Journal of Computing and Electronic Information Management
ISSN: 2413-1660 | Vol. 22, No. 1, 2026

Application and Analysis of XBoost Models Optimized with TPE in Complex System Prediction

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Abstract: This paper proposes an XGBoost model based on TPE hyperparameter optimization for constructing a system effectiveness prediction framework, focusing on integrating precise prediction with interpretable analysis. First, TPE algorithm-based hyperparameter optimization enhances the XGBoost models predictive performance, elevating the models decision coefficient from the baseline 0.827 to 0.875. Second, a Monte Carlo simulation combined with confidence interval estimation constructs an uncertainty-quantified prediction system, effectively overcoming limitations of traditional methods to deliver more reliable result intervals. Finally, the SHAP model was applied to analyze feature importance in the XGBoost model, revealing nonlinear relationships between multidimensional features and target responses, thereby enhancing interpretability. This model quantifies the marginal effects of coaching factor inputs through hypothesis testing and develops optimal resource allocation strategies based on reward-punishment balance. The framework significantly improves prediction accuracy, interpretability depth, and strategy feasibility, providing methodological support for complex decision-making scenarios. The innovation of this research lies in integrating XGBoost with the TPE optimization algorithm, which not only enhances the predictive models performance but also overcomes the limitations of traditional point estimation. It provides a comprehensive perspective encompassing uncertainty quantification and feature analysis, offering broad application value.

Keywords: TPE hyperparameter optimization, TPE-XGBoost model, SHAP model parsing, hypothesis testing.

1. Introduction

This paper focuses on predicting effects in complex systems, aiming to enhance prediction accuracy while improving model interpretability and uncertainty quantification capabilities by introducing an XGBoost model with TPE hyperparameter optimization. Traditional forecasting methods often fail to effectively quantify uncertainty when handling complex systems and lack the ability to reveal nonlinear relationships among multidimensional features. To address these issues, this paper proposes a predictive framework combining the TPE optimization algorithm with XGBoost, aiming to improve model stability and accuracy [1].

Currently, many existing approaches employ traditional machine learning algorithms for prediction, yet they often fall short when handling high-dimensional data, particularly in assessing prediction uncertainty. To overcome these limitations, this paper adopts XGBoost as the base model and further optimizes its hyperparameters using the TPE algorithm, thereby improving model performance [2]. By integrating Monte Carlo simulations and confidence interval estimation, the paper quantitatively analyzes the uncertainty in prediction results, ensuring the reliability of outcomes.

Additionally, the SHAP model is employed to analyze feature importance within XGBoost, revealing the influence of different variables on predictions and thereby enhancing model interpretability. Hypothesis testing quantifies the impact of coaching factors on system effectiveness, leading to the proposal of a reward-punishment balanced resource allocation strategy that provides more practical decision support [3][4].

Experimental results demonstrate that the TPE-optimized XGBoost model outperforms traditional methods across multiple metrics, achieving significant improvements particularly in prediction accuracy and model interpretability. This framework effectively handles multidimensional data within complex systems, offering novel solutions for prediction and optimization in complex systems with broad application prospects.

2. Predicting and Analyzing the Olympic Medal Standings

2.1. Establishing an XGBoost Medal Prediction Model Optimized with TPE

This study attempts to build an XGBoost-based prediction model to better predict the number of Olympic medals (both gold and total medals) for each country [5]. The model provides reliable predictions of future Olympic medal distributions by learning complex temporal and feature relationships in historical data, while quantifying and analysing the prediction uncertainty in detail.

Firstly, this study first preprocessed the raw data and filled in the missing values using the support vector machine algorithm [6].

2.1.1. Dataset segmentation and training

Extract feature X and target variable Y and divide the data into training set and test set in the ratio of 9:1. $X_{\text{train}}, X_{\text{test}}, Y_{\text{test}} = \text{split}(X, Y, test\_size = 0.1)$.In this case, the training set is used for parameter learning of the model and the test set is used to evaluate the predictive performance of the model. The XGBoost model is a machine learning method commonly used for sequence prediction and consists of the following main components:

Input Feature X: The input features include the country code NOC and other significant characteristics, such as the total number of medals won over the years, the host countrys identification, the number of sports participated in, and the number of awards won in each event, denoted: $X = \{NOC, x_1, x_2, \ldots, x_n\}$.

Target Variable Y: The target variable is the medal distribution matrix, including a vector of the number of gold, silver and bronze medals, denoted: $Y = \{Gold, Silver, Bronze\}$.

Model Training: The XGBoost model was used for training and the model was trained by stochastic gradient descent (SGD) with the optimisation objective of minimising the loss function. Loss Function and Optimisation Objective: using Mean Square Error (MSE) as the loss function:

$$\mathsf{L} = \frac{1}{T}\sum_{t=1}^{T}\|y_t - \hat{y}_t\|^2 \tag{1}$$

Where N is the number of samples, is the actual value is the simulated predicted value and the model is trained by stochastic gradient descent (SGD) with the optimisation objective of minimizing L.

2.1.2. TPE hyperparameter optimisation

The hyperparameters of the XGBoost model are optimised using the TPE method, and the optimised hyperparameters include the learning rate α, the maximum depth of the tree d, the subsampling ratio p and the regularisation factor λ.

Define a reasonable search range for each hyperparameter, for example:

$$\begin{gathered}\alpha \in \{10^{-5}, 10^{-4}, 10^{-3}\}, \quad d \in \{3,4,5\}, \\ p \in [0.5, 1.0], \quad \lambda \in \{10^{-5}, 10^{-4}, 10^{-3}\}\end{gathered} \tag{2}$$

The optimisation objective is the loss function on the validation set L_{val}:

$$\theta^* = \arg\min_{\theta \in \mathsf{H}} \mathsf{L}_{\text{val}}(X, Y; \theta) \tag{3}$$

Where θ denotes the set of hyperparameters of the model.

2.1.3. Assessment of model performance

In order to assess the predictive performance of the model. R^2 was chosen as the main performance metric:

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y}_i)^2}{\sum_{i=1}^{n}(y_i - \overline{y})^2} \tag{4}$$

Where y_i is the actual observed value, $\hat{y}_i$ is the predicted value of the model, and $\overline{y}$ is the sample mean of the target variable. R^2 the closer the value is to 1, the better the model explains the target variable.

2.1.4. Analysis of forecast uncertainty

To analyse the uncertainty in the predicted values, Monte Carlo simulation combined with Confidence Interval (CI) was used to quantify the reliability of the model predictions. Using the trained XGBoost model, the input data were sampled multiple times by introducing random perturbations to generate N sets of predicted values $\{\hat{y}_1, \hat{y}_2, \ldots, \hat{y}_N\}$, and the mean and standard deviation of the prediction distribution were calculated:

$$\mu_{\hat{y}} = \frac{1}{N}\sum_{i=1}^{N}\hat{y}_i, \quad \sigma_{\hat{y}} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\hat{y}_i - \mu_{\hat{y}})^2} \tag{5}$$

Assuming that the distribution of the predicted values satisfies a normal distribution, the confidence interval for the predicted values is calculated based on a set confidence level α (e.g. 95%):

$$\mathrm{CI} = \left[\mu_{\hat{y}} - z_{\alpha/2} \cdot \sigma_{\hat{y}}, \mu_{\hat{y}} + z_{\alpha/2} \cdot \sigma_{\hat{y}}\right] \tag{6}$$

Where $z_{\alpha/2}$ is the critical value of the standard normal distribution corresponding to the confidence level α.

The stability of predicted values is evaluated based on the width of the confidence interval. A narrower interval indicates higher reliability of the models predictions. Additionally, the inclusion of the true value within the confidence interval serves as a validation of the models predictive accuracy.The XGBoost model, optimized with TPE, effectively captures Olympic medal trends and country relationships. After hyperparameter tuning, it shows strong predictive performance on the test set. Uncertainty is quantified through Monte Carlo simulations and confidence intervals, boosting credibility and applicability.

2.2. Model Solution and Result Analysis

2.2.1. Hyperparameter optimisation

A TPE-based optimization algorithm was used in the hyperparameter optimization process to systematically explore multiple hyperparameters of the model. The objective was to minimize the models loss function on the multi-classification task. By building the hyperparameter search space and performing multiple iterations, identifying an optimal set of hyperparameters. The specific optimization results are shown in Table 1.

Table 1. Model-Based Optimal Hyperparameters

Hyperparameter	Search Range	Optimal Value
$\boldsymbol{\alpha}$	[10-5, 10-2]	0.001
$\boldsymbol{h}$	[64, 512]	256
$\boldsymbol{b}$	[16, 128]	64
$\boldsymbol{\lambda}$	[10-5, 10-1]	0.0001
Encoder Layer	[1, 3]	2
Decoder Layer	[1, 3]	2
$\boldsymbol{T}$	[5, 20]	10
Activation Function	[‘ReLU’, ‘Tanh’]	ReLU

Based on the optimization results, key hyperparameters affecting model performance include the learning rate α, the number of hidden layer units h, and the batch size b. A small learning rate ensures stable convergence, while a moderate number of hidden layer units and batch size balance expressiveness and training efficiency. An appropriate regularization factor λ helps prevent overfitting. Combined with the optimal time step T and activation function choice, these hyperparameters provide a solid foundation for model performance improvement.

During the initial training of the XGBoost model with default parameter settings, the model reached value of 0.986 on the training set, while the value on the test set was only 0.827, and this significant performance difference indicated an overfitting problem of the model. To mitigate this problem, the hyperparameters of the model were optimally adjusted by TPE method, including reducing the number of hidden layer units, increasing the regularisation factor λ, and adjusting key parameters such as the batch size and time step. After these adjustments, the performance of the model was significantly improved, and the R^2-values on the training set and test set were increased to 0.987 and 0.875, respectively, effectively reducing the overfitting phenomenon.

Fig. 1 shows the initial XGBoost models excellent training performance with default parameters, where predictions closely align with the reference line. Optimizing hyperparameters with TPE reduces test set dispersion and improves accuracy and stability. Despite a slight decrease in training performance, the model now generalizes better to new data, crucial for reliable Olympic medal predictions.

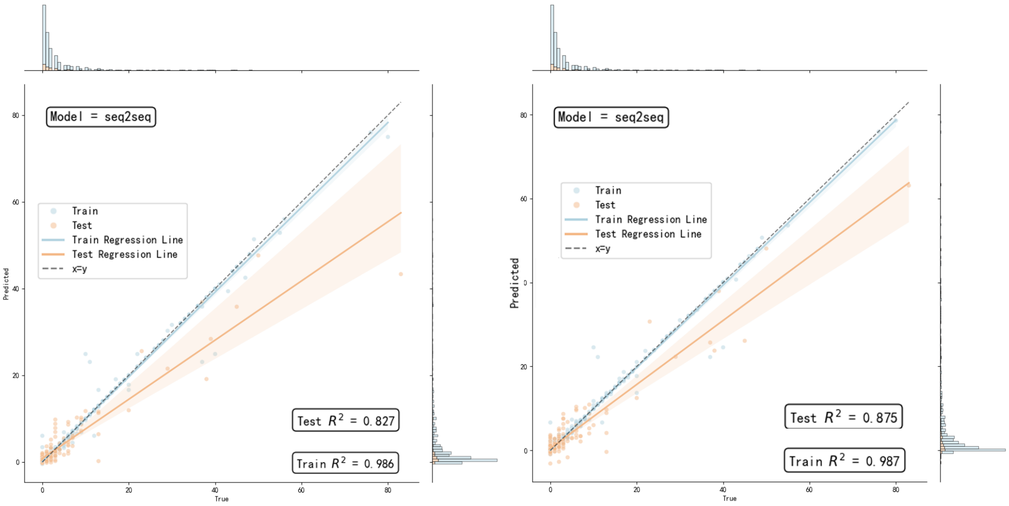

Figure 1. Comparison of training set and test set before and after model training

2.2.2. Model predictions and analysis of results

Step 1: Constructing Predictive Datasets.

To predict medals for the 2028 Los Angeles Olympics, a new input feature dataset was created by adapting 2024 Olympics data and incorporating adjustments for new events added in 2028.

Records for 2024 were extracted from the original dataset to form the base dataset X_{2024}, and data for Russia were excluded (i.e., rows with a NOC value of 113) because Russia was expected to be banned in 2028:

$$X_{2028} = X_{2024}[X_{2024}['year'] == 2024 \wedge X_{2024}['NOC'] \neq 113^2] \quad (7)$$

Index reset of filtered data to ensure consistency and neat alignment of data:

$$X_{2028} \cdot reset\_index(inplace = True, drop = True) \quad (8)$$

Adjustments are made to the corresponding number of medals based on additional sports approved by the IOC (e.g., cricket, squash, baseball, stickball, and flag rugby).

The corresponding adjustment formula is:

$$\begin{aligned} X_{2028}['Baseball'] &= X_{2028}['Baseball'] + 2 \\ X_{2028}['Softball'] &= X_{2028}['Softball'] + 2 \\ X_{2028}['Cricket'] &= X_{2028}['Cricket'] + 2 \\ X_{2028}['Sixes'] &= X_{2028}['Sixes'] + 2 \\ X_{2028}['Squash'] &= X_{2028}['Squash'] + 2 \\ X_{2028}['Flagfootball'] &= X_{2028}['Flagfootball'] + 2 \end{aligned} \quad (9)$$

Given that 2028 is a future year for the Olympic Games, the year information in the dataset needs to be updated to 2028:

$$x_{2028}['year'] = 2028 \quad (10)$$

For the United States (NOC of 147), as the host country for the 2028 Olympics, the logo needs to be set to 1, while the rest of the country stays at 0.

$$X_{2028}['Host\_Country'] = 0 \quad (11)$$

$$X_{2028}.loc[X_{2028}['NOC'] == 147, 'Host\_Country'] = 1 \quad (12)$$

Step 2: Analysis of predicted Olympic results.

Table 2 below are the results for selected countries, including gold, silver, and bronze medal counts along with their confidence intervals. Fig. 2 shows the predicted number of gold, silver, and bronze medals along with their confidence intervals (CI). Predicted values are marked by curves and scatters, while CIs are shown as shaded areas. The horizontal axis represents the data point index, and the vertical axis shows the predicted medal count. Gold, silver, and bronze predictions are indicated by yellow, grey, and brown curves, respectively, each with its corresponding CI.

2.2.3. Model testing and analysis of results

From the Fig. 2, its evident that the predicted values stabilize as the number of data points increases, but there are significant fluctuations near the initial data points, indicating high predictive uncertainty. This is confirmed by the width of the CI, where wider areas signify greater uncertainty and narrower areas indicate more accurate predictions.

Table 2. 2028 Olympics Medal Table Projections

NOC	Gold	Silver	Bronze	Gold_CI_L	Gold_CI_U	Silver_CI_L	Silver_CI_U	Bronze CI_L	Bronze_CI_U
US	39	45	43	36	40	36	45	37	43
CN	40	27	24	37	40	24	27	21	24
JP	20	13	12	14	20	11	14	9	12
AU	18	19	17	12	17	8	19	12	17
…	…	…	…	…	…	…	…	…	…
Mixed Team	1	1	2	0	1	1	2	1	2
ROC	4	2	3	0	7	0	5	0	12

By comparing the projected medal totals for 2024 and 2028, the following countries in Table 3 are expected to significantly improve their medal performance.

These countries are predicted to see a significant increase in their results in 2028, particularly ROC and Mixed team, which have both seen significant increases in their medal totals, reflecting the strong momentum in these countries and regions.

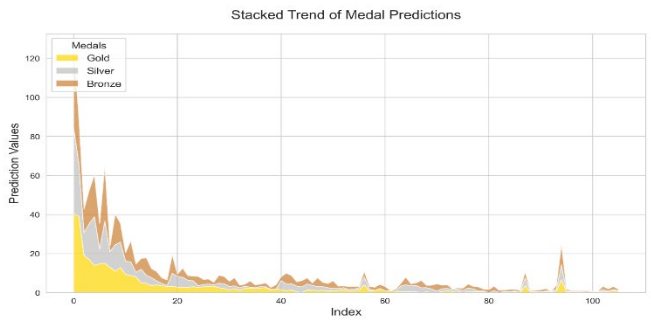

Figure 2. Confidence intervals for gold, silver and bronze medals

Table 3. Predicting Progressive National Medal Count List

NOC	2024Total	2028Total	Improvement
ROC	0	17	17
Poland	7	13	6
Jordan	1	4	3
Mixed team	0	3	3
Greece	3	6	3
Thailand	4	7	3
Mexico	4	7	3
Morocco	1	3	2
Kosovo	1	3	2
Uzbekistan	5	7	2
…	…	…	…

For countries that have not yet won a medal, the model also makes predictions and assesses which countries are likely to win a medal for the first time in 2028.The following list of countries in Table 4 was obtained by filtering out countries that had no medals in 2024 but were expected to win a medal in 2028:

Table 4. Estimated Number of First-Time Medallists

NOC	Average Probability of Winning
Zambia	0.602431
Independent Olympic Athletes	0.659130
Taiwan	0.636667
Virgin Islands	0.594907
British Indies	0.558821
Independent Olympic Participants	0.648978
Mixed team	0.752325
Ceylon	0.764092
FR Yugoslavia	0.602568
ROC	0.954915

It can be seen that ROC and Mixed team have the highest probability of winning a medal in 2028 with 0.954915 and 0.752325 respectively, indicating that they are more likely to win a medal in 2028.

2.3. SHAP Analysis of Olympic Events Impact on Medal Performance

2.3.1. SHAP modelling

This study aims to explore the correlation between Olympic sports and medal counts per country. We employed the SHAP model to analyze each sports impact on total national medals. The SHAP model quantifies the contribution of each input feature to predictions, leveraging the TPE-XGBoost models inclusion of sport types, numbers, and medal counts. SHAP draws on the Shapley value from cooperative game theory to provide a fair and transparent way of assessing the impact of each feature on the model output. The core idea is to measure the importance of a feature by considering all possible combinations of features and calculating the marginal contribution of each feature to the model output. The formula for calculating the Shapley value is as follows:

For a given feature f and model output y, Shapley value $\phi(f)$ represents the contribution of feature f to the model prediction results and is calculated as follows:

$$\phi(f)=\sum_{s\subseteq N\{f\}}\frac{|s|!(|N|-|s|-1)!}{|N|!}[f(s\cup\{f\})-f(s)] \quad (13)$$

Where S is the set of features, N is the set of all features, is to use only the feature set S Results of modelling predictions, is to add the feature f to the feature set S Post-projection results.

Shapley Values are calculated by traversing all possible combinations of features, thus fairly distributing the contribution of each feature to the prediction result.

In the application of the SHAP model, Olympic medal predictions are made using the trained TPE-XGBoost model, yielding results based on various input features. The SHAP tool then interprets the model to assess the impact of each feature (e.g., number of sports, type, historical medal distribution) on medal counts for each country. The SHAP models output identifies the most influential sports for a given country. For major sports powers like the USA and Russia, events such as athletics and swimming have a greater impact, while for emerging sports nations or smaller countries, additional events like cricket and squash may significantly affect medal predictions.

2.3.2. Solving the model

Step 1: Analysis of Olympic Program's Impact on Total Medals Won.

The SHAP model visualizes the impact of gold, silver, and bronze medals on total prizes won by countries. "NM" represents the number of items, while unlabeled items denote the number of types. The charts analyze how Olympic sports (e.g., Athletics, Swimming, Weightlifting) influence medal predictions, considering both quantity and variety.

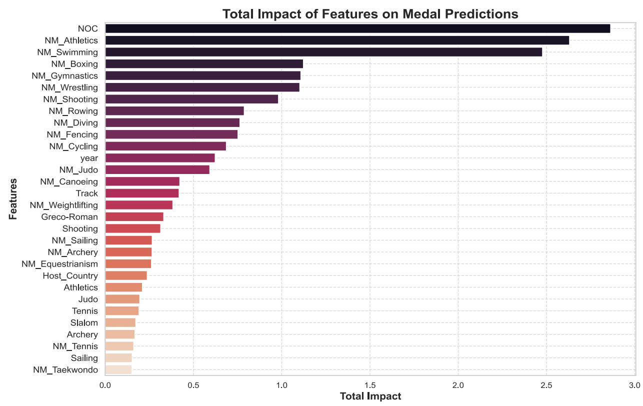

Figure 3. Impact of features on medal predictions

Fig. 3 highlights the varying impacts of sports on medals. "NM_Athletics" and "NM_Swimming" significantly influence gold and bronze, while "NM_Fencing" and "NM_Gymnastics" affect silver more. This emphasizes the importance of sports with larger participant pools and higher competitiveness. The "number of sports" (e.g., NM_Athletics, NM_Swimming) predicts overall medals, while the "number of types" (e.g., Gymnastics, Cycling) fine-tunes distribution. Increasing events like swimming and athletics boosts gold and bronze, whereas weightlifting and shooting impact silver more. The SHAP model also shows the "Host_Country" advantage, particularly in gold and silver predictions, especially in sports where the host excels, such as swimming and track.

The aggregated SHAP results for gold, silver, and bronze medals show the impact of each feature on predictions, ranked by magnitude. The chart displays each features contribution to medal counts, with "NM_" denoting the number of events, "NOC" for country codes, and "Host_Country" for host status.

From the results, Athletics and swimming are key predictors of U.S. gold medals, indicating their global influence and decisive role in gold medal wins. Wrestling, gymnastics, and shooting also significantly impact silver and bronze medals, reflecting each countrys strengths. The host country benefits from additional support and resources, enhancing medal forecasts. Lesser-impact sports like weightlifting and canoeing still contribute to specific countries med al tallies, particularly in their strongest events.

Step 2: Impact of gold, silver, and bronze medals on U.S. medal count in 2028 Olympics

The SHAP analysis of the US 2028 Olympic gold, silver, and bronze medal forecasts reveals the contributions of various factors to the medal predictions.

Fig. 4 illustrates the SHAP impact on gold medal predictions, highlighting "NM_Athletics" and "NM_Swimming" as key contributors. The Host_Country factor indicates additional U.S. support as the 2028 Olympics host. Fig. 5 shows the SHAP values for gold, silver, and bronze medals, revealing the impact of Olympic sports on U.S. medal performance. Track and field and swimming are dominant, while wrestling, fencing, shooting, and volleyball also significantly contribute to medal predictions. These insights provide a scientific basis for U.S. Olympic preparations, aiding in optimizing resource allocation and focusing on high-potential events for optimal results. Fig. 6 illustrates the SHAP impact on bronze medals, highlighting NM_Swimming and NM_Athletics as major contributors, indicating their significant influence. Shooting and Volleyball also significantly affect bronze medal count, complementing the U.S. bronze performance.

Overall, SHAP analysis of gold, silver, and bronze medals highlights the varying impact of Olympic sports on U.S. medal performance, with track and field and swimming being dominant. Contributions from wrestling, fencing, shooting, and volleyball are also significant, indicating their importance in medal prediction.

3. Great Coaching Impact Modelling and Solving

3.1. Quantitative Analysis of "Great Coach" Effect

3.1.1. Data pre-processing

Step 1: Calculate the medal score.

For each athletes medal performance, the type was converted into a numerical value using a set of mapping rules for statistical analysis. The specific mapping is as follows:

$$Medal\_score = \begin{cases} 0, Medal = 'None' \\ 1, Medal = 'Bronze' \\ 2, Medal = 'Silver' \\ 3, Medal = 'Gold' \end{cases} \tag{14}$$

Using this rule, medal types were converted into numerical values to facilitate quantitative analysis. Subsequently, the data were grouped by year, and the total medal score for each year was calculated:

$$Medal\_score_{total} = \sum_{i=1}^{n} Medal\_score_i \tag{15}$$

Where i represents each athlete within that year, and n is the total number of athletes competing in that year. By applying this method, the total medal scores of the Chinese mens ta ble tennis team in the Olympic Games each year are obtained.

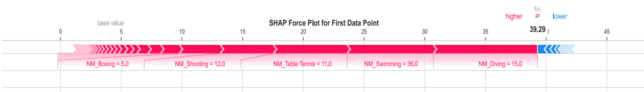

Figure 4. SHAP value impact of gold forecasts

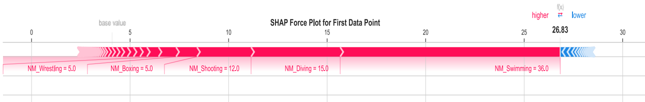

Figure 5. Impact of SHAP values for silver projections

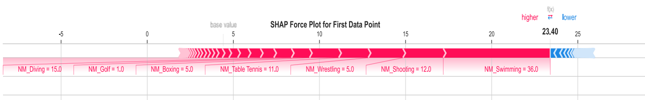

Figure 6. SHAP value impact of bronze predictions

Step 2: Constructing the "to teach or not to teach" variable.

To assess the impact of Lius coaching, a binary variable "coaching_status" was incorporated into the analysis. This variable indicates whether Liu Guoliang was coaching the Chinese mens table tennis team in a given year, based on the following criteria:

$$Coaching\ Status = \begin{cases} 0, & \text{if Year } < 2003 \\ 1, & \text{if Year } \geq 2008 \end{cases} \tag{16}$$

With this variable, the data can be divided into two parts, before and after Lius coaching, to provide data support for subsequent hypothesis testing shown in Table 5.

Table 5. Data Before and After Coaching

Year	Medal	Coaching Status
1988	0	0
1992	1	0
1996	5	0
2000	4	0
2004	3	1
2008	15	1
2012	14	1
2016	14	1

By following these steps, the dataset was transformed into a structured format that includes the "Medal_score" total score and the "teaching_status" indicator, thus providing the necessary data for subsequent hypothesis testing analysis. This pre-processing step ensured the consistency and reliability of the data, laying a solid foundation for the quantitative analysis of the "great coach" effect.

3.1.2. Modelling the great coach effect

In this section, hypothesis testing is used to quantify the "great coach" effect, specifically a paired-samples t-test to assess the significance of the change in the number of medals won by the Chinese mens table tennis team before and after Liu Guoliangs coaching. The purpose of the hypothesis test was to examine whether Liu Guoliang as head coach had a significant effect on the number of medals won by the Chinese mens table tennis team.

Model assumptions: H_0 : Before and after Liu Guoliangs coaching, there was no significant change in the total medal scores of the Chinese mens table tennis team, i.e. the effect of coaching change on the number of medals was not significant.

$$H_0 : \mu_{pre} = \mu_{post} \tag{17}$$

Where μ_{pre} denotes the average of medal scores before coaching, μ_{post} Indicates the average value of medal scores after coaching.

Alternative assumption H_1: The total medal scores of the Chinese mens table tennis team changed significantly before and after Liu Guoliangs coaching, i.e., the effect of coaching change on the number of medals is significant.

$$H_1 : \mu_{pre} \neq \mu_{post} \tag{18}$$

Paired samples t-test is used to test whether there is a significant difference between the means of two related samples. In this analysis, the data before Lius coaching and the data after his coaching were considered as paired samples for comparison. The statistic of paired-samples t-test is calculated as follows:

$$t = \frac{\bar{d}}{s_d / \sqrt{n}} \tag{19}$$

Where $\bar{d}$ is the mean of the paired differences, s_d is the standard deviation of the paired differences, n is the number of paired samples. Pairwise Difference d_i is the difference between each pair of data (pre and post coaching medal scores).

Calculation of differences: For each pair of data, calculate the difference in medal scores between pre- and post-coaching:

$$d_i = Medal\_score_{post} - Medal\_score_{pre} \tag{20}$$

Inspection Steps: Calculate the mean and standard deviation of the differences. Calculate the t-statistic and find the critical value of the t-distribution (with $n-1$ degrees of freedom). The rejection of the original hypothesis was determined based on the t-statistic and p-value.

Significance test: Set the significance level α (usually 0.05). If the p-value<α, the hypothesis is rejected and the "great coach" effect is considered significant. If the p-value $\geqslant \alpha$, the hypothesis is not rejected and the "great coach" effect is considered insignificant.

Conclusion: A paired-samples t-test showed that if the p-value was < 0.05, the effect of "great coaching" was significant and there was a significant change in the number of medals; if the p-value was≥0.05, the effect was not significant.

3.1.3. Testing of the model

In quantifying the effect of "great coaches", the core task of hypothesis testing is to test whether Liu Guoliangs coaching significantly affects the number of medals won by the Chinese mens table tennis team. This is achieved through the paired-samples t-test, and the manually derived results of the hypothesis test are analysed below.

As shown in Table 5, pre-coaching data: medal scores in 1988, 1992, 1996, 2000: 0, 1, 5, 4.Post-coaching stats: 2004, 2008, 2012, 2016 medal scores: 3, 15, 14, 14.Calculate the difference between each pair of data. For each pair of data, calculate the difference in medal scores before and after Liu Guoliangs tenure (d_i):

The p-value is obtained from the t-distribution table with $df = n - 1 = 3$. The calculated p-value is 0.0288. Given the significance level $\alpha = 0.05$, the p-value is less than α, leading to the rejection of the original hypothesis. The paired-samples t-test results indicate that Liu Guoliangs coaching significantly impacts the medal count of the Chinese mens table tennis team, supporting the "great coach" effect.

3.2.Strategic Advice on Coaching Investments

3.2.1. National coach investment priorities

Globally, proper planning of coaching investment prioritisation is essential to enhance country-specific programme performance. This study assesses the return on investment by analysing medal data, coaching experience and effects to prioritise coaching investment in table tennis. Countries with a high number of participants were selected for the study to provide recommendations for their coaching investments. By analysing previous data, data on male table tennis players were filtered and the number of players competing each year was counted according to country and year. To obtain more representative countries, the average number of participants per country was calculated and the countries were ranked according to this value. The mathematical representation of the process is:

$$\text{Average Participants}_i = \frac{1}{n}\sum_{i=1}^{n} \text{count}_{ij} \tag{21}$$

Where $Count_{ij}$ denotes the number of participants from country i in year j, and n is the total number of years in which the country participated.Return on coaching investment projections.

This study aims to quantify how coaching investment boosts medal counts and guide coaching resource allocation. Regression analysis showed that Liu Guoliangs coaching in - creased the Chinese mens table tennis teams average medal count by 9. Using this effect and other countries average medal counts, we predict medal growth from investing in top coaches.

Step 1: Calculation of the number of base medals

Calculation of the average number of medals per country by counting the total number of medals per country in each year. The specific formula is:

$$\mu_{country} = \frac{1}{n}\sum_{i=1}^{n} \text{Medal\_score}_i \tag{22}$$

Where Medal_score_i denotes the medal score in year i and n is the total number of years in which the country competed.

Step 2: Calculation of adjustment factors

During the period when Liu Guoliang was not coaching, the medal average of the Chinese mens table tennis team was = 2.5. By calculating the ratio of the medal average of each country to the medal average of China, an adjustment factor, adjust-ment_factor, was derived with the following equation:

$$\text{adjustment\_factor} = \frac{\mu_{country}}{\mu_{China}} \tag{23}$$

This adjustment factor reflects each countrys medal performance relative to Chinas performance u nder the same conditions. The larger the adjustment factor, the more competitive the country is under similar conditions.

Step 3: Projected medal growth

Calculate the predicted medal growth for each country after coaching investment using the adjustment coefficients and Lius effect value. The formula is as follows:

$$\text{PredictedGrowth\_i=adjustment\_factor}_i \times \beta_3 \quad (24)$$

Where denotes the projected medal growth for country i after investing in "good" coaches.

Step 4: Predicted number of medals

Finally, the predicted medal growth values are added to each countrys baseline medal count to obtain the predicted medal count. The specific formula is:

$$\text{Predicted Medal}_i = \mu_{country} + \text{Predicted Growth}_i \quad (25)$$

This value estimates the medals a country might win post-coaching investment, assuming the Liu Guoliang effect. Based on these calculations, the following predictions were made in Table 6. According to forecasts, South Korea, Yugoslavia, and Germany are expected to see a significant increase in medals after investing in "good" coaches, especially with the Liu Guoliang effect, which is projected to boost Germanys medal tally to 16. The Republic of Korea and Yugoslavia show more stable growth, with projected increments of 1.36 and 1.44 medals, respectively.

Table 6. Transformation of the Number of Medals after Intervention

Year	Korea	Yugoslavia	Germany	Korea_Predicted	Yugoslavia_Predicted	Germany_Predicted
1988	0	4	0	0.36	5.44	9
1992	0	0	4	0.36	1.44	13
1996	0	0	1	0.36	1.44	10
2000	0	0	0	0.36	1.44	9
2004	0	0	0	0.36	1.44	9
2008	0	0	6	0.36	1.44	15
2012	0	0	4	0.36	1.44	13
2016	0	0	3	0.36	1.44	12
2020	0	0	7	0.36	1.44	16
2024	1	0	0	0.36	1.44	9

4. Conclusion

This paper proposes an XGBoost model optimized using the TPE hyperparameter, demonstrating strong predictive accuracy and interpretability. First, by optimizing XGBoost hyperparameters via the TPE algorithm, the models predictive performance was significantly enhanced, increasing the decision coefficient from 0.827 to 0.875 while improving model stability and generalization capability. Second, by integrating Monte Carlo simulation and confidence interval estimation, this study quantifies prediction uncertainty, enabling the model to deliver more reliable forecasts when addressing complex systems. Finally, SHAP analysis reveals feature importance and uncovers nonlinear relationships between multidimensional features and target responses, thereby enhancing interpretability and decision support capabilities. Experimental results demonstrate that the optimized XGBoost model exhibits superior performance across multiple practical applications, particularly achieving high predictive accuracy in complex system effect evaluation and resource allocation optimization. By quantifying the marginal effects of coaching factors and proposing optimization strategies, this study not only provides effective tools for predictive tasks but also offers valuable references for real-world decision-making. Future research may further explore the application of TPE optimization algorithms and XGBoost across broader domains, particularly in multi-task prediction and dynamic system optimization, to enhance model adaptability and effectiveness.

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