Predict Game Sales Project

Skyler Bowthorpe

3/9/2020

##Introduction This report is a capstone project for the Data Science: Capstone course on the edx platform. This dataset has information about videogames including things like genre, publisher, and sales. The goal is to predict the number of sales a game will get based on the basic info provided. In a business context this is very useful information as developing games it time consuming and expensive.

First this script sets up the necessary libraries and imports the dataset. I will include the CSV file in the GetHub repository.

```
tinytex::reinstall_tinytex()
```

```
## If reinstallation fails, try install_tinytex() again. Then install the following packages:
##
## tinytex::tlmgr_install(c("amscls", "amsfonts", "amsmath", "atbegshi", "atveryend", "auxhook", "babel

## The directory C:\Users\47433\AppData\Roaming\TinyTeX/texmf-local is not empty. It will be backed up t

## tlmgr conf auxtrees remove "C:/PROGRA~1/R/R-36~1.1/share/texmf"

## tlmgr path remove

## Starting to install TinyTeX to C:\Users\47433\AppData\Roaming\TinyTeX. It will take a few minutes.

## Next you may see two error dialog boxes about the missing luatex.dll, and an error message like "Use

## TinyTeX installed to C:\Users\47433\AppData\Roaming\TinyTeX

## Please quit and reopen your R session and IDE (if you are using one, such as RStudio or Emacs) and ch
```

```
knitr::opts_chunk$set(echo = TRUE)
options(tinytex.verbose = TRUE)
#Introduction
#can we predict sales using other attributes?

#load libraries
options(warn =-1)
if(!require(tidyverse)) install.packages("tidyverse", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: tidyverse

## -- Attaching packages --------------------------------------------------- tidyverse 1.2.1 --

## v ggplot2 3.2.1     v purrr   0.3.2
## v tibble  2.1.3     v dplyr   0.8.3
## v tidyr   1.0.0     v stringr 1.4.0
## v readr   1.3.1     v forcats 0.4.0
```

```
## -- Conflicts ------------------------------------------------------- tidyverse_conflicts() --
## x dplyr::filter() masks stats::filter()
## x dplyr::lag()    masks stats::lag()
```

```r
if(!require(ggplot2)) install.packages("ggplot2", repos = "http://cran.us.r-project.org")
if(!require(readr)) install.packages("readr", repos = "http://cran.us.r-project.org")
if(!require(dplyr)) install.packages("dplyr", repos = "http://cran.us.r-project.org")
if(!require(caret)) install.packages("caret", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: caret

## Loading required package: lattice

##
## Attaching package: 'caret'

## The following object is masked from 'package:purrr':
##
##     lift
```

```r
if(!require(plyr)) install.packages("plyr", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: plyr

## --------------------------------------------------------------------------

## You have loaded plyr after dplyr - this is likely to cause problems.
## If you need functions from both plyr and dplyr, please load plyr first, then dplyr:
## library(plyr); library(dplyr)

## --------------------------------------------------------------------------

##
## Attaching package: 'plyr'

## The following objects are masked from 'package:dplyr':
##
##     arrange, count, desc, failwith, id, mutate, rename, summarise,
##     summarize

## The following object is masked from 'package:purrr':
##
##     compact
```

```r
if(!require(glmnet)) install.packages("glmnet", repos = "http://cran.us.r-project.org")
```

```
## Loading required package: glmnet

## Loading required package: Matrix
```

```
##
## Attaching package: 'Matrix'

## The following objects are masked from 'package:tidyr':
##
##     expand, pack, unpack

## Loaded glmnet 3.0-1
```

```r
library(tidyverse)
library(ggplot2) # for data visualization
library(readr) # for reading the CSV file
library(dplyr) # need for parts of the model
library(caret) # Backbone of the model
library(plyr) # for splitting the data into Partition
library(glmnet) # the statisital method for the model

#load data from csv
dat<-read.csv(file="Video_Games_Sales_as_at_22_Dec_2016.csv",stringsAsFactors=FALSE)

#clean up data
#change data types to more usable classes
dat<-na.omit(dat)
dat$Platform <- as.factor(as.character(dat$Platform))
dat$Genre <- as.factor(as.character(dat$Genre))
dat$Publisher <- as.factor(as.character(dat$Publisher))
dat$Name <- as.factor(as.character(dat$Name))
str(dat) #checking the dataset
```

```
## 'data.frame':    7017 obs. of  16 variables:
##  $ Name           : Factor w/ 4471 levels " Tales of Xillia 2",..: 4293 2097 4295 2574 4291 2577 209
##  $ Platform       : Factor w/ 17 levels "3DS","DC","DS",..: 13 13 13 3 13 13 3 13 15 13 ...
##  $ Year_of_Release: chr  "2006" "2008" "2009" "2006" ...
##  $ Genre          : Factor w/ 12 levels "Action","Adventure",..: 11 7 11 5 4 5 7 11 4 11 ...
##  $ Publisher      : Factor w/ 273 levels "10TACLE Studios",..: 172 172 172 172 172 172 172 172 153 1
##  $ NA_Sales       : num  41.4 15.7 15.6 11.3 14 ...
##  $ EU_Sales       : num  28.96 12.76 10.93 9.14 9.18 ...
##  $ JP_Sales       : num  3.77 3.79 3.28 6.5 2.93 4.7 4.13 3.6 0.24 2.53 ...
##  $ Other_Sales    : num  8.45 3.29 2.95 2.88 2.84 2.24 1.9 2.15 1.69 1.77 ...
##  $ Global_Sales   : num  82.5 35.5 32.8 29.8 28.9 ...
##  $ Critic_Score   : int  76 82 80 89 58 87 91 80 61 80 ...
##  $ Critic_Count   : int  51 73 73 65 41 80 64 63 45 33 ...
##  $ User_Score     : chr  "8" "8.3" "8" "8.5" ...
##  $ User_Count     : int  322 709 192 431 129 594 464 146 106 52 ...
##  $ Developer      : chr  "Nintendo" "Nintendo" "Nintendo" "Nintendo" ...
##  $ Rating         : chr  "E" "E" "E" "E" ...
##  - attr(*, "na.action")= 'omit' Named int  2 5 6 10 11 13 19 21 22 23 ...
##   ..- attr(*, "names")= chr  "2" "5" "6" "10" ...
```

```r
#I am going to focus on global sales for this analysis and we will round it to the nearest million.
dat <- dat %>% mutate(Global_Sales=round(Global_Sales,2))
dat <- dat[!(names(dat) %in% c("NA_Sales","EU_Sales","JP_Sales","Other_Sales","Year","Rank"))]
attach(dat)
head(dat)
```

```
##                         Name Platform Year_of_Release    Genre Publisher
## 1                 Wii Sports      Wii            2006   Sports  Nintendo
## 3             Mario Kart Wii      Wii            2008   Racing  Nintendo
## 4          Wii Sports Resort      Wii            2009   Sports  Nintendo
## 7      New Super Mario Bros.       DS            2006 Platform  Nintendo
## 8                   Wii Play      Wii            2006     Misc  Nintendo
## 9 New Super Mario Bros. Wii      Wii            2009 Platform  Nintendo
##   Global_Sales Critic_Score Critic_Count User_Score User_Count Developer
## 1        82.53           76           51          8        322  Nintendo
## 3        35.52           82           73        8.3        709  Nintendo
## 4        32.77           80           73          8        192  Nintendo
## 7        29.80           89           65        8.5        431  Nintendo
## 8        28.92           58           41        6.6        129  Nintendo
## 9        28.32           87           80        8.4        594  Nintendo
##   Rating
## 1      E
## 3      E
## 4      E
## 7      E
## 8      E
## 9      E
```

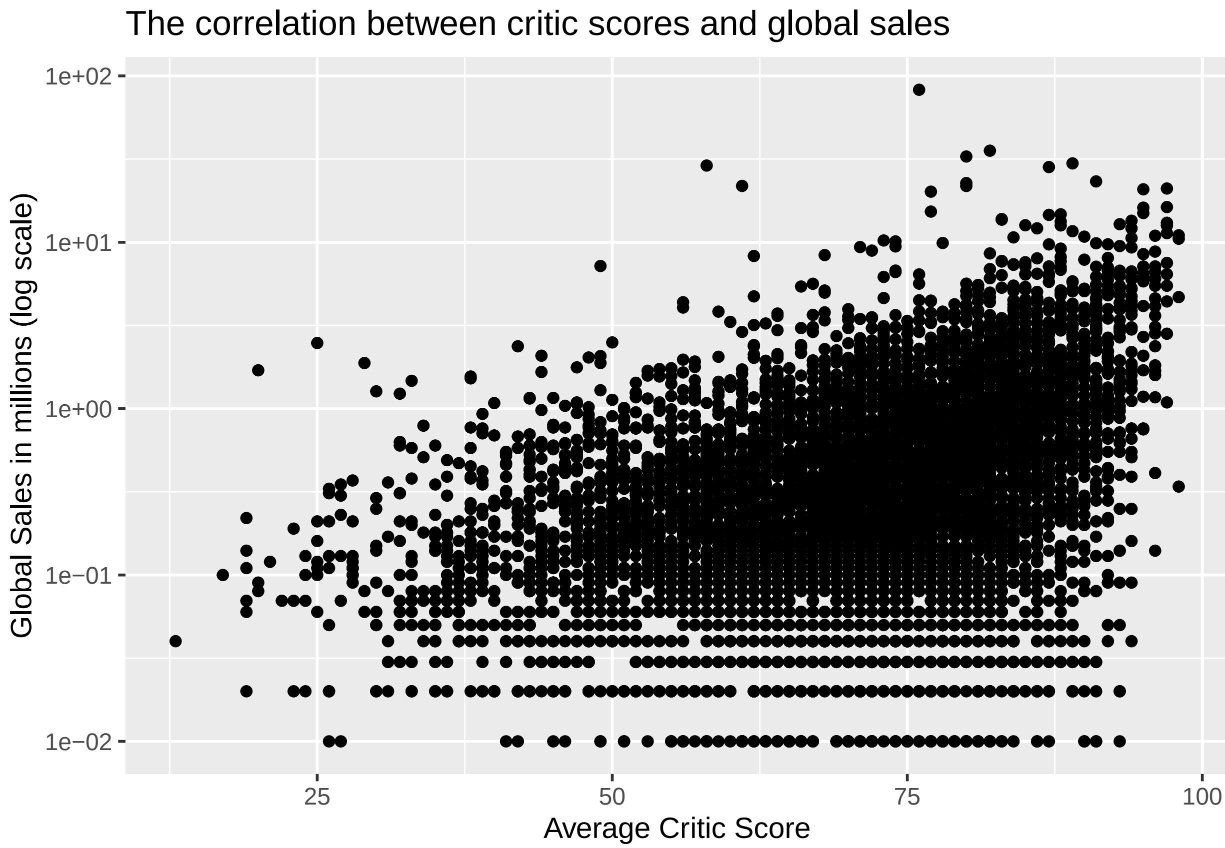
Data visualization

Next I will start exploring and visualizing the dataset. I want to clarify the variables that may help predict sales so they can be included in the prediction model.

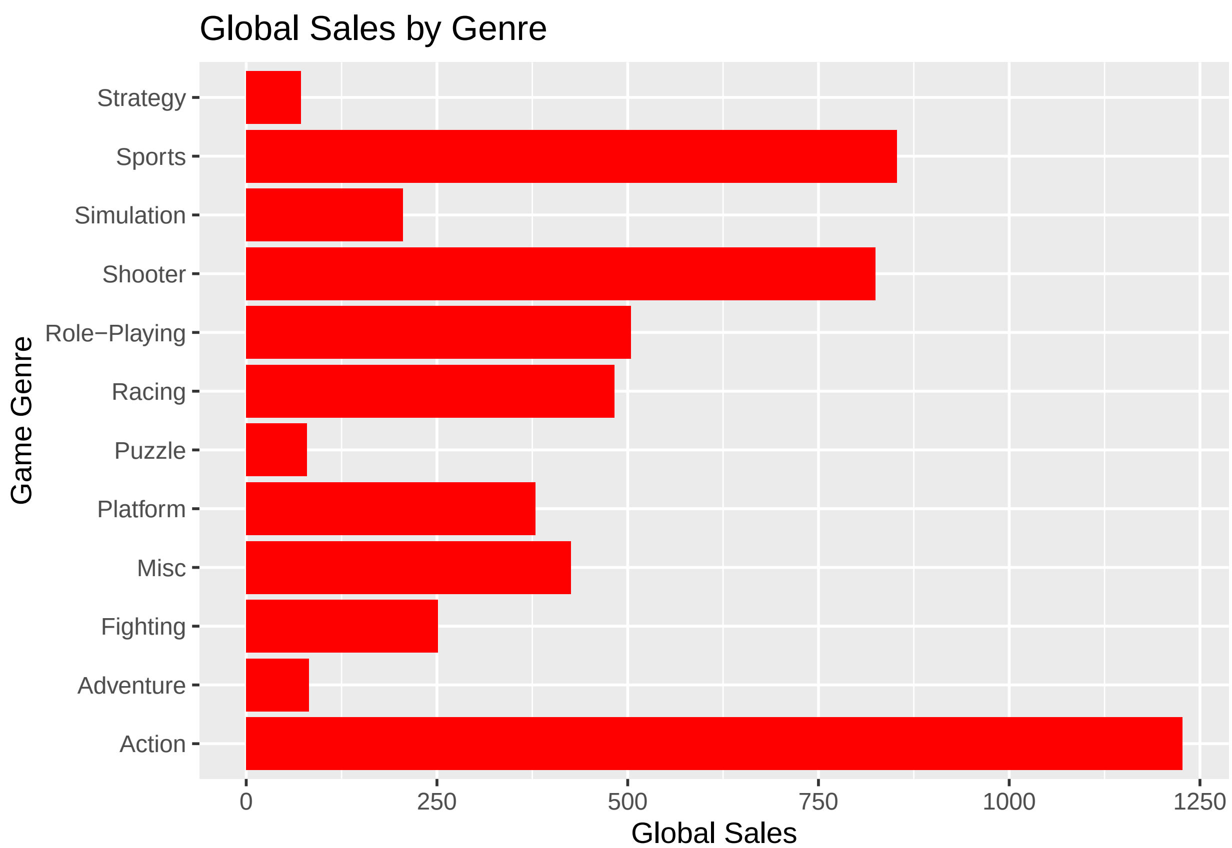
```r
#do critic scores effect sales?
#My hypothesis is that higher critic scores may influence consumers to buy certain games more.
cor(Global_Sales,Critic_Score)
```

```
## [1] 0.2369535
```

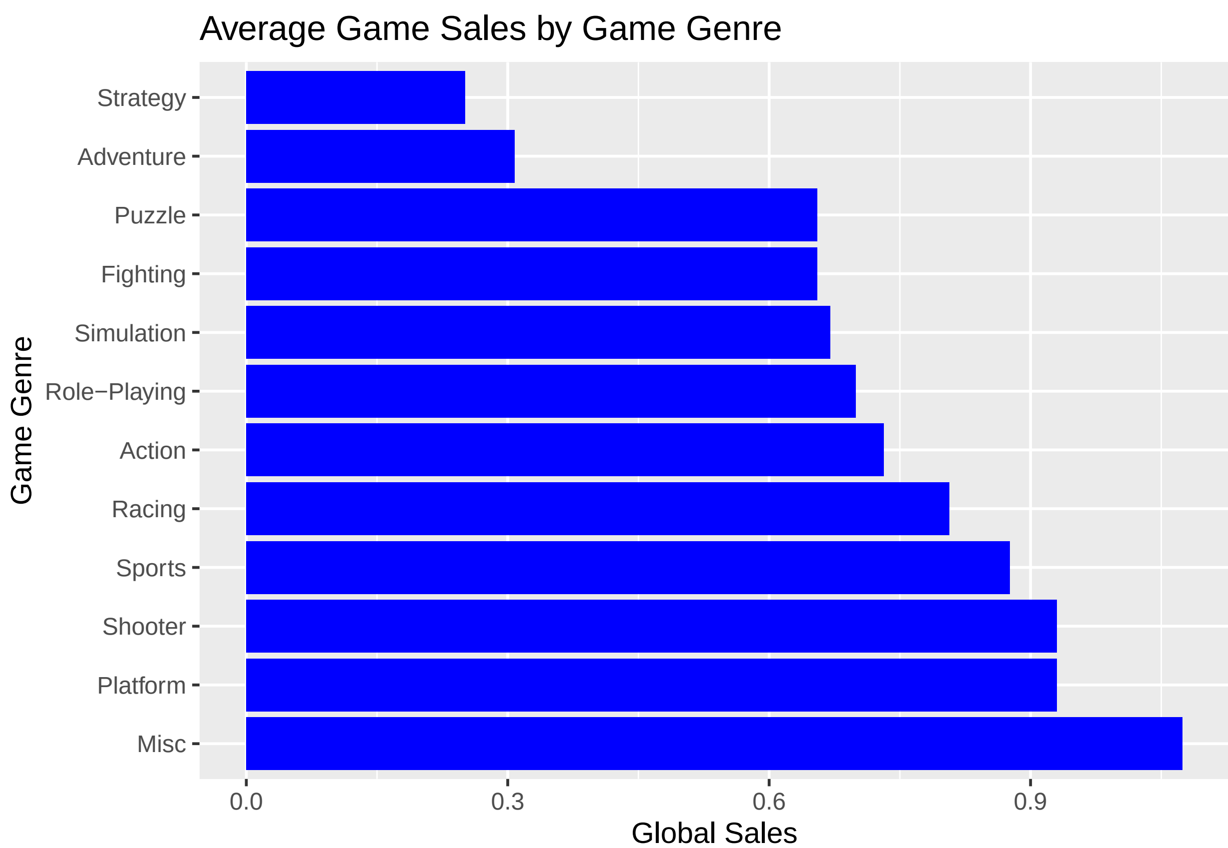
```r
#This is a lower correlation than I was expecting
#Plot the relationship to further understand the relatonship.
ggplot()+
  geom_point(aes(Critic_Score,Global_Sales))+
  scale_y_continuous(trans = "log10")+
  xlab("Average Critic Score")+
  ylab("Global Sales in millions (log scale)")+
  ggtitle("The correlation between critic scores and global sales")
```




```
dat <- dat[!(names(dat) %in% c("Critic_Score", "Critic_Count",
                               "User_Score", "User_Count",
                              "Developer", "Year_of_Release"))]
# Games seem to appeal to people differently.
# This is a good start let's explore other variables that may help predict global sales

#What are the most popular Genres?  Do games in those genres have high sales individually?
ggplot(dat, aes(Genre,Global_Sales)) +
  geom_bar(fill="red", stat="identity")+
  coord_flip()+
  xlab("Game Genre")+
  ylab("Global Sales")+
  ggtitle("Global Sales by Genre")
```




```r
# The data shows that action games have the highest
# collective sales but also a very high number of action titles.
average_rev_by_genre <- aggregate(Global_Sales~Genre,dat,mean)
arrange_by_rev2 <- arrange(average_rev_by_genre,desc(Global_Sales))
arrange_by_rev2$Genre=factor(arrange_by_rev2$Genre,levels=arrange_by_rev2$Genre)
ggplot(arrange_by_rev2,aes(Genre,Global_Sales))+
  geom_bar(fill="blue", stat="identity")+
  coord_flip()+
  xlab("Game Genre")+
  ylab("Global Sales")+
  ggtitle("Average Game Sales by Game Genre")
```

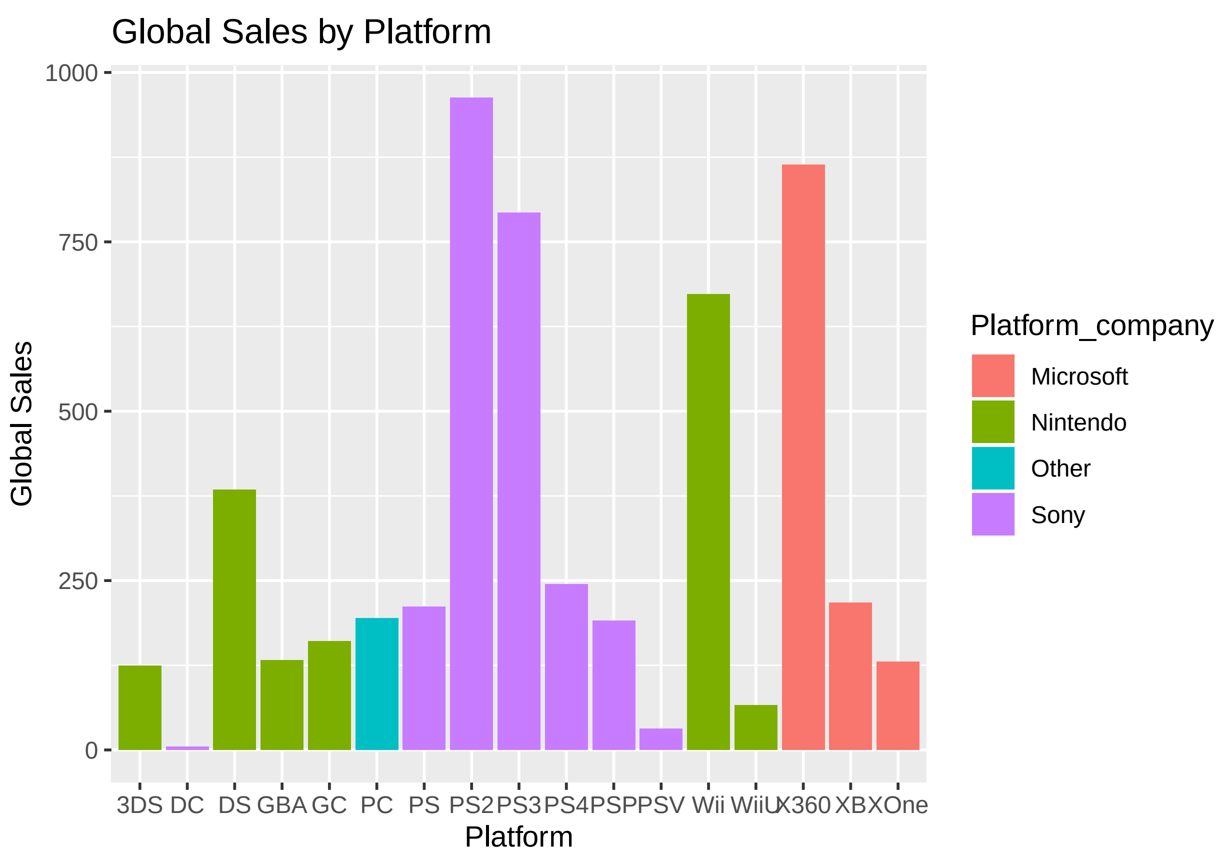



```r
# While the Adventure Genre had the most sales; Miscellaneous,
# Platforming, and Shooter games had the higher per-game performance.
# What are some of the games that are in the Miscellaneous category?

head(dat %>% filter(Genre == "Misc"), n = 10)
```

```
##                                        Name Platform Genre
## 1                                  Wii Play      Wii  Misc
## 2                        Kinect Adventures!     X360  Misc
## 3  Brain Age: Train Your Brain in Minutes a Day       DS  Misc
## 4                              Just Dance 3      Wii  Misc
## 5                              Just Dance 2      Wii  Misc
## 6                            Mario Party DS       DS  Misc
## 7                                 Wii Party      Wii  Misc
## 8                             Mario Party 8      Wii  Misc
## 9                                Just Dance      Wii  Misc
## 10                             Just Dance 4      Wii  Misc
##                 Publisher Global_Sales Rating
## 1                Nintendo        28.92      E
## 2  Microsoft Game Studios        21.81      E
## 3                Nintendo        20.15      E
## 4                 Ubisoft        10.12   E10+
## 5                 Ubisoft         9.44   E10+
## 6                Nintendo         8.91      E
## 7                Nintendo         8.38      E
## 8                Nintendo         8.27      E
```

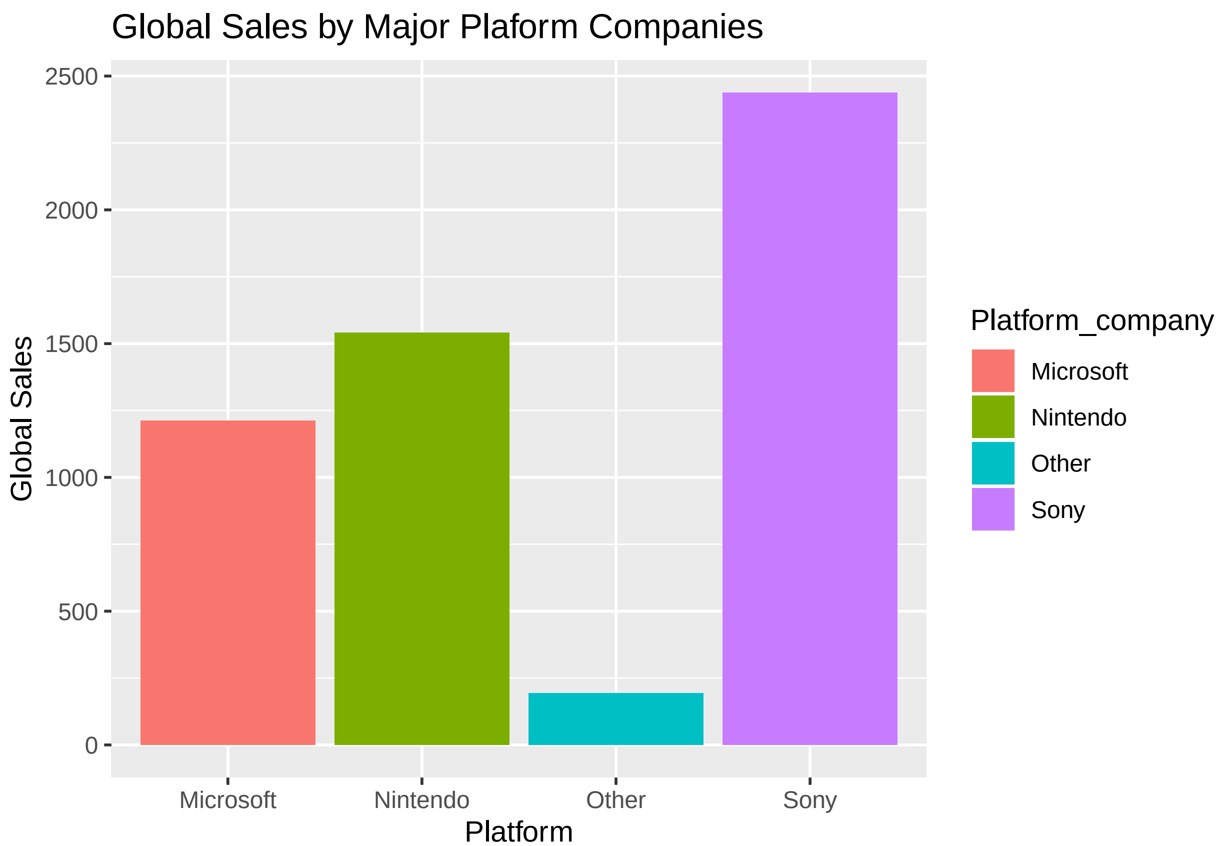
```
## 9                  Ubisoft          7.20    E10+
## 10                 Ubisoft          6.76    E10+
```

```r
#Misc includes party, music and learning type games.

# For more clarity I will categorize the platforms into major companies
# New generatoins of game systems replace the old every few years.
dat$Platform_company <- as.character(dat$Platform)
dat$Platform_company[dat$Platform_company %in% c("PS","PS2","PS3","PS4","PSP","PSV","DC")] <- "Sony"
dat$Platform_company[dat$Platform_company %in% c("XB","XOne","X360")] <- "Microsoft"
dat$Platform_company[dat$Platform_company %in% c("Wii","NES","GB","DS","SNES","GBA","3DS","N64","WiiU",
dat$Platform_company[!(dat$Platform_company  %in% c("Nintendo","Sony","Microsoft"))] <- "Other"
dat$Platform_company <- as.factor(dat$Platform_company)

#charts comparing platfoms
ggplot(dat, aes(Platform,Global_Sales,fill=Platform_company))+
  geom_bar(stat="identity")+
  xlab("Platform")+
  ylab("Global Sales")+
  ggtitle("Global Sales by Platform")
```

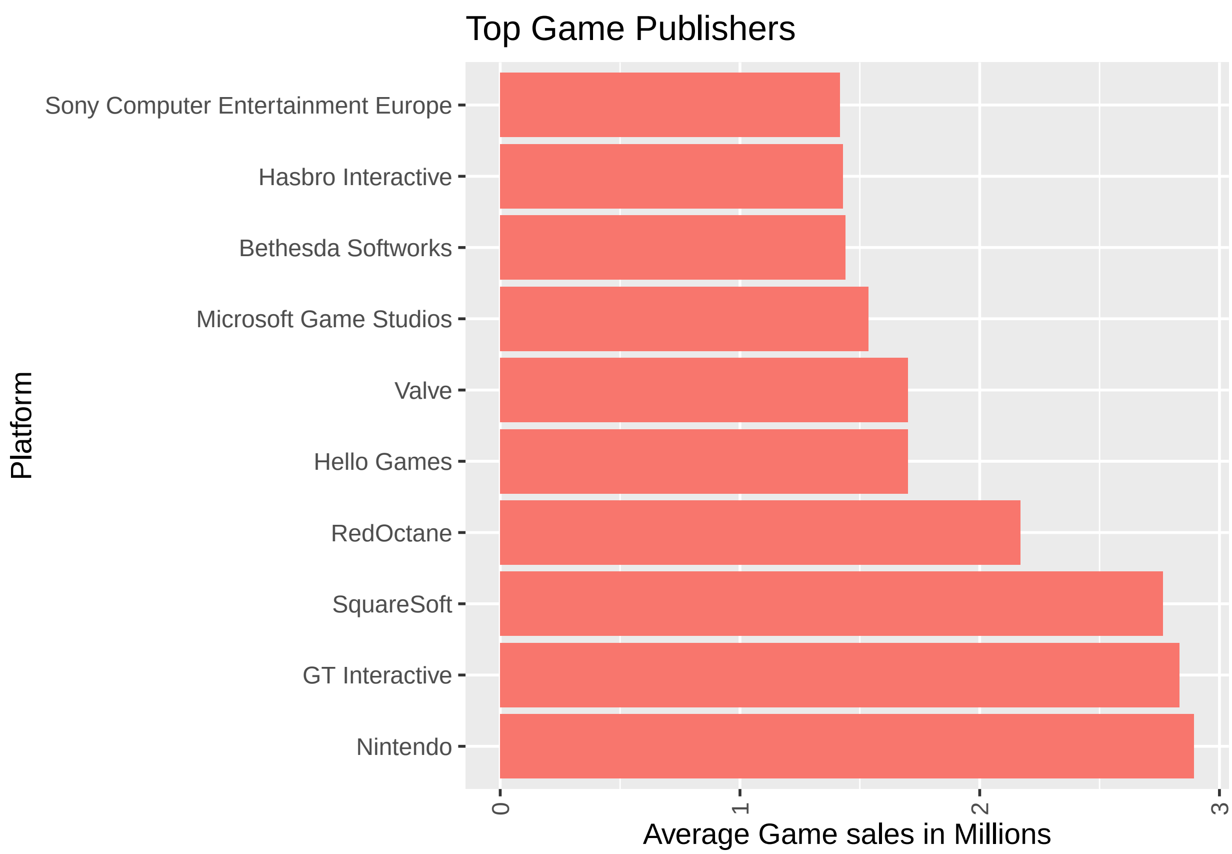



```r
#Much cleaner chart comparing platform companies.
ggplot(dat, aes(Platform_company,Global_Sales,fill=Platform_company))+
  geom_bar(stat="identity")+
  xlab("Platform")+
```

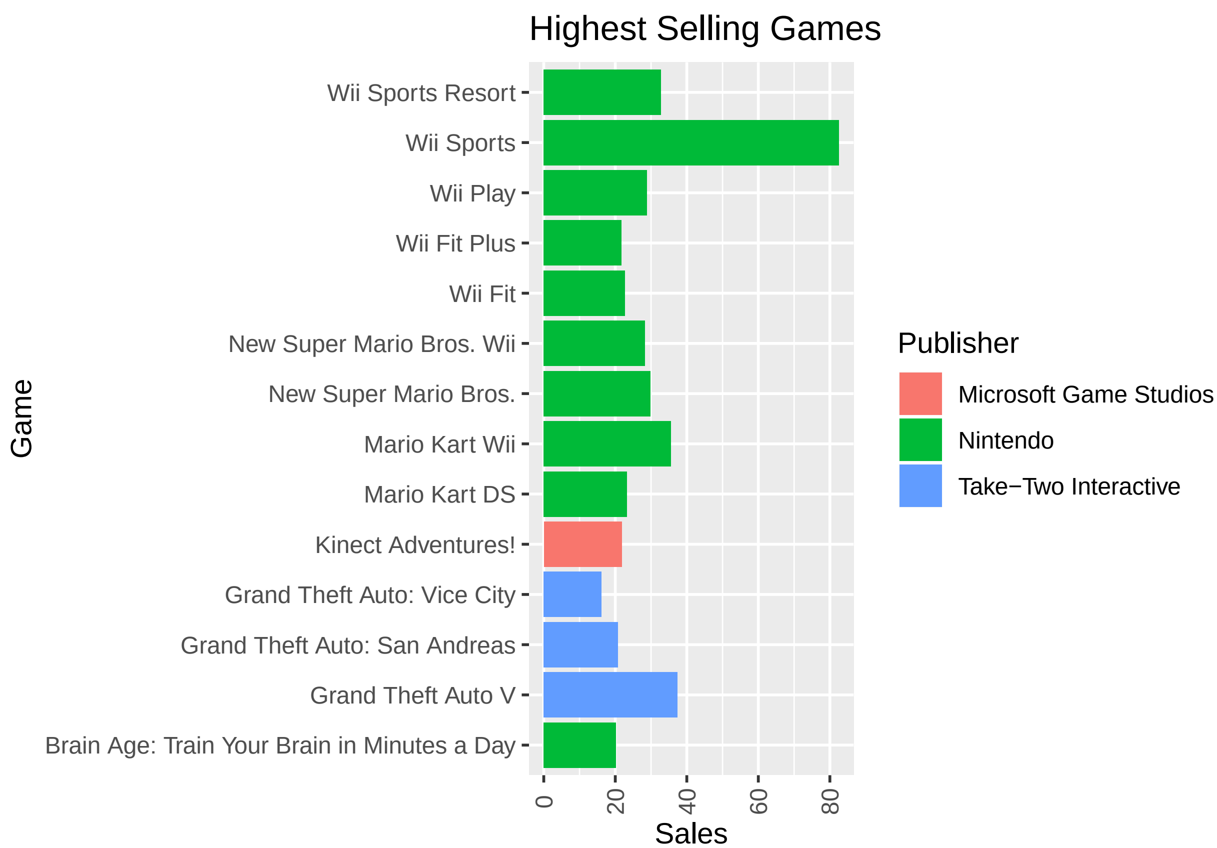
```
  ylab("Global Sales")+
  ggtitle("Global Sales by Major Plaform Companies")
```



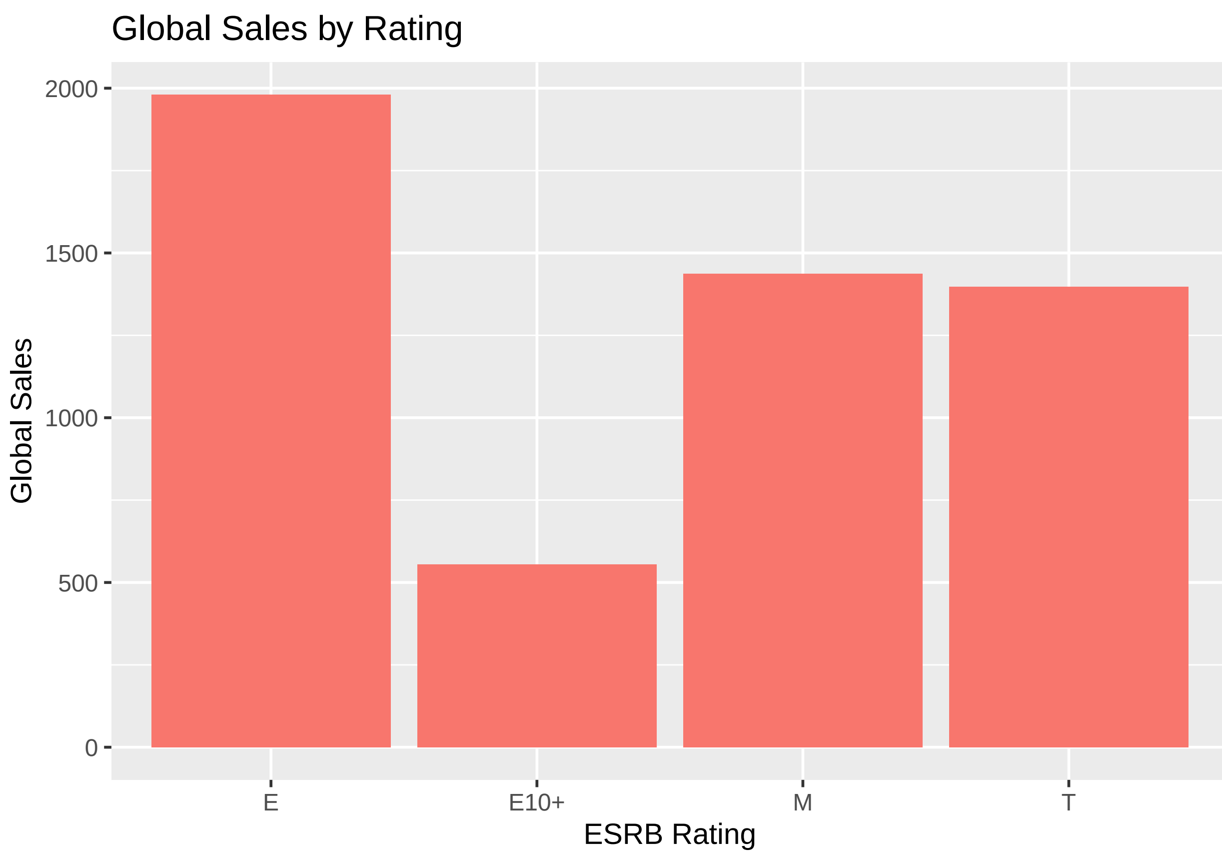

```
#There are too many publishers to plot all of them. I will show just the top ten.
top_publishers <- aggregate(Global_Sales~Publisher,dat,mean) #average of game sales per publisher
arrange_by_rev3 <- arrange(top_publishers,desc(Global_Sales))
arrange_by_rev3$Publisher = factor(arrange_by_rev3$Publisher, levels = arrange_by_rev3$Publisher)
ggplot(head(arrange_by_rev3,10),aes(Publisher,Global_Sales,fill="blue"))+
  geom_bar(stat="identity")+
  coord_flip()+
  labs(x="Platform",y="Average Game sales in Millions")+#Flipping the axis to it is more readable
  theme(axis.text.x=element_text(angle=90,vjust=0.5),legend.position="none")+
  ggtitle("Top Game Publishers")
```




```r
#Publishers vs highest sales games.
top_games_by_publisher = dat %>% select(Name,Global_Sales,Publisher) %>% arrange(desc(Global_Sales))
ggplot(head(top_games_by_publisher,15),aes(Name,Global_Sales,fill=Publisher))+
  geom_bar(stat="identity")+
  coord_flip()+
  labs(x="Platform",y="Average Game sales in Millions")+
  theme(axis.text.x = element_text(angle=90,vjust=0.5))+
  ggtitle("Highest Selling Games")+
  labs(x="Game",y="Sales")
```




```r
#What effect the parent safety ratings have on sales?
ggplot(subset(dat,Rating %in% c("E","E10+","T","M")),
  aes(Rating,Global_Sales,fill="green"))+
  geom_bar(stat="identity")+
  theme(legend.position="none")+
  xlab("ESRB Rating")+
  ylab("Global Sales")+
  ggtitle("Global Sales by Rating")
```




```
#That's enough visualization.  Lets build the model
```

Prediction model

This model will have limited accuracy because I am trying to predict a continuous variable. To help with this, I have rounded the sales to the closest million.

I ran into issues while building, I did not have a powerful enough machine to use my initial approach to building the model which is surprising because I chose that method because it is less hardware intensive than other methods. I will include a comment of the approach I would have used if my first approach was possible.

#Methodology 1. Split dataset into 80% training set and 20% training 2. Create a naïve model that is just the average of all game sales for a basis of comparison 3. Add a Genre effect that predicts higher sales if a game is in a popular genre (I learned this does not inform the prediction very well) 4. Learn I don't have enough ram to keep adding effects to the model (This project is about learning not about getting everything right) 5. Pivot and training and tuning a general linear model to predict sales 6. Test gml with the test set to measure accuracy

```
set.seed(1)
#Create training and test partitions
index <- createDataPartition(y=dat$Global_Sales, p=0.8, list=FALSE)
train <- dat[index,]
test <- dat[-index,]
validate <- test
```

```r
# Create a na?ve set for comparison
RMSE <- function(true_sales, predicted_sales){
  sqrt(mean((true_sales - predicted_sales)^2))}

mu_hat <- mean(train$Global_Sales)
naive_rmse <- RMSE(test$Global_Sales, mu_hat)
predictions <- rep(2.5, nrow(test))
rmse_results <- data_frame(method="Just the average",RMSE=naive_rmse)

#Rating effect
mu <- mean(train$Global_Sales)

genre_avgs <- train %>%
  group_by(Genre) %>%
  mutate(genre_effect = mean(Global_Sales - mu))

predicted_sales <- mu + test %>%
  left_join(genre_avgs, by="Genre") %>%
  .$genre_effect
model_1_rmse <- RMSE(predicted_sales, test$Global_Sales)
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="ESRB Rating Effect Model",
                                     RMSE = model_1_rmse ))
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	2.893235
ESRB Rating Effect Model	2.894456

```r
#I first approached this model using the lm() function to create a linear model with multiple predictor

#This is how I would have continued to test and tune the model but I received this error:
  #Error: Evaluation error: cannot allocate vector of size 3.4 Gb. and it crashed my computer.
  #I do not know of a less memory intensive way of continuing this method...

#Add platform effect to the model
#platform_avgs <- train %>%
#group_by(Platform) %>%
#mutate(platform_effect = mean(Global_Sales - mu))

#predicted_sales <- test %>%
  #full_join(genre_avgs,test, by = "Genre") %>%
  #full_join(platform_avgs,test, by = "Genre") %>%
  #mutate(pred = mu + genre_effect + platform_effect) %>%
  #.$pred
#model_2_rmse <- RMSE(predicted_sales, test$Global_Sales)
#rmse_results <- bind_rows(rmse_results,
                        #data_frame(method="Rating + Platform Effects Model",
                                   #RMSE = model_2_rmse ))
#rmse_results %>% knitr::kable()
```

```r
#New Method, hopefully my computer will handle it.
lambda <- 10^seq(2,-2,length=100)
alpha <-  seq(0,1,length=10) # I got help on a forum for this bit.
trControl <- trainControl(method = "CV",number= 10,repeats = 5)
grid = expand.grid(.alpha=alpha,.lambda=lambda)
train_model <- train(Global_Sales ~ Platform + Genre + Rating,
               data=train,
               method ='glmnet',
               tuneGrid=grid,
               trControl=trControl,
               standardize=TRUE,
               maxit= 10000)
train_model$bestTune
```

```
##         alpha     lambda
## 311 0.3333333 0.02535364
```

```r
final <- train_model$finalModel

#Make predictions with tuned model
predicted_global_sales <- predict(train_model,test,s=final$lambda.min)
#using min lamda found in train_model
check <- data.frame(Game=validate$Name, Actual=validate$Global_Sales)
prediction <- round(predicted_global_sales,2)

#check the output of GLM model
check <- check[1:length(prediction),]
check$Predicted <- abs(prediction)
check$diff <- abs(check$Predicted - check$Actual)
RMSE_glm <- sqrt(mean(check$diff^2))
# using a different method of arriving at RMSE but the answer is the same
rmse_results <- bind_rows(rmse_results,
                          data_frame(method="GLM model",
                                     RMSE = RMSE_glm ))
rmse_results %>% knitr::kable()
```

method	RMSE
Just the average	2.893235
ESRB Rating Effect Model	2.894456
GLM model	2.851813

##Conclusion I would have expected high critic ratings, ESRB rated "E" games to sell significantly more copies of a game but according to this analysis that is not the case.

This data suggests that you can directionally predict global sales of a videogame but the medium appeals to people differently and it is difficult to do with any certainty.

Thank you for the great opportunity to learn about data science and machine learning I have enjoyed these courses. This report was a great way to apply the lessons from those courses.