Lab Report 3

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```
# Insert necessary packages
library('glmnet')
library('caret')
library('ISLR')
library('plotly')
library('gridExtra')
library('tree')
## Warning: package 'tree' was built under R version 4.0.4
library('rpart')
## Warning: package 'rpart' was built under R version 4.0.4
library('MLmetrics')
## Warning: package 'MLmetrics' was built under R version 4.0.4
library('e1071')
## Warning: package 'e1071' was built under R version 4.0.4
Question 1: Classification
# Read in data
croissant <- read.csv("data/croissant.csv")[,-1]</pre>
circles <- read.csv("data/circles.csv")[,-1]</pre>
varied <- read.csv("data/varied.csv")[,-1]</pre>
Question 1.1: Preprocess and Plot
```

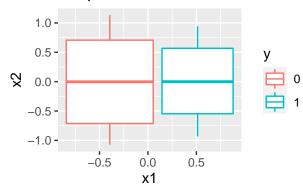
croissant\$y <- as.factor(croissant\$y)
circles\$y <- as.factor(circles\$y)
varied\$y <- as.factor(varied\$y)</pre>

```
cro <- ggplot(data = croissant) +
  geom_boxplot(aes(x = x1, y=x2, colour=y)) +
  ggtitle("Boxplot of Croissant Data")
cir <- ggplot(data = circles) +
  geom_boxplot(aes(x = x1, y=x2, colour=y)) +
  ggtitle("Boxplot of Circles Data")
var <- ggplot(data = varied) +
  geom_boxplot(aes(x = x1, y=x2, colour=y)) +
  ggtitle("Boxplot of Varied Data")
grid.arrange(cro, cir, var, ncol=2)</pre>
```

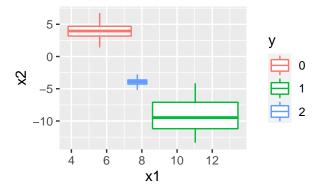
Boxplot of Croissant Data

1.0 - 0.5 - 0.0 - 0.5 - 0.0 1.5 x1

Boxplot of Circles Data



Boxplot of Varied Data

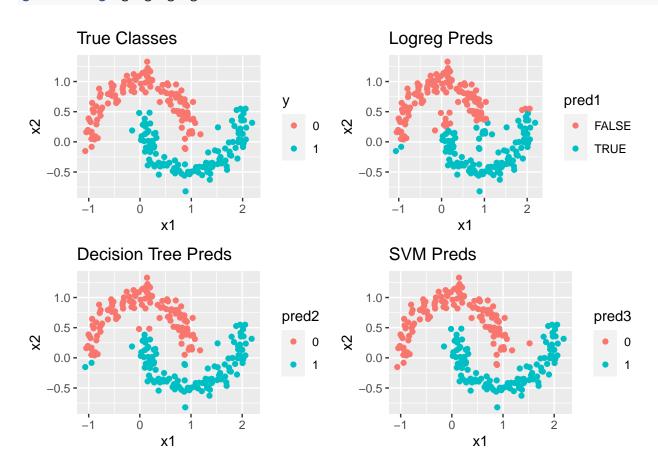


Questions 1.2-1.4 for Croissant Data

```
## Question 1.2
set.seed(112)
train_inds <- sample(1:nrow(croissant), floor(nrow(croissant)*0.5))</pre>
train <- croissant[ train_inds, ]</pre>
test <- croissant[-train_inds, ]</pre>
y.train <- train$y
x.train <- model.matrix(y ~ .,train)[,-1]</pre>
x.test <- model.matrix(y ~ .,test)[,-1]</pre>
## Question 1.3
# Logistic Regression
lreg <- glm(y ~ ., data=train, family = "binomial")</pre>
pred1 <- predict(lreg, newdata=as.data.frame(x.test), type = "response") > 0.5
lreg_acc <- mean(pred1 == (test$y==1))</pre>
lreg_con <- table(predict=pred1,actual=(test$y))</pre>
# Decision Tree
dtree <- rpart(y~., data=train)</pre>
pred2 <- predict(dtree, as.data.frame(x.test), type = "class")</pre>
dtree_acc <- Accuracy(pred2,test$y)</pre>
dtree_con <- table(predict=pred2,actual=(test$y))</pre>
# SVM
svmfit <- svm(y~.,data=train, kernel ="radial", gamma=1,cost=1)</pre>
pred3 <- predict(svmfit,as.data.frame(x.test), type="class")</pre>
print ('We chose radial as the kernel as it best fits the shape of the data
             and thus should lead to a better prediction.')
## [1] "We chose radial as the kernel as it best fits the shape of the data \n
                                                                                                 and thus
svm_acc <- Accuracy(pred3,test$y)</pre>
svm_con <- table(predict=pred3,actual=(test$y))</pre>
g1 <- ggplot(test, aes(x1,x2,colour=y)) +
  geom_point() +
  ggtitle("True Classes")
g2 <- ggplot(test, aes(x1,x2,colour=pred1)) +
  geom_point() +
  ggtitle("Logreg Preds")
g3 <- ggplot(test, aes(x1,x2,colour=pred2)) +
  geom_point() +
  ggtitle("Decision Tree Preds")
g4 <- ggplot(test, aes(x1,x2,colour=pred3)) +
  geom_point() +
```

ggtitle("SVM Preds")

grid.arrange(g1,g2,g3,g4,ncol=2)



[1] "Looking at the four plots, we can see that Logisitc Regression has \n

the most miscla

```
sprintf("Logisitc Regression Accuracy: %f", lreg_acc)
```

[1] "Logisitc Regression Accuracy: 0.904000"

sprintf("Decision Tree Accuracy: %f", dtree_acc)

[1] "Decision Tree Accuracy: 0.976000"

sprintf("SVM Accuracy: %f", svm_acc)

[1] "SVM Accuracy: 0.996000"

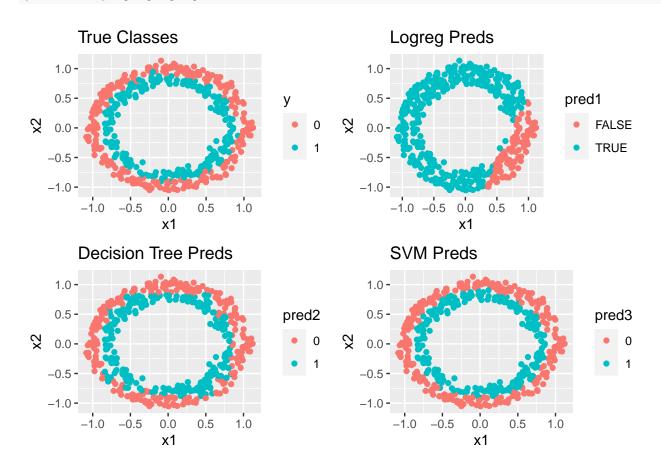
```
print("In terms of accuracy, SVM has the highest and Decision Tree was second highest.
     Logistic Regression has the lowest out of the three.")
## [1] "In terms of accuracy, SVM has the highest and Decision Tree was second highest. \n
lreg_con
##
         actual
## predict 0 1
    FALSE 112 12
##
     TRUE
           12 114
##
dtree_con
##
         actual
## predict
            0 1
##
        0 120 2
        1 4 124
##
svm_con
##
         actual
## predict 0 1
##
        0 124
##
            0 125
print("SVM was the least biased out of the three as it had zero False Positive (FP) and
     one False Negatives (FN). Decision Tree has 4 FP and 2 FN and Logistics Regression
     has 12 FP and FN.")
## [1] "SVM was the least biased out of the three as it had zero False Positive (FP) and \n
## Question 1.4 for Croissant Data
set.seed(112)
```

Questions 1.2-1.4 for Circle Data

```
## Question 1.2
set.seed(112)
train_inds <- sample(1:nrow(circles), floor(nrow(circles)*0.5))</pre>
train <- circles[ train_inds, ]</pre>
test <- circles[-train_inds, ]</pre>
y.train <- train$y
x.train <- model.matrix(y ~ .,train)[,-1]</pre>
x.test <- model.matrix(y ~ .,test)[,-1]</pre>
## Question 1.3
# Logistic Regression
lreg <- glm(y ~ ., data=train, family = "binomial")</pre>
pred1 <- predict(lreg, newdata=as.data.frame(x.test), type = "response") > 0.5
lreg_acc <- mean(pred1 == (test$y==1))</pre>
lreg_con <- table(predict=pred1,actual=(test$y))</pre>
# Decision Tree
dtree <- rpart(y~., data=train)</pre>
pred2 <- predict(dtree, as.data.frame(x.test), type = "class")</pre>
dtree_acc <- Accuracy(pred2,test$y)</pre>
dtree_con <- table(predict=pred2,actual=(test$y))</pre>
# SVM
svmfit <- svm(y~.,data=train, kernel ="radial", gamma=1,cost=1)</pre>
pred3 <- predict(svmfit,as.data.frame(x.test), type="class")</pre>
print ('We chose radial as the kernel as it best fits the shape of the data
            and thus should lead to a better prediction.')
## [1] "We chose radial as the kernel as it best fits the shape of the data \n
                                                                                                 and thus
svm_acc <- Accuracy(pred3,test$y)</pre>
svm_con <- table(predict=pred3,actual=(test$y))</pre>
g1 <- ggplot(test, aes(x1,x2,colour=y)) +
  geom_point() +
  ggtitle("True Classes")
g2 <- ggplot(test, aes(x1,x2,colour=pred1)) +
  geom_point() +
  ggtitle("Logreg Preds")
g3 <- ggplot(test, aes(x1,x2,colour=pred2)) +
  geom_point() +
  ggtitle("Decision Tree Preds")
g4 <- ggplot(test, aes(x1,x2,colour=pred3)) +
 geom_point() +
```

ggtitle("SVM Preds")

grid.arrange(g1,g2,g3,g4,ncol=2)



[1] "Looking at the four plots, we can see that Logisitc Regression has \n

a lot misclass:

sprintf("Logisitc Regression Accuracy: %f", lreg_acc)

[1] "Logisitc Regression Accuracy: 0.506000"

sprintf("Decision Tree Accuracy: %f", dtree_acc)

[1] "Decision Tree Accuracy: 0.910000"

sprintf("SVM Accuracy: %f", svm_acc)

[1] "SVM Accuracy: 0.972000"

```
print("In terms of accuracy, SVM has the highest and Decision Tree was second highest.
     Logistic Regression has the lowest out of the three.")
## [1] "In terms of accuracy, SVM has the highest and Decision Tree was second highest. \n
lreg_con
##
         actual
## predict 0 1
    FALSE 58 45
##
    TRUE 202 195
##
dtree_con
##
         actual
## predict
            0 1
        0 233 18
##
        1 27 222
##
svm_con
##
         actual
## predict 0 1
##
        0 253 7
##
        1 7 233
print("SVM was the least biased out of the three as it had 7 False Positives (FP) and
     7 False Negatives (FN). Decision Tree has 27 FP and 18 FN and Logistic Regression
     has 202 FP and 45 FN.")
## [1] "SVM was the least biased out of the three as it had 7 False Positives (FP) and \n
## Question 1.4 for Circles Data
set.seed(112)
```

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Questions 1.2-1.4 for Varied Data

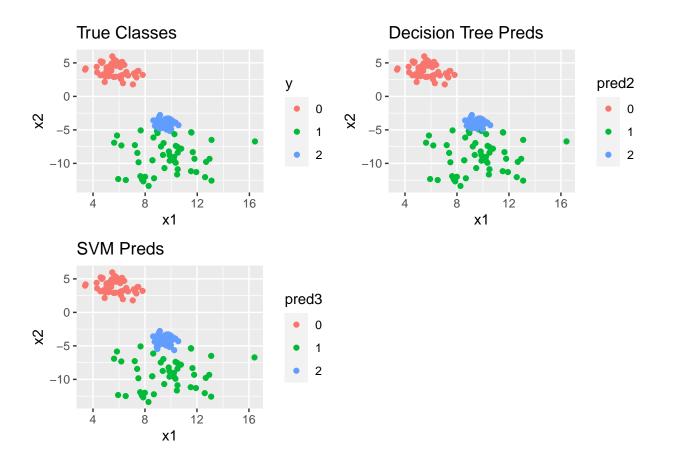
```
## Question 1.2
set.seed(112)
train_inds <- sample(1:nrow(varied), floor(nrow(varied)*0.5))</pre>
train <- varied[ train inds, ]</pre>
test <- varied[-train_inds, ]</pre>
y.train <- train$y
x.train <- model.matrix(y ~ .,train)[,-1]</pre>
x.test <- model.matrix(y ~ .,test)[,-1]</pre>
## Question 1.3
# Decision Tree
dtree <- rpart(y~., data=train)</pre>
pred2 <- predict(dtree, as.data.frame(x.test), type = "class")</pre>
dtree_acc <- Accuracy(pred2,test$y)</pre>
dtree_con <- table(predict=pred2,actual=(test$y))</pre>
# SVM
svmfit <- svm(y~.,data=train, kernel ="radial", gamma=1,cost=1)</pre>
pred3 <- predict(svmfit,as.data.frame(x.test), type="class")</pre>
print ('We chose radial as the kernel as it best fits the shape of the data
             and thus should lead to a better prediction.')
## [1] "We chose radial as the kernel as it best fits the shape of the data \n
svm_acc <- Accuracy(pred3,test$y)</pre>
svm_con <- table(predict=pred3,actual=(test$y))</pre>
g1 <- ggplot(test, aes(x1,x2,colour=y)) +
```

```
svm_acc <- Accuracy(pred3,test$y)
svm_con <- table(predict=pred3,actual=(test$y))

g1 <- ggplot(test, aes(x1,x2,colour=y)) +
    geom_point() +
    ggtitle("True Classes")
g3 <- ggplot(test, aes(x1,x2,colour=pred2)) +
    geom_point() +
    ggtitle("Decision Tree Preds")
g4 <- ggplot(test, aes(x1,x2,colour=pred3)) +
    geom_point() +
    ggtitle("SVM Preds")

grid.arrange(g1,g3,g4,ncol=2)</pre>
```

and thus



[1] "Looking at the three plots, we can see that Logisitc Regression has \n a lot misclass

sprintf("Decision Tree Accuracy: %f", dtree_acc)

[1] "Decision Tree Accuracy: 0.986667"

sprintf("SVM Accuracy: %f", svm_acc)

[1] "SVM Accuracy: 0.980000"

print("In terms of accuracy, Decision Tree performed a little bit better than SVM.")

[1] "In terms of accuracy, Decision Tree performed a little bit better than SVM."

dtree_con

```
##
         actual
## predict 0 1 2
        0 49 0 0
##
        1 0 49 2
##
        2 0 0 50
##
svm_con
##
         actual
## predict 0 1 2
##
        0 49 0 0
##
        1 0 46 0
##
        2 0 3 52
print("Decision Tree was the least biased has it had two false negatives for Class 2.
     SVM had 3 false positives for Class 1.")
## [1] "Decision Tree was the least biased has it had two false negatives for Class 2.\n
```

Question 1.4 for Varied Data

set.seed(112)

SVM

Question 2: Tree-based methods

2.1. Preprocess

```
# 1
library("ISLR")
hitters <- Hitters
hitters$Salary <- log(hitters$Salary) # Q2 (Converted to log before dataset is split)
heart <- read.csv("data/Heart.csv")[-1] # Q3 (removed row identifier)

set.seed(112)
train_inds <- sample(1:nrow(hitters), floor(nrow(hitters)*0.7))
train.hitters <- hitters[ train_inds, ]
test.hitters <- hitters[-train_inds, ]

train_inds <- sample(1:nrow(heart), floor(nrow(heart)*0.7))
train.heart <- heart[ train_inds, ]
test.heart <- heart[-train_inds, ]</pre>
```

2.2. Decision Trees for Regression

```
# 1
```

2.3. Decision Trees for Classification

```
# 1
```

2.4. Bagging: Regression

```
# 1
```

Question 2.5. Bagging: Classification

```
# 1
```

Question 2.6. Random Forest: Regression

```
# 1
```