Problem Chosen	2024 MCM/ICM Summary Sheet	Team Control Number
C		2418537

The Effect of Momentum in Tennis Matches

Summary

In the 2023 Wimbledon Gentlemen's final, the 36-year-old Grand Slam champion Novak Djokovic narrowly lost to the 20-year-old Spanish rising star Carlos Alcaraz. The incredible swings in the flow of the match are often attributed to momentum, which represent strength gained by motion or by a series of events. Based on the data from the 2023 Wimbledon men's matches, we dig into the relationship between the performance of players or the flow of play and the momentum of players.

First, we focused on the independent variables that may affect the performance of players and the flow of play to quantify the momentum of players. We used SPSS for binary logistic regression and obtained the accuracy rate about 0.66, indicating the rationality of evaluating the players' performance with these variables. Then we further validate our findings by employing some machine learning models and chose the best-perform model LGBM for further training. Depending on the trained model, we visualized the performance of players and the progress of match and analyze the importance of the selected variables.

Next, we validated the significant impact momentum had in the match by conducting correlation tests and hypothesis tests. The calculated correlation coefficient is 0.1838 and p-values are much less than 0.05, which indicates momentum does not have an absolutely significant impact on the scoring but does have a certain impact. We also validated the impact by comparison graph between momentum and match scoring, scatter diagram of average momentum and match outcomes and the state transition probabilities predicted by the Markov chain.

Then we concentrated on the factors can be controlled by human intervention to identify some indicators to help coaches and players determine when the flow of play is about to change. We selected some factors such as speed of serve, direction of serve and number of shots during the point, used MLP neural network model to identify the weights among them and give some suggestions based on the model.

Finally, we tried to test our model across more matches. Our model's average accuracy rate on other data from men's tennis matches is 74.6%, indicating our model can ensure a high level of accuracy in predicting outcomes of men's tennis matches. But for women's tennis matches, we suspected there are some reasons, for example the data from women's tennis matches contains more variables, and the original variables may not perform well under the influence of the new variables, causing the low accuracy rate about 64.37%. We improved by reselecting variables and adjusting parameters and the finally prediction accuracy rate is 72.32%. We also gave the goodness and weakness of our model in the final.

Keywords: binary logistic regression; LGBM model; Markov chain; MLP model

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1 Introduction

1.1 Problem Background

Tennis is a sport known for its elegance and competitive spirit, often hailed as the second most popular racket sport in the world. In the highly anticipated 2023 Wimbledon Gentlemen's Singles final, the 36-year-old Grand Slam champion Novak Djokovic narrowly lost to the 20-year-old Spanish rising star Carlos Alcaraz. However, what was even more surprising was the twists and turns during the match. Djokovic easily won the first set, Alcaraz won the second set in a tie-break and then easily took the third set. He began to dominate in the fourth set but was eventually overtaken, and the same thing happened in the fifth set, where Djokovic continued the edge from the fourth set but ultimately lost the match. Typically, such astonishing turns of events are attributed to "momentum", which refers to the strength gained through actions or a series of events. For tennis coaches and players, understanding the factors that can trigger positive or negative "momentum" is crucial, as it directly impacts the outcome of the match.

1.2 Restatement of the Problem

Considering the background information and related conditions, we need to analyze the data from the 2023 Wimbledon men's matches to address the following issues:

- Develop a model to capture the flow of the play and quantify the performance of the players, and provide visualizations based on the model to show the flow.
- Utilize the model to assess whether "momentum" plays a significant role in the matches.
- Develop a model using match data to predict match trends, identify the factors most closely associated with those trends, and provide strategic advice for the competition.
- Test the model across more matches to evaluate its predictive performance and generalizability, and suggest areas for improvement.

1.3 Literature Review

In the realm of sports, momentum is perceived as a bi-directional construct that can influence the probability of success in subsequent events (Cornelius *et al.*, 1997). Positive momentum arises from successful events, while negative momentum follows unsuccessful ones (Burke and Houseworth, 1995; Taylor and Demick, 1984; Vallerand *et al.*, 1988), a concept that is widely acknowledged by players, coaches, and spectators as a determinant of success (Stanimirovic and Hanrahan, 2004).

However, there is conflicting evidence regarding the actual observability of momentum in sports performance, with some studies suggesting that the perception of momentum may be a misperception by performers and viewers (Burke *et al.*, 1997; Bar Eli *et al.*, 2006). In basketball, for instance, players' scoring probabilities remain constant regardless of the outcome of their previous shots (Gilovich *et al.*, 1985; Tversky and Gilovich, 1989). Similarly, the winning streaks of NBA teams have been found to be no different from what would be expected by chance (Vergin, 2000).

Momentum is considered important in tennis, previous research has provided evidence on the positive correlation of point outcomes from previous points (Klaassen and Magnus, 2001), with some studies finding a slight decrease in the probability of winning the current point after winning the previous one (O'Donoghue and Brown, 2009). Others found no significant influence of the outcomes of the previous one to three points on the current point's outcome, but a notable effect when a player broke serve despite the server having game points; in such cases, the player was significantly more likely to hold serve in the next game, which indicates that momentum can be influenced by a series of events rather than single occurrences (Ben Moss and Peter O'Donoghue, 2017).

1.4 Our Work

The work we have done in this problem is mainly shown in the following Figure 1.

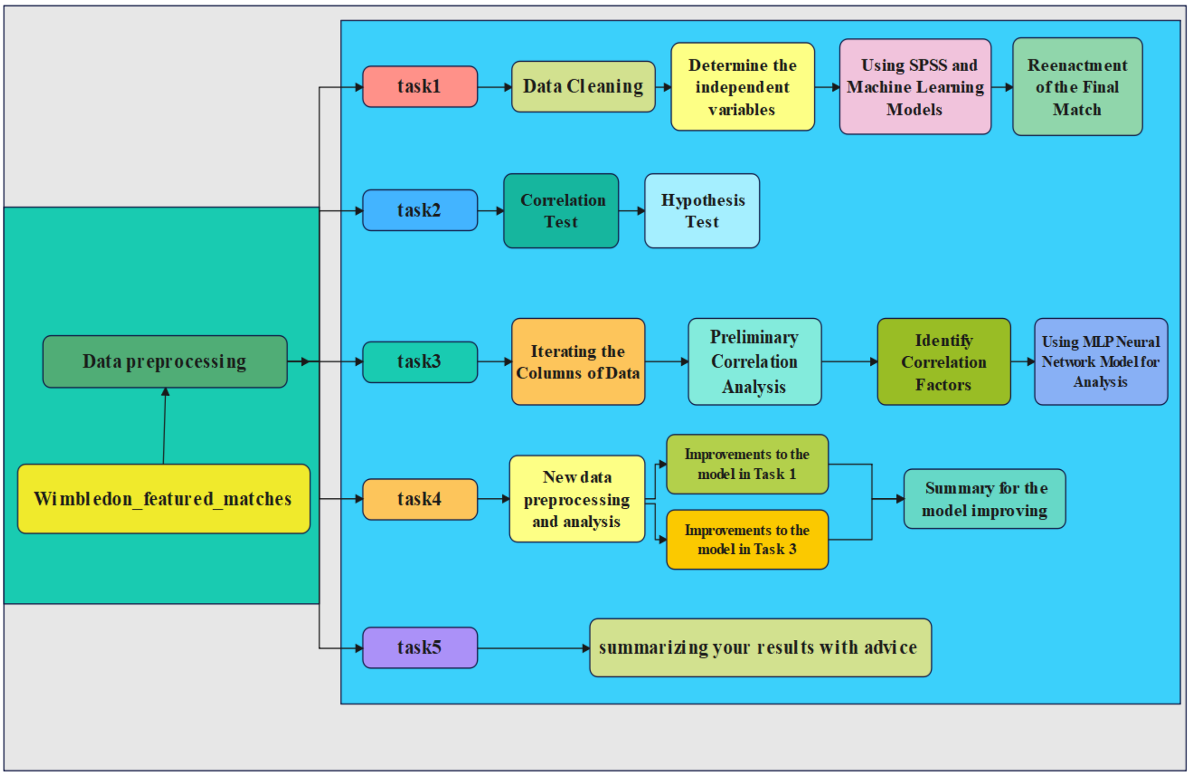

Figure 1: Our Work

2 Assumptions and Justifications

To simplify the problem and facilitate our modelling of the players' performance and momentum, we have made the following basic assumptions, each with appropriate justifications.

Assumption 1: The players' performance is not affected by external factors, for example the reaction of audience.

Justification: Professional athletes typically have undergone training to manage these external factors in order to maintain their best performance during matches.

Assumption 2: Players generally possess similar physical fitness levels, which means the more distance they run, the less remaining physical energy they have.

Justification: Professional athletes typically have undergone the professional physical training.

Assumption 3: Players are equally skilled, and thus the reason of success may lead to further success is not simply the successful player has greater abilities.

Justification: Professional athletes typically have undergone the professional skill training.

Assumption 4: The data from the 2023 Wimbledon Gentlemen's Tennis Championships is reliable and is representative of all high-level tennis matches.

Justification: As one of the four Grand Slam tennis tournaments, Wimbledon Gentlemen's Tennis Championships undoubtedly possesses reliability and representativeness.

3 Notations

The key mathematical notations used in this paper are listed in Table 1.

Table 1: Notations used in this paper

Symbol	Description
X_i	The ith correlation factor that affects winning or losing
τ	Pearson Correlation Coefficient
p_value	P-value in the hypothesis test
POT	a proportion of the test set

4 Task 1: Quantify the Flow and Performance

4.1 Data Cleaning

Considering that there are some errors in the data provided in the question and difficulties in importing it into SPSS for calculation, we have decided to clean the original data. We used Python to replace all occurrences of "AD" in the data with "50", which will facilitate subsequent data processing. Since players' distance ran during point and speed of serve have a significant impact on the momentum of the players, we appropriately filled in and modified some rows of data that are missing or contain errors.

4.2 Determine the Independent Variables

Considering that the factors affecting a player's momentum may not be limited to just the serve, we might as well think that all the indexes appearing in the data could potentially have an impact on momentum. We will select some important factors from them to quantify the player's momentum.

Table 2: Independent variables and its symbols

Independent Variables	Symbols
The number of games won in the current set	X_1
The lead in points in the current game	X_2
Whether the player is serving	X_3
Whether the player scored the last point	X_4
The lead in points in the current match	X_5
Whether the player hit an ace	X_6
Whether the player hit an untouchable winning shot	X_7
category of untouchable shot	X_8
Whether there was a double fault in the current game	X_9
Whether the player made an unforced error in the current game	X_{10}
The ratio of numbers when player made it to the net to points won while at the net	X_{11}
The ratio of numbers when player has an opportunity to win a game opponent is serving to actual points won when opponent is serving	X_{12}
The player's distance ran during the current match	X_{13}
The player's distance ran during the last three points	X_{14}
The player's distance ran during last point	X_{15}

speed of serve	X_{16}

Each of these factors may have an impact on the players' performance and the flow of the match, the explanation is as follows:

1. The number of games won in the current set: It may affect player’s confidence, pressure, and energy levels.

2. The lead in points in the current game: It may give the player an advantage, potentially affecting their opponent's mindset and increasing the pressure.

3. Whether the player is serving: Serving can be a crucial factor as it gives the player the opportunity to dictate the speed and direction of the tennis.

4. Whether the player scored the last point: Scoring the last point can boost a player's confidence and potentially increase the opponent's pressure.

5. The lead in points in the current match: A significant lead can reinforce the player's confidence.

6. Whether the player hit an ace: Aces can demoralize the opponent and boost the server's confidence.

7. Whether the player hit an untouchable winning shot: These shots can demoralize the opponent and assert serve’s dominance.

8. Category of untouchable shot: It may provide insights into a player's strengths and give him confidence.

9. Whether there was a double fault in the current game: Double faults can result in a direct loss of a point and can negatively affect a player's confidence.

10. Whether the player made an unforced error in the current game: Unforced errors can be a sign of nerves, fatigue, or lack of focus.

11. The ratio of net approaches to points won while at the net: This ratio can indicate a player's effectiveness at the net and their ability to convert opportunities into points.

12. The ratio of points won when the opponent is serving to the number of opportunities: This reflects a player's ability to break serve, which is crucial for winning sets and matches.

13. The player's distance ran during the current match: It can indicate a player's endurance and effort, which can be a deciding factor in long, grueling matches.

14. The player's distance ran during the last three points: This can show the intensity of the recent exchanges and can affect a player's energy levels.

15. The player's distance ran during the last point: This can reveals the physical demands of the point and can impact a player's readiness for the next point.

16. Speed of serve: A fast serve can make it difficult for the opponent to return and reflect the confidence of server.

We have compiled these factors into a table that can help us analyze the correlations and determine individual weights among them.

4.3 Feature Standardizing

Considering the significant differences in the units of measurement among various factors (such as running distance, serve speed, and scoring ratio), we need to standardize the data. After standardizing, we can obtain a new table.

4.4 Using SPSS for Binary Logistic Regression

To test whether the 16 factors have a significant impact on a player's scoring, we import the obtained table into SPSS for binary logistic regression analysis. The accuracy of the regression is around 0.66, which indicates that the model can be used to evaluate a player's performance.

Table 3: The accuracy rate based on SPSS binary logistic regression

Classification Table[a]					
			predict		
			label		
	actual		0	1	Correct percentage
Step 1	label	0	1857	944	66.3
		1	976	1823	65.1
	Total percentage				65.7

a.The cutoff value is .500

Table 4: Significance test of the 16 independent variables

Variables in the Equation							
		B	Standard error	Wald	Degrees of freedom	Significance	Exp(B)
Step 1[a]	x1	-.214	.099	4.683	1	.030	.807
	x2	.313	.217	2.077	1	.150	1.367
	x3	.198	.750	.070	1	.792	1.219
	x4	.093	.096	.928	1	.335	1.097
	x5	.120	.121	.994	1	.319	1.128
	x6	.994	.084	138.929	1	.000	2.703
	x7	.797	.068	138.064	1	.000	2.220
	x9	-.435	.059	54.269	1	.000	.647
	x10	.605	.086	49.862	1	.000	1.830
	x11	.022	.134	.027	1	.870	1.022
	x12	.254	.165	2.363	1	.124	1.290
	x13	-.010	.287	.001	1	.973	.990
	x14	-.184	.410	.202	1	.653	.832
	x15	-.062	.374	.027	1	.868	.940
	x16	-.416	.982	.180	1	.672	.660
	constant	-.738	.202	13.374	1	.000	.478

a. Variables inputted in the step 1:x1, x2, x3, x4, x5, x6, x7, x9, x10, x11, x12, x13, x14, x15, x16

4.5 Validation Using Machine Learning Models

We further validate our findings by employing some common machine learning models, evaluating them based on accuracy, recall, F1 score, AUC and precision, and obtained the following results:

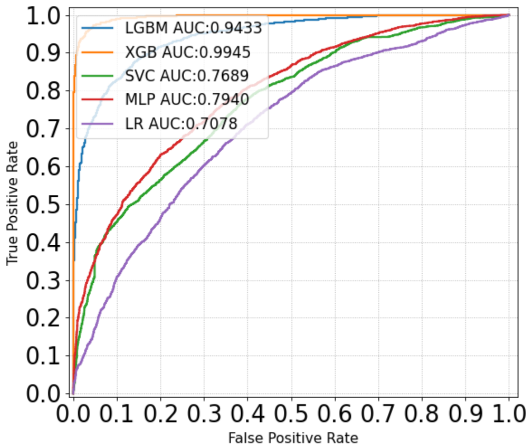

Figure 2: Results from train set

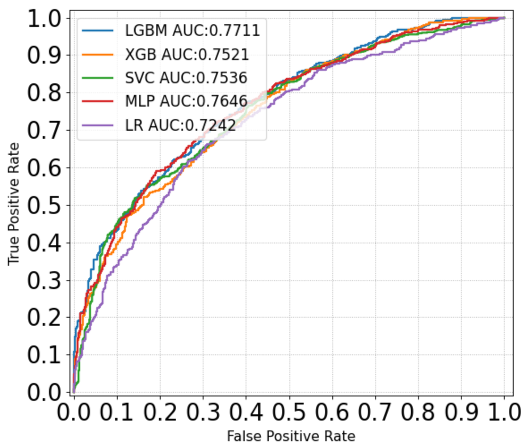

Figure 3: Results from test set

It is observed that the LGBM model have a highest AUC, so we choose this model for further training.

4.6 Reenactment of the Final Match Using the Trained Model

We use the trained model from the previous step to reenact the match described in the question and visualize the match's progression.

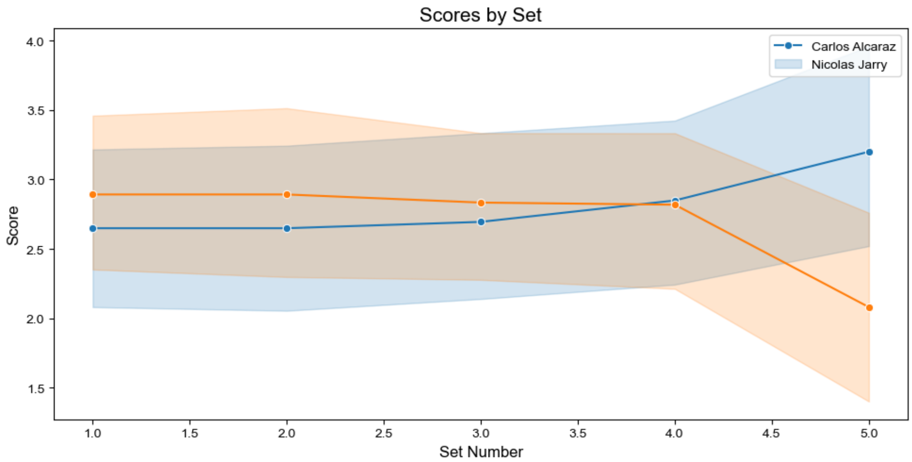

Figure 4: Visualization of the scores obtained by the players in each set

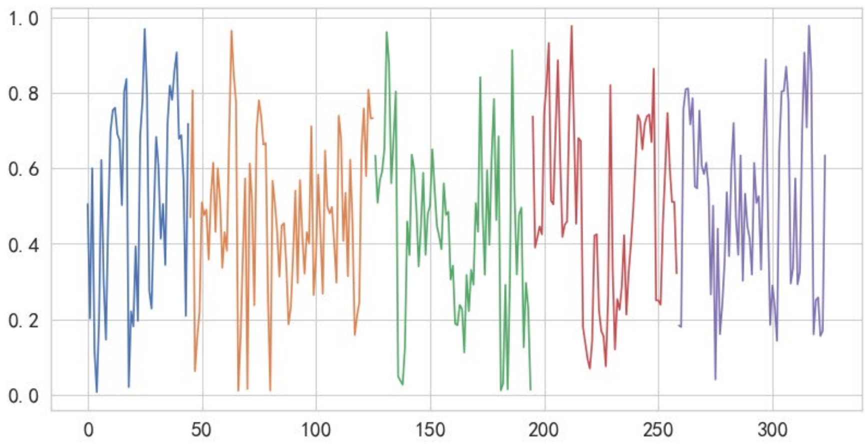

Figure 5: The performance of the player 1 in the match.

There are noticeable fluctuations in the performance of the player 1,with values oscillating between 0.0 and 1.0 ceaselessly. We know that player 1, the Spanish player Carlos Alcaraz, began to dominate in the fourth set but was eventually overtaken, and had a disadvantage at the start of the fifth set but ultimately won the match. This can be reflected in the figure where the red curve representing the fourth set shows a dip in the middle, and the purple curve representing the fifth set rises at the end. This indicates that the momentum we have quantified can influence the outcome of the match to some extent.

Then, we need to output the importance indexes of the 16 independent variables for scoring, which will reveal the importance of these 16 factors in determining the win or loss of a point.

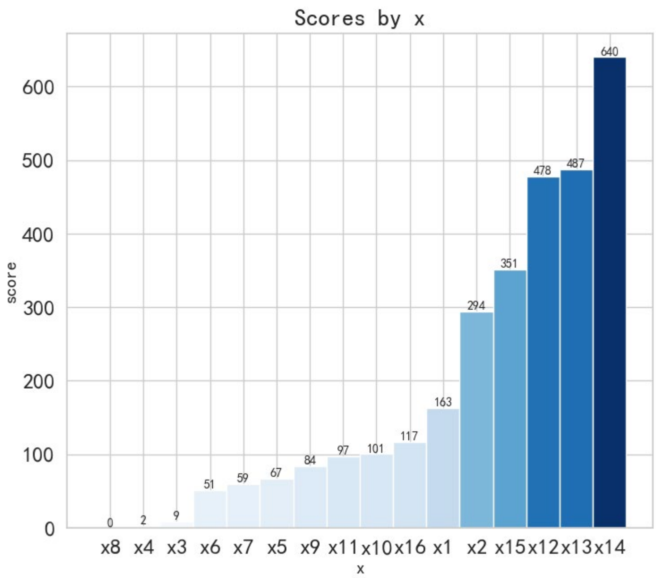

Figure 6: The importance indexes of the 16 independent variables

We can observe that the factors with the greatest impact on winning and losing are closely related to the running distance, the lead in the score, and the number of break serves, such as the player's distance ran during the last three points, the ratio of numbers when player has an opportunity to win a game opponent is serving to actual points won when opponent is serving and the lead in points in the current game, while whether the player scored the last point and whether the player hit an ace have a minor impact. This may suggest that a player's performance or the change in momentum is not significantly related to the occurrence of certain single event, but rather depends on the cumulative effect of a series of previous events. Contrary to intuition, whether the player is serving has almost no impact on the winning and losing in our model, as the server clearly holds the absolute initiative. However, when we isolate the factor of serving, we find that the win rate of the server is actually 67.31%, indicating that serving has a significant influence on the winning and losing. This influence may be diluted over the course of the match by various factors.

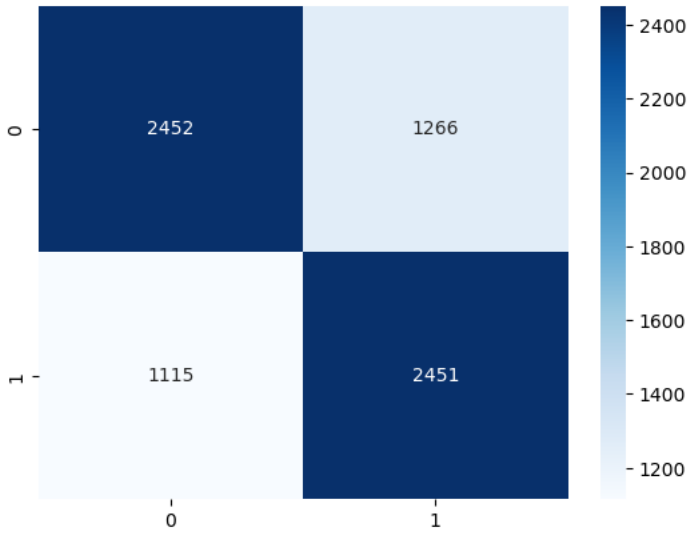

Figure 7: The win rate of the server

5 Task 2: Test the Role of Momentum in the Match

We have already quantified the momentum of the players in the first task. In the second task, we need to validate whether the momentum has a significant correlation with the turning points and the scoring in the match by conducting a correlation test and a hypothesis test.

5.1 Data Processing

We added the players' momentum quantified in the first task into the original data file for subsequent calculation. For any special or erroneous data, manual processing and adjustments are made.

5.2 Correlation Test

We imported the data and conducted the Pearson correlation test to assess the relationship between momentum and scoring.

$$\tau = \frac{\sum_{i=1}^{n}(x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum_{i=1}^{n}(x_i - \bar{x})^2 \sum_{i=1}^{n}(y_i - \bar{y})^2}}$$

The calculated correlation coefficient is approximately 0.1838, indicating that momentum does not have an absolutely significant impact on the scoring in the match. However, whether there is an effect depends on the subsequent hypothesis test.

5.3 Hypothesis Test

We conducted the hypothesis test. Our null hypothesis is that "momentum has no impact on the scoring in the match", and the alternative hypothesis is that "momentum has some impact on the scoring in the match".

The calculated p-value is 2.202×10^{-56}, which is less than our predetermined significance level of 0.05, so we reject the null hypothesis, suggesting that momentum does have some impact on the scoring in the match.

We then conducted some different hypothesis tests, including the Kolmogorov-Smirnov test, chi-square test. We used the results of these tests to plot an auto correlation graph.

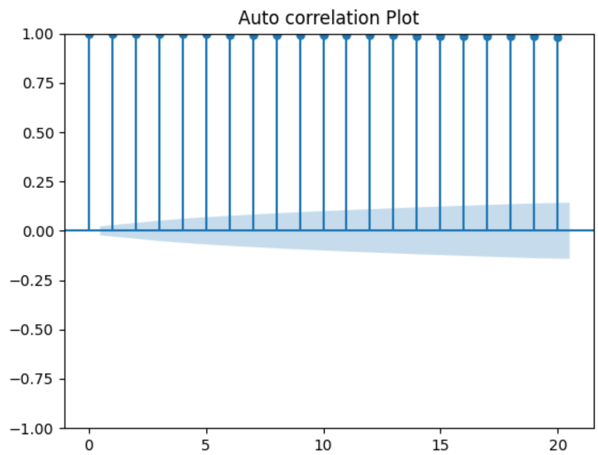

Figure 8: Auto correlation plot of different tests

The calculated p-value of chi-square test is 0.0002, and the value of Kolmogorov-Smirnov test is 9.638×10^{-35}. We found that the auto correlation plot fits the alternative hypothesis well, so we can assert that momentum has a certain impact on winning and losing in the match.

5.4 Conclusion

Based on the certain relationship between momentum and the scoring in the match, we have plotted the graph about the two during the match to compare their change.

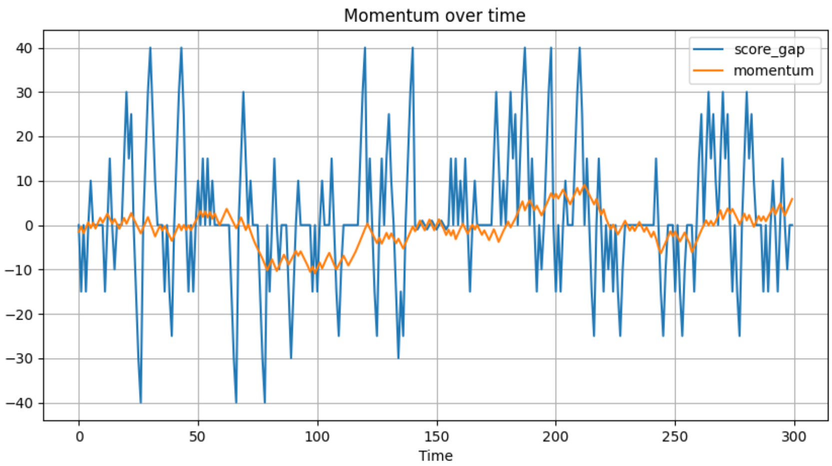

Figure 9: Momentum vs. match scoring comparison graph

We can observe that momentum does not fit well with the scoring in the match, which is consistent with the previously calculated correlation coefficient. However, since the hypothesis test was passed, we still believe there is a certain connection between the two.

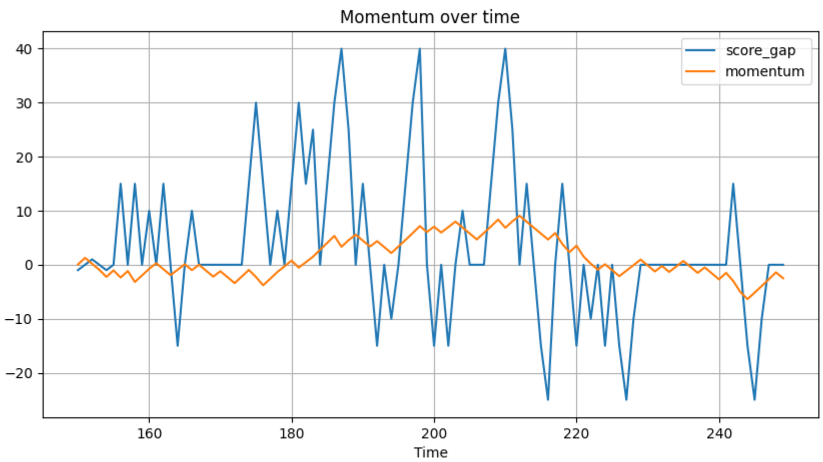

Figure 10: A certain section of the momentum vs. match scoring comparison graph

We took a specific section of the original comparison graph between momentum and scoring, and we can observe that there was a period when the player's momentum remained stable at a positive value, and during this time, the player's score was also generally leading, indicating that momentum was a significant factor in the scoring.

Furthermore, we consider the relationship between average momentum in a match and the final outcome of the match. The red dots in the diagram represent that the player with high average momentum won the match, while the blue dots represent the opposite. We find that the match outcome has an 87.1% match rate with average momentum, which is higher than the 65.7% match rate between momentum and next scoring. This suggests that the impact of momentum is more pronounced throughout the match.

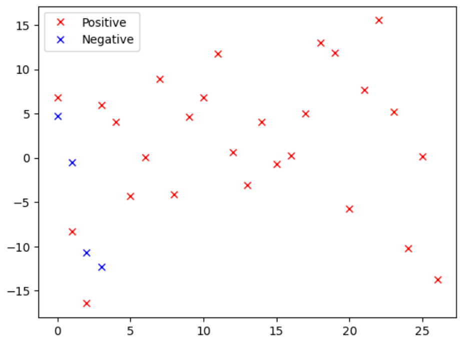

Figure 11: The scatter diagram of average momentum and match outcomes

To further probe the role of momentum in the performance of players during a match, we utilized the Markov chain to calculate the probabilities of score state transitions. There are 15 score states, such as "0:0", "2:3", etc. We analyzed these states to compute the probabilities of transitioning between them, as shown below.

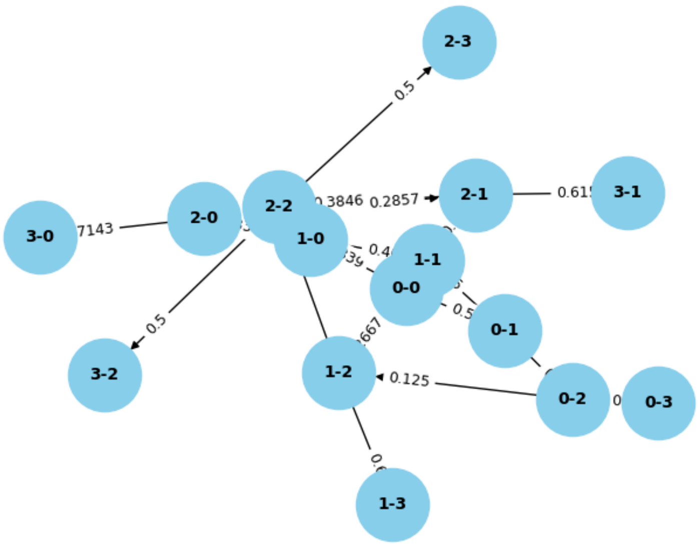

Figure 12: The state transition probabilities predicted by the Markov chain

Through the Markov chain, we can discover that momentum does have a certain impact on scoring in the match. The transition probabilities for each current score state are different. When the score is tied at "2:2", who wins or loses depends on the previous states.

In conclusion, the coach's skeptical attitude is somewhat inaccurate. Swings in play and runs of success by one player does have a certain relationship with the momentum, rather than being random as he suggested.

6 Task 3: Identify the Indicators and Give Suggestions

In this part, we need to identify some indicators to help coaches and players determine when the flow of play is about to change. We already knew that some factors, for example whether the player is serving, have a significant impact on scoring and the outcome of the match, but we generally cannot decide the player who is to serve at a certain point in the match (it is usually determined by the rules of the match). Therefore, we did not consider these uncontrollable factors.

6.1 Iterating the Columns of Data

We iterated through all the columns in the data file to calculate the correlation coefficient of each factor with the outcome of the match. We found that some factors have a small correlation coefficient, while others have a large correlation coefficient, such as whether the player is serving mentioned above, as well as the scores between players.

6.2 Preliminary Correlation Analysis

We analyzed several factors that have large correlation coefficients.

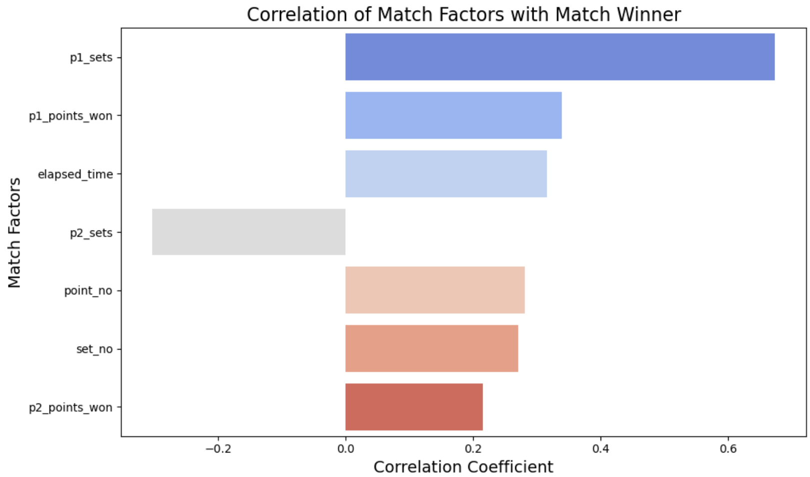

Figure 13: The correlation coefficient of some factors with the outcome of the match

We found that among these factors with large correlation coefficients, except for "elapsed_time", all other factors are uncontrollable in the match. What we aim to do is to provide coaches and players with suggestions on how to change the flow of play, so we should focus on factors that can be controlled by human intervention. Therefore, we do not analyze factors that have large correlation coefficients but are uncontrollable.

6.3 Identify Correlation Factors

We analyzed the remaining factors that have a certain degree of controllability and obtained the following results.

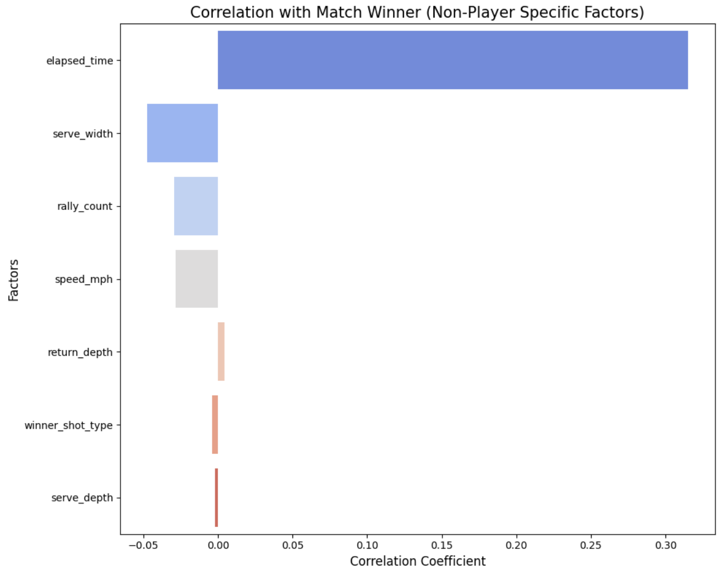

Figure 14: The correlation coefficient of controllable factors with the outcome of the match

We found that the most significant factor affecting the outcome of the match is the time elapsed since start of first point to start of current point (elapsed-time). Additionally, factors such as direction of serve (serve_width), number of shots during the point (rally_count), speed of serve (speed_mph), depth of return (return_depth), and depth of serve (serve_depth) also have a certain impact on the outcome.

6.4 Using MLP Neural Network Model for Analysis

We used MLP neural network model to analyze the factors we identified above. We imported the data into the model, filled in any missing values, split the data into a training set and a test set with the ratio of 4:1, normalized the data with different metrics, and then trained our model. The final predicted accuracy rate was 75.81%. Therefore, by using this model, we are likely to determine when to make appropriate adjustments to the player's strategy to increase their win rate.

The weights of each factor obtained from the model training are as follows.

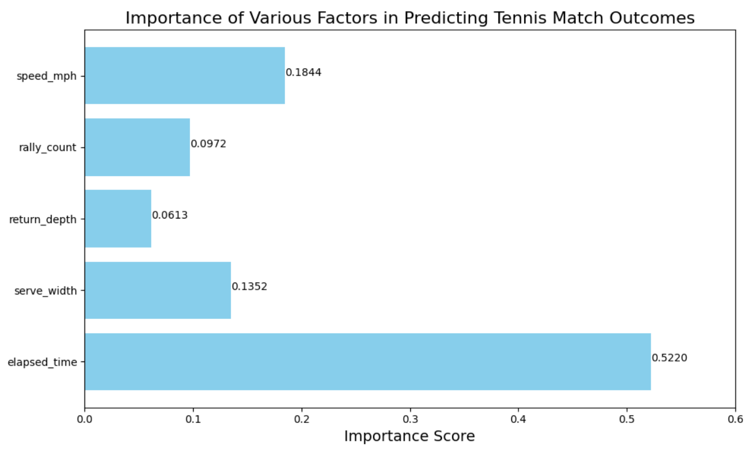

Figure 15: The weights of factors in the trained model

6.5 Conclusion and Suggestions

We found that elapsed-time has a largest weight in our model, indicating that it has the most significant impact on the scoring among the controllable factors we identified. These factors all can be strategically utilized by the coaches and players to influence the outcome of a match:

1. elapsed-time: This indicator can be used to monitor the player's fatigue levels. Coaches can analyze the elapsed-time data to determine strategies in how should the player allocate him energy over the course of a match. If the player tends to lose concentration or become exhausted as the match progresses, the coach can recommend taking strategic breaks or adjusting the player's pacing to conserve energy for crucial points.

2. serve-width: In terms of direction of serve, we can target the opponent's weaknesses and attack their vulnerable areas. Additionally, we can take advantage of natural conditions (wind direction, court conditions) to make it more difficult for the opponent to return the serve or disrupt the opponent's rhythm, potentially leading to errors or less aggressive returns. If the player is already leading in the score, he can capitalize on the above methods to reinforce his advantage and close out the game.

3. rally-count: Number of shots during the point can indicate the style of play. If the opponent is trying to win the match through rapid attacks, player should defend until entering the rallying phase. During the rallying phase, player should not rush to attack. Instead, calm down, adjust rhythm, and then look for opportunities to strike back. Or encouraging a player to end rallies more quickly with aggressive shots or by capitalizing on their opponent's weaknesses when his opponent has just gone through a prolonged point and expended a significant amount of physical energy.

4. speed-mph: A high-speed serve can make it difficult for the opponent to return, but it also comes with a higher risk of errors. Coaches can analyze speed-mph data to find the optimal speed for each player, balancing power with accuracy to maximize the chances of winning points on serve， or recommend the player hitting a fast serve if he is already leading in the score.

5. return-depth: The depth of return can dictate the difficulty for the opponent to return. Players can choose when to hit deep returns to push the opponent back or when to use a shorter return to set up an aggressive follow-up shot. But it is also important to balance the risks and the greater physical exertion involved.

By integrating these factors into a player's training and strategy, coaches can help players make more informed decisions during a match, potentially leading to improved performance and a higher win rate.

7 Task 4: Test the Model across More Matches

We searched the data of men's tennis matches from 2019 to 2022 online and test the accuracy of our model on them individually, finding that the accuracy rates are all above 70%, with an average accuracy rate of 74.6%. This indicates that for men's tennis matches, our model can still ensure a high level of accuracy in predicting outcomes.

For other matches, we found datasets for women's tennis matches (WTA) from 1968 to 2023 online. Considering timeliness, we first chose the data from the 2023 Women's Tennis Open for testing. In this dataset, in addition to the original factors, there are also some other factors, such as the type of court surface (surface), the ages of the players (age), and the dominant hand used by both players (winner-hand), etc.

7.1 Improve the Model in Task 1

We first analyzed all factors that appeared in the new dataset. We imported the data from 1968 to 2022 into the original model in Task 1 as the training set and using the 2023 data as the test set. After preprocessing the data, we trained the model and obtained a prediction accuracy rate of 64.37% for the 2023 WTA matches. We found that the accuracy rate was lower than the previous accuracy rate for men's tennis matches. We suspect there are several reasons for it:

1. The new data contains more variables, and the original variables may not perform well under the influence of the new variables.

2. Since the total number of sets in women's tennis matches is 3, while the total number of sets in our trained model is 5, this could have some impact on the outcome.

3. The new data includes indicators such as the players' ages and the dominant hand used by the players, which may have mutual influence that can not be reflected in the original model.

To address these problems, we reselected the independent variables. On the basis of the original independent variables, we added some new influential factors, such as the players' ages and the dominant hand used by the players. We retrained the model, and the resulting weights are as follows:

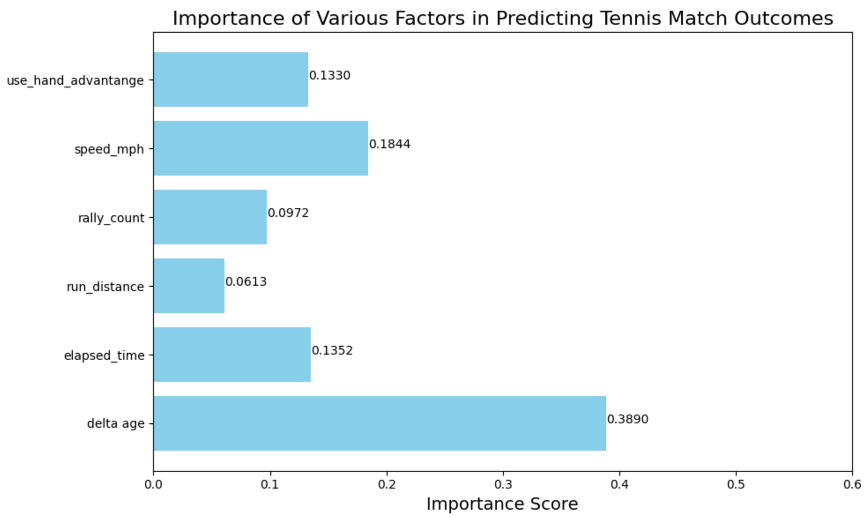

Figure 16: The weights of factors in the retrained model

We can observe that the players' age actually has a significant relationship with the scoring in the match, probably because older players have more court experience. Of course, we cannot directly determine the outcome of a match based on age alone, as 20-year-old Spanish rising star Carlos Alcaraz defeated 36-year-old Grand Slam champion Novak Djokovic in men's finals.

After adjusting the parameters and retraining, the final prediction accuracy rate for the 2023 women's tennis matches is 72.32%, still lower than the accuracy rate of the previous men's matches. We speculate that the variability of the data lead to model's instability, which can be further adjusted and optimized.

7.2 Improve the Model in Task 3

We continued to adjust and improve the second model. The second model considers only the factors that are controllable, such as the speed of serve, the direction of serve, number of shots during the point and depth of return.

Since the new independent variables are all uncontrollable, we still used the original independent variables for prediction. As expected, the correlation coefficients did not change significantly. We used the trained model to make predictions and obtained a low accuracy rate of 64.7%. This indicates that the model is not entirely applicable to women's tennis matches for providing guidance on when the flow of play is about to change.

7.3 Conclusion

Through the improving of the two models, we have drawn a general conclusion that our model cannot be applicable to all matches, for example the women's tennis matches. For more complex and variable sports like table tennis, our model is also incapable of achieving a high prediction accuracy rate. Therefore, the model may only be suitable for the data provided in our question. For datasets containing other factors, it may not yield very good prediction results.

8 Summarize Our Results and Give Some Advice

1. Emphasize the impact of winning the previous point on the current one: According to our research, the outcome of the previous point has a certain degree of influence on the current point. Therefore, coaches can emphasize to players the importance of winning each point and encourage them to stay focused and strive in every score.

2. Pay attention to turning points during the match: Since turning points in a match can significantly affect the flow of the play, coaches can help players prepare strategies to deal with these turning points, including adjusting tactics, maintaining a positive mindset, and providing technical and psychological support to address the challenges brought by turning points.

3. Value winning streaks and losing streaks: Our research indicates that winning streaks and losing streaks have a significant impact on the change of momentum. Therefore, coaches can help players increase momentum and confidence from winning streaks and provide appro-

priate support and guidance to prevent losing streaks from adversely affecting the players' psychology and performance.

4. Analyze opponent's momentum and its trend: Coaches can use our model to analyze opponent's momentum and its trend. By identifying the strengths and weaknesses of opponent, coaches can devise targeted tactics and strategies to utilize the opponent's momentum, thereby increasing the chances of victory for their players.

5. Predict match trends and provide strategic advice: Coaches can use our model to predict match trends and provide strategic advice. By identifying factors closely related to the match's flow, coaches can help players adjust their tactics and strategies to adapt to changes in the match and offer targeted advice to increase the players' chances of winning.

9 Sensitivity Analysis

For the model in task 1, we need to conduct a sensitivity analysis to test the volatility of our model. When training the model, we used a specific proportion of the test set (POT) of 0.2. To verify the reliability of our model, we changed the POT to check if the deviation of the AUC is within the expected range.

Table 5: Sensitivity analysis of different models

Model	POT=0.2	POT=0.3	POT=0.1
LGBM	0.7711	0.7598（1.47%）	0.7622（1.15%）
XGB	0.7521	0.7369（2.02%）	0.7483（0.51%）
SVC	0.7536	0.7432（1.38%）	0.7375（2.14%）
MLP	0.7646	0.7616（0.39%）	0.7600（0.60%）
LR	0.7242	0.7020（3.07%）	0.6763（6.61%）

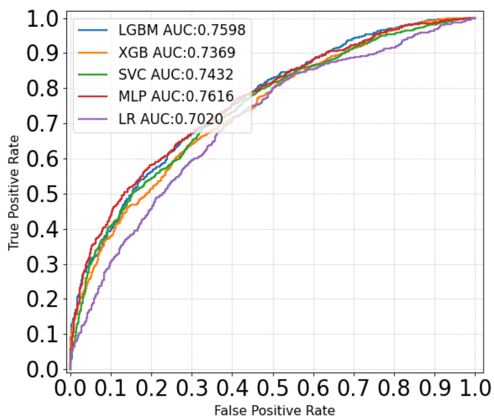

Figure 17: Model training with POT=0.3

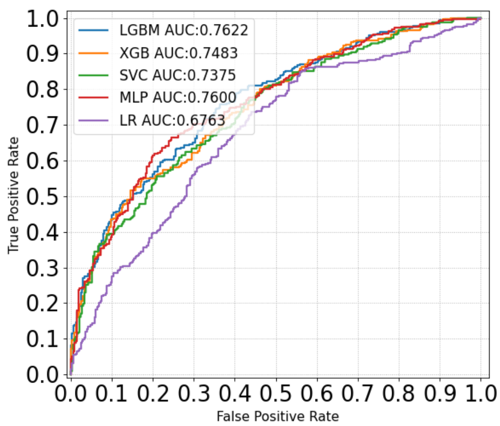

Figure 18: Model training with POT=0.1

We found that the change in POT does not significantly affect the AUC of the model, with most changes falling between 0%-5%, and only one value reaching 6.61%. Therefore, we have completed a sensitivity analysis on both the selection of the POT and the stability of the model.

10 Model Evaluation and Further Discussion

10.1 Strengths

1. The model with 16 independent variables in the first task effectively considers the factors that may influence the match and makes good use of the provided data, resulting in satisfactory outcomes.

2. The binary logistic regression classification used in SPSS requires small storage spaces, has a very small computational load and a low computational cost, making it easy to understand and implement.

3. The LGBM model has a faster computation speed compared to other models and adopts a tree growth strategy based on the Leaf-wise algorithm, which reduces a lot of unnecessary computational load and requires less memory.

4. The hypothesis test of p_value effectively examines the relationship between momentum and the scoring in the match.

5. The Pearson chi-square test effectively captures the relationship between variables.

10.2 Weaknesses

1. The 16 variables in the first task actually have certain correlations with each other, namely they are not completely independent of each other, which will lead to some bias in the calculated correlation.

2. When the feature space is large, the performance of logistic regression is not very good. Besides, binary logistic regression tends to underfit, so the accuracy rate is often low.

3. The LGBM model, when searching for the optimal solution, is based on the optimal split variable and does not take into account that the optimal solution is a combination of all features.

4. Due to the finiteness of the data provided, the p_value test cannot effectively measure the validity of the hypothesis.

5. For the Pearson chi-square test, if the expected count for individual fields is too low, it will make the probability distribution not approximate the chi-square distribution.

10.3 Further Discussion

For these models, we can make some improvements or extensions. For the models we obtained in tasks 1 and 3, we can further adjust parameters and change control factors. Regarding the applicability issues of the model in task 4, we can make further modifications to our model to achieve the desired accuracy.

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