investigate-a-dataset-template-TMDB-Szymon-Debski

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1 Project: Investigate the TMDB movie dataset.

1.1 Table of Contents

Introduction

> Dataset: TMDB movies
>
> The dataset is based on 10,000 movies from The Movie Database (TMDb).

- In the analysis, we will be focusing on one hand on the runtime of the movies and their release year which we will be comparing to earnings and budgets respectively.

  Questions:

- Does the runtime of movies impact their earnings?
- Do newer movies have bigger budgets?

[1]:
```python
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import matplotlib.cm as cm
import seaborn as sns
import warnings
warnings.simplefilter(action='ignore', category=FutureWarning)

%matplotlib inline
```

Data Wrangling

> In this section, I will load in the data, clean it and remove unnecessary columns and rows.

1.1.1 General Properties

Dataset I chose for this analysis: TMDB movies. In my analysis, I will focus on top-earning movies and movies with big budgets. I will try to answer which characteristics correspond to a high-earning and big budgets.

[39]:
```
#data set loaded
df = pd.read_csv('tmdb-movies.csv')
df.head(1)
```

[39]:
```
       id    imdb_id  popularity     budget     revenue  original_title  \
0  135397  tt0369610    32.98576  150000000  1513528810  Jurassic World

                                                cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi…

                        homepage         director             tagline  …  \
0  http://www.jurassicworld.com/  Colin Trevorrow  The park is open.  …

                                            overview runtime  \
0  Twenty-two years after the events of Jurassic …     124

                                      genres  \
0  Action|Adventure|Science Fiction|Thriller

                                production_companies release_date vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda…       6/9/15       5562

   vote_average  release_year      budget_adj      revenue_adj
0       6.50000          2015 137999939.28003 1392445892.52380

[1 rows x 21 columns]
```

1.1.2 Data Cleaning

- Dropped unneeded columns ('cast', 'homepage', 'tagline', 'keywords', 'overview', 'production_companies')
- Next I discarded missing values
- After that, I set the right date format
- Also I changed the number format which made the numbers more readable
- Next I cleaned the genres column so that it shows only the first genre
- Next step was to clean the duplicates (there was one)
- After that I deleted rows with 0 for 'budgey_adj' and 'revenue_adj'. I reasoned that replacing the values with a mean would distort the data

1.2 In the end I was left with a data frame with 3853 rows and 15 columns

[40]:
```
df.describe()
```

[40]:
```
                  id  popularity          budget         revenue      runtime  \
count   10866.00000 10866.00000     10866.00000     10866.00000  10866.00000
mean    66064.17743     0.64644  14625701.09415  39823319.79339    102.07086
std     92130.13656     1.00018  30913213.83144 117003486.58209     31.38141
min         5.00000     0.00006         0.00000         0.00000      0.00000
25%     10596.25000     0.20758         0.00000         0.00000     90.00000
50%     20669.00000     0.38386         0.00000         0.00000     99.00000
75%     75610.00000     0.71382  15000000.00000  24000000.00000    111.00000
max    417859.00000    32.98576 425000000.00000 2781505847.00000   900.00000

        vote_count  vote_average  release_year      budget_adj       revenue_adj
count  10866.00000   10866.00000   10866.00000     10866.00000       10866.00000
mean     217.38975       5.97492    2001.32266  17551039.82289    51364363.25325
std      575.61906       0.93514      12.81294  34306155.72284   144632485.03997
min       10.00000       1.50000    1960.00000         0.00000           0.00000
25%       17.00000       5.40000    1995.00000         0.00000           0.00000
50%       38.00000       6.00000    2006.00000         0.00000           0.00000
75%      145.75000       6.60000    2011.00000  20853251.08440    33697095.71731
max     9767.00000       9.20000    2015.00000 425000000.00000  2827123750.41189
```

[41]:
```
df.shape
```

[41]: (10866, 21)

[42]:
```
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
```

[43]:
```
#dropped unused columns
df.drop(['cast', 'homepage', 'tagline', 'keywords', 'overview',␣
 ↪'production_companies'], axis=1, inplace=True)
```

[44]:
```
df.head(1)
```

[44]:
```
       id    imdb_id  popularity     budget     revenue  original_title  \
0  135397  tt0369610    32.98576  150000000  1513528810  Jurassic World

          director  runtime                                     genres  \
0  Colin Trevorrow      124  Action|Adventure|Science Fiction|Thriller

  release_date  vote_count  vote_average  release_year      budget_adj  \
0       6/9/15        5562       6.50000          2015 137999939.28003

       revenue_adj
0 1392445892.52380
```

[45]:
```
# dropped missing values
df.dropna(inplace=True)
```

[46]:
```
# changed date format
df['release_date'] = pd.to_datetime(df['release_date'], format='%m/%d/%y')
```

[47]:
```
# changed number format
pd.set_option('display.float_format', lambda x: '%.5f' % x)
```

[48]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10796 entries, 0 to 10865
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              10796 non-null  int64
 1   imdb_id         10796 non-null  object
 2   popularity      10796 non-null  float64
 3   budget          10796 non-null  int64
```

```
 4   revenue         10796 non-null  int64
 5   original_title  10796 non-null  object
 6   director        10796 non-null  object
 7   runtime         10796 non-null  int64
 8   genres          10796 non-null  object
 9   release_date    10796 non-null  datetime64[ns]
 10  vote_count      10796 non-null  int64
 11  vote_average    10796 non-null  float64
 12  release_year    10796 non-null  int64
 13  budget_adj      10796 non-null  float64
 14  revenue_adj     10796 non-null  float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(4)
memory usage: 1.3+ MB
```

[49]:
```
def split(column):
    x = column.split('|')[0]
    return x
```

[52]:
```
df['genres'] = df['genres'].apply(lambda x: split(x))
```

[53]:
```
df.head(1)
```

[53]:
```
       id    imdb_id  popularity     budget     revenue  original_title  \
0  135397  tt0369610    32.98576  150000000  1513528810  Jurassic World

         director  runtime  genres release_date  vote_count  vote_average  \
0  Colin Trevorrow      124  Action   2015-06-09        5562       6.50000

   release_year      budget_adj      revenue_adj
0          2015 137999939.28003 1392445892.52380
```

[54]:
```
df.describe()
```

[54]:
```
                 id  popularity           budget           revenue      runtime  \
count   10796.00000 10796.00000      10796.00000       10796.00000 10796.00000
mean    65558.31808     0.64961   14719366.67182    40080510.64052   102.21332
std     91747.96902     1.00258   30991238.22095   117338430.76150    30.76277
min         5.00000     0.00019          0.00000           0.00000     0.00000
25%     10568.50000     0.20920          0.00000           0.00000    90.00000
50%     20454.00000     0.38551          0.00000           0.00000    99.00000
75%     74663.50000     0.71772   16000000.00000    24609991.25000   112.00000
max    417859.00000    32.98576  425000000.00000  2781505847.00000   900.00000

       vote_count  vote_average  release_year      budget_adj      revenue_adj
count 10796.00000   10796.00000   10796.00000     10796.00000      10796.00000
mean    218.68164       5.97030    2001.28677  17663691.65299   51696371.84669
std     577.25738       0.93292      12.82103  34388506.64822  145041642.43934
min      10.00000       1.50000    1960.00000         0.00000          0.00000
```

```
25%      17.00000       5.40000    1995.00000          0.00000            0.00000
50%      39.00000       6.00000    2006.00000          0.00000            0.00000
75%     147.00000       6.60000    2011.00000   21033371.65263     34097666.53813
max    9767.00000       9.20000    2015.00000 425000000.00000 2827123750.41189
```

[55]:
```python
df.query('budget_adj == 0').info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 5632 entries, 30 to 10864
Data columns (total 15 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   id              5632 non-null   int64
 1   imdb_id         5632 non-null   object
 2   popularity      5632 non-null   float64
 3   budget          5632 non-null   int64
 4   revenue         5632 non-null   int64
 5   original_title  5632 non-null   object
 6   director        5632 non-null   object
 7   runtime         5632 non-null   int64
 8   genres          5632 non-null   object
 9   release_date    5632 non-null   datetime64[ns]
 10  vote_count      5632 non-null   int64
 11  vote_average    5632 non-null   float64
 12  release_year    5632 non-null   int64
 13  budget_adj      5632 non-null   float64
 14  revenue_adj     5632 non-null   float64
dtypes: datetime64[ns](1), float64(4), int64(6), object(4)
memory usage: 704.0+ KB
```

[56]:
```python
# duplicates
sum(df.duplicated())
```

[56]: 1

[57]:
```python
df.shape
```

[57]: (10796, 15)

[58]:
```python
# dropped duplicates
df.drop_duplicates(keep ='first', inplace=True)
```

[59]:
```python
df.shape
```

[59]: (10795, 15)

[60]:
```python
# deleted rows with 0 in 'budget_adj' column
df = df[df['budget_adj'] != 0]
```

[61]:
```
df.shape
```

[61]: (5163, 15)

[62]:
```
# deleted rows with 0 in 'revenue_adj' column
df = df[df['revenue_adj'] != 0]
```

[63]:
```
df.shape
```

[63]: (3853, 15)

Exploratory Data Analysis

Now that my data is clean I will research my questions.

1.3 Does the runtime of movies impact their earnings?

[64]:
```
df['earnings'] = df['revenue_adj'] - df['budget_adj']
```

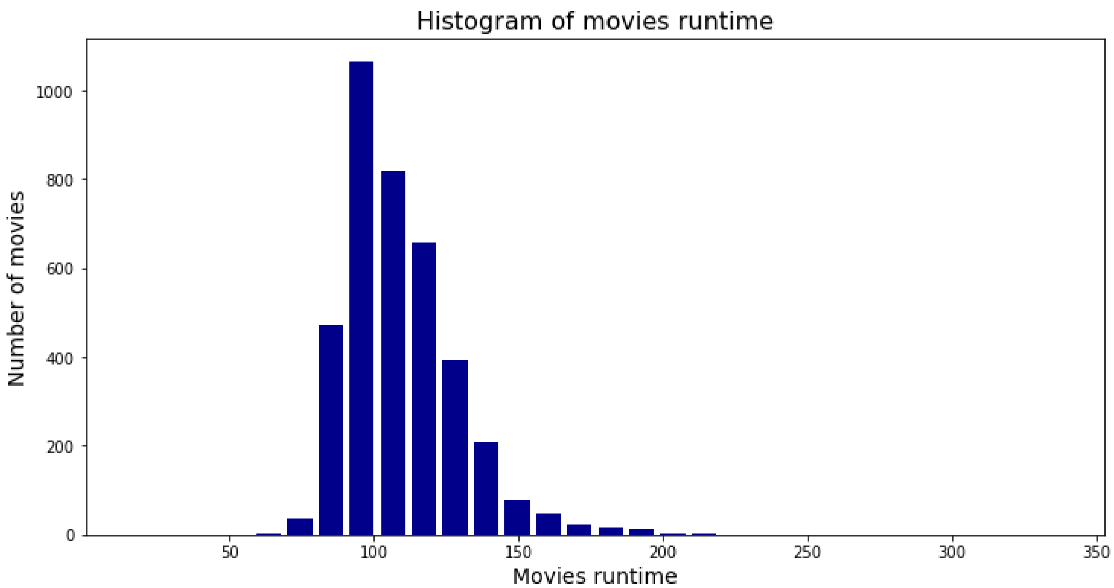
[65]:
```
df.head(1)
```

[65]:
```
       id    imdb_id  popularity     budget     revenue  original_title  \
0  135397  tt0369610    32.98576  150000000  1513528810  Jurassic World

          director  runtime  genres release_date  vote_count  vote_average  \
0  Colin Trevorrow      124  Action   2015-06-09        5562       6.50000

   release_year      budget_adj      revenue_adj          earnings
0          2015 137999939.28003 1392445892.52380 1254445953.24377
```

[66]:
```
df.shape
```

[66]: (3853, 16)

[67]:
```
plt.figure(figsize=(12,6))

plt.xlabel('Movies runtime', fontsize=14)
plt.ylabel('Number of movies', fontsize=14)
plt.title('Histogram of movies runtime', fontsize=16)
plt.hist(df['runtime'], rwidth = 0.8, bins=30, color='darkblue')
plt.show()
```

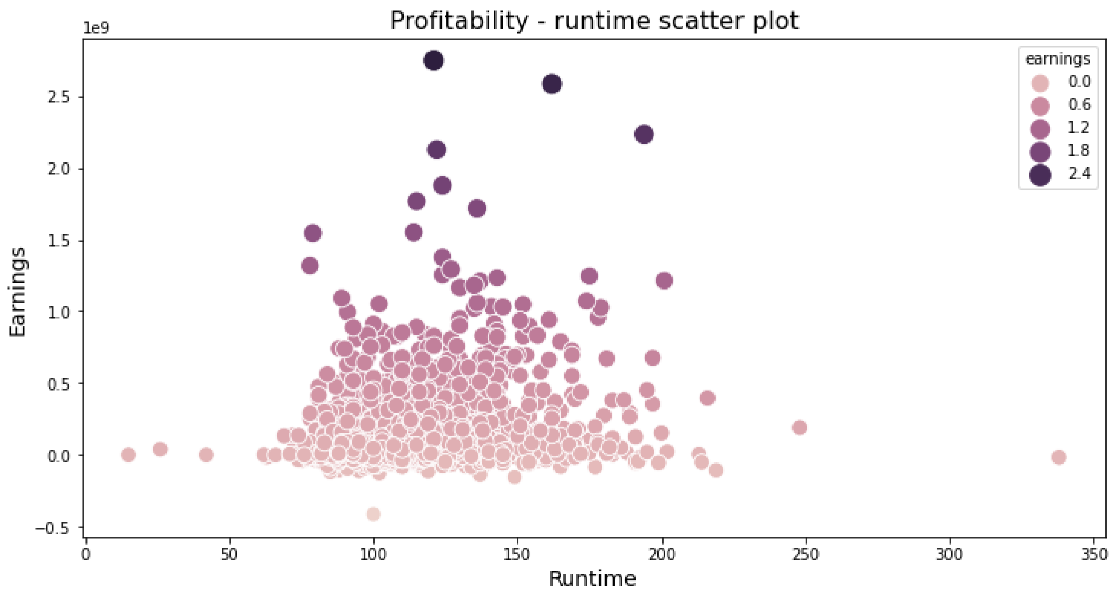


We can see that the runtime distribution is skewed to the right. Most of the movies have a runtime of 90 - 100 minutes.

[68]:
```
df.runtime.describe()
```

[68]:
```
count    3853.00000
mean      109.20893
std        19.91291
min        15.00000
25%        95.00000
50%       106.00000
75%       119.00000
max       338.00000
Name: runtime, dtype: float64
```

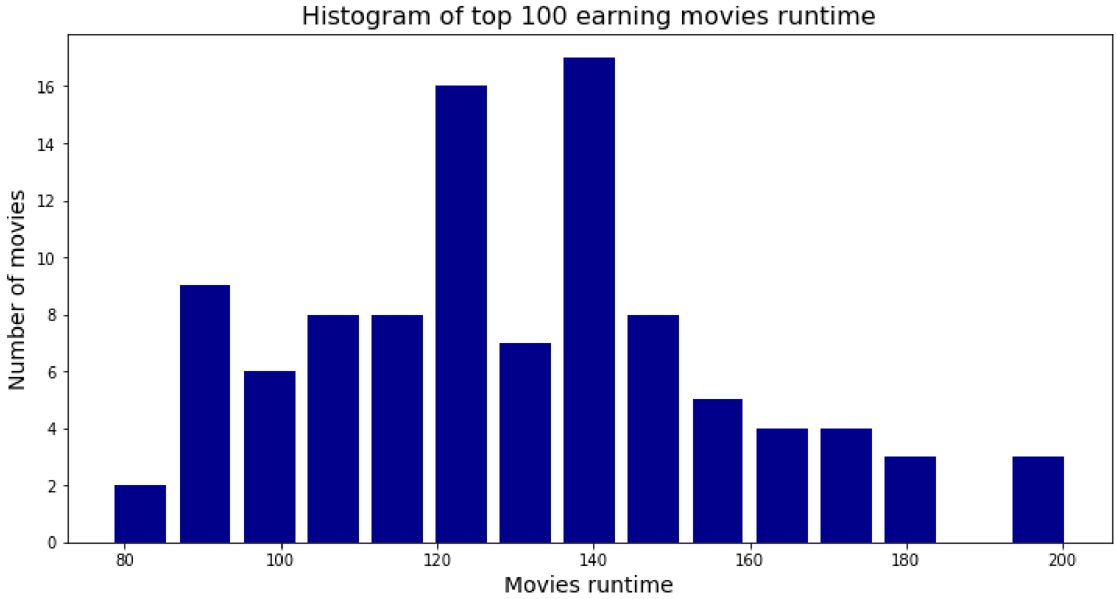
[69]:
```
plt.figure(figsize=(12,6))

plt.xlabel('Runtime', fontsize=14)
plt.ylabel('Earnings', fontsize=14)
plt.title('Profitability - runtime scatter plot', fontsize=16)

sns.scatterplot('runtime', 'earnings', data=df, hue='earnings',␣
 ↪size='earnings', sizes=(100, 200))
plt.show()
```



Above we can see a scatter plot of runtime and earnings. From the graph above we can see that the most profitable movies have a runtime greater than the mean runtime. Let's analyze it a little bit more by selecting only the top-earning movies.

[70]:
```
# created a new df only for the 100 to earners
top_100_earnings = df.sort_values(by=['earnings'], ascending = False).head(100)
```

[71]:
```
plt.figure(figsize=(12,6))

plt.xlabel('Movies runtime', fontsize=14)
plt.ylabel('Number of movies', fontsize=14)
plt.title('Histogram of top 100 earning movies runtime', fontsize=16)
plt.hist(top_100_earnings['runtime'], rwidth = 0.8, bins=15, color='darkblue')
plt.show()
```



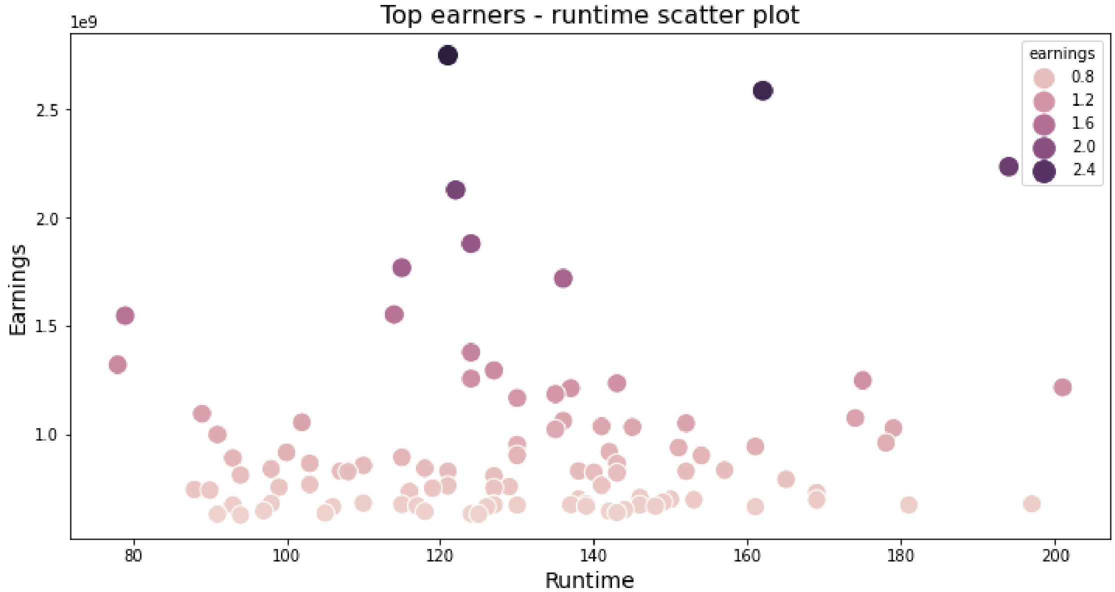
We can see from the graph above that the runtime distribution is different for top earners. It is still skewed to the right but not so much so. The biggest difference is that in this histogram most of the top-earning movies have a runtime of 140 min compared to 100 for all analyzed movies. The runtime mean for top earners is 130 minutes vs 109 for all analyzed movies.

[72]:
```
top_100_earnings.runtime.describe()
```

[72]:
```
count    100.00000
mean     130.50000
std       26.66231
min       78.00000
25%      113.00000
50%      129.50000
75%      145.25000
max      201.00000
Name: runtime, dtype: float64
```

[73]:
```
plt.figure(figsize=(12,6))

plt.xlabel('Runtime', fontsize=14)
plt.ylabel('Earnings', fontsize=14)
plt.title('Top earners - runtime scatter plot', fontsize=16)

sns.scatterplot('runtime', 'earnings', data=top_100_earnings, hue='earnings',␣
 ↪size='earnings', sizes=(150, 200))

# plt.scatter(top_100_earnings['runtime'], top_100_earnings['earnings'])
```

```
plt.show()
```



When looking at the graph above we can see that most of the top-earning movies have a runtime greater than 130 minutes.

1.3.1 We can say that although runtime does not determine that a movie will be profitable (there are movies that are long and did not earn too much or even had a loss), we can conclude that longer movies have a better chance of being profitable. This may be connected with the fact that blockbusters are generally long and and have big budgets.

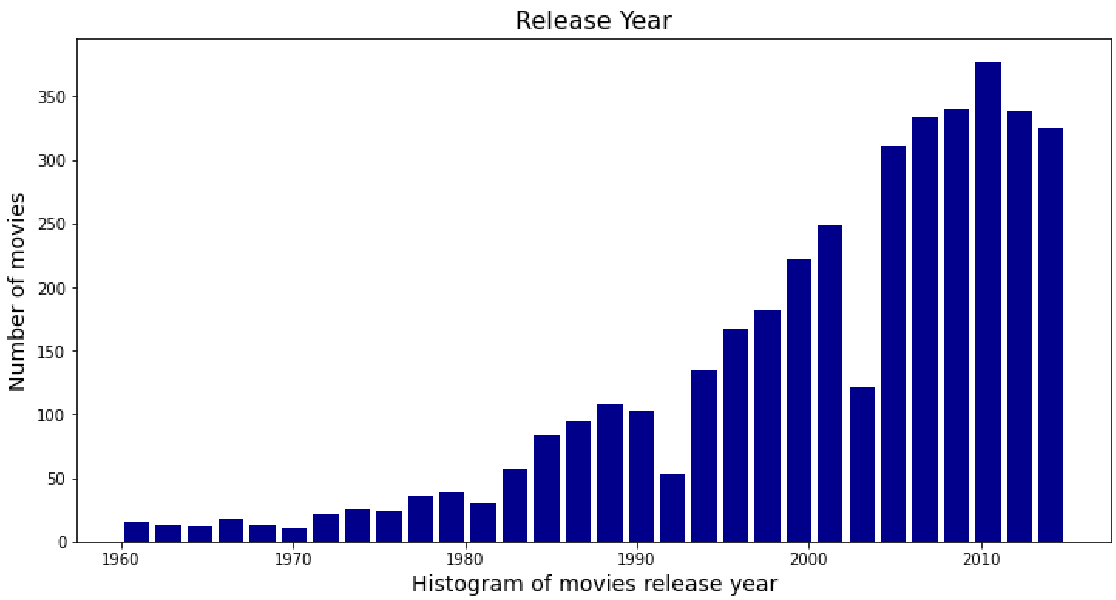
1.4 Do newer movies have bigger budgets?

[74]:
```
df.head(1)
```

[74]:
```
       id    imdb_id  popularity     budget     revenue original_title  \
0  135397  tt0369610    32.98576  150000000  1513528810 Jurassic World

          director  runtime  genres release_date  vote_count  vote_average  \
0  Colin Trevorrow      124  Action   2015-06-09        5562       6.50000

   release_year       budget_adj       revenue_adj          earnings
0          2015 137999939.28003 1392445892.52380 1254445953.24377
```

[75]:
```
plt.figure(figsize=(12,6))

plt.xlabel('Histogram of movies release year', fontsize=14)
```

```
plt.ylabel('Number of movies', fontsize=14)
plt.title('Release Year', fontsize=16)
plt.hist(df['release_year'], rwidth = 0.8, bins=30, color='darkblue')
plt.show()
```



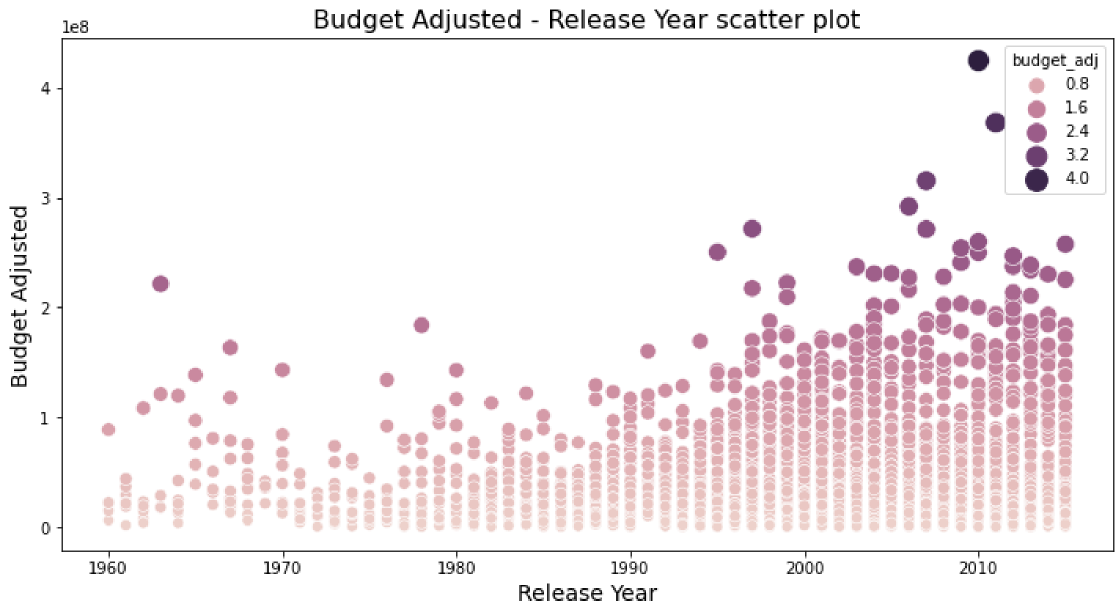
We can see that the distribution is heavily skewed to the left which is understandable - more and more movies are released every year.

[76]:
```
df.release_year.describe()
```

[76]:
```
count    3853.00000
mean     2001.25928
std        11.28352
min      1960.00000
25%      1995.00000
50%      2004.00000
75%      2010.00000
max      2015.00000
Name: release_year, dtype: float64
```

[77]:
```
plt.figure(figsize=(12,6))

plt.xlabel('Release Year', fontsize=14)
plt.ylabel('Budget Adjusted', fontsize=14)
plt.title('Budget Adjusted - Release Year scatter plot', fontsize=16)
# plt.scatter(df['release_year'], df['earnings'])
sns.scatterplot('release_year', 'budget_adj', data=df, hue='budget_adj',␣
 ↪size='budget_adj', sizes=(50, 200))
```

```
plt.show()
```



Above we can see a scatter plot of release year and budget adjusted. There is a clear indication that movies released after 1995 have a bigger budget. We can see that the movies that had the biggest budgets were released after 1995. It is worth mentioning that I'm using the budget adjusted values which means inflation did not impact the results. ## Conclusions

To answer the first question we can say that: longer movies have a better chance of being profitable.

Answering the second question we can definitely say the newer movies have bigger budgets.

1.5 Limitations:

1. We base most of our analysis on the budget_adj and revenue_adj columns. Unoftunetly we don't how they were adjusted - what were the exact assumptions. If we knew the exact calculation we could have adjusted our analysis accordingly.
2. Due to many rows of missing data for budget and revenue, we had to drop around 7000 rows which are not very good for our analysis. This limitation decreased the accuracy of the analysis tremendously.
3. The last limitation in my opinion is that data is not updated. In recent years a lot has changed in the movie industry. The newest movies in the data set are from 2015.

[ ]: