

```
In [ ]: #Do the higher budget movies achieve higher ratings ?
```

```
In [ ]: #Which features or properties can be associated with high ratings ?  
# how many rows and columns do we have ?  
# do we have a duplicated rows ?  
# what are the data types ?  
# do we have null values ?  
# what are the best year in relising movies ?
```

```
In [4]: import pandas as pd  
import numpy as np  
import matplotlib.pyplot as plt  
%matplotlib inline  
#import the pakages that we will use
```

```
In [5]: #how many rows and columns  
dfmain=pd.read_csv("movies.csv")  
dfmain.shape
```

```
Out[5]: (10866, 21)
```

```
In [6]: #we need to inquiry about the duplicated rows  
sum(dfmain.duplicated())
```

```
Out[6]: 1
```

```
In [7]: #drop the duplicated rows  
dfmain.drop_duplicates(inplace = True)
```

```
In [8]: dfmain['runtime'] = dfmain['runtime'].replace(0, np.NaN)  
dfmain['budget_adj'] = dfmain['budget_adj'].replace(0, np.NaN)  
dfmain['revenue_adj'] = dfmain['revenue_adj'].replace(0, np.NaN)  
#a great methods to replace the '0' with 'NULLS'
```

In [9]:

In [10]: dfmain.dtypes

```
Out[10]: id                int64
imdb_id                 object
popularity             float64
budget                 int64
revenue                int64
original_title         object
cast                   object
homepage               object
director               object
tagline                object
keywords               object
overview               object
runtime               float64
genres                 object
production_companies   object
release_date           object
vote_count             int64
vote_average           float64
release_year           int64
budget_adj             float64
revenue_adj            float64
dtype: object
```

```
In [11]: ## descrption of the dataset
dfmain['release_year'].describe()
#the movies release date is between 1960 and 2015 and 2011 takes the mo
st relaising movies date
```

```
Out[11]: count    10865.000000
mean      2001.321859
std       12.813260
min       1960.000000
25%      1995.000000
50%      2006.000000
75%      2011.000000
```

```
max      2015.000000
Name: release_year, dtype: float64
```

```
In [12]: #here is the amount of null values in the columns
dfmain.isnull().sum()
```

```
Out[12]: id                0
imdb_id                 10
popularity              0
budget                 0
revenue                0
original_title          0
cast                   76
homepage               7929
director                44
tagline                2824
keywords               1493
overview                4
runtime                 31
genres                 23
production_companies   1030
release_date            0
vote_count              0
vote_average            0
release_year            0
budget_adj              5696
revenue_adj             6016
dtype: int64
```

```
In [13]: # bin edges to cut the data into groups
bin_edges = [1.5, 5.4, 6.0, 6.6, 9.2]

# labels for the rating categories
bin_names = ['low', 'mediocre', 'high', 'very_high']
```

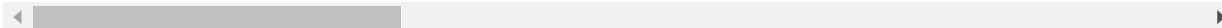
```
In [14]: # create rating categories
dfmain['rating_catagory'] = pd.cut(dfmain['vote_average'], bin_edges, l
abels=bin_names)
```

```
# confirm the creation
dfmain.head()
```

Out[14]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi...	
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy Charlize Theron Hugh Keays-Byrne Nic...	
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley Theo James Kate Winslet Ansel...	http://www
3	140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D...	http
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel Paul Walker Jason Statham Michelle ...	

5 rows × 22 columns



```
In [15]: # Description of vote_average
dfmain['vote_average'].describe()
# the vote average range from 1.5 to 9.2
```

```
Out[15]: count    10865.000000
mean         5.975012
std          0.935138
min          1.500000
```

```
25%          5.400000
50%          6.000000
75%          6.600000
max           9.200000
Name: vote_average, dtype: float64
```

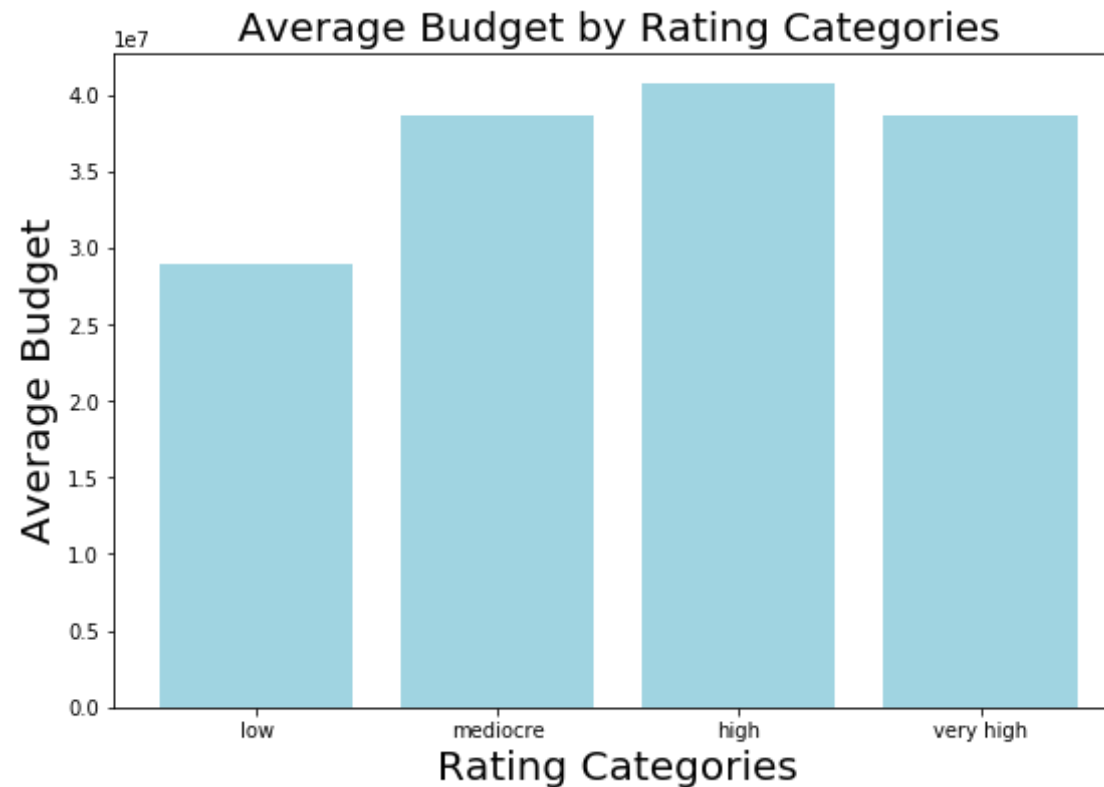
```
In [16]: # i create averages grouped by the rating categories
means = dfmain.groupby('rating_catagory')['budget_adj'].mean()
```

```
In [24]: # :Do the higher budget movies achieve higher ratings ?
```

```
In [25]: # Create a bar chart with proper labels
locations = [1,2,3,4]

heights= [means['low'],means ['mediocre'],means['high'],means['very_high']]
labels= ['low','mediocre','high','very high']
plt.figure(figsize=(9, 6))
plt.bar(locations, heights, color='#88cada', alpha=.8, tick_label=labels)
plt.title('Average Budget by Rating Categories', fontdict={'fontsize': 20})
plt.xlabel('Rating Categories', fontdict={'fontsize': 20})
plt.ylabel('Average Budget', fontdict={'fontsize': 20})
```

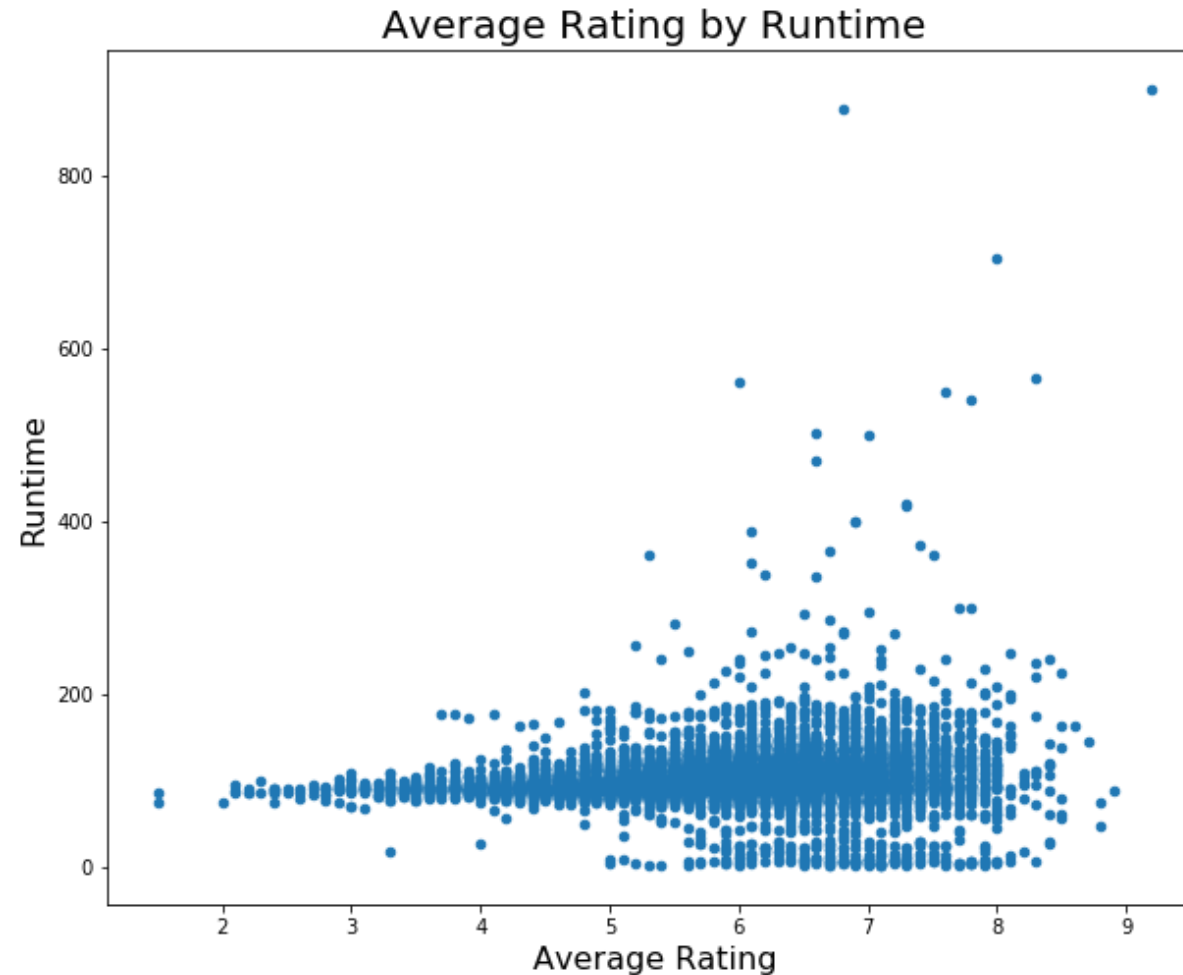
```
Out[25]: Text(0, 0.5, 'Average Budget')
```



```
In [26]: # in this visualization it shows that the movies with less budget will take a lower rating
# in the other hand it is not necessary if you have a huge budget you will guarantee the very high ratings
# the most spending budget takes the high rate by category, even though the very high has less budget
```

```
In [27]: ## I created scatterplot for runtime, popularity in combination with the average rating to identify possible correlations
dfmain.plot(y='runtime', x='vote_average', kind='scatter', figsize=(10, 8))
```

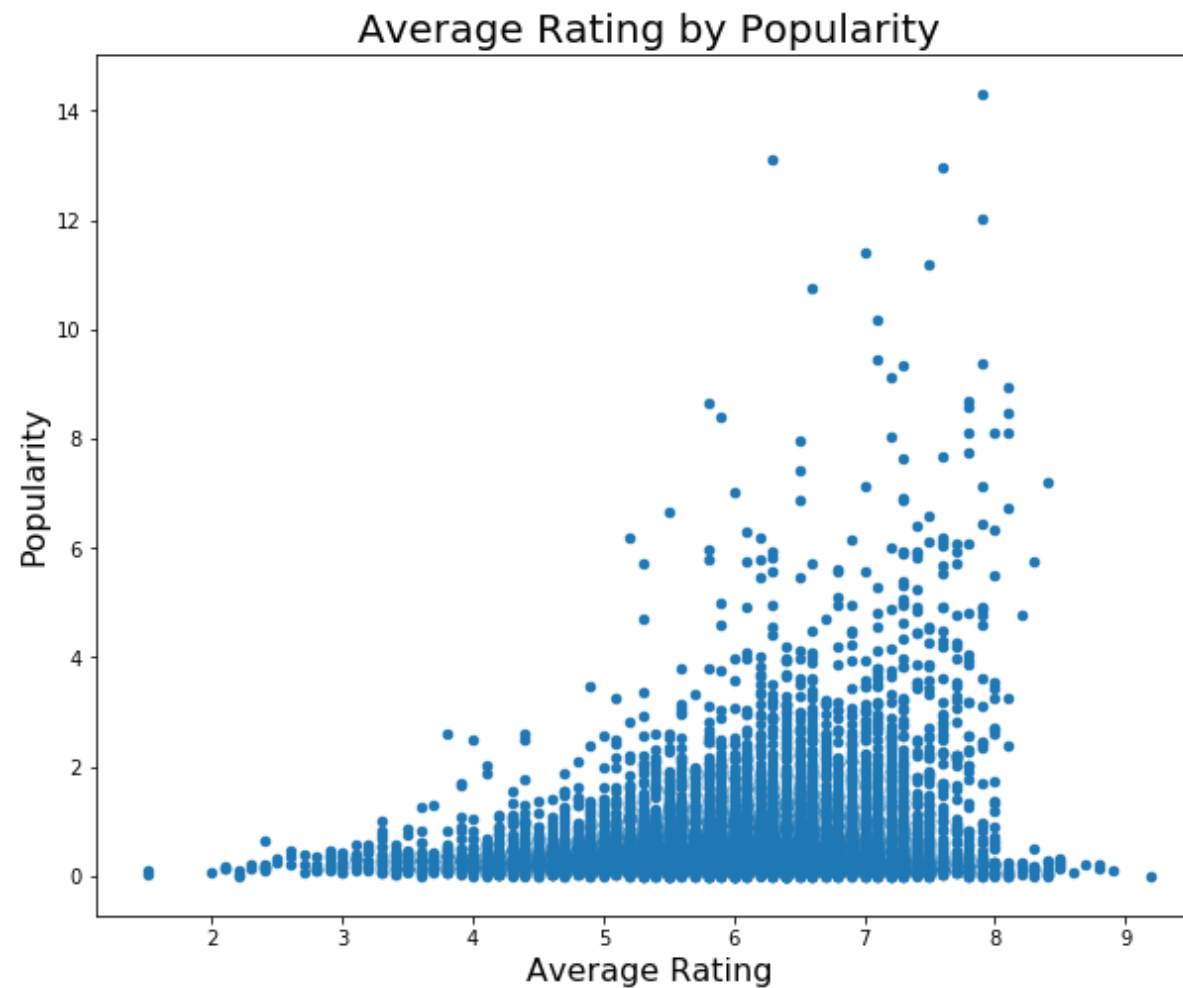
```
plt.title('Average Rating by Runtime', fontdict={'fontsize': 20})
plt.xlabel('Average Rating', fontdict={'fontsize': 16})
plt.ylabel('Runtime', fontdict={'fontsize': 16});
```



```
In [ ]: # in this scatter plot shows that most movies less than 200 minutes w
        # hitch make sense to rate it
        # the relation is strong when the movie is less than 200 min
```

```
In [39]: dfmain_pop = dfmain.query('popularity <= 15') # excluding the outliers
```

```
dfmain_pop.plot(y='popularity', x='vote_average', kind='scatter', figsize=(10, 8))
plt.title('Average Rating by Popularity', fontdict={'fontsize': 20})
plt.xlabel('Average Rating', fontdict={'fontsize': 16})
plt.ylabel('Popularity', fontdict={'fontsize': 16});
```



In []:


```
In [ ]: # the same idea from the previos scatter plot but here the relationship
        between popularity and writings
```

```
In [ ]: # Conclusions
        #The chart indicates minor differences in the average budgets, while me
        diocre and high rating categories contribute for higher average budgets
        than low and very high ratings.
        #From the visualization, a positive correlation between popularity and
        rating
```

```
In [35]: dfmain.head()
```

Out[35]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
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