

## 5 RANDOM VECTORS

Let a multivariate random variable  $X \equiv \begin{pmatrix} x_1 \\ \vdots \\ x_m \end{pmatrix} = (X_1, \dots, X_m)^T \in \mathbb{R}^m$  {also called random vector}  
with

joint cumulative distribution function:  $F(x) \equiv P[X \leq x] \stackrel{(CDF)}{=} P[X_1 \leq x_1, \dots, X_m \leq x_m]$

joint probability distribution function:  $f(x) \equiv P[X \in [x, x+dx]] \stackrel{(PDF)}{=} \frac{\partial^m F(x)}{\partial x_1 \dots \partial x_m} = f(x_1, \dots, x_m)$  where  $x = \begin{bmatrix} x_1 \\ \vdots \\ x_m \end{bmatrix}$

Then

Expectation of  $X \in \mathbb{R}^m$ :  $E[X] = \begin{bmatrix} E[X_1] \\ \vdots \\ E[X_m] \end{bmatrix} = \begin{bmatrix} \int x_1 \cdot f(x) dx \\ \vdots \\ \int x_m \cdot f(x) dx \end{bmatrix}$  where  $f(x) dx = f(x_1, \dots, x_m) dx_1 \dots dx_m$

Variation

covariance matrix

of  $X \in \mathbb{R}^m$ :  $\Sigma \equiv \text{var}[X] \equiv E[(X - E[X]) \cdot (X - E[X])^T] \equiv$

where  $\sigma_i^2 \equiv E[(X_i - E[X_i])^2] = \text{var}[X_i]$   
 $\sigma_{ij}^2 \equiv E[(X_i - E[X_i])(X_j - E[X_j])] = \text{cov}(X_i, X_j)$

$$\begin{bmatrix} \sigma_1^2 & \sigma_{12} & \dots & \sigma_{1m} \\ \sigma_{21} & \sigma_2^2 & \dots & \sigma_{2m} \\ \vdots & \vdots & \ddots & \vdots \\ \sigma_{m1} & \dots & \dots & \sigma_m^2 \end{bmatrix}$$

$\forall X \in \mathbb{R}^m$ :  $E\|X\|^2 = E[X^T X] < \infty$  iff  $E|X_i|^2 = E[X_i]^2 < \infty \forall i=1, \dots, m$

$\forall X \in \mathbb{R}^m$  with  $E[X] = \mu \in \mathbb{R}^m$ ,  $\text{var}[X] = \Sigma \in \mathbb{R}^{m \times m}$ : the  $A \cdot X \in \mathbb{R}^k$  (where  $A: \mathbb{R}^m \rightarrow \mathbb{R}^k$ ) with

$$E[AX] = A \cdot E[X] = A \cdot \mu \in \mathbb{R}^k$$

$$\text{var}[AX] = A \cdot \text{var}[X] \cdot A^T = A \cdot \Sigma \cdot A^T \in \mathbb{R}^{k \times k}$$