Movie Revenue Prediction
SML Project

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***Abstract*—In the contemporary film industry, accurately predicting a movie's earnings is paramount for maximizing profitability. This project aims to develop a machine learning model for predicting movie earnings based on input features like the movie name, the MPAA rating of the movie, the genre of the movie, year of release of the movie, IMDb Rating, the votes by the watchers, the director, writer and the leading cast, the country of production of the movie, the budget of the movie , the production company and the runtime of the movie. Through a structured methodology involving data collection, preprocessing, analysis, model selection, evaluation, and improvement, a robust predictive model is constructed. Linear Regression, Decision Trees, Random Forest Regression, Bagging, XGBoosting and Gradient Boosting have been trained and tested. Model improvement strategies include hyperparameter tuning and cross validation. The resulting model offers promising accuracy and generalization, facilitating informed decision-making in the film industry to maximize profits.**

I. Introduction

A. Motivation

Imagine you are a filmmaker or head of a movie production house and you have a big question: what makes a movie a blockbuster hit or a flop?

You might think it depends on the star power of the actors, the vision of the director, the budget of the production, or the genre of the story.

Or you might think it is simply the quality of the storytelling that captivates the audience and earns high ratings. But the answer is not straightforward or easy.

There are many factors that influence the earnings of a movie, and the true combination of these factors has not been mastered yet. That's why we have developed a machine learning model that reveals the most important factors for box office success by analyzing real data from a wide variety of movies produced around the world. With our model, filmmakers can make more informed decisions and optimize their movie production for maximum profit and popularity.

B. Rationale

We hypothesize that certain parameters hold more significance in predicting movie revenue than others. Specifically, we conjecture that the director's track record and the genre of the film carry substantial weight in this prediction model.

Our observations suggest that despite lower IMDb ratings, action-oriented films often demonstrate strong performance at the box office. Conversely, genres such as comedy or emotional dramas, despite potentially higher IMDb ratings, may not achieve comparable revenue outcomes to their action counterparts.

These insights underscore the complex interplay between film attributes and audience preferences, prompting us to assign greater importance to factors like directorial history and genre classification within our predictive framework.

C. Overview

In this project, we follow a structured methodology to build and evaluate our predictive model. We first collect a large dataset of movies and their features from various sources and custom tailor the datasets to suit our needs.

We then pre-process the data to handle missing values, outliers, and categorical variables. We perform data analysis to explore the data and understand its characteristics and relationships. We use descriptive statistics, inferential statistics, and data visualization techniques to gain insights into the data like using a graph to compare the accuracy of our model's performance of training and test data.

We then select several machine learning algorithms that are suitable for regression tasks, such as decision trees and random forests. We train and test our models using cross-validation and compare their performance using metrics such as R-squared mean error. We also apply model improvement strategies such as hyper-parameter tuning, feature selection and regularization to enhance the accuracy and generalization of our models. The resulting model offers promising results and can be used to predict the revenue of any movie based on its features.

II. Literature Review

In this section, we will see the definitions of Principal Component Analysis *(PCA)*, Label Encoder, SelectKBest features, GridSearchCV, Train Test Split and provide some literature content on the models which we are going to use. We will also explain the evaluation metrics '*R^2 score*'.

Principal Component Analysis (PCA)

PCA is a statistical procedure that uses an orthogonal transformation to convert a set of observations of possibly correlated variables into a set of values of linearly uncorrelated variables called principal components. This technique is used to emphasize variation and bring out strong patterns in a dataset.

Label Encoder

Label Encoder is a utility method to convert categorical data into numerical data. It assigns each unique category in the data to an integer value, making the data more suitable for algorithmic processing.

SelectKBest Features

SelectKBest is a feature selection method in Scikit-Learn. It selects features according to the k highest scores of a specified scoring function. It's a way to select the '*k*' best features in your dataset, where '*k*' is a parameter you choose.

GridSearchCV

GridSearchCV is a library function that is a member of sklearn's model_selection package. It helps to loop through predefined hyperparameters and fit your estimator (model) on your training set. In addition to that, you can specify the number of times for the cross-validation for each set of hyperparameters.

Train Test Split

The '*train_test_split*' function from the '*sklearn.model_selection*' module is a utility that divides a dataset into randomized training and testing subsets. Each subset is distinct, meaning that no data point can be present in both subsets. This allows for the model to be trained on one subset of the data, and then validated on an entirely separate subset. In our case, we applied an 80/20 split on our dataset for training and testing our models.

Models

A. Linear Regression

Linear Regression is a statistical approach for modelling the relationship between a dependent variable and one or more independent variables.

B. Decision Trees

A Decision Tree is a decision support tool that uses a tree-like model of decisions and their possible consequences. It is one way to display an algorithm that only contains conditional control statements.

C. Gradient Boosting

Gradient Boosting is a machine learning technique for regression and classification problems, which produces a prediction model in the form of an ensemble of weak prediction models, typically decision trees.

D. Bagging

Bootstrap Aggregating, often abbreviated as Bagging, is a meta-algorithm designed to improve the stability and accuracy of machine learning algorithms used in statistical classification and regression. It also reduces variance and helps to avoid overfitting.

E. Random Forests

Random Forests is a learning method that operates by constructing a multitude of decision trees at training time and outputting the class that is the mode of the classes (classification) or mean prediction (regression) of the individual trees.

F. XGBoosting

XGBoost is an optimized distributed gradient boosting library designed to be highly efficient, flexible and portable. It implements machine learning algorithms under the Gradient Boosting framework.

Evaluation Metrics

R² Score

The R² score, also known as the coefficient of determination, is a statistical measure that shows the proportion of the variance for a dependent variable that's explained by an independent variable or variables in a regression model. It provides an indication of goodness of fit and therefore a measure of how well unseen samples are likely to be predicted by the model.

Mean Squared Logarithmic Error (MSLE)

In Mean Squared Logarithmic Error *(MSLE)*, we begin by calculating the natural logarithm of each of the predicted. Values and calculate the mean squared error, i.e., it is called the Mean Squared Logarithmic Error *(MSLE)*. It can also be interpreted as a measure of the ratio between the actual and predicted values.

III. Dataset Selection

A. Modification of Dataset Strategy

In our initial proposal, we constructed a bespoke dataset by integrating four distinct datasets: The **Movies Industry Dataset**, **IMDb 5000 Movies Multiple Genres Dataset**, **IMDb 5000 Movies Dataset**, and **Top 500 Movies Budget**. This integration was performed sequentially, resulting in a **comprehensive dataset encompassing 7118 movies** with input variables such as budget, director, genre, leading crew, and IMDb ratings, and the output variable being gross revenue. (Refer to the **README** for a detailed explanation of the dataset construction process).

However, during the progression of our project, we identified the need to diverge from our originally proposed datasets. We opted for a refined dataset derived solely from **The Movies Industry Dataset**, achieved by excluding entries with missing values. This pivotal decision was informed by a multitude of considerations, which are detailed in the following subsections.

B. Rationale Behind the Dataset Transition

The primary challenge encountered with our initially finalized dataset was its suboptimal performance with our predictive models, reflected in lower accuracy rates. This was attributed to our initial approach of selecting input variables without a thorough analysis of the available data, leading us to force-fit the datasets into a preconceived framework of revenue determinants, thus compromising the integrity of the final dataset. Additionally, the potential for confusion due to movies sharing similar titles necessitated a cautious approach to dataset merging, which presented its own set of complexities.

Acknowledging these issues, we paused to re-evaluate our methodology. We delved into a deeper examination of the data surrounding movie revenue prediction and gained insights into structuring the dataset to train a model that is both comprehensive and robust in forecasting movie earnings. *(Graphical representations illustrating the enhancements of our current dataset compared to the previous one will be provided).*

C. Benefits of the Optimized Dataset

Our continued exploration for an ideal dataset that encapsulates the core of our research led us to ”The Movies Dataset,” which aligned perfectly with our criteria. We ensured the dataset’s reliability by eliminating entries with null values before subjecting it to our predictive models. A significant advantage of our current dataset is its ability to address the limitations of our prior data. It includes additional input variables such as Year, Production Company, and Votes *(alongside the IMDb score)*, which collectively enhance the accuracy of our machine learning model in predicting movie revenues. Moreover, sourcing the dataset from a single origin has eliminated the extraneous noise that previously arose from dataset amalgamation.

IV. Data Analysis

TABLE I: Description of Movie Dataset Features

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Feature Name	Description
Name	The title of the movie
Rating	The MPAA rating of the movie
Genre	The genre of the movie
Year	The year the movie was released
Released	The release date of the movie
Score	The IMDb rating of the movie
Votes	The number of votes the movie received
Director	The person who directed the movie
Writer	The person who wrote the movie script
Star	The main actor or actress in the movie
Country	The country where the movie was produced
Budget	The budget of the movie
Company	The production company of the movie
Runtime	The duration of the movie

In the data analysis phase, we will thoroughly examine the collected movie dataset to gain insights into its structure, distribution, and relationships between features and the target variable *(movie earnings)*. We will utilize descriptive statistics, inferential statistics, and data visualization techniques to explore the data.

A. Descriptive Statistics

We computed summary statistics such as mean, median, standard deviation, minimum, maximum, and quartiles for numerical features like budget and ratings. This gave us a general understanding of the central tendency and spread of the data.

B. Inferential Statistics

We will conduct statistical tests to analyze relationships between different features and the target variable. For example, we may use correlation analysis to examine the strength and direction of linear relationships between numerical features and earnings.

C. Data Visualization

Visualization is a powerful tool for understanding complex datasets. We created various plots and charts using Matplotlib. This includes histograms and scatter plots to visualize distributions, trends, outliers, and correlations in the data.

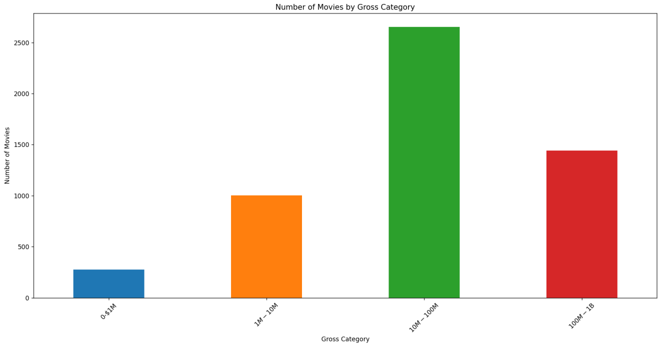


Fig. 1: Histogram of Gross Categories

V. Preprocessing

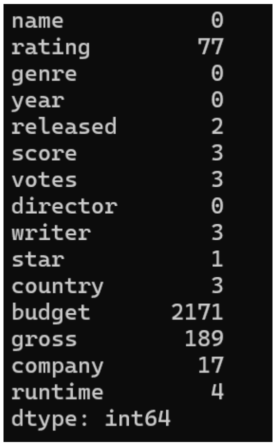
A. Dataset Parameters

We have 14 parameters, including both non-numerical and numerical data types.

1) name
2) rating
3) genre
4) year
5) released
6) score
7) votes
8) director
9) writer
10) star
11) country
12) budget
13) company
14) runtime

We have 9 non-numerical data types

1) name
2) rating



```
name           0
rating        77
genre          0
year           0
released       2
score          3
votes          3
director       0
writer         3
star           1
country        3
budget      2171
gross        189
company       17
runtime        4
dtype: int64
```

Fig. 2: Null Values

3) genre
4) released
5) director
6) writer
7) star
8) country
9) company

To prepare the data for regression models, we need to encode the non-numerical features into numerical labels. We will utilize the LabelEncoder from scikit-learn for this purpose.

LabelEncoder

The LabelEncoder is a handy tool for normalizing and transforming non-numerical labels into numerical equivalents. It's important to note that the labels should be hashable and comparable for this process to work effectively. We will begin by fitting the label encoder and obtaining the encoded labels for further processing.

Handling Null values

In the **Movie Industry Dataset**, there are 2,247 null values across the 11 parameters totalling 7669. Since budget and gross are our main parameter and output, we dropped those datasets and we were left with 5422 datasets.

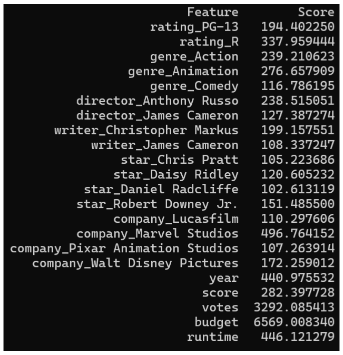
PCA

We tried to use Principal Component Analysis but we were not able to achieve significant increase in the accuracy. We believe the reason for this is that PCA works effectively when there are more parameters and datasets. It will be more useful in image or sound regression/classification as the dimensions of the image/sound will come into play. Thus, we have decided to drop PCA in our preprocessing.

Best Features

We wanted to know which features contribute more to the revenue of the movie.

So we had used SelectKBest and then categorized and predicted all the 8668 features which can be viewed in **Features Scores**.



```
                          Feature        Score
                     rating_PG-13   194.402250
                         rating_R   337.959444
                     genre_Action   239.210623
                  genre_Animation   276.657909
                     genre_Comedy   116.786195
         director_Anthony Russo   238.515051
         director_James Cameron   127.387274
     writer_Christopher Markus   199.157551
           writer_James Cameron   108.337247
               star_Chris Pratt   105.223686
              star_Daisy Ridley   120.605232
          star_Daniel Radcliffe   102.613119
         star_Robert Downey Jr.   151.485500
              company_Lucasfilm   110.297606
         company_Marvel Studios   496.764152
company_Pixar Animation Studios   107.263914
   company_Walt Disney Pictures   172.259012
                             year   440.975532
                            score   282.397728
                            votes  3292.085413
                           budget  6569.008340
                          runtime   446.121279
```

Fig. 3: K Best Features

Since there were a lot of features for us to analyse, we then printed only those features with scores greater than 100 which can be viewed in **Best Features Scores**.

As per our intuition, the budget played was the most deciding feature, with a score of about 6569. However, to our surprise, votes played the next most important role in predicting the revenue.

Additionally, runtime, year, and score also played a decent role in predicting the revenue.

Also, there were a few individual companies and individuals in the field of direction, cast and production who had an impact on the way the movies performed at the box office.

Also, there is a general trend that can be noticed where PG-13 and R-rated movies tend to do well.

Action, Animation, and Comedy are well-performing genres which also tend to increase the revenue of the movie.

VI. Model Selection

For predicting movie earnings, we have explored several regression techniques and ensemble methods like Linear Regression with and without PCA Preprocessing, Decision Trees, Gradient Boosting, Bagging, Random Forests and XGBoosting. Ensemble methods like Random Forests and Gradient Boosting are capable of handling complex interactions and non-linearities in the data.

1) Linear Regression: Initially used to explore the dataset's linear relationships and determine if a straight-line model could adequately represent the data.

2) Gradient Boosting: Employed as a predictive technique to create an ensemble model consisting of weaker prediction models (typically decision trees). Each subsequent learner in the ensemble aims to correct errors made by its predecessors. GB is known for its robustness against overfitting, making it a valuable algorithm for predictive tasks.

3) Random Forest: Utilized as an ensemble learning method for classification. RF constructs multiple decision trees and makes predictions based on the majority vote of these trees. Despite efforts to reduce dataset dimensionality, the RF model exhibited overfitting on the training set and did not outperform other models significantly.

4) Decision Tree: Employed as a hierarchical decision support model. DTs use a tree-like structure to represent decisions and their consequences, including chance events, resource costs, and utility. They provide a clear visualization of the algorithm's decision-making process.

5) Bagging: Used to improve model performance by training multiple models on random subsets of the original data. The results from these models are combined through a voting mechanism to make predictions, resulting in more accurate and robust predictions.

6) XGBoost: Applied as a popular machine learning algorithm under ensemble learning. XGBoost is effective for supervised learning tasks like regression and classification. It iteratively builds a predictive model by combining predictions from multiple individual models, often decision trees, to enhance prediction accuracy and model performance.

VII. Model Improvement

In our pursuit of enhancing the model's performance, we will employ several strategies. Let's break down the key components:

A. Standardizing Data with Standard Scaler

To ensure consistent scaling across features, we'll utilize the *Standard Scaler*. This technique standardizes each feature by subtracting the mean and dividing by the standard deviation. By applying this transformation, we bring all features to a similar scale, which can significantly improve the model's performance.

B. Feature Engineering: Logarithmic Transformations

We'll focus on two specific columns: '*budget*' and '*gross*' revenue. These columns often exhibit skewed distributions. To address this, we'll apply logarithmic transformations. Converting 'budget' and 'gross' to $\log(\text{budget})$ and $\log(\text{gross})$ using **numpy.log1p**, respectively, will stabilize their variance and enhance the model's robustness. We will also report MSLE when the above is implemented to check if the model's bias is low.

C. Hyperparameter Tuning using GridSearchCV

Now, let's delve into the details of hyperparameter tuning. *GridSearchCV* is a powerful tool that performs an exhaustive search over specified parameter values for an estimator. In our case, we're using a *Gradient Boosting Regressor* with a squared error loss function. Here's how it works:

- We define a dictionary called `param_grid` containing various hyperparameters (e.g., number of estimators, maximum depth, and learning rate).
- *GridSearchCV* systematically tests different combinations of these hyperparameters using cross-validation (in our case, 5-fold cross-validation).
- The best combination of parameters, as determined by the highest R-squared score, is extracted using the `best_params` attribute.
- Armed with these optimal parameters, we initialize the final model.
- The model is then trained on the training data and evaluated on both the training and test datasets to validate its accuracy.

By following this process, we aim to create a robust and high-performing model.

VIII. Model Evaluation

We will evaluate the performance of our models using appropriate metrics such as Mean Squared Logarithmic Error *(MSLE)* and Coefficient of Determination *(R-squared)*. These metrics provide insights into the accuracy, precision, and goodness-of-fit of our models. Additionally, we will compare the performance of our model with baseline models to assess its effectiveness.

Model	**R²**
Linear Regression	
Training Set	0.6553
Testing Set	0.6706
Decision Tree	
Training Set	0.8664
Testing Set	0.6947
Bagging	
Training Set	0.8583
Testing Set	0.7719
Gradient Boost	
Training Set	0.9158
Testing Set	0.8242
eXtreme Gradient Boosting	
Training Set	0.9079
Testing Set	0.8102
Random Forest	
Training Set	0.8728
Testing Set	0.7786

TABLE II: Model Evaluation Result

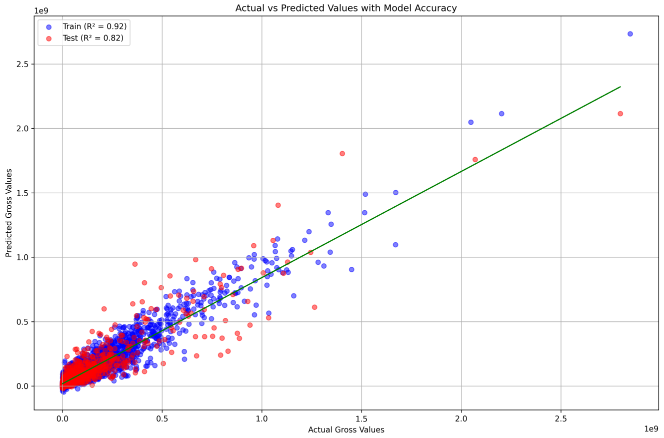


Fig. 4: Gradient Boosting Test Results

IX. Conclusion

As of now, we have found Gradient Boosting to be our best model, achieving:

- Final Training Accuracy: 91.58%

- Final Testing Accuracy: 82.42%

The model can be viewed in **Models/gradient_boost.py**.
The other models can be viewed **here**.
The accuracies of all the models can be viewed **here**.

Acknowledgment

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References

[1] Models

1) **Linear Regression**
2) **DecisionTreeRegressor**
3) **BaggingRegressor**
4) **RandomForestRegressor**
5) **XGBoost**
6) **GradientBoostingRegressor**

[2] scikit-learn Metrics

1) **r2_score**
2) **mean_squared_log_error**

[3] Kaggle Datasets

1) **Movie Industry Dataset**
2) **IMDb 5000 Movies Multiple Genres Dataset**
3) **IMDb 5000 Movies Dataset**
4) **Top 500 Movies Budget**