Data Insights to

Microsoft Movies studio

~by Jackson Munene

Next

Problem Statement

Microsoft

has decided to create a new **movie studio**, but they don't know anything about movie industries.

They need valuable insights from specific data from these three movie companies:

- Box Office Mojo
- The Numbers
- The Movies DB

GOALS

As a data scientist, here are some of the important milestones before getting to the insights

Understanding the Datasets

Cleaning the datasets

Finding patterns and visual representations of data

1) Box Office Mojo

Box office Mojo is known for its extensive collection of box office data, which includes domestic and international revenues, how different studios sell both locally and internationally. The data from Box Office Mojo is from 2010 to 2018.

There are only five features: Title, studio, domestic gross, foreign gross and year. This data defines the total amount of money a specific movie generated in the year of its release, both nationally and internationally.

Objectives

- Import and clean the dataset
- Explore how Box Office Mojo is doing both internationally and locally.
- Find out which market generates more money, whether domestic or foreign.
- Explore the studios Box Office Mojo sell through, and find out the pattern within the studios.
- Find out if domestic gross affects international gross or vice versa.

Dataset Information

This is the high level information on the data from Box Office Mojo:

There are a total of 3,387 records in the dataset, and 5 features. 3 of the features are in string data type, 1(year) is an integer and 1(domestic gross) is a floating value. Notice the inconsistency with the dataset datatype:

- Foreign gross is keyed in like a string. We need to change it to a floating value to perform calculations with it.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 3387 entries, 0 to 3386
Data columns (total 5 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   title           3387 non-null   object
 1   studio          3382 non-null   object
 2   domestic_gross  3359 non-null   float64
 3   foreign_gross   2037 non-null   object
 4   year            3387 non-null   int64
dtypes: float64(1), int64(1), object(3)
memory usage: 132.4+ KB
```

```
3   foreign_gross   2037 non-null   float64
```

Statistical Measures

Here is min, max, mean, median, standard deviation, count and quantiles of both **domestic** and **foreign gross**

	foreign_gross	domestic_gross
count	2037.0	3359.0
mean	74872810.2	28745845.1
std	137410600.8	66982498.2
min	600.0	100.0
25%	3700000.0	120000.0
50%	18700000.0	1400000.0
75%	74900000.0	27900000.0
max	960500000.0	936700000.0

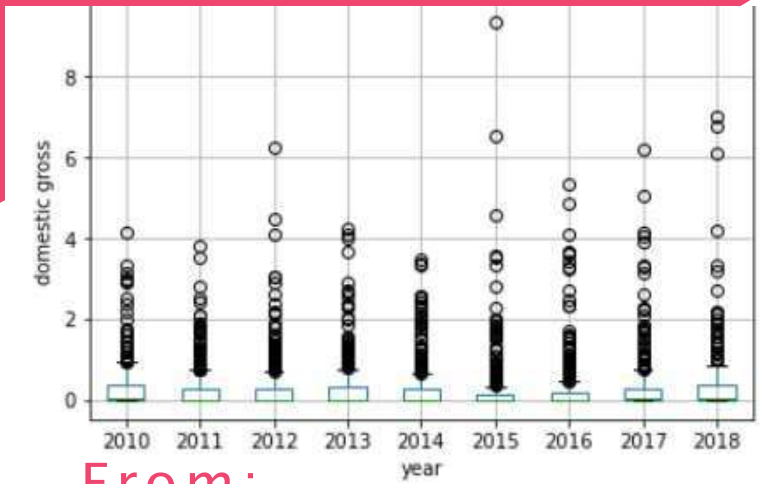
Notice the outliers, from min to the 25th percentile.

We change that by removing the outliers through getting data between 30% and 70% to look like as follows.

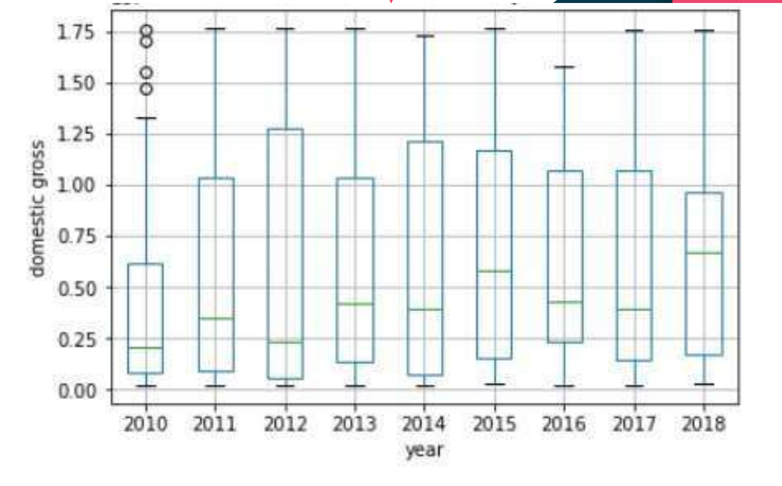
min	5300000.0	195000.0
25%	8500000.0	1100000.0

Domestic Gross

From:



To:

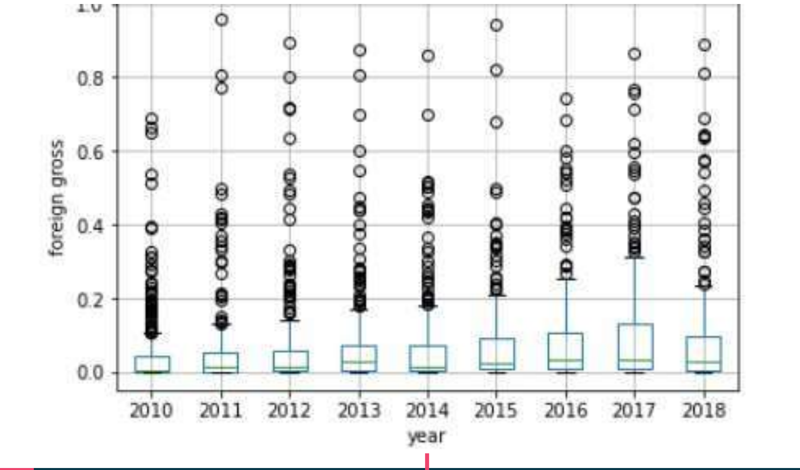


Another way to visualize these outliers is through:

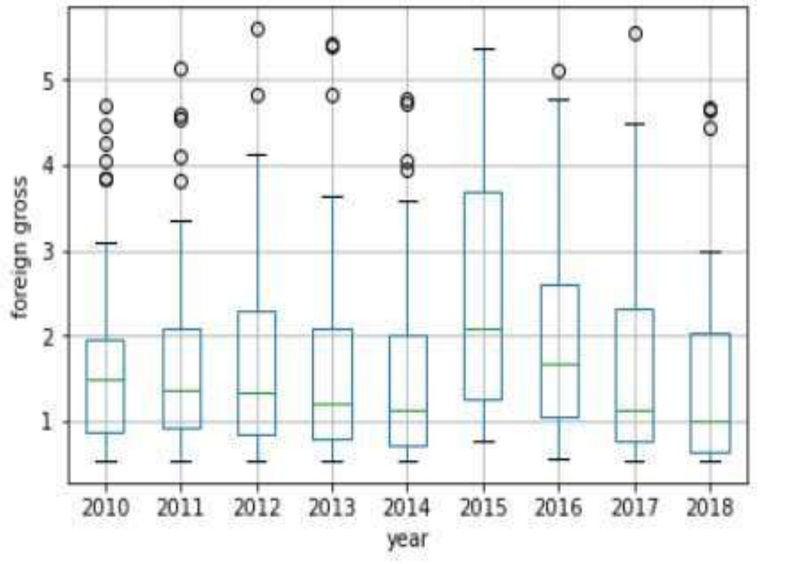
Box Plots

Foreign Gross

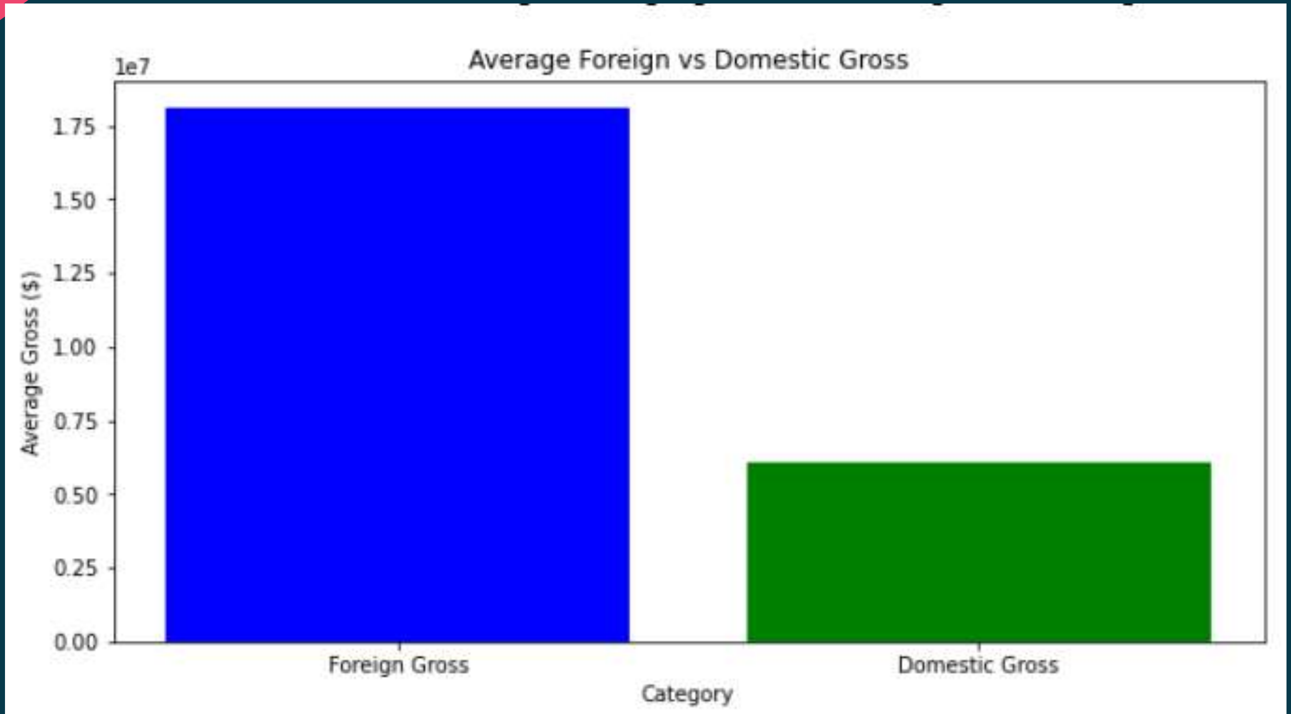
From:



To:



How big is the difference between average Foreign gross and average Domestic gross?



The blue bar represents the average foreign gross, which reaches approximately $1.75 billion. This suggests that on average, films earn significantly more from foreign markets compared to domestic ones. The green bar represents the average domestic gross, which is much shorter than the foreign gross bar, indicating a lower average movie sells in domestic markets.

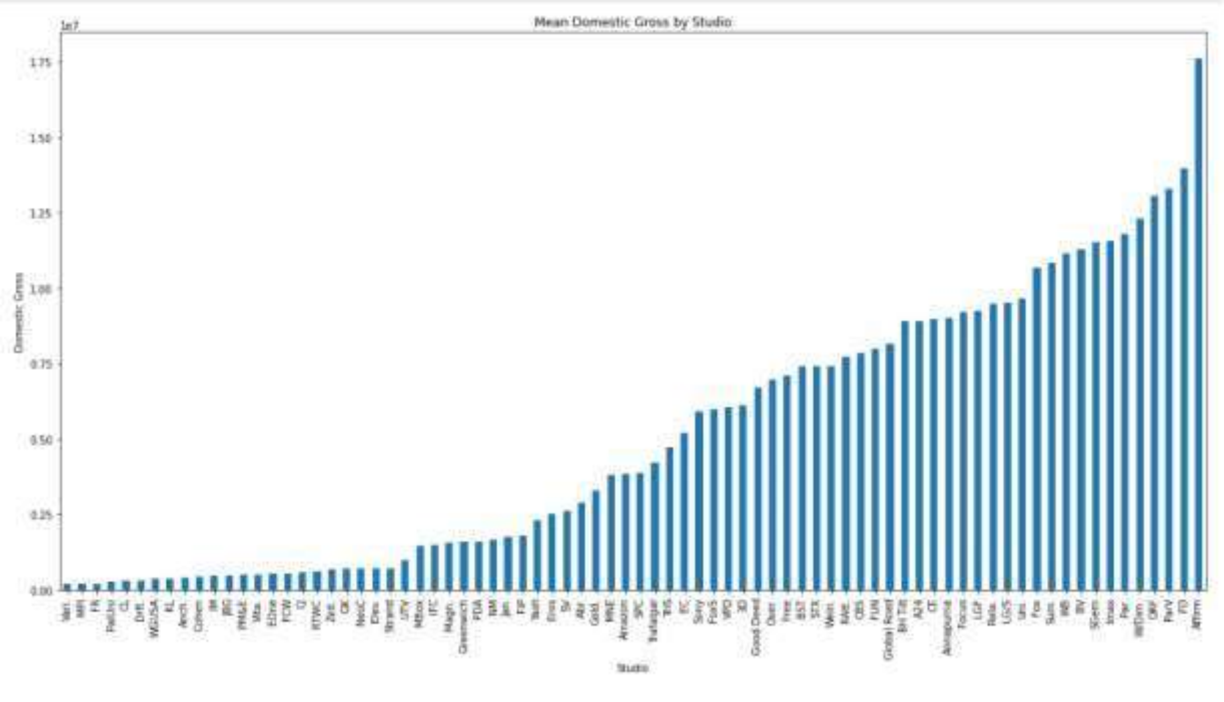
Clearly there is very big difference on how Box Office Mojo sells internationally versus how their sells are locally.

Which studio has the highest domestic gross?

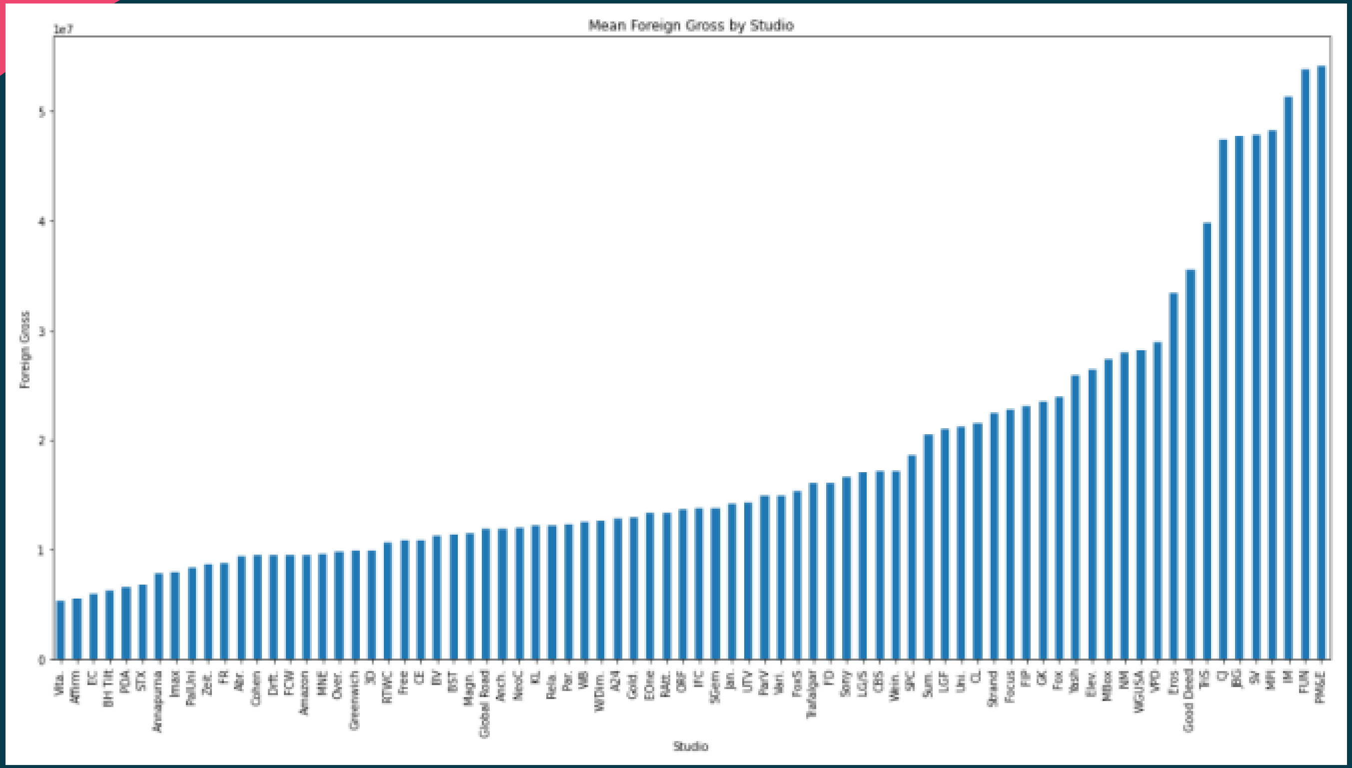
A bar graph representation for categorical feature(Studio) will be needed for this.

- 1st we'll group the **domestic gross** column by **studio.**
- Get the mean of the grouped data
- Sort the values in ascending order
- Then plot the bar graph.

We can conclude that after we removed the outliers, **Vari.** and **MPI** studios have the least while Affirm has the highest **domestic Gross**.



Which studio has the highest foreign gross?



The same will be done, but we only use Foreign Gross column in the data

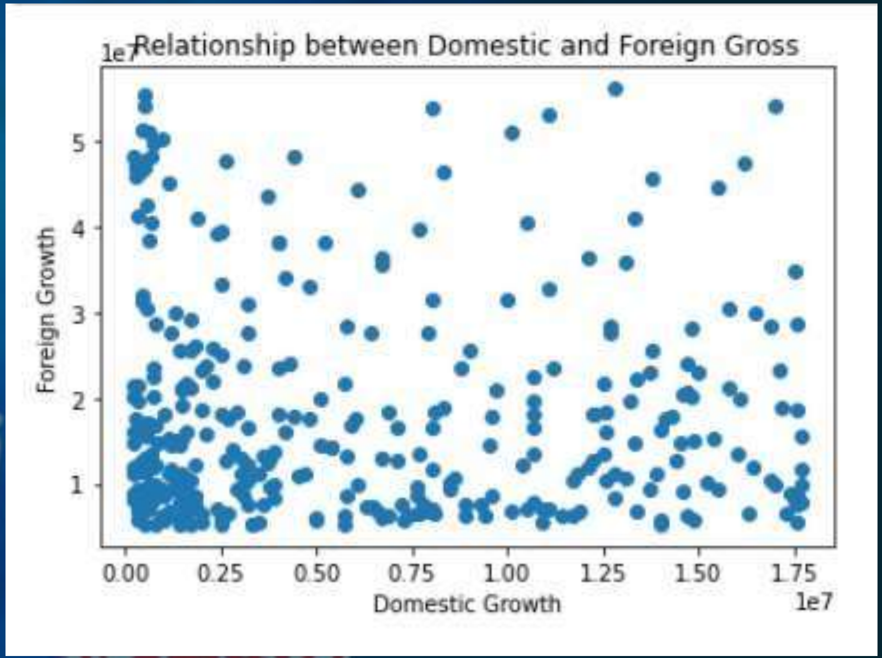
- 1st we'll group the **foreign gross** column by **studio.**
- Get the mean of the grouped data
- Sort the values in ascending order
- Then plot the bar graph.

Here, the opposite is true from the observations such that **Affirm** generates the least while **MPI** is one of the highest **Foreign gross** generator.

Gross Relationship

As much as the studios which generate the most domestic gross perform so low in foreign gross, there is no concrete connection between **domestic** and **foreign gross**.

Their correlation is: -0.01509821



Recommendations

- Microsoft should consider partnering with **Affirm** studio to generate high Domestic gross and also **MPI** and **FUN** studios for high foreign gross.
- The stakeholders should concentrate on both domestic and foreign gross, because they are both independent.
- Microsoft should focus more on releasing internationally than domestically. According to Box Office Mojo, they gain exactly $12,014,355.3 more in foreign gross than in domestic gross.

2) The Numbers

Using a dataset from “The Numbers” can be advantageous for several reasons: “The Numbers” provides detailed movie financial analysis. This data is valuable for understanding the film industry’s economics.

The Numbers offers a wide range of data, including budget, domestic and international grosses, and profitability. It is also known for its accuracy and is often cited in industry analyses.

Objectives

- First, we will import the data.
- Prepare the data through cleaning(setting the right data types, and dropping outliers.).
- Then through the available features, we add profits column from the gross and production cost.
- Analyze how we can maximize profits from the available data.

Goal

The Numbers dataset contains financial features which we will use to answer the question. How can we maximize profits in the film industry?

Dataset values

Here is a slight peek into The Numbers csv file:

There are a lot of things that have to be changed like:

- Removing **$** and comma(**,**) signs from **Production Budget**, **Domestic gross** and **worldwide gross.**
- We will also need to add few more features like **domestic profits**, **year** and **worldwide profits.**

	id	release_date	movie	production_budget	domestic_gross	worldwide_gross
0	1	Dec 18, 2009	Avatar	$425,000,000	$760,507,625	$2,776,345,279
1	2	May 20, 2011	Pirates of the Caribbean: On Stranger Tides	$410,600,000	$241,063,875	$1,045,663,875
2	3	Jun 7, 2019	Dark Phoenix	$350,000,000	$42,762,350	$149,762,350
3	4	May 1, 2015	Avengers: Age of Ultron	$330,600,000	$459,005,868	$1,403,013,963
4	5	Dec 15, 2017	Star Wars Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747

release_date	movie	production_budget	domestic_gross	worldwide_gross	domestic_profits	worldwide_profits	year
2009-12-18	Avatar	425000000.0	760507625.0	2.776345e+09	335507625.0	2.351345e+09	2009
2011-05-20	Pirates of the Caribbean: On Stranger Tides	410600000.0	241063875.0	1.045664e+09	-169536125.0	6.350639e+08	2011
2019-06-07	Dark Phoenix	350000000.0	42762350.0	1.497624e+08	-307237650.0	-2.002376e+08	2019
2015-05-01	Avengers: Age of Ultron	330600000.0	459005868.0	1.403014e+09	128405868.0	1.072414e+09	2015
2017-12-15	Star Wars Ep. VIII: The Last Jedi	317000000.0	620181382.0	1.316722e+09	303181382.0	9.997217e+08	2017

Dataset information

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   object
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   object
 4   domestic_gross     5782 non-null   object
 5   worldwide_gross    5782 non-null   object
dtypes: int64(1), object(5)
memory usage: 271.2+ KB
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 5782 entries, 0 to 5781
Data columns (total 6 columns):
 #   Column             Non-Null Count  Dtype
---  ------             --------------  -----
 0   id                 5782 non-null   int64
 1   release_date       5782 non-null   datetime64[ns]
 2   movie              5782 non-null   object
 3   production_budget  5782 non-null   float64
 4   domestic_gross     5782 non-null   float64
 5   worldwide_gross    5782 non-null   float64
dtypes: datetime64[ns](1), float64(3), int64(1), object(1)
memory usage: 271.2+ KB
```

The data has 5,782 rows and 6 columns which are all objects except from the Id.

There are a lot of things that have to be changed like:

- Changing data types of **production budget**, **domestic gross**, and **worldwide gross** to floating values.
- **Release date** should also be in datetime datatype.

MOVIE NIGHT

Statistical Measures

Before cleaning the dataset, notice the outliers from 75% percentile to max in all of the features.

We have to clean that by dropping the data so it looks as follows:

	production_budget	domestic_gross	worldwide_gross	domestic_profits	worldwide_profits
count	5782.0	5782.0	5.782000e+03	5782.0	5.782000e+03
mean	31587757.1	41873326.9	9.148746e+07	10285569.8	5.989970e+07
std	41812076.8	68240597.4	1.747200e+08	49921366.5	1.460889e+08
min	1100.0	0.0	0.000000e+00	-307237650.0	-2.002376e+08
25%	5000000.0	1429534.5	4.125415e+06	-9132757.0	-2.189071e+06
50%	17000000.0	17225945.0	2.798445e+07	-348775.5	8.550286e+06
75%	40000000.0	52348661.5	9.764584e+07	17781444.0	6.096850e+07
max	425000000.0	936662225.0	2.776345e+09	630662225.0	2.351345e+09

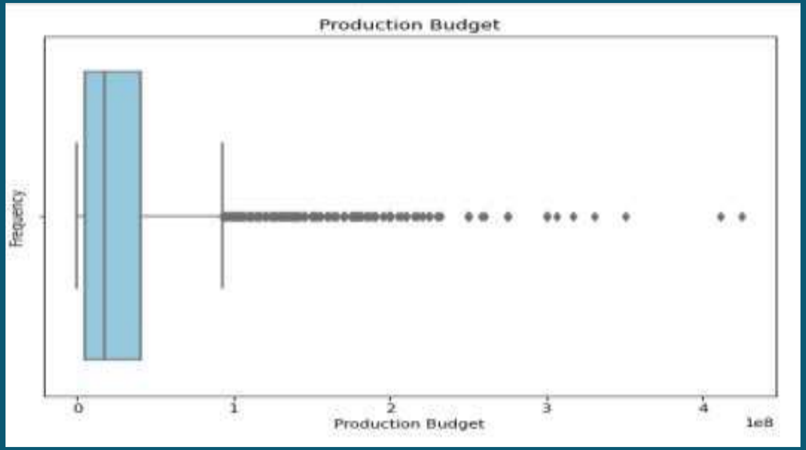
75%	25000000.0	27367976.5	39545462.2	9794648.8	22113796.0
max	35000000.0	42469946.0	76086711.0	33157856.0	62727492.0

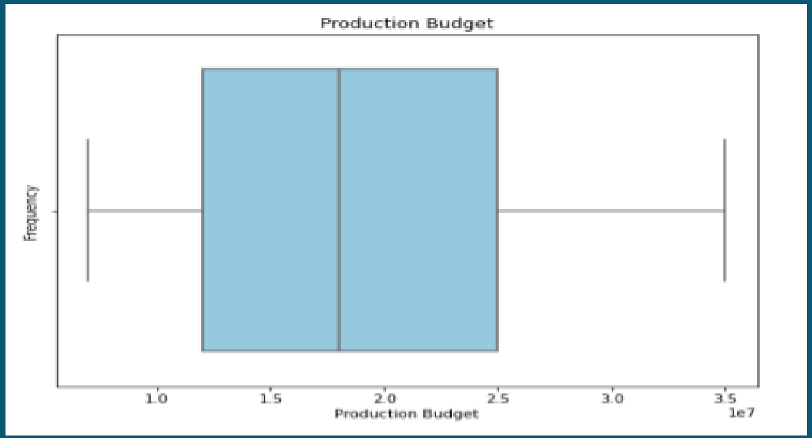
Below is another way to visualize the outliers and what will happen to the data when those outliers are removed.

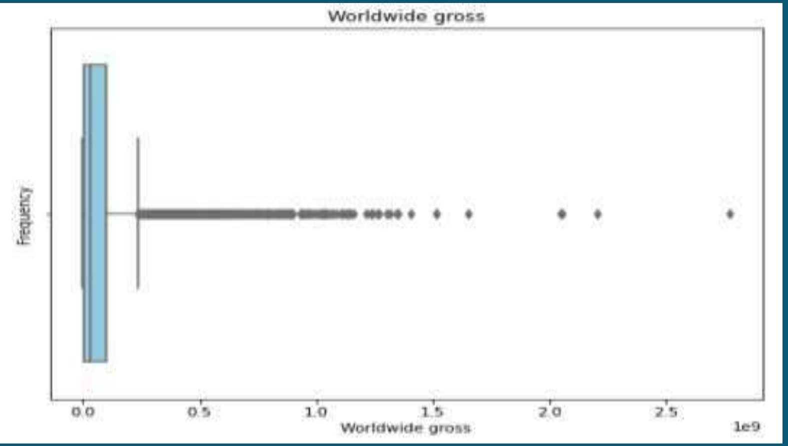
before

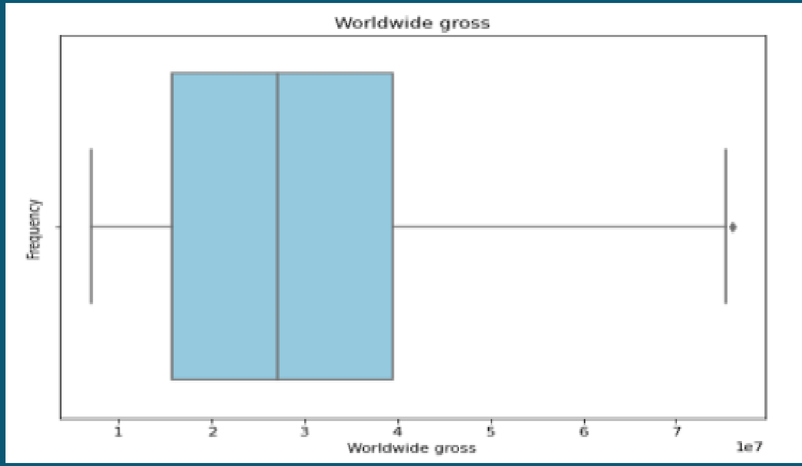
after

Box plots



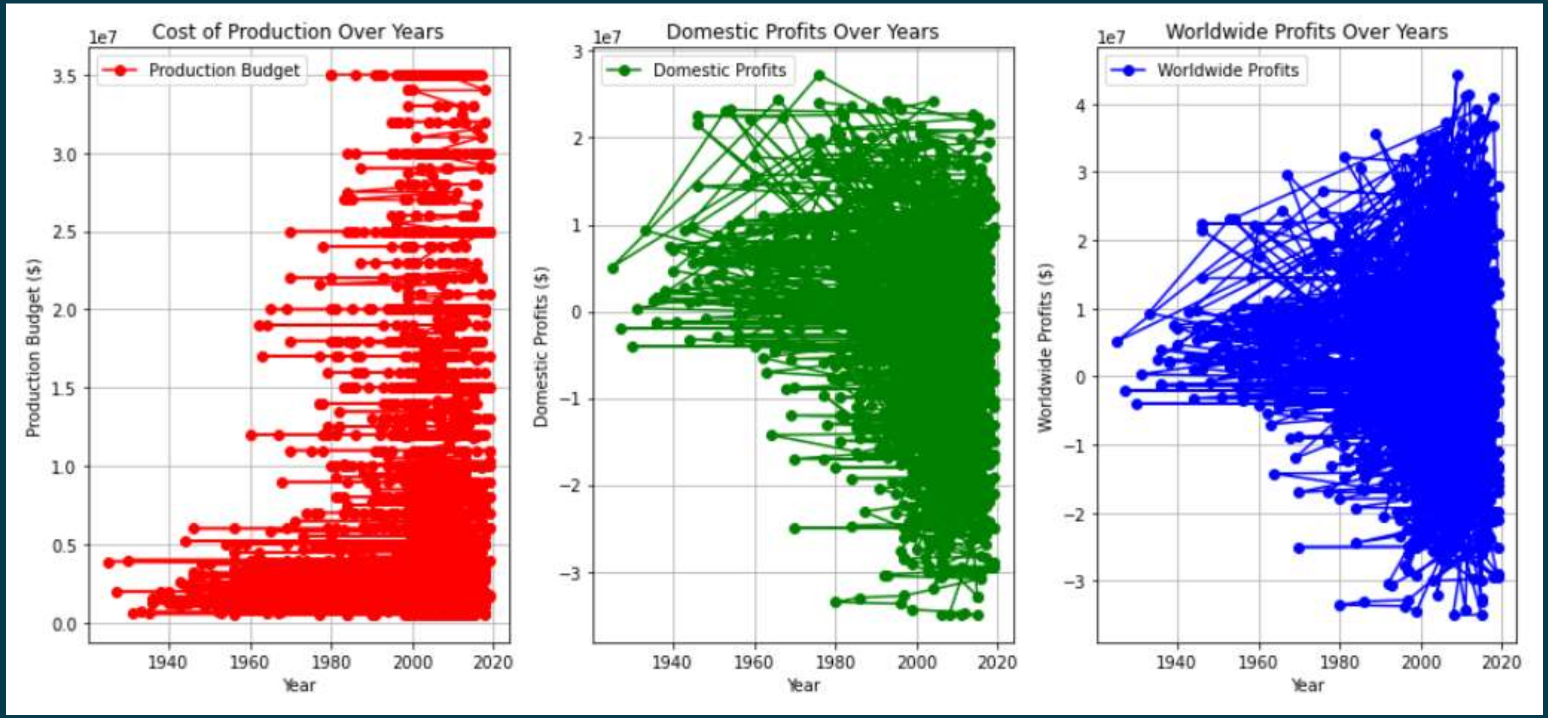






Does Production budget affect Profits?

The cost of production and the frequency of movie releases significantly impact both domestic and worldwide gross earnings. This dynamic presents a high-risk, high-reward scenario for Microsoft in the movie industry. While investing heavily in movie production offers the potential for substantial profits, it also entails the risk of significant losses.



Recommendations

- Microsoft must carefully balance its investment in movie production, considering the potential rewards against the associated risks. By strategically managing production costs and optimizing the number of movies released annually, Microsoft can maximize its chances of success while mitigating the possibility of financial setbacks. This approach acknowledges the inherent uncertainties of the movie business while positioning Microsoft to capitalize on lucrative opportunities in the ever-evolving entertainment landscape.

3) The Movie DB

The movie DB's dataset provides popularity features like how popular a movie is and how many votes the movie got. It also shows the original language of the movies.

Objectives

- Create a function to import data and clean it.
- Find out which movie language sells the highest.
- Check if votes affect popularity

Goal

Analysis to get how and why movies get so popular Analysis to find which original movie language sells the highest.

TMDB Dataset Information

In this high level overview of the data, we find that:

- We have 10 columns
- 26,517 records
- A mix of floating values and strings.
- No null values

The just need to change **release date** datatype to datetime.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 26517 entries, 0 to 26516
Data columns (total 10 columns):
 #   Column             Non-Null Count  Dtype  
---  ------             --------------  -----  
 0   Unnamed: 0         26517 non-null  int64  
 1   genre_ids          26517 non-null  object 
 2   id                 26517 non-null  int64  
 3   original_language  26517 non-null  object 
 4   original_title     26517 non-null  object 
 5   popularity         26517 non-null  float64
 6   release_date       26517 non-null  object 
 7   title              26517 non-null  object 
 8   vote_average       26517 non-null  float64
 9   vote_count         26517 non-null  int64  
dtypes: float64(2), int64(3), object(5)
memory usage: 2.0+ MB
```

```
 6   release_date       26517 non-null  datetime64[ns]
```

Statistical Measures

Notice the outliers, from min to the 25th percentile, and 75th to max.

We change that by removing the outliers through getting data between:

- 0.05 and 0.65 quantiles for **popularity**
- 0.3 and 0.8 quantiles for **Average votes**
- 0.005 and 0.65 quantiles for **vote count.**

	popularity	vote_average	vote_count
count	26517.000000	26517.000000	26517.000000
mean	3.130912	5.991281	194.224837
std	4.355229	1.852946	960.961095
min	0.600000	0.000000	1.000000
25%	0.600000	5.000000	2.000000
50%	1.374000	6.000000	5.000000
75%	3.694000	7.000000	28.000000
max	80.773000	10.000000	22186.000000

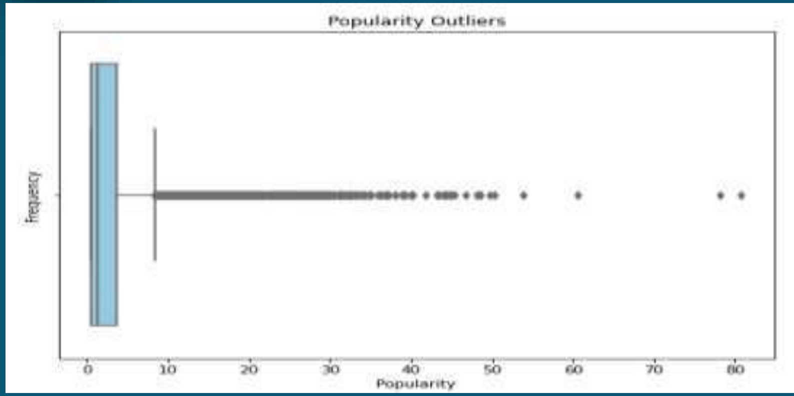
min	0.600000	5.200000	1.000000
25%	0.600000	6.000000	1.000000
50%	0.711000	6.200000	3.000000
75%	1.257000	7.000000	5.000000
max	2.235000	7.300000	13.000000

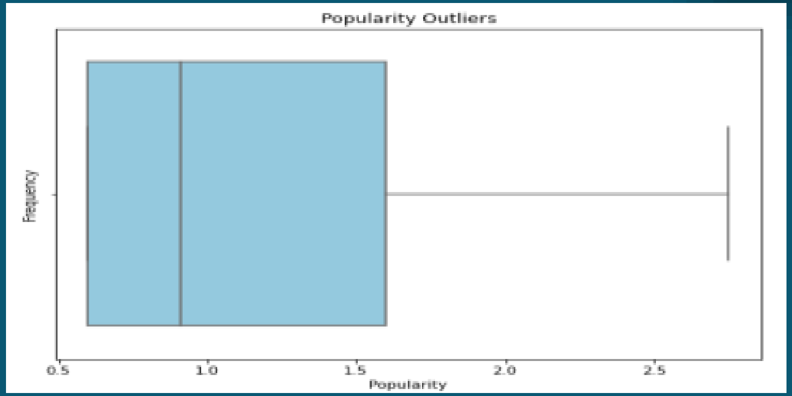
before

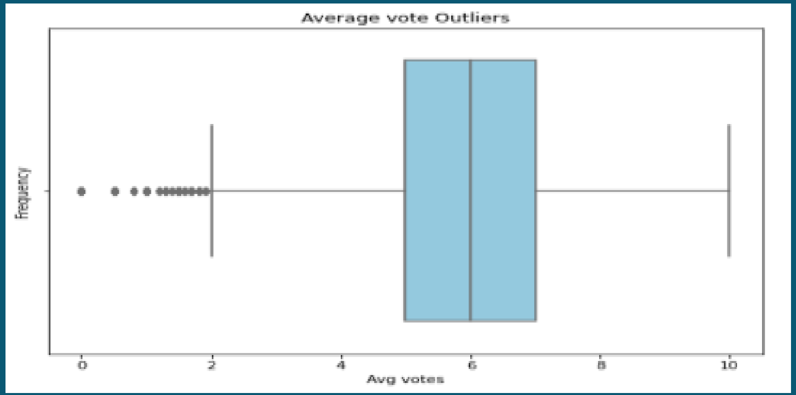
Let us visualize the outliers with a

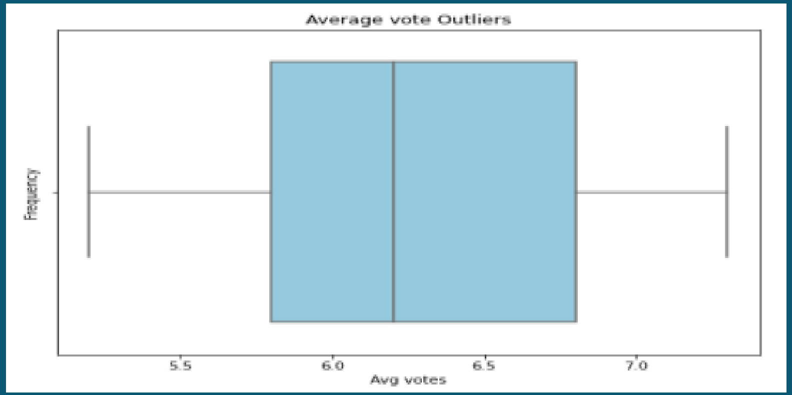
Box plots

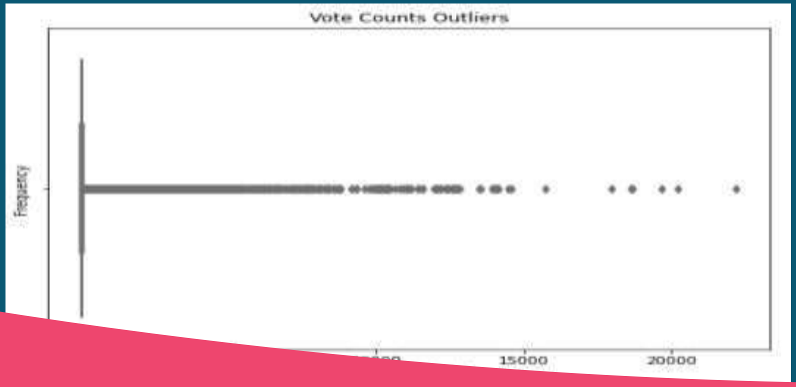
after

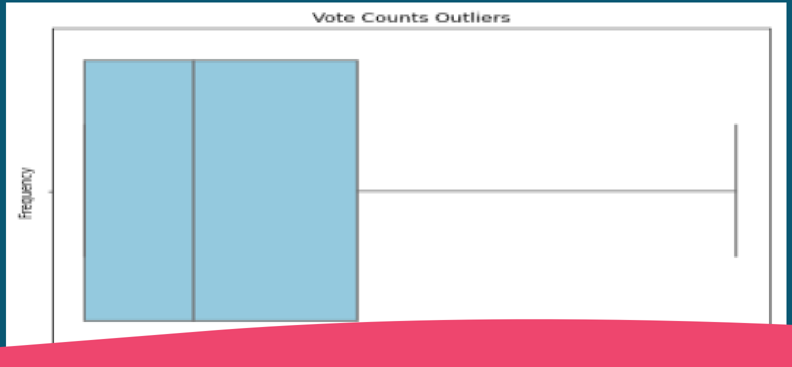




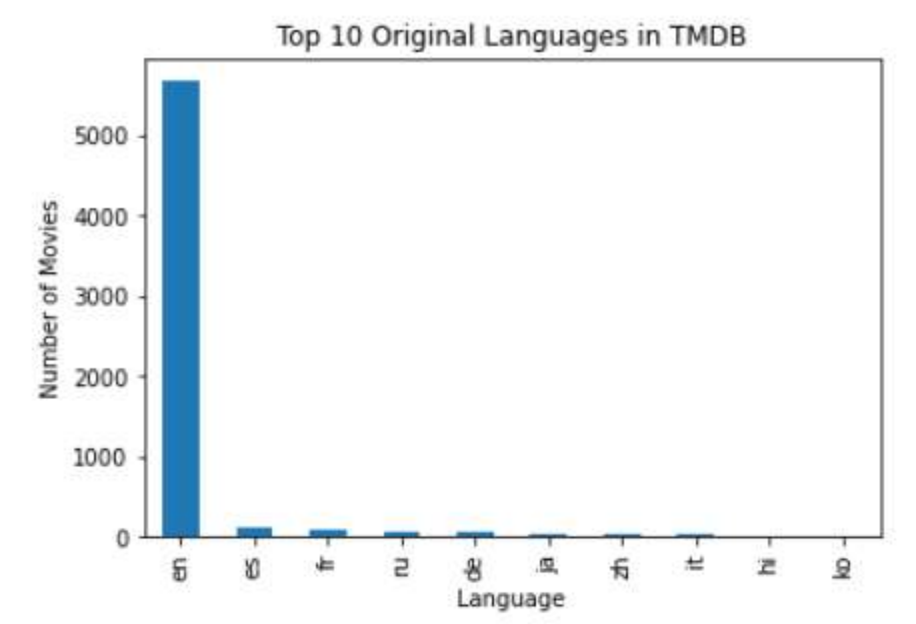








Which language is the most popular?



English movie sells the most in film industry by far.

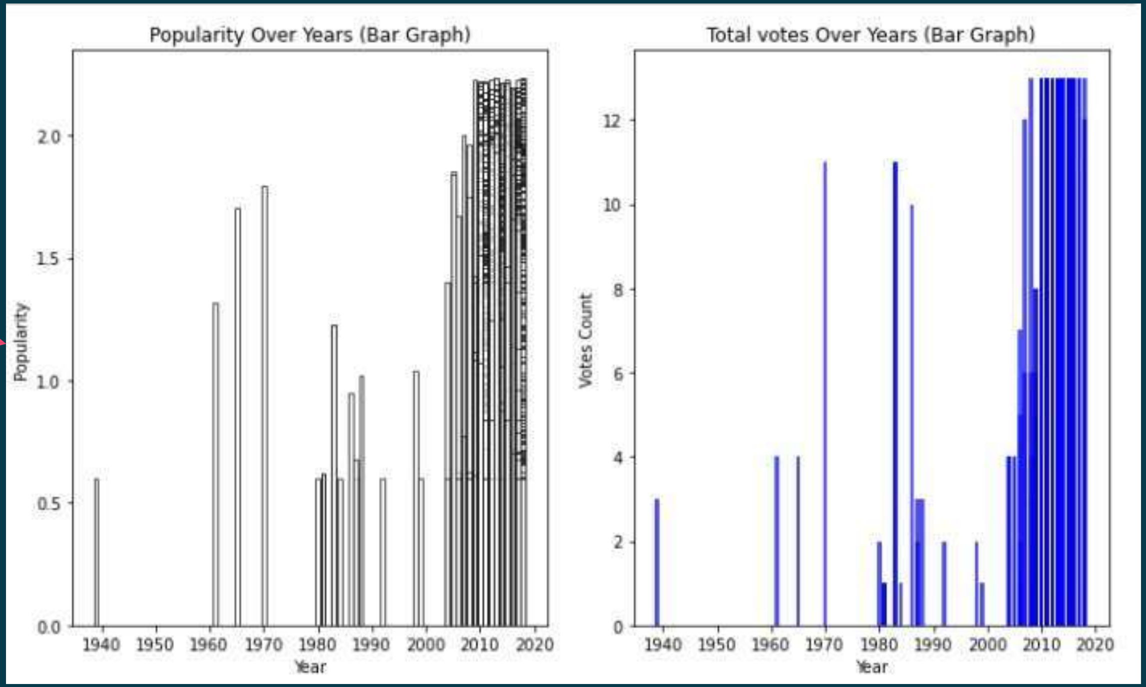
To maximize profits, Microsoft should delve into producing more English movies.

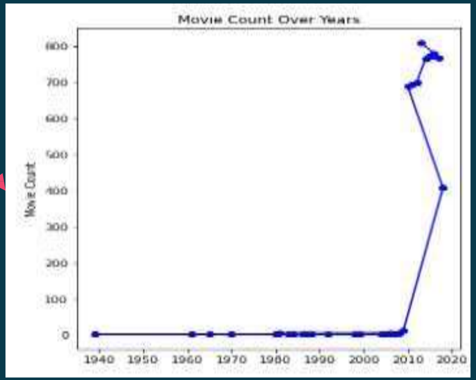
Does Vote count affect popularity?

Vote count is positively correlated to popularity, but it is not a strong correlation.

Correlation = 0.549394219698477.

The movie DB released less movies from 1940 to 2005, but started releasing a lot of movies from 2005 onwards, and gained a lot of votes and popularity there after.





Recommendations

- Given the broader market appeal, Microsoft should focus on releasing more English-language movies compared to other languages. English-language films tend to have higher sales potential and wider international distribution.
- Volume Strategy for Popularity: Releasing a high number of movies can help Microsoft gain votes and popularity on platforms like The Movie DB. The number of movies released positively correlates with audience engagement metrics, such as votes and popularity, thus enhancing the studio's visibility and reputation.

Conclusion

Microsoft can improve its success in the movie industry by focusing more on releasing movies worldwide rather than just in one country. This opens up a big opportunity to earn more money by reaching audiences all over the world.

Additionally, teaming up with the best studios, both in the U.S. and abroad, could be a smart move. By working with them, Microsoft can benefit from their knowledge and connections, helping them succeed both locally and internationally.

It's important for Microsoft to understand that selling movies globally and locally are two different things. The success of a movie and how much money it makes can depend on various factors like production costs and how often movies are released. This means Microsoft needs to be careful with their spending and release schedules to avoid big financial risks.

Focusing more on making English-language movies can also help Microsoft earn more money since they tend to be more popular worldwide. And if Microsoft releases more movies each year, it could increase their popularity and appeal to audiences.

By considering all of these factors, like where to focus their sales, how much to spend on making movies, and how often to release them, Microsoft can do better in the movie business and become a major player in entertainment.


The end