Note for Probability Theory and Statistics

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1 Distribution

Multivariate normal distribution

$$f_{\boldsymbol{x}}(x_1, \cdots, x_k) = \frac{e^{-\frac{(\boldsymbol{x}-\boldsymbol{\mu})^T \boldsymbol{C}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})}{2}}}{\sqrt{(2\pi)^k |\boldsymbol{C}|}}$$

Where,

$\boldsymbol{C}$ The symmetric covariance matrix.

$\boldsymbol{x}$ A real k-dimensional column vector.

2 Distance

2.1 Distance of Random Variables (Same Distribution, Covariance Matrix=$\sum$)

Mahalanobis Distance

(1) Distance of vector $\boldsymbol{x}$ and set:

$$D_M(\boldsymbol{x}) = \sqrt{(\boldsymbol{x}-\boldsymbol{\mu})^T \boldsymbol{C}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})}$$

If $\boldsymbol{x}$ is a k-dimensional Gaussian random vector with mean vector $\boldsymbol{\mu}$ and rank k covariance matrix $\boldsymbol{C}$, then the Mahalanobis distance $D_M^2(\boldsymbol{x})$ follows a χ^2-distribution with d degrees of freedom.

(2) Distance of two vectors $\boldsymbol{x}$ and $\boldsymbol{y}$:

$$d(\boldsymbol{x}, \boldsymbol{y}) = \sqrt{(\boldsymbol{x}-\boldsymbol{\mu})^T \boldsymbol{C}^{-1}(\boldsymbol{x}-\boldsymbol{\mu})}$$

References