## Introduction

Video Game Sales with Ratings dataset. The dataset is obtained from https://www.kaggle.com/rush4ratio/video-game-sales-with-ratings. Aim is to predict the global sales of games (Global\_Sales). First column (Name) represents the name of games. First column wasnot be used in the models. Ninth column is response/dependent variable, the global sales of games (Global Sales). Other values are predictors/independent variables.

## **Analysis**

a)

```
# Libraries
        library(glmnet)
        library(mice)
        library(caret)
        library(tidyverse)
     6
        library(rpart)
     8
        library(randomForest)
     9
    11
    12
        # import data
    13
        data <- read.csv("FinalDataset.csv", sep=";")</pre>
    14
    16
    17
        #preprocessing data
    18 - minMaxNorm <- function(x){
    19
          return \ ((x-min(x)) \ / \ (max(x) \ - \ min(x)))
    20
    21
    22
    23
        data$X=NULL
    24
        data$Global_Sales <- gsub(",", ".", data$Global_Sales)</pre>
    25
        data$Global_Sales <- as.double(data$Global_Sales)</pre>
        data$Platform <- as.factor(data$Platform)
    27
    28
        data$Genre <- as.factor(data$Genre)
    29
       data$Rating <- as.factor(data$Rating)
        data$PublisherR <- as.factor(data$PublisherR)
    30
    31
        data$Critic_Score <- minMaxNorm(data$Critic_Score)</pre>
    32
        data$Critic_Count <- minMaxNorm(data$Critic_Count)
    33
    34
        data$Global_Sales <- minMaxNorm(data$Global_Sales)</pre>
    35
    36 data <- sapply(data, unclass)</pre>
    37
        #data info
    38
    39
        cor(data)
    40
        pairs(na.omit(data))
    41 md.pattern(data)
b)
    43 # train data and test data
    44 train <- as.data.frame(data[1:1000,])
    45 test <- as.data.frame(data[1001:nrow(data),])</pre>
    46
    47
        names(train)
    48
        names(test)
    49
c)
    52 #Regression Model
       modelRegression <- lm(Global_Sales ~ ., data = train)
# coefficients, adjusted R square and F statistic of Regression the model</pre>
    53
    55 summary(modelRegression)
    56
```

```
d)
     Coefficients:
                      Estimate Std. Error t value Pr(>|t|)
1.2959120 3.7405064 0.346 0.729075
     (Intercept)
                     0.0017623 0.0013127 1.342 0.179747
-0.0006687 0.0018603 -0.359 0.719334
     Platform
     Year
                     -0.0006687
                     -0.0005454 0.0008800 -0.620 0.535517
     Genre
                     -0.0106732
                                    0.0028085 -3.800 0.000153 ***
     Rating
     PublisherR
                   -0.0034778 0.0022034
                                                  -1.578 0.114800
     Critic_Score 0.1571656 0.0220638
Critic_Count 0.0975811 0.0141178
                                                  7.123 2.02e-12 ***
                                                   6.912 8.55e-12 ***
     Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
     Residual standard error: 0.0916 on 992 degrees of freedom
Multiple R-squared: 0.1395, Adjusted R-squared: 0.1334
     Multiple R-squared: 0.1395, Adjusted R-squared: 0.
F-statistic: 22.97 on 7 and 992 DF, p-value: < 2.2e-16
e)
     59 #Regression Prediction and RMSE
     60 predictionsReg <- predict(modelRegression, test)</pre>
     61 Reg_RMSE <- RMSE(predictionsReg, test$Global_Sales)</pre>
       Result = 0.03693007
f)
         #Determine the lambda parameter using cross-validation
         Tambdas = 10^seq(3,-2,by=-.01)
modelRidgeCv <- cv.glmnet(trainRidgeLasso_x,trainRidgeLasso_y, alpha = 0, lambda = lambdas, nfolds = 10)
      96
         modelRidge <- glmnet(trainRidgeLasso_x,trainRidgeLasso_y, alpha = 0, lambda = modelRidgeCv$lambda.min) summary(modelRidge)
      98
     100
     102
     103
         #Determine the lambda parameter using cross-validation
     104
         modelLassoCV <- cv.glmnet(trainRidgeLasso_x,trainRidgeLasso_y, alpha = 1, lambda = lambdas, nfolds = 3)
         modelLassoCV$lambda.min
     105
     106
     107
     108
         modelLasso <- glmnet(trainRidgeLasso_x,trainRidgeLasso_y, alpha = 1, lambda = modelLassoCV$lambda.min)</pre>
         summary(modelLasso)
     The regression model worked more accurately.
g)
h)
      113 # Ridge and Lasso Prediction and RMSE
      114
            predictionRidge <- predict(modelRidge, testRidgeLasso_x)</pre>
            predictionLasso <- predict(modelLasso, testRidgeLasso_x)</pre>
      115
      116
             Ridge_RMSE <- RMSE(predictionRidge, testRidgeLasso_y)
      117
      118 Lasso_RMSE <- RMSE(predictionLasso, testRidgeLasso_y)
      119
      120
            Ridge_RMSE
      121
            Lasso_RMSE
     Result Ridge = 0.4610888
     Result Lasso = 0.4647719
i)
     124
      125
            #Regression Tree Model
            modelRegTree <- rpart(Global_Sales ~ ., data=train)</pre>
      126
     127
j)
```

```
130 #Regression Tree Prediction and RMSE
     131 predictionRegTree <- predict(modelRegTree, test)
132 RT_RMSE <- RMSE(predictionRegTree, test$Global_Sales)
133 RT_RMSE
    Result = 0.0433108
k)
    142 # Random Forest Prediction and RMSE
     143 predictionRF <- predict(modelRF, test)
    144 RF_RMSE <- RMSE(predictionRF, test$Global_Sales)
    Import variables is ntree=500.
I)
m)
     142 # Random Forest Prediction and RMSE
     143 predictionRF <- predict(modelRF, test)
     144 RF_RMSE <- RMSE(predictionRF, test$Global_Sales)
     145 RF_RMSE
    Result = 0.03287746
n)
    Regression RMSE = 0.03693007
    Ridge RMSE = 0.4610888
    Lasso RMSE = 0.4647719
    Regression Tree RMSE = 0.0433108
    Random Forest RMSE = 0.03287746
    Best -> Random Forest
    Worst -> Lasso
    Here's from best to worst:
    Random Forest, Regression, Regression Tree, Ridge, Lasso
```

## **Conclusion**

In general, we achieved good results from the models we obtained. The best models were Random Forest, Regression, Regression Tree.