

*CSL003P1M : Probability and Statistics*  
*Lecture 22 (Conditional Expectation and*  
*Covariance)*

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# Conditional Expectation

# Conditional Expectation

## Conditional Expectation

Recall that if  $X$  and  $Y$  are jointly discrete random variables, then the conditional probability mass function of  $X$ , given that  $Y = y$ , is defined, for all  $y$  such that  $P\{Y = y\} > 0$ , by

$$p_{X|Y}(x|y) = P\{X = x|Y = y\} = \frac{p(x, y)}{p_Y(y)}$$

It is therefore natural to define, in this case, the conditional expectation of  $X$  given that  $Y = y$ , for all values of  $y$  such that  $p_Y(y) > 0$ , by

$$\begin{aligned} E[X|Y = y] &= \sum_x xP\{X = x|Y = y\} \\ &= \sum_x x p_{X|Y}(x|y) \end{aligned}$$

## Exercise-1

If  $X$  and  $Y$  are independent binomial random variables with identical parameter  $n$  and  $p$ , calculate the conditional expected value of  $X$  given that  $X + Y = m$ .

Solution:

- We first calculate the conditional probability mass function of  $X$  given that  $X + Y = m$ . For  $k \leq \min(n, m)$ ,

$$\begin{aligned} P\{X = k | X + Y = m\} &= \frac{P\{X = k, X + Y = m\}}{P\{X + Y = m\}} \\ &= \frac{P\{X = k, Y = m - k\}}{P\{X + Y = m\}} \\ &= \frac{P\{X = k\}P\{Y = m - k\}}{P\{X + Y = m\}} \end{aligned}$$

## Exercise-1

$$\begin{aligned} \frac{P\{X = k\}P\{Y = m - k\}}{P\{X + Y = m\}} &= \\ \frac{\binom{n}{k} p^k (1-p)^{n-k} \binom{n}{m-k} p^{m-k} (1-p)^{n-m+k}}{\binom{2n}{m} p^m (1-p)^{2n-m}} \\ &= \frac{\binom{n}{k} \binom{n}{m-k}}{\binom{2n}{m}} \end{aligned}$$

which is a hypergeometric distribution with parameters  $(m, 2n, n)$ .

So,

$$E[X|X + Y = m] = \frac{mn}{2n} = \frac{m}{2}.$$

## Computing Expectations by Conditioning

- Let us denote by  $E[X|Y]$  that function of the random variable  $Y$  whose value at  $Y = y$  is  $E[X|Y = y]$ .
- Note that  $E[X|Y]$  is itself a random variable.

### Proposition

$$E[X] = E[E[X|Y]]$$

If  $Y$  is a discrete random variable, then above equation states

$$E[X] = \sum_y E[X|Y = y]P\{Y = y\}$$

# Computing Expectations by Conditioning

Proof:

- We must show that

$$E[X] = \sum_y E[X|Y = y]P\{Y = y\}.$$

Now,

$$\begin{aligned} \sum_y E[X|Y = y]P\{Y = y\} &= \sum_y \sum_x xP\{X = x|Y = y\}P\{Y = y\} \\ &= \sum_y \sum_x x \frac{P\{X = x, Y = y\}}{P\{Y = y\}} P\{Y = y\} \\ &= \sum_y \sum_x xP\{X = x, Y = y\} \\ &= \sum_x x \sum_y P\{X = x, Y = y\} \\ &= \sum_x xP\{X = x\} = E[X] \end{aligned}$$

## Exercise-2

A miner is trapped in a **mine** containing 3 doors. The first door leads to a tunnel that will take him to **safety** after under 3 hours of travel. The second door leads to a tunnel that will return him to the **mine** after 5 hours of travel. The third door leads to a tunnel that will return him to the **mine** after 7 hours. If we assume that the miner is at all times equally likely to choose any one of the doors, what is the expected length of time until he reaches **safety**?

Solution:

- Let  $X$  denote the amount of time (in hours) until the miner reaches safety.
- Let  $Y$  denote the door initially he chooses.
- Now,

$$E[X] = \sum_{r=1}^3 E[X|Y = r]P\{Y = r\}$$



## Exercise-2

$$\sum_{r=1}^3 E[X|Y=r]P\{Y=r\} = \frac{1}{3} \left( \sum_{r=1}^3 E[X|Y=r] \right)$$

However,

$$\begin{aligned} E[X|Y=1] &= 3 \\ E[X|Y=2] &= 5 + E[X] \\ E[X|Y=3] &= 7 + E[X] \end{aligned}$$

Hence,

$$E[X] = \frac{1}{3} \left( \sum_{r=1}^3 E[X|Y=r] \right) = \frac{1}{3} (3 + 5 + E[X] + 7 + E[X])$$

So,

$$E[X] = 15.$$

# Covariance

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## Covariance

The covariance between  $X$  and  $Y$ , denoted by  $\text{Cov}(X, Y)$ , is defined by

$$\text{Cov}(X, Y) = E[(X - E[X])(Y - E[Y])]$$

## Covariance

If  $X$  and  $Y$  are independent random variables,  $\text{Cov}(X, Y) = 0$ .

Solution:

$$\begin{aligned}\text{Cov}(X, Y) &= E[(X - E[X])(Y - E[Y])] \\&= E[XY - XE[Y] - YE[X] + E[Y]E[X]] \\&= E[XY] - E[X]E[Y] - E[Y]E[X] + E[X]E[Y] \\&= E[XY] - E[X]E[Y] \\&= E[X]E[Y] - E[X]E[Y] \quad (X \text{ and } Y \text{ are independent}) \\&= 0.\end{aligned}$$

The converse is not true.

## Example-1

Let  $X$  be a random variable such that

$$P\{X = 0\} = P\{X = 1\} = P\{X = -1\} = \frac{1}{3}$$

and defining

$$Y = \begin{cases} 0 & \text{if } X \neq 0 \\ 1 & \text{if } X = 0 \end{cases}$$

Now,  $XY = 0$ , so  $E[XY] = 0$ . Also  $E[X] = 0$ . Thus,

$$\text{Cov}(X, Y) = E[XY] - E[X]E[Y] = 0.$$

However,  $X$  and  $Y$  are clearly not independent.

# Covariance

## Proposition

- ①  $\text{Cov}(X, Y) = \text{Cov}(Y, X)$
- ②  $\text{Cov}(X, X) = \text{Var}(X)$
- ③  $\text{Cov}(aX, Y) = a\text{Cov}(X, Y)$
- ④  $\text{Cov}\left(\sum_{i=1}^n X_i, \sum_{j=1}^n Y_j\right) = \sum_{i=1}^n \sum_{j=1}^n \text{Cov}(X_i, Y_j)$

(Exercise!!!)

## Covariance

$$\text{Var} \left( \sum_{i=1}^n X_i \right) = \sum_{i=1}^n \text{Var}(X_i) + 2 \sum_{i < j} \text{Cov}(X_i, X_j)$$

Proof:

- It follows from 2 and 4, upon taking  $Y_j = X_j$ ,  $j = 1, \dots, n$ , that

$$\begin{aligned} \text{Var} \left( \sum_{i=1}^n X_i \right) &= \text{Cov} \left( \sum_{i=1}^n X_i, \sum_{j=1}^n X_j \right) \\ &= \sum_{i=1}^n \sum_{j=1}^n \text{Cov}(X_i, X_j) \\ &= \sum_{i=1}^n \text{Var}(X_i) + \sum_{i \neq j} \text{Cov}(X_i, X_j) \end{aligned}$$

## Covariance

Since each pair of indices  $i, j$ ,  $i \neq j$ , appears twice in the double summation, the preceding formula is equivalent to

$$\text{Var} \left( \sum_{i=1}^n X_i \right) = \sum_{i=1}^n \text{Var}(X_i) + 2 \sum_{i < j} \text{Cov}(X_i, X_j).$$

If  $X_1, \dots, X_n$  are pairwise independent, in that  $X_i$  and  $X_j$  are independent for  $i \neq j$ , then the above equation reduces to

$$\text{Var} \left( \sum_{i=1}^n X_i \right) = \sum_{i=1}^n \text{Var}(X_i).$$



# Thank You