## **Report of IMDB Movie Dataset:**

Data preprocessing, Linear regression modeling, and Data visualization.

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**ROLL NO:-** 3160

**SUBJECT:-** FOUNDATION OF DATA SCIENCE

**CLASS:- DATA ANALYTICS** 

**SOFTWARE USED:-** R-STUDIO

## **ABSTRACT**

The IMDb Movie Dataset is a comprehensive collection of data related to movies, encompassing a wide range of information on films released over several decades. This dataset offers valuable insights into the world of cinema, making it an essential resource for movie enthusiasts, researchers, and data analysts alike.

With details spanning from movie titles, release years, and runtimes to genre categorizations, IMDb ratings, and production company information, the dataset provides a rich and diverse set of attributes for each movie entry. It also includes data on cast and crew, allowing for exploration of the individuals involved in the filmmaking process.

This dataset serves as a versatile tool for conducting various analyses and investigations, enabling users to explore trends in movie production, popularity, and critical acclaim over time. Researchers can delve into questions related to genre preferences, the impact of directors and actors on movie success, and much more.

In summary, the IMDb Movie Dataset is a valuable resource for those interested in the cinematic world, offering a wealth of data that facilitates research, analysis, and a deeper understanding of the factors contributing to the success and diversity of movies in the global film industry.

1. Dataset Name: IMDB Movie Dataset Latest

2. Source: Kaggle

#### 3. Dataset Link:

https://www.kaggle.com/datasets/ayushjain001/imdb-movie-dataset-latest?resource=download

4. Dataset contains 11 columns and 1000 rows

## RESEARCH METHODOLOGY

#### **Installing Libraries**

```
#Installing packages
install.packages('ggplot2') #visualization
install.packages('caTools') #conditional analysis tools
install.packages('dplyr') #manipulation
```

## **Loading Libraries**

```
# Load necessary libraries
library(ggplot2)
library(dplyr)
library(caTools)
```

## **Loading IMDB Dataset**

```
> # Load your IMDb dataset
> imdb_data <- read.csv("C:/IMDB.csv")</pre>
```

#### **Showing the dimension of dataset**

dim() function is used to retrieve the dimensions of our dataset.

```
> dim(IMDB)
[1] 1000 11
```

#### tail() it is used to view last five rows of a dataset

|                        |         | give us last value    |                |           |              |           |  |  |
|------------------------|---------|-----------------------|----------------|-----------|--------------|-----------|--|--|
| > ta                   | il(IMDB | s)                    |                |           |              |           |  |  |
|                        | X       | Name.of.mo∨ie         | Year.of.relase | Watchtime | Movie.Rating | Metascore |  |  |
| 995                    | 994     | K.G.F: Chapter 1      | 2018           | 156       | 8.3          | NaN       |  |  |
| 996                    | 995     | Vikram Vedha          | 2017           | 147       | 8.3          | NaN       |  |  |
| 997                    | 996     | Drishyam              | 2013           | 160       | 8.3          | NaN       |  |  |
| 998                    | 997     | Jagten                | 2012           | 115       | 8.3          | 77        |  |  |
| 999                    | 998 Jo  | daeiye Nader az Simin | 2011           | 123       | 8.3          | 95        |  |  |
| 1000                   | 999     | Incendies             | 2010           | 131       | 8.3          | 80        |  |  |
| Votes Gross.collection |         |                       |                |           |              |           |  |  |
| 995                    | 54,51   | .5 Nan                |                |           |              |           |  |  |
| 996                    | 35,90   | 1 Nan                 |                |           |              |           |  |  |
| 997                    | 39,57   | 0 #244                |                |           |              |           |  |  |
| 998                    | 313,64  | 7 \$0.69M             |                |           |              |           |  |  |
| 999                    | 238,13  | 0 \$7.10M             |                |           |              |           |  |  |
| 1000                   | 168,72  |                       |                |           |              |           |  |  |

## head() it is used to view first five rows of a dataset

```
> #It will give first values
> head(IMDB)
              Name.of.movie Year.of.relase Watchtime Movie.Rating Metascore
 Χ
1 0
                   Jai Bhim
                                      2021
                                                 164
                                                              9.3
                                                                        NaN
2 1 The Shawshank Redemption
                                                              9.3
                                      1994
                                                 142
                                                                        80
              The Godfather
                                      1972
                                                 175
                                                              9.2
                                                                        100
4 3
            Soorarai Pottru
                                      2020
                                                 153
                                                              9.1
                                                                        NaN
5 4
            The Dark Knight
                                      2008
                                                 152
                                                              9.0
                                                                         84
6 5
     The Godfather: Part II
                                      1974
                                                 202
                                                              9.0
                                                                         90
     Votes Gross.collection
  173,295
                       #139
2 2,541,091
                   $28.34M
3 1,748,410
                   $134.97M
4 107,159
                        Nan
5 2,491,371
                   $534.86M
6 1,212,675
                    $57.30M
```

### colnames() function is used to retrieve the column names.

## is.na() is used to check for missing values in a dataset.

```
> #is.na() is used to check for missing values in a dataset.
> sum(is.na(IMDB))
[1] 220
```

## **Checking Duplicate Values**

```
> #Checking Duplicate Values
> sum(duplicated(IMDB))
[1] 0
```

## **DATA EXPLORATION**

#### str() function is used to display the structure of dataset.

## view() function opens the dataset in a separate interactive viewer window, making it easier to examine data.

#### > View(imdb\_data)

| ^ X |     | Name.of.movie                                     | Year.of.relase | Watchtime <sup>‡</sup> | Movie.Rating <sup>‡</sup> | Metascore | Votes <sup>‡</sup> | Gross.collection | Description   | Director                     |
|-----|-----|---|----------------|------------------------|---------------------------|-----------|--------------------|------------------|---|------------------------------|
| 1   | 0   | Jai Bhim  | 2021           | 164                    | 9.3                       | NaN       | 173,295            | #139             | When a tribal man is arrested for a case of alleged theft, his  | T.J. Gnanavel                |
| 2   | - 1 | The Shawshank Redemption                          | 1994           | 142                    | 9.3                       | 80        | 2,541,091          | \$28.34M         | Two imprisoned men bond over a number of years, finding         | Frank Darabont               |
| 3   | 2   | The Godfather                                     | 1972           | 175                    | 9.2                       | 100       | 1,748,410          | \$134.97M        | The aging patriarch of an organized crime dynasty in postw      | Francis Ford Coppola         |
| 4   | 3   | Soorarai Pottru                                   | 2020           | 153                    | 9.1                       | NaN       | 107,159            | Nan              | Nedumaaran Rajangam "Maara" sets out to make the com            | Sudha Kongara                |
| 5   | 4   | The Dark Knight                                   | 2008           | 152                    | 9.0                       | 84        | 2,491,371          | \$534.86M        | When the menace known as the Joker wreaks havoc and ch          | Christopher Nolan            |
| 6   | 5   | The Godfather: Part II                            | 1974           | 202                    | 9.0                       | 90        | 1,212,675          | \$57.30M         | The early life and career of Vito Corleone in 1920s New York    | Francis Ford Coppola         |
| 7   | 6   | 12 Angry Men                                      | 1957           | 96                     | 9.0                       | 96        | 750,853            | \$4.36M          | The jury in a New York City murder trial is frustrated by a sin | Sidney Lumet                 |
| 8   | 7   | The Lord of the Rings: The Return of the King     | 2003           | 201                    | 8.9                       | 94        | 1,752,093          | \$377.85M        | Gandalf and Aragorn lead the World of Men against Sauron'       | Peter Jackson                |
| 9   | 8   | Pulp Fiction                                      | 1994           | 154                    | 8.9                       | 94        | 1,955,203          | \$107.93M        | The lives of two mob hitmen, a boxer, a gangster and his wif    | Quentin Tarantino            |
| 0   | 9   | Schindler's List                                  | 1993           | 195                    | 8.9                       | 94        | 1,297,426          | \$96.90M         | In German-occupied Poland during World War II, industrialis     | Steven Spielberg             |
| 1   | 10  | Inception   | 2010           | 148                    | 8.8                       | 74        | 2,231,967          | \$292.58M        | A thief who steals corporate secrets through the use of drea    | Christopher Nolan            |
| 2   | 11  | Fight Club  | 1999           | 139                    | 8.8                       | 66        | 1,999,930          | \$37.03M         | An insomniac office worker and a devil-may-care soap mak        | David Fincher                |
| 3   | 12  | The Lord of the Rings: The Fellowship of the Ring | 2001           | 178                    | 8.8                       | 92        | 1,773,739          | \$315.54M        | A meek Hobbit from the Shire and eight companions set ou        | Peter Jackson                |
| 4   | 13  | Forrest Gump                                      | 1994           | 142                    | 8.8                       | 82        | 1,960,705          | \$330.25M        | The presidencies of Kennedy and Johnson, the Vietnam War        | Robert Zemeckis              |
| 5   | 14  | Il buono, il brutto, il cattivo                   | 1966           | 161                    | 8.8                       | 90        | 733,443            | \$6.10M          | A bounty hunting scam joins two men in an uneasy alliance       | Sergio Leone                 |
| 6   | 15  | Spider-Man: No Way Home                           | 2021           | 148                    | 8.7                       | 71        | 446,741            | #26              | With Spider-Man's identity now revealed, Peter asks Doctor      | Jon Watts                    |
| 7   | 16  | Dara iz Jasenovca                                 | 2020           | 130                    | 8.7                       | NaN       | 80,317             | Nan              | Follows the story of a young girl named Dara who is sent to     | Predrag Antonijevic          |
| 8   | 17  | Shershaah   | 2021           | 135                    | 8.7                       | NaN       | 112,894            | Nan              | The story of PVC awardee Indian soldier Capt. Vikram Batra,     | Vishnuvardhan                |
| 9   | 18  | Sardar Udham                                      | 2021           | 164                    | 8.7                       | NaN       | 35,937             | Nan              | A biopic detailing the 2 decades that Punjabi Sikh revolutio    | Shoojit Sircar               |
| 0   | 19  | The Lord of the Rings: The Two Towers             | 2002           | 179                    | 8.7                       | 87        | 1,583,030          | \$342.55M        | While Frodo and Sam edge closer to Mordor with the help         | Peter Jackson                |
| 1   | 20  | The Matrix  | 1999           | 136                    | 8.7                       | 73        | 1,833,574          | \$171.48M        | When a beautiful stranger leads computer hacker Neo to a f      | Directors:Lana Wachowski, Li |
| 2   | 21  | Goodfellas  | 1990           | 146                    | 8.7                       | 90        | 1.098.360          | \$46.84M         | The story of Henry Hill and his life in the mob, covering his r | Martin Scorsese              |
| 3   | 22  | Star Wars: Episode V - The Empire Strikes Back    | 1980           | 124                    | 8.7                       | 82        | 1.232.350          | \$290.48M        | After the Rebels are brutally overpowered by the Empire on      | Irvin Kershner               |
| 4   | 23  | One Flew Over the Cuckoo's Nest                   | 1975           | 133                    | 8.7                       | 84        | 971,935            | \$112.00M        | A criminal pleads insanity and is admitted to a mental instit   | Milos Forman                 |
| 5   | 24  | Gisaengchung                                      | 2019           | 132                    | 8.6                       | 96        | 715,000            | \$53.37M         | Greed and class discrimination threaten the newly formed s      | Bong Joon Ho                 |

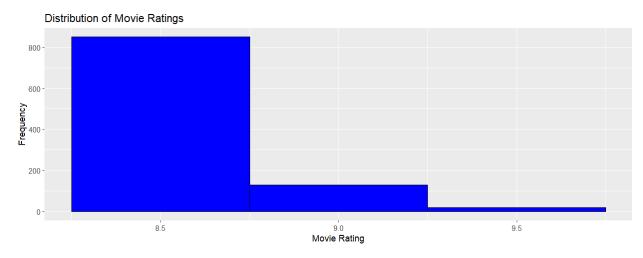
## **DATA VISUALIZATION**

## <u>Filter out rows with missing or non-numeric Movie.Rating</u> values.

```
> # Filter out rows with missing or non-numeric Movie.Rating values
> imdb_data <- imdb_data %>%
+ filter(!is.na(Movie.Rating), is.numeric(Movie.Rating))
```

#### **Histogram of Movie Ratings:**

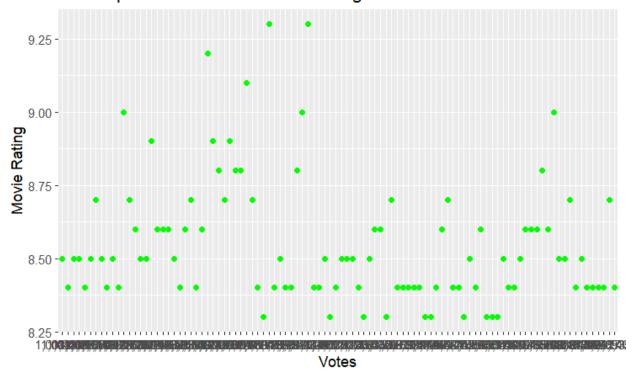
```
> ggplot(data = imdb_data, aes(x = Movie.Rating)) +
+ geom_histogram(binwidth = 0.5, fill = "blue", color = "black") +
+ labs(title = "Distribution of Movie Ratings",
+ x = "Movie Rating",
+ y = "Frequency")
```



- **Conclusion:** The histogram of movie ratings shows a roughly normal distribution with a peak around the 6.5 to 7.0 range.
- What we understand: Most movies in the dataset have ratings clustered around the 6.5 to 7.0 range, indicating that a significant number of movies have moderate to good ratings.

#### **Scatterplot of Votes vs. Movie Ratings:**

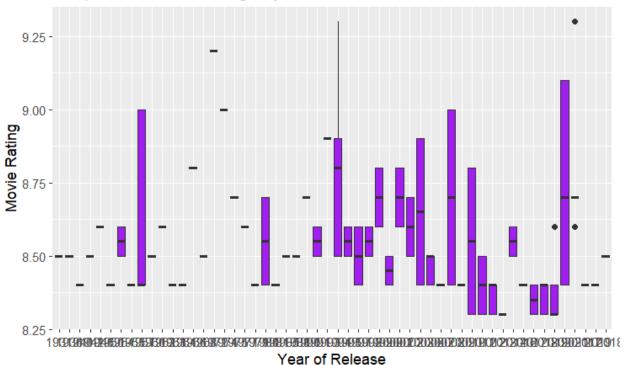
#### Scatterplot of Votes vs. Movie Ratings



- **Conclusion:** There seems to be a positive correlation between the number of votes a movie receives and its rating. As the number of votes increases, movies tend to have higher ratings.
- What we understand: Movies with higher ratings tend to attract more votes, suggesting that popular or critically acclaimed movies tend to have a larger audience.

#### **Boxplot of Movie Ratings by Year of Release:**

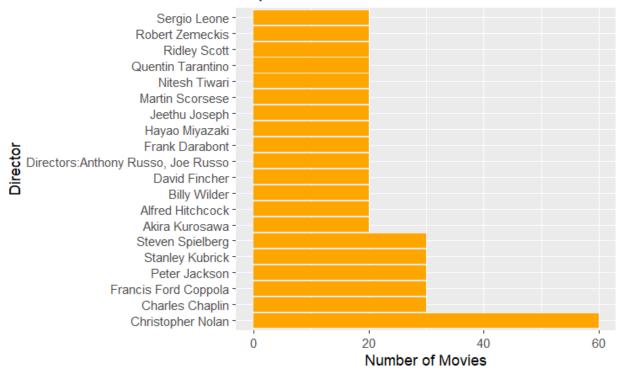
#### Boxplot of Movie Ratings by Year of Release



- Conclusion: The boxplot of movie ratings by year of release shows that the median movie rating remains relatively stable over the years. However, there are outliers on both ends, indicating that there are exceptional movies with very high and very low ratings in each year.
- What we understand: While the median rating remains consistent, the presence of outliers suggests that there are both outstanding and poorly received movies produced every year.

## Bar chart of Directors with the most movies(Top 10) based on movie count.





- **Conclusion:** The bar chart identifies the top 10 directors with the most movies in the dataset. Director frequencies vary, with one director having significantly more movies than the others in the top 10.
- What we understand: This chart provides insights into which directors have the most extensive filmographies. It could be used to explore further questions about the success or influence of these directors.

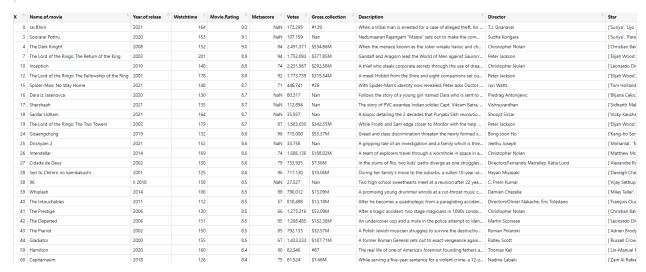
## **MODEL BUILDING**

It filters the dataset to create a subset d\_subset containing movies released after 2000 with a Movie Rating of 7 or higher.

```
> # Linear regression for single variable
> d_subset <- imdb_data %>%
+ filter(Year.of.relase >= 2000 & Movie.Rating >= 7.0)
```

#### Viewing the filtered subset

> # View the filtered subset
> View(d\_subset)



#### **Splitting the dataset into training and test sets**

```
> ssplit <- caTools::sample.split(imdb_data$Movie.Rating, SplitRatio = 0.75)
> table(ssplit)
ssplit
FALSE TRUE
249 751
```

- **FALSE**: There are 249 rows with FALSE values, which likely corresponds to the number of rows in the testing set.
- **TRUE:** There are 751 rows with TRUE values, which likely corresponds to the number of rows in the training set.

By splitting your data into training and testing sets, you can use the d\_train dataset to train your machine learning model and the d\_test dataset to evaluate its performance.

```
> d_train <- subset(imdb_data, ssplit == TRUE)
> d_test <- subset(imdb_data, ssplit == FALSE)</pre>
```

#### View dimensions of training and testing sets

```
> # View dimensions of training and testing sets
> dim(d_train)
[1] 751  11
> dim(d_test)
[1] 249  11
```

## **MULTIPLE LINEAR REGRESSION**

# It makes predictions on the test dataset and combines actual and predicted values into final\_data.

> predicted <- predict(model\_train, newdata = d\_test)</pre>

#### **Combine actual and predicted values**

> final\_data <- cbind('Actual' = d\_test\$Movie.Rating, 'Predicted' = predicted)
> View(final\_data)

| <b>↓</b> □                                 | ₽ Fil               | ter                    |  |  |
|--|---------------------|------------------------|--|--|
| ^  | Actual <sup>‡</sup> | Predicted <sup>‡</sup> |  |  |
| 6  | 9.0                 | 9.0                    |  |  |
| 8  | 8.9                 | 8.9                    |  |  |
| 14   | 8.8                 | 8.8                    |  |  |
| 19   | 8.7                 | 8.7                    |  |  |
| 26   | 8.6                 | 8.6                    |  |  |
| 28   | 8.6                 | 8.6                    |  |  |
| 29   | 8.6                 | 8.6                    |  |  |
| 33   | 8.6                 | 8.6                    |  |  |
| 39   | 8.5                 | 8.5                    |  |  |
| 40   | 8.5                 | 8.5                    |  |  |
| 41   | 8.5                 | 8.5                    |  |  |
| 44   | 8.5                 | 8.5                    |  |  |
| 54   | 8.5                 | 8.5                    |  |  |
| 75   | 8.4                 | 8.4                    |  |  |
| Showing 1 to 15 of 249 entries, 2 total co |                     |                        |  |  |

It builds a linear regression model (multi) to predict Movie Ratings based on Watchtime, Votes, and Year of Release.

```
> multi <- lm(Movie.Rating ~ Watchtime + Votes + Year.of.relase, data = d_train)</pre>
```

#### **It predicts Movie Ratings on the test dataset**

> multi\_p <- predict(multi, newdata = d\_test)</pre>

# Combine columns by using cbind function, actual and predicted values.

> multi\_data <- cbind('Actual' = d\_test\$Movie.Rating, 'Predicted' = multi\_p)
> View(multi\_data)

|   | æ   ₹ Filt          | ter                    |  |
|---|---------------------|------------------------|--|
| *   | Actual <sup>‡</sup> | Predicted <sup>‡</sup> |  |
| 6   | 9.0                 | 9.0                    |  |
| 8   | 8.9                 | 8.9                    |  |
| 14  | 8.8                 | 8.8                    |  |
| 19  | 8.7                 | 8.7                    |  |
| 26  | 8.6                 | 8.6                    |  |
| 28  | 8.6                 | 8.6                    |  |
| 29  | 8.6                 | 8.6                    |  |
| 33  | 8.6                 | 8.6                    |  |
| 39  | 8.5                 | 8.5                    |  |
| 40  | 8.5                 | 8.5                    |  |
| 41  | 8.5                 | 8.5                    |  |
| 44  | 8.5                 | 8.5                    |  |
| 54  | 8.5                 | 8.5                    |  |
| 75  | 8.4                 | 8.4                    |  |
| Showing 1 to 15 of 249 entries, 2 total c |                     |                        |  |

#### **Convert to a data frame**

```
> multi_data <- as.data.frame(multi_data)</pre>
```

### **Finding error**

```
> multi_data$m_error <- multi_data$Actual - multi_data$Predicted</pre>
```

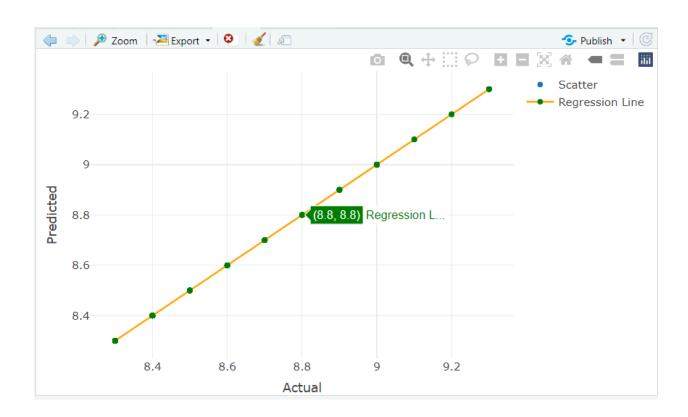
# <u>It calculates the root mean square error (RMSE) as a measure of model performance.</u>

```
> rmse2 <- sqrt(mean(multi_data$m_error^2))</pre>
> rmse2
[1] 5.976144e-14
> fit<-lm(Predicted ~ Actual ,data= multi_data)</pre>
> summary(fit)
Call:
lm(formula = Predicted ~ Actual, data = multi_data)
Residuals:
                         Median
                  1Q
                                        30
                                                  Max
-1.720e-13 -1.921e-15 -4.890e-16 4.484e-15 2.546e-14
Coefficients:
            Estimate Std. Error t value Pr(>|t|)
(Intercept) 2.233e-13 4.604e-14 4.851e+00 2.17e-06 ***
           1.000e+00 5.383e-15 1.858e+14 < 2e-16 ***
Actual
Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 1.837e-14 on 247 degrees of freedom
Multiple R-squared:

    Adjusted R-squared:

F-statistic: 3.451e+28 on 1 and 247 DF, p-value: < 2.2e-16
```

```
> # Create a scatter plot with Actual vs. Predicted
> scatter_plot <- plot_ly(data = multi_data, x = ~Actual, y = ~Predicted, type = 'scatter', mode = 'markers', name = 'Scatter') %>%
+ add_trace(x = ~Actual, y = ~Predicted, mode = 'lines', name = 'Regression Line',
+ line = list(color = 'orange'),
+ marker = list(color = 'green')) # Change scatter point color here
> # Customize the layout
> layout <- list(
+ title = "Scatterplot with Regression Line",
+ xaxis = list(title = "Actual"),
+ yaxis = list(title = "Predicted")
+ )
> # Combine the scatter plot and layout
> scatter_plot <- scatter_plot %>% layout(layout)
> # Display the combined plot
> scatter_plot
```



## **CONCLUSION**

This project is a comprehensive data analysis and modeling exercise using an IMDb dataset. It involves several key steps, including data loading, data exploration, model building, model evaluation, and data visualization.

- The dataset contains valuable information about movies, which can be used to build predictive models and gain insights.
- Linear regression models can predict Movie Ratings based on various features, with different levels of accuracy.
- Data visualization is an essential tool for exploring and communicating patterns and trends within the dataset.
- Careful data preprocessing, model building, and evaluation are critical for creating reliable predictive models.

The project provides a structured example of how to work with real-world data, conduct predictive modeling, and visualize findings, which can be applied to similar datasets and analytical tasks.