Project: Investigate a Dataset (TMDb*Movies Dataset*)

Table of Contents

Introduction

> **My logical Intuition behind this dataset, analyze, Investigating the observation, visualizing the graph plot on the TMDb_movie dataset.** About the TMDb_movie dataset it contains more than 10,000 movies records with the features rating, revenue, cast, popularity like that.
>
> In this report, I explore the following questions:

Q1.Which movies has highest and lowest popularity based on popularity feature_?

Q2.The genres popularity from the top to bottom based on the entire record?

Q3.Did movies with higher vote count received a better rating in the dataset?

Q4.Now find the Top 5 Directors with most number of movies with made the most profit?

Q5.So now taking average profit per year and total profilt over the years?

Q6.creating one more column for rating scale and checking about the rating scale?

Importing some essential dependencies/libraries

In [0]:
```
import pandas as pd
import numpy as np
from pandas import Series
import matplotlib.pyplot as plt
import seaborn as sns
```

Data Wrangling

> Now i will load the data, check for cleanliness, and then trim and clean dataset for analysis.

General Properties

In [28]:
```
df_tmdb = pd.read_csv('/content/tmdb-movies.csv')
df_tmdb.tail()
```

Out[28]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	h
10861	21	tt0060371	0.080598	0	0	The Endless Summer	Michael Hynson|Robert August|Lord 'Tally Ho' B...	N

	id	imdb_id	popularity	budget	revenue	original_title	cast	h
10862	20379	tt0060472	0.065543	0	0	Grand Prix	James Garner|Eva Marie Saint|Yves Montand|Tosh...	N
10863	39768	tt0060161	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...	N
10864	21449	tt0061177	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...	N
10865	22293	tt0060666	0.035919	19000	0	Manos: The Hands of Fate	Harold P. Warren|Tom Neyman|John Reynolds|Dian...	N

In [29]:
```
df_tmdb.shape
```

Out[29]: (10866, 21)

In [30]:
```
df_tmdb.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype
---  ------                --------------  -----
 0   id                    10866 non-null  int64
 1   imdb_id               10856 non-null  object
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64
 4   revenue               10866 non-null  int64
 5   original_title        10866 non-null  object
 6   cast                  10790 non-null  object
 7   homepage              2936 non-null   object
 8   director              10822 non-null  object
 9   tagline               8042 non-null   object
 10  keywords              9373 non-null   object
 11  overview              10862 non-null  object
 12  runtime               10866 non-null  int64
 13  genres                10843 non-null  object
 14  production_companies  9836 non-null   object
 15  release_date          10866 non-null  object
 16  vote_count            10866 non-null  int64
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

In [31]:

```
#Now we finding the missing value present in the dataset
#as we can see the missing values for each columns
df_tmdb.isnull().sum()
```

Out[31]:

```
id                         0
imdb_id                   10
popularity                 0
budget                     0
revenue                    0
original_title             0
```

```
cast                      76
homepage                7930
director                  44
tagline                 2824
keywords                1493
overview                   4
runtime                    0
genres                    23
production_companies    1030
release_date               0
vote_count                 0
vote_average               0
release_year               0
budget_adj                 0
revenue_adj                0
dtype: int64
```

In [32]:
```
sum(df_tmdb.duplicated())
```

Out[32]:
```
1
```

> Only one dublicate we have :)

In [33]:
```
df_tmdb[df_tmdb.duplicated(keep = False)]
```

Out[33]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homep

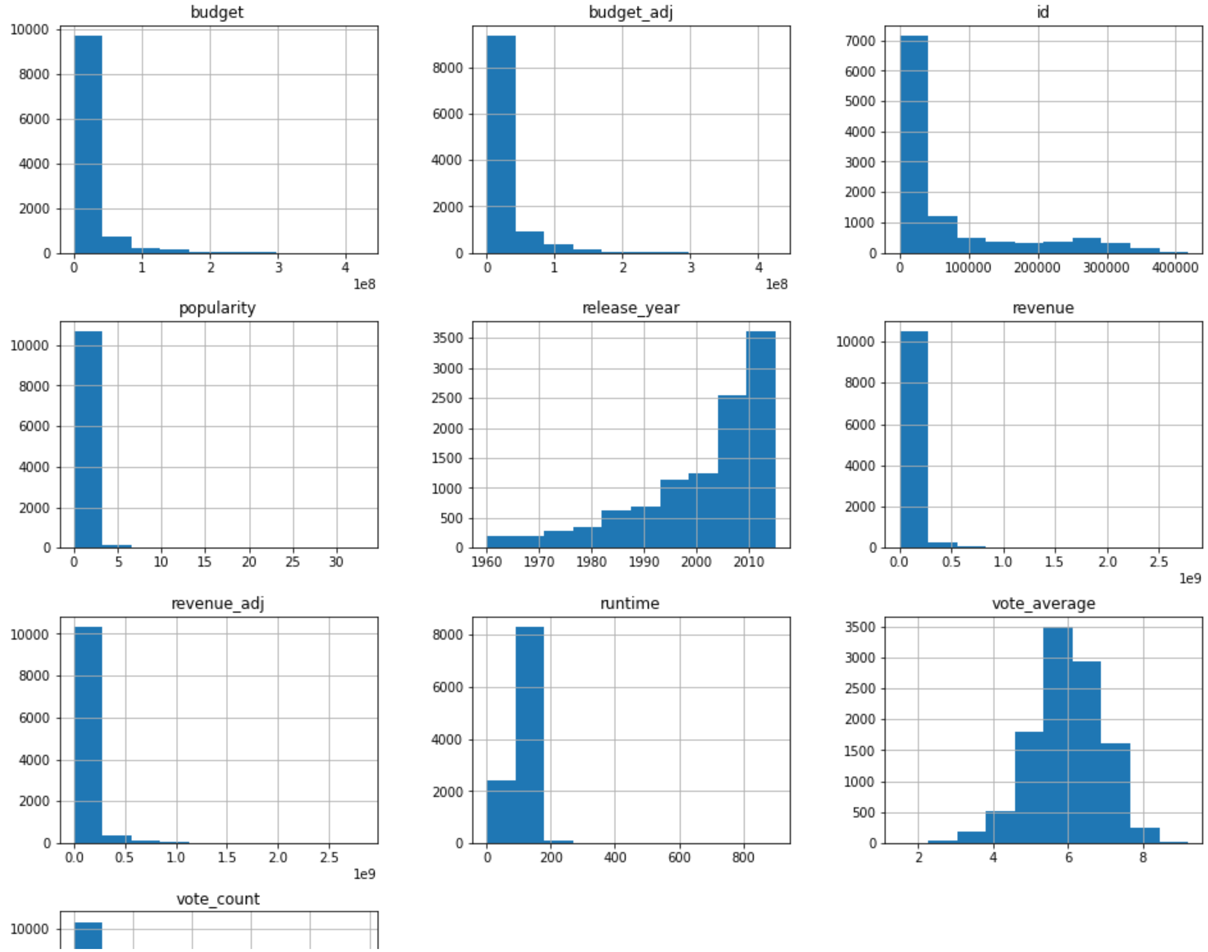
	id	imdb_id	popularity	budget	revenue	original_title	cast	homep
2089	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	NaN
2090	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	NaN

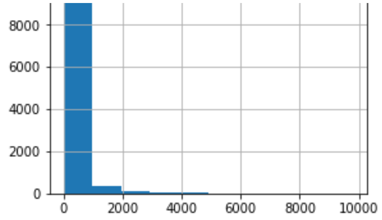
> This is duplicated record available in the TMBD dataset_

In [34]:
```
df_tmdb.hist(figsize = (16, 16))
```

Out[34]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f779bd9b2b0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f779bdc74e0
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f779bd76748
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f779bd279b0
>,
```

```
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f779bcd7c18
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f779bd0ae80
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f779bcc5128
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f779bc77358
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f779bc773c8
>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f779bbdb860
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f779bc0dac8
>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f77cbf369e8
>]],
      dtype=object)
```


budget
10000 8000 6000 4000 2000 0
0 1 2 3 4
1e8
budget_adj
8000 6000 4000 2000 0
0 1 2 3 4
1e8
id
7000 6000 5000 4000 3000 2000 1000 0
0 100000 200000 300000 400000
popularity
10000 8000 6000 4000 2000 0
0 5 10 15 20 25 30
release_year
3500 3000 2500 2000 1500 1000 500 0
1960 1970 1980 1990 2000 2010
revenue
10000 8000 6000 4000 2000 0
0.0 0.5 1.0 1.5 2.0 2.5
1e9
revenue_adj
10000 8000 6000 4000 2000 0
0.0 0.5 1.0 1.5 2.0 2.5
1e9
runtime
8000 6000 4000 2000 0
0 200 400 600 800
vote_average
3500 3000 2500 2000 1500 1000 500 0
2 4 6 8
vote_count
10000



Obeservations :\ 1.Above graph show there are some graph are positive skewed and some are negatively skewed.\ 2.also some columns are not important to analysis so we removing them while cleaning the data. 3.Data is not complicated means it realtively clean.

Data Cleaning

> 1. we will clean the our tmdb dataset. fist step is drop all duplicate record, then we will deleting the unnessesary columns like budget, cast, homepage, director, tagline, keywords, overview, production_companies.
> 2. Also dropping the zero value or filling the NAN value.

In [35]:
```
#deleting the duplicates
df_tmdb.drop_duplicates(keep = False, inplace = True)
print('Duplicated values :',sum(df_tmdb.duplicated()))
print('Checking the shape :', df_tmdb.shape)
```

```
Duplicated values : 0
Checking the shape : (10864, 21)
```

In [36]:
```
#also changing the type of the 'release date to datatime
df_tmdb['release_date'] = pd.to_datetime(df_tmdb['release_date'])
df_tmdb['release_date'].head()
```

Out[36]:
```
0   2015-06-09
1   2015-05-13
```

```
2   2015-03-18
3   2015-12-15
4   2015-04-01
Name: release_date, dtype: datetime64[ns]
```

In [37]:

```
#now we going to droop the unnessary columns
df_tmdb.drop(['id','imdb_id','homepage','tagline','keywords','overview'
,'budget','revenue','runtime', 'production_companies'],axis=1,inplace=T
rue)
df_tmdb.head(3)
```

Out[37]:

	popularity	original_title	cast	director	genres	release_d
0	32.985763	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	Action|Adventure|Science Fiction|Thriller	2015-06-0
1	28.419936	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	Action|Adventure|Science Fiction|Thriller	2015-05-1
2	13.112507	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	Adventure|Science Fiction|Thriller	2015-03-1

In [0]:

```
#replacing all the zeros with the NAN value
df_tmdb = df_tmdb.replace(to_replace=0, value=np.nan)
```

In [0]:

```
#dropping all the rows with null values
df_tmdb.dropna(how='any', axis=0, inplace=True)
```

In [40]:
```
#checking for null value
df_tmdb.isnull().sum().any()
```
Out[40]: False

In [41]:
```
#right now we don't have any  missing value
df_tmdb.describe()
```
Out[41]:

	popularity	vote_count	vote_average	release_year	budget_adj	revenue_ac
count	3848.000000	3848.000000	3848.000000	3848.000000	3.848000e+03	3.848000e+0
mean	1.193088	528.495842	6.168997	2001.255977	4.429732e+07	1.372667e+0
std	1.475783	880.422193	0.794577	11.286229	4.481883e+07	2.162187e+0
min	0.001117	10.000000	2.200000	1960.000000	9.693980e-01	2.370705e+0
25%	0.463291	71.000000	5.700000	1995.000000	1.315864e+07	1.843827e+0
50%	0.799015	205.000000	6.200000	2004.000000	3.007926e+07	6.182197e+0
75%	1.374400	581.250000	6.700000	2010.000000	6.076720e+07	1.635528e+0
max	32.985763	9767.000000	8.400000	2015.000000	4.250000e+08	2.827124e+0

In [42]:
```
df_tmdb.head(3)
```
Out[42]:

	popularity	original_title	cast	director	genres	release_d
0	32.985763	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	Action|Adventure|Science Fiction|Thriller	2015-06-0

	popularity	original_title	cast	director	genres	release_d
1	28.419936	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	Action|Adventure|Science Fiction|Thriller	2015-05-1
2	13.112507	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	Adventure|Science Fiction|Thriller	2015-03-1

In [43]:

```
#adding new columns in DF which is profit cal the revenue and budget
df_tmdb['profit'] = df_tmdb['revenue_adj'] - df_tmdb['budget_adj']
df_tmdb.head(1)
```

Out[43]:

	popularity	original_title	cast	director	genres	release_date
0	32.985763	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	Action|Adventure|Science Fiction|Thriller	2015-06-09

In [0]:

```
df_tmdb.to_csv('clean_tmdb_df.csv', index = False)
```

Exploratory Data Analysis

Research Question 1 (Which movies has highest and lowest popularity based on popularity feature_)

In [45]:
```
final_df = pd.read_csv('/content/clean_tmdb_df.csv')
final_df.head()
```

Out[45]:

	popularity	original_title	cast	director	genres	release_
0	32.985763	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	Action|Adventure|Science Fiction|Thriller	2015-06-
1	28.419936	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	Action|Adventure|Science Fiction|Thriller	2015-05-
2	13.112507	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	Adventure|Science Fiction|Thriller	2015-03-
3	11.173104	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	Action|Adventure|Science Fiction|Fantasy	2015-12-
4	9.335014	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	Action|Crime|Thriller	2015-04-

In [46]:
```
lowest_value = final_df['popularity'].idxmin()
highest_value = final_df['popularity'].idxmax()
print('highest value in popularity',final_df['original_title'][highest_
```

```
value])
print('lowest value in popularity',final_df['original_title'][lowest_va
lue])
```

```
highest value in popularity Jurassic World
lowest value in popularity Born into Brothels
```

In [47]:

```
high = pd.DataFrame(final_df.loc[highest_value,:])
low = pd.DataFrame(final_df.loc[lowest_value,:])
pd.concat([high,low],axis = 1)
```

Out[47]:

	0	2552
popularity	32.9858	0.001117
original_title	Jurassic World	Born into Brothels
cast	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Zana Briski|Avijit|Geeta Masi|Kochi|Mamuni
director	Colin Trevorrow	Zana Briski|Ross Kauffman
genres	Action|Adventure|Science Fiction|Thriller	Documentary
release_date	2015-06-09	2004-12-08
vote_count	5562	23
vote_average	6.5	6.4
release_year	2015	2004
budget_adj	1.38e+08	404056
revenue_adj	1.39245e+09	4.05795e+06
profit	1.25445e+09	3.65389e+06

> As we can see the highest value in the dataet or record is jurassic world and the

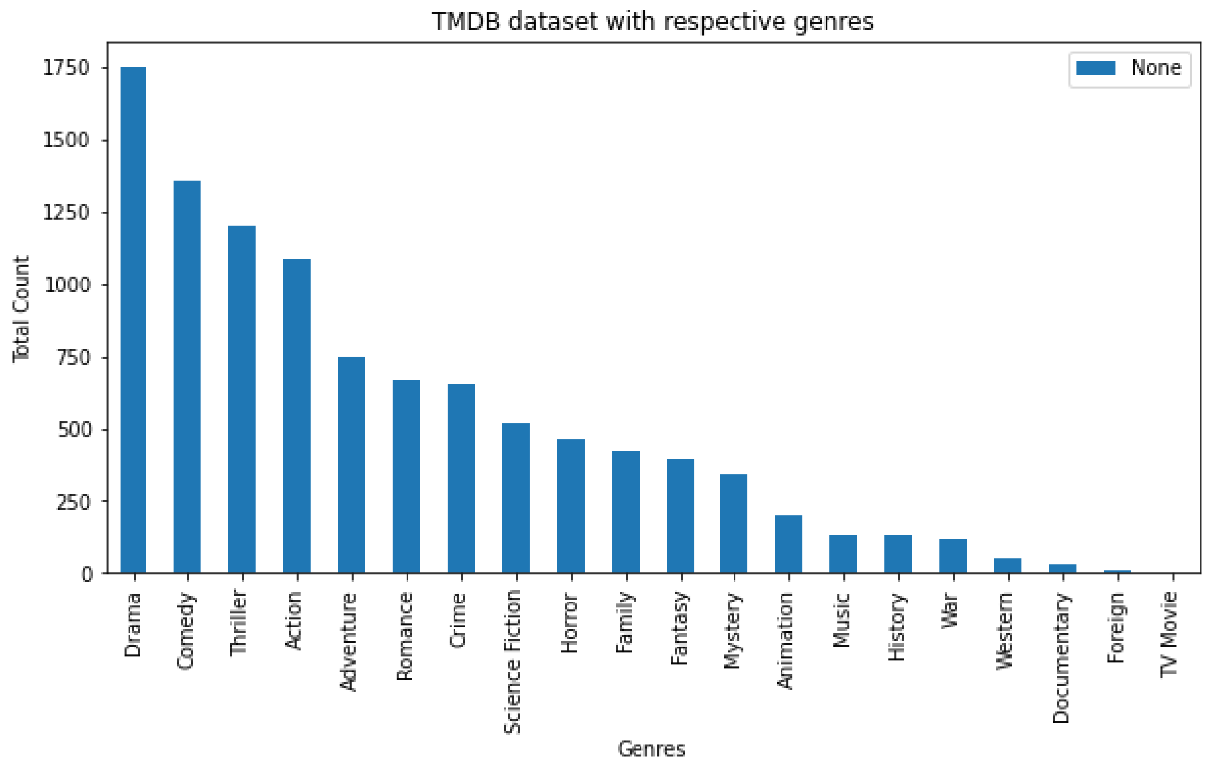
lowest value is the Born into Brothels.

Q2: The genres popularity from the top to bottom based on the entire record

In [48]:
```
def popularity(x):
    genres_data = final_df[x].str.cat(sep = '|')
    # Spliting the genres into a Pandas Series
    data_ = pd.Series(genres_data.split('|'))
    count_ = data_.value_counts(ascending = False)
    return count_

#plotting the graph
genre_count = popularity('genres') # genres column as one long string
ax = genre_count.plot.bar(figsize=(10,5), title='TMDB dataset with resp
ective genres')
ax.legend()
ax.set_xlabel("Genres") #xlabel
ax.set_ylabel("Total Count") #ylabels
plt.figure(figsize=(15,10))
```

Out[48]:
```
<Figure size 1080x720 with 0 Axes>
```




```
<Figure size 1080x720 with 0 Axes>
```

Observations :

> The record are positively skewed most lovable section is drama, comedy, thriller and action movie people liked.

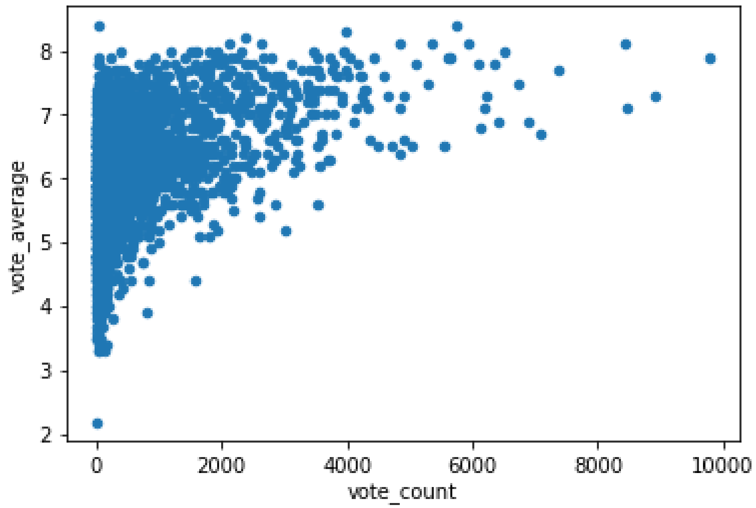
Q3. Did movies with higher vote count received a better rating in the dataset?

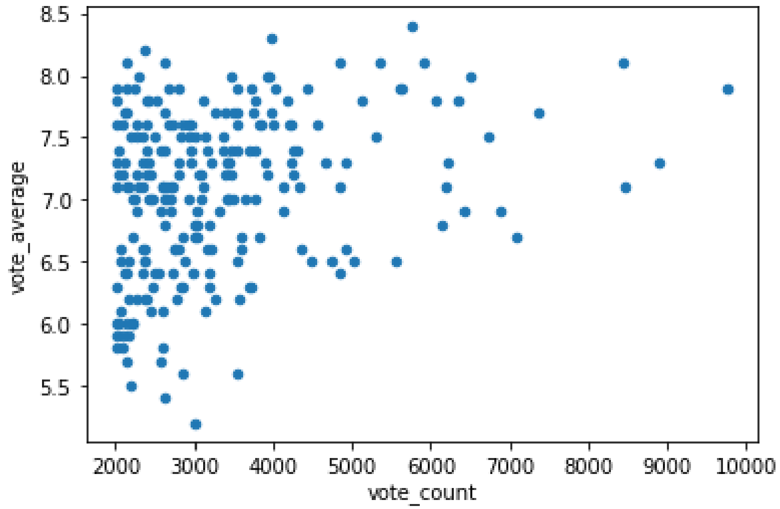
In [0]:
```
#Slicing the DataFrame to get 2 columns 'vote_average' and 'vote_count'
df_vote_count = final_df.loc[:, 'vote_count' : 'vote_average']
```

```
df_vote_count_2000 = df_vote_count[df_vote_count['vote_count'] > 2000]
#considered with more than 2000 votes
```

In [50]:
```
print(df_vote_count.plot(x='vote_count', y='vote_average', kind='scatte
r'))
print('* '*50)
print(df_vote_count.corr())
print('* '*50)
print(df_vote_count_2000.plot(x='vote_count', y='vote_average', kind='s
catter'))
print('* '*50)
print(df_vote_count_2000.corr())
```

```
AxesSubplot(0.125,0.125;0.775x0.755)
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
* * * * * * * * * * * * * *
              vote_count  vote_average
vote_count      1.000000      0.387201
vote_average    0.387201      1.000000
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
* * * * * * * * * * * * * *
AxesSubplot(0.125,0.125;0.775x0.755)
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
* * * * * * * * * * * * * *
              vote_count  vote_average
vote_count      1.000000      0.291649
vote_average    0.291649      1.000000
```





Observations :

> 1.In first graph vote_average seems to have the strongest correlation with vote_count , so it would probably do the best job predicting the value with resp to

datasets.

1. The second graph show there is less correlation bet the both. because of less record.

Q4. Now find the Top 5 Directors with most number of movies with made the most profit

In [51]:
```
#list the diretors
list_of_directors = final_df['director'].value_counts()
list_of_directors[list_of_directors > 20].head(5)
```

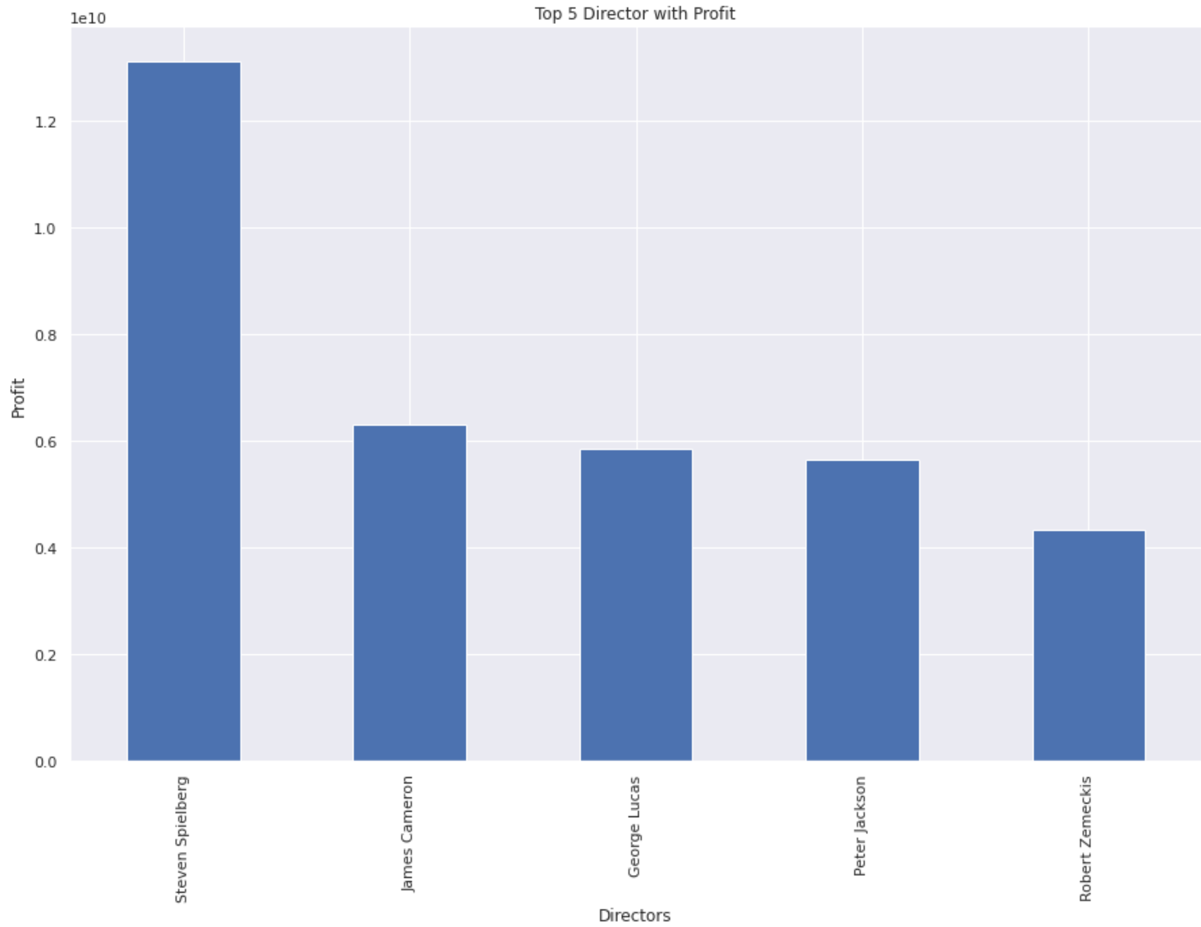
Out[51]:
```
Steven Spielberg    27
Clint Eastwood      24
Ridley Scott        21
Name: director, dtype: int64
```

In [52]:
```
#top five director with most number of movies
top_directors = final_df.groupby('director')['profit'].sum().sort_value
s(ascending=False)[:5]
top_directors
```

Out[52]:
```
director
Steven Spielberg    1.312603e+10
James Cameron       6.296578e+09
George Lucas        5.844159e+09
Peter Jackson       5.645492e+09
Robert Zemeckis     4.335995e+09
Name: profit, dtype: float64
```

In [53]:
```
sns.set()
top_directors.plot(kind='bar',figsize=(15,10))
plt.xlabel('Directors')
plt.ylabel('Profit')
plt.title('Top 5 Director with Profit')
```

Out[53]:
```
Text(0.5, 1.0, 'Top 5 Director with Profit')
```



Obervations :

> 1.the record show top 5 directors with their profits in decending order.

Q5: So now taking average profit per year and total profilt over the years

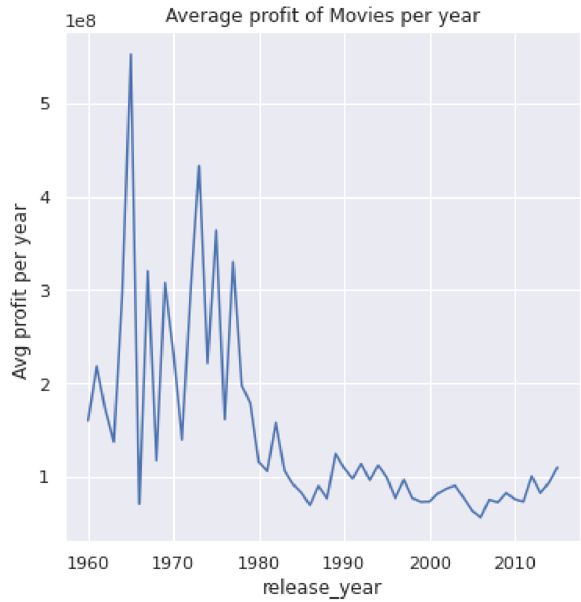
In [54]:
```
plt.figure(figsize=(20,10))
```

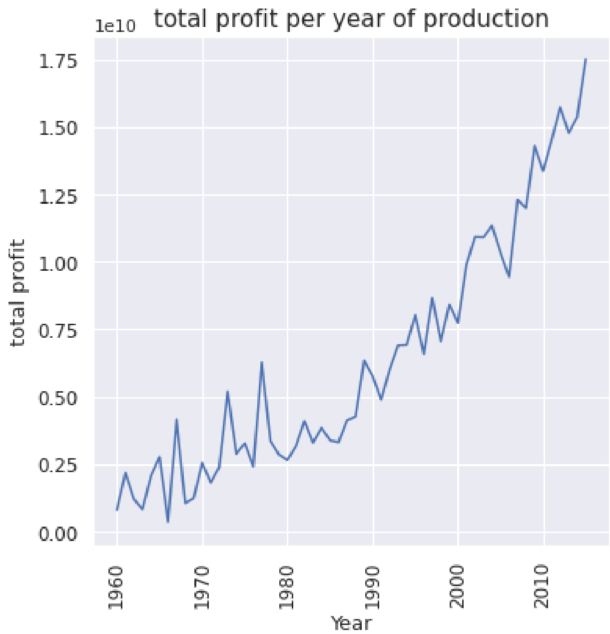
```
plt.subplot(1,2,1)


plt.xlabel('Years')
plt.ylabel('Avg profit per year ')
plt.title('Average profit of Movies per year')
final_df.groupby('release_year')['profit'].mean().plot() #plotting the
 graph using the mean
print('* '*50)
plt.subplot(1,2,2)
year_profit = final_df.groupby('release_year')['profit'].sum()
year_profit.plot(kind='line', figsize=(13,6),fontsize=12)
plt.title("total profit per year of production",fontsize=15)
plt.xticks(rotation = 90)
plt.xlabel('Year',fontsize=13)
plt.ylabel("total profit",fontsize= 13)
```

```
* * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * * *
* * * * * * * * * * * * * *
```

Out[54]: Text(0, 0.5, 'total profit')





Obervations :

> 1. So in first plot as we can see the highest profit locates in between 1960 to 1985.
> 2. from 1985 the profit graph goes down. 3.In the second graph we can see the total_profit difference is 0.25 and graph shows from 1960 the graph constantly increases.

Q6. creating one more column for rating scale and checking about the rating scale

In [55]:
```
final_df.head()
```

Out[55]:

	popularity	original_title	cast	director	genres	release_
0	32.985763	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	Action|Adventure|Science Fiction|Thriller	2015-06-
1	28.419936	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	Action|Adventure|Science Fiction|Thriller	2015-05-
2	13.112507	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	Adventure|Science Fiction|Thriller	2015-03-

	popularity	original_title	cast	director	genres	release_
3	11.173104	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	J.J. Abrams	Action|Adventure|Science Fiction|Fantasy	2015-12-
4	9.335014	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	James Wan	Action|Crime|Thriller	2015-04-

In [56]:

```
#rename the vote_average to imdb_score
final_df = final_df.rename(columns = {'vote_average' : 'imdb_score'})
final_df.head(1)
```

Out[56]:

	popularity	original_title	cast	director	genres	release_date
0	32.985763	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	Action|Adventure|Science Fiction|Thriller	2015-06-09

In [57]:

```
edges = ([1, 2, 3, 4, 5, 6, 7, 8, 9, 10])
names = (['humorous','terrible', 'not so good', 'nahhh', 'Average', 'Go
od', 'Very Good', 'Excellent', 'Awesome'])
final_df['rating_scale'] = pd.cut(final_df['imdb_score'], bins = edges,
 labels = names, include_lowest=True)
final_df.head(3)
```

Out[57]:

	popularity	original_title	cast	director	genres	release_d

	popularity	original_title	cast	director	genres	release_d
0	32.985763	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	Colin Trevorrow	Action|Adventure|Science Fiction|Thriller	2015-06-0
1	28.419936	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	George Miller	Action|Adventure|Science Fiction|Thriller	2015-05-1
2	13.112507	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	Robert Schwentke	Adventure|Science Fiction|Thriller	2015-03-1

In [58]:
```
final_df['imdb_score'].describe()
```

Out[58]:
```
count    3848.000000
mean        6.168997
std         0.794577
min         2.200000
25%         5.700000
50%         6.200000
75%         6.700000
max         8.400000
Name: imdb_score, dtype: float64
```

Observations :

> 1.ok the table show the most of the imdb_rating is in between 6 to 8.\ 2.Also 25% of movies have very low rating and 50% having average.

Conclusions

> 1.Finally completed all the obervation with respective features in that we first taking dataset applying data cleaning then applying the exploratory data analysis also applying some statastical approchs.

2.also finding which movie has highest value in popularity is Jurassic World lowest value in popularity Born into Brothels.

3.Then analysed the most movie have high revenue/profit.

4.The find out the top record 5 directors with their profits in decending order.

5.Average profit per year spike between 1960, and 1985, then it flaten. Total profit on the other hand keeps increasing over the time. this is happened due to increase number of movies everyday.

Limitations:

> 1. In the TMDB dataset i found some limitation like lots of missing value, lots of zeros in the dataset it may affect of accuracy. 2.also for the analysis I have only considered directors, popularity, genre and revenue, profit. I have not considered the impact of production companies or budget on the revenue in the analysis.

References :

> 1. Github
> 2. Stackoverflow

3. kaggle notebooks