

## STAB52, An Introduction to Probability - Tutorial 8

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Consider the set of numbers  $x_1, \dots, x_n$ . Colloquially, the average of these values is understood to be  $\bar{x} = (x_1 + \dots + x_n)/n$ . That is, we weight each value equally (probabilistically, every value  $x_i$  is equally likely to occur i.e. a discrete uniform distribution). However, what if each  $x_i$  has probability  $p_i$  of occurring ( $\sum_{i=1}^n p_i = 1$ ). Then if we average each value based on (weighting each value by) the probability of each value occurring, then the average value becomes

$$\sum_{i=1}^n p_i \cdot x_i.$$

This is the motivation behind the expected value of a random variable: "The average value that the random variable takes weighted by the probabilities of each value". More precisely, if  $X$  is discrete, then

$$\mathbb{E}(X) = \sum_{x \in \mathbb{R}} x \cdot \mathbb{P}(X = x) = \sum_{x \in \text{supp}(X)} x \cdot \mathbb{P}(X = x).$$

Similarly, the expected value for an absolutely continuous random variable with density function  $f_X(x)$  is given by

$$\mathbb{E}(X) = \int_{-\infty}^{\infty} x f_X(x) dx.$$

Notice that this is the direct analog of the discrete case since an integral is essentially a way of summing uncountably many values.

**Problem 1.** (Evans & Rosenthal, Exercise 3.1.16)

Suppose you start with one penny and repeatedly flip a fair coin. Each time you get heads, *before* the first time you get tails, your number of pennies is *doubled*. Let  $X$  be the total number of pennies you have at the end. Compute  $\mathbb{E}(X)$ .

**Solution:** Let  $Y$  be the number of heads flipped before the first tail so the  $Y \sim \text{geometric}(1/2)$ . This implies  $\mathbb{P}(Y = y) = 1/2^{y+1}$ ,  $y = 0, 1, 2, \dots$ . It then follows that  $X = 2^Y$  and so by the Theorem 3.1.1. (Evans & Rosenthal), we have

$$\mathbb{E}(X) = \mathbb{E}(2^Y) = \sum_y 2^y \mathbb{P}(Y = y) = \sum_{y=0}^{\infty} 2^y \cdot \frac{1}{2^{y+1}} = \sum_{y=0}^{\infty} \frac{1}{2} = \infty.$$

Notice here that we have an expected value of  $\infty$ ; this not uncommon result.

□

**Problem 2.** (Expectation of a random variable with natural support)

Let  $X$  be a discrete random variable whose support is the natural numbers. Prove that

$$\mathbb{E}(X) = \sum_{k=1}^{\infty} \mathbb{P}(X \geq k)$$

**Solution:** Using the definition of expectation for discrete random variables, we rewrite as

$$\mathbb{E}(X) = \sum_{k=1}^{\infty} k \cdot \mathbb{P}(X = k) = \sum_{k=1}^{\infty} \mathbb{P}(X \geq k)$$

□

**Problem 3.** (Evans & Rosenthal, Exercise 3.1.25.)

Suppose  $X$  is a discrete random variable, such that  $\mathbb{E}(\min(X, M)) = \mathbb{E}(X)$ . Prove that  $\mathbb{P}(X > M) = 0$ .

**Solution:** Allow me to first give you an incorrect solution. This is actually my first attempt at the problem (and in fact, a more natural approach to this problem). Using the definition of expectation and the given hypothesis, we compute

$$\begin{aligned}
 \sum_{x \in \mathbb{R}} x \cdot \mathbb{P}(X = x) &= \mathbb{E}(X) \\
 &= \mathbb{E}(\min(X, M)) \\
 &= \sum_{y \in \mathbb{R}} y \cdot \mathbb{P}(\min(X, M) = y) \\
 &= \sum_{y \leq M} y \cdot \mathbb{P}(\min(X, M) = y) + \sum_{y > M} y \cdot \mathbb{P}(\min(X, M) = y) \\
 &= \sum_{y \leq M} y \cdot \mathbb{P}(X = y) + \sum_{y > M} y \cdot \mathbb{P}(\emptyset) \\
 &= \sum_{y \leq M} y \cdot \mathbb{P}(X = y),
 \end{aligned}$$

which implies that  $\sum_{y > M} y \cdot \mathbb{P}(X = y) = 0$ . If we had the assumption that  $M$  was non-negative, we would be done. However, this is not the case and we cannot actually conclude anything.

Now, let us see the correct solution: Define  $Y = X - \min(X, M)$  so then  $Y$  is a discrete random variable such that  $Y \geq 0$ . By the given assumption (along with linearity of expectation), we have

$$\mathbb{E}(Y) = \sum_{y \geq 0} y \cdot \mathbb{P}(Y = y) = 0.$$

Since we are summing over  $\{y \geq 0\}$  and  $\mathbb{P}(Y = y) \geq 0$ , it must be the case that  $\mathbb{P}(Y = y) = 0$  for all  $y > 0$ . Disjoint additivity then says  $\mathbb{P}(Y > 0) = 0$  i.e.

$$0 = \mathbb{P}(X > \min(X, M)) = \mathbb{P}(X > M)$$

as required.

□

**Problem 4.** (Evans & Rosenthal, Exercise 3.1.17.a)

Let  $X \sim \text{Geometric}(\theta)$ , and let  $Y = \min(X, 100)$ . Compute  $\mathbb{E}(Y)$ .

**Solution:** We compute

$$\begin{aligned}
 \mathbb{E}(Y) &= \sum_{y=0}^{\infty} y \cdot \mathbb{P}(Y = y) \\
 &= \sum_{x=0}^{100} x \cdot \mathbb{P}(X = x) + \sum_{x=101}^{\infty} 100 \cdot \mathbb{P}(X = x) \\
 &= \theta \sum_{x=0}^{100} x \cdot (1 - \theta)^x + 100\theta \sum_{x=101}^{\infty} (1 - \theta)^x
 \end{aligned}$$

We compute the second summation as

$$\begin{aligned}
\sum_{x=101}^{\infty} (1-\theta)^x &= \sum_{x=0}^{\infty} (1-\theta)^x - \sum_{x=0}^{100} (1-\theta)^x \\
&= \frac{1}{1-(1-\theta)} - \frac{1-(1-\theta)^{100}}{\theta} \\
&= \frac{(1-\theta)^{101}}{\theta}.
\end{aligned}$$

In the first summation, we let  $S = \sum_{x=0}^{100} x \cdot (1-\theta)^x$  and hence

$$\begin{aligned}
\theta S &= S - (1-\theta)S \\
&= S - \sum_{x=0}^{100} x \cdot (1-\theta)^{x+1} \\
&= \sum_{x=0}^{100} x \cdot (1-\theta)^x - \sum_{y=1}^{101} (y-1) \cdot (1-\theta)^y \\
&= \sum_{x=1}^{100} (1-\theta)^x \\
&= \sum_{x=0}^{100} (1-\theta)^x - (1-\theta) \\
&= \frac{1-(1-\theta)^{101}}{\theta} - (1-\theta)
\end{aligned}$$

I leave the simplification of the final expression as an elementary exercise.

□