

# IMDB Movie Analysis

## *(Final Project-1)*

### Project Description:

The dataset provided by the company contains various columns of different IMDB Movies. We are required to Frame the problem. For this task, we will need to define a problem we want to shed some light on.

We can do this by asking 'What?'. This is where we frame the problem i.e. What is the problem?

We can do this by asking the following 'What?'

- What do we see happening?
- What is our hypothesis for the cause of the problem? (This will be broadly based on intuition initially)
- What is the impact of the problem on stakeholders?
- What is the impact of the problem not being solved? How to handle the things:
- Clean the data.
- Use the Data Analysis skills to explore the data set.
- Derive insights.

The things that we are going to find out through the project are movies with the highest profit, top movies as per IMDB rating, top directors, most popular genres, top foreign language films and more

### Approach:

#### **A. Cleaning the data:**

This is the most important step to perform for the better analysis of the data.

- Dropped the unwanted columns as there is no use for the analysis.
- Dropped the rows which are having null/blank.
- Removed the duplicate row values.

#### **B. Movies with highest Profit:**

‘Avatar’ movie is the highest profit in the list of data followed by ‘Jurassic World’ and ‘Titanic’.

movie_title	gross	budget	Profit
Avatar	760505847	237000000	523505847
Jurassic World	652177271	150000000	502177271
Titanic	658672302	200000000	458672302
Star Wars: Episode IV - A New Hope	460935665	11000000	449935665
E.T. the Extra-Terrestrial	434949459	10500000	424449459
The Avengers	623279547	220000000	403279547
The Avengers	623279547	220000000	403279547
The Lion King	422783777	45000000	377783777
Star Wars: Episode I - The Phantom Menace	474544677	115000000	359544677
The Dark Knight	533316061	185000000	348316061
The Hunger Games	407999255	78000000	329999255
Deadpool	363024263	58000000	305024263
The Hunger Games: Catching Fire	424645577	130000000	294645577
Jurassic Park	356784000	63000000	293784000
Despicable Me 2	368049635	76000000	292049635
American Sniper	350123553	58800000	291323553
Finding Nemo	380838870	94000000	286838870
Shrek 2	436471036	150000000	286471036
The Lord of the Rings: The Return of the King	377019252	94000000	283019252
Star Wars: Episode VI - Return of the Jedi	309125409	32500000	276625409
Forrest Gump	329691196	55000000	274691196
Star Wars: Episode V - The Empire Strikes Back	290158751	18000000	272158751
Home Alone	285761243	18000000	267761243
Star Wars: Episode III - Revenge of the Sith	380262555	113000000	267262555
Spider-Man	403706375	139000000	264706375
Minions	336029560	74000000	262029560



## C. Top 250:

Filtered the 'num\_voted\_users' column greater than 25,000.

- Created a new column named 'IMDb\_Top\_250' and stored the top 250 movies with the highest IMDb Rating (sorted the 'imdb\_score' column from the largest to the smallest).
- Added a 'Rank' containing the values 1 to 250 using the RANK() function + COUNTIFS() function.

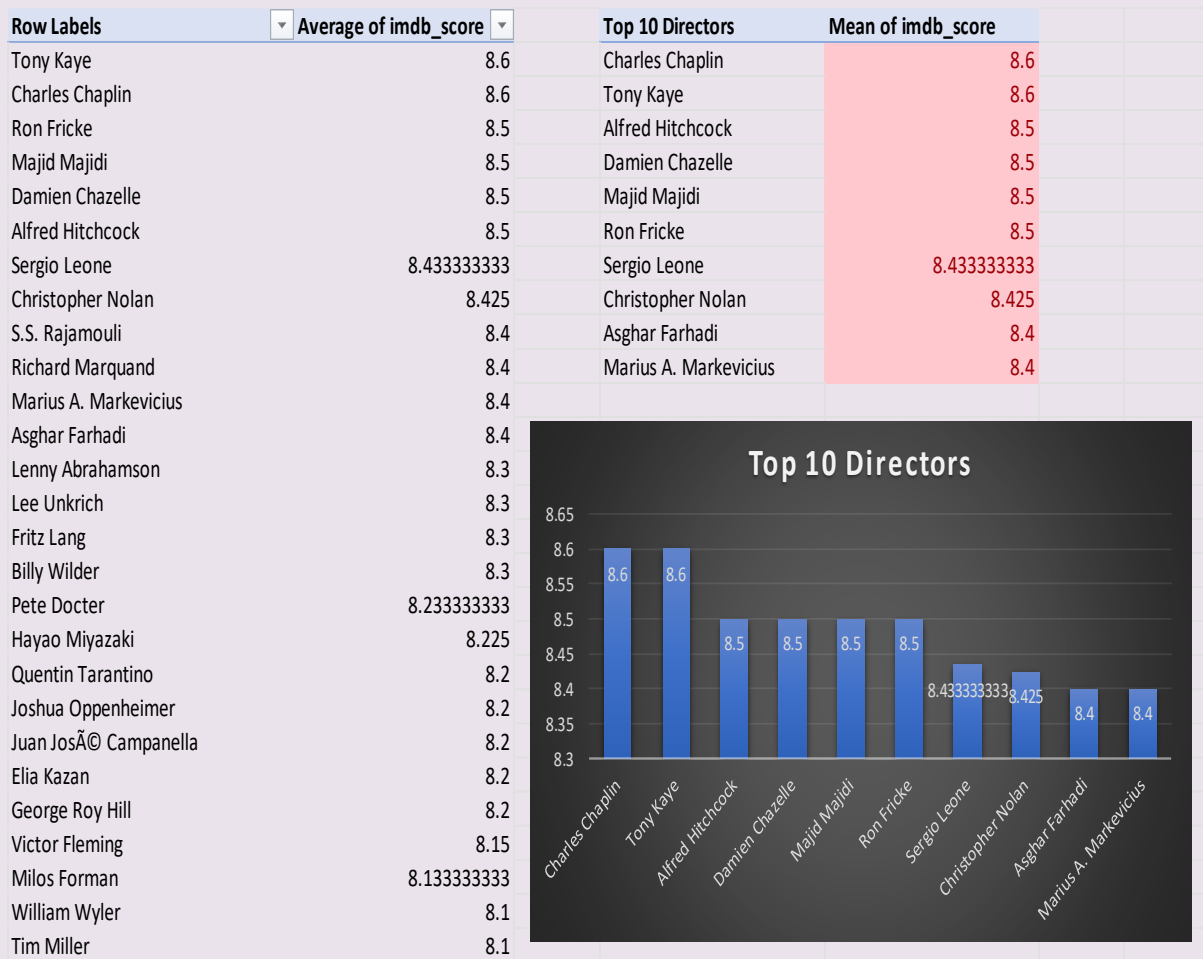
IMDb_Top_250	num_voted_users	language	imdb_score	Rank
The Shawshank Redemption	1689764	English	9.3	1
The Godfather	1155770	English	9.2	2
The Dark Knight	1676169	English	9	3
The Godfather: Part II	790926	English	9	4
Pulp Fiction	1324680	English	8.9	5
Schindler's List	865020	English	8.9	6
The Good, the Bad and the Ugly	503509	Italian	8.9	7
The Lord of the Rings: The Return of the King	1215718	English	8.9	8
Fight Club	1347461	English	8.8	9
Forrest Gump	1251222	English	8.8	10
Inception	1468200	English	8.8	11
Star Wars: Episode V - The Empire Strikes Back	837759	English	8.8	12
The Lord of the Rings: The Fellowship of the Ring	1238746	English	8.8	13
City of God	533200	Portuguese	8.7	14
Goodfellas	728685	English	8.7	15
One Flew Over the Cuckoo's Nest	680041	English	8.7	16
Seven Samurai	229012	Japanese	8.7	17
Star Wars: Episode IV - A New Hope	911097	English	8.7	18
The Lord of the Rings: The Two Towers	1100446	English	8.7	19
The Matrix	1217752	English	8.7	20
American History X	782437	English	8.6	21
Interstellar	928227	English	8.6	22
Modern Times	143086	English	8.6	23
Saving Private Ryan	881236	English	8.6	24
Se7en	1023511	English	8.6	25
Spirited Away	417971	Japanese	8.6	26

- Extracted all the movies in the IMDb\_Top\_250 column by filtering the 'language' column (unselecting English language) and stored them in a new column named 'Top\_Foreign\_Lang\_Film'.

Top_Foreign_Lang_Film	num_voted_users	imdb_score	language
The Good, the Bad and the Ugly	503509	8.9	Italian
City of God	533200	8.7	Portuguese
Seven Samurai	229012	8.7	Japanese
Spirited Away	417971	8.6	Japanese
Children of Heaven	27882	8.5	Persian
The Lives of Others	259379	8.5	German
A Separation	151812	8.4	Persian
Amélie	534262	8.4	French
Baahubali: The Beginning	62756	8.4	Telugu
Das Boot	168203	8.4	German
Oldboy	356181	8.4	Korean
Princess Mononoke	221552	8.4	Japanese
Metropolis	111841	8.3	German
The Hunt	170155	8.3	Danish
Unforgiven	248354	8.3	German
Pan's Labyrinth	80429	8.2	French
The Bridge on the River Kwai	131831	8.2	Spanish
The Thing	467234	8.2	Spanish
Warrior	214091	8.2	Japanese
Annie Hall	81644	8.1	Portuguese
In the Shadow of the Moon	65951	8.1	Danish
Sling Blade	106160	8.1	Japanese
Tae Guk Gi: The Brotherhood of War	64556	8.1	Spanish
The Best Years of Our Lives	173551	8.1	Spanish
The Imitation Game	31943	8.1	Korean
Bowling for Columbine	28951	8	Portuguese
Jaws	70194	8	French

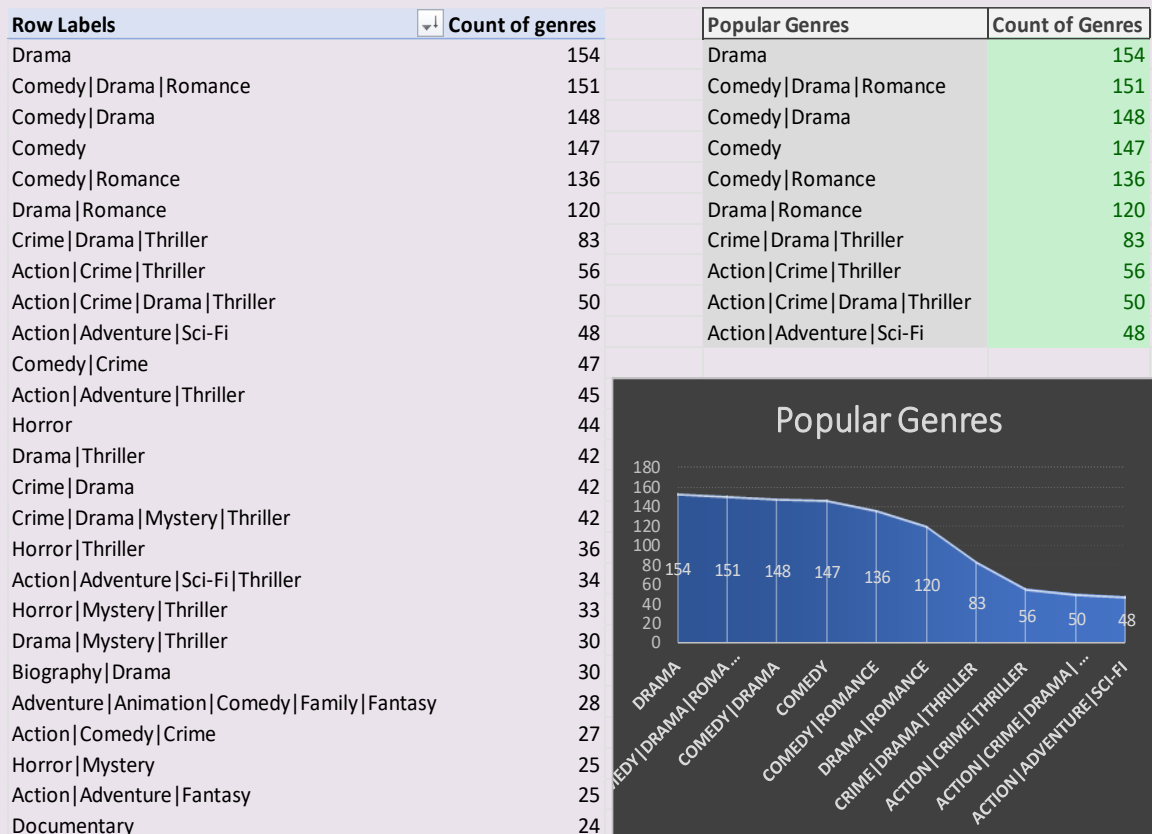
## D. Best Directors:

- Selected the cleaned dataset done and created a pivot table.
- Put the 'director\_name' into the Rows and took average of 'imdb\_score' in the Values section.
- Sorted the 'director\_name' in ascending order and then sorted the 'average of imdb\_score' (largest to smallest).
- Then selected the top 10 directors and their mean of imdb\_score in other columns.
- Finally made a Stacked Column chart of the top 10 directors for the better insights.



## E. Popular Genres:

- Selected the 'genres' column from the cleaned dataset and created a pivot table.
- In Pivot, kept the 'genres' into the Rows and took count of 'genres' in the Values section.
- After Sorted the 'Count of genres' in descending order.
- Copied the top 10 genres and their count and pasted it in the other columns.
- Made a Stacked area chart of the top 10 genres for the better insights.



## F. Charts:

### (a) Critic favourite and audience favourite actors

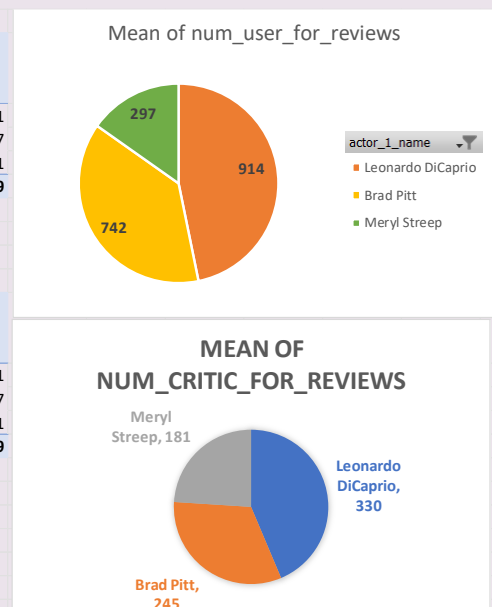
- Created 3 new columns namely, Meryl\_Streep, Leo\_Caprio, and Brad\_Pitt which contain the movies in which the actors: 'Meryl Streep', 'Leonardo DiCaprio', and 'Brad Pitt' are the lead actors using the 'actor\_1\_name' column.
- Append the rows of all these columns and stored them in a new column named 'Combined'.
- We grouped the column by the actor's name: 'Meryl Streep', 'Leonardo DiCaprio', and 'Brad Pitt'.
- Then selected the cleaned dataset done in and created a pivot table.
- In Pivot, inserted the 'actor\_1\_name' into the Rows and took mean/average of 'num\_users\_for\_review' in the Values section.
- Sorted the column from largest to smallest by mean of 'num\_users\_for\_review'.
- Made a pivot chart (bar chart) of the mean of 'num\_users\_for\_review'.
- Same procedure done for the mean of 'num\_critic\_for\_review'.

Meryl_Streep	Leo_Caprio	Brad_Pitt	Combined	Group By
Lucy	Django Unchained	Divergent	Lucy	Meryl Streep
Maleficent	Inception	Shanghai Knights	Maleficent	Meryl Streep
Transcendence	How to Train Your Dragon	The Circle	Transcendence	Meryl Streep
Down and Out with the Dolls	Pirates of the Caribbean: The Curse of the Black Pearl	42nd Street	Down and Out with the Dolls	Meryl Streep
Machine Gun Preacher	The Sessions	Fight Club	Machine Gun Preacher	Meryl Streep
Like Crazy	Frozen River	Scott Pilgrim vs. the World	Like Crazy	Meryl Streep
Brown Sugar	The Martian	Mulan	Brown Sugar	Meryl Streep
Bridge of Spies	Lethal Weapon 4	Leap Year	Bridge of Spies	Meryl Streep
True Lies	The Departed	The Kids Are All Right	True Lies	Meryl Streep
Hellboy II: The Golden Army	The Hunger Games	Connie and Carla	Hellboy II: The Golden Army	Meryl Streep
Gerry	Animal House	Star Trek Into Darkness	Gerry	Meryl Streep
	The Squid and the Whale	Sunshine State	Django Unchained	Leonardo DiCaprio
	Dream with the Fishes	Zookeeper	Inception	Leonardo DiCaprio
	Transamerica	Black Swan	How to Train Your Dragon	Leonardo DiCaprio
	The Iron Giant	Kung Fu Panda	Pirates of the Caribbean: The Curse of the Black Pearl	Leonardo DiCaprio
	Casino Royale	The Puffy Chair	The Sessions	Leonardo DiCaprio
	Hurricane Streets	It Follows	Frozen River	Leonardo DiCaprio
	The Devil Wears Prada		The Martian	Leonardo DiCaprio
	Ocean's Twelve		Lethal Weapon 4	Leonardo DiCaprio
	The Longest Yard		The Departed	Leonardo DiCaprio
	The Family Man		The Hunger Games	Leonardo DiCaprio
			Animal House	Leonardo DiCaprio
			The Squid and the Whale	Leonardo DiCaprio

Row Labels	Mean of num_user_for_reviews	Sum of num_user_for_reviews2	Count of num_user_for_reviews3
Leonardo DiCaprio	914	19204	21
Brad Pitt	742	12620	17
Meryl Streep	297	3269	11
Grand Total	716	35093	49

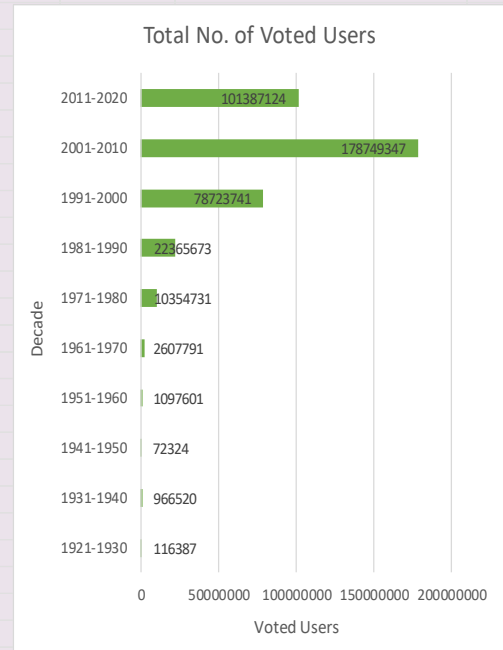
Row Labels	Mean of num_critc_for_reviews	Sum of num_critc_for_reviews2	Count of num_critc_for_reviews3
Leonardo DiCaprio	330	6934	21
Brad Pitt	245	4165	17
Meryl Streep	181	1996	11
Grand Total	267	13095	49



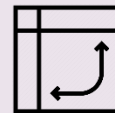
## (b) Change in number of voted users over decades

- Selected the cleaned dataset and created a pivot table.
- Insert the 'title\_year' into the Rows and took the sum of 'num\_voted\_users' in the Values section.
- Then grouped the title\_year by decade and stored in df\_by\_decade column.
- Finally plotted the total no. of voted users against the decade in a bar chart.

Row Labels	Sum of num_voted_users			
1927	111841			
1929	4546	Title_Year	df_by_decade	Total no. of voted users
1933	7921	1920s	1921-1930	116387
1935	13269	1930s	1931-1940	966520
1936	143086	1940s	1941-1950	72324
1937	133348	1950s	1951-1960	1097601
1939	507215	1960s	1961-1970	2607791
1940	161681	1970s	1971-1980	10354731
1946	46663	1980s	1981-1990	22365673
1947	19236	1990s	1991-2000	78723741
1948	3258	2000s	2001-2010	178749347
1950	3167	2010s	2011-2020	101387124
1952	9456	Grand Total		396441239
1953	11171			
1954	329902			
1957	149444			
1959	175196			
1960	422432			
1961	71919			
1962	309417			
1963	140280			
1964	493685			
1965	297839			
1966	503509			
1967	75280			



### Tech-Stack Used:



### Insights:

- ❖ There are as many as 5 outliers in the profit columns.
- ❖ The movie with the highest profit is 'Avatar'
- ❖ The Shawshank Redemption is the top-most movie with the highest IMDB rating.
- ❖ The Good, the Bad and the Ugly (Italian) is the top-most foreign language movie.
- ❖ Charles Chaplin is the top-most director followed by Tony Kaye.
- ❖ The most popular genres is Drama followed by Comedy.
- ❖ 'Leonardo DiCaprio' is the critic-favourite as well as the audience-favourite actor.
- ❖ The most users voted in the decade 2000s and the least in the decade 1940s.

## Results:

In this Project, I learned especially the “5 Why Analysis” and it helps me to think deeper to analyse and generate valuable insights. I also learned the basic and advanced excel concepts which includes statistics and functions like rank, count etc.,

Finally, It was great learning experience in entire project and very challenging too while executing the solutions.

