Investigate_a_Dataset

September 6, 2022

1 Project: Investigate TMDB Movies Dataset

1.1 Table of Contents

Introduction

1.1.1 Dataset Description

This report was generated from a dataset collection from The Movie Database (TMDb). This is a very thorough dataset of movies release between the years of 1960 and 2015. There are over 10,000 rows of data with characteristics of the film (tagline, genre, etc), financial inforamtion, popularity, and when the film was release.

1.1.2 Questions for Analysis

Have movies been getting longer year over year?

What year had the most popular releases?

Does the vote averages reflect similar results as popuarity?

```
In [1]: import numpy as np
        import pandas as pd
        import matplotlib.pyplot as plt
        import seaborn as sns
        %matplotlib inline
```

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

Data Wrangling Step 1: Gather Data

First, I used pandas to load the dataset.

```
In [3]: df_movies = pd.read_csv('Database_TMDb_movie_data/tmdb-movies.csv')
```

1.2 Data Wrangling Step 2: Assess Data

Second, I used several function to get a general understanding of the dataset. I found that there are 10,866 rows and 21 column of data. There is a mixture of numeric and string datatypes and several cells using an object data type had multiple point of thata that were separated by a bar (|). On initial glance it looked as if the majority of the omitted data was confined to the object datatype, but after review the statistical inforamtion it appears that missing numerical data simply had a "0" as a placeholder.

In [4]:
```
df_movies.shape
```

Out[4]:
```
(10866, 21)
```

In [5]:
```
df_movies.head(5)
```

Out[5]:
```
       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 [6]:
```
df_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
```

In [7]:
```
df_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  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
```

1.3 Data Wrangling Step 3: Cleaning Data

Cleaning the data for this dataset required careful consideration. I started with the easy task of removing the 1 duplicated row, as well as many of the columns that I wouldn't be using. Then explored the main columns that I wanted to explore, release year, runtime, popularity and vote average. I wanted to find where any potential outliers were, as well as if they had a placeholder to hide missing data.

In [8]:
```
sum(df_movies.duplicated())
```

Out[8]: 1

In [9]:
```
df_movies.drop_duplicates(inplace=True)
```

```
In [10]: sum(df_movies.duplicated())
```

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

```
In [11]: df_movies.drop(['imdb_id', 'budget', 'revenue', 'original_title', 'cast', 'homepage', '
         df_movies.head(10)
```

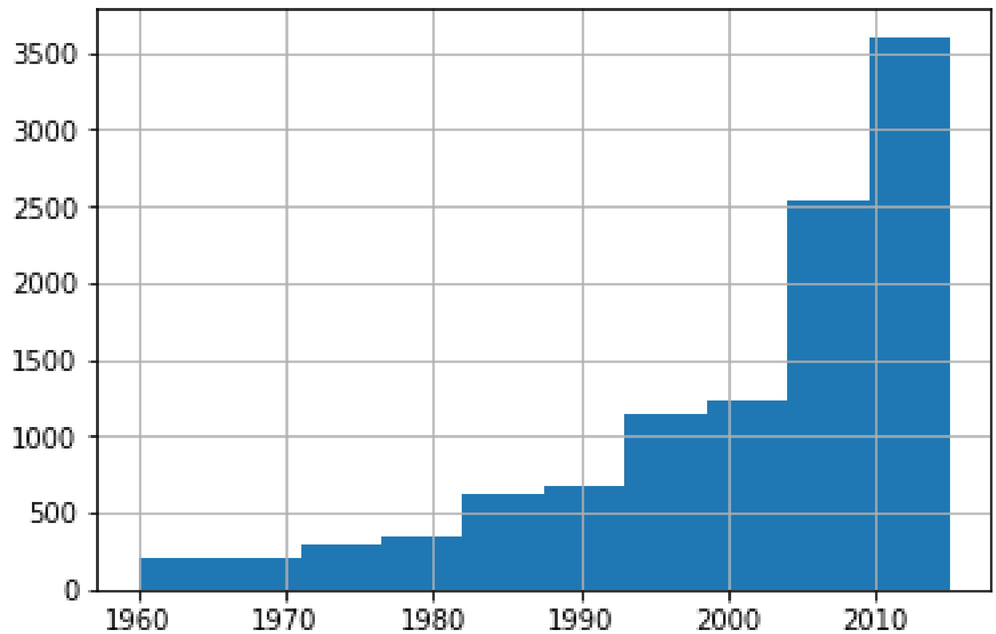
```
Out[11]:        id  popularity  runtime release_date  vote_count  vote_average  \
         0  135397   32.985763      124       6/9/15        5562           6.5
         1   76341   28.419936      120      5/13/15        6185           7.1
         2  262500   13.112507      119      3/18/15        2480           6.3
         3  140607   11.173104      136     12/15/15        5292           7.5
         4  168259    9.335014      137       4/1/15        2947           7.3
         5  281957    9.110700      156     12/25/15        3929           7.2
         6   87101    8.654359      125      6/23/15        2598           5.8
         7  286217    7.667400      141      9/30/15        4572           7.6
         8  211672    7.404165       91      6/17/15        2893           6.5
         9  150540    6.326804       94       6/9/15        3935           8.0

            release_year
         0          2015
         1          2015
         2          2015
         3          2015
         4          2015
         5          2015
         6          2015
         7          2015
         8          2015
         9          2015
```

I started with reviewing the release year and found the range to be between 1965 and 2015.

```
In [12]: df_movies['release_year'].unique()
```

```
Out[12]: array([2015, 2014, 1977, 2009, 2010, 1999, 2001, 2008, 2011, 2002, 1994,
                2012, 2003, 1997, 2013, 1985, 2005, 2006, 2004, 1972, 1980, 2007,
                1979, 1984, 1983, 1995, 1992, 1981, 1996, 2000, 1982, 1998, 1989,
                1991, 1988, 1987, 1968, 1974, 1975, 1962, 1964, 1971, 1990, 1961,
                1960, 1976, 1993, 1967, 1963, 1986, 1973, 1970, 1965, 1969, 1978,
                1966])
```

```
In [13]: df_movies['release_year'].hist();
```



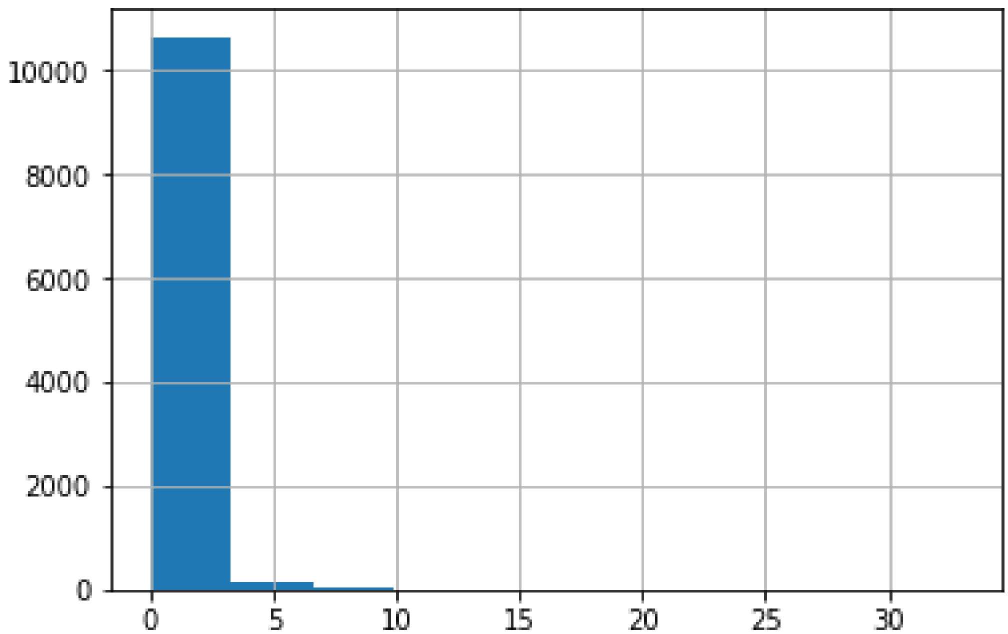
This release year histogram tells me that the number of movies made year over year has been increasing year over year with an exponential increase in the mid 2000's

Exploring the popularity column presented me with quite a challenge. It was clear by looking at the distribution and the statistical inforamtion that there are big outliers that significantly skew the data to the right. After assessing the quartiles of the data, I came to the conclusion that anything greater that a popularity of 1 is a possible outlier.

With the popularity data now in decimals, I attemped to make the analysis easier to read by multiplying the values by 100, and rounding to the nearest whole number.

I verified my assumptions about my assumptions about any possible outliers by creating another histgram with the updates and then saved it as a new dataframe.

```
In [14]: df_movies['popularity'].hist();
```




```
In [15]: df_movies['popularity'].describe()

Out[15]: count    10865.000000
         mean         0.646446
         std          1.000231
         min          0.000065
         25%          0.207575
         50%          0.383831
         75%          0.713857
         max         32.985763
         Name: popularity, dtype: float64

In [16]: pop_possible_outliers = df_movies[(df_movies['popularity'] >= 1) | (df_movies['populari
         pop_possible_outliers['popularity'].count()

Out[16]: 1854

In [17]: df_movies['pop_round_100'] = df_movies['popularity'].values
         df_movies['pop_round_100'] = np.trunc(df_movies['pop_round_100'] * 100)
         df_movies.describe()

Out[17]:                   id    popularity       runtime    vote_count  vote_average  \
         count  10865.000000  10865.000000  10865.000000  10865.000000  10865.000000
         mean   66066.374413      0.646446    102.071790    217.399632      5.975012
         std    92134.091971      1.000231     31.382701    575.644627      0.935138
         min        5.000000      0.000065      0.000000     10.000000      1.500000
```

```
25%     10596.000000      0.207575    90.000000    17.000000      5.400000
50%     20662.000000      0.383831    99.000000    38.000000      6.000000
75%     75612.000000      0.713857   111.000000   146.000000      6.600000
max    417859.000000     32.985763   900.000000  9767.000000      9.200000

       release_year  pop_round_100
count  10865.000000   10865.000000
mean    2001.321859      64.146618
std       12.813260     100.022164
min     1960.000000       0.000000
25%     1995.000000      20.000000
50%     2006.000000      38.000000
75%     2011.000000      71.000000
max     2015.000000    3298.000000
```

```
In [18]: df_pop = df_movies[(df_movies['pop_round_100'] < 100) & (df_movies['pop_round_100'] >=
         df_pop.describe()
```

```
Out[18]:                  id   popularity      runtime   vote_count  vote_average  \
         count    9011.000000  9011.000000  9011.000000  9011.000000   9011.000000
         mean    67153.272889     0.369880   100.308512    71.060260      5.891544
         std     92757.981771     0.235482    30.718330   148.513246      0.939037
         min         6.000000     0.010016     0.000000    10.000000      1.500000
         25%     11363.500000     0.187407    90.000000    15.000000      5.300000
         50%     21948.000000     0.322496    97.000000    29.000000      5.900000
         75%     74751.500000     0.513636   109.000000    72.000000      6.500000
         max    414419.000000     0.999866   877.000000  4368.000000      8.900000

                release_year  pop_round_100
         count   9011.000000    9011.000000
         mean    2000.788481      36.489291
         std       13.101088      23.549588
         min     1960.000000       1.000000
         25%     1994.000000      18.000000
         50%     2005.000000      32.000000
         75%     2011.000000      51.000000
         max     2015.000000      99.000000
```

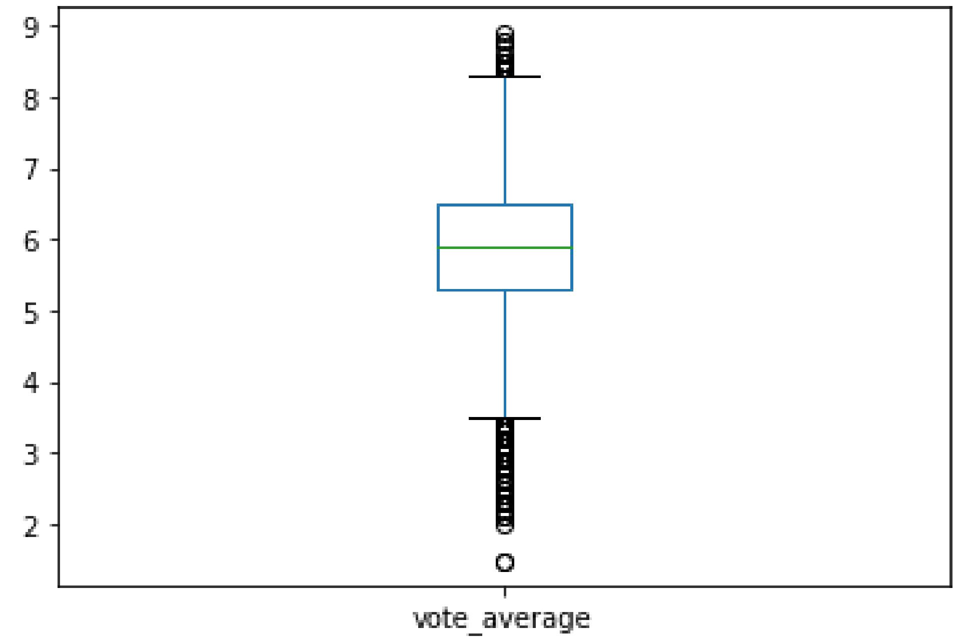
Cleaning the vote average column included verifying there was no outliers and missing data.

```
In [19]: df_pop['vote_average'].describe()
```

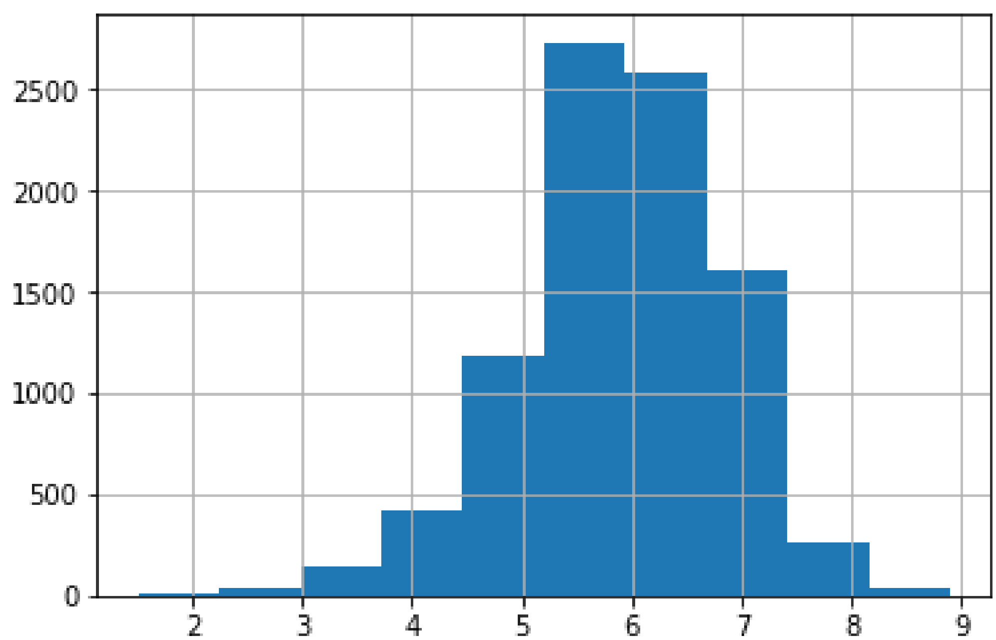
```
Out[19]: count    9011.000000
         mean        5.891544
         std         0.939037
         min         1.500000
         25%         5.300000
         50%         5.900000
```

```
75%          6.500000
max          8.900000
Name: vote_average, dtype: float64
```

```
In [20]: df_pop['vote_average'].plot(kind='box');
```



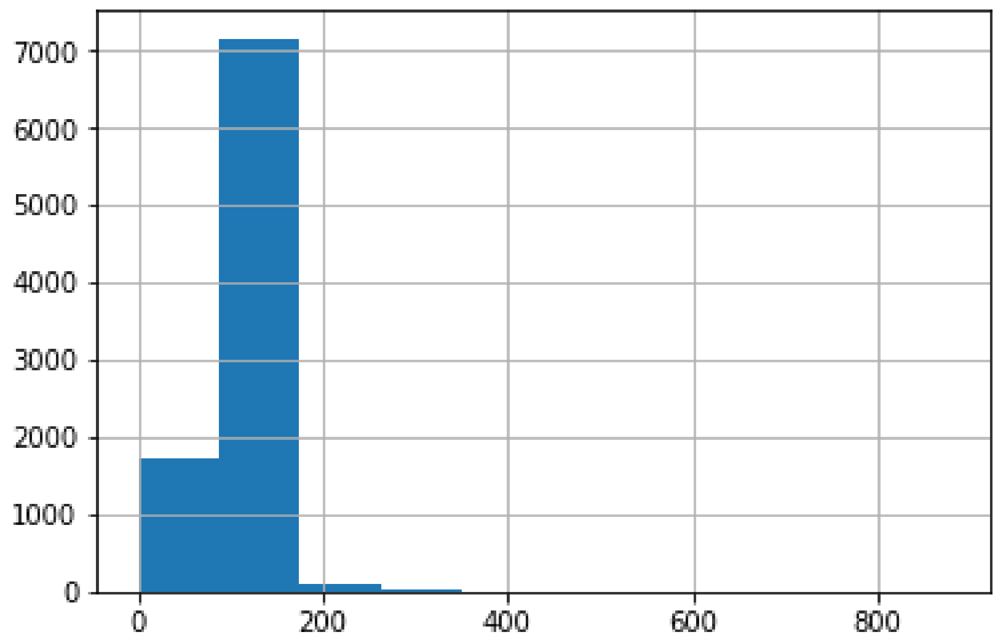

```
In [21]: df_pop['vote_average'].hist();
```



The final cleaning was for the 'runtime' column. I research film lengths I found that the Academy of Motion Picture Arts and Science defines a feature film length is over 40 minutes. Once I removed the lower limit from the dataset, I used three times the standard devation plus the mean to calulate the upper limit of the data.

This put the film runtime between 40 and 191 minutes.

In [22]:
```
df_pop['runtime'].hist();
```



In [23]:
```
df_pop['runtime'].describe()
```

Out[23]:
```
count    9011.000000
mean      100.308512
std        30.718330
min         0.000000
25%        90.000000
50%        97.000000
75%       109.000000
max       877.000000
Name: runtime, dtype: float64
```

In [24]:
```
df_feature = df_pop[df_pop['runtime'] > 40]
df_feature['runtime'].describe()
```

```
Out[24]: count    8779.000000
         mean      102.646429
         std        27.451472
         min        41.000000
         25%        90.000000
         50%        98.000000
         75%       110.000000
         max       877.000000
         Name: runtime, dtype: float64
```

```
In [25]: df_feature = df_feature[df_feature['runtime'] <= 191]
         df_feature.describe()
```

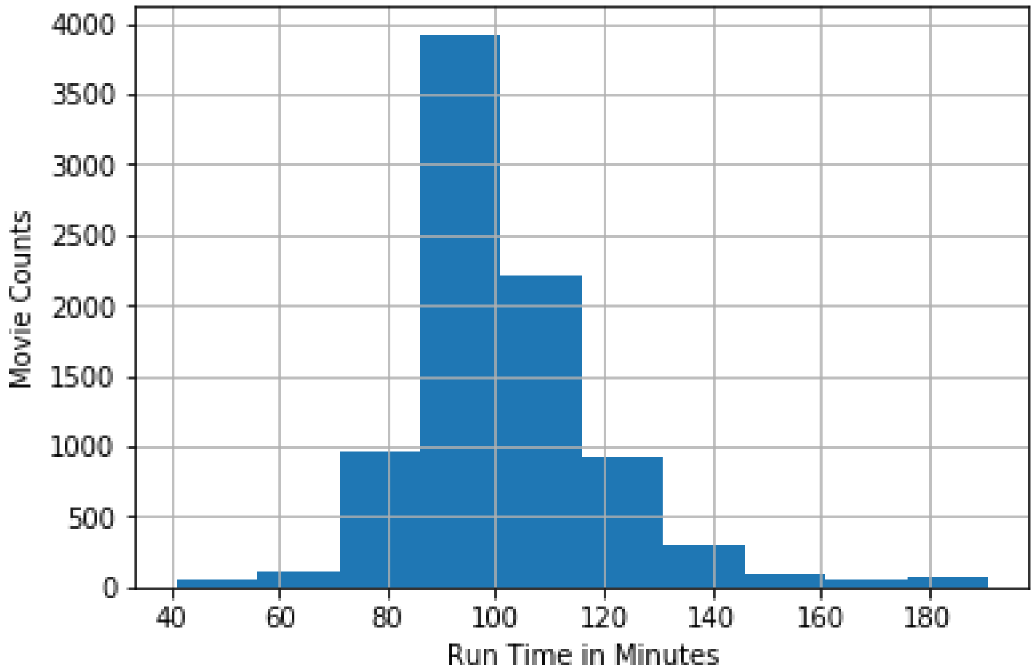
```
Out[25]:                 id   popularity      runtime   vote_count  vote_average  \
         count    8707.000000  8707.000000  8707.000000  8707.000000   8707.000000
         mean    65505.695417     0.372821   101.089009    71.991501      5.863225
         std     91623.068017     0.235435    18.214575   150.614390      0.928717
         min         6.000000     0.010016    41.000000    10.000000      1.500000
         25%     11241.500000     0.190222    90.000000    15.000000      5.300000
         50%     21183.000000     0.324081    98.000000    29.000000      5.900000
         75%     71231.000000     0.516744   109.000000    73.000000      6.500000
         max    409696.000000     0.999866   191.000000  4368.000000      8.900000

                release_year  pop_round_100
         count   8707.000000    8707.000000
         mean    2000.660503      36.784311
         std       13.116560      23.544106
         min     1960.000000       1.000000
         25%     1993.000000      19.000000
         50%     2005.000000      32.000000
         75%     2011.000000      51.000000
         max     2015.000000      99.000000
```

Exploratory Data Analysis

1.3.1 Research Question 1: Have movies been getting longer?

I wanted to be able to plot the average runtime per year by years. However 55 years was a lot of points on the plot, so I decided to put the 55 years into 5 year ranges. After that I created a function to calculate the average (in this case runtime) per year ranges.

```
In [26]: runtime_hist=df_feature['runtime'].hist()
         runtime_hist.set_ylabel('Movie Counts')
         runtime_hist.set_xlabel('Run Time in Minutes');
```



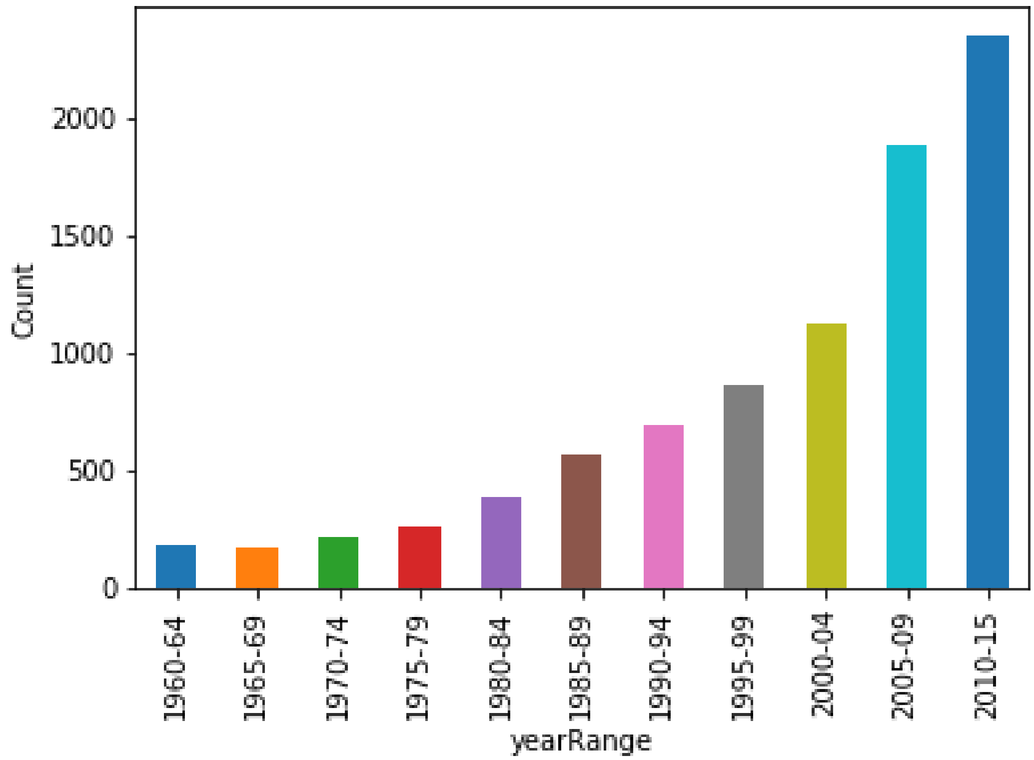
The distribution of the runtimes is slightly skewed to the right and we can see the the vast majority of movies run for about 85 to 100 minutes.

```
In [27]: df_feature['release_year'].min()
```

```
Out[27]: 1960
```

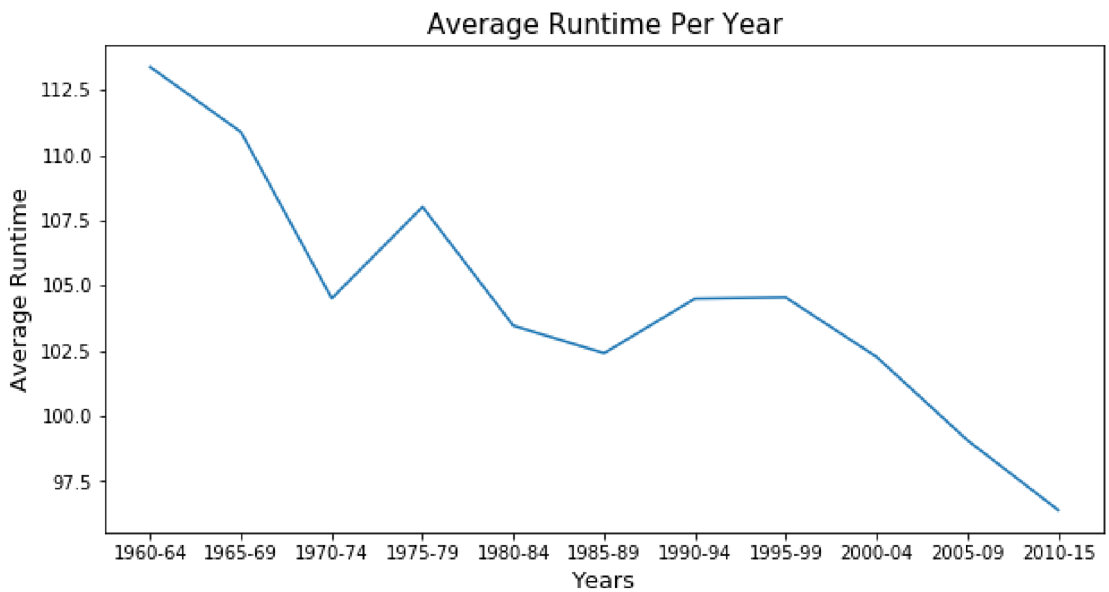
```
In [28]: year_bins = [1960, 1965, 1970, 1975, 1980, 1985, 1990, 1995, 2000, 2005, 2010, 2016]
         year_range = ['1960-64', '1965-69', '1970-74', '1975-79', '1980-84', '1985-89', '1990-9

         df_feature['yearRange'] = pd.cut(df_feature['release_year'], bins=year_bins, labels=yea
```

```
In [29]: df_feature.groupby('yearRange')['id'].count().plot(kind='bar').set_ylabel('Count');
```



This chart tells me that the amount of movies made since the last 1960's has been increasing and there was an exponential increase between the early and late 2000's.

```
In [30]: """This function calculates the average variable per year range."""
         def avg_per_year(x):
            return df_feature.groupby(df_feature.yearRange)[x].mean()

In [31]: plt.figure(figsize=(10,5))
         plt.xlabel('Years', fontsize=13)
         plt.ylabel('Average Runtime', fontsize=13)
         plt.title('Average Runtime Per Year', fontsize=15)

         plt.plot(year_range, avg_per_year(['runtime']));
```

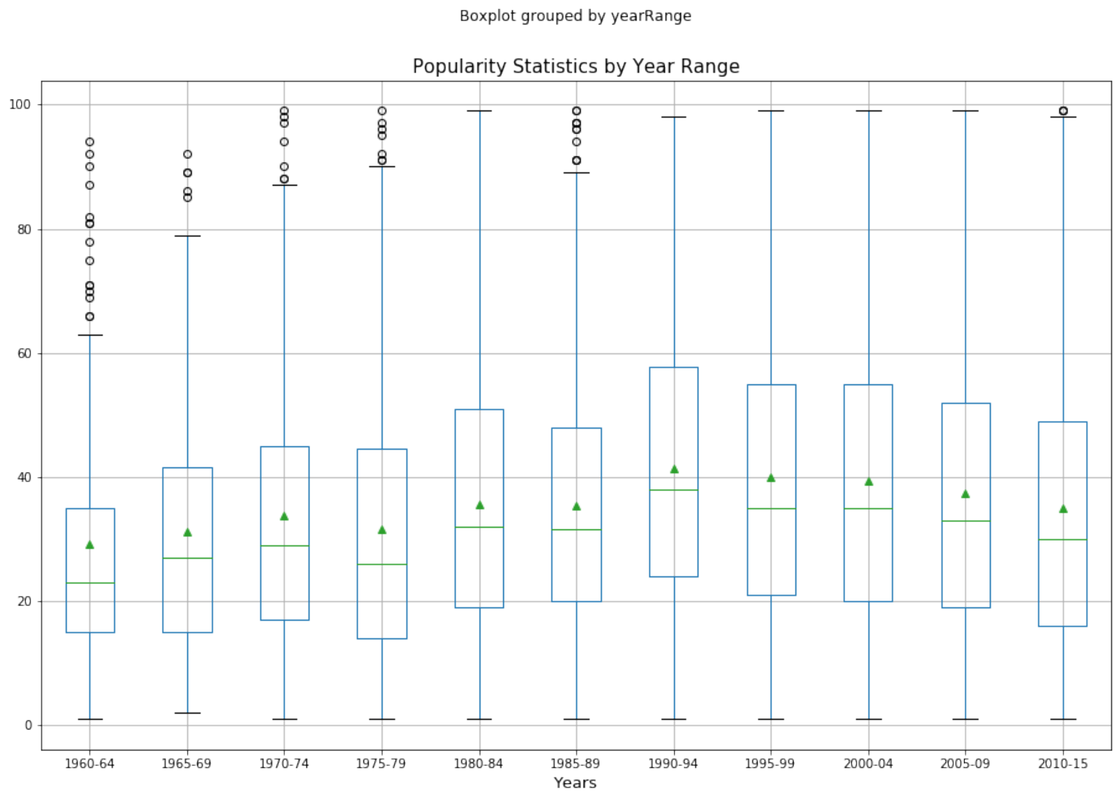


The lineplot shows that despite my initial assumption that movies have been getting longer year over year, it is actually the opposite. The average runtime per movie in early 1960's was about 113 minutes, and by the early 2010's the runtime was 17 minutes less at about 96 minutes.

1.3.2 Research Question 2 : What year had the most popular releases?

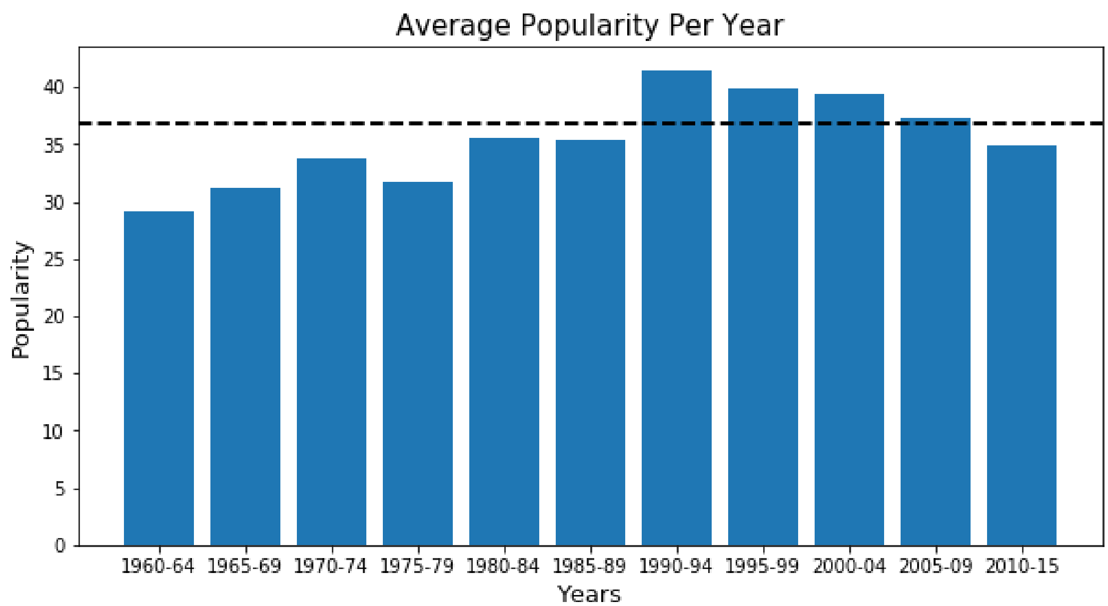
For my next question, I wanted to explore whether or not one year in particular had more popular movies than the others. I created boxplots so I could view all of the statistical information about the popularity by the year range. Next, I created a bar chart to show the average popularity per year range with a line referencing the overall average popularity.

```
In [32]: df_feature.boxplot(column=['pop_round_100'],by=['yearRange'],figsize=(15,10), showmeans
         plt.title('Popularity Statistics by Year Range', fontsize =15)
         plt.xlabel('Years', fontsize=13);
```



Viewing boxplots give a lot of helpful insites about the spread of popularity by year. We can see that the median throughout the years stays within about 10 points of eachother. We can also clearly see that the early 1990's has the most popular releases not only with the highest average, but it has the highest overall inner quartile range.

```
In [33]: plt.figure(figsize=(10,5))
         plt.xlabel('Years', fontsize=13)
         plt.ylabel('Popularity', fontsize=13)
         plt.title('Average Popularity Per Year', fontsize =15)
         plt.axhline(y=(df_feature['pop_round_100'].mean()),linewidth=2, color='k', linestyle=('
         plt.bar(year_range, df_feature.groupby(df_feature.yearRange)['pop_round_100'].mean().va
```

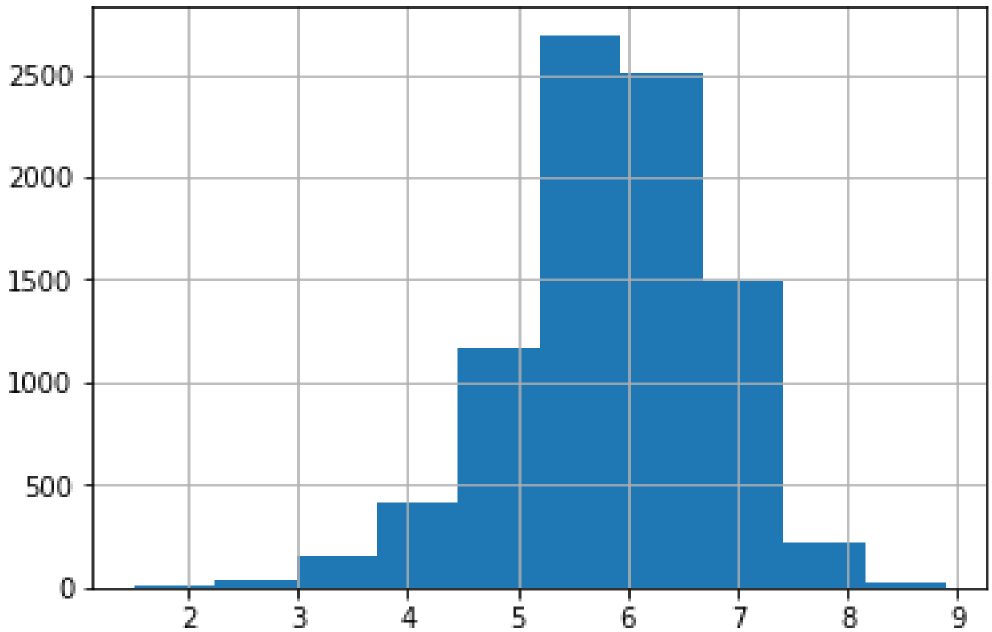


While the barchart shows very similar infomration as the boxplots it is easier to read the most popular year range as 1990-1994. It is also interesting to see the overall popularities compared to the year ranges.

1.3.3 Research Question 3 : Does the vote averages reflect similar results as popuarity?

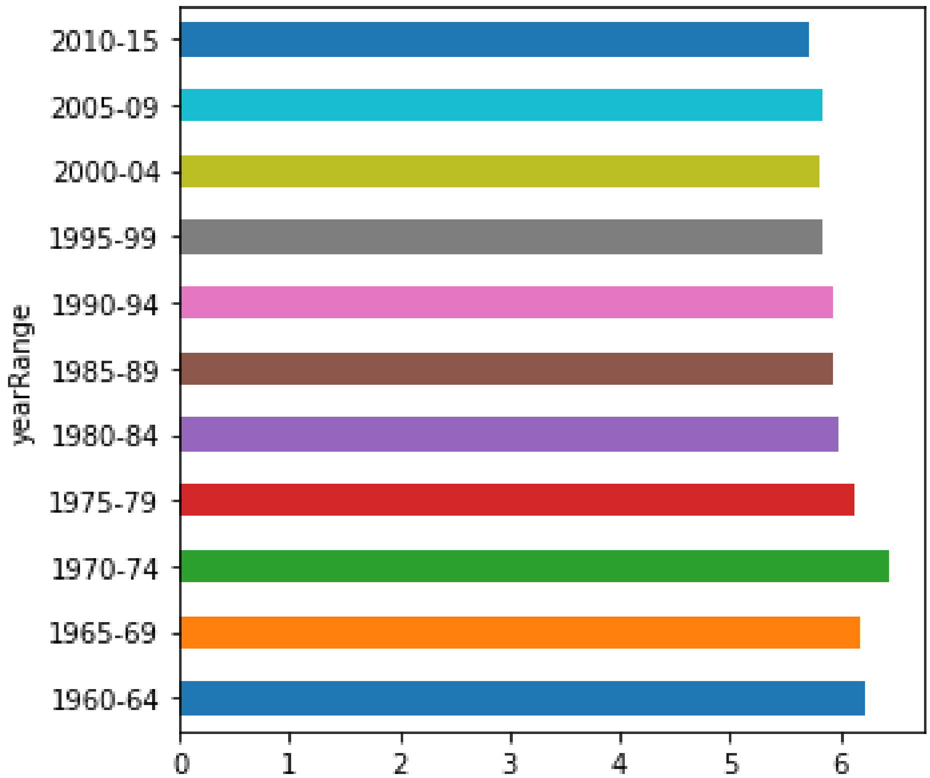
In my final question I wanted to explore if the voting averages would be a good indicator of overall popularity.

```
In [34]: df_feature['vote_average'].hist();
```



I stared by looking at the distribution, which told me that the vast majority of movies had an average vote between 5 and 7.

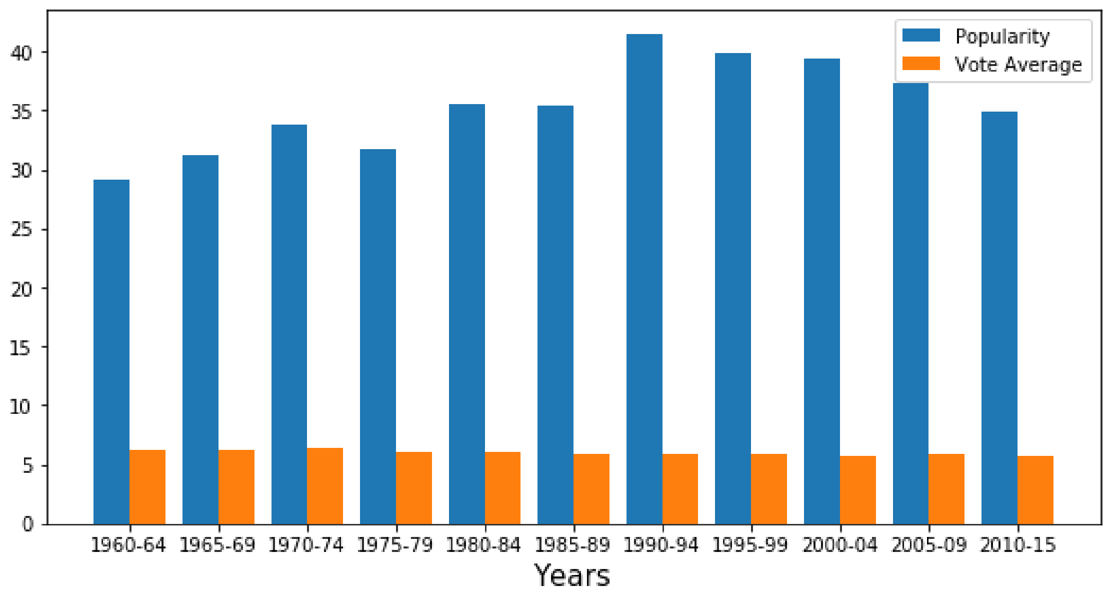
```
In [35]: avg_per_year('vote_average').plot(kind='barh', figsize=(5,5));
```



Next I looked at the data broken out by years. This was very interesting as it shows that 1970-1974 had the highest vote average, and the other years didn't have a lot of variation in their averages.

In [36]:
```
plt.figure(figsize=(10,5))


x_axis = np.arange(len(year_range))
bar1_width = x_axis - 0.2
bar2_width = x_axis + 0.2


y1_pop= avg_per_year('pop_round_100')
y2_votes=avg_per_year('vote_average')


plt.bar(bar1_width, y1_pop, 0.4, label='Popularity')
plt.bar(bar2_width, y2_votes, 0.4, label='Vote Average')

plt.xlabel('Years', fontsize=15)
plt.xticks(x_axis, year_range)
```

```
plt.legend();
```



Finally, I plotted the two points together. This data shows that the vote average is not an indicator of the overall popularity.

Conclusions

This data has lead to me to very interesting conclusions. As I was looking into the average runtimes per year my expectation was the opposite of what the data outlined. I assumed that movies overall were getting longer, but according to the data movies between 1960 and 2015 are atually getting shorter on average.

However, there are many considerations that prevent me from making this into a definitive statement. The data only has movies up until 2015, therefore we cannot make draw any concusion after that point. There are also outliers to consider. In my own data cleanup I used three times the standard devation plus the mean to remove outliers, but with a more thorough understanding of the dataset we could find that it was not the best way to handle those outliers.

The popularity graphs show that the 1990's had the most popular releases, and also that there isn't a huge variation on movie popularity in this dataset. With the overall average at 36.8, most of the years were within 5 points of the overall average. We also learned that the average votes does is not an indicator of overall popularity.

I once again cannot make this into a definitive statement because of limitation in the dataset as well as the assumptions I made in handling the outliers. I couldn't find any information about how popularity was measured which is why I tried to a second data point (vote average) to potentially have a less subjective measurement. It also made it diffcult when working on the outliers. I assumed that since 83% of the popularity measurement was less than 1 and greater than 0.01 anthing outside of this range could be considered an outlier.

```
In [37]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[37]: 0
```