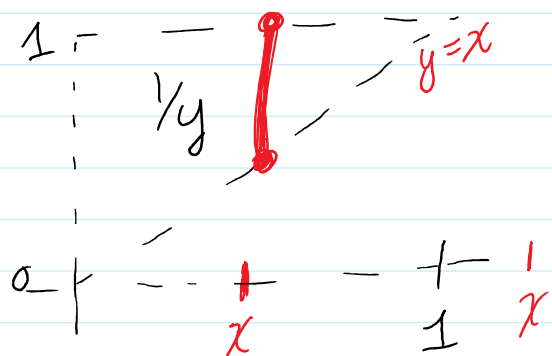


What is the marginal dist of X ?

$$f_X(x) = \int f(x,y) dy = \int_{y=x}^{y=1} \frac{1}{y} dy = \log(y) \Big|_x^1$$

$$= \log(1) - \log(x)$$

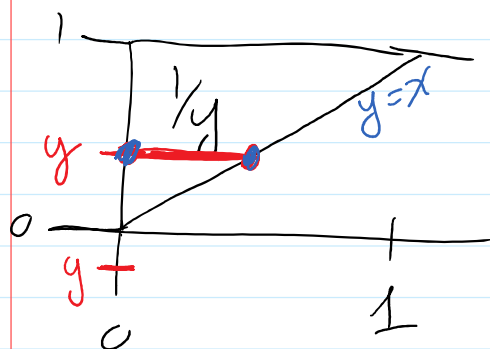


$$f_X(x) = -\log(x)$$

for $0 < x < 1$

What is the marginal PDF of Y ?

$$f_Y(y) = \int f(x,y) dx = \int_{x=0}^{x=y} \frac{1}{y} dx = \frac{1}{y} \int_0^y dx = \frac{1}{y} [x]_0^y = 1$$



So $f_Y(y) = 1$ for $0 < y < 1$

i.e. $Y \sim U(0,1) \rightarrow$

Ex.

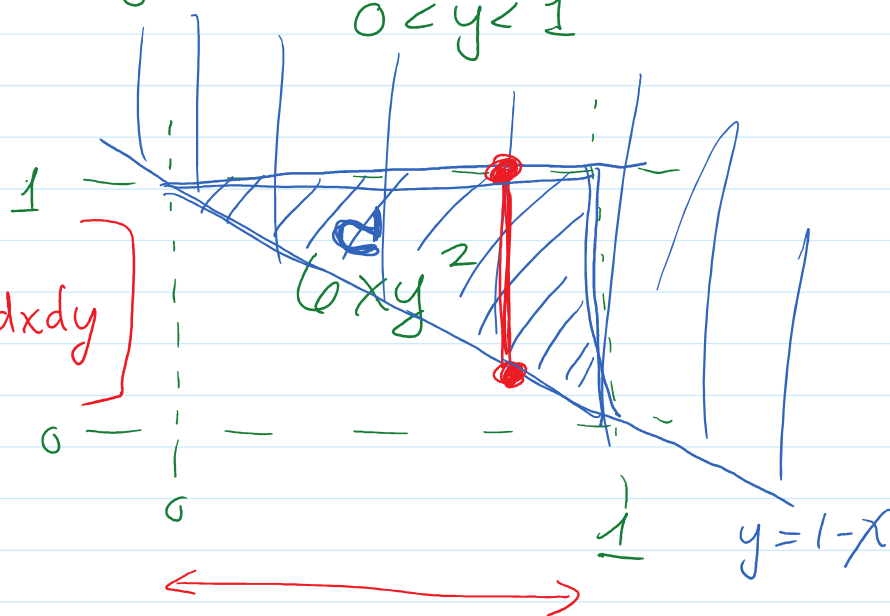
Let $f(x,y) = 6xy^2$ for $0 < x < 1$
 $0 < y < 1$

on joint pdf for $0 < y < 1$

$$P(X+Y \geq 1)$$

$$P((X,Y) \in C) = \iint_C f(x,y) dx dy$$

draw line $x+y=1$
 $y=1-x$
 $x=1-y$



$$P(X+Y \geq 1) = \int_0^1 \int_{y=1-x}^1 6xy^2 dy dx$$

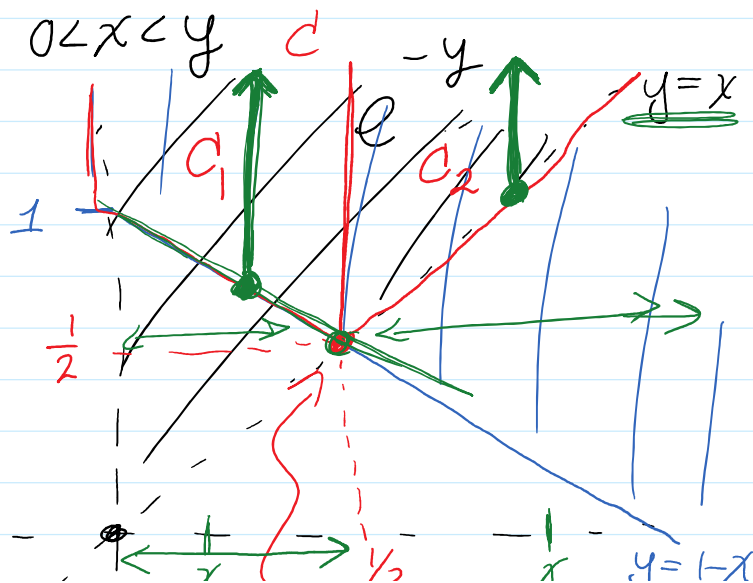
$$= \dots = \underline{\underline{9/10}}$$

Ex. $f(x,y) = e^{-y}$ for $0 < x < y$

$$P(X+Y \geq 1)$$

$$= \iint_C e^{-y} dx dy$$

$$= \int_0^1 \int_{x=0}^y e^{-y} dx dy + \int_1^{\infty} \int_{x=y-1}^y e^{-y} dx dy$$



$$\begin{aligned}
 &= \iint_{C_1} e^{-y} dx dy + \iint_{C_2} e^{-y} dx dy \\
 &= \int_0^{1/2} \int_{y=1-x}^{\infty} e^{-y} dy dx + \int_{1/2}^1 \int_{y=x}^{\infty} e^{-y} dy dx
 \end{aligned}$$

intersection of $y=1-x$ and $y=x$
 $1-x=x \Rightarrow x=1/2$

$$= \dots = \boxed{2e^{-1/2} - e^{-1}}$$

Defn: Bivariate Expectation

If (X, Y) is a BIRV and $g: \mathbb{R}^2 \rightarrow \mathbb{R}$
 then

$$\mathbb{E}[g(X, Y)] = \begin{cases} \sum_x \sum_y g(x, y) f(x, y) & (\text{discrete}) \\ \iint_{\mathbb{R}^2} g(x, y) f(x, y) dx dy & (\text{cts}) \end{cases}$$

$$\left[\text{Uni: } \mathbb{E}[g(x)] = \int_{\mathbb{R}} g(x) f(x) dx \right]$$

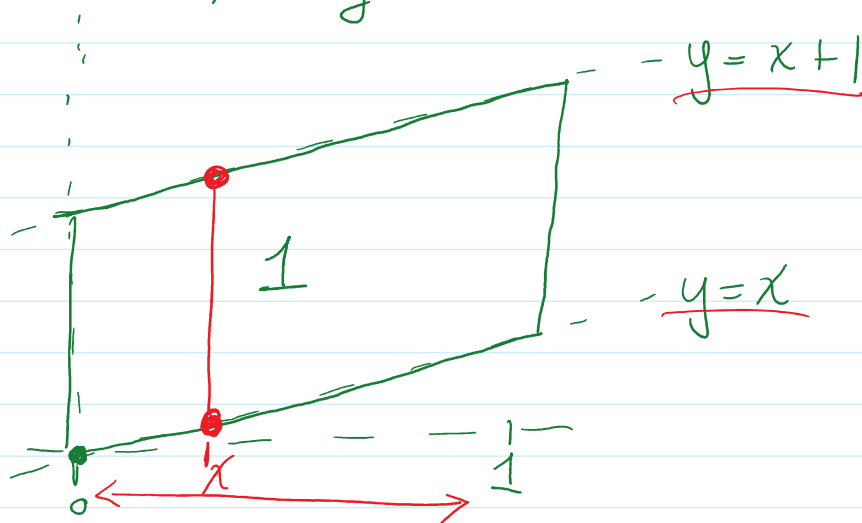
Ex. let $f(x,y) = 1$ for $0 < x < 1$
 $x < y < x+1$

$$\mathbb{E}[XY] \quad g(x,y) = xy$$

$$= \iint_{\mathbb{R}^2} g(x,y) f(x,y) dx dy$$

$$= \int_0^1 \int_{y=x}^{y=x+1} xy(1) dy dx$$

$$= \dots = 7/12$$



Theorem: Bivariate Expectation is Linear

If $g_1: \mathbb{R}^2 \rightarrow \mathbb{R}$ and $g_2: \mathbb{R}^2 \rightarrow \mathbb{R}$ and
 $a, b \in \mathbb{R}$

then

$$\mathbb{E}[a g_1(X,Y) + b g_2(X,Y)]$$

$$= a \mathbb{E}[g_1(X,Y)] + b \mathbb{E}[g_2(X,Y)]$$

Defn: Covariance

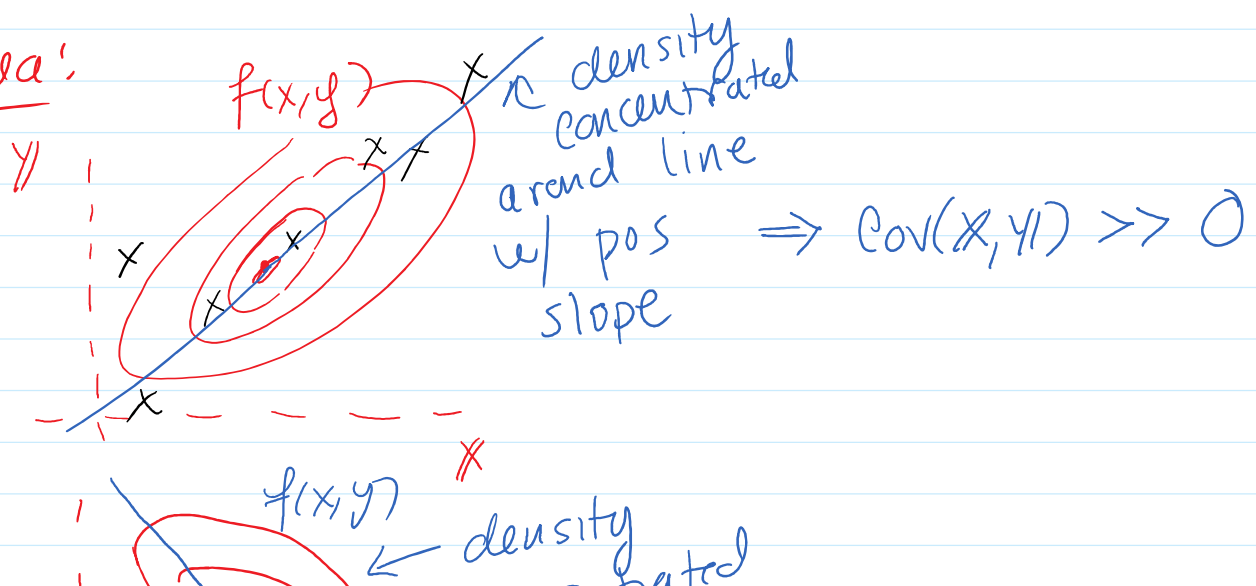
We define the covariance between two RVs X, Y as

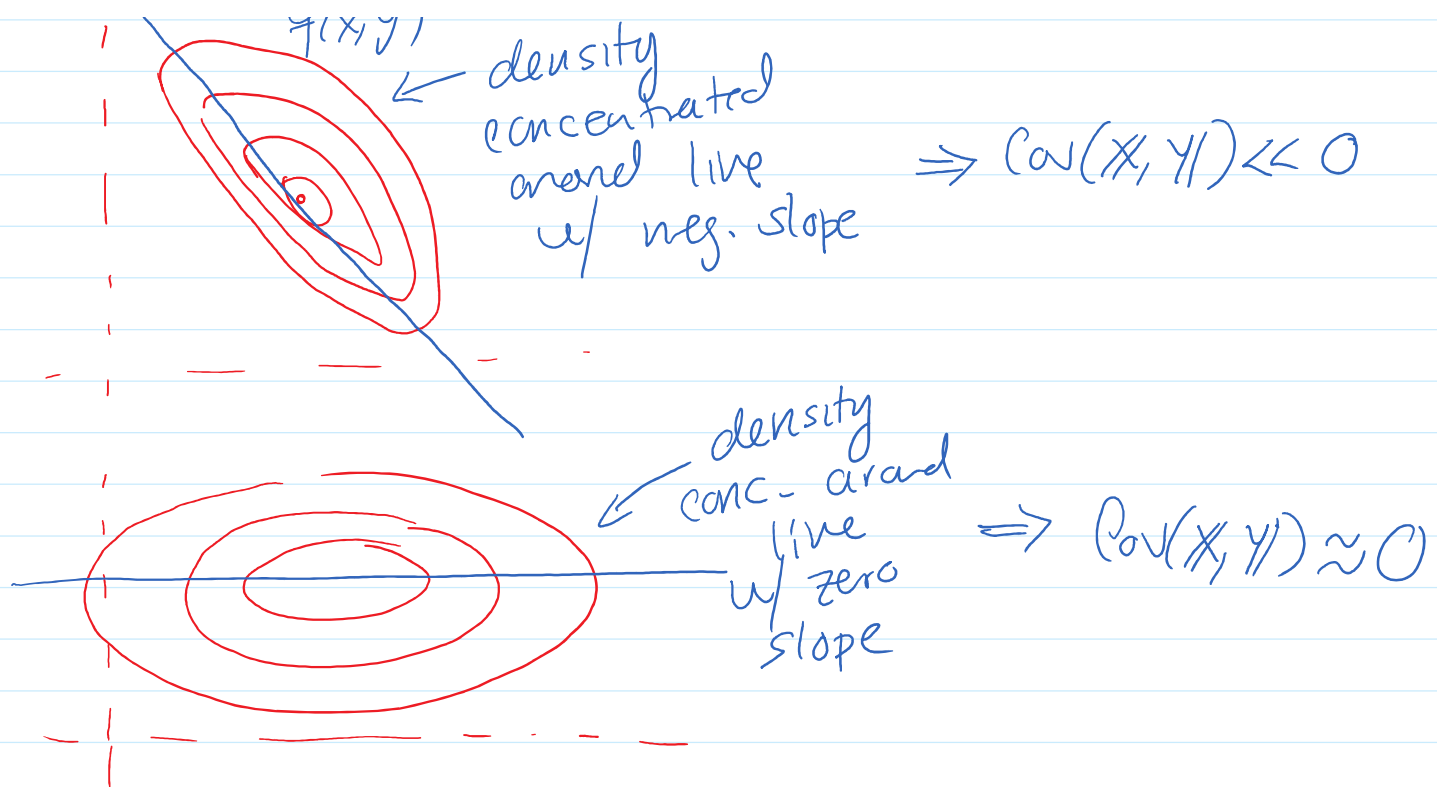
$$\begin{aligned} \text{Cov}(X, Y) &= \mathbb{E} \left[\overbrace{(X - \mathbb{E}X)}^{\mu_X = \mathbb{E}X} \overbrace{(Y - \mathbb{E}Y)}^{\mu_Y = \mathbb{E}Y} \right] \\ &= \mathbb{E}[(X - \mu_X)(Y - \mu_Y)] \\ &\quad \uparrow g(x, y) = (x - \mu_X)(y - \mu_Y) \\ &= \mathbb{E}[g(X, Y)] \end{aligned}$$

Recall: $\text{Var}(X) = \mathbb{E}[(X - \mathbb{E}X)^2]$

note: $\text{Cov}(X, X) = \text{Var}(X)$

Idea:





Cov: measuring strength of linear rel. between X and Y

Defn: Correlation

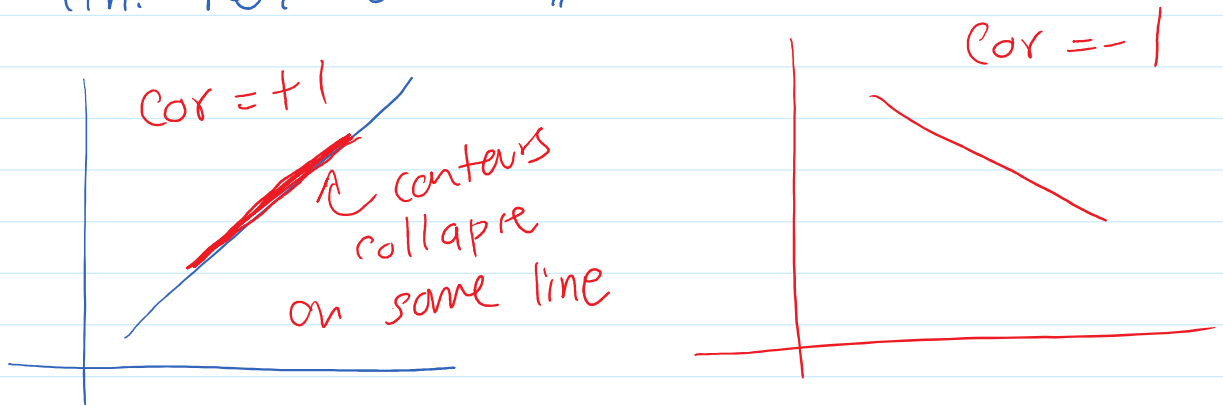
Re-scaled covariance so that it is between -1 and 1 .

$$\text{Cor}(X, Y) = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X) \text{Var}(Y)}}$$

$$\text{sd}(X) = \sqrt{\text{Var}(X)} = \frac{\text{Cov}(X, Y)}{\text{Cor}(X, Y)}$$

$$\text{sd}(X)^{-1} \cdot \text{Cov}(X, Y) = \frac{\text{Cov}(X, Y)}{\text{sd}(X) \text{sd}(Y)}$$

Note: $\text{Cor} = \pm 1$ then we have a "perfect" lin. rel. btwn X and Y



Theorem: If $a, b \in \mathbb{R}$

$$\begin{aligned} \text{Var}(aX + bY) \\ = a^2 \text{Var}(X) + b^2 \text{Var}(Y) + 2ab \text{Cov}(X, Y) \end{aligned}$$

pf. $Z = aX + bY$

$$\begin{aligned} \text{Var}(Z) &= E[(Z - E Z)^2] \\ &= E[(aX + bY - \underbrace{E[aX + bY]})^2] \end{aligned}$$

$$= \mathbb{E} \left[\left(aX + bY - (a\mathbb{E}X + b\mathbb{E}Y) \right)^2 \right]$$

$$= \mathbb{E} \left[\left(\underbrace{a(X - \mathbb{E}X)}_{\alpha} + \underbrace{b(Y - \mathbb{E}Y)}_{\beta} \right)^2 \right]$$

$$\underbrace{\hspace{10em}}_{(\alpha + \beta)^2 = \alpha^2 + \beta^2 + 2\alpha\beta}$$

$$= \mathbb{E} \left[a^2(X - \mathbb{E}X)^2 + b^2(Y - \mathbb{E}Y)^2 + 2ab(X - \mathbb{E}X)(Y - \mathbb{E}Y) \right]$$

$$= a^2 \mathbb{E}[(X - \mathbb{E}X)^2] + b^2 \mathbb{E}[(Y - \mathbb{E}Y)^2]$$

$$+ 2ab \mathbb{E}[(X - \mathbb{E}X)(Y - \mathbb{E}Y)]$$

$$= a^2 \text{Var}(X) + b \text{Var}(Y) + 2ab \text{Cov}(X, Y).$$
