TMDb

June 5, 2022

1 Project: Investigate a Movie Dataset (TMDb Movies Dataset)

1.1 Table of Contents

Introduction

1.2 This is a project towards the Udcity Data Analytics nanodegree certification

This data set contains information about 10,000 movies collected from The Movie Database (TMDb), including user ratings and revenue. - Certain columns, like 'cast' and 'genres', contain multiple values separated by pipe (|) characters. - There are some odd characters in the 'cast' column. Don't worry about cleaning them. You can leave them as is. - The final two columns ending with "_adj" show the budget and revenue of the associated movie in terms of 2010 dollars, accounting for inflation over time.

Questions ## Some questions of interest that arise from the movie features are: - Which genres are most popular? - How has movie runtime changed over the years? - Which genres generate more revenue? - How has overall movie revenue changed over the years? - which is the most popular and least popular movie? - What are the top ten most popular movies? - What genres do most producers produce? - How has the cost of movie production changed over the years?

1.3 However, we are going to answer the questions.

- How has The cost of movie production changed over the years?
- How has revenue from movie sales et'al changed over the years?
- How has profitability changed over the years?
- with respect to the 2010 inflation rate, comment on effect of inflation on overall cost overhead

we answer these questions using the actual revenue, values and the values adjusted for the 2010 value of the Dollar

1.3.1 import the needed packages

[181]:
```
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import seaborn as sns
import pprint as pp
import os
import sys
%matplotlib inline


file = 'tmdb-movies.csv'
movie_df = pd.read_csv(file)
movie_df.head(3)
```

[181]:
```
       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]
```

1.3.2 Observation

The revenue and budget have no currency specified, however, the TMDb from themoviedb, ",All currency values on TMDb is assumed to be USD."

Dimension of dtaframe

[182]:
```python
samples, features = movie_df.shape
print('The dataset has {} movie samples and {} features'.format(samples,
 ↪features))
```

```
The dataset has 10866 movie samples and 21 features
```

Summary statistics

[183]:
```python
movie_df.describe()
```

[183]:

	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

1.3.3 some deductions from the summary decription

- Most movies turn out to be profitable, althou some m
- Most movies have an average runtime of 102 mins
- The dataset contains no details of movies released after 2015 ##### Note: ##### This is a summary descriptive statistics, and is not a subtitue for the required indepth analysis and conclusion

Data Wrangling #### 1. Create a new dataframe(df) from a copy of the Movie_df #### 2. Drop duplicate movie samples #### 3. Add features relevant to the analysis

we create a new dataframe using the columns relevant to our analysis

['original_title','release_year','budget','revenue','budget_adj','revenue_adj']

Other features are important but not with respect to our analysis

1.3.4 1. create new dataframe from our old dataframe

[184]:
```
cols_to_use = np.
↪array(['original_title','release_year','budget','revenue','budget_adj','revenue_adj'])
df = movie_df[cols_to_use].copy()
df.head()
```

[184]:
```
                original_title  release_year     budget     revenue  \
0               Jurassic World          2015  150000000  1513528810
1           Mad Max: Fury Road          2015  150000000   378436354
2                    Insurgent          2015  110000000   295238201
3  Star Wars: The Force Awakens         2015  200000000  2068178225
4                    Furious 7          2015  190000000  1506249360

     budget_adj   revenue_adj
0  1.379999e+08  1.392446e+09
1  1.379999e+08  3.481613e+08
2  1.012000e+08  2.716190e+08
3  1.839999e+08  1.902723e+09
4  1.747999e+08  1.385749e+09
```

[185]:
```
df.describe()
```

[185]:
```
       release_year        budget       revenue    budget_adj   revenue_adj
count  10866.000000  1.086600e+04  1.086600e+04  1.086600e+04  1.086600e+04
mean    2001.322658  1.462570e+07  3.982332e+07  1.755104e+07  5.136436e+07
std       12.812941  3.091321e+07  1.170035e+08  3.430616e+07  1.446325e+08
min     1960.000000  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
25%     1995.000000  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
50%     2006.000000  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
75%     2011.000000  1.500000e+07  2.400000e+07  2.085325e+07  3.369710e+07
max     2015.000000  4.250000e+08  2.781506e+09  4.250000e+08  2.827124e+09
```

[186]:
```
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 6 columns):
 #   Column          Non-Null Count  Dtype
---  ------          --------------  -----
 0   original_title  10866 non-null  object
 1   release_year    10866 non-null  int64
 2   budget          10866 non-null  int64
 3   revenue         10866 non-null  int64
 4   budget_adj      10866 non-null  float64
 5   revenue_adj     10866 non-null  float64
dtypes: float64(2), int64(3), object(1)
memory usage: 509.5+ KB
```

1.3.5 clearly there are no empty cells in our new dataframe

1.3.6 2. Drop duplicate movie samples

[187]:
```
print("The new tmdb dataset has {} duplicated movie samples".format(df.
↪duplicated().sum()))
```

```
The new tmdb dataset has 2 duplicated movie samples
```

We then drop duplicate rows(samples) keeping the first instance of their occurence.

[188]:
```
df.drop_duplicates(keep='first', inplace=True)
```

Check for features with null values

[189]:
```
df.isnull().sum()
```

[189]:
```
original_title    0
release_year      0
budget            0
revenue           0
budget_adj        0
revenue_adj       0
dtype: int64
```

clearly we have no features with missing entries in our extracted DataFrame

1.3.7 3. Add feature(s) relevant to our analysis.

[190]:
```
df.insert(4,'profit',df['revenue']-df['budget'])
df.insert(7,'profit_adj',df['revenue_adj']-df['budget_adj'])
df.head()
```

[190]:
```
                   original_title  release_year     budget     revenue  \
0                  Jurassic World          2015  150000000  1513528810
1              Mad Max: Fury Road          2015  150000000   378436354
2                       Insurgent          2015  110000000   295238201
3    Star Wars: The Force Awakens          2015  200000000  2068178225
4                       Furious 7          2015  190000000  1506249360

       profit    budget_adj   revenue_adj    profit_adj
0  1363528810  1.379999e+08  1.392446e+09  1.254446e+09
1   228436354  1.379999e+08  3.481613e+08  2.101614e+08
2   185238201  1.012000e+08  2.716190e+08  1.704191e+08
3  1868178225  1.839999e+08  1.902723e+09  1.718723e+09
4  1316249360  1.747999e+08  1.385749e+09  1.210949e+09
```

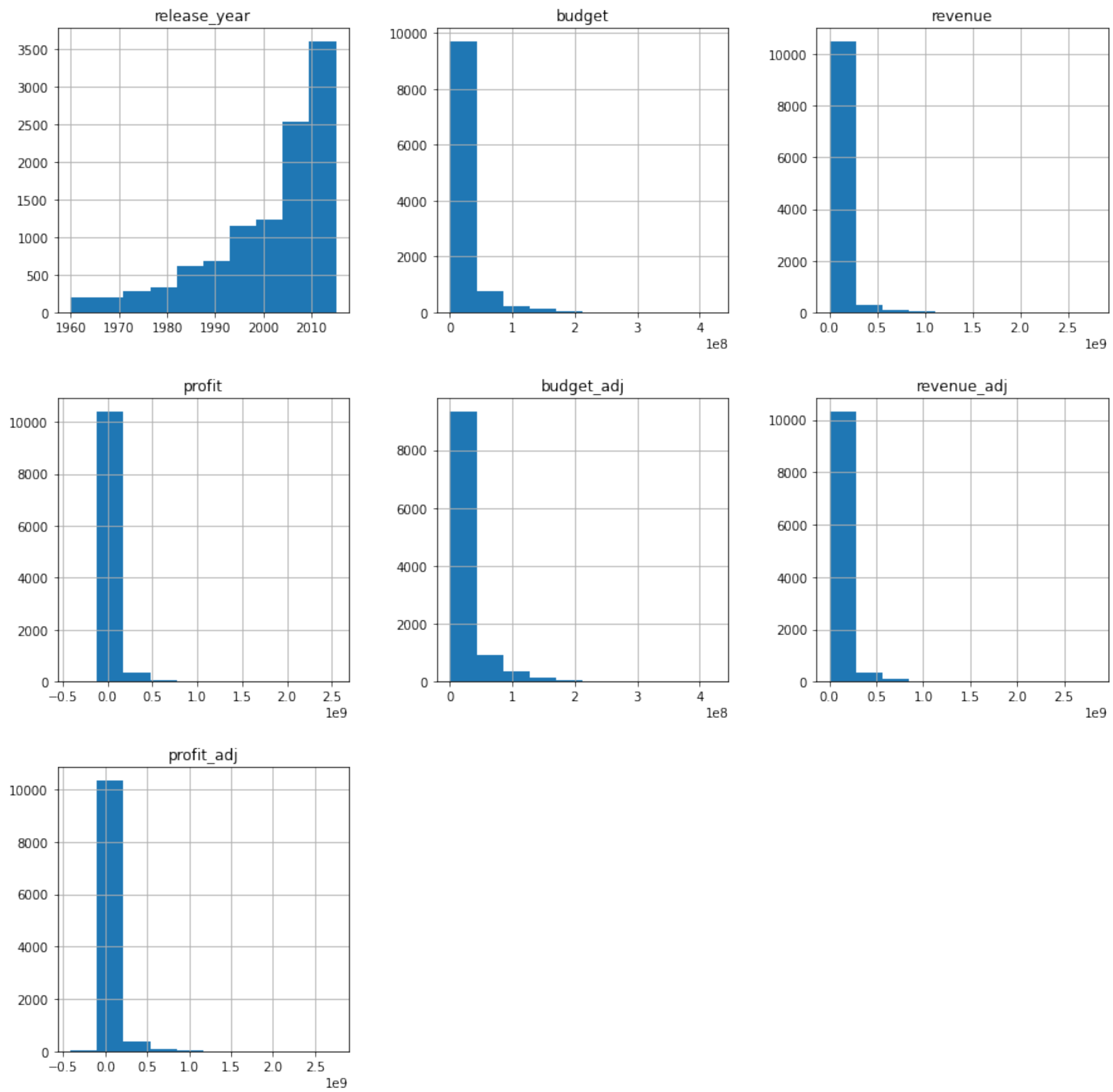
[191]:
```
df.describe()
```

[191]:
```
       release_year        budget       revenue        profit    budget_adj  \
count  10864.000000  1.086400e+04  1.086400e+04  1.086400e+04  1.086400e+04
mean    2001.320784  1.462563e+07  3.983056e+07  2.520493e+07  1.755151e+07
std       12.813360  3.091539e+07  1.170130e+08  9.659517e+07  3.430869e+07
min     1960.000000  0.000000e+00  0.000000e+00 -4.139124e+08  0.000000e+00
25%     1995.000000  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
50%     2006.000000  0.000000e+00  0.000000e+00  0.000000e+00  0.000000e+00
75%     2011.000000  1.500000e+07  2.400183e+07  9.094340e+06  2.085325e+07
max     2015.000000  4.250000e+08  2.781506e+09  2.544506e+09  4.250000e+08

        revenue_adj    profit_adj
count  1.086400e+04  1.086400e+04
mean   5.137373e+07  3.382222e+07
std    1.446442e+08  1.252247e+08
min    0.000000e+00 -4.139124e+08
25%    0.000000e+00  0.000000e+00
50%    0.000000e+00  0.000000e+00
75%    3.370925e+07  1.293994e+07
max    2.827124e+09  2.750137e+09
```

[192]:
```
df.hist(figsize=(15,15))
```

[192]:
```
array([[<AxesSubplot:title={'center':'release_year'}>,
        <AxesSubplot:title={'center':'budget'}>,
        <AxesSubplot:title={'center':'revenue'}>],
       [<AxesSubplot:title={'center':'profit'}>,
        <AxesSubplot:title={'center':'budget_adj'}>,
        <AxesSubplot:title={'center':'revenue_adj'}>],
       [<AxesSubplot:title={'center':'profit_adj'}>, <AxesSubplot:>,
        <AxesSubplot:>]], dtype=object)
```

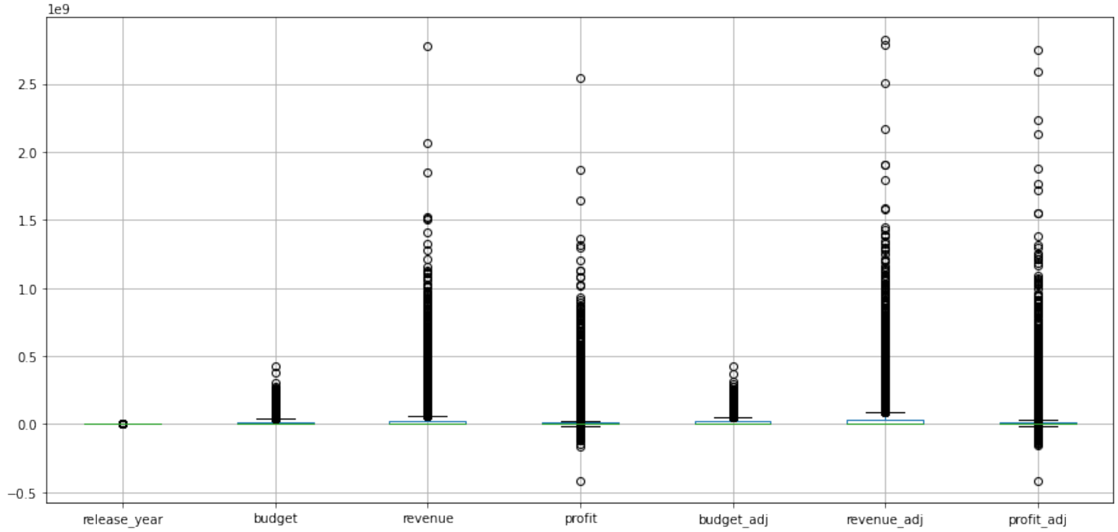


1.3.8 With the exception of the release year, all other features are skewed to the right.

- Statistically, this implies that the large values occur with a low frequency.
- Thus we can say that Movies with high budget, revenue and profit occur with very low frequencies.
- A right skewed data occurs due to peak values at initial stage which then decline with time.

[193]:
```
df.boxplot(figsize=(15,7))
```

[193]: <AxesSubplot:>



- The movie industry is a purely commercial structure (low budget, high profit)
- We can seee possible outliers at figures of 2.5e9 ~> 2.5 billion Dollars. (That's huge:))
- We can also see some losses with an outlier clsose to -0.5e9 ~> 500 million Dollars (a great loss :()
- We can also see that most movies make reasonable returns on the invested capital.
- Lastly, very few movies record losses.

Exploratory Data Analysis

1.3.9 function to compute data and make our plots

[194]:
```
def feature_info_plot(col_name):
    #data_setup
    Title = f"yearly {col_name}"
    temp_data = df.groupby('release_year')[col_name].sum()

    #plot_face
    plt.figure(figsize=(15,5))
    plt.plot(temp_data)
    plt.title(Title)
    plt.xlabel('year')
    plt.ylabel(col_name)
    plt.show()
```

1.3.10 function for max and min values

[195]:
```
def high_and_low(col_name):
    #for highest earned profit
    high= df[col_name].idxmax()
    high_details=pd.DataFrame(df.loc[high])
```

```
    #for lowest earned profit
    low= df[col_name].idxmin()
    low_details=pd.DataFrame(df.loc[low])

    #collectin data in one place
    info=pd.concat([high_details, low_details], axis=1)

    return info
```

1.3.11 function for line of best fit

[196]:
```
def plot_best_fit(col_name):
    #data setup
    Title = f"yearly {col_name}"
    temp_data = df.groupby('release_year')[col_name].sum()
    pds = pd.Series(temp_data)
    years = np.array(pds.index.values)
    yearly_values = np.array([pds[i] for i in years])
    x,y = years, yearly_values

    #gradient and intercept
    m,c = np.polyfit(x, y, 1)

    #plot of best fit
    plt.figure(figsize=(15,5))
    plt.plot(x,y,'*')
    plt.plot(x, m*x + c)
    plt.title(Title)
    plt.xlabel('year')
    plt.ylabel(col_name)
    plt.show()
```

Function for 2 variable correlation

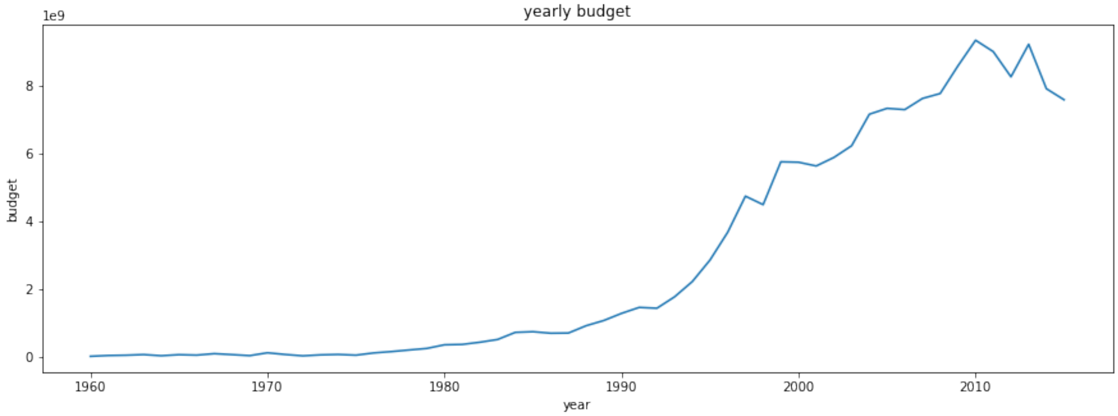
[197]:
```
def corr_plot(col1, col2):
    df.plot(x=col1, y=col2, kind='scatter')
```

1.3.12 Q1. How has the cost of movie production changed over the years?

Note: The Budget is the overhead cost of movie production.

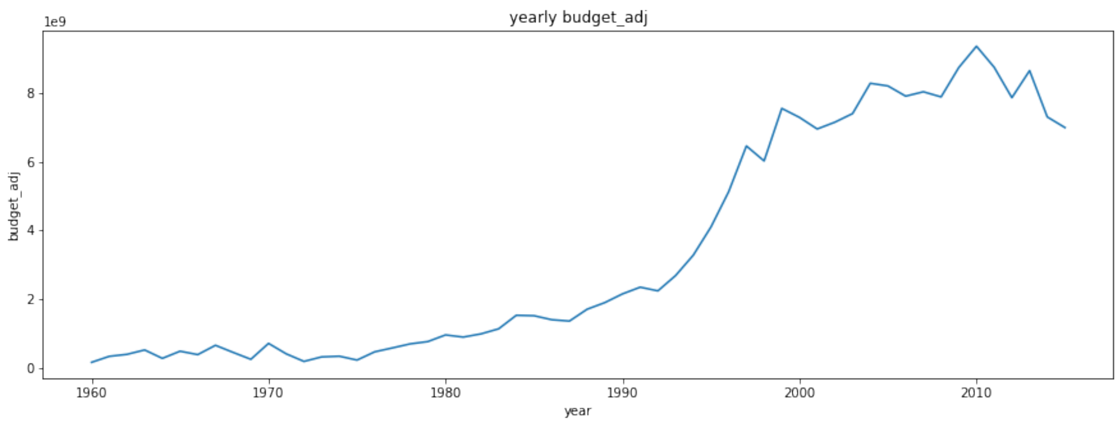
we plot for yearly budget adjusted/unadjusted

[198]:
```
feature_info_plot('budget')
```



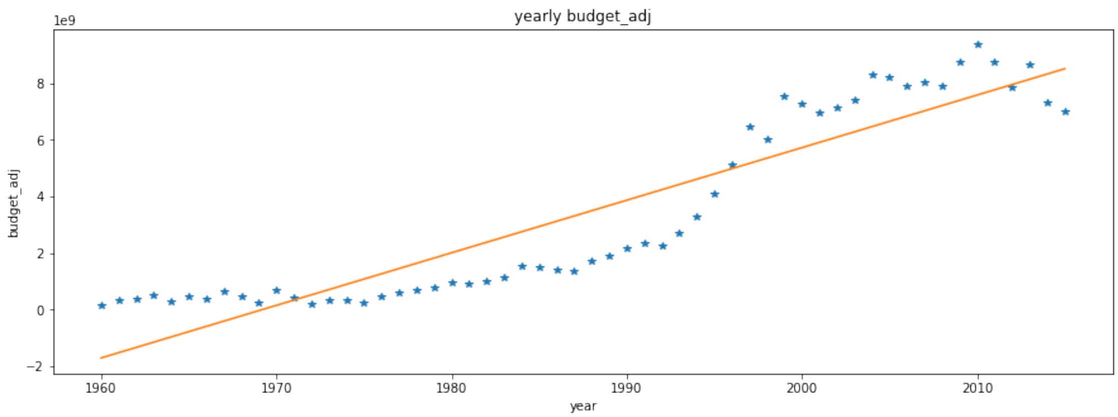
This shows a a cyclical structure with a an increasing trend

[199]:
```
feature_info_plot('budget_adj')
```



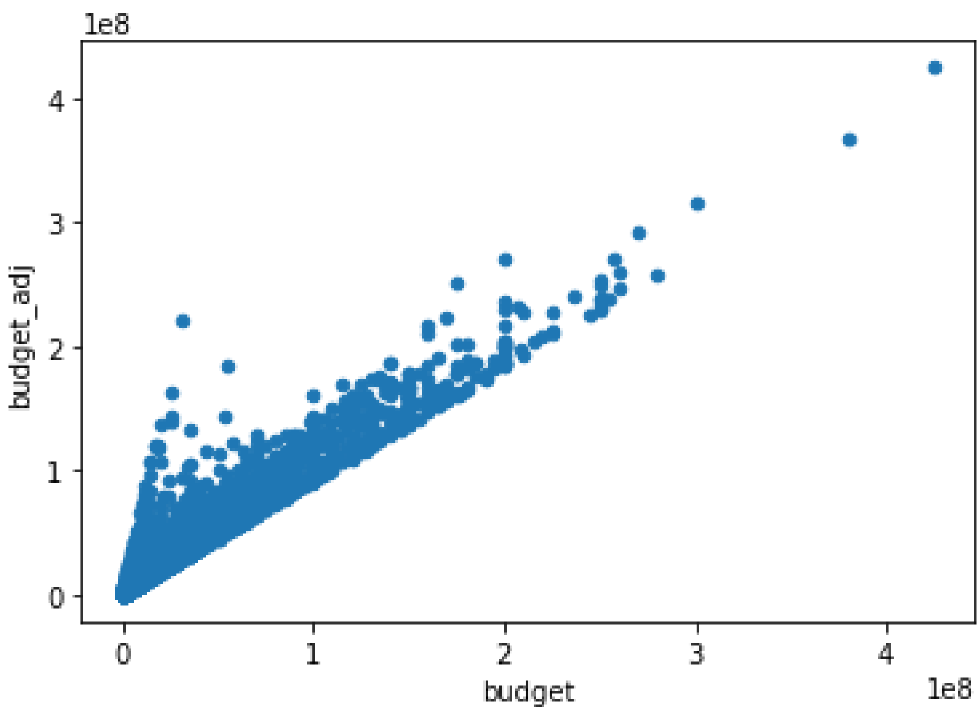
budget plot of best fit

[200]:
```
plot_best_fit('budget_adj')
```



from the plot above, we see a cyclical pattern with an increase year after year

[201]:
```
corr_plot('budget','budget_adj')
```



inflation has a significant effect on budget

[202]:
```
pd.concat([high_and_low('budget'), high_and_low('budget_adj')], axis=1)
```

[202]:

```
                        2244             30              2244  \
original_title  The Warrior's Way     Mr. Holmes  The Warrior's Way
release_year                 2010           2015              2010
budget                  425000000              0         425000000
revenue                  11087569       29355203          11087569
profit                 -413912431       29355203        -413912431
budget_adj            425000000.0            0.0       425000000.0
revenue_adj            11087569.0  27006774.877019      11087569.0
profit_adj           -413912431.0  27006774.877019    -413912431.0

                             30
original_title       Mr. Holmes
release_year               2015
budget                        0
revenue                29355203
profit                 29355203
budget_adj                  0.0
revenue_adj     27006774.877019
profit_adj      27006774.877019
```

For the adjusted and unadjusted values

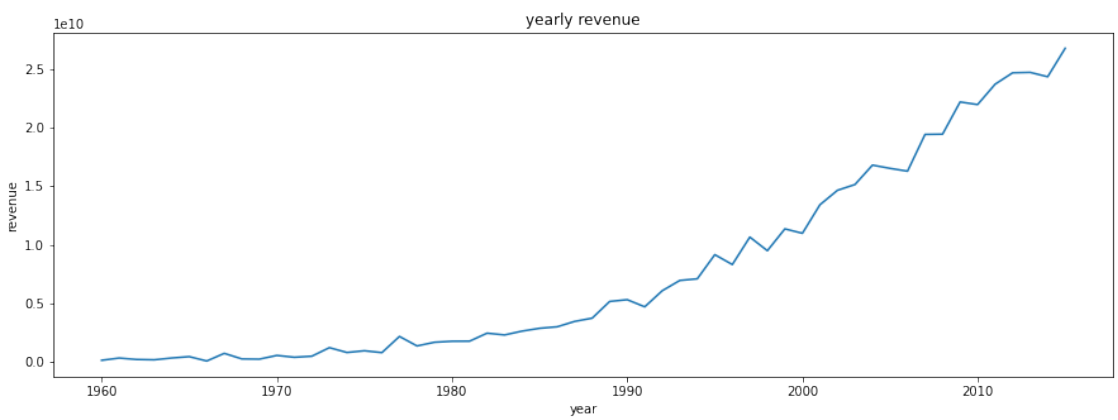
- The movie with the highest budget is The Warriors Way
- The movie with the lowest budget is Mr Holmes

1.3.13 Q2. How has revenue from movie sales and publicity changed over the the years

plot for yearly revenue unadjusted/unadjusted

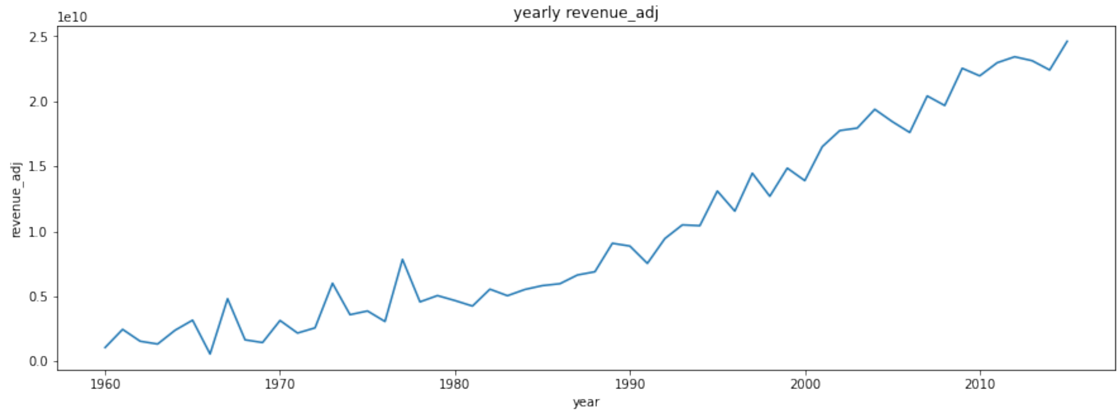
[203]:

```python
feature_info_plot('revenue')
```



This indicates an increasing trend

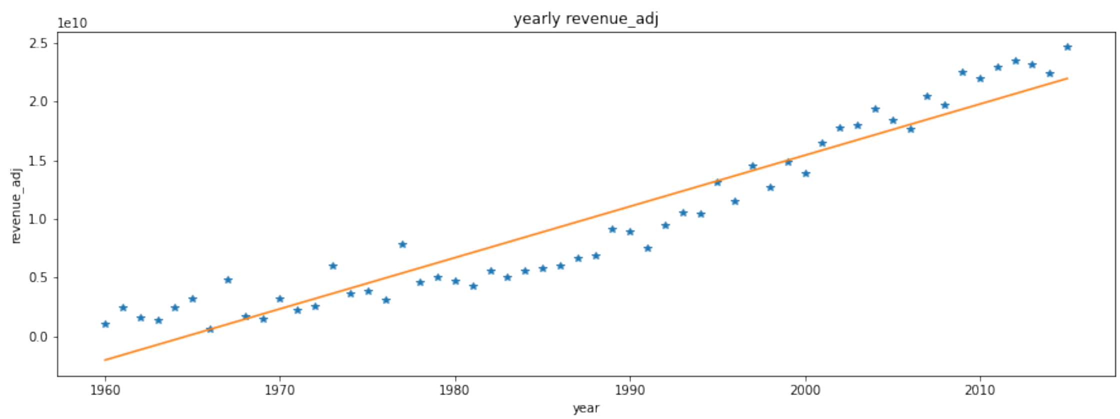
[204]:
```
feature_info_plot('revenue_adj')
```



This indicates an increasing trend

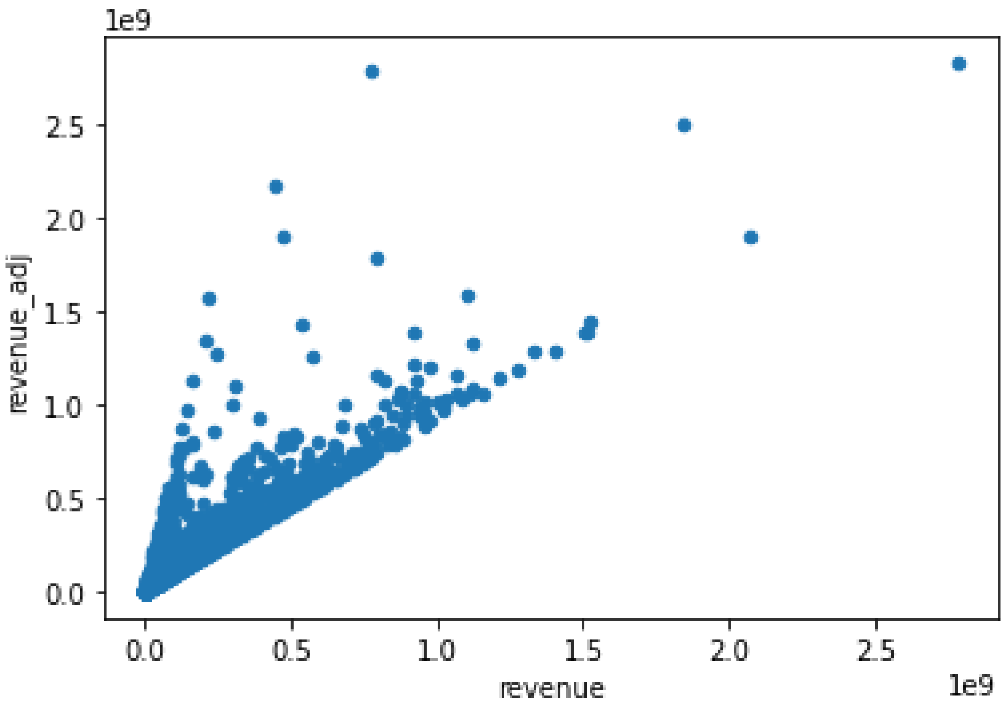
we plot for best fit

[205]:
```
plot_best_fit('revenue_adj')
```



From the above plot, we see that despite short-term seasonality, revenue continues to rise year after year

[206]:
```
corr_plot('revenue','revenue_adj')
```



Inflation has a significant effect on revenue

[207]:
```
pd.concat([high_and_low('revenue'), high_and_low('revenue_adj')], axis=1)
```

[207]:
```
                              1386              48                1386  \
original_title              Avatar       Wild Card              Avatar
release_year                  2009            2015                2009
budget                   237000000        30000000           237000000
revenue                 2781505847               0          2781505847
profit                  2544505847       -30000000          2544505847
budget_adj        240886902.887613  27599987.856005   240886902.887613
revenue_adj       2827123750.41189             0.0   2827123750.41189
profit_adj       2586236847.524277 -27599987.856005  2586236847.524277

                              48
original_title           Wild Card
release_year                  2015
budget                    30000000
revenue                          0
profit                   -30000000
budget_adj         27599987.856005
revenue_adj                    0.0
profit_adj        -27599987.856005
```

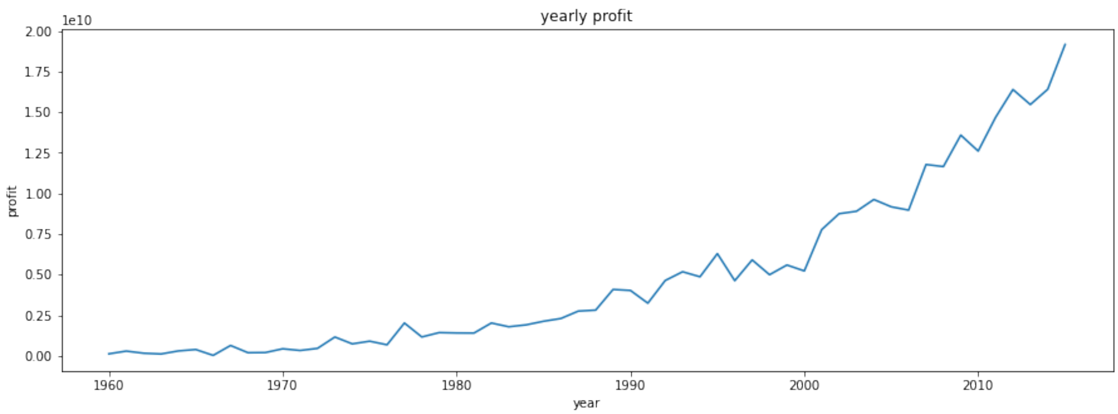
For the uadjusted and unadjusted values

- The movie with the highest revenue is Avatar ~> 2.8 billion Dollars
- The movie with the lowest revenue is Wild Card ~> 0.0 dollars

1.3.14 Q3. How Profitable has movie production been over the years.

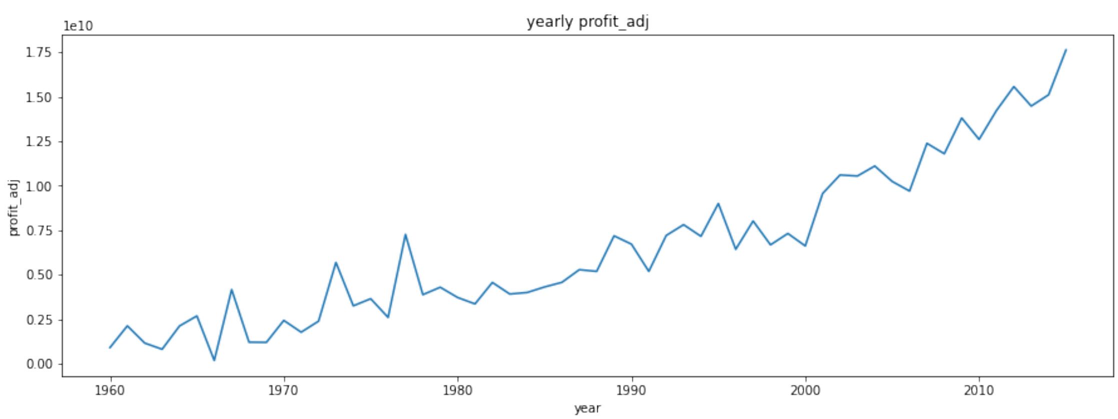
plots for profit values unadjusted

[208]:
```
feature_info_plot('profit')
```



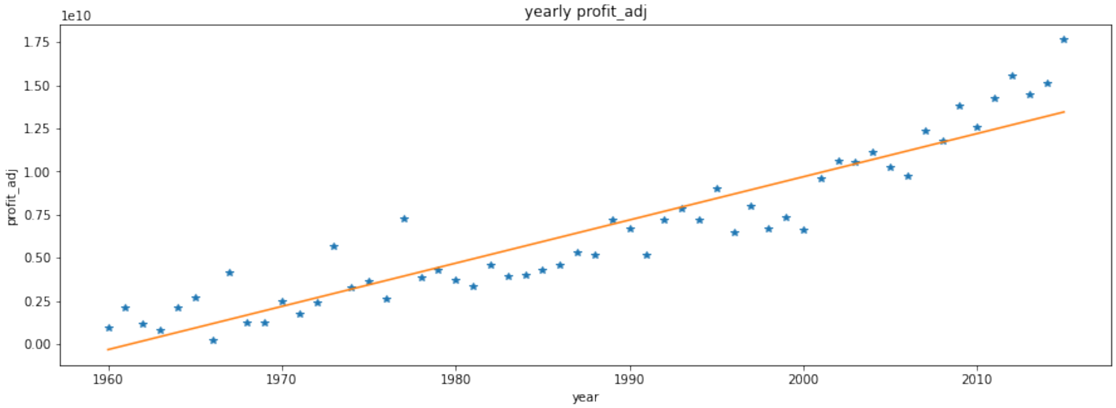
The profit has an increasing trend

[209]:
```
feature_info_plot('profit_adj')
```



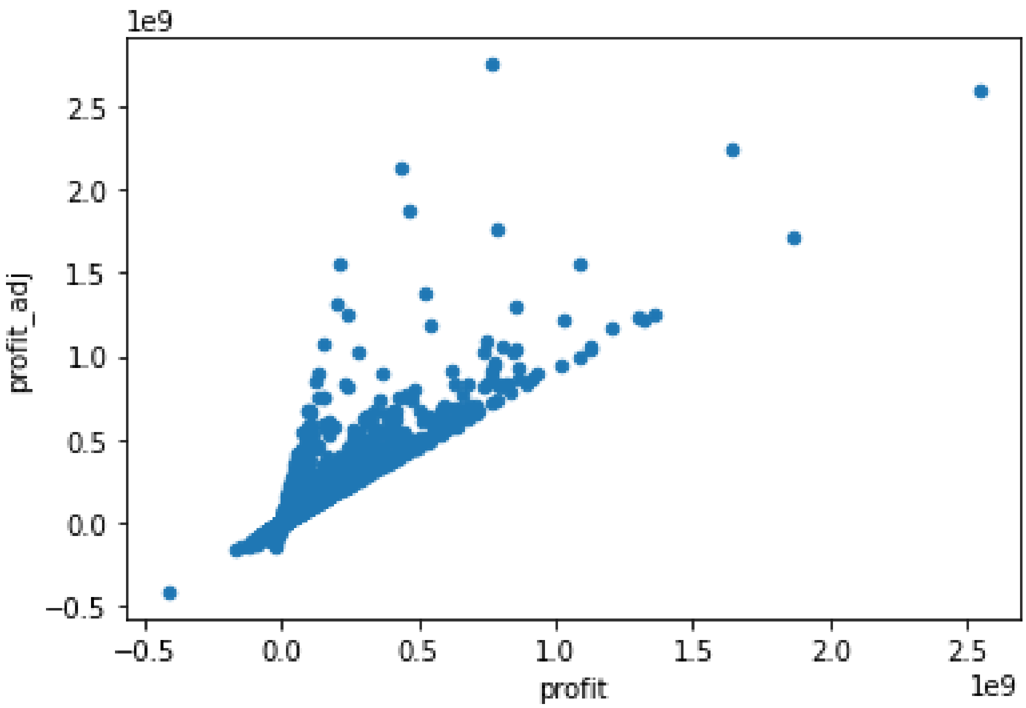
The fluctuation indicates a seasonal increase/decrease in the cumulative profit for athet year and NOT a loss profit plot of best fit

[210]:
```
plot_best_fit('profit_adj')
```



From the plot above, we see that profit continues to rise year after year

[211]:
```
corr_plot('profit','profit_adj')
```



Inflation has a significant effect on profit

[212]:
```
pd.concat([high_and_low('profit'), high_and_low('profit_adj')], axis=1)
```

[212]:
```
                                 1386               2244              1329  \
original_title                 Avatar  The Warrior's Way         Star Wars
```

```
release_year             2009          2010          1977
budget              237000000     425000000      11000000
revenue            2781505847      11087569     775398007
profit             2544505847    -413912431     764398007
budget_adj     240886902.887613   425000000.0   39575591.358274
revenue_adj    2827123750.41189    11087569.0  2789712242.27745
profit_adj    2586236847.524277  -413912431.0  2750136650.919176

                           2244
original_title  The Warrior's Way
release_year               2010
budget                425000000
revenue                11087569
profit               -413912431
budget_adj          425000000.0
revenue_adj          11087569.0
profit_adj         -413912431.0
```

For the unadjusted values

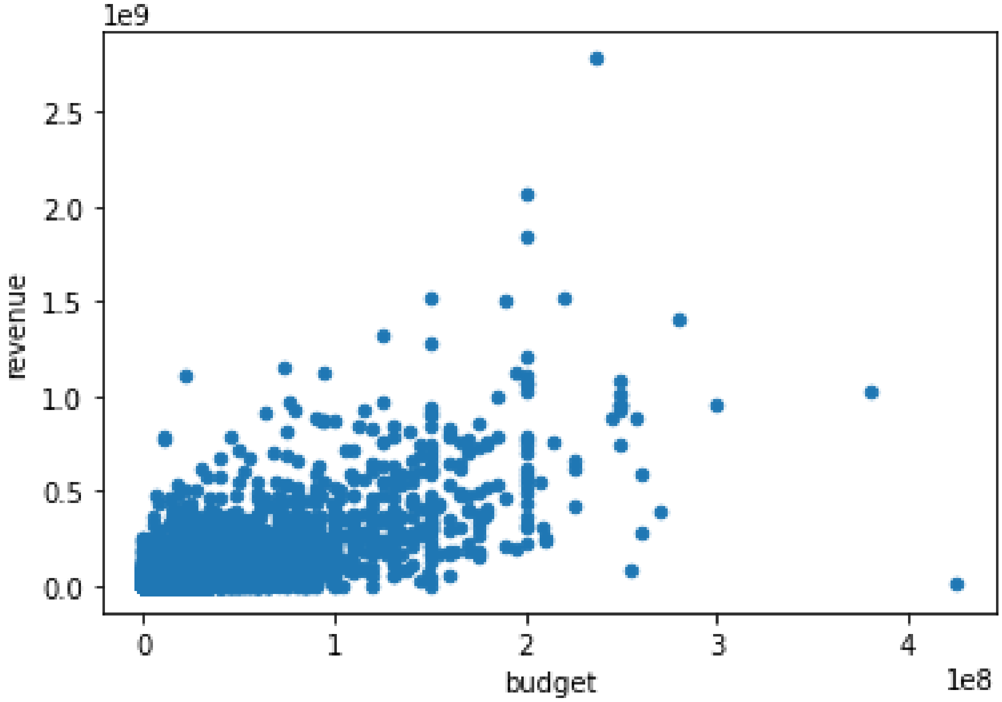
- The movie with the highest profit is Avatar ~> 2.5 billion Dollars
- The movie with the lowest profit is The Warrior's Way ~> -414 million Dollars

For the adjusted values

- The movie with the highest profit is Star Wars ~> 2.7 billion Dollars
- The movie with the lowest profit is The Warrior's Way -414 million Dollars

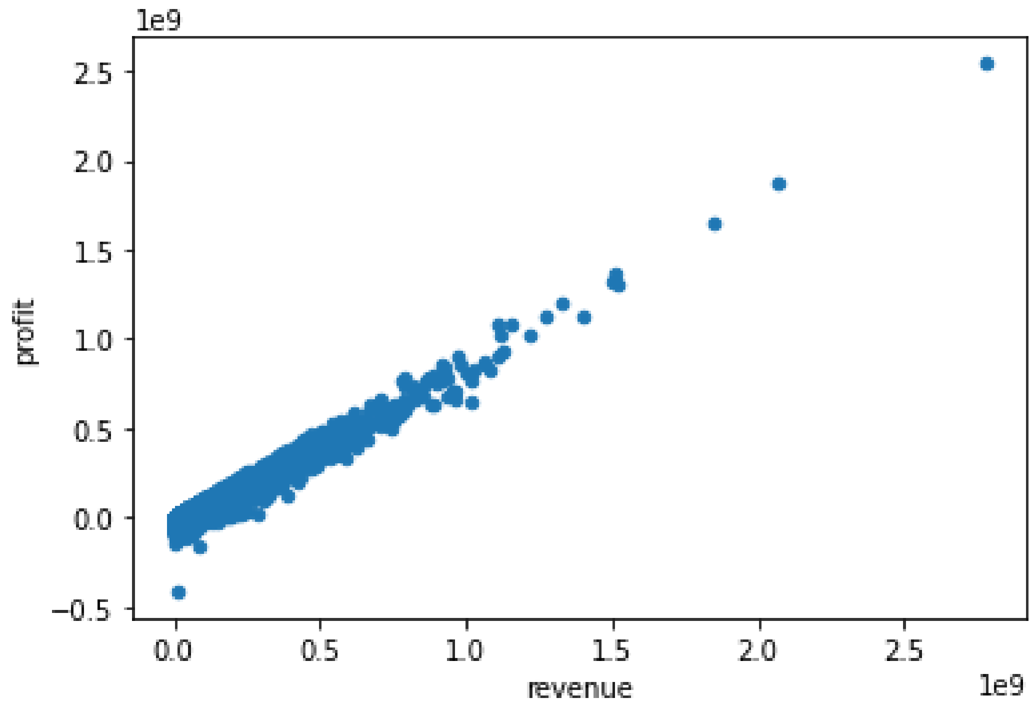
[213]:
```
df.plot(x='budget',y='revenue',kind='scatter')
```

[213]:
```
<AxesSubplot:xlabel='budget', ylabel='revenue'>
```



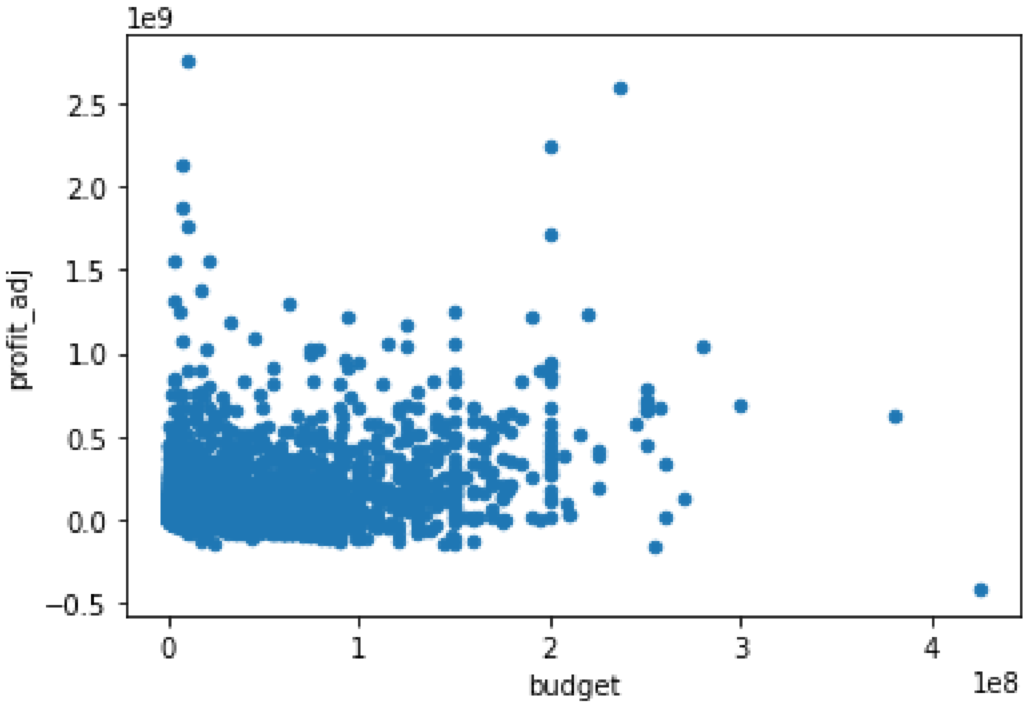
This indicates mild correlation between budget and profit thus we cannot conclude that budget affects profit

[214]:
```
corr_plot('revenue','profit')
```



We can see that revenue is a good indicator of profit. Thus high revenue == high profit and vice versa…

[215]:
```
corr_plot('budget','profit_adj')
```



There is no clear indication of inflation affecting profit

2 Conculusions

1. Budget

- There was a sharp increase in cost of movie production from te early 1990s and peaked in the year 2009-2010 and then begins to decline.
- The rising cost of movie production between the 1990s and the year 2010 could be attributed to the use of state of the art technological equipments in movie oroduction.
- The decline from the year 2010 could be attributed to increased adoption which has cut down the required manpower, thereby reducing the overall budget.

2. Revenue

- Movie revenue has seen an almost steady increase since the birth of movie production
- Inflation has had little effect on Movie Revenue.
- This shows growing interest in viewership.

3. Profit

- The overall profit shows some seasonality but has a summarily profitable trend
- from the high and low dataframes, we can see that a movie budget is not always an indicator high revenue or profit

Financial advice

- For an investor who wants to know if an investments in the movie industry is a worthy in the longterm, my answer is this since there is no significant difference in the adjusted and axctual values of the budget, revenue, and profit, the data at hand that the movie Industry is investment worthy.

Limitations

Though this analyis has been well conducted with all neccasry interpretations and visualisations,

- Since this analysis was conducted in the year 2022, the adjusted values should have been that of 2022 instead.
- Despite significant effect of inflation on each feature, there is no clear indication of inflation affecting profit so we cannot conclude that the Movie industry is worth investing into for a longterm
- NOTE:This is not to contradict the financial recommendation earlier stated