

Aim: Write a R program to implement logistic regression.

Theory:

What is Regression analysis:

Regression analysis is predictive technique used to predict a continuous quantity. A continuous variable has infinite possibilities.

Logistic Regression:

It is one of the most widely used algorithm for solving classification problem. It is a method used to predict a dependant variable (Y) given independant variable (X) such that dependant variable is categorical.

Types of Logistic Regression:

- ① Binary Logistic Regression
- ② Multinomial Regression
- ③ Ordinal Logistic Regression

Code:

```
mydata <- read.csv("binary.csv")  
head(mydata)  
xtabs (~ admit + rank, data = mydata)  
mydata$rank <- factor(mydata$rank)  
mylogit <- glm(admit ~ gre + gpa + rank,  
               data = mydata, family = "binomial")  
summary(mylogit)
```

- In the above output the first thing we see is the call, this is R reminding us what the options we specified.
- Next we see the deviance residual which are measure of model fit. This part of output, show the distribution of the deviance residual of individual cases used in model.
- Next part of output shows the coefficients their standard error, ~~the~~ the z statistic and associated P values. Both GRE and GPA are important as three terms for rank. The logistic regression coefficients gives the change in the log odds of the outcome for one unit increase in predicted variable.



Example 2:

```
install.packages('mlbench')  
install.packages('caret')  
library(caret)
```

```
data(BreastCancer, package = 'mlbench')  
bc <- BreastCancer[complete.cases(BreastCancer),]  
print(str(bc))
```

```
model <- glm(Class ~ Cell.shape, family = 'binomial',  
              data = bc)
```

```
bc <- bc[, -1]  
for (i in 1:9)  
{  
  bc[, i] <- as.numeric(as.character(bc[, i]))  
}
```

```
bc$Class <- ifelse(bc$Class == 'malignant', 1, 0)  
bc$Class <- factor(bc$Class, levels = c(0, 1))
```

```
'% ni%' <- Negate('%in%')  
options(scipen = 999)  
set.seed(100)
```

```
trainDataIndex <- createDataPartition(bc$class,  
p = 0.7, list = F)
```

```
trainData <- bc[trainDataIndex,]
```

```
testData <- bc[-trainDataIndex,]
```

```
set.seed(100)
```

```
down-train <- downSample(x = trainData[, colnames  
(trainData) %ni% "Class"],
```

```
y = trainData$class)
```

```
table(down-train$class)
```

```
set.seed(100)
```

```
up-train <- upSample(x = trainData[, colnames  
(trainData) %ni% "Class"],
```

```
y = trainData$class)
```

```
table(up-train$class)
```

```
logitmod <- glm(Class ~ Cl.thickness + Cell.size +  
Cell.Shape, family = "binomial",  
data = down-train)
```

```
summary(logitmod)
```

```
pred <- predict(logitmod, newdata = testData,  
type = "response")
```

```
pred
```



```
y-pred-num <- ifelse (pred > 0.5, 1, 0)
y-pred <- factor (y-pred-num, levels = c(0,1))
y-act <- testData$class
```

```
mean (y-pred == y-act)
```

Conclusion: Hence, we have successfully implemented the program in R for implementing logistic regression.

## Code:

```
1 #Example 1
2 #Shivam Tawari A-58
3 mydata <- read.csv("/cloud/project/binary.csv")
4 head(mydata)
5
6 xtabs (~admit + rank,data = mydata)
7
8 mydata$rank <- factor(mydata$rank)
9 mylogit <- glm(admit ~ gre + gpa + rank, data=mydata, family = "binomial")
10 summary(mylogit)
11 |
```

## Output:

```
Console Terminal x Jobs x
/cloud/project/
> #Shivam Tawari A-58
> mydata <- read.csv("/cloud/project/binary.csv")
> head(mydata)
  admit gre  gpa rank
1     0 380 3.61   3
2     1 660 3.67   3
3     1 800 4.00   1
4     1 640 3.19   4
5     0 520 2.93   4
6     1 760 3.00   2
> xtabs (~admit + rank,data = mydata)
      rank
admit  1  2  3  4
    0 28 97 93 55
    1 33 54 28 12
> mydata$rank <- factor(mydata$rank)
> mylogit <- glm(admit ~ gre + gpa + rank, data=mydata, family = "binomial")
> summary(mylogit)

Call:
glm(formula = admit ~ gre + gpa + rank, family = "binomial",
    data = mydata)

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 ***
```

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

## Code:

```
1 #Example 2
2 #Shivam Tawari A-58
3
4 install.packages('mlbench')
5 install.packages('caret')
6 library(caret)
7
8 data(BreastCancer, package='mlbench')
9 bc <- BreastCancer[complete.cases(BreastCancer),]
10
11 print(str(bc))
12
13 model <- glm(Class ~ Cell.shape, family = 'binomial', data = bc)
14
15 bc <- bc[,-1]
16 for (i in 1:9)
17 {
18   bc[,i] <- as.numeric(as.character(bc[,i]))
19 }
20
21 bc$Class <- ifelse(bc$Class == "malignant", 1, 0)
22 bc$Class <- factor(bc$Class, levels = c(0, 1))
23
24 '%ni%' <- Negate('%in%')
25 options(scipen=999)
26 set.seed(100)
27 trainDataIndex <- createDataPartition(bc$Class, p=0.7,list=F)
28 trainData <- bc[trainDataIndex,]
29
30
31 testData <- bc[-trainDataIndex,]
32
33 set.seed(100)
34 down_train <- downSample(x = trainData[, colnames(trainData) %ni% "Class"],
35                           y = trainData$Class)
36 table(down_train$Class)
37
38 set.seed(100)
39 up_train <- upSample(x = trainData[, colnames(trainData) %ni% "Class"],
40                     y = trainData$Class)
41 table(up_train$Class)
42
43 logitmod <- glm(Class ~ Cl.thickness + Cell.size + Cell.shape, family = "binomial")
44 summary(logitmod)
45
46 pred <- predict(logitmod, newdata = testData, type = "response")
47 pred
48
49 y_pred_num <- ifelse(pred > 0.5, 1, 0)
50 y_pred <- factor(y_pred_num, levels=c(0, 1))
51 y_act <- testData$Class
52
53 mean(y_pred == y_act)
```



## Output:

```
> library(caret)
> data(BreastCancer, package='mlbench')
> bc <- BreastCancer[complete.cases(BreastCancer),]
> print(str(bc))
'data.frame': 683 obs. of 11 variables:
 $ Id      : chr  "1000025" "1002945" "1015425" "1016277" ...
 $ Cl.thickness : Ord.factor w/ 10 levels "1"<"2"<"3"<"4"<...: 5 5 3 6 4 8 1 2 2 4
 ...
 $ Cell.size   : Ord.factor w/ 10 levels "1"<"2"<"3"<"4"<...: 1 4 1 8 1 10 1 1 1 2
 ...
 $ Cell.shape  : Ord.factor w/ 10 levels "1"<"2"<"3"<"4"<...: 1 4 1 8 1 10 1 2 1 1
 ...
 $ Marg.adhesion : Ord.factor w/ 10 levels "1"<"2"<"3"<"4"<...: 1 5 1 1 3 8 1 1 1 1
 ...
 $ Epith.c.size : Ord.factor w/ 10 levels "1"<"2"<"3"<"4"<...: 2 7 2 3 2 7 2 2 2 2
 ...
 $ Bare.nuclei  : Factor w/ 10 levels "1","2","3","4",...: 1 10 2 4 1 10 10 1 1 1 ...
 $ Bl.cromatin   : Factor w/ 10 levels "1","2","3","4",...: 3 3 3 3 3 9 3 3 1 2 ...
 $ Normal.nucleoli: Factor w/ 10 levels "1","2","3","4",...: 1 2 1 7 1 7 1 1 1 1 ...
 $ Mitoses       : Factor w/ 9 levels "1","2","3","4",...: 1 1 1 1 1 1 1 1 5 1 ...
 $ Class         : Factor w/ 2 levels "benign","malignant": 1 1 1 1 1 2 1 1 1 1 ...
NULL
> model <- glm(Class ~ Cell.shape, family = 'binomial', data = bc)
> bc <- bc[,-1]
> for (i in 1:9)
+ {
+   bc[,i] <- as.numeric(as.character(bc[,i]))
+ }
```

```
Console Terminal x Jobs x
/cloud/project/
> bc$Class <- ifelse(bc$Class == "malignant", 1, 0)
> bc$Class <- factor(bc$Class, levels = c(0, 1))
> '%ni%' <- Negate('%in%')
> options(scipen=999)
> set.seed(100)
> trainDataIndex <- createDataPartition(bc$Class, p=0.7,list=F)
> trainData <- bc[trainDataIndex,]
> testData <- bc[-trainDataIndex,]
> set.seed(100)
> down_train <- downSample(x = trainData[, colnames(trainData) %ni% "Class"],
+                           y = trainData$Class)
> table(down_train$Class)

 0   1
168 168
> set.seed(100)
> up_train <- upSample(x = trainData[, colnames(trainData) %ni% "Class"],
+                      y = trainData$Class)
> table(up_train$Class)

 0   1
311 311
> logitmod <- glm(Class ~ Cl.thickness + Cell.size + Cell.shape, family = "binomial",
data=down_train)
> summary(logitmod)

Call:
glm(formula = Class ~ Cl.thickness + Cell.size + Cell.shape,
    family = "binomial", data = down_train)
```

```

Deviance Residuals:
    Min       1Q   Median       3Q      Max
-3.8967 -0.2158 -0.0370  0.0631  2.7428

Coefficients:
            Estimate Std. Error z value Pr(>|z|)
(Intercept)  -7.9695     1.0724  -7.431 0.000000000000108 ***
Cl.thickness   0.7035     0.1488   4.728 0.000002264855263 ***
Cell.size      0.7201     0.2543   2.832  0.00462 **
Cell.shape     0.6974     0.2330   2.993  0.00277 **
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

(Dispersion parameter for binomial family taken to be 1)

    Null deviance: 465.795  on 335  degrees of freedom
Residual deviance:  88.447  on 332  degrees of freedom
AIC: 96.447

Number of Fisher Scoring iterations: 8

> pred <- predict(logitmod, newdata = testData, type = "response")
> pred
      1      2      3      4      6      8     12
0.045892971 0.771711712 0.011641255 0.999495516 0.999992743 0.011570800 0.005794679
      14      16      18      19      20      21      22
0.002875879 0.982359695 0.023248829 0.999875120 0.088591878 0.624845947 0.997877544
      23      26      28      29      30      32      33
0.011641255 0.285038606 0.045892971 0.005794679 0.011500766 0.005794679 0.999875120
      35      36      39      40      42      43      44

```

```

Console Terminal x Jobs x
/cloud/project/
0.088097214 0.991753010 0.045892971 0.045024787 0.102503021 0.011041255 0.011041255
602 603 604 606 607 609 610
0.002875879 0.023248829 0.931677311 0.999934926 0.023248829 0.999940110 0.045892971
611 613 614 617 619 621 622
0.982676173 0.999992743 0.024014980 0.011641255 0.023248829 0.011641255 0.623405110
624 626 627 628 629 630 631
0.002875879 0.045358096 0.966087333 0.005794679 0.005794679 0.023248829 0.446186581
632 633 634 635 636 637 638
0.045892971 0.002875879 0.995884591 0.011641255 0.087115367 0.999985602 0.283788599
640 641 642 643 644 645 648
0.045892971 0.023248829 0.011641255 0.011641255 0.002875879 0.005794679 0.002875879
649 650 652 653 654 655 656
0.999940110 0.011641255 0.005891124 0.045892971 0.023248829 0.011641255 0.011641255
658 659 660 661 662 663 664
0.871621597 0.999750296 0.002875879 0.002875879 0.023248829 0.011500766 0.011500766
666 667 668 669 670 672 673
0.002875879 0.165622432 0.011641255 0.967021128 0.999940110 0.023628875 0.005794679
674 677 678 679 680 681 682
0.289696570 0.005759402 0.045892971 0.002875879 0.005794679 0.999998223 0.999940110
684 685 686 687 688 689 691
0.002875879 0.002875879 0.002875879 0.002875879 0.011641255 0.023248829 0.002875879
692 695 696
0.999940110 0.011641255 0.005794679
> y_pred_num <- ifelse(pred > 0.5, 1, 0)
> y_pred <- factor(y_pred_num, levels=c(0, 1))
> y_act <- testData$class
> mean(y_pred == y_act)
[1] 0.9498956

```