tmdb_movies_project

June 1, 2022

1 Project: Investigation on a tmbd dataset

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Introduction **tmd-movies dataset, is a dataset containing information on 10866 movies together with 21 attributes that are linked to each movie.**
0 id :Shows the unique identification of the movie
1 imdb_id :Shows the unique identification of the movie by imdb
2 popularity :shows how popular is the movie
3 budget :describes the movies initial expenditure
4 revenue :describes the returns of the movie
5 original_title :shows the movies original name
6 cast :shows the actors in the movie
7 homepage :describes the movie's website
8 director :shows the movies director
9 tagline :describes short text to clarify a thought
10 keywords :shows main words that generally describe the movie
11 overview :shows the short description of the movie
12 runtime :shows the length of the movie
13 genres :shows the movie's themes
14 production_companies :describes the production companies
15 release_date :shows when the movie was released
16 vote_count : shows how many imbd users have voted for the movie
17 vote_average :shows the mean vote
18 release_year :shows year of release
19 budget_adj :shows adjustment to budget of the movie
20 revenue_adj :shows adjustment of revenue of the movie

1.2 Questions

1. which are the top popular movies?

2. Which are the top years in terms of movies release?

3. Who are the top directors in movies release?
4. Do popular movies happen to be top rated movies?
5. Which are the highly rated genres?
6. Does the length of a movie affect its rating?

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

Data Wrangling

1.2.1 General Properties

```
In [2]: movies = pd.read_csv('./Database_TMDb_movie_data/tmdb-movies.csv')
        movies.head()
```

```
Out[2]:       id    imdb_id  popularity     budget     revenue  \
        0  135397  tt0369610   32.985763  150000000  1513528810
        1   76341  tt1392190   28.419936  150000000   378436354
        2  262500  tt2908446   13.112507  110000000   295238201
        3  140607  tt2488496   11.173104  200000000  2068178225
        4  168259  tt2820852    9.335014  190000000  1506249360

                    original_title  \
        0                Jurassic World
        1           Mad Max: Fury Road
        2                     Insurgent
        3  Star Wars: The Force Awakens
        4                     Furious 7

                                                  cast  \
        0  Chris Pratt|Bryce Dallas Howard|Irrfan Khan|Vi...
        1  Tom Hardy|Charlize Theron|Hugh Keays-Byrne|Nic...
        2  Shailene Woodley|Theo James|Kate Winslet|Ansel...
        3  Harrison Ford|Mark Hamill|Carrie Fisher|Adam D...
        4  Vin Diesel|Paul Walker|Jason Statham|Michelle ...

                                             homepage          director  \
        0                   http://www.jurassicworld.com/   Colin Trevorrow
        1                     http://www.madmaxmovie.com/     George Miller
        2  http://www.thedivergentseries.movie/#insurgent  Robert Schwentke
        3  http://www.starwars.com/films/star-wars-episod...       J.J. Abrams
        4                         http://www.furious7.com/         James Wan

                          tagline      ...       \
```

```
0              The park is open.       ...
1             What a Lovely Day.       ...
2    One Choice Can Destroy You        ...
3  Every generation has a story.       ...
4            Vengeance Hits Home       ...

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

                                      genres  \
0  Action|Adventure|Science Fiction|Thriller
1  Action|Adventure|Science Fiction|Thriller
2         Adventure|Science Fiction|Thriller
3   Action|Adventure|Science Fiction|Fantasy
4                     Action|Crime|Thriller

                                production_companies release_date vote_count  \
0  Universal Studios|Amblin Entertainment|Legenda...       6/9/15       5562
1  Village Roadshow Pictures|Kennedy Miller Produ...      5/13/15       6185
2  Summit Entertainment|Mandeville Films|Red Wago...      3/18/15       2480
3          Lucasfilm|Truenorth Productions|Bad Robot     12/15/15       5292
4  Universal Pictures|Original Film|Media Rights ...       4/1/15       2947

   vote_average  release_year    budget_adj   revenue_adj
0           6.5          2015  1.379999e+08  1.392446e+09
1           7.1          2015  1.379999e+08  3.481613e+08
2           6.3          2015  1.012000e+08  2.716190e+08
3           7.5          2015  1.839999e+08  1.902723e+09
4           7.3          2015  1.747999e+08  1.385749e+09

[5 rows x 21 columns]
```

In [3]:
```
#function for quick general properties
def general_properties(dataset):
    print('shape :','#find rows and columns')
    print(dataset.shape)
    print('information :', '#get an overview if their might be nulls')
    print(dataset.info())
    print('description :','#get some statistics on the data')
    print( dataset.describe())
```

In [4]:
```
general_properties(movies)
```

```
shape : #find rows and columns
(10866, 21)
```

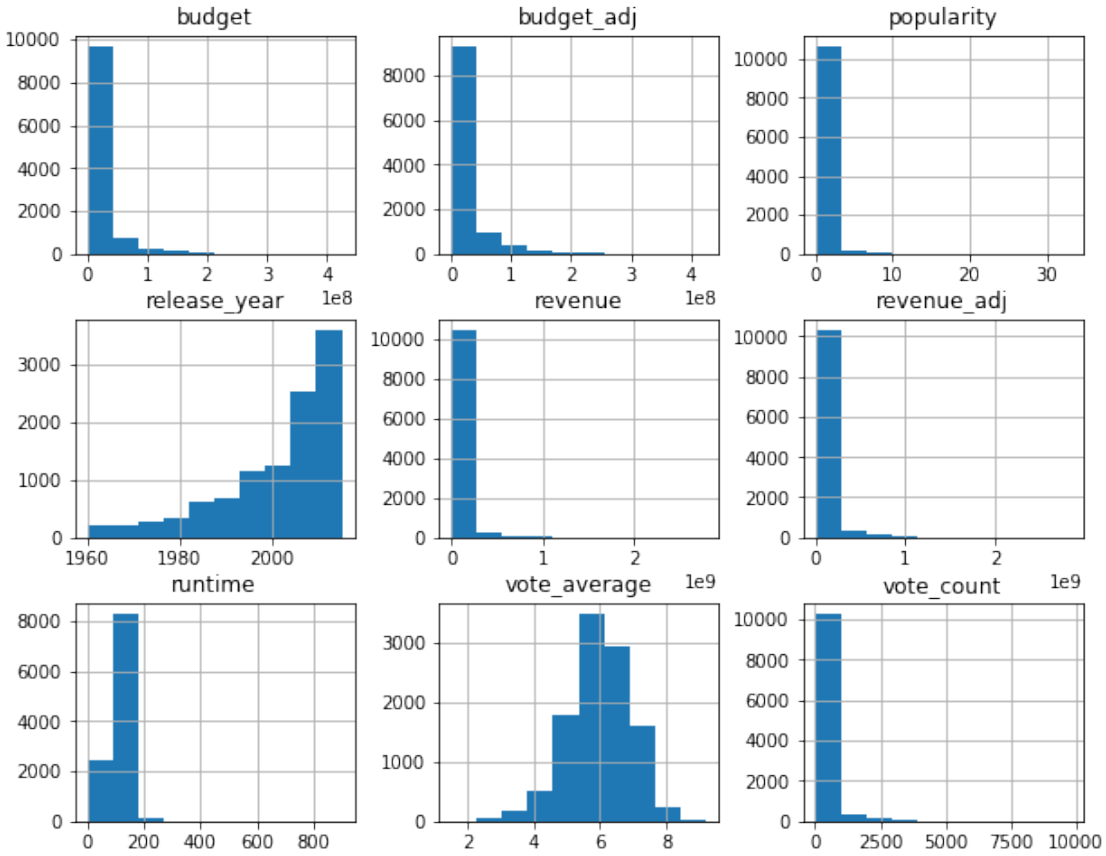
```
information : #get an overview if their might be nulls
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 10866 entries, 0 to 10865
Data columns (total 21 columns):
id                      10866 non-null int64
imdb_id                 10856 non-null object
popularity              10866 non-null float64
budget                  10866 non-null int64
revenue                 10866 non-null int64
original_title          10866 non-null object
cast                    10790 non-null object
homepage                2936 non-null object
director                10822 non-null object
tagline                 8042 non-null object
keywords                9373 non-null object
overview                10862 non-null object
runtime                 10866 non-null int64
genres                  10843 non-null object
production_companies    9836 non-null object
release_date            10866 non-null object
vote_count              10866 non-null int64
vote_average            10866 non-null float64
release_year            10866 non-null int64
budget_adj              10866 non-null float64
revenue_adj             10866 non-null float64
dtypes: float64(4), int64(6), object(11)
memory usage: 1.7+ MB
None
description : #get some statistics on the data
                  id    popularity        budget       revenue       runtime  \
count   10866.000000  10866.000000  1.086600e+04  1.086600e+04  10866.000000
mean    66064.177434      0.646441  1.462570e+07  3.982332e+07    102.070863
std     92130.136561      1.000185  3.091321e+07  1.170035e+08     31.381405
min         5.000000      0.000065  0.000000e+00  0.000000e+00      0.000000
25%     10596.250000      0.207583  0.000000e+00  0.000000e+00     90.000000
50%     20669.000000      0.383856  0.000000e+00  0.000000e+00     99.000000
75%     75610.000000      0.713817  1.500000e+07  2.400000e+07    111.000000
max    417859.000000     32.985763  4.250000e+08  2.781506e+09    900.000000

         vote_count  vote_average  release_year    budget_adj   revenue_adj
count  10866.000000  10866.000000  10866.000000  1.086600e+04  1.086600e+04
mean     217.389748      5.974922   2001.322658  1.755104e+07  5.136436e+07
std      575.619058      0.935142     12.812941  3.430616e+07  1.446325e+08
min       10.000000      1.500000   1960.000000  0.000000e+00  0.000000e+00
25%       17.000000      5.400000   1995.000000  0.000000e+00  0.000000e+00
50%       38.000000      6.000000   2006.000000  0.000000e+00  0.000000e+00
75%      145.750000      6.600000   2011.000000  2.085325e+07  3.369710e+07
max     9767.000000      9.200000   2015.000000  4.250000e+08  2.827124e+09
```

In [5]:
```
#dropping non-required columns
movies.drop(columns=['id', 'imdb_id', 'cast','cast', 'homepage', 'tagline', 'keywords',
            axis=1, inplace=True)
movies.head()
```

Out[5]:

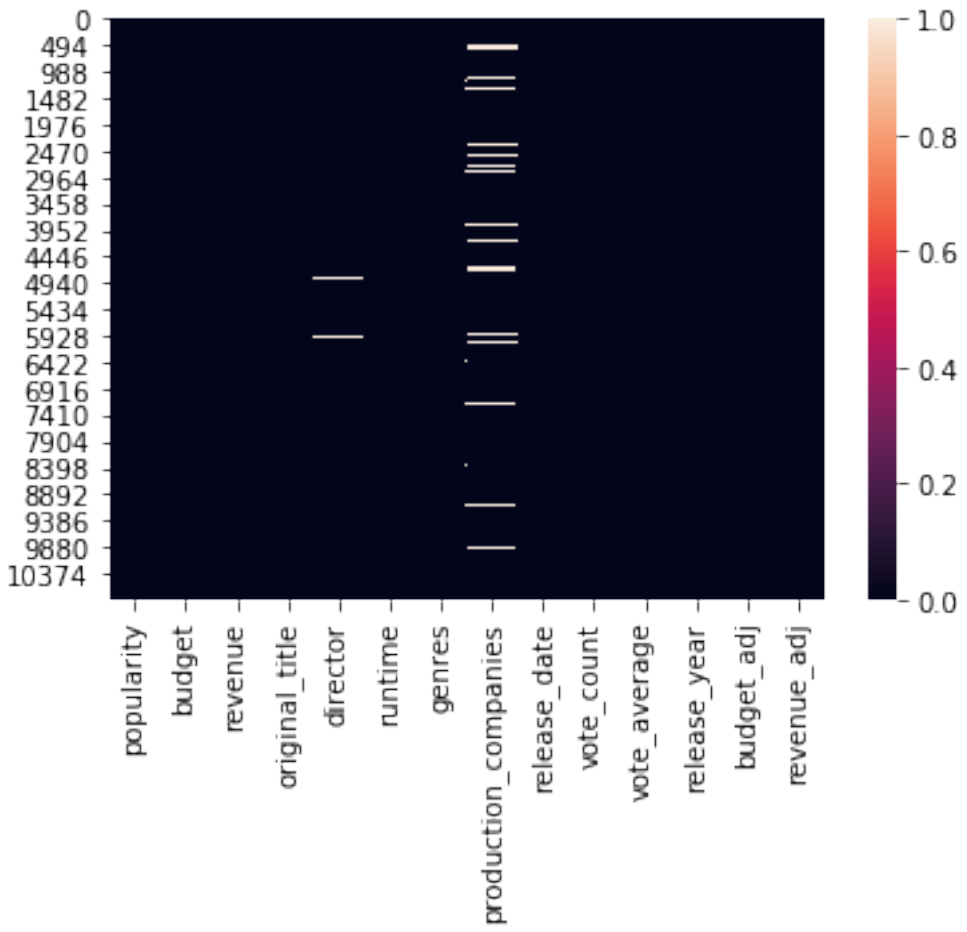
	popularity	budget	revenue	original_title	director	runtime	genres	production_companies	release_date	vote_count	vote_average	release_year	budget_adj	revenue_adj
0	32.985763	150000000	1513528810	Jurassic World	Colin Trevorrow	124	Action|Adventure|Science Fiction|Thriller	Universal Studios|Amblin Entertainment|Legenda...	6/9/15	5562	6.5	2015	1.379999e+08	1.392446e+09
1	28.419936	150000000	378436354	Mad Max: Fury Road	George Miller	120	Action|Adventure|Science Fiction|Thriller	Village Roadshow Pictures|Kennedy Miller Produ...	5/13/15	6185	7.1	2015	1.379999e+08	3.481613e+08
2	13.112507	110000000	295238201	Insurgent	Robert Schwentke	119	Adventure|Science Fiction|Thriller	Summit Entertainment|Mandeville Films|Red Wago...	3/18/15	2480	6.3	2015	1.012000e+08	2.716190e+08
3	11.173104	200000000	2068178225	Star Wars: The Force Awakens	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy	Lucasfilm|Truenorth Productions|Bad Robot	12/15/15	5292	7.5	2015	1.839999e+08	1.902723e+09
4	9.335014	190000000	1506249360	Furious 7	James Wan	137	Action|Crime|Thriller	Universal Pictures|Original Film|Media Rights ...	4/1/15	2947	7.3	2015	1.747999e+08	1.385749e+09

In [6]:
```
#getting a visualization of the general data
movies.hist(figsize=(10,8));
```



2 Data cleaning

```
In [7]: #lets see how nulls are distributed in our dataset
        sns.heatmap(movies.isnull());
```



In [8]:
```
#cheking for nulls
movies.isnull().any()
```

Out[8]:
```
popularity              False
budget                  False
revenue                 False
original_title          False
director                 True
runtime                 False
genres                   True
production_companies     True
release_date            False
vote_count              False
vote_average            False
release_year            False
budget_adj              False
revenue_adj             False
dtype: bool
```

```
In [9]: #dropping all nulls
        movies.dropna(inplace=True)

In [10]: #recheking the data
         movies.info()

<class 'pandas.core.frame.DataFrame'>
Int64Index: 9807 entries, 0 to 10865
Data columns (total 14 columns):
popularity              9807 non-null float64
budget                  9807 non-null int64
revenue                 9807 non-null int64
original_title          9807 non-null object
director                9807 non-null object
runtime                 9807 non-null int64
genres                  9807 non-null object
production_companies    9807 non-null object
release_date            9807 non-null object
vote_count              9807 non-null int64
vote_average            9807 non-null float64
release_year            9807 non-null int64
budget_adj              9807 non-null float64
revenue_adj             9807 non-null float64
dtypes: float64(4), int64(5), object(5)
memory usage: 1.1+ MB


In [11]: #counting the number of duplicates
         sum(movies.duplicated())

Out[11]: 1

In [12]: #lets drop the duplicate
         movies.drop_duplicates(inplace=True)

In [13]: #confirming changes
         sum(movies.duplicated())

Out[13]: 0

In [14]: #checking datatypes
         movies.dtypes

Out[14]: popularity             float64
         budget                   int64
         revenue                  int64
         original_title          object
         director                object
         runtime                  int64
```

```
genres                  object
production_companies    object
release_date            object
vote_count               int64
vote_average           float64
release_year             int64
budget_adj             float64
revenue_adj            float64
dtype: object
```

```
In [15]: #changing the datatype of release_date
         movies['release_date'] = pd.to_datetime(movies.release_year)
```

Exploratory Data Analysis

2.0.1 Question 1 which are the top popular movies?

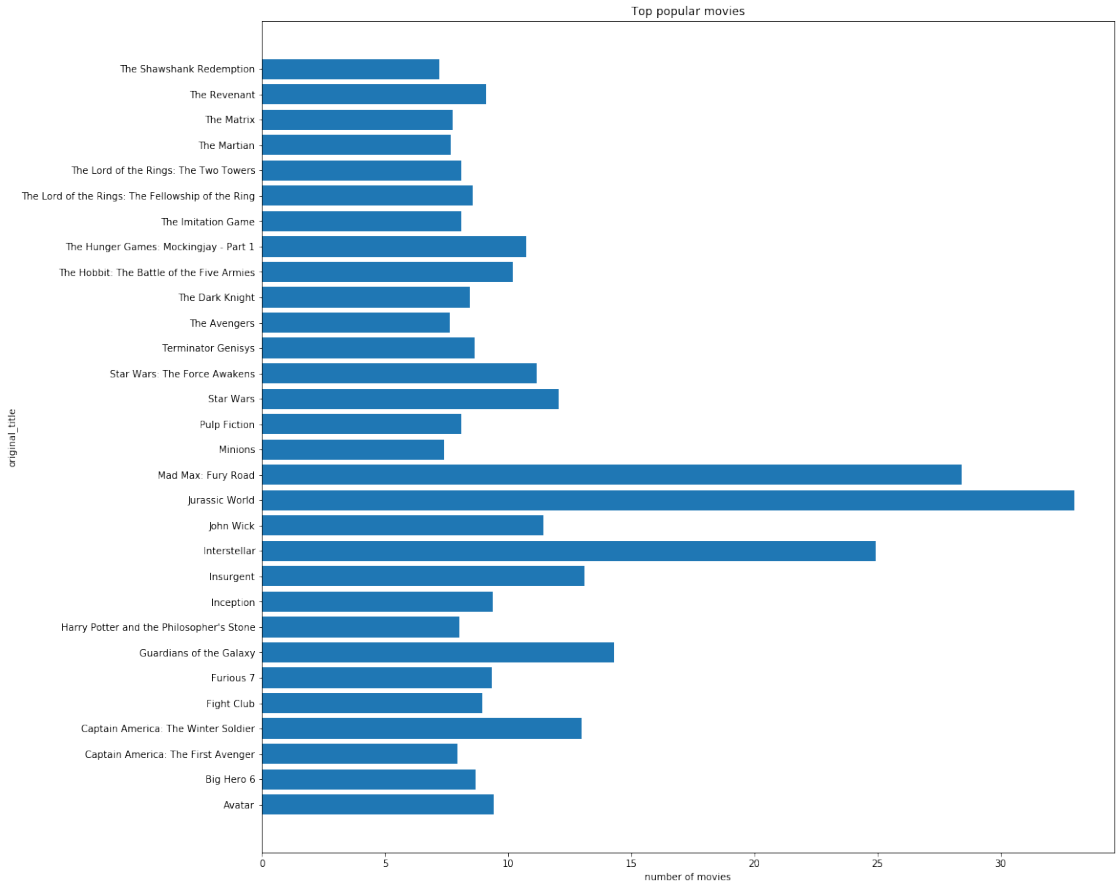
```
In [16]: #sorting movies according to their popularity using sort.values()
         #taking the top 100 movies head(20)
         #conveting it to a dataframe for easy coparisons between columns
         #dropping the annoying index after sorting using reset_index()
         movies_toppopular = movies[['popularity', 'original_title']].sort_values(by='popularity
                                                                                   ascending=False)

         movies_toppopular.reset_index(drop=True, inplace=True)
         movies_toppopular = pd.DataFrame(movies_toppopular)
         movies_toppopular
```

Out[16]:

	popularity	original_title
0	32.985763	Jurassic World
1	28.419936	Mad Max: Fury Road
2	24.949134	Interstellar
3	14.311205	Guardians of the Galaxy
4	13.112507	Insurgent
5	12.971027	Captain America: The Winter Soldier
6	12.037933	Star Wars
7	11.422751	John Wick
8	11.173104	Star Wars: The Force Awakens
9	10.739009	The Hunger Games: Mockingjay - Part 1
10	10.174599	The Hobbit: The Battle of the Five Armies
11	9.432768	Avatar
12	9.363643	Inception
13	9.335014	Furious 7
14	9.110700	The Revenant
15	8.947905	Fight Club
16	8.691294	Big Hero 6
17	8.654359	Terminator Genisys
18	8.575419	The Lord of the Rings: The Fellowship of the Ring
19	8.466668	The Dark Knight
20	8.110711	The Imitation Game

```
21    8.095275              The Lord of the Rings: The Two Towers
22    8.093754                                        Pulp Fiction
23    8.021423          Harry Potter and the Philosopher's Stone
24    7.959228               Captain America: The First Avenger
25    7.753899                                         The Matrix
26    7.667400                                        The Martian
27    7.637767                                      The Avengers
28    7.404165                                           Minions
29    7.192039                         The Shawshank Redemption
```

```
In [17]: plt.figure(figsize=(16,16))#for allocating size of the figure
         plt.title('Top popular movies')
         plt.xlabel('number of movies')
         plt.ylabel('original_title')
         plt.barh( movies_toppopular.original_title, movies_toppopular.popularity);
```



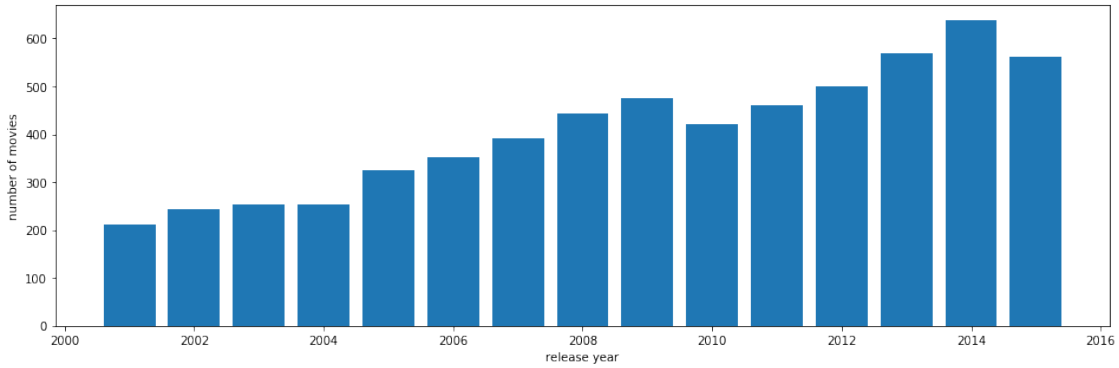
We can conclude that Jurassic World is the most popular movie and it is closely followed by Mad Max: Fury Road

2.0.2 Question 2 top years in terms of movies release

```
In [18]: top_15_years = movies.release_year.value_counts().head(15)
         top_15_years
```

```
Out[18]: 2014    638
         2013    568
         2015    561
         2012    500
         2009    474
         2011    461
         2008    443
         2010    421
         2007    392
         2006    353
         2005    324
         2003    254
         2004    253
         2002    243
         2001    212
         Name: release_year, dtype: int64
```

```
In [19]: plt.figure(figsize=(16,5))
         plt.xlabel('release year')
         plt.ylabel('number of movies')
         plt.bar(top_15_years.index, top_15_years);
```



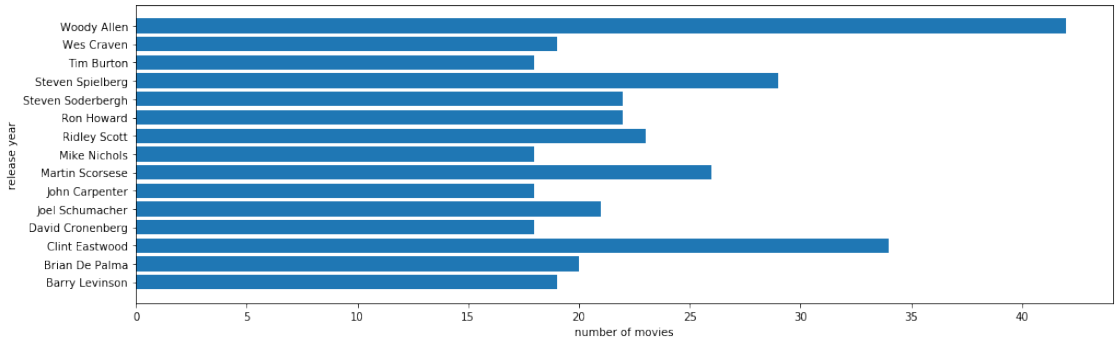
we can conclude that 2014 is the year with the highest number of releases. the general trend in movies production is increasing from the year 2001-2014

3 Question 3 Who are the top directors in movies releases?

```
In [20]: top_directors = movies.director.value_counts().head(15)
         top_directors
```

```
Out[20]: Woody Allen          42
         Clint Eastwood       34
         Steven Spielberg     29
         Martin Scorsese      26
         Ridley Scott         23
         Steven Soderbergh    22
         Ron Howard           22
         Joel Schumacher      21
         Brian De Palma       20
         Barry Levinson       19
         Wes Craven           19
         Tim Burton           18
         Mike Nichols         18
         John Carpenter       18
         David Cronenberg     18
         Name: director, dtype: int64
```

```
In [21]: plt.figure(figsize=(16,5))
         plt.xlabel('number of movies')
         plt.ylabel('release year')
         plt.barh(top_directors.index, top_directors);
```



we can conclude that Woody Allen is the top director in terms of movies releases. He has featured in 42 releases.

4 Question 4: Do popular movies happen to be top rated movies?

since Popularity is a quantative variable we need to create distinctions

```
In [22]: # View the min, 25%, 50%, 75%, max popularity values with Pandas describe
         movies.popularity.describe()
```

```
Out[22]: count    9806.000000
         mean        0.693143
         std         1.035525
```

```
min         0.000188
25%         0.231581
50%         0.418755
75%         0.774232
max        32.985763
Name: popularity, dtype: float64
```

In [23]:
```
#bin values that will be used to "cut" the data into groups
bin_values = [0.000188, 0.231581, 0.418756, 0.774231, 32.985763]
```

In [24]:
```
#labels for the four popularity levels
bin_names = ['not popular','less popular','popular','very popular']
```

In [25]:
```
#create popular level columns
movies['popularity_levels'] = pd.cut(movies['popularity'], bin_values, labels=bin_names
movies.sample(5)
```

Out[25]:

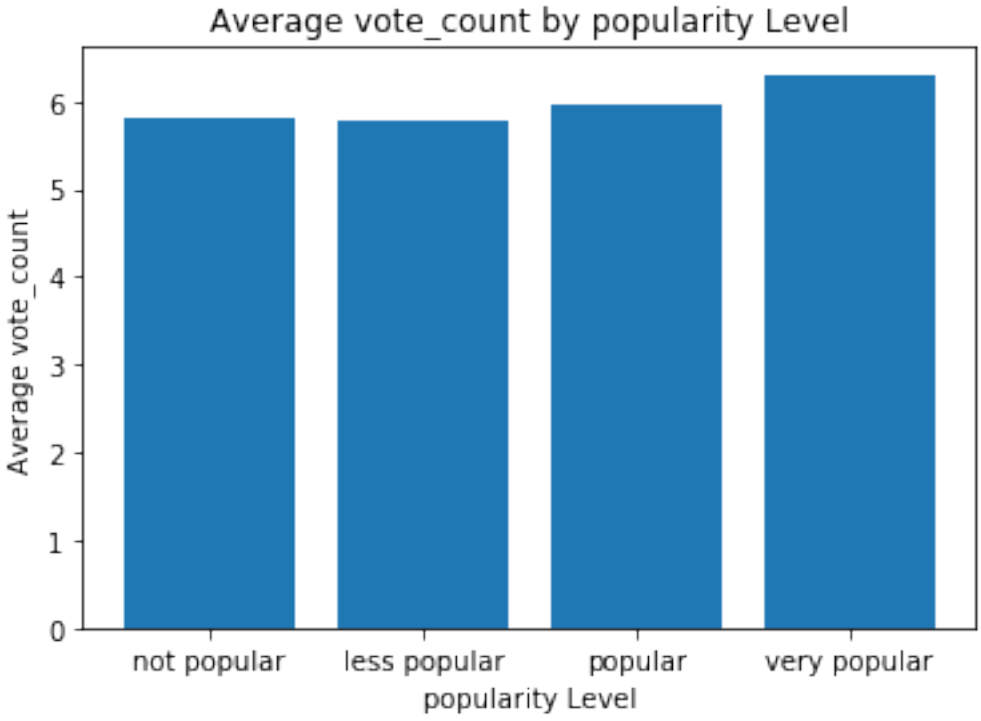
	popularity	budget	revenue	original_title	director	runtime	genres	production_companies	release_date	vote_count	vote_average	release_year	budget_adj	revenue_adj	popularity_levels
8799	0.196668	24000000	12372410	Ready to Rumble	Brian Robbins	107	Action|Comedy|Drama	Bel Air Entertainment|Warner Bros.	1970-01-01 00:00:00.000002000	16	4.4	2000	3.039101e+07	1.566709e+07	not popular
6433	0.265732	0	0	House of Fury	Stephen Fung	102	Action|Comedy|Foreign	Emperor Multimedia Group (EMG)|JCE Entertainme...	1970-01-01 00:00:00.000002005	18	6.4	2005	0.000000e+00	0.000000e+00	less popular
6696	0.575781	0	0	Hollow Man II	Claudio FÃđh	91	Horror|Action|Thriller|Science Fiction	Destination Films|Red Wagon Entertainment|Fron...	1970-01-01 00:00:00.000002006	32	5.1	2006	0.000000e+00	0.000000e+00	popular
1084	0.228495	0	0	10.000 KM	Carlos Marques-Marcet	99	Comedy|Drama|Romance	TelevisiÃşn EspaÃśola (TVE)|TelevisiÃş de Cata...	1970-01-01 00:00:00.000002014	24	6.2	2014			
10090	0.318177	0	0	I Love You to Death	Lawrence Kasdan	94	Action|Comedy|Crime	TriStar Pictures	1970-01-01 00:00:00.000001990	26	6.1	1990			

```
1084    0.000000e+00  0.000000e+00       not popular
10090   0.000000e+00  0.000000e+00      less popular
```

In [26]:
```
popularity = movies.groupby('popularity_levels').mean().vote_average
popularity
```

Out[26]:
```
popularity_levels
not popular     5.812036
less popular    5.792574
popular         5.952917
very popular    6.307993
Name: vote_average, dtype: float64
```

In [27]:
```
locations = [1, 2, 3, 4]
plt.bar(locations, popularity, tick_label=popularity.index)
plt.title('Average vote_count by popularity Level')
plt.xlabel('popularity Level')
plt.ylabel('Average vote_count');
```



Clearly we can coclude that top popular movies are also top rated.

5 Question 5: Which are the highly rated genres?

In [28]:
```
#to find this we need to label our data according to ratings(vote_average)
movies.describe().vote_average
```

```
Out[28]: count    9806.000000
         mean        5.966459
         std         0.914291
         min         1.500000
         25%         5.400000
         50%         6.000000
         75%         6.600000
         max         8.700000
         Name: vote_average, dtype: float64
```

```
In [29]: #bin values that will be used to "cut" the data into groups
         bin_values = [1.5, 5.4, 6.0, 6.6, 8.7]
```

```
In [30]: #labels for the four popularity levels
         bin_names = ['lowly_rated','average_rated','above_average_rated','highly_rated']
```

```
In [31]: movies['rating_levels'] = pd.cut(movies['vote_average'], bin_values, labels=bin_names)
         movies.sample(5)
```

Out[31]:

	popularity	budget	revenue	original_title	director	runtime	genres	production_companies	release_date	vote_count	vote_average	release_year	budget_adj	revenue_adj	popularity_levels	rating_levels
9126	0.230420	0	0	The Second Arrival	Kevin Tenney	101	Action|Adventure|Science Fiction|Thriller	Rootbeer Films|Taurus 7 Film Corporation	1970-01-01 00:00:00.000001998	11	2.9	1998	0.000000e+00	0.000000e+00	not popular	lowly_rated
10727	0.859806	3600000	44785053	Midnight Cowboy	John Schlesinger	113	Drama	United Artists|Florin Productions|Jerome Hellm...	1970-01-01 00:00:00.000001969	124	7.0	1969				
6411	0.317018	18000000	0	The Big White	Mark Mylod	100	Comedy|Crime|Drama	Capitol Films|Ascendant Pictures|Rising Star|F...	1970-01-01 00:00:00.000002005	40	6.2	2005				
10059	0.285403	0	0	Desperate Hours	Michael Cimino	105	Mystery|Thriller	Metro-Goldwyn-Mayer (MGM)	1970-01-01 00:00:00.000001990	15	5.2	1990				
8724	0.632783	83000000	59468275	The Flintstones in Viva Rock Vegas	Brian Levant	90	Science Fiction|Comedy|Family|Romance	Universal Pictures|Amblin Entertainment	1970-01-01 00:00:00.000002000	55	4.4	2000				

```
10727  2.139935e+07  2.662142e+08      very popular         highly_rated
6411   2.009814e+07  0.000000e+00      less popular  above_average_rated
10059  0.000000e+00  0.000000e+00      less popular          lowly_rated
8724   1.051022e+08  7.530421e+07           popular          lowly_rated
```

In [32]:
```
#lets create a dataframe of highly reated movies
hi_movies = movies[movies.rating_levels == 'highly_rated']
hi_movies.head()
```

Out[32]:

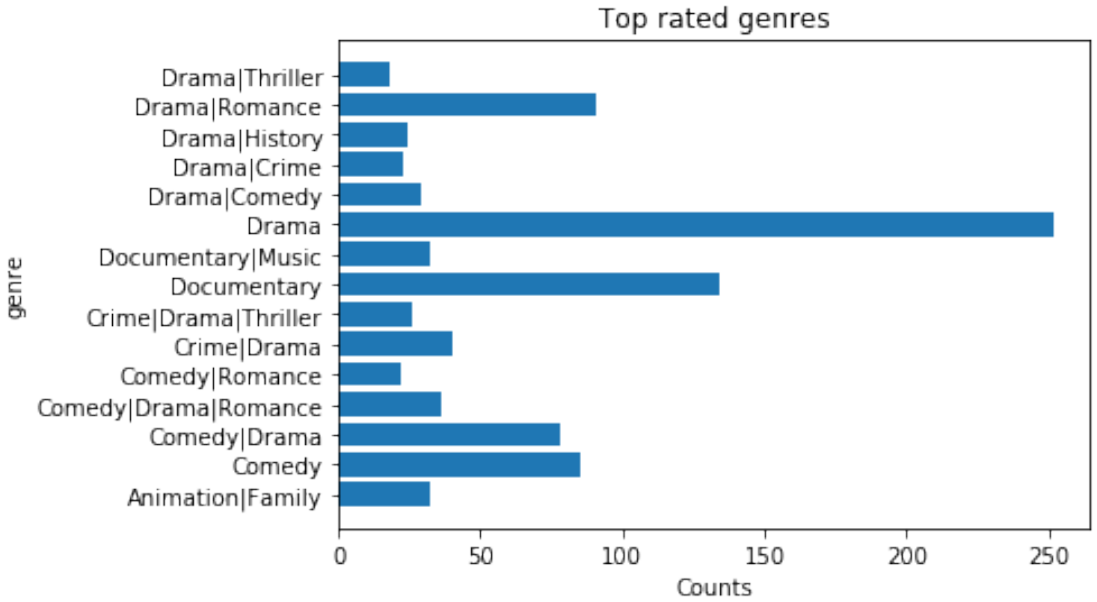
	popularity	budget	revenue	original_title	director	runtime	genres	production_companies	release_date	vote_count	vote_average	release_year	budget_adj	revenue_adj	popularity_levels	rating_levels
1	28.419936	150000000	378436354	Mad Max: Fury Road	George Miller	120	Action|Adventure|Science Fiction|Thriller	Village Roadshow Pictures|Kennedy Miller Produ...	1970-01-01 00:00:00.000002015	6185	7.1	2015	1.379999e+08	3.481613e+08	very popular	highly_rated
3	11.173104	200000000	2068178225	Star Wars: The Force Awakens	J.J. Abrams	136	Action|Adventure|Science Fiction|Fantasy	Lucasfilm|Truenorth Productions|Bad Robot	1970-01-01 00:00:00.000002015	5292	7.5	2015	1.839999e+08	1.902723e+09	very popular	highly_rated
4	9.335014	190000000	1506249360	Furious 7	James Wan	137	Action|Crime|Thriller	Universal Pictures|Original Film|Media Rights ...	1970-01-01 00:00:00.000002015	2947	7.3	2015	1.747999e+08	1.385749e+09	very popular	highly_rated
5	9.110700	135000000	532950503	The Revenant	Alejandro GonzÃąlez IÃ±Ãąrritu	156	Western|Drama|Adventure|Thriller	Regency Enterprises|Appian Way|CatchPlay|Anony...	1970-01-01 00:00:00.000002015	3929	7.2	2015	1.379999e+08	3.481613e+08	very popular	highly_rated
7	7.667400	108000000	595380321	The Martian	Ridley Scott	141	Drama|Adventure|Science Fiction	Twentieth Century Fox Film Corporation|Scott F...	1970-01-01 00:00:00.000002015	4572	7.6	2015	1.379999e+08	3.481613e+08	very popular	highly_rated

```
5  1.241999e+08  4.903142e+08      very popular  highly_rated
7  9.935996e+07  5.477497e+08      very popular  highly_rated
```

In [33]:
```
#lets group by genres
top_genres = hi_movies.genres.value_counts().head(15)
top_genres
```

Out[33]:
```
Drama                    252
Documentary              134
Drama|Romance             91
Comedy                    85
Comedy|Drama              78
Crime|Drama               40
Comedy|Drama|Romance      36
Documentary|Music         32
Animation|Family          32
Drama|Comedy              29
Crime|Drama|Thriller      26
Drama|History             24
Drama|Crime               23
Comedy|Romance            22
Drama|Thriller            18
Name: genres, dtype: int64
```

In [34]:
```
figsize=(16,16)
plt.barh(top_genres.index,top_genres)
plt.title('Top rated genres')
plt.xlabel('Counts')
plt.ylabel('genre');
```



we can conclude that drama is the most rated genre followed by documentary.

6 Question 6: Does the length of a movie affect its rating?

```
In [35]: movies.describe().runtime
```

```
Out[35]: count    9806.000000
         mean      102.744340
         std        28.134561
         min         0.000000
         25%        90.000000
         50%       100.000000
         75%       112.000000
         max       877.000000
         Name: runtime, dtype: float64
```

```
In [36]: #lets discard movies that have a runtime of 0
         #but lets make a copy first of our dataset
         movies2 = movies.copy()
         movies2 = movies2[movies.runtime != 0.0]#we are negating to remove 0 in runtime
```

```
In [37]: #lets confirm if we have 0
         movies2[movies2.runtime == 0]
```

```
Out[37]: Empty DataFrame
         Columns: [popularity, budget, revenue, original_title, director, runtime, genres, produ
         Index: []
```

```
In [38]: #lets find the median and divide the data into two groups
         movies2.runtime.median()
```

```
Out[38]: 100.0
```

```
In [39]: #using a query to find the short group
         short = movies2.query('runtime < 100')
```

```
In [40]: #finding the average between the group
         short_mean= short.vote_average.mean()
         short_mean
```

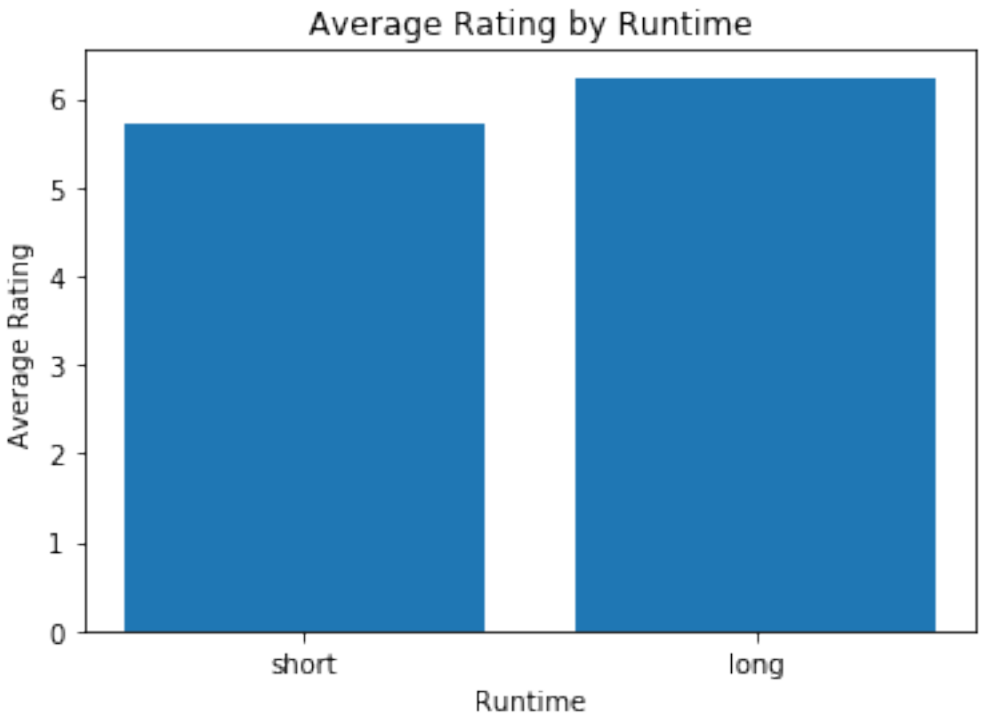
```
Out[40]: 5.7161746617466171
```

```
In [41]: #using a query to find the long group
         long = movies2.query('runtime > 100')
```

```
In [42]: #finding the average between the group
         long_mean = long.vote_average.mean()
         long_mean
```

```
Out[42]: 6.2361014744145713
```

```
In [43]: locations = [2, 1]
         heights = [long_mean, short_mean]
         labels = ['long', 'short']
         plt.bar(locations, heights, tick_label=labels)
         plt.title('Average Rating by Runtime')
         plt.xlabel('Runtime')
         plt.ylabel('Average Rating');
```



we can generally conclude that longer movies often achieve higher ratings compared to those that have shorter durations.

Conclusions I started by loading the data into my jupyter notebook, i then dug into the general properties of the data like the shape, the number of columns it contains and its summary statistics. I went further to clean the data of any nulls present, duplicates and wrong data types. I then started working on the data to answer the quetions I asked. I have worked on the assumption that removing some rows which have null data in some columns does not affect my analysis at all. And by general reasoning, I have removed rows with zero runtime since that is not sensible. The sample of data after removing nulls is not generally representitive of the whole population, same results as when the data is complete might not be observed. I have come up with these conclusions to the questions found in the introduction part:

```
Question 1 which are the top popular movies?

Jurasic World is the most popular movie followed by Mad Max. In the analysis I have shown the to
```

Question 2 Which are the top years in terms of movies release?
2014 was the year with most movie releases and the trend in movie release generally increases fr

Question 3 Who are the top directors in movies release?
Wood Allen is the top movie director in terms of movie releases, he has a record 42 movies released so far. I have shown top 15 directors who have contributed to movie release.

Question 4 Do popular movies happen to be top rated movies?
From visualization it is clearly noted that popular movies tend to being among the top rated movies.

Question 5 Which are the highly rated genres?
Drama is the best rated genre followed by documentary. I have shown further top 15 genres.

Question 6 Does the length of a movie affect its rating?
Movies with longer durations tend to receive higher ratings as compared to those with shorter du

LIMITATIONS
1.The data is not representative of the whole population. This is due to the null values in the cleaned, it has an effect on the insights generated from the data. If the data was to be free of conclusions drawn from it might be different.

2. The data I used was not enough to make very conclusive results. For example the runtime of sc i got rid of them to come up with my conclusions. We can't be able to watch a movie that does no longer.

3. The data also contains many movies with zero budgets. For sure no movie cannot generate a cos So if you are to answer questions regarding budgets the data may be misleading, unless we clear distorts some features of the data, as conclusions that will be generated do not include some mo

7 References

w3schools:https://www.w3schools.com/python/pandas/default.asp
pandas official documentantion:https://pandas.pydata.org/docs/
jovian:https://jovian.ai/learn/data-analysis-with-python-zero-to-pandas