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# Project 2:Investigate a Dataset (TMDb Movie Data)

In this project we are going to do general data analysis of data provided to us with the help of python libraries like numpy,pandas and matplotlib.

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# 1.Introduction

#### **About Dataset:**

In this project I have chosen TMDb movie data set for data analysis process. It has the details of around 10000 movies. I will analyse this data set on the basis of few questions.

#### **Questions:**

- 1. Find the movie name which has highest runtime?
- 2. How many movies have runtime less than 2hrs.(120 min) and greater than 2hrs?
- 3. Year of highest and lowest number of movie release?
- 4. Get 5 directors with highest directed movies?
- 5. What is maximum and minimum vote average?
- 6. Name the movies with maximum and minimum vote average?
- 7. Movies having vote average less than or equal to 5 and greater than 5?
- 8. What is the vote average of most popular movie?
- 9. Find the revenue of highest budget movie?
- 10. Revenue of Most Popular movie?

```
In [1]: #first of all import the required libraries before going on the next ph
    ase of data analysis.
    import pandas as pd
    import matplotlib.pyplot as plt
    import seaborn as sns
%matplotlib inline
    import numpy as np
```

# 2.Data Wrangling

In this section i will load in the data, check for cleanliness, and then trim and clean dataset for analysis.

## **General Properties**

```
In [2]: #loading data(CSV file) using pandas library
df_tmdb=pd.read_csv("tmdb-movies.csv")
```

```
In [3]: #the sumerized information about dataset
        df tmdb.info()
        <class 'pandas.core.frame.DataFrame'>
        RangeIndex: 10866 entries, 0 to 10865
        Data columns (total 21 columns):
        id
                                 10866 non-null int64
                                 10856 non-null object
        imdb id
        popularity
                                 10866 non-null float64
        budget
                                 10866 non-null int64
                                 10866 non-null int64
        revenue
                                 10866 non-null object
        original title
                                 10790 non-null object
        cast
                                 2936 non-null object
        homepage
        director
                                 10822 non-null object
        tagline
                                 8042 non-null object
                                 9373 non-null object
        keywords
                                 10862 non-null object
        overview
                                 10866 non-null int64
        runtime
                                 10843 non-null object
        genres
                                 9836 non-null object
        production companies
                                 10866 non-null object
        release date
        vote_count
                                 10866 non-null int64
        vote average
                                 10866 non-null float64
        release year
                                 10866 non-null int64
        budget adj
                                 10866 non-null float64
        revenue adj
                                 10866 non-null float64
        dtypes: float64(4), int64(6), object(11)
        memory usage: 1.7+ MB
In [4]: #First 3 rows of the dataset to take a glimpse of dataset.
        df tmdb.head(3)
Out[4]:
                  imdb_id popularity
                                     budget
                                              revenue original_title
                                                                       cast
```

	i	d i	mdb_id	popularity	budget	revenu	ue original_t	itle cast		
0	13539	7 tt0	369610	32.985763	150000000	15135288 <sup>2</sup>	10 Juras Wo	Chris ssic Pratt Bryce orld Dallas Howard Irrfan Khan Vi		
1	7634	1 tt1	392190	28.419936	150000000	37843638	54 Mad M Fury Ro			
2	26250	0 tt2	908446	13.112507	110000000	29523820	01 Insurg	Shailene ent Woodley Theo James Kate Winslet Ansel	http://www.t	
#1	<pre>3 rows × 21 columns  #last 3 rows of the dataset df tmdb.tail(3)</pre>									
		id	imdb_	_id popular	ity budget	revenue	original_title	cast	homepage	
10	<b>863</b> 3	9768	tt00601	61 0.0651	41 0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z	Nan	
10	<b>864</b> 2	1449	tt00611	77 0.0643	17 0	0	What's Up, Tiger Lily?	Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh	Nah	

In [5]:

Out[5]:

		id	popularity	budget	revenue	runtime	vote_count	vo
	75%	75610.000000	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	
	max	417859.000000	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	
4								•

## **Data Cleaning(Removing Unwanted Data)**

First we will look at the missing values in the data set

```
In [8]: #to get the missing values in the columns.
        df tmdb.isna().sum()
Out[8]: id
                                   0
                                  10
        imdb id
        popularity
        budget
        revenue
        original_title
                                  76
        cast
        homepage
                                7930
        director
                                  44
        tagline
                                2824
        keywords
                                1493
        overview
                                   4
        runtime
                                   0
        genres
                                  23
        production_companies
                                1030
        release_date
        vote count
        vote average
        release_year
        budget_adj
        revenue adj
        dtype: int64
```

we can see that 'homepage ','tagline','overview','production\_companies' has very large number of missing values.

#### **Steps To Delete Or Modify The dataset**

- 1.Remove the unused columns and rows(if necessary) with missing values.
- 2.Remove duplicate rows from the dataset.
- 3. Change format if necessary.
- 4. Treatment of outliers

#### 1.Remove the unused columns with missing values.

Since few columns which are not usable in the data analysis process.columns are: imdb\_id, keywords, homepage,tagline,overview and budget\_adj,revenue\_adj has huge number of 0 values so we can drop it. So these are the columns that are not involved in the analysis process.

```
In [9]: #removing the unused columns using drop() function.
    df_tmdb.drop(['overview','imdb_id','homepage','tagline','budget_adj','r
        evenue_adj','keywords','production_companies'],axis =1,inplace = True)

In [10]: #check rows and columns again
    #we are left with 13 columns now.
    df_tmdb.shape

Out[10]: (10866, 13)

In [11]: df_tmdb.head()

Out[11]:
    id popularity budget revenue original_title cast director runtime
```

	id	popularity	budget	revenue	original_title	cast	director	runtime
0	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	124
1	76341	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy Charlize Theron Hugh Keays- Byrne Nic	George Miller	120
2	262500	13.112507	110000000	295238201	Insurgent	Shailene Woodley Theo James Kate Winslet Ansel	Robert Schwentke	119
3	140607	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	136
4	168259	9.335014	190000000	1506249360	Furious 7	Vin Diesel Paul Walker Jason Statham Michelle 	James Wan	137
4								<b>•</b>

## 2. Remove duplicate rows from dataset

In [12]: #duplicated() function return the duplicate row as True and False
#To count the duplicate elements we use sum() function.
sum(df\_tmdb.duplicated())

Out[12]: 1

In [13]: # using drop\_duplicates() function we can remove duplicate rows.
df\_tmdb.drop\_duplicates(inplace = True)

### 3. Change format if necessary

Due to the string fromat of 'release\_date' column. we will have to change the format.

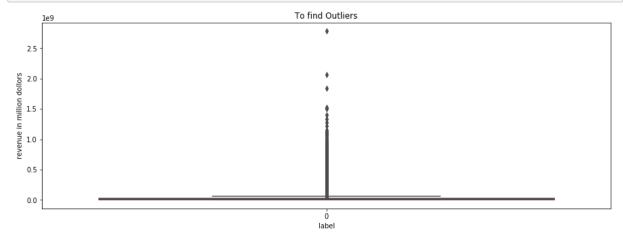
```
In [14]: #changing the format or datatype of column.
         df tmdb['release date'] = pd.to datetime(df tmdb['release date'])
In [15]: #head to verify the apllied funcution.
         df tmdb['release date'].head(2)
Out[15]: 0 2015-06-09
         1 2015-05-13
         Name: release date, dtype: datetime64[ns]
         4. Getting rid of missing values in rows
         since cast, director, genre are important columns and have missing values we should remove the
         coresponding rows
In [16]: #use dropna function to remove the missing vlaues
         df tmdb=df tmdb.dropna()
In [17]: #again recheck the missing values to varify.
         df tmdb.isna().sum()
Out[17]: id
                            0
         popularity
         budget
         revenue
         original title
         cast
         director
         runtime
         genres
         release date
         vote count
         vote average
```

```
release_year 0
dtype: int64
```

#### 4. Treatment of Outliers

Since the columns 'revenue', 'runtime' and 'budget' has outliers we need to treat them with mean, median, mode or if necessary delete the data

```
In [18]: #plotting boxplot for revenue to see the frequency of outliers
   plt.figure(figsize=(15,5))
   sns.boxplot(
         data=df_tmdb['revenue'],
         color='red')
   plt.ylabel('revenue in million dollors')
   plt.xlabel('label')
   plt.title('To find Outliers')
   plt.show()
```



with boxplot we can analyse that there is significant number of outliers and droping all of them will reduce our scope of analysis. therfore we will try to sort this problem with statistical models

```
In [19]: #calculating outlier i.e 0 in revenue column
```

```
df tmdb[df tmdb['revenue']==0].count()['id']
Out[19]: 5888
In [20]: #replace function is used to make 0 to NAN value and further dealing wi
           th nan values will be easy
           df tmdb=df tmdb.replace(0,np.NaN)
In [21]: #fill all the value of nan with mean()
           df tmdb.fillna(df tmdb.mean())
Out[21]:
                       id popularity
                                           budget
                                                        revenue
                                                                original title
                                                                                            cast
                                                                                   Chris Pratt|Bryce
                                                                     Jurassic
                0 135397 32.985763 1.500000e+08 1.513529e+09
                                                                                Dallas Howard|Irrfan Colin
                                                                       World
                                                                                        Khan|Vi...
                                                                                Tom Hardy|Charlize
                                                                   Mad Max:
                           28.419936 1.500000e+08 3.784364e+08
                                                                               Theron|Hugh Keays-
                                                                                                    Ge
                                                                   Fury Road
                                                                                       ByrnelNic...
                                                                                         Shailene
                                                                                    WoodlevlTheo
                2 262500 13.112507 1.100000e+08 2.952382e+08
                                                                    Insurgent
                                                                                       James|Kate
                                                                                    Winslet|Ansel...
                                                                   Star Wars:
                                                                                 Harrison Ford|Mark
                3 140607 11.173104 2.000000e+08 2.068178e+09
                                                                   The Force
                                                                                      Hamill|Carrie
                                                                                                     J
                                                                    Awakens
                                                                                   Fisher|Adam D...
                                                                                    Vin Diesel|Paul
                4 168259
                            9.335014 1.900000e+08 1.506249e+09
                                                                                     Walker|Jason
                                                                                                     J
                                                                    Furious 7
                                                                                Statham|Michelle ...
                                                                                        Leonardo
                                                                                     DiCaprio|Tom
                            9.110700 1.350000e+08 5.329505e+08 The Revenant
                5 281957
                                                                                        Hardy|Will
                                                                                   Poulter|Domhn...
                                                                                           Arnold
                                                                   Terminator
                                                                             Schwarzenegger|Jason
                6 87101
                            8.654359 1.550000e+08 4.406035e+08
                                                                     Genisys
```

Clarke|Emilia Clar...

	id	popularity	budget	revenue	original_title	cast	
7	286217	7.667400	1.080000e+08	5.953803e+08	The Martian	Matt Damon Jessica Chastain Kristen Wiig Jeff	F
8	211672	7.404165	7.400000e+07	1.156731e+09	Minions	Sandra Bullock Jon Hamm Michael Keaton Allison	В
9	150540	6.326804	1.750000e+08	8.537086e+08	Inside Out	Amy Poehler Phyllis Smith Richard Kind Bill Ha	F
10	206647	6.200282	2.450000e+08	8.806746e+08	Spectre	Daniel Craig Christoph Waltz Léa Seydoux Ralp	Sa
11	76757	6.189369	1.760000e+08	1.839877e+08	Jupiter Ascending	Mila Kunis Channing Tatum Sean Bean Eddie Redm	Wacł \
12	264660	6.118847	1.500000e+07	3.686941e+07	Ex Machina	Domhnall Gleeson Alicia Vikander Oscar Isaac S	Al
13	257344	5.984995	8.800000e+07	2.436371e+08	Pixels	Adam Sandler Michelle Monaghan Peter Dinklage	
14	99861	5.944927	2.800000e+08	1.405036e+09	Avengers: Age of Ultron	Robert Downey Jr. Chris Hemsworth Mark Ruffalo	Jos
15	273248	5.898400	4.400000e+07	1.557601e+08	The Hateful Eight	Samuel L. Jackson Kurt Russell Jennifer Jason 	
16	260346	5.749758	4.800000e+07	3.257714e+08	Taken 3	Liam Neeson Forest Whitaker Maggie Grace Famke	Olivie
17	102899	5.573184	1.300000e+08	5.186022e+08	Ant-Man	Paul Rudd Michael Douglas Evangeline Lilly Cor	P€

	id	popularity	budget	revenue	original_title	cast	
18	150689	5.556818	9.500000e+07	5.423514e+08	Cinderella	Lily James Cate Blanchett Richard Madden Helen	
19	131634	5.476958	1.600000e+08	6.505234e+08	The Hunger Games: Mockingjay - Part 2	Jennifer Lawrence Josh Hutcherson Liam Hemswor	
20	158852	5.462138	1.900000e+08	2.090357e+08	Tomorrowland	Britt Robertson George Clooney Raffey Cassidy	
21	307081	5.337064	3.000000e+07	9.170983e+07	Southpaw	Jake Gyllenhaal Rachel McAdams Forest Whitaker	Anto
22	254128	4.907832	1.100000e+08	4.704908e+08	San Andreas	Dwayne Johnson Alexandra Daddario Carla Gugino	В
23	216015	4.710402	4.000000e+07	5.696515e+08	Fifty Shades of Grey	Dakota Johnson Jamie Dornan Jennifer Ehle Eloi	S
24	318846	4.648046	2.800000e+07	1.333465e+08	The Big Short	Christian Bale Steve Carell Ryan Gosling Brad	Ad
25	177677	4.566713	1.500000e+08	6.823301e+08	Mission: Impossible - Rogue Nation	Tom Cruise Jeremy Renner Simon Pegg Rebecca Fe	(
26	214756	4.564549	6.800000e+07	2.158636e+08	Ted 2	Mark Wahlberg Seth MacFarlane Amanda Seyfried	N
27	207703	4.503789	8.100000e+07	4.038021e+08	Kingsman: The Secret Service	Taron Egerton Colin Firth Samuel L. Jackson Mi	
28	314365	4.062293	2.000000e+07	8.834647e+07	Spotlight	Mark Ruffalo Michael Keaton Rachel McAdams Lie	Ton

	id	popularity	budget	revenue	original_title	cast	
29	294254	3.968891	6.100000e+07	3.112569e+08	Maze Runner: The Scorch Trials	Dylan O'Brien Kaya Scodelario Thomas Brodie-Sa	
10836	38720	0.239435	3.082824e+07	8.933981e+07	Walk Don't Run	Cary Grant Samantha Eggar Jim Hutton John Stan	Char
10837	19728	0.291704	3.082824e+07	8.933981e+07	The Blue Max	George Peppard James Mason Ursula Andress Jere	John
10838	22383	0.151845	3.082824e+07	8.933981e+07	The Professionals	Burt Lancaster Lee Marvin Robert Ryan Woody St	Rich
10839	13353	0.276133	3.082824e+07	8.933981e+07	It's the Great Pumpkin, Charlie Brown	Christopher Shea Sally Dryer Kathy Steinberg A	Bil
10840	34388	0.102530	3.082824e+07	8.933981e+07	Funeral in Berlin	Michael Caine∣Paul Hubschmid∣Oskar Homolka∣Eva	Gu
10841	42701	0.264925	7.500000e+04	8.933981e+07	The Shooting	Will Hutchins Millie Perkins Jack Nicholson Wa	Mon
10842	36540	0.253437	3.082824e+07	8.933981e+07	Winnie the Pooh and the Honey Tree	Sterling Holloway Junius Matthews Sebastian Ca	F
10843	29710	0.252399	3.082824e+07	8.933981e+07	Khartoum	Charlton Heston Laurence Olivier Richard Johns	De
10844	23728	0.236098	3.082824e+07	8.933981e+07	Our Man Flint	James Coburn Lee J. Cobb Gila Golan Edward Mul	Di
10845	5065	0.230873	3.082824e+07	8.933981e+07	Carry On Cowboy	Sid James Jim Dale Angela Douglas Kenneth Will	Gera

	id	popularity	budget	revenue	original_title	cast	
10846	17102	0.212716	3.082824e+07	8.933981e+07	Dracula: Prince of Darkness	Christopher Lee Barbara Shelley Andrew Keir Fr	Tere
10847	28763	0.034555	3.082824e+07	8.933981e+07	Island of Terror	Peter Cushing Edward Judd Carole Gray Eddie By	Tere
10848	2161	0.207257	5.115000e+06	1.200000e+07	Fantastic Voyage	Stephen Boyd Raquel Welch Edmond O'Brien Donal	
10849	28270	0.206537	3.082824e+07	8.933981e+07	Gambit	Michael Caine Shirley MacLaine Herbert Lom Joh	Ron
10850	26268	0.202473	3.082824e+07	8.933981e+07	Harper	Paul Newman Lauren Bacall Julie Harris Arthur	Ji
10851	15347	0.342791	3.082824e+07	8.933981e+07	Born Free	Virginia McKenna Bill Travers Geoffrey Keen Pe	
10852	37301	0.227220	3.082824e+07	8.933981e+07	A Big Hand for the Little Lady	Henry Fonda Joanne Woodward Jason Robards Paul	Fi
10853	15598	0.163592	3.082824e+07	8.933981e+07	Alfie	Michael Caine Shelley Winters Millicent Martin	Le
10854	31602	0.146402	3.082824e+07	8.933981e+07	The Chase	Marlon Brando Jane Fonda Robert Redford E.G. M	А
10855	13343	0.141026	7.000000e+05	8.933981e+07	The Ghost & Mr. Chicken	Don Knotts Joan Staley Liam Redmond Dick Sarge	,
10856	20277	0.140934	3.082824e+07	8.933981e+07	The Ugly Dachshund	Dean Jones Suzanne Pleshette Charles Ruggles K	Nor

	id	popularity	budget	revenue	original_title	cast	
10857	5921	0.131378	3.082824e+07	8.933981e+07	Nevada Smith	Steve McQueen Karl Malden Brian Keith Arthur K	
10858	31918	0.317824	3.082824e+07	8.933981e+07	The Russians Are Coming, The Russians Are Coming	Carl Reiner Eva Marie Saint Alan Arkin Brian K	
10859	20620	0.089072	3.082824e+07	8.933981e+07	Seconds	Rock Hudson Salome Jens John Randolph Will Gee	Fran
10860	5060	0.087034	3.082824e+07	8.933981e+07	Carry On Screaming!	Kenneth Williams Jim Dale Harry H. Corbett Joa	Gera
10861	21	0.080598	3.082824e+07	8.933981e+07	The Endless Summer	Michael Hynson Robert August Lord 'Tally Ho' B	Br
10862	20379	0.065543	3.082824e+07	8.933981e+07	Grand Prix	James Garner Eva Marie Saint Yves Montand Tosh	Fran
10863	39768	0.065141	3.082824e+07	8.933981e+07	Beregis Avtomobilya	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z	Eldar
10864	21449	0.064317	3.082824e+07	8.933981e+07	What's Up, Tiger Lily?	Tatsuya Mihashi∣Akiko Wakabayashi∣Mie Hama∣Joh	W
10865	22293	0.035919	1.900000e+04	8.933981e+07	Manos: The Hands of Fate	Harold P. Warren Tom Neyman John Reynolds Dian	
10731 rd	ows × 13	3 columns					
4							•

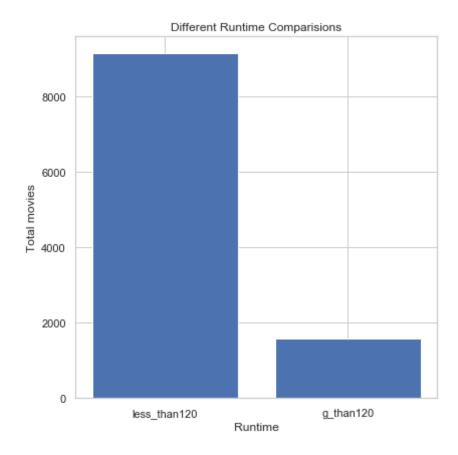
So we are done with all the introduction and data wrangling process the next step is Exploratory Data Analysis(EDA). In this section we will try to analyse our clean data with few questions.

# **3.Exploratory Data Analysis**

# Research Question 1:Find the movie name which has highest runtime?

```
In [58]: #using function to DRY:Do not repeat
         def max function(column name):
             return df tmdb[column name].max()
In [59]: #using function for 'runtime'
         max function('runtime')
Out[59]: 900.0
In [23]: #now find out the movie name coresposnding to maximum runtime value
         df tmdb[df tmdb['runtime']==max runtime]['original title']
Out[23]: 3894
                 The Story of Film: An Odyssey
         Name: original title, dtype: object
         Research Question 2: How many movies have runtime less than 2hrs.
         (120 min) and greater than 2hrs?
In [84]: #greater function is used to calculate greater values while comparing w
         ith other data
         def greater function(column name, value):
             return df tmdb[df tmdb[column name]>value].count()['id']
In [85]: #apply on rruntime column
         greater function('runtime',120)
Out[85]: 1569
In [86]: #lessfunction is used to calculate lesser or equal to given values whil
```

```
e comparing with other data
         def less function(column name, value):
              return df tmdb[df tmdb[column name] <= value].count()['id']</pre>
In [87]: #applied on runtime column
         less function('runtime',120)
Out[87]: 9134
In [88]: #visualizing and comparing the length of the movie using bar graph
         fig = plt.figure()
         ax = fig.add axes([0,0,0.5,1])
         length = ['less than120', 'g than120']
         counts = [less_function('runtime',120),greater function('runtime',120)]
         ax.bar(length, counts)
         plt.title('Different Runtime Comparisions')
         plt.xlabel('Runtime')
         plt.ylabel('Total movies')
         plt.show()
```



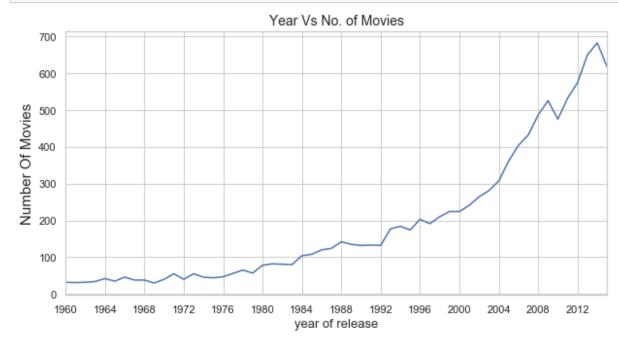
we can observe that the movies having less than or equal to 120 min is the standard movie runtime

# Research Question 3: Year of highest and lowest number of movie release?

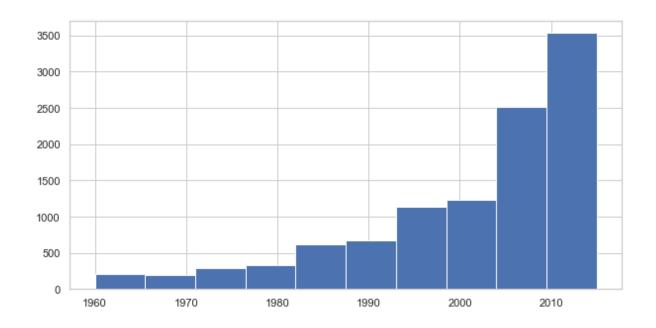
```
In [27]: #Groupby fucntion is used to get yearwise movie release
highest=df_tmdb.groupby('release_year').count()['id']
print(highest.head())
release_year
```

```
1960 32
1961 31
1962 32
1963 34
1964 42
Name: id, dtype: int64
```

# In [71]: #visualizing the comparision highest.plot(xticks = np.arange(1960,2016,4)) sns.set(rc={'figure.figsize':(10,5)}) plt.title("Year Vs No. of Movies",fontsize = 14) plt.xlabel('year of release',fontsize = 13) plt.ylabel('Number Of Movies',fontsize = 15) sns.set\_style("whitegrid")



```
In [72]: #analysis of release year using histogram
df_tmdb['release_year'].hist()
plt.show()
```



Year 1961 has 31(lowest) and 2014 has 700(highest) numbers of movie released.

The trend shows that the release of movies every year is inceasing.

# Research Question 4: Get 5 directors with highest directed movies?

print(director\_name)

director
Woody Allen 45

Clint Eastwood 34 Steven Spielberg 29 Martin Scorsese 28 Ridley Scott 23 Name: id, dtype: int64

# Research Question 5: What is maximum and minimum vote average?

```
In [60]: #max_funtion is used to calculate the maximum of vote average
    print("maximum vote average:",max_function('vote_average'))
    maximum vote average: 9.2

In [61]: #a min_func function is made to calculate the minimum value
    def min_function(column_name):
        return df_tmdb[column_name].min()

In [62]: print("minimum vote average:",min_function('vote_average'))
    minimum vote average: 1.5
```

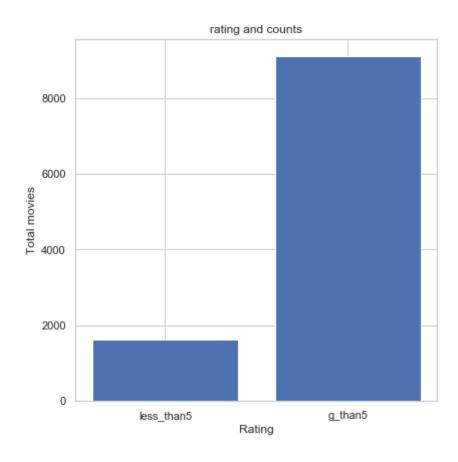
# Research Question 6: Name the movies with maximum and minimum vote average?

```
In [74]: #movie having maximum vote average
    df_tmdb[df_tmdb['vote_average']==max_function('vote_average')]['origina
    l_title']

Out[74]: 3894    The Story of Film: An Odyssey
    Name: original_title, dtype: object

In [75]: #movies with minimum vote average
    df_tmdb[df_tmdb['vote_average']==min_function('vote_average')]['origina
    l_title']
```

```
Out[75]: 7772
                             Transmorphers
                  Manos: The Hands of Fate
         10865
         Name: original title, dtype: object
         There are two movies which have same minimum rating(1.5)
         Research Question 7:Movies having vote average less than or equal
         to 5 and greater than 5?
In [91]: #Movies vote average greater than 5
         print("Number of Movies with rating greater than 5:", greater function(
         'vote average',5))
         Number of Movies with rating greater than 5: 9099
In [92]: #Movies vote average less than or equal to 5
         print("Number of Movies with rating less than or equal to 5:",less func
         tion('vote average',5))
         Number of Movies with rating less than or equal to 5: 1632
In [93]: #visualizing the rating less than or equal to 5 and greater than 5
```



Movies with rating greater than 5 has frequency higher than movies rating less than or equal to 5. It shows that directors are well aware of delivering quality content among the audience

# Research Question 8: What is the vote average of most popular movie?

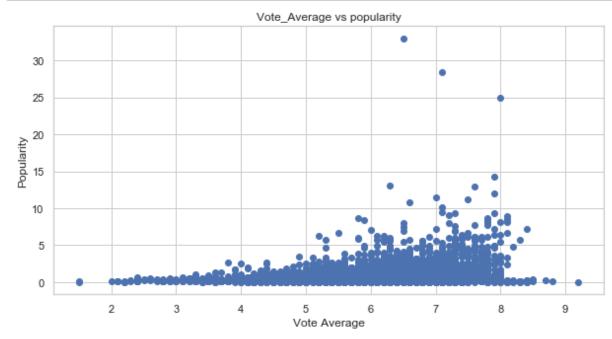
```
In [63]: #get the vote average of popular movie
    df_tmdb[df_tmdb['popularity']==max_function('popularity')]['vote_averag
    e']
Out[63]: 0     6     5
```

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```
Name: vote_average, dtype: float64
```

```
In [64]: #visualizing the data using scatter plot
    x = df_tmdb['vote_average']
    y = df_tmdb['popularity']

plt.scatter(x, y)
    plt.xlabel("Vote Average")
    plt.ylabel("Popularity")
    plt.title("Vote_Average vs popularity")
    plt.show()
```



Movies having rating greater than 5 seems to be very popular

## Research Question 9: Find the revenue of highest budget movie?

```
In [66]: #getting revenue of highest budget movie
    df_tmdb[df_tmdb['budget']==max_function('budget')]['revenue']

Out[66]: 2244    11087569.0
    Name: revenue, dtype: float64
```

## Research Question 10: Revenue of Most Popular movie?

```
In [68]: #get revenue of most popular movie
    df_tmdb[df_tmdb['popularity']==max_function('popularity')]['revenue']
Out[68]: 0    1.513529e+09
    Name: revenue, dtype: float64
```

# 4.Conclusions

- 1. The movie 'The Story of Film: An Odyssey' has runtime 900 min. This is because many parts are counted together.
- 1. Movie length less than or equal to 2hrs is the ideal length for production.
- Year 1961 has 31(lowest) and 2014 has 700(highest) numbers of movie released. This is because of evolution in technologies and public demand has raised the production of more movies year to year
- 1. According to dataset Woody Allen has directed maximum movies (45) so far.
- 1. The Story of Film: An Odyssey has the maximum vote average (9.2) whereas Transmorphers and Manos: The Hands of Fate has the lowest rating(1.5). It shows that people are interested in quality content.

- 1. Most popular movie has the rating 6.5 and revenue earned is 1513528810(\$).
- 1. Movie with highest budget had earned (11087569)(\$).

#### Limitations

- 1. This study has limitations of dealing with NaN values. It affects the process of data analysis. NAN values limit our scope of exploration when they are in significant amount. Sometimes deleting all these makes our data monotonous.
- 2. The data given to us was sufficient but columns containing outliers made the analysis less interesting.

This is how i conclude my General Data analysis of Movie data set!

In [ ]: