

# Chapter 7 part 1

## Properties of Expectations

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MATH 241

# Outline

- 1 Expectation of sums of random variable
- 2 Covariance and correlation
- 3 Conditional expectation

## Expected value of $g(X, Y)$

Recap: expectation of random variable  $g(X)$

- Discrete case  $E[g(X)] = \sum_{\text{all } x} g(x)f(x)$
- Continuous case  $E[g(X)] = \int_{-\infty}^{\infty} g(x)f(x)dx$

Suppose  $g(X, Y)$  is a real-valued function of random variables  $X$  and  $Y$ , then

- Discrete case

$$E[g(X, Y)] = \sum_{\text{all } x} \sum_{\text{all } y} g(x, y)f(x, y)$$

- Continuous case

$$E[g(X, Y)] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y)f(x, y)dxdy$$

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$$E(X + Y) = E(X) + E(Y)$$

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- It's not difficult to show that if either (or both) of the  $X, Y$  is discrete, this formula still holds.
- This results does not require  $X$  and  $Y$  to be independent.
- This can be generalized to  $n$  random variables

$$E(X_1 + X_2 + \cdots + X_n) = E(X_1) + E(X_2) + \cdots + E(X_n)$$

## Question

What's the expected value of  $X - Y$ ?

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What's the expected value of  $X - Y$ ?

$$E(X - Y) = E[X + (-Y)] = E(X) + E(-Y) = E(X) - E(Y)$$

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Let  $X$  denote the total number of matches.

$$X_i = \begin{cases} 1 & \text{if the } i \text{ th person selects his own hat} \\ 0 & \text{otherwise} \end{cases}$$

$$X = X_1 + X_2 + \cdots + X_n$$



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$$X = X_1 + X_2 + \cdots + X_n$$

For any  $i = 1, 2, \dots, n$ ,

$$E(X_i) = 1/n \implies$$

$$E(X) = E(X_1) + E(X_2) + \cdots + E(X_n) = n/n = 1$$

## Question

Let  $X_1, \dots, X_n$  be independent and identically distributed random variables having distribution function  $F$  and expected value  $\mu$ . Such a sequence of random variables is said to constitute a sample from the distribution  $F$ . Then quantity

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

is called the sample mean. Compute  $E[\bar{X}]$ .

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- The expected value of the sample mean is  $\mu$  (the distribution mean).
- When the distribution mean  $\mu$  is unknown, the sample mean is often used in statistics to estimate it.

# Recap

## Expectation of sum

$$E[X_1 + X_2 + \cdots + X_n] = E[X_1] + E[X_2] + \cdots + E[X_n]$$

$X_1, X_2, \dots, X_n$  are independent  $\implies \neq$

$$E[X_1 X_2 \cdots X_n] = E[X_1] E[X_2] \cdots E[X_n]$$

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# Covariance

## Definition

*Covariance of two random variables  $X$  and  $Y$  is defined as*

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

- Simplification

$$\begin{aligned}\text{Cov}(X, Y) &= E[(X - \mu_X)(Y - \mu_Y)] \\ &= E[XY + \mu_X\mu_Y - X\mu_Y - Y\mu_X] \\ &= E[XY] - \mu_X\mu_Y\end{aligned}$$

- Recall

$$\begin{aligned}E[XY] &= \int \int xy f(x, y) dx dy \quad \text{if continuous} \\ &= \sum_x \sum_y xy f(x, y) \quad \text{if discrete}\end{aligned}$$

# Properties of $Cov(X, Y) = E[XY] - E[X]E[Y]$

- $Cov(X, Y) = Cov(Y, X)$
- $Cov(X, c) = 0$
- $Cov(X, X) = Var(X)$
- $Cov(aX, bY) = ab Cov(X, Y)$

$$\begin{aligned} Cov(aX, bY) &= E[abXY] - E[aX]E[bY] \\ &= ab E[XY] - ab E[X]E[Y] \end{aligned}$$

- $Cov(X + a, Y + b) = Cov(X, Y)$

$$\begin{aligned} Cov(X + a, Y + b) &= E[(X + a)(Y + b)] - E[X + a]E[Y + b] \\ &= E[XY + aY + bX + ab] \\ &\quad - (E[X] + a)(E[Y] + b) \\ &= E[XY] + E[aY] + E[bX] + ab \\ &\quad - E[X]E[Y] - a E[Y] - b E[X] - ab \\ &= E[XY] - E[X]E[Y] \end{aligned}$$



# Covariance of sums of random variables

$$\text{Cov} \left( \sum_{i=1}^n X_i, \sum_{j=1}^m Y_j \right) = \sum_{i=1}^n \sum_{j=1}^m \text{Cov}(X_i, Y_j)$$

A special case

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

Some more special cases

$$\text{Var}(X + Y) = \text{Var}(X) + \text{Var}(Y) + 2\text{Cov}(X, Y)$$

$$\text{Var}(X - Y) = \text{Var}(X) + \text{Var}(Y) - 2\text{Cov}(X, Y)$$

## Question

Suppose  $Z_1$  and  $Z_2$  are two standard normal random variables. Let

$$X = Z_1 + Z_2, Y = Z_1 - Z_2$$

Find  $Cov(X, Y)$ .

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$$X = Z_1 + Z_2, Y = Z_1 - Z_2$$

Find  $Cov(X, Y)$ .

Method 1.

$$\begin{aligned} Cov(X, Y) &= Cov(Z_1 + Z_2, Z_1 - Z_2) \\ &= Cov(Z_1, Z_1) + Cov(Z_2, Z_1) + Cov(Z_1, -Z_2) + Cov(Z_2, -Z_2) \\ &= Cov(Z_1, Z_1) + Cov(Z_2, Z_1) - Cov(Z_1, Z_2) - Cov(Z_2, Z_2) \\ &= Var(Z_1) - Var(Z_2) = 0 \end{aligned}$$

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Method 2.

$$\begin{aligned} E[XY] &= E[Z_1^2 - Z_2^2] = E[Z_1^2] - E[Z_2^2] = 0 \\ E[X] &= E[Z_1] + E[Z_2] = 0, \quad E[Y] = E[Z_1] - E[Z_2] = 0 \end{aligned}$$

## Zero covariance and independence

- $X$  and  $Y$  are independent  $\implies Cov(X, Y) = 0$

$$Cov(X, Y) = E[XY] - E[X]E[Y] = E[X]E[Y] - E[X]E[Y] = 0$$

- $X_1, X_2, \dots, X_n$  are independent  $\implies$

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

- $Cov(X, Y) = 0 \not\implies X$  and  $Y$  are independent  
Counter example?

## Question

Let  $X_1, \dots, X_n$  be independent random variables having the same variance  $\sigma^2$ , and

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

Find  $\text{Var}(\bar{X})$ .

## Question

Let  $X_1, \dots, X_n$  be independent random variables having the same variance  $\sigma^2$ , and

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

Find  $Var(\bar{X})$ .

$$\begin{aligned} Var(\bar{X}) &= \frac{1}{n^2} Var \left( \sum_{i=1}^n X_i \right) \\ &= \frac{1}{n^2} \left[ \sum_{i=1}^n Var(X_i) \right] \\ &= \frac{1}{n^2} (n\sigma^2) = \frac{\sigma^2}{n} \end{aligned}$$

# Correlation

Since  $Cov(X, Y)$  depends on the magnitude of  $X$  and  $Y$  we would prefer to have a measure of association that is not effected by arbitrary changes in the scales of the random variables.

## Definition

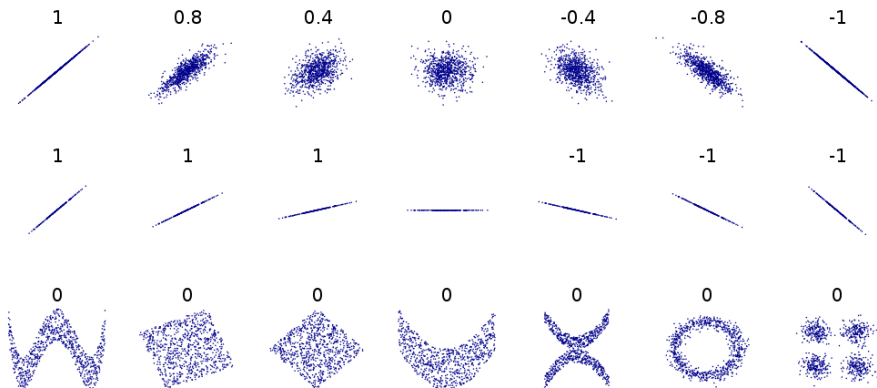
*The most common measure of linear association is **correlation** which is defined as*

$$\rho(X, Y) = \frac{Cov(X, Y)}{\sqrt{Var(X)} \sqrt{Var(Y)}}$$

- range:  $-1 \leq \rho(X, Y) \leq 1$
- the magnitude (i.e. absolute value) of the  $\rho(X, Y)$  measures the strength of the linear association
- the sign determines if it is a positive or negative relationship.
- if  $\rho(X, Y) = 0$ , then  $X$  and  $Y$  are said to be uncorrelated.



# Correlation



## Question

Find the value of  $b$  in  $Y = a + bX$  such that  $\rho(X, Y) = 1$ . What about  $\rho(X, Y) = -1$ ?

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Find the value of  $b$  in  $Y = a + bX$  such that  $\rho(X, Y) = 1$ . What about  $\rho(X, Y) = -1$ ?

$$\begin{aligned}\rho(X, a + bX) &= \frac{\text{Cov}(X, a + bX)}{\sqrt{\text{Var}(X)}\sqrt{\text{Var}(a + bX)}} \\ &= \frac{b\text{Var}(X)}{\sqrt{\text{Var}(X)}\sqrt{b^2\text{Var}(X)}} \\ &= \frac{b\text{Var}(X)}{|b|\text{Var}(X)}\end{aligned}$$

## Question

Find the value of  $b$  in  $Y = a + bX$  such that  $\rho(X, Y) = 1$ . What about  $\rho(X, Y) = -1$ ?

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 &= \frac{b\text{Var}(X)}{|b|\text{Var}(X)}
 \end{aligned}$$

- When  $b > 0$ ,  $\rho(X, a + bX) = \rho(X, Y) = 1$
- When  $b < 0$ ,  $\rho(X, a + bX) = \rho(X, Y) = -1$

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# Conditional expectation

- The discrete case: for all  $p_Y(y) > 0$ 
  - ▶ Conditional pmf:  $p_{X|Y}(x | y) = P\{X = x | Y = y\} = \frac{p(x,y)}{p_Y(y)}$

## Definition

The conditional expectation of  $X$  given that  $Y = y$  is

$$E[X | Y = y] = \sum_x x P\{X = x | Y = y\} = \sum_x x p_{X|Y}(x | y)$$

- The continuous case: for all  $f_Y(y) > 0$ 
  - ▶ Conditional pdf:  $f_{X|Y}(x | y) = \frac{f(x,y)}{f_Y(y)}$

## Definition

The conditional expectation of  $X$  given that  $Y = y$  is

$$E[X | Y = y] = \int_{-\infty}^{\infty} x f_{X|Y}(x | y) dx$$

# Properties of expectations remain

- Expectation of a function of a random variable

- ▶ The discrete case:

$$E[g(X) | Y = y] = \sum_x g(x)p_{X|Y}(x | y)$$

- ▶ The continuous case:

$$E[g(X) | Y = y] = \int_{-\infty}^{\infty} g(x)f_{X|Y}(x | y)dx$$

- Expectation of sum of random variables

$$E\left[\sum_{i=1}^n X_i | Y = y\right] = \sum_{i=1}^n E[X_i | Y = y]$$

- Think about the condition  $Y = y$  as taking expectation of  $X$  on a reduced sample space consisting only of outcomes for which  $Y = y$

# Computing expectations by conditioning

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

- A very important property of conditional expectation
- Think of  $E[X|Y]$  as a random variable (when  $Y = y$ )
- The discrete case:

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

- Intuition:
  - ▶  $E[E[X | Y]]$  is a weighted average of  $E[X | Y]$ , where weights are  $P\{Y = y\}$  (the probability of the condition)
  - ▶ Similar to the “law of total probability”  $P(E) = \sum_{i=1}^n P(E | F_i)P(F_i)$
- The continuous case:

$$E[X] = \int_{-\infty}^{\infty} E[X | Y = y]f_Y(y)dy$$



# Computing probabilities by conditioning

- Let  $E$  denote an arbitrary event, and define the indicator random variable  $X$  as

$$X = \begin{cases} 1 & \text{if } E \text{ occurs} \\ 0 & \text{if } E \text{ does not occur} \end{cases}$$

- Then  $E[X] = P(E)$ ,  $E[X | Y = y] = P(E | Y = y)$  for any random variable  $Y$
- The discrete case:

$$P(E) = \sum_y P(E|Y = y)p(Y = y)$$

related to  $P(E) = \sum_{i=1}^n P(E|F_i)P(F_i)$

- The continuous case:

$$P(E) = \int_{-\infty}^{\infty} P(E | Y = y)f_Y(y)dy$$

## Conditional variance

- Similarly to the conditional expectation, we can define the conditional variance of  $X$  given that  $Y = y$

### Definition

$$\text{Var}(X \mid Y = y) = E[(X - E[X \mid Y = y])^2 \mid Y = y]$$

- A very useful conditional variance formula

$$\text{Var}(X) = E[\text{Var}(X \mid Y)] + \text{Var}(E[X \mid Y])$$

## Question

Type  $i$  light bulbs function for a random amount of time having mean  $\mu_i$  and standard deviation  $\sigma_i$ ,  $i = 1, 2$ . A light bulb randomly chosen from a bin of bulbs is a type 1 bulb with probability  $p$  and a type 2 bulb with probability  $1 - p$ . Let  $X$  denote the lifetime of this bulb. Find (a)  $E[X]$  (b)  $Var(X)$ .

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- The mean is  $E[X] = E[E[X | Y]] = \mu_1 p + \mu_2 (1 - p)$

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- The mean is  $E[X] = E[E[X | Y]] = \mu_1 p + \mu_2 (1 - p)$
- The variance is

$$Var(X) = E[Var(X | Y)] + Var(E[X | Y])$$

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- The variance is

$$\begin{aligned} Var(X) &= E[Var(X | Y)] + Var(E[X | Y]) \\ &= E[Var(X | Y)] + E[(E[X | Y])^2] - (E[E[X | Y]])^2 \end{aligned}$$

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$$\begin{aligned}
 Var(X) &= E[Var(X | Y)] + Var(E[X | Y]) \\
 &= E[Var(X | Y)] + E[(E[X | Y])^2] - (E[E[X | Y]])^2 \\
 &= \sigma_1^2 p + \sigma_2^2(1 - p) + \mu_1^2 p + \mu_2^2(1 - p) - (\mu_1 p + \mu_2(1 - p))^2
 \end{aligned}$$