Momentum Prediction Model Combining Markov Chain And MLP

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Abstract. In sports competitions, it is common for a certain player to dominate and score consecutively, which can be described as the effect of "momentum". To portray the abstract momentum to describe the change of athletes' state during the competition, and thus provide technical support for the subsequent training of athletes, a volume prediction model combining Markov chain and MLP is proposed. Firstly, the resultant variables are calculated by the entropy value method for momentum scoring, after that, technical indicators are considered, Markov features are calculated by the Markov chain model and added into the MLP model for momentum prediction, and finally, the important factors determining the momentum are analyzed by SHAP method. The experimental results show that the accuracy of predicting athletes' state reaches 98%, which can provide credible race reviews and guidance suggestions.

Keywords: Entropy weight method, Markov Chain, Multi-Layer Perceptron, SHAP Method.

1. Introduction

In competitive sports, every shot and every point can be a turning point in the direction of the game. Behind them lies a powerful force, which can be called "momentum". The reason why "momentum" has an impact on the game is that sports are not only a competition of physical ability, but also a competition of psychological quality and strategic intelligence. momentum affects athletes' performance and game results by enhancing mental toughness, providing motivation, stimulating physiological potential, optimizing tactical execution, and exerting psychological pressure on opponents.

Current research on athletes' competitions mainly focuses on performance prediction and physical fitness assessment. Among them, the neural network method and Markov chain model become the main methods of performance prediction. Ma De et al.[1] established a hybrid genetic neural network model to predict athletes' special performance, Parfianovich E.V. et al.[2] used a neural network to predict the physical fitness of 400m athletes, Chen Bo[3] predicted the 100m running performance through the gray Markov chain model, and Long Jiayong et al.[4] also applied the GM(1,1) gray model to study the performance of 100m running. In terms of special performance prediction, the current research mostly uses the linear regression method for simple measurement, Li Ge et al.[5] proposed a method to predict the heart rate of basketball players by linear regression method, Bari Mohd Arshad et al.[6] established a multiple linear regression model to predict the effectiveness of volleyball players' serves, and Zhu Chun[7] used logistic regression method to predict athletes' joint injury. Many of the above research methods are mainly based on the a priori information of athletes' performance and do not interpret the complete game, i.e., they lack the portrayal of potential psychological influences in the game.

However, psychological factors have a key role in athlete performance[8], and quantitative representations of abstract momentum can help to understand the emergence of seemingly unusual race situations, allowing for a more comprehensive explanation. This paper introduces an MLP-based momentum prediction model that incorporates Markov modeling to describe the continuity of an athlete's state during a match and a SHAP approach to elucidate the influencing factors, thereby revealing potential momentum influences beyond physical fitness throughout the match.

2. Construction of the model

2.1. Momentum evaluation model

Usually, in the process of the game, the coaching team needs to count the technical variables and some outcome variables for subsequent analysis. Technical variables are more to explore the reasons for the change in the athlete's momentum, while the outcome variables are more like jumping out of the game to analyze the athlete's momentum from the perspective of the result. To establish the momentum index more objectively, the outcome variables are chosen as the basis, and the entropy value method is applied to establish the score evaluation model.

The entropy value method is an objective method to determine the weights according to the difference in the degree of orderliness of the information contained in the indicators. For large-scale data and a large number of comparable indicators sets, the entropy value method based on information theory can make better use of the distribution characteristics of the data itself to calculate the size of the weights of the above indicators, so as to obtain the momentum score.

First, the data are standardized. Due to the difference in the scale of each indicator and the existence of both positive and negative indicators, it is necessary to standardize the data and calculate the weights, so as to obtain a new data matrix.

Using the obtained matrix, the entropy value $e_j\left(j=1,2,\cdots,10\right)$, which measures the level of disorganization of the indicators, can be calculated:

$$e_j=-k\cdot\sum_{i=1}^{n}P_{ij}\cdot\ln\left(P_{ij}\right) \tag{1}$$

where the coefficient $k=\frac{1}{\ln n}$, the probability of occurrence of each state in the information entropy $p_{ij}=\frac{x_{ij}}{\sum_{i=1}^{n}x_{ij}}$, and the sample size are n

Based on the entropy value of the indicator, it is possible to calculate the evaluation indicator weight coefficients:

$$w_j=\frac{1-e_j}{\sum_{k=1}^{10}\left(1-e_k\right)} \tag{2}$$

The final momentum score is obtained:

$$M=\sum_{j=1}^{10}w_j x_{ij} \tag{3}$$

The implementation of the algorithm is shown in Table.1.

Table.1. The entropy weight method's pseudocode

Algorithm 1:Entropy weight method	
Input: Data Positive_indicators and Negative_indicators	
Data normalization	
for	j = 1 to $last$ indicators do
	Import data set
	Calculate the entropy for each j
	Calculate the weight coefficient for each j
end	
for	index = 1 to last piece of data do
	Import the weight coefficient for each indicator
	Calculate the momentum of each row of data
end	
Output: Weight coefficient and Momentum	

The Momentum score is a measure of an athlete's performance during a match. Since the data used is calculated on an individual basis and takes into account some of the effects of the opponent, it can be assumed that the Momentum Score describes the individual's game status. At the same time, comparing the difference between the dynamic momentum scores of both players in the same game, the momentum of the game at different moments can also be derived, thus providing a basis for further analysis and prediction.

2.2. Momentum prediction model

2.2.1 Markov Chain Model

Markov chain is a stochastic process that can be used to describe the probability of state transfer. Since the performance of an athlete is discrete in time with respect to the form of the game, and his or her momentum performance is only related to currently known information and not to past historical information, the fluctuation of momentum can be considered to be Markovian in nature and is suitable for Markov modeling. The use of the Markov model for modeling sequential data to describe the course movements in a single match can better capture the continuity of momentum present in a match and enable better predictive modeling.

Using the number of strokes as the independent variable, the corresponding state is classified as "positive momentum" and "poor state" and the state of the athlete when he returns the ball is denoted as $M'_j(j=1,2)$. The conditional probability of transforming from states is denoted as P_{ij}, thus obtaining the probability of state transfer. Matrix P.

$$P = \begin{pmatrix} P_{11} & P_{12} \\ P_{21} & P_{22} \end{pmatrix} = \begin{pmatrix} 0.9 & 0.1 \\ 0.2 & 0.8 \end{pmatrix} \tag{4}$$

Based on the property of no posteriority in Markov processes and the Bayes conditional probability formula, the probability that the player is in state M'_j at moment k after k state transfers are:

$$\pi_j(k) = \pi_j(k-1)P_{1j} + \pi_j(k-1)P_{2j} \tag{5}$$

As a result, the recursive formula for calculating the state probability one by one can be used to determine whether the player holds a momentum advantage at the kth moment based on the obtained probability, i.e., to realize the prediction of the state of the momentum value at the next time step based on the current feature value.

The prediction result of the Markov model is added as a feature to the original dataset and input to the MLP model for subsequent training and prediction.

2.2.2 MLP Model

Multi-Layer Perceptron (MLP) [9] is a feed-forward neural network consisting of multiple neurons, which organizes neurons by layers, connects network layers in a unidirectional loop-free fully connected manner, and optimizes the network weight parameters by minimizing a loss function, which provides powerful data representation and learning capabilities. Since MLP has a nonlinear activation function and a multilayer structure, it can capture nonlinear relationships well and thus perform complex feature extraction and has great advantages in nonlinear fitting. Therefore, an MLP model is built for regression fitting and prediction. The model framework is shown in Figure 1.

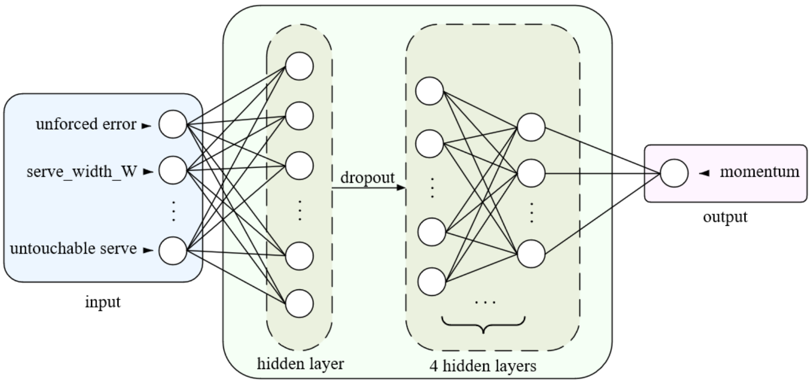


Figure 1. The architecture of MLP

The output of the neuron in the fully connected layer of the MLP model can be expressed as:

$$x_j^i = \varphi \cdot \left(\sum_{k=1}^{N_{i-1}} w_{j,k}^i x_k^{i-1} + b_j^i \right) \tag{6}$$

where, φ is the nonlinear activation function ReLU, N_{i-1} is the number of neurons in the layer $i-1$, $w_{j,k}^i$ is the weight between the neuron in layer i and the k th neuron in the layer $i-1$, x_k^{i-1} is the output of the neuron in the layer $i-1$, b_j^i is the bias term for the neuron in layer i.

2.3. Interpretability Analysis Incorporating SHAP Methods

Shaply Additive Explanations (SHAP) is a method for interpreting the prediction results of machine learning models based on cooperative game theory proposed by Lundberg et al.[10] The SHAP method calculates the SHAP value of each feature by combining and arranging different subsets of features in order to explain the effect of the value taken for that feature on the prediction. Therefore, the SHAP value can also be considered as a kind of average contribution of a feature.

For sample x_i, the SHAP value of its j th feature x_{ij} obeys the following equation:

$$\hat{y}_i = f_0 + \sum_{j=1}^{N} f_{ij} \tag{7}$$

where $\hat{y}_i$ is the predicted value of the i th sample, f_0 is the predicted mean value of all samples, and f_{ij} is the SHAP value for x_{ij}.

Distinguished from the coefficient interpretation of simple regression models, the SHAP method provides a new method of feature interpretation, which can reflect the importance of features in the model and the positivity or negativity of their effects, and enhance the interpretability of the model.

3. Results

The match data of Wimbledon 2023 Gentlemen's Singles was selected, including the match scores and the characteristics of each technical action. The 31 matches involved in this dataset were firstly divided according to the number of matches, and then data preprocessing was carried out to quantitatively represent the technical action indexes.

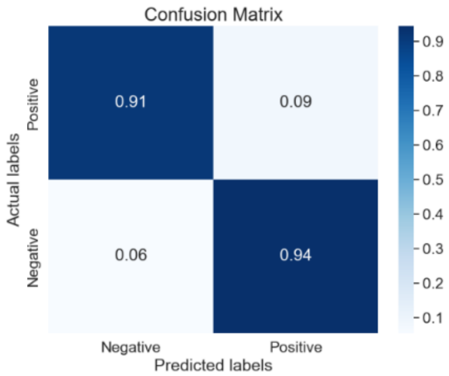
The MLP model is trained from the above dataset, and the constructed MLP consists of a total of six network layers, which are one input layer, four hidden layers, and one output layer. Specifically, the input processed 38 features and output regression function after 30 times of training are used as neurons in the output layer. For the four hidden layers, since the supplied data are positive and it is not possible to determine whether the regression function is linear or not, the nonlinear activation function Rectified Linear Unit is chosen to realize nonlinear learning. Among them, a Dropout layer is added between the first and second hidden layers to randomly reduce the weights of some neurons to prevent overfitting.

Ten-fold cross-validation is used to test the performance of the momentum prediction model, the prediction results of the MLP are divided into 10 groups, and the data of each group is used as the test set in turn, so as to obtain 10 models for repeated experiments, and the obtained MSE is shown in Table 2. After the model training and parameter tuning, the obtained average MSE reaches 3.4442.

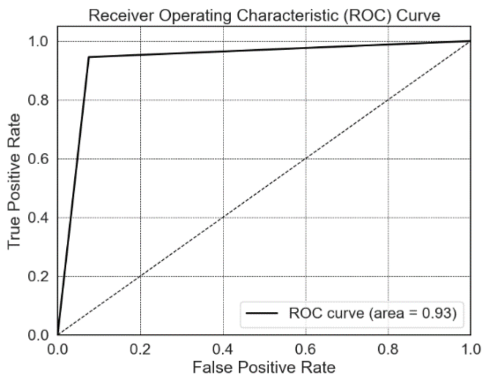
Table.2. MSE coefficient table

MSE1	MSE2	MSE3	MSE4	MSE5	MSE6	MSE7	MSE8	MSE9	MSE10
2.9998	3.5987	3.2552	3.4525	3.9853	3.7551	3.8467	3.8490	3.3353	2.3641

Considering the model's classification of whether or not the momentum is dominant, its classification accuracy reaches 98%, and the confusion matrix and ROC curve are plotted in Figure 2. The experiment shows that the model possesses a good recognition of the target samples, and the AUC reaches 93%.



Confusion matrix of momentum prediction MLP model



ROC curve of momentum prediction MLP model

Figure 2. Classification results of momentum prediction MLP model

Interpretation of the prediction results by the SHAP method, three important indicators are the current score, whether it is the serving side, and whether it is in a tie-break. Considering the above indicators and the Markov characteristics, the kernel density plot of the categorized data is shown in Figure 3. Since the score of the two sides is equal or not in a tie-break in the actual game is more common, the kernel density plot overlaps to a certain extent at 0. However, the tail distribution and the data extreme can be found that there is a significant difference between the two types of data. tail distribution and data extremes, it can be found that there are obvious differences between the two types of data. Taken together, the classification of all four indicators is good, and the two situations of positive and negative athletes show different data characteristics.

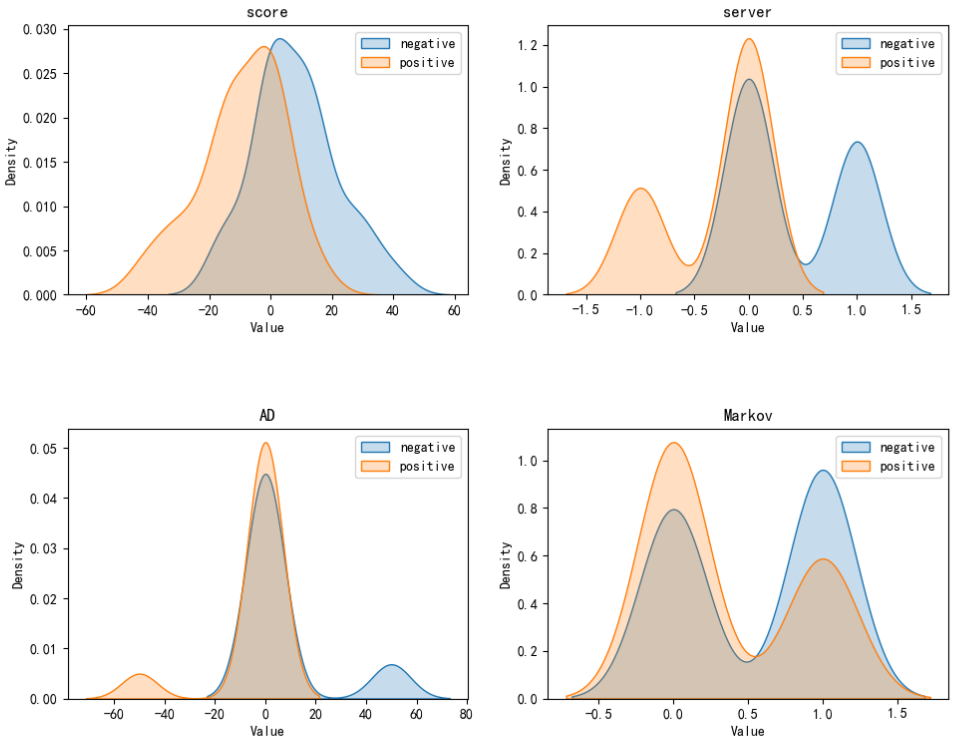


Figure 3. Nuclear density map of important indicators

Such results show strong interpretability. Consider first the indicator of whether it is the serving side. In the course of a tennis match, the serving side can better control the angle of attack as well as determine the speed of the serve, which not only controls the rhythm of the match but also restricts the opponent's return to a certain extent. The two opportunities to serve given by the rules also provide positive psychological hints for the players. Therefore, such a situation will have a positive impact on the player's condition. As for the score, the player who scores more points in a set is usually closer to victory, and he will have a more positive psychological state, which is reflected in a higher momentum value. Since this clear advantage lasts for at least one game, it is not a turning point in the course of the match. If the score is tied or in a tie-break, a player wins a key match, such a moment may be a point of momentum shift. The indicator of an Advantage game is extremely important for the fight for the advantageous points, which not only determines the final winner of the authorities' game but can also lead to a stalemate due to errors of both players.

4. Conclusions

This paper examines momentum changes in athletes during competition and the important factors that influence their form. The aim is to reveal underlying patterns in the game and provide a technical basis for analyzing the course of the game and guiding future athlete training. First, relevant match indicators were observed and categorized as either process or outcome indicators. Subsequently, the entropy method was applied to the outcome data to describe the athlete's state, quantify the abstract momentum indicators, and propose a momentum assessment model. On the basis of momentum scoring, an MLP prediction model was established by combining process indicators and introducing Markov features. The model is then applied to predict the test set data to analyze the key indicators of situation changes during the match. The evaluation results show that the model has high prediction accuracy, strong generalization ability, and practicality.

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