

Assignment 2: CS 215 Solutions

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Honor Code:

- We pledge by our honor that we will complete the assignments in a legitimate way and will not provide or receive any unauthorized help.

Instructions to run code:

- The folder 'code' contains all the code written for the assignment. Here is how we run them. From the MATLAB command line, simply typing *partA,partB,partC* will run the programs given in Question 7.
- The file *frequencyCalc.m* calculates the values of $p_{X_1}(x_1)$, $p_{X_2}(x_2)$ and $p_{X_1X_2}(x_1, x_2)$. The inputs required are the two matrices X_1, X_2 .
- The file *corCoeff.m, qmi.m*, and *anotherMeasure.m* give the values of Correlation Coefficient, QMI and the custom value. The code is commented so it can be understood easily. To be on the safe side, we have written the code for Correlation Coefficient rather than using the default routine.

Solutions:

1. There are 2 random variables X and Y having pdf $f_X(x)$ and $f_Y(y)$ and joint pdf $f_{XY}(x, y)$. To find the cdf and pdf of random variable $Z = XY$, we take $P(Z \leq a)$.

$$P(Z \leq a) = P(XY \leq a)$$
$$P(XY \leq a) = \int \int_A f_{XY}(x, y) \cdot dx \cdot dy$$

Since the function $xy = a$ has discontinuity at $x = 0$, we have to write two terms, one from $(-\infty, 0)$ and another from $(0, \infty)$ such that,

$$F_Z(a) = P(Z \leq a) = \int_{x=-\infty}^{x=0} \int_{y=\frac{a}{x}}^{y=\infty} f_{XY}(x, y) \cdot dy \cdot dx + \int_{x=0}^{x=\infty} \int_{y=-\infty}^{y=\frac{a}{x}} f_{XY}(x, y) \cdot dy \cdot dx$$

To find the pdf, we simply differentiate w.r.t. a to get,

$$f_Z(a) = \int_{x=-\infty}^{x=0} -\frac{1}{x} \cdot f_{XY}(x, \frac{a}{x}) \cdot dx + \int_{x=0}^{x=\infty} \frac{1}{x} \cdot f_{XY}(x, \frac{a}{x}) \cdot dy \cdot dx$$

Similarly, for $P(X \leq Y)$, we take $X \geq x$ and find $Y \geq X$, hence, we can write in terms of joint probability,

$$P(X \leq Y) = \int_{y=x}^{y=\infty} \int_{x=-\infty}^{x=x} f_{XY}(x, y) \cdot dx \cdot dy$$

For independent variables, we can substitute $f_{XY}(x, y) = f_X(x) \cdot f_Y(y)$

$$F_Z(a) = P(Z \leq a) = \int_{x=-\infty}^{x=0} \int_{y=\frac{a}{x}}^{y=\infty} (f_Y(y) \cdot dy) \cdot f_X(x) \cdot dx + \int_{x=0}^{x=\infty} \int_{y=-\infty}^{y=\frac{a}{x}} (f_Y(y) \cdot dy) \cdot f_X(x) \cdot dx$$

Integrating w.r.t. y first, we get,

$$\Rightarrow F_Z(a) = \int_{x=-\infty}^{x=0} \left(1 - F_Y\left(\frac{a}{x}\right)\right) \cdot f_X(x) \cdot dx + \int_{x=0}^{x=\infty} F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx$$

$$\Rightarrow F_Z(a) = F_X(0) + \int_{x=0}^{x=\infty} F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx - \int_{x=-\infty}^{x=0} F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx$$

For pdf of Z, differentiate $F_Z(a)$ with respect to a,

$$\begin{aligned}\frac{dF_Z(a)}{da} &= \frac{d}{da} \left(F_X(0) + \int_{x=0}^{x=\infty} F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx - \int_{x=-\infty}^{x=0} F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx \right) \\ \therefore f_Z(a) &= 0 + \frac{d}{da} \left(\int_{x=0}^{x=\infty} F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx \right) - \frac{d}{da} \left(\int_{x=-\infty}^{x=0} F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx \right) \\ &= \int_{x=0}^{x=\infty} \frac{\partial}{\partial a} \left(F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx \right) - \int_{x=-\infty}^{x=0} \frac{\partial}{\partial a} \left(F_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx \right) \\ f_Z(a) &= \int_{x=0}^{x=\infty} \frac{1}{x} \cdot f_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx - \int_{x=-\infty}^{x=0} \frac{1}{x} \cdot f_Y\left(\frac{a}{x}\right) \cdot f_X(x) \cdot dx\end{aligned}$$

For the case $X \leq Y$, substitute $f_{XY}(x, y) = f_X(x) \cdot f_Y(y)$ to get,

$$\begin{aligned}P(X \leq Y) &= \int_{y=x}^{y=\infty} \int_{x=-\infty}^{x=x} f_X(x) \cdot f_Y(y) \cdot dx \cdot dy \\ \implies P(X \leq Y) &= \int_x^\infty f_Y(y) \cdot dy \cdot \int_{-\infty}^x f_X(x) \cdot dx \\ \implies P(X \leq Y) &= \int_{-\infty}^\infty f_X(x) \cdot (1 - F_Y(x)) \cdot dx\end{aligned}$$

Integrating w.r.t. x , we get the final expression.

$$\therefore P(X \leq Y) = 1 - E[F_Y(x)]$$

2. X_1, X_2, \dots, X_n are n I.I.D. random variables.

Now, $Y_1 = \max(X_1, X_2, \dots, X_n)$. To provide the CDF of Y_1 , we need to find the probability that Y_1 is less than a .

So, now if we conduct an experiment to determine the value of the random variable X n times, Y_1 will be less than a only if $X_i \leq a, \forall i$.

$$P(Y_1 \leq a) = P(X_1 \leq a) \text{ and } P(X_2 \leq a) \dots \text{ and } P(X_n \leq a)$$

Since X is an I.I.D. random variable, we can simply multiply the probabilities of the right hand side since the result of one experiment doesnot affect the result of the other, we have,

$$P(Y_1 \leq a) = P(X_1 \leq a) * P(X_2 \leq a) \dots * P(X_n \leq a)$$

$$P(Y_1 \leq a) = F_X(a) * F_X(a) \dots * F_X(a) \text{ (n times)}$$

$$P(Y_1 \leq a) = (F_X(a))^n$$

Hence,

$$F_{Y_1}(a) = (F_X(a))^n$$

... (cdf of Y_1)

Differentiating w.r.t. a , we get,

$$F'_{Y_1}(a) = f_{Y_1}(a) = \frac{d(F_X(a))^n}{da} = n \cdot (F_X(a))^{n-1} \cdot f_X(a)$$

$$f_{Y_1}(a) = n \cdot (F_X(a))^{n-1} \cdot f_X(a)$$

... (pdf of Y_1)

Now, $Y_2 = \min(X_1, X_2, \dots, X_n)$

So, now if we conduct an experiment to determine the value of the random variable X n times, Y_2 will be **more** than a only if $X_i \geq a, \forall i$.

$$P(Y_2 \geq a) = P(X_1 \geq a) \text{ and } P(X_2 \geq a) \dots \text{ and } P(X_n \geq a)$$

Since X is an I.I.D. random variable, we can simply multiply the probabilities of the right hand side since the result of one experiment doesnot affect the result of the other, we have,

$$\begin{aligned} \implies P(Y_2 \geq a) &= P(X_1 \geq a) * P(X_2 \geq a) \dots * P(X_n \geq a) \\ \implies P(Y_2 \geq a) &= (1 - P(X_1 \leq a)) * (1 - P(X_2 \leq a)) \dots * (1 - P(X_n \leq a)) \\ \implies P(Y_2 \geq a) &= (1 - F_X(a)) * (1 - F_X(a)) \dots * (1 - F_X(a)) \end{aligned}$$

... (n times)

$$\begin{aligned} \implies P(Y_2 \geq a) &= (1 - (F_X(a)))^n \\ \implies 1 - F_{Y_2}(a) &= (1 - (F_X(a)))^n \\ F_{Y_2}(a) &= 1 - (1 - (F_X(a)))^n \end{aligned}$$

... (cdf of Y_2)

Differentiating w.r.t. a , we get,

$$f_{Y_2}(a) = n \cdot (1 - F_X(a))^{n-1} \cdot f_X(a)$$

... (pdf of Y_1)

3. We have to calculate the total amount one will win if n^{th} trial is successful and all others before it are unsuccessful.

Given that the amount one bets is x in the first trial. He loses the first $n-1$ trials,

Let amount lost in i^{th} trial = a_i

$$a_i = 2 \cdot a_{i-1} \text{ and } a_1 = x$$

Solving this gives:

$$\begin{aligned} a_i &= 2^{i-1} \cdot x \\ \text{Total amount lost} &= \sum_{i=1}^{n-1} a_i = x \cdot \sum_{i=1}^{n-1} 2^{i-1} \end{aligned}$$

This is the sum of a geometric progression with first term 1, common ratio 2 and $n - 1$ terms.

$$\therefore \text{Total amount lost} = x \cdot \frac{1(2^{n-1} - 1)}{(2 - 1)} = (2^{n-1} - 1)x$$

Since, the n^{th} trial is a success,

$$\text{Amount won in the } n^{th} \text{ trial} = 2 \cdot a_{n-1} = 2^{n-1}x$$

$$\text{Total amount won} = 2^{n-1}x - (2^{n-1} - 1)x = x$$

4. Let X and Y be two random independent random variables. For them, we have the following relation,

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

$$\implies E(XY) = E(X) \cdot E(Y)$$

Now, we define covariance of X, Y as,

$$\text{cov}(X, Y) = E[(X - \mu_X) \cdot (Y - \mu_Y)]$$

$$= E[XY - \mu_X Y - \mu_Y X + \mu_X \mu_Y]$$

Using linearity of the expectation value operator, we get,

$$= E[XY] - E[\mu_X Y] - E[\mu_Y X] + E[\mu_X \mu_Y]$$

$$= E[XY] - \mu_X \mu_Y - \mu_X \mu_Y + \mu_X \mu_Y$$

$$= E[XY] - E[X] \cdot E[Y]$$

Now since $E[XY] = E[X] \cdot E[Y]$, we have,

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

For the converse, we take the following two random variables,

$$X = \begin{cases} 1 & , P(X = 1) = 0.5 \\ -1 & , P(X = -1) = 0.5 \end{cases}$$

and

$$Y = \begin{cases} 0.5 & , X = 1, \text{ with } P(Y = 0.5|X = 1) = 0.5 \\ -0.5 & , X = 1, \text{ with } P(Y = -0.5|X = 1) = 0.5 \\ 0 & , X = -1, \text{ with } Y = 0 \end{cases}$$

These two random variables are obviously dependent, since if $X = 0$, we can determine Y , and similarly for $X = 1$. The covariance of these two variables will be ,

$$\text{cov}(X, Y) = \frac{\sum (X - \mu_X)(Y - \mu_Y)}{(N - 1)\sigma_X \sigma_Y} = E[XY] - E[X] \cdot E[Y]$$

Now, we have $E[X] = E[Y] = 0$, since the probability of X taking any value is equal, and same for Y . Since all the values are centered around 0, we can say the statement without calculating it. We can calculate the value very easily as well.

$$\implies \text{cov}(X, Y) = E[XY]$$

Now,

$$E[XY] = 1 * 0.5 + 1 * -0.5 + -1 * 0 = 0$$

$$\implies \text{cov}(X, Y) = E[XY] - E[X] \cdot E[Y] = 0 - 0 \cdot 0 = 0$$

$\therefore X$ and Y are dependent but have 0 covariance.

5. Shifting the values of x doesn't affect the variance. Therefore, shift the origin to $\frac{b+a}{2}$ so that the interval now becomes $[-\frac{b-a}{2}, \frac{b-a}{2}]$

$$\text{Now, } \text{Var}(X) = E(X^2) - (E(X))^2 \leq E(X^2)$$

$$\text{Var}(X) \leq E(X^2) = \int_{-\frac{b-a}{2}}^{\frac{b-a}{2}} x^2 f_X(x) dx$$

$$\text{In the given range, } x^2 \leq \left(\frac{b-a}{2}\right)^2$$

$$\therefore E(X^2) \leq \left(\frac{b-a}{2}\right)^2 \int_{-\frac{b-a}{2}}^{\frac{b-a}{2}} f_X(x) dx = \left(\frac{b-a}{2}\right)^2$$

(\because integration of a pdf over its range is 1)

$$\text{Hence, } \text{Var}(X) \leq \left(\frac{b-a}{2}\right)^2$$

6. A function $g(x)$ is a convex function. Let X be a random variable with $E[X] = \mu$. Now, let $l(x)$ be the equation of the tangent at $x = \mu$.

$$\implies l(x) = g'(\mu) \cdot (x - \mu) + g(\mu)$$

Now, we have $g(x) \geq l(x), \forall x \in \mathbb{R}$, we can write,

$$\int_{-\infty}^{\infty} g(x) \cdot f_X(x) \cdot dx \geq \int_{-\infty}^{\infty} l(x) \cdot f_X(x) \cdot dx$$

$$\implies E[g(X)] \geq E[l(X)]$$

Since $l(x)$ is a linear function of x ,

Substitute $l(X) = g'(\mu) \cdot (X - \mu) + g(\mu)$ to get ,

$$E[l(X)] = E[g'(\mu) \cdot (X - \mu) + g(\mu)]$$

$$= g'(\mu) \cdot (E[X] - \mu) + g(\mu)$$

$$= l(E[X]) = l(\mu)$$

Now, at $x = \mu, l(x) = g(x)$, so we get,

$$E[l(X)] = l(E[X]) = g(E[X])$$

$$\therefore E[g(X)] \geq g(E[X])$$

7. (a) Values computed with unaltered image -

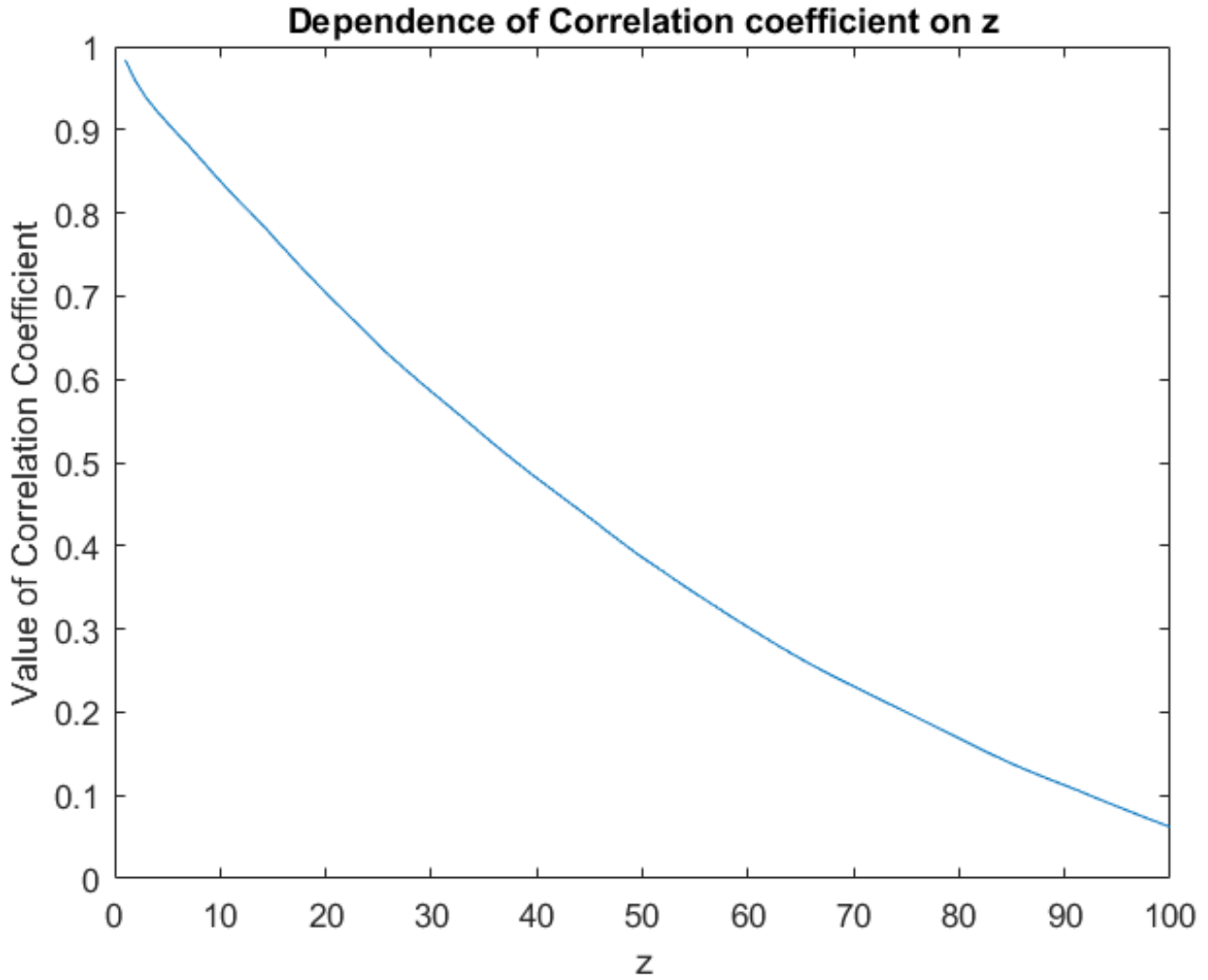
Correlation Coefficient = 0.98413

QMI = 0.035871

Another measure = 1.4736

(b) The code and instructions are provided. The graph is given below.

Figure 1: Correlation Coefficient v/s z



As the value of z increases, the neighbours are more separated and they have lesser chance of having similar intensities, and hence the correlation coefficient decreases with z .

(c) After scrambling the values, we ran the program another time and got the following results -

Table for parameters of unaltered and scrambled image.

	Unaltered image	Scrambled image
Correlation coefficient	0.98413	0.012953
QMI	0.035871	0.0012152
Another index	1.4736	0.51315

After scrambling the image, the intensities get randomized and almost all correlation is lost. Hence, the correlation coefficient decreases rapidly. Also, the random variables X_1 and X_2 become more independent and the values of $p_{XY}(x, y)$ tend to move towards $p_X(x) \cdot p_Y(y)$. Hence the other two terms tend to 0.

For the 3rd measure, the minimum value is when the random variables X_1 and X_2 are completely independent. Hence the minimum value is 0.

For the maximum value, we need to vary the difference between $p_{XY}(x, y)$ and $p_X(x) \cdot p_Y(y)$, and that happens when the 2 random variables are completely dependent on each other (for example, one variable is a deterministic function of the other).