Review Article

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Football Prediction Model Based on the Teams' Elo Ratings and Scoring Indicators

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ABSTRACT
The study focuses on proposing a solution for the 2023 Soccer Prediction Challenge organized in conjunction with the Machine Learning Journal's special issue on Machine Learning for Soccer. The challenge aimed to predict the outcomes of future matches from various leagues worldwide within a specific timeframe. In this paper, we examine the solution provided by our team" Friends of Elo" in detail. We experimented experimented with using Elo ratings and scoring indicators (goals) as arguments for the linear regression method. Poisson distribution was employed to predict the match results. The performance was evaluated based on the root mean squared error and the ranked probability score. Submitted predictions (714 matches) ranked 7th among 11 contestants in Task 1 and 5th among 13 contestants in Task 2, respectively. Futhermore, we conducted additional tests, where our model performed even greater on the expanded dataset of over 6800 matches to predict. The most significant advantage of our approach is that it does not require advanced match data, making it applicable worldwide. Overall, our study provides an in-depth analysis of the solution proposed by the" Friends of Elo" team, and we offer a superior alternative that performs well and is highly practical.

Keywords: 2023 Soccer Prediction Challenge, Soccermatics, Poisson Distribution, Elo Ranking, Linear Regression, Soccer Forecasting

Introduction

Nowadays, such scientific problems as extrapolation take a meaningful place in sport analytics to improve performance, scouting, equipment, logistics, marketing, etc. In the sports betting industry, odds setting relies on advanced modeling and analysis techniques. Since long ago, forecasting the outcomes of soccer matches has been the subject of active research. The idea of the 2023 Soccer Prediction Challenge, where advanced state-of-the-art ML methods were welcomed, is similar to the 2017 Soccer Prediction Challenge [1,2].

This study aims to conduct theoretical analysis and empirical evaluation of a model beyond the prediction of the matches in the Prediction Set provided by Organizers of the 2023 Soccer Prediction Challenge (see the set via link to GitHub repository in Program codes).

The solution was inspired by the first chapter of the book Soccermatics, where David Sumpter describes his straightforward Soccer Prediction model, which is based on the season scoring stats (namely goals scored and conceded) [3]. Professor of applied maths states the randomness of a beautiful game, eventually assuming that the number of goals scored in a football match correlates with the Poisson Distribution. His conclusions are partly connected with the Poisson limit theorem. Further research uses an efficient parameter estimator for Poisson distribution, which equals the mean of the sample or - for Poisson distribution - expected value, and Pearson's chi-squared test to confirm Sumpter's assumption [4].

Since debates about Elo ranking, which is widely used in football forecast models, have occurred justify the Elo ranking [5,6]. The obtained results show that despite the simplicity of only one number characterizing a team force, the Elo rating demonstrates a good fit.

As shown in a ranking system is not enough to predict the outcomes of soccer league matches better than a bookmaker

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does [7]. Elo rating examines team force but does not consider the style of play, whereas goals scored/conceded (and their sum, called the total) can show us whether a team is attacking or defending but misses the current state (team rating). Therefore, we decided to unite these approaches to consider more factors. Merely stated, our model generates goals as Poisson distributed random variables with a parameter including both Elo rating and scoring indicators.

We have analyzed the data from the TrainingSet (see the file" TrainingSetFINAL.xlsx" via link to GitHub repository in Program codes) provided by Organizers of the 2023 Soccer Prediction Challenge to determine the average number of goals scored and conceded at home and away (SH, CH, SA, CA) [1]. Additionally, we calculated the Elo rating for each team independently because other sources do not provide this ranking system for many lower-profile leagues. The main idea of predicting the number of team's scored and conceded goals is to generate them as the Poisson distribution with the parameter that was a linear combination of Elo Rating and goals scored and conceded. To find the most suitable coefficients, we used linear regression on the Elo rating. Beyond the Prediction Set provided by Organizers of the 2023 Soccer Prediction Challenge, our model has shown much better results on the expanded dataset (see Results. Expanded dataset) in Task 2.

Related work

The approach comes from the same Poisson ideas, but Lorenz A [8]. Gilch used nested Poisson distribution (i.e., concerning conditional probabilities). Dr. Lorenz A. Gilch builds a model based on Elo rating only (to examine the force of a team), whereas our approach, in addition to the Elo ranking system, uses "Sumpter's part" – goals scored and conceded for both teams during a time-scale of over 14 matches. This leads to considering a team's style of play. However, it could be beneficial for international cups, where the "style" is not so clear and strict to show in a few matches.

Looking into details, we predict not international tournaments without home advantage (the Copa America or Africa Cup of Nations) but long-run football leagues with games at home and away. Hence, in contrast to Gilch, we use extra summand.

Later on, in Lorenz A [9]. Gilch tried to test a slightly different approach with Nested Zero-Inflated Generalized Poisson Regression. Again, in the paper, he concentrated on national teams matches.

Theoretical analysis

Elo rating calculation

Starting from the season 24/25, the UEFA Champions League must use a variant of the Elo Ranking to balance teams' strength [10].

We have applied the Elo rating approach that was used for predicting continental football with constants K = 40, ELO_0 = 1600 [8].

Generally, these coefficients are responsible for scaling. K changes the impact of the last matches. The weight of the recent match is bigger than that of the less recent. ELO0 is the mean value among a league. In Scheme, it will be shown that K and ELO_0 were chosen correctly.

$$ELO_h = ELO_h + K \cdot G \cdot \left(W - \frac{1}{10 - \frac{\Delta ELO_{0h}}{400} + 1} \right)$$

calculated from match to match (for the next iteration (match) previous ELO_h becomes ELO_{0h}).

Here W and G depend on the result of the game as follows:

$$W = \begin{cases} 1, & \text{if a game is win} \\ 0.5, & \text{if a game is draw} \\ 0, & \text{if a game is lose} \end{cases}$$

$$G = \begin{cases} 1, & \text{if a game is draw or won by one goal} \\ 3/2, & \text{if a game is won by two goals} \\ (N + 11)/8, & \text{if a game is won by N goals, where } N \geq 3 \end{cases}$$

Finally, considering the home advantage that gives plus 100 points to the home team Δ and minus 100 points to the away team Δ, delta Elo ratings are shown in the Table 1.

Scheme

Here we provide the procedure of predicting home team goals in the match versus the away side. Analogical reasoning is accurate for an away team.

Linear regression was utilized on the delta Elo rating to determine the most suitable coefficients in the parameter. For example, the home team Poisson distribution parameter (λ_h) depends on Goals Scored Home by the home team (*SH*), Goals Conceded Away by the away team (*CA*) and the difference in Elo ratings between teams (ΔELO_h for home team).

Let G_h be the number of goals scored by home team in the match, $prG_{hs} = \frac{SH+CA}{2}$ be the predicted number of goals scored by the home team according to Sumpter's model [3], $\Delta ELO_h = ELO_h - ELO_a + 100$ be the difference between calculated Elo ratings for home team.

We intend to find how the following difference $G_h - prG_{hS}$ depends on ΔELO_h. The model aims to predict $G_h - prG_{hS}$ value by achieving the best fit regression line. Also, the error difference between the true value and predicted value should be minimized. Therefore, the b and k values should be updated to reach the best value and minimize the error between true value $G_h - prG_{hS}$ and predicted $G_h - prG_{hS}$ value. We suppose this dependence be linear: $f(\Delta ELO_h) = k \cdot \Delta ELO_h + b$. Here $G_h - prG_{hS}$ is the study or dependent variable; ΔELO_h is an explanatory or independent variable; *b* is the intercept parameter, and *k* is the slope parameter.

Overall, we use the method of least squares: $G_h - prG_{hS} = f(\Delta ELO_h) = k \cdot \Delta ELO_h + b, b \approx 0$ because *K* and ELO_0 were chosen correctly. Here $G_h - prG_{hS}$ is the study or dependent variable; ΔELO_h is an explanatory or independent variable; *b* is the intercept parameter, and *k* is the slope parameter.

- The result of regression coefficient *k*
  k ∈ [0, 0009; 0, 0014] – depends on the football league.

- Correctness of function f
  $prG_h = E(G_h) \longleftrightarrow \forall\Delta ELO_h: f(\Delta ELO_h) = E(G_h - prG_{hS})$
  $\lambda_h = prG_h = prG_{hS} + f(\Delta ELO_h) = prG_{hS} + E(G_h - prG_{hS}) = E(G_h)$
- The final Poisson distribution parameter $\lambda_h = G_h = prG_{hS} + k \cdot \Delta ELO_h$

Table 1: Parameters

Team	Scored	Conceded	prG_s	ΔELO^2	Poisson distribution parameter
Home	SH[1]	CH	$\frac{SH+CA}{2}$	$\Delta ELO_h = ELO_h - ELO_a + 100$	$\lambda_h = G_h = prG_{hS} + k \cdot \Delta ELO_h$
Away	SA	CA	$\frac{SA+CA}{2}$	$\Delta ELO_a = ELO_a - ELO_h - 100$	$\lambda_a = G_h = prG_{hS} + k \cdot \Delta ELO_h$

[1]SH, CH, SA, CA are derived from Sumpter's model described in Soccermatics [3]
[2]$\Delta ELO_a = -\Delta ELO_h$

Regarding Task 1, we have chosen the most probable values of the Poisson distributions Pois(λ_h) and Pois(λ_a) rounded them to the nearest integers as the numbers for predicted goals for the home and the away teams, respectively (see function 'MaxPoissonOne' in the file'Testing/Program.cs' of our GitHub repository Program codes).

As for Task 2, using Poisson distribution, we have converted λ_h and λ_a to the probabilities of win, draw, and lose for the home team (see function 'findVer' in the file'Testing/Program.cs' of our GitHub repository Program codes).

Results

2023 Soccer Prediction Challenge

The quality of the whole modeling was proven using RPS (The ranked probability score) and RMSE (The root mean squared error). Whereas the RMSE is widely used in statistics, RPS properly assesses football forecasting models. The probability of a draw is not the third summand as it accounts for in the equally probable distribution [11]. In terms of RMSE, which shows the correctness of the predicted exact score, we ranked 7th out of 11 participating teams (Task 1 ScoresLeaderBoard 20230503.xlsx). Concerning RPS, highlighting the correctness of the predicted probabilities of win, draw and loss, we have achieved 5th place out of 13 participants (Task 2 ScoresLeaderBoard 20230503. xlsx in GitHub).

The predictions and real match results can be viewed with "Real outcomes+Submission Friends of 3-1-0.xlsx" file.

If the current season contained 15 matches, then we have used only the last 15 matches of the current season to calculate the Elo ratings for the teams. If not, we have merged them with the previous season, replacing relegated teams with the new ones according to their places (the third team of the league below becomes the last in the league above, the second team becomes the penultimate, the first team becomes the antepenultimate).

Additional test

Expanded dataset

For further championships, we chose those where no play-off played due to uncertainty of the other tournament may be considered and strategies for these matches can differ from ordinary league matches. For empirical evaluation beyond PredictionSet, we have parsed the data from [12]. The 26 selected leagues and the seasons can be viewed in the file"Testing/config. json" (see link to GitHub repository in Program codes). Overall, 6817 matches were considered.

All these seasons contained 15 matches or more, thus, we have only used information about the current season to calculate the Elo ratings for the teams. We have used the classic approach: taking 80% of data to train the model and the remaining 20% to check its correctness with the same metrics (RMSE and RPS). Here, games count is considered instead of 'data' (see variables 'trainingSet' and 'testSet' in 'GetRPSRMSE' function in the file'Testing/ Program.cs' of our GitHub repository Program codes).

Table 2: Statistics

Index	RPS	RPS by league	RMSE[1]	RMSE by league[2]
Mean	0.1871	0.1866	1.9405	1.9383
Variance	0.0144	0.0004	5.1079	0.0566
Minimum	0.0005	0.1433	0	1.2978
0.25 Quantile	0.1120	0.1744	1	1.7961
Median	0.1570	0.1879	1.4142	1.9331
0.75 Quantile	0.2394	0.1983	2.2361	2.0817
Maximum	0.8679	0.2675	9.0554	2.9326

[1]Calculated as the sum of the square roots
[2]Calculated as the square root of the sum of squares

The most significant outcome from the Table 21 could be the RPS value (0.1871), which is much less than our result (**0.2144**) and that of the First-place team" FCSlocker" (**0.2095**) in the 2023 Soccer Prediction Challenge. Comparing to the winner of the 2017 Soccer Prediction Challenge with RPS equal to 0.2063, our model is still much better [2].

However, the RMSE value is much higher than us in competition (**1.9383 >1.8123**). It might be due to the metric RMSE evaluates the correctness of the exact score prediction, which could be far from the probabilities of win, draw and lose. This type of randomness could be in the nature of football.

Program codes

Suggested solution could be found via GitHub link (https://github.com/Gorambassador/The-2023-Soccer-Prediction-Challenge).

Discussion

We have assumed that goals are distributed by Poisson law, though the study makes it controversial [13]. It is partly because goals are not equally possible to be scored in every minute of a match. Moreover, the decision behind distribution could be made in another way. Particularly, we could take the floor or the ceiling of the Pois(λ_h) and Pois(λ_a) maximums.

Additionally, the results of this academic study show that the pi-ratings outperform considerably the widely accepted Elo ratings [5]. Thus, we may use pi-ratings instead of Elo ratings.

Conclusion

From now on, we can predict any football match result with the accuracy shown with RPS and RMSE in Results. RPS value reaches to 0.1871, which is better than that of the 2017, 2023 Soccer Prediction Challenge winners [1,2].

The novelty and the authors' contribution to the topic is caused by combining all the ideas expanded above in one solution. We describe the model that combines different approaches (Elo rating, simple scoring indicators, Poisson distribution) and demonstrates a crucial result.

Moreover, the model may be used without any deep knowledge about matches or leagues (event and tracking data) and can be implemented globally because it does not use any match statistics (shots, corners, etc.), extra data (event or tracking) or advanced metrics (Expected Goals, Expected Assists, etc).The application has the potential to forecast the results of football matches in lower-profile leagues that lack comprehensive statistical data. Our approach only requires basic soccer leagues match data and does not involve event data, tracking data or state-of-the-art advanced metrics (xT, EPV, VAEP, etc.). That is why it can be used in every league worldwide. Our philosophy is to use only goals (match results) to make the score predictor.

The future direction is to study if other methods, such as the Relational classification model, Feature-based classification model, and Feature-based regression model, might give more accurate predictions. Also, we plan to examine the studies of other participants.

Declarations

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Consent to participate

All authors whose names appear on the submission confirm the awareness of the submission to this journal and have agreed to be named as the authors.

Consent for publication

All authors whose names appear on the submission made substantial contributions to the conception or design of the work; or the acquisition, analysis, or interpretation of data; or the creation of new software used in the work; drafted the work or revised it critically for important intellectual content; approved the version to be published; and agree to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

Availability of data and materials

Please see the 2023 Soccer Prediction Challenge website [1].

Code availability Please see Program codes.

Authors' contributions

This work is the result of equal participation of both corresponding and contributing authors in all the aspects of preparation, analysis and writing of the manuscript.

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