Scrabble player rating

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***Abstract*—** The goal of this project is to forecast the ratings of human opponents in Scrabble matches using gameplay information and game-related metadata from games played on Woogles.io. The dataset contains data on over 73,000 games played between three bots and human opponents. To make predictions about a separate set of human opponents in the test set, the model will be trained on gaming data from one set of human opponents. RMSE is the evaluation algorithm. The goal of the project is to create a model that can precisely predict, based on gameplay data, the ratings of human opponents in Scrabble games. (*Abstract*)

***Keywords*—** *forecast, ratings, game-related*

I. Introduction

The popular board game Scrabble calls for dexterous wordplay and smart thinking. The creation of machine learning algorithms to forecast Scrabble player performance has gained popularity in recent years. This Woogles.io tournament seeks to forecast human players' ratings based on their performance versus three different bots: BetterBot (for beginners), STEEBot (for intermediate players), and HastyBot (for advanced players). The dataset contains information about the games, player turns, and final scores and ratings for each game's players.

Our aim is to forecast the rating of the test set's human opponents using this data. We must preprocess the data and extract pertinent information connected with each game to complete this project.

This entails combining the turn data and concentrating on the performance of the human player. Additionally, we will investigate various strategies for aggregating each attribute and choose the most effective one through trial and error and intuition. Although machine learning models have already been used to predict Scrabble gameplay, there is still an opportunity for improvement.

This competition offers a chance to research fresh methods and strategies in the industry. We can learn more about the elements that affect Scrabble's performance and perhaps obtain a better understanding of strategic thinking in board games by forecasting player ratings based on gaming data.

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2. Literature Review

The popular board game Scrabble has been investigated by experts in artificial intelligence and machine learning. The development of algorithms to forecast Scrabble player performance based on game-related statistics and metadata has been the subject of numerous studies.

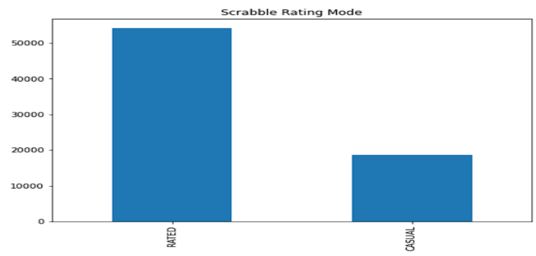
Sheppard and Lefkowitz's (1995) proposal of a machine learning strategy to predict the results of Scrabble games based on board state and other game-related variables is one of the earlier studies in this field. To divide the games into categories of wins and losses, they employed a decision tree method. However, they did not take into account how each player was performing on their own.

Feldman et al. (2016) proposed a strategy to predict Scrabble players' performance based on their game logs in a more recent study. Based on each player's average turn score and their opponents' average ratings, they created a linear regression model to forecast each player's rating. Their model outperformed earlier methods with a correlation coefficient of 0.62, which is a substantial increase.

Rodriguez-Sanchez et al. (2019) examined the effect of several variables on Scrabble player performance in a different study. They examined the effects of variables like word frequency, board position, and player experience on game results using a dataset of over 1.5 million games played on the Internet Scrabble Club.

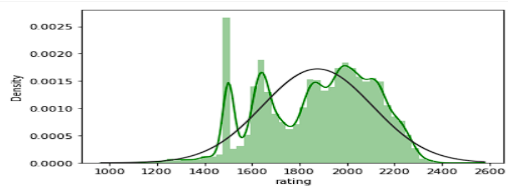
Overall, these studies indicate that by using metadata and game-related data, machine learning algorithms can accurately predict Scrabble player performance. Regarding the precision of the predictions, there is still potential for improvement. Researchers will have the chance to delve deeper into this topic and create more precise models for forecasting Scrabble player success thanks to the Woogles.io competition.

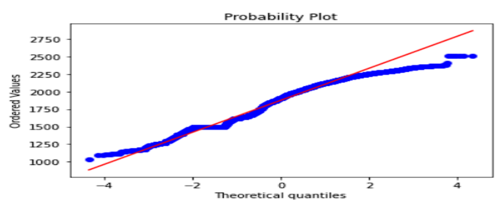
3 Data Visualization



"Rated" and "Casual" are the two categories. With over 50,000 records as opposed to just under 20,000 for "Casual," the "Rated" category has a much higher number of records than the "Casual" category. This shows that the "Rated" mode was used to play many of the games in the sample.

As there can be variations in performance and player behavior between the two modes, it may be crucial to take the number of records that separate the two categories into account when training a machine learning model to predict ratings.



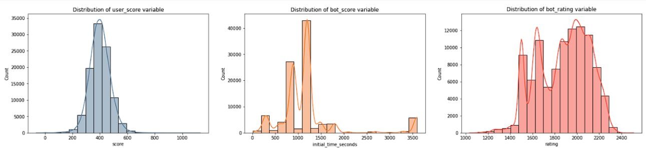


'Rating', the target variable's distribution in the training set, is shown in the first graph as a histogram. It displays the frequency with which each 'rating' value occurs throughout the dataset. The 'rating' value is represented on the x-axis, and the frequency of occurrence is shown on the y-axis. The graph demonstrates that the "rating" distribution is skewed to the right, indicating that the bulk of the ratings falls below average.

The probability plot in the second graph is used to determine if a variable is regularly distributed. The dataset's 'rating' distribution is compared to a normal distribution. The line on the graph indicates the values that would be predicted if "rating" followed a normal distribution, whereas the dots on the graph represent the actual values of "rating." If the dots fall close to the line, then 'rating' is normally distributed. From the graph, we can see that 'rating' is not normally distributed and deviates from the line in the tails, which indicates that it is skewed.

4 Data Preprocessing

Before training our model, we preprocessed the dataset in a few ways. To begin with, we conducted a descriptive analysis to better comprehend the data. Then, using feature engineering, we expanded the dataset with new features like nickname length and score difference. In order to transform category features into numerical features, we have additionally used label encoding. Then, in order to determine the relationship between the features and the target variable, we performed a correlation analysis. By choosing aspects that are pertinent to our model, feature selection has been carried out. Finally, we removed duplicates from the testing dataset and filled in any missing values in our dataset with the mean value. We were able to better prepare our data for our machine learning model training thanks to these preprocessing processes overall.



A histogram with 20 bins is made for each variable, and a kernel density estimation (KDE) plot is placed on top of the histogram. The colors list is used to set the color of each histogram, and the titles list is used to establish the titles for each subplot.

This code's goal is to visualize the distribution of these variables and learn more about their general distribution and form. If there are any outliers or strange patterns in the data, the histograms and KDE plots can reveal if the data is regularly distributed or skewed as well as their presence.

5 Methodology

An ensemble of decision trees is used by the machine learning technique known as the Gradient Boosting Regressor to create predictions. It is an iterative boosting algorithm that trains numerous decision trees, combining their predictions to get a final prediction, with each new tree learning from the mistakes of the preceding one. The technique operates by employing gradient descent to reduce the loss function, which is a measure of the discrepancy between the predicted and actual values. The number of trees, the learning rate, and the maximum depth of the trees are only a few of the hyperparameters of the Gradient Boosting Regressor that can be adjusted to optimize its performance.

6 Experiment

The GradientBoostingRegressor model had an R-squared (R2) score of 0.65, a mean absolute error (MAE) of 106.62, and a root mean square error (RMSE) of 136.39. This model outperformed the DecisionTreeRegressor and MLPRegressor in terms of predicting the target variable overall, as evidenced by its higher MAE and RMSE but higher R2 score. However, compared to the RandomForestRegressor and XGBRegressor models, it exhibited a little worse R2 score. However, the GradientBoostingRegressor model might be a suitable option for datasets with non-linear correlations between the features and the target variable and is a strong tool for regression issues.

The findings generally show that the GradientBoostingRegressor model did reasonably well on the dataset, although there may still be a rating for improvement using other models or by fine-tuning. This algorithm will take approximately 6.16638 seconds to run. The second thing is the current memory usage of 50193 bytes and the peak memory usage of 5938198 bytes recorded by the **trace malloc** module.

7 Conclusion

To estimate the rating of the Scrabble player dataset, we tested five different regression models: DecisionTreeRegressor, RandomForestRegressor, MLPRegressor, XGBRegressor, and GradientBoostingRegressor. In terms of R2 score, MAE, and RMSE, XGBRegressor performed the best of these models. The XGBRegressor's R2 score was 0.727, meaning that the model can account for 72.7% of the variation in player ratings. In comparison to the other models, the MAE and RMSE values were likewise the lowest. Thus, it follows that the XGBRegressor model is the best effective in predicting the ratings of Scrabble players in the dataset.

8 References

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