Project Report Intro to Statistical Computing STAT 610 Chess Outcome Prediction

Introduction

The goal of the project is to create a predictive model that predicts the outcome of the chess game based on the information before the game such as the players' ratings, the type of match, the tournament. The data set is available at https://www.kaggle.com/datasnaek/chess. The data set contains information about 20,000 chess games.

Objectives

- To create a predictive model that predicts the outcome of the chess game based on the information before the game such as the players' ratings, the type of match, the tournament.
- To create a pipeline that uses the data and performs the following steps:
- Data cleaning
- Data exploration
- Data visualization
- Model building
- Model evaluation

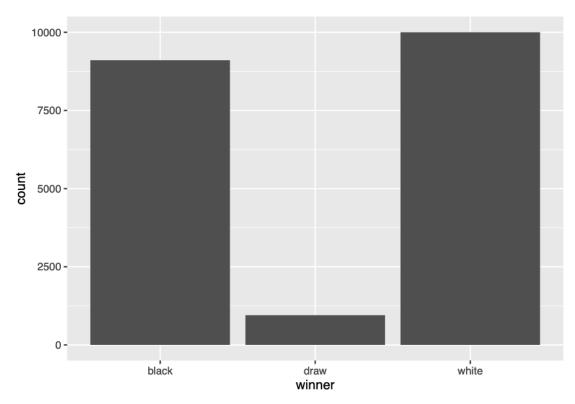


Fig 1: Distribution of the outcome of the matches in the dataset.

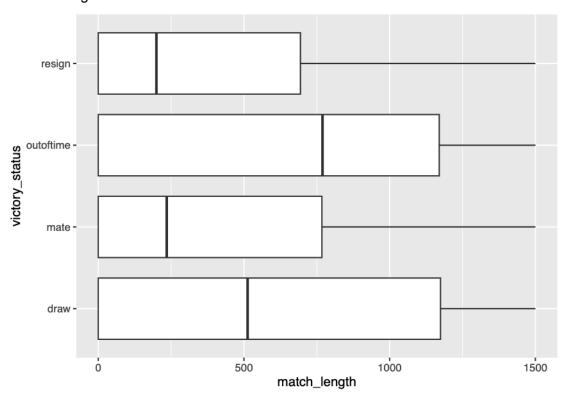


Fig 2: Distribution of match length (in seconds) vs the outcome of the match

Design Decisions

I have created a EDA notebook that performs the following steps:

- 1. Data Wrangling
 - a. Data importing
- b. Checking the data types of variables and performing necessary steps to change the data type based on relevancy.
 - c. Univariate Statistics of the variables
 - d. Dealing with null values
 - e. Outlier analysis
- 2. Data Visualization
 - a. Bivariate analysis
 - b. Correlation analysis
- 3. Feature
 - a. Chi square test
 - b. ANOVA test
 - c. Correlation test
- 4. Linear Regression
 - a. Linear Regression assumption validation
 - b. Model training
 - c. Hyperparameter tuning
 - d. Regularization
 - e. Result visualization

I have created a file "model_training.R" that performs the following steps:

- Prepare the data for model training
- Perform iterative feature selection for categorical and numerical variables
- Train the model using the selected features

```
preprocess <- function(data) {</pre>
          chess <- data
          chess$rated <- as.logical(chess$rated)</pre>
10
          chess$increment_code <- as.character(chess$increment_code)</pre>
11
          # everthing before the plus sign
12
          chess$increment_code1 <- strsplit(chess$increment_code, split = "\\+")</pre>
13
          chess$increment_code1 <- sapply(chess$increment_code1, function(x) x[1])</pre>
14
          # everything after the plus sign
15
          chess$increment_code2 <- strsplit(chess$increment_code, split = "\\+")</pre>
16
          chess$increment_code2 <- sapply(chess$increment_code2, function(x) x[2])</pre>
17
18
          chess$increment_code1 <- as.numeric(chess$increment_code1)</pre>
19
          chess$increment_code2 <- as.numeric(chess$increment_code2)</pre>
20
21
          chess$increment_code1_bin <- cut(chess$increment_code1, breaks = c(0,</pre>
22
          20, 50, 100, 200, 1000))
23
          chess$increment_code2_bin <- cut(chess$increment_code2, breaks = c(0, 20,</pre>
24
          50, 100, 200, 1000))
25
          data <- chess
26
          data$rating_diff <- data$white_rating - data$black_rating</pre>
27
28
          # Remove the draws
29
          data <- subset(data, winner != "draw")</pre>
30
          # Convert the winner column to 1 and 0
31
          data$winner <- ifelse(data$winner == "■white", 1, 0)
32
          # Remove the columns that we don't need
33
          data <- data[, c("winner", "white_rating", "black_rating",</pre>
34
           "rating_diff", "increment_code1_bin", "increment_code2_bin",
35
          "rated")]
36
          # Remove the rows with NA values
37
          data <- na.omit(data)</pre>
38
          # Return the preprocessed data
39
          return(data)
40
41
      train_model <- function(data, verbose = FALSE) {</pre>
42
        # Split the data into train and test
43
        train_index <- createDataPartition(data$winner, p = 0.7, list = FALSE)</pre>
44
        train <- data[train_index, ]</pre>
45
        test <- data[-train_index, ]</pre>
46
47
        model <- glm(winner ~ ., data = train, family = "binomial")</pre>
48
49
        pred <- predict(model, test)</pre>
50
        if (verbose) {
51
          print(model)
52
         print(summary(model))
53
          # Print the confusion matrix
54
          print(table(test$winner, pred > 0.5))
55
          # Print the accuracy
56
          print(mean(test$winner == (pred > 0.5)))
57
58
59
        return(list(model = model, accuracy = mean(test$winner == (pred > 0.5))))
```

```
iterative_sampling_num <- function(data, numerical_vars) {</pre>
         selected_vars <- c()</pre>
 84
         accuracy <- -1
         # Run the below code iteratively while adding variable if
         # the mean accuracy is greater than the previous one
         while (length(numerical_vars) > 0) {
           # Run the chi-square test on the numerical variables and
           # select the variable with the least p-value
 90
           anova_pvals <- sapply(numerical_vars,</pre>
             function(x) anova_test(data, "winner", x))
           # Select the variable with the least p-value
           anova_var <- numerical_vars[which.min(anova_pvals)]</pre>
 94
           # Run the model with the selected variable with the
           # train_model function which will return the model and the accuracy
           selected_vars <- c(selected_vars, anova_var)</pre>
           model <- train_model(data[, c("winner", selected_vars)], verbose = TRUE)</pre>
           # If the accuracy is greater than the previous one,
           # then add the variable to the model
100
           numerical vars <- numerical vars[-which(numerical vars == anova var)]</pre>
           if (model$accuracy > accuracy) {
102
             accuracy <- model$accuracy</pre>
103
           } else {
104
             # removez the last variable added to the model
105
             selected_vars <- selected_vars[-length(selected_vars)]</pre>
106
107
108
         return(selected_vars)
109
110
111
       #iterative sampling for categorical variables
112
       iterative sampling cat <- function(data, categorical vars) {</pre>
113
         selected_vars <- c()</pre>
114
         accuracy <- -1
115
         # Run the below code iteratively while adding variable if
116
         # the mean accuracy is greater than the previous one
117
         while (length(categorical_vars) > 0) {
118
           # Run the chi-square test on the categorical variables and
119
           # select the variable with the least p-value
120
           chi_pvals <- sapply(categorical_vars,</pre>
121
             function(x) chisq_test(data, "winner", x))
122
           # Select the variable with the least p-value
123
           chi_var <- categorical_vars[which.min(chi_pvals)]</pre>
124
           # Run the model with the selected variable with the
125
           # train_model function which will return the model and the accuracy
126
           selected_vars <- c(selected_vars, chi_var)</pre>
127
           model <- train_model(data[, c("winner", selected_vars)], verbose = TRUE)</pre>
128
           # If the accuracy is greater than the previous one,
129
           # then add the variable to the model
130
           categorical_vars <- categorical_vars[-which(categorical_vars == chi_var)]</pre>
131
           if (model$accuracy > accuracy) {
132
             accuracy <- model$accuracy</pre>
133
           } else {
```

I've also created a file "tests.R" that performs the following tests on the model training pipeline:

- Test the dataset that has been downloaded and has the required columns and data types
- Test the preprocessing function and the outputs of the function
- The chisquare test and the anova test
- The iterative sampling function for both the categorical and numerical variables
- The linear regression model training function

```
28
     test_preprocess <- function(file) {</pre>
29
         # Load the dataset
         data <- read.csv(file)</pre>
         # Preprocess the dataset
         data_pros <- preprocess(data) # nolint</pre>
         # Check if the dataset is not empty
33
34
         test that("Dataset is not empty", {
              expect_true(nrow(data_pros) > 0)
36
         # Check if the dataset has the right number of columns
         test_that("Dataset has the right number of columns", {
              expect_true(ncol(data_pros) == 7)
         })
41
         test_that("Dataset has the expected columns", {
42
              expect_true(sum(colnames(data_pros) == c("winner", "white_rating",
               "black_rating", "rating_diff", "increment_code1_bin",
              "increment_code2_bin", "rated")) == 7)
44
         # Check if the winner column has only 0 and 1
47
         test_that("Winner column is binary", {
              expect_true(sum(
                  data_pros$winner == 0 |
                  data_pros$winner == 1) == nrow(data_pros)
         })
         # Check if the rated column has only TRUE and FALSE
         test_that("Rated column is binary", {
54
              expect_true(sum(
56
                  data_pros$rated == TRUE |
                  data_pros$rated == FALSE) == nrow(data_pros)
58
         })
59
         # Check if there are no null values
         test_that("No null values", {
              expect_true(sum(is.na(data_pros)) == 0)
62
         })
64
```

Conclusion

Finally the output is the model that is saved in the "model.RData" file. The EDA is also saved in the pdf output. The full code is also attached in the zip file in the final submission.