

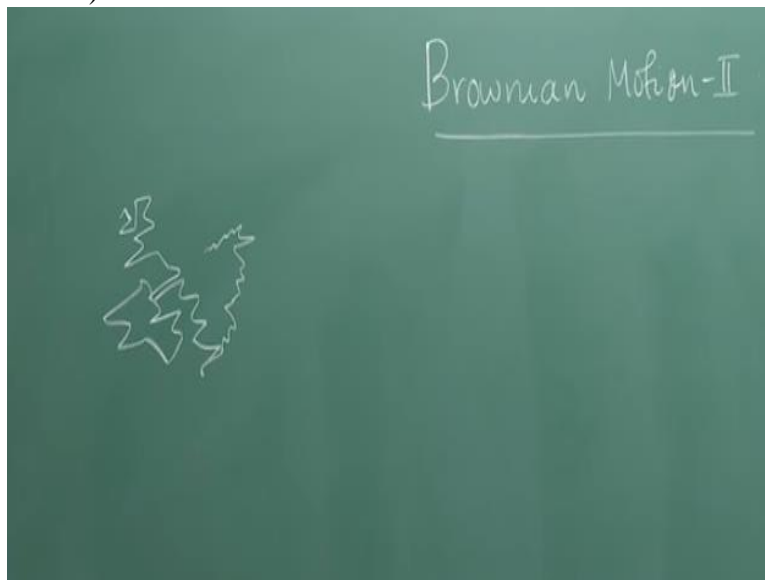
Probability and Stochastics for finance
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Lecture - 10
Brownian Motion-II

As, we have discussed in the last class, we discussed symmetric random walk and how we can scale it slightly up and down and so that we can make it more zigzag and go towards what is called a Brownian motion.

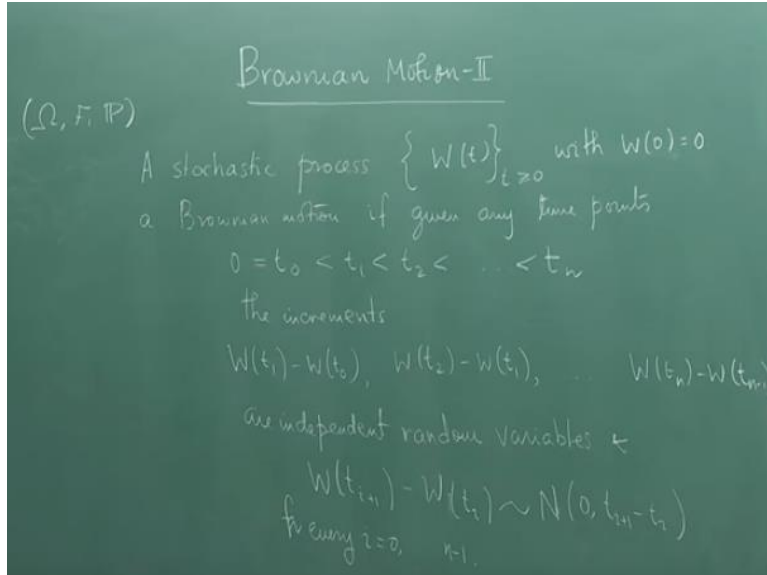
So, the Brownian motion is a continuous stochastic process which exhibits the property of a symmetric random walk. So, that is the idea of a Brownian motion. So, for example, if you look at the motion of a pollen grain in water, it would be something like this, more zigzagging than this than, I can draw. So, this is something a motion of a particle in a gas chamber a motion of a molecule.

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So, Brownian motion encapsulates lot of phenomenon. So, what did I say, the best way to remember about Brownian motion is that, Brownian motion is a continuous analog of symmetric random walk. In a continuous setting, it behaves in the way a symmetric random walk behaves in the discrete setting.

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So as usual, I will have the probability space which is written down here. So, Brownian motion, so, your stochastic process, W_t some people write W lower index t . it is up to you. it does not matter, is called a Brownian motion, if given any fine points, t is time actually, spreading time points say t_m t_n whatever. Given any time points like this the increments are independent.

The increments mean just like the way you have done increments in the symmetric random walk, the increments W_{t_1} minus W_{t_0} . W_{t_0} is actually 0, W_0 is 0 just a minute, I think, I should just change it a bit.

A stochastic process with W_0 is equal to 0. So, it does not matter. Whatever be our scenario ω , W_0 is always 0. So, it is identically a zero function. So, W_0 itself is a function. Please remember it is a random variable. So, whatever be the form of that random or whatever be this random variable, whatever be the scenario ω W of that would always be 0. That is the meaning of the whole thing.

So, this W_{t_2} minus W_{t_1} this random variable, these increments in the random variables. Hence, how much change you are having how basically, you are telling that how much zigzagging has taken place in the interval t_2 to t_1 , t_0 to t_1 , t_1 to t_2 , t_2 to t_3 and so forth. So, it is some sort of a

broad measure of the zigzagging that has taken place. How much the function value has changed at the 2 ends. These are independent random variables.

Now these are independent random variables. This is one property you know from the property of the symmetric random walk. Also, you know the symmetric random walk, the expectation of increments is 0 and the variance of the increments are the difference between the 2 time and points.

Here, actually one can prove through the Central Limit Theorem that, these increments actually follow normal distribution, which we do not prove because, that would take too much of time, it is a very short and compact course. So, these are independent random variables and $W_{t_{i+1}} - W_{t_i}$, this random variable follows normal distribution, so it means 0 and variance $t_{i+1} - t_i$.

So, if all these properties, 2 properties are followed, first that this has to be maintained whatever be the scenario, whatever be your time points increasing, if you take an increasing set of time points finite set of time points, then these things are independent and these increments themselves follow normal distribution, for every i . Of course, this has to be for every i , start from i equal to 0 to i equal to n , i equal to $n - 1$ basically.

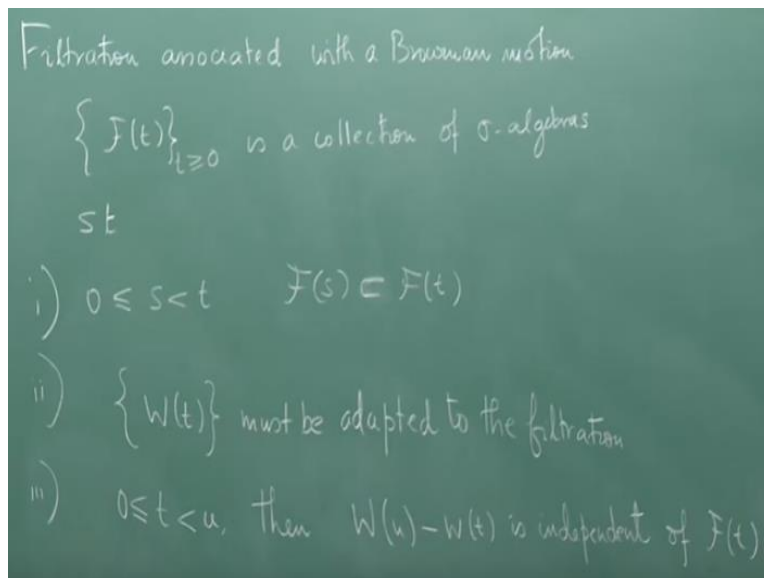
So, each of these, is following a normal distribution. So, this is what is called Brownian motion. Does stock price follow Brownian motion? The stock price truly does not follow Brownian motion, though it looks like one. Because Brownian motions can take negative values, because the symmetric random walks can also take negative values, but a stock price can never take negative value. Once a stock price is 0, that stock has to get out of the market now it is a 0-value stock.

So, stock prices are not really a model using Brownian motion, but actually these stock prices actually were modeled by Bachelier in 1900, who was the student of Henry Poincare using Brownian motion and showing that the pricing of such commodities in the stock market, of various instruments in the stock market can be achieved by solving the heat equation. So, he

linked the processing the financial markets to partial differential equations. And of course, his idea was lost and now later on he has become a very famous name.

But the interesting part is that, the way stock market or movements of stock prices are modeled that is called a geometric Brownian motion and then that is built using, that will always give you a nonnegative thing, which is built using a Brownian motion and you can understand and taking the trick that, if you want to get non-negativity always use the exponential function. So, that trick is being played in this area pretty often.

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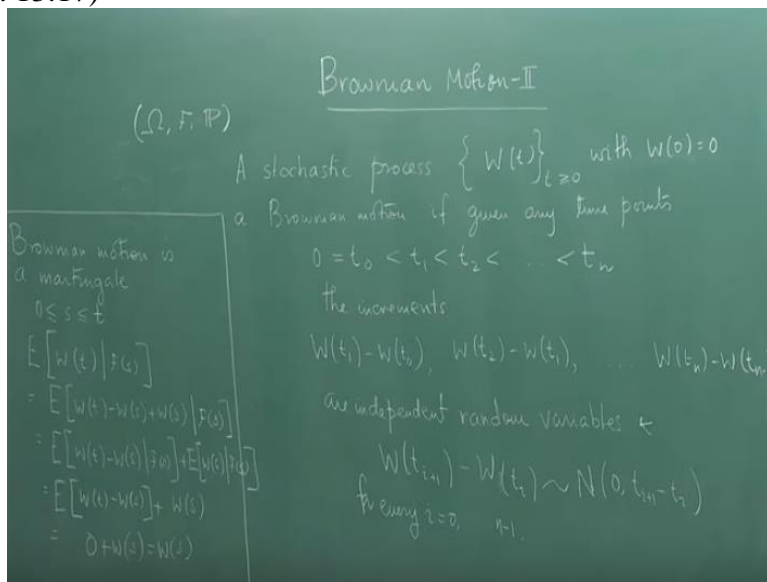
So, now we will introduce what is called, if I want to define a filtration associated with a Brownian motion, how do I define a filtration associated with a Brownian motion? So, what I will do in this filtration associated with the Brownian motion.

So, this filtration F_t is a collection of Sigma-algebras, this is a collection such that, number one, whenever t is strictly bigger than s F of s must always be contained in F_t , but you have information as time evolves. So, this should always be contained in F_t okay. Now number two, is that W_t must be adapted to the filtration. The Brownian motion must be adapted to the filtration and the third point is, so if you have this situation then, W_u minus W_t is independent of F_t .

That is, once you move beyond t , \mathcal{F}_t does not have any information about this. This is independent of what information you have in \mathcal{F}_t . \mathcal{F}_t can also be viewed in some sense as a smallest Sigma-algebra generated by the stochastic process till a given time.

So, take all the values of the random variables ω up to a given time and take the Sigma-algebra generated by them, that can be also viewed as one of the filtrations right. You could have larger filtrations also but that is essentially it is. So, once we know that that we can have some filtration defined like this, we can prove that the Brownian motion is a Martingale.

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So, again, just do like this, take t less than equal to s , so you will find that the tricks are almost similar. So, what I do is, I, and now I breakup the whole thing. You know, W_s is completely determined by \mathcal{F}_s is known. So, you have to take out what is known. So, W_s is equal to W_s into 1 you take out the W_s the expectation of 1, of constant random variable is the same so.

Now here, W_t minus W_s as the third definition, does not depend on \mathcal{F}_s . So, it is nothing but it is so there is no conditional expectation here, so is just the expectation, so this random variable is just this constant random variable plus W_s . You take the W_s out, expectation of 1 given \mathcal{F}_s expectation of 1 is 1 basically that is it. Because 1, just the constant random variable does not

depend on F_s but this you know is 0 because of this fact, 0 plus W_s which is equal to W_s and that proves that it is a Martingale.

There are several other Martingales, which are associated with the Brownian motion. A Martingale that we are going to write now, is very-very important in finance specifically in calculation of risk neutral probabilities and all those things. So, this is a very important Martingale called the exponential Martingale.

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The image shows a green chalkboard with handwritten mathematical derivations. At the top left, it says "Exponential martingale". In the top right corner, there is a boxed equation: $Z(t) = (W(t))^2 - t$ with the word "Exercise" written below it. The main derivation starts with the definition of the exponential martingale: $Z(t) = \exp\left\{\sigma W(t) - \frac{1}{2}\sigma^2 t\right\}$, where $\sigma > 0$. Below this, it shows the conditional expectation $E[Z(t) | \mathcal{F}(s)]$ for $0 \leq s \leq t$. The derivation proceeds as follows:

$$E[Z(t) | \mathcal{F}(s)] = E\left[\exp\left\{\sigma W(t) - \frac{1}{2}\sigma^2 t\right\} \mid \mathcal{F}(s)\right]$$

$$= E\left[\exp\left\{\sigma(W(t) - W(s))\right\} \exp\left\{\sigma W(s) - \frac{1}{2}\sigma^2 t\right\} \mid \mathcal{F}(s)\right]$$

$$= \exp\left\{\sigma W(s) - \frac{1}{2}\sigma^2 t\right\} E\left[\exp\left\{\sigma(W(t) - W(s))\right\} \mid \mathcal{F}(s)\right]$$

$$= \exp\left\{\sigma W(s) - \frac{1}{2}\sigma^2 t\right\} E\left[\exp\left\{\sigma(W(t) - W(s))\right\}\right]$$

$$= \exp\left\{\sigma W(s) - \frac{1}{2}\sigma^2 t\right\} \exp\left\{-\frac{1}{2}\sigma^2(t-s)\right\}$$

$$= \exp\left\{\sigma W(s) - \frac{1}{2}\sigma^2 s\right\} = Z(s)$$
 On the left side of the board, there is a boxed equation: $E\left[\exp\left\{\sigma(W(t) - W(s))\right\}\right] = \exp\left\{-\frac{1}{2}\sigma^2(t-s)\right\}$.

So, the exponential Martingale is defined like this. So, exponentiation means, E to the power, so σW_t , where σ is positive number, exponential means E to the power of this. Of course, this itself is a random variable because you are taking exponential to the power of a random variable.

So, it is, when you are taking the exponential, exponentiated by a random variable. So, this itself is a random variable. Now the idea is that if you have a filtration associated with respect to W_t then that same filtration will be associated with Z_t , because if W_t is adapted to a given filtration Z_t will also be adapted to the same filtration, because knowledge of Z_t singularly depends on the

knowledge of W_t right. The question is whether it is a Martingale. So, one has to prove that this is also a Martingale.

So, we start in the similar fashion. This proof is not as straightforward, as this proof, though similar type of approaches would be used but let us just go and do it. This ω , the σ that you see, this we will finally talk about as volatility of the stock price movement. It captures, how the randomness captures the massive movement. It really gives you a feel of the zigzagging of the path how the prices are how fast they are going and coming down so that sort of so this captures that idea basically.

So, \mathcal{F} is a filtration associated with the Brownian motion W_t (()) 18:52. Say I have added σW_t and subtracted $\sigma^2 t$ from here. Observe that $\sigma^2 t$ is nonrandom part. It is not a random variable right. So, here is the product x into y okay. So, the question is, in this sort of situations right, there are some deeper questions. If you go back to your original, where we had written down the laws of conditional expectation, the rules then, we expected this and this, this product has to be integrable because if you have to maintain the definition of conditional expectation.

Of course, product has to be integrable means you need to define, what is the meaning of integration of these two random variables okay. Are such random variables integrable? That is the question we are not going to answer right now. We will later on show that these are actually integrable, later on discuss the integrability of this, that is they are actually integrable random variables, because they will come out to be solution of certain equations.

So, and if you have a Brownian motion, how can you integrate it. Can you integrate it just like any other random variable, can you find the expectation of a Brownian motion? The answer is yes. I can find the expectation of this Brownian motion because this is 0. Can you find the expectation of this Brownian motion? The answer is expectation of Brownian this Brownian motion is this minus half $\sigma^2 t$.

Now it will be left to the reader to decide whether. Of course, there are certain little technical issues, I am not getting into, but it is clear that expect. What is meant by the meaning of integrability of a random variable? Integrability means that the expectation is finite. The expectation of this is finite, this is finite.

So, this exponential function will have the integral will be integrable and this exponential function would be also integrable. So, at the end if you look at this part. So, this is nothing but this part, but this part this is because, this has mean minus half sigma square t because, this mean is 0 and, this exponential is nothing but a constant thing, so mean of this is nothing but minus half sigma square t so this is a thing with finite mean.

Now if you take a you are taking exponentiation so basically you are taking expectation of the exponential function. If the random variable itself has a finite mean, then if you take the exponential function, that exponential function will also have a finite mean it will have finite expectation. That is why it is meaningful to apply the fact that I can take out what is known.

You see this part is known to me when, at time s , this whole part is known to me because this only depend this is just the evolution of W the random variable up to the time s . So, I will take this part out. Taking out what is known I will have exponential. So, it is very important to get certain technicalities clear, before you move, where you are actually applying the results correctly. That is an important thing, that one needs to learn as one goes on doing more mathematics. Sometimes we can do some hand waving but not always.

Now once, I have this, remember that this thing is independent of F_s , which means, I just need to calculate this. Now what is this, sorry, I would not have the F_s here sorry it is independent. Now if those, who know some probability, they will understand that, I know that W_t minus W_s is a normal distribution with mean 0 and variance t minus s and this is nothing but the moment generating function of a normal distribution.

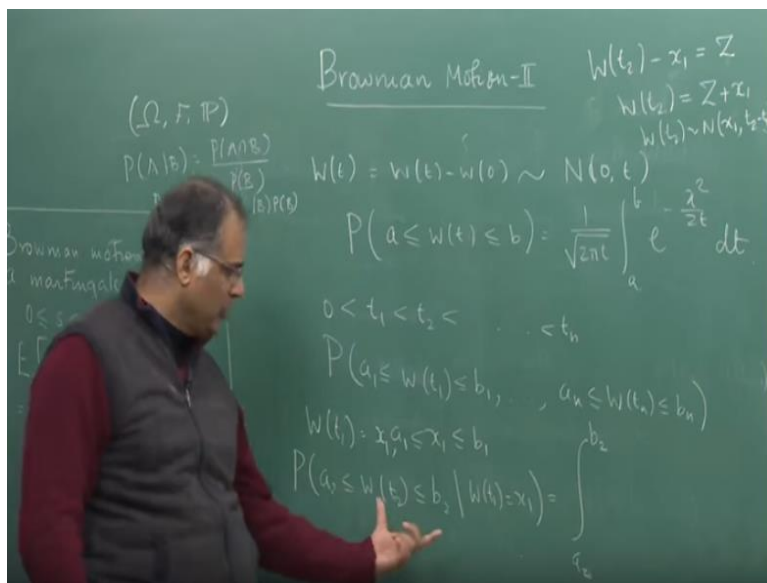
I have not spoken about moment generating function in this discussion, but if you forget about this term moment generating function, you can directly compute this expectation. I am not going to compute for you, this will come as a homework and this will appear in your assignments.

So, what I am just writing down the answer. Even this is simple integration, so I am just not going to do that. This is equal to exponential of half sigma square t minus s okay. So, this is what you will have that is the answer.

So, once you write that down then, the final answer would be the following, that if you write this as exponential so you write this as exponential sigma Ws minus half sigma square t and then you write this as exponential of sigma square t minus s, so this is nothing but exponential sigma Ws minus half sigma square s so this is nothing but Zs.

There is another Martingale which is helpful in finance is the following. It is Z_t is W square minus t . So, this will also go as an exercise in your homework assignments, to prove that this is a Martingale.

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Now we will talk about, so what is happening. We will talk about how to compute the joint probability of a Brownian motion at certain given time points. You take W_t at any t , what is the distribution of this random variable. W_t can be always written as, W_t minus W_0 and this has normal $0t$. So, if you want to know whether, at a given time t your W_t is lying between some points a and b , it is obvious you can just use the basic idea that is.

The question is, suppose I have now n time points which are greater than 0 , 0 I know where it is, so with n time points and we ask you the question, how to find sorry, say W_{t_1} , how do I do it. So, let me look at the case at the very first, this is how you compute what are called the transition probability densities let us see.

So, now suppose, you are given the information that, under the given scenario W_{t_1} , under the given scenario ω W_{t_1} ω was x okay. So, suppose I know that it is known to me that, at t_1 for the given scenario W , at time t_1 it was x where say x_1 , x_1 lying between b_1 and a_1 . So, what I now want to do is, I want to calculate the probability at W_{t_2} lies between a_2 and b_2 given that W_{t_1} is x_1 . That is what I want to do.

But, if you see, if I fixed W_{t_1} as x_1 then, what do I have. I have W_{t_2} minus x_1 as my random variable, x_1 is known to me that, at time t_1 x_1 is what happened. So, now what is the probability that W_{t_2} would lie between the value of W_{t_2} for the given scenario ω will lie between a_2 and b_2 . So, for the scenario ω t_1 I know what will happen. It was at x_1 . Now find so it is in the state x_1 so what is the probability that, the next state would lie between a_2 and b_2 . It is like sort of a computing transition probabilities.

So, here if you look at this thing, the expectation of this, this is also normal random variable, so this also follows normal random variable, but the expectation of this, is what, expectation is, so it is a , see here, we had, so this new random variable z , so W_{t_2} so, is equal to z plus x_1 . So, under this given information the expectation of W_{t_2} . So, W_{t_2} under this information follows normal x_1 with, because this is the time t_1 , so this z follows normal 0 at time $t_2 - t_1$, so W_{t_2} is nothing but x_1 plus z . So, W_{t_2} follows this one, because this expectation is 0 . So, once you know this fact then what would happen.

This means now I can compute, sorry, I should be having, so we will be applying the same idea of conditional probability, that probability of A Intersection B is probability of A into probability of B sorry, so probability of A given B is probability of A intersection B by probability of B. This is what we had learnt. So, you can always write probability of A Intersection B is probability of A given B into probability of B. That is exactly what we are going to do here.

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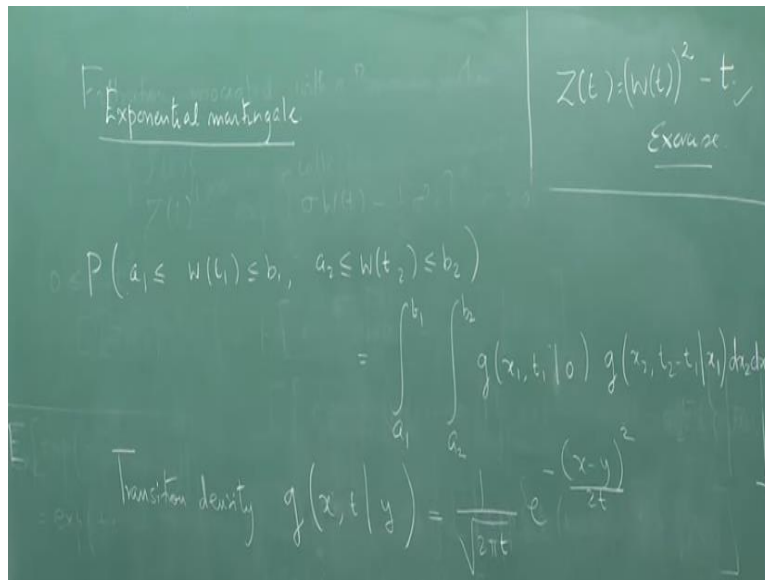
Handwritten mathematical notes on a chalkboard:

- $P(A|B) = \frac{P(A \cap B)}{P(B)}$
- $P(A \cap B) = P(A|B)P(B)$
- $W(t) = W(t) - W(0) \sim N(0, t)$
- $P(a \leq W(t) \leq b) = \frac{1}{\sqrt{2\pi t}} \int_a^b e^{-\frac{x^2}{2t}} dx$
- $0 < t_1 < t_2 < \dots < t_n$
- $P(a_1 \leq W(t_1) \leq b_1, \dots, a_n \leq W(t_n) \leq b_n)$
- $W(t_1) = x_1, a_1 \leq x_1 \leq b_1$
- $P(a_2 \leq W(t_2) \leq b_2 | W(t_1) = x_1) = \frac{1}{\sqrt{2\pi(t_2-t_1)}} e^{-\frac{(x_2-x_1)^2}{2(t_2-t_1)}} dx_2$

So first we are computing the conditional expectation and then using this we will write the joint probability. So, this conditional expectation is, 1 by the conditional probability is, 1 by x_2 is the variable that I am using for the variable x_2 , x_1 is what is the mean x_2 .

Now, if I want to write the joint probability so this is my conditional density. This is my conditional density function and thus I can write the conditional density function in a more simpler way. So, I can write the conditional density function in a compact form but let us do a general form and then we will tell you how to write the conditional density function.

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If you look at this, now I am writing this one, is a joint probability okay, and this is equal to, so first I will write, I will tell you, what is the meaning of this. So, these are the marginal probabilities, a marginal densities. So, the marginal density, in general is given like this.

So, what is the density function associated with the fact my current state is y and then in time t, I will move to the state x, at time 0 say if my current state time 0 is y in time t, I will move to the state x, what is the density function associated with that particular transition. So, this is called the transitional density function or the conditional density, transition density and that is given as, one by root 2 pi t e to the power of minus x minus y whole square by 2t.

So, this is my conditional density function. So, I would keep it as an exercise for you to write down for the case tn. How can you write it? So, here you see, from 0 my state was 0, it is always 0, W0, 0. I have come to the state X1 at t1. Given that, I am in state x1 at t1, within the time t1 to t2, I have, within the time span t2 minus t1, I have come to the state x2.

So, essential a marco process. Brownian motion is also a marco process those who know about marco process. So, we are just trying to compute, this is nothing but a conditional, this is a transitional probability actually. It tells you, given the state is at x1, what is the probability that the state is between a2 and b2 so next state. Because it is a continuous thing, you cannot say that

probability W_{t_2} is x_2 because that will become 0, so you just have to say what is in between. So, that is the whole thing.

So, I know what is at 0 I will come to the state x_1 . So, the conditional density at x_1 is the conditional density at x_2 . I am at time t_1 and I am at x_1 and at time t_2 , so within the time spend t_2 minus t_1 I have come to x_2 then what is the conditional density. So, the joint integration of this, would give me the conditional probability, which can be motivated, is motivated from this very basic idea.

Thank you very much.