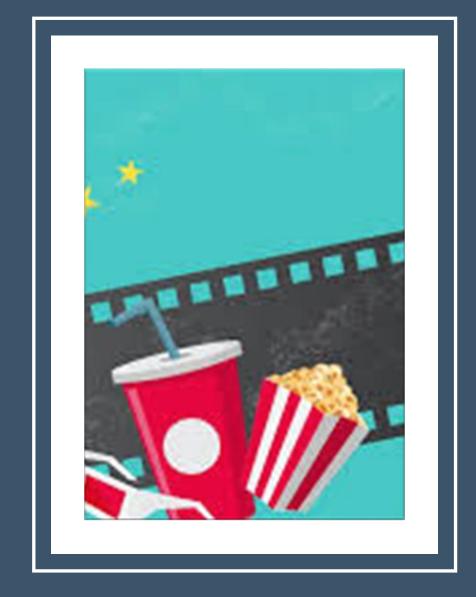
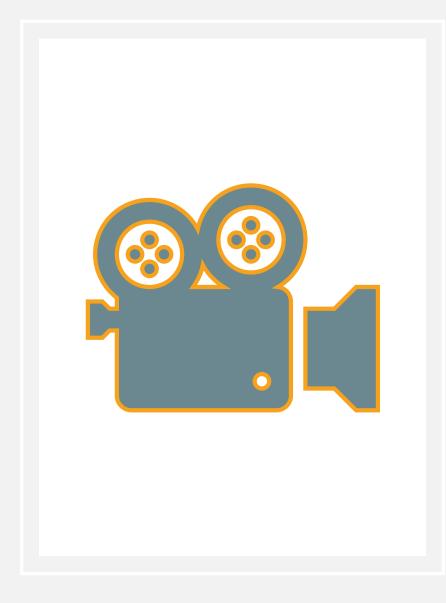
RECOMMENDATIONS FOR MOVIES PRODUCTION COMPANIES AND PREDICTING THE PROFITS OF THE MOVIES

Halah Banuqaytah || T5 bootcamp project



PROJECT GOALS:

- 1- Provide the movies production companies with recommendation to have more profits from movies streamed in cinema to keep up with the new direction streaming which is streaming platforms like Netflix.
- 2- Use machine learning algorithms to predict the profits of a movie before releasing it.



PERSONAL MOTIVATION:

This is my first ever data science project, so I thought about making the project about something I really love and enjoy which is movies and especially movies streamed only in cinema.

968 PEEU22

DATASET

58948 4635403EE B144F068EA6409E 404E4136C4FF07E

CCA58FF

DATASET INFORMATION

□Source of dataset:

Kaggle website under the name 'Movie industry'

■ Number of columns and rows:

The dataset contains 7668 rows and 15 columns

The data types of columns:9 objects ,5 float ,1 int.

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 7668 entries, 0 to 7667
Data columns (total 15 columns):
    Column
             Non-Null Count Dtype
    name 7668 non-null
                            object
    rating 7591 non-null
                            object
    genre 7668 non-null
                            object
   year 7668 non-null
                            int64
   released 7666 non-null
                            object
  score 7665 non-null
                            float64
   votes 7665 non-null
                            float64
   director 7668 non-null
                            object
  writer 7665 non-null
                            object
   star 7667 non-null
                            object
    country 7665 non-null
                            object
    budget 5497 non-null
                            float64
12 gross 7479 non-null
                           float64
13 company 7651 non-null
                            object
                            float64
14 runtime 7664 non-null
dtypes: float64(5), int64(1), object(9)
memory usage: 898.7+ KB
```

Figl: Dataset Information

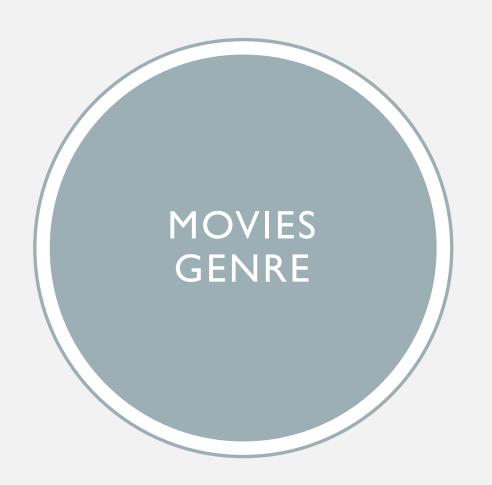
DATA CLEANING

- I- Null values: Dropping and Non dropping
- 2-Changing some data types
- 3- Rename columns

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 7409 entries, 0 to 7659
Data columns (total 15 columns):
  Column
                     Non-Null Count Dtype
    movie name
                                    object
                     7409 non-null
    rating
                     7409 non-null
                                    object
                    7409 non-null object
    genre
    imdb score
                     7409 non-null
                                    float64
    imdb votes
                     7409 non-null int64
    director
                     7409 non-null object
    writer
                     7409 non-null object
    main star
                     7409 non-null
                                    object
    country
                     7409 non-null
                                    object
                     7409 non-null
    budget
                                    int64
    profits
                    7409 non-null int64
    prod company
                                    object
                     7409 non-null
12 runtime
              7409 non-null float64
13 releasing date 7409 non-null datetime64[ns]
14 releasing country 7409 non-null object
dtypes: datetime64[ns](1), float64(2), int64(3), object(9)
memory usage: 926.1+ KB
```

Fig2: Dataset Information after Cleaning

EXPLORATORY DATA ANALYSIS AND FINDINGS

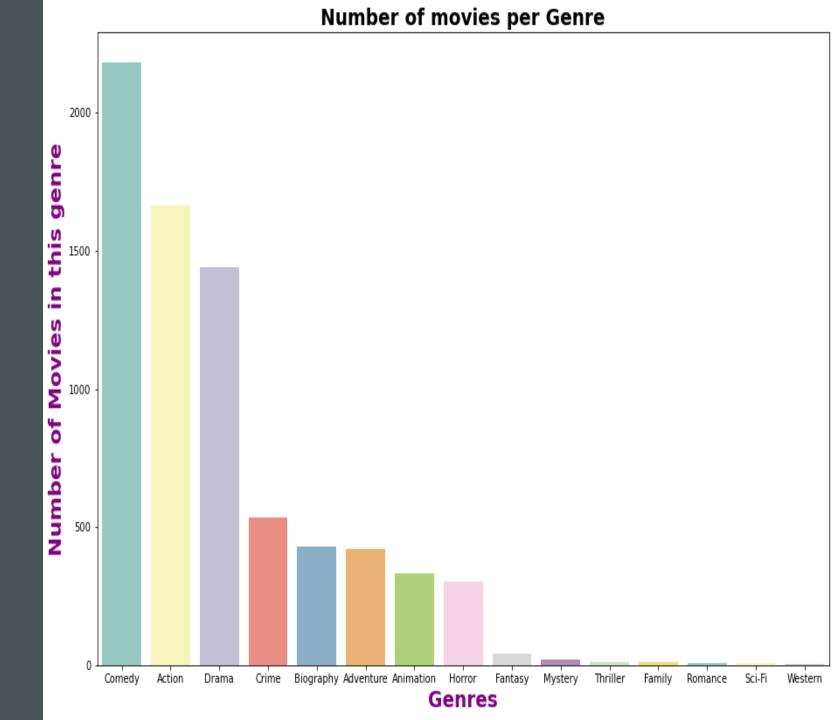


• 15 different genre which are:

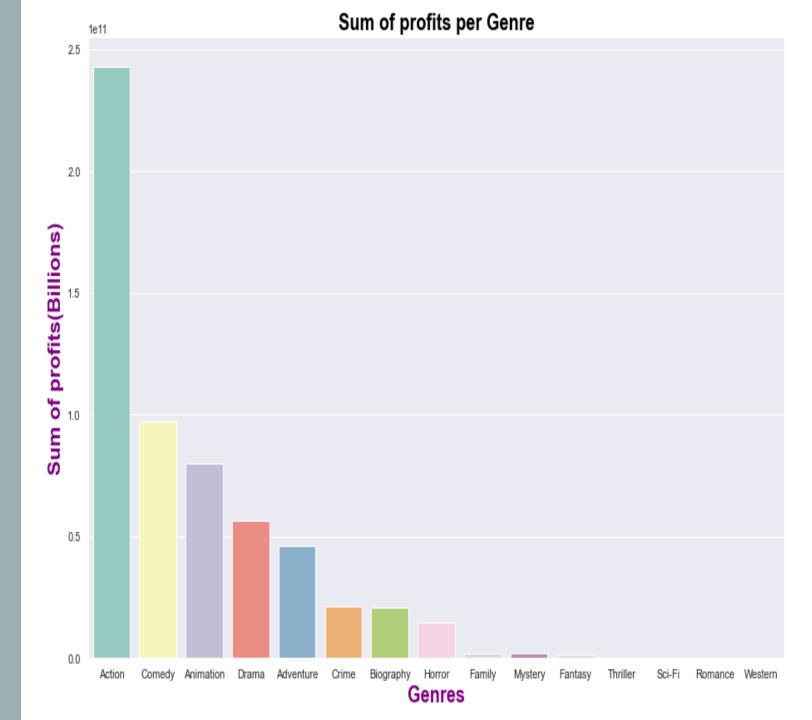
Drama, Adventure, Action, Comedy, Horror, Biography, Crime, Fantasy, Family, Animation, Romance, Western, Thriller, Sci-Fi, Mystery

- For this feature, I have the following assumptions:
- 1. Most of the movies under the fantasy genre.
- 2. The action genre is the most profitable.

MOST OF THE MOVIES UNDER THE COMEDY GENRE.



THE ACTION GENRE IS THE MOST PROFITABLE.



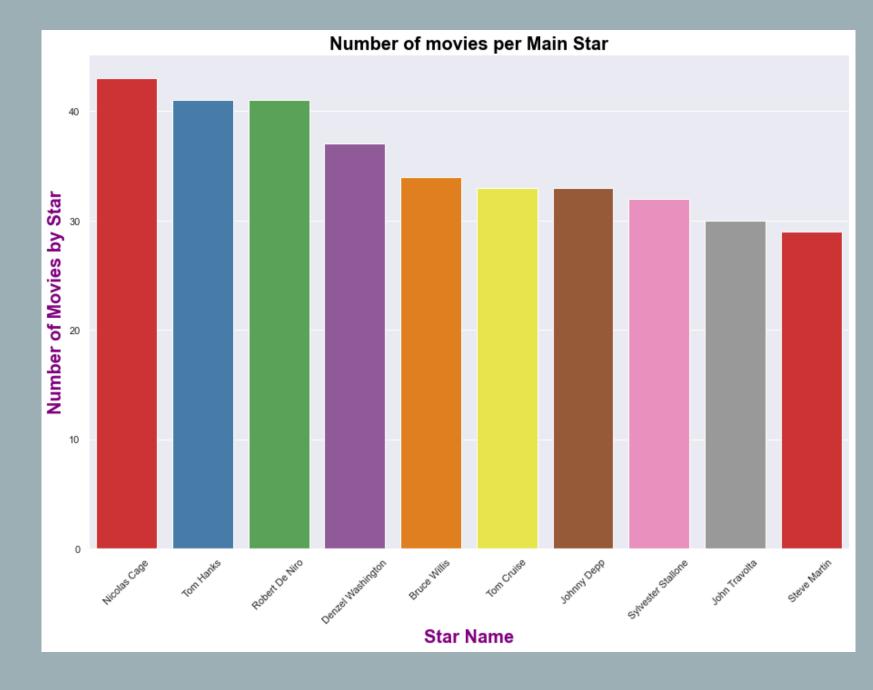


MOVIES MAIN STARS

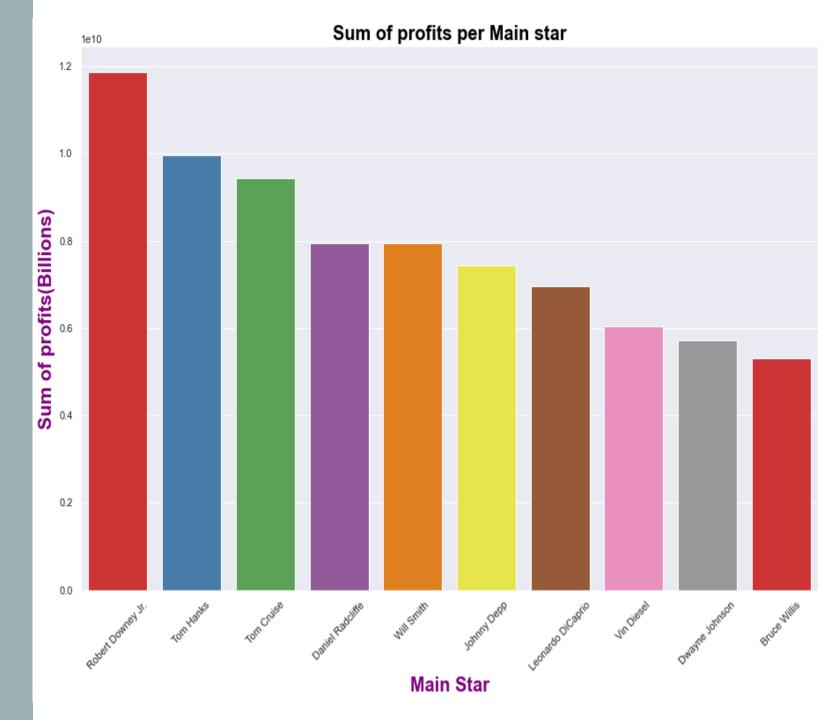
- The dataset has:
- 1. 2649 Main star
- For this feature, I have the following assumption:

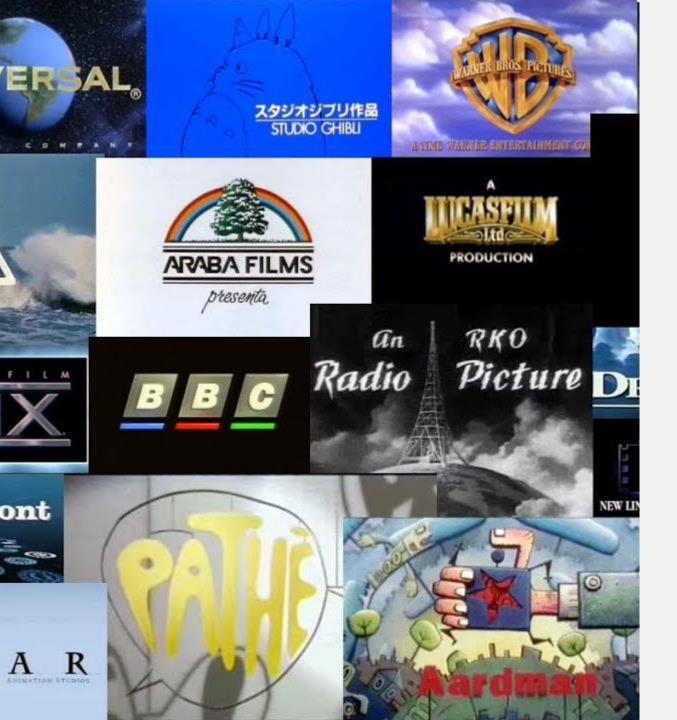
Main Stars with more movies have the highest profits.

TOPIO MAIN STARS WITH MORE MOVIES



TOPIO MAIN STARS WITH HIGHEST PROFITS

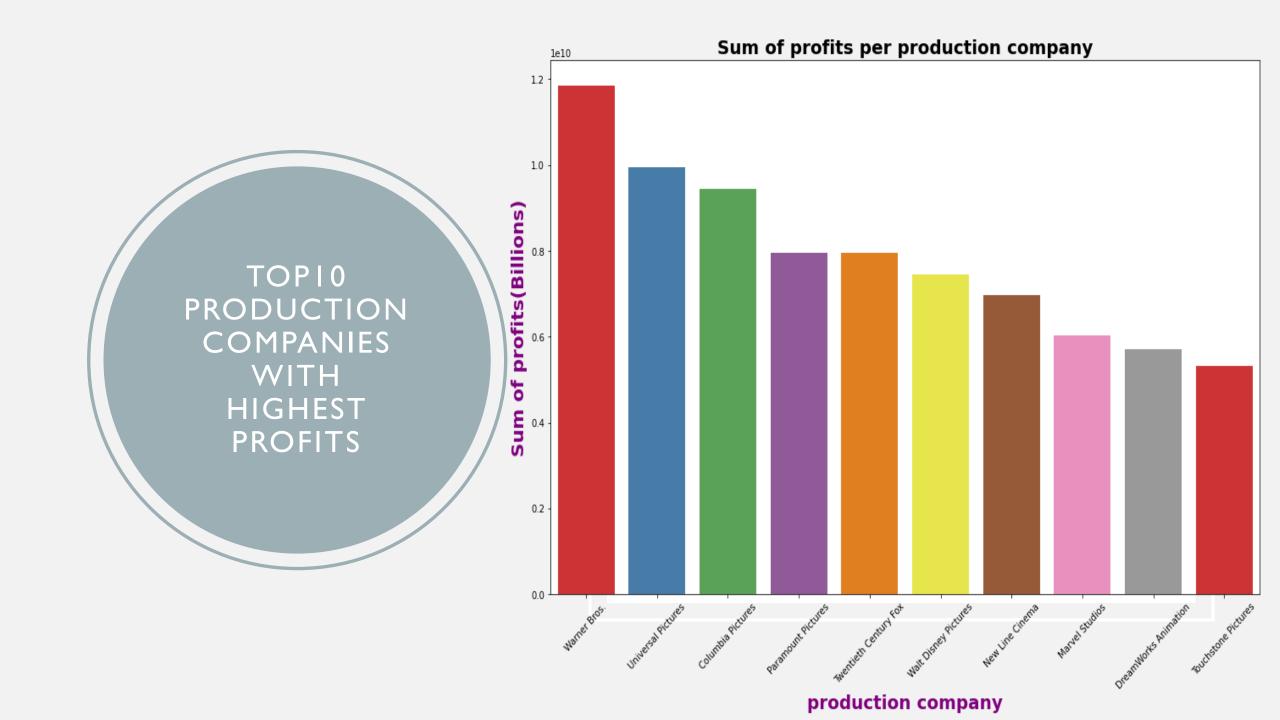




MOVIES PRODUCTION COMPANIES

- 2239 different production company.
- For this feature, I have the following assumption:

Marvel production company is the most profitable.



Month	Number of movies		
January	584		
February	584		
March	666		
April	626		
May	558		
June	547		
July	570		
August	716		
September	634		
October	724		
November	628		
December	572		

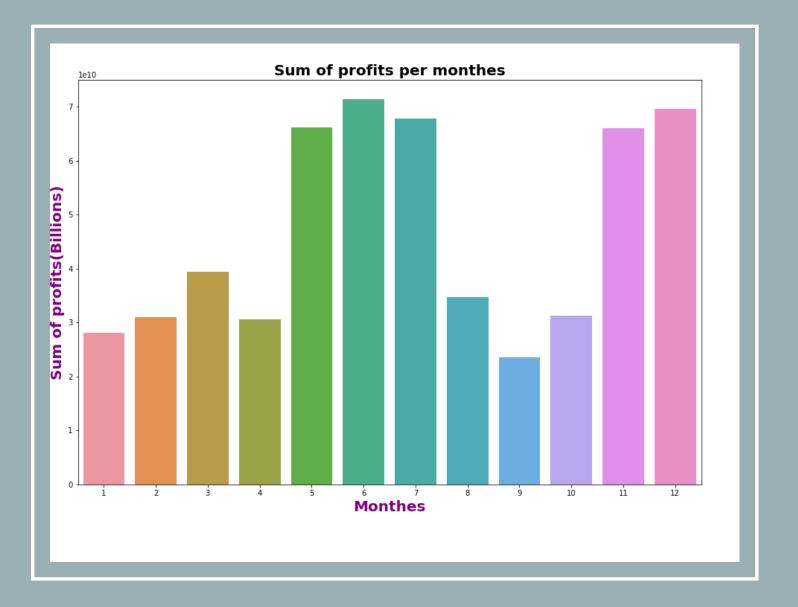
Number of movies for each month in the past 40 years.

RELEASING DATE

• For this feature, I have the following assumption:

Movies in December has the highest profits compared to other months.

JUNE IS THE BEST MONTH TO RELEASE A MOVIE



MACHINE LEARNING ALGORITHM

FEATURE SELECTION

From the heatmap, we can see that budget is the most correlated feature with the target.

Movie1 Heat Map for the Features														
movie_name	1	-0.011	0.019	0.01	0.0091	0.0068	-0.013	0.018	0.0049	0.0084	0.01	-0.00097		
rating	-0.011	1	0.12	0.014	-0.0031	0.0017	0.034	-0.17	-0.13	-0.083	0.073	-0.026		- 0.75
genre	0.019	0.12	1	-0.015	0.012	-0.0008	-0.03	-0.4	-0.25	-0.074	-0.042	-0.088		
director	0.01	0.014	-0.015	1	0.3	0.036	0.013	-0.0031	-0.014	0.0012	0.015	0.0065		- 0.50
writer	0.0091	-0.0031	0.012	0.3	1	0.025	0.012	-0.029	-0.024	0.0033	-0.0049	0.0013		- 0.25
main_star	0.0068	0.0017	-0.0008	0.036	0.025	1	-0.018	-0.017	-0.0024	0.0055	0.0083	-0.029		- 0.00
country	-0.013	0.034	-0.03	0.013	0.012	-0.018	1	0.042	0.092	0.09	-0.08	0.28	- 0.00	
budget	0.018	-0.17	-0.4	-0.0031	-0.029	-0.017	0.042	1	0.72	0.15	0.26	0.098		- -0.25
profits	0.0049	-0.13	-0.25	-0.014	-0.024	-0.0024	0.092	0.72	1	0.15	0.25	0.12		0.50
prod_company	0.0084	-0.083	-0.074	0.0012	0.0033	0.0055	0.09	0.15	0.15	1	0.03	0.088		0.50
runtime	0.01	0.073	-0.042	0.015	-0.0049	0.0083	-0.08	0.26	0.25	0.03	1	-0.0093		- -0.75
releasing_country	-0.00097	-0.026	-0.088	0.0065	0.0013	-0.029	0.28	0.098	0.12	0.088	-0.0093	1		
	movie_name	rating	genre	director	writer	main_star	country	budget	profits	prod_company	runtime	easing_country		- -1.00

LINEAR REGRESSION MODEL

R squared value for Linear Regression Table.

	Dropping budget null values	Filling budget null values
Training set	0.54	0.51
Test set	0.56	0.51

RANDOM FOREST REGRESSOR

R squared value for Random Forest Regression Table.

	Dropping budget null values	Filling budget null values
Training set	0.63	0.67
Test set	0.60	0.55

CONCLUSION



Movies production companies should focus more on action movies rather than any other genre.



The best time to release a movie will be in June or December



There is high correlation between the profits and the budget, so the production companies need to be generous with the budget to grantee the success of the movie.

FUTURE WORK

Improve the model using deep learning

Try different regression models to see if the accuracy will be higher

Adding more features from another dataset like movie's poster and plot.