

State Prob Assignment

(1) Given: $X \leftarrow P(X) = e^{\lambda} \frac{\lambda^x}{x!}$

$$Y \leftarrow P(Y) = e^{\mu} \frac{\mu^y}{y!}$$

Also given that X & Y are independent.

$$\text{So, } P\{X|X+Y=n\} = \frac{P\{X, X+Y=n\}}{P\{X+Y=n\}} = \frac{P\{X=n\} \cdot P\{Y=n\}}{P\{X+Y=n\}}$$

(1)

Assume, $Z = X+Y$

$$\text{So, } M_Z(t) = E(e^{tZ}) = E(e^{tX}) \cdot E(e^{tY}) \\ = e^{\lambda(e^{t-1})} \cdot e^{\mu(e^{t-1})} \\ = e^{(\lambda+\mu)(e^{t-1})}$$

This is a Poisson($\lambda+\mu$) distribution.

$$\text{So, } P\{X+Y\}_{Z=n} = \frac{e^{-(\lambda+\mu)} \cdot (\lambda+\mu)^n}{n!}$$

$$\therefore P(Z) = \frac{e^{-(\lambda+\mu)} (\lambda+\mu)^n}{n!}$$

So, Eqⁿ (1) becomes:

$$\frac{P\{X, X+Y=n\}}{P\{X+Y=n\}} = \frac{\left(e^{-\lambda} \cdot \lambda^x \right) \cdot \left(e^{-\mu} \cdot \mu^{n-x} \right)}{(x!) (n-x)!} \times \frac{n!}{\left(e^{-(\lambda+\mu)} \cdot (\lambda+\mu)^n \right)}$$

$$= \binom{n}{x} \cdot \left(\frac{\lambda^x \mu^{n-x}}{(\lambda+\mu)^n} \right)$$

$$= \binom{n}{x} \cdot \left(\frac{\mu}{\lambda+\mu} \right)^{n-x} \cdot \left(\frac{\lambda}{\lambda+\mu} \right)^x$$

where λ & μ given as $(1-\pi)$

$$\text{Ans} = \binom{n}{x} \cdot \pi^x \cdot (1-\pi)^{n-x}$$

Home solved.

② Given X_1, X_2, X_3, \dots

$$P\left(X_n = \frac{1}{n}\right) = 1 - \frac{1}{n^2}$$

$$P\left(X_n = n\right) = \frac{1}{n^2}$$

(i) Checking if X_n converges in probability.

$$\lim_{n \rightarrow \infty} P\{|X_n - X| \geq \epsilon\} = 0$$

$$\text{or } X_n \xrightarrow{P} X$$

$$\text{or } \lim_{n \rightarrow \infty} P\{|X_n - X| < \epsilon\} = 1$$

n is a positive integer, then
we can clearly see that as $n \rightarrow \infty$

$$P\left(X_n = \frac{1}{n}\right) \rightarrow 1$$

$$\& P\left(X_n = n\right) \rightarrow 0$$

In other words,

$$\lim_{n \rightarrow \infty} P\left(\left|X_n - \frac{1}{n}\right| < \varepsilon\right) = 1 \text{ holds}$$

$$\therefore X_n \xrightarrow{P} \frac{1}{n} = 0$$

(ii) Checking if X_n converges in quadratic mean

Now, X_n will converge in quadratic mean to X if

$$E(X_n - X)^2 \rightarrow 0$$

as

$n \rightarrow \infty$

OR

$$X_n \xrightarrow{\sqrt{m}} X$$

$$\text{here, } E(X_n - 0)^2 = E(X_n^2)$$

$$\text{where, } E(X_n^2) = 1 + \frac{1}{n^2} - \frac{1}{n^4}$$

$$\text{Now, } E(X_n^2) \rightarrow 1 \text{ as } n \rightarrow \infty.$$

Now clearly, $E(X_n - 0)^2 \rightarrow 0$ doesn't hold true.
 $\therefore X_n$ doesn't converge in q.m.

(3)

Given: $X \rightarrow$ continuous random variable
 $CDF = F$ & PDF = f .
 $P(X > 0) = 1$
 $E(X)$ exists.

To show: $E(X) = \int_0^{\infty} P(X > x) dx$

Proof: $P(X \leq x) = F(x)$
 $\& \int_0^x f(x) dx = F(x)$

$$\text{So, } P(X \leq x) = \int_0^x f(x) dx$$

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

$$\int_0^{\infty} P(X > x) dx = \int_0^{\infty} \left[\int_x^{\infty} f(x) dx \right] dx$$

OR

$$\int_0^{\infty} P(X > x) dx = \int_0^{\infty} \left[\int_x^{\infty} f(t) dt \right] dx \quad \rightarrow 0 < x < t < \infty$$

OR, $0 < t < \infty$ & $0 < x < t$

$$\int_0^{\infty} P(X > x) dx = \int_0^{\infty} \left[\int_x^t [1 - F(t)] f(t) dt \right] dx$$

$$\int_0^{\infty} P(X > x) dx = \int_0^{\infty} t f(t) dt \quad \text{--- (1)}$$

$$\text{Also, } E(X) = \int_{-\infty}^{\infty} t \cdot f(t) dt$$

$$\text{But, } P(X > \infty) = 1 \Rightarrow P(X \leq \infty) = 0$$

$$\therefore E(X) = \int_0^{\infty} t \cdot f(t) dt$$

So,  $E(X) = \int_0^{\infty} P(X > t) dt$ Hence proved.

(4) KL divergence b/w 2 Gaussians is

$$D(q(x) || p(x)) = E_{y \sim q(y)} \left(\log \frac{q(y)}{p(y)} \right)$$

$$\text{Now, } p(x) = \mathcal{N}(x | \mu, \Sigma) \quad \& \quad q(x) = \mathcal{N}(x | m, L)$$

$$D(q(x) || p(x)) = E_{y \sim q(y)} \left(\log \frac{q(y)}{p(y)} \right)$$

'cause $p(x)$ & $q(x)$ are Gaussians

$$\text{So, } p(x | \mu, \Sigma) = \frac{1}{\sqrt{(2\pi)^n |\Sigma|^{1/2}}} \exp \left[-\frac{1}{2} (x - \mu)^T \Sigma^{-1} (x - \mu) \right] \quad (1)$$

$$q(x | m, L) = \frac{1}{\sqrt{(2\pi)^n |L|^{1/2}}} \exp \left[-\frac{1}{2} (x - m)^T L^{-1} (x - m) \right] \quad (2)$$

$$\therefore \text{KL} = \int_{-\infty}^{\infty} q(x) \cdot \ln \left(\frac{q(x)}{p(x)} \right) dx = E_{q(x)} \left[\ln \frac{q(x)}{p(x)} \right] \quad (3)$$

Putting (1) & (2) in (3)

$$= E \left[\frac{1}{2} \ln \left| \frac{L}{E} \right| - \frac{1}{2} (\bar{x} - \mu)^T E^{-1} (\bar{x} - \mu) + \frac{1}{2} (\bar{x} - m)^T E^{-1} (\bar{x} - m) \right]$$

For scalar α , $\alpha = \text{trace}(A)$

$$\text{tr}(ABC) = \text{tr}(BCA) = \text{tr}(CAB)$$

$$\text{Thus, } = \frac{1}{2} \ln \frac{|L|}{|E|} - \frac{1}{2} E \left[\text{tr} (E^{-1} (\bar{x} - \mu) (\bar{x} - \mu)^T) \right]$$

$$+ \frac{1}{2} E \left[\text{tr} [L^{-1} (\bar{x} - m) (\bar{x} - m)^T] \right]$$

$$= \frac{1}{2} \ln \frac{|L|}{|E|} - \frac{1}{2} \text{tr} (E^{-1} E \left[(\bar{x} - \mu) (\bar{x} - \mu)^T \right]) + \frac{1}{2} \text{tr} (L^{-1} E \left[(\bar{x} \bar{x}^T - 2\bar{x}m^T + mm^T) \right])$$

$$E(ax) = a\mu$$

$$E(x^T ax) = \mu^T a \mu + \text{tr}(aE)$$

$$= \frac{1}{2} \ln \frac{|L|}{|E|} - \frac{1}{2} \text{tr} (E^{-1} E) + \frac{1}{2} \text{tr} (L^{-1} (E + \mu \mu^T - 2\mu m^T + mm^T))$$

$$= \frac{1}{2} \ln \frac{|L|}{|E|} - \frac{1}{2} \chi + \frac{1}{2} \text{tr} (L^{-1} E)$$

$$+ \frac{1}{2} \text{tr} (\mu^T L^{-1} \mu - 2\mu^T L^{-1} m + m^T L^{-1} m)$$

$$= \frac{1}{2} \ln |\mathbf{L}| - \frac{n}{2} + \frac{1}{2} \text{tr}(\mathbf{L}^{-1} \mathbf{E}) + \frac{1}{2} (\mathbf{m} - \boldsymbol{\mu})^T \mathbf{L}^{-1} (\mathbf{m} - \boldsymbol{\mu})$$

$$\boxed{\text{Ans} = \frac{1}{2} \left[\ln |\mathbf{L}| - n + \text{tr}(\mathbf{L}^{-1} \mathbf{E}) + (\mathbf{m} - \boldsymbol{\mu})^T \mathbf{L}^{-1} (\mathbf{m} - \boldsymbol{\mu}) \right]}$$

⑤ (X, Y) has bivariate normal distⁿ

$$f(X, Y) = \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left(\frac{-1}{2(1-\rho^2)} (x^2 - 2\rho xy + y^2)\right)$$

To show that $\text{cov}(X, Y) = \rho$ & $\text{cov}(X^2, Y^2) = \rho^2$

Now,

$$\text{cov}(X, Y) = \frac{\text{cov}(X, Y)}{\sigma_X \sigma_Y}$$

$$\& \text{cov}(X, Y) = E(XY) - E(X)E(Y)$$

$$f_X(x) = \int_{-\infty}^x f(x, y) dy \quad \text{--- ①}$$

$$\text{Let us take, } X = Z_1 \& Y = \rho Z_1 + \sqrt{1-\rho^2} Z_2$$

$$f(Z_1, Z_2) = \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left[\frac{-1}{2(1-\rho^2)} \frac{Z_1^2 - 2\rho Z_1 Z_2 + \sqrt{1-\rho^2} Z_2^2}{1+\rho^2 Z_2^2}\right]$$

$$2 \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left[\frac{-1}{2(1-\rho^2)} [(1-\rho^2)Z_1^2 + (1-\rho^2)Z_2^2]\right]$$

$$= \frac{1}{2\pi(1-\rho^2)^{1/2}} \exp\left[-\frac{1}{2}(\frac{z_1^2}{1-\rho^2} + \frac{z_2^2}{1-\rho^2})\right]$$

Now, $Z_1 = Z_2 \sim N(0, 1)$

$$\text{Var}(X) = \text{Var}(Z_1) = 1$$

$$\text{Var}(Y) = \rho^2 \text{Var}(Z_1) + (1-\rho^2) \text{Var}(Z_2) \\ = 1$$

$$\text{Cov}(X, Y) = \text{cov}(Z_1, \rho Z_1 + \sqrt{1-\rho^2} Z_2)$$

$$= \rho \text{cov}(Z_1, Z_1) + \sqrt{1-\rho^2} \text{cov}(Z_1, Z_2)$$

$$= \rho \cdot 1 + \sqrt{1-\rho^2} \cdot 0$$

$$= \rho.$$

\downarrow
 Z_1, Z_2 are independent

$\rightarrow D_{Z_1}, D_{Z_2}$

$$\boxed{\text{Cov}(X, Y) = \rho}$$

Similarly, let, $X^2 = Z_1^2$

$$Y^2 = (\rho Z_1 + \sqrt{1-\rho^2} Z_2)^2$$

$$= \rho^2 Z_1^2 + (1-\rho^2) Z_2^2 + 2\rho \sqrt{1-\rho^2} Z_1 Z_2$$

$$\text{Cov}(X^2, Y^2) = \text{cov}(Z_1^2, \rho^2 Z_1^2 + (1-\rho^2) Z_2^2)$$

$$+ 2\rho \sqrt{1-\rho^2} Z_1 Z_2$$

$$= p^2 \underbrace{\text{cov}(z_1^2, z_1^2)}_{1} + (1-p^2) \underbrace{\text{cov}(z_1^2, z_2^2)}_{0} + 2p\sqrt{1-p^2} \text{cov}(z_1^2, z_1 z_2)$$

$$\text{cov}(z_1^2, z_1^2) = p^2$$

Asked in group
& then wrote the soln

Hence proved

(6)

$$X \sim \text{gamma}(n, 3)$$

$$f(X) = \frac{1}{\sqrt{n \cdot 3^n}} \cdot x^{n-1} \cdot e^{-x/3}, x > 0$$

x is a large integer

Note from CLT for $X_1, X_2, \dots, X_n \sim \text{gamma}(n, 3)$
such that they are all i.i.d. r.v.s

$$\bar{X} = \frac{1}{n} \sum X_i$$

$$\therefore E(\bar{X}) = \frac{1}{n} E(\sum X_i) = \frac{1}{n} \cdot n\mu = \mu$$

$$\text{Var}(\bar{X}) = \frac{\sigma^2}{n}$$

$$\text{Then, } Y = \frac{\bar{X} - \mu}{\sqrt{\text{Var}(\bar{X})}} = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}} \sim N(0, 1)$$

$$M_Y(t) = E(e^{tY})$$

$$E(e^{tY}) = E\left(e^{t\left(\frac{\bar{X}-\mu}{\sigma/\sqrt{n}}\right)}\right) = E\left(e^{t\left(\frac{\sum X_i - n\mu}{\sqrt{n}\sigma}\right)}\right)$$

$$= E \left(e^{\frac{t(X_1 - \mu)}{\sqrt{n}\sigma_1}} \right) \cdot e^{\frac{t(X_2 - \mu)}{\sqrt{n}\sigma_2}}$$

$$= \prod_{i=1}^n E \left(e^{\frac{t(X_i - \mu)}{\sqrt{n}\sigma_i}} \right)$$

$$M_X(t) = \left[E \left(e^{\frac{t(X_1 - \mu)}{\sqrt{n}\sigma_1}} \right) \right]^n \quad \text{--- (1)}$$

$$\text{Say, } m(t) = E(e^{t(X-\mu)}) = e^{-\mu t} \cdot M(t)$$

$$\text{Then, } m(0) = E(e^{0(X-\mu)}) = E(1) = 1$$

$$m'(0) = -\mu e^{-\mu t} M(t) + M'(t) e^{-\mu t} \Big|_{t=0}$$

$$m'(0) = -\mu + \mu = 0$$

$$m''(0) = \mu^2 e^{-\mu t} M(t) - \mu e^{-\mu t} M'(t) \\ + M''(t) e^{-\mu t} - \mu e^{-\mu t} M'(t) \Big|_{t=0}$$

$$m''(0) = \sigma^2$$

Now, we know,

$$f(z+h) = f(z) + \frac{h}{1!} f'(z) + \frac{h^2}{2!} f''(z+h)$$

(Taylor's formula)

At $z=0$,

$$f(h) = f(0) + \frac{h}{1!} f'(0) + \frac{h^2}{2!} f''(\theta h)$$

$$\text{for, } f(h) = m(t)$$

$$m(t) = m(0) + \frac{t}{1!} m'(0) + \frac{t^2}{2!} m''(0t)$$

$$m(t) = 1 + \frac{t^2}{2!} m''(0t)$$

↓ K

$$\text{then, } 0 < K < t$$

$$\therefore m(t) = 1 + \frac{\sigma^2 t^2}{2!} - \frac{\sigma^2 t^2}{2!} + \frac{t^2}{2!} M''(K)$$

$$= 1 + \frac{\sigma^2 t^2}{2!} + \left(\frac{M''(K) - \sigma^2}{2!} \right) t^2$$

$$\text{From ①, } M_x(t) = \left[E \left(m \left(\frac{t}{\sqrt{n}\sigma} \right) \right) \right]^n$$

$$= \left[E \left(1 + \frac{\sigma^2 t^2}{2n\sigma^2} + \left(\frac{M''(K) - \sigma^2}{2} \right) \cdot \frac{t^2}{n\sigma^2} \right) \right]^n$$

$$\text{Now, } \lim_{n \rightarrow \infty} M_x(t) = \lim_{n \rightarrow \infty} \left\{ 1 + \frac{\sigma^2 t^2}{2n\sigma^2} + \underbrace{\left(\frac{M''(K) - \sigma^2}{2} \right) \cdot \frac{t^2}{n\sigma^2}}_{\text{tends to 0}} \right\}^n$$

So, 1[∞] formate

$$\lim_{n \rightarrow \infty} M_x(t) = \lim_{n \rightarrow \infty} \left\{ \frac{t^2}{2n} + \left(\frac{M''(K) - \sigma^2}{2n\sigma^2} \right) \cdot t^2 \right\}^n$$



$$= e^{\lim_{n \rightarrow \infty} \frac{t^2}{2} + \frac{m''(k) - \sigma^2}{2\sigma^2} \cdot t^2}$$

$$= e^{t^2/2 + m''(\theta) \cdot t^2}$$

$$= e^{t^2/2 + \frac{m''(\theta) - \sigma^2}{2\sigma^2} \cdot t^2}$$

Now here, $-n < \frac{t}{\sqrt{n}} < n \Rightarrow \theta t = k$

As $n \rightarrow \infty, k \rightarrow 0$

$$\left(\theta = \frac{1}{\sqrt{n}} \right)$$

then, $m''(k) - \sigma^2 \rightarrow m''(\theta) - \sigma^2 \rightarrow 0$

As $m''(\theta) \rightarrow \sigma^2$ as $n \rightarrow \infty$

Then, $M_X(t) = e^{t^2/2}$

$\therefore Y \xrightarrow{d} N(0, 1)$

This holds true for all distributions including $X \sim \text{Gamma}(n, 3)$, given $n \rightarrow \infty$.

Since, n is very very large integer, CLT holds true.

$$f(x; n, 3) = \frac{1}{\sqrt{n}} \cdot \frac{1}{3^n} \cdot x^{n-1} e^{-x/3}$$

Mean = $\alpha \beta = 3n$, Variance = $\alpha \beta^2 = 9n$ (Approximate)
 Then, $X \sim N(3n, 9n)$ for $n \rightarrow \infty$ by CLT