

Lee 20 Math 621 11/20/18

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$$\vec{Z} \sim N_n(\vec{0}_n, I_n) = \frac{1}{\sqrt{(2\pi)^n}} e^{-\frac{1}{2} \vec{Z}^T \vec{Z}}$$

Let  $A \in \mathbb{R}^{n \times n}$  and invertible,  $\vec{\mu} \in \mathbb{R}^n$ , let  $\Sigma = AA^T$

$$\vec{X} = A\vec{Z} + \vec{\mu} \sim N_n(\vec{\mu}, \Sigma) := \frac{1}{\sqrt{(2\pi)^n \det(\Sigma)}} e^{-\frac{1}{2} (\vec{X} - \vec{\mu})^T \Sigma^{-1} (\vec{X} - \vec{\mu})}$$

$$\phi_{\vec{Z}}(\vec{z}) = e^{-\frac{1}{2} \vec{z}^T \vec{z}} = e^{i\vec{z}^T \vec{0} - \frac{1}{2} \vec{z}^T I \vec{z}} \quad \phi_{\vec{X}}(\vec{x}) = e^{i\vec{x}^T \vec{\mu} - \frac{1}{2} \vec{x}^T \Sigma \vec{x}}$$

Let  $B \in \mathbb{R}^{m \times n}$ ,  $\vec{c} \in \mathbb{R}^m$

$$\vec{Y} = B\vec{X} + \vec{c} \Rightarrow \phi_{\vec{Y}}(\vec{y}) = e^{-i\vec{y}^T (B\vec{\mu} + \vec{c}) - \frac{1}{2} \vec{y}^T (B \Sigma B^T) \vec{y}}$$

$$\stackrel{(P1)}{\Rightarrow} \vec{Y} \sim N_m(B\vec{\mu} + \vec{c}, B \Sigma B^T)$$

Let  $A \in \mathbb{R}^{m \times n}$  where  $m \leq n$ ,  $A$  is full rank  $\Rightarrow AA^T = \Sigma$  invertible

$$\vec{X} = A\vec{Z} + \vec{c} \sim N_m(A\vec{0}_n + \vec{c}, A I_n A^T) = N_m(\vec{c}, AA^T) = N_m(\vec{c}, \Sigma)$$

That's the general proof!

In genl, if  $\vec{X} \sim N_n(\vec{\mu}, \Sigma)$  How is  $(\vec{X} - \vec{\mu})^T \Sigma^{-1} (\vec{X} - \vec{\mu}) \sim ?$

$$= (\vec{X} - \vec{\mu})^T (A^{-1})^T A (\vec{X} - \vec{\mu}) = \underbrace{(A^{-1}(\vec{X} - \vec{\mu}))^T}_{\vec{Z}^T} \underbrace{(A^{-1}(\vec{X} - \vec{\mu}))}_{\vec{Z}} = \vec{Z}^T \vec{Z} \sim \chi_n^2$$

Review.

Probability Distance (1936)  
analogy of 2-score  $z = \frac{x - \mu}{\sigma}$  it does

Now. let  $X \sim N_n(\vec{\mu}, \Sigma)$  and  $\vec{Y} = B\vec{X} + \vec{c} \sim ?$

Use ch.f.'s!

$$\begin{aligned}\phi_{\vec{Y}}(\vec{t}) &= e^{i\vec{t}^T \vec{c}} \phi_{\vec{X}}(B^T \vec{t}) = e^{i\vec{t}^T \vec{c}} \left( e^{i(B^T \vec{t})^T \vec{\mu} - \frac{1}{2} (B^T \vec{t})^T \Sigma (B^T \vec{t})} \right) \\ &= e^{i\vec{t}^T (B\vec{\mu} + \vec{c}) - \frac{1}{2} \vec{t}^T B \Sigma B^T \vec{t}} \stackrel{(PI)}{\Rightarrow} \vec{Y} \sim N_m(B\vec{\mu} + \vec{c}, B \Sigma B^T)\end{aligned}$$

we need to make sure  $B \Sigma B^T$  still has cov-matrix

Another cool fact about multivariate ch.f.'s

$$\vec{X} = A\vec{Z} + \vec{\mu} \sim N_m(\vec{\mu}, AA^T)$$

$$A \in \mathbb{R}^{m \times m}, \vec{\mu} \in \mathbb{R}^m$$

DUH!

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

$$\text{let } \vec{t} = \begin{bmatrix} t \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \phi_{\vec{X}}\left(\begin{bmatrix} t \\ 0 \\ \vdots \\ 0 \end{bmatrix}\right) = E[e^{i[t \ 0 \dots 0] \vec{X}}] = E[e^{itX_1}] = \phi_{X_1}(t) \stackrel{(PI)}{\Rightarrow} X_1 \sim \dots$$

this means you can find marginal distr's! No need for  $\int \dots \int f_{\vec{X}}(\vec{x}) dx_1 dx_2 \dots$

e.g.  $\vec{X} \sim N_m(\vec{\mu}, \Sigma)$  what is  $X_1 \sim ?$

$$\phi_{\vec{X}}\left(\begin{bmatrix} t \\ 0 \\ \vdots \\ 0 \end{bmatrix}\right) = e^{i[t \ 0 \dots 0] \vec{\mu} - \frac{1}{2} [t \ 0 \dots 0] \Sigma \begin{bmatrix} t \\ 0 \\ \vdots \\ 0 \end{bmatrix}} = e^{it\mu_1 - \frac{1}{2} \Sigma_{11} t^2} \Rightarrow X_1 \sim N(\mu_1, \Sigma_{11})$$

HW: multiple dimension

we will now justify the T test and F tests from linear regression

ECON 382, 387 using Math 390 manual

NOT COVERED

this was a whole class in grad school called linear model theory

ON

FINAL

$$\text{Let } \vec{Y} = X\vec{\beta} + \vec{\epsilon} \quad \text{where } \vec{X} \in \mathbb{R}^{n \times p}, \vec{\beta} \in \mathbb{R}^p$$

$$\vec{Y} = X\vec{\beta} + \vec{\epsilon}$$

$\text{rank}(\vec{X}) = p$

and

$$\vec{\epsilon}_n \sim N_n(\vec{0}, \sigma^2 I_n)$$

columns

Normal errors.

Homoskedastic error assumption