

Extra Worked Examples for Lecture 16.

The following is a collection of worked examples for the topics covered in Lecture 16, which we would have done at least partially in class if we hadn't lost 2 lectures to the weather. Please work through these independently and ask me (in person or by email) if you have any questions.

5-1.2 Marginal probability density functions

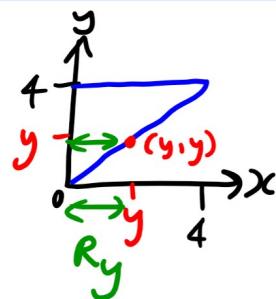
In Lecture 15 we had the following example of a joint p.d.f. for random variables X and Y :

$$f_{XY}(x,y) = \frac{1}{32}(x+y), \quad 0 < X < Y < 4.$$

From this we can find the marginal p.d.f.s of X & Y :

$$\begin{aligned} f_X(x) &= \int_{R_X} f_{XY}(x,y) dy = \int_x^4 \frac{1}{32}(x+y) dy \\ &= \left[\frac{1}{32}xy + \frac{1}{64}y^2 \right]_x^4 = \frac{x}{8} + \frac{1}{4} - \frac{1}{32}x^2 - \frac{1}{64}x^2 \\ &\quad - \frac{3x^2}{64} + \frac{x}{8} + \frac{1}{4} \end{aligned}$$

$$f_Y(y) = \int_{R_y} f_{XY}(x,y) dx = \int_0^y \frac{1}{32} (x+y) dx$$



$$= \left[\frac{1}{64} x^2 + \frac{1}{32} xy \right]_0^y = \frac{1}{64} y^2 + \frac{1}{32} y^2 = \frac{3y^2}{64}.$$

This in particular shows us that X and Y are not independent r.v.s (5-1.4) as $f_{XY}(x,y) = \frac{1}{32} (x+y)$

$$\neq f_x(x)f_y(y)$$

This fact is not surprising though since the domain of f_{XY} is not rectangular – for any fixed x , the possible values that Y can take depends on x , and for any fixed y , the possible values that X can take depends on y .

5.2 Covariance & Correlation Worked Example

Example Suppose X and Y are jointly distributed r.v.s with joint pdf

$$f_{XY}(x,y) = \begin{cases} 6 & \text{if } x^2 < y < x \\ 0 & \text{otherwise.} \end{cases}$$

Find σ_{XY} and ρ_{XY} .

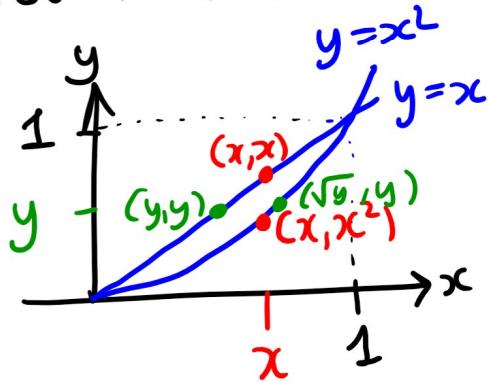
Solution Recall the formulae:

$$\sigma_{XY} = E(XY) - E(X)E(Y) \quad \text{and} \quad \rho_{XY} = \frac{\sigma_{XY}}{\sigma_X \sigma_Y}$$

$$\text{and } \sigma_X = \sqrt{E(X^2) - E(X)^2} \quad \sigma_Y = \sqrt{E(Y^2) - E(Y)^2}$$

So we need to find $E(X)$, $E(Y)$, $E(X^2)$, $E(Y^2)$, $E(XY)$.

First let's draw the domain of f_{XY} : $x^2 < y < x$



To find all of the required expectations, we can use f_{XY} .

$$\begin{aligned} E(\boxed{X}) &= \int_0^1 \int_y^{\sqrt{y}} \boxed{x} \cdot 6 \, dx \, dy = \int_0^1 [3x^2]_y^{\sqrt{y}} \, dy = \int_0^1 3\sqrt{y} - 3y^2 \, dy \\ &= \left[\frac{3y^{1/2}}{2} - y^3 \right]_0^1 = \frac{3}{2} - 1 = \frac{1}{2}. \end{aligned}$$

$$E(Y) = \int_0^1 \int_y^{\sqrt{y}} y \cdot 6 \, dx \, dy = \int_0^1 [6xy]_y^{\sqrt{y}} \, dy = \int_0^1 6y^{3/2} - 6y^2 \, dy$$

$$= \left[\frac{12y^{5/2}}{5} - 2y^3 \right]_0^1 = \frac{12}{5} - 2 = \frac{2}{5}.$$

$$E(X^2) = \int_0^1 \int_y^{\sqrt{y}} x^2 \cdot 6 \, dx \, dy = \int_0^1 [2x^3]_y^{\sqrt{y}} \, dy = \int_0^1 2y^{3/2} - 2y^3 \, dy$$

$$= \left[\frac{4y^{5/2}}{5} - \frac{y^4}{2} \right]_0^1 = \frac{4}{5} - \frac{1}{2} = \frac{3}{10}.$$

$$E(Y^2) = \int_0^1 \int_y^{\sqrt{y}} y^2 \cdot 6 \, dx \, dy = \int_0^1 [6y^2x]_y^{\sqrt{y}} \, dy = \int_0^1 6y^{5/2} - 6y^3 \, dy$$

$$= \left[\frac{12y^{7/2}}{7} - \frac{3y^4}{2} \right]_0^1 = \frac{12}{7} - \frac{3}{2} = \frac{3}{14}.$$

$$E(XY) = \int_0^1 \int_y^{\sqrt{y}} xy \cdot 6 \, dx \, dy = \int_0^1 [3x^2y]_y^{\sqrt{y}} \, dy = \int_0^1 3y^2 - 3y^3 \, dy$$

$$= \left[y^3 - \frac{3y^4}{4} \right]_0^1 = 1 - \frac{3}{4} = \frac{1}{4}.$$

Notice how every single calculation of expectation had the same form : $E(h(x,y)) = \iint h(x,y) f_{xy}(x,y) dx dy$

Whole region

$$= \int_0^1 \int_y^{\sqrt{y}} h(x,y) b dx dy.$$

$$\text{Now } \sigma_{xy} = E(xy) - E(x)E(Y) = \frac{1}{4} - \frac{1}{2} \cdot \frac{2}{5} = \frac{1}{20} = 0.05.$$

This tells us that there is some (perhaps small) positive linear relationship between X and Y .

In order to calculate f_{xy} we need first to calculate:

$$\sigma_x = \sqrt{E(X^2) - E(X)^2} = \sqrt{\frac{3}{10} - \left(\frac{1}{2}\right)^2} = \frac{1}{\sqrt{20}}$$

$$\sigma_y = \sqrt{E(Y^2) - E(Y)^2} = \sqrt{\frac{3}{14} - \left(\frac{2}{5}\right)^2} = \sqrt{\frac{19}{350}}.$$

$$\text{Now } \rho_{xy} = \frac{\sigma_{xy}}{\sigma_x \sigma_y} = \frac{1/20}{1/\sqrt{20} \sqrt{19/350}} = \frac{\cancel{\sqrt{20}} \sqrt{350}}{\cancel{\sqrt{20}} \sqrt{19}} = \sqrt{\frac{35}{38}} = 0.96.$$

The value of ρ_{xy} is 0.96 which is close to 1, so we can see that X and Y are positively correlated.

5.4 Linear Functions of Random Variables

— Key Examples

For the sake of having all the key examples in one place, here is repeated the example from class:

① Average of a collection of (independent) r.v.s.

X_1, \dots, X_n with common mean μ & variance σ^2 .

The average $\bar{X} = \frac{1}{n}(X_1 + \dots + X_n)$.

$$= \frac{1}{n}X_1 + \dots + \frac{1}{n}X_n.$$

$$\begin{aligned} \text{So } E(\bar{X}) &= \frac{1}{n}E(X_1) + \dots + \frac{1}{n}E(X_n) \\ &= \frac{1}{n}\mu + \dots + \frac{1}{n}\mu = \frac{1}{n} \cdot n \cdot \mu = \mu. \end{aligned}$$

If X_1, \dots, X_n are independent, then

$$\begin{aligned} V(\bar{X}) &= \frac{1}{n^2}V(X_1) + \dots + \frac{1}{n^2}V(X_n) \\ &= \frac{1}{n^2}\sigma^2 + \dots + \frac{1}{n^2}\sigma^2 = \frac{1}{n^2} \cdot n \cdot \sigma^2 = \frac{\sigma^2}{n}. \end{aligned}$$

So \bar{X} has mean μ , variance $\frac{\sigma^2}{n}$.

② Sum of (independent) random variables X_1, \dots, X_n with common mean μ and variance σ^2 .

The sum $X = X_1 + \dots + X_n$

$$\begin{aligned} \text{has mean } E(X) &= E(X_1) + \dots + E(X_n) \\ &= \mu + \dots + \mu = n\mu \end{aligned}$$

and, if X_1, \dots, X_n are independent, then

$$\begin{aligned} V(X) &= V(X_1) + \dots + V(X_n) \\ &= \sigma^2 + \dots + \sigma^2 = n\sigma^2. \end{aligned}$$

So X has mean $n\mu$ and variance $n\sigma^2$.

Important Fact If X_1, \dots, X_k are independent, normally distributed r.v.s then a linear combination of them $Y = c_1 X_1 + \dots + c_n X_n$ is also normally distributed.

So if $X_i \sim N(\mu_i, \sigma_i^2)$, then

$$\begin{aligned} E(Y) &= c_1 E(X_1) + \dots + c_n E(X_n) \\ &= c_1 \mu_1 + \dots + c_n \mu_n \end{aligned}$$

$$\text{and } V(Y) = c_1^2 V(X_1) + \dots + c_n^2 V(X_n) \\ = c_1^2 \sigma_1^2 + \dots + c_n^2 \sigma_n^2.$$

So $Y \sim N(c_1\mu_1 + \dots + c_n\mu_n, c_1^2\sigma_1^2 + \dots + c_n^2\sigma_n^2)$.

What if ① $Y = \bar{X}$ or ② $Y = X$ in the Special Cases above?

i.e. If $X_1, \dots, X_n \sim N(\mu, \sigma^2)$ are independent, then ① $\bar{X} \sim N(\mu, \frac{\sigma^2}{n})$
 ② $X \sim N(n\mu, n\sigma^2)$.

Pay close attention to these! ① especially we will use very often in the statistics part of the course.

Worked Example for 5.4 Linear Functions of R.V.s

Example Suppose that we have drinks bottles filled to a mean volume of 591 ml, with standard deviation 5 ml. Suppose that the volumes of the bottles are independent normal r.v.s.

- What is the probability that one bottle has less than 585 ml?
- Now 10 bottles are measured. What is the probability that their average volume is less than 585 ml?

Solution (a) Set X_i = volume of one bottle
 $\sim N(\mu, \sigma^2)$.

Part (a) is not new material:

$$\begin{aligned} \text{we need to find } P(X_i < 585) &= P\left(Z < \frac{585 - 591}{5}\right) \\ &= P(Z < -1.2) = 1 - P(Z < 1.2) \\ &= 1 - 0.88493 = 0.11507. \end{aligned}$$

(b) Set X_i = volume of bottle i ($i=1, \dots, 10$).
 $\sim N(591, 25)$.

We want $P(\bar{X} < 585)$ where $\bar{X} = \frac{1}{10}(X_1 + \dots + X_{10})$
 $\sim N(591, 2.5)$

$$\begin{aligned}
 P(\bar{X} < 585) &= P\left(Z < \frac{585 - 591}{\sqrt{2.5}}\right) \\
 &= P\left(Z < \frac{-6}{1.58}\right) = P(Z < -3.79) \\
 &= 1 - P(Z < 3.79) \\
 &= 1 - 0.999925 \\
 &= 0.000075.
 \end{aligned}$$

Notice how the probability found in part
 (b) [that the average volume of 10 bottles is

$< 585\text{ml}$] is much lower than the probability

found in part (a) [that one bottle's volume is
 $< 585\text{ml}$]. This is because of the much
 lower standard deviation for \bar{X} than for
 any individual $X_i < \sigma = 5$

$$\frac{\sigma}{\sqrt{n}} = \frac{5}{\sqrt{10}} = 1.58.$$