

Video Course on  
Stochastic Processes -1

By

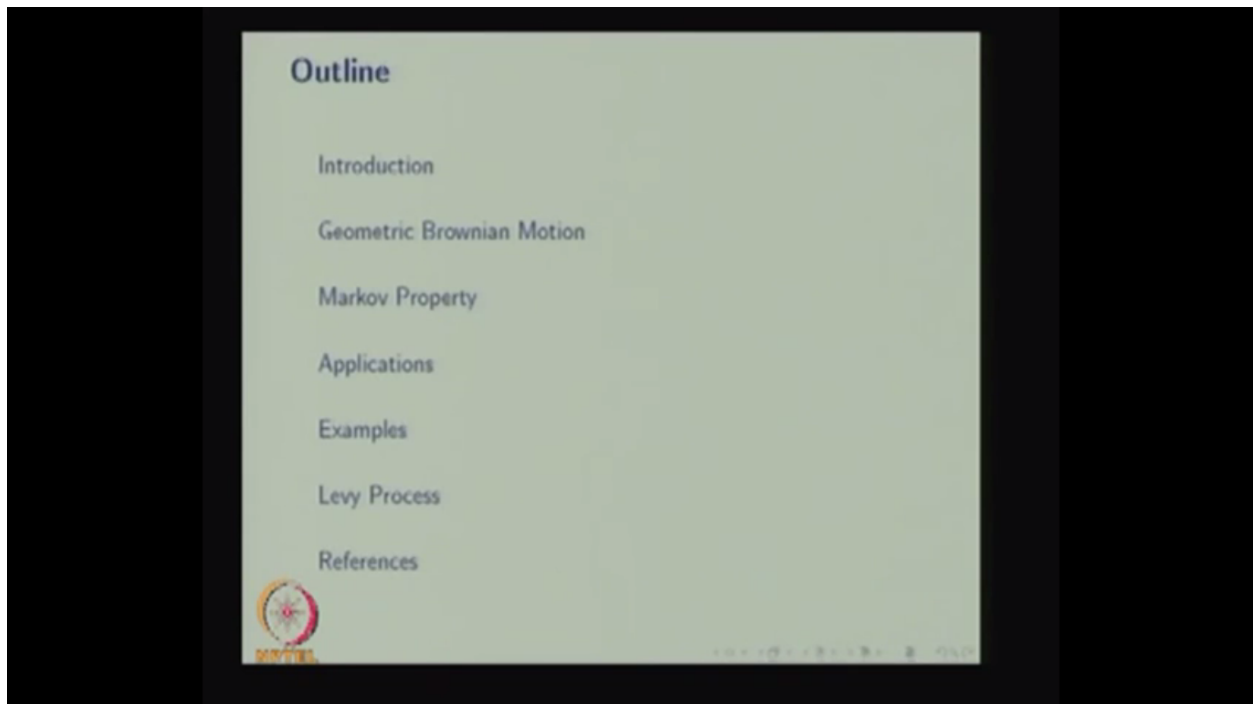
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Module #7: Brownian Motion and its Application

Lecture#2  
Processes Derived from Brownian Motion

This is a stochastic processes model 7, Brownian motion and its applications. Lecture 2; processes derived from Brownian motion.

In the lecture one we have discussed the definition and properties of Brownian motions we started with the random walk. Then the sample path of a random walk. Then we have given few properties of random walk followed by that we have made the derivation of Brownian motion through the random walk. Then we have discussed the sample path of a Brownian motion. Followed by that we have discussed a few important properties such as strict sense stationary increment, independent increment property, nowhere differentiable property, self-similar property, Markov property, between Gaussian process and the Brownian motion. Also we have discussed the Kolmogorov equation and we have given the connection with the heat equation. Then we have discussed the joint distribution of Poisson process also and finally we have discussed the Martingale property of Brownian motion. So in that lecture 1 of module 7 was completed.



In the lecture 2 we are going to cover the definition of a geometric Brownian motion. Then few properties also going to be discussed followed by that we are going to discuss the applications of geometric Brownian motion and also few examples of geometric Brownian motion.

Finally the process derived from Brownian motion that's a levy process also going to be discussed.

## Definition

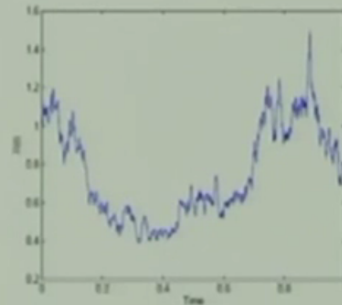
### Definition

A stochastic process  $\{X(t), t \geq 0\}$  is said to be a geometric Brownian motion if  $X(t) = X(0)e^{W(t)}$  where  $W(t)$  is a Brownian motion.



The definition of geometric Brownian motion. A stochastic process  $X_t$  is said to be a stochastic process  $X$  of  $t$  where  $t$  varies from 0 to infinity is said to be geometric Brownian motion if  $X$  of  $t$  is of the form  $X$  naught exponential of  $W$  where  $W_t$  is a Brownian motion. That means that whenever you have Brownian motion then you make another stochastic process as a function of Brownian motion but it's of the form  $X$  of  $t$  is equal to  $X$  of 0 e power  $W_t$  then the  $X$  of  $t$  is stochastic process is said to be geometric Brownian motion. You know the range of  $W_t$  that is minus 3 infinity to infinity since  $X$  of  $t$  is of the form  $X$  of 0 e power  $W_t$  therefore the range of  $X_t$  will be 0 to infinity. The range of  $X_t$  is 0 to infinity. Therefore you can use this as a model for the stock price at any time  $t$  like that you can go for modeling any pricing of any security or derivatives at time  $t$ . So the  $X_t$  can be directly used in the application of finance.

## Sample Path



You can see the sample path over the time the  $X_t$  here the range is from 0 to infinity so you can see the continuous functions. You know that the sample path of  $W_t$  is a continuous function and the  $X_t$  that is a geometric Brownian motion this is also a continuous function. [Indiscernible] [00:05:01]  $W$  of  $t$ .

## Markov property

$$\begin{aligned} X(t+h) &= X(0)e^{W(t+h)} \\ &= X(0)e^{W(t)+W(t+h)-W(t)} \\ &= X(t)e^{W(t+h)-W(t)} \end{aligned}$$

Since BM has independent increments, given  $X(t)$ , the future  $X(t+h)$  only depends on the future increment of the BM. This future is independent of the past.

► Hence, the Markov property is satisfied. Thus,  $\{X(t), t \geq 0\}$  is a Markov process.

Now we are going to discuss the very important property that is the Markov property of the geometric Brownian motion. The geometric Brownian motion is of the form  $X$  of  $t$  is equal to  $X$  naught  $e$  power  $Wt$  therefore for any  $h$  greater than 0 you can write  $X$  of  $t$  plus  $h$  is same as  $X$  naught  $e$  power in  $W$  of  $t$  plus  $h$ . I'm going to verify the Markov property therefore what I am going to do I'm going to add the  $Wt$  and subtract  $Wt$  in the exponential. Therefore the next step will be  $X$  naught  $e$  power  $Wt + W$  of  $t$  minus  $h$  minus  $Wt$ . Already we we know that  $X$  of  $t$  is equal to  $X$  naught  $E$  power  $Wt$  therefore  $X$  naught  $e$  power  $Wt$  can be replaced by  $X$  of  $t$ . Hence,  $X$  of  $t$  plus 1 is same as  $X$  of  $t$  multiplied by  $e$  power  $Wt + h$ . That means the stochastic process at the time point  $t$  plus  $h$  is same as at the time point  $t$  multiplied by exponential of the increment between the time points  $t$  to  $t$  plus  $h$  in  $W$ . We already know that the Brownian motion or Wiener process satisfies the Markov property and also the increments are independent along with increments are stationary here we are going to use independent increments are independent. That means since the Brownian motion has independent increments given  $X_t$  the future  $X$  of  $t$  plus  $h$  only depends on the future implements of Brownian motion given  $X_t$  the  $X$  of  $t$  plus 1  $t$  plus  $h$  it depends only on  $W$  of  $t$  plus  $h$  minus  $W$  of  $t$  but since  $W$  is the Brownian motion, the Brownian motion increments are independent therefore  $W$  of  $t$  plus  $h$  minus  $Wt$  is independent of 0 to  $W$ . So this feature is independent of the the positive intergers. Here the positive integers is from 0 to small time. Hence, the Markov property satisfies because the future depends only on the present not the past. Therefore the Markov property is satisfied hence then  $W$  the  $X_t$  is the [Indiscernible] [00:08:16] So this is the above result is valid for all  $h$  greater than 0 therefore the Markov property is satisfied instance the future depends only on the present not on the past or it is independent of the past. Hence the Markov property is satisfied by  $X_t$  hence the  $X_t$  is a Markov process. So the Brownian motion is also a Markov process geometric Brownian motion is a Markov process also geometric Brownian motion is also a [Indiscernible] [00:08:56].

### Mean and Variance of geometric BM

- The moment generating function of a normal distribution random variable  $X$  with mean  $\mu$  and variance  $\sigma^2$  is given by

$$M_X(s) = E(e^{sX}) = \exp\left(\mu s + \frac{1}{2}\sigma^2 s^2\right), \quad -\infty < s < \infty$$

For Brownian motion with drift, since  $W(t) \sim \mathcal{N}(\mu t, \sigma^2 t)$ , we have


$$M_{X(t)}(s) = E(e^{sX(t)}) = \exp\left(\mu t s + \frac{1}{2}\sigma^2 t s^2\right), \quad -\infty < s < \infty$$

- By using the values  $s = 1, 2$ , we get

$$E(X(t)) = X(0)M_{X(t)}(1)$$

and

$$E(X^2(t)) = X^2(0)M_{X(t)}(2)$$



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we are going to find out what is the standard [Indiscernible] [00:09:05] Brownian. We can use the moment generating function also. Here the moment generating function of a normal distribution random variable  $X$  with the mean  $\mu$  the variance is  $\sigma^2$  is given by for any random variables which is normally distributed with the mean  $\mu$  and variance [Indiscernible] [00:09:30] the moment generating function it is  $M_X(s)$  as a function of  $s$  that is nothing but expectation of  $e^{sX}$ . So this expectation exists because the random variable  $X$  is normally distributed so the moment generating function exists because of the moments of all order exist. So that is same as you can do it separately this calculation. So here I'm using the result of moment generating function of normal distribution that is same as exponential of because it's a function of [Indiscernible] [00:10:13] that's why it is  $\mu s + \frac{1}{2} \sigma^2 s^2$  where  $s$  can take the value from minus infinity to infinity.

Why we are using the moment generating function because here the geometric Brownian motion and the Brownian motion is connected in the form of  $X_t$  is  $X_0 e^{W_t}$  where  $W_t$  is a normally distributed with the mean 0 and the variance  $t$ . Hence I'm using the moment generating function of the  $X_t$  as a function of  $s$  that is expectation of  $e^{sX_t}$ . That is same as since  $W_t$  is normally distributed with the  $\mu$  times  $t$   $\sigma^2 t$  for a standard normal distribution the  $\mu$  is 0 and the variance is 1. So here you can make out that is same as exponential of the  $\mu t s + \frac{1}{2} \sigma^2 t s^2$  by replacing – by using the same the above logic here. [Indiscernible] [00:11:38] of this problem.

So sorry, there is a mistake. It is moment generating function of  $W_t$  and  $e^{sX_t}$  because  $X$  is normally distributed here it should not be exchanged with  $W_t$ . Here also  $W_t$  therefore moment generating function of  $W_t$  is same as expectation of  $e^{sW_t}$  [Indiscernible] [00:12:09] now using  $s$  equal to 1 and 2 now we are finding the mean and the variance of geometric Brownian motion because the mean of  $X_t$  is  $X_0$  times the moment generating function of  $X_t$  at 1. So we are using the moment generating function therefore we can get the mean of the geometric Brownian motion. Similarly finding the second order moment we can get the variance of geometric Brownian motion.

After simplification that means first we have to use what is the moment generating function of  $W_t$  and we have to use the form  $X_t$  is equal to  $X_0 e^{W_t}$  using that you can get that and after doing some simplification we get mean and variance of geometric Brownian motion that is a expectation of  $X_t$  is  $X_0$  times  $e^{\mu t + \frac{1}{2} \sigma^2 t}$  and first we can get the expectation of second order moment [Indiscernible] [00:13:22] and the variance is equal to expectation of [Indiscernible] [00:13:24] minus expectation of [Indiscernible] [00:13:27] then you can get the variance of  $X_t$ . So the variance of  $X_t$  is of the form  $X_0^2 e^{2\mu t + 2\sigma^2 t}$  multiplied by  $e^{2\sigma^2 t}$  minus 1. By substituting  $\mu + \sigma^2$  as a power cap upon bar you will get expectation of  $X_t$  is equal to  $X_0$  times  $e^{\mu t + \frac{1}{2} \sigma^2 t}$ . More generally you can go for expectation of  $X_t$  divided  $X_0$  that is same as  $e^{\mu t + \frac{1}{2} \sigma^2 t}$ . So in this way we are finding mean and variance of geometric Brownian motion using the moment generating motion of normal distributed randomly.