

- Moment generating ftn. Cumulant generating function
- Basic dist / properties
- Change of Variable formula : Beta, Chi-sq dist
- Quadratic form of normal dist

Def (moment generating function) given r.v. X ,

if $\exists h > 0$ s.t. $M(t) := E(e^{tX}) < \infty$ for all $t \in (-h, h)$

we say M is the moment generating function of r.v. X

Thm (a) if r.v. X has mgf, then $E X^k$ exists for all k

and $E(X^k) = M^{(k)}(0)$, and $M(t) = \sum_{k=0}^{\infty} \frac{E(X^k)t^k}{k!}$ for $t \in (-\frac{h}{2}, \frac{h}{2})$

(b) if r.v. X, Y has mgf and if $\exists h$ s.t. $M_X(t) = M_Y(t)$ for $t \in (-h, h)$

then X, Y has same distribution

(pf) (b) is beyond the scope of the lecture

fix $t \in (-h, h)$

(a) Note that $e^a = \sum_{k=0}^{\infty} a^k / k!$ $\Rightarrow |tX|^k / k! \leq e^{|tX|} \leq e^{tx} + e^{-tx}$

$\therefore |t|^k |E X^k| / k! \leq M(t) + M(-t) < \infty$

$\therefore E X^k$ exists

also by Taylor thm

$$\left| e^{tx} - \sum_{k=0}^{n-1} \frac{(tx)^k}{k!} \right|$$

$$= \left| \frac{1}{(n-1)!} \int_0^1 (1-u)^{n-1} e^{utx} du \cdot (tx)^n \right|$$

$$\leq \int_0^1 (1-u)^{n-1} e^{utx} \cdot \frac{|tx|^{n-1}}{(n-1)!} \frac{|tx|}{1!} du \leq \frac{1}{n} (e^{3tx} + e^{-3tx})$$

$\sim \sim \sim$
 $\leq e^{|tx|}$

$$\left| M(t) - \sum_{k=0}^{n-1} \frac{E X^k \cdot t^k}{k!} \right| \leq \frac{1}{n} (M(3t) + M(-3t))$$

$n \rightarrow \infty$ finishes the proof

* Suppose $M(t)$ exists in $(-h, h)$

$$\text{define } C(t) := \log M(t) = \log \mathbb{E}(e^{tX})$$

$$\text{note : } \log(1+x) = x - \frac{x^2}{2} + \frac{x^3}{3} - \dots$$

$$M(t) = 1 + M_1 t + \frac{M_2}{2} t^2 + \frac{M_3}{6} t^3 + \dots$$

$$\Rightarrow C(t) = (M_1 t + \frac{M_2}{2} t^2 + \dots) - (\dots ") \frac{1}{2} + C \dots \frac{1}{3}$$

$$= M_1 t + \frac{1}{2}(M_2 - M_1^2)t^2 + \dots$$

$$C_r(x) := C_x^{(r)}(0) \quad (r \text{ th cumulant})$$

$$\Rightarrow C_1(x) = \mathbb{E}X, \quad C_2(x) = \text{Var}(x).$$

$$\begin{aligned} * \quad C_{\frac{X-\mu}{\sigma}}(t) &= \log \mathbb{E}(e^{(tx-\mu)/\sigma}) \\ &= -\frac{\mu}{\sigma}t + C_x\left(\frac{t}{\sigma}\right) \end{aligned}$$

$$\therefore \text{for } C_1\left(\frac{X-\mu}{\sigma}\right) = 0, \quad C_2\left(\frac{X-\mu}{\sigma}\right) = 1, \quad C_r\left(\frac{X-\mu}{\sigma}\right) = C_r(x)/\sigma^r \quad (r \geq 3)$$

$$* \quad \text{when } \mu=0, \sigma=1 \quad C_3(z) = M_3(z), \quad C_4(z) = M_4(z) - 3$$

$$X \rightarrow Z = \frac{X-\mu}{\sigma} \quad \text{normalize} \quad \Rightarrow C_3(z) : \text{skewness of } X$$

$$(C_4(z)) : \text{curtosis of } X$$

• Taylor expand $M_{X(t)}$ \Rightarrow find $E X^k$

• show $M_X = M_Y$ to conclude $X \stackrel{d}{=} Y$

$$(ex) X, Y \text{ are indep} \Rightarrow E e^{t(X+Y)} = E e^{tX} E e^{tY} = M_X(t) M_Y(t)$$

if $M_X(t) M_Y(t) = M_Z(t)$, we conclude $X+Y \stackrel{d}{=} Z$

* Binomial / Bernoulli

• $X \sim \text{Bern}(p)$ $P(X=1) = p, P(X=0) = 1-p$

$$\Rightarrow EX = p \cdot 1 + (1-p) \cdot 0 = p, E X^2 = p \cdot 1^2 + (1-p) \cdot 0^2 = p \Rightarrow \text{Var} X = p(1-p)$$

$$M_X(t) = E e^{tX} = p e^t + (1-p)$$

• $X \sim B(n, p)$ $P(X=k) = \binom{n}{k} p^k (1-p)^{n-k}$ ($k = 0, 1, 2, \dots, n$)

$$\begin{aligned} EX &= \sum_{k=0}^n k \binom{n}{k} p^k (1-p)^{n-k} = \sum_{l=0}^{n-1} n \binom{n-1}{l} p^l p \cdot (1-p)^{(n-1)-l} \\ &\quad \uparrow \quad \uparrow \quad " \quad n \binom{n-1}{k-l} \\ &= np (p + (1-p))^{n-1} = np \end{aligned}$$

Note that $X \stackrel{d}{=} Z_1 + \dots + Z_n$ when $Z_i \stackrel{iid}{\sim} \text{Bern}(p)$

$$M_X(t) = (M_Z(t))^n = (p e^t + (1-p))^n$$

• $X \sim \text{multi}(n, P)$ $P = (p_1, \dots, p_k)^T$ with $p_1 + \dots + p_k = 1$ ($k \geq 3$)

"
(X_1, \dots, X_k)

$$\left[\begin{array}{lll} EX_e = np_e, \quad \text{Var}(X_e) = np_e(1-p_e) & \text{Cov}(X_e, X_m) = -np_e p_m \\ \text{mgf}_X(t_1, \dots, t_k) (= E e^{t_1 X_1 + \dots + t_k X_k}) = (p_1 e^{t_1} + \dots + p_k e^{t_k})^n \end{array} \right]$$

$X \stackrel{d}{=} Z_1 + \dots + Z_n$ $Z_i \stackrel{iid}{\sim} \text{multi}(1, P)$

$Z_i = (Z_{i1}, \dots, Z_{ik})$

$$E Z_{ie} = p_e \quad E Z_{ie} Z_{im} = 0 \quad , \quad M_Z(t) = p_1 e^{t_1} + \dots + p_k e^{t_k}$$

$$E Z_i = \begin{pmatrix} p_1 \\ \vdots \\ p_k \end{pmatrix} \quad \text{Var } Z_i = \begin{pmatrix} p_1(1-p_1) & & \\ & \ddots & \\ & & p_k(1-p_k) \end{pmatrix}$$

* Poisson process

Let N_t be number of certain event occurs between 0 and t . If following conditions are satisfied, we call $\{N_t | t \geq 0\}$ a Poisson Process with occurrence rate λ

(a) Stationarity $N_t \equiv N_{t-\tau} N_\tau$, $N_0 = 0$

(b) Independent increment N_t and $N_{t+h} - N_t$ is indep for any $h > 0$

(c) Proportionality $P(N_h=1) = \lambda h + o(h)$ as $h \rightarrow 0$

(d) Pareness $P(N_h \geq 2) = o(h)$

Claim. $P(N_t = k) = e^{-\lambda t} (\lambda t)^k / k!$

$$\begin{aligned} P(N_{t+h} = k) &= P(N_{t+h} = k, N_t = k) + P(N_{t+h} = k, N_t = k-1) \\ &\quad + P(N_{t+h} = k, N_t \leq k-2) \end{aligned}$$

Sketch of Pf

$$\begin{aligned} &= P(N_t = k, N_{t+h} - N_t = 0) + P(N_t = k-1, N_{t+h} - N_t = 1) \\ &\quad + \dots, h \text{ " } \geq 2 \end{aligned}$$

$$\begin{aligned} &= P(N_t = k) (1 - \lambda h - o(h)) + P(N_t = k-1) (\lambda h + o(h)) \\ &\quad + P(N_t \leq k-2) o(h) \end{aligned}$$

$$\therefore \lim_{h \rightarrow 0} \frac{P(N_{t+h} = k) - P(N_t = k)}{h} = \lambda (P(N_t = k-1) - P(N_t = k))$$

$$\text{let } g(k, t) = P(N_t = k) \cdot e^{\lambda t} / \lambda^k$$

$$\Rightarrow \frac{\partial}{\partial t} g(k, t) = g(k-1, t)$$

$$g(0, 0) = 1, \quad g(1, 0) = g(2, 0) = \dots = 0$$



$$f(x) = e^{-\lambda} \lambda^x / x! \quad x = 0, 1, 2, \dots \quad (\lambda > 0) \quad \text{i.e. pdf of Poisson dist.}$$

$$X \sim \text{Pois}(\lambda)$$

$$\textcircled{1} \quad \mathbb{E}e^{tx} = \sum_{x=0}^{\infty} e^{tx-\lambda} \frac{\lambda^x}{x!} = e^{-\lambda} \cdot \sum_{x=0}^{\infty} (\lambda e^t)^x / x! = e^{\lambda e^t - \lambda}$$

$$\textcircled{2} \quad \mathbb{E}X = \lambda, \quad \text{Var } X = \lambda \quad \leftarrow \text{ how to use C.g.f}$$

$$\textcircled{3} \quad X_1 \sim \text{Pois}(\lambda_1), \quad X_2 \sim \text{Pois}(\lambda_2), \quad X_1, X_2 \text{ indep}$$

$$\Rightarrow M_{X_1+X_2}(t) = M_{X_1}(t) M_{X_2}(t) = e^{(\lambda_1+\lambda_2)e^t - (\lambda_1+\lambda_2)}$$

$$\Rightarrow X_1+X_2 \sim \text{Pois}(\lambda_1+\lambda_2)$$

* exp / gamma distribution

$$\Gamma(\alpha) = \int_0^{\infty} x^{\alpha-1} e^{-x} dx \quad \rightarrow \quad y = x\beta$$

$$\Gamma(\alpha) = \int_0^{\infty} \beta^{1-\alpha} y^{\alpha-1} e^{-y/\beta} dy / \beta$$

$$\therefore \int_0^{\infty} \frac{1}{\Gamma(\alpha)\beta^\alpha} y^{\alpha-1} e^{-y/\beta} dy = 1$$

$\underbrace{\quad}_{\text{p.a.f of}} \quad \text{Gamma}(\alpha, \beta)$

One can easily prove $\Gamma(\alpha) = (\alpha-1)T(\alpha-1) \quad \alpha > 1$

$$\begin{aligned} \text{(a)} \quad \mathbb{E}X^k &= \int_0^{\infty} x^{\alpha+k-1} e^{-x/\beta} \frac{1}{\Gamma(\alpha)\beta^\alpha} dx \\ &= \frac{\Gamma(\alpha+k)\beta^{\alpha+k}}{\Gamma(\alpha)\beta^\alpha} \underbrace{\int_0^{\infty} x^{\alpha+k-1} e^{-x/\beta} \frac{1}{\Gamma(\alpha+k)\beta^{\alpha+k}} dx}_{=1} \\ &= \alpha(\alpha+1) \cdots (\alpha+k-1) \beta^{k\alpha} \end{aligned}$$

$$\Rightarrow \mathbb{E}X = \alpha\beta \quad \text{Var } X = \alpha\beta^2 \quad \left(\frac{1}{\beta} - t \right)x = y$$

$$\begin{aligned} \text{(b)} \quad \mathbb{E}e^{tx} &= \frac{1}{\Gamma(\alpha)\beta^\alpha} \int_0^{\infty} x^{\alpha-1} e^{tx - x/\beta} dx \\ &= \frac{1}{\Gamma(\alpha)\beta^\alpha} \cdot (1/\beta - t)^{-\alpha} \underbrace{\int_0^{\infty} y^{\alpha-1} e^{-y} dy}_{\Gamma(\alpha)} \\ &= (1 - \beta t)^{-\alpha} \end{aligned}$$

if $\frac{1}{\beta} - t > 0$

$$\text{(c)} \quad \text{Similarly } X_i \sim \text{Gam}(\alpha_i, \beta) \quad , \quad X_1, X_2 \text{ indep} \Rightarrow X_1+X_2 \sim \text{Gam}(\alpha_1+\alpha_2, \beta)$$

Let $\{N_t | t \geq 0\}$ be poisson process. Let W_1 be time till first event.

$$P(W_1 \leq t) = 1 - P(N_t = 0) = 1 - e^{-\lambda t}$$

\Rightarrow pdf will be $\lambda e^{-\lambda t} \leftarrow$ exp dist.

$$\hookrightarrow \text{Gamma}(1, \frac{1}{\lambda})$$

* Normal dist

$$\phi(z) = \frac{1}{\sqrt{2\pi}} e^{-\frac{z^2}{2}} \quad \frac{1}{6} \phi\left(\frac{x-\mu}{\sigma}\right) = \frac{1}{\sqrt{2\pi} \cdot 6} e^{-\frac{1}{2} \left(\frac{x-\mu}{\sigma}\right)^2}$$

$$\begin{aligned} (a) \quad \mathbb{E} e^{tx} &= \int e^{tx} \frac{1}{6} \phi\left(\frac{x-\mu}{\sigma}\right) dx \\ &= \int e^{t(6z+\mu)} \phi(z) dz \\ &= e^{\mu t + \frac{1}{2} \sigma^2 t} \underbrace{\int \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(z-6t)^2} dz}_{=1} \end{aligned}$$

$$(b) \quad X_1 + X_2 \sim N(\mu_1 + \mu_2, 6\sigma^2) \quad (\text{Similarly})$$

$$(c) \quad \mathbb{E}x = \mu, \quad \text{Var } x = \sigma^2$$

* Change of Variables formula

Thm 1. X is continuous k -dimensional r.v. $u = (u_1, \dots, u_k)^T : \mathcal{X} \rightarrow \mathcal{Y}$

with (a) $P(X \in \mathcal{X}) = 1$.

(b) $u : \mathcal{X} \rightarrow \mathcal{Y}$ is bijective ($1-1$ correspondence)

(c) \mathcal{X} is open set in \mathbb{R}^k . u is continuously differentiable

with non-singular Jacobian matrix

$$(J_{u_j}(x) = \left| \frac{\partial}{\partial x_i} u_j(x) \right| \neq 0 \quad \text{for all } x \in \mathcal{X})$$

Let $Y = u(x)$. Then

$$\text{pdf}_Y(y) = \text{pdf}_X(x) / |J_{u^{-1}}(y)|$$

2. with (a) $P(X \in \mathcal{X}) = 1$

(b) $u: \mathcal{X} \rightarrow \mathcal{Y}$ is $m-1$ correspondence

(c) $\mathcal{X} = \bigcup_{i=1}^m \mathcal{X}_i$ when each \mathcal{X}_i is open

$u|_{\mathcal{X}_i}$ is 1-1 correspondence with nonsingular Jacobian

let $T = u(x)$ then

$$\text{pdf}_Y(y) = \sum_{x: u(x)=y} \text{pdf}_X(x) |\det \left(\frac{\partial y}{\partial x} \right)|^{-1}$$

(ex) location parameter / scale parameter

r.v Z with pdf $f(z)$, $\sigma > 0$, $\mu \in \mathbb{R}$

let $X = \sigma Z + \mu$

$$\text{then } \text{pdf}_X(x) = f(z) \left| \frac{dx}{dz} \right| = \frac{1}{\sigma} f\left(\frac{x-\mu}{\sigma}\right)$$

$N(\mu, \sigma^2)$, Gamma(α, β)
loc \uparrow scale \uparrow

(ex) $Z_1 \sim \text{Gamma}(\alpha_1, \beta)$, $Z_2 \sim \text{Gamma}(\alpha_2, \beta)$, indep

$Z_1/Z_1+Z_2 \sim ?$

$$\text{pdf}_{Z_1/Z_2}(z_1, z_2) = \Gamma(\alpha_1)^{-1} \Gamma(\alpha_2)^{-1} \beta^{-(\alpha_1+\alpha_2)} z_1^{\alpha_1-1} z_2^{\alpha_2-1} e^{-(z_1+z_2)/\beta} I_{(z_1, z_2) > 0}$$

$$Y_1 = Z_1/Z_1+Z_2, Y_2 = Z_1+Z_2$$

$$X = \{ (x_1, x_2) \mid x_1, x_2 > 0 \}, Y = \{ (y_1, y_2) \mid 0 < y_1 < 1, y_2 > 0 \}$$

$$u^{-1}(y_1, y_2) = (y_1 y_2, (1-y_1)y_2)'$$

$$\Rightarrow J_{u^{-1}} = \begin{vmatrix} y_2 & -y_2 \\ y_1 & 1-y_1 \end{vmatrix} = y_2$$

$$\Rightarrow \text{pdf}_{Y_1, Y_2}(y_1, y_2) = \cdots \cdot (y_1 y_2)^{\alpha_1-1} ((1-y_1)y_2)^{\alpha_2-1} e^{-y_2/\beta} |y_2| I_{y_1 > 0} I_{y_2 > 0}$$

$$= \underbrace{\left(\Gamma(\alpha_1 + \alpha_2) \beta^{-(\alpha_1 + \alpha_2)} y_1^{\alpha_1 + \alpha_2 - 1} e^{-y_1/\beta} I_{(y_1 > 0)} \right)}_{Y_1 \sim \text{Gamma}(\alpha_1 + \alpha_2, \beta)} \cdot \underbrace{\frac{\Gamma(\alpha_1 + \alpha_2)}{\Gamma(\alpha_1)\Gamma(\alpha_2)} y_1^{\alpha_1 - 1} (1 - y_1)^{\alpha_2 - 1} I_{(y_1 < 1)}}_{\text{pdf of Beta}(\alpha_1, \alpha_2)}$$

(ex) $X \sim N(0,1)$ $Y = X^2$

except for $X=0$ (measure 0) it satisfies the condition

$$\text{pdf}_Y(y) = \sum_{x: x^2 = y} \frac{1}{\sqrt{2\pi}} e^{-\frac{x^2}{2}} \left| \frac{dx}{dy} \right|^{-1} = \underbrace{\frac{1}{\sqrt{2\pi}} y^{-1/2} e^{-y/2}}_{\hookrightarrow \text{Gamma}(1/2, 1/2)}$$

If $X_1, \dots, X_n \stackrel{iid}{\sim} N(0,1)$

$$Y = X_1^2 + \dots + X_n^2 \sim \text{Gamma}(n/2, 1/2) \text{ or } \chi^2(n)$$

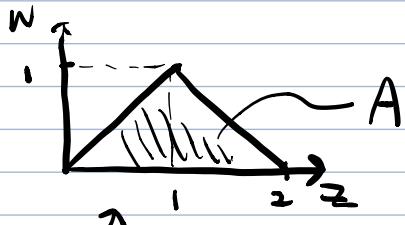
(ex) $X_{(n)} + X_{(1)}$ for unif $[0,1]$.

$$f_{X_{(1)}, X_{(n)}}(x, y) = n(n-1)(y-x)^{n-2} I_{(0 < x < y < 1)}$$

$$Z = X_{(1)} + X_{(n)}$$

$$W = X_{(n)} - X_{(1)}$$

$$\hookrightarrow 0 < Z-W < Z+W < 2$$



$$|J_{w,z}| = |(J_w)| = \left| \begin{smallmatrix} 1 & 0 \\ 0 & 1 \end{smallmatrix} \right|$$

$$= \frac{1}{2}$$

$$f_{Z,W}(z,w) = n(n-1) w^{n-2} \cdot \frac{1}{2} \cdot I_A(z,w)$$

$$f_Z(z) = \int_0^z n(n-1) w^{n-2} \frac{1}{2} dw = \frac{1}{2} n z^{n-1}$$

$$\int_0^{2-z} dw = \frac{1}{2} n (2-z)^{n-1}$$

$$\text{Var}(Z) = \int_0^2 (z-1)^2 f_Z(z) dz = \int_0^1 (z^2 - 2z + 1) z^{n-1} \frac{n}{2} dz \quad) \textcircled{1}$$

$$+ \int_1^2 (z-1)^2 (2-z)^{n-1} \frac{n}{2} dz \quad) \textcircled{2}$$

$$\textcircled{1}: \frac{n}{2} \left(\frac{1}{n+2} - \frac{2}{n+1} + \frac{1}{n} \right) \quad \textcircled{2}: \frac{n}{2} \int_0^1 (y-1)^2 y^{n-1} \frac{n}{2} dy$$

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

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

When χ^2 -dist appear in stat.

Thm A is $n \times n$ matrix which is symmetric ($A^T = A$), idempotent ($A^2 = A$) and $X \sim N(0, I_n)$ $\Rightarrow X^T A X \sim \chi^2_{\text{tr}(A)}$

(Pf) A is real, symmetric \Rightarrow diagonalizable. $A = UDU^T$ where $UU^T = I_n$.

$D = \text{diag } (\lambda_1, \dots, \lambda_n)$ where λ_i 's are eigenvalues of A

$$Av = \lambda v \Rightarrow \lambda v = Av = A^2 v = A(\lambda v) = \lambda(Av) = \lambda^2 v$$

$$\therefore \lambda = 0 \text{ or } 1.$$

Note that $U^T X \sim N(U^T 0, U^T I_n U) = N(0, I_n)$

$$\therefore U^T X = (z_1, \dots, z_n)' \text{ where } z_i \stackrel{\text{iid}}{\sim} N(0, 1)$$

$$X^T A X = (U^T X)^T D (U^T X) = \sum \lambda_i z_i^2 = \chi^2_{(\#\text{of } \lambda_i = 1)}$$

$$\text{tr}(A) = \text{tr}(UDU^T) = \text{tr}(DU^T U) = \text{tr}(U) = \#\text{ of } \lambda_i = 1$$

$$(Ex) S^2 = \sum (x_i - \bar{x})^2 / (n-1)$$

$(n-1)S^2 / \sigma^2$ is known to follow $\chi^2_{(n-1)}$

$$\text{choose } A = I_n - \frac{1}{n} \mathbb{1} \mathbb{1}^T = I_n - \frac{1}{n} \begin{pmatrix} 1 & 1 & \cdots & 1 \\ 1 & 1 & \cdots & 1 \\ \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & \cdots & 1 \end{pmatrix}$$