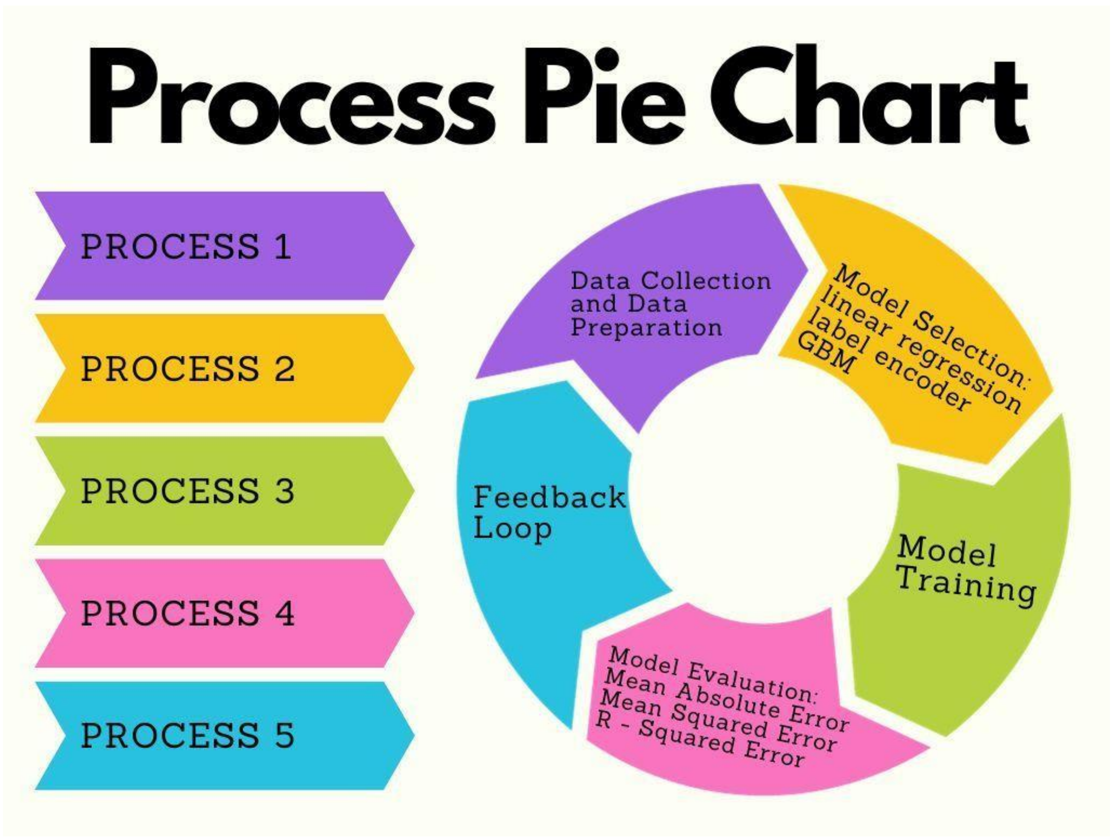
IMDb SCORE PREDICTION

(PHASE-5)

Introduction:

Predicting IMDb scores for movies or TV shows is a complex task that often involves a combination of factors, including the quality of the content, marketing, critical reception, and audience reception. Estimate the popularity of movies. This estimation is based on certain features, including genre, premiere date, runtime, and language. In other words, to build a model that can predict how well a movie is likely to be rated on IMDb.

Pie chart:


Process Pie Chart
PROCESS 1
PROCESS 2
PROCESS 3
PROCESS 4
PROCESS 5
Data Collection and Data Preparation
Model Selection: linear regression label encoder GBM
Model Training
Model Evaluation: Mean Absolute Error Mean Squared Error R - Squared Error
Feedback Loop

Data Collection:

- **Movie/TV Show Information:** List all relevant details about the project, including title, release date, director, writer, cast, genre, budget, box office performance (if applicable), production company, and any notable awards or nominations.

- **Historical IMDb Data:** Mention any historical IMDb scores for similar movies or TV shows that will be used as benchmarks.

Dataset Link:

https://www.kaggle.com/datasets/luiscorter/netflix-original-films-imdb-scores

The given dataset contains 6 columns ,584 rows. It comprises of 27% Documentary,13% Drama and 60% Films . It includes movies of various languages such as English, Hindi and foreign languages. The given details are correlated to each other.

Factors Affecting IMDb Scores

- Cast Significance:
  Discuss the importance of the cast, their star power, and acting talent.
- Genre Impact:

  Explain how the chosen genre may influence IMDb scores.

- Budget and Production Values:
  Describe the relationship between budget and production values and how they can impact audience perception.
- Marketing and Promotion:
  Discuss the role of effective marketing and promotion in generating audience interest.
- Early Reviews and Previews:
  Explain how critical and audience reactions from early reviews and preview screenings can provide insights.
- Box Office Performance:
  Mention whether box office performance is a relevant factor and how it correlates with IMDb scores.

Data preparation:

Clean and preprocess the data, handling missing values, outliers, and encoding categorical variables

1. **Handling Missing Values:**

- Decide on a strategy for dealing with missing data. Common options include:
- Removing rows or columns with too many missing values.
- Imputing missing values with the mean, median, mode, or a predictive model.
- Using domain knowledge to infer missing values

2. **Data Cleaning:**

- Address data inconsistencies and errors. This may involve:
- Correcting typos and spelling mistakes.
- Standardizing categorical variables.
- Handling duplicates.
- Removing irrelevant or redundant features.

Model selection:

Once you have identified your features, you need to select a machine learning model to train. Some popular models for predicting IMDb scores include:

- Linear regression
- Label encoder
- Gradient boosting machines

Linear Regression:

Linear regression is a widely used statistical method for modeling the relationship between a dependent variable (also called the target or outcome variable) and one or more independent variables (also called predictors or features). It is a fundamental technique in the field of machine learning and statistics, often employed for tasks like predicting numerical values, understanding correlations, and making forecasts.

Label Encoder:

A label encoder is a preprocessing technique used in machine learning and data analysis to convert categorical or textual data into numerical values. Categorical data consists of labels or categories that do not have any inherent numerical meaning, such as colors, car brands, or job titles. Machine learning algorithms often require numerical inputs, so label encoding is used to represent categorical data in a format that can be used for model training.

Gradient boosting machines:

Gradient Boosting Machines (GBM) is a powerful machine learning technique used for both regression and classification tasks. It's an ensemble learning method that builds a predictive model by combining the predictions of multiple individual models, typically decision trees. GBM has gained popularity in the field of machine learning due to its high predictive accuracy and robustness.

Model Training:

Split our data into training and testing sets. Train our model on the training data. - Split our dataset into training and testing subsets (typically 70-80% for training and the rest for testing). This separation helps evaluate the model's generalization performance. - Train each selected model on the training data, using techniques like cross-validation to prevent overfitting.

Model Evaluation :

Assess the performance of each model using appropriate regression evaluation metrics:

- **Mean Absolute Error (MAE):** Measures the average absolute difference between predicted and actual IMDb scores. Mean Absolute Error (MAE) is a commonly used metric instatistics and machine learning to evaluate the accuracy of a predictive model. It quantifies
the average absolute difference between predicted values and actual values. In other words, itmeasures how close the model's predictions are to the true values in terms of magnitude, without considering the direction (overestimation or underestimation).

- **Mean Squared Error (MSE):** Measures the average squared difference between predicted and actual scores, giving more weight to large errors. Mean Squared Error (MSE) isa widely used metric in statistics and machine learning to measure the average squared difference between predicted values and actual values. It quantifies the accuracy of a predictive model, with larger errors receiving more weight due to the squaring operation.

- **R-squared (R^2):** Evaluates how well the model fits the data. A higher R^2 indicates a better fit. R-squared, also known as the coefficient of determination, is a statistical measure used to evaluate the goodness of fit of a regression model. It provides information about howwell the model explains the variation in the dependent variable. R-squared is a value between0 and 1, with higher values indicating a better fit of the model to the data.

Feedback Loop :

- Incorporate user feedback into the model's improvement cycle, allowing for adjustmentsto the feature set, model selection, and hyperparameters.

- Maintain a feedback loop to gather user ratings and incorporate them into the datasetfor continuous model improvement.

Data Cleaning:

Data cleaning, also referred to as data cleansing and data scrubbing, isone of the most important steps

Data cleansing is a subprocess of the data science process that focuseson removing errors in the data so that the data becomes a true and consistent representation of the processes it originates from.

The first type is the interpretation error, such as incorrect use of terminologies.

The second type of error points to inconsistencies between data sourcesor against your company’s standardized values.

Data cleaning is the process of fixing or removing

- Corrupted data
- Incorrectly formatted
- Duplicate
- Incomplete data

If data is incorrect, outcomes and algorithms are unreliable, even though they may look correct. There is no one absolute way to prescribe the exact steps in the data cleaning process because the processes will vary fromdataset to dataset.

Joining Tables:

Joining tables is used to combine the information of one observation foundin one table with the information that was found in another table.

Appending Tables:

Appending or stacking tables is effectively adding observations from onetable to another table.

Transforming Data:

Certain models require their data to be in a certain shape. So the datas canbe changed according to our need. Data transformation is the process of converting data from one format or structure into another. Transformation processes can also be referred to as data wrangling, or data munging, transforming and mapping data from one "raw" data form into another formatfor warehousing and analyzing

When the dataset is summarized range index, total number of columns,datatypes, column heading and memory usage are viewed.

Feature engineering:

Feature engineering refers to manipulation — addition, deletion, combination, mutation — of the data set to improve machinelearning model training, leading to better performance and greater accuracy.

Creating new features gives a deeper understanding of the data and results in more valuable insights. When done correctly,feature engineering is one of the most valuable techniques of data science, but it is also one of the most challenging

Feature engineering in ML contains mainly four processes:

- Feature Creation
- Transformations
- Feature Extraction
- Feature Selection

Feature Creation:

Feature creation is finding the most useful variables tobe used in a predictive model. The process is subjective, and it requires human creativity and intervention.

Transformations:

The transformation step of feature engineering involvesadjusting the predictor variable to improve the accuracy and performance of the model.

Feature Extraction:

Feature extraction is an automated feature engineering process that generates new variables by extracting them from the rawdata. The main aim of this step is to reduce the volume of data so thatit can be easily used and managed for data modelling. Feature extraction methods include cluster analysis, text analytics, edge detection algorithms, and principal components analysis (PCA).

Feature Selection:

Reducing the input variable to your model by using onlyrelevant data and getting rid of noise in data. It is the process of automatically choosing relevant data and getting rid of noise in data.

Model training:

Model training is the phase in the data science development lifecycle where practitioners try to fit the best combination of weights and bias to a machine learning algorithm to minimize a loss function over the prediction range. Train the selectedmodel using the training dataset. The model learns the relationships between the input features (movie attributes) and the target variable(IMDb scores).

There are 3 steps to train a machine learning model

Step 1: Begin with existing data.

Step 2: Analysis data to identify patterns.

Step 3: Make predictions.

Evaluation:

To evaluate the model's performance, we can use metrics like Mean Absolute Error (MAE), Mean Squared Error (MSE) or R-squared. These metrics measure how well your model's predictions match the actual IMDb scores.

PROCEDURE:

Step 1: The required libraries are imported.

Step2: The given dataset is loaded in the program.

Step 3: To check whether the uploaded dataset is correct, a sample data is displayed in the output.

Step 4: The information from the dataset is summarized for better understanding.

Step 5: Then preprocessing is done, in which missing data, duplicate data are checked.

Step 6: If any modify the data or print False.

Step7:Then the features are extacted from the given data sheet.

Step 8:Split the data into training and testing sets.

Step 9:Initialize the regression algorithm.

Step 10:The set is trained and evaluated.

Step 11:The model is completed.

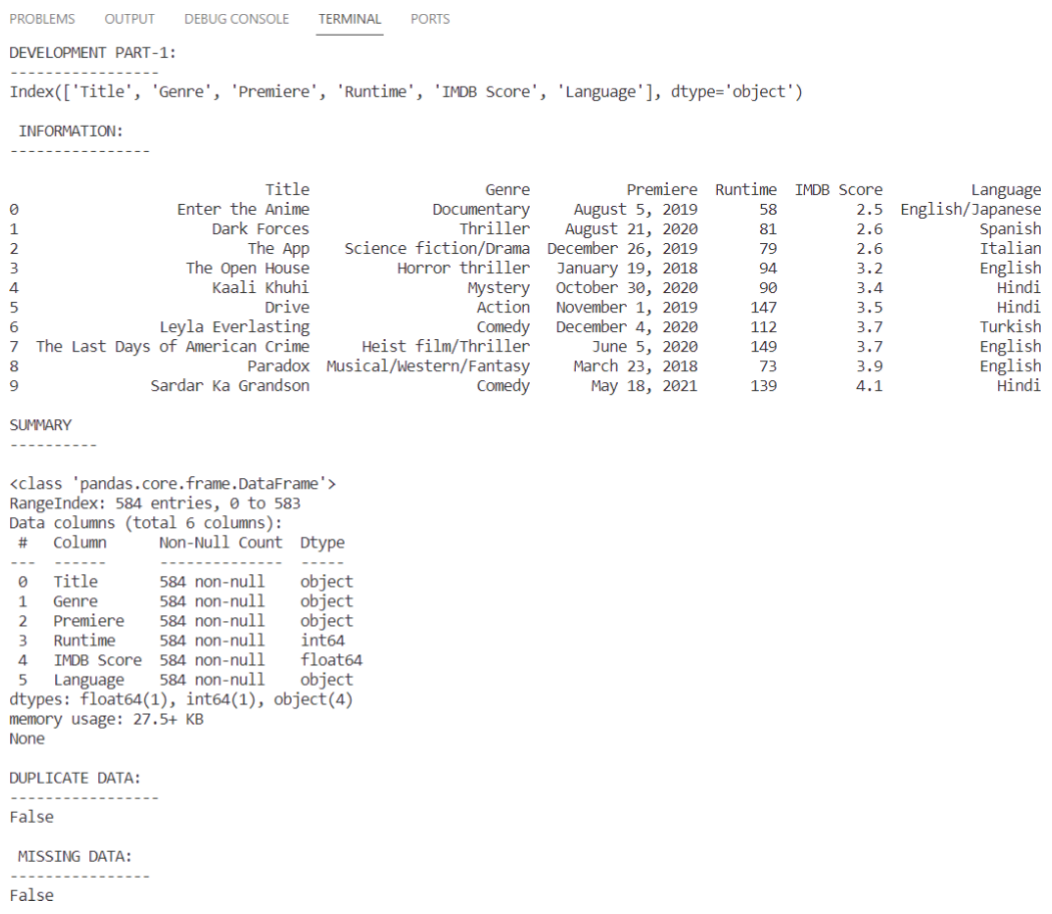
PROGRAM:

```
import pandas as pd

import numpy as np

from sklearn.model_selection import train_test_split
from sklearn.preprocessing  import  LabelEncoder
from sklearn.linear_model  import  LinearRegression
from sklearn.ensemble import  RandomForestRegressor
from sklearn.metrics import  mean_absolute_error, mean_squared_error, r2_score
from sklearn.ensemble  import GradientBoostingRegressor

# loading the data set
data = pd.read_csv("NetflixOriginals.csv",encoding='latin-1')
print('\n')

print('DEVELOPMENT PART-1:')
print('-----------------')
print(data.columns)
print('\n INFORMATION:')
print('----------------\n')
print(data.head(10))

# getting the information about the data for bettter understanding
print('\nSUMMARY')
print('---------- \n')
print(data.info())
print('\nDUPLICATE DATA:')
print('-----------------')

# checking for any duplicate data in the data set
print(data.duplicated().any())

# encoding the categorical features
label_encoder = LabelEncoder()
```

```
 data['Genre'] = label_encoder.fit_transform(data['Genre'])
 data['Language'] = label_encoder.fit_transform(data['Language'])


 # encoding the premiere data since they contain month date, year and month date. year
 data['Premiere_comma'] = pd.to_datetime(data['Premiere'], format='%B %d, %Y',
errors='coerce')
 data['Premiere_period'] = pd.to_datetime(data['Premiere'], format='%B %d. %Y',
errors='coerce')


 # Merge the two columns into a single datetime column
 data['Premiere'] = data['Premiere_comma'].combine_first(data['Premiere_period'])


 # Drop the temporary columns
 data.drop(['Premiere_comma', 'Premiere_period'], axis=1, inplace=True)


 # Convert valid datetime values to timestamps and handle NaT values
 data['Premiere'] = data['Premiere'].apply(lambda x: x.timestamp() if not pd.isna(x) else
None)
 data.head()
 print('\n MISSING DATA:')
 print('----------------')
 # checking for any missing data in the premiere
 print(data.isnull().values.any())
 print('\n')
 print('DEVELOPMENT PART 2')
 print('-------------------\n')


 # Split data into features (X) and target (y)
 X = data[['Genre','Premiere','Runtime', 'Language']]
 y = data['IMDB Score']
```

```
# Split the data into training and testing sets
X_train, X_test, y_train, y_test = train_test_split(X, y, test_size=0.2, random_state=42)
print('Linear Regression model')
print('------------------------\n')
# Choose a regression algorithm
model = LinearRegression()

# Initialize the Gradient Boosting Regressor
gb_regressor = GradientBoostingRegressor()

# Model Training
model.fit(X_train, y_train)

# Fit the model to your training data
gb_regressor.fit(X_train, y_train)

# Model Evaluation
y_pred = model.predict(X_test)

# Make predictions
predictions = gb_regressor.predict(X_test)
# by using LinearRegression method
mae = mean_absolute_error(y_test, y_pred)
mse = mean_squared_error(y_test, y_pred)
r2 = r2_score(y_test, y_pred)



print("Mean Absolute Error:", mae)
print("Mean Squared Error:", mse)
print("R-squared:", r2)

print('\nGradient Boosting Regressor')
print('----------------------------\n')

# by using Gradient Boosting Regressor
mae = mean_absolute_error(y_test, predictions)
mse = mean_squared_error(y_test, predictions)
r2 = r2_score(y_test, predictions)

print(f'Mean Absolute Error: {mae}')
print(f'Mean Squared Error: {mse}')
print(f'R-squared: {r2}')
```

OUTPUT:



```
DEVELOPMENT PART-1:
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Index(['Title', 'Genre', 'Premiere', 'Runtime', 'IMDB Score', 'Language'], dtype='object')

 INFORMATION:
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                           Title                Genre           Premiere  Runtime  IMDB Score          Language
0                Enter the Anime          Documentary     August 5, 2019       58         2.5  English/Japanese
1                    Dark Forces             Thriller    August 21, 2020       81         2.6           Spanish
2                        The App  Science fiction/Drama  December 26, 2019       79         2.6           Italian
3                 The Open House      Horror thriller   January 19, 2018       94         3.2           English
4                    Kaali Khuhi              Mystery   October 30, 2020       90         3.4             Hindi
5                          Drive               Action   November 1, 2019      147         3.5             Hindi
6               Leyla Everlasting               Comedy   December 4, 2020      112         3.7           Turkish
7  The Last Days of American Crime     Heist film/Thriller       June 5, 2020      149         3.7           English
8                        Paradox  Musical/Western/Fantasy     March 23, 2018       73         3.9           English
9             Sardar Ka Grandson               Comedy       May 18, 2021      139         4.1             Hindi

SUMMARY
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<class 'pandas.core.frame.DataFrame'>
RangeIndex: 584 entries, 0 to 583
Data columns (total 6 columns):
 #   Column      Non-Null Count  Dtype
---  ------      --------------  -----
 0   Title       584 non-null    object
 1   Genre       584 non-null    object
 2   Premiere    584 non-null    object
 3   Runtime     584 non-null    int64
 4   IMDB Score  584 non-null    float64
 5   Language    584 non-null    object
dtypes: float64(1), int64(1), object(4)
memory usage: 27.5+ KB
None

DUPLICATE DATA:
-----------------
False

 MISSING DATA:
----------------
False
```

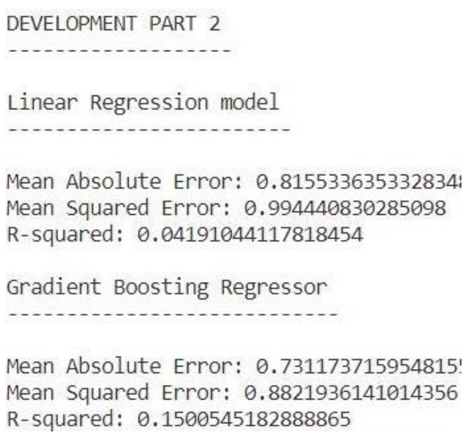

```
DEVELOPMENT PART 2
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Linear Regression model
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Mean Absolute Error: 0.815533635332834
Mean Squared Error: 0.994440830285098
R-squared: 0.04191044117818454

Gradient Boosting Regressor
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Mean Absolute Error: 0.731173715954815
Mean Squared Error: 0.8821936141014356
R-squared: 0.1500545182888865
```