Investigating Trends in Movies

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Introduction

> I will investigate the TMDb movie dataset to try and identify any trends that exist between table attributes. Specifically, I will focus on the attribute `vote_average` to see if there is any correlation between this attribute and any of the other columns. I would like to know if there is a correlation between the financial columns of `budget_adj` and `revenue_adj` , and how well a movie scores in the `vote_average` field. I will also compare the `vote_average` score and the TMDb attribute `popularity` to see if these two columns are predictive of one another. Finally, I will investigate a dataset consisting of the top 10% of the `vote_average` column to see what type of attributes are associated with movies that are in this 'A' grade grouping.

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

Data Wrangling

General Properties

In [2]:
```
# Load data from file into a dataframe
filename = 'C:/Users/securitycontrol/My Documents/WGU/C749/Project 1/tmdb-movi
es.csv'
all_movies_df = pd.read_csv(filename)
```

In [3]:
```
## preview the table
all_movies_df.head(5)
```

Out[3]:

	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...	htt
4	168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel|Paul Walker|Jason Statham|Michelle ...	

5 rows × 21 columns

In [4]:
```
## preview the table
all_movies_df.describe()
```

Out[4]:

	id	popularity	budget	revenue	runtime	vote_count	vo
count	10866.000000	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10
mean	66064.177434	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	
std	92130.136561	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	
25%	10596.250000	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	
50%	20669.000000	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	
75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	
max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	

The two above cells give a preview of the type of data that is in each column in the dataset. We can see we are going to have several columns that have values of 0 in columns like `budget` , `revenue` , `runtime` , `budget_adj` , and `revenue_adj` . A lack of values in these columns will have an impact on any trends and calculations that involve rows with those values. My investigation is also focusing on `vote_average` , which is related to `vote_count` . We can see that some of the records in this dataset have as few as 10 votes counting towards the `vote_average` score. In order to have more statsitical significance, I would like to have a minimum of 100 people who voted for each movie, to include that movie in my analysis.

In [5]:
```
## get a count of how many rows have a 0 in the adjusted budget column
len(all_movies_df[all_movies_df['budget_adj']==0])
```

Out[5]: 5696

In [6]:
```
## get a count of how many rows have a 0 in the adjusted revenue column
len(all_movies_df[all_movies_df['revenue_adj']==0])
```

Out[6]: 6016

In [7]:
```
## check to see if any duplicate rows exist in the DataFrame
all_movies_df[all_movies_df.duplicated()]
```

Out[7]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	d
2090	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo|Kelly Overton|Cary-Hiroyuki Tagawa|Ian...	NaN	I

1 rows × 21 columns

The previous few cells took a closer look at the data within the dataset to see if any abnormalities could be located. Since I intend to work with the financial columns `budget_adj` and `revenue_adj` , I thought it would be beneficial to check for invalid entries, such as rows without any finacial data. I also checked the dataset for any duplicate rows and found that one row was in fact a duplicate row in the dataset and will need to be removed.

In [8]:
```
## check the data types and non null column count
all_movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
 #   Column                Non-Null Count  Dtype  
---  ------                --------------  -----  
 0   id                    10866 non-null  int64  
 1   imdb_id               10856 non-null  object 
 2   popularity            10866 non-null  float64
 3   budget                10866 non-null  int64  
 4   revenue               10866 non-null  int64  
 5   original_title        10866 non-null  object 
 6   cast                  10790 non-null  object 
 7   homepage              2936 non-null   object 
 8   director              10822 non-null  object 
 9   tagline               8042 non-null   object 
 10  keywords              9373 non-null   object 
 11  overview              10862 non-null  object 
 12  runtime               10866 non-null  int64  
 13  genres                10843 non-null  object 
 14  production_companies  9836 non-null   object 
 15  release_date          10866 non-null  object 
 16  vote_count            10866 non-null  int64  
 17  vote_average          10866 non-null  float64
 18  release_year          10866 non-null  int64  
 19  budget_adj            10866 non-null  float64
 20  revenue_adj           10866 non-null  float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
```

The above cell looks at the content of the dataframe to show us the column names, data types, and the count of non-null columns. We can see that columns such as `homepage` have nearly 8000 rows with null values. My analysis does not rely on most of these columns so they will be removed from my refined dataset. The following cells will take a look at a few rows in the dataset to help illustrate this information.

In [9]:
```
## view the dataframe sorted by the homepage column with NaNs first
all_movies_df.sort_values(by='homepage', ascending=False, na_position='first')
.head(5)
```

Out[9]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	home
18	150689	tt1661199	5.556818	95000000	542351353	Cinderella	Lily James|Cate Blanchett|Richard Madden|Helen...	
21	307081	tt1798684	5.337064	30000000	91709827	Southpaw	Jake Gyllenhaal|Rachel McAdams|Forest Whitaker...	
26	214756	tt2637276	4.564549	68000000	215863606	Ted 2	Mark Wahlberg|Seth MacFarlane|Amanda Seyfried|...	
32	254470	tt2848292	3.877764	29000000	287506194	Pitch Perfect 2	Anna Kendrick|Rebel Wilson|Hailee Steinfeld|Br...	
33	296098	tt3682448	3.648210	40000000	162610473	Bridge of Spies	Tom Hanks|Mark Rylance|Amy Ryan|Alan Alda|Seba...	

5 rows × 21 columns

The above cell looks at the first 5 rows that are sorted by `homepage` , in descending order, with NaN (null) values listed first.

In [10]:
```
## view the dataframe sorted by the tagline column with NaNs first
all_movies_df.sort_values(by='tagline', ascending=False, na_position='first').
head(5)
```

Out[10]:

	id	imdb_id	popularity	budget	revenue	original_title	cast	
42	321697	tt2080374	3.079522	30000000	34441873	Steve Jobs	Michael Fassbender|Kate Winslet|Seth Rogen|Kat...	
53	274479	tt2446980	2.793297	60000000	101134059	Joy	Jennifer Lawrence|Bradley Cooper|Robert De Nir...	htt
72	284289	tt2911668	2.272044	0	45895	Beyond the Reach	Michael Douglas|Jeremy Irvine|Hanna Mangan Law...	
74	347096	tt3478232	2.165433	0	0	Mythica: The Darkspore	Melanie Stone|Kevin Sorbo|Adam Johnson|Jake St...	http://wwv
92	370687	tt3608646	1.876037	0	0	Mythica: The Necromancer	Melanie Stone|Adam Johnson|Kevin Sorbo|Nicola ...	http://wwv

5 rows × 21 columns

The previous cell also looked at 5 rows from our data set, but this time organized by `tagline` with NaN values listed first.

Data Cleaning - Removing duplicates, rows/columns with 0 or NaN values, and less than 100 voters

In [11]:
```
## Drop any columns that are not relevant to analysis
all_movies_df = all_movies_df.drop(columns=['imdb_id', 'budget', 'revenue', 'c
ast', 'homepage', 'director', 'tagline', 'keywords', 'overview', 'genres', 'pr
oduction_companies', 'release_date', 'release_year'])
```

In [12]:
```
## Preview the dataframe
all_movies_df.head(5)
```

Out[12]:

	id	popularity	original_title	runtime	vote_count	vote_average	budget_adj	revenue_a
0	135397	32.985763	Jurassic World	124	5562	6.5	137999939.3	1.392446e+
1	76341	28.419936	Mad Max: Fury Road	120	6185	7.1	137999939.3	3.481613e+
2	262500	13.112507	Insurgent	119	2480	6.3	101199955.5	2.716190e+
3	140607	11.173104	Star Wars: The Force Awakens	136	5292	7.5	183999919.0	1.902723e+
4	168259	9.335014	Furious 7	137	2947	7.3	174799923.1	1.385749e+

The first of the previous two cells removed all of the columns from the dataset that are not relevant for my investigation. I have choosen to keep the `id` and `original_title` columns becase they are identifiers useful for showing what the row represents. The cell directly above shows the contents of our dataset with columns removed.

In [13]:
```
## removes any duplicate rows in the DataFrame
movies_df = all_movies_df.drop_duplicates(keep='first')
```

The cell above created a new DataFrame from the existing one and only kept the first instance of a duplicate row. So we now have refined our DataFrame to only include unique row entries.

In [14]:
```
## removes any records with 0 for budget_adj or revenue_adj, or those records
 with less than 100 votes in vote_count
bad_data = (movies_df[(movies_df['budget_adj']==0) | (movies_df['revenue_adj']
==0) | (movies_df['vote_count'] < 100)])
print (len(bad_data))
```

```
8257
```

The above cell used our new DataFrame, `movies_df` , to create another DataFrame called `bad_data` . This set of bad data includes any row from our dataset that has a 0 value for `budget_adj` or `revenue_adj` . It also includes any row that has a `vote_count` of less than 100 people. There are 8257 rows that meet these 3 criteria.

In [15]:
```
## Creates a new DataFrame by removing the entries that are also in the bad_da
ta series
cleaned_movies_df = movies_df.append(bad_data).drop_duplicates(keep=False)
len(cleaned_movies_df)
```

Out[15]: 2608

The above cell creates a DataFrame that has been cleaned up to exclude any rows that are in the `bad_data` DataFrame. It takes the `movies_df` and appends all the records from the `bad_data` dataframe. Since the `bad_data` dataframe is based on the `movies_df`, it will include duplicates because the records would exist in both tables. I chose to keep none of these duplicates and the resulting dataframe is now cleaned and ready to use. This dataframe has 2608 rows.

In [16]:
```
## preview our cleaned dataset
cleaned_movies_df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 2608 entries, 0 to 10770
Data columns (total 8 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              2608 non-null   int64
 1   popularity      2608 non-null   float64
 2   original_title  2608 non-null   object
 3   runtime         2608 non-null   int64
 4   vote_count      2608 non-null   int64
 5   vote_average    2608 non-null   float64
 6   budget_adj      2608 non-null   float64
 7   revenue_adj     2608 non-null   float64
dtypes: float64(4), int64(3), object(1)
memory usage: 183.4+ KB
```

The above cell shows that we now have 8 columns that all contain non-null data that we can use for our investigation. The following cell will give a preview of what is now in the dataset.

In [17]:
```
## preview the contents of our cleaned dataset
cleaned_movies_df.head(5)
```

Out[17]:

	id	popularity	original_title	runtime	vote_count	vote_average	budget_adj	revenue_a
0	135397	32.985763	Jurassic World	124	5562	6.5	137999939.3	1.392446e+
1	76341	28.419936	Mad Max: Fury Road	120	6185	7.1	137999939.3	3.481613e+
2	262500	13.112507	Insurgent	119	2480	6.3	101199955.5	2.716190e+
3	140607	11.173104	Star Wars: The Force Awakens	136	5292	7.5	183999919.0	1.902723e+
4	168259	9.335014	Furious 7	137	2947	7.3	174799923.1	1.385749e+

In [18]:
```
## takes a panda series and returns a series with outliers removed
def find_outliers(data):
    q1 = data.quantile(.25)
    q3 = data.quantile(.75)
    iqr = q3 - q1
    lower_range = q1 - (1.5 * iqr)
    higher_range = q3 + (1.5 * iqr)

    my_list = data.tolist()

    useful_data = []
    for i in range(len(my_list)):
        if (my_list[i] >= lower_range) & (my_list[i] <= higher_range):
            useful_data.append(my_list[i])

    my_series = pd.Series(useful_data)
    return my_series
```

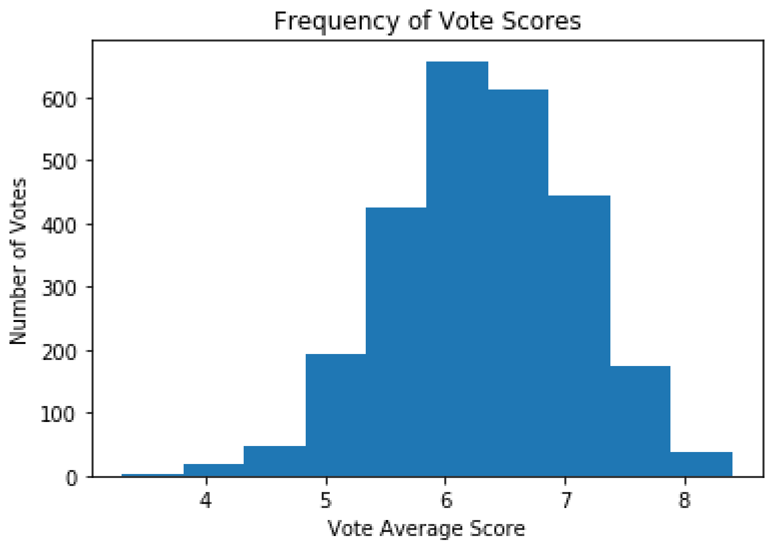
The above function was created to remove outliers from a dataset. This will remove values from both the high and low extremes. We will use this function later in my analysis.

Exploratory Data Analysis

What relationships exists between a movie's vote average score and other table properties?

Does having a higher budget correlate to a better vote average score?

In [19]:
```
## plot a histogram
plt.hist(cleaned_movies_df['vote_average'], bins=10)
plt.xlabel('Vote Average Score')
plt.ylabel('Number of Votes')
plt.title('Frequency of Vote Scores')
plt.show()
```



In [20]:
```
cleaned_movies_df['vote_average'].mode()
```

Out[20]:
```
0    6.5
dtype: float64
```

I wanted to start by viewing the distribution of `vote_average` scores that we have in our dataset. The previous cell shows the frequency of each `vote_score` . The mode of this set was determined in the cell above to be 6.5 and this can be seen in our histogram with the majority of votes falling in the 6-7 range. Next I will start looking at the relationship between variables.

In [21]:
```
## establish an independent variable, x, to represent the vote_average values
x = cleaned_movies_df['vote_average']
```

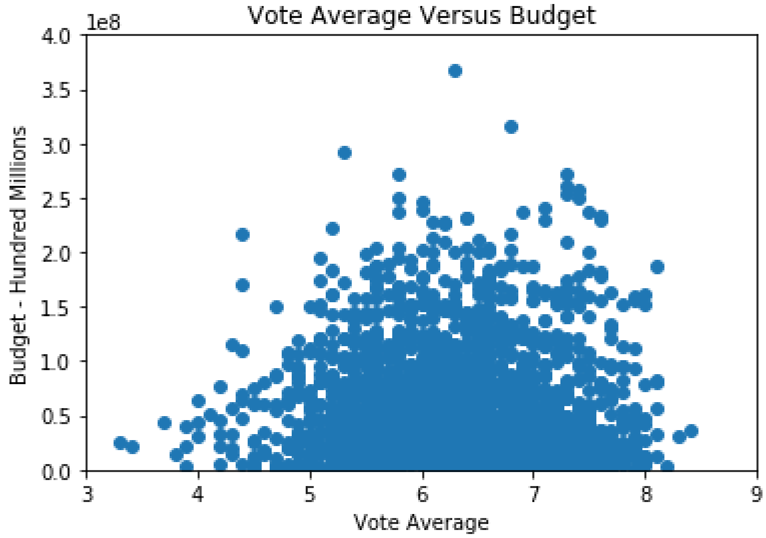
In [22]:
```
## define an dependent variable to contain the budget_adj values
y = cleaned_movies_df['budget_adj']
```

In [23]:
```
## Calculate Pearson's R, the correlation coefficient
np.corrcoef(x,y)[0,1]
```

Out[23]:
```
-0.03821466752418816
```

In [24]:
```
plt.scatter(x,y)
plt.ylabel('Budget - Hundred Millions')
plt.xlabel('Vote Average')
plt.axis([3, 9, 0, 400000000])
plt.title('Vote Average Versus Budget')
```

Out[24]: Text(0.5, 1.0, 'Vote Average Versus Budget')



The above cells calculated Pearson's R, the correlation coefficient, between scores in the `vote_average` column and their corresponding expenses from the `budget_adj` column. A coefficient of -0.0382 is indicative of practically no correlation between the two attributes. Therefore, increasing the amount of money that is spent on a movie has no correlation with how well that movie will be liked by the general population.

Does earning more revenue correlate to a better vote average score?

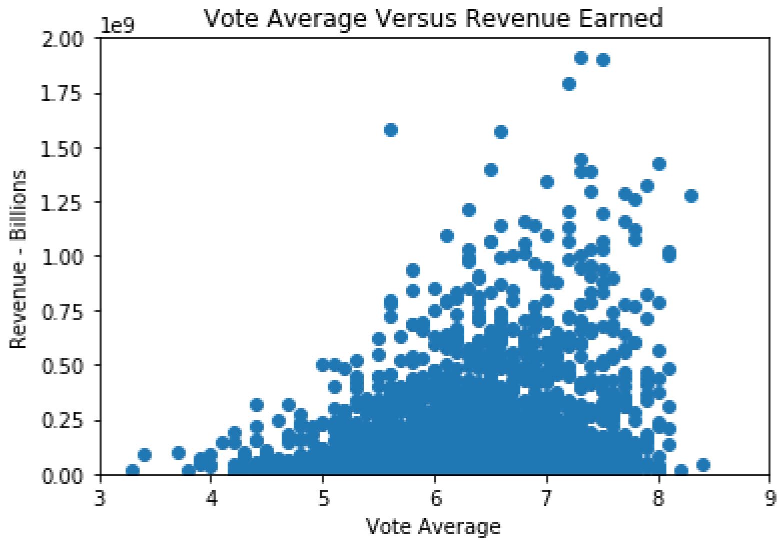
In [25]:
```
## redefine y to be the revenue_adj column
y = cleaned_movies_df['revenue_adj']
```

In [26]:
```
## Calculate Pearson's R, the correlation coefficient
np.corrcoef(x,y)[0,1]
```

Out[26]: 0.23135541337120782

In [27]:
```
plt.scatter(x,y)
plt.ylabel('Revenue - Billions')
plt.xlabel('Vote Average')
plt.axis([3, 9, 0, 2000000000])
plt.title('Vote Average Versus Revenue Earned')
```

Out[27]:
```
Text(0.5, 1.0, 'Vote Average Versus Revenue Earned')
```



The above cells calculated the correlation coeffient between the `vote_average` column and the `revenue_adj` column. There is a small positive correlation of 0.231 between the two attributes. I expected the relationship to be stronger since it would logically makes sense for a more popular movie to earn more money.

Does a movies popularity score correlate to a similar vote_average score?

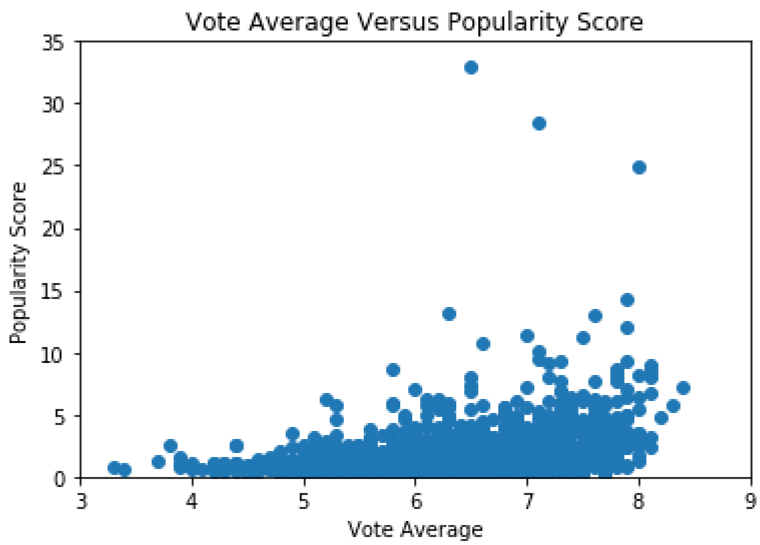
In [28]:
```
## redefine y to be the popularity column
y = cleaned_movies_df['popularity']
```

In [29]:
```
## Calculate Pearson's R, the correlation coefficient
np.corrcoef(x,y)[0,1]
```

Out[29]:
```
0.3064894733733035
```

In [30]:
```
## plot a scatterplot
plt.scatter(x,y)
plt.ylabel('Popularity Score')
plt.xlabel('Vote Average')
plt.axis([3, 9, 0, 35])
plt.title('Vote Average Versus Popularity Score')
```

Out[30]:
```
Text(0.5, 1.0, 'Vote Average Versus Popularity Score')
```

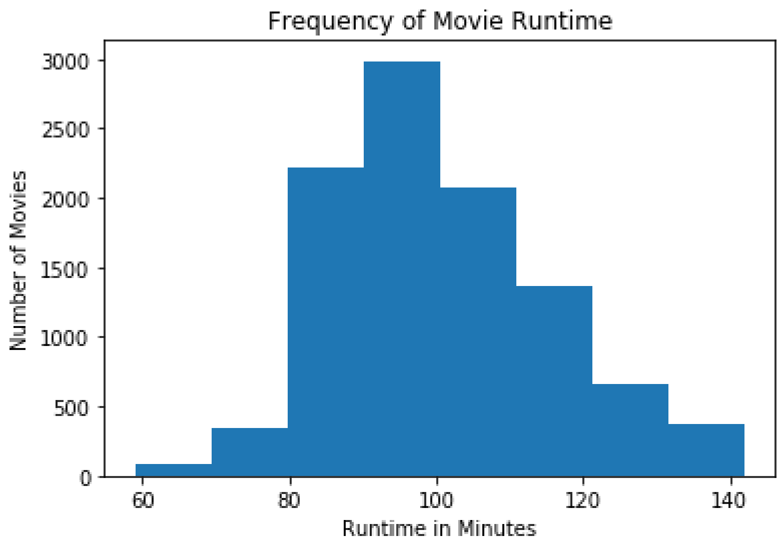


The above cells looked at the relationship between `vote_average` and `popularity` . A correlation score of 0.306 shows their is a medium correlation between the two variables. The scatterplot also shows there is a slightly positive relationship trend.

What trends exist for movies that are 'A' rated?

In [31]:
```
## remove any outliers from the runtime column
runtime_minus_outliers = find_outliers(movies_df['runtime'])
```

In [32]:
```
## plot a histogram
plt.hist(runtime_minus_outliers, bins=8)
plt.xlabel('Runtime in Minutes')
plt.ylabel('Number of Movies')
plt.title('Frequency of Movie Runtime')
plt.show()
```



The above cells created a new Panda Series that held the values from the runtime column once outliers had been removed from the data set. I used the DataFrame - `movies_df` , that I created earlier, which had removed one duplicate row from the original dataframe. We now have a larger sample of 10865 to use in our results. This is then plotted on a histogram to show the frequency of movies at a certain time length. The most common length being between 90 and 100 minutes. Next I will refine this set to include only `vote_average` scores with 100 or more voters in the `vote_count` column.

In [33]:
```
## create a dataframe where all movies have at least 100 votes
vote_count_df = movies_df[movies_df['vote_count']>=100]
```

In [34]:
```
## create a DataFrame to hold the A list movies
top_10_perc_by_vote_average=vote_count_df[vote_count_df['vote_average'] >= vot
e_count_df['vote_average'].quantile(.9)]
```

I created a `vote_count_df` from our existing dataset to include only those rows with at least 100 people that voted for the movie average score. From this newly created dataset, I then created a `top_10_perc_by_vote_average` dataset that holds all records for movies that are above the 90th percentile; the top 10 % of movies, or an 'A' rated movies set.

In [35]:
```
##describe this variable
top_10_perc_by_vote_average.describe()
```

Out[35]:

	id	popularity	runtime	vote_count	vote_average	budget_adj	revenu
count	373.000000	373.000000	373.000000	373.000000	373.000000	3.730000e+02	3.73000
mean	62506.123324	2.495170	117.726542	1480.882038	7.561930	4.290360e+07	2.50028
std	96667.654995	2.566219	52.348966	1635.556484	0.236003	5.557902e+07	3.83944
min	11.000000	0.028875	3.000000	101.000000	7.300000	0.000000e+00	0.00000
25%	650.000000	0.814857	99.000000	272.000000	7.300000	4.741411e+06	9.92017
50%	9800.000000	1.650848	118.000000	804.000000	7.500000	2.152877e+07	8.97484
75%	90369.000000	3.425628	135.000000	2131.000000	7.700000	5.526546e+07	3.19263
max	355338.000000	24.949134	705.000000	9767.000000	8.400000	2.716921e+08	2.78971

The resulting set above shows some general information about this 'A' list of movies. We can see that we have 373 rows in our dataset and that the average runtime for movies in this 'A' group is 117.73 minutes.

In [36]:
```
##Create a Series to hold runtime data minus outliers
A_list_outliers = find_outliers(top_10_perc_by_vote_average['runtime'])
```

In [37]:
```
## describe the variables
A_list_outliers.describe()
```

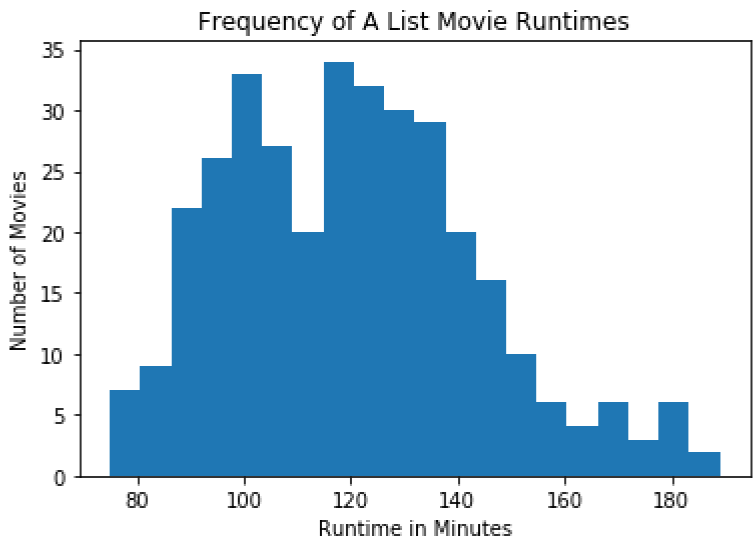
Out[37]:
```
count    342.000000
mean     120.286550
std       23.629838
min       75.000000
25%      102.000000
50%      120.000000
75%      135.000000
max      189.000000
dtype: float64
```

I then used the `find_outliers` function to remove outliers from our A list set to further refine the dataset. The average movie length in this group is about 120 minutes.

In [38]:
```
## fine the mode of this dataset
A_list_outliers.mode()
```

Out[38]:
```
0    117
dtype: int64
```

In [39]:
```
## plot a histogram
plt.hist(A_list_outliers, bins=20)
plt.xlabel('Runtime in Minutes')
plt.ylabel('Number of Movies')
plt.title('Frequency of A List Movie Runtimes')
plt.show()
```



The above cell is a visual representation of the 'A' list movies runtime frequencies. The mode was calculated in one of the above cells to be at 117 minutes and the histogram shows there is approximately 33 movies within the span of 117-122 minutes in length.

Conclusions

Limitations

> Some of the issues I encountered while working with this dataset involved a significant chunk of missing data values in the budgetary columns. Approximately two-thirds of the dataset had a value of 0 in the `budget_adj` and/or `revenue_adj` columns so this limited my sample set significantly. I still believe the sample of 2608 that I used for much of my analysis was adequate for the calculation of my results.
>
> Another limitiation that I worked around was not understanding how the column `popularity` was determined. I decided to use the `average_vote` column because it was a simple rating from 1-10 for each movie that was then averaged among the sample of voters. It was unclear how `popularity` was calcuated or what factors went into determining the ratings. I simply chose to investigate the relationship between `popularity` and `average_score` without being able to dive much further into it.

Summarizing Results

My investigation has lead me to believe that there is no correlation between vote_average