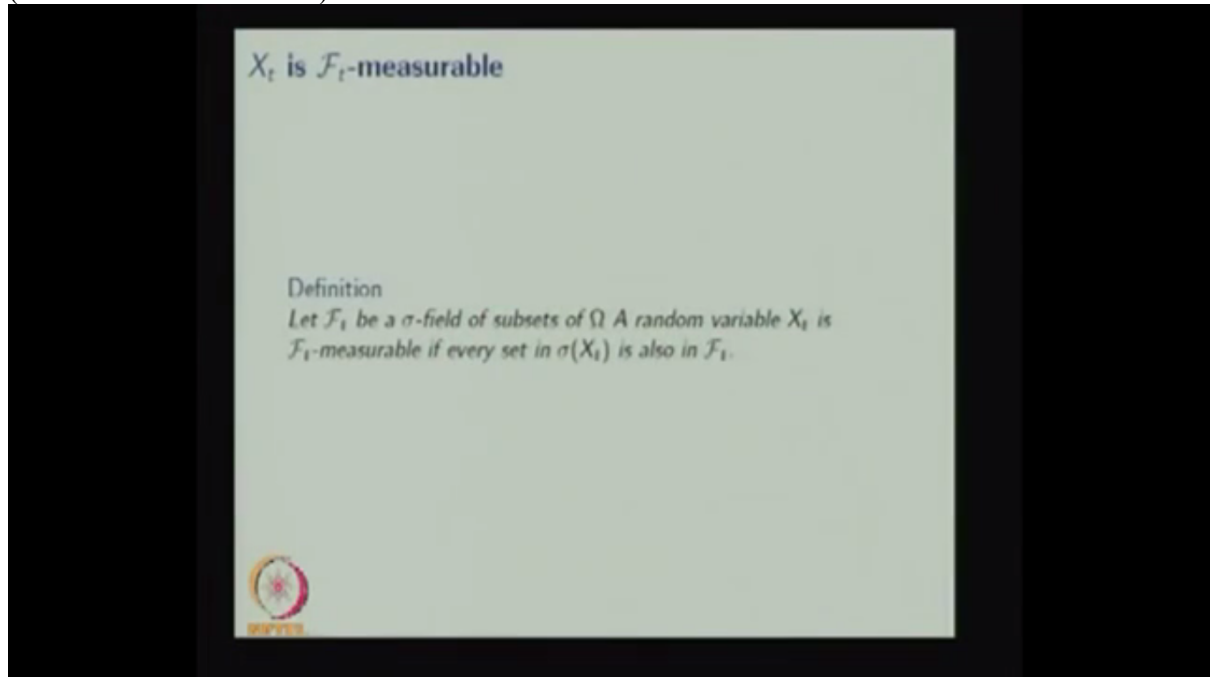


Remarks of Conditional Expectation and Adaptability

by

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To verify the given stochastic process as the Markov, sorry, as the Martingale property, each random variable X_t must be a F_t measurable. So we will see the definition of when the random variable X_t is going to be the F_t measurable. For that the definition is as follows.

Let F_t be a σ -field of subsets of Ω . A random variable X_t is F_t measurable if every set in σ -field generated by the random variable X of t is also in F_t . We have a non-empty set, that is a collection of possible outcomes and we have created the σ -field on Ω and the random variable is said to be a F_t measurable, the random variable X_t is said to be a F_t measurable if the σ -field, if every set in σ -field generated by the random variable X_t is also in F of t . If this condition is satisfied, then this random variable is going to be call it as a F_t measurable.

Obviously, F of t is contained in $\sigma(X_t)$. So here every element, every set in σ -field generated by the random variable X_t is also in F_t . That means it's other way around. So if that property is also satisfied, then this random variable is a F_t measurable.

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Some Remarks on X_t is \mathcal{F}_t -measurable

- ▶ A random variable is \mathcal{F}_t -measurable if and only if the information in \mathcal{F}_t is sufficient to determine the value of X_t .
- ▶ When a random variable X_t is not \mathcal{F}_t -measurable, the information contained in σ -field \mathcal{F}_t can not determine the values of the random variable X_t .
- ▶ If X_t is \mathcal{F}_t -measurable and g is Borel measurable function, then $g(X_t)$ is also \mathcal{F}_t -measurable.
- ▶ When \mathcal{F}_t is σ -field of all subsets of Ω (the power set of Ω) and Ω is finite or countably infinite, random variable defined on Ω is always \mathcal{F}_t -measurable.



Some remarks on X_t is \mathcal{F}_t measurable. The first remark, a random variable is -- a random variable X_t is \mathcal{F}_t measurable if and only if the information in \mathcal{F}_t of t is sufficiently to determine the value of X of t . The \mathcal{F}_t of t is nothing but the collection of the information up to the time. So whenever we say the random variable is \mathcal{F}_t measurable if and only if the information in \mathcal{F}_t is sufficient to determine the value of X of t .

The second remark, when a random variable X_t is not a \mathcal{F}_t measurable, then the information contained in σ -field \mathcal{F}_t cannot determine the values of the random variable X_t . Whenever the random variable is not a \mathcal{F}_t measurable, the conclusion is the information contained in the σ -field \mathcal{F}_t of t cannot determine the values of the random variable whereas X_t is a random -- is a \mathcal{F}_t measurable if and only if it has the sufficient information to determine the value of X of t .

Third remark, if X_t is \mathcal{F}_t measurable and g is a Borel measurable function, then $g(X_t)$ is also \mathcal{F}_t measurable. We know that X is a random variable. Then, and g is a Borel measurable function. Then $g(X)$ is a random variable. So here we are saying if X_t is \mathcal{F}_t measurable and g is a Borel measurable function, then $g(X_t)$ is also a \mathcal{F}_t measurable. Obviously, $g(X_t)$ is also a random variable. Since X_t is \mathcal{F}_t measurable, then $g(X_t)$ is also \mathcal{F}_t measurable.

The fourth remark, we are not giving the proof for this remark. The fourth one, when \mathcal{F}_t is a σ -field of all subsets of Ω , that is the power set of Ω and the Ω is finite or countably infinite, then the random variable defined on Ω is always \mathcal{F}_t measurable. Whenever the σ -field \mathcal{F}_t is the power set or the largest σ -field, in that case the random variable defined on Ω is always a \mathcal{F}_t measurable. We know that whenever \mathcal{F}_t is the largest σ -field, then any real valued function is going to be a random variable. Here, whenever \mathcal{F}_t is a σ -field, which is a largest σ -field or the power set of Ω and additional condition, and Ω is a finite or countably infinite, then the random variable is always \mathcal{F}_t measurable.

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Adaptability

Definition

The stochastic process $\{X_t, t \geq 0\}$ is said to be adapted to the filtration $\{\mathcal{F}_t, t \geq 0\}$ if

$$\sigma(X_t) \subset \mathcal{F}_t, \text{ for all } t \geq 0$$

i.e., X_t is \mathcal{F}_t -measurable for each $t \geq 0$. In such case, all events concerning the sample paths of an adapted process until time t are contained in \mathcal{F}_t .

In discrete case, we say that a stochastic process $\{X_n, n = 0, 1, \dots\}$ is adapted to the filtration $\{\mathcal{F}_n, n = 0, 1, \dots\}$ if $\sigma(X_n) \subset \mathcal{F}_n$ for every n .

For instance, suppose S_n is the price of a stock at the end of n th day then the price process $\{S_n, n = 0, 1, \dots\}$ is adapted to natural filtration $\{\mathcal{F}_n, n = 0, 1, \dots\}$ where \mathcal{F}_n is the history up to the end of n th day.

Based on X_t is \mathcal{F}_t measurable, we discuss adaptability of the stochastic process. The stochastic process X_t over the t greater than or equal to zero is said to be adapted to the filtration F of t if the σ -field generated by the random variable X_t , which is contained in F of t for all t greater than or equal to zero. So this condition is nothing but X_t is \mathcal{F}_t measurable. Whenever X_t is \mathcal{F}_t measurable, then the collection of random variable X of t is adapted to the filtration F of t . If this condition is not satisfied, in that case X_t is not a \mathcal{F}_t measurable. If X_t is not a \mathcal{F}_t measurable, then the collection of random variable, the collection of random variables X of t is not going to be adapted to the filtration.

Suppose it is X_t is \mathcal{F}_t measurable, in such cases, all events concerning the sample paths of adapted process until time t are contained in F of t . It says \mathcal{F}_t has the collection -- has the information up to the time t . Whenever X_t is \mathcal{F}_t measurable, then all the events concerning the sample paths of the adapted process until time t are contained in \mathcal{F}_t . It's the same meaning here. The σ -field generated by the X of t which is contained in F of t whenever the stochastic process is adapted.

In a discrete case, we say that stochastic process X suffix n , n can takes a value 0, 1, 2 and so on is adapted to the filtration F suffix n . So instead of F of t , I am using F suffix n for discrete type and similarly the random variable is also discrete type. Instead of t I'm using small n . If the σ -field generated by the random variable X_n which is contained in the σ -field \mathcal{F}_n for every n , it has to satisfy for every n , then only this collection of a stochastic, sorry, this collection of random variable or this stochastic process is adapted to this filtration \mathcal{F}_n .

For instance, suppose S_n is the price of a stock at the n^{th} day, then the price process S_n , n is equal to 0, 1 and so on is adapted to the natural filtration \mathcal{F}_n , $n = 0, 1$ and so on where \mathcal{F}_n is the history up to the end of n^{th} day.

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Conditional Expectation of X given \mathcal{F}

Definition

Let (Ω, \mathcal{S}, P) be a given probability space. Let X be an integrable random variable and \mathcal{F} be a sub σ -field of \mathcal{S} . The conditional expectation of X given \mathcal{F} , denoted by $E(X | \mathcal{F})$, is the unique random variable satisfying

- ▶ $E(X | \mathcal{F})$ is measurable with respect to \mathcal{F} .
- ▶ $\int_A E(X | \mathcal{F}) dP = \int_A X dP$ for all $A \in \mathcal{F}$.



Now we see the definition of a Conditional Expectation of random variable X given σ -field \mathcal{F} . Earlier we have defined the conditional expectation of the random variable X given other random variable Y takes the value small y . The definition as follows.

Let (Ω, \mathcal{S}, P) be the given probability space. Let X be an integrable random variable and \mathcal{F} be a sub σ -field of \mathcal{S} . So here I am defining a probability space with the Ω and this is the σ -field \mathcal{S} and P is the probability measure and the random variable which is integrable and \mathcal{F} be the sub σ -field of \mathcal{S} .

The conditional expectation of X given \mathcal{F} , so to distinguish the σ -fields \mathcal{F} and \mathcal{S} , I am giving the \mathcal{S} is a σ -field and \mathcal{F} is the sub σ -field, and we are defining the conditional expectation for the random variable X given the sub σ -field of \mathcal{S} , that is \mathcal{F} , that is denoted by $E(X | \mathcal{F})$, expectation of X given \mathcal{F} . It's a unique random variable. The way I discuss the conditional expectation is a random variable. So here the conditional expectation of X given the σ -field, that is also a random variable. It's a unique random variable satisfying the conditional expectation of X given σ -field is a measurable with respect to the σ -field \mathcal{F} . This is a measurable.

Also the integration over any set A where A is belonging to \mathcal{F} , the expectation of X given \mathcal{F} integration with respect to the probability measure P , that is same as integration with respect to the probability measure P of the integrand is simply X integration over A . Both are one and the same.

Note that the conditional expectation given the σ -field \mathcal{F} is a random variable satisfying these two properties and we are defining the conditional expectation given the sub σ -field of \mathcal{S} where this is the probability space.

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Notes on $E(X | \mathcal{F})$

- ▶ Note that the conditional expectation $E(X | \mathcal{F})$ is a random variable, while the expectation $E(X)$ is a real number.
- ▶ When \mathcal{F} is the σ -field generated by Y , then we also write $E(X | \mathcal{F})$ for the random variable $E(X | Y)$. Thus $E(X | \mathcal{F})$ is the expected value of X given the information \mathcal{F} .



Notes on conditional expectation of X given the σ -field \mathcal{F} . Note that the conditional expectation, expectation of X given \mathcal{F} is a random variable while expectation X is a real number. Similarly, conditional expectation of X given other random variables also a random variable, not a constant.

When \mathcal{F} is the σ -field generated by Y , then we also write conditional expectation of X given \mathcal{F} for the random variable X , expectation of X given Y . Whenever \mathcal{F} is the σ -field generated by Y , you can replace \mathcal{F} by Y . Thus expectation of X given \mathcal{F} is the expected value of X given the information \mathcal{F} . That means you can replace the random variable Y by \mathcal{F} whenever the \mathcal{F} is the σ -field generated by the random variable Y . That is same as the expectation -- expected value of X given the information \mathcal{F} . Whenever we say the σ -field, that is nothing but the information.

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Example 4

Let $\Omega = \{a, b, c, d\}$, $\mathcal{S} = \mathcal{P}(\Omega)$ and $P(\{w\}) = \frac{1}{4}$, $w \in \Omega$

Define

$$X(w) = \begin{cases} 0, & w = a, d \\ -1, & w = b \\ 1, & w = c \end{cases}$$

Let $\mathcal{F} = \{\emptyset, \Omega\}$.

Given \mathcal{F} is the trivial σ -field. The only random variables which are measurable with respect to the trivial σ -field are constants. Hence,

$$E(X | \mathcal{F}) = E(X) = k$$

where k is a constant.



We discussed the conditional expectation of the random variable given σ -field through two examples. The first example is as follows. Omega consists of four elements. S, that is a largest σ -field, power set on Ω and the P of $\{w\}$ is equal to $1/4$ where w belonging to Ω . So, therefore, this is the set function probability measure. We are defining a real valued function. You can cross-check this is a random variable.

Let F that's a σ -field, it's a trivial one. It consists of two elements, empty set and the whole set. Given F is a trivial σ -field, the only random variables which are measurable with respect to the trivial σ -fields or constant. The only random variables which are measurable with respect to the trivial σ -fields are constant. Hence, the expectation of X given the σ -field F where F is a trivial one, that is same as the expectation of X that is equal to constant. That constant you can find out by using the probability and the possible values of 0, -1 and 1, you can find out what is the constant.

So here the conclusion is whenever the σ -field is a trivial one, then the conditional expectation over the trivial σ -field, that is a constant and that constant is same as the expectation of X because it is no more random variable.

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Example 5

Let $\Omega = \{a, b, c\}$, $\mathcal{S} = \mathcal{P}(\Omega)$ and $P(\{w\}) = \frac{1}{3}$, $w \in \Omega$

Define

$$X(w) = \begin{cases} 0, & w = a, b \\ 2, & w = c \end{cases}$$

Let $\mathcal{F} = \{\emptyset, \{a\}, \{b, c\}, \Omega\}$.

Define

$$Y(w) = \begin{cases} 0, & w = a \\ 1, & w = b, c \end{cases}$$

Then, we claim that $E(X | \mathcal{F}) = E(X | Y)$. In fact, Y is \mathcal{F} -measurable, since

$$Y^{-1}((-\infty, x]) = \begin{cases} \emptyset & -\infty < x < 0 \\ \{a\} & 0 \leq x < 1 \\ \Omega & 1 \leq x < \infty \end{cases}$$



The second example is as follows. Here the Ω consists of three elements. \mathcal{S} is the largest σ -field. Probability measure is defined on Ω in each sample itself with the probability $1/3$. X is the random variable. \mathcal{F} is not the trivial one here. \mathcal{F} is the σ -field which is not a trivial one, and I am defining another random variable Y and that takes a value 0 or 1, and here I am claiming that expectation of X given \mathcal{F} is same as expectation of X given Y because the Y is the σ -field generated -- because the \mathcal{F} is the σ -field generated by the random variable Y .

If you -- if you create the σ -field generated by the Y , you may land up empty set, element a , element b and c and the whole set and that is same as \mathcal{F} . Therefore, you can replace expectation of X given \mathcal{F} by expectation of X given Y . Here Y is the \mathcal{F} measurable. You can check Y is a random variable also by finding the inverse images.

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Properties

Let (Ω, \mathcal{S}, P) be a probability space. Let \mathcal{F} be a sub σ -field of \mathcal{S} . It satisfies

- ▶ $E(X | \mathcal{F}) \geq 0$ if $X \geq 0$
- ▶ $E(\alpha X + \beta Z | \mathcal{F}) = \alpha E(X | \mathcal{F}) + \beta E(Z | \mathcal{F})$ where α and β are constants.
- ▶ $E(E(X | \mathcal{F})) = E(X)$
- ▶ If X is independent of \mathcal{F} , then $E(X | \mathcal{F}) = E(X)$
the events $\{X \leq x\}$ and A are independent for any $x \in \mathbb{R}$ and $A \in \mathcal{F}$



The other properties of the first one, the conditional expectation is always greater than or equal to zero if X is greater than or equal to zero. Then the linear property similar to the conditional expectation as I discussed earlier. Then this also I have discussed. Instead of a σ -field, I have discussed with the random variable. If they are independent, then both are same.

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Properties ...

- ▶ If X_1 is \mathcal{F} -measurable, then $E(X_1 X_2 | \mathcal{F}) = X_1 E(X_2 | \mathcal{F})$
(taking out what is known)
- ▶ If \mathcal{G} is a sub σ -field of \mathcal{F} , then

$$E(E(X | \mathcal{F}) | \mathcal{G}) = E(X | \mathcal{G})$$

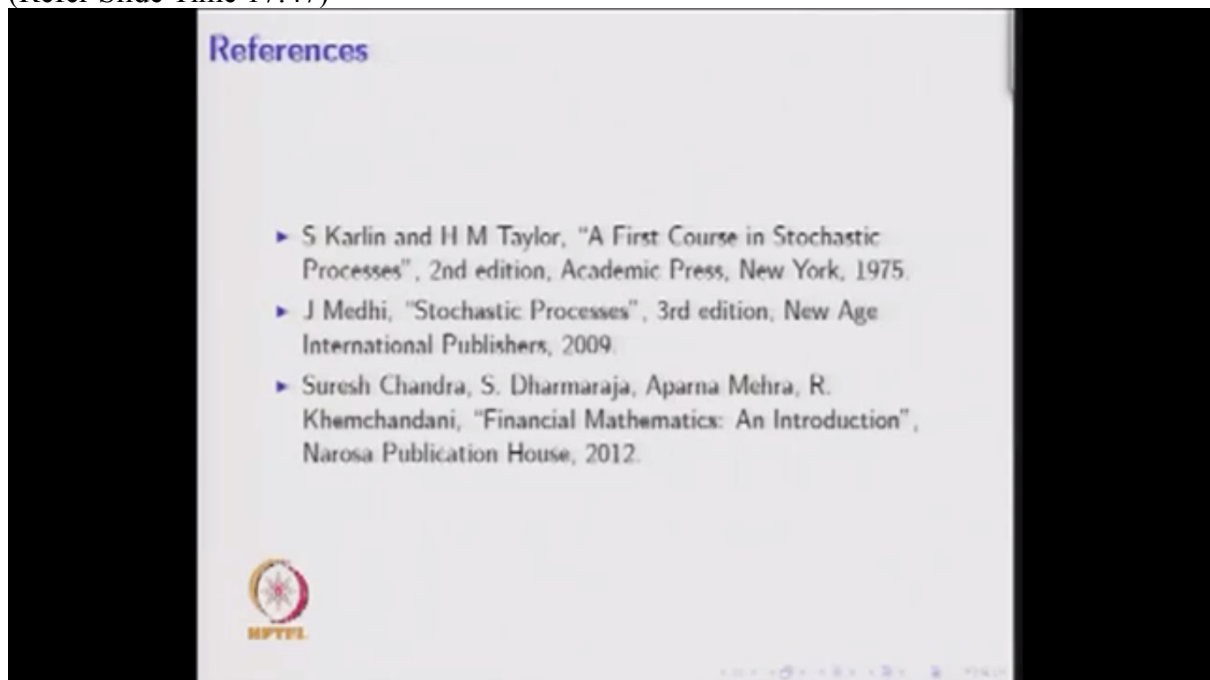
(tower property)



The last two properties, if X_1 is \mathcal{F}_1 measurable, then the multiplication, the X_1 taken out which is what is known. So since X_1 is known because X_1 is a \mathcal{F} measurable, so X_1 will be coming outside, X_1 times the conditional expectation.


If \mathcal{G} is a sub σ -field, then this expectation, conditional expectation is same as the conditional expectation and this is called the tower property. I am not going to give the proof of this.

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Here is the reference. Thanks.

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