Lecture 04.09 Expectation

Recall that a random variable is a function $X : \Omega \to \mathbb{R}$ that maps from the sample space to the reals. Random variables are the arguments of probability mass functions (PMFs) and probability density functions (PDFs).

The *expected value* (or *expectation*) of a random variable is akin to its "average value" and depends on its PMF or PDF. The expected value of a random variable X is denoted $\langle x \rangle$ or E(X). There are two definitions of the expectation, one for a discrete random variable, the other for a continuous random variable. Before we define, them, however, it is useful to predefine the most fundamental property of a random variable, its *mean*.

expected value expectation

mean

Definition 04.09.1: mean

The mean of a random variable X is defined as

 $\mathfrak{m}_X = \mathsf{E}(X).$

Let's begin with a discrete random variable.

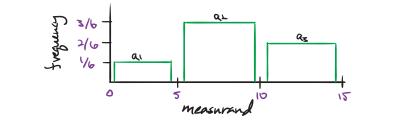
Definition 04.09.2: expectation of a discrete random variable

Let K be a discrete random variable and f its PMF. The *expected value* of K is defined as

$$\mathsf{E}(\mathsf{K}) = \sum_{\forall k} \mathsf{k}\mathsf{f}(k).$$

Example 04.09-1 expectation of a discrete random variable

Given a discrete random variable K with PMF shown below, what is its mean $\mu_K?$

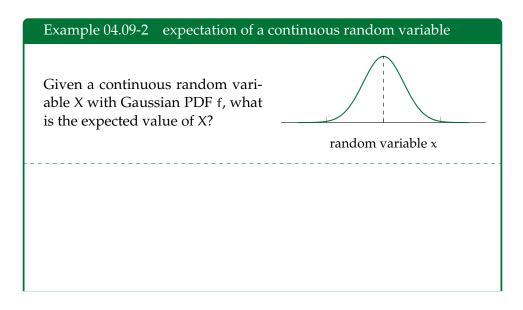


Let us now turn to the expectation of a continuous random variable.

Definition 04.09.3: expectation of a continuous random variable

Let X be a continuous random variable and f its PDF. The *expected value* of X is defined as

$$\mathsf{E}(\mathsf{X}) = \int_{-\infty}^{\infty} \mathsf{x}\mathsf{f}(\mathsf{x})\mathsf{d}\mathsf{x}.$$



Due to its sum or integral form, the expected value $E(\cdot)$ has some familiar properties for random variables X and Y and reals a and b.

$$\mathsf{E}(\mathfrak{a}) = \mathfrak{a} \tag{04.9a}$$

$$E(X + a) = E(X) + a$$
 (04.9b)

$$E(aX) = aE(X) \tag{04.9c}$$

$$E(E(X)) = E(X)$$
 (04.9d)

$$E(aX + bY) = aE(X) + bE(Y).$$
 (04.9e)