

Final Project: Analysis of Video Games Sales

Hai Le and Zack Frazier

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Welcome to our tutorial! Are you a video games lover/enthusiast, a game developer with the aspiration of making millions, or just have a quest for knowledge for the business aspect of video games? Given the appropriate data, analysis via the power of **Data Science** can provide a deep insights into almost any real-life applications, including video games! Questions like how the sales of a specific genre fluctuated over time; what is the most popular video game publisher; what factor constitutes a high grossing video games, and many others can be answer with important data science concepts!

Sounds exciting right? Now let's talk **Data Science**!!

Data Science consists of a set of tasks that convert raw data into human readable information. The data science pipeline consists of: data curation, parsing, and management; exploratory data analysis; hypothesis testing and machine learning to provide analysis. In this tutorial, we will walk you through these 5 important steps to construct a successful project!

Here are the steps:

1. **Find** and **collect** data
2. **Process** the data, **tidy** the data, and deal with missing data
3. **Exploratory analysis** and **data visualization**
4. Perform **analysis**, **hypothesis testing**, and **machine learning**
5. Curation of a message or messages covering **insights** learned via the 4 steps above.

Step 1: Find and Collect the Data

Finding relevant data to your problem in the first implied step! In this case, we are diving in to the business end of video games.

Data set URL: <https://www.kaggle.com/gregorut/videogamesales/data>

The website that we used: kaggle.com is a great source of data for a wide range of topics! The dataset that we chose contains a list of video games with sales greater than 100,000 copies. The different fields included within this dataset are:

- Rank - Ranking of overall sales
- Name - The games name
- Platform - Platform of the games release (i.e. PC, PS4, etc.)
- Year - Year of the game's release
- Genre - Genre of the game
- Publisher - Publisher of the game
- NA_Sales - Sales in North America (in millions)
- EU_Sales - Sales in Europe (in millions)
- JP_Sales - Sales in Japan (in millions)
- Other_Sales - Sales in the rest of the world (in millions)
- Global_Sales - Total worldwide sales.

How will we collect this set of data?

This project will be in R; therefore you will need to go to the installation process for R and Rstudio. After you've installed R and Rstudio, you will need the following libraries for the tasks that we will be covering:

```
* tidyverse * rvest * ggplot2 * lubridate * caret * e1071 * party
```

These libraries can be installed via this command: `install.packages("")` in your RStudio's console. Replace the with the libraries metioned above)

Now let us load in the raw data in RStudio!

```
raw_data <- read.csv("C:/Users/letha/Desktop/CMSC320/vgsales.csv")
head(raw_data)
```

##	Rank	Name	Platform	Year	Genre	Publisher	NA_Sales
## 1	1	Wii Sports	Wii	2006	Sports	Nintendo	41.49
## 2	2	Super Mario Bros.	NES	1985	Platform	Nintendo	29.08
## 3	3	Mario Kart Wii	Wii	2008	Racing	Nintendo	15.85
## 4	4	Wii Sports Resort	Wii	2009	Sports	Nintendo	15.75
## 5	5	Pokemon Red/Pokemon Blue	GB	1996	Role-Playing	Nintendo	11.27
## 6	6	Tetris	GB	1989	Puzzle	Nintendo	23.20

##	EU_Sales	JP_Sales	Other_Sales	Global_Sales
## 1	29.02	3.77	8.46	82.74
## 2	3.58	6.81	0.77	40.24
## 3	12.88	3.79	3.31	35.82
## 4	11.01	3.28	2.96	33.00
## 5	8.89	10.22	1.00	31.37
## 6	2.26	4.22	0.58	30.26

Step 2: Data Processing

Looking at the raw data above, there are some N/A entries and unwanted columns. We will properly encode the N/A entries and remove the unwanted columns ~ Rank, NA_Sales, EU_Sales, JP_Sales, Other_sales

```
tidy_data <- raw_data
# cleaning the N/A entries
tidy_data[tidy_data == "N/A"] = NA
tidy_data <- drop_na(tidy_data)

# removing unwanted columns
tidy_data <- tidy_data[-c(1,7,8,9,10)]
head(tidy_data)
```

##	Name	Platform	Year	Genre	Publisher	Global_Sales
## 1	Wii Sports	Wii	2006	Sports	Nintendo	82.74
## 2	Super Mario Bros.	NES	1985	Platform	Nintendo	40.24
## 3	Mario Kart Wii	Wii	2008	Racing	Nintendo	35.82
## 4	Wii Sports Resort	Wii	2009	Sports	Nintendo	33.00
## 5	Pokemon Red/Pokemon Blue	GB	1996	Role-Playing	Nintendo	31.37
## 6	Tetris	GB	1989	Puzzle	Nintendo	30.26

Step 3: Exploratory Analysis and Data Visualization

Exploratory Data Analysis is the last step before statistical analysis and machine learning. In this steps, we will cover the basics of visualizing datas through different graphing techniques and applications of linear regressions. Analyzing how pairs of variables interact gives important insights into different aspects of your data. Furthermore, data analysis will help us to find assumptions for the predications we will be making.

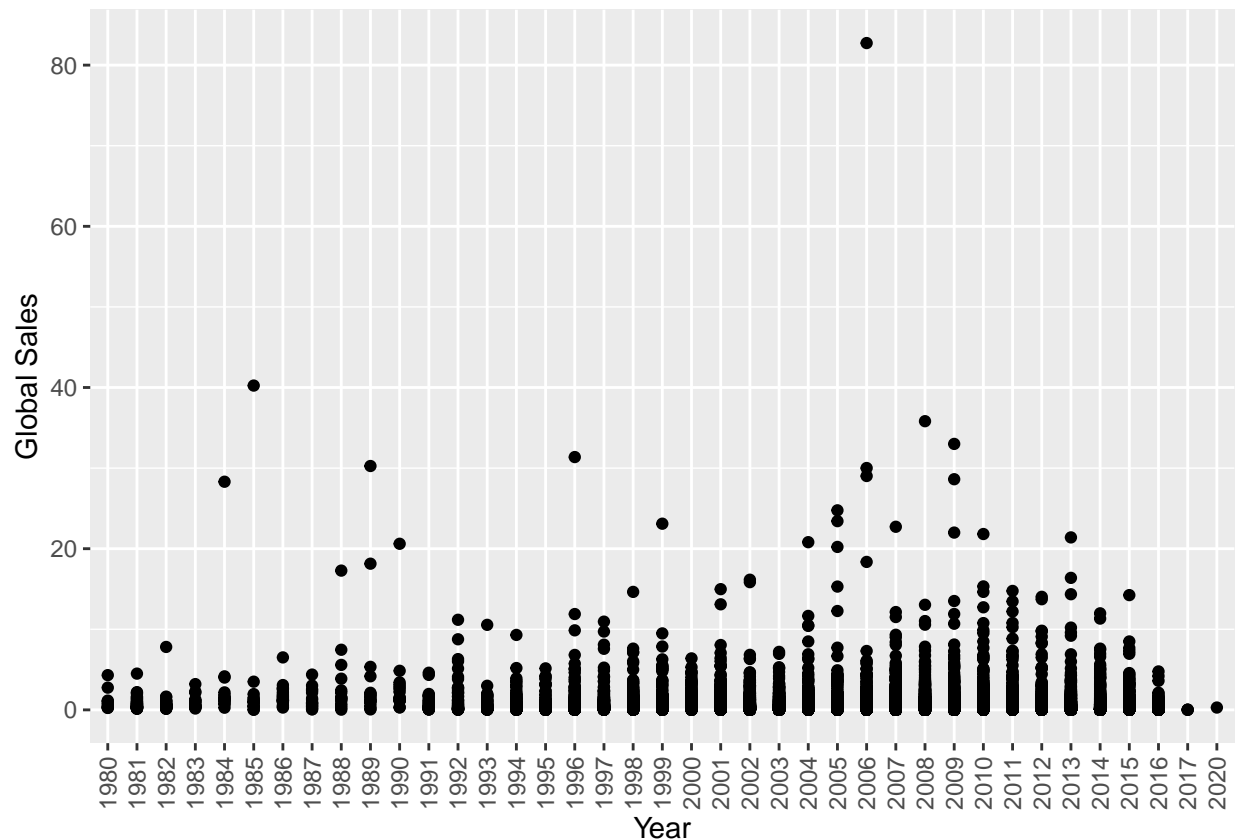
We are going to visualize the raw data in a variety of different *scopes*, including:

* Global Sales vs. Years * Global Sales vs. Different Genres * Global Sales vs. Different Publishers

Global Sales vs. Years

First, let's take a look at the relationship between global sales and years. Has the video game businesses gathered more money as time goes by? or has it decreased? This question can be answered after we analyze/visualize global sales vs. year.

```
plot <- tidy_data %>%  
  ggplot(mapping = aes(x= paste(Year), y = Global_Sales)) +  
  geom_point()  
plot +  
  xlab("Year") + ylab("Global Sales") +  
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5))
```



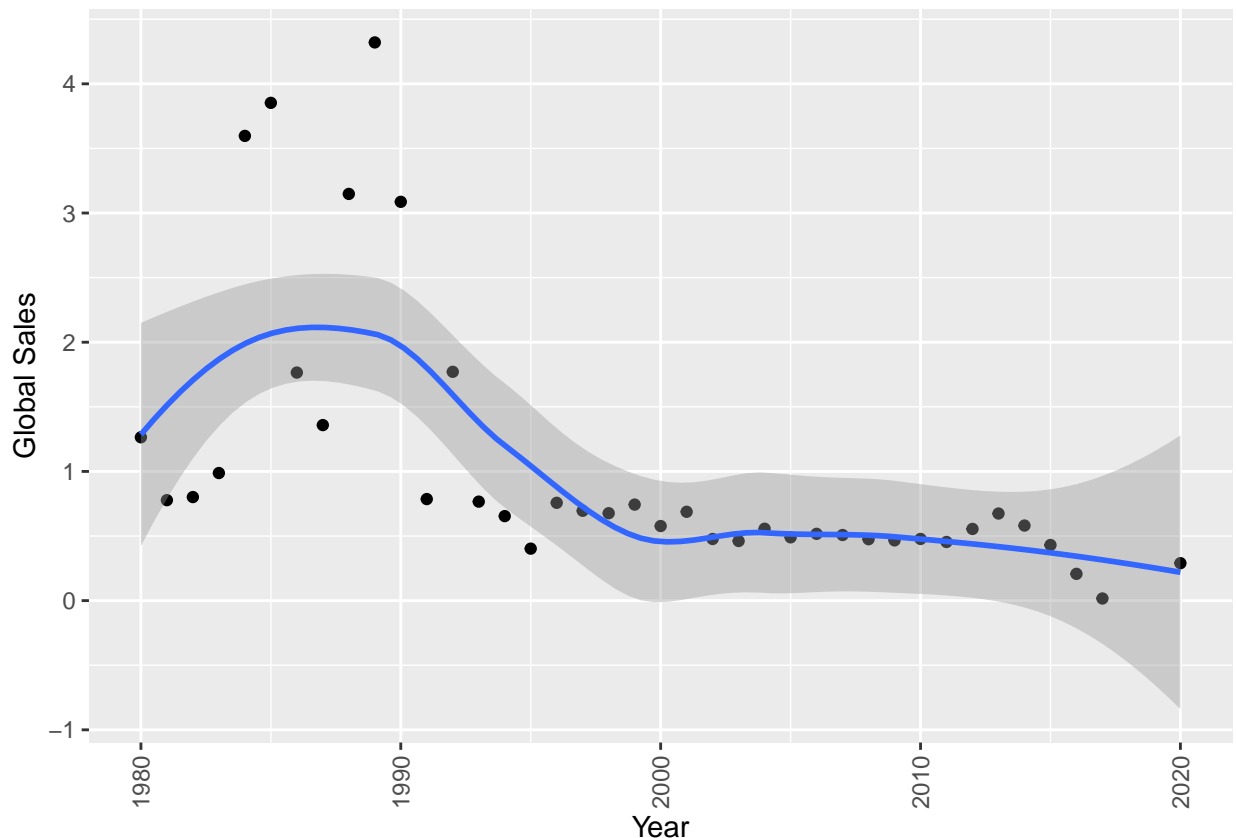
Okay, that's a lot of data. There's spikes during some years, but it's difficult to tell what's happening. Let's visualize the sales better by taking the average global sales of each year!

```
# find the average of the 6th column ~ Global Sales across the years
avg_data <- aggregate(tidy_data[6], list(tidy_data$Year), mean)
# renaming from Group.1 to Year appropriately
names(avg_data)[1] <- "Year"
view(avg_data)
```

With the data above, we can easily visualize the trend of global sales throughout the year. Let's plot this new data frame and see what happens!

```
# mutating the year to the appropriate numeric type
avg_data <- avg_data %>%
  mutate(Year = as.numeric(as.character(Year)))

avg_plot <- avg_data %>%
  ggplot(mapping = aes(x = (Year), y = Global_Sales)) +
  geom_point () +
  geom_smooth(method='loess', formula=y~x)
avg_plot +
  xlab("Year") + ylab("Global Sales") +
  theme(axis.text.x = element_text(angle = 90, hjust = 1, vjust = 0.5))
```



This is much better to look at! We can see a huge spike in video games sales between the years of 1981-1992. The years prior to that spike remains relatively “stable”, hovering around the .5 mark in global sales. Interestingly, the lowest average video game global sales happened in 2017.

Global Sales vs. Different Genres

We now want to examine the global sales in terms of different genres. With this data we can answer certain questions, like which genres produce the most revenue, or which genres are the most popular over time.

The first thing we must do is sum the global sales grouped by the genre. This will allow us to summarize which genres people have been more popular over time

```
sales_by_genre <- aggregate(Global_Sales~Genre, tidy_data, sum)
head(sales_by_genre)
```

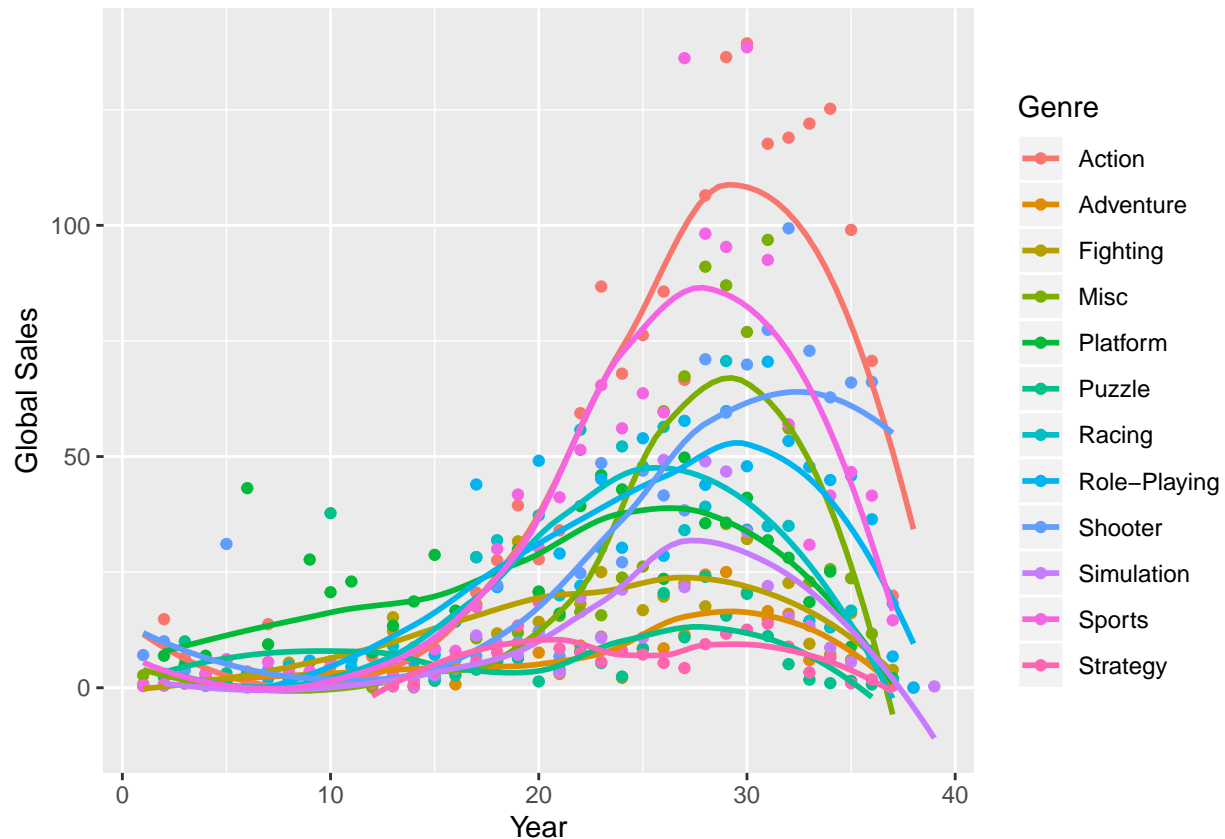
```
##      Genre Global_Sales
## 1   Action      1722.84
## 2 Adventure      234.59
## 3 Fighting      444.05
## 4    Misc       789.87
## 5 Platform      829.13
## 6  Puzzle       242.21
```

So this is interesting. It seems action-games are the most popular genres, followed by sports-games and then shooters. But this just summarizes the data taken as a whole, something more insightful might be to visualize the popularity of each genre over time. To do this we're going to

1. summarize the data's global sales in terms of Genre and Year
2. graph the data grouped by it's genre

```
sales_by_genre_and_time <- aggregate(Global_Sales~Genre+Year,
                                     tidy_data, sum) %>%
# must mutate the data into non-factors to be graphed
mutate(Year = as.numeric(Year)) %>%
mutate(Genre = as.character(Genre))

genre_time_plot <- sales_by_genre_and_time %>%
  ggplot(mapping = aes(x=Year, y=Global_Sales, color=Genre)) +
  geom_point() +
  geom_smooth(method='loess', formula=y~x, se=F)
genre_time_plot +
  xlab("Year") + ylab("Global Sales")
```

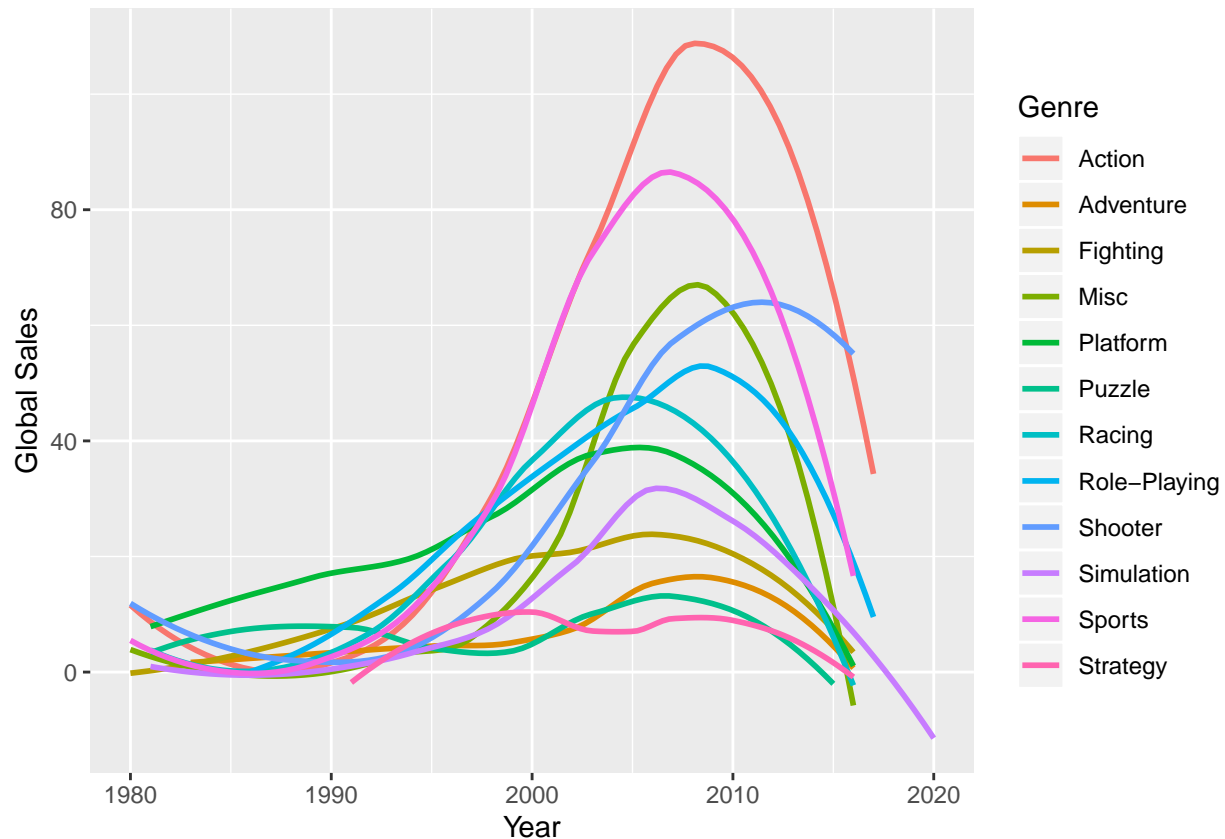


This plot is interesting, but's an absolute mess. Furthermore, our years are off now. Why is that? Well when you cast a factor like the Year to a number, it converts it into the magnitude of the factor instead of behaving as we would expect. To solve this, we will cast our Year variable to a character first, then cast that to an integer. To make our plot more readable, we will remove all of the data points and just make this a line graph.

```
sales_by_genre_and_time <- aggregate(Global_Sales~Genre+Year,
                                     tidy_data, sum) %>%
# convert the Years into characters, then to numbers
mutate(Year = as.numeric(as.character(Year))) %>%
mutate(Genre=as.character(Genre))

genre_time_plot <- sales_by_genre_and_time %>%
  ggplot(mapping = aes(x=Year, y=Global_Sales, color=Genre)) +
  geom_smooth(method='loess', formula=y~x, se=F)

genre_time_plot +
  xlab("Year") + ylab("Global Sales")
```



As can be seen, the action genre is the most popular from a holistic view, and its popularity has consistently grown over time, followed closely by the sports genre. However, in the late 2010's, shooter games rose to the top in grossing!

Global Sales vs. Different Publishers

Now we wish to analyze sales by publisher. Let's begin by analyzing sales over time for a select few publishers.

```
# filtering our desired data
targets = c("Bethesda Softworks", "Atari", "Activision",
            "Nintendo", "Sony Computer Entertainment", "Sega")

sales_pub <- aggregate(Global_Sales~Year+Publisher, tidy_data, sum) %>%

# convert the Years into characters, then to numbers
mutate(Year = as.numeric(as.character(Year))) %>%
mutate(Publisher=as.character(Publisher))

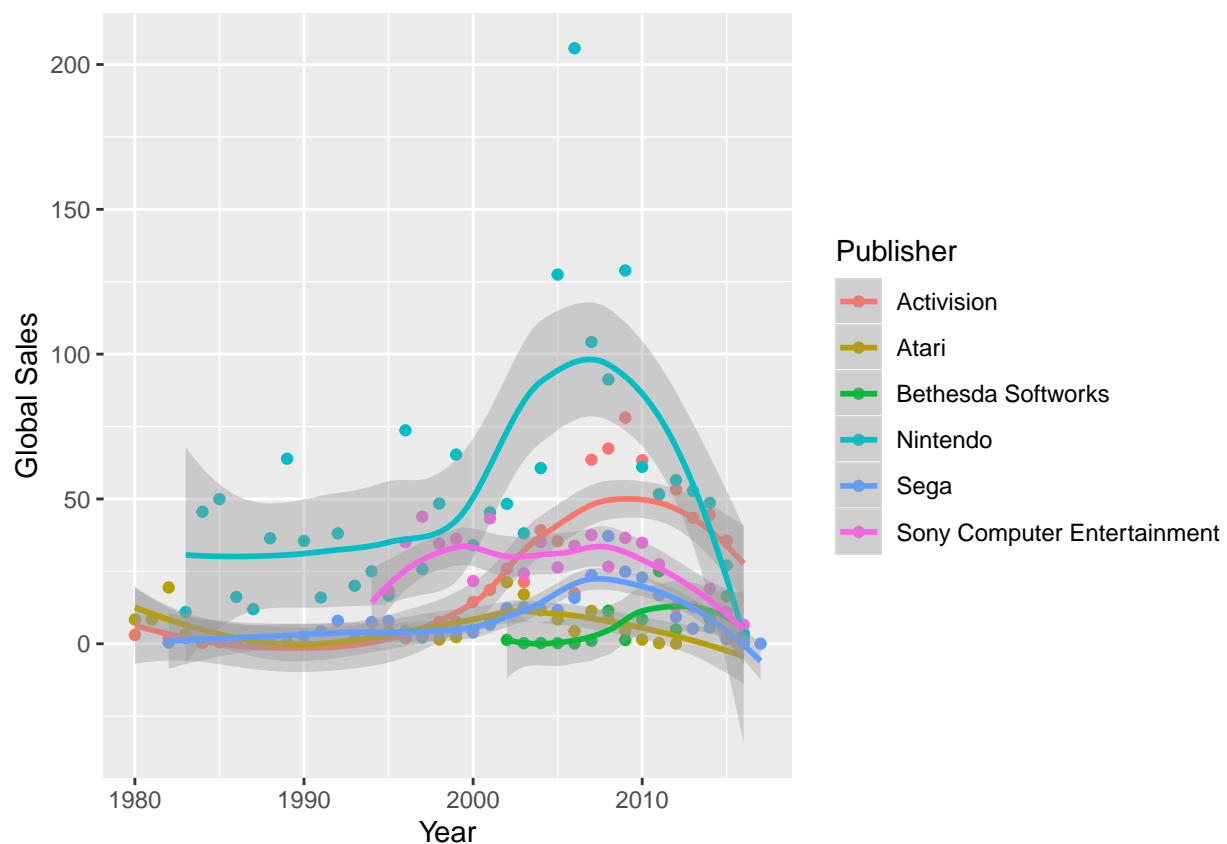
sales_pub <- sales_pub %>%
filter(Publisher %in% targets)
head(sales_pub)

##   Year Publisher Global_Sales
## 1 1980 Activision      3.02
## 2 1981 Activision      8.50
```

```
## 3 1982 Activision      1.86
## 4 1983 Activision      1.94
## 5 1984 Activision      0.27
## 6 1985 Activision      0.48
```

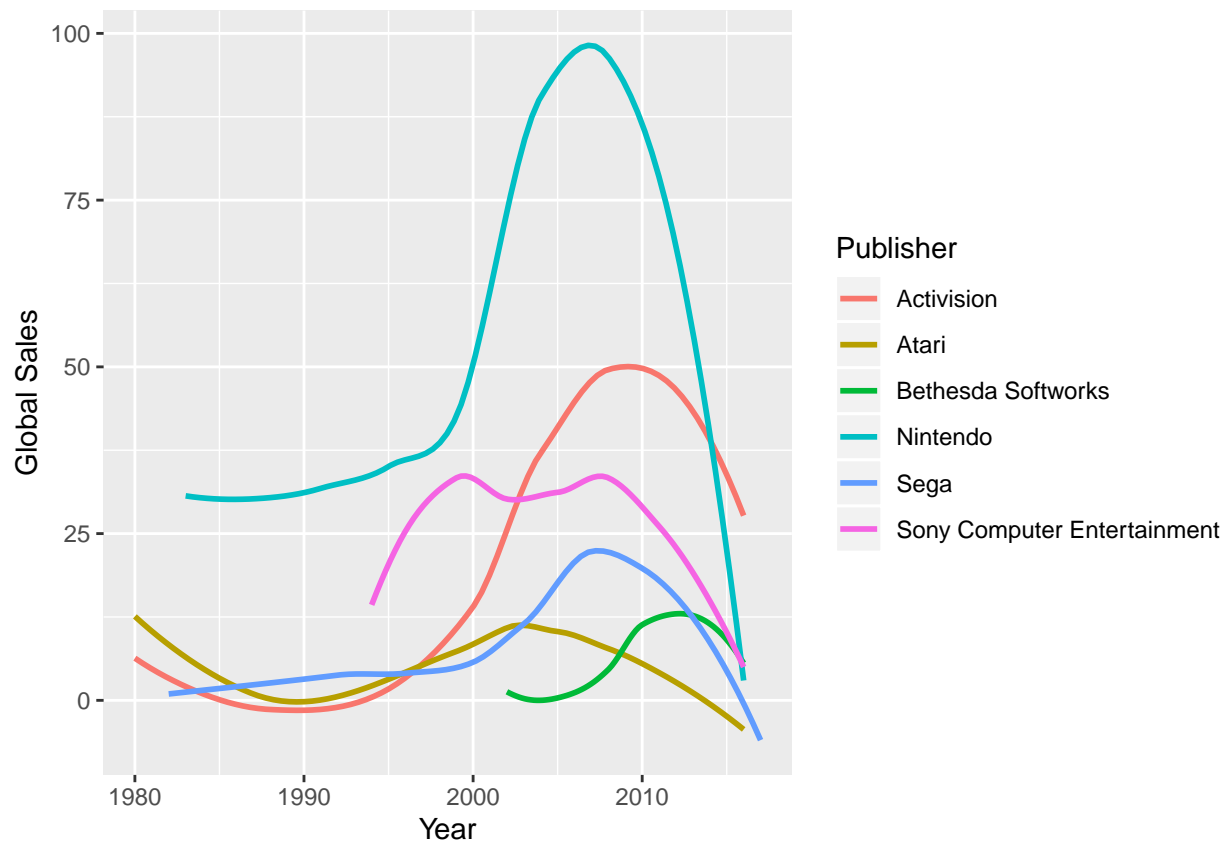
Now that we have our desired filtered data, let's visualize this data!

```
pub_time_plot <- sales_pub %>%
  ggplot(mapping = aes(x=Year, y=Global_Sales, color=Publisher)) +
  geom_point() +
  geom_smooth(method='loess')
pub_time_plot +
  xlab("Year") + ylab("Global Sales")
```



That already looks very good. However, let's remove these dots and solely focus on the trends of these publisher!

```
pub_time_plot <- sales_pub %>%
  ggplot(mapping = aes(x=Year, y=Global_Sales, color=Publisher)) +
  geom_smooth(method='loess', formula=y~x, se=F)
pub_time_plot +
  xlab("Year") + ylab("Global Sales")
```

From this graph, Nintendo holistically has been at the top of video game publisher when it comes to global sales. However, Activision rose to the top as of recent times (which corresponds to the rise of shooting games since Activision is known for First-Person-Shooter games).

Step 4: Analysis, Hypothesis Testing and Machine Learning

Hypothesis Testing

Hypothesis testing is an essential procedure in statistics. A hypothesis test evaluates two mutually exclusive statements about a population to determine which statement is best supported by the sample data. **Hypothesis Testing** uses the important mathematical concepts like the *Law of Large Numbers* and *Central Limit Theorem* to decipher whether your hypothesis is the case or not.

Let's think about what to hypothesize within our data! Looking at the history of video games and the major events within its short 40 years time line, the 2 major events for console gaming was: the introduction of game cartridge vs. CD's. The introduction of game cartridge was popularized via Nintendo Entertainment System, or NES. The NES was released in 1985. On the other hand, CD's was popularized via the Playstation, or PS1. The PS1 was released in 1995. Both are groundbreaking events in the world of videogames! Which was more popular (measured via global sales)? With that in mind, that will be our hypotheses.

Null Hypothesis: The release of PS1 (or the introduction of gaming CDs) received more global sales

Alternative Hypothesis: The release of the NSE (or the introduction of gaming cartridges) received more global sales

We will use a *paired t-test* to test our hypothesis. The paired samples t-test is used to compare the means between two related groups of samples. As regards to our rejection value, we will reject our null hypothesis if our calculated p-value is less than 0.05

```

# filtering out all of the PS and NES games
ps_vec <- filter(tidy_data, Platform == "PS")$Global_Sales
nes_vec <- filter(tidy_data, Platform == "NES")$Global_Sales

ps_vec <- sort(ps_vec, decreasing = TRUE)
# since NES only has 98 entries, we filtered out the top 98 grossed games of PS
ps_vec <- ps_vec[1:98]
nes_vec <- sort(nes_vec, decreasing = TRUE)

# performing the t-test
t_test <- t.test(ps_vec, nes_vec, paired = TRUE, alternative = "greater")
# divide by 2 because one-tailed t-test
t_test$p.value/2

```

```
## [1] 0.01013816
```

Since we are performing a *one-tailed t-test*, we would need to divide the p value in half. A one-tailed test allots all of your alpha to testing the statistical significance in the one direction of interest. In this case, we are only testing whether or not the release of PS1 gathered more income than the release of NES, or vice versa; but not **both**.

Based on our hypothesis testing, our p value is 0.01013816, which is less than 0.05. Therefore, we reject the null hypothesis. Our data suggests that the amount of global sales gathered from the introduction of the PS1 is *greater* than the amount with NES.

Machine Learning

Analysis and Machine Learning is a very important topic within data science. A precise prediction of said values can be of huge importance in many different aspects. In our case, let's say we want to create a program to estimate the global sales of your game. One can achieve this through the power of Machine Learning! You can train a model to look at the attributes of the game and determine its probable sales.

The first thing we need to do is to define our data in terms of one of two values. What I'm going to do is standardize the data and create a new variable that is True or False dependent on whether the global sales were at least average for their year. We'll only take a sample of the data, about 5% of it. This is a large enough sample that the accuracy of the model will be guaranteed by the *Central Limit Theorem*.

```

standard_df <- tidy_data %>%
  mutate(Z_Sales = NA)

for(y in 1980:2020) {
  stdev <- sd(filter(standard_df, Year==y)$Global_Sales)
  avg <- mean(filter(standard_df, Year == y)$Global_Sales)
  standard_df <- standard_df %>%
    mutate(Z_Sales = ifelse(Year == y, ((Global_Sales - avg)/stdev), Z_Sales))
}

# a sample size of 815 data points from the 16,000 total points
standard_df <- standard_df[sample(nrow(standard_df), 815),]
head(standard_df)

```

```

##                               Name Platform Year   Genre
## 15588                        Dead to Rights   GBA 2004 Shooter
## 470                     The Sims: Livin Large   PC 2000   Misc

```

```
## 7937 Vampire Savior: The Lord of Vampire SAT 1998 Fighting
## 1253 Rock Band 2 PS3 2008 Misc
## 12164 Blur PC 2010 Racing
## 10468 LEGO Rock Raiders PS 1999 Strategy
## Publisher Global_Sales Z_Sales
## 15588 Zoo Digital Publishing 0.02 -0.4209435
## 470 Electronic Arts 2.99 2.7309024
## 7937 Capcom 0.18 -0.3972663
## 1253 MTV Games 1.50 0.7875649
## 12164 Activision 0.06 -0.3221462
## 10468 LEGO Media 0.10 -0.3825697
```

Next we want to categorize our data. We will denote the Success_Level as above average or below average in terms of global sales. So if a game sold above or equal to the global average for that year, which is signified by it's Z_Sales being greater than or equal to zero, then we will mark it as above average. If a game sold below average, which means it's Z_Sales variable is below zero, then we will denote as below average appropriately.

```
standard_df <- standard_df %>%
  mutate(Success_Level = ifelse(Z_Sales >= 0, 'Above Average', 'Below Average')) %>%
  select(-Global_Sales, -Name)
head(standard_df)
```

```
## Platform Year Genre Publisher Z_Sales Success_Level
## 1 GBA 2004 Shooter Zoo Digital Publishing -0.4209435 Below Average
## 2 PC 2000 Misc Electronic Arts 2.7309024 Above Average
## 3 SAT 1998 Fighting Capcom -0.3972663 Below Average
## 4 PS3 2008 Misc MTV Games 0.7875649 Above Average
## 5 PC 2010 Racing Activision -0.3221462 Below Average
## 6 PS 1999 Strategy LEGO Media -0.3825697 Below Average
```

The next thing we need to do is divide our data into a training set and a testing set. We will use the training set to train our model, then test our model on the testing set to determine it's accuracy.

```
set.seed(1234)

partitionRule <- createFolds(standard_df$Success_Level, k=10, list=F)
trainingSet <- standard_df[partitionRule,]
testingSet <- standard_df[-partitionRule,]

names(trainingSet) <- make.names(colnames(trainingSet))
names(testingSet) <- make.names(colnames(testingSet))
```

Now we build the model. We will be using a K-Nearest-Neighbor model for our predictions.

```
knn_fit <- train(as.factor(Success_Level)~., data=trainingSet, method='knn')
knn_predict <- predict(knn_fit, newdata=testingSet)
confusionMatrix(knn_predict, as.factor(testingSet$Success_Level))
```

```
## Confusion Matrix and Statistics
##
## Reference
```

```

## Prediction      Above Average Below Average
##   Above Average          69          70
##   Below Average          90          576
##
##               Accuracy : 0.8012
##               95% CI : (0.772, 0.8283)
##   No Information Rate : 0.8025
##   P-Value [Acc > NIR] : 0.5563
##
##               Kappa : 0.3418
##
## Mcnemar's Test P-Value : 0.1331
##
##               Sensitivity : 0.43396
##               Specificity : 0.89164
##   Pos Pred Value : 0.49640
##   Neg Pred Value : 0.86486
##   Prevalence : 0.19752
##   Detection Rate : 0.08571
##   Detection Prevalence : 0.17267
##   Balanced Accuracy : 0.66280
##
##   'Positive' Class : Above Average
##

```

Step 5: Analysis

Here are the information gathered from the steps above:

- Huge spike of video global sales in the period of 1981-1992. The average grossing peaked at the late 90's. The years after that initial spike remained relative static.
- From a holistic view, action games is undoubted the most popular amongst the variety of other genres. However, in the late 2010's, shooter game rose to the top in terms of grossing.
- From a holistic view, Nintendo has been at the top of video game publisher when it comes to global sales. However, Activision rose to the top as of recent times (which corresponds to the rise of shooting games since Activision is known for First-Person-Shooter games).
- The first release of gaming CDs via PS1 gathered more interest/popularity (measured by global sales) than the first release of gaming cartridges via NES.
- A ML model that predicts the grossing of a game base on certain factors.

From those information gathered, one can synthesize that: the global sales peaked in the late 90s, and thus the introduction of CD-ROM was also in the late 90's (popularized by PS1 in 1995). Therefore, the introduction of CD's possibly aided the peaked grossing in the late 90's. This would make sense due to the increase in accessibility for the customer. Furthermore, gaming CD's are still of use in today's video game world. Therefore, one could say that another revolutionary change in the way we play games could see another spike in video game grossing (something to the extent of CD-ROM). Recently, cloud gaming and digital distribution unsurprisingly seems to be gaining popularity due to convenience purposes. Will it cause another spike in video game grossing? We shall see :)

Moreover, FPS or shooter games seems to be the highest grossing genre as of recent time. With its high demands, aspiring game makers could potentially exploit more on this genre (with other factors demonstrated from the ML), and thus earn a lot of revenue!

That concludes our tutorial. Thank you so much for making it all the way through this tutorial! We hope that you learned something new from this, and start your own data adventure sometime soon :)