Data Analysis process

Questions

Wrangle Data

Exploratory Data Analysis

Draw Conclusion

Communicate your results

```
# importing the requried packages
import pandas as pd
import numpy as np
#import matplotlib.pyplot as plt
import seaborn as sns
```

```
import matplotlib
matplotlib.use
import matplotlib.pyplot as plt
plt.style.use('ggplot')
```

Data Wrangling

```
# overview of the data
movie_data = pd.read_csv('tmdb-movies.csv')
movie_data.head(5)
```

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...	http://www.jurassicworld.com/	Colin Trevorrow	The park is open.
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...	http://www.madmaxmovie.com/	George Miller	What a Lovely Day.
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thedivergentseries.movie/#insurgent	Robert Schwentke	One Choice Can Destroy You
						Star Wars: The	Harrison Ford|Mark	http://www.starwars.com/films/star-wars-	J.J.	Every generation

```
movie_data.shape   # getting the shape of the data
```

    (10866, 21)

checking column labels and data types

Statham|Michelle Wan Hits Home

```
movie_data.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
```

Filter DropNull, Dedupe

```
movie_data.columns
```

```
Index(['id', 'imdb_id', 'popularity', 'budget', 'revenue', 'original_title',
       'cast', 'homepage', 'director', 'tagline', 'keywords', 'overview',
       'runtime', 'genres', 'production_companies', 'release_date',
       'vote_count', 'vote_average', 'release_year', 'budget_adj',
       'revenue_adj'],
      dtype='object')
```

Dealing with duplicates

cheaking the duplicates in the data

```
sum(movie_data.duplicated())
```

```
1
```

so we have one duplicate value

droping the duplicate

```
movie_data.drop_duplicates(inplace = True)
```

```
sum(movie_data.duplicated())
```

```
0
```

checking null values in each column

```
movie_data.isnull().sum()
```

```
id                         0
imdb_id                   10
popularity                 0
budget                     0
revenue                    0
original_title             0
cast                      76
homepage                7929
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
```

Mean of null values

```
movie_data.isnull().mean()
```

```
id                      0.000000
imdb_id                 0.000920
popularity              0.000000
budget                  0.000000
revenue                 0.000000
original_title          0.000000
cast                    0.006995
homepage                0.729775
director                0.004050
tagline                 0.259917
keywords                0.137414
overview                0.000368
runtime                 0.000000
genres                  0.002117
production_companies    0.094800
release_date            0.000000
vote_count              0.000000
vote_average            0.000000
```

```
release_year            0.000000
budget_adj              0.000000
revenue_adj             0.000000
dtype: float64
```

Droping null values

```
movie_data.dropna(inplace = True)
```

Data set rows are redused to 1992 rows after droping the null values

```
movie_data.shape
```

```
(1992, 21)
```

Extraneous columns

Getting rid of Extraneous columns

```
# data set contains  extranrous columns like homepage, cast, tagline, overview.

movie_data.drop(['homepage', 'cast', 'tagline', 'overview'], axis = 1, inplace = True)
```

checking the columns to confirm

```
print(movie_data.columns)
print(movie_data.shape)
```

```
Index(['id', 'imdb_id', 'popularity', 'budget', 'revenue', 'original_title',
       'director', 'keywords', 'runtime', 'genres', 'production_companies',
       'release_date', 'vote_count', 'vote_average', 'release_year',
       'budget_adj', 'revenue_adj'],
      dtype='object')
(1992, 17)
```

Fixing column data types

```
#changing release_data column to datetime format
movie_data['release_date'] = pd.to_datetime(movie_data['release_date'])
```

```
movie_data['release_date']
```

```
0       2015-06-09
1       2015-05-13
2       2015-03-18
3       2015-12-15
4       2015-04-01
           ...
10724   2069-12-12
10759   1978-10-25
10760   1978-07-27
10817   1978-05-01
10819   1978-07-28
Name: release_date, Length: 1992, dtype: datetime64[ns]
```

Corelations in movie_data set

This discribes the +ve and -ve corelations between each column

```
movie_data.corr()
```

	id	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	budget_adj	revenue_adj
id	1.000000	0.022330	-0.166067	-0.125101	-0.025016	-0.069752	-0.066973	0.507116	-0.208151	-0.165386
popularity	0.022330	1.000000	0.513553	0.641346	0.220787	0.774226	0.298066	0.002262	0.504971	0.600277
budget	-0.166067	0.513553	1.000000	0.747273	0.269480	0.649130	0.118651	0.068611	0.988433	0.630719
revenue	-0.125101	0.641346	0.747273	1.000000	0.257756	0.804788	0.258208	-0.031835	0.752853	0.925494
runtime	-0.025016	0.220787	0.269480	0.257756	1.000000	0.280602	0.243699	-0.078525	0.282257	0.257378
vote_count	-0.069752	0.774226	0.649130	0.804788	0.280602	1.000000	0.379345	0.006364	0.642077	0.741541
vote_average	-0.066973	0.298066	0.118651	0.258208	0.243699	0.379345	1.000000	-0.152250	0.128789	0.274923
release_year	0.507116	0.002262	0.068611	-0.031835	-0.078525	0.006364	-0.152250	1.000000	-0.027940	-0.237684
budget_adj	-0.208151	0.504971	0.988433	0.752853	0.282257	0.642077	0.128789	-0.027940	1.000000	0.669152
revenue_adj	-0.165386	0.600277	0.630719	0.925494	0.257378	0.741541	0.274923	-0.237684	0.669152	1.000000

Stastical Overview

```
movie_data.describe()
```

	id	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	1992.000000	1992.000000	1.992000e+03	1.992000e+03	1992.000000	1992.000000	1992.000000	1992.000000	1.992000e+03	1.992000e+03
mean	71652.152108	1.316763	3.454924e+07	1.152153e+08	106.040161	643.616968	6.178614	2007.796687	3.627376e+07	1.302391e+08
std	92355.883915	1.873563	5.061878e+07	2.202887e+08	29.234592	1092.355998	0.881955	7.549224	5.129783e+07	2.564338e+08
min	11.000000	0.000620	0.000000e+00	0.000000e+00	0.000000	10.000000	2.100000	1961.000000	0.000000e+00	0.000000e+00
25%	9699.000000	0.384079	0.000000e+00	0.000000e+00	92.000000	51.000000	5.600000	2006.000000	0.000000e+00	0.000000e+00
50%	35112.500000	0.774223	1.500000e+07	2.578782e+07	102.000000	210.000000	6.200000	2010.000000	1.524601e+07	2.806370e+07
75%	83573.000000	1.538639	4.800000e+07	1.278787e+08	116.000000	688.250000	6.800000	2012.000000	5.064450e+07	1.393645e+08
max	414419.000000	32.985763	4.250000e+08	2.781506e+09	705.000000	9767.000000	8.300000	2015.000000	4.250000e+08	2.827124e+09

Exploratory Data Analysis

```
movie_data.head(5)
```

	id	imdb_id	popularity	budget	revenue	original_title	director	keywords	runtime	genres
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Colin Trevorrow	monster|dna|tyrannosaurus rex|velociraptor|island	124	Action|Adventure|Science Fiction|Thriller
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	George Miller	future|chase|post-apocalyptic|dystopia|australia	120	Action|Adventure|Science Fiction|Thriller
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Robert Schwentke	based on novel|revolution|dystopia|sequel|dyst...	119	Adventure|Science Fiction|Thriller
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	J.J. Abrams	android|spaceship|jedi|space opera|3d	136	Action|Adventure|Science Fiction|Fantasy
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	James Wan	car race|speed|revenge|suspense|car	137	Action|Crime|Thriller

Data Visulization

Questions based on data

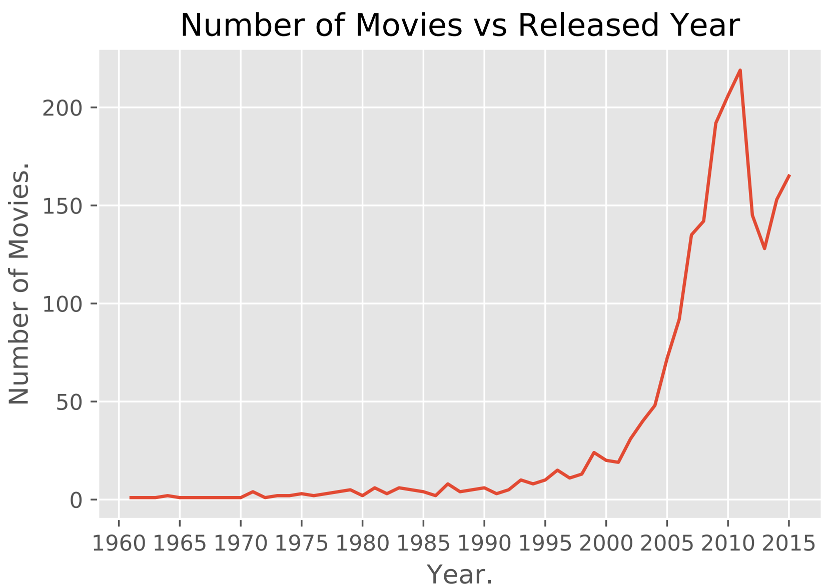
Q1 - Which year has highest number of movies released?

```
#movie_data['release_year'].value_counts()
data = movie_data.groupby('release_year').count()['id']
data
```

```
release_year
1961     1
1962     1
1963     1
1964     2
1965     1
1967     1
1969     1
1970     1
1971     4
1972     1
1973     2
1974     2
1975     3
1976     2
1977     3
1978     4
1979     5
1980     2
1981     6
1982     3
1983     6
1984     5
1985     4
1986     2
1987     8
1988     4
1989     5
1990     6
1991     3
1992     5
1993    10
1994     8
1995    10
1996    15
1997    11
1998    13
1999    24
2000    20
```

```
2001     19
2002     31
2003     40
2004     48
2005     72
2006     92
2007    135
2008    142
2009    192
2010    206
2011    219
2012    145
2013    128
2014    153
2015    165
Name: id, dtype: int64
```

```
plt.xticks(np.arange(1960,2020,5))
plt.xlabel("Year.")
plt.ylabel("Number of Movies.")
plt.title("Number of Movies vs Released Year")
plt.plot(data)
plt.show()
```



the above graph describe the no of movies released in each year

it seems the highest no of movies released in 2011

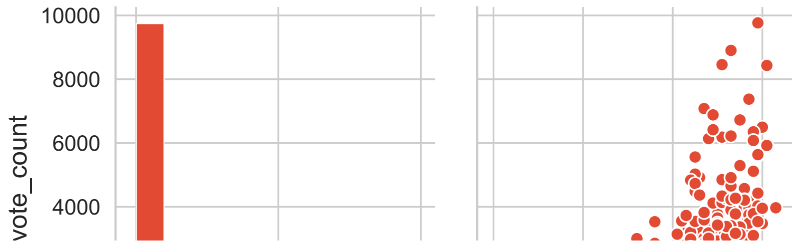
Did movies with higher vote count received a better rating?

```
#Slice DataFrame to get 2 columns 'vote_count' and 'vote_average'
df_vote = movie_data.loc[:, 'vote_count' : 'vote_average']
#To compare results only entries are considered with more than 2000 votes
df_vote_2000 = df_vote[df_vote['vote_count'] > 2000]
df_vote.tail()
```

	vote_count	vote_average
10724	258	6.4
10759	522	7.3
10760	230	6.7
10817	33	8.0
10819	13	6.0

```
sns.set_style('whitegrid')
sns.pairplot(df_vote[['vote_count','vote_average']])
```

```
<seaborn.axisgrid.PairGrid at 0x27f5f3af310>
```



the graphs describe that vote count and vote average has positive correlaion

[ ] ↳ 2 cells hidden

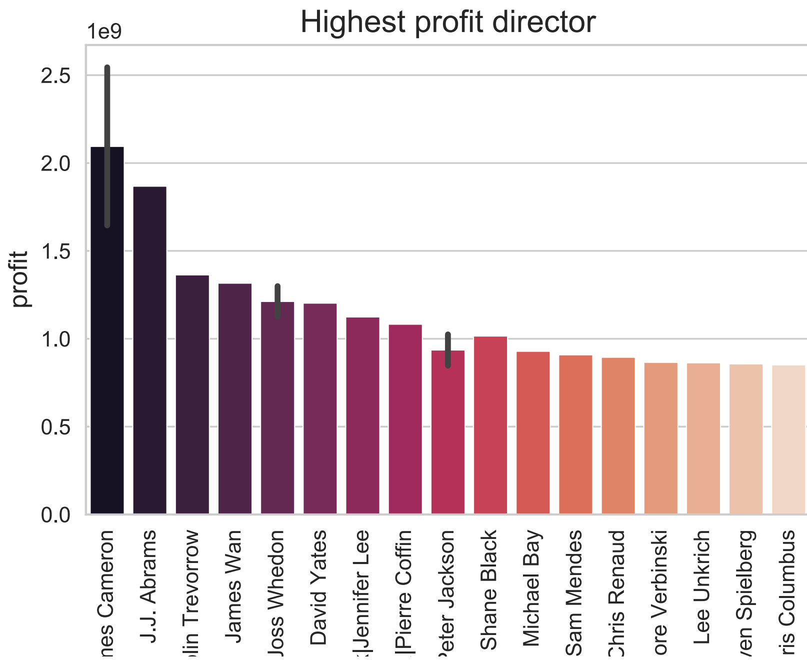
Which director has heighest profit margin?

```
movie_data['profit'] = movie_data['revenue'] - movie_data['budget']
movie_data[['profit']].head()
```

	profit
0	1363528810
1	228436354
2	185238201
3	1868178225
4	1316249360

```
def director_with_profit():
    data  = pd.DataFrame(movie_data[['director', 'profit']].sort_values(by = 'profit',              ascending = False))
    print(f'Director with highest profit {data.head().max()}')
    sns.barplot(x= 'director', y= 'profit', palette="rocket", data = data[:20])
    plt.xticks(rotation = 90)
    plt.title('Highest profit director')
director_with_profit()
```

```
Director with highest profit director     James Wan
profit      2544505847
dtype: object
```



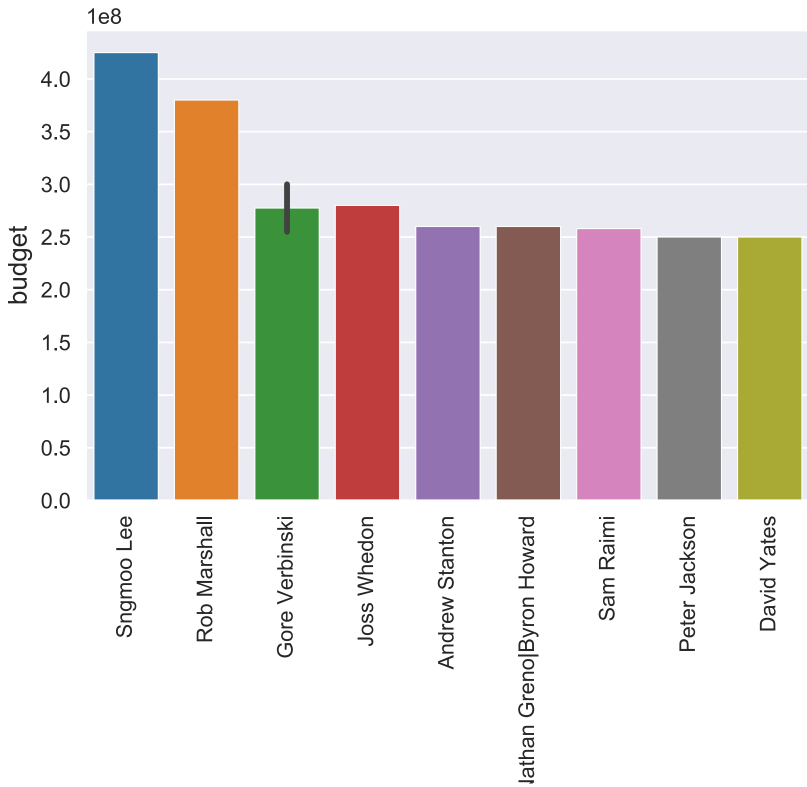
the above bar graph says that James Cameron has highest profit

The director who made movies with highest budget

```
data_2 = movie_data[['director','budget']]
directors = data_2.sort_values(by = 'budget', ascending = False)
directors.head(1)
```

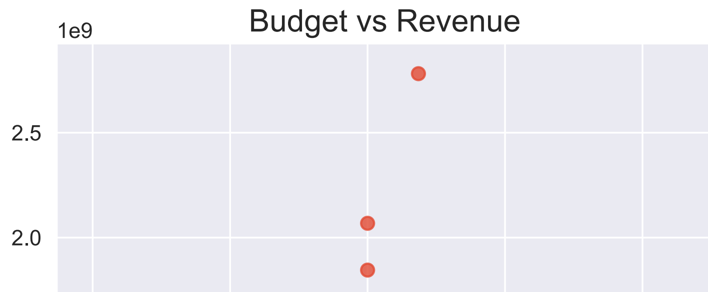
	director	budget
2244	Sngmoo Lee	425000000

```
sns.barplot(x = 'director', y ='budget',palette="tab10", data = directors[:10].sort_values(by = 'budget', ascending = False));
plt.xticks(rotation = 90);
```




```
sns.set_style('darkgrid')
sns.lmplot(x="budget", y="revenue", data=movie_data);
plt.title('Budget vs Revenue')
```

```
Text(0.5, 1, 'Budget vs Revenue')
```




```
data = movie_data[['popularity','revenue','budget','vote_count','vote_average','release_year']]
data.head()
```

	popularity	revenue	budget	vote_count	vote_average	release_year
0	32.985763	1513528810	150000000	5562	6.5	2015
1	28.419936	378436354	150000000	6185	7.1	2015
2	13.112507	295238201	110000000	2480	6.3	2015
3	11.173104	2068178225	200000000	5292	7.5	2015
4	9.335014	1506249360	190000000	2947	7.3	2015

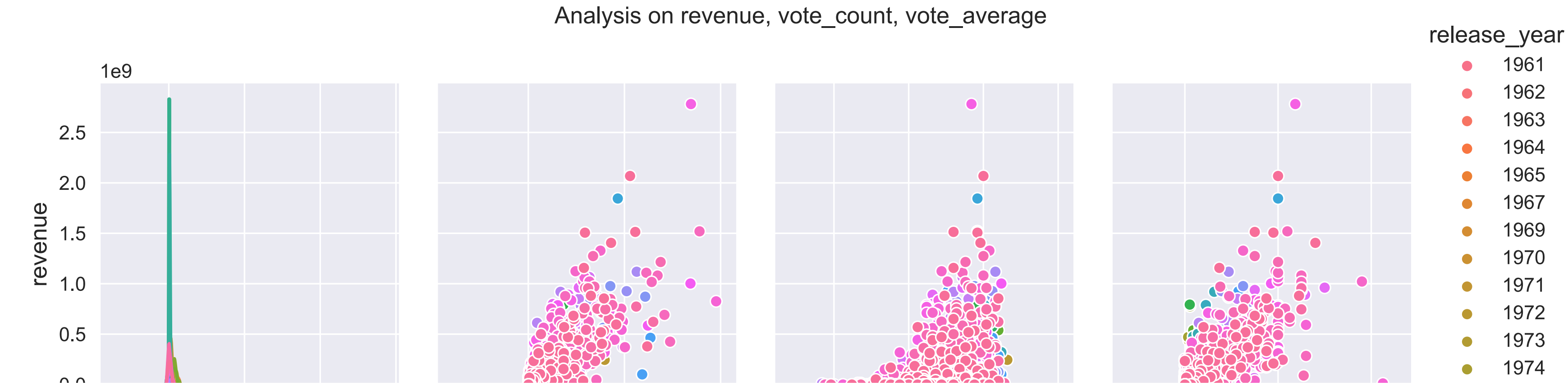
0 1 2 3 4

```
sns.lineplot(x = data['release_year'], y = data['budget'], palette="tab10", linewidth=2.5)
sns.lineplot(x = data['release_year'], y = data['revenue'], palette="tab10",linewidth=2.5)
```

```
<matplotlib.axes._subplots.AxesSubplot at 0x27f62e95d90>
```

```python
t = sns.pairplot(data[['revenue','release_year','vote_count','vote_average','budget']],hue='release_year');
t.fig.suptitle('Analysis on revenue, vote_count, vote_average', y = 1.05)
```

```
Text(0.5, 1.05, 'Analysis on revenue, vote_count, vote_average')
```



"'Looks like there is a positive correlation between budget and revenue, and a very slight positive correlation with release year and budget. --> With average rating slightly positive influenced by budget. These are only slight though, so the analysis here is limited. This does not indicate a causation in improvement in revenue/rating and a much deeper analysis would be required to find any correlation'"

Limitations and assumptions :

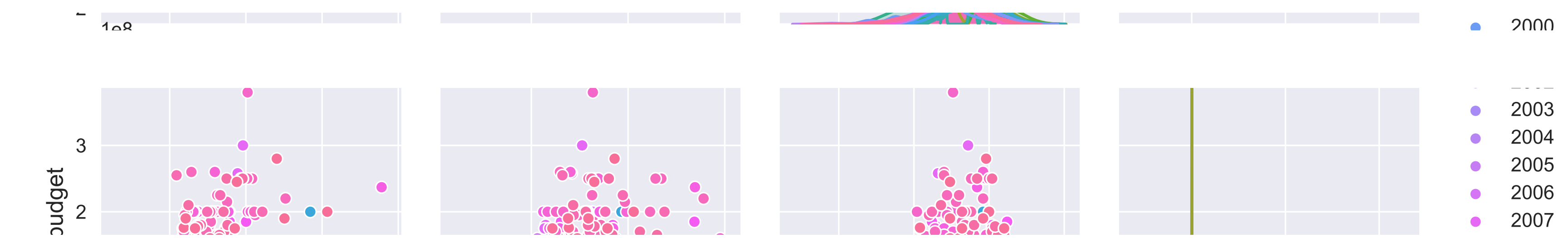
1.The coorelation between revenue and budget is 0.747273

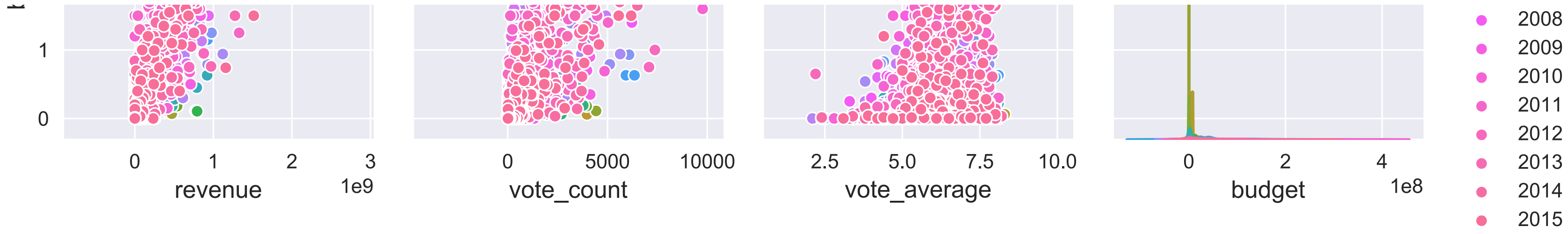
2. Director james Cameron has heighest profit margin 2544505847.

3. In year 2014 max number of movie is released i.e. 700 and In year 1961 and 1969 lowest number of movie is released i.e. 31.

4. Top five genres according to their budgets are listed above in which comedy genre has heighest budget. The mean of the Comedy Budget are 2.632826e+07.

5. Assumimng 0 revenue and 0 budget are actually missing values and not actually 0 revenue and 0 budget.





1
0
0
1
2
3
1e9
revenue
0
5000
10000
vote_count
2.5
5.0
7.5
10.0
vote_average
0
2
4
1e8
budget
2008
2009
2010
2011
2012
2013
2014
2015