# Datasta Tietoon, Autumn 2007

## EXERCISE PROBLEMS 3

[ Nov 23rd 2007, Nov 28th 2007 ]

#### H3 / 1. (MLE-regression)

We have n pairs of observations (y(i), x(i)), i = 1, ..., n of some variables x, y which are believed to be linearly related by the model  $y = \theta x$ . However, the observations contain some errors:  $y(i) = \theta x(i) + \epsilon(i)$  where  $\epsilon(i)$  is the observation error ("noise") at the *i*:th point. Assume that the observation error  $\epsilon(i)$  is gaussian distributed with mean value 0 and standard deviation  $\sigma$ .

Solve the parameter  $\theta$  in the model using Maximum Likelihood estimation.

## H3 / 2. (Bayes regression)

Let us add some prior knowledge to the previous problem. 1. Suppose that the parameter  $\theta$  is roughly equal to 1. We model this uncertainty by assuming a gaussian prior density with mean value 1 and standard deviation 0.5.

2. Suppose that the regression line may not pass through the origin after all, but it has the form  $y = \alpha + \theta x$ . The relation between our observations is then  $y(i) = \alpha + \theta x(i) + \epsilon(i)$ . We model the uncertainty related to the new parameter  $\alpha$  by assuming that is has a gaussian prior density with mean value 0 and standard deviation 0.1. Compute the Bayes estimates for the parameters  $\alpha, \theta$ .

## H3 / 3. (Nearest neighbor classifier)

In the following picture there are 2 classes (circles and squares) in 2 dimensions. Plot the decision boundary (border between classes) of the NN classifier.



#### H3 / 4. (Bayes classifier)

Assume two classes for a scalar variable x. The class densities  $p(x|\omega_1), p(x|\omega_2)$  are gaussian such that both have mean value 0 but different standard deviations  $\sigma_1, \sigma_2$ . The prior probabilities are  $P(\omega_1), P(\omega_2)$ . Plot the densities. Where would you place the decision boundaries? Then, derive the decision boundaries of the Bayes classifier.

#### H3 / 5. (Bayes classifier for binary data)

As shown in the lecture, we derive the Bayes classifier for binary vectors  $\mathbf{x} = (x_1, ..., x_d)^T$ , with each  $x_i$  equal to either 0 or 1. There are two classes, and in class  $\omega_1$  the probability of having one is p and in class  $\omega_2$  it is q < p. We may assume that the elements of the vector are independent. The prior probabilities are  $P(\omega_1), P(\omega_2)$ .

a) Denote by N the number of ones in vector  $\mathbf{x}$ . Derive the probability of vector  $\mathbf{x}$  in class 1 and class 2 in terms of N.

b) Derive the Bayes classifier giving decision regions for N.