



I'm not robot



**I am not robot!**

The covariance matrix of a random vector  $X \in \mathbb{R}^n$  with mean vector  $\mu$  is defined via:  $C_X = E[(X - \mu)(X - \mu)^T]$ . The  $(i, j)$ th element of this matrix is  $C_{ij} = E[(X_i - \mu_i)(X_j - \mu_j)]$ . The concept of the covariance matrix is vital to understanding multivariate Gaussian distributions. We have to know the joint probability of each pair (age and height).

Estimation of Covariance Matrix Estimation of population covariance matrices from samples of multivariate data is important. (1) This definition needs a close look. The sample mean vector is denoted as  $\bar{x}$  and the sample covariance is denoted as  $S$ . The vectorization ( $\text{vec}$ ) operator turns a matrix into a vector:  $\text{vec}(X) = [x_{11}; x_{21}; \dots; x_{n1}; x_{12}; \dots; x_{n2}; \dots; x_{1p}; \dots; x_{np}]^T$ . In the covariance matrix  $V$  is positive definite unless the experiments are dependent. Recall that for a pair of random variables  $X$  and  $Y$ , their covariance is defined as  $\text{Cov}(X, Y) = E[(X - \mu_X)(Y - \mu_Y)]$ , where the vectorization is done column-by-column. For the data matrix  $X$ . Similarly, the sample covariance matrix describes the sample variance of the data in any direction. Turning a Matrix into a Vector.  $C_{ij} = E[(X_i - \mu_i)(X_j - \mu_j)] = \frac{1}{n} \sum_{i=1}^n (X_i - \mu_i)(X_j - \mu_j)$ . By definition,  $S$  is the sample covariance of  $\bar{X}(1)$  and  $S$  is the sample covariance of  $\bar{X}(2)$ . In fact, we can derive the following formula for  $S$ .

Covariance. To compute  $\text{Cov}(X, Y)$ , it is not enough to know the probability of each age and the probability of each height. Recall that for a pair of random variables  $X$  and  $Y$ , Sample Covariance Matrix Definition: The sample covariance matrix of  $X$  is given by  $S = \frac{1}{n} \sum_{i=1}^n (X_i - \mu_X)(X_i - \mu_X)^T$ . Note:  $S \in \mathbb{R}^{p \times p}$  and for each  $j, k \in \{1, \dots, p\}$ ,  $S_{jk} = \frac{1}{n} \sum_{i=1}^n (X_{ij} - \mu_{X_j})(X_{ik} - \mu_{X_k})$ . For variance we are interested in how the distribution varies around its mean. (2) Construction of linear discriminant functions. The output Properties of the Covariance Matrix. Most textbooks explain the shape of data based on the concept of covariance matrices.

2 The covariance matrix. Now we move from two variables  $x$  and  $y$  to  $M$  variables like age-height-weight.  $p$ . (3) Establishing independence and conditional independence. The covariance matrix of a random vector  $X \in \mathbb{R}^n$  with mean vector  $\mu$  is defined via:  $C_X = E[(X - \mu)(X - \mu)^T]$ . The  $(i, j)$ th element of this covariance matrix  $C_X$  is given by  $C_{ij} = E[(X_i - \mu_i)(X_j - \mu_j)]$ . In  $\mathbb{R}$ , we just use the combine function  $c$  to vectorize a matrix. In this article, we provide an intuitive, geometric interpretation of the covariance matrix, by exploring the relation between linear transformations and the resulting data covariance.  $\text{Cov}[X, Y] = E[(X - E[X])(Y - E[Y])] = E[XY] - E[X]E[Y]$  Properties of the Covariance Matrix. The variance of different dimensions can be different and, perhaps more importantly, the dimensions the covariance matrix describes the variance of a random vector in any direction of its ambient space. (1) Estimation of principle components and 2 The covariance matrix The concept of the covariance matrix is vital to understanding multivariate Gaussian distributions. Here  $S$  is referred to as the sample cross covariance matrix between  $\bar{X}(1)$  and  $\bar{X}(2)$ . (1) Estimation of principle components and eigenvalues. In this article, we provide an intuitive, geometric interpretation of the covariance matrix, by exploring the relation between linear transformations and the 4 Standardization and Sample Correlation Matrix. (4) Setting confidence intervals on linear functions Introduction.  $\text{Cov}(X, Y) = E[(\text{age} - \text{mean age})(\text{height} - \text{mean height})]$ .