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$$\vec{X} = \begin{bmatrix} x_1 \\ \vdots \\ x_n \end{bmatrix} \in \mathbb{R}^{n+1} \quad E(\vec{X}) = \begin{bmatrix} E(x_1) \\ \vdots \\ E(x_n) \end{bmatrix} = \vec{\mu}$$

$$X = \begin{bmatrix} x_{11} & \dots & x_{1m} \\ \vdots & & \vdots \\ x_{n1} & \dots & x_{nm} \end{bmatrix} \in \mathbb{R}^{n \times m} \quad E(X) = \begin{bmatrix} \mu_{11} & \dots & \mu_{1m} \\ \vdots & & \vdots \\ \mu_{n1} & \dots & \mu_{nm} \end{bmatrix}$$

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

$$\sigma^2 = \text{Var}(X) = E[(X - \mu)(X - \mu)]$$

$$= E[(X - \mu)^2] \quad \text{Scalar}$$

$$= E \begin{bmatrix} (x_1 - \mu_1)^2 & (x_1 - \mu_1)(x_2 - \mu_2) & \dots \\ (x_2 - \mu_2)(x_1 - \mu_1) & (x_2 - \mu_2)^2 & \dots \\ \vdots & \vdots & \ddots \\ & & (x_n - \mu_n)^2 \end{bmatrix}$$

$$= \begin{bmatrix} \sigma_1^2 & \sigma_{1,2} & \dots \\ \sigma_{2,1} & \sigma_2^2 & \dots \\ \vdots & \vdots & \ddots \\ \vdots & \vdots & \vdots & \sigma_n^2 \end{bmatrix} = \Sigma \quad \left| \begin{array}{l} (a+b)^T = a^T + b^T \\ \Sigma \end{array} \right.$$

Symmetric

$$= \Sigma = E[(X - \mu)(X - \mu)^T] = E[(X - \mu)(X^T - \mu^T)]$$

$$= E(\underbrace{XX^T}_{n \times n} - \underbrace{\mu X^T}_{n \times 1} - \underbrace{X \mu^T}_{1 \times n} + \underbrace{\mu \mu^T}_{1 \times 1})$$

$$= E(XX^T) + E(-\mu X^T) + E(-X\mu^T) + E(\mu\mu^T)$$

$$X \in \mathbb{R}^{n \times m} \quad A \in \mathbb{R}^{p \times n}$$

$$AX \in \mathbb{R}^{p \times m}, \quad E(AX) = E \begin{bmatrix} a_{11} \dots a_{1n} \\ \vdots \\ a_{p1} \dots a_{pn} \end{bmatrix} \begin{bmatrix} x_{11} \dots x_{1m} \\ \vdots \\ x_{n1} \dots x_{nm} \end{bmatrix}$$

$$= E \begin{bmatrix} a_{11}x_{11} + a_{12}x_{21} + \dots + a_{1n}x_{n1} \\ \vdots \\ a_{p1}x_{11} + a_{p2}x_{21} + \dots + a_{pn}x_{n1} \end{bmatrix} = \begin{bmatrix} a_{11}\mu_{11} + a_{12}\mu_{21} + \dots + a_{1n}\mu_{n1} \\ \vdots \\ a_{p1}\mu_{11} + a_{p2}\mu_{21} + \dots + a_{pn}\mu_{n1} \end{bmatrix}$$

$$A = \begin{bmatrix} \leftarrow a_{1\cdot} \rightarrow \\ \leftarrow a_{2\cdot} \rightarrow \\ \vdots \\ \leftarrow a_{p\cdot} \rightarrow \end{bmatrix} = \begin{bmatrix} \uparrow & \uparrow & \uparrow \\ a_{11} & a_{12} & \dots & a_{1n} \\ \downarrow & \downarrow & \downarrow \end{bmatrix}$$

$$E(a_{1\cdot} x_{11}) = E(a_{11}x_{11} + \dots + a_{1n}x_{n1}) = a_{11}\mu_{11} + \dots + a_{1n}\mu_{n1} = a_{1\cdot}\mu_{1\cdot}$$

$$= \begin{bmatrix} a_{1\cdot} \\ a_{2\cdot} \\ \vdots \\ a_{p\cdot} \end{bmatrix} [\mu_{11} \mu_{12} \dots \mu_{1n}] = A E(X)$$

$$XB, \quad E(XB) = E(X)B$$

$$X + C = \begin{bmatrix} x_{11} & \dots & x_{1m} \\ \vdots & & \vdots \\ x_{n1} & \dots & x_{nm} \end{bmatrix} + \begin{bmatrix} c_{11} & \dots & c_{1m} \\ \vdots & & \vdots \\ c_{n1} & \dots & c_{nm} \end{bmatrix} =$$

$$E(X+C) = E(X) + C$$

$$= E(XX^T - \mu X^T - X\mu^T + \mu\mu^T)$$

$$= E(XX^T) + E(-\mu X^T) + E(-X\mu^T) + E(\mu\mu^T)$$

$$\Sigma = E(XX^T) - \mu\mu^T - \mu\mu^T + \mu\mu^T$$

$$\sigma^2 = E(X^2) - \mu^2$$

Consider

$$\begin{aligned} \text{Var}(\vec{A}X) &= \text{Cov}(\vec{A}^T X) = E[(\vec{A}^T X)(\vec{A}^T X)^T] - E(\vec{A}^T X)E(\vec{A}^T X)^T \\ &= E(\vec{A}^T X X^T \vec{A}) - \vec{A}^T E(X) (E(X)^T)^T \\ &= \vec{A}^T E(X X^T) \vec{A} - \vec{A}^T \mu \mu^T \vec{A} \\ &= \vec{A}^T (E(X X^T) - \mu \mu^T) \vec{A} = \vec{A}^T \Sigma \vec{A} \end{aligned}$$

$$\text{Var}(\vec{a}^T \vec{X}) = \vec{a}^T \overset{\text{determining matrix}}{\text{Var}}(\vec{X}) \vec{a} \quad \text{one quadratic form.}$$

$n \times 1 \quad n \times n \quad n \times 1$

$$\text{Var}[AX] = A \Sigma A^T$$

$$z_1, \dots, z_n \stackrel{iid}{\sim} N(0, 1) \quad E(z) = \vec{0}$$

$$\vec{z} = \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix} \sim N_n(\vec{0}, I_n) = \prod_{i=1}^n f(z_i) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{z_i^2}{2}}$$

$n=0$ multivariate normal (MVN)
of dim n .

$$E(\vec{z}) = n\vec{\mu} = n \cdot \vec{0} = \vec{0}$$

$$\text{Var}(\vec{z}) = \begin{bmatrix} 1 & 0 & \dots & 0 \\ 0 & 1 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & 1 \end{bmatrix} = I_n$$

$$\vec{\mu} \in \mathbb{R}^n, \quad \Sigma \in \dots \quad \text{Supp}(\vec{z}) = \mathbb{R}^n$$

$$f_{z_1, \dots, z_n}(z_1, \dots, z_n) = f_{z_1}(z_1) \dots f_{z_n}(z_n) = \prod_{i=1}^n f(z_i)$$

$$= \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{z_i^2}{2}} = \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \sum z_i^2}$$

$$= \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \vec{z}^T \vec{z}}$$

multivariate normal
density
of dim n

$$f_{\vec{x}}(\vec{x}) \quad \vec{x} = \vec{z} + \vec{c}, \quad E(\vec{x}) = \vec{0} + \vec{c},$$

$$\text{Var}(\vec{x}) = I_n \Rightarrow \vec{x} \sim N(\vec{c}, I_n)$$

$$f_{x_1, \dots, x_n}(x_1, \dots, x_n) = \prod_{i=1}^n \frac{1}{\sqrt{2\pi}} e^{-\frac{1}{2}(x_i - \mu_i)^2}$$

$$= \frac{1}{(2\pi)^{n/2}} e^{-\frac{1}{2} \sum (x_i - \mu_i)^2}$$

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

$$\vec{X} = A \vec{Z} \quad \vec{Z} \in \mathbb{R}^{n \times 1}, A \in \mathbb{R}^{m \times n}$$

$$E(\vec{X}) = A E(\vec{Z}) = A \vec{0}_n = \vec{0}_m$$

$$\Sigma = \text{Var}(\vec{X}) = A \text{Var}(\vec{Z}) A^T = A I A^T = A A^T$$

$$\begin{aligned} \vec{X} = A \vec{Z} &= \begin{bmatrix} a_{11} & \dots & a_{1n} \\ \vdots & & \vdots \\ a_{m1} & \dots & a_{mn} \end{bmatrix} \begin{bmatrix} z_1 \\ \vdots \\ z_n \end{bmatrix} = \begin{bmatrix} a_{11}z_1 + a_{12}z_2 + \dots + a_{1n}z_n \\ \vdots \\ a_{m1}z_1 + a_{m2}z_2 + \dots + a_{mn}z_n \end{bmatrix} \begin{matrix} \sim N(0, \sigma_{a_{1i}}^2) \\ \vdots \\ \sim N(0, \sigma_{a_{mi}}^2) \end{matrix} \\ &= \begin{bmatrix} x_1 \\ \vdots \\ x_{nm} \end{bmatrix} \end{aligned}$$

$$\text{Cov}(x_i, x_j) = \sum \sigma_i$$

$$\text{Cov}(x_1, x_2) = \sum_{12} = \delta_{1,2}$$

Assume $A \in \mathbb{R}^{n \times m}$ Also assume A is full rank.

$$\vec{x} = A\vec{z} = g(\vec{z}), \quad \vec{z} = h(\vec{x}) = A^{-1}\vec{x}$$