

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

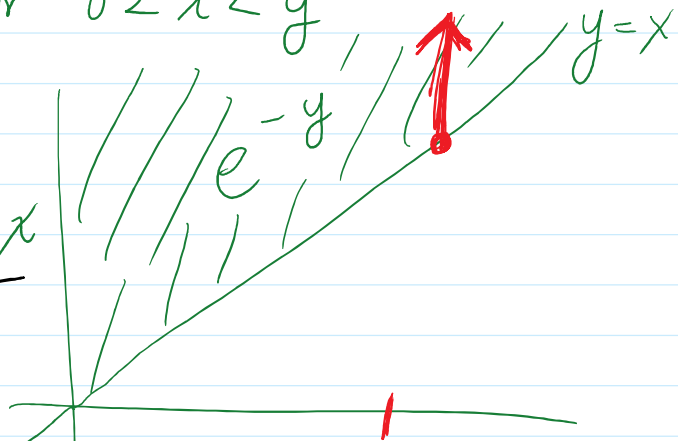
$$E[g(X) | Y=y] = \begin{cases} \sum_x g(x) f(x|y) & \text{discrete} \\ \int_{\mathbb{R}} g(x) f(x|y) dx & \text{cts} \end{cases}$$

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

Had shown:

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

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



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



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

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

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.

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

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

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

$$\begin{aligned}
 &= (x^2 + 2x + 2) - (1 + x)^2 \\
 &= \cancel{x^2} + \cancel{2x} + 2 - \cancel{x^2} - \cancel{2x} - 1 \\
 &= 2 - 1 \\
 &= 1
 \end{aligned}$$

Independence

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

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

For RVs

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

Product Spaces

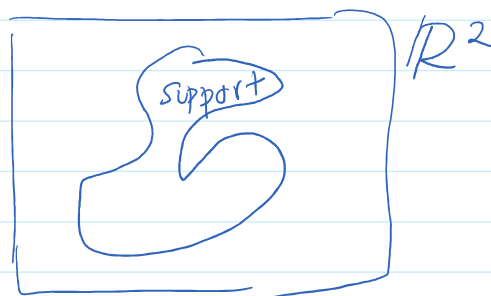
$$\text{Support}(X, Y) = \{(x, y) \mid f(x, y) > 0\}$$

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

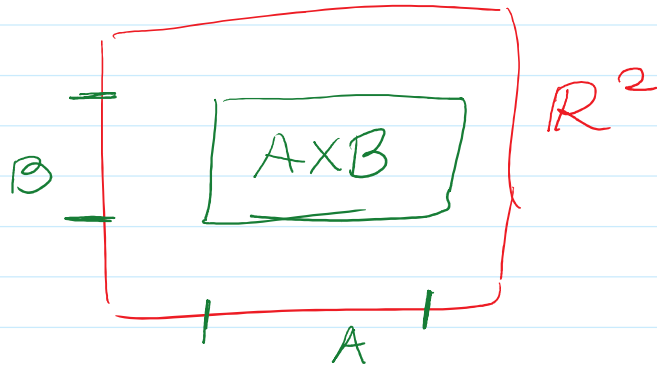
for $x \in A$ and $y \in B$

doesn't
depend on y

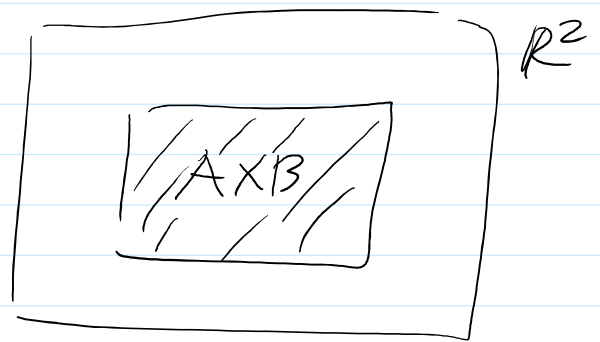
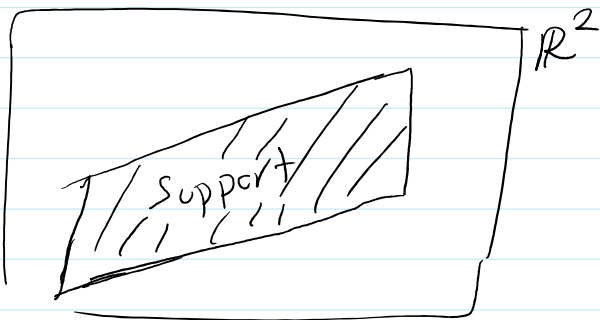
doesn't
depend on x



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 $F(x, y) = F_X(x) F_Y(y)$
or $f(x, y) = f_X(x) f_Y(y)$

$\epsilon x.$	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		$\frac{1}{10}$	$\frac{1}{10}$	$\frac{2}{10}$
					f_y
			10	20	\times

Q: $\times \perp y$?

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

So $\times \not\perp y$

Corollary:

$\times \perp y$

iff

① support is a product space

$$\textcircled{2} f(x,y) = g(x)h(y)$$

some fn only of x

h fn only of y

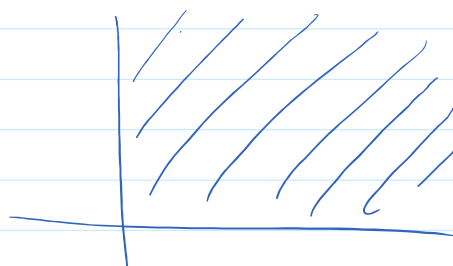
Ex.

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

$X \perp Y$?

① product space? Yes

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



$$\begin{aligned} \textcircled{2} f(x,y) &= \frac{1}{384} x^2 e^{-y - (x/2)} \\ &= \frac{1}{384} x^2 e^{-y} e^{-(x/2)} \\ &= \underbrace{\left(\frac{1}{384} x^2 e^{-x/2} \right)}_{g(x)} \underbrace{(e^{-y})}_{h(y)} \end{aligned}$$

So $X \perp Y$.

w/o this theorem, need

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

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

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

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

For RVs: $X \perp Y$ then

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

$$\text{Pf. } f(x|y) = \frac{f(x,y)}{f_Y(y)} = \frac{f_X(x) \cancel{f_Y(y)}}{\cancel{f_Y(y)}} = f_X(x)$$

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

$$\mathbb{E}[g_1(X)g_2(Y)] = \mathbb{E}[g_1(X)]\mathbb{E}[g_2(Y)].$$

pf. (cts)

$$\begin{aligned}\mathbb{E}[g_1(X)g_2(Y)] &= \iint_{A \times B} g_1(x)g_2(y)f(x,y) dx dy \\ &\quad \uparrow \text{independence} \\ &= \iint_{A \times B} g_1(x)g_2(y)f_X(x)f_Y(y) dx dy \\ &= \int_B \left[\int_A g_1(x)f_X(x) dx \right] g_2(y)f_Y(y) dy \\ &= \underbrace{\int_A g_1(x)f_X(x) dx}_{\mathbb{E}[g_1(X)]} \underbrace{\int_B g_2(y)f_Y(y) dy}_{\mathbb{E}[g_2(Y)]}\end{aligned}$$

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

↑
independent identically distributed

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

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

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

rearrange

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

Theorem: MGF of Sum of Independent

If $X \perp Y$ then

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

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

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

$$\begin{aligned} M_{X+Y}(t) &= \mathbb{E}[e^{t(X+Y)}] \\ &= \mathbb{E}[e^{tX} e^{tY}] \\ &= \underbrace{\mathbb{E}[e^{tX}]}_{M_X(t)} \underbrace{\mathbb{E}[e^{tY}]}_{M_Y(t)} \end{aligned}$$

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

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