

MA203: Covariance, Correlation and Conditional Expectation

Let X and Y are continuous RVs. The joint moment of order $m + n$ is defined as

$$E[\underbrace{X^m Y^n}] = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \underbrace{x^m y^n}_{\text{}} \underbrace{f_{X,Y}(x, y)}_{\text{}} \underbrace{dx dy}_{\text{}}.$$

$$\left\{ \begin{aligned} E[X^m] &= \int_{-\infty}^{+\infty} x^m f_X(x) dx \end{aligned} \right.$$

The joint central moment of order $m + n$ is defined as

$$E[\underbrace{(X - \mu_X)^m (Y - \mu_Y)^n}] = \int_{-\infty}^{+\infty} \int_{-\infty}^{+\infty} \underbrace{(x - \mu_X)^m (y - \mu_Y)^n}_{\text{}} \underbrace{f_{X,Y}(x, y)}_{\text{}} \underbrace{dx dy}_{\text{}}$$

where $\mu_X = E[X]$ and $\mu_Y = E[Y]$.

$m = n = 1$; $E[XY] =$ Second order moment

$$E[(X - \mu_X)^m] = \int_{-\infty}^{+\infty} (x - \mu_X)^m f_X(x) dx$$

Let X and Y are discrete RVs. The joint moment of order $m + n$ is defined as

$$E[X^m Y^n] = \sum \sum_{(x,y) \in R_X \times R_Y} x^m y^n p_{X,Y}(x, y).$$

The joint central moment of order $m + n$ is defined as

$$E[(X - \mu_X)^m (Y - \mu_Y)^n] = \sum \sum_{(x,y) \in R_X \times R_Y} \underbrace{(x - \mu_X)^m}_{\text{wavy line}} \underbrace{(y - \mu_Y)^n}_{\text{wavy line}} \underbrace{p_{X,Y}(x, y)}_{\text{wavy line}}$$

where $\mu_X = \underline{E[X]}$ and $\mu_Y = \underline{E[Y]}$.

Covariance of Two RVs: The covariance of two RVs X and Y is defined as

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

$\text{Cov}(X, Y)$ is also denoted as $\sigma_{X,Y}$.

$$\underline{\text{Cov}(X, Y)} \quad \underline{\sigma_{X,Y}}$$

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

Properties:

1. $\underline{Cov(X, Y)} = \underline{Cov(Y, X)}$

2. $\underline{Cov(X, X)} = \underline{var(X)}$

3. $\underline{Cov(aX, Y)} = a\underline{Cov(X, Y)}$ a is constant

4. $\underline{Cov(\sum_{i=1}^m X_i, \sum_{j=1}^n Y_j)} = \underline{\sum_{i=1}^m \sum_{j=1}^n Cov(X_i, Y_j)}$

$$Var(X) = E[(X - \mu_X)^2]$$

Ex:-

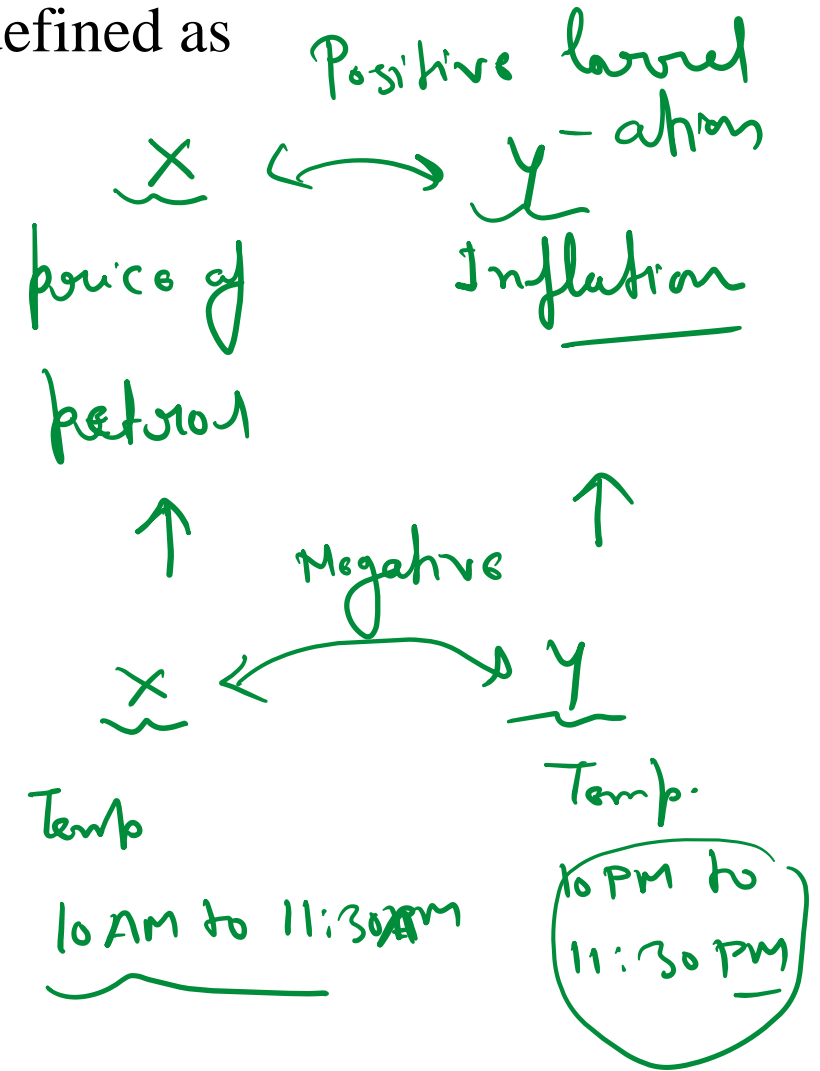
$$\begin{aligned} Cov(X_1 + X_2, Y_1 + Y_2) &= \sum_{i=1}^2 \sum_{j=1}^2 Cov(X_i, Y_j) \\ &= \sum_{i=1}^2 \{Cov(X_i + Y_1) + Cov(X_i + Y_2)\} \\ &= Cov(X_1, Y_1) + Cov(X_1, Y_2) + Cov(X_2, Y_1) \\ &\quad + \underline{Cov(X_2, Y_2)} \end{aligned}$$

Correlation Co-efficient: The covariance of two RVs X and Y is defined as

Correlation Co-efficient

$$\rho_{X,Y} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

$$\begin{aligned} \rho_{X,Y} &= \frac{E[XY] - \mu_X \mu_Y}{\sigma_X \sigma_Y} \\ &= \frac{E[XY] - \mu_X \mu_Y}{\sqrt{E[(X - \mu_X)^2]} \sqrt{E[(Y - \mu_Y)^2]}} \end{aligned}$$



Properties:

1. $\rho_{X,Y} = \rho_{Y,X}$ ✓
2. $|\rho_{X,Y}| \leq 1$ ✓ $\Rightarrow -1 \leq \rho_{X,Y} \leq +1$
3. $\rho_{X,X} = 1$
4. $\rho_{X,-X} = -1$
5. $\rho_{aX+b,Y} = \rho_{X,Y}$ where a and b are constants and $a > 0$



Uncorrelated RVs: Two RVs X and Y are called uncorrelated if

$$\text{Cov}(X, Y) = 0$$

$$\rho_{X,Y} = 0$$

$$\Rightarrow \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y} = 0$$

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

$$\text{or } \boxed{E[\underline{XY}] = \underline{\mu_X \mu_Y}}$$

$\Rightarrow X$ & Y are independent, $E[XY] = \mu_X \mu_Y$, therefore independent RVs are always uncorrelated.

\Rightarrow But if X & Y are uncorrelated, then it is not necessary they are independent.

Example 2: The joint PMF of X and Y is given in the Table. Find $\rho_{X,Y}$?

$y \backslash x$	0	1	2	$p_Y(y)$
0	$1/8$	$1/8$	0	$1/4$
1	$1/8$	$1/4$	$1/8$	$1/2$
2	0	$1/8$	$1/8$	$1/4$
$p_X(x)$	$1/4$	$1/2$	$1/4$	

$$R_X = \{0, 1, 2\}$$

$$R_Y = \{0, 1, 2\}$$

$$\rho_{X,Y} = \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E[XY] - \mu_X \mu_Y}{\sqrt{E[X^2] - \mu_X^2} \sqrt{E[Y^2] - \mu_Y^2}}$$

$$E[X] = \sum_{x \in R_X} x p_X(x) = 0 \times p_X(0) + 1 \times p_X(1) + 2 \times p_X(2) = 0 + 1 \times \frac{1}{2} + 2 \times \frac{1}{4} = 1$$

$$E[Y] = \sum_{y \in R_Y} y p_Y(y) = 1$$

$$E[XY] = \sum_{(x,y) \in R_X \times R_Y} xy p_{X,Y}(x,y) = \sum_{x \in R_X} x \left\{ 0 \cdot p_{X,Y}(x,0) + 1 \cdot p_{X,Y}(x,1) + 2 \cdot p_{X,Y}(x,2) \right\}$$

$$= 0 + 1 \cdot \left\{ 1 \cdot p_{X,Y}(1,1) + 2 \cdot p_{X,Y}(1,2) \right\} + 2 \cdot \left\{ 1 \cdot p_{X,Y}(2,1) + 2 \cdot p_{X,Y}(2,2) \right\}$$

$$E[xy] = 5/4$$

$$E[x^2] = \sum_{x \in R_x} x^2 p_x(x) = 1 \times p_x(1) + 2^2 \times p_x(2) = 1 \times \frac{1}{2} + 4 \times \frac{1}{4} = 3/2$$

$$E[y^2] = \sum_{y \in R_y} y^2 p_y(y) = 3/2$$

$$\begin{aligned} \rho_{x,y} &= \frac{E[xy] - \mu_x \mu_y}{\sqrt{E[x^2] - \mu_x^2} \sqrt{E[y^2] - \mu_y^2}} = \frac{5/4 - 1}{\sqrt{\frac{3}{2} - 1} \sqrt{\frac{3}{2} - 1}} \\ &= \frac{1/4}{\frac{1}{\sqrt{2}} \cdot \frac{1}{\sqrt{2}}} = \underline{\underline{1/2}} \end{aligned}$$

Conditional Expectation

If X and Y are continuous RVs, then the conditional PDF of Y given $X = x$ given by

$$f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)}; \text{ provided that } f_X(x) \neq 0.$$

The conditional expectation of Y given $X = x$ is defined as

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

If X and Y are discrete RVs, then the PMF of Y given $X = x$ given by

$$p_{Y|X}(y|x) = \frac{p_{X,Y}(x,y)}{p_X(x)}; \text{ provided that } p_X(x) \neq 0.$$

The conditional expectation of Y given $X = x$ is defined as

$$\mu_{Y|X=x} = E[Y|X = x] = \sum_{y \in R_Y} y p_{Y|X}(y|x)$$

Example 1: The joint PMF of RVs X and Y are given in the Table. Find $E[Y|X = 2]$?

$y \backslash x$	0	1	2	$p_y(y)$
0	0.25	0.10	0.15	0.50
1	0.14	0.35	0.01	0.50
$p_x(x)$	0.39	0.45	0.16	

$$\mu_{Y|X} = E[Y|X=2] = \sum_{y \in R_Y} y p_{Y|X}(y|2)$$

$$R_Y = \{0, 1\}$$

$$E[Y|X=2] = \sum_{y \in R_Y} y p_{Y|X}(y|2)$$

$$= 0 \cdot \cancel{p_{Y|X}(0|2)} + 1 \cdot p_{Y|X}(1|2)$$

$$= p_{Y|X}(1|2)$$

$$= \frac{p_{X,Y}(\underline{2,1})}{p_X(2)} = \frac{0.01}{0.16}$$

$$= 1/16$$

Example 4: Suppose X and Y are jointly uniform RVs with the joint PDF given by

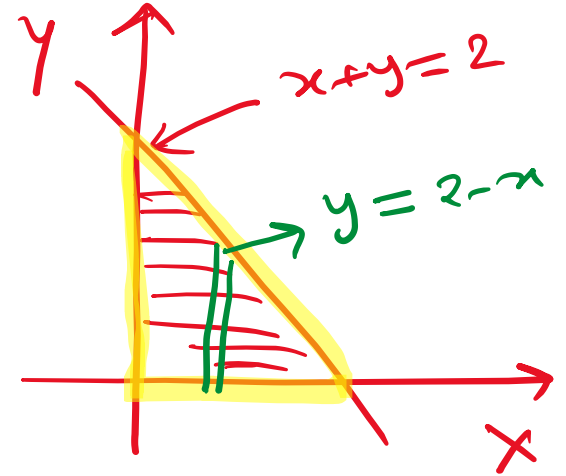
$$f_{X,Y}(x,y) = \begin{cases} \frac{1}{2}; & 0 \leq x, 0 \leq y, x+y \leq 2 \\ 0; & \text{o.w.} \end{cases}$$

Find $E[Y|X=x]$?

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

$$\underbrace{f_{Y|X}(y|x)} = \frac{f_{X,Y}(x,y)}{\underbrace{f_X(x)}} \checkmark$$

$$\underbrace{f_X(x)} = \int_{-\infty}^{+\infty} f_{X,Y}(x,y) dy = \int_0^{2-x} \frac{1}{2} dy = \frac{1}{2} (2-x)$$



$$f_{Y|X}(y|x) = \frac{f_{X,Y}(x,y)}{f_X(x)} = \frac{1/2}{\frac{1}{2}(2-x)} = \frac{1}{2-x}$$

$$\begin{aligned} E[Y|X] &= \int_{-\infty}^{+\infty} y \cdot \frac{1}{2-x} dy = \int_0^{2-x} \frac{y}{2-x} dy \\ &= \frac{1}{2-x} \left\{ \frac{y^2}{2} \right\}_0^{2-x} = \underline{\underline{\frac{2-x}{2}}} \end{aligned}$$

$$E[Y|X] = g(x) = \frac{2-x}{2}$$

Total Expectation Theorem: $EE[Y|X] = E[Y]$ and $EE[X|Y] = E[X]$

$$f_{X,Y}(x,y) = f_X(x) \cdot f_{Y|X}(y|x)$$

$$E[Y|X] = \underline{g(X)}$$

$$E[g(X)] = \int_{-\infty}^{+\infty} \underbrace{g(x)}_{\text{red}} f_X(x) dx = \int_{-\infty}^{+\infty} \underbrace{E[Y|X=x]}_{\text{green}} f_X(x) dx$$

$$= \int_{-\infty}^{+\infty} \left\{ \int_{-\infty}^{+\infty} y f_{Y|X}(y|x) dy \right\} f_X(x) dx$$

$$= \int_{-\infty}^{+\infty} y \int_{-\infty}^{+\infty} \underbrace{f_X(x) \cdot f_{Y|X}(y|x)}_{\text{red}} dy dx$$

$$= \int_{-\infty}^{+\infty} y \underbrace{\int_{-\infty}^{+\infty} f_{X,Y}(x,y) dx}_{\text{red}} dy = \int_{-\infty}^{+\infty} y \underbrace{f_Y(y)}_{\text{red}} dy = \underline{E[Y]}$$