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Abstract

In the realm of competitive sports, few events captivate the world's attention like a high-stakes tennis match. The atmosphere crackles with anticipation as two athletes step onto the hallowed grass courts of Wimbledon, ready to engage in a battle of skill, endurance, and mental fortitude. It is within these intense exchanges that the elusive concept of momentum reveals itself, dictating the ebb and flow of the game, and often defying logic and expectations.

As we analyze the extraordinary twists and turns of this monumental clash, one term lingers in our minds: momentum. This intangible force, described as the "strength or force gained by motion or a series of events," is often attributed to the shifts in a player's performance during a match. But can it truly be quantified and understood? Can we decipher the underlying factors that give rise to these remarkable momentum swings and predict their occurrence?

In this study, we aim to develop a deeper understanding of momentum in tennis through quantitative modeling and analysis, embarking on a quest to unravel the mysteries of momentum in tennis. Leveraging a comprehensive dataset from the Wimbledon 2023 Men's Doubles matches, we seek to build a predictive model that can track the ebb and flow of a match in real-time. Specifically, the model aims to identify which player is performing better at any given moment and quantify the extent of their advantage, two objectives that touch on the nebulous concept of momentum. In bringing numerical rigor to bear on momentum, this study also aims to transform an intuitive yet elusive concept into actionable intelligence. The findings seek to offer fresh analytical and strategic insights into the finer points of match play dynamics.

To achieve these goals, we implement logistic regression due to its interpretable, binary and intuitive nature. Innovative dimensionality reduction techniques, the notions of win factors, performance metrics, marks, and feature weights, are also explored to accelerate model fitting and are designed to condense the input space while preserving predictive power. By representing momentum as a concrete variable output rather than an abstract phenomenon, our approach allows the shifting tides of a match to be measured objectively. Performance and Momentum successfully predicted the switch in Alcaraz and Djokovic's final competitions. This has meaningful practical applications, enabling players and coaches to formally assess advantages in real-time.

Furthermore, we explore the claims of skeptics who argue that these swings in play are merely random occurrences, by comparing model predictions to random point outcomes, we're more than 99% sure momentum is not random. Besides, we endeavor to equip coaches with valuable indicators that foreshadow shifts in the flow of play: Players should focus more on playing games as a receiver, higher frequency of attacking as a receiver will lead to momentum drop while controlling the competitor will lead to momentum increase.

The momentum model, which was trained exclusively on the initial Wimbledon data, made predictions for each external match without any further updating of its learned weights. The accuracy of these predictions versus actual outcomes showed the degree to which the parameterized relationships generalized. This helped validate that the key determinants of dynamic advantages our model identified could transfer beyond a single tournament.

While further refinement may be possible, the success in predicting shifting momentum across tournaments is an encouraging step toward demystifying this elusive phenomenon. Advice are given towards our analysis in the process, by transforming momentum into a measurable parameter, players and coaches can make strategic adjustments informed by data-driven insights into the fluctuating tides that dictate victory or defeat.

Contents

1 Introduction

Tennis is a highly dynamic and competitive sport where the flow of play can significantly impact a player's performance and the outcome of a match. Coaches and players alike are constantly seeking ways to understand and predict these momentum shifts to gain a strategic advantage. In this report, we aim to develop a model that captures the flow of play in Wimbledon 2023 men's matches, assess the role of momentum, and provide insights to coaches on how to respond to events that impact the match's flow.

To accomplish this, models are developed to:

- Identify which player is performing better at any given time.
- Predict swings in momentum from one player to another.
- Test the generalizability of the models on other matches.

It is hoped that the data-driven modeling approach proposed here provides coaches and players with analytical tools to identify advantageous moments as well as turning points where adjustments may be needed. The results also further scientific understanding of momentum and competitiveness in one of the world's most prestigious tennis tournaments.

1.1 Problem Background

The concept of momentum in tennis suggests that a player who is performing well and winning consecutive points or games is likely to continue their success, while the opponent may struggle to regain their footing. Coaches and players often try to identify indicators or patterns that signal a change in momentum, enabling them to adapt their strategies accordingly.

To start a match, a coin is tossed to determine who serves first or chooses which side of the court to play on. The server stands behind the baseline and hits the ball over the net into the diagonally opposite service area on one bounce. A valid serve must land inbounds within this area. Players get two chances per point to get the serve in, otherwise it's a fault. Stepping over the baseline or missing the service area results in a re-serve. Once the serve is returned, a rally ensues with players hitting the ball back and forth. Points are scored if a shot lands before the first bounce or after one bounce only. Players must wait for the ball to cross the net on their side of the court.[1]

Games are won by being the first to four points, except when scores reach deuce (40-40) which triggers a point-by-point play. Sets are won by six games except in tiebreakers which occur at six games all. Matches are best of three sets for most events or best of five for Grand Slams. A variety of shots like forehands, backhands, lobs, slices and smashes are employed to maneuver opponents around the court. Consistent serves and returns are key to putting pressure on opponents. Advanced skills like volleying and overheads near the net also influence match outcomes.

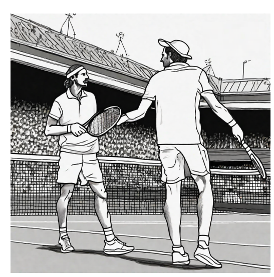

Figure 1: Players on Court

In tennis matches, it is traditionally believed that ”momentum” or being ”in the groove” would impact the match outcome. But this claim lacks statistical and data support. Some tennis coaches are skeptical about it and think the periods when one player dominates in a tennis match is actually random. In that case, they would love to know if there are any indicators that can predict when the flow of play in a tennis match may shift from favoring one player to the other. This is important for both coaches and players.

Wimbledon provides data for every single point played in men's singles matches after the third round, which provides a valuable sample for research. Using statistical modeling and data analysis methods can provide more compelling quantitative evidence for this debated issue, rather than just subjective experiences. If factors and indicators for predicting momentum shifts can be identified, it will help coaches develop coping strategies and assist players in adapting to changing situations during matches. The research results are conducive not only for tennis but also other racket sports.

The data provided contains 46 variables, which comprehensively capture the match processes occurring after the first two rounds. Directly applying regression approaches to problems with such high dimensionality can be inadvisable, as it risks over-fitting and reduced interpretability of results. Dimensionality reduction is a prudent first step to focus the modeling on the most meaningful predictors.

The literature on match-level tennis analytics and expert domain knowledge was consulted to inform the variable selection process[2]. Specifically, correlations between columns were examined to identify representative or composite metrics. Also, variables were assessed for their theoretical relationship to in-match performance dynamics.

Through this analysis, the dataset was distilled into a more parsimonious set of predictors, retaining those most interpretably related to the objectives of profiling competitive balances and momentum shifts over time. The reduced covariate set focuses on key aspects like serving efficacy, break point conversions, recent scoring differentials, and other aggregated attributes demonstrated to strongly associate with scoring outcomes. This preliminary dimensionality reduction prepares a streamlined feature space for subsequent modeling while maintaining integrity of the original data. It allows leveraging of regression techniques like logistic regression and time series analysis by limiting overfitting concerns that could arise with the full variable set.

1.2 Literature Review

> ”Momentum is the positive or negative change in cognition, affect, physiology, and behavior caused by an event or series of events that affects either the perceptions of the competitors or, perhaps, the quality of performance and the outcome of the competition.”

In tennis, the tide can turn quickly and surprise both players and onlookers. Momentum has the power to propel an athlete to great success and lead them to ultimate victory. However, in an instant, that momentum can vanish, allowing the opponent to seize the opportunity and capitalize on the wave of success previously enjoyed by their adversary. While momentum clearly plays a role in tennis matches, scientists have yet to draw definitive conclusions about its effects. The ever-shifting nature of momentum makes it a complex phenomenon to study scientifically.

A study by scientists at the University of Georgia analyzed data from multipleXA Tour events and found that players were more likely to score consecutive points when serving to go up in the match or holding serve to open a game[3]. This suggests momentum can impact an athlete's psychology and performance. However, momentum has also been shown to be difficult to quantify and sustain long-term. As one researcher noted, various on-court variables like weather, ball bounce, and more can influence the flow of a match, making momentum difficult to point to as the sole factor determining outcomes[4]. While momentum appears to play a role, definitive conclusions about its effects have yet to be drawn. As with its onset, the fickle nature of momentum means its influence remains complex to study scientifically. More empirical research is still needed to fully illuminate how momentum psychologically and physically impacts tennis players.

Another study by Lionel [5], investigated the effects of momentum shifts on match outcomes in tennis. The researchers analyzed a dataset of matches from various tournaments and found that momentum swings, characterized by a shift in dominance from one player to another, were often associated with dramatic changes in the final result. The study highlighted the importance of capitalizing on momentum shifts and the potential for a player to regain control even when facing adversity.

Further research is needed to elucidate the complexities of momentum in tennis and its impact on player performance and match outcomes. By gaining a deeper understanding of this phenomenon, coaches and athletes can potentially develop strategies to harness and maintain momentum, ultimately improving their chances of success on the court.

1.3 Our Work

What sets our work apart is our unique approach to measuring player performance by utilizing data over an extended period of time. Unlike traditional methods that focus on short-term performance, we take into account a player's performance and progress over a longer duration. This comprehensive analysis provides a more accurate and holistic understanding of a player's abilities. To measure player performance, we gather and analyze data from various source. By considering performance trends and patterns over an extended period, we can quickly identify strengths, weaknesses, and areas of improvement for each player without any prior knowledge.

In addition to analyzing historical data, we also incorporate real-world scenarios and practical considerations into our evaluations. We understand that tennis is a dynamic sport influenced by numerous factors such as court conditions, opponent strategies, and mental resilience. By simulating and analyzing these scenarios, we provide a more realistic assessment of a player's ability to adapt and perform under different circumstances. Based on this analysis, we provide personalized insights and recommendations to players and coaches. Our goal is to empower athletes with valuable information that can help them enhance their performance, refine their strategies, and make informed decisions during matches.

2 Simplifying Assumptions

From further study and the background1.1 on this topic, we gain these assumptions.

- A player's performance in a match is determined by both how they play as well as how their opponent performs. The performances are fully independent when the players directly interact with each other.
- Key performance metrics like aces, double faults, break points saved/missed are largely independent for each player, as they depend on the individual's serving/returning ability rather than their opponent on that specific point, which are illustrated as in column ['p1_double_default'] to column ['p2_break_pt_missed'] [6].

- The server has a statistical advantage to win a point due to the nature of serving, but their actual likelihood of winning also depends on the opponent's returning ability. The prior potential is deemed equal between players.
- Momentum is affected mainly by a **player's own status**, as well as the ever-changing tide of a match. Long rallies or break chances gained/lost can impact momentum in either direction. Momentum is not independent of serving/returning and interactions between the players. Players can gain confidence from big points won that extends beyond just their own play, while lost opportunities can weigh on both players' momentum in a more interconnected way, frankly speaking:
  - Both players of the match share the same starting momentum.
  - Momentum also does not completely reset between games/sets and can carry over to some degree. During the break of games, player's momentum will get close to the starting point.
- The advantage of the server in winning a point is well-established in tennis[7]. The nature of serving allows the server to dictate the pace and placement of the ball, putting the receiver under pressure. However, it is important to note that the actual likelihood of winning a point also depends on the opponent's returning ability. While the server has a statistical advantage, the opponent's skill and strategy can diminish that advantage.

3 Preparation of the Models

3.1 Data Processing

Comprehensive data preprocessing was performed prior to modeling the Wimbledon 2023 match data[6]. As is standard practice, any typographical errors or logically inconsistent values were investigated and cleared from the dataset to ensure a clean training sample.

The discrete scoring values used in tennis - love, 15, 30, 40, and advantage - were properly mapped to a ordinal integer scale of 0 to 4 to simplify modeling tasks without loss of informational content. This normalization addresses the non-standard scoring nomenclature. Time stamps indicating point start times were also normalized by converting to seconds. This improved the calculation of derived sequential and temporal features over the course of matches.

To augment the dataset for more robust model training, each match was split into two independent player-specific datasets. Each split dataset designated one player as the server for that sample, with all other player designation features set to zero. This doubling of the dataset allowed for model training to be conducted separately for each player, better capturing server vs returner dynamics. It also facilitated the collection of twice as many predictions to evaluate model performance.

Several such derived features capturing historical player performance context were also extracted. These included the relative distance each player ran up to that point, previous point scores, and running point totals/ratios. These higher-level indicators aimed to characterize player fatigue and moment-um trends. After preliminary modeling, less informative features could also be systematically eliminated via regularization and pruning techniques to refine the models.

3.2 Notation

- P Performance, refers to a quantitative measure of how well a player executes their skills on the court.
- P_{win} the probability of wining a game given by logistic regression
- S_{win} refers to the overall percentage of games won as a server, which is a constant calculated by$\frac{\#\ games\ won\ as\ server}{\#\ gameswon}$, with this constant we can diminish the factor caused by serving when given performance to a player
- d_s indicator function, equal to 1 when serving else $\frac{1-S_{win}}{S_{win}}$
- $\vec{M}$ The initial form of momentum, a 1*3 list, as described in 4.2.2
- f_{pp}, the Point_Point Weighted function in 4.2.2
- f_{gg}, d_{gg}, $\vec{m}$ represent the Game vs Game Weighted function described in Section 4.2.2. This function outputs indicators of relative momentum between opponents in a match, where f_{gg} is +1 if the momentum factor for player 1 is greater than the mean momentum $\vec{m}$, and -1 if less than the mean. Specifically: f_{gg} = +1 if $d_{gg} > \vec{m}$, -1 if $d_{gg} < \vec{m}$
- M the momentum extracted from $\vec{M}$, which is a changing value as match goes on.
- M_{12} the momentum difference between $player_1$ and $player_2$.
- T_h the turning point of M_{12} when it reaches its peak.
- T_l the turning point of M_{12} when it reaches its valley.

4 Tennis Momentum Model

4.1 Model Principle

The given rich dataset enables us to analyze various factors that influence match dynamics, including player performance, serving advantage, and momentum swings. By leveraging this data, we can develop a model that identifies the player performing better at a given time in the match and quantifies the extent of their performance advantage.

As per Assumption 2, the predictors included in our model - such as first serve percentage, break point conversions, and recent score differentials - represent independent aspects of player and situational traits. Additionally, the outcome variable encoding which player wins the current point is binary in nature. Given the independence of predictors and binary output, logistic regression is well-suited for this regression problem, which assesses the influence of each factor on point outcome probabilities while controlling for other attributes. Specifically, a logistic regression model was developed to predict the probability a player wins each point based on score situation as well as the past momentum for these reasons.

- The coefficients learned by the logistic regression model directly indicate the influence of each predictor variable on the probability of the outcome (point win/loss). Larger positive or negative coefficients correspond to stronger effects. By examining the coefficients, we can immediately see whether a predictor increases or decreases the log-odds of the outcome and compare the relative impacts of different predictors.

- We can apply the coefficients in the logistic regression formula to easily calculate and compare the predicted probabilities of different outcomes corresponding to different levels of each predictor.

- The logistic regression model will learn the likelihood of one player outperforming their opponent at any juncture based on their relative strengths across key in-match performance indicators. This will provide quantitative insights into how performance advantages emerge and transition over the course of a tennis match.

- Compared to other supervised learning models, logistic regression provides better interpretability, which is crucial for understanding how advantages emerge and shift over a match.

- By modeling each predictor separately, logistic regression allows us to examine the individual contribution of each performance indicator, furthering our understanding of what drives match flow. The predictor variables like serve percentage and break point conversion rate represent independent aspects of player performance and situational traits. Logistic regression assumes predictor independence, aligning with the data properties.

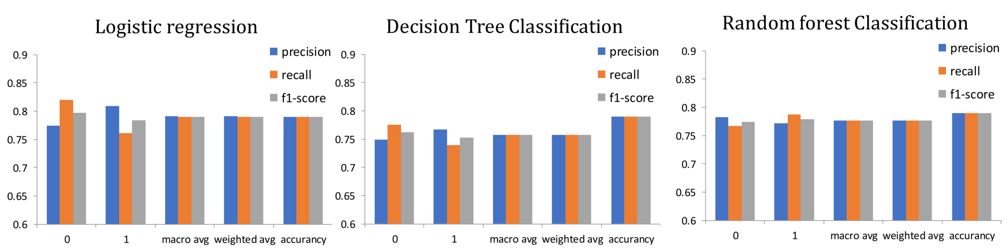

Figure 2: Comparison Between the Three Approaches.

While logistic regression showed promise based on its interpretability advantages, it is worthwhile to evaluate additional models for performance comparisons before making a final selection. Random forests and neural networks are commonly applied to classification problems and warrant consideration here due to their strong predictive capabilities on complex data. Random forests apply ensemble methods to derive relatively interpretable structure from data. Neural networks can capture highly nonlinear relationships through deep representation learning. However, he primary aim is maximizing prediction accuracy to inform analytics and insights. As parsimony is also valued in deployable solutions, the simplest high-performing method may prove most desirable[8]. In that case, logistic regression is chosen to be the main method of this model.

4.2 Model Construction

4.2.1 Performance Representative

In this model, the metric P used to measure a player's performance, denoted as 3.2, is independent of the player's final victory or the opponent they competed against. Therefore, the data used for this model is limited to process-related values, allowing us to score each player and create a profile of their performance.

The 31 games given by dataset[6] is separated as 30 games for training and one game for testing randomly when the model goes through every game. Each regression result is the prediction after training 30 games and test on the left one. This process is repeated for all 31 matches, resulting in a total of 31 regression results analyzed across according points.

Logistic regression is employed to determine the probability of winning a game, which serves as the basic of performance metric. However, due to the limited and almost determined information provided by the dataset, Sometimes the predicted result is polarized, for instance, it produced a probability=99.8% when player shot an untouchable winning shot. or have probability=0.1% when it said that a player missed an opportunity to win a game. To eliminate polarization the scores, a adjusted log function is applied in each subdivision, and the Performance evaluation function is as follow:

$$P = \frac{\sum_{i=i-2}^{i} log(10 * P_{win} * d_s * S_{win} + 1)}{3 * log(10 * S_{win} + 1)} \tag{1}$$

This function increments the variable by one, ensuring a positive value as the final goal. $P_{win} * d_s$ serves as a weight, which help give a higher performance value when a player is served. The denominator is to make sure the ratio is between $[0, 1]$, since the performance still varies greatly, we calculate the mean of the latest 3 games as the current performance of the player.

4.2.2 Momentum Representative

According to the definition of Momentum, it is a "strength or force gained by motion or by a series of events",hence we need to capture the strength showed by player and also use data in the past. To capture its strength, Performance is a good choice. However, other factors, like the ratio of games, are not included in P, to make it more comprehensively, we included another 2 factors that might affect strength, and 3 factors in total:

Current Performance P: as calculated in 4.2.1.

Mark: mark used to express the influence of scores on athletes' psychology, which is mainly composed of two factors.

- The first is the absolute mark. We found that the closer an athlete is to the winning score (7 for games and 3 for sets), the more drastic the momentum change of the athlete. We evaluated the three mark indicators of "sets", "games" and "score", and calculated the absolute mark item as follows:

$$\text{Absolute mark} = 50\% \times (\text{score}/5) + 30\% \times (\text{games}/7) + 20\% \times (\text{sets}/3) \tag{2}$$

- The second is the mark gap between opponents. The rules of tennis match determine that the prerequisite for a player to win is to lead the opponent by two points, so we assume that the two players are evenly matched within two points, and leading by two points or trailing by two points will have a greater impact on the momentum of the players. The mark gap item is calculated as follows:

$$\text{Mark\_gap\_factor} = 10\% * [50\% \times \text{score\_gap} + 30\% \times \text{games\_gap} + 20\% \times \text{sets\_gap}] \tag{3}$$

where gaps are the more than two parts of the difference between two players scores: gap = player1_score − player2_score if player1_score − player2_score > 2

Then mark item can be calculated as Mark = Absolute_mark × (Mark_gap_factor + 1)

Win Factor: Win Factor is designed to reward winning streak and punish losing streak[9], calculated as follows:

$$\text{Win Factor} = 20\% * (60\% \times \text{score win} + 40\% \times \text{games win}) \tag{4}$$

We record the number of winning and losing streaks as a "win" parameter during data processing.

Now we have the initial of Momentum: $\vec{M_i} = [Performance_i, Mark_i, Win\_factor_i]$

$\vec{M}$ is initialized using each factor's mean value, then it was thrown to the flowchart below to capture time series data. Point-Point Weighted function is generated based on Gaussian distribution. Game-Game weighted function imitates the break during games, regressing the momentum to the initial status.

$$f_{pp} = \frac{1}{2\pi} exp\{\frac{(\vec{x}-1)^2}{2}\} * \vec{M} \tag{5}$$

where $\vec{x}$ is a vector that indicate the vertical length of $\vec{M}$. i.e., length=4, then $\vec{x} = [1, 2, 3, 4]$.

$$f_{gg} = m + d_{gg}(1-e)^{|\vec{M}-m|} \tag{6}$$

After processing the initial form of momentum $\vec{M}$, we use the following function to get a stable value of momentum M to explain the psychological changes of athletes.

$$M_i = Performance_i \times Mark_i \times Win\_factor_i + Performance_i + Mark_i + Win\_factor_i \tag{7}$$

We pay attention to the cumulative values of the three factors as well as the cross-terms to obtain a more comprehensive assessment.

4.3 Flowchart

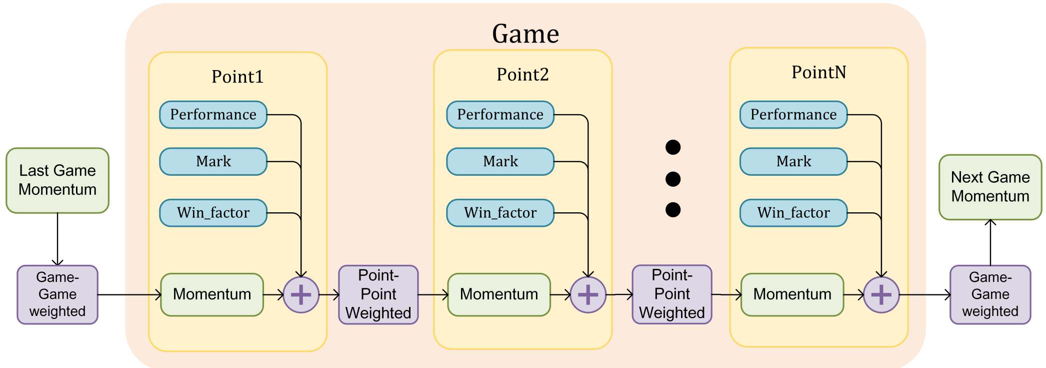

Figure 3: Tennis Momentum Model Flowchart: This flowchart mostly reflects how we can calculate each player's momentum, which is a cumulative amount of time (as opposed to performance, which depends only on a moment in time), We derive a stable value of Momentum by adjusting the three parameters "Performance", "Mark" and "Win_factor" for each moment, as well as the aforementioned "Point-Point" and "Game-Game" weighted method.

4.4 Results Presentation and Discussion

4.4.1 Performance Analysis

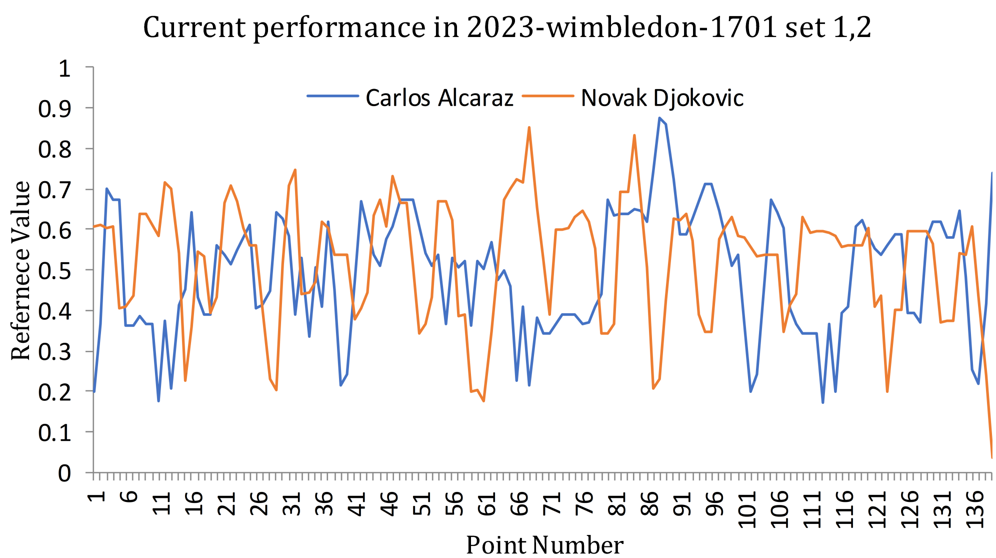

Figure 4: Current Performance: The players performance only relevant to the present moment

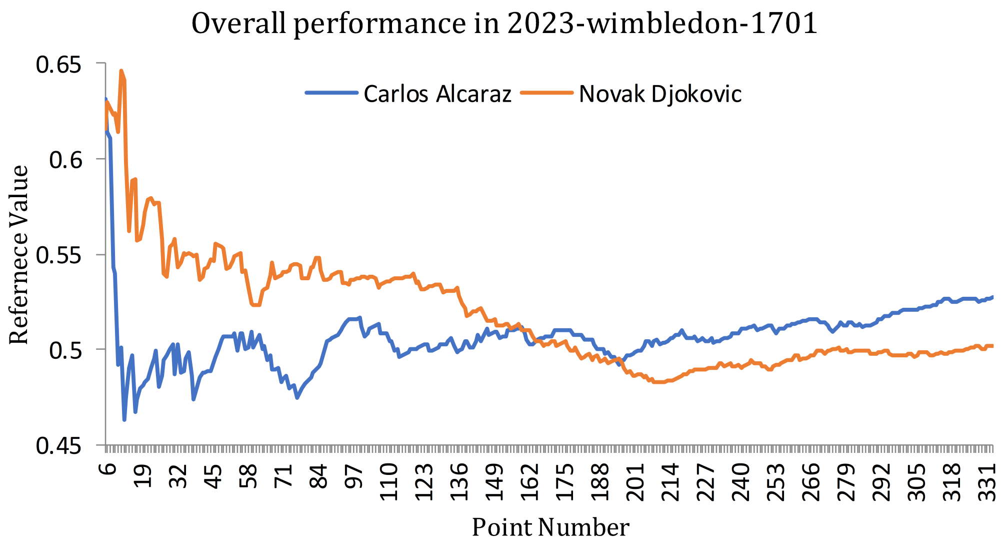

Figure 5: Overall Performance: Combine the players' cumulative performance

4.4.2 Momentum Analysis

As real match shows, Djokovic plays much better at first, having a really good 'momentum', However, as march went on, Alcaraz's momentum seems gradually increase in an unstable way. as shown in Figure 6

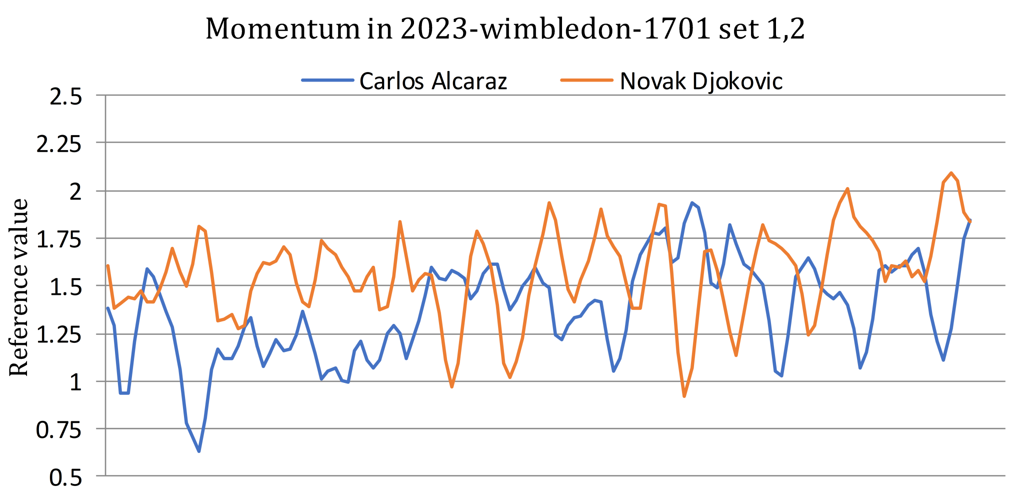

Figure 6: Two player Momentum: This figure reflects the swing of the momentum of the two players, indicating that the two players have a good state at some moments, while the state is poor at other times, providing an indicator for good analysis of the status of the players.
Note: the performance of the last match (Alcaraz : Djokovic), only shows the first half of the match to make it less complex

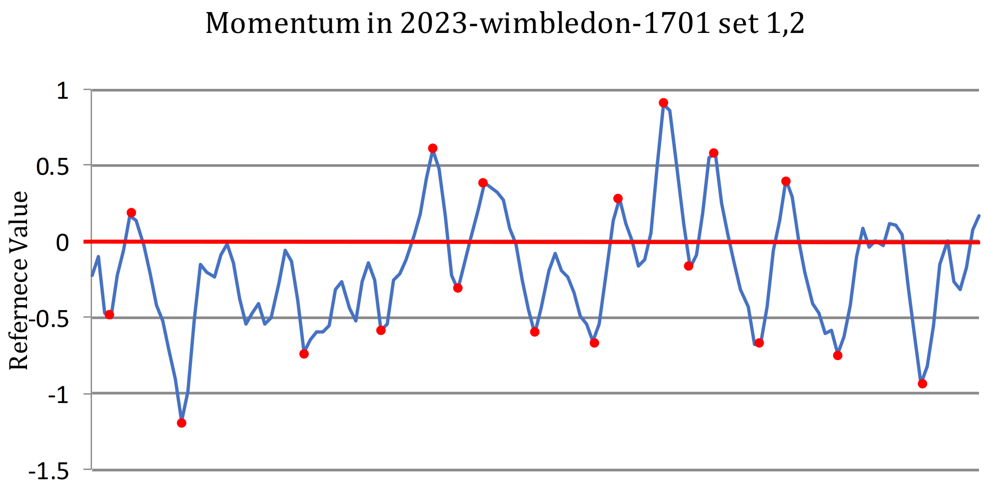

Figure 7: Momentum flow of this match: This indicator comes from the subtraction of momentum between two players, when momentum is above the X-axis we think the first player has more potential to win, and vice versa.

4.5 Is "Momentum" a Random Value?

To test the randomness of momentum, we try to convert our momentum to a distribution, then test whether the distribution of our data is the same to the distribution of random sample, since random sample always follows a same distribution in big dataset.

To make it possible, we first change M to 0-1 data: if $M = 1$, then the player's momentum is higher than the other, similarly, if $M = 0$, the current observing player's momentum is lower. We simplified the data while still preserving momentum's status. given the assumption that the momentum of game is random, the simulated data is produced by outputting 0 and 1 randomly.

To convert momentum and random samples to distribution while preserving the time series information, we applied Run-Length Encoding method, and then data of distributions was generated. Anderson-Darling was applied to test the hypothesis.

The hypotheses for Anderson-Darling test is defined as follows:

- **Null Hypothesis (H0):** The 2 given data follows the same particular probability distribution,
- **Alternative Hypothesis (H1):** 2 data do not have the same probability distribution.

Test Statistic:

$$A^2 = -n - \frac{1}{n}\sum_{i=1}^{n}\left[(2i-1)\left(\ln(F(X_i)) + \ln(1 - F(Y_i))\right)\right] \tag{8}$$

where n is the number in sample size, X_i and Y_i arr the empirical distribution of the 2 sample data.

We set $\alpha = 0.01$ and test the random data (size=100,000) with all the matches we have. and **all** tests got a **rejected** result. Hence we're more than 99% percent sure momentum is not at random. the details of distribution is shown in Fig 8, the distribution of this momentum is a sum of all the distribution of each match, as the picture suggests, momentum last much longer than random data.

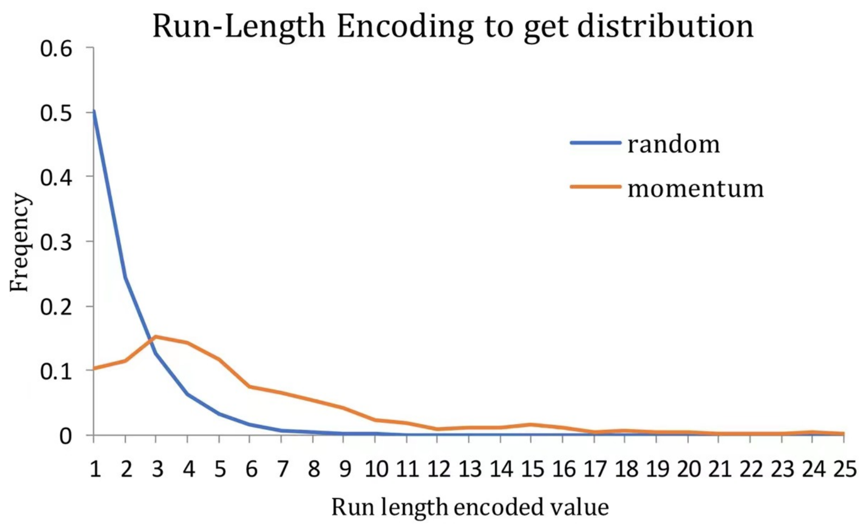

Figure 8: Run-Length Encoding to get distribution.

5 Turning Point Model

5.1 Model Principal

In the context of momentum, as illustrated in Figure 7, the inflection point occurs when the momentums of the two players intersect. It's important to note that momentum is a slowly changing metric, heavily influenced by historical data. Therefore, reaching the point of momentum equality implies that one player has been consistently underperforming over an extended period, vise versa. And that may not truly reflect the changing momentum. To make it more precisely, we choose **the peak value of p1-p2's momentum as the exact turning point**, and try to mine the patterns behind it using by data analysis and inferences .

5.2 Model Construction

The core algorithm we use to construct the model is shown in the flow chart 5.3, as it describes, we first sorted M_{12}, and choose the first 10% and last 10% momentum data as the potential turning point. Then applied Non-Maximum Suppression Algorithm, setting the minimum index distance = 5, after that, the turning point is selected. This figure shows the turning point chosen by our algorithm in Djokovic and Alcarez's competition. Although we did not find all the exact turning point. These points are generally representative.

After getting the turning point for all matches, we collected them together, and also included the its neighbors (2 points around the selected point, since the exact turning point is vague to some extent due to the delay of momentum). then extracting its origin features of T_h and T_l separately. Besides, we use the all samples in 'Wimbledon_featured_matches.csv' and collected the same features as control group, averaging each feature in each data group. and identifying the significant features.

- Features are directly selected using the 'Wimbledon_featured_matches.csv' dataset, which are column['set_no'] to column['return_depth'], T_l and T_h only uses the corresponding row, while the control group used all the rows.
- We assume a feature is significant when the ratio of the same feature in T_h and T_l are higher than 2 or lower than 0.5. Some of the significant data are shown in Section 5.4.

5.3 Flowchart

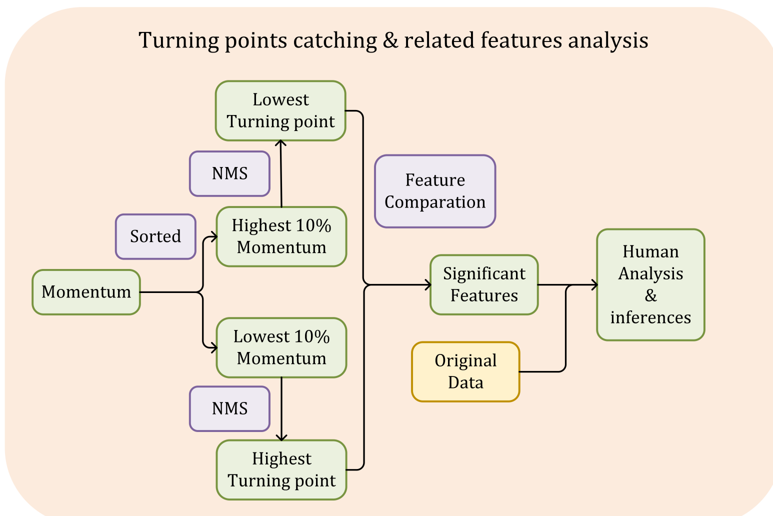

Figure 9: Turning Point Model Flowchart: This process is mainly divided into two steps. The first step is turning points catching, which uses the momentum generated by the previous model to find high-value turning points and low-value turning points. The second step is related features analysis, combining with the original data. Analyze which indicators are related to the generation of turning points.

5.4 Results Presentation and Discussion

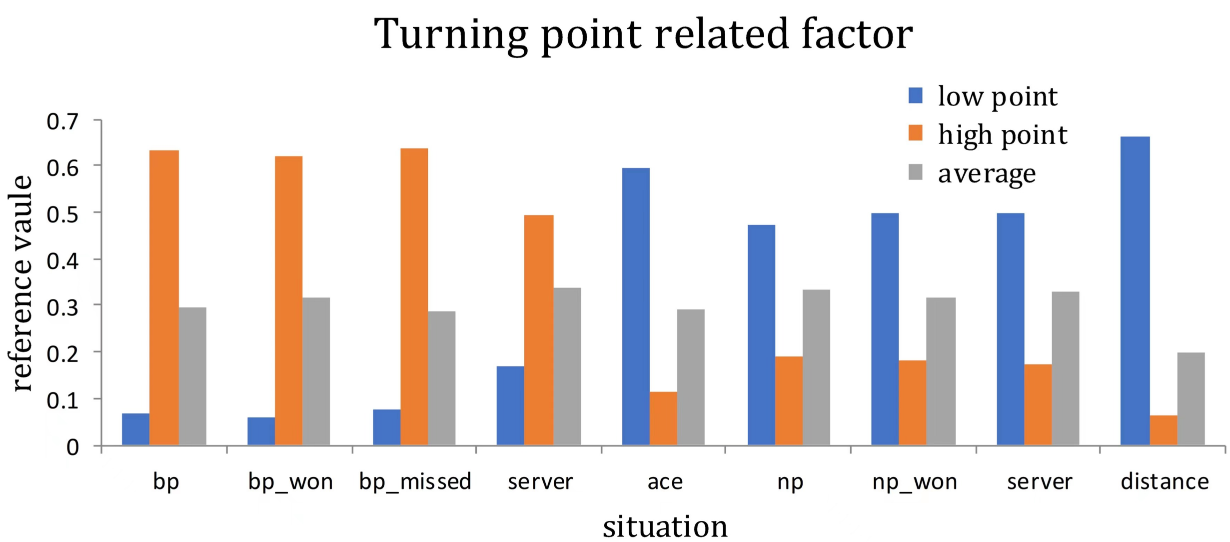

Figure 10: Turning point related factor.

For T_h, we found that factors like break_pt, break_pt_won, break_pt_missed, are extensively higher than the value of T_l and controlling group, the frequently occurring break points, no matter win or lose, implies the game is quite fierce and the current player is trying to attack the other more frequently. At the same time, we observed that player_2 serves more at T_h, implying **player 1 is trying to be the attack side quickly even though he is the receiving.**

For T_l, we found factors like ace, net_pt, net_pt_won and server are extensively higher than the value of T_h and controlling group, meaning that player_1 is giving more untouchable winning shot and volley wisely. Furthermore, player_1 serves more and player_1's walking distance is much smaller than player 2, implying player_1 had more power controlling the tennis at that time and hence controlling the game. Generally speaking, when T_l occurs, **player_1 is controlling the game, making the pace of game slows down and wait for opportunities to get an untouchable winning shot or made it to the net to give a shot.**

After we analysed the general pattern of T_h and T_l, we dived to analysis single player's momentum-turning point to better give advises to him. In this paper, we choose Carlos Alcaraz as our target.

As table.1 shows, compared to general data, p1_server, is more extreme, while other features are not as extreme as the general one (close to 1 is less extreme). Hence Alcaraz's performance is more robust, and his tragic might be consistent. However, the turning point is highly affected by p1_server, indicating Alcaraz's lowest turning point have a higher probability to come when he is serving. This result is consistent to the match since there're two 6:1 matches. For other less significant features, Alcaraz's performance is generally non-significant. Implying

- We might not find the exact turning point for Alcaraz.(it might be the case why this game is so fasinating and intricate)
- Alcaraz's momentum is more robust compared to others.

Feature	high_to_low	high_to_low_Carlos Alcaraz
p1_ace	0.19188	0.00000
p1_net_pt	0.40527	0.51429
p1_net_pt_won	0.36499	0.90000
p1_server	0.34512	0.18000
p1_break_pt	9.04586	3.60000
p1_break_pt_won	10.55351	inf
p1_break_pt_missed	8.44280	2.40000
p2_server	2.91198	2.02500

Table 1: comparison: general M_l, M_h data and Carlos Alcaraz's M_l, M_h data

- Alcaraz should pay more attention to receiving when fighting with big guys like Djokovic.

Different to the large dataset, for Carlos Alcaraz's single game, we only have 66 samples for analysis, lots of features, like p1_ace, equals to zero, hence the result may not be robust. To make it more precisely when predicting a simple player's momentum or behavior, more samples of that player should be included.

Generally speaking, all players should care about receiving since it affects the turning point of momentum a lot. Besides, a receiver should not attack the server frequently, that usually lead to a turning point at the peak. A defensing tactic might be more useful. As for server, take good use of your advantage and try to control your competitor. Seeking chances to shot but don't be impatience.

5.5 Advice Derived from the Findings

From all analysis above, we can identify indicators that can help determine when the flow of play is about to change, signaling a shift in favor of one player over the other. By analyzing the data for at least one match, we will develop a model that predicts these swings in the match and explore the factors that appear to be most related to such changes.[10]

6 Model Evaluation

6.1 Evaluation on Given Dataset

Since the given dataset starts from game after two rounds, we test it on the first rounds datasets[6], but only obtain an accuracy of 54%. The reasons can be drawn as:

- When calculating **Performance**, the information about the effect of serves on performance was specifically removed due to the consideration of serves. However, when we reintroduced the performance score information, the accuracy increased to 68%. This suggests that momentum alone provides relatively limited information for predicting match winners.

- Momentum, being a sense or feeling, is a relatively stable value that doesn't change drastically with the win/loss of a game. As a result, it may not be a strong predictor of match outcomes.

- If our goal is to predict winners and losers in authoritative matches, we can directly optimize logistic regression with comments to achieve an accuracy rate of 92%. This suggests that there are alternative approaches that may yield better results.

Given these limitations, it becomes evident that we need more features to have a comprehensive understanding of players' defensive abilities. In this process, it is crucial to gather more specific information, such as the location of each ball hit, the movement patterns when hitting the ball, and the depth, direction, and speed of each shot. This will help us identify the weaknesses of players in different matchups and provide better advice and predictions. Instead of solely relying on serve results, a more comprehensive approach is needed. If feasible, incorporating additional prior information, such as historical head-to-head results between different players in previous years, would further enhance the accuracy and reliability of predictions.

To improve the prediction accuracy, it is necessary to include more detailed and specific information about players' performance, shot dynamics, and historical data. By doing so, we can gain deeper insights into players' strengths and weaknesses, leading to more accurate predictions and better recommendations.

6.2 Generalization Analysis

Additional matches showed similar predictive performance, though certain players proved harder to model than others, highlighting individual traits not captured. Models may generalize best within tournaments on the same surface. Applying the best Momentum model to other matches yielded comparable results, indicating some portability across events.

Datasets	#Description	#Rounds	#Accuracy
Wimbledon 2023 men's matches[6]	The given processed data	31	78%
Tennis ATP Queens Doubles 2019[11]	Authentic Dataset from Kaggle	-	69%
Tennis ATP Tour Australian 2019[12]	Authentic Dataset from Kaggle	-	71%

Table 2: Overview of used datasets

The Kaggle data set is different from the origin one, it is not a continuous data set describing one single game. it is a mixture of different players. hence here we can merely use 'server', 'serve_depth','return_depth' ,'rally_count','hitting type' to make predictions, thus the precision of the generalized model is lower.

Limitations remain around capturing individual traits. The results obtained from additional matches demonstrated consistent predictive performance, although certain players presented challenges for the modeling process. This highlights the importance of individual characteristics that are not fully captured by the models. It is worth noting that the models may perform better when applied within tournaments on the same surface, suggesting that surface type plays a significant role in match outcomes.

Interestingly, when the best performing Momentum model was applied to Women's matches, comparable results were obtained. This indicates some level of portability across different events. However, it is important to acknowledge that the weakness of our model lies in its lack of access to personal prior information about each player. The datasets used for modeling purposes rely heavily on precise pre-processing approaches rather than incorporating individual player-specific information. To enhance statistical research in this field, it would be beneficial to include additional information about each player, which could potentially improve the accuracy and effectiveness of the models. Future work expanding datasets across multiple tournaments and integrating player attributes could generate more accurate and generalizable models. As a whole, these statistical techniques provide objective tools supplementing traditional tennis wisdom.

7 Memo

Re: Role of Momentum in Tennis Matches
Advice to Coaches

Dear Madam or Sir:

We are writing to share the findings of our research team's analysis of professional tennis matches, focusing on the concept of "momentum" during gameplay. Our study utilized a quantitative model to gain insights into the impact of momentum shifts on match outcomes. We have summarized our core findings and included recommendations for coaches on how to leverage momentum in player preparation.

Our model successfully tracked momentum shifts between opponents by analyzing statistical relationships within match data. Contrary to the prevailing belief that momentum is merely a subjective perception, we found that momentum fluctuations were predictive of eventual match outcomes, going beyond random chance. Certain metrics like serve speed, winners/errors, and break points captured that have been evaluated were key determinants of momentum. These metrics were found to be critical factors in understanding and predicting momentum shifts during matches. We found that momentum build-up was gradual but reversals could be sudden, which can not fully explained by the data.

Through logistic regression modeling of match statistics, our model found momentum variations correlated more strongly with eventual match outcomes than random chance, highlighting momentum's meaningful influence. Trough the Turning point model, the best strategy can be figure out when some special events happening.

From all that speculated, we highly recommend to focus training on the serve and return - strong serving boosts momentum. Emphasize consistency and minimizing errors - this slows opponent's momentum. Monitor metrics like winners/errors to gauge momentum shifts. Prepare players psychologically for momentum swings - don't let it negatively impact mindset and effort. Use strategic timeouts to disrupt surges in the opponent's momentum. Remind players that fast momentum shifts are possible - never lose hope.

Certain metrics emerged as primary determinants of changing fortunes, including serve speed, winner-to-error ratio, and break point conversion percentage. Monitoring these indicators in real-time may help gauge momentum shifts. While advantages accumulated gradually over time, our results also showed momentum reversals could occur abruptly due to intangible factors not fully captured by the available data.

Momentum is a real phenomenon in tennis that impacts match outcomes. By quantifying momentum and identifying contributors, our model provides data-driven advice for coaches to train players optimally. Preparing for momentum swings, both mentally and strategically, will give players an edge to prevail.

Based on these insights, we recommend emphasizing serving strength and return play via dedicated training to facilitate momentum building. Given the strong correlation between serving performance and momentum, we highly recommend focusing training efforts on developing a powerful and consistent serve. Additionally, emphasizing effective return play can help players gain momentum by putting pressure on their opponents. Emphasizing consistency and minimizing unforced errors can disrupt the opponent's momentum and help players regain control of the match. Monitoring metrics like winners/errors can provide valuable insights into momentum shifts during gameplay. Drills focusing on consistency while minimizing unforced errors could help stall opponents' surging momentum.

What's more, players should be mentally prepared for momentum swings, ensuring that they maintain a positive mindset and high level of effort throughout the match. Coaches can provide mental skills training to help athletes cope with momentum fluctuations and stay focused on their performance. Strategic timeouts can be used as a tool to disrupt the opponent's momentum and regain control of the match. Coaches should encourage players to take timeouts strategically when necessary.

Our statistical modeling confirms the meaningful impact of momentum on match outcomes. By quantifying and identifying the determinants of momentum, our model provides data-driven insights that can optimize training strategies. We recommend a holistic approach to managing momentum fluctuations, combining technical training, psychological preparedness, and strategic decision-making during matches. The actionable insights gleaned can help optimize training to both seize momentum opportunities and withstand opponent runs. A data-driven, holistic approach to managing momentum fluctuations may assist your players in achieving their full potential.

We hope these insights will be valuable for your coaching team. Should you have any further questions or require additional information, please feel free to reach out to us. We look forward to hearing from you.

Regards,
Research Team 2400691
Date: 02/05/2024

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