

Statistical Analysis

in Physics

* Randomness and Random Variable:-

- When you take any data, you take out central tendencies → mean, mode, median.
- When you perform any experiment, for eg. finding out the value of "g" due to gravity, $g = 9.8 \text{ m/s}^2$ or 10 m/s^2
or

Time period of a simple pendulum.

$$\text{L.C.} = 0.01 \text{ s}$$

(stopwatch)

$$T = 2\pi \sqrt{\frac{l}{g}}$$

4 people are taking

"Observation"

t_{20} (20 Observat's)

RRRR
 $s_1 \ s_2 \ s_3 \ s_4$

s_1	24.13
s_2	24.22
s_3	23.98
s_4	11?

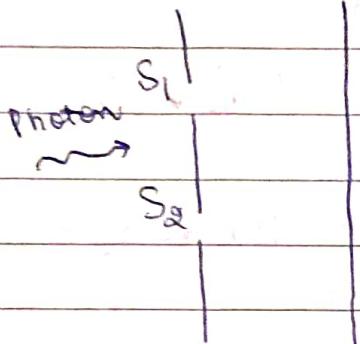
We cannot tell exactly

This phenomenon is called randomness.

* Random experiments:- Random experiment is one in which you cannot predict exactly what your next observation would be even if you

have previous data. (but we know possible outcomes).

E.g. ② Double-slit experiment with photons



we can't predict from which slit photon would go through?

③ Radioactivity → Spontaneous random experiment



④ Tossing a coin

⑤ Taking a card out of deck of cards.

→ Non Random Experiment :-

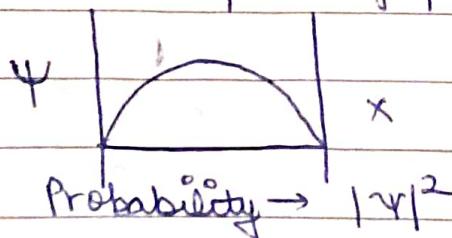
Digital Electronics experiments

S	R	G
0	1	0
1	0	1

Deterministic

⑥ Quantum Mechanics :-

Particle in a box → undeterministic
(pos? of particle)



★ Randomness is the fundamental property in Quantum Mechanics.

(Just a function which allocates a real no./value which is associated with each sample point) 1/1

* Random Variable: $(X) \quad (n \rightarrow f(x))$ (probability distribution)

$X: S \rightarrow R$
 \downarrow (Real no.)
 Sample space

Eg:- Expt: Tossing 2 coins

$$S = \{HH, TT, TH, HT\}$$

$X = \text{no. of heads} - \text{no. of tails}$

$$X = \{2, -2, 0, 0\}$$

Find probability distribut. (probability of getting each value of random variable)

X	$P(X)$	x^2	$x^2 P(X)$	$\sum P(X) = 1$
2	$\frac{1}{4}$	4	1	$\sum P(X) = 1$
0	$\frac{2}{4}$	0	0	
-2	$\frac{1}{4}$	4	1	
	1	2		

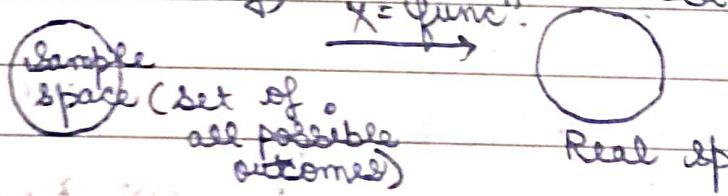
$$E(X) = \sum_{i=1}^3 X_i P(X_i) \quad (\text{discrete distribut.})$$

$$\mu = E(X) = 2 \times \frac{1}{4} + 0 \times \frac{2}{4} - 2 \times \frac{1}{4} = 0$$

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

$$= 2 - 0 = 2$$

\Rightarrow Mathematically,



* Types of Probability distributions:-

Discrete
 Binomial Poisson

$$f(x_k) > 0$$

$$\sum f(x_k) = 1$$

continuous
 Beta Gamma Normal

$$f(x_i) > 0$$

$$\int_{-\infty}^{\infty} f(x) dx = 1$$

* Expectation Values:-

$$\mu = E(X) = \sum_{\text{discrete}} x_i f(x_i)$$

(mean) (discrete)

$$E(X^2) = \sum_{\text{discrete}} x_i^2 f(x_i)$$

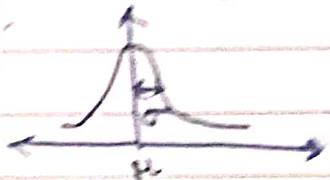
$$E(x) = \int x f(x) dx$$

(continuous)

$$E(x^2) = \int x^2 f(x) dx$$

* Normal Distribution:- (Gaussian Distribution)

$$N(x; \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}} e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$



$$X \sim N(\mu; 15, 2^2)$$

$$P(X > z) = \int_z^{\infty} f(x) dx$$

[95% Confidence Interval] = $\mu - 1.96\sigma, \mu + 1.96\sigma$

→ Standard Normal Variable, $Z = \frac{X-\mu}{\sigma}$

→ Find mean and variance of Beta and Gamma functions respectively.

$$\text{Beta } (\alpha, \beta) = \frac{\Gamma_{\alpha+\beta}}{\Gamma_{\alpha}\Gamma_{\beta}} x^{\alpha-1} (1-x)^{\beta-1} \quad (x \text{ range } \rightarrow [0, 1])$$

$$\text{Gamma } (x; r, \gamma) = \frac{1}{\Gamma_r} x^{r-1} e^{-\gamma x} \quad (x \rightarrow [0, \infty))$$

For Beta $\rightarrow \mu = E(x)$

$$= \int_0^1 x f(x) dx$$

we know $\int_0^1 f(x) dx = 1$

$$= \int_0^1 x \frac{\Gamma_{\alpha+\beta}}{\Gamma_{\alpha}\Gamma_{\beta}} x^{\alpha-1} (1-x)^{\beta-1} dx$$

$$= \frac{\Gamma_{\alpha+\beta}}{\Gamma_{\alpha}\Gamma_{\beta}} \int_0^1 x^{\alpha} (1-x)^{\beta-1} dx$$

$$\begin{aligned}
 &= \frac{\Gamma_{\alpha+\beta}}{\Gamma_{\alpha} \Gamma_{\beta}} \int x^{\alpha+1} (1-x)^{\beta-1} \times \left(\frac{\Gamma_{\alpha+\beta+1}}{\Gamma_{\alpha+1}} \right) \times \left(\frac{\Gamma_{\alpha+1}}{\Gamma_{\alpha+1}} \right) dx \\
 &= \frac{\Gamma_{\alpha+\beta+1}}{\Gamma_{\alpha} (\Gamma_{\beta} \times \Gamma_{\alpha+\beta+1})} \times \frac{\Gamma_{\alpha+1}}{\Gamma_{\alpha+1}} \times \int x^{(\alpha+1)-1} (1-x)^{\beta-1} f(x) dx
 \end{aligned}$$

$$= \frac{\Gamma_{\alpha+\beta+1} \times \Gamma_{\alpha+1}}{\Gamma_{\alpha} \times \Gamma_{\beta+1}} = \frac{\Gamma_{\alpha+\beta} \times \alpha}{\Gamma_{\alpha} \times (\alpha+\beta)} \frac{\Gamma_{\alpha}}{\Gamma_{\beta}}$$

Mean = $\frac{\alpha}{\alpha+\beta}$
(Beta)

Similarly, $E(X^2) = \int_0^\infty x^2 f(x) dx$

$$\begin{aligned}
 &= \int_0^\infty x^2 \frac{\Gamma_{\alpha+\beta}}{\Gamma_{\alpha} \Gamma_{\beta}} x^{\alpha-1} (1-x)^{\beta-1} dx \\
 &= \int_0^\infty \frac{\Gamma_{\alpha+\beta} \times (\Gamma_{\alpha+\beta+2})}{\Gamma_{\alpha} \Gamma_{\beta} \Gamma_{\alpha+\beta+2}} \times \frac{\Gamma_{\alpha+2}}{\Gamma_{\alpha+2}} \times x^{(\alpha+2)-1} (1-x)^{\beta-1} dx \\
 &= \frac{\Gamma_{\alpha+\beta} \Gamma_{\alpha+2}}{\Gamma_{\alpha} \Gamma_{\alpha+\beta+2}} = \frac{\Gamma_{\alpha+\beta} \alpha (\alpha+1)}{\Gamma_{\alpha} (\alpha+\beta+1) (\alpha+\beta)} \frac{\Gamma_{\alpha}}{\Gamma_{\beta}} \\
 &= \frac{\alpha (\alpha+1)}{(\alpha+\beta) (\alpha+\beta+1)}
 \end{aligned}$$

Variance = $E(X^2) - (E(X))^2$

$$= \frac{\alpha (\alpha+1)}{(\alpha+\beta) (\alpha+\beta+1)} - \frac{\alpha^2}{(\alpha+\beta)^2}$$

$$= \frac{(\alpha^2+\alpha)(\alpha+\beta+1) - \alpha^2(\alpha+\beta)}{(\alpha+\beta)^2}$$

$$= \frac{\alpha^3 + \alpha^2 \beta + \alpha^2 + \alpha^2 + \alpha \beta + \alpha - \alpha^3 - \alpha^2 \beta}{(\alpha+\beta)^2}$$

$$\text{Variance} = \frac{\alpha\beta(\alpha+\beta+1)}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

see

$$\frac{\alpha\beta}{(\alpha+\beta)^2(\alpha+\beta+1)}$$

\Rightarrow for Gamma :-

$$\begin{aligned} E(x) &= \int x f(x) dx \\ &= \int_0^\infty x \left(\frac{v^r}{\Gamma_r} x^{r-1} e^{-vx} \right) dx \\ &= \frac{v^r}{\Gamma_r} \int_0^\infty x^{r+1} e^{-vx} dx \\ &= \frac{v^r}{\Gamma_r} \times \frac{\Gamma_{r+1}}{v^{r+1}} \times \cancel{e^{-v(r+1)}} \\ &= \frac{v^r}{\Gamma_r} \times \frac{\Gamma_{r+1}}{v^{r+1}} \times \cancel{e^{-v(r+1)}} \\ &= \frac{v^r}{v^r v} \times r \frac{\Gamma_r}{\Gamma_r} \times \cancel{\frac{e^{-v(r+1)}}{e^{-v(r+1)}}} \end{aligned}$$

$$\mu = \text{Mean} = \frac{r}{v}$$

(Gamma)

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

(Gamma)

$$\begin{aligned} E(X^2) &= \int x^2 \frac{v^r}{\Gamma_r} x^{r-1} e^{-vx} dx \\ &= \frac{v^r}{\Gamma_r} \int_0^\infty x^{r+2} e^{-vx} \frac{v^{r+2}}{v^{r+2}} \frac{\Gamma_{r+2}}{\Gamma_{r+2}} dx \\ &= \frac{v^r}{v^r v^2} \times (r+1) \frac{\Gamma_r}{\Gamma_r} = \frac{r(r+1)}{v^2} \end{aligned}$$

$$\text{Variance} (\sigma^2) = \frac{1}{N} \sum_{i=1}^N (x_i - \bar{x})^2 = \frac{\sum_{i=1}^N (x_i - \bar{x})^2}{N}$$

$$= \frac{\sum_{i=1}^N (x_i^2 - 2\bar{x}x_i + \bar{x}^2)}{N} = \frac{\sum_{i=1}^N x_i^2 - N\bar{x}^2}{N} = \frac{\sum_{i=1}^N x_i^2}{N} - \bar{x}^2$$

Numericals:-

(i) Conditional Probability

- 1) A dice is rolled. Find the probability of getting even given that roll always gives more than 2.

$$\Rightarrow S = \{1, 2, 3, 4, 5, 6\}$$

A: Getting even

B: more than 2

$$B \rightarrow (\text{sample space reduce}) = \{3, 4, 5, 6\}$$

$$A \cap B = \{4, 6\}$$

$$P(A/B) = \frac{P(A \cap B)}{P(B)} = \frac{2/6}{4/6} = \frac{1}{2}$$

- 2) A bag contains 5 white and 4 red balls. Find probability of drawing a red ball in second draw given that white ball is drawn in first draw.

$$\Rightarrow$$

$$\begin{array}{l} 0.5W \\ 0.4R \end{array}$$

$$P(WR/W-) = ?$$

$$P(W \cap R) = \frac{5/9 \times 4/8}{5/9 \times 4/8 + 5/9 \times 4/8} = \frac{1}{2}$$

3)

$$\begin{array}{l} 10 \text{ White} \\ 15 \text{ Blue} \end{array}$$

$$P(WB) (\text{without replacement}) = ?$$

$$P(WB) = \frac{\frac{1}{2} \times \frac{1}{3}}{\frac{25}{30}} = \frac{1}{4}$$

- 4) A couple has two children. Find probability that

Both are boys if it is known that one child is a boy.

$$\Rightarrow S = \{BB, GG, GB, BG\}$$

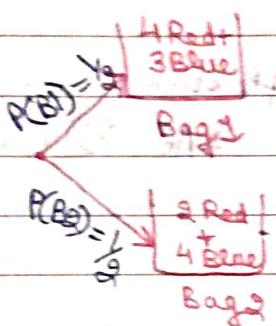
A: Both are boys : {BB}

B: One child is a boy $\rightarrow \{BB, BG, GB\}$

$$P(A/B) = \frac{P(A \cap B)}{P(B)} = \frac{\frac{1}{4}}{\frac{3}{4}} = \frac{1}{3}$$

\rightarrow Total Probability

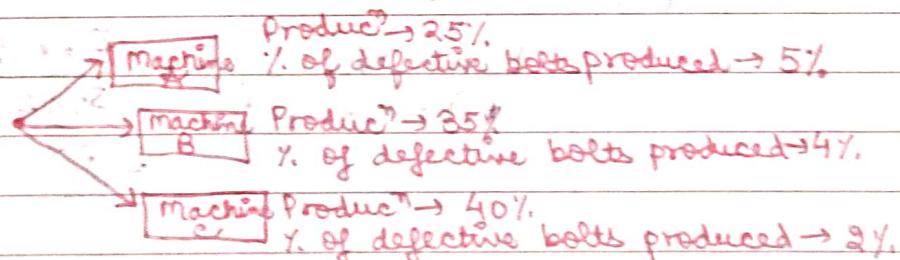
5:



One ball from one bag
(choosing one bag
and then one ball)

$$\begin{aligned} P(\text{Red}) &= P(B) P(R/B) + P(B_2) P(R/B_2) \\ &= \frac{1}{2} \times \frac{4}{7} + \frac{1}{2} \times \frac{2}{5} \\ &= \frac{2}{7} + \frac{1}{5} = \frac{10+7}{35} = \frac{17}{35} \end{aligned}$$

6:



$$\therefore P(M_A) = \frac{25}{100} = \frac{1}{4} \quad P(D/M_A) = \frac{5}{100} = \frac{1}{20}$$

$$P(M_B) = \frac{7}{20}$$

$$P(M_C) = \frac{4}{5} = \frac{20}{25}$$

$$P(D/M_B) = \frac{4}{100} = \frac{1}{25}$$

$$P(D/M_C) = \frac{2}{100} = \frac{1}{50}$$

$$P(D) = \frac{1}{4} \times \frac{1}{20} + \frac{7}{20} \times \frac{1}{25} + \frac{2}{5} \times \frac{1}{50} = 0.0345$$

\Rightarrow Baye's Rule :-

\Rightarrow In Q6, if bolt is found to be defective, find the probability that it is manufactured from machine A?

$\Rightarrow A \Rightarrow$ Machine A manufactured

$B \Rightarrow$ Defective

$$P(A/B) = \frac{P(B/A) P(A)}{P(B)} = \frac{0.20 \times \frac{1}{4}}{0.0345} = 0.362$$

Q7 Lab test \rightarrow 99% effective (disease detected)

$$P(+/\text{D}) = 0.99$$

$$P(\text{D}) = 0.005$$

$$(i) P(+) = ?$$

$$(ii) P(\text{D}/+) = ?$$

$$\Rightarrow (i) P(+) = 0.005 \times 0.99 + 0.01 \times 0.995$$

$$= 0.0149$$

$$(ii) P(\text{D}/+) = \frac{P(+/\text{D}) P(\text{D})}{P(+)} = \frac{0.99 \times 0.005}{0.0149}$$

$$= 0.3322$$

* Continuous Probability Distribut' Func'

PDF (Probability Density Func')

Discrete \rightarrow PMF (Probability Mass Func')

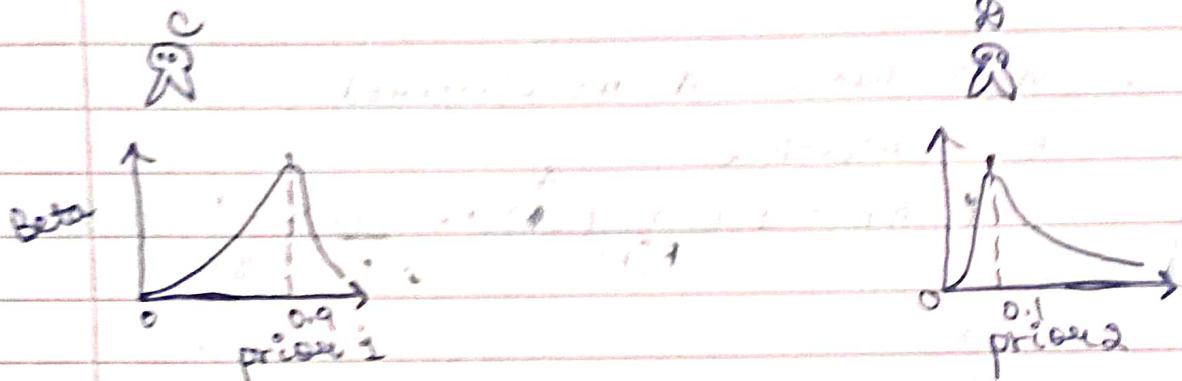
* Bayesian Statistics:-

Posterior Distribution	of Prior (Personal Bias Distribut'')	\times Likelihood [Real data (for eg. survey)]
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For eg. there are 2 political parties A and B.
Person C believes strongly that A would win because he talked to people of this region and also

prior

admire it strongly (personal bias). Person B believes it would not win because he doesn't like it (personal bias).



We take a survey of 10 people regarding it in Yes or No.

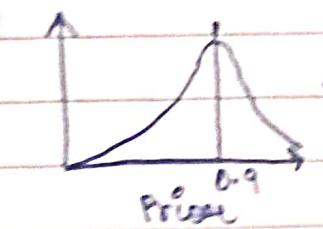
Out of 10 people, 3 people said yes or it winning (likelihood). ($n=10$ (binomial)
 $k=3$)

$$Bin(n, \theta) = {}^n C_k \theta^k (1-\theta)^{n-k}$$

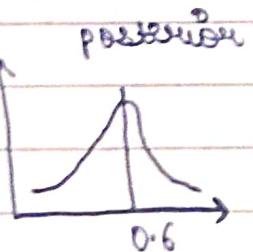
posterior of prior \times likelihood

$$\propto Bin(3) \times {}^{10} C_3 \theta^3 (1-\theta)^{10-3}$$

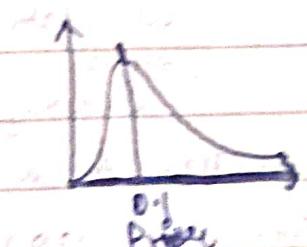
→ Person C



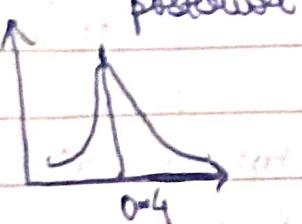
\times likelihood \Rightarrow



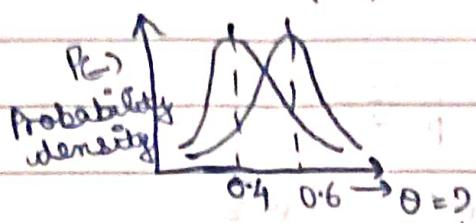
→ Person D



\times likelihood \Rightarrow



Training these two graphs,



Now,

Prior

Beta(d, p)

Gamma(r, v)

Normal(μ, σ^2)

Likelihood

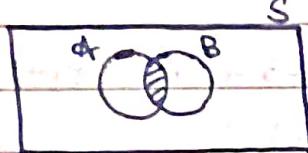
~~Binomial~~ Binomial(n, θ)

~~Gamma~~ Poisson(λ)

Normal(μ, σ^2)

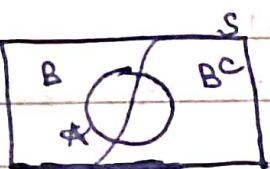
* Different Formulas:-

1.▷



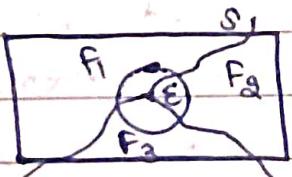
$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad (\text{conditional probability})$$

2.▷



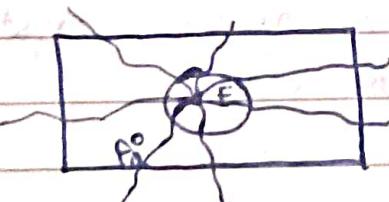
$$P(A) = P(A \cap B) + P(A \cap B^c) \quad (\text{total probability})$$

3.▷



$$\begin{aligned} P(E) &= P(E \cap F_1) + P(E \cap F_2) + P(E \cap F_3) \\ P(E) &= P(E|F_1)P(F_1) + P(E|F_2)P(F_2) + \\ &\quad P(E|F_3)P(F_3) \end{aligned}$$

4.▷



$$P(E) = \sum_{i=1}^n P(E|F_i) P(F_i)$$

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

(Bayes' Theorem)

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

* Frequentist

$$P(F_i | E) = \frac{P(F_i \cap E)}{P(E)}$$

$$= \frac{P(E|F_i) P(F_i)}{\sum_{j=1}^n P(E|F_j) P(F_j)}$$

* Bayesian Approach \Rightarrow likelihood prior

$$(Probability density) g(\theta|y) = \frac{f(y|\theta) \times g(\theta)}{\int f(y|\theta) g(\theta) d\theta}$$

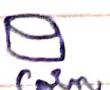
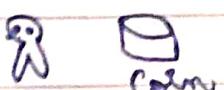
$\underbrace{f(y|\theta)}_{\text{posterior}}$

- Generally, θ can be parameter (Probability/ mean/ variance/ regress coefficients)
- Let's take θ as probability.
- Eg. suppose θ is probability of getting heads on tossing coin.

A tosses coin 5 times and he gets heads all the time. (So, for A, $\theta = 1$) (Frequentist approach)

But, if B says one more time and 6th time A gets tail, so θ becomes $5/6$. (Frequentist)

Frequentist Approach \Rightarrow For a given system, θ is fixed but unknown to me.



coin
 $\theta = \text{const.}$
(unknown)

$$5 \text{ times} || 6 \text{ times} - - - \rightarrow \log \theta \\ \theta = 1 \quad | \quad \theta = 5/6 \quad | \quad \theta = \frac{6520}{1000}$$

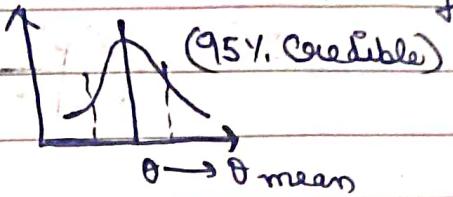
[More no. of trials means more closer value to the true value of θ]

\Rightarrow Bayesian Approach :- θ = not const.

θ = unknown

(Random variable)

\Rightarrow Probability density



$$\mu = E(\theta) = \int_{-\infty}^{\infty} \theta g(\theta) d\theta$$

$\theta \rightarrow \theta = ??$

Given, prior = Beta(3, 2)

Likelihood ($n=10, y=6$) \rightarrow Binomial(n, θ)

$$g(\theta|y) = \frac{\text{Beta}(3, 2) \times \text{Bin}(10, \theta)}{\int_0^1 \text{Beta}(3, 2) \text{Bin}(10, \theta) d\theta}$$

$$\text{Beta}(3, 2) = \frac{\Gamma_5}{\Gamma_3 \Gamma_2} \theta^{3-1} (1-\theta)^{2-1}$$

$$\text{Bin}(10, \theta) = {}^{10}C_6 \theta^6 (1-\theta)^{10-6}$$

$$\therefore g(\theta|y) = \frac{\frac{\Gamma_5}{\Gamma_3 \Gamma_2} \times \theta^{3-1} (1-\theta)^{2-1} \times {}^{10}C_6 \times \theta^6 \times (1-\theta)^{10-6}}{\int_0^1 \frac{\Gamma_5}{\Gamma_3 \Gamma_2} \theta^{3-1} (1-\theta)^{2-1} \times {}^{10}C_6 \times \theta^6 \times (1-\theta)^{10-6} d\theta}$$

$$= \theta^{9-1} \times (1-\theta)^{6-1} \times \frac{\Gamma_{10+6}}{\Gamma_{10+6}} \times \frac{\Gamma_9 \times \Gamma_6}{\Gamma_9 \times \Gamma_6}$$

$$= \theta^{9-1} \times (1-\theta)^{6-1}$$

4

$$g(\theta|y) \underset{?}{=} \text{Beta}(9, 6)$$

$$E[\mu] = \int \theta g(\theta/\bar{y}) d\theta = \frac{\alpha' \beta'}{\alpha' + \beta'}$$

$$\text{Mean} = \frac{q}{q+6} = \frac{9}{15} = 0.6$$

$$\sigma^2 = \frac{\alpha' \beta'}{(\alpha' + \beta')^2 (\alpha' + \beta' + 1)}$$

Q) In a study of water supply from a stream, $n=16$ samples were taken from different sites. Out of these, $y=9$ had high bacteria level. Let θ be true probability that a sample of water from this stream has a high bacteria level.

(a) Use beta "distribution" $\text{Beta}(1, 10)$ as prior for θ , calculate posterior "distribution".

\Rightarrow prior $\rightarrow \text{Beta}(1, 10)$

$$= \left[\frac{\Gamma_1 \Gamma_{10}}{\Gamma_1 \Gamma_{10}} \times \theta^{1-1} (1-\theta)^{10-1} \right]$$

Likelihood $\Rightarrow \text{Bin}(16, \theta)$

$$= \left[\frac{16}{24} \times \theta^{24} (1-\theta)^{152} \right]$$

Posterior = prior \times likelihood

$$= \frac{\Gamma_1}{\Gamma_1 \Gamma_{10}} \times \theta^0 (1-\theta)^9 \times \frac{16}{24} \times \theta^{24} (1-\theta)^{152}$$

$$= \frac{\int_0^1 \frac{\Gamma_1}{\Gamma_1 \Gamma_{10}} \times \theta^0 (1-\theta)^9 \times \frac{16}{24} \times \theta^{24} (1-\theta)^{152}}{\Gamma_1 \Gamma_{10}}$$

$$= \theta^{25-1} (1-\theta)^{162-1} \times \frac{\Gamma_{25+162}}{\Gamma_{25+162}} \times \frac{\Gamma_{25}}{\Gamma_{25}} \times \frac{\Gamma_{162}}{\Gamma_{162}}$$

$$\left\{ \int_0^1 \theta^{25-1} (1-\theta)^{162-1} \right\} \downarrow$$

$$\downarrow \left(\because \int_0^1 f(x) dx = 1 \text{ (Beta)} \right)$$

posterior = Beta(25, 162)

(b) Find posterior mean and variance.

$$\rightarrow \text{Mean} = \frac{\alpha}{\alpha + \beta} = \frac{25}{25 + 162} = 0.133$$

$$\text{Variance} = \frac{\alpha \beta}{(\alpha + \beta)^2 (\alpha + \beta + 1)} = \frac{25 \times 162}{(25 + 162)^2 (25 + 162 + 1)} \\ = 0.000616$$

(c) Approximate Posterior distribution to Normal distribution using posterior μ & σ^2 as normal μ and σ^2 and find 95% credible interval.

$$\Rightarrow \mu = 0.133$$

$$\sigma^2 = 0.000616 \Rightarrow \sigma = 0.0248$$

$$95\% \text{ Credible interval} \Rightarrow (\mu - 1.96\sigma, \mu + 1.96\sigma) \\ (\text{Normal})$$

$$= (0.133 - 1.96 \times 0.0248, 0.133 + 1.96 \times 0.0248)$$

$$= (0.084392, 0.181608)$$

★ Poisson Distribution :- No. of count in given time interval (t)

or

limiting case of Binomial distribution in which $n \rightarrow \infty$ and $\theta \rightarrow 0$. (A very rare occurrence). For eg. accidents happening on the road.

Frequentist $\Rightarrow \lambda$ fixed (const.)
(unbiased)

Bayesian $\Rightarrow \lambda \infty$ Random Variable
(not fixed)
(unbiased)

Free e.g. count of nuclei decaying per hour,
5, 20, 0, 23, 10

$$y_1, y_2, y_3, y_4, y_5 \dots \text{ if } (y_1, y_2, y_3, \dots \sim y_i / \lambda) \\ \Rightarrow \frac{y_1}{\lambda} e^{-\lambda}, \frac{y_2}{\lambda} e^{-\lambda}, \dots, \frac{y_i}{\lambda} e^{-\lambda}, \dots$$

$$\frac{\prod_{i=1}^n y_i}{\lambda^n} e^{-n\lambda}$$

\Rightarrow Beta \Rightarrow gamma

$$g(\lambda) = \text{gamma}(\lambda; r, v) \\ = \frac{1}{\Gamma_r} \lambda^{r-1} e^{-v\lambda}$$

$$\rightarrow \text{posterior} = \frac{\prod_{i=1}^n y_i}{\lambda^n} \times \frac{\prod_{i=1}^n \lambda^{r-1} e^{-v\lambda}}{\Gamma_r}$$

$$\int_0^\infty \frac{\prod_{i=1}^n \lambda^{r-1} e^{-v\lambda} \prod_{i=1}^n y_i}{\Gamma_r} \lambda^{r-1} e^{-v\lambda} d\lambda$$

$$N \left(\frac{(r+\sum y_i)}{(v+n)}, \frac{(v+n)}{(v+n)^2 + \sum y_i} \right)$$

$$\int_0^\infty \lambda^{(r+\sum y_i)-1} e^{-(v+n)\lambda} d\lambda$$

$$= \text{gamma}(\lambda; (v+\sum y_i), (v+n))$$

$$[\text{Mode (beta)} = \frac{\alpha - 1}{\alpha + \beta - 2}]$$

Gamma → Mean = $\frac{n}{\lambda}$
 Variance = $\frac{n}{\lambda^2}$

$$\text{Modal value} = \frac{n-1}{\lambda}$$

* Binomial → mean = $n\theta$
 Variance = $n\theta(1-\theta)$

Poisson → mean = λ
 Variance = λ

Q → Find mean and variance of binomial and poisson.

$$\Rightarrow \text{Binomial} = \sum_{x=0}^n {}^n C_x \theta^x (1-\theta)^{n-x} = f(x)$$

$$\text{For mean, } E(x) = \sum_{x=0}^n x f(x)$$

$$= \sum_{x=0}^n x {}^n C_x \theta^x (1-\theta)^{n-x}$$

$$= 0 + \sum_{x=1}^n x \times \frac{n!}{(n-x)! x!} \theta^x (1-\theta)^{n-x}$$

$$= 0 + \sum_{x=1}^n x \times \frac{n!}{(n-x)! x! (x-1)!} \theta^x (1-\theta)^{n-x}$$

$$= \sum_{x=1}^n \frac{n! (n-1)!}{((n-1)-(x-1))! (x-1)!} \times \theta^x \times \theta \times (1-\theta)^{n-x} \times (1-\theta)$$

$$= \boxed{n\theta} \quad (\text{since } \sum_{x=0}^n f(x) = 1)$$

for variance,

$$\text{Variance} = E(x^2) - [E(x)]^2 = [E(x^2) - \mu^2]$$

$$E(x^2) = E(x^2 - x + x)$$

$$= E(x(x-1)+x) = E(x(x-1)) + E(x)$$

$$= E(x(x-1)) + \mu$$

$$E(x^2) = E(x(x-1)) + \mu$$

$$E(x(x-1)) = \sum_{x=0}^n x(x-1)^m C_2 \theta^x (1-\theta)^{n-x}$$

$$= 0 + \sum_{x=1}^n x(x-1) \frac{n!}{(n-x)! x(x-1)(x-2)!} \theta^x (1-\theta)^{n-x}$$

$$= \sum_{x=1}^n \frac{n(n-1)(n-2)!}{(n-2)-(x-2)! (x-2)!} \times \theta^x \times \frac{\theta^2}{\theta^2} \times (1-\theta)^{n-2-(x-2)}$$

$$= n(n-1)\theta^2 = \boxed{n^2\theta^2 - n\theta^2}$$

$$\text{Variance} = n^2\theta^2 - n\theta^2 - \cancel{n\theta^2} + \mu$$

$$= n\theta - n\theta^2$$

$$= \boxed{n\theta(1-\theta)} = \boxed{npq}$$



Poisson :- $f(x) = \frac{\lambda^x e^{-\lambda}}{x!}$

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

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

$$= \boxed{\lambda}$$

$$\text{Var} = E(x^2) - \mu^2$$

$$E(x^2) = E(x(x-1)) + \mu$$

$$E(x(x-1)) = \sum_{n=1}^{\infty} (x-1)x^n e^{-\lambda} \frac{x^n}{n(n-1)(n-2)!} \times \frac{x^2}{x^2}$$

$$= x^2$$

$$E(x^2) = \lambda^2 + \lambda(\mu)$$

$$\text{Var} = \lambda^2 + \boxed{\lambda} - \lambda^2$$

likelihood	parameters	Prior	Posterior
Binomial	$\text{Bin}(n, \theta)$	Beta(α, β)	Beta($\alpha' + \beta'$)
Poisson	$\text{Poi}(\lambda)$	$\text{Gamma}(\gamma, \gamma)$	$\text{Gamma}(\gamma' + \gamma')$
Normal	$N(\mu, \sigma^2)$	$\text{Normal}(\mu_0, \sigma_0^2)$	$\text{Normal}(\mu', \sigma'^2)$

★ Normal \rightarrow likelihood $\rightarrow N(m, \sigma^2)$

Normal \rightarrow Prior $\rightarrow N(\mu_0, \sigma_0^2)$ given

\rightarrow likelihood $\rightarrow w_1, w_2, w_3, \dots, w_n \sim N(\mu, \sigma^2)$

$$\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(w_i - \mu)^2}{2\sigma^2}} \quad (\text{Similarly for all data points})$$

$$\text{likelihood} = \left(\frac{1}{\sqrt{2\pi}\sigma} \right)^n e^{-\frac{\sum (w_i - \mu)^2}{2\sigma^2}}$$

\rightarrow Prior, $g(\mu) \sim N(m, \sigma^2) \rightarrow \frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\mu - m)^2}{2\sigma^2}}$

that
to find
(whatever
is written
here is
variable)

Posterior

$$\frac{1}{\sqrt{2\pi}\sigma} e^{-\frac{(\mu - m)^2}{2\sigma^2}} \cdot \left(\frac{1}{\sqrt{2\pi}\sigma} \right)^n e^{-\frac{\sum (w_i - \mu)^2}{2\sigma^2}}$$

$$\int_{-\infty}^{\infty} \dots d\mu$$

$$= \left[e^{-\frac{m}{2\sigma^2} [\mu - \bar{y}]^2} \cdot e^{-\frac{(\mu - m)^2}{2\sigma^2}} \right] (\bar{y} = \sum \frac{y_i}{n})$$

$$\int \dots d\mu$$

$$= e^{-\frac{m}{2\sigma^2} [\mu - \bar{y}]^2 + \frac{1}{2\sigma^2} [\mu - m]^2}$$

$$= e^{-\frac{m}{2\sigma^2} [m\mu^2 + \bar{y}^2 - 2\mu\bar{y}] + \frac{1}{2\sigma^2} [\mu^2 + m^2 - 2\mu m]}$$

$$= e^{-[\frac{m}{2\sigma^2} + \frac{1}{2\sigma^2}] \mu^2 + (\frac{m\bar{y}^2 + m^2}{2\sigma^2}) - 2\mu(\frac{m\bar{y}}{\sigma^2} + \frac{m}{2\sigma^2})}$$

$$= e^{-[\frac{m}{2\sigma^2} + \frac{1}{2\sigma^2}] \left(\mu^2 - 2\mu \left(\frac{m\bar{y}}{\sigma^2} + \frac{m}{2\sigma^2} \right) \right)} \text{const.}$$

$$= e^{-[\frac{m}{2\sigma^2} + \frac{1}{2\sigma^2}] \left(\mu^2 - 2\mu \left(\frac{m\bar{y}}{\sigma^2} + \frac{m}{2\sigma^2} \right) + \frac{(m\bar{y} + m)^2}{2\sigma^2} \right)} \text{const.}$$

$$= e^{-[\frac{m}{2\sigma^2} + \frac{1}{2\sigma^2}] \left(\mu^2 - 2\mu \left(\frac{m\bar{y}}{\sigma^2} + \frac{m}{2\sigma^2} \right) + \frac{(m\bar{y} + m)^2}{2\sigma^2} \right)} \text{const.}$$

$$= e^{-\frac{1}{2} \left(\frac{m}{\sigma^2} + \frac{1}{2\sigma^2} \right) \left(\mu - \left(\frac{m\bar{y} + m}{\frac{m}{\sigma^2} + \frac{1}{2\sigma^2}} \right) \right)^2}$$

$$\text{Prior} = e^{-\frac{1}{2} \left(\frac{m}{\sigma^2} + \frac{1}{2\sigma^2} \right) \left(\mu - \left(\frac{m\bar{y} + m}{\frac{m}{\sigma^2} + \frac{1}{2\sigma^2}} \right) \right)^2}$$

$$\begin{aligned} \sigma^{1/2} &= \left(\frac{1}{\sigma^2} + \frac{m}{\sigma^2} \right)^{-1} \\ \frac{1}{\sigma^{1/2}} &= \frac{1}{\sigma^2} + \frac{m}{\sigma^2} \end{aligned}$$

$$\mu' = \frac{m}{\frac{1}{\sigma^2} + \frac{m}{\sigma^2}} \cdot m \left(\frac{\frac{1}{\sigma^2}}{\frac{1}{\sigma^2} + \frac{m}{\sigma^2}} \right) + \left(\frac{\frac{m}{\sigma^2}}{\frac{1}{\sigma^2} + \frac{m}{\sigma^2}} \right) \bar{y}$$

→ Data (given) $\xrightarrow{\text{prior, } \sigma^2 \text{ like}}$
 likelihood $\sim N(\mu, \sigma^2)$ $\xrightarrow{\text{given}}$

$$\text{prior} \sim N(\mu_{\text{prior}}, \frac{\sigma^2}{n} \text{ prior})$$

$$\text{posterior} \sim N(\mu^{\text{post}}, \sigma^2_{\text{post}})$$

$$\left[\frac{1}{\sigma^2_{\text{Post}}} = \frac{1}{\sigma^2_{\text{Prior}}} + \frac{n}{\sigma^2_{\text{likelihood}}} \right]$$

$$\left[\mu^{\text{post}} = \frac{\frac{1}{\sigma^2_{\text{prior}}} \times \mu_{\text{prior}} + \frac{n}{\sigma^2_{\text{like}}} \times \bar{x}}{\frac{1}{\sigma^2_{\text{Prior}}} + \frac{n}{\sigma^2_{\text{like}}}} \right] \quad \begin{matrix} \uparrow \text{Mean} \\ \text{of data set} \end{matrix}$$

★ Probability Mass func:— Let X be a discrete random variable such that $P(X=x)=P_i$, then P_i is said to be probability Mass func if it satisfies following conditions:

- (i) $P_i \geq 0$ | for pdf (probability density func), (i) $f(x) \geq 0$
- (ii) $\sum P_i = 1$ | $\int_{-\infty}^{\infty} f(x) dx = 1$

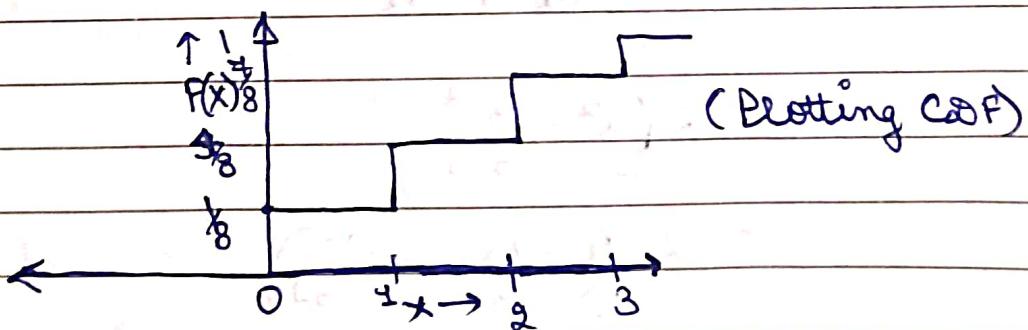
★ Cumulative Distribut Func:— $F(x)$

Let X be a discrete random variable such that its cdf is defined as $F(x) = \sum P_i = P(x \leq x)$.

for eg.

$$F(x) = \begin{cases} \frac{1}{8} & x \leq 0 \\ \frac{4}{8} & x \leq 1 \\ \frac{7}{8} & x \leq 2 \\ 1 & x \leq 3 \end{cases}$$

for eg,
 x (No. of heads) | 0 | 1 | 2 | 3
 P | $\frac{1}{8}$ | $\frac{3}{8}$ | $\frac{3}{8}$ | $\frac{1}{8}$



Q → If x is a continuous Random Variable with the following pdf

$$f(x) = \begin{cases} \alpha(2x-x^2) & 0 < x < 2 \\ 0 & \text{elsewhere} \end{cases}$$

(i) find α

(ii) $P(x > 1)$

\Rightarrow (i) By defⁿ of pdf, $\int_{-\infty}^{\infty} f(x) dx = 1$

$$= \int_{-\infty}^0 f(x) dx + \int_0^2 f(x) dx + \int_2^{\infty} f(x) dx = 1$$

$$= \int_0^2 \alpha(2x-x^2) dx = 1$$

$$= \alpha \left[2 \frac{x^2}{2} - \frac{x^3}{3} \right]_0^2 = 1$$

$$= \alpha \left[4 - \frac{8}{3} \right] = 1$$

$$\alpha = \frac{3}{4} \quad \text{(1)}$$

(ii) $P(x > 1)$

$$= \int_1^2 f(x) dx + \int_2^{\infty} f(x) dx$$

$$= \alpha \int_1^2 (2x-x^2) dx$$

$$= \alpha \left[2 \frac{x^2}{2} - \frac{x^3}{3} \right]_1^2$$

$$= \alpha \left(\left(4 - \frac{8}{3} \right) - \left(1 - \frac{1}{3} \right) \right)$$

$$= \alpha \left(4 - \frac{8}{3} - 1 + \frac{1}{3} \right) = \alpha \left(3 - \frac{7}{3} \right) = \alpha \left(\frac{2}{3} \right)$$

$$= \frac{2}{3} \times \frac{1}{2} = 0.5 \text{ Ans}$$

Cumulative Distribut" Func" (cdf):- (Continuous R.V.)

Let x be continuous random variable.

Having pdf $f(x)$ then $F_x(x)$ will be a
continuous distribut" func" of x if

$$F_x(x) = P(X \leq x) = \int_{-\infty}^x f(x) dx$$

cdf

→ Rel" b/w cumulative distribut" func" (cdf) and
probability density func" (pdf):-

$$\left[\frac{d}{dx} F(x) = f(x) \right]$$

→ Probability dist. density func" of Random
Variable x if

$$f(x) = \begin{cases} x, & 0 \leq x \leq 1 \\ 2-x, & 1 < x \leq 2 \\ 0, & \text{o/w} \end{cases}$$

① find $P(X \geq 1.5)$

② find cdf (cumulative distribut" func").

$$\begin{aligned} \Rightarrow ① P(X \geq 1.5) &= \int_{1.5}^{\infty} f(x) dx \\ &= \int_{1.5}^2 f(x) dx + \int_2^{\infty} f(x) dx \\ &= \int_{1.5}^2 (2-x) dx \\ &= 2 \left[x - \frac{x^2}{2} \right]_{1.5}^2 = 2 \left((2-2) - (1.5 - \frac{2.25}{2}) \right) \\ &= 0.125 \end{aligned}$$

② Cdf

$$x \leq 0$$

$$P(X \leq x) = \int_{-\infty}^x f(x) dx$$

$$0 < x < 1$$

$$f(x) = \int_{-\infty}^0 f(x) dx + \int_0^x f(x) dx$$
$$= 0 + \int_0^x x dx = \frac{x^2}{2}$$

$$x \leq 2$$

$$f(x) = \int_{-\infty}^0 f(x) dx + \int_0^1 f(x) dx + \int_1^x f(x) dx$$
$$= \int_0^x x dx + \int_x^2 (2-x) dx$$
$$= -1 + 2x - \frac{x^2}{2}$$

$$x > 2$$

$$f(x) = \int_{-\infty}^0 f(x) dx + \int_0^1 f(x) dx + \int_1^x f(x) dx$$
$$\int_2^\infty f(x) dx$$

$$F(x) = \begin{cases} 0, & -\infty < x < 0 \\ \frac{x^2}{2}, & x \leq 1 \\ -1 + 2x - \frac{x^2}{2}, & x \geq 2 \end{cases}$$

$$\left[\text{Find } P(X \geq 1.5) \Rightarrow -1 + 2(1.5) - \frac{1.5^2}{2} = 0.125 \right]$$

— / —

★ Variance = $E(x - \bar{x})^2$

$$\begin{aligned}
 &= E(x^2 - 2x\bar{x} + \bar{x}^2) \\
 &= E(x^2) - 2\bar{x}E(x) + \bar{x}^2 \\
 &= E(x^2) - 2\bar{x}\bar{x} + \bar{x}^2 \\
 &= \boxed{E(x^2) - \bar{x}^2}
 \end{aligned}$$

$\rightarrow \int_0^\infty x^{n-1} e^{-ax} dx = \frac{1}{a^n}$

★ Bivariate Random Variable:-
 Let S be a sample space associated w/
 random experiment. Let $X(t), Y(t)$ be two
 random func's each assigning a real no.
 to each outcome $t \in S$.

Then (X, Y) is called a Bivariate or two
 dimensional Random Variable.

★ Joint Probability Mass Func of (X, Y) :-
 If (X, Y) is a two-dimensional discrete
 Random Variable, where $X = x_i$ & $Y = y_j$, $i, j = 1, 2, 3, \dots$
 Then $P(X = x_i, Y = y_j) = P_{ij}$ is called
 PMF of (X, Y) provided

$$① P_{ij} \geq 0$$

$$② \sum_{i=1}^m \sum_{j=1}^n P_{ij} = 1$$

The set of triple (x_i, y_j, P_{ij}) is
 called Joint Probability of (X, Y)

\Rightarrow Marginal Probability mass func of x :-

$$P(X = x_i) = \sum_j P_{ij} = P_{i1} + P_{i2} + \dots$$

• collect of pair (x_i, P_i) \rightarrow Marginal PMF of x .

Similarly, $P(Y = y_j) = \sum_i P_{ij} = P_{1j} + P_{2j} + \dots$

Pair $(x,y, P_{xy}) \rightarrow$ Marginal Probability of y

If X & Y are independent,
 $\text{if } P_{xy}(x,y) = P_x(x)P_y(y)$

Q → Two balls are selected at random from a box containing three red, two green and four white balls. If X and Y are no. of red balls & green balls respectively, find

① Joint Probability of X & Y

② Marginal Probabilities of X & Y

③ Conditional distribution of X given $Y=1$

\Rightarrow ①



X	$P(X)$	Y	$P(Y)$
0	$\frac{6C_0}{9C_2} / \frac{4C_2}{9C_2}$	0	$\frac{7C_0}{9C_2} / \frac{4C_2}{9C_2}$
1	$\frac{3C_1 \times 6C_0}{9C_2} / \frac{4C_2}{9C_2}$	1	$\frac{2C_1 \times 7C_0}{9C_2} / \frac{4C_2}{9C_2}$
2	$\frac{3C_2 \times 6C_0}{9C_2} / \frac{4C_2}{9C_2}$	2	$\frac{2C_2 \times 7C_0}{9C_2} / \frac{4C_2}{9C_2}$
3			

Don't do like this

$X \setminus Y$	0	1	2	Total
0	$1/6$	$2/6$	$1/36$	$15/36$
1	$1/3$	$1/6$	0	$18/36$
2	$1/12$	0	0	$3/36$
Total	$25/36$	$14/36$	$1/36$	1

$$P(0,0) = \frac{4C_0}{9C_2} / \frac{4C_2}{9C_2}$$

② Marginal Prob. of x :

x	$P(x)$
0	$15/36$
1	$18/36$
2	$3/36$

Marginal Prob. of y :

y	$P_y(y)$
0	$5/36$
1	$14/36$
2	$1/36$

$$P(X=Y=1) = \frac{P(X \cap Y=1)}{P(Y=1)} \text{ Total}$$

③

Conditional dist' of X given $Y=1$

X	$P(X Y=1)$
0	$\frac{24}{14/36} = 4/7$
1	$6/14$
2	0

Q → Joint PMF of (X, Y) is given by

$$P(x, y) = K(2x+3y)$$

$$x=0, 1, 2, \quad y=1, 2, 3$$

- find ① K ② Marginal Prob of x and y
 ③ Conditional Prob of X given $Y=1$
 ④ " " " $Y=2$ " " $X=2$ "
 ⑤ Prob. of distrib' of $X+Y$

=> ①

$X \setminus Y$	1	2	3	Total
0	3K	6K	9K	18K
1	5K	8K	11K	24K
2	7K	10K	13K	30K
Total	15K	24K	33K	72K

$$K = 1/72$$

②

X	$P(x)$	$X \rightarrow$	$Y \Rightarrow Y$	$P_y(y)$
0	$18/72$		1	$15/72$
1	$24/72$		2	$24/72$
2	$30/72$		3	$33/72$

③

same as previous ques'

④

$Z=X+Y$	$P(Z)$
1	$3/72$
2	$11/72$
3	$24/72$
4	$21/72$
5	$13/72$

Q) Are X and Y independent?
Marginal Prob.

X	$P(X)$	Y	$P_Y(Y)$
0	$18/72$	1	$15/72$
1	$24/72$	2	$24/72$
2	$30/72$	3	$33/72$

By defⁿ of independence,
 $P_{XY}(x,y) = P_X(x)P_Y(y)$

LHS

$$P_{XY}(0,1) = P_X(0)P_Y(1)$$

$$P_{XY}(0,1) = 3/72 \text{ (from joint prob. table)}$$

$$P_X(0) = 18/72, P_Y(1) = 15/72$$

$$P_X(0) \times P_Y(1) = 5/96 \neq P_{XY}(0,1)$$

(Not independent)
(X & Y)

Q) Two random variables X and Y have following pdf:-

$$f(x,y) = \begin{cases} 2-x-y, & 0 \leq x \leq 1, 0 \leq y \leq 1 \\ 0, & \text{otherwise} \end{cases}$$

→ Find marginal distⁿ of x & y .

⇒ for x ,

$$f_X(x) = \int_0^1 (2-x-y) dy = 3/2 - x, 0 < x < 1$$

$$\text{for } y, f_Y(y) = \int_0^{2-y} (2-x-y) dx = 2 - \frac{1}{2}y - y$$

$$= 3/2 - y, 0 < y < 1$$

$$Q \rightarrow f(x, y) = \begin{cases} 2e^{-2x}e^{-y}, & \text{if } x > 0, y > 0 \\ 0, & \text{otherwise} \end{cases}$$

→ find probability that $0 \leq x \leq 1, 1 \leq y \leq 2$.

$$\underline{\text{Soln}} \rightarrow \int_0^1 \int_1^2 2e^{-2x}e^{-y} dx dy$$

~~f(x)~~

$$= 2 \int_0^1 e^{-2x} \left[\frac{e^{-y}}{-1} \right]_1^2 dx$$

$$= 2 \left[\frac{e^{-2x}}{-2} \right]_0^1 \times \left[\frac{e^{-y}}{-1} \right]_1^2$$

$$= \frac{2}{-2} \left[(e^{-2} - 1) \times (e^{-2} - e^{-1}) \right]$$

$$= \left(\frac{1}{e^2} - 1 \right) \left(\frac{1}{e^2} - \frac{1}{e} \right) = \left(\frac{1-e^2}{e^2} \right) \times \left(\frac{1-e}{e^2} \right)$$

* Properties:-

Joint PDF: $f_{x,y}(x, y) = P(X \leq x, Y \leq y)$

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

Valid joint PDF

$$f_{x,y}(x, y) \geq 0$$

$$\iint_{(x,y)} f_{x,y}(x, y) dx dy = 1$$

Marginal PDF

$$X, Y \Rightarrow f_{x,y}(x, y)$$

$$f_x(x) = \int_y f_{x,y}(x, y) dy$$

$$f_y(y) = \int_x f_{x,y}(x, y) dx$$

Conditional Probability, joint probability of randomly

$$f(x|y) = \frac{f(x,y)}{f(y)} \rightarrow \text{Marginal distn of } f$$

Independence of R.V.s

$$f(x,y) = f(x)f(y)$$

Joint Probability = product of marginal probabilities

or

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

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

Properties of Variance of Random Variable

→ If x is a random variable & $a, b \rightarrow$ constts, then $\text{var}(ax + b) = a^2 \text{var}(x) + \text{var}(b)$

→ If x_1 and x_2 are independent variables, then

$$(a) \text{var}(x_1 + x_2) = \text{var}(x_1) + \text{var}(x_2)$$

$$(b) \text{var}(x_1 - x_2) = \text{var}(x_1) + \text{var}(x_2)$$

Moments for discrete random variables:-

→ Moment about origin :- $\mu'_0 = E[x^0]$

$$\mu'_1 = E[x], \mu'_2 = E[x^2], \mu'_3 = E[x^3], \mu'_4 = E[x^4]$$

mean

→ Moment about any other pt. a :- $\mu''_0 = E[x-a]^0$

$$\mu''_1 = E[x-a] \quad \mu''_3 = E[x-a]^3$$

$$\mu''_2 = E[x-a]^2 \quad \mu''_4 = E[x-a]^4$$

— / —

→ Moment about mean :- $\mu_0 = E[(x - \bar{x})^0]$

$$\mu_0 = 1 \\ \mu_1 = E[x - \bar{x}] = E[x] - E[\bar{x}] = E[x] - \bar{x}$$

\uparrow first moment
about mean
is zero.

$$\mu_2 = E[(x - \bar{x})^2] = \sigma^2 = \text{variance}$$

Note → Mean is first moment about origin and variance is second moment about mean.

$$\rightarrow \mu_2 = E[x^2 + \bar{x}^2 - 2x\bar{x}] \\ = E[x^2] + E(\bar{x}^2) - E(2x\bar{x}) \\ = E(x^2) + \bar{x}^2 - 2\bar{x}^2 \\ = E(x^2) - E(E(x))^2$$

$$\rightarrow \mu_2 = \mu'_2 - (\mu'_1)^2$$

$$\rightarrow \mu_3 = E(x - \bar{x})^3 = E(x^3 - 3x^2\bar{x} + 3x\bar{x}^2 - \bar{x}^3) \\ = E(x^3) - 3\bar{x}E(x^2) + 3\bar{x}^2E(x) - \bar{x}^3 \\ = E(x^3) - 3\bar{x}E(x^2) + 2\bar{x}^3$$

$$\mu_3 = \mu'_3 - 3\mu'_2\mu'_1 + 2(\mu'_1)^3$$

$$\rightarrow \mu_4 = E(x - \bar{x})^4 \\ = E(x^4 - 4c_1x^3\bar{x} + 6c_2x^2\bar{x}^2 - 4c_3x\bar{x}^3 + 4c_4\bar{x}^4) \\ = E(x^4) - 4\bar{x}E(x^3) + 6\bar{x}^2E(x^2) - 4\bar{x}^3E(x) + \bar{x}^4 \\ = E(x^4) - 4\bar{x}E(x^3) + 6\bar{x}^2E(x^2) - 3\bar{x}^4$$

$$[\mu_4 = \mu'_4 - 4\mu'_1\mu'_3 + 6(\mu'_1)^2\mu'_2 - 3(\mu'_1)^4]$$



Moment for continuous R.V.

(i) Moment about a point 'a'

$$\mu''_a = \int_{-\infty}^{\infty} (x-a)^n f(x) dx$$

(ii) Moment about mean

$$\mu_a = \int_{-\infty}^{\infty} (x - \bar{x})^a f(x) dx$$

(iii) Moment about origin

$$\mu_0 = \int_{-\infty}^{\infty} (x - 0)^a f(x) dx$$

→ Calculate first four moments about mean
for following distribution

$X: 6, 7, 8, 9, 10, 11, 12$

$f: 3, 6, 9, 13, 8, 5, 4$

$$\bar{x} = \frac{\sum xf}{\sum f} = \frac{6 \times 3 + 7 \times 6 + 8 \times 9 + 9 \times 13 + 10 \times 8 + 11 \times 5 + 12 \times 4}{3 + 6 + 9 + 13 + 8 + 5 + 4}$$

$$= [9]$$

$$\rightarrow \mu_1 = E(x - \bar{x}) = 0$$

$$\mu_2 = E(x - \bar{x})^2 = \frac{\sum (x - \bar{x})^2 \cdot f}{\sum f} = \frac{18}{48} = 0.375$$

★ Covariance: - If X and Y → random variables
(measurement of joint variance of X and Y)
 $(E(X^2) < \infty \rightarrow \text{finite second moment})$

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

If X and Y are independent, then

$$E(XY) = E(X)E(Y)$$

$$\therefore \text{Cov}(X, Y) = E(X)E(Y) - E(X)E(Y) = 0$$

$$(\text{Correl}^n \text{ coefficient} = \frac{\text{Cov}(X, Y)}{\sqrt{\text{Var}(X)\text{Var}(Y)}})$$

→ No linear relation
btw X and Y

* Covariance Matrix = $\begin{bmatrix} \text{Var}(x_1) & \dots & \text{cov}(x_n, x_1) \\ \vdots & \ddots & \vdots \\ \text{cov}(x_1, x_n) & \dots & \text{Var}(x_n) \end{bmatrix}$

* Correlation matrix :- Table showing correlation coefficients b/w different sets of variables.
(Values of correlation coefficient range from -1 to 1)

$$(\text{cov}(x, x) = 1) \cdot (\text{cov}(x, y) = \text{cov}(y, x))$$

For eg.

Correlat ⁿ	Height	Weight	Age
Height	1	0.87	0.65
Weight	0.87	1	0.62
Age	0.65	0.62	1

* Properties of Covariance :-

$$\text{cov}(x, y) = \text{cov}(y, x)$$

* Linearity:-

$$\text{cov}(ax + b, y) = a \cdot \text{cov}(x, y)$$

$$\text{cov}(x + z, y) = \text{cov}(x, y) + \text{cov}(z, y)$$

$$\text{cov}(x, x) = \text{Var}(x)$$

$$\text{cov}(x, y) = 0 \quad (x \& y \text{ are independent})$$

$$\text{cov}(ax, by) = ab \cdot \text{cov}(x, y)$$

* Properties of Correlatⁿ Coefficient :- (1)

$$1 \geq r \leq 1$$

$$r(x, y) = r(y, x)$$

$$r(ax + b, cy + d) = r(x, y)$$

* Eigenvalue Decomposition auf Kovarianz-Matrizen

For eg. $A = \begin{bmatrix} 4 & 1 \\ 2 & 3 \end{bmatrix}$

$$\det(A - \lambda I) = 0 \rightarrow (\text{Eigenvalue})$$

$$(4 - \lambda)(3 - \lambda) - 2 = 0$$

$$12 - 4\lambda - 3\lambda + \lambda^2 - 2 = 0$$

$$4\lambda^2 - 14\lambda + 10 = 0$$

$$2\lambda^2 - 7\lambda + 5 = 0$$

$$2\lambda^2 - 5\lambda - 2\lambda + 5 = 0$$

$$2\lambda(\lambda - 5) - (\lambda - 5) = 0$$

$$(\lambda - 1)(\lambda - 5) = 0$$

$$\lambda^2 - 7\lambda + 10 = 0$$

$$\lambda_1 = 5 \quad \lambda_2 = 2 \rightarrow \text{Eigenvalues}$$

→ For Eigen vector ..

$$AX = \lambda X$$

eigenvektoren

Let eigenvektors be a & b

→ For $\lambda_1 = 5$,

$$\begin{bmatrix} 4 & 1 \\ 2 & 3 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = 5 \begin{bmatrix} a \\ b \end{bmatrix}$$

$$4a + b = 5a$$

$$(a = b)$$

$$2a + 3b = 5b$$

$$2a = 2b \Rightarrow (a = b)$$

$$\lambda_1 = 5 \begin{bmatrix} 1 \\ 1 \end{bmatrix}$$

$$\rightarrow \text{For } \lambda_2 = 2$$

$$\begin{bmatrix} 4 & 1 \\ 2 & 3 \end{bmatrix} \begin{bmatrix} a \\ b \end{bmatrix} = 2 \begin{bmatrix} a \\ b \end{bmatrix}$$

$$4a + b = 2a + 2b \quad \text{or} \quad 2a = b$$

$$2a + b = 0 \quad \text{or} \quad 3a = -b$$

$$(3a = -b)$$

$$\text{From Eq } 2a + 3b = 2b$$

$$(2a = -b)$$

$$x_2 = b \begin{bmatrix} 1 \\ -3 \end{bmatrix}$$

* So, we can decompose co-variance matrix like this and we can write it as:-

$$\Sigma = Q \Lambda Q^{-1} \text{ or } Q \Lambda Q^T \quad (\text{Since } Q^{-1} = Q^T)$$

(Covariance matrix) (Orthogonal matrix)

Diagonal Matrix with
diagonal elements
as eigenvalues

\rightarrow Orthogonal matrix

[with eigenvalues
as columns.]

* Quantiles :- suppose we have a probability distribution.

Quantiles divide dataset into equal-sized intervals.

$\rightarrow Q_1$ (25th Percentile) (0.25 or 25% of total area covered)

$\rightarrow Q_2$ (50th Percentile) \rightarrow (median)

$\rightarrow Q_3$ (75th Percentile) \rightarrow (75% of area)

* Point Estimation:-

- Provides a single best guess for unknown parameters.
- Eg. Suppose we survey 100 students & find their average height $\rightarrow 168\text{ cm}$
point estimate of populatⁿ mean height $\rightarrow 168\text{ cm}$
- (Estimating the populatⁿ mean (μ) using sample mean (\bar{x}))

* Interval Estimation:- (Precision)

- Provides range of values (confidence interval) within which a parameter is likely to lie.
- More reliable than point estimatⁿ bcz it accounts for uncertainty.

Eg. From above eg., instead of saying 'avg. height is 168cm', we say; Avg height is b/w 165cm and 171cm with 95% confidence.

* Central Limit Theorem

- ⇒ Statement:- It states that regardless of the shape of populⁿ distributⁿ, the sampling distributⁿ of sample mean approaches normal distributⁿ as sample size (n) increases, provided samples are independent and identically distributed.

Mathematically if X_1, X_2, \dots, X_n are independent R.V. with mean μ and variance σ^2 , then standardized normal mean or standard normal variate:

$$Z = \frac{\bar{X} - \mu}{\sigma / \sqrt{n}}$$

converges to a std. normal distribⁿ
 $N(0, 1)$ as $n \rightarrow \infty$.

* Consequences :-

- 1) Justifies the use of Normal approximⁿ
 (sample mean follows "n" distribⁿ even if original data is not "n". Allows Normal based inferences in statistics)
- 2) Enables Practical Statistical Analysis
 (Real world datasets \rightarrow not normal
 Helps in converting them into normal)
- 3) Empowers Power with Larger Sample
- 4) Supports Inferential Statistics (t -tests, regression, ANOVA etc.)

* Limitations :-

- 1) High Sample Size Requirement (for non-normal or large error observⁿ)
- 2) Independence of samples Assumptⁿ
- 3) Finite Variance Requirement
 (Cauchy-Sorenson distribⁿ \rightarrow CTD)