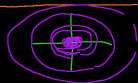


$$\frac{\bar{X} - \mu}{\frac{S}{\sqrt{n}}} = \frac{\bar{X} - \mu}{\frac{1}{\sqrt{n}} \sqrt{S^2 \frac{\sigma^2}{n-1} \frac{n-1}{\sigma^2}}} = \frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}} \sqrt{\frac{n-1}{\sigma^2} S^2}} = \frac{\frac{\bar{X} - \mu}{\frac{\sigma}{\sqrt{n}}}}{\sqrt{\frac{n-1}{\sigma^2} S^2}} \left\{ \begin{array}{l} Z \sim N(0,1) \\ U \sim \chi^2_{n-1} \end{array} \right\} \sim T_{n-1}$$

due to Cochran's thm, if X_i 's are iid $N(\mu, \sigma^2) \Rightarrow$
 \bar{X} and S^2 are independent and thus numerator and denominator here are independent

The Multivariate Normal rv (MVN)



$$\vec{Z} = \begin{bmatrix} Z_1 \\ \vdots \\ Z_n \end{bmatrix} \text{ s.t. } Z_1, \dots, Z_n \stackrel{iid}{\sim} N(0,1), \quad E[\vec{Z}] = \vec{0}_n, \quad \text{Var}[\vec{Z}] = \mathbf{I}_n$$

$$\vec{Z} \sim f_{\vec{Z}}(\vec{z}) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-z_i^2/2} = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \vec{z}^T \vec{z}} = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \vec{z}^T \mathbf{I} \vec{z}} = N_n(\vec{0}, \mathbf{I})$$

$$\text{let } \vec{\mu} \in \mathbb{R}^n, \quad \vec{X} = \vec{Z} + \vec{\mu} = \begin{bmatrix} Z_1 + \mu_1 \\ \vdots \\ Z_n + \mu_n \end{bmatrix} \sim N_n(\vec{\mu}, \mathbf{I})$$

$$\text{let } A = \begin{bmatrix} 1 & 0 & 0 & \dots & 0 \\ 1 & 1 & 0 & \dots & 0 \\ 1 & 1 & 1 & \dots & 0 \\ \vdots & \vdots & \vdots & \ddots & \vdots \\ 1 & 1 & 1 & \dots & 1 \end{bmatrix}_{n \times n}, \quad \vec{X} = A \vec{Z} = \begin{bmatrix} Z_1 \\ Z_1 + Z_2 \\ Z_1 + Z_2 + Z_3 \\ \vdots \\ Z_1 + Z_2 + \dots + Z_n \end{bmatrix} \sim N_n(\vec{0}, \mathbf{I})$$

$$\sigma_{1,2} = \text{Cov}[X_1, X_2] = \text{Cov}[Z_1, Z_1 + Z_2] = \text{Cov}[Z_1, Z_1] + \text{Cov}[Z_1, Z_2] = 1 + 0 = 1$$

$$\text{Var}[A \vec{Z}] = A \text{Var}[\vec{Z}] A^T = A A^T$$

General rule to figure out variance-covariance matrix of matrix A times rv vector X:

$$\begin{aligned} \text{Var}[A \vec{X}] &:= E[A \vec{X} (A \vec{X})^T] - E[A \vec{X}] E[A \vec{X}]^T \\ &= E[A \vec{X} \vec{X}^T A^T] - E[A \vec{X}] E[A \vec{X}]^T \\ &= A E[\vec{X} \vec{X}^T] A^T - A E[\vec{X}] (A E[\vec{X}])^T \\ &= A E[\vec{X} \vec{X}^T] A^T - A E[\vec{X}] E[\vec{X}]^T A^T \\ &= A \left(\underbrace{E[\vec{X} \vec{X}^T] - E[\vec{X}] E[\vec{X}]^T}_{\Sigma} \right) A^T \\ &= A \Sigma A^T \end{aligned}$$

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

$$\downarrow$$

$$\vec{Z} = \underbrace{A^{-1}}_{B} (\vec{X} - \vec{\mu}) = h(\vec{X}) \quad \text{In order for } g \text{ to be 1:1, the matrix } A \text{ must be invertible.}$$

$$B \vec{X} - B \vec{\mu} \Rightarrow \begin{aligned} h_1(\vec{X}) &= \vec{b}_1 \cdot \vec{X} - \vec{b}_1 \cdot \vec{\mu} \\ h_n(\vec{X}) &= \vec{b}_n \cdot \vec{X} - \vec{b}_n \cdot \vec{\mu} \end{aligned} \quad B$$

$$J_h = \det \begin{bmatrix} \partial h_1 / \partial x_1 & \dots & \partial h_1 / \partial x_n \\ \vdots & & \vdots \\ \partial h_n / \partial x_1 & \dots & \partial h_n / \partial x_n \end{bmatrix} = \det \begin{bmatrix} b_{11} & b_{12} & \dots & b_{1n} \\ b_{21} & b_{22} & \dots & b_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ b_{n1} & b_{n2} & \dots & b_{nn} \end{bmatrix} = \det[A^{-1}]$$

$$\text{Note: } A A^{-1} = \mathbf{I} \Rightarrow \det[A A^{-1}] = 1 \Rightarrow \det[A] \det[A^{-1}] = 1 \Rightarrow \det[A^{-1}] = \frac{1}{\det[A]}$$

$$\begin{aligned} f_{\vec{X}}(\vec{x}) &= f_{\vec{Z}}(h(\vec{x})) |J_h| = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} (A^{-1}(\vec{x} - \vec{\mu}))^T (A^{-1}(\vec{x} - \vec{\mu}))} \frac{1}{|\det[A]|} \\ &= \frac{1}{\sqrt{(2\pi)^n \det[A]^2}} e^{-\frac{1}{2} (\vec{x} - \vec{\mu})^T (A^{-1})^T A^{-1} (\vec{x} - \vec{\mu})} = \frac{1}{\sqrt{(2\pi)^n \det[A]^2}} e^{-\frac{1}{2} (\vec{x} - \vec{\mu})^T \Sigma^{-1} (\vec{x} - \vec{\mu})} \end{aligned}$$

$$\Sigma = \text{Var}[\vec{X}] = A A^T \Rightarrow \Sigma^{-1} = (A A^T)^{-1} = (A^T)^{-1} A^{-1}$$

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

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

Does this work if A is m x n? The answer is no... but we will solve that another way.

Multivariate chf's.

$$\begin{aligned} \phi_{\vec{X}}(\vec{t}) &:= E[e^{i \vec{t}^T \vec{X}}] = E[e^{i(t_1 X_1 + \dots + t_n X_n)}] = E[e^{i t_1 X_1} e^{i t_2 X_2} \dots e^{i t_n X_n}] \\ &\stackrel{X_1, \dots, X_n \text{ indep.}}{=} E[e^{i t_1 X_1}] E[e^{i t_2 X_2}] \dots E[e^{i t_n X_n}] = \phi_{X_1}(t_1) \phi_{X_2}(t_2) \dots \phi_{X_n}(t_n) \end{aligned}$$

$$\textcircled{P0} \phi_{\vec{X}}(\vec{0}) = 1$$

$$\textcircled{P1} \text{ yes!}$$

$$\begin{aligned} \textcircled{P2} \vec{Y} = A \vec{X} + \vec{b} \Rightarrow \phi_{\vec{Y}}(\vec{t}) &= E[e^{i \vec{t}^T (A \vec{X} + \vec{b})}] = E[e^{i \vec{t}^T A \vec{X}} e^{i \vec{t}^T \vec{b}}] \\ &= e^{i \vec{t}^T \vec{b}} \phi_{\vec{X}}(\vec{t}^T A) = e^{i \vec{t}^T \vec{b}} \phi_{\vec{X}}(A^T \vec{t}) \end{aligned}$$

Let's find the chf of the standard MVN, $\vec{Z} \sim N_n(\vec{0}, \mathbf{I})$

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

$$\vec{X} = A \vec{Z} + \vec{\mu} \sim N_n(\vec{\mu}, A A^T), \quad \phi_{\vec{X}}(\vec{t}) \stackrel{\textcircled{P2}}{=} e^{i \vec{t}^T \vec{\mu}} \phi_{\vec{Z}}(A^T \vec{t}) = e^{i \vec{t}^T \vec{\mu}} e^{-\frac{1}{2} (\vec{t}^T A^T) A \vec{t}} = e^{i \vec{t}^T \vec{\mu} - \frac{1}{2} \vec{t}^T \Sigma \vec{t}}$$

$$\vec{X} \sim N_n(\vec{\mu}, \Sigma), \quad \vec{Y} = B \vec{X} + \vec{c}, \quad B \in \mathbb{R}^{m \times n}, \quad \vec{c} \in \mathbb{R}^m$$

$$\phi_{\vec{Y}}(\vec{t}) \stackrel{\textcircled{P2}}{=} e^{i \vec{t}^T \vec{c}} e^{i (\vec{t}^T B)^T \vec{\mu} - \frac{1}{2} (B^T \vec{t})^T \Sigma (B^T \vec{t})}$$

$$= e^{i \vec{t}^T (B \vec{\mu} + \vec{c}) - \frac{1}{2} \vec{t}^T B \Sigma B^T \vec{t}} \stackrel{\textcircled{P1}}{\Rightarrow} \vec{Y} \sim N_m(B \vec{\mu} + \vec{c}, B \Sigma B^T)$$

$$\vec{X} \sim N_n(\vec{\mu}, \Sigma), \quad \underbrace{(\vec{X} - \vec{\mu})^T \Sigma^{-1} (\vec{X} - \vec{\mu})}_{\text{scalar rv}} \sim ? \quad \text{If } n=1, \quad (x - \mu) \frac{1}{\sigma^2} (x - \mu)$$

$$\begin{aligned} \text{Assume: } A A^T &\rightarrow \parallel \\ (A A^T)^{-1} &= (A^T)^{-1} A^{-1} \rightarrow \parallel \\ &= (A^{-1} (\vec{X} - \vec{\mu}))^T (A^{-1} (\vec{X} - \vec{\mu})) \\ &= \vec{Z}^T \vec{Z} \sim \chi^2_n \end{aligned}$$

the squared "z-score"

Mahalanobis Distance (1936)