

1. Random Variables

We would like to say that a random variable X is a “numerical outcome of a complicated experiment.” This is not sufficient. For example, suppose you sample 1,500 people at random and find that their average age is 25. Is $X = 25$ a “random variable”? Surely there is nothing random about the number 25!

What is random? The procedure that led to 25. This procedure, for a second sample, is likely to lead to a different number. Procedures are functions, and thence

Definition 8.1. A random variable is a function X from Ω to some set D which is usually [for us] a subset of the real line \mathbf{R} , or d -dimensional space \mathbf{R}^d .

In order to understand this, let us construct a random variable that models the number of dots in a roll of a fair six-sided die.

Define the sample space,

$$\Omega = \{1, 2, 3, 4, 5, 6\}.$$

We assume that all outcome are equally likely [fair die].

Define $X(\omega) = \omega$ for all $\omega \in \Omega$, and note that for all $k = 1, \dots, 6$,

$$P(\{\omega \in \Omega : X(\omega) = k\}) = P(\{k\}) = \frac{1}{6}. \quad (5)$$

This probability is zero for other values of k . Usually, we write $\{X \in A\}$ in place of the set $\{\omega \in \Omega : X(\omega) \in A\}$. In this notation, we have

$$P\{X = k\} = \begin{cases} \frac{1}{6} & \text{if } k = 1, \dots, 6, \\ 0 & \text{otherwise.} \end{cases} \quad (6)$$

This is a math model for the result of a coin toss.

2. General notation

Suppose X is a random variable, defined on some probability space Ω . By the *distribution* of X we mean the collection of probabilities $P\{X \in A\}$, as A ranges over all sets in \mathcal{F} .

If X takes values in a finite, or countably-infinite set, then we say that X is a *discrete random variable*. Its distribution is called a *discrete distribution*. The function

$$p(x) = P\{X = x\}$$

is then called the *mass function* of X . Note that $p(x) = 0$ for all but a countable number of values of x . The values x for which $p(x) > 0$ are called the *possible values* of X .

Some important properties of mass functions:

- $0 \leq p(x) \leq 1$ for all x . [Easy]
- $\sum_x p(x) = 1$. Proof: $\sum_x p(x) = \sum_x P\{X = x\}$, and this is equal to $P(\cup_x \{X = x\}) = P(\Omega)$, since the union is a countable disjoint union.

3. The binomial distribution

Suppose we perform n independent trials; each trial leads to a “success” or a “failure”; and the probability of success per trial is the same number $p \in (0, 1)$.

Let X denote the total number of successes in this experiment. This is a discrete random variable with possible values $0, \dots, n$. We say then that X is a binomial random variable [$X = \text{Bin}(n, p)$].

Math modelling questions:

- Construct an Ω .
- Construct X on this Ω .

Let us find the mass function of X . We seek to find $p(x)$, where $x = 0, \dots, n$. For all other values of x , $p(x) = 0$.

Now suppose x is an integer between zero and n . Note that $p(x) = P\{X = x\}$ is the probability of getting exactly x successes and $n - x$ failures. Let S_i denote the event that the i th trial leads to a success. Then,

$$p(x) = P(S_1 \cap \dots \cap S_x \cap S_{x+1}^c \cap \dots \cap S_n^c) + \dots$$

where we are summing over all possible ways of distributing x successes and $n - x$ failures in n spots. By independence, each of these probabilities is

$p^x(1-p)^{n-x}$. The number of probabilities summed is the number of ways we can distributed x successes and $n-x$ failures into n slots. That is, $\binom{n}{x}$. Therefore,

$$p(x) = P\{X = x\} = \begin{cases} \binom{n}{x} p^x (1-p)^{n-x} & \text{if } x = 0, \dots, n, \\ 0 & \text{otherwise.} \end{cases}$$

Note that $\sum_x p(x) = 1$ by the binomial theorem. So we have not missed anything.

3.1. An example. Consider the following sampling question: *Ten percent of a certain population smoke. If we take a random sample [without replacement] of 5 people from this population, what are the chances that at least 2 people smoke in the sample?*

Let X denote the number of smokers in the sample. Then $X = \text{Bin}(n, p)$ [“success” = “smoker”]. Therefore,

$$\begin{aligned} P\{X \geq 2\} &= 1 - P\{X \leq 1\} \\ &= 1 - P(\{X = 0\} \cup \{X = 1\}) \\ &= 1 - [p(0) + p(1)] \\ &= 1 - \left[\binom{n}{0} p^0 (1-p)^{n-0} + \binom{n}{1} p^1 (1-p)^{n-1} \right] \\ &= 1 - [1 - p + np(1-p)^{n-1}] \\ &= p - np(1-p)^{n-1}. \end{aligned}$$

Alternatively, we can write

$$P\{X \geq 2\} = P(\{X = 2\} \cup \dots \cup \{X = n\}) = \sum_{j=2}^n p(j),$$

and then plug in $p(j) = \binom{n}{j} p^j (1-p)^{n-j}$.

4. The geometric distribution

A p -coin is a coin that tosses heads with probability p and tails with probability $1-p$. Suppose we toss a p -coin until the first time heads appears. Let X denote the number of tosses made. Then X is a so-called geometric random variable [“ $X = \text{Geom}(p)$ ”].

Evidently, if n is an integer greater than or equal to one, then $P\{X = n\} = (1-p)^{n-1}p$. Therefore, the mass function of X is given by

$$p(x) = \begin{cases} p(1-p)^{x-1} & \text{if } x = 1, 2, \dots, \\ 0 & \text{otherwise.} \end{cases}$$