma^2} [2jm\sigma^2 \omega a - \sigma^4 \omega^2 a^2]$$

$$\text{Thus, } E(e^{j\omega a X}) = e^{j\omega m a - \sigma^2 \omega^2 a^2 / 2} \int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-[x - (m + j\sigma^2 \omega a)]^2 / 2\sigma^2} dx$$

$$\Rightarrow E(e^{j\omega a X}) = e^{j\omega m a - \sigma^2 \omega^2 a^2 / 2} \underbrace{\int_{-\infty}^{\infty} \frac{1}{\sqrt{2\pi}\sigma} e^{-[x - (m + j\sigma^2 \omega a)]^2 / 2\sigma^2} dx}_{=1}$$

$$\text{Therefore, } \phi_Y(\omega) = e^{j\omega b} e^{j\omega m a - \sigma^2 \omega^2 a^2 / 2}$$

$$= e^{j\omega(b+ma) - \omega^2 \sigma^2 a^2 / 2}$$

Mean $\frac{d}{d\omega} \phi_Y(\omega) = [j(b+ma) - \omega \sigma^2 a^2] e^{j\omega(b+ma) - \omega^2 \sigma^2 a^2 / 2}$

$$\Rightarrow \frac{1}{j} \frac{d}{d\omega} \phi_Y(\omega) \Big|_{\omega=0} = \frac{1}{j} [j(b+ma)] (1) = \underline{b+ma}$$

$$E(Y) = b+ma \text{ as expected.}$$

EE306: Signals and Systems II

Lecture 5

* Probability bounds

→ Markov bound: For X non-negative

$$P[X \geq a] \leq \frac{E(X)}{a}.$$

→ Chebyshev bound: $E(X) = m$, $V(X) = \sigma^2$

$$P[|X - m| \geq a] \leq \frac{\sigma^2}{a^2} \text{ (better bound).}$$

→ Chernoff bound:

$$P[X \geq a] \leq e^{-sa} E(e^{sX}).$$

Q How can we prove Markov bound?

Ex 1 Compare the Markov bound and the exact probability for the event $\{X > c\}$ as a function of c for X being a binomial RV with $p = 0.5$, $n = 10$.

Sol. Markov bound: $P[X \geq c] \leq \frac{E(X)}{c} = \frac{np}{c}$.

$$\begin{aligned} P[X > c] &= P[X \geq c] - P[X = c] \\ &\leq \frac{np}{c} - \binom{n}{c} p^c (1-p)^{n-c}. \end{aligned}$$

$$\begin{aligned} \text{Exact prob. : } P[X > c] &= 1 - P[X \leq c] \\ &= 1 - \sum_{k=0}^c \binom{n}{k} p^k (1-p)^{n-k}. \end{aligned}$$

→ Bound vs exact for $p=0.5$:

$$\frac{n}{2c} - \binom{n}{c} (0.5)^n \geq 1 - \sum_{k=0}^c \binom{n}{k} (0.5)^n$$

$$\Rightarrow \frac{n}{2c} \geq 1 - \sum_{k=0}^{c-1} \binom{n}{k} (0.5)^n.$$

Now set $n=10$: $c=1$ LHS=5, RHS=some prob.
 $c=10$ LHS=0.5, RHS= $(0.5)^{10}$.

Q What is your comment about the bound?

EX 2 Let X be the number of successes in n Bernoulli trials, where the prob. of success is p . Let $Y = X/n$ be the average no. of successes per trial. Apply Chebyshev bound to the event $\{|Y-p| > a\}$. What happens as $n \rightarrow \infty$?

Sol. Chebyshev bound: $P(|Y-m| \geq a) \leq \frac{\sigma^2}{a^2}$.

$$m = \mu_Y = E(X/n) = \frac{1}{n} E(X) = \frac{1}{n} (np) = p$$

since X is a binomial RV.

$$\sigma^2 = \sigma_Y^2 = \frac{1}{n^2} V(X) = \frac{1}{n^2} (np(1-p)) = \frac{p(1-p)}{n}$$

$$\text{Thus, } P(|Y-p| > a) = P(|Y-m| > a)$$

$$\leq P(|Y-m| \geq a) \leq \frac{\sigma^2}{a^2} = \frac{p(1-p)}{na^2}$$

As $n \rightarrow \infty$, $P(|Y-p| > a) \rightarrow 0 \Rightarrow$ useful bound.

* Chebyshev bound relies on mean and variance.

Since a is arbitrary, y converges to $m=p$ as $n \rightarrow \infty$.

* Recursion

→ Find probability via $p = f(p)$.

→ Find expectation via $E = f(E)$.

→ Avoid searching for underlying distributions.

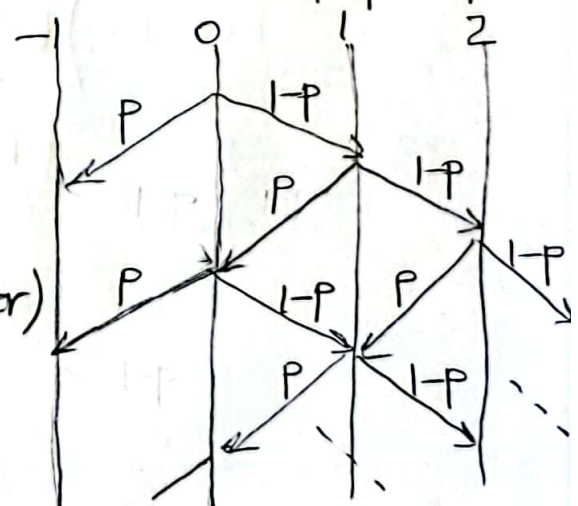
Ex 3 A man is playing chess games vs an online program at some difficulty level. The man loses a game with prob- p , and wins a game with prob- $1-p$, where p is fixed. He starts with a score of 0. His score increases (decreases) by 1 if he wins (loses) a game. As long as his score is non-neg., he keeps playing indefinitely. Once his score drops below 0, the online program blocks him.

→ Find the prob. the man is blocked if $p = \frac{1}{4}$.

Sol. Let $P(\text{blocked}) = P_b$.

$P_b = P(\text{loses first game}) + P(\text{wins it but be blocked later})$

$$\Rightarrow P_b = p + (1-p)P_{1 \rightarrow 0} P_{0 \rightarrow -1}$$



But $P_{1 \rightarrow 0} = P_{0 \rightarrow 1} = P_b$. Therefore,

$$P_b = p + (1-p)P_b^2 \Rightarrow P_b = \frac{1 \pm \sqrt{1-4(1-p)p}}{2(1-p)}$$

$$\Rightarrow P_b = \frac{1 \pm \sqrt{1-4p+4p^2}}{2(1-p)} = \frac{1 \pm (1-2p)}{2(1-p)}$$

$$\Rightarrow \underbrace{P_b = 1}_{\text{for } p > \frac{1}{2}} \text{ or } \underbrace{P_b = \frac{p}{1-p}}_{\text{for } p \leq \frac{1}{2}} \Rightarrow P_b = \frac{1/4}{3/4} = \underline{\underline{\frac{1}{3}}}$$

EX 4 Find the expected number of fair coin tosses needed to get three successive tails.

Sol. $E(\text{TTT}) = E = \sum_i E(\text{TTT} | A_i) P(A_i)$.

Thus, $E = (E+1)(\frac{1}{2})$

$+ (E+2)(\frac{1}{4})$

$+ (E+3)(\frac{1}{8})$

$+ (3)(\frac{1}{8}) \Rightarrow$

$$E = \left(\frac{4+2+1}{8}\right)E + \left(\frac{4+4+3+3}{8}\right)$$

$$\Rightarrow \frac{1}{8}E = \frac{14}{8}. \text{ Thus, } E = \underline{\underline{14}}.$$

