

# Statistical Learning Project

## Technical Appendix

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January 2021

### Introduction

This is the **Technical Appendix** for the *Statistical Learning Project*.

This document contains a list of theoretical concepts that were used inside the project along with all the model formulae.

### 1 Multiple Linear Regression

In our project we used extensively the *Multiple Linear Regression* instead of the *Simple Linear Regression* because we had a lot of predictors, each contributing to our model.

The generalization from *Simple* to *Multiple Linear Regression* is given by the following formula:

$$Y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \dots + \beta_p x_{ip} + \epsilon_i \quad (1)$$

In particular, if we use matrix notation, the model can be written as:

$$Y = X\beta + \epsilon \quad (2)$$

And the  $\beta$  coefficients are calculated minimizing the residual sum of squares:

$$\hat{\beta} = (X^T X)^{-1} X^T y \quad (3)$$

where  $y$  is the value of the response variable.

### 2 Adjusted $R^2$

The adjusted  $R^2$ , denoted by  $\bar{R}^2$  is a modified version of  $R^2$  that adjust for the number of explanatory terms in a model relative to the number of data points. Unlike  $R^2$ ,  $\bar{R}^2$  increases only when the increase in  $R^2$  (due to the inclusion of a new explanatory variable) is more than one would expect to see by chance.

To compute  $\bar{R}^2$  the following formula is used:

$$\bar{R}^2 = 1 - (1 - R^2) \left( \frac{n - 1}{n - p - 1} \right) \quad (4)$$

### 3 Backward Step-wise Selection

In order to apply variable selection in our models we used *Backward Step-wise Selection*.

It works as following:

- let  $M_p$  be our full model containing all  $p$  predictors
- For  $k = p, p - 1, \dots, 1$  :
  - Consider all  $k$  models that contains all but one of the predictors in  $M_k$ , for a total of  $k - 1$  predictors
  - Choose the best among these  $k$  models, and call it  $M_{k-1}$
- Select a single best model from  $M_0, \dots, M_p$  using cross-validated prediction error, AIC, BIC, or Adjusted  $R^2$

### 4 Linear Discriminant Analysis

As a comparison to our classification model we implemented a *Linear Discriminant Analysis (LDA)* algorithm to our training data and used to predict directly a categorical class.

The class assignment process of the algorithm works as follows:

$$\delta_j(x) = x \frac{\mu_j}{\sigma^2} - \frac{\mu_j^2}{2\sigma^2} + \log(\pi_j) \quad (5)$$

where:

- $\delta_j(x)$  : discriminant score for  $x$  to belong to class  $j$
- $1 < j < |G|$
- $G$  : the set of distinct classes that  $x$  can assume

Once that for every  $x$  all the  $\delta_j(x)$  are computed, the highest is selected and that is the qualitative prediction for the data point  $x$ .

## 5 Methods Formulae

### 5.1 Model 1

$$Y_i = \beta_0 + \beta_1 x_{i,a} + \beta_2 x_{i,h} + \beta_3 x_{i,o} + \beta_4 x_{i,ce} + \sum_{l \in L} \beta_l x_{i,l} + \beta_{10} x_{i,ga(y)} + \beta_{11} x_{i,go(y)} + \beta_{12} x_{i,mi(y)} + \beta_{13} x_{i,as(y)} + \beta_{14} x_{i,y(y)} + \beta_{15} x_{i,o(y)} + \beta_{16} x_{i,r(y)} + \epsilon_i \quad (6)$$

- $Y_i$  : market value
- $x_{i,a}$  : age
- $x_{i,h}$  : height
- $x_{i,o}$  : offensive ( dummy variable )
- $x_{i,ce}$  : contract expires
- $x_{i,l}$  : current league ( 6-1 dummy variables ), for  $l \in L = \{Leagues\}$
- $x_{i,ga(y)}$  : games 20/21
- $x_{i,go(y)}$  : goals 20/21
- $x_{i,mi(y)}$  : minutes 20/21
- $x_{i,as(y)}$  : assists 20/21
- $x_{i,y(y)}$  : yellow player 20/21 ( dummy variable )
- $x_{i,o(y)}$  : orange player 20/21 ( dummy variable )
- $x_{i,r(y)}$  : red player 20/21 (dummy variable )
- $(y) := 2021$ .
- Parameters =  $1+4+(6-1)+7 = 17$

#### 5.1.1 Model 1.1

$$\log(Y_i) = \beta_0 + \beta_1 x_{i,a} + \beta_2 x_{i,h} + \beta_3 x_{i,o} + \beta_4 x_{i,ce} + \sum_{l \in L} \beta_l x_{i,l} + \beta_{10} x_{i,ga(y)} + \beta_{11} x_{i,go(y)} + \beta_{12} x_{i,mi(y)} + \beta_{13} x_{i,as(y)} + \beta_{14} x_{i,y(y)} + \beta_{15} x_{i,o(y)} + \beta_{16} x_{i,r(y)} + \epsilon_i \quad (7)$$

where here we just log-transformed the response variable  $Y_i$  to  $\log(Y_i)$ .

## 5.2 Model 2

$$\begin{aligned} \log(Y_i) = & \beta_0 + \beta_1 x_{i,a} + \beta_2 x_{i,h} + \beta_3 x_{i,o} + \beta_4 x_{i,ce} + \sum_{l \in L} \beta_l x_{i,l} + \\ & \sum_{y \in Y} [ \beta_j x_{i,ga(y)} + \beta_{j+1} x_{i,go(y)} + \beta_{j+2} x_{i,mi(y)} + \beta_{j+3} x_{i,as(y)} + \\ & \beta_{j+4} x_{i,y(y)} + \beta_{j+5} x_{i,o(y)} + \beta_{j+6} x_{i,r(y)} ] + \epsilon_i \end{aligned} \quad (8)$$

- $y \in Y = \{2021, 2020\}$
- $j = (2021 - y) \times 7 + 10$  (counter for the  $\beta$  inside the second sum)
- Parameters =  $1+4+(6-1)+7 \times 2 = 24$

## 5.3 Model 3

$$\begin{aligned} \log(Y_i) = & \beta_0 + \beta_1 x_{i,a} + \beta_2 x_{i,h} + \beta_3 x_{i,o} + \beta_4 x_{i,ce} + \sum_{l \in L} \beta_l x_{i,l} + \\ & \sum_{y \in Y} [ \beta_j x_{i,ga(y)} + \beta_{j+1} x_{i,go(y)} + \beta_{j+2} x_{i,mi(y)} + \beta_{j+3} x_{i,as(y)} + \\ & \beta_{j+4} x_{i,y(y)} + \beta_{j+5} x_{i,o(y)} + \beta_{j+6} x_{i,r(y)} ] + \epsilon_i \end{aligned} \quad (9)$$

- $y \in Y = \{2021, 2020, 2019\}$
- $j = (2021 - y) \times 7 + 10$  (counter for the  $\beta$  inside the second sum)
- Parameters =  $1+4+(6-1)+7 \times 3 = 31$

## 5.4 Model 4

$$\begin{aligned} \log(Y_i) = & \beta_0 + \beta_1 x_{i,a} + \beta_2 x_{i,h} + \beta_3 x_{i,o} + \beta_4 x_{i,ce} + \sum_{l \in L} \beta_l x_{i,l} + \\ & \sum_{y \in Y} [ \beta_j x_{i,ga(y)} + \beta_{j+1} x_{i,go(y)} + \beta_{j+2} x_{i,mi(y)} + \beta_{j+3} x_{i,as(y)} + \\ & \beta_{j+4} x_{i,y(y)} + \beta_{j+5} x_{i,o(y)} + \beta_{j+6} x_{i,r(y)} ] + \epsilon_i \end{aligned} \quad (10)$$

- $y \in Y = \{2021, 2020, 2019, 2018\}$
- $j = (2021 - y) \times 7 + 10$  (counter for the  $\beta$  inside the second sum)
- Parameters =  $1+4+(6-1)+7 \times 4 = 38$

### 5.5 Model 5

$$\begin{aligned} \log(Y_i) = & \beta_0 + \beta_1 x_a + \beta_2 x_h + \beta_3 x_o + \beta_4 x_{ce} + \sum_{l \in L} \beta_l x_l + \\ & \beta_{10} x_{ga} + \beta_{11} x_{go} + \beta_{12} x_{mi} + \beta_{13} x_{as} + \\ & \beta_{14} x_y + \beta_{15} x_o + \beta_{16} x_r + \epsilon_i \end{aligned} \quad (11)$$

- $x_{i,a}$  : age
- $x_{i,h}$  : height
- $x_{i,o}$  : offensive ( dummy variable )
- $x_{i,ce}$  : contract expires
- $x_{i,l}$  : current league ( 6-1 dummy variables ), for  $l \in L = \{Leagues\}$
- $x_{i,ga}$  : total games
- $x_{i,go}$  : total goals
- $x_{i,mi}$  : total minutes
- $x_{i,as}$  : total assists
- $x_{i,y}$  : total yellows
- $x_{i,o}$  : total oranges
- $x_{i,r}$  : total reds
- Parameters =  $1+4+(6-1)+7 = 17$

### 5.6 Final Reduced Model

$$\begin{aligned} \log(Y_i) = & \beta_0 + \beta_1 x_a + \beta_2 x_h + \beta_3 x_o + \beta_4 x_{ce} + \sum_{l \in L} \beta_l x_l + \\ & \beta_{10} x_{ga} + \beta_{11} x_{go} + \beta_{12} x_{as} + \beta_{13} x_y + \epsilon_i \end{aligned} \quad (12)$$

- Parameters =  $1+4+(6-1)+4 = 14$