

# Statistical Signal Processing

Mid-Semester Test, Spring 2021-22

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Q1a

Here it is given that  $F_X(x)$  is a distribution function. Since  $F$  is a distribution function, it is non-decreasing.

Let  $Y = F_X(X)$ .

then we can find the distribution function of  $Y$  by,

$$\begin{aligned} G_Y(y) &= P(Y \leq y) = P[F(X) \leq y] \\ &= P[X \leq F^{-1}(y)] \end{aligned}$$

Since,  $F$  is non-decreasing & given to be continuous, the inverse exists.

$$\therefore G_Y(y) = F[F^{-1}(y)]$$

$$\Rightarrow \boxed{G_Y(y) = y}$$

$\therefore$  The probability distribution function of

$$Y = F(X)$$

$$g_Y(y) = \frac{d}{dy} [G_Y(y)] = 1$$

Since  $F$  is a distribution function its range is always  $[0, 1]$ .

Hence  $g_Y(y) = 1, 0 \leq y \leq 1 \Rightarrow Y$  is a uniform variate on  $[0, 1]$ .

Q20 = Here, using the moment generating functions (mgf) of  $x$  &  $y$  random variables.

$$M_x(t) = E(e^{tx}) = \frac{e^{t^2/2}}{\sqrt{2\pi}} e^{t^2/2}$$

$$M_y(t) = E(e^{ty}) = \frac{e^{t^2/2}}{\sqrt{2\pi}} e^{t^2/2}$$

$$M_z(t) = E(e^{tz}) = E\left\{e^{t(x+y)}\right\}$$

$$= E\left(e^{tx} e^{ty}\right)$$

$$= M_x(t) M_y(t) \text{ since } x \& y \text{ are independent.}$$

$$= e^{\frac{1}{2}(1+1)t^2}$$

the above is the moment generating function of a normal random variable with mean 0 & variance 2.

By using the uniqueness theorem of the mgf  $Z \sim N(0, 2)$ .

So, the pdf of  $Z = N(0, 2)$ .

Q2.

Given,

$$V(t) = X \cos(\omega t) + Y \sin \omega t$$
$$N(0, \sigma^2) = \frac{1}{\sqrt{2\pi} \sigma} e^{-\frac{t^2}{2\sigma^2}} = X = Y$$

$$(a) \quad V(t) = \frac{e^{-\frac{t^2}{2\sigma^2}}}{\sigma \sqrt{2\pi}} \left[ \cos \omega t + \sin \omega t \right]$$
$$= \frac{e^{-t^2/2\sigma^2}}{\sqrt{\pi} \sigma} \cos(\omega t - \pi/4)$$

(b)

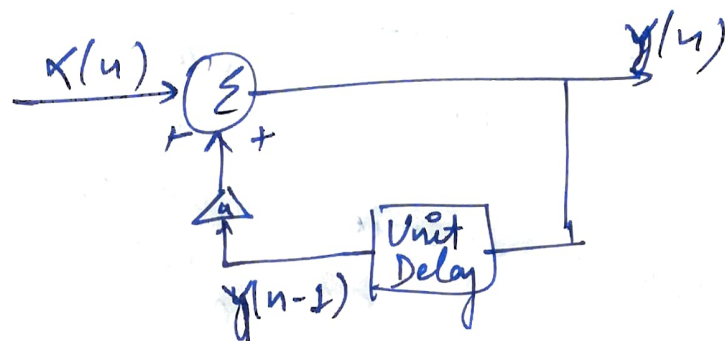
By comparison,

$$R = \frac{e^{-t^2/2\sigma^2}}{\sqrt{\pi} \sigma}$$

$$\theta = \frac{\pi}{4}$$

$\therefore$  'R' & 'θ' are independent.

Q40



Here,  $Y(n) = aY(n-1) + x(n).$

The impulse response of the system =  
 $h(n) = ah(n-1) + \delta(n).$

$$\Rightarrow h(n) = a^n u(n)$$

where  $u(n) = \begin{cases} 1 & n \geq 0 \\ 0 & n < 0 \end{cases}$ .  
 unit step sequence.

Taking fourier transform, we obtain

$$H(\omega) = \sum_{n=0}^{\infty} a^n e^{-j\omega n} = \frac{1}{1 - ae^{-j\omega}} \quad |a| < 1, |\omega| < \pi$$

$$S_{xx}(\omega) = \sigma^2 \quad |-\omega| < \pi$$

↳ power spectrum

∴ The power spectral density of the output  $Y(n)$

$$\begin{aligned}
 S_{YY}(\omega) &= |H(\omega)|^2 S_{XX}(\omega) \\
 &= \frac{H(\omega) H^*(\omega) S_{XX}(\omega)}{\sigma^2} \\
 &= \frac{\sigma^2}{(1 - ae^{-j\omega})(1 - ae^{j\omega})} \\
 &= \frac{\sigma^2}{1 + a^2 - 2a\cos\omega} \quad |\omega| < \pi
 \end{aligned}$$

Taking inverse fourier transform,

$$R_{YY}(k) = \frac{\sigma^2}{1 - a^2} a^{|k|}$$

Thus, the average power of  $Y(n)$  is

$$E[Y^2(n)] = R_{YY}(0) = \frac{\sigma^2}{1 - a^2}$$

Q6.

Proof:

Let  $a$  be an arbitrary (nonzero)  $M \times 1$  complex valued vector. We define the scalar random variable  $y$  as the inner product of  $a$  and the observation vector  $u(n)$ , by

$$y = a^H u(n).$$

Taking the Hermitian transpose of both sides & assuming  $y$  is a scalar, we get

$$y^* = u^H(n) \cdot a \quad \left\{ * \rightarrow \text{complex conjugate} \right\}$$

The mean-square value of the random variable  $y$  is

$$\begin{aligned} E[y^2] &= E[yy^*] \\ &= E[a^H u(n) u^H(n) a] \\ &= a^H E[u(n) u^H(n)] a \\ &= a^H R a \end{aligned}$$

where  $R$  is the correlation matrix,  $R = E[u(n) u^H(n)]$

The expression  $a^H R a$  is known as Hermitian form.

Since  $E[y^2] \geq 0$

$$a^H R a \geq 0$$

So, a hermitian form that satisfies this condition for every nonzero  $a$  is said to be non-negative definite or positive semidefinite.

Accordingly we may state that the correlation matrix of a discrete-time stochastic process is always non-negative definite.