Investigate_a_Dataset

October 27, 2022

1 Project: Investigate a Dataset - [TMDb Movie Dataset]

1.1 Table of Contents

Introduction

1.1.1 Dataset Description

The TMDb Movies dataset is a dataset containing over 10,000 movies collected from The Movie Database(TMDb) with various features regarding this movies with which we will use to generate useful insights such as feautures that determine popularity of movies, the profits, losses, revenues, budget and their correlations. The dataset contains the following columns and its descriptions

1.2 Columns and its description

- id - Identification Number.
- imdb_id - IMDb Identification Number.
- popularity - A numeric quantity specifying the movie popularity.
- budget - The budget of the movie.
- revenue - The revenue generated by the movie.
- original_title - The title of the movie before translation or adaptation.
- cast - The name of lead and supporting actors separated by "|".
- homepage - The link to the homepage of the movie.
- director - Director of the movie.
- tagline - A catchprase describing the movie.
- keywords - The keywords or tags related to the movie.
- overview - A brief description/summary of the movie.
- runtime - The running time of the movie in minutes.
- genre - The genre of the movie i.e Action, Comedy, Romance, Thriller etc separated by "|".
- production_companies - The production compan(y/of the movie.
- release_date - The date on which the movie was released.
- vote_count- The number of person that voted the movie.

- vote_average - The average ratings the movie recieved.
- release_year - The year the movie was released.
- budget_adj - Movie Budget including 2010 inflnation.
- revenue_adj - Movie Revenue including 2010 inflnation.

1.2.1 Question(s) for Analysis

1. Do movies with higher budget get better popularity?
2. Which genres are most popular?
3. Which year has the highest number of movies released ?
4. Which genre has the highest count of movies released?
5. What features are associated with high revenue movies ?

```
In [1]: # Importing necessary packages for analysis
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import seaborn as sns

        %matplotlib inline
```

```
In [2]: !pip install --upgrade pandas
```

```
Requirement already up-to-date: pandas in /opt/conda/lib/python3.6/site-packages (1.1.5)
Requirement already satisfied, skipping upgrade: numpy>=1.15.4 in /opt/conda/lib/python3.6/site-
Requirement already satisfied, skipping upgrade: pytz>=2017.2 in /opt/conda/lib/python3.6/site-p
Requirement already satisfied, skipping upgrade: python-dateutil>=2.7.3 in /opt/conda/lib/python
Requirement already satisfied, skipping upgrade: six>=1.5 in /opt/conda/lib/python3.6/site-packa
```

Data Wrangling

> **Tip**: In this section of the report, you will load in the data, check for cleanliness, and then trim and clean your dataset for analysis. Make sure that you **document your data cleaning steps in mark-down cells precisely and justify your cleaning decisions.**

1.2.2 General Properties of the Dataset

```
In [3]: #loading the movie dataset and printing the first 5 columns
        tmov=pd.read_csv('tmdb-movies.csv')
        tmov.head()
```

```
Out[3]:        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 [4]:
```
#printing dimensions of tmdb dataset
print(tmov.shape)
```

```
(10866, 21)
```

The dataset contains 10,866 rows and 21 columns. Exploring the data further,lets display a concise information about the dataset

In [5]:
```
tmov.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
```

for better understing of columns information,see above columns and its descriptions

In [6]:
```
#descriptive statistics for each column
tmov.describe()
```

Out[6]:

	id	popularity	budget	revenue	runtime
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000

	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	10866.000000	10866.000000	10866.000000	1.086600e+04	1.086600e+04
mean	217.389748	5.974922	2001.322658	1.755104e+07	5.136436e+07
std	575.619058	0.935142	12.812941	3.430616e+07	1.446325e+08
min	10.000000	1.500000	1960.000000	0.000000e+00	0.000000e+00
25%	17.000000	5.400000	1995.000000	0.000000e+00	0.000000e+00
50%	38.000000	6.000000	2006.000000	0.000000e+00	0.000000e+00
75%	145.750000	6.600000	2011.000000	2.085325e+07	3.369710e+07
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

From the above table, we know the maximum,minimum,mean of various columns,e.g The maximum popularity is 32.985763 while the minimum is 0.000065

Lets check for - null values - duplicates - unique values - columns correlations - columns distributions

In [7]:
```
# inspecting for null values
tmov.isnull().sum().sort_values(ascending=False)
```

Out[7]:
```
homepage                7930
tagline                 2824
keywords                1493
production_companies    1030
cast                      76
director                  44
genres                    23
imdb_id                   10
overview                   4
popularity                 0
budget                     0
revenue                    0
original_title             0
revenue_adj                0
budget_adj                 0
runtime                    0
```

```
release_date              0
vote_count                0
vote_average              0
release_year              0
id                        0
dtype: int64
```

observation:homepage,tagline,keywords,production_companies,cast,director,genres,imdb_id and overview all contain null values

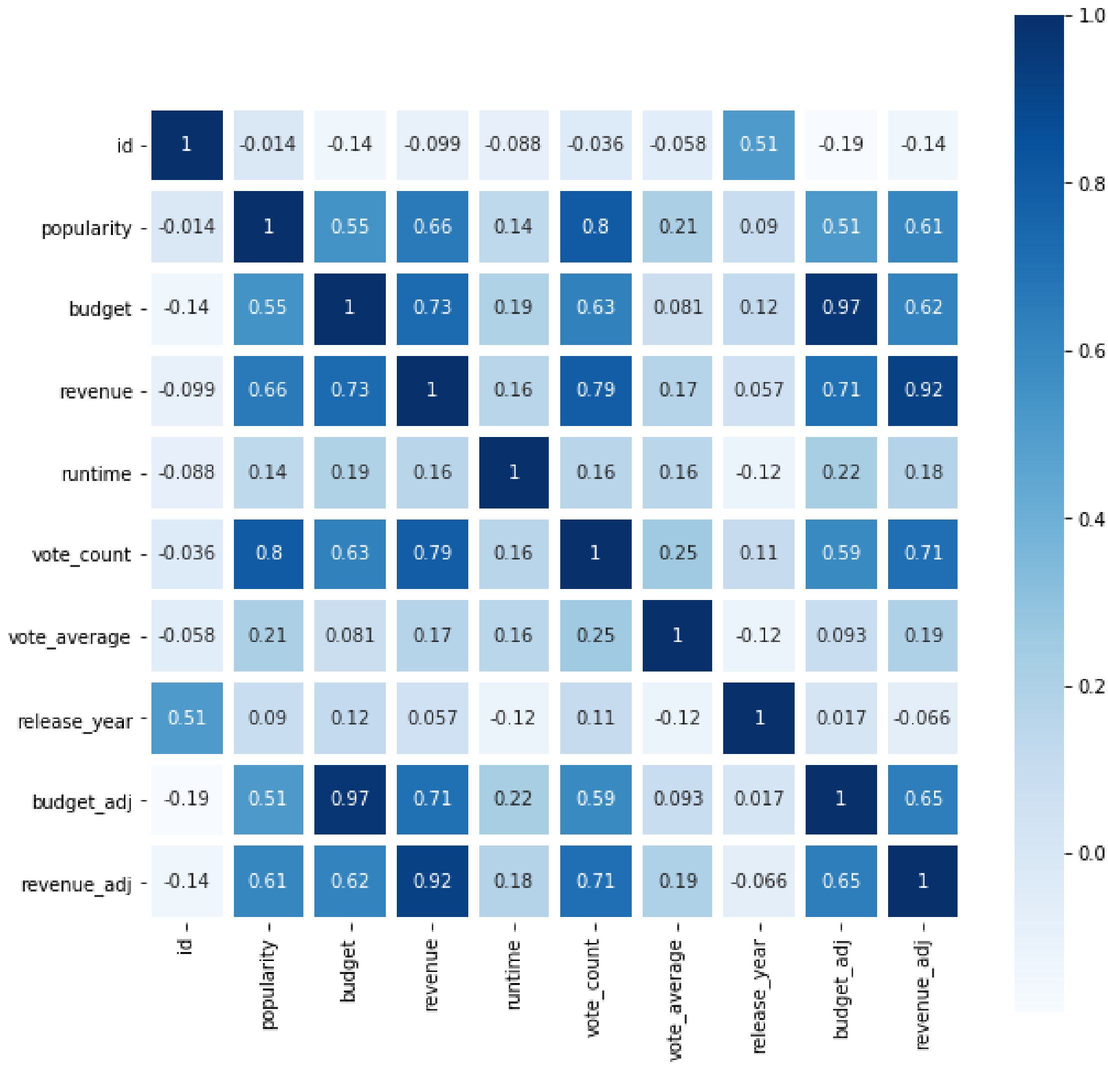
```
In [8]: #inspecting for duplicate values
        sum(tmov.duplicated())
```

```
Out[8]: 1
```

```
In [9]: #inspecting for unique values across columns
        tmov.nunique()
```

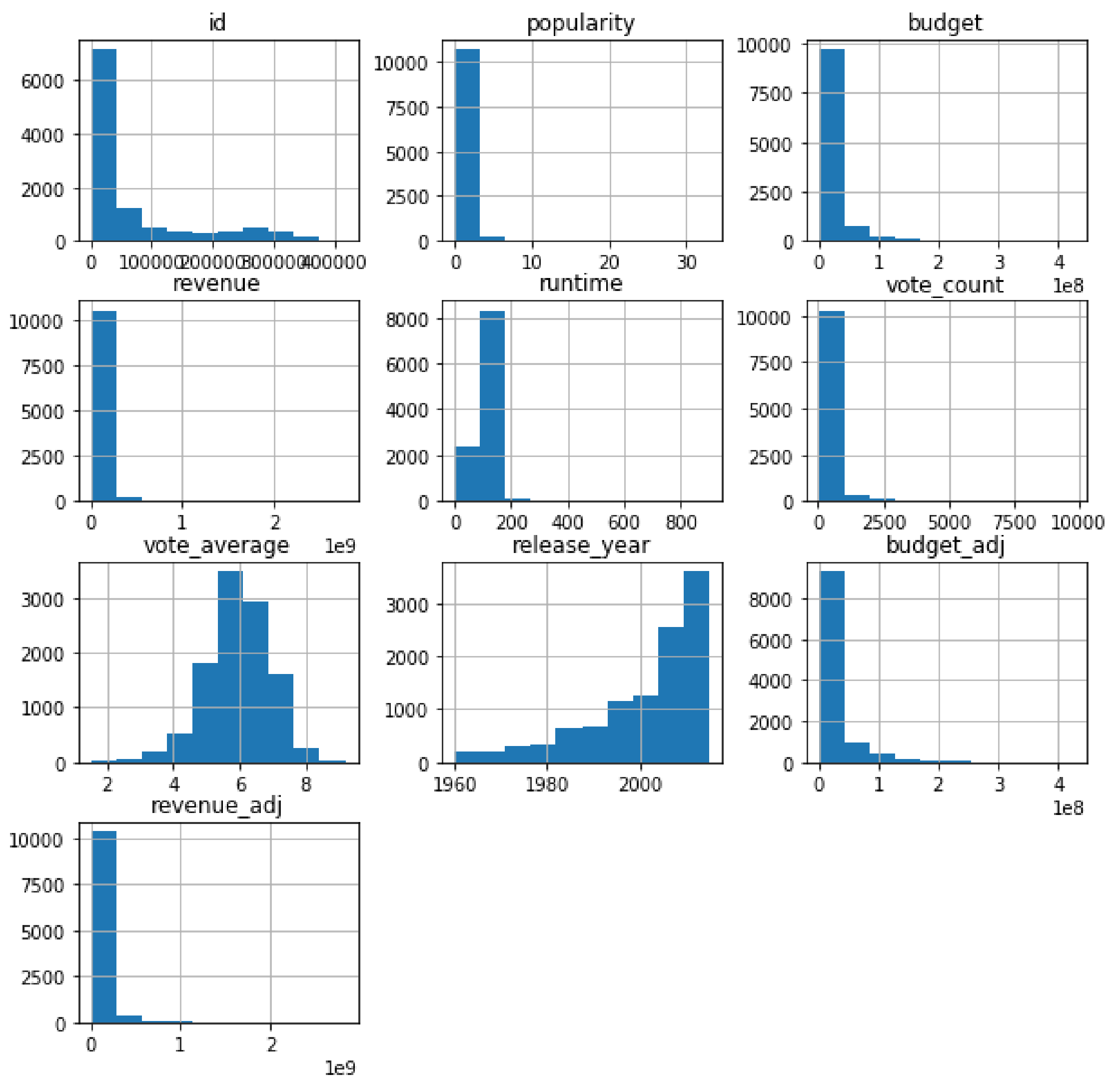
```
Out[9]: id                      10865
        imdb_id                 10855
        popularity              10814
        budget                    557
        revenue                  4702
        original_title          10571
        cast                    10719
        homepage                 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
```

```
In [10]: # Visualizing the correlation matrix of the different colums in our dataset
         fig,hm=plt.subplots(figsize=(10,10))         # Sample figsize in inches
         hm=sns.heatmap(tmov.corr(),cmap="Blues",square=True,linewidth=5, annot=True);
```



From the above matrix,figures closest to 1 indicate strong positive correlation while negative values indicate the columns are negatively correlated.

```
In [11]: # visualizing the columns distributions
         tmov.hist(figsize=(10,10));
```



1.2.3 Data Cleaning

In this stage,i will be executing the following; * Dropping columns not necessary for analysis * Dropping duplicate values * Dealing with missing values * Changing datatype where necessary(e.g-release date column) * Changing hybrid data input to single input

1. Dropping unnecessary columns

In [12]:
```
#using pandas drop function
tmov.drop(['imdb_id','homepage','tagline','overview','budget_adj','revenue_adj','keywor
tmov.head()
```

Out[12]:
```
       id  popularity     budget     revenue                original_title  \
0  135397   32.985763  150000000  1513528810                Jurassic World
```

```
1   76341   28.419936  150000000   378436354           Mad Max: Fury Road
2  262500   13.112507  110000000   295238201                    Insurgent
3  140607   11.173104  200000000  2068178225  Star Wars: The Force Awakens
4  168259    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                                      genres release_date  \
0      124  Action|Adventure|Science Fiction|Thriller       6/9/15
1      120  Action|Adventure|Science Fiction|Thriller      5/13/15
2      119         Adventure|Science Fiction|Thriller      3/18/15
3      136   Action|Adventure|Science Fiction|Fantasy     12/15/15
4      137                      Action|Crime|Thriller       4/1/15

   vote_count  vote_average  release_year
0        5562           6.5          2015
1        6185           7.1          2015
2        2480           6.3          2015
3        5292           7.5          2015
4        2947           7.3          2015
```

2. Dropping duplicates

In [13]:
```
#To drop the 1 no duplicate row observed in the data wrangling section,
dup=tmov.drop_duplicates(inplace=True)
```

In [14]:
```
shape=tmov.shape
print("The shape of the dataset after dropping unwanted column and removing duplicates
```

```
The shape of the dataset after dropping unwanted column and removing duplicates is (10865, 13)
```

3. Dealing with missing values

In [15]:
```
tmov.isnull().sum().sort_values(ascending=False)
```

Out[15]:
```
cast             76
director         44
genres           23
release_year      0
vote_average      0
vote_count        0
release_date      0
runtime           0
```

```
original_title     0
revenue            0
budget             0
popularity         0
id                 0
dtype: int64
```

In [16]:
```
#Given the size of the dataset, will drop null values for cast,director and genres colu
tmov.dropna(inplace=True)
```

In [17]:
```
#checking for any null values
tmov.isnull().sum().sort_values(ascending=False)
```

Out[17]:
```
release_year      0
vote_average      0
vote_count        0
release_date      0
genres            0
runtime           0
director          0
cast              0
original_title    0
revenue           0
budget            0
popularity        0
id                0
dtype: int64
```

4. Ensuring appropriate datatypes

In [18]:
```
tmov.dtypes
```

Out[18]:
```
id                  int64
popularity        float64
budget              int64
revenue             int64
original_title     object
cast               object
director           object
runtime             int64
genres             object
release_date       object
vote_count          int64
vote_average      float64
release_year        int64
dtype: object
```

In [19]:
```
#changing the release date datatype to datetime
tmov['release_date']=pd.to_datetime(tmov['release_date'])
```

```
In [20]: #checking
         tmov.dtypes
```

```
Out[20]: id                         int64
         popularity               float64
         budget                     int64
         revenue                    int64
         original_title            object
         cast                      object
         director                  object
         runtime                    int64
         genres                    object
         release_date      datetime64[ns]
         vote_count                 int64
         vote_average             float64
         release_year               int64
         dtype: object
```

```
In [21]: type(tmov['genres'][0])
```

```
Out[21]: str
```

5. Cleaning genres column The genre column contains various genres separated by "|", using the split finction to give each genre its individual row

```
In [22]: tmov.head()
```

```
Out[22]:        id  popularity     budget     revenue                original_title  \
         0  135397   32.985763  150000000  1513528810                Jurassic World
         1   76341   28.419936  150000000   378436354            Mad Max: Fury Road
         2  262500   13.112507  110000000   295238201                     Insurgent
         3  140607   11.173104  200000000  2068178225  Star Wars: The Force Awakens
         4  168259    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                                     genres release_date  \
         0      124  Action|Adventure|Science Fiction|Thriller   2015-06-09
         1      120  Action|Adventure|Science Fiction|Thriller   2015-05-13
         2      119         Adventure|Science Fiction|Thriller   2015-03-18
         3      136   Action|Adventure|Science Fiction|Fantasy   2015-12-15
         4      137                      Action|Crime|Thriller   2015-04-01
```

```
   vote_count  vote_average  release_year
0        5562           6.5          2015
1        6185           7.1          2015
2        2480           6.3          2015
3        5292           7.5          2015
4        2947           7.3          2015
```

In [23]:
```
# split the column genre by separator
tmov['genres']= tmov.genres.str.split('|')
```

In [24]:
```
tmov['genres']
```

Out[24]:
```
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]
                               ...
10861                                      [Documentary]
10862                         [Action, Adventure, Drama]
10863                                  [Mystery, Comedy]
10864                                   [Action, Comedy]
10865                                           [Horror]
Name: genres, Length: 10731, dtype: object
```

In [25]:
```
# using the explode function to give each genre its row
tmov_m=tmov.explode('genres')
tmov_m.tail(20)
```

Out[25]:
```
          id  popularity  budget  revenue  \
10856  20277    0.140934       0        0
10856  20277    0.140934       0        0
10857   5921    0.131378       0        0
10857   5921    0.131378       0        0
10858  31918    0.317824       0        0
10858  31918    0.317824       0        0
10859  20620    0.089072       0        0
10859  20620    0.089072       0        0
10859  20620    0.089072       0        0
10859  20620    0.089072       0        0
10860   5060    0.087034       0        0
10861     21    0.080598       0        0
10862  20379    0.065543       0        0
10862  20379    0.065543       0        0
10862  20379    0.065543       0        0
10863  39768    0.065141       0        0
10863  39768    0.065141       0        0
10864  21449    0.064317       0        0
10864  21449    0.064317       0        0
```

```
10865  22293    0.035919   19000        0

                                        original_title  \
10856                               The Ugly Dachshund
10856                               The Ugly Dachshund
10857                                     Nevada Smith
10857                                     Nevada Smith
10858  The Russians Are Coming, The Russians Are Coming
10858  The Russians Are Coming, The Russians Are Coming
10859                                          Seconds
10859                                          Seconds
10859                                          Seconds
10859                                          Seconds
10860                              Carry On Screaming!
10861                               The Endless Summer
10862                                       Grand Prix
10862                                       Grand Prix
10862                                       Grand Prix
10863                              Beregis Avtomobilya
10863                              Beregis Avtomobilya
10864                         What's Up, Tiger Lily?
10864                         What's Up, Tiger Lily?
10865                         Manos: The Hands of Fate

                                                    cast            director  \
10856  Dean Jones|Suzanne Pleshette|Charles Ruggles|K...        Norman Tokar
10856  Dean Jones|Suzanne Pleshette|Charles Ruggles|K...        Norman Tokar
10857  Steve McQueen|Karl Malden|Brian Keith|Arthur K...     Henry Hathaway
10857  Steve McQueen|Karl Malden|Brian Keith|Arthur K...     Henry Hathaway
10858  Carl Reiner|Eva Marie Saint|Alan Arkin|Brian K...     Norman Jewison
10858  Carl Reiner|Eva Marie Saint|Alan Arkin|Brian K...     Norman Jewison
10859  Rock Hudson|Salome Jens|John Randolph|Will Gee...  John Frankenheimer
10859  Rock Hudson|Salome Jens|John Randolph|Will Gee...  John Frankenheimer
10859  Rock Hudson|Salome Jens|John Randolph|Will Gee...  John Frankenheimer
10859  Rock Hudson|Salome Jens|John Randolph|Will Gee...  John Frankenheimer
10860  Kenneth Williams|Jim Dale|Harry H. Corbett|Joa...      Gerald Thomas
10861  Michael Hynson|Robert August|Lord 'Tally Ho' B...        Bruce Brown
10862  James Garner|Eva Marie Saint|Yves Montand|Tosh...  John Frankenheimer
10862  James Garner|Eva Marie Saint|Yves Montand|Tosh...  John Frankenheimer
10862  James Garner|Eva Marie Saint|Yves Montand|Tosh...  John Frankenheimer
10863  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...     Eldar Ryazanov
10863  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...     Eldar Ryazanov
10864  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...        Woody Allen
10864  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...        Woody Allen
10865  Harold P. Warren|Tom Neyman|John Reynolds|Dian...    Harold P. Warren

       runtime          genres release_date  vote_count  vote_average  \
10856       93           Drama   2066-02-16          14           5.7
```

```
10856        93            Family   2066-02-16          14           5.7
10857       128            Action   2066-06-10          10           5.9
10857       128           Western   2066-06-10          10           5.9
10858       126            Comedy   2066-05-25          11           5.5
10858       126               War   2066-05-25          11           5.5
10859       100           Mystery   2066-10-05          22           6.6
10859       100   Science Fiction   2066-10-05          22           6.6
10859       100          Thriller   2066-10-05          22           6.6
10859       100             Drama   2066-10-05          22           6.6
10860        87            Comedy   2066-05-20          13           7.0
10861        95       Documentary   2066-06-15          11           7.4
10862       176            Action   2066-12-21          20           5.7
10862       176         Adventure   2066-12-21          20           5.7
10862       176             Drama   2066-12-21          20           5.7
10863        94           Mystery   2066-01-01          11           6.5
10863        94            Comedy   2066-01-01          11           6.5
10864        80            Action   2066-11-02          22           5.4
10864        80            Comedy   2066-11-02          22           5.4
10865        74            Horror   2066-11-15          15           1.5

       release_year
10856          1966
10856          1966
10857          1966
10857          1966
10858          1966
10858          1966
10859          1966
10859          1966
10859          1966
10859          1966
10860          1966
10861          1966
10862          1966
10862          1966
10862          1966
10863          1966
10863          1966
10864          1966
10864          1966
10865          1966
```

In [26]:
```
g=tmov_m['genres'].nunique()
print('We have {} unique genres'.format(g))
```

```
We have 20 unique genres
```

Exploratory Data Analysis

1.2.4 Research Question 1 - Do movies with higher budget get better popularity?

In [27]:
```
# To answer this question,i will create a new dataframe for budget column != 0
tmov_budg=tmov_m[tmov_m['budget']!=0].copy()
```

In [28]:
```
#create two category for budget using the median
tmov_budg.budget.median()
```

Out[28]: 20000000.0

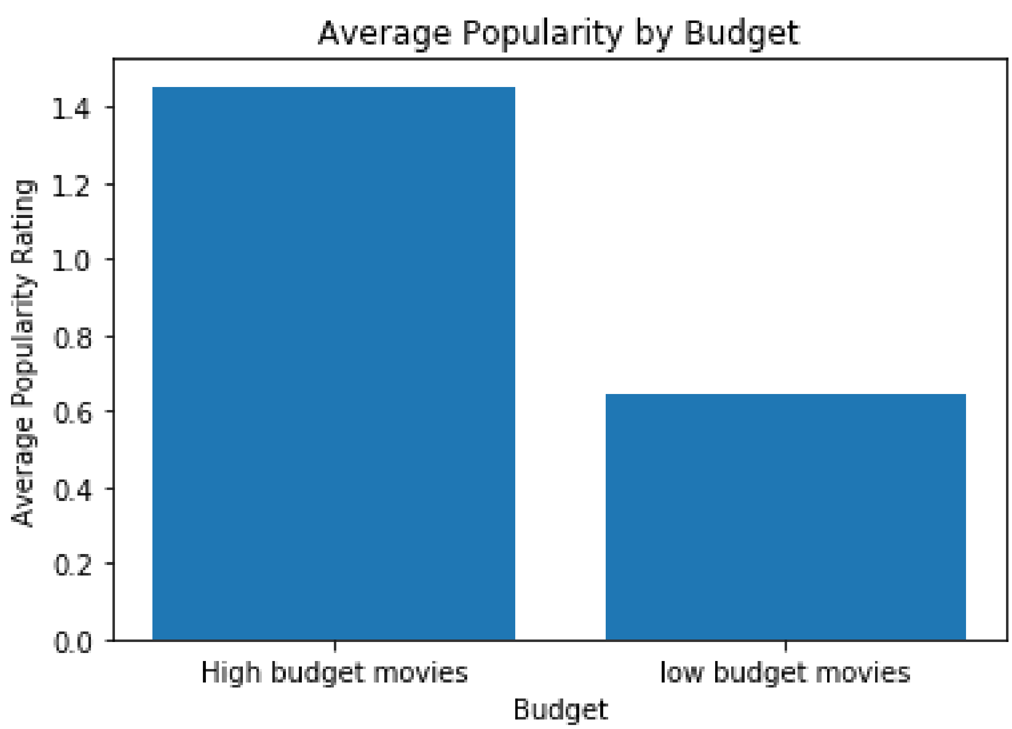
In [29]:
```
High_budget_movies=tmov_budg.query('budget >= 20000000.0') #movies with budget greater

Low_budget_movies=tmov_budg.query('budget < 20000000.0') #movies with budget less than
```

In [30]:
```
samples_count=tmov_budg.shape[0]
samples_count== High_budget_movies['budget'].count()+ Low_budget_movies['budget'].count
```

Out[30]: True

In [31]:
```
#next step is to get the mean popularity and compare for both budget groups
High_Budget=High_budget_movies.popularity.mean()
Low_Budget=Low_budget_movies.popularity.mean()
```

In [32]:
```
# Plot a bar chart to reflect mean values for both groups
locations = [1, 2]
heights = [High_Budget, Low_Budget]
labels = ['High budget movies', 'low budget movies']
plt.bar(locations, heights, tick_label=labels)
plt.title('Average Popularity by Budget')
plt.xlabel('Budget')
plt.ylabel('Average Popularity Rating');
```



1.2.5 Observation

From the above chart,we could say High budget movies are more popular, this can be attributed to higher awareness/marketing expense compared to low budget movies

1.2.6 Research Question 2 -Which genres are most popular?

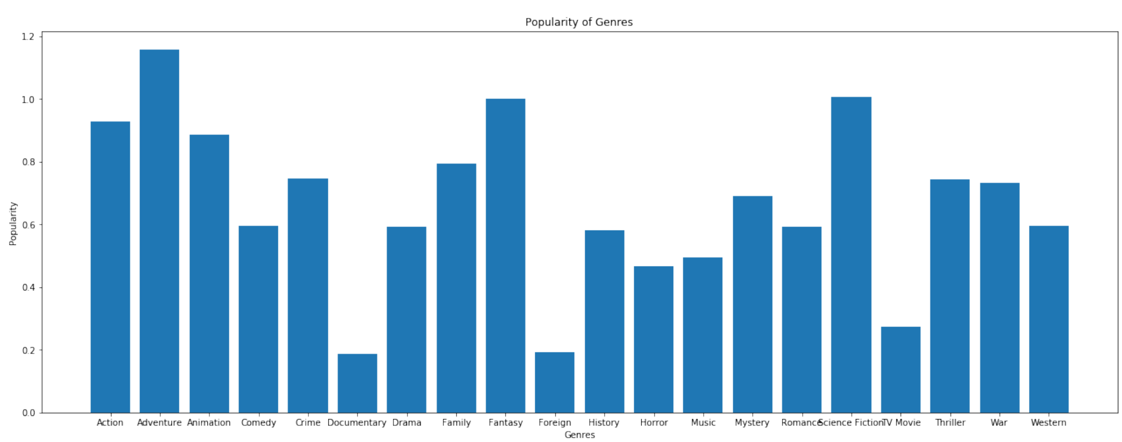
```
In [33]: # Using a copy of the original dataframe tmov_m and groupby finction()
         tmov_pop=tmov_m.copy()
         pop_gen=tmov_pop.groupby(['genres'])['popularity'].mean().reset_index()
```

```
In [34]: pop_gen.head()
```

```
Out[34]:       genres  popularity
         0     Action    0.929040
         1  Adventure    1.158480
         2  Animation    0.885913
         3     Comedy    0.594795
         4      Crime    0.745331
```

```
In [35]: pop_gen_sorted=pop_gen.sort_values('popularity')
```

```
In [36]: plt.subplots(figsize=(22,8))
         plt.bar(pop_gen_sorted['genres'],pop_gen_sorted['popularity'])
         plt.title('Popularity of Genres')
         plt.xlabel('Genres')
         plt.ylabel('Popularity');
```

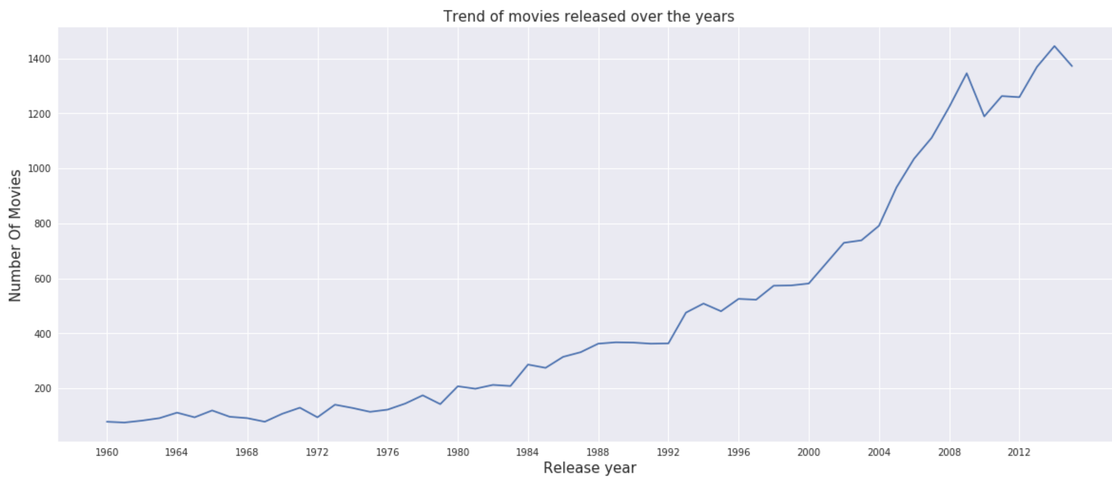


Observation: The most popular genre over the years is **Adventure**

1.2.7 Research Question 3 - Which year has the highest number of movies released ?

```
In [37]: # To answer this question, will use the groupby and count function
         rel_mov=tmov_m.groupby('release_year').count()['id']
```

```
In [39]: rel_mov.plot(xticks = np.arange(1960,2016,4))
         sns.set(rc={'figure.figsize':(20,8)})
         plt.title("Trend of movies released over the years",fontsize = 15)
         plt.xlabel('Release year',fontsize = 15)
         plt.ylabel('Number Of Movies',fontsize = 15);
```



Observation: From the plot above,we can conclude that year 2014 year has the highest release of movies (1445) followed by year 2015 (1372) and year 2013 (1369).

1.2.8 Research Question 4 - Which genre has the highest count of movies released?

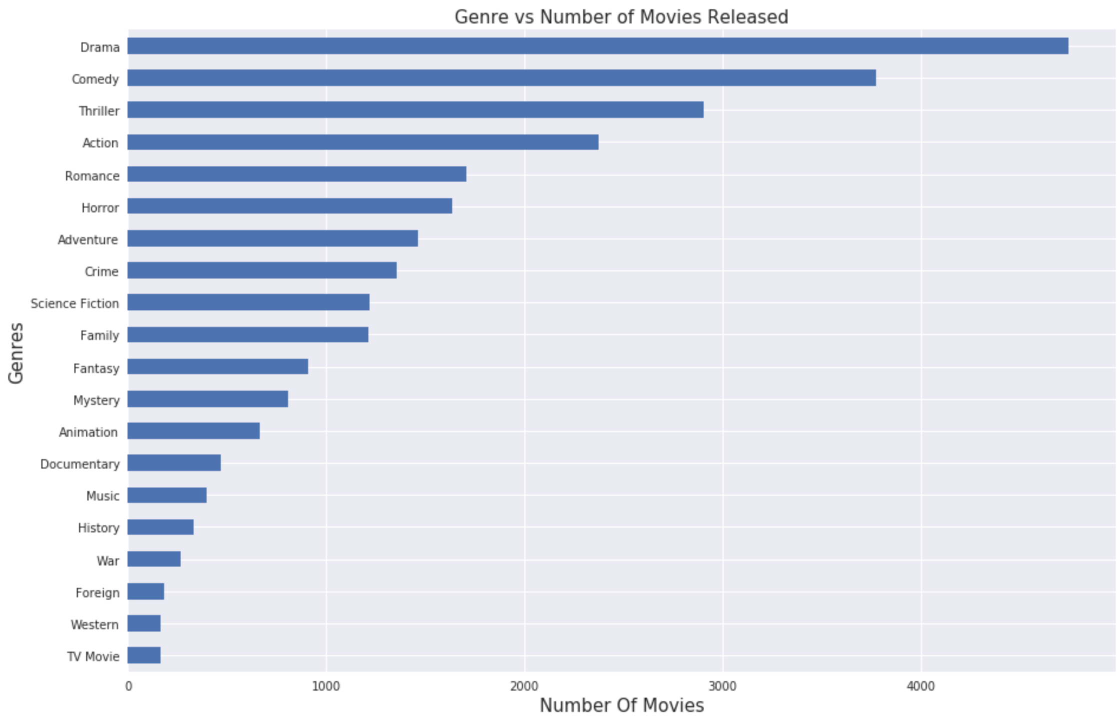
```
In [40]: # To answer this question, will use the groupby and count function
         gen_mov=tmov_m.groupby('genres').count()['id']
```

```
In [41]: gen_mov.head(10)
```

```
Out[41]: genres
         Action         2376
         Adventure      1465
         Animation       664
         Comedy         3775
         Crime          1353
         Documentary     470
         Drama          4746
         Family         1214
         Fantasy         908
         Foreign         184
         Name: id, dtype: int64
```

```
In [42]: gen_mov_sorted=gen_mov.sort_values()
```

```
In [43]: #plot a 'bar' plot using plot function for 'genre vs number of movies'.
         gen_mov_sorted.plot(kind='barh',figsize=(15,10))
         plt.title("Genre vs Number of Movies Released",fontsize=15)
         plt.xlabel('Number Of Movies',fontsize=15)
         plt.ylabel("Genres",fontsize= 15);
```



Observation: from the above bar chart, the genre with the highest number of movies released is **Action**, followed by **Comedy** and then **Thriller**

1.2.9 Research Question 5 -What features are associated with high revenue movies ?

```
In [44]: # To answer this question, i will use scatter plots
         tmov_m1=tmov_m[tmov_m['revenue']!=0]
         tmov_m2=tmov_m1[tmov_m1['budget']!=0]   # the new dataframe has no zeros in the adjusted
         tmov_m2['profit']= tmov_m2.revenue-tmov_m2.budget
         tmov_m2.corr()
```

```
/opt/conda/lib/python3.6/site-packages/ipykernel_launcher.py:4: SettingWithCopyWarning:
A value is trying to be set on a copy of a slice from a DataFrame.
Try using .loc[row_indexer,col_indexer] = value instead

See the caveats in the documentation: https://pandas.pydata.org/pandas-docs/stable/user_guide/in
  after removing the cwd from sys.path.
```

```
Out[44]:                    id  popularity    budget   revenue   runtime  vote_count  \
         id           1.000000    0.205898  0.007078  0.022228 -0.033027    0.131098
         popularity   0.205898    1.000000  0.443153  0.616056  0.209704    0.769579
         budget       0.007078    0.443153  1.000000  0.679284  0.245218    0.567217
         revenue      0.022228    0.616056  0.679284  1.000000  0.245288    0.762819
         runtime     -0.033027    0.209704  0.245218  0.245288  1.000000    0.275186
         vote_count   0.131098    0.769579  0.567217  0.762819  0.275186    1.000000
         vote_average 0.017882    0.324335  0.040128  0.245308  0.339506    0.403349
         release_year 0.475232    0.189948  0.306925  0.165425 -0.117776    0.231856
         profit       0.023975    0.596622  0.517349  0.979459  0.218653    0.733674

                      vote_average  release_year    profit
         id               0.017882      0.475232  0.023975
         popularity       0.324335      0.189948  0.596622
         budget           0.040128      0.306925  0.517349
         revenue          0.245308      0.165425  0.979459
         runtime          0.339506     -0.117776  0.218653
         vote_count       0.403349      0.231856  0.733674
         vote_average     1.000000     -0.124584  0.275029
         release_year    -0.124584      1.000000  0.108570
         profit           0.275029      0.108570  1.000000
```

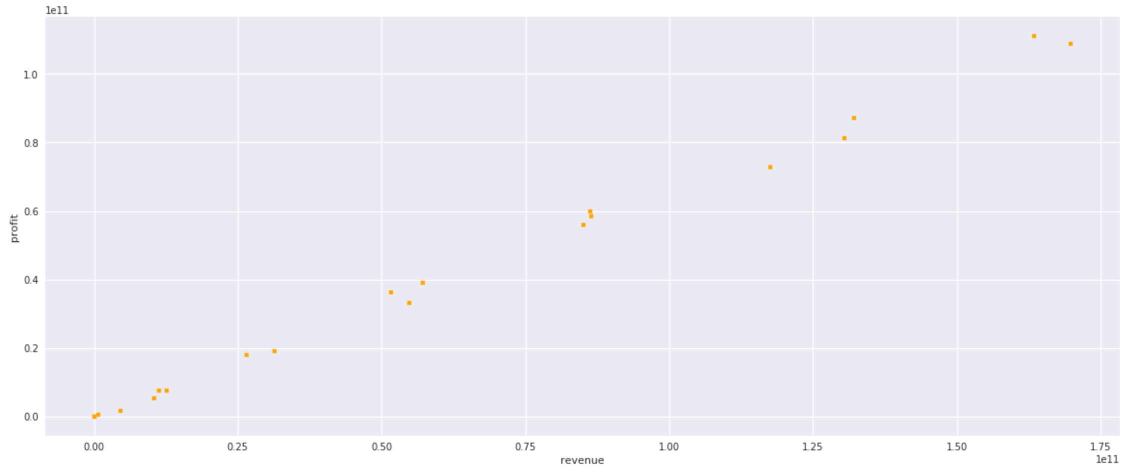
```
In [45]: #group the genre
         tmov_m2=tmov_m2.groupby('genres',as_index=False).agg({'budget':'sum','revenue':'sum','p
```

```
In [46]: tmov_m2= tmov_m2.sort_values(by='revenue',ascending=False)
         tmov_m2
```

```
Out[46]:              genres       budget       revenue        profit  popularity
         0            Action  61237880460  169886215114  108648334654    1.567116
         1         Adventure  52384245998  163500596287  111116350289    1.867693
         3            Comedy  44957919603  132172056333   87214136730    1.012958
         6             Drama  49250304629  130507076351   81256771722    1.002834
         17         Thriller  44899698604  117679503931   72779805327    1.259835
         8           Fantasy  28004091035   86420717216   58416626181    1.754315
         7            Family  26553641134   86340257365   59786616231    1.459043
         15  Science Fiction  29057157068   85081292714   56024135646    1.873294
         14          Romance  18188468254   57182921352   38994453098    0.956101
         4             Crime  21506267460   54777153159   33270885699    1.123961
         2         Animation  15464231010   51681421541   36217190531    1.710622
         13          Mystery  12061923123   31319746667   19257823544    1.142613
         11           Horror   8596200752   26524253059   17928052307    0.854005
         18              War   5028445000   12617816329    7589371329    1.246129
         12            Music   3500860040   11242189360    7741329320    0.909718
         10          History   5250972856   10501275508    5250302652    0.970674
         19          Western   2747414033    4545471891    1798057858    1.134246
         5       Documentary    161848148     754345448     592497300    0.316224
         9           Foreign    118418692     133507449      15088757    0.182271
         16         TV Movie      5000000      42000000      37000000    0.273628
```

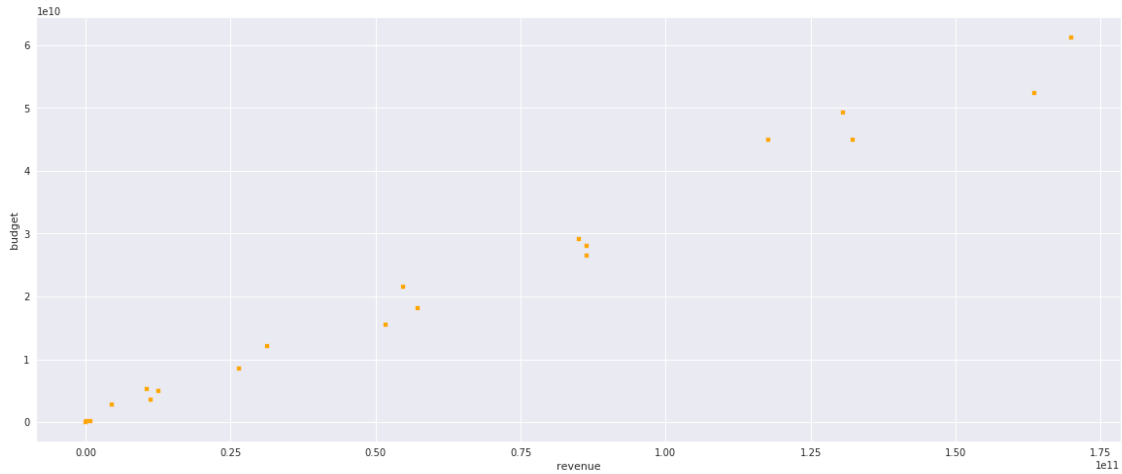
```
In [47]: def scatter_plot(arg1,arg2):
             tmov_m2.plot(x=arg1,y=arg2,kind='scatter',color="orange",marker='s');



         scatter_plot('revenue','profit')
         print("Strong Positive Correlation")
```

```
Strong Positive Correlation
```



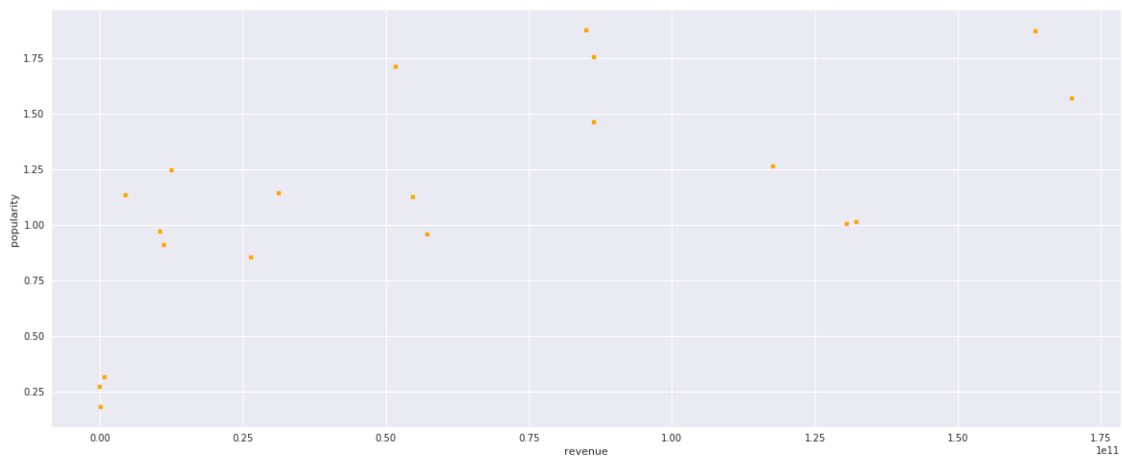

```
In [48]: scatter_plot('revenue','budget')
         print("Strong Positive Correlation")
```

```
Strong Positive Correlation
```



```
In [49]: scatter_plot('revenue','popularity')
         print("No Correlation")
```

```
No Correlation
```



Conclusions From the above EDA, The following are the answers to the question in the introduction section 1. Movies with higher budget tends to have better popularity 2. The 3 most popular genres are Adventure,science fiction and fantasy 3. The year 2014 year has the highest release of movies (1445) followed by year 2015 (1372) and year 2013 (1369). 4. The genre with the highest number of movies released is Action, followed by Comedy and then Thriller 5. The scatter plots indicates the movies with higher revenues are associated with higher budget and high profits

1.3 Limitations of the dataset:

1. Many columns had missing data
2. The budget and revenue columns had 50% rows with zero values as input
3. Each movie had multiple genres,movie genre classification being based on the main genre would have provided a better analysis.

1.4 References

- online documentations of pandas,matplotlib,seaborn
- Stackoverflow discussion platform
- Youtube video on markdown links

1.5 Submitting your Project

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

```
In [ ]:
```