# 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.

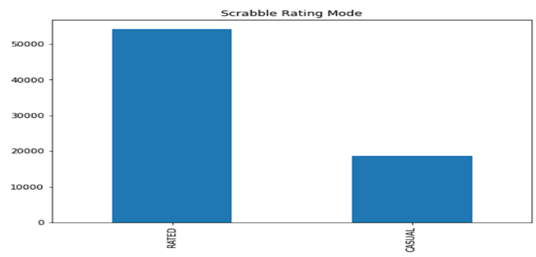
Sheppard and Lefkowitz's (1995) proposal of a machine learning strategy to predict the results of Scrabble games based on board state and other game-related variables is one of the earlier studies in this field. To divide the games into categories of wins and losses, they employed a decision tree method. 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.

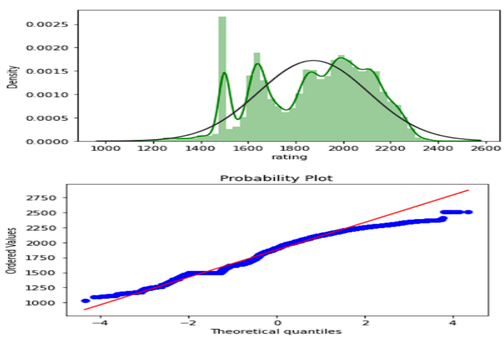
Overall, these studies indicate that by using metadata and game-related data, machine learning algorithms can accurately predict Scrabble player performance. Regarding the precision of the predictions, there is still potential for improvement. Researchers will have the chance to delve deeper into this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

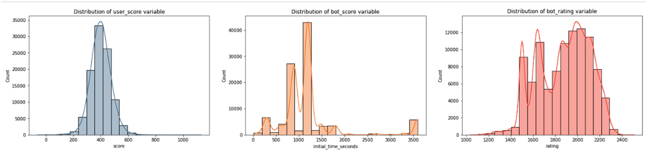


'Rating', the target variable's distribution in the training set, is shown in the first graph as a histogram. It displays the frequency with which each 'rating' value occurs throughout the dataset. The 'rating' value is represented on the x-axis, and the frequency of occurrence is shown on the y-axis. 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

By reducing the coefficients of the features towards zero, the regularisation approach known as Lasso Regression can be used to lessen the complexity of a regression model. The loss function in Lasso Regression is increased with the total absolute value of the coefficients before being minimized during training. By doing so, the most crucial elements can be distinguished from the unnecessary ones. To apply Lasso Regression, we used the LassoRegressor() method from the scikit-learn library. The model was trained on the same training dataset with the same features and target variables as the other models. After training, we made predictions on the test dataset and evaluated the model's performance using MAE, RMSE, and R2 score metrics.

## 6 Experiments

In order to avoid overfitting, the model, the linear regression technique known as Lasso regression employs L1 regularisation. In this study, the rating of the Scrabble player was predicted using the LassoRegressor methodology. The model obtained an R2 score of 0.46, a mean absolute error (MAE) of 137.23, and a root mean squared error (RMSE) of 169.51. These findings suggest that compared to some of the other models employed in this study, the Lasso model did not do as well in predicting the ratings of Scrabble players in Sydney. The dataset's enormous number of features may have influenced the Lasso model, increased bias, and decreased accuracy. Although the Lasso model can be a valuable tool for analyzing data with high-dimensional feature sets and determining key features for a particular model, even though it may have limited applications for predicting ratings of Scrabble players. This algorithm will take approximately 0.01150 seconds to run. The second thing is the current memory usage of 5525 bytes and the peak memory usage of 8461550 bytes recorded by the **trace malloc** module.

## 7 Conclusion

Finally, nine alternative regression models were employed to predict the ratings of Scrabble players. Based on the models' MAE, RMSE, and R2 score criteria, each model was assessed. The outcomes demonstrated that certain models outperformed others. The models with the lowest MAE and RMSE values and the greatest R2 score values were the XGBRegressor and RandomForestRegressor. The XGBRegressor and RandomForestRegressor models outperformed the MLPRegressor and GradientBoostingRegressor, though not as well. The Ridge Regressor and Lasso Regressor models, on the other hand, underperformed when compared to the other models. They had the lowest R2 score values and the greatest MAE and RMSE values. Overall, the findings indicate that while RidgeRegressor and LassoRegressor may not be the ideal options for this type of prediction job, ensemble models like XGBRegressor and RandomForestRegressor are well-suited for predicting rating.

## 8 References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