

# Univariate Gaussian Classifier

Ole Marius Hoel Rindal  
email [omrindal@ifi.uio.no](mailto:omrindal@ifi.uio.no)

November 5, 2015

Some notation; We have a feature  $x$  and a set  $\{w_1, w_2, \dots, w_j\}$  of  $j$  classes. In the univariate case,  $x$  is one dimensional,  $x \in \mathbb{R}$ .

According to Bayes rule, the posterior probability for class  $j$  can be computed as

$$P(w_j|x) = \frac{P(x|w_j)P(w_j)}{P(x)} \quad (1)$$

where

$$P(x) = \sum_{j=1} P(x|w_j)P(w_j) \quad (2)$$

and  $P(w_j)$  is the a priori probability. A priori probability means the probability given in advance. For example, if we have two classes  $w_1$  and  $w_2$  and we know that it has a 75% chance of getting class  $w_1$  and 25% chance of getting class  $w_2$  we have  $P(w_1) = 0.75$  and  $P(w_2) = 0.25$ .

We want to classify a feature  $x$  to the class with the highest posterior probability. That is decide  $w_i$  if  $P(w_i|x) \geq P(w_j|x)$  for all  $j \neq i$ .

This can be written as I classify  $x$  as  $w_i$  if  $g_i(x) \geq g_j(x)$ , where possible discriminant functions are:

$$g_i(x) = P(w_i|x) = \frac{P(x|w_i)P(w_i)}{P(x)} \quad (3)$$

or

$$g_i(x) = P(x|w_i)P(w_i) \quad (4)$$

or

$$g_i(x) = \ln(P(x|w_i)P(w_i)) \quad (5)$$

All these discriminant functions will have the maximum for the same  $x$ . Let's choose to use

$$g_i(x) = P(x|w_i)P(w_i) \quad (6)$$

Figure 1: This is what you need to implement and let's use the univariate gaussian distribution

$$P(x|w_i) = \frac{1}{\sigma_i \sqrt{2\pi}} e^{-\frac{(x-\mu_i)^2}{2\sigma_i^2}} \quad (7)$$

where  $\mu_i$  is the mean for class  $i$  and  $\sigma_i$  is the standard deviation for class  $i$ . So, every class will have a mean value  $\mu_i$  and a variance  $\sigma_i^2$  estimated from the training data, giving every class a probability distribution  $P(x|w_i)$ . To classify a feature value  $x$ , choose the the class with the highest posterior probability  $g_i(x) = P(x|w_i)P(w_i)$ .