TMDB Movie Analysis - P1

August 18, 2022

1 Project: Investigate a Dataset - [TMDB Movie Analysis]

1.1 Table of Contents

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2.1 Introduction

2.1.1 Dataset Description

This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue. Column names include; - id - a unique code for identifying every row in the dataset. - tmdb_id - a unique code for identifying the movies on the imdb platform - popularity - popularity of the movies in number - budget - overall amount spent on the movie - revenue - overall amount received after the release of the movie - original_title - original title of the movie - cast - actors and actresses featured in the movie - homepage - homepage of the movie website - director - individual who directed the movie - tagline - the advertising slogan - keywords - unique words that describe the movie - overview - a brief summary of the movie - runtime - time from which the movie run from start to finish - genres - movie classification - production_companies - company that made the production of the movie - release_date - date the movie was released - vote_count - the amount of people that voted for the movie - vote_average - the average amount of vote per movie ou of ten - release_year - the year the movie was released - budget_adj - the amount of money spent for the budget in terms of 2010 dollars(inflation) - revenue_adj - the amount of money received for the revenue in terms of 2010 dollars(inflation).

2.1.2 Question(s) for Analysis

- what is the relationship between the vote count and the runtime
- what is the relationship between the popularity and the runtime
- what is the relationship between the popularity and the votecount

In [1]:
```
# importing the modules to be used for the analysis of this data
import pandas as pd
```

```
import matplotlib.pyplot as plt
import seaborn as sns
%matplotlib inline
```

Data Wrangling

```
In [2]: # Loading my dataset
        movies = pd.read_csv('tmdb-movies.csv')
        movies.head()
```

```
Out[2]:        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 [3]:
```
#Checking the shape of the datasets
movies.shape
```

Out[3]:
```
(10866, 21)
```

In [4]:
```
movies.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 information shown above, it is shown that there are missing information in the datasets, some of which will not be useful in this particular analysis. Also the release year is supposed to be in datetime, so it has to be changed.

```
In [5]: #Changing the release year from 'int' to 'date_time'
        movies['release_year'] = pd.to_datetime(movies['release_year'])
```

```
In [6]: # Checking to see if the change has been made
        movies.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 datetime64[ns]
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: datetime64[ns](1), float64(4), int64(5), object(11)
```

```
memory usage: 1.7+ MB
```

```
In [7]: #Using the describe function to check for the overall mean and percentiles of each colum
        movies.describe()
```

```
Out[7]:                 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    budget_adj   revenue_adj
        count  10866.000000  10866.000000  1.086600e+04  1.086600e+04
        mean     217.389748      5.974922  1.755104e+07  5.136436e+07
        std      575.619058      0.935142  3.430616e+07  1.446325e+08
        min       10.000000      1.500000  0.000000e+00  0.000000e+00
        25%       17.000000      5.400000  0.000000e+00  0.000000e+00
        50%       38.000000      6.000000  0.000000e+00  0.000000e+00
        75%      145.750000      6.600000  2.085325e+07  3.369710e+07
        max     9767.000000      9.200000  4.250000e+08  2.827124e+09
```

```
In [8]: #Checking for duplicated values
        sum(movies.duplicated())
```

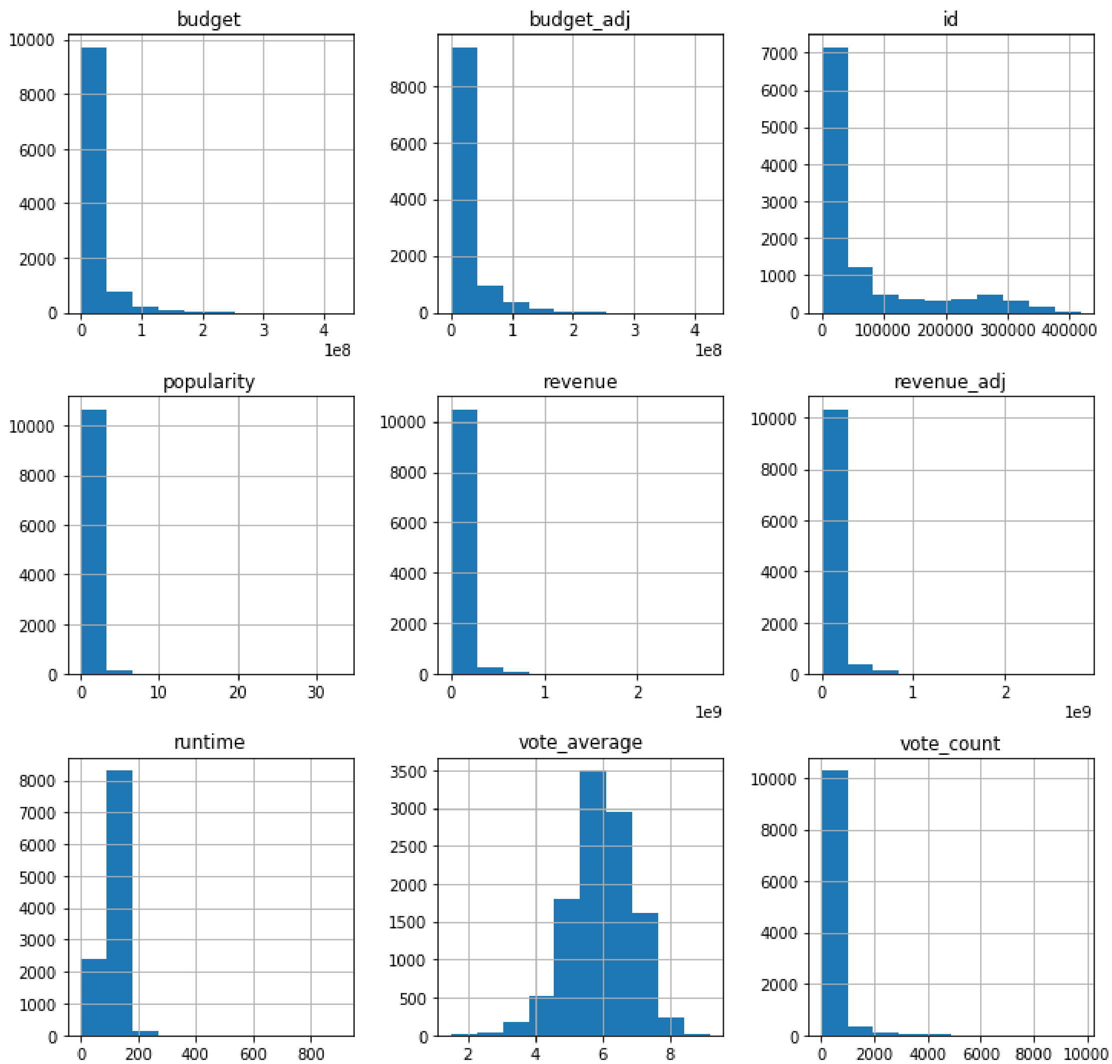
```
Out[8]: 1
```

```
In [9]: #Dropping the duplicated values
        movies.drop_duplicates(inplace=True)
```

```
In [10]: #Confirmation to check if duplicated values have been dropped
         sum(movies.duplicated())
```

```
Out[10]: 0
```

```
In [11]: #Checking the distribution for each column on the dataset
         movies.hist(figsize=(12,12));
```



2.1.3 Data Cleaning

```
In [12]: #Dropping some columns which will not be used in this analysis
         movies.drop(['id', 'imdb_id', 'homepage', 'tagline', 'keywords', 'overview', 'release_d
```

```
In [13]: #Checking for the new structure of the data after dropping some columns
         movies.head()
```

```
Out[13]:    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                                      genres  \
0      124  Action|Adventure|Science Fiction|Thriller
1      120  Action|Adventure|Science Fiction|Thriller
2      119         Adventure|Science Fiction|Thriller
3      136   Action|Adventure|Science Fiction|Fantasy
4      137                      Action|Crime|Thriller

                               production_companies  vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...        5562
1  Village Roadshow Pictures|Kennedy Miller Produ...        6185
2  Summit Entertainment|Mandeville Films|Red Wago...        2480
3          Lucasfilm|Truenorth Productions|Bad Robot        5292
4  Universal Pictures|Original Film|Media Rights ...        2947

   vote_average                  release_year
0           6.5 1970-01-01 00:00:00.000002015
1           7.1 1970-01-01 00:00:00.000002015
2           6.3 1970-01-01 00:00:00.000002015
3           7.5 1970-01-01 00:00:00.000002015
4           7.3 1970-01-01 00:00:00.000002015
```

In [14]:
```python
# Checking the description of the datasets after dropping some columns
movies.describe()
```

Out[14]:
```
         popularity        budget       revenue       runtime    vote_count  \
count  10865.000000  1.086500e+04  1.086500e+04  10865.000000  10865.000000
mean       0.646446  1.462429e+07  3.982690e+07    102.071790    217.399632
std        1.000231  3.091428e+07  1.170083e+08     31.382701    575.644627
min        0.000065  0.000000e+00  0.000000e+00      0.000000     10.000000
25%        0.207575  0.000000e+00  0.000000e+00     90.000000     17.000000
50%        0.383831  0.000000e+00  0.000000e+00     99.000000     38.000000
75%        0.713857  1.500000e+07  2.400000e+07    111.000000    146.000000
max       32.985763  4.250000e+08  2.781506e+09    900.000000   9767.000000

       vote_average
count  10865.000000
mean       5.975012
std        0.935138
min        1.500000
25%        5.400000
50%        6.000000
```

```
75%          6.600000
max          9.200000
```

From the table above, it is shown that there are many null values in the budget, revenue and runtime columns. The budget and revenue columns can be dropped since they wouldn't be used in this analysis while the null values in the runtime column can be replaced with its mean

```
In [15]: # Dropping the budget and revenue columns
         movies.drop(['budget', 'revenue'], axis = 1, inplace = True)
```

```
In [16]: # Replacing the zero values with the mean
         movies.replace(0,movies.mean(axis=0),inplace=True)
```

The above code was gotten from stackoverflow.

```
In [17]: # Checking to see the decription of the dataset again to confirm if the columns have be
         movies.describe()
```

Out[17]:

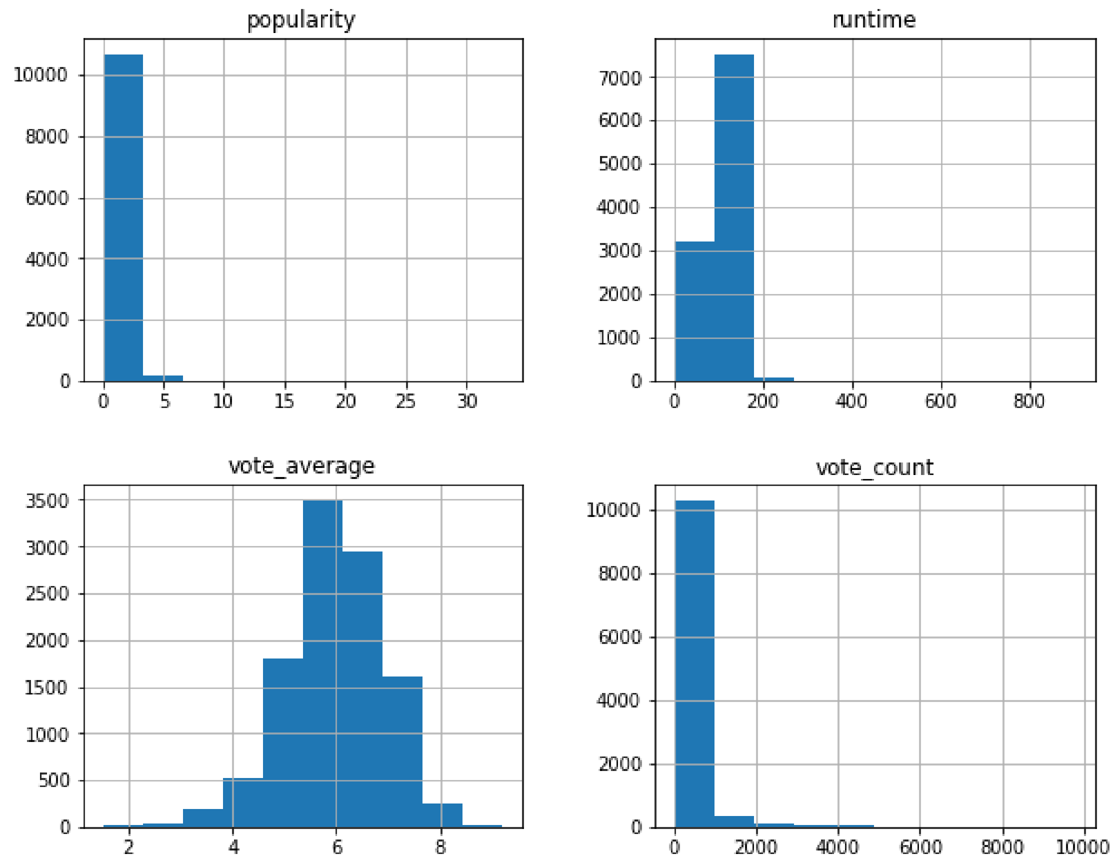
	popularity	runtime	vote_count	vote_average
count	10865.000000	10865.000000	10865.000000	10865.000000
mean	0.646446	102.363021	217.399632	5.975012
std	1.000231	30.904043	575.644627	0.935138
min	0.000065	2.000000	10.000000	1.500000
25%	0.207575	90.000000	17.000000	5.400000
50%	0.383831	99.000000	38.000000	6.000000
75%	0.713857	111.000000	146.000000	6.600000
max	32.985763	900.000000	9767.000000	9.200000

From the description above, it is shown that the zero values in the runtime column have been replaced by the mean. Also, the revenue and budget columns have been dropped so we are now left with a concise and precise dataset relavant to the questions to be answered

```
In [18]: movies.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10865 entries, 0 to 10865
Data columns (total 10 columns):
popularity              10865 non-null float64
original_title          10865 non-null object
cast                    10789 non-null object
director                10821 non-null object
runtime                 10865 non-null float64
genres                  10842 non-null object
production_companies    9835 non-null object
vote_count              10865 non-null int64
vote_average            10865 non-null float64
release_year            10865 non-null datetime64[ns]
dtypes: datetime64[ns](1), float64(3), int64(1), object(5)
memory usage: 933.7+ KB
```

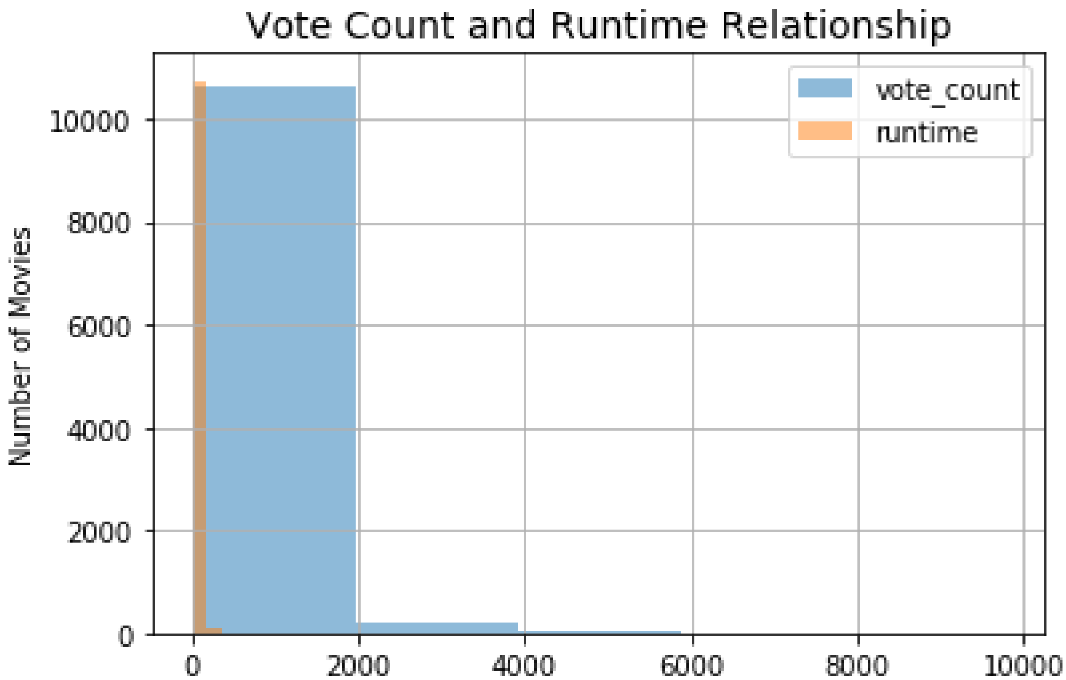
```
In [19]: #Checking the distribution of the dataset after cleaning has been done
         movies.hist(figsize=(10,8));
```



The graph above shows that the distribution did not change much after cleaning the dataset

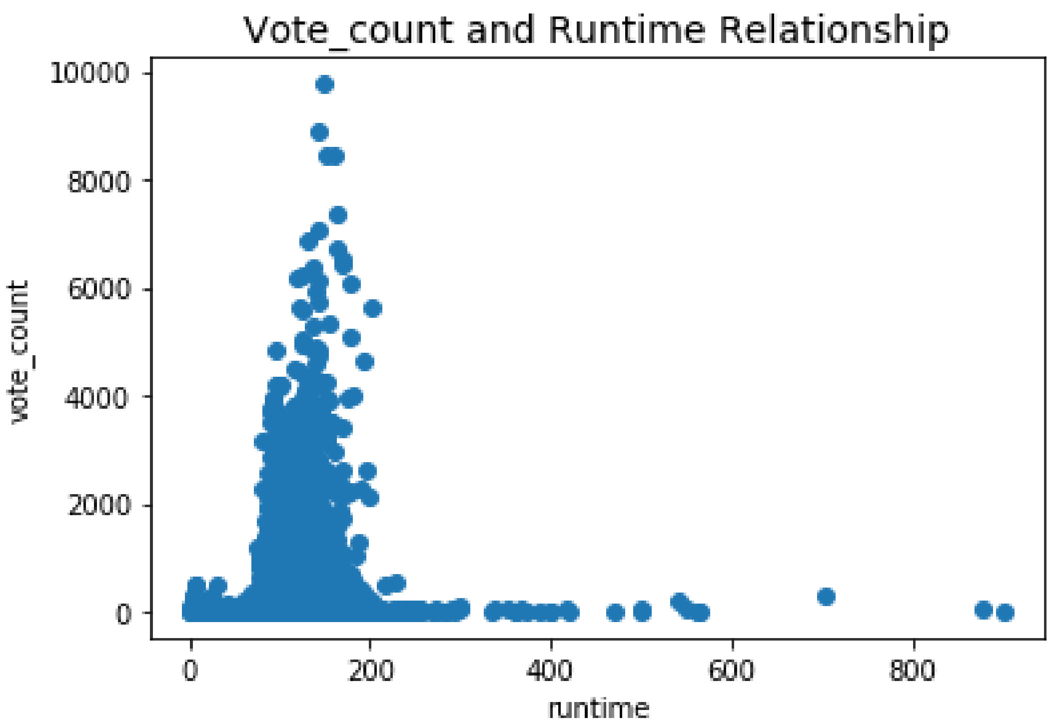
2.1.4 Question 1: what is the relationship between the vote count and the runtime?

```
In [20]: # defining the x axis
         V_C = movies['vote_count']
         # corresponding y axis values
         R = movies['runtime']

         movies.vote_count.hist(alpha=0.5, bins=5, label='vote_count')
         movies.runtime.hist(alpha=0.5, bins=5, label='runtime')
         plt.title("Vote Count and Runtime Relationship", fontsize=14);
         plt.ylabel("Number of Movies")
         plt.legend();
```



The graph above shows the relationship of the vot count and runtime on the dataset, it shows that there is a similar correlation between the vote count and runtime

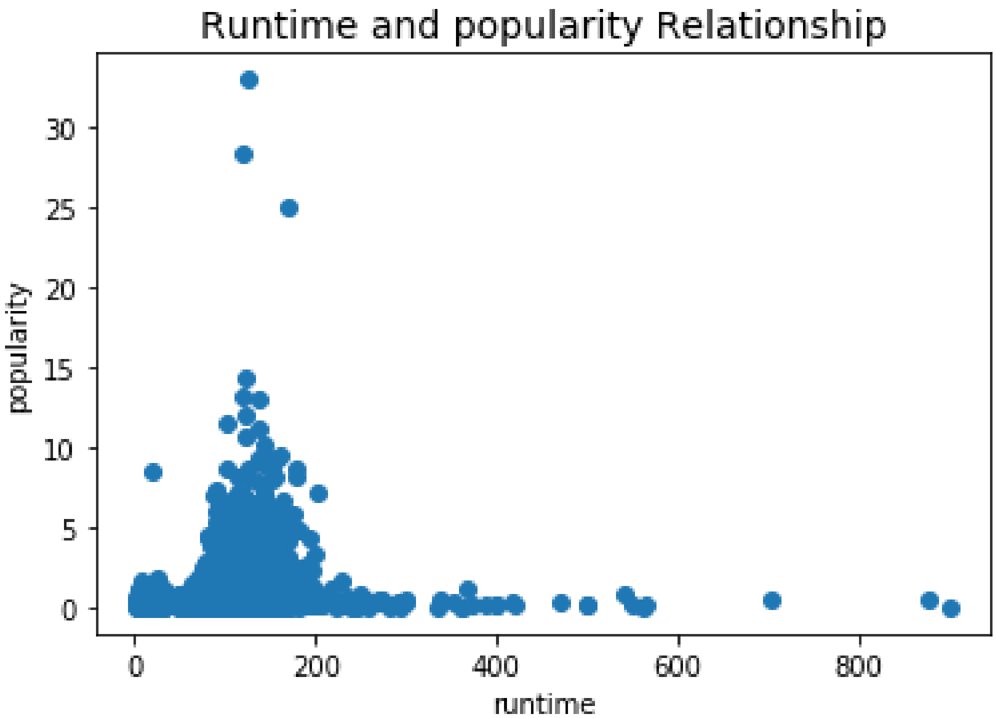
In [44]:
```
#Also using a scatterplot for verification
def scatter_plot(arg1, arg2, arg3, arg4, arg5):

# plotting the points
    plt.scatter(arg1, arg2)

# naming the x axis
    plt.xlabel(arg3)
# naming the y axis
    plt.ylabel(arg4)

#Giving the plot a title
    plt.title(arg5, fontsize=14);
    plt.show()


scatter_plot(R, V_C, 'runtime', 'vote_count', "Vote_count and Runtime Relationship")
```



The scatterplot shows that there is a similar correlation as shown in the previous graph as the graph is skewed to the right.

2.1.5 Question 2: what is the relationship between the popularity and the runtime

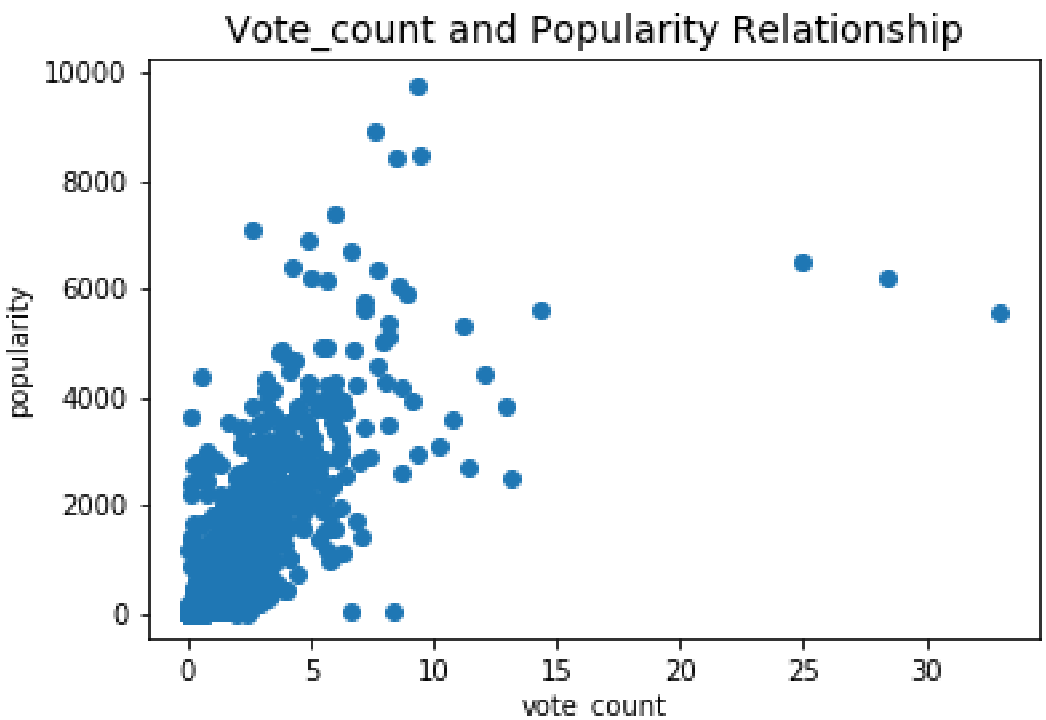
In [45]:
```
# Using a scatterplot to check the relationship
P = movies['popularity']

scatter_plot(R, P, 'runtime', 'popularity', "Runtime and popularity Relationship")
```



The scatterplot graph above shows some skewness to the right and also shows that majority of the movie relased have their runtime to be less than 200 minutes

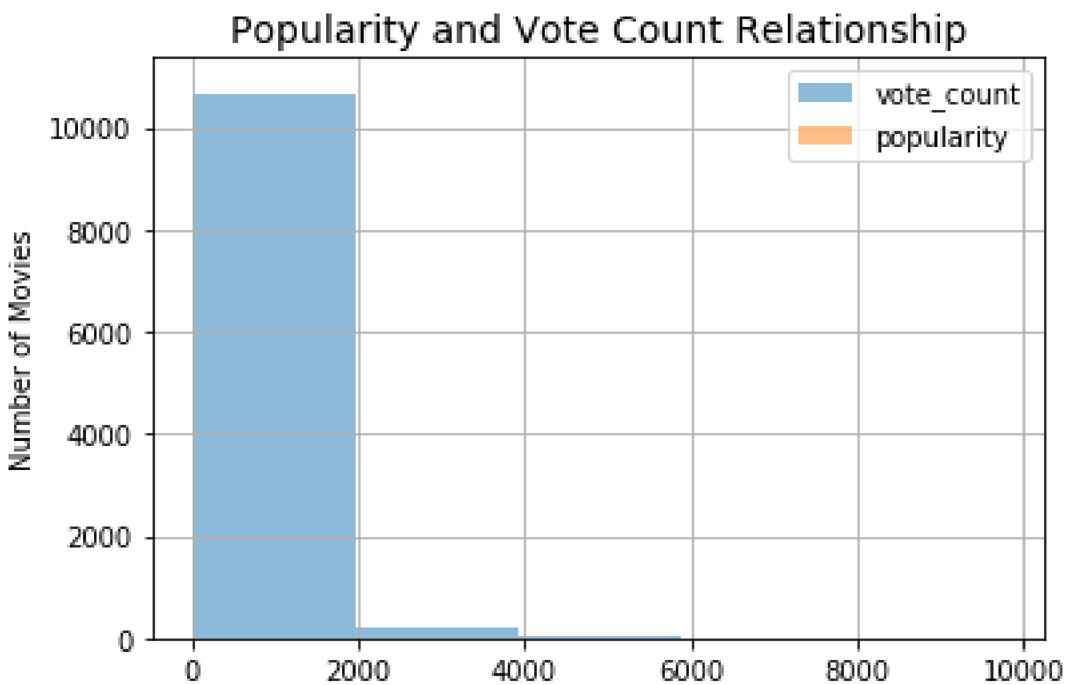
2.1.6 Question 3: what is the relationship between the popularity and the votecount

In [47]:
```
# Using scatterplot to show the relationship between popularity and votecount
scatter_plot(P, V_C, 'vote_count', 'popularity', "Vote_count and Popularity Relationshi
```



The scatterplot graph above shows the relationship between the popularity and the vote count. It shows that the vote count of the movie did not really determine how popular the movie would be

```
In [48]: #Bar graph to confirm if there are any correlation between the popularity and vote coun
         P_VC2 = movies.vote_count.hist(alpha=0.5, bins=5, label='vote_count')
         movies.popularity.hist(alpha=0.5, bins=5, label='popularity')
         plt.title("Popularity and Vote Count Relationship", fontsize=14);
         plt.ylabel("Number of Movies")
         plt.legend();
```



The bar graph above also shows that there isn't really any correlation between the popularity and the vote count of the movie

```
In [49]: #Using another method for comfirmation
         movies.describe().vote_count
```

```
Out[49]: count    10865.000000
         mean       217.399632
         std        575.644627
         min         10.000000
         25%         17.000000
         50%         38.000000
         75%        146.000000
         max       9767.000000
         Name: vote_count, dtype: float64
```

```
In [50]: # minumum to maximum percentiles values for the vote_count
         bin_edges = [10, 18, 46, 173, 9767]
```

```
In [51]: # Classifying the minimun to maximum percentiles to words
         bin_names = ['high', 'mod_high', 'medium', 'low']
```

```
In [52]: # Adding as a new column
         movies['vote_levels'] = pd.cut(movies['vote_count'], bin_edges, labels=bin_names)
         movies.head()
```

Out[52]:
```
   popularity                original_title  \
0   32.985763                Jurassic World
1   28.419936            Mad Max: Fury Road
2   13.112507                     Insurgent
3   11.173104  Star Wars: The Force Awakens
4    9.335014                     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  \
0    124.0  Action|Adventure|Science Fiction|Thriller
1    120.0  Action|Adventure|Science Fiction|Thriller
2    119.0         Adventure|Science Fiction|Thriller
3    136.0   Action|Adventure|Science Fiction|Fantasy
4    137.0                      Action|Crime|Thriller

                                production_companies  vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...        5562
1  Village Roadshow Pictures|Kennedy Miller Produ...        6185
2  Summit Entertainment|Mandeville Films|Red Wago...        2480
3          Lucasfilm|Truenorth Productions|Bad Robot        5292
4  Universal Pictures|Original Film|Media Rights ...        2947

   vote_average                  release_year vote_levels
0           6.5 1970-01-01 00:00:00.000002015         low
1           7.1 1970-01-01 00:00:00.000002015         low
2           6.3 1970-01-01 00:00:00.000002015         low
3           7.5 1970-01-01 00:00:00.000002015         low
4           7.3 1970-01-01 00:00:00.000002015         low
```

In [53]:
```
# Checking again to see if the votes correlate with popularity
movies.groupby('vote_levels').mean().popularity
```

Out[53]:
```
vote_levels
high        0.223352
mod_high    0.324672
medium      0.552263
low         1.659346
Name: popularity, dtype: float64
```

It is shown from above that very popular movies had low votes

In [54]:
```
# Checking again to see if the votes correlate with runtime
movies.groupby('vote_levels').mean().runtime
```

```
Out[54]: vote_levels
         high         98.263774
         mod_high    100.684334
         medium      101.246961
         low         110.301678
         Name: runtime, dtype: float64
```

It is also shown from above that movies with lower runtime had higher votes
Conclusions

From the dataset chosen, some columns had to be dropped because they were not relevant to the question posed so some inspection and cleaning had to be done in which i had to replace zero values with their mean. There were not much duplicates in the datasets, there were many zero values in the revenue and budget column which is a very important aspect of the data scope so I had to drop the columns to work with others because if i dropped the rows, it would eliminate almost half of the dataset.

From the EDA, it is concluded that;

- Movies with high vote count had lower runtime
- Movies that were popular did not have any correlation with the runtime
- Movies that were popular did not have any correlation with the vote count i.e. movies with low popularity was shown to have higher vote count

2.1.7 Limitations

- The dataset had many zeros in the revenue and budget columns