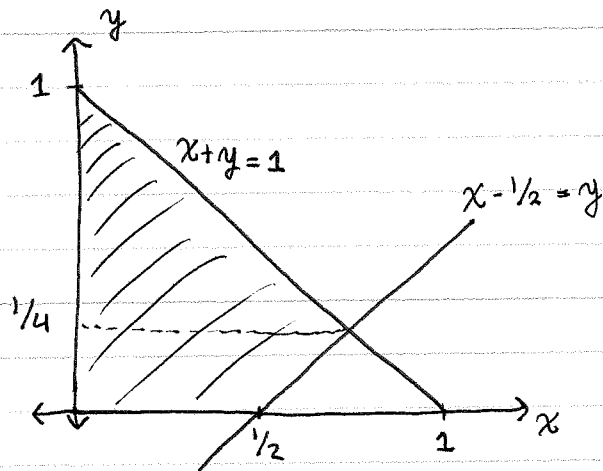


c) Find $\Pr(X - 1/2 \leq Y)$

$$\Pr(X - 1/2 \leq Y) = \iint_{X - 1/2 \leq Y} f_{X,Y}(x,y) dx dy$$



$$\Pr(X - 1/2 \leq Y) = \int_0^{1/4} \int_0^{y+1/2} 6x dx dy$$

$$+ \int_{1/4}^1 \int_0^{1-y} 6x dx dy$$

$$= \int_0^{1/4} \left. \frac{6x^2}{2} \right|_0^{y+1/2} dy$$

$$+ \int_{1/4}^1 \left. \frac{6x^2}{2} \right|_0^{1-y} dy$$

$$= \int_0^{1/4} 3(y + 1/2)^2 dy + \int_{1/4}^1 3(1 - y^2)^2 dy$$

$$= \frac{3u^3}{3} \Big|_{1/2}^{3/4} + \int_0^{3/4} 3v^2 dv$$

$$u^2 = y + 1/2 \quad v = 1 - y$$

$$= \frac{3u^3}{3} \Big|_{1/2}^{3/4} + \frac{3v^3}{3} \Big|_0^{3/4}$$

Note: Let $Z = X - Y$. How can we find the cdf of Z ?

$$F_Z(z) = \Pr(Z \leq z)$$

$$= \Pr(X - Y \leq z)$$

$$= \Pr(X - z \leq Y)$$

Can repeat the analysis from c) to find $F_Z(z)$

Conditional cdf, pdf, and pmf

As stated before, can find the conditional

pdf of X given Y as

$$f_{X|Y}(x|y) = \frac{f_{X,Y}(x,y)}{f_Y(y)}, \quad f_Y(y) > 0$$

Can also derive a total probability ~~expr~~ expression for this conditional pdf

$$f_{X,Y}(x,y) = f_{X|Y}(x|y) f_Y(y)$$

$$\Rightarrow \int_{-\infty}^{\infty} f_{X,Y}(x,y) dy = \int_{-\infty}^{\infty} f_{X|Y}(x|y) f_Y(y) dy$$

$$\Rightarrow f_X(x) = \int_{-\infty}^{\infty} f_{X|Y}(x|y) f_Y(y) dy$$

Total Probability for pdfs \uparrow

Bayes Rule for pdfs

$$f_{X|Y}(x|y) = \frac{f_{Y|X}(y|x) f_X(x)}{f_Y(y)}$$

Let X and Y be discrete r.v.s. The conditional pmf of X given Y is

$$P_{X|Y}(x_i|y_j) = \Pr(X=x_i | Y=y_j)$$

$$\Rightarrow P_{X|Y}(x_i|y_j) = \frac{P_{X,Y}(x_i, y_j)}{P_Y(y_j)} \quad (P_Y(y_j) > 0)$$

$$P_{Y|X}(y_j|x_i) = \frac{P_{X,Y}(x_i, y_j)}{P_X(x_i)} \quad (P_X(x_i) > 0)$$

Total Probability for pmfs

$$P_Y(y_j) = \sum_{x_i} P_{Y|X}(y_j|x_i) P_X(x_i)$$

Bayes Rule for pmfs

$$P_{X|Y}(x_i|y_j) = \frac{P_{Y|X}(y_j|x_i) P_X(x_i)}{P_Y(y_j)}$$

Independence of R.V.

Let X and Y be r.v.s. We say X and Y are independent if

$$\Pr(X \in A, Y \in B) = \Pr(X \in A) \Pr(Y \in B)$$

for all $A, B \subset \mathbb{R}$

Following statements are equivalent:

(1) X and Y are independent r.v.s

(2) $f_{X,Y}(x,y) = f_X(x) f_Y(y)$ for all x and y

(3) $f_{X|Y}(x|y) = f_X(x)$ for all x, y with $f_Y(y) > 0$

(4) $f_{Y|X}(y|x) = f_Y(y)$ for all x, y with $f_X(x) > 0$

(5) $f_{X,Y}(x,y) = a(x) b(y)$ for all x, y ,

where $a(x)$ and $b(y)$ are functions.

If X, Y are independent then $g(X), h(Y)$ are also independent. This implies

$$E[g(X)h(Y)] = E[g(X)]E[h(Y)]$$

$$\Rightarrow E[XY] = E[X]E[Y]$$

Correlation of R.V.s

Let X, Y be r.v.s. The correlation between

$$X \text{ and } Y \text{ is } E[XY] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} xy f_{X,Y}(x,y) dx dy$$

The covariance between X and Y is

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

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (x - \mu_X)(y - \mu_Y) f_{X,Y}(x,y) dx dy$$

Note: $\text{Cov}[X, X] = \text{Var}[X]$

$$\text{Cov}[X, Y] = \text{Cov}[Y, X]$$

X and Y are uncorrelated r.v.s if

$$\text{Cov}[X, Y] = 0 \Leftrightarrow E[XY] = E[X]E[Y]$$

Follows from $\text{Cov}[X, Y] = E[XY] - E[X]E[Y]$

Independence \Rightarrow Uncorrelated

Uncorrelated $\not\Rightarrow$ Independence

The r.v.s X and Y are orthogonal if

$$E[XY] = 0$$

The covariance of X and Y measures the correlation between the behavior of X and Y .

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

If there is a tendency for

$$\left. \begin{array}{l} (X - \mu_X) > 0 \quad \text{when} \quad (Y - \mu_Y) > 0 \\ \text{or} \\ (X - \mu_X) < 0 \quad \text{when} \quad (Y - \mu_Y) < 0 \end{array} \right\} \Rightarrow \text{Cov}[X, Y] > 0$$

If there is a tendency for

$$\left. \begin{array}{l} (X - \mu_X) < 0 \quad \text{when} \quad (Y - \mu_Y) > 0 \\ \text{or} \\ (X - \mu_X) > 0 \quad \text{when} \quad (Y - \mu_Y) < 0 \end{array} \right\} \Rightarrow \text{Cov}[X, Y] < 0$$