Home Court Advantage and Fan Attendance: Evidence from NBA 2020-2021 Season

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Abstract

For this project, we utilized a fixed effect regression model and a random forest model to investigate the impact of fan support on home court advantage in the NBA during the 2020-2021 regular season. Our research provides compelling evidence that fan support has a statistically significant influence on home court advantage. Specifically, games with fan attendance resulted in home teams scoring an additional 3.113 points and winning 11.6% more frequently compared to games without fans. Thus, increasing fan numbers and occupancy can have a substantial effect on home court advantage. Furthermore, we demonstrate that our random forest models can predict win rates with around 70% accuracy. If we employ specific team data, the model's performance could potentially improve.

Introduction

In the United States, the sports industry has always been a popular topic of continuous interest among people, with team sports such as NBA and MLB being the most popular. Almost every restaurant you go to, you can see the television broadcasting sports games, and hear the announcers and commentators analyzing the game intensely. In the end, one team wins and gets everyone's applause. It makes us wonder; what factors actually affect the outcome of the game? Needless to say, the players' skills can lead the team to victory. However, in these games with a large audience, fans watching the game play an important role in an intangible way. You often hear players say in post-game interviews that it is the support of the fans at the venue that allows us to perform so well. This seemingly polite remark begs the question of whether it actually has an impact on the game.

In many professional sports leagues, home venues play a significant role in influencing the win rate of matches. Typically, the home team receives several advantages, such as fan support, venue familiarity, and an unneutral referee. These factors, combined, propel the home team to victory. After accounting for two unquantifiable variables, namely, the familiarity of the home court and the potential bias of the referees, fan support seems to be the most likely data that we can obtain for analysis. Therefore, we plan to investigate how fan support affects the outcome of games. However, in most games, popular teams are often in high demand, with every seat filled regardless of the time of day, while unpopular teams may not see a significant increase in attendance even during the playoffs. Such little variation in the data is not favorable for prediction.

Nevertheless, Covid-19 created a unique opportunity to address this problem. Several professional sports leagues were affected due to anti-epidemic policies in several countries, which led to restrictions on fan attendance in many courts to avoid swarm infections. In this project, we use data from the 2020-21 National Basketball Association (NBA) matches to identify the impact of fan attendance on the home-court advantage and predict the outcome of game by fan attendance. Most matches this season limited fan attendance, with only a few allowing thousands of fans. The crowd size was extremely low compared to past years due to health regulations.

From the results, we find strong evidence that fan support significantly influences home-court advantage. Compared to games without fans, the home team scores more than 3.564 points, and the home team's win rate increases by 12.1% with fan attendance. Moreover, using random forest model to predict the win rate, we have about 70% prediction accuracy. In conclusion, the fan support could effectively be used to predict the home-court advantage.

Data

This paper analyzes data from the 2020-2021 NBA regular season, including limitations on fan attendance at each court and NBA in-game data. The data was procured from https://www.basketball-reference.com. Our database includes detailed information for each game, such as date, home team, and away team. We also consider other influential factors, such as whether the game is on the weekend or is back-to-back. Moreover, the most vital variables, fan attendance, court capacity, home points, and away points, are also in our database.

We removed the data for games where the Toronto Raptors were the home team because they played on a court in the United States instead of their court. This may have caused problems with fan attendance, as we cannot assume that most fans came from Canada.

This project only focuses on data from the regular season instead of playoff games because most playoff games had no limitations on fan attendance, making the courts full. If we also considered data from playoff games, the independent variable, fan attendance, would have little variation without the health policy restrictions. Thus, to ensure that our model could predict the results well, it is essential to exclude playoff games.

Methods

Part I: Fixed Effect Model

The primary objective of this project is to predict the home-court advantage by fan support. To accomplish this, we must first define the fan support. We utilize the attendance of fans, which is provided by the basketball-reference website, as it is a suitable indicator of fan support, assuming that most fans support the home team. In our estimation, we utilize three variables to represent fan attendance, including the number of fans divided by one thousand, the number of fans divided by the court capacity, and the total number of fans in attendance.

Additionally, it is crucial to clearly define the dependent variable of home court advantage. For this purpose, we use a straightforward measure of the point differential between the home team and the visiting team, which we refer to as "home margin" in this paper. We also include another variable, "home win," to assess the impact of fan support on the home team's win rate. To precisely estimate the effect of fan support, we conduct two separate regressions using the independent variables of home margin and home win.

We simply estimate two fixed effects regression models of the following form:

$$home\ court\ advantage_{i,k,t} = \beta_0 + \beta_1 attendence_{i,k,t} + \beta_2 hb_{i,t} + \beta_3 vb_{k,t} + X + e_{\ i,k,t} \quad (1)$$

where $home\ court\ advantage_{i,k,t}$ measures the home court advantage in two variables, home margin and home win. $attendence_{i,k,t}$ represent fan attendance in three variables mentioned above. $hb_{i,t}$ and $vb_{k,t}$ are whether home team and visitor team facing back-to-back game, appending these two variables in estimation because back-to-back game probably influenced the performance of players. It fluctuates with time t, home team i and visitor team k. Besides, X gives a matrix of covariates including home team fixed effects, visitor team fixed effects and time fixed effects. In addition, we use robust standard error and cluster in home team level, to allowing team performance are correlated.

Part II: Random Forest Model

This part we utilized the random forest model, considering the heterogeneity of variable types. Moreover, conducting the random forest would be able to find and consider each interaction and combination of team characteristics in our data. In the model, the complexity parameter was set at 0.002 and 300 trees was used. For cross-validation, the data (nbafans) is split into training and testing sets with 20% of the data reserved for testing.

Variable pt_diff refers to the dependent variable. Variables v_btb, h_btb, weekend, startet, strong_home, note, finish, att_rate, month and homeneutral account as the independent variables. The complexity parameter for the decision tree model is placed at 0.02; Minimum observations for the split are set at 300; Max depth is set at 4. For the random forest, the complexity parameter is set at 0.002 and the number of trees is set at 300. For cross-validation, the data is split into testing and training sets with 20% of the data reserved for testing.

Writing equation for the random forest model:

pt_diff / fg_diff ~ v_btb + h_btb + weekend + startet + strong_home + note + finish + att_rate + month

- *pt_diff*: score of the home team minus the score of the visitor team
- *fg_diff*: the difference between the home team’s and visitor team’s field goal percentage, 3-pointer percentage, and free throw percentage
- *v_btb*: equal 1 if the visitor team plays a back-to-back game

- *h_btb*: equal 1 if the home team plays a back-to-back game
- *weekend*: equal 1 if the game is played on the weekend
- *startet*: the time (ET) of the game started
- *strong_home*: equal 1 if the home team's winning game count is higher than that of the visitor team
- *finish*: whether it's an over-time game
- *att_rate*: audience attendance rate
- month: the month when the game is held

Results

Part I: Descriptive analysis

To begin our analysis, we opt to examine our data in a straightforward manner. As previously mentioned, the home-court advantage is a prevalent phenomenon in many professional sports, including the NBA. We can observe this trend from the summary statistics presented in Table 1. Specifically, we note that the home team had a win rate of 54% during the 2020-2021 regular season, and the average point differential between the home team and the visiting team was 0.924. Due to government policies, nearly half of the games were played without any fan attendance, which provided us with a significant amount of variation in fan numbers.

Furthermore, we found that the average fan attendance during the season was 1397, and the average occupancy rate was 7.6%. These statistics provide us with a starting point for understanding the relationship between fan support and home court advantage in the NBA.

Table 1: Summary statistics

	Mean	Std. Dev.	Min	Max	Obs.
Home margin	.924	15.207	-57	48	1044
Home win	.547	.498	0	1	1044
Fan attendance	.471	.499	0	1	1044
Fan number/1000	1.397	1.733	0	8.359	1044
Occupancy	.076	.094	0	.463	1044
Home team b-t-b	.205	.404	0	1	1044
Visitor team b-t-b	.213	.409	0	1	1044

Part II: Fixed Effect Model

In this section, we will present the results of the fixed effects regression models (1) discussed in the previous section. Table 2 displays the effect of fan support on the point differential. On average, fan attendance leads to the home team winning by 3.113 more points than the visiting team, and this effect is statistically significant at the 95% confidence level. Specifically, an increase of one thousand fans results in the home team winning by an additional 0.834 points. Additionally, compared to games played in vacant arenas, games played in full arenas result in the home team winning by an additional 15.586 points.

Table 2: Regression result of home team margin

	(1)	(2)	(3)
Fan	3.113**		
attendance	(1.449)		
Fan number		0.834	
/1000		(0.529)	
Occupancy			15.586
			(9.684)
Home team	0.377	0.353	0.357
b-t-b	(1.060)	(1.044)	(1.042)
Visitor team	1.684	1.591	1.590
b-t-b	(1.115)	(1.143)	(1.143)
Host FE	Yes	Yes	Yes
Visitor FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
R-squared	0.240	0.238	0.238
Observations	1044	1044	1044

Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

Table 3 presents the results of the second model where the dependent variable is whether the home team wins, using the same independent variables. Based on the results in Table 3, we observe that fan attendance increases the home team's win rate by 11.6% compared to games played in vacant arenas, and this effect is statistically significant at the 95% confidence level. On average, a one-thousand increase in fan attendance results in a 2.9% increase in the home team's win rate. Furthermore, games played in full arenas result in a 55.9% increase in the home team's win rate compared to games played in vacant arenas. Both of these effects are statistically significant at the 90% confidence level.

Table 3: Regression results of home team win

	(1)	(2)	(3)
Fan attendance	0.116** (0.047)		
Fan number /1000		0.029* (0.016)	
Occupancy			0.559* (0.299)
Home team b-t-b	0.024 (0.041)	0.023 (0.041)	0.023 (0.041)
Visitor team b-t-b	0.092*** (0.034)	0.088** (0.035)	0.088** (0.035)
Host FE	Yes	Yes	Yes
Visitor FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
R-squared	0.195	0.193	0.193
Observations	1044	1044	1044

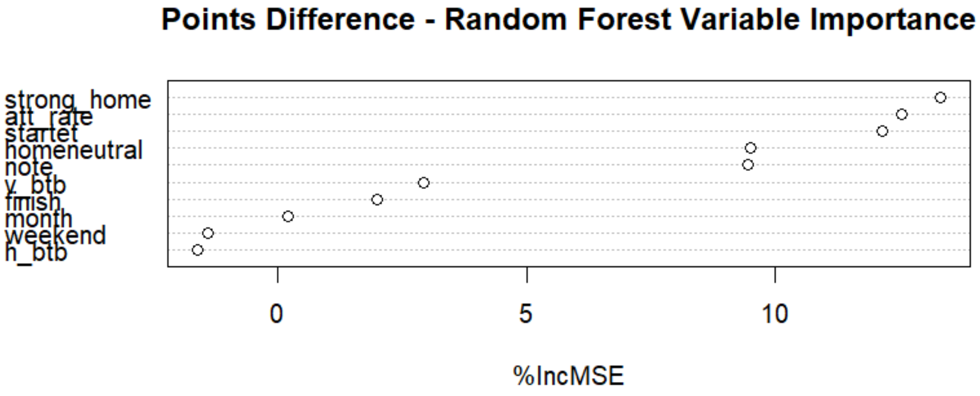
Standard errors in parentheses

* p<0.1, ** p<0.05, *** p<0.01

The results of both fixed effects regression models provide strong evidence that fan support has a significant impact on home court advantage in professional basketball, even after controlling for time, home team, and visitor team fixed effects. The findings demonstrate that fan attendance increases the home team's point difference and win rate, which confirms the influence of fan support on home court advantage with statistical significance.

Part III: Random Forest Model

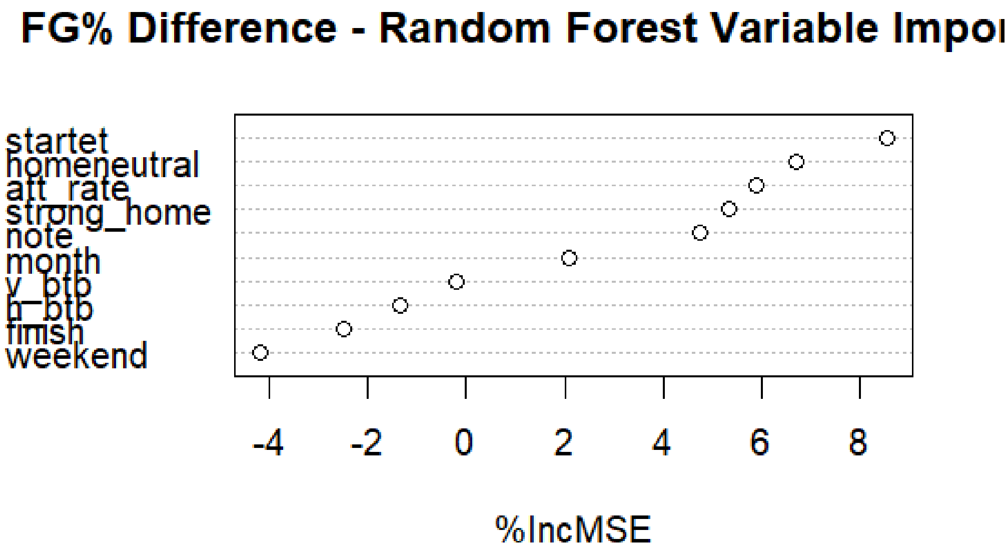
A. Points Difference



Model	RMSE
Tree	14.81312
Forest	14.64038

According to the table above, an out-of-sample root means squared error (RMSE) of 14.64038 is observed. Although we suspect that the back-to-back game and games on the weekend bias the model in favor of points, the variable importance plot above shows that the back-to-back game and games on the weekend are the least important variables to our model's accuracy.

B. Field Goal Percentage (FG%)



Model	RMSE
Tree	0.2550250
Forest	0.2484069

From the table above, an RMSE of 0.2484069 is observed. Similar to the variable importance plot of points difference, playing back-to-back games, games on the weekend and overtime games are the least important variables to our model's accuracy.

Subsample of Teams in Texas – Mavericks, Spurs & Rockets (see graphs in appendix)

A. Points Difference

Model	RMSE
Mavericks Forest	11.61502
Spurs Forest	19.09986
Rockets Forest	13.55703

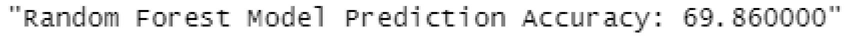
The model conducted previously controls for homeneutral (home team), while more robust findings are observed when splitting off the data. The result of separating the teams shows that different teams seem to be affected by different variables. Moreover, the negative values of variables for the Spurs and Rockets are observed because both teams were "tanking" in the 2021-2022 season. Furthermore, playing over-time games plays an important role when determining the effect of home-court advantage on Maverick's box score. Focusing on each team separately allows the model to test the more accurate importance of each predictor. The RMSE results show that the effect of home-court advantage on points difference (points advantage) can be predicted for Mavericks and Rockets much more precisely than for the Spurs.

B. FG %

Model	RMSE
Mavericks Forest	0.1747844
Spurs Forest	0.2375517
Rockets Forest	0.2651354

Similar to the results of the team points difference importance plots, more robust findings for the Mavericks are observed when splitting off the data. Also, audience attendance rate plays an important role when determining the effect of home-court advantage on the Maverick's field goal percentage, 3-pointer percentage and free throw percentage.

Model Building - Winning Outcome



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"Random Forest Model Prediction Accuracy: 69.860000"
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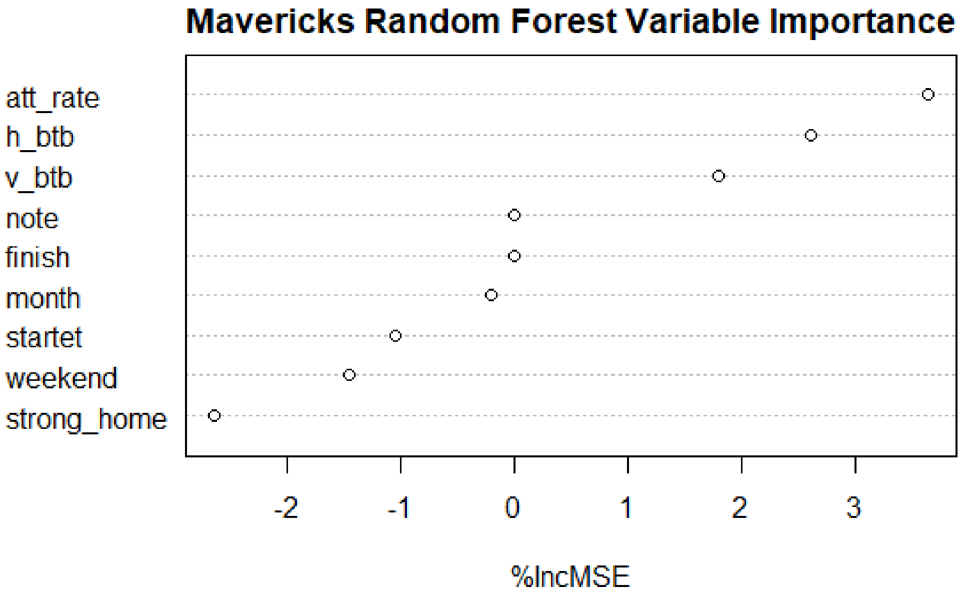
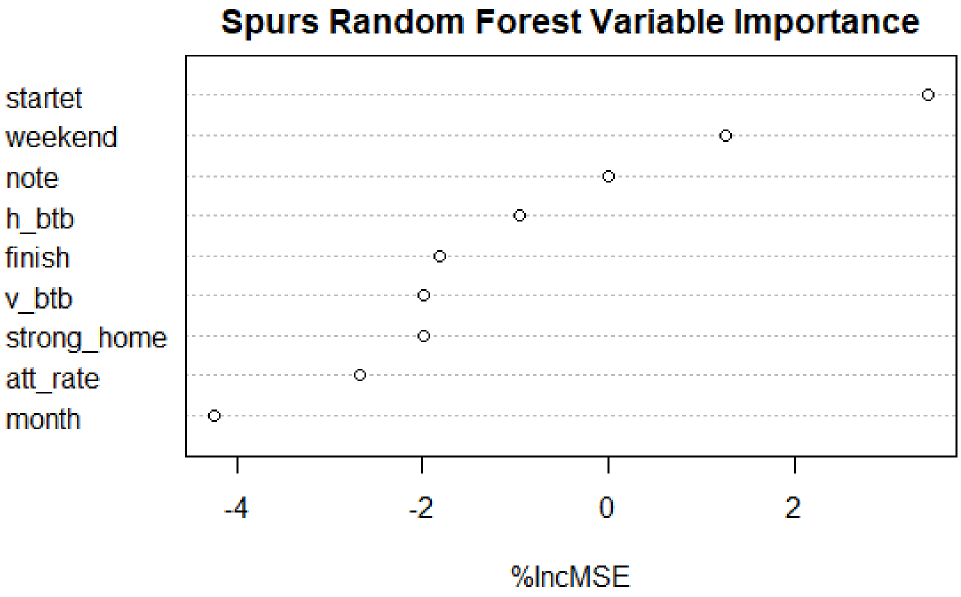
In addition to predicting score differentials and free throw differentials, we also employed a random forest model to predict game outcomes. With variables such as fan attendance rates and home/away team data, our model has a 70% chance of accurately predicting the winner of an NBA game.

Conclusion

In this project, we employed a fixed effect regression model and random forest model to examine the impact of fan support on home court advantage and predict the home-court advantage by the fan support in the NBA during the 2020-2021 regular season. Our findings reveal compelling evidence that fan support has a statistically significant influence on home court advantage. Specifically, compared to games without fans, games with fan attendance resulted in home teams scoring 3.113 more points and winning 11.6% more often. Thus, increasing fan numbers and occupancy can significantly affect home court advantage. Moreover, we also show that our random forest models have about 70% prediction accuracy of predicting win rates. Additionally, if we use specific team data to predict their outcome, it would probably have better performance.

Appendix


Mavericks Random Forest Variable Importance
att_rate
h_btb
v_btb
note
finish
month
startet
weekend
strong_home
-2
-1
0
1
2
3
%IncMSE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note
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v_btb
strong_home
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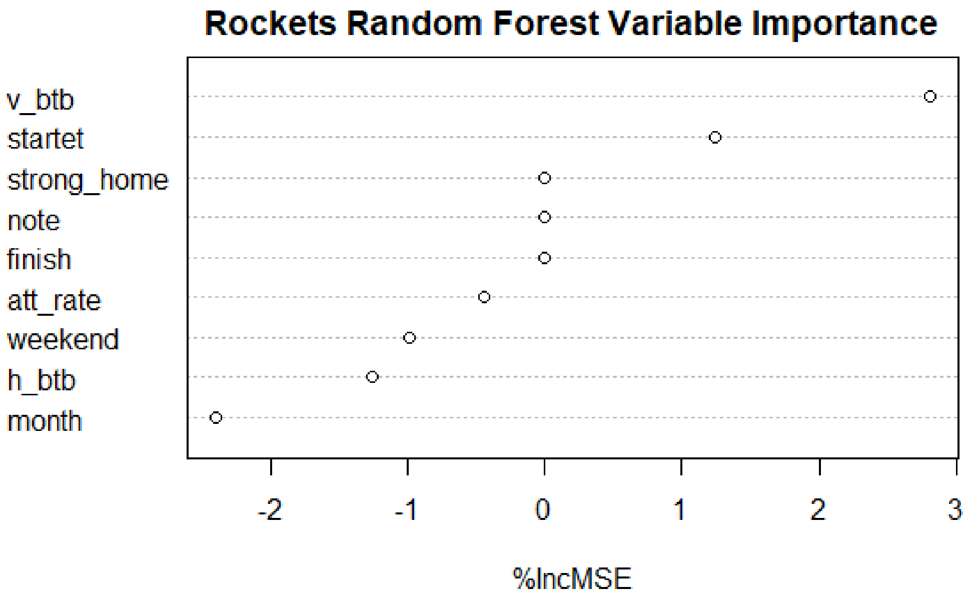
Rockets Random Forest Variable Importance
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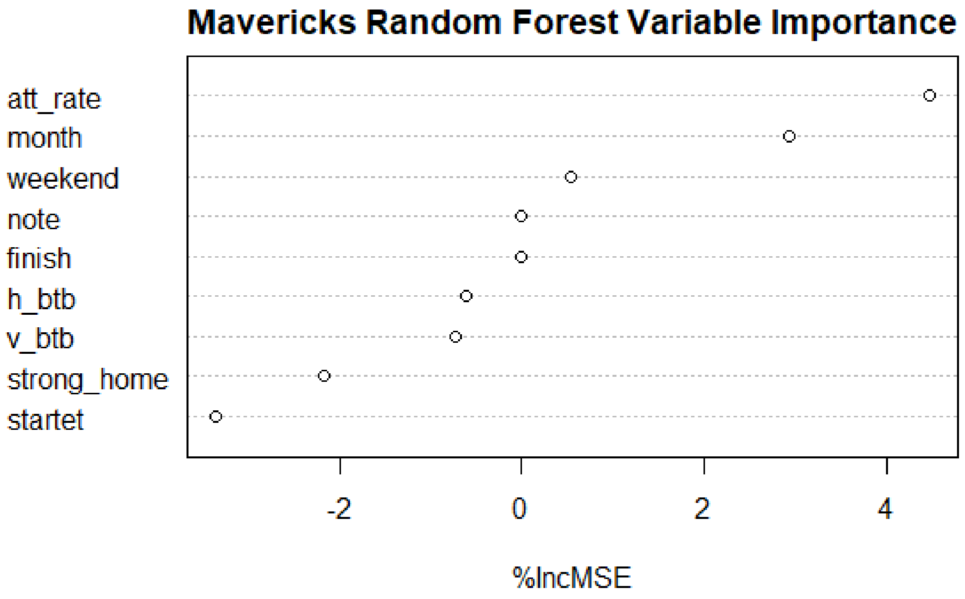
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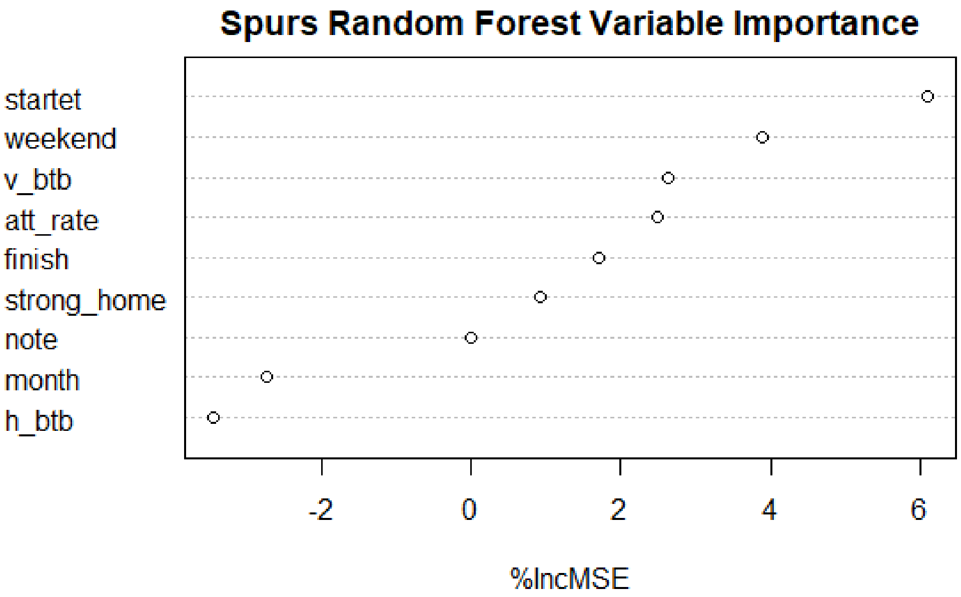
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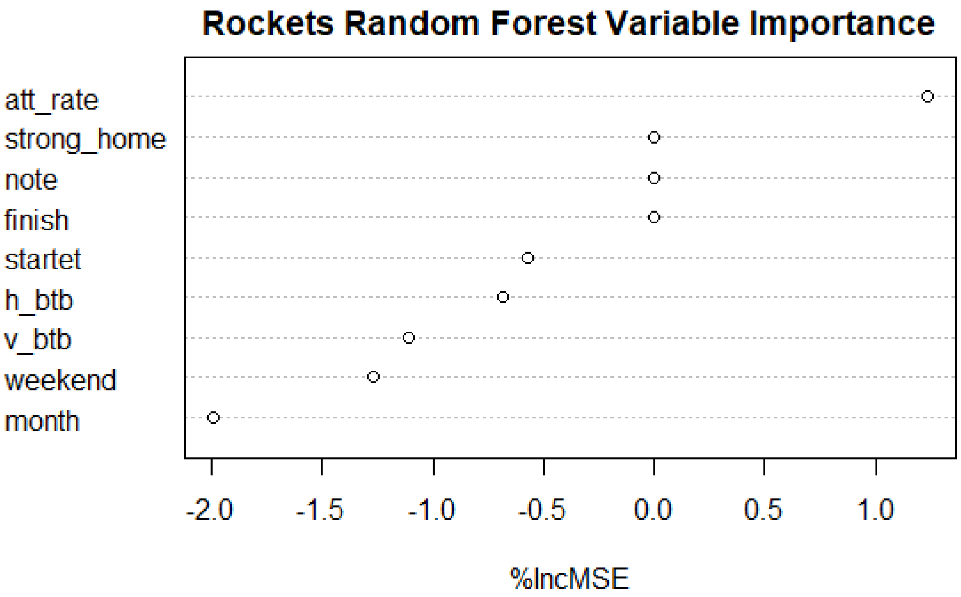
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-0.5
0.0
0.5
1.0
%IncMSE