

# 1 Basic

## 1.1 Gaussian Distributions

$$p(x) = \frac{1}{\sigma\sqrt{2\pi}} \exp\left(-\frac{1}{2}\left(\frac{x-\mu}{\sigma}\right)^2\right)$$

$$p(x) = (2\pi)^{-\frac{d}{2}} |\Sigma|^{-\frac{1}{2}} \exp\left(-\frac{1}{2}(x-\mu)^\top \Sigma^{-1}(x-\mu)\right)$$

$$p\left(\begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{bmatrix}\right) = \mathcal{N}\left(\begin{bmatrix} \mathbf{a}_1 \\ \mathbf{a}_2 \end{bmatrix} \mid \begin{bmatrix} \mathbf{u}_1 \\ \mathbf{u}_2 \end{bmatrix}, \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}\right)$$

$$p(\mathbf{a}_2 | \mathbf{a}_1 = \mathbf{z}) = \mathcal{N}(\mathbf{a}_2 | \mathbf{u}_2 + \Sigma_{21} \Sigma_{11}^{-1}(\mathbf{z} - \mathbf{u}_1), \Sigma_{22} - \Sigma_{21} \Sigma_{11}^{-1} \Sigma_{12})$$

## 1.2 Derivations

$$\frac{d\mathbf{x}^\top \mathbf{B}}{dx} = \mathbf{B}$$

$$\frac{d\mathbf{x}^\top \mathbf{b}}{dx} = \mathbf{b}$$

$$\frac{d\mathbf{x}^\top \mathbf{x}}{dx} = 2\mathbf{x}$$

$$\frac{d\mathbf{x}^\top \mathbf{B} \mathbf{x}}{dx} = 2\mathbf{B} \mathbf{x}$$

$$\frac{\partial \mathbf{x}^\top \mathbf{B} \mathbf{x}}{\partial x} = \mathbf{x}^\top \mathbf{x}$$

$$\frac{d}{dx} \mathbf{B} \mathbf{x} \rightarrow \frac{d}{dx} \mathbf{x}^\top \mathbf{B}^\top$$

## 1.3 Taylor approximation

$$f(x) \approx f(a) + (x-a)^\top \nabla f(a) + (x-a)^\top H_f(a)(x-a)$$

## 1.4 Sylvester's criterion

Checks whether a symmetric/hermitian matrix is positive semi definite: M is positive definite if and only if all the following matrices have a positive determinant:

- the upper left 1-by-1 corner of  $M$
- the upper left 2-by-2 corner of  $M$
- the upper left 3-by-3 corner of  $M$
- $\vdots$
- $M$  itself.

## 1.5 Determinant

$$|A| = \begin{vmatrix} a & b \\ c & d \end{vmatrix} = ad - bc$$

$$|A| = \begin{vmatrix} a & b & c \\ d & e & f \\ g & h & i \end{vmatrix} = a \begin{vmatrix} e & f \\ h & i \end{vmatrix} - b \begin{vmatrix} d & f \\ g & i \end{vmatrix} + c \begin{vmatrix} d & e \\ g & h \end{vmatrix}$$