investigate_a_dataset_s_salami

August 19, 2022

1 Investigating the TMDb Movie Data

Udacity alx Data Analyst Nanodegree

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1.1 Introduction

This project investigates the profitability of movies, the relationship between profit, popularity, and movie runtime. This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue.

The specific questions being investigated here are: * Are movies still profitable? * What are the top 10 profitable movies? * How are profits and average votes related?

1.2 Data wrangling

- In this section, we load the data, present, and observe the data to begin the analysis.

[1]:
```
# load required libraries

import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
%matplotlib inline
```

[2]:
```
# load dataset

path = "https://d17h27t6h515a5.cloudfront.net/topher/2017/October/
  ↪59dd1c4c_tmdb-movies/tmdb-movies.csv"
df = pd.read_csv(path)
```

[3]:
```
df.head(3)
```

[3]:

	id	imdb_id	popularity	budget	revenue	original_title	\
0	135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	
1	76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	
2	262500	tt2908446	13.112507	110000000	295238201	Insurgent	

```
                                                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…

                                       homepage           director  \
0                  http://www.jurassicworld.com/   Colin Trevorrow
1                    http://www.madmaxmovie.com/     George Miller
2  http://www.thedivergentseries.movie/#insurgent  Robert Schwentke

                     tagline  …  \
0          The park is open.  …
1         What a Lovely Day.  …
2  One Choice Can Destroy You  …

                                          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

                                    genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|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

   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 rows x 21 columns]
```

The data appears to have loaded correctly and we can proceed with the next steps.

- In this section, we will explore the dataset to identify its size, features, missing values, duplicate rows and unique values before we commence our analysis.

[4]:
```
df.shape
```

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

[5]:
```
list(df.columns)
```

[5]:
```
['id',
 'imdb_id',
 'popularity',
 'budget',
 'revenue',
 'original_title',
 'cast',
 'homepage',
 'director',
 'tagline',
 'keywords',
 'overview',
 'runtime',
 'genres',
 'production_companies',
 'release_date',
 'vote_count',
 'vote_average',
 'release_year',
 'budget_adj',
 'revenue_adj']
```

[188]:
```
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
```

[6]:
```
df.isna().sum()
```

[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
```

[7]:
```
df.duplicated().sum()
```

[7]:
```
1
```

- From the initial checks, there are 10866 observations, and 21 features.
- The data types appears to be in order.
- There are some missing values, but they are not in major features.
- The unused features will be dropped.
- The missing values in genres will also be droppped.
- The duplicate rows will also be dropped.

[8]:
```
df.drop(columns = ['imdb_id', 'tagline', 'homepage', 'cast',␣
 ↪'production_companies', 'keywords', 'overview' ], inplace=True)
```

[9]:
```
df.drop_duplicates(inplace=True)
df.shape
```

[9]:
```
(10865, 14)
```

[10]:
```
df.dropna(how='any', subset=['genres'], inplace=True)
df.shape
```

[10]:
```
(10842, 14)
```

[11]:
```
df.describe()
```

[11]:

	id	popularity	budget	revenue	runtime	\
count	10842.000000	10842.000000	1.084200e+04	1.084200e+04	10842.000000	
mean	65870.675521	0.647461	1.465531e+07	3.991138e+07	102.138443	
std	91981.355752	1.001032	3.093971e+07	1.171179e+08	31.294612	
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000	
25%	10589.250000	0.208210	0.000000e+00	0.000000e+00	90.000000	
50%	20557.000000	0.384532	0.000000e+00	0.000000e+00	99.000000	
75%	75186.000000	0.715393	1.500000e+07	2.414118e+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	10842.000000	10842.000000	10842.000000	1.084200e+04	1.084200e+04
mean	217.823649	5.974064	2001.314794	1.758712e+07	5.147797e+07
std	576.180993	0.934257	12.813617	3.433437e+07	1.447723e+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%	146.000000	6.600000	2011.000000	2.092507e+07	3.387838e+07
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

[12]:
```
df.isna().sum()
```

[12]:
```
id                0
popularity        0
budget            0
revenue           0
original_title    0
director         42
runtime           0
genres            0
release_date      0
vote_count        0
vote_average      0
release_year      0
budget_adj        0
revenue_adj       0
dtype: int64
```

1.3 Are movies still profitable?

We will define profit as the difference between revenue and budget using the adjusted values. Before we proceed, we will explore the distribution of the two features using a histgram.

[13]:
```
df.describe()
```

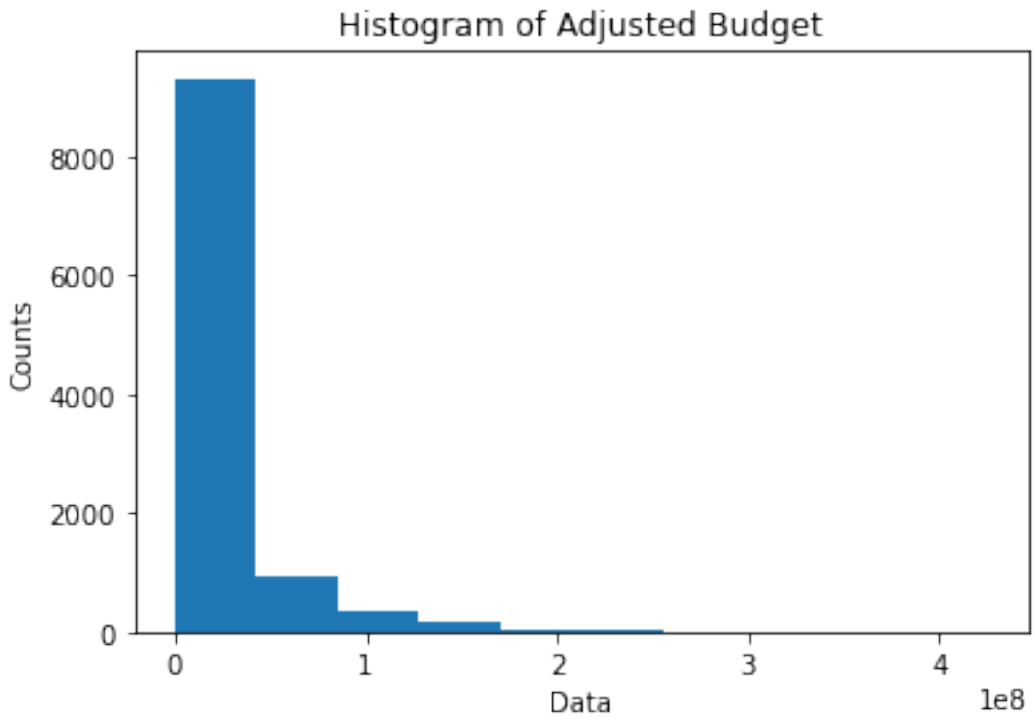
[13]:

	id	popularity	budget	revenue	runtime
count	10842.000000	10842.000000	1.084200e+04	1.084200e+04	10842.000000
mean	65870.675521	0.647461	1.465531e+07	3.991138e+07	102.138443
std	91981.355752	1.001032	3.093971e+07	1.171179e+08	31.294612
min	5.000000	0.000065	0.000000e+00	0.000000e+00	0.000000
25%	10589.250000	0.208210	0.000000e+00	0.000000e+00	90.000000
50%	20557.000000	0.384532	0.000000e+00	0.000000e+00	99.000000
75%	75186.000000	0.715393	1.500000e+07	2.414118e+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	10842.000000	10842.000000	10842.000000	1.084200e+04	1.084200e+04
mean	217.823649	5.974064	2001.314794	1.758712e+07	5.147797e+07
std	576.180993	0.934257	12.813617	3.433437e+07	1.447723e+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%	146.000000	6.600000	2011.000000	2.092507e+07	3.387838e+07
max	9767.000000	9.200000	2015.000000	4.250000e+08	2.827124e+09

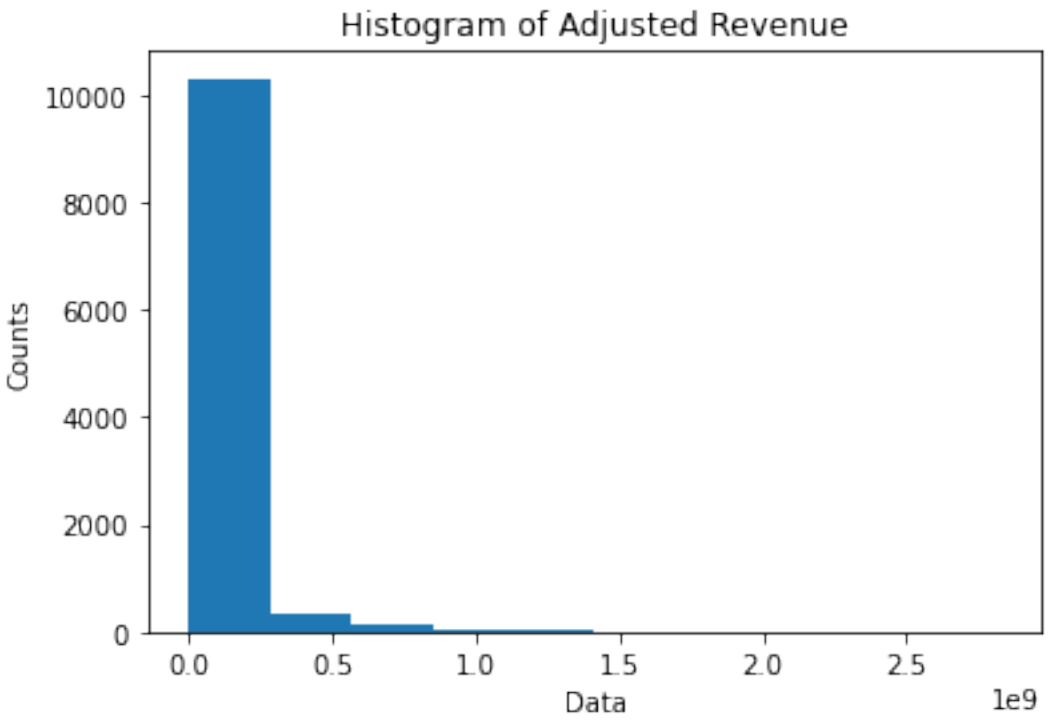
[14]:
```
plt.hist(df["budget_adj"])
plt.title('Histogram of Adjusted Budget')
plt.ylabel('Counts')
plt.xlabel('Data')
```

[14]:
```
Text(0.5, 0, 'Data')
```



[15]:
```
plt.hist(df["revenue_adj"])
plt.title('Histogram of Adjusted Revenue')
plt.ylabel('Counts')
plt.xlabel('Data')
```

[15]: Text(0.5, 0, 'Data')



- There appears to be a lot of values around the zero point which might indicate budget and revenue of zero.
- Since, revenue could be zero, we will drop all zero values under budget_adj.

[16]:
```
df.query("budget_adj <= 0")["budget_adj"].count()
```

[16]: 5674

[17]:
```
df.query("revenue_adj <= 0")["revenue_adj"].count()
```

[17]: 5993

[18]:
```
df_clean = df.query("budget_adj > 0")
```

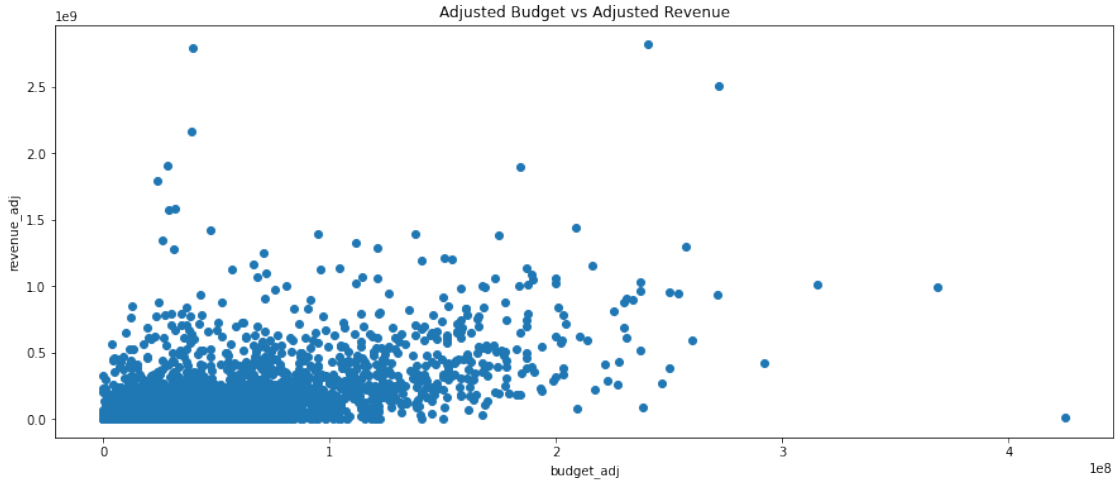
[19]:
```
df_clean.shape
```

[19]: (5168, 14)

- The new dataset has a significatly low size than the original, however, for the purposes of our analysis, we continue with this new subset.
- We will first explore the relationship between the budget and revenue, then evaluate the profit as revenue_adj - budget_adj

[20]:
```
# sctter plot of adjusted revenue and budget
```

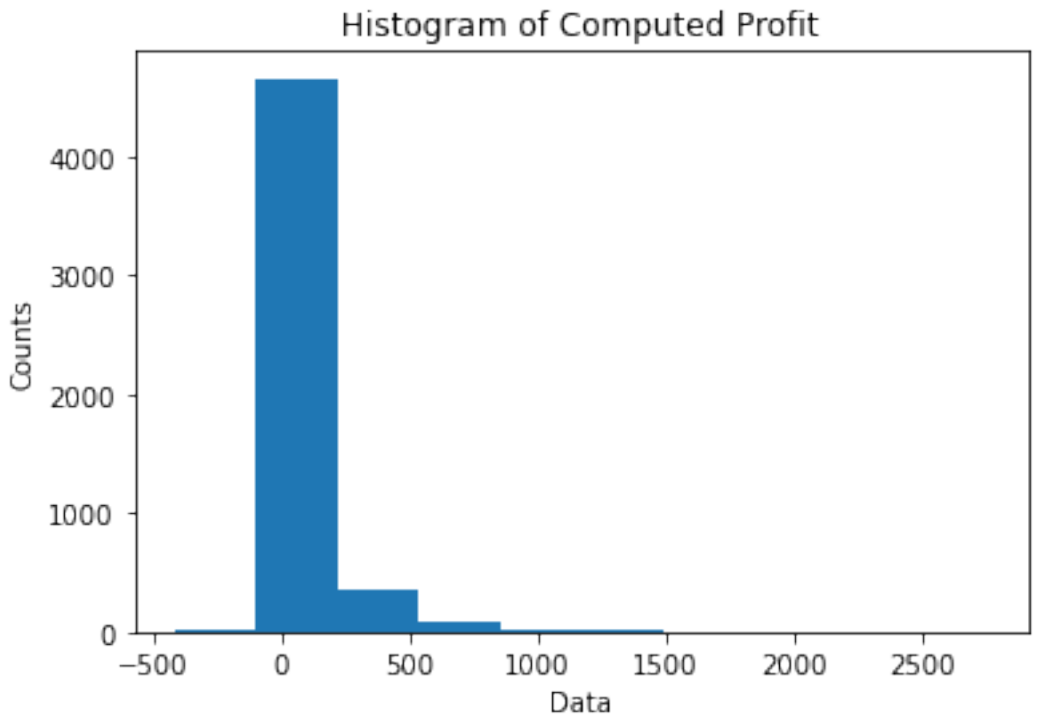
```
plt.figure(figsize = (15, 6))
plt.scatter(df_clean["budget_adj"], df_clean["revenue_adj"])
plt.title('Adjusted Budget vs Adjusted Revenue')
plt.xlabel('budget_adj')
plt.ylabel('revenue_adj')
plt.show()
```



[21]:
```
import warnings
warnings.filterwarnings('ignore') # disable warnings from computation

# compute profit from adjusted budjet and revenue

df_clean["profit"] = (df_clean["revenue_adj"] - df_clean["budget_adj"])/1000000
```

[22]:
```
# histogram of profit

plt.hist(df_clean["profit"])
plt.title('Histogram of Computed Profit')
plt.ylabel('Counts')
plt.xlabel('Data')
```

[22]:
```
Text(0.5, 0, 'Data')
```



- There is a positive correlation between adjusted budget and revenue from the scatter plot.
- Profit is computed and scaled into millions.
- Profit can be seen to be right skewed with smal negative values that indicate losses.
- Thus, we observe that most movies make profit although there are sometimes losses or rather minimal profit

[23]:
```
# what proportion of the movies make losses or break even

df_clean.query("profit <= 0")["profit"].count() / df_clean.shape[0]
```

[23]:
```
0.46246130030959753
```

- About 46% of the movies do not make profit
- We will now explore further to know whether there is a trend in years of the profit.

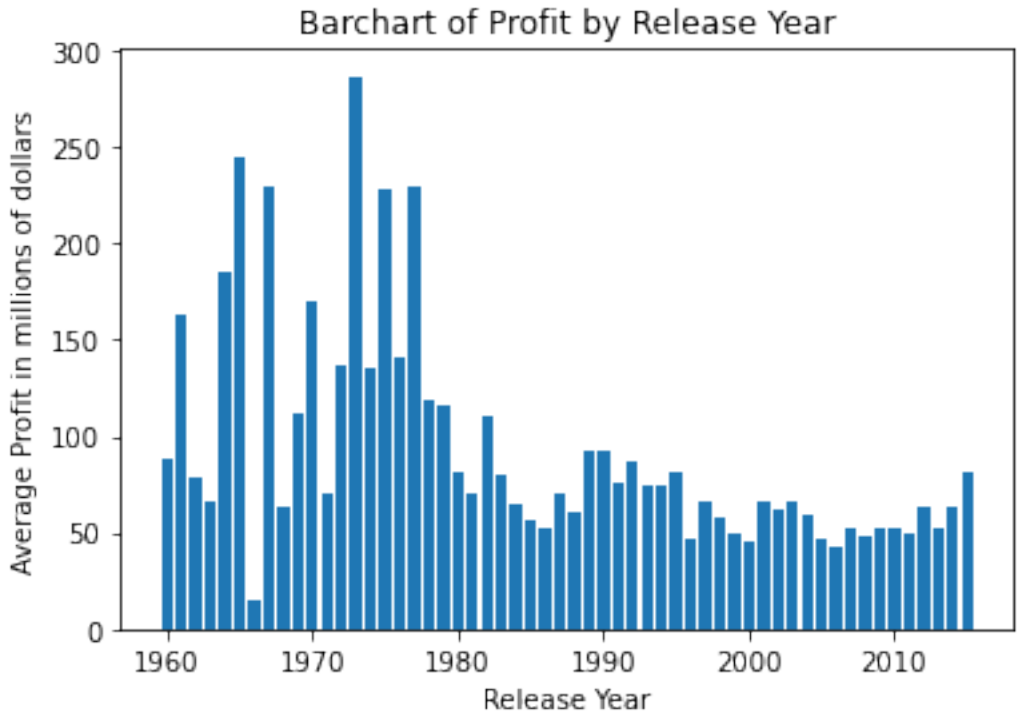
[24]:
```
# group year of release by average profit

df_profit_year = df_clean.groupby("release_year")["profit"].mean()
df_profit_year.head()
```

[24]:
```
release_year
1960     87.613834
1961    163.619914
1962     78.061179
```

```
1963     66.797239
1964    184.787631
Name: profit, dtype: float64
```

[25]:
```
# bar chart of year and average profit

plt.bar(df_profit_year.index, df_profit_year)
plt.title('Barchart of Profit by Release Year')
plt.ylabel('Average Profit in millions of dollars')
plt.xlabel('Release Year')
```

[25]:
```
Text(0.5, 0, 'Release Year')
```



- We notice that profits have been rather inconsistent over the year, reaching a peak in the early year of 1960 to 1980
- However, profit have remained stable since the 1990's with a few exceptions
- We can conclude that movies are still profitable. However the profitability has some what reduced over the year
- What has been the most profitable movies?

1.4 What are the top 10 profitable movies?

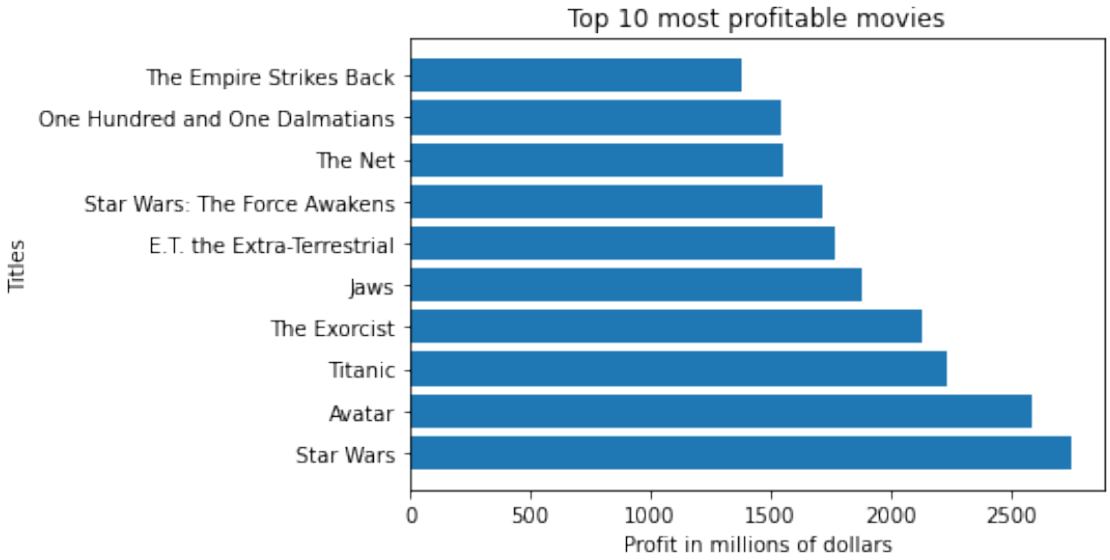
[26]:
```
# sort data by profit, and select top 10

top = df_clean[["release_year","original_title", "genres","profit"]].
 ↪sort_values('profit', ascending=False)[0:10]
top
```

[26]:

	release_year	original_title	genres	profit
1329	1977	Star Wars	Adventure|Action|Science Fiction	2750.136651
1386	2009	Avatar	Action|Adventure|Fantasy|Science Fiction	2586.236848
5231	1997	Titanic	Drama|Romance|Thriller	2234.713671
10594	1973	The Exorcist	Drama|Horror|Thriller	2128.035625
9806	1975	Jaws	Horror|Thriller|Adventure	1878.643094
8889	1982	E.T. the Extra-Terrestrial	Science Fiction|Adventure|Family|Fantasy	1767.968064
3	2015	Star Wars: The Force Awakens	Action|Adventure|Science Fiction|Fantasy	1718.723211
8094	1995	The Net	Crime|Drama|Mystery|Thriller|Action	1551.568265
10110	1961	One Hundred and One Dalmatians	Adventure|Animation|Comedy|Family	1545.635295
7309	1980	The Empire Strikes Back	Adventure|Action|Science Fiction	1376.997526

[27]:
```
# bar chart of top 10 profitable movies

plt.barh(top["original_title"], top["profit"])
plt.title('Top 10 most profitable movies')
plt.ylabel('Titles')
plt.xlabel('Profit in millions of dollars')
```

[27]:
```
Text(0.5, 0, 'Profit in millions of dollars')
```



- We observe that, 6 out of the 10 top profitable movies were release before the 1980's
- This confirms our early conclusion of the early movies bieng more profitable than the later and newer movies

1.5 What are the top 10 profitable movie genres?

[28]:
```
# function to split the genre feature and return a new dataframe with genre␣
↪listed in rows.

def col_to_list(df,col):
    new_df = df[col].str.split('|')
    new_df = new_df.apply(pd.Series)
    return new_df
```

[29]:
```
# applying col_to_list function

df_genre = col_to_list(df_clean, 'genres')
df_genre.head(2)
```

[29]:

	0	1	2	3	4
0	Action	Adventure	Science Fiction	Thriller	NaN
1	Action	Adventure	Science Fiction	Thriller	NaN

[30]:
```
# merge df_genre and df_clean tables

df_genre = df_genre.merge(df_clean, left_index=True, right_index = True)
df_genre.head(2)
```

[30]:
```
        0          1                2         3    4       id  popularity  \
0  Action  Adventure  Science Fiction  Thriller  NaN  135397   32.985763
1  Action  Adventure  Science Fiction  Thriller  NaN   76341   28.419936

      budget     revenue      original_title         director  runtime  \
0  150000000  1513528810      Jurassic World  Colin Trevorrow      124
1  150000000   378436354  Mad Max: Fury Road    George Miller      120

                                     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

   vote_average  release_year    budget_adj   revenue_adj       profit
0           6.5          2015  1.379999e+08  1.392446e+09  1254.445953
1           7.1          2015  1.379999e+08  3.481613e+08   210.161353
```

[31]:
```
# unpivot genres from columns into rows

df_genre = df_genre.
 ↪melt(id_vars=['id','popularity','budget','revenue','original_title','director','runtime','g
                        value_name="movie_genre")
df_genre.head(2)
```

[31]:
```
       id  popularity     budget     revenue      original_title  \
0  135397   32.985763  150000000  1513528810      Jurassic World
1   76341   28.419936  150000000   378436354  Mad Max: Fury Road

          director  runtime                                     genres  \
0  Colin Trevorrow      124  Action|Adventure|Science Fiction|Thriller
1    George Miller      120  Action|Adventure|Science Fiction|Thriller

  release_date  vote_count  vote_average  release_year    budget_adj  \
0       6/9/15        5562           6.5          2015  1.379999e+08
1      5/13/15        6185           7.1          2015  1.379999e+08

    revenue_adj       profit variable movie_genre
0  1.392446e+09  1254.445953        0      Action
1  3.481613e+08   210.161353        0      Action
```

[32]:
```
# drop  unused columns
df_genre.drop(['genres','variable'],axis=1,inplace=True)
```

[33]:
```
# see new size of dataframe

df_genre.shape
```

[33]:
```
(25840, 15)
```

[34]:
```
# drop missing values
df_genre.isna().sum()
df_genre.dropna(how='any', subset=['movie_genre'], inplace=True)
df_genre.shape
```

[34]:
```
(13601, 15)
```

[35]:
```
# see final dataframe

df_genre.sort_values(by='original_title').head(5)
```

[35]:

	id	popularity	budget	revenue	original_title	director	runtime	release_date	vote_count	vote_average	release_year	budget_adj	revenue_adj	profit	movie_genre
482	19913	3.244139	7500000	60722734	(500) Days of Summer	Marc Webb	95	7/17/09	1778	7.3	2009	7.623003e+06	6.171861e+07	54.09561	Comedy
5650	19913	3.244139	7500000	60722734	(500) Days of Summer	Marc Webb	95	7/17/09	1778	7.3	2009	7.623003e+06	6.171861e+07	54.09561	Drama
10818	19913	3.244139	7500000	60722734	(500) Days of Summer	Marc Webb	95	7/17/09	1778	7.3	2009	7.623003e+06	6.171861e+07	54.09561	Romance
6144	4951	1.769152	16000000	53478166	10 Things I Hate About You	Gil Junger	97	3/30/99	947	7.2	1999	2.094485e+07	7.000575e+07	49.06090	Romance
11312	4951	1.769152	16000000	53478166	10 Things I Hate About You	Gil Junger	97	3/30/99	947	7.2	1999	2.094485e+07	7.000575e+07	49.06090	Drama

[36]:
```
# summary of movie genres counts

genre_values = df_genre['movie_genre'].value_counts(ascending=False)
genre_values
```

[36]:
```
Drama              2316
Comedy             1740
Thriller           1641
Action             1428
Adventure           906
Romance             861
Crime               823
Horror              765
Science Fiction     701
Family              523
```

```
Fantasy             508
Mystery             440
Animation           260
History             183
Music               169
War                 155
Western              74
Documentary          64
Foreign              35
TV Movie              9
Name: movie_genre, dtype: int64
```

[37]:
```
# create data frame of movie genre counts and proportion

df_g = {'counts' : genre_values}

genre_counts = pd.DataFrame(df_g, columns = ['counts'])
genre_counts['proportion'] = ((genre_counts['counts'] / genre_counts['counts'].
  ↪sum()) * 100).round(2)
genre_counts
```

[37]:

	counts	proportion
Drama	2316	17.03
Comedy	1740	12.79
Thriller	1641	12.07
Action	1428	10.50
Adventure	906	6.66
Romance	861	6.33
Crime	823	6.05
Horror	765	5.62
Science Fiction	701	5.15
Family	523	3.85
Fantasy	508	3.74
Mystery	440	3.24
Animation	260	1.91
History	183	1.35
Music	169	1.24
War	155	1.14
Western	74	0.54
Documentary	64	0.47
Foreign	35	0.26
TV Movie	9	0.07

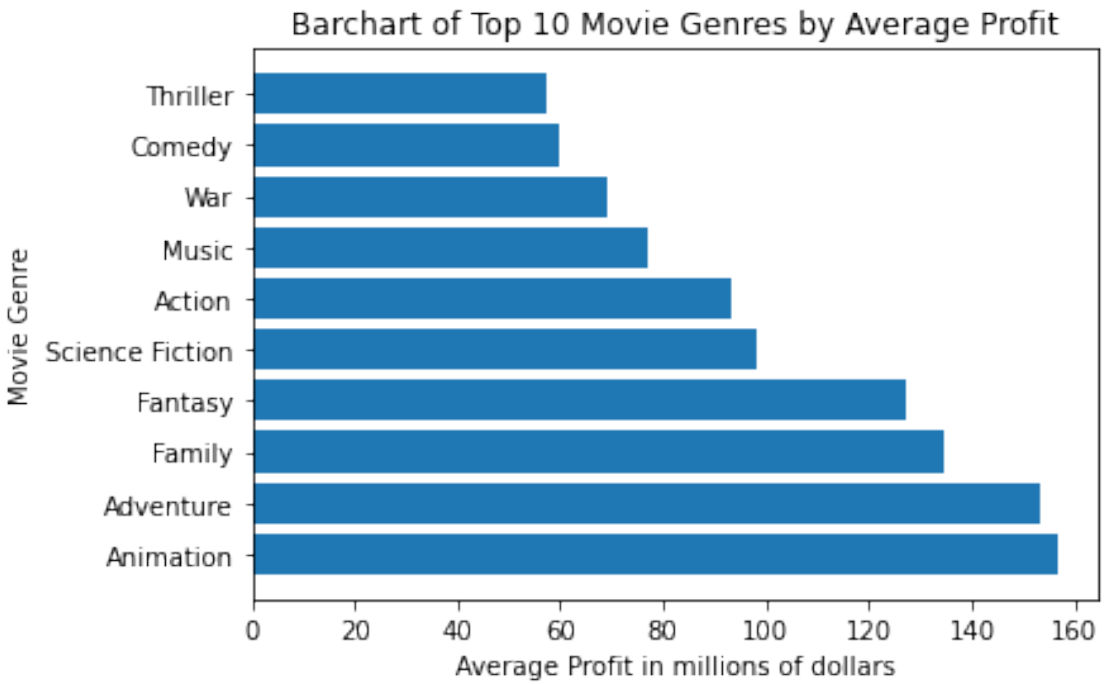
[38]:
```
# group movie genre by average profit

df_profit_genre = df_genre.groupby("movie_genre")["profit"].mean().
  ↪sort_values(ascending=False)[0:10]
```

```
df_profit_genre.head()
```

[38]:
```
movie_genre
Animation          156.926863
Adventure          153.037941
Family             134.737820
Fantasy            127.385585
Science Fiction     97.906035
Name: profit, dtype: float64
```

[39]:
```
# bar chart of movie genres and average profit

plt.barh(df_profit_genre.index, df_profit_genre)
plt.title('Barchart of Top 10 Movie Genres by Average Profit')
plt.xlabel('Average Profit in millions of dollars')
plt.ylabel('Movie Genre')
```

[39]:
```
Text(0, 0.5, 'Movie Genre')
```



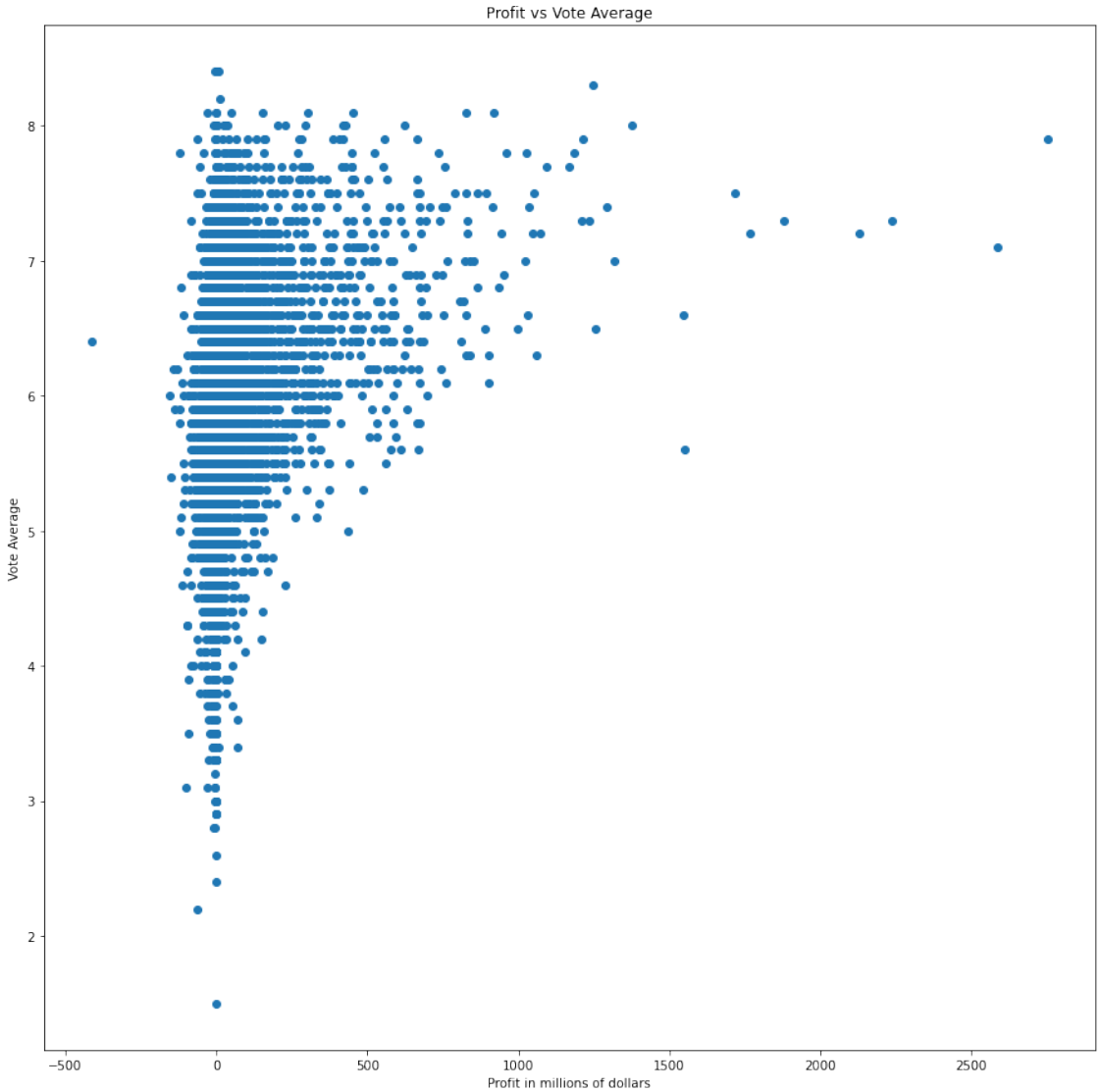
- These rankings are not entirely accurate since is includes multiple double couting for several movies
- However, the top genres are closely related to the top 10 most profitable movies except for the Animation which doesn't feature in the movies list
- Moreover, it is interesting to find that the Drama genre, although it has the highest proportion in the movie count isn't in the top 10 by profit.

- Finally, Animation which is only 1.91% of all the movies makes the highest average profit among the movie genres

1.6 How are profits and average votes related?

[40]:
```
# scatter plot of profit vs vote average

plt.figure(figsize = (15, 15))

plt.scatter(df_clean['profit'], df_clean['vote_average'])
plt.title('Profit vs Vote Average')
plt.xlabel("Profit in millions of dollars")
plt.ylabel('Vote Average')
```

[40]:
```
Text(0, 0.5, 'Vote Average')
```



- From the results, we can see that the most profitable movies have relatively high vote average

1.7 Conclusions and Limitations

This project analysed the profitability of 10,000 movies collected from The Movie Database (TMDb) by answering the following questions:

- Are movies still profitable?
- What are the top 10 profitable movies?
- How are profits and average votes related?

In conclusion, it can be said that, generally movies are still profitable. * However, the level of profitable has rather reduced over time * Modern movies are not as profitable as movies made between the 1960's and 1980's * 60% of the top 10 most profitable movies were release before 1980 * The most profitable movie genre is Animation although it is only about 2% of all the movies in the data * There appear to be a slight correlation between profit and movie votes. * The most profitable movies have relatively higher vote average than other movies.

The following are some of the limitation of this report: * A significant portion of the data was dropped becasue of missing values * The results on the most profitable movie genres is not entirely accurate due to double counting * Most of the variables were categorical which did not allow for a more vigorous statistical analysis * The movies in the database are limited up to 2015, thus newer movies will cause significant changes in the results presented here.

[ ]: