TMDb-Movies Dataset Investigation

By: Jeremiah Tindana

Table of Contents

- Introduction
- Data Wrangling
- Exploratory Data Analysis
- Conclusions

Introduction

Dataset Description

This project the details the cleaning, exploration and deduction of a data set from **The Movie Database(Tmdb)**.The data set holds the data concerning 10,000 different movies, along with their user ratings and revenue generated from said movies. The data set is characterized by 21 columns, each holding data on varying characteristics of each movie. The movie title, starring cast, movie director,revenue, runtime, release date and release year are captured.

Per the data set, each movie has its unique ID captured in the **'id'** columns, and an ID from imdb captured in the **'imdb_id'** column.

The **'popularity'** column describes the popularity rating of the movies.

The **'budget'** column captures values equivalent to the monetary value of the resources spent in the creation of the movies. This feature could analysed to ascertain a relationship between the success of a movie and the movie budget.

The **'tagline'**, **'keywords'** and **'overview'** columns contain brief descriptions of the movie. The tagline captures a single catch phrase that best describes the movie, while the overview contains a paragraph of summary of the movie. **'keywords'** hold a list of words that describe dominant features in the movies. Keywords can be used to describe the genre of each movie. For example, a movie about a monster ravaging a city could have a keyword, 'monster'.

'runtime' holds numeric values equivalent to the length of each movie in minutes. This feature could play an interesting role in the success of a movie. Do movies with shorter runtimes have higher ratings?

'genres' holds a set of genres that the movie falls in. This column is simialar in structure to the **'keywords'** column.

'production_companies' holds details on the names of the production companies that cooperated to produce the movie.

'release_date' and **'release_year'** hold the dates of release and year of release of each movie.

Movie patronizers were asked to rate the movies. **'vote_count'** holds the number of patronizers who cast votes. They were asked to rate the movies with scores from 1 to 10, where 10 is the highest score, and 1 is the least score. **'vote_average'** holds the mean rating of each movie.

The final two columns **'budget_adj'** and **'revenue_adj'** show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.

Question(s) for Analysis

The data set in this case study has the prospects to answer a plethora of questions. In this investigation however, we will be limiting ourselves to 3 questions built upon 2 dependent (**popularity** and **revenue**) variables and 3 independent variables (**budget, runtime, and genre**). **Questions**:

1. What is the relationship between the budget of a particular movie and its popularity?
2. How does the popularity of a movie affect its revenue?
3. Have more movies been made over the years? Do older movies have higher equivalent revenue than newer ones?

In [1]:
```
# To begin, we import are necessary functions, i.e., pandas, numpy, and matplotlib.
# We include the matplotlib inline to ensure that our graphs appear in our notebook workspace

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

In [2]:
```
# Upgrade pandas to use dataframe.explode() function.
!pip install --upgrade pandas==0.25.0
```

```
Requirement already up-to-date: pandas==0.25.0 in /opt/conda/lib/python3.6/site-packages (0.25.0)
Requirement already satisfied, skipping upgrade: numpy>=1.13.3 in /opt/conda/lib/python3.6/site-packages (from pandas==0.25.0) (1.19.5)
Requirement already satisfied, skipping upgrade: python-dateutil>=2.6.1 in /opt/conda/lib/python3.6/site-packages (from pandas==0.25.0) (2.6.1)
Requirement already satisfied, skipping upgrade: pytz>=2017.2 in /opt/conda/lib/python3.6/site-packages (from pandas==0.25.0) (2017.3)
Requirement already satisfied, skipping upgrade: six>=1.5 in /opt/conda/lib/python3.6/site-packages (from python-dateutil>=2.6.1->pandas==0.25.0) (1.11.0)
```

Data Wrangling

In this section, we will take a look at our data and prepare it for analysis. We will scan through the data, carry out some data cleaning where necessary, and trim our data to suit the objectives of this work.

In [3]:
```
# # Here, we load our data into this notebook and perform operations to inspect the data.
# We shall acheive this by printing out a few lines of the data and performing a few
# exploratory operations.
df = pd.read_csv('tmdb-movies.csv')
```

In [4]:
```
df.head()
```

Out[4]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagli
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 ope
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	Wha Love Da
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley|Theo James|Kate Winslet|Ansel...	http://www.thedivergentseries.movie/#insurgent	Robert Schwentke	O Choi C Destr Y
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...	http://www.starwars.com/films/star-wars-episod...	J.J. Abrams	Eve generati has sto
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	http://www.furious7.com/	James Wan	Vengean Hits Hor

5 rows × 21 columns

In [5]:
```
# Let us inspect the data set
df.shape
```

Out[5]:(10866, 21)

With the **df.shape** command, we see the shape of the data frame. The tuple generated from this command shows us the number of rows and columns of our data set. This data set has 10866 rows and 21 columns, indicating that there are, or should be 10866 entries.

In [6]:
```
# Let us take a dive into certain statistics about our data
df.describe()
```

Out[6]:

	id	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	budget_adj	revenue_adj
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10866.000000	10866.000000	1.086600e+04	1.086600e+04
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	5.974922	2001.322658	1.755104e+07	5.136436e+07
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	0.935142	12.812941	3.430616e+07	1.446325e+08
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	1.500000	1960.000000	0.000000e+00	0.000000e+00
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	5.400000	1995.000000	0.000000e+00	0.000000e+00
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	6.000000	2006.000000	0.000000e+00	0.000000e+00
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	6.600000	2011.000000	2.085325e+07	3.369710e+07
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

df.describe() presents some statistics about our data. We see our mean, minimum and maximum values. **Popularity:** About 71%, 38%, and 21% of our entries are in the 75th, 50th, and 25th popularity percentile of our data. **Budget:** The maximum budget amount for the movies in our data set is 425 Million, and the minimum budget is 0. The average budget is 146.257 Million. **Revenue:** The maximum revenue generated from any movie in our data set is about 2.78 Billion while the minimum is 0. The average revenue is about 40 Million. **Runtime:** The average runtime for the movies in our data set is about 102 minutes. The longest and shortest movies have 900 minutes and 0 minutes respectively.

In [7]:
```
# Let us check for missing entries in our data frame
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
```

We see that from the results that certain features have missing data. **imdb_id**, **cast**, **homepage**, **director**, **tagline**, **keywords,** overview**,** genres**, and** production companies** have missing entries.

Data Cleaning

> We can see from the printout from **df.info()** that all data types appear to be in order, except for the **'release_date'** which should prefereably be in datetime form. However, the **'release_date'** column in this data is not a key feature as per the objectives of this exercise. For this reason only, we can either ignore or drop this column. All other columns that will play no important role in our analysis can be dropped as well to trim the data, leaving only the necessary features. After dropping the unnecessary columns, the next step will be to handle the null data.

In [8]:
```python
# Let's take a look at our data again to trim the rows we do not need.
df.head(0)
```

Out[8]:

id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline	...	overview	runtime	genres	production_companies	rele

0 rows × 21 columns

In [9]:
```python
# We can delete the cast, homepage, director, tagline, overview, production companies and release date columns
# We acheive this with pandas' drop() function.
df.drop(['cast','homepage','director','tagline','overview','production_companies','release_date'],axis=1, inplace=True)
```

In [10]:
```python
# Let's confirm the changes
df.head()
```

Out[10]:

	id	imdb_id	popularity	budget	revenue	original_title	keywords	runtime	genres	vote_cour
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	monster|dna|tyrannosaurus rex|velociraptor|island	124	Action|Adventure|Science Fiction|Thriller	556
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	future|chase|post-apocalyptic|dystopia|australia	120	Action|Adventure|Science Fiction|Thriller	618
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	based on novel|revolution|dystopia|sequel|dyst...	119	Adventure|Science Fiction|Thriller	248
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	android|spaceship|jedi|space opera|3d	136	Action|Adventure|Science Fiction|Fantasy	529
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	car race|speed|revenge|suspense|car	137	Action|Crime|Thriller	294

In [11]:
```python
# Oops! Let's drop the keyword column too. Also, we will not be using the 'budget_adj' column for our analysis
df.drop(['keywords','budget_adj'],axis=1, inplace=True)
```

In [12]:
```python
# confirm changes. We can print only the headers
df.head(0)
```

Out[12]:

id	imdb_id	popularity	budget	revenue	original_title	runtime	genres	vote_count	vote_average	release_year	revenue_adj

In [13]:
```python
# Take a look at the new shape of the dataframe
df.shape
```

Out[13]:(10866, 12)

Now that our data frame is neatly trimmed, we have our number of columns reduced from 21 to 11. Next, let's handle null or missing data.

In [14]:
```python
# Take a look at the rows with missing data
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 12 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
runtime         10866 non-null int64
genres          10843 non-null object
vote_count      10866 non-null int64
vote_average    10866 non-null float64
release_year    10866 non-null int64
revenue_adj     10866 non-null float64
dtypes: float64(3), int64(6), object(3)
memory usage: 1018.8+ KB
```

Only 2 features have missing values, i.e., 'imdb_id' and 'genres'. Since the **imdb_id** values are unique values assigned to each movie, replacing null values with the mean will not be of any benefit. The plausible option here would be to drop those rows. We do same for the **genres** column.

In [15]:
```
# Drop null rows using pandas' dropna. Confirm for changes
df.dropna(inplace=True)
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10835 entries, 0 to 10865
Data columns (total 12 columns):
id              10835 non-null int64
imdb_id         10835 non-null object
popularity      10835 non-null float64
budget          10835 non-null int64
revenue         10835 non-null int64
original_title  10835 non-null object
runtime         10835 non-null int64
genres          10835 non-null object
vote_count      10835 non-null int64
vote_average    10835 non-null float64
release_year    10835 non-null int64
revenue_adj     10835 non-null float64
dtypes: float64(3), int64(6), object(3)
memory usage: 1.1+ MB
```

In [16]:
```
df.head()
```

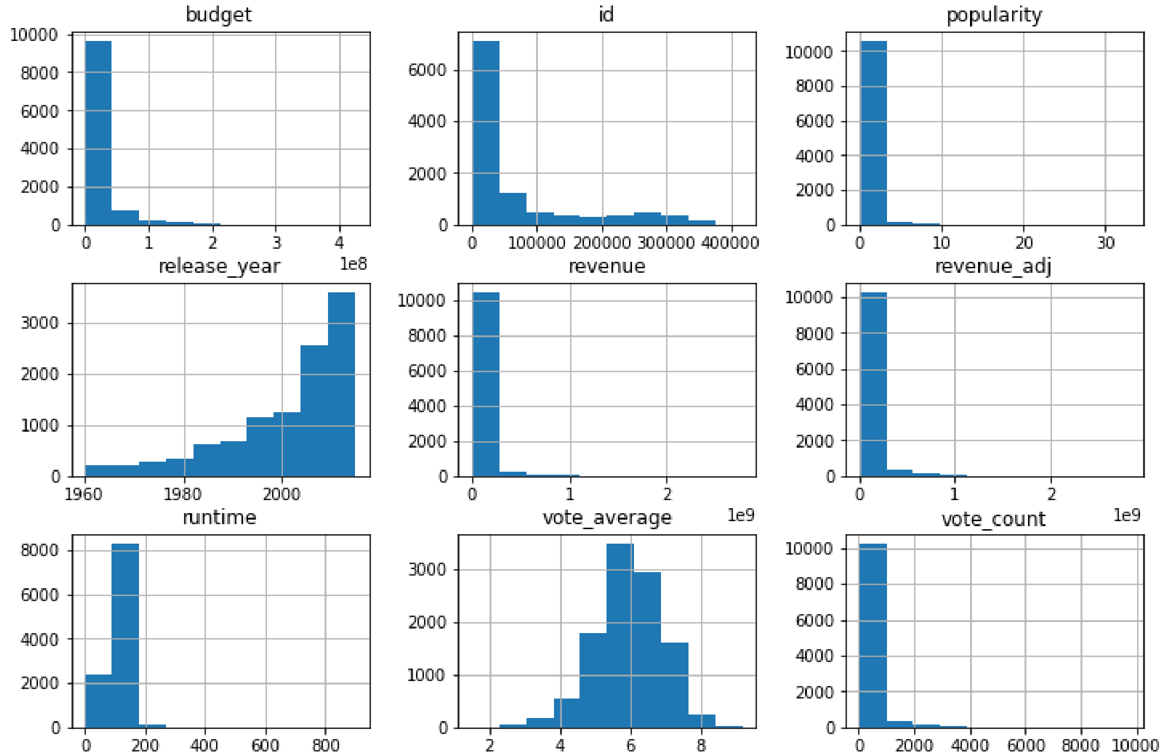
Out[16]:

	id	imdb_id	popularity	budget	revenue	original_title	runtime	genres	vote_count	vote_average	release_year	rev
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	124	Action|Adventure|Science Fiction|Thriller	5562	6.5	2015	1.39
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	120	Action|Adventure|Science Fiction|Thriller	6185	7.1	2015	3.48
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	119	Adventure|Science Fiction|Thriller	2480	6.3	2015	2.71
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	136	Action|Adventure|Science Fiction|Fantasy	5292	7.5	2015	1.90
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	137	Action|Crime|Thriller	2947	7.3	2015	1.38

Our data seems to be in pretty good shape. Now, we can delve into our Exploratory Data Analysis. But before that, let's plot some graphical representations of our data just to have an overview of the current state.

In [17]:
```
# We'll plot histograms to study our distributions
df.hist(figsize =(12,8))
```

```
Out[17]:array([[<matplotlib.axes._subplots.AxesSubplot object at 0x7f10d892d5f8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f10d891de48>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f10d88d8dd8>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f10d88c2390>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f10d884f0b8>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f10d884f0f0>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x7f10d87bf128>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f10d8777208>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x7f10d87a1908>]],
      dtype=object)
```



Interpreting the Graphs

The graph give us some comfort that our analysis have so far been on the right path. Our graphs make a lot of sense, and we see no severe deviations or abnormalities. Most of our graphs are skewed. The greater part of the movie budgets are less than 1 billion. The popularity of most of the movies is between 0 and 10. The graph for the release year is skewed to the left, indicating that most of the movies were release after the year 2000, and a number of them between 1960 and 2000. The graph of revenues is very skewed to the right. Almost all our movies have revenues less than 500 Million. Only a few movies have runtimes above 200 minutes.

Exploratory Data Analysis

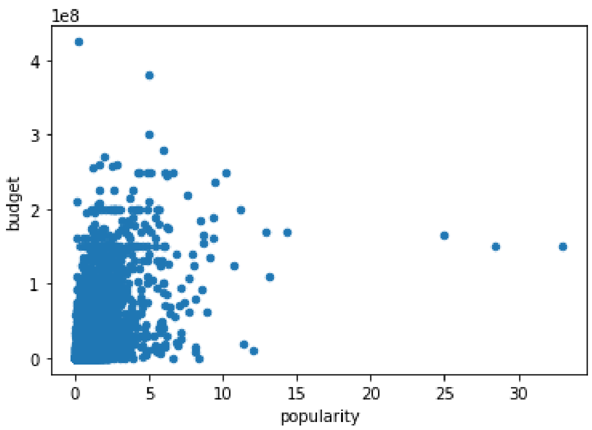
1. What is the relationship between the budget of a particular movie and its popularity?

Dependent Variable - Popularity

First of all let us plot a scatter graph of **budget** and **popularity** to check for correlation. Since we will performing this task a number of times in our analysis, we need to make this task less cumbersome. We will acheive this by creating a function.

In [18]:
```python
# Create a function to plot scatter graphs
def scatter_graph(arg):
    df.plot(x='popularity',y=arg,kind='scatter')

scatter_graph('budget')
```



Our scatter shows a level of positive correlation between budget and popularity. We can explore this relationship even further.

In [19]:
```python
# Let's take a look at our dependent variable
```

```
df.popularity.max(), df.popularity.median(), df.popularity.min()
```

Out[19]:(32.985763, 0.38461799999999996, 6.500000000000001e-05)

Our maximum, median and minimum popularity are as shown above. Let's look at our median popularity.

In [20]:
```
median = df.popularity.median()
median
```

Out[20]:0.38461799999999996

Let's see how many movies had popularity above the median popularity

In [21]:
```
popular = df.query('popularity>{}'.format(median))
unpopular = df.query('popularity<{}'.format(median))
```

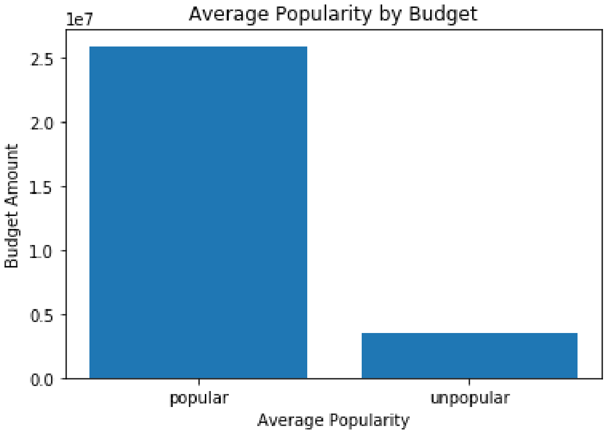
In [22]:
```
# Let's find the mean for each group in relation to budget
mean_popular = popular['budget'].mean()
mean_unpopular = unpopular['budget'].mean()
mean_popular, mean_unpopular
```

Out[22]:(25892745.875392284, 3443115.780321211)

Now that we have our means, let us create a bar chart to visualize the relationships in our data.

In [23]:
```
# Creating a bar chart
locations = [1,2]
heights = [mean_popular, mean_unpopular]
labels = ['popular','unpopular']
plt.bar(locations,heights,tick_label=labels)
plt.title('Average Popularity by Budget')
plt.xlabel('Average Popularity')
plt.ylabel('Budget Amount')
```

Out[23]:Text(0,0.5,'Budget Amount')

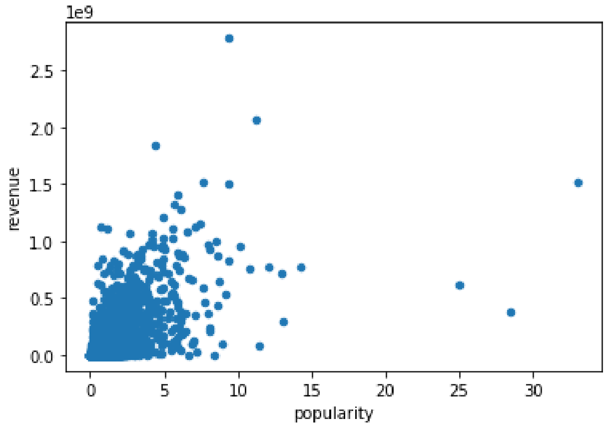


The bar chart provides more conclusive and substantial results. The most popular movies appear to have higher budget amounts that the unpopular movies. The budget of the movies whose mean popularity are above the median are greater than those whose popularity are below the median.

2. How does the popularity of a movie affect its revenue?

Like before, we shall begin by checking for correlation using a scatter plot

In [24]:
```
# Creating a scatter plot of revenue and popularity
scatter_graph('revenue')
```



It would make sense to assume that the most popular movies would have higher revenues. However, let's not be quick to assume. The scatter graph shows some positive correlation. We can go further to get more ascertive results.

In [25]:
```
# Take a look at some descriptive statistics of our revenue data
df.revenue.describe()
```

```
Out[25]:count    1.083500e+04
        mean     3.993726e+07
        std      1.171513e+08
        min      0.000000e+00
        25%      0.000000e+00
        50%      0.000000e+00
        75%      2.417286e+07
        max      2.781506e+09
        Name: revenue, dtype: float64
```

The mean revenue is 39937260 (about 40 Million)

```
In [26]: mean_rev = df.revenue.mean()
```

We can go ahead to divide the revenue set into different levels. We can create a new column called **revenue_level** and place in there the level of revenue generated, either **'high'** or **'low'**. The low and high categories will created with regards to the mean.

```
In [27]: # We use a for loop to create our new column in the data frame
         revenue_level = []
         for value in df['revenue']:
             if value >= mean_rev:
                 revenue_level.append('high')
             else:
                 revenue_level.append('low')

         df['revenue_level'] = revenue_level

         # We need to check if our changes have taken effect
         df.revenue_level
```

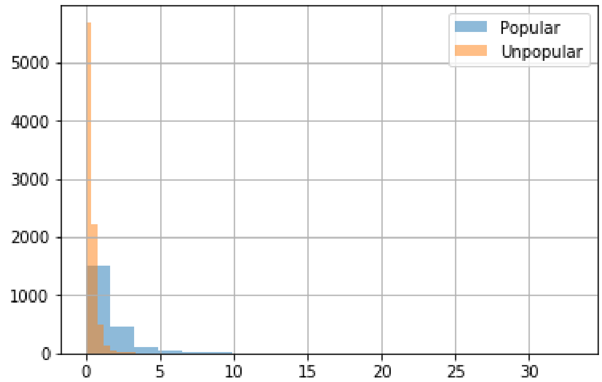
```
Out[27]:0        high
        1        high
        2        high
        3        high
        4        high
                 ...
        10861    low
        10862    low
        10863    low
        10864    low
        10865    low
        Name: revenue_level, Length: 10835, dtype: object
```

Since our changes have taken effect, we can proceed.

```
In [28]: # Let's proceed to fish out our two groups
         high_rev = df[df['revenue'] >=mean_rev]
         low_rev = df[df['revenue'] <mean_rev]
```

```
In [29]: high_rev['popularity'].hist(alpha=0.5,bins=20,label='Popular')
         low_rev['popularity'].hist(alpha=0.5,bins=20,label='Unpopular')
         plt.legend()
```

```
Out[29]:<matplotlib.legend.Legend at 0x7f10d7700a58>
```



Look at that! Our data does not agree with the initial assumption! Looking at our double plot, we can see that on the average, per our data set, the unpopular movies seem to have a higher average revenue that the popular ones. That is surprising isn't it? Well it can be explained. In the two new data sets we created, **high_rev** and **low_rev**, we see that our criteria for splitting the data wasn't the most appropriate. That is because our data is skewed, and most of the entries in the data set are on the low side. This would mean that even if the popular ones have higher revenues, the overwhelming number of unpopular ones would cause inaccurate results. A solution to this would be to create more than 2 groups, to ensure that the data is split somewhat evenly.

3. Have more movies been made over the years? Do older movies have higher equivalent revenue than newer ones?

With this question, we want to compare the years in our movie data by checking their revenues. We must take note however that the value of money changes from year to year. Luckily we have the revenue_adj column which is the monetary equivalent in 2010 for all the years.

```
In [30]: # Let's view our data again
         df.head(2)
```

Out[30]:

	id	imdb_id	popularity	budget	revenue	original_title	runtime	genres	vote_count	vote_average	release_year	rev
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	124	Action|Adventure|Science Fiction|Thriller	5562	6.5	2015	1.39
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	120	Action|Adventure|Science Fiction|Thriller	6185	7.1	2015	3.48

In [31]:
```
# Let's explore our release_year column
df.release_year.describe()
```

Out[31]:
```
count    10835.000000
mean      2001.308999
std         12.815519
min       1960.000000
25%       1995.000000
50%       2006.000000
75%       2011.000000
max       2015.000000
Name: release_year, dtype: float64
```

So the least year of release captured in our data is 1960, and the latest year is 2015. Let's look at the unique years in our data set.

In [32]:
```
# we will use the unique function
df['release_year'].nunique()
```

Out[32]:56

To break the data down into years, we can look at the amount of data in each year. We will use the value_counts() function

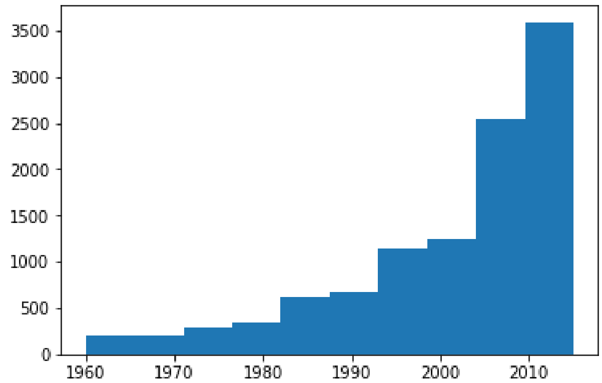
In [33]:
```
df['release_year'].value_counts()
```

```
Out[33]:2014    699
        2013    655
        2015    626
        2012    583
        2011    540
        2009    529
        2008    495
        2010    487
        2007    436
        2006    408
        2005    363
        2004    307
        2003    281
        2002    266
        2001    241
        2000    226
        1999    224
        1998    210
        1996    203
        1997    192
        1994    184
        1993    178
        1995    174
        1988    145
        1989    136
        1992    133
        1991    133
        1990    132
        1987    125
        1986    121
        1985    109
        1984    105
        1981     82
        1982     81
        1983     80
        1980     78
        1978     65
        1979     57
        1977     57
        1971     55
        1973     55
        1976     47
        1974     46
        1966     46
        1975     44
        1964     42
        1970     40
        1967     40
        1972     40
        1968     39
        1965     35
        1963     34
        1962     32
        1960     32
        1969     31
        1961     31
        Name: release_year, dtype: int64
```

Here, we can see that the movies across the years from 1961 forward keep increasing. Let's plot a histogram to visualize this trend.

In [34]:
```
plt.hist(df['release_year'])
```

```
Out[34]:(array([ 206.,  196.,  287.,  339.,  621.,  679., 1141., 1238., 2538.,
            3590.]),
         array([1960. , 1965.5, 1971. , 1976.5, 1982. , 1987.5, 1993. , 1998.5,
            2004. , 2009.5, 2015. ]),
         <a list of 10 Patch objects>)
```



Skewed data! Our graph of release years is skewed to the left. This proves that as the years went by, more and more movies were produced. The movie industry has grown largely over the decades. But by how much?

In [35]:
```
# Find the percentage increase between 1961 and 2014. Select data from release year value counts
mov_1961 = 31
mov_2014 = 699
perc_inc = (mov_2014 / mov_1961) * 100
perc_inc
```

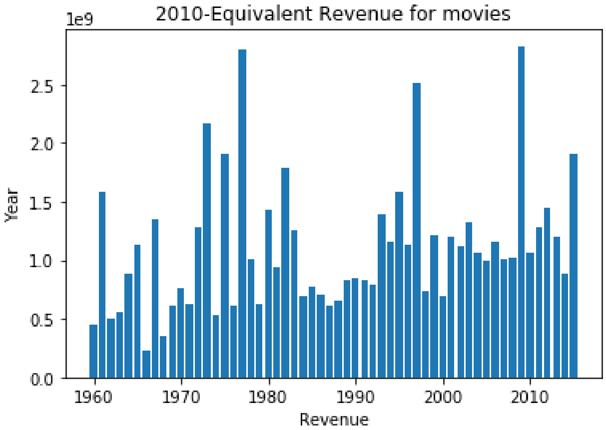
Out[35]:2254.838709677419

The movie industry has grown by over 2000%!

Now let's take a look at the relationship between revenue_adj and the movies across the years

In [36]:
```
plt.bar(df['release_year'],df['revenue_adj'])
plt.title('2010-Equivalent Revenue for movies')
plt.xlabel('Revenue')
plt.ylabel('Year')
```

Out[36]:Text(0,0.5,'Year')



No conclusive results can be drawn from the graph. Converting all revenue values from all years to equivalent values of money, each year had its revenue independent. The revenue generated from movies depends on some other factors, but not the year.

Conclusions

1. What is the relationship between the budget of a particular movie and its popularity?

   Movies with higher budgets tend to end up with more popularity than those with low budgets.

2. How does the popularity of a movie affect its revenue?

   The group of unpopular movies seem to have a higher average revenue that the popular ones.

3. Have more movies been made over the years? Do older movies have higher equivalent revenue than newer ones?

   The movie industry has grown by over 2000%! Older movies did not appear to have more or less equivalent revenue than the new ones.

   ## Limitations

4. In the two new data sets created in the second analysis, high_rev and low_rev, we see that our criteria for splitting the data wasn't the most appropriate. That is because our data is skewed, and most of the entries in the data set are on the low side. This would mean that even if the popular ones have higher revenues, the overwhelming number of unpopular ones would cause inaccurate results. A solution to this would be to create more than 2 groups, to ensure that the data is split almost evenly.

5. The same can be said about the popular and unpopular data sets in the first analysis.

In [38]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

Out[38]:0

In [ ]: