final_project_pdf

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I collected data on all players of FIFA2019 on the kaggle website data set, including height, weight, and various ability values. As one of the most popular football games, it introduces many variables to measure the ability of players. In this project, I found that each player has their own ***Preferred Foot***, the number of players with the preferred left foot is less, but the average and median of their multiple ability values are greater than the players with the preferred right foot, I guess this is an official setting of the game. For this binary variable of "predominant foot", I tried to analyze whether it is possible for us to predict the player's preferred foot through various ability values of each player. Of course, this is based on the setting of official FIFA games. It does not mean the same result in reality.

Abstract

My question is: Can we predict the preferred foot of a player based on his various abilities? If I could, I could know where the strengths of different footed players are. I used **LASSO**, **Logistics model (based on AIC and CV)**, **stepwise function**, **RandomForest model** to predict this binary variable (in most cases, each player should have only one dominant foot from left foot or right foot, but due to the missing data of some players, this data set does not show their data, we will filter out these in the data preprocessing), and finally we came to a conclusion based on the ROC curve graph, AUC core and f1 Score.

Introduction

I extracted the player's age, height, weight, and various ability values (such as dribbling, crossing, etc.) In this project, I set a binary variable **preferred foot index**, when the player's dominant foot is the right foot, this index is 1, otherwise it is 0.

Let's first look at a data comparison of preferred left foot and preferred right foot players (In this project we analyze the player's other ability values):

we first browse the summary of players' abilities whose dominant foot is left foot, which are in the appendix (end of this project).

Then we browse the summary of players' abilities whose dominant foot is right foot, which are also in the appendix(end of this project):

This tables shows how many left-footed players and right-footed players in the dataset.

Table 1: Number of preferred foot

Analyzed_data$Preferred.Foot	n
Left	4162
Right	13756

We can see that in terms of almost all abilities, left-footed players and right-footed players are different (left-footed palyers's ability values are higher in most cases), as evidenced by both the median and mean.

Of course, we have to mention one important thing, there are far fewer left-footed players than right-footed players. But based on this difference, I tried to use machine learning to predict the player's dominant foot by calculating various ability values of a player.

Potential Significance: Since left-footed players have higher stats than right-footed players in terms of most ability, if we predict based on a player's stats that his dominant foot is the left foot but his dominant foot is actually the right foot, it means that under the same circumstances, He probably surpasses someone of the same ability but is right footed, in other words, at his own level, he is better in terms of preferred foot, otherwise the model would estimate he is right footed. This can be used as a form of self-encouragement.

I split the initial data set into train set and test set, and the splitting ratio is 0.8.

Methods

The data we mainly use in this project include:

Dependent variable: **perfoot_index**, preferred left foot is 0, preferred right foot is 1.

Independent variable: **Age, height_cm, weight_amount_2, Crossing, Finishing, HeadingAccuracy** and other ability values.

I mainly use 3 methods, LASSO method (based on AIC and based on cross-validation), logistic model, and random forest model. First, I split dataset into training set and test set. Second, I use these methods and do regression. Third, I use the estimated regression model and test their accuracy based on test set. Finally, I create a ROC curve and f1 score for each model, judge which is the best model to complete my goal.

LASSO model

I first use `gamlr` package to do the regression, and I choose the coefficient based on the AIC measurement. In this part, I will show the plots of regression result, and the plot of AIC depends on different lambda.

we can show min_lambda and how many coefficient is not equal to 0 under this LASSO model with AIC approximation, since we will use these info to do prediction for testing data set.

```
## [1] "minimum lambda is:"
```

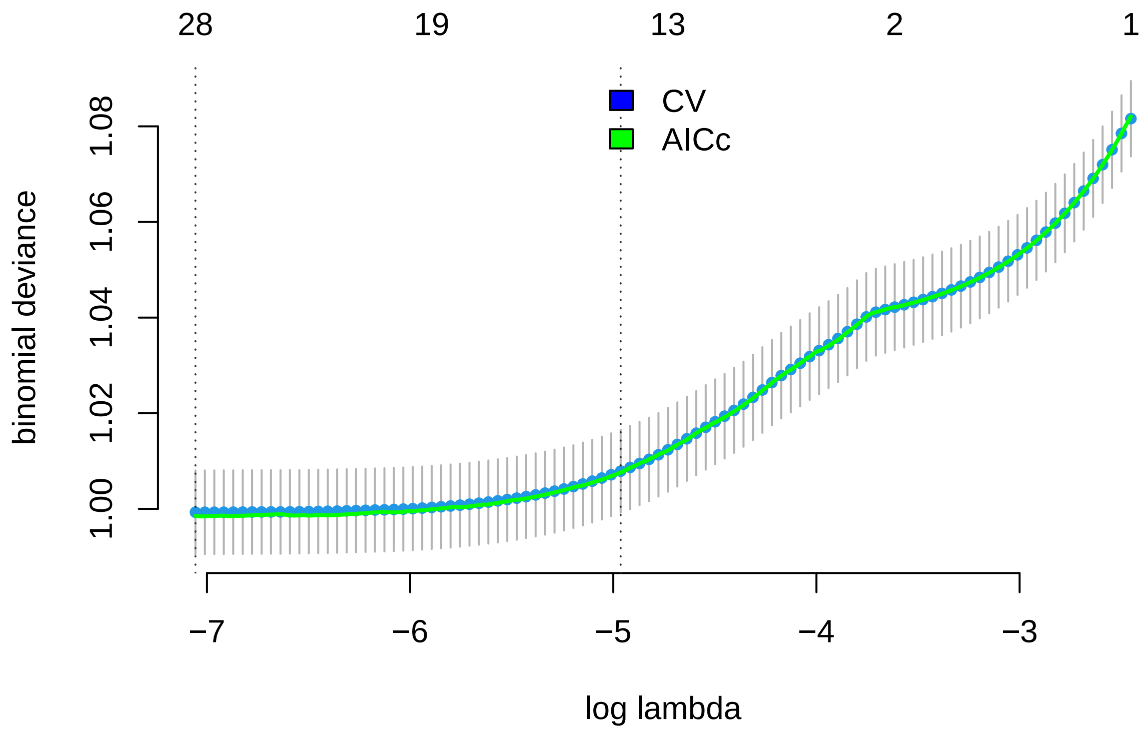
```
##    seg199
## -7.033917
```

```
## [1] "number of coefficient that is not equal to 0"
```

```
## [1] 27
```

Now I try LASSO regression without AIC approximation, but based on cross validation. Then I plot the comparison plot between AICc and Cross Validation. In this case, I set `nfold=10`

```
## fold 1,2,3,4,5,6,7,8,9,10,done.
```



I use Lasso do some prediction, in this case I use the coefficient chose on 1 standard error through LASSO cross validation result. And I set `ifelse(lasso_predict > 0.5, 1, 0)`, and it shows the result like:

Table 2: LASSO based on cross validation

	0	1
0	765	80
1	2144	595

logistic regression

In this part, I try logistic model to estimate players' preferred feet. And it provides the result like (under `ifelse(log_prediction > 0.5, 1, 0)`):

Table 3: logistic model prediction

	0	1
0	232	613
1	245	2494

stepwise function

I use the step wise function to estimate players' preferred feet.In this case, I chose forward selection method. My initial regression is `null = glm(perfoot_index ~ 1, data=Y_train, family=binomial)`, and my final regression is `full = glm(perfoot_index ~ ., data=Y_train, family=binomial)`. It will do the estimation step by step. Below it gives part of prediction result, under `ifelse(stepwise_pred>0.5, 1, 0)`.

Table 4: step wise function prediction

	0	1
0	237	608
1	237	2502

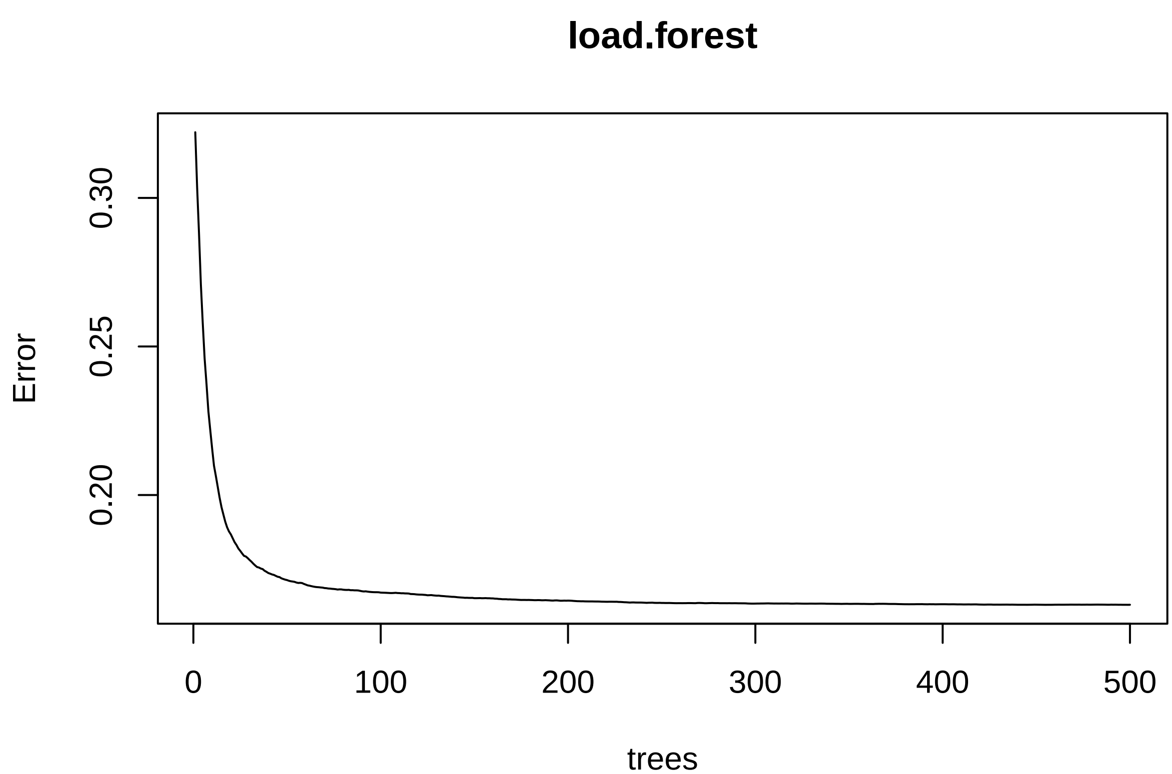
Tree model

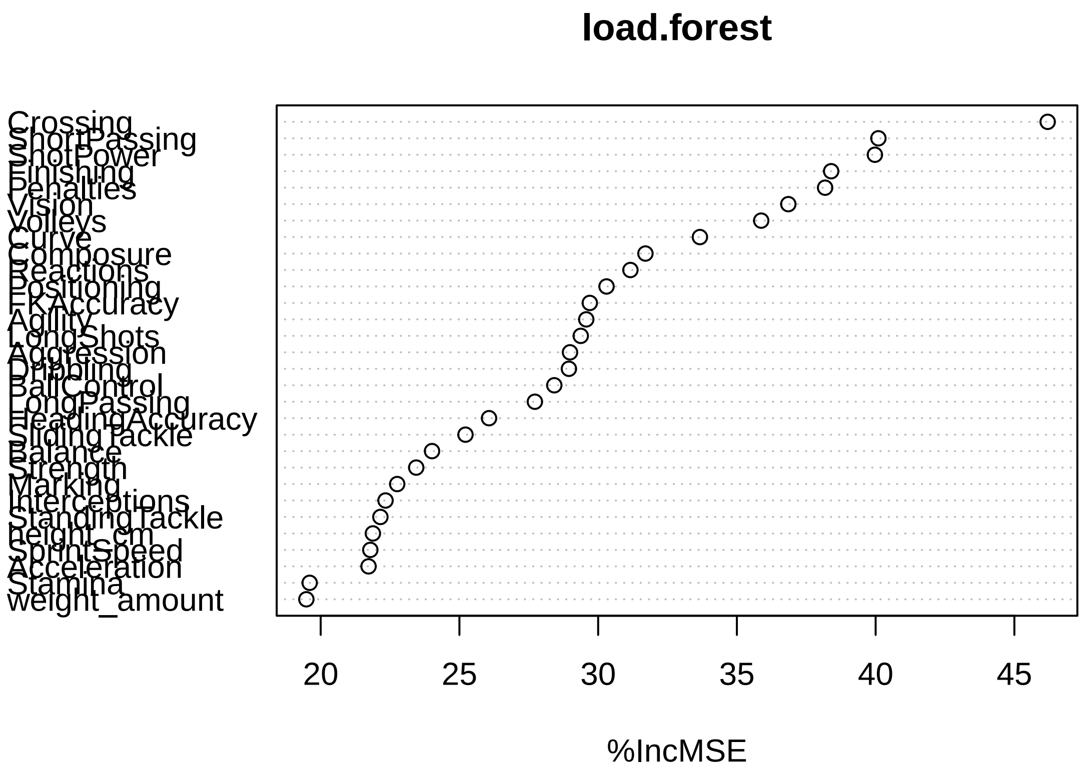
I use random forest tree model to do the regression. I first create a mannual tree model, but I don't know how to decide complexity parameter, so I just use random forest model, but I still keep the code in case readers want to check is there any difference between these two methods. It also provide some prediction result(under `ifelse(rf_pred > 0.5, 1, 0)`):

Table 5: random forest tree model

	0	1
0	81	764
1	61	2678

In this case, I plot the regression result and Variable Importance Plot, since it would be more straightforward to check the result.






```
##                  %IncMSE
## Age             19.45453
## height_cm       21.88043
## weight_amount   19.48345
## Crossing        46.20152
## Finishing       38.39721
## HeadingAccuracy 26.06686
## ShortPassing    40.09950
## Volleys         35.87688
## Dribbling       28.94598
## Curve           33.66718
## FKAccuracy      29.69850
## LongPassing     27.71975
## BallControl     28.41921
## Acceleration    21.72477
## SprintSpeed     21.78819
## Agility         29.57120
## Reactions       31.16217
## Balance         24.01283
## ShotPower       39.97368
## Jumping         15.79028
## Stamina         19.60274
## Strength        23.44281
## LongShots       29.37322
## Aggression      28.98504
## Interceptions   22.33696
```

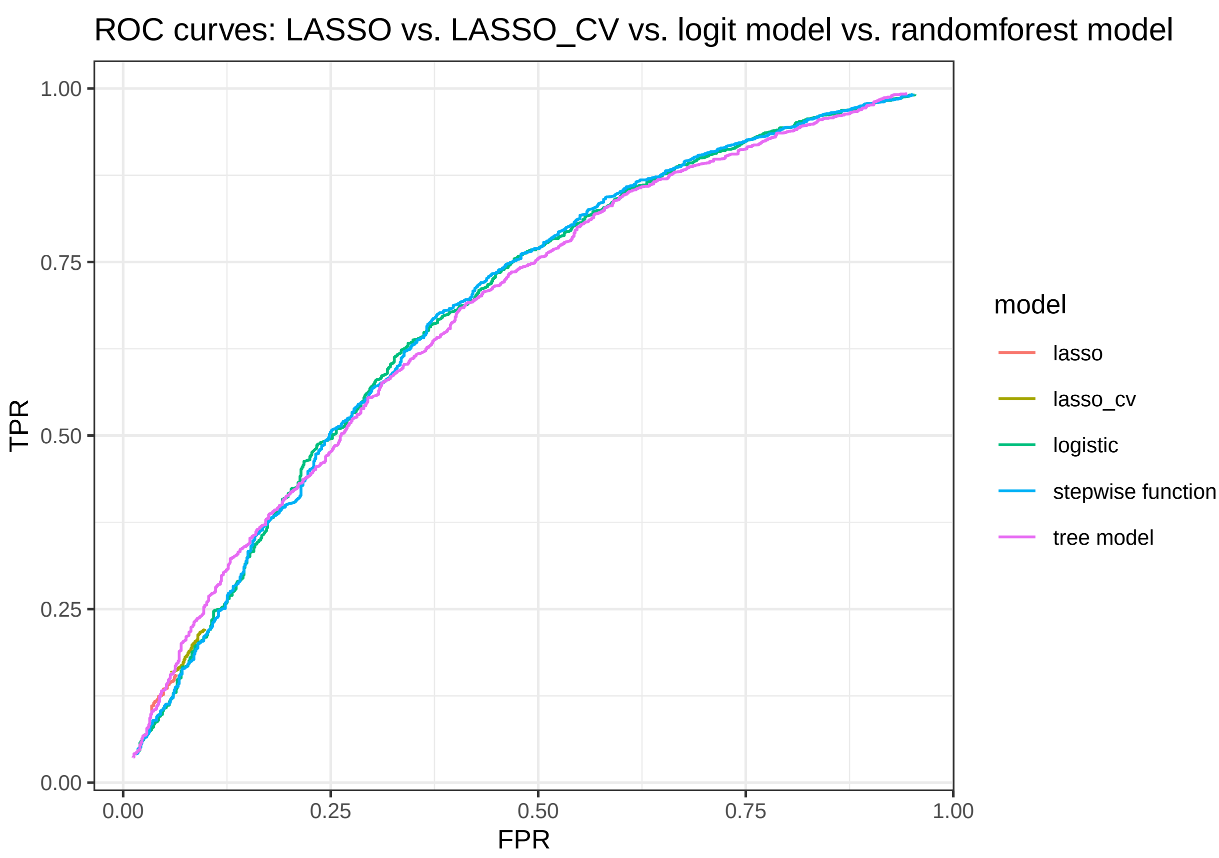
```
## Positioning     30.30167
## Vision          36.85349
## Penalties       38.17904
## Composure       31.70369
## Marking         22.75808
## StandingTackle  22.15167
## SlidingTackle   25.21856
## GKDiving        11.29414
## GKHandling      13.90679
## GKKicking       15.81053
## GKPositioning   10.62919
## GKReflexes      14.26065
```

result

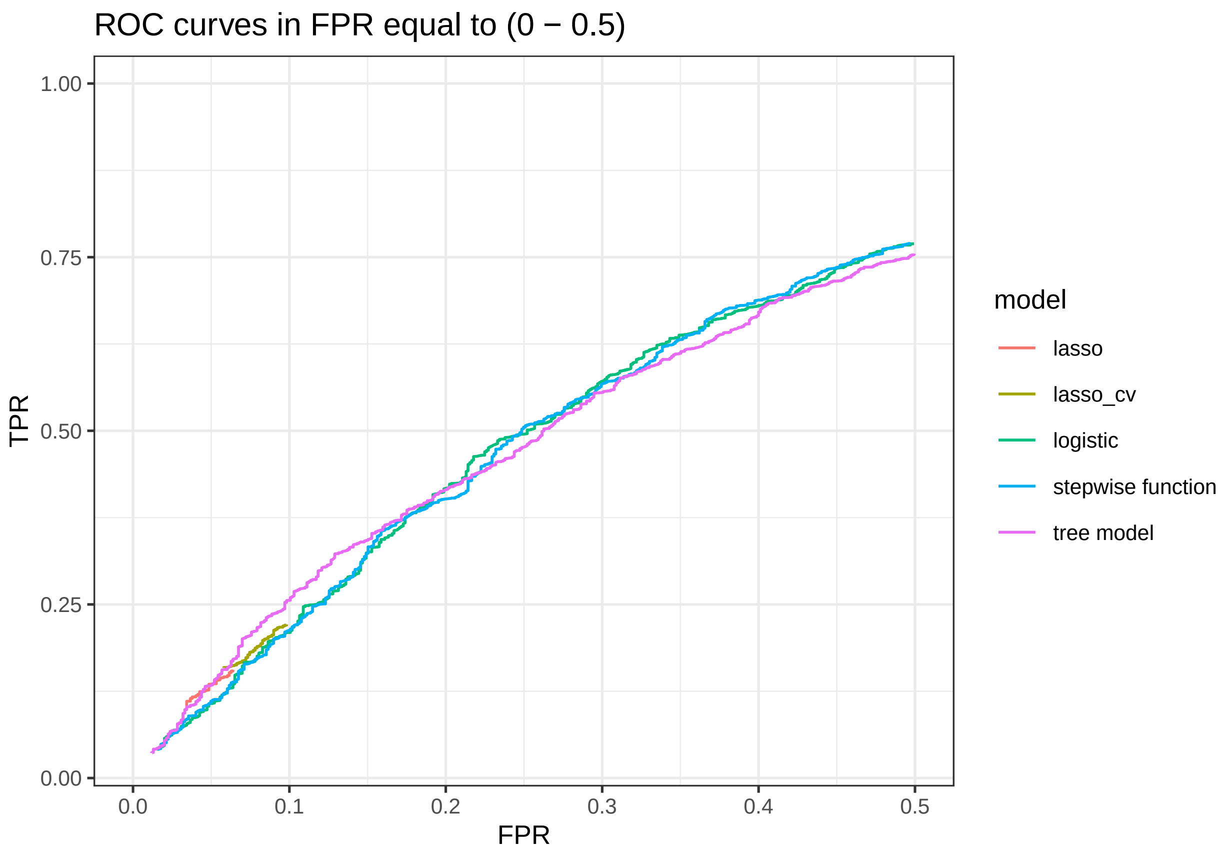
I use two different methods **ROC curve and AUC value** & **f1 Score** to make comparison with various models, and both of them give me same answer, **step wise** model's performance is the best one. So we can use it to make prediction for a player's dominant foot.

ROC curve

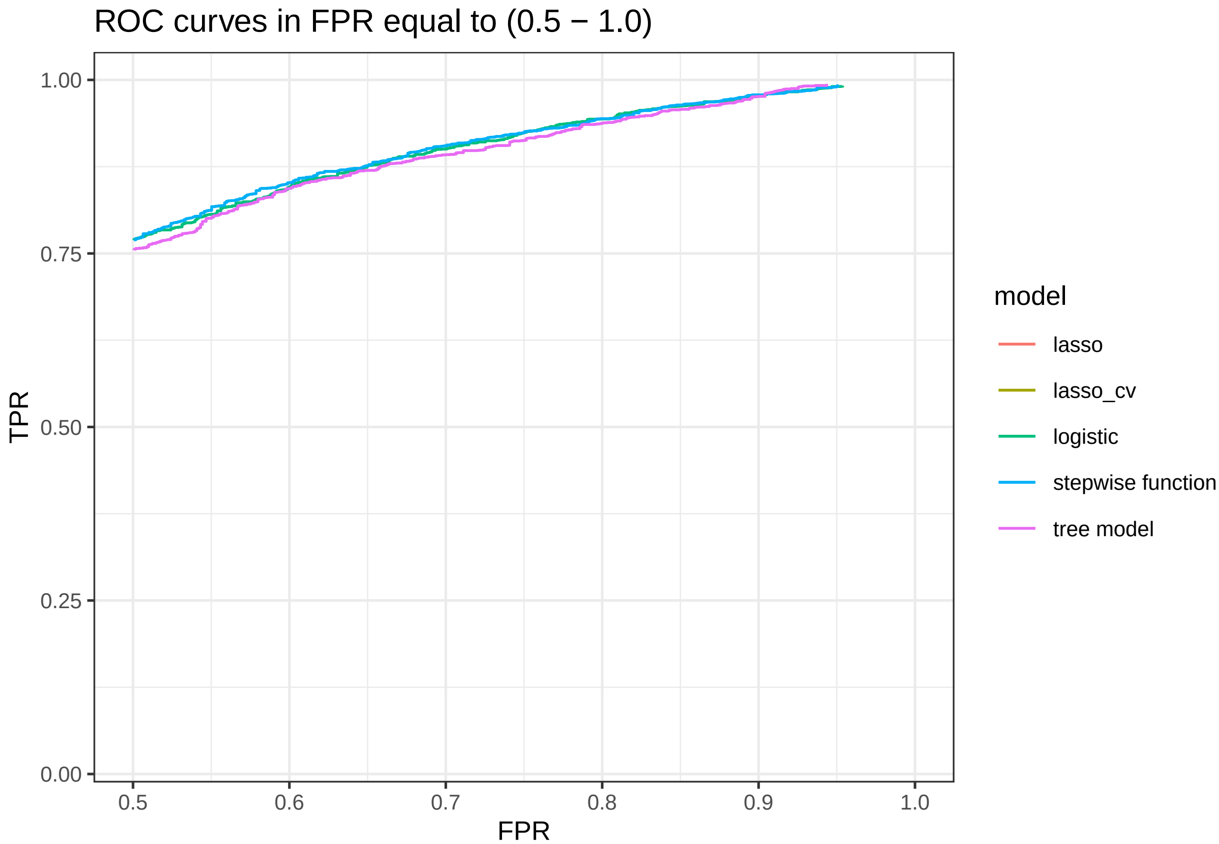
Since we cannot judge any model's accuracy based on single threshold in terms of the binomial variable (left or right), so I create a ROC curve and see their performance. In this case, I set a series of thresholds for the final binomial variable determination, which is a series of data `thresh_grid = seq(0.94, 0.45, by=-0.001)`. Since different models ROC curves are overlapping, so I just separate them into two plots in terms of two FPR intervals.



```
## Warning: Removed 7688 row(s) containing missing values (geom_path).
```




```
## Warning: Removed 16817 row(s) containing missing values (geom_path).
```



Over all, It shows almost ROC curves of **logistic model**, **stepwise model** and **random forest model** are overlapped for each threshold, but **stepwise** function's performance is a little better since its curve is always above other models' curves. To make our final judgement, we introduce *AUC Score* and **f1 score** to do deeper analysis.

AUC Score

AUC represents the probability that a random positive example is positioned to the right of a random negative example, it stands for "Area under the ROC Curve.".

```
## Setting levels: control = 0, case = 1

## Warning in roc.default(response, predictor, auc = TRUE, ...): Deprecated use a
## matrix as predictor. Unexpected results may be produced, please pass a numeric
## vector.

## Setting direction: controls < cases
## Setting levels: control = 0, case = 1

## Warning in roc.default(response, predictor, auc = TRUE, ...): Deprecated use a
## matrix as predictor. Unexpected results may be produced, please pass a numeric
## vector.

## Setting direction: controls < cases
## Setting levels: control = 0, case = 1

## Setting direction: controls < cases

## Setting levels: control = 0, case = 1
```

```
## Setting direction: controls < cases
## Setting levels: control = 0, case = 1
## Setting direction: controls < cases
```

Table 6: AUC value for different models

modelname	AUC_value
LASSO_AIC	0.6869738
LASSO_CV	0.6803921
Logistic	0.6843844
stepwise	0.6850740
randomforest	0.6817611

According to the AUC values table, we cannot say that which models are best models to determine a player's dominant foot based on his various abilities, as their AUC score is very close. On the other hand, we can say that almost all models' performance are similar in terms of AUC score.

f1 score

I introduced f1 score for further comparison. The F1-score combines the precision and recall of a classifier into a single metric by taking their harmonic mean. It is primarily used to compare the performance of two classifiers. In general, higher a model's F1-score, better performance for this model.

Table 7: f1 score summary for different models

modelname	f1SCore
LASSO_AIC	0.2604361
LASSO_CV	0.3485647
Logistic	0.8676020
stepwise	0.8670427
randomforest	0.8665265

According to the result, we can see that step wise model and logistic model has largest f1 scores(much higher than LASSO models, but random forest model would also be a good choice, its F1-score always close to step wise and logistic models), which make sure step wise model has better performance than other models for our problem. (This conclusion is based on each split process, and sometimes the f1 score of the step wise model is higher than any one model)

coefficient comparison

I also post each model's coefficients value below:

Table 8: different models coefficient summary

Ability Name	LASSO_AIC	LASSO_CV	Logistic	stepwise
(Intercept)	NA	NA	2.254	3.251
Acceleration	0.008	0.000	0.007	0.008
Age	0.039	0.024	0.009	0.010
Aggression	0.119	0.024	0.007	0.007
Agility	0.000	0.000	-0.001	NA

Ability Name	LASSO_AIC	LASSO_CV	Logistic	stepwise
Balance	0.040	0.000	0.003	NA
BallControl	0.000	0.000	-0.001	NA
Composure	0.000	0.000	-0.001	NA
Crossing	-0.843	-0.732	-0.047	-0.046
Curve	-0.235	-0.083	-0.014	-0.013
Dribbling	-0.107	0.000	-0.011	-0.010
Finishing	0.194	0.176	0.011	0.012
FKAccuracy	-0.330	-0.179	-0.021	-0.020
GKDiving	0.000	0.000	-0.004	NA
GKHandling	0.000	0.000	-0.002	NA
GKKicking	0.000	0.000	0.002	NA
GKPositioning	0.000	0.000	-0.001	NA
GKReflexes	0.000	0.000	0.001	NA
HeadingAccuracy	-0.030	0.000	-0.005	NA
height_cm	-0.033	0.000	-0.005	-0.012
intercept	1.334	1.286	NA	NA
Interceptions	0.000	0.000	0.001	NA
Jumping	0.059	0.044	0.006	0.005
LongPassing	0.045	0.000	0.004	NA
LongShots	0.008	0.000	0.001	NA
Marking	0.023	0.000	0.002	NA
Penalties	0.036	0.000	0.004	NA
Positioning	0.024	0.000	0.003	NA
Reactions	0.012	0.019	0.003	NA
ShortPassing	0.338	0.127	0.026	0.028
ShotPower	0.000	0.000	0.000	NA
SlidingTackle	-0.185	-0.017	-0.018	-0.017
SprintSpeed	-0.116	-0.015	-0.013	-0.013
Stamina	0.099	0.000	0.006	0.007
StandingTackle	0.000	0.000	0.008	0.010
Strength	0.015	0.000	0.003	NA
Vision	0.204	0.158	0.015	0.017
Volleys	0.260	0.152	0.016	0.017
weight_amount	-0.020	0.000	-0.002	NA

From the table, we can see that there exists some difference for models' coefficients, since different model set different intercepts. Step wise model uses fewer variable and set a larger intercept. Unfortunately, we cannot get the coefficients from random forest model, since it is another kind of estimation.

On the other hand, we can see that the absolute value of coefficients for different model has some similarities. According to the Variable Importance Plot from the random forest model, we know that **Crossing**, **ShortPassing**, **ShotPower** are top 3 most important variable, according to the coefficient table, **Crossing**, **ShortPassing** 's coefficients absolute value are relative larger than other variables' in terms of these 4 models.

Conclusion

The results show that the **step wise** and **logistic** models can give the better prediction results, but it does not mean that we can directly use these model's coefficient values. For example, each time we split data, it create a different test set, which could make selected variables by step wise different, and their coefficients may also be different. In theory, I should do many groupings and then calculate the average AUC and F1score for each model to avoid the problem of chance, but my computer limits me to doing so.

Because we use many models, we can make confident inferences based on similarities in model results. A plausible speculation is that, FIFA game officials tend to give left-footed players higher stats on **Crossing**, **FKAccuracy**, **SlidingTackle**, **Curve**, **SprintSpeed**, because the coefficients of these variables in almost all models are negative and much smaller than the other negative coefficients. Note that in our model, 0 is a left-footed player and 1 is a right-footed player. In addition, right-footed players always have a better **ShortPassing**, **Volleys**, **Vision**, **Finishing** ability, since these abilities' coefficients are positive and larger than others.

Interestingly, we can see where the specific advantages of different footed players are based on the coefficient table, which can also eliminate our common misconceptions. For me, I always think left-footed players are better at dribbling because most defenders are right-footed, but FIFA game officials don't think so. It does make left-footed players have a higher dribbling ability, but it is far less advantageous than Crossing.

Another aspect that I would have liked to cover, but it is really difficult to deal with, is the correlation between the various abilities of the players, in other words, the endogeneity problem. I try to use intersection for different variables, but my computer can't run such a large-scale calculation.

Appendix

left-footed players summary:

```
##  perfoot_index      Age          height_cm      weight_amount      Crossing
##  Min.   :0     Min.   :16.00   Min.   :157.5   Min.   :110.0   Min.   : 8.00
##  1st Qu.:0     1st Qu.:21.00   1st Qu.:175.3   1st Qu.:154.0   1st Qu.:49.00
##  Median :0     Median :25.00   Median :180.3   Median :163.0   Median :60.50
##  Mean   :0     Mean   :25.08   Mean   :180.2   Mean   :163.9   Mean   :56.61
##  3rd Qu.:0     3rd Qu.:28.00   3rd Qu.:185.4   3rd Qu.:174.0   3rd Qu.:67.00
##  Max.   :0     Max.   :41.00   Max.   :203.2   Max.   :218.0   Max.   :91.00
##    Finishing  HeadingAccuracy  ShortPassing      Volleys        Dribbling
##  Min.   : 5   Min.   : 7.00   Min.   :11.00   Min.   : 4.00   Min.   : 5.0
##  1st Qu.:33   1st Qu.:46.00   1st Qu.:57.00   1st Qu.:32.00   1st Qu.:55.0
##  Median :50   Median :55.00   Median :63.00   Median :45.00   Median :63.0
##  Mean   :47   Mean   :53.65   Mean   :61.42   Mean   :44.58   Mean   :59.9
##  3rd Qu.:61   3rd Qu.:64.00   3rd Qu.:69.00   3rd Qu.:57.00   3rd Qu.:70.0
##  Max.   :95   Max.   :91.00   Max.   :93.00   Max.   :90.00   Max.   :97.0
##      Curve         FKAccuracy      LongPassing     BallControl
##  Min.   : 6.00   Min.   : 3.00   Min.   :10.00   Min.   : 8.00
##  1st Qu.:40.00   1st Qu.:34.00   1st Qu.:49.00   1st Qu.:58.00
##  Median :55.00   Median :47.00   Median :58.00   Median :64.00
##  Mean   :52.55   Mean   :47.63   Mean   :55.74   Mean   :61.89
##  3rd Qu.:66.00   3rd Qu.:62.00   3rd Qu.:65.00   3rd Qu.:70.00
##  Max.   :93.00   Max.   :94.00   Max.   :89.00   Max.   :96.00
##   Acceleration    SprintSpeed        Agility        Reactions
##  Min.   :15.00   Min.   :15.00   Min.   :19.00   Min.   :30.00
##  1st Qu.:62.00   1st Qu.:62.00   1st Qu.:59.00   1st Qu.:57.00
##  Median :70.00   Median :70.00   Median :68.00   Median :63.00
##  Mean   :67.81   Mean   :67.84   Mean   :66.41   Mean   :62.25
##  3rd Qu.:76.00   3rd Qu.:76.00   3rd Qu.:76.00   3rd Qu.:68.00
##  Max.   :97.00   Max.   :96.00   Max.   :95.00   Max.   :95.00
##     Balance        ShotPower        Jumping         Stamina
##  Min.   :16.00   Min.   : 9.00   Min.   :27.00   Min.   :12.00
##  1st Qu.:59.00   1st Qu.:48.00   1st Qu.:57.25   1st Qu.:60.00
##  Median :68.00   Median :61.00   Median :66.00   Median :68.00
##  Mean   :66.45   Mean   :57.79   Mean   :64.69   Mean   :65.87
##  3rd Qu.:76.00   3rd Qu.:69.00   3rd Qu.:73.00   3rd Qu.:75.00
```

```
## Max.   :96.00   Max.   :94.00   Max.   :93.00   Max.   :94.00
##    Strength      LongShots      Aggression     Interceptions    Positioning
## Min.   :28.00   Min.   : 5.0   Min.   :12.00   Min.   : 6.00   Min.   : 4.00
## 1st Qu.:57.00   1st Qu.:36.0   1st Qu.:48.00   1st Qu.:35.00   1st Qu.:45.00
## Median :66.00   Median :53.0   Median :60.00   Median :56.00   Median :57.00
## Mean   :64.43   Mean   :49.9   Mean   :57.72   Mean   :50.54   Mean   :53.24
## 3rd Qu.:73.00   3rd Qu.:64.0   3rd Qu.:69.00   3rd Qu.:65.00   3rd Qu.:65.00
## Max.   :94.00   Max.   :94.0   Max.   :94.00   Max.   :89.00   Max.   :94.00
##     Vision        Penalties       Composure       Marking      StandingTackle
## Min.   :10.00   Min.   : 9.00   Min.   :13.0   Min.   : 5.00   Min.   : 7.00
## 1st Qu.:46.00   1st Qu.:41.00   1st Qu.:53.0   1st Qu.:37.00   1st Qu.:35.00
## Median :56.00   Median :50.00   Median :60.0   Median :56.00   Median :60.00
## Mean   :55.01   Mean   :50.22   Mean   :59.8   Mean   :50.99   Mean   :52.08
## 3rd Qu.:65.00   3rd Qu.:61.00   3rd Qu.:67.0   3rd Qu.:65.00   3rd Qu.:67.00
## Max.   :94.00   Max.   :90.00   Max.   :96.0   Max.   :93.00   Max.   :93.00
## SlidingTackle      GKDiving      GKHandling       GKKicking    GKPositioning
## Min.   : 6.00   Min.   : 1.00   Min.   : 1.00   Min.   : 1.0   Min.   : 1.00
## 1st Qu.:33.00   1st Qu.: 8.00   1st Qu.: 8.00   1st Qu.: 8.0   1st Qu.: 8.00
## Median :57.00   Median :11.00   Median :11.00   Median :11.0   Median :11.00
## Mean   :50.33   Mean   :13.32   Mean   :13.21   Mean   :13.1   Mean   :13.16
## 3rd Qu.:65.00   3rd Qu.:13.00   3rd Qu.:14.00   3rd Qu.:13.0   3rd Qu.:13.00
## Max.   :90.00   Max.   :88.00   Max.   :91.00   Max.   :91.0   Max.   :86.00
##   GKReflexes
## Min.   : 1.00
## 1st Qu.: 8.00
## Median :11.00
## Mean   :13.33
## 3rd Qu.:14.00
## Max.   :92.00
```

right-footed players summary:

```
## perfoot_index      Age          height_cm     weight_amount      Crossing
## Min.   :1     Min.   :16.00   Min.   :154.9   Min.   :110.0   Min.   : 5.00
## 1st Qu.:1     1st Qu.:21.00   1st Qu.:177.8   1st Qu.:154.0   1st Qu.:35.00
## Median :1     Median :25.00   Median :182.9   Median :165.0   Median :51.50
## Mean   :1     Mean   :25.11   Mean   :181.6   Mean   :166.6   Mean   :47.67
## 3rd Qu.:1     3rd Qu.:28.00   3rd Qu.:185.4   3rd Qu.:176.0   3rd Qu.:62.00
## Max.   :1     Max.   :45.00   Max.   :205.7   Max.   :243.0   Max.   :93.00
##   Finishing     HeadingAccuracy  ShortPassing      Volleys
## Min.   : 2.00   Min.   : 4.00   Min.   : 7.00   Min.   : 4.00
## 1st Qu.:29.00   1st Qu.:44.00   1st Qu.:52.00   1st Qu.:29.00
## Median :48.00   Median :56.00   Median :62.00   Median :43.00
## Mean   :45.15   Mean   :51.88   Mean   :57.89   Mean   :42.43
## 3rd Qu.:62.00   3rd Qu.:65.00   3rd Qu.:68.00   3rd Qu.:56.00
## Max.   :94.00   Max.   :94.00   Max.   :93.00   Max.   :90.00
##   Dribbling         Curve        FKAccuracy     LongPassing     BallControl
## Min.   : 4.00   Min.   : 6.0   Min.   : 4.00   Min.   : 9.00   Min.   : 5.00
## 1st Qu.:46.00   1st Qu.:33.0   1st Qu.:30.00   1st Qu.:41.00   1st Qu.:53.00
## Median :60.00   Median :47.0   Median :40.00   Median :55.00   Median :62.00
## Mean   :54.05   Mean   :45.6   Mean   :41.45   Mean   :51.81   Mean   :57.36
## 3rd Qu.:67.00   3rd Qu.:60.0   3rd Qu.:55.00   3rd Qu.:64.00   3rd Qu.:69.00
## Max.   :96.00   Max.   :94.0   Max.   :93.00   Max.   :93.00   Max.   :95.00
##  Acceleration    SprintSpeed       Agility        Reactions
## Min.   :12.00   Min.   :12.00   Min.   :14.00   Min.   :21.00
```

```
##  1st Qu.:55.00   1st Qu.:55.00   1st Qu.:54.00   1st Qu.:55.00
##  Median :66.00   Median :67.00   Median :65.00   Median :62.00
##  Mean   :63.63   Mean   :63.78   Mean   :62.65   Mean   :61.69
##  3rd Qu.:74.00   3rd Qu.:74.00   3rd Qu.:73.00   3rd Qu.:68.00
##  Max.   :97.00   Max.   :96.00   Max.   :96.00   Max.   :96.00
##     Balance        ShotPower        Jumping         Stamina         Strength
##  Min.   :16.00   Min.   : 2.0   Min.   :15.00   Min.   :13.0   Min.   :17.00
##  1st Qu.:55.00   1st Qu.:45.0   1st Qu.:58.00   1st Qu.:55.0   1st Qu.:58.00
##  Median :65.00   Median :59.0   Median :66.00   Median :66.0   Median :67.00
##  Mean   :63.21   Mean   :54.8   Mean   :65.25   Mean   :62.4   Mean   :65.59
##  3rd Qu.:73.00   3rd Qu.:68.0   3rd Qu.:73.00   3rd Qu.:74.0   3rd Qu.:74.00
##  Max.   :96.00   Max.   :95.0   Max.   :95.00   Max.   :96.0   Max.   :97.00
##    LongShots       Aggression     Interceptions    Positioning
##  Min.   : 3.00   Min.   :11.00   Min.   : 3.00   Min.   : 2.00
##  1st Qu.:31.00   1st Qu.:42.00   1st Qu.:24.00   1st Qu.:35.00
##  Median :51.00   Median :58.00   Median :50.00   Median :55.00
##  Mean   :46.29   Mean   :55.32   Mean   :45.53   Mean   :49.02
##  3rd Qu.:62.00   3rd Qu.:69.00   3rd Qu.:64.00   3rd Qu.:64.00
##  Max.   :93.00   Max.   :95.00   Max.   :92.00   Max.   :95.00
##      Vision        Penalties       Composure        Marking
##  Min.   :10.00   Min.   : 5.00   Min.   : 3.00   Min.   : 3.00
##  1st Qu.:43.00   1st Qu.:38.00   1st Qu.:51.00   1st Qu.:28.00
##  Median :55.00   Median :49.00   Median :59.00   Median :51.00
##  Mean   :52.98   Mean   :48.04   Mean   :58.31   Mean   :46.14
##  3rd Qu.:64.00   3rd Qu.:60.00   3rd Qu.:67.00   3rd Qu.:63.00
##  Max.   :94.00   Max.   :92.00   Max.   :95.00   Max.   :94.00
##  StandingTackle  SlidingTackle      GKDiving       GKHandling
##  Min.   : 2.00   Min.   : 3.00   Min.   : 1.00   Min.   : 1.00
##  1st Qu.:24.00   1st Qu.:22.00   1st Qu.: 8.00   1st Qu.: 8.00
##  Median :53.00   Median :49.00   Median :11.00   Median :11.00
##  Mean   :46.35   Mean   :44.22   Mean   :17.58   Mean   :17.32
##  3rd Qu.:66.00   3rd Qu.:63.00   3rd Qu.:14.00   3rd Qu.:14.00
##  Max.   :92.00   Max.   :91.00   Max.   :90.00   Max.   :92.00
##    GKKicking      GKPositioning     GKReflexes
##  Min.   : 1.00   Min.   : 1.00   Min.   : 1.0
##  1st Qu.: 8.00   1st Qu.: 8.00   1st Qu.: 8.0
##  Median :11.00   Median :11.00   Median :11.0
##  Mean   :17.14   Mean   :17.33   Mean   :17.7
##  3rd Qu.:14.00   3rd Qu.:14.00   3rd Qu.:14.0
##  Max.   :91.00   Max.   :90.00   Max.   :94.0
```