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Applied Data Science

IST687 Intro to Data Science, Spring 2019
Due Date: 06/4/2019
Homework: 9

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#R Code - unexecuted

```
## Homework Week 9: Support Vector Machines

#--- Preprocess Steps:--------------------------------------------------------------------

### Clear objects from Memory
rm(list=ls())
### Clear Console:
cat("\014")
### Set Working Directory
setwd("C:\\workspaces\\ms_datascience_su\\IST687-IntroDataScience\\R_workspace\\hw")

#---- Global Variable Assignments --------------------------------------------


#---- Load Required Packages -----------------------------------------------
if(!require("devtools")) {install.packages("devtools")}
devtools::install_github("dkahle/ggmap")
if(!require("ggplot2")){install.packages("ggplot2")}
if(!require("dplyr")) {install.packages("dplyr")}
if(!require("e1071")) {install.packages("e1071")}
```

```
if(!require("arulesViz")) {install.packages("arulesViz")}
if(!require("gridExtra")) {install.packages("gridExtra")}
if(!require("caret")) {install.packages("caret")}
if(!require("kernlab")) {install.packages("kernlab")}
if(!require("arules")) {install.packages("arules")}


#---- Step 1: Load the data -------------------------
## Air Quality dataset

##-- 1.1: Clean the dataset
air <- airquality

#-- 1.2: Clean the data -------------------------------------------------

### Replace NA with column means
na.2.mean <- function(x){
  replace(x, is.na(x), mean(x, na.rm = TRUE))
}

cleanDataSet <- function(ds){
  #Make all empty cells equal to NA
  ds[ds==""] <- NA

  #Clean NA Columns from Dataframe
  ds <- ds[ ,!apply(ds,2,function(x) all(is.na(x)))]

  #Clean empty Rows from Dataframe
  ds <- ds[!apply(ds,1,function(x) all(is.na(x))),]

  # replace NA's in Ozone col with mean of col (where NA is discarded when calculating the mean)
  ds$Ozone[is.na(ds$Ozone)] <- mean(ds$Ozone,na.rm=TRUE)
```

```
  ds$Ozone <- round(ds$Ozone)
  ds$Solar.R[is.na(ds$Solar.R)] <- mean(ds$Solar.R,na.rm=TRUE)
  ds$Solar.R <- round(ds$Solar.R)

  return(ds)
}

clean.air <- cleanDataSet(air)

#-- 1.3: Understand the data --------------------------------------------
str(clean.air)
summary(clean.air)
head(clean.air)

#---- Step 2: Create train and test data sets -------------------------
# Set repeatable random seed
set.seed(4)
partitionDataSet <- function(ds, fractionOfTest = 0.3){
  randoms <- runif(nrow(ds))
  cutoff <- quantile(randoms, fractionOfTest)
  testFlag <- randoms <= cutoff
  testingData <- ds[testFlag,]
  trainingData <- ds[!testFlag,]
  dataSetSplit <- list(trainingData=trainingData, testingData=testingData)
  return(dataSetSplit)
}


## Using techniques discussed in class, create two datasets - one for training and one for testing.
dim(clean.air)
clean.air[1:5,]
randIndex <- sample(1:nrow(clean.air))
```

```
randIndex
length(randIndex)

## Create a 2/3 cutpoint and round the number
cutPoint <- floor(2*nrow(clean.air)/3)
cutPoint

## Create train data set, contains the first 2/3 of overall data
train <- clean.air[randIndex[1:cutPoint],]
dim(train)
head(train)

## Create test data set, contains the rest of the 1/3 data that remains
test <- clean.air[randIndex[(cutPoint+1):nrow(clean.air)],]
dim(test)
head(test)

## Test exact split function
airDataSetSplits <- partitionDataSet(clean.air,0.33)
dim(airDataSetSplits$trainingData)
head(airDataSetSplits$trainingData)

dim(airDataSetSplits$testingData)
head(airDataSetSplits$testingData)

#---- Step 2.1: LM Model ------------------------------------------------------------
airLmModel <- lm(Ozone ~ .,data=train)
summary(airLmModel)
airLmPred <- predict(airLmModel,test)
airLmPred

str(airLmPred)
```

```
compTable3 <- data.frame(test[,1],round(airLmPred))
colnames(compTable3) <- c("test","Pred")

# RMSE = 18.8
round(sqrt(mean((compTable3$test-compTable3$Pred)^2)),1)

#lm plot
compTable3$error <- abs(compTable3$test - compTable3$Pred)
plot3 <- data.frame(compTable3$error,test$Temp, test$Wind)
colnames(plot3) <- c("error","Temp","Wind")
plot.lm.Ozone <- ggplot(plot3, aes(x=Temp, y=Wind)) +
  geom_point(aes(size=error, color=error)) +
  ggtitle("Linear Model (LM), Airquality, Predict Ozone levels with Error dimension")
ggsave("LM_Scatter_Plot_Prediction_of_Ozone.jpg", width = 6, height = 6)
plot.lm.Ozone

#---- Step 3: Build a Model using KSVM & visualize the results -------------------------

##-- 3.1: Build a model (using the 'ksvm' function, trying to predict ozone).
#       You can use all the possible attributes, or select the attributes that
#       you think would be the most helpful.

## Training Step - Ozone is the target predicting variable
# Kernel -> rdfdot: is the kernal function that projects the low-dimensional problem into higher-dimensional space
#         i.e., getting the maximum separation of distance between Ozone cases
# results: Training error = 0.081
#       Cross validation error = 568.72
#       Support Vectors = 91
ksvmOzoneOutput <- ksvm(Ozone ~ ., data=train, kernel="rbfdot", kpar="automatic", C=10, cross=10, prob.model=TRUE )
ksvmOzoneOutput

##-- 3.2: Test the model on the testing dataset, and compute the Root Mean Squared Error
```

```r
ksvmOzonePred <- predict(ksvmOzoneOutput, test, type="votes")
ksvmOzonePred

# Create a comparison dataframe that contains the exact 'Ozone' value and the predicted 'Ozone' value
# use for RMSE calc
ksvmCompTable <- data.frame(test[,1],ksvmOzonePred[,1])
colnames(ksvmCompTable) <- c("test","Pred")
head(ksvmCompTable)

# Compute the Root Mean Squared Error - A smaller value indicates better model performance
# RMSE = 21.59642
sqrt(mean((ksvmCompTable$test - ksvmCompTable$Pred)^2))

##-- 3.3: Plot the results. Use a scatter plot. Have the x-axis represent temperature,
#	the y-axis represent wind, the point size and color represent the error,
#	as defined by the actual ozone level minus the predicted ozone level)

# Compute the absolute error for each case
ksvmCompTable$error <- abs(ksvmCompTable$test - ksvmCompTable$Pred)

# Create new dataframe contains error, temperature and wind
ksvmOzonePlotDf <- data.frame(ksvmCompTable$error, test$Temp, test$Wind, test$Ozone)
colnames(ksvmOzonePlotDf) <- c("error","Temp","Wind","Ozone")

# Plot results - using point size and color shade to illustrate how big the error is
plot.ksvm.Ozone <- ggplot(ksvmOzonePlotDf, aes(x=Temp, y=Wind)) +
  geom_point(aes(size=error, color=error)) +
  ggtitle("KSVM Scatter Plot, Prediction of Ozone with Error dimensions")
ggsave("KSVM_Scatter_Plot_Prediction_of_Ozone_With_Error.jpg", width = 6, height = 6)
plot.ksvm.Ozone

##-- 3.4: Compute models and plot the results for 'svm' (in the e1071 package)
```

```
#
## Training Step - Ozone is the target predicting variable
# Kernel -> rdfdot: is the kernal function that projects the low-dimensional problem into higher-dimensional space
#          i.e., getting the maximum separation of distance between Ozone cases
svmOzoneOutput <- svm(Ozone ~ ., data=train, kernel="radial", C=10, cross=10, prob.model=TRUE )
svmOzoneOutput

## Test the model on the testing dataset, and compute the Root Mean Squared Error
svmOzonePred <- predict(svmOzoneOutput, test)
svmOzonePred
str(svmOzonePred)

# Create a comparison dataframe that contains the exact 'Ozone' value and the predicted 'Ozone' value
# use for RMSE calc
svmCompTable <- data.frame(select(test,'Ozone'),svmOzonePred)
colnames(svmCompTable) <- c("test","Pred")
head(svmCompTable)

# Compute the Root Mean Squared Error - A smaller value indicates better model performance
# RMSE = 16.54
sqrt(mean((svmCompTable$test - svmCompTable$Pred)^2))

##-- 3.3: Plot the results. Use a scatter plot. Have the x-axis represent temperature,
#        the y-axis represent wind, the point size and color represent the error,
#        as defined by the actual ozone level minus the predicted ozone level)

# Compute the absolute error for each case
svmCompTable$error <- abs(svmCompTable$test - svmCompTable$Pred)

# Create new dataframe contains error, temperature and wind
svmOzonePlotDf <- data.frame(round(svmCompTable$error,2), test$Temp, test$Wind, test$Ozone)
colnames(svmOzonePlotDf) <- c("error","Temp","Wind","Ozone")
```

```
# Plot results - using point size and color shade to illustrate how big the error is
plot.svm.Ozone <- ggplot(svmOzonePlotDf, aes(x=Temp, y=Wind)) +
  geom_point(aes(size=error, color=error)) +
  ggtitle("SVM Scatter Plot, Prediction of Ozone with Error dimensions")
ggsave("SVM_Scatter_Plot_Prediction_of_Ozone_With_Error.jpg", width = 6, height = 6)
plot.svm.Ozone


##-- 3.5: Show all three results (charts) in one window, using the grid.arrange function
ga3 <- grid.arrange(plot.ksvm.Ozone, plot.svm.Ozone, plot.lm.Ozone, ncol=3, nrow=2, top="Step 3 Model Comparisions")
ggsave(file="Grid_Arrange_KSVM-SVM-LM.jpg", ga3, width = 24, height = 12)


#---- Step 4: Create a 'goodOzone' variable ------------------------
##-- This variable should be either 0 or 1. It should be 0 if the ozone is below the average for all
#   the data observations, and 1 if it is equal to or above the average ozone observed.

avgOzone <- round(mean(clean.air$Ozone))
avgOzone
train$goodOzone <- ifelse(train$Ozone<avgOzone,0,1)
test$goodOzone <- ifelse(test$Ozone<avgOzone,0,1)
head(train)
head(test)

#---- Step 5: See if we can do a better job predicting 'good' and 'bad' days  ------------------------
train$goodOzone <- as.factor(train$goodOzone)
test$goodOzone <- as.factor(test$goodOzone)
train <- select(train,-'Ozone')
test <- select(test,-'Ozone')
str(train)
str(test)
```

```
##-- 5.1: Build a model (using the 'ksvm' function, trying to predict 'goodozone').
#       You can use all the possible attributes, or select the attributes that you think
#       would be the most helpful.
# Output Results:
#   Training error: 0.098
#   Cross Validation error: 0.354
#   Support Vectors: 61
ksvmOzoneOutputGood <- ksvm(goodOzone ~ ., data=train, kernel="rbfdot", kpar="automatic", C=10, cross=10, prob.model=TRUE)
ksvmOzoneOutputGood

##-- 5.2: Test the model on the testing dataset, and compute the percent of 'goodOzone' that was correctly predicted.
ksvmOzonePredGood <- predict(ksvmOzoneOutputGood, test)
ksvmOzoneCompGood1 <- data.frame(select(test,'goodOzone'), ksvmOzonePredGood)
colnames(ksvmOzoneCompGood1) <- c('test','Pred')
head(ksvmOzoneCompGood1)

# Percent of goodOzone that was correctly predicted
# Output: 0.705 or 70%
percKSVMCorrect <- length(which(ksvmOzoneCompGood1$test==ksvmOzoneCompGood1$Pred))/dim(ksvmOzoneCompGood1)[1]
percKSVMCorrect

# Confusion Matrix
# result output: 0 class, 18 identified correctly, 5 identified incorrectly
# result output: 1 class, 10 identified incorrectly, 18 identified correctly
ksvmResults <- table(test=ksvmOzoneCompGood1$test, pred=ksvmOzoneCompGood1$Pred)
print(ksvmResults)
length(ksvmOzoneCompGood1$test)

# Error & Accuracy Score Rate:
ksvmErrorRate <- round((ksvmResults[1,][[2]] + ksvmResults[2,][[1]]) / nrow(ksvmOzoneCompGood1) *100,2)
ksvmErrorRate
```

```
ksvmAccuracyRate <- 100-ksvmErrorRate
ksvmAccuracyRate

##-- 5.3: Plot the results. Use a scatter plot. Have the x-axis represent temperature,
#        the y-axis represent wind, the shape representing what was predicted (good or bad day),
#        the color representing the actual value of 'goodozone' (i.e., if the actual ozone level was good)
#        and the size represent if the prediction was correct (larger symbols should be the observations the model got wrong)
ksvmOzoneCompGood1$correct <- ifelse(ksvmOzoneCompGood1$test==ksvmOzoneCompGood1$Pred,'correct','wrong')
plotksvmOzoneCompGood1 <- data.frame(ksvmOzoneCompGood1$correct,test$Temp,test$Wind,test$goodOzone,ksvmOzoneCompGood1$Pred)
colnames(plotksvmOzoneCompGood1) <- c("correct","Temp","Wind","goodOzone","Predict")
plot.ksvm.good <- ggplot(plotksvmOzoneCompGood1, aes(x=Temp,y=Wind)) +
  geom_point(aes(size=correct, color=goodOzone, shape=Predict)) +
  ggtitle("KSVM - Good/Bad Ozone Prediction")
ggsave("KSVM_Good_Bad_Ozone_Prediction.jpg", width = 6, height = 6)
plot.ksvm.good


##-- 5.3: Compute models and plot the results for 'svm' (in the e1071 package) and 'nb' (Naive Bayses)
#
## 5.3.1: Models & Plots for svm
svmOzoneOutputGood <- svm(goodOzone ~ ., data=train, kernel='radial', C=10, cross=10, prob.model=TRUE)
svmOzoneOutputGood

# Test the svm model
svmOzonePredGood <- predict(svmOzoneOutputGood, test)
svmOzoneCompGood1 <- data.frame(select(test,'goodOzone'), svmOzonePredGood)
colnames(svmOzoneCompGood1) <- c('test','Pred')
head(svmOzoneCompGood1)

# Percent of goodOzone that was correctly predicted
percSVMCorrect <- length(which(svmOzoneCompGood1$test==svmOzoneCompGood1$Pred))/dim(svmOzoneCompGood1)[1]
percSVMCorrect
```

```
# Confusion Matrix
# result output: 0 class, 21 identified correctly, 5 identified incorrectly
# result output: 1 class, 7 identified incorrectly, 18 identified correctly
svmResults <- table(test=svmOzoneCompGood1$test, pred=svmOzoneCompGood1$Pred)
print(svmResults)

# Error & Accuracy Score Rate:
svmErrorRate <- round((svmResults[1,][[2]] + svmResults[2,][[1]]) / nrow(svmOzoneCompGood1) *100,2)
svmErrorRate

svmAccuracyRate <- 100-svmErrorRate
svmAccuracyRate


## Plot the results. Use a scatter plot. Have the x-axis represent temperature,
#    the y-axis represent wind, the shape representing what was predicted (good or bad day),
#    the color representing the actual value of 'goodozone' (i.e., if the actual ozone level was good)
#    and the size represent if the prediction was correct (larger symbols should be the observations the model got wrong)
svmOzoneCompGood1$correct <- ifelse(svmOzoneCompGood1$test==svmOzoneCompGood1$Pred,'correct','wrong')
plotSvmOzoneCompGood1 <- data.frame(svmOzoneCompGood1$correct,test$Temp,test$Wind,test$goodOzone,svmOzoneCompGood1$Pred)
colnames(plotSvmOzoneCompGood1) <- c("correct","Temp","Wind","goodOzone","Predict")
plot.svm.good <- ggplot(plotSvmOzoneCompGood1, aes(x=Temp,y=Wind)) +
  geom_point(aes(size=correct, color=goodOzone, shape=Predict)) +
  ggtitle("SVM - Good/Bad Ozone Prediction")
ggsave("SVM_Good_Bad_Ozone_Prediction.jpg", width = 6, height = 6)
plot.svm.good

## 5.3.2: Models & Plots for 'nb'
nbOzoneOutputGood <- naiveBayes(goodOzone ~ ., data=train)
nbOzoneOutputGood
```

```
# Test the naiveBase model
nbOzonePredGood <- predict(nbOzoneOutputGood, test)
nbOzoneCompGood1 <- data.frame(select(test,'goodOzone'), nbOzonePredGood)
colnames(nbOzoneCompGood1) <- c('test','Pred')
head(nbOzoneCompGood1)

# Percent of goodOzone that was correctly predicted
percNBCorrect <- length(which(nbOzoneCompGood1$test==nbOzoneCompGood1$Pred))/dim(nbOzoneCompGood1)[1]
percNBCorrect

# Confusion Matrix
# result output: 0 class, 19 identified correctly, 3 identified incorrectly
# result output: 1 class, 9 identified incorrectly, 20 identified correctly
nbResults <- table(test=nbOzoneCompGood1$test, pred=nbOzoneCompGood1$Pred)
print(nbResults)

nbErrorRate <- round((nbResults[1,][[2]] + nbResults[2,][[1]]) / nrow(nbOzoneCompGood1) *100,2)
nbErrorRate

nbAccuracyRate <- 100-nbErrorRate
nbAccuracyRate


## Plot the results. Use a scatter plot. Have the x-axis represent temperature,
#     the y-axis represent wind, the shape representing what was predicted (good or bad day),
#     the color representing the actual value of 'goodozone' (i.e., if the actual ozone level was good)
#     and the size represent if the prediction was correct (larger symbols should be the observations the model got wrong)
nbOzoneCompGood1$correct <- ifelse(nbOzoneCompGood1$test==nbOzoneCompGood1$Pred,'correct','wrong')
plotNBOzoneCompGood1 <- data.frame(nbOzoneCompGood1$correct,test$Temp,test$Wind,test$goodOzone,nbOzoneCompGood1$Pred)
colnames(plotNBOzoneCompGood1) <- c("correct","Temp","Wind","goodOzone","Predict")
plot.nb.good <- ggplot(plotNBOzoneCompGood1, aes(x=Temp,y=Wind)) +
  geom_point(aes(size=correct, color=goodOzone, shape=Predict)) +
```

```
  ggtitle("Niave Baise - Good/Bad Ozone Prediction")
ggsave("NB_Good_Bad_Ozone_Prediction.jpg", width = 6, height = 6)
plot.nb.good

##-- 5.5: Show all three results (charts) in one window, using the grid.array function (have two charts in one row)
ga5 <- grid.arrange(plot.ksvm.good, plot.svm.good, plot.nb.good, ncol=3, nrow=2, top="Step 5 Model Comparisions")
ggsave(file="Grid_Arrange_Good_KSVM-SVM-NB.jpg", ga5, width = 24, height = 12)

#---- Step 6: Which are the best Models for this data? -------------------------
## Review what you have done and state which is the best and why
#
# Answer: It's observed that the SVM and Naive Baise models have the heighest accuracy ratings, measured at 76.5%,
#         for predicting the goodOzone Class. The result output calculation of Accuracy Rating for each model is shown below.
#
## Output Results ##
# Step 3 results:
# LM:   RMSE = 18.8
# KSVM: RMSE = 21.59642
# SVM:  RMSE = 16.54
#
# Step 5 results:
# KSVM:
#    Accuracy Rate: 70.59%
#    Error Rate:  29.41%
# SVM:
#    Accuracy Rate: 76.47%
#    Error Rate: 23.53%
# Naive Baise:
#    Accuracy Rate: 76.47%
#    Error Rate: 23.53%
#---------------------------------------------------------------------------------
```

#R Code – executed

```
> ### Set Working Directory
> setwd("C:\\workspaces\\ms_datascience_su\\IST687-IntroDataScience\\R_workspace\\hw")
>
> #---- Global Variable Assignments ---------------------------------------------
>
>
> #---- Load Required Packages -------------------------------------------------
> if(!require("devtools")) {install.packages("devtools")}
> devtools::install_github("dkahle/ggmap")
> if(!require("ggplot2")){install.packages("ggplot2")}
> if(!require("dplyr")) {install.packages("dplyr")}
> if(!require("e1071")) {install.packages("e1071")}
> if(!require("arulesViz")) {install.packages("arulesViz")}
> if(!require("gridExtra")) {install.packages("gridExtra")}
> if(!require("caret")) {install.packages("caret")}
> if(!require("kernlab")) {install.packages("kernlab")}
> if(!require("arules")) {install.packages("arules")}
>
>
> #---- Step 1: Load the data -------------------------
> ## Air Quality dataset
>
> ##-- 1.1: Clean the dataset
> air <- airquality
>
> #-- 1.2: Clean the data --------------------------------------------------
>
> ### Replace NA with column means
> na.2.mean <- function(x){
+   replace(x, is.na(x), mean(x, na.rm = TRUE))
+ }
>
> cleanDataSet <- function(ds){
+   #Make all empty cells equal to NA
+   ds[ds==""] <- NA
+
+   #Clean NA Columns from Dataframe
+   ds <- ds[ ,!apply(ds,2,function(x) all(is.na(x)))]
+
+   #Clean empty Rows from Dataframe
+   ds <- ds[!apply(ds,1,function(x) all(is.na(x))),]
+
+   # replace NA's in Ozone col with mean of col (where NA is discarded when calculating the mean)
```

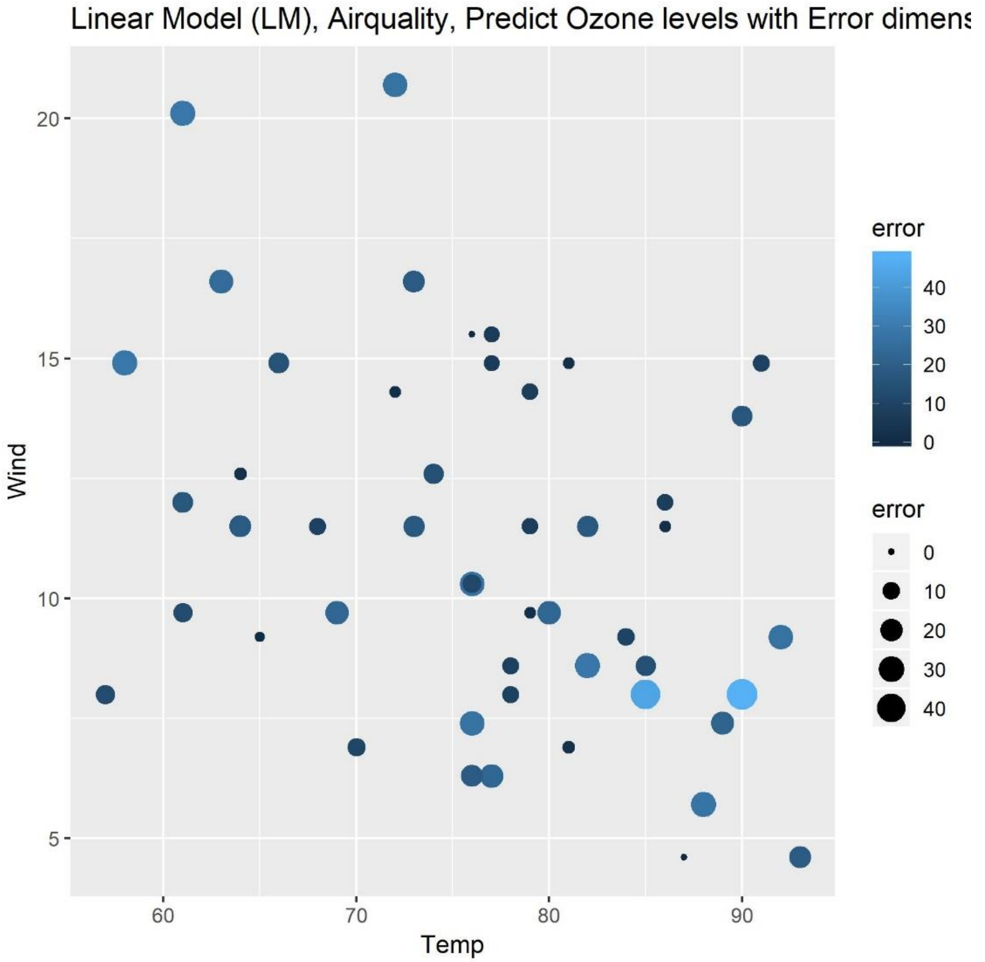
```
+   ds$Ozone[is.na(ds$Ozone)] <- mean(ds$Ozone,na.rm=TRUE)
+   ds$Ozone <- round(ds$Ozone)
+   ds$Solar.R[is.na(ds$Solar.R)] <- mean(ds$Solar.R,na.rm=TRUE)
+   ds$Solar.R <- round(ds$Solar.R)
+
+   return(ds)
+ }
>
> clean.air <- cleanDataSet(air)
>
> #-- 1.3: Understand the data ---------------------------------------------
> str(clean.air)
'data.frame':   153 obs. of  6 variables:
 $ Ozone  : num  41 36 12 18 42 28 23 19 8 42 ...
 $ Solar.R: num  190 118 149 313 186 186 299 99 19 194 ...
 $ Wind   : num  7.4 8 12.6 11.5 14.3 14.9 8.6 13.8 20.1 8.6 ...
 $ Temp   : int  67 72 74 62 56 66 65 59 61 69 ...
 $ Month  : int  5 5 5 5 5 5 5 5 5 5 ...
 $ Day    : int  1 2 3 4 5 6 7 8 9 10 ...
> summary(clean.air)
     Ozone           Solar.R           Wind             Temp           Month            Day      
 Min.   :  1.0   Min.   :  7.0   Min.   : 1.700   Min.   :56.00   Min.   :5.000   Min.   : 1.0  
 1st Qu.: 21.0   1st Qu.:120.0   1st Qu.: 7.400   1st Qu.:72.00   1st Qu.:6.000   1st Qu.: 8.0  
 Median : 42.0   Median :194.0   Median : 9.700   Median :79.00   Median :7.000   Median :16.0  
 Mean   : 42.1   Mean   :185.9   Mean   : 9.958   Mean   :77.88   Mean   :6.993   Mean   :15.8  
 3rd Qu.: 46.0   3rd Qu.:256.0   3rd Qu.:11.500   3rd Qu.:85.00   3rd Qu.:8.000   3rd Qu.:23.0  
 Max.   :168.0   Max.   :334.0   Max.   :20.700   Max.   :97.00   Max.   :9.000   Max.   :31.0  
> head(clean.air)
  Ozone Solar.R Wind Temp Month Day
1    41     190  7.4   67     5   1
2    36     118  8.0   72     5   2
3    12     149 12.6   74     5   3
4    18     313 11.5   62     5   4
5    42     186 14.3   56     5   5
6    28     186 14.9   66     5   6
>
> #---- Step 2: Create train and test data sets -------------------------
> # Set repeatable random seed
> set.seed(4)
> partitionDataSet <- function(ds, fractionOfTest = 0.3){
+   randoms <- runif(nrow(ds))
+   cutoff <- quantile(randoms, fractionOfTest)
+   testFlag <- randoms <= cutoff
+   testingData <- ds[testFlag,]
+   trainingData <- ds[!testFlag,]
```

```
+   dataSetSplit <- list(trainingData=trainingData, testingData=testingData)
+   return(dataSetSplit)
+ }
>
>
> ## Using techniques discussed in class, create two datasets - one for training and one for testing.
> dim(clean.air)
[1] 153   6
> clean.air[1:5,]
  Ozone Solar.R Wind Temp Month Day
1    41     190  7.4   67     5   1
2    36     118  8.0   72     5   2
3    12     149 12.6   74     5   3
4    18     313 11.5   62     5   4
5    42     186 14.3   56     5   5
> randIndex <- sample(1:nrow(clean.air))
> randIndex
  [1]  90   2  45  42 122  39 107 133 138  11 108  41  15 134  58  63 140  80 130 103  96 132  67  64  84 147  62 128  65  66  70
30 126  79 139
 [36] 115  54  73 151   1 121  28 145  20  99  10  97  95  76  59 142  77  91  81  82 150  18  17  85 123  53   7  78  83  21  56
92 118  69 109
 [71]  29  52  34 112 124 117  25 100 110 143 131 129 137 125 111   4  68 120  14  60  13   8  33 146  89   5  44 102 152  38  94
61  93  27  23
[106] 136  32  74  57  36  12 135  43  75 149  40  98 153  47   3 119 106  50 127 105 104  31   6  51   9  46  72 148 116  16  19
71  22  87 114
[141]  48  24 101  49  55 144 113  26  35  37 141  88  86
> length(randIndex)
[1] 153
>
> ## Create a 2/3 cutpoint and round the number
> cutPoint <- floor(2*nrow(clean.air)/3)
> cutPoint
[1] 102
>
> ## Create train data set, contains the first 2/3 of overall data
> train <- clean.air[randIndex[1:cutPoint],]
> dim(train)
[1] 102   6
> head(train)
    Ozone Solar.R Wind Temp Month Day
90     50     275  7.4   86     7  29
2      36     118  8.0   72     5   2
45     42     332 13.8   80     6  14
42     42     259 10.9   93     6  11
122    84     237  6.3   96     8  30
```

```
39     42     273  6.9   87     6   8
>
> ## Create test data set, contains the rest of the 1/3 data that remains
> test <- clean.air[randIndex[(cutPoint+1):nrow(clean.air)],]
> dim(test)
[1] 51  6
> head(test)
    Ozone Solar.R Wind Temp Month Day
93     39      83  6.9   81     8   1
27     42     186  8.0   57     5  27
23      4      25  9.7   61     5  23
136    28     238  6.3   77     9  13
32     42     286  8.6   78     6   1
74     27     175 14.9   81     7  13
>
> ## Test exact split function
> airDataSetSplits <- partitionDataSet(clean.air,0.33)
> dim(airDataSetSplits$trainingData)
[1] 102   6
> head(airDataSetSplits$trainingData)
  Ozone Solar.R Wind Temp Month Day
1    41     190  7.4   67     5   1
3    12     149 12.6   74     5   3
5    42     186 14.3   56     5   5
6    28     186 14.9   66     5   6
7    23     299  8.6   65     5   7
8    19      99 13.8   59     5   8
>
> dim(airDataSetSplits$testingData)
[1] 51  6
> head(airDataSetSplits$testingData)
   Ozone Solar.R Wind Temp Month Day
2     36     118  8.0   72     5   2
4     18     313 11.5   62     5   4
13    11     290  9.2   66     5  13
14    14     274 10.9   68     5  14
15    18      65 13.2   58     5  15
16    14     334 11.5   64     5  16
>
> #---- Step 2.1: LM Model ----------------------------------------------------------------
> airLmModel <- lm(Ozone ~ .,data=train)
> summary(airLmModel)

Call:
lm(formula = Ozone ~ ., data = train)
```

```
Residuals:
    Min      1Q  Median      3Q     Max 
-43.127 -13.609  -2.886   9.752  95.716 

Coefficients:
             Estimate Std. Error t value Pr(>|t|)    
(Intercept) -32.72841   25.60172  -1.278   0.2042    
Solar.R       0.06502    0.02694   2.413   0.0177 *  
Wind         -3.19521    0.75902  -4.210 5.76e-05 ***
Temp          1.35679    0.31707   4.279 4.44e-05 ***
Month        -2.30716    1.78393  -1.293   0.1990    
Day           0.35835    0.24086   1.488   0.1401    
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 21.92 on 96 degrees of freedom
Multiple R-squared:  0.5078,	Adjusted R-squared:  0.4822 
F-statistic: 19.81 on 5 and 96 DF,  p-value: 1.615e-13

> airLmPred <- predict(airLmModel,test)
> airLmPred
       93        27        23       136        32        74        57        36        12       135        43        
75       149 
 42.422477  29.280078  17.374036  50.983276  50.733316  29.449796  51.271145  57.373034  39.305852  21.237579  69.412436  50.9182
21  41.301254 
       40        98       153        47         3       119       106        50       127       105       104        
31         6 
 53.591597  66.400856  27.273631  28.445118  26.641619  69.622565  41.588951  30.340388  71.712818  45.734955  45.537288  64.4563
85  11.919004 
       51         9        46        72       148       116        16        19        71        22        87         1 
14        48 
 39.708682 -21.263113  50.181500  47.879066 -10.796395  47.391629  33.275326  38.997316  63.193195  30.430706  49.483178  11.0361
58   9.533987 
       24       101        49        55       144       113        26        35        37       141        88        
86 
 14.739633  62.047943  21.080146  61.269998  16.081890  28.126647  13.433045  51.530140  34.238725  24.918465  44.469998  64.3449
64 
> 
> str(airLmPred)
 Named num [1:51] 42.4 29.3 17.4 51 50.7 ...
 - attr(*, "names")= chr [1:51] "93" "27" "23" "136" ...
> compTable3 <- data.frame(test[,1],round(airLmPred))
> colnames(compTable3) <- c("test","Pred")
> 
```

```
> # RMSE = 18.8
> round(sqrt(mean((compTable3$test-compTable3$Pred)^2)),1)
[1] 18.8
>
> #lm plot
> compTable3$error <- abs(compTable3$test - compTable3$Pred)
> plot3 <- data.frame(compTable3$error,test$Temp, test$Wind)
> colnames(plot3) <- c("error","Temp","Wind")
> plot.lm.Ozone <- ggplot(plot3, aes(x=Temp, y=Wind)) +
+   geom_point(aes(size=error, color=error)) +
+   ggtitle("Linear Model (LM), Airquality, Predict Ozone levels with Error dimension")
> ggsave("LM_Scatter_Plot_Prediction_of_Ozone.jpg", width = 6, height = 6)
> plot.lm.Ozone
```

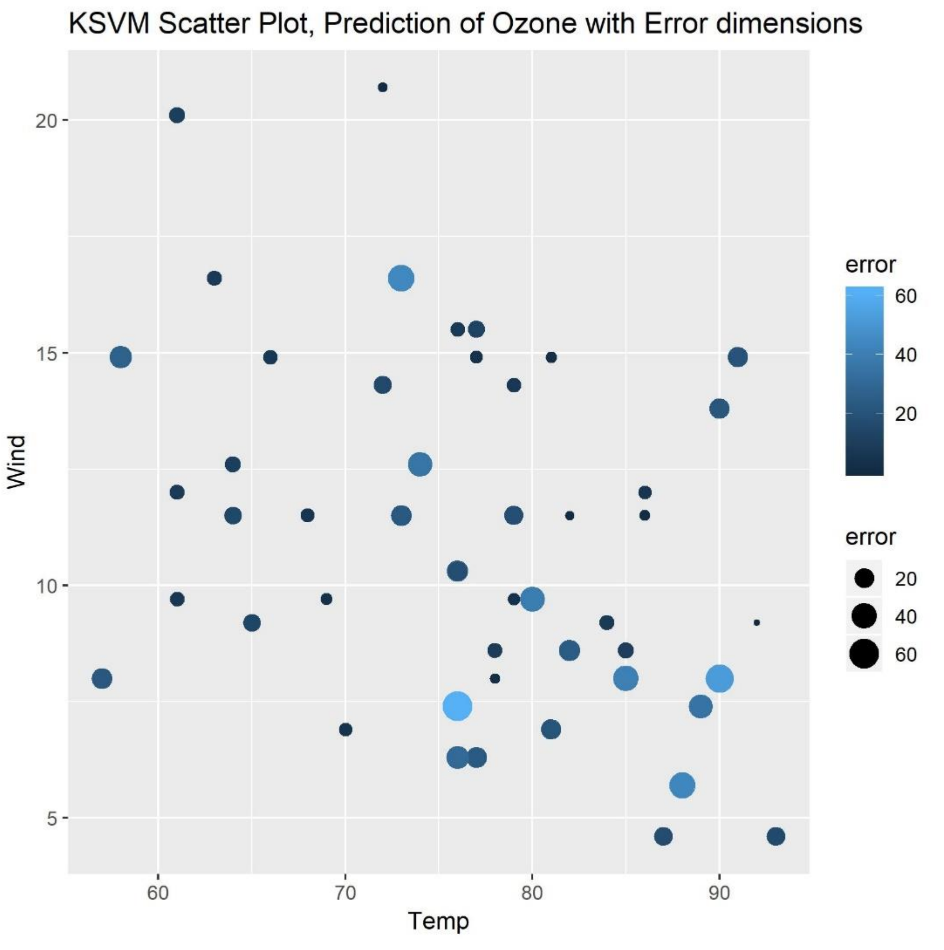



```
>
> #---- Step 3: Build a Model using KSVM & visualize the results -------------------------
>
> ##-- 3.1: Build a model (using the 'ksvm' function, trying to predict ozone).
> #         You can use all the possible attributes, or select the attributes that
> #         you think would be the most helpful.
>
> ## Training Step - Ozone is the target predicting variable
> # Kernel -> rdfdot: is the kernal function that projects the low-dimensional problem into higher-dimensional space
```

```
> #            i.e., getting the maximum separation of distance between Ozone cases
> # results: Training error = 0.081
> #          Cross validation error = 568.72
> #          Support Vectors = 91
> ksvmOzoneOutput <- ksvm(Ozone ~ ., data=train, kernel="rbfdot", kpar="automatic", C=10, cross=10, prob.model=TRUE )
> ksvmOzoneOutput
Support Vector Machine object of class "ksvm"

SV type: eps-svr  (regression)
 parameter : epsilon = 0.1  cost C = 10

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  0.220439906185414

Number of Support Vectors : 89

Objective Function Value : -149.9922
Training error : 0.073994
Cross validation error : 549.7396
Laplace distr. width : 46.05834
>
> ##-- 3.2: Test the model on the testing dataset, and compute the Root Mean Squared Error
> ksvmOzonePred <- predict(ksvmOzoneOutput, test, type="votes")
> ksvmOzonePred
           [,1]
 [1,] 18.166951
 [2,] 64.455104
 [3,] 10.950205
 [4,] 51.717998
 [5,] 50.727273
 [6,] 29.994896
 [7,] 43.561524
 [8,] 31.858064
 [9,] 12.435743
[10,] 28.666047
[11,] 41.849001
[12,] 62.588736
[13,] 35.126635
[14,] 49.318547
[15,] 83.397686
[16,] 18.111359
[17,] 25.381528
[18,] 47.930125
[19,] 85.677968
[20,] 25.732833
```

```
[21,] 34.860444
[22,] 74.933268
[23,] 28.909551
[24,] 46.429706
[25,] 98.285913
[26,] 35.394158
[27,] 37.294241
[28,] -2.640910
[29,] 23.822402
[30,] 23.763612
[31,] 22.429212
[32,] 49.031397
[33,] 28.316769
[34,] 36.086531
[35,] 50.183269
[36,] 55.290535
[37,] 44.862748
[38,] 24.706120
[39,] 35.732445
[40,] 40.480157
[41,] 57.484816
[42,]  5.916529
[43,] 72.844627
[44,] 23.595645
[45,] 33.838382
[46,] 69.411286
[47,] 33.658825
[48,] 34.473067
[49,] 30.457873
[50,] 57.916715
[51,] 67.121088
>
> # Create a comparison dataframe that contains the exact 'Ozone' value and the predicted 'Ozone' value
> # use for RMSE calc
> ksvmCompTable <- data.frame(test[,1],ksvmOzonePred[,1])
> colnames(ksvmCompTable) <- c("test","Pred")
> head(ksvmCompTable)
  test     Pred
1   39 18.16695
2   42 64.45510
3    4 10.95020
4   28 51.71800
5   42 50.72727
6   27 29.99490
>
```

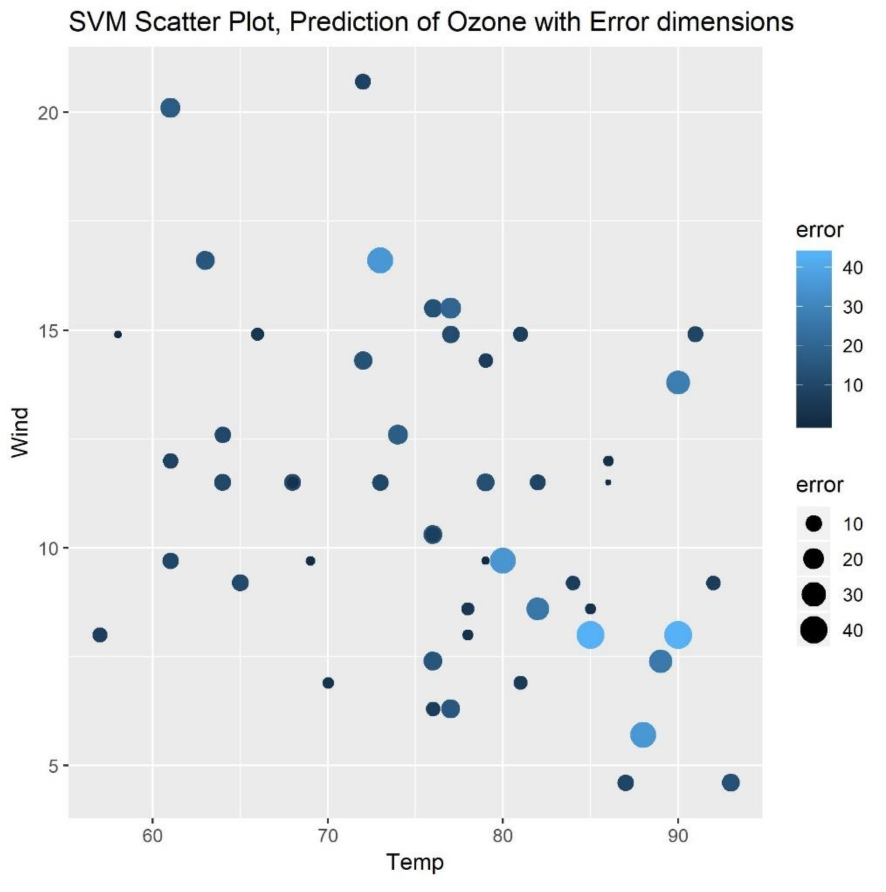
```
> # Compute the Root Mean Squared Error - A smaller value indicates better model performance
> # RMSE = 21.59642
> sqrt(mean((ksvmCompTable$test - ksvmCompTable$Pred)^2))
[1] 22.26252
>
> ##-- 3.3: Plot the results. Use a scatter plot. Have the x-axis represent temperature,
> #         the y-axis represent wind, the point size and color represent the error,
> #         as defined by the actual ozone level minus the predicted ozone level)
>
> # Compute the absolute error for each case
> ksvmCompTable$error <- abs(ksvmCompTable$test - ksvmCompTable$Pred)
>
> # Create new dataframe contains error, temperature and wind
> ksvmOzonePlotDf <- data.frame(ksvmCompTable$error, test$Temp, test$Wind, test$Ozone)
> colnames(ksvmOzonePlotDf) <- c("error","Temp","Wind","Ozone")
>
> # Plot results - using point size and color shade to illustrate how big the error is
> plot.ksvm.Ozone <- ggplot(ksvmOzonePlotDf, aes(x=Temp, y=Wind)) +
+   geom_point(aes(size=error, color=error)) +
+   ggtitle("KSVM Scatter Plot, Prediction of Ozone with Error dimensions")
> ggsave("KSVM_Scatter_Plot_Prediction_of_Ozone_With_Error.jpg", width = 6, height = 6)
> plot.ksvm.Ozone
```




```
>
> ##-- 3.4: Compute models and plot the results for 'svm' (in the e1071 package)
> #
> ## Training Step - Ozone is the target predicting variable
> # Kernel -> rdfdot: is the kernal function that projects the low-dimensional problem into higher-dimensional space
> #           i.e., getting the maximum separation of distance between Ozone cases
> svmOzoneOutput <- svm(Ozone ~ ., data=train, kernel="radial", C=10, cross=10, prob.model=TRUE )
Warning message:
In cret$cresults * scale.factor :
  Recycling array of length 1 in vector-array arithmetic is deprecated.
```

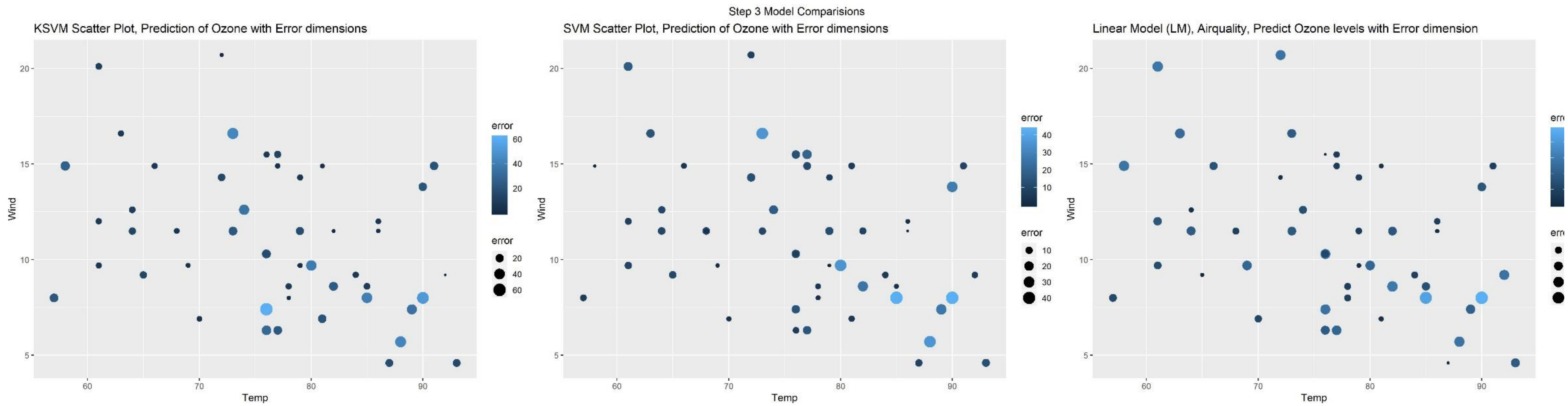
```
  Use c() or as.vector() instead.

> svmOzoneOutput

Call:
svm(formula = Ozone ~ ., data = train, kernel = "radial", C = 10, cross = 10, prob.model = TRUE)


Parameters:
   SVM-Type:  eps-regression 
 SVM-Kernel:  radial 
       cost:  1 
      gamma:  0.2 
    epsilon:  0.1 


Number of Support Vectors:  82

> 
> ## Test the model on the testing dataset, and compute the Root Mean Squared Error
> svmOzonePred <- predict(svmOzoneOutput, test)
> svmOzonePred
       93        27        23       136        32        74        57        36        12       135        43        75       149 
40 
33.049942 34.904249 13.695370 43.430237 37.549640 34.098356 44.226325 39.501597 17.253211 34.748474 48.616004 51.163768 32.850975 
43.206289 
       98       153        47         3       119       106        50       127       105       104        31         6        51 
9 
75.356836 31.218378 32.640250 29.662234 77.516778 29.834708 22.189763 77.718924 36.941442 44.071532 51.688922 32.682183 27.935125 
25.465356 
       46        72       148       116        16        19        71        22        87       114        48        24       101 
49 
29.382416 31.848861 29.087265 44.566448 24.371959 27.090378 58.732153 46.392391 45.646845 22.748363 45.517584 23.780091 66.941354 
8.899384 
       55       144       113        26        35        37       141        88        86 
48.469430 23.204711 41.317757 42.347772 35.325172 35.352311 20.619950 50.217865 64.976495 
> str(svmOzonePred)
 Named num [1:51] 33 34.9 13.7 43.4 37.5 ...
 - attr(*, "names")= chr [1:51] "93" "27" "23" "136" ...
> 
> # Create a comparison dataframe that contains the exact 'Ozone' value and the predicted 'Ozone' value
> # use for RMSE calc
> svmCompTable <- data.frame(select(test,'Ozone'),svmOzonePred)
> colnames(svmCompTable) <- c("test","Pred")
> head(svmCompTable)
```

```
    test     Pred
93    39 33.04994
27    42 34.90425
23     4 13.69537
136   28 43.43024
32    42 37.54964
74    27 34.09836
>
> # Compute the Root Mean Squared Error - A smaller value indicates better model performance
> # RMSE = 16.54
> sqrt(mean((svmCompTable$test - svmCompTable$Pred)^2))
[1] 16.5422
>
> ##-- 3.3: Plot the results. Use a scatter plot. Have the x-axis represent temperature,
> #         the y-axis represent wind, the point size and color represent the error,
> #         as defined by the actual ozone level minus the predicted ozone level)
>
> # Compute the absolute error for each case
> svmCompTable$error <- abs(svmCompTable$test - svmCompTable$Pred)
>
> # Create new dataframe contains error, temperature and wind
> svmOzonePlotDf <- data.frame(round(svmCompTable$error,2), test$Temp, test$Wind, test$Ozone)
> colnames(svmOzonePlotDf) <- c("error","Temp","Wind","Ozone")
>
> # Plot results - using point size and color shade to illustrate how big the error is
> plot.svm.Ozone <- ggplot(svmOzonePlotDf, aes(x=Temp, y=Wind)) +
+   geom_point(aes(size=error, color=error)) +
+   ggtitle("SVM Scatter Plot, Prediction of Ozone with Error dimensions")
> ggsave("SVM_Scatter_Plot_Prediction_of_Ozone_With_Error.jpg", width = 6, height = 6)
> plot.svm.Ozone
```




```
>
>
> ##-- 3.5: Show all three results (charts) in one window, using the grid.arrange function
> ga3 <- grid.arrange(plot.ksvm.Ozone, plot.svm.Ozone, plot.lm.Ozone, ncol=3, nrow=2, top="Step 3 Model Comparisions")
> ggsave(file="Grid_Arrange_KSVM-SVM-LM.jpg", ga3, width = 24, height = 12)
```

```
>
```

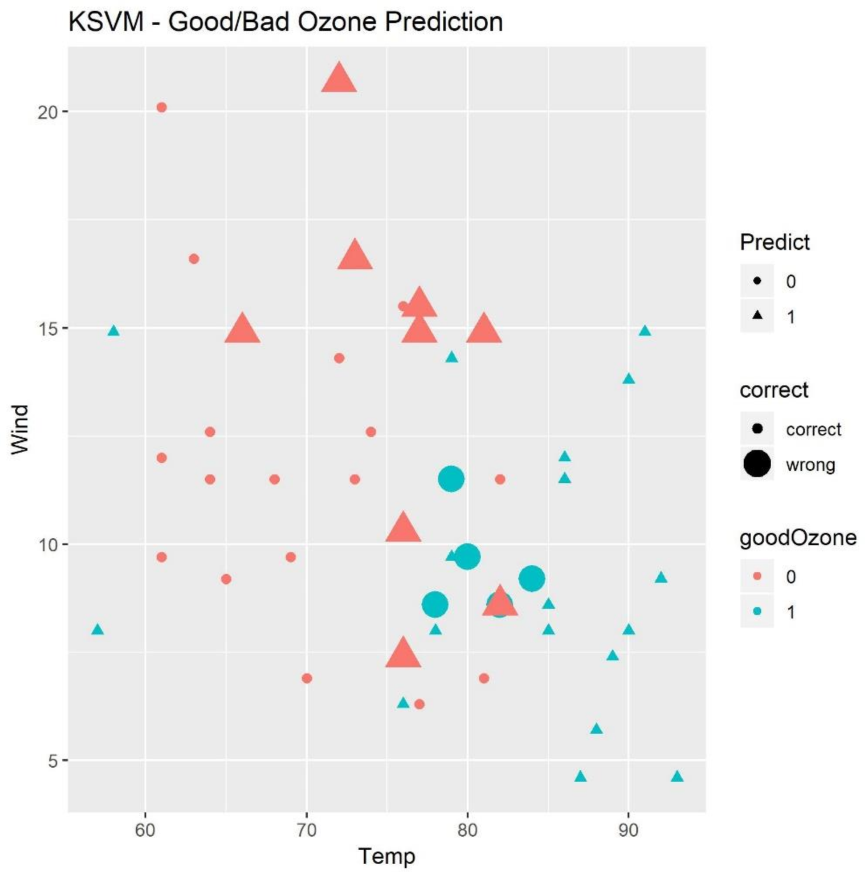



```
>
> #---- Step 4: Create a 'goodOzone' variable -------------------------
> ##-- This variable should be either 0 or 1. It should be 0 if the ozone is below the average for all
> #   the data observations, and 1 if it is equal to or above the average ozone observed.
>
> avgOzone <- round(mean(clean.air$Ozone))
> avgOzone
[1] 42
> train$goodOzone <- ifelse(train$Ozone<avgOzone,0,1)
> test$goodOzone <- ifelse(test$Ozone<avgOzone,0,1)
> head(train)
    Ozone Solar.R Wind Temp Month Day goodOzone
90     50     275  7.4   86     7  29         1
2      36     118  8.0   72     5   2         0
45     42     332 13.8   80     6  14         1
42     42     259 10.9   93     6  11         1
122    84     237  6.3   96     8  30         1
39     42     273  6.9   87     6   8         1
> head(test)
    Ozone Solar.R Wind Temp Month Day goodOzone
93     39      83  6.9   81     8   1         0
27     42     186  8.0   57     5  27         1
23      4      25  9.7   61     5  23         0
```

```
136     28      238  6.3   77      9  13          0
32      42      286  8.6   78      6   1          1
74      27      175 14.9   81      7  13          0
>
> #---- Step 5: See if we can do a better job predicting 'good' and 'bad' days  -------------------------
> train$goodOzone <- as.factor(train$goodOzone)
> test$goodOzone <- as.factor(test$goodOzone)
> train <- select(train,-'Ozone')
> test <- select(test,-'Ozone')
> str(train)
'data.frame':  102 obs. of  6 variables:
 $ Solar.R  : num  275 118 332 259 237 273 64 259 112 186 ...
 $ Wind     : num  7.4 8 13.8 10.9 6.3 6.9 11.5 9.7 11.5 6.9 ...
 $ Temp     : int  86 72 80 93 96 87 79 73 71 74 ...
 $ Month    : int  7 5 6 6 8 6 8 9 9 5 ...
 $ Day      : int  29 2 14 11 30 8 15 10 15 11 ...
 $ goodOzone: Factor w/ 2 levels "0","1": 2 1 2 2 2 2 2 1 1 1 ...
> str(test)
'data.frame':  51 obs. of  6 variables:
 $ Solar.R  : num  83 186 25 238 286 175 127 220 256 259 ...
 $ Wind     : num  6.9 8 9.7 6.3 8.6 14.9 8 8.6 9.7 15.5 ...
 $ Temp     : int  81 57 61 77 78 81 78 85 69 76 ...
 $ Month    : int  8 5 5 9 6 7 6 6 5 9 ...
 $ Day      : int  1 27 23 13 1 13 26 5 12 12 ...
 $ goodOzone: Factor w/ 2 levels "0","1": 1 2 1 1 2 1 2 2 1 1 ...
> ##-- 5.1: Build a model (using the 'ksvm' function, trying to predict 'goodozone').
> #         You can use all the possible attributes, or select the attributes that you think
> #         would be the most helpful.
> # Output Results:
> #   Training error: 0.098
> #   Cross Validation error: 0.354
> #   Support Vectors: 61
> ksvmOzoneOutputGood <- ksvm(goodOzone ~ ., data=train, kernel="rbfdot", kpar="automatic", C=10, cross=10, prob.model=TRUE)
> ksvmOzoneOutputGood
Support Vector Machine object of class "ksvm"

SV type: C-svc  (classification)
 parameter : cost C = 10

Gaussian Radial Basis kernel function.
 Hyperparameter : sigma =  0.155172599536458

Number of Support Vectors : 58

Objective Function Value : -339.667
```

```
Training error : 0.117647
Cross validation error : 0.331818
Probability model included.
>
> ##-- 5.2: Test the model on the testing dataset, and compute the percent of 'goodOzone' that was correctly predicted.
> ksvmOzonePredGood <- predict(ksvmOzoneOutputGood, test)
> ksvmOzoneCompGood1 <- data.frame(select(test,'goodOzone'), ksvmOzonePredGood)
> colnames(ksvmOzoneCompGood1) <- c('test','Pred')
> head(ksvmOzoneCompGood1)
    test Pred
93     0    0
27     1    1
23     0    0
136    0    0
32     1    0
74     0    1
>
> # Percent of goodOzone that was correctly predicted
> # Output: 0.705 or 70%
> percKSVMCorrect <- length(which(ksvmOzoneCompGood1$test==ksvmOzoneCompGood1$Pred))/dim(ksvmOzoneCompGood1)[1]
> percKSVMCorrect
[1] 0.7254902
>
> # Confusion Matrix
> # result output: 0 class, 18 identified correctly, 5 identified incorrectly
> # result output: 1 class, 10 identified incorrectly, 18 identified correctly
> ksvmResults <- table(test=ksvmOzoneCompGood1$test, pred=ksvmOzoneCompGood1$Pred)
> print(ksvmResults)
    pred
test  0  1
   0 19  9
   1  5 18
> length(ksvmOzoneCompGood1$test)
[1] 51
>
> # Error & Accuracy Score Rate:
> ksvmErrorRate <- round((ksvmResults[1,][[2]] + ksvmResults[2,][[1]]) / nrow(ksvmOzoneCompGood1) *100,2)
> ksvmErrorRate
[1] 27.45
>
> ksvmAccuracyRate <- 100-ksvmErrorRate
> ksvmAccuracyRate
[1] 72.55
>
> ##-- 5.3: Plot the results. Use a scatter plot. Have the x-axis represent temperature,
```

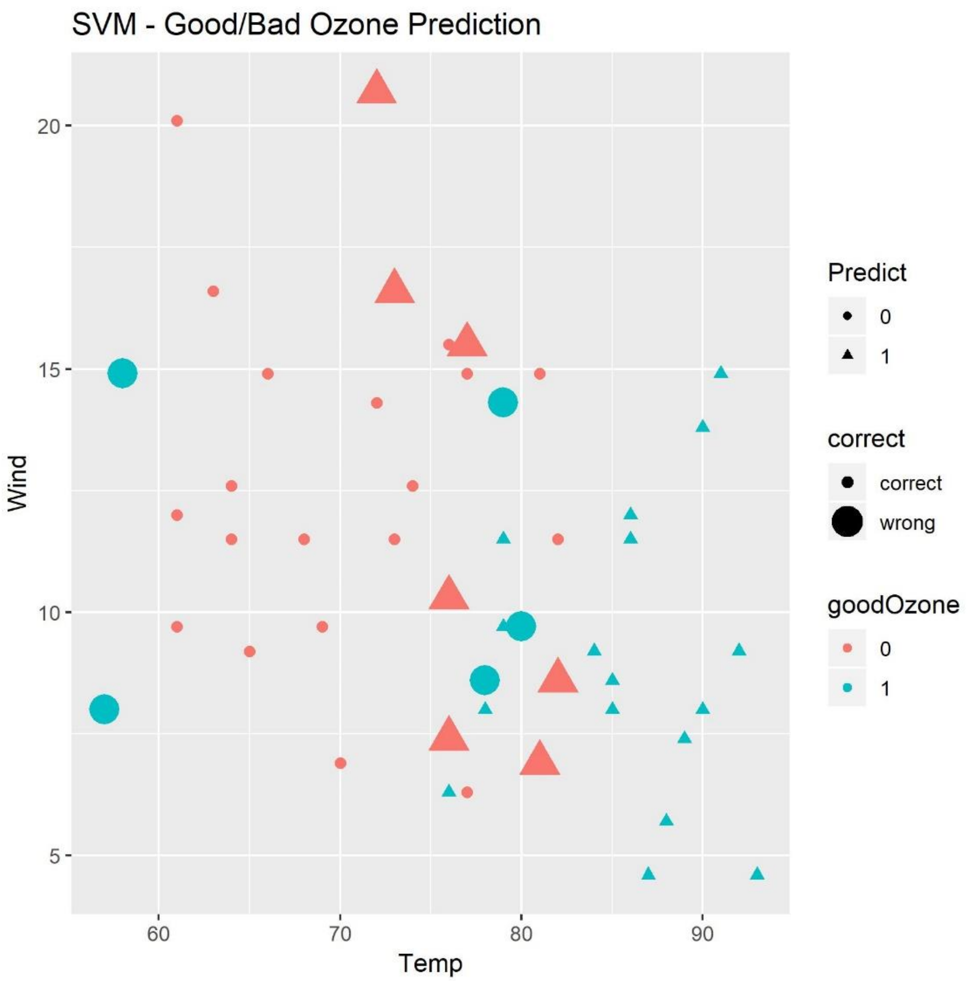
```
> #         the y-axis represent wind, the shape representing what was predicted (good or bad day),
> #         the color representing the actual value of 'goodozone' (i.e., if the actual ozone level was good)
> #         and the size represent if the prediction was correct (larger symbols should be the observations the model got wrong)
> ksvmOzoneCompGood1$correct <- ifelse(ksvmOzoneCompGood1$test==ksvmOzoneCompGood1$Pred,'correct','wrong')
> plotksvmOzoneCompGood1 <- data.frame(ksvmOzoneCompGood1$correct,test$Temp,test$Wind,test$goodOzone,ksvmOzoneCompGood1$Pred)
> colnames(plotksvmOzoneCompGood1) <- c("correct","Temp","Wind","goodOzone","Predict")
> plot.ksvm.good <- ggplot(plotksvmOzoneCompGood1, aes(x=Temp,y=Wind)) +
+   geom_point(aes(size=correct, color=goodOzone, shape=Predict)) +
+   ggtitle("KSVM - Good/Bad Ozone Prediction")
> ggsave("KSVM_Good_Bad_Ozone_Prediction.jpg", width = 6, height = 6)
Warning message:
Using size for a discrete variable is not advised.
> plot.ksvm.good
```




```
>
>
> ##-- 5.3: Compute models and plot the results for 'svm' (in the e1071 package) and 'nb' (Naive Bayses)
> #
> ## 5.3.1: Models & Plots for svm
> svmOzoneOutputGood <- svm(goodOzone ~ ., data=train, kernel='radial', C=10, cross=10, prob.model=TRUE)
> svmOzoneOutputGood

Call:
svm(formula = goodOzone ~ ., data = train, kernel = "radial", C = 10, cross = 10, prob.model = TRUE)
```

```
Parameters:
   SVM-Type:  C-classification
 SVM-Kernel:  radial
       cost:  1
      gamma:  0.2

Number of Support Vectors:  73

>
> # Test the svm model
> svmOzonePredGood <- predict(svmOzoneOutputGood, test)
> svmOzoneCompGood1 <- data.frame(select(test,'goodOzone'), svmOzonePredGood)
> colnames(svmOzoneCompGood1) <- c('test','Pred')
> head(svmOzoneCompGood1)
    test Pred
93     0    1
27     1    0
23     0    0
136    0    0
32     1    0
74     0    0
>
> # Percent of goodOzone that was correctly predicted
> percSVMCorrect <- length(which(svmOzoneCompGood1$test==svmOzoneCompGood1$Pred))/dim(svmOzoneCompGood1)[1]
> percSVMCorrect
[1] 0.7647059
>
> # Confusion Matrix
> # result output: 0 class, 21 identified correctly, 5 identified incorrectly
> # result output: 1 class, 7 identified incorrectly, 18 identified correctly
> svmResults <- table(test=svmOzoneCompGood1$test, pred=svmOzoneCompGood1$Pred)
> print(svmResults)
    pred
test  0  1
   0 21  7
   1  5 18
>
> # Error & Accuracy Score Rate:
> svmErrorRate <- round((svmResults[1,][[2]] + svmResults[2,][[1]]) / nrow(svmOzoneCompGood1) *100,2)
> svmErrorRate
[1] 23.53
>
> svmAccuracyRate <- 100-svmErrorRate
> svmAccuracyRate
[1] 76.47
```

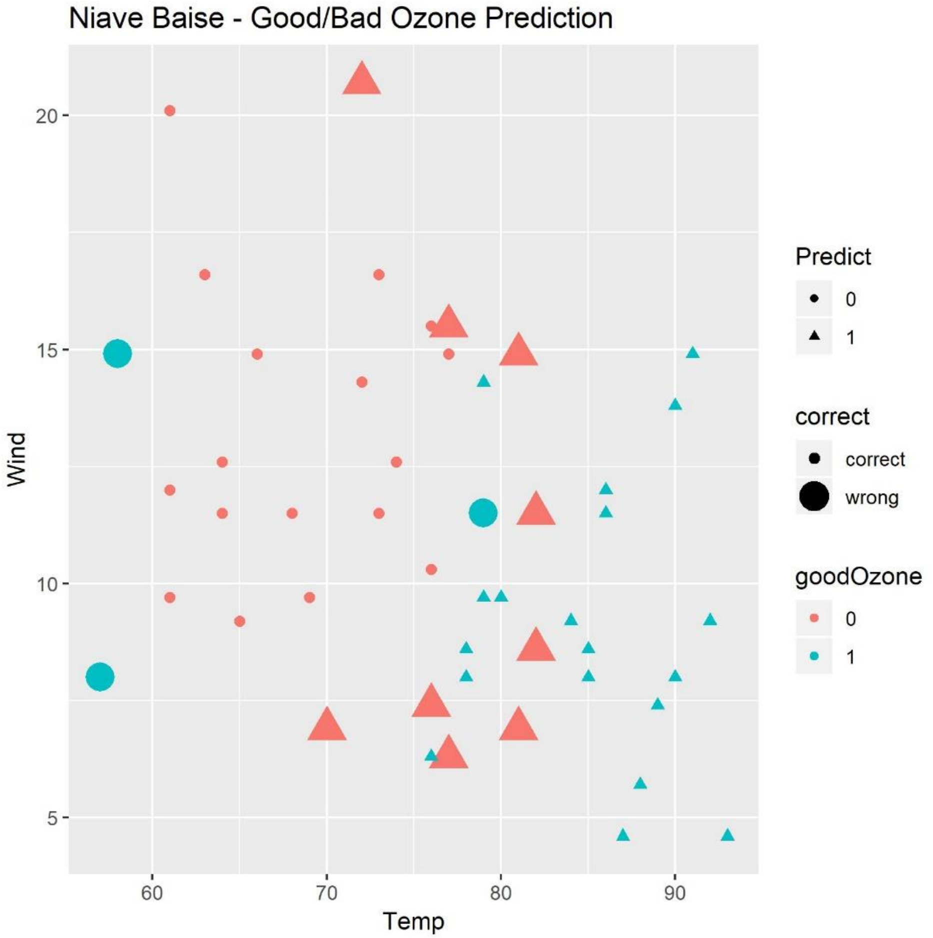
```
>
>
> ## Plot the results. Use a scatter plot. Have the x-axis represent temperature,
> #     the y-axis represent wind, the shape representing what was predicted (good or bad day),
> #     the color representing the actual value of 'goodozone' (i.e., if the actual ozone level was good)
> #     and the size represent if the prediction was correct (larger symbols should be the observations the model got wrong)
> svmOzoneCompGood1$correct <- ifelse(svmOzoneCompGood1$test==svmOzoneCompGood1$Pred,'correct','wrong')
> plotSvmOzoneCompGood1 <- data.frame(svmOzoneCompGood1$correct,test$Temp,test$Wind,test$goodOzone,svmOzoneCompGood1$Pred)
> colnames(plotSvmOzoneCompGood1) <- c("correct","Temp","Wind","goodOzone","Predict")
> plot.svm.good <- ggplot(plotSvmOzoneCompGood1, aes(x=Temp,y=Wind)) +
+   geom_point(aes(size=correct, color=goodOzone, shape=Predict)) +
+   ggtitle("SVM - Good/Bad Ozone Prediction")
> ggsave("SVM_Good_Bad_Ozone_Prediction.jpg", width = 6, height = 6)
Warning message:
Using size for a discrete variable is not advised.
> plot.svm.good
```




```
>
> ## 5.3.2: Models & Plots for 'nb'
> nbOzoneOutputGood <- naiveBayes(goodOzone ~ ., data=train)
> nbOzoneOutputGood

Naive Bayes Classifier for Discrete Predictors

Call:
```

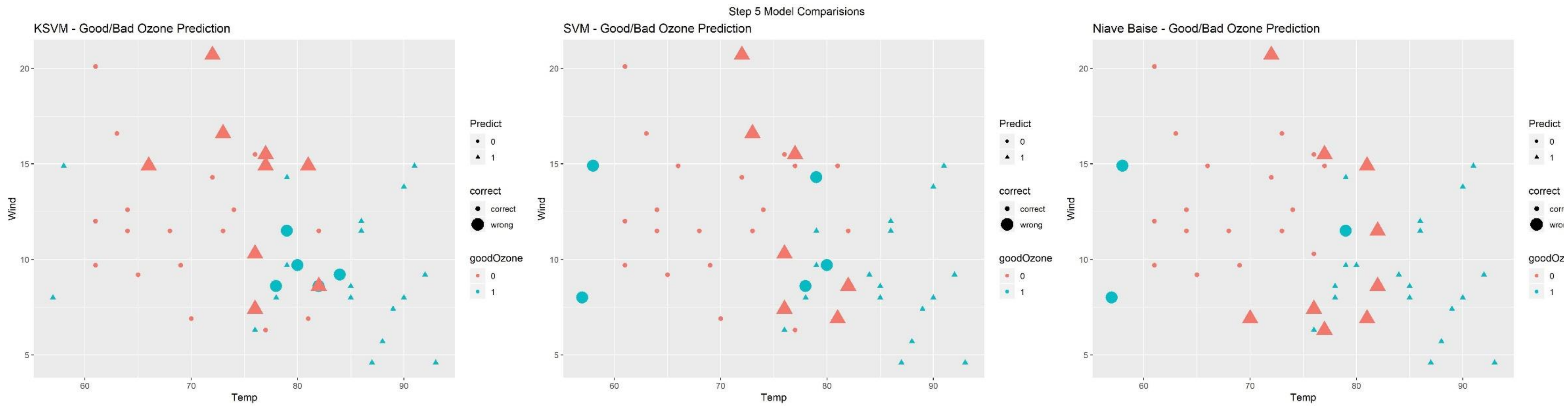
```
naiveBayes.default(x = X, y = Y, laplace = laplace)

A-priori probabilities:
Y
        0         1 
0.4313725 0.5686275 

Conditional probabilities:
   Solar.R
Y       [,1]      [,2]
  0 161.7727 100.59448
  1 200.3448  74.10508

   Wind
Y        [,1]     [,2]
  0 10.625000 2.548609
  1  8.532759 3.577188

   Temp
Y       [,1]     [,2]
  0 73.31818 8.083209
  1 82.63793 8.313376

   Month
Y       [,1]     [,2]
  0 7.113636 1.701106
  1 7.103448 1.149976

   Day
Y       [,1]      [,2]
  0 13.56818  7.531014
  1 17.01724 10.089931

> 
> # Test the naiveBase model
> nbOzonePredGood <- predict(nbOzoneOutputGood, test)
> nbOzoneCompGood1 <- data.frame(select(test,'goodOzone'), nbOzonePredGood)
> colnames(nbOzoneCompGood1) <- c('test','Pred')
> head(nbOzoneCompGood1)
    test Pred
93     0    1
27     1    0
23     0    0
136    0    1
32     1    1
```

```
74     0    1
>
> # Percent of goodOzone that was correctly predicted
> percNBCorrect <- length(which(nbOzoneCompGood1$test==nbOzoneCompGood1$Pred))/dim(nbOzoneCompGood1)[1]
> percNBCorrect
[1] 0.7647059
>
> # Confusion Matrix
> # result output: 0 class, 19 identified correctly, 3 identified incorrectly
> # result output: 1 class, 9 identified incorrectly, 20 identified correctly
> nbResults <- table(test=nbOzoneCompGood1$test, pred=nbOzoneCompGood1$Pred)
> print(nbResults)
    pred
test  0  1
   0 19  9
   1  3 20
>
> nbErrorRate <- round((nbResults[1,][[2]] + nbResults[2,][[1]]) / nrow(nbOzoneCompGood1) *100,2)
> nbErrorRate
[1] 23.53
>
> nbAccuracyRate <- 100-nbErrorRate
> nbAccuracyRate
[1] 76.47
>
>
> ## Plot the results. Use a scatter plot. Have the x-axis represent temperature,
> #     the y-axis represent wind, the shape representing what was predicted (good or bad day),
> #     the color representing the actual value of 'goodozone' (i.e., if the actual ozone level was good)
> #     and the size represent if the prediction was correct (larger symbols should be the observations the model got wrong)
> nbOzoneCompGood1$correct <- ifelse(nbOzoneCompGood1$test==nbOzoneCompGood1$Pred,'correct','wrong')
> plotNBOzoneCompGood1 <- data.frame(nbOzoneCompGood1$correct,test$Temp,test$Wind,test$goodOzone,nbOzoneCompGood1$Pred)
> colnames(plotNBOzoneCompGood1) <- c("correct","Temp","Wind","goodOzone","Predict")
> plot.nb.good <- ggplot(plotNBOzoneCompGood1, aes(x=Temp,y=Wind)) +
+   geom_point(aes(size=correct, color=goodOzone, shape=Predict)) +
+   ggtitle("Niave Baise - Good/Bad Ozone Prediction")
> ggsave("NB_Good_Bad_Ozone_Prediction.jpg", width = 6, height = 6)
Warning message:
Using size for a discrete variable is not advised.
> plot.nb.good
```




```
>
> ##-- 5.5: Show all three results (charts) in one window, using the grid.array function (have two charts in one row)
> ga5 <- grid.arrange(plot.ksvm.good, plot.svm.good, plot.nb.good, ncol=3, nrow=2, top="Step 5 Model Comparisions")
Warning messages:
1: Using size for a discrete variable is not advised.
2: Using size for a discrete variable is not advised.
3: Using size for a discrete variable is not advised.
> ggsave(file="Grid_Arrange_Good_KSVM-SVM-NB.jpg", ga5, width = 24, height = 12)
```

```
>
```




```
> #---- Step 6: Which are the best Models for this data? -------------------------
> ## Review what you have done and state which is the best and why
> #
> # Answer: It's observed that the SVM and Naive Baise models have the heighest accuracy ratings, measured at 76.5%,
> #         for predicting the goodOzone Class. The result output calculation of Accuracy Rating for each model is shown below.
> #
> ## Output Results ##
> # Step 3 results:
> # LM:   RMSE = 18.8
> # KSVM: RMSE = 21.59642
> # SVM:  RMSE = 16.54
> #
> # Step 5 results:
> # KSVM:
> #    Accuracy Rate: 70.59%
> #    Error Rate:  29.41%
> # SVM:
> #    Accuracy Rate: 76.47%
> #    Error Rate: 23.53%
> # Naive Baise:
> #    Accuracy Rate: 76.47%
> #    Error Rate: 23.53%
> #--------------------------------------------------------------------------------
```

>