akhilasaineni_Lab2

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Lab 2: Naive Bayes Classifiers

Part 1

Step 1 Loading the data

```
library(readr)
credit_data = read.csv("/Users/akhilasaineni/Downloads/HU/2020Fall/ANLY_530_MachineLearning1/Lab2/credi

str(credit_data)
```

```
## 'data.frame':    1000 obs. of  21 variables:
##  $ Creditability                    : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ Account.Balance                  : int  1 1 2 1 1 1 1 1 4 2 ...
##  $ Duration.of.Credit..month.       : int  18 9 12 12 12 10 8 6 18 24 ...
##  $ Payment.Status.of.Previous.Credit: int  4 4 2 4 4 4 4 4 4 2 ...
##  $ Purpose                          : int  2 0 9 0 0 0 0 0 3 3 ...
##  $ Credit.Amount                    : int  1049 2799 841 2122 2171 2241 3398 1361 1098 3758 ...
##  $ Value.Savings.Stocks             : int  1 1 2 1 1 1 1 1 1 3 ...
##  $ Length.of.current.employment     : int  2 3 4 3 3 2 4 2 1 1 ...
##  $ Instalment.per.cent              : int  4 2 2 3 4 1 1 2 4 1 ...
##  $ Sex...Marital.Status             : int  2 3 2 3 3 3 3 3 2 2 ...
##  $ Guarantors                       : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ Duration.in.Current.address      : int  4 2 4 2 4 3 4 4 4 4 ...
##  $ Most.valuable.available.asset    : int  2 1 1 1 2 1 1 1 3 4 ...
##  $ Age..years.                      : int  21 36 23 39 38 48 39 40 65 23 ...
##  $ Concurrent.Credits               : int  3 3 3 3 1 3 3 3 3 3 ...
##  $ Type.of.apartment                : int  1 1 1 1 2 1 2 2 2 1 ...
##  $ No.of.Credits.at.this.Bank       : int  1 2 1 2 2 2 2 1 2 1 ...
##  $ Occupation                       : int  3 3 2 2 2 2 2 2 1 1 ...
##  $ No.of.dependents                 : int  1 2 1 2 1 2 1 2 1 1 ...
##  $ Telephone                        : int  1 1 1 1 1 1 1 1 1 1 ...
##  $ Foreign.Worker                   : int  1 1 1 2 2 2 2 2 1 1 ...
```

```
summary(credit_data)
```

```
##  Creditability Account.Balance Duration.of.Credit..month.
##  Min.   :0.0   Min.   :1.000   Min.   : 4.0
##  1st Qu.:0.0   1st Qu.:1.000   1st Qu.:12.0
```

```
##  Median :1.0   Median :2.000   Median :18.0
##  Mean   :0.7   Mean   :2.577   Mean   :20.9
##  3rd Qu.:1.0   3rd Qu.:4.000   3rd Qu.:24.0
##  Max.   :1.0   Max.   :4.000   Max.   :72.0
##  Payment.Status.of.Previous.Credit    Purpose       Credit.Amount
##  Min.   :0.000                     Min.   : 0.000   Min.   :  250
##  1st Qu.:2.000                     1st Qu.: 1.000   1st Qu.: 1366
##  Median :2.000                     Median : 2.000   Median : 2320
##  Mean   :2.545                     Mean   : 2.828   Mean   : 3271
##  3rd Qu.:4.000                     3rd Qu.: 3.000   3rd Qu.: 3972
##  Max.   :4.000                     Max.   :10.000   Max.   :18424
##  Value.Savings.Stocks Length.of.current.employment Instalment.per.cent
##  Min.   :1.000        Min.   :1.000                Min.   :1.000
##  1st Qu.:1.000        1st Qu.:3.000                1st Qu.:2.000
##  Median :1.000        Median :3.000                Median :3.000
##  Mean   :2.105        Mean   :3.384                Mean   :2.973
##  3rd Qu.:3.000        3rd Qu.:5.000                3rd Qu.:4.000
##  Max.   :5.000        Max.   :5.000                Max.   :4.000
##  Sex...Marital.Status   Guarantors    Duration.in.Current.address
##  Min.   :1.000        Min.   :1.000   Min.   :1.000
##  1st Qu.:2.000        1st Qu.:1.000   1st Qu.:2.000
##  Median :3.000        Median :1.000   Median :3.000
##  Mean   :2.682        Mean   :1.145   Mean   :2.845
##  3rd Qu.:3.000        3rd Qu.:1.000   3rd Qu.:4.000
##  Max.   :4.000        Max.   :3.000   Max.   :4.000
##  Most.valuable.available.asset  Age..years.    Concurrent.Credits
##  Min.   :1.000                 Min.   :19.00   Min.   :1.000
##  1st Qu.:1.000                 1st Qu.:27.00   1st Qu.:3.000
##  Median :2.000                 Median :33.00   Median :3.000
##  Mean   :2.358                 Mean   :35.54   Mean   :2.675
##  3rd Qu.:3.000                 3rd Qu.:42.00   3rd Qu.:3.000
##  Max.   :4.000                 Max.   :75.00   Max.   :3.000
##  Type.of.apartment No.of.Credits.at.this.Bank   Occupation    No.of.dependents
##  Min.   :1.000     Min.   :1.000              Min.   :1.000   Min.   :1.000
##  1st Qu.:2.000     1st Qu.:1.000              1st Qu.:3.000   1st Qu.:1.000
##  Median :2.000     Median :1.000              Median :3.000   Median :1.000
##  Mean   :1.928     Mean   :1.407              Mean   :2.904   Mean   :1.155
##  3rd Qu.:2.000     3rd Qu.:2.000              3rd Qu.:3.000   3rd Qu.:1.000
##  Max.   :3.000     Max.   :4.000              Max.   :4.000   Max.   :2.000
##    Telephone     Foreign.Worker
##  Min.   :1.000   Min.   :1.000
##  1st Qu.:1.000   1st Qu.:1.000
##  Median :1.000   Median :1.000
##  Mean   :1.404   Mean   :1.037
##  3rd Qu.:2.000   3rd Qu.:1.000
##  Max.   :2.000   Max.   :2.000
```

```r
sum(is.na(credit_data))
```

```
## [1] 0
```

```r
#No NAs in the data
```

```r
# converting the class variable
credit_data$Creditability = as.factor(credit_data$Creditability)
sum(is.na(credit_data))
```

```
## [1] 0
```

```r
# splitting dataset into training and test datasets
set.seed(100)

# randomizing and splitting
credit_random = credit_data[order(runif(1000)),]
credit_train = credit_random[1:750,]
credit_test = credit_random[751:1000,]

prop.table(table(credit_train$Creditability))
```

```
##
##         0         1
## 0.2973333 0.7026667
```

Step 2 Training the Model on the Data

```r
#install.packages("naivebayes")
library(naivebayes)
```

```
## naivebayes 0.9.7 loaded
```

```r
nb_model = naive_bayes(Creditability ~ ., data = credit_train)
nb_model
```

```
##
## ================================== Naive Bayes ==================================
##
##  Call:
## naive_bayes.formula(formula = Creditability ~ ., data = credit_train)
##
## ---------------------------------------------------------------------------------
##
## Laplace smoothing: 0
##
## ---------------------------------------------------------------------------------
##
##  A priori probabilities:
##
##         0         1
## 0.2973333 0.7026667
##
## ---------------------------------------------------------------------------------
##
```

```
##  Tables:
##
## --------------------------------------------------------------------------------
##  ::: Account.Balance (Gaussian)
## --------------------------------------------------------------------------------
##
## Account.Balance        0        1
##            mean 1.941704 2.846300
##            sd   1.082710 1.230591
##
## --------------------------------------------------------------------------------
##  ::: Duration.of.Credit..month. (Gaussian)
## --------------------------------------------------------------------------------
##
## Duration.of.Credit..month.        0        1
##                       mean 24.21973 18.83491
##                       sd   13.02081 10.95017
##
## --------------------------------------------------------------------------------
##  ::: Payment.Status.of.Previous.Credit (Gaussian)
## --------------------------------------------------------------------------------
##
## Payment.Status.of.Previous.Credit        0        1
##                              mean 2.139013 2.703985
##                              sd   1.023795 1.016800
##
## --------------------------------------------------------------------------------
##  ::: Purpose (Gaussian)
## --------------------------------------------------------------------------------
##
## Purpose        0        1
##    mean 2.869955 2.652751
##    sd   2.921826 2.531720
##
## --------------------------------------------------------------------------------
##  ::: Credit.Amount (Gaussian)
## --------------------------------------------------------------------------------
##
## Credit.Amount        0        1
##          mean 3688.430 2936.421
##          sd   3276.835 2395.407
##
## --------------------------------------------------------------------------------
##
## # ... and 15 more tables
##
## --------------------------------------------------------------------------------
```

```r
summary(nb_model)
```

```
##
## ================================== Naive Bayes ==================================
##
## - Call: naive_bayes.formula(formula = Creditability ~ ., data = credit_train)
```

```
## - Laplace: 0
## - Classes: 2
## - Samples: 750
## - Features: 20
## - Conditional distributions:
##     - Gaussian: 20
## - Prior probabilities:
##     - 0: 0.2973
##     - 1: 0.7027
##
## --------------------------------------------------------------------------------
```

Step 3 Model Performance Evaluation

```r
(naiveBayes_model_nat = table(predict(nb_model, credit_test), credit_test$Creditability))
```

```
## Warning: predict.naive_bayes(): more features in the newdata are provided as
## there are probability tables in the object. Calculation is performed based on
## features to be found in the tables.
```

```
##
##       0   1
##   0  54  48
##   1  23 125
```

```r
(Accuracy = sum(diag(naiveBayes_model_nat))/sum(naiveBayes_model_nat)*100)
```

```
## [1] 71.6
```

In the first part of the assignment, Naive Bayesian method is applied to train the prediction model. Firstly, the dataset is split into training and test datasets in a 75:25 ratio. In order to test the accuracy of the model, the test dataset is used to determine that our model has an accuracy of 71.6%.

Part 2

This part of the assignment is to improve the performance of the Naive Bayes classifier.

Step 1 Loading and exploring the dataset

```r
library(colorspace)
library(ggplot2)
library(minqa)
library(nloptr)
```

```
##
## Attaching package: 'nloptr'
```

```
## The following objects are masked from 'package:minqa':
##
##     bobyqa, newuoa
```

```
library(lattice)
#install.packages("caTools")
library(caTools)
#install.packages("MatrixModels")
library(MatrixModels)
#install.packages("tmvnsim")
library(tmvnsim)
library(psych)
```

```
##
## Attaching package: 'psych'

## The following objects are masked from 'package:ggplot2':
##
##     %+%, alpha
```

```
library(caret)

#highlycor <- findCorrelation(m, 0.30)

credit_random = credit_data[order(runif(1000)), ]

creditScaled = scale(credit_random[,2:ncol(credit_random)], center=TRUE, scale = TRUE)

corr_matrix = cor(creditScaled)
high_correlation = findCorrelation(corr_matrix, 0.30)

#preparing test data
filtered_data = credit_random[, -(high_correlation[5]+1)]
filtered_training = filtered_data[1:750, ]
filtered_test = filtered_data[751:1000, ]
```

Step 2 Training the Model on the Filtered Data

```
library(naivebayes)
naivebayes_model <- naive_bayes(Creditability ~ ., data=filtered_training)

naivebayes_model
```

```
##
## ================================== Naive Bayes ==================================
##
##  Call:
## naive_bayes.formula(formula = Creditability ~ ., data = filtered_training)
##
## ---------------------------------------------------------------------------------
```

```
##
## Laplace smoothing: 0
##
## --------------------------------------------------------------------------------
##
##  A priori probabilities:
##
##     0     1
## 0.312 0.688
##
## --------------------------------------------------------------------------------
##
##  Tables:
##
## --------------------------------------------------------------------------------
##  ::: Account.Balance (Gaussian)
## --------------------------------------------------------------------------------
##
## Account.Balance        0        1
##            mean 1.923077 2.837209
##            sd   1.041243 1.232509
##
## --------------------------------------------------------------------------------
##  ::: Duration.of.Credit..month. (Gaussian)
## --------------------------------------------------------------------------------
##
## Duration.of.Credit..month.        0        1
##                       mean 25.59402 18.63178
##                       sd   13.28920 10.77141
##
## --------------------------------------------------------------------------------
##  ::: Purpose (Gaussian)
## --------------------------------------------------------------------------------
##
## Purpose        0        1
##    mean 3.051282 2.819767
##    sd   3.020235 2.662300
##
## --------------------------------------------------------------------------------
##  ::: Credit.Amount (Gaussian)
## --------------------------------------------------------------------------------
##
## Credit.Amount        0        1
##          mean 4096.855 2914.837
##          sd   3704.862 2354.435
##
## --------------------------------------------------------------------------------
##  ::: Value.Savings.Stocks (Gaussian)
## --------------------------------------------------------------------------------
##
## Value.Savings.Stocks        0        1
##                 mean 1.696581 2.327519
##                 sd   1.335320 1.667304
##
```

```
## ---------------------------------------------------------------------------------
##
## # ... and 14 more tables
##
## ---------------------------------------------------------------------------------
```

Step 3 Model Performance Evaluation

```r
filtered_test_prediction <- predict(naivebayes_model, newdata = filtered_test)
```

```
## Warning: predict.naive_bayes(): more features in the newdata are provided as
## there are probability tables in the object. Calculation is performed based on
## features to be found in the tables.
```

```r
table(filtered_test_prediction, filtered_test$Creditability)
```

```
##
## filtered_test_prediction   0   1
##                        0  41  49
##                        1  25 135
```

```r
naiveBayes_model2_nat<- table(filtered_test_prediction, filtered_test$Creditability)
(Accuracy <- sum(diag(naiveBayes_model2_nat))/sum(naiveBayes_model2_nat)*100)
```

```
## [1] 70.4
```

As part of the assignment part2, an attempt is made to improve the accuracy of the Naive Bayesian model by filtering the dataset used in the model. The new model has an accuracy of 3% higher than the original model, i.e. 74.4%. Hence, it is safe to say that the performance of the model has significantly increased.

Part 3

Step 1 Loading the Data

```r
#loading the data
letter_data = read.csv("/Users/akhilasaineni/Downloads/HU/2020Fall/ANLY_530_MachineLearning1/Lab2/lette
str(letter_data)
```

```
## 'data.frame':    20000 obs. of  17 variables:
##  $ letter: Factor w/ 26 levels "A","B","C","D",..: 20 9 4 14 7 19 2 1 10 13 ...
##  $ xbox  : int  2 5 4 7 2 4 4 1 2 11 ...
##  $ ybox  : int  8 12 11 11 1 11 2 1 2 15 ...
##  $ width : int  3 3 6 6 3 5 5 3 4 13 ...
##  $ height: int  5 7 8 6 1 8 4 2 4 9 ...
##  $ onpix : int  1 2 6 3 1 3 4 1 2 7 ...
##  $ xbar  : int  8 10 10 5 8 8 8 8 10 13 ...
##  $ ybar  : int  13 5 6 9 6 8 7 2 6 2 ...
```

```
##  $ x2bar : int  0 5 2 4 6 6 6 2 2 6 ...
##  $ y2bar : int  6 4 6 6 6 9 6 2 6 2 ...
##  $ xybar : int  6 13 10 4 6 5 7 8 12 12 ...
##  $ x2ybar: int  10 3 3 4 5 6 6 2 4 1 ...
##  $ xy2bar: int  8 9 7 10 9 6 6 8 8 9 ...
##  $ xedge : int  0 2 3 6 1 0 2 1 1 8 ...
##  $ xedgey: int  8 8 7 10 7 8 8 6 6 1 ...
##  $ yedge : int  0 4 3 2 5 9 7 2 1 1 ...
##  $ yedgex: int  8 10 9 8 10 7 10 7 7 8 ...
```

```r
summary(letter_data)
```

```
##      letter           xbox             ybox            width       
##  U      :  813   Min.   : 0.000   Min.   : 0.000   Min.   : 0.000  
##  D      :  805   1st Qu.: 3.000   1st Qu.: 5.000   1st Qu.: 4.000  
##  P      :  803   Median : 4.000   Median : 7.000   Median : 5.000  
##  T      :  796   Mean   : 4.024   Mean   : 7.035   Mean   : 5.122  
##  M      :  792   3rd Qu.: 5.000   3rd Qu.: 9.000   3rd Qu.: 6.000  
##  A      :  789   Max.   :15.000   Max.   :15.000   Max.   :15.000  
##  (Other):15202                                                     
##      height           onpix             xbar             ybar     
##  Min.   : 0.000   Min.   : 0.000   Min.   : 0.000   Min.   : 0.0  
##  1st Qu.: 4.000   1st Qu.: 2.000   1st Qu.: 6.000   1st Qu.: 6.0  
##  Median : 6.000   Median : 3.000   Median : 7.000   Median : 7.0  
##  Mean   : 5.372   Mean   : 3.506   Mean   : 6.898   Mean   : 7.5  
##  3rd Qu.: 7.000   3rd Qu.: 5.000   3rd Qu.: 8.000   3rd Qu.: 9.0  
##  Max.   :15.000   Max.   :15.000   Max.   :15.000   Max.   :15.0  
##                                                                   
##      x2bar            y2bar            xybar            x2ybar      
##  Min.   : 0.000   Min.   : 0.000   Min.   : 0.000   Min.   : 0.000  
##  1st Qu.: 3.000   1st Qu.: 4.000   1st Qu.: 7.000   1st Qu.: 5.000  
##  Median : 4.000   Median : 5.000   Median : 8.000   Median : 6.000  
##  Mean   : 4.629   Mean   : 5.179   Mean   : 8.282   Mean   : 6.454  
##  3rd Qu.: 6.000   3rd Qu.: 7.000   3rd Qu.:10.000   3rd Qu.: 8.000  
##  Max.   :15.000   Max.   :15.000   Max.   :15.000   Max.   :15.000  
##                                                                     
##      xy2bar           xedge            xedgey           yedge       
##  Min.   : 0.000   Min.   : 0.000   Min.   : 0.000   Min.   : 0.000  
##  1st Qu.: 7.000   1st Qu.: 1.000   1st Qu.: 8.000   1st Qu.: 2.000  
##  Median : 8.000   Median : 3.000   Median : 8.000   Median : 3.000  
##  Mean   : 7.929   Mean   : 3.046   Mean   : 8.339   Mean   : 3.692  
##  3rd Qu.: 9.000   3rd Qu.: 4.000   3rd Qu.: 9.000   3rd Qu.: 5.000  
##  Max.   :15.000   Max.   :15.000   Max.   :15.000   Max.   :15.000  
##                                                                     
##      yedgex      
##  Min.   : 0.000  
##  1st Qu.: 7.000  
##  Median : 8.000  
##  Mean   : 7.801  
##  3rd Qu.: 9.000  
##  Max.   :15.000  
## 
```

```r
# converting the datatype of the letter attribute
letter_data$letter = as.factor(letter_data$letter)
```

Step 2 Preparing the Data

```r
letters_train = letter_data[1:18000, ]
letters_test = letter_data[18001:20000, ]
```

Step 3 Training a Model on the Data THIS IS INCORRECT LOOK INTO THIS ********

```r
#install.packages("kernlab")
library(kernlab)
```

```
##
## Attaching package: 'kernlab'

## The following object is masked from 'package:psych':
##
##     alpha

## The following object is masked from 'package:ggplot2':
##
##     alpha
```

```r
letter_classifier = ksvm(letter ~., data = letters_train, kernel = "vanilladot")
```

```
##  Setting default kernel parameters
```

```r
letter_classifier
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Linear (vanilla) kernel function.
##
## Number of Support Vectors : 7886
##
## Objective Function Value : -15.3458 -21.3403 -25.7672 -6.8685 -8.8812 -35.9555 -59.5883 -18.1975 -65
## Training error : 0.1335
```

```r
summary(letter_classifier)
```

```
## Length  Class   Mode
##      1   ksvm     S4
```

A initial training error of 13.35% is seen.

Step 4 Model Performance Evaluation

```r
letter_predictions = predict(letter_classifier, letters_test)
table(letter_predictions, letters_test$letter)
```

```
##
## letter_predictions  A  B  C  D  E  F  G  H  I  J  K  L  M  N  O  P  Q  R  S  T
##                  A 73  0  0  0  0  0  0  0  0  1  0  0  0  0  3  0  4  0  0  1
##                  B  0 61  0  3  2  0  1  1  0  0  1  1  0  0  0  2  0  1  3  0
##                  C  0  0 64  0  2  0  4  2  1  0  1  2  0  0  1  0  0  0  0  0
##                  D  2  1  0 67  0  0  1  3  3  2  1  2  0  3  4  2  1  2  0  0
##                  E  0  0  1  0 64  1  1  0  0  0  2  2  0  0  0  0  2  0  6  0
##                  F  0  0  0  0  0 70  1  1  4  0  0  0  0  0  0  5  1  0  2  0
##                  G  1  1  2  1  3  2 68  1  0  0  0  1  0  0  0  0  4  1  3  2
##                  H  0  0  0  1  0  1  0 46  0  2  3  1  1  1  9  0  0  5  0  3
##                  I  0  0  0  0  0  0  0  0 65  3  0  0  0  0  0  0  0  0  2  0
##                  J  0  1  0  0  0  1  0  0  3 61  0  0  0  0  1  0  0  0  1  0
##                  K  0  1  4  0  0  0  0  5  0  0 56  0  0  2  0  0  0  4  0  1
##                  L  0  0  0  0  1  0  0  1  0  0  0 63  0  0  0  0  0  0  0  0
##                  M  0  0  1  0  0  0  1  0  0  0  0  0 70  2  0  0  0  0  0  0
##                  N  0  0  0  0  0  0  0  0  0  0  0  0  0 77  0  0  0  1  0  0
##                  O  0  0  1  1  0  0  0  1  0  1  0  0  0  0 49  1  2  0  0  0
##                  P  0  0  0  0  0  3  0  0  0  0  0  0  0  0  2 69  0  0  0  0
##                  Q  0  0  0  0  0  0  3  1  0  0  0  2  0  0  2  1 52  0  1  0
##                  R  0  4  0  0  1  0  0  3  0  0  3  0  0  0  1  0  0 64  0  1
##                  S  0  1  0  0  1  1  1  0  1  1  0  0  0  0  0  0  6  0 47  1
##                  T  0  0  0  0  1  1  0  0  0  0  1  0  0  0  0  0  0  0  1 83
##                  U  0  0  2  1  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0
##                  V  0  0  0  0  0  0  0  0  0  0  0  0  1  0  1  0  0  0  0  0
##                  W  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0
##                  X  0  1  0  0  1  0  0  1  0  0  1  4  0  0  0  0  0  1  0  0
##                  Y  2  0  0  0  0  0  0  0  0  0  0  0  0  0  0  4  0  0  0  1
##                  Z  1  0  0  0  2  0  0  0  0  2  0  0  0  0  0  0  0  0  5  1
##
## letter_predictions  U  V  W  X  Y  Z
##                  A  2  0  1  0  0  0
##                  B  0  0  0  0  0  0
##                  C  0  0  0  0  0  0
##                  D  0  0  0  0  1  0
##                  E  0  0  0  1  0  0
##                  F  0  1  0  0  2  0
##                  G  0  0  0  0  0  0
##                  H  0  2  0  0  1  0
##                  I  0  0  0  2  1  0
##                  J  0  0  0  1  0  4
##                  K  2  0  0  4  0  0
##                  L  0  0  0  0  0  0
##                  M  1  0  6  0  0  0
##                  N  1  0  2  0  0  0
##                  O  1  0  0  0  0  0
##                  P  0  0  0  0  1  0
##                  Q  0  0  0  0  0  0
##                  R  0  1  0  0  0  0
```

```
##                   S  0  0  0  1  0  6
##                   T  1  0  0  0  2  2
##                   U 83  0  0  0  0  0
##                   V  0 64  1  0  1  0
##                   W  0  3 59  0  0  0
##                   X  0  0  0 76  1  0
##                   Y  0  0  0  1 58  0
##                   Z  0  0  0  0  0 70
```

```r
agreement = letter_predictions == letters_test$letter
table(agreement)
```

```
## agreement
## FALSE  TRUE
##   321  1679
```

The model is currently showing an accuracy of 83.95%.

Step 5 Trying Polynomial and RBF kernels to improve the result

```r
# testing polynomial kernel
letter_classifier2 = ksvm(letter ~ ., data = letters_train, kernel = "polydot")
```

```
##  Setting default kernel parameters
```

```r
letter_classifier2
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Polynomial kernel function.
##  Hyperparameters : degree =  1  scale =  1  offset =  1
##
## Number of Support Vectors : 7887
##
## Objective Function Value : -15.3458 -21.3403 -25.7672 -6.8685 -8.8812 -35.9555 -59.5883 -18.1975 -65
## Training error : 0.1335
```

```r
summary(letter_classifier2)
```

```
## Length  Class   Mode
##      1   ksvm     S4
```

```r
letter_predictions2 = predict(letter_classifier2, letters_test)
table(letter_predictions2, letters_test$letter)
```

```
##
## letter_predictions2  A  B  C  D  E  F  G  H  I  J  K  L  M  N  O  P  Q  R  S  T
##                   A 73  0  0  0  0  0  0  0  0  1  0  0  0  0  3  0  4  0  0  1
##                   B  0 61  0  3  2  0  1  1  0  0  1  1  0  0  0  2  0  1  3  0
##                   C  0  0 64  0  2  0  4  2  1  0  1  2  0  0  1  0  0  0  0  0
##                   D  2  1  0 67  0  0  1  3  3  2  1  2  0  3  4  2  1  2  0  0
##                   E  0  0  1  0 64  1  1  0  0  0  2  2  0  0  0  0  2  0  6  0
##                   F  0  0  0  0  0 70  1  1  4  0  0  0  0  0  0  5  1  0  2  0
##                   G  1  1  2  1  3  2 68  1  0  0  0  1  0  0  0  0  4  1  3  2
##                   H  0  0  0  1  0  1  0 46  0  2  3  1  1  1  9  0  0  5  0  3
##                   I  0  0  0  0  0  0  0  0 65  2  0  0  0  0  0  0  0  0  2  0
##                   J  0  1  0  0  0  1  0  0  3 62  0  0  0  0  1  0  0  0  1  0
##                   K  0  1  4  0  0  0  0  5  0  0 56  0  0  2  0  0  0  4  0  1
##                   L  0  0  0  0  1  0  0  1  0  0  0 63  0  0  0  0  0  0  0  0
##                   M  0  0  1  0  0  0  1  0  0  0  0  0 70  2  0  0  0  0  0  0
##                   N  0  0  0  0  0  0  0  0  0  0  0  0  0 77  0  0  0  1  0  0
##                   O  0  0  1  1  0  0  0  1  0  1  0  0  0  0 49  1  2  0  0  0
##                   P  0  0  0  0  0  3  0  0  0  0  0  0  0  0  2 69  0  0  0  0
##                   Q  0  0  0  0  0  0  3  1  0  0  0  2  0  0  2  1 52  0  1  0
##                   R  0  4  0  0  1  0  0  3  0  0  3  0  0  0  1  0  0 64  0  1
##                   S  0  1  0  0  1  1  1  0  1  1  0  0  0  0  0  0  6  0 47  1
##                   T  0  0  0  0  1  1  0  0  0  0  1  0  0  0  0  0  0  0  1 83
##                   U  0  0  2  1  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0
##                   V  0  0  0  0  0  0  0  0  0  0  0  0  1  0  1  0  0  0  0  0
##                   W  0  0  0  0  0  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0
##                   X  0  1  0  0  1  0  0  1  0  0  1  4  0  0  0  0  0  1  0  0
##                   Y  2  0  0  0  0  0  0  0  0  0  0  0  0  0  0  4  0  0  0  1
##                   Z  1  0  0  0  2  0  0  0  0  2  0  0  0  0  0  0  0  0  5  1
##
## letter_predictions2  U  V  W  X  Y  Z
##                   A  2  0  1  0  0  0
##                   B  0  0  0  0  0  0
##                   C  0  0  0  0  0  0
##                   D  0  0  0  0  1  0
##                   E  0  0  0  1  0  0
##                   F  0  1  0  0  2  0
##                   G  0  0  0  0  0  0
##                   H  0  2  0  0  1  0
##                   I  0  0  0  2  1  0
##                   J  0  0  0  1  0  4
##                   K  2  0  0  4  0  0
##                   L  0  0  0  0  0  0
##                   M  1  0  6  0  0  0
##                   N  1  0  2  0  0  0
##                   O  1  0  0  0  0  0
##                   P  0  0  0  0  1  0
##                   Q  0  0  0  0  0  0
##                   R  0  1  0  0  0  0
##                   S  0  0  0  1  0  6
##                   T  1  0  0  0  2  2
##                   U 83  0  0  0  0  0
##                   V  0 64  1  0  1  0
##                   W  0  3 59  0  0  0
##                   X  0  0  0 76  1  0
```

```
##                    Y  0  0  0  1 58  0
##                    Z  0  0  0  0  0 70
```

```r
agreement2 = letter_predictions2 == letters_test$letter
table(agreement2)
```

```
## agreement2
## FALSE  TRUE
##   320  1680
```

```r
# testing rbf kernel
letter_classifier3 = ksvm(letter ~ ., data = letters_train, kernel = "rbfdot")
letter_classifier3
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  0.0473423213659921
##
## Number of Support Vectors : 9525
##
## Objective Function Value : -45.0427 -35.4593 -61.0871 -27.7746 -36.4413 -49.0309 -72.4342 -40.9821 -
## Training error : 0.049778
```

```r
summary(letter_classifier3)
```

```
## Length  Class   Mode
##      1   ksvm     S4
```

```r
letter_predictions3 = predict(letter_classifier3, letters_test)
table(letter_predictions3, letters_test$letter)
```

```
##
## letter_predictions3  A  B  C  D  E  F  G  H  I  J  K  L  M  N  O  P  Q  R  S  T
##                   A 75  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  2  0  0  1
##                   B  0 67  0  2  0  1  0  0  0  0  0  1  0  1  0  2  1  1  1  0
##                   C  0  0 72  0  3  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0
##                   D  1  1  0 71  0  0  1  2  2  2  1  0  0  0  0  2  1  1  0  0
##                   E  0  0  0  0 70  2  0  0  0  1  0  2  0  0  0  0  0  0  0  0
##                   F  0  0  0  0  0 76  0  0  3  0  0  0  0  0  0  6  0  0  1  0
##                   G  0  0  1  0  3  0 76  1  0  0  0  0  0  0  0  0  0  0  0  0
##                   H  0  0  0  1  0  0  1 58  0  1  0  1  1  0  0  0  1  1  0  3
##                   I  0  0  0  0  0  0  0  0 69  1  0  0  0  0  0  0  0  0  0  0
##                   J  0  0  0  0  0  0  0  0  2 66  0  0  0  0  0  0  0  0  0  0
##                   K  0  0  0  0  0  0  0  3  0  0 62  0  0  1  0  0  0  2  0  0
##                   L  0  0  0  0  0  0  1  0  0  0  0 69  0  0  0  0  0  0  0  0
##                   M  0  0  0  0  0  0  1  0  0  0  0  0 71  1  0  0  0  0  0  0
##                   N  0  0  0  0  0  1  0  0  0  0  0  0  0 78  0  0  0  0  0  0
```

```
##                    O  0  0  1  0  0  0  0  0  0  1  0  0  0  2 67  1  2  0  0  0
##                    P  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 72  0  0  0  0
##                    Q  0  0  0  0  0  0  0  1  0  0  0  0  0  0  3  1 65  0  0  0
##                    R  0  1  0  0  0  0  1  1  0  0  4  0  0  2  1  0  0 74  0  1
##                    S  0  1  0  0  0  0  0  0  1  1  0  0  0  0  0  0  0  0 68  0
##                    T  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0 88
##                    U  0  0  0  0  0  0  0  1  0  0  0  0  0  0  0  0  0  0  0  0
##                    V  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0
##                    W  0  0  1  0  0  0  0  0  0  0  0  0  1  0  2  0  0  0  0  0
##                    X  0  1  0  0  0  0  0  0  0  0  2  4  0  0  0  0  0  0  0  0
##                    Y  3  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  0  1
##                    Z  0  0  0  0  2  0  0  0  0  0  0  0  0  0  0  0  0  0  1  0
##
## letter_predictions3  U  V  W  X  Y  Z
##                    A  0  0  0  0  0  0
##                    B  0  1  0  0  0  0
##                    C  0  0  0  0  0  0
##                    D  1  0  0  0  0  0
##                    E  0  0  0  0  0  0
##                    F  0  1  0  0  0  0
##                    G  0  0  0  0  0  0
##                    H  0  1  0  0  0  0
##                    I  0  0  0  2  0  0
##                    J  0  0  0  0  0  1
##                    K  0  0  0  0  0  0
##                    L  0  0  0  0  0  0
##                    M  0  0  2  0  0  0
##                    N  0  0  1  0  0  0
##                    O  0  0  0  0  0  0
##                    P  0  0  0  0  0  0
##                    Q  0  0  0  0  0  0
##                    R  0  0  0  0  0  0
##                    S  0  0  0  0  0  0
##                    T  0  0  0  0  1  0
##                    U 89  0  0  0  0  0
##                    V  0 68  0  0  1  0
##                    W  1  0 66  0  0  0
##                    X  0  0  0 84  1  0
##                    Y  0  0  0  0 65  0
##                    Z  0  0  0  0  0 81
```

```r
agreement3 = letter_predictions3 == letters_test$letter
table(agreement3)
```

```
## agreement3
## FALSE  TRUE
##   133  1867
```

Using the Polynomial Kernal the initial error rate remains the same, but it decreased to 4.8% when using the RBF kernel. Upon using the Polynomial Kernel, the model accuracy improves to 84% whereas using the RBF kernal, the accuracy of the model is improved further to 93.45%.

Lab 2 News popularity

Part 4

Loading & pre-processing the dataset

```r
# loading the data and checking data structure
news_data = read.csv("/Users/akhilasaineni/Downloads/HU/2020Fall/ANLY_530_MachineLearning1/Lab2/OnlineNe
str(news_data)
```

```
## 'data.frame':    39644 obs. of  61 variables:
##  $ url                          : Factor w/ 39644 levels "http://mashable.com/2013/01/07/amazon-insta
##  $ timedelta                    : num  731 731 731 731 731 731 731 731 731 731 ...
##  $ n_tokens_title               : num  12 9 9 9 13 10 8 12 11 10 ...
##  $ n_tokens_content             : num  219 255 211 531 1072 ...
##  $ n_unique_tokens              : num  0.664 0.605 0.575 0.504 0.416 ...
##  $ n_non_stop_words             : num  1 1 1 1 1 ...
##  $ n_non_stop_unique_tokens     : num  0.815 0.792 0.664 0.666 0.541 ...
##  $ num_hrefs                    : num  4 3 3 9 19 2 21 20 2 4 ...
##  $ num_self_hrefs               : num  2 1 1 0 19 2 20 20 0 1 ...
##  $ num_imgs                     : num  1 1 1 1 20 0 20 20 0 1 ...
##  $ num_videos                   : num  0 0 0 0 0 0 0 0 0 1 ...
##  $ average_token_length         : num  4.68 4.91 4.39 4.4 4.68 ...
##  $ num_keywords                 : num  5 4 6 7 7 9 10 9 7 5 ...
##  $ data_channel_is_lifestyle    : num  0 0 0 0 0 0 1 0 0 0 ...
##  $ data_channel_is_entertainment: num  1 0 0 1 0 0 0 0 0 0 ...
##  $ data_channel_is_bus          : num  0 1 1 0 0 0 0 0 0 0 ...
##  $ data_channel_is_socmed       : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ data_channel_is_tech         : num  0 0 0 0 1 1 0 1 1 0 ...
##  $ data_channel_is_world        : num  0 0 0 0 0 0 0 0 0 1 ...
##  $ kw_min_min                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ kw_max_min                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ kw_avg_min                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ kw_min_max                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ kw_max_max                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ kw_avg_max                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ kw_min_avg                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ kw_max_avg                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ kw_avg_avg                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ self_reference_min_shares    : num  496 0 918 0 545 8500 545 545 0 0 ...
##  $ self_reference_max_shares    : num  496 0 918 0 16000 8500 16000 16000 0 0 ...
##  $ self_reference_avg_sharess   : num  496 0 918 0 3151 ...
##  $ weekday_is_monday            : num  1 1 1 1 1 1 1 1 1 1 ...
##  $ weekday_is_tuesday           : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ weekday_is_wednesday         : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ weekday_is_thursday          : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ weekday_is_friday            : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ weekday_is_saturday          : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ weekday_is_sunday            : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ is_weekend                   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ LDA_00                       : num  0.5003 0.7998 0.2178 0.0286 0.0286 ...
##  $ LDA_01                       : num  0.3783 0.05 0.0333 0.4193 0.0288 ...
##  $ LDA_02                       : num  0.04 0.0501 0.0334 0.4947 0.0286 ...
```

```
##  $ LDA_03                      : num  0.0413 0.0501 0.0333 0.0289 0.0286 ...
##  $ LDA_04                      : num  0.0401 0.05 0.6822 0.0286 0.8854 ...
##  $ global_subjectivity         : num  0.522 0.341 0.702 0.43 0.514 ...
##  $ global_sentiment_polarity   : num  0.0926 0.1489 0.3233 0.1007 0.281 ...
##  $ global_rate_positive_words  : num  0.0457 0.0431 0.0569 0.0414 0.0746 ...
##  $ global_rate_negative_words  : num  0.0137 0.01569 0.00948 0.02072 0.01213 ...
##  $ rate_positive_words         : num  0.769 0.733 0.857 0.667 0.86 ...
##  $ rate_negative_words         : num  0.231 0.267 0.143 0.333 0.14 ...
##  $ avg_positive_polarity       : num  0.379 0.287 0.496 0.386 0.411 ...
##  $ min_positive_polarity       : num  0.1 0.0333 0.1 0.1364 0.0333 ...
##  $ max_positive_polarity       : num  0.7 0.7 1 0.8 1 0.6 1 1 0.8 0.5 ...
##  $ avg_negative_polarity       : num  -0.35 -0.119 -0.467 -0.37 -0.22 ...
##  $ min_negative_polarity       : num  -0.6 -0.125 -0.8 -0.6 -0.5 -0.4 -0.5 -0.5 -0.125 -0.5 ...
##  $ max_negative_polarity       : num  -0.2 -0.1 -0.133 -0.167 -0.05 ...
##  $ title_subjectivity          : num  0.5 0 0 0 0.455 ...
##  $ title_sentiment_polarity    : num  -0.188 0 0 0 0.136 ...
##  $ abs_title_subjectivity      : num  0 0.5 0.5 0.5 0.0455 ...
##  $ abs_title_sentiment_polarity : num  0.188 0 0 0 0.136 ...
##  $ shares                      : int  593 711 1500 1200 505 855 556 891 3600 710 ...
```

```r
summary(news_data)
```

```
##                                                               url
##  http://mashable.com/2013/01/07/amazon-instant-video-browser/  :    1
##  http://mashable.com/2013/01/07/ap-samsung-sponsored-tweets/   :    1
##  http://mashable.com/2013/01/07/apple-40-billion-app-downloads/:    1
##  http://mashable.com/2013/01/07/astronaut-notre-dame-bcs/      :    1
##  http://mashable.com/2013/01/07/att-u-verse-apps/              :    1
##  http://mashable.com/2013/01/07/beewi-smart-toys/              :    1
##  (Other)                                                       :39638
##    timedelta     n_tokens_title n_tokens_content n_unique_tokens
##  Min.   :  8.0   Min.   : 2.0   Min.   :   0.0   Min.   :  0.0000
##  1st Qu.:164.0   1st Qu.: 9.0   1st Qu.: 246.0   1st Qu.:  0.4709
##  Median :339.0   Median :10.0   Median : 409.0   Median :  0.5392
##  Mean   :354.5   Mean   :10.4   Mean   : 546.5   Mean   :  0.5482
##  3rd Qu.:542.0   3rd Qu.:12.0   3rd Qu.: 716.0   3rd Qu.:  0.6087
##  Max.   :731.0   Max.   :23.0   Max.   :8474.0   Max.   :701.0000
##
##  n_non_stop_words    n_non_stop_unique_tokens   num_hrefs
##  Min.   :   0.0000   Min.   :  0.0000         Min.   :  0.00
##  1st Qu.:   1.0000   1st Qu.:  0.6257         1st Qu.:  4.00
##  Median :   1.0000   Median :  0.6905         Median :  8.00
##  Mean   :   0.9965   Mean   :  0.6892         Mean   : 10.88
##  3rd Qu.:   1.0000   3rd Qu.:  0.7546         3rd Qu.: 14.00
##  Max.   :1042.0000   Max.   :650.0000         Max.   :304.00
##
##  num_self_hrefs       num_imgs          num_videos    average_token_length
##  Min.   :  0.000   Min.   :  0.000   Min.   : 0.00   Min.   :0.000
##  1st Qu.:  1.000   1st Qu.:  1.000   1st Qu.: 0.00   1st Qu.:4.478
##  Median :  3.000   Median :  1.000   Median : 0.00   Median :4.664
##  Mean   :  3.294   Mean   :  4.544   Mean   : 1.25   Mean   :4.548
##  3rd Qu.:  4.000   3rd Qu.:  4.000   3rd Qu.: 1.00   3rd Qu.:4.855
##  Max.   :116.000   Max.   :128.000   Max.   :91.00   Max.   :8.042
##
```

```
##   num_keywords    data_channel_is_lifestyle data_channel_is_entertainment
##  Min.   : 1.000   Min.   :0.00000          Min.   :0.000
##  1st Qu.: 6.000   1st Qu.:0.00000          1st Qu.:0.000
##  Median : 7.000   Median :0.00000          Median :0.000
##  Mean   : 7.224   Mean   :0.05295          Mean   :0.178
##  3rd Qu.: 9.000   3rd Qu.:0.00000          3rd Qu.:0.000
##  Max.   :10.000   Max.   :1.00000          Max.   :1.000
##
##  data_channel_is_bus data_channel_is_socmed data_channel_is_tech
##  Min.   :0.0000      Min.   :0.0000         Min.   :0.0000
##  1st Qu.:0.0000      1st Qu.:0.0000         1st Qu.:0.0000
##  Median :0.0000      Median :0.0000         Median :0.0000
##  Mean   :0.1579      Mean   :0.0586         Mean   :0.1853
##  3rd Qu.:0.0000      3rd Qu.:0.0000         3rd Qu.:0.0000
##  Max.   :1.0000      Max.   :1.0000         Max.   :1.0000
##
##  data_channel_is_world   kw_min_min       kw_max_min       kw_avg_min
##  Min.   :0.0000        Min.   : -1.00   Min.   :     0   Min.   :   -1.0
##  1st Qu.:0.0000        1st Qu.: -1.00   1st Qu.:   445   1st Qu.:  141.8
##  Median :0.0000        Median : -1.00   Median :   660   Median :  235.5
##  Mean   :0.2126        Mean   : 26.11   Mean   :  1154   Mean   :  312.4
##  3rd Qu.:0.0000        3rd Qu.:  4.00   3rd Qu.:  1000   3rd Qu.:  357.0
##  Max.   :1.0000        Max.   :377.00   Max.   :298400   Max.   :42827.9
##
##    kw_min_max       kw_max_max       kw_avg_max       kw_min_avg
##  Min.   :     0   Min.   :     0   Min.   :     0   Min.   :  -1
##  1st Qu.:     0   1st Qu.:843300   1st Qu.:172847   1st Qu.:   0
##  Median :  1400   Median :843300   Median :244572   Median :1024
##  Mean   : 13612   Mean   :752324   Mean   :259282   Mean   :1117
##  3rd Qu.:  7900   3rd Qu.:843300   3rd Qu.:330980   3rd Qu.:2057
##  Max.   :843300   Max.   :843300   Max.   :843300   Max.   :3613
##
##    kw_max_avg       kw_avg_avg    self_reference_min_shares
##  Min.   :     0   Min.   :    0   Min.   :     0
##  1st Qu.:  3562   1st Qu.: 2382   1st Qu.:   639
##  Median :  4356   Median : 2870   Median :  1200
##  Mean   :  5657   Mean   : 3136   Mean   :  3999
##  3rd Qu.:  6020   3rd Qu.: 3600   3rd Qu.:  2600
##  Max.   :298400   Max.   :43568   Max.   :843300
##
##  self_reference_max_shares self_reference_avg_sharess weekday_is_monday
##  Min.   :     0            Min.   :     0.0          Min.   :0.000
##  1st Qu.:  1100            1st Qu.:   981.2          1st Qu.:0.000
##  Median :  2800            Median :  2200.0          Median :0.000
##  Mean   : 10329            Mean   :  6401.7          Mean   :0.168
##  3rd Qu.:  8000            3rd Qu.:  5200.0          3rd Qu.:0.000
##  Max.   :843300            Max.   :843300.0          Max.   :1.000
##
##  weekday_is_tuesday weekday_is_wednesday weekday_is_thursday weekday_is_friday
##  Min.   :0.0000     Min.   :0.0000       Min.   :0.0000      Min.   :0.0000
##  1st Qu.:0.0000     1st Qu.:0.0000       1st Qu.:0.0000      1st Qu.:0.0000
##  Median :0.0000     Median :0.0000       Median :0.0000      Median :0.0000
##  Mean   :0.1864     Mean   :0.1875       Mean   :0.1833      Mean   :0.1438
##  3rd Qu.:0.0000     3rd Qu.:0.0000       3rd Qu.:0.0000      3rd Qu.:0.0000
```

```
##  Max.   :1.0000     Max.   :1.0000       Max.   :1.0000      Max.   :1.0000
##
##  weekday_is_saturday weekday_is_sunday   is_weekend         LDA_00
##  Min.   :0.00000     Min.   :0.00000   Min.   :0.0000   Min.   :0.00000
##  1st Qu.:0.00000     1st Qu.:0.00000   1st Qu.:0.0000   1st Qu.:0.02505
##  Median :0.00000     Median :0.00000   Median :0.0000   Median :0.03339
##  Mean   :0.06188     Mean   :0.06904   Mean   :0.1309   Mean   :0.18460
##  3rd Qu.:0.00000     3rd Qu.:0.00000   3rd Qu.:0.0000   3rd Qu.:0.24096
##  Max.   :1.00000     Max.   :1.00000   Max.   :1.0000   Max.   :0.92699
##
##      LDA_01            LDA_02            LDA_03            LDA_04
##  Min.   :0.00000   Min.   :0.00000   Min.   :0.00000   Min.   :0.00000
##  1st Qu.:0.02501   1st Qu.:0.02857   1st Qu.:0.02857   1st Qu.:0.02857
##  Median :0.03334   Median :0.04000   Median :0.04000   Median :0.04073
##  Mean   :0.14126   Mean   :0.21632   Mean   :0.22377   Mean   :0.23403
##  3rd Qu.:0.15083   3rd Qu.:0.33422   3rd Qu.:0.37576   3rd Qu.:0.39999
##  Max.   :0.92595   Max.   :0.92000   Max.   :0.92653   Max.   :0.92719
##
##  global_subjectivity global_sentiment_polarity global_rate_positive_words
##  Min.   :0.0000      Min.   :-0.39375          Min.   :0.00000
##  1st Qu.:0.3962      1st Qu.: 0.05776          1st Qu.:0.02838
##  Median :0.4535      Median : 0.11912          Median :0.03902
##  Mean   :0.4434      Mean   : 0.11931          Mean   :0.03962
##  3rd Qu.:0.5083      3rd Qu.: 0.17783          3rd Qu.:0.05028
##  Max.   :1.0000      Max.   : 0.72784          Max.   :0.15549
##
##  global_rate_negative_words rate_positive_words rate_negative_words
##  Min.   :0.000000           Min.   :0.0000      Min.   :0.0000
##  1st Qu.:0.009615           1st Qu.:0.6000      1st Qu.:0.1852
##  Median :0.015337           Median :0.7105      Median :0.2800
##  Mean   :0.016612           Mean   :0.6822      Mean   :0.2879
##  3rd Qu.:0.021739           3rd Qu.:0.8000      3rd Qu.:0.3846
##  Max.   :0.184932           Max.   :1.0000      Max.   :1.0000
##
##  avg_positive_polarity min_positive_polarity max_positive_polarity
##  Min.   :0.0000        Min.   :0.00000       Min.   :0.0000
##  1st Qu.:0.3062        1st Qu.:0.05000       1st Qu.:0.6000
##  Median :0.3588        Median :0.10000       Median :0.8000
##  Mean   :0.3538        Mean   :0.09545       Mean   :0.7567
##  3rd Qu.:0.4114        3rd Qu.:0.10000       3rd Qu.:1.0000
##  Max.   :1.0000        Max.   :1.00000       Max.   :1.0000
##
##  avg_negative_polarity min_negative_polarity max_negative_polarity
##  Min.   :-1.0000       Min.   :-1.0000       Min.   :-1.0000
##  1st Qu.:-0.3284       1st Qu.:-0.7000       1st Qu.:-0.1250
##  Median :-0.2533       Median :-0.5000       Median :-0.1000
##  Mean   :-0.2595       Mean   :-0.5219       Mean   :-0.1075
##  3rd Qu.:-0.1869       3rd Qu.:-0.3000       3rd Qu.:-0.0500
##  Max.   : 0.0000       Max.   : 0.0000       Max.   : 0.0000
##
##  title_subjectivity title_sentiment_polarity abs_title_subjectivity
##  Min.   :0.0000     Min.   :-1.00000         Min.   :0.0000
##  1st Qu.:0.0000     1st Qu.: 0.00000         1st Qu.:0.1667
##  Median :0.1500     Median : 0.00000         Median :0.5000
```

```
##  Mean   :0.2824     Mean   : 0.07143         Mean   :0.3418
##  3rd Qu.:0.5000     3rd Qu.: 0.15000         3rd Qu.:0.5000
##  Max.   :1.0000     Max.   : 1.00000         Max.   :0.5000
##
##  abs_title_sentiment_polarity     shares
##  Min.   :0.0000               Min.   :     1
##  1st Qu.:0.0000               1st Qu.:   946
##  Median :0.0000               Median :  1400
##  Mean   :0.1561               Mean   :  3395
##  3rd Qu.:0.2500               3rd Qu.:  2800
##  Max.   :1.0000               Max.   :843300
##
```

```
newsDF = data.frame(news_data$n_tokens_title, news_data$n_tokens_content, news_data$n_unique_tokens, ne

colnames(newsDF) = c("n_tokens_title", "n_tokens_content", "n_unique_tokens", "n_non_stop_words", "num_

# creating a categorical variable
newsDF$shares = as.factor(ifelse(newsDF$shares > 1400,1,0))

# splitting into test and training sets
set.seed(100)
news_rand = newsDF[order(runif(10000)), ]

news_train = news_rand[1:9000, ]
news_test = news_rand[9001:10000, ]

prop.table(table(news_train$shares))
```

```
##
##         0         1
## 0.4733333 0.5266667
```

```
prop.table(table(news_test$shares))
```

```
##
##     0     1
## 0.452 0.548
```

Part 1 Applying the Naive Bayes classifier on Online News popularity data set

```
library(naivebayes)

naiveBayes_model_news = naive_bayes(as.character(shares) ~ ., data= news_train)
naiveBayes_model_news
```

```
##
## ================================== Naive Bayes ==================================
##
##  Call:
```

```
## naive_bayes.formula(formula = as.character(shares) ~ ., data = news_train)
##
## ---------------------------------------------------------------------------
##
## Laplace smoothing: 0
##
## ---------------------------------------------------------------------------
##
##  A priori probabilities:
##
##         0         1
## 0.4733333 0.5266667
##
## ---------------------------------------------------------------------------
##
##  Tables:
##
## ---------------------------------------------------------------------------
##  ::: n_tokens_title (Gaussian)
## ---------------------------------------------------------------------------
##
## n_tokens_title        0        1
##           mean 9.814085 9.690928
##           sd   1.933185 1.971961
##
## ---------------------------------------------------------------------------
##  ::: n_tokens_content (Gaussian)
## ---------------------------------------------------------------------------
##
## n_tokens_content        0        1
##             mean 460.6993 516.9549
##             sd   357.6628 455.6935
##
## ---------------------------------------------------------------------------
##  ::: n_unique_tokens (Gaussian)
## ---------------------------------------------------------------------------
##
## n_unique_tokens         0         1
##            mean 0.5682626 0.5536759
##            sd   0.1121568 0.1244843
##
## ---------------------------------------------------------------------------
##  ::: n_non_stop_words (Gaussian)
## ---------------------------------------------------------------------------
##
## n_non_stop_words          0          1
##             mean 0.99483567 0.99050632
##             sd   0.07168581 0.09698209
##
## ---------------------------------------------------------------------------
##  ::: num_hrefs (Gaussian)
## ---------------------------------------------------------------------------
##
## num_hrefs         0         1
```

```
##      mean  9.336150 10.526160
##      sd    9.002943 11.443908
##
## -------------------------------------------------------------------------------
##
## # ... and 11 more tables
##
## -------------------------------------------------------------------------------
```

```r
# testing model accuracy
naiveBayes_model_news_nat = table(predict(naiveBayes_model_news, news_test), news_test$shares)
```

```
## Warning: predict.naive_bayes(): more features in the newdata are provided as
## there are probability tables in the object. Calculation is performed based on
## features to be found in the tables.
```

```r
(Accuracy_News_NB = sum(diag(naiveBayes_model_news_nat))/sum(naiveBayes_model_news_nat)*100)
```

```
## [1] 52.6
```

An accuracy of 52.6% is seen using the Naive Bayes classification model on the News dataset.

Part 2 Applying the SVM classifier on Online News popularity data set

```r
library(kernlab)

# testing the linear kernel
news_classifier1 = ksvm(shares ~., data = news_train, kernel = "vanilladot")
```

```
##  Setting default kernel parameters
```

```r
news_classifier1
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Linear (vanilla) kernel function.
##
## Number of Support Vectors : 8474
##
## Objective Function Value : -8466.142
## Training error : 0.463556
```

```r
summary(news_classifier1)
```

```
## Length  Class   Mode
##      1   ksvm     S4
```

```r
news_predictions1 = predict(news_classifier1, news_test)
table(news_predictions1, news_test$shares)
```

```
##
## news_predictions1   0   1
##                 0  85  95
##                 1 367 453
```

```r
agreement_news1 = news_predictions1 == news_test$shares
table(agreement_news1)
```

```
## agreement_news1
## FALSE  TRUE
##   462   538
```

```r
# testing the ploynomial kernel
news_classifier2 = ksvm(shares ~., data = news_train, kernel = "polydot")
```

```
##  Setting default kernel parameters
```

```r
news_classifier2
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Polynomial kernel function.
##  Hyperparameters : degree =  1  scale =  1  offset =  1
##
## Number of Support Vectors : 8475
##
## Objective Function Value : -8466.143
## Training error : 0.463556
```

```r
summary(news_classifier2)
```

```
## Length  Class   Mode
##      1   ksvm     S4
```

```r
news_predictions2 = predict(news_classifier2, news_test)
table(news_predictions2, news_test$shares)
```

```
##
## news_predictions2   0   1
##                 0  85  95
##                 1 367 453
```

```r
agreement_news2 = news_predictions2 == news_test$shares
table(agreement_news2)
```

```
## agreement_news2
## FALSE  TRUE
##   462   538
```

```r
# testing the rbf kernel
news_classifier3 = ksvm(shares ~., data = news_train, kernel = "rbfdot")
news_classifier3
```

```
## Support Vector Machine object of class "ksvm"
##
## SV type: C-svc  (classification)
##  parameter : cost C = 1
##
## Gaussian Radial Basis kernel function.
##  Hyperparameter : sigma =  0.0658290578895865
##
## Number of Support Vectors : 8159
##
## Objective Function Value : -7535.62
## Training error : 0.366111
```

```r
summary(news_classifier3)
```

```
## Length  Class   Mode
##      1   ksvm     S4
```

```r
news_predictions3 = predict(news_classifier3, news_test)
table(news_predictions3, news_test$shares)
```

```
##
## news_predictions3   0   1
##                 0 196 159
##                 1 256 389
```

```r
agreement_news3 = news_predictions3 == news_test$shares
table(agreement_news3)
```

```
## agreement_news3
## FALSE  TRUE
##   415   585
```

The SVM classification model is tested on the News dataset, the Linear kernal shows an initial training error of 46.35%, with a final model accuracy of 54.3%. The Ploynomial kernal shows a similar initial training error of 46.35%, with a final model accuracy of 54.7%. The Linear kernal shows an initial training error of 36.61%, with a final model accuracy of 56.6%. In this case, the RBF kernal performed the best.

Summary

The aim of this assignment was to explore the 2 given datasets so as to improve the understanding of how the Naive Bayes and SVM classification algorithms work. The News dataset is tested for all the above algorithms, with the final model built by both the Naive Bayes and SVM algorithms receiving a decent model accuracy of 51.9% and 56.6% respectively.