Homework 5

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R packages

```
library(tidyverse)
library(caret)
library(tidymodels)
library(ISLR)
library(e1071)
```

1. auto.csv data

In this problem, we will apply support vector machines to predict whether a given car gets high or low gas mileage based on the dataset "auto.csv" (used in Homework 3; see Homework 3 for more details of the dataset). The response variable is mpg cat. The predictors are cylinders, displacement, horsepower, weight, acceleration, year, and origin. Split the dataset into two parts: training data (70%) and test data (30%).

Input dataset

```
dat<-read_csv("./data/auto.csv")%>%
  mutate(
    mpg_cat = as.factor(mpg_cat),
    origin = as.factor(origin))
dat <- dat%>%
  na.omit()
```

Response: mpg_cat

```
contrasts(dat$mpg_cat)
```

```
##      low
## high   0
## low    1
```

Split the dataset into two parts: training data (70%) and test data (30%).

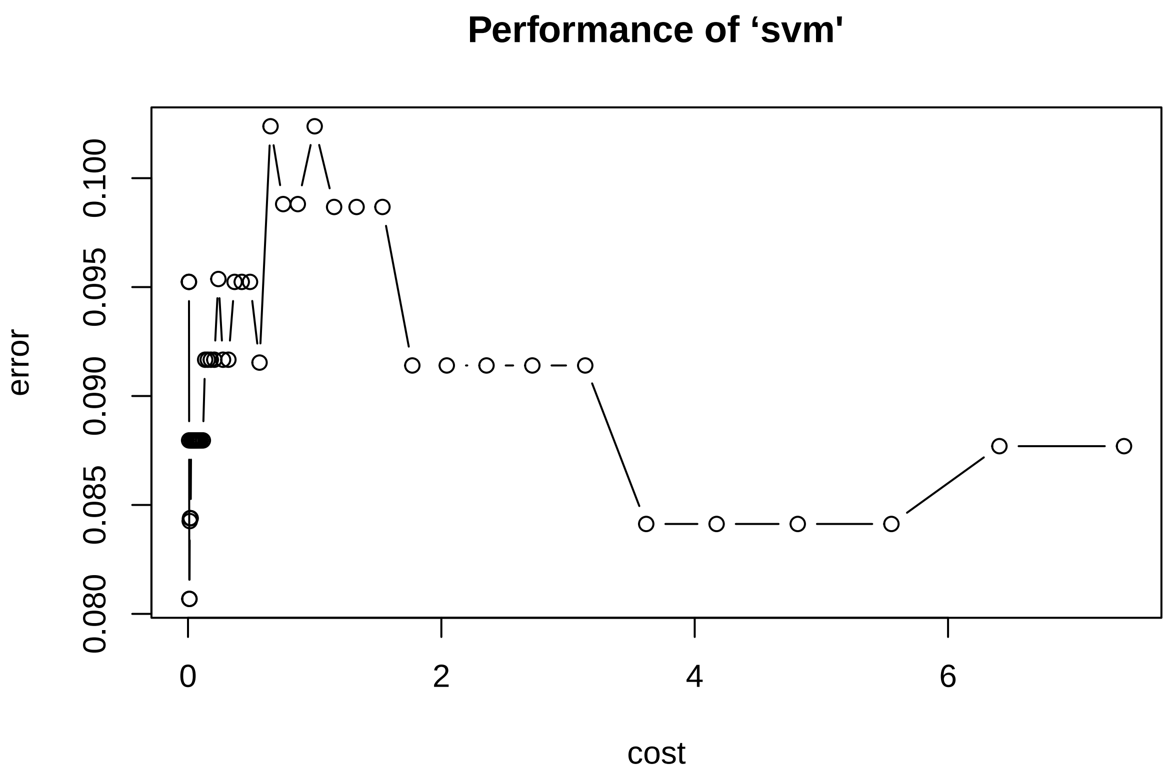
```
set.seed(1)
data_split <- initial_split(dat, prop = 0.7)

# Extract the training and test data
training_data <- training(data_split)
testing_data <- testing(data_split)
```

```r
ctrl <- trainControl(method = "cv", number = 10,
                     summaryFunction = twoClassSummary,
                     classProbs = TRUE)
```

(a) Fit a support vector classifier to the training data. What are the training and test error rates?

```r
set.seed(1)
linear.tune <- tune.svm(mpg_cat ~ . ,
                        data = training_data,
                        kernel = "linear",
                        cost = exp(seq(-5,2, len = 50)),
                        scale = TRUE)
plot(linear.tune)
```




```r
# summary(linear.tune)
linear.tune$best.parameters
```

```
##          cost
## 5 0.01193152
```

```r
best.linear <- linear.tune$best.model
summary(best.linear)
```

```
##
```

```
## Call:
## best.svm(x = mpg_cat ~ ., data = training_data, cost = exp(seq(-5,
##     2, len = 50)), kernel = "linear", scale = TRUE)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  0.01193152
##
## Number of Support Vectors:  123
##
##  ( 62 61 )
##
##
## Number of Classes:  2
##
## Levels:
##  high low
```

```
pred.linear <- predict(best.linear, newdata = testing_data)

confusionMatrix(data = pred.linear,
                reference = testing_data$mpg_cat)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction high low
##       high   56  10
##       low     1  51
##
##                Accuracy : 0.9068
##                  95% CI : (0.8393, 0.9525)
##     No Information Rate : 0.5169
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.8143
##
##  Mcnemar's Test P-Value : 0.01586
##
##             Sensitivity : 0.9825
##             Specificity : 0.8361
##          Pos Pred Value : 0.8485
##          Neg Pred Value : 0.9808
##              Prevalence : 0.4831
##          Detection Rate : 0.4746
##    Detection Prevalence : 0.5593
##       Balanced Accuracy : 0.9093
##
##        'Positive' Class : high
##
```

The **training error rate** is 0.0119.

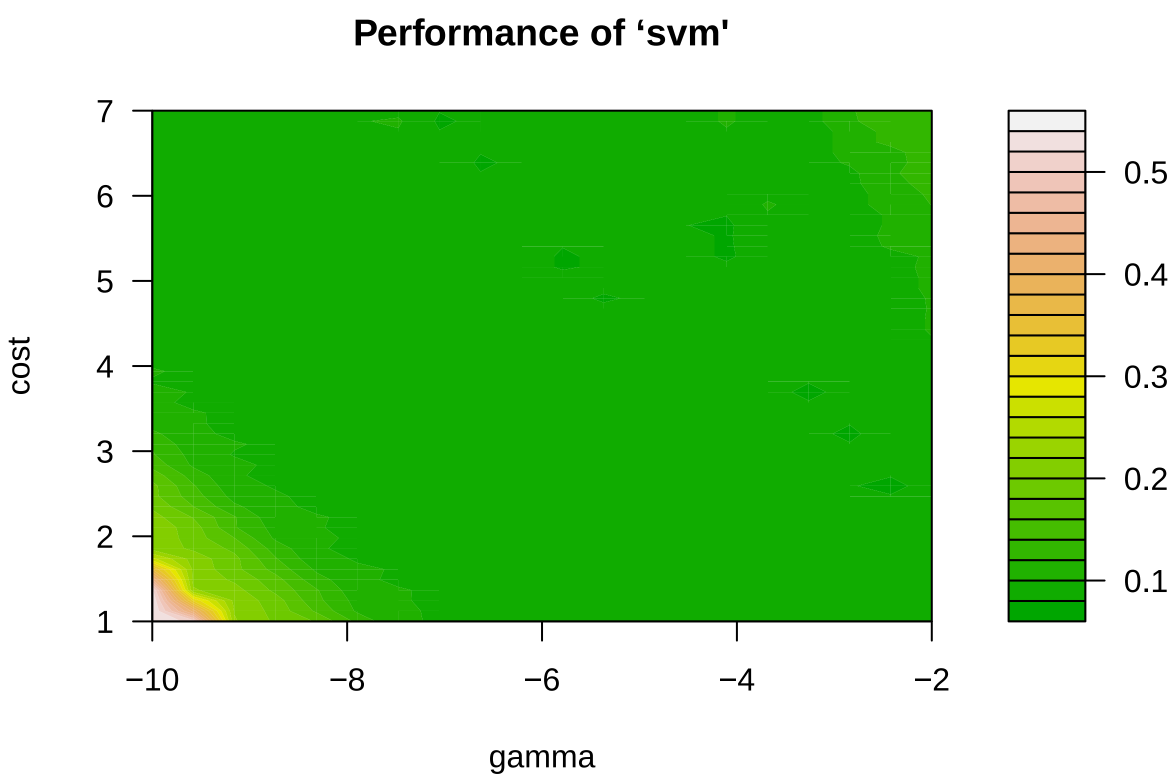
Test Error Rate $= 1 - Accuracy = 1 - 0.9068 = 0.0932$

The **test error rate** for the model on the testing data is approximately 0.0932.

(b) Fit a support vector machine with a radial kernel to the training data. What are the training and test error rates?

```
set.seed(1)
radial.tune <- tune.svm(mpg_cat ~ . ,
                        data = training_data,
                        kernel = "radial",
                        cost = exp(seq(1, 7, len = 50)),
                        gamma = exp(seq(-10, -2,len = 20)))

plot(radial.tune, transform.y = log, transform.x = log,
     color.palette = terrain.colors)
```




```
# summary(radial.tune)

radial.tune$best.parameters
```

```
##          gamma     cost
## 715 0.01648568 197.4952
```

```
best.radial <- radial.tune$best.model
summary(best.radial)
```

```
##
## Call:
## best.svm(x = mpg_cat ~ ., data = training_data, gamma = exp(seq(-10,
##     -2, len = 20)), cost = exp(seq(1, 7, len = 50)), kernel = "radial")
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  radial
##        cost:  197.4952
##
## Number of Support Vectors:  63
##
##  ( 32 31 )
##
##
## Number of Classes:  2
##
## Levels:
##  high low
```

```
# Predict on the training data using the best model
pred.radial.train <- predict(best.radial, newdata = training_data)

# Calculate the confusion matrix for the training predictions
conf.matrix.train <- confusionMatrix(data = pred.radial.train,
                                     reference = training_data$mpg_cat)

# Extract and print the training error rate
train.error.rate <- 1 - conf.matrix.train$overall['Accuracy']
print(train.error.rate)
```

```
##  Accuracy
## 0.0620438
```

```
pred.radial <- predict(best.radial, newdata = testing_data)

confusionMatrix(data = pred.radial,
                reference = testing_data$mpg_cat)
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction high low
##       high   56   9
##       low     1  52
##
##                Accuracy : 0.9153
##                  95% CI : (0.8497, 0.9586)
##     No Information Rate : 0.5169
##     P-Value [Acc > NIR] : < 2e-16
##
##                   Kappa : 0.8311
```

```
##
##  Mcnemar's Test P-Value : 0.02686
##
##             Sensitivity : 0.9825
##             Specificity : 0.8525
##          Pos Pred Value : 0.8615
##          Neg Pred Value : 0.9811
##              Prevalence : 0.4831
##          Detection Rate : 0.4746
##    Detection Prevalence : 0.5508
##       Balanced Accuracy : 0.9175
##
##        'Positive' Class : high
##
```

The **training error rate** is 0.062.

Test Error Rate $= 1 - Accuracy = 1 - 0.9153 = 0.0847$

The **test error rate** for the model on the testing data is approximately 0.0847.

2. USArrests data

(a) Using hierarchical clustering with complete linkage and Euclidean distance, cluster the states. Cut the dendrogram at a height that results in three distinct clusters. Which states belong to which clusters?

(b) Hierarchically cluster the states using complete linkage and Euclidean distance, after scaling the variables to have standard deviation one.

(c) Does scaling the variables change the clustering results? Why? In your opinion, should the variables be scaled before the inter-observation dissimilarities are com- puted?