

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	Type	Description
DBNOs		Number of enemy players knocked.
assists		Number of enemy players this player damaged that were killed by teammates.

Column Name	Type	Description
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.
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.

Column Name	Type	Description
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 classifier 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 and 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 ***
```

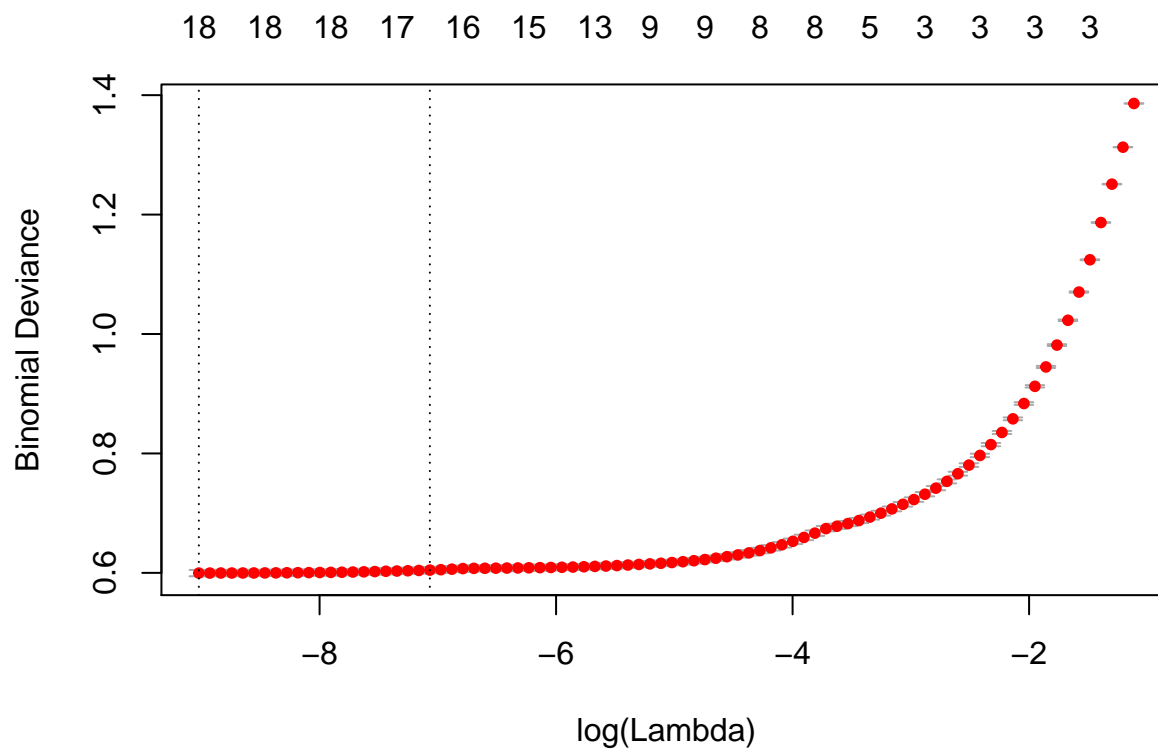
```
## killPoints      -1.578e-03  2.606e-04  -6.055  1.41e-09 ***
## rankPoints      3.995e-03  3.056e-04  13.074  < 2e-16 ***
## winPoints       5.282e-03  3.949e-04  13.376  < 2e-16 ***
## longestKill     -1.896e-03  4.007e-04  -4.732  2.22e-06 ***
## swimDistance    1.503e-03  3.705e-04  4.056  5.00e-05 ***
## 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:



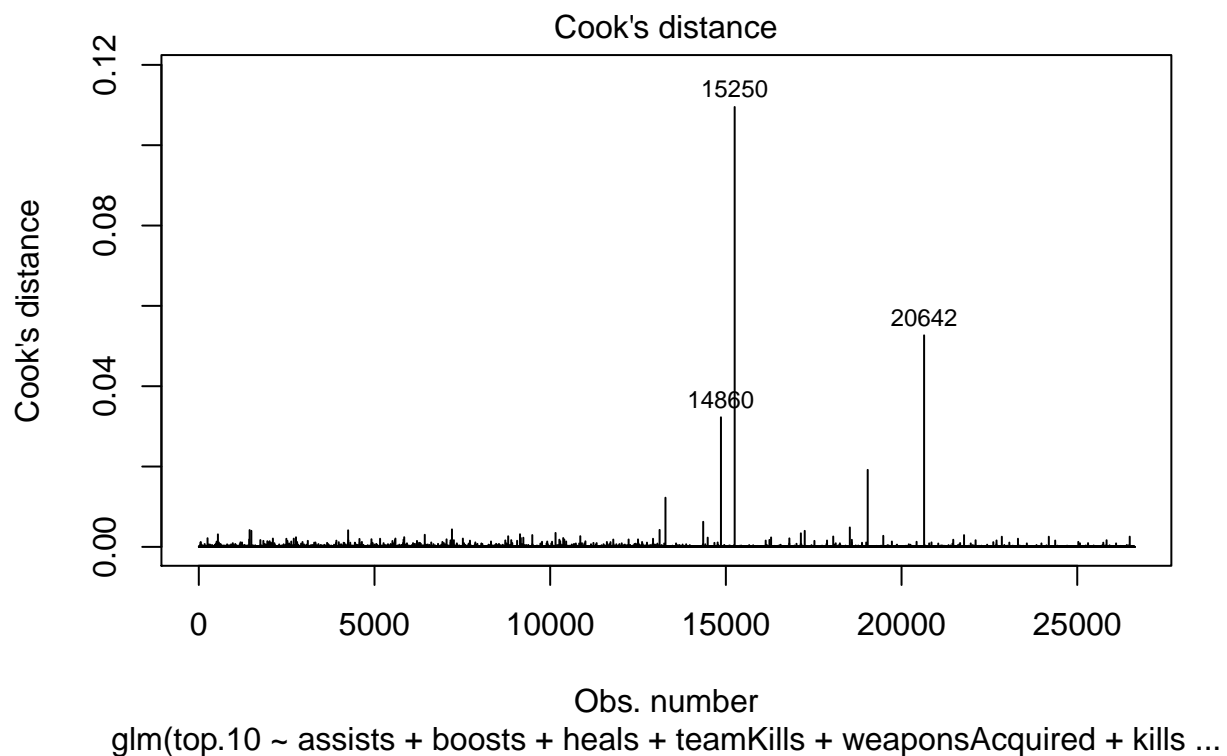
```
## 21 x 1 sparse Matrix of class "dgCMatrix"
##                               s0
## (Intercept)    -0.6733424558
## (Intercept)      .
## assists         0.6465602204
## boosts          0.3247910863
## heals           -0.0291791887
## teamKills       -1.9070440684
## weaponsAcquired 0.0445136944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

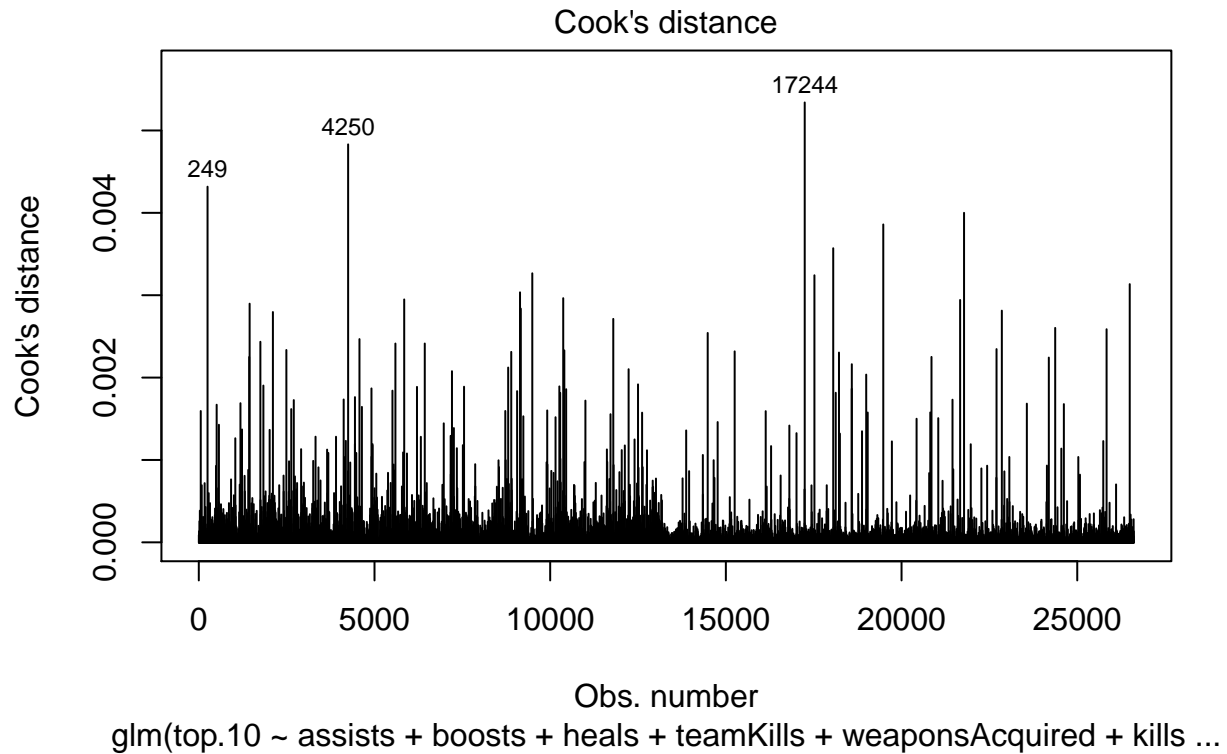
3.4 Final Iterations

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 coefficient 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 permutations 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. Fortunately, our data set had no null values to speak of which may have posed more of a problem.

4.2.2.2 Random Forest Results

The out-of-bag estimate of the error rate was 9.71% which seems to be consistent with our results against the test data not used to train the model with.

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

- Accuracy : 0.8964
- Sensitivity : 0.91811
- Specificity : 0.89384
- AUC : 0.90598

4.2.2.3 Random Forest Conclusion

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

The following arguments were important to address bias/ variance issues that we observed when using the default settings. Trial and error 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. Or rather, when it was in the top 10%, how often did we predict that it was and when it was in the bottom 90%, how often did we predict that it was respectively

- `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)
```

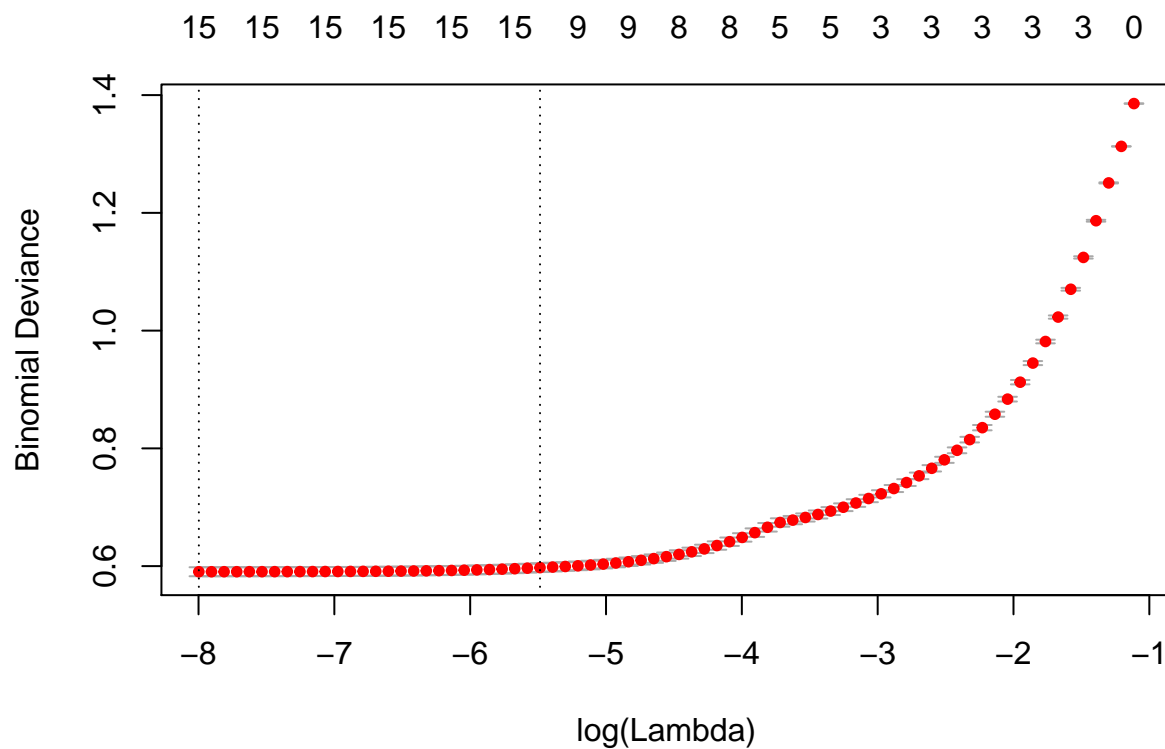
```
grid=10^seq(10,-2, length =100)
```

```
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"
```

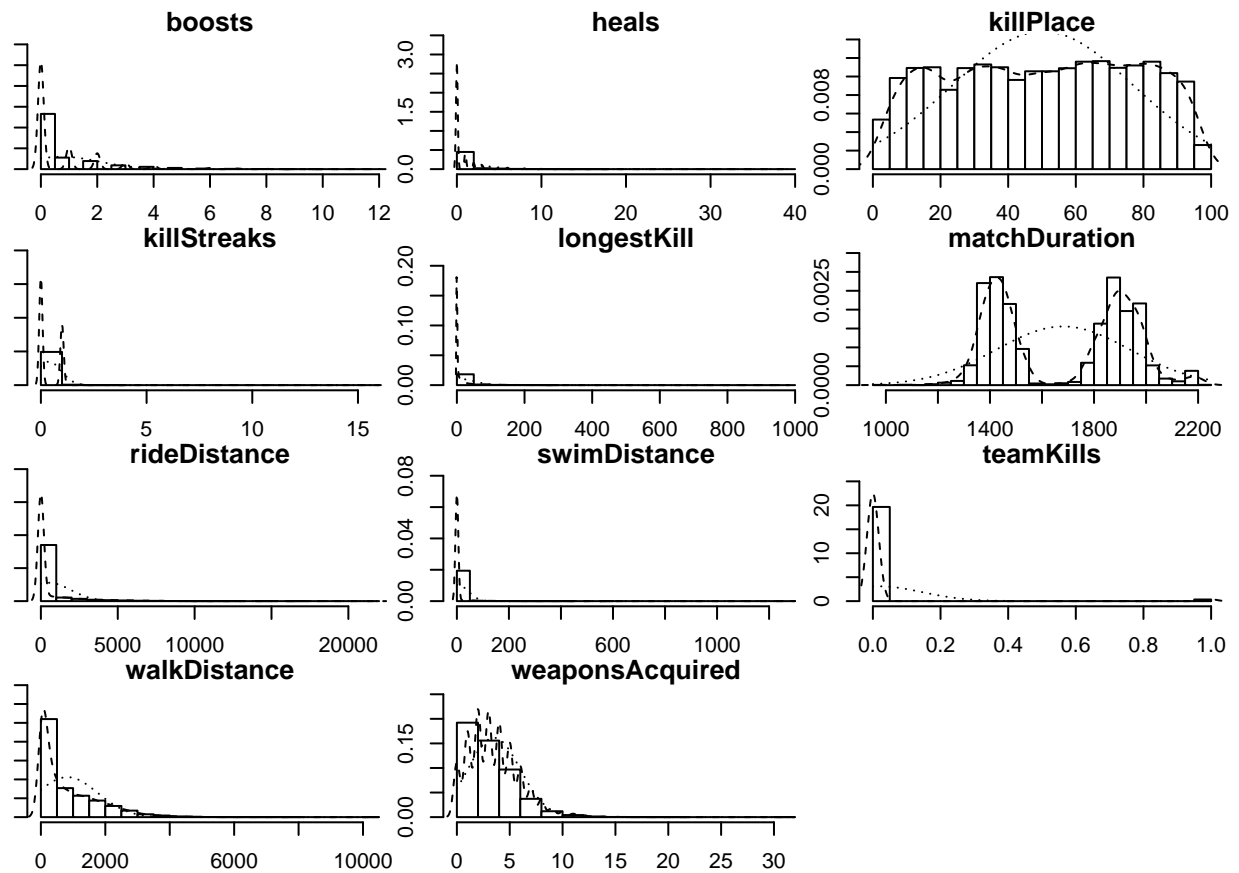
```
##              1
## (Intercept)  3.091783e+00
## boosts      2.672920e-01
## heals       -2.784586e-03
## killPlace    -8.033586e-02
## kills        .
## killStreaks -1.117635e+00
## longestKill  -5.733176e-05
## matchDuration -1.609689e-03
## rankPoints   1.034136e-05
## rideDistance  1.948066e-04
## roadKills     .
## swimDistance  5.967117e-04
## teamKills     -1.509184e+00
## vehicleDestroys .
## walkDistance  8.511812e-04
```

```
## weaponsAcquired 5.746021e-02
```

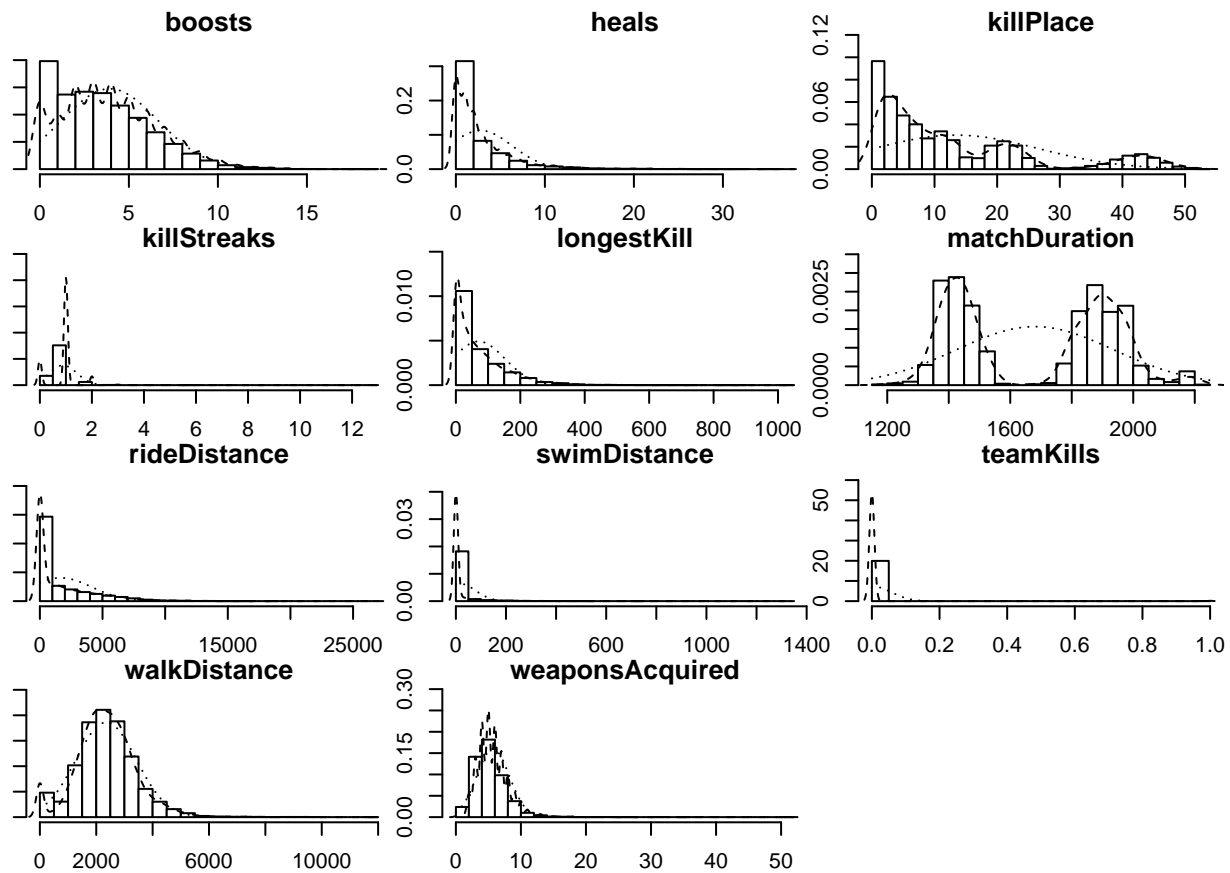
```
# Removing the kills, roadKills, and vehicleDestroys as shown above  
# Also removing rankPoints because  
# (a) the majority of the players in these data aren't ranked and  
# (b) the Kaggle description says "This ranking is inconsistent and is being deprecated in the API's next version"  
train_final <- 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
```

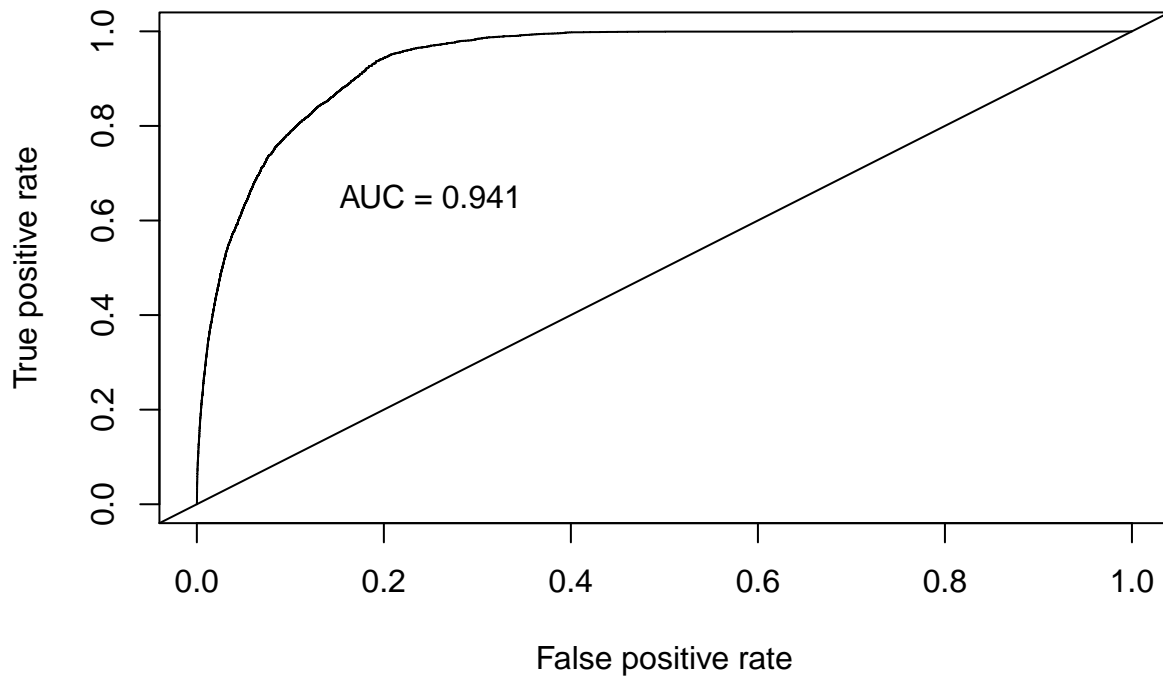
```
##
##           Kappa : 0.5582
##
## McNemar's Test P-Value : 3.998e-15
##
##           Sensitivity : 0.57479
##           Specificity : 0.96099
##           Pos Pred Value : 0.63221
##           Neg Pred Value : 0.95091
##           Prevalence : 0.10448
##           Detection Rate : 0.06006
##           Detection Prevalence : 0.09499
##           Balanced Accuracy : 0.76789
##
##           'Positive' Class : 1
##
```

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

# Evaluate the model
pred <- prediction(predict.posterioriors[,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 = ""))
```

ROC Curve – LDA



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
```

```

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 ...

```

```

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.posterior <- as.data.frame(predict$posterior)

```

```

# Evaluate the model

```

```

pred <- prediction(predict.posterior[,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 = ""))
```

