InvestigateADatasetProjectRRoot

July 15, 2020

1 Project: Investigate Cinema Correlations

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Introduction I chose to investigate the "The Movie Database" (TMDb) cinema dataset. As a movie lover, this dataset seemed the most appealing to me. My intent was to explore the data and see what information it contained, refine which information I was interested in, find correlations in that information, and gleam what observations I could to from it. As with any data, it is essential to know where it came came from. A simple internet search gave me access to the following quote from the TMDb project's website:

"Where did all of your data come from?

You! Since starting this project in 2008, we've been lucky enough to have users just like you add and edit missing/incorrect data. Think of TMDb as a very specialised version of Wikipedia where everything is editable but very specialised around only movie, TV and actor data. We started with an initial data contribution from a project called omdb with only 10,000 movies in 2009. Everything added and edited since then has been users just like you!

In October 2013, we finally added TV. Since we didn't want to start with an empty database we opted to bring an intial import of data from Freebase. Freebase is made up of a number of different sources but primarily those from Wikipedia, The TVDb and TV Rage." ('https://www.themoviedb.org/faq/general', 6/2020)

In addition to that information, Udacity provides some initial facts about the dataset I chose. The following is from Udacity's project documentation:

- *"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, account.” (https://video.udacity-data.com/topher/2018/July/5b57919a_data-set-options/data-set-options.pdf, 6/2020)

Reviewing and Wrangling the Data With some basics given to me, my next step was to explore the TMDb data. I started by displaying the top and bottom 3 rows using a Pandas data frame. I also defined the imports I will need for my analysis (updating these as needed).

[1]:
```
# Define Imports
import pandas as pd
import numpy as np
import matplotlib.pyplot as plt
import pprint as pp
import seaborn as sns

# Reconfigure dataframe display
pd.set_option('max_colwidth', 100)
pd.set_option('display.max_columns', None)
pd.options.display.float_format = '{:.0f}'.format  # Suppress scientific␣
 ↪notation and remove cents

# Load the data and print out a few lines.
print('Top 3 rows of data:')
movie_dframe = pd.read_csv('Data/tmdb-movies.csv')
pd.DataFrame(movie_dframe)[0:3]
```

```
Top 3 rows of data:
```

[1]:
```
       id    imdb_id  popularity     budget     revenue      original_title  \
0  135397  tt0369610          33  150000000  1513528810      Jurassic World
1   76341  tt1392190          28  150000000   378436354  Mad Max: Fury Road
2  262500  tt2908446          13  110000000   295238201           Insurgent

                                                                     cast  \
0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vincent D'Onofrio|Nick Robinson
1        Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nicholas Hoult|Josh Helman
2           Shailene Woodley|Theo James|Kate Winslet|Ansel Elgort|Miles Teller

                                         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

                                                         keywords  \
0          monster|dna|tyrannosaurus rex|velociraptor|island
1           future|chase|post-apocalyptic|dystopia|australia
2  based on novel|revolution|dystopia|sequel|dystopic future

              overview  \
0  Twenty-two years after the events of Jurassic Park, Isla Nublar now features
a fully functioning…
1  An apocalyptic story set in the furthest reaches of our planet, in a stark
desert landscape wher…
2  Beatrice Prior must confront her inner demons and continue her fight against
a powerful alliance…

   runtime                                     genres  \
0      124  Action|Adventure|Science Fiction|Thriller
1      120  Action|Adventure|Science Fiction|Thriller
2      119         Adventure|Science Fiction|Thriller

production_companies  \
0  Universal Studios|Amblin Entertainment|Legendary Pictures|Fuji Television
Network|Dentsu
1                                       Village Roadshow Pictures|Kennedy Miller
Productions
2                      Summit Entertainment|Mandeville Films|Red Wagon
Entertainment|NeoReel

  release_date  vote_count  vote_average  release_year  budget_adj  \
0       6/9/15        5562             6          2015   137999939
1      5/13/15        6185             7          2015   137999939
2      3/18/15        2480             6          2015   101199955

   revenue_adj
0   1392445893
1    348161292
2    271619025
```

[2]:
```python
print('Bottom 3 rows of data:')
pd.DataFrame(movie_dframe)[-3:]
```

```
Bottom 3 rows of data:
```

[2]:
```
          id    imdb_id  popularity  budget  revenue  \
10863  39768  tt0060161           0       0        0
10864  21449  tt0061177           0       0        0
```

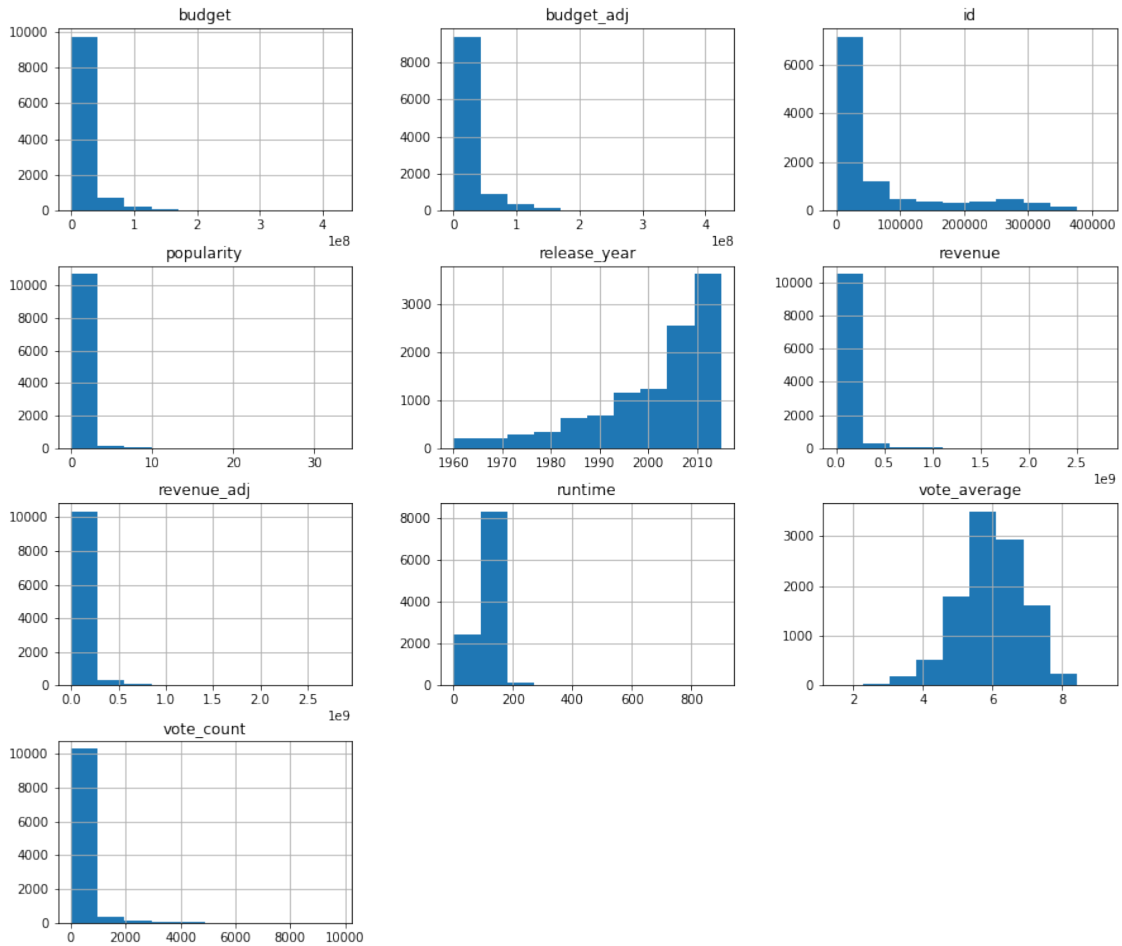
```
10865  22293  tt0060666          0   19000       0

                 original_title  \
10863       Beregis Avtomobilya
10864    What's Up, Tiger Lily?
10865  Manos: The Hands of Fate

           cast  \
10863  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Zhzhyonov|Olga
Aroseva|Lyubov Dobrzhanskaya
10864                  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|John
Sebastian|Tadao Nakamaru
10865                  Harold P. Warren|Tom Neyman|John Reynolds|Diane
Mahree|Stephanie Nielson

      homepage          director  \
10863      NaN    Eldar Ryazanov
10864      NaN       Woody Allen
10865      NaN  Harold P. Warren

                                            tagline  \
10863                                           NaN
10864                       WOODY ALLEN STRIKES BACK!
10865  It's Shocking! It's Beyond Your Imagination!

                                  keywords  \
10863             car|trolley|stealing car
10864                                spoof
10865  fire|gun|drive|sacrifice|flashlight

                  overview  \
10863  An insurance agent who moonlights as a carthief steals cars various
crooks and never from the co…
10864  In comic Woody Allen's film debut, he took the Japanese action film
"International Secret Police…
10865  A family gets lost on the road and stumbles upon a hidden, underground,
devil-worshiping cult le…

       runtime          genres     production_companies release_date  \
10863       94  Mystery|Comedy                  Mosfilm       1/1/66
10864       80   Action|Comedy  Benedict Pictures Corp.      11/2/66
10865       74          Horror                Norm-Iris     11/15/66

       vote_count  vote_average  release_year  budget_adj  revenue_adj
10863          11             6          1966           0            0
10864          22             5          1966           0            0
10865          15             2          1966      127642            0
```

Next, I wanted to see if there was anything that stood out within data. I started with a simple call to Pandas' decribe() function and did a quick review.

[3]:
```
movie_dframe.describe()  # Get an general overview of the data's stats
```

[3]:
```
           id  popularity     budget     revenue  runtime  vote_count  \
count   10866       10866      10866       10866    10866       10866
mean    66064           1   14625701    39823320      102         217
std     92130           1   30913214   117003487       31         576
min         5           0          0           0        0          10
25%     10596           0          0           0       90          17
50%     20669           0          0           0       99          38
75%     75610           1   15000000    24000000      111         146
max    417859          33  425000000  2781505847      900        9767

       vote_average  release_year  budget_adj  revenue_adj
count         10866         10866       10866        10866
mean              6          2001    17551040     51364363
std               1            13    34306156    144632485
min               2          1960           0            0
25%               5          1995           0            0
50%               6          2006           0            0
75%               7          2011    20853251     33697096
max               9          2015   425000000   2827123750
```

[4]:
```
movie_dframe.hist(figsize=(15,13));
```



Since some of the standard stats provided by Pandas' describe() function were either not of interest to me or needed better formatting, I created my own function to extract what I wanted called get_simple_stats(). I also created a class with ANSI escape codes, a function for printing messages, and another function to get a simple histogram. I did this to improve the presentation of my results and make them more consistent.

[5]:
```
class ffont:
    '''
    This class enumerates a list of ANSI Escape codes for font formating
    (ref: http://ascii-table.com/ansi-escape-sequences.php
     and https://godoc.org/github.com/whitedevops/colors)
    '''
    normal = '\033[0m'
    bold = '\033[1m'
    underline = '\033[4m'
    blue = '\033[94m'
    red = '\033[91m'
    black = '\033[30m'
```

```python
# print a message using my "Note" format
# defined with my "formated font" class ffont
def print_msg(message_type = '', text = ''):
    # Set message type format and print the type
    if message_type.lower() == 'info':
        print(ffont.bold,ffont.blue)
    elif message_type.lower() == 'note':
        print(ffont.bold,ffont.black)
    elif message_type.lower() == 'warning':
        print(ffont.bold,ffont.red)
    else:
        print(ffont.normal,end='')
    print(message_type + ': ',end='')
    # Set text format and print the text
    print(ffont.normal,end='')
    print(text)


# Get a Histogram conformed to this notebooks design format
def get_simple_hist(data_frame, key_for_stats, figsize=(6,3), bins=10):
    axis = data_frame.hist(column=key_for_stats,figsize=figsize,bins=bins,)

# Get a basic set of Stats
def get_simple_stats(data_frame, key_for_stats, show_basic_hist=False, bins=10␣
↪):
    ''' This functions shows statistics for a attribute in a givent dataframe␣
↪'''
    # Configure presenation
    print(ffont.bold,ffont.red)

    # print stats for all types
    data = data_frame[key_for_stats]
    print('Statistics for {k}:'.format(k = key_for_stats.title()))
    print(ffont.normal,end='')
    print('Count: {c:<} of {t}'.format(c = np.count_nonzero(data), t =␣
↪len(data)))
    print('Null or Zero: {c:<}'.format(c = len(data) - np.count_nonzero(data)))

    # Print stats for numeric data types
    try:
        print('Minimum: {mi:<10.2f}'.format(mi = np.min(data)))
        print('Maximum: {mx:<10.2f}'.format(mx = np.max(data)))
        print('Mean: {m:<10.2f}'.format(m = np.mean(data)))
        print('Std Dev: {sd:<10.2f}'.format(sd = np.std(data)))
    except:
        print()
```

```
    # Optionally show a histiogram
    if show_basic_hist:
        get_simple_hist(data_frame, key_for_stats, bins=bins)
```

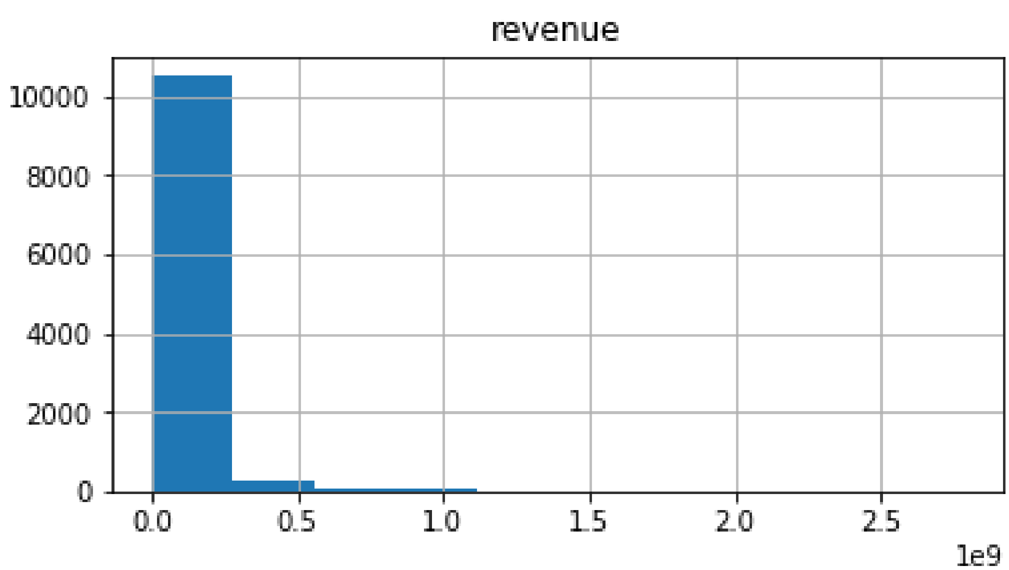
With my new functions and class in place, it was time to look for the measurable attributes. I looked for these first since they have the values used for calculations.

1.0.1 Reviewing Revenue

I figured revenue would be my best metric for analysis, so I reviewed its values first.

[6]:
```
print_msg('Note','Revenue over all years')
get_simple_stats(movie_dframe,key_for_stats='revenue', show_basic_hist=True)
```

```
Note: Revenue over all years


Statistics for Revenue:

Count: 4850 of 10866
Null or Zero: 6016
Minimum: 0.00
Maximum: 2781505847.00
Mean: 39823319.79
Std Dev: 116998102.53
```



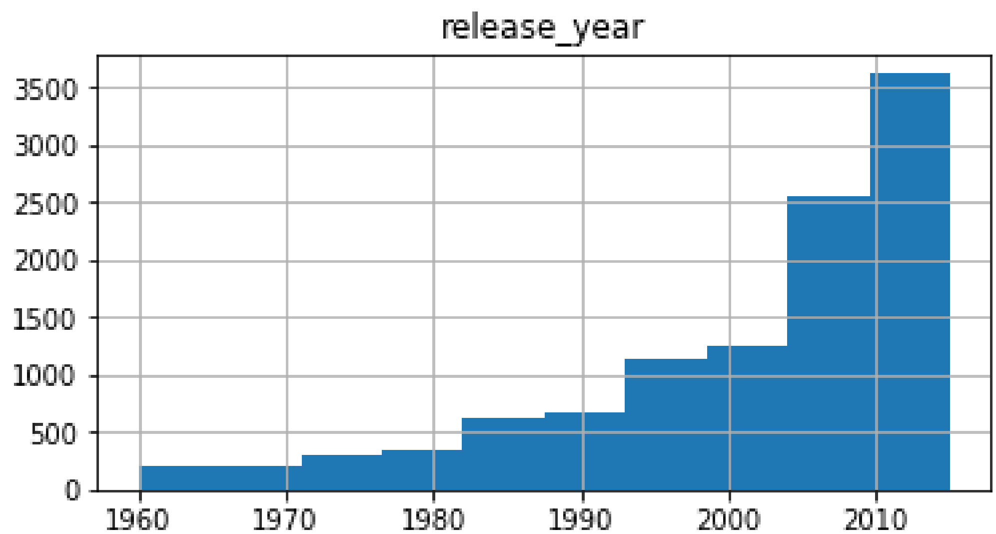
Examining the Revenue by Release Year Reviewing this data, I noticed the it was very skewed and contained many zero values. This, made me wonder why there were so many zeros and did that happen with mostly older movies?

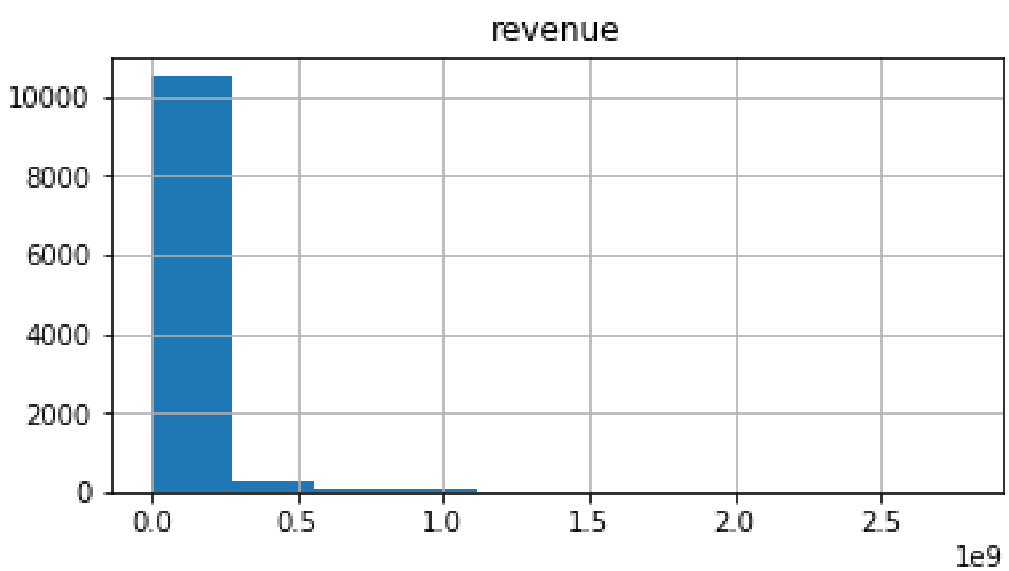
So, I started looking at revenues based on different years. Sure enough, I saw that most revenue values with zero were associated with older films. It was obvious that newer movies had much more revenue than could be reasonably explained by the increase in theater prices or population.

I decided to do a more focused look at this data. So, I created a filtered dataframe to reduce noise and increase performance, then got some basic statistics about the revenue by release year.

[7]:
```
keep_these = ['revenue','release_year']
year_revenue_movie_dframe = movie_dframe[keep_these]
get_simple_stats(year_revenue_movie_dframe,key_for_stats='release_year',␣
 ↪show_basic_hist=True)
get_simple_stats(year_revenue_movie_dframe,key_for_stats='revenue',␣
 ↪show_basic_hist=True)
```

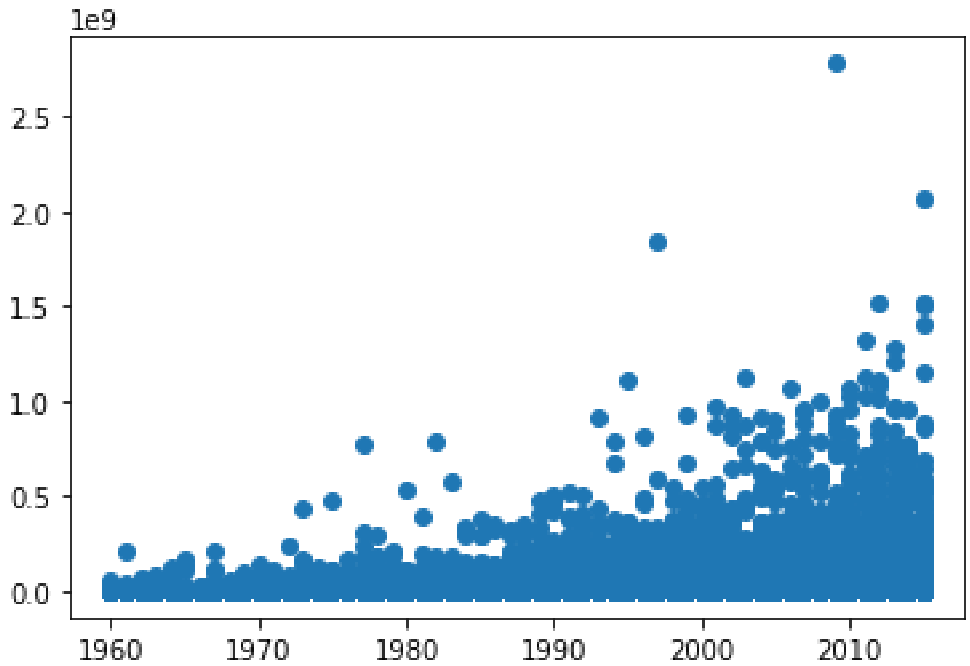
```
Statistics for Release_Year:

Count: 10866 of 10866
Null or Zero: 0
Minimum: 1960.00
Maximum: 2015.00
Mean: 2001.32
Std Dev: 12.81

Statistics for Revenue:

Count: 4850 of 10866
Null or Zero: 6016
Minimum: 0.00
Maximum: 2781505847.00
Mean: 39823319.79
Std Dev: 116998102.53
```





[8]:
```
plt.
 ↪scatter(year_revenue_movie_dframe['release_year'],year_revenue_movie_dframe['revenue']␣
 ↪)
```

[8]: <matplotlib.collections.PathCollection at 0x1da4ff88f48>



I could now visualize how revenue values were strongly skewed toward the later years in the dataset and suspected that earlier years like 1966 had many more zeros.

[9]:
```
year_revenue_movie_dframe
```

[9]:
```
          revenue  release_year
0      1513528810          2015
1       378436354          2015
2       295238201          2015
3      2068178225          2015
4      1506249360          2015
…             …             …
10861           0          1966
10862           0          1966
10863           0          1966
10864           0          1966
10865           0          1966

[10866 rows x 2 columns]
```

I removed the rows with zero revenue values and looked again, only to find that there were several revenue values that were disproportionately lower than the ones in 2015.

[10]:
```
year_revenue_movie_dframe =␣
↪year_revenue_movie_dframe[year_revenue_movie_dframe['revenue'] != 0]
```

```
year_revenue_movie_dframe
```

[10]:

```
          revenue  release_year
0      1513528810          2015
1       378436354          2015
2       295238201          2015
3      2068178225          2015
4      1506249360          2015
…             …           …
10822    33736689          1966
10828    13000000          1966
10829     6000000          1966
10835    20000000          1966
10848    12000000          1966

[4850 rows x 2 columns]
```

1.0.2 Filtering by the Release Year

After more investigation, I was confident that revenue was strongly skewed toward the year 2015 and that the total revenues dropped considerably after 2005. I now felt that if I wanted to have good comparisons between attributes that correlated to revenues, it would be best to compare revenues for movies between 2005 and 2015. So, I sliced the data by that date range making revenue more useful when calculated by attributes like actors, genre, or production companies.

[11]:

```
# Filter by years
print_msg('Info', 'Revenue by Years 2005 to 2015' )

years=range(2005,2016)
filtered_dframe = year_revenue_movie_dframe[movie_dframe != 0].
 ↪query('release_year in (@years)')
get_simple_stats(filtered_dframe,key_for_stats='revenue')

print_msg('Individule Years', '' )

# Filter by each year
for year in years:
    print_msg('For', year)
    year_filter = [year]
    filtered_dframe = year_revenue_movie_dframe[movie_dframe != 0].
 ↪query('release_year in (@year_filter)')
    get_simple_stats(filtered_dframe,key_for_stats='revenue')
```

Info: Revenue by Years 2005 to 2015

Statistics for Revenue:

Count: 2354 of 2354
Null or Zero: 0
Minimum: 3.00
Maximum: 2781505847.00
Mean: 101927511.27
Std Dev: 192952136.40
Individule Years:
For: 2005

Statistics for Revenue:

Count: 184 of 184
Null or Zero: 0
Minimum: 10289.00
Maximum: 895921036.00
Mean: 89765408.20
Std Dev: 141301396.84
For: 2006

Statistics for Revenue:

Count: 206 of 206
Null or Zero: 0
Minimum: 144.00
Maximum: 1065659812.00
Mean: 79008443.62
Std Dev: 134114685.89
For: 2007

Statistics for Revenue:

Count: 195 of 195
Null or Zero: 0
Minimum: 46.00
Maximum: 961000000.00
Mean: 99547018.82
Std Dev: 166627621.43
For: 2008

Statistics for Revenue:

Count: 206 of 206

Null or Zero: 0
Minimum: 3.00
Maximum: 1001921825.00
Mean: 94328617.17
Std Dev: 152605754.71
For: 2009

Statistics for Revenue:

Count: 200 of 200
Null or Zero: 0
Minimum: 80.00
Maximum: 2781505847.00
Mean: 110900852.80
Std Dev: 249997481.73
For: 2010

Statistics for Revenue:

Count: 218 of 218
Null or Zero: 0
Minimum: 10.00
Maximum: 1063171911.00
Mean: 100733938.28
Std Dev: 177750473.13
For: 2011

Statistics for Revenue:

Count: 241 of 241
Null or Zero: 0
Minimum: 15.00
Maximum: 1327817822.00
Mean: 98321956.76
Std Dev: 177805798.77
For: 2012

Statistics for Revenue:

Count: 216 of 216
Null or Zero: 0
Minimum: 30.00
Maximum: 1519557910.00
Mean: 114205689.00
Std Dev: 219570579.85
For: 2013

Statistics for Revenue:

```
Count: 244 of 244
Null or Zero: 0
Minimum: 11.00
Maximum: 1274219009.00
Mean: 101244397.61
Std Dev: 196025760.48
For: 2014
```

Statistics for Revenue:

```
Count: 228 of 228
Null or Zero: 0
Minimum: 2710.00
Maximum: 955119788.00
Mean: 106715570.98
Std Dev: 180621612.15
For: 2015
```

Statistics for Revenue:

```
Count: 216 of 216
Null or Zero: 0
Minimum: 4444.00
Maximum: 2068178225.00
Mean: 123900233.88
Std Dev: 267924981.33
```

I noted that the standard deviation was huge since this skewed data had a "long tail." I decided I would likely want only data less than 2 standard deviation from the mean.

[12]:

```
for year in years:
    print_msg('For', year)
    year_filter = [year]
    filtered_dframe = year_revenue_movie_dframe[movie_dframe != 0].
 ↪query('release_year in (@year_filter)')

# Remove the tail data
    mean_less_one_std =  int(abs(np.mean(filtered_dframe['revenue']) - np.
 ↪std(filtered_dframe['revenue'])))

    print('Min', filtered_dframe['revenue'].min())
    print('Mean less two std: ', mean_less_one_std * 2)
    print('Range between {0:,} max and {1:,} is {2:,} billion'.format(
                 int(filtered_dframe['revenue'].max()),
                 int(filtered_dframe['revenue'].min()),
```

```
                int(filtered_dframe['revenue'].max() -␣
↪filtered_dframe['revenue'].min())/1000000000)
        )
    print('Range between {0:,} max and {1:,} is {2:,} billion '.format(
                int(filtered_dframe['revenue'].max()),
                int(mean_less_one_std * 2),
                int(filtered_dframe['revenue'].max() - (mean_less_one_std *␣
↪2))/1000000000)
        )
    print()
```

```
For: 2005
Min 10289
Mean less two std:  103071976
Range between 895,921,036 max and 10,289 is 0.895910747 billion
Range between 895,921,036 max and 103,071,976 is 0.79284906 billion

For: 2006
Min 144
Mean less two std:  110212484
Range between 1,065,659,812 max and 144 is 1.065659668 billion
Range between 1,065,659,812 max and 110,212,484 is 0.955447328 billion

For: 2007
Min 46
Mean less two std:  134161204
Range between 961,000,000 max and 46 is 0.960999954 billion
Range between 961,000,000 max and 134,161,204 is 0.826838796 billion

For: 2008
Min 3
Mean less two std:  116554274
Range between 1,001,921,825 max and 3 is 1.001921822 billion
Range between 1,001,921,825 max and 116,554,274 is 0.885367551 billion

For: 2009
Min 80
Mean less two std:  278193256
Range between 2,781,505,847 max and 80 is 2.781505767 billion
Range between 2,781,505,847 max and 278,193,256 is 2.503312591 billion

For: 2010
Min 10
Mean less two std:  154033068
Range between 1,063,171,911 max and 10 is 1.063171901 billion
Range between 1,063,171,911 max and 154,033,068 is 0.909138843 billion
```

```
For: 2011
Min 15
Mean less two std:  158967684
Range between 1,327,817,822 max and 15 is 1.327817807 billion
Range between 1,327,817,822 max and 158,967,684 is 1.168850138 billion

For: 2012
Min 30
Mean less two std:  210729780
Range between 1,519,557,910 max and 30 is 1.51955788 billion
Range between 1,519,557,910 max and 210,729,780 is 1.30882813 billion

For: 2013
Min 11
Mean less two std:  189562724
Range between 1,274,219,009 max and 11 is 1.274218998 billion
Range between 1,274,219,009 max and 189,562,724 is 1.084656285 billion

For: 2014
Min 2710
Mean less two std:  147812082
Range between 955,119,788 max and 2,710 is 0.955117078 billion
Range between 955,119,788 max and 147,812,082 is 0.807307706 billion

For: 2015
Min 4444
Mean less two std:  288049494
Range between 2,068,178,225 max and 4,444 is 2.068173781 billion
Range between 2,068,178,225 max and 288,049,494 is 1.780128731 billion
```

Oddly, the tail was so long that there seemed to be little advantage to removing the tail, at least when using revenue to compare if one movie generated proportionally more money than another. Still, if the data set was larger it would have a performance impact so I resolved to remove the tail anyway.

1.1 Using a Priority Matrix for the Review

I performed similar tests on the other columns to identify what each one's data would be of interest, while also noting the difficulty in cleansing or validating the data.

I next defined a status of keep or remove, along with my reasons for the determination, and created a simple priority matrix to help refine my choices, as shown below.

**Note: The Difficulty and Benefit Index scales are from low(1) to high(5)

[13]:
```
# Get Matrix data from file
print_msg('Prioritization Matrix', '')
```

```python
pmatrix_dframe = pd.read_csv('./Data/Prioritization Matrix.csv')
pd.DataFrame(pmatrix_dframe)  # Display data from file
# ** Note: The Difficulty and Benefit Index scales are from low(1) to high(5)
```

```
Prioritization Matrix:
```

[13]:

```
              Attribute  Difficulty  Benefit  Status  \
0               imdb_id           1        5    Keep
1            popularity           2        5    Keep
2                budget           3        3  Remove
3               revenue           3        5    Keep
4        original_title           1        5    Keep
5                  cast           3        5    Keep
6              homepage           2        2  Remove
7              director           2        5    Keep
8               tagline           3        3  Remove
9              keywords           3        3  Remove
10             overview           1        1  Remove
11              runtime           1        5    Keep
12               genres           2        5    Keep
13 production_companies           1        4    Keep
14         release_date           1        4  Remove
15           vote_count           1        3  Remove
16         vote_average           3        3  Remove
17         release_year           1        5    Keep
18           budget_adj           2        3  Remove
19          revenue_adj           2        3  Remove

              Reasoning
0
Provides granular lookup.
1             Measure of interest. Has undefined scale and missing data issues.
Population size unknown.
2   Measure of interest. Has a lot missing data. Most data is skewed to a small
set of attribute values
3   Measure of interest. Has a lot missing data. Most data is skewed to a small
set of attribute values
4                                                        Attribute if interest.
Human Friendly Identifier.
5                                                         Attribute of interest. Is
a collection of values
6                                                  Attribute of interest. A two-
thirds of the data is null
7
Attribute of interest.
8                                                                Attribute of
interest. Missing data issues.
```

```
9                Attribute of interest. Must be parsed to group. Too many
variations for easy grouping.
10               Attribute of interest. Must be parsed to group. Too many
variations for easy grouping.
11                                                     Measure of interest.
Provides objective values.
12                                                Attribute of interest.
Provides subjective grouping.
13                                                 Attribute of interest.
Provides objective grouping.
14                    Attribute of interest. Provides objective grouping. Too
fine a grain for my needs
15    Measure of interest. Provides objective values. Demographics unknown.
Population size too varied.
16    Measure of interest. Provides subjective values. Demographics unknown.
Population size too varied
17                             Attribute of interest. Transform to string.
Provides objective grouping.
18
Measure of interest.
19                                                   Measure of interest.
Provides objective grouping.
```

1.2 Completing my Review

I completed my review and made note of the following problems, solutions, and questions that might be asked with this data.

1.2.1 Problems with the Data:

- p1 - Some attributes have a lot of null or zero values
- p2 - Some rows have a lot of null or zero attribute values
- p3 - Some attributes are not needed or their data is suspect
- p4 - The definition of the popularity score is not clear
- p5 - It is unknown if the inflation calculation for revenue and budget values are already included
- p6 - Denomination of the revenue and budget values are not known
- p7 - Data values vary a greatly based on release date.

1.2.2 Solutions for the Problems:

- p1 - Replace nulls with zero values were appropate
- p2 - Remove rows with lots of null or zero attribute values
- p3 - Remove non needed or suspect attributes
- p4 - Remove non needed or suspect attributes
- p5 - Assume that it is not pre-calculated and keep the budget_adj and revenue_adj attributes
- p6 - Assume the values are in US dollars, but make sure to use this in relational comparisons
- p7 - Remove rows not in the last 10 years to make better comparisons

1.2.3 Questions on the Data:

Now was the time to decided which questions to ask of the data. Several came to mind:

- What are the most popular genres per decade?
- What effect does tagline have?
- What correlations are there between budget and revenue?
- Did the inclusion of homepages have any impact on popularity?
- Did runtime have any impact on popularity, and has that changed over time?
- Did production company names impact popularity and revenue?
- Which actors were most popular or generated the most revenue?

Of these, I decided to focus on the correlations between revenue vs actors and production company between the years 2005 to 2015. So, my final questions I wanted to investigate for this assignment were:

- Which actor's movies generated the most revenue between 2005 and 2015?
- Which production company's movies generated the most revenue between 2005 and 2015?

(Back to Table of Contents) ## Data Cleaning Before examining the questions, I wanted to filter and cleanse the data that I would need.

1.2.4 Reducing the Data

I used Pandas drop() function to remove all the attributes I did not need or want. What I wanted was defined by my questions about the revenues based on actors and production companies over the years 2005 to 2015. I also included the title as the values key identifier.

I reloaded the data from the file to make sure I was starting from the baseline and use the needed filtering to create the dataframe I needed for my reports.

[14]:
```
movie_dframe = pd.read_csv('Data/tmdb-movies.csv')

keep_these =␣
↪['revenue','cast','release_year','production_companies','original_title']
movie_dframe = movie_dframe[keep_these]

print_msg('Warning','Columns are now filtered by Revenue, Cast, Release Year,␣
↪Production Companies and Original Title')
movie_dframe
```

```
Warning: Columns are now filtered by Revenue, Cast, Release Year, Production
Companies and Original Title
```

[14]:
```
           revenue  \
0       1513528810
1        378436354
2        295238201
3       2068178225
```

```
4      1506249360
…           …
10861           0
10862           0
10863           0
10864           0
10865           0

           cast  \
0                  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vincent
D'Onofrio|Nick Robinson
1                        Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nicholas
Hoult|Josh Helman
2                           Shailene Woodley|Theo James|Kate Winslet|Ansel
Elgort|Miles Teller
3                             Harrison Ford|Mark Hamill|Carrie Fisher|Adam
Driver|Daisy Ridley
4                        Vin Diesel|Paul Walker|Jason Statham|Michelle
Rodriguez|Dwayne Johnson
…
…
10861            Michael Hynson|Robert August|Lord 'Tally Ho' Blears|Bruce
Brown|Chip Fitzwater
10862                    James Garner|Eva Marie Saint|Yves Montand|ToshirÅ
Mifune|Brian Bedford
10863  Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Zhzhyonov|Olga
Aroseva|Lyubov Dobrzhanskaya
10864                  Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|John
Sebastian|Tadao Nakamaru
10865                  Harold P. Warren|Tom Neyman|John Reynolds|Diane
Mahree|Stephanie Nielson

       release_year  \
0              2015
1              2015
2              2015
3              2015
4              2015
…            …
10861          1966
10862          1966
10863          1966
10864          1966
10865          1966

production_companies  \
0      Universal Studios|Amblin Entertainment|Legendary Pictures|Fuji Television
```

```
Network|Dentsu
1                                          Village Roadshow Pictures|Kennedy
Miller Productions
2                          Summit Entertainment|Mandeville Films|Red Wagon
Entertainment|NeoReel
3                                                     Lucasfilm|Truenorth
Productions|Bad Robot
4                    Universal Pictures|Original Film|Media Rights
Capital|Dentsu|One Race Films
…
…
10861
Bruce Brown Films
10862                          Cherokee Productions|Joel Productions|Douglas &
Lewis Productions
10863
Mosfilm
10864                                                                        Benedict
Pictures Corp.
10865
Norm-Iris

                    original_title
0                   Jurassic World
1               Mad Max: Fury Road
2                        Insurgent
3       Star Wars: The Force Awakens
4                        Furious 7
…                              …
10861           The Endless Summer
10862                   Grand Prix
10863          Beregis Avtomobilya
10864       What's Up, Tiger Lily?
10865      Manos: The Hands of Fate

[10866 rows x 5 columns]
```

Next, I filtered the data so that only films released between 2005 and 2015 were included. I noted that the earliest movies in that range started in 2007,

[15]:
```
# Sort by year and revenue
movie_dframe.sort_values(by=['release_year','revenue'], inplace=True,␣
 ↪ascending=False)

# Slice by year
years=range(2005,2016)
movie_dframe = movie_dframe.query('release_year in (@years)')
```

```
# review the results
ymin = movie_dframe['release_year'].min()
ymax = movie_dframe['release_year'].max()
print_msg('Warning','Rows are now filtered by Release Years ' + str(ymin) + '␣
↪to ' + str(ymax))
movie_dframe
```

```
Warning: Rows are now filtered by Release Years 2005 to 2015
```

[15]:
```
         revenue  \
3     2068178225
0     1513528810
4     1506249360
14    1405035767
8     1156730962
…            …
6548           0
6549           0
6551           0
6552           0
6553           0

       cast  \
3                          Harrison Ford|Mark Hamill|Carrie Fisher|Adam
Driver|Daisy Ridley
0                Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vincent
D'Onofrio|Nick Robinson
4                     Vin Diesel|Paul Walker|Jason Statham|Michelle
Rodriguez|Dwayne Johnson
14              Robert Downey Jr.|Chris Hemsworth|Mark Ruffalo|Chris
Evans|Scarlett Johansson
8                        Sandra Bullock|Jon Hamm|Michael Keaton|Allison
Janney|Steve Coogan
…
…
6548                      Debbie Doebereiner|Omar Cowan|Dustin James
Ashley|Phyllis Workman
6549
Daniel Johnston
6551  Catherine Frot|AndrÃ© Dussollier|GeneviÃ¨ve Bujold|Laurent
Terzieff|ValÃ©rie Kaprisky
6552         JosÃ© Garcia|Isabelle CarrÃ©|RenÃ©e Le Calm|FranÃ§ois Cluzet|Michel
Vuillermoz
6553                                              Shah Rukh Khan|Rani
Mukerji|Naseeruddin Shah
```

```
      release_year  \
3             2015
0             2015
4             2015
14            2015
8             2015
…              …
6548          2005
6549          2005
6551          2005
6552          2005
6553          2005

production_companies  \
3                                                     Lucasfilm|Truenorth
Productions|Bad Robot
0     Universal Studios|Amblin Entertainment|Legendary Pictures|Fuji Television
Network|Dentsu
4                  Universal Pictures|Original Film|Media Rights
Capital|Dentsu|One Race Films
14                                            Marvel Studios|Prime
Focus|Revolution Sun Studios
8                                                 Universal Pictures|Illumination
Entertainment
…
…
6548                                                                Magnolia
Pictures|Extension 765
6549
NaN
6551                                                           RhÃ´ne-Alpes
CinÃ©ma|France2 CinÃ©ma
6552
NaN
6553                                                                  Red Chillies
Entertainment

                     original_title
3       Star Wars: The Force Awakens
0                     Jurassic World
4                          Furious 7
14           Avengers: Age of Ultron
8                            Minions
…                                …
6548                          Bubble
6549  The Devil and Daniel Johnston
```

```
6551     Mon petit doigt m'a dit…
6552                Quatre Ã©toiles
6553                         Paheli

[5845 rows x 5 columns]
```

Lastly, I reduced the data set by over 4 thousand rows, by removing what I considered to be films with insignificant revenue.

[16]:
```
mean_less_one_std =  int(abs(np.mean(movie_dframe['revenue']) - np.
 ↪std(movie_dframe['revenue'])))
movie_dframe =  movie_dframe[movie_dframe['revenue'] > mean_less_one_std * 2]
movie_dframe
```

[16]:
```
         revenue  \
3     2068178225
0     1513528810
4     1506249360
14    1405035767
8     1156730962
…            …
6213   211643158
6280   202026112
6232   192452832
6306   190320568
6297   186438883

cast  \
3                   Harrison Ford|Mark Hamill|Carrie Fisher|Adam Driver|Daisy
Ridley
0        Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vincent D'Onofrio|Nick
Robinson
4             Vin Diesel|Paul Walker|Jason Statham|Michelle Rodriguez|Dwayne
Johnson
14      Robert Downey Jr.|Chris Hemsworth|Mark Ruffalo|Chris Evans|Scarlett
Johansson
8                 Sandra Bullock|Jon Hamm|Michael Keaton|Allison Janney|Steve
Coogan
…
…
6213              Orlando Bloom|Eva Green|Jeremy Irons|Marton Csokas|Brendan
Gleeson
6280                  Jim Carrey|TÃ©a Leoni|Alec Baldwin|Richard Jenkins|Angie
Harmon
6232        Peter Sallis|Helena Bonham Carter|Ralph Fiennes|Nicholas Smith|Liz
Smith
6306                           Adam Sandler|Chris Rock|Burt Reynolds|Michael
```

```
Irvin|Nelly
6297  Joaquin Phoenix|Reese Witherspoon|Ginnifer Goodwin|Robert Patrick|Tyler
Hilton

      release_year  \
3             2015
0             2015
4             2015
14            2015
8             2015
…              …
6213          2005
6280          2005
6232          2005
6306          2005
6297          2005

     production_companies  \
3
Lucasfilm|Truenorth Productions|Bad Robot
0                Universal Studios|Amblin Entertainment|Legendary Pictures|Fuji
Television Network|Dentsu
4                             Universal Pictures|Original Film|Media Rights
Capital|Dentsu|One Race Films
14                                                       Marvel Studios|Prime
Focus|Revolution Sun Studios
8                                                            Universal
Pictures|Illumination Entertainment
…
…
6213  Studio Babelsberg|Twentieth Century Fox Film Corporation|Scott Free
Productions|Kanzaman|Dune Films
6280                                  Imagine Entertainment|Columbia Pictures
Corporation|JC 23 Entertainment
6232                                                                  Aardman
Animations|DreamWorks Animation
6306  Paramount Pictures|Columbia Pictures Corporation|MTV Films|Happy Madison
Productions|Callahan Fi…
6297        Tree Line Films|Konrad Pictures|Catfish Productions|Fox 2000
Pictures|Mars Media Beteiligungs

                    original_title
3     Star Wars: The Force Awakens
0                   Jurassic World
4                        Furious 7
14         Avengers: Age of Ultron
8                          Minions
```

```
…                                …
6213              Kingdom of Heaven
6280          Fun with Dick and Jane
6232  The Curse of the Were-Rabbit
6306                The Longest Yard
6297                   Walk the Line

[364 rows x 5 columns]
```

1.2.5 Cleaning the values

That still left me with null, (NaN), and zero values to transform, so I next worked on those.

[17]:
```
# replace nulls with the following values
values = {'revenue': 0,
          'cast': 'Unknown',
          'release_year': 0,
          'production_companies':'Unknown',
          'original_title': 'Unknown'}
movie_dframe.fillna(value = values)

# reset the index number
movie_dframe = movie_dframe.reset_index(drop=True)

# Show the results of the transformations
get_simple_stats(movie_dframe,key_for_stats='revenue')
movie_dframe
```

```
Statistics for Revenue:

Count: 364 of 364
Null or Zero: 0
Minimum: 183018522.00
Maximum: 2781505847.00
Mean: 443786815.81
Std Dev: 301129908.15
```

[17]:
```
         revenue  \
0     2068178225
1     1513528810
2     1506249360
3     1405035767
4     1156730962
..           …
359    211643158
360    202026112
```

```
361   192452832
362   190320568
363   186438883

cast  \
0                  Harrison Ford|Mark Hamill|Carrie Fisher|Adam Driver|Daisy
Ridley
1       Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vincent D'Onofrio|Nick
Robinson
2             Vin Diesel|Paul Walker|Jason Statham|Michelle Rodriguez|Dwayne
Johnson
3     Robert Downey Jr.|Chris Hemsworth|Mark Ruffalo|Chris Evans|Scarlett
Johansson
4                 Sandra Bullock|Jon Hamm|Michael Keaton|Allison Janney|Steve
Coogan
..
…
359               Orlando Bloom|Eva Green|Jeremy Irons|Marton Csokas|Brendan
Gleeson
360                  Jim Carrey|TÃ©a Leoni|Alec Baldwin|Richard Jenkins|Angie
Harmon
361         Peter Sallis|Helena Bonham Carter|Ralph Fiennes|Nicholas Smith|Liz
Smith
362                        Adam Sandler|Chris Rock|Burt Reynolds|Michael
Irvin|Nelly
363  Joaquin Phoenix|Reese Witherspoon|Ginnifer Goodwin|Robert Patrick|Tyler
Hilton

     release_year  \
0            2015
1            2015
2            2015
3            2015
4            2015
..            …
359          2005
360          2005
361          2005
362          2005
363          2005

    production_companies  \
0
Lucasfilm|Truenorth Productions|Bad Robot
1               Universal Studios|Amblin Entertainment|Legendary Pictures|Fuji
Television Network|Dentsu
2                             Universal Pictures|Original Film|Media Rights
```

```
Capital|Dentsu|One Race Films
3                                                      Marvel Studios|Prime
Focus|Revolution Sun Studios
4                                                          Universal
Pictures|Illumination Entertainment
..
…
359  Studio Babelsberg|Twentieth Century Fox Film Corporation|Scott Free
Productions|Kanzaman|Dune Films
360                              Imagine Entertainment|Columbia Pictures
Corporation|JC 23 Entertainment
361                                                                Aardman
Animations|DreamWorks Animation
362  Paramount Pictures|Columbia Pictures Corporation|MTV Films|Happy Madison
Productions|Callahan Fi…
363        Tree Line Films|Konrad Pictures|Catfish Productions|Fox 2000
Pictures|Mars Media Beteiligungs

                   original_title
0    Star Wars: The Force Awakens
1                  Jurassic World
2                       Furious 7
3         Avengers: Age of Ultron
4                         Minions
..                            …
359             Kingdom of Heaven
360          Fun with Dick and Jane
361  The Curse of the Were-Rabbit
362               The Longest Yard
363                  Walk the Line

[364 rows x 5 columns]
```

Finally, I was ready to start analysing my data for answers to my questions:

- Which actors generated the most revenue between 2005 and 2015?
- Which production company generated the most revenue between 2005 and 2015?

(Back to Table of Contents) ## Data Analysis

I started analysing the data using revenue, cast and production companies. Since both actors and production companies were stored as multi-valued fields I created a function to split that data and provide the sums for a specified column.

[18]:
```
# Create a function for analysing sums in a multi-valued columns
def split_dataframe_string_and_sum(dframe,key_to_split,key_to_sum,␣
 ↪split_char='|'):
    '''This function creates a two-column pandas dataframe
       with the sum totals for each member of a complex string'''
```

```
    results = {}
    for i, data in dframe.iterrows():
        for key_in_process in str(data[key_to_split]).split(split_char):
            k = key_in_process
            v = data[key_to_sum]
            if k in results.keys():
                results[k] += data[key_to_sum]
            else:
                results[k] = data[key_to_sum]
    #Create a new simple two-column data frame for analysis
    output_dframe = pd.DataFrame(list(results.items())
                                 ,columns = [key_to_split
                                 ,key_to_sum])
    return output_dframe
```

1.2.6 Question 1 : Which actor's movies generated the most revenue between 2005 and 2015?

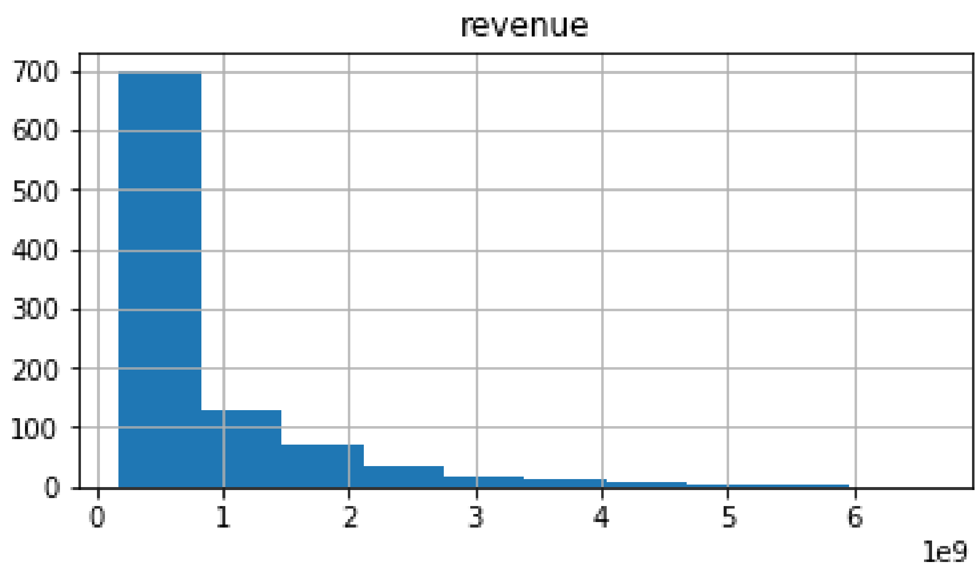
This question needed to be answered by associating each movie's revenue to each actor listed in its cast. Since the cast was a collection of data, I needed to separate each actor and associate a revenue value with that actor. I decided that since I had no information on how much each actor in the collection earned for each film, I decided that each actor would be mapped to the full revenue regardless of their contribution.

[19]:
```
# Separate the individual actors from each film.
# Each actor will be ranked by the total revenue of each of their films.
revenue_by_actor_dframe = split_dataframe_string_and_sum(dframe=movie_dframe
                                                         ,key_to_split = 'cast'
                                                         ,key_to_sum = 'revenue'
                                                         ,split_char='|'
                                                         )


# Change cast to actor
revenue_by_actor_dframe = revenue_by_actor_dframe.rename(columns={'cast':
 ↪'actor'},inplace=False)

# sort and reset the index numbers
revenue_by_actor_dframe = revenue_by_actor_dframe.sort_values(by=['revenue'],␣
 ↪ascending= False)
print_msg('Note', 'The number of actors in this data is %s' %␣
 ↪revenue_by_actor_dframe['revenue'].count())
revenue_by_actor_dframe = revenue_by_actor_dframe.reset_index(drop=True)

# review my results
get_simple_stats(revenue_by_actor_dframe,key_for_stats='revenue',show_basic_hist=True)
revenue_by_actor_dframe.style.format({"revenue": "${:20,.0f}"})
```

```
Note: The number of actors in this data is 977
```

```
Statistics for Revenue:

Count: 977 of 977
Null or Zero: 0
Minimum: 183018522.00
Maximum: 6607638376.00
Mean: 826706248.50
Std Dev: 900695834.44
```

[19]: <pandas.io.formats.style.Styler at 0x1da4fe08988>



Most of this data was so skewed to the left that having the so many outliers seemed pointless. So I decided to once again only use data two standard deviations from the mean. This removed about 90% of the actors. Making less than 10 percent of the actors the highest earners!

[20]:
```
# Remove the tail data
rev_ref = revenue_by_actor_dframe['revenue']
two_std = np.std(rev_ref) * 2
stdv = abs(np.mean(rev_ref) - two_std)
revenue_by_actor_dframe =␣
↪revenue_by_actor_dframe[revenue_by_actor_dframe['revenue'] > two_std]

# Display the resulting stats
```

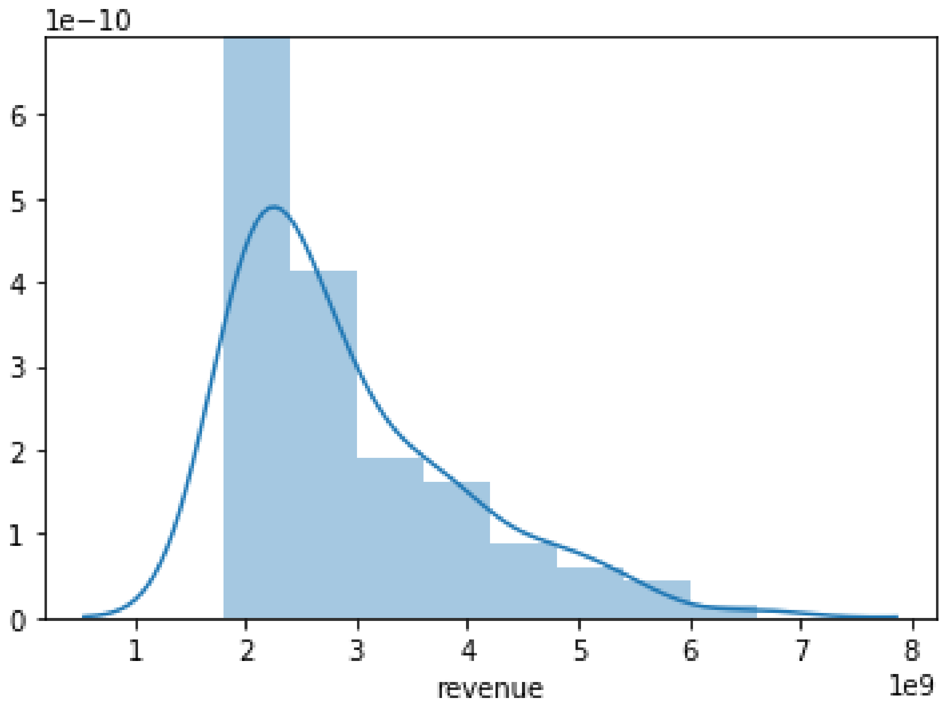
```
revenue_by_actor_dframe = revenue_by_actor_dframe.reset_index(drop=True)  #␣
↪reset the index number
actor_cnt = revenue_by_actor_dframe['actor'].count()
print_msg('Warning', 'The number of actors in this data is now reduced to %s' %␣
↪actor_cnt)
get_simple_stats(revenue_by_actor_dframe, key_for_stats='revenue',␣
↪show_basic_hist=False)
revenue_by_actor_dframe

# Use a Seaborn chart to make it easier to see the data is more normal␣
↪distributed within this top earners
sns.distplot(revenue_by_actor_dframe['revenue'])
```

Warning: The number of actors in this data is now reduced to 113

Statistics for Revenue:

Count: 113 of 113
Null or Zero: 0
Minimum: 1802235867.00
Maximum: 6607638376.00
Mean: 2907451941.56
Std Dev: 1013006191.32

[20]: <matplotlib.axes._subplots.AxesSubplot at 0x1da501ba648>



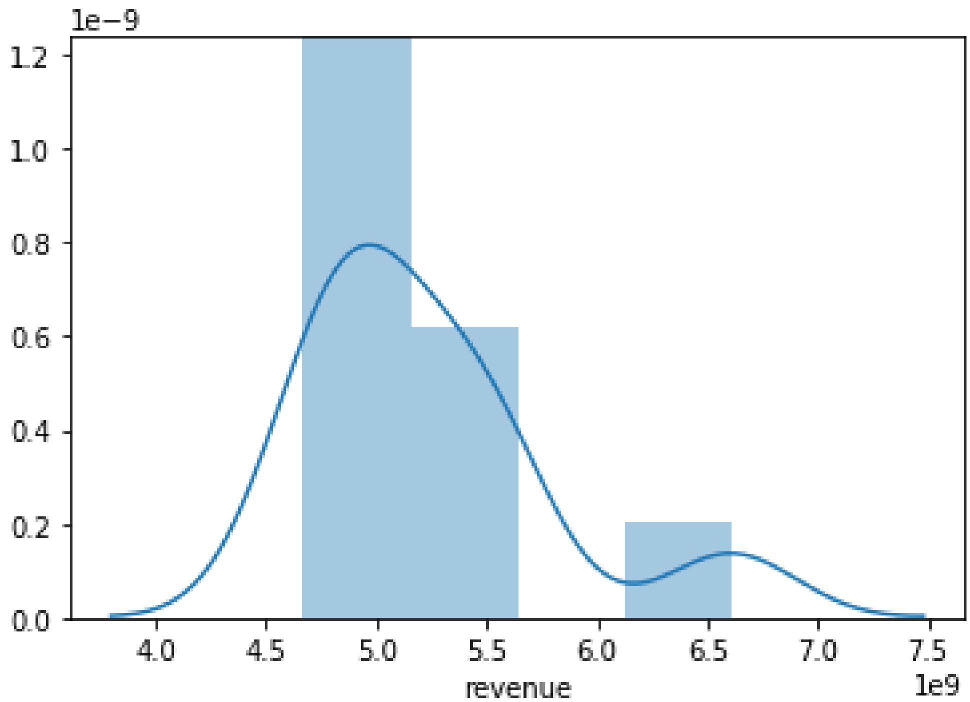
Of these actors, who are the top 10 earners base on combined movie revenue?

[21]:
```
# Top 10 actors based on movie revenue
revenue_by_actor_dframe = revenue_by_actor_dframe.reset_index(drop=True)  #␣
 ↪reset the index number
top_ten_actors = revenue_by_actor_dframe.head(10)
top_ten_actors.style.format({"revenue": "${:20,.0f}"})
```

[21]: <pandas.io.formats.style.Styler at 0x1da501b5cc8>

[22]:
```
sns.distplot(top_ten_actors['revenue'])
```

[22]: <matplotlib.axes._subplots.AxesSubplot at 0x1da50228308>



The top actor in this result was Robert Downey Jr., so I looked up which movies he was in. As you can see there were 8 of them, which is a lot for a 10 year period!

These were almost all "Super Hero" movies by Marvel Studio. It seems that landing the role of "Iron Man" with an amazing break for this actor!

[23]:
```
rdj_dframe = movie_dframe[movie_dframe['cast'].str.contains('Robert Downey Jr.
↪', regex=False)]
rdj_dframe = rdj_dframe.reset_index(drop=True)  # reset the index number
rdj_dframe.style.format({"revenue": "${:20,.0f}"})
```

[23]:
```
<pandas.io.formats.style.Styler at 0x1da502109c8>
```

Another interesting point was how the young actors from the Harry Potter movies all made this top 10 list!. While there were only 4 of these movies in the ten year span, those movies generated a lot of revenue! Considering each actor's age, this was also and amazing break!

[24]:
```
hp_dframe = movie_dframe[movie_dframe['original_title'].str.contains('Harry␣
↪Potter', regex=False)]
hp_dframe.reset_index(drop=True, inplace=True)
hp_dframe.style.format({"revenue": "${:20,.0f}"})
```

[24]:
```
<pandas.io.formats.style.Styler at 0x1da501becc8>
```

1.2.7 Question 2 : Which Company's Movies generated the most revenue between 2005 and 2015?

Similar to question one, this question needed to be answered by associating each movie's revenue to each production company listed in the production_companies collection.

Once again I decided to give equal revenue to each company listed reguardless of this participation or profit from the revenue.

[25]:
```
revenue_by_company_dframe = split_dataframe_string_and_sum(dframe = movie_dframe ␣
    ↪,key_to_split='production_companies' ␣
    ↪,key_to_sum='revenue')

# Change cast to actor
revenue_by_company_dframe = revenue_by_company_dframe.
    ↪rename(columns={'production_companies':'company'}
                                                    ,inplace=False)

# sort and reset the index numbers
revenue_by_company_dframe = revenue_by_company_dframe.
    ↪sort_values(by=['revenue'], ascending= False)
print_msg('Note', 'The number of production companies in this data is %s' %
                    revenue_by_company_dframe['company'].count())

revenue_by_company_dframe = revenue_by_company_dframe.reset_index(drop=True)
revenue_by_company_dframe.style.format({"revenue": "${:20,.0f}"})
```

```
Note: The number of production companies in this data is 420
```

[25]:
```
<pandas.io.formats.style.Styler at 0x1da4f3cde48>
```

Similar to the Actors data set there was another long tail in this data, so one again I removed it.

[26]:
```
# Remove the tail data
rev_ref = revenue_by_company_dframe['revenue']
two_std = np.std(rev_ref) * 2
stdv = abs(np.mean(rev_ref) - two_std)
revenue_by_company_dframe =␣
    ↪revenue_by_company_dframe[revenue_by_company_dframe['revenue'] > two_std]

# Display the resulting stats
revenue_by_company_dframe = revenue_by_company_dframe.reset_index(drop=True)  #␣
    ↪reset the index number
company_cnt = revenue_by_company_dframe['company'].count()
```

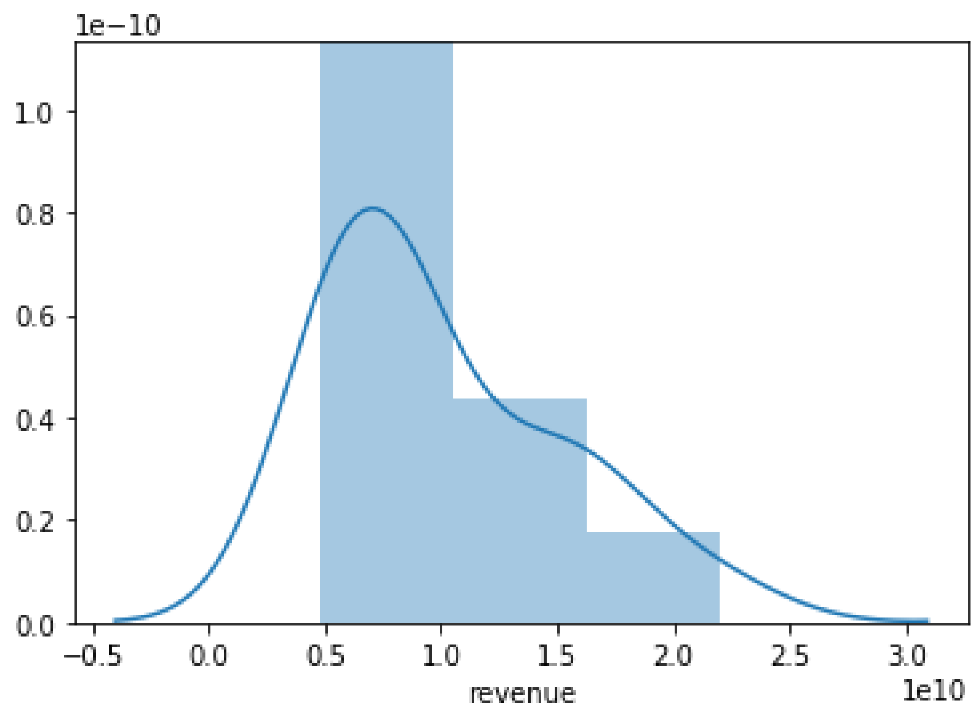
```
print_msg('Warning', 'The number of companies in this data is now reduced to␣
↪%s' % company_cnt)
get_simple_stats(revenue_by_company_dframe, key_for_stats='revenue',␣
↪show_basic_hist=False)


# Use a Seaborn chart to make it easier to see the data is more normal␣
↪distributed within this top earners
sns.distplot(revenue_by_company_dframe['revenue'])
```

Warning: The number of companies in this data is now reduced to 20

Statistics for Revenue:

Count: 20 of 20
Null or Zero: 0
Minimum: 4832902904.00
Maximum: 22054929039.00
Mean: 10065305980.85
Std Dev: 4946489452.64

[26]: <matplotlib.axes._subplots.AxesSubplot at 0x1da50426608>



This time I saw that only 5 percent of the companyies were associated with the most revenue. The top ten here were:

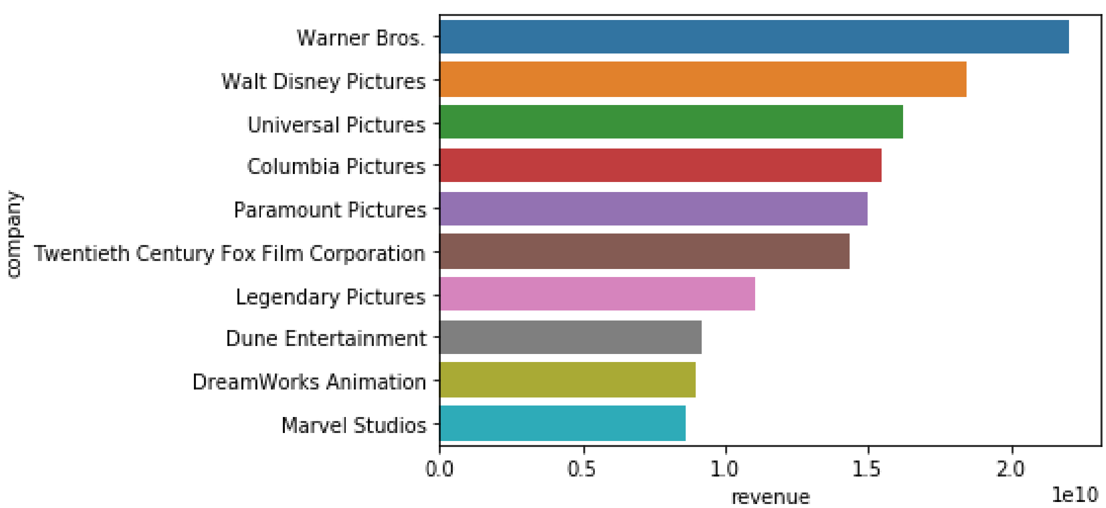
[27]:
```
# Top 10 companies based on movie revenue
print_msg('Note', 'The top ten movie revenue by company')
top_ten_companies_dframe = revenue_by_company_dframe.head(10)
top_ten_companies_dframe.style.format({"revenue": "${:20,.0f}"})
```

```
Note: The top ten movie revenue by company
```

[27]: <pandas.io.formats.style.Styler at 0x1da504bd208>

[28]:
```
sns.barplot(y="company", x="revenue", data=top_ten_companies_dframe)
```

[28]: <matplotlib.axes._subplots.AxesSubplot at 0x1da502c43c8>



I now had my answer for which production companie's movies generated the most total movie revenue. The top company in this result was Warner Bros. I counted up which movies they had produced and found 47 of them in this 10 year period! An averate of 4.7 per year.

[29]:
```
columns_of_interest = ['production_companies', 'original_title']
company_by_movies_dframe = movie_dframe[columns_of_interest]

company_by_movies_dframe = pd.DataFrame(company_by_movies_dframe.
 ↪production_companies.str.split('|').tolist()
                        ,index=company_by_movies_dframe.original_title).stack()

company_by_movies_dframe = company_by_movies_dframe.reset_index([0,␣
 ↪'original_title'])
```

```
company_by_movies_dframe.columns = ['movie_count', 'company']

company_by_movies_dframe.sort_values(by=['company'], inplace=True)
company_by_movies_dframe

count_by_company_dframe = company_by_movies_dframe.groupby('company').count()
count_by_company_dframe.sort_values(by=['movie_count'], inplace=True,␣
↪ascending=False)
count_by_company_dframe[:10]
```

[29]:

	movie_count
company	
Warner Bros.	47
Universal Pictures	41
Columbia Pictures	41
Paramount Pictures	37
Twentieth Century Fox Film Corporation	35
Walt Disney Pictures	33
Relativity Media	26
Legendary Pictures	23
Dune Entertainment	21
Village Roadshow Pictures	19

So, what were the movie counts corrolate with revenue?

[30]:
```
#  pd.merge(left, right, how='outer', on=['key1', 'key2'])
revenue_by_count_dframe = pd.merge(count_by_company_dframe,␣
↪revenue_by_company_dframe, on=['company','company'], how='inner')
revenue_by_count_dframe.style.format({"revenue": "${:20,.0f}"})
revenue_by_count_dframe = revenue_by_count_dframe.sort_values(by=['revenue'],␣
↪ascending= False)
revenue_by_count_dframe
```

[30]:

	company	movie_count	revenue
0	Warner Bros.	47	22054929039
5	Walt Disney Pictures	33	18428127396
1	Universal Pictures	41	16219387733
2	Columbia Pictures	41	15463098173
3	Paramount Pictures	37	15011188391
4	Twentieth Century Fox Film Corporation	35	14379844891
7	Legendary Pictures	23	11056090648
8	Dune Entertainment	21	9144964294
10	DreamWorks Animation	18	8937057404
14	Marvel Studios	11	8650272139
6	Relativity Media	26	8104174816
11	New Line Cinema	18	7209118046
18	Heyday Films	9	6881159722

```
9                 Village Roadshow Pictures          19   6837850883
15                  Pixar Animation Studios          10   6429562448
16                  Ingenious Film Partners          10   6171154562
17                     Amblin Entertainment           9   5428131481
13                            Original Film          11   5125260008
19                                   Dentsu           8   4941844639
12                Metro-Goldwyn-Mayer (MGM)          11   4832902904
```

It seemed obvious now, that most of the time a company with the most movies is likely to have the highest revenue, but I decided to double check this correlation using the built- in correlation function to get the Pearson correlation coefficient. It's result at close to 1, confirmed that in this small data set there it was indeed strong!

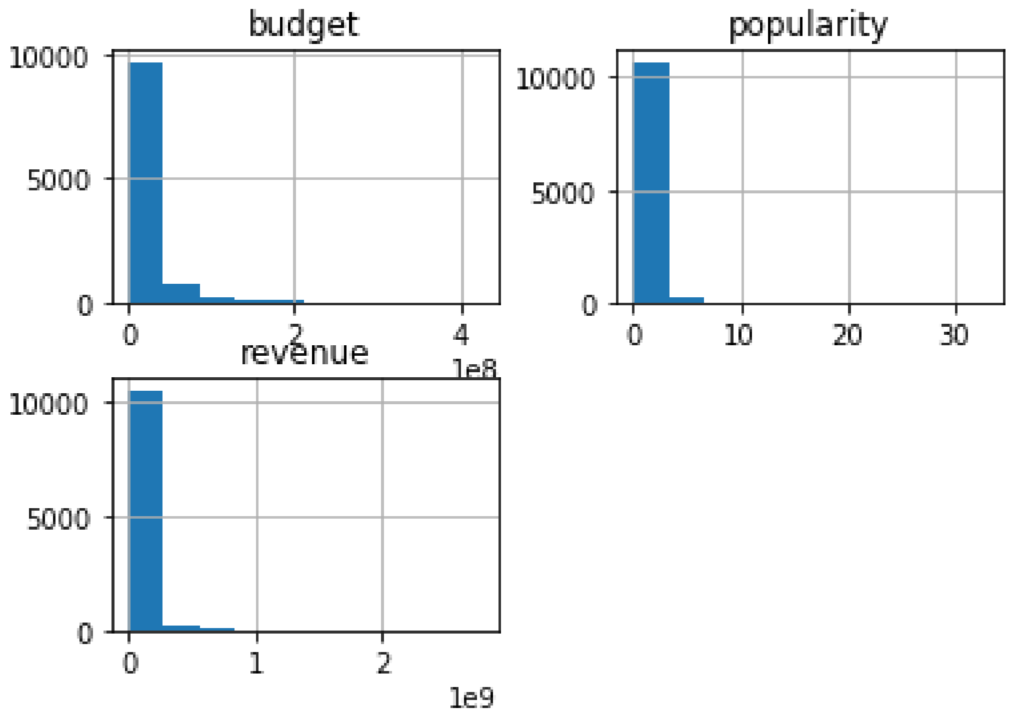
[31]:
```
column_1 = revenue_by_count_dframe['movie_count']
column_2 = revenue_by_count_dframe['revenue']
pcc_val = column_1.corr(column_2)
pcc_val
```

[31]:
```
0.9347756278868806
```

Other things that I would like to compare revenue too were a film's budget and popularity. Though I did not feel completely confident about its quality, the fact that their graphs are quite similar is intriguing.

[33]:
```
movie_dframe = pd.read_csv('Data/tmdb-movies.csv')
keep_these = ['revenue','budget','popularity']
movie_dframe = movie_dframe[keep_these]
movie_dframe.hist()
```

[33]:
```
array([[<matplotlib.axes._subplots.AxesSubplot object at 0x000001DA50210A08>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001DA5013F688>],
       [<matplotlib.axes._subplots.AxesSubplot object at 0x000001DA4FC3FB48>,
        <matplotlib.axes._subplots.AxesSubplot object at 0x000001DA5076BF88>]],
      dtype=object)
```



(Back to Table of Contents) ## Conclusions

In this report I looked at the correlation between revenue, actors, and production companies. I found that a small percentage of actors are part of the movies that generate the highest revenues, at least for the movies in this dataset between 2005 and 2015.

This could indicate that certain actors are a major factor in generating more revenue, or it could be that these actors just happened to be part of the cast of a movie that generated more revenue.

Given the fact that many of the revenues that contributed the top ten actors' totals were part of a series (ie. Iron Man/Avengers and Harry Potter) and the fact that some actors were greatly experienced while others were not, I believe that it is likely that being on the "right" movie was more important than having a certain actor in that movie.

Still, I cannot feel too confident in this analysis, since each actor was given a movie's total revenue without regard to their participation. For example, I cannot tell which of the Harry Potter actors generated the most money or if any one of them generated more than Robert Downey Jr..

It was also true that a small percentage of production companies produced movies with the highest revenues. Here it seemed a bit clearer that certain production companies produce movies with the highest revenue, but it could also be that the companies that produce the most films have the highest revenue.

There was a definite correlation between the number of films and the generated revenue, which makes sense, given that the odds of having a "hit" movie are higher for a company producing 100 movies versus 1 movie. What is less clear to me is if a company's other actions has much to do with the revenue as does its quantity of movies. Does one company do a better job of producing movies and so generates more revenue? If one company can invest the more money does it increase revenue? If a company's budget data was cleaner or each film's popularity scores were better defined, perhaps I could make a stronger correlation between those attributes, at this point I do not feel confident in the results.

What I do feel confident in saying is that a small percent of the actors and companies in this dataset are disproportionately associated with revenue. Rather that should be the case or what is the root cause of this difference is still unknown to me.

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1.3 References:

- TMDB Movie Metadata, https://www.kaggle.com/tmdb/tmdb-movie-metadata
- Pandas Online documents, https://pandas.pydata.org/pandas-docs/stable/user_guide/style.html
- Offical Seaborn Tutorial, https://seaborn.pydata.org/tutorial.html
- Creating Histograms using Pandas, https://mode.com/example-gallery/python_histogram/
- How To Make Histogram in Python with Pandas and Seaborn?, https://cmdlinetips.com/2019/02/how-to-make-histogram-in-python-with-pandas-and-seaborn/
- Python Histogram Plotting: NumPy, Matplotlib, Pandas & Seaborn, https://realpython.com/python-histograms/
- How to Drop Rows with NaN Values in Pandas DataFrame, https://datatofish.com/dropna/

[ ]:

```

```