

STAT 4198 Final Project

STAT 4198 Data Mining

Final Project

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Dataset input

```
data <- read.csv(file = "D:/file/STAT4198 Final/fordTrain.csv",stringsAsFactors=TRUE)
indexes <- read.csv(file = "D:/file/STAT4198 Final/indexes.csv",header=FALSE,
stringsAsFactors=TRUE)
# G49803308
last.two.digits<- 08
k<-last.two.digits+1

newdata<-data.frame(data[data[,1]%in%indexes[k,], ])
summary(newdata)
```

```
##      TrialID      ObsNum      IsAlert      P1
## Min.   : 0.0   Min.   : 0.0   Min.   :0.000   Min.   : 22.35
## 1st Qu.: 99.0   1st Qu.: 302.0   1st Qu.:0.000   1st Qu.: 31.59
## Median :274.0   Median : 604.0   Median :1.000   Median : 34.13
## Mean   :245.3   Mean   : 603.9   Mean   :0.575   Mean   : 35.22
## 3rd Qu.:357.0   3rd Qu.: 906.0   3rd Qu.:1.000   3rd Qu.: 37.14
## Max.   :505.0   Max.   :1210.0   Max.   :1.000   Max.   :100.15
##      P2      P3      P4      P5
## Min.   :-23.239   Min.   : 504   Min.   : 24.83   Min.   : 0.04800
## 1st Qu.: 9.988   1st Qu.: 788   1st Qu.: 50.00   1st Qu.: 0.09081
## Median :11.479   Median :1000   Median : 60.00   Median : 0.10379
## Mean   :12.035   Mean   :1017   Mean   : 64.45   Mean   : 0.21511
## 3rd Qu.:13.694   3rd Qu.:1200   3rd Qu.: 76.14   3rd Qu.: 0.14011
## Max.   :29.082   Max.   :2416   Max.   :119.05   Max.   :27.20220
##      P6      P7      P8      E1
## Min.   :140.0   Min.   : 22.42   Min.   :0   Min.   : 0.00
## 1st Qu.:648.0   1st Qu.: 68.49   1st Qu.:0   1st Qu.: 0.00
## Median :768.0   Median : 78.12   Median :0   Median : 0.00
## Mean   :789.3   Mean   : 80.59   Mean   :0   Mean   :10.95
## 3rd Qu.:876.0   3rd Qu.: 92.59   3rd Qu.:0   3rd Qu.:28.63
## Max.   :2676.0   Max.   :428.57   Max.   :0   Max.   :38.62
##      E2      E3      E4      E5
## Min.   : 0.00   Min.   :0.000   Min.   : -250.000   Min.   :0.00800
## 1st Qu.: 0.00   1st Qu.:0.000   1st Qu.: -8.000   1st Qu.:0.01562
## Median : 0.00   Median :0.000   Median : 0.000   Median :0.01600
```

```
## Mean : 95.91 Mean :0.336 Mean : -2.336 Mean :0.01629
## 3rd Qu.:196.63 3rd Qu.:0.000 3rd Qu.: 6.000 3rd Qu.:0.01688
## Max. :359.82 Max. :4.000 Max. : 250.000 Max. :0.02394
## E6 E7 E8 E9
## Min. :260.0 Min. : 0.000 Min. :0.000 Min. :0.0000
## 1st Qu.:350.0 1st Qu.: 0.000 1st Qu.:0.000 1st Qu.:1.0000
## Median :366.0 Median : 1.000 Median :1.000 Median :1.0000
## Mean :359.1 Mean : 1.503 Mean :1.252 Mean :0.8941
## 3rd Qu.:367.0 3rd Qu.: 2.000 3rd Qu.:2.000 3rd Qu.:1.0000
## Max. :513.0 Max. :20.000 Max. :9.000 Max. :1.0000
## E10 E11 V1 V2
## Min. : 0.00 Min. : 0.000 Min. : 0.00 Min. : -4.20000
## 1st Qu.: 44.00 1st Qu.: 0.000 1st Qu.: 23.64 1st Qu.: -0.07000
## Median : 65.00 Median : 0.000 Median : 99.88 Median : 0.00000
## Mean : 60.16 Mean : 1.293 Mean : 75.73 Mean : -0.02632
## 3rd Qu.: 72.00 3rd Qu.: 0.000 3rd Qu.:108.13 3rd Qu.: 0.07000
## Max. :117.00 Max. :32.800 Max. :123.88 Max. : 2.83500
## V3 V4 V5 V6
## Min. : 240 Min. : 0.000 Min. :0.0000 Min. : 531
## 1st Qu.: 255 1st Qu.: 1.488 1st Qu.:0.0000 1st Qu.:1068
## Median : 497 Median : 3.019 Median :0.0000 Median :1982
## Mean : 568 Mean : 34.079 Mean :0.1247 Mean :1708
## 3rd Qu.: 767 3rd Qu.: 9.012 3rd Qu.:0.0000 3rd Qu.:2137
## Max. :1023 Max. :479.981 Max. :1.0000 Max. :3466
## V7 V8 V9 V10 V11
## Min. :0 Min. : 0.00 Min. :0 Min. :1.000 Min. : 3.506
## 1st Qu.:0 1st Qu.: 0.00 1st Qu.:0 1st Qu.:2.000 1st Qu.: 7.498
## Median :0 Median :12.10 Median :0 Median :4.000 Median :10.796
## Mean :0 Mean :12.18 Mean :0 Mean :3.276 Mean :11.179
## 3rd Qu.:0 3rd Qu.:21.00 3rd Qu.:0 3rd Qu.:4.000 3rd Qu.:15.232
## Max. :0 Max. :62.10 Max. :0 Max. :7.000 Max. :19.711

sum(is.na(newdata))

## [1] 0
```

The entire data has no missing value

Exploratory Data Analysis

1.Remove features which do not change their values

delete: P8, V7, V9

```
drops <- c("P8", "V7", "V9")
newdata<-newdata[ , !(names(newdata) %in% drops)]
```

2.For each feature

Due to the lack of dataset decription, I can only determine whether a variable is continuous or categorical by checking how many levels the variable has. For example, if a variable is

continuous, then it could have as many levels as the sample size. Otherwise, if a variable is categorical, then it could have much fewer numbers of levels compared to the sample size.

TrialID: From the dataset description, variable “TrialID” is a code for a subject, which means such variable is categorical. And the specific levels for variable “TrialID” are listing as following:

```
TrialID <- as.factor(newdata$TrialID)
levels(TrialID)

## [1] "0" "8" "17" "29" "35" "36" "44" "60" "63" "78" "83"
## [12] "91" "99" "100" "146" "155" "170" "180" "208" "225" "235" "244"
## [23] "256" "258" "268" "274" "290" "291" "296" "308" "315" "320" "322"
## [34] "324" "325" "338" "352" "357" "359" "392" "395" "405" "411" "416"
## [45] "422" "425" "438" "450" "452" "505"
```

ObsNum: Based on the dataset description, variable “ObsNum” is the number of new sample. Therefore, this variable has no influence on the analysis. Range from 0 to 1211.

IsAlert: Based in the dataset description, this variable is the response variable. This variable only concludes two levels – 1 for having alert, and 0 for not having alert

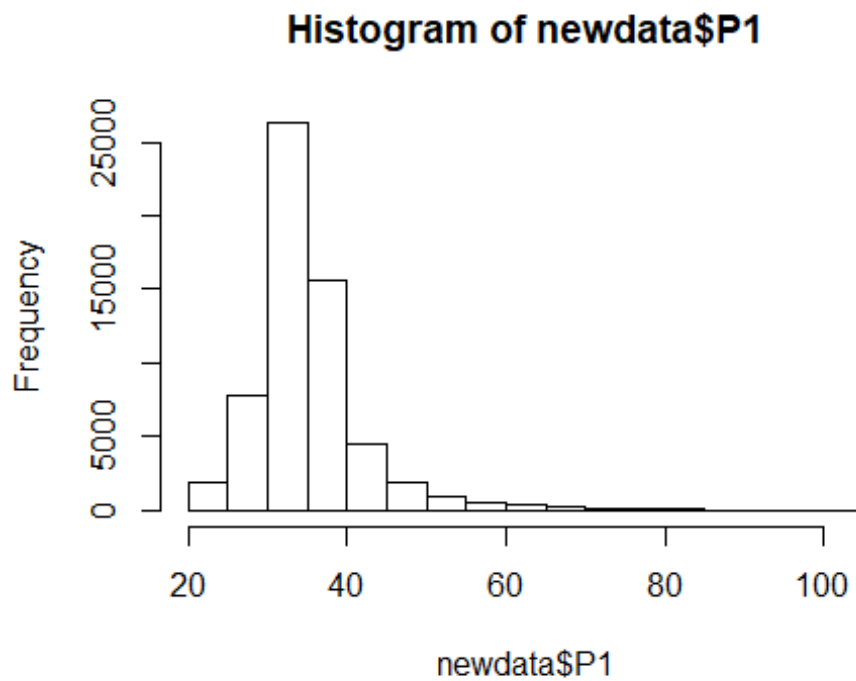
```
table(newdata$IsAlert)

##
##      0      1
## 25686 34756
```

There are 25686 observations have no alert, and 34756 observations have alert.

Physical data: P1: Variable “P1” is continuous, and has symmetry distribution.

```
#P1 <- as.factor(newdata$P1)
#levels(P1)
hist(newdata$P1)
```



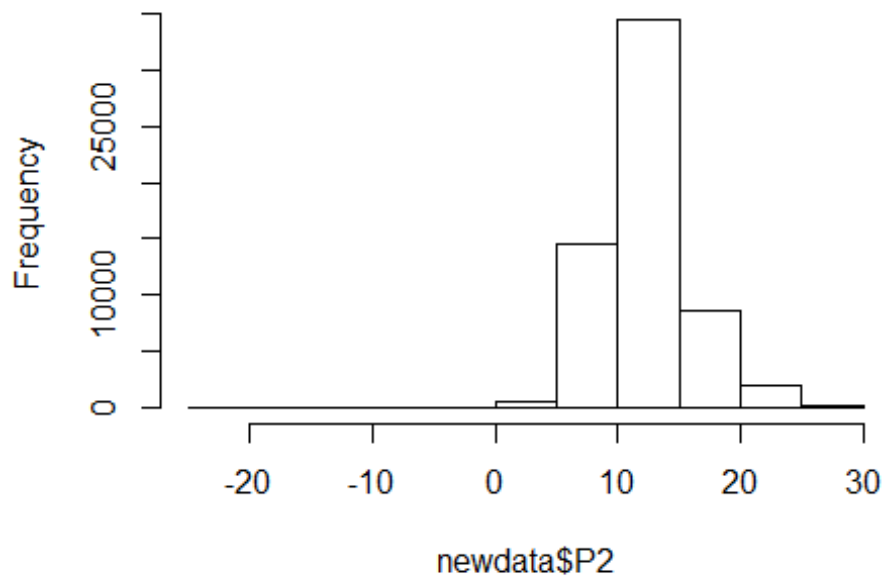
```
summary(newdata$P1)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  22.35   31.59   34.13   35.22   37.14  100.15
```

P2: Variable "P2" is continuous, and has symmetry distribution.

```
#P2 <- as.factor(newdata$P2)
#levels(P2)
hist(newdata$P2)
```

Histogram of newdata\$P2

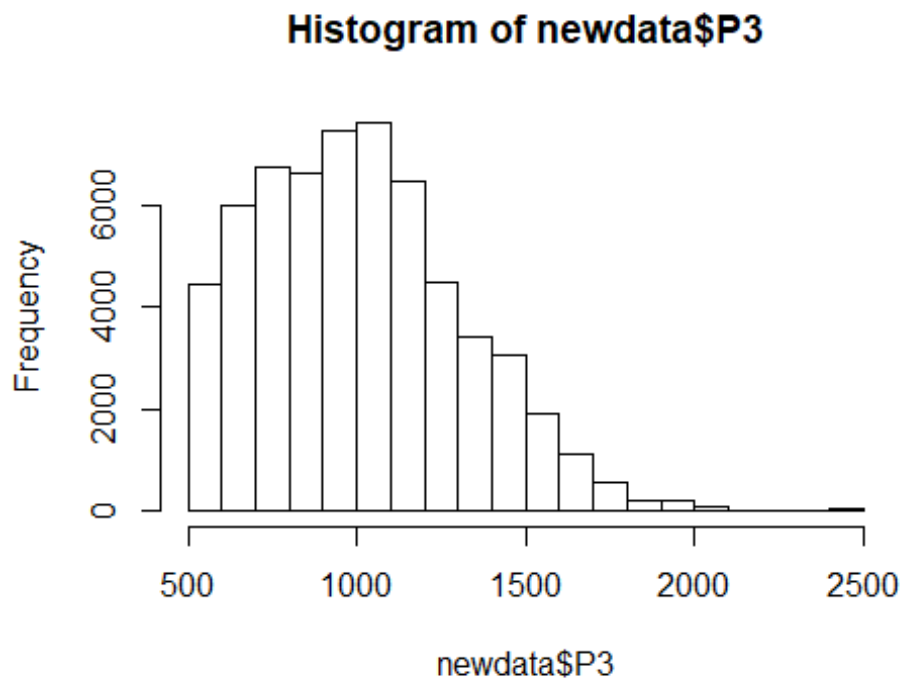


```
summary(newdata$P2)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -23.239   9.988   11.479   12.035   13.694   29.082
```

P3: Variable "P3" is continuous, and has symmetry distribution.

```
#P3 <- as.factor(newdata$P3)
#levels(P3)
hist(newdata$P3)
```



```
#barplot(table(newdata$P3),xlab= 'P3')
```

```
summary(newdata$P3)
```

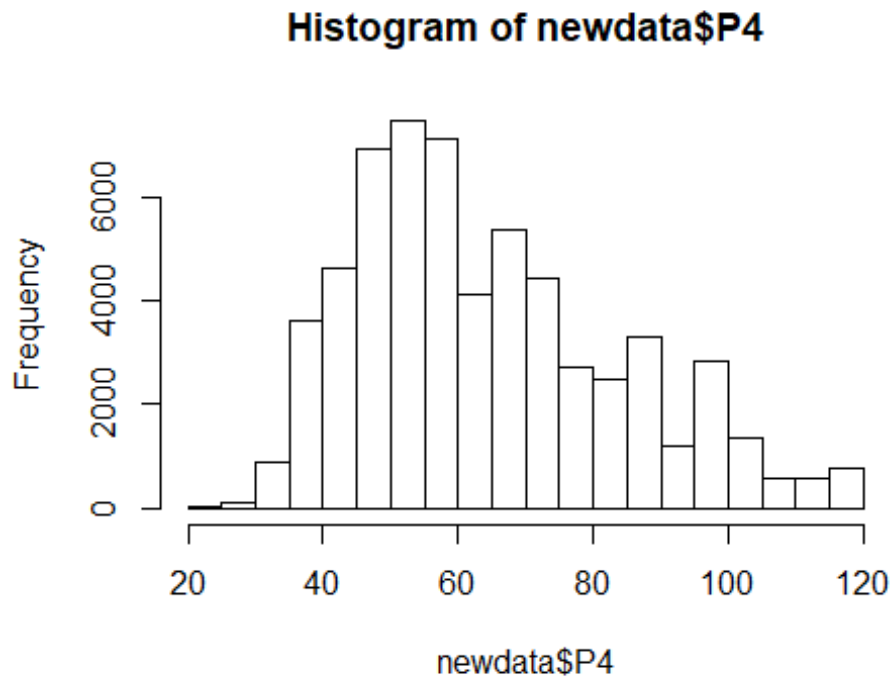
##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	504	788	1000	1017	1200	2416

P4: Variable “P4” is continuous, and has symmetry distribution.

```
#P4 <- as.factor(newdata$P4)
```

```
#levels(P4)
```

```
hist(newdata$P4)
```

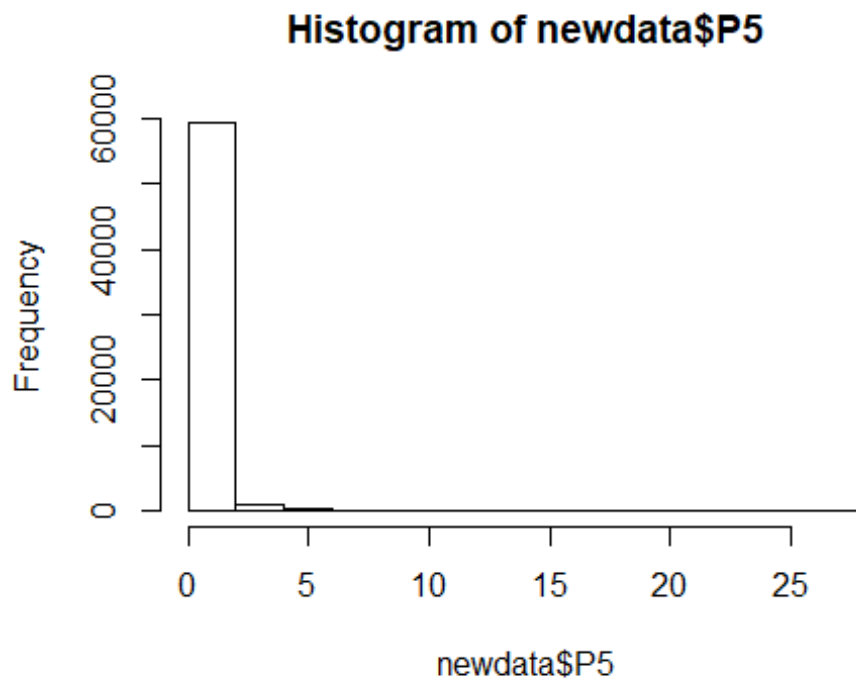


```
#barplot(table(newdata$P4),xlab= 'P4')
summary(newdata$P4)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	24.83	50.00	60.00	64.45	76.14	119.05

P5: Variable “P5” is continuous, and has right-skewed distribution.

```
#P5 <- as.factor(newdata$P5)
#levels(P5)
hist(newdata$P5)
```

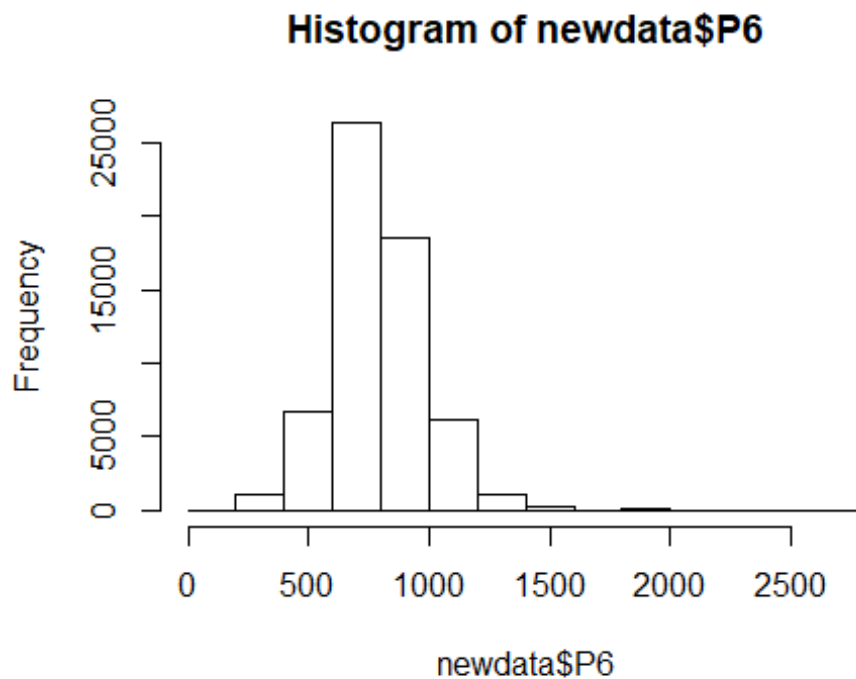


```
#barplot(table(newdata$P5),xLab= 'P5')
summary(newdata$P5)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.04800 0.09081 0.10379 0.21511 0.14011 27.20220
```

P6: Variable “P6” is continuous, and has symmetry distribution.

```
#P6 <- as.factor(newdata$P6)
#levels(P6)
hist(newdata$P6)
```

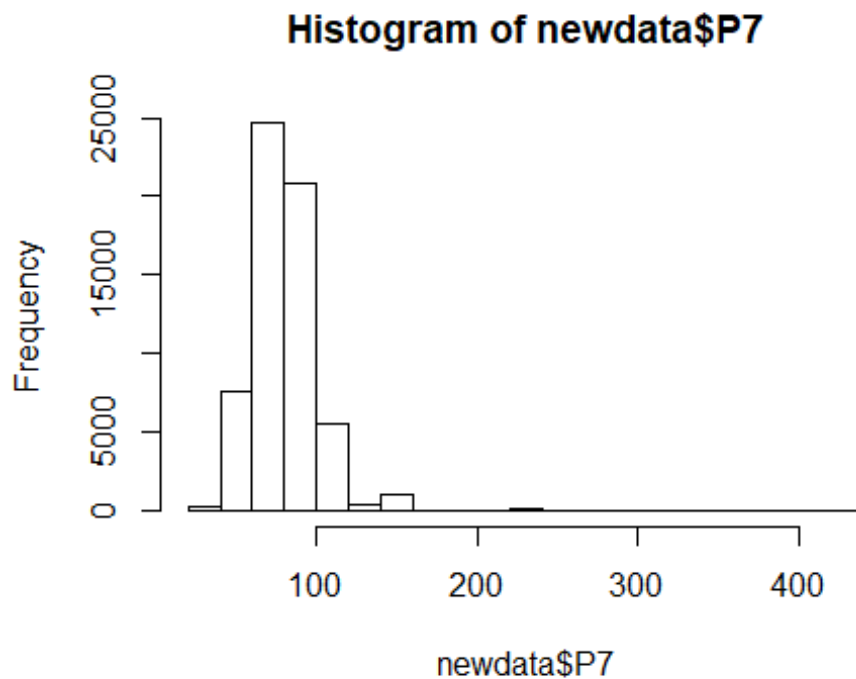



```
#barplot(table(newdata$P6),xLab= 'P6')
summary(newdata$P6)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	140.0	648.0	768.0	789.3	876.0	2676.0

P7: Variable “P7” is continuous, and has symmetry distribution.

```
#P7 <- as.factor(newdata$P7)
#levels(P7)
hist(newdata$P7)
```



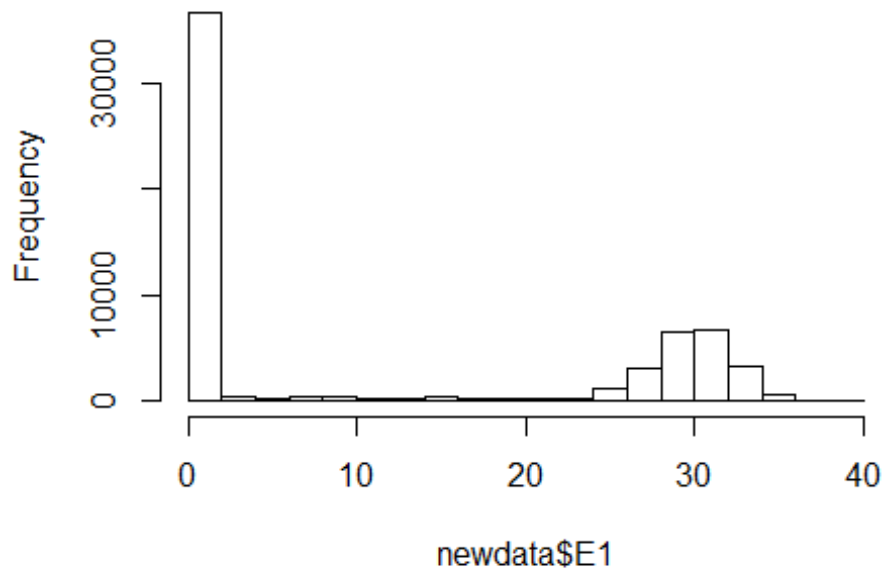
```
#barplot(table(newdata$P7),xlab= 'P7')
summary(newdata$P7)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	22.42	68.49	78.12	80.59	92.59	428.57

E1: Variable “E1” is continuous, and has multimodality distribution.

```
#E1 <- as.factor(newdata$E1)
#levels(E1)
hist(newdata$E1)
```

Histogram of newdata\$E1



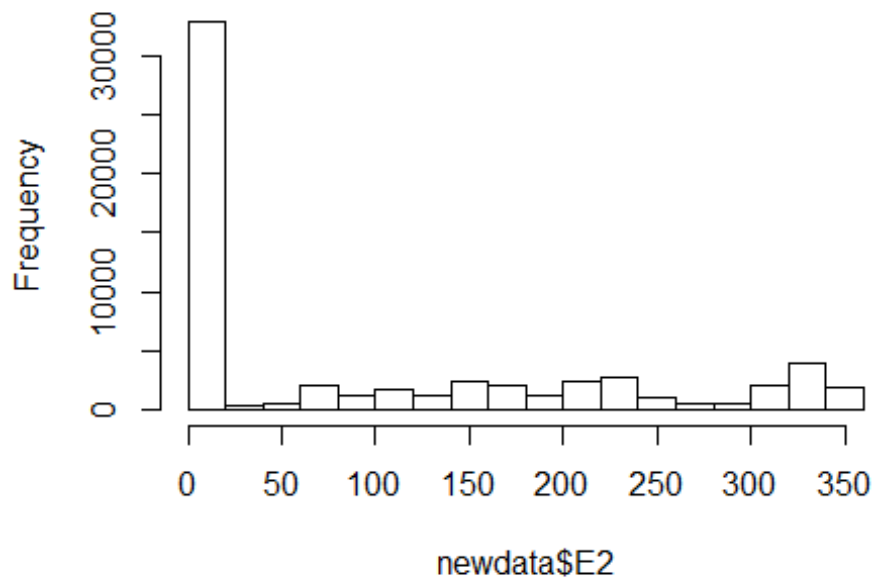
```
#barplot(table(newdata$E1),xlab= 'E1')
summary(newdata$E1)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.00   0.00   0.00  10.95  28.63   38.62
```

E2: Variable “E2” is continuous, and has multimodality distribution.

```
#E2 <- as.factor(newdata$E2)
#levels(E2)
hist(newdata$E2)
```

Histogram of newdata\$E2



```
#barplot(table(newdata$E2),xlab= 'E2')
summary(newdata$E2)

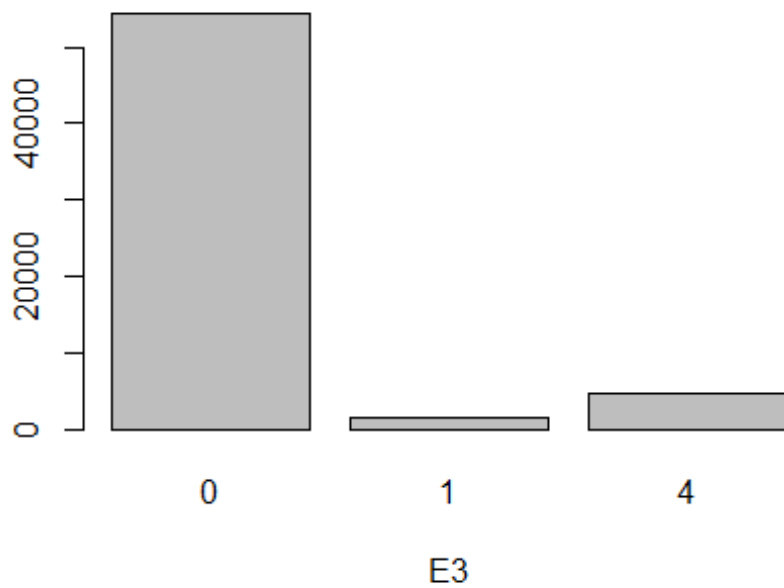
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.00   0.00   0.00  95.91 196.63 359.82
```

E3: Variable “E3” is categorical, with 3 levels.

```
E3 <- as.factor(newdata$E3)
levels(E3)

## [1] "0" "1" "4"

#hist(newdata$E3)
barplot(table(newdata$E3),xlab= 'E3')
```

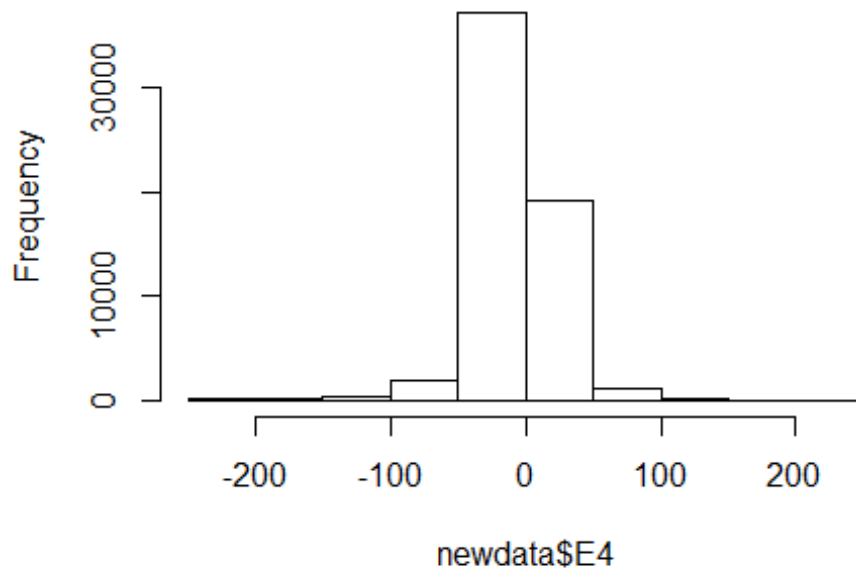


```
#summary(newdata$E3)
```

E4: Variable "E4" is continuous, and has symmetry distribution.

```
#E4 <- as.factor(newdata$E4)
#levels(E4)
hist(newdata$E4)
```

Histogram of newdata\$E4



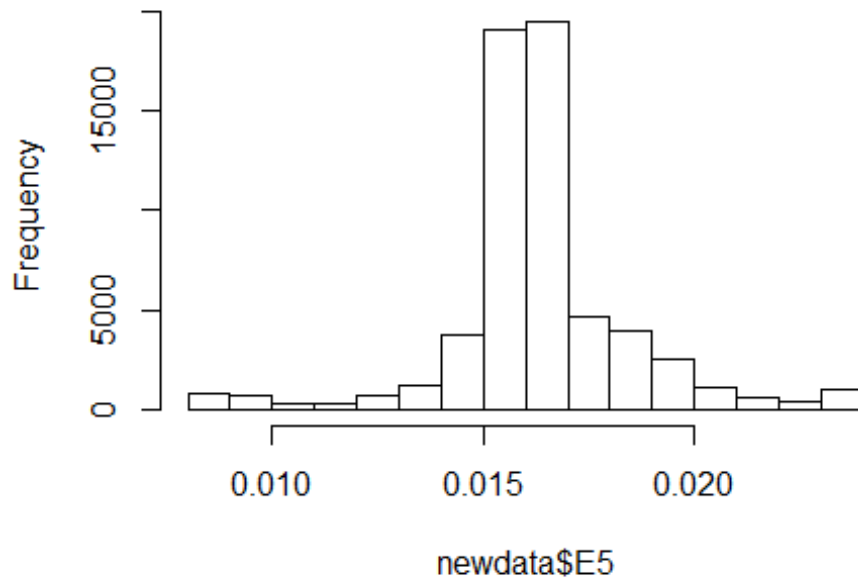
```
#barplot(table(newdata$E4),xlab= 'E4')
summary(newdata$E4)

##      Min.   1st Qu.   Median     Mean   3rd Qu.    Max.
## -250.000   -8.000    0.000   -2.336    6.000   250.000
```

E5: Variable "E5" is continuous, and has symmetry distribution.

```
#E5 <- as.factor(newdata$E5)
#levels(E5)
hist(newdata$E5)
```

Histogram of newdata\$E5



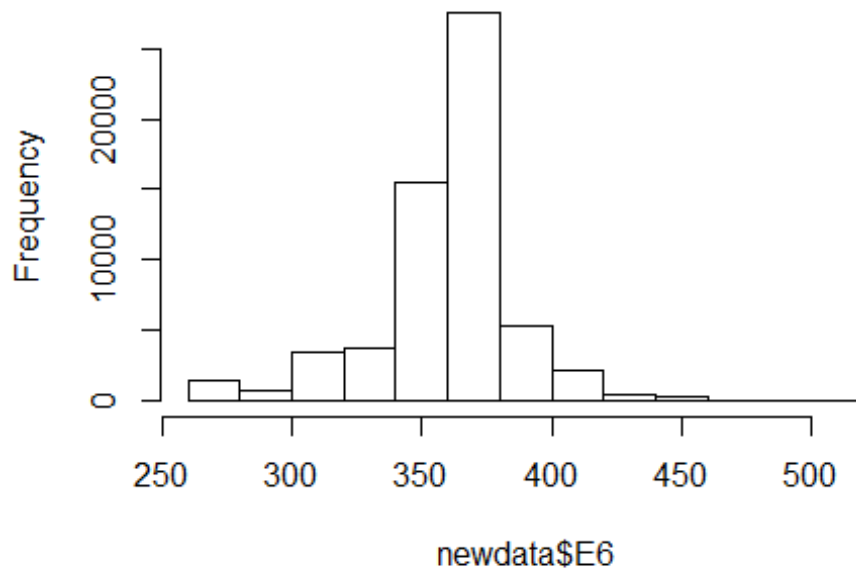
```
#barplot(table(newdata$E5),xlab= 'E5')
summary(newdata$E5)

##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 0.00800 0.01562 0.01600 0.01629 0.01688 0.02394
```

E6: Variable "E6" is continuous, and has symmetry distribution.

```
#E6 <- as.factor(newdata$E6)
#levels(E6)
hist(newdata$E6)
```

Histogram of newdata\$E6



```
#barplot(table(newdata$E6),xlab= 'E6')
```

```
summary(newdata$E6)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## 260.0   350.0   366.0   359.1  367.0   513.0
```

E7: Variable “E7” is categorical, with 18 levels. because all values of E7 are integers, and the values follow an order from 1 to 16 and the last one is 20.

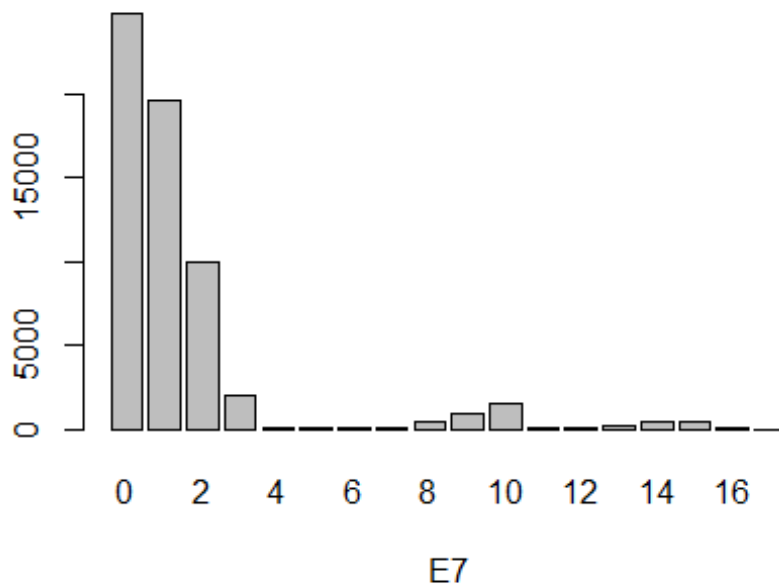
```
E7 <- as.factor(newdata$E7)
```

```
levels(E7)
```

```
##  [1] "0"  "1"  "2"  "3"  "4"  "5"  "6"  "7"  "8"  "9"  "10" "11" "12" "13"
## [15] "14" "15" "16" "20"
```

```
#hist(newdata$E7)
```

```
barplot(table(newdata$E7),xlab= 'E7')
```

```
#summary(newdata$E7)
```

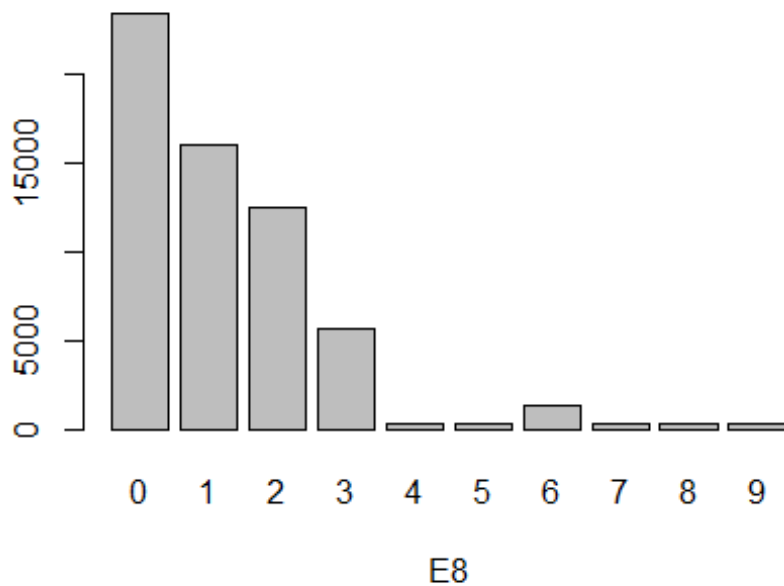
E8: Variable "E8" is categorical, with 10 levels.

```
E8 <- as.factor(newdata$E8)  
levels(E8)
```

```
## [1] "0" "1" "2" "3" "4" "5" "6" "7" "8" "9"
```

```
#hist(newdata$E8)
```

```
barplot(table(newdata$E8),xlab= 'E8')
```



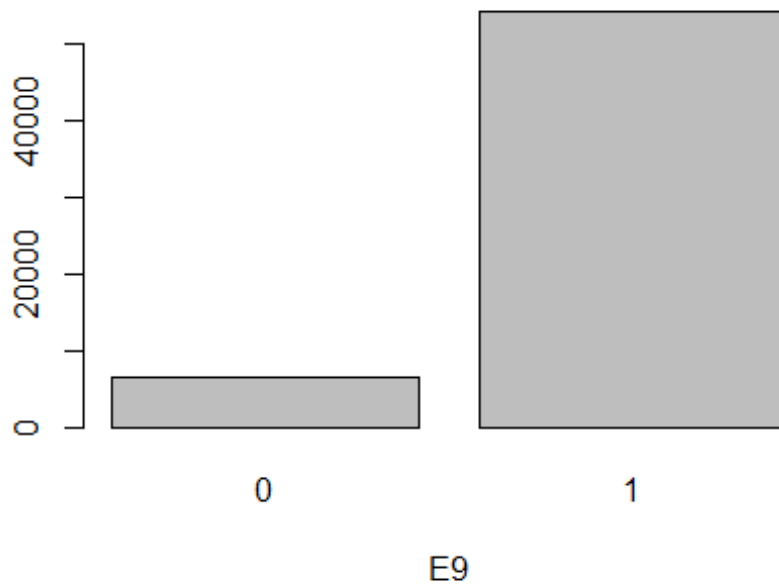
```
#summary(newdata$E8)
```

E9: Variable "E9" is categorical, with 2 levels.

```
E9 <- as.factor(newdata$E9)  
levels(E9)
```

```
## [1] "0" "1"
```

```
#hist(newdata$E9)  
barplot(table(newdata$E9), xlab= 'E9')
```

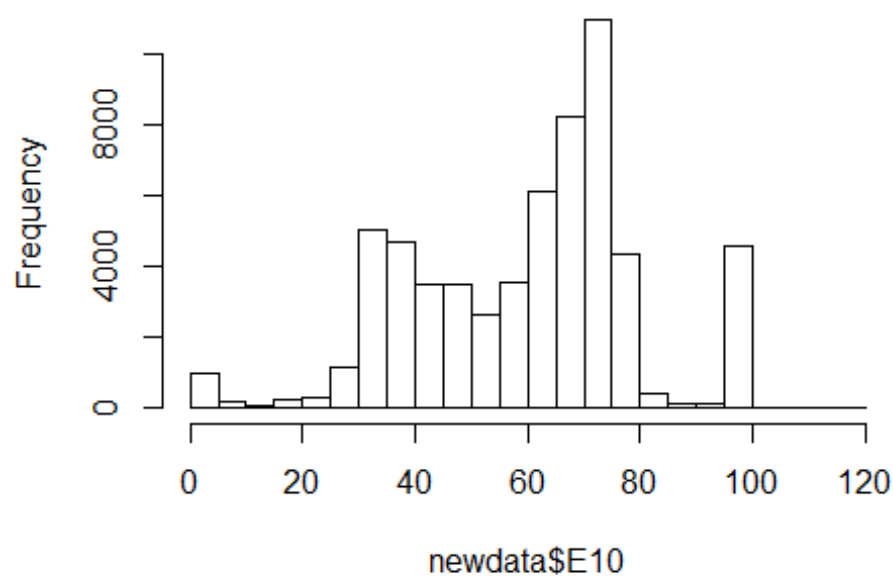


```
#summary(newdata$E9)
```

E10: Variable “E10” is continuous, and has multimodality distribution.

```
#E10 <- as.factor(newdata$E10)  
#levels(E10)  
hist(newdata$E10)
```

Histogram of newdata\$E10



```
#barplot(table(newdata$E10),xlab= 'E10')
```

```
summary(newdata$E10)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.00   44.00   65.00   60.16   72.00   117.00
```

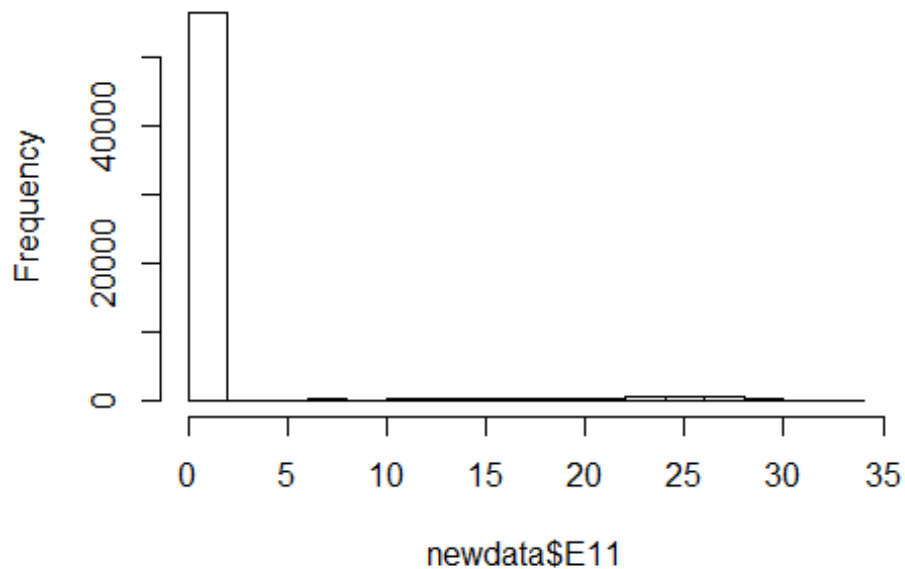
E11: Variable “E11” is continuous, and has right-skewed distribution.

```
#E11 <- as.factor(newdata$E11)
```

```
#levels(E11)
```

```
hist(newdata$E11)
```

Histogram of newdata\$E11



```
#barplot(table(newdata$E11),xlab= 'E11')
```

```
summary(newdata$E11)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.000   0.000   0.000   1.293   0.000   32.800
```

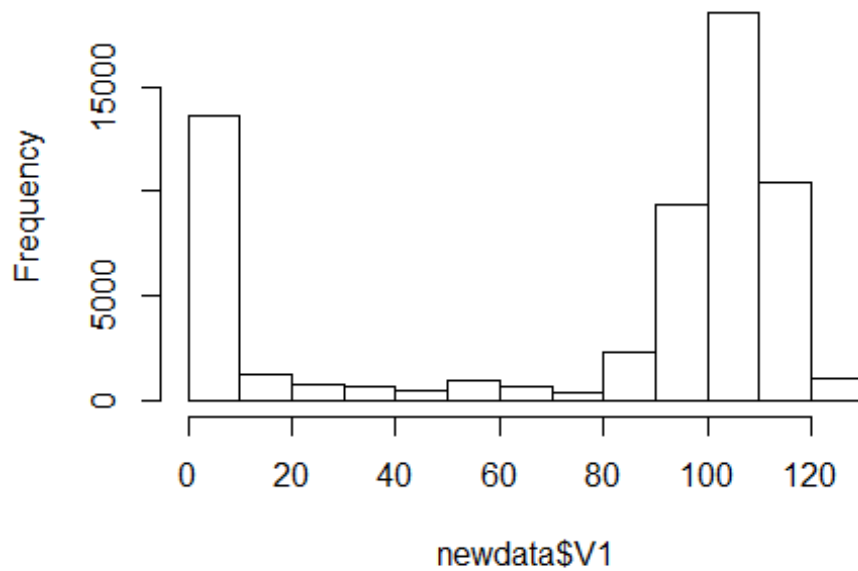
V1: Variable "V1" is continuous, and has multimodality distribution.

```
#V1 <- as.factor(newdata$V1)
```

```
#levels(V1)
```

```
hist(newdata$V1)
```

Histogram of newdata\$V1



```
#barplot(table(newdata$V1),xlab= 'V1')
```

```
summary(newdata$V1)
```

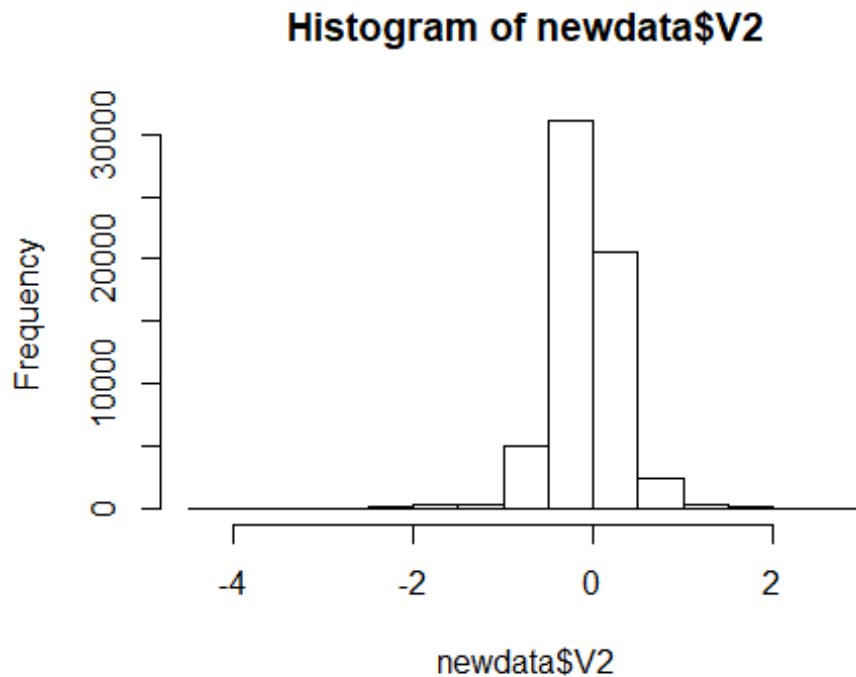
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.00   23.64   99.88   75.73  108.13  123.88
```

V2: Variable "V2" is continuous, and has symmetry distribution.

```
#V2 <- as.factor(newdata$V2)
```

```
#levels(V2)
```

```
hist(newdata$V2)
```



```
#barplot(table(newdata$V2),xlab= 'V2')
```

```
summary(newdata$V2)
```

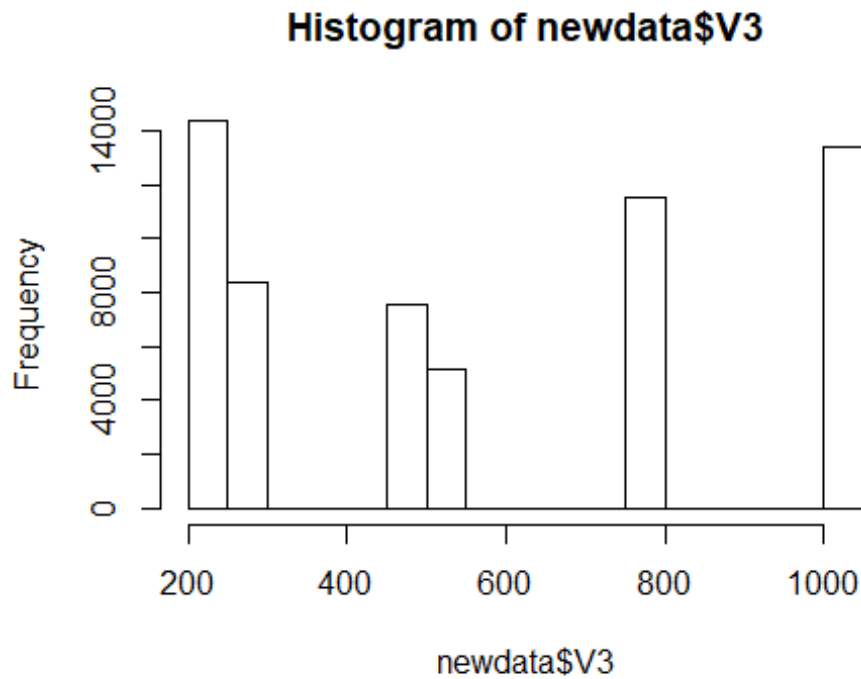
```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
## -4.20000 -0.07000  0.00000 -0.02632  0.07000  2.83500
```

V3: Variable "V3" is continuous, and has multimodality distribution.

```
#V3 <- as.factor(newdata$V3)
```

```
#levels(V3)
```

```
hist(newdata$V3)
```



```
#barplot(table(newdata$V3),xlab= 'V3')
```

```
summary(newdata$V3)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	240	255	497	568	767	1023

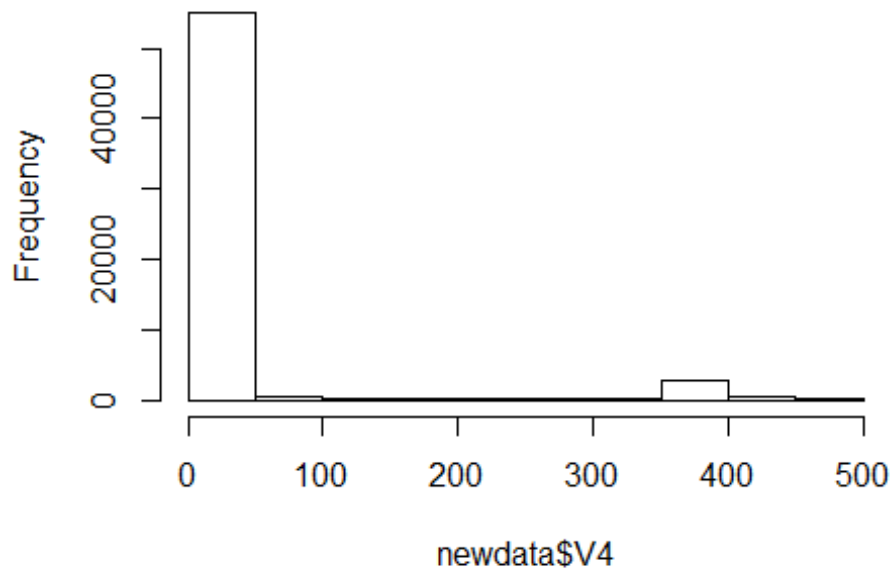
V4: Variable "V4" is continuous, and has right-skewed distribution.

```
#V4 <- as.factor(newdata$V4)
```

```
#levels(V4)
```

```
hist(newdata$V4)
```


Histogram of newdata\$V4



```
#barplot(table(newdata$V4),xlab= 'V4')
summary(newdata$V4)

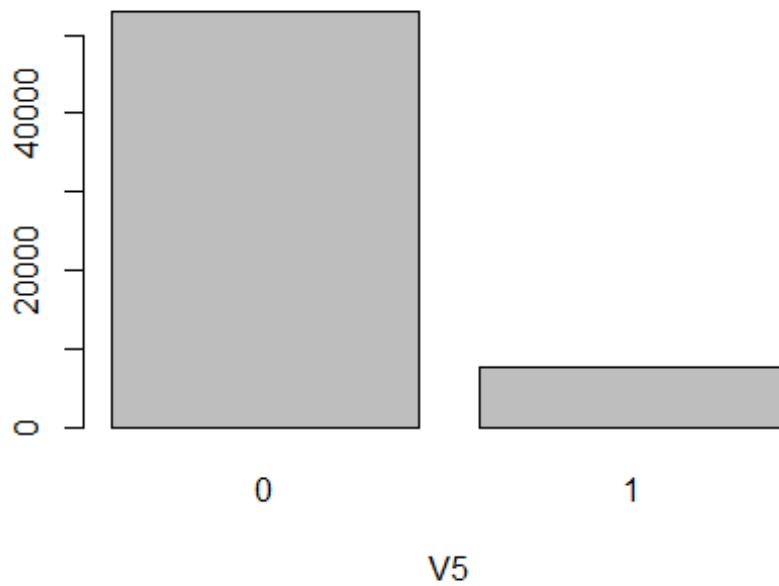
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##    0.000   1.488   3.019   34.079   9.012  479.981
```

V5: Variable "V5" is categorical, with 2 levels.

```
V5 <- as.factor(newdata$V5)
levels(V5)

## [1] "0" "1"

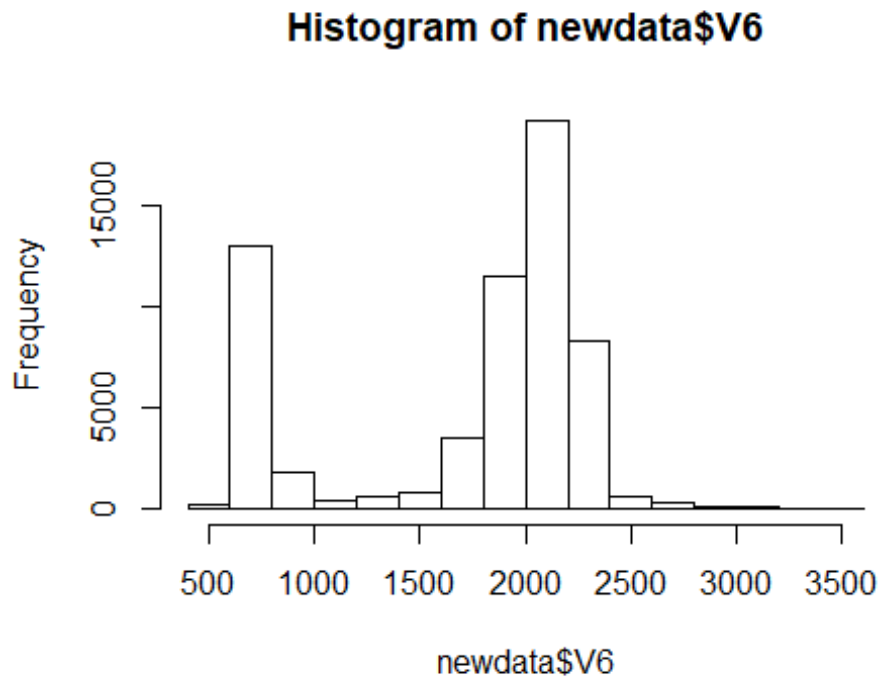
#hist(newdata$V5)
barplot(table(newdata$V5),xlab= 'V5')
```



```
#summary(newdata$V5)
```

V6: Variable "V6" is continuous, and has multimodality distribution.

```
#V6 <- as.factor(newdata$V6)
#levels(V6)
hist(newdata$V6)
```



```
#barplot(table(newdata$V6),xlab= 'V6')
```

```
summary(newdata$V6)
```

##	Min.	1st Qu.	Median	Mean	3rd Qu.	Max.
##	531	1068	1982	1708	2137	3466

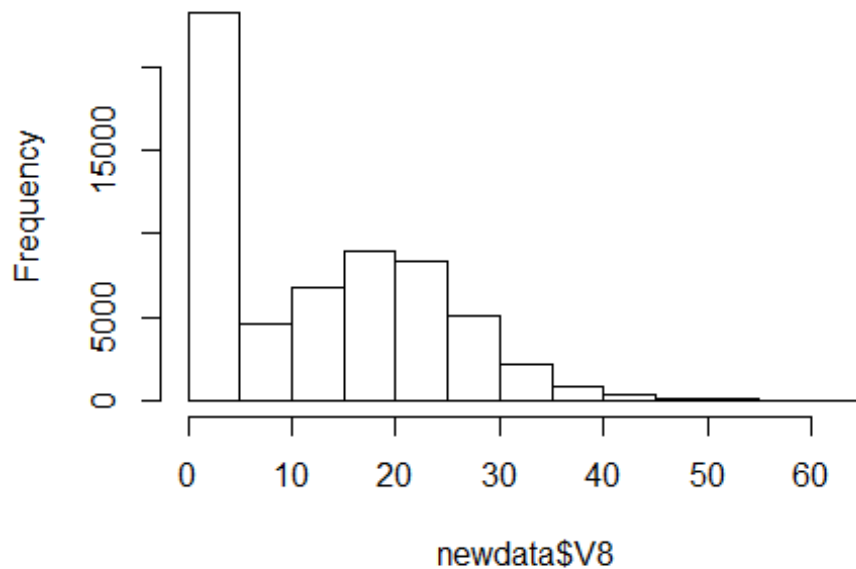
V8: Variable "V8" is continuous, and has right-skewed distribution.

```
#V8 <- as.factor(newdata$V8)
```

```
#levels(V8)
```

```
hist(newdata$V8)
```

Histogram of newdata\$V8



```
#barplot(table(newdata$V8),xlab= 'V8')
summary(newdata$V8)

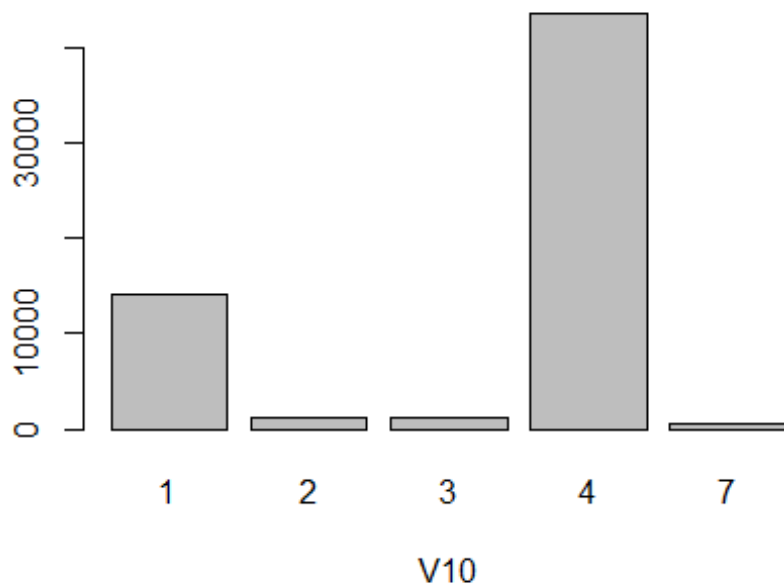
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##      0.00   0.00   12.10   12.18  21.00   62.10
```

V10: Variable "V10" is categorical, with 5 levels.

```
V10 <- as.factor(newdata$V10)
levels(V10)

## [1] "1" "2" "3" "4" "7"

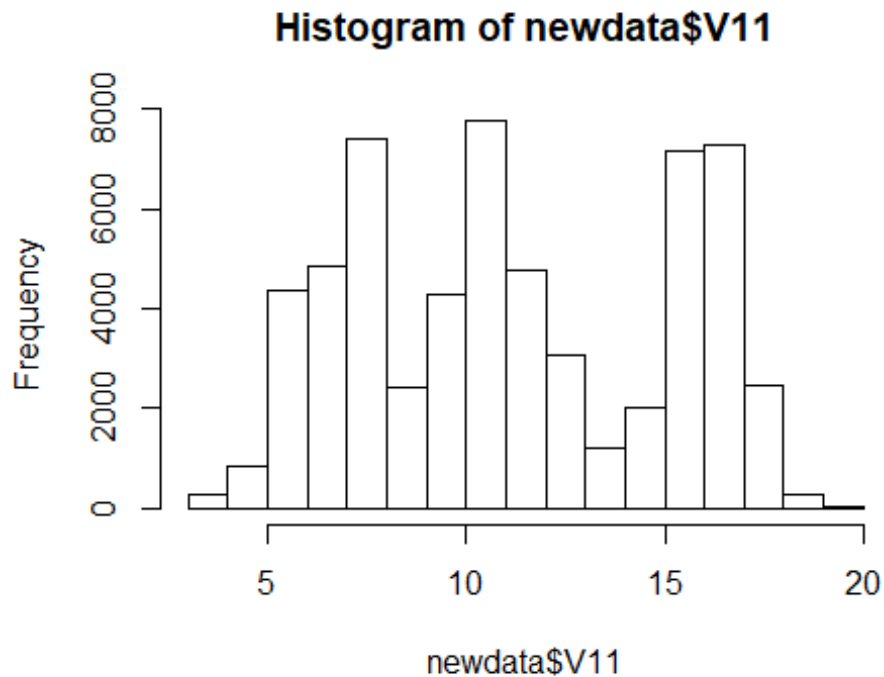
#hist(newdata$V10)
barplot(table(newdata$V10),xlab= 'V10')
```



```
#summary(newdata$V10)
```

V11: Variable "V11" is continuous, and has multimodality distribution.

```
#V11 <- as.factor(newdata$V11)
#levels(V11)
hist(newdata$V11)
```



```
#barplot(table(newdata$V11),xlab= 'V11')
```

```
summary(newdata$V11)
```

```
##      Min. 1st Qu.  Median    Mean 3rd Qu.    Max.
##  3.506   7.498   10.796   11.179   15.232   19.711
```

3.Graphical investigation to whether the feature has a relationship with the response

```
library(gridExtra)
```

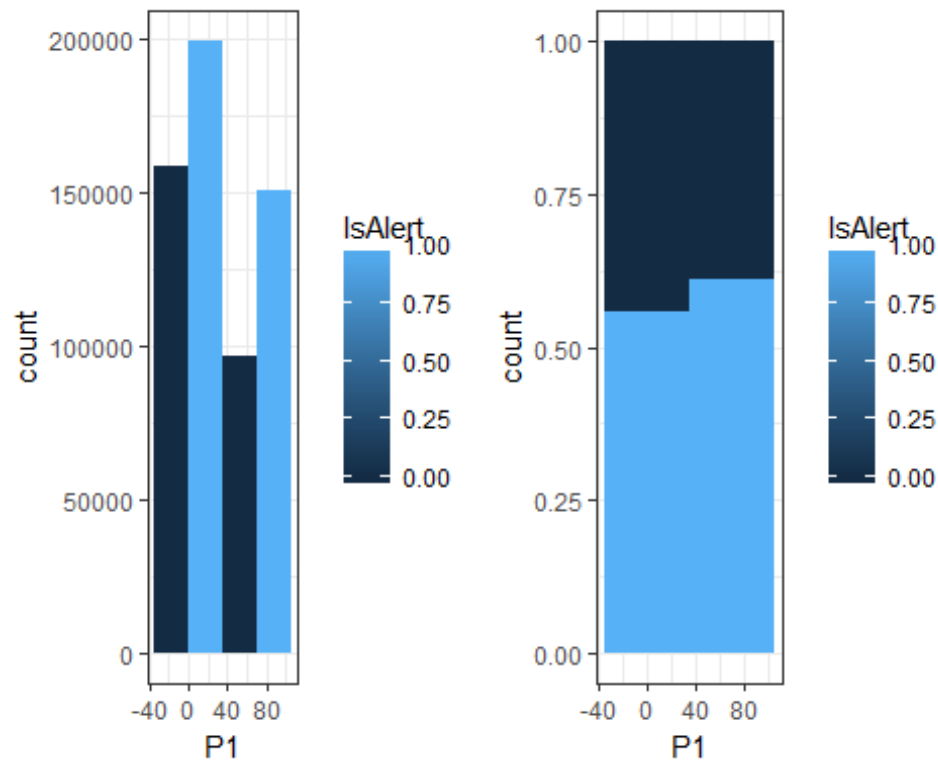
```
library(ggplot2)
```

```
#P1
```

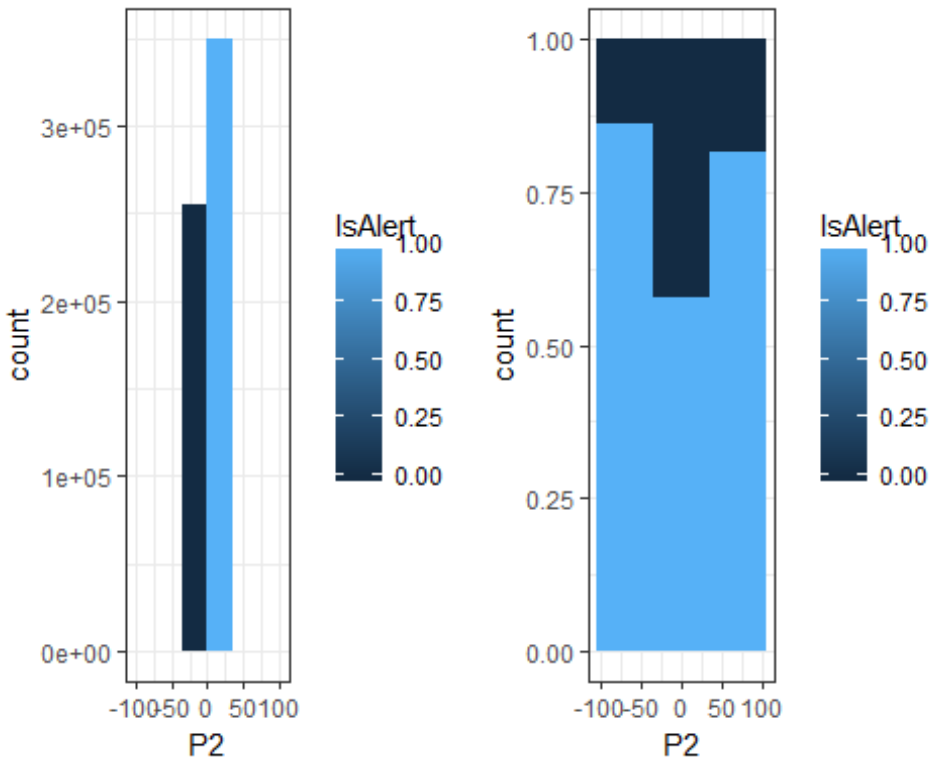
```
p1_1<-ggplot(data,aes(x=P1,group=IsAlert,fill=IsAlert))+ geom_histogram(position="dodge",binwidth=70)+theme_bw()
```

```
p1_2<-ggplot(data,aes(x=P1,group=IsAlert,fill=IsAlert))+ geom_histogram(position="fill",binwidth=70)+theme_bw()
```

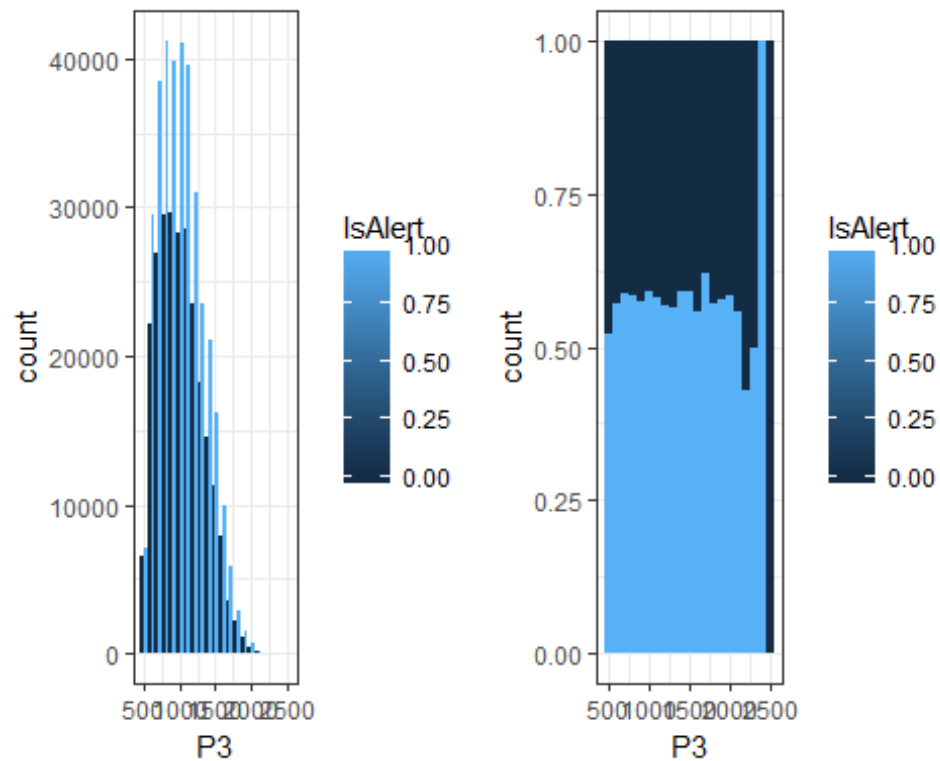
```
grid.arrange(p1_1, p1_2, ncol=2)
```



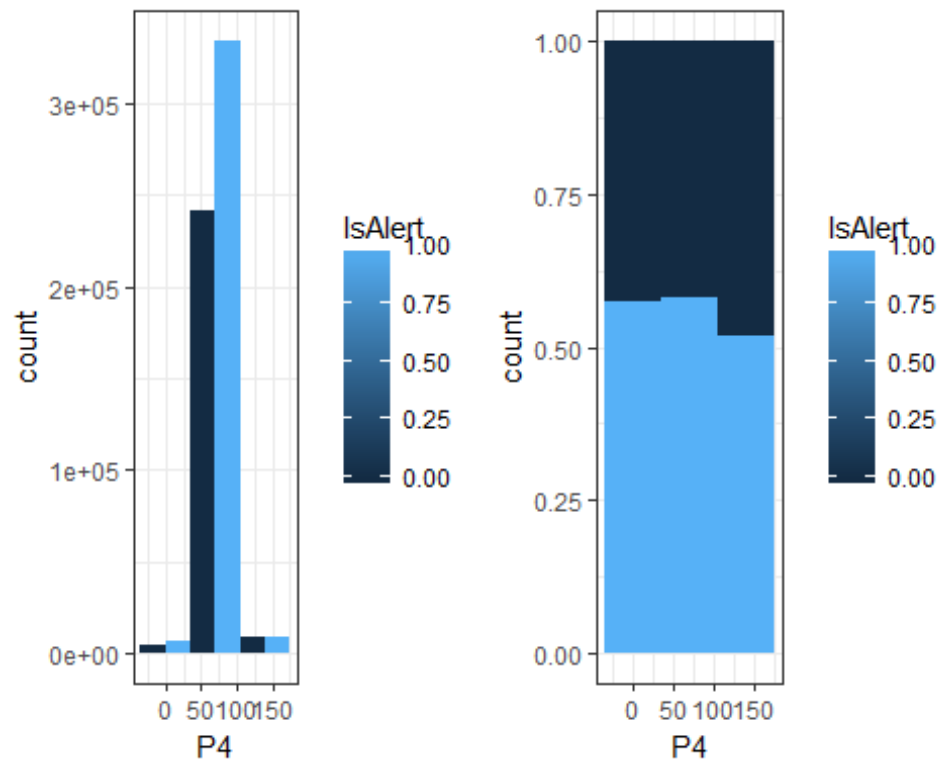
```
#P2
p2_1<-ggplot(data,aes(x=P2,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
p2_2<-ggplot(data,aes(x=P2,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(p2_1, p2_2, ncol=2)
```



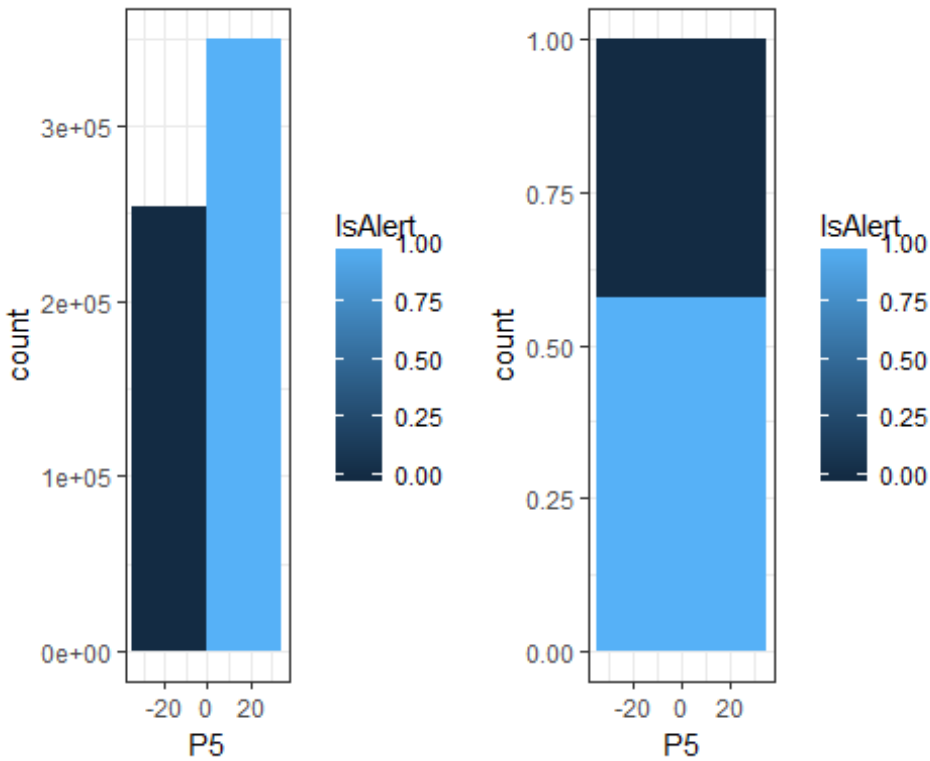
```
#P3
p3_1<-ggplot(data,aes(x=P3,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=100)+theme_bw()
p3_2<-ggplot(data,aes(x=P3,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=100)+theme_bw()
grid.arrange(p3_1, p3_2, ncol=2)
```

```
#P4
p4_1<-ggplot(data,aes(x=P4,group=IsAlert,fill=IsAlert))+ geom_histogram(position="dodge",binwidth=70)+theme_bw()
p4_2<-ggplot(data,aes(x=P4,group=IsAlert,fill=IsAlert))+ geom_histogram(position="fill",binwidth=70)+theme_bw()
grid.arrange(p4_1, p4_2, ncol=2)
```



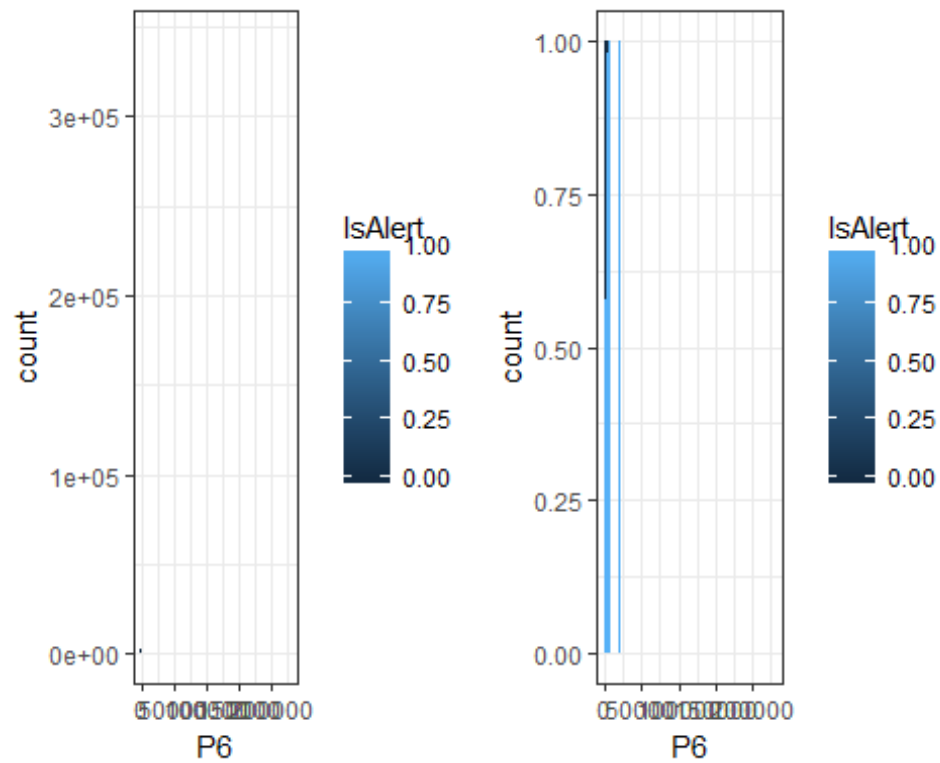
```
#P5
p5_1<-ggplot(data,aes(x=P5,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
p5_2<-ggplot(data,aes(x=P5,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(p5_1, p5_2, ncol=2)
```



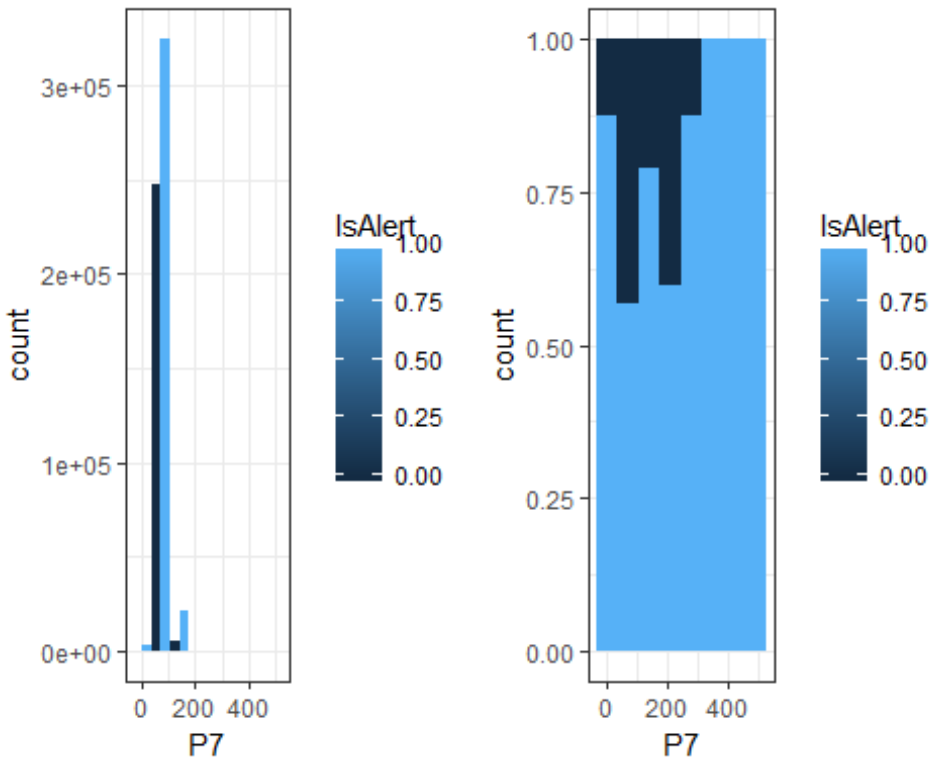
#P6

```
p6_1<-ggplot(data,aes(x=P6,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=1000)+theme_bw()
p6_2<-ggplot(data,aes(x=P6,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=1000)+theme_bw()
grid.arrange(p6_1, p6_2, ncol=2)
```

Warning: Removed 440 rows containing missing values (geom_bar).



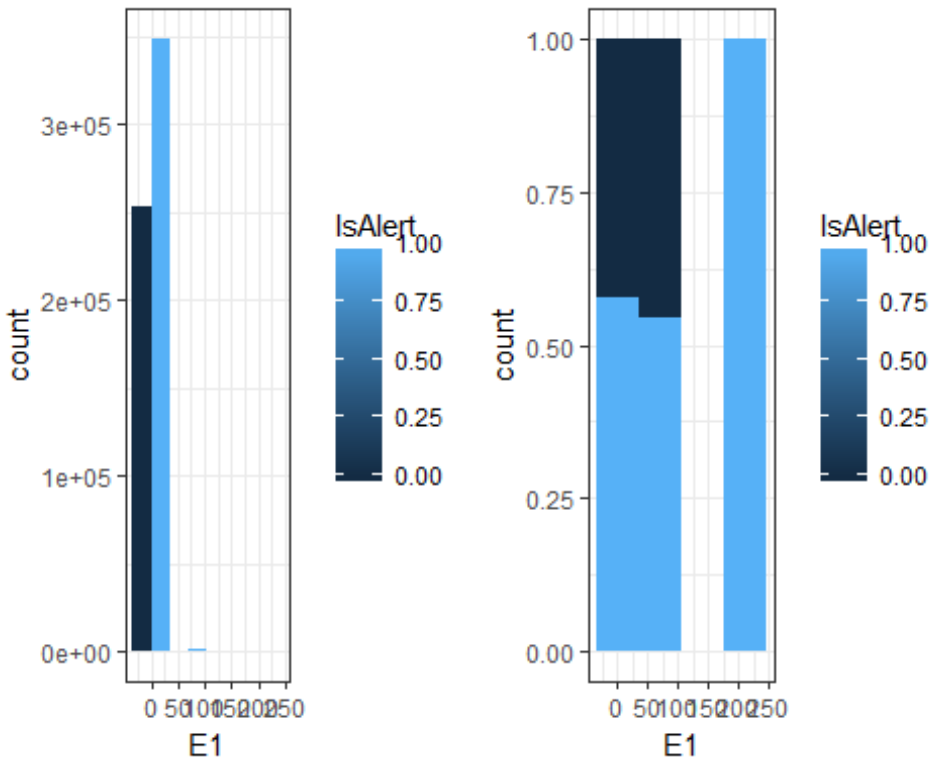
```
#P7
p7_1<-ggplot(data,aes(x=P7,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
p7_2<-ggplot(data,aes(x=P7,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(p7_1, p7_2, ncol=2)
```



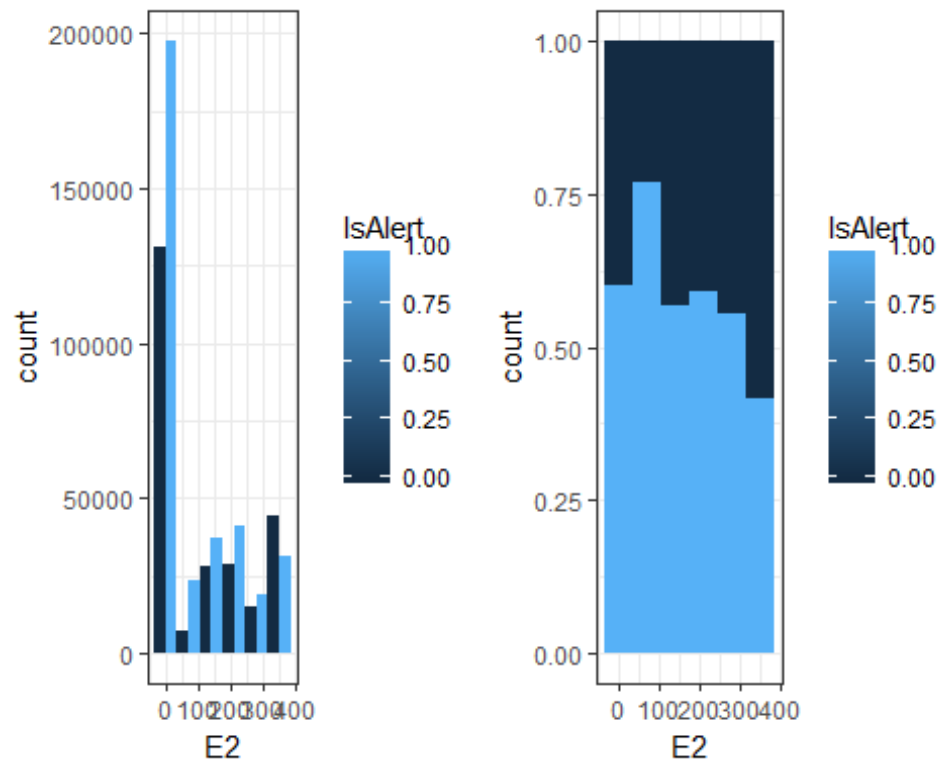
Among all Physical data, the change of P5 has no effect on the change of response variable, which indicates that P5 has no relationship with response variable

```
#E1
e1_1<-ggplot(data,aes(x=E1,group=IsAlert,fill=IsAlert))+ geom_histogram(position="dodge",binwidth=70)+theme_bw()
e1_2<-ggplot(data,aes(x=E1,group=IsAlert,fill=IsAlert))+ geom_histogram(position="fill",binwidth=70)+theme_bw()
grid.arrange(e1_1, e1_2, ncol=2)

## Warning: Removed 2 rows containing missing values (geom_bar).
```

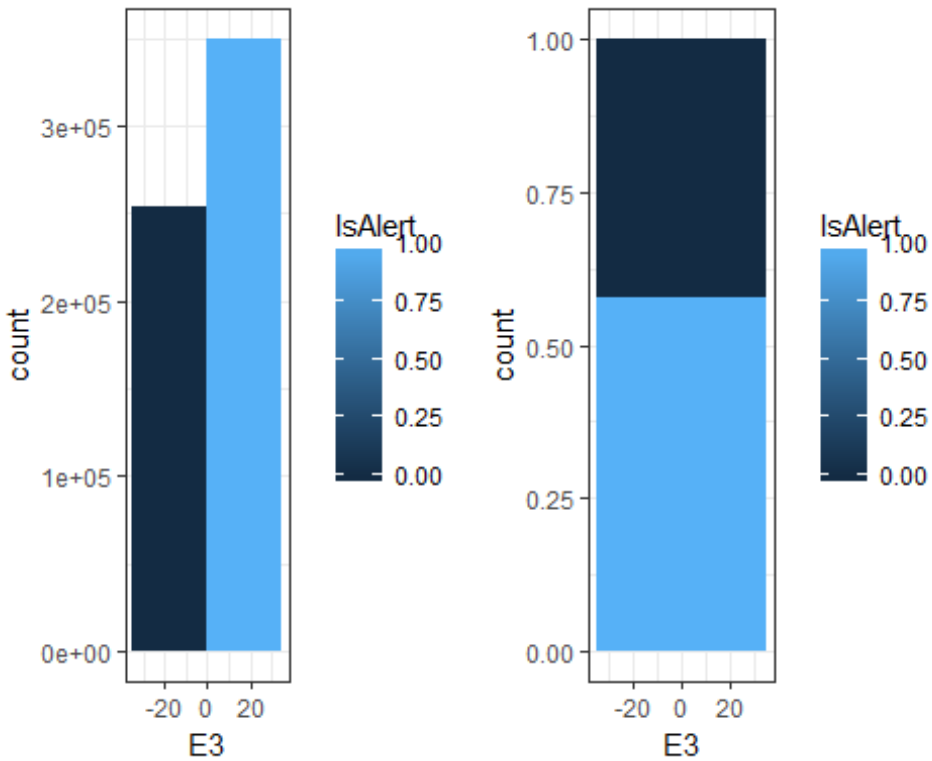


```
#E2
e2_1<-ggplot(data,aes(x=E2,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
e2_2<-ggplot(data,aes(x=E2,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(e2_1, e2_2, ncol=2)
```



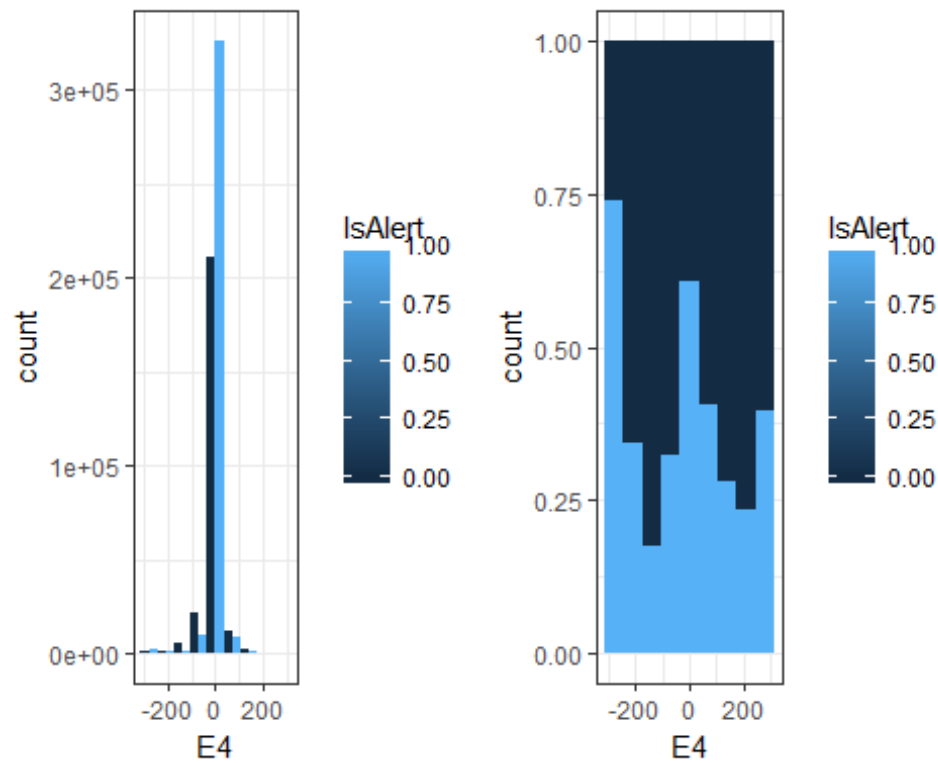
#E3

```
e3_1<-ggplot(data,aes(x=E3,group=IsAlert,fill=IsAlert))+ geom_histogram(position="dodge",binwidth=70)+theme_bw()
e3_2<-ggplot(data,aes(x=E3,group=IsAlert,fill=IsAlert))+ geom_histogram(position="fill",binwidth=70)+theme_bw()
grid.arrange(e3_1, e3_2, ncol=2)
```



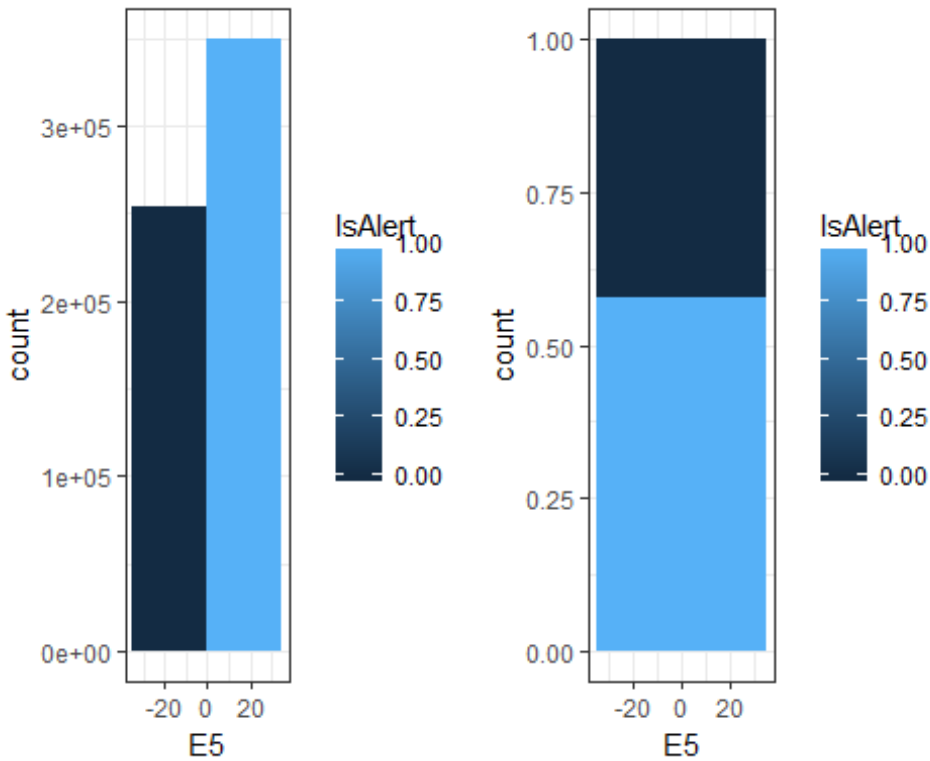
#E4

```
e4_1<-ggplot(data,aes(x=E4,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
e4_2<-ggplot(data,aes(x=E4,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(e4_1, e4_2, ncol=2)
```

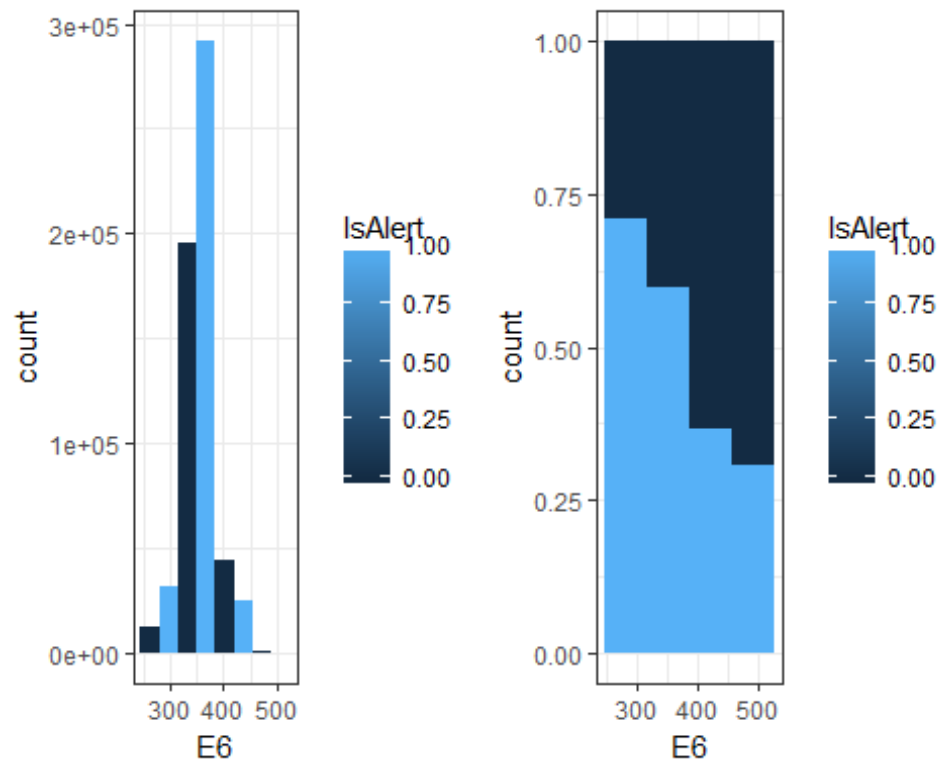
#E5

```
e5_1<-ggplot(data,aes(x=E5,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
e5_2<-ggplot(data,aes(x=E5,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(e5_1, e5_2, ncol=2)
```

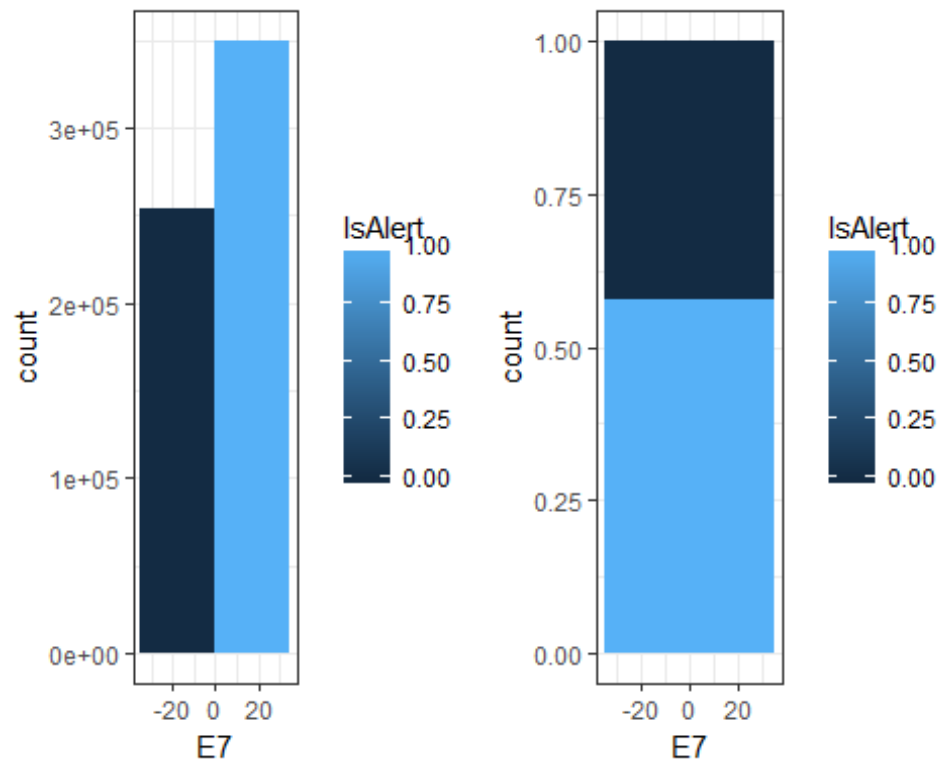


#E6

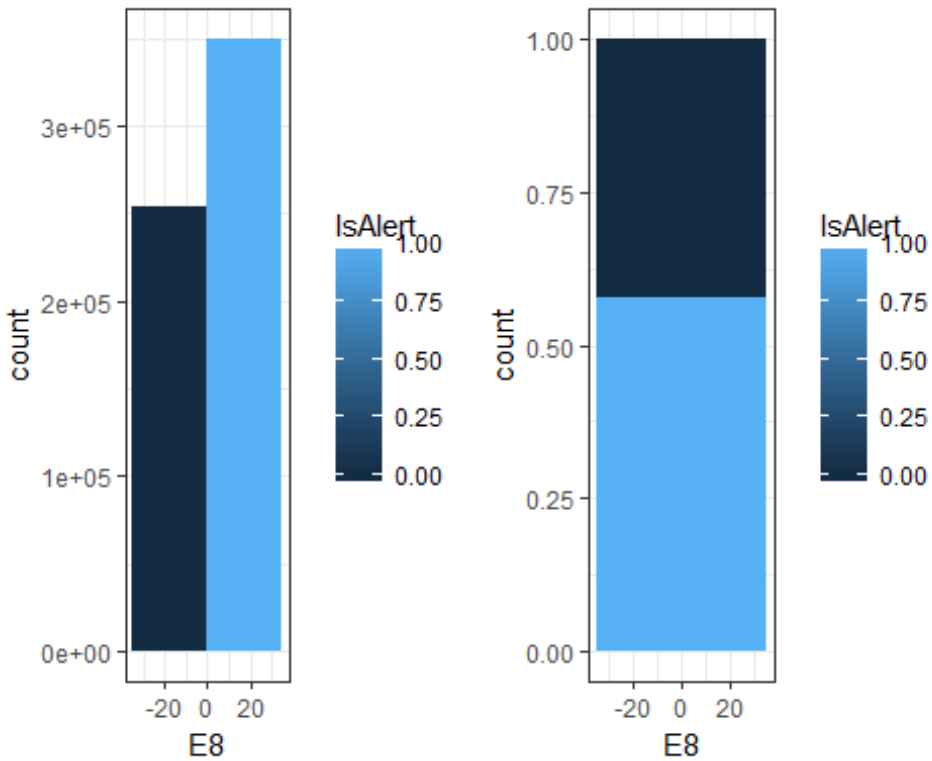
```
e6_1<-ggplot(data,aes(x=E6,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
e6_2<-ggplot(data,aes(x=E6,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(e6_1, e6_2, ncol=2)
```



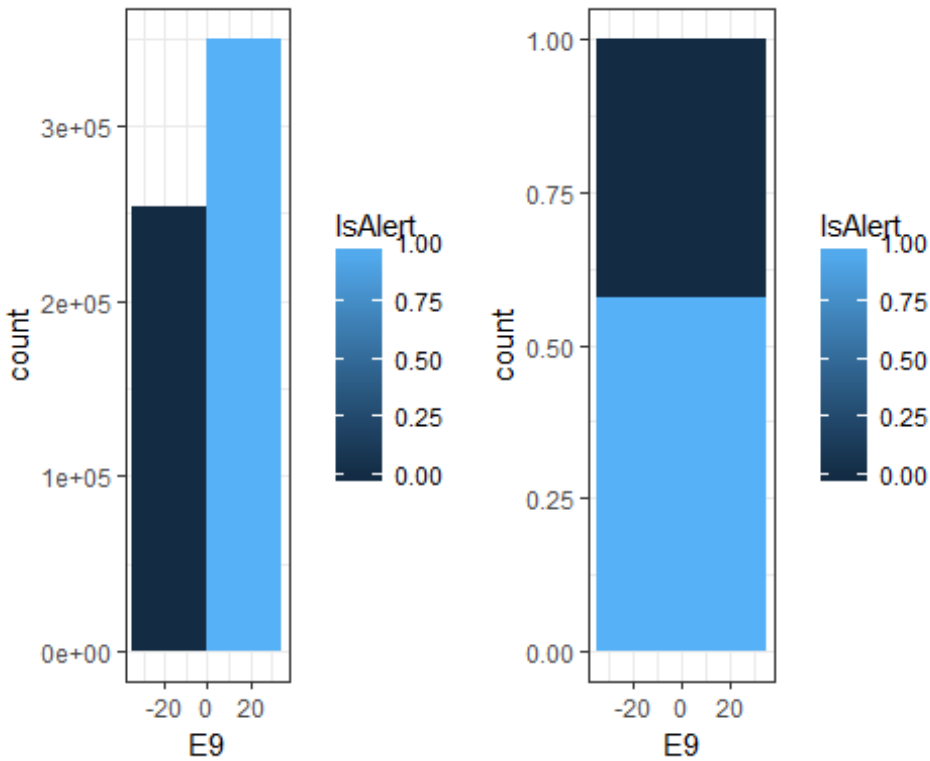
```
#E7
e7_1<-ggplot(data,aes(x=E7,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
e7_2<-ggplot(data,aes(x=E7,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(e7_1, e7_2, ncol=2)
```



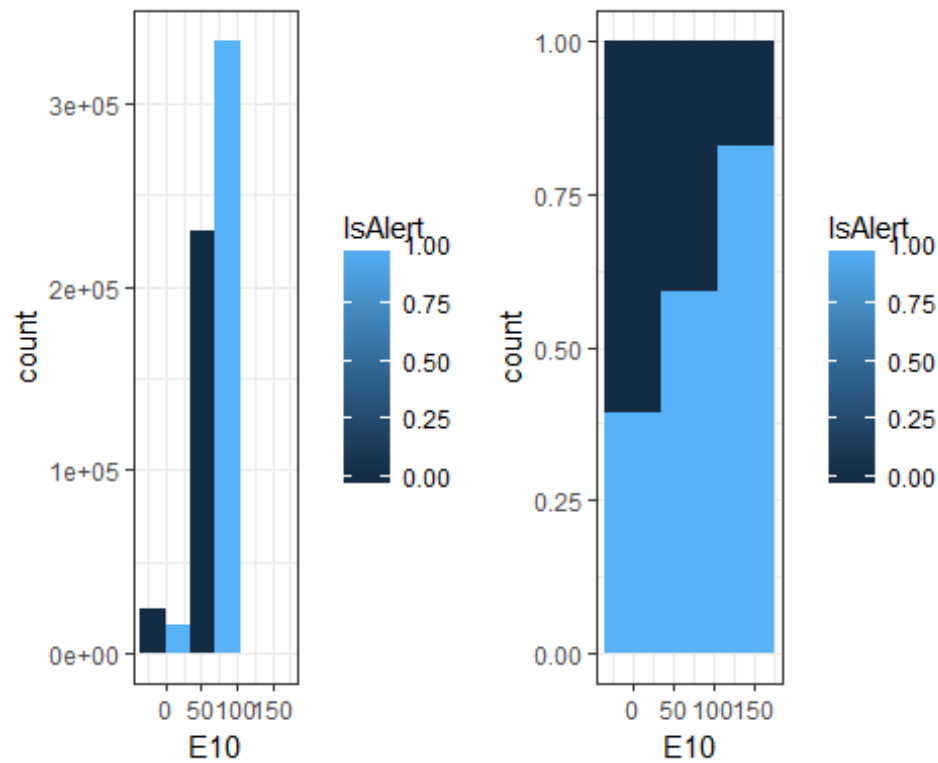
```
#E8
e8_1<-ggplot(data,aes(x=E8,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
e8_2<-ggplot(data,aes(x=E8,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(e8_1, e8_2, ncol=2)
```



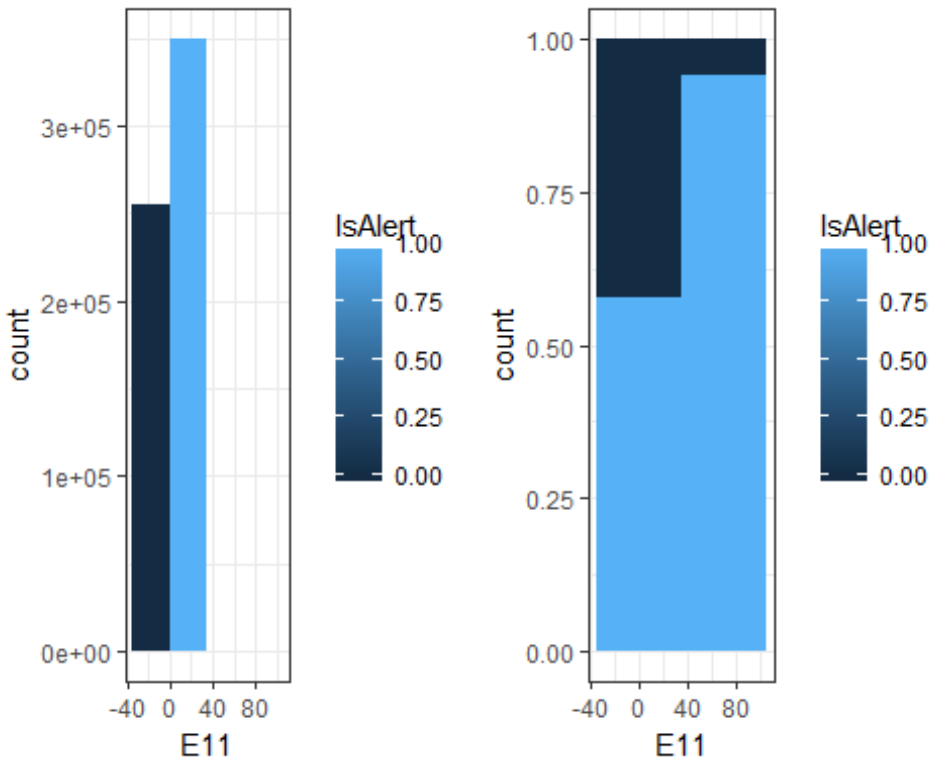
```
#E9
e9_1<-ggplot(data,aes(x=E9,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
e9_2<-ggplot(data,aes(x=E9,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(e9_1, e9_2, ncol=2)
```



```
#E10
e10_1<-ggplot(data,aes(x=E10,group=IsAlert,fill=IsAlert))+ geom_histogram(po
sition="dodge",binwidth=70)+theme_bw()
e10_2<-ggplot(data,aes(x=E10,group=IsAlert,fill=IsAlert))+ geom_histogram(po
sition="fill",binwidth=70)+theme_bw()
grid.arrange(e10_1, e10_2, ncol=2)
```



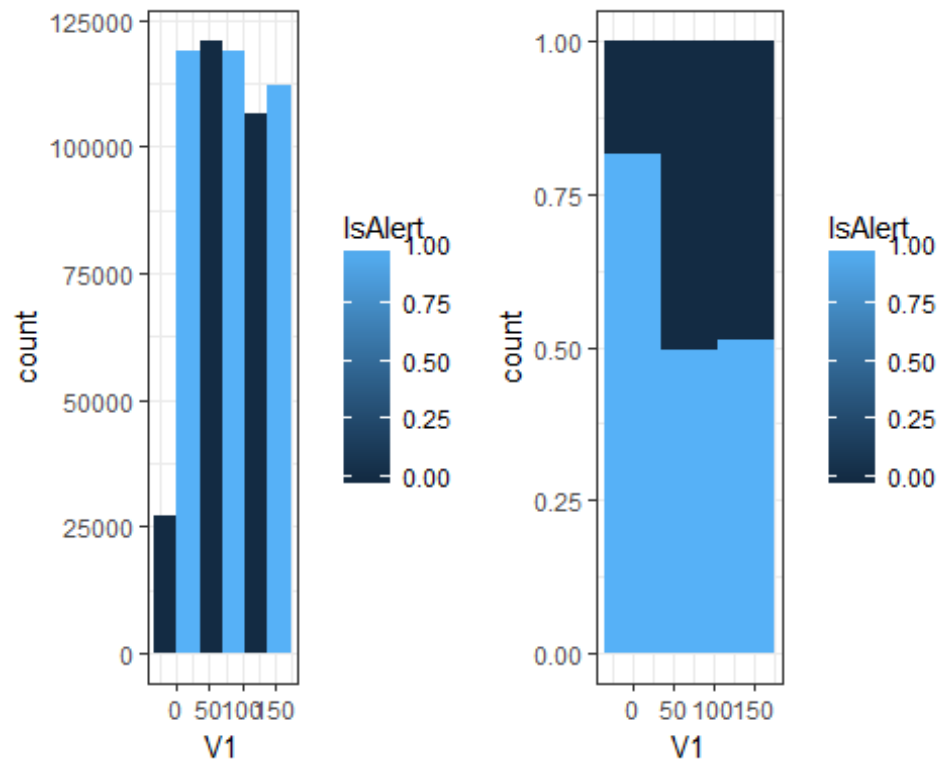
```
#E11
e11_1<-ggplot(data,aes(x=E11,group=IsAlert,fill=IsAlert))+ geom_histogram(po
sition="dodge",binwidth=70)+theme_bw()
e11_2<-ggplot(data,aes(x=E11,group=IsAlert,fill=IsAlert))+ geom_histogram(po
sition="fill",binwidth=70)+theme_bw()
grid.arrange(e11_1, e11_2, ncol=2)
```



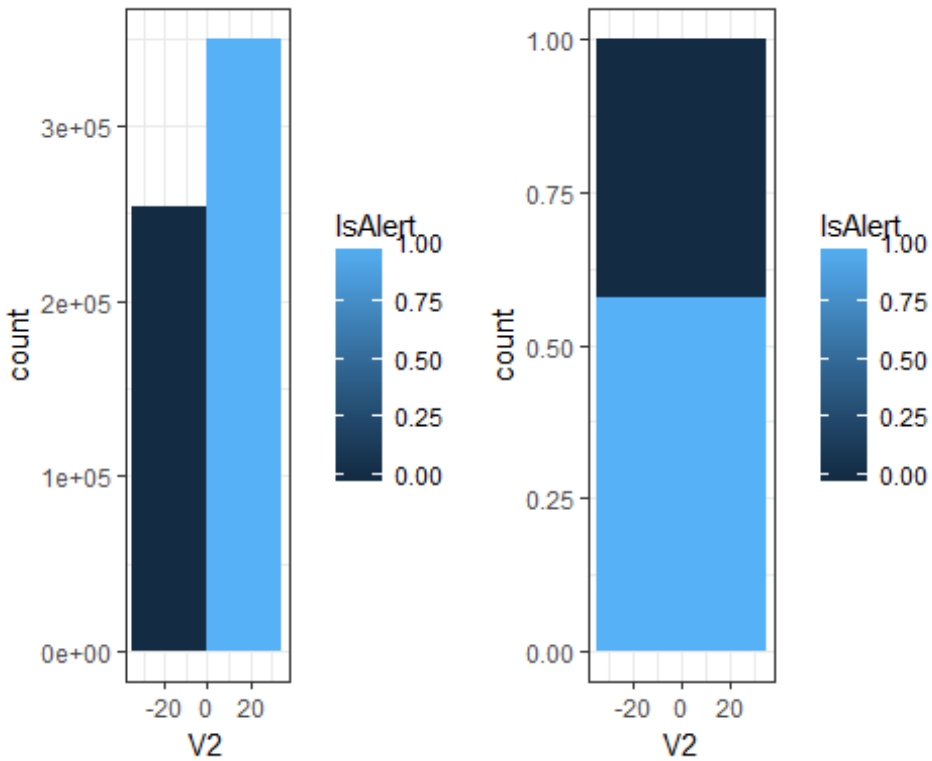
E3, E5, E7, E8, E9

have no relationship with response variable. However, considered some of them are categorical variables, we cannot simply delete them from dataset.

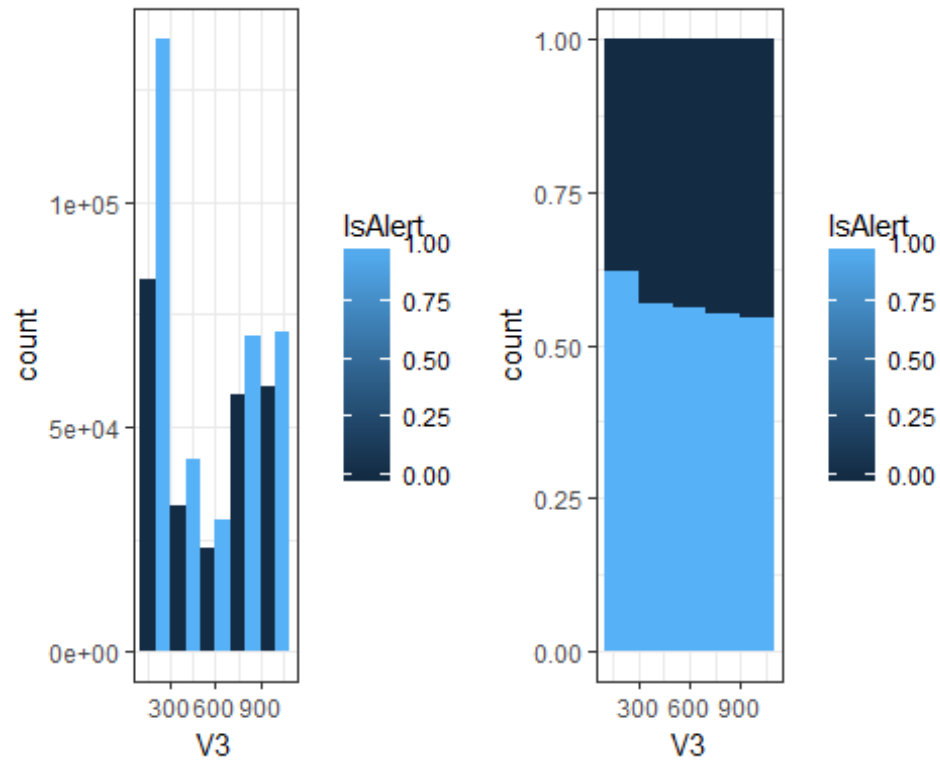
```
#V1
v1_1<-ggplot(data,aes(x=V1,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
v1_2<-ggplot(data,aes(x=V1,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(v1_1, v1_2, ncol=2)
```

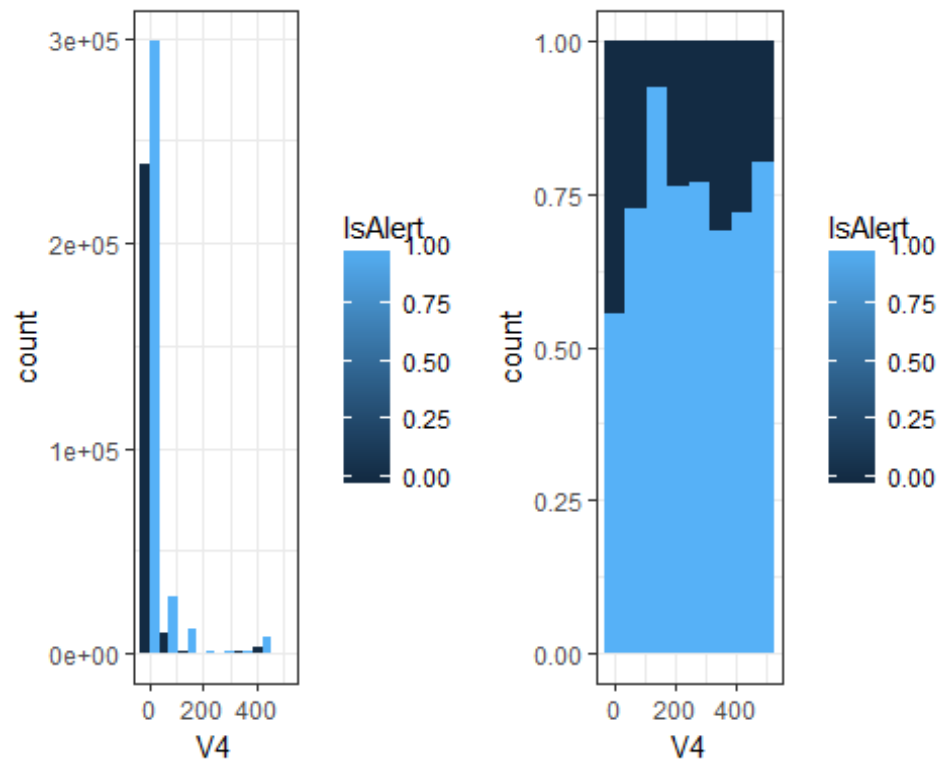
```
#V2
v2_1<-ggplot(data,aes(x=V2,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
v2_2<-ggplot(data,aes(x=V2,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(v2_1, v2_2, ncol=2)
```



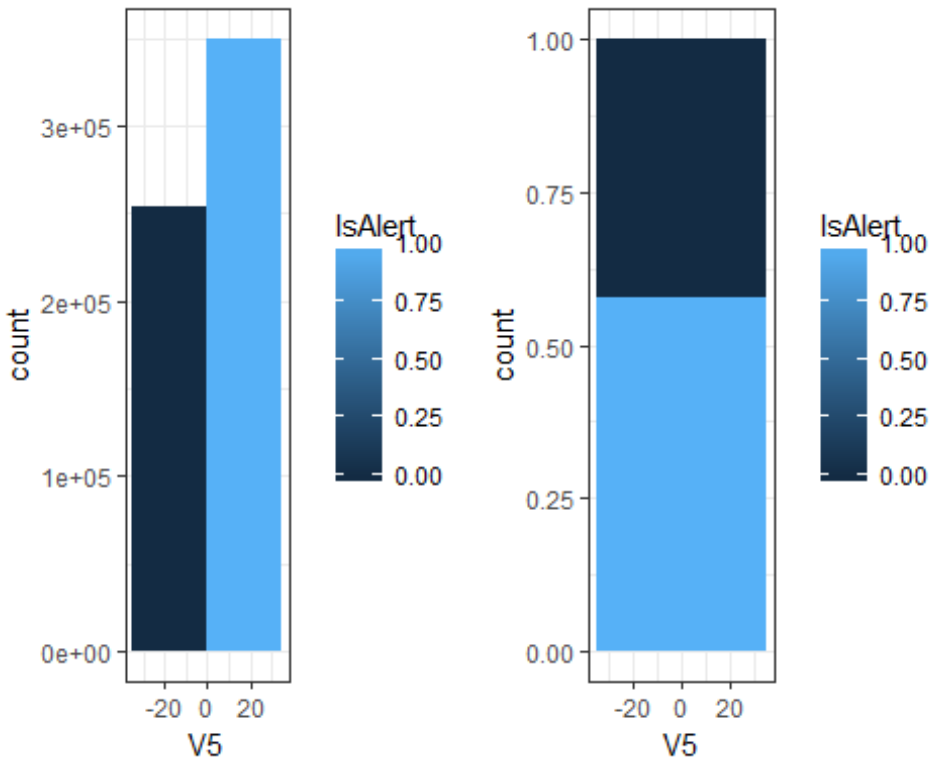
```
#V3
v3_1<-ggplot(data,aes(x=V3,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=200)+theme_bw()
v3_2<-ggplot(data,aes(x=V3,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=200)+theme_bw()
grid.arrange(v3_1, v3_2, ncol=2)
```



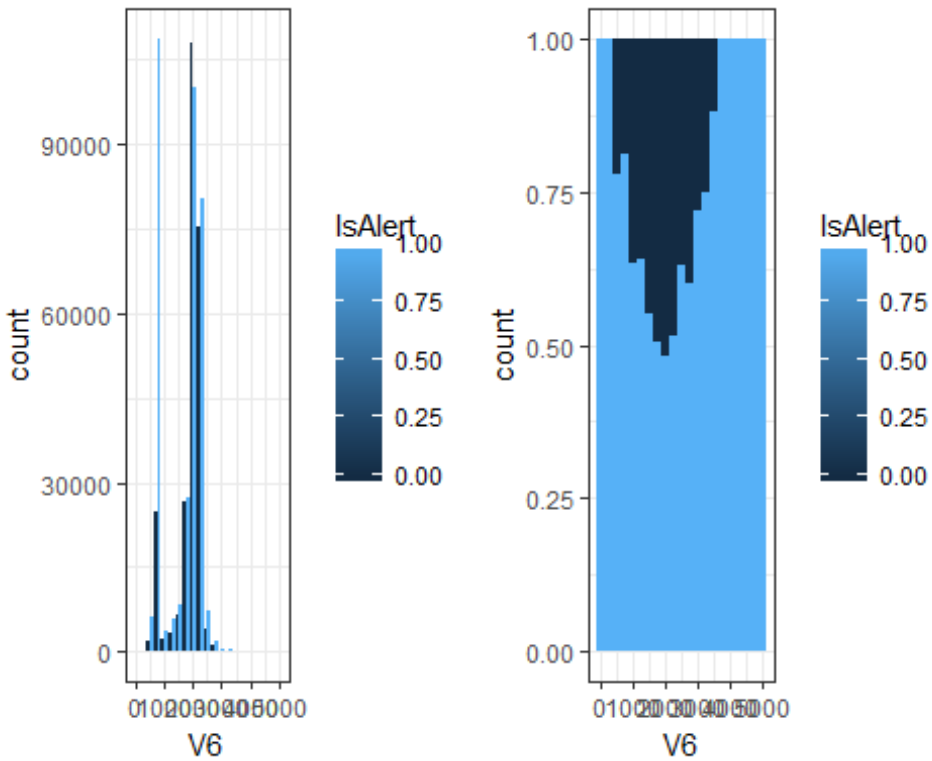
```
#V4
v4_1<-ggplot(data,aes(x=V4,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
v4_2<-ggplot(data,aes(x=V4,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(v4_1, v4_2, ncol=2)
```



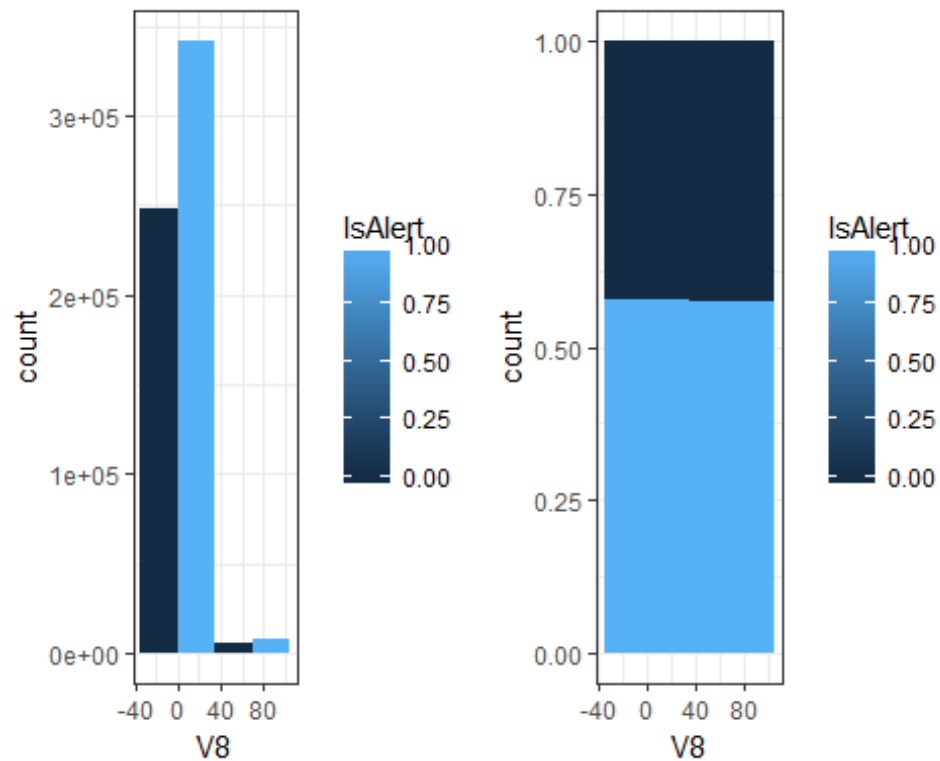
```
#V5
v5_1<-ggplot(data,aes(x=V5,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
v5_2<-ggplot(data,aes(x=V5,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(v5_1, v5_2, ncol=2)
```



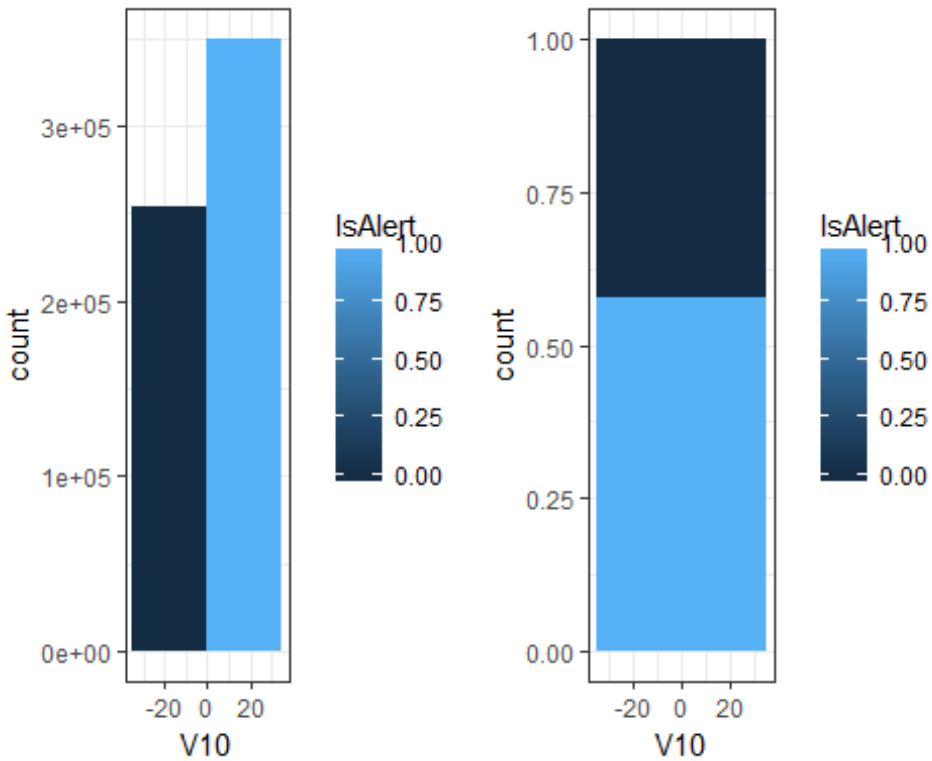
```
#V6
v6_1<-ggplot(data,aes(x=V6,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=250)+theme_bw()
v6_2<-ggplot(data,aes(x=V6,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=250)+theme_bw()
grid.arrange(v6_1, v6_2, ncol=2)
```



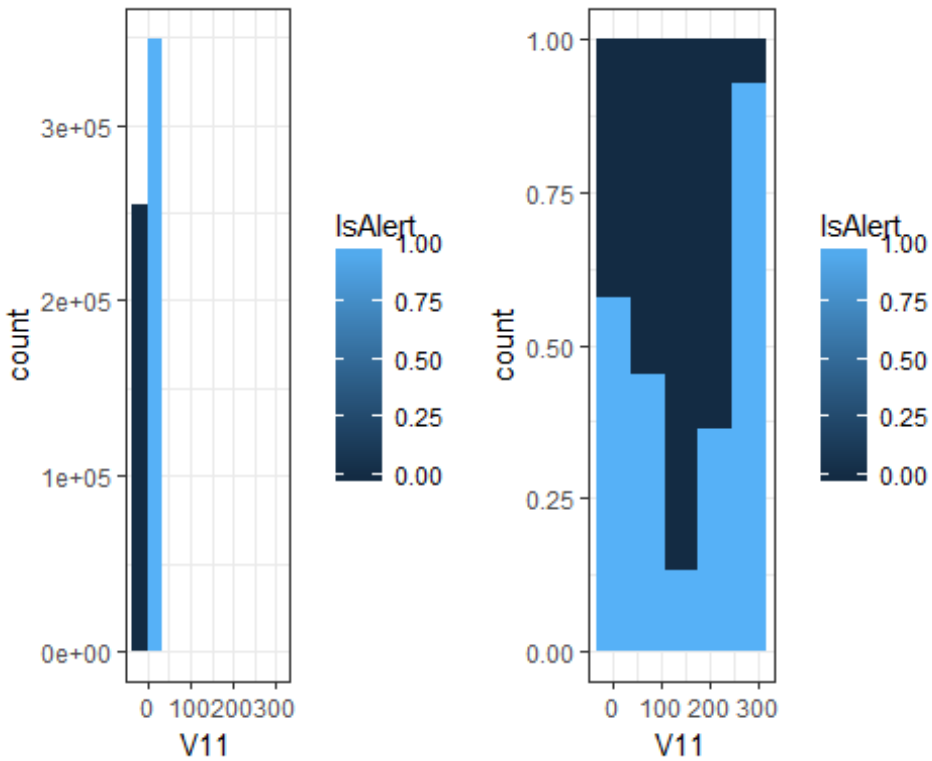
```
#V8
v8_1<-ggplot(data,aes(x=V8,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="dodge",binwidth=70)+theme_bw()
v8_2<-ggplot(data,aes(x=V8,group=IsAlert,fill=IsAlert))+ geom_histogram(posi
tion="fill",binwidth=70)+theme_bw()
grid.arrange(v8_1, v8_2, ncol=2)
```



```
#V10
v10_1<-ggplot(data,aes(x=V10,group=IsAlert,fill=IsAlert))+ geom_histogram(po
sition="dodge",binwidth=70)+theme_bw()
v10_2<-ggplot(data,aes(x=V10,group=IsAlert,fill=IsAlert))+ geom_histogram(po
sition="fill",binwidth=70)+theme_bw()
grid.arrange(v10_1, v10_2, ncol=2)
```



```
#V11
v11_1<-ggplot(data,aes(x=V11,group=IsAlert,fill=IsAlert))+ geom_histogram(po
sition="dodge",binwidth=70)+theme_bw()
v11_2<-ggplot(data,aes(x=V11,group=IsAlert,fill=IsAlert))+ geom_histogram(po
sition="fill",binwidth=70)+theme_bw()
grid.arrange(v11_1, v11_2, ncol=2)
```

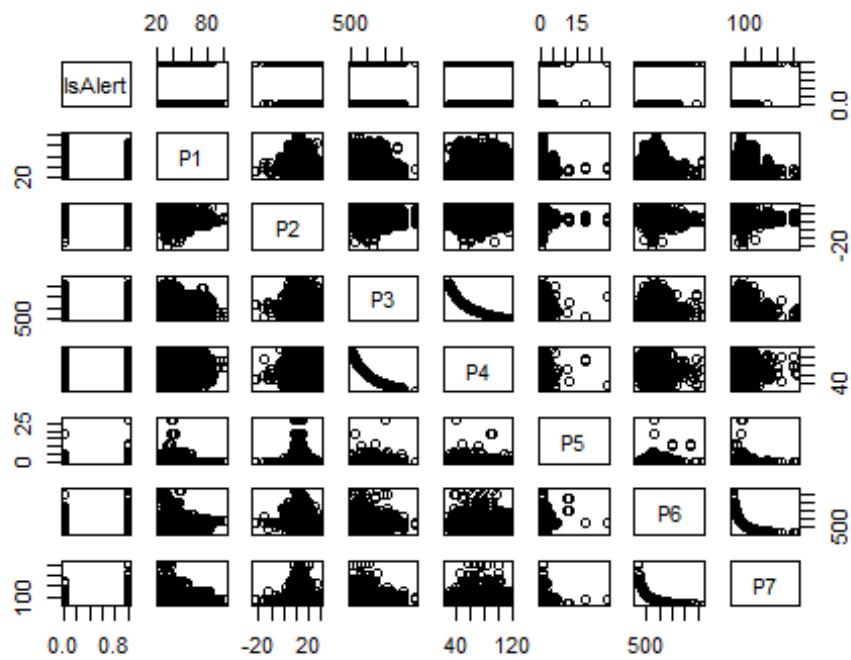
V2, V5, V8, V10

have no relationship with response variable. Similarly, we have to consider the categorical data.

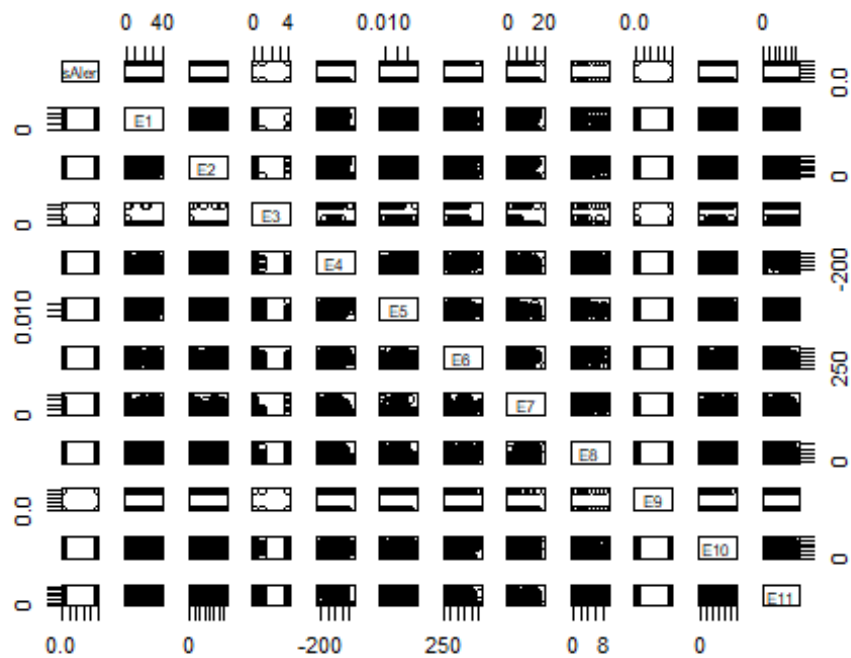
4. Identify pairs of features which are related to each other

#P~

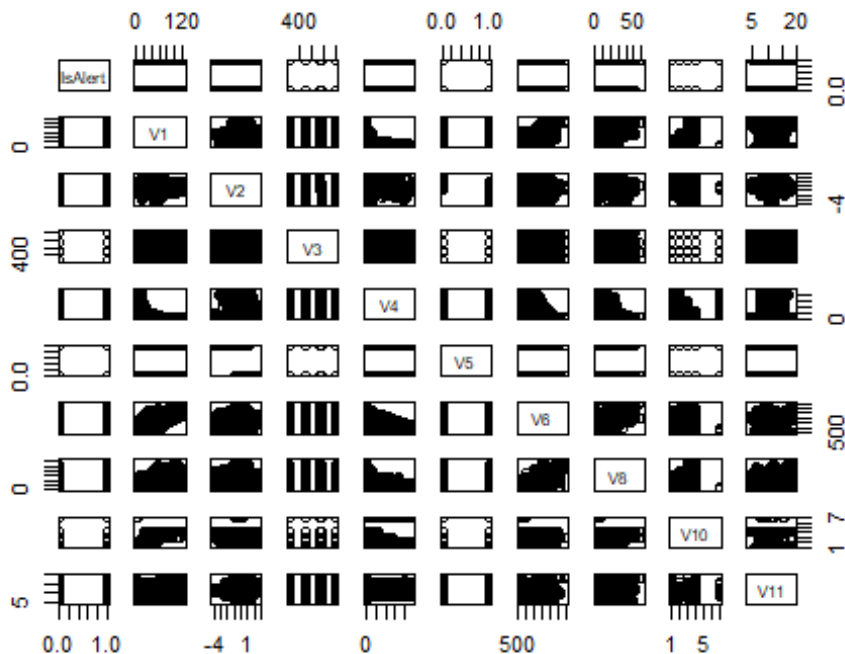
```
pairs(newdata[,c(3,4,5,6,7,8,9,10)])
```



```
#E~
pairs(newdata[,c(3,11, 12,13,14,15,16,17,18,19,20,21)])
```



```
#V~
pairs(newdata[,c(3,22, 23,24,25,26,27,28, 29, 30)])
```



5. Dimension reduction

1). Remove the features which have no relationship with the response Becasue variables E1 to E11 are environmental data, which is reasonable to consider that certain environmental features could have no relationship with response variable. And to determine the specific variables which have no relationship with response variable, we need to check scatter plot matrix. And for those who have no relationship with response variable, the distribution of dots for "1" and "0" would be same. Therefore, I decide to delete the following variables: E1 E2 E5 E10 E11

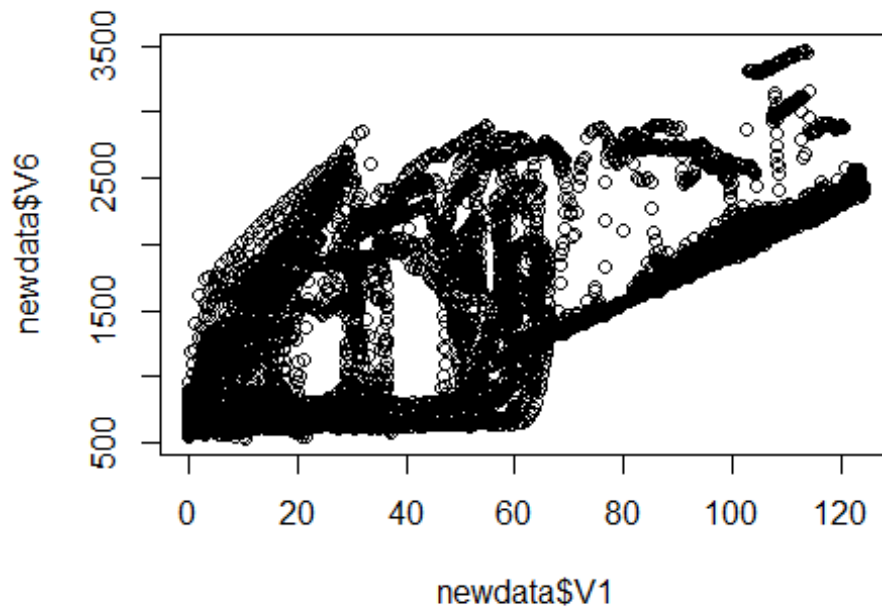
```
drops <- c("E1", "E2", "E5", "E10", "E11")
newdata<-newdata[ , !(names(newdata) %in% drops)]
```

2). Remove a feature(s) that has a perfect relationship to another one P3 - P4, drop P4 P6 - P7, drop P7

```
drops <- c("P4", "P7")
newdata<-newdata[ , !(names(newdata) %in% drops)]
```

3)Reduce the number of features which are significantly related to each other in some non-linear way V1 - V6, drop V6

```
plot(newdata$V1, newdata$V6)
```



```
drops <- c("V6")
newdata<-newdata[ , !(names(newdata) %in% drops)]
```

4) Transform a set of highly correlated features into a smaller set, by using wrapper method

```
#install.packages("caret", repos = "http://cran.r-project.org", dependencies
= c("Depends", "Imports", "Suggests"))
#install.packages("ggplot2", dependencies = TRUE)
#install.packages("Rcpp", dependencies = TRUE)
library(ggplot2)
library(caret)

library(randomForest)

## randomForest 4.6-14

## Type rfNews() to see new features/changes/bug fixes.

##
## Attaching package: 'randomForest'

## The following object is masked from 'package:ggplot2':
##
##     margin

## The following object is masked from 'package:gridExtra':
##
##     combine
```

```

temp_train <- newdata[1:100,]
temp_train$IsAlert <- as.factor(temp_train$IsAlert)
#Feature selection using rfe in caret
control <- rfeControl(functions = rfFuncs,method = "repeatedcv",repeats = 3,
verbose = FALSE)
outcomeName<-'IsAlert'
predictors<-names(temp_train)[!names(temp_train) %in% outcomeName]
result <- rfe(temp_train[,predictors], temp_train[,outcomeName],rfeControl =
control)
result

##
## Recursive feature selection
##
## Outer resampling method: Cross-Validated (10 fold, repeated 3 times)
##
## Resampling performance over subset size:
##
## Variables Accuracy Kappa AccuracySD KappaSD Selected
##      4    0.9926 0.9667    0.04057  0.1826      *
##      8    0.9796 0.9237    0.05089  0.2081
##     16    0.9661 0.8806    0.05705  0.2228
##     21    0.9661 0.8806    0.05705  0.2228
##
## The top 4 variables (out of 4):
##      E4, ObsNum, V1, E6

```

Now we have four variables which might have significant influence on response variable. they are E3, ObsNum, V1, and E6. However, F=four variables are insufficient to make analysis, So I will still keep as 22 variables.

Until now, we have 22 variables as following: P1:continuous P2:continuous P3:continuous P5:continuous P6:continuous E3:categorical, with 3 levels E4:continuous E6:continuous E7:categorical, with 18 levels E8:categorical, with 10 levels E9:categorical, with 2 levels V1:continuous V2:continuous V3:continuous V4:continuous V5:categorical, with 2 levels V8:continuous V10:categorical, with 5 levels V11:continuous

Basic Model building

#Check indicator variables

```
unique(newdata$E3)
```

```
## [1] 1 0 4
```

```
unique(newdata$E7)
```

```
## [1] 1 0 6 5 3 13 14 15 16 12 11 2 10 9 8 7 4 20
```

```
unique(newdata$E8)
```

```
## [1] 1 0 4 7 2 3 5 8 6 9
```

```

unique(newdata$E9)

## [1] 1 0

unique(newdata$V5)

## [1] 0 1

unique(newdata$V10)

## [1] 4 3 7 1 2

#Create indicator variable
newdata$E3_1 = c(rep(0, length(newdata$IsAlert)))
newdata$E3_0 = newdata$E3_4 = newdata$E7_low = newdata$E7_high = newdata$E8_low = newdata$E8_high = newdata$E9_0 = newdata$E9_1 = newdata$V5_0 = newdata$V5_1 = newdata$V10_low = newdata$V10_high = newdata$E3_1

for (i in 1:length(newdata$IsAlert)) {
#E3
if(newdata$E3[i] == 1) newdata$E3_1[i] <- 1
if(newdata$E3[i] == 0) newdata$E3_0[i] <- 1
if(newdata$E3[i] == 4) newdata$E3_4[i] <- 1

#E7
if(newdata$E7[i] <= 10) newdata$E7_low[i] <- 1
if(newdata$E7[i] > 10) newdata$E7_high[i] <- 1

#E8
if(newdata$E8[i] <= 4) newdata$E7_low[i] <- 1
if(newdata$E8[i] > 4) newdata$E7_high[i] <- 1

#E9
if(newdata$E9[i] == 1) newdata$E9_1[i] <- 1
if(newdata$E9[i] == 0) newdata$E9_0[i] <- 1

#V5
if(newdata$V5[i] == 1) newdata$V5_1[i] <- 1
if(newdata$V5[i] == 0) newdata$V5_0[i] <- 1

#V10
if(newdata$E8[i] <= 3) newdata$V10_low[i] <- 1
if(newdata$E8[i] > 3) newdata$V10_high[i] <- 1
}

# Minimax transform the continuous variables
#P1
newdata$P1_mm <- (newdata$P1 - min(newdata$P1)) / (max(newdata$P1) - min(newdata$P1))
#P2
newdata$P2_mm <- (newdata$P2 - min(newdata$P2)) / (max(newdata$P2) - min(newdata$P2))

```

```

ata$P2))
#P3
newdata$P3_mm <- (newdata$P3 - min(newdata$P3)) / (max(newdata$P3) - min(newd
ata$P3))
#P5
newdata$P5_mm <- (newdata$P5 - min(newdata$P5)) / (max(newdata$P5) - min(newd
ata$P5))
#P6
newdata$P6_mm <- (newdata$P6 - min(newdata$P6)) / (max(newdata$P6) - min(newd
ata$P6))
#E4
newdata$E4_mm <- (newdata$E4 - min(newdata$E4)) / (max(newdata$E4) - min(newd
ata$E4))
#E6
newdata$E6_mm <- (newdata$E6 - min(newdata$E6)) / (max(newdata$E6) - min(newd
ata$E6))
#V1
newdata$V1_mm <- (newdata$V1 - min(newdata$V1)) / (max(newdata$V1) - min(newd
ata$V1))
#V2
newdata$V2_mm <- (newdata$V2 - min(newdata$V2)) / (max(newdata$V2) - min(newd
ata$V2))
#V3
newdata$V3_mm <- (newdata$V3 - min(newdata$V3)) / (max(newdata$V3) - min(newd
ata$V3))
#V4
newdata$V4_mm <- (newdata$V4 - min(newdata$V4)) / (max(newdata$V4) - min(newd
ata$V4))
#V8
newdata$V8_mm <- (newdata$V8 - min(newdata$V8)) / (max(newdata$V8) - min(newd
ata$V8))
#V11
newdata$V11_mm <- (newdata$V11 - min(newdata$V11)) / (max(newdata$V11) - min(
newdata$V11))

#new dataset
mydata_nn <- newdata[, -c(4:22)]
mydata_nn <- mydata_nn[, -c(1, 2)]
mydata_nn <- mydata_nn[1:10000,]
#training data
training <- mydata_nn[1:7000, ]
#testing data
testing <- mydata_nn[7001:10000,]

```

Neural Network

1) Constructing and comparing model

```

library(nnet) # Requires package nnet
set.seed(2018)
myNewFrame <- data.frame(node = integer(0),maxit = integer(0), decay = intege
r(0) ,misscls.train = integer(0), misscls.test = integer(0))

```

```

for (m in c(10, 100, 10000)) {
  for (d in c(0, 0.1, 0.2)) {
    for (s in c(5, 10, 15)) {
      net.dat <- nnet(IsAlert~., data = training, size = s, decay = d, maxit
= m)
      #table(round(net.dat$fitted.values, 1))

      estimated_isAlert=as.numeric(net.dat$fitted.values>0.5)

      T = table(estimated_isAlert,training$IsAlert)

      misscls.train<-sum((estimated_isAlert - training$IsAlert)^2)/length(tr
aining$IsAlert)
      misscls.train
      presdicted.testing<-as.numeric(predict(net.dat,testing )>0.5)
      Ttest = table(presdicted.testing, testing$IsAlert)
      misscls.test<-sum((presdicted.testing - testing$IsAlert)^2)/length(tes
ting$IsAlert)
      misscls.test

      df <- data.frame(s, m, d, misscls.train, misscls.test)
      names(df)<-c("node", "maxit", "decay", "misscls.train", "misscls.test"
)
      myNewFrame <- rbind(myNewFrame, df)

    }
  }
}

## # weights:  141
## initial  value 1306.799428
## final  value 396.000000
## converged
## # weights:  281
## initial  value 2012.521226
## final  value 1744.000000
## converged
## # weights:  421
## initial  value 2549.624964
## final  value 1744.000000
## converged
## # weights:  141
## initial  value 2029.279725
## iter  10 value 1281.854021
## final  value 1281.854021
## stopped after 10 iterations
## # weights:  281
## initial  value 2391.598699

```



```
## iter 10 value 1495.701339
## final value 1495.701339
## stopped after 10 iterations
## # weights: 421
## initial value 1465.568100
## iter 10 value 421.075809
## final value 421.075809
## stopped after 10 iterations
## # weights: 141
## initial value 2107.655542
## iter 10 value 1503.434091
## final value 1503.434091
## stopped after 10 iterations
## # weights: 281
## initial value 3246.847111
## iter 10 value 1527.330158
## final value 1527.330158
## stopped after 10 iterations
## # weights: 421
## initial value 2786.487949
## iter 10 value 1678.682384
## final value 1678.682384
## stopped after 10 iterations
## # weights: 141
## initial value 1410.739557
## final value 396.000000
## converged
## # weights: 281
## initial value 1257.845833
## final value 396.000000
## converged
## # weights: 421
## initial value 1381.157690
## iter 10 value 361.583794
## iter 20 value 351.994633
## iter 30 value 345.572434
## iter 40 value 334.199224
## iter 50 value 317.929717
## iter 60 value 305.379378
## iter 70 value 292.090277
## iter 80 value 272.128459
## iter 90 value 258.600778
## iter 100 value 249.058926
## final value 249.058926
## stopped after 100 iterations
## # weights: 141
## initial value 1406.774649
## iter 10 value 509.934431
## iter 20 value 376.834567
## iter 30 value 364.277056
```

```
## iter 40 value 363.897512
## iter 50 value 363.637781
## iter 60 value 363.539481
## iter 70 value 363.338802
## iter 80 value 363.243296
## iter 90 value 363.059820
## iter 100 value 363.007993
## final value 363.007993
## stopped after 100 iterations
## # weights: 281
## initial value 1941.192597
## iter 10 value 1576.397392
## iter 20 value 430.834136
## iter 30 value 380.908419
## iter 40 value 365.992123
## iter 50 value 364.144361
## iter 60 value 363.447173
## iter 70 value 363.247153
## iter 80 value 363.168043
## iter 90 value 363.029031
## iter 100 value 362.885454
## final value 362.885454
## stopped after 100 iterations
## # weights: 421
## initial value 1343.584185
## iter 10 value 420.587566
## iter 20 value 366.720145
## iter 30 value 363.656050
## iter 40 value 363.260930
## iter 50 value 363.146127
## iter 60 value 362.951359
## iter 70 value 362.762791
## iter 80 value 362.564508
## iter 90 value 362.474733
## iter 100 value 362.442954
## final value 362.442954
## stopped after 100 iterations
## # weights: 141
## initial value 1390.434380
## iter 10 value 428.396901
## iter 20 value 374.731388
## iter 30 value 369.920856
## iter 40 value 369.261492
## iter 50 value 368.834084
## iter 60 value 368.635723
## iter 70 value 368.576908
## iter 80 value 368.574660
## iter 90 value 368.574445
## iter 100 value 368.574282
## final value 368.574282
```

```
## stopped after 100 iterations
## # weights: 281
## initial value 2328.470687
## iter 10 value 1412.431944
## iter 20 value 473.096669
## iter 30 value 389.573877
## iter 40 value 375.330528
## iter 50 value 370.561815
## iter 60 value 369.156849
## iter 70 value 368.813227
## iter 80 value 368.611964
## iter 90 value 368.491813
## iter 100 value 368.387404
## final value 368.387404
## stopped after 100 iterations
## # weights: 421
## initial value 2547.952114
## iter 10 value 1679.176969
## iter 20 value 466.734073
## iter 30 value 374.596332
## iter 40 value 368.846596
## iter 50 value 368.383504
## iter 60 value 368.255936
## iter 70 value 368.223781
## iter 80 value 368.218594
## iter 90 value 368.212747
## iter 100 value 368.206357
## final value 368.206357
## stopped after 100 iterations
## # weights: 141
## initial value 2850.854771
## final value 1744.000000
## converged
## # weights: 281
## initial value 2009.172362
## final value 1744.000000
## converged
## # weights: 421
## initial value 2526.940767
## final value 1744.000000
## converged
## # weights: 141
## initial value 3591.169029
## iter 10 value 1572.849814
## iter 20 value 415.484227
## iter 30 value 369.150964
## iter 40 value 364.322632
## iter 50 value 364.124594
## iter 60 value 363.844907
## iter 70 value 363.673686
```

```
## iter 80 value 363.564042
## iter 90 value 363.423684
## iter 100 value 363.213267
## iter 110 value 362.876440
## iter 120 value 362.771216
## iter 130 value 362.539276
## iter 140 value 362.469943
## iter 150 value 362.455320
## iter 160 value 362.446853
## iter 170 value 362.443819
## iter 180 value 362.438245
## iter 190 value 362.436594
## iter 200 value 362.436126
## iter 210 value 362.432247
## iter 220 value 362.430566
## iter 230 value 362.429535
## iter 240 value 362.428531
## iter 250 value 362.428054
## final value 362.428020
## converged
## # weights: 281
## initial value 1292.209168
## iter 10 value 663.247708
## iter 20 value 387.227913
## iter 30 value 366.227343
## iter 40 value 364.219362
## iter 50 value 363.657815
## iter 60 value 363.264071
## iter 70 value 363.023963
## iter 80 value 362.916812
## iter 90 value 362.815893
## iter 100 value 362.717704
## iter 110 value 362.601341
## iter 120 value 362.550526
## iter 130 value 362.518659
## iter 140 value 362.490773
## iter 150 value 362.462390
## iter 160 value 362.447005
## iter 170 value 362.436124
## iter 180 value 362.429136
## iter 190 value 362.423164
## iter 200 value 362.417193
## iter 210 value 362.412477
## iter 220 value 362.408908
## iter 230 value 362.406278
## iter 240 value 362.405085
## iter 250 value 362.404442
## iter 260 value 362.403808
## iter 270 value 362.403495
## iter 280 value 362.401943
```

```
## iter 290 value 362.401233
## iter 300 value 362.400974
## iter 310 value 362.400838
## final value 362.400138
## converged
## # weights: 421
## initial value 1401.399696
## iter 10 value 408.648049
## iter 20 value 373.341776
## iter 30 value 365.027901
## iter 40 value 363.788715
## iter 50 value 363.333385
## iter 60 value 363.180033
## iter 70 value 363.060518
## iter 80 value 362.752318
## iter 90 value 362.519441
## iter 100 value 362.463256
## iter 110 value 362.450330
## iter 120 value 362.444239
## iter 130 value 362.441093
## iter 140 value 362.436359
## iter 150 value 362.427218
## iter 160 value 362.422082
## iter 170 value 362.418903
## iter 180 value 362.416198
## iter 190 value 362.414841
## iter 200 value 362.413345
## iter 210 value 362.412703
## iter 220 value 362.412166
## iter 230 value 362.411581
## iter 240 value 362.411267
## iter 250 value 362.411077
## iter 260 value 362.410935
## iter 270 value 362.410794
## iter 280 value 362.410598
## iter 290 value 362.410253
## iter 300 value 362.409644
## iter 310 value 362.409345
## iter 320 value 362.409148
## iter 330 value 362.408767
## iter 340 value 362.408669
## iter 350 value 362.408514
## final value 362.408506
## converged
## # weights: 141
## initial value 1324.431307
## iter 10 value 413.369813
## iter 20 value 371.472711
## iter 30 value 368.742135
## iter 40 value 368.586511
```

```
## iter 50 value 368.575998
## iter 60 value 368.575654
## iter 70 value 368.574568
## final value 368.573533
## converged
## # weights: 281
## initial value 2848.781381
## iter 10 value 1602.822447
## iter 20 value 976.212020
## iter 30 value 459.292679
## iter 40 value 417.234153
## iter 50 value 372.060190
## iter 60 value 369.043194
## iter 70 value 368.574584
## iter 80 value 368.387506
## iter 90 value 368.341836
## iter 100 value 368.314161
## iter 110 value 368.294447
## iter 120 value 368.283180
## iter 130 value 368.278502
## iter 140 value 368.276798
## iter 150 value 368.276392
## iter 160 value 368.276280
## iter 170 value 368.276145
## final value 368.276009
## converged
## # weights: 421
## initial value 1591.958396
## iter 10 value 413.185743
## iter 20 value 389.890075
## iter 30 value 373.016553
## iter 40 value 369.645385
## iter 50 value 368.702181
## iter 60 value 368.433782
## iter 70 value 368.321278
## iter 80 value 368.274693
## iter 90 value 368.246836
## iter 100 value 368.234059
## iter 110 value 368.226857
## iter 120 value 368.219032
## iter 130 value 368.213343
## iter 140 value 368.208683
## iter 150 value 368.205179
## iter 160 value 368.202874
## iter 170 value 368.201806
## iter 180 value 368.200935
## iter 190 value 368.200451
## iter 200 value 368.199774
## iter 210 value 368.199313
## iter 220 value 368.198918
```

```
## iter 230 value 368.198663
## final value 368.198511
## converged
```

```
myNewFrame
```

##	node	maxit	decay	misscls.train	misscls.test
## 1	5	10	0.0	0.05657143	0.1033333
## 2	10	10	0.0	0.24914286	0.1190000
## 3	15	10	0.0	0.24914286	0.1190000
## 4	5	10	0.1	0.24914286	0.1190000
## 5	10	10	0.1	0.24914286	0.1190000
## 6	15	10	0.1	0.05657143	0.1033333
## 7	5	10	0.2	0.24914286	0.1190000
## 8	10	10	0.2	0.24914286	0.1190000
## 9	15	10	0.2	0.24914286	0.1190000
## 10	5	100	0.0	0.05657143	0.1033333
## 11	10	100	0.0	0.05657143	0.1033333
## 12	15	100	0.0	0.04000000	0.1143333
## 13	5	100	0.1	0.05657143	0.1033333
## 14	10	100	0.1	0.05657143	0.1033333
## 15	15	100	0.1	0.05657143	0.1033333
## 16	5	100	0.2	0.05657143	0.1033333
## 17	10	100	0.2	0.05657143	0.1033333
## 18	15	100	0.2	0.05657143	0.1033333
## 19	5	10000	0.0	0.24914286	0.1190000
## 20	10	10000	0.0	0.24914286	0.1190000
## 21	15	10000	0.0	0.24914286	0.1190000
## 22	5	10000	0.1	0.05657143	0.1033333
## 23	10	10000	0.1	0.05657143	0.1033333
## 24	15	10000	0.1	0.05657143	0.1033333
## 25	5	10000	0.2	0.05657143	0.1033333
## 26	10	10000	0.2	0.05657143	0.1033333
## 27	15	10000	0.2	0.05657143	0.1033333

Based on the output, I would choose the best model with 5 nodes, maxit as 100, and decay as 0.

```
best_nn <- nnet(IsAlert~., data = newdata, size = 5, decay = 0, maxit = 100)
```

```
## # weights: 246
## initial value 17630.923600
## iter 10 value 14460.156899
## iter 20 value 14199.861982
## iter 30 value 13520.782083
## iter 40 value 13451.497230
## iter 50 value 13400.787369
## iter 60 value 12849.881837
## iter 70 value 12392.392073
## iter 80 value 12073.870893
## iter 90 value 11418.815823
```

```
## iter 100 value 10581.357555
## final value 10581.357555
## stopped after 100 iterations

misscls.train<-sum((estimated_isAlert - training$IsAlert)^2)/length(training$IsAlert)
misscls.train

## [1] 0.05657143

presdicted.testing<-as.numeric(predict(net.dat,testing )>0.5)
Ttest = table(presdicted.testing, testing$IsAlert)
misscls.test<-sum((presdicted.testing - testing$IsAlert)^2)/length(testing$IsAlert)
misscls.test

## [1] 0.1033333

presdicted.testing.all<-as.numeric(predict(net.dat, newdata )>0.5)
Ttest = table(presdicted.testing.all, newdata$IsAlert)
misscls.test.all<-sum((presdicted.testing.all - newdata$IsAlert)^2)/length(newdata$IsAlert)
misscls.test.all

## [1] 0.3264452
```

the best Neural Network model has 5 nodes, decay = 0, maxit = 100, the missclassification rate for training data : 0.05657143 the missclassification rate for testing data : 0.1033333 the missclassification rate for entire data : 0.3264452

Logistic Regression

```
#new data set
drops <- c("E3", "E7", "E8", "E9" , "V5","V10")
mydata_lm<-newdata[ , !(names(newdata) %in% drops)]
mydata_lm <- mydata_lm[ , -c(30:42)]

mydata_lm <- mydata_lm[1:1000,]
#training data
training <- mydata_lm[1:700, ]
#testing data
testing <- mydata_lm[701:1000,]

summary(training)
```

##	TrialID	ObsNum	IsAlert	P1
##	Min. :0	Min. : 0.0	Min. :0.0000	Min. :25.38
##	1st Qu.:0	1st Qu.:174.8	1st Qu.:1.0000	1st Qu.:34.15
##	Median :0	Median :349.5	Median :1.0000	Median :35.24
##	Mean :0	Mean :349.5	Mean :0.8457	Mean :35.89
##	3rd Qu.:0	3rd Qu.:524.2	3rd Qu.:1.0000	3rd Qu.:37.35
##	Max. :0	Max. :699.0	Max. :1.0000	Max. :44.82


```

##          P2          P3          P5          P6
## Min.    : 6.137   Min.    : 516   Min.    :0.2335   Min.    :556.0
## 1st Qu.:10.936   1st Qu.: 816   1st Qu.:0.2672   1st Qu.:592.0
## Median :12.783   Median :1084   Median :0.2789   Median :612.0
## Mean    :12.844   Mean    :1081   Mean    :0.2782   Mean    :617.3
## 3rd Qu.:14.753   3rd Qu.:1400   3rd Qu.:0.2919   3rd Qu.:632.0
## Max.    :18.524   Max.    :1816   Max.    :0.3140   Max.    :732.0
##          E4          E6          V1          V2
## Min.    :-20.0000   Min.    :260.0   Min.    : 93.36   Min.    : -0.6650
## 1st Qu.: -6.0000   1st Qu.:317.0   1st Qu.: 97.01   1st Qu.: 0.0000
## Median : 0.0000   Median :320.0   Median : 99.61   Median : 0.0000
## Mean    : 0.6857   Mean    :319.9   Mean    : 99.47   Mean    : 0.0568
## 3rd Qu.: 8.0000   3rd Qu.:324.0   3rd Qu.:102.30   3rd Qu.: 0.0700
## Max.    : 36.0000   Max.    :332.0   Max.    :104.97   Max.    : 0.8750
##          V3          V4          V8          V11
## Min.    : 240.0   Min.    : 0.000   Min.    : 0.00   Min.    :14.08
## 1st Qu.: 240.0   1st Qu.: 3.019   1st Qu.: 7.95   1st Qu.:14.83
## Median : 496.0   Median : 4.506   Median :14.70   Median :14.94
## Mean    : 536.8   Mean    : 3.952   Mean    :13.70   Mean    :14.95
## 3rd Qu.: 767.0   3rd Qu.: 4.506   3rd Qu.:20.60   3rd Qu.:15.05
## Max.    :1023.0   Max.    :10.500   Max.    :28.60   Max.    :15.60
##          E3_1          V10_high V10_low V5_1
## Min.    :0.0000   Min.    :0   Min.    :1   Min.    :0.000000
## 1st Qu.:1.0000   1st Qu.:0   1st Qu.:1   1st Qu.:0.000000
## Median :1.0000   Median :0   Median :1   Median :0.000000
## Mean    :0.9857   Mean    :0   Mean    :1   Mean    :0.005714
## 3rd Qu.:1.0000   3rd Qu.:0   3rd Qu.:1   3rd Qu.:0.000000
## Max.    :1.0000   Max.    :0   Max.    :1   Max.    :1.000000
##          V5_0          E9_1          E9_0          E8_high
## Min.    :0.0000   Min.    :0.0000   Min.    :0.00000   Min.    :0
## 1st Qu.:1.0000   1st Qu.:1.0000   1st Qu.:0.00000   1st Qu.:0
## Median :1.0000   Median :1.0000   Median :0.00000   Median :0
## Mean    :0.9943   Mean    :0.9886   Mean    :0.01143   Mean    :0
## 3rd Qu.:1.0000   3rd Qu.:1.0000   3rd Qu.:0.00000   3rd Qu.:0
## Max.    :1.0000   Max.    :1.0000   Max.    :1.00000   Max.    :0
##          E8_low E7_high E7_low E3_4 E3_0
## Min.    :0   Min.    :0   Min.    :1   Min.    :0   Min.    :0.00000
## 1st Qu.:0   1st Qu.:0   1st Qu.:1   1st Qu.:0   1st Qu.:0.00000
## Median :0   Median :0   Median :1   Median :0   Median :0.00000
## Mean    :0   Mean    :0   Mean    :1   Mean    :0   Mean    :0.01429
## 3rd Qu.:0   3rd Qu.:0   3rd Qu.:1   3rd Qu.:0   3rd Qu.:0.00000
## Max.    :0   Max.    :0   Max.    :1   Max.    :0   Max.    :1.00000

```

```

logistic.model <- glm(IsAlert~., data = training, family = binomial(link="log
it"))
summary(logistic.model)

##
## Call:
## glm(formula = IsAlert ~ ., family = binomial(link = "logit"),

```

```

##      data = training)
##
## Deviance Residuals:
##      Min        1Q      Median        3Q        Max
## -2.9021    0.1444    0.3130    0.5397    1.5659
##
## Coefficients: (11 not defined because of singularities)
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept)  3.733e+01  1.686e+03   0.022 0.982335
## TrialID              NA          NA      NA      NA
## ObsNum         8.934e-04  1.137e-03   0.786 0.432118
## P1              7.744e-02  1.345e-01   0.576 0.564902
## P2              2.972e-02  4.806e-02   0.618 0.536281
## P3             -1.408e-03  4.476e-04  -3.145 0.001659 **
## P5             -4.477e+01  8.113e+00  -5.519 3.42e-08 ***
## P6              2.204e-03  5.182e-03   0.425 0.670534
## E4              2.433e-02  1.371e-02   1.774 0.076050 .
## E6              5.952e-02  1.755e-02   3.392 0.000693 ***
## V1              1.121e-01  5.888e-02   1.904 0.056877 .
## V2              3.510e+00  1.104e+00   3.181 0.001467 **
## V3             -1.404e-03  4.887e-04  -2.873 0.004070 **
## V4             -6.796e-01  1.737e-01  -3.912 9.15e-05 ***
## V8              2.384e-02  1.801e-02   1.323 0.185720
## V11             -1.561e+00  1.743e+00  -0.896 0.370507
## E3_1           -1.559e+01  1.150e+03  -0.014 0.989190
## V10_high              NA          NA      NA      NA
## V10_low              NA          NA      NA      NA
## V5_1                1.474e+01  1.944e+03   0.008 0.993948
## V5_0                NA          NA      NA      NA
## E9_1              -1.427e+01  1.232e+03  -0.012 0.990763
## E9_0                NA          NA      NA      NA
## E8_high              NA          NA      NA      NA
## E8_low              NA          NA      NA      NA
## E7_high              NA          NA      NA      NA
## E7_low              NA          NA      NA      NA
## E3_4                NA          NA      NA      NA
## E3_0                NA          NA      NA      NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 602.10  on 699  degrees of freedom
## Residual deviance: 452.36  on 682  degrees of freedom
## AIC: 488.36
##
## Number of Fisher Scoring iterations: 16

```

To preserve only the significant variables: P3, P6, E4, E6, V1, V2, V3, V4, E9_1

```

logistic.model.cur <- glm(IsAlert~P3 + P6 + E4 + E6 + V1 +V2 + V3 + V4 + E9_1
, data = training, family = binomial(link="logit"))
summary(logistic.model.cur)

##
## Call:
## glm(formula = IsAlert ~ P3 + P6 + E4 + E6 + V1 + V2 + V3 + V4 +
##      E9_1, family = binomial(link = "logit"), data = training)
##
## Deviance Residuals:
##      Min       1Q   Median       3Q      Max
## -2.7354   0.2117   0.3612   0.6086   1.5315
##
## Coefficients:
##              Estimate Std. Error z value Pr(>|z|)
## (Intercept) -1.755e+01  7.935e+02  -0.022  0.982356
## P3           -1.734e-03  3.923e-04  -4.419  9.90e-06 ***
## P6            3.365e-03  4.706e-03   0.715  0.474574
## E4            3.596e-02  1.300e-02   2.767  0.005653 **
## E6            6.314e-02  1.528e-02   4.132  3.60e-05 ***
## V1            1.599e-01  4.734e-02   3.377  0.000733 ***
## V2            3.201e+00  1.025e+00   3.124  0.001786 **
## V3           -6.224e-04  4.015e-04  -1.550  0.121054
## V4           -5.903e-01  1.251e-01  -4.720  2.36e-06 ***
## E9_1         -1.416e+01  7.935e+02  -0.018  0.985759
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##      Null deviance: 602.10  on 699  degrees of freedom
## Residual deviance: 499.65  on 690  degrees of freedom
## AIC: 519.65
##
## Number of Fisher Scoring iterations: 15

library(MASS)
set.seed(10)
birthwt.step <- stepAIC(logistic.model.cur, trace = 1, direction="both")

## Start:  AIC=519.65
## IsAlert ~ P3 + P6 + E4 + E6 + V1 + V2 + V3 + V4 + E9_1
##
##           Df Deviance    AIC
## - P6       1    500.18 518.18
## - E9_1      1    501.11 519.11
## <none>      0    499.65 519.65
## - V3       1    502.05 520.05
## - E4       1    507.70 525.70
## - V2       1    509.74 527.74

```

```

## - V1      1    512.03 530.03
## - E6      1    518.91 536.91
## - P3      1    520.11 538.11
## - V4      1    523.50 541.50
##
## Step:  AIC=518.18
## IsAlert ~ P3 + E4 + E6 + V1 + V2 + V3 + V4 + E9_1
##
##           Df Deviance    AIC
## - E9_1    1    501.67 517.67
## <none>      500.18 518.18
## - V3      1    502.81 518.81
## + P6      1    499.65 519.65
## - E4      1    509.05 525.05
## - V2      1    510.52 526.52
## - V1      1    512.04 528.04
## - E6      1    524.16 540.16
## - V4      1    524.31 540.31
## - P3      1    525.01 541.01
##
## Step:  AIC=517.67
## IsAlert ~ P3 + E4 + E6 + V1 + V2 + V3 + V4
##
##           Df Deviance    AIC
## <none>      501.67 517.67
## + E9_1    1    500.18 518.18
## - V3      1    504.60 518.60
## + P6      1    501.11 519.11
## - E4      1    510.48 524.48
## - V1      1    513.18 527.18
## - V2      1    513.32 527.32
## - E6      1    525.59 539.59
## - V4      1    526.80 540.80
## - P3      1    527.33 541.33

birthwt.step$anova

## Stepwise Model Path
## Analysis of Deviance Table
##
## Initial Model:
## IsAlert ~ P3 + P6 + E4 + E6 + V1 + V2 + V3 + V4 + E9_1
##
## Final Model:
## IsAlert ~ P3 + E4 + E6 + V1 + V2 + V3 + V4
##
##
##           Step Df  Deviance Resid. Df Resid. Dev      AIC
## 1              690    499.6475 519.6475

```

```
## 2 - P6 1 0.5342874      691    500.1818 518.1818
## 3 - E9_1 1 1.4860335    692    501.6679 517.6679
```

the best Logistic Regression model has variables as following P3 + E4 + E6 + V1 + V2 + V3 + V4

```
logistic.model.best <- glm(IsAlert~P3 + E4 + E6 + V1 +V2 + V3 + V4, data = training, family = binomial(link="logit"))
estimated_isAlert<- predict(logistic.model.best, training, type = "response")
misscls.train<-sum((estimated_isAlert-training$IsAlert)^2)/ length(training$IsAlert)
misscls.train

## [1] 0.1102006

presdicted.testing <- predict(logistic.model.best, testing, type = "response")
misscls.test<-sum((presdicted.testing - testing$IsAlert)^2)/length(testing$IsAlert)
misscls.test

## [1] 0.1379455

presdicted.testing.all <- predict(logistic.model.best, mydata_lm, type = "response")
misscls.test.all<-sum((presdicted.testing.all - mydata_lm$IsAlert)^2)/length(mydata_lm$IsAlert)
misscls.test.all

## [1] 0.1185241
```

the missclassification rate for training data : 0.1102006 the missclassification rate for testing data : 0.1379455 the missclassification rate for entire data : 0.1185241

Decision Tree

```
#new data set
mydata_tree <- newdata[ , 3:22]
mydata_tree <- mydata_tree[1:1000,]
#training data
training <- mydata_tree[1:700, ]
#testing data
testing <- mydata_tree[701:1000,]
```

```
summary(training)
```

```
##      IsAlert      P1      P2      P3
## Min.   :0.0000  Min.   :25.38  Min.   : 6.137  Min.   : 516
## 1st Qu.:1.0000  1st Qu.:34.15  1st Qu.:10.936  1st Qu.: 816
## Median :1.0000  Median :35.24  Median :12.783  Median :1084
## Mean   :0.8457  Mean   :35.89  Mean   :12.844  Mean   :1081
## 3rd Qu.:1.0000  3rd Qu.:37.35  3rd Qu.:14.753  3rd Qu.:1400
```

```
## Max. :1.0000 Max. :44.82 Max. :18.524 Max. :1816
## P5 P6 E3 E4
## Min. :0.2335 Min. :556.0 Min. :0.0000 Min. : -20.0000
## 1st Qu.:0.2672 1st Qu.:592.0 1st Qu.:1.0000 1st Qu.: -6.0000
## Median :0.2789 Median :612.0 Median :1.0000 Median : 0.0000
## Mean :0.2782 Mean :617.3 Mean :0.9857 Mean : 0.6857
## 3rd Qu.:0.2919 3rd Qu.:632.0 3rd Qu.:1.0000 3rd Qu.: 8.0000
## Max. :0.3140 Max. :732.0 Max. :1.0000 Max. : 36.0000
## E6 E7 E8 E9
## Min. :260.0 Min. :0.0000 Min. :0.0000 Min. :0.0000
## 1st Qu.:317.0 1st Qu.:1.0000 1st Qu.:1.0000 1st Qu.:1.0000
## Median :320.0 Median :1.0000 Median :1.0000 Median :1.0000
## Mean :319.9 Mean :0.9914 Mean :0.9914 Mean :0.9886
## 3rd Qu.:324.0 3rd Qu.:1.0000 3rd Qu.:1.0000 3rd Qu.:1.0000
## Max. :332.0 Max. :1.0000 Max. :1.0000 Max. :1.0000
## V1 V2 V3 V4
## Min. : 93.36 Min. : -0.6650 Min. : 240.0 Min. : 0.000
## 1st Qu.: 97.01 1st Qu.: 0.0000 1st Qu.: 240.0 1st Qu.: 3.019
## Median : 99.61 Median : 0.0000 Median : 496.0 Median : 4.506
## Mean : 99.47 Mean : 0.0568 Mean : 536.8 Mean : 3.952
## 3rd Qu.:102.30 3rd Qu.: 0.0700 3rd Qu.: 767.0 3rd Qu.: 4.506
## Max. :104.97 Max. : 0.8750 Max. :1023.0 Max. :10.500
## V5 V8 V10 V11
## Min. :0.000000 Min. : 0.00 Min. :4 Min. :14.08
## 1st Qu.:0.000000 1st Qu.: 7.95 1st Qu.:4 1st Qu.:14.83
## Median :0.000000 Median :14.70 Median :4 Median :14.94
## Mean :0.005714 Mean :13.70 Mean :4 Mean :14.95
## 3rd Qu.:0.000000 3rd Qu.:20.60 3rd Qu.:4 3rd Qu.:15.05
## Max. :1.000000 Max. :28.60 Max. :4 Max. :15.60
```

```
IsAlert=ifelse(mydata_tree$IsAlert == 1," yes"," No ")
mydata_tree <- data.frame(mydata_tree[,-1],IsAlert)
summary(mydata_tree)
```

```
## P1 P2 P3 P5
## Min. :25.38 Min. : 6.137 Min. : 516 Min. :0.2335
## 1st Qu.:34.46 1st Qu.:10.873 1st Qu.: 800 1st Qu.:0.2672
## Median :35.81 Median :12.840 Median :1000 Median :0.2763
## Mean :36.22 Mean :12.838 Mean :1048 Mean :0.2768
## 3rd Qu.:37.59 3rd Qu.:14.629 3rd Qu.:1232 3rd Qu.:0.2896
## Max. :44.82 Max. :20.608 Max. :1816 Max. :0.3321
## P6 E3 E4 E6
## Min. :556 Min. :0.00 Min. : -24.000 Min. :260
## 1st Qu.:600 1st Qu.:1.00 1st Qu.: -6.000 1st Qu.:317
## Median :616 Median :1.00 Median : 0.000 Median :320
## Mean :625 Mean :0.99 Mean : 1.072 Mean :321
## 3rd Qu.:632 3rd Qu.:1.00 3rd Qu.: 8.000 3rd Qu.:324
## Max. :892 Max. :1.00 Max. : 36.000 Max. :393
## E7 E8 E9 V1
## Min. :0.00 Min. :0.000 Min. :0.000 Min. : 93.36
```

```
## 1st Qu.:1.00 1st Qu.:1.000 1st Qu.:1.000 1st Qu.: 97.51
## Median :1.00 Median :1.000 Median :1.000 Median :101.09
## Mean :1.04 Mean :1.036 Mean :0.976 Mean :100.26
## 3rd Qu.:1.00 3rd Qu.:1.000 3rd Qu.:1.000 3rd Qu.:102.86
## Max. :6.00 Max. :7.000 Max. :1.000 Max. :106.11
## V2 V3 V4 V5
## Min. :-0.665000 Min. : 240.0 Min. : 0.000 Min. :0.000
## 1st Qu.: -0.070000 1st Qu.: 255.0 1st Qu.: 1.488 1st Qu.:0.000
## Median : 0.000000 Median : 752.0 Median : 3.019 Median :0.000
## Mean : 0.005565 Mean : 595.7 Mean : 3.209 Mean :0.006
## 3rd Qu.: 0.070000 3rd Qu.: 767.0 3rd Qu.: 4.506 3rd Qu.:0.000
## Max. : 0.875000 Max. :1023.0 Max. :10.500 Max. :1.000
## V8 V10 V11 IsAlert
## Min. : 0.00 Min. :4 Min. :14.08 No :150
## 1st Qu.: 8.40 1st Qu.:4 1st Qu.:14.87 yes:850
## Median :15.20 Median :4 Median :15.02
## Mean :14.01 Mean :4 Mean :15.01
## 3rd Qu.:19.50 3rd Qu.:4 3rd Qu.:15.14
## Max. :28.60 Max. :4 Max. :15.60
```

```
library(tree)
```

```
tree.mydata_tree =tree(IsAlert~.,data=mydata_tree )
```

```
summary (tree.mydata_tree )
```

```
##
```

```
## Classification tree:
```

```
## tree(formula = IsAlert ~ ., data = mydata_tree)
```

```
## Variables actually used in tree construction:
```

```
## [1] "V1" "E6" "V4" "E4" "P1" "P6" "V8" "V2" "P5"
```

```
## Number of terminal nodes: 25
```

```
## Residual mean deviance: 0.098 = 95.55 / 975
```

```
## Misclassification error rate: 0.023 = 23 / 1000
```

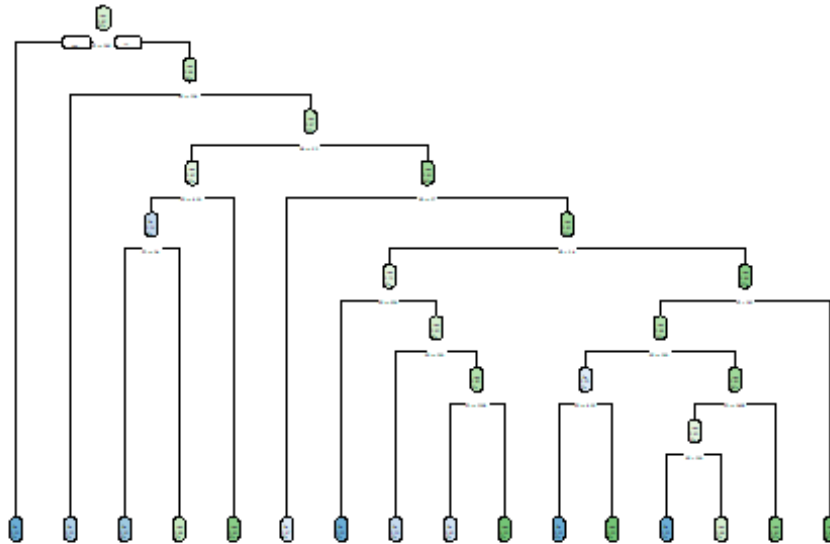
```
#plot(tree.mydata_tree)
```

```
#text(tree.mydata_tree ,pretty =0)
```

```
library(rpart.plot)
```

```
rpart.plot::rpart.plot(rpart(IsAlert~ .,data = mydata_tree),main = "Tree")
```

Tree



```
ntrain=700
set.seed(2020)
train=sample(1: nrow(mydata_tree ),ntrain )
training = mydata_tree[train,]
testing=mydata_tree[-train ,]
tree.one =tree(IsAlert~.,data=training )
summary (tree.one )

##
## Classification tree:
## tree(formula = IsAlert ~ ., data = training)
## Variables actually used in tree construction:
## [1] "V4" "V1" "E6" "E4" "P2" "V8" "P3" "P6" "V2" "P5" "P1"
## Number of terminal nodes: 25
## Residual mean deviance: 0.1242 = 83.81 / 675
## Misclassification error rate: 0.02857 = 20 / 700

IsAlert.test=IsAlert[-train ]
tree.pred=predict(tree.one, testing,type="class")
table(tree.pred ,IsAlert.test)

##           IsAlert.test
## tree.pred  No   yes
##          No   29  12
##          yes  11 248
```

the missclassification rate for testing data :

$$\frac{12 + 11}{29 + 12 + 11 + 248} = 0.076667$$

```

set.seed (2021)
cv.one =cv.tree(tree.one ,FUN=prune.misclass )
names(cv.one )

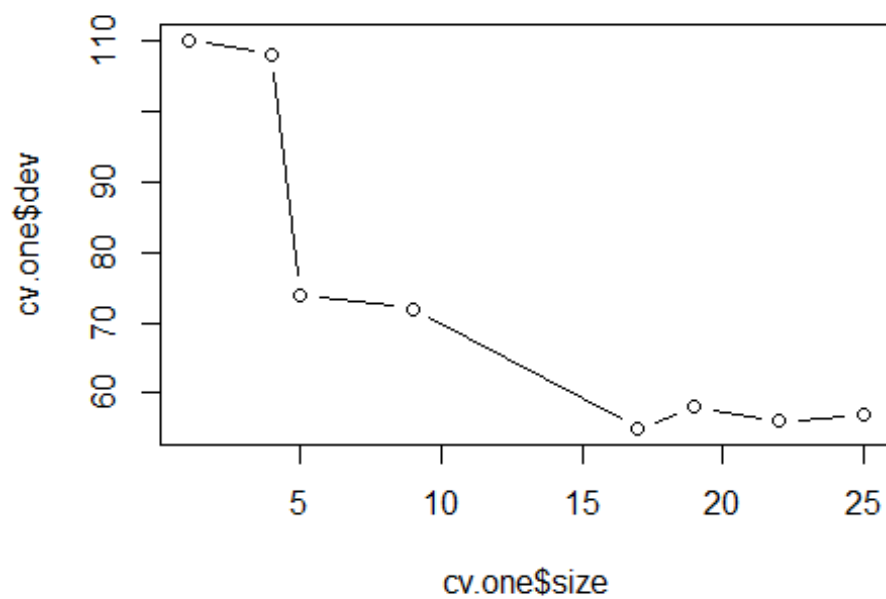
## [1] "size"    "dev"      "k"        "method"

cv.one

## $size
## [1] 25 22 19 17 9 5 4 1
##
## $dev
## [1] 57 56 58 55 72 74 108 110
##
## $k
## [1] -Inf 0.0000000 0.6666667 2.0000000 3.6250000 4.0000000
## [7] 9.0000000 10.0000000
##
## $method
## [1] "misclass"
##
## attr(,"class")
## [1] "prune"      "tree.sequence"

plot(cv.one$size ,cv.one$dev ,type="b")

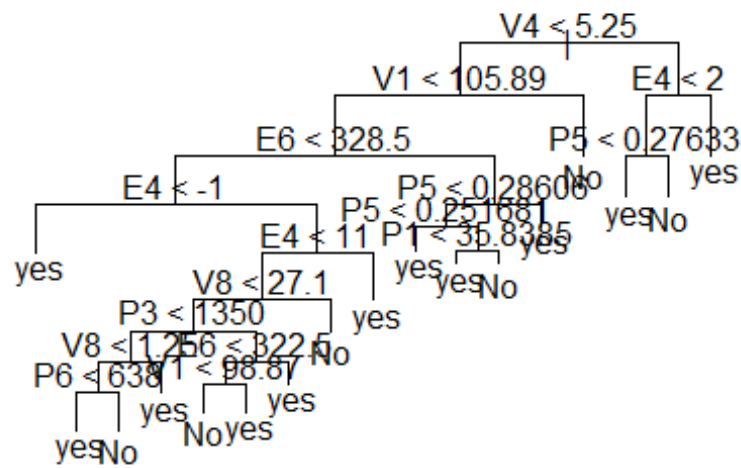
```



The best node size

is 17.

```
mybest = 17
prune.one = prune.misclass (tree.one ,best = mybest)
plot(prune.one)
text(prune.one ,pretty =0)
```



```
summary(prune.one)
```

```
##
## Classification tree:
## snip.tree(tree = tree.one, nodes = c(7L, 16L, 75L, 273L, 12L,
## 549L))
## Variables actually used in tree construction:
## [1] "V4" "V1" "E6" "E4" "V8" "P3" "P6" "P5" "P1"
## Number of terminal nodes: 17
## Residual mean deviance: 0.243 = 166 / 683
## Misclassification error rate: 0.03714 = 26 / 700
```

```
IsAlert.train=IsAlert[train ]
tree.pred=predict(prune.one, training,type="class")
table(tree.pred ,IsAlert.train)
```

```
##           IsAlert.train
## tree.pred  No   yes
##           No    89   5
##           yes   21 585
```

```
IsAlert.test=IsAlert[-train ]
tree.pred=predict(prune.one, testing,type="class")
table(tree.pred ,IsAlert.test)
```

```
##           IsAlert.test
## tree.pred  No   yes
```

```
##      No    26    5
##      yes   14  255
```

After we reduce the size of nodes,
the missclassification rate for training data:

$$\frac{21 + 5}{89 + 21 + 5 + 585} = 0.037143$$

the missclassification rate for testing data:

$$\frac{14 + 5}{26 + 14 + 5 + 255} = 0.063333$$

After reducing the size of nodes, the missclassification has reduced.

Random Forest Boost

```
library(randomForest)
bag.one = randomForest(IsAlert~., data=mydata_tree, subset = train , mtry=4, ntree = 200, importance=TRUE)
IsAlert.test=IsAlert[-train]
tree.pred = predict ( bag.one , newdata =mydata_tree[-train ,], type="class")
table(tree.pred , IsAlert.test)

##      IsAlert.test
## tree.pred  No   yes
##      No    33    0
##      yes    7  260
```

the missclassification rate for testing data:

$$\frac{7 + 0}{33 + 7 + 0 + 260} = 0.02333333$$

Esemble

```
library("mlbench")

## Warning: package 'mlbench' was built under R version 3.4.4

library("pROC")

## Warning: package 'pROC' was built under R version 3.4.4
## Type 'citation("pROC")' for a citation.

##
## Attaching package: 'pROC'

## The following objects are masked from 'package:stats':
##
##      cov, smooth, var
```

```

library(caret)
#names(getModelInfo())

set.seed(2022)
mydata_last <- newdata[1:10000, ]
mydata_last$IsAlert <- as.factor(ifelse(mydata_last$IsAlert == 0, "No", "Yes"
))

inTrain <- createDataPartition(y = mydata_last$IsAlert, p = .75, list = FALSE
)
trainSet <- mydata_last[ inTrain,]
testSet <- mydata_last[-inTrain,]

#Defining the training controls for multiple models
fitControl <- trainControl(
  method = "cv",
  number = 5,
  savePredictions = 'final',
  classProbs = T)

#Defining the predictors and outcome
#based on the result from logistic regression
predictors<-c("P3", "E4", "E6", "V1", "V2", "V3", "V4")
outcomeName<-'IsAlert'

#Training the random forest model
model_rf<-train(trainSet[,predictors],trainSet[,outcomeName],method = 'rf')

#Predicting using random forest model
testSet$pred_rf<-predict(object = model_rf,testSet[,predictors],na.action = n
a.pass)

#Checking the accuracy of the random forest model
confusionMatrix(testSet$IsAlert,testSet$pred_rf)

## Confusion Matrix and Statistics
##
##           Reference
## Prediction    No  Yes
##           No   504   21
##           Yes    1 1973
##
##               Accuracy : 0.9912
##               95% CI : (0.9867, 0.9945)
##       No Information Rate : 0.7979
##       P-Value [Acc > NIR] : < 2.2e-16
##
##               Kappa : 0.9731

```

```

## McNemar's Test P-Value : 5.104e-05
##
##          Sensitivity : 0.9980
##          Specificity : 0.9895
##          Pos Pred Value : 0.9600
##          Neg Pred Value : 0.9995
##          Prevalence : 0.2021
##          Detection Rate : 0.2017
##          Detection Prevalence : 0.2101
##          Balanced Accuracy : 0.9937
##
##          'Positive' Class : No
##

#Training the knn model
model_knn<-train(trainSet[,predictors],trainSet[,outcomeName],method='knn')

#Predicting using knn model
testSet$pred_knn<-predict(object = model_knn,testSet[,predictors])

#Checking the accuracy of the random forest model
confusionMatrix(testSet$IsAlert,testSet$pred_knn)

## Confusion Matrix and Statistics
##
##          Reference
## Prediction   No  Yes
##          No   377 148
##          Yes   71 1903
##
##          Accuracy : 0.9124
##          95% CI : (0.9006, 0.9232)
##          No Information Rate : 0.8207
##          P-Value [Acc > NIR] : < 2.2e-16
##
##          Kappa : 0.7209
##          McNemar's Test P-Value : 2.812e-07
##
##          Sensitivity : 0.8415
##          Specificity : 0.9278
##          Pos Pred Value : 0.7181
##          Neg Pred Value : 0.9640
##          Prevalence : 0.1793
##          Detection Rate : 0.1509
##          Detection Prevalence : 0.2101
##          Balanced Accuracy : 0.8847
##
##          'Positive' Class : No
##

```

```

#Training the Logistic regression model
model_lr<-train(trainSet[,predictors],trainSet[,outcomeName],method='glm')

#Predicting using Logistic regression model
testSet$pred_lr<-predict(object = model_lr,testSet[,predictors])

#Checking the accuracy of the random forest model
confusionMatrix(testSet$IsAlert,testSet$pred_lr)

## Confusion Matrix and Statistics
##
##              Reference
## Prediction    No  Yes
##          No   271  254
##          Yes    29 1945
##
##              Accuracy : 0.8868
##              95% CI   : (0.8737, 0.8989)
##          No Information Rate : 0.88
##          P-Value [Acc > NIR] : 0.1548
##
##              Kappa   : 0.5951
##  Mcnemar's Test P-Value : <2e-16
##
##              Sensitivity : 0.9033
##              Specificity : 0.8845
##              Pos Pred Value : 0.5162
##              Neg Pred Value : 0.9853
##              Prevalence : 0.1200
##              Detection Rate : 0.1084
##          Detection Prevalence : 0.2101
##              Balanced Accuracy : 0.8939
##
##              'Positive' Class : No
##

```

Random forest model has accuracy as 0.9912; knn model has accuracy as 0.9124; Logistic regression model has accuracy as 0.8868.

```

#Defining the training control
fitControl <- trainControl(
method = "cv",
number = 10,
savePredictions = 'final', # To save out of fold predictions for best parameter combinations
classProbs = T # To save the class probabilities of the out of fold predictions
)

```

#Training the random forest model

```
model_rf<-train(trainSet[,predictors],trainSet[,outcomeName],method='rf',trControl=fitControl,tuneLength=3)
```

#Training the knn model

```
model_knn<-train(trainSet[,predictors],trainSet[,outcomeName],method='knn',trControl=fitControl,tuneLength=3)
```

#Training the logistic regression model

```
model_lr<-train(trainSet[,predictors],trainSet[,outcomeName],method='glm',trControl=fitControl,tuneLength=3)
```

#Predicting the out of fold prediction probabilities for training data

```
trainSet$OOF_pred_rf<-model_rf$pred$Y[order(model_rf$pred$rowIndex)]
```

```
trainSet$OOF_pred_knn<-model_knn$pred$Y[order(model_knn$pred$rowIndex)]
```

```
trainSet$OOF_pred_lr<-model_lr$pred$Y[order(model_lr$pred$rowIndex)]
```

#Predicting probabilities for the test data

```
testSet$OOF_pred_rf<-predict(model_rf,testSet[predictors],type='prob')$Y
```

```
testSet$OOF_pred_knn<-predict(model_knn,testSet[predictors],type='prob')$Y
```

```
testSet$OOF_pred_lr<-predict(model_lr,testSet[predictors],type='prob')$Y
```

#Predictors for top layer models

```
predictors_top<-c('OOF_pred_rf','OOF_pred_knn','OOF_pred_lr')
```

#GBM as top layer model

```
model_gbm<-
```

```
train(trainSet[,predictors_top],trainSet[,outcomeName],method='gbm')
```

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8380	nan	0.1000	0.0892
##	2	0.7189	nan	0.1000	0.0599
##	3	0.6286	nan	0.1000	0.0448
##	4	0.5579	nan	0.1000	0.0355
##	5	0.4975	nan	0.1000	0.0304
##	6	0.4466	nan	0.1000	0.0254
##	7	0.4043	nan	0.1000	0.0206
##	8	0.3673	nan	0.1000	0.0190
##	9	0.3345	nan	0.1000	0.0165
##	10	0.3058	nan	0.1000	0.0141
##	20	0.1507	nan	0.1000	0.0044
##	40	0.0839	nan	0.1000	0.0005
##	60	0.0738	nan	0.1000	0.0001
##	80	0.0710	nan	0.1000	-0.0000
##	100	0.0695	nan	0.1000	-0.0000
##	120	0.0679	nan	0.1000	0.0001
##	140	0.0665	nan	0.1000	-0.0001
##	150	0.0660	nan	0.1000	-0.0001
##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve

##	1	0.8388	nan	0.1000	0.0872
##	2	0.7190	nan	0.1000	0.0609
##	3	0.6279	nan	0.1000	0.0449
##	4	0.5544	nan	0.1000	0.0359
##	5	0.4942	nan	0.1000	0.0304
##	6	0.4429	nan	0.1000	0.0259
##	7	0.3989	nan	0.1000	0.0218
##	8	0.3619	nan	0.1000	0.0186
##	9	0.3291	nan	0.1000	0.0166
##	10	0.3009	nan	0.1000	0.0141
##	20	0.1467	nan	0.1000	0.0042
##	40	0.0802	nan	0.1000	0.0003
##	60	0.0661	nan	0.1000	-0.0000
##	80	0.0619	nan	0.1000	-0.0001
##	100	0.0583	nan	0.1000	-0.0001
##	120	0.0538	nan	0.1000	0.0001
##	140	0.0499	nan	0.1000	0.0000
##	150	0.0491	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8368	nan	0.1000	0.0905
##	2	0.7163	nan	0.1000	0.0606
##	3	0.6251	nan	0.1000	0.0453
##	4	0.5517	nan	0.1000	0.0364
##	5	0.4910	nan	0.1000	0.0296
##	6	0.4401	nan	0.1000	0.0250
##	7	0.3969	nan	0.1000	0.0221
##	8	0.3595	nan	0.1000	0.0190
##	9	0.3272	nan	0.1000	0.0160
##	10	0.2978	nan	0.1000	0.0142
##	20	0.1429	nan	0.1000	0.0044
##	40	0.0740	nan	0.1000	0.0007
##	60	0.0590	nan	0.1000	-0.0001
##	80	0.0545	nan	0.1000	-0.0001
##	100	0.0494	nan	0.1000	0.0001
##	120	0.0457	nan	0.1000	-0.0000
##	140	0.0421	nan	0.1000	-0.0000
##	150	0.0403	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8754	nan	0.1000	0.0867
##	2	0.7536	nan	0.1000	0.0602
##	3	0.6598	nan	0.1000	0.0466
##	4	0.5831	nan	0.1000	0.0377
##	5	0.5209	nan	0.1000	0.0317
##	6	0.4671	nan	0.1000	0.0265
##	7	0.4228	nan	0.1000	0.0220
##	8	0.3843	nan	0.1000	0.0193
##	9	0.3497	nan	0.1000	0.0171
##	10	0.3207	nan	0.1000	0.0142

##	20	0.1595	nan	0.1000	0.0041
##	40	0.0878	nan	0.1000	0.0005
##	60	0.0771	nan	0.1000	0.0000
##	80	0.0736	nan	0.1000	-0.0000
##	100	0.0717	nan	0.1000	-0.0001
##	120	0.0702	nan	0.1000	0.0000
##	140	0.0689	nan	0.1000	-0.0001
##	150	0.0683	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8732	nan	0.1000	0.0882
##	2	0.7499	nan	0.1000	0.0607
##	3	0.6549	nan	0.1000	0.0463
##	4	0.5789	nan	0.1000	0.0377
##	5	0.5155	nan	0.1000	0.0309
##	6	0.4623	nan	0.1000	0.0267
##	7	0.4170	nan	0.1000	0.0226
##	8	0.3779	nan	0.1000	0.0194
##	9	0.3434	nan	0.1000	0.0172
##	10	0.3137	nan	0.1000	0.0146
##	20	0.1527	nan	0.1000	0.0041
##	40	0.0835	nan	0.1000	0.0005
##	60	0.0707	nan	0.1000	0.0001
##	80	0.0661	nan	0.1000	-0.0001
##	100	0.0602	nan	0.1000	-0.0000
##	120	0.0570	nan	0.1000	0.0000
##	140	0.0544	nan	0.1000	-0.0001
##	150	0.0533	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8722	nan	0.1000	0.0899
##	2	0.7481	nan	0.1000	0.0605
##	3	0.6528	nan	0.1000	0.0479
##	4	0.5762	nan	0.1000	0.0382
##	5	0.5128	nan	0.1000	0.0312
##	6	0.4595	nan	0.1000	0.0265
##	7	0.4139	nan	0.1000	0.0229
##	8	0.3743	nan	0.1000	0.0198
##	9	0.3399	nan	0.1000	0.0173
##	10	0.3104	nan	0.1000	0.0145
##	20	0.1477	nan	0.1000	0.0044
##	40	0.0764	nan	0.1000	0.0004
##	60	0.0619	nan	0.1000	-0.0000
##	80	0.0555	nan	0.1000	-0.0001
##	100	0.0497	nan	0.1000	0.0000
##	120	0.0465	nan	0.1000	0.0000
##	140	0.0405	nan	0.1000	-0.0000
##	150	0.0391	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8325	nan	0.1000	0.0872
##	2	0.7131	nan	0.1000	0.0593
##	3	0.6243	nan	0.1000	0.0449
##	4	0.5512	nan	0.1000	0.0371
##	5	0.4911	nan	0.1000	0.0302
##	6	0.4412	nan	0.1000	0.0246
##	7	0.3975	nan	0.1000	0.0217
##	8	0.3600	nan	0.1000	0.0186
##	9	0.3284	nan	0.1000	0.0158
##	10	0.3005	nan	0.1000	0.0139
##	20	0.1454	nan	0.1000	0.0039
##	40	0.0770	nan	0.1000	0.0006
##	60	0.0655	nan	0.1000	-0.0000
##	80	0.0624	nan	0.1000	0.0000
##	100	0.0605	nan	0.1000	-0.0001
##	120	0.0591	nan	0.1000	-0.0000
##	140	0.0584	nan	0.1000	-0.0000
##	150	0.0581	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8305	nan	0.1000	0.0919
##	2	0.7105	nan	0.1000	0.0601
##	3	0.6192	nan	0.1000	0.0450
##	4	0.5464	nan	0.1000	0.0370
##	5	0.4863	nan	0.1000	0.0298
##	6	0.4357	nan	0.1000	0.0256
##	7	0.3918	nan	0.1000	0.0218
##	8	0.3544	nan	0.1000	0.0186
##	9	0.3218	nan	0.1000	0.0164
##	10	0.2934	nan	0.1000	0.0139
##	20	0.1411	nan	0.1000	0.0037
##	40	0.0731	nan	0.1000	0.0002
##	60	0.0597	nan	0.1000	0.0001
##	80	0.0545	nan	0.1000	0.0001
##	100	0.0496	nan	0.1000	-0.0001
##	120	0.0482	nan	0.1000	0.0001
##	140	0.0438	nan	0.1000	-0.0001
##	150	0.0427	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8303	nan	0.1000	0.0872
##	2	0.7098	nan	0.1000	0.0606
##	3	0.6176	nan	0.1000	0.0456
##	4	0.5448	nan	0.1000	0.0367
##	5	0.4840	nan	0.1000	0.0299
##	6	0.4331	nan	0.1000	0.0253
##	7	0.3895	nan	0.1000	0.0217
##	8	0.3518	nan	0.1000	0.0186
##	9	0.3196	nan	0.1000	0.0164
##	10	0.2910	nan	0.1000	0.0142

##	20	0.1357	nan	0.1000	0.0043
##	40	0.0656	nan	0.1000	0.0004
##	60	0.0507	nan	0.1000	0.0001
##	80	0.0437	nan	0.1000	-0.0001
##	100	0.0379	nan	0.1000	-0.0000
##	120	0.0353	nan	0.1000	-0.0001
##	140	0.0330	nan	0.1000	0.0000
##	150	0.0511	nan	0.1000	0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8413	nan	0.1000	0.0894
##	2	0.7208	nan	0.1000	0.0593
##	3	0.6284	nan	0.1000	0.0455
##	4	0.5561	nan	0.1000	0.0362
##	5	0.4953	nan	0.1000	0.0303
##	6	0.4442	nan	0.1000	0.0259
##	7	0.4018	nan	0.1000	0.0208
##	8	0.3627	nan	0.1000	0.0192
##	9	0.3299	nan	0.1000	0.0162
##	10	0.3013	nan	0.1000	0.0143
##	20	0.1442	nan	0.1000	0.0041
##	40	0.0750	nan	0.1000	0.0005
##	60	0.0662	nan	0.1000	0.0001
##	80	0.0643	nan	0.1000	-0.0000
##	100	0.0623	nan	0.1000	-0.0000
##	120	0.0609	nan	0.1000	-0.0000
##	140	0.0599	nan	0.1000	-0.0001
##	150	0.0592	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8396	nan	0.1000	0.0899
##	2	0.7188	nan	0.1000	0.0608
##	3	0.6258	nan	0.1000	0.0460
##	4	0.5519	nan	0.1000	0.0373
##	5	0.4905	nan	0.1000	0.0304
##	6	0.4383	nan	0.1000	0.0259
##	7	0.3940	nan	0.1000	0.0221
##	8	0.3563	nan	0.1000	0.0189
##	9	0.3231	nan	0.1000	0.0166
##	10	0.2942	nan	0.1000	0.0142
##	20	0.1403	nan	0.1000	0.0039
##	40	0.0733	nan	0.1000	0.0007
##	60	0.0618	nan	0.1000	0.0001
##	80	0.0569	nan	0.1000	-0.0001
##	100	0.0480	nan	0.1000	-0.0002
##	120	0.0439	nan	0.1000	-0.0000
##	140	0.0414	nan	0.1000	-0.0002
##	150	0.0407	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8389	nan	0.1000	0.0924
##	2	0.7172	nan	0.1000	0.0610
##	3	0.6249	nan	0.1000	0.0461
##	4	0.5507	nan	0.1000	0.0366
##	5	0.4891	nan	0.1000	0.0302
##	6	0.4371	nan	0.1000	0.0258
##	7	0.3929	nan	0.1000	0.0222
##	8	0.3547	nan	0.1000	0.0191
##	9	0.3214	nan	0.1000	0.0163
##	10	0.2923	nan	0.1000	0.0145
##	20	0.1349	nan	0.1000	0.0045
##	40	0.0659	nan	0.1000	0.0004
##	60	0.0525	nan	0.1000	-0.0016
##	80	0.0445	nan	0.1000	-0.0000
##	100	0.0405	nan	0.1000	-0.0001
##	120	0.0361	nan	0.1000	0.0000
##	140	0.0336	nan	0.1000	-0.0001
##	150	0.0371	nan	0.1000	0.0002

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8513	nan	0.1000	0.0880
##	2	0.7322	nan	0.1000	0.0586
##	3	0.6403	nan	0.1000	0.0465
##	4	0.5668	nan	0.1000	0.0358
##	5	0.5055	nan	0.1000	0.0292
##	6	0.4543	nan	0.1000	0.0259
##	7	0.4112	nan	0.1000	0.0216
##	8	0.3731	nan	0.1000	0.0189
##	9	0.3412	nan	0.1000	0.0160
##	10	0.3119	nan	0.1000	0.0143
##	20	0.1544	nan	0.1000	0.0045
##	40	0.0857	nan	0.1000	0.0006
##	60	0.0752	nan	0.1000	-0.0000
##	80	0.0713	nan	0.1000	0.0000
##	100	0.0694	nan	0.1000	-0.0000
##	120	0.0677	nan	0.1000	-0.0001
##	140	0.0662	nan	0.1000	-0.0000
##	150	0.0659	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8521	nan	0.1000	0.0896
##	2	0.7301	nan	0.1000	0.0595
##	3	0.6378	nan	0.1000	0.0452
##	4	0.5638	nan	0.1000	0.0362
##	5	0.5020	nan	0.1000	0.0308
##	6	0.4507	nan	0.1000	0.0263
##	7	0.4071	nan	0.1000	0.0216
##	8	0.3684	nan	0.1000	0.0190
##	9	0.3348	nan	0.1000	0.0166
##	10	0.3056	nan	0.1000	0.0146

##	20	0.1513	nan	0.1000	0.0040
##	40	0.0827	nan	0.1000	0.0004
##	60	0.0703	nan	0.1000	0.0001
##	80	0.0635	nan	0.1000	-0.0001
##	100	0.0585	nan	0.1000	-0.0001
##	120	0.0546	nan	0.1000	-0.0000
##	140	0.0520	nan	0.1000	-0.0001
##	150	0.0502	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8501	nan	0.1000	0.0874
##	2	0.7278	nan	0.1000	0.0616
##	3	0.6354	nan	0.1000	0.0455
##	4	0.5606	nan	0.1000	0.0371
##	5	0.4993	nan	0.1000	0.0302
##	6	0.4472	nan	0.1000	0.0260
##	7	0.4029	nan	0.1000	0.0218
##	8	0.3650	nan	0.1000	0.0188
##	9	0.3315	nan	0.1000	0.0167
##	10	0.3024	nan	0.1000	0.0144
##	20	0.1443	nan	0.1000	0.0046
##	40	0.0754	nan	0.1000	0.0004
##	60	0.0622	nan	0.1000	0.0001
##	80	0.0550	nan	0.1000	0.0000
##	100	0.0459	nan	0.1000	0.0000
##	120	0.0425	nan	0.1000	-0.0001
##	140	0.0409	nan	0.1000	0.0001
##	150	0.0391	nan	0.1000	0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8357	nan	0.1000	0.0877
##	2	0.7160	nan	0.1000	0.0603
##	3	0.6243	nan	0.1000	0.0451
##	4	0.5515	nan	0.1000	0.0366
##	5	0.4908	nan	0.1000	0.0295
##	6	0.4404	nan	0.1000	0.0255
##	7	0.3964	nan	0.1000	0.0216
##	8	0.3581	nan	0.1000	0.0190
##	9	0.3258	nan	0.1000	0.0156
##	10	0.2971	nan	0.1000	0.0139
##	20	0.1411	nan	0.1000	0.0046
##	40	0.0723	nan	0.1000	0.0004
##	60	0.0629	nan	0.1000	0.0000
##	80	0.0607	nan	0.1000	0.0000
##	100	0.0592	nan	0.1000	-0.0001
##	120	0.0580	nan	0.1000	-0.0001
##	140	0.0571	nan	0.1000	-0.0001
##	150	0.0567	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8338	nan	0.1000	0.0902
##	2	0.7128	nan	0.1000	0.0600
##	3	0.6209	nan	0.1000	0.0465
##	4	0.5476	nan	0.1000	0.0367
##	5	0.4865	nan	0.1000	0.0312
##	6	0.4352	nan	0.1000	0.0252
##	7	0.3912	nan	0.1000	0.0217
##	8	0.3537	nan	0.1000	0.0185
##	9	0.3207	nan	0.1000	0.0164
##	10	0.2918	nan	0.1000	0.0143
##	20	0.1367	nan	0.1000	0.0044
##	40	0.0696	nan	0.1000	0.0003
##	60	0.0582	nan	0.1000	0.0001
##	80	0.0520	nan	0.1000	-0.0001
##	100	0.0495	nan	0.1000	-0.0002
##	120	0.0471	nan	0.1000	-0.0001
##	140	0.0458	nan	0.1000	-0.0001
##	150	0.0449	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8340	nan	0.1000	0.0892
##	2	0.7131	nan	0.1000	0.0611
##	3	0.6207	nan	0.1000	0.0452
##	4	0.5465	nan	0.1000	0.0366
##	5	0.4852	nan	0.1000	0.0307
##	6	0.4339	nan	0.1000	0.0248
##	7	0.3896	nan	0.1000	0.0223
##	8	0.3514	nan	0.1000	0.0192
##	9	0.3182	nan	0.1000	0.0164
##	10	0.2891	nan	0.1000	0.0143
##	20	0.1341	nan	0.1000	0.0042
##	40	0.0642	nan	0.1000	0.0005
##	60	0.0513	nan	0.1000	0.0000
##	80	0.0468	nan	0.1000	0.0000
##	100	0.0434	nan	0.1000	0.0000
##	120	0.0398	nan	0.1000	-0.0000
##	140	0.0373	nan	0.1000	-0.0002
##	150	0.0363	nan	0.1000	-0.0002

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8584	nan	0.1000	0.0904
##	2	0.7349	nan	0.1000	0.0608
##	3	0.6413	nan	0.1000	0.0488
##	4	0.5653	nan	0.1000	0.0380
##	5	0.5037	nan	0.1000	0.0305
##	6	0.4510	nan	0.1000	0.0262
##	7	0.4058	nan	0.1000	0.0224
##	8	0.3667	nan	0.1000	0.0195
##	9	0.3321	nan	0.1000	0.0172
##	10	0.3032	nan	0.1000	0.0142

##	20	0.1423	nan	0.1000	0.0043
##	40	0.0709	nan	0.1000	0.0005
##	60	0.0616	nan	0.1000	0.0000
##	80	0.0590	nan	0.1000	-0.0002
##	100	0.0573	nan	0.1000	-0.0001
##	120	0.0556	nan	0.1000	-0.0000
##	140	0.0549	nan	0.1000	-0.0000
##	150	0.0545	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8567	nan	0.1000	0.0906
##	2	0.7330	nan	0.1000	0.0606
##	3	0.6384	nan	0.1000	0.0475
##	4	0.5617	nan	0.1000	0.0369
##	5	0.4988	nan	0.1000	0.0313
##	6	0.4464	nan	0.1000	0.0262
##	7	0.4010	nan	0.1000	0.0226
##	8	0.3620	nan	0.1000	0.0190
##	9	0.3280	nan	0.1000	0.0168
##	10	0.2980	nan	0.1000	0.0145
##	20	0.1368	nan	0.1000	0.0047
##	40	0.0676	nan	0.1000	0.0004
##	60	0.0554	nan	0.1000	0.0000
##	80	0.0479	nan	0.1000	-0.0001
##	100	0.0453	nan	0.1000	-0.0000
##	120	0.0431	nan	0.1000	-0.0001
##	140	0.0402	nan	0.1000	-0.0000
##	150	0.0392	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8566	nan	0.1000	0.0915
##	2	0.7327	nan	0.1000	0.0621
##	3	0.6381	nan	0.1000	0.0468
##	4	0.5614	nan	0.1000	0.0382
##	5	0.4984	nan	0.1000	0.0318
##	6	0.4450	nan	0.1000	0.0267
##	7	0.3989	nan	0.1000	0.0229
##	8	0.3597	nan	0.1000	0.0196
##	9	0.3252	nan	0.1000	0.0170
##	10	0.2952	nan	0.1000	0.0150
##	20	0.1330	nan	0.1000	0.0040
##	40	0.0621	nan	0.1000	0.0002
##	60	0.0481	nan	0.1000	-0.0003
##	80	0.0412	nan	0.1000	-0.0001
##	100	0.0380	nan	0.1000	-0.0001
##	120	0.0352	nan	0.1000	-0.0001
##	140	0.0323	nan	0.1000	-0.0000
##	150	0.0315	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8451	nan	0.1000	0.0880
##	2	0.7241	nan	0.1000	0.0602
##	3	0.6312	nan	0.1000	0.0466
##	4	0.5564	nan	0.1000	0.0358
##	5	0.4956	nan	0.1000	0.0293
##	6	0.4446	nan	0.1000	0.0250
##	7	0.4021	nan	0.1000	0.0216
##	8	0.3635	nan	0.1000	0.0189
##	9	0.3307	nan	0.1000	0.0163
##	10	0.3031	nan	0.1000	0.0139
##	20	0.1460	nan	0.1000	0.0049
##	40	0.0743	nan	0.1000	0.0004
##	60	0.0633	nan	0.1000	0.0001
##	80	0.0611	nan	0.1000	-0.0000
##	100	0.0593	nan	0.1000	-0.0000
##	120	0.0582	nan	0.1000	-0.0000
##	140	0.0571	nan	0.1000	-0.0001
##	150	0.0568	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8426	nan	0.1000	0.0865
##	2	0.7222	nan	0.1000	0.0596
##	3	0.6295	nan	0.1000	0.0458
##	4	0.5554	nan	0.1000	0.0368
##	5	0.4941	nan	0.1000	0.0307
##	6	0.4423	nan	0.1000	0.0255
##	7	0.3976	nan	0.1000	0.0224
##	8	0.3593	nan	0.1000	0.0191
##	9	0.3261	nan	0.1000	0.0164
##	10	0.2967	nan	0.1000	0.0146
##	20	0.1405	nan	0.1000	0.0040
##	40	0.0697	nan	0.1000	0.0006
##	60	0.0573	nan	0.1000	0.0001
##	80	0.0535	nan	0.1000	0.0001
##	100	0.0502	nan	0.1000	-0.0000
##	120	0.0485	nan	0.1000	-0.0000
##	140	0.0462	nan	0.1000	0.0000
##	150	0.0454	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8426	nan	0.1000	0.0910
##	2	0.7205	nan	0.1000	0.0619
##	3	0.6274	nan	0.1000	0.0468
##	4	0.5528	nan	0.1000	0.0371
##	5	0.4912	nan	0.1000	0.0305
##	6	0.4390	nan	0.1000	0.0264
##	7	0.3943	nan	0.1000	0.0221
##	8	0.3562	nan	0.1000	0.0187
##	9	0.3227	nan	0.1000	0.0168
##	10	0.2933	nan	0.1000	0.0142

##	20	0.1358	nan	0.1000	0.0042
##	40	0.0647	nan	0.1000	0.0005
##	60	0.0521	nan	0.1000	-0.0000
##	80	0.0453	nan	0.1000	-0.0001
##	100	0.0395	nan	0.1000	-0.0001
##	120	0.0350	nan	0.1000	-0.0000
##	140	0.0323	nan	0.1000	-0.0000
##	150	0.1469	nan	0.1000	0.0002

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8549	nan	0.1000	0.0901
##	2	0.7345	nan	0.1000	0.0600
##	3	0.6420	nan	0.1000	0.0456
##	4	0.5674	nan	0.1000	0.0368
##	5	0.5069	nan	0.1000	0.0302
##	6	0.4553	nan	0.1000	0.0255
##	7	0.4124	nan	0.1000	0.0211
##	8	0.3734	nan	0.1000	0.0190
##	9	0.3394	nan	0.1000	0.0169
##	10	0.3099	nan	0.1000	0.0146
##	20	0.1546	nan	0.1000	0.0044
##	40	0.0849	nan	0.1000	0.0005
##	60	0.0739	nan	0.1000	0.0001
##	80	0.0714	nan	0.1000	0.0001
##	100	0.0702	nan	0.1000	-0.0001
##	120	0.0693	nan	0.1000	-0.0000
##	140	0.0682	nan	0.1000	-0.0000
##	150	0.0677	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8540	nan	0.1000	0.0899
##	2	0.7317	nan	0.1000	0.0608
##	3	0.6383	nan	0.1000	0.0456
##	4	0.5642	nan	0.1000	0.0366
##	5	0.5027	nan	0.1000	0.0302
##	6	0.4504	nan	0.1000	0.0261
##	7	0.4065	nan	0.1000	0.0225
##	8	0.3679	nan	0.1000	0.0197
##	9	0.3342	nan	0.1000	0.0166
##	10	0.3049	nan	0.1000	0.0144
##	20	0.1500	nan	0.1000	0.0042
##	40	0.0815	nan	0.1000	0.0003
##	60	0.0661	nan	0.1000	0.0001
##	80	0.0616	nan	0.1000	-0.0002
##	100	0.0568	nan	0.1000	-0.0001
##	120	0.0543	nan	0.1000	-0.0001
##	140	0.0514	nan	0.1000	-0.0001
##	150	0.0501	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8531	nan	0.1000	0.0899
##	2	0.7308	nan	0.1000	0.0601
##	3	0.6375	nan	0.1000	0.0468
##	4	0.5634	nan	0.1000	0.0373
##	5	0.5012	nan	0.1000	0.0312
##	6	0.4486	nan	0.1000	0.0263
##	7	0.4039	nan	0.1000	0.0221
##	8	0.3647	nan	0.1000	0.0190
##	9	0.3318	nan	0.1000	0.0161
##	10	0.3030	nan	0.1000	0.0145
##	20	0.1448	nan	0.1000	0.0042
##	40	0.0739	nan	0.1000	0.0006
##	60	0.0577	nan	0.1000	0.0000
##	80	0.0513	nan	0.1000	-0.0002
##	100	0.0482	nan	0.1000	-0.0001
##	120	0.0455	nan	0.1000	0.0000
##	140	0.0426	nan	0.1000	0.0001
##	150	0.0407	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8526	nan	0.1000	0.0897
##	2	0.7339	nan	0.1000	0.0601
##	3	0.6417	nan	0.1000	0.0459
##	4	0.5685	nan	0.1000	0.0367
##	5	0.5065	nan	0.1000	0.0305
##	6	0.4557	nan	0.1000	0.0254
##	7	0.4115	nan	0.1000	0.0223
##	8	0.3733	nan	0.1000	0.0187
##	9	0.3402	nan	0.1000	0.0164
##	10	0.3122	nan	0.1000	0.0138
##	20	0.1524	nan	0.1000	0.0041
##	40	0.0833	nan	0.1000	0.0005
##	60	0.0726	nan	0.1000	0.0000
##	80	0.0695	nan	0.1000	-0.0000
##	100	0.0675	nan	0.1000	-0.0000
##	120	0.0657	nan	0.1000	-0.0000
##	140	0.0646	nan	0.1000	-0.0001
##	150	0.0640	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8512	nan	0.1000	0.0886
##	2	0.7304	nan	0.1000	0.0597
##	3	0.6382	nan	0.1000	0.0462
##	4	0.5635	nan	0.1000	0.0374
##	5	0.5017	nan	0.1000	0.0300
##	6	0.4493	nan	0.1000	0.0262
##	7	0.4050	nan	0.1000	0.0224
##	8	0.3670	nan	0.1000	0.0190
##	9	0.3333	nan	0.1000	0.0168
##	10	0.3040	nan	0.1000	0.0145

##	20	0.1478	nan	0.1000	0.0039
##	40	0.0805	nan	0.1000	0.0006
##	60	0.0643	nan	0.1000	0.0003
##	80	0.0584	nan	0.1000	-0.0001
##	100	0.0543	nan	0.1000	-0.0001
##	120	0.0503	nan	0.1000	-0.0001
##	140	0.0478	nan	0.1000	-0.0000
##	150	0.0464	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8512	nan	0.1000	0.0910
##	2	0.7293	nan	0.1000	0.0606
##	3	0.6363	nan	0.1000	0.0466
##	4	0.5615	nan	0.1000	0.0385
##	5	0.4997	nan	0.1000	0.0302
##	6	0.4476	nan	0.1000	0.0260
##	7	0.4039	nan	0.1000	0.0217
##	8	0.3656	nan	0.1000	0.0189
##	9	0.3316	nan	0.1000	0.0166
##	10	0.3022	nan	0.1000	0.0144
##	20	0.1436	nan	0.1000	0.0041
##	40	0.0739	nan	0.1000	0.0002
##	60	0.0596	nan	0.1000	-0.0001
##	80	0.0622	nan	0.1000	-0.0000
##	100	2701721.6555	nan	0.1000	0.0003
##	120	inf	nan	0.1000	nan
##	140	inf	nan	0.1000	nan
##	150	inf	nan	0.1000	nan

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8284	nan	0.1000	0.0878
##	2	0.7109	nan	0.1000	0.0587
##	3	0.6217	nan	0.1000	0.0439
##	4	0.5493	nan	0.1000	0.0368
##	5	0.4905	nan	0.1000	0.0295
##	6	0.4409	nan	0.1000	0.0247
##	7	0.3987	nan	0.1000	0.0213
##	8	0.3621	nan	0.1000	0.0181
##	9	0.3315	nan	0.1000	0.0154
##	10	0.3036	nan	0.1000	0.0139
##	20	0.1551	nan	0.1000	0.0044
##	40	0.0903	nan	0.1000	0.0004
##	60	0.0802	nan	0.1000	-0.0001
##	80	0.0778	nan	0.1000	0.0000
##	100	0.0759	nan	0.1000	-0.0001
##	120	0.0746	nan	0.1000	0.0000
##	140	0.0735	nan	0.1000	-0.0001
##	150	0.0731	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8282	nan	0.1000	0.0885
##	2	0.7089	nan	0.1000	0.0601
##	3	0.6185	nan	0.1000	0.0451
##	4	0.5465	nan	0.1000	0.0362
##	5	0.4876	nan	0.1000	0.0292
##	6	0.4381	nan	0.1000	0.0251
##	7	0.3960	nan	0.1000	0.0209
##	8	0.3594	nan	0.1000	0.0184
##	9	0.3272	nan	0.1000	0.0162
##	10	0.2993	nan	0.1000	0.0141
##	20	0.1507	nan	0.1000	0.0038
##	40	0.0861	nan	0.1000	0.0004
##	60	0.0736	nan	0.1000	0.0001
##	80	0.0679	nan	0.1000	-0.0001
##	100	0.0636	nan	0.1000	-0.0000
##	120	0.0585	nan	0.1000	-0.0000
##	140	0.0561	nan	0.1000	-0.0001
##	150	0.0547	nan	0.1000	0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8273	nan	0.1000	0.0915
##	2	0.7082	nan	0.1000	0.0598
##	3	0.6182	nan	0.1000	0.0450
##	4	0.5463	nan	0.1000	0.0364
##	5	0.4871	nan	0.1000	0.0301
##	6	0.4367	nan	0.1000	0.0252
##	7	0.3936	nan	0.1000	0.0211
##	8	0.3563	nan	0.1000	0.0187
##	9	0.3243	nan	0.1000	0.0157
##	10	0.2966	nan	0.1000	0.0139
##	20	0.1463	nan	0.1000	0.0039
##	40	0.0805	nan	0.1000	0.0005
##	60	0.0643	nan	0.1000	-0.0001
##	80	0.0582	nan	0.1000	0.0002
##	100	0.0540	nan	0.1000	-0.0001
##	120	0.0516	nan	0.1000	-0.0000
##	140	0.0476	nan	0.1000	0.0001
##	150	0.0453	nan	0.1000	0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8434	nan	0.1000	0.0908
##	2	0.7211	nan	0.1000	0.0608
##	3	0.6279	nan	0.1000	0.0475
##	4	0.5537	nan	0.1000	0.0380
##	5	0.4920	nan	0.1000	0.0304
##	6	0.4405	nan	0.1000	0.0258
##	7	0.3965	nan	0.1000	0.0225
##	8	0.3590	nan	0.1000	0.0189
##	9	0.3252	nan	0.1000	0.0166
##	10	0.2965	nan	0.1000	0.0146

##	20	0.1374	nan	0.1000	0.0043
##	40	0.0672	nan	0.1000	0.0006
##	60	0.0562	nan	0.1000	0.0001
##	80	0.0537	nan	0.1000	-0.0000
##	100	0.0521	nan	0.1000	-0.0000
##	120	0.0509	nan	0.1000	-0.0000
##	140	0.0498	nan	0.1000	-0.0001
##	150	0.0492	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8433	nan	0.1000	0.0941
##	2	0.7209	nan	0.1000	0.0611
##	3	0.6273	nan	0.1000	0.0470
##	4	0.5527	nan	0.1000	0.0368
##	5	0.4902	nan	0.1000	0.0312
##	6	0.4384	nan	0.1000	0.0256
##	7	0.3936	nan	0.1000	0.0226
##	8	0.3553	nan	0.1000	0.0188
##	9	0.3215	nan	0.1000	0.0169
##	10	0.2924	nan	0.1000	0.0143
##	20	0.1357	nan	0.1000	0.0042
##	40	0.0628	nan	0.1000	0.0004
##	60	0.0490	nan	0.1000	0.0003
##	80	0.0450	nan	0.1000	-0.0000
##	100	0.0420	nan	0.1000	-0.0000
##	120	0.0397	nan	0.1000	0.0000
##	140	0.0381	nan	0.1000	-0.0000
##	150	0.0372	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8417	nan	0.1000	0.0892
##	2	0.7183	nan	0.1000	0.0616
##	3	0.6247	nan	0.1000	0.0465
##	4	0.5496	nan	0.1000	0.0374
##	5	0.4871	nan	0.1000	0.0300
##	6	0.4350	nan	0.1000	0.0256
##	7	0.3901	nan	0.1000	0.0218
##	8	0.3516	nan	0.1000	0.0192
##	9	0.3178	nan	0.1000	0.0163
##	10	0.2888	nan	0.1000	0.0142
##	20	0.1291	nan	0.1000	0.0043
##	40	0.0563	nan	0.1000	0.0004
##	60	0.0432	nan	0.1000	0.0000
##	80	0.0391	nan	0.1000	-0.0001
##	100	0.0362	nan	0.1000	-0.0001
##	120	0.0336	nan	0.1000	-0.0001
##	140	0.0316	nan	0.1000	0.0000
##	150	0.0300	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8462	nan	0.1000	0.0869
##	2	0.7257	nan	0.1000	0.0592
##	3	0.6346	nan	0.1000	0.0447
##	4	0.5607	nan	0.1000	0.0365
##	5	0.4996	nan	0.1000	0.0302
##	6	0.4493	nan	0.1000	0.0256
##	7	0.4064	nan	0.1000	0.0212
##	8	0.3667	nan	0.1000	0.0193
##	9	0.3345	nan	0.1000	0.0157
##	10	0.3052	nan	0.1000	0.0149
##	20	0.1470	nan	0.1000	0.0044
##	40	0.0791	nan	0.1000	0.0006
##	60	0.0685	nan	0.1000	0.0001
##	80	0.0663	nan	0.1000	-0.0001
##	100	0.0643	nan	0.1000	-0.0000
##	120	0.0627	nan	0.1000	-0.0000
##	140	0.0614	nan	0.1000	-0.0000
##	150	0.0608	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8442	nan	0.1000	0.0886
##	2	0.7230	nan	0.1000	0.0599
##	3	0.6308	nan	0.1000	0.0458
##	4	0.5568	nan	0.1000	0.0360
##	5	0.4961	nan	0.1000	0.0297
##	6	0.4435	nan	0.1000	0.0261
##	7	0.3991	nan	0.1000	0.0221
##	8	0.3616	nan	0.1000	0.0187
##	9	0.3282	nan	0.1000	0.0164
##	10	0.2992	nan	0.1000	0.0146
##	20	0.1439	nan	0.1000	0.0040
##	40	0.0754	nan	0.1000	0.0005
##	60	0.0607	nan	0.1000	0.0001
##	80	0.0560	nan	0.1000	0.0001
##	100	0.0532	nan	0.1000	-0.0001
##	120	0.0503	nan	0.1000	0.0000
##	140	0.0478	nan	0.1000	0.0000
##	150	0.0470	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8441	nan	0.1000	0.0898
##	2	0.7222	nan	0.1000	0.0612
##	3	0.6294	nan	0.1000	0.0456
##	4	0.5547	nan	0.1000	0.0361
##	5	0.4931	nan	0.1000	0.0311
##	6	0.4414	nan	0.1000	0.0258
##	7	0.3972	nan	0.1000	0.0220
##	8	0.3585	nan	0.1000	0.0191
##	9	0.3251	nan	0.1000	0.0165
##	10	0.2958	nan	0.1000	0.0145

##	20	0.1366	nan	0.1000	0.0042
##	40	0.0684	nan	0.1000	0.0007
##	60	0.0540	nan	0.1000	0.0001
##	80	0.0484	nan	0.1000	-0.0000
##	100	0.0449	nan	0.1000	-0.0001
##	120	0.0402	nan	0.1000	-0.0001
##	140	0.0382	nan	0.1000	0.0000
##	150	0.0370	nan	0.1000	0.0001

##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8525	nan	0.1000	0.0882
##	2	0.7313	nan	0.1000	0.0604
##	3	0.6381	nan	0.1000	0.0464
##	4	0.5636	nan	0.1000	0.0371
##	5	0.5024	nan	0.1000	0.0306
##	6	0.4507	nan	0.1000	0.0260
##	7	0.4066	nan	0.1000	0.0220
##	8	0.3679	nan	0.1000	0.0192
##	9	0.3356	nan	0.1000	0.0160
##	10	0.3064	nan	0.1000	0.0147
##	20	0.1478	nan	0.1000	0.0041
##	40	0.0805	nan	0.1000	0.0005
##	60	0.0707	nan	0.1000	-0.0000
##	80	0.0680	nan	0.1000	-0.0000
##	100	0.0658	nan	0.1000	-0.0001
##	120	0.0642	nan	0.1000	-0.0000
##	140	0.0628	nan	0.1000	-0.0000
##	150	0.0623	nan	0.1000	0.0000

##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8511	nan	0.1000	0.0886
##	2	0.7289	nan	0.1000	0.0617
##	3	0.6362	nan	0.1000	0.0476
##	4	0.5614	nan	0.1000	0.0375
##	5	0.4997	nan	0.1000	0.0310
##	6	0.4475	nan	0.1000	0.0262
##	7	0.4026	nan	0.1000	0.0222
##	8	0.3646	nan	0.1000	0.0190
##	9	0.3309	nan	0.1000	0.0168
##	10	0.3027	nan	0.1000	0.0143
##	20	0.1449	nan	0.1000	0.0040
##	40	0.0747	nan	0.1000	0.0006
##	60	0.0604	nan	0.1000	-0.0004
##	80	0.0556	nan	0.1000	-0.0001
##	100	0.0515	nan	0.1000	-0.0003
##	120	0.0462	nan	0.1000	-0.0001
##	140	0.0444	nan	0.1000	-0.0001
##	150	0.0432	nan	0.1000	-0.0001

##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve

##	1	0.8495	nan	0.1000	0.0902
##	2	0.7275	nan	0.1000	0.0611
##	3	0.6340	nan	0.1000	0.0458
##	4	0.5590	nan	0.1000	0.0367
##	5	0.4973	nan	0.1000	0.0315
##	6	0.4453	nan	0.1000	0.0263
##	7	0.4009	nan	0.1000	0.0220
##	8	0.3620	nan	0.1000	0.0192
##	9	0.3277	nan	0.1000	0.0169
##	10	0.2974	nan	0.1000	0.0147
##	20	0.1405	nan	0.1000	0.0041
##	40	0.0694	nan	0.1000	0.0005
##	60	0.0548	nan	0.1000	0.0000
##	80	0.0475	nan	0.1000	-0.0000
##	100	0.0427	nan	0.1000	-0.0000
##	120	0.0387	nan	0.1000	-0.0001
##	140	0.0361	nan	0.1000	-0.0001
##	150	0.0345	nan	0.1000	-0.0004

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8408	nan	0.1000	0.0879
##	2	0.7230	nan	0.1000	0.0598
##	3	0.6311	nan	0.1000	0.0458
##	4	0.5573	nan	0.1000	0.0372
##	5	0.4957	nan	0.1000	0.0304
##	6	0.4451	nan	0.1000	0.0255
##	7	0.4015	nan	0.1000	0.0222
##	8	0.3637	nan	0.1000	0.0187
##	9	0.3306	nan	0.1000	0.0160
##	10	0.3028	nan	0.1000	0.0134
##	20	0.1483	nan	0.1000	0.0043
##	40	0.0822	nan	0.1000	0.0004
##	60	0.0725	nan	0.1000	-0.0000
##	80	0.0698	nan	0.1000	-0.0001
##	100	0.0679	nan	0.1000	-0.0000
##	120	0.0664	nan	0.1000	-0.0000
##	140	0.0654	nan	0.1000	-0.0001
##	150	0.0648	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8397	nan	0.1000	0.0895
##	2	0.7193	nan	0.1000	0.0603
##	3	0.6276	nan	0.1000	0.0465
##	4	0.5541	nan	0.1000	0.0364
##	5	0.4936	nan	0.1000	0.0307
##	6	0.4417	nan	0.1000	0.0254
##	7	0.3980	nan	0.1000	0.0222
##	8	0.3604	nan	0.1000	0.0186
##	9	0.3277	nan	0.1000	0.0162
##	10	0.2990	nan	0.1000	0.0141

##	20	0.1463	nan	0.1000	0.0037
##	40	0.0772	nan	0.1000	0.0006
##	60	0.0640	nan	0.1000	0.0002
##	80	0.0602	nan	0.1000	-0.0001
##	100	0.0547	nan	0.1000	-0.0000
##	120	0.0519	nan	0.1000	-0.0001
##	140	0.0492	nan	0.1000	-0.0000
##	150	0.0516	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8388	nan	0.1000	0.0899
##	2	0.7179	nan	0.1000	0.0594
##	3	0.6266	nan	0.1000	0.0463
##	4	0.5531	nan	0.1000	0.0373
##	5	0.4922	nan	0.1000	0.0291
##	6	0.4401	nan	0.1000	0.0259
##	7	0.3962	nan	0.1000	0.0217
##	8	0.3584	nan	0.1000	0.0184
##	9	0.3254	nan	0.1000	0.0164
##	10	0.2970	nan	0.1000	0.0139
##	20	0.1428	nan	0.1000	0.0045
##	40	0.0739	nan	0.1000	0.0005
##	60	0.0590	nan	0.1000	0.0001
##	80	0.0527	nan	0.1000	0.0000
##	100	0.0487	nan	0.1000	0.0000
##	120	0.0457	nan	0.1000	-0.0001
##	140	0.0430	nan	0.1000	-0.0000
##	150	0.0423	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8637	nan	0.1000	0.0902
##	2	0.7420	nan	0.1000	0.0595
##	3	0.6493	nan	0.1000	0.0477
##	4	0.5752	nan	0.1000	0.0365
##	5	0.5153	nan	0.1000	0.0293
##	6	0.4624	nan	0.1000	0.0266
##	7	0.4174	nan	0.1000	0.0224
##	8	0.3790	nan	0.1000	0.0192
##	9	0.3450	nan	0.1000	0.0169
##	10	0.3166	nan	0.1000	0.0138
##	20	0.1528	nan	0.1000	0.0044
##	40	0.0826	nan	0.1000	0.0006
##	60	0.0729	nan	0.1000	0.0000
##	80	0.0701	nan	0.1000	-0.0001
##	100	0.0683	nan	0.1000	0.0000
##	120	0.0670	nan	0.1000	-0.0001
##	140	0.0656	nan	0.1000	-0.0001
##	150	0.0650	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8615	nan	0.1000	0.0894
##	2	0.7396	nan	0.1000	0.0619
##	3	0.6459	nan	0.1000	0.0463
##	4	0.5703	nan	0.1000	0.0367
##	5	0.5079	nan	0.1000	0.0317
##	6	0.4557	nan	0.1000	0.0259
##	7	0.4106	nan	0.1000	0.0226
##	8	0.3717	nan	0.1000	0.0192
##	9	0.3375	nan	0.1000	0.0170
##	10	0.3082	nan	0.1000	0.0148
##	20	0.1503	nan	0.1000	0.0040
##	40	0.0795	nan	0.1000	0.0003
##	60	0.0670	nan	0.1000	0.0000
##	80	0.0621	nan	0.1000	0.0000
##	100	0.0578	nan	0.1000	-0.0001
##	120	0.0558	nan	0.1000	-0.0001
##	140	0.0539	nan	0.1000	-0.0000
##	150	0.0519	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8610	nan	0.1000	0.0878
##	2	0.7389	nan	0.1000	0.0602
##	3	0.6449	nan	0.1000	0.0461
##	4	0.5693	nan	0.1000	0.0377
##	5	0.5065	nan	0.1000	0.0312
##	6	0.4538	nan	0.1000	0.0262
##	7	0.4087	nan	0.1000	0.0224
##	8	0.3695	nan	0.1000	0.0196
##	9	0.3359	nan	0.1000	0.0170
##	10	0.3056	nan	0.1000	0.0152
##	20	0.1455	nan	0.1000	0.0041
##	40	0.0721	nan	0.1000	0.0005
##	60	0.0586	nan	0.1000	-0.0001
##	80	0.0527	nan	0.1000	0.0001
##	100	0.0489	nan	0.1000	-0.0001
##	120	0.0527	nan	0.1000	-0.0025
##	140	0.0410	nan	0.1000	0.0000
##	150	0.0395	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8499	nan	0.1000	0.0880
##	2	0.7294	nan	0.1000	0.0618
##	3	0.6371	nan	0.1000	0.0459
##	4	0.5631	nan	0.1000	0.0365
##	5	0.5009	nan	0.1000	0.0306
##	6	0.4497	nan	0.1000	0.0261
##	7	0.4052	nan	0.1000	0.0223
##	8	0.3674	nan	0.1000	0.0189
##	9	0.3347	nan	0.1000	0.0165
##	10	0.3057	nan	0.1000	0.0144

##	20	0.1503	nan	0.1000	0.0046
##	40	0.0829	nan	0.1000	0.0005
##	60	0.0735	nan	0.1000	-0.0001
##	80	0.0704	nan	0.1000	-0.0001
##	100	0.0688	nan	0.1000	-0.0000
##	120	0.0676	nan	0.1000	-0.0001
##	140	0.0663	nan	0.1000	0.0000
##	150	0.0659	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8480	nan	0.1000	0.0899
##	2	0.7269	nan	0.1000	0.0615
##	3	0.6338	nan	0.1000	0.0464
##	4	0.5594	nan	0.1000	0.0374
##	5	0.4972	nan	0.1000	0.0305
##	6	0.4455	nan	0.1000	0.0262
##	7	0.4013	nan	0.1000	0.0220
##	8	0.3635	nan	0.1000	0.0186
##	9	0.3305	nan	0.1000	0.0165
##	10	0.3019	nan	0.1000	0.0146
##	20	0.1463	nan	0.1000	0.0042
##	40	0.0781	nan	0.1000	0.0006
##	60	0.0650	nan	0.1000	0.0001
##	80	0.0572	nan	0.1000	-0.0000
##	100	0.0520	nan	0.1000	-0.0002
##	120	0.0490	nan	0.1000	0.0000
##	140	0.0458	nan	0.1000	-0.0001
##	150	0.0450	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8483	nan	0.1000	0.0885
##	2	0.7256	nan	0.1000	0.0608
##	3	0.6329	nan	0.1000	0.0473
##	4	0.5587	nan	0.1000	0.0379
##	5	0.4970	nan	0.1000	0.0312
##	6	0.4445	nan	0.1000	0.0265
##	7	0.4004	nan	0.1000	0.0217
##	8	0.3621	nan	0.1000	0.0194
##	9	0.3287	nan	0.1000	0.0166
##	10	0.2996	nan	0.1000	0.0144
##	20	0.1429	nan	0.1000	0.0042
##	40	0.0737	nan	0.1000	0.0005
##	60	0.0526	nan	0.1000	0.0004
##	80	0.0458	nan	0.1000	0.0000
##	100	0.0410	nan	0.1000	-0.0000
##	120	0.0379	nan	0.1000	-0.0000
##	140	0.0351	nan	0.1000	-0.0000
##	150	0.0340	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8527	nan	0.1000	0.0895
##	2	0.7293	nan	0.1000	0.0613
##	3	0.6355	nan	0.1000	0.0466
##	4	0.5605	nan	0.1000	0.0370
##	5	0.4980	nan	0.1000	0.0312
##	6	0.4464	nan	0.1000	0.0257
##	7	0.4028	nan	0.1000	0.0218
##	8	0.3644	nan	0.1000	0.0191
##	9	0.3302	nan	0.1000	0.0170
##	10	0.3011	nan	0.1000	0.0147
##	20	0.1383	nan	0.1000	0.0049
##	40	0.0662	nan	0.1000	0.0005
##	60	0.0561	nan	0.1000	-0.0001
##	80	0.0531	nan	0.1000	0.0000
##	100	0.0507	nan	0.1000	-0.0001
##	120	0.0499	nan	0.1000	-0.0001
##	140	0.0485	nan	0.1000	-0.0000
##	150	0.0480	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8513	nan	0.1000	0.0880
##	2	0.7277	nan	0.1000	0.0620
##	3	0.6338	nan	0.1000	0.0468
##	4	0.5581	nan	0.1000	0.0383
##	5	0.4957	nan	0.1000	0.0308
##	6	0.4433	nan	0.1000	0.0265
##	7	0.3989	nan	0.1000	0.0220
##	8	0.3595	nan	0.1000	0.0195
##	9	0.3254	nan	0.1000	0.0173
##	10	0.2955	nan	0.1000	0.0147
##	20	0.1348	nan	0.1000	0.0041
##	40	0.0644	nan	0.1000	0.0003
##	60	0.0519	nan	0.1000	-0.0000
##	80	0.0474	nan	0.1000	0.0000
##	100	0.0439	nan	0.1000	-0.0000
##	120	0.0427	nan	0.1000	-0.0001
##	140	0.0412	nan	0.1000	-0.0001
##	150	0.0397	nan	0.1000	-0.0002

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8503	nan	0.1000	0.0897
##	2	0.7264	nan	0.1000	0.0620
##	3	0.6325	nan	0.1000	0.0480
##	4	0.5570	nan	0.1000	0.0373
##	5	0.4937	nan	0.1000	0.0314
##	6	0.4408	nan	0.1000	0.0261
##	7	0.3953	nan	0.1000	0.0222
##	8	0.3559	nan	0.1000	0.0193
##	9	0.3213	nan	0.1000	0.0170
##	10	0.2912	nan	0.1000	0.0149

##	20	0.1286	nan	0.1000	0.0043
##	40	0.0557	nan	0.1000	0.0004
##	60	0.0428	nan	0.1000	-0.0000
##	80	0.0385	nan	0.1000	0.0000
##	100	0.0379	nan	0.1000	0.0002
##	120	0.0345	nan	0.1000	-0.0000
##	140	0.0315	nan	0.1000	-0.0001
##	150	0.0301	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8660	nan	0.1000	0.0868
##	2	0.7432	nan	0.1000	0.0605
##	3	0.6502	nan	0.1000	0.0459
##	4	0.5742	nan	0.1000	0.0383
##	5	0.5118	nan	0.1000	0.0313
##	6	0.4596	nan	0.1000	0.0261
##	7	0.4145	nan	0.1000	0.0223
##	8	0.3763	nan	0.1000	0.0192
##	9	0.3432	nan	0.1000	0.0162
##	10	0.3131	nan	0.1000	0.0148
##	20	0.1504	nan	0.1000	0.0042
##	40	0.0782	nan	0.1000	0.0006
##	60	0.0681	nan	0.1000	0.0001
##	80	0.0648	nan	0.1000	0.0000
##	100	0.0625	nan	0.1000	0.0001
##	120	0.0611	nan	0.1000	-0.0000
##	140	0.0599	nan	0.1000	-0.0000
##	150	0.0594	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8644	nan	0.1000	0.0891
##	2	0.7417	nan	0.1000	0.0627
##	3	0.6480	nan	0.1000	0.0464
##	4	0.5723	nan	0.1000	0.0375
##	5	0.5088	nan	0.1000	0.0314
##	6	0.4551	nan	0.1000	0.0270
##	7	0.4094	nan	0.1000	0.0225
##	8	0.3693	nan	0.1000	0.0195
##	9	0.3354	nan	0.1000	0.0167
##	10	0.3058	nan	0.1000	0.0150
##	20	0.1450	nan	0.1000	0.0043
##	40	0.0745	nan	0.1000	0.0006
##	60	0.0622	nan	0.1000	0.0000
##	80	0.0580	nan	0.1000	0.0002
##	100	0.0523	nan	0.1000	-0.0000
##	120	0.0499	nan	0.1000	0.0000
##	140	0.0463	nan	0.1000	-0.0002
##	150	0.0452	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
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##	1	0.8630	nan	0.1000	0.0890
##	2	0.7396	nan	0.1000	0.0618
##	3	0.6445	nan	0.1000	0.0473
##	4	0.5685	nan	0.1000	0.0379
##	5	0.5048	nan	0.1000	0.0313
##	6	0.4518	nan	0.1000	0.0264
##	7	0.4059	nan	0.1000	0.0228
##	8	0.3665	nan	0.1000	0.0199
##	9	0.3325	nan	0.1000	0.0167
##	10	0.3024	nan	0.1000	0.0150
##	20	0.1404	nan	0.1000	0.0042
##	40	0.0680	nan	0.1000	0.0004
##	60	0.0551	nan	0.1000	0.0001
##	80	0.0748	nan	0.1000	0.0001
##	100	0.0712	nan	0.1000	0.0002
##	120	inf	nan	0.1000	nan
##	140	inf	nan	0.1000	nan
##	150	inf	nan	0.1000	nan

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8414	nan	0.1000	0.0860
##	2	0.7227	nan	0.1000	0.0582
##	3	0.6315	nan	0.1000	0.0448
##	4	0.5588	nan	0.1000	0.0363
##	5	0.4996	nan	0.1000	0.0296
##	6	0.4486	nan	0.1000	0.0256
##	7	0.4061	nan	0.1000	0.0216
##	8	0.3678	nan	0.1000	0.0189
##	9	0.3360	nan	0.1000	0.0156
##	10	0.3068	nan	0.1000	0.0145
##	20	0.1501	nan	0.1000	0.0040
##	40	0.0821	nan	0.1000	0.0005
##	60	0.0717	nan	0.1000	0.0001
##	80	0.0693	nan	0.1000	-0.0001
##	100	0.0676	nan	0.1000	-0.0001
##	120	0.0664	nan	0.1000	-0.0000
##	140	0.0653	nan	0.1000	-0.0000
##	150	0.0647	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8412	nan	0.1000	0.0908
##	2	0.7208	nan	0.1000	0.0607
##	3	0.6290	nan	0.1000	0.0464
##	4	0.5549	nan	0.1000	0.0363
##	5	0.4938	nan	0.1000	0.0307
##	6	0.4424	nan	0.1000	0.0251
##	7	0.3988	nan	0.1000	0.0217
##	8	0.3614	nan	0.1000	0.0186
##	9	0.3287	nan	0.1000	0.0163
##	10	0.3000	nan	0.1000	0.0141

##	20	0.1463	nan	0.1000	0.0039
##	40	0.0781	nan	0.1000	0.0005
##	60	0.0656	nan	0.1000	0.0002
##	80	0.0636	nan	0.1000	-0.0042
##	100	0.0533	nan	0.1000	0.0001
##	120	0.0498	nan	0.1000	-0.0001
##	140	0.0458	nan	0.1000	-0.0001
##	150	0.0471	nan	0.1000	-0.0023

##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8400	nan	0.1000	0.0897
##	2	0.7197	nan	0.1000	0.0597
##	3	0.6272	nan	0.1000	0.0456
##	4	0.5530	nan	0.1000	0.0369
##	5	0.4919	nan	0.1000	0.0311
##	6	0.4408	nan	0.1000	0.0253
##	7	0.3969	nan	0.1000	0.0220
##	8	0.3595	nan	0.1000	0.0186
##	9	0.3263	nan	0.1000	0.0161
##	10	0.2969	nan	0.1000	0.0143
##	20	0.1411	nan	0.1000	0.0039
##	40	0.0707	nan	0.1000	0.0003
##	60	0.0586	nan	0.1000	0.0000
##	80	0.0508	nan	0.1000	-0.0004
##	100	0.0448	nan	0.1000	0.0000
##	120	0.0413	nan	0.1000	0.0000
##	140	0.0380	nan	0.1000	-0.0001
##	150	0.0369	nan	0.1000	-0.0000

##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8523	nan	0.1000	0.0882
##	2	0.7309	nan	0.1000	0.0604
##	3	0.6367	nan	0.1000	0.0461
##	4	0.5618	nan	0.1000	0.0365
##	5	0.4997	nan	0.1000	0.0310
##	6	0.4472	nan	0.1000	0.0264
##	7	0.4020	nan	0.1000	0.0225
##	8	0.3640	nan	0.1000	0.0191
##	9	0.3295	nan	0.1000	0.0174
##	10	0.2993	nan	0.1000	0.0146
##	20	0.1392	nan	0.1000	0.0046
##	40	0.0681	nan	0.1000	0.0005
##	60	0.0580	nan	0.1000	0.0000
##	80	0.0557	nan	0.1000	-0.0000
##	100	0.0543	nan	0.1000	-0.0000
##	120	0.0531	nan	0.1000	-0.0001
##	140	0.0519	nan	0.1000	-0.0000
##	150	0.0517	nan	0.1000	-0.0000

##					
##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve

##	1	0.8496	nan	0.1000	0.0888
##	2	0.7267	nan	0.1000	0.0614
##	3	0.6327	nan	0.1000	0.0466
##	4	0.5573	nan	0.1000	0.0372
##	5	0.4951	nan	0.1000	0.0311
##	6	0.4426	nan	0.1000	0.0261
##	7	0.3977	nan	0.1000	0.0224
##	8	0.3589	nan	0.1000	0.0192
##	9	0.3252	nan	0.1000	0.0165
##	10	0.2954	nan	0.1000	0.0150
##	20	0.1360	nan	0.1000	0.0044
##	40	0.0661	nan	0.1000	0.0007
##	60	0.0535	nan	0.1000	-0.0001
##	80	0.0495	nan	0.1000	-0.0000
##	100	0.0470	nan	0.1000	-0.0000
##	120	0.0452	nan	0.1000	-0.0000
##	140	0.0431	nan	0.1000	0.0000
##	150	0.0422	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8491	nan	0.1000	0.0913
##	2	0.7259	nan	0.1000	0.0619
##	3	0.6313	nan	0.1000	0.0477
##	4	0.5560	nan	0.1000	0.0377
##	5	0.4934	nan	0.1000	0.0297
##	6	0.4405	nan	0.1000	0.0269
##	7	0.3951	nan	0.1000	0.0227
##	8	0.3563	nan	0.1000	0.0192
##	9	0.3223	nan	0.1000	0.0167
##	10	0.2925	nan	0.1000	0.0148
##	20	0.1323	nan	0.1000	0.0042
##	40	0.0598	nan	0.1000	0.0003
##	60	0.0490	nan	0.1000	0.0001
##	80	0.0430	nan	0.1000	-0.0001
##	100	0.0393	nan	0.1000	-0.0000
##	120	0.0371	nan	0.1000	-0.0000
##	140	0.0345	nan	0.1000	-0.0000
##	150	0.0336	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8476	nan	0.1000	0.0867
##	2	0.7282	nan	0.1000	0.0586
##	3	0.6375	nan	0.1000	0.0449
##	4	0.5651	nan	0.1000	0.0363
##	5	0.5058	nan	0.1000	0.0299
##	6	0.4555	nan	0.1000	0.0245
##	7	0.4119	nan	0.1000	0.0217
##	8	0.3742	nan	0.1000	0.0187
##	9	0.3408	nan	0.1000	0.0166
##	10	0.3114	nan	0.1000	0.0147

##	20	0.1561	nan	0.1000	0.0046
##	40	0.0868	nan	0.1000	0.0005
##	60	0.0770	nan	0.1000	-0.0001
##	80	0.0739	nan	0.1000	-0.0001
##	100	0.0715	nan	0.1000	-0.0000
##	120	0.0701	nan	0.1000	-0.0000
##	140	0.0689	nan	0.1000	-0.0001
##	150	0.0685	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8472	nan	0.1000	0.0873
##	2	0.7267	nan	0.1000	0.0594
##	3	0.6347	nan	0.1000	0.0456
##	4	0.5612	nan	0.1000	0.0363
##	5	0.4999	nan	0.1000	0.0302
##	6	0.4480	nan	0.1000	0.0257
##	7	0.4048	nan	0.1000	0.0212
##	8	0.3664	nan	0.1000	0.0190
##	9	0.3330	nan	0.1000	0.0163
##	10	0.3043	nan	0.1000	0.0143
##	20	0.1494	nan	0.1000	0.0044
##	40	0.0823	nan	0.1000	0.0006
##	60	0.0697	nan	0.1000	0.0000
##	80	0.0648	nan	0.1000	-0.0000
##	100	0.0587	nan	0.1000	-0.0001
##	120	0.0557	nan	0.1000	0.0000
##	140	0.0524	nan	0.1000	0.0000
##	150	0.0514	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8471	nan	0.1000	0.0883
##	2	0.7258	nan	0.1000	0.0612
##	3	0.6340	nan	0.1000	0.0453
##	4	0.5594	nan	0.1000	0.0366
##	5	0.4979	nan	0.1000	0.0308
##	6	0.4460	nan	0.1000	0.0258
##	7	0.4025	nan	0.1000	0.0219
##	8	0.3645	nan	0.1000	0.0185
##	9	0.3309	nan	0.1000	0.0164
##	10	0.3021	nan	0.1000	0.0143
##	20	0.1457	nan	0.1000	0.0038
##	40	0.0756	nan	0.1000	0.0005
##	60	0.0628	nan	0.1000	-0.0001
##	80	0.0564	nan	0.1000	-0.0001
##	100	0.0494	nan	0.1000	0.0000
##	120	0.0462	nan	0.1000	-0.0001
##	140	0.0438	nan	0.1000	-0.0000
##	150	0.0442	nan	0.1000	0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
----	------	---------------	---------------	----------	---------

##	1	0.8513	nan	0.1000	0.0886
##	2	0.7304	nan	0.1000	0.0616
##	3	0.6375	nan	0.1000	0.0458
##	4	0.5641	nan	0.1000	0.0362
##	5	0.5028	nan	0.1000	0.0312
##	6	0.4514	nan	0.1000	0.0256
##	7	0.4082	nan	0.1000	0.0215
##	8	0.3690	nan	0.1000	0.0190
##	9	0.3354	nan	0.1000	0.0166
##	10	0.3065	nan	0.1000	0.0143
##	20	0.1499	nan	0.1000	0.0041
##	40	0.0832	nan	0.1000	0.0006
##	60	0.0738	nan	0.1000	0.0000
##	80	0.0711	nan	0.1000	-0.0000
##	100	0.0691	nan	0.1000	0.0000
##	120	0.0676	nan	0.1000	0.0000
##	140	0.0668	nan	0.1000	-0.0001
##	150	0.0662	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8506	nan	0.1000	0.0894
##	2	0.7283	nan	0.1000	0.0613
##	3	0.6354	nan	0.1000	0.0462
##	4	0.5617	nan	0.1000	0.0366
##	5	0.5001	nan	0.1000	0.0314
##	6	0.4486	nan	0.1000	0.0257
##	7	0.4046	nan	0.1000	0.0220
##	8	0.3659	nan	0.1000	0.0192
##	9	0.3321	nan	0.1000	0.0167
##	10	0.3027	nan	0.1000	0.0146
##	20	0.1468	nan	0.1000	0.0039
##	40	0.0795	nan	0.1000	0.0007
##	60	0.0662	nan	0.1000	-0.0001
##	80	0.0608	nan	0.1000	-0.0001
##	100	0.0560	nan	0.1000	-0.0001
##	120	0.0520	nan	0.1000	-0.0001
##	140	0.0480	nan	0.1000	-0.0000
##	150	0.0468	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8509	nan	0.1000	0.0884
##	2	0.7285	nan	0.1000	0.0613
##	3	0.6355	nan	0.1000	0.0465
##	4	0.5604	nan	0.1000	0.0378
##	5	0.4983	nan	0.1000	0.0309
##	6	0.4461	nan	0.1000	0.0262
##	7	0.4013	nan	0.1000	0.0222
##	8	0.3628	nan	0.1000	0.0194
##	9	0.3297	nan	0.1000	0.0166
##	10	0.3001	nan	0.1000	0.0144

##	20	0.1429	nan	0.1000	0.0045
##	40	0.0738	nan	0.1000	0.0004
##	60	0.0619	nan	0.1000	-0.0000
##	80	0.0541	nan	0.1000	0.0003
##	100	0.0499	nan	0.1000	0.0002
##	120	0.0438	nan	0.1000	-0.0000
##	140	0.0393	nan	0.1000	-0.0001
##	150	0.0377	nan	0.1000	0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8615	nan	0.1000	0.0901
##	2	0.7393	nan	0.1000	0.0613
##	3	0.6452	nan	0.1000	0.0469
##	4	0.5702	nan	0.1000	0.0365
##	5	0.5076	nan	0.1000	0.0313
##	6	0.4557	nan	0.1000	0.0260
##	7	0.4103	nan	0.1000	0.0225
##	8	0.3716	nan	0.1000	0.0194
##	9	0.3378	nan	0.1000	0.0168
##	10	0.3077	nan	0.1000	0.0147
##	20	0.1481	nan	0.1000	0.0047
##	40	0.0784	nan	0.1000	0.0004
##	60	0.0679	nan	0.1000	0.0000
##	80	0.0660	nan	0.1000	-0.0001
##	100	0.0643	nan	0.1000	-0.0000
##	120	0.0634	nan	0.1000	-0.0001
##	140	0.0623	nan	0.1000	-0.0000
##	150	0.0617	nan	0.1000	0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8604	nan	0.1000	0.0876
##	2	0.7375	nan	0.1000	0.0612
##	3	0.6433	nan	0.1000	0.0471
##	4	0.5673	nan	0.1000	0.0376
##	5	0.5041	nan	0.1000	0.0311
##	6	0.4510	nan	0.1000	0.0261
##	7	0.4056	nan	0.1000	0.0225
##	8	0.3665	nan	0.1000	0.0196
##	9	0.3326	nan	0.1000	0.0167
##	10	0.3027	nan	0.1000	0.0148
##	20	0.1427	nan	0.1000	0.0041
##	40	0.0748	nan	0.1000	0.0004
##	60	0.0625	nan	0.1000	0.0001
##	80	0.0552	nan	0.1000	0.0000
##	100	0.0515	nan	0.1000	-0.0002
##	120	0.0464	nan	0.1000	-0.0000
##	140	0.0441	nan	0.1000	-0.0001
##	150	0.0428	nan	0.1000	-0.0000

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
----	------	---------------	---------------	----------	---------

##	1	0.8593	nan	0.1000	0.0893
##	2	0.7361	nan	0.1000	0.0629
##	3	0.6418	nan	0.1000	0.0476
##	4	0.5657	nan	0.1000	0.0381
##	5	0.5026	nan	0.1000	0.0310
##	6	0.4494	nan	0.1000	0.0266
##	7	0.4037	nan	0.1000	0.0221
##	8	0.3642	nan	0.1000	0.0196
##	9	0.3302	nan	0.1000	0.0171
##	10	0.3007	nan	0.1000	0.0147
##	20	0.1406	nan	0.1000	0.0044
##	40	0.0696	nan	0.1000	0.0002
##	60	0.0549	nan	0.1000	-0.0001
##	80	0.0448	nan	0.1000	-0.0000
##	100	0.0381	nan	0.1000	0.0001
##	120	0.0352	nan	0.1000	-0.0000
##	140	0.0319	nan	0.1000	-0.0001
##	150	0.0310	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8618	nan	0.1000	0.0913
##	2	0.7393	nan	0.1000	0.0609
##	3	0.6449	nan	0.1000	0.0474
##	4	0.5700	nan	0.1000	0.0371
##	5	0.5066	nan	0.1000	0.0318
##	6	0.4536	nan	0.1000	0.0261
##	7	0.4085	nan	0.1000	0.0223
##	8	0.3702	nan	0.1000	0.0192
##	9	0.3360	nan	0.1000	0.0172
##	10	0.3070	nan	0.1000	0.0145
##	20	0.1475	nan	0.1000	0.0042
##	40	0.0783	nan	0.1000	0.0006
##	60	0.0679	nan	0.1000	0.0000
##	80	0.0657	nan	0.1000	-0.0001
##	100	0.0638	nan	0.1000	0.0000
##	120	0.0632	nan	0.1000	-0.0001
##	140	0.0623	nan	0.1000	0.0001
##	150	0.0623	nan	0.1000	-0.0001

##	Iter	TrainDeviance	ValidDeviance	StepSize	Improve
##	1	0.8611	nan	0.1000	0.0885
##	2	0.7371	nan	0.1000	0.0629
##	3	0.6431	nan	0.1000	0.0463
##	4	0.5669	nan	0.1000	0.0379
##	5	0.5033	nan	0.1000	0.0314
##	6	0.4503	nan	0.1000	0.0265
##	7	0.4052	nan	0.1000	0.0223
##	8	0.3658	nan	0.1000	0.0198
##	9	0.3319	nan	0.1000	0.0165
##	10	0.3021	nan	0.1000	0.0150

```
##      20      0.1435      nan      0.1000      0.0044
##      40      0.0738      nan      0.1000      0.0005
##      60      0.0603      nan      0.1000     -0.0001
##      80      0.0561      nan      0.1000     -0.0000
##     100      0.0534      nan      0.1000      0.0000
##     120      0.0474      nan      0.1000     -0.0000
##     140      0.0443      nan      0.1000     -0.0000
##     150      0.0427      nan      0.1000     -0.0001
##
```

```
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      0.8615      nan      0.1000      0.0875
##      2      0.7375      nan      0.1000      0.0617
##      3      0.6431      nan      0.1000      0.0480
##      4      0.5660      nan      0.1000      0.0388
##      5      0.5027      nan      0.1000      0.0320
##      6      0.4495      nan      0.1000      0.0269
##      7      0.4038      nan      0.1000      0.0226
##      8      0.3645      nan      0.1000      0.0197
##      9      0.3303      nan      0.1000      0.0169
##     10      0.3005      nan      0.1000      0.0147
##     20      0.1401      nan      0.1000      0.0042
##     40      0.0693      nan      0.1000      0.0004
##     60      0.0571      nan      0.1000     -0.0000
##     80      0.0482      nan      0.1000     -0.0000
##    100      0.0444      nan      0.1000     -0.0003
##    120      0.0408      nan      0.1000      0.0000
##    140      0.0391      nan      0.1000     -0.0001
##    150      0.0376      nan      0.1000     -0.0001
##
```

```
## Iter   TrainDeviance   ValidDeviance   StepSize   Improve
##      1      0.8509      nan      0.1000      0.0896
##      2      0.7297      nan      0.1000      0.0608
##      3      0.6374      nan      0.1000      0.0467
##      4      0.5633      nan      0.1000      0.0360
##      5      0.5027      nan      0.1000      0.0301
##      6      0.4518      nan      0.1000      0.0253
##      7      0.4090      nan      0.1000      0.0219
##      8      0.3704      nan      0.1000      0.0194
##      9      0.3378      nan      0.1000      0.0161
##     10      0.3084      nan      0.1000      0.0147
##     20      0.1516      nan      0.1000      0.0047
##     40      0.0812      nan      0.1000      0.0005
##     50      0.0741      nan      0.1000      0.0002
```

#Logistic regression as top layer model

```
model_glm<-
```

```
train(trainSet[,predictors_top],trainSet[,outcomeName],method='glm')
```

#predict using GBM top layer model

```
testSet$gbm_stacked<-predict(model_gbm,testSet[,predictors_top])
```

```
#predict using logistic regression top layer model
testSet$glm_stacked<-predict(model_glm,testSet[,predictors_top])
```

```
confusionMatrix(testSet$IsAlert,testSet$gbm_stacked)
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##           Reference
```

```
## Prediction    No  Yes
```

```
##           No   515   10
```

```
##           Yes    9 1965
```

```
##
```

```
##               Accuracy : 0.9924
```

```
##               95% CI : (0.9882, 0.9954)
```

```
##       No Information Rate : 0.7903
```

```
##       P-Value [Acc > NIR] : <2e-16
```

```
##
```

```
##               Kappa : 0.9771
```

```
## Mcnemar's Test P-Value : 1
```

```
##
```

```
##               Sensitivity : 0.9828
```

```
##               Specificity : 0.9949
```

```
##               Pos Pred Value : 0.9810
```

```
##               Neg Pred Value : 0.9954
```

```
##               Prevalence : 0.2097
```

```
##               Detection Rate : 0.2061
```

```
##       Detection Prevalence : 0.2101
```

```
##       Balanced Accuracy : 0.9889
```

```
##
```

```
##       'Positive' Class : No
```

```
##
```

```
confusionMatrix(testSet$IsAlert,testSet$glm_stacked)
```

```
## Confusion Matrix and Statistics
```

```
##
```

```
##           Reference
```

```
## Prediction    No  Yes
```

```
##           No   514   11
```

```
##           Yes    3 1971
```

```
##
```

```
##               Accuracy : 0.9944
```

```
##               95% CI : (0.9906, 0.9969)
```

```
##       No Information Rate : 0.7931
```

```
##       P-Value [Acc > NIR] : < 2e-16
```

```
##
```

```
##               Kappa : 0.983
```

```
## Mcnemar's Test P-Value : 0.06137
```

```
##
```

```
##               Sensitivity : 0.9942
```

```
##          Specificity : 0.9945
##          Pos Pred Value : 0.9790
##          Neg Pred Value : 0.9985
##          Prevalence : 0.2069
##          Detection Rate : 0.2057
##          Detection Prevalence : 0.2101
##          Balanced Accuracy : 0.9943
##
##          'Positive' Class : No
##
```

When GBM model at top layer, the ensemble model has accuracy as 0.9924. When logistic model at top layer, the ensemble model has accuracy as 0.9944. they both are good, but I prefer using logistic model as top layer model.