$$\mathbf{X} = \begin{pmatrix} X_1 \\ X_2 \\ \dots \\ X_n \end{pmatrix} - \begin{array}{c} n\text{-dimensional} \\ \text{random vector} \\ \end{pmatrix}$$

$$E(\mathbf{X}) = \boldsymbol{\mu}_{\mathbf{X}} = \begin{pmatrix} \boldsymbol{\mu}_1 \\ \boldsymbol{\mu}_2 \\ \dots \\ \boldsymbol{\mu}_n \end{pmatrix}$$

Covariance matrix:

$$\boldsymbol{\Sigma}_{\mathbf{X}} = \begin{pmatrix} \sigma_{11} & \sigma_{12} & \dots & \sigma_{1n} \\ \sigma_{21} & \sigma_{22} & \dots & \sigma_{2n} \\ \dots & \dots & \dots \\ \sigma_{n1} & \sigma_{n2} & \dots & \sigma_{nn} \end{pmatrix}$$

$$\sigma_{ij} = \text{Cov}(X_i, X_j)$$

$$\Sigma_{\mathbf{X}} = \text{E}[(\mathbf{X} - \boldsymbol{\mu})(\mathbf{X} - \boldsymbol{\mu})^{\text{T}}]$$

$$\Sigma_{\mathbf{X}} - \text{symmetric, nonnegative-definite}$$

$$n = 1$$

$$n = 2$$

$$\mathbf{X} = (\mathbf{X})$$

$$\mathbf{\mu_X} = \begin{pmatrix} \mathbf{X}_1 \\ \mathbf{X}_2 \end{pmatrix}$$

$$\mathbf{\mu_X} = \begin{pmatrix} \mu_1 \\ \mu_2 \end{pmatrix}$$

$$\mathbf{\Sigma_X} = \begin{pmatrix} \operatorname{Var}(\mathbf{X}_1) & \operatorname{Cov}(\mathbf{X}_1, \mathbf{X}_2) \\ \operatorname{Cov}(\mathbf{X}_1, \mathbf{X}_2) & \operatorname{Var}(\mathbf{X}_2) \end{pmatrix} = \begin{pmatrix} \sigma_1^2 & \rho \sigma_1 \sigma_2 \\ \rho \sigma_1 \sigma_2 & \sigma_2^2 \end{pmatrix}$$

Let
$$\mathbf{Y} = \mathbf{A} \mathbf{X} + \mathbf{b}$$
,

where

 $\mathbf{A} - m \times n$ (non-random) matrix,

 $\mathbf{b} \in \mathbf{R}^m$ – (non-random) vector

Then
$$E(Y) = \mu_Y = A \mu_X + b$$
 $\Sigma_Y = A \Sigma_X A^T$

$$\mathbf{a} = \begin{pmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \\ \dots \\ \mathbf{a}_n \end{pmatrix} \qquad \mathbf{a}_1 \mathbf{X}_1 + \mathbf{a}_2 \mathbf{X}_2 + \dots + \mathbf{a}_n \mathbf{X}_n = \mathbf{a}^T \mathbf{X}$$

$$\mathbf{E}(\mathbf{a}^T \mathbf{X}) = \mathbf{a}^T \mathbf{\mu}_{\mathbf{X}} \qquad \mathbf{Var}(\mathbf{a}^T \mathbf{X}) = \mathbf{a}^T \mathbf{\Sigma}_{\mathbf{X}} \mathbf{a} \ge 0$$

Example: Consider a random vector
$$\vec{\mathbf{X}} = \begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix}$$
 with mean $\mathbf{E}(\vec{\mathbf{X}}) = \vec{\boldsymbol{\mu}} = \begin{pmatrix} 5 \\ 1 \\ 3 \end{pmatrix}$ and variance-covariance matrix $\mathbf{Cov}(\vec{\mathbf{X}}) = \boldsymbol{\Sigma} = \begin{pmatrix} 9 & 2 & -3 \\ 2 & 4 & -2 \\ 3 & 2 & 16 \end{pmatrix}$.

Then
$$\operatorname{Var}(X_1) = 9$$
, $\operatorname{Var}(X_2) = 4$, $\operatorname{Var}(X_3) = 16$,
$$\rho_{12} = \frac{2}{\sqrt{9} \cdot \sqrt{4}} = \frac{1}{3}, \quad \rho_{13} = \frac{-3}{\sqrt{9} \cdot \sqrt{16}} = -\frac{1}{4}, \quad \rho_{23} = \frac{-2}{\sqrt{4} \cdot \sqrt{16}} = -\frac{1}{4}.$$

Consider
$$2X_1 - 3X_2 - X_3 = (2 - 3 - 1)\begin{pmatrix} X_1 \\ X_2 \\ X_3 \end{pmatrix}$$
.

$$E(2X_1 - 3X_2 - X_3) = 2\mu_1 - 3\mu_2 - \mu_3 = (2 -3 -1)\begin{pmatrix} \mu_1 \\ \mu_2 \\ \mu_3 \end{pmatrix} = 2 \cdot 5 - 3 \cdot 1 - 1 \cdot 3 = 4.$$

$$Var(2X_{1}-3X_{2}-X_{3}) = \begin{pmatrix} 2 & -3 & -1 \end{pmatrix} \begin{pmatrix} 9 & 2 & -3 \\ 2 & 4 & -2 \\ -3 & -2 & 16 \end{pmatrix} \begin{pmatrix} 2 \\ -1 \end{pmatrix}$$
$$= \begin{pmatrix} 15 & -6 & -16 \end{pmatrix} \begin{pmatrix} 2 \\ -3 \\ -1 \end{pmatrix} = 64.$$

OR

$$Var(2X_1 - 3X_2 - X_3) = 4 Var(X_1) + 9 Var(X_2) + Var(X_3)$$
$$-12 Cov(X_1, X_2) - 4 Cov(X_1, X_3) + 6 Cov(X_2, X_3)$$
$$= 36 + 36 + 16 - 24 + 12 - 12 = 64.$$