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GENBUS 656 Final Project

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Problem Statement

In the NFL, data analytics has greatly impacted on-field decisions and strategies, however, analysis for special teams plays has not advanced as quickly as they have for offense and defense. Many football coaches say special teams are a third of the game and are crucial to the field position battle within a game. Punt returns exemplify this, as they are now more common than kickoff returns and one long return can completely change the game.

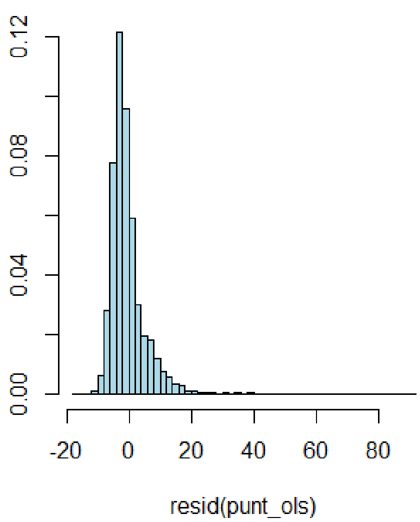
We have run the following analysis to predict results of punt returns and to determine what factors of the game indicate a long return. NFL teams and analysts can use our findings to formulate strategies on punt returns, from the type of punt to kick to whether the returner should call a fair catch or return the ball.

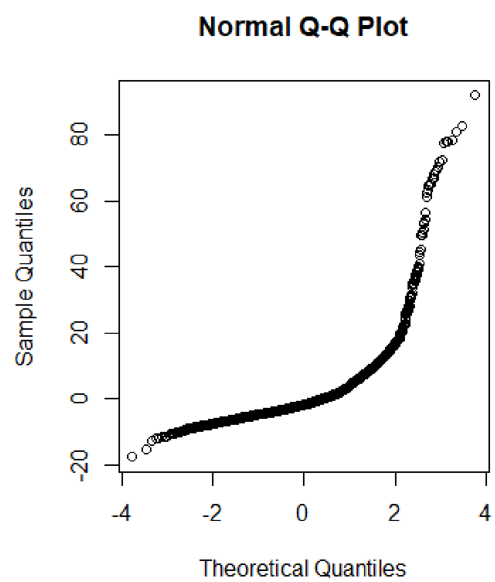
Analysis

To begin exploring the relationship between punt return yards and performance of the punting team, we started with a simple linear regression with the entire dataset. The model was to predict the number of punt return yards but it performed very poorly. This first linear regression model produced an R-squared of only 0.087, but it was more useful to learn which variables were the best predictors of punt return yardage to use going forward. Kick length, hang time and a binary variable for punt type were the most significant predictors. Kick length had a small, positive coefficient so as kick length increased, so did return yards by the other team. The same relationship was found between return yards and the binary variable for punt type, but we found that lower operation times and hang times decreased punt return yards. The linear regression model's full performance can be seen below.

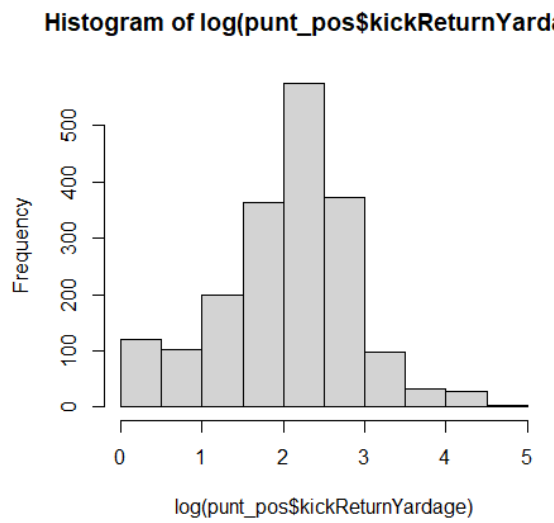
```
Coefficients: (1 not defined because of singularities)
                Estimate Std. Error t value Pr(>|t|)    
(Intercept)      1.01879    2.26790   0.449   0.6533    
kickLength       0.23369    0.01258  18.577  < 2e-16 ***
snapTime         2.04840    1.80119   1.137   0.2555    
operationTime   -1.88567    1.01287  -1.862   0.0627 .  
hangTime        -1.80136    0.22809  -7.898 3.37e-15 ***
blocked               NA         NA      NA       NA    
snapOK           0.76606    0.37270   2.055   0.0399 *  
normalKickType   1.57211    0.23582   6.667 2.86e-11 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 7.584 on 5864 degrees of freedom
  (49 observations deleted due to missingness)
Multiple R-squared:  0.087,	Adjusted R-squared:  0.08607 
F-statistic: 93.13 on 6 and 5864 DF,  p-value: < 2.2e-16
```

So now that we know which predictors are best and their relationships with return yards, we re-ran the linear regression model with only kick length, hang time and the normal kick type variable. This model performed slightly worse, with an R-squared of 0.086, and we can see on the plots below that the residuals for this model's predictions are not normally distributed.

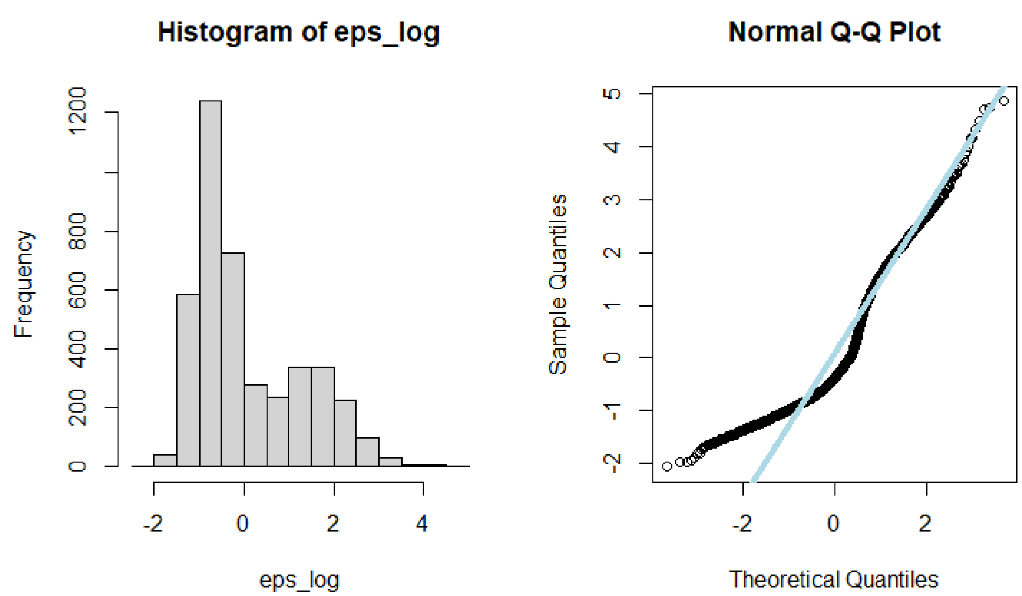




Because of this poor performance, we began exploring whether transforming our data could improve a linear regression's prediction power. We discovered that there were very few negative values for punt return yards so we decided to convert all negative values to zero, and then added one to all punt return yard values so we could do a log transformation. The distribution of log transformed punt return yards is much more normal and we proceeded using the transformed data.



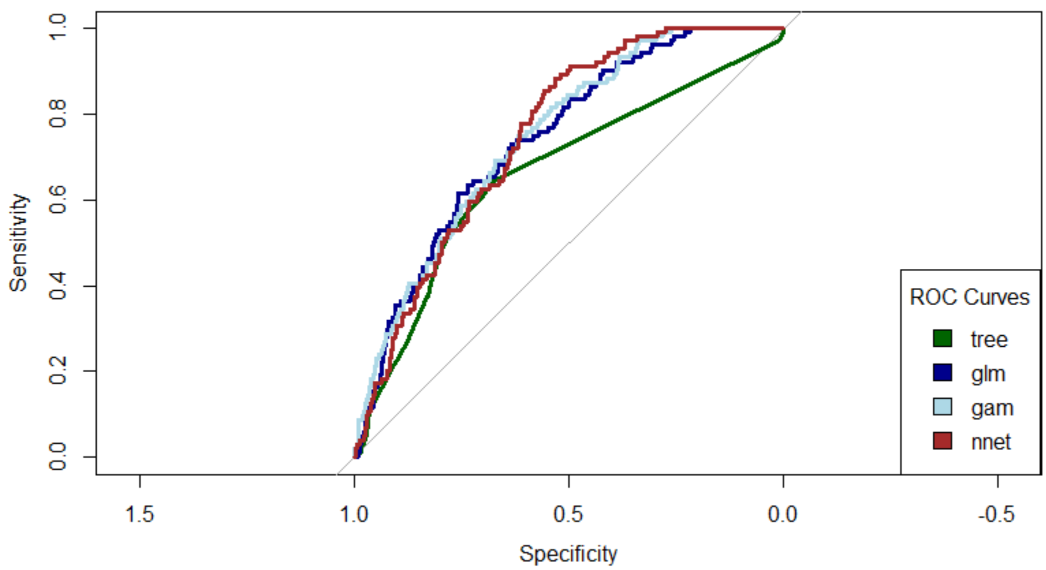
We created another linear regression model, now predicting the logarithm of punt return yards, and only using kick length, hang time and normal kick type as predictors like we did previously. This model produced the best R-squared so far at 0.1477. The in-sample and out-of-sample RMSE for this model were also very close, and the out-of-sample RMSE was 1.194. For out-of-sample performance, we can also see that the distribution of the residuals has evened out in the graphs below. The model performance is still not adequate, but it is markedly improved.



We subsequently ran ridge regression and LASSO regression models with the transformed data, but still only saw marginal improvement. In hopes of improving prediction power of return yards, we pivoted to using classification models. We created a new binary variable for explosive returns, or returns greater than 15 yards, to now predict. We also liked that these models could be more easily interpreted, and believe it would be more useful to predict long returns rather than the difference between a five-yard or ten-yard return.

The first classification model we ran was a logistic regression model, and again found that kick length, hang time and normal kick type were the most important predictors. The logistic regression model produced an ROC of 74.28 percent, which is significant improvement over the linear regression models.

To continue, we then created a classification tree, but this decreased our area under the curve to 66.38 percent. We proceeded to create general additive and neural net models, and the performance for all of our classification models is plotted below, based on ROC.



The classification tree struggled with correctly identifying explosive returns, but the other classification models performed similarly and fairly well, all with areas under the curve close to 75 percent. Because the neural net was slightly more successful at correctly predicting explosive returns, we would recommend this model using this model to evaluate punt returns.

Results

With this analysis, NFL teams and analysts can now know that longer kicks can lead to longer returns, as well as using a normal kick type. Hang time, however, has been proven to decrease explosive returns as it increases.

For teams punting, we recommend they now consider using rugby-style punts to decrease the chance of an explosive return. They should also not punt the ball so far that their coverage players are not able to pressure the returner, but punters should try to maximize hang time on their punts.

For when teams are receiving the ball, they can use this model to determine when to return the ball. If a returner sees that a punt is traveling far but is low with little hang time, then they should return the ball because they have a better chance at a return greater than 15 yards.

Coaches and analysts now have a more comprehensive way of evaluating their special teams units than they did before. They can also be more confident in which metrics to use when evaluating their team and making on-field decisions. With the recommended neural net model, they can use their teams' punt data to predict whether they, or the opposing team, are likely to give up explosive returns.