

Ex-1  $X \sim \exp(\lambda_1)$  &  $Y \sim \exp(\lambda_2)$

1) Let the r.v.  $Z = \min(X, Y)$ . Let's find the CDF of  $Z$

$$P(Z \leq z) = P(\min(X, Y) \leq z) = 1 - P(\min(X, Y) > z)$$

We know that if  $\min(a, b) > c$ , then  $a > c$  &  $b > c$

Also for r.v.  $X \sim \exp(\lambda)$ ,  $P(X > x) = e^{-\lambda x}$

$$\begin{aligned} \text{Thus, } P(Z \leq z) &= 1 - P((X > z) \cap (Y > z)) = 1 - P(X > z) P(Y > z) \\ &= 1 - e^{-\lambda_1 z} \cdot e^{-\lambda_2 z} \quad \text{as } X \text{ \& } Y \text{ are independent} \\ &= 1 - e^{-(\lambda_1 + \lambda_2)z} \rightarrow \text{s.t. } z > 0 \text{ \& } 0 \text{ o/w} \end{aligned}$$

Since the p.d.f.  $f_z(z) = \frac{\partial}{\partial z} (P(Z \leq z))$ , we have:

$$f_z(z) = \frac{\partial}{\partial z} (1 - e^{-(\lambda_1 + \lambda_2)z}) = \boxed{(\lambda_1 + \lambda_2) e^{-(\lambda_1 + \lambda_2)z}}$$

Thus,  $Z \sim \exp(\lambda_1 + \lambda_2)$

2) Let the r.v.  $Z = \max(X, Y)$ . Let's find the CDF of  $Z$

$$P(Z \leq z) = P(\max(X, Y) \leq z) = P(X \leq z) P(Y \leq z)$$

Using same arg. as before, & result  $P(X \leq x) = 1 - e^{-\lambda x}$  for  $X \sim \exp(\lambda)$

$$P(Z \leq z) = (1 - e^{-\lambda_1 z})(1 - e^{-\lambda_2 z}) = 1 - e^{-\lambda_1 z} - e^{-\lambda_2 z} + e^{-(\lambda_1 + \lambda_2)z}$$

$$f_z(z) = \frac{\partial}{\partial z} (P(Z \leq z)) = \boxed{\lambda_1 e^{-\lambda_1 z} + \lambda_2 e^{-\lambda_2 z} - (\lambda_1 + \lambda_2) e^{-(\lambda_1 + \lambda_2)z}}$$

$\hookrightarrow$  s.t.  $z > 0$ , 0 o/w

Ex-2 Given probabilities  $p_W = \frac{3}{14}$ ,  $p_R = \frac{6}{14}$  &  $p_O = \frac{5}{14}$ , & 6 draws.

Since it's given that  $Y=3$ , other three draws could have only W or R with probabilities:  $p'_W = \frac{3}{3+6} = \frac{1}{3}$  &  $p'_R = \frac{6}{3+6} = \frac{2}{3}$ . So for the remaining 3 draws,  $P(X=i) \sim \text{Binomial}(3, \frac{1}{3})$

$$\Rightarrow E[X|Y=3] = E[\text{Binomial}(3, \frac{1}{3})] = \boxed{1} \quad \text{as } E[\text{bin}(n, p)] = np$$

Ex-3 Since  $X_1 \sim \text{bin}(n_1, p)$  &  $X_2 \sim \text{bin}(n_2, p)$  share same param  $p$ ,  
 $(X_1 + X_2) \sim (n_1 + n_2, p)$ . We need to find  $P(X_1 = i | X_1 + X_2 = m)$

If  $X_1 = i$  &  $X_1 + X_2 = m$ , then  $X_2 = m - i$   
 $\Rightarrow P(X_1 = i | X_1 + X_2 = m) = \frac{P(X_1 = i) P(X_2 = m - i)}{P(X_1 + X_2 = m)}$

$$= \frac{\binom{n_1}{i} p^i (1-p)^{n_1-i} \cdot \binom{n_2}{m-i} p^{m-i} (1-p)^{n_2-m+i}}{\binom{n_1+n_2}{m} p^m (1-p)^{n_1+n_2-m}} = \boxed{\frac{\binom{n_1}{i} \binom{n_2}{m-i}}{\binom{n_1+n_2}{m}}}$$

Ex-4 Consider  $X \sim \text{Uniform}(-1, 1) \Rightarrow f_X(x) = \begin{cases} 1/2 & x \in [-1, 1] \\ 0 & \text{o/w} \end{cases}$

Now define  $Y = X^2$ . Clearly  $Y$  &  $X$  are dependent

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

$$= E[X^3] - E[X]E[X^2] = \int_{-1}^1 \frac{x^3}{2} dx - \int_{-1}^1 \frac{x}{2} dx \int_{-1}^1 \frac{x^2}{2} dx$$

$$= \boxed{0}$$

(As  $x^3$  &  $x$  are odd func)

Thus,  $X$  &  $Y$  are uncorrelated but not independent.

Ex-5 Given  $X \sim \text{Pois}(\lambda)$  &  $\lambda \sim \exp(1)$

$$\text{Thus } P(X=n | \lambda=x) = \frac{e^{-x} x^n}{n!}$$

$$\text{Since } P(X=n) = \int_0^\infty P(X=n | \lambda=x) f_\lambda(x) dx$$

$$= \int_0^\infty \frac{e^{-x} x^n}{n!} dx \quad \begin{array}{l} \text{Substitute } t = 2x \\ \Rightarrow dt = 2dx \end{array}$$

$$= \frac{1}{2^{n+1} \cdot n!} \int_0^\infty e^{-t} t^n dt \quad \begin{array}{l} \text{We know} \\ \Gamma(z) = \int_0^\infty e^{-x} x^{z-1} dx \end{array}$$

$$= \frac{1}{2^{n+1} n!} \Gamma(n+1) = \frac{1}{2^{n+1} n!} \cdot n!$$

$$= \boxed{\frac{1}{2^{n+1}}}$$

Since for +ve integer  $n$ ,  
 $\Gamma(n) = (n-1)!$

Ex-6 Given  $f_{x,y}(x,y) = \begin{cases} c(1+xy), & (x,y) \in [2,3] \times [1,2] \\ 0, & \text{otherwise} \end{cases}$

1) We know that  $\int_{-\infty}^{\infty} \int_{-\infty}^{\infty} f_{x,y}(x,y) dx dy = 1$

$$\Rightarrow 1 = c \int_1^2 \int_2^3 (1+xy) dx dy = c \int_1^2 \left[ x + y \frac{x^2}{2} \right]_2^3 dy$$

$$= c \int_1^2 \left( 1 + \frac{5y}{2} \right) dy = c \left[ y + \frac{5y^2}{4} \right]_1^2$$

$$\Rightarrow 1 = c \left( 1 + \frac{15}{4} \right) \Rightarrow \boxed{c = \frac{4}{19}}$$

2)  $f_X(x) = \int_{-\infty}^{\infty} f_{x,y}(x,y) dy = \frac{4}{19} \int_1^2 (1+xy) dy$

$$= \boxed{\frac{4}{19} \left( 1 + \frac{3}{2}x \right)}$$

$$f_Y(y) = \int_{-\infty}^{\infty} f_{x,y}(x,y) dx = \frac{4}{19} \int_2^3 (1+xy) dx = \boxed{\frac{4}{19} \left( 1 + \frac{5y}{2} \right)}$$

Ex-7 Let a r.v. **N** denote no. of accidents per year  
given,  $(N|\lambda) \sim \text{Pois}(\lambda)$  &  $\lambda \sim g(\lambda) = \text{gamma}(\lambda), \lambda \geq 0$

Thus,  $P(N=n) = \int_0^{\infty} P(N=n|\lambda) g(\lambda) d\lambda$

$$\Rightarrow P(N=n) = \int_0^{\infty} \frac{e^{-\lambda} \lambda^n}{n!} \lambda e^{-\lambda} d\lambda = \int_0^{\infty} \frac{e^{-2\lambda} \lambda^{n+1}}{n!} d\lambda$$

Substitute  $t=2\lambda$   
 $\Rightarrow dt = 2d\lambda$

$$= \int_0^{\infty} \frac{e^{-t} t^{n+1}}{2^{n+2} n!} dt = \frac{\Gamma(n+2)}{2^{n+2} n!}$$

$$= \frac{(n+1)!}{2^{n+2} n!} = \boxed{\frac{n+1}{2^{n+2}}}$$

Ex-8 Let  $T$  be total no. of people visiting a yoga studio on a day  
 Also, let  $M$  be no. of men &  $N$  be no. of women s.t.  $M+N=T$   
 Given,  $T \sim \text{Poisson}(\lambda)$  &  $N \sim \text{Binomial}(T, p)$

$$\begin{aligned} \text{Thus } P(M=m, N=n) &= P(T=m+n) \cdot P(N=n | T=m+n) \\ &= \frac{e^{-\lambda} \lambda^{m+n}}{(m+n)!} \cdot \binom{m+n}{n} p^n (1-p)^m \end{aligned}$$

$$\Rightarrow P(M=m, N=n) = \boxed{\frac{e^{-\lambda} \cdot \lambda^{m+n} \cdot p^n (1-p)^m}{m! n!}}$$

Ex-9 1) Show  $\text{Cov}(aX_1+b, cX_2+b) = ac \text{Cov}(X_1, X_2)$

$$\text{LHS: } \text{Cov}(aX_1+b, cX_2+b) = E[(aX_1+b) - E[aX_1+b]] \cdot E[cX_2+b - E[cX_2+b]]$$

$$= E[a(X_1 - E[X_1])] \cdot E[c(X_2 - E[X_2])]$$

$$= ac E[X_1 - E[X_1]] \cdot E[X_2 - E[X_2]] = \boxed{ac \text{Cov}(X_1, X_2) = \text{RHS}}$$

2) Show  $\text{Cov}(X_1 + X_2, X_3) = \text{Cov}(X_1, X_3) + \text{Cov}(X_2, X_3)$

$$\text{LHS: } \text{Cov}(X_1 + X_2, X_3) = E[X_1 + X_2 - E[X_1 + X_2]] \cdot E[X_3 - E[X_3]]$$

$$= E[(X_1 - E[X_1]) + (X_2 - E[X_2])] \cdot E[X_3 - E[X_3]]$$

$$= (E[X_1 - E[X_1]] + E[X_2 - E[X_2]]) \cdot E[X_3 - E[X_3]]$$

$$= E[X_1 - E[X_1]] E[X_3 - E[X_3]] + E[X_2 - E[X_2]] \cdot E[X_3 - E[X_3]]$$

$$= \boxed{\text{Cov}(X_1, X_3) + \text{Cov}(X_2, X_3) = \text{RHS}}$$

Ex-10 Given  $n=100$  samples of iid. r.v.  $X$  &  $\hat{\mu} = 0.45$   
 1) We have the result  $P(|\hat{\mu} - \mu| > \epsilon) \leq 2e^{-2n\epsilon^2}$ ,  $\epsilon > 0$   
 for confidence interval  $\mu \in [\hat{\mu} - \epsilon, \hat{\mu} + \epsilon]$  Hoeffding's inequality  
 for  $> 0.95$  confidence,  $P(|\hat{\mu} - \mu| > \epsilon) \leq 0.05$   
 $\Rightarrow 2e^{-2n\epsilon^2} \leq 0.05 \Rightarrow 2n\epsilon^2 \geq -\log(0.025)$   
 Thus,  $\epsilon^2 \geq \frac{-\log(0.025)}{200} = 0.0184$

$\Rightarrow \epsilon \geq 0.136$ . We have tightest interval with  $\boxed{\epsilon = 0.136}$   
 Thus,  $\mu \in (0.314, 0.586)$  with 95% confidence

2) for interval of half length,  $\epsilon' = \frac{\epsilon}{2} = 0.068$

Also  $2n\epsilon'^2 \geq -\log(0.025)$   
 $\Rightarrow n \geq \frac{-\log(0.025)}{2\epsilon'^2} = 4 \cdot \left( \frac{-\log(0.025)}{2\epsilon^2} \right) = 400$

$\Rightarrow \boxed{n \geq 400}$  Thus at least 400 samples are needed.

Since we already have 100, we need 300 more samples.

Source: [Hoeffding's inequality for confidence intervals](#)

1<sup>st</sup> part with lower bound from the slides

Ex-10 Given  $n=100$  samples of iid. r.v.  $X$  &  $\hat{\mu} = 0.45$   
 1) We have the result  $P(|\hat{\mu} - \mu| > \epsilon) \leq 2e^{-n\epsilon^2}$ ,  $\epsilon > 0$   
 for confidence interval  $\mu \in [\hat{\mu} - \epsilon, \hat{\mu} + \epsilon]$   
 for  $> 0.95$  confidence,  $P(|\hat{\mu} - \mu| > \epsilon) \leq 0.05$   
 $\Rightarrow 2e^{-n\epsilon^2} \leq 0.05 \Rightarrow n\epsilon^2 \geq -\log(0.025)$   
 Thus,  $\epsilon^2 \geq \frac{-\log(0.025)}{100} = 0.0369$

$\Rightarrow \epsilon \geq 0.192$ . We have tightest interval with  $\boxed{\epsilon = 0.192}$   
 Thus,  $\mu \in (0.258, 0.642)$  with 95% confidence