PUBG Top 10% Placement Analysis

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1 Introduction

PlayerUnknown's Battlegrounds, colloquially referred to as PUBG, is an online battle royale-style shooter that is one of the best-selling video games of all time. The game's developer has created an API (application program interface) where others have collected data on over 65,000 matches and made that data available on the popular online competition site *Kaggle*[1]. The project team will be utilizing logistic regression, linear and quadratic discriminant analyses, and random forest methods to attempt to create the best model for predicting whether or not an individual player in a solo match will place in the top 10 finishers or not.

2 Data Description

The source data is available on Kaggle.com under the competition PUBG Finish Placement Prediction. The files used in our analysis were transformed to fit the requirements of a binomial logistic regression classifier. The data has also been pre-split into training and test files for consistency when comparing our different model types. Additionally, as the percentage-based nature of the top 10% of players is inherently unbalanced, we've also downsampled the higher frequency data to match that over the lower frequency outcome of the top 10% of players.

`pubg_solo_game_types.csv`

- Filtered for solo only game types

`pubg_solo_game_types_test_full.csv`

- Pre-split for test data

`pubg_solo_game_types_train_full.csv`

- Pre-split for train data without downsampling for the unbalanced response variable

`pubg_solo_game_types_train_downsampled.csv`

- Pre-split for train data with downsampling for the unbalanced response variable

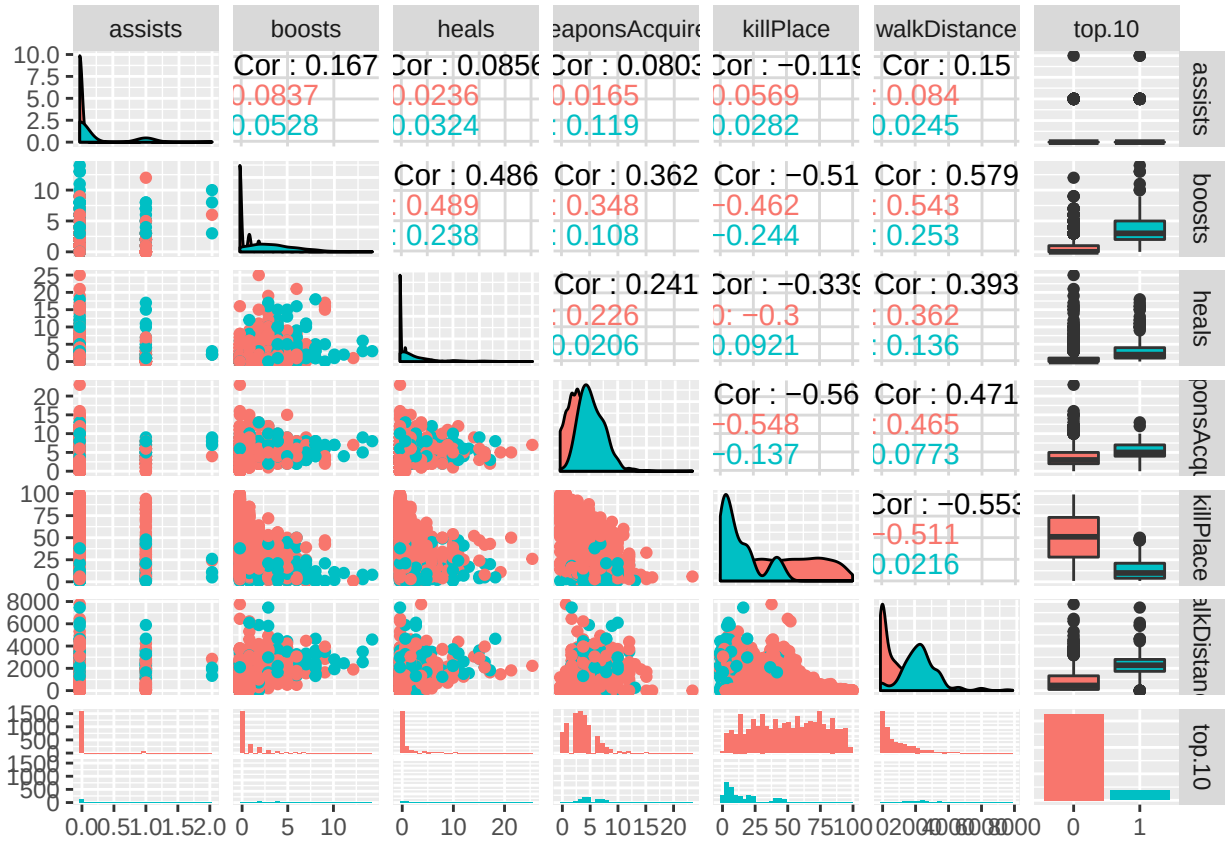
2.1 Data Dictionary

Column Name	Description
DBNOs	Number of enemy players knocked.
assists	Number of enemy players this player damaged that were killed by teammates.
boosts	Number of boost items used.
damageDealt	Total damage dealt. Note: Self inflicted damage is subtracted.

Column Name	Description
headshotKills	Number of enemy players killed with headshots.
heals	Number of healing items used.
Id	Players Id
killPlace	Ranking in match of number of enemy players killed.
killPoints	Kills-based external ranking of player. (Think of this as an Elo ranking where only kills matter.) If there is a value other than -1 in rankPoints, then any 0 in killPoints should be treated as a None.
killStreaks	Max number of enemy players killed in a short amount of time.
kills	Number of enemy players killed.
longestKill	Longest distance between player and player killed at time of death.
matchDuration	Duration of match in seconds.
matchId	ID to identify match. There are no matches that are in both the training and testing set.
matchType	String identifying the game mode that the data comes from.
rankPoints	Elo-like ranking of player.
revives	Number of times this player revived teammates.
rideDistance	Total distance traveled in vehicles measured in meters.
roadKills	Number of kills while in a vehicle.
swimDistance	Total distance traveled by swimming measured in meters.
teamKills	Number of times this player killed a teammate.
vehicleDestroys	Number of vehicles destroyed.
walkDistance	Total distance traveled on foot measured in meters.
weaponsAcquired	Number of weapons picked up.
winPoints	Win-based external ranking of player. (Think of this as an Elo ranking where only winning matters.) If there is a value other than -1 in rankPoints, then any 0 in winPoints should be treated as a None.
groupId	ID to identify a group within a match. If the same group of players plays in different matches, they will have a different groupId each time.
numGroups	Number of groups we have data for in the match.
maxPlace	Worst placement we have data for in the match. This may not match with numGroups, as sometimes the data skips over placements.
winPlacePerc	This is a percentile winning placement, where 1 corresponds to 1st place, and 0 corresponds to last place in the match. (to be removed from our binomial classfier so as not to influence our predictive results)
top.10	The target of prediction. This is a percentile winning placement, where 1 corresponds to a top 10% placement a 0 in the lower 90%.

2.2 Exploratory Data Analysis

The data full data set has 65,000 matches, each with data on the players in that match and statistics based on that individual match with only minor exceptions. We have data on how much damage was dealt, how many kills a player got, and other information like distance travelled and weapons acquired. Below is a pairs plot for some of our core variables.



A complete set of pair plots and box plots are available in the EDA appendix. There are a number of frequency tables in the DescriptiveTables script, but it was quite lengthy so it is not included here.

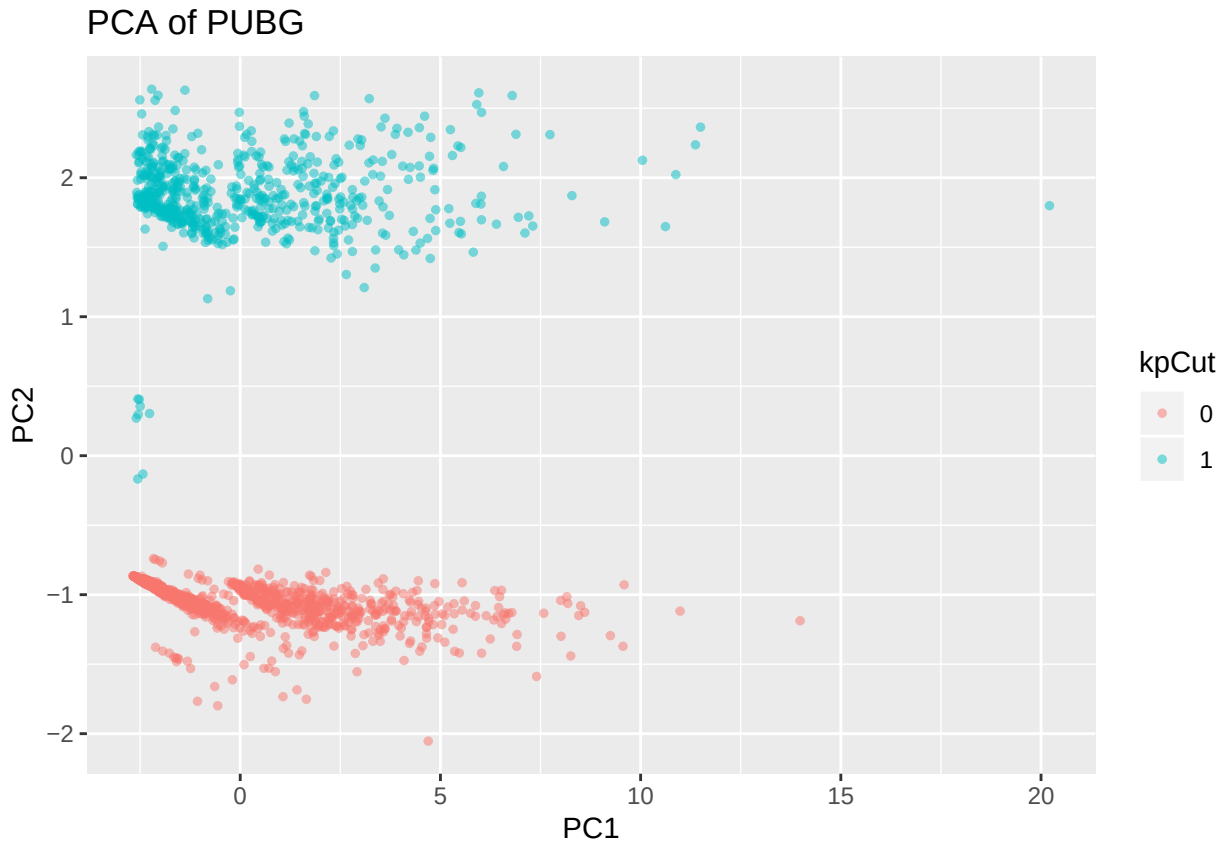
A number of variables are not useful for prediciton. Id, groupID, and matchId are identifiers. MatchType, DBNOs, and Revives are not relevant because we are focusing on the Solo match type. Finally, our response variable, top.10, is derived from winPlacePerc, so we cannot use it for prediction.

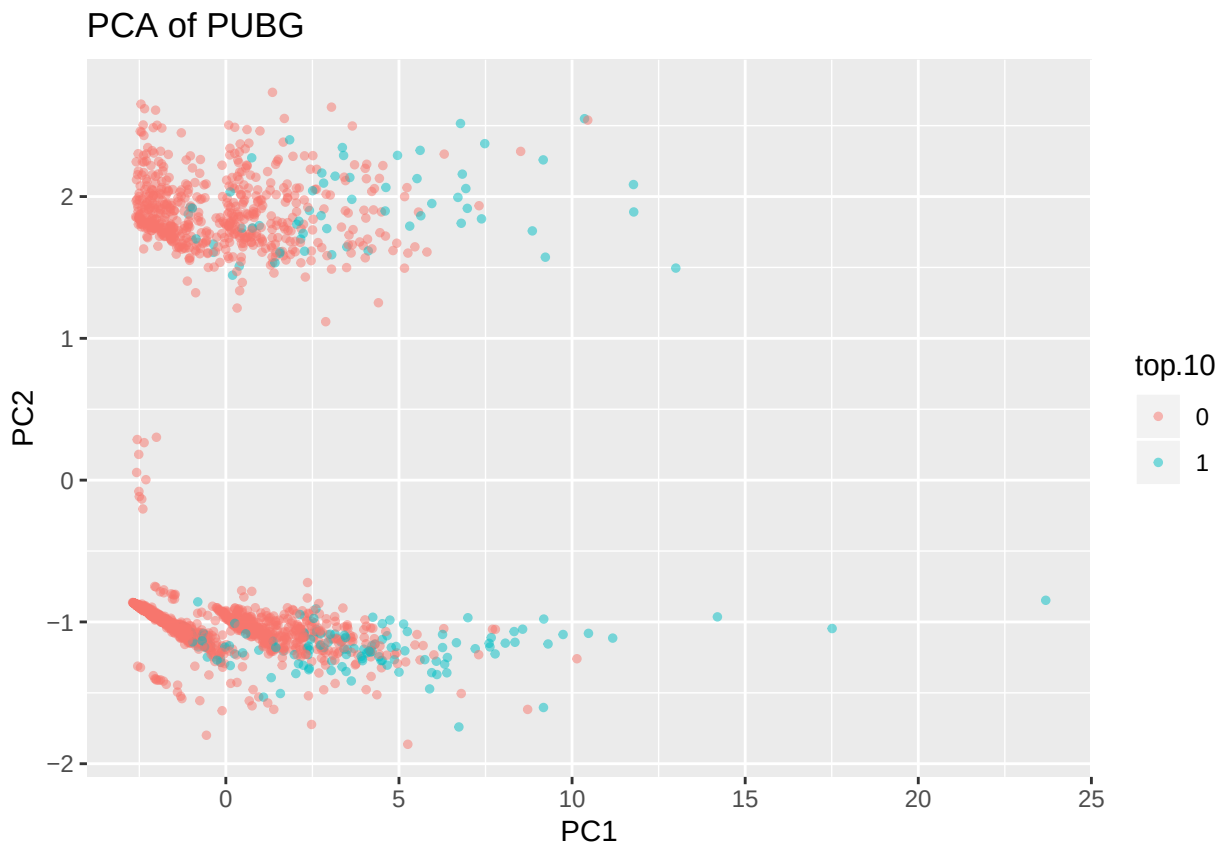
2.2.1 PCA

Principle Components Analysis can help us reduce numerical predictors to a few components. These groupings might help us find key variables to use for modeling

```
##                      PC1           PC2         PC3
## assists       0.093464896  0.0341204724 -0.07248995
## boosts        0.284017732 -0.0187724920 -0.27993293
## damageDealt   0.354025626 -0.0006752358  0.16342595
## headshotKills 0.272432205  0.0058796339  0.19810172
```

```
## heals            0.172891815 -0.0314204736 -0.36832274
## killPlace       -0.328110631  0.0417139011  0.05106409
## killPoints       0.025713144  0.7026339764 -0.04743269
## kills            0.366152434  0.0064308394  0.19503487
## killStreaks      0.320309798  0.0146912776  0.20189572
## longestKill      0.282653385 -0.0104638751  0.06734322
## rideDistance     0.125792347 -0.0328766270 -0.36531789
## roadKills        0.058565079  0.0099295744  0.01992678
## swimDistance     0.038039360 -0.0055821852 -0.19718801
## teamKills        0.005310582 -0.0529793299 -0.10953494
## vehicleDestroys  0.054284130 -0.0255527144 -0.10946179
## walkDistance     0.245857081 -0.0176610089 -0.41203730
## weaponsAcquired  0.194128985 -0.0430771084 -0.35785321
## winPoints        0.015164472  0.7032363836 -0.05351414
## killsPK          0.327801875  0.0166732303  0.33144634
## damageKill       0.163661873 -0.0015941934  0.13894088
```

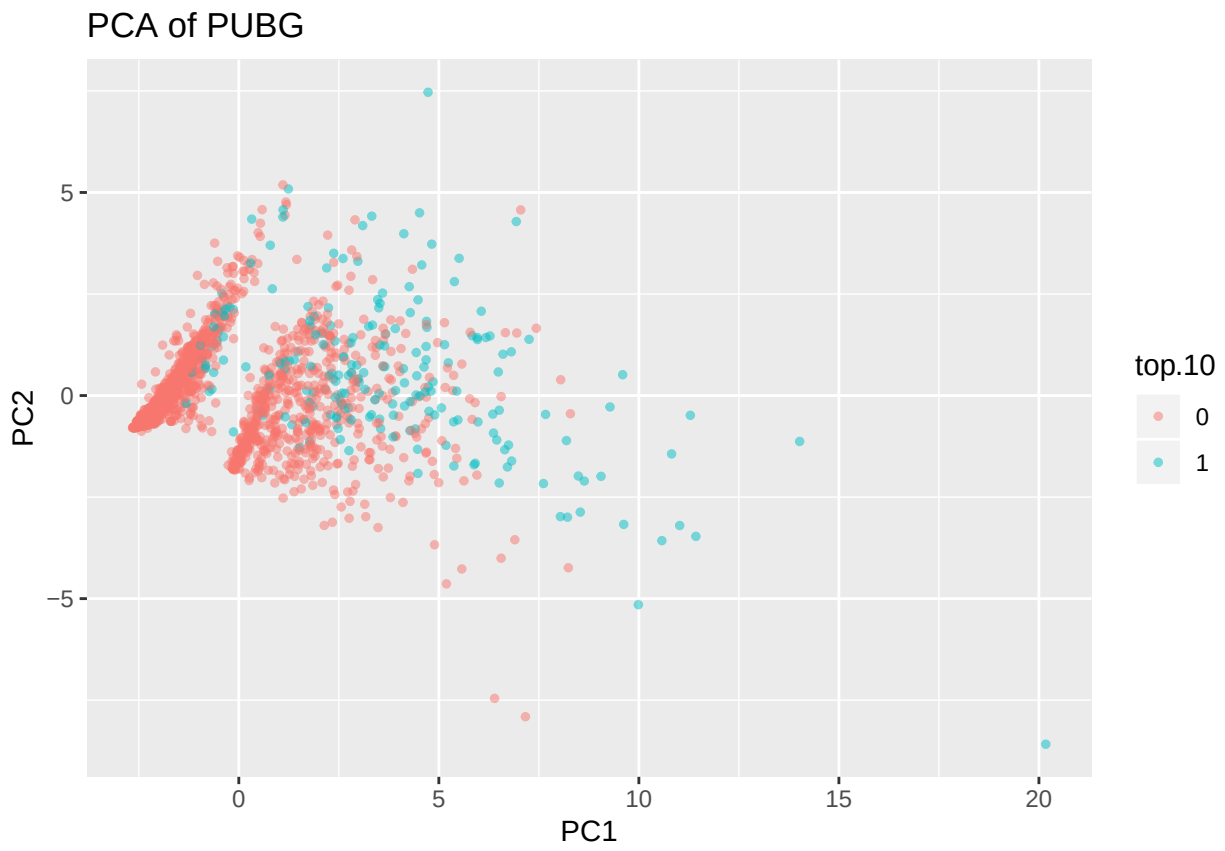




We see kills based measures are pretty strong in PC1, and killPoints/Winpoints dominate PC2. Looking at the graph, we get a strange separation. The killPoints variable can explain this, with one group having killPoints = 0 and the other being killPoints > 0. Lets try it one more time without killpoints.

```
##                        PC1         PC2         PC3
## assists          0.093288398  0.06828606  0.04474120
## boosts           0.284134067  0.28016254  0.07277247
## damageDealt      0.354186391 -0.16308792 -0.01079849
## headshotKills    0.272532648 -0.19811583  0.01739273
## heals            0.173041804  0.36948689  0.05346143
## killPlace       -0.328486849 -0.05445813 -0.06225663
## kills            0.366260701 -0.19513648 -0.01676471
## killStreaks      0.320325015 -0.20251783 -0.03788582
## longestKill      0.282828105 -0.06637903  0.02458407
## rideDistance     0.125910114  0.36697769 -0.30903984
## roadKills        0.058526280 -0.02081518 -0.39810562
## swimDistance     0.038043527  0.19662593  0.24080577
## teamKills        0.005560085  0.11493992 -0.57603084
## vehicleDestroys  0.054393599  0.11187784 -0.54205238
## walkDistance     0.245894336  0.41172283  0.17098240
## weaponsAcquired  0.194340503  0.36034996  0.10634883
```

```
## killsPK          0.327856167 -0.33177097 -0.07024240
## damageKill       0.163742912 -0.13812684  0.01166277
```



We are still getting some separation, but it has much improved. We are not getting 100$ separation of the top.10 variable, so PCA alone is not giving us a clear answer as to what makes a top 10 player.

3 Objective I Analysis

3.1 Problem Statement

We would like to predict if a player finished in the top 10 of a PUBG match based on their stats during the match. Our response variable is top.10, which is 1 if the player finished in the top 10 and 0 if they did not. We will start with a logistic regression model before moving into more complex methods.

3.2 Establishing the Initial Model

During EDA, we discovered a number of variables that would not be useful for prediction, either because they were ID columns or match characteristics that were not relevant to individual player performance. Removing those, our first model contains all the remaining variables.

```
##
## Call:
## glm(formula = top.10 ~ assists + boosts + heals + teamKills +
```

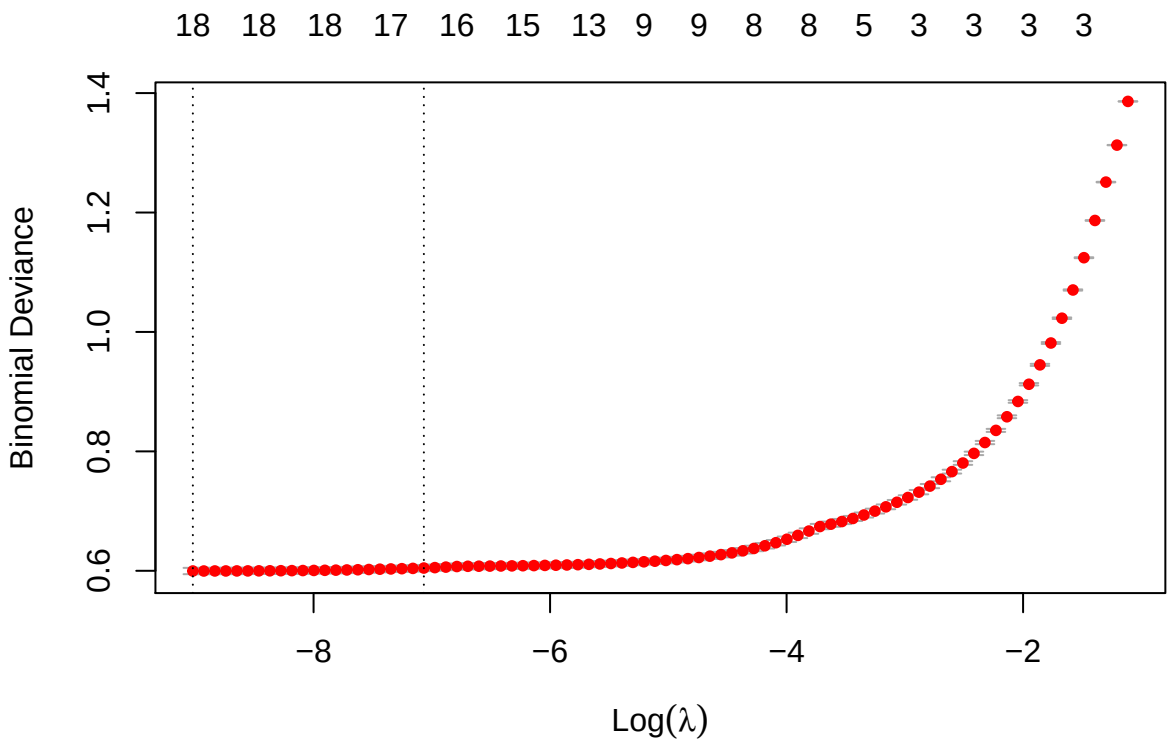
```
##     weaponsAcquired + damageDealt + headshotKills + kills + killStreaks +
##     roadKills + vehicleDestroys + killPlace + killPoints + rankPoints +
##     winPoints + longestKill + swimDistance + rideDistance + walkDistance,
##     family = binomial(link = "logit"), data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5064  -0.2621   0.0017   0.4644   5.1751
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -5.335e+00  4.679e-01 -11.402  < 2e-16 ***
## assists          6.767e-01  7.031e-02   9.624  < 2e-16 ***
## boosts           3.279e-01  1.265e-02  25.930  < 2e-16 ***
## heals           -3.521e-02  6.748e-03  -5.217 1.82e-07 ***
## teamKills       -2.027e+00  2.315e-01  -8.757  < 2e-16 ***
## weaponsAcquired  4.750e-02  8.215e-03   5.782 7.36e-09 ***
## damageDealt      6.655e-05  2.758e-04   0.241  0.80935
## headshotKills    4.061e-02  3.300e-02   1.231  0.21841
## kills           -5.179e-02  3.254e-02  -1.591  0.11151
## killStreaks     -1.210e+00  5.375e-02 -22.509  < 2e-16 ***
## roadKills       -2.286e-01  1.223e-01  -1.870  0.06148 .
## vehicleDestroys -4.657e-01  1.674e-01  -2.783  0.00539 **
## killPlace       -9.337e-02  1.817e-03 -51.380  < 2e-16 ***
## killPoints      -1.578e-03  2.606e-04  -6.055 1.41e-09 ***
## rankPoints       3.995e-03  3.056e-04  13.074  < 2e-16 ***
## winPoints        5.282e-03  3.949e-04  13.376  < 2e-16 ***
## longestKill     -1.896e-03  4.007e-04  -4.732 2.22e-06 ***
## swimDistance     1.503e-03  3.705e-04   4.056 5.00e-05 ***
## rideDistance     1.316e-04  1.011e-05  13.026  < 2e-16 ***
## walkDistance     8.866e-04  2.384e-05  37.197  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 15916  on 26594  degrees of freedom
## AIC: 15956
##
## Number of Fisher Scoring iterations: 6
```

We can see some insignificant variables, and the vif (Appendix: Logistic Model) will show some correlation. This model performance of this model is as follows:

Model	AUC	Sensitivity	Specificity	Error Rate (1 - Accuracy)
Initial	0.941	0.891	0.843	15.2%

3.3 Variable Selection

Next, we use lasso to narrow these down to the most important variables. First, we used cv.glmnet to search for the ideal value of lambda for the lasso regression (Appendix: Logistic Regression). We selected the lambda.1se value, which will hopefully eliminate the most variables. Using that value for lambda, lasso produced this output:



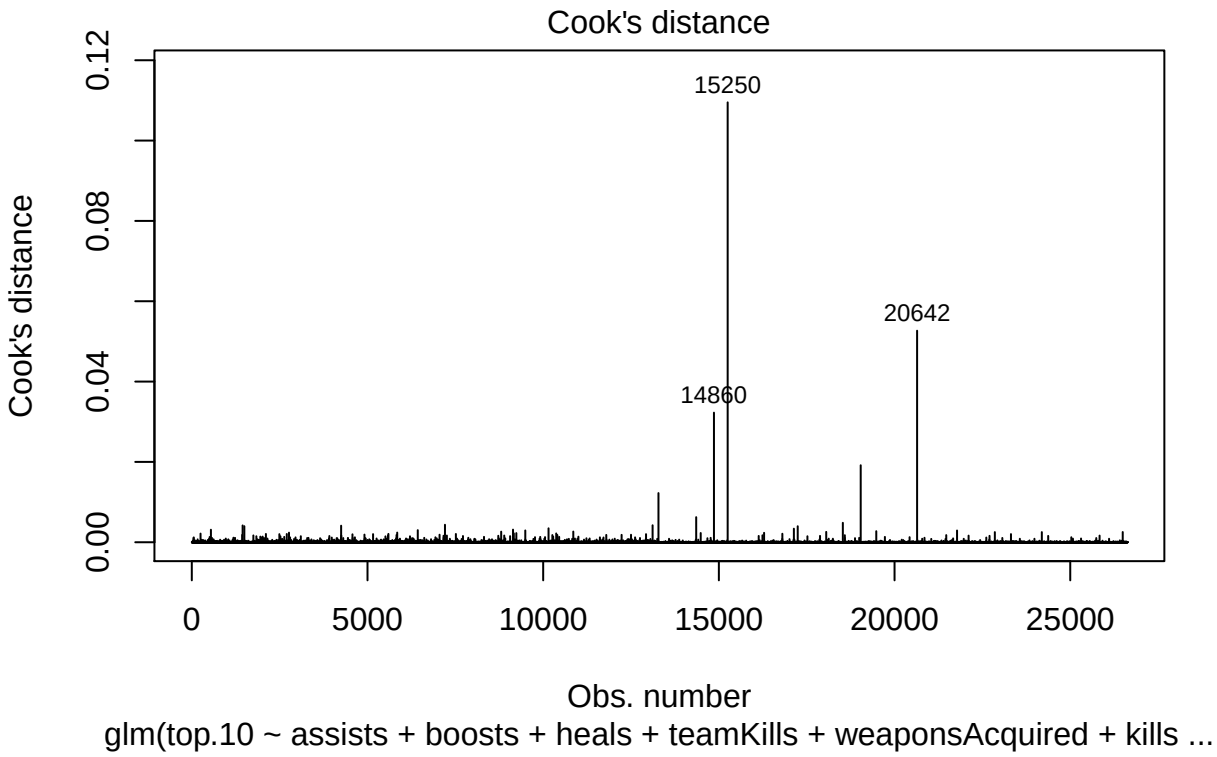

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                              s0
## (Intercept)     -0.6733424558
## (Intercept)      .
## assists          0.6465602204
## boosts           0.3247910863
## heals           -0.0291791887
## teamKills       -1.9070440684
## weaponsAcquired  0.0445136944
## damageDealt      .
## headshotKills    .
```

```
## kills           -0.0262597549
## killStreaks     -1.1450786717
## roadKills       -0.1971398791
## vehicleDestroys -0.4170561352
## killPlace       -0.0876942534
## killPoints       .
## rankPoints       0.0008663913
## winPoints        0.0008998702
## longestKill     -0.0014955118
## swimDistance     0.0013710884
## rideDistance     0.0001344144
## walkDistance     0.0008663011
```

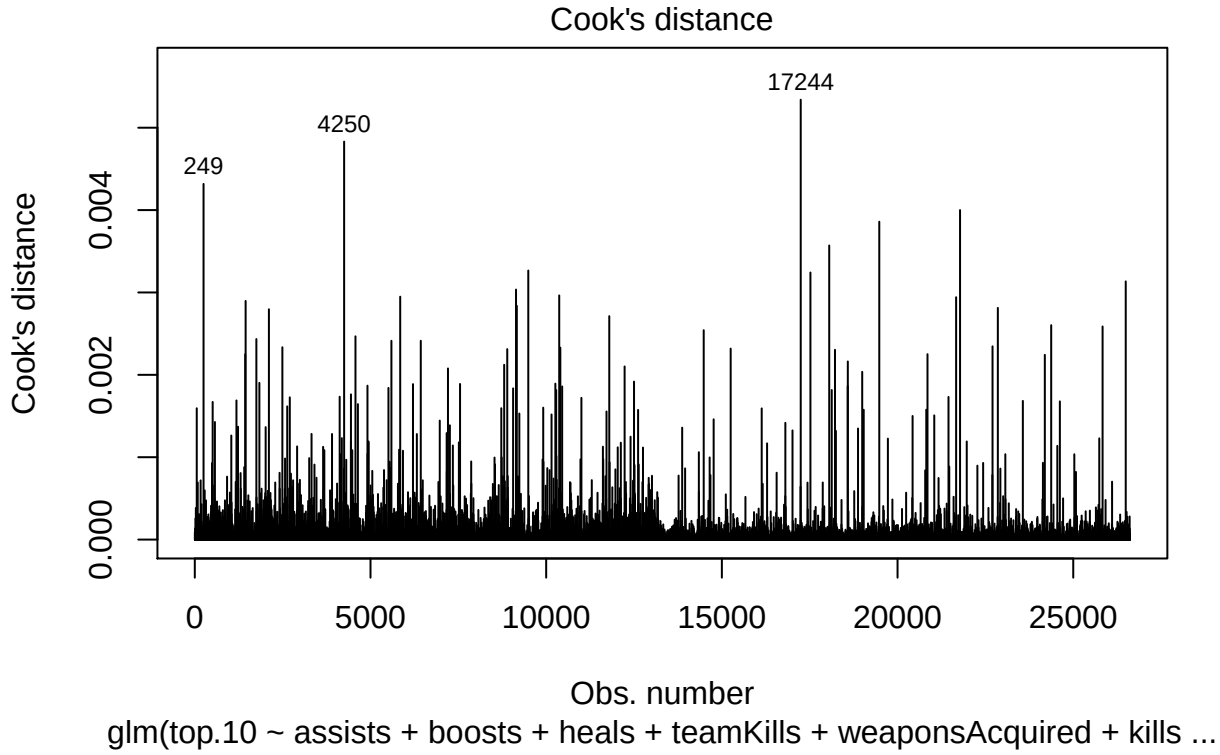
3.4 Final Iterations

The selection eliminated damageDealt, headshotKills, and killPoints. We created a model using just the variables from lasso and found two issues. First, winPoints and rankPoints have high VIFs. Removing them individually found that when one is missing, the other is no longer significant. We decided to remove them both. Second, the cooksD plot shows 3 potentially influential points. All three points have high values (> p99 threshold) for roadKills and killStreaks, and I also found through adding and removing variables that swimDistance contributes influential points. We chose to remove these variables, as a very small part of the population has high values in these metrics, and it negatively effects the model.

Here we can see influential points from the Cook's D chart.


Cook's distance
Cook's distance
0.00
0.04
0.08
0.12
15250
20642
14860
0
5000
10000
15000
20000
25000
Obs. number
glm(top.10 ~ assists + boosts + heals + teamKills + weaponsAcquired + kills ...

After removing roadKills , killStreaks, and swimDistance



Final Model Coefficients

```
##
## Call:
## glm(formula = top.10 ~ assists + boosts + heals + weaponsAcquired +
##     killPlace + walkDistance, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.3664  -0.3759  -0.0174   0.4865   2.6092
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -5.934e-01  5.982e-02  -9.919  < 2e-16 ***
## assists          6.225e-01  6.666e-02   9.339  < 2e-16 ***
## boosts           3.067e-01  1.158e-02  26.493  < 2e-16 ***
## heals           -2.276e-02  6.449e-03  -3.529 0.000418 ***
## weaponsAcquired  7.900e-02  7.742e-03  10.205  < 2e-16 ***
## killPlace       -6.216e-02  1.192e-03 -52.172  < 2e-16 ***
```

```
## walkDistance     7.415e-04  2.073e-05  35.775  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 17365  on 26607  degrees of freedom
## AIC: 17379
##
## Number of Fisher Scoring iterations: 6
```

3.5 Comparing Competing Models

Model	AUC	Sensitivity	Specificity	Error Rate (1 - Accuracy)
Initial	0.941	0.891	0.843	15.2%
Lasso	0.941	0.892	0.843	15.2%
Inf. Points	0.936	0.892	0.842	15.3%
Final	0.932	0.863	0.841	15.6%

3.6 Model Interpretation

We prefer the final model because it simplifies the previous versions without significant loss in accuracy. The variable interpretations are found in the table below.

Variable	Interpretation
assists	The log-odds of placing in the top 10 increase by 0.6225 for each additional assist
boosts	The log-odds of placing in the top 10 increase by 0.3067 for each additional boost
heals	The log-odds of placing in the top 10 decrease by -0.0228 for each additional heal
weaponsAcquired	The log-odds of placing in the top 10 increase by 0.0790 for each additional weapon acquired
killPlace	The log-odds of placing in the top 10 increase by 0.0622 for each additional rank in kills (lower is better for killPlace)
walkDistance	The log-odds of placing in the top 10 increase by 0.0007 for each additional meter walked

3.7 Conclusion

Players who do well in kill placement and who travel far tend to win games. Travel distance probably is a proxy for time alive, as players eliminated early would probably not travel far. Acquiring in game items like boosts or weapons also help. The negative coeffient on heals is odd, perhaps indicating that taking more damage is detrimental to placement. We will try to improve on the final model using more complex methods.

4 Objective II Analysis

4.1 Question of Interest

As we stated in the Problem Statement, we would like to predict if a player finished in the top 10 of a PUBG match based on their stats during the match. The next three methods of prediction we will present areLogistic Regression using more complicated terms than what were presented in Objective 1, Linear Discriminant Analysis (LDA), and Random Forest. These different techniques are all going to help us answer the question: What model is has the highest predicitve accuracy for classifying players as top 10 finishers?

4.2 Model Selection

4.2.1 Logistic Regression with complex terms

4.2.1.1 Objective

In the first logistic regression we used terms that were easier to interpret, now we will add more complex terms. The final model from the previous section was:

top.10 ~ assists + boosts + heals + weaponsAcquired + killPlace + walkDistance

Additional terms considered in the more complex model are as follows: * Dichotomized variables: Two level versions of the original variables, with cutoffs determined by EDA to try to separate top.10 from the rest of the group

- Binned Variables: These have more levels than the dichotomized versions, to try to capture more complexity
- Ratios: Key variables are compared against each other in ratio format. For instance, does damage dealt per kill make a difference?
- Interactions: multiplicative relationships between key variables. For instance, does increased damage matter if the player is above the boosts cut point?
- Full definitions of new variables can be found in Appendix: Complex Logistic Regression

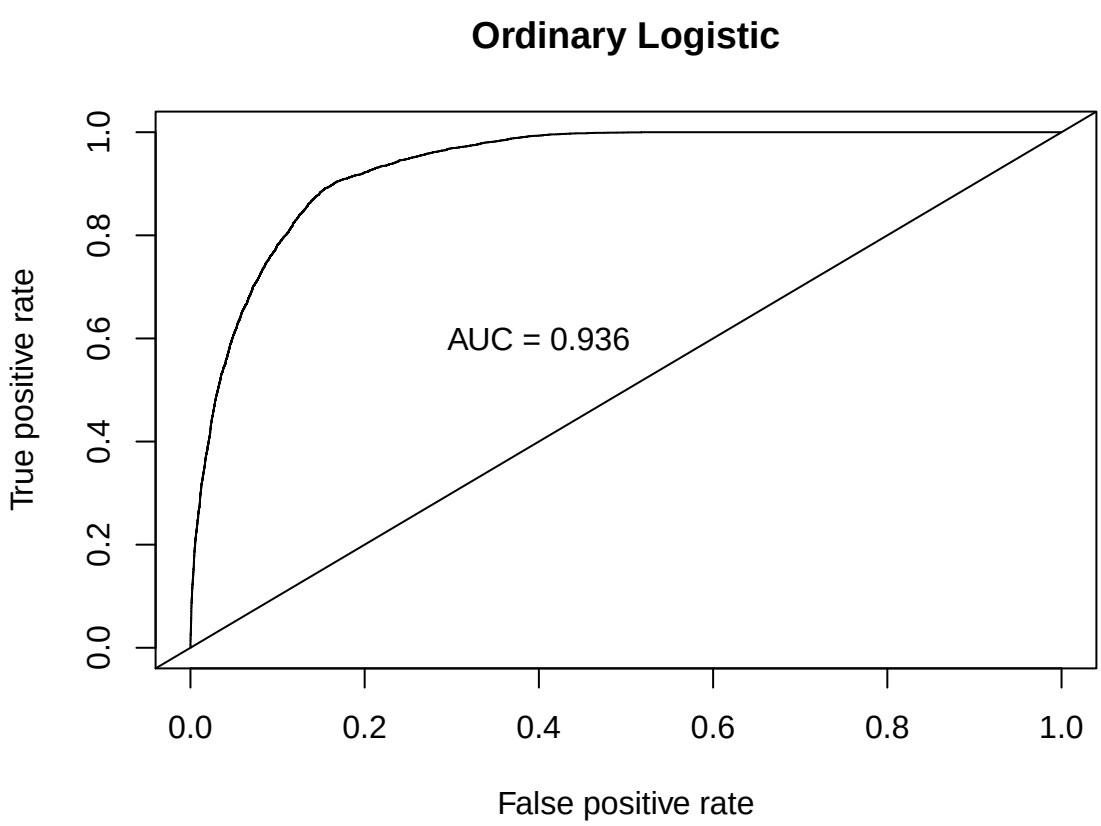
4.2.1.2 Model Selection

We ran a total of 8 additional logistic models, with the following results:

Model	AUC	Sensitivity	Specificity	Error Rate (1 - Accuracy)
Model 01	0.932	0.873	0.836	16.0%
Model 02	0.932	0.862	0.841	15.7%
Model 03	0.932	0.885	0.832	16.2%
Model 04	0.936	0.889	0.827	16.6%
Model 05	0.932	0.864	0.841	15.6%
Model 06	0.939	0.888	0.836	15.8%
Model 07	0.936	0.895	0.840	15.4%
Model 08	0.936	0.894	0.838	15.6%
Obj1 Final	0.932	0.863	0.841	15.6%

The most successful model was number 7, which had the best accuracy with no warnings. The model coefficients and performance are in the figures below:

```
##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + killsPK, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5511  -0.3216  -0.0002   0.4906   2.9651
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.866e-01  7.051e-02   4.064 4.82e-05 ***
## boosts           3.581e-01  1.159e-02  30.896  < 2e-16 ***
## assists          7.086e-01  6.731e-02  10.526  < 2e-16 ***
## weaponsAcquired  6.123e-02  7.994e-03   7.659 1.87e-14 ***
## killPlace       -7.958e-02  1.471e-03 -54.091  < 2e-16 ***
## walkDistance     6.951e-04  2.127e-05  32.683  < 2e-16 ***
## killsPK         -7.938e-01  3.420e-02 -23.213  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 16839  on 26607  degrees of freedom
## AIC: 16853
##
## Number of Fisher Scoring iterations: 6
```




```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 41066   600
##          1  7813  5103
##
##                Accuracy : 0.8459
##                  95% CI : (0.8428, 0.8489)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4715
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.89479
##             Specificity : 0.84016
##          Pos Pred Value : 0.39509
##          Neg Pred Value : 0.98560
##              Prevalence : 0.10448
```

```
##          Detection Rate : 0.09349
##    Detection Prevalence : 0.23663
##       Balanced Accuracy : 0.86747
##
##        'Positive' Class : 1
##
```

The additional variable for this model is killsPK, or kills per kilometer. It is a ratio designed to separate players who are aggressive and engaging other players during the match vs. those who travel far but play a more stealthy strategy. The model suggests each additional unit of killsPK would decrease the log odds of entering the top 10 by 0.794

4.2.1.3 Conclusions for Logistic Regression

Of the models we tried, none achieved an increase in accuracy that would justify the additional complexity. We also ran into issues with complex variables. The rank deficient error suggest some values of the combination of two categorical variables did not have any observations assigned. In this case it would make sense to code a special variable to account for this. The other warning suggests some combination of variables allowed for perfrect seperation of top.10, but which variables was not clear from the EDA. For logistic regression, the best model we found was the one at the end of objective one.

4.2.2 Linear Discriminant Analysis

Our next prediction tool is Linear Discriminant Analysis (LDA) for classifying the player as Top 10 or not. We have taken a subset of the continuous variables from our EDA to build the LDA off of. Before running the LDA, we will cover two things: a LASSO call to eliminate less important variables and assumption checking.

4.2.2.1 LASSO

The LASSO call plus manual variable selection reduced the predictors considered for the LDA model to: boosts, heals, killPlace, killStreaks, longestKill, matchDuration, rideDistance, swimDistance, teamKills, walkDistance, weaponsAcquired. See see the Appendix - LDA for the output of the LASSO call.

4.2.2.2 Assumption Checking

LDA performs optimally when the assumptions of MANOVA are met. That is,

1. The predictors are normally distributed for each class of the response.
2. The covariance matrices for each class of the response are homogeneous.

When we check the first assumption for the predictors that are to be included in the LDA model, we see that the assumption is not met, as shown in the histograms of the variables as shown in the Appendix - LDA. Most of the predictors are right skewed. The variable matchDuration is bimodal. To remedy this, we tried transforming the variables, but it did not help our overall prediction accuracy. However, because issues of normality exist, we will explore QDA as well as LDA.

We also checked the homogeneity of correlation matrices, shown in the Appendix - LDA. We find that, overall, there are no major departures from homogeneity. The variables walkDistance and killPlace show the greatest

deviances from homogenous correlations between bottom 90 and top 10 placements. Consequently, we tried removing those variables from the model. However, removing those variables reduced our prediction accuracy.

Thus, we will proceed with the variables selected and see if LDA or QDA performs better.

4.2.2.3 LDA Results

LDA has a prediction accuracy of 0.9206, with a sensitivity of 0.57479 and a specificity of 0.96099. The area under the ROC curve is 0.941. Output of the LDA call and the ROC curve are shown in Appendix - LDA. The confusion matrix is shown below for comparison with QDA.

```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 46972  2425
##   1  1907  3278
##
##                Accuracy : 0.9206
##                  95% CI : (0.9183, 0.9229)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5582
##
##  Mcnemar's Test P-Value : 3.998e-15
##
##             Sensitivity : 0.57479
##             Specificity : 0.96099
##          Pos Pred Value : 0.63221
##          Neg Pred Value : 0.95091
##              Prevalence : 0.10448
##          Detection Rate : 0.06006
##    Detection Prevalence : 0.09499
##       Balanced Accuracy : 0.76789
##
##        'Positive' Class : 1
##
```

4.2.2.4 QDA Results

QDA has a prediction accuracy of 0.8779, with a sensitivity of 0.68262 and a specificity of 0.90071. The area under the ROC curve is 0.912 .Output of the QDA call and the ROC curve are shown in Appendix - LDA. The confusion matrix is shown below for comparison with LDA.

```
## Confusion Matrix and Statistics
```

```
##
##
##         0     1
##   0 46972  2425
##   1  1907  3278
##
##                Accuracy : 0.9206
##                  95% CI : (0.9183, 0.9229)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5582
##
##  Mcnemar's Test P-Value : 3.998e-15
##
##             Sensitivity : 0.57479
##             Specificity : 0.96099
##          Pos Pred Value : 0.63221
##          Neg Pred Value : 0.95091
##              Prevalence : 0.10448
##          Detection Rate : 0.06006
##    Detection Prevalence : 0.09499
##       Balanced Accuracy : 0.76789
##
##        'Positive' Class : 1
##
```

4.2.2.5 LDA Conclusion

Although the QDA is better at predicting the top 10 placements that were true top 10 than LDA (QDA sensitivity of 0.68 > LDA sensitivity of 0.57), QDA predicts many more incorrect top 10 placements than LDA does (1907 LDA false positives < 4853 QDA false positives). Because LDA has a better overall accuracy (0.9206 for LDA > 0.8779 for QDA), we think the LDA is a stronger model for prediction than QDA.

4.2.3 Random Forest

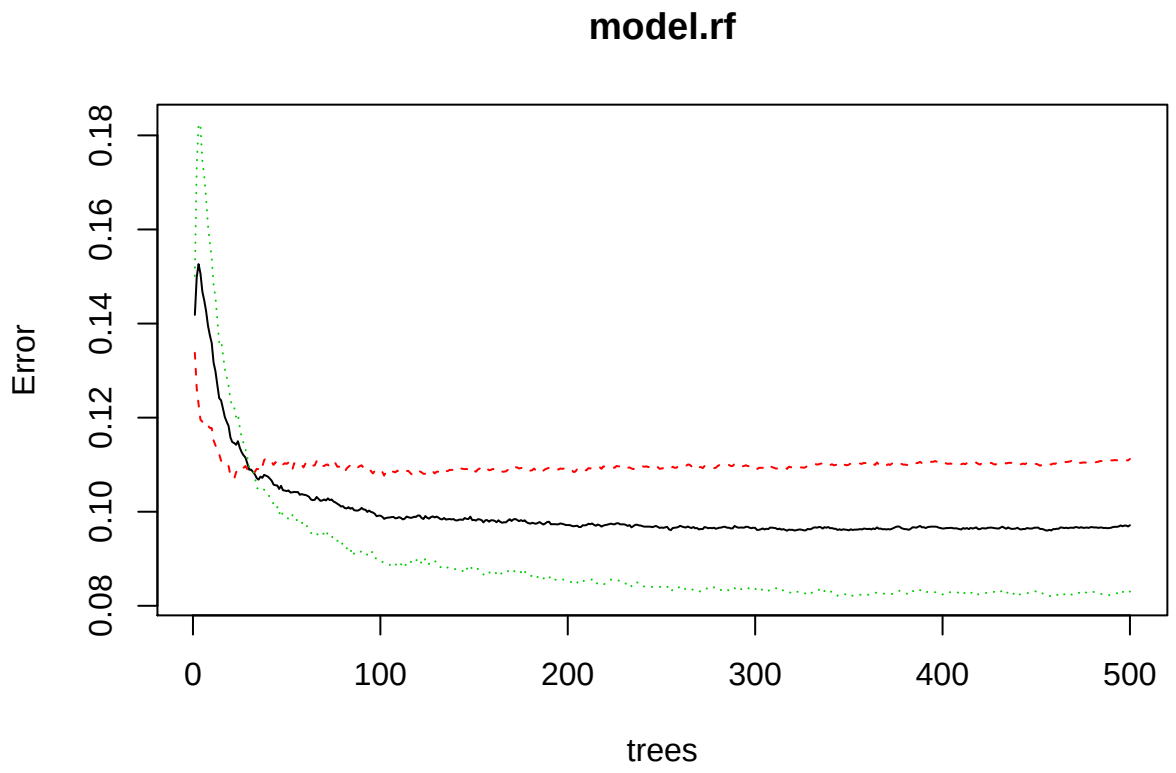
We then tried our first non-parametrical model with Random Forest, which averages out the results of many Decision Trees to provide the lowest error rates across all of the permuations attempted.

4.2.3.1 Assumption Checking

Random Forest methods do not have the same level of assumption restrictions as many of the parametrical models we reviewed. Fotunately, our data set had no null values to speak of which may have posed more of a problem.

4.2.3.2 Error Rates by No. of Trees

The model could likely be tuned further as you can see there's no additional payoff from having the `ntree` value set so high. In fact, it could be harming the performance by setting it to such a high value as you can see the error rates starting to trend upwards at the far-right edge of the graph.



4.2.3.3 Variable Importance

Similar features were confirmed as having the best predictive outcomes from the variable importance output. (i.e. . . Kill Place, Walking Distance, etc..)

Column.Name	Overall.Score
assists	43.62334
boosts	1157.86767
damageDealt	587.86497
headshotKills	61.26146
heals	209.00441
killPlace	5172.69584
killPoints	155.16722
kills	635.76974
killStreaks	159.01334
longestKill	386.08015
matchDuration	105.38803
maxPlace	326.37764
numGroups	367.23582
rankPoints	289.94210
rideDistance	270.77805
roadKills	13.37229
swimDistance	96.74467
teamKills	22.79068
vehicleDestroys	13.58180
walkDistance	2802.62385
weaponsAcquired	261.50104
winPoints	155.96105

4.2.3.4 Random Forest Results

The out-of-bag estimate of the error rate was 9.71% which wasconsistent with our finding from classifying the test data not used to train the model with. This should allow us to better guage what real-world performance would be like with new data to apply the model to.

When running our model against the hold out test data set, we received the following performance metrics.

Model	AUC	Sensitivity	Specificity	Error Rate (1 - Accuracy)
RF	0.963	0.918	0.894	10.4%

4.2.3.5 Random Forest Conclusion

The Random Forest approach required that the model be tuned with parameters better suited to the provided data set.

The following arguments were important to address bias/ variance issues that were observed when using the default settings. Trial and error techniques along with tuning libraries in `caret` and native to the `randomForest` library allowed us to better optimize the results. We were able to get a roughly 90/90 split between our sensitivity and specificity performance measures. Or rather, when it was in the top 10%, the model was able to accurately predict that it was roughly 90% of the time. The same could be said for the specificity metric.

From the library documentation:

- `ntree` : Number of trees to grow
- `mtry` : Number of variables randomly sampled as candidates at each split.
- `cutoff` : A vector of length equal to number of classes.

4.3 Overall Comparison of Models and Conclusion

Model	AUC	Sensitivity	Specificity	Error Rate (1 - Accuracy)
Logistic regression (simple - final)	0.932	0.863	0.841	15.6%
Logistic regression (complex - model 7)	0.936	0.895	0.840	15.4%
LDA	0.941	0.575	0.961	7.94%
Random forest	0.963	0.918	0.894	10.4%

The logistic regression models both performed well on all four metrics of interest (AUC, sensitivity, specificity, and error rate). Due to the fact that the simple logistic regression model is easier to interpret than the complex version, we prefer this simple model over the complex one. LDA had the highest AUC and lowest error rate. However, due to its low sensitivity, it was the worst model in terms of answering our question of interest: how can we best predict top 10 finishers. Random forest outperformed the logistic models in most categories and perhaps further hyperparameter tuning could improve this model.

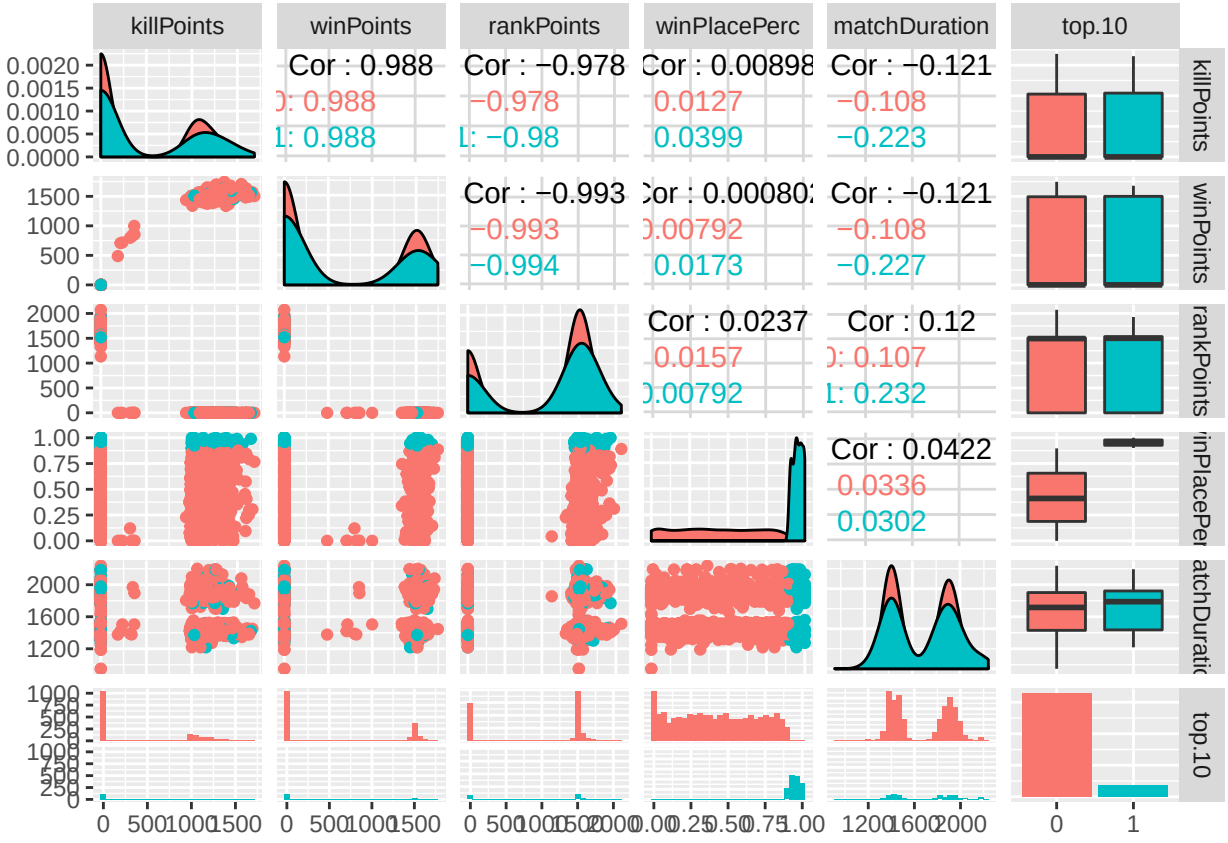
However, due to its overall simplicity and easy interpretability, our preferred model is the simple logistic regression model. Logistic regression in this format allows us to specify the log-odds of placing in the top 10,

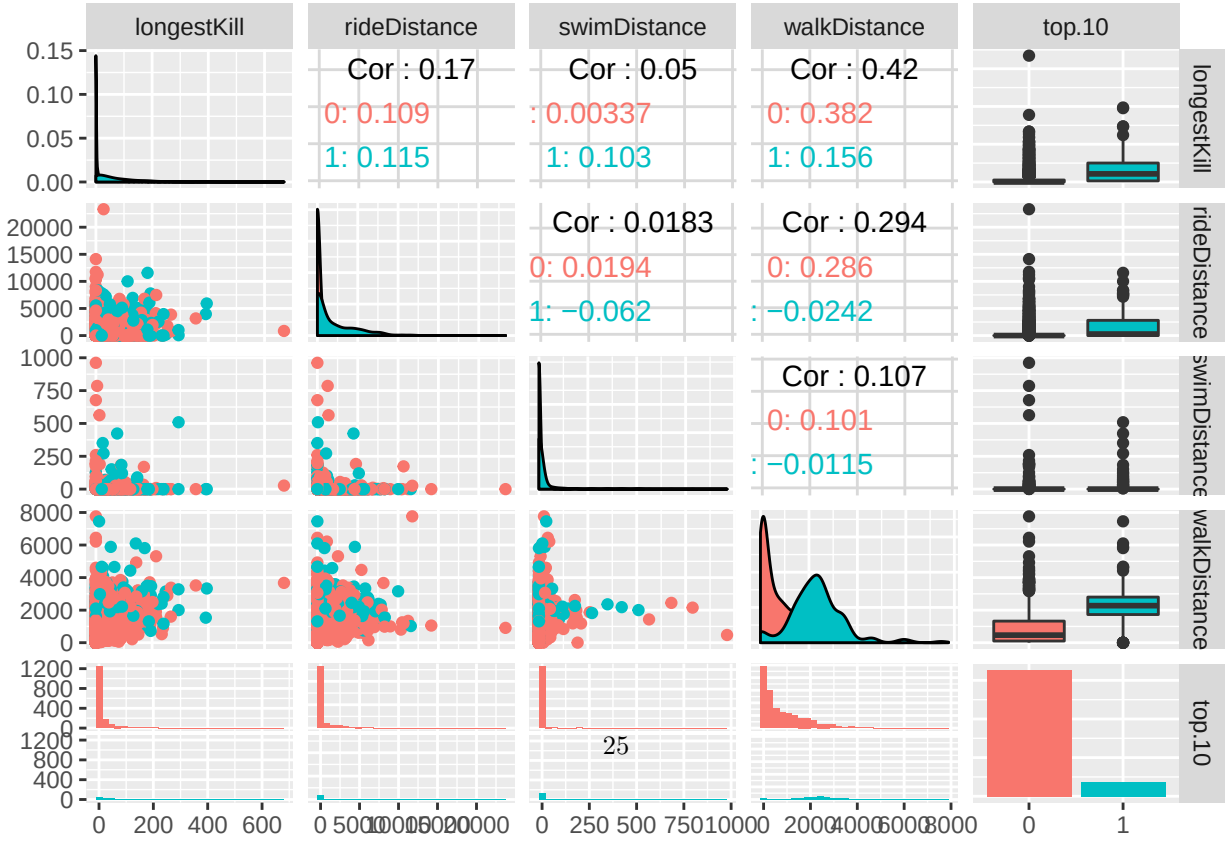
as shown in the Model Interpretation section of Objective 1. Based on the information we gathered from all four methods of modeling this data, we recommend to PUBG players to rank highly in the number of kills per match, walk a lot (or stay in the match long enough to walk a lot), and use boost items to your advantage.

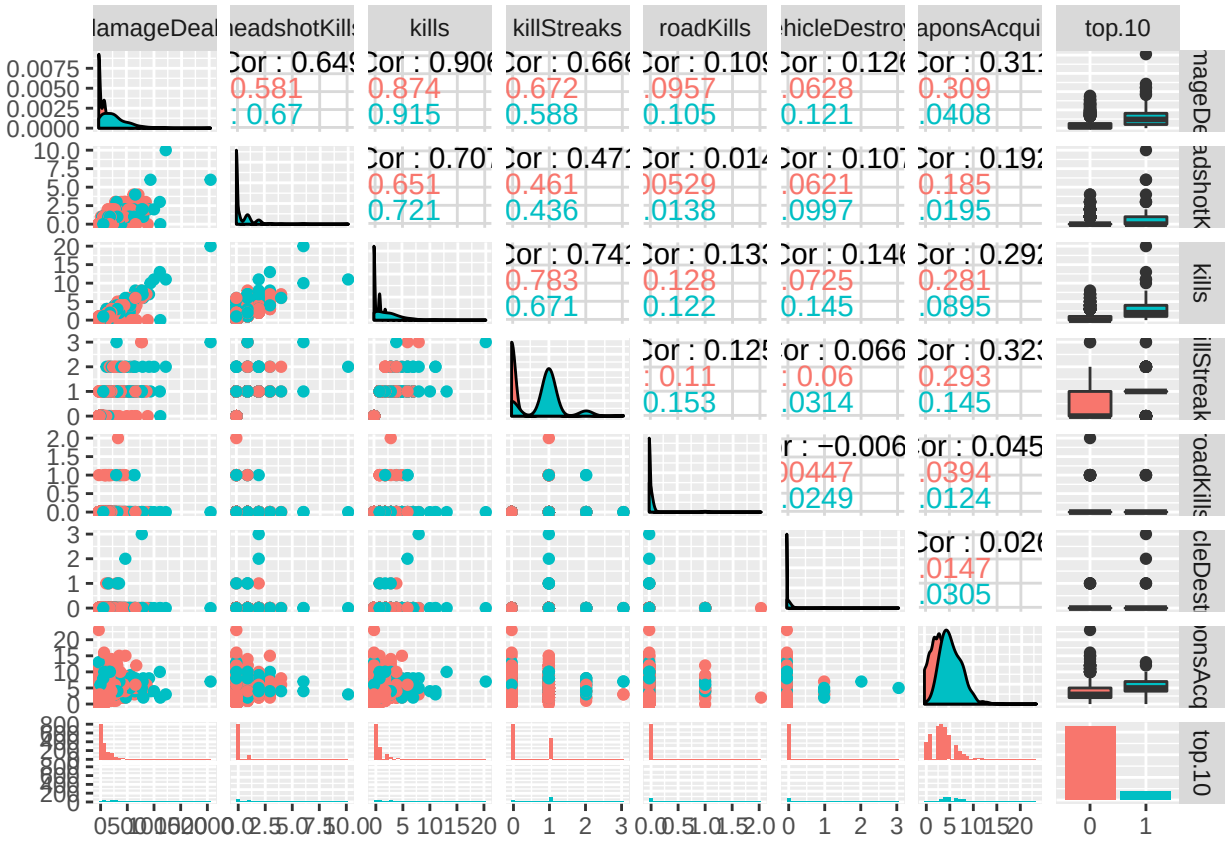
5 Appendix

5.1 Exploratory Data Analysis

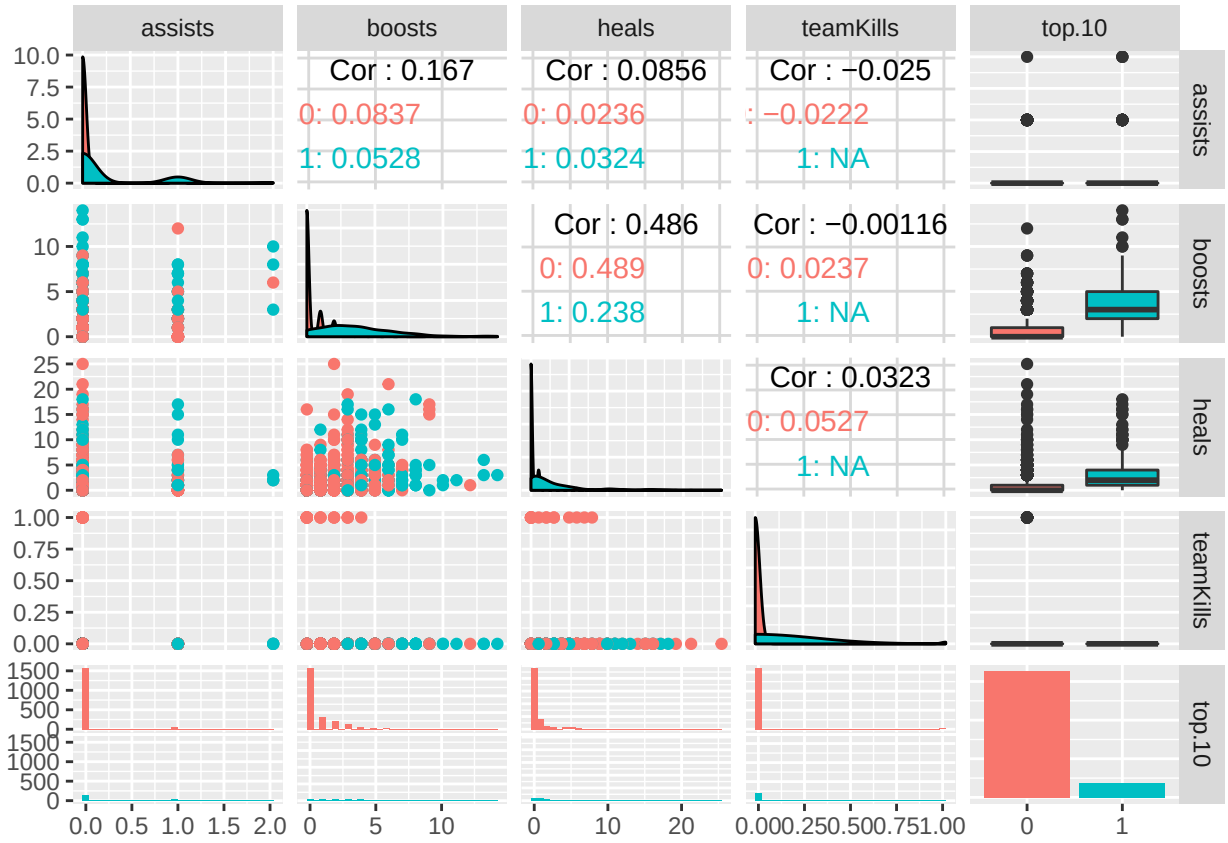
5.1.1 Pairs Plots



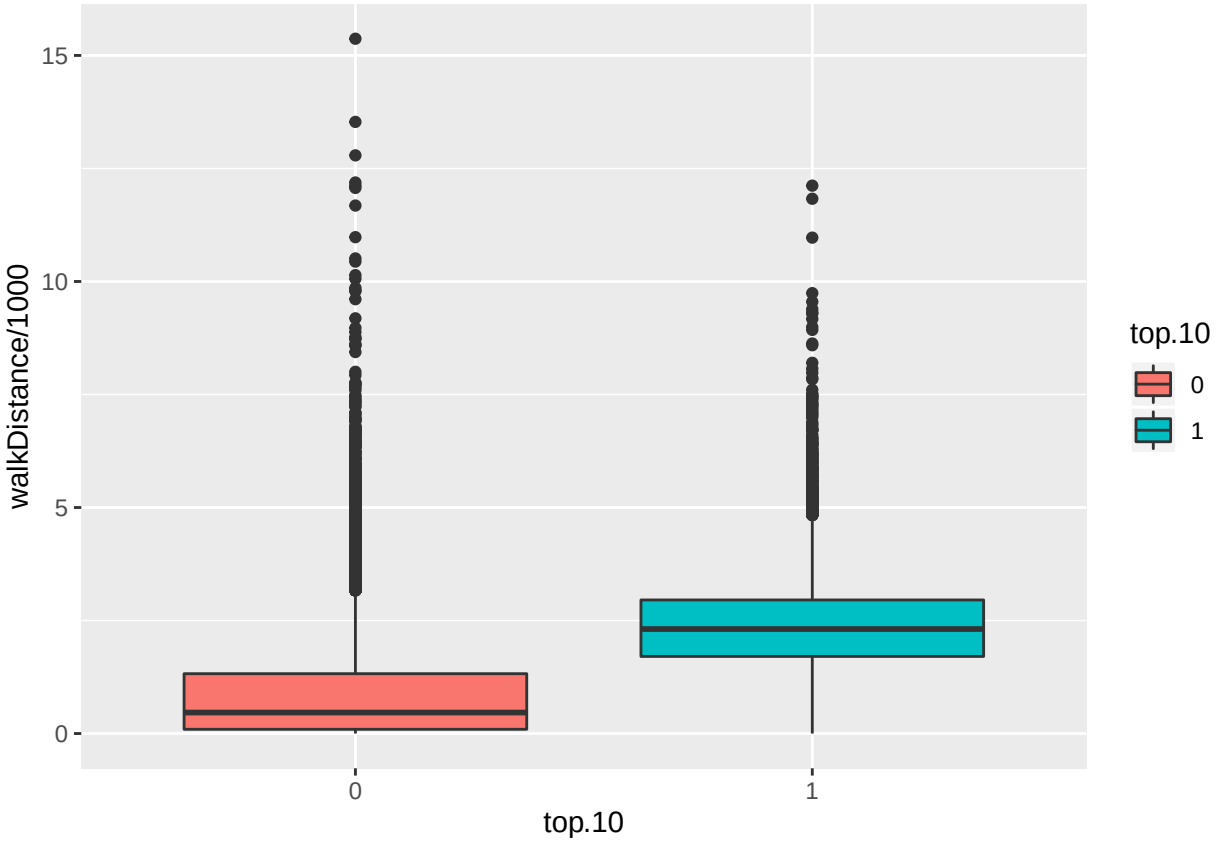


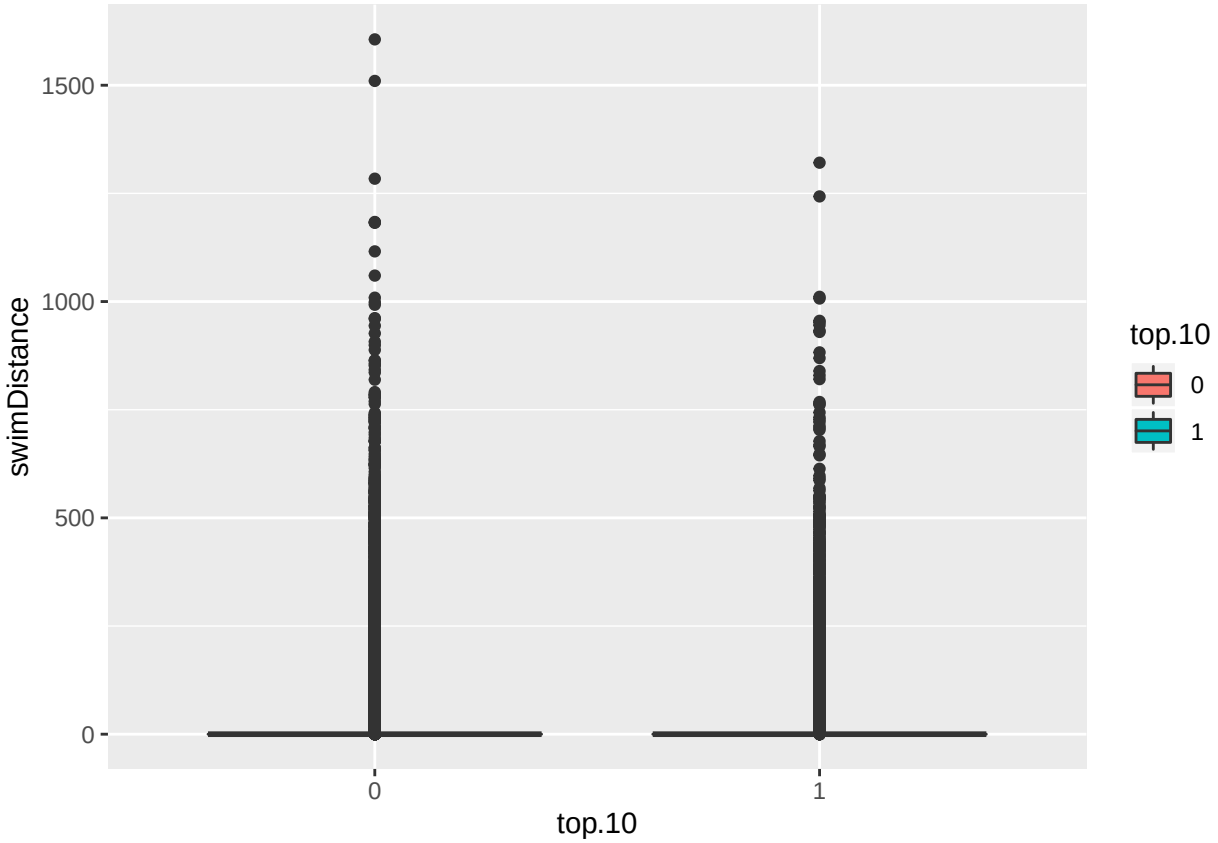


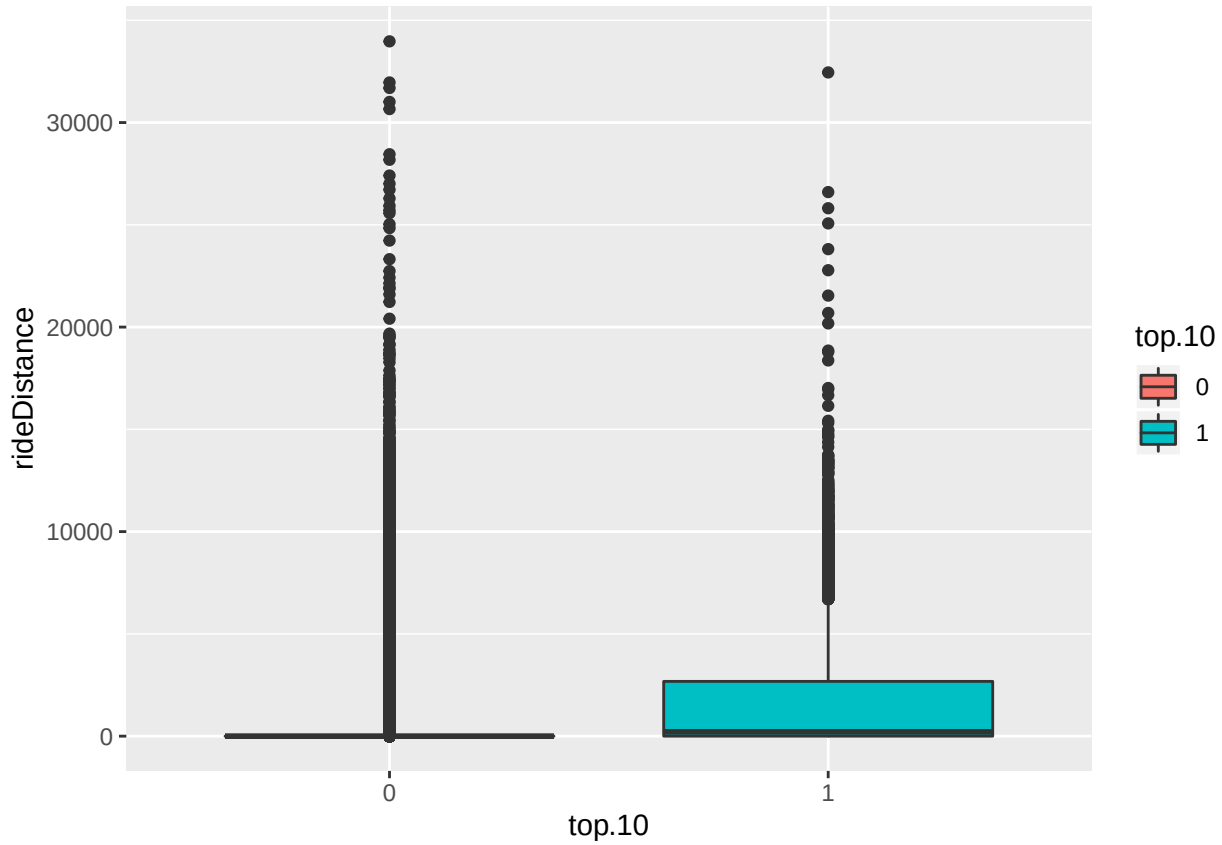

```
## Warning in cor(x, y, method = method, use = use): the standard deviation is zero

## Warning in cor(x, y, method = method, use = use): the standard deviation is zero

## Warning in cor(x, y, method = method, use = use): the standard deviation is zero
```

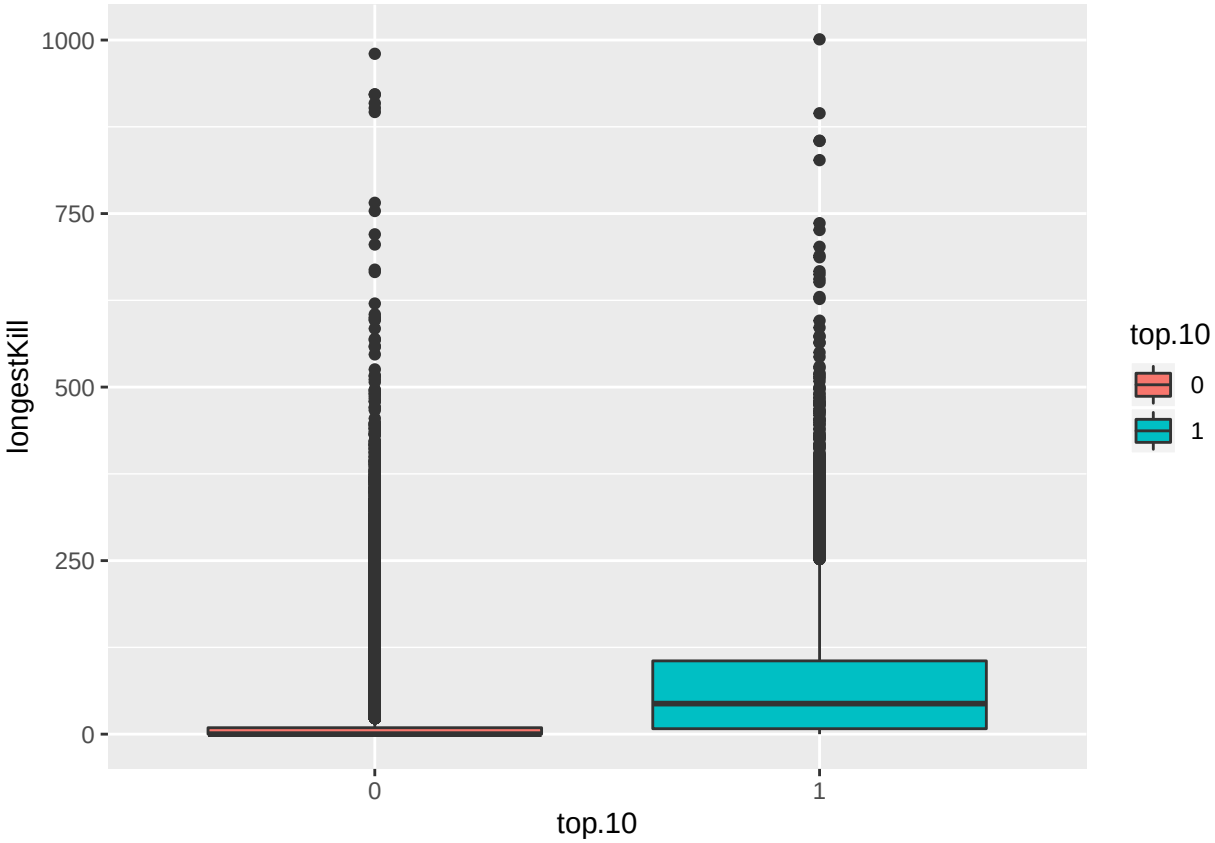

assists
boosts
heals
teamKills
top.10
Cor : 0.167
0: 0.0837
1: 0.0528
Cor : 0.0856
0: 0.0236
1: 0.0324
Cor : −0.025
: −0.0222
1: NA
Cor : 0.486
0: 0.489
1: 0.238
Cor : −0.00116
0: 0.0237
1: NA
Cor : 0.0323
0: 0.0527
1: NA

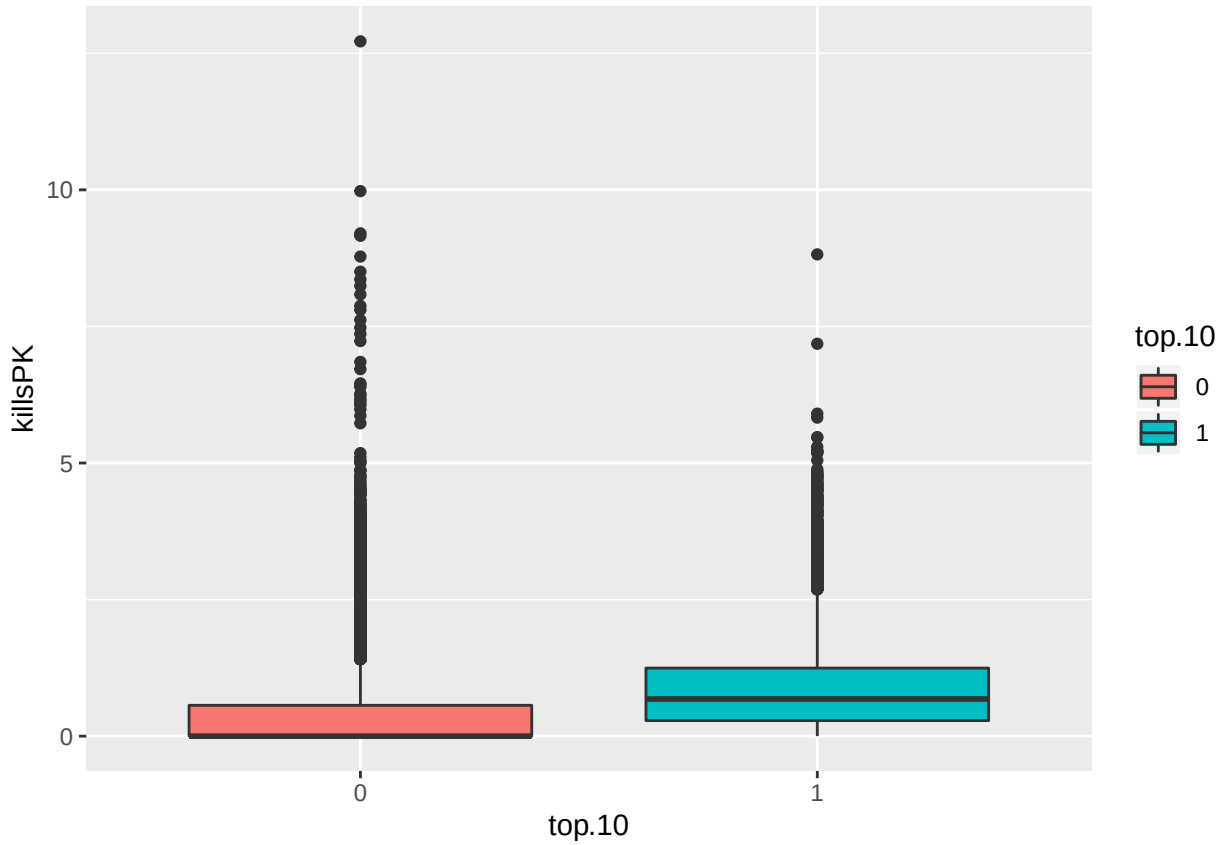
5.1.2 Box Plots

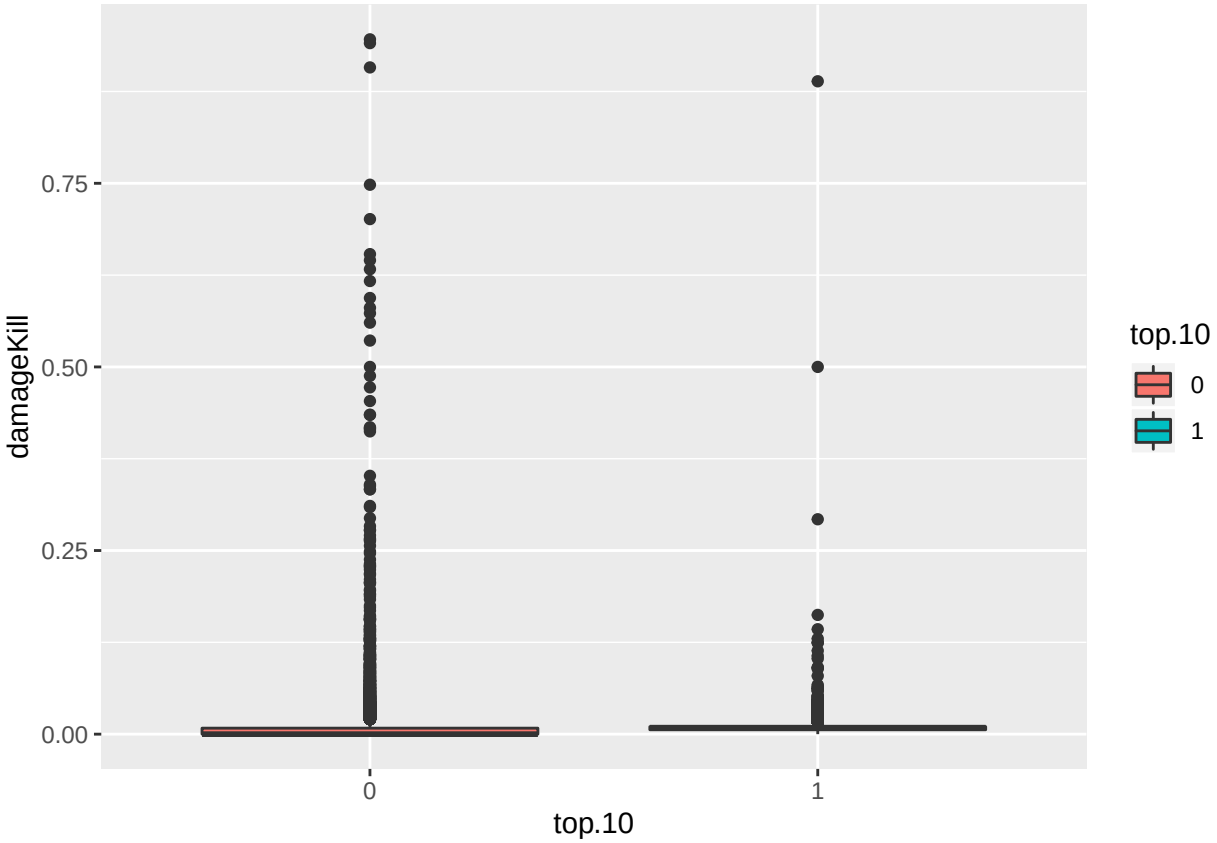


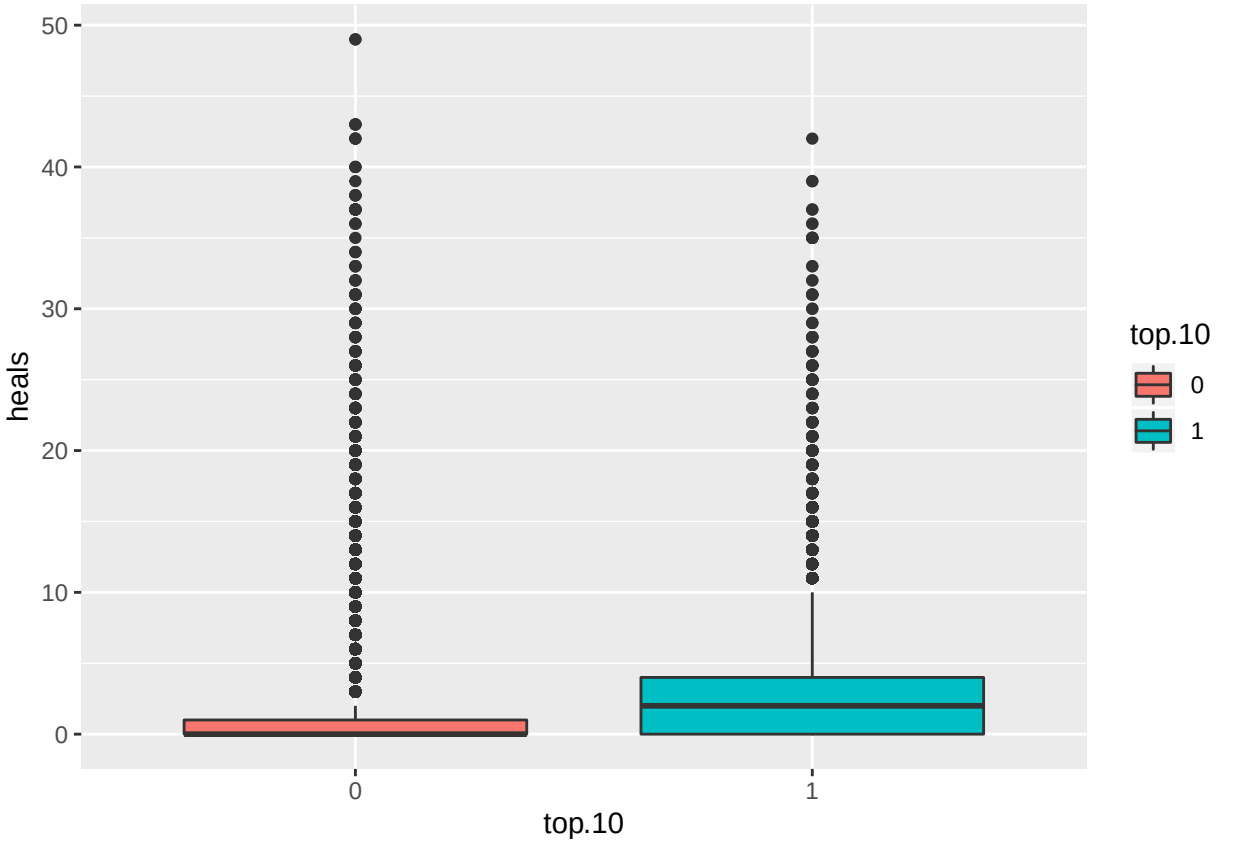


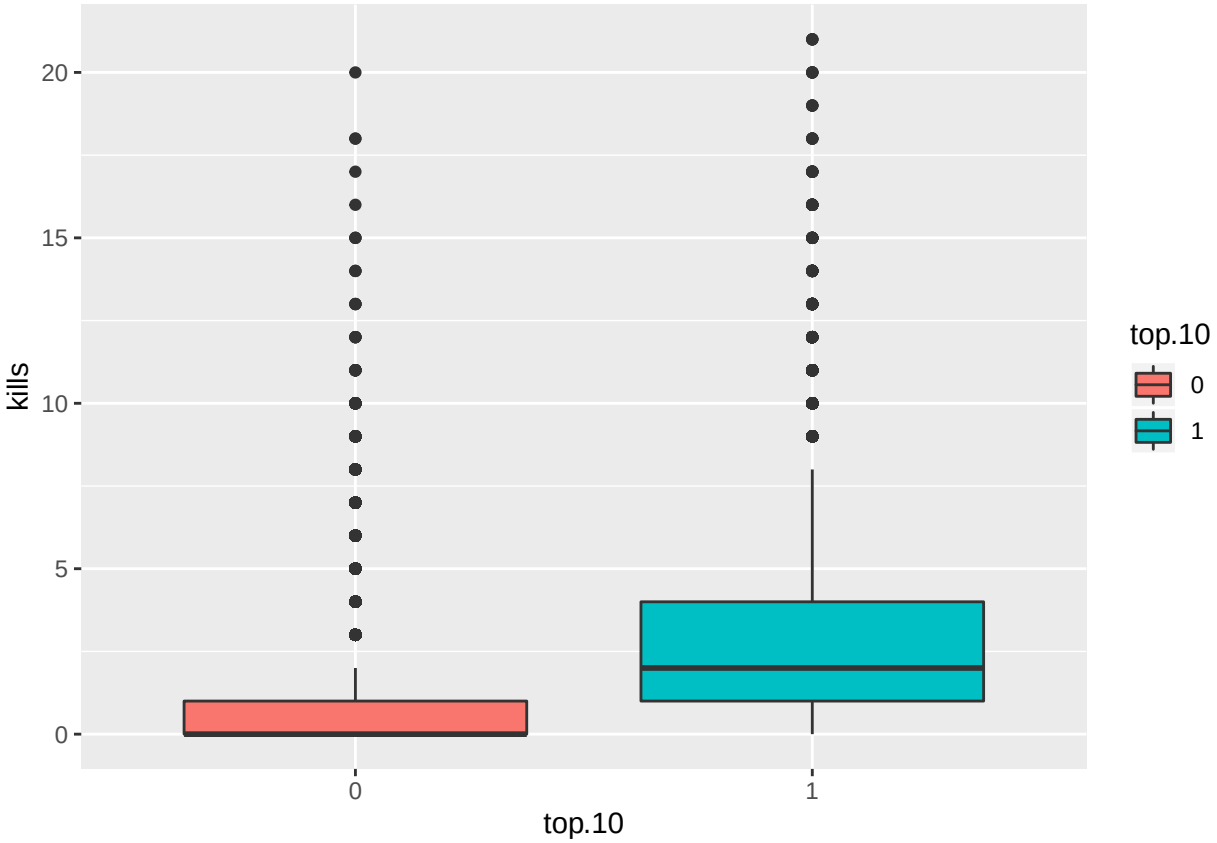

30000
20000
10000
0
rideDistance
0
1
top.10
top.10
0
1

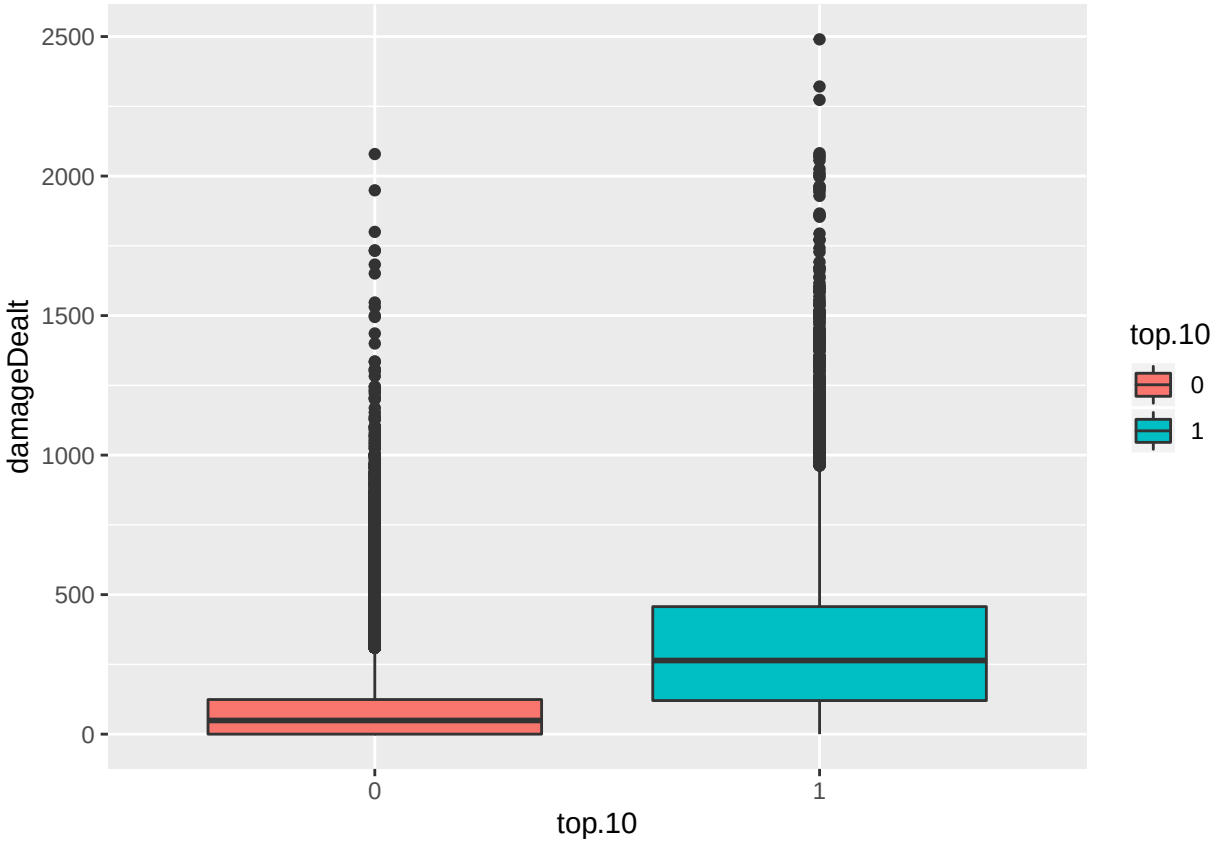

1000
750
500
250
0
longestKill
0
1
top.10
top.10
0
1

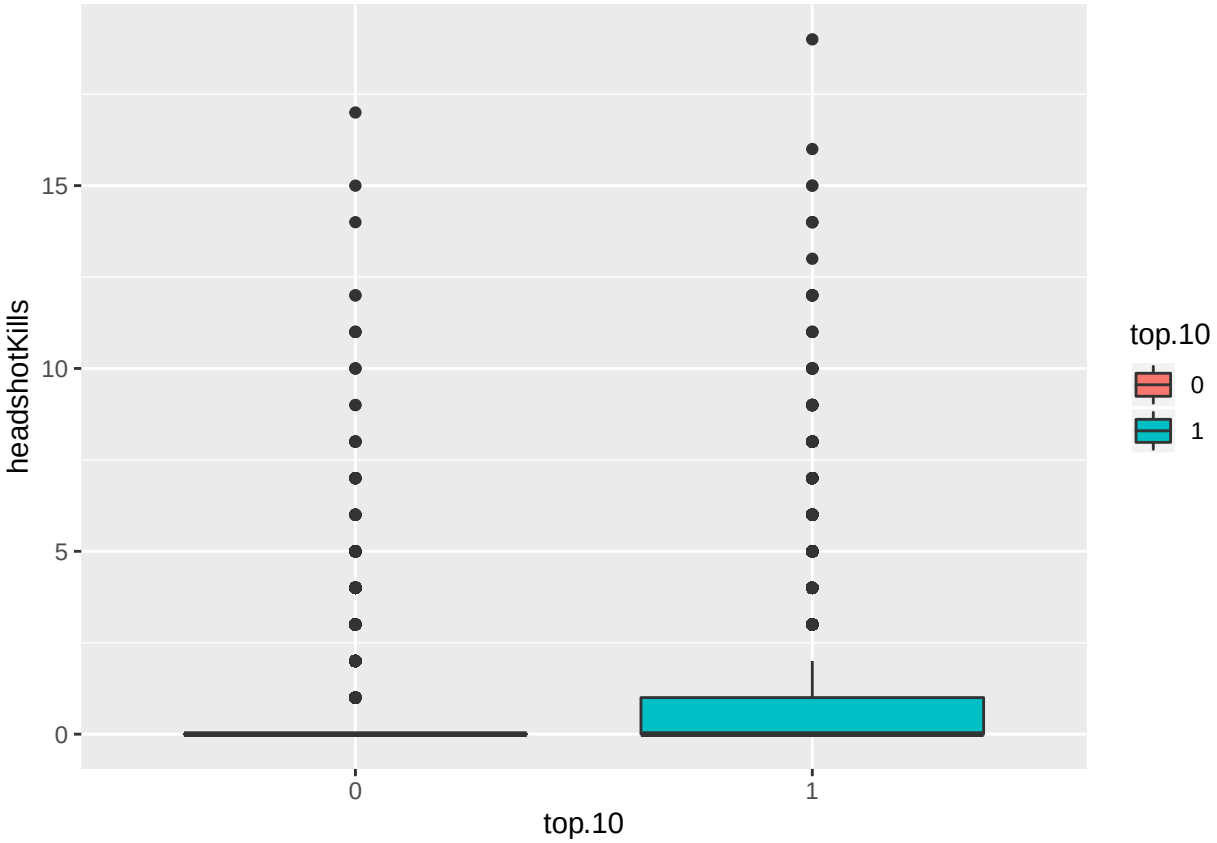

killsPK
10
5
0
0
1
top.10
top.10
0
1

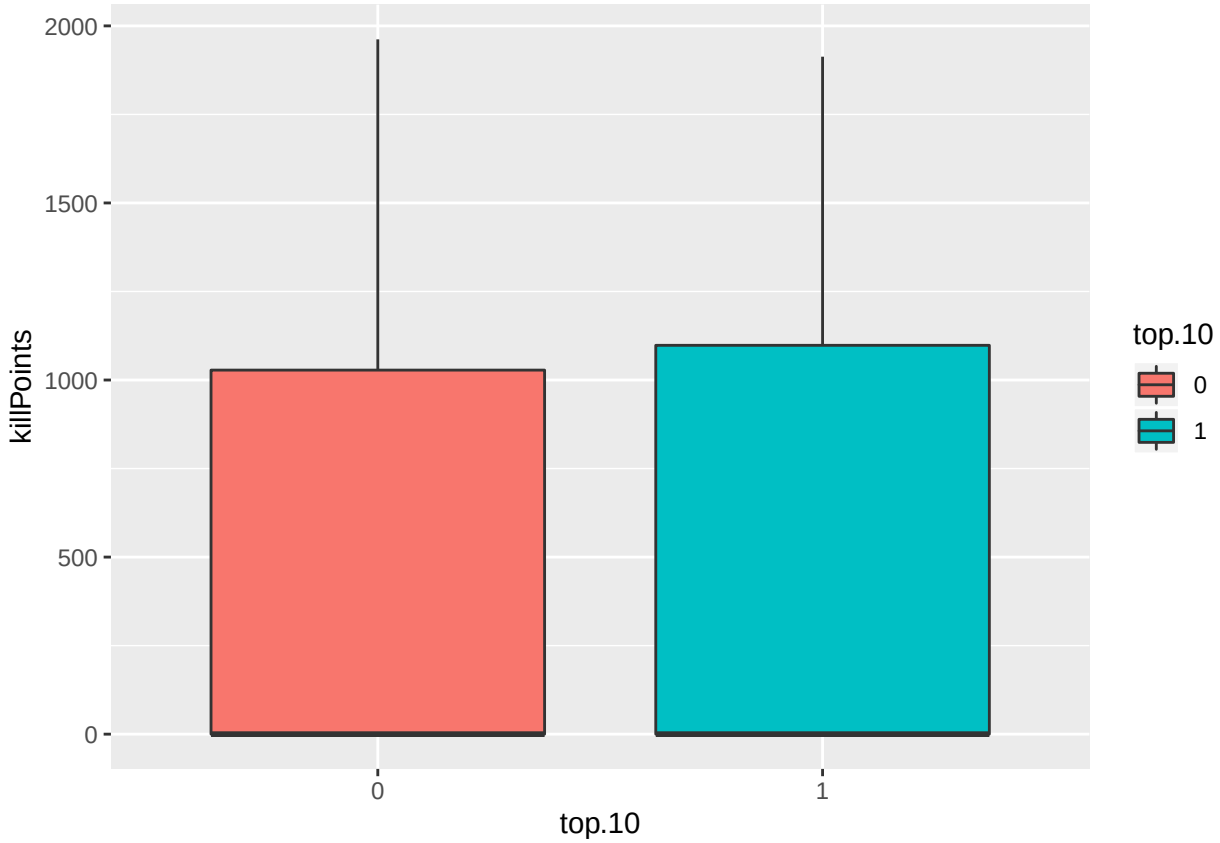

damageKill
0.75
0.50
0.25
0.00
0
1
top.10
top.10
0
1

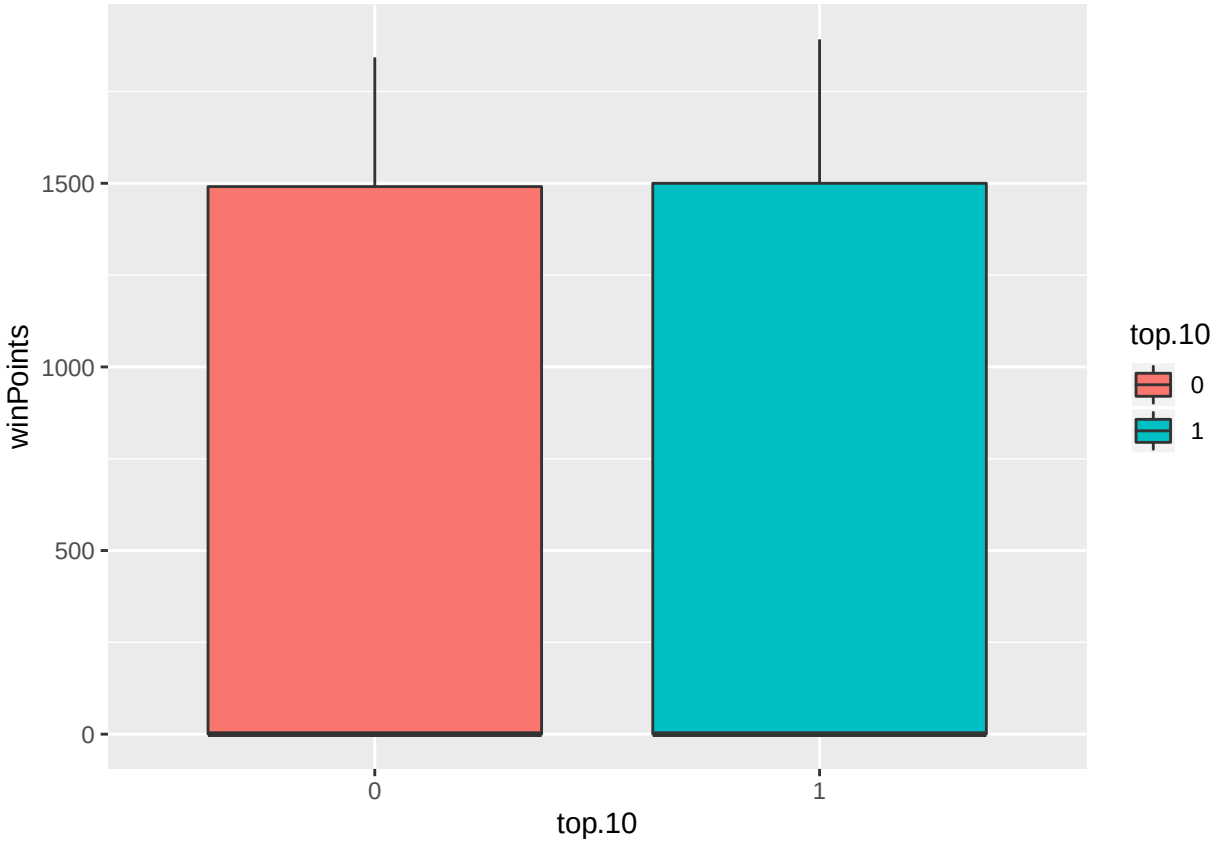

50
40
30
20
10
0
heals
0
1
top.10
top.10
0
1

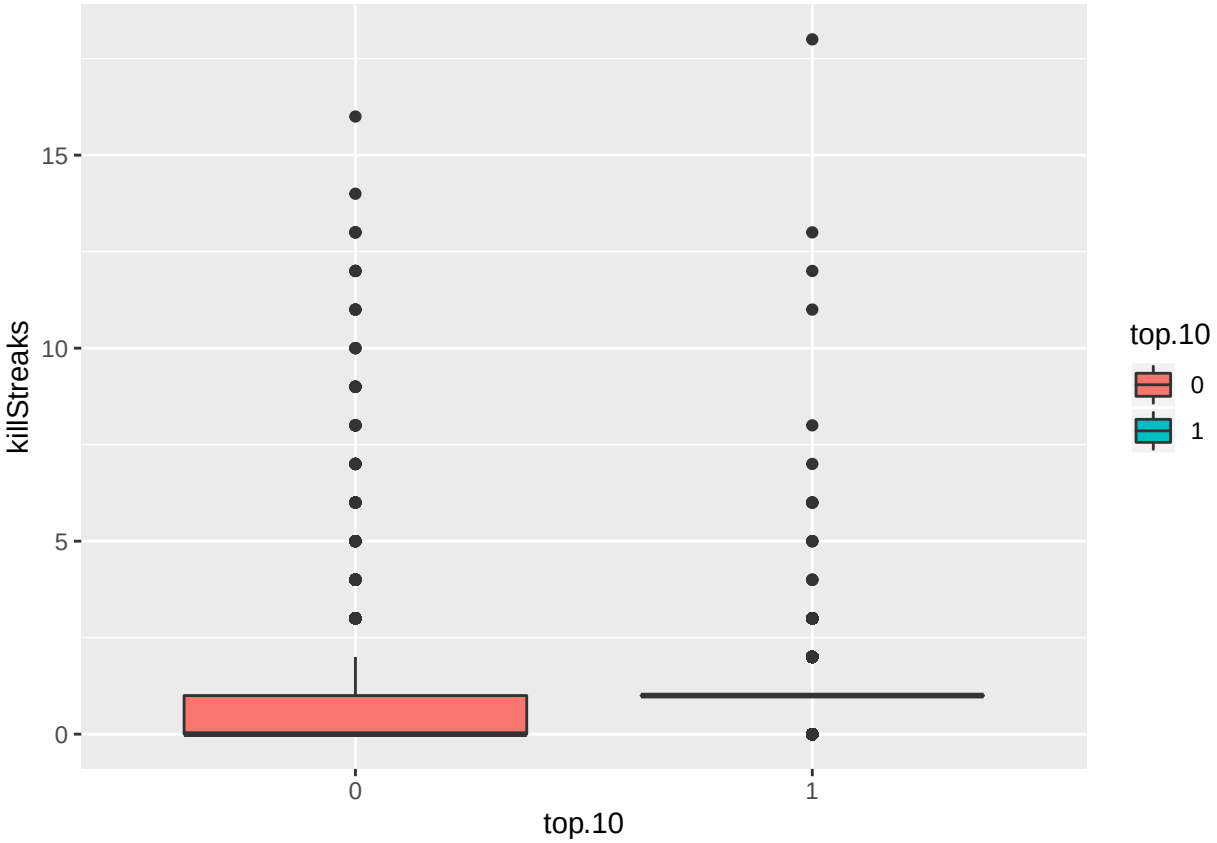

kills
20
15
10
5
0
0
1
top.10
top.10
0
1

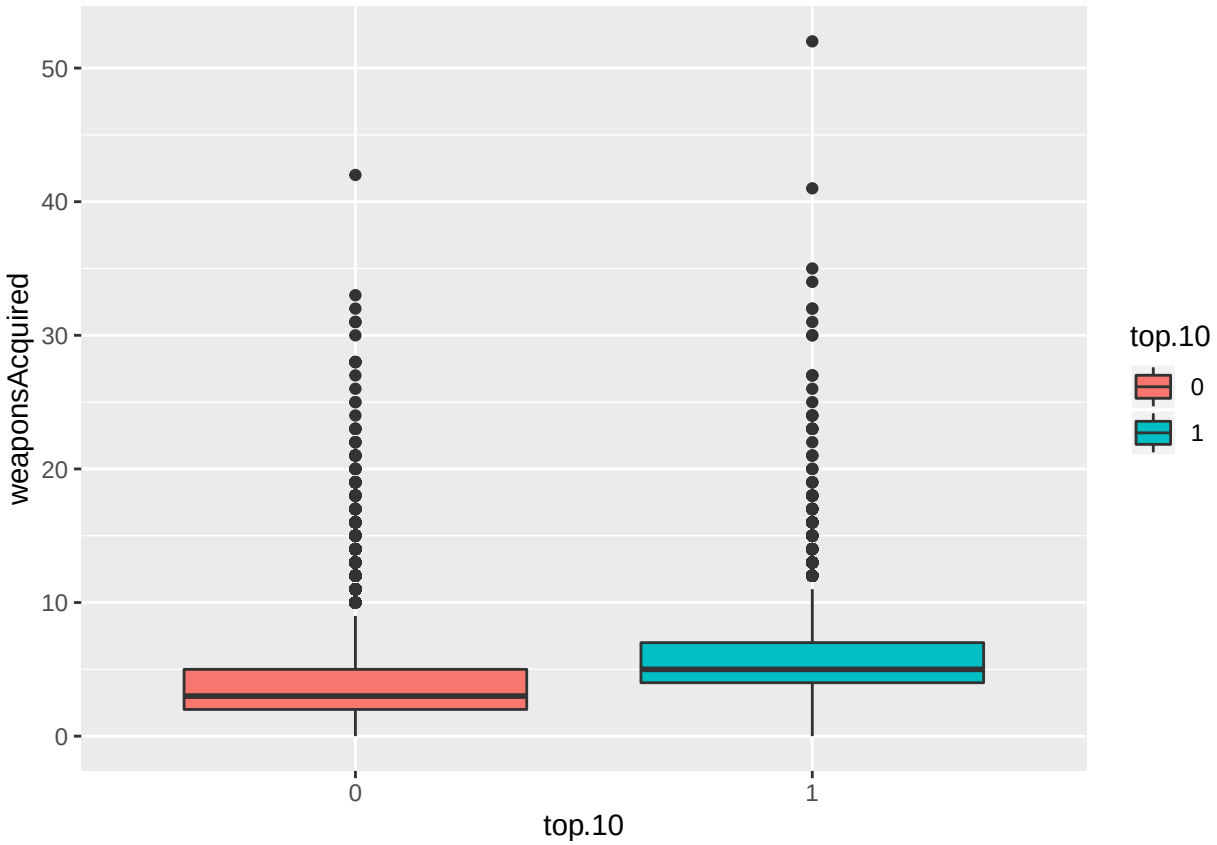

2500
2000
1500
1000
500
0
damageDealt
0
1
top.10
top.10
0
1

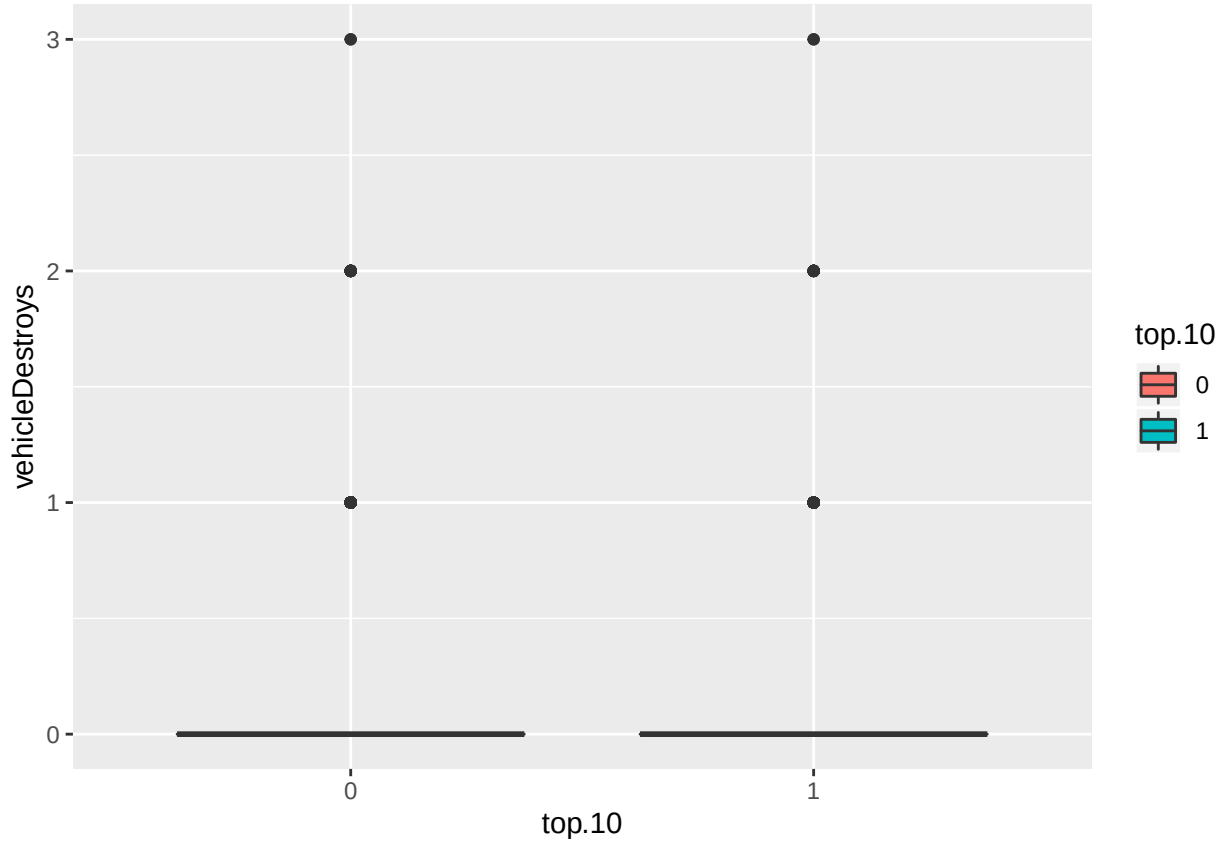

headshotKills
15
10
5
0
0
1
top.10
top.10
0
1


2000
1500
1000
500
0
killPoints
0
1
top.10
top.10
0
1


winPoints
1500
1000
500
0
0
1
top.10
top.10
0
1


killStreaks
15
10
5
0
0
1
top.10
top.10
0
1


50
40
30
20
10
0
weaponsAcquired
0
1
top.10
top.10
0
1



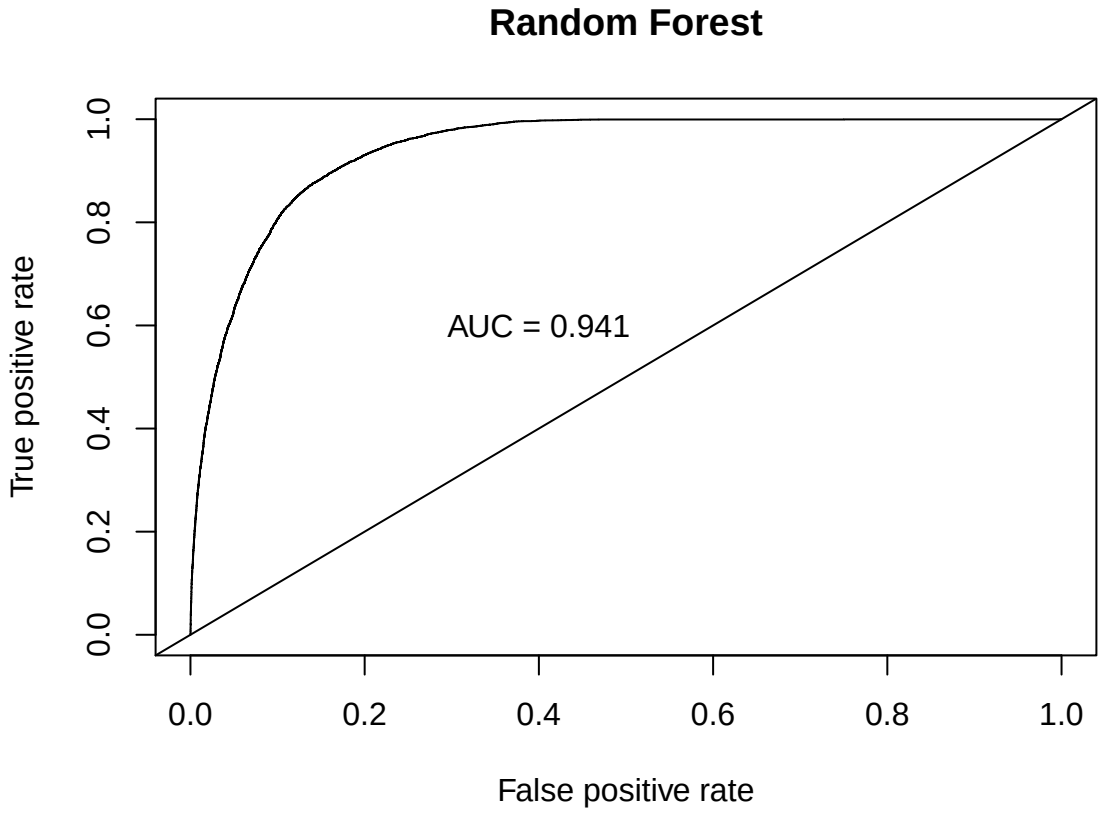
Logistic Regression

5.1.2.1 Original logistic model with VIF

```
##
## Call:
## glm(formula = top.10 ~ assists + boosts + heals + teamKills +
##     weaponsAcquired + damageDealt + headshotKills + kills + killStreaks +
##     roadKills + vehicleDestroys + killPlace + killPoints + rankPoints +
##     winPoints + longestKill + swimDistance + rideDistance + walkDistance,
##     family = binomial(link = "logit"), data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5064  -0.2621   0.0017   0.4644   5.1751
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -5.335e+00  4.679e-01 -11.402  < 2e-16 ***
## assists          6.767e-01  7.031e-02   9.624  < 2e-16 ***
## boosts           3.279e-01  1.265e-02  25.930  < 2e-16 ***
## heals           -3.521e-02  6.748e-03  -5.217 1.82e-07 ***
```

```
## teamKills       -2.027e+00  2.315e-01  -8.757  < 2e-16 ***
## weaponsAcquired  4.750e-02  8.215e-03   5.782 7.36e-09 ***
## damageDealt      6.655e-05  2.758e-04   0.241  0.80935
## headshotKills    4.061e-02  3.300e-02   1.231  0.21841
## kills           -5.179e-02  3.254e-02  -1.591  0.11151
## killStreaks     -1.210e+00  5.375e-02 -22.509  < 2e-16 ***
## roadKills       -2.286e-01  1.223e-01  -1.870  0.06148 .
## vehicleDestroys -4.657e-01  1.674e-01  -2.783  0.00539 **
## killPlace       -9.337e-02  1.817e-03 -51.380  < 2e-16 ***
## killPoints      -1.578e-03  2.606e-04  -6.055 1.41e-09 ***
## rankPoints       3.995e-03  3.056e-04  13.074  < 2e-16 ***
## winPoints        5.282e-03  3.949e-04  13.376  < 2e-16 ***
## longestKill     -1.896e-03  4.007e-04  -4.732 2.22e-06 ***
## swimDistance     1.503e-03  3.705e-04   4.056 5.00e-05 ***
## rideDistance     1.316e-04  1.011e-05  13.026  < 2e-16 ***
## walkDistance     8.866e-04  2.384e-05  37.197  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 15916  on 26594  degrees of freedom
## AIC: 15956
##
## Number of Fisher Scoring iterations: 6
```

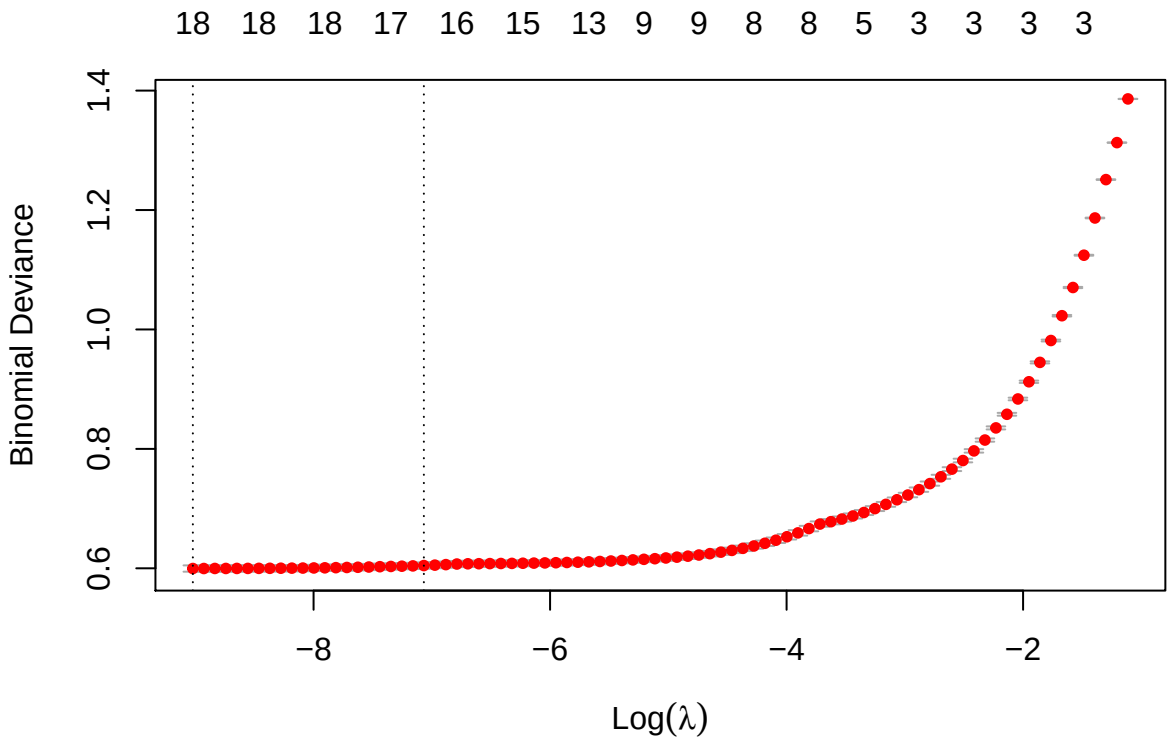
```
##         assists          boosts           heals       teamKills weaponsAcquired
##        1.056570        1.457881        1.190480        1.012404        1.036598
##     damageDealt   headshotKills           kills     killStreaks       roadKills
##        7.068001        1.996675        9.407337        2.283736        1.056648
## vehicleDestroys       killPlace      killPoints      rankPoints       winPoints
##        1.030448        2.142370       54.408050      124.018858      204.493531
##     longestKill    swimDistance    rideDistance    walkDistance
##        1.703710        1.016534        1.137564        1.387638
```




```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 41211   619
##          1  7668  5084
##
##                Accuracy : 0.8482
##                  95% CI : (0.8451, 0.8512)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4752
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.89146
##             Specificity : 0.84312
##          Pos Pred Value : 0.39868
##          Neg Pred Value : 0.98520
##              Prevalence : 0.10448
```

```
##          Detection Rate : 0.09314
##    Detection Prevalence : 0.23363
##       Balanced Accuracy : 0.86729
##
##        'Positive' Class : 1
##
```

5.1.2.2 Full Lasso Variable Reduction




```
## [1] 0.0001208403
```

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                              1
## (Intercept)     -4.3850198039
## (Intercept)      .
## assists           0.6746223715
## boosts            0.3272759414
## heals            -0.0342697309
## teamKills        -2.0062930907
## weaponsAcquired   0.0470239834
## damageDealt       .
## headshotKills     0.0333622719
```

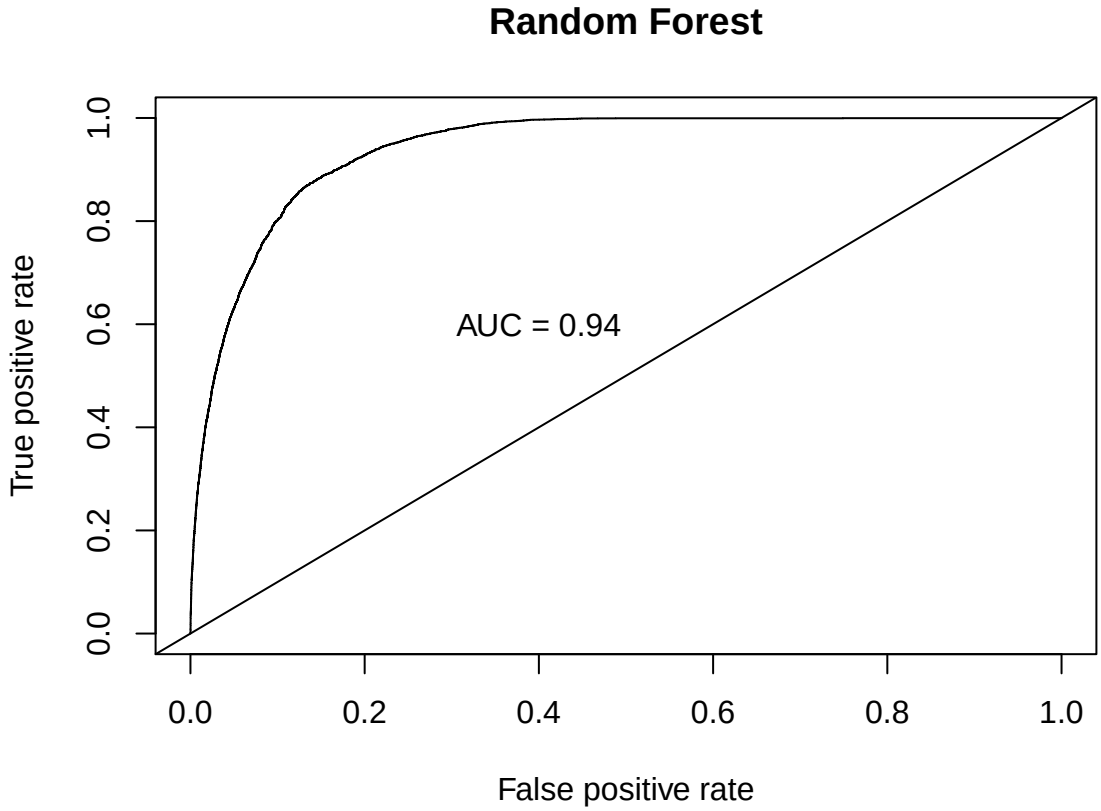
```
## kills           -0.0440824065
## killStreaks     -1.1987929481
## roadKills       -0.2242257360
## vehicleDestroys -0.4592145376
## killPlace       -0.0923410748
## killPoints      -0.0011652837
## rankPoints       0.0033626431
## winPoints        0.0043254560
## longestKill     -0.0018193615
## swimDistance     0.0014831701
## rideDistance     0.0001321729
## walkDistance     0.0008825722
```

```
## [1] 0.0008525043
```

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                              1
## (Intercept)     -0.6697250551
## (Intercept)      .
## assists          0.6465141635
## boosts           0.3247444750
## heals           -0.0291869321
## teamKills       -1.9071380400
## weaponsAcquired  0.0445041552
## damageDealt      .
## headshotKills    .
## kills           -0.0263675957
## killStreaks     -1.1451581898
## roadKills       -0.1971800303
## vehicleDestroys -0.4170606837
## killPlace       -0.0877153549
## killPoints       .
## rankPoints       0.0008643892
## winPoints        0.0008978790
## longestKill     -0.0014961791
## swimDistance     0.0013709914
## rideDistance     0.0001344471
## walkDistance     0.0008664751
```

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                             s0
## (Intercept)     -0.6733424558
## (Intercept)      .
## assists          0.6465602204
## boosts           0.3247910863
```

```
## heals           -0.0291791887
## teamKills       -1.9070440684
## weaponsAcquired  0.0445136944
## damageDealt      .
## headshotKills    .
## kills           -0.0262597549
## killStreaks     -1.1450786717
## roadKills       -0.1971398791
## vehicleDestroys -0.4170561352
## killPlace       -0.0876942534
## killPoints       .
## rankPoints       0.0008663913
## winPoints        0.0008998702
## longestKill     -0.0014955118
## swimDistance     0.0013710884
## rideDistance     0.0001344144
## walkDistance     0.0008663011
```




```
##
##     0     1
## 48879  5703
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 43486   972
##          1  5393  4731
##
##                Accuracy : 0.8834
##                  95% CI : (0.8807, 0.8861)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.5358
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.82956
##             Specificity : 0.88967
##          Pos Pred Value : 0.46731
##          Neg Pred Value : 0.97814
##              Prevalence : 0.10448
##          Detection Rate : 0.08668
##    Detection Prevalence : 0.18548
##       Balanced Accuracy : 0.85961
##
##        'Positive' Class : 1
##

##
## Call:
## glm(formula = top.10 ~ assists + boosts + heals + teamKills +
##     weaponsAcquired + kills + killStreaks + roadKills + vehicleDestroys +
##     killPlace + rankPoints + winPoints + longestKill + swimDistance +
##     rideDistance + walkDistance, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5204  -0.2625   0.0021   0.4641   5.1861
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -4.884e+00  4.571e-01 -10.683  < 2e-16 ***
## assists          6.792e-01  6.870e-02   9.886  < 2e-16 ***
```

```
## boosts           3.257e-01  1.260e-02  25.842  < 2e-16 ***
## heals           -3.475e-02  6.734e-03  -5.160 2.47e-07 ***
## teamKills       -2.034e+00  2.308e-01  -8.811  < 2e-16 ***
## weaponsAcquired  4.852e-02  8.216e-03   5.905 3.52e-09 ***
## kills           -4.373e-02  1.800e-02  -2.430  0.01510 *
## killStreaks     -1.212e+00  5.305e-02 -22.839  < 2e-16 ***
## roadKills       -2.466e-01  1.211e-01  -2.036  0.04177 *
## vehicleDestroys -4.814e-01  1.672e-01  -2.880  0.00398 **
## killPlace       -9.255e-02  1.765e-03 -52.432  < 2e-16 ***
## rankPoints       3.695e-03  2.989e-04  12.360  < 2e-16 ***
## winPoints        3.764e-03  3.018e-04  12.472  < 2e-16 ***
## longestKill     -1.755e-03  3.962e-04  -4.429 9.47e-06 ***
## swimDistance     1.534e-03  3.714e-04   4.130 3.63e-05 ***
## rideDistance     1.304e-04  1.009e-05  12.934  < 2e-16 ***
## walkDistance     8.889e-04  2.378e-05  37.382  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 15953  on 26597  degrees of freedom
## AIC: 15987
##
## Number of Fisher Scoring iterations: 6
```

```
##         assists          boosts           heals       teamKills weaponsAcquired
##        1.011919        1.453020        1.189852        1.012041        1.036222
##           kills     killStreaks       roadKills vehicleDestroys       killPlace
##        2.912014        2.236310        1.053813        1.028168        2.026555
##      rankPoints       winPoints     longestKill    swimDistance    rideDistance
##      118.368517      118.867443        1.677517        1.015841        1.136265
##    walkDistance
##        1.381498
```

5.1.2.3 Final Model for Objective 1

```
##
## Call:
## glm(formula = top.10 ~ assists + boosts + heals + weaponsAcquired +
##     killPlace + walkDistance, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
```

```
## -3.3664  -0.3759  -0.0174   0.4865   2.6092
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)     -5.934e-01  5.982e-02  -9.919  < 2e-16 ***
## assists          6.225e-01  6.666e-02   9.339  < 2e-16 ***
## boosts           3.067e-01  1.158e-02  26.493  < 2e-16 ***
## heals           -2.276e-02  6.449e-03  -3.529 0.000418 ***
## weaponsAcquired  7.900e-02  7.742e-03  10.205  < 2e-16 ***
## killPlace       -6.216e-02  1.192e-03 -52.172  < 2e-16 ***
## walkDistance     7.415e-04  2.073e-05  35.775  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 17365  on 26607  degrees of freedom
## AIC: 17379
##
## Number of Fisher Scoring iterations: 6
```

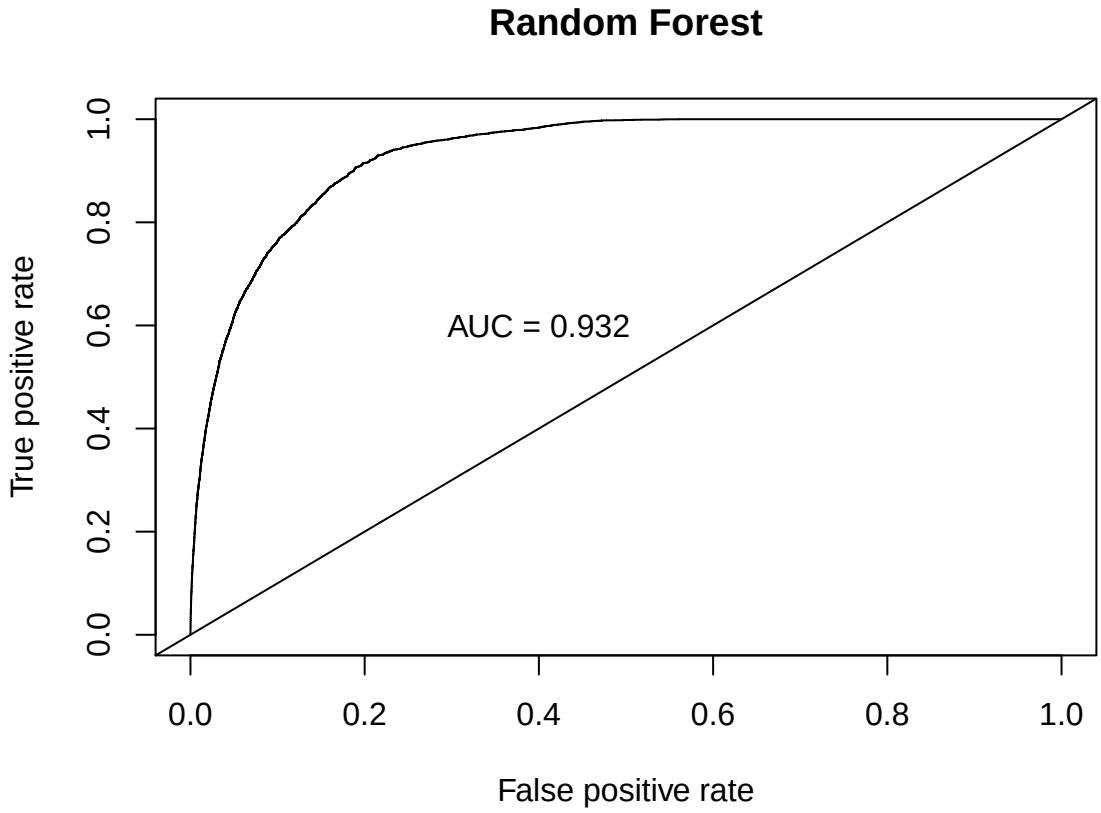
5.1.3 Complex Logistic Regression

5.1.3.1 Variable Definitions

```
#train_obj1 <- train %>% mutate(
#  DurationCut = as.factor(ifelse(matchDuration > 1600,1,0)),
#  kpCut = as.factor(ifelse(killPoints > 0,1,0)),
#  wpCut = as.factor(ifelse(winPoints > 0,1,0)),
#  rpCut = as.factor(ifelse(rankPoints > -1,1,0)),
#  boostCut = as.factor(ifelse(boosts >= 2,1,0)),
#  healCut = as.factor(ifelse(heals >= 2,1,0)),
#  walkCut = as.factor(ifelse(walkDistance >= 1250,1,0)),
#  weaponCut = as.factor(ifelse(weaponsAcquired >= 3,1,0)),
#  killCut = as.factor(ifelse(kills >= 2,1,0)),
#  assistCut = as.factor(ifelse(assists >= 2,1,0)),
#  damageCut = as.factor(ifelse(damageDealt >= 250,1,0)),
#  streakCut = as.factor(ifelse(killStreaks >= 1,1,0)),
#  killsPK = kills/(walkDistance/1000+1),
#  damageKill = kills/(damageDealt+1)
#)
```

5.1.3.2 Full Model List

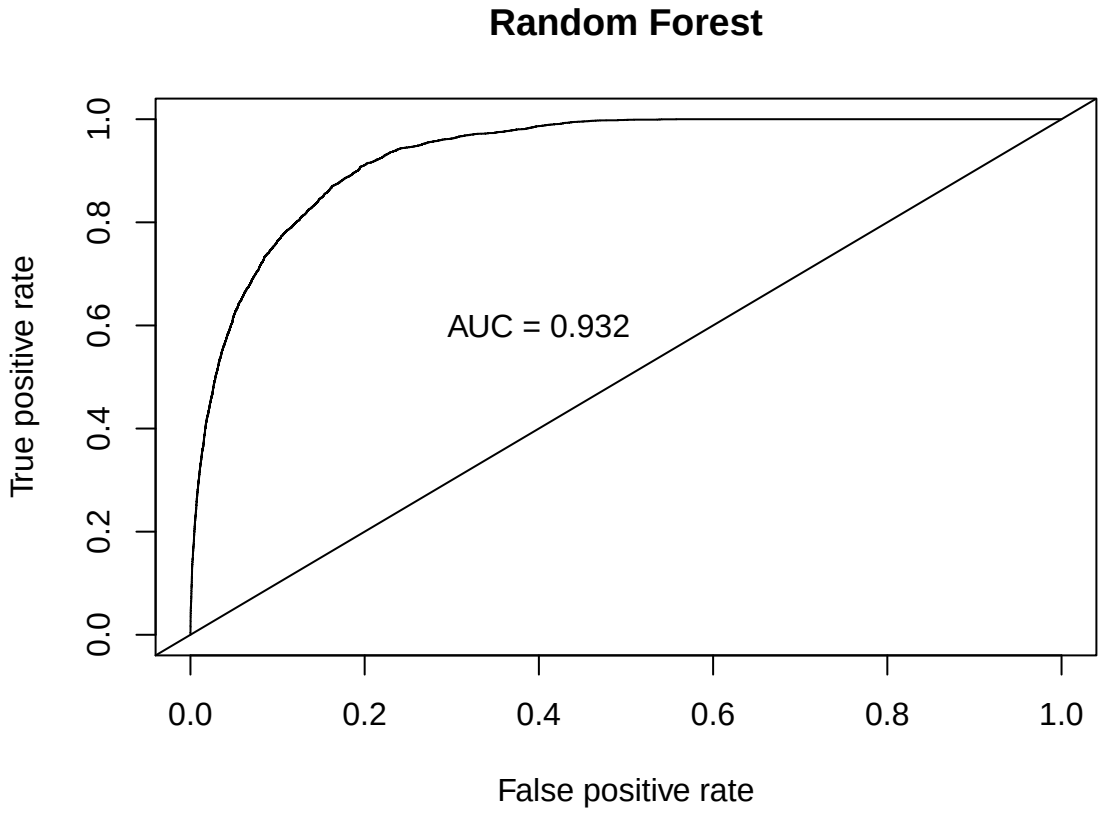
```
##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + boostCut:killPlace, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.2453  -0.3495  -0.0074   0.4957   2.6710
##
## Coefficients:
##                       Estimate Std. Error z value Pr(>|z|)
## (Intercept)         -4.788e-01  6.177e-02  -7.751 9.10e-15 ***
## boosts               2.398e-01  1.263e-02  18.993  < 2e-16 ***
## assists              6.233e-01  6.676e-02   9.336  < 2e-16 ***
## weaponsAcquired      7.619e-02  7.777e-03   9.796  < 2e-16 ***
## killPlace           -6.813e-02  1.476e-03 -46.155  < 2e-16 ***
## walkDistance         7.288e-04  2.068e-05  35.241  < 2e-16 ***
## killPlace:boostCut1  1.303e-02  1.703e-03   7.652 1.98e-14 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 17319  on 26607  degrees of freedom
## AIC: 17333
##
## Number of Fisher Scoring iterations: 6
```




```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 40845   727
##          1  8034  4976
##
##                Accuracy : 0.8395
##                  95% CI : (0.8364, 0.8426)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4522
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.87252
##             Specificity : 0.83563
##          Pos Pred Value : 0.38248
##          Neg Pred Value : 0.98251
##              Prevalence : 0.10448
```

```
##          Detection Rate : 0.09117
##    Detection Prevalence : 0.23836
##       Balanced Accuracy : 0.85408
##
##        'Positive' Class : 1
##
```

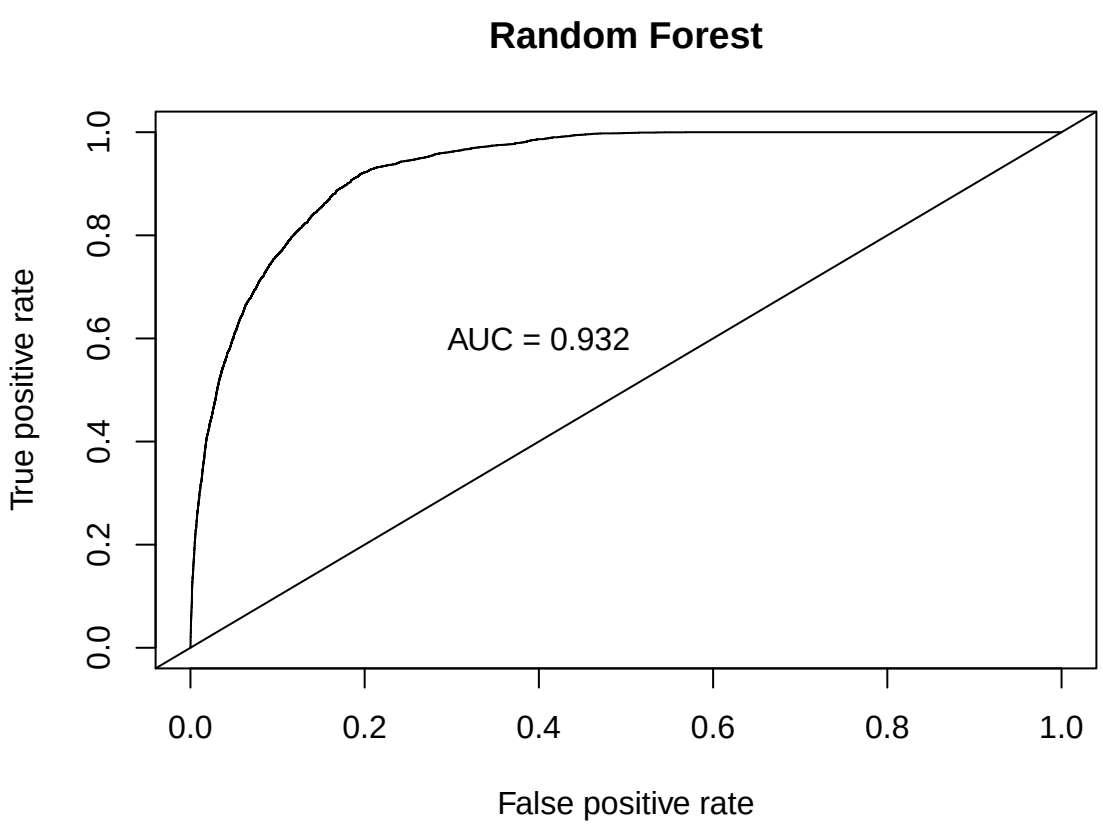
```
##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + kpCut:killPlace, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.3510  -0.3752  -0.0173   0.4860   2.6179
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -5.951e-01  5.983e-02  -9.946   <2e-16 ***
## boosts            2.943e-01  1.096e-02  26.854   <2e-16 ***
## assists           6.196e-01  6.666e-02   9.294   <2e-16 ***
## weaponsAcquired   7.865e-02  7.739e-03  10.164   <2e-16 ***
## killPlace        -6.259e-02  1.298e-03 -48.225   <2e-16 ***
## walkDistance      7.334e-04  2.057e-05  35.646   <2e-16 ***
## killPlace:kpCut1  1.079e-03  1.400e-03   0.771    0.441
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 17377  on 26607  degrees of freedom
## AIC: 17391
##
## Number of Fisher Scoring iterations: 6
```




```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 41103   785
##          1  7776  4918
##
##                Accuracy : 0.8432
##                  95% CI : (0.8401, 0.8462)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4562
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.8624
##             Specificity : 0.8409
##          Pos Pred Value : 0.3874
##          Neg Pred Value : 0.9813
##              Prevalence : 0.1045
```

```
##          Detection Rate : 0.0901
##    Detection Prevalence : 0.2326
##       Balanced Accuracy : 0.8516
##
##        'Positive' Class : 1
##
```

```
##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + walkDistance * killPlace, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.9357  -0.3234  -0.0021   0.5071   2.7891
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -1.125e-01  7.102e-02  -1.584    0.113
## boosts                  3.150e-01  1.108e-02  28.434   <2e-16 ***
## assists                 6.477e-01  6.671e-02   9.709   <2e-16 ***
## weaponsAcquired         6.775e-02  7.839e-03   8.643   <2e-16 ***
## killPlace              -8.444e-02  2.314e-03 -36.484   <2e-16 ***
## walkDistance            4.135e-04  3.191e-05  12.957   <2e-16 ***
## killPlace:walkDistance  1.432e-05  1.183e-06  12.110   <2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 17219  on 26607  degrees of freedom
## AIC: 17233
##
## Number of Fisher Scoring iterations: 7
```

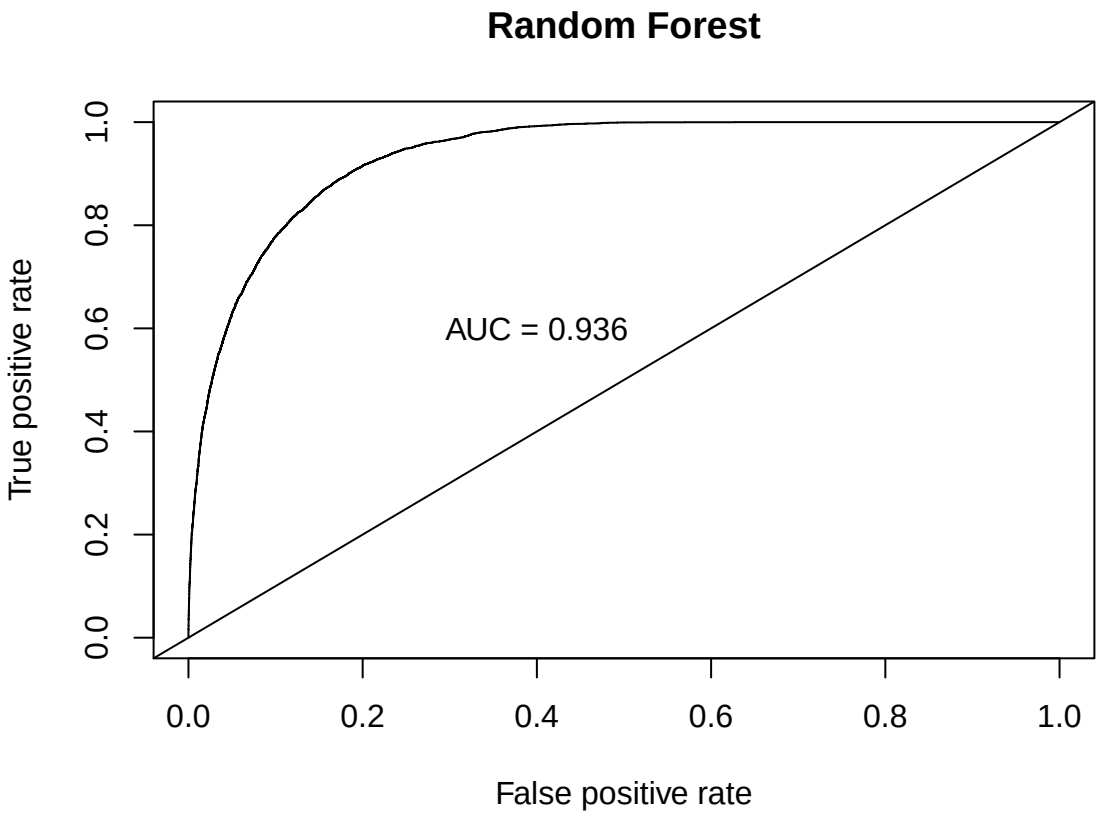



```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 40687   654
##          1  8192  5049
##
##                Accuracy : 0.8379
##                  95% CI : (0.8348, 0.841)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4532
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.8853
##             Specificity : 0.8324
##          Pos Pred Value : 0.3813
##          Neg Pred Value : 0.9842
##              Prevalence : 0.1045
```

```
##          Detection Rate : 0.0925
##    Detection Prevalence : 0.2426
##       Balanced Accuracy : 0.8589
##
##        'Positive' Class : 1
##
```

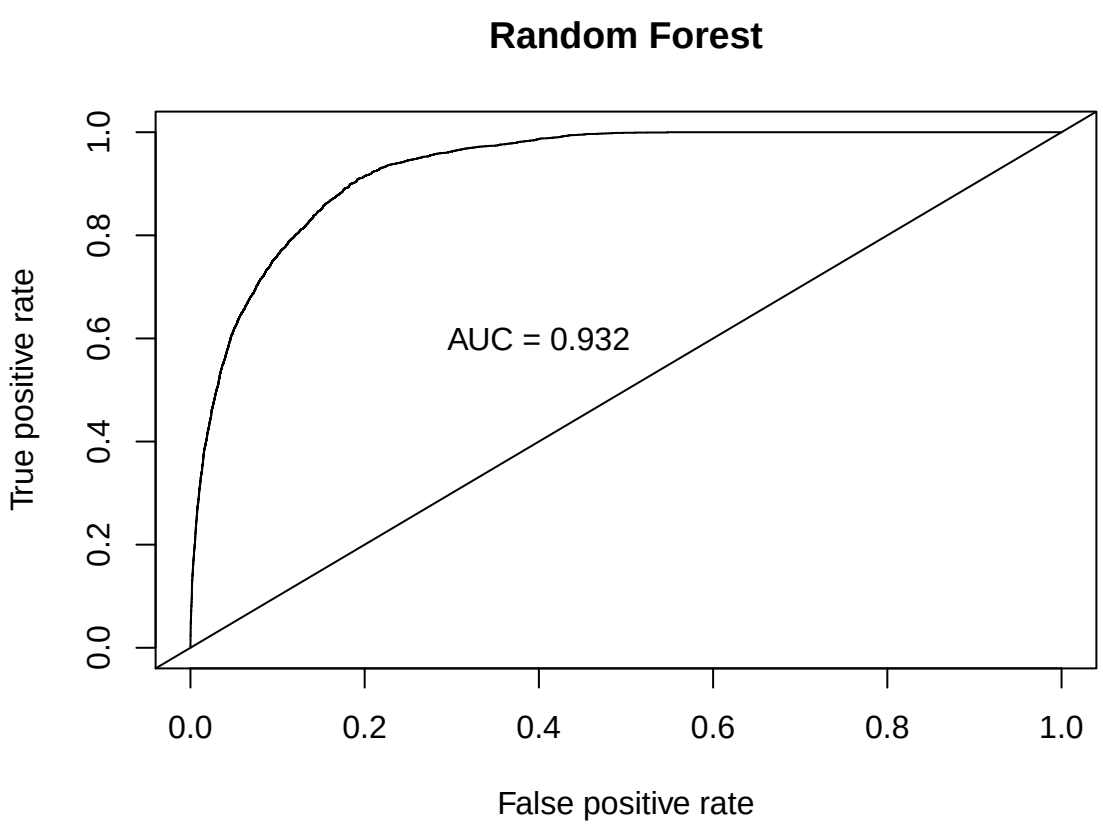
```
##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + walkBin, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.1290  -0.2718   0.1166   0.4911   2.9315
##
## Coefficients:
##                          Estimate Std. Error z value Pr(>|z|)
## (Intercept)            -1.8990163  0.1206717 -15.737  < 2e-16 ***
## boosts                  0.2958458  0.0113382  26.093  < 2e-16 ***
## assists                 0.6267201  0.0669282   9.364  < 2e-16 ***
## weaponsAcquired         0.0374587  0.0090652   4.132 3.59e-05 ***
## killPlace              -0.0532964  0.0012909 -41.285  < 2e-16 ***
## walkDistance            0.0006996  0.0001289   5.426 5.78e-08 ***
## walkBin(500,1e+03]      0.8116992  0.1374167   5.907 3.49e-09 ***
## walkBin(1e+03,1.5e+03]  1.4153735  0.1718194   8.238  < 2e-16 ***
## walkBin(1.5e+03,2e+03]  1.6105048  0.2222116   7.248 4.24e-13 ***
## walkBin(2e+03,2.5e+03]  1.5435278  0.2788404   5.536 3.10e-08 ***
## walkBin(2.5e+03,3e+03]  1.4517335  0.3393104   4.278 1.88e-05 ***
## walkBin(3e+03,3.5e+03]  1.4327575  0.4041083   3.545 0.000392 ***
## walkBin(3.5e+03,4e+03]  1.0128776  0.4709296   2.151 0.031492 *
## walkBin(4e+03,4.5e+03]  0.9021646  0.5469129   1.650 0.099033 .
## walkBin(4.5e+03,5e+03]  0.4101287  0.6243381   0.657 0.511244
## walkBin(5e+03,2e+04]   -0.0089293  0.7459099  -0.012 0.990449
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 34792  on 25102  degrees of freedom
## Residual deviance: 15745  on 25087  degrees of freedom
##   (1511 observations deleted due to missingness)
## AIC: 15777
```

```
##
## Number of Fisher Scoring iterations: 7
```




```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 37382   611
##          1  7796  4869
##
##                Accuracy : 0.834
##                  95% CI : (0.8308, 0.8373)
##     No Information Rate : 0.8918
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4543
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.88850
##             Specificity : 0.82744
```

```
##          Pos Pred Value : 0.38445
##          Neg Pred Value : 0.98392
##              Prevalence : 0.10818
##          Detection Rate : 0.09612
##    Detection Prevalence : 0.25001
##       Balanced Accuracy : 0.85797
##
##        'Positive' Class : 1
##

##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + kpCut + kpCut:killPlace, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.3065  -0.3720  -0.0150   0.4891   2.6470
##
## Coefficients:
##                    Estimate Std. Error z value Pr(>|z|)
## (Intercept)      -4.829e-01  6.256e-02  -7.719 1.17e-14 ***
## boosts            2.992e-01  1.103e-02  27.134  < 2e-16 ***
## assists           6.274e-01  6.671e-02   9.405  < 2e-16 ***
## weaponsAcquired   7.646e-02  7.762e-03   9.851  < 2e-16 ***
## killPlace        -6.674e-02  1.494e-03 -44.660  < 2e-16 ***
## walkDistance      7.525e-04  2.096e-05  35.907  < 2e-16 ***
## kpCut1           -4.442e-01  7.149e-02  -6.213 5.21e-10 ***
## killPlace:kpCut1  1.371e-02  2.457e-03   5.582 2.38e-08 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 17339  on 26606  degrees of freedom
## AIC: 17355
##
## Number of Fisher Scoring iterations: 6
```

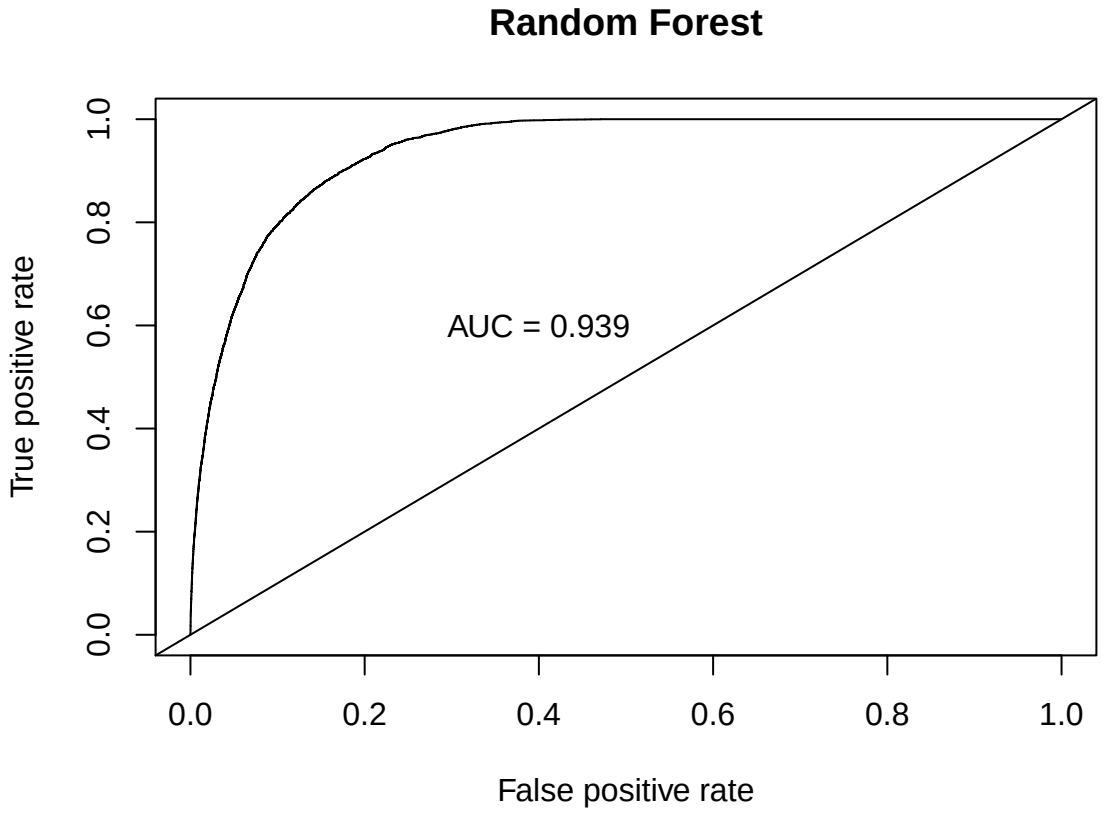



```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 41140   774
##          1  7739  4929
##
##                Accuracy : 0.844
##                  95% CI : (0.841, 0.8471)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4586
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.8643
##             Specificity : 0.8417
##          Pos Pred Value : 0.3891
##          Neg Pred Value : 0.9815
##              Prevalence : 0.1045
```

```
##          Detection Rate : 0.0903
##    Detection Prevalence : 0.2321
##       Balanced Accuracy : 0.8530
##
##        'Positive' Class : 1
##
```

```
##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + damageCut:streakCut, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.6348  -0.2734  -0.0068   0.4847   2.5701
##
## Coefficients: (1 not defined because of singularities)
##                         Estimate Std. Error z value Pr(>|z|)
## (Intercept)           -1.077e+00  7.153e-02 -15.062   <2e-16 ***
## boosts                 3.599e-01  1.174e-02  30.645   <2e-16 ***
## assists                7.779e-01  6.885e-02  11.299   <2e-16 ***
## weaponsAcquired        5.215e-02  8.279e-03   6.299    3e-10 ***
## killPlace             -9.611e-02  1.810e-03 -53.093   <2e-16 ***
## walkDistance           9.176e-04  2.355e-05  38.968   <2e-16 ***
## damageCut0:streakCut0  2.188e+00  7.842e-02  27.904   <2e-16 ***
## damageCut1:streakCut0  1.638e+00  1.941e-01   8.438   <2e-16 ***
## damageCut0:streakCut1  4.937e-01  5.585e-02   8.839   <2e-16 ***
## damageCut1:streakCut1         NA         NA      NA       NA
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 16238  on 26605  degrees of freedom
## AIC: 16256
##
## Number of Fisher Scoring iterations: 6
```

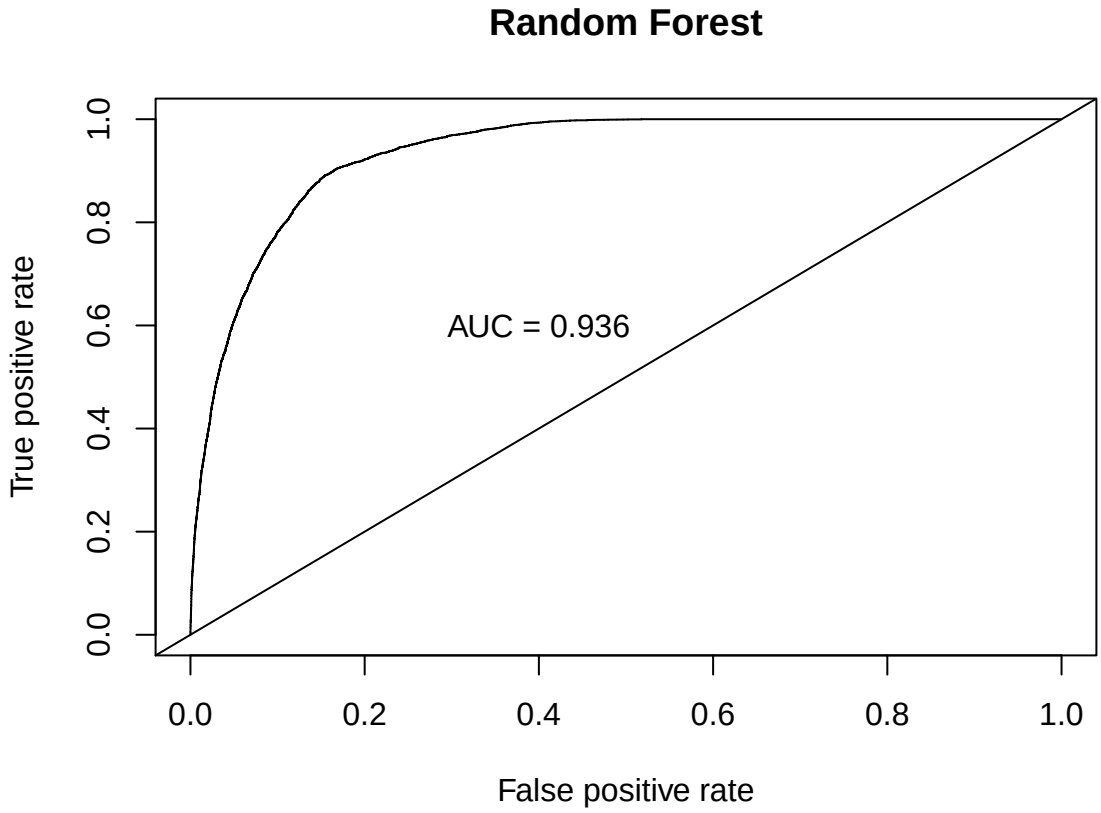
```
## Warning in predict.lm(object, newdata, se.fit, scale = 1, type = if (type == :
## prediction from a rank-deficient fit may be misleading
```




```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 40879   639
##          1  8000  5064
##
##                Accuracy : 0.8417
##                  95% CI : (0.8386, 0.8448)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4613
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.88795
##             Specificity : 0.83633
##          Pos Pred Value : 0.38763
##          Neg Pred Value : 0.98461
##              Prevalence : 0.10448
```

```
##          Detection Rate : 0.09278
##    Detection Prevalence : 0.23935
##       Balanced Accuracy : 0.86214
##
##        'Positive' Class : 1
##
```

```
##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + killsPK, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5511  -0.3216  -0.0002   0.4906   2.9651
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      2.866e-01  7.051e-02   4.064 4.82e-05 ***
## boosts           3.581e-01  1.159e-02  30.896  < 2e-16 ***
## assists          7.086e-01  6.731e-02  10.526  < 2e-16 ***
## weaponsAcquired  6.123e-02  7.994e-03   7.659 1.87e-14 ***
## killPlace       -7.958e-02  1.471e-03 -54.091  < 2e-16 ***
## walkDistance     6.951e-04  2.127e-05  32.683  < 2e-16 ***
## killsPK         -7.938e-01  3.420e-02 -23.213  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 16839  on 26607  degrees of freedom
## AIC: 16853
##
## Number of Fisher Scoring iterations: 6
```

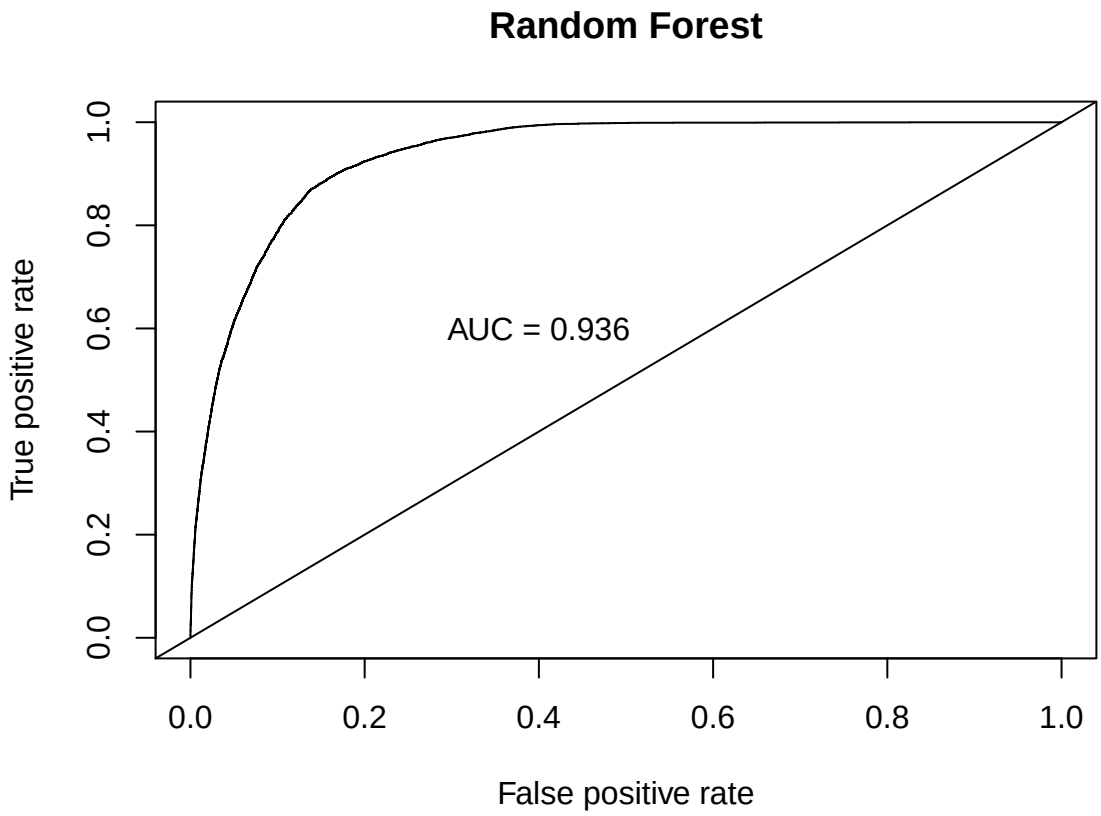



```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 41066   600
##          1  7813  5103
##
##                Accuracy : 0.8459
##                  95% CI : (0.8428, 0.8489)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4715
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.89479
##             Specificity : 0.84016
##          Pos Pred Value : 0.39509
##          Neg Pred Value : 0.98560
##              Prevalence : 0.10448
```

```
##          Detection Rate : 0.09349
##    Detection Prevalence : 0.23663
##       Balanced Accuracy : 0.86747
##
##        'Positive' Class : 1
##
```

```
## Warning: glm.fit: fitted probabilities numerically 0 or 1 occurred
```

```
##
## Call:
## glm(formula = top.10 ~ boosts + assists + weaponsAcquired + killPlace +
##     walkDistance + damageKill + killsPK, family = binomial(link = "logit"),
##     data = train_obj1)
##
## Deviance Residuals:
##     Min       1Q   Median       3Q      Max
## -3.5382  -0.3095   0.0055   0.4915   8.4904
##
## Coefficients:
##                   Estimate Std. Error z value Pr(>|z|)
## (Intercept)      4.936e-01  7.445e-02   6.630 3.36e-11 ***
## boosts           3.565e-01  1.160e-02  30.740  < 2e-16 ***
## assists          6.536e-01  6.773e-02   9.650  < 2e-16 ***
## weaponsAcquired  5.806e-02  8.057e-03   7.206 5.74e-13 ***
## killPlace       -8.295e-02  1.534e-03 -54.067  < 2e-16 ***
## walkDistance     7.371e-04  2.203e-05  33.454  < 2e-16 ***
## damageKill      -3.780e+01  4.138e+00  -9.133  < 2e-16 ***
## killsPK         -6.874e-01  3.653e-02 -18.820  < 2e-16 ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## (Dispersion parameter for binomial family taken to be 1)
##
##     Null deviance: 36895  on 26613  degrees of freedom
## Residual deviance: 16738  on 26606  degrees of freedom
## AIC: 16754
##
## Number of Fisher Scoring iterations: 7
```




```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction     0     1
##          0 40958   602
##          1  7921  5101
##
##                Accuracy : 0.8438
##                  95% CI : (0.8408, 0.8469)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4674
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.89444
##             Specificity : 0.83795
##          Pos Pred Value : 0.39172
##          Neg Pred Value : 0.98551
##              Prevalence : 0.10448
```

```
##          Detection Rate : 0.09346
##    Detection Prevalence : 0.23858
##       Balanced Accuracy : 0.86619
##
##        'Positive' Class : 1
##
```

5.1.4 LDA

5.1.4.1 LASSO

```
# Reduce variables to relevant continuous variables
train1<-train[,c(5:6,8:10,12:15,19,21:27,29:30)]
test1<-test[,c(5:6,8:10,12:15,19,21:27,29:30)]
# train2 <- train1[,c(1,4:19)]
# test2 <- test1[,c(1,4:19)]
train2_alt <- train1[,c(1,4:17,19)]
test2_alt <- test1[,c(1,4:17,19)]
```

```
# Get data in format for LASSO
x=model.matrix(top.10~.,train2_alt)[,-1]
y=as.numeric(train2_alt$top.10)

xtest<-model.matrix(top.10~.,test2_alt)[,-1]
ytest<-as.numeric(test2_alt$top.10)

grid=10^seq(10,-2, length =100)
lasso.mod=glmnet(x,y,alpha=1, lambda =grid)

set.seed(23) #removes kills roadKills vehicleDestroys
lda.cv.out=cv.glmnet(x,y,alpha=1,family="binomial") #alpha=1 performs LASSO
# plot(lda.cv.out)

# simplest model
lda.lasso.model.coef<-coef(cv.out, cv.out$lambda.1se)
# lda.lasso.model.coef
```

```
lda.lasso.model.coef
```

```
## 16 x 1 sparse Matrix of class "dgCMatrix"
##                               1
## (Intercept)      3.091783e+00
## boosts           2.672920e-01
## heals           -2.784586e-03
## killPlace       -8.033586e-02
## kills            .
```

```
## killStreaks     -1.117635e+00
## longestKill     -5.733176e-05
## matchDuration   -1.609689e-03
## rankPoints       1.034136e-05
## rideDistance     1.948066e-04
## roadKills        .
## swimDistance     5.967117e-04
## teamKills       -1.509184e+00
## vehicleDestroys  .
## walkDistance     8.511812e-04
## weaponsAcquired  5.746021e-02
```

```
# Removing the kills, roadKills, and vehicleDestroys as shown above
# Also removing rankPoints because
# (a) the majority of the players in these data aren't ranked and
# (b) the Kaggle descrption says "This ranking is inconsistent and is being deprecated in the API's nex
train_final <- train2_alt[,c(-4,-8,-10,-13)]
```

5.1.4.2 Assumption Checking

```
train_final_no <- train_final[which(train_final$top.10==0),]
train_final_yes <- train_final[which(train_final$top.10==1),]

# nrow(train_final)
# nrow(train_final_no)
# nrow(train_final_yes)

max_cols<-ncol(train_final)
no_matrix<-as.matrix(train_final_no[,-max_cols])
yes_matrix<-as.matrix(train_final_yes[,-max_cols])

no_hist<-multi.hist(no_matrix)
yes_hist<-multi.hist(yes_matrix)
# par(mfrow=c(1,1))
```

```
no_hist
```

```
## NULL
```

```
yes_hist
```

```
## NULL
```

```
#http://www.sthda.com/english/wiki/ggplot2-quick-correlation-matrix-heatmap-r-software-and-data-visuali
get_upper_tri <- function(cormat){
  cormat[lower.tri(cormat)]<- NA
  return(cormat)
```

```
}

custom_corr_plot <- function(cormat){

  upper_tri <- get_upper_tri(cormat)
  # Melt the correlation matrix
  melted_cormat <- melt(upper_tri, na.rm = TRUE)
  # Create a ggheatmap
  ggheatmap <- ggplot(melted_cormat, aes(Var2, Var1, fill = value))+
    geom_tile(color = "white")+
    scale_fill_gradient2(low = "blue", high = "red", mid = "white",
                         midpoint = 0, limit = c(-1,1), space = "Lab",
                         name="Pearson\nCorrelation") +
    theme_minimal()+ # minimal theme
    theme(axis.text.x = element_text(angle = 45, vjust = 1,
                                     size = 12, hjust = 1))+
    coord_fixed()


  p<-ggheatmap +
    geom_text(aes(Var2, Var1, label = value), color = "black", size = 4) +
    theme(
      axis.title.x = element_blank(),
      axis.title.y = element_blank(),
      panel.grid.major = element_blank(),
      panel.border = element_blank(),
      panel.background = element_blank(),
      axis.ticks = element_blank(),
      legend.justification = c(1, 0),
      legend.position = c(0.6, 0.7),
      legend.direction = "horizontal")+
    guides(fill = guide_colorbar(barwidth = 7, barheight = 1,
                                 title.position = "top", title.hjust = 0.5))

  return(p)
}

cormat <- round(cor(no_matrix),2)
lda.no <- custom_corr_plot(cormat)

cormat <- round(cor(yes_matrix),2)
lda.yes <- custom_corr_plot(cormat)
```

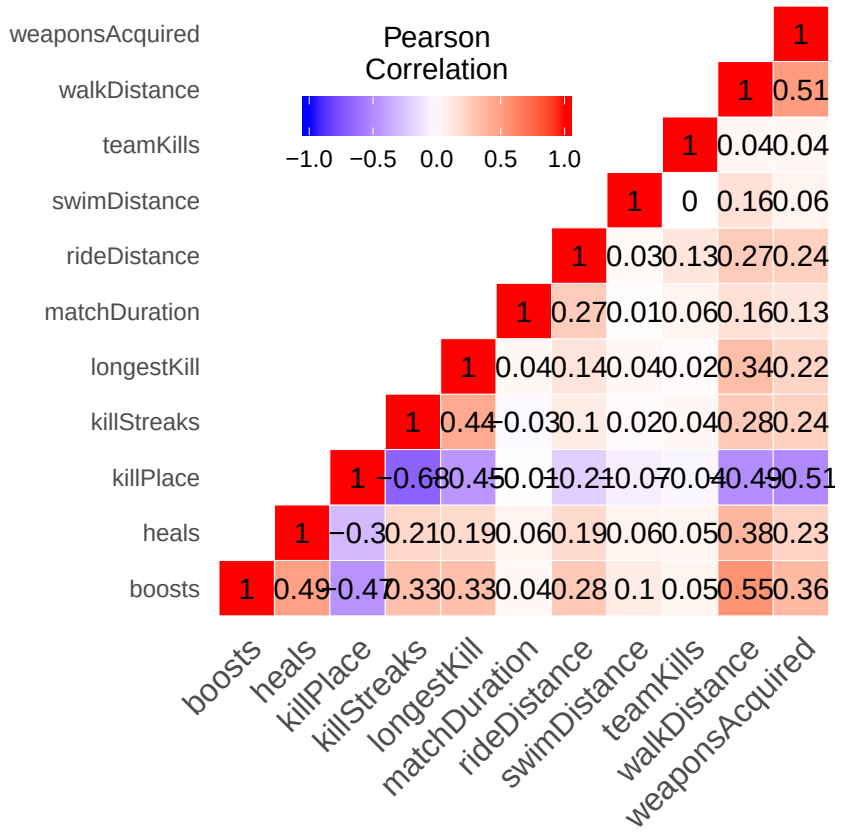


Figure 1: (#fig:code.lda.no)Correlation Matrix for Bottom 90 of Training Dataset

```
lda.no
```

```
lda.yes
```

5.1.4.3 LDA Results

```
# Run LDA
lda <- lda(top.10 ~ . , data=train_final, prior=c(.9,.1))

lda
```

```
## Call:
## lda(top.10 ~ ., data = train_final, prior = c(0.9, 0.1))
##
## Prior probabilities of groups:
##   0   1
## 0.9 0.1
##
## Group means:
```

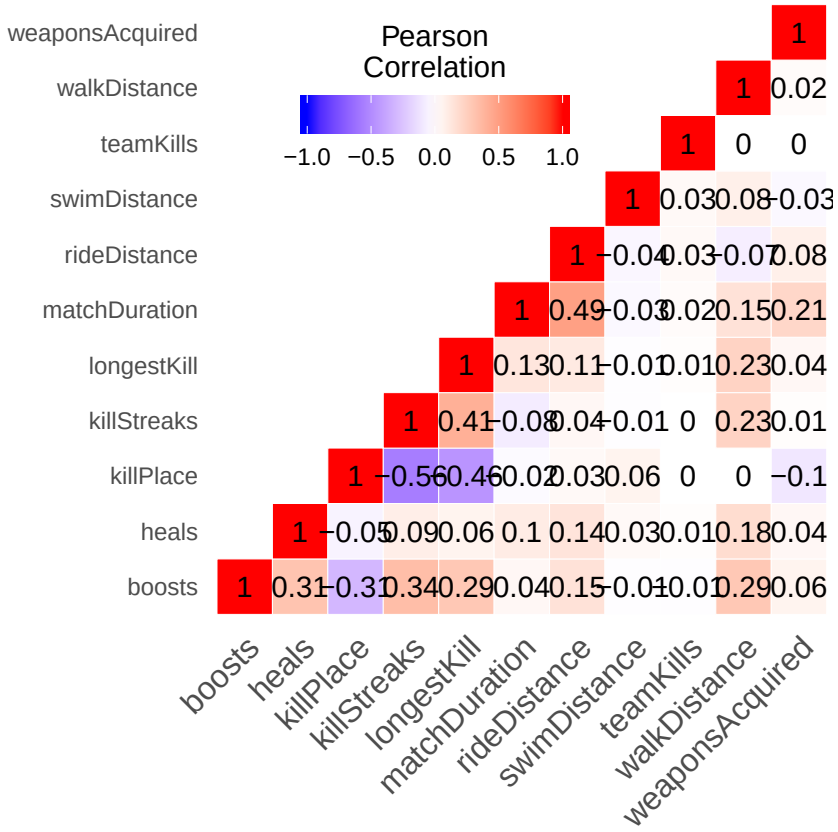


Figure 2: (#fig:code.lda.yes)Correlation Matrix for Top 90 of Training Dataset

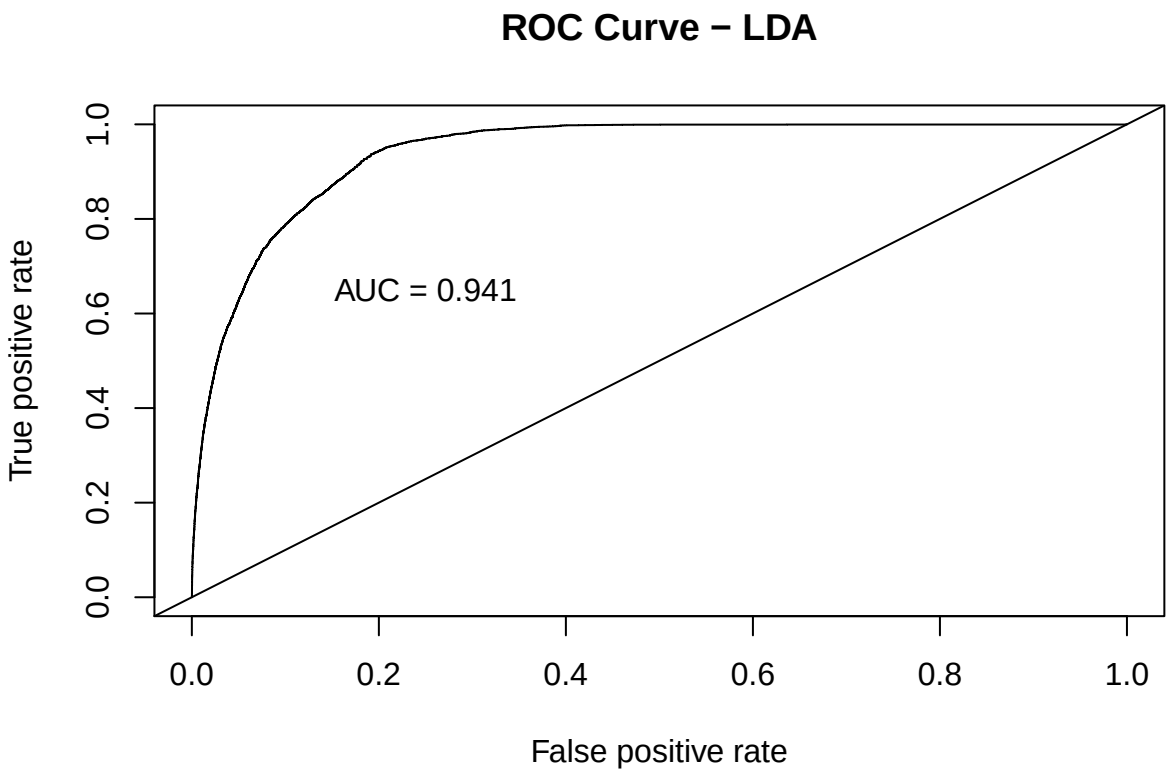
```
##      boosts     heals killPlace killStreaks longestKill matchDuration
## 0 0.7381078 0.8007815  50.25445   0.3915984    15.00272      1681.215
## 1 3.9244758 2.7710228  13.42301   0.8962200    70.77070      1680.553
##   rideDistance swimDistance   teamKills walkDistance weaponsAcquired
## 0     515.6142     5.365372 0.016908394     823.7333        3.517848
## 1    1666.6767    16.136750 0.003005937    2351.6425        5.710528
##
## Coefficients of linear discriminants:
##                            LD1
## boosts           0.1636559657
## heals           -0.0071779101
## killPlace       -0.0313509817
## killStreaks     -0.4645084746
## longestKill      0.0003963294
## matchDuration   -0.0007443145
## rideDistance     0.0001033605
## swimDistance     0.0006812726
## teamKills       -1.0147862026
## walkDistance     0.0004217550
## weaponsAcquired  0.0155413057
```

```
predict <- predict(lda,newdata=test)

test_final <- test
test_final$predcited_place <- as.vector(predict$class)
test_final$top.10<-as.factor(test_final$top.10)
test_final$predcited_place<-as.factor(test_final$predcited_place)

xtab<-table(test_final$predcited_place,test_final$top.10)
confusionMatrix(xtab, positive="1")
```

```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 46972  2425
##   1  1907  3278
##
##                Accuracy : 0.9206
##                  95% CI : (0.9183, 0.9229)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5582
```

```
##
##  Mcnemar's Test P-Value : 3.998e-15
##
##             Sensitivity : 0.57479
##             Specificity : 0.96099
##          Pos Pred Value : 0.63221
##          Neg Pred Value : 0.95091
##              Prevalence : 0.10448
##          Detection Rate : 0.06006
##    Detection Prevalence : 0.09499
##       Balanced Accuracy : 0.76789
##
##        'Positive' Class : 1
##
```

```r
predict.posteriors <- as.data.frame(predict$posterior)

# Evaluate the model
pred <- prediction(predict.posteriors[,2], test$top.10)
roc.perf = performance(pred, measure = "tpr", x.measure = "fpr")
auc.train <- performance(pred, measure = "auc")
auc.train <- auc.train@y.values


# Plot
plot(roc.perf, main="ROC Curve - LDA")
abline(a=0, b= 1)
text(x = .25, y = .65 ,paste("AUC = ", round(auc.train[[1]],3), sep = ""))
```



5.1.4.4 QDA Results

```
qda <- qda(top.10 ~ . , data=train_final, prior=c(.9,.1))

qda
```

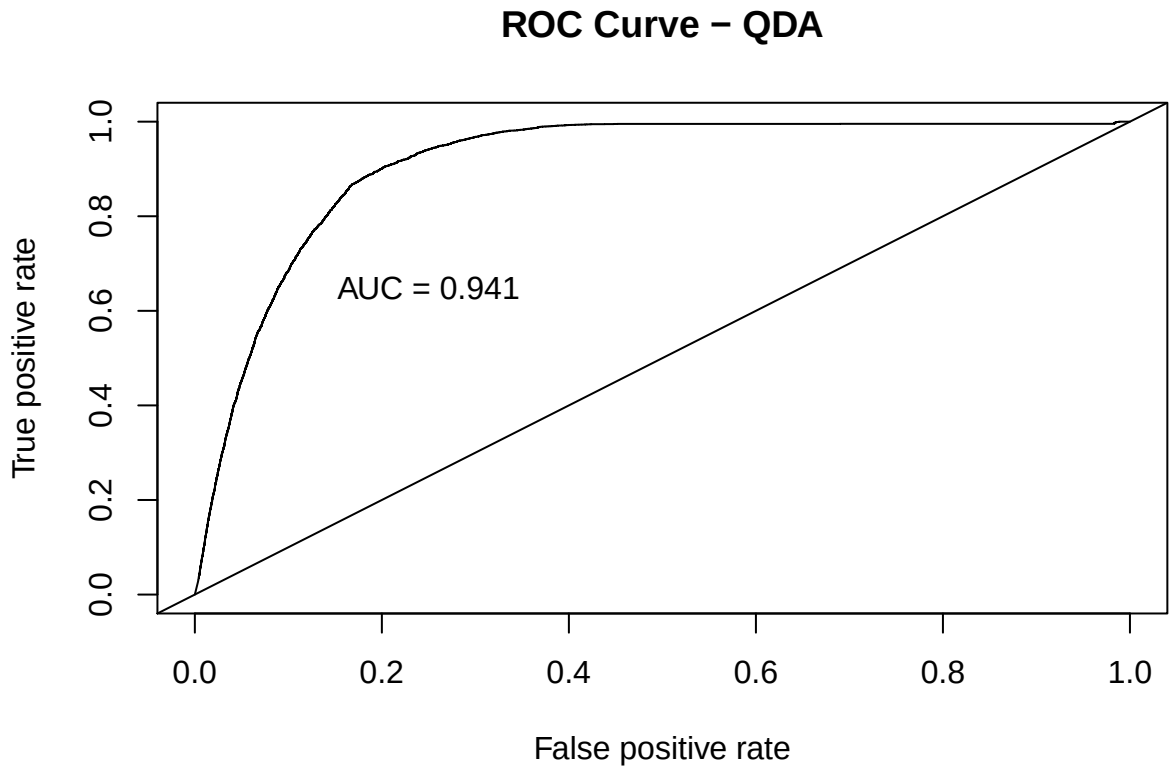
```
## Call:
## qda(top.10 ~ ., data = train_final, prior = c(0.9, 0.1))
##
## Prior probabilities of groups:
##   0   1
## 0.9 0.1
##
## Group means:
##      boosts     heals killPlace killStreaks longestKill matchDuration
## 0 0.7381078 0.8007815  50.25445   0.3915984    15.00272      1681.215
## 1 3.9244758 2.7710228  13.42301   0.8962200    70.77070      1680.553
##   rideDistance swimDistance   teamKills walkDistance weaponsAcquired
## 0     515.6142     5.365372 0.016908394     823.7333        3.517848
## 1    1666.6767    16.136750 0.003005937    2351.6425        5.710528
```

```r
predict.qda <- predict(qda,newdata=test)

# test_final <- test
test_final$predcited_place.qda <- as.vector(predict$class)
# test_final$top.10<-as.factor(test_final$top.10)
test_final$predcited_place.qda<-as.factor(test_final$predcited_place.qda)
# test_final$predcited_place<-as.factor(test_final$predcited_place)
# str(test_final)

xtab.qda<-table(test_final$predcited_place.qda,test_final$top.10)
confusionMatrix(xtab.qda, positive="1")
```

```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 46972  2425
##   1  1907  3278
##
##                Accuracy : 0.9206
##                  95% CI : (0.9183, 0.9229)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : < 2.2e-16
##
##                   Kappa : 0.5582
##
##  Mcnemar's Test P-Value : 3.998e-15
##
##             Sensitivity : 0.57479
##             Specificity : 0.96099
##          Pos Pred Value : 0.63221
##          Neg Pred Value : 0.95091
##              Prevalence : 0.10448
##          Detection Rate : 0.06006
##    Detection Prevalence : 0.09499
##       Balanced Accuracy : 0.76789
##
##        'Positive' Class : 1
##
```

```r
predict.posteriors.qda <- as.data.frame(predict.qda$posterior)

# Evaluate the model
pred.qda <- prediction(predict.posteriors.qda[,2], test$top.10)
```

```
roc.perf.qda = performance(pred.qda, measure = "tpr", x.measure = "fpr")
auc.train.qda <- performance(pred.qda, measure = "auc")
auc.train.qda <- auc.train.qda@y.values


# Plot
plot(roc.perf.qda, main="ROC Curve - QDA")
abline(a=0, b= 1)
text(x = .25, y = .65 ,paste("AUC = ", round(auc.train[[1]],3), sep = ""))
```



5.1.5 Random Forest

5.1.5.1 Model

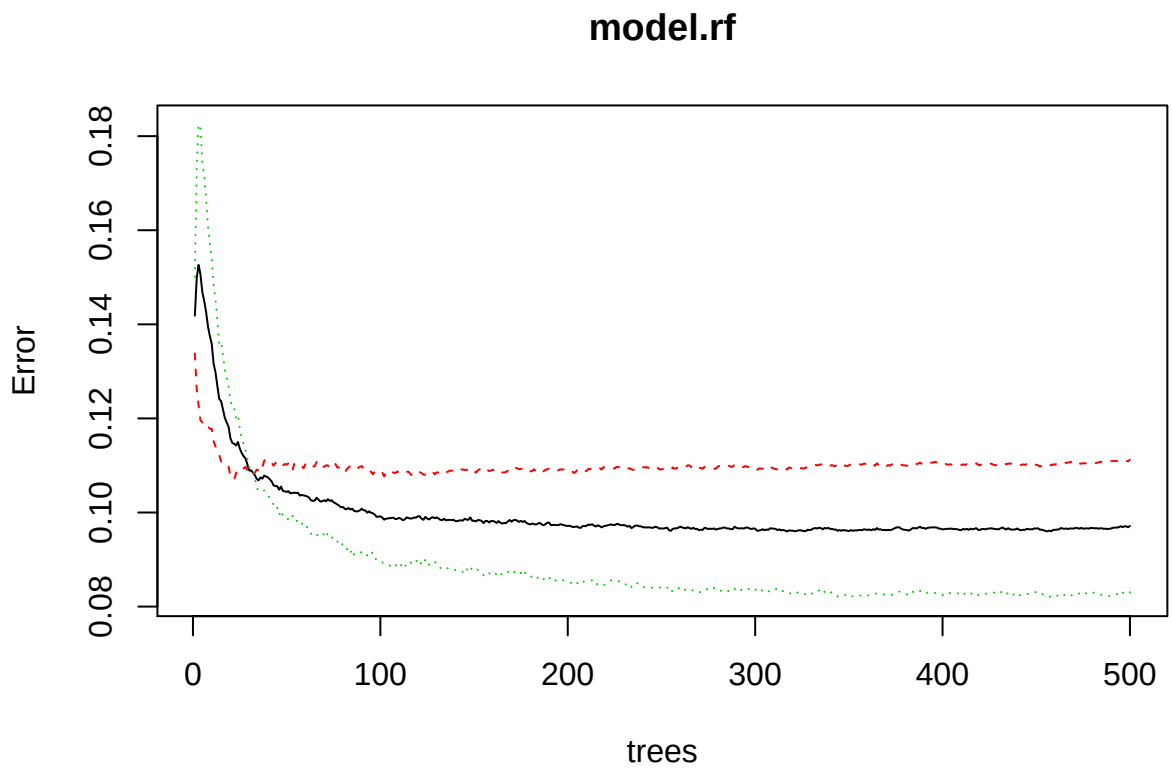
```
# results='hide', message=FALSE, include=FALSE, echo=FALSE
rf_cols_to_remove = c("Id", "groupId", "matchId", "matchType", "DBNOs", "revives", "winPlacePerc")

train.rf <- train %>%
  dplyr::select(-rf_cols_to_remove) %>%
  mutate(kills  = kills * 100 / numGroups) %>% # Normalized Kills
  mutate(matchDuration = as.factor(ifelse(matchDuration < mean(matchDuration), "Low", "High"))) %>%
  mutate(top.10 = factor(top.10, labels = c("No", "Yes")))
```

```r
test.rf <- test %>%
  dplyr::select(-rf_cols_to_remove) %>%
  mutate(kills  = kills * 100 / numGroups) %>% # Normalized Kills
  mutate(matchDuration = as.factor(ifelse(matchDuration < mean(matchDuration), "Low", "High"))) %>%
  mutate(top.10 = factor(top.10, labels = c("No", "Yes")))

set.seed(1234)
model.rf <- randomForest(as.factor(top.10) ~ .,
                                data = train.rf,
                                ntree = 500,
                                mtry = 12,
                                cutoff = c(0.4,1-0.40))


model.rf
```

```
##
## Call:
##  randomForest(formula = as.factor(top.10) ~ ., data = train.rf,      ntree = 500, mtry = 12, cutoff =
##                Type of random forest: classification
##                      Number of trees: 500
## No. of variables tried at each split: 12
##
##         OOB estimate of  error rate: 9.71%
## Confusion matrix:
##        No   Yes class.error
## No  11827  1480   0.1112197
## Yes  1105 12202   0.0830390
```

5.1.5.2 Tuning Plot

```r
plot(model.rf)
```



5.1.5.3 Variable Importance

```
# varImp(model.rf)

rf.imp.variables <-data.frame(varImp(model.rf))

# rf.imp.variables[order(rf.imp.variables$Overall,decreasing = T),]

kable(data.frame('Column Name' = rownames(rf.imp.variables),
                 'Overall Score'= rf.imp.variables$Overall),
      "latex", booktabs = T)  %>%
  kable_styling(position = "center")
```

Column.Name	Overall.Score
assists	43.62334
boosts	1157.86767
damageDealt	587.86497
headshotKills	61.26146
heals	209.00441
killPlace	5172.69584
killPoints	155.16722
kills	635.76974
killStreaks	159.01334
longestKill	386.08015
matchDuration	105.38803
maxPlace	326.37764
numGroups	367.23582
rankPoints	289.94210
rideDistance	270.77805
roadKills	13.37229
swimDistance	96.74467
teamKills	22.79068
vehicleDestroys	13.58180
walkDistance	2802.62385
weaponsAcquired	261.50104
winPoints	155.96105

5.1.5.4 Predict

```
prd.rf.train <- predict(model.rf, train.rf)
prd.rf.test <- predict(model.rf, test.rf)
```

5.1.5.5 Confusion Matrix

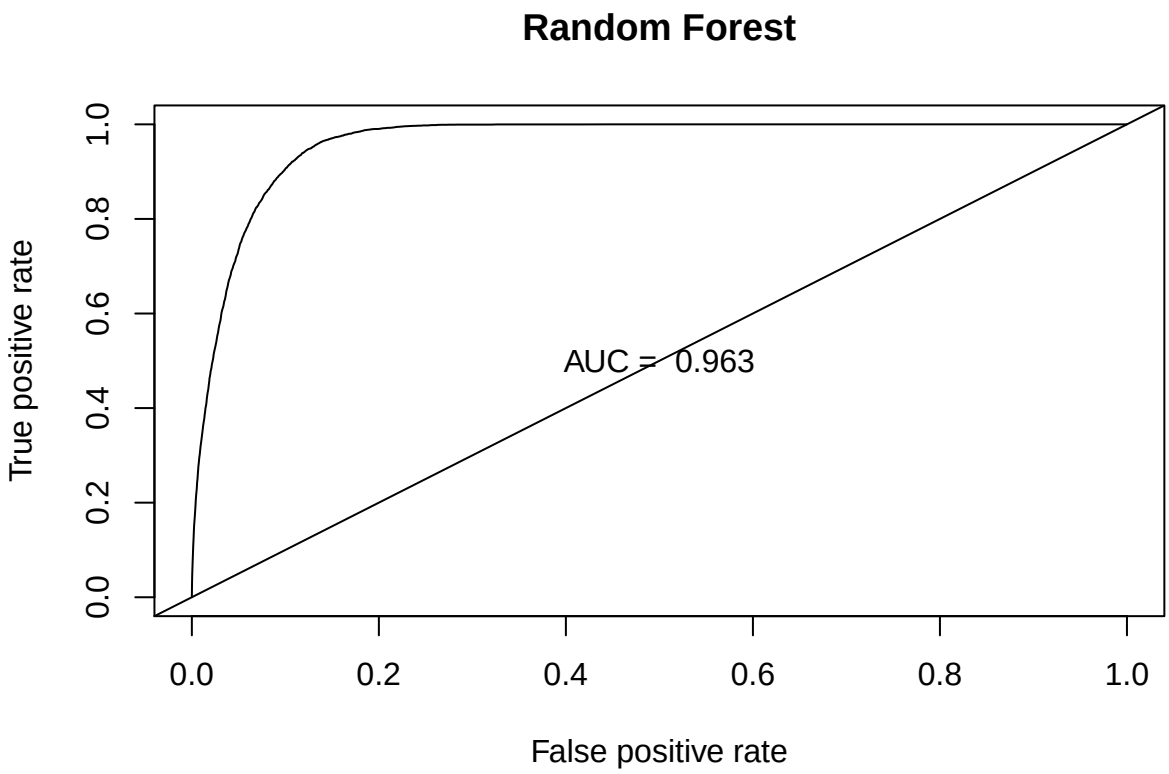
```
confusionMatrix(data=prd.rf.test,
                reference=test.rf$top.10, "Yes")
```

```
## Confusion Matrix and Statistics
##
##           Reference
## Prediction    No   Yes
##        No  43690   467
##        Yes  5189  5236
##
##                Accuracy : 0.8964
##                  95% CI : (0.8938, 0.8989)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 0.258
##
##                   Kappa : 0.5945
```

```
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.91811
##             Specificity : 0.89384
##          Pos Pred Value : 0.50225
##          Neg Pred Value : 0.98942
##              Prevalence : 0.10448
##          Detection Rate : 0.09593
##    Detection Prevalence : 0.19100
##       Balanced Accuracy : 0.90598
##
##        'Positive' Class : Yes
##
```

5.1.5.6 ROC Curve

```
prd.rf.test <- predict(model.rf, test.rf, type = "prob")

predictions <- as.vector(prd.rf.test[,2])

pred <- prediction(predictions, test$top.10)

perf_AUC <- performance(pred,"auc") #Calculate the AUC value
AUC=perf_AUC@y.values[[1]]

perf_ROC=performance(pred,"tpr","fpr") #plot the actual ROC curve
plot(perf_ROC, main="Random Forest")
text(0.5,0.5,paste("AUC = ",format(AUC, digits=3, scientific=FALSE)))
abline(a=0, b= 1) #Ref line indicating poor performance
```



References

[1] Kaggle (2019). Kaggle2019. Data retrieved from the Kaggle website, https://www.kaggle.com/c/pubg-finish-placement-prediction/data.