Session 16 – Assignment

1. Use the below given data set
Data Set
2. Perform the below given activities:
a. Predict the no of comments in next H hrs
Note:-
1. Use LASSO, Elastic Net and Ridge and other regression techniques that are covered in the module
2. Report the training accuracy and test accuracy
3. compare with linear models and report the accuracy
4. create a graph displaying the accuracy of all models

Attribute Information:

(39 - This describes the H hrs, for which we have the target variable/ comments received.

, 54 -Target Variable - Decimal Target The no of comments in next H hrs(H is given in Feature no 39).

39
H Local
ï¿½Decimal(0-23) Encoding
Other feature
This describes the H hrs, for which we have the target variable/ comments received.

54
Target Variable
Decimal
Target
The no of comments in next H hrs(H is given in Feature no 39).

Prediction Accuracy

A good learner is the one which has good prediction accuracy; in other words, which has the smallest prediction error.
Let us try to understand the prediction problem intuitively. Consider the simple case of fitting a linear regression model to the observed data. A model is a good fit, if it provides a high R^2 value.

1. Use LASSO, Elastic Net and Ridge and other regression techniques that are covered in the module

```
library(tidyverse)

library(caret)

library(glmnet)

# Load the data

setwd("~/Dataset/Dataset/Training")


Features_Variant_1 <-
read.csv("C:/users/seshan/Documents/Dataset/Dataset/Training/Features_Variant_1.csv")

View(Features_Variant_1)

Features.data <- na.omit(Features_Variant_1)

# Split the data into training and test set

set.seed(123)

training.samples <- Features$X0.19 %>%

  createDataPartition(p = 0.8, list = FALSE)

train.data  <- Features_Variant_1[training.samples, ]

test.data <- Features_Variant_1[-training.samples, ]

# Predictor variables

x <- model.matrix(X0.19~., train.data)[,-1]

# Outcome variable

y <- train.data$X0.19

glmnet(x, y, alpha = 1, lambda = NULL)

# Find the best lambda using cross-validation

set.seed(123)

cv <- cv.glmnet(x, y, alpha = 0)

# Display the best lambda value
```

```
cv$lambda.min

plot(cv$lambda.min)

# Fit the final model on the training data

model <- glmnet(x, y, alpha = 0, lambda = cv$lambda.min)

plot(model)

# Display regression coefficients

coef(model)


# Make predictions on the test data

x.test <- model.matrix(X0.19 ~., test.data)[,-1]

predictions <- model %>% predict(x.test) %>% as.vector()

# Model performance metrics

data.frame(

  RMSE = RMSE(predictions, test.data$X0.19),

  Rsquare = R2(predictions, test.data$X0.19)

)


#Computing lasso regression

# Find the best lambda using cross-validation

set.seed(123)

cv <- cv.glmnet(x, y, alpha = 1)

# Display the best lambda value

cv$lambda.min

# Fit the final model on the training data

model <- glmnet(x, y, alpha = 1, lambda = cv$lambda.min)
```

```
# Dsiplay regression coefficients

coef(model)

# Make predictions on the test data

x.test <- model.matrix(X0.19 ~., test.data)[,-1]

predictions <- model %>% predict(x.test) %>% as.vector()

# Model performance metrics

data.frame(

  RMSE = RMSE(predictions, test.data$X0.19),

  Rsquare = R2(predictions, test.data$X0.19))

#Computing elastic net regession

# Build the model using the training set

set.seed(123)

model <- train(X0.19  ~., data = train.data, method = "glmnet",

  trControl = trainControl("cv", number = 10),

  tuneLength = 10

)

# Best tuning parameter

model$bestTun

plot(model$bestTun)

# Coefficient of the final model. You need

# to specify the best lambda

coef(model$finalModel, model$bestTune$lambda)

# Make predictions on the test data

x.test <- model.matrix(X0.19 ~., test.data)[,-1]

predictions <- model %>% predict(x.test)
```

```
# Model performance metrics
data.frame(
  RMSE = RMSE(predictions, test.data$X0.19),
  Rsquare = R2(predictions, test.data$X0.19)
)
#Comparing the different models
#Using caret package
#Setup a grid range of lambda values:
  lambda <- 10^seq(-3, 3, length = 100)
#Compute ridge regression
  # Build the model
  set.seed(123)
  ridge <- train(
    X0.19 ~., data = train.data, method = "glmnet",
    trControl = trainControl("cv", number = 10),
    tuneGrid = expand.grid(alpha = 0, lambda = lambda)
  )
  # Model coefficients
  coef(ridge$finalModel, ridge$bestTune$lambda)
  # Make predictions
  predictions <- ridge %>% predict(test.data)
  plot(predictions)
  # Model prediction performance
  data.frame(
    RMSE = RMSE(predictions, test.data$X0.19),
```

```
  Rsquare = R2(predictions, test.data$X0.19)
)

#Compute lasso regression
# Build the model
set.seed(123)
lasso <- train(
  X0.19 ~., data = train.data, method = "glmnet",
  trControl = trainControl("cv", number = 10),
  tuneGrid = expand.grid(alpha = 1, lambda = lambda)
)
plot( lasso)
# Model coefficients
coef(lasso$finalModel, lasso$bestTune$lambda)
  # Make predictions
predictions <- lasso %>% predict(test.data)
# Model prediction performance
data.frame(
  RMSE = RMSE(predictions, test.data$X0.19),
  Rsquare = R2(predictions, test.data$X0.19)
)
#Elastic net regression
# Build the model
set.seed(123)
elastic <- train(
```

```
  X0.19 ~., data = train.data, method = "glmnet",
  trControl = trainControl("cv", number = 10),
  tuneLength = 10
)
# Model coefficients
coef(elastic$finalModel, elastic$bestTune$lambda)

# Make predictions
predictions <- elastic %>% predict(test.data)
plot( predictions)
# Model prediction performance
data.frame(
  RMSE = RMSE(predictions, test.data$X0.19),
  Rsquare = R2(predictions, test.data$X0.19)
)
#Comparing models performance:
models <- list(ridge = ridge, lasso = lasso, elastic = elastic)
resamples(models) %>% summary( metric = "RMSE")



#k-fold Cross Validation
# load the library
library(caret)

# define training control
```

```
train_control <- trainControl(method="cv", number=10)

# fix the parameters of the algorithm

grid <- expand.grid(.fL=c(0), .usekernel=c(FALSE))

# train the model

model <- train(X0.19~., data=Features_Variant_1, trControl=train_control, method="nb",
tuneGrid=grid)

# summarize results

print(model)


# load the library

library(caret)


# define training control

train_control <- trainControl(method="repeatedcv", number=10, repeats=3)

# train the model

model <- train(X0.19~., data=Features_Variant_1, trControl=train_control, method="nb")

# summarize results

print(model)


#create a graph displaying the accuracy of all models

plot(model)

plot(varImp(ridge$finalModel))

plot(cv)

plot(ridge)

hist(Features$X0.19,col = "green")

hist(Features$X24,col = "red")
```

hist(Features$X11.291044776119403,col = 'yellow')

fit = glmnet(x, y)

plot(fit)

cvfit = cv.glmnet(x, y)

plot(cvfit)

tfit=glmnet(x,y,lower=-.7,upper=.5)

plot(tfit)

```
> library(tidyverse)
> library(caret)
> library(glmnet)
> # Load the data
> setwd("~/Dataset/Dataset/Training")
>
> Features_Variant_1 <- read.csv("C:/users/seshan/Documents/Dataset/Dataset/Training/
Features_Variant_1.csv")
> View(Features_Variant_1)
> Features.data <- na.omit(Features_Variant_1)
> # Split the data into training and test set
> set.seed(123)
> training.samples <- Features$X0.19 %>%
+   createDataPartition(p = 0.8, list = FALSE)
> train.data  <- Features_Variant_1[training.samples, ]
> test.data <- Features_Variant_1[-training.samples, ]
> # Predictor variables
> x <- model.matrix(X0.19~., train.data)[,-1]
> # Outcome variable
> y <- train.data$X0.19
> glmnet(x, y, alpha = 1, lambda = NULL)

Call:  glmnet(x = x, y = y, alpha = 1, lambda = NULL)

       Df    %Dev    Lambda
  [1,]  0 0.00000 18.250000
  [2,]  1 0.04881 16.630000
  [3,]  1 0.08933 15.150000
  [4,]  1 0.12300 13.810000
  [5,]  1 0.15090 12.580000
  [6,]  1 0.17410 11.460000
  [7,]  1 0.19330 10.440000
  [8,]  1 0.20930  9.516000
  [9,]  1 0.22260  8.671000
 [10,]  1 0.23360  7.900000
 [11,]  1 0.24270  7.198000
```

```
 [12,]  1 0.25030  6.559000
 [13,]  1 0.25660  5.976000
 [14,]  2 0.26350  5.445000
 [15,]  2 0.26950  4.962000
 [16,]  3 0.27660  4.521000
 [17,]  3 0.28290  4.119000
 [18,]  4 0.28840  3.753000
 [19,]  4 0.29290  3.420000
 [20,]  4 0.29670  3.116000
 [21,]  6 0.30040  2.839000
 [22,]  6 0.30370  2.587000
 [23,]  6 0.30640  2.357000
 [24,]  7 0.30870  2.148000
 [25,]  7 0.31060  1.957000
 [26,]  8 0.31210  1.783000
 [27,]  8 0.31350  1.625000
 [28,]  8 0.31490  1.480000
 [29,]  8 0.31610  1.349000
 [30,]  8 0.31710  1.229000
 [31,]  8 0.31790  1.120000
 [32,]  8 0.31860  1.020000
 [33,]  8 0.31920  0.929700
 [34,]  8 0.31970  0.847100
 [35,]  9 0.32020  0.771900
 [36,]  9 0.32060  0.703300
 [37,]  9 0.32090  0.640800
 [38,]  9 0.32120  0.583900
 [39,] 10 0.32150  0.532000
 [40,] 10 0.32180  0.484800
 [41,] 11 0.32200  0.441700
 [42,] 11 0.32240  0.402500
 [43,] 11 0.32270  0.366700
 [44,] 12 0.32290  0.334100
 [45,] 12 0.32320  0.304400
 [46,] 13 0.32330  0.277400
 [47,] 14 0.32370  0.252800
 [48,] 16 0.32390  0.230300
 [49,] 17 0.32420  0.209800
 [50,] 17 0.32440  0.191200
 [51,] 18 0.32460  0.174200
 [52,] 22 0.32480  0.158700
 [53,] 22 0.32500  0.144600
 [54,] 23 0.32520  0.131800
 [55,] 24 0.32540  0.120100
 [56,] 24 0.32550  0.109400
 [57,] 26 0.32570  0.099690
 [58,] 29 0.32590  0.090830
 [59,] 29 0.32600  0.082770
 [60,] 30 0.32620  0.075410
 [61,] 30 0.32630  0.068710
 [62,] 30 0.32640  0.062610
 [63,] 31 0.32640  0.057050
 [64,] 31 0.32650  0.051980
 [65,] 34 0.32660  0.047360
 [66,] 35 0.32660  0.043150
 [67,] 36 0.32680  0.039320
 [68,] 36 0.32700  0.035830
 [69,] 37 0.32730  0.032640
 [70,] 38 0.32750  0.029740
 [71,] 37 0.32770  0.027100
 [72,] 40 0.32790  0.024690
 [73,] 40 0.32820  0.022500
 [74,] 45 0.32840  0.020500
 [75,] 45 0.32880  0.018680
```

```
 [76,] 46 0.32930  0.017020
 [77,] 46 0.32960  0.015510
 [78,] 47 0.32980  0.014130
 [79,] 47 0.33000  0.012880
 [80,] 47 0.33010  0.011730
 [81,] 47 0.33030  0.010690
 [82,] 47 0.33040  0.009740
 [83,] 47 0.33050  0.008875
 [84,] 47 0.33060  0.008086
 [85,] 48 0.33070  0.007368
 [86,] 48 0.33080  0.006713
 [87,] 48 0.33090  0.006117
 [88,] 48 0.33090  0.005574
 [89,] 48 0.33100  0.005078
 [90,] 48 0.33100  0.004627
 [91,] 48 0.33110  0.004216
 [92,] 48 0.33110  0.003842
 [93,] 49 0.33120  0.003500
 [94,] 49 0.33120  0.003189
 [95,] 49 0.33120  0.002906
 [96,] 49 0.33120  0.002648
 [97,] 49 0.33130  0.002413
 [98,] 49 0.33130  0.002198
 [99,] 49 0.33130  0.002003
[100,] 49 0.33130  0.001825
> # Find the best lambda using cross-validation
> set.seed(123)
> cv <- cv.glmnet(x, y, alpha = 0)
> # Display the best lambda value
> cv$lambda.min
[1] 3.189382
> plot(cv$lambda.min)
> # Fit the final model on the training data
> model <- glmnet(x, y, alpha = 0, lambda = cv$lambda.min)
> plot(model)
> # Display regression coefficients
> coef(model)
54 x 1 sparse Matrix of class "dgCMatrix"
                               s0
(Intercept)         -2.538449e+00
X634995              4.086976e-08
X0                  -2.391902e-05
X463                -1.118531e-05
X1                   7.735292e-04
X0.0                 1.350121e-02
X806.0               1.553809e-03
X11.291044776119403  9.304117e-03
X1.0                 1.793778e-04
X70.49513846124168   2.001045e-02
X0.0.1              -1.965736e-02
X806.0.1            -1.021345e-03
X7.574626865671642   2.932718e-02
X0.0.2               1.122924e-01
X69.435826365571    -3.244738e-03
X0.0.3              -7.678915e-03
X76.0               -2.361222e-04
X2.6044776119402986  2.333540e-02
X0.0.4               1.156420e-01
X8.50550186882253    4.524854e-03
X0.0.5              -1.178544e-02
X806.0.2            -1.639273e-03
X10.649253731343284 -3.665694e-03
X1.0.1              -1.572424e-02
X70.25478763764251   5.195732e-03
```

```
X.69.0                1.960444e-04
X806.0.3             -5.160122e-04
X4.970149253731344    4.298933e-02
X0.0.6               -3.755897e-02
X69.85058043098057    4.831630e-03
X0.1                  3.362289e-03
X0.2                  1.151692e-01
X0.3                  2.359120e-02
X0.4                  5.274079e-04
X0.5                  6.427015e-02
X65                  -1.912346e-01
X166                  2.483775e-04
X2                    1.745596e-03
X0.6                  .
X24                   3.970945e-01
X0.7                 -8.263988e-01
X0.8                 -4.301798e-01
X0.9                 -4.379730e-01
X1.1                  7.482821e-01
X0.10                 4.288169e-01
X0.11                 5.881030e-01
X0.12                -2.262055e-01
X0.13                -5.948819e-01
X0.14                 4.781008e-01
X0.15                -7.372765e-02
X0.16                 1.043352e+00
X0.17                -1.065425e-01
X0.18                -2.291072e-01
X1.2                 -5.230538e-01
>
> # Make predictions on the test data
> x.test <- model.matrix(X0.19 ~., test.data)[,-1]
> predictions <- model %>% predict(x.test) %>% as.vector()
> # Model performance metrics
> data.frame(
+   RMSE = RMSE(predictions, test.data$X0.19),
+   Rsquare = R2(predictions, test.data$X0.19)
+ )
      RMSE   Rsquare
1 34.21296 0.3043655
>
> #Computing lasso regression
> # Find the best lambda using cross-validation
> set.seed(123)
> cv <- cv.glmnet(x, y, alpha = 1)
> # Display the best lambda value
> cv$lambda.min
[1] 0.7033004
> # Fit the final model on the training data
> model <- glmnet(x, y, alpha = 1, lambda = cv$lambda.min)
> # Dsiplay regression coefficients
> coef(model)
54 x 1 sparse Matrix of class "dgCMatrix"
                               s0
(Intercept)           5.0667129773
X634995               .
X0                    .
X463                  .
X1                    .
X0.0                  .
X806.0                .
X11.291044776119403   .
X1.0                  .
X70.49513846124168    0.0131953053
```

```
x0.0.1                  .
x806.0.1                .
x7.574626865671642      0.0278254674
x0.0.2                  0.0955320465
x69.435826365571        .
x0.0.3                  .
x76.0                   .
x2.6044776119402986     .
x0.0.4                  0.1082157028
x8.5055018682253        .
x0.0.5                  .
x806.0.2                .
x10.649253731343284     .
x1.0.1                  .
x70.25478763764251      .
x.69.0                  .
x806.0.3                .
x4.970149253731344      .
x0.0.6                  .
x69.85058043098057      .
x0.1                    .
x0.2                    0.1661874069
x0.3                    .
x0.4                    .
x0.5                    0.0264102499
x65                    -0.1704729896
x166                    .
x2                      0.0007766533
x0.6                    .
x24                     0.0658390632
x0.7                    .
x0.8                    .
x0.9                    .
x1.1                    .
x0.10                   .
x0.11                   .
x0.12                   .
x0.13                   .
x0.14                   .
x0.15                   .
x0.16                   .
x0.17                   .
x0.18                   .
x1.2                    .
> # Make predictions on the test data
> x.test <- model.matrix(X0.19 ~., test.data)[,-1]
> predictions <- model %>% predict(x.test) %>% as.vector()
> # Model performance metrics
> data.frame(
+   RMSE = RMSE(predictions, test.data$X0.19),
+   Rsquare = R2(predictions, test.data$X0.19))
      RMSE   Rsquare
1 34.35851 0.2981491
> #Computing elastic net regession
> # Build the model using the training set
> set.seed(123)
> model <- train(X0.19  ~., data = train.data, method = "glmnet",
+   trControl = trainControl("cv", number = 10),
+   tuneLength = 10
+ )
> # Best tuning parameter
> model$bestTun
   alpha    lambda
96     1 0.5547923
```

```
> plot(model$bestTun)
> # Coefficient of the final model. You need
> # to specify the best lambda
> coef(model$finalModel, model$bestTune$lambda)
54 x 1 sparse Matrix of class "dgCMatrix"
                                1
(Intercept)           3.243771e+00
X634995               .
X0                   -1.451030e-06
X463                  .
X1                    .
X0.0                  .
X806.0                .
X11.291044776119403   .
X1.0                  .
X70.49513846124168    1.537445e-02
X0.0.1                .
X806.0.1              .
X7.574626865671642    2.330706e-02
X0.0.2                1.020902e-01
X69.435826365571      .
X0.0.3                .
X76.0                 .
X2.6044776119402986   .
X0.0.4                1.150414e-01
X8.50550186882253     .
X0.0.5                .
X806.0.2              .
X10.649253731343284   .
X1.0.1                .
X70.25478763764251    .
X.69.0                .
X806.0.3              .
X4.970149253731344    .
X0.0.6                .
X69.85058043098057    .
X0.1                  .
X0.2                  1.650641e-01
X0.3                  .
X0.4                  .
X0.5                  2.819936e-02
X65                  -1.762485e-01
X166                  .
X2                    9.079099e-04
X0.6                  .
X24                   1.461588e-01
X0.7                  .
X0.8                  .
X0.9                  .
X1.1                  .
X0.10                 .
X0.11                 .
X0.12                 .
X0.13                 .
X0.14                 .
X0.15                 .
X0.16                 .
X0.17                 .
X0.18                 .
X1.2                  .
> # Make predictions on the test data
> x.test <- model.matrix(X0.19 ~., test.data)[,-1]
> predictions <- model %>% predict(x.test)
> # Model performance metrics
```

```
> data.frame(
+   RMSE = RMSE(predictions, test.data$X0.19),
+   Rsquare = R2(predictions, test.data$X0.19)
+ )
      RMSE   Rsquare
1 34.31238 0.2993523
> #Comparing the different models
> #Using caret package
> #Setup a grid range of lambda values:
>   lambda <- 10^seq(-3, 3, length = 100)
> #Compute ridge regression
>   # Build the model
>   set.seed(123)
>   ridge <- train(
+     X0.19 ~., data = train.data, method = "glmnet",
+     trControl = trainControl("cv", number = 10),
+     tuneGrid = expand.grid(alpha = 0, lambda = lambda)
+   )
>   # Model coefficients
>   coef(ridge$finalModel, ridge$bestTune$lambda)
54 x 1 sparse Matrix of class "dgCMatrix"
                                1
(Intercept)         -2.780069e+00
X634995              5.350956e-08
X0                  -2.364834e-05
X463                -1.329873e-05
X1                   6.216835e-04
X0.0                 2.038074e-02
X806.0               1.700351e-03
X11.291044776119403  8.550170e-03
X1.0                -4.004515e-03
X70.49513846124168   2.306081e-02
X0.0.1              -5.381912e-02
X806.0.1            -1.655099e-03
X7.574626865671642   2.994944e-02
X0.0.2               1.245636e-01
X69.435826365571    -7.884156e-03
X0.0.3               2.622963e-02
X76.0               -3.747457e-04
X2.6044776119402986  2.978466e-02
X0.0.4               1.358288e-01
X8.50550186882253    3.211969e-03
X0.0.5              -1.596299e-02
X806.0.2            -2.000906e-03
X10.649253731343284 -3.364991e-03
X1.0.1              -1.984096e-02
X70.25478763764251   7.880343e-03
X.69.0              -2.562913e-04
X806.0.3             9.298950e-05
X4.970149253731344   5.279758e-02
X0.0.6              -3.668527e-02
X69.85058043098057   3.578648e-03
X0.1                 2.690513e-03
X0.2                 1.241846e-01
X0.3                 3.087028e-02
X0.4                -5.186126e-03
X0.5                 6.542507e-02
X65                 -1.911067e-01
X166                 2.396281e-04
X2                   1.857963e-03
X0.6                 .
X24                  4.067486e-01
X0.7                -8.764705e-01
X0.8                -4.849690e-01
```

```
X0.9                   -4.740900e-01
X1.1                    7.672004e-01
X0.10                   4.799051e-01
X0.11                   6.261735e-01
X0.12                  -2.236307e-01
X0.13                  -6.182879e-01
X0.14                   5.103142e-01
X0.15                  -3.737265e-02
X0.16                   1.097674e+00
X0.17                  -1.186700e-01
X0.18                  -2.627125e-01
X1.2                   -5.621735e-01
>   # Make predictions
>   predictions <- ridge %>% predict(test.data)
>   plot(predictions)
>   # Model prediction performance
>   data.frame(
+     RMSE = RMSE(predictions, test.data$X0.19),
+     Rsquare = R2(predictions, test.data$X0.19)
+   )
      RMSE   Rsquare
1 34.15522 0.3061988
>
>   #Compute lasso regression
>   # Build the model
>   set.seed(123)
>   lasso <- train(
+     X0.19 ~., data = train.data, method = "glmnet",
+     trControl = trainControl("cv", number = 10),
+     tuneGrid = expand.grid(alpha = 1, lambda = lambda)
+   )

In nominalTrainWorkflow(x = x, y = y, wts = weights, info = trainInfo,  :
  There were missing values in resampled performance measures.
>   plot( lasso)
>   # Model coefficients
>   coef(lasso$finalModel, lasso$bestTune$lambda)
54 x 1 sparse Matrix of class "dgCMatrix"
                                    1
(Intercept)             2.988187e+00
X634995                 .
X0                     -2.504262e-06
X463                    .
X1                      .
X0.0                    .
X806.0                  .
X11.291044776119403     .
X1.0                    .
X70.49513846124168      1.574129e-02
X0.0.1                  .
X806.0.1                .
X7.574626865671642      2.257750e-02
X0.0.2                  1.029959e-01
X69.435826365571        .
X0.0.3                  .
X76.0                   .
X2.6044776119402986     .
X0.0.4                  1.160087e-01
X8.50550186882253       .
X0.0.5                  .
X806.0.2                .
X10.649253731343284     .
X1.0.1                  .
X70.25478763764251      .
```

```
X.69.0                .
X806.0.3              .
X4.970149253731344    .
X0.0.6                .
X69.85058043098057    .
X0.1                  .
X0.2                  1.649295e-01
X0.3                  .
X0.4                  .
X0.5                  2.844279e-02
X65                  -1.770593e-01
X166                  .
X2                    9.269250e-04
X0.6                  .
X24                   1.574830e-01
X0.7                  .
X0.8                  .
X0.9                  .
X1.1                  .
X0.10                 .
X0.11                 .
X0.12                 .
X0.13                 .
X0.14                 .
X0.15                 .
X0.16                 .
X0.17                 .
X0.18                 .
X1.2                  .
>     # Make predictions
>   predictions <- lasso %>% predict(test.data)
>   # Model prediction performance
>   data.frame(
+     RMSE = RMSE(predictions, test.data$X0.19),
+     Rsquare = R2(predictions, test.data$X0.19)
+   )
     RMSE   Rsquare
1 34.3056 0.2995397
>   #Elastic net regression
>   # Build the model
>   set.seed(123)
>   elastic <- train(
+     X0.19 ~., data = train.data, method = "glmnet",
+     trControl = trainControl("cv", number = 10),
+     tuneLength = 10
+   )
>   # Model coefficients
>   coef(elastic$finalModel, elastic$bestTune$lambda)
54 x 1 sparse Matrix of class "dgCMatrix"
                                 1
(Intercept)           3.243771e+00
X634995               .
X0                   -1.451030e-06
X463                  .
X1                    .
X0.0                  .
X806.0                .
X11.291044776119403   .
X1.0                  .
X70.49513846124168    1.537445e-02
X0.0.1                .
X806.0.1              .
X7.574626865671642    2.330706e-02
X0.0.2                1.020902e-01
```

```
x69.435826365571      .
x0.0.3                .
x76.0                 .
x2.6044776119402986   .
x0.0.4                1.150414e-01
x8.50550186882253     .
x0.0.5                .
x806.0.2              .
x10.649253731343284   .
x1.0.1                .
x70.25478763764251    .
x.69.0                .
x806.0.3              .
x4.970149253731344    .
x0.0.6                .
x69.85058043098057    .
x0.1                  .
x0.2                  1.650641e-01
x0.3                  .
x0.4                  .
x0.5                  2.819936e-02
x65                  -1.762485e-01
x166                  .
x2                    9.079099e-04
x0.6                  .
x24                   1.461588e-01
x0.7                  .
x0.8                  .
x0.9                  .
x1.1                  .
x0.10                 .
x0.11                 .
x0.12                 .
x0.13                 .
x0.14                 .
x0.15                 .
x0.16                 .
x0.17                 .
x0.18                 .
x1.2                  .
>
>   # Make predictions
>   predictions <- elastic %>% predict(test.data)
>   plot( predictions)
>   # Model prediction performance
>   data.frame(
+     RMSE = RMSE(predictions, test.data$X0.19),
+     Rsquare = R2(predictions, test.data$X0.19)
+   )
      RMSE   Rsquare
1 34.31238 0.2993523
>   #Comparing models performance:
>   models <- list(ridge = ridge, lasso = lasso, elastic = elastic)
>   resamples(models) %>% summary( metric = "RMSE")

Call:
summary.resamples(object = ., metric = "RMSE")

Models: ridge, lasso, elastic
Number of resamples: 10

RMSE
            Min.  1st Qu.   Median     Mean  3rd Qu.     Max. NA's
ridge   21.64890 25.52171 28.01852 27.99756 30.88915 35.66276    0
```

```
lasso   21.52017 25.58002 28.07640 27.93523 30.71819 35.53640    0
elastic 21.51814 25.58351 28.07020 27.93467 30.72364 35.53586    0

>
>
>   #k-fold Cross Validation
>   # load the library
>   library(caret)
>
>   # define training control
>   train_control <- trainControl(method="cv", number=10)
>   # fix the parameters of the algorithm
>   grid <- expand.grid(.fL=c(0), .usekernel=c(FALSE))
>   # train the model
>   model <- train(X0.19~., data=Features_Variant_1, trControl=train_control, method=
"nb", tuneGrid=grid)
>   # summarize results
>   print(model)
glmnet

32760 samples
   53 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 29484, 29485, 29484, 29484, 29483, 29484, ...
Resampling results across tuning parameters:

  alpha  lambda        RMSE      Rsquared   MAE
  0.1     0.008432348  28.00932  0.3176368   8.073572
  0.1     0.019479818  28.00913  0.3176396   8.072474
  0.1     0.045000908  28.00646  0.3176551   8.050171
  0.1     0.103957936  28.00846  0.3174455   8.016234
  0.1     0.240156321  28.00059  0.3176130   7.975161
  0.1     0.554792263  27.98067  0.3181937   7.923823
  0.1     1.281642117  27.96815  0.3182085   7.868204
  0.1     2.960759592  27.97201  0.3179401   7.737538
  0.1     6.839738840  28.04120  0.3164505   7.526685
  0.1    15.800684229  28.33270  0.3138865   7.217222
  0.2     0.008432348  28.01765  0.3172223   8.072621
  0.2     0.019479818  28.01210  0.3174223   8.061405
  0.2     0.045000908  28.00976  0.3174643   8.039239
  0.2     0.103957936  28.00648  0.3174175   7.996145
  0.2     0.240156321  27.98642  0.3180788   7.943594
  0.2     0.554792263  27.96948  0.3183579   7.887480
  0.2     1.281642117  27.95241  0.3186087   7.775205
  0.2     2.960759592  27.96450  0.3182276   7.562917
  0.2     6.839738840  28.09348  0.3170458   7.222323
  0.2    15.800684229  28.65765  0.3151025   7.133642
  0.3     0.008432348  28.00299  0.3177588   8.065477
  0.3     0.019479818  28.00437  0.3177326   8.057176
  0.3     0.045000908  28.01072  0.3174032   8.031060
  0.3     0.103957936  28.00038  0.3176307   7.975466
  0.3     0.240156321  27.97652  0.3183974   7.915900
  0.3     0.554792263  27.95698  0.3186058   7.846411
  0.3     1.281642117  27.94976  0.3185072   7.683206
  0.3     2.960759592  27.97534  0.3181303   7.400328
  0.3     6.839738840  28.17680  0.3172627   6.985857
  0.3    15.800684229  29.13696  0.3103036   7.570747
  0.4     0.008432348  28.01830  0.3172446   8.079680
  0.4     0.019479818  28.00882  0.3176078   8.058608
  0.4     0.045000908  28.01072  0.3173242   8.019561
  0.4     0.103957936  27.99402  0.3178502   7.957537
  0.4     0.240156321  27.96938  0.3185741   7.892792
```

0.4	0.554792263	27.94835	0.3187576	7.805517
0.4	1.281642117	27.94390	0.3185641	7.599557
0.4	2.960759592	27.99377	0.3179287	7.243370
0.4	6.839738840	28.28988	0.3165676	6.848175
0.4	15.800684229	29.67198	0.2994897	7.987755
0.5	0.008432348	28.01315	0.3174913	8.081913
0.5	0.019479818	28.00741	0.3176329	8.055975
0.5	0.045000908	28.00761	0.3174288	8.007801
0.5	0.103957936	27.98665	0.3181211	7.942926
0.5	0.240156321	27.96218	0.3187504	7.873342
0.5	0.554792263	27.94327	0.3188512	7.760826
0.5	1.281642117	27.94205	0.3185650	7.519772
0.5	2.960759592	28.02238	0.3174298	7.096167
0.5	6.839738840	28.45004	0.3134711	6.885703
0.5	15.800684229	30.10478	0.2911250	8.323360
0.6	0.008432348	28.01123	0.3175588	8.077084
0.6	0.019479818	28.00535	0.3177547	8.051417
0.6	0.045000908	28.00633	0.3174460	7.995543
0.6	0.103957936	27.98081	0.3183217	7.929786
0.6	0.240156321	27.95596	0.3188777	7.854967
0.6	0.554792263	27.94107	0.3188351	7.718358
0.6	1.281642117	27.94808	0.3183242	7.443956
0.6	2.960759592	28.05422	0.3169109	6.963000
0.6	6.839738840	28.64667	0.3078443	7.060181
0.6	15.800684229	30.45088	0.2909322	8.582636
0.7	0.008432348	28.01327	0.3174691	8.070577
0.7	0.019479818	28.00938	0.3175657	8.046031
0.7	0.045000908	28.00293	0.3175654	7.982522
0.7	0.103957936	27.97610	0.3184735	7.917651
0.7	0.240156321	27.95104	0.3189454	7.835833
0.7	0.554792263	27.94103	0.3187177	7.678114
0.7	1.281642117	27.95454	0.3181156	7.369797
0.7	2.960759592	28.09005	0.3163118	6.846891
0.7	6.839738840	28.85612	0.3001402	7.277639
0.7	15.800684229	30.85446	0.2909322	8.878579
0.8	0.008432348	28.01238	0.3175718	8.070449
0.8	0.019479818	28.00936	0.3175163	8.039224
0.8	0.045000908	28.00020	0.3176370	7.972411
0.8	0.103957936	27.97254	0.3185722	7.906252
0.8	0.240156321	27.94734	0.3189795	7.817664
0.8	0.554792263	27.94076	0.3186304	7.640068
0.8	1.281642117	27.96246	0.3178774	7.295586
0.8	2.960759592	28.13781	0.3151418	6.755044
0.8	6.839738840	29.02499	0.2946305	7.449163
0.8	15.800684229	31.33025	0.2909322	9.216728
0.9	0.008432348	28.01155	0.3175817	8.069278
0.9	0.019479818	28.01019	0.3174714	8.033794
0.9	0.045000908	27.99737	0.3177359	7.963507
0.9	0.103957936	27.96951	0.3186458	7.895521
0.9	0.240156321	27.94458	0.3189922	7.800738
0.9	0.554792263	27.93743	0.3186621	7.602655
0.9	1.281642117	27.97328	0.3175364	7.223312
0.9	2.960759592	28.19981	0.3131783	6.691255
0.9	6.839738840	29.16270	0.2914991	7.572163
0.9	15.800684229	31.88869	0.2909322	9.602631
1.0	0.008432348	28.00984	0.3176179	8.064194
1.0	0.019479818	28.01048	0.3174197	8.027480
1.0	0.045000908	27.99330	0.3178932	7.955851
1.0	0.103957936	27.96647	0.3187201	7.885657
1.0	0.240156321	27.94291	0.3189672	7.784590
1.0	0.554792263	27.93467	0.3186856	7.565986
1.0	1.281642117	27.98635	0.3171131	7.153438
1.0	2.960759592	28.26663	0.3108182	6.661504
1.0	6.839738840	29.27235	0.2909322	7.666803

```
  1.0    15.800684229  32.54609  0.2909322  10.044511

RMSE was used to select the optimal model using the smallest value.
The final values used for the model were alpha = 1 and lambda = 0.5547923.
>
>   # load the library
>   library(caret)
>
>   # define training control
>   train_control <- trainControl(method="repeatedcv", number=10, repeats=3)
>   # train the model
>   model <- train(X0.19~., data=Features_Variant_1, trControl=train_control, method=
"nb")
>   # summarize results
>   print(model)
glmnet

32760 samples
   53 predictor

No pre-processing
Resampling: Cross-Validated (10 fold)
Summary of sample sizes: 29484, 29485, 29484, 29484, 29483, 29484, ...
Resampling results across tuning parameters:

  alpha  lambda        RMSE      Rsquared   MAE
  0.1     0.008432348  28.00932  0.3176368   8.073572
  0.1     0.019479818  28.00913  0.3176396   8.072474
  0.1     0.045000908  28.00646  0.3176551   8.050171
  0.1     0.103957936  28.00846  0.3174455   8.016234
  0.1     0.240156321  28.00059  0.3176130   7.975161
  0.1     0.554792263  27.98067  0.3181937   7.923823
  0.1     1.281642117  27.96815  0.3182085   7.868204
  0.1     2.960759592  27.97201  0.3179401   7.737538
  0.1     6.839738840  28.04120  0.3164505   7.526685
  0.1    15.800684229  28.33270  0.3138865   7.217222
  0.2     0.008432348  28.01765  0.3172223   8.072621
  0.2     0.019479818  28.01210  0.3174223   8.061405
  0.2     0.045000908  28.00976  0.3174643   8.039239
  0.2     0.103957936  28.00648  0.3174175   7.996145
  0.2     0.240156321  27.98642  0.3180788   7.943594
  0.2     0.554792263  27.96948  0.3183579   7.887480
  0.2     1.281642117  27.95241  0.3186087   7.775205
  0.2     2.960759592  27.96450  0.3182276   7.562917
  0.2     6.839738840  28.09348  0.3170458   7.222323
  0.2    15.800684229  28.65765  0.3151025   7.133642
  0.3     0.008432348  28.00299  0.3177588   8.065477
  0.3     0.019479818  28.00437  0.3177326   8.057176
  0.3     0.045000908  28.01072  0.3174032   8.031060
  0.3     0.103957936  28.00038  0.3176307   7.975466
  0.3     0.240156321  27.97652  0.3183974   7.915900
  0.3     0.554792263  27.95698  0.3186058   7.846411
  0.3     1.281642117  27.94976  0.3185072   7.683206
  0.3     2.960759592  27.97534  0.3181303   7.400328
  0.3     6.839738840  28.17680  0.3172627   6.985857
  0.3    15.800684229  29.13696  0.3103036   7.570747
  0.4     0.008432348  28.01830  0.3172446   8.079680
  0.4     0.019479818  28.00882  0.3176078   8.058608
  0.4     0.045000908  28.01072  0.3173242   8.019561
  0.4     0.103957936  27.99402  0.3178502   7.957537
  0.4     0.240156321  27.96938  0.3185741   7.892792
  0.4     0.554792263  27.94835  0.3187576   7.805517
  0.4     1.281642117  27.94390  0.3185641   7.599557
  0.4     2.960759592  27.99377  0.3179287   7.243370
```

```
  0.4     6.839738840  28.28988  0.3165676   6.848175
  0.4    15.800684229  29.67198  0.2994897   7.987755
  0.5     0.008432348  28.01315  0.3174913   8.081913
  0.5     0.019479818  28.00741  0.3176329   8.055975
  0.5     0.045000908  28.00761  0.3174288   8.007801
  0.5     0.103957936  27.98665  0.3181211   7.942926
  0.5     0.240156321  27.96218  0.3187504   7.873342
  0.5     0.554792263  27.94327  0.3188512   7.760826
  0.5     1.281642117  27.94205  0.3185650   7.519772
  0.5     2.960759592  28.02238  0.3174298   7.096167
  0.5     6.839738840  28.45004  0.3134711   6.885703
  0.5    15.800684229  30.10478  0.2911250   8.323360
  0.6     0.008432348  28.01123  0.3175588   8.077084
  0.6     0.019479818  28.00535  0.3177547   8.051417
  0.6     0.045000908  28.00633  0.3174460   7.995543
  0.6     0.103957936  27.98081  0.3183217   7.929786
  0.6     0.240156321  27.95596  0.3188777   7.854967
  0.6     0.554792263  27.94107  0.3188351   7.718358
  0.6     1.281642117  27.94808  0.3183242   7.443956
  0.6     2.960759592  28.05422  0.3169109   6.963000
  0.6     6.839738840  28.64667  0.3078443   7.060181
  0.6    15.800684229  30.45088  0.2909322   8.582636
  0.7     0.008432348  28.01327  0.3174691   8.070577
  0.7     0.019479818  28.00938  0.3175657   8.046031
  0.7     0.045000908  28.00293  0.3175654   7.982522
  0.7     0.103957936  27.97610  0.3184735   7.917651
  0.7     0.240156321  27.95104  0.3189454   7.835833
  0.7     0.554792263  27.94103  0.3187177   7.678114
  0.7     1.281642117  27.95454  0.3181156   7.369797
  0.7     2.960759592  28.09005  0.3163118   6.846891
  0.7     6.839738840  28.85612  0.3001402   7.277639
  0.7    15.800684229  30.85446  0.2909322   8.878579
  0.8     0.008432348  28.01238  0.3175718   8.070449
  0.8     0.019479818  28.00936  0.3175163   8.039224
  0.8     0.045000908  28.00020  0.3176370   7.972411
  0.8     0.103957936  27.97254  0.3185722   7.906252
  0.8     0.240156321  27.94734  0.3189795   7.817664
  0.8     0.554792263  27.94076  0.3186304   7.640068
  0.8     1.281642117  27.96246  0.3178774   7.295586
  0.8     2.960759592  28.13781  0.3151418   6.755044
  0.8     6.839738840  29.02499  0.2946305   7.449163
  0.8    15.800684229  31.33025  0.2909322   9.216728
  0.9     0.008432348  28.01155  0.3175817   8.069278
  0.9     0.019479818  28.01019  0.3174714   8.033794
  0.9     0.045000908  27.99737  0.3177359   7.963507
  0.9     0.103957936  27.96951  0.3186458   7.895521
  0.9     0.240156321  27.94458  0.3189922   7.800738
  0.9     0.554792263  27.93743  0.3186621   7.602655
  0.9     1.281642117  27.97328  0.3175364   7.223312
  0.9     2.960759592  28.19981  0.3131783   6.691255
  0.9     6.839738840  29.16270  0.2914991   7.572163
  0.9    15.800684229  31.88869  0.2909322   9.602631
  1.0     0.008432348  28.00984  0.3176179   8.064194
  1.0     0.019479818  28.01048  0.3174197   8.027480
  1.0     0.045000908  27.99330  0.3178932   7.955851
  1.0     0.103957936  27.96647  0.3187201   7.885657
  1.0     0.240156321  27.94291  0.3189672   7.784590
  1.0     0.554792263  27.93467  0.3186856   7.565986
  1.0     1.281642117  27.98635  0.3171131   7.153438
  1.0     2.960759592  28.26663  0.3108182   6.661504
  1.0     6.839738840  29.27235  0.2909322   7.666803
  1.0    15.800684229  32.54609  0.2909322  10.044511

RMSE was used to select the optimal model using the smallest value.
```

```
The final values used for the model were alpha = 1 and lambda = 0.5547923.
>
>   #create a graph displaying the accuracy of all models
>   plot(model)
>   plot(varImp(ridge$finalModel))
>   plot(cv)
>   plot(ridge)
>   hist(Features$X0.19,col = "green")
>   hist(Features$X24,col = "red")
>   hist(Features$X11.291044776119403,col = 'yellow')
>   fit = glmnet(x, y)
>   plot(fit)
>   cvfit = cv.glmnet(x, y)
>   plot(cvfit)
>   tfit=glmnet(x,y,lower=-.7,upper=.5)
>   plot(tfit)
```

#compare with linear models and report the accuracy

cor(Features_Variant_1$X0.19,Features_Variant_1$X24)

mod=lm(Features_Variant_1$X0.19~Features_Variant_1$X1)

predict(mod)

Features_Variant_1$error=mod$residuals

library(car)

dwt(mod)

plot(Features_Train$X0.19,Features_Train$X24,
abline(lm(Features_Variant_1$X0.19~Features_Variant_1$X1),col='red'))

#Assumption1 Linearity

plot(Features_Variant_1$X0.19,Features_Variant_1$error, xlab="X24",ylab="Residuals",
main="Linearity")

#Assumption - Normality

hist(Features_Variant_1$error, xlab = "Residuals",main= "Histogram of Residuals", col="yellow")

#Running Regression

fit<-lm(X0.19~X24+X463+X11.291044776119403+X1.0+X70.49513846124168, data=Features_Variant_1)

fit

#Prediction Accuracy- the one which has good prediction accuracy; in other words, which

#has the smallest prediction error. Consider the simple case of fitting a linear regression model to the observed data. #A model is a good fit, if it provides a high R2 value.

#Coefficients, Significance of slope, R Square, Model Fit

summary(fit)

#Multicollinearity

vif(fit)

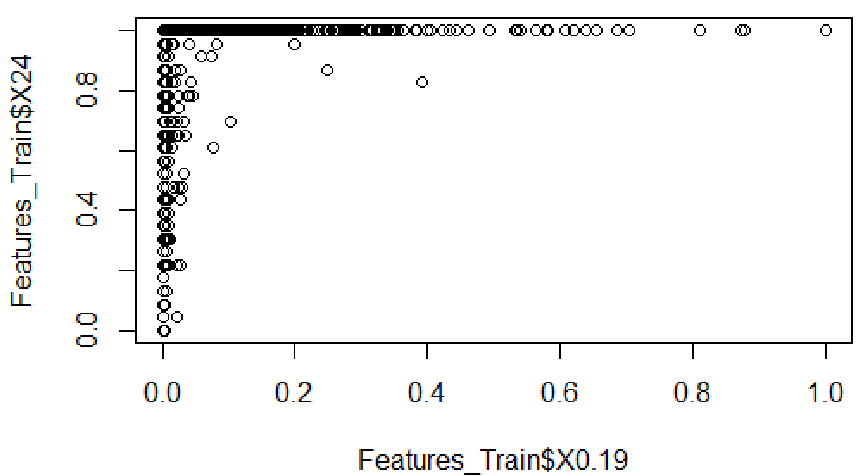
```
  > cor(Features_Variant_1$X0.19,Features_Variant_1$X24)
[1] 0.01258501
> mod=lm(Features_Variant_1$X0.19~Features_Variant_1$X1)
> summary(mod)

Call:
lm(formula = Features_Variant_1$X0.19 ~ Features_Variant_1$X1)

Residuals:
    Min      1Q  Median      3Q     Max
 -10.37   -8.27   -6.32   -3.03 1295.68

Coefficients:
                       Estimate Std. Error t value Pr(>|t|)
(Intercept)           10.502642   0.275383   38.14   <2e-16 ***
Features_Variant_1$X1 -0.131088   0.008768  -14.95   <2e-16 ***
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 35.4 on 40946 degrees of freedom
Multiple R-squared:  0.005429, Adjusted R-squared:  0.005404
F-statistic: 223.5 on 1 and 40946 DF,  p-value: < 2.2e-16
```

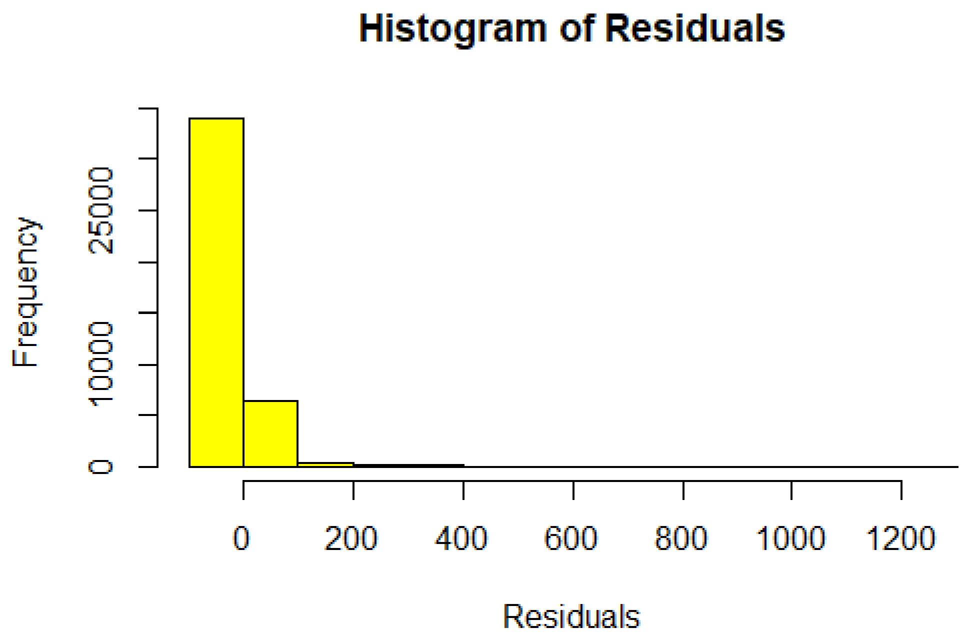
```
> predict(mod)
```

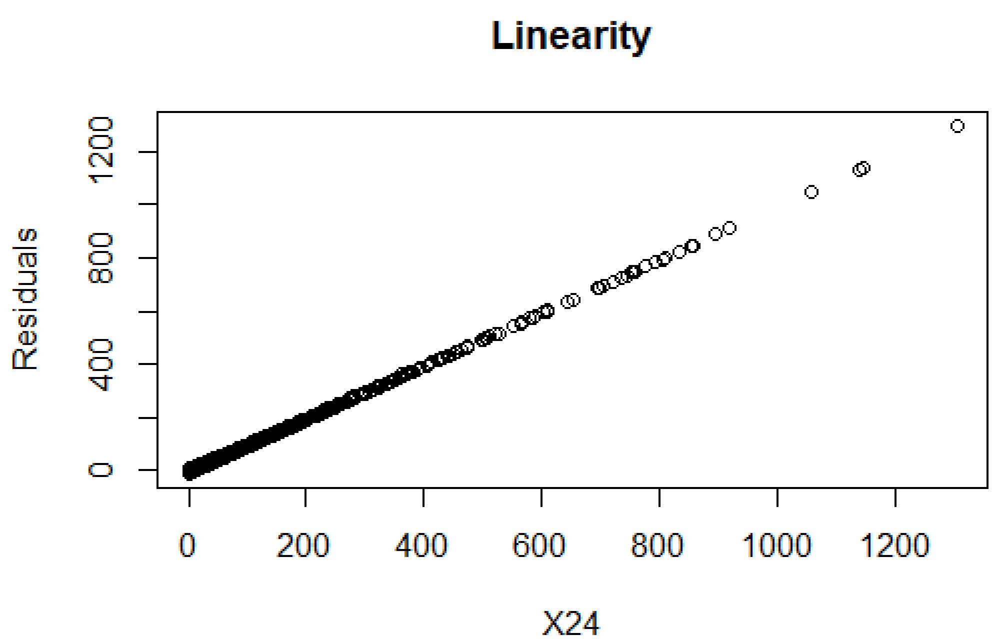
```
> Features_Variant_1$error=mod$residuals
> library(car)
Loading required package: carData
```

```
Attaching package: 'car'

The following object is masked from 'package:dplyr':

    recode

The following object is masked from 'package:purrr':

    some

>    dwt(mod)
 lag Autocorrelation D-W Statistic p-value
   1        0.125323      1.749352       0
 Alternative hypothesis: rho != 0
```

```
> plot(Features_Train$X0.19,Features_Train$X24, abline(lm(Features_Variant_1$
X0.19~Features_Variant_1$X1),col='red'))
> hist(Features_Variant_1$error, xlab = "Residuals",main= "Histogram of Resid
uals", col="yellow")
> plot(Features_Variant_1$X0.19,Features_Variant_1$error, xlab="X24",ylab="Re
siduals", main="Linearity")
```








```
> fit<-lm(X0.19~X24+X463+X11.291044776119403+X1.0+X70.49513846124168, data=Fe
atures_Variant_1)
> fit<-lm(X0.19~X24+X463+X11.291044776119403+X1.0+X70.49513846124168, data=Fe
atures_Variant_1)
> fit
```

```
Call:
lm(formula = X0.19 ~ X24 + X463 + X11.291044776119403 + X1.0 +
    X70.49513846124168, data = Features_Variant_1)

Coefficients:
        (Intercept)                   X24                  X463  X11.2910447761
19403
         -1.765e+01             7.229e-01             3.037e-06              6.93
0e-02
               X1.0    X70.49513846124168
          5.878e-02             2.513e-02
```

```
> summary(fit)

Call:
lm(formula = X0.19 ~ X24 + X463 + X11.291044776119403 + X1.0 +
    X70.49513846124168, data = Features_Variant_1)

Residuals:
    Min      1Q  Median      3Q     Max
-235.02   -5.38   -1.03    0.17 1266.57

Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
(Intercept)         -1.765e+01  2.079e+00  -8.490  < 2e-16 ***
X24                  7.229e-01  8.654e-02   8.354  < 2e-16 ***
X463                 3.037e-06  1.785e-06   1.701 0.088916 .
X11.291044776119403  6.930e-02  1.775e-02   3.905 9.46e-05 ***
X1.0                 5.878e-02  1.530e-02   3.841 0.000123 ***
X70.49513846124168   2.513e-02  7.821e-03   3.213 0.001315 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 33.41 on 40942 degrees of freedom
Multiple R-squared:  0.1141,   Adjusted R-squared:  0.114
F-statistic:  1054 on 5 and 40942 DF,  p-value: < 2.2e-16
```

```
> vif(fit)
                X24                X463 X11.291044776119403                X1
.0
           1.012425            1.438330           87.332985             42.0345
25
 X70.49513846124168
          14.928307
```

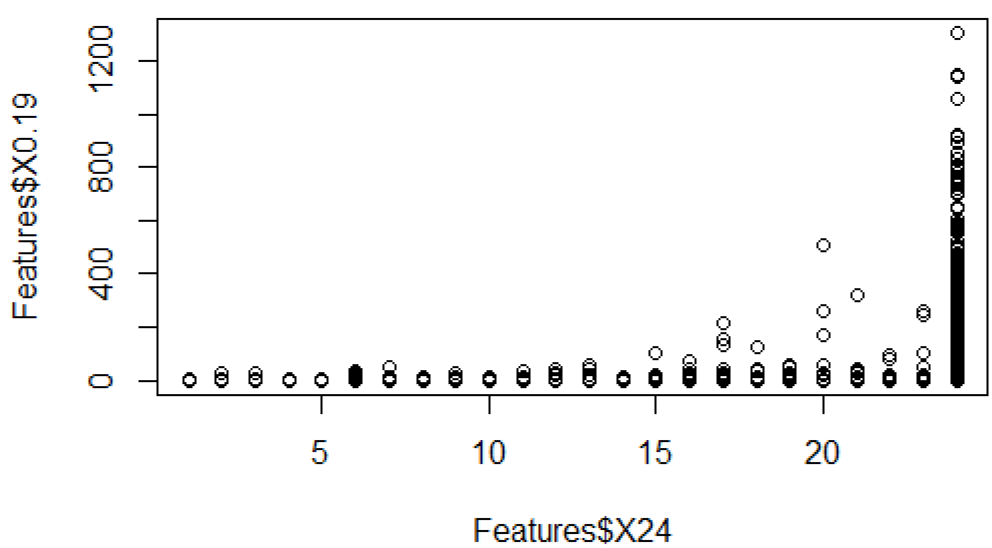
plot(cv$lambda.min)

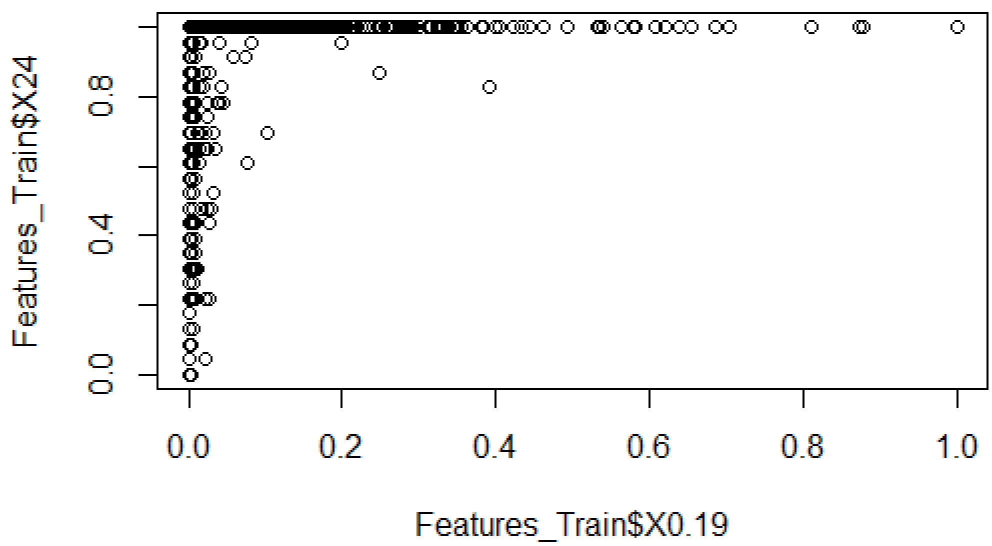
plot(model)

plot(model$bestTun)

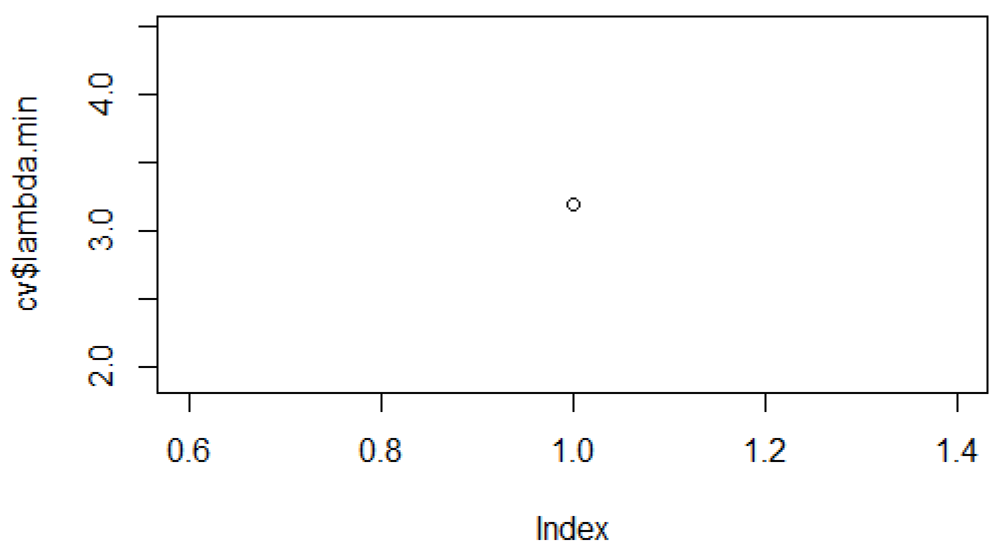
plot(model)

```
plot(varImp(ridge$finalModel))


plot(cv)

plot(ridge)

hist(Features$X0.19,col = "green")

hist(Features$X24,col = "red")

hist(Features$X11.291044776119403,col = 'yellow')

fit = glmnet(x, y)

plot(fit)

cvfit = cv.glmnet(x, y)

plot(cvfit)

tfit=glmnet(x,y,lower=-.7,upper=.5)

plot(tfit)
```

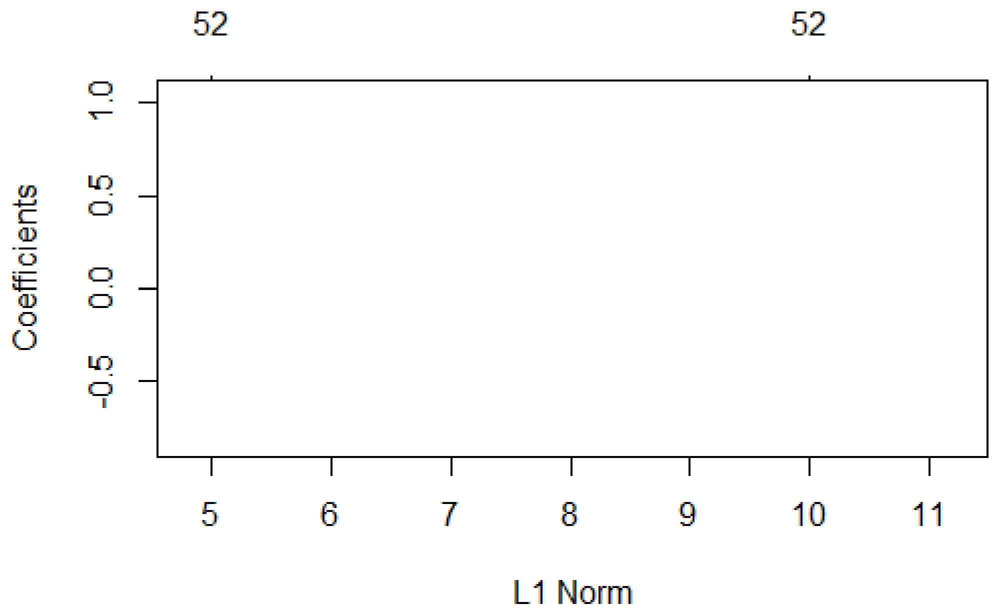


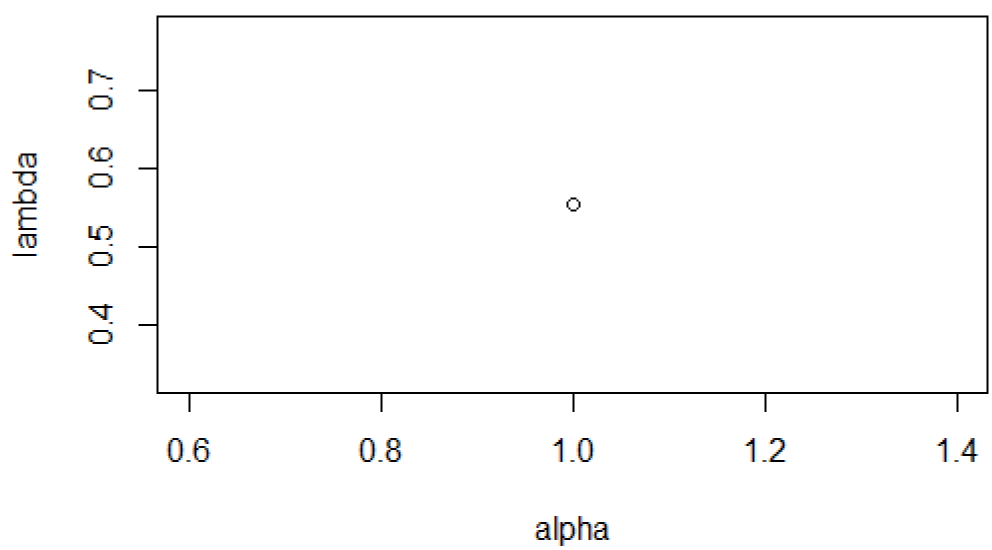


Features_Train$X24
0.0
0.4
0.8
0.0
0.2
0.4
0.6
0.8
1.0
Features_Train$X0.19

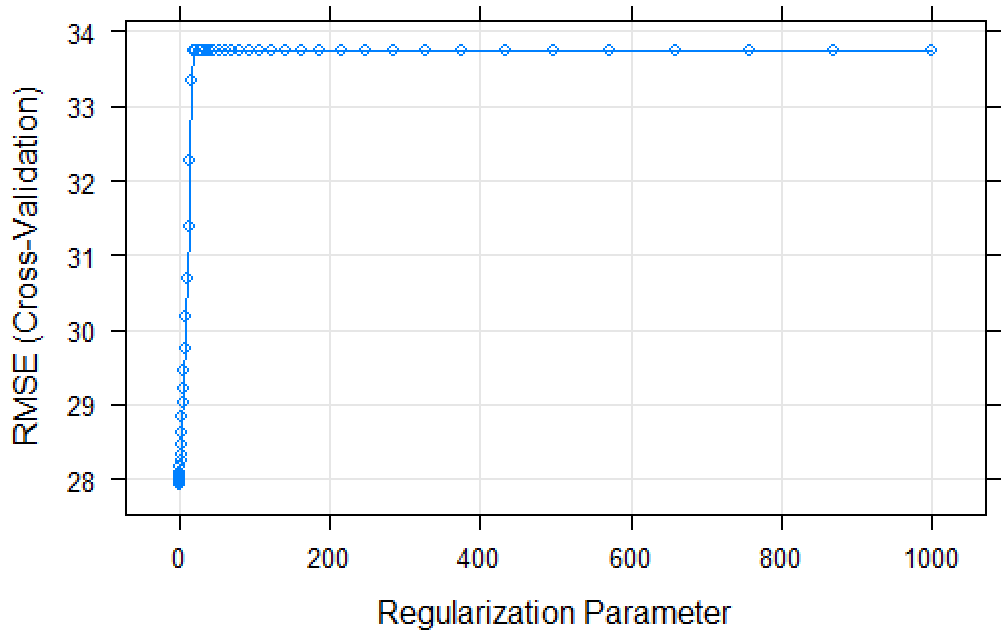


cv$lambda.min
2.0
3.0
4.0
0.6
0.8
1.0
1.2
1.4
Index

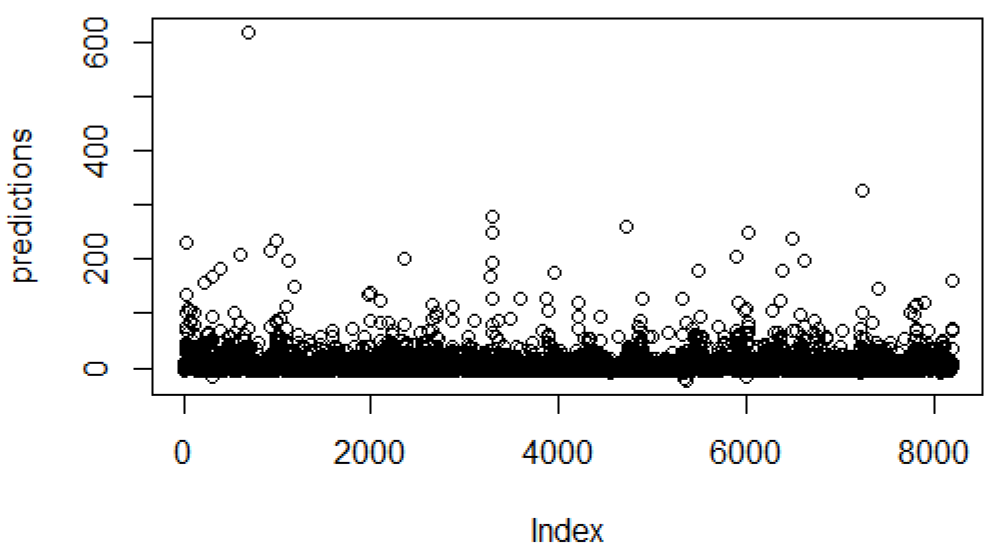

52
52
Coefficients
1.0
0.5
0.0
-0.5
5
6
7
8
9
10
11
L1 Norm


lambda
0.7
0.6
0.5
0.4
0.6
0.8
1.0
1.2
1.4
alpha

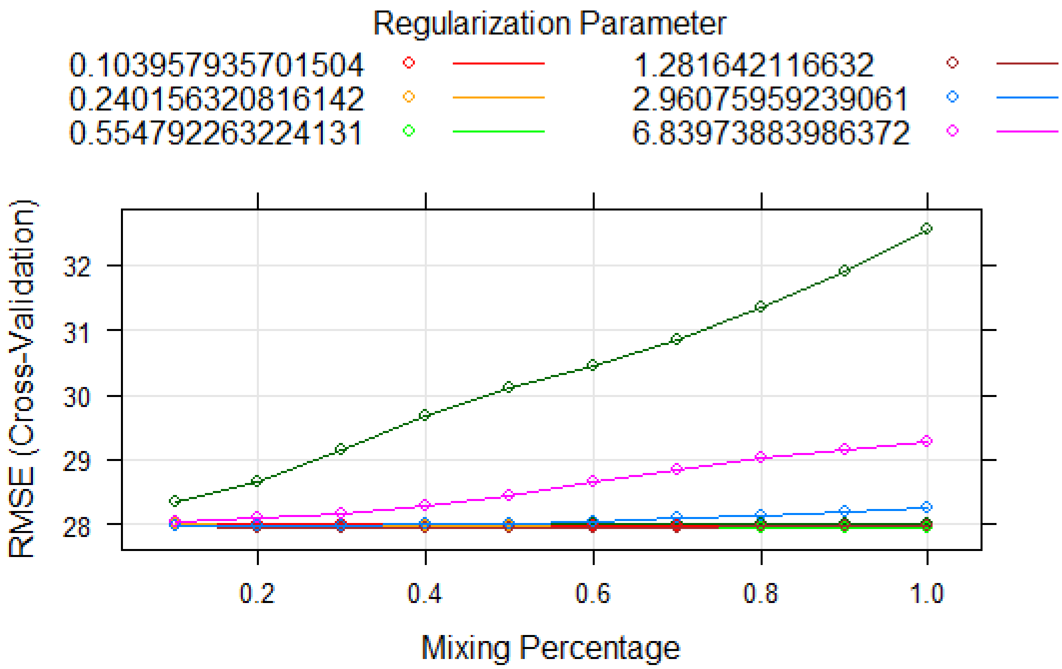
plot(lasso)



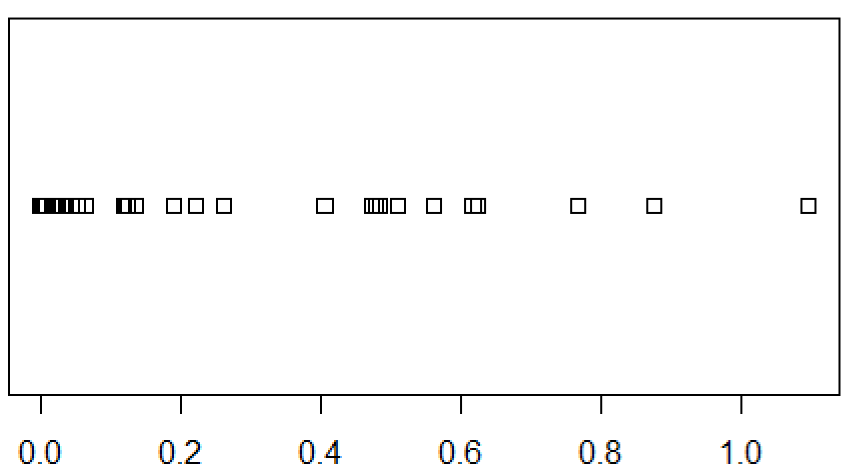
plot(predictions)



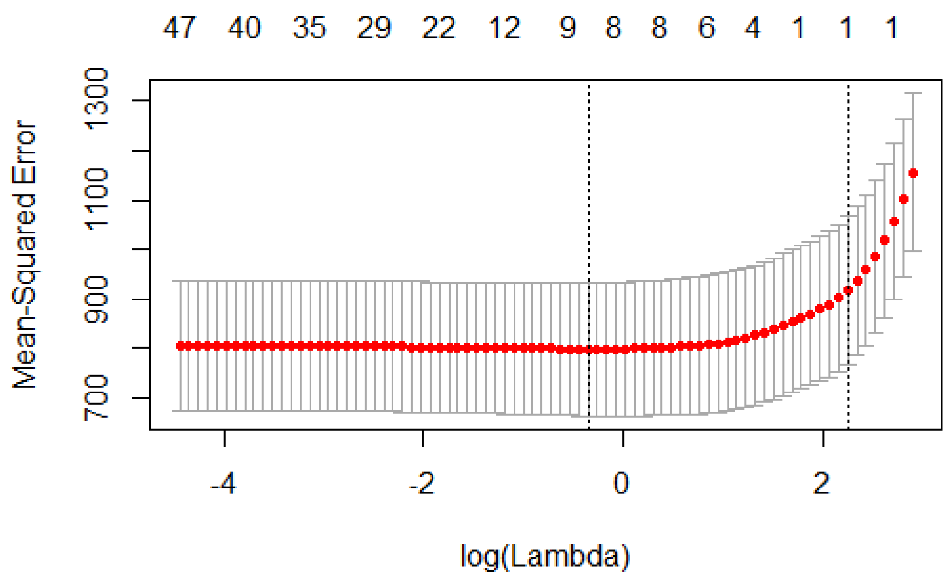
plot(model)



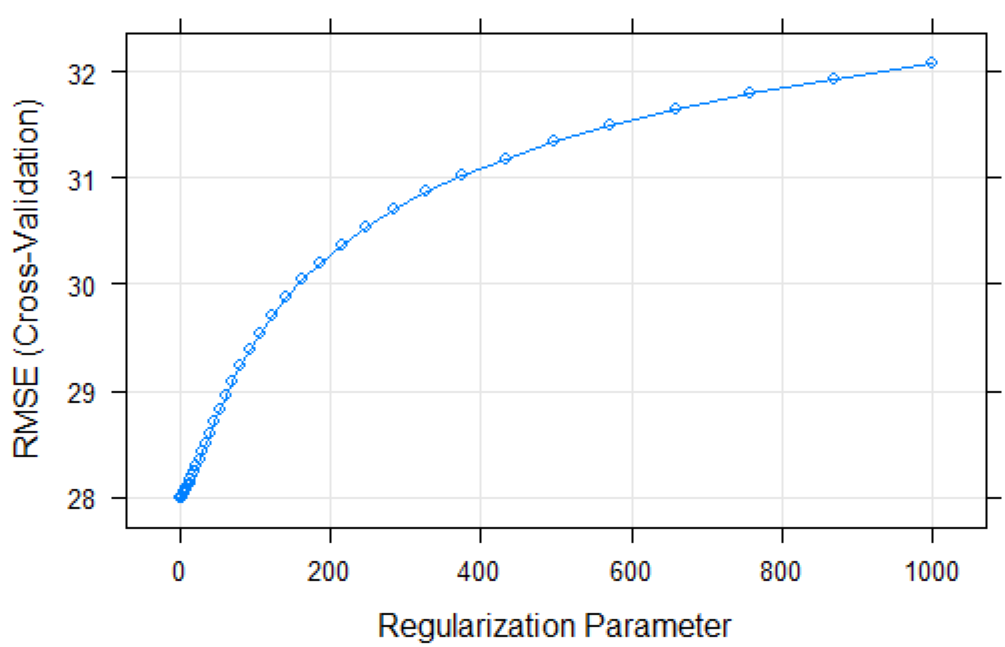
plot(varImp(ridge$finalModel))

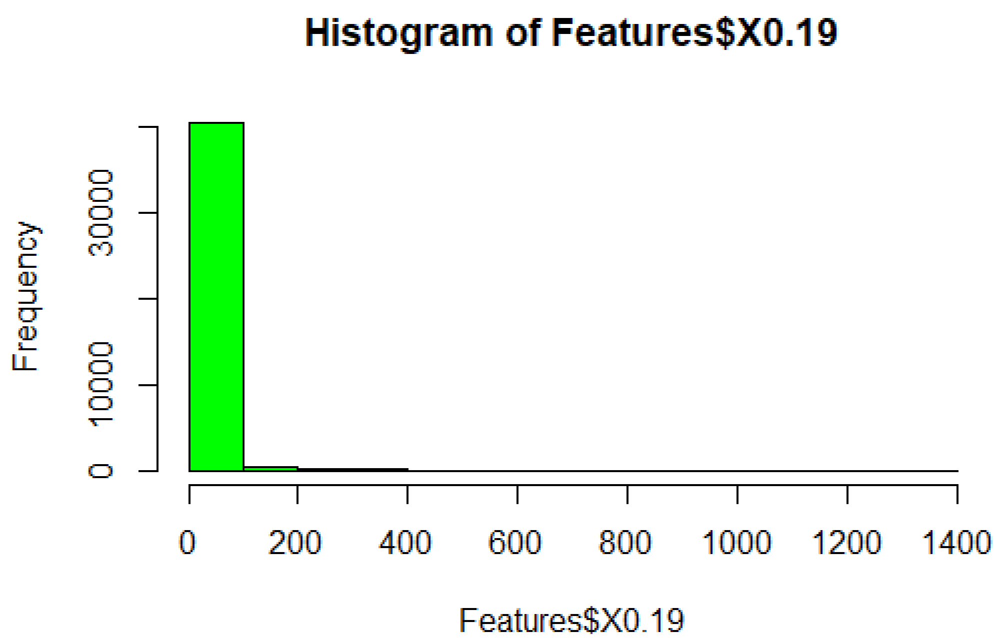


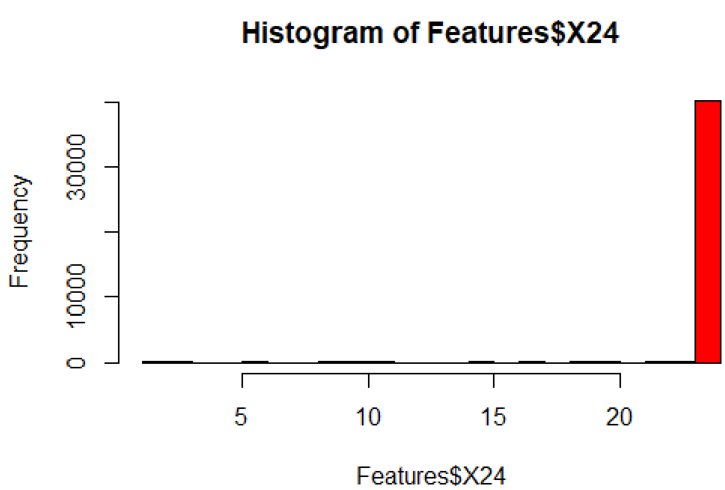
plot(cv)

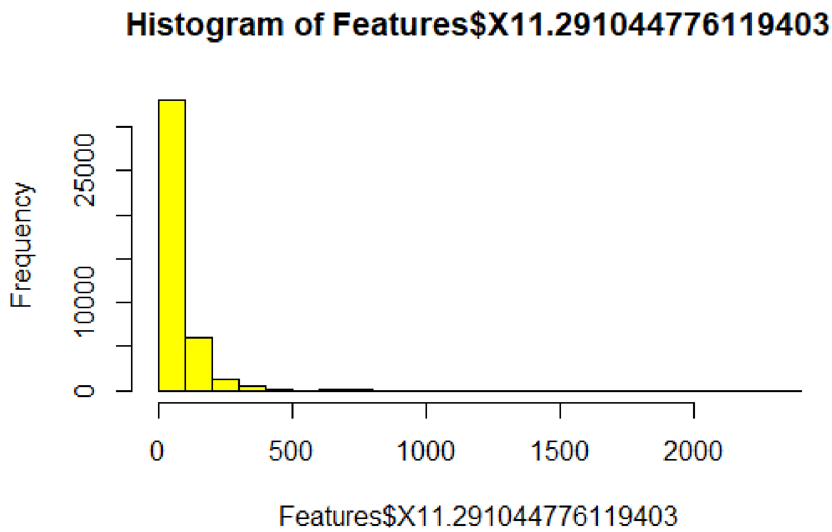


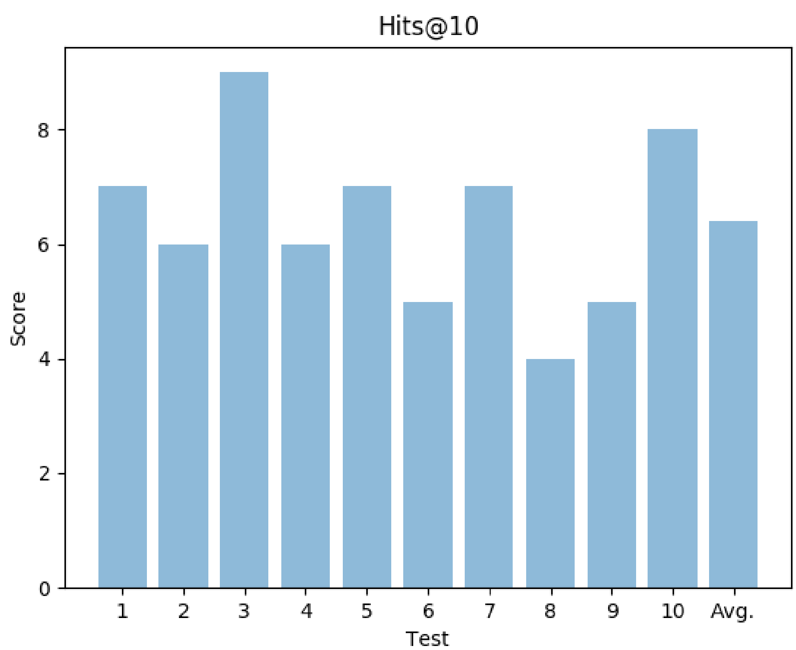
plot(ridge)




Histogram of Features$X0.19
Frequency
0
10000
30000
0
200
400
600
800
1000
1200
1400
Features$X0.19

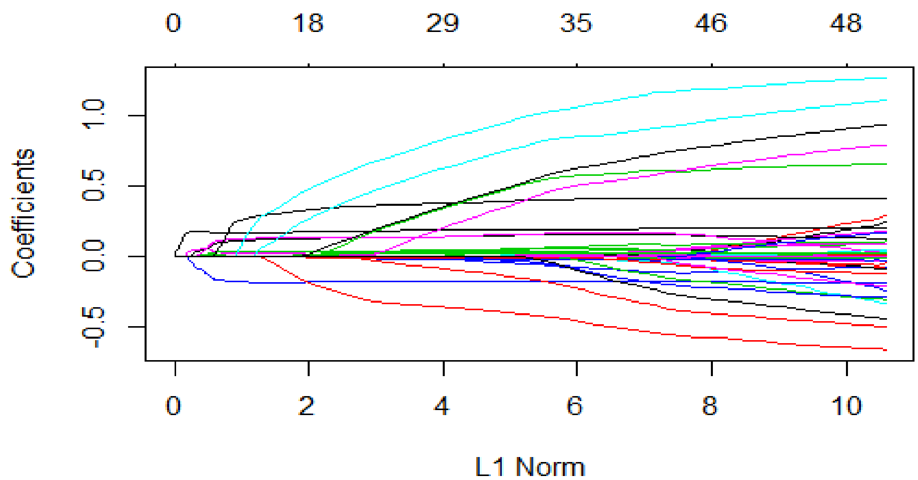

Histogram of Features$X24
Frequency
0
10000
30000
5
10
15
20
Features$X24


Histogram of Features$X11.291044776119403
Frequency
0
10000
25000
0
500
1000
1500
2000
Features$X11.291044776119403


Hits@10
Score
0
2
4
6
8
1
2
3
4
5
6
7
8
9
10
Avg.
Test

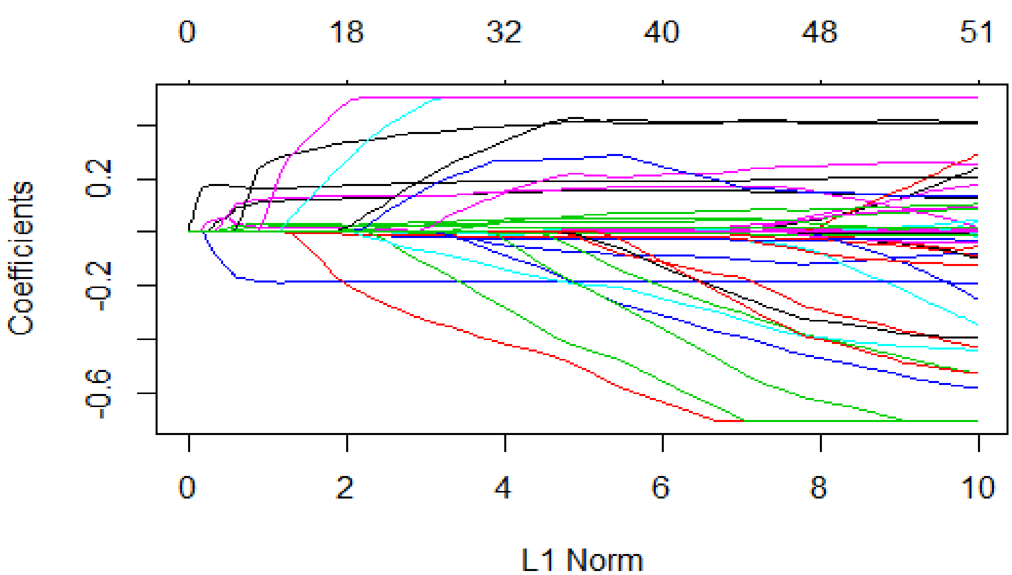
fit = glmnet(x, y)

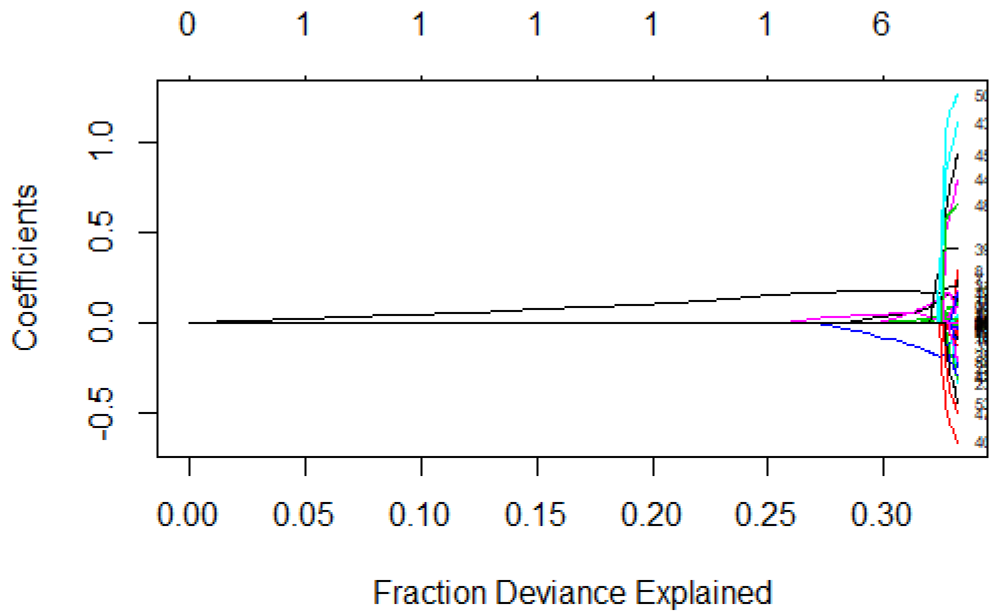
plot(fit)

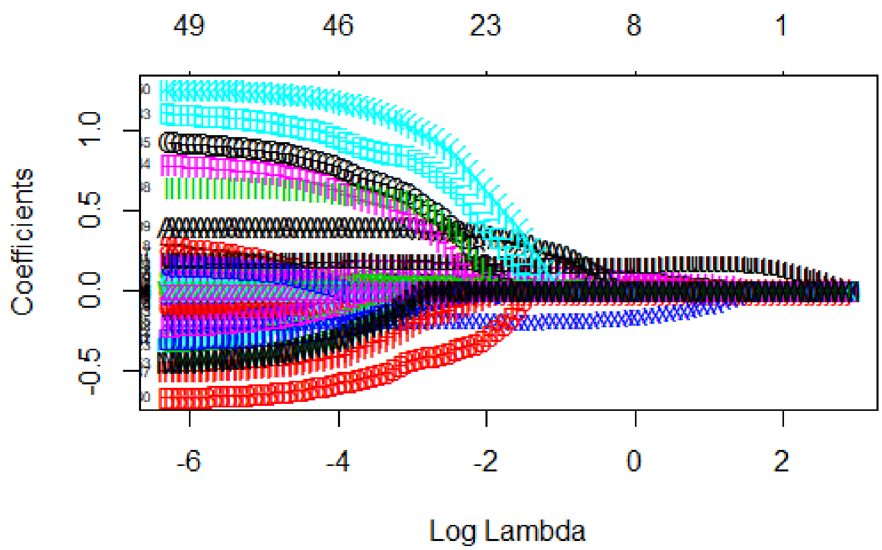


tfit=glmnet(x,y,lower=-.7,upper=.5)

plot(tfit)




0 1 1 1 1 1 6
Coefficients
1.0
0.5
0.0
-0.5
0.00 0.05 0.10 0.15 0.20 0.25 0.30
Fraction Deviance Explained


49 46 23 8 1
Coefficients
1.0
0.5
0.0
-0.5
-6 -4 -2 0 2
Log Lambda