

Joint m.g.f.

$$\underline{X} = (X_1, \dots, X_p)'$$

Joint m.g.f.

$$M_{\underline{X}}(\underline{t}) = E(e^{\underline{t}' \underline{X}}) = E(e^{t_1 X_1 + \dots + t_p X_p})$$

\nearrow
 (t_1, \dots, t_p)

provided the expectation exists in some

nbhd of $\underline{0}_{p \times 1}$

$$M_{\underline{X}}(\underline{t}) = \int \dots \int e^{\sum_{i=1}^p t_i x_i} f_{\underline{X}}(\underline{x}) dx_1 \dots dx_p \quad \text{for continuous case}$$

$$= \sum_{x_1} \dots \sum_{x_p} e^{\sum_{i=1}^p t_i x_i} P(\underline{X} = \underline{x}) \quad \text{for discrete case}$$

$$\mu'_{k_1, \dots, k_p} = E(X_1^{k_1} \dots X_p^{k_p}) = \frac{\partial^{k_1 + \dots + k_p} M_{\underline{X}}(\underline{t})}{\partial t_1^{k_1} \dots \partial t_p^{k_p}} \bigg|_{\underline{t} = \underline{0}}$$

\nearrow
joint moment of order $k_1 + \dots + k_p$

k_i 's are non-negative integers

Note that we can get marginal distⁿ m.g.f.s from the joint m.g.f.

$$M_{\underline{X}}(0, \dots, 0, t_i, 0, \dots, 0) = E(e^{t_i X_i}) = M_{X_i}(t_i)$$

\nearrow
ith position

Any marginal joint m.g.f. for any subset can be obtained from $M_{\underline{X}}(\underline{t})$.

Note: m.g.f. of $X_1 + \dots + X_K$ for $K \leq p$ can be obtained from $M_{\underline{X}}(\underline{t})$

Remark: X_1, \dots, X_p are independent iff

$$M_{\underline{X}}(\underline{t}) = \prod_{i=1}^p M_{X_i}(t_i)$$

M.g.f. of $N_p(\underline{\mu}, \Sigma)$

$$M_{\underline{X}}(\underline{t}) = E(e^{\underline{t}'\underline{X}})$$

$$= M_{\underline{t}'\underline{X}}(1)$$

$$= e^{\underline{t}'\underline{\mu} + \frac{1}{2}\underline{t}'\Sigma\underline{t}}$$

$$\underline{t}'\underline{X} \sim N_1(\underline{t}'\underline{\mu}, \underline{t}'\Sigma\underline{t})$$

m.g.f.

$$M_{\underline{t}'\underline{X}}(z) = E(e^{z(\underline{t}'\underline{X})})$$

$$= e^{z(\underline{t}'\underline{\mu}) + \frac{z^2}{2}(\underline{t}'\Sigma\underline{t})}$$

• Marginal m.g.f.s can be derived using the above.

M.g.f. of trinomial (n, θ_1, θ_2)

$$\underline{X} = (X_1, X_2) \sim \text{trinomial}(n, \theta_1, \theta_2)$$

$$M_{\underline{X}}(t_1, t_2) = E(e^{t_1 X_1 + t_2 X_2})$$

$$= \sum_{x_1=0}^n \sum_{x_2=0}^{n-x_1} e^{t_1 x_1 + t_2 x_2} \frac{n!}{x_1! x_2! (n-x_1-x_2)!} \theta_1^{x_1} \theta_2^{x_2} (1-\theta_1-\theta_2)^{n-x_1-x_2}$$

$$= \sum_{x_1=0}^n \frac{n!}{x_1! (n-x_1)!} (\theta_1 e^{t_1})^{x_1} \sum_{x_2=0}^{n-x_1} \frac{(n-x_1)!}{x_2! (n-x_1-x_2)!} (\theta_2 e^{t_2})^{x_2} (1-\theta_1-\theta_2)^{n-x_1-x_2}$$

$$= \sum_{x_1=0}^n \binom{n}{x_1} (\theta_1 e^{t_1})^{x_1} (1-\theta_1-\theta_2 + \theta_2 e^{t_2})^{n-x_1}$$

$$= (1-\theta_1-\theta_2 + \theta_1 e^{t_1} + \theta_2 e^{t_2})^n$$

By \uparrow $(X_1, \dots, X_{p-1}) \sim \text{mult}(n, \theta_1, \theta_2, \dots, \theta_{p-1})$

$$M_{\underline{X}}(t_1, \dots, t_{p-1}) = (1-\theta_1-\theta_2-\dots-\theta_{p-1} + \theta_1 e^{t_1} + \dots + \theta_{p-1} e^{t_{p-1}})^n$$

Marginal m.g.f.s can be derived.

DISTⁿ of $X_i + X_j$ can be derived thro joint m.g.f.

Conditional expectation

Consider a bivariate setup $(X, Y) \rightarrow$ j.t. p.d.f $f_{X,Y}(x,y)$

marginal p.d.f.s: $f_X(x)$, $f_Y(y)$

Conditional p.d.f.s: $f_{X|Y}(x)$, $f_{Y|X}(y)$

Note that

$$f_{X,Y}(x,y) = f_X(x) f_{Y|X}(y) \\ = f_Y(y) f_{X|Y}(x)$$

let $g(x,y)$ be some fⁿ of x & y

$E(g(x,y)|x)$: Conditional expectation of $g(x,y)$

$E(g(x,y)|y)$: Conditional expectation ^{given x} of $g(x,y)$ given y

$$E(g(x,y)|x) = E_{Y|X}(g(x,y)|x)$$

$$= \int_{-\infty}^{\infty} g(x,y) f_{Y|X}(y) dy \rightarrow \text{fⁿ of } x \text{ only} \\ = \phi(x), \text{ say}$$

$$E_X(\phi(x)) = E_X E_{Y|X}(g(x,y)|x)$$

$$= \int_{-\infty}^{\infty} \phi(x) f_X(x) dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f_{Y|X}(y) f_X(x) dy dx$$

$$= \int_{-\infty}^{\infty} \int_{-\infty}^{\infty} g(x,y) f_{X,Y}(x,y) dy dx \\ = E_{X,Y}(g(x,y))$$

$$\text{i.e. } E_X E_{Y|X} (g(x, y) | X) = E_{X, Y} (g(x, y))$$

Sp. case : $g(x, y) = Y$ say

$$E E(Y | X) = E(Y)$$

slly $E E(X | Y) = E(X)$

Sp. case : $g(x, y) = (y - E(Y))^2$

$$E (Y - E(Y))^2 = E_X E_{Y|X} ((Y - E(Y))^2 | X)$$

Note that

$$E (Y - E(Y))^2 | X$$

$$= E (Y - E(Y|X) + E(Y|X) - E(Y))^2 | X$$

$$= E (Y - E(Y|X))^2 | X + (E(Y|X) - E(Y))^2$$

$$+ 2 E ((Y - E(Y|X)) | X) (E(Y|X) - E(Y))$$

$$0 \text{ (as } E(Y - E(Y|X)) | X = E(Y|X) - E(Y|X) = 0)$$

$$= V(Y|X) + (E(Y|X) - E(Y))^2$$

$$\Rightarrow E E [(Y - E(Y))^2 | X] (= V(Y))$$

$$= E (V(Y|X)) + V(E(Y|X))$$

i.e. $V(Y) = E(V(Y|X)) + V(E(Y|X))$

Note: Joint m.g.f. can be derived through m.g.f. of conditional distⁿ using conditional expectation

e.g. $(X_1, X_2) \sim N_2(\mu_1, \mu_2, \sigma_1^2, \sigma_2^2, \rho)$

$$\begin{aligned} M_{X_1, X_2}(t_1, t_2) &= E(e^{t_1 X_1 + t_2 X_2}) ; \quad q(X_1, X_2) = e^{t_1 X_1 + t_2 X_2} \\ &= E E(e^{t_1 X_1 + t_2 X_2} | X_1) \\ &= E_{X_1} \left(e^{t_1 X_1} \left(E_{X_2 | X_1} e^{t_2 X_2} | X_1 \right) \right) \end{aligned}$$

Now, use the fact that

$$X_2 | X_1 \sim N\left(\mu_2 + \rho \frac{\sigma_2}{\sigma_1} (x_1 - \mu_1), \sigma_2^2 (1 - \rho^2)\right).$$