DCP 1206: Probability Lecture 17 — Covariance, Conditional Distributions, and Bivariate Normal

Ping-Chun Hsieh

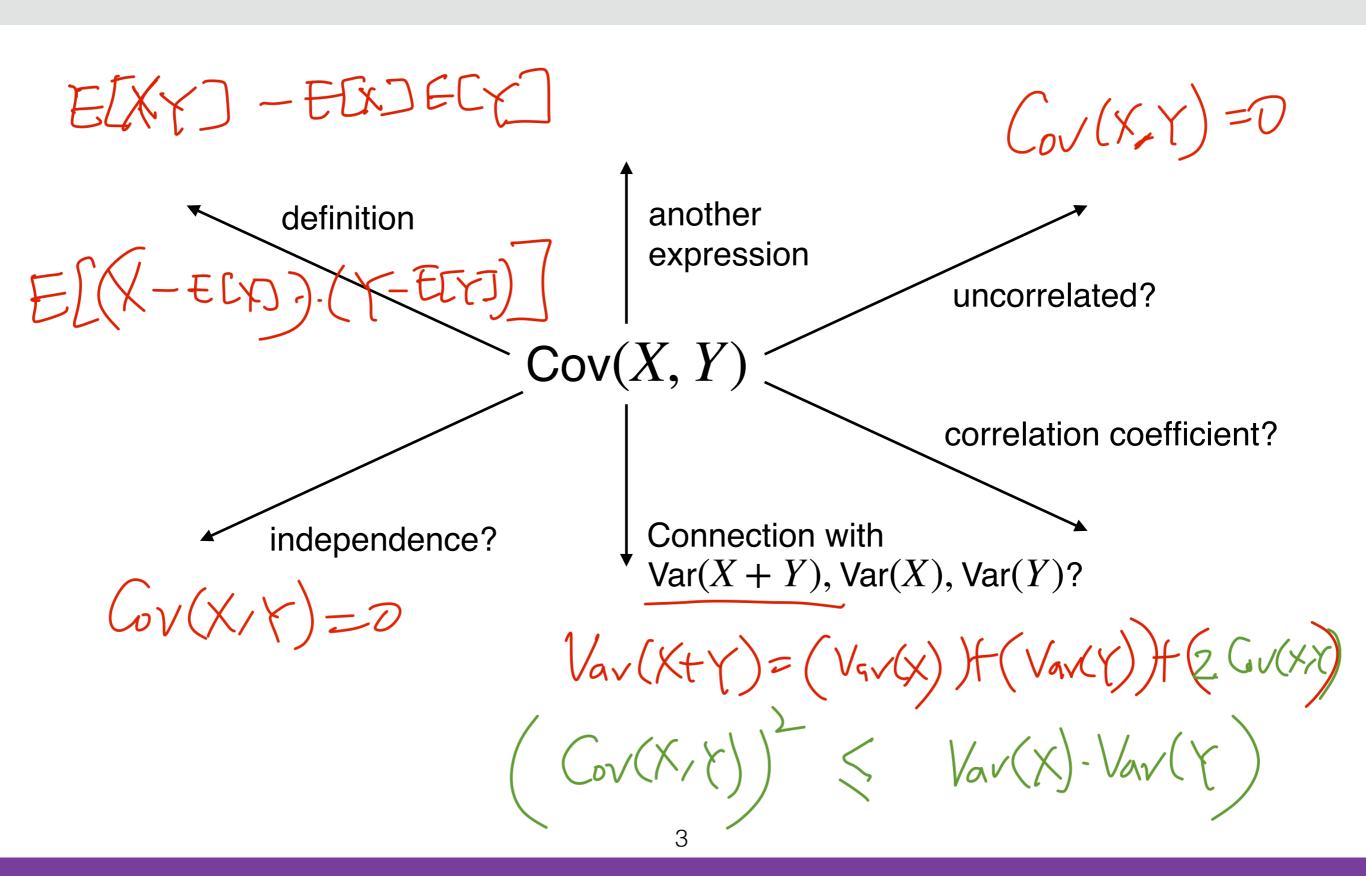
November 15, 2019

Announcements

- HW4 is posted on E3
 - Part 1: due on 11/22 (Friday)
 - Part 2: due on 11/27 (Wednesday)

- Midterm exam booklet will be returned today after class
 - 4:30pm 5:30pm @ EC122

Quick Review: Covariance



This Lecture

1. Covariance and Correlation Coefficient

2. Conditional Distributions

3. Bivariate Normal Random Variables

Reading material: Chapter 8.3,10.3, and 10.5

1. Covariance and Correlation Coefficient

Covariance is Sensitive to the Units

- Property: $Cov(aX, aY) \neq a^2 (Cov(X, Y))$
 - *a*: scaling factor due to change of unit

Question: Any suggested solution?

Correlation Coefficient

• Correlation Coefficient: Let X, Y be two random variables with finite variance $\sigma_X^2 > 0$ and $\sigma_Y^2 > 0$. Then, the correlation coefficient of X and Y is defined as

$$\rho(X,Y) = \frac{\text{Cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{\text{Cov}(X,Y)}{\sqrt{\sqrt{\chi}}}$$

• Question: Do we have $\rho(X,Y) = \rho(aX,aY)$, for any $a \neq 0$?

$$P(X,Y) = \frac{GoV(X,Y)}{G_XG_Y}$$

$$P(AX,AY) = \frac{GoV(AX,AY)}{G_{AX} \cdot G_{AY}} = \frac{A^2 \cdot GoV(X,Y)}{(A \cdot G_Y)} = P(X,Y)$$

A Property of Correlation Coefficient

Property:

$$-1 \le \rho(X, Y) \le 1$$

$$\sqrt{(\chi(X, Y))} = \sqrt{(\chi(X) - \chi(X))}$$

Question: How to prove this?

Example: Correlation Coefficient

- Example: Let X be a continuous uniform r.v. on [0,1].
 - ▶ Define $Y = X^2$

$$\rho(X,Y) = ?$$

$$\rho(X,Y) = \frac{G_{V}(X,Y)}{V_{GV}(X) \cdot V_{GV}(Y)} = \frac{E[XY] - E[X] \cdot E[Y]}{E[X^{3}] - E[X] \cdot E[X^{2}]}$$

$$= \frac{E[X^{3}] - E[X] \cdot E[X^{2}]}{E[X^{2}] - (E[X^{2}])^{2}}$$

2. Conditional Distributions

Example: Using Joint PMF to Find Conditional PMF

- Example: Bus #2 (NCTU Mackay Train Station)
 - X = traveling time from NCTU to Mackay
 - Y = traveling time from Mackay to Train Station

•	P(X =	10 Y = 15	= ?

	Joint PMF	X=10	X=15	X=20
	Y=10	0.1	0.1	0.05
4	Y=15	0.1	0.3	0.1
	Y=20	0.05	0.1	0.1

$$P(X=10 | Y=15) = \frac{P(X=10 \text{ and } Y=15)}{P(Y=15)}$$

$$P(X=15|Y=15) = \frac{0.7}{0.5} = 0.2$$

$$P(X=15|Y=15) = \frac{0.3}{0.5} = 0.6$$

$$P(X=\infty|Y=15) = \frac{0.7}{0.5} = 0.2$$

Conditional PMF (Formally)

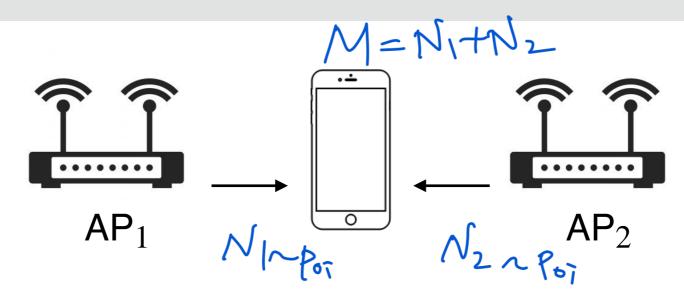
ightharpoonup Conditional PMF: Let X, Y be two discrete random variables with joint PMF $p_{XY}(x, y)$ When P(Y = y) > 0, the conditional

PMF of
$$X$$
 given $Y = y$ is
$$p_{X|Y}(x|y) \stackrel{\leftarrow}{=} \frac{p_{XY}(x,y)}{p_{Y}(y)}$$

• Question: Conditional PMF of
$$Y$$
 given $X = x$?

$$P_{Y|X}(y|x) = P_{X}(x|y)$$
• Question:
$$\sum_{x} p_{X|Y}(x|y) = \int_{x} P_{X}(x|y) dx$$

Example: Conditioning and Sum of Poisson

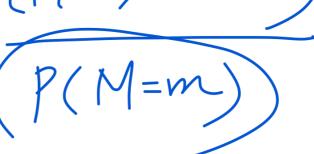


- Let N_1 and N_2 be the # of bits transmitted by ${\sf AP}_1$ and ${\sf AP}_2$ in a time interva(T), respectively
 - N_1 and N_2 are Poisson with rates λ_1 and λ_2 , respectively.
 - Moreover, N_1 and N_2 are independent
 - Define $M = N_1 + N_2$

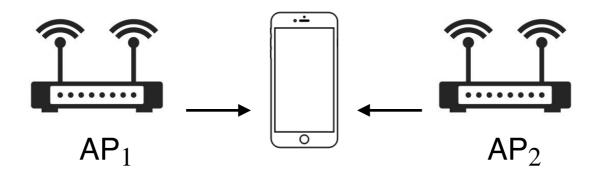
Question: Conditional PMF
$$p_{N_1|M}(n|m) = ?$$

$$p(N_1=N) M=m$$

$$p(M=M) = (P(M=M)) = (P(M=M))$$



Example: Conditioning and Sum of Poisson



- Conditional PMF $p_{N_1|M}(n \mid m)$

Conditional CDF: Discrete Case (Formally)

▶ Question: Given $p_{X|Y}(x | y)$, how to find $P(X \le t | Y = y)$?

• Conditional CDF: Let X, Y be two discrete random variables with joint PMF $p_{XY}(x,y)$. When P(Y=y)>0, the conditional CDF of X given Y=y is defined as

$$F_{X|Y}(x|y) = P(X \le x | Y = y) =$$

Conditional Expectation: Discrete Case (Formally)

• Conditional Expectation: Let X, Y be two discrete random variables. When P(Y = y) > 0, the conditional expected value of X given Y = y is

$$E(X | Y = y) = \sum_{x} x \cdot P(X = x | Y = y) =$$

• Question: Conditional expectation of Y given X = x?

Conditional PDF (Formally)

• Conditional PDF: Let X, Y be two continuous random variables with joint PDF $f_{XY}(x, y)$. When $f_Y(y) > 0$, the conditional PDF of X given Y = y is

$$f_{X|Y}(x|y) = \frac{f_{XY}(x,y)}{f_{Y}(y)}$$

• Question: Conditional PDF of Y given X = x?

Example: Find Conditional PDF From Joint PDF

Example: $f(x,y) = \begin{cases} 2 & \text{, if } 0 < y < x < 1 \\ 0 & \text{, otherwise} \end{cases}$ $f(x,y) = \begin{cases} 2 & \text{, if } 0 < y < x < 1 \\ 0 & \text{, otherwise} \end{cases}$

Conditional CDF: Continuous Case (Formally)

▶ Conditional CDF: Let X, Y be two continuous random variables and $f_{X|Y}(x|y)$ be the conditional PDF of X given Y = y. The conditional CDF of X given Y = y is $F_{X|Y}(x|y) = P(X \le x | Y = y) =$

Conditional Expectation: Continuous Case (Formally)

• Conditional Expectation: Let X, Y be two continuous random variables. When $f_Y(y) > 0$, the conditional expected value of X given Y = y is

$$E(X | Y = y) =$$

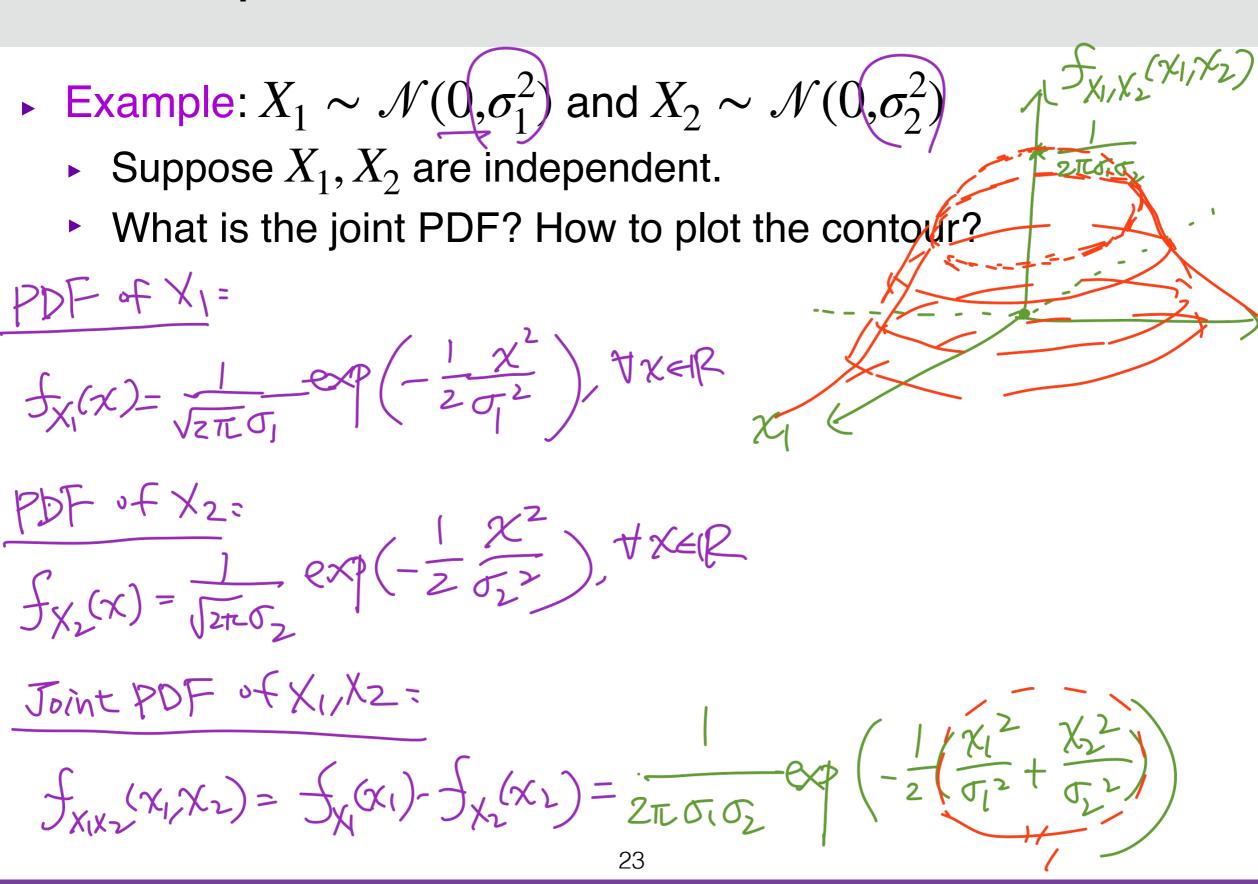
• Question: Conditional expectation of Y given X = x?

Example: Find Conditional Expectation

- Example: $f(x,y) = \begin{cases} 2, & \text{if } 0 < y < x < 1 \\ 0, & \text{otherwise} \end{cases}$
- E[X | Y = 0.5] = ?

3. Bivariate Normal Random Variables

Two Independent Normal Random Variables



Two Dependent Normal Random Variables

- Example: Suppose we want to construct X_1, X_2 such that
 - $X_1 \sim \mathcal{N}(0, \sigma_1^2)$ and $X_2 \sim \mathcal{N}(0, \sigma_2^2)$
 - $\rho(X_1, X_2) \neq 0$
 - How to achieve this?

Joint PDF of Bivariate Normal Random Variables

Joint PDF of Bivariate Normal (With Zero Mean):

$$f_{X_1X_2}(x_1, x_2) = \frac{1}{2\pi\sigma(\sigma_2)\sqrt{1 - \rho^2}} \exp\left[-\frac{1}{2(1 - \rho^2)} \left(\frac{x_1^2}{\sigma_1^2} - 2\rho\frac{x_1x_2}{\sigma_1\sigma_2} + \frac{x_2^2}{\sigma_2^2}\right)\right]$$



Two Dependent Normal Random Variables (Cont.)

- ► Goal: $X_1 \sim \mathcal{N}(0, \sigma_1^2)$, $X_2 \sim \mathcal{N}(0, \sigma_2^2)$, and $\rho(X_1, X_2) \neq 0$
- Idea: Let Z, W be 2 independent standard normal r.v.s

$$X_1 = \sigma_1 Z$$

$$X_2 = \sigma_2 \left(\rho Z + \sqrt{1 - \rho^2} W \right)$$

Linear Transformation of 2 Random Variables

Theorem: Let U_1,U_2,V_1,V_2 be random variables that satisfy $V_1=aU_1+bU_2$ and $V_2=cU_1+dU_2$. Define the matrix

$$A = \begin{bmatrix} a & b \\ c & d \end{bmatrix}$$
. Then, we have

$$f_{V_1V_2}(v_1, v_2) = \frac{1}{|\det(A)|} f_{U_1U_2}(A^{-1}[v_1, v_2]^T)$$

Joint PDF of X_1 and X_2

$$X_1 = \sigma_1 Z$$

$$X_2 = \sigma_2 \left(\rho Z + \sqrt{1 - \rho^2} W \right) \quad f_{X_1 X_2}(x_1, x_2) = \frac{1}{|\det(A)|} f_{ZW}(A^{-1}[x_1, x_2]^T)$$

1-Minute Summary

1. Covariance and Correlation Coefficient

• $\rho(X, Y) = \text{Cov}(X, Y)/(\sigma_X \sigma_Y)$, and $-1 \le \rho(X, Y) \le 1$

2. Conditional Distributions

Conditional PMF / CDF / PDF

3. Bivariate Normal Random Variables

- Construction from 2 independent standard normal
- Joint PDF