# تمرین اول احتمال

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# پرسش ۱

- 2. \* Cov(X + Z, Y) = Cov(X, Y) + Cov(Z, Y) proof:

#### E is linear

 $\begin{array}{l} Cov(X+Z,Y) = E[(X+Y-E[X]-E[Y])(Z-E[Z])] = \\ = E[(X-E[X])(Z-E[Z]) + (Y-E[Y])(Z-E[Z])] = \\ = E[(X-E[X])(Z-E[Z])] + E[(Y-E[Y])(Z-E[Z])] = Cov(X,Z) + \\ Cov(Y,Z) \end{array}$ 

\* Cov(X, X) = Var(X)

$$*Cov(X,Y) = Cov(Y,X)$$

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#### lets think that both X,Y have distribution like Z

$$Cov(X+Y,X-Y) = Cov(X,X) + Cov(Y,X) - Cov(Y,Y) - Cov(X,Y) = Var(X) - Var(Y) = Var(Z) - Var(Z) = 0$$

- 1. \*  $\int x^k dx = \frac{x^{k+1}}{k+1} = \int_0^1 x^k dx = \frac{1}{k+1}$  $\int_0^1 G(s)ds = \int_0^1 E(s^X)ds = \int \int_0^1 f(x)s^x ds dx = \int f(x)\frac{1}{x+1}dx = E[\frac{1}{1+x}]$
- 2. \*  $M_X(t) = E[e^{tX}] = e^{t\mu + \frac{(t\sigma)^2}{2}}$  so  $Y = log(X) => E[X] = E[e^Y] = M_1(Y) = e^{\mu + \frac{\sigma^2}{2}}$   $var(X) = E[X^2] E[X]^2$

$$var(X) = E[X^{2}] - E[X]^{2}$$

$$E[X^{2}] = E[e^{2Y}] = M_{2}(Y) = e^{2\mu + \frac{4\sigma^{2}}{2}}$$

$$var(X) = e^{2\mu + \frac{4\sigma^{2}}{2}} - (e^{\mu + \frac{\sigma^{2}}{2}})^{2}$$

پرسش 
$$*e^x = \Sigma \frac{x^n}{n!}$$
  $*M_X^{(k)}(0) = E[X^k]$ 

\* $M_X$  for normal standard is:  $e^{\,\overline{\,2\,}}$ we use its moment generative function  $e^{\frac{t^2}{2}} = \Sigma_{n=0} \frac{t^{2^n}}{2^n n!}$  so we derive it k times:

$$e^{\frac{t^2}{2}} = \sum_{n=0}^{\infty} \frac{t^{2^n}}{2^n n!}$$

so we derive it k times: 
$$e^{\frac{t^2}{2}} = \sum_{n \geq \frac{k}{2}} \frac{2n \times (2n-1)... \times (2n-k+1)t^{2n-k}}{2^n n!}$$
 ee if k is 2j+1 and t=0 then all the elements are equal to the content of the second of the content of the cont

as we can see if k is 2j+1 and t=0 then all the elements are equal to zero but if its 2j then the first one is  $t^{2n-2j}$  and for t=0,n= $\frac{k}{2}$ =j its equal to one so its coefficient is the sum of whole sigma which is equal to:  $\frac{2j\times(2j-1)...\times 1}{2^{2j}(2j)!}=\frac{(2j)!}{2^{2j}(2j)!}$ 

$$\frac{2j \times (2j-1)... \times 1}{2^{2j}(2j)!} = \frac{(2j)!}{2^{2j}(2j)!}$$

$$X_i \text{ if toss number i is head} \\ M_n = \frac{X_1 + \ldots + X_n}{n} \\ Var(M_n) = \frac{\sigma_X^2}{n} \\ P|M_n - f| > 0.1 \leq 0.1 \\ \text{by Chebyshev we have: } P(|M_n - f| > \epsilon) \leq \frac{\sigma_M^2}{\epsilon^2} => \\ P(|M_n - f| > 0.1) \leq \frac{\sigma_M^2}{0.01} \leq 0.1 => \\ \sigma_M^2 \leq 0.001 => \frac{p.(1-p)}{n} \leq 0.001 => n \geq 250 \\ \end{cases}$$

1. as it says:  $P(limX_n = c) = 1$ 

if we want to say that it also converge in probability, we have to show

that:  $\forall \epsilon > 0 : lim P(|X_n - c| > \epsilon) = 0$ 

if we show  $limP(|X_n-c|=0)=1$  so we have prove the above theorem. by the definition:  $P(limX_n=c)=1 => limP(X_n=c)=1 => limP(X_n-c=0)=1 => limP(|X_n-c|=0)=1$ 

2. we use central limit theorem and try to use standard normal RV to get the answer

as  $X_i$  are independent and identical with  $\mu = 0, \sigma^2 = \frac{1}{12}$ 

 $S_n = \Sigma X_i = P(S_n \le 5) = \Phi(\frac{5 - n\mu}{\sigma\sqrt{n}}), n = 100 = \Phi(\sqrt{3}) = 0.9584$ 

so the answer is  $1 - \Phi(1.732) \approx 0.0416$ 

we have this formula in book and as the result of similarity of sum of n number of random variable to normal distribution

- 1.
- 2. as the CDF of exponential is  $1 e^{-\lambda x}$  for positive x

$$P\{X \le k\} = 1 - e^{-k\lambda}$$

$$W = min(X, Y) = > F_W(w) = 1 - P(X > w, Y > w) =$$

$$\begin{aligned} & Y = K_Y - 1 - e \\ & W = min(X,Y) => F_W(w) = 1 - P(X > w, Y > w) = \\ & 1 - P\{X > w\} P\{Y > w\} = 1 - (1 - F_X(w))(1 - F_Y(w)) = 1 - e^{-2w\lambda} => \\ & f_W(w) = F' = 2\lambda e^{-2w\lambda} \end{aligned}$$

so its just like a exponential with parameter  $2\lambda$ 

$$E[W] = \frac{1}{2\lambda}$$

 $E[W] = \frac{1}{2\lambda}$  now for second one  $P\{X <= k\} = 1 - e^{-k\lambda}$ 

$$W = min(2X, Y) = F_W(w) = 1 - P(X > \frac{w}{2}, Y > w) = 0$$

$$1 - P\{X > w\}P\{Y > w\} = 1 - (1 - F_X(w))(1 - F_Y(w)) = 1 - e^{-\frac{3}{2}w\lambda} = > f_W(w) = F' = \frac{3}{2}\lambda e^{-\frac{3}{2}w\lambda}$$

so its just like a exponential with parameter  $\frac{3}{2}\lambda$ 

$$E[W] = \frac{2}{3\lambda}$$

### پرسش ۷

1.  $E[|X - Y|] = \int \int_{x>y} x - y dx dy + \int \int_{y>x} y - x dx dy = 2 \int \int_{x>y} x - y dx dy$  $2\int_{0}^{\alpha} (\int_{y}^{\alpha} x dx - y \int_{y}^{\alpha} dx) dy = 2\int_{0}^{\alpha} (\frac{\alpha^{2}}{2} - \frac{y^{2}}{2} - y\alpha + y^{2}) dy =$ 

$$2(\frac{\alpha^3}{2} - \frac{\alpha^3}{6} - \frac{\alpha^3}{2} + \frac{\alpha^3}{3}) = \frac{\alpha^3}{3}$$

**2.** max(a,b) - min(a,b) = |a-b|

directly from last part we get  $\frac{1}{3}$ 

$$max(a,b) + min(a,b) = a + b$$

so its the PMF of sum of two uniform and we use the convolution on them:

$$f_{X+Y}(Z) = \int f_X(z-y) f_Y(y) dy$$

as we solve it before, there is two case: 0 < z < 1, 1 < z < 2

its only important when  $f_Y(y)=1$  other place its 0, so:  $0 \le z < 1$  :

$$\int_{0}^{1} f_{X}(z-y)dy = \int_{0}^{z} dy = z$$

$$\int_0^1 f_X(z-y)dy = \int_0^z dy = z$$

$$1 \le z \le 2 : \int_0^1 f_X(z-y)dy = \int_{z-1}^1 dy = 2 - z$$

$$f_{X+Y}(z) = z : 0 \le z < 1, f_{X+Y}(z) = 2 - z : 1 \le z \le 2$$

for any two  $X_i$  we know the probability of  $X_i > X_j$  as they are iid, it means it must be  $\frac{1}{2}$   $P(X_i > X_{i-1}, X_i > X_{i-2}, ... X_i > X_1) = P(X_i > X_{i-1}) \times ... \times P(X_i > X_1) = \frac{1}{2^i}$  so  $Y_i$ : person i do record  $E[\Sigma Y_i] = \Sigma E[Y_i] = 1 + \frac{1}{2} + ... = 2$   $E[Y_i^2] = 1^2 \times P(record) + 0^2 \times (1 - P(record)) = E[Y_i]$   $Y_i \text{ are independent so}$   $var(\Sigma Y_i) = \Sigma var(Y_i) = \Sigma E[Y^2] - E[Y]^2 = \Sigma_{i=1} \frac{1}{2^{i-1}} - \frac{1}{2^i} = 1 - \frac{1}{2^n}$ 

- 1. \*  $E[Cos(\theta)]=0$  as it is odd between 0 and  $2\pi$  so  $f_{\theta}(a)=\frac{1}{2\pi}$   $Cov(Sin(\theta),Cos(\theta))=E[Sin(\theta)Cos(\theta)]-E[Sin(\theta)]E[Cos(\theta)]=E[Sin(\theta)Cos(\theta)]=\int_{0}^{2\pi}cos(x)sin(x)\frac{1}{2\pi}dx=\frac{1}{2\pi}\int\frac{1}{2}sin(2x)=\frac{-1}{8\pi}cos(2x)from(0,2\pi)=0=>uncorrelated$
- 2. \* var(X + Y) = var(X) + var(Y) 2cov(X, Y) $\rho(X + Y, X - Y) = \frac{cov(X + Y, X - Y)}{\sigma_{X + Y}\sigma_{X - Y}} = \frac{var(X) - var(Y)}{\sigma_{X + Y}\sigma_{X - Y}} = \frac{var(X) - var(Y)}{\sqrt{var(X + Y)var(X - Y)}} = \frac{var(X) - var(Y)}{\sqrt{var(X)^2 + var(Y)^2 + 2var(x)var(y)}} = \frac{var(X) - var(Y)}{\sqrt{(var(X) + var(y))^2}} = \frac{var(X) - var(Y)}{var(X) + var(Y)}$

1. 
$$f_X(x) = \int f(x,y) dy = \int \frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}} e^{-z} dy$$

$$z = \frac{1}{2(1-\rho^2)} \times [(\frac{x-{\mu_x}^2}{\sigma_x}) - (\frac{2\rho(x-{\mu_x})(y-{\mu_y})}{\sigma_x\sigma_y}) + (\frac{y-{\mu_y}^2}{\sigma_y})]$$
we can prove that it integral is equal to:

$$\frac{1}{\sqrt{2\pi}\sigma_x}e^{-\frac{(x-\mu_x)^2}{2\sigma_x^2}}$$

 $\frac{1}{\sqrt{2\pi}\sigma_x}e^{-\frac{(x-\mu_x)^2}{2\sigma_x^2}}$  which is exactly the normal distribution with mean  $\mu_x$  and variance  $\sigma_x^2$ same for y we have:

same for y we have: 
$$f_Y(y)=\int\frac{1}{2\pi\sigma_x\sigma_y\sqrt{1-\rho^2}}e^{-z}dx=\frac{1}{\sqrt{2\pi}\sigma_y}e^{-\frac{(y-\mu_y)^2}{2\sigma_y^2}}$$
 prove:

2.