

# Lecture Notes for Math 210 – 22 October 2007

Shannon Starr

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## Chapter 5: Tools in Probability Theory

### Conditional Probability and Conditional Expectation

Remember that for one sample space  $\Omega$ , there can be different event spaces ( $\sigma$ -fields)  $\mathcal{F}$ .

A random variable  $X : \Omega \rightarrow \mathbb{R}$  is said to be  $\mathcal{F}$ -measurable if all the sets  $\{\omega \in \Omega : X(\omega) = x\}$  are in  $\mathcal{F}$  for all  $x \in \mathbb{R}$ .

This is an abstract idea, but consider the following simple example.

Example 1. Let  $X$  be the outcome of rolling 1 fair die, and let  $Y$  be the outcome of rolling another fair die.

So we could say

$$\Omega = \{(i, j) : i, j = 1, 2, \dots, 6\}.$$

Let  $\mathcal{F}_1$  be the full event space consisting of all possible subsets of  $\Omega$ .

Let  $\mathcal{F}_2$  be the event space generated by  $X$ , by itself.

So, some events in  $\mathcal{F}_2$  are

$$\begin{aligned} E_1 &= \{(1, j) : j = 1, \dots, 6\}, \\ E_2 &= \{(2, j) : j = 1, \dots, 6\}, \\ &\vdots \\ E_6 &= \{(6, j) : j = 1, \dots, 6\}. \end{aligned}$$

All other events in  $\mathcal{F}_2$  are unions of some of these sets, or the empty set  $\emptyset$ .

(The empty set  $\emptyset$  is always in every event space).

Note that using events in  $\mathcal{F}_2$  we can ask the question “Is  $X = 4$ ?” or even “What is  $X$ ?” but we cannot specify anything about  $Y$ .

So  $X$  is  $\mathcal{F}_2$ -measurable, but  $Y$  is not  $\mathcal{F}_2$ -measurable.

But both  $X$  and  $Y$  are  $\mathcal{F}_1$ -measurable.

Fact: Suppose  $\Omega$  is some sample space

and that  $\mathcal{F}_1$  and  $\mathcal{F}_2$  are two event spaces

such that  $\mathcal{F}_2 \subseteq \mathcal{F}_1$ .

If  $X$  is a random variable which is  $\mathcal{F}_1$ -measurable,

then there is always another random variable, called  $\mathbf{E}[X | \mathcal{F}_2]$ ,

which is  $\mathcal{F}_2$ -measurable, and such that for any other  $\mathcal{F}_2$  measurable function,  $Y$ ,

we have

$$\mathbf{E}[Y \cdot \mathbf{E}[X | \mathcal{F}_2]] = \mathbf{E}[Y \cdot X].$$

This is also a somewhat abstract definition, but in particular cases calculating  $\mathbf{E}[X | \mathcal{F}_2]$  is usually a very concrete problem.

In case  $\mathcal{F}_2$  is the event space generated by some other random variable  $Y$ , we usually write  $\mathbf{E}[X | Y]$  instead of  $\mathcal{F}_2$ .

Usually, when we calculate  $\mathbf{E}[X | Y]$ , we find that it is an explicit function of  $Y$ .

Example 1 (cont.) Let us reconsider example 1 where  $X$  and  $Y$  are the results of rolling independent fair dice.

So,

$$\mathbf{P}\{X = i, Y = j\} = \frac{1}{36} \quad \text{for all } i, j = 1, \dots, 6.$$

Let  $Z = X + Y$ .

Note that the possible outcomes for  $Z$  are  $k = 2, 3, \dots, 12$ .

Also,

$$\mathbf{P}\{Z = k\} = \frac{n(k)}{36},$$

where  $n(k) = 6 - |7 - k|$ .

$k$	2	3	4	5	6	7	8	9	10	11	12
$n(k)$	1	2	3	4	5	6	5	4	3	2	1

Let us calculate

(a)  $\mathbf{E}[X | Z]$ ,

(b)  $\mathbf{E}[X^2 | Z]$ .

**A:** The answer to (a) is actually easy using a trick:

By symmetry we should have  $\mathbf{E}[X | Z] = \mathbf{E}[Y | Z]$ .

But we also know that

$$\mathbf{E}[X | Z] + \mathbf{E}[Y | Z] = \mathbf{E}[X + Y | Z] = \mathbf{E}[Z | Z].$$

But  $Z$  is already measurable with respect to the event space generated by  $Z$ , by definition.

So  $\mathbf{E}[Z | Z] = Z$ .

Therefore,

$$\mathbf{E}[X | Z] = \frac{1}{2} \mathbf{E}[X + Y | Z] = \frac{Z}{2}.$$

So that is the answer.

To solve (b) is not as trivial.

Actually, what we have to do is first calculate the conditional probability.

We have

$$\mathbf{P}(\{X = i\} | Z) = \mathbf{E}[I_{X=i} | Z],$$

where  $I_{\{X=i\}}$  is the indicator random variable:

$$I_{\{X=i\}} = \begin{cases} 1 & \text{if } X = i, \\ 0 & \text{otherwise.} \end{cases}$$

We remember the famous formula for conditional probability

$$\mathbf{P}(\{X = i\} | \{Z = k\}) = \frac{\mathbf{P}\{X = i, Z = k\}}{\mathbf{P}\{Z = k\}}.$$

In our new, abstract notation, we actually *define* the conditional probability as

$$\mathbf{P}(\{X = i\} | \{Z = k\}) = g(k),$$

where  $g$  is the function such that  $\mathbf{P}(\{X = i\} | Z) = g(Z)$ .

But we do not have to get caught up in notation.

What we get is

$$\mathbf{P}(\{X = i\} | \{Z = k\}) = \begin{cases} 1/n(k) & \text{if } i = \frac{k-n(k)+1}{2}, \dots, \frac{k+n(k)-1}{2}, \\ 0 & \text{otherwise.} \end{cases}$$

E.g., if  $k = 5$  then we have  $n(k) = 6 - 2 = 4$ . So

$$\mathbf{P}(\{X = i\} | \{Z = 5\}) = \frac{1}{4} \quad \text{for } i = \frac{5-4+1}{2}, \dots, \frac{5+4-1}{2} = 1, \dots, 4.$$

Using this and the formula

$$\sum_{i=1}^n i^2 = \frac{n(n+1)(2n+1)}{6},$$

it is straightforward, but tedious, to calculate

$$\mathbf{E}[X^2 | \{Z = k\}] = \frac{k(k^2 + 3(n(k))^2 - 3)}{12n(k)}.$$

So technically, we should have

$$\mathbf{E}[X^2 | Z] = \frac{Z(Z^2 + 3(6 - |7 - Z|)^2 - 3)}{12(6 - |7 - Z|)}.$$

(There may be a simpler formula. Also, there is some possibility that this formula has a small error. The point is not to derive the formula for this complicated problem, but to illustrate the notation using this problem.)