

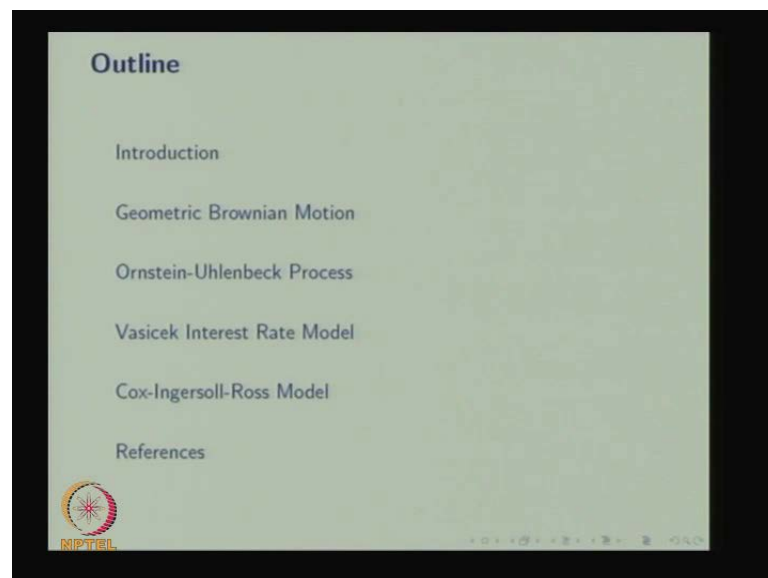
Stochastic Processes
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Module No - 7
Brownian Motion and its Applications
Lecture No - 6
Some Important SDE's and Their Solutions

This is stochastic processes, module 7, Brownian motion and its applications. This is lecture 6, some important stochastic differential equations and their solutions. The last 5 lectures we have discussed Brownian motion and its properties. Then process derived from the Brownian motion, then we have discussed stochastic differential equation. That is related to Brownian motion, only then we have discussed the Ito integral. That is the integral integration with respect to the Brownian motion.

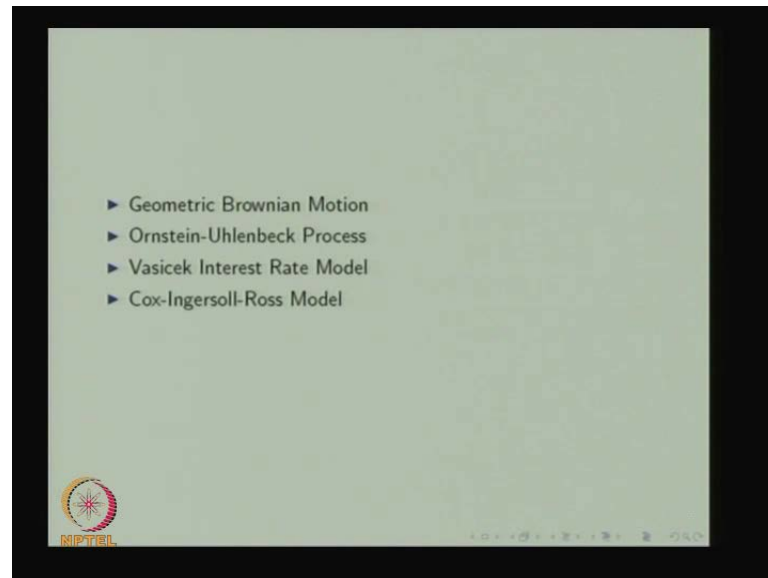
Then, we discussed Ito formula that is the 1. We can use to solve the some special cases of stochastic differential equations at the end as the lecture 6. We are going to discuss some important stochastic differential equations with their solutions in this stochastic differential equations arises in the application of mathematical finance.

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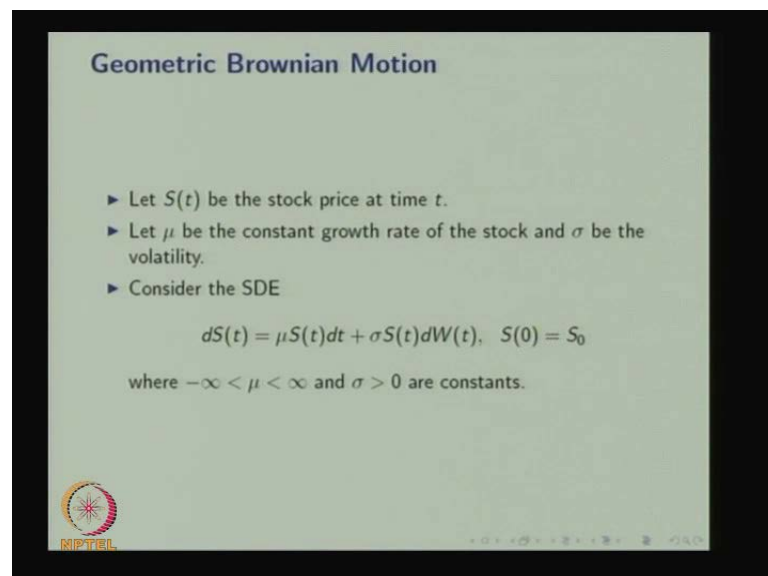
In this lecture, we are going to discuss four different stochastic differential equations. All are related to the applications of financial mathematics. The first one is geometric Brownian motion.

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That is the stochastic process, this is this stochastic differential equation the corresponding stochastic differential equation is called Black-Scholes model. The second model is Ornstein-Uhlenbeck process. The third and fourth are the interest rate model. So, these four models we are going to discuss in this lecture in detail.

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The first model this is nothing but Black-Scholes model. Let $S(t)$ be the stock price at time t . Let μ be the constant growth rate of stock and σ be the volatility. Consider the stochastic differential equation that is $dS(t)$ is equal to μ times $S(t) dt$ plus σ times $S(t) dW(t)$ at S and 0 you will know the value that is S naught. So, here we made the assumption μ σ is a volatility, which is the constant but in the real world scenario, the volatile it is not a constant.

But for the this particular Black-Scholes model, we have chosen volatility is a constant in general volatility is a random variable. Therefore, over the time, that is a stochastic process. Also, it is a stochastic volatility the corresponding model is a stochastic volatility model. But, here the volatility we treated as a constant therefore, it is a sigma time S of t not a function of t and the growth rate that is μ . That is also a constant, so the μ can take the value from minus infinity to infinity. Whereas, σ is volatility, so this is greater than 0, both are constant.

So, the corresponding stochastic differential equation, that is increment of S is μ times S of $t dt$ plus σ times S of $t dW(t)$ because of this $W(t) dW(t)$, this equation is a stochastic differential equation. we are going to relate, we are going to find out the solution of this stochastic differential equation. The solution is a stochastic process, that is nothing but the geometric Brownian motion and corresponding this model is called Black-Scholes model.

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Geometric Brownian Motion ...

► Assume that $S(t) = f(t, W(t))$. Using Ito's formula (version 2)

$$dS(t) = f_t dt + f_x dW(t) + \frac{1}{2} f_{xx} dt$$

$$f_x = \sigma f \text{ and } f_t + \frac{1}{2} f_{xx} = \mu f$$


$$f = e^{\sigma x} k(t), f_{xx} = \sigma^2 f, f_t = k'(t) e^{\sigma x}$$

$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) f$$

►

$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) e^{\sigma x} k(t)$$

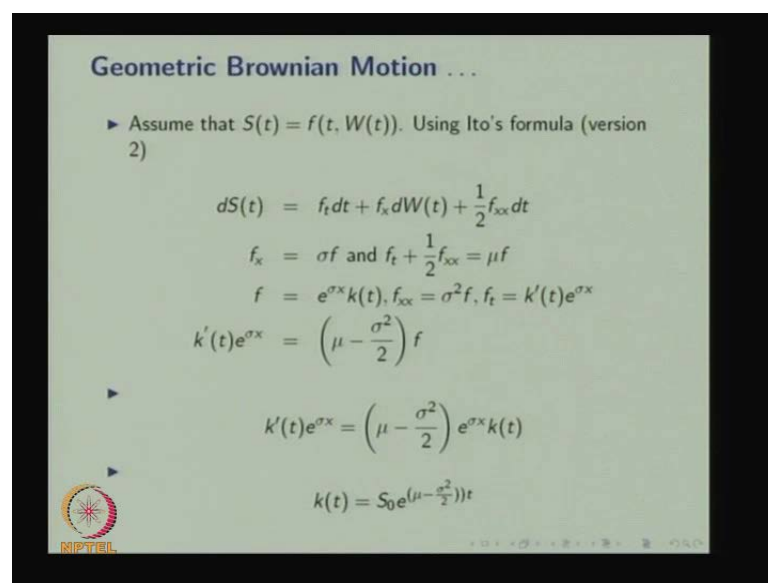
►

$$k(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t}$$


Assume that the solution S of t is a function of t comma $W t$, now you can use the Ito formula version 2. That is nothing but $dS t$ is equal to first derivative with respect to t dt , first derivative with respect to x $dW t$ and half times first derivative with respect to second derivative with respect to x dt . Therefore, we will have a two terms with respect equation $d t$ and one term with the factor $d W t$. Now, you can compare this with the given stochastic differential equation.

So, this is a given stochastic differential equation d of $S t$ is equal to this one.

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Geometric Brownian Motion ...

- Assume that $S(t) = f(t, W(t))$. Using Ito's formula (version 2)

$$dS(t) = f_t dt + f_x dW(t) + \frac{1}{2} f_{xx} dt$$


$$f_x = \sigma f \text{ and } f_t + \frac{1}{2} f_{xx} = \mu f$$

$$f = e^{\sigma x} k(t), f_{xx} = \sigma^2 f, f_t = k'(t) e^{\sigma x}$$

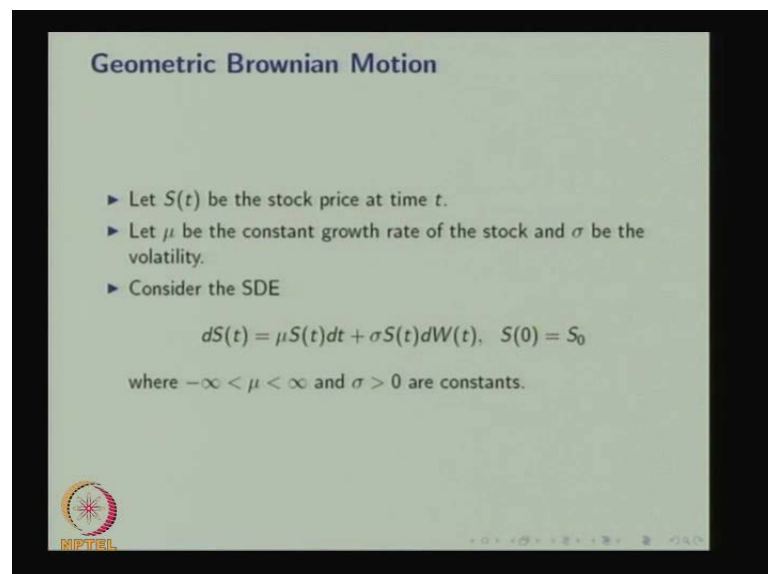
$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) f$$

$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) e^{\sigma x} k(t)$$

$$k(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t}$$



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Geometric Brownian Motion

- Let $S(t)$ be the stock price at time t .
- Let μ be the constant growth rate of the stock and σ be the volatility.
- Consider the SDE

$$dS(t) = \mu S(t) dt + \sigma S(t) dW(t), \quad S(0) = S_0$$

where $-\infty < \mu < \infty$ and $\sigma > 0$ are constants.



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Geometric Brownian Motion . . .

► Assume that $S(t) = f(t, W(t))$. Using Ito's formula (version 2)


$$dS(t) = f_t dt + f_x dW(t) + \frac{1}{2} f_{xx} dt$$

$$f_x = \sigma f \text{ and } f_t + \frac{1}{2} f_{xx} = \mu f$$

$$f = e^{\sigma x} k(t), f_{xx} = \sigma^2 f, f_t = k'(t) e^{\sigma x}$$

$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) f$$

$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) e^{\sigma x} k(t)$$

$$k(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t}$$


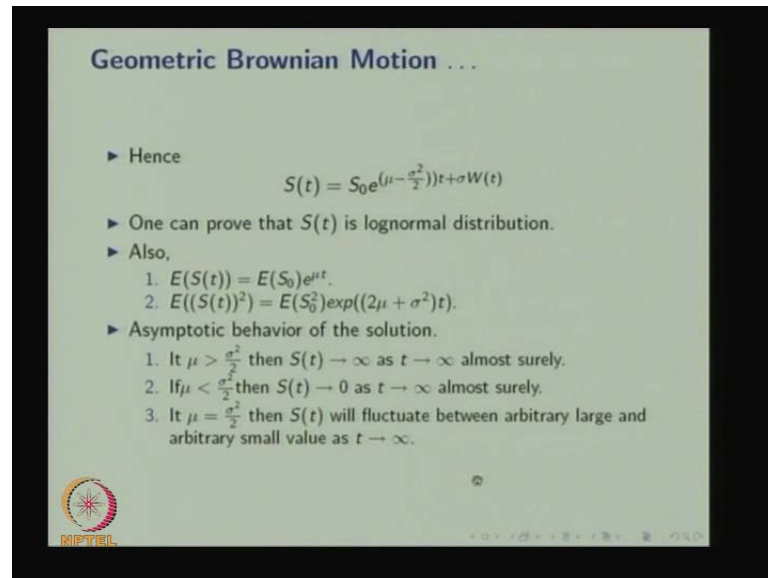
Whereas, by Ito formula, the d of $S(t)$ is given by this one; so you can compare this equation with the given stochastic differential equation. So, you will get f the partial derivative with respect to x . That is nothing but the coefficient of $dW(t)$ that is σ times $S(t)$. That is σ times f . Here the coefficient of dt is f_t plus half, so you can differentiate with respect to x . So, therefore f_t plus half times f double derivative with respect to x , that is μ times f times $S(t)$ that is μ times f . So, you can solve this equation f_x is equal to σ times f by solving you will get f is equal to $e^{\sigma x}$ times some function of t because this is derivative with respect to x partial, partial derivative with respect to x . Therefore, the function is $e^{\sigma x}$ times some function of t .

You can take a second partial derivative with respect to x , therefore we will get f_{xx} . f_{xx} will be $\sigma^2 f$. Here you can take a partial derivative with respect to t . Therefore, we will get $k'(t) e^{\sigma x}$. So, you can substitute f_t here f_{xx} here. Therefore, you will get $k'(t) e^{\sigma x}$ is same as μ times f minus half $\sigma^2 f$.

Therefore, substituting f_t and f_{xx} in this equation, you will get $k'(t) e^{\sigma x}$ is equal to μ minus σ^2 by 2 times f . Still $k(t)$ is unknown, you have to find out the k of t . Then you can get the f . So, substitute f is equal to $e^{\sigma x}$ times k of t . Therefore, you will have an equation, the only for the equation you get k of t . Therefore, we can solve that equation and get the k of t . So, k of t is nothing but $S_0 e^{(\mu - \frac{\sigma^2}{2})t}$.

naught, that is S at point. S initially at 0 e power μ minus σ^2 square t . So, you substitute this in the here, therefore you have f of t comma $W(t)$ is e power σ times $W(t)$, S naught e power μ minus σ^2 square t .

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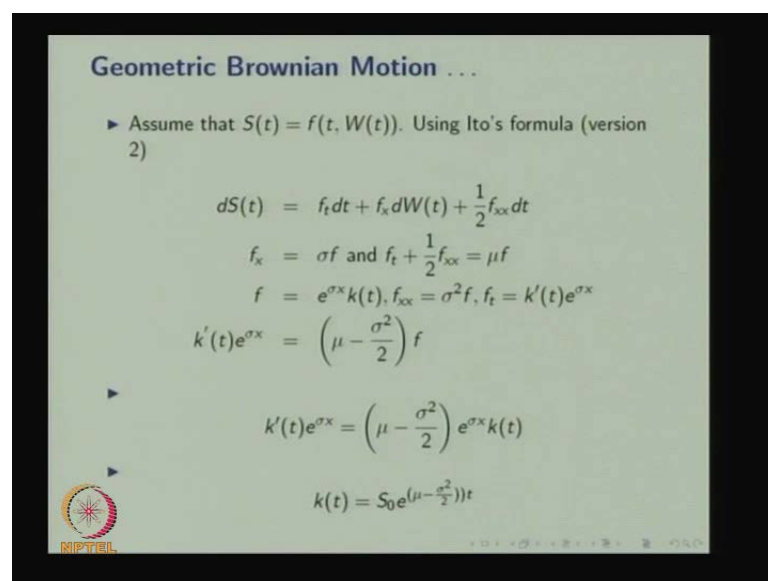
Geometric Brownian Motion ...

- ▶ Hence

$$S(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma W(t)}$$
- ▶ One can prove that $S(t)$ is lognormal distribution.
- ▶ Also,
 1. $E(S(t)) = E(S_0) e^{\mu t}$.
 2. $E((S(t))^2) = E(S_0^2) \exp((2\mu + \sigma^2)t)$.
- ▶ Asymptotic behavior of the solution.
 1. If $\mu > \frac{\sigma^2}{2}$ then $S(t) \rightarrow \infty$ as $t \rightarrow \infty$ almost surely.
 2. If $\mu < \frac{\sigma^2}{2}$ then $S(t) \rightarrow 0$ as $t \rightarrow \infty$ almost surely.
 3. If $\mu = \frac{\sigma^2}{2}$ then $S(t)$ will fluctuate between arbitrary large and arbitrary small value as $t \rightarrow \infty$.

Therefore, S of t will be S naught e power μ minus σ^2 square t plus σ times $W(t)$, substituting k of t in the in this equation f is equal to e power σ x $k(t)$, where x is nothing but $W(t)$.

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Geometric Brownian Motion ...

- ▶ Assume that $S(t) = f(t, W(t))$. Using Ito's formula (version 2)

$$dS(t) = f_t dt + f_x dW(t) + \frac{1}{2} f_{xx} dt$$

$$f_x = \sigma f \text{ and } f_t + \frac{1}{2} f_{xx} = \mu f$$

$$f = e^{\sigma x} k(t), f_{xx} = \sigma^2 f, f_t = k'(t) e^{\sigma x}$$

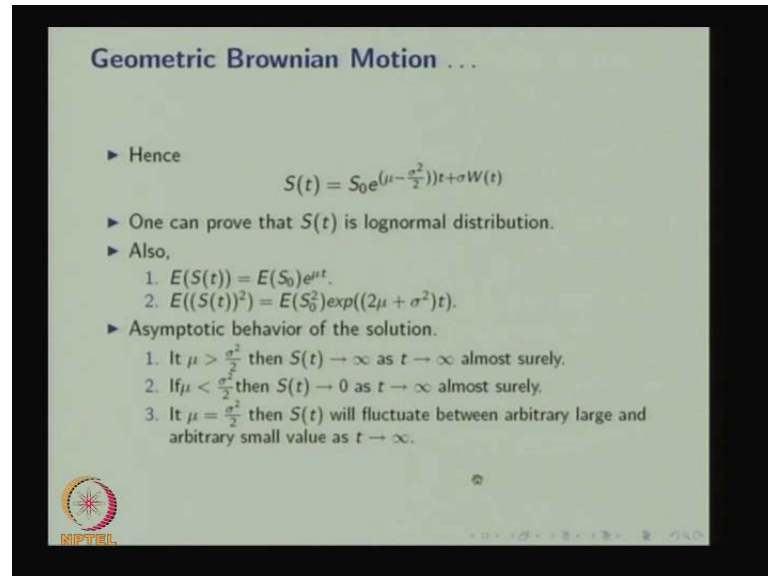
$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) f$$
- ▶

$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) e^{\sigma x} k(t)$$
- ▶

$$k(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t}$$

Therefore, your solution is $S_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma W(t)}$.

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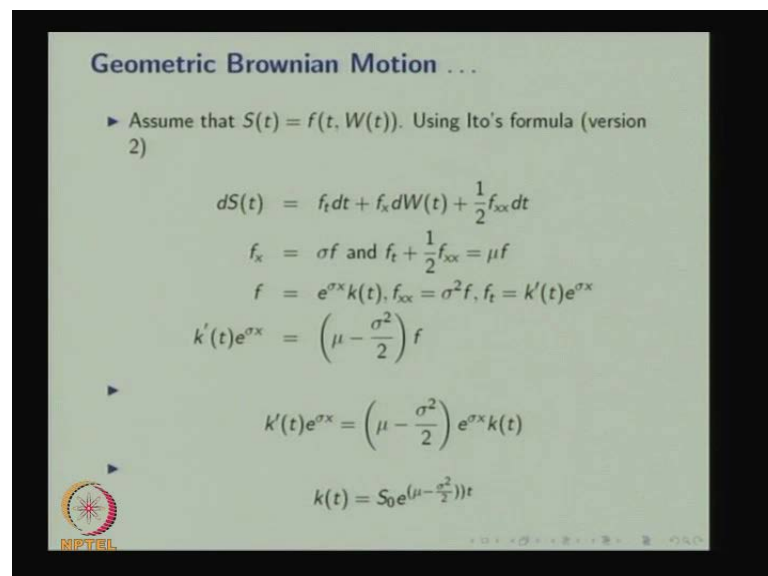
Geometric Brownian Motion ...

- ▶ Hence

$$S(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma W(t)}$$
- ▶ One can prove that $S(t)$ is lognormal distribution.
- ▶ Also,
 1. $E(S(t)) = E(S_0) e^{\mu t}$.
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- ▶ Asymptotic behavior of the solution.
 1. If $\mu > \frac{\sigma^2}{2}$ then $S(t) \rightarrow \infty$ as $t \rightarrow \infty$ almost surely.
 2. If $\mu < \frac{\sigma^2}{2}$ then $S(t) \rightarrow 0$ as $t \rightarrow \infty$ almost surely.
 3. If $\mu = \frac{\sigma^2}{2}$ then $S(t)$ will fluctuate between arbitrary large and arbitrary small value as $t \rightarrow \infty$.

So, this is a solution of given stochastic differential equation. This will be got by using the Ito formula.

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Geometric Brownian Motion ...

- ▶ Assume that $S(t) = f(t, W(t))$. Using Ito's formula (version 2)

$$dS(t) = f_t dt + f_x dW(t) + \frac{1}{2} f_{xx} dt$$

$$f_x = \sigma f \text{ and } f_t + \frac{1}{2} f_{xx} = \mu f$$

$$f = e^{\sigma x} k(t), f_{xx} = \sigma^2 f, f_t = k'(t) e^{\sigma x}$$

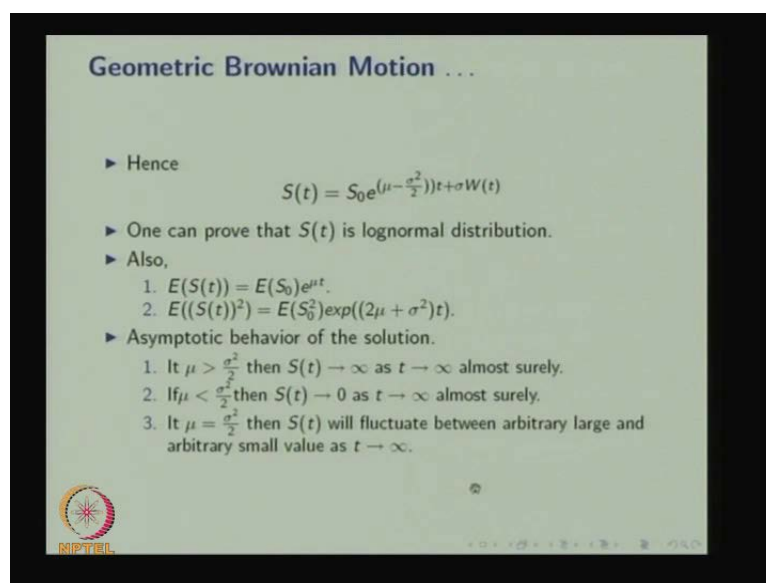
$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) f$$
- ▶

$$k'(t) e^{\sigma x} = \left(\mu - \frac{\sigma^2}{2} \right) e^{\sigma x} k(t)$$
- ▶

$$k(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t}$$

By using the Ito formula version 2 without solving the stochastic differential equation by using the Ito formula, we are finding the solution of given stochastic differential equation.

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Geometric Brownian Motion ...

- ▶ Hence
$$S(t) = S_0 e^{(\mu - \frac{\sigma^2}{2})t + \sigma W(t)}$$
- ▶ One can prove that $S(t)$ is lognormal distribution.
- ▶ Also,
 1. $E(S(t)) = E(S_0) e^{\mu t}$.
 2. $E((S(t))^2) = E(S_0^2) \exp((2\mu + \sigma^2)t)$.
- ▶ Asymptotic behavior of the solution.
 1. If $\mu > \frac{\sigma^2}{2}$ then $S(t) \rightarrow \infty$ as $t \rightarrow \infty$ almost surely.
 2. If $\mu < \frac{\sigma^2}{2}$ then $S(t) \rightarrow 0$ as $t \rightarrow \infty$ almost surely.
 3. If $\mu = \frac{\sigma^2}{2}$ then $S(t)$ will fluctuate between arbitrary large and arbitrary small value as $t \rightarrow \infty$.

One can prove that S of t is log normal distribution because W t is normal distribution with mean 0. Variance t and this is of the form $e^{\mu t - \frac{\sigma^2}{2}t + \sigma W(t)}$. Therefore, the S of t will be lognormal distribution and also you can find out mean and variance. So, the mean will be expectation of S not $e^{\mu t}$. Similarly, you can find out the expectation of S of t whole square using this two. We can find out the variance of S of t also. For this Black-Scholes model, we are finding the solution of S of t , also we are finding the distribution of S of t that is a log normal distribution. We know the mean and variance in terms of μ and σ^2 .

We can also discuss, what is a asymptotic behavior of the solution because the solution is $e^{\mu t - \frac{\sigma^2}{2}t + \sigma W(t)}$ as t tends to infinity, what happens? If μ is greater than $\frac{\sigma^2}{2}$, if μ is greater than $\frac{\sigma^2}{2}$ as t tends to infinity S of t will tends to infinity.

If μ is less than $\frac{\sigma^2}{2}$, then as t tends to infinity S of t tends to 0 because the whole term is in the $e^{\mu t - \frac{\sigma^2}{2}t}$ exponential of power. If μ is equal to $\frac{\sigma^2}{2}$, as t tends to infinity S of t will fluctuate between arbitrary large and arbitrary small value. Note that μ is, μ is a constant growth rate of the stock and σ is a volatility. So, as t tends to infinity if based on these three conditions accordingly, S of t tends to infinity or S of t tends to 0 or S of t will be fluctuating as t tends to infinity.

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Application in Finance

- Consider European Call Option written on time $t = 0$ with maturity $t = T$ and strike price K .
- Let the interest rate r and the volatility $\sigma > 0$ be constant.
- Let $S(t)$ be the stock price at any time t .
- Let

$$S(t) = S(0)e^{(r - \frac{1}{2}\sigma^2)t + \sigma W(t)}$$

be a geometric Brownian motion with mean rate of return r , where the initial stock price $S(0)$ is positive and $W(t)$ is a Brownian motion.

- Value of the option at time T is $(S(T) - K)^+$ where $X^+ = \max(X, 0)$



This is application in finance consider European call option written on t is equal to 0 with maturity t is equal to capital T and the strike price capital K . So, you can choose the μ is nothing but the interest rate with the notation r and the volatility is σ that is the constant and the $S(t)$ be the stock price. Therefore, $S(t)$ the solution S of zero e power here replaced μ by r . Therefore, r is a interest rate here. So, r minus half σ square t plus σ times $W(t)$ be the geometric Brownian motion with the mean rate of return r , where the initial stock price is $S(0)$ is positive and $W(t)$ is a Brownian motion.

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Application in Finance . . .

► One can show that, for $T > 0$,

$$E \left[e^{-rT} (S(T) - K)^+ \right] = S(0) \Phi(d_+(T, S(0))) - Ke^{-rT} \Phi(d_-(T, S(0)))$$

where $X^+ = \max(X, 0)$,

$$d_{\pm}(T, S(0)) = \frac{1}{\sigma\sqrt{T}} \left[\log \frac{S(0)}{K} + \left(r \pm \frac{\sigma^2}{2} \right) T \right],$$

and Φ is the cumulative standard normal distribution function

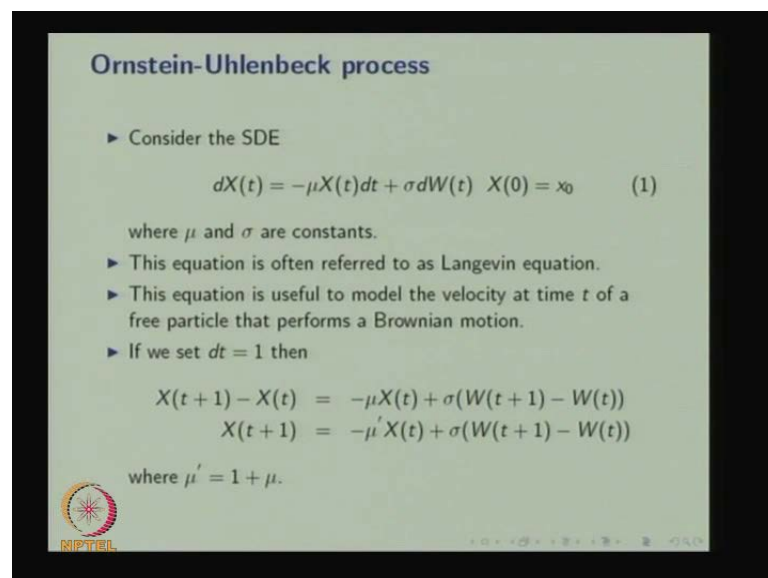
$$\Phi(y) = \frac{1}{\sqrt{2\pi}} \int_{-\infty}^y e^{-\frac{1}{2}z^2} dz = \frac{1}{\sqrt{2\pi}} \int_{-y}^{\infty} e^{-\frac{1}{2}z^2} dz.$$

So, it has direct application in the finance. Suppose, we choose K is positive constant, which is strike price at the maturity date capital T , value of the option at time t at time capital T is S of capital T minus K superscript plus, where x superscript plus means maximum of x comma 0 . Then, one can show that t is greater than 0 .

The expectation of $e^{\text{power minus } r \text{ times capital } T}$, the random variable is S of capital T minus K power superscript plus that means is a maximum of x comma 0 for x superscript plus that means it will return the value 0 or whatever the x for the maximum. That is nothing but x of 0 psi of d suffix plus t comma S of 0 minus K times $e^{\text{power minus } r \text{ of capital } T}$ psi of d minus T minus S of 0 , where T plus and T minus are defined in this form and psi is the cumulative standard normal distribution function.

Psi of y is defined as a probability between minus infinity to till y in the standard normal distributed random variable. So, either minus infinity to y or minus y to infinity because of it is symmetric. So, it is expectation this is discounted $1 e^{\text{power minus } r T}$. So, the expected written will be calculated using the c d f of normal, standard normal distribution. You should know the strike price value capital K and maturity date capital T and also the interest rate r and the volatility sigma square also sigma also.

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Ornstein-Uhlenbeck process

- Consider the SDE

$$dX(t) = -\mu X(t)dt + \sigma dW(t) \quad X(0) = x_0 \quad (1)$$
 where μ and σ are constants.
- This equation is often referred to as Langevin equation.
- This equation is useful to model the velocity at time t of a free particle that performs a Brownian motion.
- If we set $dt = 1$ then

$$X(t+1) - X(t) = -\mu X(t) + \sigma(W(t+1) - W(t))$$

$$X(t+1) = -\mu' X(t) + \sigma(W(t+1) - W(t))$$
 where $\mu' = 1 + \mu$.



Now we are moving into the second model, that is Ornstein-Uhlenbeck process. Consider the stochastic differential equation dx is equal to minus μ times x dt plus sigma times dW , where μ and sigma are constants. This equation is also referred as

Langevin equation. This equation is useful to model the velocity at time t of a free particle that performs a Brownian motion. If we described as the dt is equal to 1, then you will get the increment is nothing but x of $t+1$ minus x of t . That is dx is equal to 1. Therefore, this increment is W of $t+1$ minus W of t . Therefore, if you label μ dash t is equal to $1 + \mu$, then you can transform the equation in the discretized version.

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Ornstein-Uhlenbeck Process . . .

- ▶ This time series model can be considered as a discrete analogue at the solution of the Langevin equation (1).
- ▶ The stochastic differential equation (1) is interpreted as the following stochastic integral equation

$$X(t) = x_0 + \sigma W(t) - \mu \int_0^t X(s) ds.$$

- ▶ The computation is somewhat complicated. Here, we derive the solution using Ito's formula which is easy.
- ▶ Let $f(t, x) = e^{\mu t} x$. Then

$$\frac{\partial f}{\partial t} = \mu e^{\mu t} x, \quad \frac{\partial f}{\partial x} = e^{\mu t}, \quad \frac{\partial^2 f}{\partial x^2} = 0.$$



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Ornstein-Uhlenbeck process

- ▶ Consider the SDE
$$dX(t) = -\mu X(t)dt + \sigma dW(t) \quad X(0) = x_0 \quad (1)$$

where μ and σ are constants.
- ▶ This equation is often referred to as Langevin equation.
- ▶ This equation is useful to model the velocity at time t of a free particle that performs a Brownian motion.
- ▶ If we set $dt = 1$ then
$$X(t+1) - X(t) = -\mu X(t) + \sigma(W(t+1) - W(t))$$

$$X(t+1) = -\mu' X(t) + \sigma(W(t+1) - W(t))$$

where $\mu' = 1 + \mu$.



So, this time series model can be considered as a discrete analogue at the solution of the same equation 1. You can, you can in the you can develop the time series model. Then by discretizing the above stochastic differential equation and this stochastic differential equation can be interpreted to the integral equation also. Because it is dx_t is equal to $-\mu x_t dt + \sigma dW_t$.

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Ornstein-Uhlenbeck Process . . .

- ▶ This time series model can be considered as a discrete analogue at the solution of the Langevin equation (1).
- ▶ The stochastic differential equation (1) is interpreted as the following stochastic integral equation

$$X(t) = x_0 + \sigma W(t) - \mu \int_0^t X(s) ds.$$

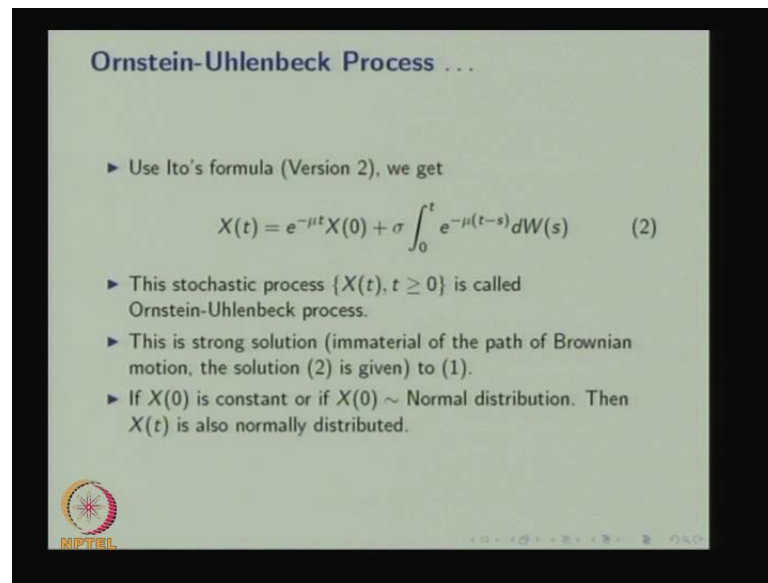
- ▶ The computation is somewhat complicated. Here, we derive the solution using Ito's formula which is easy.
- ▶ Let $f(t, x) = e^{\mu t} x$. Then

$$\frac{\partial f}{\partial t} = \mu e^{\mu t} x, \frac{\partial f}{\partial x} = e^{\mu t}, \frac{\partial^2 f}{\partial x^2} = 0.$$



Therefore you can write down this has the x_t is equal to x_0 plus σW_t minus μ times integration 0 to t of $X(s) ds$. $X(s)$ is unknown. Therefore, this is an integral equation. It is very difficult to get the solution, but now here we are using the Ito formula, which is easy to get the solution. Assume that the solution is of the form $e^{\mu t} x$. So, use the version 2 of Ito formula; that means you have to find out first derivative with respect to t , first derivative with respect to x , second derivative with respect to x . Find out those things, then substitute, substitute in the equation.

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Ornstein-Uhlenbeck Process ...

- ▶ Use Ito's formula (Version 2), we get

$$X(t) = e^{-\mu t} X(0) + \sigma \int_0^t e^{-\mu(t-s)} dW(s) \quad (2)$$

- ▶ This stochastic process $\{X(t), t \geq 0\}$ is called Ornstein-Uhlenbeck process.
- ▶ This is strong solution (immaterial of the path of Brownian motion, the solution (2) is given) to (1).
- ▶ If $X(0)$ is constant or if $X(0) \sim \text{Normal distribution}$. Then $X(t)$ is also normally distributed.

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Then you can get the solution of x of t , that is x of t is equal to e power minus μt x of 0 plus σ times the integration 0 to t e power minus μt minus S $dW(S)$. Note that this is a Ito integral because this is a integration with respect to $W(S)$, but the integrand is non random function of non random function of time. Therefore, it is easy to get the solution, we have already discussed as an example how to solve the Ito integral the integrand is a non random function?


So, you can refer that example and you can get the solution and this is strong solution immaterial of the path of Brownian motion, the solution for the equation one. We know that the, this is whenever the integrand is a non random function; the Ito integral with the deterministic integrand is normally distributed with the mean 0 and the variance in terms of integration.

So, you can conclude when x of t is constant or x of 0 is normally distributed random variable, normally distributed random variable, you can conclude x of t is also normal distributed random variable. If x of 0 is constant or if x of 0 is normal distributed random variable, then x of t , one can prove that is also normally distributed random variable. You have to use the Ito integral of non random function of time.

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Ornstein-Uhlenbeck Process ...

- ▶ If $X(0) = 0$, then $E(X(t)) = 0$; $Var(X(t)) = \frac{\sigma^2}{2\mu}(e^{-2\mu t} - 1)$ and $Cov(X(t), X(s)) = \frac{\sigma^2}{2\mu}(e^{-\mu(t+s)} - e^{-\mu(t-s)})$, $s < t$. Since $\{X(t), t \geq 0\}$ is a zero-mean Gaussian process, the covariance function is characteristic for the Ornstein-Uhlenbeck process.



So, you can find if x of 0 is equal to 0 , you can find the mean of x of t .


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Ornstein-Uhlenbeck Process ...

- ▶ Use Ito's formula (Version 2), we get

$$X(t) = e^{-\mu t}X(0) + \sigma \int_0^t e^{-\mu(t-s)} dW(s) \quad (2)$$

- ▶ This stochastic process $\{X(t), t \geq 0\}$ is called Ornstein-Uhlenbeck process.
- ▶ This is strong solution (immaterial of the path of Brownian motion, the solution (2) is given) to (1).
- ▶ If $X(0)$ is constant or if $X(0) \sim$ Normal distribution. Then $X(t)$ is also normally distributed.



Mean of x of t , so this will be 0 and this is normally distributed, normally distributed random variable with mean 0 .

(Refer Slide Time: 21:04)

Ornstein-Uhlenbeck Process . . .

- If $X(0) = 0$, then $E(X(t)) = 0$; $Var(X(t)) = \frac{\sigma^2}{2\mu}(e^{-2\mu t} - 1)$
and $Cov(X(t), X(s)) = \frac{\sigma^2}{2\mu}(e^{-\mu(t+s)} - e^{-\mu(t-s)})$, $s < t$.



Therefore, the mean of $x(t)$ will be 0 and the variance also one can find. Before that you should find out the expectation of $x(t)$ whole square using the formula of variance of $x(t)$ is equal to expectation of $x(t)$ whole square minus expectation of t whole square. You can find out the variance of $x(t)$ and also you can find out the covariance between two random variables $x(t)$ and $x(s)$.

(Refer Slide Time: 21:37)

Ornstein-Uhlenbeck Process . . .

- The $\{X(t), t \geq 0\}$ is a Markov process with Gaussian transition probability densities

$$p(t; x, y) = \frac{1}{\sqrt{2\pi}\sigma(t)} \exp \left\{ -\frac{(y - e^{-\mu t}x)^2}{2\sigma^2(t)} \right\}$$

when $\mu > 0$, which is the stable case,

$$\lim_{t \rightarrow \infty} \sigma^2(t) = \frac{\sigma^2}{2\mu} = \theta$$

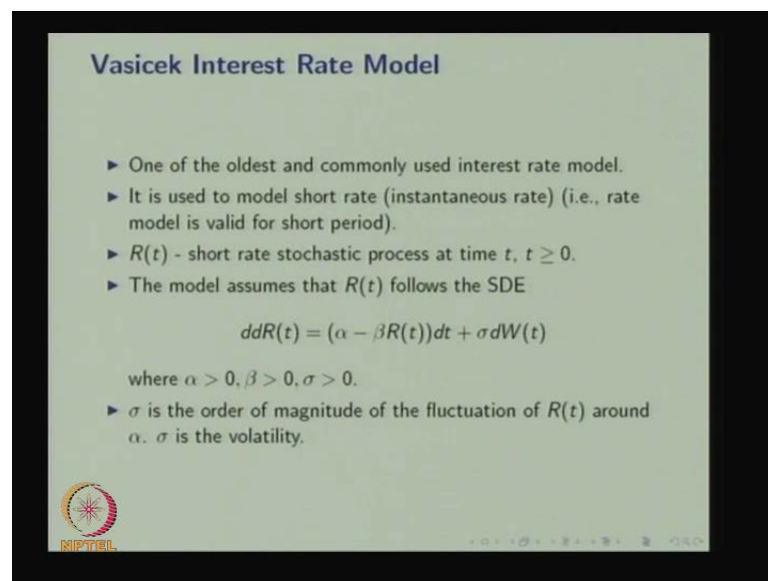
and

$$\lim_{t \rightarrow \infty} p(t; x, y) = \frac{1}{\sqrt{2\pi\theta}} \exp \left\{ -\frac{y^2}{2\theta} \right\}$$
The NPTEL logo, which consists of a stylized circular emblem with a star-like pattern inside, and the word "NPTEL" in orange capital letters below it.

Also, we can prove this, this solution $x(t)$ is a Markov process with a Gaussian transition probability density is in this form. The stable case has tends to infinity you can make

sigma square t is nothing but some theta, then you can find out the limiting distribution the transition probability density, that is standard normal distribution, sorry that is normal distribution with the mean 0 and the variance sigma the variance theta. So, you can you can prove the x t is a Markov process with Gaussian transition probability density, as well as t tends to infinity, you can prove the transition probability. So, the normal this is normal distributed random variable with the mean 0 and variance theta.

(Refer Slide Time: 22:52)




Vasicek Interest Rate Model

- ▶ One of the oldest and commonly used interest rate model.
- ▶ It is used to model short rate (instantaneous rate) (i.e., rate model is valid for short period).
- ▶ $R(t)$ - short rate stochastic process at time t , $t \geq 0$.
- ▶ The model assumes that $R(t)$ follows the SDE

$$dR(t) = (\alpha - \beta R(t))dt + \sigma dW(t)$$

where $\alpha > 0, \beta > 0, \sigma > 0$.

- ▶ σ is the order of magnitude of the fluctuation of $R(t)$ around α . σ is the volatility.

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Now, we are moving into the third important stochastic differential equation. This is the one of the oldest and commonly used interest rate model Vasicek interest rate model. It is used to model short rate, that is the instantaneous rate; that is the rate model is valid for a short period. So, suppose capital R of t that is a short rate stochastic process at time t, then this model assumes the following stochastic differential equation.

That is d r t is equal to alpha minus beta times r of t multiplied by d t plus sigma d W t, where the alpha greater than 0, beta greater than 0, sigma greater than 0. Sigma is the order of magnitude of the fluctuation of r of t around alpha sigma is the volatility. So, we are going to find the solution of this stochastic differential equation.


(Refer Slide Time: 24:11)

Vasicek Interest Rate Model ...

- ▶ Assume that Lipschitz condition is satisfied.
- ▶ Start with

$$\begin{aligned}
 d(e^{\beta t} R(t)) &= e^{\beta t} dR(t) + \beta e^{\beta t} R(t) dt \\
 &= e^{\beta t} (\alpha - \beta R(t)) dt + e^{\beta t} \sigma dW(t) + \beta e^{\beta t} R(t) dt \\
 e^{\beta t} R(t) &= R(0) + \alpha \int_0^t e^{\beta s} ds + \sigma \int_0^t e^{\beta s} dW(s)
 \end{aligned}$$

- ▶ The strong solution is

$$R(t) = R(0)e^{-\beta t} + \frac{\alpha}{\beta}(1 - e^{-\beta t}) + \sigma e^{-\beta t} \int_0^t e^{\beta s} dW(s)$$


Assume that Lipschitz condition is satisfied, so here we are not going to use Ito's formula, but we are going to use the increment concept. So, increment of $e^{\beta t} R(t)$ will have 2 terms. Then substitute $dR(t)$ will form the stochastic differential equation. The previous is stochastic differential equation. We substitute $dR(t)$ from here in this place. So, it is $e^{\beta t} dR(t)$ is replaced by the given stochastic differential equation, so that is nothing but this one plus beta times $e^{\beta t} R(t) dt$.

That is nothing but some terms will be cancelled out, so you will get $e^{\beta t} R(t)$ is nothing but because this is a differential form, so we are making an integral form. Therefore, $e^{\beta t} R(t)$ will be $R(0) + \alpha \int_0^t e^{\beta s} ds + \sigma \int_0^t e^{\beta s} dW(s)$. So, this is a Riemann integral, $\sigma \int_0^t e^{\beta s} dW(s)$. This is a Riemann, this is an Ito integral, but the integrand is a non-random function of time. Therefore, this is a strong solution for a given stochastic differential equation.

Therefore, the $R(t)$ will be $R(0)e^{-\beta t} + \frac{\alpha}{\beta}(1 - e^{-\beta t}) + \sigma e^{-\beta t} \int_0^t e^{\beta s} dW(s)$ plus this term and the last term, so this is an Ito integral, but the integrand is the non-random function. You know that Ito integral with non-random function of time has an integrand, that will be a normal distributed random variable. Therefore, you can find out the distribution of $R(t)$ also.

(Refer Slide Time: 26:19)


Vasicek Interest Rate Model ...

- ▶ If $R(0)$ is constant, then $R(t)$ is Gaussian distributed with

$$E(R(t)) = R(0)e^{-\beta t} + \frac{\alpha}{\beta}(1 - e^{-\beta t})$$

$$\text{Var}(R(t)) = \frac{\sigma^2}{2\beta}(1 - e^{-2\beta t})$$
- ▶ As $t \rightarrow \infty$

$$R(t) \sim \mathcal{N}\left(\frac{\alpha}{\beta}, \frac{\sigma^2}{2\beta}\right)$$
- ▶ If $R(t) \gg \frac{\alpha}{\beta}$ then the process will bring it down back to $\frac{\alpha}{\beta}$ and if $R(t) \ll \frac{\alpha}{\beta}$ then also the process will bring it up to $\frac{\alpha}{\beta}$. Hence, this model is also known as mean reverting Ornstein-Uhlenbeck process.



So, if $R(0)$ is constant, then you can find out the distribution of $R(t)$ which is Gaussian or normal distributed random variable with mean and variance is given in this form.

(Refer Slide Time: 26:37)

Vasicek Interest Rate Model ...


- ▶ Assume that Lipschitz condition is satisfied.
- ▶ Start with

$$d(e^{\beta t} R(t)) = e^{\beta t} dR(t) + \beta e^{\beta t} R(t) dt$$

$$= e^{\beta t} (\alpha - \beta R(t)) dt + e^{\beta t} \sigma dW(t) + \beta e^{\beta t} R(t) dt$$

$$e^{\beta t} R(t) = R(0) + \alpha \int_0^t e^{\beta s} ds + \sigma \int_0^t e^{\beta s} dW(s)$$
- ▶ The strong solution is

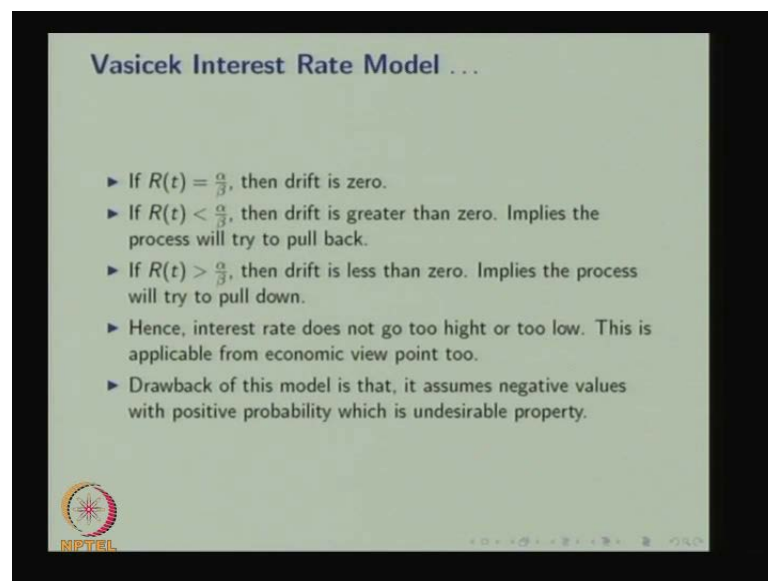
$$R(t) = R(0)e^{-\beta t} + \frac{\alpha}{\beta}(1 - e^{-\beta t}) + \sigma e^{-\beta t} \int_0^t e^{\beta s} dW(s)$$



One can find out the mean and variance from. The, this solution term by term we can find out and we can find out the mean of $R(t)$. So, here you can find the variance of $R(t)$ and you can discuss as t tends to infinity what is a distribution of $R(t)$ also. When $R(t)$ is much much greater than α/β , then the process will bring down back to


alpha by beta. If $R(t)$ is very very smaller comparing with alpha by beta, then also the process will bring it up to the alpha by beta. That means this model is known as mean reverting OU process because of this property. If $R(t)$ is much much higher than alpha by beta, the process will bring it down back to the alpha by beta. If $R(t)$ is much much lower than alpha by beta, then also the process will bring it up to the alpha by beta. Therefore, it is called the mean reverting OU process.

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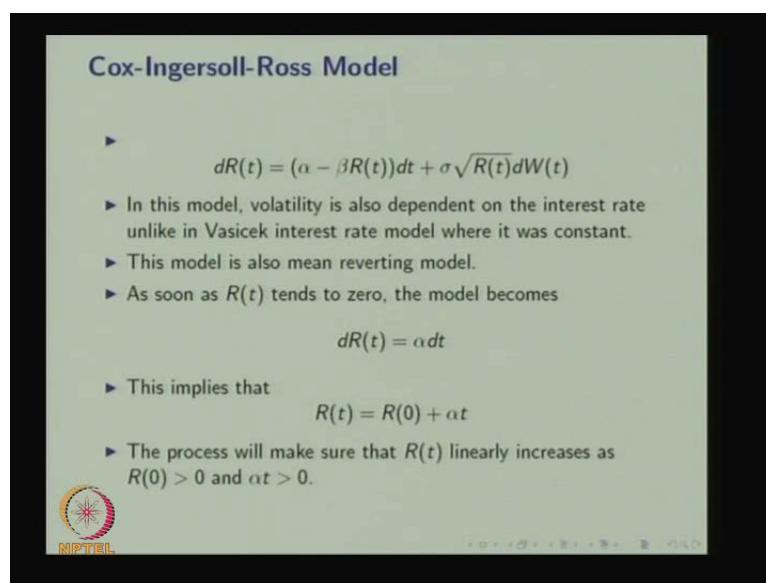
Vasicek Interest Rate Model ...

- ▶ If $R(t) = \frac{\alpha}{\beta}$, then drift is zero.
- ▶ If $R(t) < \frac{\alpha}{\beta}$, then drift is greater than zero. Implies the process will try to pull back.
- ▶ If $R(t) > \frac{\alpha}{\beta}$, then drift is less than zero. Implies the process will try to pull down.
- ▶ Hence, interest rate does not go too high or too low. This is applicable from economic view point too.
- ▶ Drawback of this model is that, it assumes negative values with positive probability which is undesirable property.

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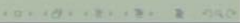
If $R(t)$ is equal to alpha by beta, then the drift is 0. If $R(t)$ is less than alpha by beta then the drift is greater than 0, implies the process will try to pull back. If $R(t)$ is greater than alpha by beta, then the drift is less than 0 implies the process will try to pull down. So, these all are the behavior based on $R(t)$ is with the alpha by beta. Hence, interest rate does not go too high or too low. So, this is applicable from a economic view point also. The drawback of this model is that it assumes negative values with positive probability, which is undesirable property. The Vasicek interest rate model is a mean reverting OU process, but the drawback is it takes negative value with the positive probability which is undesirable property.

(Refer Slide Time: 29:15)



Cox-Ingersoll-Ross Model

- ▶
$$dR(t) = (\alpha - \beta R(t))dt + \sigma \sqrt{R(t)}dW(t)$$
- ▶ In this model, volatility is also dependent on the interest rate unlike in Vasicek interest rate model where it was constant.
- ▶ This model is also mean reverting model.
- ▶ As soon as $R(t)$ tends to zero, the model becomes
$$dR(t) = \alpha dt$$
- ▶ This implies that
$$R(t) = R(0) + \alpha t$$
- ▶ The process will make sure that $R(t)$ linearly increases as $R(0) > 0$ and $\alpha t > 0$.

Now, we are moving into the CIR model, this is also the interest rate model and this also has application in financial mathematics. So, the underlying stochastic differential equation is $dR(t)$ is equal to $\alpha - \beta R(t)$ times dt plus $\sigma \sqrt{R(t)}$ times $dW(t)$. You cannot use the Ito formula to solve the stochastic differential equation. This is a stochastic differential equation, but we are finding the solution to the increments. In this model the volatility also depends on the interest rate. Earlier the volatility here it is σ , but here it is σ times square root of $R(t)$.

So, the volatility also depends on the interest rate unlike Vasicek interest model where it was constant. This model is also mean reverting model because of this $\alpha - \beta R(t)$ times dt . Therefore, this model is also called a mean reverting model. As soon as $R(t)$ tends to 0, the model becomes $dR(t)$ is equal to α times dt . This implies $R(t)$, if you solve this equation you will get $R(t) = R(0) + \alpha t$. That means this process will make sure that $R(t)$ linearly increases as $R(0) > 0$ and $\alpha t > 0$. So, this is the observation as $R(t)$ tends to 0.

(Refer Slide Time: 31:12)

Cox-Ingersoll-Ross Model . . .

- ▶ The model does not have a closed form solution. Only numerical schemes can be used to solve the CIR model.
- ▶ $E(R(t))$ can be obtained as follows:

$$d(e^{\beta t} R(t)) = \beta e^{\beta t} R(t) dt + e^{\beta t} dR(t) + 0 dR(t) dR(t)$$

$$\begin{aligned} e^{\beta t} R(t) &= R(0) + \int_0^t \beta e^{\beta s} R(s) ds \\ &\quad + \int_0^t e^{\beta s} ((\alpha - \beta R(s)) ds + \sigma \sqrt{R(s)} dW(s)) \\ &= R(0) + \int_0^t \alpha e^{\beta s} ds + \int_0^t \sigma \sqrt{R(s)} dW(s) \\ &= R(0) + \frac{\alpha}{\beta} (e^{\beta t} - 1) + \int_0^t \sigma \sqrt{R(s)} dW(s) \end{aligned}$$



Now, we are discussing the solution. This model does not have a closed form solution only the numerical schemes can be used to solve the CIR model. So, we are finding what is the expectation of R of t ; so, we cannot use a Ito formula to get the solution, only numerical schemes can be used to solve the CIR model. Now, we are finding the expectation of R of t , for that we are taking the increment of $e^{\beta t} R(t)$, get the terms. Then substitute R of d of $R(t)$ from the previous equation.

(Refer Slide Time: 32:38)

Cox-Ingersoll-Ross Model . . .

- ▶ We know that $\int_0^t \sigma \sqrt{R(s)} dW(s)$ is an Ito integral and is a martingale. Hence, expectation is zero.
- ▶
$$E(e^{\beta t} R(t)) = R(0) + \frac{\alpha}{\beta} (e^{\beta t} - 1)$$
- ▶
$$E(R(t)) = R(0)e^{-\beta t} + \frac{\alpha}{\beta} (1 - e^{-\beta t})$$
- ▶ Variance of $R(t)$ is given by
$$\text{Var}(R(t)) = \frac{\sigma^2}{\beta} R(0)(e^{-\beta t} - e^{-2\beta t}) + \frac{\alpha \sigma^2}{2\beta^2} (1 - 2e^{-\beta t} + e^{-2\beta t})$$

⏮ ⏪ ⏩ ⏭ ⏴ ⏵ ⏶ ⏷ ⏸ ⏹ ⏺ ⏻ ⏼ ⏽ ⏾ ⏿

Therefore, you will get $e^{\beta t}$ power by converting into the Ito integral, sorry by converting into integral equation you will get $e^{\beta t}$ power βt $R(t)$ is equal to $R(0)$ integration βt to times $e^{\beta s}$ $R(s) ds$.

Substitute you can get the mean of, we know that... So, basically we should find a mean and variance of the Ito integral 0 to t σ times square root of $R(s) dW(s)$. Since, this is Ito integral that is also a martingale. Hence, expectation will be 0 because this integration, if you make it as i of t . Since, it is a martingale the expectation of i of t is same as expectation of i of 0 , and the expectation of i of 0 is 0 . Therefore, the expectation of i of t will be 0 .

(Refer Slide Time: 33:25)

Cox-Ingersoll-Ross Model ...

- The model does not have a closed form solution. Only numerical schemes can be used to solve the CIR model.
- $E(R(t))$ can be obtained as follows:

$$d(e^{\beta t} R(t)) = \beta e^{\beta t} R(t) + e^{\beta t} R(t) + 0 dR(t) dR(t)$$

$$\begin{aligned} e^{\beta t} R(t) &= R(0) + \int_0^t \beta e^{\beta s} R(s) ds \\ &\quad + \int_0^t e^{\beta s} ((\alpha - \beta R(s)) ds + \sigma \sqrt{R(s)} dW(s)) \\ &= R(0) + \int_0^t \alpha e^{\beta s} ds + \int_0^t \sigma \sqrt{R(s)} dW(s) \\ &= R(0) + \frac{\alpha}{\beta} (e^{\beta t} - 1) + \int_0^t \sigma \sqrt{R(s)} dW(s) \end{aligned}$$


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Therefore, from the previous equation expectation of $R(t)$ will be $R(0) e^{\beta t}$ minus βt . This term multiplied by $e^{\beta t}$ minus βt this whole Ito integral multiplied by $e^{\beta t}$ minus βt . Since, this expectation is 0 , therefore, expectation of $R(t)$ with the multiplication $e^{\beta t}$ βt will be $R(0)$ plus α by β $e^{\beta t}$ minus 1 .

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Cox-Ingersoll-Ross Model ...

- ▶ We know that $\int_0^t \sigma \sqrt{R(s)} dW(s)$ is an Ito integral and is a martingale. Hence, expectation is zero.
- ▶
$$E(e^{\beta t} R(t)) = R(0) + \frac{\alpha}{\beta} (e^{\beta t} - 1)$$
- ▶
$$E(R(t)) = R(0)e^{-\beta t} + \frac{\alpha}{\beta} (1 - e^{-\beta t})$$
- ▶ Variance of $R(t)$ is given by
$$\text{Var}(R(t)) = \frac{\sigma^2}{\beta} R(0)(e^{-\beta t} - e^{-2\beta t}) + \frac{\alpha \sigma^2}{2\beta^2} (1 - 2e^{-\beta t} + e^{-2\beta t})$$




Therefore, expectation of R of t will be multiplied this side with the e power minus beta t , so nearly one can find out the variance of R of t .

(Refer Slide Time: 34:16)

Cox-Ingersoll-Ross Model ...

- ▶ The model does not have a closed form solution. Only numerical schemes can be used to solve the CIR model.
- ▶ $E(R(t))$ can be obtained as follows:

$$d(e^{\beta t} R(t)) = \beta e^{\beta t} R(t) + e^{\beta t} R(t) + 0 dR(t) dR(t)$$


$$\begin{aligned} e^{\beta t} R(t) &= R(0) + \int_0^t \beta e^{\beta s} R(s) ds \\ &\quad + \int_0^t e^{\beta s} ((\alpha - \beta R(s)) ds + \sigma \sqrt{R(s)} dW(s)) \\ &= R(0) + \int_0^t \alpha e^{\beta s} ds + \int_0^t \sigma \sqrt{R(s)} dW(s) \\ &= R(0) + \frac{\alpha}{\beta} (e^{\beta t} - 1) + \int_0^t \sigma \sqrt{R(s)} dW(s) \end{aligned}$$


For that we have to find out expectation of R of t whole square. So, for that you have to find out the increment.

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Cox-Ingersoll-Ross Model . . .

- ▶ We know that $\int_0^t \sigma \sqrt{R(s)} dW(s)$ is an Ito integral and is a martingale. Hence, expectation is zero.
- ▶
$$E(e^{\beta t} R(t)) = R(0) + \frac{\alpha}{\beta} (e^{\beta t} - 1)$$
- ▶
$$E(R(t)) = R(0)e^{-\beta t} + \frac{\alpha}{\beta} (1 - e^{-\beta t})$$
- ▶ Variance of $R(t)$ is given by
$$\text{Var}(R(t)) = \frac{\sigma^2}{\beta} R(0)(e^{-\beta t} - e^{-2\beta t}) + \frac{\alpha \sigma^2}{2\beta^2} (1 - 2e^{-\beta t} + e^{-2\beta t})$$




So, on secondary increment, then find out the expectation of R of t whole square, then you can find out the variance of R of t . So in this c, CIR model you have not giving the closed form solution because the ito formula does not satisfy, does not work, whereas, we are finding the mean and variance of R of t , using the using the mean and variance of ito integral. Now, we are discussing as t tends to infinity, what happens?

(Refer Slide Time: 35:00)

Cox-Ingersoll-Ross Model . . .


- ▶ As $t \rightarrow \infty$, we have
$$E(R(t)) = \frac{\alpha}{\beta}; \quad \text{Var}(R(t)) = \frac{\alpha \sigma^2}{2\beta^2}$$
- ▶ If we choose α and β appropriately, we can bring down variance and hence bringing more stability to the model.
- ▶ The bond pricing equation can be solved explicitly.



(Refer Slide Time: 35:10)

Cox-Ingersoll-Ross Model . . .


- ▶ We know that $\int_0^t \sigma \sqrt{R(s)} dW(s)$ is an Ito integral and is a martingale. Hence, expectation is zero.
- ▶
$$E(e^{\beta t} R(t)) = R(0) + \frac{\alpha}{\beta} (e^{\beta t} - 1)$$
- ▶
$$E(R(t)) = R(0)e^{-\beta t} + \frac{\alpha}{\beta} (1 - e^{-\beta t})$$
- ▶ Variance of $R(t)$ is given by
$$\text{Var}(R(t)) = \frac{\sigma^2}{\beta} R(0)(e^{-\beta t} - e^{-2\beta t}) + \frac{\alpha \sigma^2}{2\beta^2} (1 - 2e^{-\beta t} + e^{-2\beta t})$$



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Cox-Ingersoll-Ross Model . . .

- ▶ As $t \rightarrow \infty$, we have
$$E(R(t)) = \frac{\alpha}{\beta}; \quad \text{Var}(R(t)) = \frac{\alpha \sigma^2}{2\beta^2}$$
- ▶ If we choose α and β appropriately, we can bring down variance and hence bringing more stability to the model.
- ▶ The bond pricing equation can be solved explicitly.




As a t tends to infinity from this equation you can make out this is expectation of R of t , as t tends to infinity, you will get with the assumption R of 0 is equal to 0 . So, expectation of R of t is equal to α by β . As t tends to infinity with R of 0 is equal to 0 expectation of t will be λ by, sorry α by β .

(Refer Slide Time: 35:43)

Cox-Ingersoll-Ross Model ...

- ▶ We know that $\int_0^t \sigma \sqrt{R(s)} dW(s)$ is an Ito integral and is a martingale. Hence, expectation is zero.
- ▶
$$E(e^{\beta t} R(t)) = R(0) + \frac{\alpha}{\beta} (e^{\beta t} - 1)$$
- ▶
$$E(R(t)) = R(0)e^{-\beta t} + \frac{\alpha}{\beta} (1 - e^{-\beta t})$$
- ▶ Variance of $R(t)$ is given by
$$\text{Var}(R(t)) = \frac{\sigma^2}{\beta} R(0)(e^{-\beta t} - e^{-2\beta t}) + \frac{\alpha \sigma^2}{2\beta^2} (1 - 2e^{-\beta t} + e^{-2\beta t})$$




Similarly, you can find out the variance of R of t that is as t tends to infinity, you will get this term and R of 0 is equal to 0.

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Cox-Ingersoll-Ross Model ...

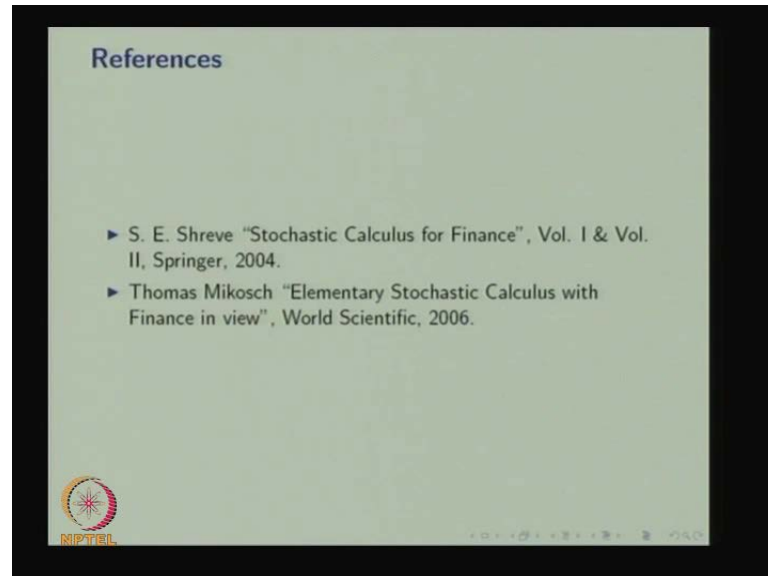
- ▶ As $t \rightarrow \infty$, we have
$$E(R(t)) = \frac{\alpha}{\beta}; \quad \text{Var}(R(t)) = \frac{\alpha \sigma^2}{2\beta^2}$$
- ▶ If we choose α and β appropriately, we can bring down variance and hence bringing more stability to the model.
- ▶ The bond pricing equation can be solved explicitly.



Therefore, you will get α times σ^2 by $2\beta^2$. So, this is a asymptotic behavior of R of t with the assumption R of 0 is equal to 0. If we choose α and β appropriately, we can bring down variance because the variance is longer run, variance is in terms of α and β . So, you can bring down the variance and hence bringing more stability to the model. You can make the model stable by properly choosing α and

beta. This CIR model has lot of application in particular, the bond pricing model. So, using CIR model the bond pricing equation can be solved explicitly.

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With this, we have completed 6 lectures in Brownian motion and its application, starting with the Brownian motion, definition and the properties. Then process derived from the Brownian motion. In particular we have discussed geometric Brownian motion, Levy processes and in the third lecture, we have discussed stochastic differential equation. The fourth lecture we have discussed ito integral and few properties of ito integral. We have discussed few examples also in the ito integrals.

The fourth lecture we have discussed, in the the fourth lecture we have discusses ito integral and the fifth lecture we have discussed the ito formula. That is useful to solve some special cases of stochastic differential equation. In the last lecture, we have discussed some important stochastic differential equation and their solutions. Here the important means this stochastic differential equations are having applications in mathematical finance.

The first model is a Black-Scholes model we have discussed, the second model is OU process and the third and fourth one are the models for the interest rate. Some standard differential equations, we solved using this ito formula and in one model. We have not given the closed form solution, which does not exist in that case. We have discussed the

mean and variance and a asymptotic behavior, with this the model 7 Brownian motion and its application is completed.