

# EE3731C Tutorial - Statistical Signal I

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1. (a) For a discrete random variable  $x$ , the probability mass function  $p(x)$  is  $\geq 0$  for all  $x$  and  $\sum_x p(x) = 1$ . Consequently,  $p(x) \leq 1$  for all  $x$ . To see this, suppose  $p(x_0) > 1$  for some  $x_0$ , then  $\sum_x p(x) > 1$ . In class, I might sometimes refer to the probability mass function  $p(x)$  as the “probability distribution of  $x$ ”, where I have dropped “mass function” for brevity.

For a continuous random variable  $z$ , the probability distribution function  $p(z)$  also has to be  $\geq 0$  for all  $z$  and  $\int_z p(z) = 1$ . Unlike the discrete case,  $p(z)$  can be  $> 1$  for certain  $z$ . For example,  $p(z) = 2$  for  $0 \leq z \leq 0.5$  is a valid probability distribution function. In class, I might refer to the probability distribution function  $p(z)$  as the “probability distribution of  $z$ ”, where I have dropped “function” for brevity.

In this problem,  $p(x, y)$  is a valid distribution because

- $p(x, y) \geq 0$  for all  $x, y$
- $\int_0^1 \int_0^1 p(x, y) dx dy = \int_0^1 \int_0^1 x + y dx dy = \int_0^1 x dx + \int_0^1 y dy = 1/2 + 1/2 = 1$

(b)

$$\begin{aligned} p(x) &= \int_0^1 p(x, y) dy \text{ for } 0 \leq x \leq 1 \\ &= \int_0^1 x + y dy \\ &= \int_0^1 x dy + \int_0^1 y dy \\ &= x + \int_0^1 y dy \\ &= x + \frac{1}{2} \end{aligned}$$

Note that  $p(x) = 0$  for  $x < 0$  or  $x > 1$ . By symmetry,

$$p(y) = \begin{cases} y + 1/2 & 0 \leq y \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

Using the definition of conditional probability

$$\begin{aligned} p(x|y) &= \frac{p(x, y)}{p(y)} \\ &= \begin{cases} \frac{x+y}{y+1/2} & \text{for } 0 \leq x, y \leq 1 \\ 0 & \text{otherwise} \end{cases} \end{aligned}$$

(c)  $p(x|y) \neq p(x)$ . Therefore  $x$  and  $y$  are not independent.

(d)  $E(x) = E(y)$ , so we will just calculate  $E(x)$

$$\begin{aligned} E(x) &= \int_0^1 xp(x)dx \\ &= \int_0^1 x(x + 1/2)dx \\ &= \left[ \frac{x^3}{3} + \frac{x^2}{4} \right]_0^1 \\ &= \frac{1}{3} + \frac{1}{4} = \frac{7}{12} \end{aligned}$$

(e)  $Var(x) = Var(y)$ , so we will just calculate  $Var(x)$ . First let's calculate

$$\begin{aligned} E(x^2) &= \int_0^1 x^2p(x)dx \\ &= \int_0^1 x^2\left(x + \frac{1}{2}\right)dx \\ &= \left[ \frac{x^4}{4} + \frac{x^3}{6} \right]_0^1 \\ &= \frac{1}{4} + \frac{1}{6} = \frac{5}{12} \end{aligned}$$

Therefore  $Var(x) = E(x^2) - (E(x))^2 = \frac{5}{12} - \left(\frac{7}{12}\right)^2 = 11/144$ .

(f)

$$\begin{aligned} E(xy) &= \int_0^1 \int_0^1 xyp(x, y)dxdy = \int_0^1 \int_0^1 xy(x + y)dxdy \\ &= \int_0^1 \int_0^1 x^2y + xy^2dxdy \\ &= \int_0^1 \left[ \frac{x^3}{3}y + \frac{x^2y^2}{2} \right]_0^1 dy \\ &= \int_0^1 \frac{y}{3} + \frac{y^2}{2} dy \\ &= \left[ \frac{y^2}{6} + \frac{y^3}{6} \right]_0^1 = \frac{1}{6} + \frac{1}{6} = \frac{1}{3} \end{aligned}$$

Therefore  $Cov(x, y) = E(xy) - E(x)E(y) = \frac{1}{3} - \frac{7}{12}\frac{7}{12} = -\frac{1}{144}$

$$(g) \ p(x|y = 0.5) = \begin{cases} x + 0.5 & \text{for } 0 \leq x \leq 1 \\ 0 & \text{otherwise} \end{cases}$$

We can verify that  $\int_0^1 p(x|y = 0.5)dx = 1$  and is therefore a valid probability distribution. Therefore

$$\begin{aligned} E(x^2|y = 0.5) &= \int_0^1 x^2 p(x|y = 0.5)dx \\ &= \int_0^1 x^3 + 0.5x^2 dx \\ &= \left[ \frac{1}{4}x^4 + \frac{1}{6}x^3 \right]_0^1 \\ &= \frac{1}{4} + \frac{1}{6} = 5/12 \end{aligned}$$

2.

$$\begin{aligned} &E_{p(x)}(x - a)^2 \\ &= E_{p(x)}(x^2 + a^2 - 2ax) \\ &= E_{p(x)}(x^2) + E_{p(x)}(a^2) - E_{p(x)}(2ax) \quad \text{linearity of expectation} \\ &= E_{p(x)}(x^2) + a^2 - 2a\mu_x \quad \text{more linearity of expectation} \\ &= E_{p(x)}(x^2) + (a - \mu_x)^2 - \mu_x^2 \quad \text{completing the square} \\ &= Var(x) + (a - \mu_x)^2 \\ &\geq Var(x) \text{ with equality achieved when } a = \mu_x \end{aligned}$$

3.

$$\begin{aligned} Var(cx) &= E((cx)^2) - (E(cx))^2 && \text{Definition of variance} \\ &= E(c^2x^2) - (cE(x))^2 && \text{Expand first term and linearity of expectation second term} \\ &= c^2E(x^2) - c^2(E(x))^2 && \text{Linearity of expectation first term and expand second term} \\ &= c^2(E(x^2) - (E(x))^2) && \text{collect terms} \\ &= c^2Var(x) && \text{Definition of variance} \end{aligned}$$

4. (a) By linearity of expectation,  $E(2x + 3y) = 2E(x) + 3E(y) = 2 \times 5 + 3 \times 3 = 19$

(b) Using Q3 and the fact that  $Var(x) = E(x^2) - (E(x))^2$ , we get  $Var(2x) = 4Var(x) = 4[E(x^2) - (E(x))^2] = 4(30 - 5^2) = 20$

(c)  $Cov(x, y) = E(xy) - E(x)E(y) = 4 - (5 \times 3) = -11$

(d)  $Cov(x, y) \neq 0 \implies x$  and  $y$  are not independent

5. Consider two random variables  $x$  and  $y$  with joint distribution  $p(x, y)$ . Let

$$\begin{aligned} p(5, 5) &= 2/5 & p(-5, -5) &= 2/5 \\ p(-10, 10) &= 1/10 & p(10, -10) &= 1/10 \\ p(x, y) &= 0, \text{ otherwise} \end{aligned}$$

Clearly  $x$  and  $y$  are not independent, since knowing one completely determines the other. However,

$$E(XY) = \sum_x \sum_y xyp(x, y) = 25 \times \frac{2}{5} + 25 \times \frac{2}{5} - 100 \times \frac{1}{10} - 100 \times \frac{1}{10} = 0$$

Furthermore, observe that  $p(x) = p(y)$ , where  $p(x = -5) = p(x = 5) = 2/5$  and  $p(x = -10) = p(x = 10) = 1/10$ . Therefore

$$\begin{aligned} E(x) &= \sum_x xp(x) = 5 \times \frac{2}{5} - 5 \times \frac{2}{5} - 10 \times \frac{1}{10} + 10 \times \frac{1}{10} = 0 \\ E(Y) &= \sum_y yp(y) = 5 \times \frac{2}{5} - 5 \times \frac{2}{5} + 10 \times \frac{1}{10} - 10 \times \frac{1}{10} = 0 \end{aligned}$$

Therefore  $Cov(X, Y) = E(XY) - E(X)E(Y) = 0$ .

The webpage ([http://en.wikipedia.org/wiki/Correlation\\_and\\_dependence](http://en.wikipedia.org/wiki/Correlation_and_dependence)) shows various examples of continuous distributions where  $Cov(x, y) = 0$ , but  $x$  and  $y$  are not independent. Here's a more formal example. Let  $x \sim U[-1/2, 1/2]$  (uniform distribution between  $-1/2$  and  $1/2$ ).

Let  $y = x^2 + \epsilon$ , where  $\epsilon \sim \mathcal{N}(0, 1)$ , so we can think of  $y$  as equal to  $x^2$  plus some Gaussian noise. Then  $p(y|x) \sim \mathcal{N}(x^2, 1)$ . Therefore  $x$  and  $y$  are not independent. Let's compute  $E(xy)$

$$\begin{aligned} E(xy) &= \int_{-0.5}^{0.5} \int_{-\infty}^{\infty} xyp(x)p(y|x)dydx \\ &= \int_{-0.5}^{0.5} \int_{-\infty}^{\infty} xy \frac{1}{\sqrt{2\pi}} e^{-\frac{(y-x^2)^2}{2}} dydx \\ &= \int_{-0.5}^{0.5} x \int_{-\infty}^{\infty} y \frac{1}{\sqrt{2\pi}} e^{-\frac{(y-x^2)^2}{2}} dydx \\ &= \int_{-0.5}^{0.5} x \int_{-\infty}^{\infty} (u - x^2) \frac{1}{\sqrt{2\pi}} e^{-\frac{u^2}{2}} du dx \quad \text{substitute } u = y - x^2 \\ &= - \int_{-0.5}^{0.5} x^3 dx \\ &= 0 \end{aligned}$$

Note that  $E(x) = 0$ . Therefore  $Cov(x, y) = E(xy) - E(x)E(y) = 0$ .