

Defn: Conditional PMF/PDF

Given  $X$  and  $Y$  then the conditional PMF/PDF of  $X | Y = y$  is

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

Defn: Conditional Expectation

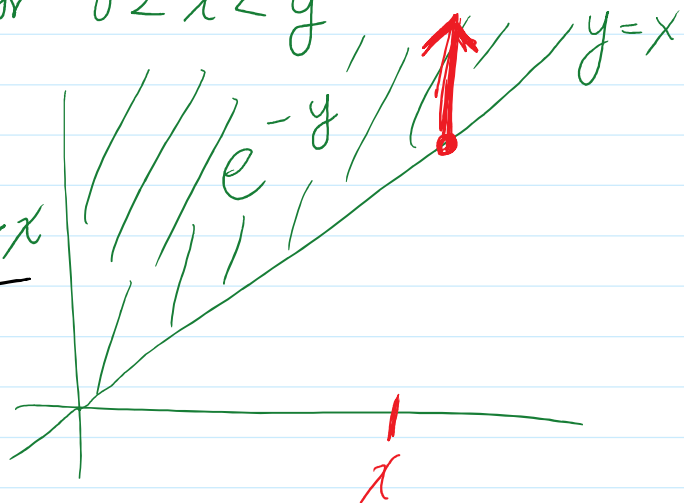
If  $g: \mathbb{R} \rightarrow \mathbb{R}$  then the conditional expectation of  $g(X)$  given  $Y = y$  is

$$E[g(X) | Y = y] = \begin{cases} \sum_x g(x) f(x|y) & \text{discrete} \\ \int_{\mathbb{R}} g(x) f(x|y) dx & \text{cts} \end{cases}$$

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

Had shown:

$$f(y|x) = e^{-(y-x)} \text{ for } y > x$$



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

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

$$= \int_x^{\infty} y e^{-(y-x)} dy = \dots = 1+x$$

Defn: Conditional Variance

$$\text{Var}(Y|X=x) = E[(Y - E[Y|X=x])^2 | X=x]$$

Short-cut formula:

$$\text{Var}(Y|X=x) = E[Y^2|X=x] - E[Y|X=x]^2$$

Ex.  $E[Y^2|X=x] = \int_{\mathbb{R}} y^2 f(y|x) dy$

$$= \int_x^{\infty} y^2 e^{-(y-x)} dy = \dots = x^2 + 2x + 2$$

$$\begin{aligned} \text{Var}(Y|X=x) &= E[Y^2|X=x] - E[Y|X=x]^2 \\ &= (x^2 + 2x + 2) - (1+x)^2 \\ &= x^2 + 2x + 2 - x^2 - 2x - 1 \\ &= 2 - 1 \\ &= 1 \end{aligned}$$

### Independence

For events: If  $A, B \subset S$  then

$$A \perp B \Leftrightarrow P(AB) = P(A)P(B)$$

For RVs

$$\begin{aligned} X \perp Y &\Leftrightarrow P(X \in A, Y \in B) = P(X \in A)P(Y \in B) \\ &\quad \forall A, B \subset \mathbb{R} \end{aligned}$$

## Product Spaces

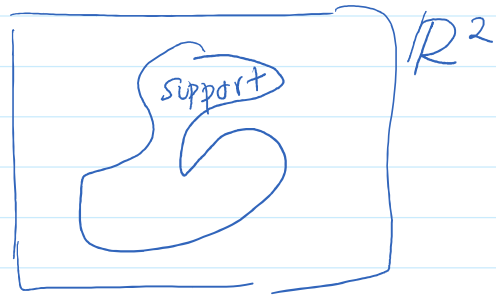
$$\text{Support}(X, Y) = \{(x, y) \mid f(x, y) > 0\}$$

If  $f(x, y) = \text{wavy}$

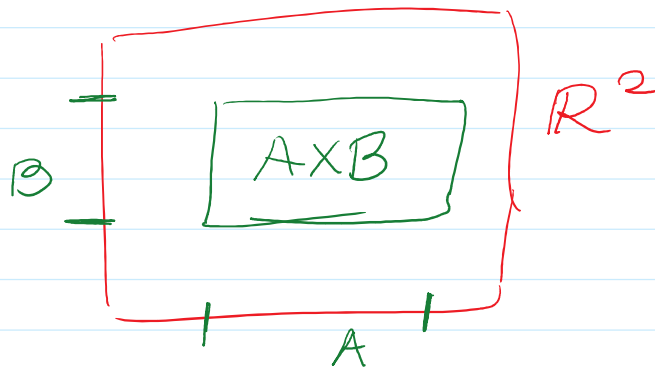
for  $x \in A$  and  $y \in B$

doesn't  
depend on  $y$

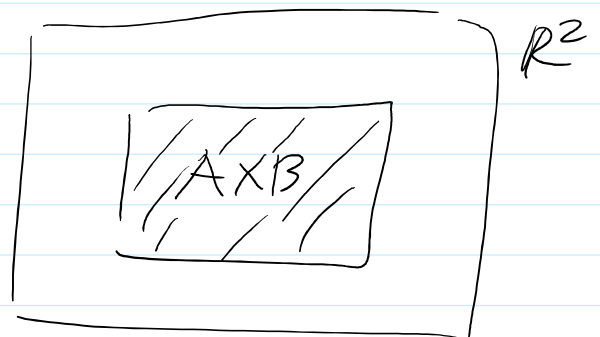
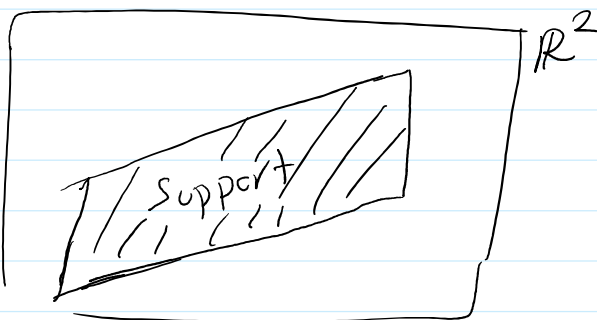
doesn't  
depend on  $x$



then the support is a product space  $A \times B$



Two different support examples



## Theorem: Factorization Theorem

$$X \perp\!\!\!\perp Y$$

iff

(1) support of  $X$  and  $Y$  is a product space

(2) either  $F(x,y) = F_X(x) F_Y(y)$

$$\text{or } f(x,y) = f_X(x) f_Y(y)$$

<u>Ex.</u>	$Y$	$f_X$	$\frac{1}{2}$	$\frac{1}{2}$	
	3		$\frac{1}{5}$	$\frac{3}{10}$	$\frac{5}{10}$
	2		$\frac{1}{5}$	$\frac{1}{10}$	$\frac{3}{10}$
	1		$\frac{1}{10}$	$\frac{1}{10}$	$\frac{2}{10}$
			10	20	$X$

$f_Y$

Q:  $X \perp\!\!\!\perp Y$ ?

(1) Product space? Yes:  $A = \{10, 20\}$ ,  $B = \{1, 2, 3\}$   
then  $A \times B$  is my support

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

Ex.  $f(10,3) = \frac{1}{5} \neq f_X(10) f_Y(3) = \left(\frac{1}{2}\right)\left(\frac{1}{2}\right) = \frac{1}{4}$

Ex.  $f(10, 3) = \frac{1}{5} \neq f_x(10) f_y(3) = (\frac{1}{2})(\frac{1}{2}) = \frac{1}{4}$

So  $X \not\perp Y$

Corollary:

$X \perp Y$

iff

① support is a product space

②  $f(x, y) = g(x) h(y)$

some fn only of  $x$

h fn only of  $y$

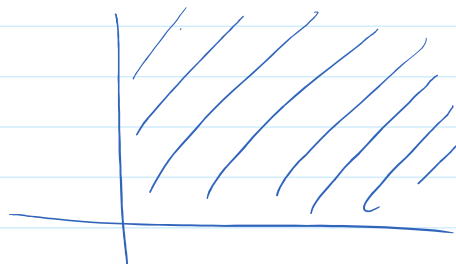
Ex.

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

$X \perp Y$ ?

① product space? Yes

Support =  $(0, \infty) \times (0, \infty)$



(2)

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

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

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

So  $X \perp Y$ .

w/o this theorem, need

$$f_X(x) = \int_0^{\infty} \frac{1}{384} x^2 e^{-(x/2) - y} dy$$

$$f_Y(y) = \int_0^{\infty} \frac{1}{384} x^2 e^{-x/2 - y} dx$$

Fact:  $A, B \subset \Omega$  and  $A \perp B$  then

$$P(A|B) = P(A)$$

For RVs:  $X \perp Y$  then

$$f(x|y) = f_x(x)$$

Pf.  $f(x|y) = \frac{f(x,y)}{f_y(y)} = \frac{f_x(x) \cancel{f_y(y)}}{\cancel{f_y(y)}} = f_x(x)$

Theorem: Expectation of Product of Independent

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)

$$\begin{aligned} E[g_1(X)g_2(Y)] &= \iint_{A \times B} g_1(x)g_2(y) f(x,y) dx dy \\ &\quad \updownarrow \text{independence} \\ &= \iint g_1(x)g_2(y) f_x(x) f_y(y) dx dy \end{aligned}$$



$$= \iint_{A \times B} g_1(x) g_2(y) f_x(x) f_y(y) dx dy$$

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

$$= \underbrace{\int_A g_1(x) f_x(x) dx}_{\mathbb{E}[g_1(X)]} \underbrace{\int_B g_2(y) f_y(y) dy}_{\mathbb{E}[g_2(Y)]}$$

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

↑  
independent identically distributed

means:  $X \perp Y$ ,  $X \sim \text{Exp}(1)$   
 $Y \sim \text{Exp}(1)$

$$\mathbb{E}[X^2 Y] = \overset{(1+1)}{\mathbb{E}[X^2]} \overset{(1)}{\mathbb{E}[Y]} = (2)(1) = 2$$

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

rearrange

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

Theorem: MGF of Sum of Independent

## Theorem: MGF of Sum of Independent

If  $X \perp Y$  then

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

pf:  $M_X(t) = \mathbb{E}[e^{tX}]$

$$M_Y(t) = \mathbb{E}[e^{tY}]$$

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

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

$$= \underbrace{\mathbb{E}[e^{tX}]}_{M_X(t)} \underbrace{\mathbb{E}[e^{tY}]}_{M_Y(t)}$$

Ex.  $X \sim N(\mu, \sigma^2)$  and  $Y \sim N(\delta, \tau^2)$

assume  $X \perp Y$ .

What is the dist. of  $X+Y$ ?

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

$$= e^{\mu t + \frac{\sigma^2 t^2}{2}} e^{\delta t + \frac{\tau^2 t^2}{2}}$$

$$= e^{\mu t + \delta t + \frac{\sigma^2 t^2}{2} + \frac{\tau^2 t^2}{2}}$$

$$= e^{(\mu + \delta)t + (\sigma^2 + \tau^2)t^2/2}$$

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

i.e.  $\boxed{X + Y \sim N(\mu + \delta, \sigma^2 + \tau^2)}$