Problem Chosen	2024 MCM/ICM Summary Sheet	Team Control Number
C		2409015

The Secret of Tennis Players' Momentum: Is It Personal Ability, or Is There More to It?

Summary

This project aims to analyze factors influencing the change in player momentum during tennis matches, intending to provide pre-match advice and post-match analysis for tennis coaches. In physics, momentum reflects the energy and trend of motion. In tennis, when two players are of comparable skill level, the player with higher morale is likely to win the next point or even several points, thereby impacting the deeper layers of the match outcome.

All our research is based on the quantitative calculation of momentum. Drawing on relevant literature and past experience, we established a momentum score model in the first question. This model can calculate the quantitative increase or decrease of momentum for both players at the end of any rally in a match. It comprehensively takes into account linear adjustments for consecutive scoring, linear adjustments for winning consecutive games, exponential adjustments for significant score differences, linear adjustments for small score differences, as well as the impact of missing break opportunities, breaking and being broken, stroke count, and the running distance of both players. We used exponential moving averages to smooth the changes in momentum score, making it more conducive for subsequent machine learning processes.

In response to some coaches' skepticism about whether changes in momentum are random, we employed random process simulation and hypothesis testing methods to evaluate the hypothesis. Finally, through the Kolmogorov-Smirnov test and statistical hypothesis testing, we determined that momentum shifts in actual matches significantly differ from random occurrences, thus refuting the randomness of momentum changes.

Based on the model from the first question, we can identify crucial turning points in matches by finding significant intersections in the model. We used the momentum score derived from the model as the label for the prediction model in the third question. We selected additional relevant features for machine learning, fitting a random forest regression model, thereby identifying the most related factors. By applying strict conditions to the intersections, we filtered out the points that either intensified or resolved the match's deadlock as turning points and analyzed their rationality in actual games. After verifying with over twenty matches, we believe the prediction model effectively identifies match turning points. Subsequently, we focused on analyzing the strategies at these turning points and provided general recommendations.

In relation to our model, we conducted a generalizability analysis using the dataset from the 2018 Australian Open mixed doubles matches. Despite the limitations of the dataset being incomplete and lacking in certain features, which restricted the optimal performance of our prediction model, it still demonstrated a relatively good prediction accuracy. This indicates that our prediction model possesses strong generalizability.

Contents

1 Introduction

1.1 Problem Background

In today's society, tennis has evolved into one of the most visually appealing and fan-favorite sports globally. As of 2022, the sport has reached an impressive milestone in terms of global participation. There are over 100 million tennis players worldwide, encompassing all levels from amateur to professional, a figure that has been steadily increasing over the past decade. Moreover, the long history of tennis is marked by many memorable matches due to their uniqueness, intensity, or historical significance. For instance, the 2023 Wimbledon men's singles final was a case in point. In this match, 20-year-old Spanish rising star Carlos Alcaraz triumphed over 36-year-old Novak Djokovic, thereby ending the spectacular record of one of the greatest Grand Slam players in history. This match was characterized by its dramatic twists and turns and continuous excitement. Both players experienced incredible fluctuations in performance, at times dominating the play and at others being dominated. This phenomenon may relate to the concept of 'momentum' experienced by a team or player in a sport. In this report, our team aims to use scientific and mathematical methods to measure and predict this seemingly intangible concept in the context of the match.

1.2 Restatement of the Problem

In this study, our team obtained data for every point played in the men's singles matches at Wimbledon 2023, starting from the third round onwards. This data acquisition was aimed at addressing the following questions:

- Create a model leveraging existing datasets to analyze and identify the dominating player or team at certain points in a match. This model should quantify their advantage and include a visualization feature. Moreover, the model should be customized for various sports. For instance, in tennis matches, it should reflect the server's higher likelihood of scoring. This approach will showcase the model's adaptability across different sports.
- Employ the developed model to evaluate a coach's viewpoint by analyzing if the fluctuations in a player's 'momentum' during a match are due to random changes.
- Based on existing data, create a new model to predict fluctuations in player performance during a match and identify the indicators most closely related to shifts in the game's dynamics. Simultaneously, use the data on past fluctuations in players' 'momentum' to provide strategies for upcoming matches between two players.
- Conduct trials of the model across different matches and sports to assess its effectiveness in prediction and its applicability to sports beyond tennis. Following these trials, identify the model's limitations and propose additional factors that might influence its performance.

- Compile the insights from your experiments to offer guidance about 'momentum' to tennis coaches and players. This will aid them in developing strategies for handling situations that affect the course of tennis matches.

1.3 Our Work

In athletic competitions, 'momentum' typically signifies the cumulative 'force' or 'drive' generated from various events. Although it's an intangible concept and challenging to measure, this task involves investigating how to quantify momentum using match data. We'll examine the impact of different events on momentum shifts and, using our results, offer targeted strategies for tennis coaches and players. Our key responsibilities include:

1. By harnessing point-by-point data from the 2023 Wimbledon men's singles (beyond the initial two rounds) and integrating it with publicly accessible match statistics online, we aim to gather detailed player profiles and match data. This approach will facilitate a more precise quantification and examination of momentum.

2. Based on the existing data, develop a model that can quantitatively determine which player or team has the advantage at specific times during a match. Visualize this model to assess the randomness of fluctuations throughout the course of the game.

3. Develop a forecast model aimed at predicting variations in players' performances throughout a match, pinpointing key elements that are significantly related to pivotal moments in the match.

4. Gather and systematize match data across diverse events and sports types to evaluate the predictive accuracy of the model and its applicability beyond tennis. Additionally, enhance the model by including elements that were initially overlooked.

5. Based on the model's results, provide specific advice and strategies for coaches and players in the sport of tennis.

2 General Assumptions

Considering that practical problems always contain many complex factors, first of all, we need to make reasonable assumptions to simplify the model, and each hypothesis is closely followed by its corresponding explanation:

Assumption **1: At the beginning of a tennis match, the 'momentum' for each player or team is equally established at a value of 0.**

Explanation: In tennis matches, it's important to note that under certain circumstances, there can be a significant difference in 'momentum' between the players before the match even begins. An example is a match between someone completely unfamiliar with tennis and a world champion, where their 'momentum' could differ significantly before the start.

However, to simplify the model, reduce the difficulty of data collection and processing, our team has decided that ’momentum’ in the match will only be related to the players’ behavior during the game and not influenced by external factors. Therefore, we have set the initial ’momentum’ values for both sides to be the same.

Assumption **2: In tennis, matches played repeatedly between the same pair of players are treated as separate and independent events with no influence on each other.**
Explanation:The second hypothesis builds upon the first. For model simplification and to ease the data collection and processing efforts, our team’s analysis is concentrated on the shifts in ’momentum’ within the confines of ’sets’, ’games’, and ’points’ during a single tennis match. Consequently, it’s established that the initial ’momentum’ for both players is identical and does not vary, irrespective of the number of times they have competed against each other.

Assumption **3: The variations in ’momentum’ for a particular player during a tennis match are predictable.**
Explanation:While a player’s momentum in tennis is linked to both competitors’ actions, individual factors like habits, physical condition, and preferences mean that a particular player’s skill and tactical approach tend to remain stable across various matches. Consequently, our team can use historical data on a specific player’s ’momentum’ fluctuations to forecast future game data changes, enabling us to offer tailored recommendations before upcoming matches.

3 Notations

Some important mathematical notations used in this paper are listed in Table 1.

4 Data

4.1 Data Collection

For this project, we have already obtained data for every point after the first two rounds of the 2023 Wimbledon men’s singles. However, to test the generalizability of our team’s model as required by the task, we have still sourced some publicly available match data on the internet, which includes 2018 Australian Open Mixed Doubles.

Table 1: Notations used in this paper

Symbol	Description
X_t	The positive contribution to momentum by a player's actions at time point 't'
Y_t	The negative contribution to momentum by a player's actions at time point 't'
t	The time from now
M_t	The comprehensive momentum score
S_t	The score corrections at time 't' for a player in 'sets'
G_t	The score corrections at time 't' for a player in 'games'
P_t	The score corrections at time 't' for a player in 'points'
D_t	The scoring adjustment for a player's physical fitness at time 't'
S_n	The counts of consecutive sets won by the player at time 't'
G_n	The counts of consecutive games won by the player at time 't'
P_n	The counts of consecutive points won by the player at time 't'
D_n	The total running distance of the player at time point 't'
R_n	The cumulative stroke count at time point 't'

*There are some variables that are not listed here and will be discussed in detail in each section.

Table 2: Data and Database Websites

Database Names	**Database Websites**
all Wimbledon 2023 men's matches	Obtained from the topic
2018 Australian Open Mixed Doubles	https://ausopen.com/

4.2 Data Processing

In the data cleansing phase, our team executed various cleaning operations. For instance, in the dataset of every point post the first two rounds of the 2023 Wimbledon men's singles, we found missing entries in Serve speed, serve direction, serve depth and return depth, amounting to 752, 54, 54, and 1309 values respectively. We compensated for these gaps by averaging and judiciously removing data, and also eliminated outliers in parameters such as movement distance and stroke count using both mathematical methods and manual review. This cleaning procedure was similarly applied to additional datasets sourced from the web.

5 Model Preparation I

According to the task requirements, our team, using the available data, has developed a model that can quantitatively determine which player or team is more dominant at specific times in a match. Clearly, this 'dominance' is what we refer to as the player's

’momentum’, an abstract concept influenced by multiple factors. Facing this seemingly intangible concept in matches, our team’s most crucial goal is to quantify it. With this objective in mind, we initiated the next phase of our work.

5.1 Engineering of Features

It’s evident that we’re dealing with a ’big data’ challenge here. Our team dedicated a lot of time and effort to data analysis and processing in hopes of deriving valid indicators. A pivotal part of this task and the foundation of our model — quantifying ’momentum’ — led us to extensively review scholarly articles and literature. However, we discovered that in tennis, there isn’t a standardized definition or quantifiable measure for a player’s ’momentum’. The dictionary defines ’momentum’ as ’force accumulated through movement or a sequence of events’, and in the realm of sports, coaches and athletes typically use ’momentum’ to denote a kind of advantage during a match.

Based on previous discussions and data we researched online, our team concludes that in tennis, ’momentum’ for players is shaped by short-term aspects like specific technical moves (for example, the server scoring, as mentioned in the task) and long-term elements such as a series of successful points. These factors collectively manifest as a player’s dominance over the flow of the match, signifying their advantage. It naturally follows that a player with this advantage has a higher chance of winning the rally, and there’s a strong correlation between the two. Therefore, we infer that elements significantly impacting a player’s chance of winning might also heavily influence their ’momentum’. Our team aims to uncover these influential factors to serve as metrics for evaluating and quantifying a player’s ’momentum’.

Based on the 2023 Wimbledon men’s singles data provided in the task, our team used the win rate that can be directly calculated from the dataset to identify the features that most positively impact player win rates. First, we calculated the win rate for each player on a ’point’ basis within a match. To comprehensively evaluate players’ win rates, we extracted corresponding data for each player from the available dataset, such as the number of serves, break points, and net approaches, and constructed a correlation matrix: Serving rights, successful first serves, points won on first serves, successful second serves, points won on second serves, faults on second serves, frequency of breaking serves, missed opportunities to break serves, total strokes, number of quality shots played, total distance run by both players, success at the net, errors at the net, players’ winning streaks in ’sets’, ’games’, and ’points’, and the magnitude of the score gap between the players.

Based on the correlation matrix, we noted significant correlations among certain features and the presence of numerous variables in the dataset. This necessitates the application of dimensionality reduction techniques to these variables:

As indicated in the previous graph, the cumulative contribution of the first nine principal components accounts for 90% of the variance. For the sake of simplifying our analysis, we will omit the components beyond the ninth. Next, we assess the correlation between these nine principal components and the players’ winning probabilities, as depicted in

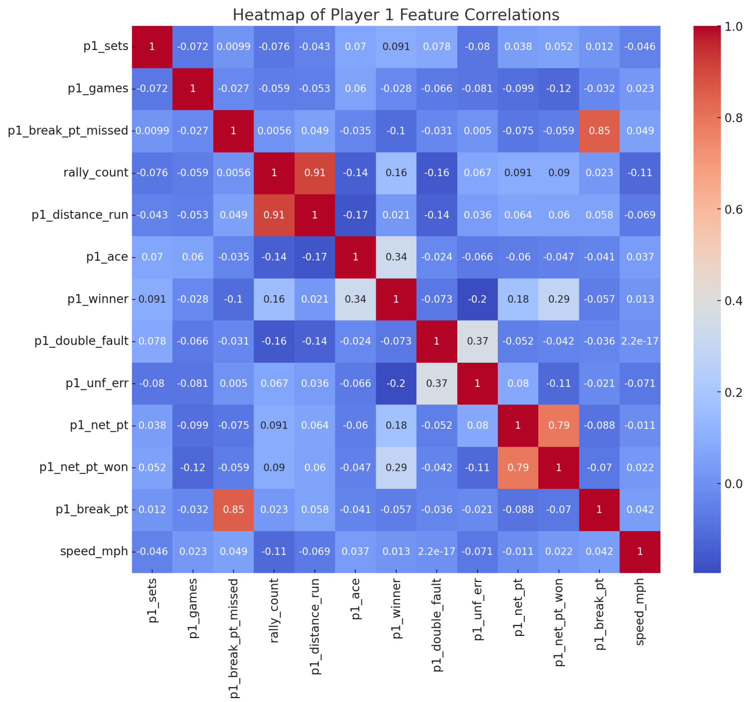

Figure 1: Correlation matrix

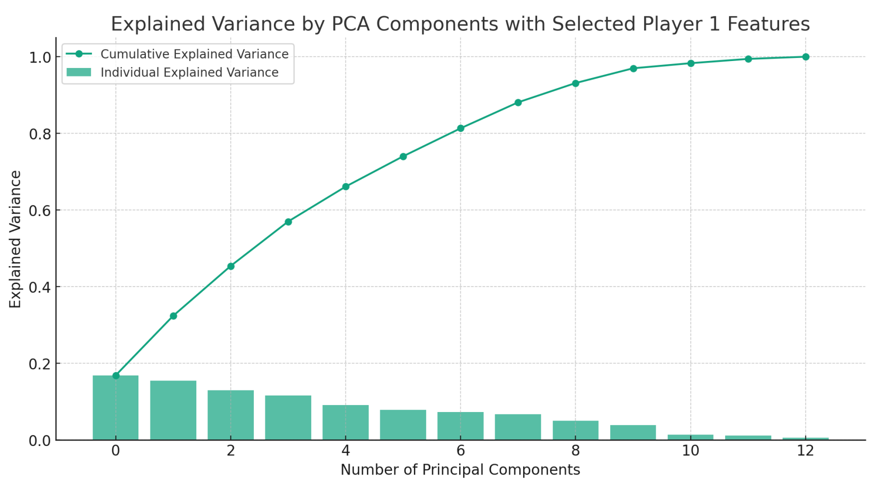

Figure 2: PCA

the subsequent graph:

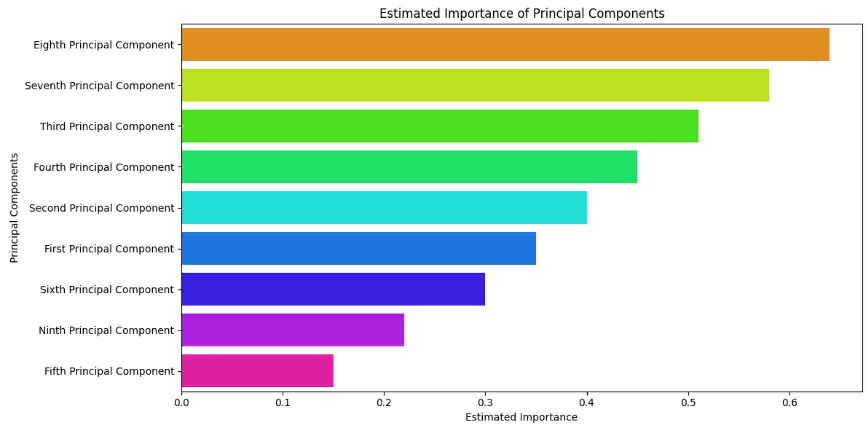

Figure 3: Estimated Importance of Principal components

The first six principal components depicted in the graph are arguably the most significant factors affecting players' win rates within our dataset. By examining the linear associations between these six principal components and the initial features, we can pinpoint the most relevant features to these principal components. These key features will act as the primary metrics for evaluating 'momentum' in our model.

Additionally, our feature extraction endeavor extends beyond the initial steps. We explored various scholarly articles and publications available online that might relate to our study. In this exploration, we discovered several technical metrics, such as the success rate of first serves, scoring on return against the first serve, serving speed, scoring rate on first serves, effectiveness in saving break points, success rate at the net, and scoring percentage from the baseline. These indicators were extracted and processed from the existing data, undergoing evaluations similar to the aforementioned processes. Due to the complexity of these procedures, I won't delve into the details here.

As a result, our team, informed by the existing data, relevant scholarly work, and our collective insight into players' 'momentum' during tennis matches, has identified the following key evaluation metrics:

5.2 Model Construction

Evidently, in the context of this project, the pivotal aspect of our model lies in quantifying the 'momentum' of a player. From our feature extraction efforts, we've pinpointed several elements that impact a player's 'momentum'. Thus, our team adopted a fundamental and direct approach to assessment. We perceive a player's 'momentum' as their on-court advantage. A player should earn 'momentum' points for performing advantageous technical actions or achieving a series of scores that elevate their spirit, and conversely lose points otherwise. The basic premise of our team's model can be encapsulated in the subsequent formula:

$$M_t = \alpha X_t - \beta Y_t \tag{1}$$

In this formula, M_t represents the comprehensive momentum score, X_t indicates the positive contribution to momentum by a player's actions at time point 't', and Y_t represents the negative contribution to momentum by a player's actions at time point 't'. α and β are weight parameters that need to be obtained through training.

Based on the indicators previously selected by our team, we have also specified scoring for each type of action. Firstly, there's the basic scoring part: if a player wins a 'point' in a 'game' during the match, their 'momentum' score increases by one, and conversely, there's a corresponding deduction for losing a point. Secondly, considering that a player might score consecutively or even win several 'games' or 'sets' in a row, we took into account the impact of consecutive scoring and winning streaks on momentum. Our team also considered how the margin of victory during a winning streak affects momentum. For the scoring of consecutive points and game victories, we adopted a linear adjustment method. In terms of the impact of the score difference on player momentum, our team conducted numerous trials and manual adjustments. We ultimately concluded that the impact of score differences in 'sets' and 'games' on player momentum is distinct. Clearly, in matches, the difference in the number of sets won has a greater impact on a player's performance. Therefore, our team has chosen the following formula:

$$S_t = \alpha * S_n + \beta * 2^{S_n} \tag{2}$$

$$G_t = \alpha * G_n \tag{3}$$

$$P_t = \alpha * P_n \tag{4}$$

In this formula,S_t ,G_t and P_t signifie the score corrections at time 't' for a player on a winning streak for their consecutive victories in 'sets', 'games', and 'points'. S_n ,G_n and P_n indicate the counts of consecutive sets, games, and points won by the player at time 't'. As before, α,β and γ are the weighting parameters, which require calibration through model training.

Based on our feature extraction work, we have thoroughly considered the physical aspect of players during the match. Our team combined the number of strokes exchanged between players and the distance they ran, resulting in the following formula:

$$D_t = \alpha R_n + \beta D_n \tag{5}$$

In this context, D_t indicates the scoring adjustment for a player's physical fitness at time 't'. R_n and D_n denotes the cumulative stroke count and the total running distance of the player at that same time point. As with previous components, α and β are the weighting factors which require calibration via model training.

In regard to the features we selected during the feature extraction phase, we have also developed corresponding weighted formulas. For positive contributions, we have metrics like successful first serves, scoring on first serves, and net play scoring. For negative contributions, we include double faults, missed hitting opportunities, and being scored on by first serves. The formulas for these metrics are broadly similar, involving the multiplication of match data with respective weights. Thus, the positive and negative contributions corresponding to these metrics are essentially the weighted sums of the indicators.

How then are the weights in these formulas determined? To address this, our team treated the problem as a time-series learning task. We used a standard encoder-decoder network architecture to build a regression model and employed mean squared error as the loss function. Finally, we ensured model regularization through manual adjustments and cross-validation.

It's worth mentioning that to account for the advantageous position of the server in tennis matches, our team manually adjusted the weights for serve scoring and break scoring. We relatively reduced the weight for serve scoring and increased the weight for break scoring. This adjustment reflects the ubiquity of serve scoring and the higher difficulty of break scoring in influencing a player's 'momentum'.

5.3 Results

Our team equipped this model with visualization capabilities to enhance the presentation of its outcomes. We deployed it in numerous matches, consistently obtaining positive results. We will now focus on the match referenced in this topic, specifically the one where Carlos Alcaraz triumphed over Novak Djokovic in match number 1701, for our demonstration.

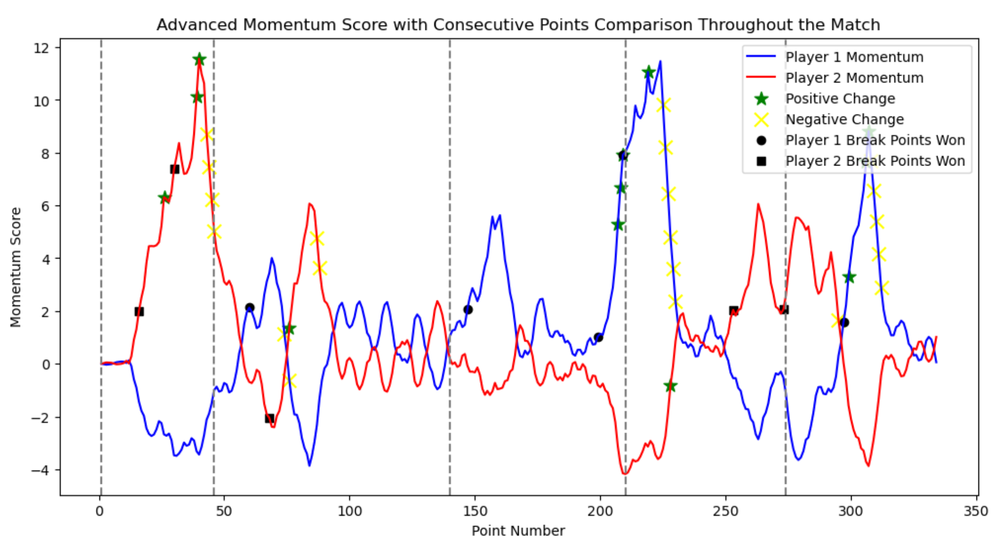

Figure 4: Estimated Importance of Principal components

The visualization clearly demonstrates that our model's evaluation of player momentum is consistent with both the match description and the actual data. In this match, Djokovic, labeled as player 2, won the first set with ease. The tension escalated in the second set, as depicted by the intertwined lines in our visualization. Alcaraz, player 1, easily won the third set, a reversal from the first. The beginning of the fourth set saw Alcaraz dominating, but the tide turned in Djokovic's favor. The final set concluded with Alcaraz's victory. This shows that our model's assessment of player momentum closely mirrors the real-life events of the match.

6 Volatility stochastic assessment

In this task, a coach hypothesizes that the fluctuations in a player's 'momentum' and consecutive winning events during a match are random. To evaluate this hypothesis, we employed methods of random process simulation and hypothesis testing. First, we calculated momentum scores based on real match data and our completed model. Next, we generated a distribution of momentum scores by simulating numerous random matches using the same model. Finally, we used statistical hypothesis testing to determine if the momentum shifts in actual matches significantly differ from random occurrences.

The approach for this task is relatively straightforward. We have already demonstrated the real data in 'Model I'. For the random process simulation, our team opted to perform Gaussian sampling within the value range of the actual data indicators to ensure randomness. We then generated new momentum scores using this random data. Lastly, we conducted a KS (Kolmogorov-Smirnov) test to analyze the distribution of momentum scores in the match data, with the following result:

Table 3: Data and Database Websites

Players	KS statistic	P-value
1	0.362994	1.3839928931388789e-39
2	0.448952	2.1703747469076462e-61

As a result, the hypothesis test clearly shows a P-value significantly lower than 0.05, leading us to reject the coach's hypothesis, thereby indicating that the momentum shifts in the matches are not random.

7 Model Preparation II

7.1 Model Construction

In our initial inquiries, we developed a momentum score framework predicated on specific metrics observed during gameplay, enabling the computation of each competitor's momentum at the conclusion of every round within a given match. The objective of discerning the match's pivotal juncture, the round where the dynamics notably shift,

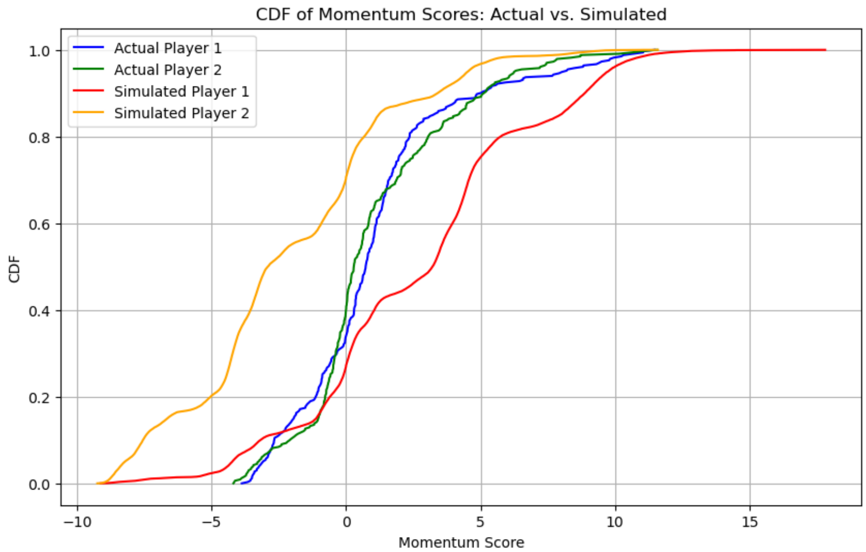

Figure 5: Hypothesis testing visualization

necessitates an understanding of the on-court realities and the strategies employed by both the offensive and defensive players that contribute to this shift. This logically extends from our primary question, directing our attention to the intersection of the two momentum trajectories. Yet, this approach surfaces two pertinent challenges:

1. The foundational model, as established in our primary query, is anchored in assumptions that are straightforward and intuitively resonant. For the third query, where the focus is on pinpointing match turning points, our predictive model must integrate a broader array of features pertinent to serving and returning dynamics (such as 'p1_ace', 'p2_ace', 'p1_double_fault', 'p2_double_fault', 'serve_width_B', and others). This necessitates employing machine learning techniques to assimilate these feature weights effectively into the momentum curve modeling.

2. Our initial model presupposes that momentum scores are contingent on recent round performances, interpreting 'momentum' as an expression of a player's arousal state. Given the fluctuating fortunes in elite tennis matches, momentum shifts are expected to be frequent. This results in an overabundance of intersection points on the momentum curves. To address this, it becomes imperative to develop methodologies that filter out insignificant, repetitive stalemate points, thereby concentrating on rounds that signify a transition into or out of a deadlock.

For the first issue, we employed a random forest regressor to train our model using data processed through the momentum score model established in the first question. The momentum score serves as a crucial label in the supervised learning process. We used the R^2 score as the evaluation metric and observed the importance of features post-training. To prevent model overfitting and enhance the generalizability of our predictive model, it's essential to select primary features for further training.

Regarding the second issue, we first identify all intersection points where the change in momentum is not less than a certain threshold. Then, we select those points that do not have any other intersection points in their vicinity, meaning there are no further momentum crosses in several rounds before or after these points. We locate these turning points and, in conjunction with the specific on-court situations, analyze the rationality of our predictions.

7.2 Results

The figure6 shows the ranking of feature importance after the initial training.

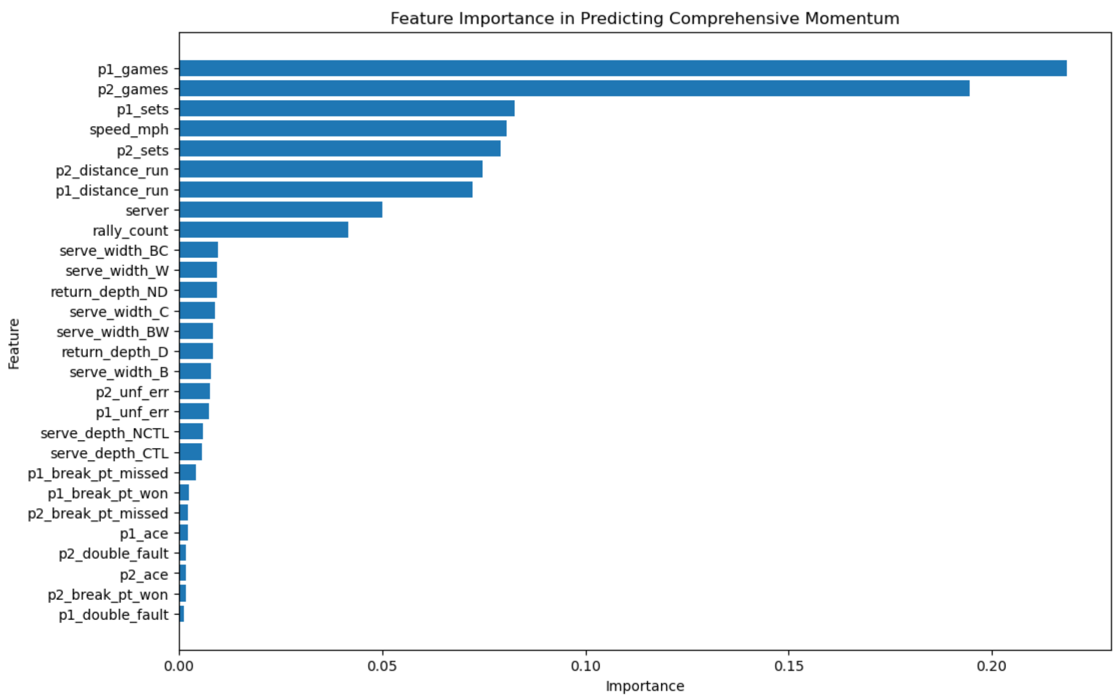

Figure 6: Feature Inportance

Select the top 10 features with the highest importance for retraining. Then, obtain the actual and fitted momentum curves7 for Player1 and Player2.

In the process of pinpointing crucial junctures and evaluating the dynamics of the game, let's consider the match labeled as 1302. The players involved in this encounter are Alexander Zverev, designated as Player 1 (P1), and Matteo Berrettini, referred to as Player 2 (P2).

7.3 suggestion

Although there is ambiguity in the increase or decrease of momentum for individual points, considering the trend of the momentum curve and the actual events on the court,

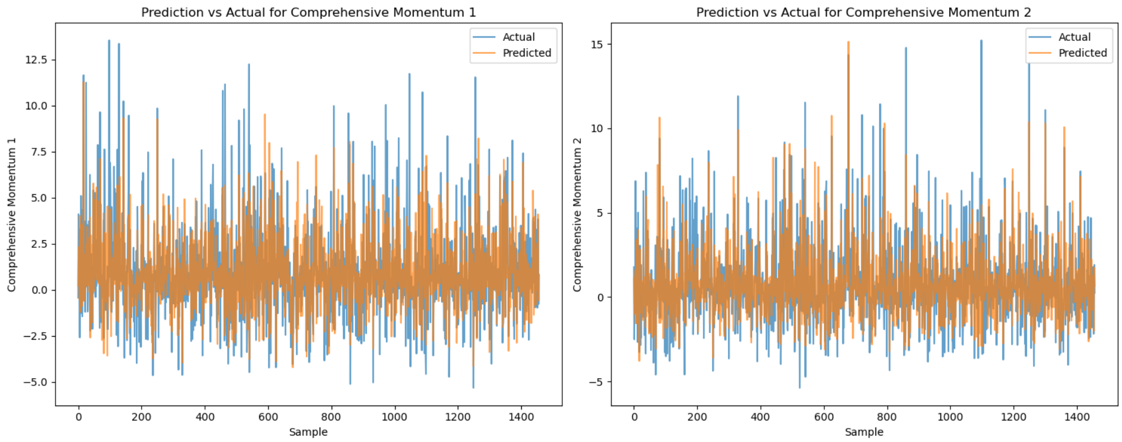

Figure 7: Predicted curves vs Actual curves

Intersection	Game Point	Momentum 1	Momentum 2	Set	Game	Current Point
1	26	0.65	-0.71	0-0	1-2	40:15 (1st)
2	44	-0.47	0.64	0-0	3-4	15:30 (1st)
3	64	0.36	-0.44	0-1	1-1	40:0 (1st)
4	112	-0.81	0.82	0-1	6-6	15:40 (1st)
5	135	2.16	-3.30	0-2	1-1	30:40 (2nd)

Table 4: Tennis Match Detailed Analysis

we believe our predictive model has successfully identified the key turning points that significantly affect the momentum of the match. Once these turning points are identified, we can extract them separately and analyze actual game strategies such as the types of serves and returns, the number of strokes, running distance, etc.

7.4 Recommendations for the Serving Player

1. Enhance First Serve Success: Increasing the success rate of first serves generally correlates with a stronger offensive position and reduced pressure.

2. Diversify Serve Tactics: Utilizing a variety of serve trajectories (B, BC, BW, C, W) and depths (CTL, NCTL), servers are advised to dynamically alter their serving strategies to bewilder their opponents.

3. Dictate Match Tempo: The rally_count's positive impact implies that prolonging rallies may contribute to building momentum, likely linked to patient play, capitalizing on opponent errors, or generating scoring opportunities.

Intersection	Result	Model Prediction
1	Player 1 holds serve, 2-2	After this, Player 2 has the upper hand
2	Player 2 scores, Player 1 error, 15-40	Player 2 further extends lead
3	Player 1 ace, 2-1	Player 1 turns the tide
4	Player 1 ace, 30-40	Player 2 retains advantage
5	Player 2 holds serve, 1-2	Match reaches stalemate

Table 5: Tennis Match Detailed Analysis(supplement)

Table 6: Player1 as Server: Model Coefficients and Accuracy

Feature	Coefficient
p1_sets	-0.660716
p2_sets	1.079027
p1_games	0.523895
p2_games	-0.461889
p1_double_fault	0.360961
p1_unf_err	-0.310627
p2_unf_err	-0.924556
rally_count	0.404886
speed_mph	-0.641765
serve_width_B	-0.342782
serve_width_BC	-0.237314
serve_width_BW	-0.029538
serve_width_C	0.361789
serve_width_W	0.111184
serve_depth_CTL	-0.393256
serve_depth_NCTL	0.391367
distance_diff	-0.314234
p2_distance_run	-0.570710
p1_distance_run	-0.515582

Model Accuracy: 0.75

4. Limit Unforced Errors: The significance of minimizing unforced errors, as indicated by the negative impact of p1_unf_err, highlights the need for consistency and error reduction.

Table 7: Player1 as Receiver: Model Coefficients and Accuracy

Feature	Coefficient
p1_sets	0.124868
p2_sets	-0.149697
p1_games	0.519961
p2_games	-0.155793
p2_double_fault	0.643224
p1_unf_err	-0.136075
p2_unf_err	-0.087853
rally_count	-0.305280
speed_mph	0.205257
return_depth_D	0.259512
return_depth_ND	0.372136
distance_diff	-0.093827
p2_distance_run	0.399639
p1_distance_run	0.333224

Model Accuracy: 0.782608695652174

7.5 Guidance for the Receiving Player

1. Emphasize Defense and Counterplay: With their data reflecting the opponent's serve, receivers should prioritize defensive and responsive strategies.

2. Strengthen Second Serve Returns: The coefficient related to p2_double_fault suggests an opportunity to increase aggression on second serve returns, targeting the opponent's weaknesses.

3. Modify Return Techniques: Based on return_depth_D and return_depth_ND, receivers should adapt their positioning and return tactics in response to ongoing match conditions.

4. Optimize Movement Efficiency: By effectively managing movement on the court, receivers can reduce unnecessary exertion, preserving energy and focus.

8 Model generalization detection

8.1 Test Dataset Description

In order to evaluate the generalizability and overall applicability of our model, we have chosen a dataset from the Australian Open's mixed doubles matches. This contrasts with Wimbledon's grass courts, as the Australian Open utilizes hard courts. Grass courts are known for their quick ball speeds and lower bounces, whereas hard courts provide an average ball speed, offering a fairer playfield for players of varying styles. Mixed doubles games, unlike men's singles, generally have more rhythm changes, focusing more on coordination and a variety of tactics, potentially affecting the game's momentum differently. Additionally, our dataset includes a limited number of features, requiring the model to be more stable. Thus, we consider the selection of this dataset for testing our model to be both logical and effective.

8.2 Model I

To verify the plausibility of the momentum score outcomes, we chose to analyze trend images of momentum scores from various matches alongside the actual progression of those matches. In these images, different sets within a single match are delineated using dashed lines.

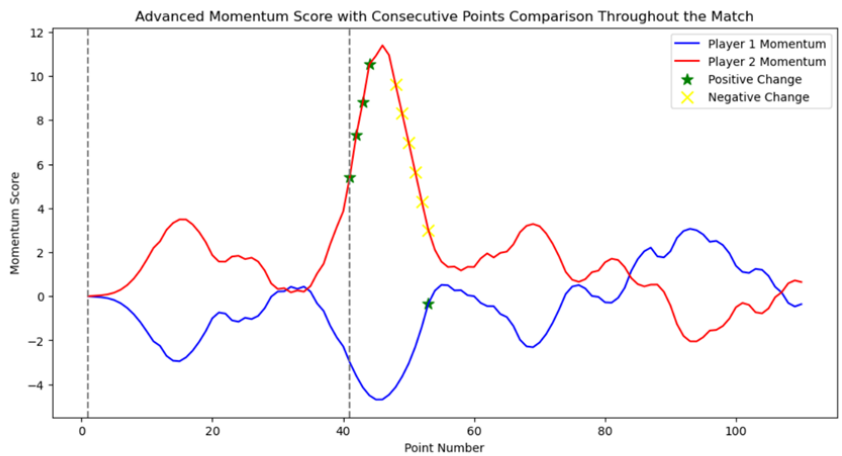

Figure 8: Match 1

In Match 1, the duo represented by the red curve, Team 2, easily prevailed over Team 1, indicated by the blue curve, with a dominant 2:0 scoreline. Throughout most of the match, Team 2 maintained a higher momentum score compared to Team 1, aligning with the final result of the match. A closer examination of the match reveals that in the first set, Team 2 quickly gained momentum, securing an early lead in game scores. This was followed by a period of alternating game scores, after which Team 2 comfortably won two consecutive games, securing the first set. This sequence of events was reflected in the trend of the momentum curve. In the second set, Team 2's momentum peaked after winning two games and successfully breaking the opponent's serve, but then dipped following a lost service game. The subsequent part of the set saw alternating scores between the teams, with Team 2 clinching the second set by a slim margin. The match's progression was in broad agreement with the shifts in the momentum curve.

In Match 2, Team 1, indicated by the blue curve, managed a challenging 2:1 victory over Team 2. In the early stages of both the first and second sets, Team 2, represented by the red curve, was the dominant team, securing the first set and initially leading in

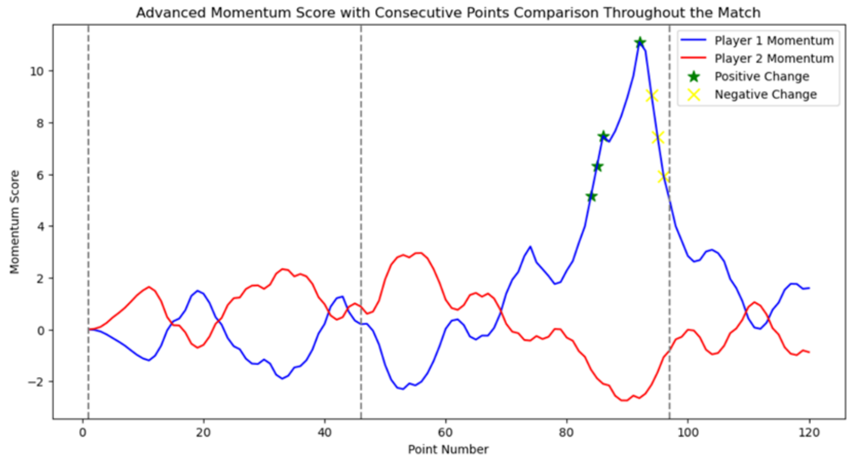

Figure 9: Match 2

the second. However, the match dynamics dramatically shifted as Team 1 made a series of successful breaks, turning the tide to win the second set and maintaining pressure for most of the third set, ultimately winning the match. The momentum curve we developed closely mirrors the match's overall progression, with the timing of momentum peaks aligning with key moments in the game. In summary, through extensive testing with abundant data, we conclude that our model can vividly and accurately depict momentum swings throughout the match in the test dataset, showcasing its generalization capability.

8.3 Model II

In applying this model, we integrated an analysis of the match progression, data, and result visualization images. In Match 3, Team 2, represented by the yellow curve, won against Team 1, shown by the blue curve, with a 2:0 scoreline. Yet, the match was not as straightforward as the score implied. Throughout the match, Team 2's superiority was not distinctly evident, leading to prolonged periods of intense competition. The imagery from Match 3, segmented into five stages by four pivotal moments, showed Team 2's clearer advantage in stages 1, 3, and 5, while stages 2 and 4 were tightly contested. The depicted match dynamics closely mirrored the actual match trajectory. The first turning point was marked by Team 1's break, and the second by Team 2's increased serve speed and deeper serve placements. These key moments and tactical shifts reflected the evolving direction of the match. In conclusion, our model's testing on data sets indicates its ability to realistically and dynamically predict momentum shifts and pivotal moments in matches, highlighting its robust generalization capabilities.

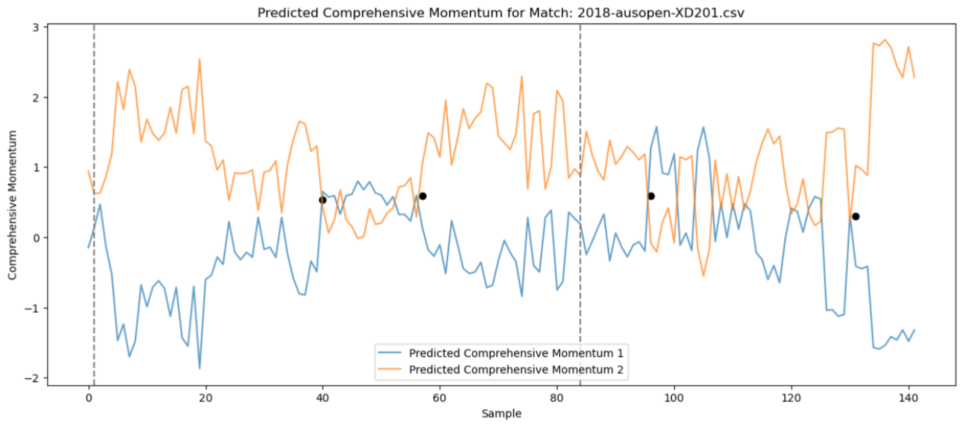

Figure 10: Match 3

8.4 Model's Adaptability to Various Match Types

The elements influencing the progression and volatility of various match types can differ, and our prior experiments have shown the model's general applicability and versatility to some degree. Should the model show inadequate adaptability to diverse match formats, we could enhance its suitability by modifying the choice of features and adjusting the model's parameters to cater to particular types of matches.

9 Memo

To: Tennis coach
From: MCM Team #2409015
Dtae: Feb 5th 2024
Subject: The Secret of Tennis Players' Momentum
Esteemed Coach,
Greetings!

I seize this moment to impart our latest tennis-related research insights, aspiring to enhance your coaching and the athletes' training. Our meticulous analysis of various matches has yielded vital recommendations, specifically tailored for both servers and receivers. Below are our detailed findings and advice:

Server's Guidelines:

- Enhance First Serve Success Rate: A pivotal correlation exists between a higher first serve success rate and increased chances of victory. A proficient first serve not only augments offensive strength but also alleviates mental stress during the game. Athletes are encouraged to refine their foundational serve training, boosting precision and quality of their first serve.
- Diversify Serve Trajectories and Pace: Varying serve directions (including B, BC, BW, C, W) and serve depths (CTL, NCTL) can adeptly perplex opponents and dis-

rupt their tempo. We advise athletes to master diverse serving styles and adapt their serving strategies based on game dynamics and the opponent's responses.
- Dictate Game Rhythm: Rally counts are positively linked to controlling the match's tempo. Prolonging rallies, while patiently anticipating opponents' errors, helps athletes gradually establish momentum. We recommend enhancing endurance and strategic planning in practice to manage and extend rally duration.
- Curtail Unforced Errors: The negative correlation of the p1_unf_err coefficient underlines minimizing errors' significance. Athletes should emphasize training for consistency and stability, particularly remaining composed during crucial points to prevent unforced errors.

Receiver's Recommendations:

- Prioritize Defense and Counterattacks: With the inclusion of the opponent's serve in their data, receivers must concentrate on developing defensive and counterattacking skills. We advocate for simulated practices to elevate adaptability to various serves and enhance counterattack quality.
- Optimize Response to Second Serves: The analysis of the p2_double_fault coefficient suggests an aggressive stance when facing an opponent's second serve, exploiting their instability. Athletes are encouraged to amplify their offensive approach following a first serve error to seize control.
- Modify Return Position and Tactics: Based on return_depth_D and retur_depth_ND observations, athletes should adjust their stance and return strategies as per match specifics. Training should focus on adapting to different return positions, enabling athletes to swiftly and effectively realign based on match rhythm and opponents' serving patterns.
- Reduce Redundant Movement: Minimizing unnecessary motion aids in preserving energy and concentration. Athletes are advised to scrutinize their court mobility via video analysis, identifying and diminishing non-essential movements to ensure adequate energy for crucial offensive or defensive plays.

These recommendations aim to leverage athletes' strengths and ameliorate weaknesses through scientific training. Recognizing the diversity in each athlete's style and technique, our advice should be tailored to individual needs.

In executing these strategies, we also recognize the importance of mental conditioning, real-time strategic adjustments, and opponent strategy analysis as crucial match influencers. Apart from physical and technical enhancements, mental and tactical comprehension should be nurtured.

Moreover, thorough match preparation and recovery are vital. Athletes should engage in comprehensive warm-ups pre-match and focus on recovery and nutrition post-match.

We appreciate your support for our research and eagerly await your feedback to refine our studies and further support you and your athletes. Please contact us for any queries or in-depth guidance.

Best wishes for your training endeavors!

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