

$$\begin{aligned}
 \textcircled{1} \text{ (a) } & \mathbb{P} \left[u_1 \leq u, \dots, u_n \leq u \right] \\
 &= \mathbb{E} \left[1 \left[u_1 \leq u, \dots, u_n \leq u \right] \right] \\
 &= \mathbb{E} \left[\mathbb{E} \left[1 \left[u_1 \leq u, \dots, u_n \leq u \right] \mid u \right] \right] \quad (\text{Iterated conditioning}) \\
 &= \mathbb{E} \left[\mathbb{P} \left[u_1 \leq u, \dots, u_n \leq u \mid u \right] \right] \\
 &= \mathbb{E} \left[\mathbb{P} \left[u_1 \leq u, \dots, u_n \leq u \mid u = u \right]_{u=u} \right] \\
 &= \mathbb{E} \left[\mathbb{P} \left[u_1 \leq u, \dots, u_n \leq u \right]_{u=u} \right] \quad (\because u \perp u_i, i=1, \dots, n) \\
 &= \mathbb{E} \left[\left(\prod_{i=1}^n \mathbb{P}(u_i \leq u) \right)_{u=u} \right] \quad (u_i \text{'s are Mutually Independent}) \\
 &= \mathbb{E} \left[u^n 1(0 \leq u < 1) \right] \\
 &= \int_0^1 u^n du = \left. \frac{u^{n+1}}{n+1} \right|_0^1 = \frac{1}{n+1} //
 \end{aligned}$$

(b) For $1 \leq i \leq n$,

$$\begin{aligned}
 & \mathbb{P} \left[u_i \leq u \right] \\
 &= \mathbb{E} \left[1 \left[u_i \leq u \right] \right] \\
 &= \mathbb{E} \left[\mathbb{E} \left[1 \left[u_i \leq u \right] \mid u \right] \right] \\
 &= \mathbb{E} \left[\mathbb{P} \left[u_i \leq u \mid u \right] \right] \\
 &= \mathbb{E} \left[u \right] \\
 &= \frac{1}{2}
 \end{aligned}$$

Hence, $\prod_{i=1}^n \mathbb{P}(u_i \leq u) = \left(\frac{1}{2}\right)^n \neq \mathbb{P}[u_1 \leq u, \dots, u_n \leq u]$

$\therefore$ The random variables $1[u_1 \leq u], \dots, 1[u_n \leq u]$ are not Mutually Independent.

(1.c) Consider $Y = \sum_{l=1}^n 1[u_l \leq u]$. It is evident that the

support of Y , $S_Y = \{0, 1, \dots, n\}$ ($\because$ each indicator function can take only one of $\{0, 1\}$ values)

In the event $Y = x$, out of the random variables $1[u_l \leq u]$, $l=1, \dots, n$, x are equal to one and the remaining $(n-x)$ are zero. And since the random variables are iid, the probability of getting x 1's and $(n-x)$ 0's is the same for all $\binom{n}{x}$ possible ways of picking x .

$$\therefore P[Y = x], \quad x \in \{0, 1, \dots, n\}$$

$$= \binom{n}{x} P[u_1 \leq u, u_2 \leq u, \dots, u_x \leq u, u_{x+1} > u, \dots, u_n > u]$$

$$= \binom{n}{x} P\left[1[u_1 \leq u, \dots, u_x \leq u, u_{x+1} > u, \dots, u_n > u]\right]$$

$$= \binom{n}{x} P\left[P[u_1 \leq u, \dots, u_x \leq u, u_{x+1} > u, \dots, u_n > u \mid u]\right]$$

$$= \binom{n}{x} P\left[\left(\prod_{i=1}^x P[u_i \leq u]\right) \left(\prod_{j=x+1}^n P[u_j > u]\right) \mid u = u\right]$$

$$= \binom{n}{x} P\left[u^x (1-u)^{n-x}\right]$$

$$= \binom{n}{x} \int_0^1 u^x (1-u)^{n-x} du$$

$$= \binom{n}{x} \left\{ \frac{-u^x (1-u)^{n-x+1}}{n-x+1} \Big|_0^1 + \int_0^1 \frac{x}{n-x+1} u^{x-1} (1-u)^{n-x+1} du \right\}$$

$$= \binom{n}{x} \cdot \frac{x}{(n-x+1)} \int_0^1 u^{x-1} (1-u)^{n-x+1} du$$

$\therefore$ (By iterative integration by parts)

$$= \binom{n}{x} \times \frac{x!}{(n-x+1) \dots n} \int_0^1 (1-u)^n du$$

$$= \frac{n!}{(n-x)! x!} \times \frac{x! (n-x)!}{n!} \times \frac{1}{n+1}$$

$$= \frac{1}{n+1} //$$

This is a uniform distribution. The probabilities do not depend on x

$$(3) (a) \quad g_{\Lambda}(t) = \lambda e^{-\lambda t}, \quad t > 0$$

$$\begin{aligned} \therefore \mathbb{P}(N=k) &= \int_0^{\infty} \mathbb{P}(N=k | \Lambda=t) g_{\Lambda}(t) dt, \quad k=0,1,\dots \\ &= \int_0^{\infty} \frac{t^k}{k!} e^{-t} \cdot \lambda e^{-\lambda t} dt \\ &= \frac{\lambda}{k!} \int_0^{\infty} t^k e^{-(1+\lambda)t} dt \\ &= \frac{\lambda}{k!(1+\lambda)} \int_0^{\infty} t^k (1+\lambda) e^{-(1+\lambda)t} dt \\ &= \frac{\lambda}{k!(1+\lambda)} \left[\frac{k!}{(1+\lambda)^k} \right] \quad \left(\text{By moments of the exponential distribution} \right) \\ &= \frac{\lambda}{(1+\lambda)} \times \frac{1}{(1+\lambda)^k} \\ &= \left(\frac{\lambda}{1+\lambda} \right) \left[1 - \left(\frac{\lambda}{1+\lambda} \right) \right]^k \end{aligned}$$

$\Rightarrow$

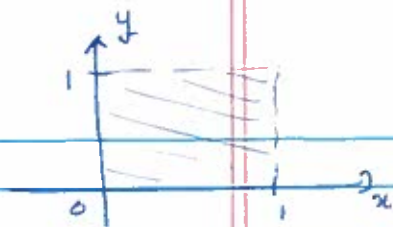
$$N \sim \text{geometric} \left(\frac{\lambda}{1+\lambda} \right) //$$

$$\begin{aligned} (b) \quad f_{\Lambda|N}(t | N=k) &= \frac{\mathbb{P}(N=k | \Lambda=t) g_{\Lambda}(t)}{\mathbb{P}(N=k)}, \quad t > 0 \\ &= \frac{\frac{t^k}{k!} e^{-t} \cdot \lambda e^{-\lambda t}}{\frac{\lambda}{(1+\lambda)} \left[\frac{k!}{(1+\lambda)^k} \right]} \\ &= \frac{t^k (1+\lambda)^{k+1} e^{-(1+\lambda)t}}{k!} // \end{aligned}$$

This is a Gamma distributions with parameters $\Gamma[k+1, 1+\lambda]$

$$\begin{aligned} (c) \quad \mathbb{E}(N\Lambda) &= \mathbb{E}(\mathbb{E}(N\Lambda | \Lambda)) \quad (\text{Iterated Conditioning}) \\ &= \mathbb{E}[\Lambda \mathbb{E}(N | \Lambda)] \\ &= \mathbb{E}[\Lambda^2] \quad (\because \mathbb{E}(N | \Lambda) = \Lambda, \because N \text{ is poisson with parameter } \Lambda) \\ &= \frac{2}{\lambda^2} // \end{aligned}$$

$$(4) f(x, y) = \begin{cases} x+y & \text{if } 0 < x, y < 1 \\ 0 & \text{o/w} \end{cases}$$



$$\begin{aligned} (4.a) f_x(x) &= \int_{-\infty}^{\infty} f_{xy}(x, y) dy \\ &= \int_0^1 (x+y) dy \quad (\text{for } 0 < x < 1) \\ &= \left(xy + \frac{y^2}{2} \right)_0^1 \\ &= x + \frac{1}{2} \end{aligned}$$

Similarly,

$$f_x(x) = \begin{cases} x + \frac{1}{2} & , 0 < x < 1 \\ 0 & , \text{o/w} \end{cases} //$$

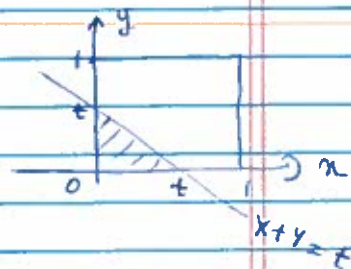
$$f_y(y) = \begin{cases} y + \frac{1}{2} & , 0 < y < 1 \\ 0 & , \text{o/w} \end{cases} //$$

(4.b) When $0 < x, y < 1$,

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

Hence, X and Y are not independent.

$$(4.c) 0 < t \leq 1$$



$$\begin{aligned} P(X+Y \leq t) &= \int_0^t \int_0^t (x+y) dy dx \\ &= \int_0^t \left(xy + \frac{y^2}{2} \right)_0^t dx \\ &= \int_0^t \left(xt + \frac{t^2}{2} \right) dx \\ &= \left(\frac{t \cdot x^2}{2} + \frac{t^2 \cdot x}{2} \right)_0^t \\ &= \frac{t^3}{3} // \end{aligned}$$

$$\begin{aligned} (4.d) E(X) &= \int_0^1 x f_x(x) dx \\ &= \int_0^1 x \left(x + \frac{1}{2} \right) dx \\ &= \left(\frac{x^3}{3} + \frac{x^2}{4} \right)_0^1 \\ &= \frac{7}{12} // \end{aligned}$$

$$\begin{aligned}
 E(X^2) &= \int_0^1 x^2 \left(x + \frac{1}{2} \right) dx \\
 &= \int_0^1 \left(x^3 + \frac{x^2}{2} \right) dx \\
 &= \left(\frac{x^4}{4} + \frac{x^3}{6} \right) \Big|_0^1 \\
 &= \frac{5}{12}
 \end{aligned}$$

$$\begin{aligned}
 \text{Var}(X) &= E(X^2) - (E(X))^2 \\
 &= \frac{5}{12} - \left(\frac{7}{12} \right)^2 \\
 &= \frac{11}{144} //
 \end{aligned}$$

$$\begin{aligned}
 E(XY) &= \int_0^1 \int_0^1 xy(x+y) dx dy \\
 &= \int_0^1 y \int_0^1 \left(\frac{x^3}{3} + \frac{yx^2}{2} \right) dx dy \\
 &= \int_0^1 y \left(\frac{1}{3} + \frac{y}{2} \right) dy \\
 &= \left(\frac{y^2}{6} + \frac{y^3}{6} \right) \Big|_0^1 \\
 &= \frac{1}{3}
 \end{aligned}$$

$$\begin{aligned}
 \text{Cov}(XY) &= E(XY) - E(X) \cdot E(Y) \\
 &= \frac{1}{3} - \left(\frac{7}{12} \right)^2 \\
 &= \frac{48 - 49}{144} \\
 &= \frac{-1}{144} //
 \end{aligned}$$

(5) $\{X_k, k=1, 2, \dots\}$ iid rvs and $Y_k = X_{k+1} - X_k, k=1, 2, \dots$

(5.a) $X \sim N(0, 1)$

Consider, $S_X = X_1 + \dots + X_n$. Since $X_i \sim N(0, 1)$, iid

$$S_X \sim N(0, n)$$

$$\begin{aligned} a_n &= IP[S_X > 0] \\ &= 1 - \Phi\left(\frac{0}{n}\right) \\ &= 1 - \Phi(0) \\ &= 1/2 // \end{aligned}$$

$$\begin{aligned} S_Y &= Y_1 + \dots + Y_n \\ &= (X_2 - X_1) + (X_3 - X_2) + \dots + (X_{n+1} - X_n) \\ &= X_{n+1} - X_1 \end{aligned}$$

$$\Rightarrow S_Y \sim N(0, 2) \text{ for } n=1, 2, \dots$$

$$\begin{aligned} \text{Hence, } b_n &= IP[S_Y > 0] \\ &= 1 - \Phi(0) \\ &= 1/2 // \end{aligned}$$

(5.b) $E(X) = 0, E(|X|^2) = 1$

The Central Limit Theorem: If $E(X) = \mu, \text{Var}(X) = \sigma^2$,
$$Z_n = \frac{X_1 + \dots + X_n - n\mu}{\sigma\sqrt{n}}$$

Then,

$$\lim_{n \rightarrow \infty} IP[Z_n \leq z] = \Phi(z) \quad \left(\text{The CDF of } Z_n \text{ converges to the standard normal CDF} \right)$$

In the given problem, $E(X) = 0$ and $\text{Var}(X) = E(X^2) - (E(X))^2 = 1$

$$\Rightarrow Z_n = \frac{X_1 + \dots + X_n}{\sqrt{n}}$$

By the Central Limit Theorem,
$$\lim_{n \rightarrow \infty} IP\left[\frac{X_1 + \dots + X_n}{\sqrt{n}} \leq z\right] = \Phi(z)$$

In particular, when $g = 0$,

$$\lim_{n \rightarrow \infty} \mathbb{P} \left[\frac{X_1 + \dots + X_n}{\sqrt{n}} \leq 0 \right] = \Phi(0)$$

$$\lim_{n \rightarrow \infty} \mathbb{P} [X_1 + \dots + X_n \leq 0] = \Phi(0) = 1/2$$

$$\Rightarrow \lim_{n \rightarrow \infty} \mathbb{P} [X_1 + \dots + X_n > 0] = 1/2 //$$

Hence, when n is large,

$$\mathbb{P} [X_1 + \dots + X_n > 0] \approx 1/2 //$$

$$(5c) \quad S_Y = Y_1 + \dots + Y_n \\ = X_{n+1} - X_1$$

$$\begin{aligned} & \mathbb{P} [S_Y > 0] \\ &= \mathbb{P} [X_{n+1} - X_1 > 0] \\ &= \mathbb{P} [X_{n+1} > X_1] \end{aligned}$$

Since $X_1, \dots, X_n, \dots$ are iid, $\mathbb{P} [X_{n+1} > X_1] = \mathbb{P} [X_1 > X_{n+1}]$

But,

$$\mathbb{P} (X_{n+1} > X_1) + \mathbb{P} (X_{n+1} < X_1) + \mathbb{P} (X_{n+1} = X_1) = 1$$

$\Rightarrow \mathbb{P} (X_{n+1} > X_1) = \mathbb{P} (X_{n+1} < X_1) = 1/2$ (Assuming X is continuous)

$$\therefore \mathbb{P} [Y_1 + \dots + Y_n > 0] = 1/2 \text{ for } \forall n$$

Hence

$$\lim_{n \rightarrow \infty} \mathbb{P} [Y_1 + \dots + Y_n > 0] = 1/2 //$$

This value is the same as the one obtained in 5.b.

• Note that in this case the claim is true for all n , not only in the limiting value!

(6) The sample space can be constructed as the ordered pairs
 { Choice of coin, Sequence of observations }

(a)

$$\Omega = \left\{ (m, (y_1, y_2, \dots, y_L)) \mid 1 \leq m \leq M, y_i \in \{0, 1\} \atop 1 \leq i \leq L \right\}$$

(We represent an observation of Heads by 1 and tails by 0)

If the event of selecting coin m is A_m ,

$$IP[(y_1, y_2, \dots, y_L) \mid A_m] = p_m^{\sum_{i=1}^L y_i} (1-p_m)^{L - \sum_{i=1}^L y_i} \text{ and}$$

$$IP[A_m] = a_m$$

Hence, the probability of the singleton events in the sample space,

$$\begin{aligned} IP[\{\omega\}] &= IP[(m, (y_1, y_2, \dots, y_L))] \\ &= IP[(y_1, y_2, \dots, y_L) \mid A_m] IP[A_m] \\ &= a_m \cdot p_m^{\sum_{i=1}^L y_i} (1-p_m)^{L - \sum_{i=1}^L y_i} \quad // \end{aligned}$$

Since Ω is countable, $\mathcal{F}$ = Power Set (2^Ω)

(b) $IP[E_L] = \sum_{m=1}^M IP[E_L \mid A_m] IP[A_m] \quad (\text{Law of Total Probabilities})$

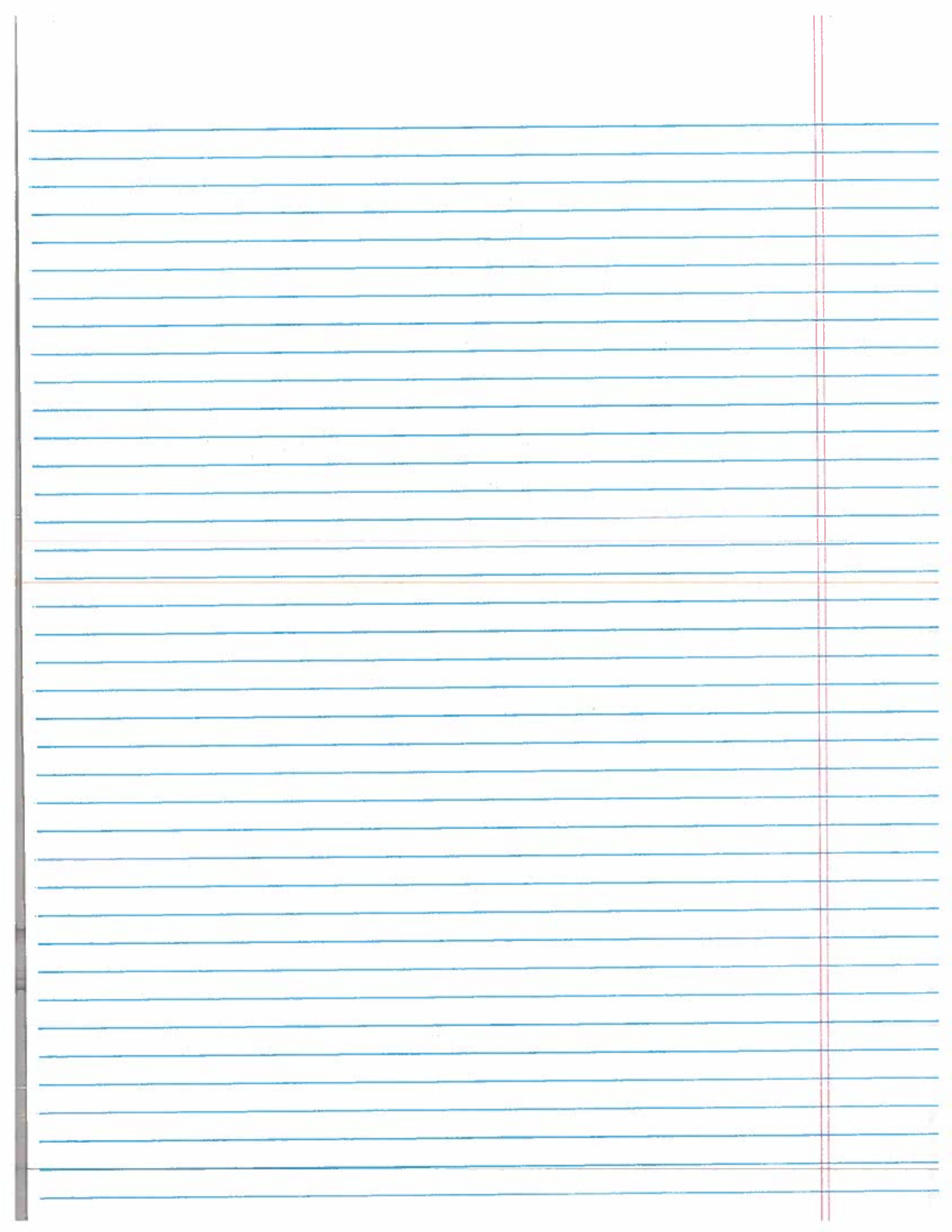
$$= \sum_{m=1}^M p_m \cdot a_m \quad \text{for } 1 \leq L \leq L$$

$$\begin{aligned} IP[E_1, E_2, \dots, E_L] &= \sum_{m=1}^M IP[E_1, E_2, \dots, E_L \mid A_m] IP[A_m] \\ &= \sum_{m=1}^M p_m^L \cdot a_m \\ &\neq \left(\sum_{m=1}^M p_m a_m \right)^L = \prod_{l=1}^L IP[E_L] \end{aligned}$$

Hence, the events $E_1, E_2, \dots, E_L$ are not mutually independent.

$$\begin{aligned}
 (c) \quad IP[A_m | E_1] &= \frac{IP[E_1 | A_m] IP[A_m]}{IP[E_1]} \\
 &= \frac{p_m a_m}{\sum_{k=1}^M p_k a_k} \quad (\text{from (b)}) \\
 &\quad //
 \end{aligned}$$

$$\begin{aligned}
 (d) \quad IP[E_2 | E_1] &= \frac{IP[E_1, E_2]}{IP[E_1]} \\
 &= \frac{\sum_{m=1}^M p_m^2 a_m}{\sum_{m=1}^M p_m a_m} \quad (\text{from (b)}) \\
 &\quad //
 \end{aligned}$$



$$\gamma) P[N=n] = (1-p)p^{n-1}, \quad n=1,2,\dots$$

$$f_{X|N}(t|n) = \frac{\lambda(\lambda t)^{n-1}}{(n-1)!} e^{-\lambda t}, \quad t \geq 0, \quad n=1,2,\dots$$

a) We can write pdf of N as:

$$f_N(n) = \sum_{n_0=1}^{\infty} P[N=n] \cdot \delta(n-n_0) \quad [\text{where } \delta \text{ is the Dirac-delta } \delta^*]$$

Now, for $t \geq 0$,

$$f_X(t) = \int_{n=-\infty}^{\infty} f_{X|N}(t|n) dn$$

$$= \int_{n=-\infty}^{\infty} f_{X|N}(t|n) \cdot f_N(n) dn$$

$$= \int_{n=-\infty}^{\infty} \lambda \frac{(\lambda t)^{n-1}}{(n-1)!} e^{-\lambda t} \cdot \sum_{n_0=1}^{\infty} P[N=n] \cdot \delta(n-n_0) dn$$

$$= \int_{n=-\infty}^{\infty} \sum_{n_0=1}^{\infty} \lambda \frac{(\lambda t)^{n-1}}{(n-1)!} e^{-\lambda t} \cdot (1-p) p^{n-1} \delta(n-n_0) dn$$

$$= \sum_{n_0=1}^{\infty} \int_{n=-\infty}^{\infty} \lambda \frac{(\lambda t)^{n-1}}{(n-1)!} e^{-\lambda t} (1-p) p^{n-1} \delta(n-n_0) dn \quad [\text{by Fubini's theorem, we can interchange the sum and integral if } |f_X(t)| < \infty]$$

$$= \sum_{n_0=1}^{\infty} \lambda \frac{(\lambda t)^{n_0-1}}{(n_0-1)!} e^{-\lambda t} (1-p) p^{n_0-1} \quad [\text{by property of Delta } \delta^*]$$

$$= \lambda e^{-\lambda t} (1-p) \sum_{n_0=1}^{\infty} \frac{(\lambda t p)^{n_0-1}}{(n_0-1)!}$$

$$= \lambda e^{-\lambda t} (1-p) \sum_{m=0}^{\infty} \frac{(\lambda t p)^m}{m!} \quad [\text{changing the index using } m = n_0 - 1]$$

$$= \lambda e^{-\lambda t} (1-p) \cdot e^{\lambda t p}$$

$$= \lambda(1-p) \cdot e^{-\lambda(1-p)t}$$

Clearly, $f_X(t) = 0$ for $t < 0$ because $f_{X|N}(t|n) = 0$ if $t < 0$ and

$$f_X(t) = \int_{n=-\infty}^{\infty} f_{X|N}(t|n) f_N(n) dn.$$

So, $X \sim \exp(\lambda(1-p))$.

b) For each $t > 0$, $n=1, 2, \dots$,

$$\begin{aligned}\mathbb{P}[N=n | X=t] &= \frac{f_{X|N}(t|n) \cdot \mathbb{P}[N=n]}{f_X(t)} \\ &= \frac{\lambda(1-p)^{n-1}}{(n-1)!} e^{-\lambda t} \cdot (1-p)p^{n-1} \cdot \frac{1}{\lambda(1-p)e^{-\lambda t(1-p)}} \\ &= \frac{(\lambda tp)^{n-1}}{(n-1)!} e^{-\lambda tp}, \quad n=1, 2, \dots\end{aligned}$$

$$\text{So, } \mathbb{P}[N=1+m | X=t] = \frac{(\lambda tp)^m}{m!} e^{-\lambda tp}, \quad m=0, 1, 2, \dots$$

$$\Rightarrow \mathbb{P}[N-1=m | X=t] = \frac{(\lambda tp)^m}{m!} e^{-\lambda tp}, \quad m=0, 1, 2, \dots$$

Thus, the conditional pmf of N given $X=t$, $t > 0$, is related to Poisson distribution.

In particular,

the rv $(N-1) | X=t \sim \text{Pois}(\lambda tp)$, $t > 0$

$$\begin{aligned}e) \quad \mathbb{E}[XN] &= \int_{t=0}^{\infty} \sum_{n=1}^{\infty} tn \cdot \mathbb{P}[N=n | X=t] \cdot f_X(t) dt && [\text{by def}^n \text{ of expectation of product of two rvs}] \\ &= \int_{t=0}^{\infty} \sum_{n=1}^{\infty} tn \cdot \frac{(\lambda tp)^{n-1}}{(n-1)!} e^{-\lambda tp} \cdot \lambda(1-p)e^{-\lambda(1-p)t} dt && [\text{by results obtained in (7.a) \& (7.b)}] \\ &= \int_{t=0}^{\infty} \sum_{n=1}^{\infty} tn \frac{(\lambda tp)^{n-1}}{(n-1)!} \lambda(1-p)e^{-\lambda t} dt \\ &= \int_{t=0}^{\infty} \left[\sum_{n=1}^{\infty} n \frac{(\lambda tp)^{n-1}}{(n-1)!} \right] \cdot t \lambda(1-p)e^{-\lambda t} dt\end{aligned}$$

$$\begin{aligned}\text{Now, } \sum_{n=1}^{\infty} n \cdot \frac{(\lambda tp)^{n-1}}{(n-1)!} &= \sum_{n=1}^{\infty} n \cdot \frac{\mu^{n-1}}{(n-1)!} \quad [\text{where } \mu := \lambda tp] \\ &= \sum_{m=0}^{\infty} (m+1) \cdot \frac{\mu^m}{m!} \quad [\text{where } m := n-1] \\ &= \sum_{m=0}^{\infty} m \frac{\mu^m}{m!} + \sum_{m=0}^{\infty} \frac{\mu^m}{m!} \\ &= \sum_{m=1}^{\infty} m \frac{\mu^m}{m!} + e^{\mu}\end{aligned}$$

$$= \sum_{m=2}^{\infty} \frac{\mu^m}{(m-1)!} + e^{\mu}$$

$$= \mu \sum_{m=1}^{\infty} \frac{\mu^{m-1}}{(m-1)!} + e^{\mu}$$

$$= \mu e^{\mu} + e^{\mu}$$

$$= \lambda t p \cdot e^{\lambda t p} + e^{\lambda t p}$$

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

By differentiating both sides w.r.t. x

$$\Rightarrow e^x = \sum_{m=0}^{\infty} \frac{m x^{m-1}}{m!}$$

$$= \sum_{m=1}^{\infty} \frac{m x^{m-1}}{m!}$$

$$= \sum_{m=1}^{\infty} \frac{x^{m-1}}{(m-1)!}$$

$$\text{So, } E[X_N] = \int_{t=0}^{\infty} e^{\lambda t p} (\lambda t p + 1) \cdot t \lambda (1-p) e^{-\lambda t} dt$$

$$= \lambda p \int_0^{\infty} t^2 \lambda (1-p) e^{-\lambda (1-p)t} dt + \int_0^{\infty} t \cdot \lambda (1-p) e^{-\lambda (1-p)t} dt$$

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

$$= \lambda p \cdot \frac{2}{[\lambda (1-p)]^2} + \frac{1}{\lambda (1-p)}$$

$$= p \cdot \frac{2}{\lambda (1-p)^2} + \frac{1}{\lambda (1-p)}$$

$$= \frac{1}{\lambda (1-p)} \left(\frac{2p}{1-p} + 1 \right)$$

$$= \frac{(1+p)}{(1-p)} \cdot \frac{1}{\lambda}$$

[$\because$ The first integrand is 2nd moment of exponential distribution with parameter $\lambda(1-p)$ and the second integrand is mean of $\text{exp}(\lambda(1-p))$]

$$8) f_{X,Y}(x,y) = \Gamma \cdot e^{-(ax^2+cy^2-2bxy)}, \quad \forall x,y \in \mathbb{R}, \Gamma > 0.$$

$$a, c > 0, b^2 < ac.$$

$$\begin{aligned} a) \iint_{x,y} f_{X,Y}(x,y) dx dy &= 1 \Rightarrow \iint_{x,y} \Gamma \cdot e^{-(ax^2+cy^2-2bxy)} dx dy = 1 \\ &\Rightarrow \frac{1}{\Gamma} = \iint_{x,y} e^{-(ax^2+cy^2-2bxy)} dx dy \end{aligned}$$

Now, by property of bivariate Normal distribution,

$$\begin{aligned} 1 &= \iint_{x,y} \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} e^{-\frac{1}{2(1-\rho^2)}\left\{\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2 - 2\rho\frac{(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y}\right\}} dx dy \\ &\Rightarrow \iint_{x,y} e^{-\frac{1}{2(1-\rho^2)}\left\{\left(\frac{x-\mu_x}{\sigma_x}\right)^2 + \left(\frac{y-\mu_y}{\sigma_y}\right)^2 - 2\rho\frac{(x-\mu_x)(y-\mu_y)}{\sigma_x\sigma_y}\right\}} dx dy = 2\pi\sigma_x\sigma_y\sqrt{1-\rho^2} \end{aligned}$$

where $\mu_x, \mu_y \in \mathbb{R}, \sigma_x, \sigma_y > 0, \rho^2 < 1$.

Comparing, $ax^2 + by^2 - 2bxy = \left\{ \left(\frac{x - \mu_x}{\sigma_x} \right)^2 + \left(\frac{y - \mu_y}{\sigma_y} \right)^2 - 2\rho \frac{(x - \mu_x)(y - \mu_y)}{\sigma_x \sigma_y} \right\} \cdot \frac{1}{2(1 - \rho^2)}$

we get,

$$\mu_x = \mu_y = 0$$

$$a = \frac{1}{\sigma_x^2 \cdot 2(1 - \rho^2)}$$

$$c = \frac{1}{\sigma_y^2 \cdot 2(1 - \rho^2)}$$

$$b = \frac{\rho}{\sigma_x \sigma_y \cdot 2(1 - \rho^2)}$$

$$\text{So, } ac = \frac{1}{\sigma_x^2 \sigma_y^2 (2(1 - \rho^2))^2}$$

$$\Rightarrow \sqrt{ac} = \pm \frac{1}{\sigma_x \sigma_y \cdot 2(1 - \rho^2)}$$

$$\Rightarrow b = \pm \rho \cdot \sqrt{ac}$$

$$\Rightarrow \rho = \pm \frac{b}{\sqrt{ac}}$$

$$\Rightarrow \rho^2 = \frac{b^2}{ac} < 1 \quad [\because b^2 < ac]$$

Hence, $\iint_{x,y} e^{-(ax^2 + by^2 - 2bxy)} dx dy = 2\pi \sigma_x \sigma_y \sqrt{1 - \rho^2}$

Now, $b = \frac{\rho}{\sigma_x \sigma_y \cdot 2(1 - \rho^2)} \Rightarrow \sigma_x \sigma_y \cdot 2\sqrt{1 - \rho^2} = \frac{\rho \pi}{b \sqrt{1 - \rho^2}}$

$$= \frac{\frac{b}{\sqrt{ac}} \pi \cdot \frac{1}{b \sqrt{1 - \frac{b^2}{ac}}}}{1}$$

$$= \frac{\pi}{\sqrt{ac - b^2}}$$

$$\therefore \iint_{x,y} e^{-(ax^2 + by^2 - 2bxy)} dx dy = \frac{\pi}{\sqrt{ac - b^2}}$$

$$\Rightarrow \frac{1}{\Gamma} = \frac{\pi}{\sqrt{ac - b^2}}$$

$$\Rightarrow \Gamma = \frac{\sqrt{ac - b^2}}{\pi}$$

$$\therefore f_{x,y}(x,y) = \frac{\sqrt{ac - b^2}}{\pi} e^{-(ax^2 + by^2 - 2bxy)}, \quad \forall x, y \in \mathbb{R}.$$

$$\begin{aligned}
 b) \quad f_Y(y) &= \int_{-\infty}^{\infty} f_{X,Y}(x,y) dx, \quad y \in \mathbb{R}. \\
 &= \frac{\sqrt{ac-b^2}}{\pi} \int_{-\infty}^{\infty} e^{-(ax^2+cy^2-2bxy)} dx \\
 &= \frac{\sqrt{ac-b^2}}{\pi} \cdot e^{-cy^2} \int_{-\infty}^{\infty} e^{-(ax^2-x \cdot 2by)} dx
 \end{aligned}$$

$$\text{Now, } (ax^2 - x \cdot 2by) = \left(x\sqrt{a} - \frac{yb}{\sqrt{a}}\right)^2 - \left(\frac{yb}{\sqrt{a}}\right)^2$$

$$\begin{aligned}
 \therefore f_Y(y) &= \frac{\sqrt{ac-b^2}}{\pi} e^{-cy^2} \cdot e^{\left(\frac{yb}{\sqrt{a}}\right)^2} \int_{-\infty}^{\infty} e^{-\left(x\sqrt{a} - \frac{yb}{\sqrt{a}}\right)^2} dx \\
 &= \frac{\sqrt{ac-b^2}}{\pi} e^{-y^2\left(c - \frac{b^2}{a}\right)} \int_{-\infty}^{\infty} e^{-\frac{1}{2}\left(\frac{x}{\frac{1}{\sqrt{2a}}} - \frac{\frac{by}{a}}{\frac{1}{\sqrt{2a}}}\right)^2} dx \\
 &= \frac{\sqrt{ac-b^2}}{\pi} e^{-y^2\left(c - \frac{b^2}{a}\right)} \cdot \sqrt{2\pi} \cdot \frac{1}{\sqrt{2a}} \left[\because 1 = \frac{1}{\sqrt{2\pi}\sigma} \int_{-\infty}^{\infty} e^{-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2} dx, \right. \\
 &\quad \left. \text{take } \sigma = \frac{1}{\sqrt{2a}}, \mu = \frac{by}{a} \right] \\
 &= \sqrt{\frac{ac-b^2}{\pi a}} e^{-y^2\left(c - \frac{b^2}{a}\right)}, \quad \forall y \in \mathbb{R}.
 \end{aligned}$$

c) For each $y \in \mathbb{R}$,

$$\begin{aligned}
 f_{X|Y}(x|y) &= \frac{f_{X,Y}(x,y)}{f_Y(y)}, \quad \forall x \in \mathbb{R} \\
 &= \frac{\frac{\sqrt{ac-b^2}}{\pi} e^{-(ax^2+cy^2-2bxy)}}{\sqrt{\frac{ac-b^2}{\pi a}} e^{-y^2\left(c - \frac{b^2}{a}\right)}} \\
 &= \sqrt{\frac{a}{\pi}} e^{-(ax^2 - 2bxy - \frac{b^2}{a}y^2)}, \quad x \in \mathbb{R}.
 \end{aligned}$$

$$\begin{aligned}
 d) \quad E[Y] &= \int_{-\infty}^{\infty} y f_Y(y) dy = \int_{-\infty}^{\infty} y \cdot \sqrt{\frac{ac-b^2}{\pi a}} e^{-y^2\left(c - \frac{b^2}{a}\right)} dy \\
 &= 0. \quad [\text{since the integrand is an odd f}^{\text{th}} \text{ w.r.t. } y]
 \end{aligned}$$

By symmetry of the problem in x and y ,

$$f_X(x) = \sqrt{\frac{ac-b^2}{\pi a}} e^{-x^2\left(a - \frac{b^2}{c}\right)}, \quad \forall x \in \mathbb{R}$$

and $E[X] = 0$ by a similar argument as $E[Y]$.

$$e) \quad E[XY] = \iint_{x,y} xy f_{X,Y}(x,y) dx dy \quad \left[\text{Be careful here as to not write} \right. \\ \left. \iint_{x,y} xy f_X(x) f_Y(y) dx dy \right]$$

$$= \iint xy \cdot \Gamma \cdot e^{-(ax^2 - 2bxy + cy^2)} dx dy$$

$$= \Gamma \int_{y=-\infty}^{\infty} y e^{-cy^2} \left[\int_{x=-\infty}^{\infty} x e^{-(ax^2 - 2bxy)} dx \right] dy$$

As shown in the part (8.b), the term inside the $[\]$ bracket, can be calculated by:

$$\frac{1}{\sqrt{2\pi} \cdot \frac{1}{\sqrt{2a}}} \int_{-\infty}^{\infty} x e^{-(ax^2 - 2bxy)} dx = \frac{1}{\sqrt{2\pi} \cdot \frac{1}{\sqrt{2a}}} e^{\frac{y^2 b^2}{a}} \int_{-\infty}^{\infty} x e^{-\frac{1}{2} \left(\frac{x}{\frac{1}{\sqrt{2a}}} - \frac{yb/a}{\frac{1}{\sqrt{2a}}} \right)^2} dx \\ = e^{\frac{y^2 b^2}{a}} \cdot \frac{yb}{a} \quad \left[\text{by expectation of a Normal rv. with } \sigma = \frac{1}{\sqrt{2a}}, \mu = \frac{yb}{a} \right]$$

$$\Rightarrow \int_{-\infty}^{\infty} x e^{-(ax^2 - 2bxy)} dx = \sqrt{\frac{a}{\pi}} \cdot e^{\frac{y^2 b^2}{a}} \cdot \frac{yb}{a}$$

$$\therefore E[XY] = \Gamma \int_{-\infty}^{\infty} y e^{-cy^2} \cdot \sqrt{\frac{a}{\pi}} e^{\frac{y^2 b^2}{a}} \cdot \frac{yb}{a} dy$$

$$= \Gamma \cdot \frac{b}{a} \cdot \sqrt{\frac{a}{\pi}} \int_{-\infty}^{\infty} y^2 e^{-y^2 \left(c - \frac{b^2}{a} \right)} dy$$

$$= \Gamma \cdot \frac{b}{\sqrt{a\pi}} \int_{-\infty}^{\infty} y^2 e^{-\frac{1}{2} \cdot y^2 \cdot 2 \left(c - \frac{b^2}{a} \right)} dy$$

$$= \Gamma \cdot \frac{b}{\sqrt{a\pi}} \cdot \sqrt{2\pi} \cdot \sigma \int_{-\infty}^{\infty} y^2 \cdot \frac{1}{\sqrt{2\pi} \cdot \sigma} e^{-\frac{y^2}{2\sigma^2}} dy \quad \left[\text{where } \sigma^2 = \frac{1}{2 \left(c - \frac{b^2}{a} \right)} \right]$$

$$= \Gamma \cdot \frac{b}{\sqrt{a\pi}} \cdot \sqrt{2\pi} \cdot \sigma \cdot (\sigma^2 + 0) \quad \left[\because \text{The integral is 2nd moment of a Normal rv with mean 0 and variance } \sigma^2 \right]$$

$$= \Gamma \cdot \frac{b}{\sqrt{a}} \cdot \sqrt{2} \sigma^3 = \frac{ab}{2\pi(ac - b^2)}$$

9) An useful result:

$$\int_0^{\infty} e^{-\alpha t} \cdot t^{(n-1)} dt = \frac{(n-1)!}{\alpha^n}, \text{ where } \alpha > 0, n = 1, 2, \dots \quad \text{--- (A)}$$

Proof:

$$\begin{aligned} \text{Let } y &= \alpha t \\ \text{Then } \int_0^{\infty} e^{-\alpha t} \cdot t^{(n-1)} dt &= \int_0^{\infty} e^{-y} y^{n-1} \cdot \alpha^{-(n-1)} \cdot \alpha^{-1} dy \\ &= \alpha^{-n} \int_0^{\infty} e^{-y} \cdot y^{n-1} dy \\ &= \alpha^{-n} \cdot (n-1)! \quad [\text{Recall: } \int_0^{\infty} t^n e^{-t} dt = n!, n \geq 1] \end{aligned}$$

Now the problem:

$$\begin{aligned} \Lambda &\sim \exp(\lambda), \lambda > 0 \\ \Rightarrow f_{\Lambda}(t) &= \begin{cases} \lambda e^{-\lambda t} & , t \geq 0 \\ 0 & , t < 0 \end{cases} \end{aligned}$$

For each $t > 0$,

$$\mathbb{P}[X=x | \Lambda=t] = \frac{t^x}{x!} e^{-t}, \quad x=0,1,\dots$$

$$a) \mathbb{P}[X=x], \quad x=0,1,\dots$$

$$= \int_{-\infty}^{\infty} \mathbb{P}[X=x | \Lambda=t] f_{\Lambda}(t) dt$$

$$= \int_0^{\infty} \frac{t^x}{x!} e^{-t} \cdot \lambda e^{-\lambda t} dt$$

$$= \frac{\lambda}{x!} \int_0^{\infty} t^x \cdot e^{-(\lambda+1)t} dt$$

$$= \frac{\lambda}{x!} \cdot \frac{x!}{(\lambda+1)^{x+1}} \quad [\text{using (A) with } n-1=x, \alpha=\lambda+1 > 0]$$

$$= \frac{\lambda}{(\lambda+1)^{x+1}}$$

$$= \frac{\lambda}{\lambda+1} \left(\frac{1}{\lambda+1} \right)^x$$

$$= \frac{\lambda}{\lambda+1} \left(1 - \frac{\lambda}{\lambda+1} \right)^x, \quad x=0,1,\dots$$

$$\therefore X \sim \text{Geo}\left(\frac{\lambda}{\lambda+1}\right) \text{ on } \mathbb{N}_0.$$

b) With $x=0,1,\dots$,

$$f_{\lambda|x}(t|x) = \frac{\mathbb{P}[X=x|\Lambda=t] f_{\lambda}(t)}{\mathbb{P}[X=x]}$$

$$\therefore f_{\lambda|x}(t|x) = 0 \text{ if } t < 0 \text{ [} \because f_{\lambda}(t) = 0 \text{ if } t < 0 \text{]}$$

For $t \geq 0$,

$$\begin{aligned} f_{\lambda|x}(t|x) &= \frac{\frac{t^x}{x!} e^{-t} \cdot \lambda e^{-\lambda t}}{\frac{\lambda}{(\lambda+1)^{x+1}}} \\ &= \frac{t^x}{x!} e^{-(\lambda+1)t} \cdot (\lambda+1)^{x+1} \\ &= \frac{[(\lambda+1)t]^x}{x!} e^{-(\lambda+1)t} \cdot (\lambda+1) \end{aligned}$$

c) $\mathbb{E}[e^{-ax\Lambda} | X=x]$, $x=0,1,\dots; a>0$

$$= \int_{t=-\infty}^{\infty} e^{-axt} \cdot f_{\lambda|x}(t|x) dt$$

$$= \int_{t=0}^{\infty} e^{-axt} \cdot \frac{t^x}{x!} e^{-(\lambda+1)t} \cdot (\lambda+1)^{x+1} dt \quad [\text{from result of (9.b)}]$$

$$= \frac{(\lambda+1)^{x+1}}{x!} \int_0^{\infty} e^{-(ax+\lambda+1)t} \cdot t^x dt$$

$$= \frac{(\lambda+1)^{x+1}}{x!} \cdot \frac{x!}{(ax+\lambda+1)^{x+1}} \quad [\text{from (1)}]$$

$$= \left(\frac{\lambda+1}{ax+\lambda+1} \right)^{x+1}, \quad x=0,1,\dots$$

$$\begin{aligned}
 10) \quad & X \sim \exp(\lambda) \\
 & Y \sim \exp(\mu) \\
 & X \perp\!\!\!\perp Y \\
 & \lambda, \mu > 0 \\
 & R = \begin{cases} \frac{\sqrt{X}}{\sqrt{X} + \sqrt{Y}} & , \text{ if } X > 0, Y > 0 \\ 0 & , \text{ o/w} \end{cases}
 \end{aligned}$$

$$\begin{aligned}
 a) \quad & X \sim \exp(\lambda) \Rightarrow \mathbb{P}[X > 0] = 1 \\
 & Y \sim \exp(\mu) \Rightarrow \mathbb{P}[Y > 0] = 1 \\
 & X \perp\!\!\!\perp Y \Rightarrow \mathbb{P}[X > 0, Y > 0] = \mathbb{P}[X > 0] \cdot \mathbb{P}[Y > 0] = 1 \\
 & \Rightarrow \mathbb{P}[\{X > 0, Y > 0\}^c] = 0.
 \end{aligned}$$

Clearly,

$$\begin{aligned}
 & \mathbb{P}[R \leq r] = 0, \text{ if } r \leq 0 \\
 & \text{and } \mathbb{P}[R \leq r] = 1, \text{ if } r \geq 1
 \end{aligned}$$

For $r \in (0, 1)$,

$$\begin{aligned}
 \mathbb{P}[R \leq r] &= \mathbb{P}[R \leq r, \{X > 0, Y > 0\}] + \mathbb{P}[R \leq r, \{X > 0, Y > 0\}^c] \\
 &= \mathbb{P}[R \leq r, \{X > 0, Y > 0\}] + 0 \quad [\because R \leq r, \{X > 0, Y > 0\}^c \\
 &\quad \subseteq \{X > 0, Y > 0\}^c \\
 &\quad \text{and } \mathbb{P}[\{X > 0, Y > 0\}^c] = 0] \\
 &= \mathbb{P}\left[\frac{\sqrt{X}}{\sqrt{X} + \sqrt{Y}} \leq r, X > 0, Y > 0\right] \\
 &= \mathbb{P}[\sqrt{X}(1-r) \leq r\sqrt{Y}, X > 0, Y > 0] \\
 &= \mathbb{P}[X(1-r)^2 \leq r^2 Y, X > 0, Y > 0] \\
 &= \mathbb{P}\left[X \leq \left(\frac{r}{1-r}\right)^2 Y, X > 0, Y > 0\right] \\
 &= \mathbb{P}\left[Y > 0, 0 < X \leq \left(\frac{r}{1-r}\right)^2 Y\right] \\
 &= \mathbb{E}\left[1[Y > 0, 0 < X \leq \left(\frac{r}{1-r}\right)^2 Y]\right] \\
 &= \mathbb{E}\left[\left(\mathbb{E}\left[1[Y > 0] \cdot 1\left[0 < X \leq \left(\frac{r}{1-r}\right)^2 Y\right] \mid Y=y\right]\right)_{y=Y}\right] \\
 &= \mathbb{E}\left[\left(\mathbb{E}\left[1[Y > 0] \cdot 1\left[0 < X \leq \left(\frac{r}{1-r}\right)^2 Y\right] \mid Y=y\right]\right)_{y=Y}\right]
 \end{aligned}$$

$$= \mathbb{E} \left[\mathbb{1}[Y > 0] \cdot \mathbb{E} \left[\mathbb{1} \left[0 < X \leq \left(\frac{p}{1-p} \right)^2 Y \right] \right]_{Y=Y} \right] \quad [\because X \perp Y]$$

$$= \mathbb{E} \left[\mathbb{1}[Y > 0] \cdot \left(\mathbb{P} \left[0 < X \leq \left(\frac{p}{1-p} \right)^2 Y \right]_{Y=Y} \right) \right]$$

$$= \mathbb{E} \left[\mathbb{1}[Y > 0] \cdot \left(\mathbb{P} \left[X \leq \left(\frac{p}{1-p} \right)^2 Y \right]_{Y=Y} \right) \right] \quad [\because X \sim \exp(\lambda) \Rightarrow \mathbb{P}[X \leq x] = 0 \quad \forall x < 0]$$

$$= \mathbb{E} \left[\mathbb{1}[Y > 0] \cdot \left(1 - e^{-\lambda \left(\frac{p}{1-p} \right)^2 Y} \right)_{Y=Y} \right] \quad [\because X \sim \exp(\lambda) \Rightarrow \mathbb{P}[X \leq x] = 1 - e^{-\lambda x}, x > 0]$$

$$= \mathbb{E} \left[\mathbb{1}[Y > 0] \cdot \left(1 - e^{-\lambda \left(\frac{p}{1-p} \right)^2 Y} \right) \right]$$

$$= \int_0^{\infty} \left(1 - e^{-\lambda \left(\frac{p}{1-p} \right)^2 y} \right) \mu e^{-\mu y} dy$$

$$= \int_0^{\infty} \mu e^{-\mu y} dy - \int_0^{\infty} \mu e^{-\left(\lambda \left(\frac{p}{1-p} \right)^2 + \mu \right) y} dy$$

$$= 1 - \frac{\mu}{\mu + \lambda \left(\frac{p}{1-p} \right)^2}$$

$$\text{So, } \mathbb{P}[R \leq r] = \begin{cases} 0, & \text{if } r \leq 0 \\ 1 - \frac{\mu}{\mu + \lambda \left(\frac{p}{1-p} \right)^2}, & \text{if } 0 < r < 1 \\ 1, & \text{if } r \geq 1 \end{cases}$$

b) Clearly $F_R(r) = \mathbb{P}[R \leq r]$ is continuous and differentiable w.r.t. r .

So, R is a continuous r.v.

$$f_R(r) = \frac{d}{dr} F_R(r) = \frac{d}{dr} \left(1 - \frac{\mu}{\mu + \lambda \left(\frac{p}{1-p} \right)^2} \right), \quad 0 < r < 1$$

$$= \frac{d}{dr} \left(\frac{\lambda p^2}{r^2 \lambda + \mu (1-p)^2} \right), \quad 0 < r < 1$$

$$= \begin{cases} 2\mu\lambda \frac{r(1-p)}{(\lambda r^2 + \mu(1-p)^2)^2}, & 0 < r < 1 \\ 0, & \text{o/w.} \end{cases}$$

Now, $\lambda = \mu$.

$$c) F_R(r) = \begin{cases} 0, & r \leq 0 \\ 1 - \frac{1}{1 + \left(\frac{r}{1-r}\right)^2}, & 0 < r < 1 \\ 1, & r \geq 1 \end{cases}$$

If $|x| > \frac{1}{2}$,

$$\mathbb{P}[R \leq \frac{1}{2} - |x|] = 0 \quad [\because \frac{1}{2} - |x| < 0]$$

$$\begin{aligned} \text{and } \mathbb{P}[R \geq \frac{1}{2} + |x|] &= 1 - \mathbb{P}[R \leq \frac{1}{2} + |x|] \\ &= 1 - 1 \quad [\because \frac{1}{2} + |x| > 1] \\ &= 0. \end{aligned}$$

$$\Rightarrow \mathbb{P}[R \leq \frac{1}{2} - |x|] = \mathbb{P}[R \geq \frac{1}{2} + |x|], \quad \forall |x| > \frac{1}{2}.$$

If $|x| < \frac{1}{2}$,

$$\mathbb{P}[R \leq \frac{1}{2} - |x|] = 1 - \frac{1}{1 + \left(\frac{\frac{1}{2} - |x|}{1 - \frac{1}{2} + |x|}\right)^2} = 1 - \frac{1}{1 + \left(\frac{\frac{1}{2} - |x|}{\frac{1}{2} + |x|}\right)^2} = 1 - \frac{(\frac{1}{2} + |x|)^2}{(\frac{1}{2} + |x|)^2 + (\frac{1}{2} - |x|)^2}$$

$$\text{and } \mathbb{P}[R \geq \frac{1}{2} + |x|] = 1 - \mathbb{P}[R \leq \frac{1}{2} + |x|]$$

$$= 1 - \left(1 - \frac{1}{1 + \left(\frac{\frac{1}{2} + |x|}{1 - \frac{1}{2} - |x|}\right)^2}\right)$$

$$= \frac{1}{1 + \left(\frac{\frac{1}{2} + |x|}{\frac{1}{2} - |x|}\right)^2}$$

$$= \frac{(\frac{1}{2} - |x|)^2}{(\frac{1}{2} - |x|)^2 + (\frac{1}{2} + |x|)^2}$$

$$= 1 - \frac{(\frac{1}{2} + |x|)^2}{(\frac{1}{2} + |x|)^2 + (\frac{1}{2} - |x|)^2} = \mathbb{P}[R \leq \frac{1}{2} - |x|]$$

$$\text{So, } \mathbb{P}[R \leq \frac{1}{2} - |x|] = \mathbb{P}[R \geq \frac{1}{2} + |x|] \quad \forall |x| \geq 0.$$

Hence, the distribution of R is symmetric about $\frac{1}{2}$.

$$\therefore E[R] = \frac{1}{2}.$$

$$\begin{aligned} d) \text{Cov}[R, \sqrt{X} + \sqrt{Y}] &= E[R(\sqrt{X} + \sqrt{Y})] - E[R] \cdot E[\sqrt{X} + \sqrt{Y}] \\ &= E[R(\sqrt{X} + \sqrt{Y})] - E[R] \cdot (E[\sqrt{X}] + E[\sqrt{Y}]) \end{aligned}$$

$$\text{Now, } E[R(\sqrt{X} + \sqrt{Y})]$$

$$\begin{aligned} &= E[R(\sqrt{X} + \sqrt{Y}) \cdot 1[X > 0, Y > 0] + R(\sqrt{X} + \sqrt{Y}) \cdot 1[\{X > 0, Y > 0\}^c]] \\ &= E[R(\sqrt{X} + \sqrt{Y}) \cdot 1[X > 0, Y > 0]] + E[R(\sqrt{X} + \sqrt{Y}) \cdot 1[\{X > 0, Y > 0\}^c]] \\ &= E\left[\frac{\sqrt{X}}{\sqrt{X} + \sqrt{Y}} \cdot (\sqrt{X} + \sqrt{Y}) \cdot 1[X > 0] \cdot 1[Y > 0]\right] + E[0 \cdot (\sqrt{X} + \sqrt{Y}) \cdot 1[\{X > 0, Y > 0\}^c]] \\ &= E[\sqrt{X} \cdot 1[X > 0] \cdot 1[Y > 0]] \\ &= E\left[\left(E[1[Y > 0] \sqrt{X} \cdot 1[X > 0] \mid Y = y]\right)_{y=Y}\right] \\ &= E\left[\left(E[1[Y > 0] \sqrt{X} \cdot 1[X > 0] \mid Y = y]\right)_{y=Y}\right] \\ &= E\left[\left(1[Y > 0] \cdot E[\sqrt{X} \cdot 1[X > 0] \mid Y = y]\right)_{y=Y}\right] \\ &= E\left[\left(1[Y > 0] \cdot E[\sqrt{X} \cdot 1[X > 0]]\right)_{y=Y}\right] \quad [\because X \perp Y] \\ &= E[1[Y > 0] \cdot E[\sqrt{X} \cdot 1[X > 0]]] \\ &= E[1[Y > 0]] \cdot E[\sqrt{X} \cdot 1[X > 0]] \quad [\because \text{The inner expectation is a constant}] \\ &= P[Y > 0] \cdot E[\sqrt{X} \cdot 1[X > 0]] \\ &= E[\sqrt{X} \cdot 1[X > 0]] \quad [\because X \sim \text{Exp}(1) \Rightarrow P[Y > 0] = 1] \end{aligned}$$

$$= \int_0^{\infty} x^{1/2} \cdot \lambda e^{-\lambda x} dx$$

$$= E[\sqrt{X}].$$

$$\therefore \text{Cov}[R, \sqrt{X} + \sqrt{Y}] = E[\sqrt{X}] - E[R] \cdot (E[\sqrt{X}] + E[\sqrt{Y}])$$

$$= E[\sqrt{X}] - \frac{1}{2}(E[\sqrt{X}] + E[\sqrt{Y}])$$

$$= \frac{1}{2} (E[\sqrt{X}] + E[\sqrt{Y}]).$$

$$E[\sqrt{X}] = \int_0^{\infty} x^{1/2} \cdot \lambda e^{-\lambda x} dx$$

$$= \lambda \int_0^{\infty} x^{\frac{3}{2}-1} e^{-\lambda x} dx$$

$$= \lambda \cdot \frac{\Gamma(\frac{3}{2})}{(\lambda)^{3/2}} \quad [\text{Gamma integral } \int_0^{\infty} e^{-ax} \cdot x^{p-1} dx = \frac{\Gamma(p)}{a^p}, p \in \mathbb{Q} \text{ (set of rationals)}]$$

$$= \frac{1}{\sqrt{\lambda}} \cdot \frac{1}{2} \sqrt{\frac{\pi}{2}}$$

$$= \frac{\sqrt{\pi}}{2\sqrt{\lambda}}.$$

$$\text{Similarly, } E[\sqrt{Y}] = \frac{\sqrt{\pi}}{2\sqrt{\mu}}.$$

$$\therefore \text{Cov}[R, \sqrt{X} + \sqrt{Y}] = \frac{1}{2} \left(\frac{\sqrt{\pi}}{2\sqrt{\lambda}} + \frac{\sqrt{\pi}}{2\sqrt{\mu}} \right)$$

$$= \frac{\sqrt{\pi}}{4} \left(\frac{1}{\sqrt{\lambda}} + \frac{1}{\sqrt{\mu}} \right)$$

If $\lambda = \mu$,

$$\text{Cov}[R, \sqrt{X} + \sqrt{Y}] = \frac{\sqrt{\pi}}{4} \cdot \frac{2}{\sqrt{\lambda}} = \frac{\sqrt{\pi}}{2\sqrt{\lambda}}.$$

