

Statistic Learning Assignment 2

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- Question 10 in Section 4.7 of ISLR
 - (a)
 - (b)
 - (c)
 - (d)
 - (e)
 - (f)
 - (g)
 - (h)
 - (i)
- Question 5 of Section 9.7 in ISLR
 - (a)
 - (b)
 - (c)
 - (d)
 - (e)
 - (f)
 - (g)
 - (h)
 - (i)
- Reproduction the Example in Section 9.3.3 of ISLR

Question 10 in Section 4.7 of ISLR

(a)

```
library("ISLR")
library("car")
```

```
## 载入需要的程辑包: carData
```

```
data(Weekly)
summary(Weekly)
```

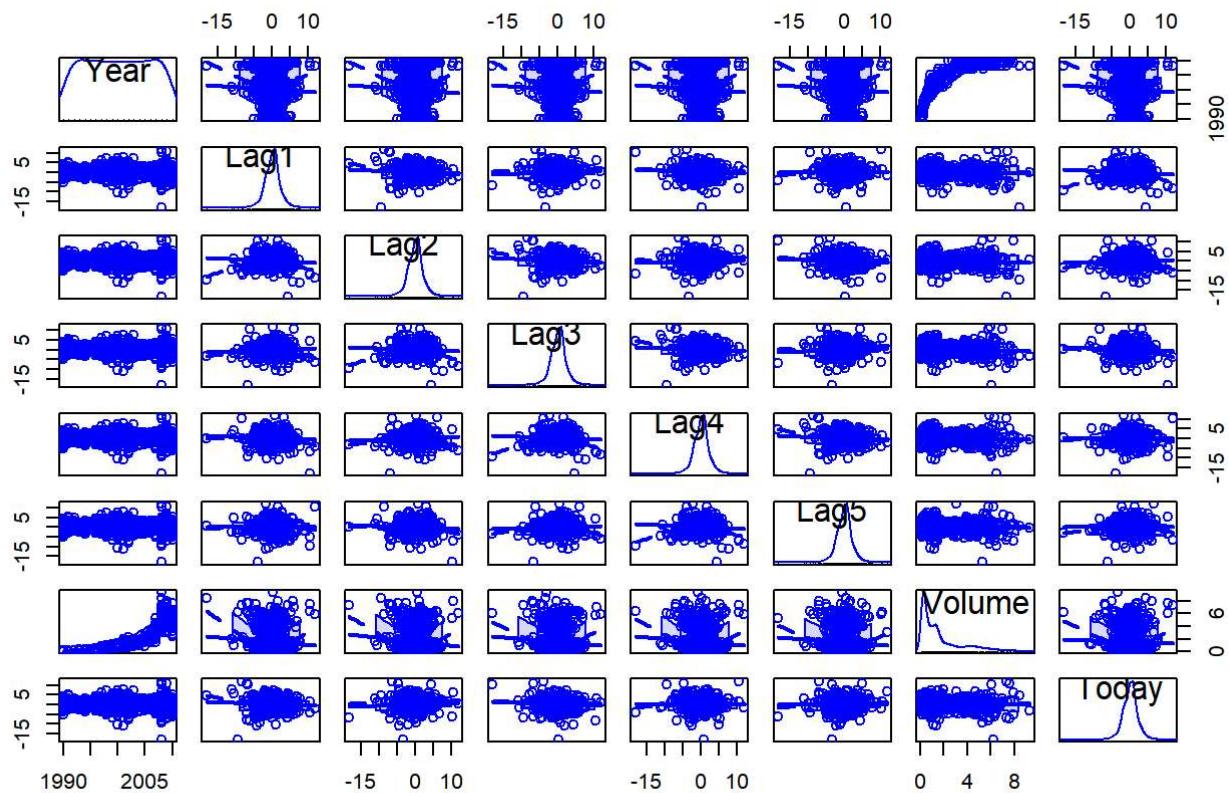
```
cor(Weekly[, -9])
```

```
##          Year      Lag1      Lag2      Lag3      Lag4
## Year  1.00000000 -0.032289274 -0.03339001 -0.03000649 -0.031127923
## Lag1 -0.03228927  1.000000000 -0.07485305  0.05863568 -0.071273876
## Lag2 -0.03339001 -0.074853051  1.00000000 -0.07572091  0.058381535
## Lag3 -0.03000649  0.058635682 -0.07572091  1.00000000 -0.075395865
## Lag4 -0.03112792 -0.071273876  0.05838153 -0.07539587  1.000000000
## Lag5 -0.03051910 -0.008183096 -0.07249948  0.06065717 -0.075675027
## Volume 0.84194162 -0.064951313 -0.08551314 -0.06928771 -0.061074617
## Today -0.03245989 -0.075031842  0.05916672 -0.07124364 -0.007825873
##          Lag5      Volume      Today
## Year  -0.03051910  0.84194162 -0.032459894
## Lag1 -0.008183096 -0.06495131 -0.075031842
## Lag2 -0.072499482 -0.08551314  0.059166717
## Lag3  0.060657175 -0.06928771 -0.071243639
## Lag4 -0.075675027 -0.06107462 -0.007825873
## Lag5  1.000000000 -0.05851741  0.011012698
## Volume -0.058517414  1.000000000 -0.033077783
## Today   0.011012698 -0.03307778  1.000000000
```

As one would expect, the correlations between the lag variables and today's returns are close to zero. In other words, there appears to be little correlation between today's returns and previous days' returns. The only substantial correlation is between Year and Volume, which is approximately 0.84. By plotting the data we see that Volume is increasing over time. In other words, the average number of shares traded weekly increased from 1990 to 2010.

```
scatterplotMatrix(Weekly[,-9], spread=FALSE, lty.smooth=2, main="Scatter Plot Matrix")
```

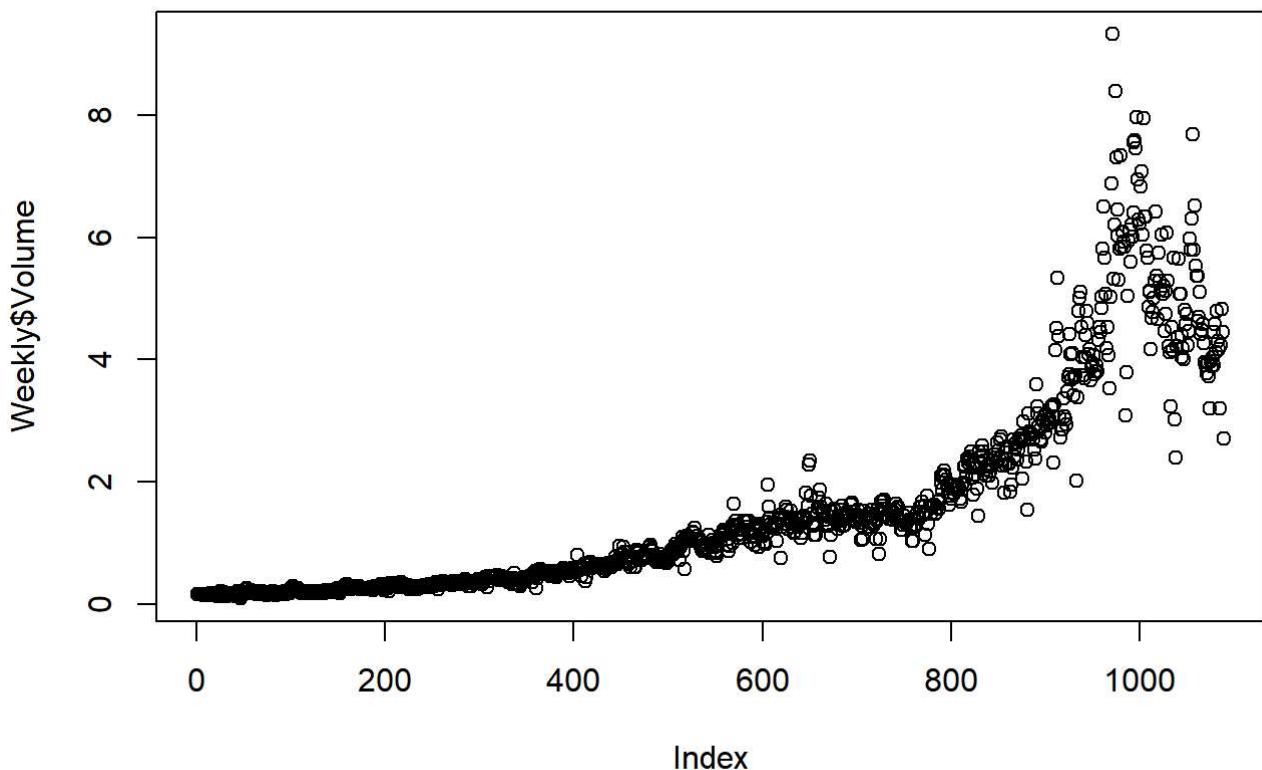
Scatter Plot Matrix



From the scatter plot matrix we can discover that there is little linear relationship between today's returns and previous days' returns, which is consistent with the conclusion we drew to previously. Then we plot Volume with time.

```
plot(Weekly$Volume, main = "Volume with Time")
```

Volume with Time



Thus, From the plot we can figure out that there is an increasing trend pattern between Volume and Year.

(b)

```
log.fit <- glm(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 + Volume,  
                  family = binomial(), data = Weekly)  
summary(log.fit)
```

```

## Call:
## glm(formula = Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5 +
##       Volume, family = binomial(), data = Weekly)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) 0.26686   0.08593   3.106   0.0019 **
## Lag1        -0.04127   0.02641  -1.563   0.1181
## Lag2         0.05844   0.02686   2.175   0.0296 *
## Lag3        -0.01606   0.02666  -0.602   0.5469
## Lag4        -0.02779   0.02646  -1.050   0.2937
## Lag5        -0.01447   0.02638  -0.549   0.5833
## Volume      -0.02274   0.03690  -0.616   0.5377
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 1496.2 on 1088 degrees of freedom
## Residual deviance: 1486.4 on 1082 degrees of freedom
## AIC: 1500.4
##
## Number of Fisher Scoring iterations: 4

```

We maintain that the Intercept and Lag2 is significant. The positive coefficient of Lag2 suggests that if the market had a positive return the day before yesterday, then it is more likely to go up today.

(c)

```

glm.probs <- predict(log.fit, type = "response")
contrasts(Weekly$Direction)

```

```

##      Up
## Down  0
## Up    1

```

```

glm.pred <- rep("Down", 1089)
glm.pred[glm.probs>0.5] <- "Up"

```

The confusion matrix is as follows.

```
table(glm.pred, Weekly$Direction)
```

```

## 
## glm.pred Down Up
##      Down   54  48
##      Up    430 557

```

The overall fraction of correct predictions is computed as follows.

```
mean(glm.pred == Weekly$Direction)  
  
## [1] 0.5610652
```

- In this case, logistic regression correctly predicted the movement of the market 56.1% of the time. The diagonal elements of the confusion matrix indicate correct predictions, while the off-diagonals represent incorrect predictions. Hence our model correctly predicted that the market would go up on 557 days and that it would go down on 54 days, for a total of $557 + 54 = 611$ correct predictions. In other words, there are 48 sample points which should have been classified as “Up” but be wrongly predicted as “Down” and 430 points which should have been classified as “Down” but be wrongly predicted as “Up”.
- TPR: $557/(557+48) = 0.92$
- FPR: $430/(430+54) = 0.89$

(d)

```
train <- subset(Weekly, Year %in% 1990:2008)  
test <- subset(Weekly, Year %in% c(2009, 2010))  
  
log.fit2 <- glm(Direction ~ Lag2, data = train, family = binomial())  
glm.probs2 <- predict(log.fit2, test, type = "response")  
glm.pred2 <- rep("Down", nrow(test))  
glm.pred2[glm.probs2 > 0.5] <- "Up"
```

The confusion matrix is as follows.

```
table(glm.pred2, test$Direction)  
  
##  
##  glm.pred2 Down Up  
##    Down     9   5  
##    Up      34  56
```

The overall fraction of correct predictions is computed as follows.

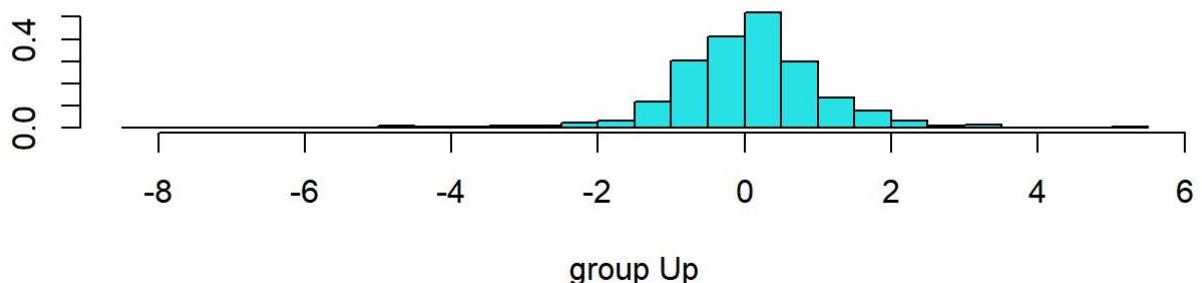
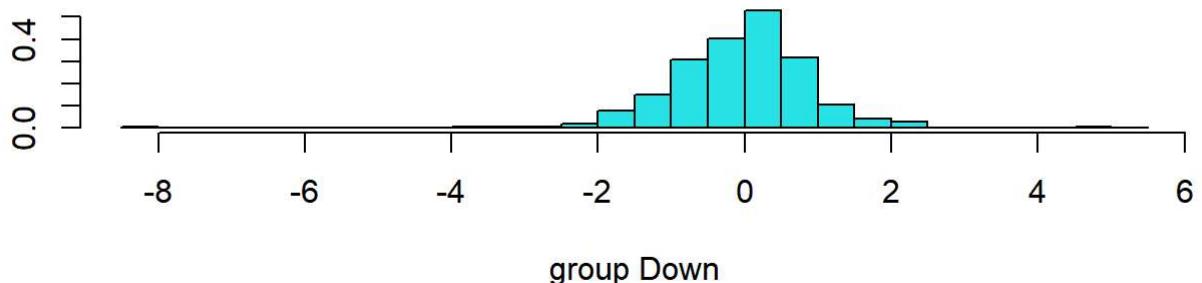
```
mean(glm.pred2 == test$Direction)  
  
## [1] 0.625
```

(e)

```
library(MASS)
lda.fit <- lda(Direction ~ Lag2, data = train)
lda.fit
```

```
## Call:
## lda(Direction ~ Lag2, data = train)
##
## Prior probabilities of groups:
##       Down      Up
## 0.4477157 0.5522843
##
## Group means:
##           Lag2
## Down -0.03568254
## Up   0.26036581
##
## Coefficients of linear discriminants:
##           LD1
## Lag2 0.4414162
```

```
plot(lda.fit)
```



```
prob <- predict(lda.fit, test, type = "response")
names(prob)
```

```
## [1] "class"      "posterior"  "x"
```

```
lda.class <- preb$class
```

The confusion matrix is as follows.

```
table(lda.class, test$Direction)
```

```
##  
## lda.class Down Up  
##      Down     9   5  
##      Up      34  56
```

The overall fraction of correct predictions is computed as follows.

```
mean(lda.class == test$Direction)
```

```
## [1] 0.625
```

(f)

```
qda.fit <- qda(Direction ~ Lag2, data = train)  
qda.fit
```

```
## Call:  
## qda(Direction ~ Lag2, data = train)  
##  
## Prior probabilities of groups:  
##      Down      Up  
## 0.4477157 0.5522843  
##  
## Group means:  
##      Lag2  
## Down -0.03568254  
## Up   0.26036581
```

```
preb <- predict(qda.fit, test, type = "response")  
names(preb)
```

```
## [1] "class"      "posterior"
```

```
qda.class <- preb$class
```

The confusion matrix is as follows.

```
table(qda.class, test$Direction)
```

```
##  
## qda.class Down Up  
##      Down     0  0  
##      Up      43 61
```

The overall fraction of correct predictions is computed as follows.

```
mean(qda.class == test$Direction)  
  
## [1] 0.5865385
```

(g)

```
library(class)  
train.X <- cbind(train$Lag2)  
test.X <- cbind(test$Lag2)  
train.Y <- train$Direction  
set.seed(1)  
knn.pred <- knn(train.X, test.X, train.Y, k = 1)
```

The confusion matrix is as follows.

```
table(knn.pred, test$Direction)  
  
##  
## knn.pred Down Up  
##      Down     21 30  
##      Up      22 31
```

The overall fraction of correct predictions is computed as follows.

```
mean(knn.pred == test$Direction)  
  
## [1] 0.5
```

(h)

d. logistic regression model using a training data period from 1990 to 2008, with Lag2 as the only predictor and (e)LDA model using a training data period from 1990 to 2008, with Lag2 as the only predictor provide the best results on this data, since they have the greatest overall fraction of correct predictions.

(i)

KNN with k = 5

```
train.X <- cbind(train$Lag2)
test.X <- cbind(test$Lag2)
train.Y <- train$Direction
set.seed(1)
knn.pred <- knn(train.X, test.X, train.Y, k = 5)
table(knn.pred, test$Direction)
```

```
## 
## knn.pred Down Up
##   Down   16 21
##   Up     27 40
```

```
mean(knn.pred == test$Direction)
```

```
## [1] 0.5384615
```

KNN with k = 10

```
train.X <- cbind(train$Lag2)
test.X <- cbind(test$Lag2)
train.Y <- train$Direction
set.seed(1)
knn.pred <- knn(train.X, test.X, train.Y, k = 10)
table(knn.pred, test$Direction)
```

```
## 
## knn.pred Down Up
##   Down   17 21
##   Up     26 40
```

```
mean(knn.pred == test$Direction)
```

```
## [1] 0.5480769
```

LDA with all Lag variables

```
library(MASS)
lda.fit <- lda(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5, data = train)
lda.fit
```

```

## Call:
## lda(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5, data = train)
##
## Prior probabilities of groups:
##      Down      Up
## 0.4477157 0.5522843
##
## Group means:
##           Lag1      Lag2      Lag3      Lag4      Lag5
## Down  0.289444444 -0.03568254 0.17080045 0.15925624 0.21409297
## Up   -0.009213235 0.26036581 0.08404044 0.09220956 0.04548897
##
## Coefficients of linear discriminants:
##           LD1
## Lag1 -0.27604838
## Lag2  0.26309706
## Lag3 -0.04233861
## Lag4 -0.11994755
## Lag5 -0.15335694

```

```

preb <- predict(lda.fit, test, type = "response")
names(preb)

```

```

## [1] "class"      "posterior"   "x"

```

```

lda.class <- preb$class
table(lda.class, test$Direction)

```

```

##
## lda.class Down Up
##      Down   9 13
##      Up    34 48

```

```

mean(lda.class == test$Direction)

```

```

## [1] 0.5480769

```

QDA with all Lag variables

```

library(MASS)
qda.fit <- qda(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5, data = train)
qda.fit

```

```
## Call:  
## qda(Direction ~ Lag1 + Lag2 + Lag3 + Lag4 + Lag5, data = train)  
##  
## Prior probabilities of groups:  
##      Down      Up  
## 0.4477157 0.5522843  
##  
## Group means:  
##           Lag1      Lag2      Lag3      Lag4      Lag5  
## Down  0.289444444 -0.03568254 0.17080045 0.15925624 0.21409297  
## Up   -0.009213235 0.26036581 0.08404044 0.09220956 0.04548897
```

```
preb <- predict(qda.fit, test, type = "response")  
names(preb)
```

```
## [1] "class"      "posterior"
```

```
qda.class <- preb$class  
table(qda.class, test$Direction)
```

```
##  
## qda.class Down Up  
##      Down   10 23  
##      Up     33 38
```

```
mean(qda.class == test$Direction)
```

```
## [1] 0.4615385
```

QDA with all Lag variables and their interaction

```
qda.fit <- qda(Direction ~ (Lag1 + Lag2 + Lag3 + Lag4 + Lag5)^2, data = train)  
qda.fit
```

```

## Call:
## qda(Direction ~ (Lag1 + Lag2 + Lag3 + Lag4 + Lag5)^2, data = train)
##
## Prior probabilities of groups:
##      Down      Up
## 0.4477157 0.5522843
##
## Group means:
##           Lag1      Lag2      Lag3      Lag4      Lag5  Lag1:Lag2
## Down  0.289444444 -0.03568254 0.17080045 0.15925624 0.21409297 -0.8014495
## Up   -0.009213235 0.26036581 0.08404044 0.09220956 0.04548897 -0.1393632
##           Lag1:Lag3  Lag1:Lag4  Lag1:Lag5  Lag2:Lag3  Lag2:Lag4  Lag2:Lag5
## Down -0.006554329 -0.4724269  0.3615693 -0.1937158  0.78824608 -0.3132494
## Up    0.687742739 -0.2036205 -0.1833118 -0.6405132  0.04407141 -0.3497535
##           Lag3:Lag4  Lag3:Lag5  Lag4:Lag5
## Down -0.991496916  0.4913572 -0.3686248
## Up   0.007162822  0.3137873 -0.4945795

```

```

preb <- predict(qda.fit, test, type = "response")
names(preb)

```

```

## [1] "class"      "posterior"

```

```

qda.class <- preb$class
table(qda.class, test$Direction)

```

```

##
## qda.class Down Up
##      Down 19 13
##      Up   24 48

```

```

mean(qda.class == test$Direction)

```

```

## [1] 0.6442308

```

Logistic regression with Lag1, Lag2, Volume and their interaction

```

log.fit <- glm(Direction ~ (Lag1 + Lag2 + Volume)^2,
                 family = binomial(), data = Weekly)

```

```

glm.probs <- predict(log.fit, type = "response")
contrasts(Weekly$Direction)

```

```

##      Up
## Down 0
## Up   1

```

```
glm.pred <- rep("Down", 1089)
glm.pred[glm.probs>0.5] <- "Up"
table(glm.pred, Weekly$Direction)
```

```
##
##  glm.pred Down  Up
##    Down    43   35
##    Up     441  570
```

```
mean(glm.pred == Weekly$Direction)
```

```
## [1] 0.5629017
```

We discover that the best prediction results are the qda model with all Lag variables, with its correct rate 0.644.

Question 5 of Section 9.7 in ISLR

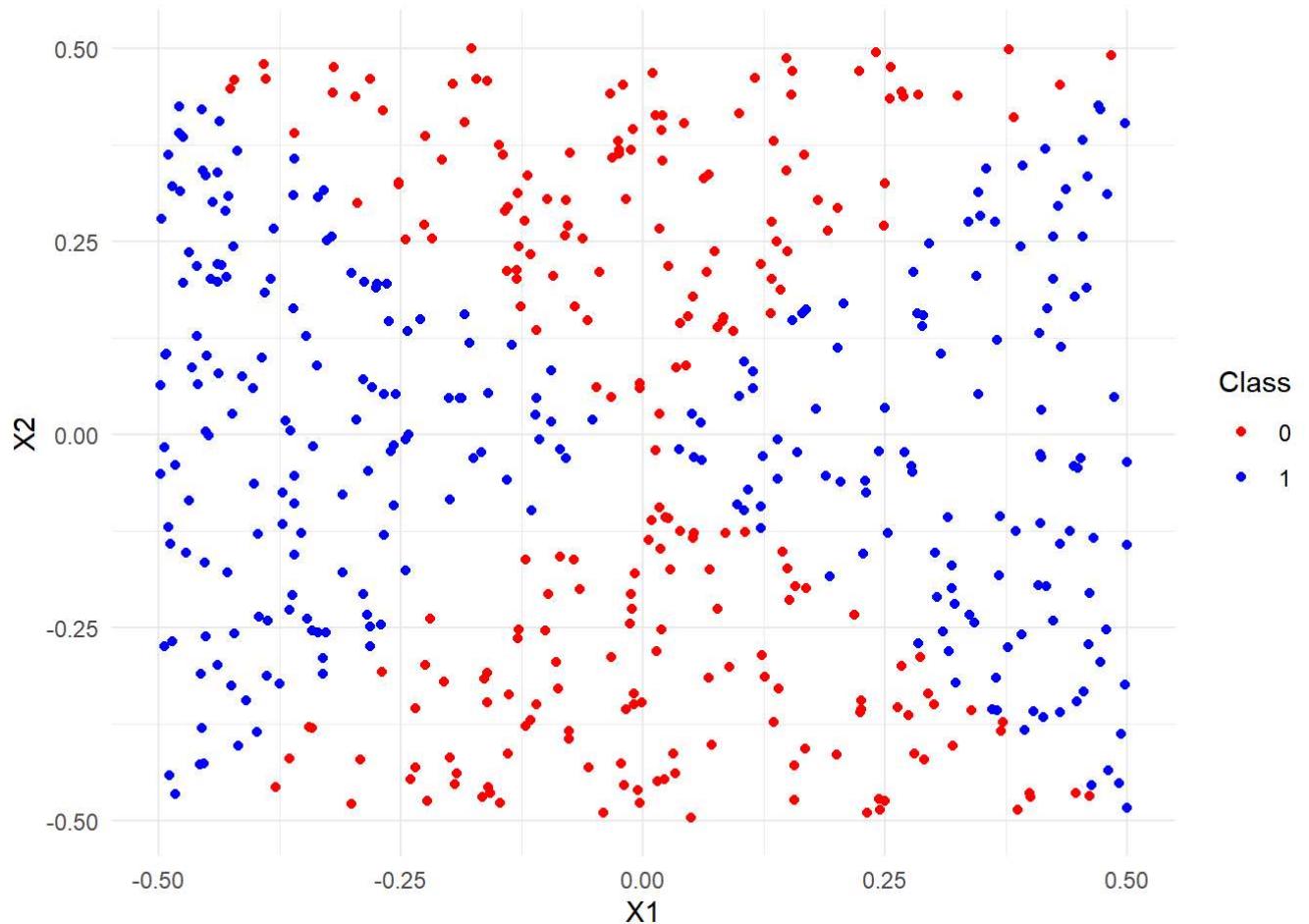
(a)

```
set.seed(37)
x1=runif(500) -0.5
x2=runif(500) -0.5
y=1*(x1^2-x2^2 > 0)
```

(b)

```
# Create a data frame
data1 <- data.frame(X1 = x1, X2 = x2, Class = as.factor(y))

# Plot the observations colored by class labels
library(ggplot2)
ggplot(data1, aes(x = X1, y = X2, color = Class)) +
  geom_point() +
  scale_color_manual(values = c("red", "blue")) +
  labs(x = "X1", y = "X2", color = "Class") +
  theme_minimal()
```



(c)

```
log.fit <- glm(Class ~ X1 + X2, family = binomial(), data = data1)
summary(log.fit)
```

```
##
## Call:
## glm(formula = Class ~ X1 + X2, family = binomial(), data = data1)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept) 0.125279  0.090235  1.388  0.1650
## X1          -0.603122  0.307581 -1.961  0.0499 *
## X2          -0.006648  0.315593 -0.021  0.9832
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 690.83 on 499 degrees of freedom
## Residual deviance: 686.94 on 497 degrees of freedom
## AIC: 692.94
##
## Number of Fisher Scoring iterations: 4
```

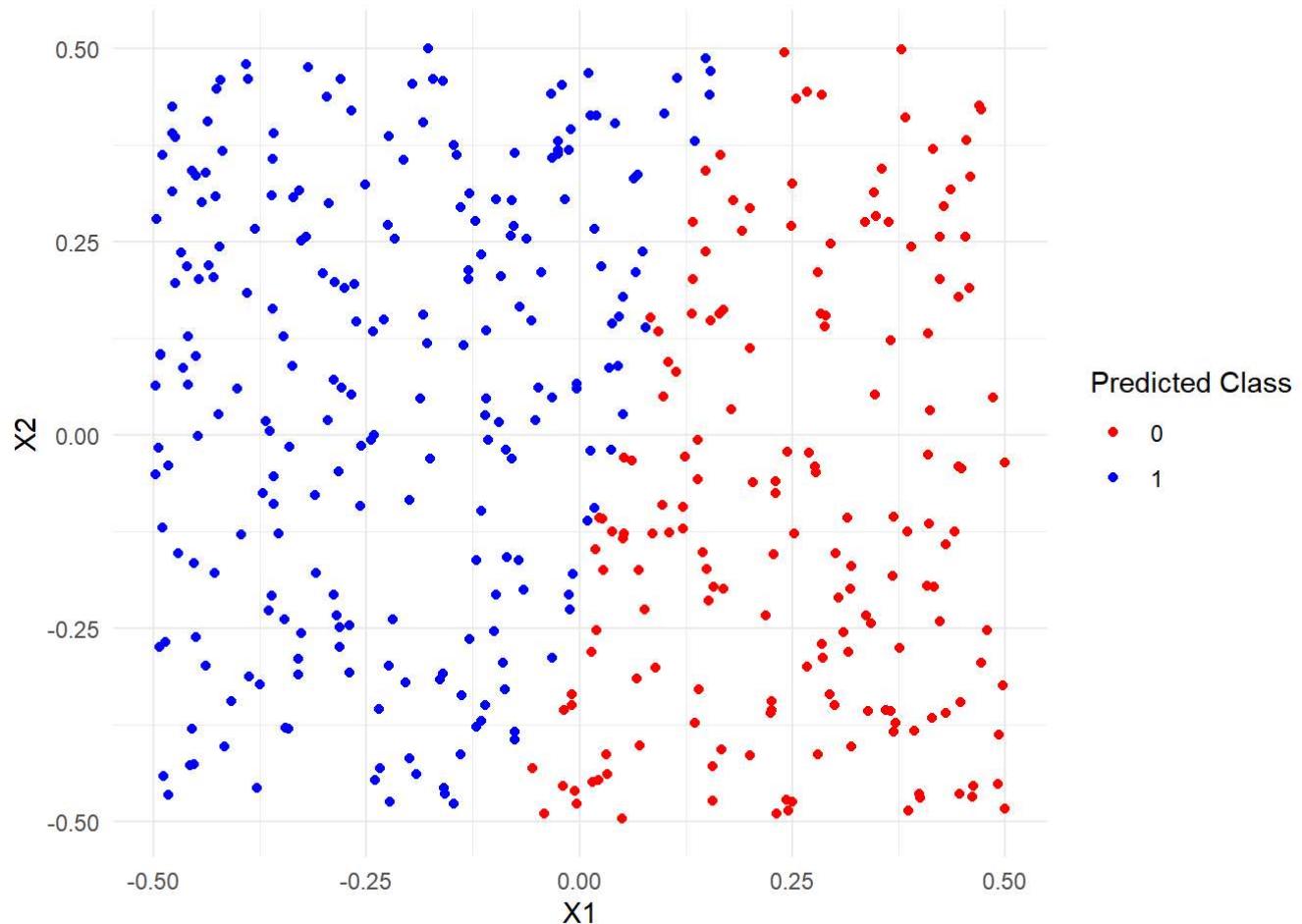
(d)

```
train <- data1[c(1:400), ]
test <- data1[c(401:500), ]
log.fit2 <- glm(Class ~ X1 + X2, data = train, family = binomial())
summary(log.fit2)
```

```
##
## Call:
## glm(formula = Class ~ X1 + X2, family = binomial(), data = train)
##
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)
## (Intercept)  0.02884   0.10084   0.286   0.7748
## X1          -0.63663   0.35217  -1.808   0.0706 .
## X2           0.15678   0.34976   0.448   0.6540
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
## Null deviance: 554.36 on 399 degrees of freedom
## Residual deviance: 550.60 on 397 degrees of freedom
## AIC: 556.6
##
## Number of Fisher Scoring iterations: 3
```

```
# Use the model to predict class labels for training data
train$predicted_class <- predict(log.fit2, data = train, type = "response") > 0.5
train$predicted_class[train$predicted_class == "FALSE"] <- 0
train$predicted_class[train$predicted_class == "TRUE"] <- 1
train$predicted_class <- as.factor(train$predicted_class)

# Plot the observations colored by predicted class labels
ggplot(train, aes(x = X1, y = X2, color = predicted_class)) +
  geom_point() +
  scale_color_manual(values = c("red", "blue")) +
  labs(x = "X1", y = "X2", color = "Predicted Class") +
  theme_minimal()
```



(e)

```
fit2 <- glm(Class ~ I(X1^2) + I(X1*X2) + log(X2^2) , data = data1, family = binomial())
```

```
## Warning: glm.fit:拟合機率算出来是数值零或一
```

```
summary(fit2)
```

```

## 
## Call:
## glm(formula = Class ~ I(X1^2) + I(X1 * X2) + log(X2^2), family = binomial(),
##      data = data1)
## 
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)    
## (Intercept) -10.7155    1.1637  -9.208 <2e-16 ***
## I(X1^2)      50.0615    5.1604   9.701 <2e-16 ***
## I(X1 * X2)    3.0451    1.9992   1.523   0.128    
## log(X2^2)    -2.2545    0.2686  -8.393 <2e-16 ***
## ---    
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
## Null deviance: 690.83 on 499 degrees of freedom
## Residual deviance: 206.25 on 496 degrees of freedom
## AIC: 214.25
## 
## Number of Fisher Scoring iterations: 7

```

(f)

```
fit3 <- glm(Class ~ I(X1^2) + I(X1*X2) + log(X2^2) , data = train, family = binomial())
```

```
## Warning: glm.fit:拟合機率算出来是数值零或一
```

```
summary(fit3)
```

```

## 
## Call:
## glm(formula = Class ~ I(X1^2) + I(X1 * X2) + log(X2^2), family = binomial(),
##      data = train)
## 
## Coefficients:
##             Estimate Std. Error z value Pr(>|z|)    
## (Intercept) -11.4231    1.4542  -7.855 3.98e-15 ***
## I(X1^2)      56.1497    6.7155   8.361 < 2e-16 ***
## I(X1 * X2)    7.1839    2.5784   2.786  0.00533 ** 
## log(X2^2)    -2.3583    0.3296  -7.154 8.41e-13 ***
## ---    
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
## 
## (Dispersion parameter for binomial family taken to be 1)
## 
## Null deviance: 554.36 on 399 degrees of freedom
## Residual deviance: 155.12 on 396 degrees of freedom
## AIC: 163.12
## 
## Number of Fisher Scoring iterations: 8

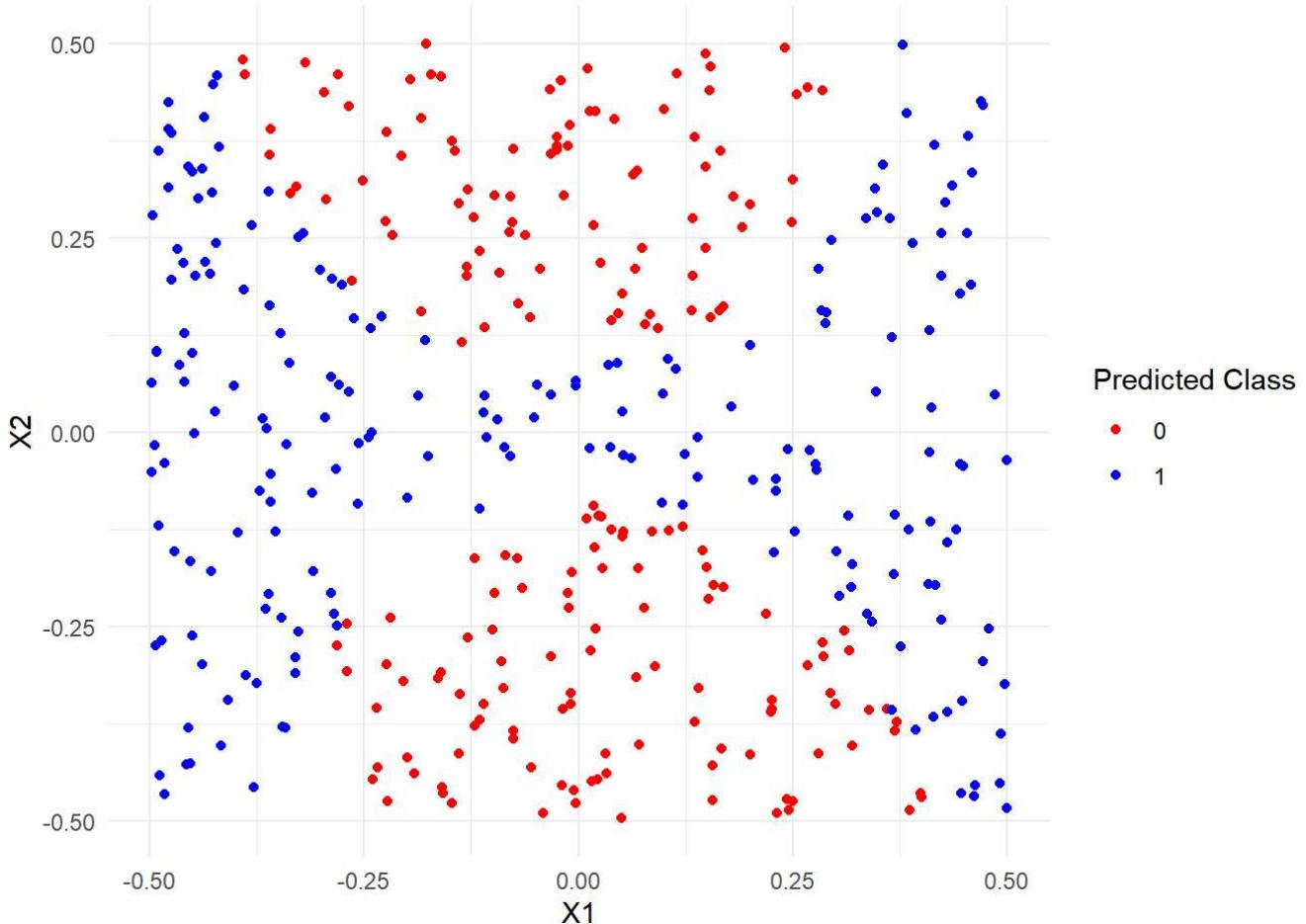
```

```

train$predicted_class <- predict(fit3, data = train, type = "response") > 0.5
train$predicted_class[train$predicted_class == "FALSE"] <- 0
train$predicted_class[train$predicted_class == "TRUE"] <- 1
train$predicted_class <- as.factor(train$predicted_class)

# Plot the observations colored by predicted class labels
ggplot(train, aes(x = X1, y = X2, color = predicted_class)) +
  geom_point() +
  scale_color_manual(values = c("red", "blue")) +
  labs(x = "X1", y = "X2", color = "Predicted Class") +
  theme_minimal()

```



```

glm.probs2 <- predict(fit3, test, type = "response")
glm.pred2 <- rep("0", nrow(test))
glm.pred2[glm.probs2 > 0.5] <- 1
table(glm.pred2, test$Class)

```

```

##
## glm.pred2  0  1
##             0 33  3
##             1  4 60

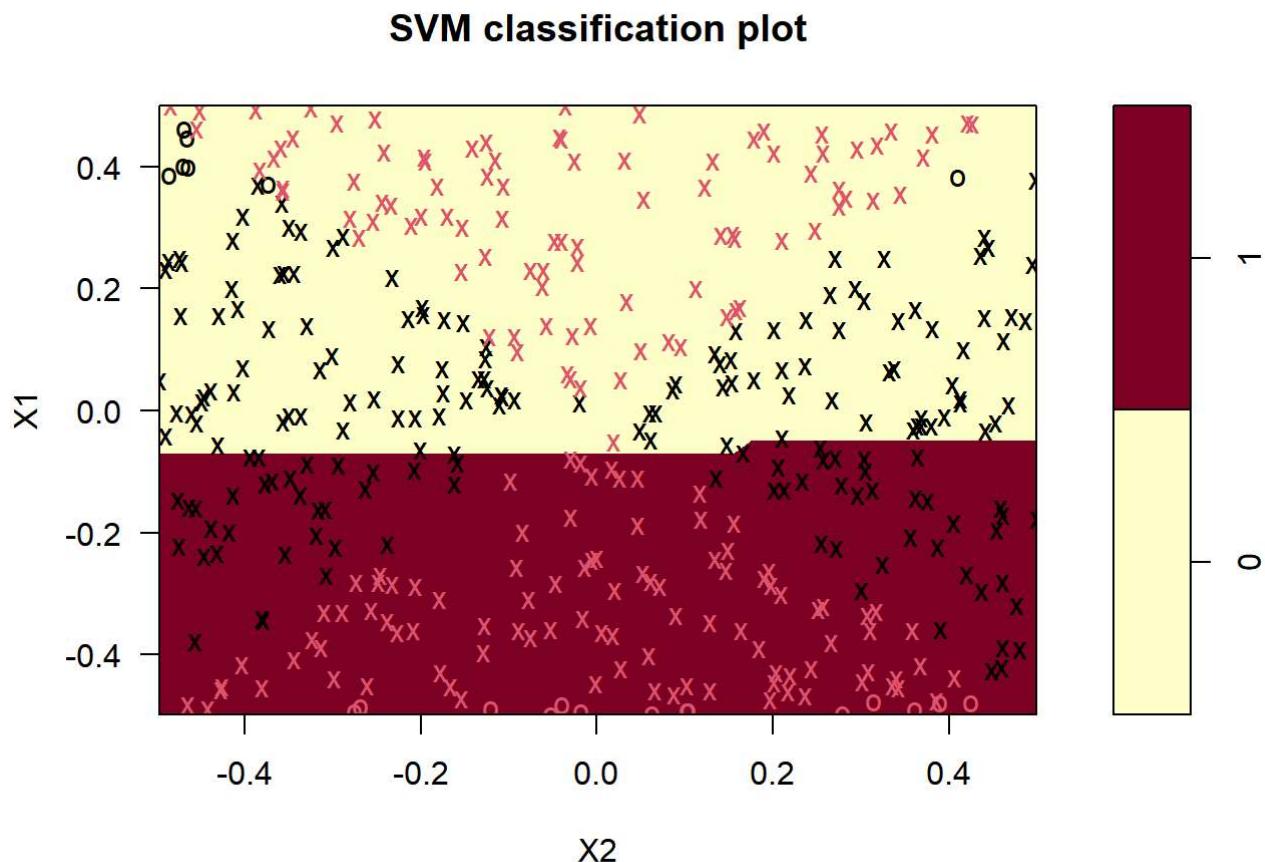
```

```
mean(glm.pred2 == test$Class)
```

```
## [1] 0.93
```

(g)

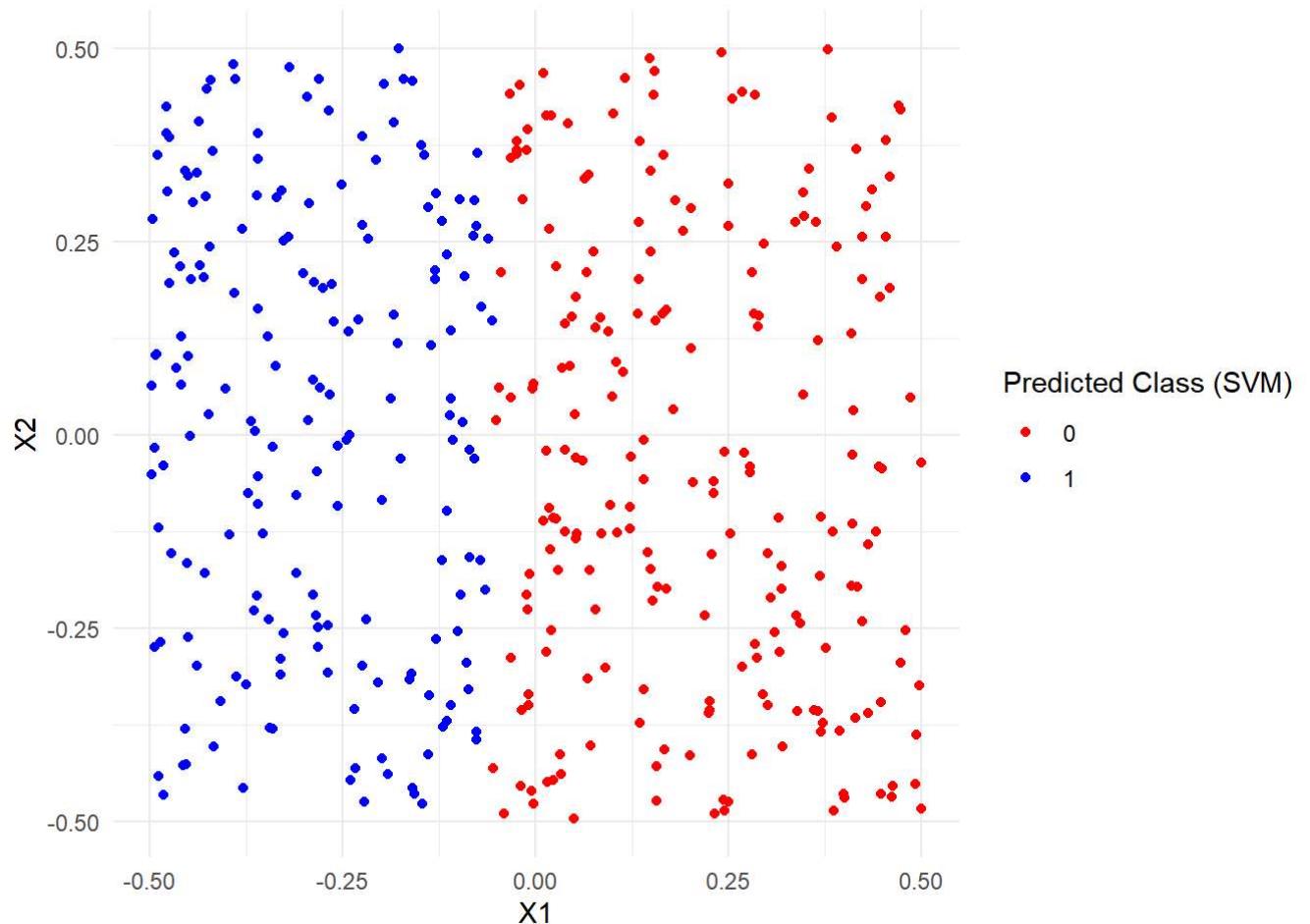
```
train <- data1[c(1:400), ]  
test <- data1[c(401:500), ]  
  
library(e1071)  
svc.fit <- svm(Class ~ ., data = train, kernel = "linear", cost = 5, scale = FALSE)  
plot(svc.fit, train)
```



```
summary(svc.fit)
```

```
##  
## Call:  
## svm(formula = Class ~ ., data = train, kernel = "linear", cost = 5,  
##       scale = FALSE)  
##  
##  
## Parameters:  
##   SVM-Type: C-classification  
##   SVM-Kernel: linear  
##   cost: 5  
##  
## Number of Support Vectors: 379  
##  
## ( 189 190 )  
##  
##  
## Number of Classes: 2  
##  
## Levels:  
## 0 1
```

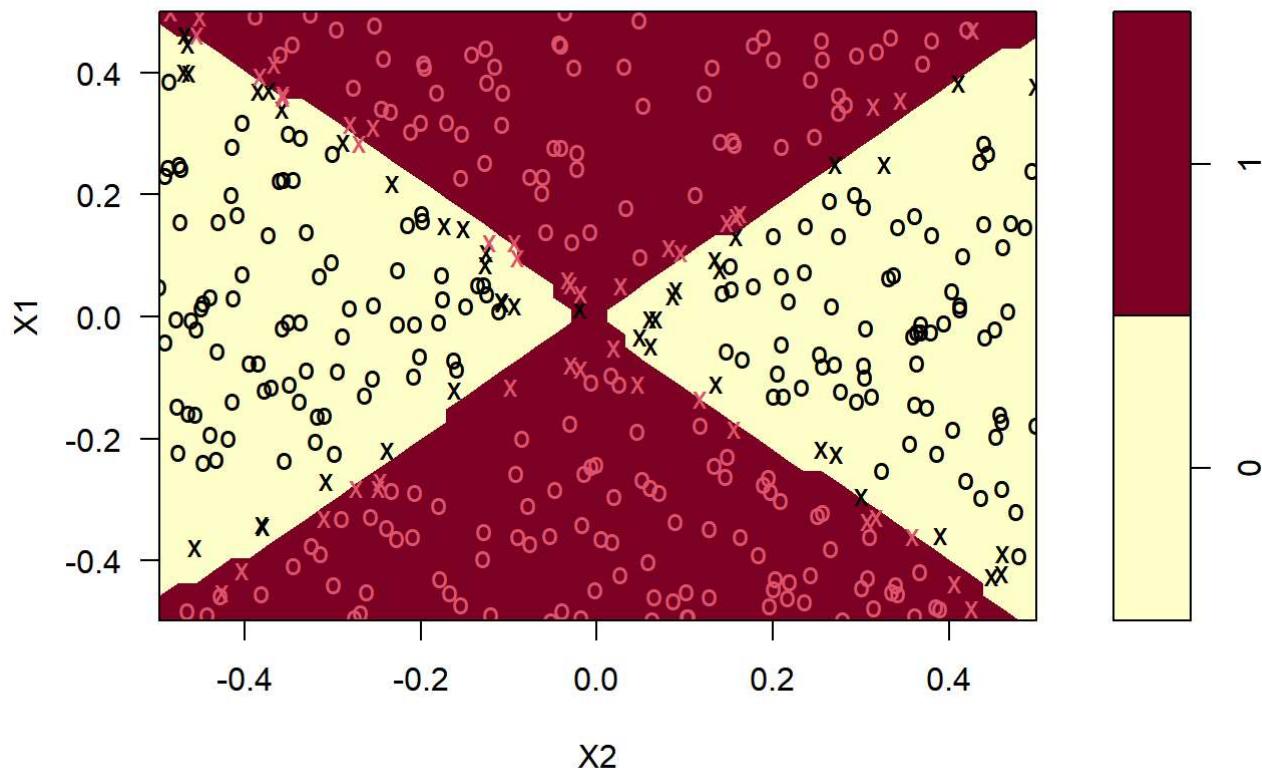
```
# Use the model to predict class labels for training data  
train$predicted_class_svm <- predict(svc.fit, data = train)  
  
# Plot the observations, colored by predicted class labels  
ggplot(train, aes(x = X1, y = X2, color = predicted_class_svm)) +  
  geom_point() +  
  scale_color_manual(values = c("red", "blue")) +  
  labs(x = "X1", y = "X2", color = "Predicted Class (SVM)") +  
  theme_minimal()
```



(h)

```
train <- data1[c(1:400),]
test <- data1[c(401:500),]
svm.fit <- svm(Class~, data = train, kernel = "radial", cost = 5, gamma = 1)
plot(svm.fit, train)
```

SVM classification plot



```
summary(svm.fit)
```

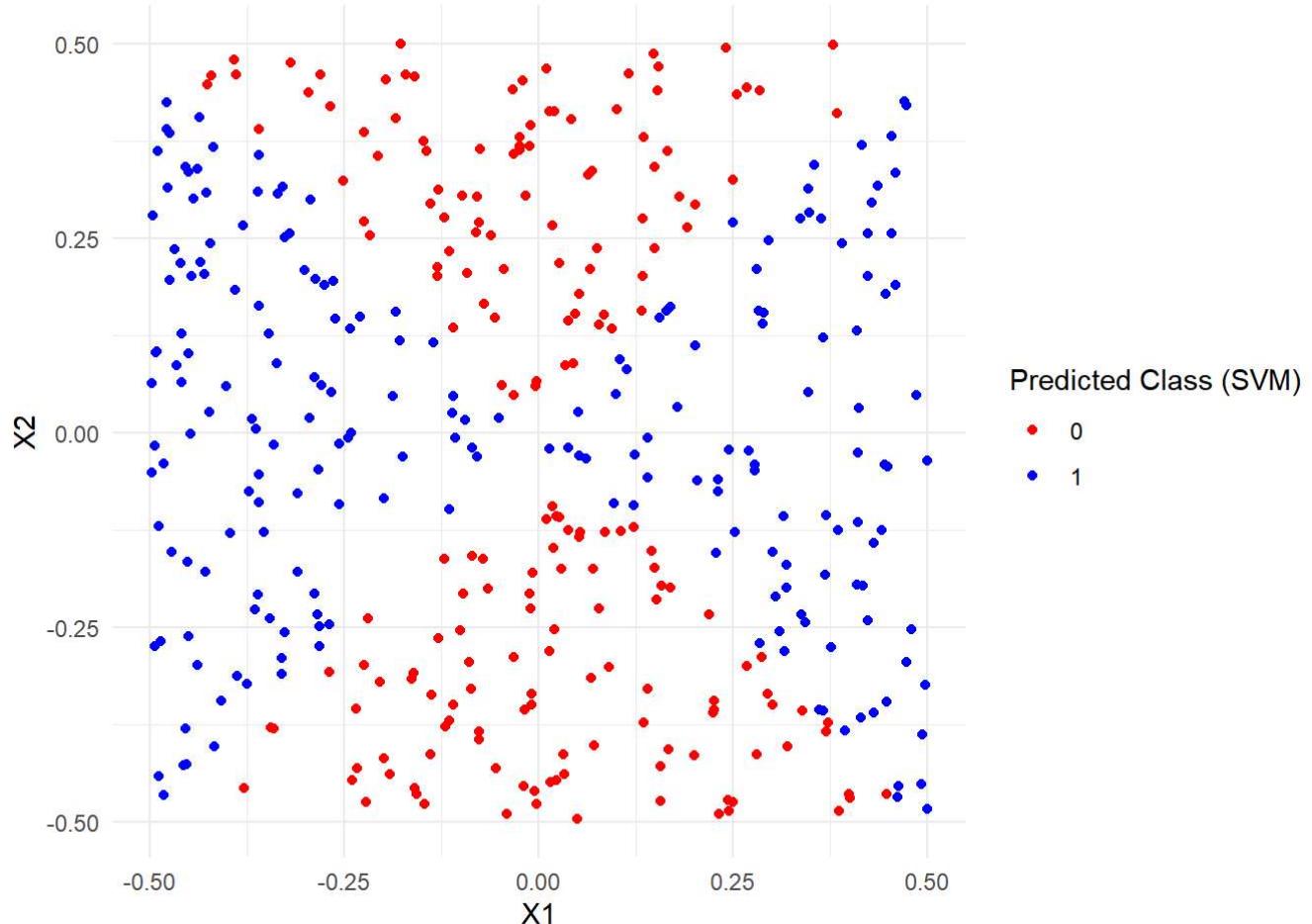
```
##  
## Call:  
## svm(formula = Class ~ ., data = train, kernel = "radial", cost = 5,  
##       gamma = 1)  
##  
##  
## Parameters:  
##   SVM-Type: C-classification  
##   SVM-Kernel: radial  
##   cost: 5  
##  
##   Number of Support Vectors: 87  
##  
##   ( 44 43 )  
##  
##  
##   Number of Classes: 2  
##  
##   Levels:  
##   0 1
```

```

# Use the model to predict class labels for training data
train$predicted_class_svm <- predict(svm.fit, data = train)

# Plot the observations, colored by predicted class labels
ggplot(train, aes(x = X1, y = X2, color = predicted_class_svm)) +
  geom_point() +
  scale_color_manual(values = c("red", "blue")) +
  labs(x = "X1", y = "X2", color = "Predicted Class (SVM)") +
  theme_minimal()

```



(i)

When simulating data with a quadratic decision boundary, a logistic model with quadratic transformations of the variables and an svm model with a quadratic kernel both produce much better (and similar fits) than standard linear methods.

Reproduction the Example in Section 9.3.3 of ISLR

First, we introduce the dataset and remove missing observations.

```
data <- read.csv("C:/Users/Lenovo/Desktop/统计学习/Heart.csv")
data <- na.omit(data)

data$AHD[data$AHD == "Yes"] <- 1
data$AHD[data$AHD == "No"] <- 0

data$AHD <- as.numeric(data$AHD)
```

Then we randomly split it into 207 training and 90 test observations.

```
set.seed(5)

train_indices <- sample(1:nrow(data), 207)
train_data <- data[train_indices, ]
test_data <- data[-train_indices, ]
```

ROC curves for Heart data on training set.

```

par(mfrow = c(1, 2))

library(ROCR)

library(e1071)
svc.fit <- svm(AHD~. -X, data = train_data, kernel = "polynomial", d = 1,
                 cost = 1e-1, scale = TRUE)
prob0 <- predict(svc.fit, train_data, type = "response")
predict0 <- prediction(prob0, train_data$AHD)
per0 <- performance(predict0, measure = "tpr", x.measure = "fpr")
plot(per0, col = "red")
abline(a = 0, b = 1, lty = 2)
legend("bottomright", legend = c("Support Vector Classifier", "LDA"),
       fill = c("red", "blue"), cex = 0.6
)

```

```

library(MASS)
lda.fit <- lda(AHD~. -X, data = train_data)

```

```

lda.prob <- predict(lda.fit, train_data, type = "response")
lda.preb <- prediction(lda.prob$posterior[, 2], train_data$AHD)
lda.per <- performance(lda.preb, measure = "tpr", x.measure = "fpr")
plot(lda.per, col = "blue", add = TRUE)

```

```

library(e1071)

```

```

plot(per0, col = "red")
legend("bottomright", legend = c("Support Vector Classifier", "SVM γ = 0.1",
                                 "SVM γ = 0.01", "SVM γ = 0.001"),
       fill = c("red", "blue", "green", "black"), cex = 0.6
)

```

```

svm.fit <- svm(AHD ~. -X, data = train_data, kernel = "radial",
                 cost = 1e-1, scale = TRUE, gamma = 0.1)
prob <- predict(svm.fit, train_data, type = "response")
predict <- prediction(prob, train_data$AHD)
per <- performance(predict, measure = "tpr", x.measure = "fpr")
plot(per, col = "blue", add = TRUE)
abline(a = 0, b = 1, lty = 2)

```

```

svm.fit2 <- svm(AHD ~. -X, data = train_data, kernel = "radial",
                 cost = 1e-1, scale = TRUE, gamma = 0.01)
prob2 <- predict(svm.fit2, train_data, type = "response")
predict2 <- prediction(prob2, train_data$AHD)
per2 <- performance(predict2, measure = "tpr", x.measure = "fpr")
plot(per2, col = "green", add = TRUE)

```

```

svm.fit3 <- svm(AHD ~. -X, data = train_data, kernel = "radial",

```

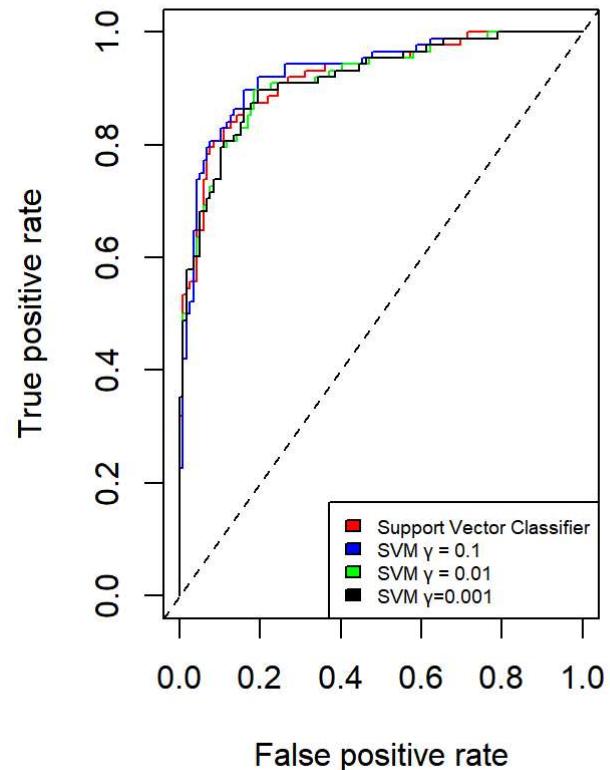
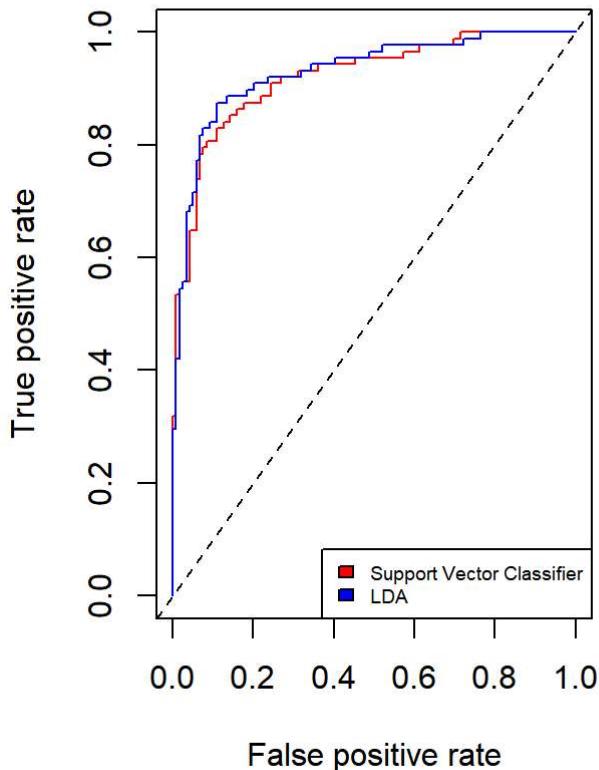
```

cost = 1e-1, scale = TRUE, gamma = 0.001)
prob3 <- predict(svm.fit3, train_data, type = "response")
predict3 <- prediction(prob3, train_data$AHD)
per3 <- performance(predict3, measure = "tpr", x.measure = "fpr")
plot(per3, col = "black", add = TRUE)

mtext("ROC curves for Heart data on training set", side = 3, line = -2, outer = TRUE, cex = 1.
5)

```

ROC curves for Heart data on training set



ROC curves for Heart data on testing set.

```

par(mfrow = c(1, 2))

library(ROCR)

library(e1071)
svc.fit <- svm(AHD~. -X, data = train_data, kernel = "polynomial", d = 1,
                 cost = 1e-1, scale = TRUE)
prob0 <- predict(svc.fit, test_data, type = "response")
predict0 <- prediction(prob0, test_data$AHD)
per0 <- performance(predict0, measure = "tpr", x.measure = "fpr")
plot(per0, col = "red")
abline(a = 0, b = 1, lty = 2)
legend("bottomright", legend = c("Support Vector Classifier", "LDA"),
       fill = c("red", "blue"), cex = 0.6
)

```

```

library(MASS)
lda.fit <- lda(AHD~. -X, data = train_data)

```

```

lda.prob <- predict(lda.fit, test_data, type = "response")
lda.preb <- prediction(lda.prob$posterior[, 2], test_data$AHD)
lda.per <- performance(lda.preb, measure = "tpr", x.measure = "fpr")
plot(lda.per, col = "blue", add = TRUE)

```

```

library(e1071)

```

```

plot(per0, col = "red")
legend("bottomright", legend = c("Support Vector Classifier", "SVM γ = 0.1",
                                 "SVM γ = 0.01", "SVM γ = 0.001"),
       fill = c("red", "blue", "green", "black"), cex = 0.6
)

```

```

svm.fit <- svm(AHD ~. -X, data = train_data, kernel = "radial",
                 cost = 1e-1, scale = TRUE, gamma = 0.1)
prob <- predict(svm.fit, test_data, type = "response")
predict <- prediction(prob, test_data$AHD)
per <- performance(predict, measure = "tpr", x.measure = "fpr")
plot(per, col = "blue", add = TRUE)
abline(a = 0, b = 1, lty = 2)

```

```

svm.fit2 <- svm(AHD ~. -X, data = train_data, kernel = "radial",
                 cost = 1e-1, scale = TRUE, gamma = 0.01)
prob2 <- predict(svm.fit2, test_data, type = "response")
predict2 <- prediction(prob2, test_data$AHD)
per2 <- performance(predict2, measure = "tpr", x.measure = "fpr")
plot(per2, col = "green", add = TRUE)

```

```

svm.fit3 <- svm(AHD ~. -X, data = train_data, kernel = "radial",

```

```

cost = 1e-1, scale = TRUE, gamma = 0.001)
prob3 <- predict(svm.fit3, test_data, type = "response")
predict3 <- prediction(prob3, test_data$AHD)
per3 <- performance(predict3, measure = "tpr", x.measure = "fpr")
plot(per3, col = "black", add = TRUE)

mtext("ROC curves for Heart data on testing set", side = 3, line = -2, outer = TRUE, cex = 1.5)

```

ROC curves for Heart data on testing set

