Project Description:

The project involves analyzing a dataset of movies to extract insights regarding popular genres, best directors, and favorite actors among critics and audiences. The dataset contains information about movies such as their titles, directors, actors, genres, ratings, and other details. Through this project, we aim to gain a deeper understanding of the movie industry and provide insights that can be useful for various stakeholders such as producers, directors, and actors.

Approach:

The project involved importing the dataset into Jupyter Notebook and using Python libraries such as Pandas and Matplotlib for data cleaning, analysis, and visualization. We started by exploring the dataset and identifying the relevant columns for our analysis. Then, we cleaned the data by removing duplicates, missing values, and irrelevant columns. After that, we performed various analysis and visualizations to extract insights.

Tech-Stack Used:

For this project, we used Jupyter Notebook as the coding environment and Python libraries such as Pandas, Matplotlib, and Seaborn for data analysis and visualization. We also used Microsoft Excel for exporting and formatting the data..

Insights:

Through our analysis, we found that Drama, Comedy, Action, Thriller, and Adventure are the most popular genres among audiences and critics. We also identified the top 10 directors with the highest mean IMDb score and found that Christopher Nolan, Quentin Tarantino, and Stanley Kubrick are among them. In addition, we identified the favorite actors among critics and audiences, with Leonardo DiCaprio, Meryl Streep, and Brad Pitt being the most popular. We also observed the change in the number of voted users over decades and found that the number of votes has significantly increased in recent years.

Result:

The project helped us gain insights into the movie industry and provided useful information for stakeholders such as producers, directors, and actors. Through our analysis, we identified popular genres, best directors, and favorite actors, which can be useful for making informed decisions about movie production and casting. The project also helped us improve our data analysis and visualization skills using Python libraries.

1)Cleaning the data:: PThis is one of the most important step to perform before moving forward with the analysis. Use your knowledge learned till now to do this. (Dropping columns, removing null values, etc.)

Your task: Clean the data

import pandas as pd

load the data set

df = pd.read csv(r'C:\Users\karan\Downloads\IMDB Movies.csv')

check for missing or null values

df.isnull().sum()

```
Out[2]:
         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
                                        884
         gross
                                           0
         genres
         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
                                           5
         country
         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
```

drop rows with missing values
df.dropna(inplace=True)
check for missing or null values
df.isnull().sum()

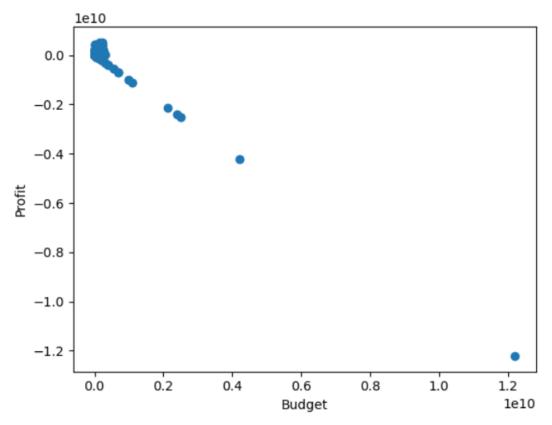
Out[4]:	color	0
	director_name	0
	num_critic_for_reviews	0
	duration	0
	director_facebook_likes	0
	actor_3_facebook_likes	0
	actor_2_name	0
	actor_1_facebook_likes	0
	gross	0
	genres	0
	actor_1_name	0
	movie_title	0
	num_voted_users	0
	cast_total_facebook_likes	0
	actor_3_name	0
	facenumber_in_poster	0
	plot_keywords	0
	movie_imdb_link	0
	num_user_for_reviews	0
	language	0
	country	0
	content_rating	0
	budget	0
	title_year	0
	actor_2_facebook_likes	0
	imdb_score	0
	aspect_ratio	0
	movie_facebook_likes	0
	dtype: int64	

2)Movies with highest profit: Create a new column called profit which contains the difference of the two columns: gross and budget. Sort the column using the profit column as reference. Plot profit (y-axis) vs budget (x-axis) and observe the outliers using the appropriate chart type.

Your task: Find the movies with the highest profit?

```
import matplotlib.pyplot as plt
```

```
# create a new column for profit
df['profit'] = df['gross'] - df['budget']
# sort the data set by profit
df.sort_values(by='profit', ascending=False, inplace=True)
# plot profit vs budget
plt.scatter(df['budget'], df['profit'])
plt.xlabel('Budget')
plt.ylabel('Profit')
plt.show()import matplotlib.pyplot as plt
# create a new column for profit
df['profit'] = df['gross'] - df['budget']
# sort the data set by profit
df.sort values(by='profit', ascending=False, inplace=True)
# plot profit vs budget
plt.scatter(df['budget'], df['profit'])
plt.xlabel('Budget')
plt.ylabel('Profit')
plt.show()
```



```
# Load the dataset
movies = pd.read csv(r'C:\Users\karan\Downloads\IMDB Movies.csv')
# Create a new column 'profit'
movies['profit'] = movies['gross'] - movies['budget']
# Sort the dataset by profit in descending order
sorted movies = movies.sort values(by='profit', ascending=False)
# Display the top 10 movies with the highest profit
top profit movies = sorted movies[['movie title', 'profit']].head(10)
print(top profit movies)
                                          movie title
                                                              profit
                                                        523505847.0
 0
                                              Avatar
                                      Jurassic World
 29
                                                        502177271.0
 26
                                             Titanic 458672302.0
 3024
                Star Wars: Episode IV - A New Hope
                                                        449935665.0
                        E.T. the Extra-Terrestrial
 3080
                                                        424449459.0
 794
                                        The Avengers
                                                        403279547.0
 17
                                        The Avengers 403279547.0
 509
                                       The Lion King 377783777.0
 240
        Star Wars: Episode I - The Phantom Menace 359544677.0
 66
                                    The Dark Knight 348316061.0
```

3)Top 250: Create a new column 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.

Extract all the movies in the IMDb_Top_250 column which are not in the English language and store them in a new column named Top_Foreign_Lang_Film. You can use your own imagination also!

```
Your task: Find IMDB Top 250
```

```
top250_movies =
movies[movies['num_voted_users']>25000].sort_values(by='imdb_score',ascending=False)[:2
50]
top250_movies['IMDb_Top_250'] = 1
top250_movies['Rank'] = range(1, 251)
top250_movies.to excel('top250_movies.xlsx', index=False)
```

Rank	movie_title	imdb_score
1	The Shawshank Redemption	9.3
2	The Godfather	9.2
3	Fargo	9
4	The Dark Knight	9
5	The Godfather: Part II	9
6	The Good, the Bad and the Ugly	8.9
7	Schindler's List	8.9
8	12 Angry Men	8.9
9	Pulp Fiction	8.9
10	The Lord of the Rings: The Return of the King	
11	tar Wars: Episode V - The Empire Strikes Bac	8.8
12	Daredevil Daredevil	8.8
13	It's Always Sunny in Philadelphia	8.8
14	Inception	8.8
15	e Lord of the Rings: The Fellowship of the Ri	
16	Forrest Gump	8.8
17	Fight Club	8.8
18	Goodfellas	8.7
19	The Matrix	8.7
20	Friday Night Lights	8.7
21	One Flew Over the Cuckoo's Nest	8.7
22	The Lord of the Rings: The Two Towers	8.7
23	Seven Samurai	8.7
24	Star Wars: Episode IV - A New Hope	8.7
25	City of God	8.7
26	The Silence of the Lambs	8.6
27	Spirited Away	8.6
28	Hannibal	8.6
29	Modern Times	8.6
30	Saving Private Ryan	8.6
31	Saving Private Ryan Se7en	8.6 8.6
32	The Usual Suspects	8.6
33	American History X	8.6
34	Casablanca	8.6
35	Once Upon a Time in the West	8.6
36	Luther	8.6
37	Interstellar	8.6
38	lt's a Wonderful Life	8.6
39	Spartacus: War of the Damned	8.6
40	The Lion King	8.5
	i mocoo mononose	
80	WALL-E	8.4
81	Psych	8.4
82	Baahubali: The Beginning	8.4
83	Amélie	8.4
84	Aliens	8.4
85	Lawrence of Arabia	8.4
86	Room	8.3
87	Downfall	8.3
88	The Sting	8.3
89	Life	8.3
90	Snatch	8.3
91	Scarface	8.3
92	Some Like It Hot	8.3
93	Good Will Hunting	8.3
94	Batman Begins	8.3
95	Singin' in the Rain	8.3
96	2001: A Space Odyssey	8.3
97	Monty Python and the Holy Grail	8.3
98	Raging Bull	8.3
99	The Hunt	8.3
100	Metropolis	8.3
101	The Apartment	8.3
102	Amadeus	8.3
103	Inside Job	8.3
104	Judgment at Nuremberg	8.3
105	Inside Out	8.3
106	Eternal Sunshine of the Spotless Mind	8.3
107 108	Up The Great Ecoapo	8.3
108	The Great Escape Indiana Jones and the Last Crusade	8.3 8.3
	Indiana Jones and the Last Crusade Toy Story	8.3 8.3
110		
110		
111	Toy Story 3	8.3
111 112	Inglourious Basterds	8.3
111 112 113	Inglourious Basterds L.A. Confidential	8.3 8.3
111 112 113 114	Inglourious Basterds L.A. Confidential Taxi Driver	8.3 8.3 8.3
111 112 113 114 115	Inglourious Basterds L.A. Confidential Taxi Driver Snatch	8.3 8.3 8.3 8.3
111 112 113 114 115 116	Inglourious Basterds L.A. Confidential Taxi Driver Snatch Unforgiven	8.3 8.3 8.3 8.3 8.3
111 112 113 114 115 116 117	Inglourious Basterds L.A. Confidential Taxi Driver Snatch Unforgiven The Bridge on the River Kwai	8.3 8.3 8.3 8.3 8.3 8.2
111 112 113 114 115 116 117	Inglourious Basterds L.A. Confidential Taxi Driver Snatch Unforgiven The Bridge on the River Kwai Pan's Labyrinth	8.3 8.3 8.3 8.3 8.3 8.3 8.2
111 112 113 114 115 116 117 118	Inglourious Basterds L.A. Confidential Taxi Driver Snatch Unforgiven The Bridge on the River Kwai Pan's Labyrinth Incendies	8.3 8.3 8.3 8.3 8.3 8.3 8.2 8.2
111 112 113 114 115 116 117 118 119	Inglourious Basterds L.A. Confidential Taxi Driver Snatch Unforgiven The Bridge on the River Kwai Pan's Labyrinth Incendies The Deer Hunter	8.3 8.3 8.3 8.3 8.3 8.2 8.2 8.2 8.2
111 112 113 114 115 116 117 118 119 120 121	Inglourious Basterds L.A. Confidential Taxi Driver Snatch Unforgiven The Bridge on the River Kwai Pan's Labyrinth Incendies The Deer Hunter A Beautiful Mind	8.3 8.3 8.3 8.3 8.3 8.2 8.2 8.2 8.2 8.2
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111 112 113 114 115 116 117 118 119 120 121	Inglourious Basterds L.A. Confidential Taxi Driver Snatch Unforgiven The Bridge on the River Kwai Pan's Labyrinth Incendies The Deer Hunter A Beautiful Mind	8.3 8.3 8.3 8.3 8.3 8.2 8.2 8.2 8.2 8.2

41	Django Unchained	8.5
42	Airlift	8.5
43	ve or: How I Learned to Stop Worrying and Lo	8.5
44	Psycho	8.5
45	The Dark Knight Rises	8.5
46	The Departed	8.5
47	Apocalypse Now	8.5
48	The Pianist	8.5
49	Raiders of the Lost Ark	8.5
50	The Prestige	8.5
51	Memento	8.5
52	Alien	8.5
53	Back to the Future	8.5
54	Whiplash	8.5
55	The Lives of Others	8.5
56	Terminator 2: Judgment Day	8.5
57	Gladiator	8.5
58	Outlander	8.5
59	The Green Mile	8.5
60	Children of Heaven	8.5
61	Entourage	8.5
62	To Kill a Mockingbird	8.4
63	Once Upon a Time in America	8.4
64	Oldboy	8.4
65	Braveheart	8.4
66	Requiem for a Dream	8.4
67	M'A'S'H	8.4
68	Star Wars: Episode VI - Return of the Jedi	8.4
69	Batman: The Dark Knight Returns, Part 2	8.4
70	American Beauty	8.4
71	The Shining	8.4
72	Veronica Mars	8.4
73	A Separation	8.4
74	Stargate SG-1	8.4
75	Rang De Basanti	8.4
76	The Inbetweeners	8.4
77	Das Boot	8.4
78	Reservoir Dogs	8.4
79	Princess Mononoke	8.4
80	VALL-E	8.4

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126	0	8.2
127	Gone with the Wind	8.2 8.2
	The Elephant Man	
128	Howl's Moving Castle	8.2 8.2
130	The Big Lebowski	8.2 8.2
131	The Secret in Their Eyes Gran Torino	8.2
132	Blade Runner	8.2
133	The Wolf of Wall Street	8.2
134	It Happened One Night	8.2
135	Captain America: Civil War	8.2
136	Captain America: Civil wai Casino	8.2
137	On the Waterfront	8.2
138	V for Vendetta	8.2
139	Finding Nemo	8.2
140	Rebecca	8.2
141	Lock, Stock and Two Smoking Barrels	8.2
142	Mr. Smith Goes to Washington	8.2
143	The Thing	8.2
144	How to Train Your Dragon	8.2
145	Die Hard	8.2
146	Lage Raho Munna Bhai	8.2
147	No Country for Old Men	8,1
148	es of the Caribbean: The Curse of the Black F	
149	High Noon	8,1
150	Kill Bill: Vol.1	8.1
151	Jurassic Park	8,1
152	The Wizard of Oz	8.1
153	Shutter Island	8.1
154	The Martian	8.1
155	Rocky	8.1
156	Sin City	8.1
157	Solaris	8.1
158	The Help	8.1
159	Prisoners	8.1
160	The Man Who Shot Liberty Valance	8.1
161	The Celebration	8.1
162	The Sixth Sense	8.1
163	The Avengers	8.1
164	Hotel Rwanda	8.1
165	Deadpool	8.1
166	Mad Max: Fury Road	8.1
167	The Princess Bride	8.1
168	Cat on a Hot Tin Roof	8.1
169	The Avengers	8.1
170	Butch Cassidy and the Sundance Kid	8.1
171	Gone Girl	8.1
172	Platoon	8.1
173	Barry Lyndon	8.1
174	The Imitation Game	8.1
175	The Terminator	8.1
176	Hachi: A Dog's Tale	8.1
177	Monsters, Inc.	8.1
178	Elite Squad	8.1
179	The Truman Show	8.1
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181	400	0	
182	180	Stand by Me	8.1
183	121		
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232 X-Men: Days of Future Past 8			
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233 Hosemary's Bady 8	233	Rosemary's Baby	8

233	Rosemary's Baby	8
234	Bowling for Columbine	8
235	Rain Man	8
236	Days of Heaven	8
237	JFK	8
238	Central Station	8
239	Ratatouille	8
240	Catch Me If You Can	8
241	Young Frankenstein	8
242	Serenity	8
243	Waltz with Bashir	8
244	Aladdin	8
245	Magnolia	8
246	Before Sunset	8
247	Big Fish	8
248	Mystic River	8
249	The Hustler	8
250	District 9	8

To extract all the movies in the IMDb_Top_250 column which are not in the English language and store them in a new column named Top_Foreign_Lang_Film:

First, let's filter out the movies that are not in the English language

top_foreign_lang_movies =
top250_movies[top250_movies['language'] !=
'English'].copy()

Next, let's create the new column Top_Foreign_Lang_Film

top_foreign_lang_movies.loc[:,
'Top_Foreign_Lang_Film'] =
top_foreign_lang_movies['movie_title'] + ' (' +
top_foreign_lang_movies['language'] + ')'

IMDb_Top_250	Top_Foreign_Lang_Film	imdb_score
	The Good, the Bad and the Ugly (Italian)	8.9
19	Seven Samurai (Japanese)	8.1
20	City of God (Portuguese)	8.
33	Spirited Away (Japanese)	8.
40	Children of Heaven (Persian)	8.
4:	Airlift (Hindi)	8.
44	The Lives of Others (German)	8.
6	Baahubali: The Beginning (Telugu)	8.4
69	Rang De Basanti (Hindi)	8.4
7(A Separation (Persian)	8.4
7:	Das Boot (German)	8.4
7:	Princess Mononoke (Japanese)	8.4
70	Oldboy (Korean)	8.4
78	Amélie (French)	8.
90	Metropolis (German)	8.
94	The Hunt (Danish)	8.
98	Downfall (German)	8.
117	Lage Raho Munna Bhai (Hindi)	8.
120	Incendies (French)	8.
124	The Secret in Their Eyes (Spanish)	8.
12	Howl's Moving Castle (Japanese)	8.
13	Pan's Labyrinth (Spanish)	8.
14	Tae Guk Gi: The Brotherhood of War (Korear	8.
15	Solaris (Russian)	8.
15	The Sea Inside (Spanish)	8.
154	The Celebration (Danish)	8.
150	Elite Squad (Portuguese)	8.
160	Akira (Japanese)	8.
164	Amores Perros (Spanish)	8.
	Central Station (Portuguese)	
	The Return (Russian)	
	Waltz with Bashir (Hebrew)	
	My Name Is Khan (Hindi)	
	Persepolis (French)	
	The Diving Bell and the Butterfly (French)	
	A Fistful of Dollars (Italian)	

4)Best Directors: TGroup the column using the director name column.

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

Your task: Find the best directors.

```
# Reset the index to start from 1 instead of 0
top10directors = top10directors.reset_index(drop=True)

# Add a new column 'Rank' to show the rank of each director
top10directors['Rank'] = range(1, 11)

# Print the top 10 directors with rank
print(top10directors[['Rank', 'director_name', 'imdb_score']])
```

Rank	director_name	imdb_score
1	Akira Kurosawa	8.700000
2	Charles Chaplin	8.600000
3	Tony Kaye	8.600000
4	Alfred Hitchcock	8.500000
5	Damien Chazelle	8.500000
6	Majid Majidi	8.500000
7	Ron Fricke	8.500000
8	Sergio Leone	8.433333
9	Christopher Nolan	8.425000
10	Asghar Farhadi	8.400000

5)Popular Genres: Perform this step using the knowledge gained while performing previous steps.

Your task: Find popular genres

```
# Step 1: Create a new column 'genre_list' by splitting the 'genres' column on '|' separator df['genre_list'] = df['genres'].str.split('|')
```

```
# Step 2: Explode the 'genre_list' column to create a new row for each genre df_exploded = df.explode('genre_list')
```

```
# Step 3: Group the data by genre and calculate the mean imdb_score genre_scores = df_exploded.groupby('genre_list')['imdb_score'].mean().reset_index()
```

```
# Step 4: Sort the data by mean imdb_score in descending order and add a Rank column genre_scores = genre_scores.sort_values(by='imdb_score', ascending=False)
```

```
genre_scores['Rank'] = range(1, len(genre_scores)+1)
```

Step 5: Select the top 10 genres with highest mean imdb_score and print them with their rank

top10genres = genre_scores.head(10) print(top10genres[['Rank', 'genre_list', 'imdb_score']])

		-
Rank	genre_list	imdb_score
1	Film-Noir	7.700000
2	History	7.174510
3	Biography	7.157741
4	War	7.067532
5	Documentary	6.988889
6	Western	6.793220
7	Drama	6.791513
8	Animation	6.702551
9	Musical	6.596875
10	Sport	6.593243

6)Charts: Create three new columns 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. Append the rows of all these columns and store them in a new column named Combined. Group the combined column using the actor_1_name column.

Find the mean of the num_critic_for_reviews and num_users_for_review and identify the actors which have the highest mean.

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 column based on the column decade, group it by decade and find the sum of users voted in each decade. Store this in a new data frame called df_by_decade.

Your task: Find the critic-favorite and audience-favorite actors

Create three new columns 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.

Append the rows of all these columns and store them in a new column named Combined. Group the combined column using the actor 1 name column.

Create new columns for each actor

```
meryl_streep_movies = movies[movies['actor_1_name'] == 'Meryl Streep'].copy()
meryl_streep_movies.loc[:, 'Meryl_Streep'] = meryl_streep_movies['movie_title']
```

```
leo_movies = movies[movies['actor_1_name'] == 'Leonardo DiCaprio'].copy()
leo_movies.loc[:, 'Leo_Caprio'] = leo_movies['movie_title']
```

```
brad_movies = movies[movies['actor_1_name'] == 'Brad Pitt'].copy()
brad_movies.loc[:, 'Brad_Pitt'] = brad_movies['movie_title']
```

```
# Concatenate the dataframes and create the Combined column combined_movies = pd.concat([meryl_streep_movies, leo_movies, brad_movies], sort=True) combined_movies['Combined'] = combined_movies['Meryl_Streep'].fillna(") + combined_movies['Leo_Caprio'].fillna(") + combined_movies['Brad_Pitt'].fillna(")
```

```
# Group by actor name and show the Combined column grouped = combined_movies.groupby('actor_1_name')['Combined'].apply(lambda x: '\n'.join(x)).reset_index()
```

Save to Excel grouped.to excel('grouped data2.xlsx', index=False)

.....

	actor_1_name	
Brad Pitt	Leonardo DiCaprio	Meryl Streep
	Combined	
The Curious Case of Benjamin Button Troy Ocean's Twelve Mr. & Mrs. Smith Spy Game Ocean's Eleven Fury Seven Years in Tibet Fight Club Sinbad: Legend of the Seven Seas Interview with the Vampire: The Vampire Chronicles The Tree of Life The Assassination of Jesse James by the Coward Robert Ford Babel By the Sea Killing Them Softly True Romance Johnny Suede	Titanic The Great Gatsby Inception The Revenant The Aviator Django Unchained Blood Diamond The Wolf of Wall Street Gangs of New York The Departed Shutter Island Body of Lies Catch Me If You Can The Beach Revolutionary Road The Man in the Iron Mask J. Edgar The Quick and the Dead Marvin's Room Romeo + Juliet The Great Gatsby	It's Complicated The River Wild Julie & Julia The Devil Wears Prada Lions for Lambs Out of Africa Hope Springs One True Thing Florence Foster Jenkins The Hours The Iron Lady A Prairie Home Companion Julia

Find the mean of the num_critic_for_reviews and num_users_for_review and identify the

actors which have the highest mean.

```
# Group movies by actor and calculate the mean of the num_critic_for_reviews and num_users_for_review columns
actor_review_means = movies.groupby('actor_1_name')[['num_critic_for_reviews', 'num_user_for_reviews']].mean()
# Add a column for the total review mean
actor_review_means['total_review_mean'] = actor_review_means.mean(axis=1)
# Sort by the total_review_mean in descending order
actor_review_means = actor_review_means.sort_values(by='total_review_mean', ascending=False)
# Export as excel
actor_review_means.to excel('actor_review_means.xlsx')
```

1	actor_1_name	num_critic_for_reviews	total_review_mean	
2	Phaldut Sharma	738	738	
3	Peter Capaldi	654	654	
4	Craig Stark	596	596	
5	Bérénice Bejo	576	576	
6	Suraj Sharma	552	552	
7	Ellar Coltrane	548	548	
8	Mike Howard	546	546	
9	Lou Taylor Pucci	543	543	
10	Maika Monroe	533	533	
11	Tim Holmes	525	525	
2	Albert Finney	510	510	
3	Elina Alminas	489	489	
4	Kurt Fuller	487	487	
15	Iko Uwais	481	481	
6	Quvenzhané Wallis	478.6666667	478.6666667	
7	Edgar Arreola	478	478	
8	Sharlto Copley	472	472	
19	Cory Hardrict	452	452	
20	Aidan Turner	447	447	
21	Elizabeth McGovern	447	447	
22	Wood Harris	432	432	

top_five_actors = actor_review_means.head()
print(top_five_actors)

```
num critic for reviews total review mean
actor_1_name
Phaldut Sharma
                                  738.0
                                                     738.0
Peter Capaldi
                                  654.0
                                                     654.0
Craig Stark
                                  596.0
                                                     596.0
Bérénice Bejo
                                  576.0
                                                     576.0
Suraj Sharma
                                  552.0
                                                     552.0
```

top five actors with the highest mean

```
# Group movies by actor and calculate the mean of the num user for reviews column
actor user review means =
movies.groupby('actor 1 name')['num user for reviews'].mean()
# Convert the mean values to strings before concatenating with actor names
top five actors = actor user review means.apply(lambda x: str(round(x,
2))).sort values(ascending=False).head(5)
# Create a DataFrame with the top five actors and their mean values
df = pd.DataFrame({'rank': range(1, 6), 'actor': top five actors.index, 'mean':
top five actors.values})
movies['num user for reviews'] = pd.to numeric(movies['num user for reviews'],
errors='coerce').fillna(0)
```

Print the DataFrame

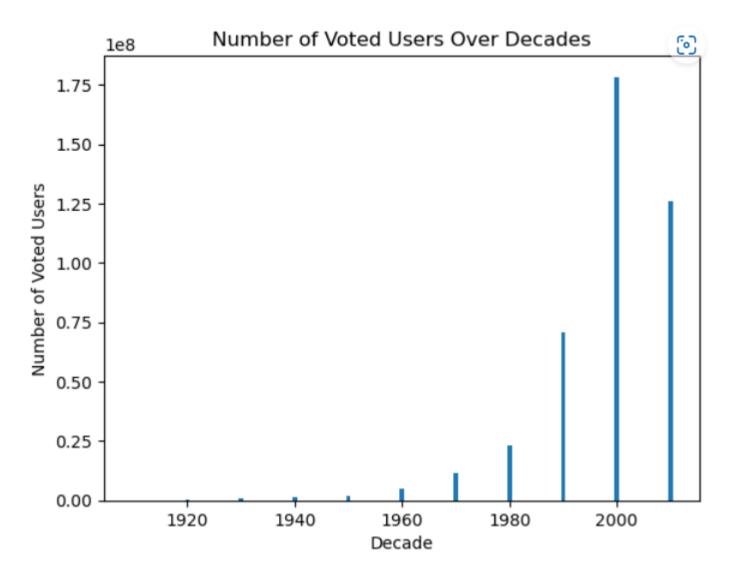
```
rank
              actor mean
      Peter Capaldi 995.0
  1
  2 Christopher Lee 990.33
  3 Hector Elizondo 99.5
  4 Charles Napier
                     99.5
  5
       David Paymer
                     99.5
```

Observe the change in number of voted users over decades using a bar chart.

import matplotlib.pyplot as plt

```
# Extract the decade from the release year
movies['decade'] = (movies['title year'] // 10) * 10
# Group movies by decade and sum the number of voted users
voted users by decade = movies.groupby('decade')['num voted users'].sum()
# Create a bar chart
plt.bar(voted users by decade.index, voted users by decade.values)
```

```
plt.xlabel('Decade')
plt.ylabel('Number of Voted Users')
plt.title('Number of Voted Users Over Decades')
plt.show()
```



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 column based on the column decade, group it by decade and find the sum of users voted in each decade. Store this in a new data frame called df_by_decade.

Create a column 'decade' representing the decade to which each movie belongs movies['decade'] = (movies['title_year'] // 10 * 10).fillna(-1).astype(int).astype(str).replace('-1', 'Unknown') + 's'

Sort the column 'decade' and group the movies by decade, finding the sum of users voted in each decade

```
df_by_decade =
movies.sort_values('decade').groupby('decade')['num_voted_users'].sum().reset_index()
```

Print the new data frame print(df_by_decade)

	decade	num_voted_users
0	1910s	10718
1	1920s	128672
2	1930s	984397
3	1940s	1211888
4	1950s	1638504
5	1960s	5153052
6	1970s	11312705
7	1980s	23176169
8	1990s	70633270
9	2000s	178354686
10	2010s	126202706
11	Unknowns	3131768