

14-10-20

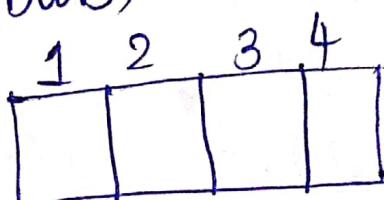
CSP30-Assignment - 2

Sanjay Marreddi
1904119
CSE

1) CONDITIONAL PROBABILITY:

1) Analysing Monty Hall Problem if there are 4 Gates (Doors)

* Let us denote Goats in 3 doors as G_1, G_2, G_3 .



* Treasure as T.

→ Let us assume the case where HOST opens only 1 Door.

→ Sample Space (Ω)

$$\Omega = \{ (G_1, G_2), (G_1, G_3), (G_2, G_1), (G_2, G_3), (G_3, G_1), (G_3, G_2), (T, G_1), (T, G_2), (T, G_3) \}$$

In our Sample Space (a, b)

First One

represents the option
Chosen by
Contestant

Second one

represents the
option chosen
by
HOST.

Let us find Probabilities of each element in S_2 .

$$P((G_1, G_2)) = \frac{1}{4} \times \frac{1}{2} = \frac{1}{8}$$

Contestant
can choose any
1 door from
4.

Once Contestant chooses
Door with Goat;
Host has to choose
from rem. two.

Similarly for

$$P((G_1, G_3)) = \frac{1}{8}$$

$$P((G_2, G_1)) = \frac{1}{8}$$

$$P((G_2, G_3)) = \frac{1}{8}$$

$$P((G_3, G_1)) = \frac{1}{8}$$

$$P((G_3, G_2)) = \frac{1}{8}$$

Now;

$$P((T, G_1)) = \frac{1}{4} \times \frac{1}{3} = \frac{1}{12}$$

Once Contestant chooses
Door with treasure;
he has 3 options

Similarly;

$$P((T, G_2)) = \frac{1}{12}$$

$$P((T, G_3)) = \frac{1}{12}$$

Now;

* Probability of Winning when Person sticks to his

$$\text{Initial choice} = P(C_T, G_{11}) + P(C_T, G_{12}) + P(C_T, G_{13})$$

$$= \frac{1}{12} + \frac{1}{12} + \frac{1}{12} = \frac{3}{12}$$

$$= \frac{1}{4}$$

* Probability of Winning when Person chooses to switch from Initial choice =

$$= P(C_{G_1}, G_{12}) + P(C_{G_1}, G_{13}) + P(G_{12}, G_{13}) + P(G_{12}, G_{11}) \\ + P(C_{G_3}, G_{12}) + P(C_{G_3}, G_{11})$$

$$= \frac{1}{8} + \frac{1}{8} + \frac{1}{8} + \frac{1}{8} + \frac{1}{8} + \frac{1}{8}$$

$$\Rightarrow \frac{6}{8} = \frac{3}{4}$$

∴ The probability that person wins is more when person chooses to switch from

Initial choice ($\frac{3}{4} > \frac{1}{4}$)

Switch

NOT switch.

NOTE:- There is other case where HOST opens 2 doors out of 4.

I have simulated this case in Question 2.

③ Aim:- Pairwise independence for several events is not sufficient for claiming Full independence.

We know;

Three events X, Y, Z are said to be INDEPENDENT if it satisfies the below 4 eqns:-

$$1) P(X \cap Y \cap Z) = P(X)P(Y)P(Z)$$

$$2) P(X \cap Y) = P(X) \cdot P(Y)$$

$$3) P(Y \cap Z) = P(Y) \cdot P(Z)$$

$$4) P(X \cap Z) = P(Z) \cdot P(X)$$

If only 2,3,4 hold & 1 does not hold we say X, Y, Z are only PAIRWISE INDEPENDENT.

Let's take an example:

* Two independent fair coin tosses

Event X: 1st toss shows Head

Event Y: 2nd toss shows Head

Event Z: 1st & 2nd tosses give same result.

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

$$P(X) = \frac{2}{4} = \frac{1}{2}$$

$$P(Y) = \frac{2}{4} = \frac{1}{2}$$

$$P(Z) = \frac{2}{4} = \frac{1}{2}$$

③ Now;

$$P(X \cap Y) = \frac{1}{4} = \frac{1}{2} \times \frac{1}{2} = P(X) \cdot P(Y)$$

$$P(X \cap Z) = \frac{1}{4} = \frac{1}{2} \times \frac{1}{2} = P(X) \cdot P(Z)$$

$$P(Y \cap Z) = \frac{1}{4} = \frac{1}{2} \times \frac{1}{2} = P(Y) \cdot P(Z)$$

\therefore Here; X, Y, Z are pairwise independent.

Now; let us check;

$$P(X \cap Y \cap Z) = \frac{1}{4}$$

$$P(X) \cdot P(Y) \cdot P(Z) = \frac{1}{2} \times \frac{1}{2} \times \frac{1}{2} = \frac{1}{8}$$

$$\therefore P(X \cap Y \cap Z) \neq P(X) \cdot P(Y) \cdot P(Z)$$

Hence; X, Y, Z are not INDEPENDENT.

Here; Pairwise Independence of events X, Y, Z is not implying complete independence

\therefore Pairwise Independence is not sufficient to claim full independence.

(4) AIM:-

$P(E_1, E_2, \dots, E_n) = \prod_{i=1}^n P(E_i)$ is not enough to claim pairwise independence.

lets take an example :-

Consider two independent rolls of a fair SIX sided dice

Event A : First roll is 1/2/3.

Event B : Second roll is 3/4/5.

Event C : Sum of two rolls is 9.

$$\Omega = \{(1,1), (1,2), (1,3), (1,4), (1,5), (1,6), (2,1), (2,2), (2,3), (2,4), (2,5), (2,6), (3,1), (3,2), (3,3), (3,4), (3,5), (3,6), (4,1), (4,2), (4,3), (4,4), (4,5), (4,6), (5,1), (5,2), (5,3), (5,4), (5,5), (5,6), (6,1), (6,2), (6,3), (6,4), (6,5), (6,6)\}$$

$$P(A) = \frac{6+6+6}{36} = \frac{18}{36} = \frac{1}{2}$$

$$P(B) = \frac{6+6+6}{36} = \frac{18}{36} = \frac{1}{2}$$

$$P(C) = P(\{(3,6), (6,3), (5,4), (4,5)\})$$

$$P(C) = \frac{4}{36} = \frac{1}{9}$$

$$P(A) \cdot P(B) \cdot P(C) = \frac{1}{36}$$

$$P(A \cap B \cap C) = P((3,6)) = \frac{1}{36}$$

$$\therefore P(A \cap B \cap C) = P(A) \cdot P(B) \cdot P(C)$$

Now, let's check whether it is implying
pairwise independence.

$$P(A \cap B) = \frac{6}{36} = \frac{1}{6}$$

$$P(A \cap C) = \frac{1}{36}$$

$$P(B \cap C) = \frac{3}{36}$$

$$P(A) \cdot P(B) = \frac{1}{2} \times \frac{1}{2} = \frac{1}{4}$$

$$P(A) \cdot P(C) = \frac{1}{2} \times \frac{1}{9} = \frac{1}{18}$$

$$P(B) \cdot P(C) = \frac{1}{2} \times \frac{1}{9} = \frac{1}{18}$$

It is clear from above that;

$$P(A \cap B) \neq P(A) \cdot P(B)$$

$$P(A \cap C) \neq P(A) \cdot P(C)$$

$$P(B \cap C) \neq P(B) \cdot P(C)$$

Hence; this example shows that the

condition; $P(E_1, E_2, \dots, E_n) = \prod_{i=1}^n P(E_i)$ is

not enough to claim pairwise
independence.

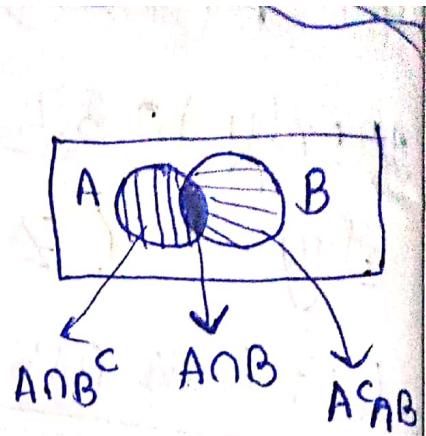
⑤ Given ; A & B are independent;

$$\Rightarrow P(A \cap B) = P(A) \cdot P(B)$$

a) $P(A \cap B^c) = P(A) - P(A \cap B)$

$$= P(A) - P(A) \cdot P(B)$$

$$= P(A)(1 - P(B))$$



$$P(A \cap B^c) = P(A)P(B^c)$$

Hence A & B^c are independent.

$$b) P(A^c \cap B) = P(B) - P(A \cap B)$$

$$= P(B) - P(A)P(B)$$

$$= P(B)(1 - P(A))$$

$$\boxed{P(A^c \cap B) = P(A^c) \cdot P(B)}$$

Hence, A^c and B are also independent.

$$c) P(A^c \cap B^c) = 1 - P(A \cup B)$$

$$= 1 - (P(A) + P(B) - P(A \cap B))$$

$$= (1 - P(A)) + (1 - P(B)) \\ + P(A \cap B)$$

$$= (1 - P(A)) + P(A)P(B) - P(B)$$

$$= (1 - P(A)) + P(B)(P(A) - 1)$$

$$= (1 - P(A))(1 - P(B))$$

$$\boxed{P(A^c \cap B^c) = P(A^c) \cdot P(B^c)}$$

Hence ; A^c & B^c are also independent.

⑥ Let us assume an event A. Conditioned on other event B.

From definition of Conditional Probability;

$$P(A|B) = \frac{P(A \cap B)}{P(B)} \quad \text{with } P(B) \geq 0$$

I) NON NEGATIVITY AXIOM

We know; If 'S' is an event $P(S) \geq 0$

$$\therefore P(A \cap B) \geq 0$$

We also know $P(B) \geq 0$

$\therefore P(A|B) \geq 0$ Hence 1st axiom is proved

II) NORMALIZATION

$$P(\Omega) = 1$$

$$\text{Now; } P(\Omega|B) = \frac{P(\Omega \cap B)}{P(B)} = \frac{P(B)}{P(B)} = 1$$

$$\therefore P(\Omega|B) = 1$$

$$\text{Also; } P(\emptyset) = 0$$

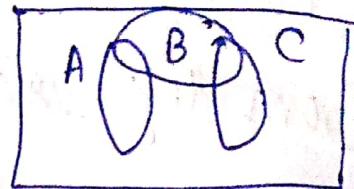
$$\text{Now; } P(\emptyset|B) = \frac{P(\emptyset \cap B)}{P(B)} = \frac{P(\emptyset)}{P(B)} = 0$$

$$\therefore P(\emptyset|B) = 0$$

Hence 2nd axiom is proved.

ii) Let A & C be two mutually exclusive events.
 - B is a conditional event

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



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

Since; A & C are mutually exclusive events;
 A ∩ B & C ∩ B are also mutually exclusive.

$$\begin{aligned} &\because (A \cap B) \cap (C \cap B) \\ &\Rightarrow (A \cap B) \cap B = \emptyset \end{aligned}$$

∴ By Probability axiom;

$$P((A \cap B) \cup (C \cap B)) = P(A \cap B) + P(C \cap B)$$

$$\therefore P(A \cup C | B) = \frac{P(A \cap B) + P(C \cap B)}{P(B)}$$

$$P(A \cup C | B) = \frac{P(A \cap B)}{P(B)} + \frac{P(C \cap B)}{P(B)}$$

$$\boxed{P(A \cup C | B) = P(A | B) + P(C | B)}$$

This proves Axiom-3

* Hence; Conditional Probability obeys all the axioms of Probability.

7) AIM :- UNCONDITIONAL INDEPENDENCE does not necessarily imply CONDITIONAL INDEPENDENCE.

Let consider an example :-

Two independent tosses of a fair coin:

Event A: 1st toss shows H

Event B: 2nd toss shows H

Event C: Both tosses show same result.

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

$$P(A) = \frac{2}{4} = \frac{1}{2} \quad | \quad P(B) = \frac{2}{4} = \frac{1}{2} \quad | \quad P(C) = \frac{2}{4} = \frac{1}{2}$$

$$P(A \cap B) = \frac{1}{4} = \frac{1}{2} \times \frac{1}{2} = P(A) \cdot P(B)$$

\therefore A & B are UNCONDITIONALLY INDEPENDENT.

Now; assume 'C' happened :-

$$P(A|C) = \frac{P(A \cap C)}{P(C)} = \frac{1/4}{1/2} = 1/2$$

$$P(B|C) = \frac{P(B \cap C)}{P(C)} = \frac{1/4}{1/2} = 1/2$$

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

$$\therefore P(A|C) \cdot P(B|C) = \frac{1}{2} \cdot \frac{1}{2} = \frac{1}{4}$$

$$\therefore P(A \cap B|C) \neq P(A|C) \cdot P(B|C)$$

\therefore A & B are CONDITIONALLY DEPENDENT.

This proves the fact that;

Unconditional Independence does not necessarily imply Conditional Independence.

8) AIM:- Conditional INDEPENDENCE does not necessarily imply UNCONDITIONAL INDEPENDENCE.

Ex:- Assume we have two coins.

1st coin is regular & unbiased : $P(H) = \frac{1}{2}$

2nd coin is irregular (Head) : $P(H) = 1$

First we will choose a coin & then toss it two times.

A: 1st coin toss results H

B: 2nd coin toss results H

C: Coin 1 (perfect) is selected

$$P(A|C) = \frac{1}{2} \quad P(B|C) = \frac{1}{2}$$

$$P(A \cap B|C) = \frac{1}{4} = \frac{1}{2} \times \frac{1}{2} = P(A|C) \cdot P(B|C)$$

$\therefore A \& B$ are conditionally independent

$$\text{Now}; P(A) = P(A|C)P(C) + P(A|C^c)P(C^c)$$

$$= \frac{1}{2} \times \frac{1}{2} + 1 \times \frac{1}{2} = \frac{3}{4}$$

$$P(B) = P(B|C)P(C) + P(B|C^c)P(C^c)$$

$$= \frac{1}{2} \times \frac{1}{2} + 1 \times \frac{1}{2} = \frac{3}{4}$$

$$P(A \cap B) = P(A \cap B|C)P(C) + P(A \cap B|C^c)P(C^c)$$

$$= \frac{1}{2} \times \frac{1}{2} \times \frac{1}{2} + 1 \times 1 \times \frac{1}{2} = \frac{5}{8}$$

$$P(A) \cdot P(B) = \frac{9}{16} \neq \frac{5}{8} = P(A \cap B)$$

Hence; It proves the fact that;

Conditional Independence does not necessarily imply Unconditional Independence.

II DISCRETE RANDOM VARIABLES:-

$$\textcircled{1} \quad \lim_{n \rightarrow \infty} \lim_{m \rightarrow \infty} 2^{m-n} \neq \lim_{m \rightarrow \infty} \lim_{n \rightarrow \infty} (2^{m-n})$$

$$\text{L.H.S: } - \lim_{n \rightarrow \infty} \lim_{m \rightarrow \infty} 2^{m-n} = \lim_{n \rightarrow \infty} \left(\lim_{m \rightarrow \infty} 2^{m-n} \right)$$

$$= \lim_{n \rightarrow \infty} \left(\lim_{m \rightarrow \infty} \frac{2^m}{2^n} \right) \\ = \lim_{n \rightarrow \infty} (\infty)$$

$$\therefore \boxed{\lim_{n \rightarrow \infty} \lim_{m \rightarrow \infty} 2^{m-n} \rightarrow \infty} \xrightarrow{\text{R.H.S.}} \textcircled{1}$$

R.H.S:-

$$\lim_{m \rightarrow \infty} \lim_{n \rightarrow \infty} 2^{m-n} = \lim_{m \rightarrow \infty} \left(\lim_{n \rightarrow \infty} 2^{m-n} \right)$$

$$= \lim_{m \rightarrow \infty} \left(\lim_{n \rightarrow \infty} \frac{2^m}{2^n} \right)$$

$$= \lim_{m \rightarrow \infty} 0$$

$$\boxed{\therefore \lim_{m \rightarrow \infty} \lim_{n \rightarrow \infty} 2^{m-n} = 0} \xrightarrow{\text{R.H.S.}} \textcircled{2}$$

from eq. $\textcircled{1}$ & $\textcircled{2}$; it can be proved that

$$\lim_{n \rightarrow \infty} \lim_{m \rightarrow \infty} (2^{m-n}) \neq \lim_{m \rightarrow \infty} \lim_{n \rightarrow \infty} (2^{m-n})$$

③

a) Bernoulli Random Variable :-

We know;

A random variable ' X ' is called Bernoulli Random Variable, if

$$P_X(0) = 1 - p$$

$$P_X(1) = p$$

where

$0 \leq p \leq 1$ is the probability that the trial is a 'success'

*

$$E[X] = \sum_x x P_X(x)$$

$$= 0 \times (1-p) + 1 \times p$$

$$\boxed{E[X] = p}$$

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

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

$$= \sum_x (x - p)^2 P_X(x)$$

$$= (0 - p)^2 \times (1 - p) + (1 - p)^2 \times p$$

$$= (1 - p)p^2 + (1 - p)^2 p$$

$$\text{Var}[X] = (1 - p)p (p + 1 - p) = \boxed{p(1 - p)}$$

b) Binomial Random Variable :-

Let ' p ' is Probability of Success.

' X ' is a Binomial RV which is equal to no. of successes

$$P_X(x) = \binom{n}{x} p^x (1-p)^{n-x} \quad \text{in } n \text{ independent trials}$$

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

Let us define some Random Variables :-

$$X_i = \begin{cases} 1; & \text{if success in trial } i, \\ 0; & \text{otherwise} \end{cases}$$

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

$$\text{We can write } X = \sum_i X_i$$

$$\text{We know; } E[X] = E\left[\sum_i X_i\right]$$

$$= \sum_i E[X_i] = \sum_i p$$

$$\boxed{E[X] = np}$$

Now;

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

$$= E[X_i] - (E[X_i])^2$$

$$= P - P^2 = P(1-P)$$

$$\therefore \boxed{\text{Var}(X_i) = P(1-P)}$$

From our definition of X_i 's ; it is clear
that X_i 's are independent of each other.

$$\therefore \text{Var}(X) = \text{Var}(\sum_i X_i)$$

$$= \sum_i \text{Var}(X_i)$$

$$= \sum_i P(1-P)$$

$$\boxed{\text{Var}(X) = nP(1-P)}$$

c) Geometric Random Variable :-

Let ' p ' is the probability of success.

X be the number of trials required until the first success; then ' X ' is said to be a Geometric R.V.

$$P_X(x) = \begin{cases} (1-p)^{x-1} p, & x = 1, 2, 3, \dots \\ 0, & \text{otherwise} \end{cases}$$

$$E[X] = \sum_{x=1}^{\infty} x (1-p)^{x-1} p$$

Let $(1-p) = q$

$$= \sum_{x=1}^{\infty} x (q^{x-1}) p$$

$$= p \sum_{x=1}^{\infty} x (q^{x-1})$$

$$= p \sum_{x=1}^{\infty} \frac{d q^x}{dq}$$

$$= p \sum_{x=1}^{\infty} \frac{d}{dq} (q^x)$$

Exchanging Summation
to ∞ & derivative
is similar to end-limits

In general Interchanging limits is not a correct way.
As proven in Q-1. But in some cases;
It will yield correct result.

$$\therefore E[X] = P \frac{d}{dq} \left(\sum_{x=1}^{\infty} q^x \right)$$

$$= P \frac{d}{dq} \left(\frac{q}{1-q} \right)$$

$$= P \times \frac{(1-q)x_1 - q(-1)}{(1-q)^2}$$

$$= \frac{P(1/q+q)}{(1-q)^2} = \frac{P}{(1-q)^2}$$

Since $1-P=q \Rightarrow 1-q=P$

$$= \frac{P}{P^2} = \frac{1}{P}$$

$$\therefore E[X] = \frac{1}{P}$$

Now;

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

$$\text{Now, } E[X^2] = \sum_{x=1}^{\infty} x^2 P_X(x)$$

$$= \sum_{x=1}^{\infty} x^2 P(1-P)^{x-1}$$

$$= P \sum_{x=1}^{\infty} x^2 (1-P)^{x-1} \quad (1-P=q)$$

$$E[X^2] = P \sum_{x=1}^{\infty} x^2 q^{x-1}$$

$$q = 1 - P$$

We Know;

$$\sum_{x=1}^{\infty} x^2 q^{x-1} = \frac{1+q}{(1-q)^3}$$

$$\because q < 1$$

$$\therefore E[X^2] = P \frac{(1+q)}{(1-q)^3}$$

$$\therefore 1-q = P$$

$$= P \frac{(1+1-P)}{P^3}$$

$$E[X^2] = \frac{P(2-P)}{P^3} = \frac{2-P}{P^2}$$

We had $E[X] = \frac{1}{P}$

$$\therefore \text{Var}(X) = \left(\frac{2-P}{P^2}\right) - \left(\frac{1}{P}\right)^2$$

$$\boxed{\text{Var}(X) = \frac{1-P}{P^2}}$$

d) Poisson Random Variable :-

A Random Variable X ; taking on one of the values $0, 1, 2$ is said to be a Poisson RV with λ for

$$P_X(k) = P(X=k) = e^{-\lambda} \frac{\lambda^k}{k!} \quad \lambda > 0 \rightarrow \text{Rate Parameter}$$

$$X \in \{0, 1, 2, \dots\}$$

Now;

$$E[X] = \sum_{x=0}^{\infty} x P_X(x)$$

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

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

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

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

$$E[X] = \lambda e^{-\lambda} \sum_{x=1}^{\infty} \frac{\lambda^{x-1}}{(x-1)!}$$

Now; let $y = x - 1$

$$E[X] = \lambda e^{\lambda} \sum_{y=0}^{\infty} \frac{\lambda^y}{y!}$$

We know;

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

$$E[X] = (\lambda e^{-\lambda}) (e^{\lambda})$$

$$E[X] = \lambda e^{(\lambda-\lambda)}$$

$$\therefore E[X] = \lambda$$

Now; $\text{Var}(X) = E(X^2) - (E(X))^2$

$$E(X^2) = \sum_{x=2}^{\infty} x^2 \frac{\lambda^x e^{-\lambda}}{x!} \quad ?$$

First let us find;

$$E[X(X-1)] = \sum_{x=2}^{\infty} x(x-1) \frac{\lambda^x e^{-\lambda}}{x!}$$

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

(When $x=0$,
 $x=1$
terms become
0)

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

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

$$\text{③ d) } E[X(X-1)] = e^{-\lambda} \lambda^2 \sum_{x=2}^{\infty} \frac{\lambda^{x-2}}{(x-2)!}$$

$$\text{Let } y = x-2$$

$$E[X(X-1)] = \lambda^2 e^{-\lambda} \sum_{y=0}^{\infty} \frac{\lambda^y}{y!}$$

$$E[X(X-1)] = \lambda^2 e^{-\lambda} \lambda^2 \left(\because \sum_{y=0}^{\infty} \frac{\lambda^y}{y!} = e^\lambda \right)$$

$$E[X(X-1)] = \lambda^2$$

$$E[X^2 - X] = \lambda^2$$

$$E[X^2] - E[X] = \lambda^2$$

$$E[X^2] = \lambda^2 + E[X] = \lambda^2 + \lambda$$

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

$$= \lambda^2 + \lambda - (\lambda)^2$$

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

$$\boxed{\text{Var}(X) = \lambda}$$

Q.

Assignment - 2

5) $[Ch-2; Ex:-6]$

Given; 5 fair coins are tossed.

E' : Event that all coins land heads

$$I_E = \begin{cases} 1 & \text{if } E \text{ occurs} \\ 0 & \text{if } E^c \text{ occurs} \end{cases}$$

$$\Omega = \{ (H, H, H, H, H), (H, H, H, H, T), (H, H, H, T, T), \dots, (H, H, T, T, H) \}$$

$$\Omega = \{ 0H, 1H, 2H, 3H, 4H, 5H \}$$

$\downarrow \quad \downarrow \quad \downarrow \quad \downarrow \quad \downarrow \quad \downarrow$

$1 \text{ way} \quad 5C_1 \text{ ways} \quad 5C_2 \text{ ways} \quad 5C_3 \text{ ways} \quad 5C_4 \text{ ways.} \quad 1 \text{ way (} 5C_5 \text{)}$

1) $I_E = 1$ if the outcome is 5 Heads
i.e; (H, H, H, H, H)

2) $P\{I_E = 1\} = \frac{1}{(5C_0 + 5C_1 + 5C_2 + 5C_3 + 5C_4 + 5C_5)}$

$$P\{I_E = 1\} = \frac{1}{(1+5+10+10+5+1)} = \frac{1}{32}$$

6) $[ch-2; ex:-8]$

Distribution funcⁿ of (X) is

$$F(b) = \begin{cases} 0; & b < 0 \\ \frac{1}{2}; & 0 \leq b < 1 \\ 1; & 1 \leq b < \infty \end{cases}$$

We know;

$$\begin{aligned} F(b) &= P(X \leq b) \\ &= \sum_{x \leq b} P_X(x) \quad (\text{For Discrete R.V.}) \end{aligned}$$

$$F(b) = P(X = b) + P(X < b)$$

We know;

$$P(a) = P(X=a) = F(a) - F(a^-)$$

$$\begin{aligned} \text{Let } a &= b; \\ a &= 0 \end{aligned}$$

$$\begin{aligned} * P(b=0) &= F(b=0) - F(b<0) \\ &= \frac{1}{2} - 0 \end{aligned}$$

$$P(b=0) = \frac{1}{2}$$

$$\begin{aligned} * P(b=1) &= F(b=1) - F(b<1) \\ &= 1 - 1/2 \end{aligned}$$

$$= 1/2$$

$$\therefore P(b=1) = \frac{1}{2}$$

$P(b) = 0$ for all other b .

$$\therefore P_X(x) = \begin{cases} \frac{1}{2}; & b=0 \\ \frac{1}{2}; & b=1 \\ 0; & \text{else} \end{cases}$$

7) ch: 2 ex: 9

Given; Distribution funcⁿ of X ; $F(x)$

$$F(b) = \begin{cases} 0, & b < 0 \\ \frac{1}{2}, & 0 \leq b < 1 \\ \frac{3}{5}, & 1 \leq b < 2 \\ \frac{4}{5}, & 2 \leq b < 3 \\ \frac{9}{10}, & 3 \leq b < 3.5 \\ 1, & b \geq 3.5 \end{cases}$$

Now;
we know; $F(b) = P(X \leq b)$

$P(x=a) = F(x=a) - F(x < a)$

Now;

* $P(x=0) = F(x=0) - F(x < 0)$

$$P(x=0) = \frac{1}{2} - 0 = \frac{1}{2}$$

* $P(x=1) = F(x=1) - F(x < 1)$

$$P(x=1) = \frac{3}{5} - \frac{1}{2} = \frac{6-5}{10} = \frac{1}{10}$$

* $P(x=2) = F(x=2) - F(x < 2)$

$$P(x=2) = \frac{4}{5} - \frac{3}{5} = \frac{1}{5}$$

* $P(x=3) = F(x=3) - F(x < 3)$

$$P(x=3) = \frac{9}{10} - \frac{4}{5} = \frac{9-8}{10} = \frac{1}{10}$$

$$7) P(x=3.5) = F(x=3.5) - F(x<3.5)$$

$$P(x=3.5) = 1 - \frac{9}{10} = 1 - 0.9 = \frac{1}{10}$$

∴ The Probability mass func of X

$$P_X(x) = \left\{ \begin{array}{ll} \frac{1}{2}; & x=0 \\ \frac{1}{10}; & x=1 \\ \frac{1}{5}; & x=2 \\ \frac{1}{10}; & x=3 \\ \frac{1}{10}; & x=3.5 \end{array} \right\}$$

8) Ch:P Err:- 13

A fair coin is flipped 10 times.

Let 'X' is a R.V which has the value of no. of coins the person correctly predicted.

Given;

Person claims to have ESP \Rightarrow X = 7

If it is so clear that the individual would have done at least this well if he had no ESP

$$\text{is } P(X=7) + P(X=8) + P(X=9) + P(X=10)$$

(or) In short if $P(X \geq 7)$.

Note that;

Our defined Random Variable 'X';
obeys Binomial Distribution

$$\text{ie;} P_X(x) = \binom{n}{x} \left(\frac{1}{2}\right)^{n-x} \left(\frac{1}{2}\right)^x$$

Here; $n = 10$

Since coin is fair;

$$P(H) = P(T) = \frac{1}{2}$$

$$P(\text{correctly predicting}) = P(\text{not correct}) = \frac{1}{2}$$

$$\therefore P_X(x) = \binom{10}{x} \left(\frac{1}{2}\right)^{10}$$

$$n_C_r = \frac{n!}{r!(n-r)!}$$

Now;

$$P(X \geq 7) = \sum_{x=7}^{10} \binom{10}{x} \left(\frac{1}{2}\right)^{10}$$

$$= \left(\frac{1}{2^{10}}\right) \left(\binom{10}{7} + \binom{10}{8} + \binom{10}{9} + \binom{10}{10} \right)$$

$$\begin{aligned} &= \binom{10}{7} + \binom{10}{8} + \binom{10}{9} + \binom{10}{10} \\ &= \frac{10!}{7!3!} + \frac{10!}{8!2!} + \frac{10!}{9!1!} + \frac{10!}{10!0!} \\ &= 120 + 45 + 10 + 1 \\ &= 176 \end{aligned}$$

$$P(X \geq 7) = \frac{176}{2^{10}} = 0.171875$$

9) Ch:2 Ex:17

Given; an experiment can result in one of n possible outcomes with i th outcome having ' P_i ' Prob.

$$\sum_{i=1}^n P_i = 1$$

* If ' n ' of these experiments are performed & if outcome of any one of the ' n ' does not affect outcome of the other $n-1$ experiments;

\Rightarrow Probability that 1st outcome appears x_1 times
 2nd " " x_2 " . . .
 r th " " x_r " if

Now; probability that 1st outcome appears x_1 times among n experiments;
 $P(1)$

$$P(1) = \frac{n!}{x_1! (n-x_1)!} (P_1)^{x_1}$$

Similarly;
 Probability that 2nd outcome appears x_2 times among $(n-x_1)$ experiments is

$$P(2) = \frac{(n-x_1)!}{x_2! (n-x_1-x_2)!} (P_2)^{x_2}$$

Similarly for r th outcome.

Since 1st, 2nd, --- r th Outcomes are independent of each other;

Probability that 1st outcome appears x_1 times,

(P) 2nd " " x_2 times

r th " " x_r times if

$$P = \left[nC_{x_1} (P_1)^{x_1} \right] \left[(n-x_1)C_{x_2} (P_2)^{x_2} \right] \left[(n-x_1-x_2)C_{x_3} (P_3)^{x_3} \right]$$

$$\cdot \left[(n-(x_1+x_2+\dots+x_{r-1}))C_{x_r} (P_r)^{x_r} \right]$$

$$P = \left(nC_{x_1} \quad (n-x_1)C_{x_2} \quad (n-(x_1+x_2))C_{x_3} \quad \dots \quad (n-(x_1+x_2+\dots+x_{r-1}))C_{x_r} \right)$$

$$\cdot ((P_1)^{x_1} (P_2)^{x_2} (P_3)^{x_3} \dots (P_r)^{x_r})$$

We also have; $x_1 + x_2 + \dots + x_{r-1} + x_r = n$

$$P = \left(nC_{x_1} \quad (n-x_1)C_{x_2} \quad (n-(x_1+x_2))C_{x_3} \quad \dots \quad (n-(x_1+x_2+\dots+x_{r-1}))C_{x_r} \right)$$

$$\cdot ((P_1)^{x_1} (P_2)^{x_2} \dots (P_r)^{x_r})$$

We have;

$$nC_r = \frac{n!}{r!(n-r)!}$$

$$\therefore P = \frac{n!}{x_1!(n-x_1)!} \cdot \frac{(n-x_1)!}{x_2!(n-x_1-x_2)!} \cdot \frac{(n-x_1-x_2)!}{x_3!(n-x_1-x_2-x_3)!} \cdots \frac{x_r!}{x_r! 0!} \cdot (P_1^{x_1} \cdot P_2^{x_2} \cdots P_r^{x_r})$$

$$P = \frac{n!}{x_1! x_2! x_3! \cdots x_r!} P_1^{x_1} P_2^{x_2} \cdots P_r^{x_r}$$

Hence Proved.

Q) Let X_i denote the number of times the i^{th} type outcome occurs ; $i=1, 2, \dots, r-1$

for $0 \leq j \leq n$;

$$P(X_i = x_i, i=1, 2, \dots, r-1 \mid X_r = j)$$

We know; From definition of Conditional Probability;

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

therefore;

$$P(X_i = x_i ; i=1, 2, \dots, r-1 \mid X_r = j) = \frac{P(X_r = j \text{ and } X_i = x_i)}{P(X_r = j)}$$

We also know that

Events ;

$$(X_i = x_i; i = 1, 2, \dots, r-1) : A$$

and $(X_r = j) : B$ are independent of each other.

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

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

$$\Rightarrow P(X_1 = x_1 \text{ for } i=1, 2, \dots, r-1 \mid X_r = j) \\ = P(X_i = x_i, i = 1, 2, \dots, r-1)$$

$$= P(X_1 = x_1) \cdot P(X_2 = x_2) \cdot \dots \cdot P(X_{r-1} = x_{r-1})$$

1st outcome occurs x_1 times.

$(r-1)^{\text{th}}$ outcome occurs x_{r-1} times.

$$= P_1^{x_1} P_2^{x_2} \cdots P_{r-1}^{x_{r-1}}$$

Hence;

$$P(X_i = x_i, i=1, 2, \dots, r-1 | X_r = j)$$

$$= P_1^{x_1} P_2^{x_2} \cdots P_{r-1}^{x_{r-1}}$$

ii) Ch: 2, Ex: 23

$$\rightarrow P(\text{Head}) = P$$

\rightarrow Coin is flipped successively until the r th head appears

$\rightarrow X = \text{No. of flips required}$

for $n \geq r$,

$$P(X=n) = \binom{n-1}{r-1} P^r (1-P)^{n-r}$$

We know that;

In order for 'X' to be equal to 'n';

The first $(n-1)$ flips must have $(r-1)$ heads

and in the n th flip we must have head

so that we stop our experiment at n flips.

Let event; A: first $(n-1)$ flips must have $(r-1)$ heads

B: n th flip resulted in Head.

Our task is done if both A & B happens;

$$P(A \cap B) = P(A) \cdot P(B) \quad (\text{Since } A \text{ & } B \text{ are independent})$$

$$\therefore P(X=n) = \binom{n-1}{r-1} P^{r-1} (1-P)^{(n-1)-(r-1)} \times P$$

$$P(X=n) = \binom{n-1}{r-1} P^r (1-P)^{n-r}, n \geq r$$

* Hence Proved

12) ch: 2, Ex: 24

Given; Probability Mass function of 'X' is given by:

$$P(X) = \binom{r+k-1}{r-1} p^r (1-p)^k$$

$k = 0, 1, \dots$

$$P(X) = \binom{r+k-1}{r-1} p^{r-1} \cdot P \cdot (1-p)^{(r+k-1)-(r-1)}$$

Let us assume we have a coin

* $P(\text{Heads}) = P$.

* Coin is successively flipped until the r th head appears.

Now; A Random Variable 'X' be the ~~X~~ number that must be added to 'r'

So that the number of flips required

will be $(r+k)$. ~~[$r+k$ in general]~~

$$\therefore P(X=k) = \binom{r+k-1}{r-1} p^{r-1} \cdot (1-p)^{(r+k-1)-r+1}$$

implies $(r+k)$ flips are req.

So; Among $(\tau+k)$ flips;

We must have $(r-1)$ Heads in $(\tau+k-1)$ flips & the last flip must be head.

$$\therefore P(X=k) = \binom{\tau+k-1}{r-1} p^{r-1} (1-p)^{(\tau+k-1)-(r-1)} \times P$$

$$P(X=k) = \binom{\tau+k-1}{r-1} p^r (1-p)^k. \quad k=0, 1, \dots$$

Hence an interpretation of X is done !!