

$$\text{Var}(U) = \text{Cov}(U, U) = \text{Cov}(\underline{a}^T \underline{x}, \underline{a}^T \underline{x}) = \underline{a}^T \underline{\Sigma} \underline{a}$$

$$= \sum_{i=1}^n a_i^2 \sigma_i^2$$

Basics:

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

$$\text{Cov}(X, Y) = \text{Cov}(Y, X)$$

Conditional Distribution:

$$\text{Discrete: } P(X=x | Y=y) = \frac{P(X=x \wedge Y=y)}{P(Y=y)}$$

$$\text{Continuous: } f_{X|Y}(x|y) = \frac{f_{XY}(x, y)}{f_Y(y)}$$

why? We want to predict

- the HL
- election
- wealth
- Future

Ex Discrete

X	Y			
	0	1	2	
1	.15	.10	0	.25
2	.25	.30	.20	.75
	.4	.40	.20	

joint prob

$$P(X=x | Y=y)$$

X	Y		
	0	1	2
1	$\frac{.15}{.40}$	$\frac{.10}{.40}$	0
2	$\frac{.25}{.40}$	$\frac{.30}{.40}$	$\frac{.20}{.20}$

$$E(X=x | Y=y)$$

$$\boxed{E_X} E(X | Y=1) = \sum_{\text{all } x} x P(X=x | Y=1) = 1 \cdot \frac{1}{4} + 2 \cdot \frac{3}{4} = \frac{7}{4}$$

- 390 391 today
- Data Scraping
 - Modeling
- 1) Independence
 - 2) Covariance
 - 3) Cond. Dist.

Check X and Y are independent:

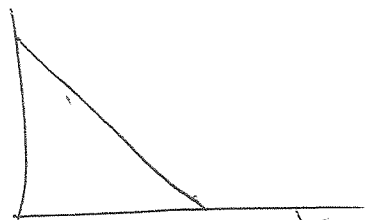
- Discrete $P(X=x, Y=y) = P_X(x) P_Y(y)$

- Continuous $F_{XY}(x, y) = F_X(x) F_Y(y)$

$\Rightarrow f_{XY}(x, y) = f_X(x) f_Y(y) *$

Check the support/joint contours
 X & Y are ^{not} independent if the support is ^{not} "□" or "O"

Ex. $f_{XY}(x, y) = 60x^2y \quad 0 < x < 1, xy < 1, x+y < 1$



Ex. #1

	Y			
X	0	1	2	
1	.15	.10	0	.25
2	.25	.30	.20	.75
	.40	.40	.20	

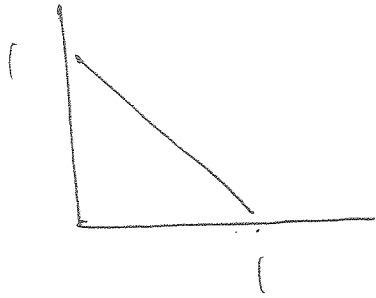
Check independence

$P(X=1, Y=2) = 0 \neq$

$P(X=1) P(Y=2)$

Ex #2

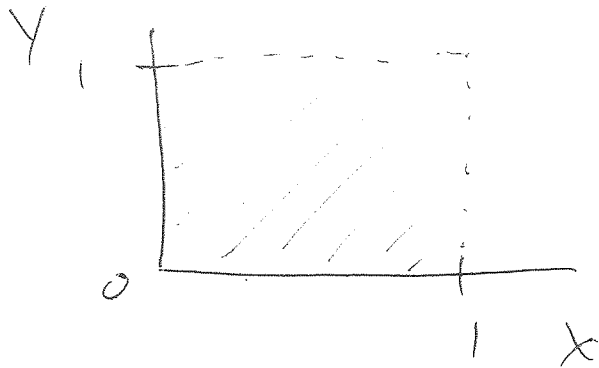
$$f_{xy}(x,y) = 60x^2y, 0 < x < 1, 0 < y < 1, x+y < 1$$



Not rectangle. X and Y are dependent

Ex #3

$$f_{xy} = \begin{cases} x+y, & 0 < x < 1, 0 < y < 1 \\ 0 & \text{o.w.} \end{cases}$$



$$f_X(x) = \int_0^1 (x+y) dy = \frac{1}{2}x + \frac{1}{2}, 0 < x < 1$$

$$f_Y(y) = \int_0^1 (x+y) dx = y + \frac{1}{2}, 0 < y < 1$$

$$f_{xy} = (x+y) \neq f_X f_Y = \left(x + \frac{1}{2}\right) \left(y + \frac{1}{2}\right)$$

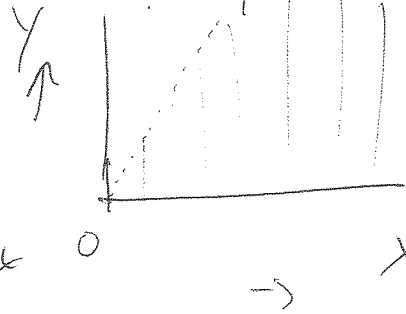
$\Rightarrow X$ and Y are dependent OR not independent

Ex #4 Suppose X and Y are independent

$X \sim \exp(\alpha)$, $Y \sim \exp(\beta)$ Find $P(2X > Y)$.

$$f_X(x) = \alpha e^{-\alpha x}, x > 0 \quad \therefore f_Y(y) = \beta e^{-\beta y}, y > 0$$

$$f_{X,Y} = f_X f_Y$$



$$P(2X > Y) = \int_0^{\infty} \int_0^{2x} f_{X,Y}(x,y) dy dx$$

$$= \int_0^{\infty} \int_0^{2x} f_X(x) f_Y(y) dy dx = \int_0^{\infty} \alpha e^{-\alpha x} \left(\int_0^{2x} \beta e^{-\beta y} dy \right) dx$$

$$= \frac{2\beta}{\alpha + 2\beta}$$

Ex #5

Let X and Y be independent R.v.'s

$X \sim \text{Geometric}(p = \frac{1}{3})$, $Y \sim \text{Poisson}(\lambda = 3)$

$$P_X(x) = \frac{1}{3} \left(\frac{2}{3}\right)^{x-1}, x=1, 2, \dots \quad P_Y(y) = \frac{3^y e^{-3}}{y!}, y=0, 1, 2, \dots$$

$$a) P(X=Y) = \sum_{k=1}^{\infty} P_{XY}(X=k, Y=k) = \sum_{k=1}^{\infty} P_X(X=k) P_Y(Y=k)$$

$$= \sum_{k=1}^{\infty} \frac{1}{3} \left(\frac{2}{3}\right)^{k-1} \frac{3^k e^{-3}}{k!} = e^{-3} \sum_{k=1}^{\infty} \frac{2^{k-1}}{k!} \cdot \frac{2}{2} = \frac{e^{-3}}{2} \sum_{k=1}^{\infty} \frac{2^k}{k!}$$

\uparrow
starts at 1

$$= \frac{e^{-3}}{2} \left(\sum_{k=0}^{\infty} \frac{2^k}{k!} - 1 \right)$$

$$= \frac{e^{-3}}{2} (e^2 - 1) \approx .159$$

$$b) P(X=2Y) = \sum_{k=1}^{\infty} P_{XY}(X=2k, Y=k) = \sum_{k=1}^{\infty} P_X(X=2k) P_Y(Y=k)$$

$$= \sum_{k=1}^{\infty} \frac{1}{3} \left(\frac{2}{3}\right)^{2k-1} \frac{3^k e^{-3}}{k!} = \sum_{k=1}^{\infty} \frac{1}{3} \left(\frac{2}{3}\right)^{2k} \frac{3}{2} \cdot \frac{3^k e^{-3}}{k!}$$

$$= \frac{e^{-3}}{2} \sum_{k=1}^{\infty} \frac{2^{2k}}{3^{2k}} \frac{3}{2} \cdot \frac{3^k}{k!} = \frac{e^{-3}}{2} \sum_{k=1}^{\infty} \frac{4^k}{3^k} \frac{1}{k!} = \frac{e^{-3}}{2} \sum_{k=1}^{\infty} \left(\frac{4}{3}\right)^k \frac{1}{k!}$$

$$= \frac{e^{-3}}{2} (e^{4/3} - 1)$$

Covariance

$$\begin{aligned}\text{Cov}(X, Y) &= E[(X - \mu_X)(Y - \mu_Y)] \\ &= E(XY) - [E(X)][E(Y)] \\ &= E(XY) - \mu_X \mu_Y\end{aligned}$$

* Measure of ~~un~~standardized linear association

Correlation

$$\rho_{XY} = \frac{\text{Cov}(X, Y)}{\sigma_X \sigma_Y}$$

* standardized measure of linear association

If X and Y are independent $\Rightarrow \text{Cov}(X, Y) = 0$

Pf $E(XY) = E(X)E(Y)$

The converse is not true.

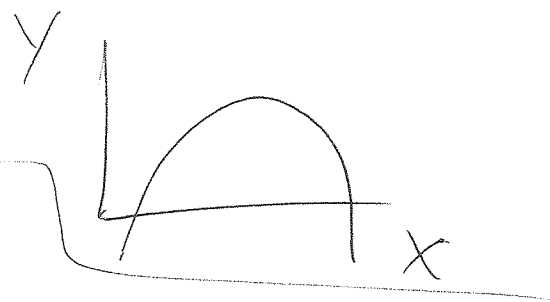
Covariances of linear combs of r.v.s

• $\text{Cov}(aX + bY, cX + dY) ?$

$$= ac \text{Var}(X) + bd \text{Var}(Y) + (ad + bc) \text{Cov}(X, Y) *$$

• $\text{Cov}(a_1 X_1 + a_2 X_2, b_1 X_1 + b_2 X_2)$

$$\underline{X} = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}, \quad \underline{a} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}, \quad \underline{b} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}$$



$$\text{Cov}(a_1 X_1 + a_2 X_2, b_1 X_1 + b_2 X_2) = \underline{a}^T \underline{\Sigma} \underline{b} \quad *$$

$$\underline{X} = \begin{bmatrix} X_1 \\ X_2 \end{bmatrix}, \quad \underline{a} = \begin{bmatrix} a_1 \\ a_2 \end{bmatrix}, \quad \underline{b} = \begin{bmatrix} b_1 \\ b_2 \end{bmatrix}, \quad \underline{\mu} = \begin{bmatrix} \mu_1 \\ \mu_2 \end{bmatrix}$$

- symmetric $\underline{\Sigma} = \underline{\Sigma}^T$
- p.s.d.

$\underline{\Sigma}$ = Variance - covariance matrix

$$= \begin{bmatrix} \text{Var}(X_1) & \text{Cov}(X_1, X_2) \\ \text{Cov}(X_1, X_2) & \text{Var}(X_2) \end{bmatrix}$$

$$= E[(\underline{X} - \underline{\mu})(\underline{X} - \underline{\mu})^T] \quad (\text{Hint } \underline{X} - \underline{\mu} = \begin{bmatrix} X_1 - \mu_1 \\ X_2 - \mu_2 \end{bmatrix})$$

Ex a) Find in terms of $\sigma_x^2, \sigma_y^2, \sigma_{xy}$

$$\text{Cov}(2X + 3Y, X - 2Y) \quad \underline{a} = \begin{bmatrix} 2 \\ 3 \end{bmatrix}, \quad \underline{b} = \begin{bmatrix} 1 \\ -2 \end{bmatrix}$$

$$= \underline{a}^T \underline{\Sigma} \underline{b}$$

$$\underline{\Sigma} = \begin{bmatrix} \sigma_x^2 & \sigma_{xy} \\ \sigma_{xy} & \sigma_y^2 \end{bmatrix}$$

$$\sigma_x^2 = 1, \quad \sigma_y^2 = 2, \quad \sigma_{xy} = 1$$

$$= \begin{bmatrix} 2 & 3 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix}$$

$$= \begin{bmatrix} 2 & 3 \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 2 \end{bmatrix} \begin{bmatrix} 1 \\ -2 \end{bmatrix}$$

b) Suppose X_1, \dots, X_n are independent w/ ~~mean~~ variances

$\sigma_1^2, \dots, \sigma_n^2$. Let $U = \sum_{i=1}^n a_i X_i$. Find $\text{Var}(U)$.

$$\underline{a} = \begin{bmatrix} a_1 \\ \vdots \\ a_n \end{bmatrix}, \quad \underline{a} = \underline{b}, \quad \underline{\Sigma} \text{ is diagonal } \neq 1 \quad \underline{\Sigma} = \begin{bmatrix} \sigma_1^2 & 0 & 0 \\ 0 & \ddots & 0 \\ 0 & 0 & \sigma_n^2 \end{bmatrix} = \text{Cov}(U, U)$$

Conditional Expectation

$$\cancel{E(x)} \quad E(Y|x) = \sum_{\text{all } y} y \, p(Y=y|x=x)$$

$$E(Y|x) = \int y f_Y(y|x) dy$$