

# Investigate\_a\_Dataset

January 1, 2022

## 1 Project: Investigate a Dataset - TDP Movies

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## Introduction

**Dataset Description** 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.

**Columns:** Imdb\_id - - original\_title cast - - popularity director - - production\_companies release\_year - - revenue budget\_adj - - revenue\_adj

#### 1.1.1 Question(s) for Analysis

Which actor achieve revenue in their movies

who the director has top successful movies

production companies revenue vs budget (loss or gain)

import statements for all of the packages we need to run the project

```
In [3]: # import statements for all of the packages
```

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

```
In [2]: # 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 3.2MB/s eta 0:00:01 33% | | 3.5MB 28.7MB/s eta 0:00:01
```

```
Collecting numpy>=1.13.3 (from pandas==0.25.0)
```

```
  Downloading https://files.pythonhosted.org/packages/45/b2/6c7545bb7a38754d63048c7696804a0d9473
100% || 13.4MB 2.7MB/s eta 0:00:01 24% | | 3.2MB 27.3MB/s eta 0:00:01
```

```
Requirement already satisfied, skipping upgrade: python-dateutil>=2.6.1 in /opt/conda/lib/python
```

```
Requirement already satisfied, skipping upgrade: pytz>=2017.2 in /opt/conda/lib/python3.6/site-p
```

```
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

### 1.1.2 General Properties

Load data from tmdb-movies.csv file

```
In [4]: df= pd.read_csv('Database_TMDb_movie_data/tmdb-movies.csv')
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

```

Check the statistics for the data frame

```
In [5]: df.describe()
```

```

Out[5]:
      count      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

      count  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

```

Check the number of columns and rows for the dataframe

```
In [6]: # Check the number of columns and rows for the dataframe
df.shape
```

```
Out[6]: (10866, 21)
```

Get the number of NA/Null values for each feature

```
In [7]: # Get the number of NA/Null values for each feature
df.isnull().sum()
```

```

Out[7]: id                0
        imdb_id          10

```

popularity	0
budget	0
revenue	0
original_title	0
cast	76
homepage	7930
director	44
tagline	2824
keywords	1493
overview	4
runtime	0
genres	23
production_companies	1030
release_date	0
vote_count	0
vote_average	0
release_year	0
budget_adj	0
revenue_adj	0
dtype:	int64

### 1.1.3 Data Cleaning

**Which data to be dropped** For the questions about cast and director, it will be necessary to drop the rows has NA values. Production\_companies will dropped in the question number 3.

**which data to be filled** The production companies missing data will be filled with "Other companies" value

**Columns to be dropped** The columns home page, tagline and keywords NA values will be dropped because it is not included in the calculations

```
In [8]: ''' Drop the cast and directors NA values from
         the dataframe to calculate the average revenue and top rated movies
         '''
         df.dropna(subset=['cast','director'], how='any',inplace=True)
```

```
In [11]: df.drop(['homepage','tagline','keywords'],axis=1, inplace=True)
```

Check features after drop the NA

```
In [12]: # Check features after drop the NA
         df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10752 entries, 0 to 10865
Data columns (total 18 columns):
id                10752 non-null int64
```

```

imdb_id          10746 non-null object
popularity       10752 non-null float64
budget           10752 non-null int64
revenue          10752 non-null int64
original_title   10752 non-null object
cast             10752 non-null object
director         10752 non-null object
overview         10749 non-null object
runtime          10752 non-null int64
genres           10732 non-null object
production_companies 9780 non-null object
release_date     10752 non-null object
vote_count       10752 non-null int64
vote_average     10752 non-null float64
release_year     10752 non-null int64
budget_adj       10752 non-null float64
revenue_adj      10752 non-null float64
dtypes: float64(4), int64(6), object(8)
memory usage: 1.9+ MB

```

```
In [19]: df.drop_duplicates()
```

```

Out[19]:
   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
5  281957  tt1663202    9.110700  135000000   532950503
6    87101  tt1340138    8.654359  155000000   440603537
7  286217  tt3659388    7.667400  108000000   595380321
8  211672  tt2293640    7.404165   74000000  1156730962
9  150540  tt2096673    6.326804  175000000   853708609
10  206647  tt2379713    6.200282  245000000   880674609
11   76757  tt1617661    6.189369  176000003   183987723
12  264660  tt0470752    6.118847   15000000   36869414
13  257344  tt2120120    5.984995   88000000   243637091
14   99861  tt2395427    5.944927  280000000  1405035767
15  273248  tt3460252    5.898400   44000000   155760117
16  260346  tt2446042    5.749758   48000000   325771424
17  102899  tt0478970    5.573184  130000000   518602163
18  150689  tt1661199    5.556818   95000000   542351353
19  131634  tt1951266    5.476958  160000000   650523427
20  158852  tt1964418    5.462138  190000000   209035668
21  307081  tt1798684    5.337064   30000000    91709827
22  254128  tt2126355    4.907832  110000000   470490832
23  216015  tt2322441    4.710402   40000000   569651467

```

24	318846	tt1596363	4.648046	28000000	133346506
25	177677	tt2381249	4.566713	150000000	682330139
26	214756	tt2637276	4.564549	68000000	215863606
27	207703	tt2802144	4.503789	81000000	403802136
28	314365	tt1895587	4.062293	20000000	88346473
29	294254	tt4046784	3.968891	61000000	311256926
...	...	...	...	...	...
10836	38720	tt0061170	0.239435	0	0
10837	19728	tt0060177	0.291704	0	0
10838	22383	tt0060862	0.151845	0	0
10839	13353	tt0060550	0.276133	0	0
10840	34388	tt0060437	0.102530	0	0
10841	42701	tt0062262	0.264925	75000	0
10842	36540	tt0061199	0.253437	0	0
10843	29710	tt0060588	0.252399	0	0
10844	23728	tt0059557	0.236098	0	0
10845	5065	tt0059014	0.230873	0	0
10846	17102	tt0059127	0.212716	0	0
10847	28763	tt0060548	0.034555	0	0
10848	2161	tt0060397	0.207257	5115000	12000000
10849	28270	tt0060445	0.206537	0	0
10850	26268	tt0060490	0.202473	0	0
10851	15347	tt0060182	0.342791	0	0
10852	37301	tt0060165	0.227220	0	0
10853	15598	tt0060086	0.163592	0	0
10854	31602	tt0060232	0.146402	0	0
10855	13343	tt0059221	0.141026	700000	0
10856	20277	tt0061135	0.140934	0	0
10857	5921	tt0060748	0.131378	0	0
10858	31918	tt0060921	0.317824	0	0
10859	20620	tt0060955	0.089072	0	0
10860	5060	tt0060214	0.087034	0	0
10861	21	tt0060371	0.080598	0	0
10862	20379	tt0060472	0.065543	0	0
10863	39768	tt0060161	0.065141	0	0
10864	21449	tt0061177	0.064317	0	0
10865	22293	tt0060666	0.035919	19000	0

	original_title \
0	Jurassic World
1	Mad Max: Fury Road
2	Insurgent
3	Star Wars: The Force Awakens
4	Furious 7
5	The Revenant
6	Terminator Genisys
7	The Martian
8	Minions

9	Inside Out
10	Spectre
11	Jupiter Ascending
12	Ex Machina
13	Pixels
14	Avengers: Age of Ultron
15	The Hateful Eight
16	Taken 3
17	Ant-Man
18	Cinderella
19	The Hunger Games: Mockingjay - Part 2
20	Tomorrowland
21	Southpaw
22	San Andreas
23	Fifty Shades of Grey
24	The Big Short
25	Mission: Impossible - Rogue Nation
26	Ted 2
27	Kingsman: The Secret Service
28	Spotlight
29	Maze Runner: The Scorch Trials
...	...
10836	Walk Don't Run
10837	The Blue Max
10838	The Professionals
10839	It's the Great Pumpkin, Charlie Brown
10840	Funeral in Berlin
10841	The Shooting
10842	Winnie the Pooh and the Honey Tree
10843	Khartoum
10844	Our Man Flint
10845	Carry On Cowboy
10846	Dracula: Prince of Darkness
10847	Island of Terror
10848	Fantastic Voyage
10849	Gambit
10850	Harper
10851	Born Free
10852	A Big Hand for the Little Lady
10853	Alfie
10854	The Chase
10855	The Ghost & Mr. Chicken
10856	The Ugly Dachshund
10857	Nevada Smith
10858	The Russians Are Coming, The Russians Are Coming
10859	Seconds
10860	Carry On Screaming!
10861	The Endless Summer

10862	Grand Prix
10863	Beregis Avtomobilya
10864	What's Up, Tiger Lily?
10865	Manos: The Hands of Fate

	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 ...
5	Leonardo DiCaprio Tom Hardy Will Poulter Domhn...
6	Arnold Schwarzenegger Jason Clarke Emilia Clar...
7	Matt Damon Jessica Chastain Kristen Wiig Jeff ...
8	Sandra Bullock Jon Hamm Michael Keaton Allison...
9	Amy Poehler Phyllis Smith Richard Kind Bill Ha...
10	Daniel Craig Christoph Waltz LÃa Seydoux Ralp...
11	Mila Kunis Channing Tatum Sean Bean Eddie Redm...
12	Domhnall Gleeson Alicia Vikander Oscar Isaac S...
13	Adam Sandler Michelle Monaghan Peter Dinklage ...
14	Robert Downey Jr. Chris Hemsworth Mark Ruffalo...
15	Samuel L. Jackson Kurt Russell Jennifer Jason ...
16	Liam Neeson Forest Whitaker Maggie Grace Famke...
17	Paul Rudd Michael Douglas Evangeline Lilly Cor...
18	Lily James Cate Blanchett Richard Madden Helen...
19	Jennifer Lawrence Josh Hutcherson Liam Hemswor...
20	Britt Robertson George Clooney Raffey Cassidy ...
21	Jake Gyllenhaal Rachel McAdams Forest Whitaker...
22	Dwayne Johnson Alexandra Daddario Carla Gugino...
23	Dakota Johnson Jamie Dornan Jennifer Ehle Eloi...
24	Christian Bale Steve Carell Ryan Gosling Brad ...
25	Tom Cruise Jeremy Renner Simon Pegg Rebecca Fe...
26	Mark Wahlberg Seth MacFarlane Amanda Seyfried ...
27	Taron Egerton Colin Firth Samuel L. Jackson Mi...
28	Mark Ruffalo Michael Keaton Rachel McAdams Lie...
29	Dylan O'Brien Kaya Scodelario Thomas Brodie-Sa...
...	...
10836	Cary Grant Samantha Eggar Jim Hutton John Stan...
10837	George Peppard James Mason Ursula Andress Jere...
10838	Burt Lancaster Lee Marvin Robert Ryan Woody St...
10839	Christopher Shea Sally Dryer Kathy Steinberg A...
10840	Michael Caine Paul Hubschmid Oskar Homolka Eva...
10841	Will Hutchins Millie Perkins Jack Nicholson Wa...
10842	Sterling Holloway Junius Matthews Sebastian Ca...
10843	Charlton Heston Laurence Olivier Richard Johns...
10844	James Coburn Lee J. Cobb Gila Golan Edward Mul...
10845	Sid James Jim Dale Angela Douglas Kenneth Will...
10846	Christopher Lee Barbara Shelley Andrew Keir Fr...



10847 Peter Cushing|Edward Judd|Carole Gray|Eddie By...  
 10848 Stephen Boyd|Raquel Welch|Edmond O'Brien|Donal...  
 10849 Michael Caine|Shirley MacLaine|Herbert Lom|Joh...  
 10850 Paul Newman|Lauren Bacall|Julie Harris|Arthur ...  
 10851 Virginia McKenna|Bill Travers|Geoffrey Keen|Pe...  
 10852 Henry Fonda|Joanne Woodward|Jason Robards|Paul...  
 10853 Michael Caine|Shelley Winters|Millicent Martin...  
 10854 Marlon Brando|Jane Fonda|Robert Redford|E.G. M...  
 10855 Don Knotts|Joan Staley|Liam Redmond|Dick Sarge...  
 10856 Dean Jones|Suzanne Pleshette|Charles Ruggles|K...  
 10857 Steve McQueen|Karl Malden|Brian Keith|Arthur K...  
 10858 Carl Reiner|Eva Marie Saint|Alan Arkin|Brian K...  
 10859 Rock Hudson|Salome Jens|John Randolph|Will Gee...  
 10860 Kenneth Williams|Jim Dale|Harry H. Corbett|Joa...  
 10861 Michael Hynson|Robert August|Lord 'Tally Ho' B...  
 10862 James Garner|Eva Marie Saint|Yves Montand|Tosh...  
 10863 Innokentiy Smoktunovskiy|Oleg Efremov|Georgi Z...  
 10864 Tatsuya Mihashi|Akiko Wakabayashi|Mie Hama|Joh...  
 10865 Harold P. Warren|Tom Neyman|John Reynolds|Dian...

	director \
0	Colin Trevorrow
1	George Miller
2	Robert Schwentke
3	J.J. Abrams
4	James Wan
5	Alejandro Gonz��lez I����rritu
6	Alan Taylor
7	Ridley Scott
8	Kyle Balda Pierre Coffin
9	Pete Docter
10	Sam Mendes
11	Lana Wachowski Lilly Wachowski
12	Alex Garland
13	Chris Columbus
14	Joss Whedon
15	Quentin Tarantino
16	Olivier Megaton
17	Peyton Reed
18	Kenneth Branagh
19	Francis Lawrence
20	Brad Bird
21	Antoine Fuqua
22	Brad Peyton
23	Sam Taylor-Johnson
24	Adam McKay
25	Christopher McQuarrie
26	Seth MacFarlane

27	Matthew Vaughn
28	Tom McCarthy
29	Wes Ball
...	...
10836	Charles Walters
10837	John Guillermin
10838	Richard Brooks
10839	Bill Melendez
10840	Guy Hamilton
10841	Monte Hellman
10842	Wolfgang Reitherman
10843	Basil Dearden Eliot Elisofon
10844	Daniel Mann
10845	Gerald Thomas
10846	Terence Fisher
10847	Terence Fisher
10848	Richard Fleischer
10849	Ronald Neame
10850	Jack Smight
10851	James Hill
10852	Fielder Cook
10853	Lewis Gilbert
10854	Arthur Penn
10855	Alan Rafkin
10856	Norman Tokar
10857	Henry Hathaway
10858	Norman Jewison
10859	John Frankenheimer
10860	Gerald Thomas
10861	Bruce Brown
10862	John Frankenheimer
10863	Eldar Ryazanov
10864	Woody Allen
10865	Harold P. Warren

		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	
5	In the 1820s, a frontiersman, Hugh Glass, sets...		156	
6	The year is 2029. John Connor, leader of the r...		125	
7	During a manned mission to Mars, Astronaut Mar...		141	
8	Minions Stuart, Kevin and Bob are recruited by...		91	
9	Growing up can be a bumpy road, and it's no ex...		94	
10	A cryptic message from Bondâs past sends him...		148	
11	In a universe where human genetic material is ...		124	

12	Caleb, a 26 year old coder at the world's larg...	108
13	Video game experts are recruited by the milita...	105
14	When Tony Stark tries to jumpstart a dormant p...	141
15	Bounty hunters seek shelter from a raging bliz...	167
16	Ex-government operative Bryan Mills finds his ...	109
17	Armed with the astonishing ability to shrink i...	115
18	When her father unexpectedly passes away, youn...	112
19	With the nation of Panem in a full scale war, ...	136
20	Bound by a shared destiny, a bright, optimisti...	130
21	Billy "The Great" Hope, the reigning junior mi...	123
22	In the aftermath of a massive earthquake in Ca...	114
23	When college senior Anastasia Steele steps in ...	125
24	The men who made millions from a global econom...	130
25	Ethan and team take on their most impossible m...	131
26	Newlywed couple Ted and Tami-Lynn want to have...	115
27	The story of a super-secret spy organization t...	130
28	The true story of how The Boston Globe uncover...	128
29	Thomas and his fellow Gladers face their great...	132
...	...	...
10836	British industrialist Sir William Rutland - "B...	114
10837	A young pilot in the German air force of 1918,...	156
10838	The Professionals is a 1966 American Western f...	117
10839	This classic "Peanuts" tale focuses on the thu...	25
10840	Colonel Stok, a Soviet intelligence officer re...	102
10841	A hired gun seeks to enact revenge on a group ...	82
10842	Christopher Robin's bear attempts to raid a be...	25
10843	English General Charles George Gordon, a devou...	134
10844	When scientists use eco-terrorism to impose th...	108
10845	Stodge City is in the grip of the Rumpo Kid an...	93
10846	Whilst vacationing in the Carpathian Mountain,...	90
10847	A small island community is overrun with creep...	89
10848	The science of miniaturization has been unlock...	100
10849	Harry Dean (Michael Caine) has a perfect plan ...	109
10850	Harper is a cynical private eye in the best tr...	121
10851	Born Free (1966) is an Open Road Films Ltd./Co...	95
10852	A naive traveler in Laredo gets involved in a ...	95
10853	The film tells the story of a young man who le...	114
10854	Most everyone in town thinks that Sheriff Cald...	135
10855	Luther Heggs aspires to being a reporter for h...	90
10856	The Garrisons (Dean Jones and Suzanne Pleshett...	93
10857	Nevada Smith is the young son of an Indian mot...	128
10858	Without hostile intent, a Soviet sub runs agro...	126
10859	A secret organisation offers wealthy people a ...	100
10860	The sinister Dr Watt has an evil scheme going...	87
10861	The Endless Summer, by Bruce Brown, is one of ...	95
10862	Grand Prix driver Pete Aron is fired by his te...	176
10863	An insurance agent who moonlights as a carthie...	94
10864	In comic Woody Allen's film debut, he took the...	80

10865 A family gets lost on the road and stumbles up...

74

```

                                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
5      Western|Drama|Adventure|Thriller
6      Science Fiction|Action|Thriller|Adventure
7      Drama|Adventure|Science Fiction
8      Family|Animation|Adventure|Comedy
9      Comedy|Animation|Family
10     Action|Adventure|Crime
11     Science Fiction|Fantasy|Action|Adventure
12     Drama|Science Fiction
13     Action|Comedy|Science Fiction
14     Action|Adventure|Science Fiction
15     Crime|Drama|Mystery|Western
16     Crime|Action|Thriller
17     Science Fiction|Action|Adventure
18     Romance|Fantasy|Family|Drama
19     War|Adventure|Science Fiction
20     Action|Family|Science Fiction|Adventure|Mystery
21     Action|Drama
22     Action|Drama|Thriller
23     Drama|Romance
24     Comedy|Drama
25     Action
26     Comedy
27     Crime|Comedy|Action|Adventure
28     Drama|Thriller|History
29     Action|Science Fiction|Thriller
...
10836     Comedy|Romance
10837     War|Action|Adventure|Drama
10838     Action|Adventure|Western
10839     Family|Animation
10840     Thriller
10841     Western
10842     Animation|Family
10843     Adventure|Drama|War|History|Action
10844     Adventure|Comedy|Fantasy|Science Fiction
10845     Comedy|Western
10846     Horror
10847     Science Fiction|Horror
10848     Adventure|Science Fiction
10849     Action|Comedy|Crime
```

10850	Action Drama Thriller Crime Mystery
10851	Adventure Drama Action Family Foreign
10852	Western
10853	Comedy Drama Romance
10854	Thriller Drama Crime
10855	Comedy Family Mystery Romance
10856	Comedy Drama Family
10857	Action Western
10858	Comedy War
10859	Mystery Science Fiction Thriller Drama
10860	Comedy
10861	Documentary
10862	Action Adventure Drama
10863	Mystery Comedy
10864	Action Comedy
10865	Horror

	production_companies	release_date	\
0	Universal Studios Amblin Entertainment Legenda...	6/9/15	
1	Village Roadshow Pictures Kennedy Miller Produ...	5/13/15	
2	Summit Entertainment Mandeville Films Red Wago...	3/18/15	
3	Lucasfilm Truenorth Productions Bad Robot	12/15/15	
4	Universal Pictures Original Film Media Rights ...	4/1/15	
5	Regency Enterprises Appian Way CatchPlay Anony...	12/25/15	
6	Paramount Pictures Skydance Productions	6/23/15	
7	Twentieth Century Fox Film Corporation Scott F...	9/30/15	
8	Universal Pictures Illumination Entertainment	6/17/15	
9	Walt Disney Pictures Pixar Animation Studios W...	6/9/15	
10	Columbia Pictures Danjaq B24	10/26/15	
11	Village Roadshow Pictures Dune Entertainment A...	2/4/15	
12	DNA Films Universal Pictures International (UP...	1/21/15	
13	Columbia Pictures Happy Madison Productions	7/16/15	
14	Marvel Studios Prime Focus Revolution Sun Studios	4/22/15	
15	Double Feature Films The Weinstein Company Fil...	12/25/15	
16	Twentieth Century Fox Film Corporation M6 Film...	1/1/15	
17	Marvel Studios	7/14/15	
18	Walt Disney Pictures Genre Films Beagle Pug Fi...	3/12/15	
19	Studio Babelsberg StudioCanal Lionsgate Walt D...	11/18/15	
20	Walt Disney Pictures Babieka A113	5/19/15	
21	Escape Artists Riche-Ludwig Productions	6/15/15	
22	New Line Cinema Village Roadshow Pictures Warn...	5/27/15	
23	Focus Features Trigger Street Productions Mich...	2/11/15	
24	Paramount Pictures Plan B Entertainment Regenc...	12/11/15	
25	Paramount Pictures Skydance Productions China ...	7/23/15	
26	Universal Pictures Media Rights Capital Fuzzy ...	6/25/15	
27	Twentieth Century Fox Film Corporation Marv Fi...	1/24/15	
28	Participant Media Open Road Films Anonymous Co...	11/6/15	
29	Gotham Group Temple Hill Entertainment TSG Ent...	9/9/15	

...	...	...
10836	Columbia Pictures Corporation	1/1/66
10837	Twentieth Century Fox Film Corporation	6/21/66
10838	Columbia Pictures	11/1/66
10839	Warner Bros. Home Video	10/27/66
10840	Lowndes Productions Limited	12/22/66
10841	Proteus Films	10/23/66
10842	NaN	1/1/66
10843	Julian Blaustein Productions Ltd.	6/9/66
10844	20th Century Fox	1/16/66
10845	Peter Rogers Productions	3/1/66
10846	Seven Arts Productions Hammer Film Productions	1/9/66
10847	Planet Film Productions Protelco	6/20/66
10848	Twentieth Century Fox Film Corporation	8/24/66
10849	Universal Pictures	12/16/66
10850	Warner Bros.	2/23/66
10851	High Road	6/22/66
10852	Eden Productions Inc.	5/31/66
10853	NaN	3/29/66
10854	Horizon Pictures Columbia Pictures Corporation	2/17/66
10855	Universal Pictures	1/20/66
10856	Walt Disney Pictures	2/16/66
10857	Paramount Pictures Solar Productions Embassy P...	6/10/66
10858	The Mirisch Corporation	5/25/66
10859	Gibraltar Productions Joel Productions John Fr...	10/5/66
10860	Peter Rogers Productions Anglo-Amalgamated Fil...	5/20/66
10861	Bruce Brown Films	6/15/66
10862	Cherokee Productions Joel Productions Douglas ...	12/21/66
10863	Mosfilm	1/1/66
10864	Benedict Pictures Corp.	11/2/66
10865	Norm-Iris	11/15/66

	vote_count	vote_average	release_year	budget_adj	revenue_adj	\
0	5562	6.5	2015	1.379999e+08	1.392446e+09	
1	6185	7.1	2015	1.379999e+08	3.481613e+08	
2	2480	6.3	2015	1.012000e+08	2.716190e+08	
3	5292	7.5	2015	1.839999e+08	1.902723e+09	
4	2947	7.3	2015	1.747999e+08	1.385749e+09	
5	3929	7.2	2015	1.241999e+08	4.903142e+08	
6	2598	5.8	2015	1.425999e+08	4.053551e+08	
7	4572	7.6	2015	9.935996e+07	5.477497e+08	
8	2893	6.5	2015	6.807997e+07	1.064192e+09	
9	3935	8.0	2015	1.609999e+08	7.854116e+08	
10	3254	6.2	2015	2.253999e+08	8.102203e+08	
11	1937	5.2	2015	1.619199e+08	1.692686e+08	
12	2854	7.6	2015	1.379999e+07	3.391985e+07	
13	1575	5.8	2015	8.095996e+07	2.241460e+08	
14	4304	7.4	2015	2.575999e+08	1.292632e+09	

15	2389	7.4	2015	4.047998e+07	1.432992e+08
16	1578	6.1	2015	4.415998e+07	2.997096e+08
17	3779	7.0	2015	1.195999e+08	4.771138e+08
18	1495	6.8	2015	8.739996e+07	4.989630e+08
19	2380	6.5	2015	1.471999e+08	5.984813e+08
20	1899	6.2	2015	1.747999e+08	1.923127e+08
21	1386	7.3	2015	2.759999e+07	8.437300e+07
22	2060	6.1	2015	1.012000e+08	4.328514e+08
23	1865	5.3	2015	3.679998e+07	5.240791e+08
24	1545	7.3	2015	2.575999e+07	1.226787e+08
25	2349	7.1	2015	1.379999e+08	6.277435e+08
26	1666	6.3	2015	6.255997e+07	1.985944e+08
27	3833	7.6	2015	7.451997e+07	3.714978e+08
28	1559	7.8	2015	1.839999e+07	8.127872e+07
29	1849	6.4	2015	5.611998e+07	2.863562e+08
...	...	...	...	...	...
10836	11	5.8	1966	0.000000e+00	0.000000e+00
10837	12	5.5	1966	0.000000e+00	0.000000e+00
10838	21	6.0	1966	0.000000e+00	0.000000e+00
10839	49	7.2	1966	0.000000e+00	0.000000e+00
10840	13	5.7	1966	0.000000e+00	0.000000e+00
10841	12	5.5	1966	5.038511e+05	0.000000e+00
10842	12	7.9	1966	0.000000e+00	0.000000e+00
10843	12	5.8	1966	0.000000e+00	0.000000e+00
10844	13	5.6	1966	0.000000e+00	0.000000e+00
10845	15	5.9	1966	0.000000e+00	0.000000e+00
10846	16	5.7	1966	0.000000e+00	0.000000e+00
10847	13	5.3	1966	0.000000e+00	0.000000e+00
10848	42	6.7	1966	3.436265e+07	8.061618e+07
10849	14	6.1	1966	0.000000e+00	0.000000e+00
10850	14	6.0	1966	0.000000e+00	0.000000e+00
10851	15	6.6	1966	0.000000e+00	0.000000e+00
10852	11	6.0	1966	0.000000e+00	0.000000e+00
10853	26	6.2	1966	0.000000e+00	0.000000e+00
10854	17	6.0	1966	0.000000e+00	0.000000e+00
10855	14	6.1	1966	4.702610e+06	0.000000e+00
10856	14	5.7	1966	0.000000e+00	0.000000e+00
10857	10	5.9	1966	0.000000e+00	0.000000e+00
10858	11	5.5	1966	0.000000e+00	0.000000e+00
10859	22	6.6	1966	0.000000e+00	0.000000e+00
10860	13	7.0	1966	0.000000e+00	0.000000e+00
10861	11	7.4	1966	0.000000e+00	0.000000e+00
10862	20	5.7	1966	0.000000e+00	0.000000e+00
10863	11	6.5	1966	0.000000e+00	0.000000e+00
10864	22	5.4	1966	0.000000e+00	0.000000e+00
10865	15	1.5	1966	1.276423e+05	0.000000e+00

MainActor

0	Chris Pratt
1	Tom Hardy
2	Shailene Woodley
3	Harrison Ford
4	Vin Diesel
5	Leonardo DiCaprio
6	Arnold Schwarzenegger
7	Matt Damon
8	Sandra Bullock
9	Amy Poehler
10	Daniel Craig
11	Mila Kunis
12	Domhnall Gleeson
13	Adam Sandler
14	Robert Downey Jr.
15	Samuel L. Jackson
16	Liam Neeson
17	Paul Rudd
18	Lily James
19	Jennifer Lawrence
20	Britt Robertson
21	Jake Gyllenhaal
22	Dwayne Johnson
23	Dakota Johnson
24	Christian Bale
25	Tom Cruise
26	Mark Wahlberg
27	Taron Egerton
28	Mark Ruffalo
29	Dylan O'Brien
...	...
10836	Cary Grant
10837	George Peppard
10838	Burt Lancaster
10839	Christopher Shea
10840	Michael Caine
10841	Will Hutchins
10842	Sterling Holloway
10843	Charlton Heston
10844	James Coburn
10845	Sid James
10846	Christopher Lee
10847	Peter Cushing
10848	Stephen Boyd
10849	Michael Caine
10850	Paul Newman
10851	Virginia McKenna
10852	Henry Fonda



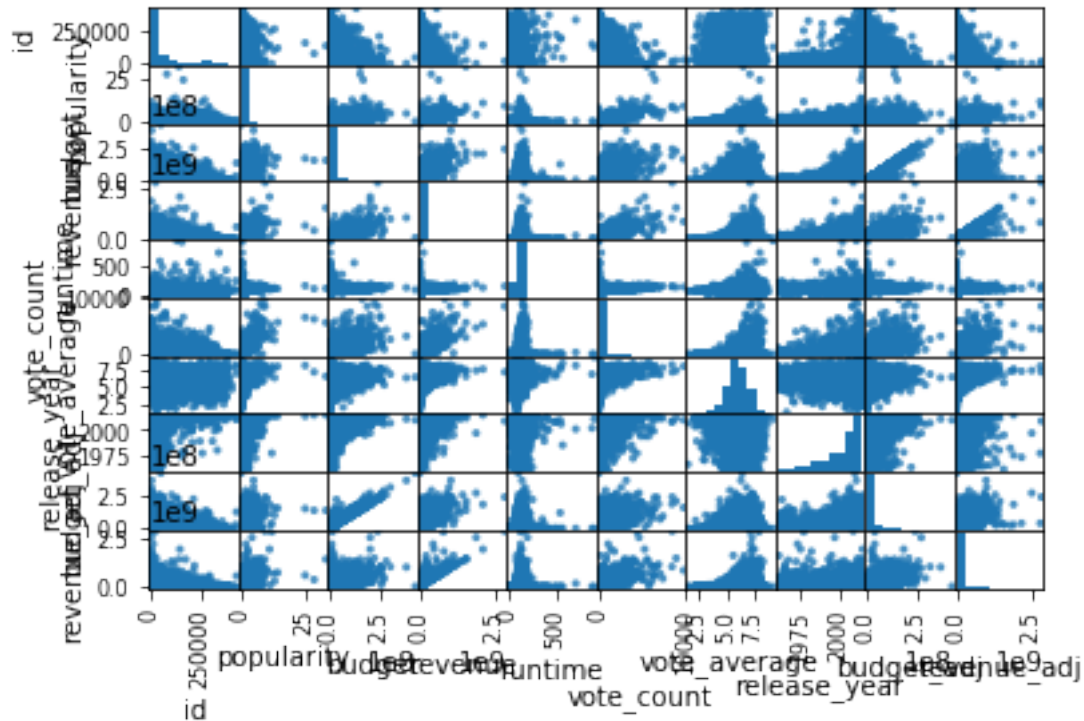
10853	Michael Caine
10854	Marlon Brando
10855	Don Knotts
10856	Dean Jones
10857	Steve McQueen
10858	Carl Reiner
10859	Rock Hudson
10860	Kenneth Williams
10861	Michael Hynson
10862	James Garner
10863	Innokentiy Smoktunovskiy
10864	Tatsuya Mihashi
10865	Harold P. Warren

[10751 rows x 19 columns]

```
In [20]: df.isnull().sum()
```

```
Out[20]: id                0
imdb_id                  6
popularity               0
budget                  0
revenue                 0
original_title          0
cast                    0
director                0
overview                3
runtime                 0
genres                  20
production_companies    972
release_date            0
vote_count              0
vote_average            0
release_year            0
budget_adj              0
revenue_adj             0
MainActor              0
dtype: int64
```

```
In [37]: pd.plotting.scatter_matrix(df, alpha=0.8);
```



Add new column Main Actor by applying lamda function to split the cast cell by | and get the first one

```
In [21]: # Add column Main Actor/Actress by applying lamda function to split the cast cell by |
df['MainActor']= df['cast'].apply(lambda x: x.split('|')[0])
# another way to get the Main actor df['MainActor']=[ act.split('|')[0] for act in df['cast']]
```

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

```
Out[15]:
```

	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      director \
```

0	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi...	Colin Trevorrow
1	Tom Hardy Charlize Theron Hugh Keays-Byrne Nic...	George Miller
2	Shailene Woodley Theo James Kate Winslet Ansel...	Robert Schwentke
3	Harrison Ford Mark Hamill Carrie Fisher Adam D...	J.J. Abrams
4	Vin Diesel Paul Walker Jason Statham Michelle ...	James Wan

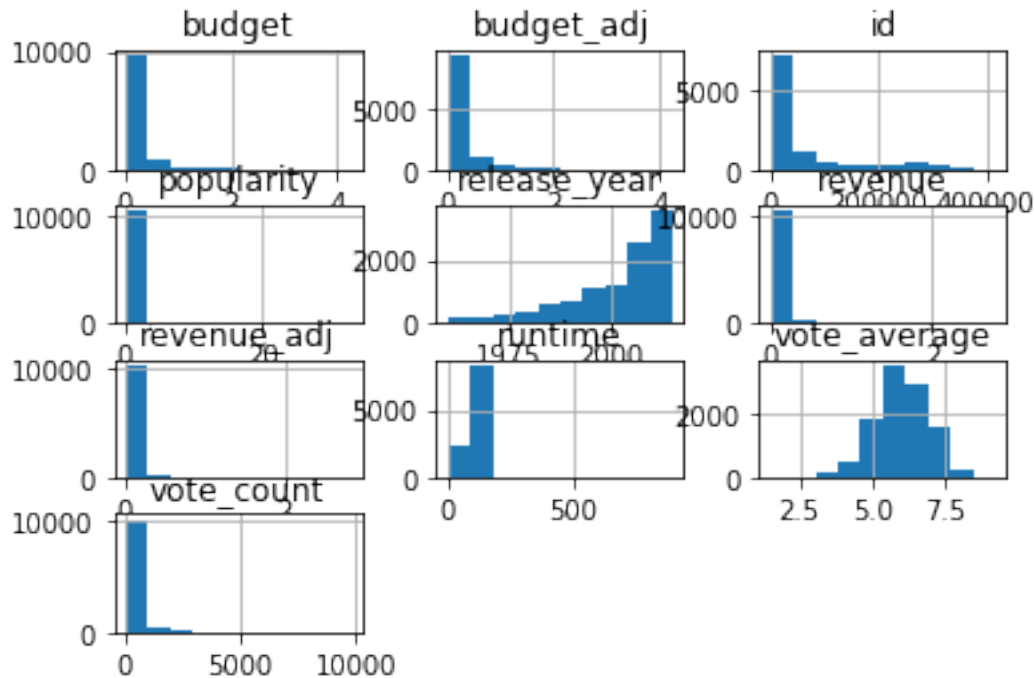
	overview	runtime \
0	Twenty-two years after the events of Jurassic ...	124
1	An apocalyptic story set in the furthest reach...	120
2	Beatrice Prior must confront her inner demons ...	119
3	Thirty years after defeating the Galactic Empi...	136
4	Deckard Shaw seeks revenge against Dominic Tor...	137

	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	MainActor
0	6.5	2015	1.379999e+08	1.392446e+09	Chris Pratt
1	7.1	2015	1.379999e+08	3.481613e+08	Tom Hardy
2	6.3	2015	1.012000e+08	2.716190e+08	Shailene Woodley
3	7.5	2015	1.839999e+08	1.902723e+09	Harrison Ford
4	7.3	2015	1.747999e+08	1.385749e+09	Vin Diesel

```
In [27]: df.hist();
```



## Exploratory Data Analysis

#### 1.1.4 Research Question 1 (top actors achieved revenue in their movies)

group by Main actor and sum the revenue per actor.

```
In [22]: #group by Main actor and sum the revenue per actor.
         top_actors = df.groupby('MainActor')['revenue'].sum().sort_values(ascending=False)
```

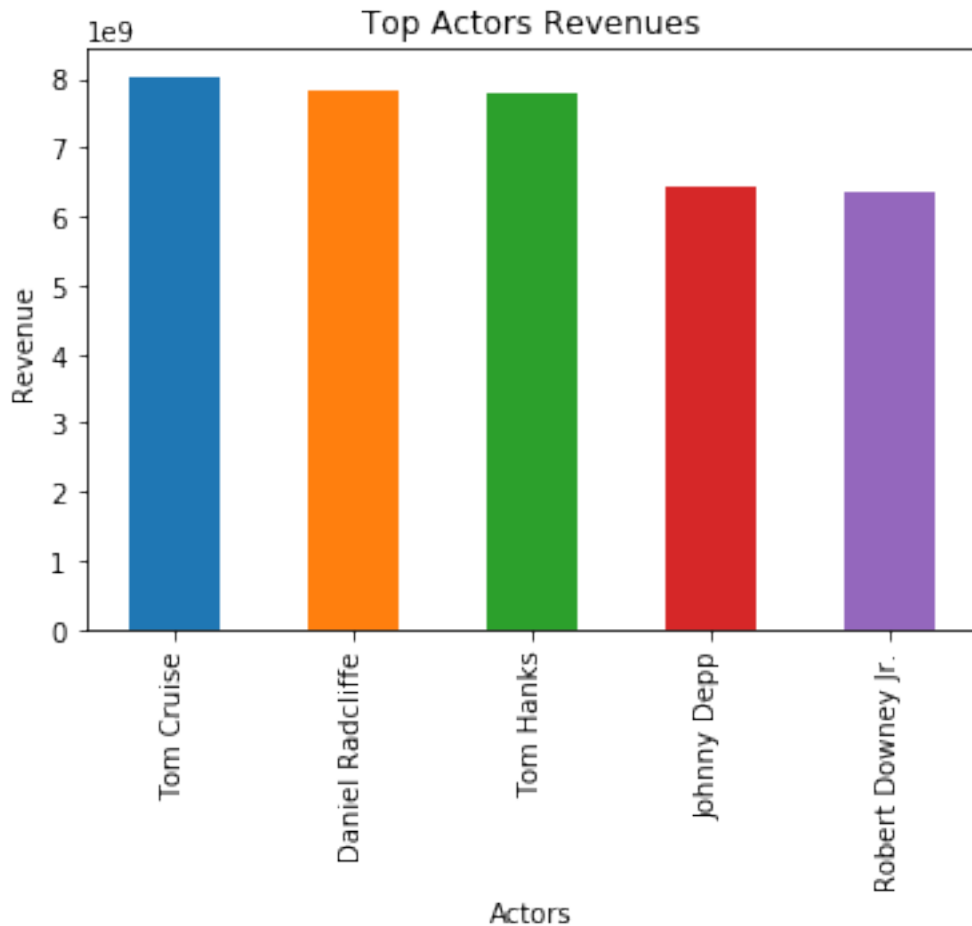
Get Top 5 actors

```
In [23]: top_actors = top_actors.head(5)
```

Present the 5 actors with top revenues

```
In [24]: top_actors.plot(kind='bar',title="Top Actors Revenues", label='Actor');
         plt.xlabel("Actors")
         plt.ylabel('Revenue')
```

```
Out[24]: Text(0,0.5, 'Revenue')
```



The above chart, shows that, Tom cruise has the most successfull movies based on revenues

### 1.1.5 Research Question 2 (who the director has top rated movies)

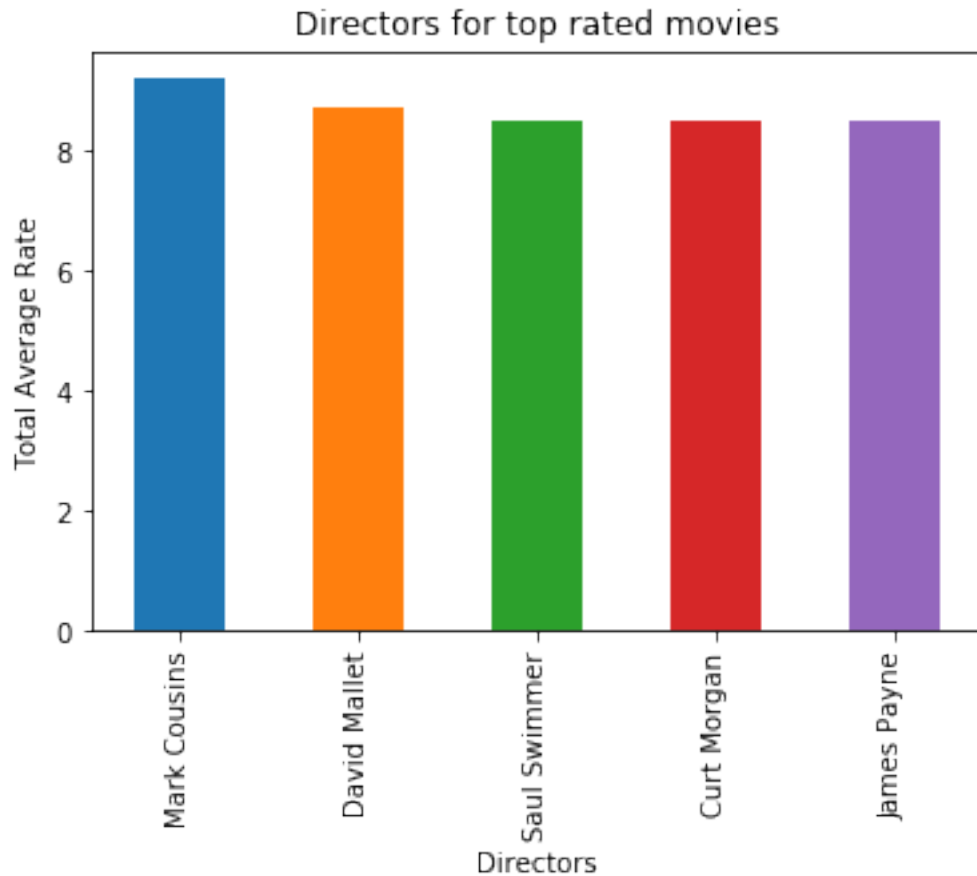
group by directors to get the average of the vote average column for all movies directed by them.

```
In [15]: # group by directors to get the average of the vote average column for all movies directed by them
top_five_directors=df.groupby('director')['vote_average'].mean().sort_values(ascending=False)
```

Present the directors have top rated movies

```
In [16]: top_five_directors.plot(kind='bar',title="Directors for top rated movies", label='Directors')
plt.xlabel("Directors")
plt.ylabel('Total Average Rate')
```

```
Out[16]: Text(0,0.5,'Total Average Rate')
```



The chart above shows that the top rated movies has directed by Mark Cousins

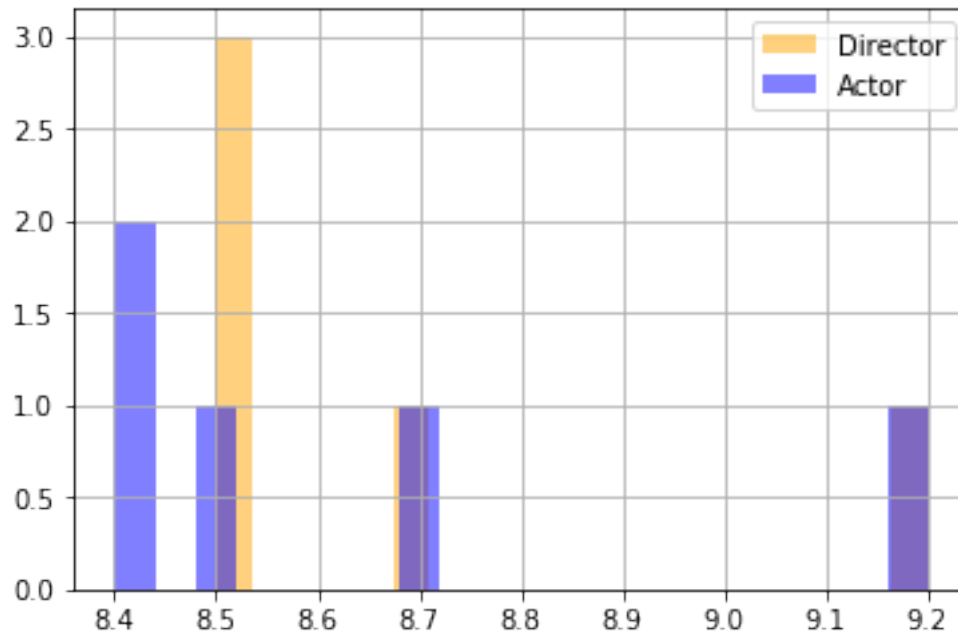
### 1.1.6 Extra Step

Comparing between the actors and directors for the top rated movies

```
In [17]: top_five_actors=df.groupby('MainActor')['vote_average'].mean().sort_values(ascending=False)
```

the below chart view the relation between top rated movies for actors vs top rated movies for directors, if the blue and orange are the same height , then both director and actor the cause to succuss this movie

```
In [18]: top_five_directors.hist(alpha=0.5, bins=20, color='orange', label='Director');
top_five_actors.hist(alpha=0.5, bins=20, color='blue', label='Actor');
plt.legend();
```



The chart above shows the relations between famous actor and director, how can affect the popularity of a good movie

### 1.1.7 Question 3 (production companies revenue vs budget (loss or gain))

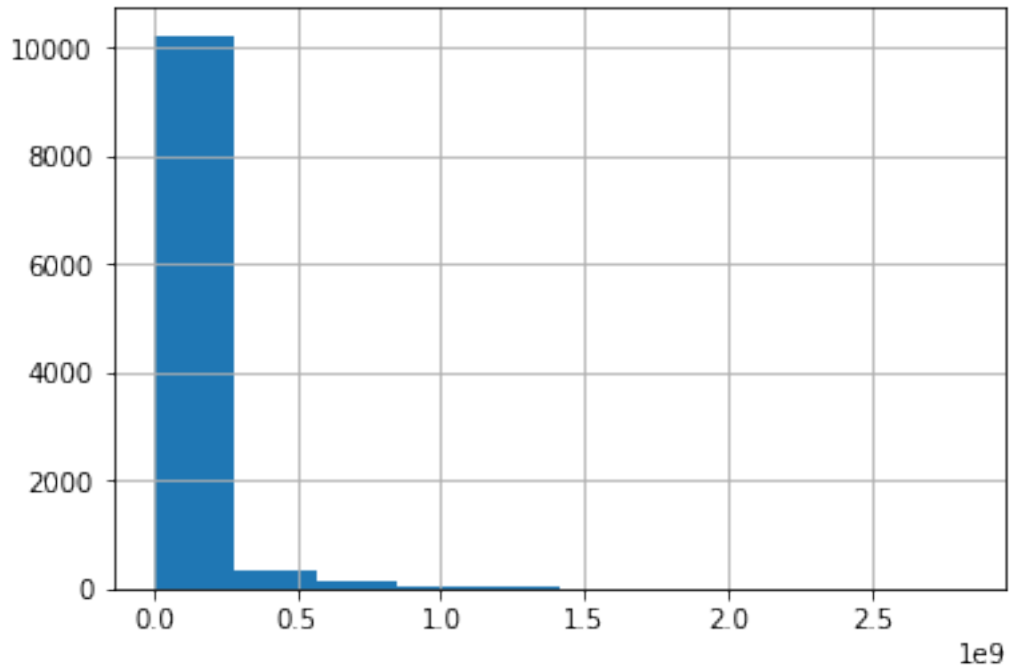
this question show the relation between budget and revenue for production companies, is the companies gaining profit or lose

```
In [19]: def fillNAWithValue(df,colName,ValueToFill):
        '''
        This function to fill the Na values in column
        with specific word
        args:
            df : the dataframe
            colName: the column name will be filled
            ValueToFill: the value will be used to fill the NA
        '''
        df[colName].fillna(ValueToFill, inplace=True)
```

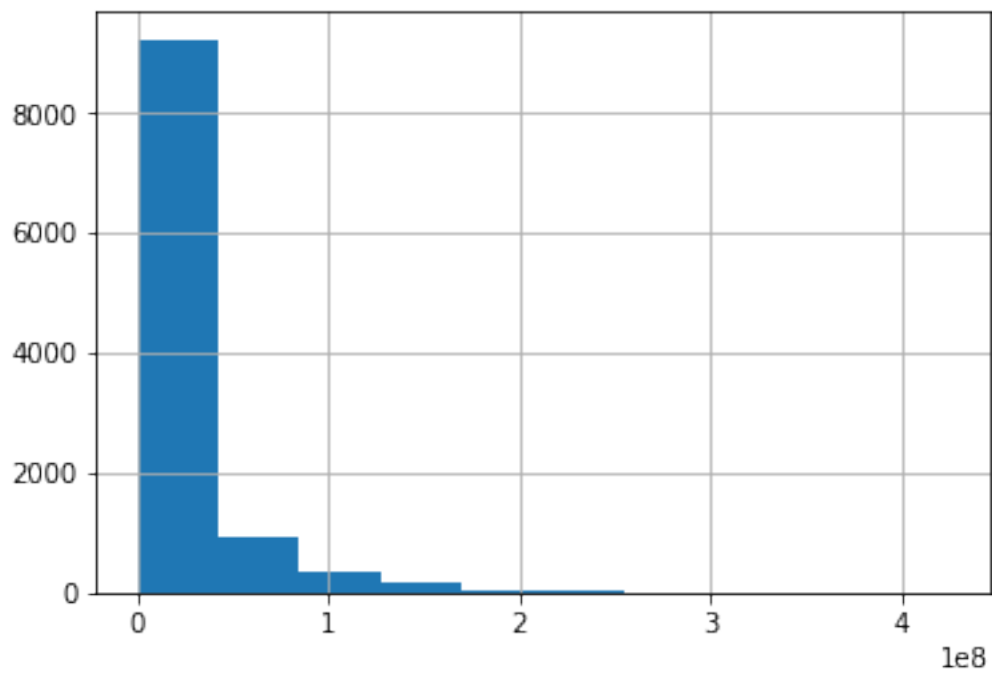
fill the NA in production companies to be Other companies

```
In [20]: #Fill NA with Other word
        fillNAWithValue(df,'production_companies','Other')
```

```
In [28]: df['revenue_adj'].hist();
```



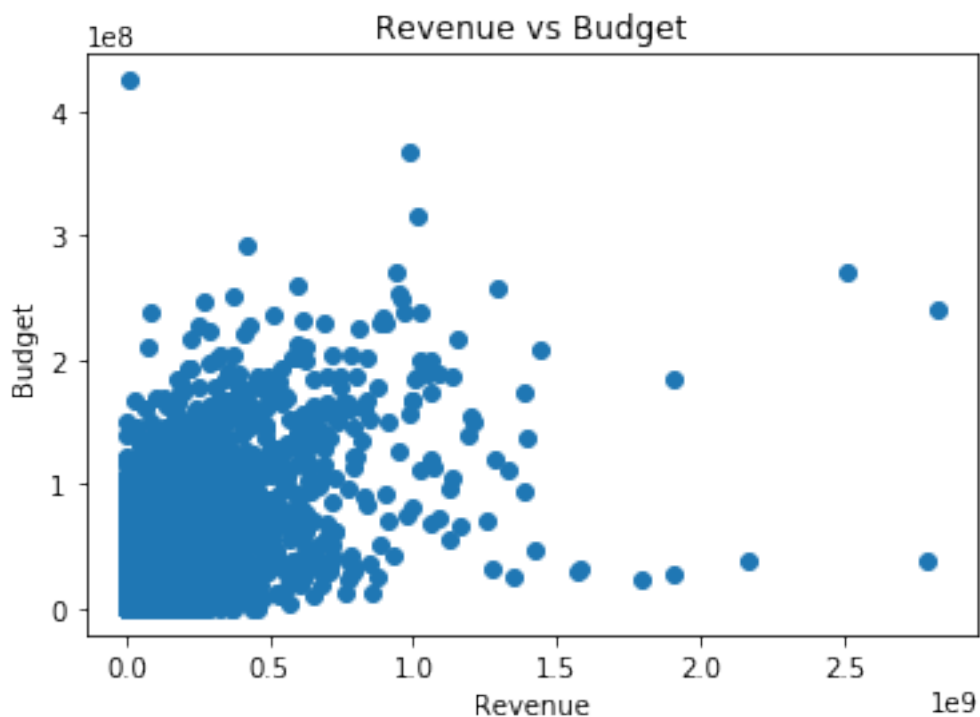
```
In [29]: df['budget_adj'].hist();
```



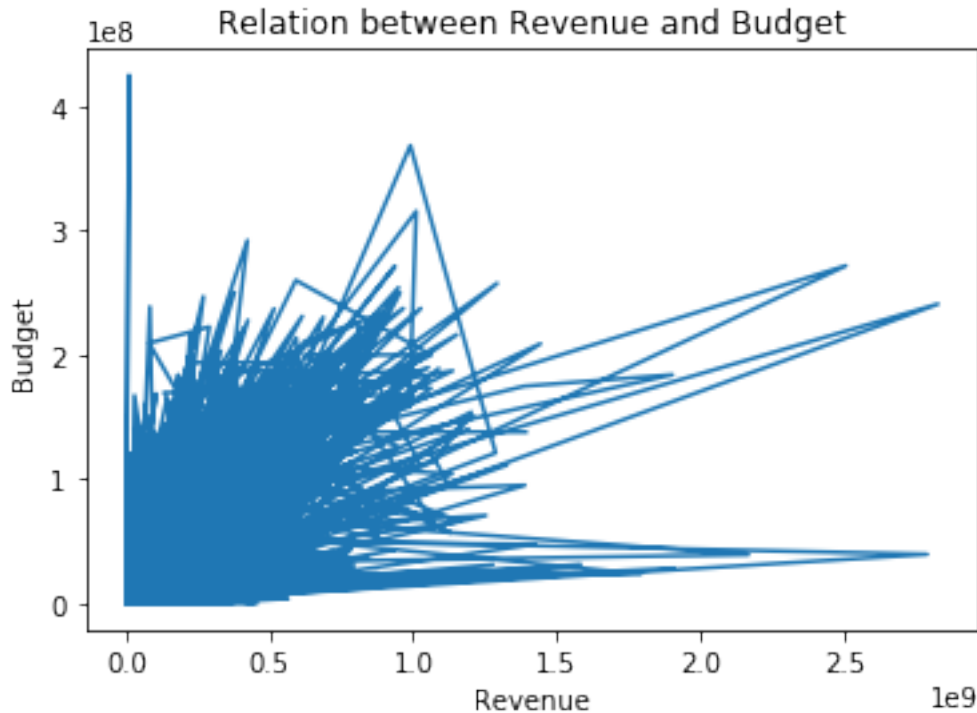


Both Budget and Revenue are right skewed, so if the budget increased the propability of the revenue increase

```
In [25]: plt.scatter(data = df, x = 'revenue_adj', y = 'budget_adj');  
plt.xlabel('Revenue')  
plt.ylabel('Budget')  
plt.title("Revenue vs Budget");
```



```
In [34]: plt.plot(df['revenue_adj'], df['budget_adj'])  
plt.xlabel('Revenue')  
plt.ylabel('Budget')  
plt.title('Relation between Revenue and Budget')  
plt.show()
```



Revenue vs budget are skewed to the right, that means few companies are having most of the profits from the movies production

## Conclusions

Last, after reviewing the movies and the revenue, we got the below:

The data sample contains data for movies with cast, production movies, titles, revenue, and budget.

In this exploratory, I choose to check the success of movies based on rate and revenue, to check which actor or director has the most successful movies.

Also checked the companies revenues, and the relation between how much they spend in production and the revenue.

findings:

1- popular actor and good director may be great factor to increase the revenue and get numerous positive ratings. 2- few companies in the movies production gaining most of the revenue, but they have huge budgets.

## 2 Limitations

We can't get the revenue per company, because there a lot of companies unions in the movies production.

### 2.1 Submitting your Project

```
In [24]: from subprocess import call
         call(['python', '-m', 'nbconvert', 'Investigate_a_Dataset.ipynb'])
```

```
Out[24]: 0
```

```
In [ ]:
```