

lec 20 MATH 20/600

1

Joint / Multivariate ch. f.'s! let \vec{X} be an n -dim vector rv

$$\begin{aligned} \text{Def: } \phi_{\vec{X}}(\vec{t}) &:= E[e^{i\vec{t}^T \vec{X}}] \\ &= E[e^{i(t_1 X_1 + \dots + t_n X_n)}] \\ &= E[e^{it_1 X_1 + \dots + it_n X_n}] \\ &= E[e^{it_1 X_1} \dots e^{it_n X_n}] \\ &\stackrel{\text{if } X_1, \dots, X_n \text{ ind}}{\rightarrow} E[e^{it_1 X_1}] \dots E[e^{it_n X_n}] \end{aligned}$$

Properties analogous

to Lemma 5 $X_1, \dots, X_n \text{ ind} \stackrel{\text{only one-dim } t!}{\Rightarrow} \phi_{X_1, \dots, X_n}(\vec{t}) \stackrel{\text{only one-dim } t!}{=} \phi_{X_1}(\vec{t}) \dots \phi_{X_n}(\vec{t}) \neq \phi_{X_1}(\vec{t}) \dots \phi_{X_n}(\vec{t}) = \phi_{X_1 + \dots + X_n}(\vec{t})$

(P0) $\phi_{\vec{X}}(\vec{0}) = E[e^{i\vec{0}^T \vec{X}}] = E[1] = 1$

(P1) $\phi_{\vec{X}}(\vec{t}) = \phi_{\vec{Y}}(\vec{t}) \iff \vec{X} \stackrel{d}{=} \vec{Y}$ due to multivariate Fourier transform theorem (unproven)

(P2) let $A \in \mathbb{R}^{m \times n}$, $\vec{b} \in \mathbb{R}^m$, $\vec{Y} = A\vec{X} + \vec{b}$ where $\dim(\vec{Y}) = m$

$$\phi_{\vec{Y}}(\vec{t}) = E[e^{i\vec{t}^T (A\vec{X} + \vec{b})}] = E[e^{i\vec{t}^T A\vec{X}} e^{i\vec{t}^T \vec{b}}] = e^{i\vec{t}^T \vec{b}} E[e^{i(\vec{t}^T A)\vec{X}}] = e^{i\vec{t}^T \vec{b}} \phi_{\vec{X}}(\underbrace{(\vec{t}^T A)^T}_{\substack{\text{row } i \text{ of } A \\ \text{dim } m}} \vec{t})$$

(P3) $\vec{T} = \vec{X}_1 + \dots + \vec{X}_k$ where $\vec{X}_1, \dots, \vec{X}_k \stackrel{\text{ind}}{\rightarrow} \vec{X}_1, \dots, \vec{X}_k \stackrel{\text{ind}}{\rightarrow}$

$$\phi_{\vec{T}}(\vec{t}) = E[e^{i\vec{t}^T (\vec{X}_1 + \dots + \vec{X}_k)}] = E[e^{i\vec{t}^T \vec{X}_1} \dots e^{i\vec{t}^T \vec{X}_k}] = \phi_{\vec{X}_1}(\vec{t}) \dots \phi_{\vec{X}_k}(\vec{t}) = \left(\phi_{\vec{X}}(\vec{t})\right)^k$$

Ⓟ Moment Lemma

(2)

$$h_i(\vec{t}) := \frac{\partial}{\partial t_i} [\phi_{\vec{X}}(\vec{t})] = E \left[\frac{\partial}{\partial t_i} [e^{itX_1} \dots e^{itX_i} \dots e^{itX_n}] \right]$$

$$= E [iX_i (e^{itX_1} \dots e^{itX_n})]$$

$$\Rightarrow h_i(\vec{0}) = E[iX_i] \Rightarrow E[X_i] = \frac{h_i(\vec{0})}{i}$$

$$\text{Hw: } h_{i,l}(\vec{t}) := \frac{\partial^l}{\partial t_i^l} (\phi_{\vec{X}}(\vec{t})) \Rightarrow E[X_i^l] = \frac{h_{i,l}(\vec{0})}{i^l}$$

Further ... Consider

$$h_{i,j,l} := \frac{\partial^2}{\partial t_i \partial t_j} [\phi_{\vec{X}}(\vec{t})] = E \left[\frac{\partial^2}{\partial t_i \partial t_j} [e^{itX_1} \dots e^{itX_i} \dots e^{itX_j} \dots e^{itX_n}] \right]$$

$$= E \left[iX_i \frac{\partial}{\partial t_j} [e^{itX_1} \dots e^{itX_j} \dots e^{itX_n}] \right]$$

$$= E [i^2 X_i X_j (e^{itX_1} \dots e^{itX_n})]$$

$$\Rightarrow h_{i,j,l}(\vec{0}) = E[i^2 X_i X_j] \Rightarrow E[X_i X_j] = \frac{h_{i,j,l}(\vec{0})}{i^2}$$

This allows you to get any moment product you wish! For example...

$$E[X_{17}^3 X_{37}^5 X_{41}^2] = \frac{h_{17,3,37,5,41,2}(\vec{0})}{i^{3+5+2}}$$

$$\text{where } h_{17,3,37,5,41,2}(\vec{t}) = \frac{\partial^{3+5+2}}{\partial t_{17}^3 \partial t_{37}^5 \partial t_{41}^2} [\phi_{\vec{X}}(\vec{t})]$$

(P5) Existence and Boundedness

H.W.: $|\phi_{\vec{x}}(\vec{t})| \in [-1, 1]$ due to $|e^{i\vec{t}^T \vec{x}}| = |i \sin(\vec{t}^T \vec{x}) + \cos(\vec{t}^T \vec{x})| = \sin^2(\vec{t}^T \vec{x}) + \cos^2(\vec{t}^T \vec{x}) = 1$

(P6) Inversion

$\phi_{\vec{x}}(\vec{t}) \in L^1 \Rightarrow f_{\vec{x}}(\vec{x}) = \frac{1}{(2\pi)^n} \int_{\mathbb{R}^n} e^{-i\vec{t}^T \vec{x}} \phi_{\vec{x}}(\vec{t}) d\vec{t}$ difficult!!

(P7) Continuity (beyond scope of course)

(P8) Levy CLT formula (11)

NEW
(P9) Marginalization

note $\phi_{\vec{x}} \left(\begin{pmatrix} 0 \\ 0 \\ \vdots \\ 0 \end{pmatrix} \right) = E[e^{i(0)X_1} \dots e^{i(0)X_{i-1}} e^{it_i X_i} e^{i(0)X_{i+1}} \dots e^{i(0)X_n}] = E[e^{it_i X_i}] = \phi_{X_i}(t_i)$

only position

Further...

$\phi_{\vec{x}} \left(\begin{pmatrix} 0 \\ 0 \\ \vdots \\ t_i \\ 0 \\ \vdots \\ 0 \end{pmatrix} \right) = E[e^{it_i X_i} e^{i(0)X_j}] = \phi_{\begin{pmatrix} X_i \\ X_j \end{pmatrix}} \left(\begin{pmatrix} t_i \\ 0 \end{pmatrix} \right)$

the ch.f. of the joint component!!

subset joint
You can get any ch.f. you want...

↓ dunk

$$\vec{X} \sim \text{Multinomial}(n, \vec{p}) := \binom{n}{x_1, \dots, x_k} p_1^{x_1} \dots p_k^{x_k}$$

$$\phi_{\vec{X}}(\vec{t}) = E[e^{i\vec{t}^T \vec{X}}] = \sum_{\vec{x} \in S_X} e^{it_1 x_1} \dots e^{it_k x_k} \binom{n}{x_1, \dots, x_k} p_1^{x_1} \dots p_k^{x_k}$$

$$= \sum_{\vec{x} \in S_X} \binom{n}{x_1, \dots, x_k} (e^{it_1} p_1)^{x_1} \dots (e^{it_k} p_k)^{x_k}$$

by multinomial thm \rightarrow

$$= (p_1 e^{it_1} + \dots + p_k e^{it_k})^n$$

Lee 8

$$\vec{X}_1, \dots, \vec{X}_k \stackrel{\text{iid}}{\sim} \text{Multinomial}(1, \vec{p}) \Rightarrow \phi_{\vec{X}}(\vec{t}) = p_1 e^{it_1} + \dots + p_k e^{it_k}$$

$$\vec{T} = \vec{X}_1 + \dots + \vec{X}_k \Rightarrow \phi_{\vec{T}}(\vec{t}) \stackrel{(P3)}{=} (\phi_{\vec{X}}(\vec{t}))^n = (p_1 e^{it_1} + \dots + p_k e^{it_k})^n \stackrel{(P1)}{\Rightarrow} \vec{T} \sim \text{Multinomial}(n, \vec{p})$$

~~$$\vec{X} \sim \text{Multinomial}(n, \vec{p})$$~~
~~$$\text{Cov}[X_i, X_j] := E[X_i X_j] - E[X_i] E[X_j]$$~~

~~difficult... 3D math!~~

~~$$\text{by (P7), } E[X_i X_j] = \frac{h_{ij} h_{ji}(\vec{a})}{i! j!}$$~~

~~$$h_{ij,ij}(\vec{t}) = \frac{\partial^2}{\partial t_i \partial t_j} [(p_1 e^{it_1} + \dots + p_k e^{it_k})^n]$$~~

~~$$= ip_i e$$~~

$$\vec{X} \sim \text{Multinomial}(n, \vec{p}), X_i \sim ?$$

by (P9)

$$\phi_{\vec{X}} \left(\begin{pmatrix} 0 \\ \vdots \\ t_i \\ \vdots \\ 0 \end{pmatrix} \right) = (p_1 e^{i0} + \dots + p_{i-1} e^{i0} + p_i e^{it_i} + p_{i+1} e^{i0} + \dots + p_k e^{i0})^n$$

$$= (p_1 + \dots + p_{i-1} + p_{i+1} + \dots + p_k + p_i e^{it_i})^n$$

$$= (1 - p_i + p_i e^{it_i})^n$$

$$\stackrel{(P1)}{\Rightarrow} X_i \sim \text{bin}(n, p_i)$$

$$\vec{X} \sim \text{Multinomial}(1, \vec{p})$$

$$(\text{diff-able}) = 0 \quad p_i \quad p_j$$

5

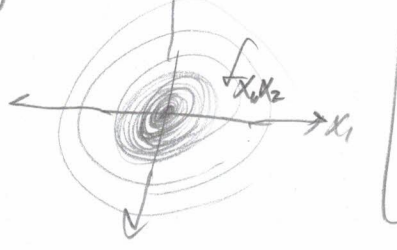
When we have density $\text{Cov}[X_i, X_j] := E[X_i X_j] - E[X_i]E[X_j]$

lets use (11) now...

$$E[X_i X_j] = \frac{h_{i,j}(\vec{0}_K)}{i^2}$$

$$h_{i,j}(\vec{0}) = \frac{\partial^2}{\partial t_i \partial t_j} [p_1 e^{it_1} + \dots + p_K e^{it_K}] = \frac{\partial}{\partial t_j} [ip_i e^{it_i}] = 0 \Rightarrow E[X_i X_j] = 0 \quad \checkmark$$

let $z_1, \dots, z_n \stackrel{iid}{\sim} N(0,1)$, $\vec{z} = \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix}$ n -dim vector rv

$$E[\vec{z}] = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} = \vec{0}_n \quad \text{Var}[\vec{z}] = \begin{bmatrix} \text{Var}(z_1) & \text{Cov}(z_1, z_2) & \dots \\ \text{Cov}(z_2, z_1) & \text{Var}(z_2) & \dots \\ \vdots & \vdots & \ddots \\ \text{Cov}(z_n, z_1) & \dots & \text{Var}(z_n) \end{bmatrix} = \begin{bmatrix} 1 & 0 & \dots \\ 0 & 1 & \dots \\ \vdots & \vdots & \ddots \\ 0 & \dots & 1 \end{bmatrix} = I_n$$


$$f_{\vec{z}}(\vec{z}) = \prod_{i=1}^n f(z_i) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{z_i^2}{2}} = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \sum_{i=1}^n z_i^2} = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \vec{z}^T \vec{z}} = N(\vec{0}_n, I_n)$$

Standard Multivariate normal (rv)

$$AA^{-1} = I \Rightarrow \det(AA^{-1}) = \det(I) = 1$$

$$\Rightarrow 1 = \det(A) \det(A^{-1}) \Rightarrow \det(A^{-1}) = \frac{1}{\det(A)}$$

Consider $\vec{a} \in \mathbb{R}^n$, $A \in \mathbb{R}^{n \times n}$ and full rank. Let $\vec{x} = \vec{a} + A\vec{z}$

$f_{\vec{x}}(\vec{x}) = ?$ Let's use multivariate change of variables.

$$\vec{x} = g(\vec{z}) = \vec{a} + A\vec{z} \Rightarrow \vec{x} - \vec{a} = A\vec{z} = \vec{z} = h(\vec{x}) = \underbrace{A^{-1}}_B (\vec{x} - \vec{a})$$

$$h_1(\vec{x}) = \vec{b}_{1\cdot} (\vec{x} - \vec{a}) = \vec{b}_{1\cdot} \vec{x} - \vec{b}_{1\cdot} \vec{a}$$

$$h_2(\vec{x}) = \vec{b}_{2\cdot} (\vec{x} - \vec{a}) = \vec{b}_{2\cdot} \vec{x} - \vec{b}_{2\cdot} \vec{a}$$

$$\vdots$$

$$h_n(\vec{x}) = \vec{b}_{n\cdot} (\vec{x} - \vec{a}) = \vec{b}_{n\cdot} \vec{x} - \vec{b}_{n\cdot} \vec{a}$$

$$J_h = \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \frac{\partial h_1}{\partial x_2} & \dots & \frac{\partial h_1}{\partial x_n} \\ \frac{\partial h_2}{\partial x_1} & \frac{\partial h_2}{\partial x_2} & \dots & \frac{\partial h_2}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial h_n}{\partial x_1} & \frac{\partial h_n}{\partial x_2} & \dots & \frac{\partial h_n}{\partial x_n} \end{bmatrix} = \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ b_{21} & b_{22} & \dots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \dots & b_{nn} \end{bmatrix} = B$$

$$f_{\vec{X}}(\vec{x}) = f_{\vec{Z}}(h(\vec{x})) |J_h| = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} (A^{-1}(\vec{x}-\vec{\mu}))^T (A^{-1}(\vec{x}-\vec{\mu}))} \det(A^{-1})$$

$$= \frac{1}{(2\pi)^{n/2} \det[A]} e^{-\frac{1}{2} (\vec{x}-\vec{\mu})^T (A^{-1})^T A^{-1} (\vec{x}-\vec{\mu})}$$

$$\text{Let } \Sigma = AA^T \Rightarrow \Sigma^{-1} = (AA^T)^{-1} = (A^T)^{-1} A^{-1} = (A^{-1})^T A^{-1}$$

$$I = AA^{-1} \Rightarrow I^T = (AA^{-1})^T = (A^{-1})^T A^T = I \Rightarrow (A^T)^{-1} = (A^{-1})^T$$

$$\det[\Sigma] = \det[AA^T] = \det[A] \det[A^T] = \det[A]^2$$

$$\Rightarrow \det[A] = \sqrt{\det[\Sigma]}$$

$$= \frac{1}{\sqrt{(2\pi)^n \det[\Sigma]}} e^{-\frac{1}{2} (\vec{x}-\vec{\mu})^T \Sigma^{-1} (\vec{x}-\vec{\mu})} = N_n(\vec{\mu}, \Sigma)$$

general MVN rv

Does Σ have any special meaning??

(If $\vec{\mu} = \vec{0}_n$ and $\Sigma = I_n$ standard mvn)

$$E(\vec{X}) = E(\vec{\mu} + A\vec{Z}) = \vec{\mu} + E[A\vec{Z}] = \vec{\mu} + A\vec{0}_n = \vec{\mu}$$

In general (not just for MVN), let \vec{Y} be a vector rv with dimension n . Let $A \in \mathbb{R}^{m \times n}$,

$$E[A\vec{Y}] = E \begin{bmatrix} \vec{a}_1 \cdot \vec{Y} \\ \vec{a}_2 \cdot \vec{Y} \\ \vdots \\ \vec{a}_m \cdot \vec{Y} \end{bmatrix} = \begin{bmatrix} E[\vec{a}_1 \cdot \vec{Y}] \\ E[\vec{a}_2 \cdot \vec{Y}] \\ \vdots \\ E[\vec{a}_m \cdot \vec{Y}] \end{bmatrix} = \begin{bmatrix} \vec{a}_1 \cdot \vec{\mu} \\ \vec{a}_2 \cdot \vec{\mu} \\ \vdots \\ \vec{a}_m \cdot \vec{\mu} \end{bmatrix} = A\vec{\mu} \quad \text{by same logic}$$

$$E[\vec{Y}A^T] = E[(A\vec{Y})^T] = (E[A\vec{Y}])^T = (A\vec{\mu})^T = \vec{\mu}^T A^T = E[\vec{Y}]^T A^T$$

$$\text{Var}(\vec{X}) = ?$$

The above proof also works for matrix rv's Y .