Study of tennis performance on different surfaces and factors that affect wins

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Abstract

This study explores how player rankings and aces affect tennis match outcomes using the Association of Tennis Professionals (ATP) data. The first research topic examines the impact of ranking differences on match duration. The research then evolves to investigate the relationship between the number of aces by a tennis player and that player's odds of winning.

Methodology to the study includes exploratory data analysis combined with linear and logistic regression models, supported by visualizations. These findings highlight the connection between player rankings, aces, and match outcomes, while emphasizing the interactive impact of surface type.

Results show that larger ranking gaps lead to shorter matches, though surface type and match conditions also influence duration. Additionally, the findings indicate that hitting more aces improves the odds of winning, with surface types like clay and hard courts playing a significant role in this relationship.

Introduction

A substantial body of research has explored the prediction of tennis match outcomes using statistical models, highlighting the importance of player attributes and match statistics. Early studies, such as those by Newton and Keller (2005)[2], O'Malley (2008)[3], and Riddle (1988)[4], demonstrate that under the assumption of independent and identically distributed (iid) point outcomes on a player's serve, the probability of winning a match can be derived from the probabilities of winning points on serve.

Kovalchik (2016) [5] conducted a comparison of 11 published tennis prediction models, categorizing them into three classes: point-based models relying on the iid assumption, regression-based models, and paired comparison models. The study found that while point-based models had lower accuracy and higher log loss, regression and paired comparison models generally outperformed them.

Methods

Data and preprocessing

The dataset utilized in this study is the Tennis ATP Dataset curated by Jeff Sackmann (Sackmann, 2021) [1]. This dataset serves as a comprehensive repository of professional tennis data, encompassing a wide range of player information, historical rankings, match outcomes, and statistical metrics. Specifically, it includes a player file containing detailed biographical data, such as unique player identifiers, names, handedness, birth dates, nationalities, and physical attributes like height. Additionally, ranking files provide a historical record of ATP rankings over time, while the results file covers match outcomes across tour-level, challenger, and futures events. This dataset forms a robust foundation for exploring various aspects of professional tennis performance and trends.

The dataset selected includes ATP match data from 2014-2024, the subset chosen are challenger matches and professional and tournament class A such as Davis Cup, Roland Garros and others. The records from this period consist in 116,103 matches where each match has 49 variables.

The initial collection of data contains features at the match level, therefore it has information from the winner player and the loser player. In order to analyze the effect of match win this structured has been modified to portray the results at the player level, including both win and loss outcomes.

In order to improve the quality of the data, those players that do not have a rank and rank points have been set to zero as the data dictionary explains that unranked players are new to these tournaments. To handle missing values in height, an imputation technique is used where player height is estimated using the average of the country of birth of the player.

Furthermore, rows where the number of aces played is missing have been removed as this is key information in our research questionanalyzing that matches whose number of aces for the winner nor the loser are missing lack all the statistical information from the the other aspects of the match therefore those records have been filtered. The same rationale applies to the serving games as it signals records that have missing information overall therefore those records have been filtered out from the analysis data.

Lastly, for highly correlated information, ratios have been computed to continue to capture granularity in information, but also reduce the number of variables needed in any model, minimizing multicollinearity.

Variable selection

Taking as reference previous research regarding the most relevant features involved in the outcome of a tennis match (Newton et al., 2005[1]; O'Malley 2008[2]; Kovalchik, 2016) a pre selection was made observing the limitation of the available data. In order to further refine the process of feature selection exploratory data analysis was conducted using correlation plots, box plots and scatterplots.

Modeling and evaluation

The present study focuses on the effects of the duration of a match using linear regression to evaluate inference capabilities and determining the principal factors for a match win using logistic regression to evaluate the probability of a win. Variance Inflation Factor (VIF) was used to test multi-colinearity. For the linear regression task the assumptions for the model are tested via residual vs fitted plots and normal q-q plots, furthermore, the performance of the model is evaluated using the adjusted r squared metric. In terms of logistic regression, accuracy, recall sensitivity and specificity are used to evaluate the model. Lasso Regularization is implemented to prevent overfitting of the model due to too many variables. The

AIC score is also used to evaluate the model, incorporating the number of predictors into the overall score.

Results

Overview of key variables of interest

The dataset has a fairly even distribution of players that Win (101746) and Lose (111621), implying that there would not be more information gain in one outcome over the other. The surface types do not have as balanced of a distribution. Majority of the matches are played on a Hard or Clay surface, accounting for 53.5% and 41.1% of the matches. About 5% of the matches are played on Grass and only 0.2% on Carpet. Below we consider the distribution of the key continuous variables:

Table 1: Summary Statistics for Variables

Variable	Minimum	Quantile.1	Mean	Median	Quantile.3	Maximum
minutes	0	74	100.490937	94	123	4756
rank	0	98	268.974804	200	343	2257
aces	0	2	4.745965	4	7	75

Research question 1: Effects of the difference in ranking over the length in minutes for a tennis match

Research question 2: Aces and court surface type influence in match outcome

The results for the final fitted model for win prediction are in the Anex I since the table is large. The selected variables along with the interaction term of the type of surface was included. Multiple iterations to find the best model were performed and multicolinearity evaluations were used to assess the model. To evaluate multicollinearity, the VIF score was used on a logistic regression model. The raw variables representing a player's total serve points, number of first serve points made, number of first serve points won, number of second serve points won, number of break points faced, number of break points saved, total draw size in the tournament and the tournament level were all highly correlated. To address the multicollinearity in serve variables, ratios of successful serves for the first and second attempt were generated. Similarly, the break points saved ratio is used in place of the overall counts. Lastly, between draw size and tournament level, draw size is only used as there is more granular information derived from draw size than tournament level.

Apart from the VIF scores, Lasso Regularization is also performed to prevent the model from overfitting as the number of variables used is large. Using the optimal lambda value in the cross validation process, extraneous variables are identified. However, this approach did not result in the removal of any variables, rather specific binary variables representing a category like whether or not the surface is grass were deemed insignificant. Hence, Lasso Regularization is not used in the final model. The model function is:

$$
\begin{aligned}
\log\left(\frac{P(\text{win})}{1-P(\text{win})}\right) = \beta_0 \\
&+ \beta_1 \cdot \text{draw size} \\
&+ \beta_2 \cdot \text{left-handed player} \\
&+ \beta_3 \cdot \text{right-handed player} \\
&+ \beta_4 \cdot \text{undefined-handed player} \\
&+ \beta_5 \cdot \text{player height} \\
&+ \beta_6 \cdot \text{player age} \\
&+ \beta_7 \cdot \text{rank} \\
&+ \beta_8 \cdot \text{rank points} \\
&+ \beta_9 \cdot \text{aces} \\
&+ \beta_{10} \cdot \text{clay surface} \\
&+ \beta_{11} \cdot \text{grass surface} \\
&+ \beta_{12} \cdot \text{hard surface} \\
&+ \beta_{13} \cdot \text{double faults} \\
&+ \beta_{14} \cdot \text{first serve win ratio} \\
&+ \beta_{15} \cdot \text{second serve win ratio} \\
&+ \beta_{16} \cdot \text{break points saved ratio} \\
&+ \beta_{17} \cdot (\text{aces} \cdot \text{clay surface}) \\
&+ \beta_{18} \cdot (\text{aces} \cdot \text{grass surface}) \\
&+ \beta_{19} \cdot (\text{aces} \cdot \text{hard surface})
\end{aligned}
$$

Below is a summary of the final logistic regression model:

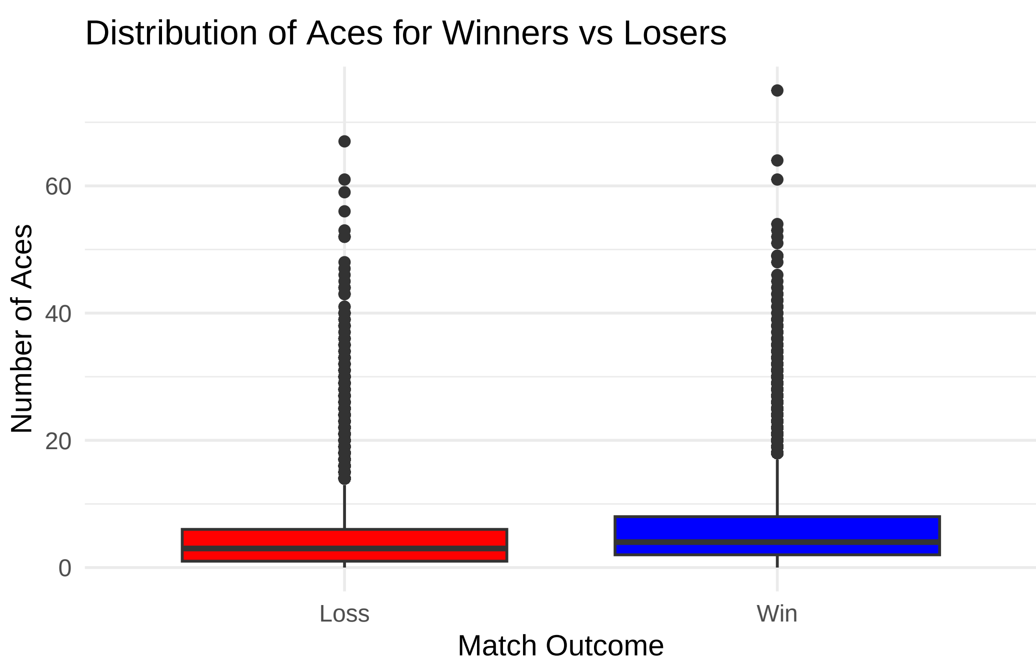
Table 2: Logistic Regression Coefficients, Odds Ratios, and P-values

Variable	Coefficient	Odds Ratio	P-value
(Intercept)	-0.3636746	0.6951173	0.5729598
draw_size	-0.0024621	0.9975409	0.0000000
player_handL	2.2698780	9.6782204	0.0001411
player_handR	2.2755000	9.7327838	0.0001354
player_handU	2.0070022	7.4409776	0.0007650
player_height	-0.0191927	0.9809903	0.0000000
player_age	-0.0154771	0.9846421	0.0000000
rank	-0.0005144	0.9994858	0.0000000
rank_points	0.0001543	1.0001543	0.0000000
aces	0.0966552	1.1014805	0.0000005
surfaceClay	0.7382147	2.0921969	0.0001173
surfaceGrass	0.3250532	1.3841042	0.0956714
surfaceHard	0.5582932	1.7476870	0.0035779
double_faults	-0.1403072	0.8690912	0.0000000
break_pt_save_ratio	2.5465202	12.7626151	0.0000000
aces:surfaceClay	0.0048078	1.0048194	0.8041908
aces:surfaceGrass	-0.0242897	0.9760029	0.2163763
aces:surfaceHard	-0.0169552	0.9831877	0.3794067

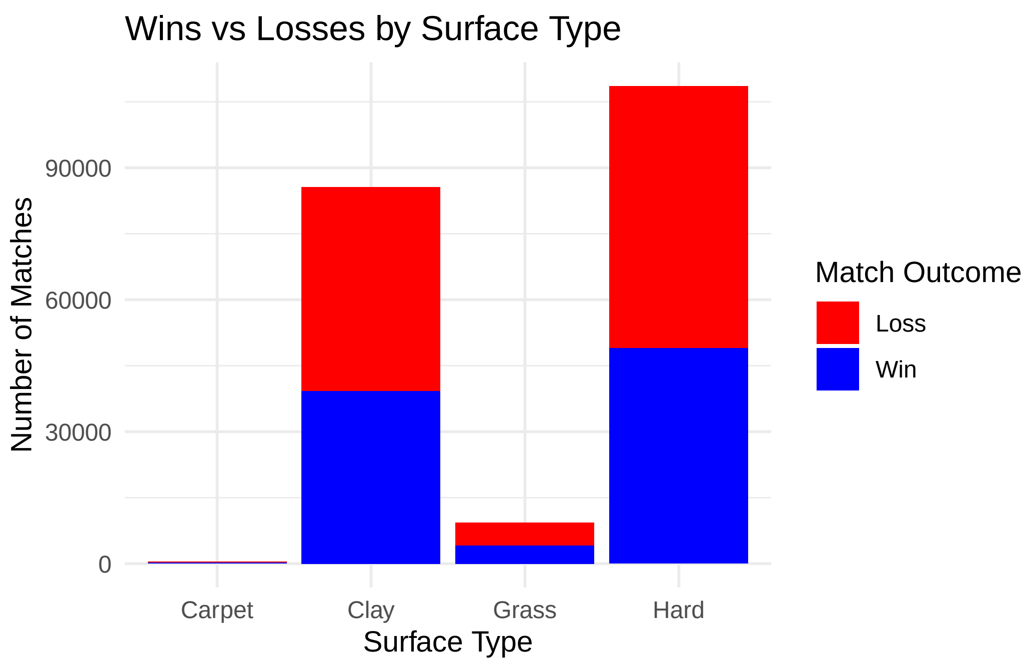
Analyzing the variables of interest aces and surface, holding every other variable constant, applying exponential we have an effect of 1.1 times increase in odds of winning for every extra ace point. Similarly matches on Clay and Hard surfaces increase the odds of winning in comparison to playing on a Carpet by 2.1 and 1.7 times respectively. Surprisingly, the impact of every extra ace point is not statistically significant between the different surface types. Another statistically significant variable impacting the odds of winning is the right vs left-handed stature of the player. Specifically being Right or Left Handed (as opposed to undefined) is associated with approximately 9.7 times increase in odds of winning.

Metric	Value
Accuracy	0.6838672
Precision	0.6899683
Recall	0.7648834
F1 Score	0.7254970
Specificity	0.5863642
Sensitivity	0.7648834
Positive Predictive Value	0.6899683
Negative Predictive Value	0.6745036

The performance of the logistic regression model was evaluated using standard classification metrics, including accuracy, precision, recall, and F1 score. The model achieved an accuracy of 0.8117, indicating that approximately 81.17% of predictions matched the true outcomes. The precision of the model was 0.8230, reflecting its ability to correctly identify positive cases while minimizing false positives. The recall was measured at 0.8155, demonstrating the model's capability to correctly identify a high proportion of actual positive cases. Finally, the F1 score, a harmonic mean of precision and recall, was calculated to be 0.8192, indicating a balanced performance between these two metrics. Together, these results suggest the model performs reliably in predicting match outcomes based on the given features.



The distribution of aces played by Winners is slightly higher valued than the distribution of aces by Losers. This supports the model estimates and the slight increase in odds of winning (by 1.1 times) for every additional ace played.



Conclusion

References

[1] Sackmann, J. (n.d.). Tennis databases, files, and algorithms [Data set]. Tennis Abstract. Licensed under a Creative Commons Attribution-NonCommercial-ShareAlike 4.0 International License. Based on a work at https://github.com/JeffSackmann.

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