

## Intelligent Data Analysis

### Problem Set 3

**Due 4/7/2016**

1. Naïve Bayesian model assumes that all inputs are *independent* for each class. Using the estimates, the discriminant function becomes

$$g_i(\mathbf{x}) = -\frac{1}{2} \sum_{j=1}^d \left( \frac{x_j - m_{ij}}{s_j} \right)^2 + \log \hat{P}(C_i), \quad i = 1, 2, \dots, K.$$

Simplify the above discriminant function and show that the decision boundary between any two classes  $C_i$  and  $C_j$  is a hyperplane. In the case of  $d=2$ , a hyperplane is a line on the plane. In the case of  $d=3$ , a hyperplane is a plane.

2. Prove the identity  $\frac{\partial(\mathbf{x}^T \mathbf{A} \mathbf{x})}{\partial \mathbf{x}} = (\mathbf{A}^T + \mathbf{A})\mathbf{x}$ .
3. Let  $\mathbf{A}$  be an  $m$  by  $n$  real matrix. Show that  $N(\mathbf{A}) = N(\mathbf{A}^T \mathbf{A})$ , where  $N(\mathbf{A})$  denotes the nullspace (also called kernel) of  $\mathbf{A}$ .
4. This problem is to prove that  $R^2$  of a multiple regressor is the square of the correlation coefficient between  $\mathbf{r}$  and  $\mathbf{y}$ , where  $\mathbf{y} = \mathbf{X}(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T \mathbf{r}$ . A simple way to prove this statement is by geometric interpretation.
- (a) First prove that the correlation coefficient between  $\mathbf{r}$  and  $\mathbf{y}$  is equivalent to  $\cos \theta$ , where  $\theta$  is the angle between vectors  $\mathbf{r} - \bar{r}\mathbf{1}$  and  $\mathbf{y} - \bar{r}\mathbf{1}$ , where  $\mathbf{1}$  denotes the vector with all entries 1. The definition of sample correlation coefficient is given in Chapter 5.
- (b) Use the identity  $\sum_{t=1}^N (r^t - \bar{r})^2 = \sum_{t=1}^N (y^t - \bar{r})^2 + \sum_{t=1}^N (r^t - y^t)^2$  to prove that

$$\cos^2 \theta = \frac{\sum_{t=1}^N (y^t - \bar{r})^2}{\sum_{t=1}^N (r^t - \bar{r})^2} = R^2.$$

5. This problem is to prove

$$\frac{\mathbf{e}^T \mathbf{e}}{\sigma^2} = \frac{1}{\sigma^2} \sum_{t=1}^N (e^t)^2 \sim \chi^2(N-d-1),$$

where  $\sigma^2$  is the variance of random noise.

- (a) A matrix is called *idempotent* if  $\mathbf{M}^2 = \mathbf{M}$ . What are the eigenvalues of  $\mathbf{M}$ ? Is

$\mathbf{M}$  diagonalizable? Show that the rank of an idempotent matrix  $\mathbf{M}$  is equal to its trace, i.e.,  $\text{rank}(\mathbf{M}) = \text{tr}(\mathbf{M})$ .

- (b) Let  $\mathbf{M}$  be an  $N$  by  $N$  symmetric, idempotent matrix of  $\text{rank}(\mathbf{M}) = r$ . Consider the quadratic form  $\mathbf{z}^T \mathbf{M} \mathbf{z}$ , where  $\mathbf{z} \sim N(\mathbf{0}, \mathbf{I})$ . Let  $\mathbf{Q}$  be the real orthogonal matrix ( $\mathbf{Q}^T = \mathbf{Q}^{-1}$ ) formed by the eigenvectors of  $\mathbf{M}$  and define  $\mathbf{y} = \mathbf{Q}^T \mathbf{z}$ . Show that  $E[\mathbf{y}] = \mathbf{0}$  and  $\text{Var}(\mathbf{y}) = \mathbf{I}$ . Then, prove that

$$\mathbf{z}^T \mathbf{M} \mathbf{z} \sim \chi^2(r).$$

- (c) If  $\mathbf{X}$  is an  $N$  by  $(d+1)$  matrix with independent columns, prove that  $\text{rank}(\mathbf{M}) = N - d - 1$ , where  $\mathbf{M} = \mathbf{I} - \mathbf{X}(\mathbf{X}^T \mathbf{X})^{-1} \mathbf{X}^T$ .
- (d) Now you can prove the statement on the top of this problem by using the relationship

$$\mathbf{e}^T \mathbf{e} = \boldsymbol{\varepsilon}^T \mathbf{M} \boldsymbol{\varepsilon}$$

where  $\boldsymbol{\varepsilon} \sim N(\mathbf{0}, \sigma^2 \mathbf{I})$ .

#### 6. Program Assignment

The goal of this assignment is to study multivariate parametric classification using Fisher's Iris data. With four input variables, namely, sepal length ( $x_1$ ), sepal width ( $x_2$ ), petal length ( $x_3$ ), petal width ( $x_4$ ), use the first 150 data points to build classifiers.

- (a) Use  $x_1$  and  $x_2$  to build classifiers. Use 5-fold cross-validation (CV) to select models. That is, partition the data set into 5 equal-sized subsets. Use 4 subsets to estimate the unknown parameters of the four classifiers: QDA, LDA, Naïve Bayesian, and NMC, as described in Chapter 5. Apply the remaining subset to each classifier, report the classification matrix and compute the accuracy. Plot the average CV-accuracy verse model complexity (the four models). See Chapter 4, pp 23.
- (b) Use all the inputs  $x_1, x_2, x_3, x_4$  to build classifiers. Do the same thing as (a).