Investigate_a_Dataset_TMDB

May 31, 2022

1 Project: Investigate a Dataset - [TMDB Movie Data]

1.1 Table of Contents

Introduction

1.1.1 Dataset Description

This dataset contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue.

The columns of the dataset are listed below with their respective significance.

id - unique id of the movie
imdb_id - id of the movie by IMDB
popularity - popularity score of the movie
budget - budget used to make the movie
revenue - revenue brought in by the movie
original_title - movie title
cast - list/names of actors in the movie
homepage - website of the movie
director - person who directed the movie
tagline - movie's advertising slogan
keywords - words to easily find a movie title
overview - summary of movie storyline
runtime - total time of the movie
genres - categorization of movie based on plot, story etc.
production_companies - production company of movie
release_date - date of release
vote_count - total number of votes
vote_average - average rating of votes
release_year - year of movie release
budget_adj - budget adjustment due to inflation
revenue_adj - revenue adjustment due to inflation

1.1.2 Questions for Analysis

The following questions will be explored and analysed in this report.

1. Are very popular movies high revenue/grossing movies?
2. Do movies with high budgets get the highest revenues?
3. Do lower user ratings translate to low revenues for movies?
4. How has movie revenue changed over the years?
5. How has movie popularity changed over the years?
6. How has movie budget evolved over the years?
7. Which years were most profitable for movies?

In [1]:
```
# Import all necessary packages (Numpy, Pandas, Matplotlib and Seaborn)
import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns

% matplotlib inline
```

In [10]:
```
# Upgrade pandas to use dataframe.explode() function.
!pip install --upgrade pandas==0.25.0
```

```
Collecting pandas==0.25.0
  Downloading https://files.pythonhosted.org/packages/1d/9a/7eb9952f4b4d73fbd75ad1d5d6112f407e69
    100% || 10.5MB 1.6MB/s eta 0:00:01   12% |                                | 1.3MB 22.2MB/s eta 0
Requirement already satisfied, skipping upgrade: pytz>=2017.2 in /opt/conda/lib/python3.6/site-p
Collecting numpy>=1.13.3 (from pandas==0.25.0)
  Downloading https://files.pythonhosted.org/packages/45/b2/6c7545bb7a38754d63048c7696804a0d9473
    100% || 13.4MB 2.8MB/s eta 0:00:01   25% |                           | 3.4MB 18.0MB/s eta 0:00:0
Requirement already satisfied, skipping upgrade: python-dateutil>=2.6.1 in /opt/conda/lib/python
Requirement already satisfied, skipping upgrade: six>=1.5 in /opt/conda/lib/python3.6/site-packa
tensorflow 1.3.0 requires tensorflow-tensorboard<0.2.0,>=0.1.0, which is not installed.
Installing collected packages: numpy, pandas
  Found existing installation: numpy 1.12.1
    Uninstalling numpy-1.12.1:
      Successfully uninstalled numpy-1.12.1
  Found existing installation: pandas 0.23.3
    Uninstalling pandas-0.23.3:
      Successfully uninstalled pandas-0.23.3
Successfully installed numpy-1.19.5 pandas-0.25.0
```

Data Wrangling

1.1.3 General Properties

In [2]:
```
#load TMDB movies dataset
df = pd.read_csv('tmdb_movies.csv')
```

```
#inspect few lines
df.head()
```

Out[2]:

```
       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 [3]:
```
#Show the size of dataframe (number of rows and columns)
df.shape
```

Out[3]: (10866, 21)

In [4]:
```
#Display information about the dataframe (column labels, data types and number of cells
df.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 [5]: #Shows brief statistical summary of features(columns) in dataframe
        df.describe()
```

```
Out[5]:                   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
```

1.1.4 Data Cleaning

In the next few cells, I will be cleaning the data by dropping columns that I believe are not relevant to my analysis and also rows of missing data and converting datatypes where necessary.

```
In [6]: #Drop columns that will not be used in analysis

        df.drop(['id', 'imdb_id', 'cast', 'homepage', 'keywords', 'tagline', 'overview', 'origin
```

```
In [7]: #check shape of dataframe after dropping columns
        df.shape
```

```
Out[7]: (10866, 10)
```

```
In [8]: #check dataframe information again
        df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 10 columns):
popularity      10866 non-null float64
budget          10866 non-null int64
revenue         10866 non-null int64
genres          10843 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(4), object(2)
memory usage: 849.0+ KB
```

```
In [9]: df.isnull().sum()
```

```
Out[9]: popularity       0
        budget           0
        revenue          0
        genres          23
        release_date     0
        vote_count       0
        vote_average     0
        release_year     0
        budget_adj       0
        revenue_adj      0
        dtype: int64
```

The df.info() and df.isnull().sum() shows that genres column is missing some data in some rows. Therefore, we will drop those rows too.

```
In [10]: #Drop null rows from dataframe
         df.dropna(inplace=True)
```

```
In [11]: df.isnull().sum().sum()
```

```
Out[11]: 0
```

There are no null values in the dataframe. Let's finally check for duplicates and drop any duplicates we may find.

```
In [12]: sum(df.duplicated())
```

```
Out[12]: 1
```

```
In [13]: df.drop_duplicates(inplace=True)
```

```
In [14]: sum(df.duplicated())
```

```
Out[14]: 0
```

Let's finally run df.info() and df.describe() again

```
In [15]: df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10842 entries, 0 to 10865
Data columns (total 10 columns):
popularity      10842 non-null float64
budget          10842 non-null int64
revenue         10842 non-null int64
genres          10842 non-null object
release_date    10842 non-null object
vote_count      10842 non-null int64
vote_average    10842 non-null float64
release_year    10842 non-null int64
budget_adj      10842 non-null float64
revenue_adj     10842 non-null float64
dtypes: float64(4), int64(4), object(2)
memory usage: 931.7+ KB
```

```
In [16]: df.describe()
```

```
Out[16]:          popularity        budget       revenue    vote_count  vote_average  \
        count  10842.000000  1.084200e+04  1.084200e+04  10842.000000  10842.000000
        mean       0.647461  1.465531e+07  3.991138e+07    217.823649      5.974064
        std        1.001032  3.093971e+07  1.171179e+08    576.180993      0.934257
        min        0.000065  0.000000e+00  0.000000e+00     10.000000      1.500000
        25%        0.208210  0.000000e+00  0.000000e+00     17.000000      5.400000
        50%        0.384532  0.000000e+00  0.000000e+00     38.000000      6.000000
        75%        0.715393  1.500000e+07  2.414118e+07    146.000000      6.600000
        max       32.985763  4.250000e+08  2.781506e+09   9767.000000      9.200000

               release_year    budget_adj   revenue_adj
        count  10842.000000  1.084200e+04  1.084200e+04
        mean    2001.314794  1.758712e+07  5.147797e+07
        std       12.813617  3.433437e+07  1.447723e+08
        min     1960.000000  0.000000e+00  0.000000e+00
        25%     1995.000000  0.000000e+00  0.000000e+00
        50%     2006.000000  0.000000e+00  0.000000e+00
        75%     2011.000000  2.092507e+07  3.387838e+07
        max     2015.000000  4.250000e+08  2.827124e+09
```

It looks like the min, 25% and 50% are returning zeros which look like errors. it is likely that there are so many zeros for budget and revenue in the dataframe and this is very unlikely for movies. To continue I'll drop all the rows with zero.

```
In [17]: df = df.replace(0, np.nan)
         df = df.dropna()
```

Let's run df.info() and df.describe() one last time to complete our data cleaning process

```
In [18]: df.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 3854 entries, 0 to 10848
Data columns (total 10 columns):
popularity      3854 non-null float64
budget          3854 non-null float64
revenue         3854 non-null float64
genres          3854 non-null object
release_date    3854 non-null object
vote_count      3854 non-null int64
vote_average    3854 non-null float64
release_year    3854 non-null int64
budget_adj      3854 non-null float64
revenue_adj     3854 non-null float64
dtypes: float64(6), int64(2), object(2)
memory usage: 331.2+ KB


In [19]: df.describe()

Out[19]:         popularity        budget       revenue   vote_count  vote_average  \
         count  3854.000000  3.854000e+03  3.854000e+03  3854.000000   3854.000000
         mean      1.191554  3.720370e+07  1.076866e+08   527.720291      6.168163
         std       1.475162  4.220822e+07  1.765393e+08   879.956821      0.794920
         min       0.001117  1.000000e+00  2.000000e+00    10.000000      2.200000
         25%       0.462368  1.000000e+07  1.360003e+07    71.000000      5.700000
         50%       0.797511  2.400000e+07  4.480000e+07   204.000000      6.200000
         75%       1.368324  5.000000e+07  1.242125e+08   580.000000      6.700000
         max      32.985763  4.250000e+08  2.781506e+09  9767.000000      8.400000

                release_year    budget_adj   revenue_adj
         count   3854.000000  3.854000e+03  3.854000e+03
         mean    2001.261028  4.423999e+07  1.370647e+08
         std       11.282575  4.480925e+07  2.161114e+08
         min     1960.000000  9.693980e-01  2.370705e+00
         25%     1995.000000  1.309053e+07  1.835735e+07
         50%     2004.000000  3.001611e+07  6.173068e+07
         75%     2010.000000  6.061307e+07  1.632577e+08
         max     2015.000000  4.250000e+08  2.827124e+09

In [20]: df.shape

Out[20]: (3854, 10)
```

In [21]:
```
#Resetting the index to make the numbering correct
df = df.reset_index(drop=True)
```

Before we confirm if the index has been reset correctly, **let's create a simple function that will display few values at both ends of the TMDB dataframe.** This can now help us not to run df.tail() and df.head() individually all the time.

In [22]:
```
#This function when called anytime will display both df.head() and df.tail() together.

def df_ends(df, x=5):
    return df.head(x).append(df.tail(x))
```

In [24]:
```
#Now let's call our new function 'df_ends' to confirm that the index has been reset cor

df_ends(df,2)
```

Out[24]:
```
      popularity       budget       revenue  \
0      32.985763  150000000.0  1.513529e+09
1      28.419936  150000000.0  3.784364e+08
3852    0.299911   12000000.0  2.000000e+07
3853    0.207257    5115000.0  1.200000e+07

                                        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
3852         Action|Adventure|Drama|War|Romance     12/20/66          28
3853                  Adventure|Science Fiction      8/24/66          42

      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
3852           7.0          1966  8.061618e+07  1.343603e+08
3853           6.7          1966  3.436265e+07  8.061618e+07
```

Yes, our function works great!

Our data cleaning process is complete. All NaN values, duplicates and columns that are not relevant have been dropped. We also dropped rows for budget and revenue which had zeros as it is unlikely that this is possible in real life scenario and we would want to analyse data where those values for said columns are not zero.

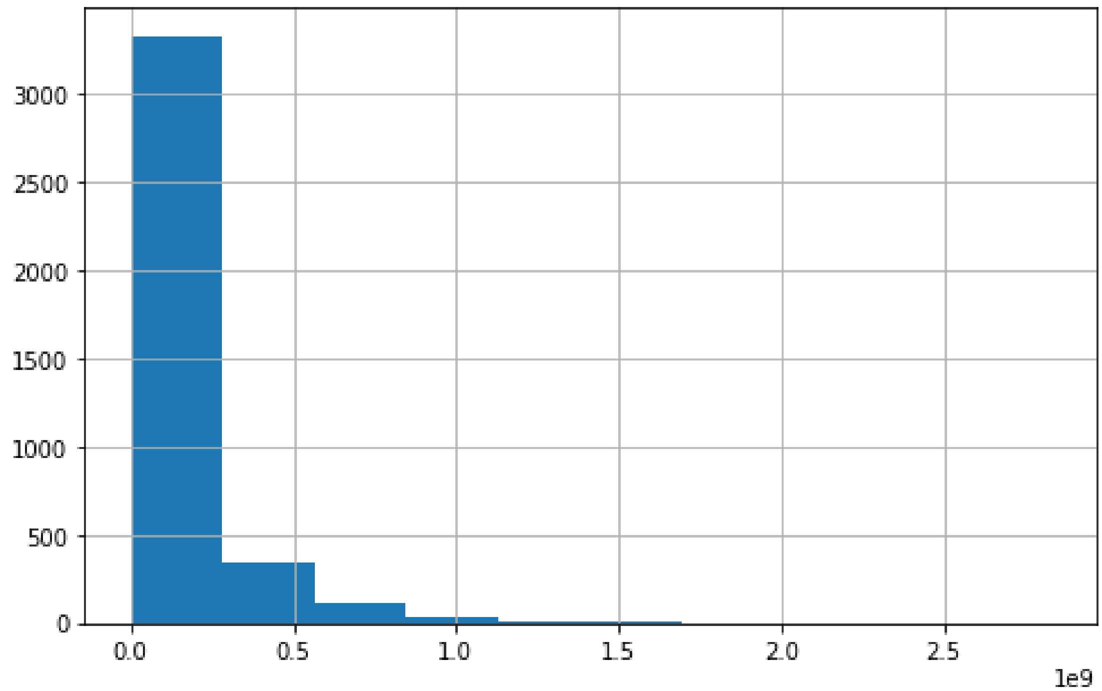
Exploratory Data Analysis

1.1.5 Research Question 1 (Which features can be most associated with high revenue?)

Sub questions: 1. Are very popular movies high revenue/grossing movies? 2. Do movies with high budgets get the highest revenues? 3. Do lower user ratings translate to low revenues for movies?

Please note that for the purposes of the exploratory data analysis, the columns 'revenue_adj' and 'budget_adj' will be used as revenue and budget values respectively and not 'revenue' and 'budget' columns.

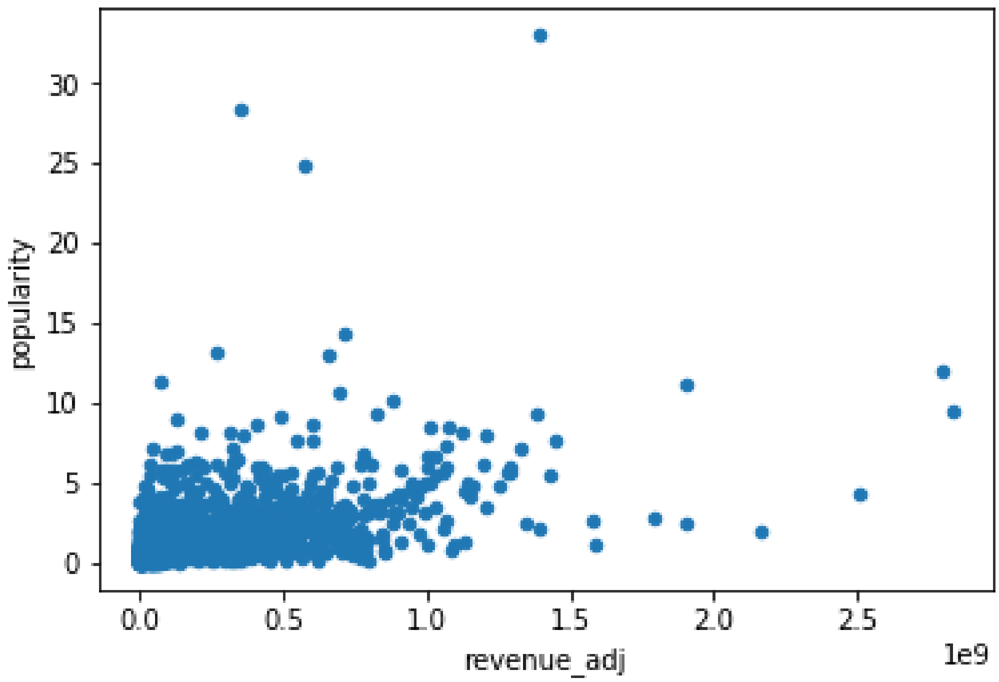
```
In [25]: # Explore the revenue_adj feature using a histogram and dataframe.describe()

         df.revenue_adj.hist(figsize = (8, 5));
```



The revenue_adj histogram appears very skewed to the right

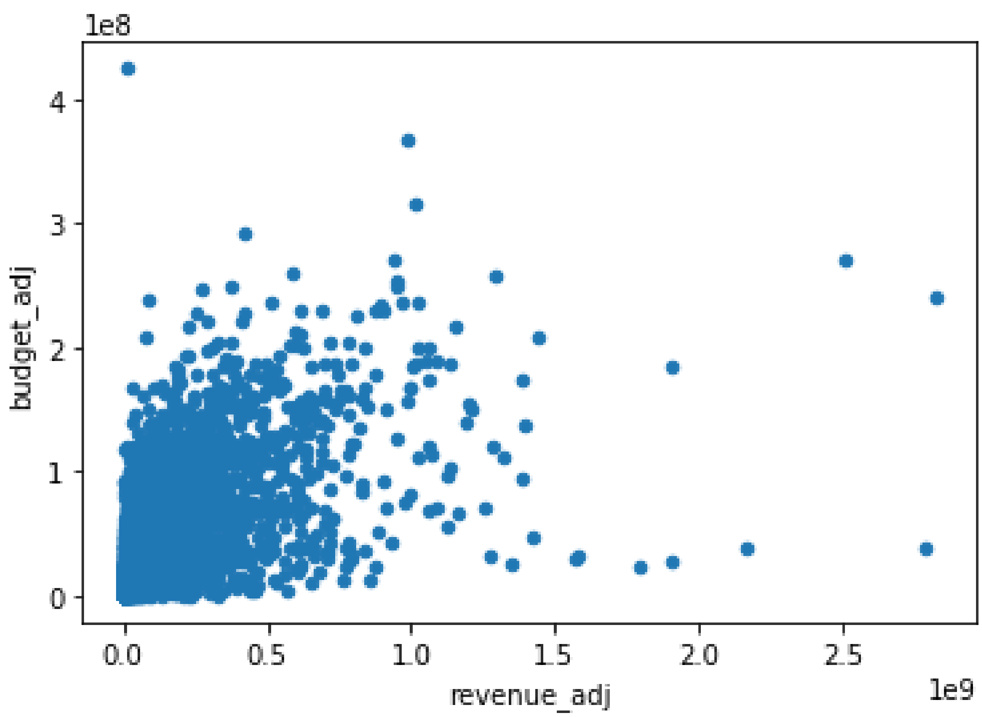
Let's quickly explore the relationship between revenue_adj and a few features using the scatter diagram.

```
In [26]: df.plot(x = 'revenue_adj', y = 'popularity', kind = 'scatter');
```



It looks like popularity for most movies is low regardless of revenue. This will however be explored in more details.

```
In [27]: df.plot(x = 'revenue_adj', y = 'budget_adj', kind = 'scatter');
```



From initial observations, it looks like bugdet largely has a positive correlation with revenue.

```
In [28]: df.plot(x = 'revenue_adj', y = 'vote_average', kind = 'scatter');
```

From initial observations, it looks like vote_average (user ratings) has a weak correlation with revenue. We will need to do more detailed exploration.

```
In [29]: #Statistics of revenue feature

         df.revenue_adj.describe()

Out[29]: count    3.854000e+03
         mean     1.370647e+08
         std      2.161114e+08
         min      2.370705e+00
         25%      1.835735e+07
         50%      6.173068e+07
         75%      1.632577e+08
         max      2.827124e+09
         Name: revenue_adj, dtype: float64
```

Level of movie revenue:
High: 75% to max
Moderately High: 50% to 75%

Medium: 25% to 50%
Low: min to 25%

In [30]:
```
# Cutting the data from revenue_adj into groups from the describe results
bin_edges = [2.370705e+00, 1.835735e+07, 6.173068e+07, 1.632577e+08, 2.827124e+09]
```

We are grouping the revenue_adj data to create a new feature.

In [31]:
```
# We create labels for the four different revenue levels and name each revenue level
bin_names = ['low', 'medium', 'moderately high', 'high']
```

The new feature will need new values as found in the cell above.

In [32]:
```
# Creates revenue_levels column
df['revenue_levels'] = pd.cut(df['revenue_adj'], bin_edges, labels=bin_names)
```

We have successfully created a new column called 'revenue_levels' where 'revenue_adj' values have been categorised in terms of high, moderately high, medium and low.

In [35]:
```
#Let's check if the revenue_levels column is showing

df_ends(df,2)
```

Out[35]:
```
      popularity       budget       revenue  \
0      32.985763  150000000.0  1.513529e+09
1      28.419936  150000000.0  3.784364e+08
3852    0.299911   12000000.0  2.000000e+07
3853    0.207257    5115000.0  1.200000e+07

                                        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
3852         Action|Adventure|Drama|War|Romance     12/20/66          28
3853                 Adventure|Science Fiction      8/24/66          42

      vote_average  release_year    budget_adj   revenue_adj   revenue_levels
0              6.5          2015  1.379999e+08  1.392446e+09             high
1              7.1          2015  1.379999e+08  3.481613e+08             high
3852           7.0          1966  8.061618e+07  1.343603e+08  moderately high
3853           6.7          1966  3.436265e+07  8.061618e+07  moderately high
```

Now let's use groupby to do more exploration of revenue levels with the following features; vote_average, popularity and budget_adj

In [36]:
```
# So we will first find the mean popularity of each revenue level with groupby
df.groupby('revenue_levels')['popularity'].mean()
```

Out[36]:
```
revenue_levels
low                0.559361
medium             0.808519
moderately high    1.148874
high               2.249021
Name: popularity, dtype: float64
```

We see that the level of revenue that receives the highest mean popularity score is 'high'

In [37]:
```
# Next, we will find the mean user rating/vote_average of each revenue level with group
df.groupby('revenue_levels')['vote_average'].mean()
```

Out[37]:
```
revenue_levels
low                 5.958299
medium              6.066355
moderately high     6.188681
high                6.459232
Name: vote_average, dtype: float64
```

We see that the level of revenue that receives the highest mean vote average is 'high'

In [38]:
```
# Finally, we will find the mean budget of each revenue level with groupby
df.groupby('revenue_levels')['budget_adj'].mean()
```

Out[38]:
```
revenue_levels
low                 1.599161e+07
medium              2.947073e+07
moderately high     4.449050e+07
high                8.699208e+07
Name: budget_adj, dtype: float64
```

Again, we see that the level of revenue with the highest mean budget is 'high'

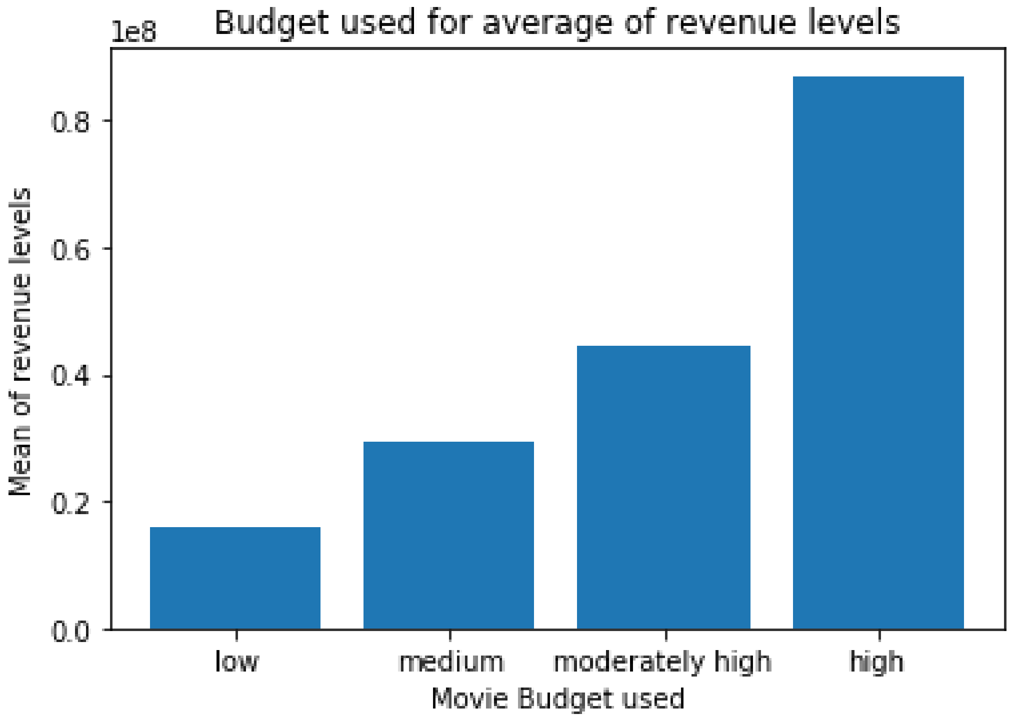
Let's explore both revenue level means and budget means, popularity means and vote average means again using Matplotlib visualisation.

Let's create more plots using Matplotlib

In [39]:
```
revenue_levels_means = df.groupby('revenue_levels')['budget_adj'].mean()
```

In [40]:
```
# Create a bar chart with proper labels
locations = [1, 2, 3, 4]
heights = revenue_levels_means
labels = ['low', 'medium', 'moderately high', 'high']
plt.bar(locations, heights, tick_label=labels)
plt.title('Budget used for average of revenue levels')
plt.xlabel('Movie Budget used')
plt.ylabel('Mean of revenue levels')
```

Out[40]:
```
Text(0,0.5,'Mean of revenue levels')
```

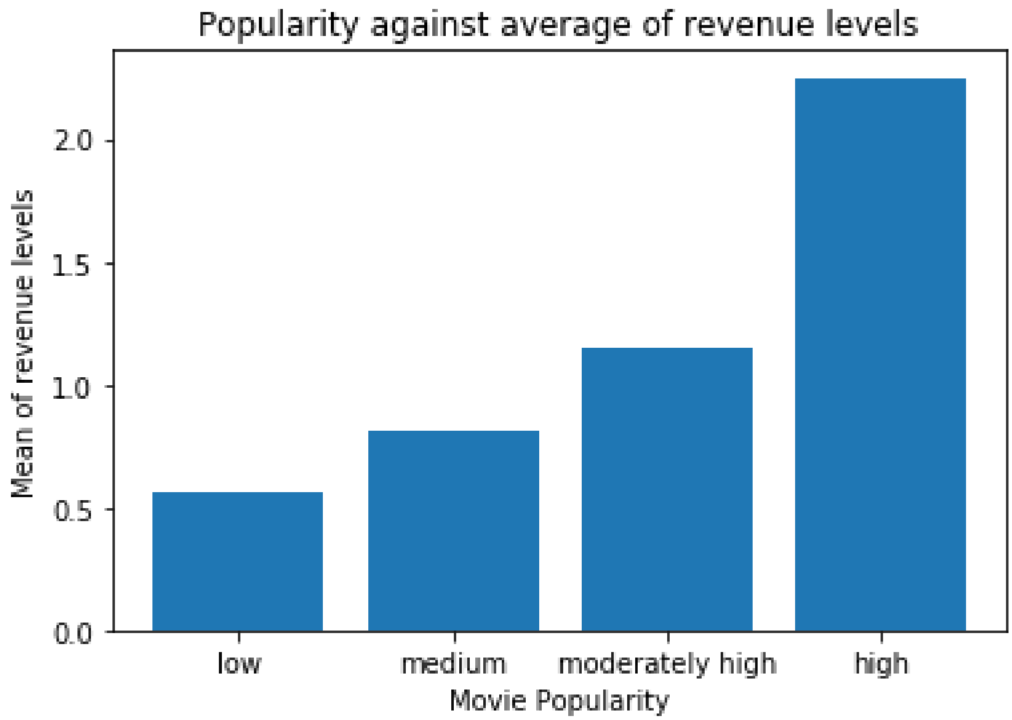


From the plot above, we see that averagely higher budget movies are associated with higher revenue levels.

```
In [41]: revenue_levels_means1 = df.groupby('revenue_levels')['popularity'].mean()
```

```
In [42]: # Create a bar chart with proper labels
         locations = [1, 2, 3, 4]
         heights = revenue_levels_means1
         labels = ['low', 'medium', 'moderately high', 'high']
         plt.bar(locations, heights, tick_label=labels)
         plt.title('Popularity against average of revenue levels')
         plt.xlabel('Movie Popularity')
         plt.ylabel('Mean of revenue levels')
```

```
Out[42]: Text(0,0.5,'Mean of revenue levels')
```

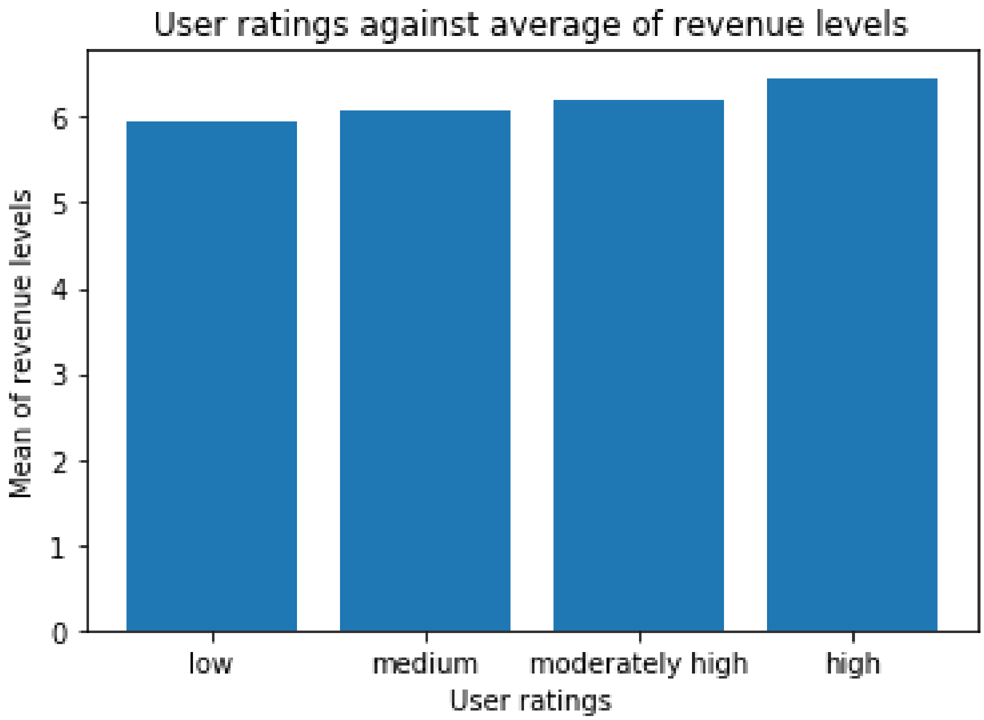


We observe from the plot above that averagely high revenue level movies seem to be associated with high popularity.

```
In [43]: revenue_levels_means2 = df.groupby('revenue_levels')['vote_average'].mean()
```

```
In [44]: # Create a bar chart with proper labels
         locations = [1, 2, 3, 4]
         heights = revenue_levels_means2
         labels = ['low', 'medium', 'moderately high', 'high']
         plt.bar(locations, heights, tick_label=labels)
         plt.title('User ratings against average of revenue levels')
         plt.xlabel('User ratings')
         plt.ylabel('Mean of revenue levels')
```

```
Out[44]: Text(0,0.5,'Mean of revenue levels')
```



We observe that the revenue levels doesn't seem to be affected by user ratings.
This marks the end of the first major part of our data exploration.

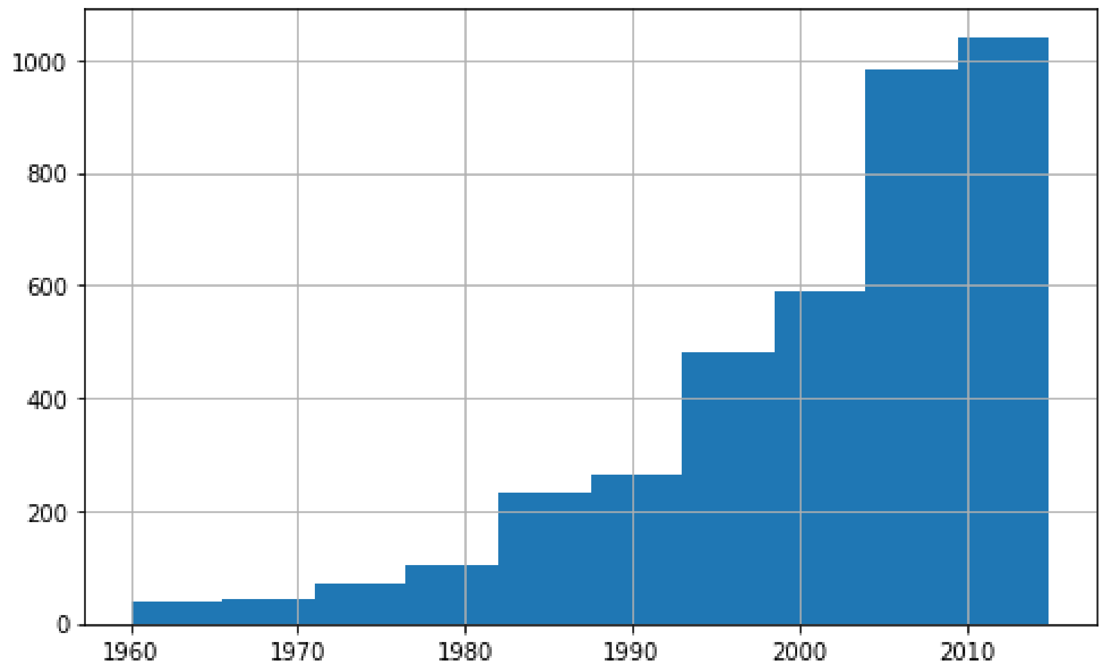
1.1.6 Research Question 2 (How has movie success changed over the years?

Sub questions:

1. How has movie revenue changed over the years?
2. How has movie budgets changed over the years?
3. How has popularity changed over the years?
4. Which years were most profitable for movies?

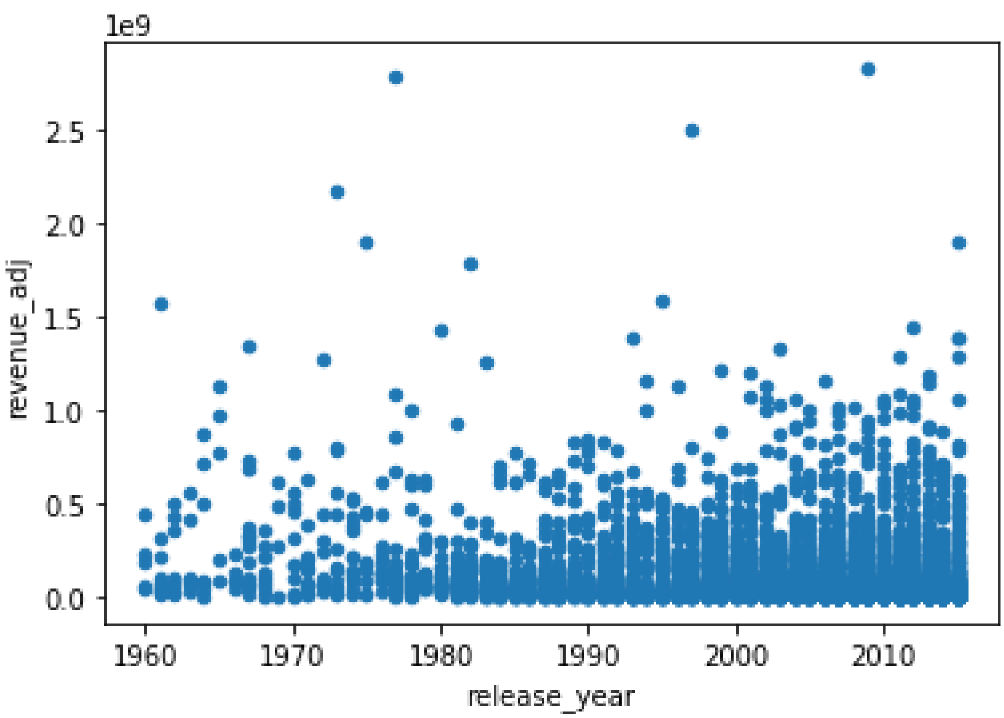
We shall use histograms, scatter plots and bar charts to investigate the way movies have changed over the years in terms of budget, revenue, profit and popularity.

```
In [45]: df.release_year.hist(figsize = (8, 5));
```



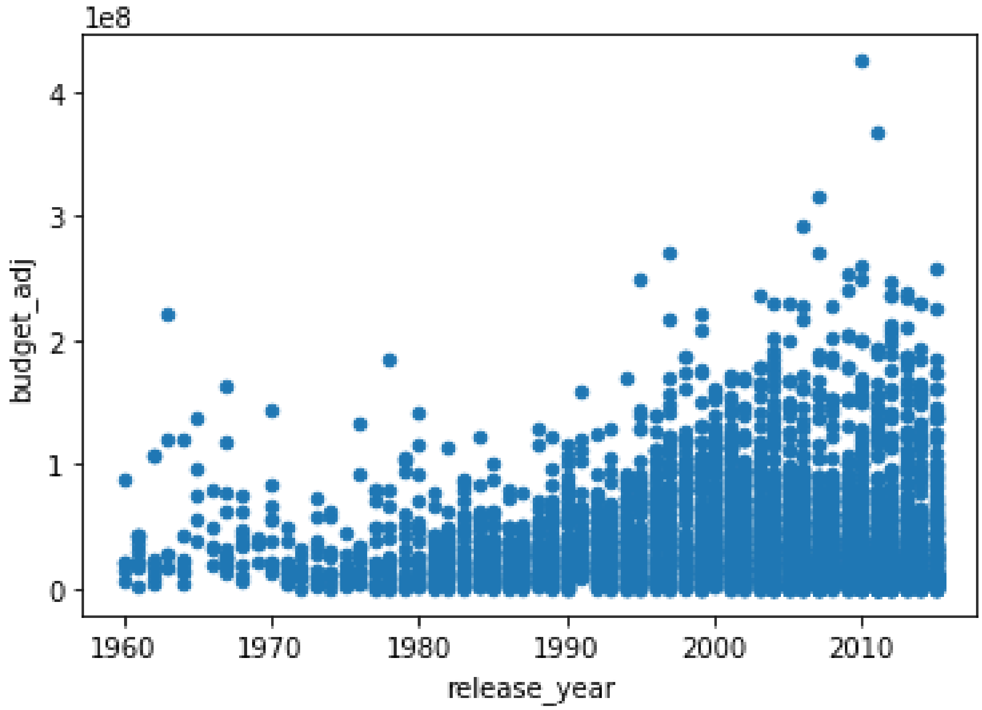
Firstly, we observe that the release year histogram is skewed to the left.
Let's create some scatter plots related to our questions

```
In [46]: df.plot(x = 'release_year', y = 'revenue_adj', kind = 'scatter');
```



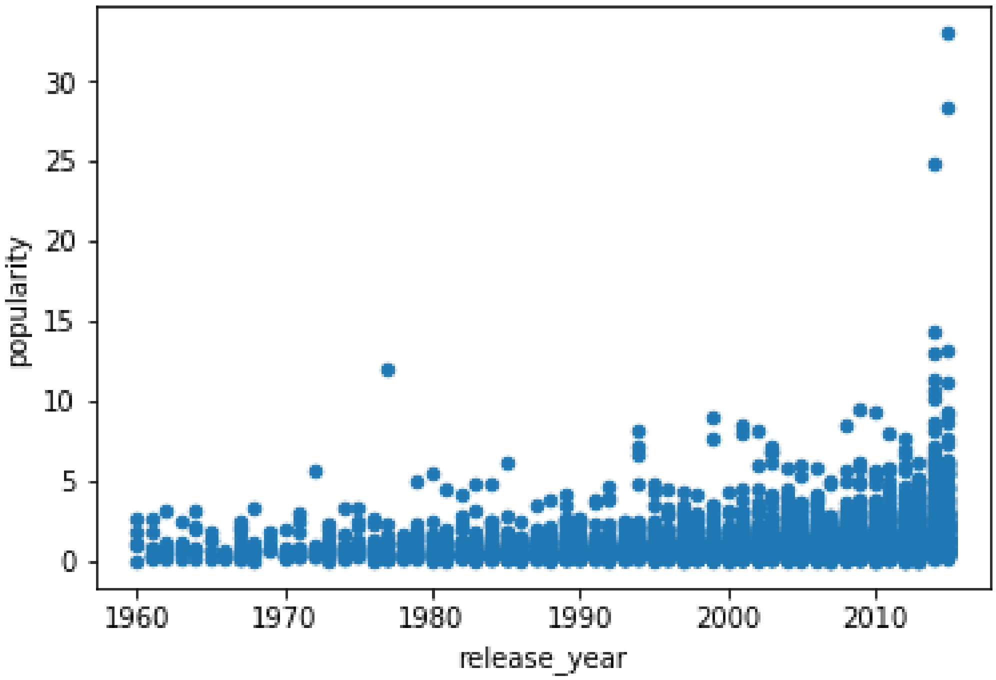
From the scatter plot it looks like revenue has increased overall between 1960s and 2010s. However, there were some individual years were revenue was very high.

```
In [47]: df.plot(x = 'release_year', y = 'budget_adj', kind = 'scatter');
```



From the scatter plot it looks like movie budget has also increased overall between 1960s and 2010s.

```
In [48]: df.plot(x = 'release_year', y = 'popularity', kind = 'scatter');
```



The scatter plot shows there is a positive correlation between popluarity and the increase of years, although it appears the trend appears slow.

We have about 56 years of movie data. It will be much better to investigate the long term change over the years in terms of decades. For this we will need to group the years into decades and create a new column in the dataframe called 'decades'.

```
In [49]: # Group/'cut' the years into decades
         bin_edges = [1960, 1970, 1980, 1990, 2000, 2010, 2015]

In [50]: # Label the new decades
         bin_names = ['1960s', '1970s', '1980s', '1990s', '2000s', '2010s']

In [51]: # Create the new 'decade' column
         df['decade'] = pd.cut(df['release_year'], bin_edges, labels=bin_names)

In [52]: df.head(2)

Out[52]:    popularity       budget       revenue  \
         0   32.985763  150000000.0  1.513529e+09
         1   28.419936  150000000.0  3.784364e+08

                                         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 revenue_levels  \
```

```
0           6.5          2015  1.379999e+08  1.392446e+09            high
1           7.1          2015  1.379999e+08  3.481613e+08            high

  decade
0  2010s
1  2010s
```

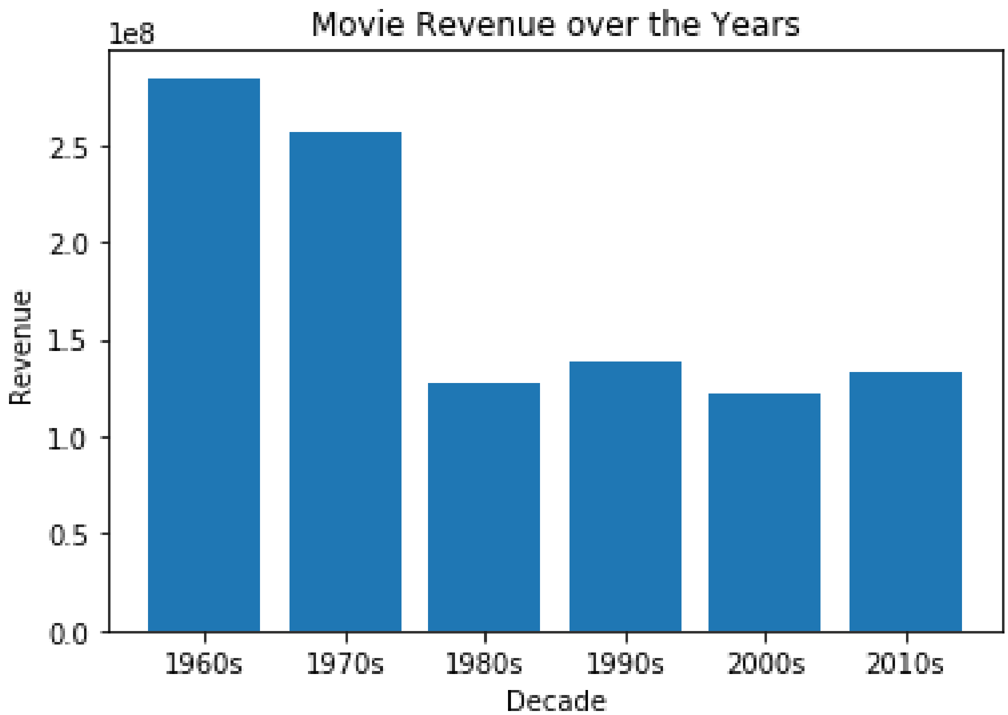
Last two cells are for checking if our new column was successfully created.
Let's plot a bar chart using Matplotlib to show correlation between Decades and Revenue

In [54]:
```
df.groupby('decade')['revenue_adj'].mean()
```

Out[54]:
```
decade
1960s    2.842694e+08
1970s    2.567380e+08
1980s    1.274362e+08
1990s    1.380226e+08
2000s    1.225630e+08
2010s    1.330990e+08
Name: revenue_adj, dtype: float64
```

In [55]:
```
# We plot the bar chart to explore the mean revenue generated in the various decades
revenue_during_decade = df.groupby('decade')['revenue_adj'].mean()

plt.bar(revenue_during_decade.index, revenue_during_decade.values)
plt.title('Movie Revenue over the Years')
plt.xlabel('Decade')
plt.ylabel('Revenue')
```

Out[55]:
```
Text(0,0.5,'Revenue')
```



From the bar chart above, we see that average movie revenue was highest in the 1960s and 1970s and has steadily come down to half of that over the rest of the decades.

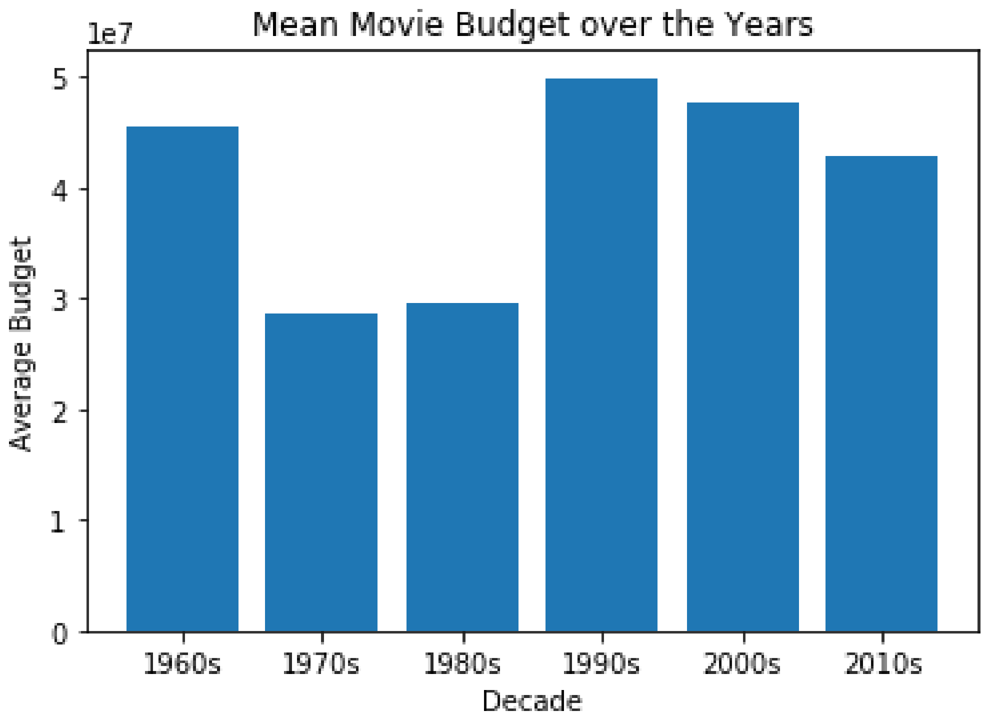
Let's plot a bar chart using Matplotlib to show correlation between Decades and Mean Budget used

In [56]:
```
df.groupby('decade')['budget_adj'].mean()
```

Out[56]:
```
decade
1960s    4.546152e+07
1970s    2.851827e+07
1980s    2.957904e+07
1990s    4.988054e+07
2000s    4.766348e+07
2010s    4.271093e+07
Name: budget_adj, dtype: float64
```

In [57]:
```
# We plot the bar chart to explore the mean budget used over the various decades
budget_during_decade = df.groupby('decade')['budget_adj'].mean()

plt.bar(budget_during_decade.index, budget_during_decade.values)
plt.title('Mean Movie Budget over the Years')
plt.xlabel('Decade')
plt.ylabel('Average Budget')
```

Out[57]:
```
Text(0,0.5,'Average Budget')
```



From the bar chart, we see that budget used has high in the 1960s, then it came low through the 1970s and 1980s and eventually went up in 1990s and is still high till 2010s although there is a very small decline between 1990s and 2010s.

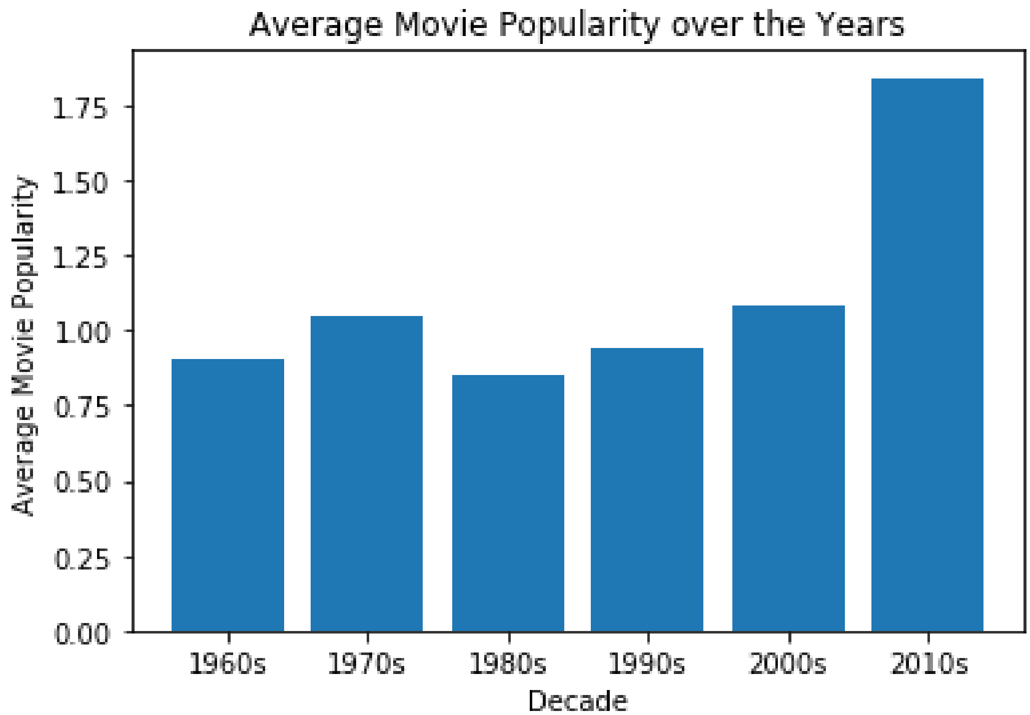
Let's plot a bar chart using Matplotlib to show Average Popularity of movies over the Decades

In [58]:
```
df.groupby('decade')['popularity'].mean()
```

Out[58]:
```
decade
1960s    0.900749
1970s    1.044932
1980s    0.848137
1990s    0.938220
2000s    1.082989
2010s    1.841155
Name: popularity, dtype: float64
```

In [59]:
```
# We plot the bar chart to explore the mean budget used over the various decades
popularity_during_decade = df.groupby('decade')['popularity'].mean()

plt.bar(popularity_during_decade.index, popularity_during_decade.values)
plt.title('Average Movie Popularity over the Years')
plt.xlabel('Decade')
plt.ylabel('Average Movie Popularity')
```

Out[59]:
```
Text(0,0.5,'Average Movie Popularity')
```



We see from the chart above that movies have relatively maintained their popularity over the decades until the 2010s where they seem to have gone up.

One more way we want to explore our data over the decades is in terms of profits made from the movies. We define profit here as 'revenue_adj - budget_adj'.

Let's create a new column in the dataframe called 'profit'

```
In [60]: df['profit'] = df['revenue_adj'] - df['budget_adj']
```

```
In [62]: #Let's confirm that the 'profit' column has been created.
         df_ends(df,2)
```

```
Out[62]:       popularity        budget        revenue  \
         0      32.985763   150000000.0   1.513529e+09
         1      28.419936   150000000.0   3.784364e+08
         3852    0.299911    12000000.0   2.000000e+07
         3853    0.207257     5115000.0   1.200000e+07

                                                   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
         3852          Action|Adventure|Drama|War|Romance     12/20/66          28
         3853                   Adventure|Science Fiction      8/24/66          42

               vote_average  release_year    budget_adj   revenue_adj   revenue_levels  \
         0              6.5          2015  1.379999e+08  1.392446e+09             high
```

```
1               7.1          2015  1.379999e+08  3.481613e+08             high
3852            7.0          1966  8.061618e+07  1.343603e+08  moderately high
3853            6.7          1966  3.436265e+07  8.061618e+07  moderately high

     decade        profit
0     2010s  1.254446e+09
1     2010s  2.101614e+08
3852  1960s  5.374412e+07
3853  1960s  4.625353e+07
```

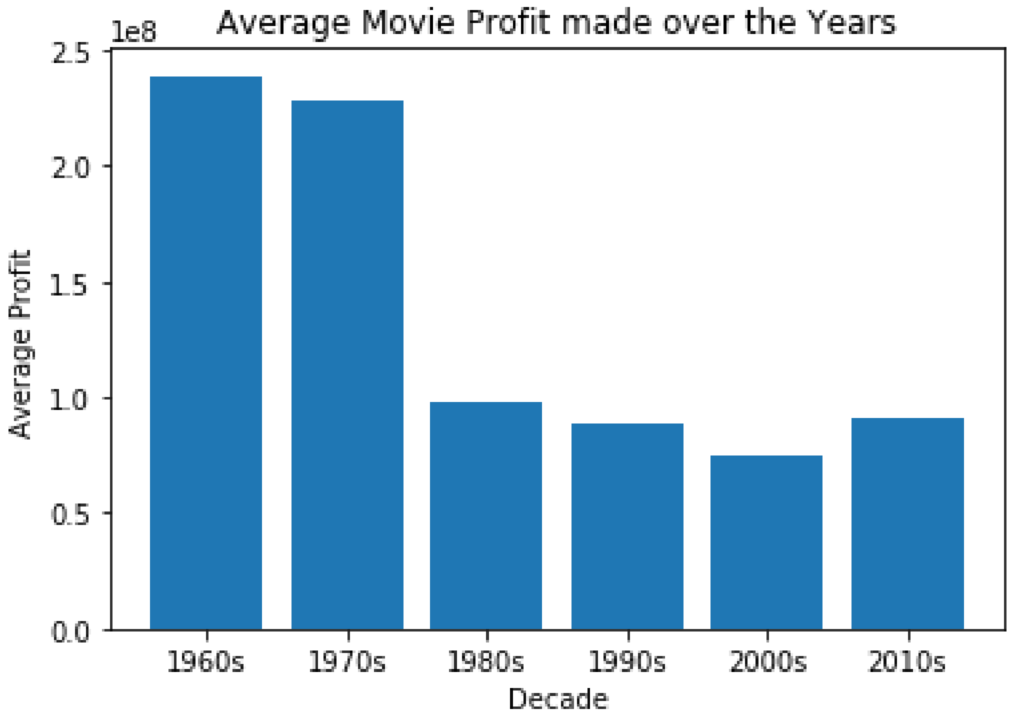
Let's plot a bar chart using Matplotlib to show Average Popularity of movies over the Decades

In [63]:
```
df.groupby('decade')['profit'].mean()
```

Out[63]:
```
decade
1960s    2.388079e+08
1970s    2.282197e+08
1980s    9.785714e+07
1990s    8.814204e+07
2000s    7.489950e+07
2010s    9.038803e+07
Name: profit, dtype: float64
```

In [64]:
```
# We plot the bar chart to see the average profit made over the various decades
profit_during_decade = df.groupby('decade')['profit'].mean()

plt.bar(profit_during_decade.index, profit_during_decade.values)
plt.title('Average Movie Profit made over the Years')
plt.xlabel('Decade')
plt.ylabel('Average Profit')
```

Out[64]:
```
Text(0,0.5,'Average Profit')
```



From the plot above, the 1960s and 1970s look to have been the most profitable years for movies. The subsequent decades show even less than half of that average profit.

Conclusions

Main question 1: Which features can be most associated with high revenue? (1 to 3)

1. Are very popular movies high revenue/grossing movies?

   It can be deduced from the exploratory analysis that on average, higher revenue levels can be associated with slightly higher popularity levels.

2. Do movies with high budgets get the highest revenues?

   From the data exploration, we see that averagely, higher budget movies are associated with higher revenue levels.

3. Do lower user ratings translate to low revenues for movies?

   It can be inferred from the exploration of data that user ratings (vote average) does not directly influence the revenue levels of movies.

Main question 2: How has movie success changed over the years? (4 to 7)

4. How has movie revenue changed over the years?

   The bar chart of average movie revenue for the various decades shows that average movie revenue was highest in the 1960s and 1970s and steadily came down to half of that over the rest of the decades.

5. How has movie popularity changed over the years?

   The exploratory analysis shows that movies have relatively maintained their popularity level over the decades until the 2010s where the popularity appears to have doubled.

6. How has movie budget evolved over the years?

   From the analysis, movie budget was high in the 1960s, then it came low through the 1970s and 1980s and eventually went up in 1990s and is still high till 2010s although there is a very small decline between 1990s and 2010s.

7. Which years were most profitable for movies?

   The analysis shows that the 1960s and 1970s look to have been the most profitable years for movies. The subsequent decades show even less than half of that average profit.

Additional comments under conclusion > The genre column can be explored to investigate it's relationship with revenue levels as well as it's popularity over the decades.

1.1.7 Limitations

1. The data had a lot of zero values and null values which resulted in deletion of many rows. Out of the initial 10866 rows of data, only 3854 was used in the analysis after cleaning. This may have resulted in loss of valuable data.
2. Although, budget_adj and revenue_adj were two of the main columns used in the dataframe for analysis, the currencies of the vlaues were not added. This means that the values may not be very accurate for analysis.

1.2 Reference

1. https://pandas.pydata.org/docs/user_guide/index.html#user-guide
2. https://stackoverflow.com/questions/22649693/drop-rows-with-all-zeros-in-pandas-data-frame
3. https://classroom.udacity.com

Extra note: This updated .ipynb file has the specified change recommnended from the 1st review, which is the creation of a function.

```
In [66]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset_TMDB.ipynb'])

Out[66]: 0

In [ ]:
```