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**Machine Learning with Python-From Linear Models to Deep Learning**[Course](#)[Progress](#)[Dates](#)[Discussion](#)[Resources](#)[Course](#) / [Unit 4. Unsupervised Learning \(2 weeks\)](#) / [Lecture 15. Generative Models](#)[< Previous](#)

## 9. Gaussian Generative models

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Exercises due Apr 19, 2023 08:59 -03 Completed

**Gaussian Generative Models****Video**
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**Multivariate Gaussian Random Vector**

A random vector  $\mathbf{X} = (X^{(1)}, \dots, X^{(d)})^T$  is a **Gaussian vector**, or **multivariate Gaussian**, if any linear combination of its components is a (univariate) Gaussian variable or a constant (a Gaussian variable with zero variance), i.e., if  $\alpha^T \mathbf{X}$  is (univariate) Gaussian or constant for any  $\alpha \in \mathbb{R}^d$ .

The distribution of  $\mathbf{X}$ , the  **$d$ -dimensional Gaussian or normal distribution**, is completely determined by its vector mean  $\mu = \mathbf{E}[\mathbf{X}] = (\mathbf{E}[X^{(1)}], \dots, \mathbf{E}[X^{(d)}])^T$  and the  $d \times d$  covariance matrix  $\Sigma$ . Then the pdf of  $\mathbf{X}$  is

$$f_{\mathbf{X}}(\mathbf{x}) = \frac{1}{\sqrt{(2\pi)^d \det(\Sigma)}} e^{-\frac{1}{2}(\mathbf{x}-\mu)^T \Sigma^{-1}(\mathbf{x}-\mu)}, \quad \mathbf{x} \in \mathbb{R}^d$$

[< Previous](#)[Next >](#)

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