

Theorem: Cov/Cor of Independent

If  $X \perp Y$  then  $\text{Cov}(X, Y) = \text{Cor}(X, Y) = 0$ .


Pf.

$$\begin{aligned} \text{Cov}(X, Y) &= E[XY] - E[X]E[Y] \\ &\stackrel{\text{independence}}{=} E[X]E[Y] - \dots = 0 \end{aligned}$$

Cor is just re-scaled cov, so it is also zero.

Converse is generally false

If  $\text{Cor}(X, Y) = 0$  then  $X$  and  $Y$  may or may not be independent.

Ex.  $X \sim N(0, 1)$  and  $Y = X^2$ .  
  
 not independent

however

$$\begin{aligned} \text{Cov}(X, Y) &= E[XY] - EXEY \\ &= E[XX^2] - EXEY \end{aligned}$$

$\underbrace{\quad}_{-1.27} \quad \underbrace{\quad}_{\nearrow 0} \quad \underbrace{\quad}_{-2}$

odd fn

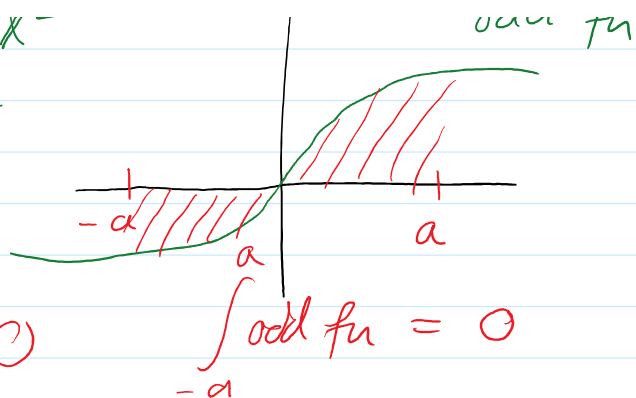
$$= E[XX^*] - E[X]E[X^*]$$

$$= E[X^3] - E[X]E[X^2]$$

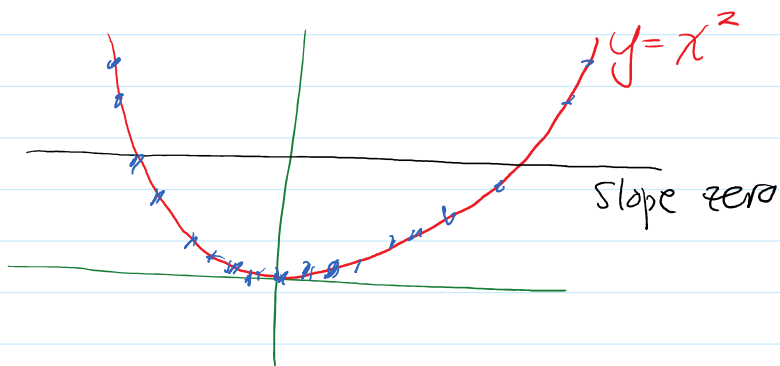
$$= E[X^3]$$

$$E[X^3] = \int_{\mathbb{R}} \underbrace{x^3}_{\text{odd}} \underbrace{\frac{1}{\sqrt{2\pi}} e^{-x^2}}_{\text{even fn}} dx = 0$$

odd fn



$$\downarrow = 0 \quad \text{so} \quad \text{Cor}(X, Y) = 0$$



Bayes' Theorem:

Events:  $P(A|B) = \frac{P(B|A)P(A)}{P(B)}$

RV:  $f(x|y) = \frac{f(y|x)f_x(x)}{f_y(y)}$

## Law of Total Prob:

Events:  $(C_i)$  partition  $S$  then

$$P(A) = \sum_i P(A|C_i)P(C_i)$$

RVs:

$$(\text{discrete}) \quad f(y) = \sum_x f(y|x) f(x)$$

$$(\text{cts}) \quad f(y) = \int_{\mathbb{R}} f(y|x) f(x) dx$$

Pf: (cts case)

$$(1) \quad f(y|x) = \frac{f(x,y)}{f(x)}$$



$$\underline{f(y|x) f(x) = f(x,y)}$$

$$(2) \quad \boxed{f(y)} = \int_{\mathbb{R}} f(x,y) dx = \boxed{\int_{\mathbb{R}} f(y|x) f(x) dx}$$

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Ex.  $\left\{ \begin{array}{l} X \sim \text{Exp}(\lambda) \rightarrow f(x) = \lambda e^{-\lambda x} \\ Y|X=x \sim \text{Pois}(x) \rightarrow f(y|x) = \frac{x^y e^{-x}}{y!} \end{array} \right\}$

$$(Y|X=x \sim \text{Pois}(x) \rightarrow f(y|x) = \frac{x^y e^{-x}}{y!})$$

What is the dist of  $Y$ ?

Law of Tot. Prob.

$$f(y) = \int_{\mathcal{R}} f(y|x) f(x) dx$$

$$= \int_0^{\infty} \frac{x^y e^{-x}}{y!} \lambda e^{-\lambda x} dx$$

$$= \frac{\lambda}{y!} \int_0^{\infty} x^{y+1} e^{-(\lambda+1)x} dx$$

$$= \frac{\lambda}{y!} \frac{P(a)}{b^{a-1}} \int_0^{\infty} \frac{x^{a-1} e^{-bx} b^{a-1}}{P(a)} dx$$

integrate to 1

$$= \frac{\lambda}{y!} \frac{P(y+1)}{(\lambda+1)^y}$$

$$= \frac{\lambda}{y!} \frac{y!}{(\lambda+1)^y} = \frac{\lambda}{(\lambda+1)^y} \quad \text{for } y=0,1,2,\dots$$

$$= f(y)$$

The form  $x^{a-1} e^{-bx}$  is basically a Gamma RV PPF

↓

$$\text{Gamma}(a, b) \text{ PPF}$$

$$\frac{(bx)^{a-1} b e^{-bx}}{\Gamma(a)}$$

$$a-1 = y$$

$$a = y+1$$

$$b = \lambda+1$$

Ex.

$$Y \sim \text{Pois}(\lambda)$$

$$X|Y=y \sim \text{Bin}(y, p)$$

$$0 < p < 1$$

Notice:  $0 \leq X \leq Y$

$$\binom{y}{x} \frac{1}{y!} = \frac{y!}{x!(y-x)!} \frac{1}{y!}$$
$$= \frac{1}{x!(y-x)!}$$

What is the dist of  $Y$ ?

$$f(x) = \sum_y \underbrace{f(x|y)}_{\text{Bin}(y,p)} \underbrace{f(y)}_{\text{Pois}(\lambda)} = \sum_{y=x}^{\infty} \binom{y}{x} p^x (1-p)^{y-x} \frac{\lambda^y e^{-\lambda}}{y!}$$

$$= \sum_{y=x}^{\infty} \frac{1}{x!(y-x)!} p^x (1-p)^{y-x} \lambda^y e^{-\lambda}$$

$$= \frac{e^{-\lambda} p^x \lambda^x}{x!} \sum_{y=x}^{\infty} \frac{1}{(y-x)!} (1-p)^{y-x} \lambda^{y-x}$$

$$= \frac{e^{-\lambda} p^x \lambda^x}{x!} \sum_{y=0}^{\infty} \frac{1}{y!} \underbrace{[(1-p)\lambda]^y}_{z}$$

$$e^z = \sum_{i=0}^{\infty} \frac{z^i}{i!}$$

$$e^{(1-p)\lambda}$$

$$= \frac{e^{-\lambda} p^x \lambda^x}{x!} e^{(1-p)\lambda}$$

$$f(x) = \frac{(p\lambda)^x e^{-(p\lambda)}}{x!}$$

$$X \sim \text{Pois}(p\lambda)$$

Theorem: Iterated Expectation

If  $X$  and  $Y$  are RVs then

$$E[X] = E[E[X|Y]]$$

$$E[X|Y=y] = \int_{\mathbb{R}} x f(x|y) dx \leftarrow \text{depends on } y$$

For each  $y \in \mathbb{R}$  we get some value

This defines a function

$$g(y) = E[X|Y=y]$$

↑ a number

We can plug  $Y$  into  $g$

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

↑ weird notation

$$g(y) = y^2 \leftarrow \text{a number}$$

$$g(Y) = Y^2$$

↑ a RV

↑ weird notation

$$= E[X|Y]$$

↑ a RV.

Basically:

- ①  $E[X|Y=y]$  is a number
- ②  $E[X|Y]$  is a RV

Ex.  $E[X|Y=y] = \log(y)$

$$E[X|Y] = \log(Y)$$

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Ex.  $Y \sim \text{Pois}(\lambda)$

$X|Y=y \sim \text{Bin}(y, p)$

What is  $E[X]$ ? ( $= \lambda p$ )

① get  $E[X|Y=y] = yp$

②  $E[X|Y] = Yp$

③  $E[X] = E[E[X|Y]] = E[Yp]$

$$= p EY$$

$$= p \lambda$$

pf.  $E[X] = E[E[X|Y]]$  [cts case]

$$(1) f(x) = \int f(x,y) dy$$

$$(2) f(x|y) = \frac{f(x,y)}{f(y)} \Leftrightarrow \underline{f(x,y) = f(x|y)f(y)}$$

$$(3) E[X|Y=y] = \int x f(x|y) dx$$

$$E[X] = \int x f(x) dx \stackrel{(1)}{=} \int x \int f(x,y) dy dx$$

$$\stackrel{(2)}{=} \int x \int f(x|y) f(y) dy dx$$

$$= \int \underbrace{\int x f(x|y) dx}_{E[X|Y=y] = g(y)} f(y) dy$$

$$= \int g(y) f(y) dy$$

$$= E[g(Y)] \quad \text{called this } E[X|Y]$$

$E[X] = E[E[X|Y]]$



Ex.  $P \sim \text{Beta}(\alpha, \beta)$

$$X|P=p \sim \text{Bin}(n, p)$$

↑ known

$E[X]?$

①  $E[X|P=p] = np$

②  $E[X|P] = nP$

③  $EX = E[E[X|P]] = E[nP]$

$$= nEP$$

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

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Theorem: Law of Total Variance

$$\text{Var}(X) = E[\text{Var}(X|Y)] + \text{Var}(E[X|Y])$$



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Ex. Continue prev.

$\text{Var}(X)?$

①  $E[X|P=p] = np$

$$\text{Var}(X|P=p) = np(1-p)$$

$$(2) E[X|P] = nP$$

$$\text{Var}(X|P) = nP(1-P)$$

$$(3) \text{Var}(X) = E[\text{Var}(X|P)] + \text{Var}(E[X|P])$$

$$= E[nP(1-P)] + \text{Var}(nP)$$

$$= n(E[P] - E[P^2]) + n^2 \text{Var}(P)$$

$$P \sim \text{Beta}(\alpha, \beta) \rightarrow \text{plug in}$$

$$= \dots = n \frac{\alpha\beta}{(\alpha+\beta)(\alpha+\beta+1)} + \frac{n^2\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$