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BPFNN Based Football Player Value Prediction by Introducing Historic Information

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ABSTRACT

With extensively successful applications of artificial neural networks in many scenarios of classification and prediction, research related to the world most popular sport - football - has undoubtedly attracted researchers to carry out their works with aid of such powerful tools. Despite that most of these works are oriented to predict match results and game strategies, only very a few are designed for player value prediction, which is of great importance with the rapid growth of the football players' transfer market. In this paper, we propose a BP feedforward neural network framework which integrates both the empirically determined variables and some historical information. Comparative ablation experiments on one dataset FINAL verified the necessity of some factors especially the highest_values which inspired the inclusion of available historical information into the framework. For further verifying the efficiency of integrating historical information, we embedded the value columns of FIFA17 to FIFA21 into the data of FIFA22. Comparative experiments showed an 11% improvement on the precision with the help of historical values, verifying the efficiency of this strategy. Experiments were also conducted for determining the choice of the number of layers, the ratio of the training set and test set, the learning rate, and the process of the missed information.

KEYWORDS

Football player value prediction; Deep neural network; BPFNN

1. INTRODUCTION

Football attracts most fans in the world [1]. Football clubs invest a great amount of money annually for buying or releasing players. A player's market value reflects his financial value the employers attribute to his performance [2]. However, since assessing players' values is extremely subjective, great challenge presents in estimating players' values accurately and consistently.

Traditional methods for predicting players' values are usually based on experiences of club managers or owners [3-7]. Some reference platforms such as Transfermarkt.com determine the transfer fees of players based on its members' opinions. These methods have obvious drawbacks: (1) The accuracy of estimation depends totally on the experience of the decision-making members, while everybody's experience is limited; (2) Experience is usually applicable for the famous players who are familiar to the consultants while inapplicable to the players serving in minor leagues or the newly recruited ones whose performance is rarely viewed and thus hard to predict; (3) The experts' decision depends on the priority they hold against the performance factors of one player without scientific guarantee.

The limitation of traditional player's value prediction has been supplemented by data-driven estimation methods with more and more datasets are collected. Since most data-driven methods rely on the choice of evaluation factors such as players' positions, ages, average goals etc., some researchers focus mainly on analyzing the how different parameters make sense [8-11]. The ordinary data-driven prediction models are either statistics-based or machine learning methods.

2. RELATED WORKS

Franck and Nu¨esch [12] concluded that non-performance-related popularity and talent are both correlated with their market value by leveraging OLS regression with 20 parameters. Kiefer [13] claimed that the performance in a big contest can increase a player's popularity greatly and consequently his market value as well. Herm et al. [14] proposed an econometric model to estimate football players' transfer fee, which is proved to be consistent with the community's estimations. Majewski [15] leveraged a generalized least squared model to study how different variables affect the values of forward players, and reported that assists and the number of goals etc. play significant roles. Mu¨ller et al. [8] designed a multi-level regression model for testing the factors influencing players' values which was reported to perform well for the lower 90% transfers and poor for the top 10% maybe due to the unpredictability of the superstar's nonlinearly increasing commercial values. Singh and Lamba [16] made a deep analysis of several machine learning methods based on a considerate selection of the features using correlation. Yigit et al. [17] found that only age correlated with the target value nonlinearly after analyzing several regression methods based on a dataset collected from a football manager simulation game. Felipe et al. [18] also reported the effect of age on the players' market values in addition to that of several other factors like the birth month and the playing position by regression analysis. Iman Behravan and Seyed Mohammad Razavi [19] proposed to determine the keen variables for different player groups by automatic categorizing and regression analysis. Christer Thrane [20] claimed that composite performance factors impact football players' market values both statistically and practically.

With the development of artificial intelligence especially artificial neural networks (ANN), ANN has become the most commonly utilized approach in sports analytics and sports prediction [21-23]. The basic units of ANN are neurons which accept real values as inputs and output one or several values which are usually the values of some nonlinear functions of the inputs multiplied by weights [24]. The weights are trained through supervised or unsupervised learning on the training data and the resulting model is used for future predicting. Different architectures are designed to tackle different applications, e.g., Feedforward ANN, which is a straight forward neural network that takes the information as inputs via the input neurons, then transfers the information through the hidden layers, and eventually triggers the output neurons [25]. Each neuron receives inputs from the neurons in the last layer, sums up the inputs multiplied by the weights of the links between the two layers with a bias, calculates the value of a usually nonlinear function of the biased summation, and then delivers the values to the neurons in the next layer.

Although there are some works that apply ANN for sports prediction, e.g., the game result prediction, works that apply ANN to predict soccer player values are very rare. In [23], the researchers applied the data from FIFA 19 for predicting football players' prices through considerately investigating the parameter settings and model optimization of the neural networks, and reported a 95% accuracy and a 0.037 mse. In [26], the authors presented a design which is a mixture of qualitative selection of factors and quantitative prediction based on these factors through radial neural networks. The authors in [27] developed a MLP framework to predict football players' values and reported an 87.2% top-five accuracy within 119 pricing classes.

Since ANN has shown its power in many predicting tasks including game result predicting, we further investigate its application in football player value prediction. Considering that a player's history data should be very correlated to its current value, a LSTM structure is suitable for fulfilling this task. However, LSTM usually needs an enough large time window for both training and prediction, which we found unavailable for current known football player data. Through experiments, we found that a player's historic highest_value has very large correlation with its current value, which inspires us that players' historic values may be a suitable representation of historic data. Hence, we alternatively incorporate historic values into a BP feedforward neural network, BPFNN for short, structure. Experiments on two datasets verified the efficiency of this proposed idea. We also investigated the impacts of the proposed parameters on the prediction and found that age is another most important factor influencing the players' values in addition to highest_value or historic values, which is in accordance with the findings in other works [8, 17, 28, 29, 30].

3. MATERIALS AND METHODS

3.1. Datasets

This study utilizes two datasets which are downloaded from Kaggle. The first dataset, we call it FINAL, is downloaded from https://www.kaggle.com/datasets/khanghunhnguyntrng/football-players-transfer-fee-prediction-dataset. This data comprises the information of players serving in several top global football leagues. The detailed information of these super leagues can be found at the website. The original data has 22 columns corresponding to players' appearances and statistics such as height, age, goals, and assists etc. For applying our ANN model, we change the names of teams into integer numbers. Since there is a 'position_encoded' column, we do not take the 'position' column into consideration. The second dataset, we call it FIFA, downloaded from https://www.kaggle.com/datasets/bryanb /fifa-player-stats-database, comprises the information of players from FIFA 17 to FIFA 22. We do not use the set FIFA 23 presented by the website since the information in this set is very rare. This annual dataset includes a wealth of features and a large number of players from around the world with a total of 63 columns. The names of the columns are listed in Table1. Since our purpose is to predict players' values, we omitted the variables which are evidently unrelated, e.g., ID, name, photo, etc. Also, we change the string variables into integers for fulfilling the ANN task, i.e., 'body type', 'position', 'best position', 'weight', 'height', and 'value'. For the missing data, we assign them to zeros.

Table 1. Features presented in FIFA.

ID	Position	Reactions
Name	Jersey Number	Balance
Age	Joined	ShotPower
Photo	Loaned From	Jumping
Nationality	Contract Valid Until	Stamina Strength
Flag	Height	LongShots
Overall Potential	Weight	Aggression
Club	Crossing	Interceptions
Club Logo	Finishing	Positioning
Value	Heading	Vision
Wage	Accuracy	Penalties
Special	ShortPassing	Composure
Preferred Foot	Volleys	Marking
International	Dribbling	StandingTackle
Reputation	Curve	SlidingTackle
Weak Foot	FKAccuracy	GKDiving
Skill	LongPassing	GKHandling
Moves	BallControl	GKKicking
Work Rate	Acceleration	GKPositioning
Body Type	SprintSpeed	GKReflexes
Real Face	Agility	Best Position
		Best Overall Rating

3.2. Architecture

In this paper, we leverage back propagation feed-forward neural network, BPFNN, as the architecture to train the features and predict the outputs. The structure of a typical three-layered BPFNN is illustrated in Fig. 1. In the forward flow, the neutrons in each layer receive the input from each neuron of previous layer and feed an output to each neuron of next layer. The weights are adjusted according to the differences of the final outputs and the real values in such a way that these differences are reduced as efficiently as possible, e.g., in the negative gradient direction of the optimization function of the outputs. BPFNN is utilized for many applications including speech, image recognition, and sports. The given model is implemented with the help of TensorFlow library in python. The MinMaxScaler is applied for data preprocessing since the values in some columns may vary in a great extent. Train_test_split is used for data random splitting into to training and test parts. The activation functions are relu and sigmoid. The optimizer is Adam, and the loss is mse.

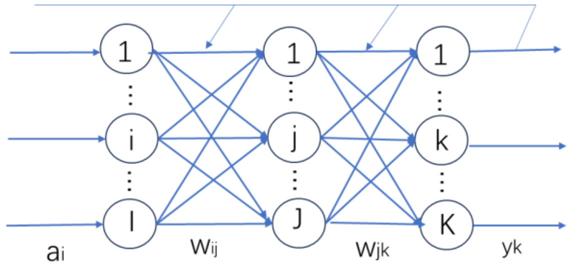

Figure 1. Structure of a Three-Layered BPFNN.

3.3. Evaluation Metrics

Since predicting exact values is almost impossible, we apply the corrcoef in numpy as one metric to evaluate the prediction accuracy. The corrcoef of two variables x and y is defined as:

$$corrcoef(x, y) = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}} \tag{1}$$

Despite the correlation level, we also test the proportion of the x% correctly predicted values, denoted as x% accuracy, as the evaluation criteria, where a value is called x% correctly predicted if the absolute difference between the predicted value and the true value is no more than 1-x% of the maximum between the predicted value and the true value. For example, if the true value is 10000, the predicted value is 9000, then the absolute difference is 1000, 10% of the max {10000, 9000}. In this case, this value is a 1-10% = 90% correctly predicted sample. In our experiments, we consider the 100%, 95%, 90%, 85%, 80%, 70%, 60%, 50%, and 10% accuracy correspondingly. Notice that even with a 10% accuracy, the magnitudes of the prediction value and the true value are almost the same.

$$x\%\ accuracy = \frac{number\ of\ x\%\ correctly\ predicted\ values}{total\ number\ of\ values} \tag{2}$$

4. RESULTS AND DISCUSSION

4.1. Experiments on FINAL

The experiments were first carried out on the FINAL dataset which was downloaded from https://www.kaggle.com/datasets/khanghunhnguyntrng/football-players-transfer-fee-prediction-dataset. Through experiments, we set the splitting ratio between the training set and the test set as 07 vs. 0.3, the learning rate as 0.001, the number of layers as four with two relu layers and two sigmoid layers. For evaluating the importance of each variable, except the experiment with all the variables included, we also did the ablation experiments in each one variable is deleted. After 100 epochs of iteration, the loss in each experiment was stabilized at almost 0.01. The experiments results are summarized in Table 2.

Table 2. The results of the ablation experiments. All variables mean the experiment in which all the variables are considered. -x means the experiment in which the variable x is deleted.

experiment	100% acc	95% acc	90% acc	85% acc	80% acc	70% acc	60% acc	50% acc	10% acc	*corrcoef*
All varaibles	0.0	0.0787	0.162	0.242	0.315	0.4676	0.594	0.7208	0.97	0.9536
-height	0.0	0.0707	0.134	0.2061	0.2761	0.4224	0.5535	0.6712	0.951	0.9559
-age	**0.0**	**0.0533**	**0.1112**	**0.1748**	**0.2368**	**0.3604**	**0.4620**	**0.5680**	**0.9262**	**0.8467**
-appearance	0.0	0.0617	0.1292	0.1999	0.2646	0.3898	0.5042	0.6074	0.9235	0.9527
-goals	0.0	0.0700	0.1456	0.2203	0.3037	0.4571	0.5971	0.7134	0.9625	0.9528
-assists	0.0	0.0552	0.1168	0.1866	0.2529	0.3719	0.4723	0.5748	0.9352	0.9532
-yellow cards	0.0	0.0638	0.1363	0.2089	0.2798	0.4211	0.5569	0.6836	0.9473	0.9545
-second yellow cards	0.0	0.0725	0.1534	0.2262	0.2919	0.4115	0.5187	0.6219	0.9405	0.9551
-red card	0.0	0.0784	0.1553	0.2358	0.3040	0.4199	0.5386	0.6405	0.939	0.9541
-goals conceded	0.0	0.0852	0.1664	0.2448	0.3105	0.4555	0.5891	0.7121	0.9606	0.9570
-clean sheets	0.0	0.0697	0.1314	0.2020	0.2730	0.4016	0.5404	0.6675	0.9665	0.956
-minutes played	0.0	0.0645	0.1298	0.1996	0.2606	0.401	0.5469	0.6898	0.9733	0.941
-days_injured	0.0	0.0719	0.1453	0.2203	0.2938	0.4372	0.5668	0.6725	0.9405	0.9537
-games_injured	**0.0**	**0.0369**	**0.0744**	**0.1181**	**0.1596**	**0.2622**	**0.3725**	**0.4949**	**0.9839**	**0.9535**
-award	0.0	0.0778	0.1549	0.2234	0.2925	0.4168	0.5426	0.648	0.9359	0.9529
-position_encoded	0.0	0.0883	0.1738	0.2578	0.3316	0.4747	0.6083	0.7034	0.9575	0.9556
-winger	0.0	0.0744	0.159	0.2392	0.3198	0.4689	0.6207	0.7456	0.9693	0.9543
-higest_value	**0.0**	**0.0304**	**0.0651**	**0.10289**	**0.1379**	**0.2064**	**0.2919**	**0.3867**	**0.8943**	**0.7104**

From the experiment results shown in Table 2., we can see that almost all the factors contribute more or less to the prediction except the position_encoded which is in accordance with the real case that the value of a soccer player is almost irrelevant to the positions they usually hold. The bold numbers tell us that age, especially highest_value have significant impact on the prediction accuracy the deletion of which induced great decreases with all the criteria, which is in accordance with that reported in [8, 17, 28, 29, 30]. Although the absence of Games_injured also brought decreases with 100% to 50% accuracy, the 10% accuracy and the corrcoef increased instead with a small margin. The reason may be that whether a player tends to be injured easily may bring about a great gap to his value, and a player who is easy to get injured may unpredictably bring uncertainness to the host team and therefore is evaluated much lower than those who are stronger although with the similar skill abilities. Age is evidently a critical factor which influences a player's value greatly. The value of a football star usually decreases sharply after the age of 30 [31][32]. Although we had supposed that the highest_value would influence the prediction of current value, but we did not expect it in such a great extent, which implies that the historic values of a player would also make sense in current value prediction. Therefore, when sufficient historic data of players are not available for admitting a LSTM, we speculate that introducing some historic values may help improve the performance of predicting models. We verified this hypothesis through experiments on the dataset FIFA.

4.2. Experiments on FIFA

This data is downloaded from https://www.kaggle.com/datasets/bryanb/fifa-player-stats-database with collections of 17560 soccer players' 63 variables. In the experiments on FIFA, we chose three relu layers and three sigmoid layers, and we set the learning rate still as 0.001, and the splitting rate as 0.3. We set the absent values as zeros. After 100 epochs of iteration, the loss of both experiments decreased to about 0.01. In Table 3., we present the x% accuracies and the corrcoef of the experiments. From the numbers in Table 3., we can see that introducing the values of FIFA17 to FIFA21 has evidently improved all the x% accuracies although decreased the corrcoef value. The plotting figures in Fig 2. illustrate this phenomenon, i.e., in the left figure of experiment on FIFA22, the lines of real values (red) and the lines of predicted values (blue) are in more similar trends than those in the right figure, which corresponds to the experiment with values from FIFA17 to FIFA21 introduced. However, in the right figure, some predicted values are more reaching the real values which help with the better performance in x% accuracies. The reason may be that introducing historic values help improve the prediction of most players who perform stably while may also bring some noise since some players' values may change greatly in FIFA22 due to some unpredicted performances or events.

Table 3. The experiment results on FIFA. In experiment FIFA22, only variables in FIFA22 are involved, while in experiment +historic values the values from FIFA 17 to FIFA21 are also included.

experiment	100% acc	95% acc	90% acc	85% acc	80% acc	70% acc	60% acc	50% acc	10% acc	*corrcoef*
FIFA22	0.0	0.0559	0.1079	0.1541	0.1940	0.2511	0.3179	0.3854	0.8048	**0.8483**
+historic values	**0.0**	**0.0636**	**0.1362**	**0.2139**	**0.2794**	**0.4316**	**0.5414**	**0.6461**	**0.8972**	0.7769

From Table 2. and Table 3., we can notice that the performance of the method with all the variables considered on FINAL is much better than that on FIFA with historic values. However, when the highest_value is deleted from FINAL, the performance becomes much worse than that on FIFA22 with historic values but comparable to that on FIFA22 only. This suggests that highest_value plays more crucial roles in predicting soccer players' current values than just a few proceeding years' values, while even only a few proceeding years' values can also contribute more than 11% increase on the x% accuracies to the case with no historic value information.

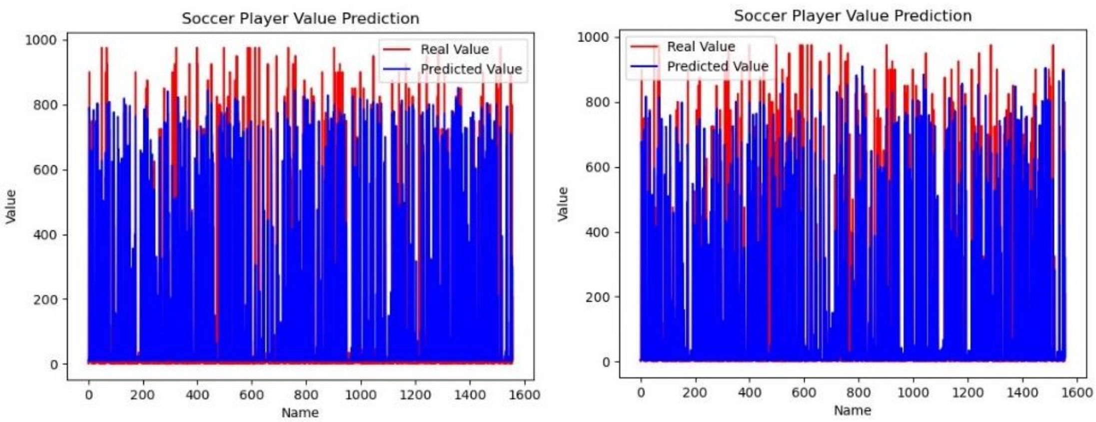

Figure 2. Plotting results on FIFA22 and FIFIA22+historic values.

5. CONCLUSION

In this paper, we study the problem of football player value prediction and propose a BPFNN method with historic information introduced. Ablation experiments on the FINAL dataset suggest the importance of age, games_injured, especially highest_value, which inspires us that proceeding years' values may be a delegate of the historic information. Experiments on the FIFA dataset verified this hypothesis by presenting an over 11% increase on the x% accuracies with the inclusion of proceeding years' values and even better performance with historic highest_value. We will further study the influence of introducing more historic information by conducting experiments on more datasets and we expect to find sufficient data to study the performance of LSTM model for predicting soccer player's values.

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