PUBG Top 10% Placement Analysis

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1 Introduction

[Intro]

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.
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.

Column Name	Description
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

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 ***
```

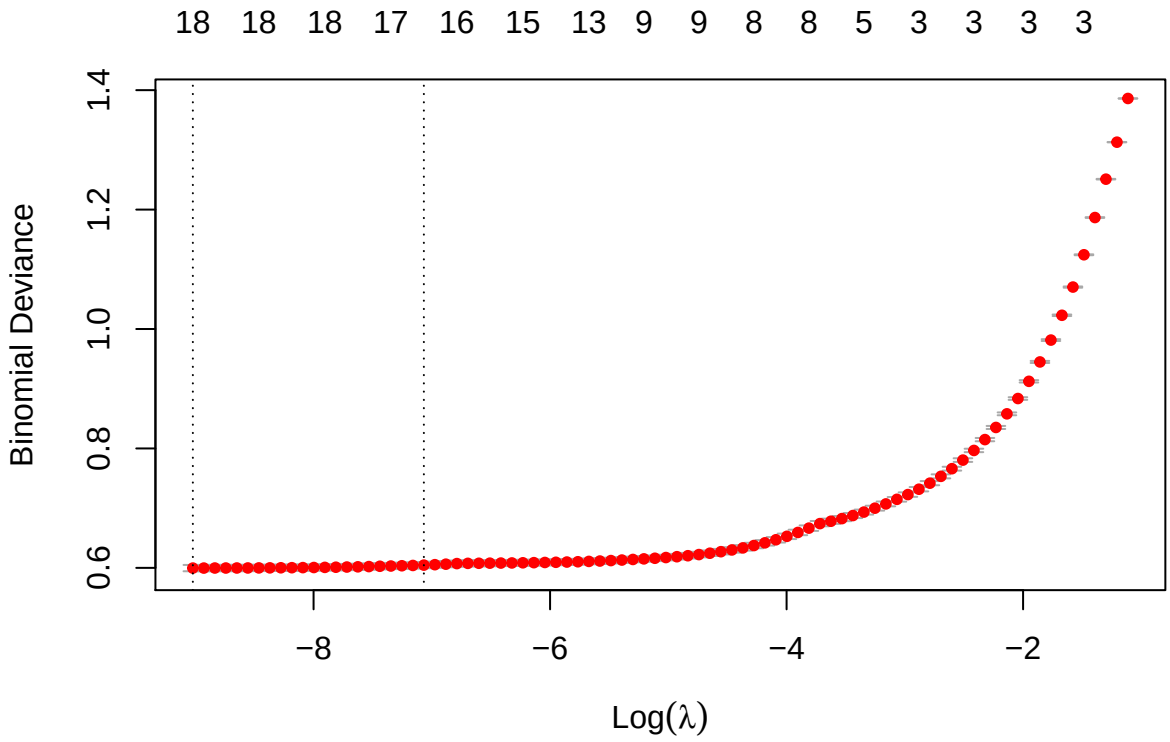
```
## winPoints        5.282e-03  3.949e-04  13.376  < 2e-16 ***
## longestKill     -1.896e-03  4.007e-04  -4.732 2.22e-06 ***
## swimDistance     1.503e-03  3.705e-04   4.056 5.00e-05 ***
## rideDistance     1.316e-04  1.011e-05  13.026  < 2e-16 ***
## walkDistance     8.866e-04  2.384e-05  37.197  < 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 Ref) 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 Reference). We selected the lambda.1se value, which will hopefully eliminate the most variables. Using that value for lambda, lasso produced this output:



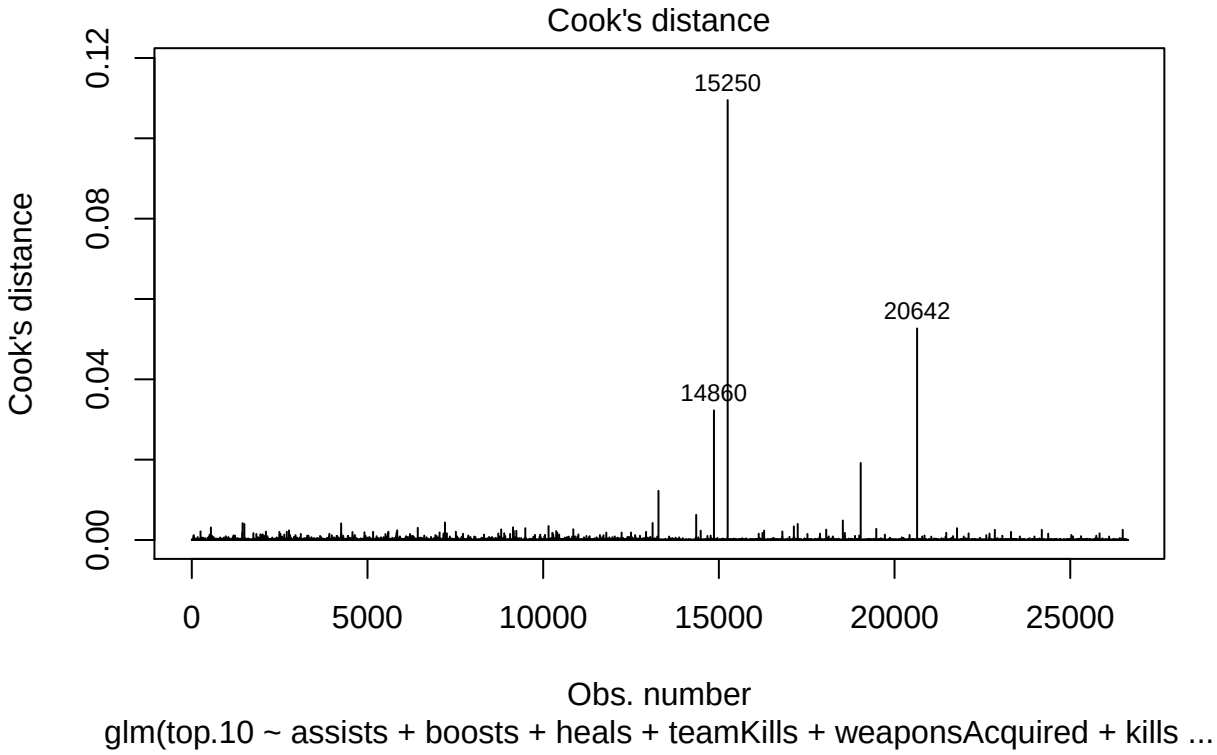

```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                              s0
## (Intercept)     -0.6733424558
## (Intercept)      .
## assists          0.6465602204
## boosts           0.3247910863
## heals           -0.0291791887
## teamKills       -1.9070440684
## weaponsAcquired  0.0445136944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

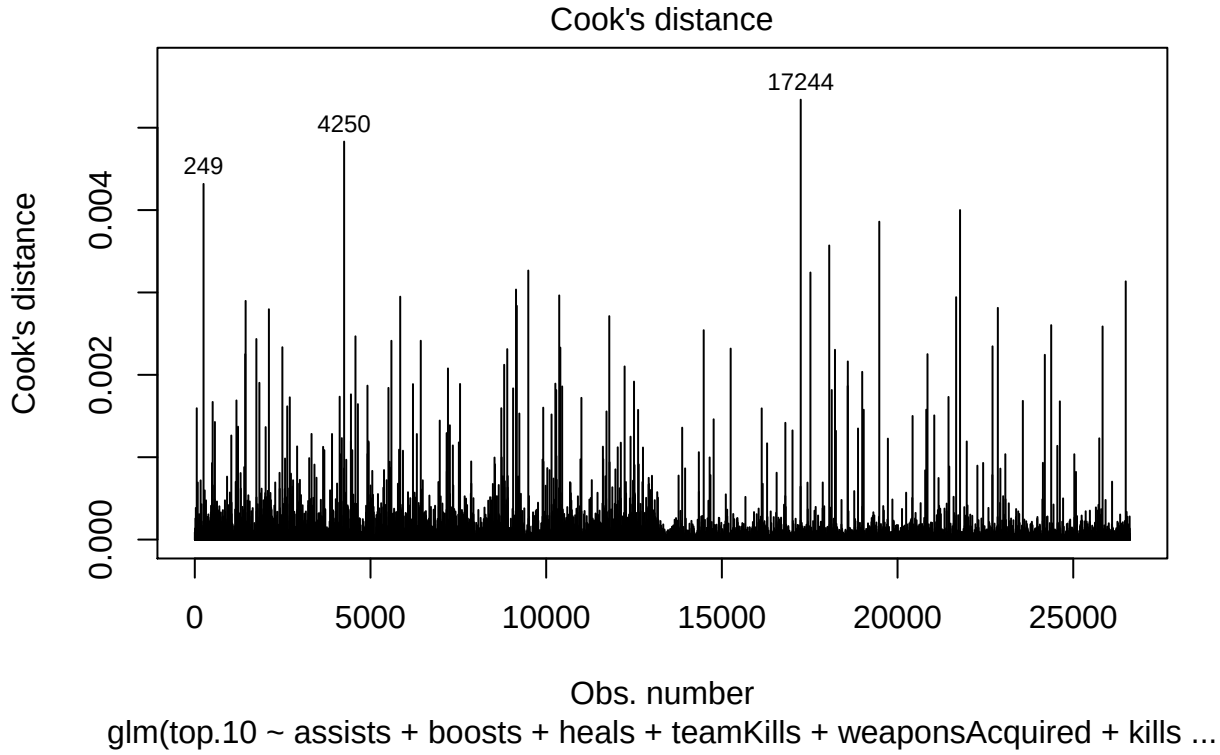
3.4 Final Iterations

The selection eliminated damageDealt, headshotKills, and killPoints. We created a model using just the variables from lasso (ref) 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.



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

4.2 Model Selection

4.2.1 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.

4.2.1.1 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.

4.2.1.2 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. 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. 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.

4.2.1.3 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.

4.2.1.4 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.

4.2.1.5 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.

4.2.2 Random Forest

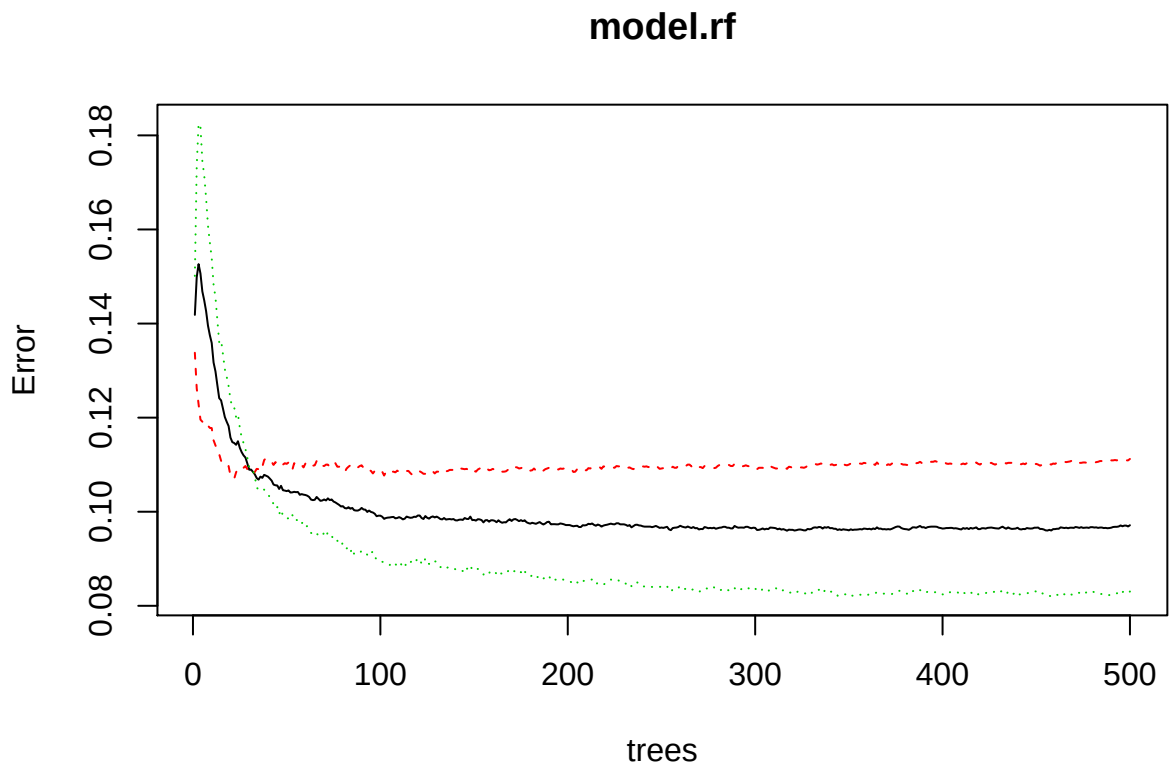
We then tried our first non-parametrical model with Random Forest, which averages out the results of many Decision Trees to provide the lowest error rates across all of the permuations attempted.

4.2.2.1 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.

4.2.2.2 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.



4.2.2.3 Variable Importance

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

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

4.2.2.4 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	0.906	0.918	0.894	10.4%

4.2.2.5 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 Comparing Competing Models

4.4 Model Interpretation

4.5 Conclusion

5 Appendix

5.1 Exploratory Data Analysis

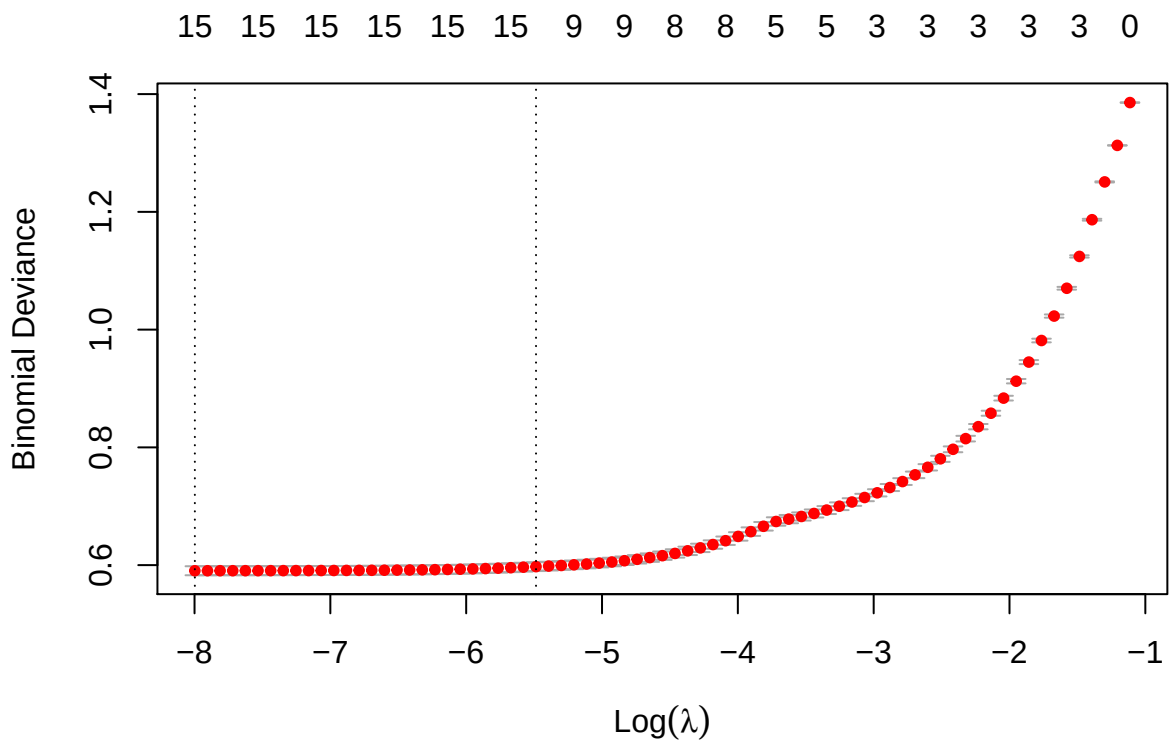
5.2 Code

5.2.1 LDA

5.2.1.1 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
cv.out=cv.glmnet(x,y,alpha=1,family="binomial") #alpha=1 performs LASSO
lda.lasso<-plot(cv.out)
```




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

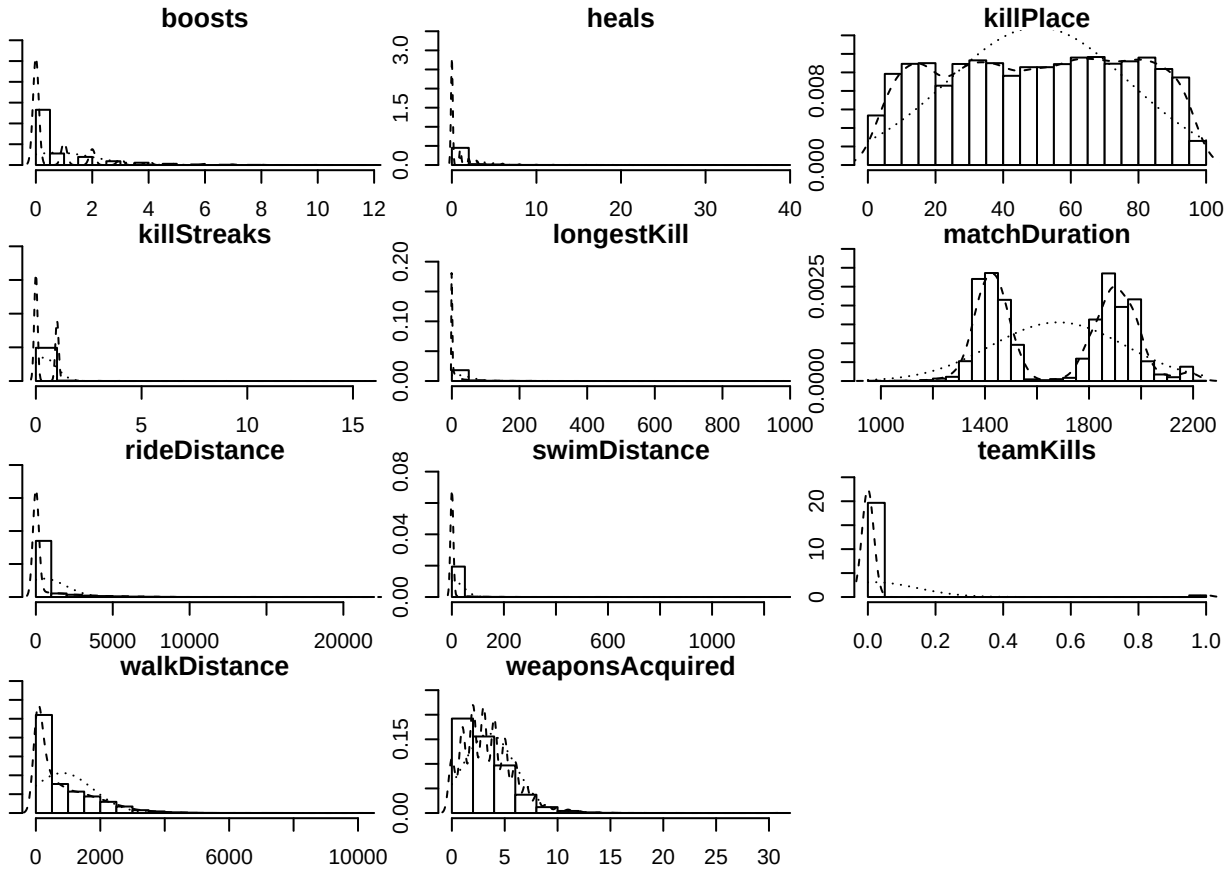
```
## 16 x 1 sparse Matrix of class "dgCMatrix"
##                               1
## (Intercept)      3.091783e+00
## boosts           2.672920e-01
## heals           -2.784586e-03
## killPlace       -8.033586e-02
## kills            .
## killStreaks     -1.117635e+00
## longestKill     -5.733176e-05
## 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
```

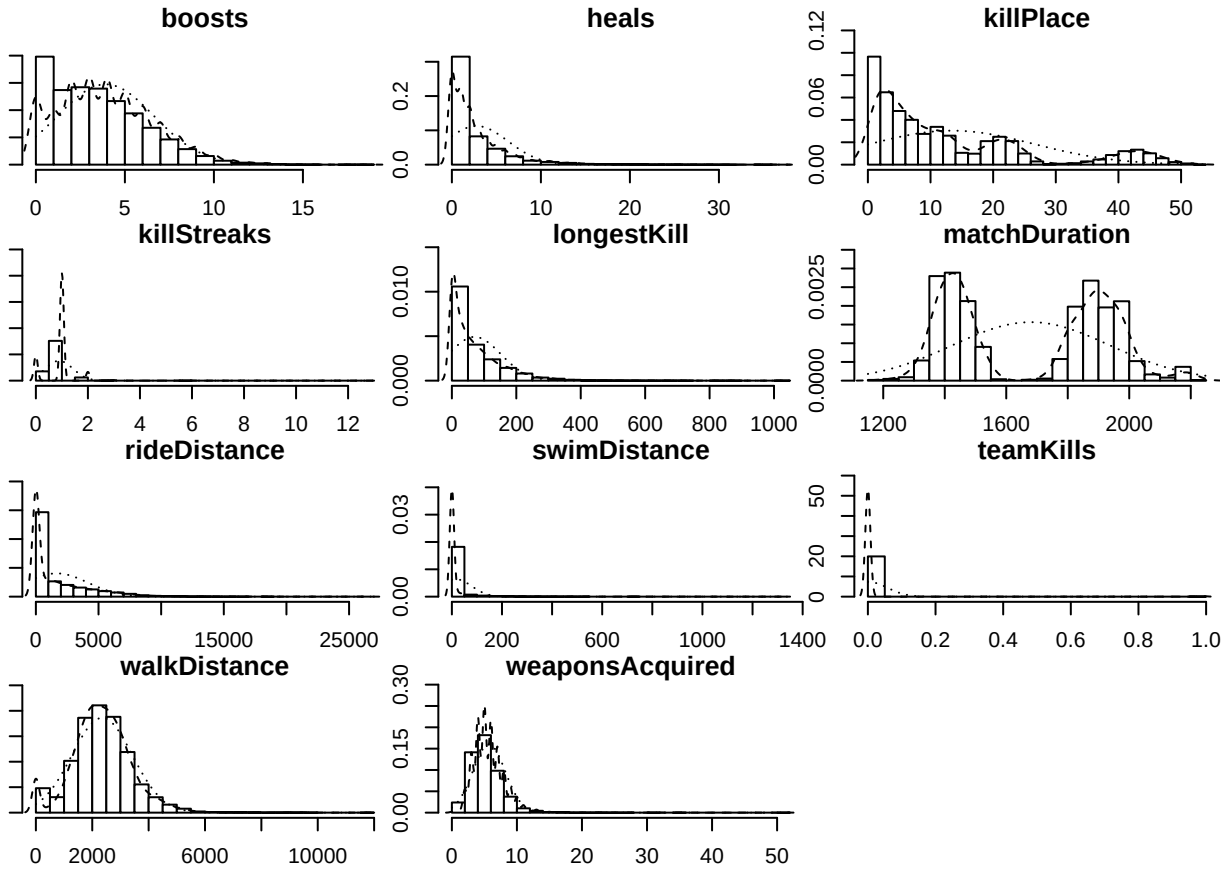
```
# Removing the kills, roadKills, and vehicleDestroys as shown above
# Also removing rankPoints because
# (a) the majority of the players in these data aren't ranked and
# (b) the Kaggle descrption says "This ranking is inconsistent and is being deprecated in the API's nex
train_final <- train2_alt[,c(-4,-8,-10,-13)]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

5.2.1.2 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))
```

```
#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)
no <- custom_corr_plot(cormat)

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

5.2.1.3 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
##
```

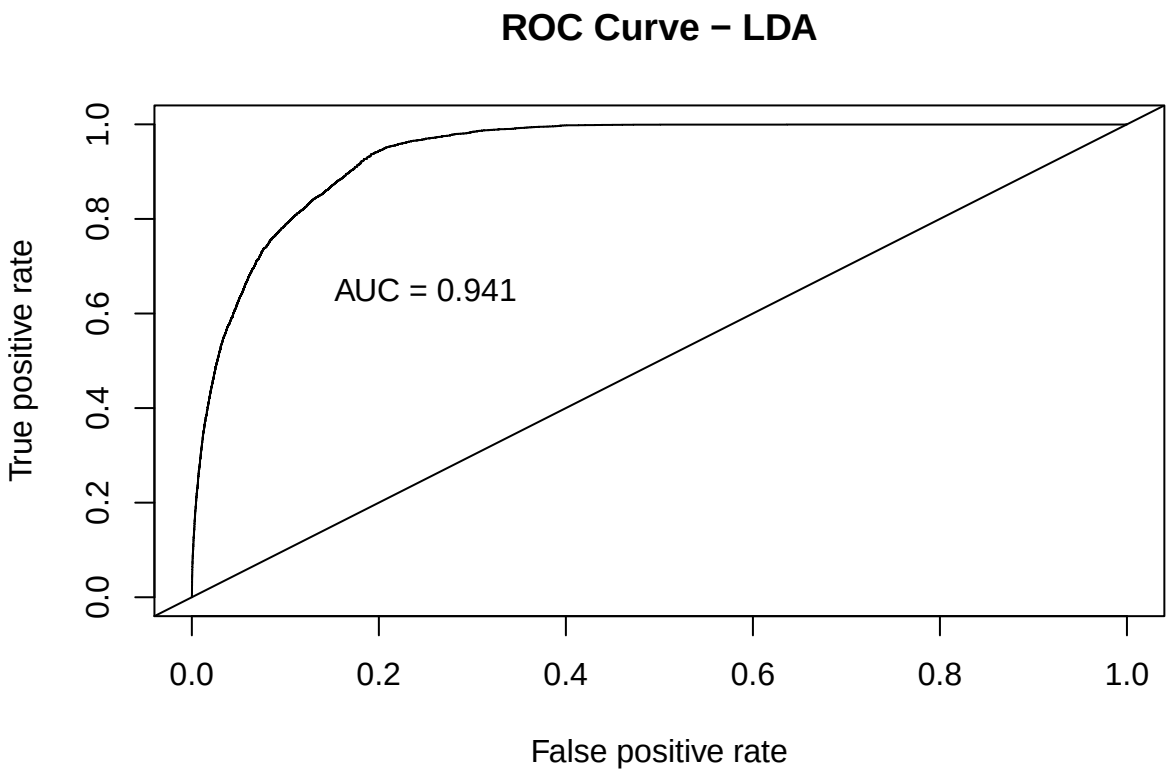
```
## Group means:
##      boosts     heals killPlace killStreaks longestKill matchDuration
## 0 0.7381078 0.8007815  50.25445   0.3915984    15.00272      1681.215
## 1 3.9244758 2.7710228  13.42301   0.8962200    70.77070      1680.553
##   rideDistance swimDistance   teamKills walkDistance weaponsAcquired
## 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 = ""))
```



5.2.1.4 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
```

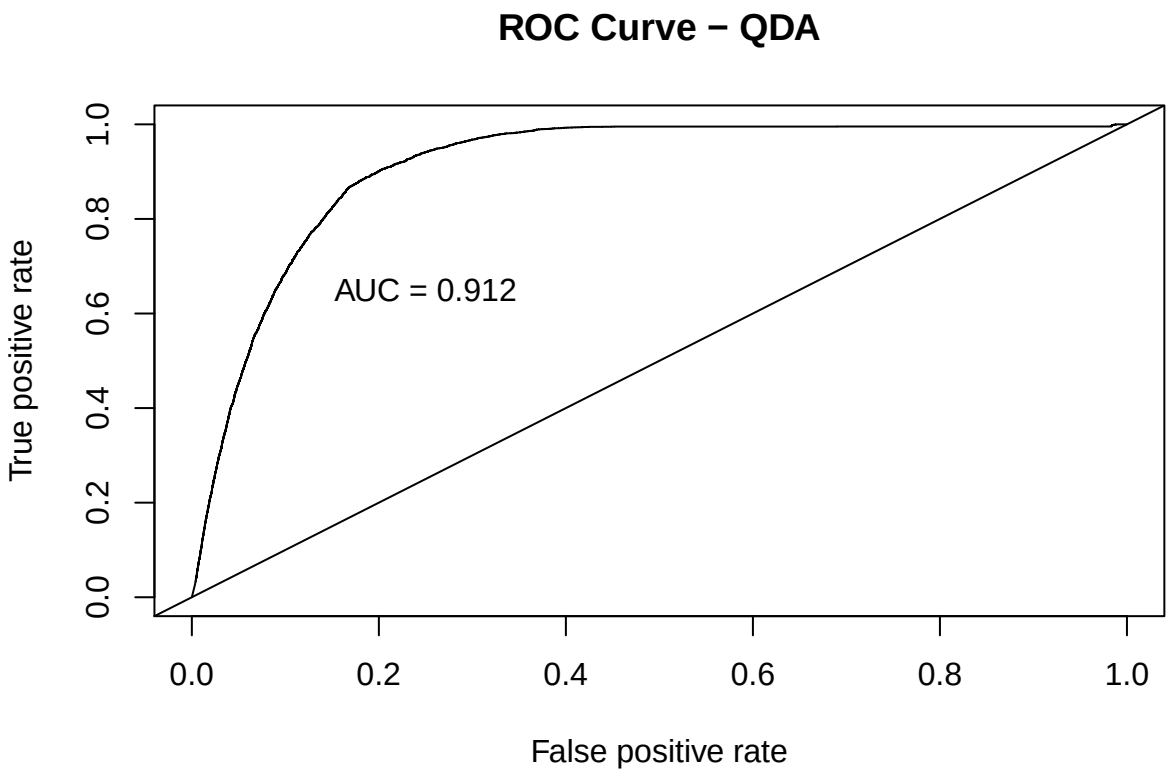
```r
predict <- predict(qda,newdata=test)

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)
# test_final$predcited_place<-as.factor(test_final$predcited_place)
str(test_final)
```

```
## 'data.frame':    54582 obs. of  31 variables:
##  $ Id             : chr  "5fd62798396ca8" "d08ce24e7a7973" "50820adcefc866" "029a693a75ef57" ...
##  $ groupId        : chr  "bb19a05801d30d" "d57ed9de010a4e" "212fc68772a25a" "11d78ae0ca90b6" ...
##  $ matchId        : chr  "9e3c46f8acde82" "1eda9747e31f1f" "c9259d5a2a4f19" "bfccecf5202cc8" ...
##  $ assists        : int  0 0 0 1 0 0 0 0 0 0 ...
##  $ boosts         : int  0 0 9 1 2 1 6 1 0 1 ...
##  $ damageDealt    : num  36 0 167.4 568.7 29.1 ...
##  $ DBNOs          : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ headshotKills  : int  0 0 1 1 0 0 0 0 0 0 ...
##  $ heals          : int  0 0 5 0 3 5 3 2 0 0 ...
##  $ killPlace      : int  84 65 12 3 53 60 16 69 52 57 ...
##  $ killPoints     : int  0 0 0 1339 1180 0 1297 977 0 0 ...
##  $ kills          : int  0 0 2 5 0 0 2 0 0 0 ...
##  $ killStreaks    : int  0 0 1 1 0 0 1 0 0 0 ...
##  $ longestKill    : num  0 0 82.6 92.8 0 ...
##  $ matchDuration  : int  1999 1471 1801 1964 1381 1892 1439 1976 1436 2190 ...
##  $ matchType      : chr  "solo" "solo" "solo" "solo" ...
##  $ maxPlace       : int  94 99 91 98 95 94 95 91 96 93 ...
##  $ numGroups      : int  92 94 85 92 93 90 93 87 92 91 ...
##  $ rankPoints     : int  1507 1500 1500 -1 -1 1500 -1 0 1492 1507 ...
##  $ revives        : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ rideDistance   : num  0 0 4146 5187 1093 ...
##  $ roadKills      : int  0 0 0 1 0 0 0 0 0 0 ...
##  $ swimDistance   : num  0 0 0 0 0 0 0 0 0 0 ...
##  $ teamKills      : int  0 0 0 0 0 0 0 0 0 0 ...
##  $ vehicleDestroys: int  0 0 0 0 0 0 0 0 0 0 ...
##  $ walkDistance   : num  293 871 3592 827 1135 ...
##  $ weaponsAcquired: int  1 3 7 4 2 5 2 2 3 4 ...
##  $ winPoints      : int  0 0 0 1537 1546 0 1596 1485 0 0 ...
##  $ winPlacePerc   : num  0.107 0.388 0.922 0.598 0.692 ...
##  $ top.10         : Factor w/ 2 levels "0","1": 1 1 2 1 1 1 1 1 1 1 ...
##  $ predcited_place: Factor w/ 2 levels "0","1": 1 1 2 2 1 1 2 1 1 1 ...
```

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

```
## Confusion Matrix and Statistics
##
##
##         0     1
##   0 44026  1810
##   1  4853  3893
##
##                Accuracy : 0.8779
##                  95% CI : (0.8752, 0.8807)
##     No Information Rate : 0.8955
##     P-Value [Acc > NIR] : 1
##
##                   Kappa : 0.4721
##
##  Mcnemar's Test P-Value : <2e-16
##
##             Sensitivity : 0.68262
##             Specificity : 0.90071
##          Pos Pred Value : 0.44512
##          Neg Pred Value : 0.96051
##              Prevalence : 0.10448
##          Detection Rate : 0.07132
##    Detection Prevalence : 0.16024
##       Balanced Accuracy : 0.79167
##
##        'Positive' Class : 1
##
```

```
# confusionMatrix(test_final$predcited_place, test_final$top.10)

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 - QDA")
abline(a=0, b= 1)
text(x = .25, y = .65 ,paste("AUC = ", round(auc.train[[1]],3), sep = ""))
```



5.2.2 Random Forest

5.2.2.1 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")))


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
```

5.2.2.2 Tuning Plot

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

5.2.2.3 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")
```

5.2.2.4 Predict

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

5.2.2.5 Confusion Matrix

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

5.2.2.6 ROC Curve

```
plotRoc <- function(preds, truth) {
  pred <- prediction(preds, truth)
  roc.perf = performance(pred, measure = "tpr", x.measure = "fpr")
  auc.train <- performance(pred, measure = "auc")
  auc.train <- auc.train@y.values
  #Plot ROC
  par(mar=c(4,4,4,4))
```

```
  plot(roc.perf,main="Random Forest")
  abline(a=0, b= 1) #Ref line indicating poor performance
  text(x = .40, y = .6,paste("AUC = ", round(auc.train[[1]],3), sep = ""))
  table(test$top.10, useNA = "ifany")
}



plotRoc(as.integer(prd.rf.test),as.integer(test.rf$top.10))

# ?randomForest
```