MTH6101 Introduction to Machine Learning

Laboratory week nine

The aim of this practice is to build different classifiers on the same data set and to compare them. The file glass.data has measurements of 10 variables in seven different types of glass. This file has 11 columns, and the last column is the type of glass. We are interested in classifying headlamps (type of glass equals seven) against all the other types of glass.

When you start your session, open RStudio and install/load the following libraries: cvTools, class, tree, MASS, pROC.

1. Reading the data and adapting the file for analysis.

Read the data using the command read.csv(file = "glass.data",header = FALSE), store it in a variable termed X. Save the last column of X in a variable called Y and remove the first column. Then center and scale the matrix X using the command scale, saving it in X.

Now we will prepare the output for analysis. The variable Y will be used twice, first as 0/1 variable then as "Yes"/"No". Replace Y by (Y==7)*1 and substitute the last column of X for this value of Y.

At this point, the first 9 columns of X have the centered values and the last one has 0/1 values. Give names to the columns of X according to colnames(X)<-c("RI", "Na", "Mg", "A1", "Si", "K", "Ca", "Ba", "Fe", "Type")

Finally, convert the variable Y to "Yes"/"No" by the commands Y[Y==1]<-"Yes";
Y[Y==0]<-"No". Merge X and Y in a data frame called DAT by DAT<-data.frame(X,Y).

- 2. Now we create the partition of data into training and testing datasets. For this, we create a partition 66:33. Set seed equal to zero and using cvFolds from cvTools, create variables Train and Test for the training and testing partition respectively. See the notes where this has been done in virtually every example.
- 3. Using the training data, fit the logistic classifier for the response variable Type using all but the last column of the data (i.e. DAT[Train,-11]). Save the fitted model in variable M1. Then predict the response using the fitted model M1 and the test partition. Save this in a variable called P1.
- 4. Examine the fitted classifier and identify variables that are not important for the response. Using only those variables that were found significant in the

- first logistic model, fit a second **logistic classifier** and a second prediction set. These are to be called M11 and P11.
- 5. Fit a K nearest neighbors classifier. Here use three nearest neighbors in the function knn from the library class and recall that only columns 1:9 of the data frame contain variables. Call this model M2 and recall that M2 already contains the predicted classes.
- 6. Fit a tree classifier to the data using the function tree from library tree. The response is Y and here the column ten from the data frame is not to be used (i.e. DAT[Train,-10]). Save the fitted model in variable called M3. Predict output with option type="class" and save it in a variable called P3.
- 7. Fit a linear discriminant classifier using the function lda from library MASS. Use the training data except the last column (i.e. DAT[Train,-11]) to fit variable Type and save the output in a variable termed M4. Using the test data, predict output using the fitted model and save results in variable termed P4.
- 8. Now we prepare to compare all classifiers. To this end, recall that we can do ROC curve for **logistic** and **linear discriminant** classifiers. For KNN and tree we will compute only points in ROC graph. Using the function roc from the library pROC, compute and ROC for models M1, M11 and M4 and save the results in variables R1, R11 and R4.
- For each of KNN and tree classifiers, compute the confusion matrix using the command table. In each case, compute the figures TPR and FPR. Save results in variables TPR2, FPR2 and TPR3, FPR3.
- 10. In a single ROC graph, plot ROC curves for logistic and linear discriminant classifiers; add points for the KNN and tree classifiers. Compute AUC for the classifiers M1, M11 and M4 and summarize your results.
- 11. (Extra) Plot the tree for classifier M3 and interpret it.