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Supervised Learning Techniques

Course Project

Instructions:

In this project, you will:

- Use linear discriminant analysis.
- Build a logit model and an ordered logit model.
- Examine Naïve Bayes for classification.
- Examine how to use support vector machines.
- Develop the skills to use all these techniques in R.

Except as indicated, use this document to record all your project work and responses to any questions. At a minimum, you will need to turn in a digital copy of this document to your facilitator as part of your project completion. You may also have additional supporting documents that you will need to submit. Your facilitator will provide feedback to help you work through your findings.

Note: Though your work will only be seen by those grading the course and will not be used or shared outside the course, you should take care to obscure any information you feel might be of a sensitive or confidential nature.

Complete each project part as you progress through the course. Wait to submit the project until all parts are complete. Begin your course project by completing Part One below. You will find directions to submit this project on the last Course Project assignment page. Do not hesitate to contact your facilitator if you have any questions about the project.

Part One
Building a Model

In this part of the project, you will focus on building a model to understand who might make a good product technician if hired using linear discriminate analysis logit and ordered logit modeling. The data set you will be using is in the file HRdata2groups.csv, contained in the RStudio instance.

This part of the project requires some work in RStudio, located on the project page in Canvas. Use that space, along with the provided scripts and data file, to perform the work, then use this document to answer questions on what you discover.

1. The four performance scores in PerfScore have been mapped into two new categories of Satisfactory and Unsatisfactory under the heading of CollapseScore. Assume that levels 1 and 2 are unacceptable and levels 3 and 4 are acceptable. Build a linear discriminant analysis using regression with these two categories as the dependent variable. The purpose of this question is for you to examine the independent variables and conclude which one to include in the regression model. Several are not useful. Remember that when we do this, only the coefficients in the model are useful. You may use the function lm() which has the syntax lm(dependent variable ~ independent variable 1+ independent variable 2+…, data=frame). This function is part of the package caret: hence you will need to use the command library(caret).

   Notice that you have a several variables that might be used as independent variables. You should pick the variables to include based on how effective they are at explaining the variability in the dependent variable as well as which variables might be available should you need to use this model to determine if a candidate is likely to make a good employee. You may assume that the verbal and mechanical scores will be available at the point where a decision about hiring is to be made. In this question, please give us the linear discriminate model you have developed.

```
Call:
lda(Score ~ EmpStatusID + EmpSatisfaction + Aptitude, data = hr_data)

Prior probabilities of groups:
        0         1
0.1088083 0.8911917

Group means:
  EmpStatusID EmpSatisfaction  Aptitude
0    3.095238        3.238095  64.41122
1    2.691860        3.970930 124.64620

Coefficients of linear discriminants:
                       LD1
EmpStatusID     0.00271593
EmpSatisfaction 0.25572719
Aptitude        0.03966111
```

2. Explain the variables you decided to use in the model described above and why.

The employee's hiring status (EmpStatusID) in conjunction with the employee's satisfaction (EmpSatisfaction) and average aptitude score are used in the model.

Averaging the mechanical and verbal scores row over row creates a new (Aptitude) column with these values. Mechanical and verbal aptitude scores are omitted because of their high between-predictor relationships. MechanicalApt vs. VerbalApt yields an $r = 0.96$. Once the scores are averaged and passed into one column, the problem of multicollinearity is removed. Termd is also omitted because its correlation with EmpStatusID is $r = 0.96$.

3. The regression model can be used to classify each of the individuals in the dataset. As discussed in the videos, you will need to find the cutoff value for the regression value that separates the unsatisfactory performers from the satisfactory performers. Find this value and determine whether individual 5 is predicted to be satisfactory or not.

In R you can use the predict command to use the regression function with the data associated with each individual in the dataset. For example:
pred=predict(model, frame) stores the predicted values from the regression function into the variable pred when the regression model has been assigned to the variable model as in this statement:
model <-lm(dependent variable ~ independent variable 1+ independent variable 2+…, data=frame).

You may then find the mean value of the regression for all observations of unsatisfactory employees using the command
meanunsat=mean(pred[frame$CollapseScore==0]). You may do the parallel step for the satisfactory employees. Suppose you have stored this value as meansat.

The cutoff value is then computed in r as follows:
cutoff<-0.5(meanunsat+meansat).

If you want to compare what your model says verses whether they were found to be satisfactory or unsatisfactory you may add the prediction to the data frame using cbind(frame, pred). This will make the predictions part of the dataset.

	EmpStatusID	EmpSatisfaction	CollapseScore	Score	Aptitude	pred
1	1	5	Acceptable	1	180.89209	1.3147863
2	1	3	Acceptable	1	106.66625	0.7863039
3	5	4	Acceptable	1	152.34146	1.1041458
4	1	2	Unacceptable	0	46.98597	0.3851682
5	1	5	Unacceptable	0	41.8677	0.4714585

Individual 5 has unacceptable/unsatisfactory performance, and the model predicts the same with a probability of 0.471, which is below the cutoff of 0.737.

4. Construct a logit model using the two performance groups. Compare this model and the discriminant analysis done in step 1. To construct the logit model, use the function lrm() in the library rms.

```
Logistic Regression Model

lrm(formula = Score ~ MechanicalApt + VerbalApt, data = hr_data)

                       Model Likelihood     Discrimination    Rank Discrim.
                             Ratio Test            Indexes          Indexes
Obs             193    LR chi2      109.40     R2        0.870    C        0.991
 0               21    d.f.              2     R2(2,193)0.427    Dxy      0.983
 1              172    Pr(> chi2) <0.0001    R2(2,56.1)0.852    gamma    0.983
max |deriv| 3e-06                              Brier     0.017    tau-a    0.192

              Coef     S.E.    Wald Z Pr(>|Z|)
Intercept     -33.7121 11.5108 -2.93  0.0034
MechanicalApt   0.4697  0.1689  2.78  0.0054
VerbalApt      -0.0865  0.0743 -1.16  0.2443
```

The linear discriminant analysis model does not use mechanical aptitude and/or verbal aptitude as standalone independent variables. The scores are averaged to create one column for general aptitude.

5. Build an ordered logit model for the full four categories for performance. When you call the function lrm() you will use the original categories PerScoreID. What is the probability that individual two is in each of the four performance categories? You can use the function predict() to do this. The form of the call is predict(name of the model you used when you created the model, data=frame, type="fitted.ind").

```
lrm(formula = PerfScoreID ~ Termd + EmpStatusID + EmpSatisfaction,
    data = hr_data)
Frequencies of Responses
  1   2   3   4
  8  13 148  24
                      Model Likelihood      Discrimination    Rank Discrim.
                            Ratio Test             Indexes          Indexes
Obs             193    LR chi2      12.13      R2        0.077    C        0.634
max |deriv| 8e-09      d.f.             3      R2(3,193)0.046    Dxy      0.268
                       Pr(> chi2) 0.0070     R2(3,105.5)0.083    gamma    0.298
                                               Brier     0.086    tau-a    0.105
                Coef    S.E.   Wald Z Pr(>|Z|)
y>=2             1.0880 0.9065  1.20  0.2300
y>=3            -0.0130 0.8869 -0.01  0.9883
y>=4            -4.3212 0.9741 -4.44  <0.0001
Termd           -1.2239 1.1992 -1.02  0.3075
EmpStatusID      0.1560 0.3152  0.49  0.6208
EmpSatisfaction  0.5872 0.2086  2.81  0.0049
```

The respective probabilities that individual two will be in each of the four performance categories are:

```
PerfScoreID=1 PerfScoreID=2 PerfScoreID=3 PerfScoreID=4
   0.04717017    0.08241392    0.78751439    0.08290152
```

Part Two

Using Naïve Bayes to Predict a Performance Score

In this part of the project, you will use Naïve Bayes to predict a performance score. This part continues the scenario from Part One and uses the same modified version of the human resources data set available on the Kaggle website. The data set you will be using is in the file NaiveBayesHW.csv file. Over the course of this project, your task is to gain insight into who might be a "high" performer if hired.

This part of the project requires some work in RStudio, located on the project page in Canvas. Use that space, along with the provided scripts and data files, to perform the work, then use this document to answer questions on what you discover.

1. Using only the mechanical aptitude score, use Naïve Bayes to predict the performance score for each employee. Professor Nozick discretized the mechanical scores into four classes.

   Notice only three of four classes have observations. This discretization is in the data file NaiveBayesHW.csv. The function to create the model is naiveBayes().

```
naive_df <- read.csv('NaiveBayesHW.csv') # read in the dataset
# inspect the dataset
head(naive_df)

    EmpID  Termd  EmpStatusID  PerfScoreID  EmpSatisfaction  PerfScore  MechanicalApt
 1    1      0         1            4              5           Class4       Level4
 2    2      0         1            3              3           Class3       Level3
 3    3      1         5            3              4           Class3       Level4
 4    4      0         1            1              2           Class1       Level1
 5    5      0         1            1              5           Class1       Level1
 6    6      0         1            4              4           Class4       Level3

nbmodel <- naiveBayes(PerfScore~MechanicalApt, data=naive_df)
print(nbmodel)

# type = raw' specifies that R should return the probability that a point is in
# each risk group. Not specifying a type would print the most likely category
# that each point would fall into.

pred_bayes <- predict(nbmodel, naive_df, type='raw')
head(pred_bayes)

Naive Bayes Classifier for Discrete Predictors

Call:
```

```
naiveBayes.default(x = X, y = Y, laplace = laplace)

A-priori probabilities:
Y
    Class1     Class2     Class3     Class4
0.04145078 0.06735751 0.76683938 0.12435233

Conditional probabilities:
        MechanicalApt
Y            Level1    Level3    Level4
  Class1 1.0000000 0.0000000 0.0000000
  Class2 0.0000000 0.0000000 1.0000000
  Class3 0.0000000 0.6554054 0.3445946
  Class4 0.0000000 0.3333333 0.6666667

           Class1       Class2     Class3      Class4
 [1,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
 [2,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
 [3,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
 [4,] 9.773977e-01 0.0015882712 0.01808186 0.002932193
 [5,] 9.773977e-01 0.0015882712 0.01808186 0.002932193
 [6,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
 [7,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
 [8,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
 [9,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
[10,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
```

2. Using this modeling approach, what is your assessment of the probability that individual 10 will evolve into each of the four probability classes if hired? This can be done using the model created above and the pred() function.

   The arguments for that function are the model name, data and for type use “raw”. This question is parallel to the Practice using Naïve Bayes activity you completed in R.

The probability that individual 10 will evolve into each of the four probability classes if hired is as follows:

```
individual10 <- pred_bayes[10,]
individual10 <- data.frame(individual10)
colnames(individual10) <- c('Probability')
individual10
           Probability
 Class 1     0.00009999
 Class 2     0.16248375
 Class 3     0.63743626
 Class 4     0.19998000
```

Part Three

Building Classification Trees

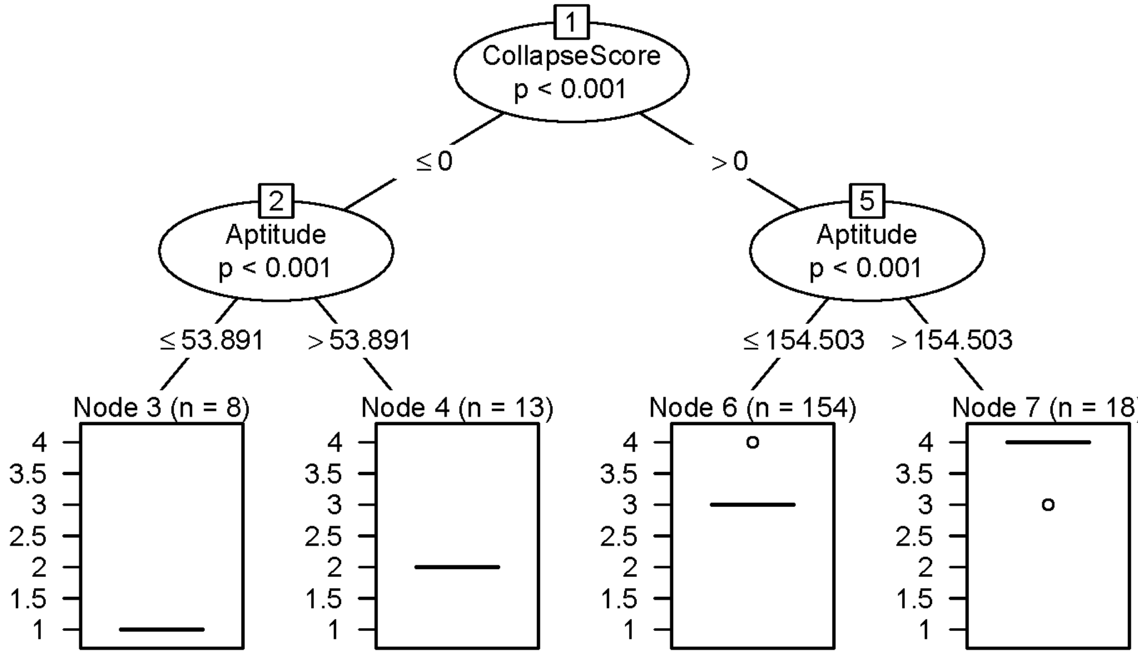
In this part of the project, you will build classification trees. This part continues the scenario from Parts One and Two, as it uses the same modified version of the human resources data set available on the Kaggle website. Use the HRdata4groups.csv data set to predict each individual's performance (Performance Score ID) using classification trees. In the space below, you will explain the model you have developed and describe how well it performs.

This part of the project requires some work in RStudio, located on the project page in Canvas. Use that space, along with the provided scripts and data files, to perform the work, then use this document to answer questions on what you discover.

1. In the space below, explain the model you developed. It is sufficient to use the function ctree() in R to accomplish this in the style of the codio exercise Practice: Building a Classification Tree in R—Small Example.

Before modeling can commence, it is important to establish between-predictor relationships and the potential presence of multicollinearity, because this is a refined dataset from a new .csv file. The classification trees model is developed from all variables except for mechanical aptitude and verbal aptitude. Verbal aptitude exhibits a noticeably high correlation of *r* = 0.96 with mechanical aptitude. However, rather than omitting this one variable, both aptitude columns are replaced with a new column by the name of aptitude which has been averaged from their results.

```
# build the classification tree
ctout <- ctree(PerfScoreID ~ ., data=hrgroups_final)
ctout

Model formula:
PerfScoreID ~ EmpStatusID + CollapseScore + PayRate + Age + JobTenure +
    EngagementSurvey + EmpSatisfaction + Aptitude

Fitted party:
[1] root
|   [2] CollapseScore <= 0
|   |   [3] Aptitude <= 53.89066: 1.000 (n = 8, err = 0.0)
|   |   [4] Aptitude > 53.89066: 2.000 (n = 13, err = 0.0)
|   [5] CollapseScore > 0
|   |   [6] Aptitude <= 154.50311: 3.052 (n = 154, err = 7.6)
|   |   [7] Aptitude > 154.50311: 3.889 (n = 18, err = 1.8)

Number of inner nodes:    3
Number of terminal nodes: 4

 Correct Classification of Data Point: 0.1088083
```



2. In the space below, describe how well your model performs.

Whenever a CollapseScore is less than or equal to zero, it is classified as unacceptable or unsatisfactory performance. Thus, under this umbrella category, aptitude scores less than or equal to 53.89 (level 1) exhibit no error (third node), where *n* = 8. Aptitude scores greater than 53.89066 (level 2) exhibit no error, where *n* = 13.

Whenever a CollapseScore is greater than 0, employee performance is classified as acceptable or satisfactory. This, under this umbrella category, aptitude scores less than or equal to 154.50 reach a node level of 3.052, with an error of 7.6, where *n* = 154 observations. Aptitude scores greater than 154.50 reach a higher node level of 3.89, where there are *n* = 18 observations, and a lower error rate of 1.8.

There are three inner nodes and four terminal nodes, with a correct classification of data points at approximately 11%. The performance is low, and this model warrants iterative refinement.

Part Four

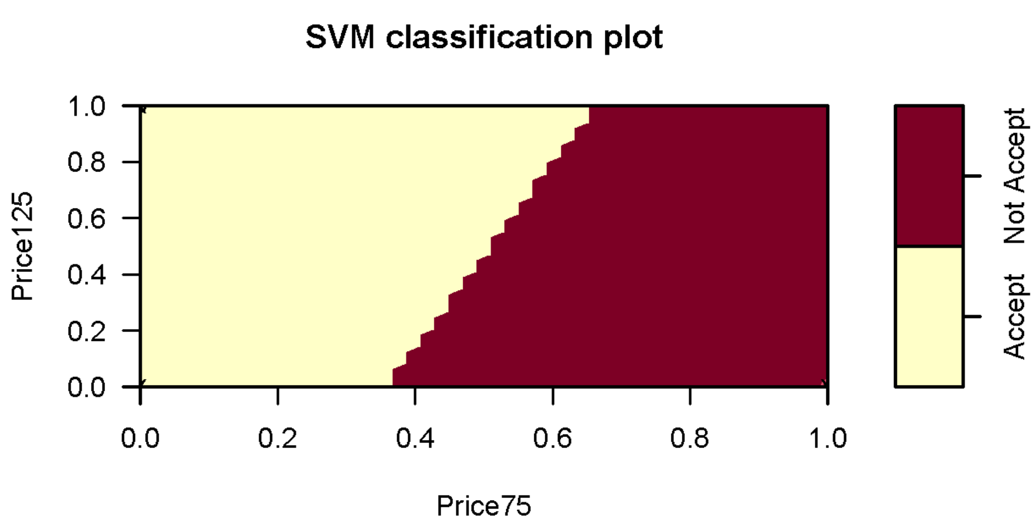
Applying SVM to a Data Set

In this part of the project, you will apply SVM to a data set. The RStudio instance contains the file acquisitionacceptanceSVM.csv, which includes information about whether or not homeowners accepted a government offer to purchase their home. This part of the project requires some work in RStudio, located on the project page in Canvas. Use that space, along with the provided scripts and data files, to perform the work, then use this document to answer questions on what you discover.

1. Apply the tool SVM to the acquisition data set in the CSV file acquisitionacceptanceSVM.csv to predict which homeowners will most likely accept the government's offer. What variables did you choose to use in your analysis?

Inspecting the dataframe for near zero variance predictors from a visual standpoint alone identifies current market value (CurMarketValue) to be a variable that exhibits such behavior. However, the nearZeroVar() function from the caret library does not expose such variables. Near zero variance measures the fraction of unique values in the columns across the dataset. Moreover, the correlation matrix does not expose any sources of high between-predictor relationships (beyond the cutoff point of r = 0.75). This relegates the variable selection process to Principal Component Analysis (PCA), but this is a dimensionality reduction technique; there are only 12 variables and 1,531 rows of data.

Casting the target (Accept) variable to a factor is done to categorize the data. There are enough rows in this dataset to carry out a train-test split, and so it is done, with 70% partitioned into the training set, and the remaining 30% into the test set. The e1071 package does not allow for a printout of variable importance varImp for feature selection, the caret package is used to accomplish this task. The model's cost and kernel hyperparameters are tuned over the training data with a 10-fold cross validation sampling method. Price75 and Price125 are the top two variables surpassing a score of 80 in importance and are thus selected for the soft-margin support vector machine.



2. How good was your model at correctly predicting who would and who would not accept the offer?

The confusion matrix is used to obtain the first measure of model performance (accuracy) using the following equation.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision (specificity) measures out of everyone who accepted a government offer to purchase their home, how many actually accepted? It is calculated as follows.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

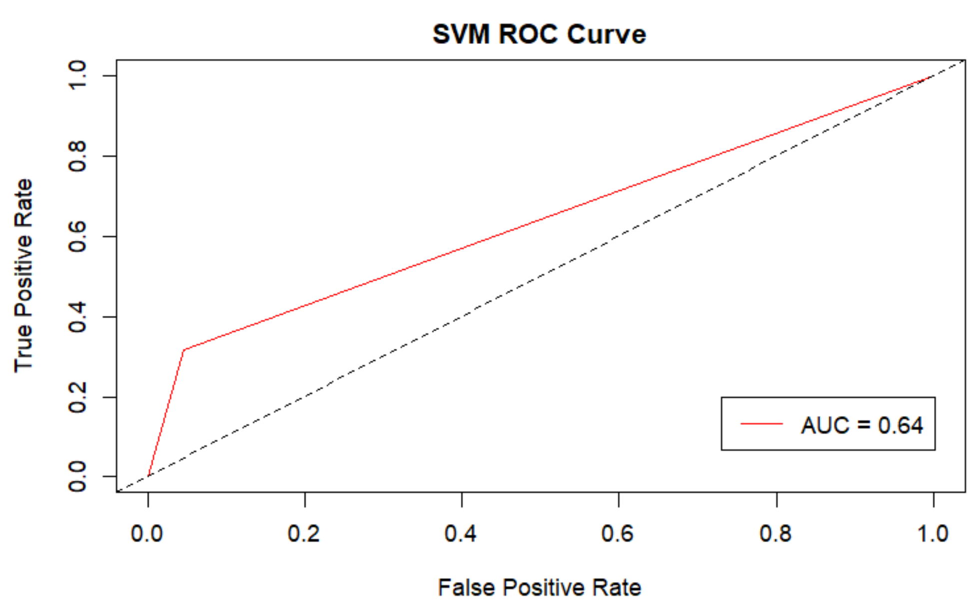
Recall (sensitivity) measures the true positive rate (TPR), which is the number of correct predictions in the `Accept` class divided by the total number of `Accept` instances. It is calculated as follows:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

The *f1*-score is the harmonic mean of precision and recall, and is calculated as follows:

$$f1 = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

Using the test data (30% hold out), the model's accuracy is only 15% improvement above baseline, coming out to 65%. However, the model's ability to correctly classify the 'Accept' class is effectively high at 95% specificity. The ROC Curve calculates an AUC (area under the curve) score of ~64%, so model performance is quite low. Moreover, the ROC Curve below shows that as the true positive rate increases, so does the false positive rate, so, for every increase in the false positive rate, there is a greater increase in false alarms.



3. When building models, we often use part of the data to estimate the model and use the remainder for prediction. Why do we do this? It is not necessary to do this for each of the problems above. It is essential to realize that you will need to do this in practice.

We are interested in seeing how the model performs on unseen data. Thus, we partition the data into a train-test split. Ideally, there are enough rows of data to conduct a three-way train-validation-test split such that the train-validation set becomes the development set. However, we are working with a smaller amount of data, so we are using a two-way split, where the training set (development set) is the larger portion of data (70-80%), and the remaining 30% is allocated to the test set. Anything can be done repeatedly to the development set (e.g., iteration, hyperparameterization, experimentation, etc.), as long as the test set remains uncontaminated (unseen). Once the model is finalized through the training set, it can be predicted on the remaining test set.

To submit this assignment, please refer to the instructions in the course.

Supervised Learning Techniques Course Project

Cornell University - CEEM585

Leonid Shpaner

January 1, 2023

```r
# function for loading necessary libraries and installing them if they have not
# yet been installed

pack <- function(lib){

    new.lib <- lib[!(lib %in%
                     installed.packages()[, 'Package'])]
  if (length(new.lib))
     install.packages(new.lib, dependencies = TRUE)
  sapply(lib, require, character.only = TRUE)

  }

packages <- c('partykit', 'e1071', 'caret', 'corrplot', 'MASS', 'car', 'DT',
              'ggplot2', 'cowplot', 'ggpubr', 'rms', 'pander', 'ROCR', 'pROC')

pack(packages) # run function
```

```
## partykit    e1071    caret corrplot     MASS      car       DT  ggplot2
##     TRUE     TRUE     TRUE     TRUE     TRUE     TRUE     TRUE     TRUE
##  cowplot   ggpubr      rms   pander     ROCR     pROC
##     TRUE     TRUE     TRUE     TRUE     TRUE     TRUE
```

```r
# set working directory by concatenating long string
string1 <- 'C:/Users/lshpaner/OneDrive/Cornell University/Coursework'
string2 <- '/Data Science Certificate Program/CEEM585 '
string3 <- '- Supervised Learning Techniques'

# concatenate each string
working_dir = paste(string1, string2, string3, sep = '')

# set the working directory by calling function
setwd(working_dir)

# confirm working directory
getwd()
```

[1] "C:/Users/lshpaner/OneDrive/Cornell University/Coursework/Data Science Certificate Program/CEEM585 - Supervised Learning Techniques"

Part One

Building A Model

In this part of the project, you will focus on building a model to understand who might make a good product technician if hired using linear discriminate analysis logit and ordered logit modeling. The data set you will be using is in the file `HRdata2groups.csv`, contained in the RStudio instance.

1. The four performance scores in `PerfScore` have been mapped into two new categories of Satisfactory and Unsatisfactory under the heading of `CollapseScore`. Assume that levels 1 and 2 are unacceptable and levels 3 and 4 are acceptable. Build a linear discriminant analysis using regression with these two categories as the dependent variable. The purpose of this question is for you to examine the independent variables and conclude which one to include in the regression model. Several are not useful. Remember that when we do this, only the coefficients in the model are useful. You may use the function `lm()` which has the syntax `lm(dependent variable ~ independent variable 1+ independent variable 2+..., data=frame)`. This function is part of the package caret: hence you will need to use the command `library(caret)`.

   Notice that you have a several variables that might be used as independent variables. You should pick the variables to include based on how effective they are at explaining the variability in the dependent variable as well as which variables might be available should you need to use this model to determine if a candidate is likely to make a good employee. You may assume that the verbal and mechanical scores will be available at the point where a decision about hiring is to be made. In this question, please give us the linear discriminate model you have developed.

The dataset is inspected and the categorical classes of `Acceptable` and `Unacceptable` are cast to the Performance Score `PerfScoreID` in a new column named `CollapseScore`. However, since supervised learning models need to learn from a numerical, though, binarized target column, a new column of `Score` is thus created. Extraneous or otherwise not useful columns like `Employee ID`, `CollapseScore` and `Score` are removed such that a numerical only dataframe is created for subsequent distribution analysis.

```
# read in the data
hr_data <- read.csv('HRdata2groups.csv')

# Adding column based on other column:
# inspect first five rows of the dataset
pandoc.table(head(hr_data), style = 'grid', split.table = Inf)
```

EmpID	Termd	EmpStatusID	PerfScoreID	EmpSatisfaction	MechanicalApt	VerbalApt
1	0	1	4	5	174.6	187.2
2	0	1	3	3	110.6	102.7
3	1	5	3	4	148.6	156.1
4	0	1	1	2	49.11	44.86
5	0	1	1	5	42.15	41.59
6	0	1	4	4	133	130.2

```
# cast categorical classes to Performance Score
hr_data$CollapseScore <- ifelse(hr_data$PerfScoreID >= 3, 'Acceptable',
                                                           'Unacceptable')
# numerically binarize these performance scores
hr_data$Score <- ifelse(hr_data$CollapseScore == 'Acceptable', 1, 0)
pandoc.table(head(hr_data), style = 'grid')
```

Table 2: Table continues below

EmpID	Termd	EmpStatusID	PerfScoreID	EmpSatisfaction
1	0	1	4	5
2	0	1	3	3
3	1	5	3	4
4	0	1	1	2
5	0	1	1	5
6	0	1	4	4

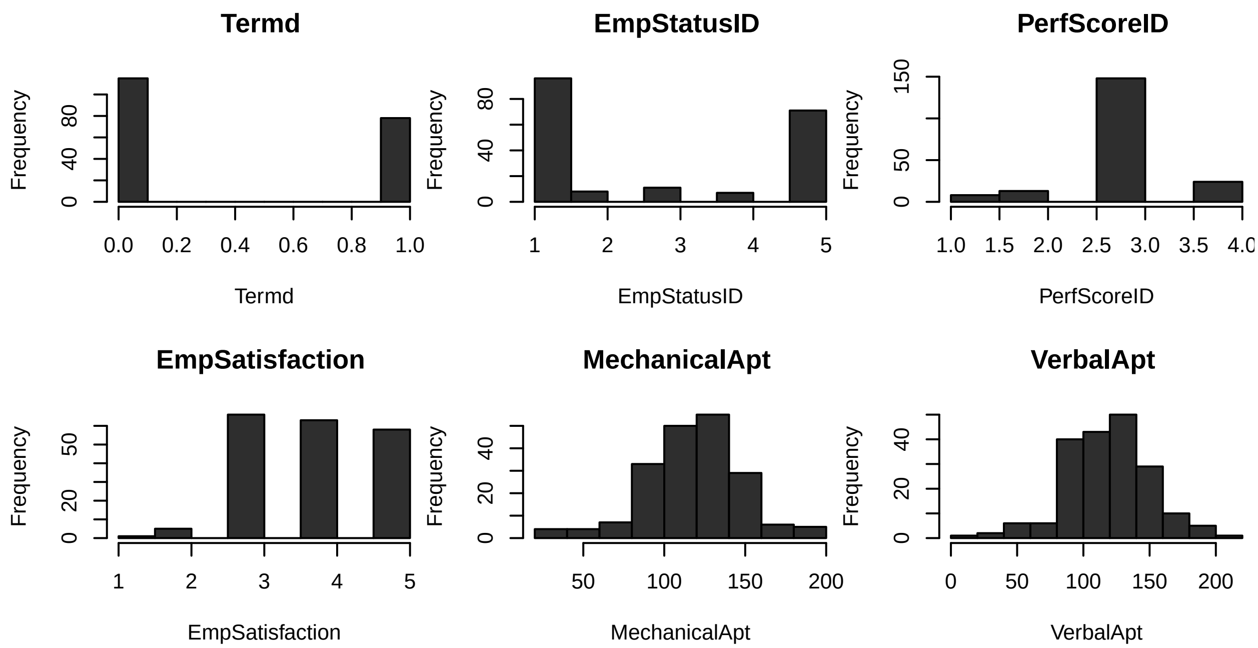
MechanicalApt	VerbalApt	CollapseScore	Score
174.6	187.2	Acceptable	1
110.6	102.7	Acceptable	1
148.6	156.1	Acceptable	1
49.11	44.86	Unacceptable	0
42.15	41.59	Unacceptable	0
133	130.2	Acceptable	1

```r
# extract meaningful data (i.e., remove categorical data types)
hr_data_numeric <- subset(hr_data, select = -c(EmpID, CollapseScore, Score))
```

The histogram distributions below do not yield or uncover any near-zero-variance predictors, but it is worth noting that `Termd` has only two class labels. `MechanicalApt` and `VerbalApt` exhibit normality; other variables approach the same trend.

```r
# create function for plotting histograms to check for near-zero variance
# in distributions where input `df` is a dataframe of interest
nearzerohist <- function(df, x, y) {

  # x rows by y columns & adjust margins
  par(mfrow = c(x, y), mar = c(4, 4, 4, 0))
  for (i in 1:ncol(df)){
    hist(df[, i],
         xlab = names(df[i]),
         main = paste(names(df[i]), ''),
         col = 'gray18')
  }

  # check for near zero variance predictors using if-else statement
  nearzero_names <- nearZeroVar(df)
  if (length(nearzero_names) == 0) {
     print('There are no near-zero variance predictors.')
  } else {
    cat('The following near-zero variance predictors exist:',
    print(nearzero_names))
  }
}
```

```r
# call the `nearzerohist()` function
nearzerohist(hr_data_numeric, x = 2, y = 3)
```

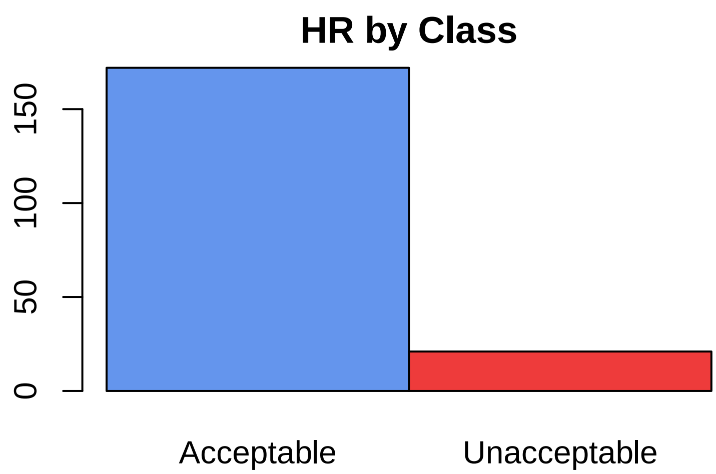



```
## [1] "There are no near-zero variance predictors."
```

Examining the `Score` column separately yields an imbalanced dataset where 172 `Acceptable` cases outweigh the 21 `Unacceptable` classes. However, no solution is rendered for this outcome. The data is treated as-is.

```
# function for generating class balance table and barplot
# inputs -->   feat: feature or column of interest
#              title: plot title
#                 x: x-axis label
#                 y: y-axis label

class_balance <- function(feat, title, x, y) {

   # check target column's class balance
   # parse target variable into table showcasing class distribution
   feat_table <- table(unname(feat)) # generate table for column

   # fix plot margins
   par(mar = c (2, 2, 2, 1))
      # plot the counts (values) of each respective class on barplot
   barplot(feat_table, main = title, space = c(0), horiz = FALSE,
           names.arg = c(x, y),
           col = c('cornflowerblue', 'brown2'))

   return (feat_table)

}
```

```
class_balance(feat = hr_data$CollapseScore, title = 'HR by Class',
                 x = 'Acceptable', y = 'Unacceptable')
```




```
##
##   Acceptable Unacceptable
##          172           21
```

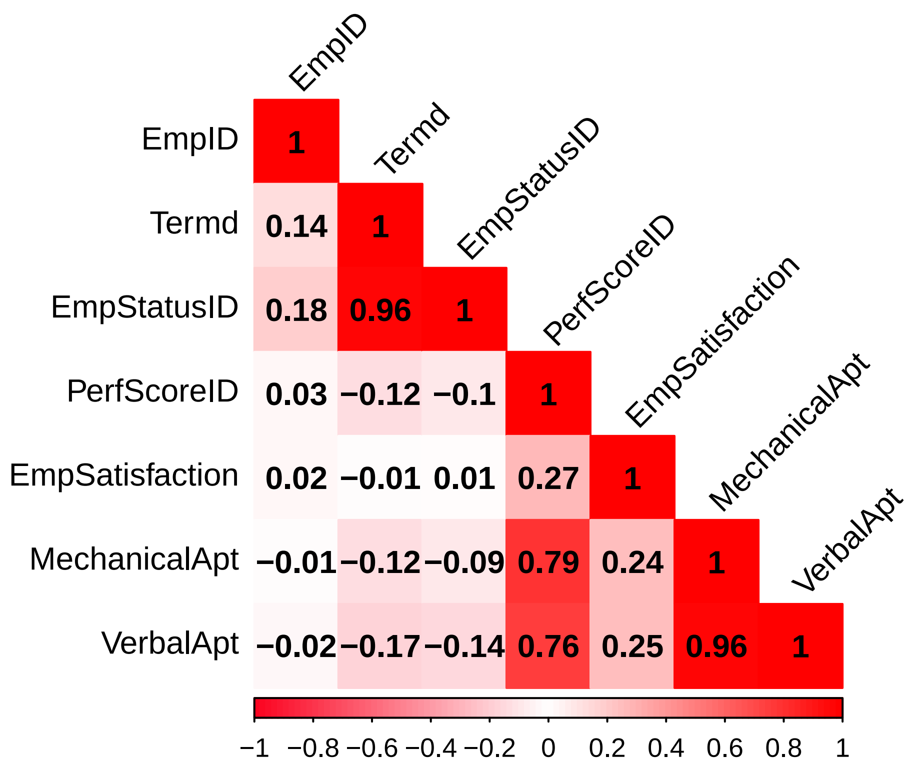
Explain the variables you decided to use in the model described above and why.

The employee's hiring status `EmpStatusID` in conjunction with the employee's satisfaction `EmpSatisfaction` and average aptitude score are used in the model.

Averaging the mechanical and verbal scores row over row creates a new `Aptitude` column with these values. Mechanical and verbal aptitude scores are omitted because of their high between-predictor relationships. `MechanicalApt` vs. `VerbalApt` yields an $r = 0.96$. Once the scores are averaged and passed into one column, the problem of multicollinearity is removed. `Termd` is also omitted because its correlation with `EmpStatusID` is $r = 0.96$.

```
# create function to plot correlation matrix and establish multicollinearity
# takes one input (df) to pass in dataframe of interest

multicollinearity <- function(df) {

      # Examine between predictor correlations/multicollinearity
      corr <- cor(df)
      corrplot(corr, mar = c(0, 0, 0, 0), method = 'color',
                     col = colorRampPalette(c('#FC0320', '#FFFFFF',
                                              '#FF0000'))(100),
                     addCoef.col = 'black', tl.srt = 45, tl.col = 'black',
                     type = 'lower')

      # assign variable to count how many highly correlated
      # variables there exist based on 0.75 threshold
      highCorr <- findCorrelation(corr, cutoff = 0.75)

      # find correlated names
      highCorr_names <- findCorrelation(corr, cutoff = 0.75, names = TRUE)
      cat(' The following variables should be omitted:',
      paste('\n', unlist(highCorr_names)))

}
```

```r
# determine multicollinearity
multicollinearity(hr_data[c(1:7)])
```



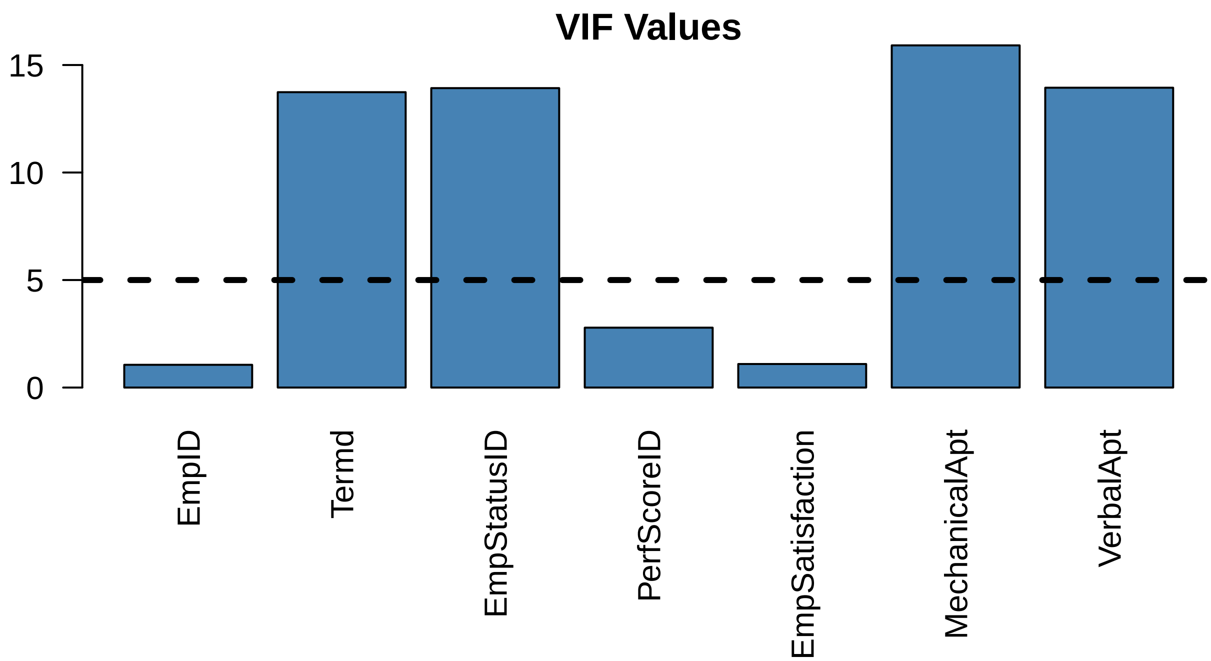

```
##  The following variables should be omitted:
##  VerbalApt
##  MechanicalApt
##  Termd
```

Variance Inflation Factor (VIF) scores confirm similar behavior, exhibiting high multicollinearity once a threshold of five is reached and surpassed. A linear model (lm) is used to test this behavior.

```r
# use generalized linear model to determine confirm multicollinearity w/ VIF
model_all <- lm(Score ~ . - CollapseScore, data = hr_data) # remove CollapseScore
                                                           # since it is target
# and we are only interested in comparing between-predictor relationships

# use car library to extract VIF and parse it into a pandoc table using the
# linear model as a proxy for analysis
pandoc.table(vif(model_all), style = 'grid', split.table = Inf)
```

EmpID	Termd	EmpStatusID	PerfScoreID	EmpSatisfaction	MechanicalApt	VerbalApt
1.058	13.74	13.93	2.785	1.096	15.91	13.94

```r
# create vector of VIF values for plotting
vif_values <- vif(model_all)

par(mar = c(7.5, 2, 1, 1)) # fix plot margins
# create column chart to display each VIF value
barplot(vif_values, main = 'VIF Values', horiz = FALSE, col = 'steelblue',
        las = 2)

# add vertical line at 5 as after 5 there is severe correlation
abline(h = 5, lwd = 3, lty = 2)
```




```r
# create average score since result of both scores creates multicollinearity
hr_data$Aptitude <- rowMeans(hr_data[, c(6, 7)], na.rm = TRUE)

# create a final dataframe with selected columns of interest for modeling
hr_data_final <- hr_data[, c(3, 5, 8, 9, 10)]
```

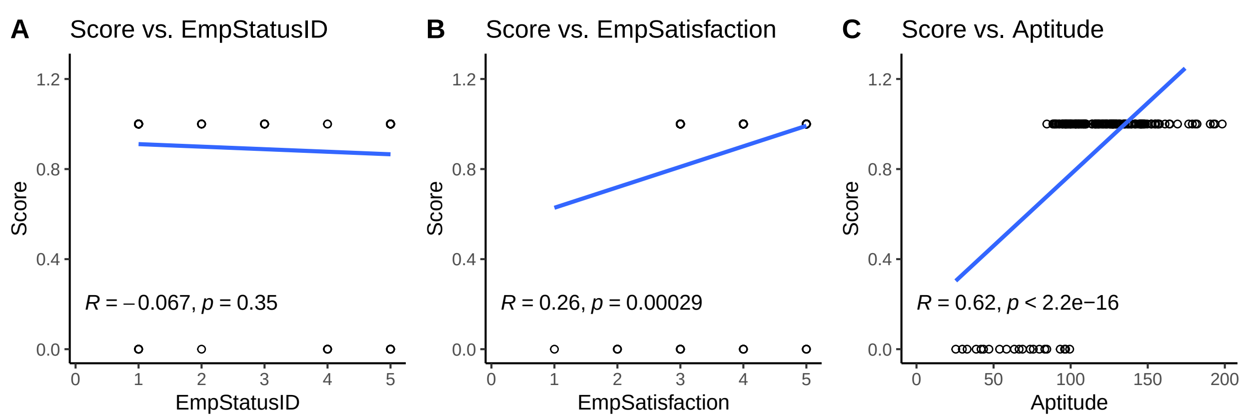
```r
# Re-examine between predictor correlations/multicollinearity
highCorr <- findCorrelation(cor(hr_data_final[c(1, 2, 5)]), cutoff = 0.75,
                            names = TRUE)
cat(' The following variables should be omitted:',
paste('\n', unlist(highCorr)))
```

```
##  The following variables should be omitted:
##
```

The Score vs. Aptitude scatterplot below exhibits a moderate correlation of $r = 0.62$. Employee satisfaction exhibits a much weaker relationship of $r = 0.26$, and there is almost no relationship between Score and Employee Status ID where $r =$ -0.067.

```r
# create function for plotting correlations between variables
# inputs: xvar: independent variable, yvar: dependent variable,
#          title: plot title, xlab: x-axis label, ylab: y-axis label
correl_plot <- function(df, xvar, yvar, title, xlab, ylab) {

  ggplot(df, aes(x = xvar, y = yvar)) +
  ggtitle(title) +
  xlab(xlab) + ylab(ylab) +
  geom_point(pch = 1) + ylim(0, 1.25) +
  geom_smooth(method = 'lm', se = FALSE) +
  theme_classic() +
  stat_cor(method = 'pearson', label.x = 0.15, label.y = 0.20) # correl coeff.

}
```

```r
# create three correlation plots on same grid
plot1 <- correl_plot(hr_data_final, xvar = hr_data_final$EmpStatusID,
                     yvar = hr_data_final$Score, title = 'Score vs. EmpStatusID',
                     xlab = 'EmpStatusID', ylab = 'Score')

plot2 <- correl_plot(hr_data_final, xvar = hr_data_final$EmpSatisfaction,
                     yvar = hr_data_final$Score,
                     title = 'Score vs. EmpSatisfaction',
                     xlab = 'EmpSatisfaction', ylab = 'Score')

plot3 <- correl_plot(hr_data_final, xvar = hr_data_final$Aptitude,
                     yvar = hr_data_final$Score, title = 'Score vs. Aptitude',
                     xlab = 'Aptitude', ylab = 'Score')

# plot all correlations together
plot_grid(plot1, plot2, plot3, labels = 'AUTO', ncol = 3, align = '')
```

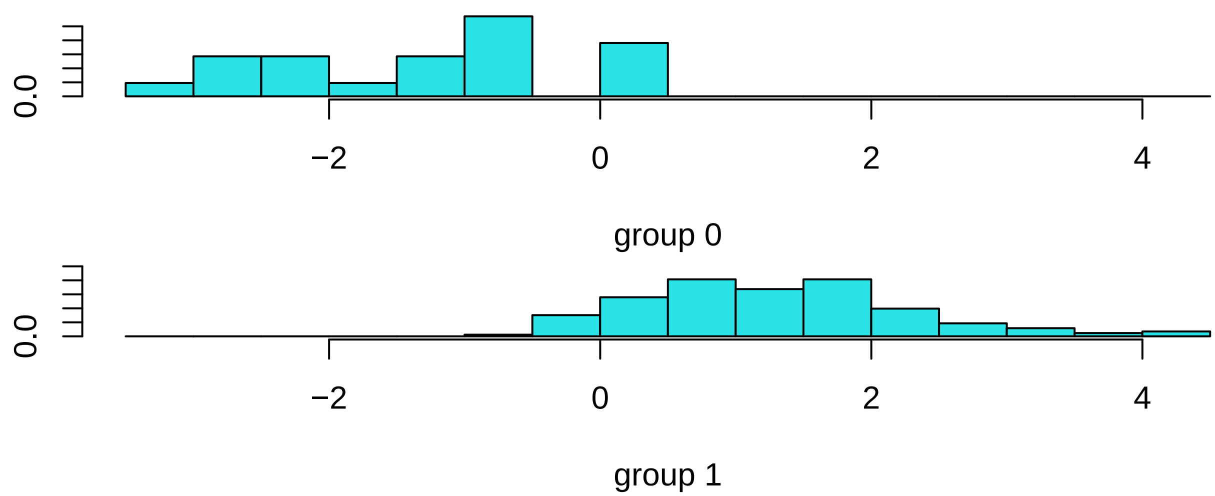


Fitting the linear discriminant analysis model produces the following results.

```r
par(mar = c(4, 2, 0, 0)) # fix plot margins
# Fit the Linear Discriminant Analysis (LDA) model
lda_fit <- lda(Score ~  EmpStatusID + EmpSatisfaction + Aptitude,
               data = hr_data_final); lda_fit
```

```
## Call:
## lda(Score ~ EmpStatusID + EmpSatisfaction + Aptitude, data = hr_data_final)
##
## Prior probabilities of groups:
##         0         1
## 0.1088083 0.8911917
##
## Group means:
##   EmpStatusID EmpSatisfaction  Aptitude
## 0    3.095238        3.238095  64.41122
## 1    2.691860        3.970930 124.64620
##
## Coefficients of linear discriminants:
##                        LD1
## EmpStatusID     0.00271593
## EmpSatisfaction 0.25572719
## Aptitude        0.03966111
```

```
plot(lda_fit) # plot the lda model
```



3. The regression model can be used to classify each of the individuals in the dataset. As discussed in the videos, you will need to find the cutoff value for the regression value that separates the unsatisfactory performers from the satisfactory performers. Find this value and determine whether individual 5 is predicted to be satisfactory or not.

   In R you can use the predict command to use the regression function with the data associated with each individual in the dataset. For example: `pred=predict(model, frame)` stores the predicted values from the regression function into the variable pred when the regression model has been assigned to the variable model as in this statement: `model <-lm(dependent variable ~ independent variable 1+ independent variable 2+..., data=frame)`.

   You may then find the mean value of the regression for all observations of unsatisfactory employees using the command `meanunsat=mean(pred[frame$CollapseScore==0])`.

   The cutoff value is then computed in r as follows: `cutoff<-0.5(meanunsat+meansat)`.

   If you want to compare what your model says verses whether they were found to be satisfactory or unsatisfactory you may add the prediction to the data frame using `cbind(frame, pred)`. This will make the predictions part of the dataset.

A generalized linear model is fitted accordingly, a column of predictions is appended to the dataframe, and a cutoff value is determined accordingly. Individual 5 has unacceptable/unsatisfactory performance, and the model predicts the same with a probability of 0.471, which is below the cutoff of 0.737.

```r
# Fit a regression model
reg_model <- lm(Score ~ EmpStatusID + EmpSatisfaction + Aptitude,
                data = hr_data_final)

# stores the predicted values from the regression function into the variable
# pred when the regression model has been assigned to the variable reg_model
pred <- predict(reg_model, hr_data_final)

# find the mean value of the regression for all observations of unsatisfactory
# and satisfactory employees
meanunsat <- mean(pred[hr_data_final$Score == 0])
meansat <- mean(pred[hr_data_final$Score == 1])
cat(' Mean of Satisfactory Results =', meansat, '\n',
    'Mean of Unsatisfactory Results =', meanunsat, '\n')
```

Mean of Satisfactory Results = 0.9340495 Mean of Unsatisfactory Results = 0.540166

```r
# determine the cutoff value
cutoff <- 0.5*(meanunsat + meansat)
cat(' Cutoff Value =', cutoff)
```

Cutoff Value = 0.7371078

```r
cbind_hrdatafinal <- cbind(hr_data_final, pred)
pandoc.table(head(cbind_hrdatafinal), style = 'grid', split.table = Inf)
```

EmpStatusID	EmpSatisfaction	CollapseScore	Score	Aptitude	pred
1	5	Acceptable	1	180.9	1.315
1	3	Acceptable	1	106.7	0.7863
5	4	Acceptable	1	152.3	1.104
1	2	Unacceptable	0	46.99	0.3852
1	5	Unacceptable	0	41.87	0.4715
1	4	Acceptable	1	131.6	0.9764

4. Construct a logit model using the two performance groups. Compare this model and the discriminant analysis done in step 1. To construct the logit model, use the function `lrm()` in the library rms.

```r
# Construct a logit model using the two performance groups
logit <- lrm(Score ~ MechanicalApt + VerbalApt, data = hr_data); logit
```

```
## Logistic Regression Model
##
##  lrm(formula = Score ~ MechanicalApt + VerbalApt, data = hr_data)
##
##                          Model Likelihood     Discrimination    Rank Discrim.
##                                Ratio Test            Indexes          Indexes
```

```
## Obs           193    LR chi2     109.40     R2       0.870     C       0.991
##  0             21    d.f.             2     R2(2,193)0.427     Dxy     0.983
##  1            172    Pr(> chi2) <0.0001    R2(2,56.1)0.852     gamma   0.983
## max |deriv| 3e-06                           Brier    0.017     tau-a   0.192
##
##                Coef     S.E.    Wald Z Pr(>|Z|)
## Intercept     -33.7121 11.5108 -2.93  0.0034
## MechanicalApt   0.4697  0.1689  2.78  0.0054
## VerbalApt      -0.0865  0.0743 -1.16  0.2443
##
```

The linear discriminant analysis model does not use mechanical aptitude and/or verbal aptitude as standalone independent variables. The scores are averaged to create one column for general aptitude.

5. Build an ordered logit model for the full four categories for performance. When you call the function `lrm()` you will use the original categories `PerScoreID`. What is the probability that individual two is in each of the four performance categories? You can use the function `predict()` to do this. The form of the call is `predict(name of the model you used when you created the model, data=frame, type="fitted.ind")`.

```
# Build an ordered logit model for the full four categories for performance
ologit <- lrm(PerfScoreID ~ Termd + EmpStatusID + EmpSatisfaction, data = hr_data)
ologit
```

```
## Logistic Regression Model
##
##  lrm(formula = PerfScoreID ~ Termd + EmpStatusID + EmpSatisfaction,
##      data = hr_data)
##
##
##  Frequencies of Responses
##
##    1   2   3   4
##    8  13 148  24
##
##                       Model Likelihood      Discrimination    Rank Discrim.
##                             Ratio Test             Indexes          Indexes
## Obs           193    LR chi2      12.13      R2       0.077    C       0.634
## max |deriv| 8e-09    d.f.             3      R2(3,193)0.046    Dxy     0.268
##                      Pr(> chi2) 0.0070    R2(3,105.5)0.083    gamma   0.298
##                                              Brier    0.086    tau-a   0.105
##
##                 Coef    S.E.   Wald Z Pr(>|Z|)
## y>=2             1.0880 0.9065  1.20  0.2300
## y>=3            -0.0130 0.8869 -0.01  0.9883
## y>=4            -4.3212 0.9741 -4.44  <0.0001
## Termd           -1.2239 1.1992 -1.02  0.3075
## EmpStatusID      0.1560 0.3152  0.49  0.6208
## EmpSatisfaction  0.5872 0.2086  2.81  0.0049
##
```

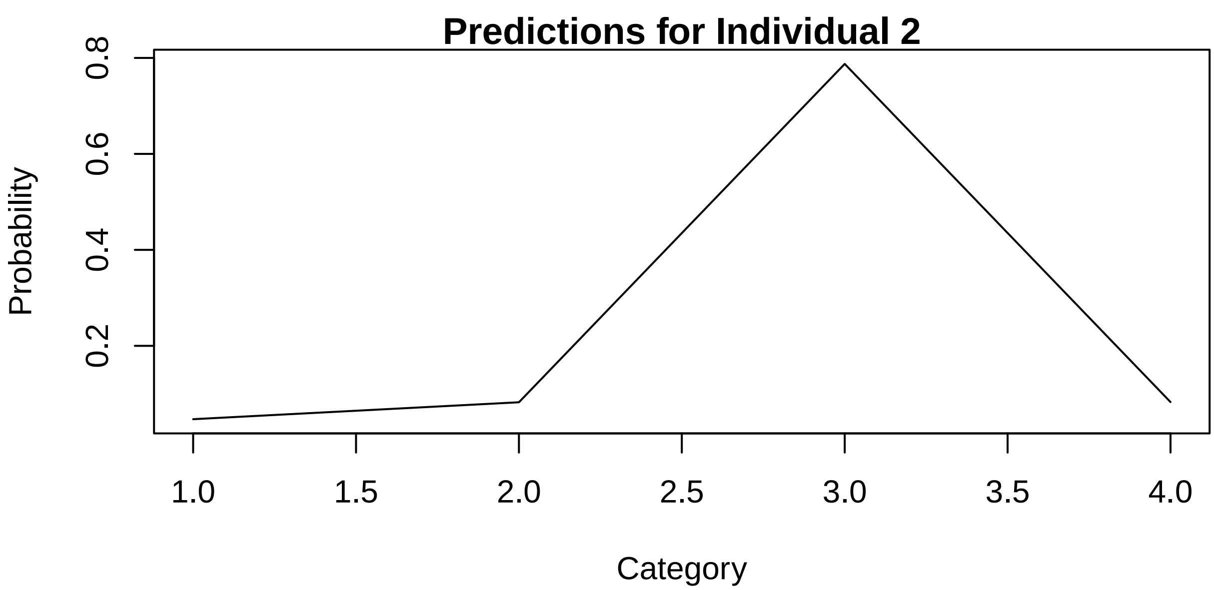
```r
# probability that individual two is in each of the four performance categories
pred_ologit <- predict(ologit, data = hr_data, type = 'fitted.ind')
```

```r
# inspect the dataframe
pandoc.table(head(pred_ologit), style = 'grid', split.table = Inf, round = 4)
```

PerfScoreID=1	PerfScoreID=2	PerfScoreID=3	PerfScoreID=4
0.0151	0.0289	0.7297	0.2263
0.0472	0.0824	0.7875	0.0829
0.0477	0.0833	0.787	0.0819
0.0818	0.1295	0.7409	0.0478
0.0151	0.0289	0.7297	0.2263
0.0268	0.0496	0.7837	0.1399

```r
# get predictions only for second individual
individual2 <- pred_ologit[2, ]; cat('\n')
```

```r
par(mar = c(4, 4, 1, 1)) # fix plot margins
plot(individual2, type = 'l', main = 'Predictions for Individual 2',
     xlab = 'Category', ylab = 'Probability')
```




```r
pandoc.table(individual2, style = 'grid', split.table = Inf, round = 4)
```

PerfScoreID=1	PerfScoreID=2	PerfScoreID=3	PerfScoreID=4
0.0472	0.0824	0.7875	0.0829

The respective probabilities that individual two will be in each of the four performance categories are 0.0471702, 0.0824139, 0.7875144, 0.0829015.

Part Two

Using Naïve Bayes to Predict a Performance Score

In this part of the project, you will use Naïve Bayes to predict a performance score. This part continues the scenario from Part One and uses the same modified version of the human resources data set available on the Kaggle website. The data set you will be using is in the file `NaiveBayesHW.csv` file. Over the course of this project, your task is to gain insight into who might be a "high" performer if hired.

1. Using only the mechanical aptitude score, use Naïve Bayes to predict the performance score for each employee. Professor Nozick discretized the mechanical scores into four classes. Notice only three of four classes have observations. This discretization is in the data file `NaiveBayesHW.csv`. The function to create the model is `naiveBayes()`.

```r
naive_df <- read.csv('NaiveBayesHW.csv') # read in the dataset

# inspect the dataset
pandoc.table(head(naive_df), style = 'simple', split.table = Inf)
```

EmpID	Termd	EmpStatusID	PerfScoreID	EmpSatisfaction	PerfScore	MechanicalApt
1	0	1	4	5	Class4	Level4
2	0	1	3	3	Class3	Level3
3	1	5	3	4	Class3	Level4
4	0	1	1	2	Class1	Level1
5	0	1	1	5	Class1	Level1
6	0	1	4	4	Class4	Level3

```r
# assign the naivebayes function to a new variable
nbmodel <- naiveBayes(PerfScore ~ MechanicalApt, data = naive_df)
print(nbmodel)
```

```
##
## Naive Bayes Classifier for Discrete Predictors
##
## Call:
## naiveBayes.default(x = X, y = Y, laplace = laplace)
##
## A-priori probabilities:
## Y
##     Class1     Class2     Class3     Class4
## 0.04145078 0.06735751 0.76683938 0.12435233
##
## Conditional probabilities:
##         MechanicalApt
## Y           Level1    Level3    Level4
##   Class1 1.0000000 0.0000000 0.0000000
##   Class2 0.0000000 0.0000000 1.0000000
##   Class3 0.0000000 0.6554054 0.3445946
##   Class4 0.0000000 0.3333333 0.6666667
```

```r
# predict the naive bayes model
# type = raw' specifies that R should return the probability that a point is in
# each risk group. Not specifying a type would print the most likely category
# that each point would fall into.

pred_bayes <- predict(nbmodel, naive_df, type = 'raw')
head(pred_bayes, 20) # inspect the first 10 rows
```

```
##             Class1       Class2     Class3      Class4
##  [1,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
##  [2,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
##  [3,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
##  [4,] 9.773977e-01 0.0015882712 0.01808186 0.002932193
##  [5,] 9.773977e-01 0.0015882712 0.01808186 0.002932193
##  [6,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
##  [7,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
##  [8,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
##  [9,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
## [10,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
## [11,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
## [12,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
## [13,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
## [14,] 7.617524e-05 0.0001237848 0.92362480 0.076175241
## [15,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
## [16,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
## [17,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
## [18,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
## [19,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
## [20,] 9.999000e-05 0.1624837516 0.63743626 0.199980002
```

2. Using this modeling approach, what is your assessment of the probability that individual 10 will evolve into each of the four probability classes if hired? This can be done using the model created above and the `pred()` function. The arguments for that function are the model name, data and for type use "raw". This question is parallel to the Practice using Naïve Bayes activity you completed in R.

The probability that individual 10 will evolve into each of the four probability classes if hired is as follows:

```r
# table the probabilities of each respective class for the individual
# get the 10th row only
individual10 <- pred_bayes[10, ]
# assign to a dataframe
individual10 <- data.frame(individual10)
# rename the column
colnames(individual10) <- c('Probability')
# show the table
individual10
```

```
##        Probability
## Class1  0.00009999
## Class2  0.16248375
## Class3  0.63743626
## Class4  0.19998000
```

Part Three

Building Classification Trees

In this part of the project, you will build classification trees. This part continues the scenario from Parts One and Two, as it uses the same modified version of the human resources data set available on the Kaggle website. Use the `HRdata4groups.csv` data set to predict each individual's performance (Performance Score ID) using classification trees. In the space below, you will explain the model you have developed and describe how well it performs.

1. In the space below, explain the model you developed. It is sufficient to use the function `ctree()` in R to accomplish this in the style of the codio exercise Practice: Building a Classification Tree in R—Small Example.

```
hrdata_groups <- read.csv('HRdata4groups.csv') # read in the dataset

# inspect the first five rows of the dataset
pandoc.table(head(hrdata_groups, 5), style = 'grid')
```

Table 9: Table continues below

EmpStatusID	PerfScoreID	CollapseScore	PayRate	Age	JobTenure
1	4	1	23	43	8
1	3	1	16	50	8
5	3	1	21	37	9
1	1	0	20	53	6
1	1	0	18	31	5

EngagementSurvey	EmpSatisfaction	MechanicalApt	VerbalApt
5	5	174.6	187.2
5	3	110.6	102.7
2	4	148.6	156.1
1.12	2	49.11	44.86
1.56	5	42.15	41.59

```
str(hrdata_groups) # print out the structure of the dataframe
```

```
## 'data.frame':    193 obs. of  10 variables:
##  $ EmpStatusID     : int  1 1 5 1 1 1 1 5 5 5 ...
##  $ PerfScoreID     : int  4 3 3 1 1 4 4 3 3 3 ...
##  $ CollapseScore   : int  1 1 1 0 0 1 1 1 1 1 ...
##  $ PayRate         : num  23 16 21 20 18 16 20 24 15 22 ...
##  $ Age             : int  43 50 37 53 31 40 46 50 48 37 ...
##  $ JobTenure       : int  8 8 9 6 5 6 6 9 8 7 ...
##  $ EngagementSurvey: num  5 5 2 1.12 1.56 3.39 4.76 3.49 3.08 3.18 ...
##  $ EmpSatisfaction : int  5 3 4 2 5 4 4 4 4 3 ...
##  $ MechanicalApt   : num  174.6 110.6 148.6 49.1 42.2 ...
##  $ VerbalApt       : num  187.2 102.7 156.1 44.9 41.6 ...
```

Before modeling can commence, it is important to establish between-predictor relationships and the potential presence of multicollinearity, because this is a refined dataset from a new .csv file. The classification trees model is developed from all variables except for mechanical aptitude and verbal aptitude. Verbal aptitude exhibits a noticeably high correlation of $r = 0.96$ with mechanical aptitude. However, rather than omitting this one variable, both aptitude columns are replaced with a new column by the name of aptitude which has been averaged from their results.

```
# Examine between predictor correlations/multicollinearity
highCorr <- findCorrelation(cor(hrdata_groups[c(-2)]), cutoff = 0.75,
                            names = TRUE)
cat(' The following variables should be omitted: \n', paste(unlist(highCorr)))
```

```
##  The following variables should be omitted:
##  VerbalApt
```

`VerbalApt` exhibits multicollinearity, so it is averaged with `MechanicalApt`, just like in part one. A replacement column called `Aptitude` is once again created on this refined dataset.

```
# create aptitude from averaged MechanicalApt and VerbalApt scores
hrdata_groups$Aptitude <- rowMeans(hrdata_groups[, c(9, 10)], na.rm = TRUE)
# mechanical aptitude, and verbal aptitude are omitted
hrgroups_final <- hrdata_groups[, c(-9, -10)] # finalize dataframe for modeling
```

Between-predictor relationships are once again re-examined to ensure no residual multicollinearity is detected.

```
# Re-examine between predictor correlations/multicollinearity
highCorr <- findCorrelation(cor(hrgroups_final[, c(-2)]), cutoff = 0.75,
                            names = TRUE)
cat(' The following variables should be omitted:', '\n',
paste(unlist(highCorr)))
```

```
##  The following variables should be omitted:
##
```

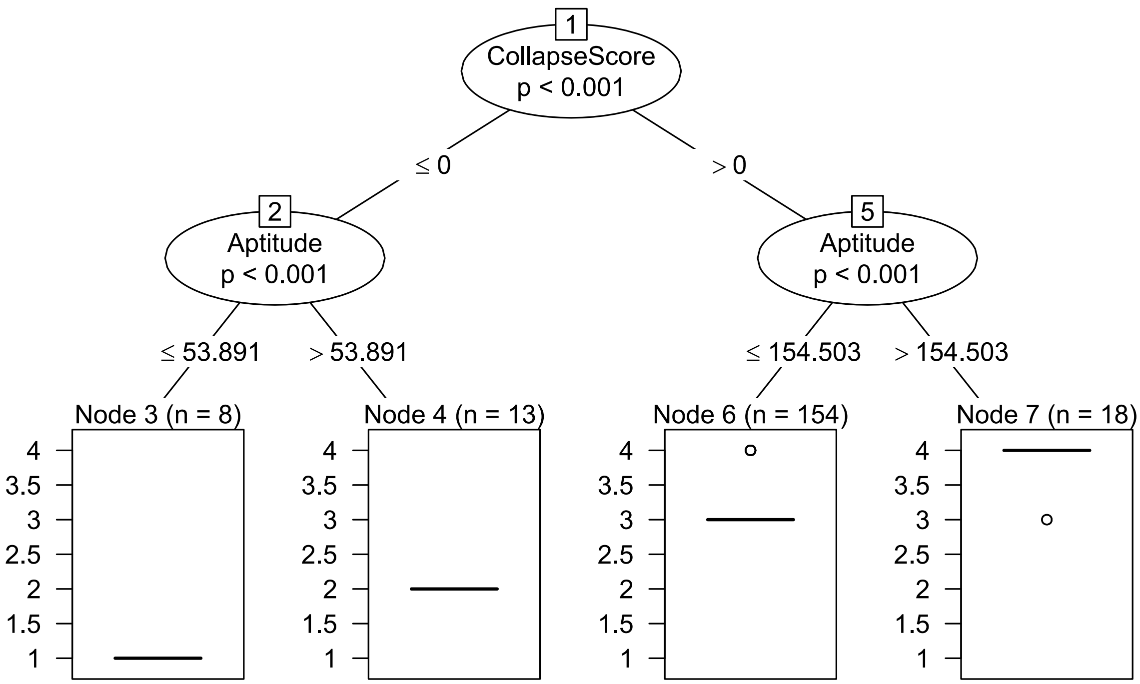
```
# build the classification tree
ctout <- ctree(PerfScoreID ~ ., data = hrgroups_final)
ctout
```

```
##
## Model formula:
## PerfScoreID ~ EmpStatusID + CollapseScore + PayRate + Age + JobTenure +
##     EngagementSurvey + EmpSatisfaction + Aptitude
##
## Fitted party:
## [1] root
## |   [2] CollapseScore <= 0
## |   |   [3] Aptitude <= 53.89066: 1.000 (n = 8, err = 0.0)
## |   |   [4] Aptitude > 53.89066: 2.000 (n = 13, err = 0.0)
## |   [5] CollapseScore > 0
## |   |   [6] Aptitude <= 154.50311: 3.052 (n = 154, err = 7.6)
## |   |   [7] Aptitude > 154.50311: 3.889 (n = 18, err = 1.8)
##
## Number of inner nodes:    3
## Number of terminal nodes: 4
```

```r
# predict the performance score based on all input features of final df
ctpred <- predict(ctout, hrgroups_final)

# Check the percentage of time that the classification tree correctly classifies
# a data point
cat('Correct Classification of Data Point:',
    mean(ctpred == hrgroups_final$PerfScoreID))
```

```
## Correct Classification of Data Point: 0.1088083
```

```r
plot(ctout) # plot the classification tree
```



2. In the space below, describe how well your model performs.

Whenever a `CollapseScore` is less than or equal to zero, it is classified as unacceptable or unsatisfactory performance. Thus, under this umbrella category, aptitude scores less than or equal to 53.89 (level 1) exhibit no error (third node), where $n = 8$. Aptitude scores greater than 53.89066 (level 2) exhibit no error, where $n = 13$.

Whenever a `CollapseScore` is greater than 0, employee performance is classified as acceptable or satisfactory. Under this umbrella category, aptitude scores less than or equal to 154.50 reach a node level of 3.052, with an error of 7.6, where $n = 154$ observations. Aptitude scores greater than 154.50 reach a higher node level of 3.89, where there are $n = 18$ observations, and a lower error rate of 1.8.

There are three inner nodes and four terminal nodes, with a correct classification of data points at approximately 11%. The performance is low, and this model warrants iterative refinement.

Part Four

Applying SVM to a Data Set

In this part of the project, you will apply SVM to a data set. The RStudio instance contains the file `acquisitionacceptanceSVM.csv`, which includes information about whether or not homeowners accepted a government offer to purchase their home.

1. Apply the tool SVM to the acquisition data set in the CSV file `acquisitionacceptanceSVM.csv` to predict which homeowners will most likely accept the government's offer. What variables did you choose to use in your analysis?

```
acquisition <- read.csv('acquisitionacceptanceSVM.csv') # read in the dataset

# inspect the dataframe
pandoc.table(head(acquisition), style = 'grid')
```

Table 11: Table continues below

Distance	Floodplain	HomeTenure	Education345	CurMarketValue
162.8	1	1	1	650000
108.3	1	14	0	30000
4.55	1	19	1	50000
81.28	1	37	1	78000
183.2	1	9	1	127300
32.05	1	57	0	35000

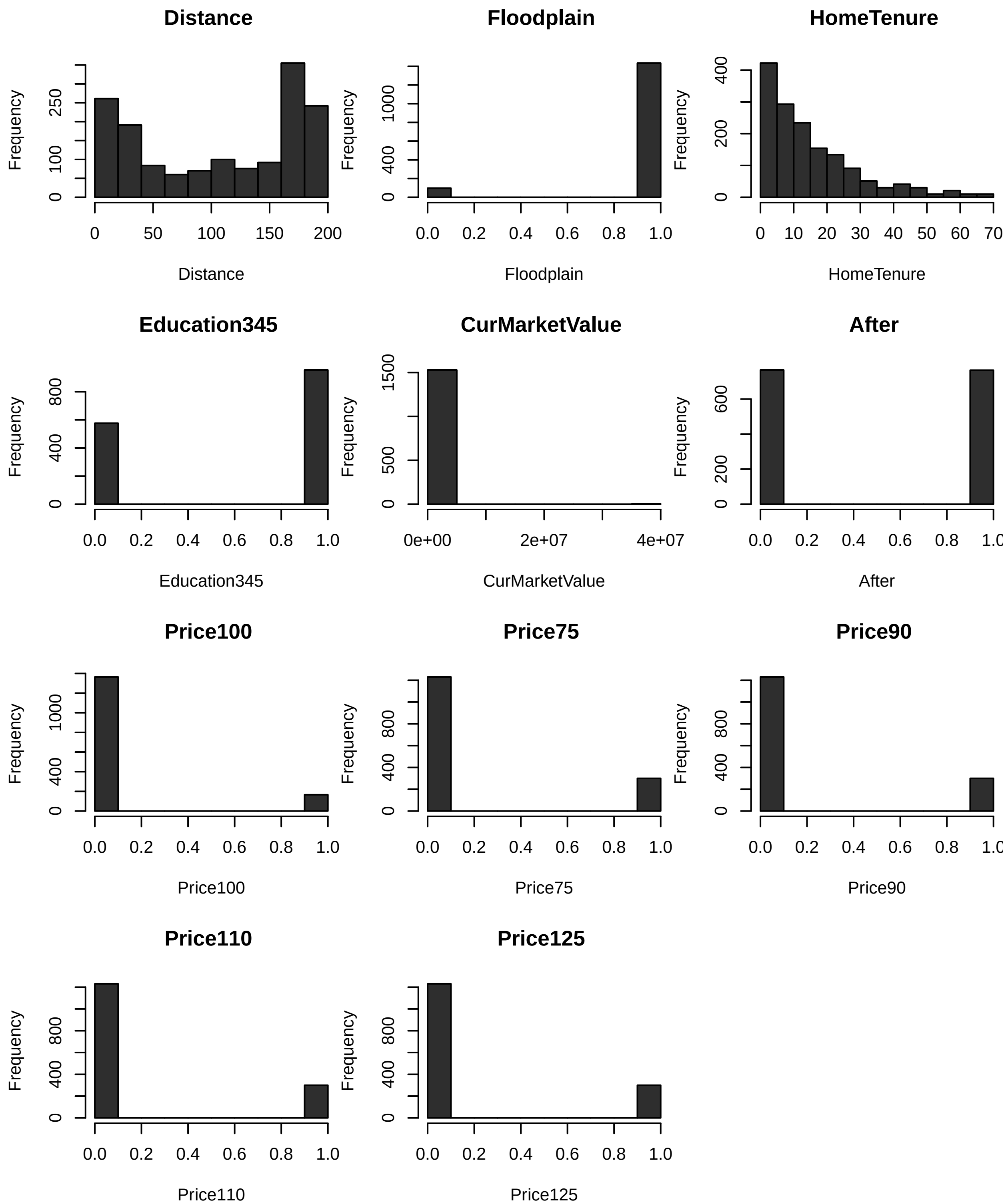
After	Price100	Price75	Price90	Price110	Price125	Accept
0	1	0	0	0	0	0
0	1	0	0	0	0	0
0	1	0	0	0	0	0
0	1	0	0	0	0	1
0	1	0	0	0	0	0
0	1	0	0	0	0	1

```
str(acquisition) # obtain the structure of the dataframe
```

```
## 'data.frame':    1531 obs. of  12 variables:
##  $ Distance      : num  162.75 108.26 4.55 81.28 183.21 ...
##  $ Floodplain    : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ HomeTenure    : int  1 14 19 37 9 57 11 65 1 25 ...
##  $ Education345  : int  1 0 1 1 1 0 0 0 1 1 ...
##  $ CurMarketValue: int  650000 30000 50000 78000 127300 35000 400000 80000 360000 300000 ...
##  $ After         : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Price100      : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ Price75       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Price90       : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Price110      : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Price125      : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ Accept        : int  0 0 0 1 0 1 0 0 0 0 ...
```

```r
nearzerohist(acquisition[c(-12)], x = 4, y = 3)
```

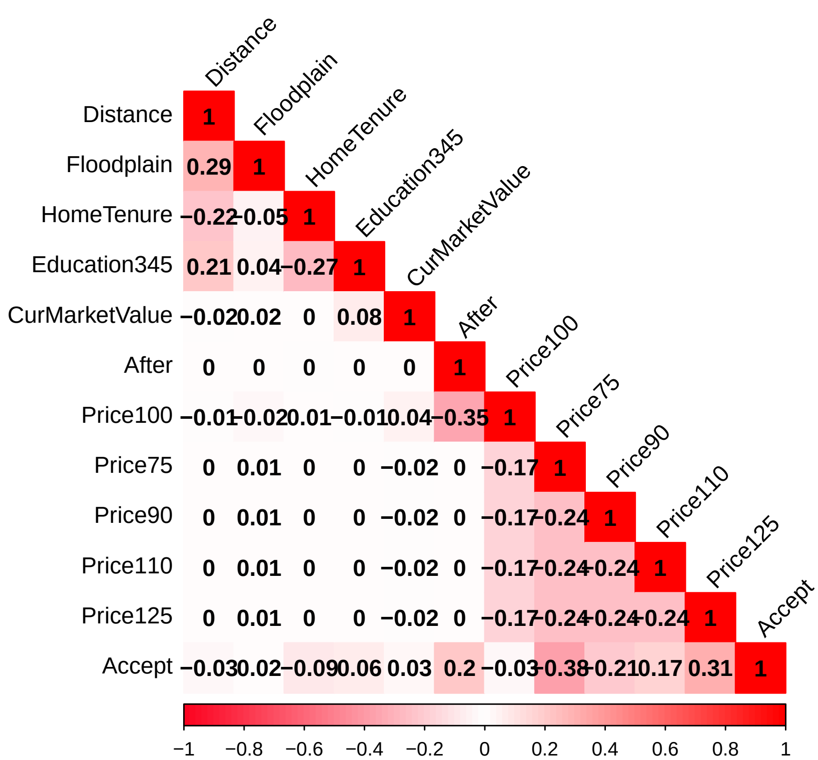
```
## [1] "There are no near-zero variance predictors."
```



Inspecting the dataframe for near zero variance predictors from a visual standpoint alone identifies current market value `CurMarketValue` to be a variable that exhibits such behavior. However, the `nearZeroVar` function from the ‘caret‘ library does not expose such variables. Near zero variance measures the fraction of unique values in the columns across the dataset.

Moreover, the correlation matrix does not expose any sources of high between-predictor relationships (beyond the cutoff point of $r = 0.75$). This relegates the variable selection process to Principal Component Analysis (PCA), but this is a dimensionality reduction technique; there are only 12 variables and 1,531 rows of data.

```
multicollinearity(acquisition)
```




```
##  The following variables should be omitted:
##
```

Casting the target `Accept` variable to a factor is done to categorize the data. There are enough rows in this dataset to carry out a train-test split, and so it is done, with 70% partitioned into the training set, and the remaining 30% into the test set.

```
acquisition$Accept <- as.factor(acquisition$Accept)
acquisition$Accept <- ifelse(acquisition$Accept == 1, 'Accept', 'Not Accept')
acquisition$Accept <- as.factor(acquisition$Accept)
```

```
set.seed(222) # set seed for reproducibility

# Use 70% of dataset as training set and remaining 30% as testing set
```

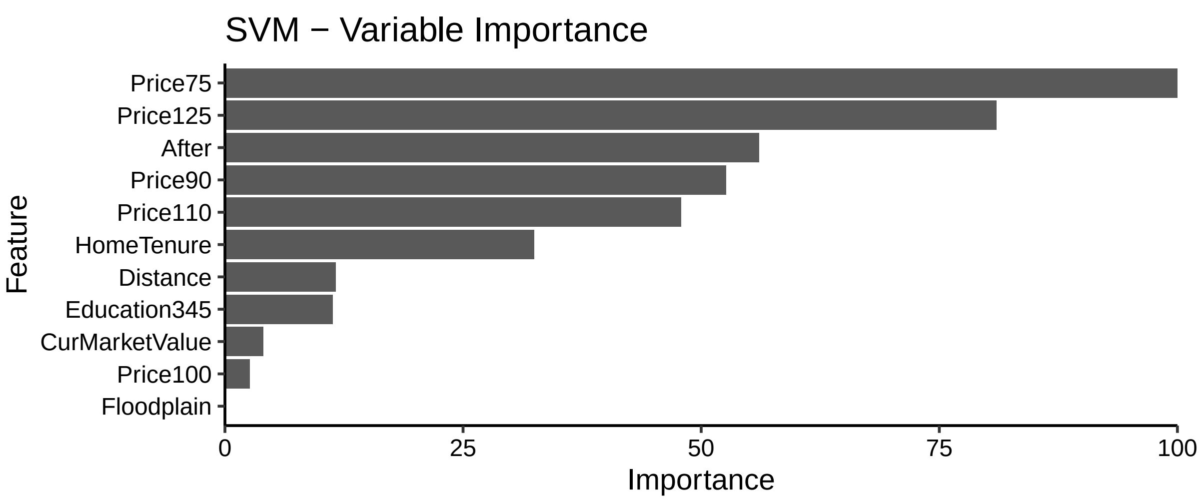
```r
sample <- sample(c(TRUE, FALSE), nrow(acquisition), replace = TRUE,
                 prob = c(0.7, 0.3))
train_acquisition <- acquisition[sample, ] # training set
test_acquisition <- acquisition[!sample, ] # test set

cat(' Training Dimensions:', dim(train_acquisition),
    '\n Testing Dimensions:', dim(test_acquisition), '\n',
    '\n Training Dimensions Percentage:', round(nrow(train_acquisition) /
                                                nrow(acquisition), 2),
    '\n Testing Dimensions Percentage:', round(nrow(test_acquisition) /
                                               nrow(acquisition), 2))
```

```
##  Training Dimensions: 1067 12
##  Testing Dimensions: 464 12
##
##  Training Dimensions Percentage: 0.7
##  Testing Dimensions Percentage: 0.3
```

```r
predictors <- train_acquisition[, c(-12)] # extract ind. var. from train set
target <- train_acquisition[, c(12)] # extract dep. var. from train set
target <- as.factor(target) # cast target as factor
```

Since the `e1071` package does not allow for a printout of variable importance (`varImpt()`) for feature selection, the `caret` package is used to accomplish this task, and the results are shown below. `Price75` and `Price125` are the top two variables surpassing a score of 80 in importance and are thus selected for the soft-margin support vector machine.

```r
# Support Vector Machines via caret
model_svm  <- train(predictors, target, method = 'svmLinear', verbose = FALSE)
# plot the variable importance
svm_varimp <- varImp(object = model_svm)
ggplot2::ggplot(varImp(object = model_svm)) +
  ggtitle('SVM - Variable Importance') +
  scale_y_continuous(expand = c(0, 0)) +
  theme_classic() + theme(plot.margin = unit(c(0, 1, 0, 0), 'cm')) +
  theme(axis.text = element_text(color = 'black'),
        axis.title = element_text(color = 'black'))
```



The model's cost and kernel hyperparameters are tuned over the training data with a 10-fold cross validation sampling method. The optimal hyperparameter values are shown in table below.

```r
train_df <- train_acquisition[, c(8, 11, 12)]
test_df <- test_acquisition[, c(8, 11, 12)]

# column names of df to confirm cols
pandoc.table(colnames(train_df))
```

Price75	Price125	Accept

```r
# tune the support vector machine, optimizing the hyperparameters
# of gamma, cost, and epsilon
set.seed (222) # set seed for reproducibility
tune.out <- tune(svm, Accept ~ Price75 + Price125, data = train_df,
                ranges = list(cost = 10 ^ seq(-3, 3),
                              kernel = c('linear', 'polynomial',
                                         'radial')))

bestparam <- tune.out$best.parameters # best hyperparamaters
bestmod <- tune.out$best.model # best model based on tuning parameters
pandoc.table(bestparam, style = 'grid') # print out the best hyperparamaters
```

	cost	kernel
2	0.01	linear

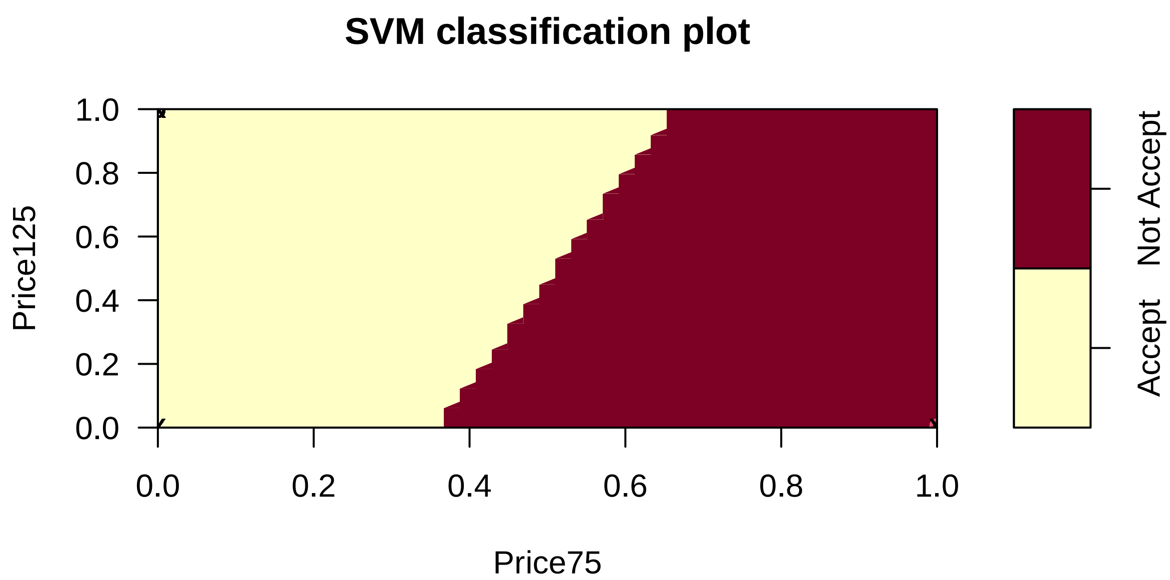
These hyperparameters are used to create a soft margin support vector machine.

```r
# Construct Soft Margin SVM
acquisition_result <- svm(Accept ~ Price125 + Price75, kernel = 'linear',
                          gamma = 0.001, cost = 0.01, epsilon = 0,
                          data = train_df, decision.values = TRUE)
print(acquisition_result)
```

```
##
## Call:
## svm(formula = Accept ~ Price125 + Price75, data = train_df, kernel = "linear",
##     gamma = 0.001, cost = 0.01, epsilon = 0, decision.values = TRUE)
##
##
## Parameters:
##    SVM-Type:  C-classification
##  SVM-Kernel:  linear
##        cost:  0.01
##
## Number of Support Vectors:  802
```

The classification results are visualized below.

```r
# Visualize the SVM decision boundary using only the training data using price75
# and price125 as features
plot(acquisition_result, data = train_df)
```




```r
# create function for outputting a confusion matrix in a pandoc-style format
# where inputs --> df1: model df
#                  df2: dataset
#                  feat: target column
#                  x: H0  column (i.e., 'yes', 'accept' '1', etc.)
#                  y: H1  column (i.e., 'no', 'not accept', '0', etc.)
#                  custom_name: any string you want to pass into table name

conf_matrix <- function(df1, df2, feat, x, y, custom_name) {

    prediction <- predict(df1, newdata = df2)
    # Evaluate the model on the training data and inspect first six rows
    pred_table <- table(prediction, feat)
    # print out pander-grid-style table with performance results
    metrics <- c(x, y)
    h0 <- c(pred_table[1], pred_table[2])
    h1 <- c(pred_table[3], pred_table[4])
    # create table as dataframe from above variables
    table <- data.frame(metrics, h0, h1)
    # change column names of table
    colnames(table) <- c('\n', x, y)
    table %>% pander(style = 'grid', caption = sprintf('Confusion Matrix for %s',
                                                        custom_name))

}
```

```r
conf_matrix(df1 = acquisition_result, df2 = train_df, feat = train_df$Accept,
            x = 'Accept', y = 'Not Accept', custom_name = 'Train Set')
```

Table 15: Confusion Matrix for Train Set

	Accept	Not Accept
Accept	498	350
Not Accept	25	194

```r
conf_matrix(df1 = acquisition_result, df2 = test_df, feat = test_df$Accept,
            x = 'Accept', y = 'Not Accept', custom_name = 'Test Set')
```

Table 16: Confusion Matrix for Test Set

	Accept	Not Accept
Accept	233	150
Not Accept	11	70

The confusion matrix is used to obtain the first effective measure of model performance (accuracy) using the following equation.

$$\text{Accuracy} = \frac{\text{TP} + \text{TN}}{\text{TP} + \text{TN} + \text{FP} + \text{FN}}$$

Precision (specificity) measures out of everyone who accepted a government offer to purchase their home, how many actually accepted? It is calculated as follows.

$$\text{Precision} = \frac{\text{TP}}{\text{TP} + \text{FP}}$$

Recall (sensitivity) measures the true positive rate (TPR), which is the number of correct predictions in the `Accept` class divided by the total number of `Accept` instances. It is calculated as follows:

$$\text{Recall} = \frac{\text{TP}}{\text{TP} + \text{FN}}$$

The *f1*-score is the harmonic mean of precision and recall, and is calculated as follows:

$$f1 = \frac{\text{TP}}{\text{TP} + \frac{1}{2}(\text{FP+FN})}$$

```r
#
#
#
#
# create function for calculating model performance metrics that takes in the
# following inputs --> df1: model df
#                      df2: dataset
#                      feat: target column
#                      custom_name: any string you want to pass into table name
#
```

```r
perf_metrics <- function(df1, df2, feat, custom_name) {

  prediction <- predict(df1, newdata = df2)
  # Evaluate the model on the training data and inspect first six rows
  df <- table(prediction, feat)

  tp <- df[1] # position of true positives
  tn <- df[4] # position of true negatives
  fp <- df[3] # position of false positives
  fn <- df[2] # position of false negatives

  # calculate model performance metrics
  accuracy <- round((tp + tn)/(tp + tn + fp + fn),2) # calculate accuracy
  spec <- round((tp) / (tp + fp),2) # calculate specificity (precision)
  sens <- round((tp) / (tp + fn),2) # calculate sensitivity (recall)
  f1 <- round((tp) / (tp+0.5*(fp+fn)),2) # calculate f1-score

  # print out pander-grid-style table with performance results
  metrics <- c('Accuracy', 'Specificity', 'Sensitivity', 'F1-Score')
  values <- c(accuracy, spec, sens, f1)
  table <- data.frame(Metric = metrics, Value = values)
  table %>% pander(style = 'grid',
                   caption = sprintf('Performance Metrics for %s', custom_name))

}
```

```r
# call the `perf_metrics` function to establish performance metrics for train set
perf_metrics(df1 = acquisition_result, df2 = train_df, feat = train_df$Accept,
             custom_name = 'Training Set')
```

Table 17: Performance Metrics for Training Set

Metric	Value
Accuracy	0.65
Specificity	0.59
Sensitivity	0.95
F1-Score	0.73

```r
# call the `perf_metrics` function to establish performance metrics for test set
perf_metrics(df1 = acquisition_result, df2 = test_df, feat = test_df$Accept,
             custom_name = 'Test Set')
```

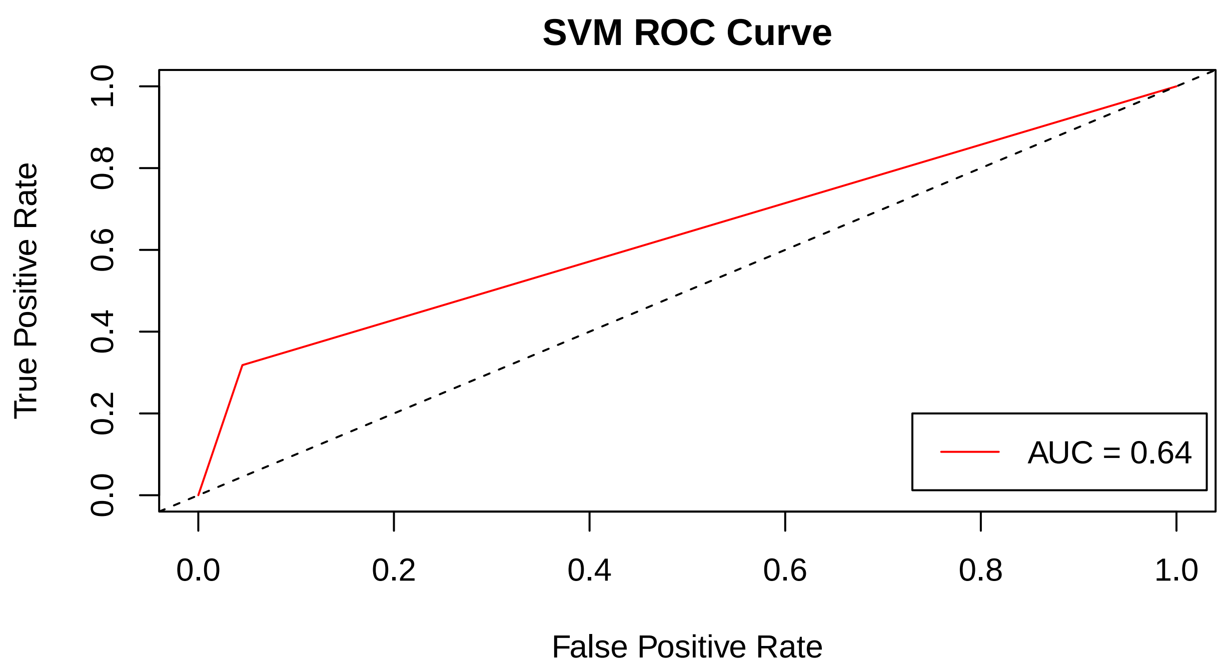
Table 18: Performance Metrics for Test Set

Metric	Value
Accuracy	0.65
Specificity	0.61
Sensitivity	0.95
F1-Score	0.74

2. How good was your model at correctly predicting who would and who would not accept the offer?

Using the test data (30% hold out), the model's accuracy is only 15% improvement above baseline, coming out to 65%. However, the model's ability to correctly classify the `Accept` class is effectively high at 95% specificity. The ROC Curve calculates an AUC (area under the curve) score of 64%, so model performance is quite low. Moreover, the ROC Curve below shows that as the true positive rate increases, so does the false positive rate, so, for every increase in the false positive rate, there is a greater increase in false alarms.

```
test_prob  <- predict(acquisition_result, test_df, type = 'decision')
pr <-prediction(as.numeric(test_prob), as.numeric(test_df$Accept))
prf <- performance(pr, measure = 'tpr', x.measure = 'fpr')
test_roc <- roc(test_df$Accept ~ as.numeric(test_prob), print.auc = TRUE)
auc <- round(as.numeric(test_roc$auc), 2); par(mar = c (4, 4, 2, 1))
plot(prf, main = 'SVM ROC Curve', col = 'red', xlab = 'False Positive Rate',
                                             ylab = 'True Positive Rate')
abline(0, 1, col = 'black', lty = 2, lwd = 1)
legend(0.73, 0.2, legend = paste('AUC =', rev(auc)), lty = c(1), col = c('red'))
```



3. When building models, we often use part of the data to estimate the model and use the remainder for prediction. Why do we do this? It is not necessary to do this for each of the problems above. It is essential to realize that you will need to do this in practice.

We are interested in seeing how the model performs on unseen data. Thus, we partition the data into a train-test split. Ideally, there are enough rows of data to conduct a three-way train-validation-test split such that the train-validation set becomes the development set. However, we are working with a smaller amount of data, so we are using a two-way split, where the training set (development set) is the larger portion of data (70-80%), and the remaining 30% is allocated to the test set. Anything can be done repeatedly to the development set (e.g., iteration, hyperparameterization, experimentation, etc.), as long as the test set remains uncontaminated (unseen). Once the model is finalized through the training set, it can be predicted on the remaining test set.