

```
In [141... # Supress Warnings

import warnings
warnings.filterwarnings('ignore')
```

```
In [243... # Import the numpy and pandas packages

import numpy as np
import pandas as pd
import matplotlib.pyplot as plt
import seaborn as sns
```

This projects is based on the IMDB dataset and we have find some insights out of the Data. Steps going to be taken:

- 1. View the data and Understand
- 2. Cleaning the DATA
- 3. Make Changes in the Dataset for further analysis.
- 4. Performing EDA on the DataSet
- 5. Visualising the Results using a Graph or a Chart
- 6. Providng Conclusions

## Task 1: Reading and Inspection

- ### Subtask 1.1: Import and read

Import and read the movie database. Store it in a variable called `movies` .

```
In [143... movies = pd.read_csv(r"C:\Users\eva\Desktop\assignments\imdb\IMDB_Movies.csv")
movies
```

	color	director_name	num_critc_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2
0	Color	James Cameron	723.0	178.0	0.0	855.0	Joel
1	Color	Gore Verbinski	302.0	169.0	563.0	1000.0	O
2	Color	Sam Mendes	602.0	148.0	0.0	161.0	Rory K
3	Color	Christopher Nolan	813.0	164.0	22000.0	23000.0	Christia
4	NaN	Doug Walker	NaN	NaN	131.0	NaN	Rob \
...	...	...	...	...	...	...	
5038	Color	Scott Smith	1.0	87.0	2.0	318.0	D ;
5039	Color	NaN	43.0	43.0	NaN	319.0	Valorie
5040	Color	Benjamin Roberds	13.0	76.0	0.0	0.0	M
5041	Color	Daniel Hsia	14.0	100.0	0.0	489.0	Daniel H

	color	director_name	num_critic_for_reviews	duration	director_facebook_likes	actor_3_facebook_likes	actor_2_
5042	Color	Jon Gunn	43.0	90.0	16.0	16.0	Her:

5043 rows × 28 columns

- ### Subtask 1.2: Inspect the dataframe

Inspect the dataframe's columns, shapes, variable types etc.

In [144...

```
print('Columns')
print(movies.columns)

print('Shapes')

print(movies.shape)

print('Variable_types')

print(movies.dtypes)
```

Columns

```
Index(['color', 'director_name', 'num_critic_for_reviews', 'duration',
       'director_facebook_likes', 'actor_3_facebook_likes', 'actor_2_name',
       'actor_1_facebook_likes', 'gross', 'genres', 'actor_1_name',
       'movie_title', 'num_voted_users', 'cast_total_facebook_likes',
       'actor_3_name', 'facenumber_in_poster', 'plot_keywords',
       'movie_imdb_link', 'num_user_for_reviews', 'language', 'country',
       'content_rating', 'budget', 'title_year', 'actor_2_facebook_likes',
       'imdb_score', 'aspect_ratio', 'movie_facebook_likes'],
      dtype='object')
```

Shapes

```
(5043, 28)
```

Variable\_types

```
color                                object
director_name                       object
num_critic_for_reviews              float64
duration                           float64
director_facebook_likes             float64
actor_3_facebook_likes             float64
actor_2_name                       object
actor_1_facebook_likes             float64
gross                              float64
genres                             object
actor_1_name                       object
movie_title                        object
num_voted_users                    int64
cast_total_facebook_likes          int64
actor_3_name                       object
facenumber_in_poster              float64
plot_keywords                      object
movie_imdb_link                   object
num_user_for_reviews              object
language                          object
country                           object
content_rating                    object
budget                             float64
title_year                        float64
actor_2_facebook_likes            float64
imdb_score                        float64
aspect_ratio                      float64
```

```
movie_facebook_likes      int64
dtype: object
```

## Task 2: Cleaning the Data

- ### Subtask 2.1: Inspect Null values

Find out the number of Null values in all the columns and rows. Also, find the percentage of Null values in each column. Round off the percentages upto two decimal places.

In [145...

```
print(movies.isnull().sum(axis = 0))

# Table contains lot of Null Values most of them accumulated in certain columns
```

```
color      19
director_name  104
num_critic_for_reviews  50
duration    15
director_facebook_likes  104
actor_3_facebook_likes  23
actor_2_name  13
actor_1_facebook_likes  7
gross      884
genres      0
actor_1_name  7
movie_title  0
num_voted_users  0
cast_total_facebook_likes  0
actor_3_name  23
facenumber_in_poster  13
plot_keywords  153
movie_imdb_link  0
num_user_for_reviews  20
language    12
country     5
content_rating  303
budget      492
title_year  108
actor_2_facebook_likes  13
imdb_score  0
aspect_ratio  329
movie_facebook_likes  0
dtype: int64
```

In [146...

```
print(movies.isnull().sum(axis = 1))
```

```
0      0
1      0
2      0
3      0
4     13
..
5038    4
5039    5
5040    4
5041    2
5042    0
Length: 5043, dtype: int64
```

In [147...

```
Null_by_coloumns = movies.isnull().sum(axis = 0)
Null_by_coloumns = Null_by_coloumns.to_frame()
Null_by_coloumns = Null_by_coloumns.rename(columns= {0: 'Num_of_Nulls'})
```

```
Total_null_values = Null_by_coloumns.Num_of_Nulls.sum()
print(Total_null_values)
Null_by_coloumns['Null_per'] = round(((Null_by_coloumns.Num_of_Nulls/Total_null_values)*100)
print(Null_by_coloumns)
```

*# Calculated the percentage of Null Values in each coloumn for better understanding*

```
2697
                                Num_of_Nulls  Null_per
color                               19         0.70
director_name                     104         3.86
num_critic_for_reviews             50         1.85
duration                           15         0.56
director_facebook_likes           104         3.86
actor_3_facebook_likes             23         0.85
actor_2_name                       13         0.48
actor_1_facebook_likes              7         0.26
gross                             884        32.78
genres                             0         0.00
actor_1_name                        7         0.26
movie_title                        0         0.00
num_voted_users                    0         0.00
cast_total_facebook_likes          0         0.00
actor_3_name                       23         0.85
facenumber_in_poster              13         0.48
plot_keywords                     153         5.67
movie_imdb_link                   0         0.00
num_user_for_reviews              20         0.74
language                           12         0.44
country                            5         0.19
content_rating                    303        11.23
budget                            492        18.24
title_year                        108         4.00
actor_2_facebook_likes            13         0.48
imdb_score                         0         0.00
aspect_ratio                       329        12.20
movie_facebook_likes              0         0.00
```

- **### Subtask 2.2: Drop unnecessary columns**

For this assignment, you will mostly be analyzing the movies with respect to the ratings, gross collection, popularity of movies, etc. So many of the columns in this dataframe are not required. So it is advised to drop the following columns.

- color
- director\_facebook\_likes
- actor\_1\_facebook\_likes
- actor\_2\_facebook\_likes
- actor\_3\_facebook\_likes
- actor\_2\_name
- cast\_total\_facebook\_likes
- actor\_3\_name
- duration
- facenumber\_in\_poster
- content\_rating
- country
- movie\_imdb\_link
- aspect\_ratio

- plot\_keywords

In [148...

```
movies_new = movies.drop(['color', 'director_facebook_likes', 'actor_1_facebook_likes', 'ac
movies_new
```

Out[148...

	director_name	num_critic_for_reviews	gross	genres	actor_1_name	movie_title	nu
0	James Cameron	723.0	760505847.0	Action Adventure Fantasy Sci-Fi	CCH Pounder	Avatar	
1	Gore Verbinski	302.0	309404152.0	Action Adventure Fantasy	Johnny Depp	Pirates of the Caribbean: At World's End	
2	Sam Mendes	602.0	200074175.0	Action Adventure Thriller	Christoph Waltz	Spectre	
3	Christopher Nolan	813.0	448130642.0	Action Thriller	Tom Hardy	The Dark Knight Rises	
4	Doug Walker	NaN	NaN	Documentary	Doug Walker	Star Wars: Episode VII - The Force Awakens ...	
...	...	...	...	...	...	...	
5038	Scott Smith	1.0	NaN	Comedy Drama	Eric Mabius	Signed Sealed Delivered	
5039	NaN	43.0	NaN	Crime Drama Mystery Thriller	Natalie Zea	The Following	
5040	Benjamin Roberds	13.0	NaN	Drama Horror Thriller	Eva Boehnke	A Plague So Pleasant	
5041	Daniel Hsia	14.0	10443.0	Comedy Drama Romance	Alan Ruck	Shanghai Calling	
5042	Jon Gunn	43.0	85222.0	Documentary	John August	My Date with Drew	

5043 rows × 13 columns

- ### Subtask 2.3: Drop unnecessary rows using columns with high Null percentages

Now, on inspection you might notice that some columns have large percentage (greater than 5%) of Null values. Drop all the rows which have Null values for such columns.

In [149...

```
Greater_5per_columns = set(Null_by_coloumns.loc[(Null_by_coloumns['Null_per'] > 5)].index)
movies_new_columns = set(movies_new.columns)
Greater_5per_columns
movies_new_columns

intersection = list(Greater_5per_columns & movies_new_columns)
intersection

actual_data = movies_new.dropna(subset = intersection)
actual_data
```

```
actual_data.language.isnull().sum()
```

```
# Dropping Null Values for Columns that have high Null Value percentage
```

Out[149... 3

- ### Subtask 2.4: Fill NaN values

You might notice that the `language` column has some NaN values. Here, on inspection, you will see that it is safe to replace all the missing values with `'English'`.

In [150...

```
pd.options.mode.chained_assignment = None
# (To disable the copy warning)

actual_data['language'].fillna("English", inplace = True)
print(actual_data)
actual_data.language.isnull().sum()

# Hadling some of the Null Values by either replacing or deleting
```

	director_name	num_critic_for_reviews	gross	\
0	James Cameron	723.0	760505847.0	
1	Gore Verbinski	302.0	309404152.0	
2	Sam Mendes	602.0	200074175.0	
3	Christopher Nolan	813.0	448130642.0	
5	Andrew Stanton	462.0	73058679.0	
...	...	...	...	
5033	Shane Carruth	143.0	424760.0	
5034	Neill Dela Llana	35.0	70071.0	
5035	Robert Rodriguez	56.0	2040920.0	
5037	Edward Burns	14.0	4584.0	
5042	Jon Gunn	43.0	85222.0	

	genres	actor_1_name	\
0	Action Adventure Fantasy Sci-Fi	CCH Pounder	
1	Action Adventure Fantasy	Johnny Depp	
2	Action Adventure Thriller	Christoph Waltz	
3	Action Thriller	Tom Hardy	
5	Action Adventure Sci-Fi	Daryl Sabara	
...	...	...	
5033	Drama Sci-Fi Thriller	Shane Carruth	
5034	Thriller	Ian Gamazon	
5035	Action Crime Drama Romance Thriller	Carlos Gallardo	
5037	Comedy Drama	Kerry Bishé	
5042	Documentary	John August	

	movie_title	num_voted_users	\
0	Avatar	886204	
1	Pirates of the Caribbean: At World's End	471220	
2	Spectre	275868	
3	The Dark Knight Rises	1144337	
5	John Carter	212204	
...	...	...	
5033	Primer	72639	
5034	Cavite	589	
5035	El Mariachi	52055	
5037	Newlyweds	1338	
5042	My Date with Drew	4285	

	num_user_for_reviews	language	budget	title_year	imdb_score	\
0	3054	English	237000000.0	2009.0	7.9	
1	1238	English	300000000.0	2007.0	7.1	

2	994	English	245000000.0	2015.0	6.8
3	2701	English	250000000.0	2012.0	8.5
5	738	English	263700000.0	2012.0	6.6
...	...	...	...	...	...
5033	371	English	7000.0	2004.0	7.0
5034	35	English	7000.0	2005.0	6.3
5035	130	Spanish	7000.0	1992.0	6.9
5037	14	English	9000.0	2011.0	6.4
5042	84	English	1100.0	2004.0	6.6

	movie_facebook_likes
0	33000
1	0
2	85000
3	164000
5	24000
...	...
5033	19000
5034	74
5035	0
5037	413
5042	456

```
[3891 rows x 13 columns]
0
```

Out[150...

- ### Subtask 2.5: Check the number of retained rows

You might notice that two of the columns viz. `num_critic_for_reviews` and `actor_1_name` have small percentages of NaN values left. You can let these columns as it is for now. Check the number and percentage of the rows retained after completing all the tasks above.

In [151...

```
print(len(actual_data.index))
print((len(actual_data.index)/len(movies.index))*100)
```

```
3891
77.15645449137418
```

**Checkpoint 1:** You might have noticed that we still have around 77% of the rows!

## Task 3: Data Analysis

In this Part We will be performing most of the detailed Analysis

- ### Subtask 3.1: Change the unit of columns

Convert the unit of the `budget` and `gross` columns from \$ to million \$.

In [152...

```
actual_data.budget = round(actual_data["budget"]/1000000,2)
actual_data.gross = round(actual_data["gross"]/1000000,2)
print(actual_data)

# Changing the Unit of Gross and Budget Fields so that we can read the data easily
```

	director_name	num_critic_for_reviews	gross	\
0	James Cameron	723.0	760.51	
1	Gore Verbinski	302.0	309.40	
2	Sam Mendes	602.0	200.07	
3	Christopher Nolan	813.0	448.13	
5	Andrew Stanton	462.0	73.06	

```

...
5033      Shane Carruth      143.0      0.42
5034      Neill Dela Llana    35.0       0.07
5035      Robert Rodriguez    56.0       2.04
5037      Edward Burns       14.0       0.00
5042      Jon Gunn           43.0       0.09

...
genres      actor_1_name \
0      Action|Adventure|Fantasy|Sci-Fi      CCH Pounder
1      Action|Adventure|Fantasy      Johnny Depp
2      Action|Adventure|Thriller      Christoph Waltz
3      Action|Thriller      Tom Hardy
5      Action|Adventure|Sci-Fi      Daryl Sabara
...
5033      Drama|Sci-Fi|Thriller      Shane Carruth
5034      Thriller      Ian Gamazon
5035      Action|Crime|Drama|Romance|Thriller      Carlos Gallardo
5037      Comedy|Drama      Kerry Bishé
5042      Documentary      John August

...
movie_title      num_voted_users \
0      Avatar      886204
1      Pirates of the Caribbean: At World's End      471220
2      Spectre      275868
3      The Dark Knight Rises      1144337
5      John Carter      212204
...
5033      Primer      72639
5034      Cavite      589
5035      El Mariachi      52055
5037      Newlyweds      1338
5042      My Date with Drew      4285

...
num_user_for_reviews      language      budget      title_year      imdb_score \
0      3054      English      237.00      2009.0      7.9
1      1238      English      300.00      2007.0      7.1
2      994      English      245.00      2015.0      6.8
3      2701      English      250.00      2012.0      8.5
5      738      English      263.70      2012.0      6.6
...
5033      371      English      0.01      2004.0      7.0
5034      35      English      0.01      2005.0      6.3
5035      130      Spanish      0.01      1992.0      6.9
5037      14      English      0.01      2011.0      6.4
5042      84      English      0.00      2004.0      6.6

...
movie_facebook_likes
0      33000
1      0
2      85000
3      164000
5      24000
...
5033      19000
5034      74
5035      0
5037      413
5042      456

```

[3891 rows x 13 columns]

- ### Subtask 3.2: Find the movies with highest profit



- 1. Create a new column called profit which contains the difference of the two columns: gross and budget .
- 2. Sort the dataframe using the profit column as reference.
- 3. Plot profit (y-axis) vs budget (x- axis) and observe the outliers using the appropriate chart type.
- 4. Extract the top ten profiting movies in descending order and store them in a new dataframe - top10

In [153...

actual\_data['profit']= actual\_data.gross-actual\_data.budget  
actual\_data

Out[153...

	director_name	num_critic_for_reviews	gross	genres	actor_1_name	movie_title	n
0	James Cameron	723.0	760.51	Action Adventure Fantasy Sci-Fi	CCH Pounder	Avatar	
1	Gore Verbinski	302.0	309.40	Action Adventure Fantasy	Johnny Depp	Pirates of the Caribbean: At World's End	
2	Sam Mendes	602.0	200.07	Action Adventure Thriller	Christoph Waltz	Spectre	
3	Christopher Nolan	813.0	448.13	Action Thriller	Tom Hardy	The Dark Knight Rises	
5	Andrew Stanton	462.0	73.06	Action Adventure Sci-Fi	Daryl Sabara	John Carter	
...	...	...	...	...	...	...	...
5033	Shane Carruth	143.0	0.42	Drama Sci-Fi Thriller	Shane Carruth	Primer	
5034	Neill Dela Llana	35.0	0.07	Thriller	Ian Gamazon	Cavite	
5035	Robert Rodriguez	56.0	2.04	Action Crime Drama Romance Thriller	Carlos Gallardo	El Mariachi	
5037	Edward Burns	14.0	0.00	Comedy Drama	Kerry Bishé	Newlyweds	
5042	Jon Gunn	43.0	0.09	Documentary	John August	My Date with Drew	

3891 rows × 14 columns

In [154...

print(actual\_data.sort\_values('profit', ascending = False))

	director_name	num_critic_for_reviews	gross	genres	actor_1_name
0	James Cameron	723.0	760.51		
29	Colin Trevorrow	644.0	652.18		
26	James Cameron	315.0	658.67		
3024	George Lucas	282.0	460.94		
3080	Steven Spielberg	215.0	434.95		
...	...	...	...		
2334	Katsuhiro Ôtomo	105.0	0.41		
2323	Hayao Miyazaki	174.0	2.30		
3005	Lajos Koltai	73.0	0.20		
3859	Chan-wook Park	202.0	0.21		
2988	Joon-ho Bong	363.0	2.20		

0		Action Adventure Fantasy Sci-Fi	CCH Pounder
29		Action Adventure Sci-Fi Thriller	Bryce Dallas Howard
26		Drama Romance	Leonardo DiCaprio
3024		Action Adventure Fantasy Sci-Fi	Harrison Ford
3080		Family Sci-Fi	Henry Thomas
...		...	...
2334	Action Adventure Animation Family Sci-Fi Thriller		William Hootkins
2323	Adventure Animation Fantasy		Minnie Driver
3005	Drama Romance War		Marcell Nagy
3859	Crime Drama		Min-sik Choi
2988	Comedy Drama Horror Sci-Fi		Doona Bae

	movie_title	num_voted_users	\
0	Avatar	886204	
29	Jurassic World	418214	
26	Titanic	793059	
3024	Star Wars: Episode IV - A New Hope	911097	
3080	E.T. the Extra-Terrestrial	281842	
...	...	...	
2334	Steamboy	13727	
2323	Princess Mononoke	221552	
3005	Fateless	5603	
3859	Lady Vengeance	53508	
2988	The Host	68883	

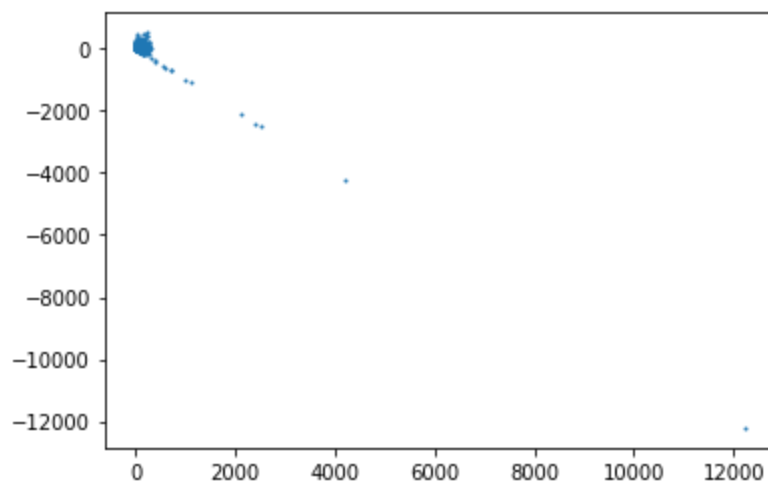
	num_user_for_reviews	language	budget	title_year	imdb_score	\
0	3054	English	237.00	2009.0	7.9	
29	1290	English	150.00	2015.0	7.0	
26	2528	English	200.00	1997.0	7.7	
3024	1470	English	11.00	1977.0	8.7	
3080	515	English	10.50	1982.0	7.9	
...	...	...	...	...	...	
2334	79	Japanese	2127.52	2004.0	6.9	
2323	570	Japanese	2400.00	1997.0	8.4	
3005	45	Hungarian	2500.00	2005.0	7.1	
3859	131	Korean	4200.00	2005.0	7.7	
2988	279	Korean	12215.50	2006.0	7.0	

	movie_facebook_likes	profit
0	33000	523.51
29	150000	502.18
26	26000	458.67
3024	33000	449.94
3080	34000	424.45
...	...	...
2334	973	-2127.11
2323	11000	-2397.70
3005	607	-2499.80
3859	4000	-4199.79
2988	7000	-12213.30

[3891 rows x 14 columns]

In [155...

```
plt.scatter(actual_data.budget, actual_data.profit, s=1)
plt.figure(figsize=(20,20))
plt.show()
```



<Figure size 1440x1440 with 0 Axes>

In [156..

```
top10 = actual_data.sort_values('profit', ascending=False).head(10)
print(top10)

# We used Python library functions to find out the profit and the movies with the highest
```

	director_name	num_critic_for_reviews	gross	\
0	James Cameron	723.0	760.51	
29	Colin Trevorrow	644.0	652.18	
26	James Cameron	315.0	658.67	
3024	George Lucas	282.0	460.94	
3080	Steven Spielberg	215.0	434.95	
794	Joss Whedon	703.0	623.28	
17	Joss Whedon	703.0	623.28	
509	Roger Allers	186.0	422.78	
240	George Lucas	320.0	474.54	
66	Christopher Nolan	645.0	533.32	

	genres	actor_1_name	\
0	Action Adventure Fantasy Sci-Fi	CCH Pounder	
29	Action Adventure Sci-Fi Thriller	Bryce Dallas Howard	
26	Drama Romance	Leonardo DiCaprio	
3024	Action Adventure Fantasy Sci-Fi	Harrison Ford	
3080	Family Sci-Fi	Henry Thomas	
794	Action Adventure Sci-Fi	Chris Hemsworth	
17	Action Adventure Sci-Fi	Chris Hemsworth	
509	Adventure Animation Drama Family Musical	Matthew Broderick	
240	Action Adventure Fantasy Sci-Fi	Natalie Portman	
66	Action Crime Drama Thriller	Christian Bale	

	movie_title	num_voted_users	\
0	Avatar	886204	
29	Jurassic World	418214	
26	Titanic	793059	
3024	Star Wars: Episode IV - A New Hope	911097	
3080	E.T. the Extra-Terrestrial	281842	
794	The Avengers	995415	
17	The Avengers	995415	
509	The Lion King	644348	
240	Star Wars: Episode I - The Phantom Menace	534658	
66	The Dark Knight	1676169	

	num_user_for_reviews	language	budget	title_year	imdb_score	\
0	3054	English	237.0	2009.0	7.9	
29	1290	English	150.0	2015.0	7.0	
26	2528	English	200.0	1997.0	7.7	
3024	1470	English	11.0	1977.0	8.7	
3080	515	English	10.5	1982.0	7.9	

794	1722	English	220.0	2012.0	8.1
17	1722	English	220.0	2012.0	8.1
509	656	English	45.0	1994.0	8.5
240	3597	English	115.0	1999.0	6.5
66	4667	English	185.0	2008.0	9.0

	movie_facebook_likes	profit
0	33000	523.51
29	150000	502.18
26	26000	458.67
3024	33000	449.94
3080	34000	424.45
794	123000	403.28
17	123000	403.28
509	17000	377.78
240	13000	359.54
66	37000	348.32

- ### Subtask 3.3: Drop duplicate values

After you found out the top 10 profiting movies, you might have noticed a duplicate value. So, it seems like the dataframe has duplicate values as well. Drop the duplicate values from the dataframe and repeat Subtask 3.2 . Note that the same `movie_title` can be there in different languages.

In [161...

# Write your code for dropping duplicate values here
actual\_data = actual\_data.drop\_duplicates()
actual\_data

Out[161...

	director_name	num_critic_for_reviews	gross	genres	actor_1_name	movie_title	n
0	James Cameron	723.0	760.51	Action Adventure Fantasy Sci-Fi	CCH Pounder	Avatar	
1	Gore Verbinski	302.0	309.40	Action Adventure Fantasy	Johnny Depp	Pirates of the Caribbean: At World's End	
2	Sam Mendes	602.0	200.07	Action Adventure Thriller	Christoph Waltz	Spectre	
3	Christopher Nolan	813.0	448.13	Action Thriller	Tom Hardy	The Dark Knight Rises	
5	Andrew Stanton	462.0	73.06	Action Adventure Sci-Fi	Daryl Sabara	John Carter	
...	...	...	...	...	...	...	...
5033	Shane Carruth	143.0	0.42	Drama Sci-Fi Thriller	Shane Carruth	Primer	
5034	Neill Dela Llana	35.0	0.07	Thriller	Ian Gamazon	Cavite	
5035	Robert Rodriguez	56.0	2.04	Action Crime Drama Romance Thriller	Carlos Gallardo	El Mariachi	
5037	Edward Burns	14.0	0.00	Comedy Drama	Kerry Bishé	Newlyweds	
5042	Jon Gunn	43.0	0.09	Documentary	John August	My Date with Drew	

In [174...

```
# Write code for repeating subtask 2 here
top10 = actual_data.sort_values('profit', ascending=False).head(10).reset_index()
print(top10)

# Since we missed to filter some of the Duplicate Values in the DataSet,
# we had to remove them now and redo some of the tasks.
# Below is the Dataset displaying the Top 10 movies based on the Profit Earning.
```

index	director_name	num_critic_for_reviews	gross	\
0	James Cameron	723.0	760.51	
1	Colin Trevorrow	644.0	652.18	
2	James Cameron	315.0	658.67	
3	George Lucas	282.0	460.94	
4	Steven Spielberg	215.0	434.95	
5	Joss Whedon	703.0	623.28	
6	Roger Allers	186.0	422.78	
7	George Lucas	320.0	474.54	
8	Christopher Nolan	645.0	533.32	
9	Gary Ross	673.0	408.00	

	genres	actor_1_name	\
0	Action Adventure Fantasy Sci-Fi	CCH Pounder	
1	Action Adventure Sci-Fi Thriller	Bryce Dallas Howard	
2	Drama Romance	Leonardo DiCaprio	
3	Action Adventure Fantasy Sci-Fi	Harrison Ford	
4	Family Sci-Fi	Henry Thomas	
5	Action Adventure Sci-Fi	Chris Hemsworth	
6	Adventure Animation Drama Family Musical	Matthew Broderick	
7	Action Adventure Fantasy Sci-Fi	Natalie Portman	
8	Action Crime Drama Thriller	Christian Bale	
9	Adventure Drama Sci-Fi Thriller	Jennifer Lawrence	

	movie_title	num_voted_users	\
0	Avatar	886204	
1	Jurassic World	418214	
2	Titanic	793059	
3	Star Wars: Episode IV - A New Hope	911097	
4	E.T. the Extra-Terrestrial	281842	
5	The Avengers	995415	
6	The Lion King	644348	
7	Star Wars: Episode I - The Phantom Menace	534658	
8	The Dark Knight	1676169	
9	The Hunger Games	701607	

num_user_for_reviews	language	budget	title_year	imdb_score	\
3054	English	237.0	2009.0	7.9	
1290	English	150.0	2015.0	7.0	
2528	English	200.0	1997.0	7.7	
1470	English	11.0	1977.0	8.7	
515	English	10.5	1982.0	7.9	
1722	English	220.0	2012.0	8.1	
656	English	45.0	1994.0	8.5	
3597	English	115.0	1999.0	6.5	
4667	English	185.0	2008.0	9.0	
1959	English	78.0	2012.0	7.3	

movie_facebook_likes	profit	
33000	523.51	
150000	502.18	
26000	458.67	
33000	449.94	
34000	424.45	

5	123000	403.28
6	17000	377.78
7	13000	359.54
8	37000	348.32
9	140000	330.00

**Checkpoint 2:** You might spot two movies directed by James Cameron in the list.

- ### Subtask 3.4: Find IMDb Top 250

1. Create a new dataframe `IMDb_Top_250` and store the top 250 movies with the highest IMDb Rating (corresponding to the column: `imdb_score`). Also make sure that for all of these movies, the `num_voted_users` is greater than 25,000. Also add a `Rank` column containing the values 1 to 250 indicating the ranks of the corresponding films.
2. Extract all the movies in the `IMDb_Top_250` dataframe which are not in the English language and store them in a new dataframe named `Top_Foreign_Lang_Film`.

In [178...

```
# Write your code for extracting the top 250 movies as per the IMDb score here. Make sure
# and name that dataframe as 'IMDb_Top_250'

IMDb_Top_250 = actual_data[actual_data['num_voted_users'] > 25000].sort_values("imdb_score")
IMDb_Top_250['Rank'] = [int(x) for x in IMDb_Top_250['imdb_score'].rank(ascending = False)]
print(IMDb_Top_250)

# Created a Dataset displaying the Top 250 Movies based on there IMDb score and number of
```

	director_name	num_critic_for_reviews	gross	\
1937	Frank Darabont	199.0	28.34	
3466	Francis Ford Coppola	208.0	134.82	
2837	Francis Ford Coppola	149.0	57.30	
66	Christopher Nolan	645.0	533.32	
4498	Sergio Leone	181.0	6.10	
...	...	...	...	
4931	John Carney	232.0	9.44	
2605	Ang Lee	287.0	128.07	
3029	David O. Russell	410.0	93.57	
2177	Tim Burton	111.0	56.36	
2487	George Cukor	82.0	72.00	

	genres	actor_1_name	\
1937	Crime Drama	Morgan Freeman	
3466	Crime Drama	Al Pacino	
2837	Crime Drama	Robert De Niro	
66	Action Crime Drama Thriller	Christian Bale	
4498	Western	Clint Eastwood	
...	...	...	
4931	Drama Music Romance	Glen Hansard	
2605	Action Drama Romance	Chen Chang	
3029	Biography Drama Sport	Christian Bale	
2177	Fantasy Romance	Johnny Depp	
2487	Drama Family Musical Romance	Jeremy Brett	

	movie_title	num_voted_users	num_user_for_reviews	\
1937	The Shawshank Redemption	1689764	4144	
3466	The Godfather	1155770	2238	
2837	The Godfather: Part II	790926	650	
66	The Dark Knight	1676169	4667	
4498	The Good, the Bad and the Ugly	503509	780	
...	...	...	...	
4931	Once	90827	329	
2605	Crouching Tiger, Hidden Dragon	217740	1641	
3029	The Fighter	275869	389	

2177		Edward Scissorhands			357581	588
2487		My Fair Lady			66959	258

	language	budget	title_year	imdb_score	movie_facebook_likes	profit	\
1937	English	25.00	1994.0	9.3	108000	3.34	
3466	English	6.00	1972.0	9.2	43000	128.82	
2837	English	13.00	1974.0	9.0	14000	44.30	
66	English	185.00	2008.0	9.0	37000	348.32	
4498	Italian	1.20	1966.0	8.9	20000	4.90	
...	...	...	...	...	...	...	
4931	English	0.18	2007.0	7.9	26000	9.26	
2605	Mandarin	15.00	2000.0	7.9	0	113.07	
3029	English	25.00	2010.0	7.9	36000	68.57	
2177	English	20.00	1990.0	7.9	16000	36.36	
2487	English	17.00	1964.0	7.9	0	55.00	

	Rank
1937	1
3466	2
2837	3
66	3
4498	6
...	...
4931	228
2605	228
3029	228
2177	228
2487	228

[250 rows x 15 columns]

In [179...

```
# Write your code to extract top foreign language films from 'IMDb_Top_250' here

Top_Foreign_Lang_Film = IMDb_Top_250[IMDb_Top_250["language"] != "English"]
print(Top_Foreign_Lang_Film)

# Displayed the top Foreings Films.
```

	director_name	num_critic_for_reviews	gross	\
4498	Sergio Leone	181.0	6.10	
4747	Akira Kurosawa	153.0	0.27	
4029	Fernando Meirelles	214.0	7.56	
2373	Hayao Miyazaki	246.0	10.05	
4259	Florian Henckel von Donnersmarck	215.0	11.28	
4921	Majid Majidi	46.0	0.93	
2323	Hayao Miyazaki	174.0	2.30	
2970	Wolfgang Petersen	96.0	11.43	
4105	Chan-wook Park	305.0	2.18	
4659	Asghar Farhadi	354.0	7.10	
1329	S.S. Rajamouli	44.0	6.50	
1298	Jean-Pierre Jeunet	242.0	33.20	
2734	Fritz Lang	260.0	0.03	
4033	Thomas Vinterberg	349.0	0.61	
2829	Oliver Hirschbiegel	192.0	5.50	
2551	Guillermo del Toro	406.0	37.62	
4000	Juan José Campanella	262.0	20.17	
3550	Denis Villeneuve	226.0	6.86	
2047	Hayao Miyazaki	212.0	4.71	
2830	Alejandro Amenábar	157.0	2.09	
2914	Je-kyu Kang	86.0	1.11	
4461	Thomas Vinterberg	98.0	1.65	
3553	José Padilha	142.0	0.01	
3423	Katsuhiko Ôtomo	150.0	0.44	
4267	Alejandro G. Iñárritu	157.0	5.38	
3456	Vincent Paronnaud	242.0	4.44	

3344	Karan Johar	210.0	4.02
4144	Walter Salles	71.0	5.60
4284	Ari Folman	231.0	2.28
4897	Sergio Leone	122.0	3.50
1171	Yimou Zhang	283.0	0.08
2863	Clint Eastwood	251.0	13.75
3264	Michael Haneke	447.0	0.23
3510	Yash Chopra	29.0	2.92
3677	Christophe Barratier	112.0	3.63
4415	Fabián Bielinsky	94.0	1.22
4640	Cristian Mungiu	233.0	1.19
2605	Ang Lee	287.0	128.07

	genres \
4498	Western
4747	Action Adventure Drama
4029	Crime Drama
2373	Adventure Animation Family Fantasy
4259	Drama Thriller
4921	Drama Family
2323	Adventure Animation Fantasy
2970	Adventure Drama Thriller War
4105	Drama Mystery Thriller
4659	Drama Mystery
1329	Action Adventure Drama Fantasy War
1298	Comedy Romance
2734	Drama Sci-Fi
4033	Drama
2829	Biography Drama History War
2551	Drama Fantasy War
4000	Drama Mystery Thriller
3550	Drama Mystery War
2047	Adventure Animation Family Fantasy
2830	Biography Drama Romance
2914	Action Drama War
4461	Drama
3553	Action Crime Drama Thriller
3423	Action Animation Sci-Fi
4267	Drama Thriller
3456	Animation Biography Drama War
3344	Adventure Drama Thriller
4144	Drama
4284	Animation Biography Documentary Drama History War
4897	Action Drama Western
1171	Action Adventure History
2863	Drama History War
3264	Drama Romance
3510	Drama Musical Romance
3677	Drama Music
4415	Crime Drama Thriller
4640	Drama
2605	Action Drama Romance

	actor_1_name	movie_title \
4498	Clint Eastwood	The Good, the Bad and the Ugly
4747	Takashi Shimura	Seven Samurai
4029	Alice Braga	City of God
2373	Bunta Sugawara	Spirited Away
4259	Sebastian Koch	The Lives of Others
4921	Bahare Seddiqi	Children of Heaven
2323	Minnie Driver	Princess Mononoke
2970	Jürgen Prochnow	Das Boot
4105	Min-sik Choi	Oldboy
4659	Shahab Hosseini	A Separation
1329	Tamannaah Bhatia	Baahubali: The Beginning
1298	Mathieu Kassovitz	Amélie



2734	Brigitte Helm	Metropolis
4033	Thomas Bo Larsen	The Hunt
2829	Thomas Kretschmann	Downfall
2551	Ivana Baquero	Pan's Labyrinth
4000	Ricardo Darín	The Secret in Their Eyes
3550	Lubna Azabal	Incendies
2047	Christian Bale	Howl's Moving Castle
2830	Belén Rueda	The Sea Inside
2914	Min-sik Choi	Tae Guk Gi: The Brotherhood of War
4461	Ulrich Thomsen	The Celebration
3553	Wagner Moura	Elite Squad
3423	Mitsuo Iwata	Akira
4267	Adriana Barraza	Amores Perros
3456	Catherine Deneuve	Persepolis
3344	Shah Rukh Khan	My Name Is Khan
4144	Fernanda Montenegro	Central Station
4284	Ari Folman	Waltz with Bashir
4897	Clint Eastwood	A Fistful of Dollars
1171	Jet Li	Hero
2863	Yuki Matsuzaki	Letters from Iwo Jima
3264	Isabelle Huppert	Amour
3510	Shah Rukh Khan	Veer-Zaara
3677	Jean-Baptiste Maunier	The Chorus
4415	Ricardo Darín	Nine Queens
4640	Anamaria Marinca	4 Months, 3 Weeks and 2 Days
2605	Chen Chang	Crouching Tiger, Hidden Dragon

	num_voted_users	num_user_for_reviews	language	budget	title_year	\
4498	503509	780	Italian	1.20	1966.0	
4747	229012	596	Japanese	2.00	1954.0	
4029	533200	749	Portuguese	3.30	2002.0	
2373	417971	902	Japanese	19.00	2001.0	
4259	259379	407	German	2.00	2006.0	
4921	27882	130	Persian	0.18	1997.0	
2323	221552	570	Japanese	2400.00	1997.0	
2970	168203	426	German	14.00	1981.0	
4105	356181	809	Korean	3.00	2003.0	
4659	151812	264	Persian	0.50	2011.0	
1329	62756	410	Telugu	18.03	2015.0	
1298	534262	1314	French	77.00	2001.0	
2734	111841	413	German	6.00	1927.0	
4033	170155	249	Danish	3.80	2012.0	
2829	248354	564	German	13.50	2004.0	
2551	467234	1083	Spanish	13.50	2006.0	
4000	131831	231	Spanish	2.00	2009.0	
3550	80429	156	French	6.80	2010.0	
2047	214091	330	Japanese	24.00	2004.0	
2830	64556	140	Spanish	10.00	2004.0	
2914	31943	224	Korean	12.80	2004.0	
4461	65951	258	Danish	1.30	1998.0	
3553	81644	107	Portuguese	4.00	2007.0	
3423	106160	430	Japanese	1100.00	1988.0	
4267	173551	361	Spanish	2.00	2000.0	
3456	70194	158	French	7.30	2007.0	
3344	69759	235	Hindi	12.00	2010.0	
4144	28951	257	Portuguese	2.90	1998.0	
4284	46107	156	Hebrew	1.50	2008.0	
4897	147566	235	Italian	0.20	1964.0	
1171	149414	841	Mandarin	31.00	2002.0	
2863	132149	316	Japanese	19.00	2006.0	
3264	70382	190	French	8.90	2012.0	
3510	34449	119	Hindi	7.00	2004.0	
3677	44151	110	French	5.50	2004.0	
4415	38215	125	Spanish	1.50	2000.0	
4640	44763	172	Romanian	0.59	2007.0	
2605	217740	1641	Mandarin	15.00	2000.0	

	imdb_score	movie_facebook_likes	profit	Rank
4498	8.9	20000	4.90	6
4747	8.7	11000	-1.73	17
4029	8.7	28000	4.26	17
2373	8.6	28000	-8.95	24
4259	8.5	39000	9.28	37
4921	8.5	0	0.75	37
2323	8.4	11000	-2397.70	54
2970	8.4	11000	-2.57	54
4105	8.4	43000	-0.82	54
4659	8.4	48000	6.60	54
1329	8.4	21000	-11.53	54
1298	8.4	39000	-43.80	54
2734	8.3	12000	-5.97	73
4033	8.3	60000	-3.19	73
2829	8.3	14000	-8.00	73
2551	8.2	27000	24.12	96
4000	8.2	33000	18.17	96
3550	8.2	37000	0.06	96
2047	8.2	13000	-19.29	96
2830	8.1	0	-7.91	130
2914	8.1	0	-11.69	130
4461	8.1	5000	0.35	130
3553	8.1	11000	-3.99	130
3423	8.1	0	-1099.56	130
4267	8.1	11000	3.38	130
3456	8.0	14000	-2.86	179
3344	8.0	27000	-7.98	179
4144	8.0	0	2.70	179
4284	8.0	0	0.78	179
4897	8.0	0	3.30	179
1171	7.9	0	-30.92	228
2863	7.9	5000	-5.25	228
3264	7.9	33000	-8.67	228
3510	7.9	2000	-4.08	228
3677	7.9	0	-1.87	228
4415	7.9	0	-0.28	228
4640	7.9	14000	0.60	228
2605	7.9	0	113.07	228

**Checkpoint 3:** Can you spot Veer-Zaara in the dataframe?

- ### Subtask 3.5: Find the best directors

1. Group the dataframe using the `director_name` column.
2. Find out the top 10 directors for whom the mean of `imdb_score` is the highest and store them in a new dataframe `top10director`. In case of a tie in IMDb score between two directors, sort them alphabetically.

In [183...

```
# Write your code for extracting the top 10 directors here

top10director = actual_data.groupby('director_name')['imdb_score'].mean().sort_values(ascending=False)
print(top10director)

# We made a list of top 10 best Directors of all time and Charles Chaplin tops the list.
```

director_name	
Charles Chaplin	8.600000
Tony Kaye	8.600000
Alfred Hitchcock	8.500000
Ron Fricke	8.500000
Damien Chazelle	8.500000

Majid Majidi	8.500000
Sergio Leone	8.433333
Christopher Nolan	8.425000
S.S. Rajamouli	8.400000
Marius A. Markevicius	8.400000
Name: imdb_score, dtype: float64	

**Checkpoint 4:** No surprises that Damien Chazelle (director of Whiplash and La La Land) is in this list.

- ### Subtask 3.6: Find popular genres

You might have noticed the `genres` column in the dataframe with all the genres of the movies separated by a pipe ( `|` ). Out of all the movie genres, the first two are most significant for any film.

1. Extract the first two genres from the `genres` column and store them in two new columns: `genre_1` and `genre_2` . Some of the movies might have only one genre. In such cases, extract the single genre into both the columns, i.e. for such movies the `genre_2` will be the same as `genre_1` .
2. Group the dataframe using `genre_1` as the primary column and `genre_2` as the secondary column.
3. Find out the 5 most popular combo of genres by finding the mean of the gross values using the `gross` column and store them in a new dataframe named `PopGenre` .

In [189...

```
# Write your code for extracting the first two genres of each movie here

actual_data[['genre_1', 'genre_2', 'remaining']] = actual_data['genres'].str.split('|', n=
actual_data.drop('remaining', inplace=True, axis=1)
actual_data["genre_2"] = actual_data["genre_2"].fillna(actual_data["genre_1"])
print(actual_data)

# Since we had Movie Genre given in a Single Column, we had to split the Genre into Genre
```

	director_name	num_critic_for_reviews	gross	\
0	James Cameron	723.0	760.51	
1	Gore Verbinski	302.0	309.40	
2	Sam Mendes	602.0	200.07	
3	Christopher Nolan	813.0	448.13	
5	Andrew Stanton	462.0	73.06	
...	...	...	...	
5033	Shane Carruth	143.0	0.42	
5034	Neill Dela Llana	35.0	0.07	
5035	Robert Rodriguez	56.0	2.04	
5037	Edward Burns	14.0	0.00	
5042	Jon Gunn	43.0	0.09	

	genres	actor_1_name	\
0	Action Adventure Fantasy Sci-Fi	CCH Pounder	
1	Action Adventure Fantasy	Johnny Depp	
2	Action Adventure Thriller	Christoph Waltz	
3	Action Thriller	Tom Hardy	
5	Action Adventure Sci-Fi	Daryl Sabara	
...	...	...	
5033	Drama Sci-Fi Thriller	Shane Carruth	
5034	Thriller	Ian Gamazon	
5035	Action Crime Drama Romance Thriller	Carlos Gallardo	
5037	Comedy Drama	Kerry Bishé	
5042	Documentary	John August	

	movie_title	num_voted_users	\
0	Avatar	886204	
1	Pirates of the Caribbean: At World's End	471220	
2	Spectre	275868	
3	The Dark Knight Rises	1144337	
5	John Carter	212204	

```

...
5033          Primer          72639
5034          Cavite          589
5035      El Mariachi      52055
5037      Newlyweds      1338
5042      My Date with Drew      4285

```

```

      num_user_for_reviews language budget title_year imdb_score \
0          3054 English 237.00      2009.0      7.9
1          1238 English 300.00      2007.0      7.1
2           994 English 245.00      2015.0      6.8
3          2701 English 250.00      2012.0      8.5
5           738 English 263.70      2012.0      6.6
...
5033          371 English    0.01      2004.0      7.0
5034           35 English    0.01      2005.0      6.3
5035          130 Spanish    0.01      1992.0      6.9
5037           14 English    0.01      2011.0      6.4
5042           84 English    0.00      2004.0      6.6

```

```

      movie_facebook_likes profit genre_1 genre_2
0          33000 523.51      Action Adventure
1              0   9.40      Action Adventure
2          85000 -44.93      Action Adventure
3         164000 198.13      Action  Thriller
5          24000 -190.64      Action Adventure
...
5033         19000   0.41      Drama  Sci-Fi
5034           74   0.06  Thriller  Thriller
5035            0   2.03      Action   Crime
5037          413  -0.01      Comedy   Drama
5042          456   0.09 Documentary Documentary

```

[3856 rows x 16 columns]

In [191...

```

# Write your code for grouping the dataframe here

movies_by_segment = actual_data.groupby(['genre_1', 'genre_2'])

```

In [193...

```

# Write your code for getting the 5 most popular combo of genres here

PopGenre = movies_by_segment.gross.mean()
PopGenre = PopGenre.sort_values(ascending = False)
print(PopGenre)

# Here we were able to find out the best combination of the two genres and it was Family

```

```

genre_1  genre_2      gross
Family    Sci-Fi    434.950000
Adventure Sci-Fi    228.628750
          Family    118.918824
          Animation  116.998462
Action    Adventure  109.595510
...
Horror     Musical     0.140000
Romance    Romance     0.105000
Thriller    Thriller     0.040000
Sci-Fi     Sci-Fi     0.020000
Adventure   War         0.010000
Name: gross, Length: 103, dtype: float64

```

**Checkpoint 5:** Well, as it turns out. Family + Sci-Fi is the most popular combo of genres out there!

- ### Subtask 3.7: Find the critic-favorite and audience-favorite actors

1. Create three new dataframes namely, `Meryl_Streep`, `Leo_Caprio`, and `Brad_Pitt` which contain the movies in which the actors: 'Meryl Streep', 'Leonardo DiCaprio', and 'Brad Pitt' are the lead actors. Use only the `actor_1_name` column for extraction. Also, make sure that you use the names 'Meryl Streep', 'Leonardo DiCaprio', and 'Brad Pitt' for the said extraction.
2. Append the rows of all these dataframes and store them in a new dataframe named `Combined`.
3. Group the combined dataframe using the `actor_1_name` column.
4. Find the mean of the `num_critic_for_reviews` and `num_users_for_review` and identify the actors which have the highest mean.
5. Observe the change in number of voted users over decades using a bar chart. Create a column called `decade` which represents the decade to which every movie belongs to. For example, the `title_year` year 1923, 1925 should be stored as 1920s. Sort the dataframe based on the column `decade`, group it by `decade` and find the sum of users voted in each decade. Store this in a new dataframe called `df_by_decade`.

In [226...

```
# Write your code for creating three new dataframes here

Meryl_Streep = actual_data[actual_data['actor_1_name'] == "Meryl Streep"]
print(Meryl_Streep)

# Include all movies in which Meryl_Streep is the lead
```

	director_name	num_critic_for_reviews	gross	\
410	Nancy Meyers	187.000	112.700	
1106	Curtis Hanson	42.000	46.820	
1204	Nora Ephron	252.000	94.130	
1408	David Frankel	208.000	124.730	
1483	Robert Redford	227.000	15.000	
1575	Sydney Pollack	66.000	87.100	
1618	David Frankel	234.000	63.540	
1674	Carl Franklin	64.000	23.210	
1925	Stephen Daldry	174.000	41.600	
2781	Phyllida Lloyd	331.000	29.960	
3135	Robert Altman	211.000	20.340	

	genres	actor_1_name	\
410	Comedy Drama Romance	Meryl Streep	
1106	Action Adventure Crime Thriller	Meryl Streep	
1204	Biography Drama Romance	Meryl Streep	
1408	Comedy Drama Romance	Meryl Streep	
1483	Drama Thriller War	Meryl Streep	
1575	Biography Drama Romance	Meryl Streep	
1618	Comedy Drama Romance	Meryl Streep	
1674	Drama	Meryl Streep	
1925	Drama Romance	Meryl Streep	
2781	Biography Drama History	Meryl Streep	
3135	Comedy Drama Music	Meryl Streep	

	movie_title	num_voted_users	num_user_for_reviews	\
410	It's Complicated	69860	214	
1106	The River Wild	32544	69	
1204	Julie & Julia	79264	277	
1408	The Devil Wears Prada	286178	631	
1483	Lions for Lambs	41170	298	
1575	Out of Africa	52339	200	
1618	Hope Springs	34258	178	
1674	One True Thing	9283	112	
1925	The Hours	102123	660	
2781	The Iron Lady	82327	350	

	language	budget	title_year	imdb_score	movie_facebook_likes	profit	\
410	English	85.000	2009.000	6.600	0	27.700	
1106	English	45.000	1994.000	6.300	0	1.820	
1204	English	40.000	2009.000	7.000	13000	54.130	
1408	English	35.000	2006.000	6.800	0	89.730	
1483	English	35.000	2007.000	6.200	0	-20.000	
1575	English	31.000	1985.000	7.200	0	56.100	
1618	English	30.000	2012.000	6.300	0	33.540	
1674	English	30.000	1998.000	7.000	592	-6.790	
1925	English	25.000	2002.000	7.600	0	16.600	
2781	English	13.000	2011.000	6.400	18000	16.960	
3135	English	10.000	2006.000	6.800	683	10.340	

	genre_1	genre_2
410	Comedy	Drama
1106	Action	Adventure
1204	Biography	Drama
1408	Comedy	Drama
1483	Drama	Thriller
1575	Biography	Drama
1618	Comedy	Drama
1674	Drama	Drama
1925	Drama	Romance
2781	Biography	Drama
3135	Comedy	Drama

In [227...

```
Leo_Caprio = actual_data[actual_data['actor_1_name'] == "Leonardo DiCaprio"]
print(Leo_Caprio)
```

	director_name	num_critic_for_reviews	gross	\
26	James Cameron	315.000	658.670	
50	Baz Luhrmann	490.000	144.810	
97	Christopher Nolan	642.000	292.570	
179	Alejandro G. Iñárritu	556.000	183.640	
257	Martin Scorsese	267.000	102.610	
296	Quentin Tarantino	765.000	162.800	
307	Edward Zwick	166.000	57.370	
308	Martin Scorsese	606.000	116.870	
326	Martin Scorsese	233.000	77.680	
361	Martin Scorsese	352.000	132.370	
452	Martin Scorsese	490.000	127.970	
641	Ridley Scott	238.000	39.380	
911	Steven Spielberg	194.000	164.440	
990	Danny Boyle	118.000	39.780	
1114	Sam Mendes	323.000	22.880	
1422	Randall Wallace	83.000	56.880	
1453	Clint Eastwood	392.000	37.300	
1560	Sam Raimi	63.000	18.640	
2067	Jerry Zaks	45.000	12.780	
2757	Baz Luhrmann	106.000	46.340	
3476	Baz Luhrmann	490.000	144.810	

	genres	actor_1_name	\
26	Drama Romance	Leonardo DiCaprio	
50	Drama Romance	Leonardo DiCaprio	
97	Action Adventure Sci-Fi Thriller	Leonardo DiCaprio	
179	Adventure Drama Thriller Western	Leonardo DiCaprio	
257	Biography Drama	Leonardo DiCaprio	
296	Drama Western	Leonardo DiCaprio	
307	Adventure Drama Thriller	Leonardo DiCaprio	
308	Biography Comedy Crime Drama	Leonardo DiCaprio	
326	Crime Drama	Leonardo DiCaprio	
361	Crime Drama Thriller	Leonardo DiCaprio	

452	Mystery Thriller	Leonardo DiCaprio
641	Action Drama Thriller	Leonardo DiCaprio
911	Biography Crime Drama	Leonardo DiCaprio
990	Adventure Drama Thriller	Leonardo DiCaprio
1114	Drama Romance	Leonardo DiCaprio
1422	Action Adventure	Leonardo DiCaprio
1453	Biography Crime Drama	Leonardo DiCaprio
1560	Action Thriller Western	Leonardo DiCaprio
2067	Drama	Leonardo DiCaprio
2757	Drama Romance	Leonardo DiCaprio
3476	Drama Romance	Leonardo DiCaprio

	movie_title	num_voted_users	num_user_for_reviews	\
26	Titanic	793059	2528	
50	The Great Gatsby	362912	753	
97	Inception	1468200	2803	
179	The Revenant	406020	1188	
257	The Aviator	264318	799	
296	Django Unchained	955174	1193	
307	Blood Diamond	400292	657	
308	The Wolf of Wall Street	780588	1138	
326	Gangs of New York	314033	1166	
361	The Departed	873649	2054	
452	Shutter Island	786092	964	
641	Body of Lies	174248	263	
911	Catch Me If You Can	525801	667	
990	The Beach	176169	548	
1114	Revolutionary Road	152591	414	
1422	The Man in the Iron Mask	125219	244	
1453	J. Edgar	102728	279	
1560	The Quick and the Dead	69197	216	
2067	Marvin's Room	20163	71	
2757	Romeo + Juliet	167750	506	
3476	The Great Gatsby	362933	753	

	language	budget	title_year	imdb_score	movie_facebook_likes	profit	\
26	English	200.000	1997.000	7.700	26000	458.670	
50	English	105.000	2013.000	7.300	115000	39.810	
97	English	160.000	2010.000	8.800	175000	132.570	
179	English	135.000	2015.000	8.100	190000	48.640	
257	English	110.000	2004.000	7.500	0	-7.390	
296	English	100.000	2012.000	8.500	199000	62.800	
307	English	100.000	2006.000	8.000	14000	-42.630	
308	English	100.000	2013.000	8.200	138000	16.870	
326	English	100.000	2002.000	7.500	0	-22.320	
361	English	90.000	2006.000	8.500	29000	42.370	
452	English	80.000	2010.000	8.100	53000	47.970	
641	English	70.000	2008.000	7.100	0	-30.620	
911	English	52.000	2002.000	8.000	15000	112.440	
990	English	50.000	2000.000	6.600	0	-10.220	
1114	English	35.000	2008.000	7.300	0	-12.120	
1422	English	35.000	1998.000	6.400	0	21.880	
1453	English	35.000	2011.000	6.600	16000	2.300	
1560	English	32.000	1995.000	6.400	0	-13.360	
2067	English	23.000	1996.000	6.700	1000	-10.220	
2757	English	14.500	1996.000	6.800	10000	31.840	
3476	English	105.000	2013.000	7.300	115000	39.810	

	genre_1	genre_2
26	Drama	Romance
50	Drama	Romance
97	Action	Adventure
179	Adventure	Drama
257	Biography	Drama
296	Drama	Western
307	Adventure	Drama

308	Biography	Comedy
326	Crime	Drama
361	Crime	Drama
452	Mystery	Thriller
641	Action	Drama
911	Biography	Crime
990	Adventure	Drama
1114	Drama	Romance
1422	Action	Adventure
1453	Biography	Crime
1560	Action	Thriller
2067	Drama	Drama
2757	Drama	Romance
3476	Drama	Romance

In [224..

```
Brad_Pitt = actual_data[actual_data['actor_1_name'] == "Brad Pitt"]
print(Brad_Pitt)
```

	director_name	num_critic_for_reviews	gross	\
101	David Fincher	362.000	127.490	
147	Wolfgang Petersen	220.000	133.230	
254	Steven Soderbergh	198.000	125.530	
255	Doug Liman	233.000	186.340	
382	Tony Scott	142.000	0.030	
400	Steven Soderbergh	186.000	183.410	
470	David Ayer	406.000	85.710	
611	Jean-Jacques Annaud	76.000	37.900	
683	David Fincher	315.000	37.020	
792	Patrick Gilmore	98.000	26.290	
940	Neil Jordan	120.000	105.260	
1490	Terrence Malick	584.000	13.300	
1722	Andrew Dominik	273.000	3.900	
2204	Alejandro G. Iñárritu	285.000	34.300	
2333	Angelina Jolie Pitt	131.000	0.530	
2682	Andrew Dominik	414.000	14.940	
2898	Tony Scott	122.000	12.280	

	genres	actor_1_name	\
101	Drama Fantasy Romance	Brad Pitt	
147	Adventure	Brad Pitt	
254	Crime Thriller	Brad Pitt	
255	Action Comedy Crime Romance Thriller	Brad Pitt	
382	Action Crime Thriller	Brad Pitt	
400	Crime Thriller	Brad Pitt	
470	Action Drama War	Brad Pitt	
611	Adventure Biography Drama History War	Brad Pitt	
683	Drama	Brad Pitt	
792	Adventure Animation Comedy Drama Family Fantas...	Brad Pitt	
940	Drama Fantasy Horror	Brad Pitt	
1490	Drama Fantasy	Brad Pitt	
1722	Biography Crime Drama History Western	Brad Pitt	
2204	Drama	Brad Pitt	
2333	Drama Romance	Brad Pitt	
2682	Crime Thriller	Brad Pitt	
2898	Action Crime Drama Romance Thriller	Brad Pitt	

	movie_title	num_voted_users	\
101	The Curious Case of Benjamin Button	459346	
147	Troy	381672	
254	Ocean's Twelve	284852	
255	Mr. & Mrs. Smith	348861	
382	Spy Game	121259	
400	Ocean's Eleven	402645	
470	Fury	303185	
611	Seven Years in Tibet	96385	



683		Fight Club	1347461
792	Sinbad: Legend of the Seven Seas		36144
940	Interview with the Vampire: The Vampire Chroni...		239752
1490	The Tree of Life		136367
1722	The Assassination of Jesse James by the Coward...		136104
2204	Babel		243799
2333	By the Sea		7976
2682	Killing Them Softly		111625
2898	True Romance		163492

	num_user_for_reviews	language	budget	title_year	imdb_score	\
101	822	English	150.000	2008.000	7.800	
147	1694	English	175.000	2004.000	7.200	
254	627	English	110.000	2004.000	6.400	
255	798	English	120.000	2005.000	6.500	
382	361	English	92.000	2001.000	7.000	
400	845	English	85.000	2001.000	7.800	
470	701	English	68.000	2014.000	7.600	
611	119	English	70.000	1997.000	7.000	
683	2968	English	63.000	1999.000	8.800	
792	91	English	60.000	2003.000	6.700	
940	406	English	60.000	1994.000	7.600	
1490	975	English	32.000	2011.000	6.700	
1722	415	English	30.000	2007.000	7.500	
2204	908	English	25.000	2006.000	7.500	
2333	61	English	10.000	2015.000	5.300	
2682	369	English	15.000	2012.000	6.200	
2898	460	English	13.000	1993.000	8.000	

	movie_facebook_likes	profit	genre_1	genre_2
101	23000	-22.510	Drama	Fantasy
147	0	-41.770	Adventure	Adventure
254	0	15.530	Crime	Thriller
255	0	66.340	Action	Comedy
382	0	-91.970	Action	Crime
400	0	98.410	Crime	Thriller
470	82000	17.710	Action	Drama
611	0	-32.100	Adventure	Biography
683	48000	-25.980	Drama	Drama
792	880	-33.710	Adventure	Animation
940	11000	45.260	Drama	Fantasy
1490	39000	-18.700	Drama	Fantasy
1722	0	-26.100	Biography	Crime
2204	0	9.300	Drama	Drama
2333	0	-9.470	Drama	Romance
2682	20000	-0.060	Crime	Thriller
2898	15000	-0.720	Action	Crime

In [228...

```
# Write your code for combining the three dataframes here
Combined = pd.concat([Meryl_Streep, Leo_Caprio, Brad_Pitt], axis = 0)
print(Combined)

# We Created a Dataset only with movies that had Meryl_Streep, Leo_Caprio, Brad_Pitt as tl
```

	director_name	num_critic_for_reviews	gross	\
410	Nancy Meyers	187.000	112.700	
1106	Curtis Hanson	42.000	46.820	
1204	Nora Ephron	252.000	94.130	
1408	David Frankel	208.000	124.730	
1483	Robert Redford	227.000	15.000	
1575	Sydney Pollack	66.000	87.100	
1618	David Frankel	234.000	63.540	
1674	Carl Franklin	64.000	23.210	
1925	Stephen Daldry	174.000	41.600	
2781	Phyllida Lloyd	331.000	29.960	

3135	Robert Altman	211.000	20.340
26	James Cameron	315.000	658.670
50	Baz Luhrmann	490.000	144.810
97	Christopher Nolan	642.000	292.570
179	Alejandro G. Iñárritu	556.000	183.640
257	Martin Scorsese	267.000	102.610
296	Quentin Tarantino	765.000	162.800
307	Edward Zwick	166.000	57.370
308	Martin Scorsese	606.000	116.870
326	Martin Scorsese	233.000	77.680
361	Martin Scorsese	352.000	132.370
452	Martin Scorsese	490.000	127.970
641	Ridley Scott	238.000	39.380
911	Steven Spielberg	194.000	164.440
990	Danny Boyle	118.000	39.780
1114	Sam Mendes	323.000	22.880
1422	Randall Wallace	83.000	56.880
1453	Clint Eastwood	392.000	37.300
1560	Sam Raimi	63.000	18.640
2067	Jerry Zaks	45.000	12.780
2757	Baz Luhrmann	106.000	46.340
3476	Baz Luhrmann	490.000	144.810
101	David Fincher	362.000	127.490
147	Wolfgang Petersen	220.000	133.230
254	Steven Soderbergh	198.000	125.530
255	Doug Liman	233.000	186.340
382	Tony Scott	142.000	0.030
400	Steven Soderbergh	186.000	183.410
470	David Ayer	406.000	85.710
611	Jean-Jacques Annaud	76.000	37.900
683	David Fincher	315.000	37.020
792	Patrick Gilmore	98.000	26.290
940	Neil Jordan	120.000	105.260
1490	Terrence Malick	584.000	13.300
1722	Andrew Dominik	273.000	3.900
2204	Alejandro G. Iñárritu	285.000	34.300
2333	Angelina Jolie Pitt	131.000	0.530
2682	Andrew Dominik	414.000	14.940
2898	Tony Scott	122.000	12.280

	genres	actor_1_name \
410	Comedy Drama Romance	Meryl Streep
1106	Action Adventure Crime Thriller	Meryl Streep
1204	Biography Drama Romance	Meryl Streep
1408	Comedy Drama Romance	Meryl Streep
1483	Drama Thriller War	Meryl Streep
1575	Biography Drama Romance	Meryl Streep
1618	Comedy Drama Romance	Meryl Streep
1674	Drama	Meryl Streep
1925	Drama Romance	Meryl Streep
2781	Biography Drama History	Meryl Streep
3135	Comedy Drama Music	Meryl Streep
26	Drama Romance	Leonardo DiCaprio
50	Drama Romance	Leonardo DiCaprio
97	Action Adventure Sci-Fi Thriller	Leonardo DiCaprio
179	Adventure Drama Thriller Western	Leonardo DiCaprio
257	Biography Drama	Leonardo DiCaprio
296	Drama Western	Leonardo DiCaprio
307	Adventure Drama Thriller	Leonardo DiCaprio
308	Biography Comedy Crime Drama	Leonardo DiCaprio
326	Crime Drama	Leonardo DiCaprio
361	Crime Drama Thriller	Leonardo DiCaprio
452	Mystery Thriller	Leonardo DiCaprio
641	Action Drama Thriller	Leonardo DiCaprio
911	Biography Crime Drama	Leonardo DiCaprio
990	Adventure Drama Thriller	Leonardo DiCaprio

1114	Drama Romance	Leonardo DiCaprio
1422	Action Adventure	Leonardo DiCaprio
1453	Biography Crime Drama	Leonardo DiCaprio
1560	Action Thriller Western	Leonardo DiCaprio
2067	Drama	Leonardo DiCaprio
2757	Drama Romance	Leonardo DiCaprio
3476	Drama Romance	Leonardo DiCaprio
101	Drama Fantasy Romance	Brad Pitt
147	Adventure	Brad Pitt
254	Crime Thriller	Brad Pitt
255	Action Comedy Crime Romance Thriller	Brad Pitt
382	Action Crime Thriller	Brad Pitt
400	Crime Thriller	Brad Pitt
470	Action Drama War	Brad Pitt
611	Adventure Biography Drama History War	Brad Pitt
683	Drama	Brad Pitt
792	Adventure Animation Comedy Drama Family Fantas...	Brad Pitt
940	Drama Fantasy Horror	Brad Pitt
1490	Drama Fantasy	Brad Pitt
1722	Biography Crime Drama History Western	Brad Pitt
2204	Drama	Brad Pitt
2333	Drama Romance	Brad Pitt
2682	Crime Thriller	Brad Pitt
2898	Action Crime Drama Romance Thriller	Brad Pitt

	movie_title	num_voted_users \
410	It's Complicated	69860
1106	The River Wild	32544
1204	Julie & Julia	79264
1408	The Devil Wears Prada	286178
1483	Lions for Lambs	41170
1575	Out of Africa	52339
1618	Hope Springs	34258
1674	One True Thing	9283
1925	The Hours	102123
2781	The Iron Lady	82327
3135	A Prairie Home Companion	19655
26	Titanic	793059
50	The Great Gatsby	362912
97	Inception	1468200
179	The Revenant	406020
257	The Aviator	264318
296	Django Unchained	955174
307	Blood Diamond	400292
308	The Wolf of Wall Street	780588
326	Gangs of New York	314033
361	The Departed	873649
452	Shutter Island	786092
641	Body of Lies	174248
911	Catch Me If You Can	525801
990	The Beach	176169
1114	Revolutionary Road	152591
1422	The Man in the Iron Mask	125219
1453	J. Edgar	102728
1560	The Quick and the Dead	69197
2067	Marvin's Room	20163
2757	Romeo + Juliet	167750
3476	The Great Gatsby	362933
101	The Curious Case of Benjamin Button	459346
147	Troy	381672
254	Ocean's Twelve	284852
255	Mr. & Mrs. Smith	348861
382	Spy Game	121259
400	Ocean's Eleven	402645
470	Fury	303185
611	Seven Years in Tibet	96385

683		Fight Club	1347461
792	Sinbad: Legend of the Seven Seas		36144
940	Interview with the Vampire: The Vampire Chroni...		239752
1490	The Tree of Life		136367
1722	The Assassination of Jesse James by the Coward...		136104
2204	Babel		243799
2333	By the Sea		7976
2682	Killing Them Softly		111625
2898	True Romance		163492

	num_user_for_reviews	language	budget	title_year	imdb_score	\
410	214	English	85.000	2009.000	6.600	
1106	69	English	45.000	1994.000	6.300	
1204	277	English	40.000	2009.000	7.000	
1408	631	English	35.000	2006.000	6.800	
1483	298	English	35.000	2007.000	6.200	
1575	200	English	31.000	1985.000	7.200	
1618	178	English	30.000	2012.000	6.300	
1674	112	English	30.000	1998.000	7.000	
1925	660	English	25.000	2002.000	7.600	
2781	350	English	13.000	2011.000	6.400	
3135	280	English	10.000	2006.000	6.800	
26	2528	English	200.000	1997.000	7.700	
50	753	English	105.000	2013.000	7.300	
97	2803	English	160.000	2010.000	8.800	
179	1188	English	135.000	2015.000	8.100	
257	799	English	110.000	2004.000	7.500	
296	1193	English	100.000	2012.000	8.500	
307	657	English	100.000	2006.000	8.000	
308	1138	English	100.000	2013.000	8.200	
326	1166	English	100.000	2002.000	7.500	
361	2054	English	90.000	2006.000	8.500	
452	964	English	80.000	2010.000	8.100	
641	263	English	70.000	2008.000	7.100	
911	667	English	52.000	2002.000	8.000	
990	548	English	50.000	2000.000	6.600	
1114	414	English	35.000	2008.000	7.300	
1422	244	English	35.000	1998.000	6.400	
1453	279	English	35.000	2011.000	6.600	
1560	216	English	32.000	1995.000	6.400	
2067	71	English	23.000	1996.000	6.700	
2757	506	English	14.500	1996.000	6.800	
3476	753	English	105.000	2013.000	7.300	
101	822	English	150.000	2008.000	7.800	
147	1694	English	175.000	2004.000	7.200	
254	627	English	110.000	2004.000	6.400	
255	798	English	120.000	2005.000	6.500	
382	361	English	92.000	2001.000	7.000	
400	845	English	85.000	2001.000	7.800	
470	701	English	68.000	2014.000	7.600	
611	119	English	70.000	1997.000	7.000	
683	2968	English	63.000	1999.000	8.800	
792	91	English	60.000	2003.000	6.700	
940	406	English	60.000	1994.000	7.600	
1490	975	English	32.000	2011.000	6.700	
1722	415	English	30.000	2007.000	7.500	
2204	908	English	25.000	2006.000	7.500	
2333	61	English	10.000	2015.000	5.300	
2682	369	English	15.000	2012.000	6.200	
2898	460	English	13.000	1993.000	8.000	

	movie_facebook_likes	profit	genre_1	genre_2
410	0	27.700	Comedy	Drama
1106	0	1.820	Action	Adventure
1204	13000	54.130	Biography	Drama
1408	0	89.730	Comedy	Drama

1483	0	-20.000	Drama	Thriller
1575	0	56.100	Biography	Drama
1618	0	33.540	Comedy	Drama
1674	592	-6.790	Drama	Drama
1925	0	16.600	Drama	Romance
2781	18000	16.960	Biography	Drama
3135	683	10.340	Comedy	Drama
26	26000	458.670	Drama	Romance
50	115000	39.810	Drama	Romance
97	175000	132.570	Action	Adventure
179	190000	48.640	Adventure	Drama
257	0	-7.390	Biography	Drama
296	199000	62.800	Drama	Western
307	14000	-42.630	Adventure	Drama
308	138000	16.870	Biography	Comedy
326	0	-22.320	Crime	Drama
361	29000	42.370	Crime	Drama
452	53000	47.970	Mystery	Thriller
641	0	-30.620	Action	Drama
911	15000	112.440	Biography	Crime
990	0	-10.220	Adventure	Drama
1114	0	-12.120	Drama	Romance
1422	0	21.880	Action	Adventure
1453	16000	2.300	Biography	Crime
1560	0	-13.360	Action	Thriller
2067	1000	-10.220	Drama	Drama
2757	10000	31.840	Drama	Romance
3476	115000	39.810	Drama	Romance
101	23000	-22.510	Drama	Fantasy
147	0	-41.770	Adventure	Adventure
254	0	15.530	Crime	Thriller
255	0	66.340	Action	Comedy
382	0	-91.970	Action	Crime
400	0	98.410	Crime	Thriller
470	82000	17.710	Action	Drama
611	0	-32.100	Adventure	Biography
683	48000	-25.980	Drama	Drama
792	880	-33.710	Adventure	Animation
940	11000	45.260	Drama	Fantasy
1490	39000	-18.700	Drama	Fantasy
1722	0	-26.100	Biography	Crime
2204	0	9.300	Drama	Drama
2333	0	-9.470	Drama	Romance
2682	20000	-0.060	Crime	Thriller
2898	15000	-0.720	Action	Crime

In [229...

```
# Write your code for grouping the combined dataframe here

movies_by_lead_actor = Combined.groupby(['actor_1_name'])

movies_by_lead_actor
```

Out[229...

	num_critic_for_reviews	num_user_for_reviews
actor_1_name		
Brad Pitt	245.000	48362909575284482650084176409630425793076528152...
Leonardo DiCaprio	330.190	12041682287199465949590673927567270018268705975...
Meryl Streep	181.455	1951752511936200083592242528256.000

In [230...

```
# Write the code for finding the mean of critic reviews and audience reviews here
```

```
print(movies_by_lead_actor.num_critic_for_reviews.mean())
print(movies_by_lead_actor.num_user_for_reviews.mean())
```

```
actor_1_name
Brad Pitt      245.000
Leonardo DiCaprio  330.190
Meryl Streep    181.455
Name: num_critic_for_reviews, dtype: float64
actor_1_name
Brad Pitt      48362909575284482650084176409630425793076528152...
Leonardo DiCaprio  12041682287199465949590673927567270018268705975...
Meryl Streep      1951752511936200083592242528256.000
Name: num_user_for_reviews, dtype: float64
```

**Checkpoint 6:** Leonardo has aced both the lists!

In [232...

```
Movies_by_decade=actual_data.copy(deep=True)
Movies_by_decade['decade']=Movies_by_decade['title_year'].apply(lambda x:10*(int(x/10)))
Movies_by_decade

# In this part we are trying to understand how movies have changed in each Decade.
```

Out[232...

	director_name	num_critic_for_reviews	gross	genres	actor_1_name	movie_title
0	James Cameron	723.000	760.510	Action Adventure Fantasy Sci-Fi	CCH Pounder	Avatar
1	Gore Verbinski	302.000	309.400	Action Adventure Fantasy	Johnny Depp	Pirates of the Caribbean: At World's End
2	Sam Mendes	602.000	200.070	Action Adventure Thriller	Christoph Waltz	Spectre
3	Christopher Nolan	813.000	448.130	Action Thriller	Tom Hardy	The Dark Knight Rises
5	Andrew Stanton	462.000	73.060	Action Adventure Sci-Fi	Daryl Sabara	John Carter
...	...	...	...	...	...	...
5033	Shane Carruth	143.000	0.420	Drama Sci-Fi Thriller	Shane Carruth	Primer
5034	Neill Dela Llana	35.000	0.070	Thriller	Ian Gamazon	Cavite
5035	Robert Rodriguez	56.000	2.040	Action Crime Drama Romance Thriller	Carlos Gallardo	El Mariachi
5037	Edward Burns	14.000	0.000	Comedy Drama	Kerry Bishé	Newlyweds
5042	Jon Gunn	43.000	0.090	Documentary	John August	My Date with Drew

3856 rows × 7 columns

In [233...

```
# Write your code for creating the data frame df_by_decade here

Movies_by_decade = Movies_by_decade.groupby('decade',as_index=False)['num_voted_users'].sum()
Movies_by_decade
```

```
# As we can see, the number of Users voted in the IMDB site has been increasing rapidly as
```

Out[233...

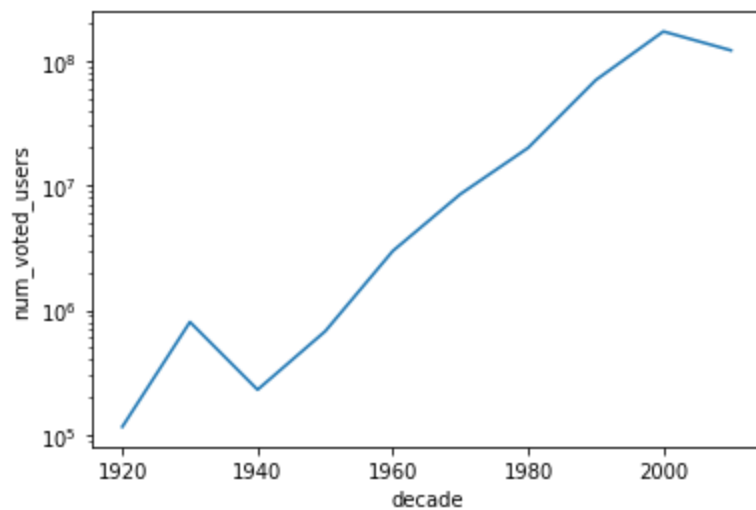
	decade	num_voted_users
0	1920	116392
1	1930	804839
2	1940	230838
3	1950	678336
4	1960	2983442
5	1970	8524102
6	1980	19987476
7	1990	69735679
8	2000	170908676
9	2010	120640994

In [242...

```
# Write your code for plotting number of voted users vs decade
```

```
sns.lineplot(data= Movies_by_decade, x='decade', y='num_voted_users')  
plt.yscale('log')  
plt.ylabel("num_voted_users")  
plt.xlabel("decade")  
plt.show()
```

```
# Though the number of Users voted has been since 1900s, but there has been slight dip in
```



In [ ]: