

Introduction to Random Variables + Probability Distributions

1. Mapping
 - a. Mapping is a way of converting the possibilities contained in a sample space to real numbers
 - b. Given a sample space, S , and a random variable, X , we say that X maps every element of S to a real number
 - c. You plug the elements of S into X and X outputs a number, i.e. $X(S)$
2. Discrete Random Variables
 - a. A discrete random variable is a variable that can only take on a finite number of values or a countably infinite sequence of values
 - b. The sets $X = \{0.5, 3.23, 10, -1\}$ and $Y = \{0, 1, 2, 3, \dots\}$ are both examples of discrete random variables
 - c. A discrete distribution is the discrete random variable and its corresponding probabilities
 - d. A random variable has a discrete distribution if that random variable is a discrete random variable according to the definition in the bullet point a.
3. Probability Mass Function (PMF)
 - a. A function that maps an element of a random variable to its associated probability
 - b. $PMF = f(x) = Pr(X = x)$ for all possible values of x
4. Cumulative Probabilities
 - a. We can use summations to figure out the probability of one of multiple events occurring
 - b. Say X , a discrete random variable, is the set $\{0, 1, 2, 3\}$
 - c. We can find the probability of X being at most 2 by summing up the probabilities of each independent element:
$$Pr(X \leq 2) = Pr(0) + Pr(1) + Pr(2)$$
 - d. This summation can be done for any accumulation of events, i.e. $Pr(1 < X < 4) = Pr(2) + Pr(3)$
 - e. The sum of all probabilities of all possible events for a discrete random variable must be 1

Outlier

- f. This fact can be used to calculate a cumulative probability in another way
- g. Instead of adding up all the desired probabilities, you could subtract the undesired probabilities from 1
- h.
$$Pr(X \leq 2) = 1 - Pr(3)$$
- i. This could be useful for discrete random variables with many elements
- j. If X ranges from 1 to 100 and you want to know the probability of X taking on a value less than or equal to 98, you don't have to add up all 98 probabilities. You could instead just calculate $1 - Pr(100) - Pr(99)$

Expectations of Discrete Random Variables

1. Expected Value

- a. The expected value is the weighted average of all possible values where the weights are the probabilities of each value
- b. Written as $E[X]$ or μ
- c.
$$\mu = \sum_{all\ x} x \cdot Pr(x)$$
- d. Over many trials, the average of all trials will approach the expected value

2. Variance

- a. $V[X] = \sigma^2 = E[X^2] - (E[X])^2 = E[X^2] - \mu^2$
- b.
$$E[X^2] = \sum_{all\ x} x^2 \cdot Pr(x)$$

3. Standard Deviation

- a.
$$\sigma = \sqrt{V[X]} = \sqrt{E[X^2] - \mu^2}$$
- b. The standard deviation is on the same order as the data, making it usually more useful than the variance

Binomial Distribution

1. Bernoulli Experiment
 - a. A random experiment with only 2 possible outcomes
 - b. Success or Failure
 - c. The probability of success is the same for each time you try the experiment
 - d. The discrete random variable, X , can only take on the values 0 or 1
2. Binomial Distribution
 - a. Sum of all successes over independent Bernoulli experiments
 - b. There are two parameters in this distribution
 - c. n : number of trials
 - d. p : probability of success
3. Probability Mass Function (PMF) of a Binomial Distribution
 - a. $f(x) = \Pr(X = x) = \binom{n}{x} p^x (1 - p)^{n-x}$
 - b. This is the probability of x successes in n trials
 - c. n = number of trials
 - d. x = number of successes (observed value of X) = 0, 1, 2, ..., n
 - e. $n - x$ = number failures
 - f. p = probability of success
 - g. $1 - p$ = probability of failure
 - h. $\binom{n}{x} = \frac{n!}{x!(n-x)!}$ = number of possible ways to get x successes in n trials
 - i. $\binom{n}{x}$ is pronounced "n choose x"
 - j. $\binom{n}{x} \neq \binom{n}{n-x}$
4. Mean, Variance, and Standard Deviation of the Binomial Distribution
 - a. Mean: $\mu = np$
 - b. Variance: $\sigma^2 = np(1 - p)$

Outlier

c. Standard Deviation: $\sigma = \sqrt{np(1-p)}$