MS_MOVIES_ANALSYS

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Overview

THE file contains the crystal view of data from the resouurce IMBD in terms of business, statics, data, methods and recomendations

Business Problem

Microsoft, the tech company is now jumping into the entertainment industry. thus, before making a high budget feature film, it is a good practice to analyse data from past and then make right decision.

**the company wants to make a movie as a symbol of creating MICROSOFT STUDIOS, thys, the type of fims is really important to stand in the crowd.* *the data used in this project is completely from IMDB, the datasets are the records of popular movies with respect to following aspects: region, director, writer, ratings, votes, language etc. though,, some records are not useful. *this project analuse the data and create graphs to show information such as: most rated movies, most popular writer, director, highest number of movies by year and so on.* *this information will help the stakeholders to make a right decision about choosing genre of the movie, director for movie, region to release in.

Data Understanding

Questions to consider:

- Where did the data come from, and how do they relate to the data analysis questions?
- Data in this project belongs to IMDB. Dataframes contains information such as release year, writer, director, revenue of the movies.
- What is the target variable?
- Target variables are "popular writer", "popular director", "average ratings". "votes" etc.
- What are the properties of the variables you intend to use?
- The variables are complete strings and integers. It is a good practice to format data with respect to each other in order to make and understand a trend.

In [1]:

```
# Import standard packages
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns

%matplotlib inline
```

In [2]:

```
import gzip
import csv
```

In [3]:

```
# import files which contains data about rating, titles etc.
df_r=pd.read_csv('imdb.title.ratings.csv.gz')
df_c=pd.read_csv('imdb.title.crew.csv.gz')
df_a=pd.read_csv('imdb.title.akas.csv.gz')
df_b=pd.read_csv('imdb.name.basics.csv.gz')
```

In [4]:

```
#checking info and a overview of the datasets
df_r.head(2)
```

Out[4]:

	tconst	averagerating	numvotes
0	tt10356526	8.3	31
1	tt10384606	8.9	559

In [5]:

```
df_c.head(2)
```

Out[5]:

	tconst	directors	writers
0	tt0285252	nm0899854	nm0899854
1	tt0438973	NaN	nm0175726,nm1802864

In [6]:

```
df_a.head(2)
```

Out[6]:

	title_id	ordering	title	region	language	types	attributes	is_original_title
0	tt0369610	10	Джурасик свят	BG	bg	NaN	NaN	0.0
1	tt0369610	11	Jurashikku warudo	JP	NaN	imdbDisplay	NaN	0.0

In [7]:

```
# changing columns name from title id to tconst
new_df=df_a.rename(columns={'title_id':'tconst'})
```

In [8]:

```
#all three data sets have one common attribute whihc is title.
```

In [9]:

```
#merging all datasets in to one dataset
dfm1=df_r.merge(df_c)
dfm=dfm1.merge(new_df)
```

In [10]:

```
dfm
```

Out[10]:

	tconst	averagerating	numvotes	directors	
0	tt1042974	6.4	20	nm1915232	nm1
1	tt1042974	6.4	20	nm1915232	nm1
2	tt1042974	6.4	20	nm1915232	nm1
3	tt1043726	4.2	50352	nm0001317	nm0393517,nm0316417,nm0001317,nm1
4	tt1043726	4.2	50352	nm0001317	nm0393517,nm0316417,nm0001317,nm1
...	...	...	...	...	
261801	tt9691896	6.3	21	nm0663605	
261802	tt9844256	7.5	24	nm0849465	nm0849465,nm1
261803	tt9844256	7.5	24	nm0849465	nm0849465,nm1
261804	tt9844256	7.5	24	nm0849465	nm0849465,nm1
261805	tt9844256	7.5	24	nm0849465	nm0849465,nm1

261806 rows × 12 columns

In [11]:

```
#checking for duplicate entries
dfm.duplicated().value_counts()
```

Out[11]:

```
False    261806
dtype: int64
```

In [12]:

```
# filetring movies having average rating more than 7
df_average=dfm.loc[(dfm['averagerating']>7)]
df_average
```

Out[12]:

	tconst	averagerating	numvotes	directors	writers	ordering	
55	tt1156528	7.2	265	nm0121203	nm0121203	1	S
56	tt1156528	7.2	265	nm0121203	nm0121203	2	Fanta
57	tt1156528	7.2	265	nm0121203	nm0121203	3	S sile
58	tt1156528	7.2	265	nm0121203	nm0121203	4	Fanta
59	tt1156528	7.2	265	nm0121203	nm0121203	5	I sor
...	...	...	...	...	...	...	
261777	tt9526152	7.6	29	nm1425958	nm8916539	6	Gekij da mot
261802	tt9844256	7.5	24	nm0849465	nm0849465,nm1287521	1	(Lelc Re Epis
261803	tt9844256	7.5	24	nm0849465	nm0849465,nm1287521	2	(Lelc Re Epis
261804	tt9844256	7.5	24	nm0849465	nm0849465,nm1287521	3	(Lelc Reb (
261805	tt9844256	7.5	24	nm0849465	nm0849465,nm1287521	4	(Lelc Reb Er

72211 rows × 12 columns

In [13]:

```
# now, we will take the title id of directors and writers having most number of movies
# most frequent value in Team
df_average['writers'].value_counts().idxmax()
```

Out[13]:

```
'nm0604555,nm0860155'
```

In [14]:

```
# most frequent value in Team
df_average['directors'].value_counts().idxmax()
```

Out[14]:

```
'nm0000229'
```

In [15]:

```
#dropping column which are not important
final=df_average.drop(['is_original_title'],axis=1)
```

In [16]:

```
final
```

Out[16]:

	tconst	averagerating	numvotes	directors	writers	ordering	
55	tt1156528	7.2	265	nm0121203	nm0121203	1	S
56	tt1156528	7.2	265	nm0121203	nm0121203	2	Fanta
57	tt1156528	7.2	265	nm0121203	nm0121203	3	S sile
58	tt1156528	7.2	265	nm0121203	nm0121203	4	Fanta
59	tt1156528	7.2	265	nm0121203	nm0121203	5	I sor
...	...	...	...	...	...	...	
261777	tt9526152	7.6	29	nm1425958	nm8916539	6	Gekij da mot
261802	tt9844256	7.5	24	nm0849465	nm0849465,nm1287521	1	(Lelc Re Epis
261803	tt9844256	7.5	24	nm0849465	nm0849465,nm1287521	2	(Lelc Re Epis
261804	tt9844256	7.5	24	nm0849465	nm0849465,nm1287521	3	(Lelc Reb (
261805	tt9844256	7.5	24	nm0849465	nm0849465,nm1287521	4	(Lelc Reb Er

72211 rows × 11 columns

In [17]:

```
# #now, we will filter the movies which has these writers or directors as crew
crew=final[(final["directors"] == 'nm0000229') | (final["writers"] == "nm0604555,nm0860
crew.head(2)
```

Out[17]:

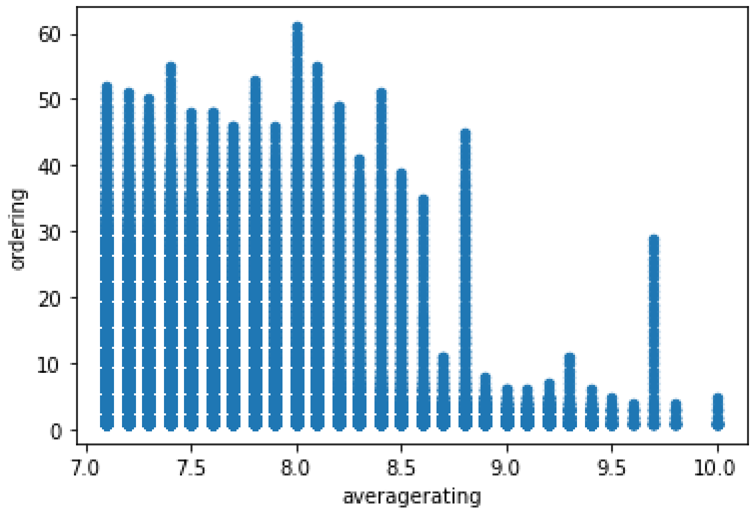
	tconst	averagerating	numvotes	directors	writers	ordering	title
4384	tt0443272	7.4	228701	nm0000229	nm1065785,nm0329447	10	Lincoln
4385	tt0443272	7.4	228701	nm0000229	nm1065785,nm0329447	11	Lincoln

In [18]:

```
final.plot(x ='averagerating', y='ordering', kind = 'scatter')
```

Out[18]:

```
<AxesSubplot:xlabel='averagerating', ylabel='ordering'>
```



In [19]:

```
# here we can see that the most orderd movies are the ones whihc are rated arround 8 and
# this gives insights that extreme rated movies are not much popular.
```

In [20]:

```
# so, no we will check the title of the movies having rating arround 8 and 8.5
final.loc[final['directors'] =='nm0000229', ['title']]
```

Out[20]:

	title
4384	Lincoln
4385	Lincoln
4386	Lincoln
4387	Lincoln
4388	Лінкольн
...	...
253805	War Horse
253806	Caballo de guerra
253807	Caballo de batalla
253808	Gefährten
253809	Бойовий кінь

222 rows × 1 columns

In [21]:

```
## from above data and internet, it is concluded that Steven Spielberg is a good choice
```

In [22]:

```
# now, we will check this data set from kaggle
```

In [23]:

```
df_k=pd.read_csv('archive.zip')
```

In [24]:

```
# to check the view to dataset
df_k.head(2)
```

Out[24]:

	Rank	Title	Genre	Description	Director	Actors	Year	Runtime (Minutes)	Rat
0	1	Guardians of the Galaxy	Action,Adventure,Sci-Fi	A group of intergalactic criminals are forced ...	James Gunn	Chris Pratt, Vin Diesel, Bradley Cooper, Zoe S...	2014	121	
1	2	Prometheus	Adventure,Mystery,Sci-Fi	Following clues to the origin of mankind, a te...	Ridley Scott	Noomi Rapace, Logan Marshall-Green, Michael Fa...	2012	124	

In [25]:

```
df_k.describe()
```

Out[25]:

	Rank	Year	Runtime (Minutes)	Rating	Votes	Revenue (Millions)	Metas
count	1000.000000	1000.000000	1000.000000	1000.000000	1.000000e+03	872.000000	936.00(
mean	500.500000	2012.783000	113.172000	6.723200	1.698083e+05	82.956376	58.985
std	288.819436	3.205962	18.810908	0.945429	1.887626e+05	103.253540	17.19
min	1.000000	2006.000000	66.000000	1.900000	6.100000e+01	0.000000	11.00(
25%	250.750000	2010.000000	100.000000	6.200000	3.630900e+04	13.270000	47.00(
50%	500.500000	2014.000000	111.000000	6.800000	1.107990e+05	47.985000	59.50(
75%	750.250000	2016.000000	123.000000	7.400000	2.399098e+05	113.715000	72.00(
max	1000.000000	2016.000000	191.000000	9.000000	1.791916e+06	936.630000	100.00(

In [26]:

```
#check the columns and create a varribale to for movies over 180mis of runtime
df_k.columns
```

Out[26]:

```
Index(['Rank', 'Title', 'Genre', 'Description', 'Director', 'Actors', 'Yea
r',
       'Runtime (Minutes)', 'Rating', 'Votes', 'Revenue (Millions)',
       'Metascore'],
      dtype='object')
```

In [27]:

```
df_k[df_k['Runtime (Minutes)']>=180]['Title']
```

Out[27]:

```
82      The Wolf of Wall Street
88            The Hateful Eight
311              La vie d'Adèle
828                  Grindhouse
965               Inland Empire
Name: Title, dtype: object
```

In [28]:

```
#checking votes for movies with respect to year
df_k.groupby('Year')['Votes'].mean().sort_values(ascending=False)
```

Out[28]:

```
Year
2012    285226.093750
2008    275505.384615
2006    269289.954545
2009    255780.647059
2010    252782.316667
2007    244331.037736
2011    240790.301587
2013    219049.648352
2014    203930.224490
2015    115726.220472
2016     48591.754209
Name: Votes, dtype: float64
```

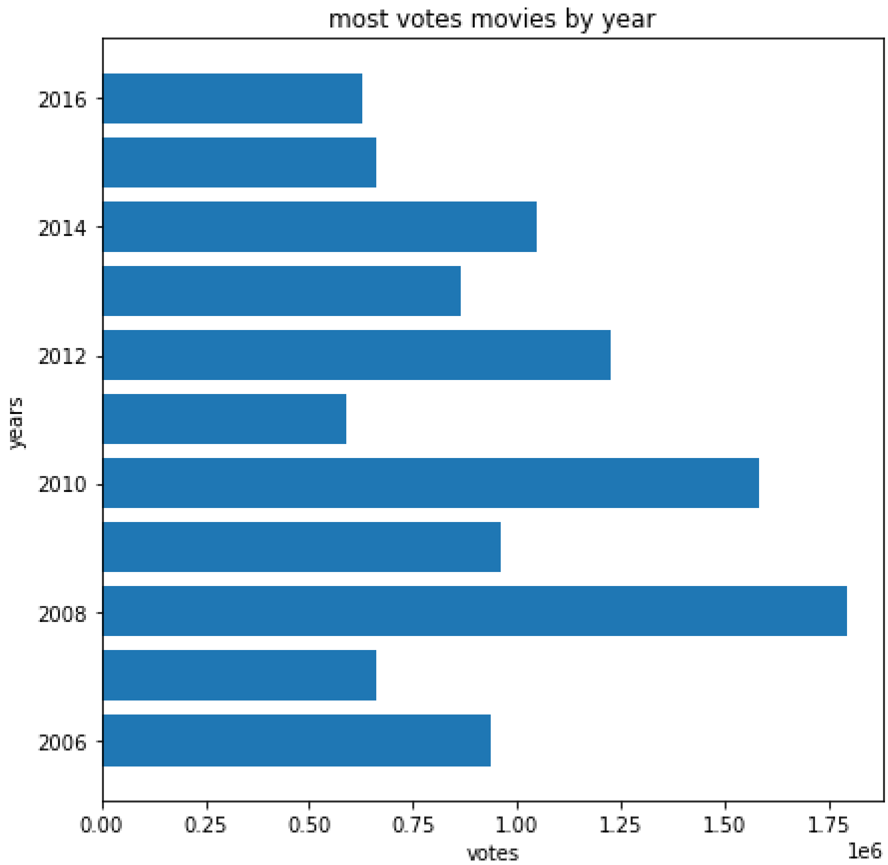
In [29]:

```
a=df_k['Year']
b=df_k['Votes']

# creating the bar plot
fig, ax = plt.subplots(figsize =(7, 7))
ax.barh(a,b)
ax.set_title('most votes movies by year')
ax.set_xlabel('votes')
ax.set_ylabel('years')
```

Out[29]:

```
Text(0, 0.5, 'years')
```



In [30]:

```
#finding movies which are top rated and checking the name of directors
h_r=df_k.nlargest(10,'Rating')[['Title','Rating','Director','Metascore','Runtime (Minute
.set_index('Title')
h_r
```

Out[30]:

Title	Rating	Director	Metascore	Runtime (Minutes)
The Dark Knight	9.0	Christopher Nolan	82.0	152
Inception	8.8	Christopher Nolan	74.0	148
Dangal	8.8	Nitesh Tiwari	NaN	161
Interstellar	8.6	Christopher Nolan	74.0	169
Kimi no na wa	8.6	Makoto Shinkai	79.0	106
The Intouchables	8.6	Olivier Nakache	57.0	112
The Prestige	8.5	Christopher Nolan	66.0	130
The Departed	8.5	Martin Scorsese	85.0	151
The Dark Knight Rises	8.5	Christopher Nolan	78.0	164
Whiplash	8.5	Damien Chazelle	88.0	107

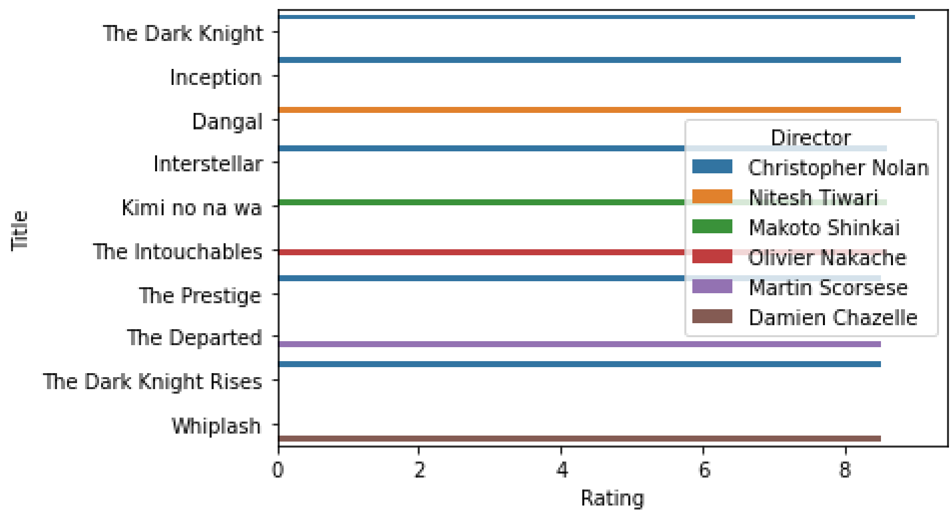
In [31]:

```
#visualize the result for better understanding
#importing seaborn library for better graphs
import seaborn as sns

# creating the bar plot
sns.barplot(x='Rating',y=h_r.index,data=h_r,hue='Director')
#the documentation for seaborn library is at https://seaborn.pydata.org/
```

Out[31]:

```
<AxesSubplot:xlabel='Rating', ylabel='Title'>
```



In [32]:

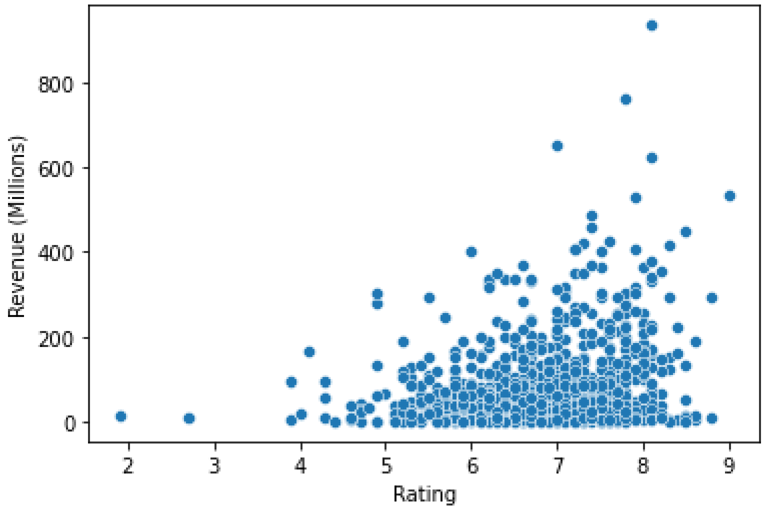
```
#we can see that the movies by christopher nolan are frequently top rated
```

In [33]:

```
#now, we will check the relation between ratings and revenue. as revenue is considered i
sns.scatterplot(x='Rating',y='Revenue (Millions)',data=df_k)
```

Out[33]:

```
<AxesSubplot:xlabel='Rating', ylabel='Revenue (Millions)'>
```



In [34]:

```
# it is concluded that rating affects revenue.
```

In [35]:

```
# let's predict the genre of the movie
g=df_k['Genre'].value_counts().idxmax()
g
```

Out[35]:

```
'Action,Adventure,Sci-Fi'
```

In [36]:

```
#it is clear that genre of the movie shoud be action revolving arround a storyline basec
```

In [37]:

```
df_k[df_k.Genre.str.contains('Action,Adventure,Sci-Fi')].shape
```

Out[37]:

```
(50, 12)
```

In [38]:

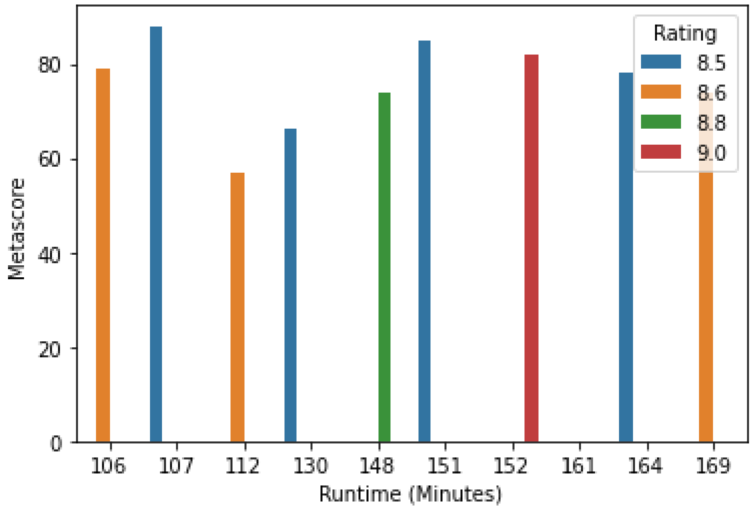
```
#50 movies are made under the category of action, scie-fi, adventure.
```

In [39]:

```
sns.barplot(x='Runtime (Minutes)',y='Metascore',data=h_r,hue='Rating')
```

Out[39]:

```
<AxesSubplot:xlabel='Runtime (Minutes)', ylabel='Metascore'>
```



In [40]:

```
#metascore is effectively high if the movie runtime is about 110 minutes, also rating
```

Data Preparation

Questions to consider:

- Were there variables you dropped or created?
- yes, dropped column named'originot title'
- How did you address missing values or outliers?
- analyzed the data, there were no outliers and missing data
- Why are these choices appropriate given the data and the business problem?
- Thses choices provides the data in seriess of mast occurence and camparisons to predict the attributes for the movie.

Data Modeling

Questions to consider:

- How did you analyze or model the data?
- we previewed the datasets and cheked the values of mean, median mode, columns,shapes etc. then we sorted and merged the datasets to create a model and performed functions on that.
- we also used one more data set from kaggle to do some extra work.

- Why are these choices appropriate given the data and the business problem?
- as all the data sets are about movies, so, there were some attributes common in each set, like title, votes etc. merging the datasets allowed to seea bigger picture, which then helped to predict the trend.

Evaluation

Evaluate how well your work solves the stated business problem.

Questions to consider:

- How do you interpret the results?
- results shos the comparisons, frequent occurence of strings in top rated movies with high revenue. this will help to understand the algorithm of a successfull movie.
- How well does your model fit your data? How much better is this than your baseline model?
- the model have all the colmns set and clean. there is no coumn whihc is not useful and the dataset contains the values of all initial sets.
- How confident are you that your results would generalize beyond the data you have?
- I can take the risk to produce this movie, and still sleep well.
- How confident are you that this model would benefit the business if put into use?
- Microsoft will be bigger than MARVEL STUDIOS.

Conclusions

Questions to consider:

- What would you recommend the business do as a result of this work?
- Microsoft should make a movie which revolves arround technology and science fiction, with the storyline of adventure and action mixed.
- What are some reasons why your analysis might not fully solve the business problem?
- entertainment industry is been always a chanllenge. audience is unpredictable. Eventhough, the pridictions are done in perfact way, there is still 0.00001 percent chance to face failure.
- What else could you do in the future to improve this project?
- as these datasets have information much old, I woould use a realtime dataset.
