CIS 490 MACHINE LEARNING HOMEWORK 2

(Full Score: **45** + 4 bonus points)

October 13, 2017 Fall

Group number: 08

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Please write your answers for each question:

1. **4 points.**
   (a) use the multiple linear regression model to fit the “Demand estimation” data below (you can copy and paste the data into a file and save it as, e.g., *.txt or *.xlsx); compute SSE, MSE; and predict the number of weekly riders of a new city, given its known values on X1 = $35, X2=$1,600,000, X3 = $12,000 and X4= $ 110.

Please (1) attach your R or Matlab codes and output in your word file as Appendices; (2) save and name your original scripts as “Group#_Reg.R” (e.g., Group1_Reg.R) or “Group#_Reg.m” (e.g., “Group1_Reg.m”).

	Y	**X1**	**X2**	**X3**	**X4**
City	**Number of weekly riders**	**Price per week**	**Population of city**	**Monthly income of riders**	**Average parking rates per month**
1	192,000	$15	1,800,000	$5,800	$50
2	190,400	$15	1,790,000	$6,200	$50
3	191,200	$15	1,780,000	$6,400	$60
4	177,600	$25	1,778,000	$6,500	$60
5	176,800	$25	1,750,000	$6,550	$60
6	178,400	$25	1,740,000	$6,580	$70
7	180,800	$25	1,725,000	$8,200	$75
8	175,200	$30	1,725,000	$8,600	$75
9	174,400	$30	1,720,000	$8,800	$75
10	173,920	$30	1,705,000	$9,200	$80
11	172,800	$30	1,710,000	$9,630	$80
12	163,200	$40	1,700,000	$10,570	$80
13	161,600	$40	1,695,000	$11,330	$85
14	161,600	$40	1,695,000	$11,600	$100
15	160,800	$40	1,690,000	$11,800	$105
16	159,200	$40	1,630,000	$11,830	$105
17	148,800	$65	1,640,000	$12,650	$105
18	115,696	$102	1,635,000	$13,000	$110
19	147,200	$75	1,630,000	$13,224	$125
20	150,400	$75	1,620,000	$13,766	$130
21	152,000	$75	1,615,000	$14,010	$150
22	136,000	$80	1,605,000	$14,468	$155
23	126,240	$86	1,590,000	$15,000	$165
24	123,888	$98	1,595,000	$15,200	$175
25	126,080	$87	1,590,000	$15,600	$175
26	151,680	$77	1,600,000	$16,000	$190
					$200
27	152,800	$63	1,610,000	$16,200	

Solution: The number of weekly riders of a new city, given its known values on X1 = $35, X2=$1,600,000, X3 = $12,000 and X4= $ 110 is 190056.7

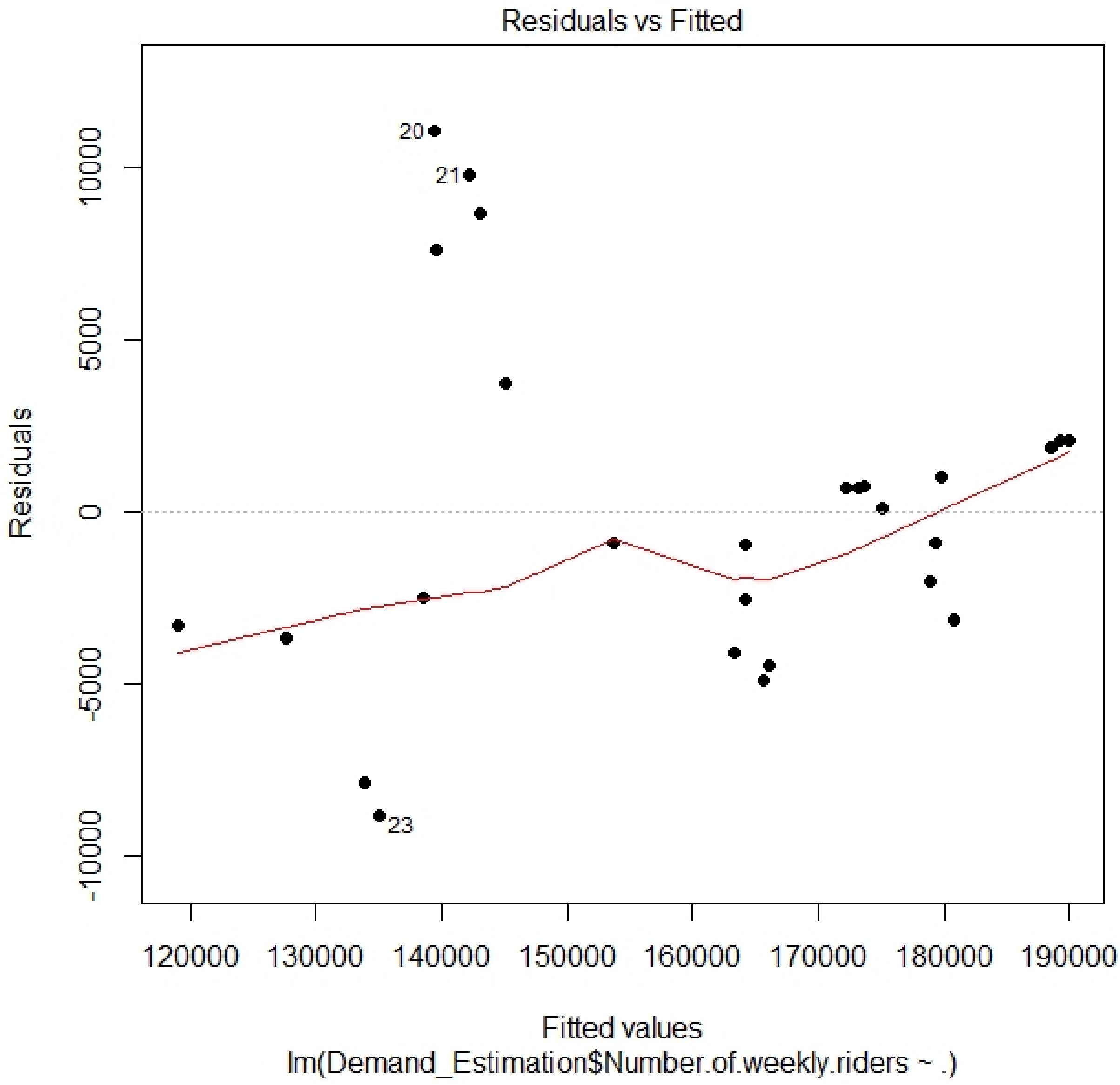
SSE: 630848248
MSE: 23364750

```
#Importing the Dataset
library(readxl)
Demand_Estimation <- read_excel("C:/Users/Kevin D'Cruz/Downloads/UMass/Sem 3/Machine Learning/Assignment 2/Demand Estimation.xlsx")
View(Demand_Estimation)

head(Demand_Estimation)

summary(Demand_Estimation)

Demand_Estimation <- data.frame(Demand_Estimation)
model1 <- lm(Demand_Estimation$Number.of.weekly.riders ~ ., data = Demand_Estimation)
summary(model1)


str(Demand_Estimation)

#Creating A Dataframe
newdf = data.frame(City = numeric(1), Price.per.week = numeric(1), Population.of.city = numeric(1), Monthly.income.of.riders = numeric(1), Average.parking.rates.per.month = numeric(1) )
newdf$City = 1
newdf$Price.per.week = 35
newdf$Population.of.city = 1600000
newdf$Monthly.income.of.riders = 12000
newdf$Average.parking.rates.per.month = 110


predict(model1, newdf)

#Computing SSE
SSE <-sum(model1$residuals^2)
SSE

#Computing MSE
MSE <-mean(model1$residuals^2)
MSE
```

1 Bonus point: Plot a graph where you have a best fit line for this dataset.

Graph:

```
#Plotting Best Fit
plot(model1, pch=16,which = 1)
```



Output Code:

```
> library(readxl)
> Demand_Estimation <- read_excel("C:/Users/Kevin D'Cruz/Downloads/UMass/Sem 3/Machine Lear
ning/Assignment 2/Demand Estimation.xlsx")
> View(Demand_Estimation)
> head(Demand_Estimation)
# A tibble: 6 x 6
   City `Number of weekly riders` `Price per week` `Population of city` `Monthly income of
riders`
  <dbl>                     <dbl>            <dbl>                <dbl>
<dbl>
1     1                    192000               15              1800000
5800
2     2                    190400               15              1790000
6200
3     3                    191200               15              1780000
6400
4     4                    177600               25              1778000
6500
5     5                    176800               25              1750000
6550
6     6                    178400               25              1740000
6580
# ... with 1 more variables: `Average parking rates per month` <dbl>
> summary(Demand_Estimation)
      City      Number of weekly riders Price per week   Population of city Monthly income
of riders
 Min.   : 1.0   Min.   :115696          Min.   : 15.00   Min.   :1590000    Min.   : 5800
 1st Qu.: 7.5   1st Qu.:149600          1st Qu.: 27.50   1st Qu.:1617500    1st Qu.: 8400
 Median :14.0   Median :161600          Median : 40.00   Median :1695000    Median :11600
 Mean   :14.0   Mean   :160026          Mean   : 49.93   Mean   :1680111    Mean   :11063
 3rd Qu.:20.5   3rd Qu.:176000          3rd Qu.: 75.00   3rd Qu.:1725000    3rd Qu.:13888
 Max.   :27.0   Max.   :192000          Max.   :102.00   Max.   :1800000    Max.   :16200
 Average parking rates per month
 Min.   : 50
 1st Qu.: 75
 Median :100
 Mean   :107
 3rd Qu.:140
 Max.   :200
> Demand_Estimation <- data.frame(Demand_Estimation)
> model1 <- lm(Demand_Estimation$Number.of.weekly.riders ~ ., data = Demand_Estimation)
> summary(model1)

Call:
lm(formula = Demand_Estimation$Number.of.weekly.riders ~ ., data = Demand_Estimation)

Residuals:
    Min      1Q  Median      3Q     Max 
-8831.7 -3194.1  -918.8  1952.5 11016.2 
```

```
Coefficients:
                                  Estimate Std. Error t value Pr(>|t|)    
(Intercept)                      1.598e+05  1.665e+05   0.960   0.3482    
City                            -1.503e+03  2.360e+03  -0.637   0.5311    
Price.per.week                  -6.979e+02  9.762e+01  -7.150 4.75e-07 ***
Population.of.city               1.520e-02  9.629e-02   0.158   0.8761    
Monthly.income.of.riders         7.002e-01  3.549e+00   0.197   0.8455    
Average.parking.rates.per.month  2.133e+02  1.214e+02   1.757   0.0935 .  
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 5481 on 21 degrees of freedom
Multiple R-squared:  0.9465,	Adjusted R-squared:  0.9338 
F-statistic: 74.34 on 5 and 21 DF,  p-value: 1.242e-12

> str(Demand_Estimation)
'data.frame':	27 obs. of  6 variables:
 $ City                           : num  1 2 3 4 5 6 7 8 9 10 ...
 $ Number.of.weekly.riders        : num  192000 190400 191200 177600 176800 ...
 $ Price.per.week                 : num  15 15 15 25 25 25 25 30 30 30 ...
 $ Population.of.city             : num  1800000 1790000 1780000 1778000 1750000 ...
 $ Monthly.income.of.riders       : num  5800 6200 6400 6500 6550 6580 8200 8600 8800 9200 
...
 $ Average.parking.rates.per.month: num  50 50 60 60 60 70 75 75 75 80 ...
> #Creating A Dataframe
> newdf = data.frame(City = numeric(1), Price.per.week = numeric(1), Population.of.city = n
umeric(1), Monthly.income.of.riders = numeric(1), Average.parking.rates.per.month = numeric
(1) )
> newdf$City = 1
> newdf$Price.per.week = 35
> newdf$Population.of.city = 1600000
> newdf$Monthly.income.of.riders = 12000
> newdf$Average.parking.rates.per.month = 110
> predict(model1, newdf)
       1 
190056.7 
> #Computing SSE
> SSE <-sum(model1$residuals^2)
> SSE
[1] 630848248
> #Computing MSE
> MSE <-mean(model1$residuals^2)
> MSE
[1] 23364750
> #Plotting Best Fit
> plot(model1, pch=16,which = 1)
```

2. 8 points

Use logistic regression model to fit the “Graduate Admission” data, in “logistic.txt” (see the data file under Homework2 in Week 6 at myCourses)

Scenario: A researcher is interested in how three variables, (X1=GRE, Graduate Record Exam scores; X2=GPA, grade point average; and X3: Rank, prestige of the undergraduate institution) effect admission into graduate school (the response variable, Y, admit/don’t admit, is a binary variable).

```
#read file named logistic
data <- read.table(file.choose(),header =T)
#data
#factor variables
data$admit <- as.factor(data$admit)
data$rank <- as.factor(data$rank)

set.seed(1234)
ind <- sample(2, nrow(data), replace = T, prob = c(0.8, 0.2))

#Logistic Regression
lrmodel <- glm(admit ~ . , data = data, family = "binomial")
summary(lrmodel)

##confusion matrix
p3 <- predict(lrmodel, data, type = "response")
p3 <- ifelse(p3>0.5,1,0)
(tab3 <- table(predicted = p3, Actual = data$admit))

#prediction if student will get admit or not Student will be admitted or not
newdf = data.frame( gre = numeric(1), gpa = double(1), rank = numeric(1) )
newdf$gre = 720
newdf$gpa = 3.8
newdf$rank= 2

newdf$rank = as.factor(newdf$rank)
str(newdf)

predict(lrmodel, newdata = newdf, interval = 'confidence')
```

(a) If a new student has X1 = 720; X2=3.8; X3= 2, do you admit or not admit him? (1 point)

Solution: From the output of the code above, the output is as follows:

1

0.02030725

This shows that, the new student gets an admit.

(b) Fill in the number of students in the confusion matrix (2 points)

	Predicted $\hat{Y}$	
Observed/True (Y)	0= don't admit	1= Admit
0= don't admit	254	97
1= Admit	19	30

(c) Compute misclassification errors, sensitivity and specificity. (3 points)

Please attach your R or Matlab code and output in your word file as Appendices. Please also save and name your scripts as "Group#_Logit.R" or "Group#_Logit.m" and any related R or Matlab output files with the same file names, e.g "Group#_Logit.xxx".

Solution:

#Misclassification rate

1 - sum(diag(tab3))/sum(tab3)

0.29

Sensitivity from the confusion matrix obtained is: 97

Specificity from the confusion matrix: 254

Output:

```
> data <- read.table(file.choose(),header =T)
> data$admit <- as.factor(data$admit)
> data$rank <- as.factor(data$rank)
> set.seed(1234)
> ind <- sample(2, nrow(data), replace = T, prob = c(0.8, 0.2))
> lrmodel <- glm(admit ~ . , data = data, family = "binomial")
> summary(lrmodel)

Call:
glm(formula = admit ~ ., family = "binomial", data = data)

Deviance Residuals:
   Min       1Q   Median       3Q      Max
-1.6268  -0.8662  -0.6388   1.1490   2.0790

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept) -3.989979   1.139951  -3.500 0.000465 *
gre          0.002264   0.001094   2.070 0.038465 *
gpa          0.804038   0.331819   2.423 0.015388 *
rank2       -0.675443   0.316490  -2.134 0.032829 *
rank3       -1.340204   0.345306  -3.881 0.000104 *
rank4       -1.551464   0.417832  -3.713 0.000205 *
---
Signif. codes:  0 ‘*’ 0.001 ‘*’ 0.01 ‘’ 0.05 ‘.’ 0.1 ‘ ’ 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 499.98  on 399  degrees of freedom
Residual deviance: 458.52  on 394  degrees of freedom
AIC: 470.52

Number of Fisher Scoring iterations: 4

> p3 <- predict(lrmodel, data, type = "response")
> p3 <- ifelse(p3>0.5,1,0)
> (tab3 <- table(predicted = p3, Actual = data$admit))
         Actual
predicted   0   1
        0 254  97
        1  19  30
> 1 - sum(diag(tab3))/sum(tab3)
[1] 0.29
> newdf = data.frame( gre = numeric(1), gpa = double(1), rank = numeric(1) )
> newdf$gre = 720
> newdf$gpa = 3.8
> newdf$rank= 2
> newdf$rank = as.factor(newdf$rank)
> str(newdf)
'data.frame':      1 obs. of  3 variables:
 $ gre : num 720
 $ gpa : num 3.8
 $ rank: Factor w/ 1 level "2": 1
> predict(lrmodel, newdata = newdf, interval = 'confidence')
         1
0.02030725
```

(d) What's relationship among probability, odds and log odds? Use an example to demonstrate their relationship. What's the range for probability, odds and log odds? (2 points)

Solution:

Probability: It gives us the fraction of times an event might occur in any number of trails, and it ranges from 0 to 1.

Odds: Odds are found by dividing the probability that the event will occur by probability that the event won't occur.

Example, consider that the probability of a event occurring is X= 0.8(i.e. 80%), then the probability of event not occurring is: Y= 1-0.8 = 0.2(i.e. 20 %)

Odds is given by, odds = X/Y

=0.8/1-0.8

=4/1

The problem of odds ratio is that, for small to moderate sample size the sampling distribution is highly skewed. To overcome the problem, we use Log Odds ratio.

Log odds: They provide another way of expressing probability, intended to simplify the process of updating them with new data or evidence.

It is difficult to convert probability to log odds. Log odds is the log of odds ratio. That is , Log odds = log(Odds) So, from the above example Log odd ratio is, Log odds = log(Odds) Log odds =log(1.5)

3. 8 **points**

(a) What is Bias-variance trade off? (0.5 point)

Solution:

Bias-variance tradeoff –It is the problem in supervised learning. The problem takes place when two sources of error prevent supervised learning algorithm from simplifying beyond their training set.

i. **Bias**

Bias is an error from inaccurate hypothesis. High bias can cause an algorithm to omission the relevant relations between structures and goal output

ii. **Variance**

Variance is an error from compassion to small variability in the training set. High variance can cause an algorithm to establish the random noise in the training data, rather than the proposed outputs

(b) What is overfitting? (0.5 point)

Solution:

Overfitting: It takes place when the model is extremely complex, such as having too many parameters relative to the numbers of observations. Overfitted model have poor predictive performance, because it exaggerates to slight variations in the training data. The existence of overfitting depends on the measures used for training the model, but it is not the same as the measures used to magistrate the usefulness of a model. The model is classically trained by maximizing its piece on some set of training data and its usefulness is determine not by its piece on the training data but by its capacity to perform well on unseen data.

(c) What are the two common types of regularization in linear regression? (0.5 point)

Solution:

i. Ridge Regression

Ridge regression is a practice for scrutinizing multiple regression data that agonize from multi regression. The multi regression take place when the smallest squares assessments are impartial, as their discrepancy are large, so they may be far from the true value, ridge regression castigates the size of the regression coefficients, the ridge regression coefficient assessment is defined as the value of ***β*** that minimizes

$$\sum_i (y_i - x_i^T \beta)^2 + \lambda \sum_{j=1}^{p} \beta_j^2$$

ii. Lasso Regression

Lasso regression is a method that accomplishes both variable collection and control because they increase the calculation, precision and accountability of the statistical model, Lasso is slightest complete contraction and collection operator. Its coefficients are the solution to the l_1 optimization problem.

Minimize $(y - \boldsymbol{Z}\beta)^T \, (y - \boldsymbol{Z}\beta)$

Such that $\sum_{j=1}^{p} |\beta_j| \leq t$

(d) Write out the objective functions for these two regularization types. Please identify which term is for SSR and which term is for shrinkage penalty term in each function. What is λ called in these regularized regressions? (2 points)

Solution:

i. **Ridge Regression**

$$\sum_{i}(y_i - x_i^T\,\beta)^2 + \lambda\sum_{j=1}^{p}\beta_j^2$$

ii. **Lasso Regression**

Minimize $(y - \boldsymbol{Z}\beta)^T\,(y - \boldsymbol{Z}\beta)$

Such that $\sum_{j=1}^{p}|\beta_j| \le t$

(e) Write out the corollaries of Ridge Regression. (0.5 point)

Solution: The solution for regular regression problem is assumed by

$\beta^{\wedge} = (X^TX + \lambda\boldsymbol{I})^{-1}\,X^Ty$

Therefore, $\beta^{\wedge} = (X^TX + \lambda\boldsymbol{I})^{-1}\,X^Ty$

Therefore, Corollary:

i. $\lambda \to 0, \beta^{\wedge\,ridge} \to \beta^{\wedge\,OLS}$

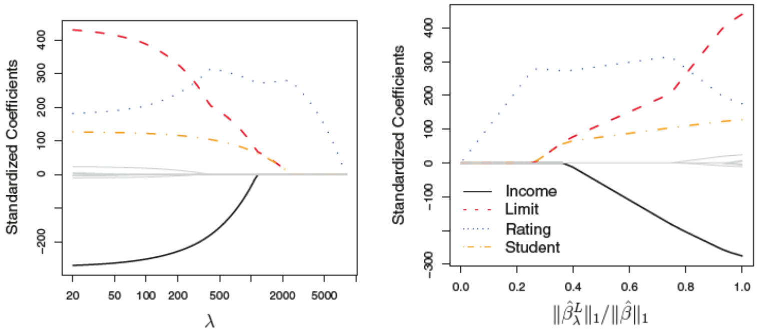
ii. $\lambda \to \infty, \beta^{\wedge\,ridge} \to 0$

(f) what is the major difference between the two regularization types? (hint: why one of them is preferred in real world practice) (1 point)

Solution:

Ridge Regression	Lasso regression
In rigid regression, the drawback is the sum of square of coefficient	In lasso it's the sum of the complete value of the coefficient
Unsteady Solution	Constant Solution
Multiple solutions may be possible	Only one solution
This is the regularization method and uses l2 regularization	This is the regularization method that uses l1 regularization
It contracts the value of coefficient but does not reaches zero, which suggests no feature selection	It contracts coefficient to zero which certainly help in feature selection

(g) Download credit data from under Homework2 in Week 6 at myCourses and use Lasso regression with cross-validation to select a parsimonious model (Occam's Razor), ie. what attributes will enter into your final Lasso regression model and what optimal value will you pick for λ? Please replicate the following two graphs. (3 points)
Please (1) attach your R or Matlab codes and output in your word file as Appendices; (2) save and name your original scripts as "Group#_Lasso.R" (e.g., Group1_Lasso.R) or "Group#_Lasso.m" (e.g., "Group1_Lasso.m").

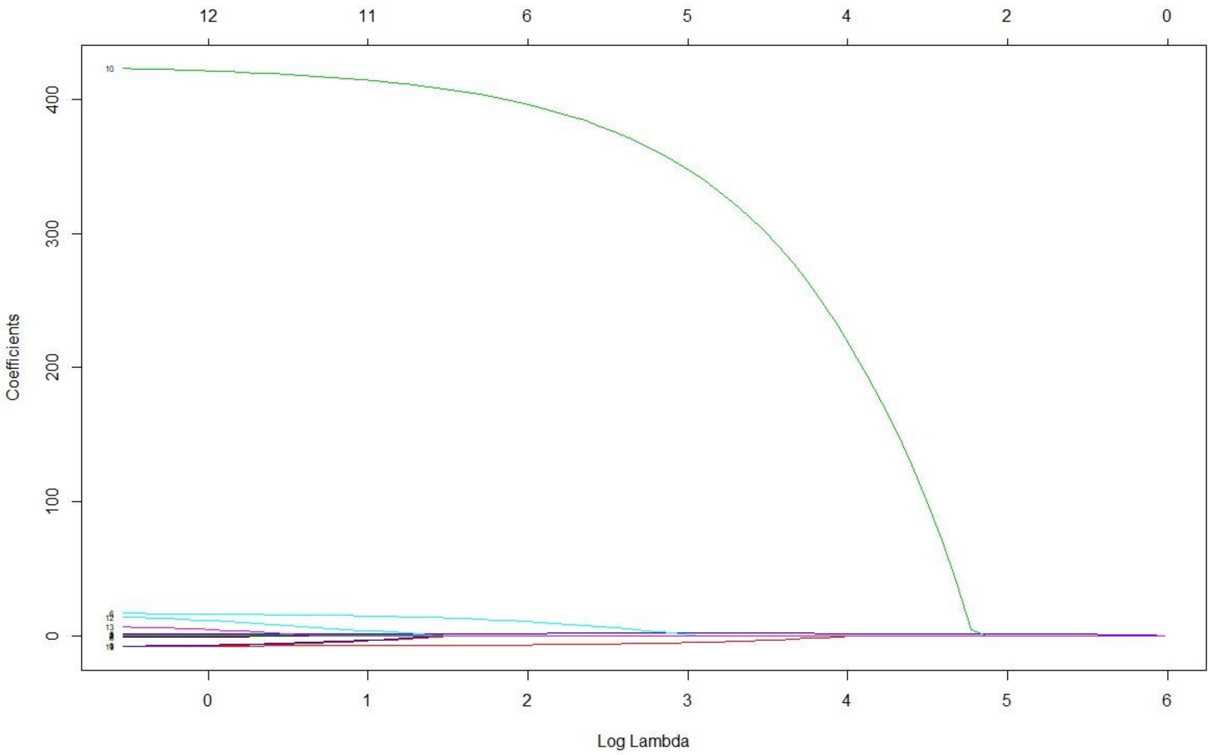


Solution(Code):

```
library(glmnet)
data <- read.csv(file.choose(), header= T)
x=model.matrix(Balance~.,data=data)
y <- as.double(as.matrix(data[, 12])) # Only class
#head(y)
set.seed(999)
```

```
cv.lasso <- cv.glmnet(x, y, alpha=1, parallel=TRUE, standardize=TRUE, type.measure='auc')
plot(cv.lasso)
plot(cv.lasso$glmnet.fit, xvar="lambda", label=TRUE)
cv.lasso$lambda.min
cv.lasso$lambda.1se
coef(cv.lasso, s=cv.lasso$lambda.1se)
coef <- coef(cv.lasso, s='lambda.1se')
coef
```

Graph:



Output:

```
library(glmnet)
> data <- read.csv(file.choose(), header= T)
> x=model.matrix(Balance~.,data=data)
> y <- as.double(as.matrix(data[, 12])) # Only class
> set.seed(999)
> cv.lasso <- cv.glmnet(x, y, alpha=1, parallel=TRUE, standardize=TRUE,
type.measure='auc')
Warning message:
In cv.elnet(list(list(a0 = c(535.825, 454.345391736194, 380.104207303334,  :
  Only 'mse', 'deviance' or 'mae'  available for Gaussian models; 'mse' used
> plot(cv.lasso)
> plot(cv.lasso$glmnet.fit, xvar="lambda", label=TRUE)
> cv.lasso$lambda.min
[1] 0.6462984
> cv.lasso$lambda.1se
[1] 8.744726
> coef(cv.lasso, s=cv.lasso$lambda.1se)
14 x 1 sparse Matrix of class "dgCMatrix"
                         1
(Intercept)       -473.4815857
(Intercept)          .
X                  .
Income             -6.6522100
Limit              0.1342854
Rating             1.7122347
Cards              9.2763395
Age               -0.2859738
Education            .
GenderFemale         .
StudentYes        391.2431284
MarriedYes           .
EthnicityAsian       .
EthnicityCaucasian   .
```

Here we get 2 values of λ , i.e. min = 0.6462984 and 1se = 8.744726. values closer to zero signify the unimportant variables.

4. 7 points

(a) What are the differences between parametric and non-parametric methods? (1.5 point)

Solution:

Parametric method	Non-parametric method
Parametric method makes several hypotheses about parameters	Non-parametric method does not make several hypotheses about parameters.
The inhabitants have the same changes.	Variant under study has inherent stability.
The parametric method emphases on the nasty difference and corresponding non-parametric test emphases on the difference between means	In non- parametric method records are changed from scores to levels or symbols

In parametric method numerical method trust on hypothesis about the shape of the distribution	In non-parametric method numerical method trust on few hypothesis about the outline of the population distribution from which the model was drawn.

(b) What is called curse of dimensionality? (0.5 point)

Solution:

Curse of dimensionality is a process that take place at the time of examining and unifying data in high-dimensional location, they do not follow in low-dimensional location, it is somewhat ambiguous in definition as it describes different but related things in different disciplines.

(c) Why should we consider rescaling the attributes when using KNN? (0.5 point)

Solution:

We consider rescaling the attribute data to value so that we can scale the range in [0,1] or [-1,1] which is useful for the optimizing algorithms and it is useful for algorithms that use distance measurement such as KNN.

(d) What options can we use to determine the class from a nearest neighbor list? (0.5 point)

Solution:

The options we can use to determine the class from a nearest neighbor list is:

i. To take Mainstream division of class labels among the k-nearest neighbors.

ii. To balance the division according to distance

Weight factor, w=1/d^2

(e) What method can we use to choose the number of k for nearest neighbor classification (0.5 point)

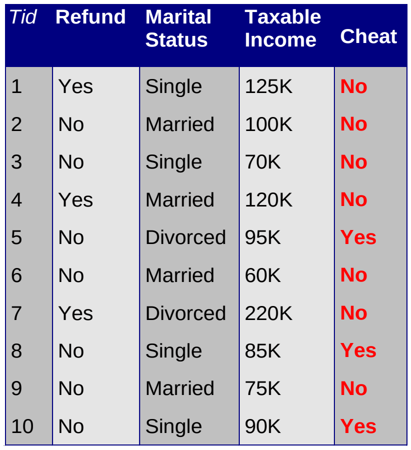
Solution:

i. **k** should be large so that error rate is minimized, if **k** is too small it will lead to noisy decision boundaries.

ii. **k** should be small enough so that only nearby models are involved.

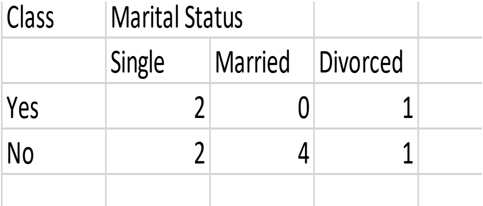
if **k** is too large it will lead to over-smoothed limitations

(d) Given data below, compute the distance between nominal attribute values: d(Married,Divorced). Please show you calculation steps below. (1 point)



Tid	**Refund**	**Marital Status**	**Taxable Income**	**Cheat**
1	Yes	Single	125K	**No**
2	No	Married	100K	**No**
3	No	Single	70K	**No**
4	Yes	Married	120K	**No**
5	No	Divorced	95K	**Yes**
6	No	Married	60K	**No**
7	Yes	Divorced	220K	**No**
8	No	Single	85K	**Yes**
9	No	Married	75K	**No**
10	No	Single	90K	**Yes**

Solution:



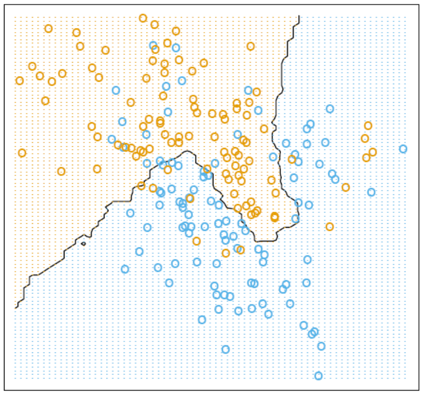
Class	Marital Status		
	Single	Married	Divorced
Yes	2	0	1
No	2	4	1

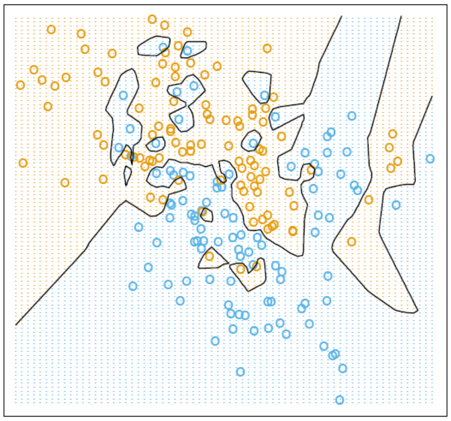
d(Married,Divorced):

$$=\left|\frac{0}{4}-\frac{1}{2}\right| + \left|\frac{4}{4}-\frac{1}{2}\right|$$

$$= 1$$

(f) KNN is a local or global method? (0.5 point) Solution:





Which decision boundary in the graph seems to derive from more nearest neighbors? (0.5 point)

(i) (ii)

Solution:

KNN is a local method because it is the simple and active method that guesses the class label of a query model based on information contained in its neighborhood

(i) is the decision boundary in the graph which seems to derive from more nearest neighbors.

(g) Please download IRIS data from UCI machine learning repository (https://archive.ics.uci.edu/ml/datasets.html), and run KNN on IRIS data, compute the misclassification error rates. (1.5 points)

Please (1) attach your R or Matlab codes and output in your word file as Appendices; (2) save and name your original scripts as "Group#_KNN.R" (e.g., Group1_KNN.R) or "Group#_KNN.m" (e.g., "Group1_IRIS.m"). (points)

Solution:

```
data("iris")
head(iris,10)
set.seed(1234)

ind <- sample(2, nrow(iris), replace = T, prob = c(0.8, 0.2))
ind
train_data <- iris[ind == 1, 1:4]
test_data <- iris[ind==2, 1:4]

train_label <- iris[ind == 1, 5]
test_label <- iris[ind==2, 5]


library(class)
iris_test_pred<-knn(train=train_data, test=test_data,cl=train_label,k=13)
iris_test_pred

tab1 <- table(predicted = iris_test_pred, Actual = test_label)
tab1

accuracy <- sum(diag(tab1)) / sum(tab1)
accuracy
misclassification_error_rate = 1 - accuracy
misclassification_error_rate
```

Since there are very few cases in the test data, we get 100% accuracy and a misclassification rate of 0.

Output:

```
data("iris")
> head(iris,10)
  Sepal.Length Sepal.Width Petal.Length Petal.Width Species
1          5.1         3.5          1.4         0.2  setosa
2          4.9         3.0          1.4         0.2  setosa
3          4.7         3.2          1.3         0.2  setosa
4          4.6         3.1          1.5         0.2  setosa
5          5.0         3.6          1.4         0.2  setosa
```

```
6         5.4       3.9       1.7       0.4  setosa
7         4.6       3.4       1.4       0.3  setosa
8         5.0       3.4       1.5       0.2  setosa
9         4.4       2.9       1.4       0.2  setosa
10         4.9       3.1       1.5       0.1  setosa
> set.seed(1234)
> ind <- sample(2, nrow(iris), replace = T, prob = c(0.8, 0.2))
> ind
  [1] 1 1 1 1 2 1 1 1 1 1 1 1 2 1 2 1 1 1 1 1 1 1 1 2 1 2 2 1 1 1 1 1 1 1 1 2 2 1 1 1 1 1
 [46] 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 2 1 1 1 1 1 1 1 1 1 1 2 1 1 1 1 1 1 1 1 2 1 1 1 1 2 1 1 1 2
 [91] 1 2 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 2 1 1 2 2 1 1 1 1 2 2 2 1 1 1 1 1 1 2 1 1 1 2
[136] 1 2 1 1 2 1 2 1 1 1 1 1 1 2 1
> train_data <- iris[ind == 1, 1:4]
> test_data <- iris[ind==2, 1:4]
> train_label <- iris[ind == 1, 5]
> test_label <- iris[ind==2, 5]
> library(class)
> iris_test_pred<-knn(train=train_data, test=test_data,cl=train_label,k=13)
> iris_test_pred
 [1] setosa     setosa     setosa     setosa     setosa     setosa     setosa     setosa
 [9] versicolor versicolor versicolor versicolor versicolor versicolor versicolor virginica
[17] virginica  virginica  virginica  virginica  virginica  virginica  virginica  virginica
[25] virginica  virginica  virginica
Levels: setosa versicolor virginica
> tab1 <- table(predicted = iris_test_pred, Actual = test_label)
> tab1
            Actual
predicted    setosa versicolor virginica
  setosa        8        0        0
  versicolor     0        7        0
  virginica      0        0       12
> accuracy <- sum(diag(tab1)) / sum(tab1)
> accuracy
[1] 1
> misclassification_error_rate = 1 - accuracy
> misclassification_error_rate
[1] 0
```

2 Bonus Points: Using the same IRIS data, use cross validation to choose the optimal number of nearest neighbors for KNN. Please (1) attach your R or Matlab codes and output in your word file as Appendices; (2) save and name your original scripts as "Group#_KNNCV.R" (e.g., Group1_KNNCV.R) or "Group#_KNNCV.m" (e.g., "Group1_KNNCV.m").

Solution(Code):

```
iris_test_pred2<-knn.cv(train=train_data,cl=train_label,k=13)
```

```
tab2 <- table(predicted = iris_test_pred2, Actual = train_label)
tab2
```

Output:

```
Actual
predicted   setosa versicolor virginica
  setosa       42        0       0
  versicolor    0       42       2
  virginica     0        1      36
```

After varying the k value, we get the least classification error for k=13

5. **6 points**

(a) What are the differences between Frequentist and Bayesian approaches? (2 point)

Solution:

Frequentist	Bayesian
In frequentist data are repeatable unplanned sample	In Bayesian data are observed from the comprehended sample
Parameters are fixed	Data are fixed
It does not use prospects for hypothesis	It uses prospects for both hypothesis and data
It depends on the possibility for both practical and unseen data	It depends on the prior and possibility of practical data
Does not require a previous	Require one to know a particular preceding
It is less computationally intensive	It is computationally intensive due to integration over many parameters

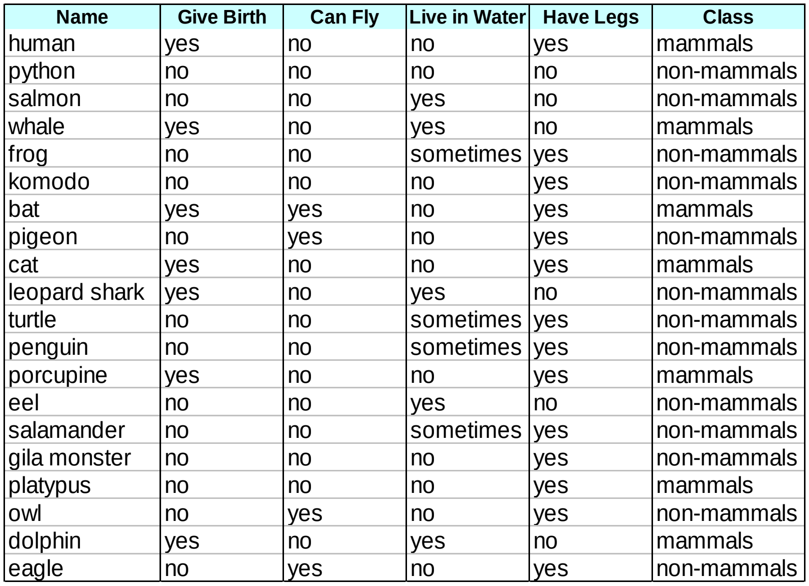
(b) What are the four terms called in the following equation from Bayesian classification approach. (1 point)

$$p(C\,|\,\mathbf{x}) = \frac{p(\mathbf{x}\,|\,C)\,p(C)}{p(\mathbf{x})}$$

Solution:

p(C|x) is called posterior probability.
p(x|C) is called likelihood.
p(C) is called prior probability.
p(x) is called evidence.

(c) Given the evidence/observed data below



Name	Give Birth	Can Fly	Live in Water	Have Legs	Class
human	yes	no	no	yes	mammals
python	no	no	no	no	non-mammals
salmon	no	no	yes	no	non-mammals
whale	yes	no	yes	no	mammals
frog	no	no	sometimes	yes	non-mammals
komodo	no	no	no	yes	non-mammals
bat	yes	yes	no	yes	mammals
pigeon	no	yes	no	yes	non-mammals
cat	yes	no	no	yes	mammals
leopard shark	yes	no	yes	no	non-mammals
turtle	no	no	sometimes	yes	non-mammals
penguin	no	no	sometimes	yes	non-mammals
porcupine	yes	no	no	yes	mammals
eel	no	no	yes	no	non-mammals
salamander	no	no	sometimes	yes	non-mammals
gila monster	no	no	no	yes	non-mammals
platypus	no	no	no	yes	mammals
owl	no	yes	no	yes	non-mammals
dolphin	yes	no	yes	no	mammals
eagle	no	yes	no	yes	non-mammals

what is the class label for a new animal with the following attribute values? Please show your calculation steps using Naïve Bayes Formulas. (3 points)

Give Birth	Can fly	Live in water	Have Legs	Class
Yes	No	yes	no	?

Solution:

X: attributes

M: Class: Mammal

N: Class: Non-Mammal

p(X|M) = (6/7) * (6/7) * (2/7) * (2/7) = 0.06

p(X|N) = (1/13) * (10/13) * (3/13) * (4/13) = 0.0042

p(X|M) * p(M) = 0.06 * (7/20) = 0.021

p(X|N) * p(N) = 0.004*(13/20) = 0.0027

p(X|M) * p(M) > p(X|N) * p(N)

Hence, the class label for a new animal with the following attribute values is **Mammal**.

6. 8 **points**

(a) What is the relationship between LDA and Naïve Bayes? (points)

Linear Discriminant Analysis (LDA) and naïve bayes both are used for linear classification. They both fall in the type of generative models and that is used to estimate the posterior probability as:

$$P(\frac{class}{x})$$

LDA and naïve bayes both accepts that Gaussian is with in class distribution. In naïve bayes, this is assumed that variables are independent while in LDA it is assumed that covariance for all the classes is same. If data is normally distributed then we can use naïve bayes and as well as LDA because it also uses normal distribution.

(b) What is the relationship between LDA and Logistic regression? (points)

Logistic regression aim is to find the conditional distribution i.e, $p(k|x)$ while linear discriminant analysis aim is to find the joint distribution as $p(k, x)$. Logistic regression maximizes the conditional likelihood while LDA maximizes the joint likelihood.

Gross outliers are not handled by LDA while logistic regression can handle non Gaussian type of data as it takes into consider few assumption.

Often similar results are obtained by both of the models, logistic regression and LDA.

(c) When do we use Logistic regression, LDA or Naïve Bayes? (points)

Logistic Regression:

It is a regression analysis and it is used when dependent variable, the variable which we need to analyze based on given data is in the form of binary that is when one of the two outcomes are needed to be predicted. Logistic regression defines the relationship between a binary dependent variable with one or many independent variables.

LDA:

Linear discriminant analysis is preferred to use when number of classes are more than 2. It works on the assumption that the provided data is in Gaussian that is a bell curve is formed for each variable if plotted and other assumption is that each variable has the same variance.

It is also used for dimensionality reduction as a preprocessing task for machine learning. Aim of this to reduce the dataset into smaller form for better class prediction in order to avoid overfitting i.e., cure of dimensionality and this also minimizes the required computational power.

Naïve Bayes:

Naïve Bayes is practically useful when we have very large dataset. It can coverage fast when conditional assumption holds so it requires less training data and less time is consumed for training the model.

(d) Please download IRIS data from UCI machine learning repository (https://archive.ics.uci.edu/ml/datasets.html), compare the misclassification error rates, false positive rates and false negative rates between Naïve Bayes and LDA. Please (1) attach your R or Matlab codes and output in your word file as Appendices; (2) save and name your original scripts as "Group#_IRIS.R" (e.g., Group1_IRIS.R) or "Group#_IRIS.m" (e.g., "Group1_IRIS.m"). (points)

R Code: Naïve Bayes

```
data <- iris

indep = iris[,-5]
dep <- iris$Species

library("caret")
library("klaR")
library("e1071")
library("MASS")

nb = train(indep,dep,'nb',trControl=trainControl(method='cv',number=8))
```

```
nb

predict(nb$finalModel,indep)
(tab1 <- table(predict(nb$finalModel,indep)$class,dep))

(missclassification_error <- 1 - sum(diag(tab1))/sum(tab1))
```

Output:

```
         dep
             setosa versicolor virginica
  setosa         50          0         0
  versicolor      0         47         3
  virginica       0          3        47
```

Misclassification Error for Naïve Bayes:

- ➢ 0.04 ➔ 4%

R Code: LDA

```
library(MASS)
data <- iris

lda_model <- lda(Species~., data)
summary(lda_model)

p1 <- predict(lda_model, data[,1:4])$class
(tab2 <- table(p1, data$Species))

(missclassification_error <- 1 - sum(diag(tab2))/sum(tab2))
```

Output:

```
p1           setosa versicolor virginica
  setosa         50          0         0
  versicolor      0         48         1
  virginica       0          2        49
```

Misclassification Error for Naïve Bayes:

- ➢ 0.02 ➔ 2%

Description:

When Naïve Bayes algorithm is applied on Iris dataset, we obtained misclassification error of 4% while LDA gave less misclassification error of 2%.

7. **4 points**

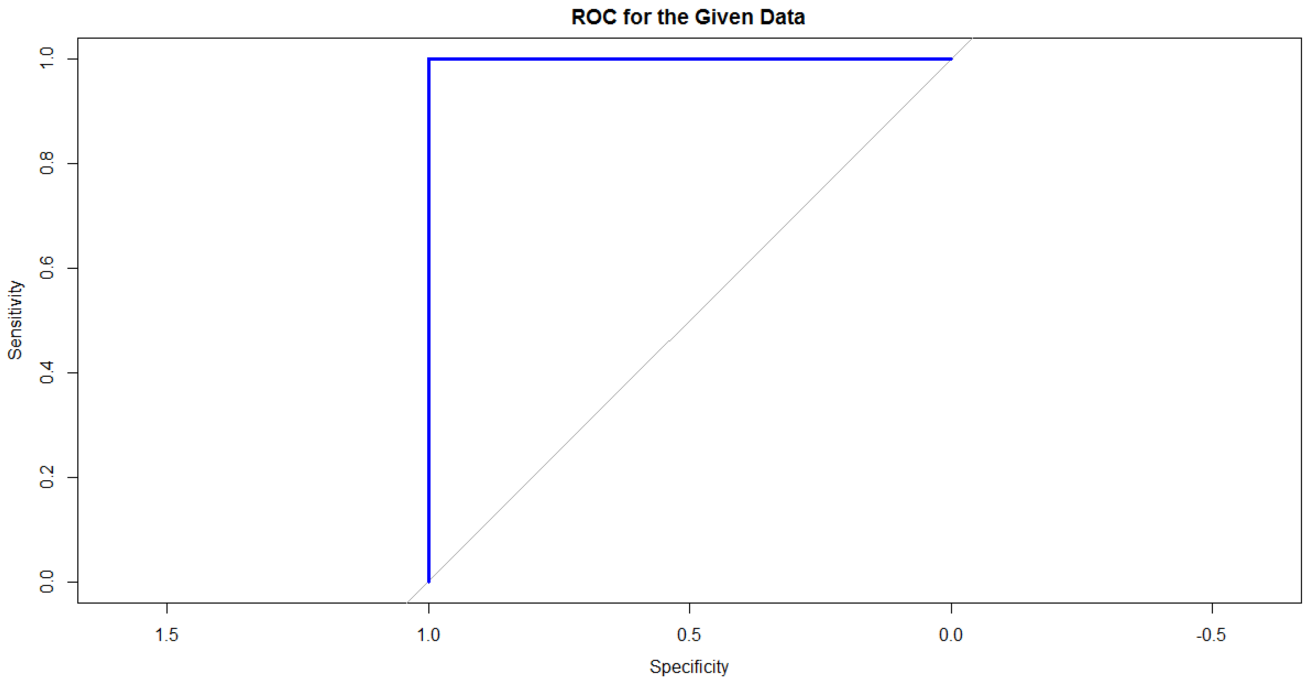
Generate ROC curve using the following tables. Please attach your R or Matlab code and output in your word file as Appendices. Please (1) attach your R or Matlab codes and output in your word file as Appendices; (2) save and name your original scripts as “Group#_ROC.R” (e.g., Group1_ROC.R) or “Group#_ROC.m” (e.g., “Group1_ROC.m”).

New measure	**Disease**	**Non-Disease**
5 or less	18	1
5.1 - 7	7	17
v7.1 - 9	4	36
9 or more	3	39
Totals:	32	93
Cut point	Sensitivity	Specificity
5	0.56	0.99
7	0.78	0.81
9	0.91	0.42

R Code: ROC

```
cutPoints <- c(5,7,9)
truePositive <- c(0.56,0.78,0.91)
falsePositive <- c(0.1, 0.19, 0.58)
library(pROC)
plot(roc(cutPoints, truePositive, falsePositive), col="blue", lwd=3, main="ROC for the Given Data")
```

ROC Curve:


ROC for the Given Data
Sensitivity
1.0
0.8
0.6
0.4
0.2
0.0
Specificity
1.5
1.0
0.5
0.0
-0.5

References:

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http://rischanlab.github.io/NaiveBayes.html

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