Football Match Outcome Prediction using DeepSet Player Aggregation

Group 12

Sayed Masoud Mousavi - 9735453
Mohammad Bahrami - 9724133

April 2, 2022

Contents

1 Problem Understanding Phase

1.1 Problem Definition and Scope

Association Football is the world's most popular sport. Each match is played between 2 teams of 11 players each. Teams try to score goals and the team scoring the more goals wins. If both teams have the same number of goals scored, the result will be a tie. The better the players of a team, the higher the chances of that team winning a match. In every match, there are events of player actions, either positive including but not limited to scoring a goal, successfully passing the ball and intercepting the ball, or negative, for instance scoring an own goal, getting a red or yellow card and etc. In addition to players' merit and quality playing, other factors such as match context, weather conditions, coaching team and players' experience, to name a few, as well as pure luck play an enormous role in determining the outcome of a match.

Each match is held at a stadium, usually filled with cheering audience applauding their favorite team. The team playing at their home stadium have an advantage since the audience will have a supporting effect and the boost in morale of the home team players will cause the home team to have a higher chance of winning.

Due to the sport's nature, predicting the outcome of a match is rather difficult. Moreover, in contrast to traditional ML problems where the output is a function of an input vector, the outcome of a match is a function of two input vectors, the home and the away feature vectors and if the players' features are to be modeled as well, there will be two sets of features for the home and the away teams. Since each team is represented as a set of players and sets are permutation-invariant, any modeling will also have to be permutation invariant.

1.2 Previous Works

Prior approaches to predict the outcome of a match are mostly statistical methods originating from zero-sum games such as chess prediction.

1.2.1 Elo Rating System

Elo rating system is one popular method that tries to calculate the relative skill level of the two teams competing in a match. A set of fixed mathematical formulas are introduced in this approach which aim to rate teams based on their previous performances. If a team has won more matches and against higher-skilled teams, their rating is higher. The ELO rating system's formulas have a number of hyper-parameters that could be tuned for better results. Initially, the teams are given a initial score. For each match, the score of participating teams of that match is updated utilizing equation 3.

To Update the Elo scores, the expected result for the home and away teams are calculated based on their current scores. The expected results for the home and away teams are also used to predict the result of a match

$$E_t^H = \frac{1}{1 + c^{(R_t^A - R_t^H)/d}} \tag{1}$$

$$E_t^A = 1 - E_t^H = \frac{1}{1 + c^{(R_t^H - R_t^A)/d}} \tag{2}$$

Where E_t^H and E_t^A are the expected result for the home and away teams at time t respectively. R_t^H and R_t^A are the ratings of home and away team at time t respectively and c and d are meta-parameters set according to the world football ratings standards.

After calculating the expected results of participating teams, their Elo scores can be updated based on the expected results and the final outcome of the match.

$$R_{t+1}^H = R_t^H + K(O_t^H - E_t^H) \tag{3}$$

where R_{t+1}^H is the rating of the home team at time $t+1$, R_t^H is the rating of the home team at time t, K is a meta-parameter set by the world football ratings standards and can be interpreted as a learning rate, O_t^H is the actual outcome of the match at time t for the home team which is set to 1 for a victory, 0.5 for a draw and 0 for a defeat and E_t^H is the expected outcome of the match for the home team at time t formulated in Eq. 1.

The rating for the away team is updated with the same rule and with respect to away team's previous rating and expected and actual outcome of the match. The predictions with this method is done at the time of calculating the expected scores. for the teams involved in a match, as the following terms:

$$Prediction = \begin{cases} \text{Draw} & \text{if } \left|E_t^H - E_t^A\right| \leq T \\ \text{Home Victory} & \text{if } E_t^H - E_t^A > T \\ \text{Home Defeat} & \text{if } E_t^H - E_t^A < T \end{cases} \tag{4}$$

where E_t^H and E_t^A are expected values of home and away and calculated from Eq. 1, 2 respectively and T is a hyperparameter called the draw threshold and tuned with the validation set and chosen from the values $0.01, 0.03, 0.1$ and 0.3 for each league.

1.2.2 Blade Chest

Other approaches combine both ML methods and statistical formulas utilizing both hidden representations and fixed mathematical relations.

Blade Chest model is one example of this approach. Each team has a vector of features obtained prior to a match. Two feed forward encoders are used to attain two hidden vectors for a team. One being the blade vector representing the offensive strategy and strength of each team and the other being the chest vector representing the defensive strategy and strength. Using a mathematical operation as the decoder, the match-up score is calculated as:

$$S = Home_{\text{blade}} \cdot Away_{\text{chest}} - Away_{\text{blade}} \cdot Home_{\text{chest}} \tag{5}$$

Using thresholds, this score can be binned into regions where higher scores correspond to the winning territory for home team and lower scores correspond to the winning territory for away team and a middle ground corresponds to ties.

1.2.3 Simple GNN

Recently and with the rising popularity of graph models, a graph based model has been used to create a message-passing network of team nodes. This model is transductive and each team has a node in the network and the edges are of types win and lose with higher edge weights corresponding to more recent matches. This weighting of edges is through fixed mathematical formulas and aims at favoring more recent match links.

1.3 Our Ideas

Our approach aims to represent each team competing in a match as a multi-set of 11 players comprising the lineup of that team. The problem will be a classification task whose target variable will be a vector of 3 possible outcomes of a match, home win, home loss and tie. The target variable will be a function of two multi-sets home and away, each containing 11 players.

Players have two sets of measures, post-game and pre-game. Pre-game measures are attributes such as market value, age and video game rating, conducted by video game companies such as EA and Konami. Post-game measures such as goals scored or minutes played are not accessible prior to the match.

Post-game measures contain a tremendous amount of information in regard to individual players. Our idea is to utilize these information through pre-game aggregates of these post-game measures. In other words, for each player, a new set of aggregate pre-game attributes are derived from the post-game measures of the last n games, n can be tuned. As a concrete example, each player's total number of successful passes in the last 3 matches is an aggregate pre-game attribute.

One key note to keep in mind is that the nature of this task is both dependent and independent of order. At intra-team level, there is no fixed point of reference and hence each team is represented as a multi-set and any subsequent modeling need to preserve this permutation invariance. In contrast, at inter-team level, for the home team advantage, order is meaningful and the home team's position need be fixed at the time of modeling.

As an increment to the universal approximation theorem, the injective multi-set theorem is utilized to map an injective function from the set of players to their team. This approach will be used to represent each team as a multi-set of its players.

Each team's multi-set is turned into a vector injectively with the following formula:

$$V_T = \mathrm{MLP}_\theta(\sum_{p \in T} \mathrm{MLP}_\phi(p)) \tag{6}$$

Where V_T is the final aggregated vector for team T and p is the player feature vector for all the players of team T.

Each MLP is a neural fully connected network with at least one hidden layer. After obtaining each team's hidden representation, the vector of both teams can be fed into another MLP whose output layer is the target variable of the match outcome

2 Data Preparation

2.1 Outlier Detection

Field players and goalkeepers are the input to our problem. 3 attributes for field players including goals scored, market value and video game rating plus 1 attribute of saves for goalkeepers are used for this section.

2.1.1 Z score

```
       postGame_goals
37467               2
50688               2
50757               2
50877               2
51107               2
...               ...
67259               4
47229               4
27278               4
26430               4
18678               5

[944 rows x 1 columns]
```

(a) player post game goals

```
       preGame_marketValueMilEuro
36                           51.5
41756                        51.5
41713                        51.5
18798                        51.5
41603                        51.5
...                           ...
65458                       525.0
67300                       525.0
69766                       525.0
69134                       525.0
65649                       525.0

[1581 rows x 1 columns]
```

(b) player pre game market value

```
       preGame_overall
66768             48.0
64234             50.0
51624             50.0
58194             50.0
53924             50.0
...                ...
42746             94.0
42882             94.0
43773             94.0
41757             94.0
43515             94.0

[312 rows x 1 columns]
```

(c) player pre game video game score

```
      postGame_save
4385           10.0
3748           10.0
4517           10.0
4626           10.0
4802           10.0
4808           10.0
5141           10.0
5198           10.0
5424           10.0
6029           10.0
6176           10.0
6810           10.0
7027           10.0
7088           10.0
7120           10.0
```

(d) goalkeeper post game saves

Figure 1: Outliers in the four selected fields with the Z score method

First, we perform a Z-score transformation on the data. Then every player that has a value greater than 3 or smaller than -3 in a specific field is considered to be a outlier. then we check the values to see if there is anything wrong with the data. which in our case, for example for the post game goals, most players do not score any goals in a specific match. This causes the other player who score goals to be recognized as outliers. Some of the outliers and their count is shown in figure 1.

2.1.2 IQR

```
       postGame_goals
39708               1
51438               1
51409               1
51407               1
51406               1
...               ...
27278               4
47229               4
49567               4
67259               4
18678               5

[8211 rows x 1 columns]
```

(a) player post game goals

```
       preGame_marketValueMilEuro
44571                        24.0
54333                        24.0
6470                         24.0
54515                        24.0
28821                        24.0
...                           ...
67300                       525.0
69313                       525.0
67346                       525.0
69766                       525.0
65458                       525.0

[6949 rows x 1 columns]
```

(b) player pre game market value

```
       preGame_overall
66768             48.0
58194             50.0
64234             50.0
51624             50.0
62214             50.0
...                ...
44999             94.0
38435             94.0
44946             94.0
28548             94.0
36068             94.0

[532 rows x 1 columns]
```

(c) player pre game video game score

```
      postGame_save
7956            8.0
4268            8.0
6609            8.0
4410            8.0
4498            8.0
...             ...
1877           13.0
6168           13.0
6971           14.0
6526           16.0
4798           17.0

[232 rows x 1 columns]
```

(d) goalkeeper post game saves

Figure 2: Outliers in the four selected fields with the IQR method

We perform the standard IQR method and we can see the values considered as outliers with this method in figure 2. The key point to note here is that this method seems to be more sensitive to outliers in our data as the number of outliers found is much greater comparing with the z-score method.

2.2 Transformation and Standardization

```
preGame_overall
Original data skewness: 0.11
After transformation if necessary data skewness: -0.053
----------------------------------------
preGame_potential
Original data skewness: 0.094
After transformation if necessary data skewness: -0.007
----------------------------------------
preGame_marketValueMilEuro
Original data skewness: 9.837
After transformation if necessary data skewness: 0.104
----------------------------------------
preGame_ageDays
Original data skewness: 0.28
After transformation if necessary data skewness: 0.067
----------------------------------------
```

(a) players' selected fields

```
preGame_overall
Original data skewness: 0.079
After transformation if necessary data skewness: -0.042
----------------------------------------
preGame_potential
Original data skewness: 0.101
After transformation if necessary data skewness: -0.004
----------------------------------------
preGame_marketValueMilEuro
Original data skewness: 3.05
After transformation if necessary data skewness: 0.173
----------------------------------------
preGame_ageDays
Original data skewness: 0.219
After transformation if necessary data skewness: 0.022
```

(b) goalkeepers' selected fields

Figure 3: Skewness of selected fields before and after choosing the best transform

Numerical non-binary fields have been chosen on which 6 candidate transforms including 3 methods of log, square root and inverse square root, each with 2 added values of 1 and 0.1, were performed and the approach with the least skewness were selected and finally all values were normalized with the z-score standardization method. Since log and inverse square root cannot accept negative or zero values, all data are added with their respective minimum and then again with either 1 or 0.1.

2.3 Reclassifying the Categorical Features

	preGame_position	preGame_rc_position
0	DC	D
1	FW	F
2	MC	M
3	MR	M
4	MC	M
...	...	...
80075	AMC	M
80076	DMC	M
80077	FW	F
80078	FW	F
80079	AMC	M

Figure 4: the pre game positions before and after reclassifying

Non-numeric categorical attributes are outnumbered by numerical attributes and are limited to 'preGame_side', 'preGame_line', 'preGame_position', 'preGame_preferredFoot', of which only 'preGame_position' could be reclassified. As a concrete example, 'FW','FWL' and 'FWR' could all be reclassified as 'F', short for 'Forward'.

2.4 Binning

```
numerical_fp = ['postGame_minPlayed',
  'preGame_overall', 'preGame_potential', 'preGame_marketValueMilEuro',
  'preGame_ageDays', 'postGame_error',
  'postGame_clearance', 'postGame_index', 'postGame_shots',
  'postGame_shots_on_target', 'postGame_shots_left_foot',
  'postGame_shots_right_foot', 'postGame_shots_head',
  'postGame_shots_other', 'postGame_goals', 'postGame_goals_left_foot',
  'postGame_goals_right_foot', 'postGame_goals_head',
  'postGame_goals_other', 'postGame_xG', 'postGame_cross',
  'postGame_cross_success', 'postGame_pass', 'postGame_pass_success',
  'postGame_pass_final_third', 'postGame_pass_final_third_success',
  'postGame_pass_forward', 'postGame_pass_forward_success',
  'postGame_dribble', 'postGame_dribble_success', 'postGame_tackle',
  'postGame_tackle_success', 'postGame_interception',
  'postGame_challenge', 'postGame_ball_recovery', 'postGame_ball_lost',
  'postGame_key_pass', 'preGame_xgpm', 'preGame_xppm',]

numerical_gk = ['postGame_minPlayed',
      'preGame_overall',
       'preGame_potential', 'preGame_marketValueMilEuro',
       'preGame_ageDays', 'preGame_xgpm',
       'preGame_xppm', 'postGame_error', 'postGame_clearance',
       'postGame_index', 'postGame_pickUp', 'postGame_punch', 'postGame_save']
```

Figure 5: All the binned features for the field players and goalkeepers

For each of the players, 2 methods of binning with equal width and equal frequency, each with 4 random bins between 3 and 9, have been used and the new binned values have been saved.

	postGame_pass	postGame_pass_binned_6
0	52	(32.667, 65.333]
1	16	(-0.196, 32.667]
2	51	(32.667, 65.333]
3	46	(32.667, 65.333]
4	98	(65.333, 98.0]
...	...	...
80075	14	(-0.196, 32.667]
80076	9	(-0.196, 32.667]
80077	22	(-0.196, 32.667]
80078	8	(-0.196, 32.667]
80079	10	(-0.196, 32.667]

(a) binned with equal width with 6 bins

	postGame_pass	postGame_pass_binned_4_ef
0	52	(44.0, 196.0]
1	16	(-0.001, 21.0]
2	51	(44.0, 196.0]
3	46	(44.0, 196.0]
4	98	(44.0, 196.0]
...	...	...
80075	14	(-0.001, 21.0]
80076	9	(-0.001, 21.0]
80077	22	(21.0, 31.0]
80078	8	(-0.001, 21.0]
80079	10	(-0.001, 21.0]

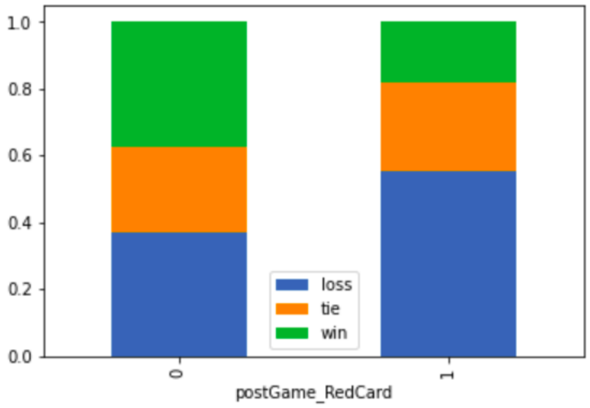
80080 rows × 2 columns

(b) binned with equal frequency with 4 bins

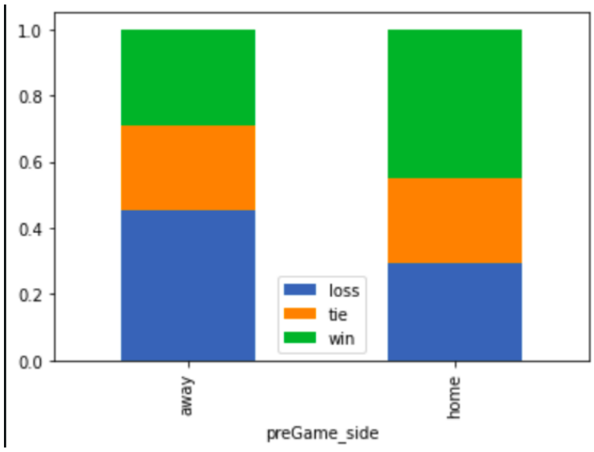
Figure 6: Players post game passes binned with two different methods and different number of bins

3 Exploratory Data Analysis

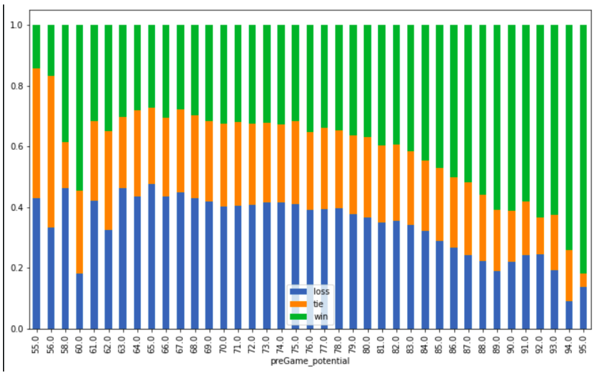
3.1 Univariate Relations with the Target Value



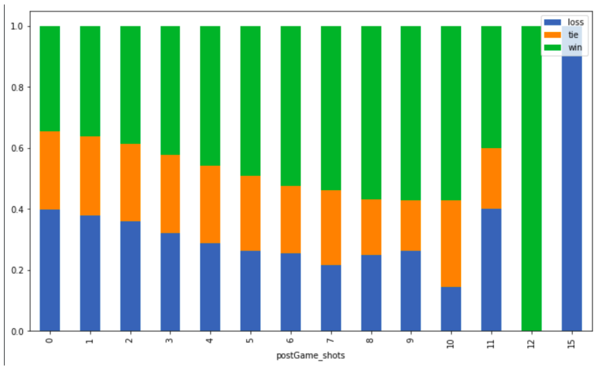
(a) weather a player received a red card or not



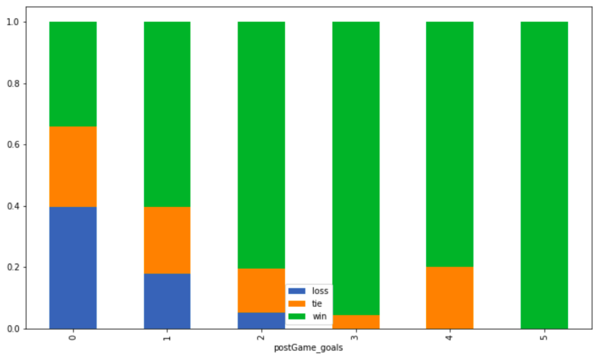
(b) weather a player is playing for the home team or not



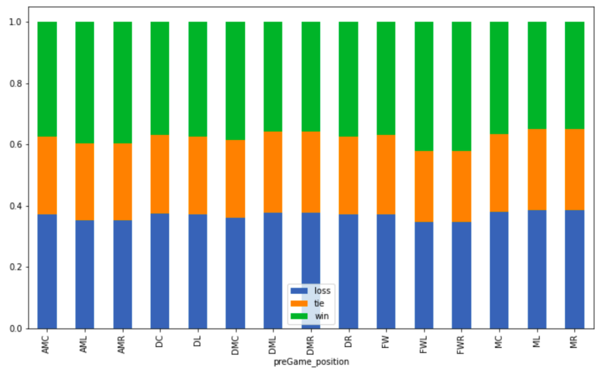
(c) pre-game potential from the video game features



(d) the number of performed shots by a player

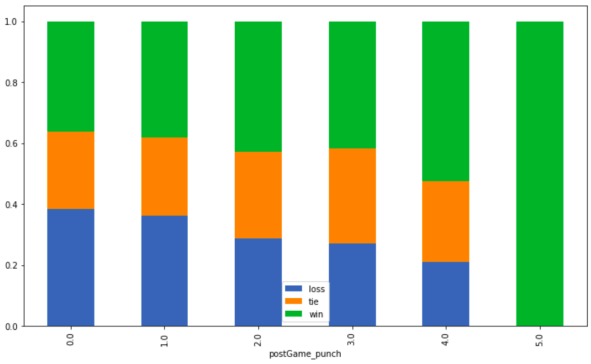


(e) the number of scored goals by a player

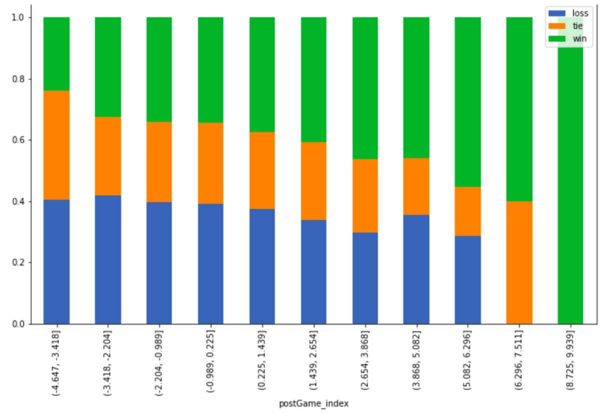


(f) the position which a player plays in

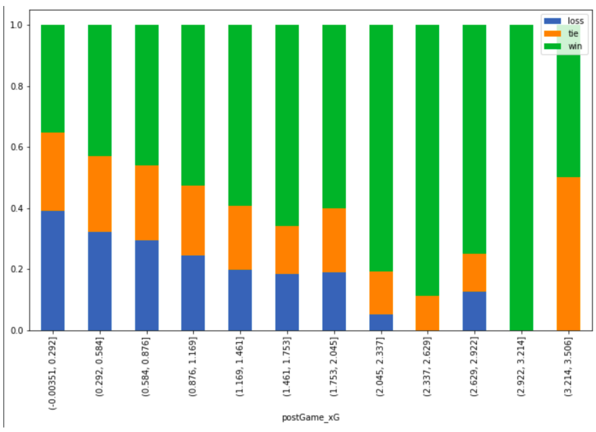
Field players who received a red card were half likely to win(figure 7a). Home players are almost 50% more likely to win(figure 7b). Players with video game rating of more than 73 seem to be more likely to be on the winning side(figure 7c). The more shots(either kind) a player has had, the more likely his team is to win the match(figure 7d). Players scoring 3 or more goals have never been on the losing side(figure 7e). Players with higher performance indices(player ratings including xG and Stephenson and pre-game expected



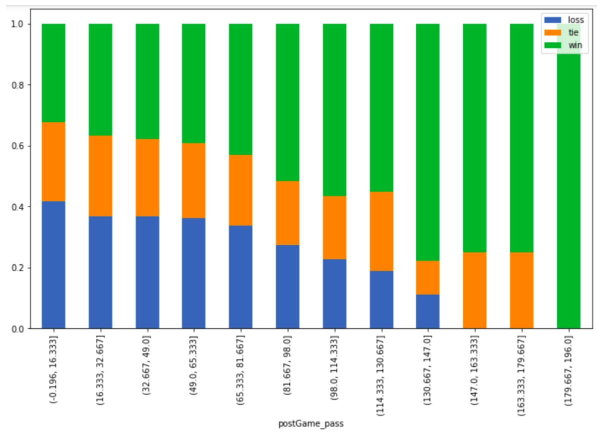
(g) the number of punches by the goalkeeper



(h) the stephenson index of a player



(i) the xG index of a player



(j) the number of passes given by a player

Figure 7: Some properties of the players in the data and their relation to the target variable

xG) have higher chances of winning(figures 7h, 7i). Players with more passes(either kind) also have higher probabilities for winning(7j). Goalkeepers having more punches are more likely on the side of the winning team(7g). Other attributes such as position(figure 7f) do not reveal any information about the result.

3.2 Multivariate Relations

Pearson correlation heatmap between the attributes indicate correlation among different measures of pass and also among goals, index and xG ratings(figure 8, figure 9a). Multivariate analysis further indicate relationship between market value, potential and overall which might incline us to drop either ones since increase in any of these attributes lead to increase in the value of their corresponding attributes as well(figure 9b).

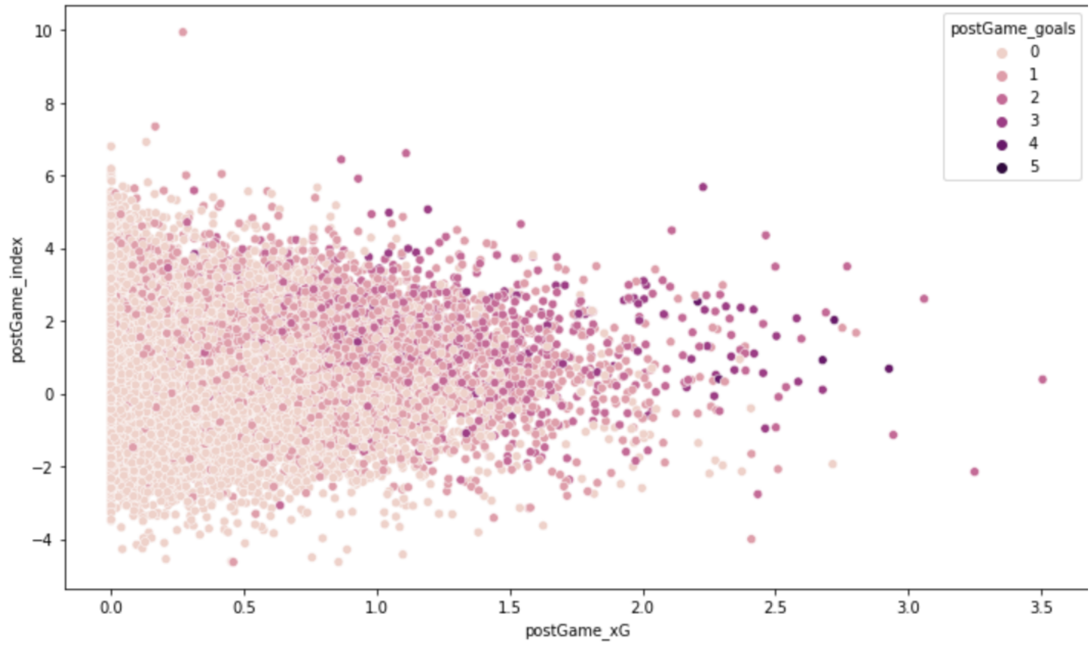
Figure 8: The heatmap of correlations between the features of each player

3.3 Binning Based on Predictive Value

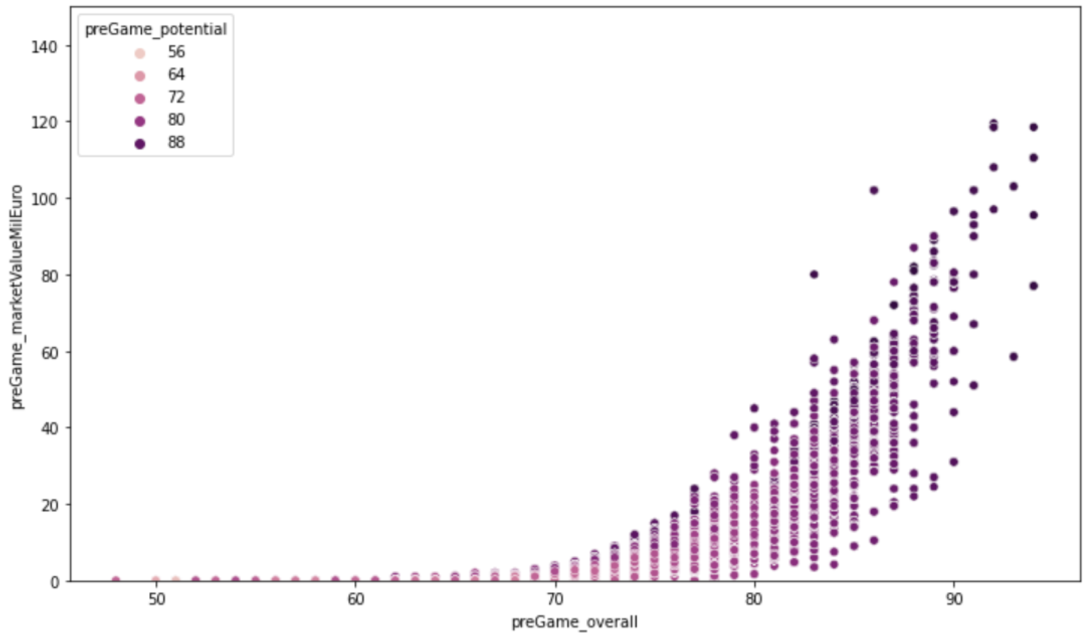
Using the analysis from the predictive variables and the target variable, custom bins were derived with a focus on the predictability of each bin with regard to the target variable. Some of the binned variables and their relation to the target variable is depicted in figure 10.

3.4 Extracting New Features

As explained earlier in the problem understanding phase, the post-game attributes are not available prior to a match taking place. However, by using a window of the values of these attributes across previous matches, a rich attribute could be derived. Each player's performance in the last 4 matches has been averaged over to provide these attributes. some of the variables created are shown in figure 11.

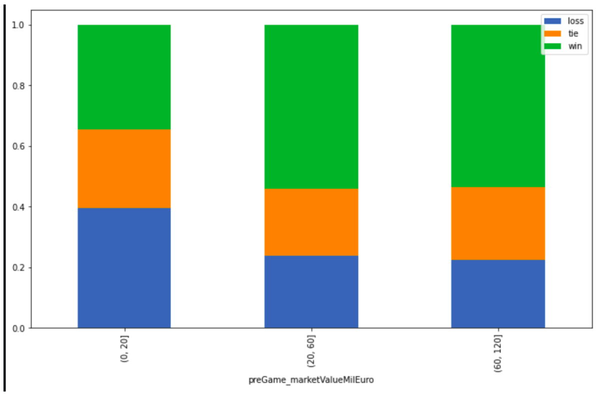


(a) the relation between stephenson index, xG index and the number of goals of a player

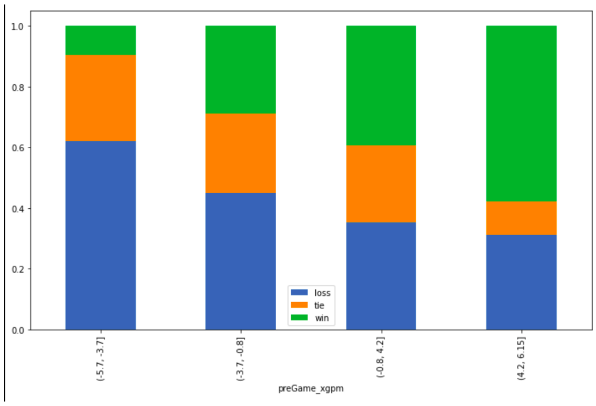


(b) the relation between overall, market value and potential video game scores

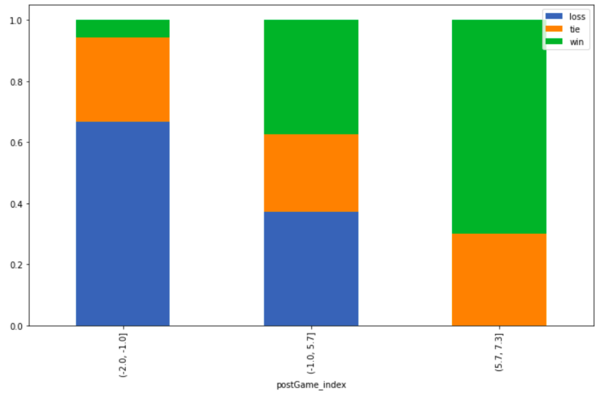
Figure 9: Multivariate correlations between some columns of player data



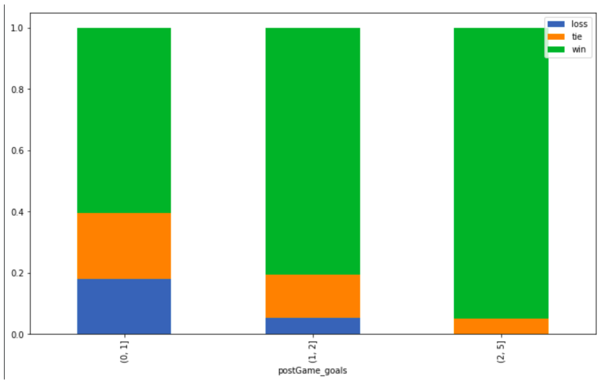
(a) Players' market value



(b) players' xGpm index



(c) the Stephenson index of the players



(d) the number of scored goals by a player

Figure 10: Some properties of the players after binning based on the predictive value and their relation to the target value

	agg_postGame_error	agg_postGame_clearance	agg_postGame_index	agg_postGame_shots	agg_postGame_shots_on_target	agg_postGame_shots_left_foot
80075	0.0	2.25	1.167869	0.5	0.25	0.0
80076	0.0	1.25	1.737601	1.5	0.75	0.5
80077	0.0	1.75	0.717848	1.0	0.75	0.5
80078	0.0	6.75	0.391377	0.0	0.00	0.0
80079	0.0	0.00	1.234975	0.0	0.00	0.0

Figure 11: Some of the aggregated post-game features that are now available before each match of a player