

# INFORMATION AND COMMUNICATION THEORY

Unit-1: Probability Theory

Unit-2: Stochastic Processes

Unit-3: Estimation & Hypothesis Testing

Unit-4: Information Theory

Unit-5: Statistical Modeling of Noise

## Module-3-Unit-2

- Stochastic Processes
- Statistical Modeling of Noise

# **Lecture-1 (Unit-2, Module-3)**

## **Stochastic Process**

# Stochastic (Random) Process

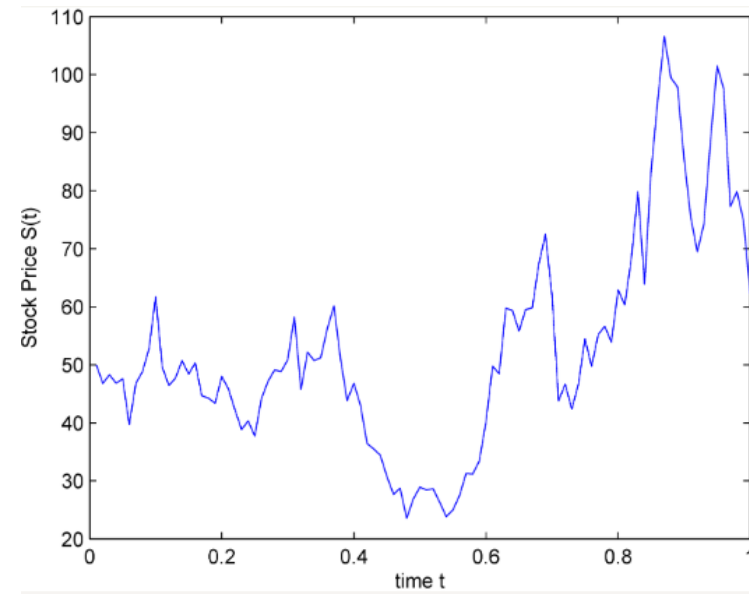
Random variable is a rule to assign a number  $x(\xi)$  to every outcome  $\xi$  of an experiment  $S$ .

A stochastic process is a rule to assign a function  $X(t, \xi)$  to every outcome  $\xi$  of an experiment  $S$ .

Stochastic process is represented by  $X(t)$ . It has following interpretations –

- It is a family (or ensemble) of functions  $X(t, \xi)$ . Here  $t$  and  $\xi$  are variables.
- It is a single time-function (or a **sample** of the given process). In this case  $t$  is a variable but  $\xi$  is fixed.
- It is the random variable equal to the state of given process at time  $t$ . In this case  $\xi$  is a variable but  $t$  is fixed.
- It is a number if both  $t$  and  $\xi$  are fixed.

At time  
 $t_1 \in [0, \infty)$   
 $t_2 \in [0, \infty)$



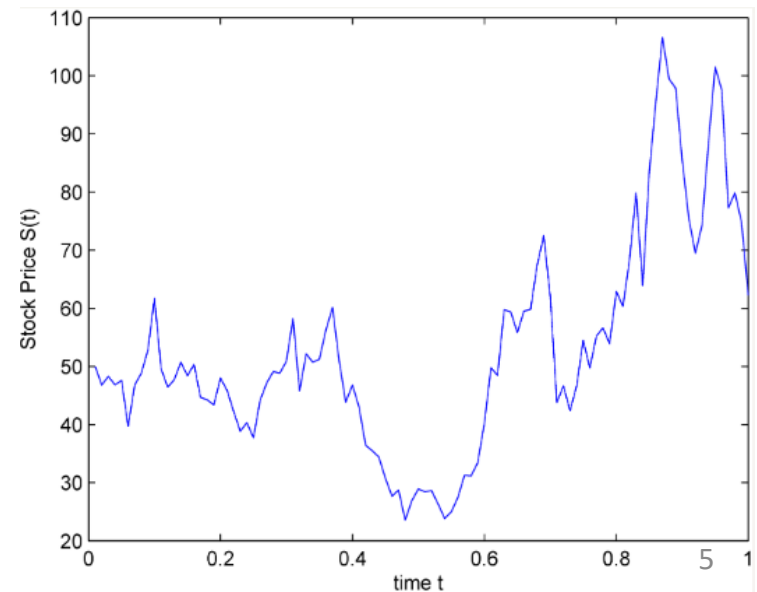
# Random Process

*In real-life applications, we are often interested in multiple observations of random values over a period of time.*

## Example:

observing the stock price of a company over the next few months. In particular, let  $S(t)$  be the stock price at time  $t \in [0, \infty)$ ,  $t = 0$  refers to current time.

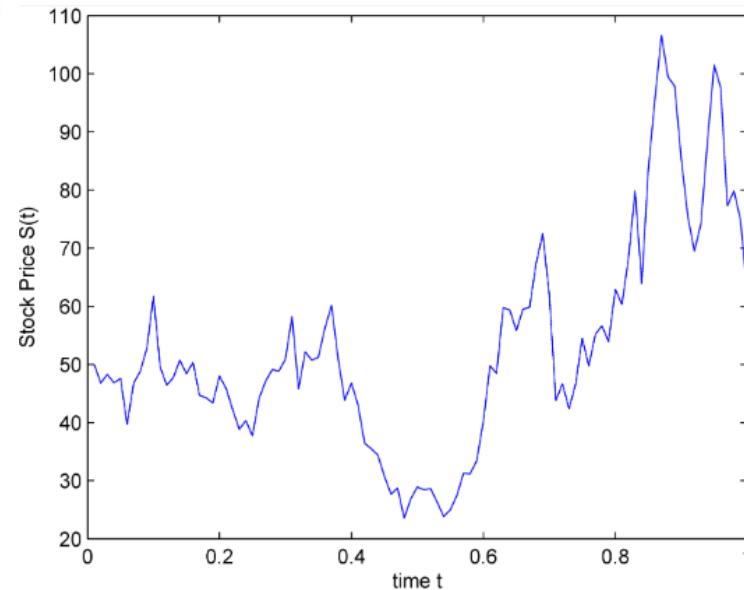
Figure shows a possible outcome of this random experiment from time  $t = 0$  to time  $t = 1$ .



A random process is a collection of random variables usually indexed by time.

At  $t_1 \in [0, \infty)$ ,  $S(t_1)$  is a random variable. At time  $t_2 \in [0, \infty)$ ,  $S(t_2)$  is another random variable could have a different PDF. The collective values of  $S(t)$  for  $t \in [0, \infty)$  is a **random process** or a **stochastic process**.

$$\{S(t), t \in [0, \infty)\}$$



The function shown in this figure is just one of the many possible outcomes of this random experiment.

We call each of these possible functions of  $S(t)$  a **sample function** or **sample path**.

# Continuous-time random processes

Let  $N(t)$  be the number of customers who have *visited a bank* from  $t = 9$  (when the bank opens at 9:00 AM) until time  $t$ , on a given day, for  $t \in [9,16]$ .

Here, we measure  $t$  in hours, but  $t$  can take any real value between 9 and 16.

We assume that  $N(9) = 0$ , and  $N(t) \in \{0,1,2, \dots\}$  for all  $t \in [9,16]$ .

Note that for any time  $t_1$ , the random variable  $N(t_1)$  is a discrete random variable.

Thus,  $N(t)$  is a *discrete-valued random process*.

However, since  $t$  can take any real value between 9 and 16,  $N(t)$  is a ***continuous-time random process***.

There are uncountable number of random variables. For example, for any given  $t_1 \in [9,16]$ ,  $N(t_1)$  is a random variable.

Thus, the ***random process  $N(t)$  consists of an uncountable number of random variables***.



# Discrete-time random processes

A discrete-time random process is a process

$\{X(t), t \in J\}$ , where  $J$  is a countable set i.e.  $J = \{t_1, t_2, \dots\}$ .

We usually define  $X(t_n) = X(n)$  or  $X(t_n) = X(n)$ , for  $n = 1, 2, \dots$ ,  
(the index values  $n$  could be from any countable set such as natural number or integers i.e.  $\mathbb{N}$  or  $\mathbb{Z}$ ).

Therefore, ***a discrete-time random process is just a sequence of random variables.***

Or, if the process is defined for all integers, then we may show the process by

$$\{X(n), n \in \mathbb{Z}\} \text{ or } \{X_n, n \in \mathbb{Z}\}$$

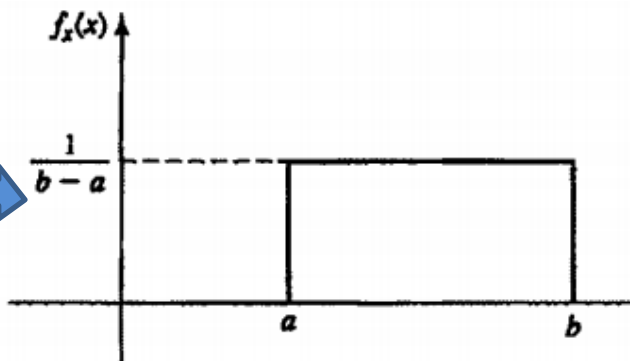
*Discrete-time processes are sometimes obtained from continuous-time processes by discretizing time (sampling at specific times).*

# Example:

You have 1000 dollars to put in an account with interest rate  $R$ , compounded annually. That is, if  $X_n$  is the value of the account at year  $n$ , then

$$X_n = 1000(1 + R)^n, \text{ for } n = 0, 1, 2, \dots$$

If  $R \sim \text{Uniform}(0.04, 0.05)$ , determine sample functions for the random process  $\{X_n, n = 0, 1, 2, \dots\}$  and the expected value of account at year three i.e.  $E[X_3]$ .



The probability density function of the continuous uniform distribution is:

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b, \\ 0 & \text{for } x < a \text{ or } x > b \end{cases}$$

# Solution:

Here, the randomness in  $X_n$  comes from the random variable  $R$ .  
Here,

$$X_n = 1000(1 + R)^n, \forall n \in \{0, 1, 2, \dots\}$$

So sample functions are of the form

$$f(n) = 1000(1 + R)^n, \text{ for } n = 0, 1, 2, \dots$$

where  $R \in (0.04, 0.05)$

For any value of  $R \in (0.04, 0.05)$  a sample function of random process  $X_n$  can be obtained.

$$X_n = 1000(1 + R)^n = 1000Y^n, \text{ thus}$$

$$Y \sim \text{Uniform}(1.04, 1.05) \text{ and}$$

$$f_Y(y) = \begin{cases} 100, & 1.04 \leq y \leq 1.05 \\ 0, & \text{elsewhere} \end{cases}$$

# Expected value of sample function at $n=3$

$$E[X_3] = E[1000Y^3]$$


We know that

## Continuous random variable

The expected value or mean of a random variable  $x$  is given as

$$E\{x\} = \int_{-\infty}^{\infty} x f(x) dx$$

$f_Y(y) = \begin{cases} 100, & 1.04 \leq y \leq 1.05 \\ 0, & \text{elsewhere} \end{cases}$

*pdf* 

$$= 1000 \int_{1.04}^{1.05} 100 y^3 dy$$

$$\approx 1141$$

# CDF of Random Process

A stochastic process is a non-countable collection of random variables, one for each  $t$ .

*For a specific  $t$ ,  $X(t)$  is random variable* with distribution

$$F(x, t) = P\{X(t) \leq x\}$$

This function depend on  $t$  and it equals the probability of the event  $\{X(t) \leq x\}$  consisting of all outcomes  $\xi$ , such that, at specific time  $t$ , the samples of  $X(t, \xi)$  of the given process does not exceed  $x$ .

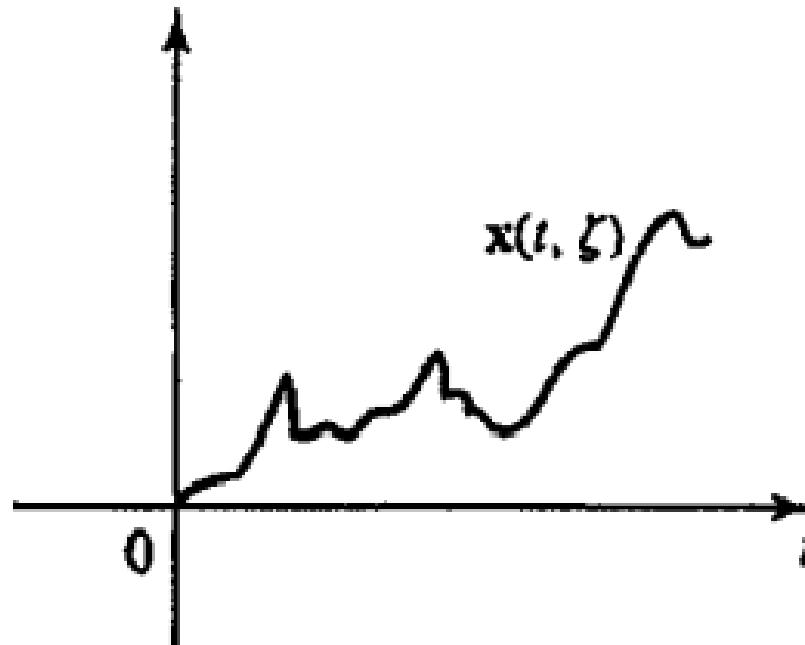
$F(x, t)$  is called first-order distribution of the process  $X(t)$

$f(x, t) = \frac{\partial F(x, t)}{\partial x}$  is the first-order density of the process  $X(t)$

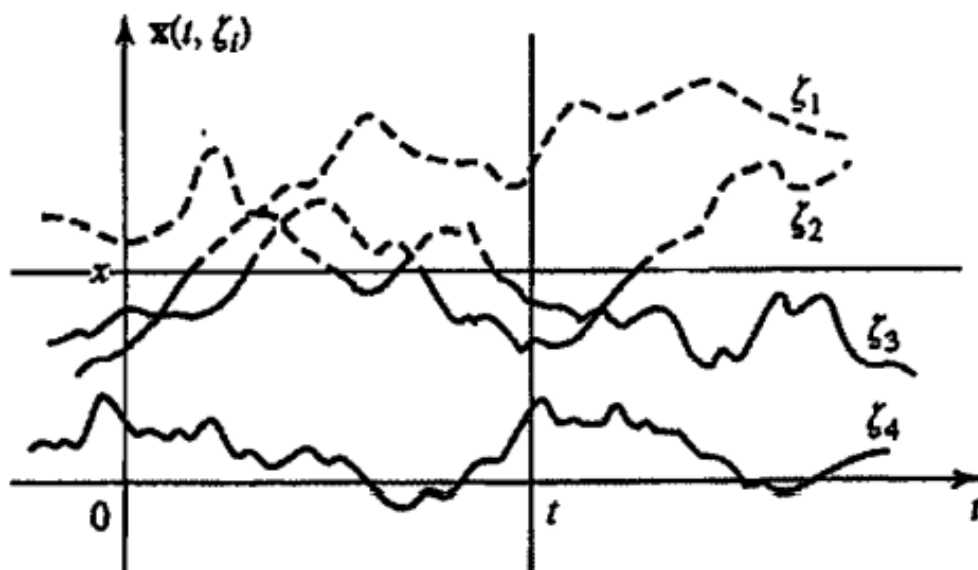
# Continued...

Consider the random process  $\{X(t), t \in J\}$ . For any  $t_0 \in J$ ,  $X(t_0)$  is a random variable, so we can write its CDF as

$$F_{X(t_0)}(x) = P\{X(t_0) \leq x\}.$$



If the experiment is performed  $n$  times, then  $n$  functions  $x(t, \varepsilon_i)$  are observed, one for each trial as shown in figure below:



If  $t_1, t_2 \in J$ , then the joint CDF  $X(t_1)$  and  $X(t_2)$  is

$$\begin{aligned} F(x_1, x_2, t_1, t_2) &= F_{X(t_1) X(t_2)}(x_1, x_2) \\ &= P\{X(t_1) \leq x_1, X(t_2) \leq x_2\} \end{aligned}$$



## Example:

Consider the random process  $\{X_n, n = 0, 1, 2, \dots\}$  in which  $X_i$ 's are i.i.d. standard normal random variables.

Find  $f_{X_n}(x)$  and  $f_{X_m, X_n}(x_1, x_2)$

**Solution:** Since  $X_n \sim N(0, 1)$ ,

PDF of normal RV is

$$f_{X_n}(x) = \frac{1}{\sigma\sqrt{2\pi}} e^{-(x-\eta)^2/2\sigma^2}$$

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

Since it is i.i.d.

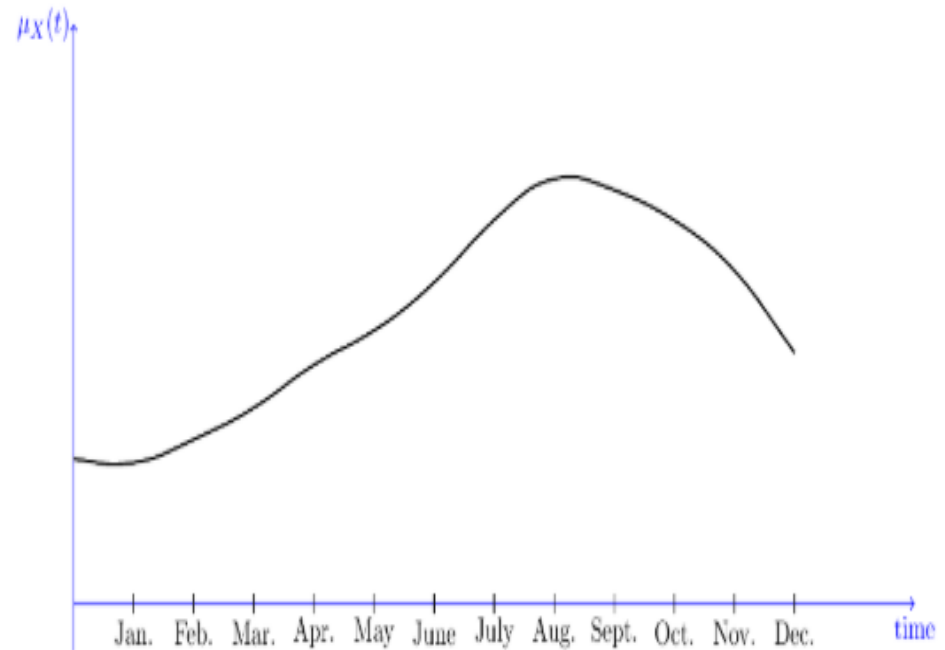
$$\begin{aligned} f_{X_m, X_n}(x_1, x_2) &= f_{X_m}(x_1) f_{X_n}(x_2) \\ &= \left( \frac{1}{\sqrt{2\pi}} e^{-x_1^2/2} \right) \left( \frac{1}{\sqrt{2\pi}} e^{-x_2^2/2} \right) \\ &= \frac{1}{\sqrt{2\pi}} e^{-(x_1^2 + x_2^2)/2} \end{aligned}$$

# Mean Functions

*The mean function gives an idea about how the random process behaves on average as time evolves.*

$$\mu_X(t) = E[X(t)] = \int_{-\infty}^{\infty} x f(x, t) dx \quad \mu_X(n) = E[X_n]$$

For example, if  $X(t)$  is the temperature in a certain city, the mean function  $\mu_X(t)$  might look like the function shown in Figure below. *(the expected value of  $X(t)$  is lowest in the winter and highest in the summer)*



# Correlation and Covariance Functions

The mean function  $\mu_X(t)$  gives the expected value of  $X(t)$  at time  $t$ , but it does not give any information about how  $X(t_1)$  and  $X(t_2)$  are related.

The **autocorrelation function**,  $R_X(t_1, t_2)$  is defined for a random process  $\{X(t), t \in J\}$

**We know that:**  $\mu_X(t) = E[X(t)] = \int_{-\infty}^{\infty} x f(x, t) dx$

$$R_X(t_1, t_2) = E[X(t_1) X(t_2)]$$
$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x_1 x_2 f(x_1, x_2, t_1, t_2) dx_1 dx_2 \quad \text{for } t_1, t_2 \in J$$



**$x_1$  and  $x_2$  are two values of  $X$  at two different time  $t_1$  and  $t_2$**

# The auto covariance function

We know that:

$$\sigma^2 = E\{(x - \eta)^2\} = \int_{-\infty}^{\infty} (x - \eta)^2 f(x) dx$$
$$\sigma^2 = E\{x^2\} - E^2\{x\}$$

**Proof:**

$$\begin{aligned}\sigma^2 &= E\{(x - \eta)^2\} = E\{x^2 - 2x\eta + \eta^2\} \\ &= E\{x^2\} - 2\eta E\{x\} + \eta^2 \\ &= E\{x^2\} - 2\eta \eta + \eta^2 \\ &= E\{x^2\} - 2\eta^2 + \eta^2 \\ &= E\{x^2\} - \eta^2\end{aligned}$$

**How?**

$$\begin{aligned}C_X(t_1, t_2) &= Cov[X(t_1) X(t_2)] \\ &= E[\{X(t_1) - E[X(t_1)]\} \{X(t_2) - E[X(t_2)]\}] \\ &= R_X(t_1, t_2) - \mu_X(t_1)\mu_X(t_2) \quad \text{for} \quad t_1, t_2 \in J\end{aligned}$$

**How?**

# HELP:

$$\begin{aligned}C_X(t_1, t_2) &= \text{Cov}[X(t_1) X(t_2)] \\&= E[\{X(t_1) - E[X(t_1)]\} \\&\quad \{X(t_2) - E[X(t_2)]\}] \\&= R_X(t_1, t_2) \\&\quad - \mu_X(t_1)\mu_X(t_2) \\&\quad \text{for } t_1, t_2 \in J\end{aligned}$$

$$= \text{COV}[X(t_1) X(t_2)]$$

$$= E[\{X(t_1) - E[X(t_1)]\} \{X(t_2) - E[X(t_2)]\}]$$

$$= E[\{X(t_1) X(t_2) - X(t_1) E[X(t_2)] - X(t_2) E[X(t_1)] + E[X(t_1)] E[X(t_2)]\}]$$

$$= E[\{X(t_1) X(t_2) - X(t_1) \mu_2 - X(t_2) \mu_1 + \mu_1 \mu_2\}]$$

$$= E[X(t_1) X(t_2)] - \mu_2 E[X(t_1)] - \mu_1 E[X(t_2)] + \mu_1 \mu_2$$

$$= R_X(t_1, t_2) - \mu_2 \mu_1 - \cancel{\mu_1 \mu_2} + \cancel{\mu_1 \mu_2}$$

$$= R_X(t_1, t_2) - \mu_2 \mu_1$$

## Continued...

The **autocovariance function**,  $C_X(t_1, t_2)$  is defined for a random process  $\{X(t), t \in J\}$

### Special condition:

If  $t_1 = t_2 = t$

$$\begin{aligned} R_X(t, t) &= E[X(t) X(t)] \\ &= E[X(t)^2] \end{aligned}$$

$$\begin{aligned} C_X(t, t) &= E[\{X(t) - E[X(t)]\} \{X(t) - E[X(t)]\}] \\ &= \text{Var}[X(t)] \end{aligned}$$

$$= R_X(t_1, t_1) - \mu_X(t_1)\mu_X(t_1)$$

for  $t_1 \in J$

# Continued...

- Intuitively,  $C_X(t_1, t_2)$  shows how  $X(t_1)$  and  $X(t_2)$  move relative to each other.
- If large values of  $X(t_1)$  tend to imply large values of  $X(t_2)$ , then  $\{X(t_1) - E[X(t_1)]\} \{X(t_2) - E[X(t_2)]\}$  is positive on average. In this case,  $C_X(t_1, t_2)$  is positive, and we say  $X(t_1)$  and  $X(t_2)$  are **positively correlated**.
- On the other hand, if large values of  $X(t_1)$  imply small values of  $X(t_2)$ , then  $\{X(t_1) - E[X(t_1)]\} \{X(t_2) - E[X(t_2)]\}$  is negative on average, and we say  $X(t_1)$  and  $X(t_2)$  are **negatively correlated**.
- If  $C_X(t_1, t_2) = 0$ , then  $X(t_1)$  and  $X(t_2)$  are **uncorrelated**.



## Example:

Find the mean, correlation and covariance function for random process  $X_n = 1000(1 + R)^n$ ,

for  $n = 0, 1, 2, \dots$ .  $R \sim \text{Uniform}(0.04, 0.05)$ .

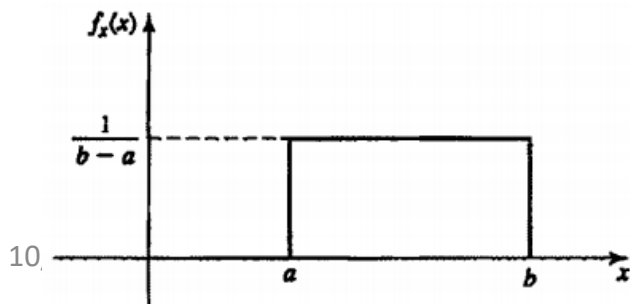
## Solution:

For any value of  $R \in (0.04, 0.05)$  a sample function of random process  $X_n$  can be obtained.

$X_n = 1000(1 + R)^n = 1000Y^n$ , thus

$Y \sim \text{Uniform}(1.04, 1.05)$  and

$$f_Y(y) = \begin{cases} \frac{1}{b-a}, & 1.04 \leq y \leq 1.05 \\ 0, & \text{elsewhere} \end{cases}$$



The [probability density function](#) of the continuous uniform distribution is:

$$f(x) = \begin{cases} \frac{1}{b-a} & \text{for } a \leq x \leq b, \\ 0 & \text{for } x < a \text{ or } x > b \end{cases}$$

# Continued...

We know that:

**Mean:**

$$f_Y(y) = \begin{cases} 100, & 1.04 \leq y \leq 1.05 \\ 0, & \text{elsewhere} \end{cases}$$

$$\mu_X(n) = E[X_n] = 1000E[Y^n]$$

$$= 1000 \int_{1.04}^{1.05} 100 y^n dy$$

$$= \frac{10^5}{n+1} [1.05^{n+1} - 1.04^{n+1}]$$

## Correlation:

$$\begin{aligned} R_X(m, n) &= E[X_m, X_n] \\ &= 10^6 E[Y^m Y^n] \end{aligned}$$

$$= 10^6 \int_{1.04}^{1.05} 100 y^{(m+n)} dy$$

$$= \frac{10^8}{m+n+1} [1.05^{m+n+1} - 1.04^{m+n+1}]$$

## Covariance:

$$C_X(m, n) = R_X(m, n) - \mu_X(m)\mu_X(n)$$

$$= \frac{10^8}{m+n+1} [1.05^{m+n+1} - 1.04^{m+n+1}]$$

$$- \left\{ \frac{10^5}{m+1} [1.05^{m+1} - 1.04^{m+1}] \right\} \left\{ \frac{10^5}{n+1} [1.05^{n+1} - 1.04^{n+1}] \right\}$$

## We know that:

$$\mu_X(n) = E[X_n] = 1000E[Y^n]$$

$$f_Y(y) = \begin{cases} 100, & 1.04 \leq y \leq 1.05 \\ 0, & \text{elsewhere} \end{cases}$$

# Multiple Random Processes

For two random processes  $\{X(t), t \in J\}$  and  $\{Y(t), t \in J\}$

The **cross-correlation function**,  $R_{XY}(t_1, t_2)$  is defined as

$$R_{XY}(t_1, t_2) = E[X(t_1) Y(t_2)] \quad \text{for} \quad t_1, t_2 \in J$$

The **cross-covariance function**,  $C_X(t_1, t_2)$  is defined as

$$\begin{aligned} C_{XY}(t_1, t_2) &= \text{Cov}[X(t_1) Y(t_2)] \\ &= R_{XY}(t_1, t_2) - \mu_X(t_1) \mu_Y(t_2) \quad \text{for} \quad t_1, t_2 \in J \end{aligned}$$

# Reference

- Athanasios Papoulis, “Probability, Random Variables, and Stochastic Processes,” 3<sup>rd</sup> edition, McGraw Hill Publication.
- <https://www.probabilitycourse.com>