

Lec 19 Mark 621 11/25/19

$$U \sim \mathcal{N}_k^T \quad E[U] = E[Z_1^2 \dots Z_k^2] = k E[Z_1^2] \quad (1) \\ = k (Var(Z) + E(Z)^2) = k Var(Z) = kI = k$$

let \vec{X} be a r.v. vector with dim n . $E[\vec{X}] = \vec{\mu}$

$$\Sigma := Var[\vec{X}] = \begin{bmatrix} Var(X_1) & Cov(X_1, X_2) & \dots & Cov(X_1, X_n) \\ Cov(X_1, X_2) & Var(X_2) & \dots & Cov(X_2, X_n) \\ \vdots & \vdots & \ddots & \vdots \\ Cov(X_n, X_1) & \dots & \dots & Var(X_n) \end{bmatrix} \quad \text{the definition} \\ = E[\underbrace{\vec{X} \vec{X}^T}_{n \times n}] - \underbrace{E[\vec{X}]}_{n \times 1} \underbrace{E[\vec{X}]^T}_{1 \times n} = Var(\vec{X})$$

let $A \in \mathbb{R}^{m \times n}$ matrix of constants

$$E[A\vec{X}] = \begin{bmatrix} E[\vec{q}_1 \cdot \vec{X}] \\ E[\vec{q}_2 \cdot \vec{X}] \\ \vdots \\ E[\vec{q}_m \cdot \vec{X}] \end{bmatrix} = \begin{bmatrix} \vec{q}_1 \cdot \vec{\mu} \\ \vec{q}_2 \cdot \vec{\mu} \\ \vdots \\ \vec{q}_m \cdot \vec{\mu} \end{bmatrix} = \begin{bmatrix} \vec{q}_1 \\ \vec{q}_2 \\ \vdots \\ \vec{q}_m \end{bmatrix} \cdot \vec{\mu} = \vec{\mu} = A\vec{\mu}$$

$$Var[A\vec{X}] = E[A\vec{X}(A\vec{X})^T] - E[A\vec{X}]E[A\vec{X}]^T$$

$$\begin{matrix} m \times n & n \times 1 \\ \hline m \times 1 \end{matrix} \quad = E[A\vec{X}\vec{X}^T A^T] - (A\vec{\mu})(A\vec{\mu})^T$$

$$\begin{matrix} m \times m \end{matrix} \quad = A E[\vec{X}\vec{X}^T] A^T - A\vec{\mu}\vec{\mu}^T A^T$$

$$= A E[\vec{X}\vec{X}^T] A^T - A\vec{\mu}\vec{\mu}^T A^T$$

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

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

$$= A \Sigma A^T$$

this generalizes the rule we learned before

let $A = \vec{a}^T$ where $\vec{a} \in \mathbb{R}^n$

$$Var[\vec{a}^T \vec{X}] = \vec{a}^T \Sigma \vec{a} = A \Sigma A^T$$

$$E[X] = E[A\vec{Z}] = A E[\vec{Z}] = A \vec{0}_n = \vec{0}_m$$

$$Var[X] = Var[A\vec{Z}] = A Var(\vec{Z}) A^T = A I_n A^T = A A^T$$

From last lecture

$$\vec{Z} = \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix} \sim \mathcal{N}_n(\vec{0}, I_n) \\ = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \vec{Z}^T \vec{Z}}$$

$$\vec{X} = A \vec{Z}$$

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

$\vec{X} = A\vec{Z} + \vec{\mu} \sim f_{\vec{X}}(\vec{x}) = ?$

Let's use change of random variable. Assuming g is 1:1 is the same as assuming A is invertible, in this case.

$\Rightarrow A\vec{Z} = \vec{X} - \vec{\mu} \Rightarrow \vec{Z} = \underbrace{A^{-1}}_B (\vec{X} - \vec{\mu}) = h(\vec{X}) = B\vec{X} - B\vec{\mu}$

$f_{\vec{X}}(\vec{x}) = f_{\vec{Z}}(h(\vec{x})) |J_h|$

$\Rightarrow h_1(\vec{x}) = \vec{b}_{11}\vec{x} - \vec{b}_{11}\vec{\mu}$

$h_n(\vec{x}) = \vec{b}_{n1}\vec{x} - \vec{b}_{n1}\vec{\mu}$

$J_h = \det \begin{bmatrix} \frac{\partial h_1}{\partial x_1} & \dots & \frac{\partial h_1}{\partial x_n} \\ \vdots & & \vdots \\ \frac{\partial h_n}{\partial x_1} & \dots & \frac{\partial h_n}{\partial x_n} \end{bmatrix} = \det \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ \vdots & \vdots & & \vdots \\ b_{n1} & b_{n2} & \dots & b_{nn} \end{bmatrix} = \det[A^{-1}]$

Note:

$AA^{-1} = I$

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

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

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

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

Recall $\text{Var}(\vec{X}) = AA^T = \Sigma$. So it would be nice to use Σ as a parameter, not A .
 Facts: $(AB)^{-1} = B^{-1}A^{-1}$

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

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

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

by def of inverse

Also... $\det(\Sigma) = \det(AA^T) = \det(A)\det(A^T) = \det(A)^2 \Rightarrow \det(A) = \sqrt{\det(\Sigma)}$

$\Rightarrow = \frac{1}{\sqrt{(2\pi)^n \det(\Sigma)}} e^{-\frac{1}{2} (\vec{x} - \vec{\mu})^T \Sigma^{-1} (\vec{x} - \vec{\mu})} = N_n(\vec{\mu}, \Sigma)$ where $\vec{\mu} \in \mathbb{R}^n$
 Σ is a valid cov matrix

General Multivariate Normal

$\vec{\mu} = \vec{0}$ and $\Sigma = I \Rightarrow$ Standard MVN

What about for $A \in \mathbb{R}^{m \times n}$ and $\vec{u} \in \mathbb{R}^m$? $\vec{X} = A \vec{Z} + \vec{u}$

We can imagine setting $A_{aug} = \begin{bmatrix} A \\ \vec{v}_{m+1} \\ \vdots \\ \vec{v}_{n-m} \end{bmatrix}$, $\vec{u}_{aug} = \begin{bmatrix} \vec{u} \\ 0 \\ \vdots \\ 0 \end{bmatrix}$ $\vec{X}_{aug} = A_{aug} \vec{Z} + \vec{u}_{aug}$

The \vec{v} 's can't be $\vec{0}$ since we need A_{aug} to be full rank \Rightarrow invertible

where $m+1, \dots, n$ dimensions are "noise" so margin them!

$$f_{\vec{X}}(\vec{x}) = \int_{\mathbb{R}} \dots \int_{\mathbb{R}} f_{\vec{X}_{aug}}(\vec{x}_{aug}) dx_{m+1} \dots dx_n$$

That integral is HARD! he will solve this problem soon...

Introducing multivariate ch.f.'s

For r.v. \vec{X} with dimension n , the ch.f. is defined as

$$\phi_{\vec{X}}(\vec{t}) := E[e^{i\vec{t}^T \vec{X}}] = E[e^{i(t_1 X_1 + \dots + t_n X_n)}] = E[e^{it_1 X_1} e^{it_2 X_2} \dots e^{it_n X_n}]$$

$$= E[e^{it_1 X_1}] E[e^{it_2 X_2}] \dots E[e^{it_n X_n}] = \phi_{X_1}(t_1) \dots \phi_{X_n}(t_n)$$

if X_1, \dots, X_n i.i.d. $\textcircled{P0} \phi_{\vec{X}}(\vec{0}_n) = 1$ $\textcircled{P1}$ holds

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

Note: not the same as

$X_1 + \dots + X_n$ since \vec{t} has dimension n !

$$\Rightarrow \phi_{\vec{Y}}(\vec{t}) = E[e^{i\vec{t}^T (A\vec{X} + \vec{b})}] = E[e^{i\vec{t}^T A \vec{X}} e^{i\vec{t}^T \vec{b}}] = e^{i\vec{t}^T \vec{b}} \phi_{\vec{X}}(A^T \vec{t})$$

\uparrow
 $\dim m$

\uparrow
 $\dim n$

Let's get ch.f. of \vec{Z} :

$$\phi_{\vec{Z}}(\vec{t}) = \prod_{i=1}^n \phi_{Z_i}(t_i) = \prod_{i=1}^n e^{-\frac{t_i^2}{2}} = e^{-\frac{1}{2} \sum t_i^2} = e^{-\frac{1}{2} \vec{t}^T \vec{t}}$$

Let's get ch.f. of \vec{X} by $\textcircled{P2}$ $\vec{X} = A\vec{Z} + \vec{u} \sim N_n(\vec{u}, \Sigma)$ let $A \in \mathbb{R}^{n \times n}$ invertible

$$\phi_{\vec{X}}(\vec{t}) = e^{i\vec{t}^T \vec{u}} \phi_{\vec{Z}}(\vec{t}^T A) = e^{i\vec{t}^T \vec{u}} e^{-\frac{1}{2} (A^T \vec{t})^T A^T \vec{t}} = e^{i\vec{t}^T \vec{u} - \frac{1}{2} \vec{t}^T A A^T \vec{t}} = e^{i\vec{t}^T \vec{u} - \frac{1}{2} \vec{t}^T \Sigma \vec{t}}$$