Investigate_a_Dataset

May 18, 2018

1 Investigate Data from The Movie Database (TMDb)

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Introduction

1.1.1 Background Information

The dataset I've selected is from the TMDb and contains data on movies, their ratings, and other characteristics.

> I'd like to answer the following questions. 1. Which months and weeks are more/less popular for movie releases? 2. How have movie genres trended over time? 3. How to measure popularity for movies?
>
> The variables of interest are listed below. - one dependent variable: **popularity** - three independent variables: **vote_count, vote_average, release_year**

Because I've only done exploratory data analysis here, my work is limited to basic data wrangling and visualization. Therefore, my conclusions in this report are tentative at best. Further statistical inference will be needed to confirm my preliminary hypotheses.

1.1.2 Resources

In addition to my Udacity lessions, I've also consulted external resources such as Stack Overflow and the Movie Database Developers API Documentation to debug my codes and to understand the data better.

```
In [1]: # import all relevant packages
        import pandas as pd
        import numpy as np
        import matplotlib.pyplot as plt
        import matplotlib.patches as mpatches
        %matplotlib inline
```

Data Wrangling

In this section, I check for data cleanliness after loading the csv file, and then trim and clean my dataset in preparation for further analysis. I have added some comments to document my steps and explain my decision-making process along the way.

1.1.3 General Properties

- Number of rows: 10866
- Number of columns: 21
- Are there duplicated rows: Yes
- Are there null values: Yes
- Interesting columns:
  - popularity
  - genres
  - vote_count
  - vote_average
  - release_year
  - budget_adj

1.1.4 Data Cleanliness

Overall, data is not too messy. There is one duplicate record and needs to be deleted. Null values are present in a number of columns; however, a close examination reveals that some columns are not important for this analysis and should be dropped before removing null values.

In [2]:
```
# load data from csv and print out the first few lines
df = pd.read_csv('tmdb_movies.csv')
df.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]:
```
# inspect data types and look for missing or possibly errant data
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
```

1.1.5 Duplicates

Only one duplicate row is found.

```
In [4]: # check for duplicates
        sum(df.duplicated())
```

```
Out[4]: 1
```

```
In [5]: # find the duplicated row
        df[df.duplicated()]
```

```
Out[5]:          id    imdb_id  popularity    budget  revenue original_title  \
        2090  42194  tt0411951     0.59643  30000000   967000         TEKKEN

                                                          cast homepage  \
        2090  Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...      NaN

                     director             tagline     ...       \
        2090  Dwight H. Little  Survival is no game     ...
```

```
                                               overview runtime  \
2090  In the year of 2039, after World Wars destroy ...      92

                                           genres    production_companies  \
2090  Crime|Drama|Action|Thriller|Science Fiction  Namco|Light Song Films

     release_date vote_count  vote_average  release_year  budget_adj  \
2090      3/20/10        110           5.0          2010  30000000.0

      revenue_adj
2090     967000.0

[1 rows x 21 columns]
```

1.1.6 Null Values

I don't believe that having null values across nine columns renders the majority of this dataset unfit for exploratory data analysis. These seven columns, 'cast', 'homepage', 'director', 'tagline', 'keywords', 'overview', and 'production_companies', consist of strings, so advanved data analysis techniques beyond the scope of this term must be deployed to deal with string vlaues. In this project, I will focus on integer and floating numbers.

In [6]:
```
# check for null values
df.isnull().sum()
```

Out[6]:
```
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
```

1.1.7 Data Cleaning

Below, I remove the one duplicate row as well as 10 rows of null values in the 'imdb_id' column and 23 rows of null values in the 'genres' column.

In [7]:
```
# drop the duplicated row
df.drop_duplicates(inplace=True)
df = df.reset_index()
```

In [8]:
```
# drop the columns that will not be investigated in this report
df = df.drop(['index', 'cast', 'homepage', 'director', 'tagline', 'keywords', 'overview'

# drop the rows with duplicates
df.dropna(inplace=True)

# confirm that operations are done properly and expect a return of False
df.isnull().sum().any()
```

Out[8]: False

In [9]:
```
# take a look at the cleaned dataset before moving on to the next section
df.head()
```

Out[9]:

	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	runtime
0	Jurassic World	124
1	Mad Max: Fury Road	120
2	Insurgent	119
3	Star Wars: The Force Awakens	136
4	Furious 7	137

	genres	release_date	vote_count
0	Action|Adventure|Science Fiction|Thriller	6/9/15	5562
1	Action|Adventure|Science Fiction|Thriller	5/13/15	6185
2	Adventure|Science Fiction|Thriller	3/18/15	2480
3	Action|Adventure|Science Fiction|Fantasy	12/15/15	5292
4	Action|Crime|Thriller	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

Exploratory Data Analysis

1.1.8 Research Question 1: Which quarters are more/less popular for movie releases?

As movie trends tend to change over time, I think it is most relevant to look at data from the past 10 years only. Seasonal trends in movie releases have been widely reported by the media. I will take this opportunity to observe what types of trends exist in movie releases. To begin, I use the 'release_date' column to create a new column named 'release_quarter'.

```
In [10]: # only interested in the past 10 years
         df = df.query('release_year >= 2006')
         pd.options.mode.chained_assignment = None # bypass the warning message

         # create a new column to allow aggregating data by quarters
         df.release_date = pd.to_datetime(df.release_date)
         df['release_quarter'] = df.release_date.apply(lambda x: x.quarter)
         df.head()
```

```
Out[10]:        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  runtime  \
         0                Jurassic World      124
         1            Mad Max: Fury Road      120
         2                     Insurgent      119
         3  Star Wars: The Force Awakens      136
         4                     Furious 7      137

                                               genres release_date  vote_count  \
         0  Action|Adventure|Science Fiction|Thriller   2015-06-09        5562
         1  Action|Adventure|Science Fiction|Thriller   2015-05-13        6185
         2         Adventure|Science Fiction|Thriller   2015-03-18        2480
         3   Action|Adventure|Science Fiction|Fantasy   2015-12-15        5292
         4                      Action|Crime|Thriller   2015-04-01        2947

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

Upon further consideration, there is a good number of "knock-off" movies produced every year. In order to minimize the potentially distorting impact of these outliers, I will limit my analysis to movies with average ratings above the mean. In other words, I will exclude roughly half of the movies whose average ratings fall below the mean.

```
In [11]: df_top = df.query('vote_average > vote_average.mean()')
         # number of movies by quarters
         df_top.groupby('release_quarter').count()['id']

Out[11]: release_quarter
         1    601
         2    580
         3    822
         4    725
         Name: id, dtype: int64

In [12]: # total adjusted revenues by quarters
         df_top.groupby(['release_quarter']).sum()['revenue_adj']

Out[12]: release_quarter
         1    2.311874e+10
         2    5.690195e+10
         3    3.420598e+10
         4    4.846137e+10
         Name: revenue_adj, dtype: float64

In [13]: # total vote counts by quarters
         df_top.groupby(['release_quarter']).sum()['vote_count']

Out[13]: release_quarter
         1    180376
         2    317779
         3    292442
         4    316621
         Name: vote_count, dtype: int64
```

In this section, I've looked at three aspects of movie releases each suggesting a somewhat different trend. According to the number of movies released by quarters, I can conclude that Q3 and Q4 are popular times to release new movies. My guess would be that because movie awards usually have a cutoff date at the end of the year, more movies are released before this deadline to be considered for such awards. Further investigation into the cause is beyond the scope of this project and requires data not included in this dataset.

The total adjusted revenues broken down by quarters suggest that Q2 is the most popular time for movie releases. This statistical summary makes economic sense since blockbusters coming out in May and June usually stay on the big screen for two to three months over the summer time when moviegoers visit theaters most frequently.

Lastly, the total vote counts by quarters suggest that movie fans are the least active in Q1 and the most active in Q2 and Q4. This is in line with my previous two observations. Movie lovers tend to vote in the summer for blockbusters generating large revenues and in the winter for films competing for the academy award and other special honors.

1.1.9 Research Question 2: How have movie genres trended over time?

In this section, I will examine whether and how movie genres have changed in popularity in the past 10 years. I will focus on particular four genres: animation, documentary, science fiction, and war. Below, I will compute the number of movies produced in each mentioned genre every year and its percentage of the total number of movies made.

In [14]:
```
# focus on only 4 genres only
genre_list = ['animation', 'documentary', 'science fiction', 'war']

# create 4 new columns to count the number of movies in each genre
for g in genre_list:
    df[g] = df.genres.apply(lambda x: g in x.lower())
df.rename(columns={'science fiction': 'science_fiction'}, inplace=True)
df.head()
```

Out[14]:
```
       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  runtime  \
0                Jurassic World      124
1            Mad Max: Fury Road      120
2                     Insurgent      119
3  Star Wars: The Force Awakens      136
4                     Furious 7      137

                                      genres release_date  vote_count  \
0  Action|Adventure|Science Fiction|Thriller   2015-06-09        5562
1  Action|Adventure|Science Fiction|Thriller   2015-05-13        6185
2         Adventure|Science Fiction|Thriller   2015-03-18        2480
3   Action|Adventure|Science Fiction|Fantasy   2015-12-15        5292
4                      Action|Crime|Thriller   2015-04-01        2947

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

   animation  documentary  science_fiction    war
0      False        False             True  False
1      False        False             True  False
2      False        False             True  False
```

```
3      False         False             True  False
4      False         False            False  False
```

In [15]:
```
# number of movies for each genre in the same release year
df_genres = df.groupby('release_year').sum()
df_genres = df_genres[df_genres.columns[-len(genre_list):]]
df_genres['num_movies'] = df.groupby('release_year').count()['id']
df_genres
```

Out[15]:

release_year	animation	documentary	science_fiction	war	num_movies
2006	39.0	16.0	30.0	7.0	408
2007	32.0	19.0	40.0	6.0	436
2008	33.0	26.0	52.0	18.0	495
2009	46.0	25.0	69.0	12.0	529
2010	50.0	35.0	45.0	7.0	486
2011	46.0	49.0	56.0	9.0	540
2012	40.0	49.0	54.0	10.0	583
2013	42.0	62.0	60.0	7.0	655
2014	36.0	73.0	62.0	23.0	699
2015	39.0	56.0	85.0	9.0	626

In [16]:
```
# each genre as a percentage of the total number of movies in the same release year
df_genres = df_genres.div(df_genres.num_movies, axis=0)
df_genres *= 100
df_genres
```

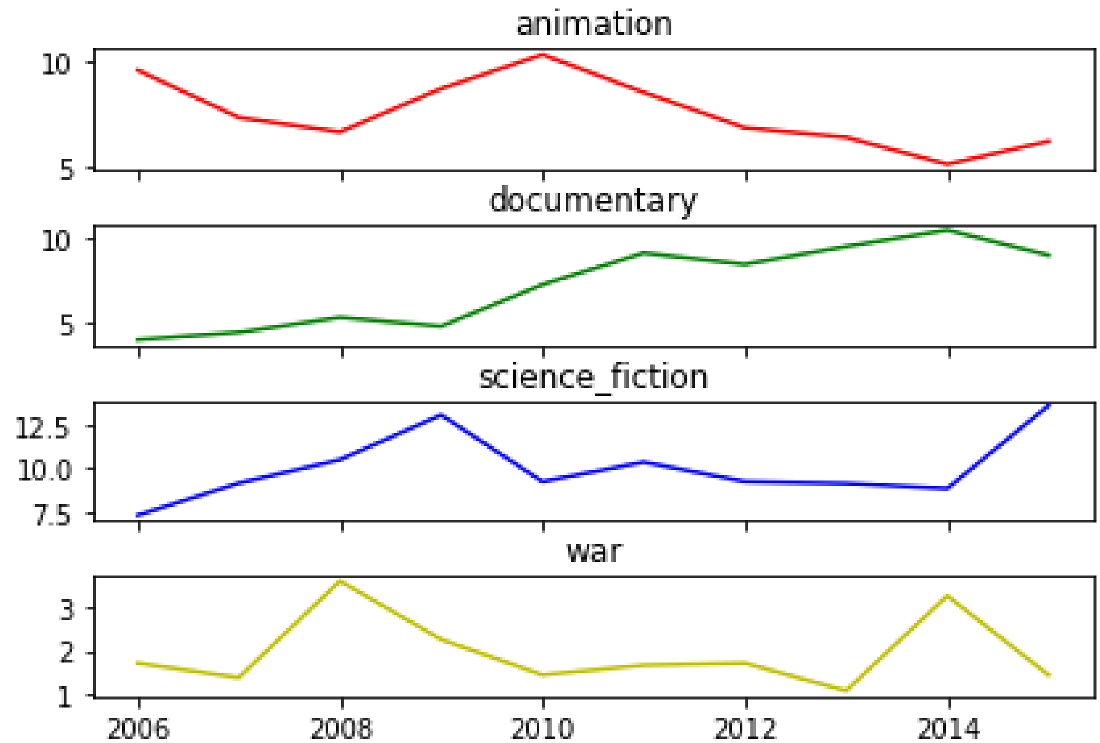
Out[16]:

release_year	animation	documentary	science_fiction	war	num_movies
2006	9.558824	3.921569	7.352941	1.715686	100.0
2007	7.339450	4.357798	9.174312	1.376147	100.0
2008	6.666667	5.252525	10.505051	3.636364	100.0
2009	8.695652	4.725898	13.043478	2.268431	100.0
2010	10.288066	7.201646	9.259259	1.440329	100.0
2011	8.518519	9.074074	10.370370	1.666667	100.0
2012	6.861063	8.404803	9.262436	1.715266	100.0
2013	6.412214	9.465649	9.160305	1.068702	100.0
2014	5.150215	10.443491	8.869814	3.290415	100.0
2015	6.230032	8.945687	13.578275	1.437700	100.0

In [17]:
```
# create 4 subplots to visualize genre trends over 10 years
fig, ax = plt.subplots(4, sharex=True)
fig.tight_layout() # optimize subplot space management

# some quick fixes to allow generating 4 subplots in a for loop
genre_list[2] = 'science_fiction'
colors = ['r', 'g', 'b', 'y']
dict_genre_color = dict(zip(genre_list, colors))
i = 0
```

```
# 4 subplots with different titles but sharing the same x-axis
for g in genre_list:
    ax[i].plot(df_genres.index, df_genres[g], color=dict_genre_color[g])
    ax[i].set_title(g)
    i += 1
```



Judging from the above tables and graphs, I can form the following conclusions. Roughly the same number of animation movies are made every year; however, because more movies are produced now than 10 years ago, animation as a percentage of total movies has trended down. Documentary has become a more popular movie genre, and this is very consistent over time. Science fiction is another genre gaining more popularity, but its trend is less consistent than that of documentary. Other than three years, 2008, 2009, and 2014, a similar number of war movies is released each year. The trend here is less obvious.

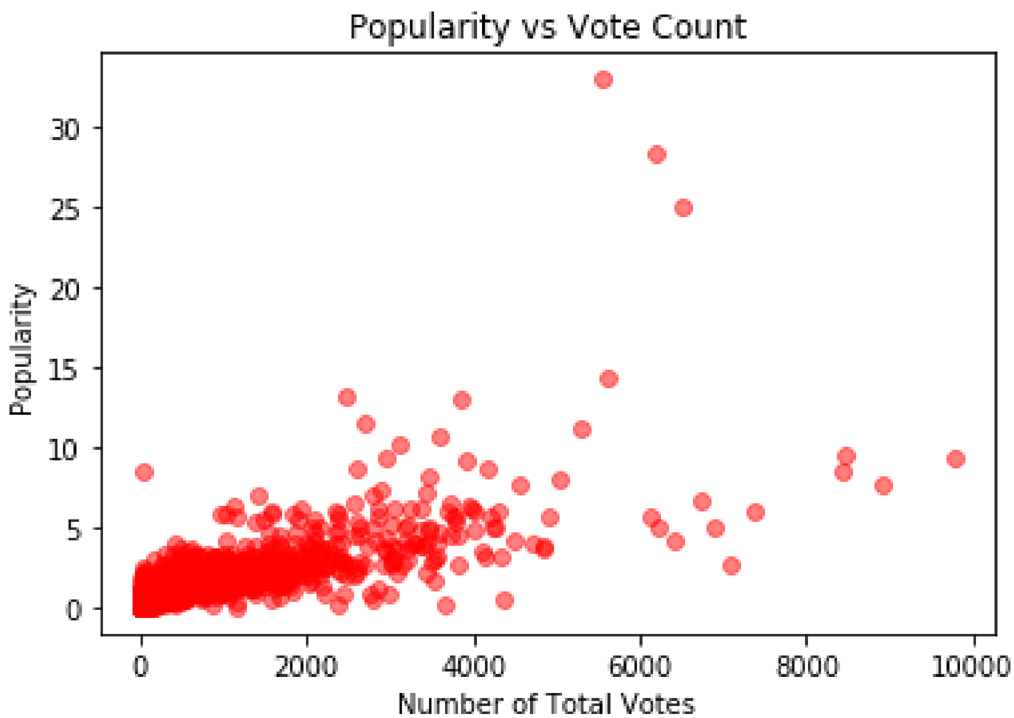
1.1.10 Research Question 3: How to measure popularity for movies??

As stated in the developers API documentation, The Movie Database uses popularity as a key metric for its recommendation model to improve search results. In this particular case, popularity for movies is based on a number of factors including the number of total votes, release date, and the number of users marking the movie as a favorite and adding it to their watchlist.

From this information, I'd like to confirm that 'popularity' is correlated with 'vote_count' and 'release_year'. In other words, I'd like to explore 'popularity' as a dependent variable and 'vote_count' and 'release_year' as independent variables. I'd also like to analyze whether a similar relationship exists between 'popularity' and 'budget_adj'.

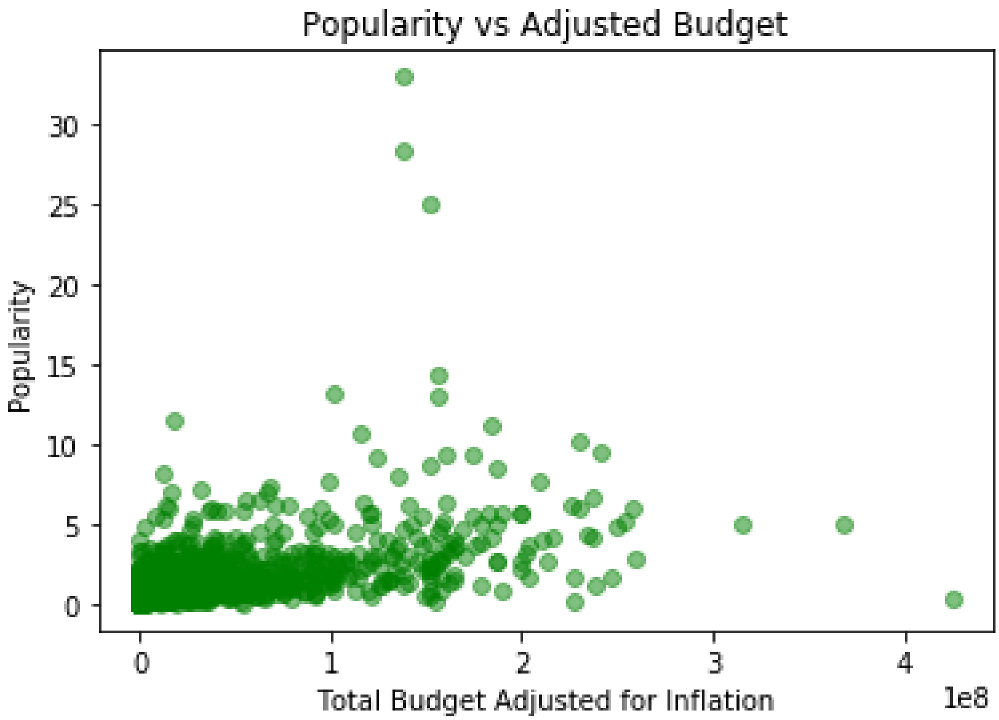
```
In [18]: x = df.vote_count
         y = df.popularity
         plt.scatter(x, y, c='r', alpha=0.5)
         plt.xlabel('Number of Total Votes')
         plt.ylabel('Popularity')
         plt.title('Popularity vs Vote Count')
```

```
Out[18]: Text(0.5,1,'Popularity vs Vote Count')
```



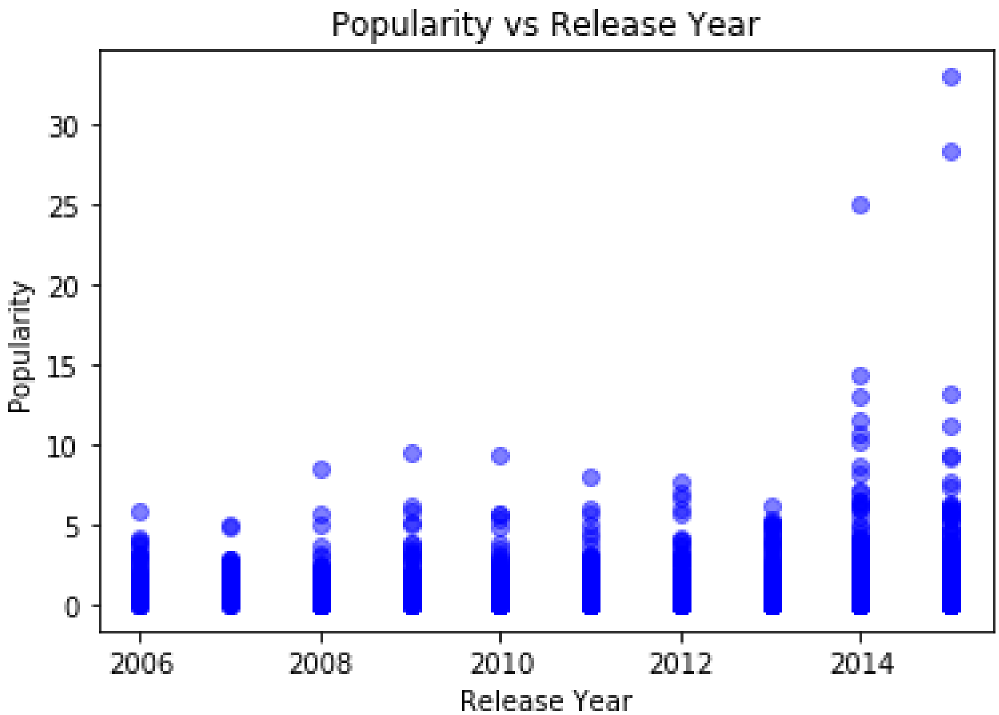

```
In [19]: x = df_top.budget_adj
         y = df_top.popularity
         plt.scatter(x, y, c='g', alpha=0.5)
         plt.xlabel('Total Budget Adjusted for Inflation')
         plt.ylabel('Popularity')
         plt.title('Popularity vs Adjusted Budget')
```

```
Out[19]: Text(0.5,1,'Popularity vs Adjusted Budget')
```




```
In [20]: x = df_top.release_year
         y = df_top.popularity
         plt.scatter(x, y, c='b', alpha=0.5)
         plt.xlabel('Release Year')
         plt.ylabel('Popularity')
         plt.title('Popularity vs Release Year')
```

```
Out[20]: Text(0.5,1,'Popularity vs Release Year')
```



Having created scatter plots for three pairs of variables, I can confirm visually that some statistical relationships exist between my dependent variables and the independent variable. Overlooking outliers, I can see a positive correlation between 'popularity' and 'vote_count' as well as between 'popularity' and 'budget_adj'. It is straightforward that if a movie receives more votes from users, it is gaining popularity. Similarly, if a movie has a larger budget, it will spend more on marketing and more users will react by looking up the movie on TMBd.

Lastly, it is quite clear from the last graph that movies released in the last two years, 2014 and 2015, are more popular than those made earlier. This is reasonable because users tend to get swayed by movie critics and commercials, both online and in other media outlets, and this effect is mostly limited to recent films. On ther other hand, this also reveals the limitation of building a popularity-based recommendation engine. Some movies from 5 or 10 years ago might be a great fit for a particular user, but it scores a low popularity and is, therefor, excluded from the recommendation results. An extension of this project would be to investigate string values in the columns removed in the data wrangling section. They provide descriptions for movies and can support a content-based recommendation system.

Conclusions

From my earlier analysis, I've found that both Q2 and Q4 are popular times to release movies.

In terms of trends in movie genres, I've learned that documentary and science fiction have gained popularity in the past 10 years while production in animation and war movies has stayed rather flat.

I've also reached the conclusion that the number of total vote counts, the total revenues adjusted for inflation, and release year all have a direct relationship with popularity. More data and further investigation are needed to understand the nature of these correlations. I believe I will be able to do so after completing the second term of the Udacity Data Analyst Nano-degree.

In [22]:
```
from subprocess import call
call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

Out[22]:
```
0
```