

# Investigate\_a\_Dataset

August 31, 2022

## 1 Project: [TMDB-MOVIE-DATA]

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## Introduction

#### 1.1.1 Dataset Description

Movies has always been one of the best forms of entertainment because they offer something for everyone. This range from intense, dramatic, comedy, action, and so much more. Whether you're feeling up or down, there's always something for everyone.

This data set contains information about 10,000 movies collected from The Movie Database (TMDB), including user ratings and revenue. The dataset contains 21 columns 10866 rows. We will be performing an exploratory analysis on the dataset. we will be exploring the data and answering questions which includes; what genres are the most popular, what levels of popularity received the highest rating, and we will also be exploring the data to check the relationship between variables.

#### 1.1.2 Import Libraries

```
In [68]: import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
% matplotlib inline

In [69]: # Upgrade pandas to use dataframe.explode() function.
#!pip install --upgrade pandas==0.25.0

In [70]: df = pd.read_csv('tmdb-movies.csv')
df.head()
```

```

Out[70]:      id      imdb_id  popularity      budget      revenue \
0  135397  tt0369610   32.985763  150000000  1513528810
1    76341  tt1392190   28.419936  150000000   378436354
2   262500  tt2908446   13.112507  110000000   295238201
3   140607  tt2488496   11.173104  200000000  2068178225
4   168259  tt2820852    9.335014  190000000  1506249360

      original_title \
0      Jurassic World
1      Mad Max: Fury Road
2      Insurgent
3  Star Wars: The Force Awakens
4      Furious 7

      cast \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...

      homepage      director \
0      http://www.jurassicworld.com/  Colin Trevorrow
1      http://www.madmaxmovie.com/    George Miller
2      http://www.thedivergentseries.movie/#insurgent  Robert Schwentke
3      http://www.starwars.com/films/star-wars-episod...  J.J. Abrams
4      http://www.furious7.com/      James Wan

      tagline      ... \
0      The park is open.      ...
1      What a Lovely Day.      ...
2      One Choice Can Destroy You      ...
3      Every generation has a story.      ...
4      Vengeance Hits Home      ...

      overview runtime \
0  Twenty-two years after the events of Jurassic ...  124
1  An apocalyptic story set in the furthest reach...  120
2  Beatrice Prior must confront her inner demons ...  119
3  Thirty years after defeating the Galactic Empi...  136
4  Deckard Shaw seeks revenge against Dominic Tor...  137

      genres \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2      Adventure|Science Fiction|Thriller
3  Action|Adventure|Science Fiction|Fantasy
4      Action|Crime|Thriller

```

	production_companies	release_date	vote_count	\
0	Universal Studios Amblin Entertainment Legenda...	6/9/15	5562	
1	Village Roadshow Pictures Kennedy Miller Produ...	5/13/15	6185	
2	Summit Entertainment Mandeville Films Red Wago...	3/18/15	2480	
3	Lucasfilm Truenorth Productions Bad Robot	12/15/15	5292	
4	Universal Pictures Original Film Media Rights ...	4/1/15	2947	

	vote_average	release_year	budget_adj	revenue_adj
0	6.5	2015	1.379999e+08	1.392446e+09
1	7.1	2015	1.379999e+08	3.481613e+08
2	6.3	2015	1.012000e+08	2.716190e+08
3	7.5	2015	1.839999e+08	1.902723e+09
4	7.3	2015	1.747999e+08	1.385749e+09

[5 rows x 21 columns]

In [71]: df.shape

Out[71]: (10866, 21)

There are 10866 rows and 21 columns in this dataset

In [72]: df.info()

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                10866 non-null int64
imdb_id           10856 non-null object
popularity        10866 non-null float64
budget            10866 non-null int64
revenue           10866 non-null int64
original_title    10866 non-null object
cast              10790 non-null object
homepage          2936 non-null object
director          10822 non-null object
tagline           8042 non-null object
keywords          9373 non-null object
overview          10862 non-null object
runtime           10866 non-null int64
genres            10843 non-null object
production_companies 9836 non-null object
release_date      10866 non-null object
vote_count        10866 non-null int64
vote_average      10866 non-null float64
release_year      10866 non-null int64
budget_adj        10866 non-null float64
revenue_adj       10866 non-null float64
```

```
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

From the info above, we can tell that cast, homepage, tagline, keywords, overview, genres, and production\_companies have missing values

```
In [73]: #checking the sum of null values
df.isnull().sum()
```

```
Out[73]: 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
```

IsNull further shows the amount of missing values. There are two ways to treat missing values; either by filling them or dropping them. Going further to explore the data, we will know which option to go with.

```
In [74]: #checking the amount of unique values in a dataset
df.nunique()
```

```
Out[74]: id                10865
imdb_id                10855
popularity              10814
budget                  557
revenue                 4702
original_title         10571
cast                   10719
homepage                2896
director                5067
```

```

tagline          7997
keywords         8804
overview         10847
runtime          247
genres           2039
production_companies 7445
release_date     5909
vote_count       1289
vote_average     72
release_year     56
budget_adj       2614
revenue_adj      4840
dtype: int64

```

The above shows the amount of unique values in each columns

```

In [75]: #checking for duplicates in Movie title
dup_title = df[df["original_title"].duplicated() == True]
dup_title['original_title'].index

```

```

Out[75]: Int64Index([ 1133,  1194,  1349,  1440,  1513,  1707,  1753,  1757,  1865,
                    2036,
                    ...,
                    10757, 10759, 10767, 10795, 10799, 10818, 10827, 10849, 10853,
                    10854],
                    dtype='int64', length=295)

```

The above code shows that there are 295 duplicates data in our dataset And we will be removing all duplicate title in the original\_title dataset. This will be done in the data cleaning session.

### 1.1.3 Data Cleaning

Following our steps above, we can see that there data cleaning is requiredd in the dataset,which includes; dropping of nan values, removal of duplicate data e.t.c.

We are going to build a wrangle function to input all our cleaning.

```

In [76]: #build a wrangle function

def wrangle(filepath):
    #read csv file
    df = pd.read_csv(filepath)

    #drop unwanted columns
    df.drop(columns = ['id', 'imdb_id', 'homepage', 'tagline', 'keywords', 'overview',

    #Drop title Duplicates
    df_dup = df.drop_duplicates('original_title', inplace = True)

    #Drop Nan values

```

```

drop_genre_na = df.dropna(subset = ['genres'], inplace = True)

#split and subset to the first index
df['genre'] = df["genres"].str.split("|", expand = True)[0]

#Drop genres column
df.drop(columns = 'genres', inplace = True)

return df

```

Inside our WRANGLE FUNCTION, the following was done to clean the data;

1. All unwanted columns which includes 'id', 'imdb\_id', 'homepage', 'tagline', 'keywords', and 'overview' was dropped.
2. All duplicate title in the original\_title was dropped
3. All empty cell in the genre column was dropped.
4. The 'genres' column was split and a new column named 'genre' was created and the old column 'genres' was dropped

In [77]: *#Loading the clean Data in the wrangle function*

```

df = wrangle('tmdb-movies.csv')
df.head()

```

```

Out[77]:
  popularity    budget    revenue  original_title \
0   32.985763  150000000  1513528810      Jurassic World
1   28.419936  150000000   378436354  Mad Max: Fury Road
2   13.112507  110000000   295238201      Insurgent
3   11.173104  200000000  2068178225  Star Wars: The Force Awakens
4    9.335014  190000000  1506249360      Furious 7

                                cast      director \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...  Colin Trevorrow
1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...   George Miller
2  Shailene Woodley|Theo James|Kate Winslet|Ansel...  Robert Schwentke
3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...   J.J. Abrams
4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...   James Wan

  runtime  release_date  vote_count  vote_average  release_year  budget_adj \
0      124      6/9/15      5562         6.5         2015  1.379999e+08
1      120      5/13/15      6185         7.1         2015  1.379999e+08
2      119      3/18/15      2480         6.3         2015  1.012000e+08
3      136     12/15/15      5292         7.5         2015  1.839999e+08
4      137      4/1/15      2947         7.3         2015  1.747999e+08

  revenue_adj  genre
0  1.392446e+09  Action
1  3.481613e+08  Action
2  2.716190e+08  Adventure

```

```
3  1.902723e+09    Action
4  1.385749e+09    Action
```

```
In [78]: df.shape
```

```
Out[78]: (10548, 14)
```

```
In [79]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10548 entries, 0 to 10865
Data columns (total 14 columns):
popularity          10548 non-null float64
budget              10548 non-null int64
revenue             10548 non-null int64
original_title      10548 non-null object
cast                10475 non-null object
director            10507 non-null object
runtime             10548 non-null int64
release_date        10548 non-null object
vote_count          10548 non-null int64
vote_average        10548 non-null float64
release_year        10548 non-null int64
budget_adj          10548 non-null float64
revenue_adj         10548 non-null float64
genre               10548 non-null object
dtypes: float64(4), int64(5), object(5)
memory usage: 1.2+ MB
```

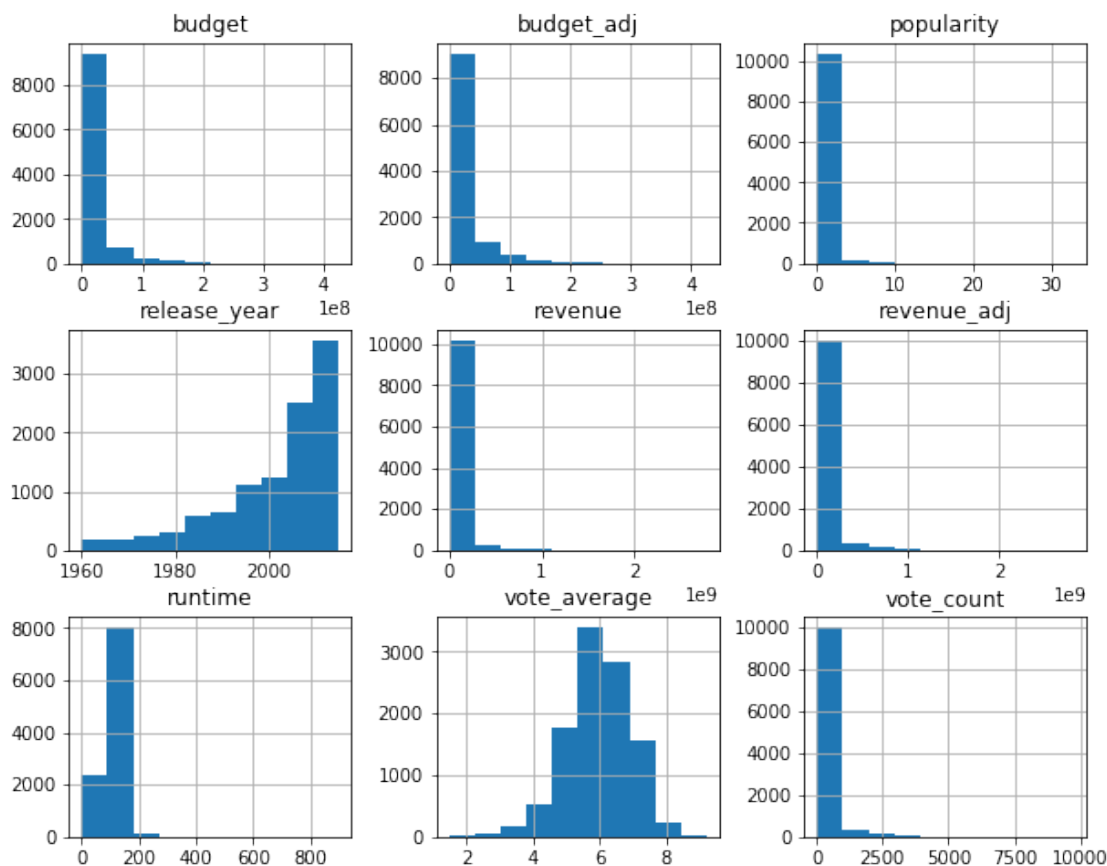
```
In [80]: #checking for duplicates in Movie title
dup_title = df[df["original_title"].duplicated() == True]
dup_title['original_title'].index
```

```
Out[80]: Int64Index([], dtype='int64')
```

After cleaning, There are 10548 rows and 14 columns remaining in the dataset, and there are no duplicate titles in the 'original\_title' dataset.

### 1.1.4 Summary Statistics of movies dataset

```
In [81]: df.hist(figsize=(10,8));
```



From the histogram above, we can see from the 'release\_year' that movies were released most in the year 2015. and 'vote\_average' appears to be closer to a normal distribution

In [82]: df.describe()

```
Out[82]:
```

	popularity	budget	revenue	runtime	vote_count
count	10548.000000	1.054800e+04	1.054800e+04	10548.000000	10548.000000
mean	0.649027	1.479945e+07	4.017399e+07	101.898369	219.320440
std	1.008401	3.116716e+07	1.175987e+08	30.253258	580.362722
min	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000
25%	0.207371	0.000000e+00	0.000000e+00	90.000000	17.000000
50%	0.384765	0.000000e+00	0.000000e+00	99.000000	38.000000
75%	0.715897	1.600000e+07	2.418657e+07	111.000000	148.000000
max	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000

	vote_average	release_year	budget_adj	revenue_adj
count	10548.000000	10548.000000	1.054800e+04	1.054800e+04
mean	5.967965	2001.635002	1.765650e+07	5.128319e+07
std	0.937372	12.594811	3.448349e+07	1.446210e+08
min	1.500000	1960.000000	0.000000e+00	0.000000e+00
25%	5.400000	1995.000000	0.000000e+00	0.000000e+00

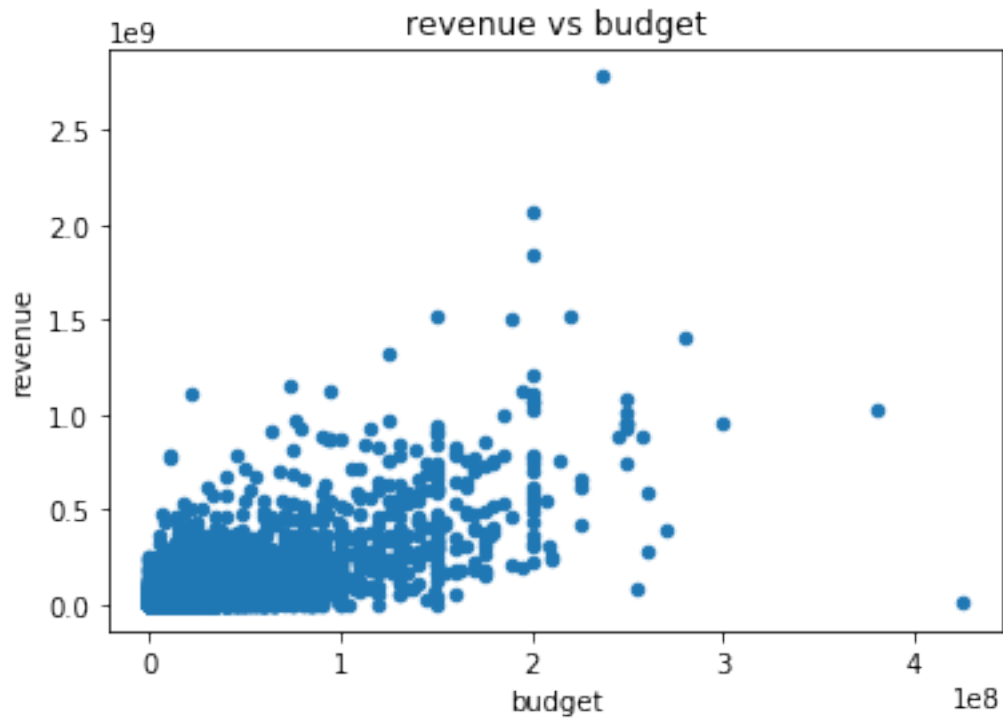


50%	6.000000	2006.000000	0.000000e+00	0.000000e+00
75%	6.600000	2011.000000	2.099042e+07	3.368783e+07
max	9.200000	2015.000000	4.250000e+08	2.827124e+09

## Exploratory Data Analysis

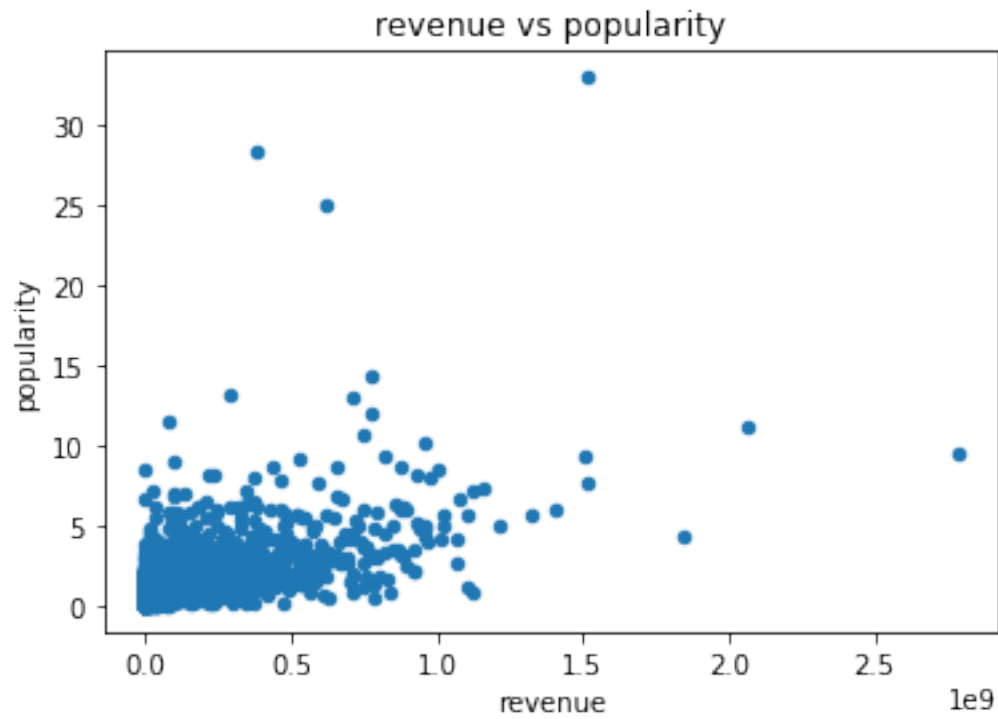
### 1.1.5 Relationship Between Variables

```
In [83]: df.plot(x = "budget", y = "revenue", kind = "scatter", title = 'revenue vs budget') ;
```



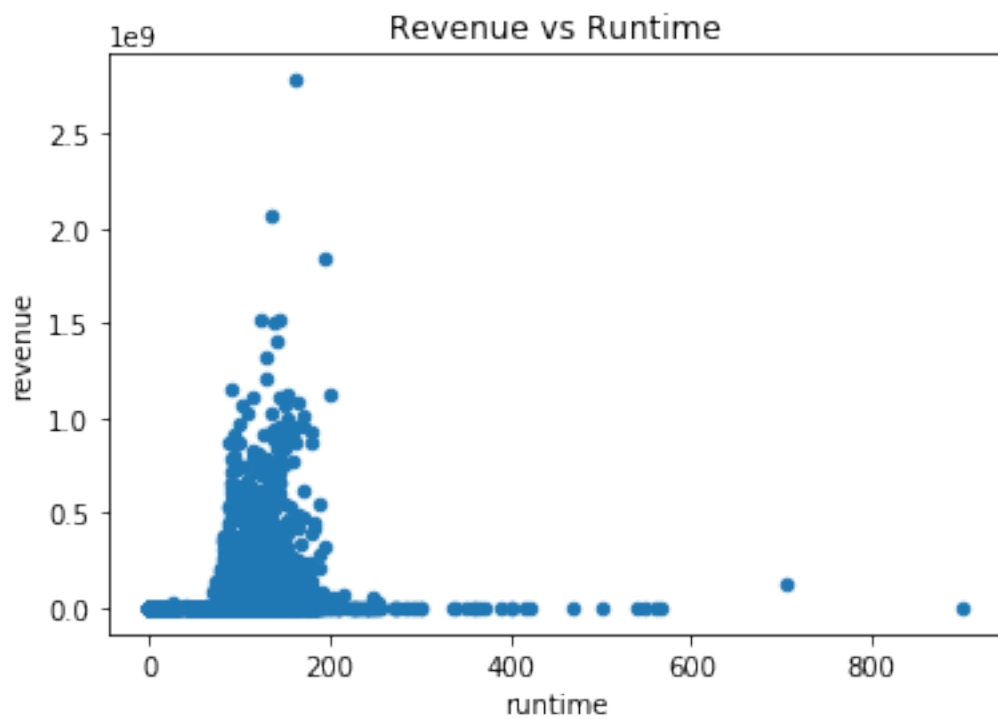
We can say that budget(investment) affects returns(investment) positively

```
In [84]: df.plot(x = "revenue", y = "popularity", kind = 'scatter', title = 'revenue vs populari
```



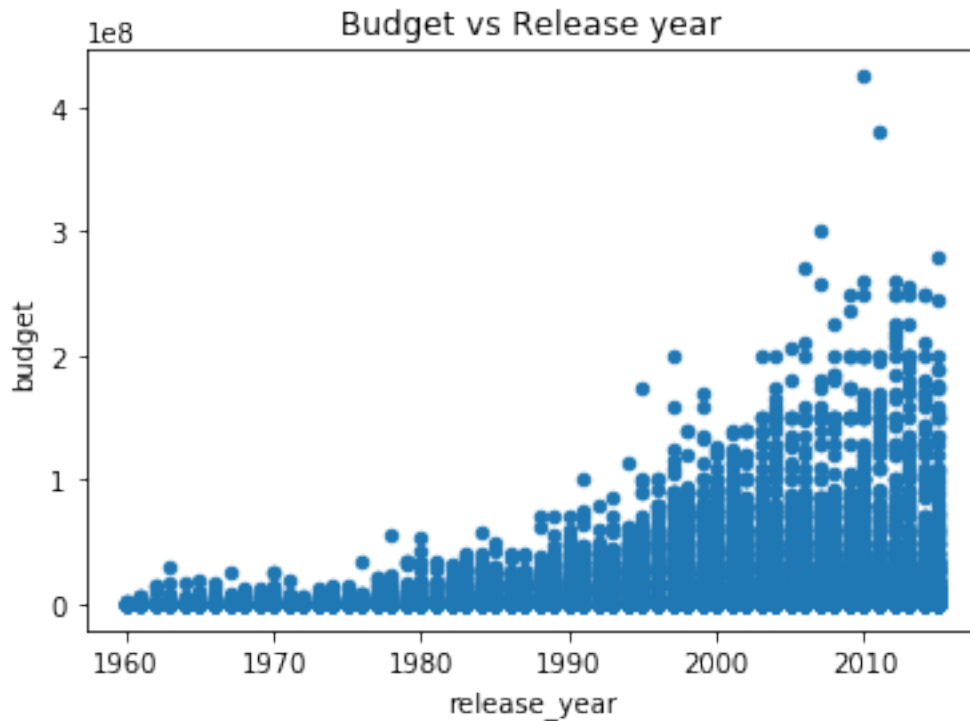
The above shows a slight increase in popularity as revenue increases

```
In [85]: df.plot(x = "runtime", y = "revenue", kind = "scatter", title = 'Revenue vs Runtime');
```



This shows that movies with runtime close to 150 minutes will possibly produce Higher returns('revenue')

```
In [86]: df.plot(x = "release_year", y = "budget", kind = "scatter", title = "Budget vs Release
```



This shows that the cost of movies increased with respect to year

### 1.1.6 What level of popularity receives the highest average rating?

```
In [87]: df['popularity'].describe()
```

```
Out[87]: count      10548.000000
         mean         0.649027
         std         1.008401
         min         0.000065
         25%         0.207371
         50%         0.384765
         75%         0.715897
         max         32.985763
         Name: popularity, dtype: float64
```

```
In [88]: # Bin edges that will be used to "cut" the data into groups
         bin_edges = [0.000065 , 0.207371, 0.384765, 0.715897, 32.985763]
         # Fill in this list with five values you just found
```

```
In [89]: bin_names = ["low", "medium", "moderate_high", "high"]

In [90]: df['popularity_levels'] = pd.cut(df['popularity'], bin_edges, labels=bin_names)
df.head()
```

```
Out[90]:
```

	popularity	budget	revenue	original_title \
0	32.985763	150000000	1513528810	Jurassic World
1	28.419936	150000000	378436354	Mad Max: Fury Road
2	13.112507	110000000	295238201	Insurgent
3	11.173104	200000000	2068178225	Star Wars: The Force Awakens
4	9.335014	190000000	1506249360	Furious 7

	cast	director \
0	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi...	Colin Trevorrow
1	Tom Hardy Charlize Theron Hugh Keays-Byrne Nic...	George Miller
2	Shailene Woodley Theo James Kate Winslet Ansel...	Robert Schwentke
3	Harrison Ford Mark Hamill Carrie Fisher Adam D...	J.J. Abrams
4	Vin Diesel Paul Walker Jason Statham Michelle ...	James Wan

	runtime	release_date	vote_count	vote_average	release_year	budget_adj \
0	124	6/9/15	5562	6.5	2015	1.379999e+08
1	120	5/13/15	6185	7.1	2015	1.379999e+08
2	119	3/18/15	2480	6.3	2015	1.012000e+08
3	136	12/15/15	5292	7.5	2015	1.839999e+08
4	137	4/1/15	2947	7.3	2015	1.747999e+08

	revenue_adj	genre	popularity_levels
0	1.392446e+09	Action	high
1	3.481613e+08	Action	high
2	2.716190e+08	Adventure	high
3	1.902723e+09	Action	high
4	1.385749e+09	Action	high

```
In [91]: df.groupby('popularity_levels').mean()['vote_average']
```

```
Out[91]: popularity_levels
low          5.896094
medium       5.798142
moderate_high 5.900341
high         6.277285
Name: vote_average, dtype: float64
```

This shows that Movies with high rating have high vote\_average

### 1.1.7 Do low runtime have the highest revenue?

```
In [92]: df['runtime'].describe()
```

```
Out[92]: count    10548.000000
mean         101.898369
```

```

std          30.253258
min           0.000000
25%          90.000000
50%          99.000000
75%         111.000000
max          900.000000
Name: runtime, dtype: float64

```

```

In [93]: low_runtime = df.query("runtime < 99")
         high_runtime = df.query("runtime >= 99")

```

```

# ensure these queries included each sample exactly once
runtime_samples = df.shape[0]
runtime_samples == low_runtime['runtime'].count() + high_runtime['runtime'].count() # s

```

```

Out[93]: True

```

```

In [94]: low_runtime.mean()['revenue']

```

```

Out[94]: 19215792.030511059

```

```

In [95]: high_runtime.mean()['revenue']

```

```

Out[95]: 60895096.031108595

```

No, low runtime do not receive high revenue

### 1.1.8 What genre is most popular?

```

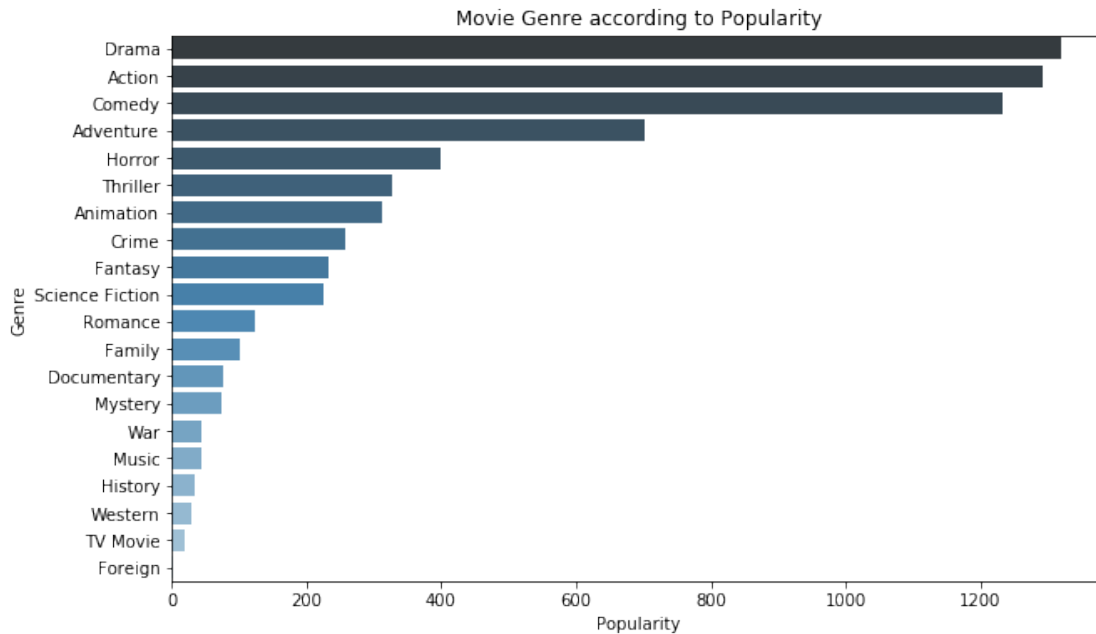
In [96]: df1 = df.groupby('genre').sum()['popularity']
         df1 = pd.DataFrame(df1)
         df1['genre'] = df1.index

```

```

In [97]: fig, ax = plt.subplots(figsize = (10,6))
         sns.barplot(x = 'popularity', y = 'genre',
                     data = df1,
                     palette = "Blues_d",
                     order = df1.sort_values('popularity',ascending = False).genre)
         plt.xlabel('Popularity')
         plt.ylabel('Genre')
         plt.title('Movie Genre according to Popularity') ;

```

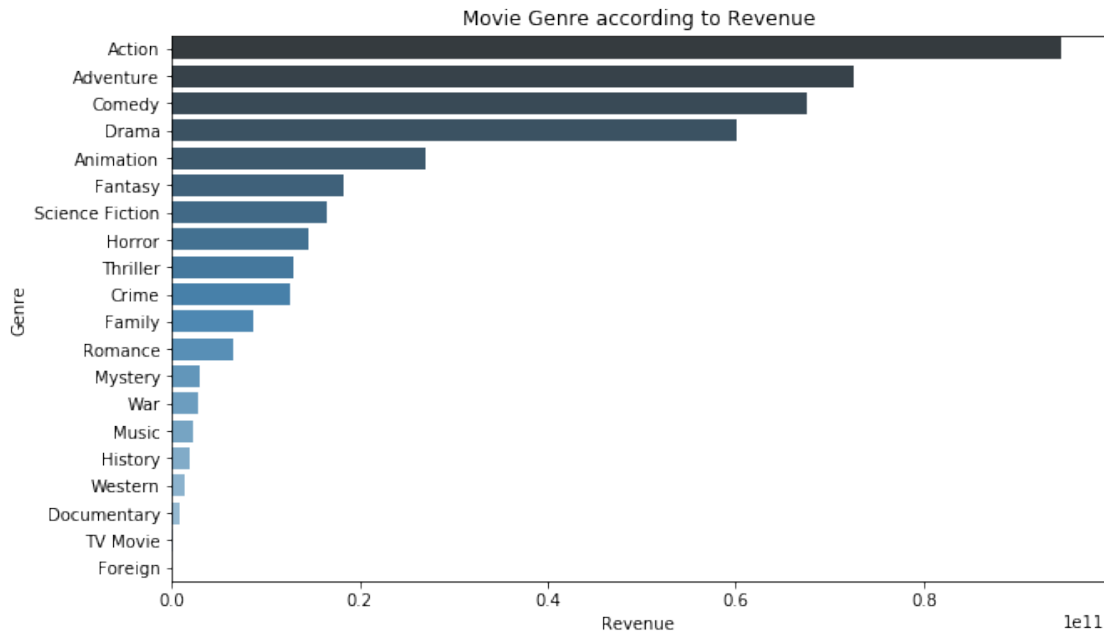


from the above analysis, we can conclude that Drama is the most popular Genre

### 1.1.9 What Genre has the highest Revenue?

```
In [98]: df1 = df.groupby('genre').sum()['revenue']
          df1 = pd.DataFrame(df1)
          df1['genre'] = df1.index

In [99]: fig, ax = plt.subplots(figsize = (10,6))
          sns.barplot(x = 'revenue', y = 'genre',
                      data = df1,
                      palette = "Blues_d",
                      order = df1.sort_values('revenue',ascending = False).genre)
          plt.xlabel('Revenue')
          plt.ylabel('Genre')
          plt.title('Movie Genre according to Revenue') ;
```



## ## Conclusions

Firstly, I carried out a summary statistics of the dataset. I found out that most movies in the data set were released in the year 2015 and most of the movies have an average runtime of 110 minutes. Furthermore, I performed an exploratory analysis checking on the relationship between variables using the scatter plot, It was clear that a high budget produces high revenue. Also, it was clear that movies with a runtime between 100 to 180 minutes produce high revenue. After that, I analyzed the level of popularity that receives the highest ratings and found out that high popularity receives high ratings. I also found out that low runtime produces low revenues. Lastly, I ran an analysis on the most popular genre according to popularity and revenue and it showed 'Drama' as the most popular and 'Action' as the genre with the highest revenue.

## ## Limitations

I noticed every movie has more than one genre so I was confused at first as to what index in the genre I needed to use but I ended up using the first row in the genre.

```
In [101]: from subprocess import call
          call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[101]: 0
```