# Project: Investigate a Dataset - [TMDB 5000 Movie data]

### **Table of Contents**

- Introduction
- Data Wrangling
- Exploratory Data Analysis
- Conclusions

# Introduction

# **Dataset Description**

This dataset was taken from the <u>The movie database (TMDb) (https://www.kaggle.com/datasets/tmdb/themoviedb.org)</u>, containing information about 10000 movies released between the years 2015 and 1960.

Number of Rows: 10866

Number of columns: 20

#### Columns:

- id : Identification number
- imdb\_id : IMDb identification number
- popularity : Popularity of the movie in numbers
- budget : Budget of the movie
- revenue : Revenue of the movie
- original title: Title of the movie
- · cast: List of actors
- homepage : Website homepage of the movie
- director : Director of the movie
- tagline : The film's advertising slogan
- **keywords** : Keywords related to the movie
- overview : Overview of the movie's plot
- runtime : Screentime/How long is the movie
- genres : Genre of the movie (Action, Comedy, Drama, Romance...)
- production\_companies : Companies that produced the movie
- release date: Release date of the movie
- vote\_count : Number of people voting for the movie on IMDb
- vote\_average : Average vote of people voting for the movie
- release\_year : Release year of the movie
- budget adj : Budget of the movie with inflation from 2010 in dollars
- revenue\_adj : Revenue of the movie with inflation from 2010 in dollars

# **Question(s) for Analysis**

After taking a look at the dataset, there are multiple questions that popped out in my mind regarding some feature and the relationships between them.

**Question 1:** Which genres are the most popular from year to year?

Question 2: Which movies have the most profit? and in which year they were released?

**Question 3:** What kind of characteristics are associated with movies having high revenues?

**Question 4:** Which movies have the highest budgets but are low on vote counts?

Question 5: Which movies have the lowest budgets but are very high on vote counts?

**Question 6:** what are the movies that flopped and topped the most in terms of profit and votes? and who was their cast/director?

**Question 7:** Is the screen runtime related to the success or flopping of the movies?

Question 8: What is the runtime of the most successful movies between the years 2015 and 1960?

Question 9: Which production companies that released the most successful movies each year?

Question 10: Do movies with more profit have more popularity as well?

Question 11: What is the relationship between Budget and other features in the dataset?

**Question 12:** Which cast participated in the most successful/flopped movies?

```
In [1]: import pandas as pd import matplotlib.pyplot as plt import numpy as np import seaborn as sns

%matplotlib inline #to make visualisations be plotted inline within the notebook
```

```
In [2]: # Upgrade pandas to use dataframe.explode() function.
#!pip install --upgrade pandas==0.25.0
```

# **Data Wrangling**

In [3]: # Load your data and print out a few lines. Perform operations to inspect data
df = pd.read\_csv('tmdb-movies.csv', index\_col='id')
df.head()

# Out[3]:

	imdb_id	popularity	budget	revenue	original_title	cast	
id							
135397	tt0369610	32.985763	150000000	1513528810	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	http://ww
76341	tt1392190	28.419936	150000000	378436354	Mad Max: Fury Road	Tom Hardy Charlize Theron Hugh Keays- Byrne Nic	http://www.
262500	tt2908446	13.112507	110000000	295238201	Insurgent	Shailene Woodley Theo James Kate Winslet Ansel	http://www.thedivergentser
140607	tt2488496	11.173104	200000000	2068178225	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	http://www.starwars.
168259	tt2820852	9.335014	190000000	1506249360	Furious 7	Vin Diesel Paul Walker Jason Statham Michelle	http:

ut[4]:	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director
	21	tt0060371	0.080598	0	0	The Endless Summer	Michael Hynson Robert August Lord 'Tally Ho' B	NaN	Bruce Brown
	20379	tt0060472	0.065543	0	0	Grand Prix	James Garner Eva Marie Saint Yves Montand Tosh	NaN	John Frankenheimer
	39768	tt0060161	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z	NaN	Eldar Ryazanov
	21449	tt0061177	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh	NaN	Woody Allen
	22293	tt0060666	0.035919	19000	0	Manos: The Hands of Fate	Harold P. Warren Tom Neyman John Reynolds Dian	NaN	Harold P. Warren

We can notice that there are some columns having values separated by '|'

```
In [5]: list_1 = ['cast', 'director', 'keywords', 'genres', 'production_companies']
```

Some information about the data:

In [4]: df.tail()

```
<class 'pandas.core.frame.DataFrame'>
Int64Index: 10866 entries, 135397 to 22293
Data columns (total 20 columns):
    Column
                          Non-Null Count
                                          Dtype
---
    -----
                          -----
                                          ----
0
    imdb_id
                          10856 non-null
                                          object
1
    popularity
                          10866 non-null float64
2
    budget
                          10866 non-null int64
3
    revenue
                          10866 non-null int64
4
    original_title
                          10866 non-null
                                          object
5
    cast
                          10790 non-null object
                                          object
6
    homepage
                          2936 non-null
7
    director
                          10822 non-null object
8
    tagline
                          8042 non-null
                                          object
9
                                          object
    keywords
                          9373 non-null
10 overview
                          10862 non-null
                                          object
11 runtime
                          10866 non-null
                                          int64
12 genres
                          10843 non-null
                                          object
13 production_companies 9836 non-null
                                          object
                                          object
14
    release_date
                          10866 non-null
15 vote_count
                          10866 non-null
                                          int64
                          10866 non-null float64
16 vote_average
17
    release_year
                          10866 non-null int64
    budget_adj
                          10866 non-null float64
18
19
    revenue_adj
                          10866 non-null float64
dtypes: float64(4), int64(5), object(11)
memory usage: 1.7+ MB
```

```
In [7]: df.shape
```

In [6]: | df.info()

Out[7]: (10866, 20)

The dataset has 10866 rows and 20 columns

In [8]: df.describe()

Out[8]:

	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	
count	10866.000000	1.086600e+04	1.086600e+04	10866.000000	10866.000000	10866.000000	10866.000000	_: :
mean	0.646441	1.462570e+07	3.982332e+07	102.070863	217.389748	5.974922	2001.322658	:
std	1.000185	3.091321e+07	1.170035e+08	31.381405	575.619058	0.935142	12.812941	;
min	0.000065	0.000000e+00	0.000000e+00	0.000000	10.000000	1.500000	1960.000000	(
25%	0.207583	0.000000e+00	0.000000e+00	90.000000	17.000000	5.400000	1995.000000	(
50%	0.383856	0.000000e+00	0.000000e+00	99.000000	38.000000	6.000000	2006.000000	(
75%	0.713817	1.500000e+07	2.400000e+07	111.000000	145.750000	6.600000	2011.000000	:
max	32.985763	4.250000e+08	2.781506e+09	900.000000	9767.000000	9.200000	2015.000000	2

We can notice that there are some movies having the budget and revenue equals to 0, these can be considered as NaN values.

### Types of features:

```
In [10]:
         df.dtypes
Out[10]: imdb_id
                                    object
         popularity
                                   float64
         budget
                                     int64
         revenue
                                     int64
                                    object
         original_title
                                    object
         cast
                                    object
         homepage
                                    object
         director
         tagline
                                    object
         keywords
                                    object
                                    object
         overview
         runtime
                                     int64
                                    object
         aenres
         production_companies
                                    object
         release_date
                                    object
         vote_count
                                     int64
         vote_average
                                   float64
         release_year
                                     int64
         budget_adj
                                   float64
         revenue_adj
                                   float64
         dtype: object
```

We can notice that the release date is an object and not in a date\_time type

### Checking for duplicate rows:

checking for the duplicated row:

In [12]:	df[df	.duplica	ted(keep=	False)]							
Out[12]:	id	imdb_id	popularity	budget	revenue	original_title	cast	homepage	director	tagline	
	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo Kelly Overton Cary- Hiroyuki Tagawa Ian	NaN	Dwight H. Little	Survival is no game	a
	42194	tt0411951	0.59643	30000000	967000	TEKKEN	Jon Foo Kelly Overton Cary- Hiroyuki Tagawa Ian	NaN	Dwight H. Little	Survival is no game	a

### Number of rows with missing data:

```
In [13]: df.isnull().values.ravel().sum()
Out[13]: 13434
```

To check if we have missing values for each feature:

```
df.isnull().sum()
In [14]:
Out[14]: imdb_id
                                     10
          popularity
                                      0
          budget
                                      0
          revenue
                                      0
          original_title
                                      0
                                     76
          cast
          homepage
                                   7930
          director
                                     44
          tagline
                                   2824
          keywords
                                   1493
          overview
                                      4
          runtime
                                      0
                                     23
          genres
          production_companies
                                   1030
          release_date
                                      0
          vote_count
                                      0
                                      0
          vote_average
          release_year
                                      0
          budget_adj
                                      0
                                      0
          revenue_adj
          dtype: int64
```

### Checking for unique values:

```
In [15]:
         df.nunique()
Out[15]: imdb_id
                                  10855
         popularity
                                  10814
         budget
                                    557
         revenue
                                   4702
         original_title
                                  10571
         cast
                                  10719
         homepage
                                   2896
         director
                                   5067
         tagline
                                   7997
         keywords
                                   8804
         overview
                                  10847
         runtime
                                    247
         aenres
                                   2039
         production_companies
                                   7445
         release_date
                                   5909
         vote_count
                                   1289
         vote_average
                                     72
                                     56
         release_year
         budget_adj
                                   2614
         revenue_adj
                                   4840
         dtype: int64
In [16]: | df['original_title'].unique() #names of unique movie titles
Out[16]: array(['Jurassic World', 'Mad Max: Fury Road', 'Insurgent', ...,
                 'Beregis Avtomobilya', "What's Up, Tiger Lily?",
                 'Manos: The Hands of Fate'], dtype=object)
In [17]: df['original_title'].nunique() #number of unique movie titles
Out[17]: 10571
```

# **Data Cleaning**

I noticed that there are some columns we might not need in further analysis such as: imdb\_id since we already have an id column, homepage, tagline, overview, and keywords since we're not doing a movie recommendation in this project.

111 [20].	ui iiica	u(±)							
Out[20]:		popularity	budget	revenue	original_title	cast	director	runtime	g
	id								
	135397	32.985763	150000000	1513528810	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	124	Action Adventure So

### **Dropping duplicates:**

```
In [21]: df.drop_duplicates(inplace=True)
```

checking for duplicates again:

In [20]: df head(1)

```
In [22]: df.duplicated().any()
```

Out[22]: False

### **Dropping null values:**

```
In [23]: df.dropna(inplace=True)
```

checking for null values again:

```
In [24]: | df.isna().any()
Out[24]: popularity
                                   False
          budget
                                   False
          revenue
                                   False
          original_title
                                   False
                                   False
          cast
          director
                                   False
          runtime
                                   False
          genres
                                   False
          production_companies
                                   False
          release_date
                                   False
          vote_count
                                   False
          vote_average
                                   False
          release_year
                                   False
          budget_adj
                                   False
          revenue_adj
                                   False
          dtype: bool
```

I noticed in the first part of this project that the release date of each movie is not in date format but in object format. So, we should change it:

```
In [25]: df['release_date'].dtype
Out[25]: dtype('0')
In [26]: release_date = pd.to_datetime(df['release_date'])
In [27]: release_date
Out[27]: id
                  2015-06-09
         135397
         76341
                  2015-05-13
         262500
                  2015-03-18
         140607
                  2015-12-15
         168259
                  2015-04-01
         21
                  2066-06-15
         20379
                  2066-12-21
         39768
                  2066-01-01
         21449
                  2066-11-02
         22293
                  2066-11-15
         Name: release_date, Length: 9772, dtype: datetime64[ns]
```

I encountered a problem where each release date written for example as '11/15/66' is going to be converted to '2066-11-15' instead of 1966 as noted in the release year

```
In [28]: | #changing the release_date year part with the release_year values :
         df['release_date'] = df.apply(lambda x: x.release_date[:-2] + str(x.release_yea
         r), axis=1)
         df['release_date'] = pd.to_datetime(df['release_date'])
         df['release_date']
Out[28]: id
         135397
                  2015-06-09
         76341
                  2015-05-13
         262500
                  2015-03-18
         140607
                  2015-12-15
         168259
                  2015-04-01
         21
                  1966-06-15
         20379
                  1966-12-21
         39768
                  1966-01-01
         21449
                  1966-11-02
         22293
                  1966-11-15
         Name: release_date, Length: 9772, dtype: datetime64[ns]
```

as noted in the first part of the notebook, i noticed that some of the budget and revenue values are zeros:

In [29]: | df.loc[(df['budget']==0.0000000e+00) & (df['revenue']==0.000000e+00)]

Out[29]:

	popularity	budget	revenue	e original_title cast		director	runtime	
id								
347096	2.165433	0	0	Mythica: The Darkspore	Melanie Stone Kevin Sorbo Adam Johnson Jake St	Anne K. Black	108	Action Adver
308369	2.141506	0	0	Me and Earl and the Dying Girl	Thomas Mann RJ Cyler Olivia Cooke Connie Britt	Alfonso Gomez-Rejon	105	Со
370687	1.876037	0	0	Mythica: The Necromancer	Melanie Stone Adam Johnson Kevin Sorbo Nicola	A. Todd Smith	0	Fantasy Actic
326359	1.724712	0	0	Frozen Fever	Kristen Bell Idina Chris Menzel Jonathan Buck Jennife Groff Josh Lee		8	Adventure Anin
254302	1.661789	0	0	High-Rise	Tom Hiddleston Sienna Miller Jeremy Irons Luke	Ben Wheatley	119	Action Dr
5060	0.087034	0	0	Carry On Screaming!	Kenneth Williams Jim Dale Harry H. Corbett Joa	Gerald Thomas	87	
21	0.080598	0	0	The Endless Summer	Michael Hynson Robert August Lord 'Tally Ho' B	Bruce Brown	95	I
20379	0.065543	0	0	Grand Prix	James Garner Eva Marie Saint Yves Montand Tosh	John Frankenheimer	176	Action Adve
39768	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z	Eldar Ryazanov	94	Mys
21449	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh	Woody Allen	80	Ac

3806 rows × 15 columns

In [30]: df.loc[df['revenue']==0.000000e+00]

Out[30]:

	popularity	budget	revenue	original_title	cast	director	runtime	
id								
265208	2.932340	30000000	0	Wild Card	Jason Statham Michael Angarano Milo Ventimigli	Simon West	92	Thriller
334074	2.331636	20000000	0	Survivor	Pierce Brosnan Milla Jovovich Dylan McDermott	James McTeigue	96	Crime  <sup>-</sup>
347096	2.165433	0	0	Mythica: The Darkspore	Melanie Stone Kevin Sorbo Adam Johnson Jake St	Anne K. Black	108	Action Adver
308369	2.141506	0	0	Me and Earl and the Dying Girl	Thomas Mann RJ Cyler Olivia Cooke Connie Britt	Alfonso Gomez-Rejon	105	Сс
370687	1.876037	0	0	Mythica: The Necromancer	Melanie Stone Adam Johnson Kevin Sorbo Nicola	A. Todd Smith	0	Fantasy Acti
21	0.080598	0	0	The Endless Summer	Michael Hynson Robert August Lord 'Tally Ho' B	Bruce Brown	95	I
20379	0.065543	0	0	Grand Prix	James Garner Eva Marie Saint Yves Montand Tosh	John Frankenheimer	176	Action Adve
39768	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z	Eldar Ryazanov	94	Mys
21449	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh	Woody Allen	80	Ac
22293	0.035919	19000	0	Manos: The Hands of Fate	Harold P. Warren Tom Neyman John Reynolds Dian	Harold P. Warren	74	

5022 rows × 15 columns

In [31]:	df.loc[df['budget']==0.000000e+00]
Out[31]:	

	popularity	budget	revenue	original_title	cast	director	runtime	
id								
280996	3.927333	0	29355203	Mr. Holmes	lan McKellen Milo Parker Laura Linney Hattie M	Bill Condon	103	Mys
339527	3.358321	0	22354572	Solace	Abbie Cornish Jeffrey Dean Morgan Colin Farrel	Afonso Poyart	101	Crime Dra
284289	2.272044	0	45895	Beyond the Reach	Michael Douglas Jeremy Irvine Hanna Mangan Law	Jean-Baptiste Léonetti	95	
347096	2.165433	0	0	Mythica: The Darkspore	Melanie Stone Kevin Sorbo Adam Johnson Jake St	Anne K. Black	108	Action Advent
308369	2.141506	0	0	Me and Earl and the Dying Girl	Thomas Mann RJ Cyler Olivia Cooke Connie Britt	Alfonso Gomez-Rejon	105	Con
						•••		
5060	0.087034	0	0	Carry On Screaming!	Kenneth Williams Jim Dale Harry H. Corbett Joa	Gerald Thomas	87	
21	0.080598	0	0	The Endless Summer	Michael Hynson Robert August Lord 'Tally Ho' B	Bruce Brown	95	D
20379	0.065543	0	0	Grand Prix	James Garner Eva Marie Saint Yves Montand Tosh	John Frankenheimer	176	Action Adver
39768	0.065141	0	0	Beregis Avtomobilya	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z	Eldar Ryazanov	94	Myste
21449	0.064317	0	0	What's Up, Tiger Lily?	Tatsuya Mihashi Akiko Wakabayashi Mie Hama Joh	Woody Allen	80	Acti

4751 rows × 15 columns

We notice that some of the movies have a revenue but the budget is zero and vice versa! and that is really odd and not realistic. We should change the value of each budget to the mean to make it more realistic, and vice versa

Checking how many zero values are there in each feature :

```
In [32]: df[['budget', 'revenue']].apply(lambda x: x == 0).sum()
```

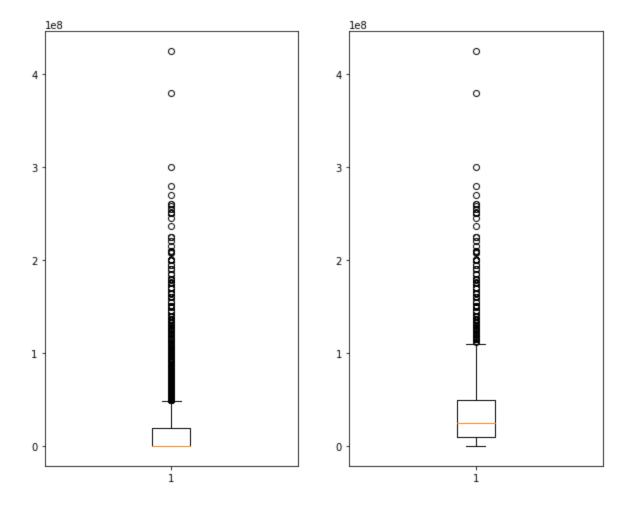
We have to see first if dropping the zero values of budgets and revenues will affect our data, and the information related to each feature:

```
In [33]:
         def entropy(Y):
             Also known as Shanon Entropy
             HHHH
             unique, count = np.unique(Y, return_counts=True, axis=0)
             prob = count/len(Y)
             en = np.sum((-1)*prob*np.log2(prob))
             return en
In [34]: entropy(df['budget'])
Out[34]: 4.59288636847125
In [35]: |entropy(df['revenue'])
Out[35]: 6.899474856143105
         df_cleaned = df[(df['budget'] != 0) & (df['revenue'] != 0)]
In [36]:
         entropy(df_cleaned['budget'])
Out[36]: 6.814872606606914
In [37]: entropy(df_cleaned['revenue'])
Out[37]: 11.833355099520029
```

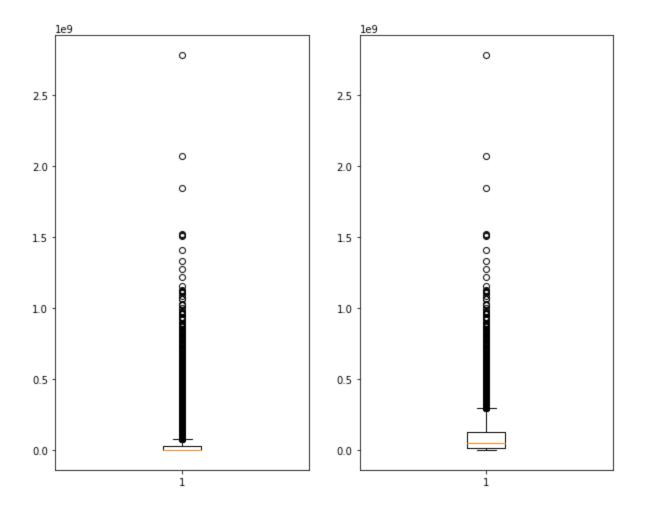
Increasing in shanon's entropy is an indication of information loss: We don't need to drop all the rows containing zeros in budget and revenue columns

we can also see this impact with boxplots:

Information loss after dropping all zero values in budget



Information loss after dropping all zero values in revenue



Grouping the budget mean by year:

```
In [40]: mean_budg = df.groupby('release_year')[['budget']].mean()
           mean_budg.head(10)
Out[40]:
                             budget
           release_year
                       6.892796e+05
                  1960
                  1961 1.537900e+06
                  1962 1.824071e+06
                  1963 2.156809e+06
                  1964 9.630039e+05
                  1965 2.064856e+06
                  1966
                       1.308064e+06
                  1967 2.795889e+06
                  1968 1.944297e+06
                  1969 1.452727e+06
```

### Grouping mean revenue by year:

```
mean_rev = df.groupby('release_year')[['revenue']].mean()
In [41]:
         mean_rev.head(10)
Out[41]:
```

### revenue

release_year	
1960	4.531406e+06
1961	1.125734e+07
1962	7.185995e+06
1963	5.511911e+06
1964	8.316629e+06
1965	1.347300e+07
1966	1.925834e+06
1967	2.049541e+07
1968	7.154945e+06
1969	8.412313e+06

### Replacing zero values of budget and revenue:

Replacing zero values in budget when revenue isn't null:

```
zero_budg = df[(df.budget == 0) & (df.revenue != 0)] #budget equal to zero when
In [42]:
         revenue isn't null
```

```
In [43]: """
Function to replace zero values in budget and revenue
"""

def replace_zeros(row : pd.DataFrame, columns : list, df: pd.DataFrame):
    if (row[columns]==0).all():
        row[columns] = df.loc[row.release_year, columns]
    return row

In [44]: zero_budg = zero_budg.apply(lambda x: replace_zeros(x, ['budget'], mean_budg),a
    xis=1) #replacing budget with mean value

In [45]: df[df.index.isin(zero_budg.index)] = zero_budg #replacing budget zero values in
    the dataset
```

check again if we filled the zero budget values when the revenue isn't null:

Do the same to revenue when budget isn't null but revenue is equal to zero:

```
In [47]: zero_revenue = df[(df.revenue == 0) & (df.budget != 0)] #revenue zero values wh
    en the budget isn't null

In [48]: zero_revenue = zero_revenue.apply(lambda x: replace_zeros(x, ['revenue'], mean_
    rev),axis=1) #replacing zero value revenues with the mean

In [49]: df[df.index.isin(zero_revenue.index)] = zero_revenue #replacing budget zero values in the dataset
```

check again if we filled the zero revenue values when the budget isn't null:

I also noticed that the runtime also has some zero values which is unrealistic! to tackle this problem we should replace each zero runtime with the mean value from each year

In [51]: zero\_runtime = df[df['runtime'] == 0]
zero\_runtime

Out[51]:

	popularity	budget	revenue	original_title	cast	director	runtime	
id								
370687	1.876037	0.0	0.000000e+00	Mythica: The Necromancer	Melanie Stone Adam Johnson Kevin Sorbo Nicola	A. Todd Smith	0	Fantasy A
361931	0.357654	0.0	0.000000e+00	Ronaldo	Cristiano Ronaldo	Anthony Wonke	0	
353345	0.218528	0.0	0.000000e+00	The Exorcism of Molly Hartley	Sarah Lind Devon Sawa Gina Holden Peter MacNei	Steven R. Monroe	0	
333653	0.176744	0.0	0.000000e+00	If There Be Thorns	Heather Graham Jason Lewis Rachael Carpani Mas	Nancy Savoca	0	Т
286372	0.037459	3250000.0	3.831440e+07	Treehouse	J. Michael Trautmann Dana Melanie Daniel Fredr	Michael G. Bartlett	0	Thriller
286256	0.036904	0.0	0.000000e+00	Tim Maia	Robson Nunes Babú Santana Alinne Moraes Cauã	Mauro Lima	0	Documenta
20414	0.082898	0.0	0.000000e+00	Grande, grosso e Verdone	Carlo Verdone Claudia Gerini Eva Riccobono Vit	Carlo Verdone	0	
289097	0.095583	0.0	0.000000e+00	Cell 213	Bruce Greenwood Eric Balfour Michael Rooker De	Stephen Kay	0	
158150	0.026459	0.0	0.000000e+00	How to Fall in Love	Brooke D'Orsay Eric Mabius Jody Thompson Gina 	Mark Griffiths	0	Come
224815	0.417739	0.0	0.000000e+00	Skinwalker Ranch	Steve Berg Kyle Davis Erin Cahill Jon Gries De	Devin McGinn	0	Thriller
248842	0.165765	0.0	0.000000e+00	The Food Guide to Love	Richard Coyle Leonor Watling Ginés GarcÃa Mi	Dominic Harari Teresa Pelegri	0	Ro
191562	0.147188	0.0	0.000000e+00	Go Goa Gone	Saif Ali Khan Anand Tiwari Vir Das Pooja Gupta	Krishna D.K. Raj Nidimoru	0	
13713	0.071872	0.0	0.000000e+00	Jean-Philippe	Fabrice Luchini Johnny Hallyday Jackie Berroye	Laurent Tuel	0	

#### Grouping the runtime by year:

```
In [52]:
          mean_runtime = df.groupby('release_year')[['runtime']].mean()
          mean_runtime.head(10)
Out[52]:
                        runtime
           release_year
                 1960
                     110.656250
                 1961 119.866667
                 1962 125.833333
                 1963 111.323529
                 1964 111.195122
                 1965 119.294118
                 1966 108.590909
                 1967 109.416667
                 1968 110.540541
                 1969 110.310345
In [53]: zero_runtime = zero_runtime .apply(lambda x: replace_zeros(x, ['runtime'], mea
          n_runtime), axis=1) #replacing runtime with mean value
          df[df.index.isin(zero_runtime.index)] = zero_runtime #replacing runtime zero va
          lues in the dataset
```

checking again for zero runtime:

I noticed that there is a row where we have two directors at the same time, So I'm going to use the pandas explode function to make two rows for each director

In [57]: explode(df, 'director')

Out[57]:

	popularity	budget	revenue	original_title	cast	director	runtime	
id								
135397	32.985763	150000000.0	1.513529e+09	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	124.0	Acti
76341	28.419936	150000000.0	3.784364e+08	Mad Max: Fury Road	Tom Hardy Charlize Theron Hugh Keays-Byrne Nic	George Miller	120.0	Acti
262500	13.112507	110000000.0	2.952382e+08	Insurgent	Shailene Woodley Theo James Kate Winslet Ansel	Robert Schwentke	119.0	
140607	11.173104	200000000.0	2.068178e+09	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	136.0	Acti
168259	9.335014	190000000.0	1.506249e+09	Furious 7	Vin Diesel Paul Walker Jason Statham Michelle	James Wan	137.0	
21	0.080598	0.0	0.000000e+00	The Endless Summer	Michael Hynson Robert August Lord 'Tally Ho' B	Bruce Brown	95.0	
20379	0.065543	0.0	0.000000e+00	Grand Prix	James Garner Eva Marie Saint Yves Montand Tosh	John Frankenheimer	176.0	Ac
39768	0.065141	0.0	0.000000e+00	Beregis Avtomobilya	Innokentiy Smoktunovskiy Oleg Efremov Georgi Z	Eldar Ryazanov	94.0	
21449	0.064317	0.0	0.000000e+00	What's Up, Tiger Lily?	Tatsuya Mihashi∣Akiko Wakabayashi Mie Hama∣Joh	Woody Allen	80.0	
22293	0.035919	19000.0	1.925834e+06	Manos: The Hands of Fate	Harold P. Warren Tom Neyman John Reynolds Dian	Harold P. Warren	74.0	

10708 rows × 15 columns

checking for statistical info about the data:

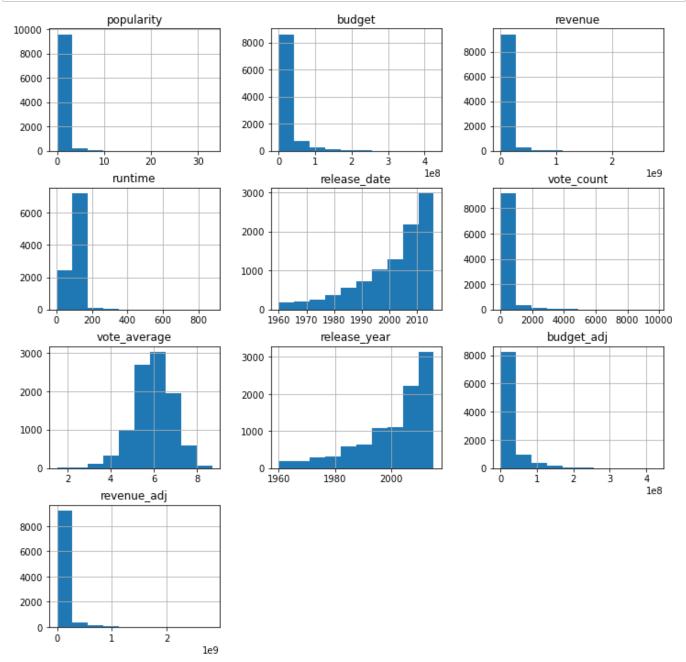
In [58]: df.describe()
Out[58]:

	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	bι
count	9772.000000	9.772000e+03	9.772000e+03	9772.000000	9772.000000	9772.000000	9772.000000	9.77
mean	0.694721	1.753632e+07	4.972249e+07	103.057654	239.312014	5.963528	2000.878428	1.94
std	1.036931	3.185817e+07	1.215553e+08	27.623684	603.011504	0.913174	13.036794	3.56
min	0.000188	0.000000e+00	0.000000e+00	3.000000	10.000000	1.500000	1960.000000	0.00
25%	0.232710	0.000000e+00	0.000000e+00	91.000000	18.000000	5.400000	1994.000000	0.00
50%	0.419762	5.000000e+06	6.865676e+06	100.000000	46.000000	6.000000	2005.000000	3.06
75%	0.776408	2.000000e+07	4.946531e+07	112.000000	173.000000	6.600000	2011.000000	2.46
max	32.985763	4.250000e+08	2.781506e+09	877.000000	9767.000000	8.700000	2015.000000	4.25

# **Exploratory Data Analysis**

Question1: Which genres are the most popular from year to year?

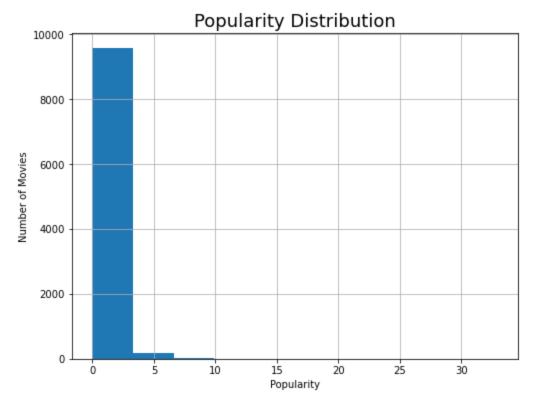
First i want to see the distribution of each feature:



we can see that there are some variables that are skewed either to the right such as : budget and budget\_adj , or to the left such as : release\_year and release\_date. But some variables have a normal distribution such as vote\_average

### **Distribution of popularity**:

```
In [60]: df.popularity.hist(figsize=(8, 6))
    plt.title("Popularity Distribution", fontsize=18);
    plt.xlabel("Popularity")
    plt.ylabel("Number of Movies")
    plt.show();
```



### Most popular movie of all between the years 2015 and 1960 :

```
In [61]: df.loc[df['popularity'].idxmax()] #idxmax : returns the index of the first occu
         rrence of maximum over requested column
Out[61]: popularity
                                                                           32.985763
         budget
                                                                         150000000.0
         revenue
                                                                        1513528810.0
         original_title
                                                                      Jurassic World
         cast
                                  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
         director
                                                                     Colin Trevorrow
         runtime
                                                                                124.0
         genres
                                          Action|Adventure|Science Fiction|Thriller
                                  Universal Studios | Amblin Entertainment | Legenda...
         production_companies
         release_date
                                                                 2015-06-09 00:00:00
         vote_count
                                                                                 5562
         vote_average
                                                                                  6.5
         release_year
                                                                                 2015
         budget_adj
                                                                    137999939.280026
         revenue_adj
                                                                     1392445892.5238
         Name: 135397, dtype: object
```

Most popular movie : Jurassic World(2015)

```
In [62]: #most popular movies :
    most_pop = df.sort_values('popularity', axis=0, ascending=False).head(10)
    most_pop
```

### Out[62]:

	popularity	budget	revenue	original_title	cast	director	runtime	
id								
135397	32.985763	150000000.0	1.513529e+09	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	124.0	<i>‡</i>
76341	28.419936	150000000.0	3.784364e+08	Mad Max: Fury Road	Tom Hardy Charlize Theron Hugh Keays- Byrne Nic	George Miller	120.0	1
157336	24.949134	165000000.0	6.217525e+08	Interstellar	Matthew McConaughey Jessica Chastain Anne Hath	Christopher Nolan	169.0	А
118340	14.311205	170000000.0	7.733124e+08	Guardians of the Galaxy	Chris Pratt Zoe Saldana Dave Bautista Vin Dies	James Gunn	121.0	
262500	13.112507	110000000.0	2.952382e+08	Insurgent	Shailene Woodley Theo James Kate Winslet Ansel	Robert Schwentke	119.0	
100402	12.971027	170000000.0	7.147666e+08	Captain America: The Winter Soldier	Chris Evans Scarlett Johansson Sebastian Stan	Joe Russo Anthony Russo	136.0	ļ
11	12.037933	11000000.0	7.753980e+08	Star Wars	Mark Hamill Harrison Ford Carrie Fisher Peter	George Lucas	121.0	ļ
245891	11.422751	20000000.0	7.873990e+07	John Wick	Keanu Reeves Michael Nyqvist Alfie Allen Wille	Chad Stahelski David Leitch	101.0	
140607	11.173104	200000000.0	2.068178e+09	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	136.0	ļ
131631	10.739009	125000000.0	7.521002e+08	The Hunger Games: Mockingjay - Part 1	Jennifer Lawrence Josh Hutcherson Liam Hemswor	Francis Lawrence	123.0	

```
In [63]: most_pop_by_year = most_pop.groupby(['release_year'])['genres'].value_counts()
most_pop_by_year
```

Out[63]:	release_year	genres	
	1977	Adventure Action Science Fiction	1
	2014	Action Adventure Science Fiction	1
		Action Science Fiction Adventure	1
		Action Thriller	1
		Adventure Drama Science Fiction	1
		Science Fiction Adventure Thriller	1
	2015	Action Adventure Science Fiction Thriller	2
		Action Adventure Science Fiction Fantasy	1
		Adventure Science Fiction Thriller	1
	Name: genres,	dtype: int64	

# Question 2: Which movies have the most profit ? and in which year they were released ?

profit of movies:

```
In [64]: | df['profit'] = df.revenue - df.budget
         df.profit.head()
Out[64]: id
         135397
                   1.363529e+09
         76341
                   2.284364e+08
         262500
                   1.852382e+08
         140607
                   1.868178e+09
         168259
                   1.316249e+09
         Name: profit, dtype: float64
In [65]:
        df.profit.describe()
Out[65]: count
                  9.772000e+03
         mean
                  3.218616e+07
         std
                  1.006611e+08
         min
                -4.139124e+08
         25%
                  0.000000e+00
         50%
                  0.000000e+00
                  3.244257e+07
         75%
         max
                  2.544506e+09
         Name: profit, dtype: float64
```

movies having the most profit (having profit > 75%):

```
successful_movies.sort_values('profit', axis=0, ascending=False).head(5)
Out[66]:
                    popularity
                                   budget
                                                revenue original title
                                                                                        director runtime
                                                                                 cast
                 id
                                                                                 Sam
                                                                       Worthington|Zoe
                                                                                         James
                                                                                                        Action|Adv
                                                                                                  162.0
             19995
                     9.432768 237000000.0 2.781506e+09
                                                              Avatar
                                                                     Saldana|Sigourney
                                                                                       Cameron
                                                                           Weaver|S...
                                                                              Harrison
                                                           Star Wars:
                                                                            Ford|Mark
                                                                                                               Α
                                                                                           J.J.
            140607
                    11.173104 200000000.0 2.068178e+09
                                                           The Force
                                                                                                  136.0
                                                                          Hamill|Carrie
                                                                                        Abrams
                                                            Awakens
                                                                       Fisher|Adam D...
                                                                       Winslet|Leonardo
                                                                                         James
               597
                     4.355219 200000000.0 1.845034e+09
                                                              Titanic
                                                                                                  194.0
                                                                       DiCaprio|Frances
                                                                                       Cameron
                                                                             Fisher|...
                                                                       Chris Pratt|Bryce
                                                             Jurassic
                                                                               Dallas
                                                                                          Colin
            135397
                    32.985763 150000000.0 1.513529e+09
                                                                                                  124.0
                                                               World
                                                                         Howard|Irrfan Trevorrow
                                                                             Khan|Vi...
                                                                        Vin Diesel|Paul
                                                                         Walker|Jason
                                                                                         James
            168259
                     9.335014 190000000.0 1.506249e+09
                                                            Furious 7
                                                                                                  137.0
                                                                       Statham|Michelle
                                                                                          Wan
In [67]:
           successful_movies.groupby('release_year')['original_title'].value_counts()
Out[67]: release_year
                             original_title
           1960
                                                                       1
                             Spartacus
                                                                       1
           1961
                             One Hundred and One Dalmatians
                             West Side Story
                                                                       1
           1962
                                                                       1
                             Dr. No
                             How the West Was Won
                                                                       1
                                                                       . .
           2015
                             Unfriended
                                                                       1
                                                                       1
                             Vacation
                             Vice
                                                                       1
                             War Room
                                                                       1
                             Woman in Gold
           Name: original_title, Length: 2443, dtype: int64
```

successful\_movies = df[df.profit >= 3.244257e+07]

In [66]:

# Question 3: What kind of characteristics are associated with movies having high revenues ?

```
In [68]:
          df.revenue.describe()
Out[68]:
         count
                   9.772000e+03
                   4.972249e+07
          mean
          std
                   1.215553e+08
          min
                   0.000000e+00
          25%
                   0.000000e+00
          50%
                   6.865676e+06
          75%
                   4.946531e+07
                   2.781506e+09
          Name: revenue, dtype: float64
```

# movies having the highest revenues (having revenues > 75%):

In [69]: high\_movies = df[df.revenue >= 4.946531e+07] high\_movies.head(5)

Out[69]:

	popularity	budget	revenue	original_title	cast	director	runtime	
id								
135397	32.985763	150000000.0	1.513529e+09	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	124.0	Action Adve
76341	28.419936	150000000.0	3.784364e+08	Mad Max: Fury Road	Tom Hardy Charlize Theron Hugh Keays- Byrne Nic	George Miller	120.0	Action Adve
262500	13.112507	110000000.0	2.952382e+08	Insurgent	Shailene Woodley Theo James Kate Winslet Ansel	Robert Schwentke	119.0	Adve
140607	11.173104	200000000.0	2.068178e+09	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	136.0	Action Adve F
168259	9.335014	190000000.0	1.506249e+09	Furious 7	Vin Diesel Paul Walker Jason Statham Michelle 	James Wan	137.0	Actior

In [70]: high\_movies.describe()

Out[70]:

	popularity	budget	revenue	runtime	vote_count	vote_average	release_year	bι
count	2389.000000	2.389000e+03	2.389000e+03	2389.000000	2389.000000	2389.000000	2389.000000	2.38
mean	1.469329	4.887598e+07	1.730065e+08	111.191712	720.071578	6.163541	2002.665132	5.55
std	1.750423	4.765504e+07	1.990198e+08	27.111858	1039.334704	0.820476	9.606977	5.03
min	0.010335	3.000000e+00	4.946990e+07	4.000000	10.000000	2.900000	1960.000000	0.00
25%	0.555793	1.500000e+07	6.064831e+07	96.000000	115.000000	5.600000	1998.000000	1.84
50%	1.042281	3.500000e+07	1.011341e+08	107.000000	333.000000	6.200000	2004.000000	4.07
75%	1.765322	6.800000e+07	1.967812e+08	122.000000	852.000000	6.700000	2010.000000	8.00
max	32.985763	3.800000e+08	2.781506e+09	705.000000	9767.000000	8.300000	2015.000000	3.68

### Out[71]:

	original_title	popularity	release_date	profit	budget	revenue	vote_average
id							
135397	Jurassic World	32.985763	2015-06-09	1.363529e+09	1.500000e+08	1.513529e+09	6.5
76341	Mad Max: Fury Road	28.419936	2015-05-13	2.284364e+08	1.500000e+08	3.784364e+08	7.1
262500	Insurgent	13.112507	2015-03-18	1.852382e+08	1.100000e+08	2.952382e+08	6.3
140607	Star Wars: The Force Awakens	11.173104	2015-12-15	1.868178e+09	2.000000e+08	2.068178e+09	7.5
168259	Furious 7	9.335014	2015-04-01	1.316249e+09	1.900000e+08	1.506249e+09	7.3
	•••						
948	Halloween	1.198849	1978-10-25	6.970000e+07	3.000000e+05	7.000000e+07	7.3
8469	Animal House	1.157930	1978-07-27	1.383000e+08	2.700000e+06	1.410000e+08	6.7
6081	Revenge of the Pink Panther	1.090065	1978-07-19	4.615309e+07	3.426181e+06	4.957927e+07	6.2
11778	The Deer Hunter	0.959754	1978-12-08	3.500000e+07	1.500000e+07	5.000000e+07	7.4
16214	Hooper	0.044675	1978-07-28	7.457382e+07	3.426181e+06	7.800000e+07	6.0

2389 rows × 7 columns

# Question 4: Which movies have the highest budgets but are low on vote counts?

### Out[72]:

	original_title	release_date	budget	vote_count
id				
254263	The Swan Princess: A Royal Family Tale	2014-02-25	3.000000e+07	14
242166	Red Sky	2014-03-12	2.500000e+07	16
33870	Mao's Last Dancer	2009-10-01	2.500000e+07	16
66193	Sinners and Saints	2010-09-14	2.221868e+07	16
48495	Double Wedding	2010-07-20	1.040024e+08	12
2071	Shattered	1991-10-11	2.200000e+07	11
6470	Fire Birds	1990-05-25	2.200000e+07	15
22414	Postcards from the Edge	1990-09-12	2.200000e+07	15
46828	Son of the Pink Panther	1993-01-01	2.500000e+07	15
33157	Waterloo	1970-10-26	2.500000e+07	10

# Question 5: Which movies have the lowest budgets but are very high on vote counts?

it seems to be that there are no low budget movies that have very high vote counts

Question 6: what are the movies that flopped and topped the most in terms of profit and votes? and who was their cast/director?

# In [74]: #successful movies: s= successful\_movies.where(successful\_movies['vote\_count']> successful\_movies[ 'vote\_count'].quantile(0.75)) s[['original\_title', 'cast', 'director', 'release\_date']].head(15)

# Out[74]:

	original_title	cast	director	release_date
id				
135397	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	2015-06-09
76341	Mad Max: Fury Road	Tom Hardy Charlize Theron Hugh Keays- Byrne Nic	George Miller	2015-05-13
262500	Insurgent	Shailene Woodley Theo James Kate Winslet Ansel	Robert Schwentke	2015-03-18
140607	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	2015-12-15
168259	Furious 7	Vin Diesel Paul Walker Jason Statham Michelle	James Wan	2015-04-01
281957	The Revenant	Leonardo DiCaprio Tom Hardy Will Poulter Domhn	Alejandro González Iñárritu	2015-12-25
87101	Terminator Genisys	Arnold Schwarzenegger Jason Clarke Emilia Clar	Alan Taylor	2015-06-23
286217	The Martian	Matt Damon Jessica Chastain Kristen Wiig Jeff	Ridley Scott	2015-09-30
211672	Minions	Sandra Bullock Jon Hamm Michael Keaton Allison	Kyle Balda Pierre Coffin	2015-06-17
150540	Inside Out	Amy Poehler Phyllis Smith Richard Kind Bill Ha	Pete Docter	2015-06-09
206647	Spectre	Daniel Craig Christoph Waltz Léa Seydoux Ralp	Sam Mendes	2015-10-26
257344	Pixels	Adam Sandler Michelle Monaghan Peter Dinklage	Chris Columbus	2015-07-16
99861	Avengers: Age of Ultron	Robert Downey Jr. Chris Hemsworth Mark Ruffalo	Joss Whedon	2015-04-22
273248	The Hateful Eight	Samuel L. Jackson Kurt Russell Jennifer Jason	Quentin Tarantino	2015-12-25
260346	Taken 3	Liam Neeson Forest Whitaker Maggie Grace Famke	Olivier Megaton	2015-01-01

```
In [75]: #flopped movies:
     flopped_movies = df[df.profit < 3.244257e+07]
     flopped_movies[['original_title', 'cast', 'director', 'release_date']].head(15)</pre>
```

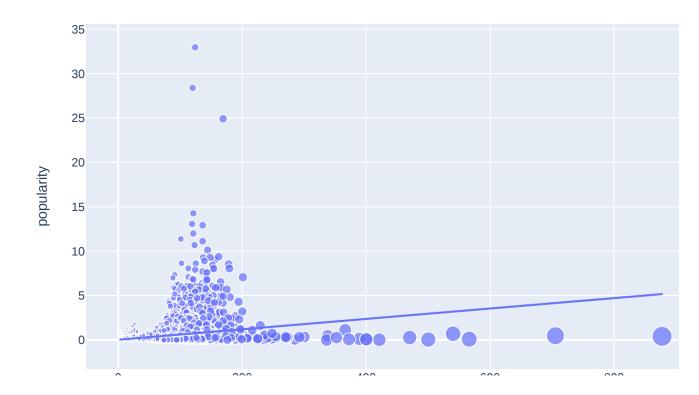
### Out[75]:

	original_title	cast	director	release_date
id				
76757	Jupiter Ascending	Mila Kunis Channing Tatum Sean Bean Eddie Redm	Lana Wachowski Lilly Wachowski	2015-02-04
264660	Ex Machina	Domhnall Gleeson Alicia Vikander Oscar Isaac S	Alex Garland	2015-01-21
158852	Tomorrowland	Britt Robertson George Clooney Raffey Cassidy	Brad Bird	2015-05-19
280996	Mr. Holmes	Ian McKellen Milo Parker Laura Linney Hattie M	Bill Condon	2015-06-19
264644	Room	Brie Larson Jacob Tremblay Joan Allen Sean Bri	Lenny Abrahamson	2015-10-16
339527	Solace	Abbie Cornish Jeffrey Dean Morgan Colin Farrel	Afonso Poyart	2015-09-03
241554	Run All Night	Liam Neeson Ed Harris Joel Kinnaman Boyd Holbr	Jaume Collet-Serra	2015-03-11
321697	Steve Jobs	Michael Fassbender Kate Winslet Seth Rogen Kat	Danny Boyle	2015-10-09
293863	The Age of Adaline	Blake Lively Michiel Huisman Harrison Ford Ell	Lee Toland Krieger	2015-04-16
325348	Hardcore Henry	Sharlto Copley Haley Bennett Danila Kozlovskiy	llya Naishuller	2015-09-12
265208	Wild Card	Jason Statham Michael Angarano Milo Ventimigli	Simon West	2015-01-14
254320	The Lobster	Colin Farrell Rachel Weisz Léa Seydoux John C	Yorgos Lanthimos	2015-10-08
258480	Carol	Cate Blanchett Rooney Mara Kyle Chandler Sarah	Todd Haynes	2015-11-20
257088	Point Break	Edgar RamÃrez Luke Bracey Teresa Palmer Delro	Ericson Core	2015-12-03
295964	Burnt	Bradley Cooper Sienna Miller Lily James Alicia	John Wells	2015-10-02

Question 7: Is the screen runtime related to the success or flopping of the movies ?

# 

# Relationship Between Runtime and Popularity



Runtime and poularity aren't correlated

Question 8: What is the runtime of the most successful movies between the years 2015 and 1960 ?

```
In [77]: | s.sort_values('popularity', axis=0, ascending=False).head(10).groupby(['runtim
         e', 'release_year'])['original_title'].sum()
Out[77]: runtime release_year
         101.0
                  2014.0
                                                               John Wick
         119.0
                  2015.0
                                                               Insurgent
         120.0
                  2015.0
                                                      Mad Max: Fury Road
         121.0
                  1977.0
                                                               Star Wars
                  2014.0
                                                 Guardians of the Galaxy
                  2014.0
                                 The Hunger Games: Mockingjay - Part 1
         123.0
         124.0
                  2015.0
                                                          Jurassic World
                                     Captain America: The Winter Soldier
         136.0
                  2014.0
                  2015.0
                                            Star Wars: The Force Awakens
         169.0
                  2014.0
                                                            Interstellar
         Name: original_title, dtype: object
```

Question 9: Do movies with more profit have more popularity as well?

In [78]: most\_pop['profit'] = df.profit

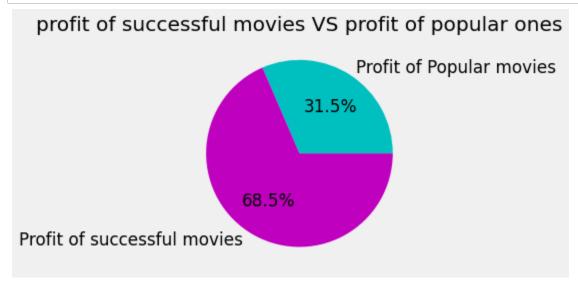
most\_successful = successful\_movies.sort\_values('profit', axis=0, ascending=Fal se).head(10)
most\_successful

## Out[78]:

	popularity	budget	revenue	original_title	cast	director	runtime	
id								
19995	9.432768	237000000.0	2.781506e+09	Avatar	Sam Worthington Zoe Saldana Sigourney Weaver S	James Cameron	162.0	Actio
140607	11.173104	200000000.0	2.068178e+09	Star Wars: The Force Awakens	Harrison Ford Mark Hamill Carrie Fisher Adam D	J.J. Abrams	136.0	
597	4.355219	200000000.0	1.845034e+09	Titanic	Kate Winslet Leonardo DiCaprio Frances Fisher	James Cameron	194.0	
135397	32.985763	150000000.0	1.513529e+09	Jurassic World	Chris Pratt Bryce Dallas Howard Irrfan Khan Vi	Colin Trevorrow	124.0	
168259	9.335014	190000000.0	1.506249e+09	Furious 7	Vin Diesel Paul Walker Jason Statham Michelle 	James Wan	137.0	
24428	7.637767	220000000.0	1.519558e+09	The Avengers	Robert Downey Jr. Chris Evans Mark Ruffalo Chr	Joss Whedon	143.0	Scio
12445	5.711315	125000000.0	1.327818e+09	Harry Potter and the Deathly Hallows: Part 2	Daniel Radcliffe Rupert Grint Emma Watson Alan	David Yates	130.0	
99861	5.944927	280000000.0	1.405036e+09	Avengers: Age of Ultron	Robert Downey Jr. Chris Hemsworth Mark Ruffalo	Joss Whedon	141.0	Acti
109445	6.112766	150000000.0	1.274219e+09	Frozen	Kristen Bell Idina Menzel Jonathan Groff Josh	Chris Buck Jennifer Lee	102.0	
1642	1.136610	22000000.0	1.106280e+09	The Net	Sandra Bullock Jeremy Northam Dennis Miller We	Irwin Winkler	114.0	Crime

id				
135397	Jurassic World	32.985763	2015-06-09	1.363529e+09
76341	Mad Max: Fury Road	28.419936	2015-05-13	2.284364e+08
157336	Interstellar	24.949134	2014-11-05	4.567525e+08
118340	Guardians of the Galaxy	14.311205	2014-07-30	6.033124e+08
262500	Insurgent	13.112507	2015-03-18	1.852382e+08
100402	Captain America: The Winter Soldier	12.971027	2014-03-20	5.447666e+08
11	Star Wars	12.037933	1977-03-20	7.643980e+08
245891	John Wick	11.422751	2014-10-22	5.873990e+07
140607	Star Wars: The Force Awakens	11.173104	2015-12-15	1.868178e+09
131631	The Hunger Games: Mockingjay - Part 1	10.739009	2014-11-18	6.271002e+08

### Pie Chart representing profit of successful movies VS profit of popular ones :



# percentage of popular movies that have highest profit :

Out[81]: 20.0

We can notice that having the most profit doesn't mean the movie is also popular, also we have only 20% of the popular movies having also the highest profit

# Question 10: Which production companies that released the most successful movies each year?

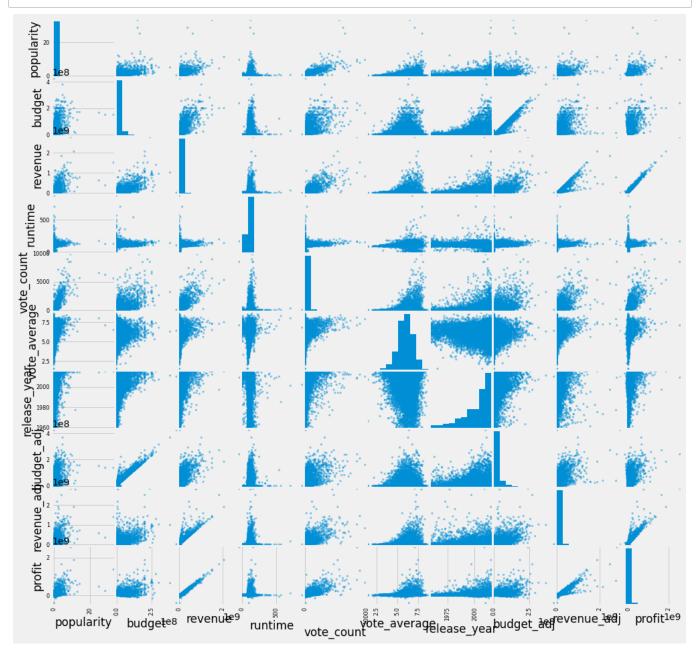
In [82]: s[['original\_title', 'production\_companies', 'release\_date']].head(15)
Out[82]:

	original_title	production_companies	release_date
id			
135397	Jurassic World	Universal Studios Amblin Entertainment Legenda	2015-06-09
76341	Mad Max: Fury Road	Village Roadshow Pictures Kennedy Miller Produ	2015-05-13
262500	Insurgent	$Summit\ Entertainment   Mandeville\ Films   Red\ Wago$	2015-03-18
140607	Star Wars: The Force Awakens	Lucasfilm Truenorth Productions Bad Robot	2015-12-15
168259	Furious 7	Universal Pictures Original Film Media Rights	2015-04-01
281957	The Revenant	${\it Regency Enterprises}   {\it Appian Way}  {\it CatchPlay}  {\it Anony}$	2015-12-25
87101	Terminator Genisys	Paramount Pictures Skydance Productions	2015-06-23
286217	The Martian	Twentieth Century Fox Film Corporation Scott F	2015-09-30
211672	Minions	Universal Pictures Illumination Entertainment	2015-06-17
150540	Inside Out	Walt Disney Pictures Pixar Animation Studios W	2015-06-09
206647	Spectre	Columbia Pictures Danjaq B24	2015-10-26
257344	Pixels	Columbia Pictures Happy Madison Productions	2015-07-16
99861	Avengers: Age of Ultron	Marvel Studios Prime Focus Revolution Sun Studios	2015-04-22
273248	The Hateful Eight	Double Feature Films The Weinstein Company Fil	2015-12-25
260346	Taken 3	Twentieth Century Fox Film Corporation M6 Film	2015-01-01

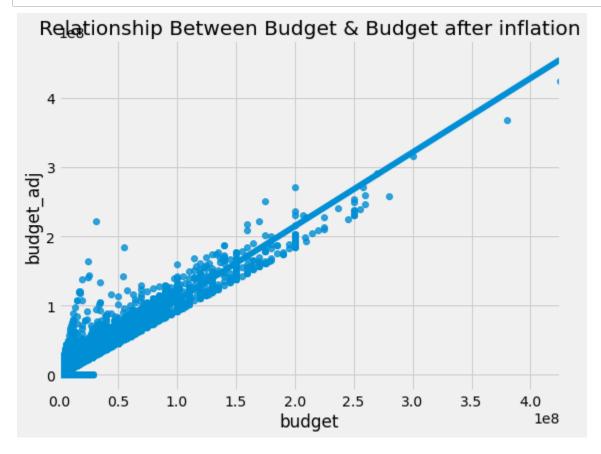
```
In [83]: | s.groupby('release_year')['production_companies'].sum()
Out[83]: release_year
         1961.0
                                               Walt Disney Productions
         1967.0
                                                  Walt Disney Pictures
                    Stanley Kubrick Productions|Metro-Goldwyn-Maye...
         1968.0
         1972.0
                                Paramount Pictures | Alfran Productions
         1973.0
                                         Warner Bros. | Hoya Productions
         1974.0
                               Paramount Pictures | The Coppola Company
                    Fantasy Films|Warner Bros.Universal Pictures|Z...
         1975.0
         1976.0
                                                        United Artists
                     Lucasfilm|Twentieth Century Fox Film Corporation
         1977.0
         1979.0
                    Twentieth Century-Fox Productions | Brandywine P...
                     Lucasfilm|Twentieth Century Fox Film Corporation
         1980.0
         1981.0
                                          Lucasfilm|Paramount Pictures
                    Universal Pictures | Amblin EntertainmentOrion P...
         1982.0
                    Lucasfilm|Twentieth Century Fox Film Corporati...
         1983.0
         1984.0
                    Orion Pictures | Pacific Western | Hemdale Film | Ci...
         1985.0
                    Universal Pictures | Amblin Entertainment | U-Driv...
                    Twentieth Century Fox Film Corporation SLM Pro...
         1986.0
         1987.0
                    Twentieth Century Fox Film Corporation|Lawrenc...
                    Twentieth Century Fox Film Corporation | Gordon ...
         1988.0
         1989.0
                    Walt Disney PicturesLucasfilm|Paramount Pictur...
                    TriStar Pictures | Carolco Pictures | Carolco Inte...
         1990.0
                    Walt Disney Pictures | Walt Disney Animation Stu...
         1991.0
                    Walt Disney PicturesTwentieth Century Fox Film...
         1992.0
                    Columbia PicturesWalt Disney Pictures | Tim Burt...
         1993.0
         1994.0
                    Miramax Films A Band Apart Jersey Films Paramou...
                    New Line Cinema|Juno Pix|Cecchi Gori PicturesW...
         1995.0
                    Twentieth Century Fox Film Corporation Centrop...
         1996.0
         1997.0
                    Paramount Pictures|Twentieth Century Fox Film ...
         1998.0
                    Paramount Pictures | Scott Rudin ProductionsJerr...
         1999.0
                    Regency Enterprises | Fox 2000 Pictures | Taurus F...
                    DreamWorks SKG|Universal Pictures|Scott Free P...
         2000.0
                    WingNut Films|New Line Cinema|The Saul Zaentz ...
         2001.0
         2002.0
                    WingNut Films | New Line Cinema | The Saul Zaentz ...
                    WingNut Films|New Line CinemaLakeshore Enterta...
         2003.0
         2004.0
                    1492 Pictures|Warner Bros.|Heyday Films|P of A...
                    Patalex IV Productions Limited|Warner Bros.|He...
         2005.0
         2006.0
                    Lakeshore Entertainment|Screen GemsWalt Disney...
         2007.0
                    Walt Disney Pictures|Jerry Bruckheimer Films|S...
                    DC Comics|Legendary Pictures|Warner Bros.|Sync...
         2008.0
         2009.0
                    Ingenious Film Partners|Twentieth Century Fox ...
         2010.0
                    Legendary Pictures | Warner Bros. | SyncopyMarvel ...
                    Marvel StudiosBold Films | Marc Platt Production...
         2011.0
                    Marvel StudiosLakeshore Entertainment|Saturn F...
         2012.0
                    Walt Disney Pictures | Walt Disney Animation Stu...
         2013.0
         2014.0
                    Paramount Pictures|Legendary Pictures|Warner B...
                    Universal Studios | Amblin Entertainment | Legenda...
         2015.0
         Name: production_companies, dtype: object
```

Question 11: What is the relationship between Budget and other features in the dataset

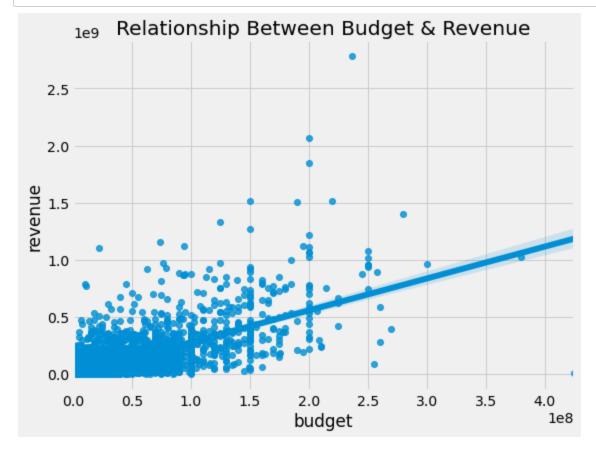
In [102]: pd.plotting.scatter\_matrix(df, figsize=(15,15));



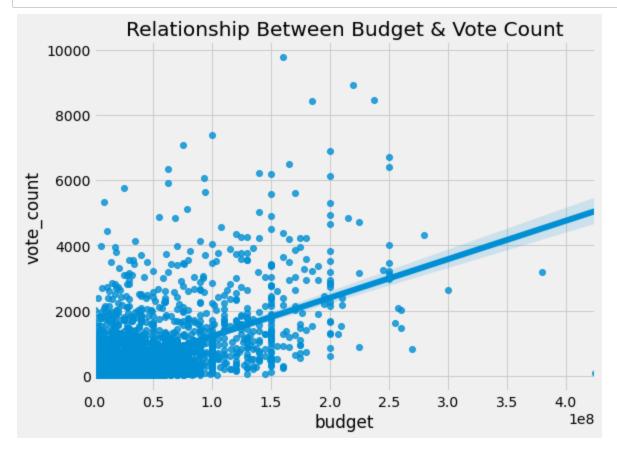
```
In [107]: plt.figure(figsize=(8, 6))
    plt.style.use('fivethirtyeight')
    plt.title("Relationship Between Budget & Budget after inflation")
    sns.regplot(x="budget", y="budget_adj", data=df)
    plt.show()
```



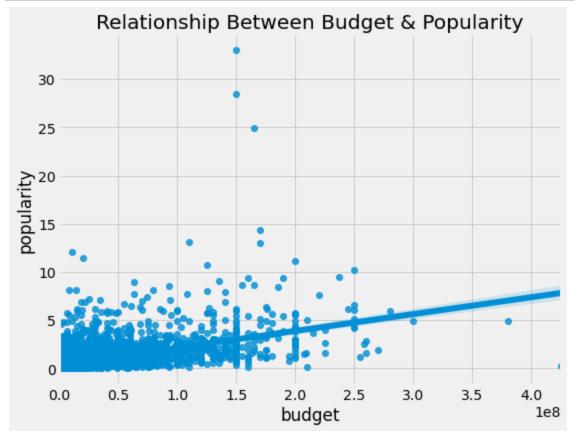
```
In [108]: plt.figure(figsize=(8, 6))
    plt.style.use('fivethirtyeight')
    plt.title("Relationship Between Budget & Revenue")
    sns.regplot(x="budget", y="revenue", data=df)
    plt.show()
```



```
In [109]: plt.figure(figsize=(8, 6))
   plt.style.use('fivethirtyeight')
   plt.title("Relationship Between Budget & Vote Count")
   sns.regplot(x="budget", y="vote_count", data=df)
   plt.show()
```



```
In [110]: plt.figure(figsize=(8, 6))
    plt.style.use('fivethirtyeight')
    plt.title("Relationship Between Budget & Popularity")
    sns.regplot(x="budget", y="popularity", data=df)
    plt.show()
```



Budget is positively correlated with 'budget\_adj', 'revenue', 'vote\_count' and 'popularity'

# Question 12: Which cast participated in the most successful/flopped movies?

name of the movie:

```
In [87]: #flopped movie:
    list_4= flopped_movies.sort_values('popularity', axis=0, ascending=True).head(1
    ).cast.values
    list_4

Out[87]: array(['George C. Scott|Diana Rigg|Richard Dysart|Barnard Hughes|Stephen Elliot
```

name of the movie:

In [88]: flopped\_movies.sort\_values('popularity', axis=0, ascending=True).head(1).origin
al\_title

Out[88]: id

32082 The Hospital

dtype=object)

Name: original\_title, dtype: object

# **Conclusions**

In this project, I tried to analyse a dataset taken from The movie database (TMDb) of 10,000 movies.

The cleaning part is what I found the most interesting to do, I noticed that there are some null values and duplicates in the dataset, as well as zero values on some data points such as budget, revenue and runtime.

There are some movies having the budget and revenue equals to 0, these can be considered as NaN values. Normally we can drop these zero values if they don't have an impact on the overall information about the dataset, but since I checked with the help of Shannon's Entropy, I found that We don't need to drop all the rows containing zeros in budget and revenue columns, since increasing in shanon's entropy is an indication of information loss. Also, some of the movies have a revenue but the budget is zero and vice versa! and that is really not realistic. So i changed the value of each budget to the mean overall budget to make it more realistic, and vice versa.

I also noticed that the release date is an object and not in a date\_time type, so I tried to change it but I encountered a problem where each release date written for example as '11/15/66' is going to be converted to '2066-11-15' instead of 1966 as noted in the release\_year, so I changed each year part in the release\_date to the year noted in the release\_year feature to solve the problem.

There were some columns I did not need in further analysis such as: imdb\_id since we already have an id column, homepage, tagline, overview, and keywords since we're not doing a movie recommendation in this project, so I dropped them.

I also noticed that the runtime also has some zero values which is unrealistic! to tackle this problem I replaced each zero runtime with the mean overall runtime from each year.

Here are answers to some questions asked earlier:

the most popular genres between 2015 and 1960 are: Action, Adventure, Science Fiction and Thriller

the top 5 movies having the most profit were: Jurassic World(2015), Mad Max:Fury Road(2015), Insurgent(2015), Star Wars:The Force Awakens(2015) and Furious 7(2015).

the top 5 movies having the highest budget but the lowest vote counts: The Swan Princess: A Royal Family Tale(2014), Red Sky(2014), Mao's Last Dancer(2009), Sinners and Saints(2010) and Double Wedding(2010).

the top 5 movies who flopped in terms of profit: Jupiter Ascending, Ex Machina, Tomorrowland, Mr. Holmes and Room.

We can assume that Runtime and poularity aren't correlated based on graphs, also we can notice that having the most profit doesn't mean the movie is also popular; only 20% of the popular movies have also the highest profit.

#### Limitations:

The dataset has alot of zero values, null values and wrong format, it makes it a bit hard for me to conduct a proper analysis, nevertherless, I found that an interesting problem to tackle.

Also, having the revenue columns filled with values when the budget columns has alot of zero values and vice versa was a non realistic thing and a problem that I found equally interesting.

Another limitation for me is conducting exploratory analysis with visualizations, I found that I'm more familiar with wrangling the data.

# **Resources:**

geeksforgeeks (https://www.geeksforgeeks.org/selecting-rows-in-pandas-dataframe-based-on-conditions/)

<u>pandas.plotting.scatter\_matrix (https://pandas.pydata.org/pandas-docs/version/1.2.4/reference/api/pandas.plotting.scatter\_matrix.html)</u>

<u>converting-object-to-datetime-format-in-python (https://stackoverflow.com/questions/38333954/converting-object-to-datetime-format-in-python)</u>

<u>entropy-calculation-in-python (https://datascience.stackexchange.com/questions/58565/conditional-entropy-calculation-in-python-hyx)</u>

pandas.DataFrame.explode (https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.explode.html)

<u>split-explode-pandas-dataframe-string-entry-to-separate-rows (https://stackoverflow.com/questions/12680754/split-explode-pandas-dataframe-string-entry-to-separate-rows)</u>

pandas.DataFrame.plot.pie. (https://pandas.pydata.org/docs/reference/api/pandas.DataFrame.plot.pie.html)

T . F . 7	
ın ı ı	
- H 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1 1	