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movie_project / Microsoft Movie Analysis.ipynb

AHMET16 Update Microsoft Movie Analysis.ipynb History

1 contributor

2765 lines (2765 sloc) | 493 KB

Microsoft Movie Analysis

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Overview

This project represents a preliminary study of the entry into the microsoft film industry. The company, which is very new in this sector, made front studies by making use of the large database containing the data of movies such as IMDB, TMDB, ROTTEN TOMATOES. We decided to examine the director, genre and movie profit. We determined which film genres had a more successful effect on the directors' profit. Using this data, Microsoft can decide which movies it would be right to start with in its new project.

Business Problem

Microsoft is the world leader in its field, but the film industry is also very new in terms of know-how, the company should decide how much budget it has outside of this project and decide on the film it will shoot. The results of the data and analyzes I have collected show the following. Genre and profit data of the directors have determined the genre that provides the least risk for companies that have just started in the film industry.

Data Understanding

Questions to consider:

Question Where did the data come from, and how do they relate to the data analysis questions?

The data is provided by Flatiron school and collected from the respective websites.

The data is collected from Box Office Mojo, IMDB, Rotten Tomatoes, and TheMovieDB.org. The data has information about movie titles, genres, directors, actors, profits, release year.

What is the target variable? Target variables are the Genre, Directors and profit.

In [724…

```
#Import the following libraries
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import plotly.express as px

import matplotlib.pyplot as plt
%matplotlib inline
```

In [725…

```
# Here you run your code to explore the data
```

```
bom_movie_gross = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/bom.movie_
imdb_name_basics = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/imdb.name
imdb_title_akas = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/imdb.title
imdb_title_basics = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/imdb.tit
imdb_title_principals = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/imdb
imdb_title_ratings = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/imdb.ti
tmdb_movies = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/tmdb.movies.cs
tn_movie_budgets = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/tn.movie_
imdb_title_crew = pd.read_csv('/Users/karaoglan/Desktop/PROJECT/imdb.title
```

In [726…

```
imdb_title_crew
```

Out[726…

	tconst	directors	writers
0	tt0285252	nm0899854	nm0899854
1	tt0438973	NaN	nm0175726,nm1802864
2	tt0462036	nm1940585	nm1940585
3	tt0835418	nm0151540	nm0310087,nm0841532
4	tt0878654	nm0089502,nm2291498,nm2292011	nm0284943
...	...	...	...
146139	tt8999974	nm10122357	nm10122357
146140	tt9001390	nm6711477	nm6711477
146141	tt9001494	nm10123242,nm10123248	NaN
146142	tt9004986	nm4993825	nm4993825
146143	tt9010172	NaN	nm8352242

146144 rows × 3 columns

In [727…

```
imdb_name_basics
```

Out[727…

	nconst	primary_name	birth_year	death_year	
0	nm0061671	Mary Ellen Bauder	NaN	NaN	miscellaneous,product
1	nm0061865	Joseph Bauer	NaN	NaN	composer,music_departme
2	nm0062070	Bruce Baum	NaN	NaN	mis
3	nm0062195	Axel Baumann	NaN	NaN	camera_department,cinematogı
4	nm0062798	Pete Baxter	NaN	NaN	production_designer,art_dep
...	...	...	...	...	
606643	nm9990381	Susan Grobes	NaN	NaN	
606644	nm9990690	Joo Yeon So	NaN	NaN	
606645	nm9991320	Madeline Smith	NaN	NaN	
606646	nm9991786	Michelle Modigliani	NaN	NaN	

606647	nm9993380	Pegasus Envoyé	NaN	NaN

606648 rows × 6 columns

In [728…

```
bom_movie_gross
```

Out[728…

	title	studio	domestic_gross	foreign_gross	year
0	Toy Story 3	BV	415000000.0	652000000	2010
1	Alice in Wonderland (2010)	BV	334200000.0	691300000	2010
2	Harry Potter and the Deathly Hallows Part 1	WB	296000000.0	664300000	2010
3	Inception	WB	292600000.0	535700000	2010
4	Shrek Forever After	P/DW	238700000.0	513900000	2010
...	...	...	...	...	...
3382	The Quake	Magn.	6200.0	NaN	2018
3383	Edward II (2018 re-release)	FM	4800.0	NaN	2018
3384	El Pacto	Sony	2500.0	NaN	2018
3385	The Swan	Synergetic	2400.0	NaN	2018
3386	An Actor Prepares	Grav.	1700.0	NaN	2018

3387 rows × 5 columns

In [729…

```
imdb_title_ratings
```

Out[729…

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559
2	tt1042974	6.4	20
3	tt1043726	4.2	50352
4	tt1060240	6.5	21
...	...	...	...
73851	tt9805820	8.1	25
73852	tt9844256	7.5	24
73853	tt9851050	4.7	14
73854	tt9886934	7.0	5
73855	tt9894098	6.3	128

73856 rows × 3 columns

In [730…

```
tmdb_movies
```

Out[730…

	Unnamed: 0	genre_ids	id	original_language	original_title	popularity	rel
0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	
1	1	[14, 12, 16, 10751]	10191	en	How to Train Your Dragon	28.734	2
2	2	[12, 28, 878]	10138	en	Iron Man 2	28.515	2
3	3	[16, 35, 10751]	862	en	Toy Story	28.005	1
4	4	[28, 878, 12]	27205	en	Inception	27.920	2
...	...	...	...	...	...	...	
26512	26512	[27, 18]	488143	en	Laboratory Conditions	0.600	2
26513	26513	[18, 53]	485975	en	_EXHIBIT_84xxx_	0.600	2
26514	26514	[14, 28, 12]	381231	en	The Last One	0.600	2
26515	26515	[10751, 12, 28]	366854	en	Trailer Made	0.600	2
26516	26516	[53, 27]	309885	en	The Church	0.600	2

26517 rows × 10 columns

In [731…

```
tn_movie_budgets
```

Out[731…

	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
			Star Wars			

4	5	Dec 15, 2017	Ep. VIII: The Last Jedi	$317,000,000	$620,181,382	$1,316,721,747
...	...	...	...	...	...	...
5777	78	Dec 31, 2018	Red 11	$7,000	$0	$0
5778	79	Apr 2, 1999	Following	$6,000	$48,482	$240,495
5779	80	Jul 13, 2005	Return to the Land of Wonders	$5,000	$1,338	$1,338
5780	81	Sep 29, 2015	A Plague So Pleasant	$1,400	$0	$0
5781	82	Aug 5, 2005	My Date With Drew	$1,100	$181,041	$181,041

5782 rows × 6 columns

Data preparation

Here are the datasets that I used for analysis:

imdb datasets: imdb_name_basics,imdb_title_akas,imdb_title_basics,imdb_title_principals,imdb_title_ratin

tmdb dataset: tmdb_movies

bom dataset: bom_movie_gross

tn dataset: tn_movie_budgets

In [732…

```
# I merged imdb related datasets on the value 'tconst'

imdb11 = pd.merge(imdb_title_basics,imdb_title_crew,how='inner',on='tconst
imdb12 = pd.merge(imdb_title_principals,imdb_title_ratings, how='inner',on
imdb13 = pd.merge(imdb11,imdb12,how='inner',on='tconst')


# I merged imdb name basics and imdb13 with nconst

IMDB = pd.merge(imdb_name_basics,imdb13,how='inner',on='nconst')

# IMDB and tmbd therefore do not have common value
# I merged it using the 'original_title'
itmb = pd.merge(tmdb_movies,IMDB, how='inner',on='original_title')
itmb.head(3)
```

Out[732…

Unnamed: 0	genre_ids	id	original_language	original_title	popularity	release_date

0	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
1	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19
2	0	[12, 14, 10751]	12444	en	Harry Potter and the Deathly Hallows: Part 1	33.533	2010-11-19

3 rows × 29 columns

In [733…

```
itmb.drop(['original_title','primary_title','Unnamed: 0','genre_ids','id',
itmb.head(3)
```

Out[733…

	popularity	title	vote_average	primary_name	primary_profession	
0	33.533	Harry Potter and the Deathly Hallows: Part 1	7.7	Steve Kloves	writer,producer,director	Adventure,F
1	33.533	Harry Potter and the Deathly Hallows: Part 1	7.7	Rupert Grint	actor,producer,soundtrack	Adventure,F
2	33.533	Harry Potter and the Deathly Hallows: Part 1	7.7	J.K. Rowling	writer,producer,soundtrack	Adventure,F

In [734…

```
#i merged it using 'title' bom_movie_gross and itmb

itmbom = pd.merge(bom_movie_gross,itmb, how='inner',on='title')
itmbom.head(3)
```

Out[734…

	title	studio	domestic_gross	foreign_gross	year	popularity	vote_average	primary_
	Toy							

0	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	Joan C
1	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	John La
2	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	Tom

In [735…

```
#i did left join because I wanted to return data in both tables
itmbomtn = pd.merge(itmbom, tn_movie_budgets, how='inner',left_on='title',
itmbomtn.head(3)
```

Out[735…

	title	studio	domestic_gross_x	foreign_gross	year	popularity	vote_average	primai
0	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	Joai
1	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	John
2	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	To

In [736…

```
# domestic_gross is an object (str), needs to be converted to integer and

itmbomtn['worldwide_gross'] = itmbomtn['worldwide_gross'].str.replace(',',
itmbomtn['worldwide_gross'].head()
```

Out[736…

```
0    1068879522
1    1068879522
2    1068879522
3    1068879522
4    1068879522
Name: worldwide_gross, dtype: int64
```

In [737…

```
# production_budget is an object (str), needs to be converted to integer a

itmbomtn['production_budget'] = itmbomtn['production_budget'].str.replace(
itmbomtn['production_budget'].head()
```

Out[737…

```
0    200000000
1    200000000
2    200000000
3    200000000
4    200000000
Name: production_budget, dtype: int64
```

Questions to consider

-what variables did you add ?

I created the profit value with worldwide_gross,production_budget

-which variables did you change ? i changed the primary_name to Director

In [738…

```
#i create profit,I subtracted product expenses from world income


itmbomtn = itmbomtn.dropna(subset=['worldwide_gross','production_budget'])
itmbomtn['profit']=itmbomtn['worldwide_gross']-itmbomtn['production_budget
itmbomtn.drop(['studio','year','domestic_gross_x','domestic_gross_y','worl
itmbomtn.head(3)
```

Out[738…

	title	popularity	vote_average	primary_name	primary_profession	
0	Toy Story 3	24.445	7.7	Joan Cusack	actress,soundtrack,writer	Adventure,Anim
1	Toy Story 3	24.445	7.7	John Lasseter	producer,writer,director	Adventure,Anim
2	Toy Story 3	24.445	7.7	Tom Hanks	producer,actor,soundtrack	Adventure,Anim

In [739…

```
itmbomtn.shape
```

Out[739…

```
(16184, 14)
```

In [740…

```
itmbom = pd.merge(bom_movie_gross,itmb, how='inner',on='title')
itmbom.head(3)
```

Out[740…

	title	studio	domestic_gross	foreign_gross	year	popularity	vote_average	primary_
0	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	Joan C
1	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	John La
2	Toy Story 3	BV	415000000.0	652000000	2010	24.445	7.7	Tom

In [741…

```
itmbomtn.head()
```

Out[741…

title	popularity	vote_average	primary_name	primary_profession

0	Toy Story 3	24.445	7.7	Joan Cusack	actress,soundtrack,writer	Adventure,Anim
1	Toy Story 3	24.445	7.7	John Lasseter	producer,writer,director	Adventure,Anim
2	Toy Story 3	24.445	7.7	Tom Hanks	producer,actor,soundtrack	Adventure,Anim
3	Toy Story 3	24.445	7.7	Andrew Stanton	writer,actor,producer	Adventure,Anim
4	Toy Story 3	24.445	7.7	Ned Beatty	actor,soundtrack	Adventure,Anim

In [742…

```
itmbomtn.shape
```

Out[742…

```
(16184, 14)
```

Data Modeling

How did you analyze or model the data? I wanted to determine the profitability ratios of different film types.

I also wanted to determine the average ratings of different movie tours.

I wanted to determine both imdb and tmdb ratings.

I wanted to identify which directors Microsoft should work with for the best profit.

What did you do to get more accurate results?

To calculate profit, I took the production budget from world Groos and determined the best genre directors with these results.

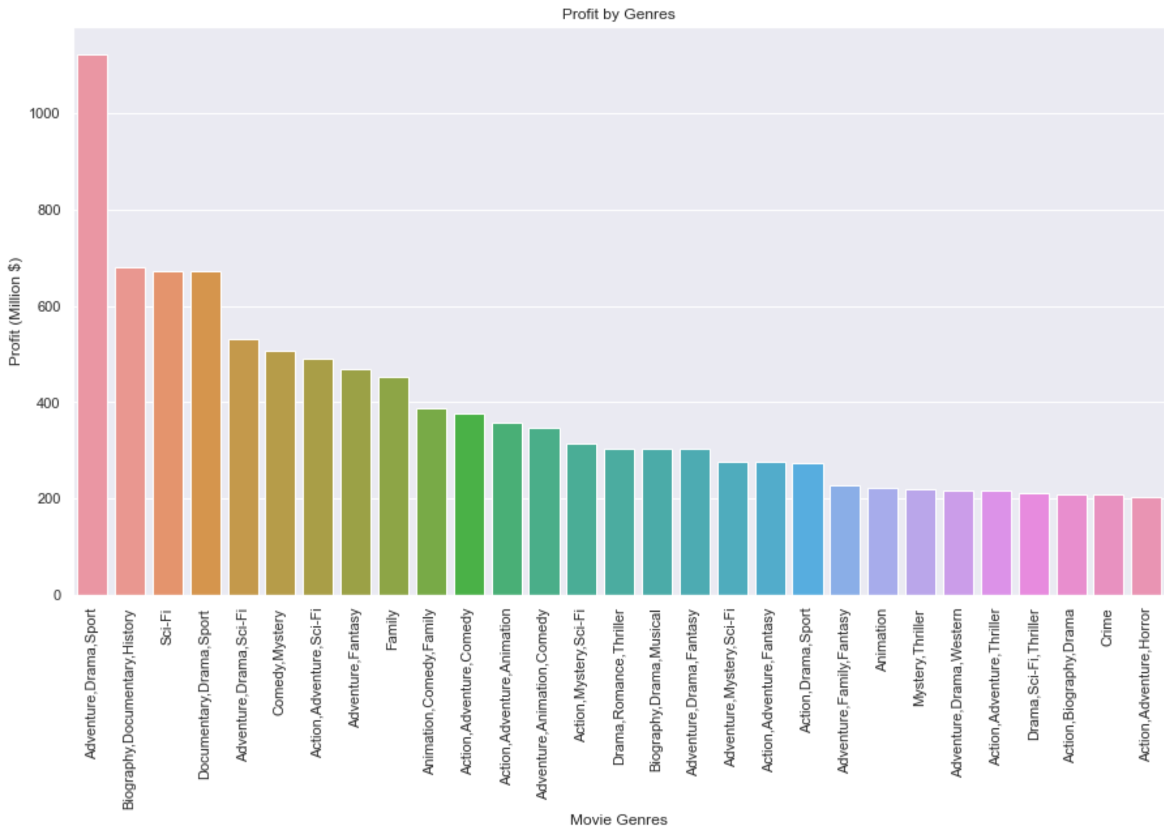
why did you use these methods?

profit and film ratings are good result data to solve our business problem.

In [747…

```
df1 = itmbomtn.groupby('genres').mean().sort_values(['profit'],ascending=F
tg = df1[df1['profit']>0.2*(10**9)]
tg1 = tg.reset_index()
tg1 ['profit'] = tg1['profit']/(10**6)
sns.set(rc = {'figure.figsize':(15,8)})
ax = sns.barplot(x='genres',y='profit',data=tg1)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
ax.set(xlabel = "Movie Genres", ylabel = "Profit (Million $)", title = 'Pr
None #don't show the label objects
```

```
plt.savefig('df1.png',bbox_inches='tight')
```



In [709…

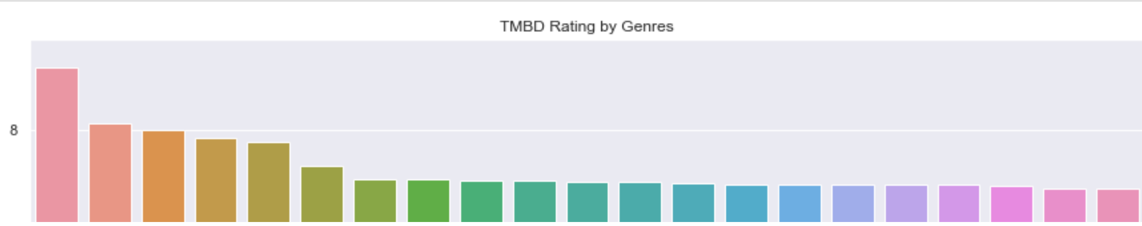
```
tg1.genres.head(10)
```

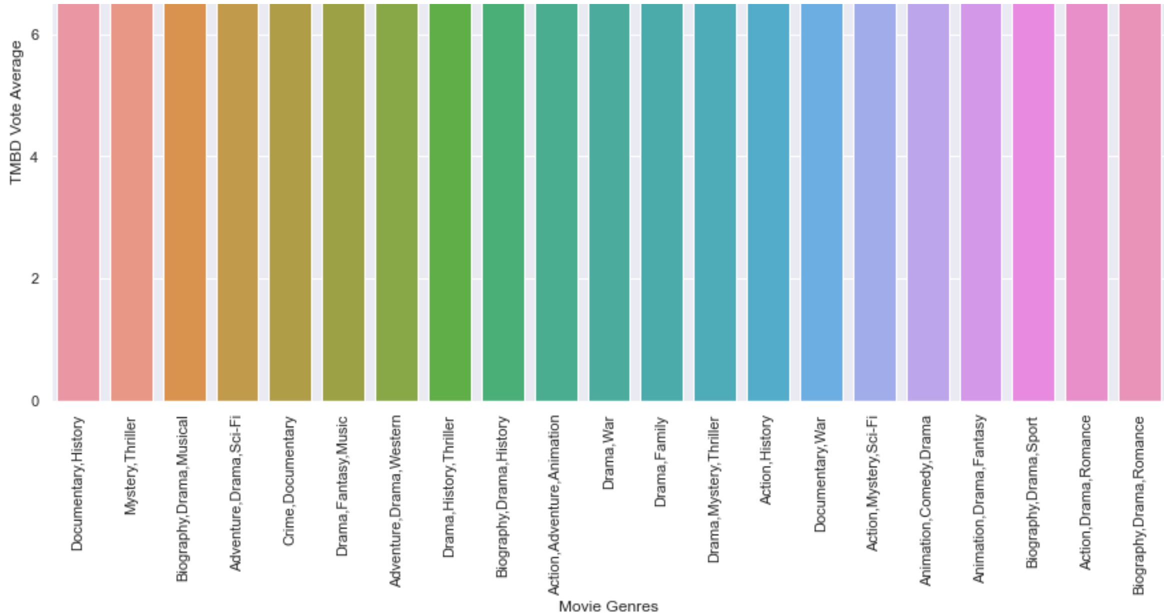
Out[709…

```
0              Adventure,Drama,Sport
1     Biography,Documentary,History
2                            Sci-Fi
3            Documentary,Drama,Sport
4             Adventure,Drama,Sci-Fi
5                     Comedy,Mystery
6            Action,Adventure,Sci-Fi
7                  Adventure,Fantasy
8                             Family
9            Animation,Comedy,Family
Name: genres, dtype: object
```

In [749…

```
df2 = itmbomtn.groupby('genres').mean().sort_values(['vote_average'],ascen
va = df2[df2['vote_average']>7]
va1 = va.reset_index()
sns.set(rc = {'figure.figsize':(15,8)})
ax = sns.barplot(x='genres',y='vote_average',data=va1)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
ax.set(xlabel = "Movie Genres", ylabel = "TMBD Vote Average", title = 'TMB
None #don't show the label objects
plt.savefig('df2.png',bbox_inches='tight')
```





In [711…

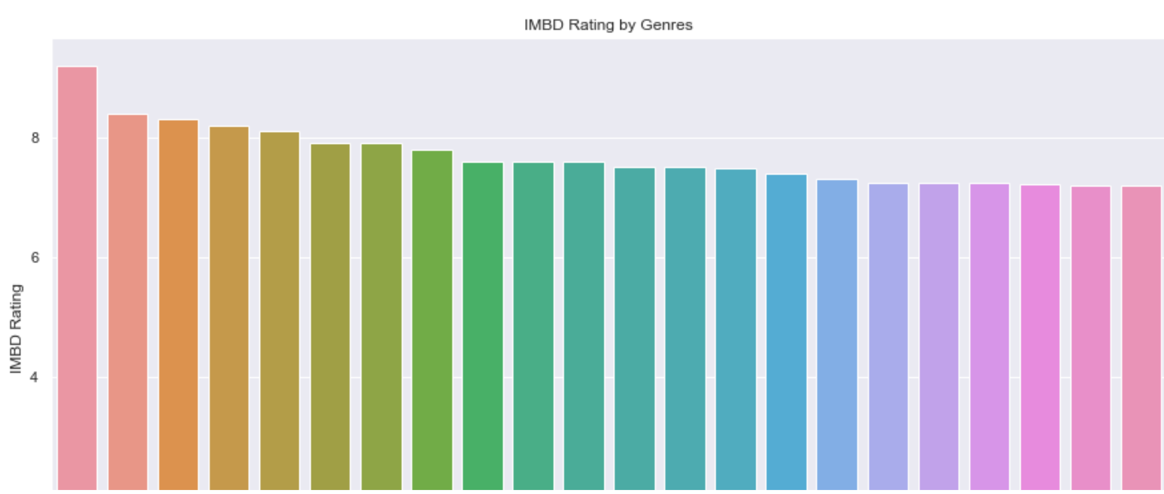
```
val.genres.head(10)
```

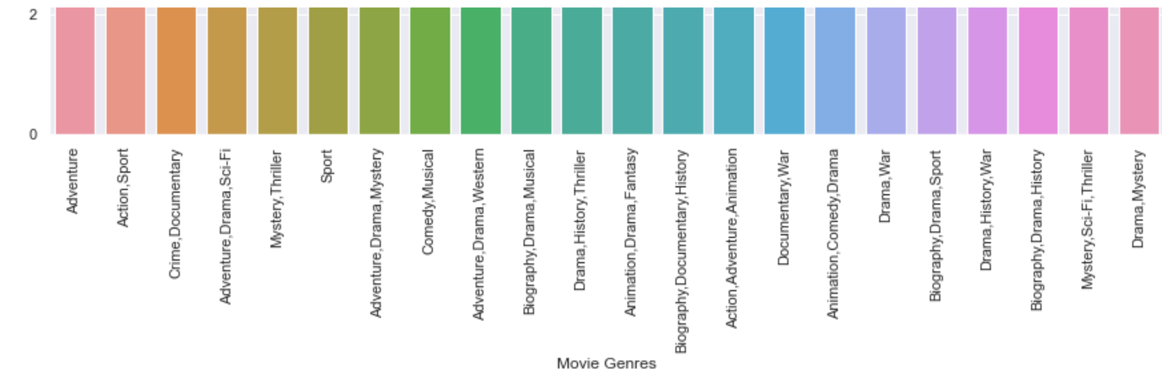
Out[711…

```
0            Documentary,History
1               Mystery,Thriller
2        Biography,Drama,Musical
3         Adventure,Drama,Sci-Fi
4              Crime,Documentary
5            Drama,Fantasy,Music
6        Adventure,Drama,Western
7         Drama,History,Thriller
8        Biography,Drama,History
9     Action,Adventure,Animation
Name: genres, dtype: object
```

In [748…

```
df3 = itmbomtn.groupby('genres').mean().sort_values(['averagerating'],asce
ar = df3[df3['averagerating']>7.2]
ar1 = ar.reset_index()
sns.set(rc = {'figure.figsize':(15,8)})
ax = sns.barplot(x='genres',y='averagerating',data=ar1)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
ax.set(xlabel = "Movie Genres", ylabel = "IMBD Rating", title = 'IMBD Rati
None #don't show the label objects
plt.savefig('df3.png',bbox_inches='tight')
```





In [713…

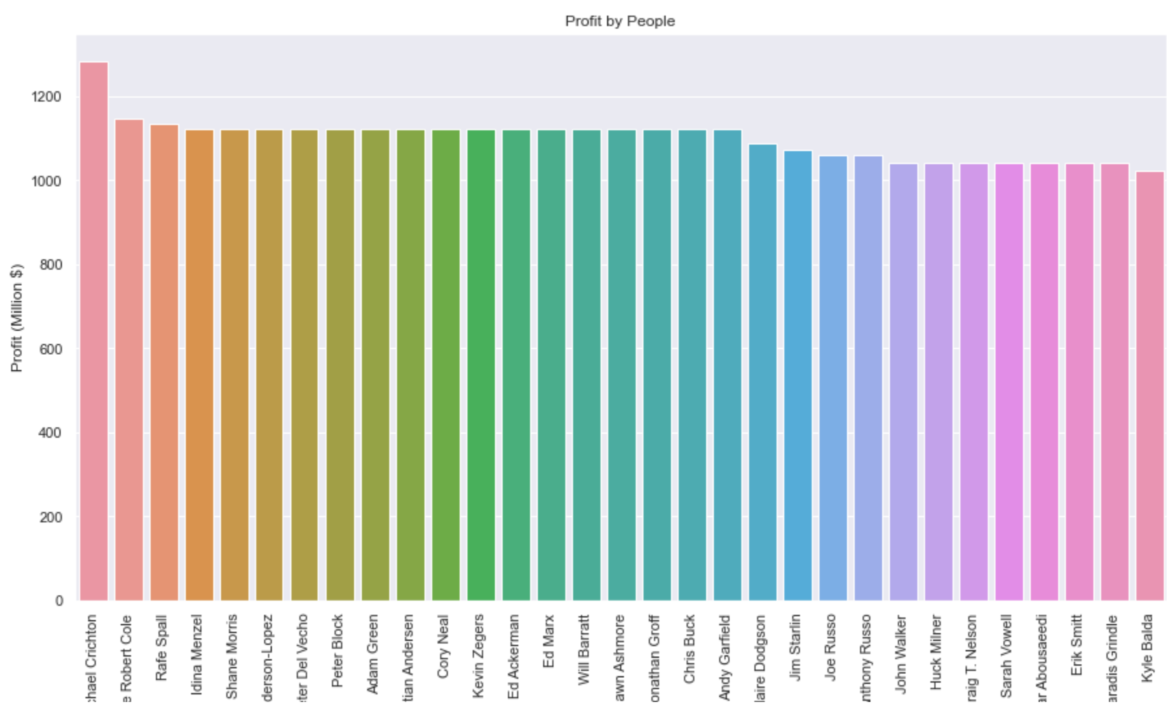
```
ar1.genres.head(10)
```

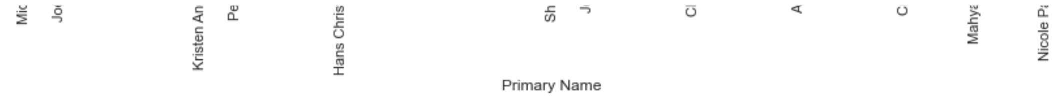
Out[713…

```
0                   Adventure
1                Action,Sport
2          Crime,Documentary
3      Adventure,Drama,Sci-Fi
4            Mystery,Thriller
5                       Sport
6     Adventure,Drama,Mystery
7              Comedy,Musical
8     Adventure,Drama,Western
9     Biography,Drama,Musical
Name: genres, dtype: object
```

In [750…

```
df4 = itmbomtn.groupby('primary_name').mean().sort_values(['profit'],ascer
tg2 = df4[df4['profit']>1*(10**9)]
tg2 = tg2.reset_index()
tg2 ['profit'] = tg2['profit']/(10**6)
sns.set(rc = {'figure.figsize':(15,8)})
ax = sns.barplot(x='primary_name',y='profit',data=tg2)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
ax.set(xlabel = "Primary Name", ylabel = "Profit (Million $)", title = 'Pr
None #don't show the label objects
plt.savefig('df4.png',bbox_inches='tight')
```





In [715…

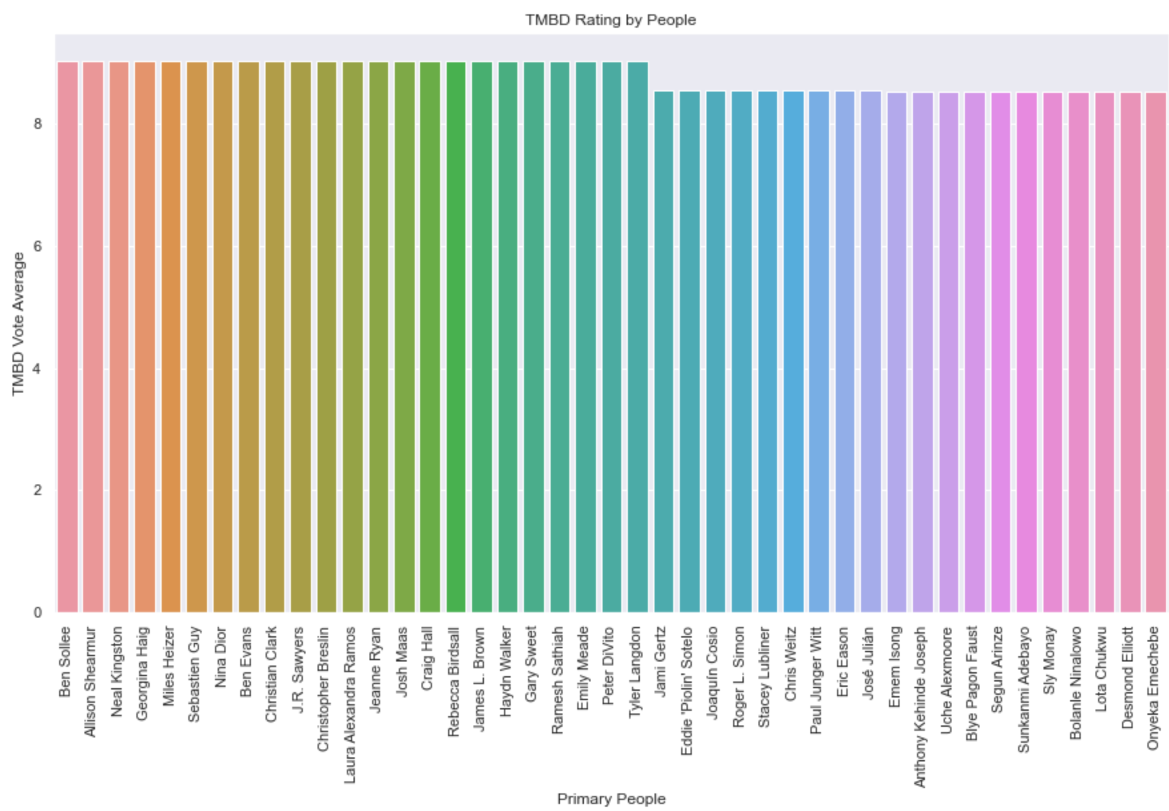
```
tg2.primary_name.head(10)
```

Out[715…

```
0            Michael Crichton
1             Joe Robert Cole
2                  Rafe Spall
3                Idina Menzel
4                Shane Morris
5      Kristen Anderson-Lopez
6             Peter Del Vecho
7                 Peter Block
8                  Adam Green
9     Hans Christian Andersen
Name: primary_name, dtype: object
```

In [755…

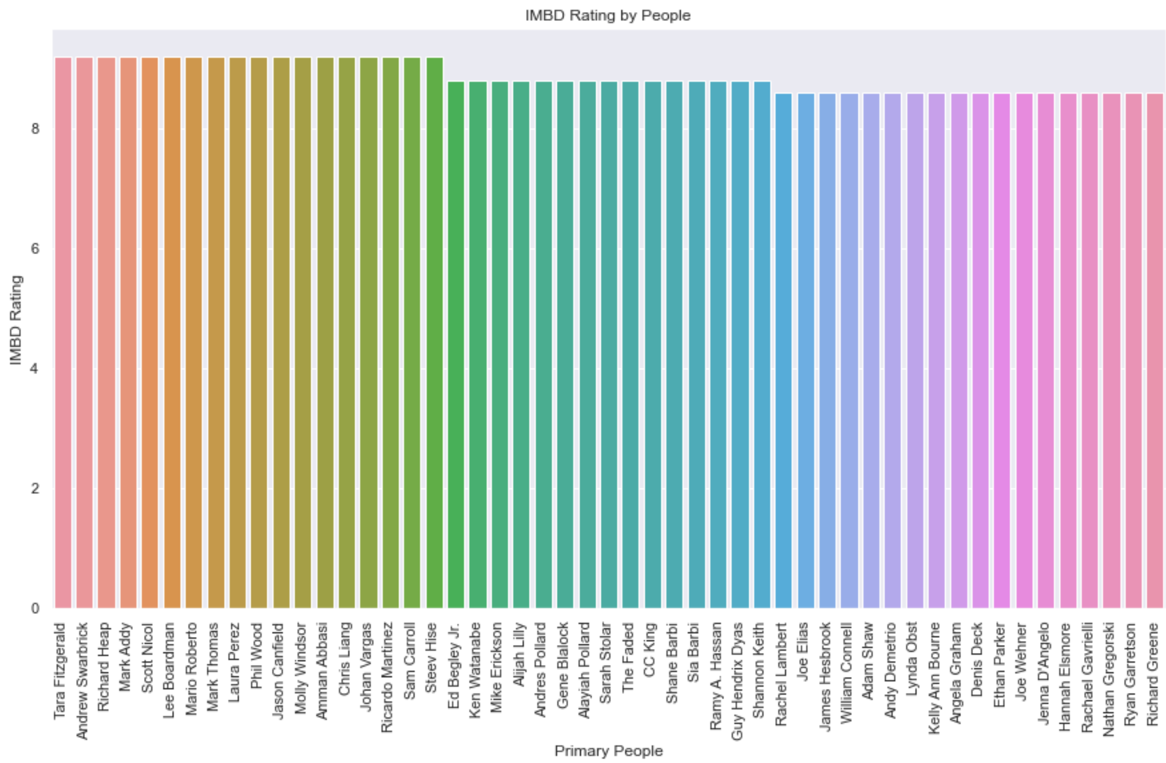
```
df5 = itmbomtn.groupby('primary_name').mean().sort_values(['vote_average']
va2 = df5[df5['vote_average']>8.5]
va2 = va2.reset_index()
sns.set(rc = {'figure.figsize':(15,8)})
ax = sns.barplot(x='primary_name',y='vote_average',data=va2)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
ax.set(xlabel = "Primary People", ylabel = "TMBD Vote Average", title = 'T
None #don't show the label objects
plt.savefig('df5.png',bbox_inches='tight')
```



In [751…

```
df6 = itmbomtn.groupby('primary_name').mean().sort_values(['averagerating'
ar2 = df6[df6['averagerating']>8.5]
ar2 = ar2.reset_index()
sns.set(rc = {'figure.figsize':(15,8)})
```

```
ax = sns.barplot(x='primary_name',y='averagerating',data=ar2)
ax.set_xticklabels(ax.get_xticklabels(),rotation = 90)
ax.set(xlabel = "Primary People", ylabel = "IMBD Rating", title = 'IMBD Ra
None #don't show the label objects
plt.savefig('df6.png',bbox_inches='tight')
```



In [721…

```
ar2.primary_name.head(10)
```

Out[721…

```
0      Tara Fitzgerald
1     Andrew Swarbrick
2         Richard Heap
3            Mark Addy
4          Scott Nicol
5         Lee Boardman
6        Mario Roberto
7          Mark Thomas
8          Laura Perez
9            Phil Wood
Name: primary_name, dtype: object
```

Evaluation

Questions to consider:

Question: How do you interpret the results?

in terms of genres and directors We have a general knowledge using profit and rating results

Question: How confident are you that your results would generalize beyond the data you have?

imdb and tmdb is a channel that gives direction to the film industry

Question: How confident are you that this model would benefit the business if put into use?

I think this analysis will be helpful in choosing genres and people to work with.

Conclusions

Questions to consider:

Question: What would you recommend the business do as a result of this work?

In terms of best imdb movie genres for the highest profit, here are the top 10 genres that I would recommend:

```
1             Adventure,Drama,Sport
2     Biography,Documentary,History
3                            Sci-Fi
4           Documentary,Drama,Sport
5            Adventure,Drama,Sci-Fi
6                    Comedy,Mystery
7           Action,Adventure,Sci-Fi
8                 Adventure,Fantasy
9                            Family
10           Animation,Comedy,Family

Writers, directors and actors in the most profitable genre
should be     worked with, the top 10 people with the highest
profit

1           Michael Crichton
2            Joe Robert Cole
3                 Rafe Spall
4               Idina Menzel
5               Shane Morris
6     Kristen Anderson-Lopez
7            Peter Del Vecho
8                Peter Block
9                 Adam Green
10    Hans Christian Andersen


IMDB and TMBD had different results on the best genres.

Top 10 genres vote average TMDB

1           Documentary,History
2              Mystery,Thriller
3       Biography,Drama,Musical
4        Adventure,Drama,Sci-Fi
5             Crime,Documentary
```

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6          Drama,Fantasy,Music
7        Adventure,Drama,Western
8      Drama,History,Thriller
9        Biography,Drama,History
10     Action,Adventure,Animation
```

Top 10 genres vote average IMDB

```
1                  Adventure
2               Action,Sport
3          Crime,Documentary
4      Adventure,Drama,Sci-Fi
5           Mystery,Thriller
6                      Sport
7     Adventure,Drama,Mystery
8             Comedy,Musical
9     Adventure,Drama,Western
10     Biography,Drama,Musical
```

IMDB and TMBD had different results on the best people to work with.

```
Top 10 people by average votes on TMDB:
1         Ben Sollee
2     Allison Shearmur
3        Neal Kingston
4        Georgina Haig
5         Miles Heizer
6        Sebastien Guy
7            Nina Dior
8            Ben Evans
9      Christian Clark
10          J.R. Sawyers
```

```
Top 10 people by averagevotes on IMDB:
1      Tara Fitzgerald
2     Andrew Swarbrick
3         Richard Heap
4            Mark Addy
5          Scott Nicol
6         Lee Boardman
7        Mario Roberto
8          Mark Thomas
9          Laura Perez
10             Phil Wood
```

Question: What are some reasons why your analysis does not fully address the business problem?

More data can be collected, they should address global economic problems over the years, natural disasters, infectious diseases, the interest of countries in cinema should also be investigated.

Question: What else could you do in the future to improve this project?

The correlation between the minimum wage and the movie ticket prices of each country should be checked, at the same time, it should be determined that the advertising budgets and how many theaters were released.

In [ ]:

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In [ ]:

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