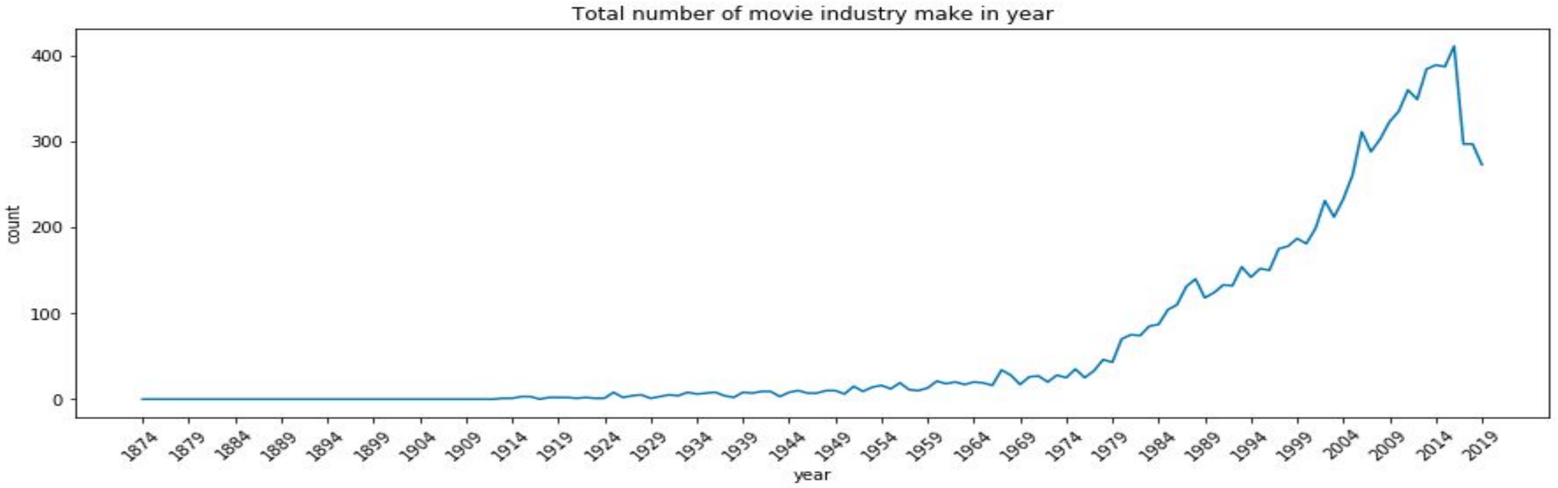
MOVIE PREDICT AND RECOMMENDATION

Word Cloud for title movie

- LIVE, LOVE, LIFE, MAN, GIRL are word was show a lot in the title name, So we can see that movie are more romantic and family.

Total number movie over year!



- Increasing at 1974

Total, Avg. revenue and number movie each year

year	Average_revenue	Total_revenue	count
2016	7.627827e+07	3.135037e+10	411
2015	7.414786e+07	2.869522e+10	387
2014	7.113407e+07	2.767116e+10	389
2013	7.039734e+07	2.703258e+10	384
2012	7.569661e+07	2.641812e+10	349
2011	6.939981e+07	2.498393e+10	360
2010	7.205477e+07	2.413835e+10	335
2009	7.440009e+07	2.403123e+10	323
2008	6.991971e+07	2.118567e+10	303
2007	7.076921e+07	2.038153e+10	288

Year was first movie

	year	title	runtime
34693	1874	Passage of Venus	1.0
34690	1878	Sallie Gardner at a Gallop	1.0
70946	1881	Athlete Swinging a Pick	1.0
41270	1883	Buffalo Running	1.0
135279	1885	L'homme machine	1.0

Year last movie in our data set

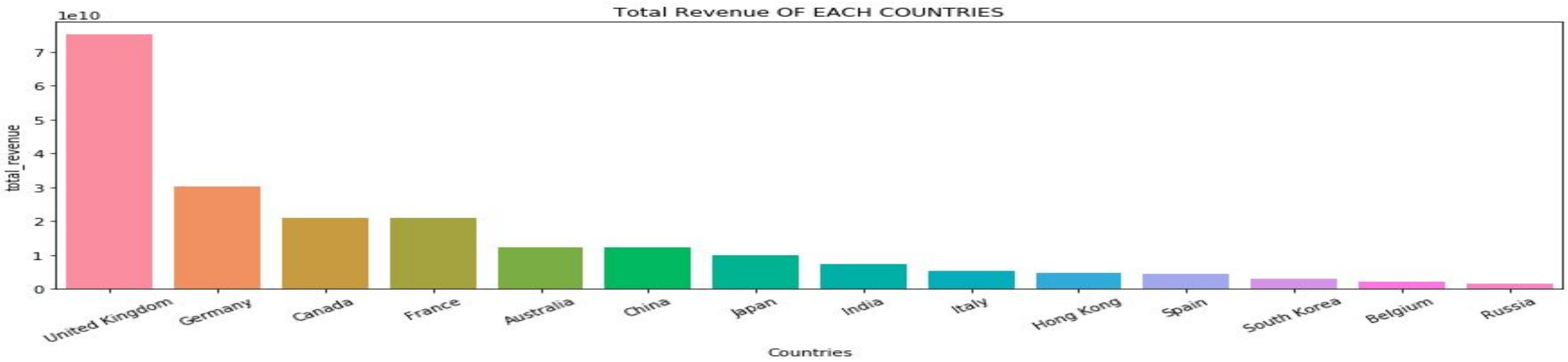
	year	title	runtime
174446	2019	Sunday	13.0
174441	2019	Queen + Béjart - Ballet For Life	58.0
126731	2019	The Ocean Washed Open Your Grave	3.0
174467	2019	Entropia	28.0
210551	2019	Jorge	20.0

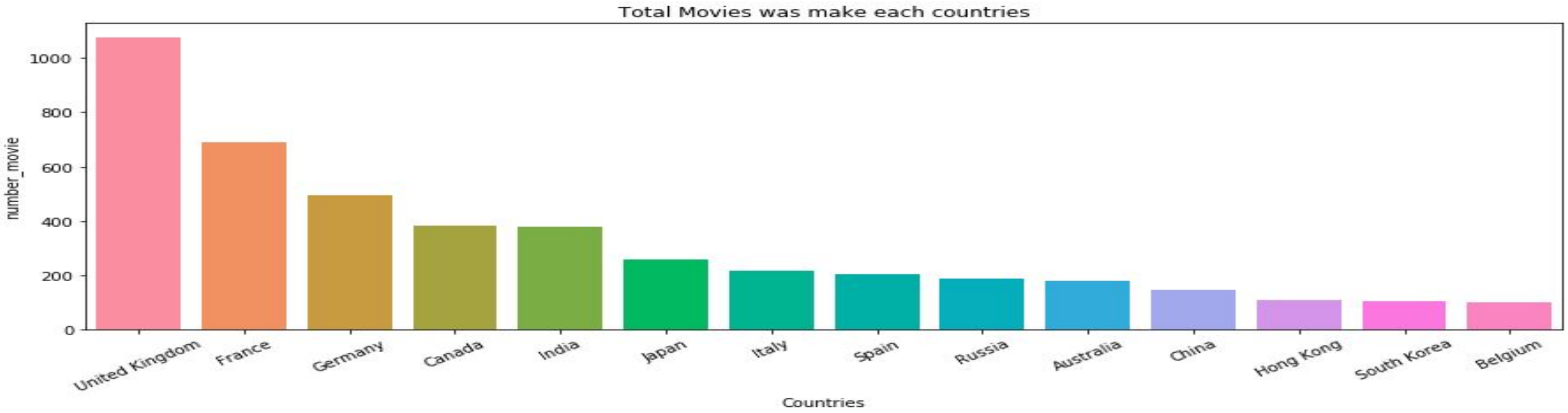
Total, Avg. revenue of each countries

Countries	average_revenue	total_revenue	number_movie
United States of America	7.714978e+07	4.976932e+11	6451
United Kingdom	6.990096e+07	7.514353e+10	1075
France	3.021624e+07	2.084921e+10	690
Germany	6.078097e+07	3.014736e+10	496
Canada	5.485054e+07	2.089806e+10	381
India	1.911960e+07	7.246328e+09	379
Japan	3.894279e+07	9.969354e+09	256
Italy	2.382187e+07	5.169346e+09	217
Spain	2.157035e+07	4.378782e+09	203
Russia	8.155989e+06	1.517014e+09	186

- **USA is number 1 have total revenue and number of movie product**

Total, Avg. revenue of each countries (continuous)



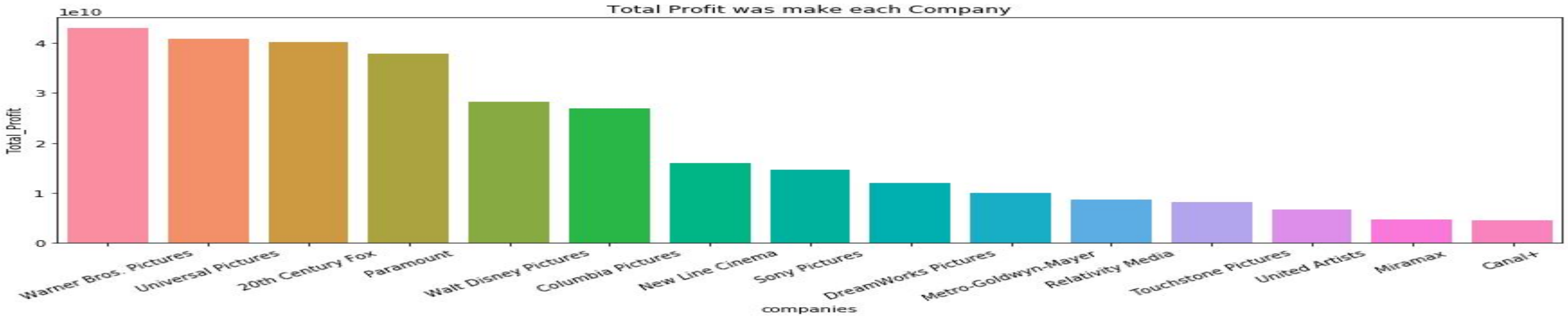


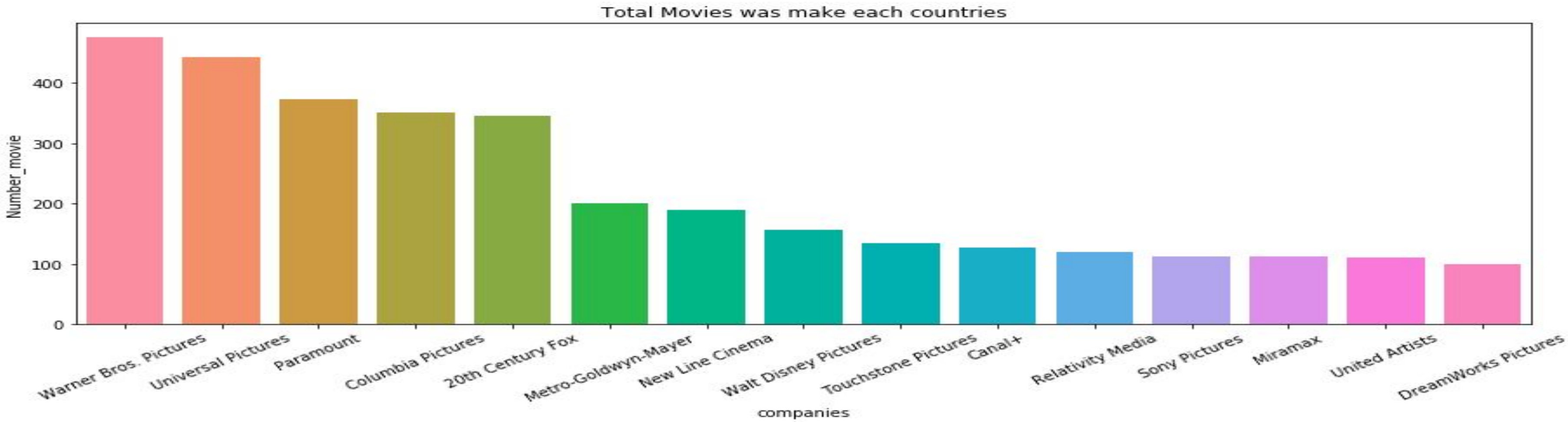
Total, Avg profit of each company

companies	Avergae_profit	Total_Profit	Number_movie
Warner Bros. Pictures	9.032809e+07	4.299617e+10	476
Universal Pictures	9.229253e+07	4.088559e+10	443
Paramount	1.014296e+08	3.793466e+10	374
Columbia Pictures	7.684656e+07	2.697314e+10	351
20th Century Fox	1.164543e+08	4.017672e+10	345
Metro-Goldwyn-Mayer	5.015126e+07	1.003025e+10	200
New Line Cinema	8.415754e+07	1.598993e+10	190
Walt Disney Pictures	1.797291e+08	2.821747e+10	157
Touchstone Pictures	6.081461e+07	8.209972e+09	135
Canal+	3.521476e+07	4.437060e+09	126

- **Warner Bros. Picture is number 1 total profit and number 1 on the make movie**
- **Second one is Universal Pictures**

Total, Avg profit of each company (continuous)



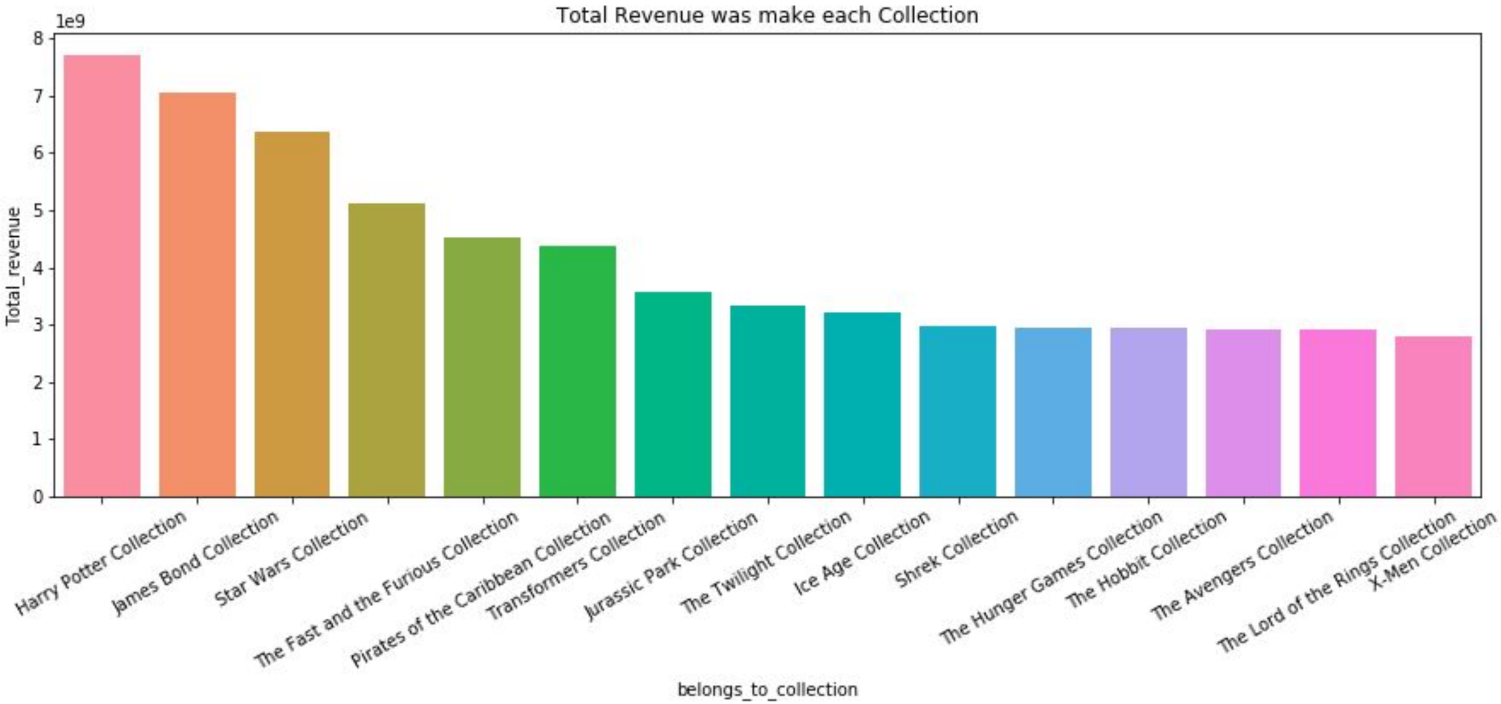


Total, Avg. of each collection of movie

belongs_to_collection	Average_revenue	Total_revenue	Total_movie
Harry Potter Collection	9.633598e+08	7.706879e+09	8
James Bond Collection	2.827486e+08	7.068715e+09	25
Star Wars Collection	9.112054e+08	6.378438e+09	7
The Fast and the Furious Collection	6.406373e+08	5.125099e+09	8
Pirates of the Caribbean Collection	9.043154e+08	4.521577e+09	5
Transformers Collection	8.758574e+08	4.379287e+09	5
Jurassic Park Collection	8.948083e+08	3.579233e+09	4
The Twilight Collection	6.686215e+08	3.343107e+09	5
Ice Age Collection	6.433533e+08	3.216767e+09	5
Shrek Collection	7.411823e+08	2.964729e+09	4

- **Harry Potter only have 8 movie, but total revenue is number 1**
- **The second is James Bond**
- **The third is Star Wars**

Total, Avg. of each collection of movie (continuous)

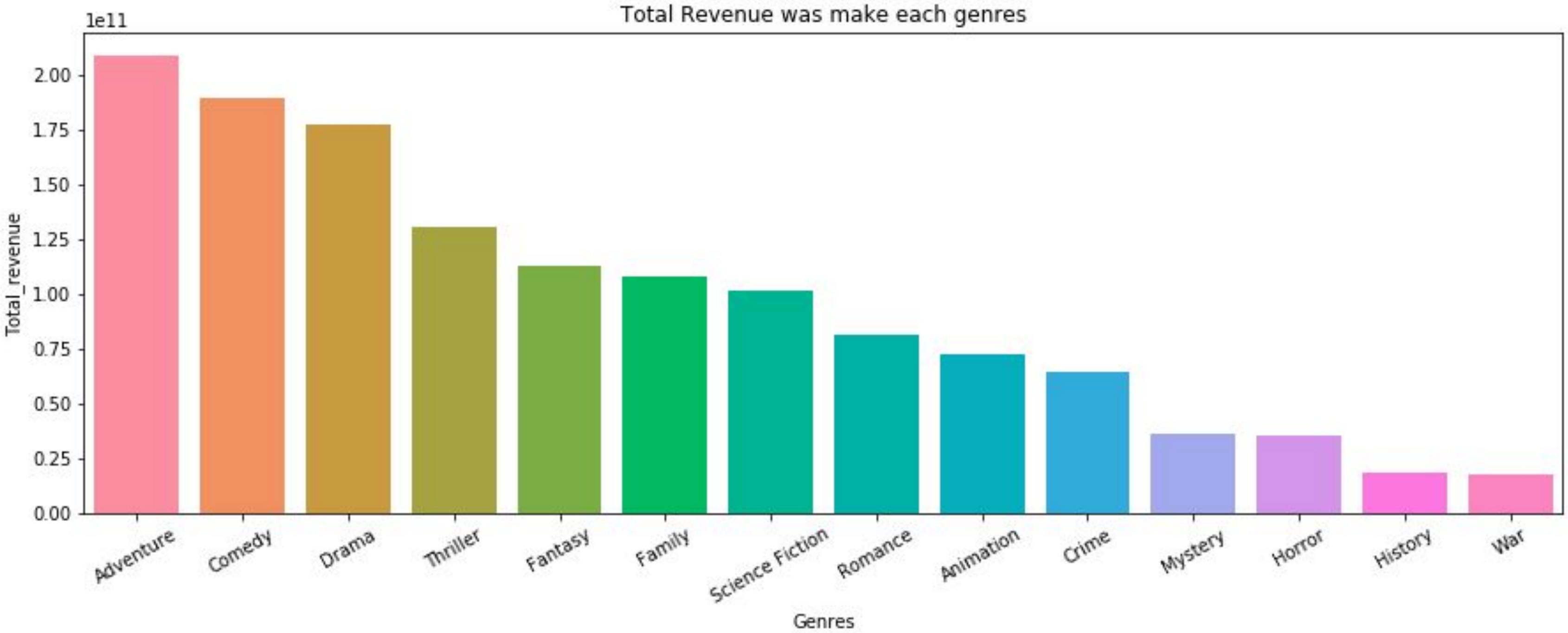


Total, Avg. of Genres of movie

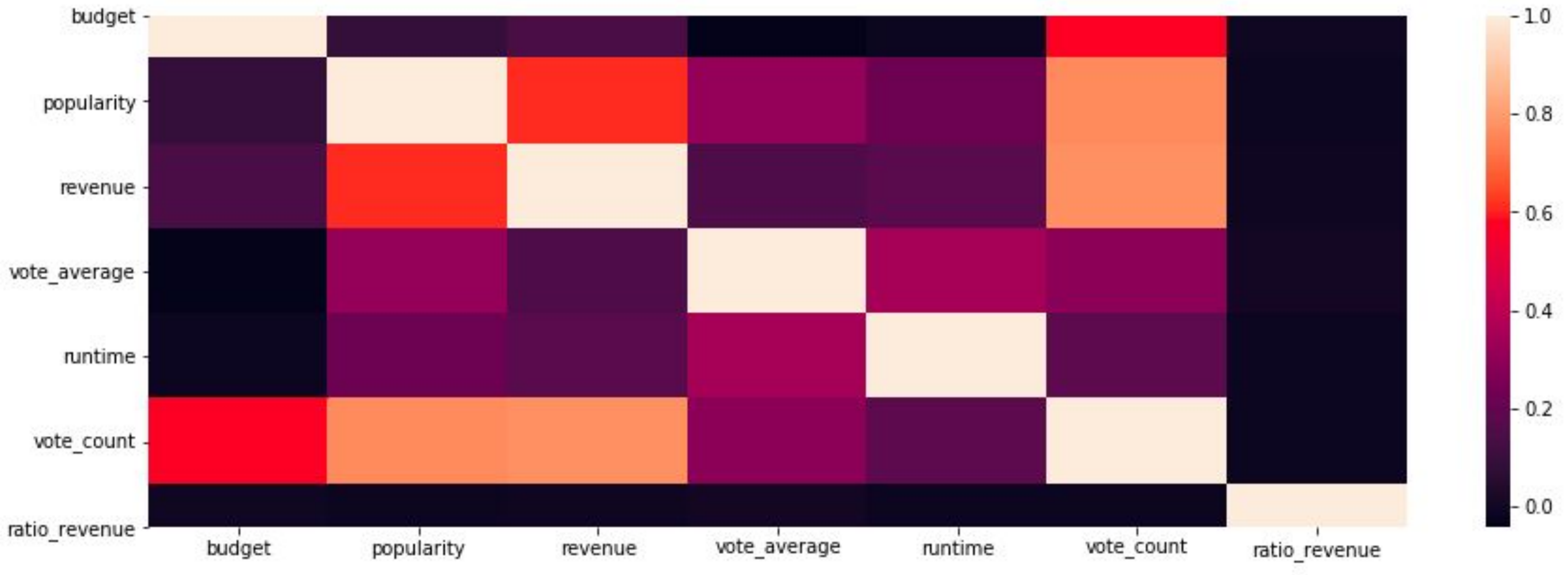
Genres	Avergae_revenue	Total_revenue	Total_movie
Action	1.025900e+08	2.134897e+11	2081
Adventure	1.640720e+08	2.086996e+11	1272
Comedy	5.798689e+07	1.889213e+11	3258
Drama	3.835340e+07	1.773078e+11	4623
Thriller	6.120269e+07	1.302393e+11	2128
Fantasy	1.463286e+08	1.122341e+11	767
Family	1.299991e+08	1.080293e+11	831
Science Fiction	1.181741e+08	1.016297e+11	860
Romance	4.568787e+07	8.073046e+10	1767
Animation	1.467283e+08	7.189686e+10	490

- **People are love Action movie, then you can see that movie action was have number 1 of total revenue.**

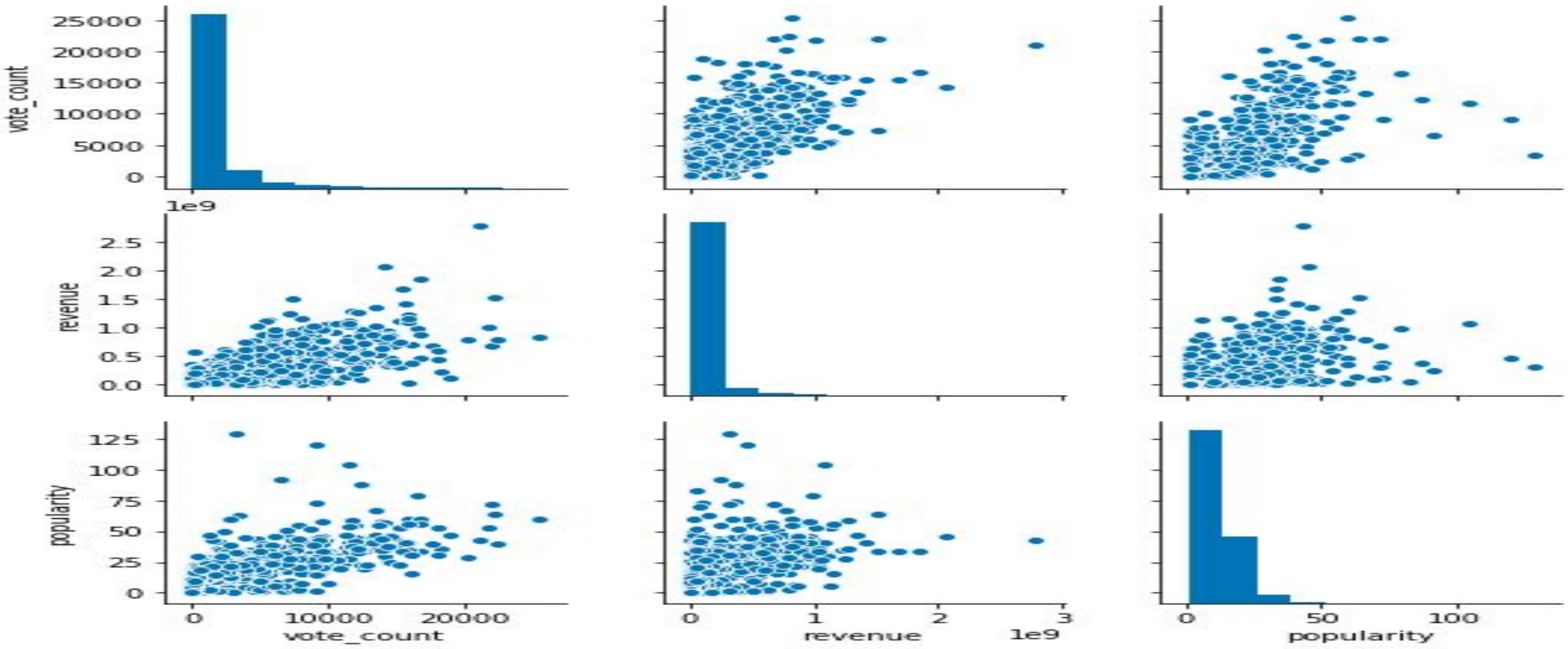
Total, Avg. of Genres of movie (continuous)



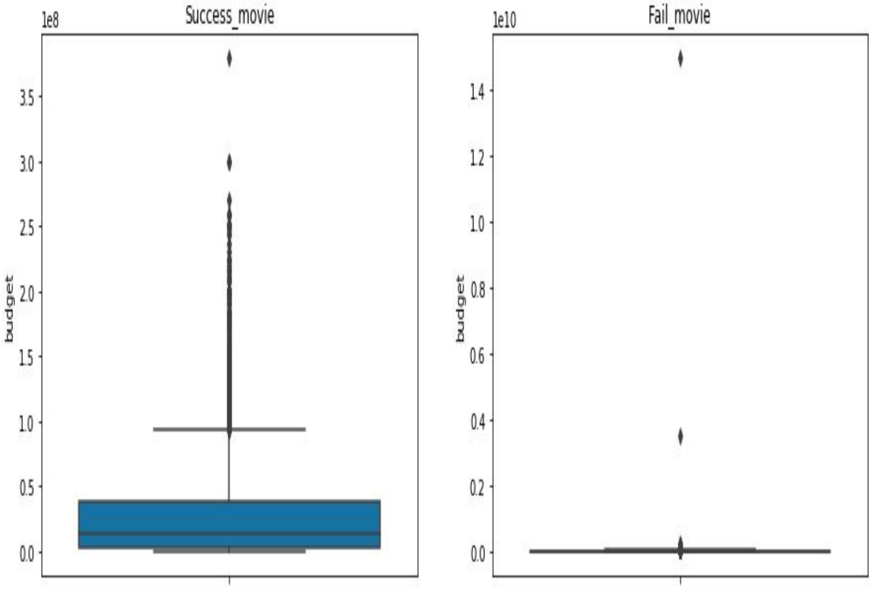
Heatmap relation of each column



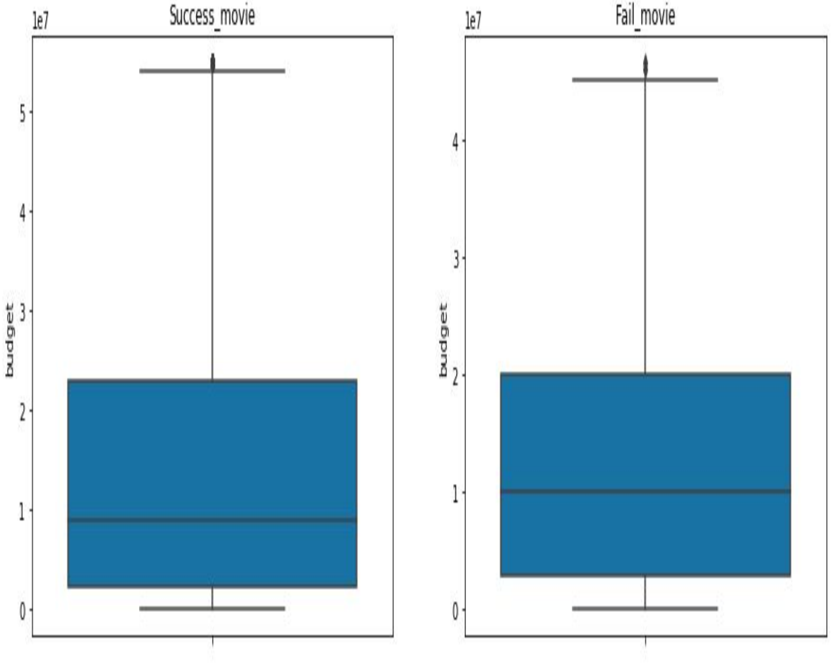
Pairplot for vote_count, revenue, popularity



Boxplot detect outlier and remove



Before remove outlier

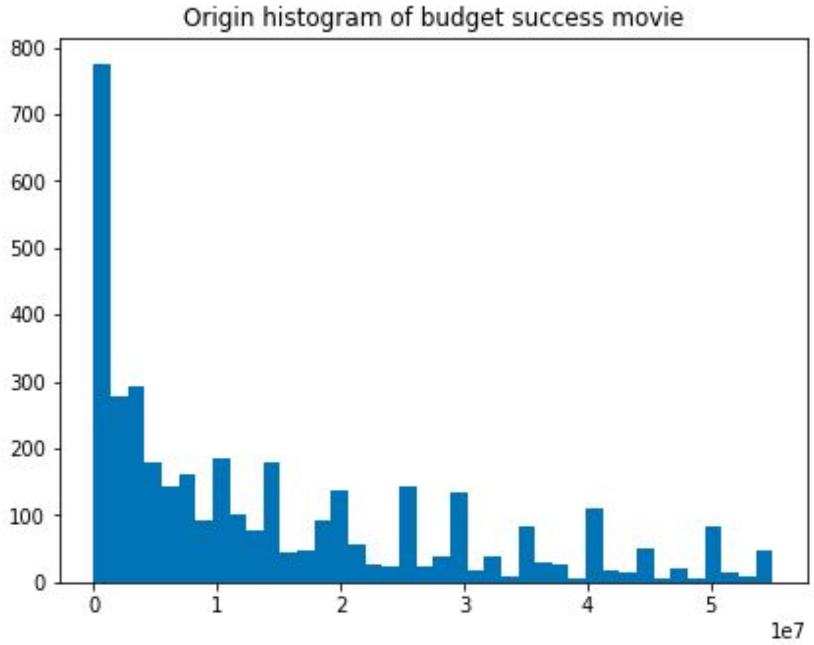


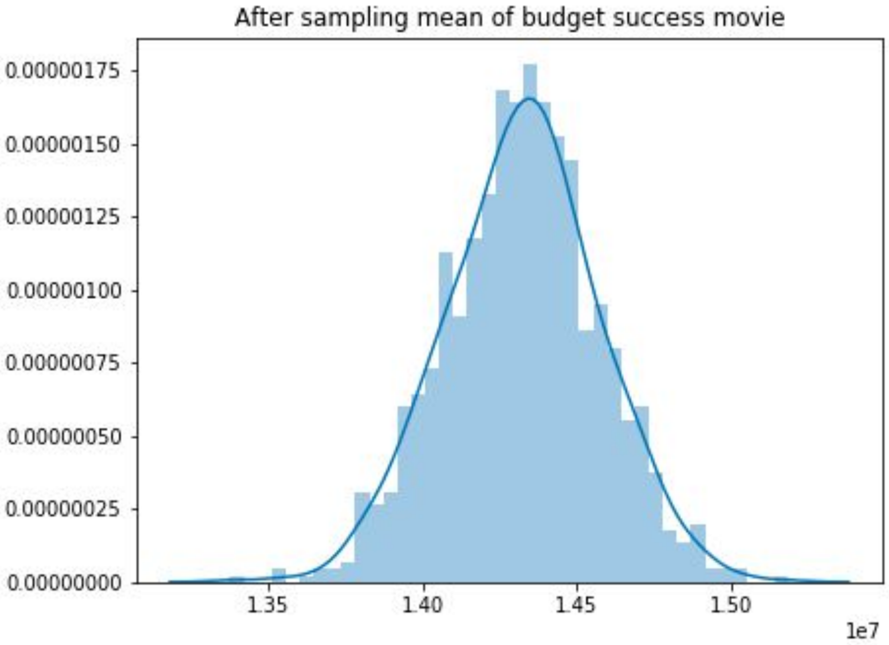
After remove outlier

Interface Statistic

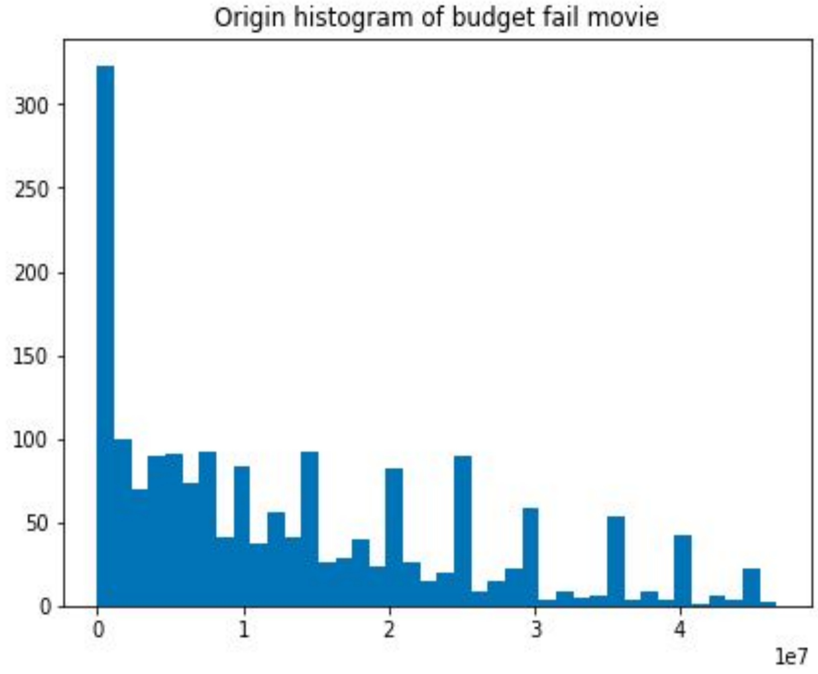
- We perform the hypothesis test to test the different mean average of success and fail movies.
  - We identified the null hypothesis and alternative hypothesis.
    - H0: the different average of success and fail is >= 1438763
    - Ha: the different average is < 1438763
  - With significant is 5% or 0.05
  - After our test and we got the p-value = 0.501
  - Then we can’t reject our null hypothesis.

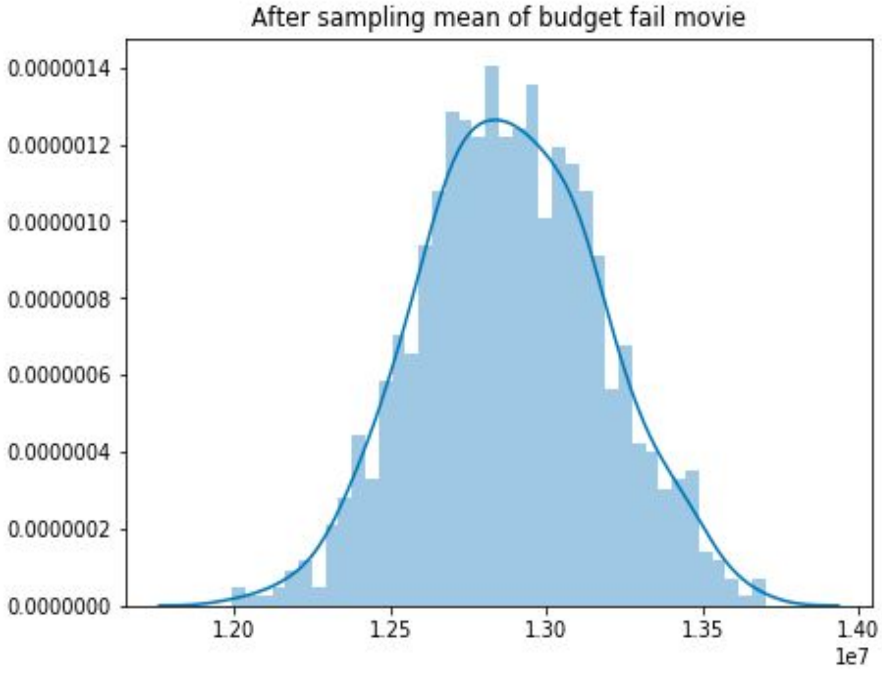
Resampling mean of success movie



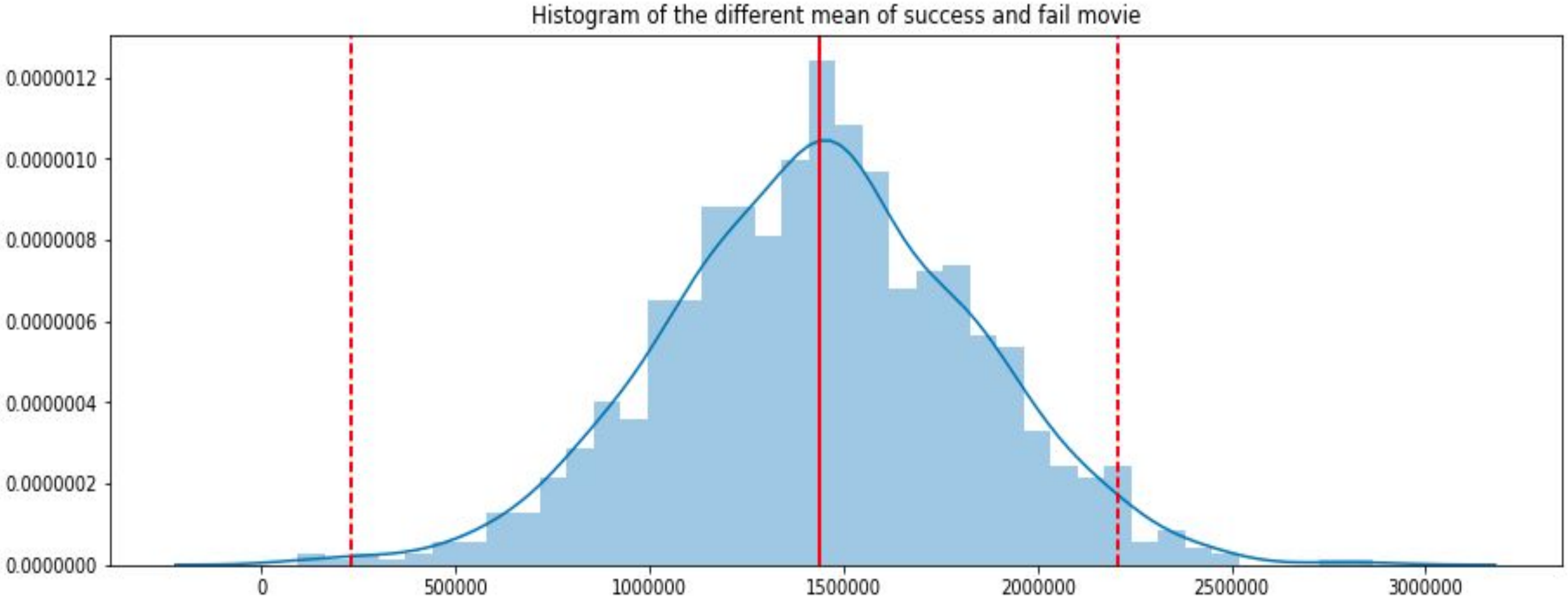


Resampling mean of fail movie





Different mean of two resampling.



PREDICT MACHINE MODEL

1. Random forest classification

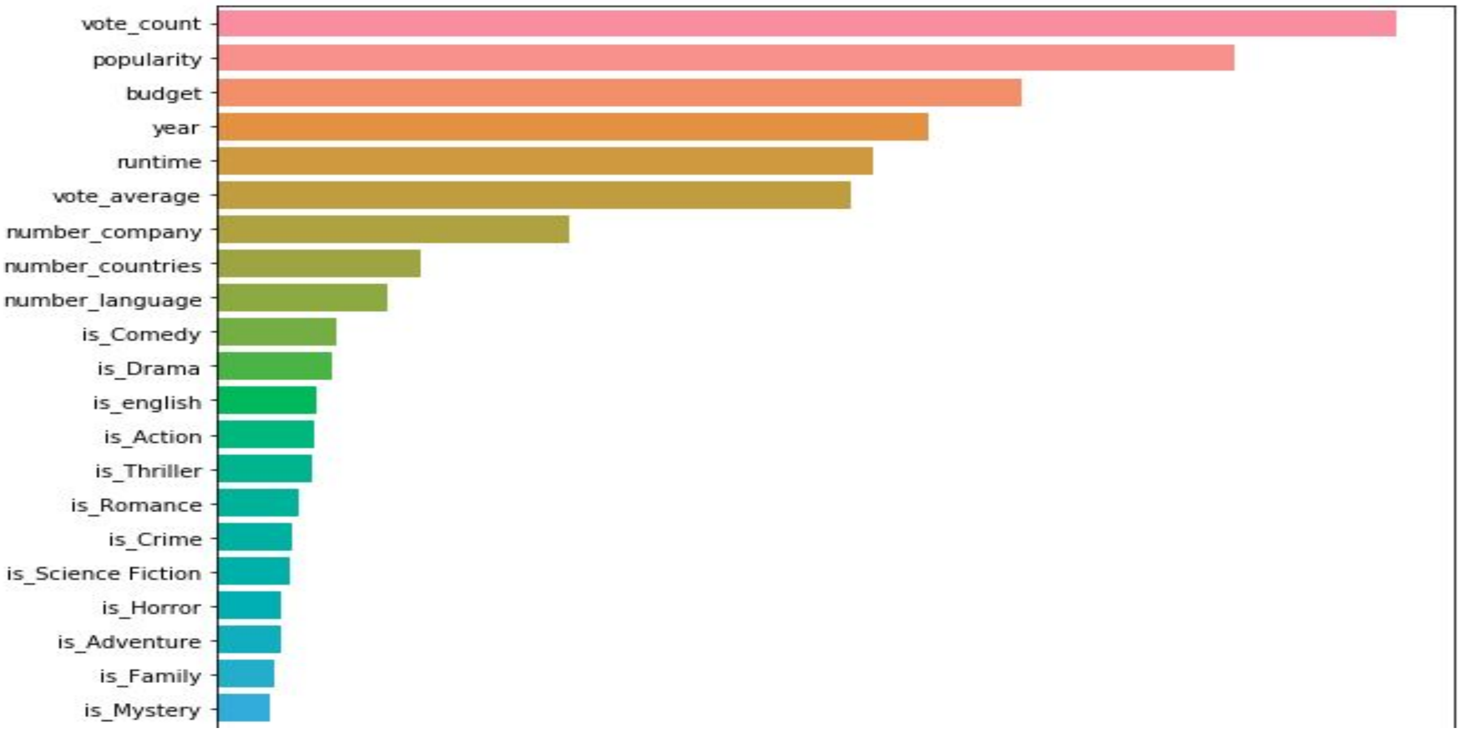
2. Gradient Boosting Classification

3. Logistic Regression model

Random Forest Classification

	precision	recall	f1-score	support
0	0.67	0.54	0.60	785
1	0.82	0.89	0.85	1860
accuracy			0.78	2645
macro avg	0.75	0.71	0.73	2645
weighted avg	0.78	0.78	0.78	2645

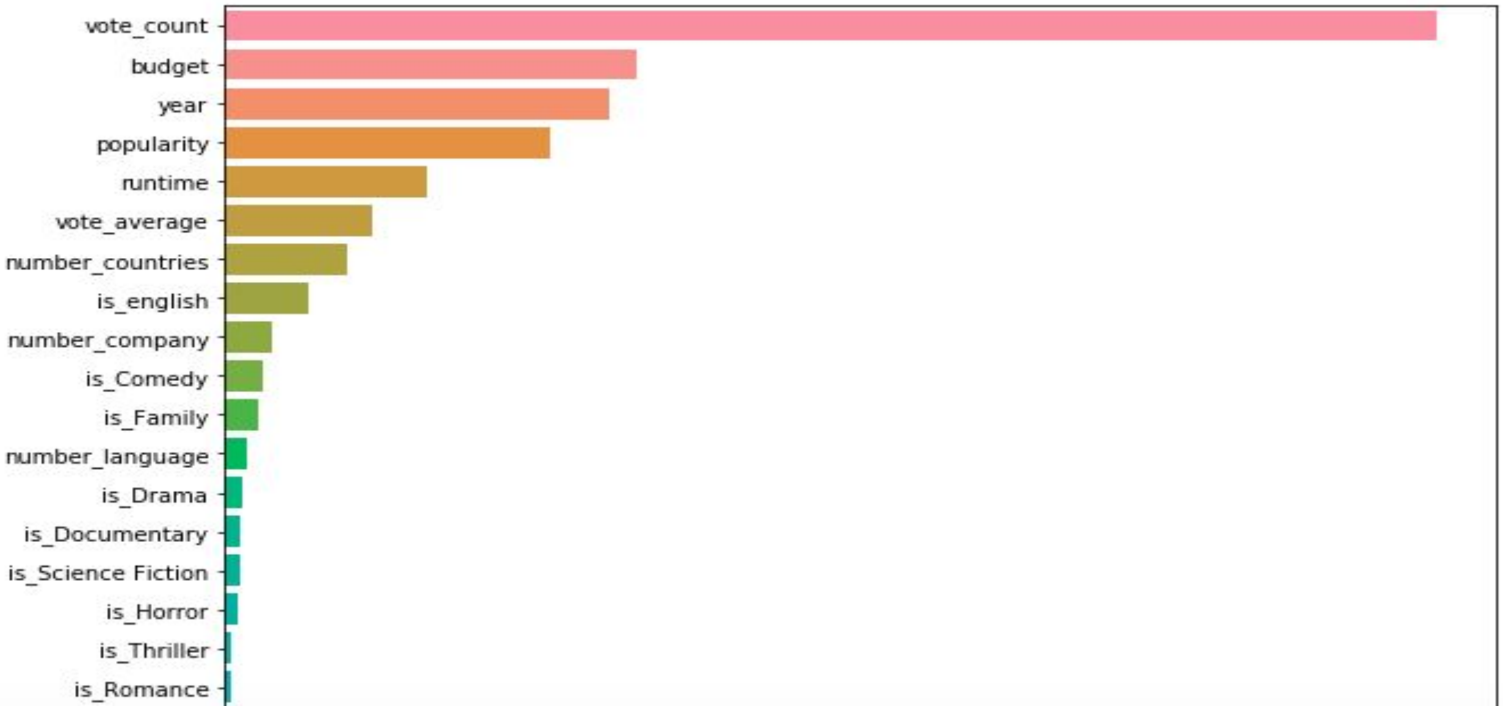
Feature importance



Gradient Boosting Classification

	precision	recall	f1-score	support
0	0.67	0.54	0.60	785
1	0.82	0.88	0.85	1860
accuracy			0.78	2645
macro avg	0.74	0.71	0.73	2645
weighted avg	0.78	0.78	0.78	2645

Feature Importance



Logistic Regression model

	precision	recall	f1-score	support
0	1.00	0.00	0.01	785
1	0.70	1.00	0.83	1860
accuracy			0.70	2645
macro avg	0.85	0.50	0.42	2645
weighted avg	0.79	0.70	0.58	2645

Conclusion

- Random forest:
  - Score: 0.78
  - Faster, and use more feature
- Gradient Boosting
  - Score: 0.78
  - Slower than random forest, and use less feature than random forest
- Logistic regression
  - Score: 0.70

RECOMMENDATION SYSTEM

- Basic recommendation
  - Top 20 movie
  - Top 15 movie for genre
- Correlation-base recommendation
- Model-based Collaborative filtering system recommendation

Basic Recommendation

- Target for new user.

- Return overall top 20 movie

- User can choose genres, and return top 15 movie of that genres

Basic Recommendation- by Top 20 movie

```
recommend_top_20_movie()
```

	title	genres
0	In a Lonely Place (1950)	Drama|Film-Noir|Mystery|Romance
1	Paperman (2012)	Animation|Comedy|Romance
2	Diabolique (Les diaboliques) (1955)	Horror|Mystery|Thriller
3	Paradise Now (2005)	Crime|Drama|Thriller|War
4	Best Years of Our Lives, The (1946)	Drama|War
5	Drunken Master (Jui kuen) (1978)	Action|Comedy
6	Inherit the Wind (1960)	Drama
7	Tell No One (Ne le dis à personne) (2006)	Crime|Drama|Mystery|Thriller
8	For the Birds (2000)	Animation|Children|Comedy
9	Wind Rises, The (Kaze tachinu) (2013)	Animation|Drama|Romance
10	Court Jester, The (1956)	Adventure|Comedy|Musical
11	Godfather, The (1972)	Crime|Drama
12	Shawshank Redemption, The (1994)	Crime|Drama
13	Tom Jones (1963)	Adventure|Comedy|Romance
14	Gladiator (1992)	Action|Drama
15	On the Waterfront (1954)	Crime|Drama
16	Kid, The (1921)	Comedy|Drama
17	When We Were Kings (1996)	Documentary
18	Carnal Knowledge (1971)	Comedy|Drama

Basic recommendation - by Genres

```
get_recommend_genre("Drama")
```

	title	genres
0	Best Years of Our Lives, The (1946)	Drama|War
1	Inherit the Wind (1960)	Drama
2	Godfather, The (1972)	Crime|Drama
3	Shawshank Redemption, The (1994)	Crime|Drama
4	Gladiator (1992)	Action|Drama
5	On the Waterfront (1954)	Crime|Drama
6	All About Eve (1950)	Drama
7	Ran (1985)	Drama|War
8	Mister Roberts (1955)	Comedy|Drama|War
9	Godfather: Part II, The (1974)	Crime|Drama
10	Paths of Glory (1957)	Drama|War
11	Lifeboat (1944)	Drama|War
12	Rush (2013)	Action|Drama
13	Modern Times (1936)	Comedy|Drama|Romance
14	Philadelphia Story, The (1940)	Comedy|Drama|Romance

Correlation base recommendation

- Use Pearson's r correlation
  - to recommend a movie that is most similar to the movie that user have early watch
- Users can search movies by name, or
- the system will recommend the next movie based on the user have been watched.

Correlation recommendation

```
get_recommendation_movie_corr('Dangerous Minds (1995)')
```

```
/Users/hungnguyen/miniconda3/lib/python3.7/site-packages/numpy/li
freedom <= 0 for slice
  c = cov(x, y, rowvar)
/Users/hungnguyen/miniconda3/lib/python3.7/site-packages/numpy/li
ero encountered in true_divide
  c *= np.true_divide(1, fact)
```

	title	genres
0	...And Justice for All (1979)	Drama|Thriller
1	127 Hours (2010)	Adventure|Drama|Thriller
2	2 Days in the Valley (1996)	Crime|Film-Noir
3	2 Fast 2 Furious (Fast and the Furious 2, The)...	Action|Crime|Thriller
4	21 (2008)	Crime|Drama|Romance|Thriller
5	300 (2007)	Action|Fantasy|War|IMAX
6	40 Days and 40 Nights (2002)	Comedy|Romance
7	About Last Night... (1986)	Comedy|Drama|Romance
8	Absolute Power (1997)	Mystery|Thriller
9	Addams Family, The (1991)	Children|Comedy|Fantasy
10	Adventureland (2009)	Comedy|Drama
11	Adventures in Babysitting (1987)	Adventure|Comedy
12	Adventures of Baron Munchausen, The (1988)	Adventure|Comedy|Fantasy
13	Aeon Flux (2005)	Action|Sci-Fi

Model-based collaborative filter system

- Use Singular Value Decomposition (SVD)

- Recommend base on model
    - Faster
    - accurate

Model-base collaborative filter system

```
model_base_recommendation('Dangerous Minds (1995)')
```

	title	genres
0	Dangerous Minds (1995)	Drama
1	Outbreak (1995)	Action|Drama|Sci-Fi|Thriller
2	Waterworld (1995)	Action|Adventure|Sci-Fi
3	Legends of the Fall (1994)	Drama|Romance|War|Western
4	Tombstone (1993)	Action|Drama|Western
5	Dances with Wolves (1990)	Adventure|Drama|Western
6	Apollo 13 (1995)	Adventure|Drama|IMAX
7	Cliffhanger (1993)	Action|Adventure|Thriller
8	Ace Ventura: Pet Detective (1994)	Comedy
9	Firm, The (1993)	Drama|Thriller
10	Speed (1994)	Action|Romance|Thriller
11	True Lies (1994)	Action|Adventure|Comedy|Romance|Thriller
12	Die Hard: With a Vengeance (1995)	Action|Crime|Thriller
13	Crimson Tide (1995)	Drama|Thriller|War
14	Net, The (1995)	Action|Crime|Thriller

THANK YOU!

THE END!