

(X, Y) has a joint density $f(x, y)$.

$$\begin{aligned} Z = X + Y \text{ has density } f_Z(z) &= \int f(z-y, y) dy \\ &= \int f(x, z-x) dx \end{aligned}$$

Special Case:

X has density f_1 , Y has density f_2 ,

X, Y - independent

$$(\Leftrightarrow) \text{ joint density } f(x, y) = f_1(x) \cdot f_2(y).$$

In this case, density of $Z = X + Y$ is

$$\begin{aligned} f_Z(z) &= \int f_1(x) \cdot f_2(z-x) dx \\ &= \int f_1(z-y) \cdot f_2(y) dy \end{aligned}$$

$f_Z = f_1 * f_2 = f_2 * f_1$ is called the **Convolution** of densities f_1 & f_2 .

Ex. $X \sim \text{Gamma}(\lambda, \alpha_1)$

$Y \sim \text{Gamma}(\lambda, \alpha_2)$

X, Y - independent

$Z = X + Y$.

$$\begin{aligned} f_1 * f_2(z) &= \int_0^z f_1(x) \cdot f_2(z-x) dx & z \in (0, \infty) \\ &= \frac{\lambda^{\alpha_1} \cdot \lambda^{\alpha_2}}{\Gamma(\alpha_1) \cdot \Gamma(\alpha_2)} \cdot \int_0^z e^{-\lambda x} \cdot e^{-\lambda(z-x)} \cdot x^{\alpha_1-1} \cdot (z-x)^{\alpha_2-1} dx. \end{aligned}$$

$$= \frac{\lambda^{\alpha_1 + \alpha_2}}{\Gamma(\alpha_1) \cdot \Gamma(\alpha_2)} \cdot e^{-\lambda z} \int_0^z x^{(\alpha_1-1)} \cdot (z-x)^{(\alpha_2-1)} dx$$

$\rightarrow u = x/z \quad \text{ie, } x = zu$
 $du = \frac{1}{z} dx \Rightarrow dx = z du$

u	x
0	0
1	z

$$= \frac{\lambda^{\alpha_1 + \alpha_2} \cdot e^{-\lambda z}}{\Gamma(\alpha_1) \cdot \Gamma(\alpha_2)} \cdot z^{\alpha_1-1} \cdot z^{\alpha_2-1} \cdot z \int_0^1 u^{\alpha_1-1} \cdot (1-u)^{\alpha_2-1} du$$

$\underbrace{\int_0^1 u^{\alpha_1-1} \cdot (1-u)^{\alpha_2-1} du}_{\beta(\alpha_1, \alpha_2)}$

$$= \frac{\lambda^{\alpha_1 + \alpha_2} \cdot e^{-\lambda z} \cdot z^{(\alpha_1 + \alpha_2) - 1}}{\Gamma(\alpha_1) \cdot \Gamma(\alpha_2)} \cdot \frac{\beta(\alpha_1, \alpha_2)}{\frac{\Gamma(\alpha_1) \cdot \Gamma(\alpha_2)}{\Gamma(\alpha_1 + \alpha_2)}}$$

$$= \frac{\lambda^{\alpha_1 + \alpha_2} \cdot e^{-\lambda z} \cdot z^{(\alpha_1 + \alpha_2) - 1}}{\cancel{\Gamma(\alpha_1)} \cdot \cancel{\Gamma(\alpha_2)}} \cdot \frac{\cancel{\Gamma(\alpha_1)} \cdot \cancel{\Gamma(\alpha_2)}}{\Gamma(\alpha_1 + \alpha_2)}$$

$f_1 * f_2(z) = \frac{\lambda^{\alpha_1 + \alpha_2}}{\Gamma(\alpha_1 + \alpha_2)} \cdot z^{(\alpha_1 + \alpha_2) - 1} \cdot e^{-\lambda z}$, which is
 the density of $\text{Gamma}(\lambda, \alpha_1 + \alpha_2)$.

Eg. $X \sim N(0, \sigma_1^2)$

$Y \sim N(0, \sigma_2^2)$

X, Y - independent.

$Z = X + Y \sim (?)$

$\int_{-\infty}^{\infty} -\frac{1}{2} \left(\frac{x^2}{\sigma_1^2} + \frac{(z-x)^2}{\sigma_2^2} \right) dx$

$$Z = X + Y \sim (?)$$

$$f_Z(z) = \frac{1}{2\pi\sigma_1\sigma_2} \cdot \int_{-\infty}^{\infty} e^{-\frac{1}{2}\left(\frac{x^2}{\sigma_1^2} + \frac{(z-x)^2}{\sigma_2^2}\right)} dx.$$

complete the square & proceed.

$$= \dots$$

$$= \frac{1}{\sqrt{2\pi(\sigma_1^2 + \sigma_2^2)}} \cdot e^{-\frac{1}{2} \cdot \frac{z^2}{\sigma_1^2 + \sigma_2^2}} \rightarrow \text{density of } N(0, \sigma_1^2 + \sigma_2^2).$$

Q: What to do for $X \sim N(\mu_1, \sigma_1^2)$ $\left\{ \begin{array}{l} \text{for any } \mu_1, \mu_2? \\ Y \sim N(\mu_2, \sigma_2^2) \end{array} \right.$
 X, Y - independent

$$- \tilde{X} = X - \mu_1 \sim N(0, \sigma_1^2)$$

$$\tilde{Y} = Y - \mu_2 \sim N(0, \sigma_2^2)$$

$$\therefore \tilde{Z} = \tilde{X} + \tilde{Y} \sim N(0, \sigma_1^2 + \sigma_2^2).$$

$$\therefore Z = X + Y = \tilde{Z} + (\mu_1 + \mu_2) \sim N(\mu_1 + \mu_2, \sigma_1^2 + \sigma_2^2).$$

Alternative way: (Using MGFs).

Result: X, Y - independent

$$\Rightarrow m_{X+Y}(t) = m_X(t) \cdot m_Y(t) \quad \forall t \text{ s.t. } m_X(t) < \infty, m_Y(t) < \infty.$$

* Note: Whenever $0 \in I := \{t: m_X(t) < \infty\}$,
 $m_X(t)$ uniquely determines the distribution.
 i.e., there should exist an open interval containing 0, for mgf to uniquely determine the distⁿ.

uniquely determine the distⁿ.

$$X \sim \text{Gamma}(\lambda, \alpha). \quad m_X(t) = \left(\frac{\lambda}{\lambda - t} \right)^\alpha, \quad t < \lambda.$$

$$X \sim N(\mu, \sigma^2). \quad m_X(t) = e^{\mu t + \frac{1}{2} \sigma^2 t^2}, \quad t \in \mathbb{R}.$$

eg. $X \sim \text{Unif}(0,1)$
 $Y \sim \text{Unif}(0,1)$
 X, Y - independent.

$$Z = X + Y \sim (?)$$

← Case where mgf is NOT helpful.

We resort back to convolution again.

Z takes values in $(0, 2)$.

Fix $z \in (0, 2)$.

$$f_Z(z) = \int_0^z f_1(x) \cdot f_2(z-x) dx, \quad z \leq 1$$

$$0 < x < 1; \quad 0 < z < 2$$

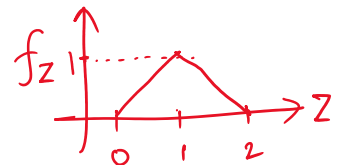
$$0 < z-x < 1 \rightarrow x > z-1$$

$$= \int_{z-1}^1 f_1(x) \cdot f_2(z-x) dx = \begin{cases} z & , 0 < z < 1 \\ 2-z & , 1 < z < 2 \end{cases}$$

$$\boxed{z-1 < x < 1}$$

→ known as "tent" density.

Note that:
 this no longer remains Uniform.

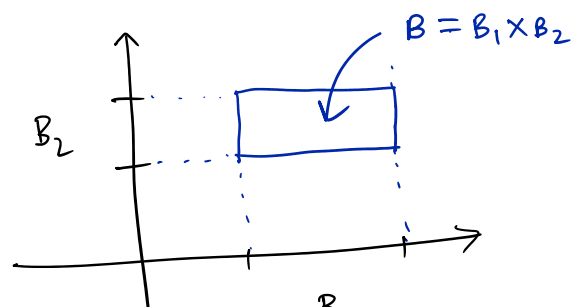


$$X, Y \text{ independent} \Leftrightarrow P(X \in B_1, Y \in B_2) = P(X \in B_1) \cdot P(Y \in B_2).$$

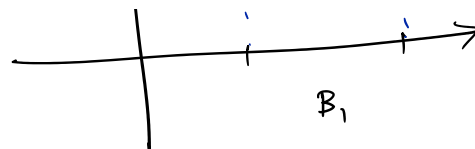
$$P((X, Y) \in B_1 \times B_2)$$

$$= P(X \in B_1) \cdot P(Y \in B_2).$$

$$B_X := \{y : (x, y) \in B\}$$



$$B_x := \{y : (x, y) \in B\}$$



$$\therefore B_x = \begin{cases} B_2, & x \in B_1 \\ \emptyset, & x \notin B_1 \end{cases}$$

$$\therefore P(Y \in B_x) = \begin{cases} P(Y \in B_2), & \text{if } x \in B_1 \\ 0, & \text{if } x \notin B_1 \end{cases}$$

$$= P(Y \in B_2) \cdot \mathbb{1}_{B_1}(x)$$

$$\therefore P(Y \in B_x) = \underbrace{\Psi(x)}_{\text{(say)}} = P(Y \in B_2) \cdot \mathbb{1}_{B_1}(x), \text{ where } \Psi: [0, 1] \rightarrow \mathbb{R}.$$

$$\therefore \begin{aligned} P((X, Y) \in B_1 \times B_2) \\ = P(X \in B_1) \cdot P(Y \in B_2). \end{aligned}$$

\Updownarrow If B is a "rectangle",
 then $P((X, Y) \in B)$
 $= E(\Psi(X))$,
 where, $\Psi(x) = P(Y \in B_x)$

\nearrow Cartesian prod of 2
 borel sets, NOT the
 geometric rectangle.

X has distribution function F_1 ,

Y has distribution function F_2 .

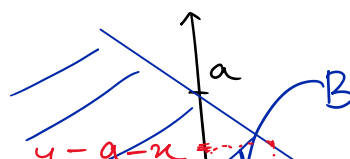
X, Y - independent.

$Z = X + Y$. What is the distribution function of Z ?

$$P(Z \leq a) = P((X, Y) \in B), \text{ where } B = \{(x, y) \in \mathbb{R}^2 : x + y \leq a\}.$$

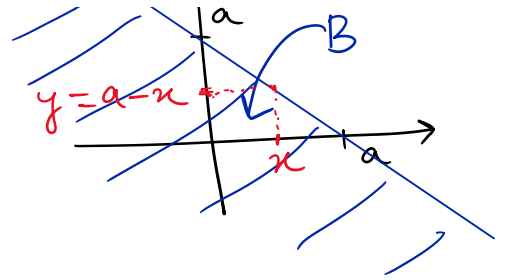
$$= E(\Psi(X))$$

$$= E(F_2(a - X))$$



$$= E(F_2(a-X))$$

$$\begin{aligned}\Psi(x) &= P(Y \in B_x) \\ &= P(Y \leq a-x) \\ &= F_2(a-x)\end{aligned}$$



Conditional Distribution and Conditional Expectation:

(X, Y) - pair of real r.v.s.

Conditional distribution of Y , given $X=x$.

$$P(Y \in B | X=x) = \Psi(x, B).$$

[→ we define it for only those x 's that belong to the support of X .]

$$\Psi(x, B) = E(1_B(Y) | X=x).$$

$\Psi(\cdot, B)$ must satisfy:

$$P(X \in A, Y \in B) = E(\Psi(X, B) \cdot 1_A(X))$$

for all $A \subset \mathbb{R}$.

Recall: Problem Sheet - 1 (Sem-2)

$$\Psi(x) = E(Y | X) \Leftrightarrow E(Y \cdot 1_A(X)) = E(\Psi(X) \cdot 1_A(X)) \quad \forall A.$$

(X, Y) - pair of real r.v.s.

Let $S = \text{support of } X$ (i.e., set of all values X can take.).

We want a fn $\Psi: S \times \{\text{Borel sets}\} \rightarrow [0, 1]$, such that,

(i) $\forall x \in S, B \mapsto \Psi(x, B)$ is a probability.

$$(ii) \quad \forall B, \quad P(X \in A, Y \in B) = E(\Psi(X, B) \cdot \mathbb{1}_A(X))$$

for all borel
 $A \subset \mathbb{R}$.

So, if such a Ψ exists, then $\Psi(x, B)$ is called $P(Y \in B \mid X = x)$.

All of this is subjected to a big "IF".

i.e., does such a Ψ exist in general?

Ans: Yes !!!

Proof: Aukat ke bahar ka

(X, Y) has density $f(x, y)$.

Let f_X - marginal density of X .

define $g(y|x) = \frac{f(x, y)}{f_X(x)} \quad \forall x \text{ s.t. } f_X(x) > 0.$

Claim: $g(y)$ is density in y .

Proof: (trivial) $g(y) = \int_{\mathbb{R}} g(y|x) dy = \int_{\mathbb{R}} \frac{f(x, y)}{f_X(x)} dy$

$\underbrace{f_X(x)}_{\text{const.}}$

$= \frac{f_X(x)}{f_X(x)} = 1 \quad \checkmark \quad \text{valid density.}$

Define $\Psi(x, B) := \int_B g(y|x) \cdot dy$

Fix $x \in S$.

$B \mapsto \Psi(x, B)$ is a probability.

$(\mathbb{R}, \mathcal{B}, \Psi(x, \cdot))$ $h: \mathbb{R} \rightarrow \mathbb{R}$ measurable.

$$E_{\Psi(x, \cdot)}(h) = E(h(Y) \mid X = x).$$