Predict Game Sales Project

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##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.

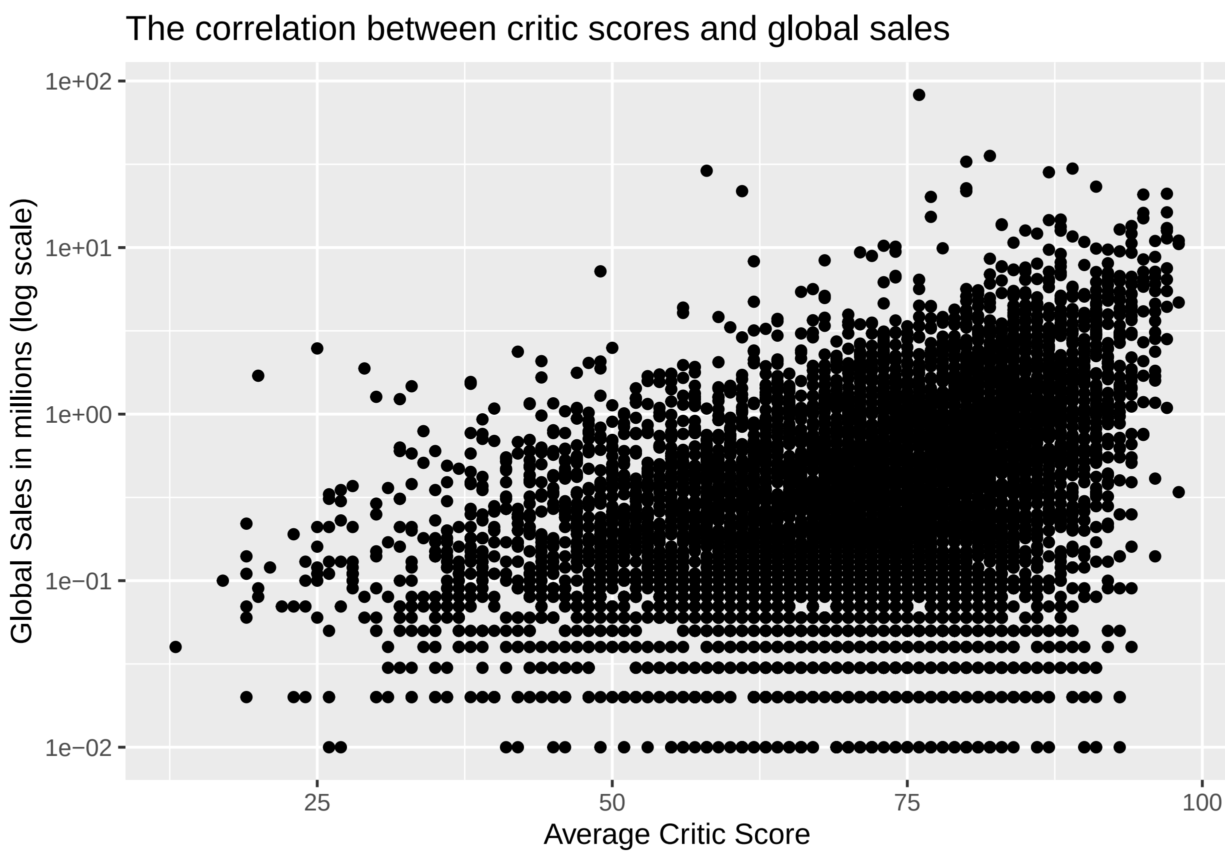
Data visualization

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.

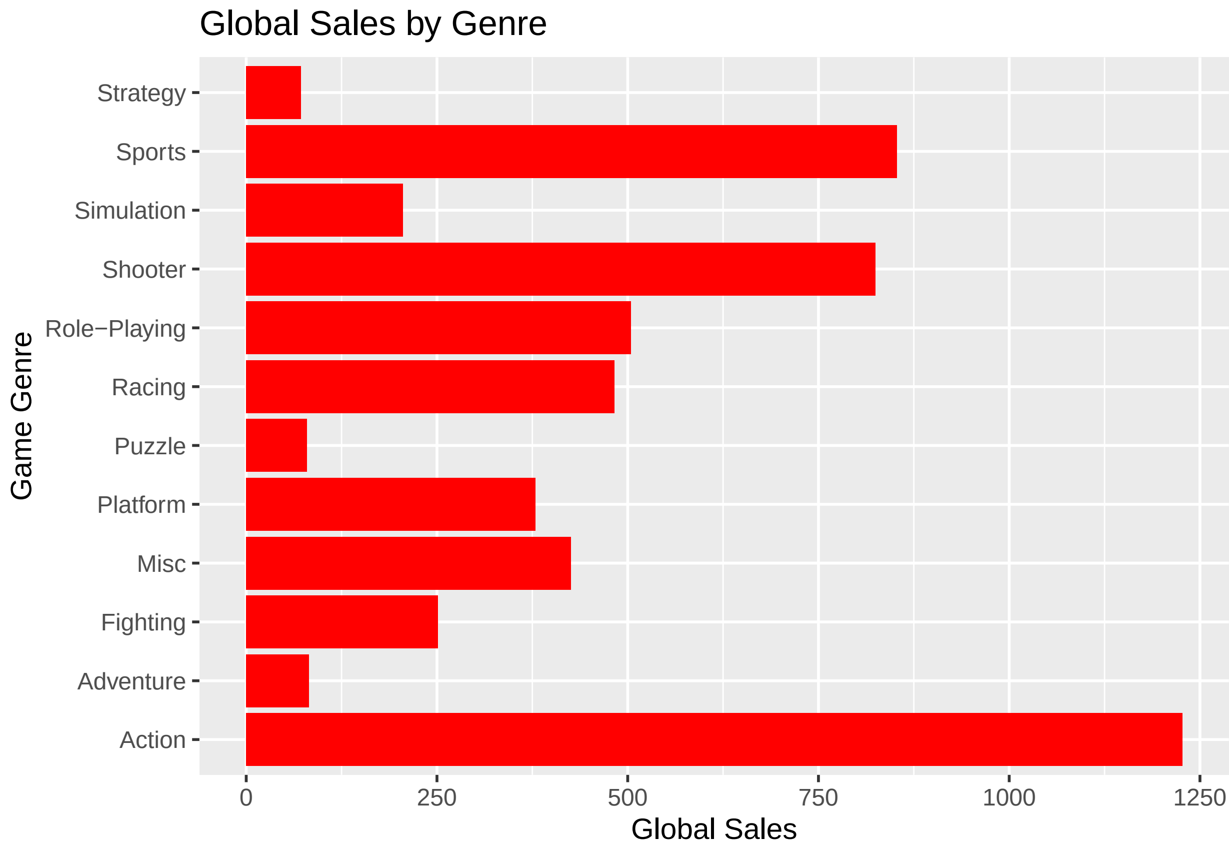
```r
#do critic scores effect sales?
#My hypothesis is that higher critic scores may influence consumers to buy certain games more.
cor(Global_Sales,Critic_Score)
```

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

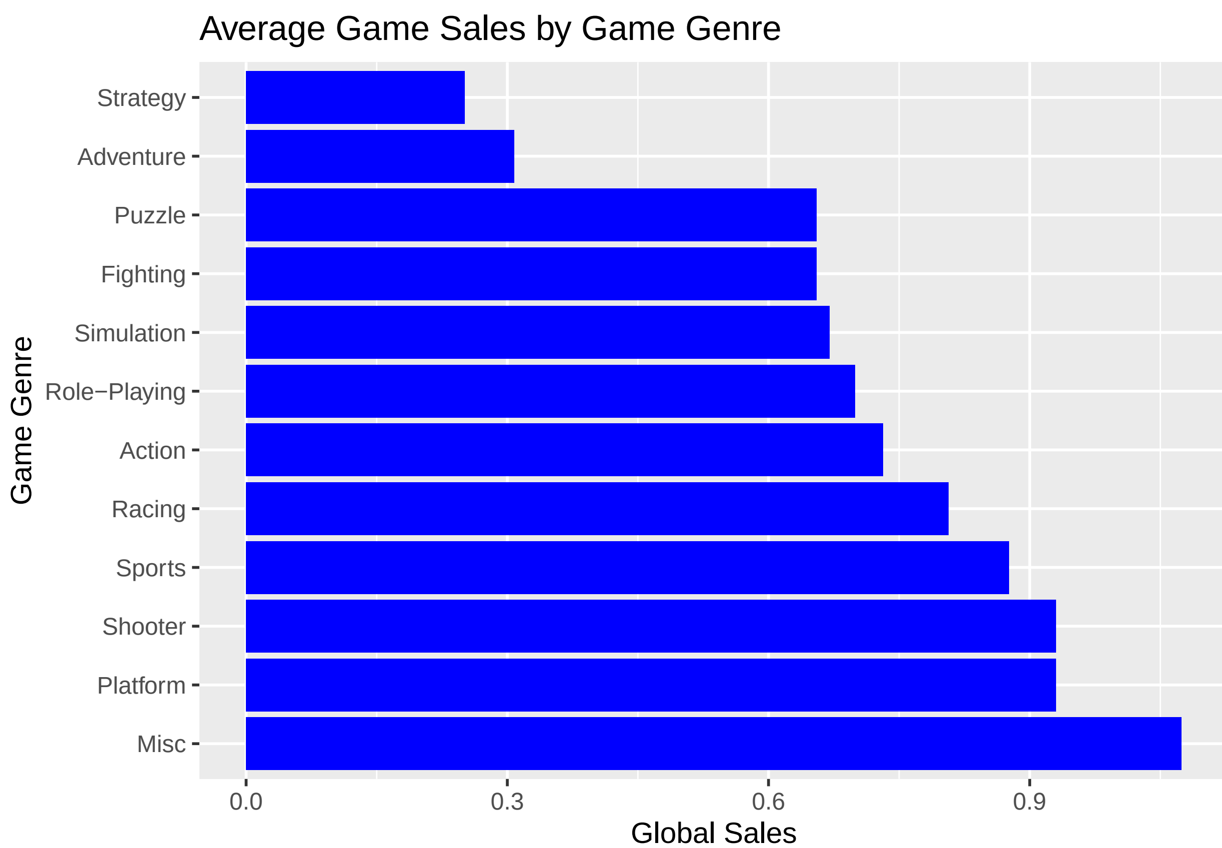
```r
#This is a lower correlation than I was expecting
#Plot the relationship to further understand the relatonship.
ggplot()+
  geom_point(aes(Critic_Score,Global_Sales))+
  scale_y_continuous(trans = "log10")+
  xlab("Average Critic Score")+
  ylab("Global Sales in millions (log scale)")+
  ggtitle("The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

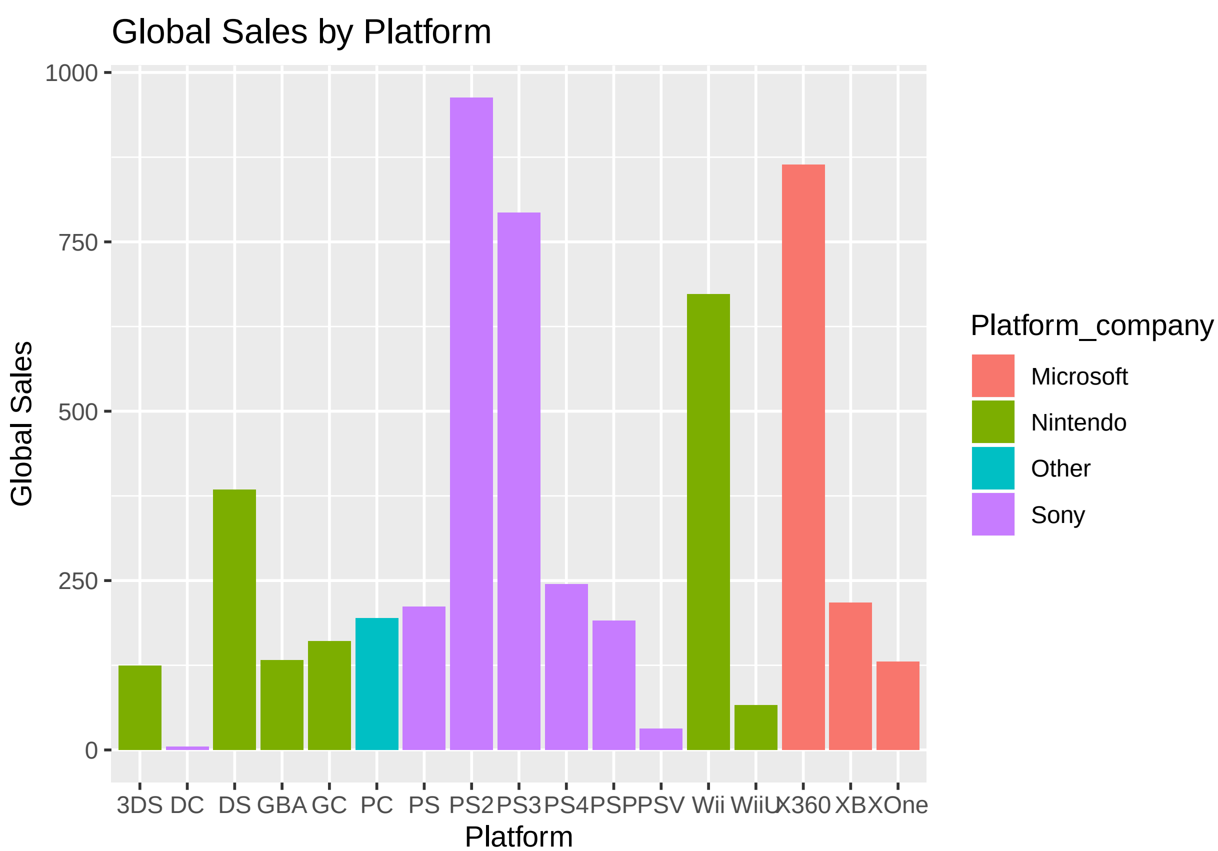



```r
# While the Adventure Genre had the most sales; Miscellaneous,
# Platforming, and Shooter games had the higher per-game performance.
# What are some of the games that are in the Miscellaneous category?

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
```

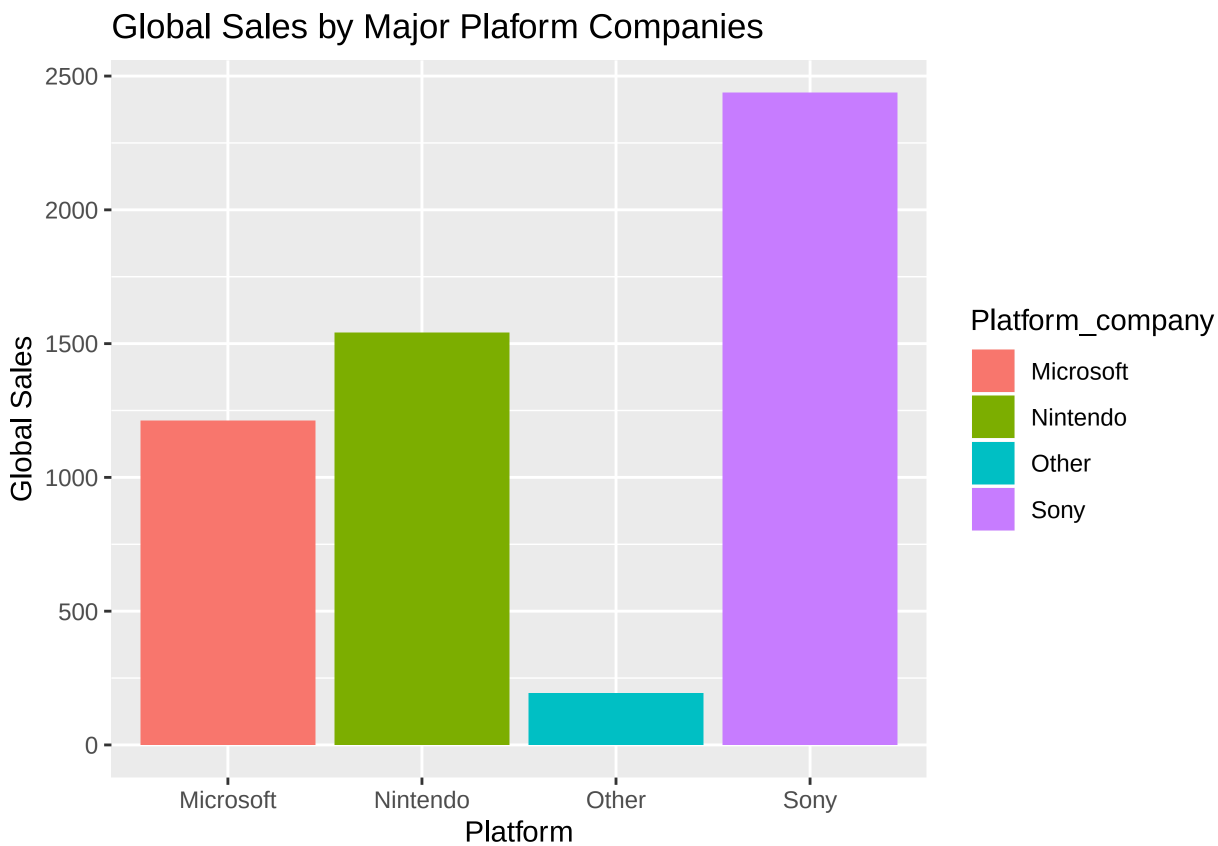
```
## 9                Ubisoft        7.20    E10+
## 10               Ubisoft        6.76    E10+
```

```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")
```

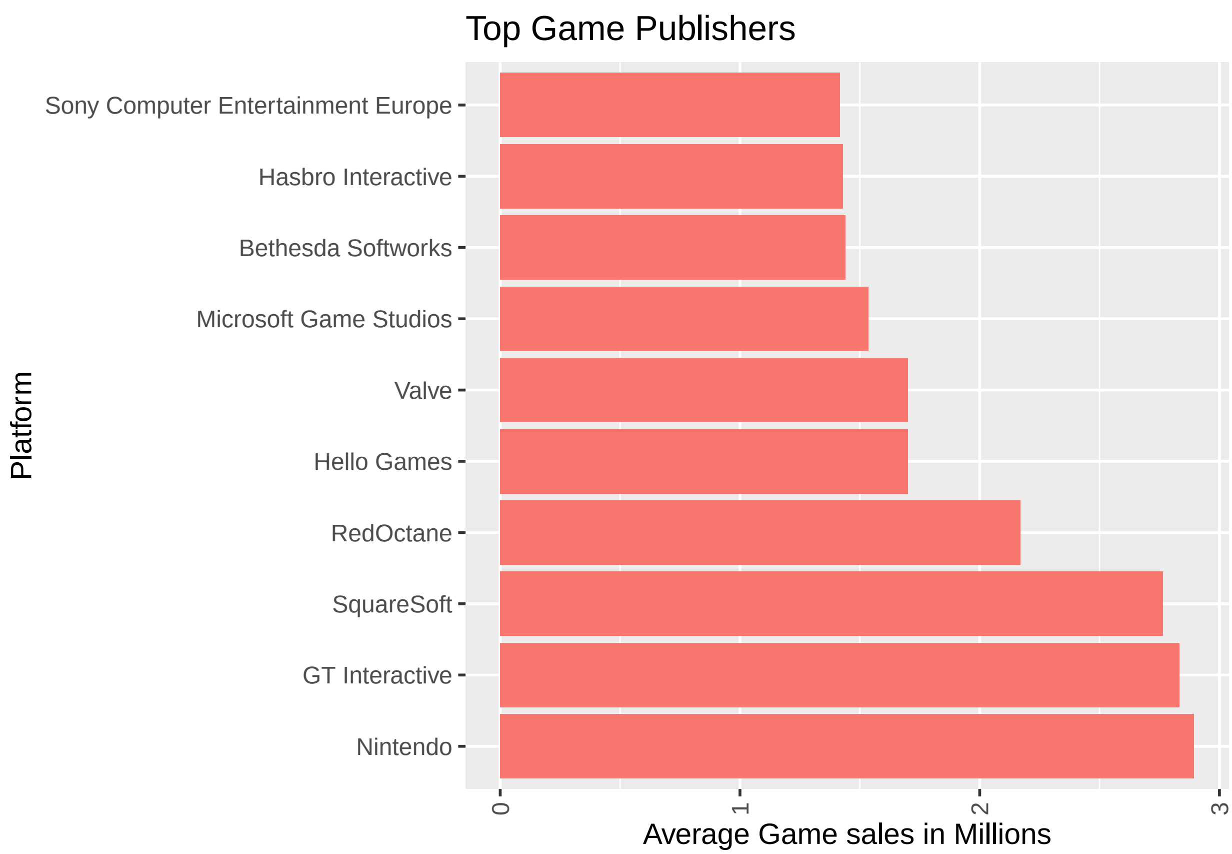



```r
#Much cleaner chart comparing platform companies.
ggplot(dat, aes(Platform_company,Global_Sales,fill=Platform_company))+
  geom_bar(stat="identity")+
  xlab("Platform")+
```

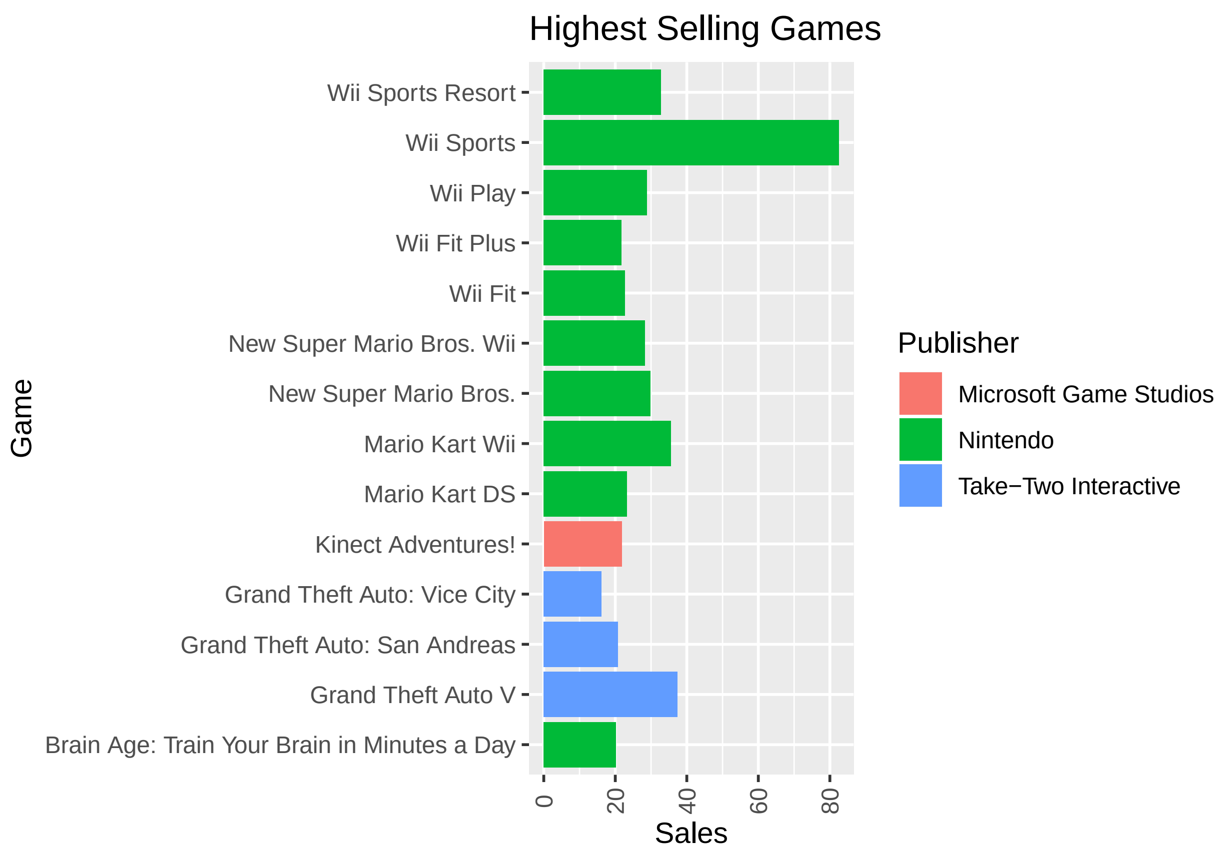
```
  ylab("Global Sales")+
  ggtitle("Global Sales by Major Plaform Companies")
```



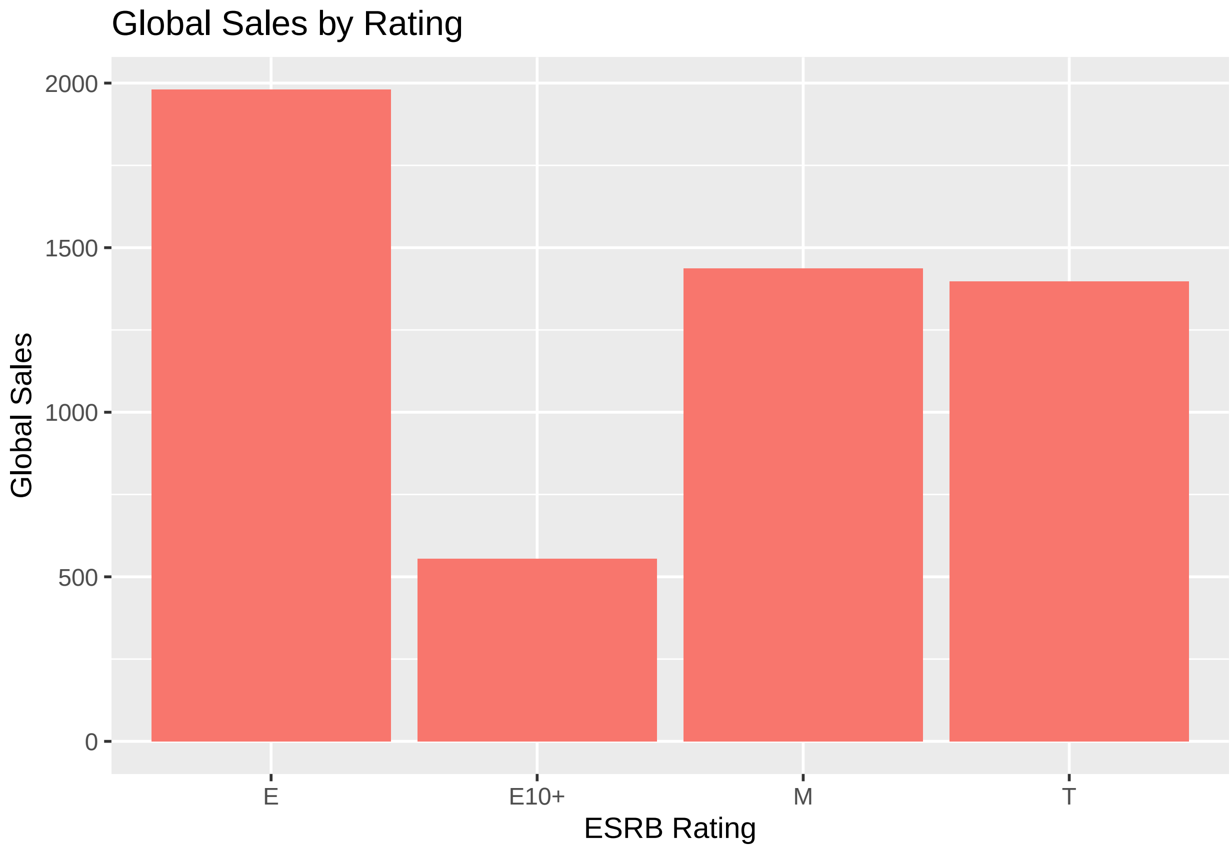

```
#There are too many publishers to plot all of them. I will show just the top ten.
top_publishers <- aggregate(Global_Sales~Publisher,dat,mean) #average of game sales per publisher
arrange_by_rev3 <- arrange(top_publishers,desc(Global_Sales))
arrange_by_rev3$Publisher = factor(arrange_by_rev3$Publisher, 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
```

```
# 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

```
#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.

For a directional recommendation it seems that E-rated, party, music or learning, Nintendo games have historically been the highest selling individual games while games for Sony consoles collectively have sold the most.

If I were consulting for a game studio on what types of game to make I would recommend making a game in the "Misc" type category because there are fewer of them but on average they sell a high number of copies.

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.