

Recap:

Q

Continuous distribution

Uniform $[a, b]$

$$f_x(x) = \begin{cases} \frac{1}{b-a} & \text{if } x \in [a, b] \\ 0 & \text{otherwise} \end{cases}$$

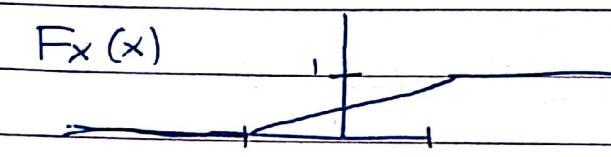


$F_x(x)$

$$F_x(x) = 0 \quad \text{if } x \leq a$$

$$= \frac{x-a}{b-a} \quad \text{if } x \in (a, b]$$

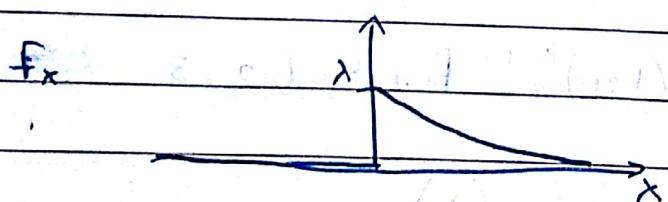
$$= 1 \quad \text{if } x > b$$



Exponential (λ); $\lambda > 0$

$$f_x(x) = \lambda e^{-\lambda x} \quad \text{if } x \geq 0$$

$$= 0 \quad \text{otherwise}$$

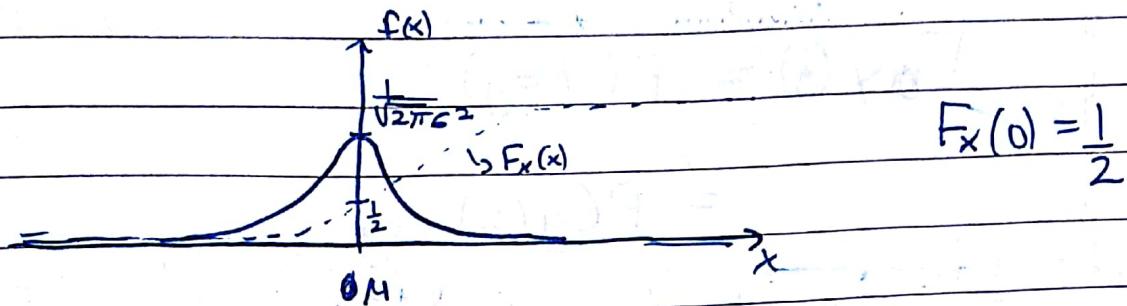


$$\lambda e^{-\lambda x} dx$$
$$-e^{-\lambda x}$$

$$\begin{aligned} 1 - e^{-\lambda x} &= F_x(x) \\ \text{if } x > 0 &= 1 - e^{-\lambda x} \\ 0 &= \text{otherwise} \end{aligned}$$

Gaussian Distribution (μ, σ^2)

$$f_x(x) = \frac{1}{\sqrt{2\pi}\sigma^2} e^{-(x-\mu)^2/2\sigma^2} \quad \forall x \in \mathbb{R}$$



Function of Random Variables:



$$Y = ax + b$$

$$X \sim F_x \quad (\text{x has distr. } F_x)$$

Find F_{xy}

$$\begin{aligned} F_{xy}(y) &= P(Y \leq y) \\ &= P(ax+b \leq y) \\ &= P(ax \leq y-b) \\ &\stackrel{\alpha}{=} P\left(x \leq \frac{y-b}{a}\right) \quad \text{if } a > 0 \rightarrow F_x\left(\frac{y-b}{a}\right) \\ &= \begin{cases} P\left(x \geq \frac{y-b}{a}\right) & \text{if } a < 0 \rightarrow 1 - P\left(x < \frac{y-b}{a}\right) \end{cases} \end{aligned}$$

$$1 - \lim_{u \rightarrow y^-} F_x\left(\frac{u-b}{a}\right)$$

Find $F_y(\cdot)$

~~$$F_y: \mathbb{R} \rightarrow [0, 1]$$~~

$$Y = g(x)$$

g is a borel measurable fn
from $\mathbb{R} \rightarrow \mathbb{R}$

$$F_{g(Y)}(y) = P(Y \leq y)$$

$$= P(g(X) \leq y)$$

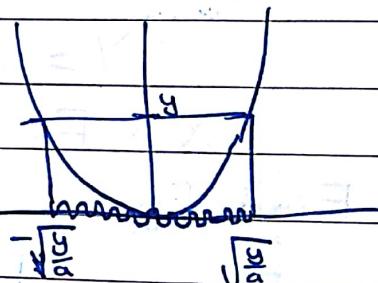
$$\text{find } x \text{ s.t. } g(x) - y \leq 0 = \{x : g(x) \leq y\}$$

$$= \tilde{g}^{-1}(y)$$

$$Y = ax^2 \quad Y \text{ is } g(x)$$

$$g(x) = ax^2$$

$$a > 0$$



$$\tilde{g}^{-1}(y) = \{x : g(x) \leq y\}$$

$$F_Y(y) = P(X \in [-\sqrt{\frac{y}{a}}, \sqrt{\frac{y}{a}}]) = F_X(\sqrt{\frac{y}{a}}) - F_X(-\sqrt{\frac{y}{a}}) + P(X = -\sqrt{\frac{y}{a}})$$

Now to find density

$$P(X=x) = P(X \leq x) - P(X < x) \quad (\text{if } A \subseteq B, \text{ then } P(B \setminus A) = P(B) - P(A))$$

$$F_Y(y) = F_X(\sqrt{\frac{y}{a}}) - F_X(-\sqrt{\frac{y}{a}})$$

$$f_Y(y) = \frac{d}{dy} [F_X(\sqrt{\frac{y}{a}}) - F_X(-\sqrt{\frac{y}{a}})]$$

$$\frac{d}{dy} F_x(\sqrt{\frac{y}{a}}) = \frac{d}{dy} \int_{-\infty}^{\sqrt{\frac{y}{a}}} f_x(u) du = f_x(\sqrt{\frac{y}{a}}) \frac{1}{\sqrt{a}} \frac{1}{\sqrt{y}} \frac{1}{2}$$

~~$$\frac{d}{dy} F_x(-\sqrt{\frac{y}{a}}) = f_x(-\sqrt{\frac{y}{a}}) \times (-1) \cdot \frac{1}{2\sqrt{ay}}$$~~

$$f_y(y) = \frac{f_x(\sqrt{\frac{y}{a}})}{2\sqrt{ya}} + \frac{f_x(-\sqrt{\frac{y}{a}})}{2\sqrt{ya}} = \frac{f_x(\sqrt{\frac{y}{a}}) + f_x(-\sqrt{\frac{y}{a}})}{2\sqrt{ya}}$$

Theorem: Let X be a continuous r.v. & let $g()$ be a differentiable fn

Then

$$f_g(y) = \sum_{k=1}^{\infty} \frac{f_x(x_k)}{|g'(x_k)|}$$

Where x_1, x_2 are at most countably many roots of $g(x) = y$, i.e. $g(x) = y \neq i$

$$y = ax^2 \quad g(x) = ax^2 \quad g'(x) = 2ax$$

$f_g(y)$ to find

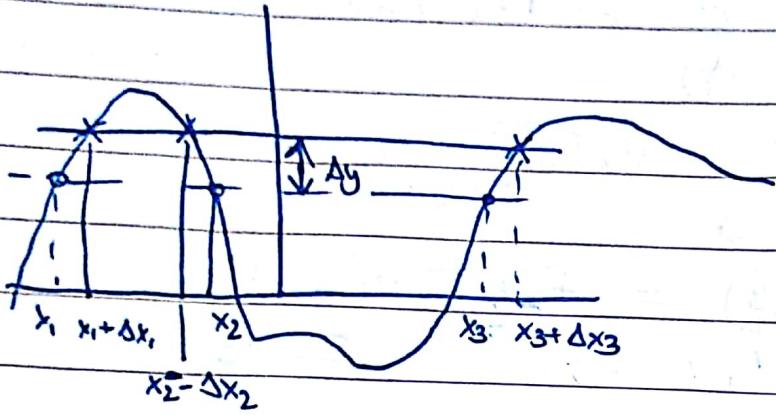
Roots of $y = ax^2$ for $y > 0$

$$x = -\sqrt{\frac{y}{a}}, \sqrt{\frac{y}{a}}$$

$$g'(\sqrt{\frac{y}{a}}) = \left| -2a\sqrt{\frac{y}{a}} \right| = 2\sqrt{ya} \quad g'(\sqrt{\frac{y}{a}}) = 2\sqrt{ya}$$

$$f_y(y) = (\text{same as above})$$

Now we can integrate to get F



$$\begin{aligned}
 f_Y(y) &= \lim_{\Delta y \downarrow 0} \frac{F_Y(y + \Delta y) - F_Y(y)}{\Delta y} \\
 &= \lim_{\Delta y \downarrow 0} P(y < Y \leq y + \Delta y) / \Delta y \\
 &= \lim_{\Delta y \downarrow 0} \underbrace{P(x_1 < X < x_1 + \Delta x)}_{\Delta y} + P(x_2 - \Delta x_2 < X < x_2) + P(x_3 < X < x_3 + \Delta x)
 \end{aligned}$$

because g is cont as $\Delta y \downarrow 0$ $\Delta x \xrightarrow{\text{def}} 0$

Expectation

$$E[x] = \int_{-\infty}^{\infty} x f_x(x) dx$$

$$E[x] = \sum_{k=1}^{\infty} a_k p\{x=a_k\}$$

Discrete r.v.

Bernoulli r.v.

$$x = 1 \text{ w prob } p$$

$$= 0 \text{ w prob } 1-p$$

$$E[x] = 1(1 \cdot p) + 0(1-p) = p$$

- Binomial

$$x = k \text{ w prob } \binom{n}{k} p^k (1-p)^{n-k}$$

$$E[x] = \sum_{k=0}^n k \cdot \binom{n}{k} p^k (1-p)^{n-k}$$

$$= n \sum_{k=1}^{n-1} \binom{n-1}{k-1} p^k (1-p)^{n-k}$$

$$= n \sum_{v=0}^n \binom{n-1}{v} p^{v+1} (1-p)^{n-v-1}$$

$$= np \sum_{v=0}^n \binom{n-1}{v} p^v (1-p)^{(n-1)-v}$$

$$= np [p + (1-p)]^n$$

$$= np$$

Poisson r.v. ($\lambda > 0$)
 $x = k$ wp $\frac{e^{-\lambda} \lambda^k}{k!}$ + $k=0, 1, \dots$

$$E[x] = \sum_{k=0}^{\infty} k e^{-\lambda} \frac{\lambda^k}{k!}$$

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

$$= \lambda \sum_{v=0}^{\infty} \frac{e^{-\lambda} \lambda^v}{v!}$$

$$= \lambda (e^{-\lambda} \times e^{\lambda}) = \lambda$$

- Uniform $[a, b]$

$$f_x(x) = \frac{1}{b-a} \quad \forall x \in [a, b]$$

$$= 0 \quad \text{otherwise}$$

$$E[x] = \int_{-\infty}^{\infty} x f_x(x) dx$$

$$= \int_a^b x f_x(x) dx = \frac{1}{b-a} \int_a^b x dx$$

$$= \frac{1}{b-a} \frac{(b^2 - a^2)}{2} = \frac{a+b}{2}$$

$$\frac{d}{dx}(-x(e^{-\lambda x})) = \lambda x e^{-\lambda x} - e^{-\lambda x}$$

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Exponential r.v. ($\lambda > 0$)

$$f_x(x) = \begin{cases} \lambda e^{-\lambda x} & \text{if } x \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

$$E[x] = \int_{-\infty}^{\infty} x f_x(x) dx$$

$$= \lambda \int_0^{\infty} x e^{-\lambda x} dx = \frac{1}{\lambda}$$

Properties of Expectation

If $x \geq 0$, then $E[x] \geq 0$

↑
Pointwise

$$X(\omega) \geq 0 \quad \forall \omega \in \Omega$$

$$E[x] = \int_{-\infty}^{\infty} x f_x(x) dx$$

$$F_x(x) = 0 \quad x < 0$$

$$\therefore f_x(x) = 0 \quad x < 0$$

$$= \int_0^{\infty} x f_x(x) dx \geq 0$$

Note $F_x(x)$ is inc
so $f_x(x)$ is +ve

If $f_x()$ is symmetric around $a \in \mathbb{R}$, i.e.

$$f_x(a-x) = f_x(a+x), \text{ then } E[x] = a$$

$$E[x] = \int_{-\infty}^{\infty} x f_x(x) dx$$

$$= \int_{-\infty}^a x f_x(x) dx + \int_a^{\infty} x f_x(x) dx$$

$$u = a - x \Rightarrow$$

$$= \int_{-\infty}^0 u f_x(-u) du + \int_0^{\infty} (a-y) f_x(a-y) dy + \int_0^{\infty} (a-y) f_x(a-y) dy$$

$$= \int_0^{\infty} (a-y) f_x(a-y) dy + \int_{-\infty}^0 (a-y) f_x(a-y) dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_x(a-y) dy (= a) +$$

$$a - \int_{-\infty}^{\infty} f_x(a-y) dy = a$$

$$- \left[\int_{-\infty}^0 y f_x(a-y) dy + \int_0^{\infty} y f_x(a-y) dy \right]$$

$$y = -u$$

$$\left[\int_{-\infty}^0 (-u) f_x(a+u) du \right]$$

$$= \left[- \int_a^0 u f_x(a-u) du + \int_a^0 y f_x(a-y) dy \right]$$

$$= \int_a^0 y f_x(a-y) dy (-1+1)$$

$$= 0$$

$$\therefore E[x] = a$$

If $x \geq 0$ then

$$E[x] = \int_0^{\infty} (1 - F_x(u)) du$$

$$E[x] = \int_{-\infty}^{\infty} x f_x(u) du$$

Discrete version

$$E[x] = \sum_{k=1}^{\infty} k P(x \geq k)$$

assuming $x \in \mathbb{N}$

$$E[x] = \sum_{k=1}^{\infty} k P(x=k)$$

$$\begin{array}{ll} K=1 & P(x=1) \\ K=2 & P(x=2) \\ K=3 & P(x=3) \end{array} + P(x=2) + P(x=3)$$

$\checkmark E[x] = P(x \geq 1) + P(x \geq 2) + P(x \geq 3)$

It's a differ notation

$$\sum_{k=1}^{\infty} k P(x=k) = \sum_{k=1}^{\infty} \left(\sum_{i=1}^k P(x=i) \right)$$

$$= \sum_{u=1}^{\infty} \sum_{k=u}^{\infty} P(x=k)$$

$\underbrace{\hspace{1cm}}$

$P(x \geq u) = P(x \geq 0)$

$$E[x] = \int_0^{\infty} x f_x(x) dx = \int_0^{\infty} \int_0^x du f_x(x) dx$$

$$f_x(x) = \lambda e^{-\lambda x} \quad \text{for } x \geq 0$$

$$F_x(x) = 1 - e^{-\lambda x} =$$

$$1 - F_x(x) = e^{-\lambda x}$$

$$E[x] = \int_0^{\infty} e^{-\lambda x} dx = -e^{-\lambda x} \Big|_0^{\infty} = \frac{1}{\lambda}$$

Law of unconscious Statistician

nontrivial result $\therefore E[g(x)] = \int_{-\infty}^{\infty} g(x) f_x(x) dx$

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

$$E[x^2] = \int_{-\infty}^{\infty} x^2 f_x(x) dx$$

To prove $\rightarrow Y = x^2$ find f_y

$$E[Y] = \int_{-\infty}^{\infty} y f_y(y) dy$$

Moments of r.v.

$$k^{\text{th}} \text{ moment } m_k = E[x^k]$$

(not necessary
 n^{th} moment exists)

Central moment

$$c_k = E[(x - Ex)^k]$$

c_2 is called variance of r.v.

$$\sigma^2 = E[(x - Ex)^2]$$

Moment generating function

$$\Psi_x(t) = E[e^{tx}] = \int_{-\infty}^{\infty} e^{tx} f_x(x) dx$$

$\Psi_x(t)$ exists if \exists to s.t. $t + t \in (0, t_0)$

$\Psi_x(t)$ is defined & finite

$$e^{tx} = 1 + tx + \frac{t^2 x^2}{2!} + \dots$$

(Assume expectation
is linear)

$$E[e^{tx}] = 1 + tE[x] + \frac{t^2 E[x^2]}{2!} + \frac{t^3 E[x^3]}{3!} \dots$$

$|E[e^{tx}]| < \infty$ only if $|E[x^k]| < \infty$ for every k

Finding moments using m.g.f. (at $t=0$ mgf = 1)

$$\frac{d}{dt} E[e^{tx}] = E[x] + tE[x^2] + \frac{t^2 E[x^3]}{2!} \dots$$

$$\lim_{t \rightarrow 0} \left(\frac{d}{dt} E[e^{tx}] \right) = E[x^2]$$

$$\lim_{t \rightarrow 0} \frac{1}{t} E[e^{tx}] = E[x]$$

- IF $E[e^{tx}] = E[e^{tx}] \neq t > 0$
then $F_x(x) = F_y(x)$ except for countably
many points (like at point of discontinuity)

Characteristics fn

$$\phi_x(t) = E[e^{jtx}] = \int_{-\infty}^{\infty} e^{jtx} f_x(x) dx$$

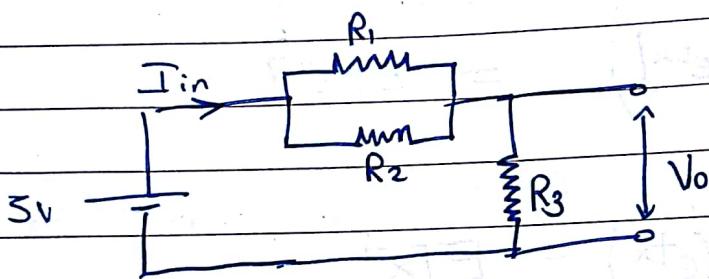
Two random variables:

X & Y

$X + Y$

$\forall \omega \in \Omega, X(\omega) + Y(\omega)$

(Both must be defined
on some probability
space.)



~~S~~ $S = \{(r_1, r_2, r_3) : r_1, r_2, r_3 \in \mathbb{R}_{\text{pos}}\}$

$$I_{in}(r_1, r_2, r_3) = \frac{5}{(r_1/r_2) + r_3}$$

$$V_0(r_1, r_2, r_3) = r_3 \cdot I_{in}(r_1, r_2, r_3)$$

For a fixed I_{in} , we may still see many values of V_0

$\therefore V_0$ & I_{in} are not functions of each other

Like knowing I_{in} I only have partial info about V_0

Even when we have all these similarities, we can't find V_0 if given I_{in}

Two Random Variables

$$X: \Omega \rightarrow \mathbb{R}_e$$

$$Y: \Omega \rightarrow \mathbb{R}_e$$

Joint distribution fn (\cap) means AND

$$F_{XY}(x, y) = P(X \leq x, Y \leq y)$$

$$\underbrace{P(\{\omega : X(\omega) \leq x\} \cap \{\omega : Y(\omega) \leq y\})}_{\in \mathcal{F} \text{ (containing } \in \mathcal{F} \text{ condition)}}$$

$$F_{XY}(-\infty, y) = F_{XY}(x, -\infty) = 0 \quad \forall x, y \in \mathbb{R}_e$$

$$F_{XY}(+\infty, y) = F_Y(y)$$

\uparrow marginal distribution fn

Partial Order

$(x_1, y_1) \leq (x_2, y_2)$ whenever $x_1 \leq x_2, y_1 \leq y_2$

Only for partial order we can talk about monotonicity

Joint Density function, $f_{xy}(x, y)$
any non-negative f^n satisfying

$$F_{xy}(x, y) = \int_{-\infty}^x \int_{-\infty}^y f_{xy}(u, v) du dv$$

$$f_{xy}(x, y) = \frac{\partial^2}{\partial x \partial y} F_{xy}(x, y)$$

Conditional distribution

$$P(X \leq x | Y \leq y)$$

$$P(X \in B_1 | Y \in B_2) = \frac{P(X \in B_1, Y \in B_2)}{P(Y \in B_2)}$$

$$F_y(y | X \in B) = \frac{P(Y \leq y, X \in B)}{P(X \in B)}$$

$$F_y(\cdot | X \in B) : R \rightarrow [0, 1]$$

Conditional Density

$$f_y(y | X \in B) = \frac{d}{dy} F_y(y | X \in B)$$

$$F_y(y | x \leq x) = \frac{F_{xy}(x, y)}{F_x(x)}$$

$$f_{by}(y | x \leq x) = \frac{1}{F_x(x)} \int_0^y F_{xy}(x, y) dy$$

—→ x —→ x —

Just a notation $\leftarrow F_y(y | x = x) = \frac{P(Y \leq y, X = x)}{P(X = x)}$

means $\lim_{\Delta x \downarrow 0} F_x(y | x \in (x, x + \Delta x))$

whenever the limit exists

$$\lim_{\Delta x \downarrow 0} \frac{P(Y \leq y, X \in [x, x + \Delta x]) / \Delta x}{P(X \in [x, x + \Delta x]) / \Delta x}$$

$$\left(\frac{\partial}{\partial x} F_{xy}(x, y) \right) \frac{1}{F_x(x)}$$

$$f_{by}(y | x = x) = \frac{1}{F_x(x)} \int_0^y F_y(y | x = x) dy$$

$$= \frac{f_{xy}(x, y)}{f_x(x)}$$

$$P(Y \leq y) = \int_{-\infty}^y f_y(y | x = x) f_x(x) dx dy$$

$$P(X \in [a, b]) = \int_a^b f_x(x) dx$$

Approx $P(X \in [a, a + \Delta]) \approx f_x(x) \Delta \rightarrow$ Approximation for small Δ .

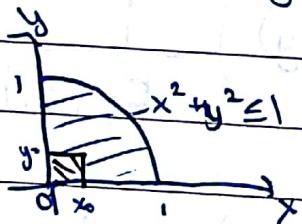
Law of total prob: $P(A) = \sum_{i=1}^n P(A|B_i) \cdot P(B_i)$

$$P(A) = \sum_{i=1}^n P(A|B_i) \cdot P(B_i)$$

Where $\{B_i\}_{i=1 \dots n}$ is partition of Ω

$$P(Y \leq y) = \int_{-\infty}^{\infty} P(Y \leq y | X=x) f_X(x) dx$$
$$= \int_{-\infty}^y f_{Y|X}(y|x) dx$$

Let (X, Y) denote the coordinates of a point chosen uniformly at random from



the shaded area

$$P((X, Y) \in \text{Black area})$$

$$f_{XY}(x, y) = c, c > 0$$



only in the shaded area

$$= 0 \quad \text{outside}$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{XY}(x, y) dx dy = 1$$

~~$\int \int f_{xy}(x, y) dx dy$~~ (done in later) To find

$$\iint f_{xy}(x, y) dx dy = \frac{1}{2} \int_0^{\sqrt{1-y^2}} dx = \frac{1}{2} C \pi = 1$$

$$\Rightarrow C = \frac{4}{\pi}$$

$$P(X \leq x_0, Y \leq y_0) = \int_{-\infty}^{x_0} \int_{-\infty}^{y_0} f_{xy}(x, y) dx dy$$

$$= \int_0^{x_0} \int_0^{y_0} f_{xy}(x, y) dy dx$$

$$= x_0 y_0 \frac{4}{\pi}$$

$$P(Y \leq y | X \leq x) = \int_0^x f_{xy}(u, y) du$$

$$\text{To show } f_Y(y | x) = \frac{f_{xy}(x, y)}{f_X(x)}$$

$$F_Y(y | x < X < x + \Delta x) = \frac{P(Y \leq y, x < X \leq x + \Delta x)}{P(x < X \leq x + \Delta x)}$$

$$f_{xy}(y | x < X \leq x + \Delta x) = \frac{1}{\Delta x} \int_x^{x+\Delta x} f_{xy}(u, y) du$$

$$\text{and since } P(x < X \leq x + \Delta x) = 1 - F_X(x)$$

$$f_Y(y | x) = \lim_{\Delta x \downarrow 0} \frac{1}{P(x < X \leq x + \Delta x)} \int_x^{x+\Delta x} f_{xy}(u, y) du / \Delta x$$

$$= \frac{f_{xy}(x, y)}{F_X(x)}$$

Law of Total Probability

$$f_Y(y) = \int_{-\infty}^{\infty} f_Y(y|x=x) f_X(x) dx$$

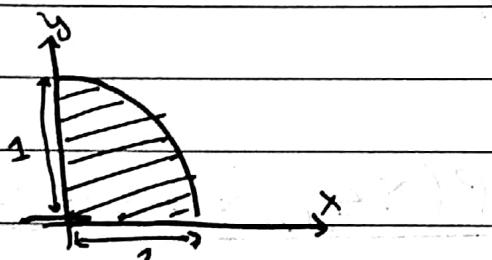
Bayes Formula

$$f_Y(y|x=x) = \frac{f_X(x|Y=y) \cdot f_Y(y)}{f_X(x)}$$

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

Conditional Expectation

$$E[Y|A] = \int_{-\infty}^{\infty} y f_Y(y|A) dy$$



(x, y) denotes co-ordinates of a point picked uniformly at random in the shaded area

$$f_{XY}(x,y) = \begin{cases} \frac{4}{\pi} & \text{if } (x,y) \in \text{Shaded area} \\ 0 & \text{otherwise} \end{cases}$$

$$f_Y(y|x=x) = \frac{f_{XY}(x,y)}{f_X(x)}$$

$$f_x(x) = \int_{-\infty}^{\infty} f_{xy}(x,y) dy$$

$$= \int_0^{\sqrt{1-x^2}} dy = \frac{1}{2} \sqrt{1-x^2}$$

$$f_x(y|x=x) = \frac{1}{\sqrt{1-x^2}} \rightarrow \text{it } x, y \in \text{Shaded area}$$

^{here} we know y is a uniform random variable between $(0, \sqrt{1-x^2})$

$$E[Y | x=x] = \frac{1}{2} \sqrt{1-x^2}$$

$$x \rightarrow x$$

$$E[g(y)|A] = \int_{-\infty}^{\infty} g(y) f_y(y|A) dy$$

Function of two random variables

$$z = x+y$$

we know $F_{xy}(x,y)$ To find $F_z(z)$

$$F_z(z) = P(z \leq z) = P(x+y \leq z)$$

~~$$\int_{-\infty}^{\infty} \int_{-\infty}^{z-x} f_{xy}(u,v) du dv$$~~

Diff approach

$$= P(x+y \leq z | x=x) f_x(x) dx$$

$$= \int_{-\infty}^{\infty} P(x+y \leq z | x=x) f_x(x) dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{z-x} f_y(u|x=x) du f_x(x) dx$$

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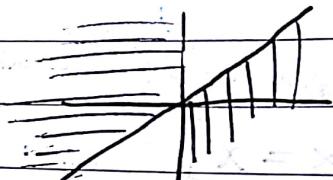
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$$\text{If } z = \frac{y}{x}$$

$$F_z(z) = P(Z \leq z) = P\left(\frac{Y}{X} \leq z\right) = P(Y \leq zx)$$

when $x > 0$

when $x < 0$



Expectation

$$E[g_{\phi}(x, y)]$$

$$\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x, y) f_{xy}(x, y) dx dy$$

2. Monotonicity of Expectation

if $x \leq y$, then $E[x] \leq E[y]$

means pointwise greater

$$Z = Y - X \geq 0$$

When $Z \geq 0$

$$E[Z] = \int z f_Z(z) dz$$

because $Z \geq 0$

$$= \int z f_Z(z) dz$$

$$E[Y - X] = \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} (y - x) f_{xy}(x, y) dx dy$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} y f_{xy}(x, y) dx dy - \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} x f_{xy}(x, y) dx dy$$

$$= \int_{-\infty}^{\infty} y f_Y(y) dy - \int_{-\infty}^{\infty} x f_X(x) dx$$

$$E[Y] - E[X]$$

Since $E[Y - X] > 0$

$$E[Y] > E[X]$$

Markov's Inequality

Let $x \geq 0$, then $\mathbb{P}[x^k \geq 1]$

Called
Tail
Probability $\rightarrow \mathbb{P}(x > \varepsilon) \leq \frac{\mathbb{E} x^k}{\varepsilon^k}$

To convert Prob. to Expectation

$$\mathbb{I}_{\{x > \varepsilon\}} = \begin{cases} 1 & \text{if } x > \varepsilon \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{I}_{\{x > \varepsilon\}}(\omega) = \begin{cases} 1 & \text{if } x(\omega) > \varepsilon \\ 0 & \text{otherwise} \end{cases}$$

$$\mathbb{E} [\mathbb{I}_{\{x > \varepsilon\}}] = 1 \cdot \mathbb{P}(\mathbb{I}_{\{x > \varepsilon\}} = 1) + 0 \cdot \mathbb{P}(\mathbb{I}_{\{x > \varepsilon\}} = 0)$$

$$= 1 \cdot \mathbb{P}(x > \varepsilon) + 0 \cdot \mathbb{P}(x \leq \varepsilon) \\ = \mathbb{P}(x > \varepsilon)$$

\therefore to show $\mathbb{E}[\mathbb{I}_{\{x > \varepsilon\}}] \leq \mathbb{E}[\frac{x^k}{\varepsilon^k}]$

Enough to Show

$$\mathbb{I}_{\{x > \varepsilon\}} \leq \frac{x^k}{\varepsilon^k} \quad \forall k \geq 1$$

~~basis~~

(Consider $\omega \in \Omega$)

Case 1: $x(\omega) > \varepsilon$

$$\frac{x(\omega)}{\varepsilon^k} \geq 1 \text{ holds since } \frac{x(\omega)}{\varepsilon} \geq 1$$

↑ cause X is positive $\forall \omega$.

Case 2: $0 \leq X(\omega) \leq \varepsilon$

$$\mathbb{I}_{\{X > \varepsilon\}}(\omega) = 0$$

$$\frac{X(\omega)}{\varepsilon} \geq 0 \quad \forall \omega$$

Chebychev's Inequality

$$\underline{P(|X - E[X]|^2 > \varepsilon)} \leq \frac{\text{Var}(X)}{\varepsilon^2}$$

$$\underline{P(|X - E[X]|^2 > \varepsilon) = P(Y > \varepsilon)} \leq \frac{E[Y^2]}{\varepsilon^2} = \frac{E(|X - E[X]|^2)}{\varepsilon^2} = \frac{\text{Var}(X)}{\varepsilon^2}$$

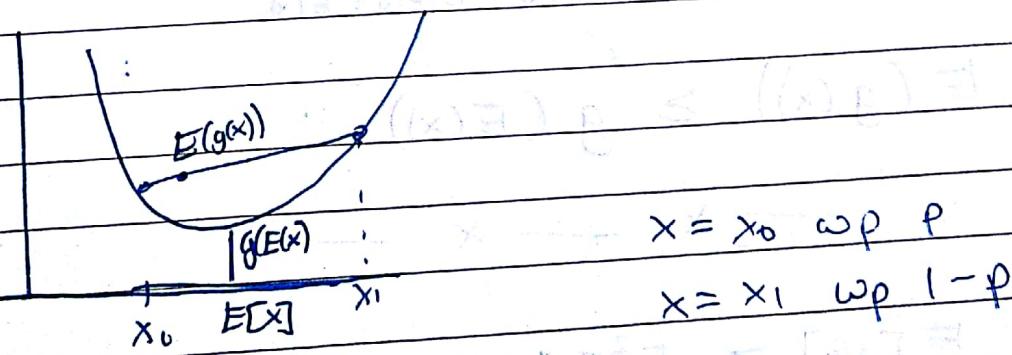
↓
Y > 0 $\kappa=2$ Apply Markov's Ineq

~~$E[g(x)] \leq g(E[x])$~~

Jensen's Inequality

If $g(x)$ is a convex fn, then

$$E[g(x)] \leq g(E[x])$$



$$E[X] = p x_0 + (1-p) x_1$$

$$g(E[X])$$

$$E[g(x)] = g(x_0)p + g(x_1)(1-p)$$

↓

$$\frac{y - g(x_0)}{x - x_0} = g'(x_0)$$

$$y = g'(x_0)(x - x_0) + g(x_0)$$

$$g(x) \geq g'(x_0)(x - x_0) + g(x_0) \quad \nexists x \perp x_0$$

$$g(x) \geq g'(x_0)(x - x_0) + g(x_0)$$

$$\text{choose } x_0 = E[x]$$

$$g(x) \geq g'(E[x]) \cdot (x - E[x]) + g(E[x])$$

$$E[g(x)] \geq E[g'(E[x]) \cdot (x - E(x))] + g(E(x))$$

$$E[g(x)] \geq g'(E[x])E(x - E[x]) + g(E(x))$$

$E[x] \quad E[E(x)] = E(x)$

$$E(g(x)) \geq g(E(x))$$

— x — x —

E.G.

$$E[x^2] \geq E^2[x]$$

$$g(x) = x^2$$

$$E(Y|X) = \int_{-\infty}^{\infty} E[Y|X=x] \delta(x-x) dx$$

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

$$= \int_{-\infty}^{\infty} y f_Y(y|X=x) dy$$

$$\frac{f_{XY}(x,y)}{f_X(x)}$$

~~REMARKS~~

$$= \int_{-\infty}^{\infty} g(x) \delta(x-x) dx$$

$$= g(x)$$

Tutorial - 2

$$1. k(1+2+4) + k(2+4+5) = 1$$

$$k(7+11) =$$

(a) $k = \frac{1}{18}$

(b) $E[x] = \int_{-\infty}^{\infty} x f_x(x) dx$ $f_x(x) = k P(x)$
 $= \frac{1 \times 1}{18} + \frac{2 \times 2}{18} + \frac{4 \times 4}{18} + \frac{2 \times 3}{18} + \frac{4 \times 5}{18} + \frac{5 \times 6}{18}$
 $= \frac{1+4+16+16+40+30}{18}$
 $= \frac{77}{18}$

$E[x^2] = \frac{1 \times 1}{18} + \frac{4 \times 2}{18} + \frac{16 \times 4}{18} + \frac{2 \times 9}{18} + \frac{4 \times 25}{18} + \frac{5 \times 36}{18}$
 $= \frac{1+8+64+18+100+180}{18}$

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$$2. \text{mean} = \int_{-\infty}^{\infty} x \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$= \frac{1}{\sqrt{2\pi\sigma^2}} \int_{-\infty}^{\infty} x e^{-\frac{(x-\mu)^2}{2\sigma^2}} dx$$

$$\frac{(x-\mu)^2}{2\sigma^2} = t$$

$$dt = \frac{d(x-\mu)}{\sigma^2}$$

$$\int_{-\infty}^{\infty} \frac{e^{-t}}{\sqrt{2\pi\sigma^2}} (x^2 dt + \mu dx)$$

$$\mu dx + \frac{\sigma^2}{\sigma^2} dt = x dx - \cancel{\mu dx}$$

$$P(X = k) = \frac{\lambda^k e^{-\lambda}}{k!}$$

$$\sum_{k=0}^{\infty} k \frac{\lambda^k e^{-\lambda}}{k!}$$

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

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

$$= e^{-\lambda} \sum_{k=0}^{\infty} \frac{\lambda^k}{k!} = e^{-\lambda} e^{\lambda} = \lambda$$

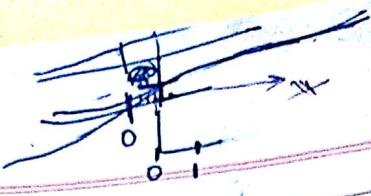
$$\text{Variance} = E(X^2) - (E(X))^2$$

$$E(X^2) = \sum_{k=0}^{\infty} k^2 \frac{\lambda^k e^{-\lambda}}{k!}$$

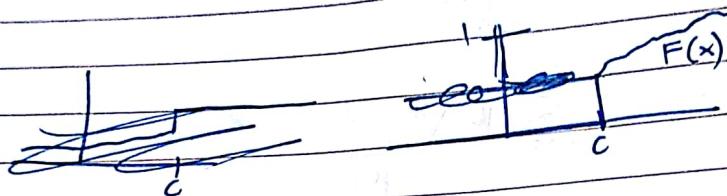
$$= e^{-\lambda} \sum_{k=0}^{\infty} k \frac{\lambda^k}{(k-1)!}$$

$$e^{-\lambda} \sum_{k=1}^{\infty} \frac{k \lambda^k}{(k-1)!} = e^{-\lambda} \sum_{k=1}^{\infty} k \frac{\lambda^{k-1}}{(k-1)!} = \sum_{k=0}^{\infty} (k+1) \frac{\lambda^k}{k!}$$

$$\frac{d}{dx} \sum_{k=0}^{\infty} \frac{\lambda^{k+1}}{k!}$$



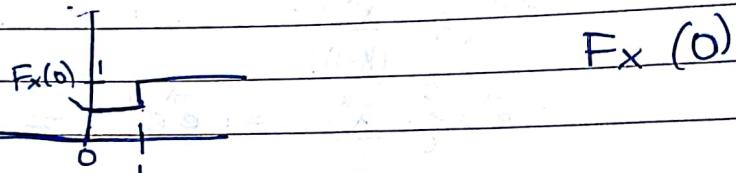
4.



$$= 0 \quad x(\omega) \leq c$$

$$= F_x(x) \quad x(\omega) \geq c$$

5.



~~1.20.~~ $\text{if } Y = -\log X$

$$\begin{aligned} Y &\leq y \\ -\log X &\leq y \end{aligned}$$

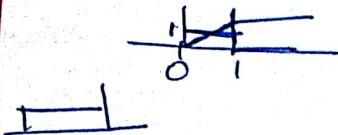
$$\begin{aligned} \log X &\geq -y \\ X &\geq e^{-y} \end{aligned}$$

as \log

as ~~$\log x$ is~~

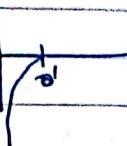
(e^y, ∞) is a Borel field so $y \leq y$ is ~~a Borel~~

Borel Set Dikhaga is suff.



$$f_y =$$

$$y =$$



$$f_x(x) = 1 \quad x \in (0, 1)$$

~~f_x(x) = 1~~

$$f_x(e^{-y}) = 1$$

$$\int f_y(\textcircled{e}^y) dy = 1$$

F_y

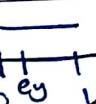
$$F_y(y) = \int_{-\infty}^{\infty} f_x(x) dx$$

$$= \int_{-\infty}^{e^y} f_x(x) dx$$

$$= \int_{-\infty}^{e^y} \cancel{f_x(x)} dx$$

$$= \int_{-\infty}^{e^y} 1 dx$$

$$= 1 - e^{-y}$$



for $y > 0$

$$3. P(x > \frac{n}{2}) \leq E\left(\frac{x}{n}\right) = \cancel{E}\frac{n}{n} = \frac{1}{n}$$

4.

Independence

$$X \perp\!\!\!\perp Y \quad (\text{if } f = p(x) \cdot p(y))$$

\uparrow
x is independent of Y

6-field generated by a r.v.

$$\begin{aligned} X^*(B) &= \{A \in \mathcal{F} \mid A \subseteq \mathbb{R} \text{ & } \exists B \in \mathcal{B} \text{ s.t. } X(A) = B\} \\ &\subseteq \mathcal{S} \end{aligned}$$

eventually required for all B

We also have $Y^*(B)$

X & Y are said to be independent if $X^*(B)$ & $Y^*(B)$ are independent collection

$$\forall A_x \in X^*(B) \text{ & } A_y \in Y^*(B)$$

$$P(A_x \cap A_y) = P(A_x) \cdot P(A_y)$$

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

$$F_{xy}(x, y) = F_x(x) \cdot F_y(y) \quad \forall x, y \in \mathbb{R}$$

$$P(X \leq x, Y \leq y) = P(X \leq x) \cdot P(Y \leq y)$$

$(-\infty, x] \quad (-\infty, y]$

Needs a proof.

It is enough to check for $(-\infty, x]$ type

If it holds, then it'll hold for all subsets of \mathcal{B} . To be proved in 3rd year

$$f_{xy}(x, y) = f_x(x) \cdot f_y(y)$$