Johnpaul Ogah(jogah3)

```
library("ggplot2")
library("plyr")
library(tm)
library(magrittr)
library(wordcloud)
library(chron)
library(scales)
library(GGally)
library(reshape2)
library(dplyr)
library(stringr)
library(timeDate)
library(lubridate)
library("cowplot")
library("gridExtra")
library("cowplot")
library(glmnet)

load("movies_merged")
movie_only_data = subset(movies_merged, Type == "movie")
movie_only_data = subset(movie_only_data, is.na(Budget)==FALSE)
movie_only_data = subset(movie_only_data, is.na(Gross)==FALSE)
movie_only_data$profit = movie_only_data$Gross - movie_only_data$Budget
movie_only_data = subset(movie_only_data, Runtime != "N/A")
movie_only_data=subset(movie_only_data, Metascore !="N/A")
movie_only_data$Metascore = sapply(movie_only_data$Metascore, as.numeric)

convert.to.numeric = function(x){
  str = strsplit(x , " ")[[1]]
  len = length(str)
  num = 0;
  if (len == 4){
    num = as.numeric(str[1]) * 60 + as.numeric(str[3])
  }
  if (len == 2){
    if ( str[2] == "h"){
      num = as.numeric(str[1]) * 60
    }
    if( str[2] == "min"){
      num = as.numeric(str[1])
    }
  }
  return(num)
}

extract.numbers = function(x){
  num = str_extract_all(x,"\\(?[0-9]+\\)?")[[1]]
  num= as.numeric(num)
  num = (sum(num))
  return(num)
```

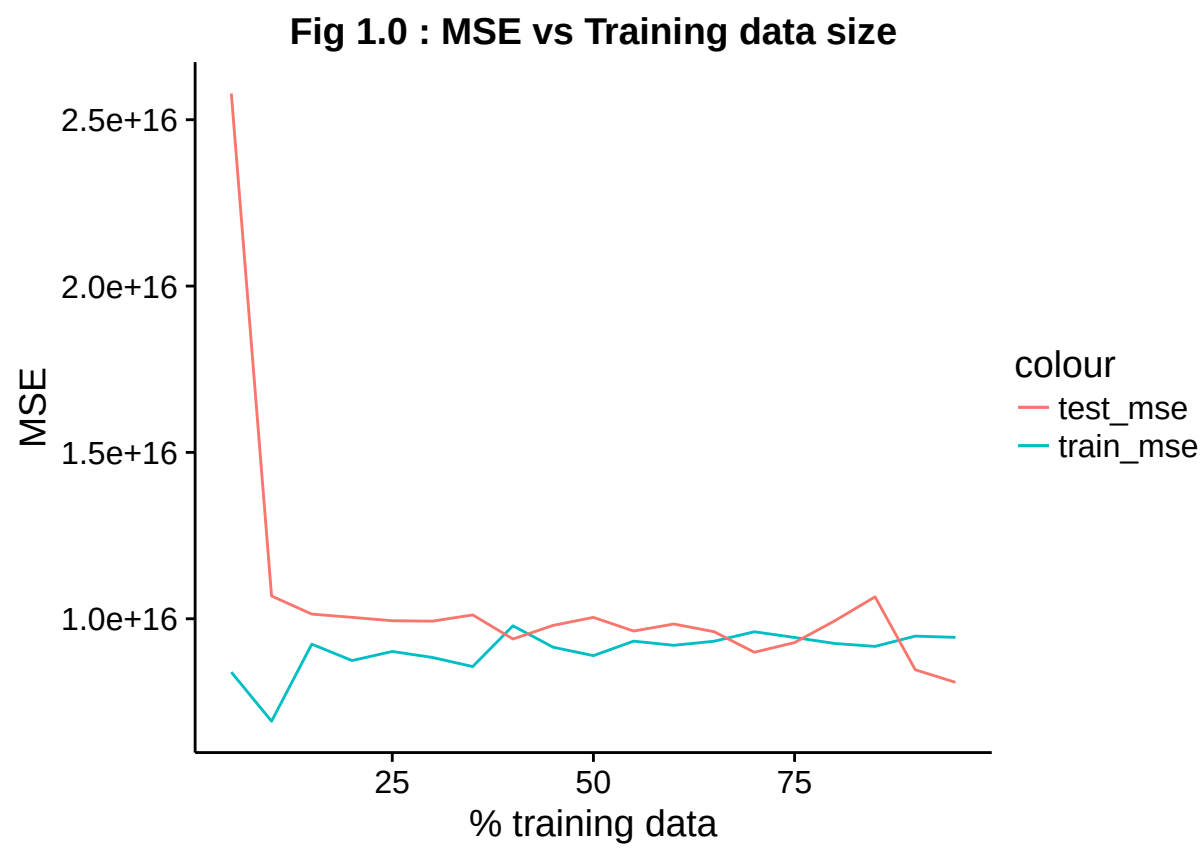
```
}

calculate_rmse = function(x , y){
  error = x - y
  result = sum(error * error)
  return(result/length(x))
}

ans = data.frame(ldply(movie_only_data[,'Runtime'], convert.to.numeric))
movie_only_data$Runtime = ans$V1
movie_only_data = na.omit(movie_only_data)
movie_only_data = subset(movie_only_data, Year >= 2000)
ans = ldply(movie_only_data[,"Awards"], extract.numbers)
movie_only_data$Awards = ans$V1
movie_only_data$is_budget_greater_than_3m = movie_only_data$Budget > 3e6

small_movie = movie_only_data[sample(1:dim(movie_only_data)[1],500),]
```

Use linear regression to predict profit based on all available numeric variables. Graph the train and test MSE as a function of the train set size (averaged over 10 random data partitions as described above)?

In figure 1.0, the mean square error decreases on the testing data as the training size increases.The best mean square error obtained was 8.088929e+15.

```
train_set = seq(5,95, by=5)

mse.on.test.data_1 = rep(0,19)
mse.on.train.data_1 = rep(0,19)
train_mse = rep(0,10)
test_mse= rep(0,10)
n_row = nrow(movie_only_data)
best_mse = 1.797693e+308
best_train_size = 0
set.seed(50)



for (num in seq(1:19)){
  for(i in seq(1:10)){
    local_var = train_set[num]
    local_var = local_var/100
  random_perm = sample(n_row,n_row)
  first_index = random_perm[1:floor(n_row*local_var)]
  second_index = random_perm[(floor(n_row * local_var)+1):n_row]
  train_data = movie_only_data[first_index,]
  test_data = movie_only_data[second_index,]
  data = train_data
  model = lm(profit~Year+Runtime+Budget+Awards+
        imdbVotes+tomatoReviews+tomatoRotten+
               tomatoUserMeter+tomatoUserReviews+
               tomatoUserRating+tomatoMeter+imdbRating+Metascore,data)
```

```
 train_mse[i]  = mean(residuals(model)^2)
 data = test_data
 test_mse[i] = calculate_rmse(test_data$profit, predict(model,data))
  }
  mse.on.train.data_1[num] = mean(train_mse)
  mse.on.test.data_1[num] = mean(test_mse)

  if (mean(test_mse) < best_mse){
   best_mse = mean(test_mse)
   best_model=model
 }
}

result = data.frame(training_data=train_set,
                    mse_train_data=mse.on.train.data_1,
                    mse_test_data=mse.on.test.data_1)

ggplot(result,aes(x=training_data)) +
  geom_line(aes(y=mse_train_data,color="train_mse")) + geom_line(aes(y=mse_test_data,color="test_mse"))+
ylab("MSE") +xlab("% training data") +
  ggtitle("Fig 1.0 : MSE vs Training data size")
```




```
cat("best MSE:", best_mse)
```

```
## best MSE: 8.088929e+15
```

Try to improve the prediction quality in (1) as much as possible by adding feature transformations of the numeric variables. Explore both numeric transformations such as power transforms and non-numeric transformations of the numeric variables like binning (e.g.,is_budget_greater_than_3M). Explain which transformations you used and why you chose them.Graph the train and test MSE as a function of the train set size (averaged over 10 random datapartitions as described above)?

The code for the question is shown below. A non linear relationship exist between tomatoReviews and profit as result the particular feature was transformed to account for the non linear relationship.Similarly imdbRating was tramformed to account for non linear relationship. Also there exist a linear relationship between the log of tomatoUserReviews and profit . Thus tomotaUserReviews was transformed with the log function.Further , I explored the interaction between the various variables with imdbVotes and Budget.imdbVotes and Budget are two features that are most correlated with profit , hence I explored interaction between the remaining features with the two variables. Figure 2.0 shows the plot of train and test MSE as a function of train set size. The best MSE obtained was 6.314433e+15 which an an improvement of 1.774496e+15 less than what was obtained in question one.Fig2.1 graph both test and train MSE for question 1 and question2 we can see the obvious improvement obtained in question 2 for both the test and train MSE.

```
with(small_movie,cor(Year,profit))
```

```
## [1] 0.1577506
```

```
with(small_movie,cor(Runtime,profit))
```

```
## [1] 0.3092
```

```
with(small_movie,cor(Budget,profit))
```

```
## [1] 0.6096132
```

```
with(small_movie,cor(Awards,profit))
```

```
## [1] 0.3515959
```

```
with(small_movie,cor(imdbVotes,profit))
```

```
## [1] 0.6649807
```

```
with(small_movie,cor(tomatoReviews,profit))
```

```
## [1] 0.5244732
```

```
with(small_movie,cor(tomatoRotten,profit))
```

```
## [1] 0.138523
```

```
with(small_movie,cor(tomatoUserMeter,profit))
```

```
## [1] 0.2200973
```

```
with(small_movie,cor(tomatoUserReviews,profit))
```

```
## [1] 0.3206703
```

```
with(small_movie,cor(tomatoUserRating,profit))
```

```
## [1] 0.3061903
```

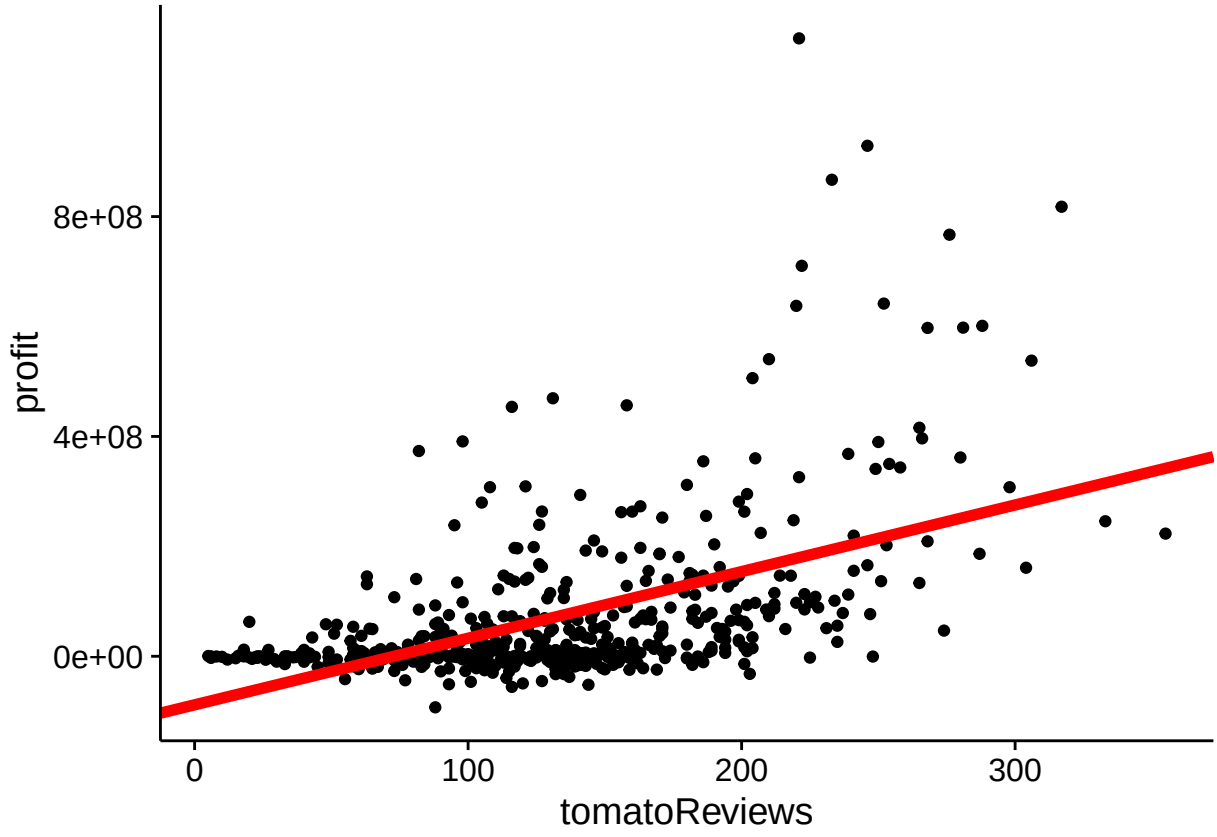
```
with(small_movie,cor(tomatoMeter,profit))
```

```
## [1] 0.1784568
```

```
with(small_movie,cor(imdbRating,profit))
```

```
## [1] 0.2055936
```

```
M1 = lm(profit ~tomatoReviews,small_movie)
theta1 = coef(M1)
print(ggplot(small_movie,aes(tomatoReviews,profit)) + geom_point() + geom_abline(intercept = theta1[1],
```



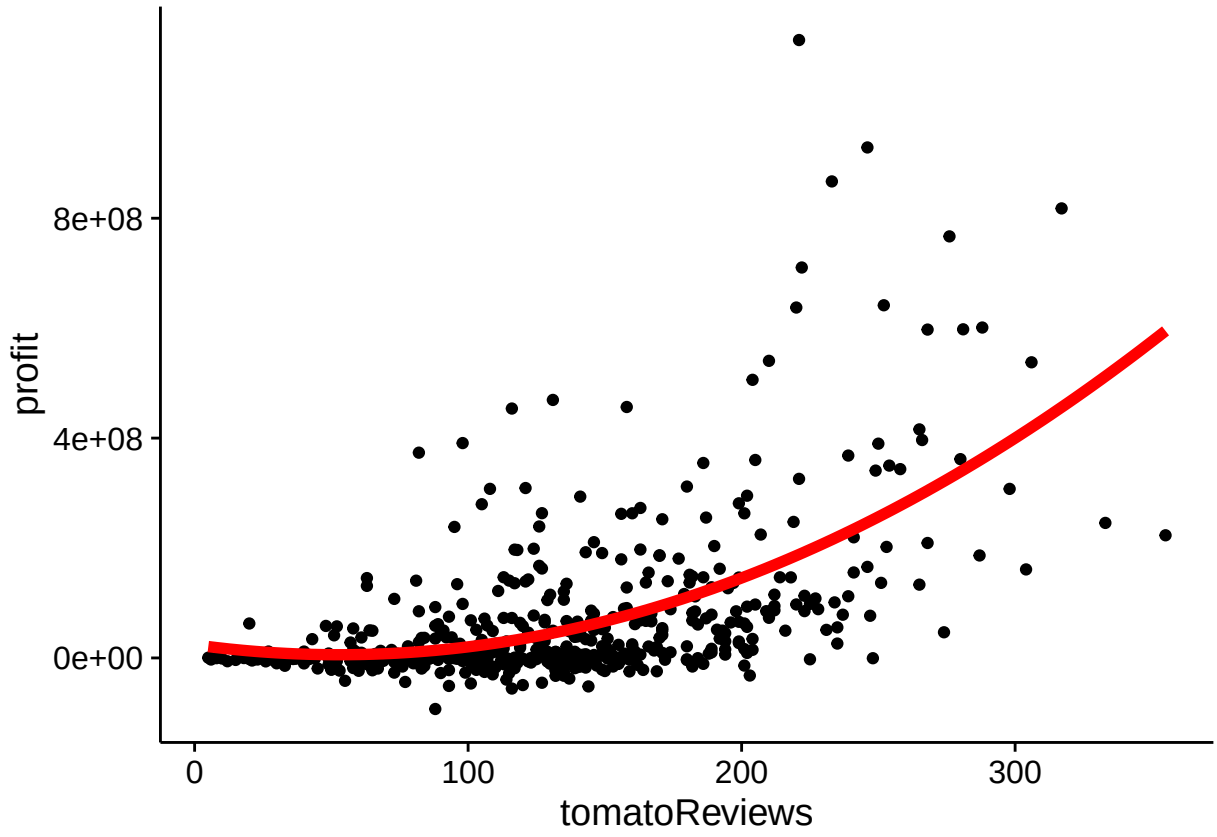

```
summary(M1)$r.squared
```

```
## [1] 0.2750722
```

```
mean(residuals(M1)^2)
```

```
## [1] 1.534508e+16
```

```
M2 = lm(profit~tomatoReviews+I(tomatoReviews^2),small_movie)
cX = seq(5,range(small_movie$tomatoReviews)[2],length=500)
theta2 = coef(M2)
cY = theta2[1] + theta2[2]*cX + theta2[3]*cX^2
print(ggplot(small_movie,aes(tomatoReviews,profit)) + geom_point() + geom_line(aes(x=cX,y=cY), size=2,c
```



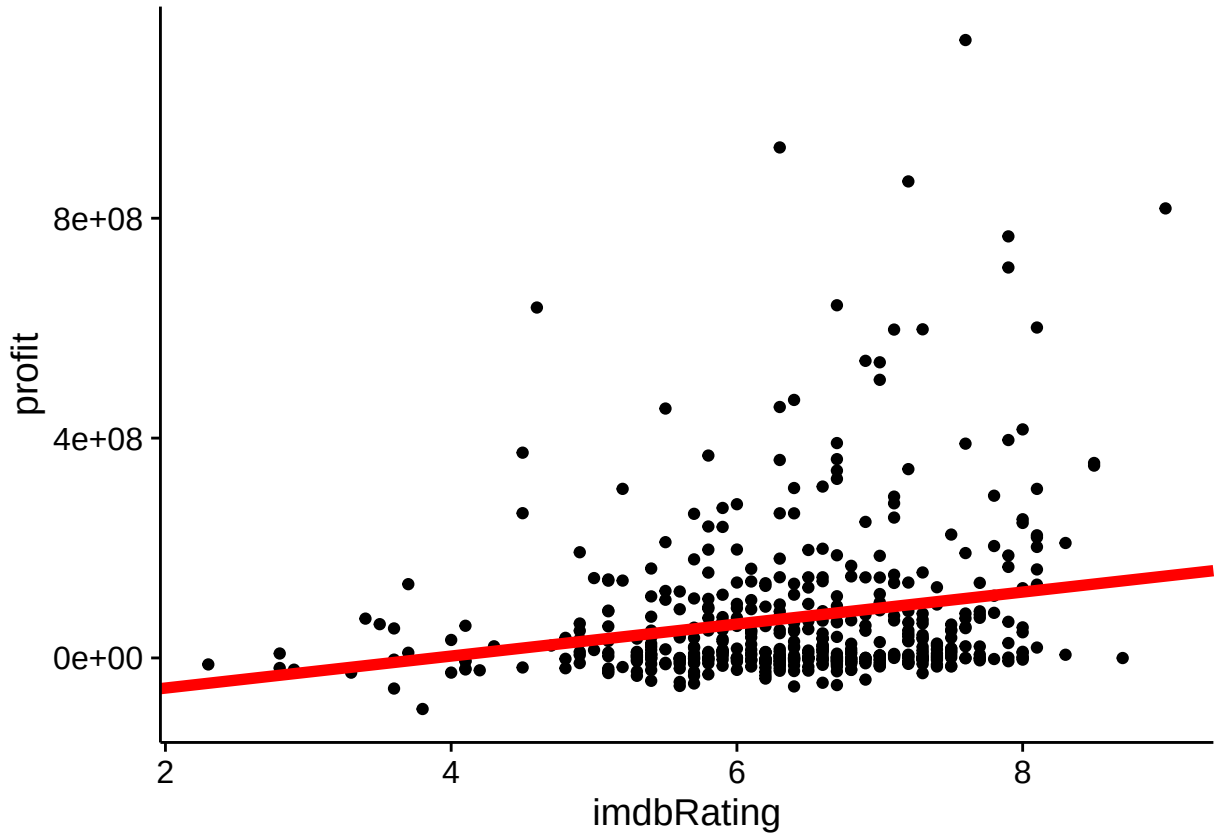

```
summary(M2)$r.squared
```

```
## [1] 0.3339782
```

```
mean(residuals(M2)^2)
```

```
## [1] 1.409817e+16
```

```
M3 = lm(profit ~imdbRating,small_movie)
theta3 = coef(M3)
print(ggplot(small_movie,aes(imdbRating,profit)) +
        geom_point() +
        geom_abline(intercept = theta3[1],
                    slope = theta3[2], size=2,color=I("red")))
```



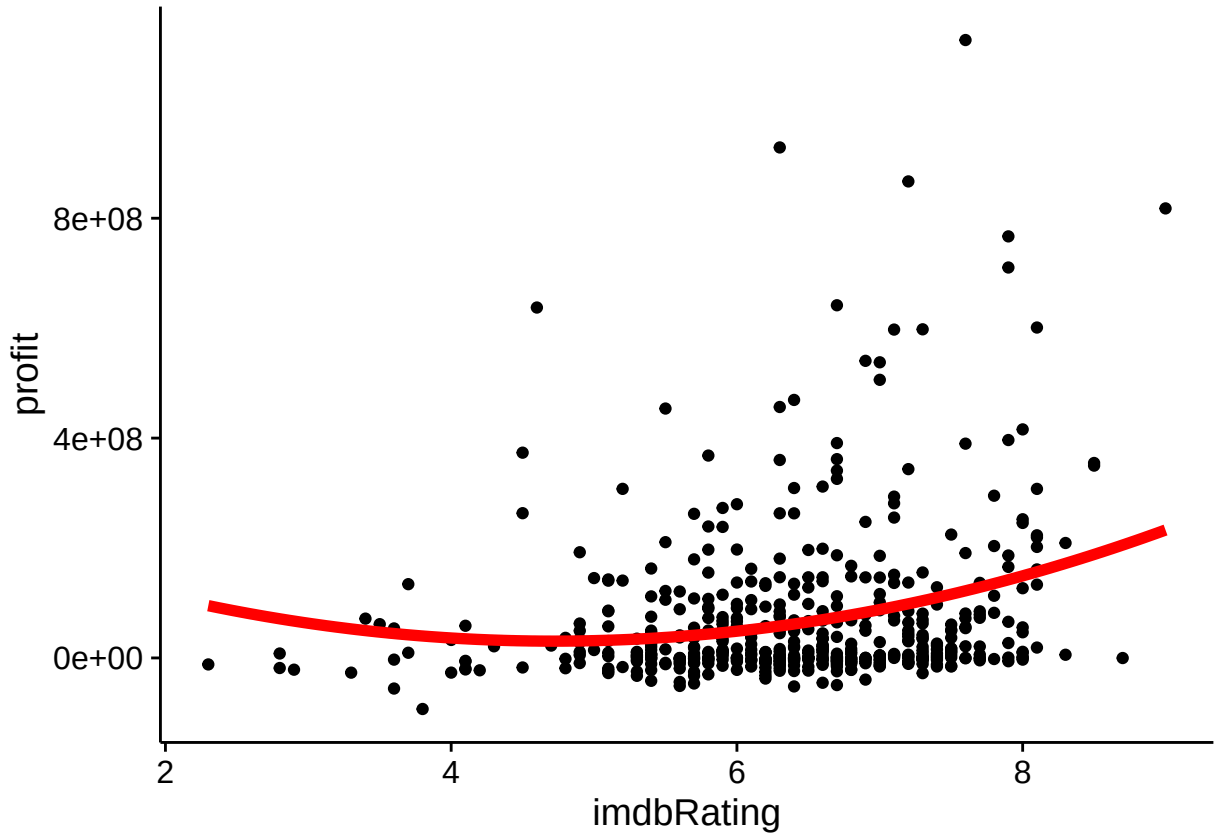

```
summary(M3)$r.squared
```

```
## [1] 0.04226872
```

```
mean(residuals(M3)^2)
```

```
## [1] 2.0273e+16
```

```
M3 = lm(profit~imdbRating+I(imdbRating^2),small_movie)
cX3 = seq(range(small_movie$imdbRating)[1],
          range(small_movie$imdbRating)[2],length=500)
theta3 = coef(M3)
cY3 = theta3[1] + theta3[2]*cX3 + theta3[3]*cX3^2
print(ggplot(small_movie,aes(imdbRating,profit)) + geom_point() + geom_line(aes(x=cX3,y=cY3), size=2,co
```



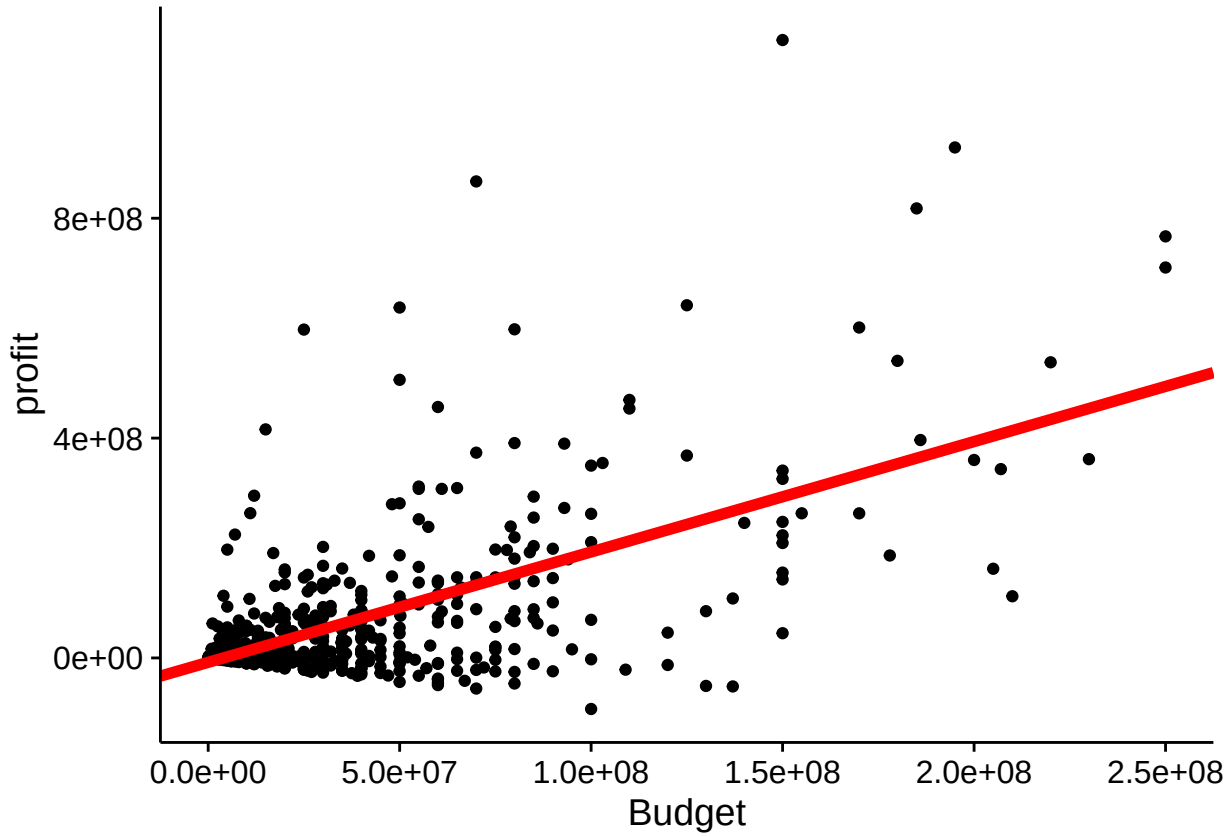

```
summary(M3)$r.squared
```

```
## [1] 0.05867443
```

```
mean(residuals(M3)^2)
```

```
## [1] 1.992573e+16
```

```
M4 = lm(profit ~Budget,small_movie)
theta4 = coef(M4)
print(ggplot(small_movie,aes(Budget,profit)) + geom_point()
      + geom_abline(intercept = theta4[1], slope = theta4[2], size=2,color=I("red")))
```



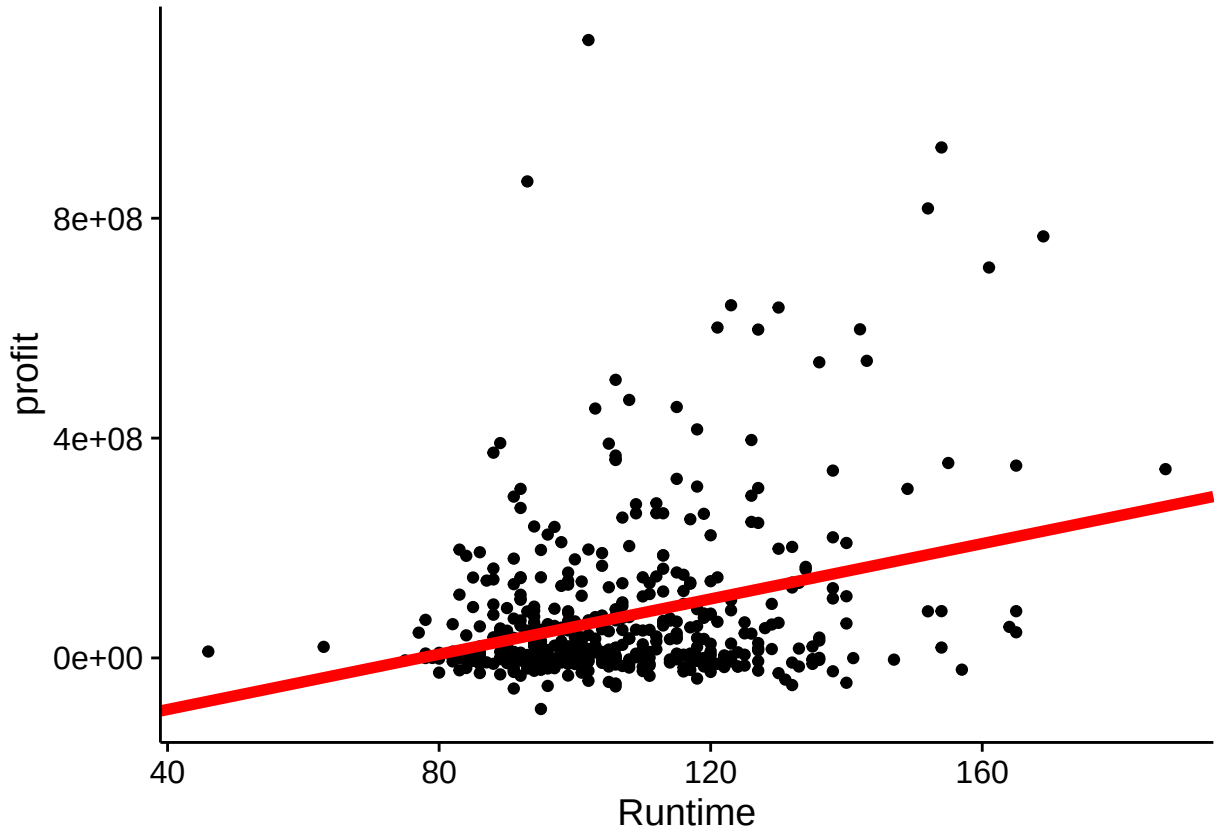

```
summary(M4)$r.squared
```

```
## [1] 0.3716283
```

```
mean(residuals(M4)^2)
```

```
## [1] 1.33012e+16
```

```
M5 = lm(profit~Runtime,small_movie)
theta5 = coef(M5)
print(ggplot(small_movie,aes(Runtime,profit)) + geom_point() +
        geom_abline(intercept = theta5[1], slope = theta5[2], size=2,color=I("red")))
```




```
summary(M5)$r.squared
```

```
## [1] 0.09560465
```

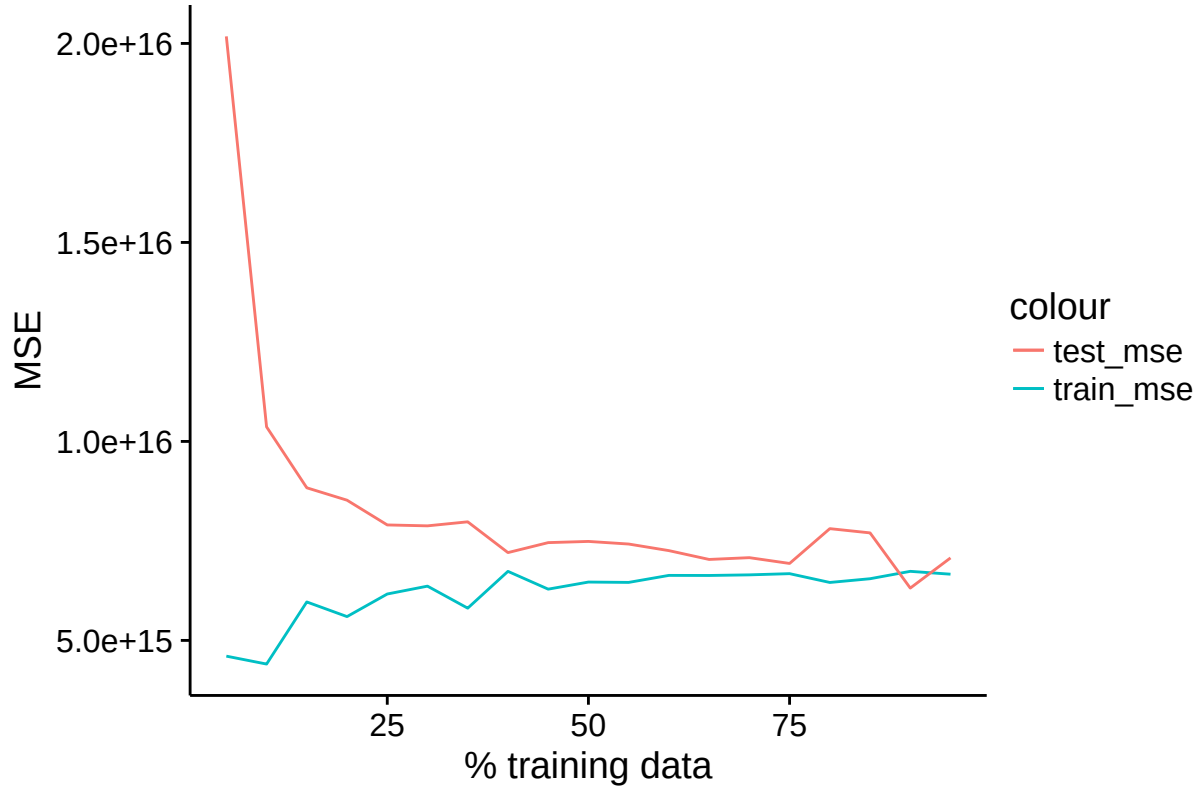
```
mean(residuals(M5)^2)
```

```
## [1] 1.9144e+16
```

```
train_set = seq(5,95, by=5)

mse.on.test.data_2 = rep(0,19)
mse.on.train.data_2 = rep(0,19)
train_mse = rep(0,10)
test_mse= rep(0,10)
n_row = nrow(movie_only_data)
best_mse = 1.797693e+308
best_train_size = 0
set.seed(50)



for (num in seq(1:19)){
  for(i in seq(1:10)){
    local_var = train_set[num]
    local_var = local_var/100
  random_perm = sample(n_row,n_row)
  first_index = random_perm[1:floor(n_row*local_var)]
  second_index = random_perm[(floor(n_row * local_var)+1):n_row]
```

```
  train_data = movie_only_data[first_index,]
  test_data = movie_only_data[second_index,]
  data = train_data
  model = lm(profit~Year+Runtime*imdbVotes+Budget+Awards+imdbVotes
             +tomatoReviews*Budget+I(tomatoReviews^2)*Budget+
               tomatoRotten*imdbVotes+tomatoUserMeter*imdbVotes+
               I(log(tomatoUserReviews))*imdbVotes+
               tomatoUserRating*Budget+tomatoMeter*Budget+
               imdbRating*imdbVotes+I(imdbRating^2)*Budget+
               I(imdbRating^3)*Budget+Metascore*imdbVotes,data)
 train_mse[i]  = mean(residuals(model)^2)
 data = test_data
 test_mse[i] = calculate_rmse(test_data$profit, predict(model,data))
  }
  mse.on.train.data_2[num] = mean(train_mse)
  mse.on.test.data_2[num] = mean(test_mse)

  if (mean(test_mse) < best_mse){
   best_mse = mean(test_mse)
   best_model=model
 }
}

result = data.frame(training_data=train_set,
                    mse_train_data=mse.on.train.data_2,
                    mse_test_data=mse.on.test.data_2)

ggplot(result,aes(x=training_data)) +
  geom_line(aes(y=mse_train_data,color="train_mse")) + geom_line(aes(y=mse_test_data,color="test_mse"))+
ylab("MSE") +xlab("% training data") +
  ggtitle("Fig 1.0 : MSE vs Training data size")
```

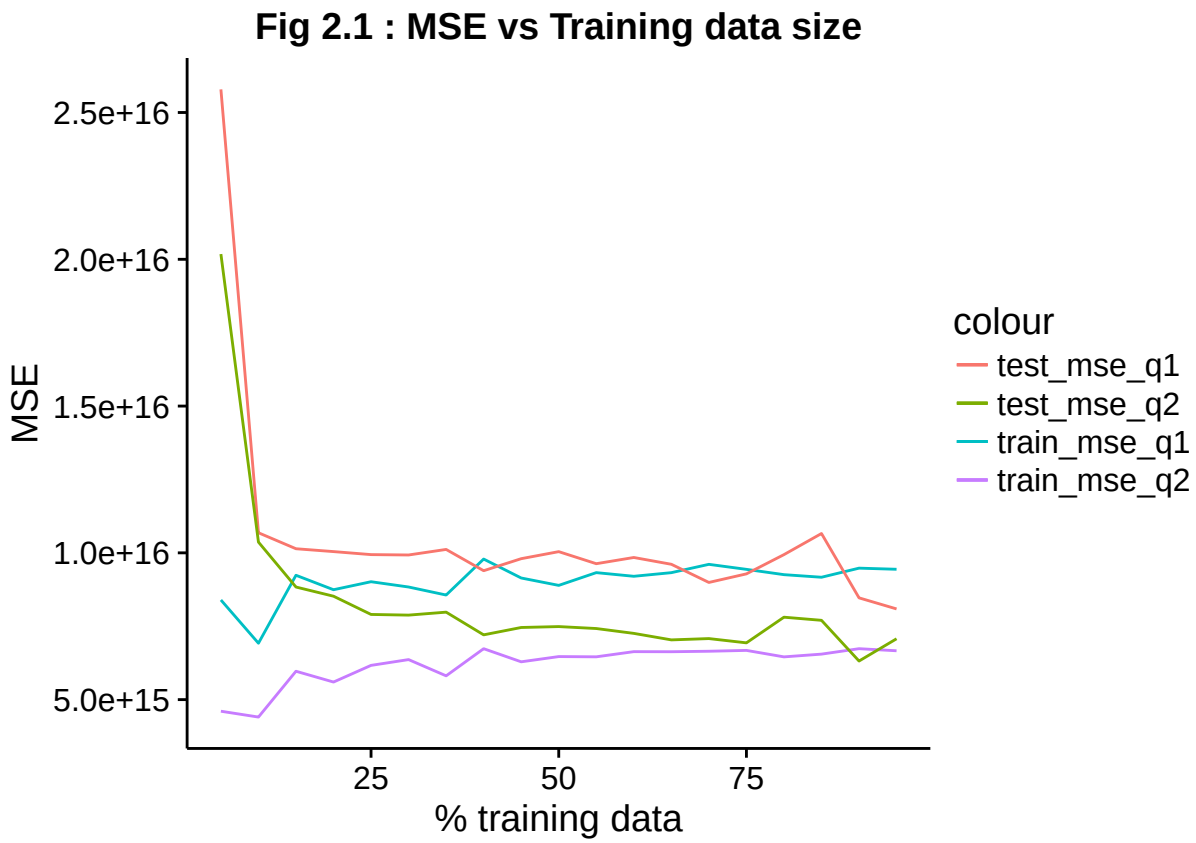
Fig 1.0 : MSE vs Training data size




```
cat("best MSE:", best_mse)
```

```
## best MSE: 6.314433e+15
```

```
result2 = data.frame(training_data=train_set,
                     mse_train_data_q1=mse.on.train.data_1,
                     mse_test_data_q1=mse.on.test.data_1,
                     mse_train_data_q2=mse.on.train.data_2,
                     mse_test_data_q2=mse.on.test.data_2)

ggplot(result2,aes(x=training_data)) + geom_line(aes(y=mse_train_data_q1,color="train_mse_q1")) + geom_
```



Write code that featurizes genre (can use code from Part-I), actors, directors, and othercategorical variables. Explain how you encoded the variables into features.

Code for the question were extracted from the code I submitted for project1.For the Genre I transformed the features into an N-dimensional vector of zeros and ones.where one represent the present of a genre and zero the absent of a genre.N is the total number of possible distinct Genre.Genre with high sparcity are dropped. The same techniques used to featurize the genre feature was used for actors, directors, country , production, tomatoImage,language and rated features as shown in the code below.

```
movie_only_data = subset(movie_only_data, Genre != "N/A")
docs = data.frame(movie_only_data$Genre)
ds = DataframeSource(docs)
rm(docs)
docs = VCorpus(ds)
docs = tm_map(docs, content_transformer(tolower))
docs = tm_map(docs, removePunctuation)
docs = tm_map(docs, removeNumbers)
docs = tm_map(docs, stripWhitespace)
dtm = DocumentTermMatrix(docs)
dtm = removeSparseTerms(dtm,0.925)
newcolumns_1 = data.frame(as.matrix(dtm))
movie_only_data = cbind(movie_only_data,newcolumns_1)
genre_features = names(newcolumns_1)

temp =  data.frame(gsub(pattern = " ", replacement = "", x = movie_only_data$Actors))
```

```
names(temp) = "Actors"
temp$Actors = as.character(temp$Actors)

docs = data.frame(temp$Actors)
ds = DataframeSource(docs)
rm(docs)
docs = VCorpus(ds)
docs = tm_map(docs, content_transformer(tolower))
toSpace = content_transformer(function(x,pattern) gsub(pattern," ",x))
docs = tm_map(docs,toSpace, ",")
docs=tm_map(docs,removePunctuation)
dtm = DocumentTermMatrix(docs)
#newcolumns_2 = data.frame(as.matrix(dtm))
#movie_only_data = cbind(movie_only_data,newcolumns_2)
#actors_features = names(newcolumns_2)

mydata = movie_only_data

temp =  data.frame(gsub(pattern = " ", replacement = "", x = movie_only_data$Director))
names(temp) = "Director"
temp$Director = as.character(temp$Director)

docs = data.frame(temp$Director)
ds = DataframeSource(docs)
rm(docs)
docs = VCorpus(ds)
docs = tm_map(docs, content_transformer(tolower))
toSpace = content_transformer(function(x,pattern) gsub(pattern," ",x))
docs = tm_map(docs,toSpace, ",")
dtm = DocumentTermMatrix(docs)
newcolumns_3 = data.frame(as.matrix(dtm))
mydata = cbind(mydata,newcolumns_3)
director_features = names(newcolumns_3)



docs = data.frame(movie_only_data$tomatoImage)
ds = DataframeSource(docs)
rm(docs)
docs = VCorpus(ds)
docs = tm_map(docs, content_transformer(tolower))
toSpace = content_transformer(function(x,pattern) gsub(pattern," ",x))
docs = tm_map(docs,toSpace, ",")
dtm = DocumentTermMatrix(docs)
newcolumns_4 = data.frame(as.matrix(dtm))
movie_only_data = cbind(movie_only_data,newcolumns_4)
tomato_image_features = names(newcolumns_4)

temp =  data.frame(gsub(pattern = " ", replacement = "", x = movie_only_data$Production))
names(temp) = "Production"
temp$Production = sapply(temp$Production, function(x){return(substr(x,1,9))})

docs = data.frame(temp$Production)
```

```
ds = DataframeSource(docs)
rm(docs)
docs = VCorpus(ds)
toSpace = content_transformer(function(x,pattern) gsub(pattern," ",x))
docs = tm_map(docs,toSpace, ",")
docs = tm_map(docs,toSpace, "/")
docs = tm_map(docs, removePunctuation)
docs = tm_map(docs, content_transformer(tolower))
toString = content_transformer(function(x, from ,to) gsub(from , to , x))
docs = tm_map(docs , toString, "sonypicut","sonypictu")

dtm = DocumentTermMatrix(docs)
dtm=removeSparseTerms(dtm,0.95)
newcolumns_5 = data.frame(as.matrix(dtm))
movie_only_data = cbind(movie_only_data,newcolumns_5)
production_features = names(newcolumns_5)




docs = data.frame(movie_only_data$Language)
ds = DataframeSource(docs)
rm(docs)
docs = VCorpus(ds)
docs = tm_map(docs, content_transformer(tolower))
toSpace = content_transformer(function(x,pattern) gsub(pattern," ",x))
docs = tm_map(docs,toSpace, ",")
dtm = DocumentTermMatrix(docs)
dtm = removeSparseTerms(dtm, 0.92)
newcolumns_6 = data.frame(as.matrix(dtm))
movie_only_data = cbind(movie_only_data,newcolumns_6)
language_features = names(newcolumns_6)



mydocs = data.frame(movie_only_data$Country)
ds = DataframeSource(mydocs)
rm(mydocs)
mydocs = VCorpus(ds)
mydocs = tm_map(mydocs, content_transformer(tolower))
#toSpace = content_transformer(function(x,pattern) gsub(pattern," ",x))
#docs = tm_map(docs,toSpace, ",")
toString = content_transformer(function(x, from ,to) gsub(from , to , x))
mydocs = tm_map(mydocs , toString, "new zealand", "new-zealand")
mydocs = tm_map(mydocs , toString, "burkina faso", "burkina-faso")
mydocs = tm_map(mydocs , toString, "united arab emirates", "united-arab-emirates")
mydocs = tm_map(mydocs , toString, "puerto rico", "puerto-rico")
mydocs = tm_map(mydocs , toString, "costa rica", "costa-rica")
mydocs = tm_map(mydocs , toString, "côte d'ivoire", "côte-d'ivoire")
mydocs = tm_map(mydocs , toString, "dominican republic", "dominican-republic")
mydocs = tm_map(mydocs , toString, "solomon islands", "solomon-islands")
mydocs = tm_map(mydocs , toString, "bosnia and herzegovina", "bosnia-and-herzegovina")
mydocs = tm_map(mydocs , toString, "soviet union", "soviet-union")
```

```
mydocs = tm_map(mydocs , toString, "east germany", "east-germany")
mydocs = tm_map(mydocs , toString, "federal republic of yugoslavia", "yugoslavia")
mydocs = tm_map(mydocs , toString, "hong kong", "hong-kong")
mydocs = tm_map(mydocs , toString, "west germany", "west-germany")
mydocs = tm_map(mydocs , toString, "the democratic republic of congo", "congo")
mydocs = tm_map(mydocs , toString, "isle of man", "isle-of-man")
mydocs = tm_map(mydocs , toString, "uk,", " united-Kingdom")
mydocs = tm_map(mydocs , toString, "trinidad and tobago", "trinidad-and-tobago")
mydocs = tm_map(mydocs , toString, "turks and caicos islands", "turks-and-caicos-islands")
mydocs = tm_map(mydocs , toString, "serbia and montenegro", "serbia-and-montenegro")
mydocs = tm_map(mydocs , toString, "south africa", "south-africa")
mydocs = tm_map(mydocs , toString, "saudi arabia", "saudi-arabia")
mydocs = tm_map(mydocs , toString, "north korea", "north-korea")
mydocs = tm_map(mydocs , toString, "papua new guinea", "papua-new-guinea")
mydocs = tm_map(mydocs , toString, "czech republic", "czech-republic")
mydocs = tm_map(mydocs , toString, "republic of macedonia", "republic-of-macedonia")
mydocs = tm_map(mydocs, removePunctuation)
dtm = DocumentTermMatrix(mydocs)
dtm = removeSparseTerms(dtm, 0.90)
newcolumns_7 = data.frame(as.matrix(dtm))
movie_only_data = cbind(movie_only_data,newcolumns_7)
country_features = names(newcolumns_7)




temp =  data.frame(gsub(pattern = " ", replacement = "", x = movie_only_data$Rated))
names(temp) = "Rated"
temp$Rated = sapply(temp$Rated,function(x){if(x=="R"){return("R-rated")}else if (x=="G"){return("G-Rate

docs = data.frame(temp$Rated)
ds = DataframeSource(docs)
rm(docs)
docs = VCorpus(ds)
docs = tm_map(docs, content_transformer(tolower))
toSpace = content_transformer(function(x,pattern) gsub(pattern," ",x))
docs = tm_map(docs,toSpace, ",")
dtm = DocumentTermMatrix(docs)
dtm = removeSparseTerms(dtm, 0.92)
newcolumns_8 = data.frame(as.matrix(dtm))
movie_only_data = cbind(movie_only_data,newcolumns_8)
Rated_features = names(newcolumns_8)




hlist =holidayNYSE(1888:2018)
hlist = c(hlist,holidayLONDON(1888:2018))
hlist = c(hlist, holidayTSX(1888:2018))
hlist = c(hlist, holidayZURICH(1888:2018))
temp1 = data.frame(isHoliday(timeDate(movie_only_data$Released), holidays =hlist ))
names(temp1) = "v1"
movie_only_data$Holidays[temp1$v1 == TRUE] = "Yes"
```

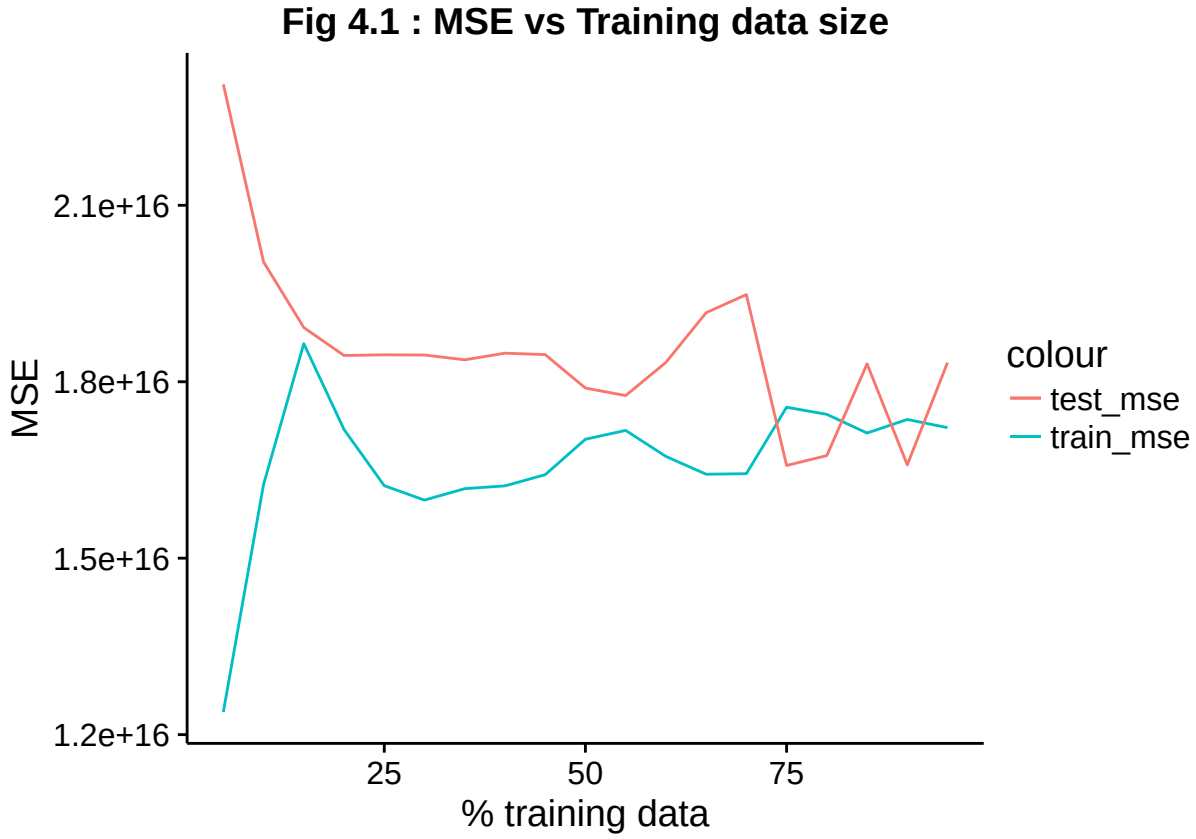
```
movie_only_data$Holidays[temp1$v1 == FALSE] = "No"
```

Use linear regression to predict profit based on all available non-numeric variables (using thetransformations in (3). Graph the train and test MSE as a function of the train set size (averagedover 10 random data partitions as described above)?

The code is shown.Fig 4.1 shows the test and train MSE , the best MSE on the test data was 1.657613e+16 which is lower than the value for question1 and question2 above.

```
features = c(genre_features,tomato_image_features,production_features,language_features,country_features

mydata = movie_only_data[,c("profit",features)]

train_set = seq(5,95, by=5)

mse.on.test.data = rep(0,19)
mse.on.train.data = rep(0,19)
train_mse = rep(0,10)
test_mse= rep(0,10)
n_row = nrow(movie_only_data)
best_mse = 1.797693e+308
best_train_size = 0
set.seed(200)



for (num in seq(1:19)){
  for(i in seq(1:10)){
    local_var = train_set[num]
    local_var = local_var/100
  random_perm = sample(n_row,n_row)
  first_index = random_perm[1:floor(n_row*local_var)]
  second_index = random_perm[(floor(n_row * local_var)+1):n_row]
  train_data = mydata[first_index,]
  test_data =  mydata[second_index,]
  data = train_data
  model = lm(profit~.,data)
 train_mse[i]  = mean(residuals(model)^2)
 data = test_data
 test_mse[i] = calculate_rmse(test_data$profit, predict(model,data))
  }
  mse.on.train.data[num] = mean(train_mse)
  mse.on.test.data[num] = mean(test_mse)


  if (mean(test_mse) < best_mse){
   best_mse = mean(test_mse)
  }

}

result = data.frame(training_data=train_set,
                    mse_train_data=mse.on.train.data,
```

```
                    mse_test_data=mse.on.test.data)

ggplot(result,aes(x=training_data)) +
  geom_line(aes(y=mse_train_data,color="train_mse")) + geom_line(aes(y=mse_test_data,color="test_mse"))+
ylab("MSE") +xlab("% training data") +
  ggtitle("Fig 4.1 : MSE vs Training data size")
```




```
cat("best MSE:", best_mse)
```

```
## best MSE: 1.657613e+16
```

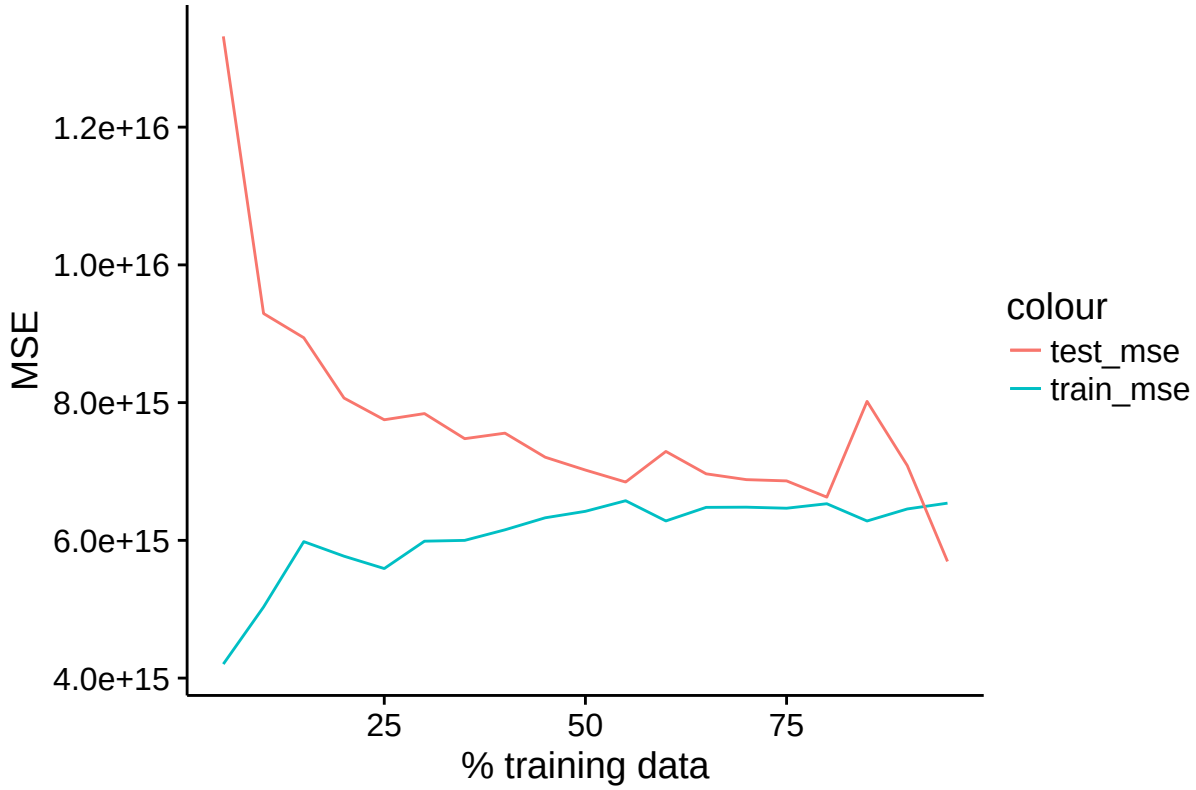
Try to improve the prediction quality in (1) as much as possible by using both numeric and non-numericvariables as well as creating additional transformed features including interactionfeatures (for example is_genre_comedy x is_budget_greater_than_3M). Explain whichtransformations you used and why you chose them. Graph the train and test MSE as a functionof the train set size (averaged over 10 random data partitions as described above)?

The code for this question is shwon below.Fig5.0 shows the test and train MSE , the best MSE was 5.694263e+15 which is a significant improvement from question2.I eliminated removed non-numeric features with very high sparcity.Fig5.1 shows the comparison between Q1,Q2 and Q5 model , overall the Q5 model performed better and has the lowest average MSE on test data.

```
train_set = seq(5,95, by=5)

mse.on.test.data_5 = rep(0,19)
mse.on.train.data_5 = rep(0,19)
```

```
train_mse = rep(0,10)
test_mse= rep(0,10)
n_row = nrow(movie_only_data)
best_mse = 1.797693e+308
best_train_size = 0
set.seed(201)



for (num in seq(1:19)){
  for(i in seq(1:10)){
    local_var = train_set[num]
    local_var = local_var/100
  random_perm = sample(n_row,n_row)
  first_index = random_perm[1:floor(n_row*local_var)]
  second_index = random_perm[(floor(n_row * local_var)+1):n_row]
  train_data = movie_only_data[first_index,]
  test_data = movie_only_data[second_index,]
  data = train_data
  model = lm(profit~Year+Runtime*imdbVotes+Budget+Awards
             +imdbVotes+tomatoReviews*Budget+
               I(tomatoReviews^2)*Budget+tomatoRotten*imdbVotes+
               tomatoUserMeter*imdbVotes+I(log(tomatoUserReviews))*
               imdbVotes+tomatoUserRating*Budget+tomatoMeter*Budget+
               imdbRating*imdbVotes+I(imdbRating^2)*Budget+
               I(imdbRating^3)*Budget+Metascore*imdbVotes+
               Holidays+action+adventure+drama+r.rated+certified,data)
 train_mse[i]  = mean(residuals(model)^2)
 data = test_data
 test_mse[i] = calculate_rmse(test_data$profit, predict(model,data))
  }
  mse.on.train.data_5[num] = mean(train_mse)
  mse.on.test.data_5[num] = mean(test_mse)

  if (mean(test_mse) < best_mse){
   best_mse = mean(test_mse)
   best_model=model
 }
}

result = data.frame(training_data=train_set,
                    mse_train_data=mse.on.train.data_5,
                    mse_test_data=mse.on.test.data_5)

ggplot(result,aes(x=training_data)) + geom_line(aes(y=mse_train_data,color="train_mse")) + geom_line(aes
```

Fig 5.0 : MSE vs Training data size




```
cat("best MSE:", best_mse)
```

```
## best MSE: 5.694263e+15
```

```
result5 = data.frame(training_data=train_set,
                     mse_train_data_q1=mse.on.train.data_1,
                     mse_test_data_q1=mse.on.test.data_1,
                     mse_train_data_q2=mse.on.train.data_2,
                     mse_test_data_q2=mse.on.test.data_2,
                     mse_train_data_q5=mse.on.train.data_5,
                     mse_test_data_q5=mse.on.test.data_5)

ggplot(result5,aes(x=training_data)) + geom_line(aes(y=mse_train_data_q1,color="train_mse_q1")) + geom_l
  geom_line(aes(y=mse_train_data_q5,color="train_mse_q5")) + geom_line(aes(y=mse_test_data_q5,color="tes
```

Fig 5.1 : MSE vs Training data size