

Lecture 19

		Joint PMF		
x	y	f_X	f_Y	
		$\frac{1}{2}$	$\frac{1}{2}$	
x	3	$\frac{1}{5}$	$\frac{3}{10}$	$\frac{1}{2}$
	2	$\frac{1}{5}$	$\frac{1}{10}$	$\frac{3}{10}$
	1	$\frac{1}{10}$	$\frac{1}{10}$	$\frac{2}{10}$
		10	20	\times

Are X and Y indep?

(1) Product Space?

Support = $\{10, 20\} \times \{1, 2, 3\}$

(2) Factor? $f(x, y) = f_X(x)f_Y(y)$

$$f(10, 2) = \frac{1}{5} \neq \left(\frac{1}{2}\right)\left(\frac{3}{10}\right) = f_X(10)f_Y(2)$$

Not independent.

Ex. $f(x,y) = \frac{1}{384} x^2 e^{-y - x/2}$
for $x > 0, y > 0$

Corollary:

$X \perp Y$ iff

① Support is product space

② $f(x,y) = g(x)h(y)$

no y no x

Ex. continue

① Yes, product space:

$$\text{Support} = (0, \infty) \times (0, \infty)$$

② $f(x,y) = \frac{1}{384} x^2 e^{-y - x/2}$

$$= \frac{1}{384} x^2 e^{-y} e^{-x/2}$$

$g(x)$

$$= \left(\frac{1}{384} x^2 e^{-x/2} \right) e^{-y}$$

$h(y)$

Theorem:

If $X \perp Y$ and $g_1: \mathbb{R} \rightarrow \mathbb{R}, g_2: \mathbb{R} \rightarrow \mathbb{R}$
then

$$E[g_1(X)g_2(Y)] = E[g_1(X)]E[g_2(Y)]$$

pf (cts)

$$E[g_1(X)g_2(Y)] = \iint_{A \times B} g_1(x)g_2(y) \underbrace{f(x,y)}_{\downarrow} dx dy$$

$$= \int_B \int_A g_1(x)g_2(y) \underbrace{f(x)}_{\downarrow} \underbrace{f(y)}_{\downarrow} dx dy$$

$$= \left[\int_A g_1(x) f(x) dx \right] \left[\int_B g_2(y) f(y) dy \right]$$

$$= E[g_1(X)]E[g_2(Y)]$$

ex $X, Y \stackrel{iid}{\sim} \text{Exp}(1)$

independent, identically distributed

$$E[X^2 Y] = E[X^2] E[Y] \\ = (2)(1) = 2$$

Theorem:

$$Z = X + Y$$

If $X \perp Y$ then

$$M_{X+Y}(t) = M_X(t) M_Y(t).$$

pf.

$$M_Z(t) =$$

$$M_{X+Y}(t) = E[e^{t(X+Y)}]$$

$$= E[e^{tX} e^{tY}]$$

$$= E[e^{tX}] E[e^{tY}]$$

$$= M_X(t) M_Y(t)$$

Theorem:

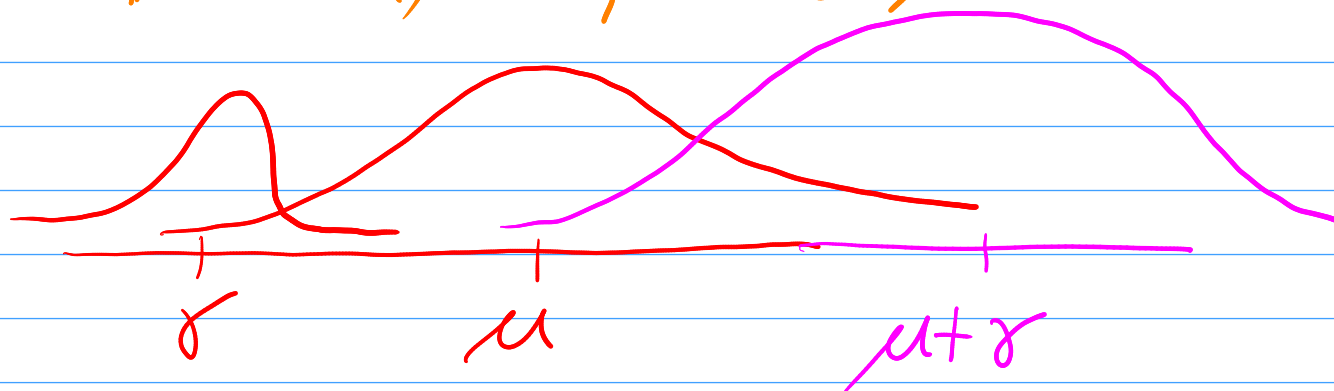
$$X \sim N(\mu, \sigma^2)$$

$$Y \sim N(\gamma, \tau^2)$$

) assume $X \perp Y$.

$$X + Y \sim N(\mu + \delta, \sigma^2 + \tau^2)$$

pf.



$$M_{X+Y}(t) = M_X(t) M_Y(t)$$

$$= \exp\left(\mu t + \frac{\sigma^2 t^2}{2}\right) \exp\left(\delta t + \frac{\tau^2 t^2}{2}\right)$$

$$= \exp\left((\mu + \delta)t + \frac{(\sigma^2 + \tau^2)t^2}{2}\right)$$

↑ MGF of $N(\mu + \delta, \sigma^2 + \tau^2)$

Theorem:

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

pf.

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

$$= E[X]E[Y] - E[X]E[Y] = 0$$

Generally, converse is false.

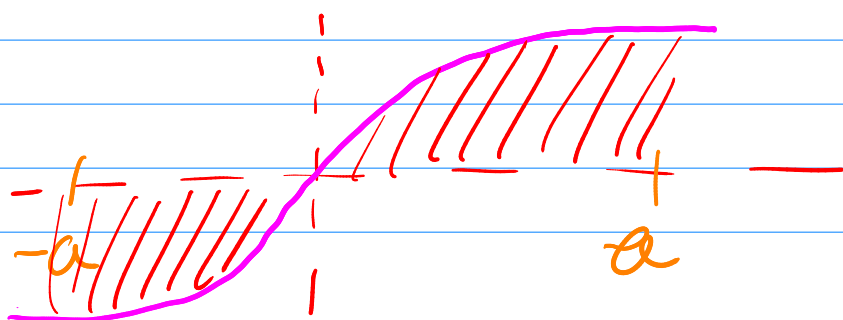
If $\text{cor}(X, Y) = 0$ then X and Y
could be dependent.

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

$$\begin{aligned}\text{Cov}(X, Y) &= E[XY] - E[X]E[Y] \\ &= E[X^3] - \underbrace{E[X]}_0 E[X^2]\end{aligned}$$

$$= E[X^3]$$

$$= \int_{\mathbb{R}} \underbrace{x^3}_{\text{odd}} \underbrace{\frac{1}{\sqrt{2\pi}} \exp(-\frac{1}{2}x^2)}_{\text{even}} dx = 0$$



For events: $A \perp B$ then $P(A|B) = P(A)$

For RVs: $X \perp Y$ then $f(x|y) = f(x)$

pf

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

Bayes' Theorem:

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

For RVs: $f(x|y) = \frac{f(y|x)f(x)}{f(y)}$

Partitioning (Total Prob.)

For events: C_i partitioned S

then

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

For RVs:

discrete : $f(y) = \sum_x f(y|x) f(x)$

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

pf. (cts)

① $f(y|x) = \frac{f(x,y)}{f(x)} \Leftrightarrow \underbrace{f(x,y)}_{\text{orange arrow}} = \underbrace{f(y|x)}_{\text{green arrow}} \underbrace{f(x)}_{\text{green arrow}}$

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

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

Ex. $X \sim \text{Exp}(\lambda)$

$Y|X=x \sim \text{Pois}(x)$

What's the dist of Y ?

$$f(y) = \int \underbrace{f(y|x)}_{\text{Pois}(x)} \underbrace{f(x)}_{\text{Exp}(\lambda)} dx$$

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

$$z \sim \text{Pois}(\mu)$$

$$f(z) = \frac{\mu^z e^{-\mu}}{z!}$$

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

Gamma(a, b)

PDF =

$$x^{\textcircled{a-1}} e^{-\textcircled{b}x} \left(\frac{b^a}{\Gamma(a)} \right)$$

$$\boxed{y = a - 1} \Rightarrow \boxed{a = y + 1}$$

$$\boxed{b = \lambda + 1}$$

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

$$\frac{\textcolor{red}{y+1}}{\textcolor{red}{(\lambda+1)}} = \frac{\textcolor{red}{P(y+1)}}{\textcolor{red}{P(y+1)}}$$

integrate to 1

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

for $y = 0, 1, 2, \dots$

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

Qx,

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

Known

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

notes:

$$X \leq Y$$

What's the dist of X ?

$$f(x) = \sum_y \overbrace{f(x|y)}^{\text{Bin}(y,p)} \overbrace{f(y)}^{\text{Pois}\lambda}$$

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

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

$$f(x) = \binom{n}{x} p^x (1-p)^{n-x}$$