Gaussian distribution

$$P(x) = (2\pi\sigma^2)^{-\frac{1}{2}} \exp\left[-\frac{1}{2}\frac{(x-\mu)^2}{\sigma^2}\right] \quad \text{1D}$$

μ = mean

σ^2 = Variance

$$P(x) = \det(2\pi\Sigma)^{-\frac{1}{2}} \exp\left[-\frac{1}{2}(x-\mu)^T \Sigma^{-1}(x-\mu)\right] \quad \text{nD}$$

μ = mean Vector

Σ = Covariance vector (Positive Semidefinite)

* **Mean:** $\boxed{\mu = \frac{1}{N}\sum_{i=1}^{N} x_i}$

* **Variance:** $\boxed{\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(x_i-\mu)^2}$

* **Covariance:** Covariance is a measure of the joint variability of two random variables. $\boxed{\operatorname{cov}(x,y) = \frac{1}{N}\sum_{i=1}^{N}(x_i-\bar{x})(y_i-\bar{y})}$

* **Covariance matrix:** It is a matrix whose element in the i, j position is the Covariance between the i^{th} and the j^{th} elements of a random vector.

$$M = \begin{array}{c c} & \begin{array}{ccc} 1 & 2 & 3 \end{array} \\ \begin{array}{c} 1 \\ 2 \\ 3 \end{array} & \begin{bmatrix} C_{11} & C_{12} & C_{13} \\ C_{21} & C_{22} & C_{23} \\ C_{31} & C_{32} & C_{33} \end{bmatrix} \end{array} \quad \begin{cases} C_{12} = C_{21} \\ C_{13} = C_{31} \\ C_{32} = C_{23} \end{cases}$$