Gaussian Naive Bayes

$D = \{ (x_1, y_1) \quad \dots \quad (x_D, y_D) \} \longrightarrow D$ samples

$\left[\begin{array}{l} y_1 \dots y_D : \text{discrete values} \\ x_1 \dots x_D : \text{continuous values} \end{array} \right.$

likelihood

$$P(D) = \prod_{d=1}^{D} \frac{P(x_d \mid y_d)\, P(y_d)}{P(x_d)}$$

MLE:

$$\max \quad \log P(D) = \sum_{d=1}^{D} \log P(x_d \mid y_d) + \sum_{d=1}^{D} \log P(y_d)$$

$$\boxed{\sum_{d=1}^{D_T} \log P(x_d \mid y_d = y_T) + \sum_{d=1}^{D_{\bar{T}}} \log P(x_d \mid y_d = y_{\bar{T}})}$$

$$\sum_{d=1}^{D_T} \log \left(\frac{1}{\sqrt{2\pi}\, \sigma_T^2} \exp\left(-\frac{1}{2} \left(\frac{x_d - \mu_T}{\sigma_T} \right)^2 \right) \right)$$

$$= \sum_{d=1}^{D_T} \left[-\log \sqrt{2\pi}\, \sigma_T^2 - \frac{1}{2} \left(\frac{x_d - \mu_T}{\sigma_T} \right)^2 \right]$$

1st derivative w.r.t. μ_T

$$\sum_{d=1}^{D_T} - \frac{x_d - \mu_T}{\sigma_T} (-1) = 0$$

$$\mu_T = \frac{\sum_{d=1}^{D_T} x_d}{D_T}$$

$$\sigma_T = ?$$