

Concept of probability

- *Random Experiment*
- *Number of Outcomes - Events*
- *Sample Space – A collection of all possible events*
- *Complement*
- *Union*
- *Intersection*

Relative Frequency and Probability

$$f(A) = \lim_{N \rightarrow \infty} \frac{N(A)}{N}$$

$$P(A) = \lim_{N \rightarrow \infty} \frac{N(A)}{N}$$

Important Results

$$P(S) = 1 \quad P(\phi) = 0$$

$$P(A \cup B) = P(A) + P(B) \quad \text{if} \quad AB = \phi$$

Mutually Exclusive



$$P(AB) = P(BA)$$

Conditional Probability and Independent Events

$$P(AB) = P(A)P(B|A)$$

$$\Rightarrow P(B|A) = \frac{P(AB)}{P(A)}$$

Similarly $P(A|B) = \frac{P(AB)}{P(B)}$

Independent Events

A and B are independent if

$$P(B|A) = P(B)$$

or $P(A|B) = P(A)$

$$\Rightarrow P(AB) = P(A)P(B)$$

Does Order Matter in a Repeated Trials Series?

Let probability of success is $p \Rightarrow$ probability of failure is $q = 1 - p$

$$P(k \text{ successes in a specific order of } n \text{ trials}) = p^k (1 - p)^{n-k}$$

$$P(k \text{ successes in } n \text{ trials}) = \binom{n}{k} p^k (1 - p)^{n-k}$$

where
$$\binom{n}{k} = \frac{n!}{k!(n-k)!}$$

Binary Symmetric Channel (BSC)

$$P(0|1) = P(1|0) = P_e$$

and $P(0|0) = P(1|1) = 1 - P_e$

Two Interesting Examples from Digital Communication

- *Concatenation increases probability of error*
[start with probability of correct decision $(1 - P_E)$]
- *Redundancy reduces probability of error*
[(start with probability of error P_E)]

Random Variable

- *Discrete Random Variables*
- *Continuous Random Variables*

Let's first look at discrete random variables

1. *Probabilities*
2. *Joint Probabilities*
3. *Conditional Probabilities*
4. *Cumulative Distribution Function*

Discrete Probabilities

$$\sum_i P_x(x_i) = 1$$

Joint Probabilities

$$\sum_i \sum_j P_{xy}(x_i, y_j) = 1$$

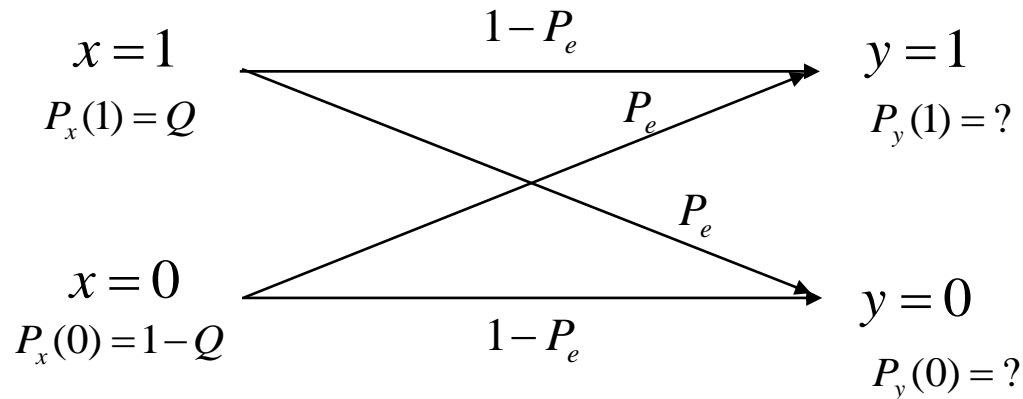
If x and y are independent

$$P_{xy}(x_i, y_j) = P_x(x_i)P_y(y_j)$$

Conditional Probabilities

$$\sum_i P_{x|y}(x_i|y_j) = \sum_j P_{y|x}(y_j|x_i) = 1$$

Binary Symmetric Channel (BSC)



We know

$$P_y(y_j) = \sum_i P_{xy}(x_i, y_j)$$

$$= \sum_i P_x(x_i) P_{y|x}(y_j | x_i)$$

$$\Rightarrow P_y(1) = P_x(0)P_{y|x}(1|0) + P_x(1)P_{y|x}(1|1)$$

$$= (1 - Q)P_e + Q(1 - P_e)$$

Cumulative Distribution Function (CDF)

$$F_X(x) = P(X \leq x)$$

Properties

$$F_X(x) \geq 0$$

$$F_X(\infty) = 1$$

$$F_X(-\infty) = 0$$

$$F_X(x_1) \leq F_X(x_2) \quad \text{for } x_1 \leq x_2$$

$$\frac{dF_X(x)}{dx} = P_X(x)$$

$$F_X(x) = \int_{-\infty}^x P_X(x) dx$$

We know that

$$F_X(\infty) = 1 \quad \Rightarrow \quad \int_{-\infty}^{\infty} P_X(x) dx = 1$$

Similarly

$$P(x_1 < X \leq x_2) = F_X(x_2) - F_X(x_1)$$

$$= \int_{-\infty}^{x_2} P_X(x) dx - \int_{-\infty}^{x_1} P_X(x) dx$$

$$= \int_{x_1}^{x_2} P_X(x) dx$$

Gaussian PDF

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

$$\Rightarrow F_X(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{x^2}{2}} dx$$

Cannot be solved analytically, so let's define

$$Q(y) = \frac{1}{\sqrt{2\pi}} \int_y^{\infty} e^{-\frac{x^2}{2}} dx \quad \text{Which is widely tabulated}$$

$$\Rightarrow F_X(x) = 1 - Q(x)$$

More General Gaussian PDF

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

$$\Rightarrow F_X(x) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^x e^{-\frac{(x-m)^2}{2\sigma^2}} dx$$

Let $(x-m)/\sigma = z$

Then

$$F_X(x) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^{(x-m)/\sigma} e^{-\frac{z^2}{2}} dz$$

$$\Rightarrow F_X(x) = 1 - Q\left(\frac{x-m}{\sigma}\right)$$

Statistical Averages (Means)

$$\bar{X} = \frac{N_1x_1 + N_2x_2 + \dots N_nx_n}{N}$$

where $N = N_1 + N_2 + \dots N_n = \sum_i N_i$

$$\bar{X} = \frac{N_1x_1}{N} + \frac{N_2x_2}{N} + \dots \frac{N_nx_n}{N} = \sum_{i=1}^n \frac{N_i}{N} x_i$$

$$= \sum_{i=1}^n P_x(x_i)x_i \quad \text{as } N \rightarrow \infty$$

If X is continuous random variable

$$\bar{X} = \int_{-\infty}^{\infty} xP_X(x)dx$$

Mean of a Function of Random Variable

$$\text{Let } Y = g(X)$$

$$\text{then } \bar{Y} = \overline{g(X)} = \int_{-\infty}^{\infty} g(X)P_X(x)dx$$

Moments and Central Moments

nth moment

$$\overline{X^n} = \int_{-\infty}^{\infty} x^n P_X(x) dx$$

nth central moment

$$\overline{(X - \bar{X})^n} = \int_{-\infty}^{\infty} (x - \bar{x})^n P_X(x) dx$$

Special Cases

$$\text{variance} = \sigma_X^2 = \int_{-\infty}^{\infty} (x - \bar{x})^2 P_X(x) dx$$

$$\text{standard deviation} = \sigma_X = \sqrt{\int_{-\infty}^{\infty} (x - \bar{x})^2 P_X(x) dx}$$

Variance of Two Independent Variables

If X and Y are independent variables

$$\text{Let } Z = X + Y$$

$$\text{Then } \sigma_Z^2 = \sigma_X^2 + \sigma_Y^2$$

$$\begin{aligned}\sigma_Z^2 &= \overline{(z - \bar{z})^2} = \overline{[x + y - (\bar{x} + \bar{y})]^2} \\ &= \overline{[(x - \bar{x}) + (y - \bar{y})]^2} \\ &= \overline{(x - \bar{x})^2} + \overline{(y - \bar{y})^2} + \overline{2(x - \bar{x})(y - \bar{y})} \\ &= \sigma_X^2 + \sigma_Y^2 + \cancel{0} \\ &= \sigma_X^2 + \sigma_Y^2\end{aligned}$$

Central Limit Theorem

Sum of large number of random variables tend to be Gaussian.

$$\text{Let } Z = X + Y$$

$$\Rightarrow Y = Z - X$$

$$F_z(z) = P(z \leq z) = P(x \leq \infty, y \leq z - x)$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{z-x} P_{XY}(x, y) dx dy$$

$$= \int_{-\infty}^{\infty} dx \int_{-\infty}^{z-x} P_{XY}(x, y) dy$$

$$p_z(z) = \frac{dF_z(z)}{dz} = \frac{d}{dz} \int_{-\infty}^{\infty} dx \int_{-\infty}^{z-x} P_{XY}(x, y) dy$$

$$\begin{aligned}
P_z(z) &= \frac{dF_z(z)}{dz} = \frac{d}{dz} \int_{-\infty}^{\infty} dx \int_{-\infty}^{z-x} P_{XY}(x, y) dy \\
&= \int_{-\infty}^{\infty} dx \frac{d}{dz} \int_{-\infty}^{z-x} P_{XY}(x, y) dy \\
\Rightarrow P_z(z) &= \int_{-\infty}^{\infty} P_{XY}(x, z-x) dx
\end{aligned}$$

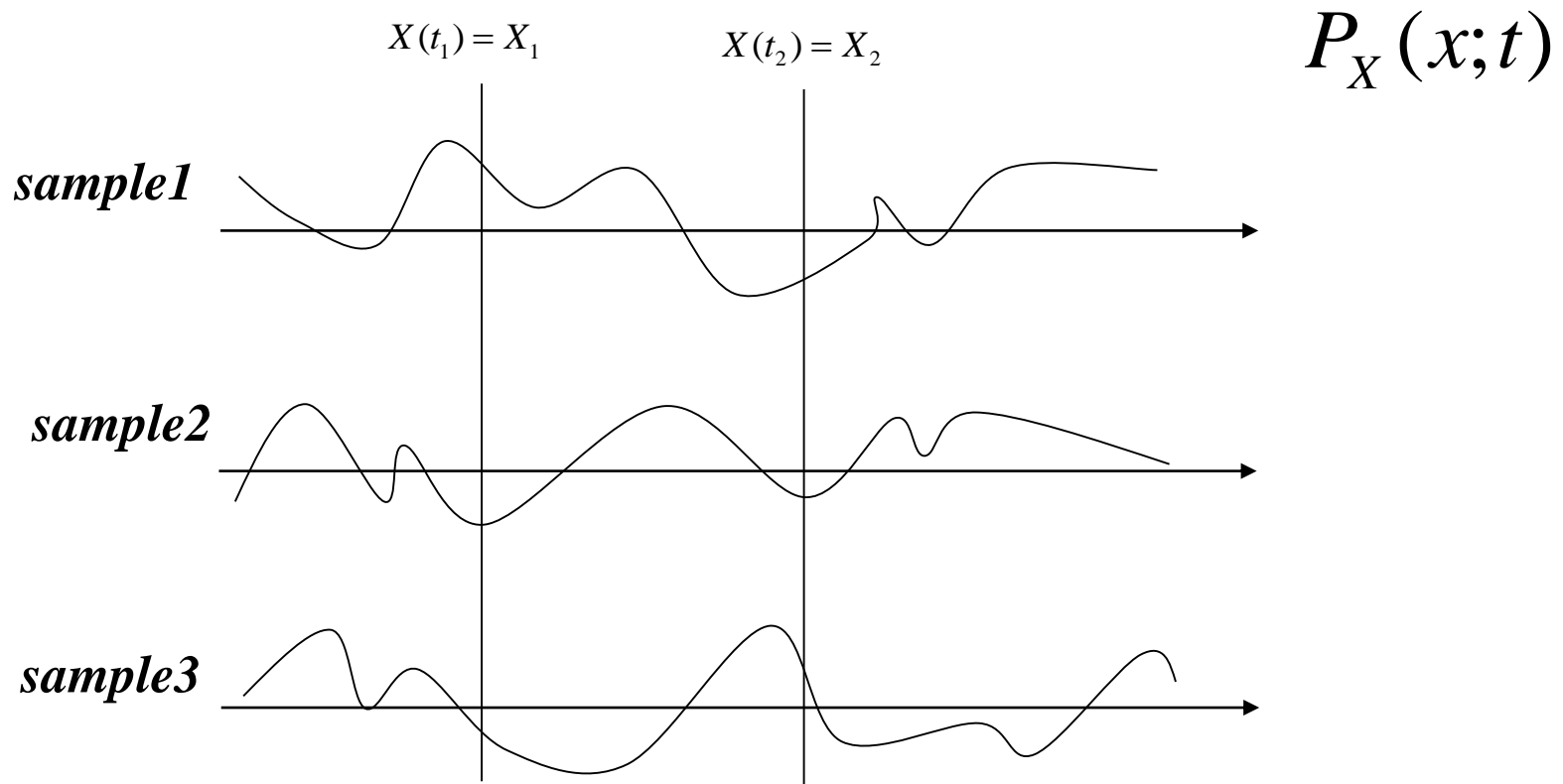
If X and Y are independent RVs, then

$$\begin{aligned}
P_{XY}(x, z-x) &= P_X(x)P_Y(z-x) \\
\Rightarrow P_z(z) &= \int_{-\infty}^{\infty} P_X(x)P_Y(z-x) dx \\
&= P_X(x) * P_Y(y)
\end{aligned}$$

Random Processes

A random variable which is a function of time is a random process.

A random Variable is X and a random Process is $X(t)$



Autocorrelation Function of A Random Process

$$\begin{aligned} R_X(t_1, t_2) &= \overline{X(t_1)X(t_2)} = \overline{X_1 X_2} \\ &= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 x_2 P_{X_1 X_2}(x_1, x_2) dx_1 dx_2 \end{aligned}$$

For stationary random processes:

$$P_X(x; t) = P_X(x)$$

and $R_X(t_1, t_2) = R_X(t_2 - t_1) = R_X(\tau)$

$$R_X(\tau) = \overline{X(t)X(t + \tau)}$$

An Example of a Random Process

$$X(t) = A \cos(\omega_c t + \Theta)$$

$$\overline{X(t)} = ? \quad \text{and} \quad R_X(\tau) = ?$$

$$\overline{X(t)} = \overline{A \cos(\omega_c t + \Theta)} = \overline{A \cos(\omega_c t + \Theta)}$$

$$\begin{aligned} \overline{\cos(\omega_c t + \Theta)} &= \int_0^{2\pi} \cos(\omega_c t + \theta) P_{\Theta}(\theta) d\theta \\ &= \frac{1}{2\pi} \int_0^{2\pi} \cos(\omega_c t + \theta) d\theta = 0 \end{aligned}$$

$$\Rightarrow \overline{X(t)} = 0$$

$$\begin{aligned}
R_X(t_1, t_2) &= \overline{A^2 \cos(\omega_c t_1 + \Theta) \cos(\omega_c t_2 + \Theta)} \\
&= \overline{A^2 \cos(\omega_c t_1 + \Theta) \cos(\omega_c t_2 + \Theta)} \\
&= \frac{A^2}{2} \{ \overline{\cos[\omega_c(t_1 - t_2)]} + \overline{\cos[\omega_c(t_1 + t_2) + 2\Theta]} \} \\
&= \frac{A^2}{2} \{ \overline{\cos[\omega_c(t_1 - t_2)]} + \overline{\cos[\omega_c(t_1 + t_2) + 2\Theta]} \}
\end{aligned}$$

$$\begin{aligned}
\overline{\cos[\omega_c(t_1 + t_2) + 2\Theta]} &= \frac{1}{2\pi} \int_0^{2\pi} \cos[\omega_c(t_1 + t_2) + 2\theta] d\theta \\
&= 0
\end{aligned}$$

$$\Rightarrow R_X(t_1, t_2) = \frac{A^2}{2} \cos \omega_c(t_1 - t_2) = \frac{A^2}{2} \cos \omega_c(\tau)$$

Autocorrelation function of a power signal

$$\mathfrak{R}_g(\tau) = \lim_{T \rightarrow \infty} \frac{1}{T} \int_{-\infty}^{\infty} g(t)g(t + \tau)dt$$

Reminder Slide

Same argument as in energy signals will prove that

$$\mathfrak{R}_g(\tau) = \mathfrak{R}_g(-\tau)$$

and $\mathfrak{R}_g(\tau) \Leftrightarrow S_g(\omega)$

also $S_y(\omega) = |H(\omega)|^2 S_g(\omega)$

if $Y(\omega) = H(\omega)G(\omega)$

Power Spectral Density of a Deterministic Signal

$$S_g(\omega) = \lim_{T \rightarrow \infty} \frac{|G_T(\omega)|^2}{T}$$

$$S_g(\omega) \Leftrightarrow R_g(\tau)$$

Power Spectral Density of Random Process

$$S_X(\omega) = \lim_{T \rightarrow \infty} \left[\frac{|X_T(\omega)|^2}{T} \right]$$

$$S_X(\omega) \Leftrightarrow R_X(\tau)$$

$$S_X(\omega) \Leftrightarrow R_X(\tau)$$

$$\Rightarrow S_X(\omega) = \int_{-\infty}^{\infty} R_X(\tau) e^{-j\omega(\tau)} d\tau$$

Also remember

$$R_X(\tau) = \overline{X(t)X(t+\tau)}$$

Let $t + \tau = \sigma$

$$\begin{aligned} R_X(-\tau) &= \overline{X(\sigma + \tau)X(\sigma)} \\ &= \overline{X(\sigma)X(\sigma + \tau)} = R_X(\tau) \end{aligned}$$

Power of a Random Process

$$P_X = \overline{X^2}$$

$$\begin{aligned} R_X(0) &= \overline{X(t)X(t)} \\ &= \overline{X^2(t)} = \overline{X^2} \end{aligned}$$

$$\Rightarrow P_X = R_X(0)$$

$$= \frac{1}{2\pi} \int_{-\infty}^{\infty} S_X(\omega) d\omega$$

$$= \frac{1}{\pi} \int_0^{\infty} S_X(\omega) d\omega$$

Example 1 – Low-Pass Random Process

$$S_X(\omega) = \frac{N}{2} \operatorname{rect}\left(\frac{\omega}{4\pi B}\right)$$

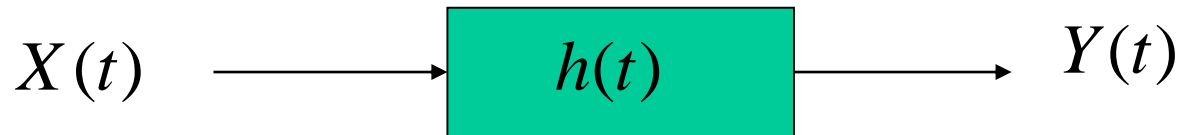
$$\Rightarrow R_X(\tau) = NB \operatorname{sinc}(2\pi B\tau)$$

$$P_X = R_X(0) = NB$$

Alternatively

$$\begin{aligned} P_X &= \frac{1}{\pi} \int_0^{\infty} S_X(\omega) d\omega = 2 \int_0^{\infty} S_X(f) df \\ &= 2 \int_0^B \frac{N}{2} df = NB \end{aligned}$$

Transmission through Linear System



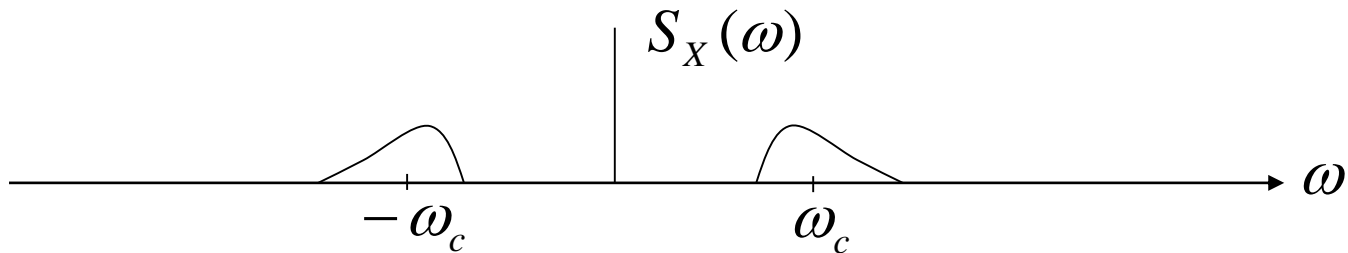
$$S_Y(\omega) = |H(\omega)|^2 S_X(\omega)$$

Sum of Independent Random Processes

$$\text{If } Z(t) = X(t) + Y(t)$$

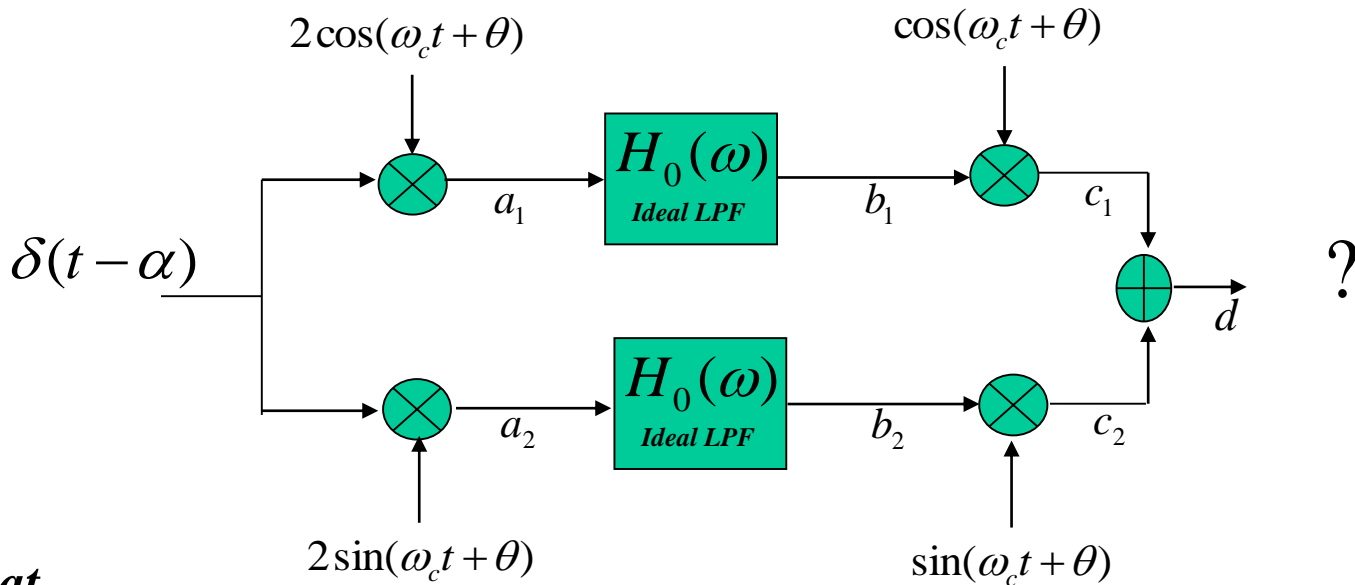
$$\text{then } S_Z(\omega) = S_X(\omega) + S_Y(\omega)$$

Bandpass Random Process



$$X(t) = X_c(t) \cos \omega_c t + X_s(t) \sin \omega_c t$$

Bandpass random process has two quadrature low pass components having equal power.



Signals at

$$a_1 = 2 \cos(\omega_c \alpha + \theta) \delta(t - \alpha)$$

$$a_2 = 2 \sin(\omega_c \alpha + \theta) \delta(t - \alpha)$$

$$b_1 = 2 \cos(\omega_c \alpha + \theta) h_0(t - \alpha)$$

$$b_2 = 2 \sin(\omega_c \alpha + \theta) h_0(t - \alpha)$$

$$c_1 = 2 \cos(\omega_c \alpha + \theta) \cos(\omega_c t + \theta) h_0(t - \alpha)$$

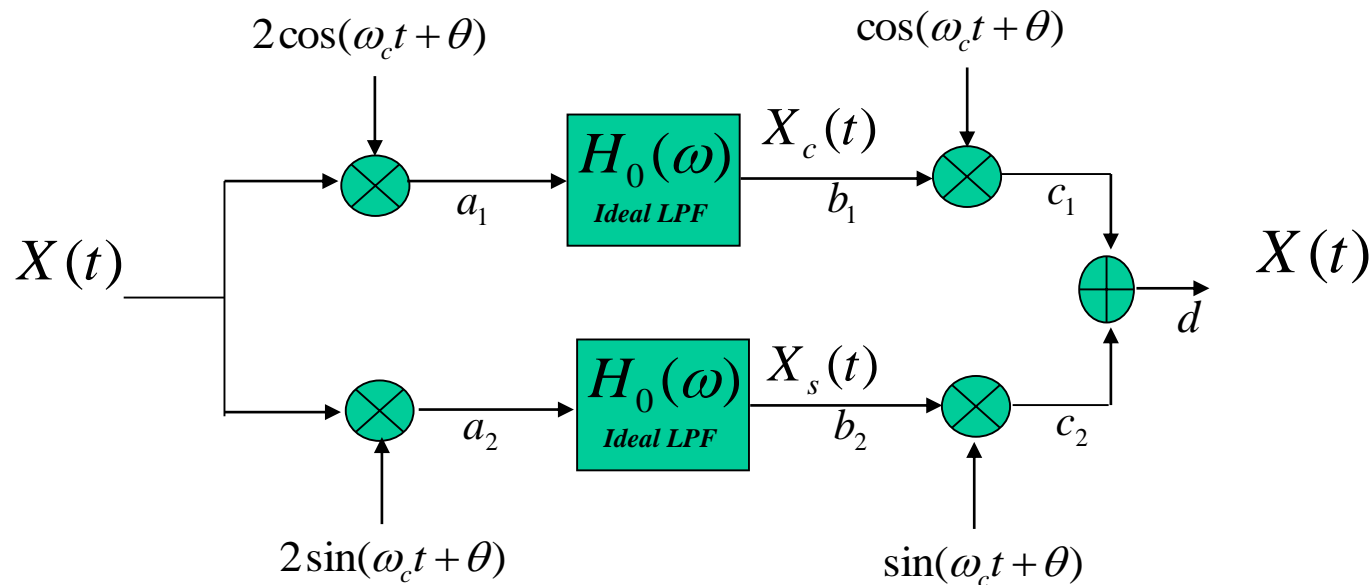
$$c_2 = 2 \sin(\omega_c \alpha + \theta) \sin(\omega_c t + \theta) h_0(t - \alpha)$$

$$d = 2h_0(t - \alpha) [\cos(\omega_c \alpha + \theta) \cos(\omega_c t + \theta) + \sin(\omega_c \alpha + \theta) \sin(\omega_c t + \theta)]$$

$$= 2h_0(t - \alpha) \cos[\omega_c(t - \alpha)]$$

$$d = 2h_0(t - \alpha) \cos[\omega_c(t - \alpha)]$$

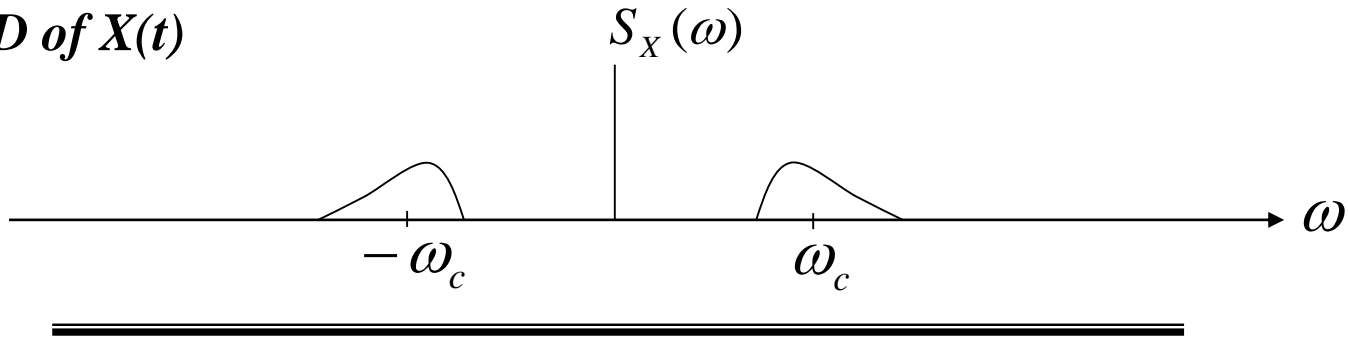
$$\Rightarrow H(\omega) = H_0(\omega + \omega_c) + H_0(\omega - \omega_c)$$



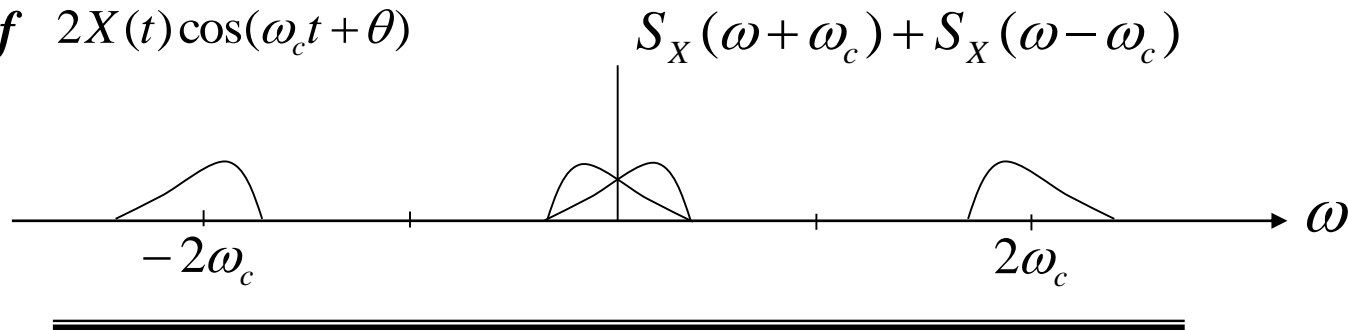
$$X(t) = X_c(t) \cos(\omega_c t + \theta) + X_s(t) \sin(\omega_c t + \theta)$$

PSD of Quadrature Components

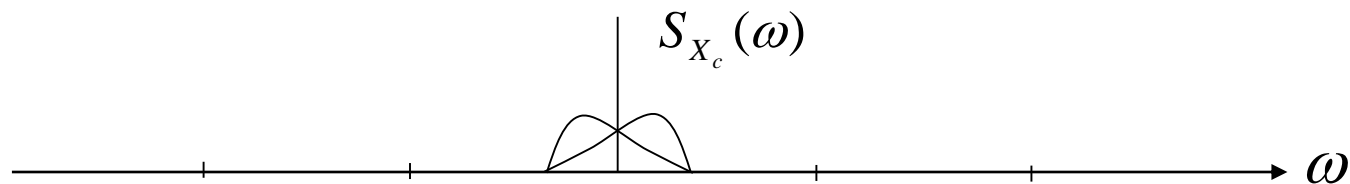
PSD of $X(t)$



PSD of $2X(t)\cos(\omega_c t + \theta)$



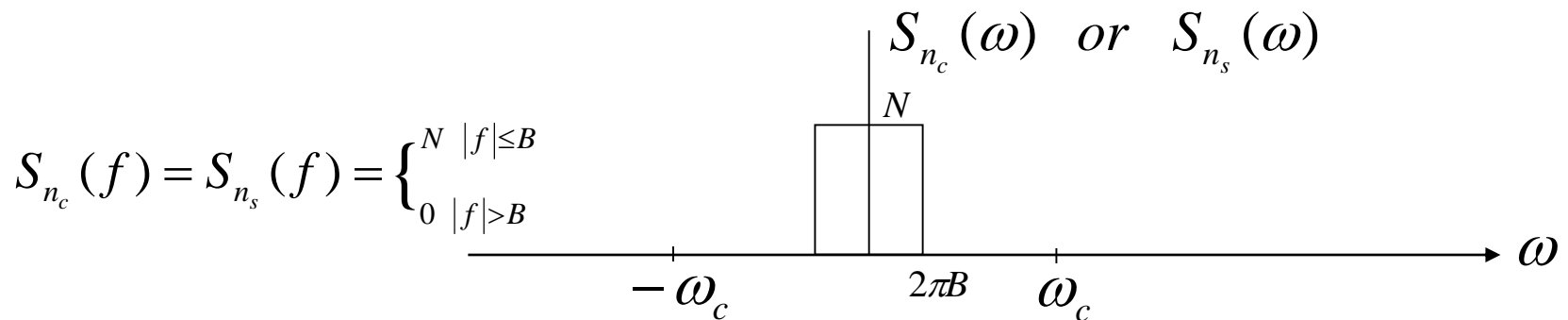
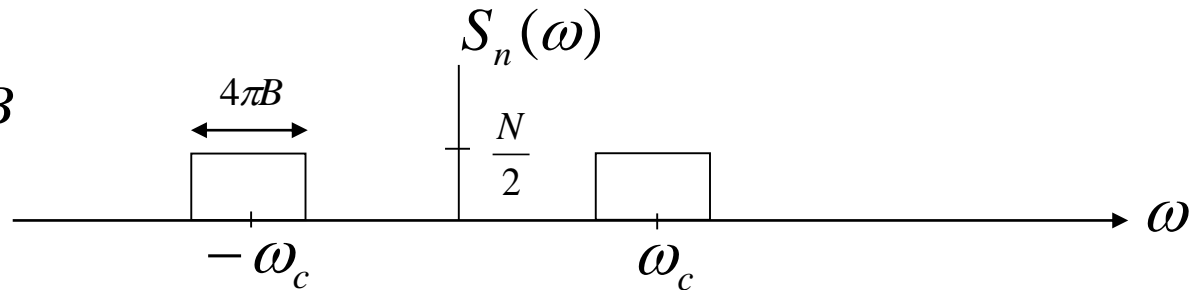
PSD of $2X(t)\cos(\omega_c t + \theta)$ after passing through LPF



$$\Rightarrow \overline{X_c^2} = \overline{X_s^2} = \overline{X^2}$$

Example – Bandpass Noise

$$\overline{n^2} = 2 \int_{f_c-B}^{f_c+B} \frac{N}{2} df = 2NB$$



$$\overline{n_c^2} = \overline{n_s^2} = 2 \int_0^B N df = 2NB$$

$$\Rightarrow \overline{n^2} = \overline{n_c^2} = \overline{n_s^2} = 2NB$$