Econ 325

Notes on Bernoulli Random Variable and Binomial Distribution¹ By Hiro Kasahara

Bernoulli Random Variable

Consider a random variable X that takes a value of zero or one with probability 1 - p and p, respectively. That is,

$$X = \begin{cases} 0 & \text{with prob. } 1 - p \\ 1 & \text{with prob. } p \end{cases}$$
(1)

The probability mass function is written as $f(x) = p^x(1-p)^{1-x}$ and we say that X has a Bernoulli distribution.

The expected value of X is

$$E(X) = \sum_{x=0,1} xp^x (1-p)^{1-x} = (0)(1-p) + (1)(p) = p$$

and the variance of X is

$$Var(X) = \sum_{x=0,1} (x-p)^2 p^x (1-p)^{1-x}$$

= $(0-p)^2 (1-p) + (1-p)^2 p$
= $p^2 (1-p) + (1-p)^2 p = (p+(1-p)) \times p(1-p) = p(1-p).$

The standard deviation of X is $\sqrt{\operatorname{Var}(X)} = \sqrt{p(1-p)}$.

Binomial Distribution

Let $X_1, X_2, ..., X_n$ be a sequence of *n* independent Bernoulli random variables, each of which has the probability of success equal to *p*, given by (1). Define a random variable *Y* by

$$Y = \sum_{i=1}^{n} X_i,$$

i.e., Y is the number of successes in n Bernoulli trials. The number of ways of selecting y positions for the y successes in the n trials is

$$\binom{n}{y} = \frac{n!}{y!(n-y)!}$$

Then, the probability mass function of Y is given by

$$f(y) = \binom{n}{y} p^{y} (1-p)^{(n-y)}.$$
 (2)

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The expected value of $Y = \sum_{i=1}^{n} X_i$ is

$$E(Y) = E(\sum_{i=1}^{n} X_i) = \sum_{i=1}^{n} E(X_i) = np$$

where the last equality follows because $E(X_i) = p$ which is a constant and $\sum_{i=1}^{n} c = nc$ for any constant c.

Let $Z_i = X_i - p$. Then, the variance of $Y = \sum_{i=1}^n X_i$ is

$$\begin{aligned} \operatorname{Var}(Y) &= E[\{(\sum_{i=1}^{n} X_{i}) - np\}^{2}] \\ &= E[\{\sum_{i=1}^{n} (X_{i} - p)\}^{2}] \\ &= E[\{\sum_{i=1}^{n} Z_{i}\}^{2}] \quad (\operatorname{Define} Z_{i} = X_{i} - p \text{ for } i = 1, ..., n) \\ &= E[Z_{1}^{2} + Z_{2}^{2} + ... + Z_{n}^{2} + 2Z_{1}Z_{2} + 2Z_{1}Z_{3} + ... + 2Z_{1}Z_{n} + ... + 2Z_{n-1}Z_{n}] \\ &= \sum_{i=1}^{n} E[Z_{i}^{2}] + 2\sum_{i=1}^{n} \sum_{j=i+1}^{n} E[Z_{i}Z_{j}] \\ &= \sum_{i=1}^{n} p(1 - p) + 2 \times 0 \quad (\operatorname{Because} E[Z_{i}^{2}] = \operatorname{Var}(X_{i}) = p(1 - p) \text{ and } E[Z_{i}Z_{j}] = 0 \text{ if } i \neq j) \\ &= np(1 - p), \end{aligned}$$

where $E[Z_i Z_j] = 0$ if $i \neq j$ because X_i and X_j is independent if $i \neq j$.

The Sample Mean of Bernoulli Random Variables

Binomial distribution is closely related to the distribution of the sample mean of Bernoulli random variables. Define

$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i,$$

where $X_1, X_2, ..., X_n$ are a sequence of *n* independent Bernoulli random variables. Then, the possible values \bar{X} can take are $\{0, 1/n, 2/n, ..., (n-1)/n, 1\}$. Further, $\bar{X} = (1/n)Y$ so that $Y = n\bar{X}$. Therefore, by letting $y = n\bar{x}$ in (2), the probability mass function of \bar{X} is given by

$$\Pr(\bar{X} = \bar{x}) = \binom{n}{(n\bar{x})} p^{n\bar{x}} (1-p)^{(n-n\bar{x})}.$$

This is the exact probability mass function of \bar{X} when X_i s are independent Bernoulli random variables. Later, we will discuss that the distribution of \bar{X} can be *approximated* by the normal distribution when n is large. We may also compute the expected value and the variance of \bar{X} from those of $Y = \sum_{i=1}^{n} X_i$. In fact,

$$E[\bar{X}] = E[(1/n)Y] = (1/n)E[Y] = (1/n)np = p,$$

and

$$Var(\bar{X}) = Var((1/n)Y) = (1/n)^2 Var(Y) = (1/n)^2 np(1-p) = \frac{p(1-p)}{n}$$

Examples

1. Flip a coin four times and let Y be the number of heads. What is the probability that the number of heads Y is equal to 2?

Answer: We have n = 4 and p = 0.5. The probability that Y = 2 is equal to

$$\binom{4}{2}(0.5)^2(1-0.5)^{(4-2)} = 6(0.5)^4 = \frac{3}{8}.$$

2. Exercise 4.40: The Minnesota Twins are to play a series of 5 games against the Red Sox. For any one game it is estimated that the probability of a Twins' win is 0.5. The outcome of the 5 games are independent of one another. (a) What is the probability that Twins will win all 5 games? (b) What is the probability that Twins will win a majority of the 5 games? (c) If the Twins win the first game, what is the probability that they will win a majority of the five games?

Answer: We have n = 5 and p = 0.5. For (a), the probability that Y = 5 is equal to

$$\Pr(Y=5) = \binom{5}{5} (0.5)^5 (1-0.5)^{(5-5)} = 1 \times (0.5)^5 \times 1 = \frac{1}{32}$$

For (b), the probability that Y = 3 and that of Y = 4 are

$$\Pr(Y=3) = \binom{5}{3} (0.5)^3 (1-0.5)^{(5-3)} = 10 \times (0.5)^5 = \frac{10}{32},$$

$$\Pr(Y=4) = \binom{5}{4} (0.5)^4 (1-0.5)^{(5-4)} = 5 \times (0.5)^5 = \frac{5}{32}.$$

Therefore, the probability that Twins will win a majority of the 5 games, namely, $Y \ge 3$ is

$$\Pr(Y \ge 3) = \Pr(Y = 3) + \Pr(Y = 4) + \Pr(Y = 5) = \frac{10}{32} + \frac{5}{32} + \frac{1}{32} = \frac{1}{2}$$

For (c), when the Twins win the first game, the Twins need to win at least 2 games out of four games to win a majority. Because the outcomes of the 5 games are independent of one another, we may define a new Binomial random variable $W = \sum_{i=1}^{n} X_i$ with n = 4 and p = 0.5, which represents the outcomes of the 4 games after the first game.

$$\Pr(W \ge 2) = \Pr(W = 2) + \Pr(W = 3) + \Pr(W = 4) = \frac{6}{16} + \frac{4}{16} + \frac{1}{16} = \frac{11}{16},$$

where, for example, $\Pr(W = 2) = \binom{4}{2}(0.5)^2(1 - 0.5)^{(4-2)} = 6(0.5)^4 = 6/16$. Therefore, the probability for the Twins to win a majority after winning the first game is 11/16.

3. Let X_1 and X_2 are two Bernoulli random variables with the probability of success p, where X_1 and X_2 are independent, and $X_i = 0$ with probability 1 - p and $X_i = 1$ with probability p for i = 1, 2. Define a random variable $Y = X_1 + X_2$. Therefore, Y follows the Binomial Distribution with n = 2 trials.

(a) Find the mean and the variance of Y.

Answer: Note that $E[X_1] = E[X_2] = p$ and $Var(X_1) = Var(X_2) = p(1-p)$ because $E[X_i] = 0 \times (1-p) + 1 \times p = p$ and $Var(X_i) = E[X_i^2] - \{E[X_i]\}^2 = p - p^2 = p(1-p)$, where $E[X_i^2] = p$ follows from $E[X_i^2] = E[X_i] = p$ with $X_i^2 = X_i$. Furthermore, because X_1 and X_2 are independent, $Cov(X_1, X_2) = 0$. Therefore, $E[Y] = E[X_1 + X_2] = E[X_1] + E[X_2] = p + p = 2p$ and $Var(Y) = Var(X_1 - X_2) = Var(X_1) + Var(X_2) + 2Cov(X_1, X_2) = p(1-p) + p(1-p) + 0 = 2p(1-p)$.

- (b) What is $E[Y|X_1 = 1]$? Answer: $E[Y|X_1 = 1] = E[X_1 + X_2|X_1 = 1] = E[X_1|X_1 = 1] + E[X_2|X_1 = 1] = 1 + E[X_2] = 1 + p$, where $E[X_1|X_1 = 1] = 1$ holds $X_1 = 1$ with probability one when we condition on the event that $X_1 = 1$ and $E[X_2|X_1 = 1] = E[X_2]$ because X_1 and X_2 are independent.
- (c) What is $E[X_1|Y=1]$?

Answer: $\Pr(X_1 = 1|Y = 1) = \Pr(X_1 = 1|X_1 + X_2 = 1) = \frac{\Pr(X_1 = 1, X_1 + X_2 = 1)}{\Pr(X_1 + X_2 = 1)}$. Note that there are four possible outcomes for (X_1, X_2) : (0, 0), (1, 0), (0, 1), and (1, 1). Now, $\Pr(X_1 = 1, X_1 + X_2 = 1) = \Pr(X_1 = 1, X_2 = 0) = p(1 - p)$ and $\Pr(X_1 + X_2 = 1) = \Pr(X_1 = 0, X_2 = 1) + \Pr(X_1 = 1, X_2 = 0) = 2p(1 - p)$. Therefore, $\Pr(X_1 = 1|Y = 1) = \frac{\Pr(X_1 = 1, X_1 + X_2 = 1)}{\Pr(X_1 + X_2 = 1)} = \frac{p(1-p)}{2p(1-p)} = 1/2$. Similarly, we may prove that $\Pr(X_1 = 0|Y = 1)$. Finally, $E[X_1|Y = 1] = E[X_1|X_1 + X_2 = 1] = \sum_{x_1 \in \{0,1\}} x_1 \Pr(X_1 = x_1|X_1 + X_2 = 1) = 0 \times (1/2) + 1 \times (1/2) = 1/2$.