

CSE 544: Probability & Statistics for Data Science,
Spring 2021

Assignment - 2

Submitted by

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i) Given that

$$\text{Cov}(x, y) = E[(x - E(x))(y - E(y))] \quad \text{--- (1)}$$

$$\text{Cov}(x, y) = E(xy) - E(x)E(y) \quad \text{--- (2)}$$

a) Let S_1 - Event of getting heads at first toss

S_2 - Event of getting heads at second toss

S_3 - Event of getting heads at third toss

Note, S_1, S_2, S_3 are mutually independent.

$$\text{i.e., } S_1 \perp S_2 \perp S_3 \quad \text{--- (3)}$$

$$\text{We have, } x = S_1(\text{or})S_2 = S_1 + S_2$$

$$y = S_2(\text{or})S_3 = S_2 + S_3$$

$$\therefore \text{Cov}(x, y) = \text{Cov}(S_1 + S_2, S_2 + S_3)$$

$$\text{We know } P(S_i) = \frac{1}{2} \text{ for } i \in [1, 2, 3]$$

We also know that coin tosses are bernoulli distribution,

$$\begin{aligned}\therefore \text{Var}(S_i) &= P(S_i)(1 - P(S_i)) \\ &= \frac{1}{2}\left(1 - \frac{1}{2}\right) = \frac{1}{4}.\end{aligned}$$

$$\text{Var}(S_i) = \frac{1}{4} \quad \text{--- (4)}$$

$$\therefore \text{cov}(S_1 + S_2, S_2 + S_3)$$

$$= E((S_1 + S_2 - E(S_1 + S_2)) (S_2 + S_3 - E(S_2 + S_3)))$$

using ①

We Know, $E(A+B) = E(A) + E(B)$.

$$\begin{aligned} \therefore E(S_1 + S_2) &= E(S_1) \\ &\quad + E(S_2) \\ E(S_2 + S_3) &= E(S_2) \\ &\quad + E(S_3) \end{aligned}$$

→ ⑤

$$\therefore \text{cov}(S_1 + S_2, S_2 + S_3)$$

$$= E((S_1 + S_2 - E(S_1) - E(S_2))$$

$$(S_2 + S_3 - E(S_2) - E(S_3)))$$

using ⑤

$$= E(((S_1 - E(S_1)) + (S_2 - E(S_2))))$$

$$(((S_2 - E(S_2)) + (S_3 - E(S_3))))$$

Multiplying,

$$\begin{aligned} &= E((S_1 - E(S_1)) (S_2 - E(S_2)) + (S_2 - E(S_2)) (S_2 - E(S_2)) \\ &\quad + (S_1 - E(S_1)) (S_3 - E(S_3)) + (S_2 - E(S_2)) \\ &\quad (S_3 - E(S_3))) \end{aligned}$$

$$\begin{aligned}
 &= E[(S_1 - E(S_1))(S_2 - E(S_2))] \\
 &\quad + E[(S_2 - E(S_2))^2] \\
 &\quad + E[(S_1 - E(S_1))(S_3 - E(S_3))] \\
 &\quad + E[(S_2 - E(S_2))(S_3 - E(S_3))]
 \end{aligned}$$

$$\begin{aligned}
 &= \text{Cov}(S_1, S_2) + E[(S_2 - E(S_2))^2] + \text{Cov}(S_1, S_3) \\
 &\quad + \text{Cov}(S_2, S_3)
 \end{aligned}$$

Since

$$\begin{aligned}
 S_1 \perp S_2 \perp S_3, \text{Cov}(S_i, S_j) = 0 \\
 \forall i, j \in [1, 3] \\
 \text{and } i \neq j
 \end{aligned}$$

We also know

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

$$\therefore \text{Cov}(x, y) = 0 + \text{Var}(S_2) + 0 + 0$$

$$\text{From (A), } \text{Var}(S_2) = 1/4$$

$$\therefore \boxed{\text{Cov}(x, y) = 1/4}$$

b) $x = \text{fair sided dice}$

$$\{-5, -2, 0, 2, 5\}$$

Let i be the face we get on outcome.

We have,

$$i = \{-5, -2, 0, 2, 5\}$$

$$\text{We have } \sum_{i=1}^5 i = 0.$$

$$\text{Also } \sum_{i=1}^5 i^3 = (-5)^3 + (-2)^3 + (0)^3 + (2)^3 + (5)^3 \\ = 0$$

From ②

$$\text{Cov}(x, y) = E(xy) - E(x) E(y)$$

$$\text{Cov}(x, x^2) = E(x^3) - E(x) E(x^2)$$

$$\text{We have, } P_i = 1/5$$

$$P_{ii} = 1/25$$

$$P_{iii} = 1/125$$

$$\begin{aligned}
 E(x) &= \sum_{i=1}^5 i p_i \\
 &= \sum_{i=1}^5 i \left(\frac{1}{5}\right) = \frac{1}{5} \sum_{i=1}^5 i \\
 &= \frac{1}{5}(0) \\
 &= 0.
 \end{aligned}$$

$$\therefore E(x) E(x^2) = 0 \times E(x^2) = 0$$

$$\therefore \text{Cov}(x, x^2) = E(x^3)$$

$$\begin{aligned}
 E(x^3) &= \sum_{i=1}^5 i^3 p_{ii} \\
 &= \sum_{i=1}^5 i^3 \left(\frac{1}{125}\right) = \frac{1}{125} \sum_{i=1}^5 i^3 \\
 &= \frac{1}{125}(0) \\
 &= 0
 \end{aligned}$$

$$\therefore \text{Cov}(x, x^2) = 0$$

Note that p_{ii} depends on p_i and still $\text{Cov}(x, x^2) = 0$.

c) No.

$\text{Cov}(x, f(x)) \neq 0$ iff $f(x)$ is linear in terms of x . Cov won't catch dependency if the two terms are not linearly dependant.

Ex Let $f(x) = x^2$.

$\text{Cov}(x, x^2) = 0$ from Q.b, still x, x^2 are dependent.

\therefore Covariance works only for linear dependency.

2) Inequalities:

(a) X is a non-negative RV

Mean = μ

Variance = σ^2

t is a real number > 0

To prove:

$$E[X] \geq \int x \cdot f(x) dx$$

Solution:

$$E[X] = \int_{-\infty}^{+\infty} x \cdot f(x) dx$$

$$\text{As } x > 0, E[X] = \int_0^{\infty} x \cdot f(x) dx$$

t is any number between 0 and ∞

$$\therefore E[X] = \underbrace{\int_0^t x \cdot f(x) dx}_{A} + \underbrace{\int_t^{\infty} x \cdot f(x) dx}_{B}$$

For A, we know $x > 0, f(x) > 0$ and $t > 0$

$$\text{Hence, } \int_0^t x \cdot f(x) dx \geq 0$$

$$\therefore E[X] = (\geq 0) + \int_t^\infty x \cdot f(x) \cdot dx$$

$$\therefore E[X] \geq \int_t^\infty x \cdot f(x) dx$$

Hence, proved

$$(b) \text{ To prove : } P(X > t) \leq \frac{E[X]}{t}$$

$$\text{From (a), } E[X] \geq \int_t^\infty x \cdot f(x) \cdot dx \rightarrow (1)$$

Given we know $t > 0, x > 0$.

Minimum value of ' x ' = t

$$\therefore x \geq t$$

Using $f(x)$ on both sides,
(applying) (where $f(x) > 0$)

$$x \cdot f(x) \geq t \cdot f(x)$$

Integrating on both sides,

$$\int_t^{\infty} x \cdot f(x) dx \geq \int_t^{\infty} t \cdot f(x) dx$$

Hence, replacing (i) with the above explanation,

$$\Rightarrow E[x] \geq \int_t^{\infty} t \cdot f(x) dx$$

$$\Rightarrow E[x] \geq t \int_t^{\infty} f(x) dx$$

$$\hookrightarrow P[x > t]$$

$$\therefore E[x] \geq t P[x > t]$$

$$\therefore \text{Hence, } P[x > t] \leq \frac{E[x]}{t}$$

Hence, Proved.

(c) To prove: $P(|X - \mu| \geq t) \leq \frac{\sigma^2}{t^2}$

Solution:

From (b), $P(X > t) \leq \frac{E[X]}{t}$

Replacing X with $(X-\mu)^2$,

$$P((X-\mu)^2 > t) \leq \frac{E[(X-\mu)^2]}{t}$$

We know, $t > 0$, hence replacing t with t^2
(inequality does not change)

$$P((X-\mu)^2 > t^2) \leq \frac{E[(X-\mu)^2]}{t^2}$$

$$\hookrightarrow |X-\mu| > |t|$$

(But $t > 0$, Hence,

$$|X-\mu| > t$$

$$(\because \sigma^2 = E[(X-\mu)^2])$$

$$\hookrightarrow \text{Hence, } P(|X-\mu| \geq t) \leq \frac{\sigma^2}{t^2}$$

(As point probabilities
are 0 for

continuous RV)

$$\begin{aligned} |X-\mu| &> t \\ \Rightarrow |X-\mu| &\geq t \end{aligned}$$

③

Given,

$x_1, x_2, \dots, x_k \Rightarrow k$ independent RVs.

Pdfs $f_{x_i}(x) = \lambda_i e^{-\lambda_i x} \quad \forall i \in \{1, 2, \dots, k\}$

Also, $Z = \min(x_1, x_2, x_3, \dots, x_k)$

$$P_Z(Z \leq z) = P_Z(\min(x_1, x_2, \dots, x_k) \leq z)$$

$= P_Z(\text{At least one element in } (x_1, \dots, x_k) \leq z)$

$$= 1 - P_Z(\text{No element in } (x_1, \dots, x_k) \leq z)$$

$$= 1 - P_Z(x_1 > z \text{ and } x_2 > z \dots x_k > z)$$

Since, x_1, x_2 are RV which are independent,

$$P_Z(Z \leq z) = 1 - [P_Z(x_1 > z) P_Z(x_2 > z) \dots P_Z(x_k > z)]$$

1

i) From definition of PDF, CDF

$$F_{x_i}(x) = P_n(x \leq x) = \text{CDF}(x_i) \quad \text{--- (2)}$$

$$\frac{F'(x)}{x_i} = f(x_i) = \text{PDF}(x_i) \quad \text{--- (3)}$$

CDF(z) from (2)

$$F_Z(z) = P_n(Z \leq z)$$

From (1)

$$F_Z(z) = 1 - \left[P_n(x_1 > z) \cdot P_n(x_2 > z) \cdots P_n(x_k > z) \right]$$

We know

$$P_n(x_i > z) = 1 - P_n(x_i \leq z)$$

$$= 1 - F_{x_i}(z)$$

$$= 1 - \text{CDF}(x_i)$$

$$\text{We have, } f_{x_i}(x) = \lambda_i e^{-\lambda_i x}$$

$$f_{x_i}(z) = \lambda_i e^{-\lambda_i z}$$

$$F_{x_i}(z) = \int_0^z \lambda_i e^{-\lambda_i z} dz$$

$$= \lambda_i \int_0^z e^{-\lambda_i z} dz$$

$$= \lambda_i \left[-\frac{1}{\lambda_i} e^{-\lambda_i z} \right]_0^z$$

$$= - \left[e^{-\lambda_i z} \right]_0^z$$

$$= - \left[e^{-\lambda_i z} - 1 \right]$$

$$F_{x_i}(z) = P_n(x_i \leq z) = 1 - e^{-\lambda_i z} \quad \text{--- (5)}$$

\therefore From (5) we have

$$P_n(x_i > z) = e^{-\lambda_i z} \quad \text{--- (6)}$$

(6) in (4),

$$F_Z(z) = 1 - \left[e^{-\lambda_1 z} \cdot e^{-\lambda_2 z} \cdots \cdots e^{-\lambda_k z} \right]$$

$$F_Z(z) = 1 - \left[e^{-(\lambda_1 + \lambda_2 + \dots + \lambda_k)z} \right]$$

From ③ Pdf(z),
 $= f_Z(z)$

$$= 0 - \left[-(\lambda_1 + \lambda_2 + \dots + \lambda_k) e^{-(\lambda_1 + \dots + \lambda_k)z} \right]$$

$$= (\lambda_1 + \lambda_2 + \dots + \lambda_k) e^{-(\lambda_1 + \lambda_2 + \dots + \lambda_k)z}$$

Let $\lambda_T = \lambda_1 + \lambda_2 + \dots + \lambda_k$

$$\therefore \text{Pdf}(z) = f_Z(z) = \lambda_T e^{-\lambda_T z}$$

where $\lambda_T = \lambda_1 + \lambda_2 + \dots + \lambda_k$.

$$\begin{aligned} \text{i)} F[z] &= \int_0^\infty z f_Z(z) dz \\ &= \int_0^\infty z \lambda_T e^{-\lambda_T z} dz \\ &= \lambda_T \int_0^\infty z e^{-\lambda_T z} dz \end{aligned}$$

Let $u = z$, $dv = e^{-\lambda_T z} dz$

$$\therefore du = dz, v = \frac{1}{\lambda_T} e^{-\lambda_T z}$$

$$\therefore E[z] = \lambda_T \left[uv - \int_0^\infty v du \right]$$

$$= \lambda_T \left[\frac{ze^{-\lambda_T z}}{-\lambda_T} \Big|_0^\infty + \int_0^\infty \frac{-1}{\lambda_T} e^{-\lambda_T z} dz \right]$$

$$= \lambda_T \left[0 + \frac{1}{\lambda_T} \int_0^\infty e^{-\lambda_T z} dz \right]$$

$$= \lambda_T \left[\frac{1}{\lambda_T} \times \frac{-1}{\lambda_T} [e^{-\lambda_T z}]_0^\infty \right]$$

$$= -\frac{1}{\lambda_T^2} [e^{-\lambda_T z}]_0^\infty$$

$$= -\frac{1}{\lambda_T} [0 - 1]$$

$$= \frac{1}{\lambda_T}$$

$$\therefore E(z) = \frac{1}{\lambda_T} = \frac{1}{(\lambda_1 + \lambda_2 + \dots + \lambda_k)}$$

iii) Similarly integrating by parts twice,

we get

$$E(x^2) \text{ for exp distribution} = \frac{1}{\lambda^2}$$

where λ is the rate.

$$\text{So } E(z^2) = \frac{1}{\lambda_T^2} = \frac{1}{(\lambda_1 + \lambda_2 + \dots + \lambda_k)^2}.$$

$$\therefore \text{Var}(z) = \frac{1}{(\lambda_1 + \lambda_2 + \dots + \lambda_k)^2}.$$

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

Given $Z = XY$

$$\therefore X = \frac{Z}{Y}, Y = \frac{Z}{X}. \quad \text{--- (1)}$$

To find
Pmf (Z)

We will use the similar approach in 3(a) to calculate Pmf(Z) by finding cdf(Z)

$$\text{cdf}(z) = F_Z(z) = P_Z(Z \leq z)$$

$$\text{cdf}(z) = P_Z(XY \leq z) \quad \text{--- (2)}$$

We have,

$$Y \geq X \quad (\text{given})$$

From (1)

$$\frac{Z}{X} > X \quad (\text{as}) \quad Y \geq \frac{Z}{X}$$

$$Y^2 \geq Z \quad (\because Y \geq 0)$$

$$\frac{Y \geq \sqrt{Z}}{\square} \quad (\because Y \geq 0, X \geq 0, XY \geq 0) \quad \text{--- (3)}$$

From ②,

$$F_z(z) = P_n(z \leq z)$$

$$= 1 - P_n(z > z)$$

$$= 1 - P_n(xy > z)$$

$$P_n(xy > z)$$

$$= \int_{y=b}^y \int_{x=a}^y f_{xy}(x, y) dx dy.$$

We need to find a, b .

One way is fix a and find b by
lower limit of y .

From ③, we have $y \geq \sqrt{bz}$ (or) $y \geq \sqrt{z}$

$$(\because z \geq z)$$

Also, From ①

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

$$\therefore P_{xy}(xy > z)$$

$$= \int_{y=\sqrt{z}}^{\infty} \int_{x=\frac{z}{y}}^y f_{xy}(x,y) dx dy.$$

$$= \int_{y=\sqrt{z}}^{\infty} \int_{x=\frac{z}{y}}^y 2 dx dy.$$

$$= 2 \left[\int_{y=\sqrt{z}}^{\infty} \int_{x=\frac{z}{y}}^y dx dy \right]$$

$$= 2 \left[\int_{y=\sqrt{z}}^{\infty} [x]_{\frac{z}{y}}^y dy \right]$$

$$= 2 \left[\int_{y=\sqrt{z}}^{\infty} \left(y - \frac{z}{y} \right) dy \right]$$

$$= 2 \left[\int_{y=\sqrt{z}}^{\infty} y dy - z \int_{y=\sqrt{z}}^{\infty} \frac{1}{y} dy \right]$$

$$= 2 \left[\left[\frac{y^2}{2} \right]'_{\sqrt{z}} - z \left[\log_e y \right]'_{\sqrt{z}} \right]$$

$$= 2 \left[\frac{1-z}{2} - z (0 - \log \sqrt{z}) \right]$$

$$= 2 \left[\frac{1-z}{2} + z \log \sqrt{z} \right]$$

$$= \left(\frac{1-z}{2} \right) 2 + 2z \log \sqrt{z}$$

$$= (1-z) + z \log_e (\sqrt{z})^2$$

$$\left(\because a \log b = \log_b a \right)$$

$$\therefore P_R(Z > z) = 1 - z + z \log_e z$$

$$\therefore CDF(z) = 1 - (1 - z + z \log_e z)$$

$$= z - z \log_e z$$

$$F'(z) = f(z) = \text{pdf}(z)$$

where $F'(z)$ is partial derivative of $F(z)$
wrt to z .

$$\therefore \text{pdf}(z) = F'(z) = 1 - \frac{\partial}{\partial z} (z \log_e z)$$

$$\frac{\partial}{\partial z} (z \log_e z) = \left(z \times \frac{1}{z} \right) + \left(\cancel{z \log_e z} \times 1 \right)$$

(by Product rule)

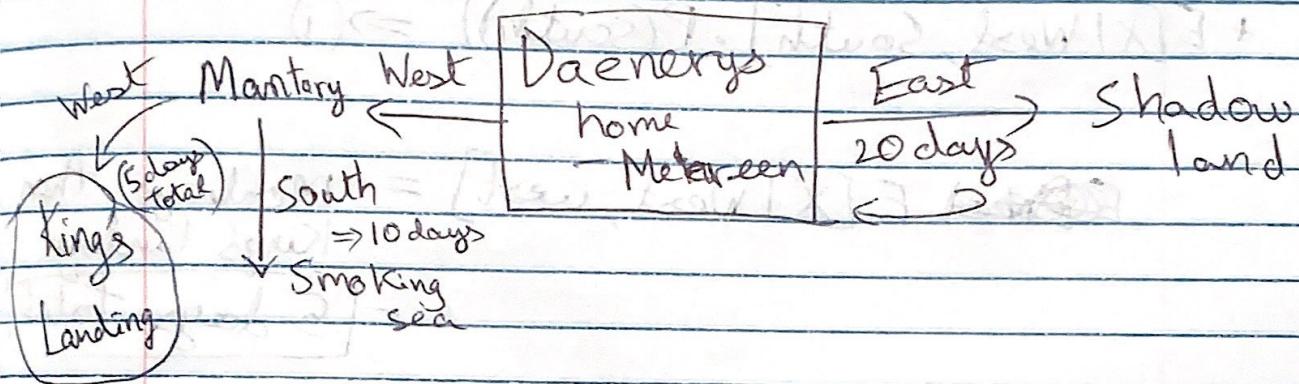
$$= 1 + \log_e z$$

$$\therefore \text{pdf}(z) = F'(z) = 1 - [1 + \log_e z]$$

$$= -\log_e z$$

$$\boxed{\therefore \text{pdf}(z) = f_z(z) = -\log_e z}$$

A)



$$\star E[X] = ?$$

(Where $X \Rightarrow$ time spent by Daenerys before reaching King's landing)

By law of total expectation,

$$E[X] = E[X | \text{east from Meereen}] \cdot \Pr(\text{east from Meereen})$$

+

$$E[X | \text{west from Meereen}] \cdot \Pr(\text{west from Meereen})$$

$$\Pr(\text{choosing any direction at a point in time}) = \frac{1}{2}$$

Further splitting the West journey,

$$E[X] = E[X | \text{east}] \cdot P(\text{east}) + \frac{1}{2} (E[X | \text{west, west}] \cdot P(\text{west}) +$$

(Contd.)

$$+ E[X | \text{West, South}] \cdot P(\text{South}) \Rightarrow (i)$$

~~E[X | West, west] = Montezuma's~~ Then
~~Kings Landing~~
= 5 days total

$$E[X | \text{West, South}] \Rightarrow \text{Smoking sea}$$

\hookrightarrow additional

$$\begin{aligned} & 10 \text{ days} \\ & = (X + 10) \end{aligned}$$

$$E[(X | \text{east})] \Rightarrow \text{Shadow lands}$$

\hookrightarrow additional 20 days

$$= X + 20$$

Substituting these values in (i),

$$= (E[X + 20]) \frac{1}{2} + \frac{1}{2} (5 \times \frac{1}{2} + E[X + 10]) \frac{1}{2}$$

Using Linearity of expectation,

$$\hookrightarrow E[X] = \frac{1}{2} E[X] + 10 + \frac{5}{4} + \frac{1}{2} E[X] + \frac{10}{4}$$

$$E[X] = \frac{3}{4} E[X] + 10 + \frac{15}{4}$$

(using LCM 4)

$$4E[X] - 3E[X] = \frac{55}{4}$$

$$\therefore E[X] = 55$$

$$(b) \quad \text{Var}[X] = ?$$

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

Obtaining $E[X^2]$ from equation (i) in part (a),

$$E[X^2] = \frac{1}{2} E[X^2 | \text{East}] + \frac{1}{2} (E[X^2 | \text{West}, \text{West}]. P(\text{West}))$$

$$E[X^2 | \text{East}] = [X] + E[X^2 | \text{West}, \text{South}]. P(\text{South})$$

$$\Rightarrow E[X^2] = \frac{1}{2} [(X+20)^2] + \frac{1}{2} \left(\frac{1}{2} \times 25 + \frac{1}{2} E[(X+10)^2] \right)$$

$$\Rightarrow E[X^2] = \frac{1}{2} E[400 + 40X + X^2] + \frac{1}{2} \left(\frac{1}{2} \cdot 25 + \frac{1}{2} E[X^2 + 100 + 20X] \right)$$

Using LOE,

$$E[X^2] = \frac{0.25}{4} + 25 + E[X^2] + 5E[X] + \\ + 20E[X] + 200$$

$$E[X^2] = \frac{3E[X^2]}{4} + 25E[X] + \frac{925}{4}$$

(using LCM 4)

$$4E[X^2] - 3E[X^2] = 100E[X] + 925$$

(Using (a), $E[X] = 55$)

$$= (100 \times 55) + 925$$

$$E[X^2] = 6425$$

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

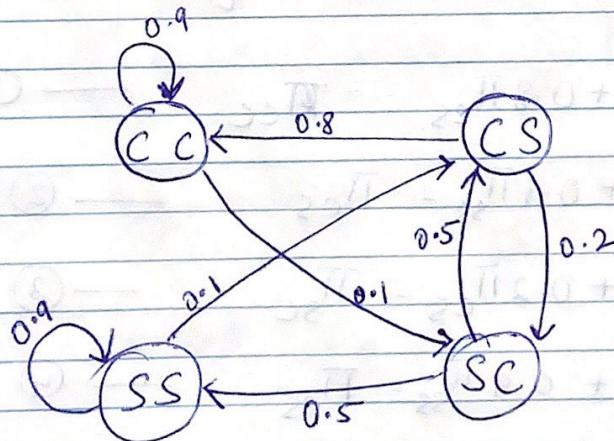
$$= 6425 - (55)^2$$

$$= 3400$$

Given \rightarrow

$$5.) \begin{aligned} P_e[C|CC] &= 0.9 \Rightarrow P_e[S|CC] = 1 - 0.9 = 0.1 \\ P_e[C|CS] &= 0.8 \Rightarrow P_e[S|CS] = 1 - 0.8 = 0.2 \\ P_e[C|SC] &= 0.5 \Rightarrow P_e[S|SC] = 1 - 0.5 = 0.5 \\ P_e[C|SS] &= 0.1 \Rightarrow P_e[S|SS] = 1 - 0.1 = 0.9 \end{aligned}$$

(a) Markov Chain:



Probability matrix \rightarrow

$$(P) = \begin{array}{c|cccc} & CC & CS & SC & SS \\ \hline CC & 0.9 & 0 & 0.1 & 0 \\ CS & 0.8 & 0 & 0.2 & 0 \\ SC & 0 & 0.5 & 0 & 0.5 \\ SS & 0 & 0.1 & 0 & 0.9 \end{array}$$

Using Global Balance

$$\rightarrow P^{n-1} \cdot P = P^n$$

$$P^{n-1} \approx P^n \quad (\text{as } n \rightarrow \infty)$$

$$\rightarrow P^{n-1} \cdot P = P^n$$

$$[\pi_{cc} \quad \pi_{cs} \quad \pi_{sc} \quad \pi_{ss}]$$

0.9	0	0.1	0
0.8	0	0.2	0
0	0.5	0	0.5
0	0.1	0	0.9

$$= [\pi_{cc} \quad \pi_{cs} \quad \pi_{sc} \quad \pi_{ss}]$$

$$\Rightarrow 0.9 \pi_{cc} + 0.8 \pi_{cs} = \pi_{cc} \quad \text{--- (1)}$$

$$0.5 \pi_{sc} + 0.1 \pi_{ss} = \pi_{cs} \quad \text{--- (2)}$$

$$0.1 \pi_{cc} + 0.2 \pi_{cs} = \pi_{sc} \quad \text{--- (3)}$$

$$0.5 \pi_{sc} + 0.9 \pi_{ss} = \pi_{ss} \quad \text{--- (4)}$$

$$\text{Also, } \sum \text{Probs} = 1$$

$$\Rightarrow \pi_{cc} + \pi_{cs} + \pi_{sc} + \pi_{ss} = 1 \quad \text{--- (5)}$$

Solving equations (1), (2), (3), (4) and (5)

$$\left\{ \begin{array}{l} \pi_{sc} = \frac{1}{15} \\ \pi_{ss} = \frac{5}{15} = \frac{1}{3} \\ \pi_{cc} = \frac{8}{15} \\ \pi_{cs} = \frac{1}{15} \end{array} \right\}$$

(b) $P_e(\text{Snowy 3 days from today}) = ?$

TP rule

$$= \pi_{cc} \times P(S|cc) + \pi_{cs} \times P(S|cs)$$
$$+ \pi_{sc} P(S|sc) + \pi_{ss} \times P(S|ss)$$

$$= \frac{8}{15} \times 0.1 + \frac{1}{15} \times 0.2 + \frac{1}{15} \times (0.5) + \frac{1}{3} (0.9)$$

$$= \frac{0.8}{15} + \frac{0.2}{15} + \frac{0.5}{15} + \cancel{0.1} \cancel{0.1} \frac{4.5}{15}$$

$$= \frac{6}{15}$$

$$= 0.4$$

5(c) Steady-State : Power iteration >>

$$\begin{bmatrix} \bar{\pi}_{cc} & \bar{\pi}_{cs} & \bar{\pi}_{sc} & \bar{\pi}_{ss} \\ 0.533333 & 0.066667 & 0.066667 & 0.333333 \end{bmatrix}$$

Complete Transition matrix with $k = 2000$
after python simulation

$$\begin{bmatrix} cc & cs & sc & ss \\ cc & 0.533333 & 0.066667 & 0.066667 & 0.333333 \\ cs & 0.533333 & 0.066667 & 0.066667 & 0.333333 \\ sc & 0.533333 & 0.066667 & 0.066667 & 0.333333 \\ ss & 0.533333 & 0.066667 & 0.066667 & 0.333333 \end{bmatrix}$$

Using the steady state that we got
from simulation to calculate part (b)

→ P_{cc} (Snowy 3 days from today) = ?

$$= \bar{\pi}_{cc} P(S|CC) + \bar{\pi}_{cs} P(S|CS) +$$

$$\bar{\pi}_{sc} P(S|SC) + \bar{\pi}_{ss} P(S|SS)$$

$$= 0.533333 \times 0.1 + 0.066667 \times 0.2 + \\ 0.066667 \times 0.5 + 0.333333 \times 0.9$$

$$= 0.399999 \approx 0.4 \quad \text{as calculated via our}$$

mathematical formulas
in part a & b.

Code execution output for (5.c)

```
harman@harmans-MacBook-Pro Hw2 % python3 a2_5.py
Transition Matrix
[[0.533333 0.066667 0.066667 0.333333]
 [0.533333 0.066667 0.066667 0.333333]
 [0.533333 0.066667 0.066667 0.333333]
 [0.533333 0.066667 0.066667 0.333333]]
[

Steady State:
[0.533333 0.066667 0.066667 0.333333]

CC: 0.533333
CS: 0.066667
SC: 0.066667
SS: 0.333333

5(b): Steady State Probability for Snow third day from today: 0.39999989999999996
harman@harmans-MacBook-Pro Hw2 %
```

6.) (a) Given $X = (X_1, X_2, \dots, X_k)$ is a multivariate normal

(i.e.) $t_1 X_1 + t_2 X_2 + \dots + t_k X_k$ is a

(2212) linear combination having Normal distribution.

$$\Rightarrow t_1 X_1 + t_2 X_2 + t_3 X_3 + \dots + t_j X_j + \dots + t_k X_k$$

Suppose in this combination all t_i 's = 0

except t_j

$$\therefore 0+0+0+\dots+t_j X_j+\dots+0 \sim \text{Normal}$$

$$\Rightarrow t_j X_j \sim \text{Normal}$$

$$\therefore X_j \sim \text{Normal}$$

(b) $X = \text{Normal}(0, 1)$

$$S = \begin{bmatrix} 1 & p=1/2 \\ -1 & p=1/2 \end{bmatrix}$$

Also, $Y = SX$ is a Normal R.V.

$$Y = SX \quad \left\{ \begin{array}{l} X \text{ with } p=1/2 \\ -X \text{ with } p=1/2 \end{array} \right.$$

Let $Z = (X, Y)$

To show Z is not a multivariate Normal we can show that some linear combination of X & Y is not Normally distributed

Let linear combinations be : $X + Y$

Now,

$$X+Y \quad \left\{ \begin{array}{l} X+(-X) \text{ with } p=1/2 \\ X+(X) \text{ with } p=1/2 \end{array} \right.$$

$$\rightarrow X+Y \quad \left\{ \begin{array}{l} 0 \text{ with } p=1/2 \\ 2X \text{ with } p=1/2 \end{array} \right.$$

As we know if a distribution is Normal then the point probabilities are 0 because Normal distribution is continuous and Point probabilities in continuous distribution

are zero.

(1, 0) bivariate \Rightarrow (d)

But here $X+Y \begin{cases} 0 & \text{with } P=1/2 \\ 2X & \text{with } P=1/2 \end{cases}$

$$P(X+Y = 0) > 0$$

$\therefore X+Y$ is not normally distributed

Similarly $X-Y$ will also not be normally distributed

$\therefore Z = (X, Y)$ will not be a multivariate Normal

Because Linear combination of X & Y are not normal.

(c) i) $Z, W \sim \text{Normal}(0, 1)$

Also Z, W are iid RV

Let $X = (Z, W)$ be a RV.

Linear combination of $Z, W \Rightarrow t_1 Z + t_2 W$

$\Rightarrow t_1 Z + t_2 W$ is also Normally distributed using Weighted Sum of Independent Normals property

Because Z & W are given iid.

So, for any t_1, t_2 $t_1 Z + t_2 W$ will have a normal distribution

∴ Using definition of Multivariate Normals

$X = (Z, W)$ will be a multivariate normal distribution.

ii) $(Z+2W, 3Z+5W)$

Let $X = (Z+2W, 3Z+5W)$

Linear combination $\Rightarrow t_1(Z+2W) + t_2(3Z+5W)$

$\Rightarrow t_1 Z + 2t_1 W + 3t_2 Z + 5t_2 W$

$\Rightarrow (t_1 + 3t_2) Z + (2t_1 + 5t_2) W$

Let $t_1 + 3t_2 = t_3$
& $2t_1 + 5t_2 = t_4$

$$\therefore \Rightarrow t_3 Z + t_4 W \sim N(0, 1)$$

Now Z & W are given i.i.d & Normals
∴ Using weighted sum of Independent Normals

$t_3 Z + t_4 W$ will be Normally distributed

$$\therefore X \sim (Z+2W, 3Z+5W)$$

is a multivariate Normal,

d) $X = (X_1, X_2, \dots, X_n)$

$Y = (Y_1, Y_2, \dots, Y_m)$ are

multivariate normals & X, Y are independent

$$\Rightarrow W = (X_1, X_2, \dots, X_n, Y_1, Y_2, \dots, Y_m)$$

$$\Rightarrow W = (X, Y)$$

Linear combination $\rightarrow t_1 X + t_2 Y$

\therefore It is given X, Y are Independent & Normally distributed.

$t_1 X + t_2 Y$ will also be Normally distributed using Weighted sum of Independent Normals

$\Rightarrow \therefore W = (X, Y)$ will be a multivariate Normal distribution.

(c) $X, Y \Rightarrow$ iid & Normal

Let $Z = (X+Y, X-Y)$

Using Fact 2 (Prop. of Covariance)

Covariance (Z) \Rightarrow Covariance ($X+Y, X-Y$)

$$= 1 \cdot 1 \operatorname{Cov}(X, X) + 1 \cdot (-1) \operatorname{Cov}(X, Y) \\ + 1 \cdot 1 \operatorname{Cov}(Y, X) + 1 \cdot (-1) \operatorname{Cov}(Y, Y)$$

$$= 1 \cdot \operatorname{Cov}(X, X) - 1 \cdot \operatorname{Cov}(X, Y) + 1 \cdot \operatorname{Cov}(Y, X) \\ - 1 \cdot \operatorname{Cov}(Y, Y)$$

$$= 1 \cdot \operatorname{Cov}(X, X) - 1 \cdot \operatorname{Cov}(Y, Y)$$

$$= \operatorname{Var}(X) - \operatorname{Var}(Y)$$

Given that X & Y are iid $\therefore \operatorname{Var}(X) - \operatorname{Var}(Y) = 0$

$\therefore \text{Covariance } (X+Y, X-Y) = 0$

$\therefore (X+Y, X-Y)$ are uncorrelated

Using Fact 1 (Uncorrelated implies independence)

$\Rightarrow (X+Y, X-Y)$ are Independent

Now let's show that $Z = (X+Y, X-Y)$

is Multivariate normal
using Fact 1 & Fact 2

NOTE :- Since $(X+Y, X-Y)$ are linearly related and their covariance is zero we can say that they are uncorrelated or Independent.

7) $X = \text{no. of days needed to complete the goal}$

Let $P_i (P_1, P_2, \dots, P_n)$ be the days to

Capture Pokemon 'i' after capturing 'i-1' Pokemon

Then, $X = P_1 + P_2 + P_3 + \dots + P_n$

P_i can be thought of as random variable with Geometric distribution as Geometric distribution indicates time to first success.

In our case, success can be said to be equivalent to capturing a Pokemon of type 'i' after some no. of days.

Also, P_1, P_2, \dots, P_n are Independent as we are calculating P_2 after P_1 has already occurred.

a) $E[X] = ?$

$$\because X = P_1 + P_2 + P_3 + \dots + P_n$$

$$\therefore E[X] = E[P_1 + P_2 + \dots + P_n]$$

Using Linearity of Expectation,

$$\Rightarrow E[X] = E[P_1] + E[P_2] + E[P_3] + \dots + E[P_n]$$

~~↳~~ P_i has a Geometric Distribution

~~↳~~ $\therefore \text{Expectation } E[P_i] = \frac{1}{\text{Probability}}$

(Already calculated in assignment 1
question - 5 (c))

Now, probability of event 1
Let's say $P_e(P_1)$ we need to find.

$$P_e(P_1) = \frac{n}{n} \quad (\text{Using counting method})$$

i.e. for first type of
Pokemon we have
'n' choices to capture
out of Total 'n' Pokemons

Similarly,

$$P_e(P_2) = \frac{n-1}{n} \quad (\text{After capturing Pokemon
of Type 1, } 'n-1' \text{ are left})$$

$$P_e(P_3) = \frac{n-2}{n}$$

$$P_e(P_n) = \frac{n-(n-1)}{n} = \frac{1}{n}$$

$$\therefore E[X] = E[P_1] + E[P_2] + \dots + E[P_n]$$

$$= \frac{1}{P_x(P_1)} + \frac{1}{P_x(P_2)} + \frac{1}{P_x(P_3)} + \dots + \frac{1}{P_x(P_n)}$$

$$= \frac{n}{n} + \frac{n}{n-1} + \frac{n}{n-2} + \dots + \frac{n}{1}$$

$$= n \left(\frac{1}{n} + \frac{1}{n-1} + \frac{1}{n-2} + \dots + \frac{1}{2} + 1 \right)$$

$$\boxed{\therefore E[X] = n \left(1 + \frac{1}{2} + \frac{1}{3} + \dots + \frac{1}{n-1} + \frac{1}{n} \right)}$$

$$(b) \quad \text{Var}[X]$$

$$\Rightarrow \text{Var}[X] = \text{Var}[P_1 + P_2 + P_3 + \dots + P_n]$$

Using Linearity of Variance, as P_i 's are Independent

$$\Rightarrow \text{Var}[X] = \text{Var}[P_1] + \text{Var}[P_2] + \text{Var}[P_3] + \dots + \text{Var}[P_n]$$

As, P_i are geometrically distributed,

$$\therefore \text{Var}[P_i] = \frac{1 - P_x(P_i)}{(P_x(P_i))^2}$$

(Already calculated
in Assignment 1
& 5(d))

$$\therefore \text{Var}[P_1] = \frac{1 - P_2(P_1)}{(P_2(P_1))^2} = \frac{1 - (n/n)}{(n/n)^2} = 0$$

$$\text{Var}[P_2] = \frac{1 - (n-1/n)}{(\frac{n-1}{n})^2} = n^2 \left(\frac{1/n}{(n-1)^2} \right)$$

$$\text{Var}[P_3] = \frac{1 - (n-2/n)}{(\frac{n-2}{n})^2} = n^2 \left(\frac{2/n}{(n-2)^2} \right)$$

$$\text{Var}[P_n] = \frac{1 - (1/n)}{(\frac{1}{n})^2} = n^2 \left((n-1)/n \right)$$

$$\Rightarrow \text{Var}[x] = \text{Var}[P_1] + \text{Var}[P_2] + \text{Var}[P_3] + \dots + \text{Var}[P_n]$$

$$= 0 + n^2 \left(\frac{1/n}{(n-1)^2} \right) + n^2 \left(\frac{2/n}{(n-2)^2} \right) + \dots + n^2 \left(\frac{(n-1)/n}{1} \right)$$

$$= n \left[\frac{1}{(n-1)^2} + \frac{2}{(n-2)^2} + \dots + \frac{(n-1)}{1} \right]$$

$$\Rightarrow \boxed{\text{Var}[x] = n \left(\frac{1}{(n-1)^2} + \frac{2}{(n-2)^2} + \dots + \frac{(n-1)}{1} \right)}$$