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Sliding-window Based ARIMA Model for Deviation Value Analysis in Olympic Medal Counts

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Abstract. There are many factors that affect the total number of national medals at the Olympics, and coaching turnover is one of the major factors. Understanding how coaching changes affect athlete performance and national competitiveness is crucial for boosting a country's standing in international tournaments. Machine learning models offer unique advantages in exploring these complex relationships. The purpose of this paper is to explore the evidence for changes in the number of medals caused by coaching turnover based on medal data. Therefore, by applying the sliding window-ARIMA (Autoregressive Integrated Moving Average) model to analyze the historical medal records of specific countries, this study provides empirical evidence supporting the significant influence of great coaches, such as Lang Ping and Béla Károlyi, on athletic performance and medal achievements. Based on the model's findings, Lang Ping significantly elevated the medal - scoring performance of the Chinese women's volleyball team by 2.29 points in 2016 and that of the U.S. women's volleyball team by 1.75 points in 2008. Similarly, Béla Károlyi made a substantial impact, augmenting the medal - scoring performance of the 1976 Romanian gymnastics team by 15.82 points and that of the 1984 U.S. gymnastics team by 14.83 points. Finally, the paper examines specific sports in select countries that could potentially benefit from the recruitment of "great coaches." Examples include sprinting in Jamaica and gymnastics in Romania, among others.

Keywords: sliding window, ARIMA model, Olympic Games, great coach

1. Introduction

As a globally renowned event that captivates the world's attention, the Olympic Games naturally make the final Olympic medal table a topic of enduring interest for people worldwide. To some degree, the Olympic medal table serves as an indicator of a nation's overall sporting prowess and the caliber of its athletes. There are many related studies that are keen on exploring the medal distribution characteristics and the competition pattern of the Olympic Games through the medal table. However, research on coaching remains limited, despite its critical significance in sports. Coaches, especially those in professional sports, have been fundamental to the growth of international professional sports. Their work is essential for optimizing management strategies and tactical arrangements, which in turn strengthen a nation’s competitiveness in international events. The case of renowned Chinese volleyball coach Lang Ping exemplifies the impact of exceptional

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coaching. Leading the Chinese women's volleyball team to victory at the 2016 Rio Olympics, her success can be attributed to her extensive professional experience coaching multiple international teams, including those in Italy, and her global perspective gained from participating in international competitions[1]. The "great coach" effect emerges due to coaches' ability to work with multiple countries, transcending national boundaries. This phenomenon is characterized by coaches guiding different nations at various times and facilitating significant breakthroughs in their sports' medal standings. For instance, Lang Ping's coaching tenures with the U.S. and Chinese volleyball teams resulted in medal - winning performances for both sides. Similarly, Béla Károlyi achieved remarkable success by coaching the Romanian and U.S. women's gymnastics teams, propelling them to outstanding results in international competitions.

Machine learning models, particularly the ARIMA model, exhibit notable advantages in analyzing time - series data, such as the number of Olympic medals. For instance, Xin et al.applied the ARIMA model to analyze the athletic performance of NBA player Jeremy Lin, thereby validating the feasibility of using time - series analysis for sports performance data[2]. Additionally, Chen leveraged the ARIMA model to conduct outlier detection in water usage data, demonstrating its versatility across different domains[3]. Meanwhile, Qin et al.proposed a novel approach integrating a sliding window technique with a weighted scoring algorithm for player re-identification, which effectively preserves image continuity and enhances the discriminative ability of local features[4].

This paper proposes a novel methodology by integrating a sliding window technique with an ARIMA model, aiming to investigate the impact of coaching turnover on a country's medal performance at the Olympics. In the research process, the study first quantifies the medal achievements of national sports programs, deriving a time series of historical medal scores. By applying the Sliding Window - ARIMA Time Series Prediction Model, it analyzes the deviations in medal scores during the year when a new coach is appointed, thereby quantifying the coach's impact. This model can identify abnormal time points in medal score fluctuations, enabling the validation of the "great coach" effect through historical comparisons. Such analysis not only facilitates the further quantification of coaching influence on medal counts but also treats the abnormal points in other years as valuable data for exploring underlying causes. Additionally, by examining historical deviation data, the study can determine which countries might benefit from recruiting "great coaches" in specific sports events, aiming to offer insights and references for Olympic-related research and practices.

2. Data and methodology

2.1. Data sources

The dataset utilized in this paper is sourced from the official website of the Olympic Committee. It encompasses the historical medal achievements of various countries across different sports, ensuring a substantial sample size. In the data preprocessing phase, the study first conducted data cleaning by removing blank characters and employed interpolation methods to address missing values. Additionally, data integration was achieved by standardizing country names; for instance, the Russian delegation competed under the neutral status of ROC (Russian Olympic Committee) in the 2024 Olympics.

Given that this paper focuses on coaches Lang Ping and Béla Károlyi, data were extracted from four specific sports programs: the U.S. Women's Volleyball Team, the Chinese Women's Volleyball Team, the U.S. Gymnastics Team, and the Romanian Gymnastics Team. The data for the Chinese

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and U.S. women's volleyball teams spanned the years 1960 - 2024, covering 17 Olympic Games. For Romanian gymnastics, data from 1932 - 2024 were selected, encompassing 24 Olympic Games, while the U.S. Gymnastics data ranged from 1936 - 2024, covering 23 Olympic Games. Since volleyball is a team - based sport, annual medal outcomes were categorized into four groups: Gold, Silver, Bronze, and No medal, and were quantitatively scored as 3, 2, 1, and 0 points, respectively. The total score was then calculated by using Formula 1. In contrast, for gymnastics, which includes both individual and team events, scores for each component were computed separately and subsequently aggregated to determine the overall total score. Table 1 presents a partial illustration of the U.S. gymnastics team's medal records.

$$score = 3*G + 2*S + 1*B \tag{1}$$

Table 1: Examples of U.S. gymnastics awards (partial) (team + individual)

YEAR	SCORE
2012	12
2016	21
2020	12
2024	15

2.2. Model overview

2.2.1. Sliding-window model

The sliding window model involves a window of either fixed or variable size applied to a data series. When analyzing Olympic medal counts, this window traverses the time-series data of historical medal counts sequentially, advancing by a predetermined step size at each iteration. During this iterative progression, targeted calculations and analyses are conducted on the data points encapsulated within each window. As depicted in Figure 1, a visual representation of the sliding window's movement over the medal score sequence is provided.

The sliding window approach is engineered to optimize the extraction of critical information, demonstrating particular efficacy in identifying short-term anomalies within medal scores. Given a time-series of annual medal scores D with a length of L, a window size of w, and a step size of s, the series can be segmented into N distinct blocks. The value of N can be approximated using the following formula:

$$N = \left\lceil \frac{L-w}{s} \right\rceil + 1 \tag{2}$$

Where: $\lceil x \rceil$ denotes the upward rounding function.

The window size w refers to the number of data points contained in the window. The choice of window size is crucial when studying the number of Olympic medals. If the window is chosen too small, the amount of data included is small, which may not accurately reflect the overall characteristics and trends of the data, leading to misjudgment of the “great coach” effect; if the window is chosen too large, the model may include too much outdated information, making the model not responsive enough to recent changes. The sliding step size s determines how far the window moves each time. The step size is usually 1, but it can be adjusted according to the actual

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situation. With a step size of 1, the window moves one data point at a time, capturing changes in the data in detail. Based on the initial window starting from the beginning of the sequence and then moving the step length s each time, for each window Wi (where $1 \leq i \leq N$) can be expressed as:

$$W_i = D[(i-1)*s \ : \min((i-1)*s, L) \tag{3}$$

Where: the $\min()$ function is used to ensure that the last window does not exceed the length of the data sequence D.

By integrating the aforementioned two formulas[5], a comprehensive framework is established for decomposing the medal score data sequence D into a sequence of windows W and computing the contents of each individual window. Moreover, when dealing with dynamic window sizes and step sizes, these formulas can be appropriately adjusted to accommodate such variations, ensuring the model's adaptability to changing data characteristics. In this study, to streamline subsequent calculations and analysis, the sliding window size was configured as the equivalent of 8 Olympic Games cycles, while the sliding step size was set to progress by 1 Olympic Games cycle at each iteration.

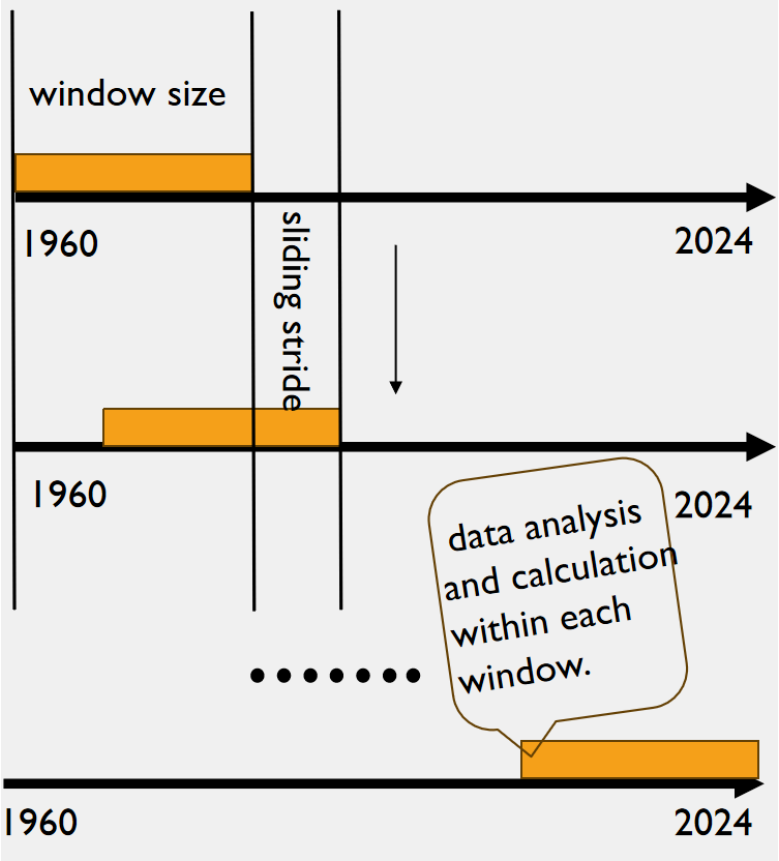

Figure1: Sliding window schematic

2.2.2. ARIMA model

The ARIMA model is a highly recognized time-series model. It primarily conducts linear regression analysis, leveraging the relationships within historical data series over time to forecast future changes in the target variable [6]. Notably, ARIMA is not a single, specific model but rather an

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umbrella term encompassing a family of models. Its configuration is typically defined by three key parameters: the autoregressive order p, the integration order d, and the moving average order q, represented as ARIMA(p,d,q). This model is composed of three fundamental components: the autoregressive model (AR), the integration model (I), and the moving average model (MA), each playing a distinct role in the overall modeling process.

(1) Autoregressive model（AR）

$$y_t = c + \sum_{i=1}^{p} \phi_i y_{t-i} + \epsilon_t \tag{4}$$

Autoregression relies on the linear relationship between the current and past values of a time series, utilizing historical values to forecast the present value.

Where: y_t denotes the observed value of the time series at time t; ϕ_i denotes the autoregressive coefficient; ϵ_t denotes the white noise error term; c denotes the constant term.

(2) Integration model（I）

$$\nabla^d y_t = \nabla \left(\nabla^{d-1} y_t \right) \tag{5}$$

The integration operation is to transform the non-smooth time series into a smooth series, so that the statistical characteristics of the data are stable for subsequent analysis.

Where: d denotes the difference order.

(3) moving average model（MA）

$$y_t = c + \epsilon_t + \sum_{i=1}^{q} \theta_i \epsilon_{t-i} \tag{6}$$

The moving average (MA) component of the ARIMA model capitalizes on the correlation among error terms. It works by characterizing the current error using past errors, thereby refining the predicted values.

Where: θ_i denotes the moving average coefficient.

The ARIMA model excels at extracting linear information from data and offers robust predictions regarding the autocorrelation and seasonality of time series. However, its performance in long - term forecasting of time - series data leaves much to be desired [7]. In this study, the sliding window technique is integrated with the ARIMA model. Specifically, the ARIMA model is employed for short - term prediction within each sliding window, a strategy that significantly reduces prediction errors. Simultaneously, considering the limited volume of data within each window, the differencing order d of the ARIMA model should be kept in check. A disproportionately large d value may lead to excessive fluctuations in the predicted results [8].

2.3. Research process

Figure 2 illustrates the comprehensive research workflow, spanning from data preprocessing to the validation of the "great coach" effect. Following the acquisition of the medal score sequence through data processing, a predefined sliding window model is applied at the start of the sequence. In this study, within each window, predictions are made to forecast the number of medals in the subsequent period of that window. The deviation values are then calculated by subtracting the predicted values from the actual ones. As the window traverses along the sequence, deviation values for all years are computed and visualized. A positive deviation value indicates a positive impact on medal performance in that year.

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Simultaneously, a threshold is established. If the absolute value of the deviation in a given year exceeds this threshold, the data point is flagged as an outlier. When a coach assumes responsibility in a particular year, and the corresponding deviation value is both positive and surpasses the threshold, it provides substantial evidence for the presence of the "great coach" effect. Moreover, the magnitude of the deviation value quantifies the extent of the coach's influence. The remaining outliers can serve as valuable data points, prompting further exploration into the underlying contributing factors.

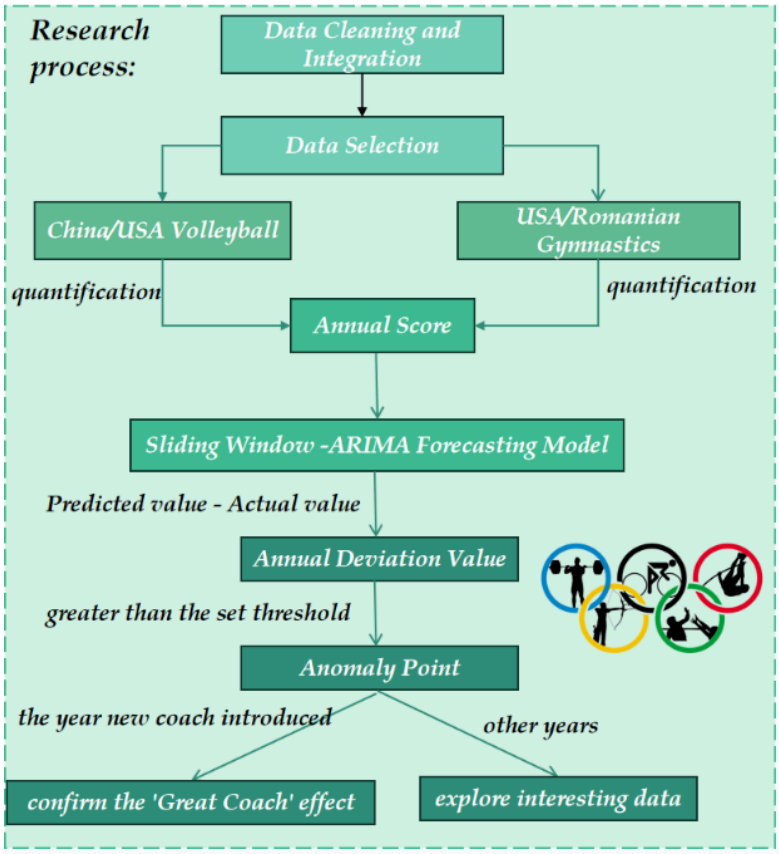

Figure 2: Process diagram of the research flow

3. Analysis of results

This study examines the "great coach" effect through the cases of Lang Ping and Béla Károlyi. For the volleyball teams coached by Lang Ping, the outlier judgment threshold was set at 1.5 points. In the context of volleyball, this threshold lies between the point values assigned to a silver and a bronze medal. Regarding the gymnastics teams coached by Károlyi, the outlier threshold was established at 10 points. For a team - based sport like gymnastics, this value is equivalent to the combined points of three gold medals and one bronze medal.

The accompanying charts depict the year-on-year deviation of the medal counts for each program. A negative deviation indicates that the actual medal score fell short of the predicted score, suggesting a subpar performance by the team in that year. Conversely, a positive deviation implies that the team outperformed expectations. The following section presents a detailed analysis of the study's findings:

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3.1. Lang Ping

3.1.1. Lang Ping coaches the U.S. women's volleyball team

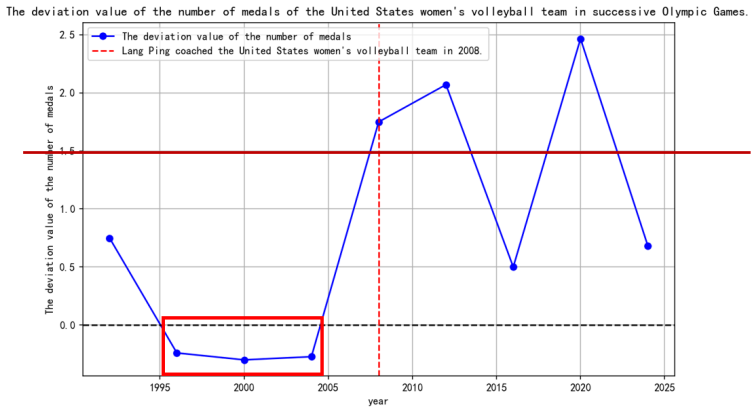

Figure 3: Yearly medal deviation of U.S. women's volleyball team under Lang Ping's coaching

Figure 3 illustrates the annual medal deviation values of the U.S. women's volleyball team during Lang Ping's tenure as coach. The figure 3 reveals that the team underperformed in the 1996, 2000, and 2004 Olympic Games, as evidenced by negative medal-score deviations. However, following Lang Ping's appointment in 2008, a notable positive shift emerged, strongly validating the "great coach" effect.

Notably, 2020 marked another high point for the U.S. women's volleyball team in terms of medal scores. This success can be largely attributed to the legendary coach Karch Kiraly. In 2020, Kiraly revamped the team's traditional offensive approach, introducing a novel "dual-core drive + three-dimensional attack-and-defense" tactical system. The implementation of this innovative strategy significantly enhanced the team's overall strength and tactical versatility. As a result, the U.S. women's volleyball team elevated its competitive level, demonstrated renewed prowess in matches, and emerged as a formidable championship contender.

3.1.2. Lang Ping coaches the Chinese women's volleyball team



Figure 4: Yearly medal deviation of Chinese women's volleyball team under Lang Ping's coaching

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Figure 4 illustrates the annual medal deviation values during Lang Ping's tenure as the coach of the Chinese women's volleyball team. The figure 4 reveals the presence of three outlier years where the deviation values exceeded the established threshold, with two of these instances directly attributable to Lang Ping's coaching influence. In 1996, the team secured a silver medal, marking the Chinese women's volleyball team's first Olympic medal in twelve years. Lang Ping's strategic approach involved comprehensive team integration and intensive training, which significantly enhanced the team's combat capabilities. Under her guidance, the team executed rapid and versatile tactics, demonstrating exceptional defensive prowess during matches. These strategic adjustments and improvements in on - court performance were pivotal in achieving remarkable results and contributing to the observed medal deviation outliers.

In 2004, the Chinese women's volleyball team reached the zenith of its strength. The emergence of numerous outstanding players during that period firmly established the team's dominance in international competitions. With a deviation value of +2.29, the team achieved an unprecedented high. In contrast, the teams in 2008 and 2012 failed to replicate such success. Notably, the team failed to secure any medals in 2012, resulting in a negative deviation value in the model. This was primarily attributed to the team being in a transitional phase between generations. The young players required time to mature and accumulate experience, leading to inconsistent performances in crucial matches.

The turning point came in 2016 at the Rio Olympics when Lang Ping resumed her coaching role. Under her leadership, the Chinese women's volleyball team claimed the gold medal, marking a triumphant return to Olympic glory after a twelve-year hiatus. The team demonstrated remarkable cohesion and tenacity in the face of adversity. Young talents were steadily developing, and core players like Zhu Ting delivered exceptional performances. Additionally, following Lang Ping's guidance, the team's secondary attackers employed a more balanced range of tactics, ensuring a consistent scoring rate[9].

However, the 2020 Tokyo Olympics presented a different narrative. The team's performance suffered due to a confluence of challenges, including the impact of the pandemic, injured attackers, and adjustments to the tactical system.

3.2. Béla Károlyi

3.2.1. Károlyi coaches Romanian gymnastics team

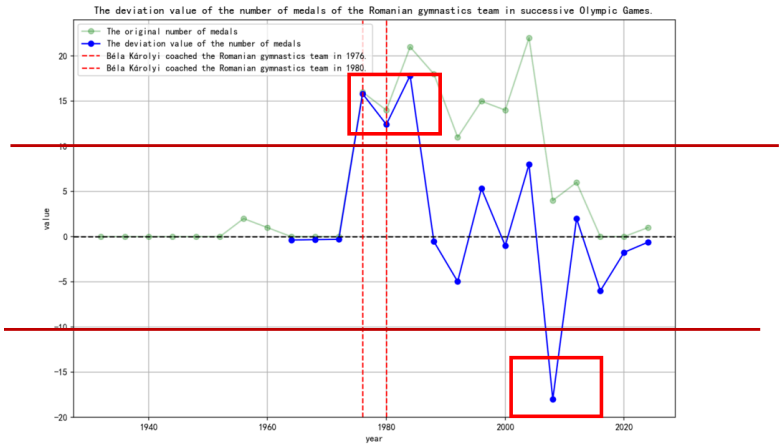

Figure 5: Yearly medal deviation of romanian gymnastics team under Béla Károlyi's coaching

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Figure 5 depicts the annual medal deviation values during Béla Károlyi's tenure as the coach of the Romanian gymnastics team. In the graph, the green line represents the original medal scores, while the blue line indicates the medal deviation values.

The graph reveals that prior to 1976, the Romanian gymnastics team had limited success in medal acquisition. However, the 1976 Montreal Olympics marked a transformative moment, as 14-year-old Nadia Comăneci stunned the world by scoring seven perfect 10s. This extraordinary achievement was inextricably linked to the innovative training methodologies implemented by coach Béla Károlyi. By introducing strength training regimens, focusing on mental toughness development, and pioneering choreographic innovations, such as integrating dance elements into free gymnastics routines, Károlyi elevated the artistic competitiveness of Romanian gymnasts. These efforts culminated in remarkable success at the 1976 and 1980 Olympics, with deviation values surpassing the established thresholds and propelling Romanian gymnastics into a period of unprecedented dominance.

Nonetheless, in 1981, Károlyi defected to the United States, taking his core training system with him and significantly contributing to the ascendancy of American gymnastics. As the 21st century unfolded, the once - glorious Romanian gymnastics dynasty entered a period of decline. In 2008, the team managed to secure only two silver and one bronze medal, registering its worst performance to date, with a deviation value of -18 points, well beyond the threshold. This decline can be attributed to multiple factors, including political upheavals that resulted in substantial cuts to the sports budget, a dearth of local talent development, and the loss of experienced coaches.

3.2.2. Károlyi coaches U.S. gymnastics team

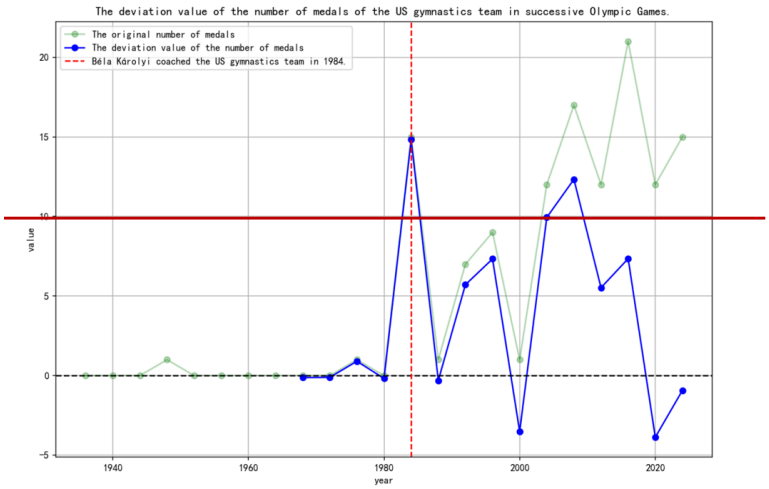

Figure 6: Yearly medal deviation of the U.S. gymnastics team under Béla Károlyi's coaching

Figure 6 illustrates the annual medal deviation values during Béla Károlyi's coaching tenure of the U.S. Gymnastics team. After relocating to the United States in 1981, Károlyi rapidly made a name for himself in the gymnastics community. His impact was immediately evident when he mentored Mary Lou Retton to secure the women's individual all - around gold medal at the 1984 Los Angeles Olympics. Additionally, he nurtured Julianna McNamara, who triumphed in the uneven bars event at the same Games.

Prior to Károlyi's arrival, the U.S. gymnastics team had a minimal presence on the Olympic medal podium. In 1984, the deviation value soared to +15 points, signifying the equivalent of five

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additional gold medals. This remarkable achievement represented a revolutionary turning point for U.S. gymnastics.

Since the onset of the 21st century, while there have been minor fluctuations in medal scores, the overall trajectory has been decidedly upward. Through the combined efforts of Béla Károlyi and his wife, Marta, the U.S. women's gymnastics team blossomed into a dominant force in the international gymnastics arena. Their hard work culminated in the team clinching gold medals at both the 2012 and 2016 Olympic Games.

Table 2 provides a comprehensive summary of the data findings. In this study, the influence of coaching is systematically quantified by analyzing the achievements of renowned coaches Lang Ping and Béla Károlyi. Through this analytical approach, the "great coach" effect is not only empirically validated but also offers a deeper understanding of the transformative role coaches play in athletic performance. Additionally, the study delves into the underlying factors contributing to the remaining outliers, uncovering intriguing insights that warrant further exploration.

Table 2: Medal impact of different coaches with different coaching periods

Coach	Time	Deviation value
Lang Ping	1996 China Women's Volleyball	1.56
Lang Ping	2008 U.S. Women's Volleyball	1.75
Lang Ping	2016 China Women's Volleyball	2.29
Béla Károlyi	1976 Romanian Gymnastics	15.82
Béla Károlyi	1984 U.S. Gymnastics	14.83

4. Discussion/recommendations

4.1. Programs that could introduce “great coaches”

The above study uses a sliding window-ARIMA time series model to quantitatively analyze the positive impact of two "great coaches" on medal counts. The model reveals the annual medal deviation values of specific countries' sports programs, showing that some traditionally strong programs have exhibited high positive deviation values historically but experienced a gradual shift to negative values in recent years, indicating declining performance. For such programs, introducing "great coaches" to optimize tactical systems, enhance management practices, and inject new vitality into athlete teams could be a viable strategy. Table 3 presents the recent medal deviation values for these sports.

Table 3: Traditionally strong sports programs with recent underperformance

Project	2008 deviation	2008 deviation	2008 deviation	2008 deviation	2008 deviation
Romanian Gymnastics	-18	2	-6	-1.74	-0.62
Jamaican sprint	10.64	11	-4	-7	-14
Bulgarian Wrestling	-2	-3	-4.86	0.12	4.88

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4.2. Limitations and improvements

4.2.1. Complexity of influencing factors

Changes in medal counts result from a confluence of factors rather than relying solely on coaching. Improvements in athletes' capabilities, advancements in training techniques, and other variables may all influence medal outcomes. Analyzing only medal count deviations during a coach's tenure risks overestimating or underestimating the "great coach" effect while overlooking other critical factors.

To address this, the corresponding solution is to establish a multidimensional comprehensive evaluation system that holistically measures factors affecting medal counts. For instance, elements such as athlete strength, tactical arrangements, and technological support can be quantified and assigned weights based on their importance to calculate a composite score. This approach employs multiple linear regression, comparing changes in the composite score before and after a coach's appointment to more comprehensively assess their impact. By integrating diverse variables, this method provides a more objective and complete evaluation of coaching contributions.

4.2.2. Accuracy of predictive models

The accuracy of predicting medal counts for the next Olympic Games directly influences the reliability of deviation values. If the prediction model is overly simplistic and fails to account for the complexity and uncertainty of time-series data, or if the dataset is too small, issues such as overfitting may arise. To address this, more sophisticated machine learning models can be employed to capture nonlinear relationships and complex patterns in the data.

Notably, deep learning methods have demonstrated superior performance in multivariate time-series prediction compared to traditional machine learning approaches[10]. Their strong capability to identify intricate patterns and learn nonlinear relationships within datasets makes them well-suited for enhancing the accuracy of medal count predictions and, consequently, the validity of deviation value analyses.

5. Conclusion

The objective of this study is to analyze quantized medal score sequences to identify anomalies and validate the "great coach" effect. This paper proposes a hybrid sliding window-ARIMA time series prediction model, which calculates annual deviation values (actual value - predicted value) through sliding window movement and ARIMA time model computations. These deviation values help reveal scoring sequence anomalies and confirm the impact of "great coaches" when introduced.

Using Lang Ping and Béla Károlyi as case studies, the research explores the influence of "great coaches." Results confirm that both coaches had a significant positive impact on the national programs they led. Additionally, by examining deviation values across multiple programs over the years, this paper identifies other programs that may benefit from introducing new coaches, aiming to provide insights for Olympic-related disciplines.

Finally, the study highlights limitations of the existing model in terms of influencing factors and prediction accuracy, suggesting the integration of multiple linear regression to develop a comprehensive model evaluation system that accounts for diverse variables. This approach seeks to enhance the model’s comprehensiveness and analytical depth.

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