

# YAPR

'Yards Above Predicted Return'

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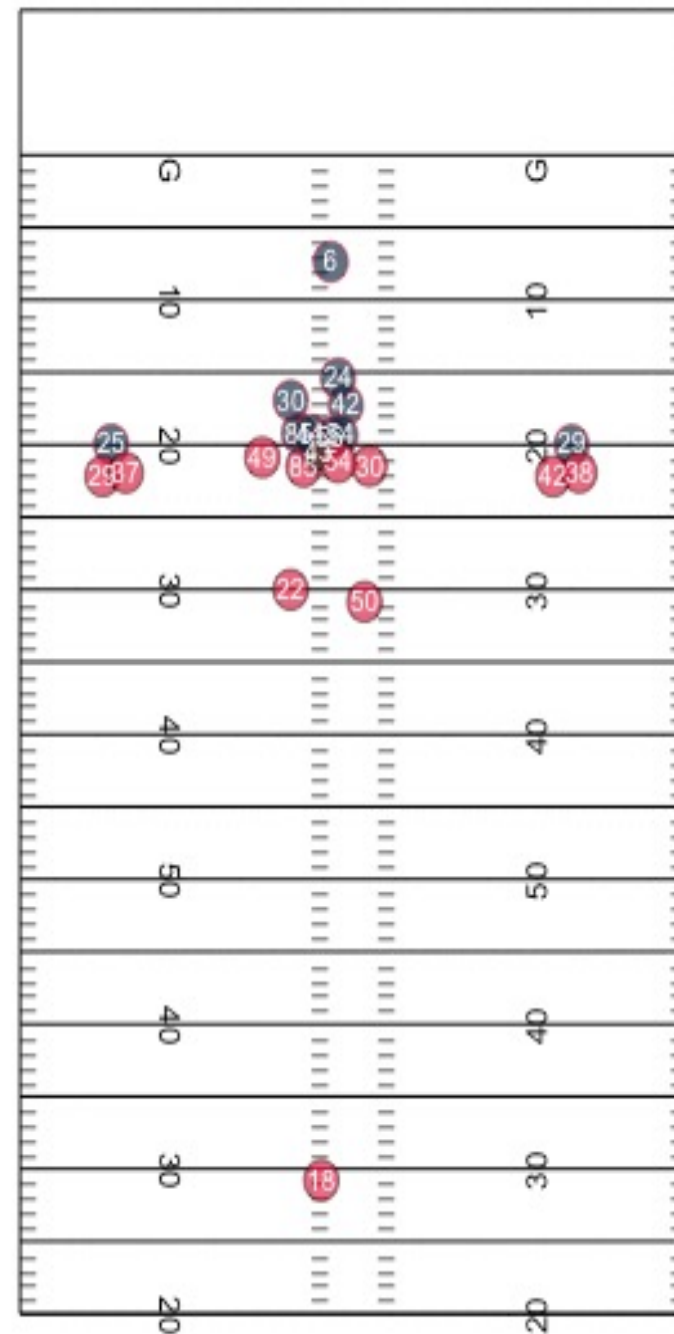






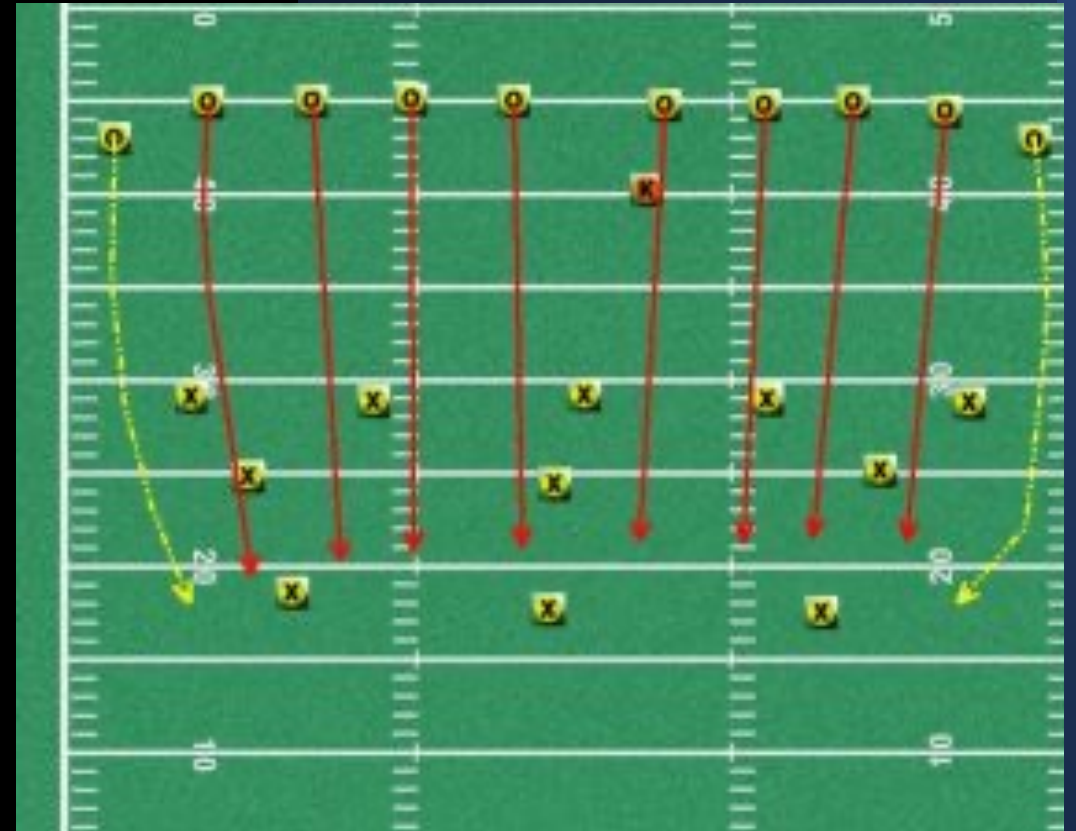
# 2022 NFL Big Data Bowl


- Annual Big Data Bowl
- Innovation with player tracking data
- Hosted by Kaggle
- The goal:
  - 1. Create a new special teams metric
  - 2. Quantify special teams strategy
  - 3. Rank special teams players



# Expected Return Yards

- How many yards will the returner gain at the moment they receive the ball?
- Variables used to determine Expected Return Yards
  - The yard line the ball was kicked to
  - The location the returner received the ball
  - Distance between returner and defenders (kickoff team)
  - Speed of defenders
  - Kick Type (Flat, Deep, or Pooch)
  - Catch Type (Dropped or Caught)





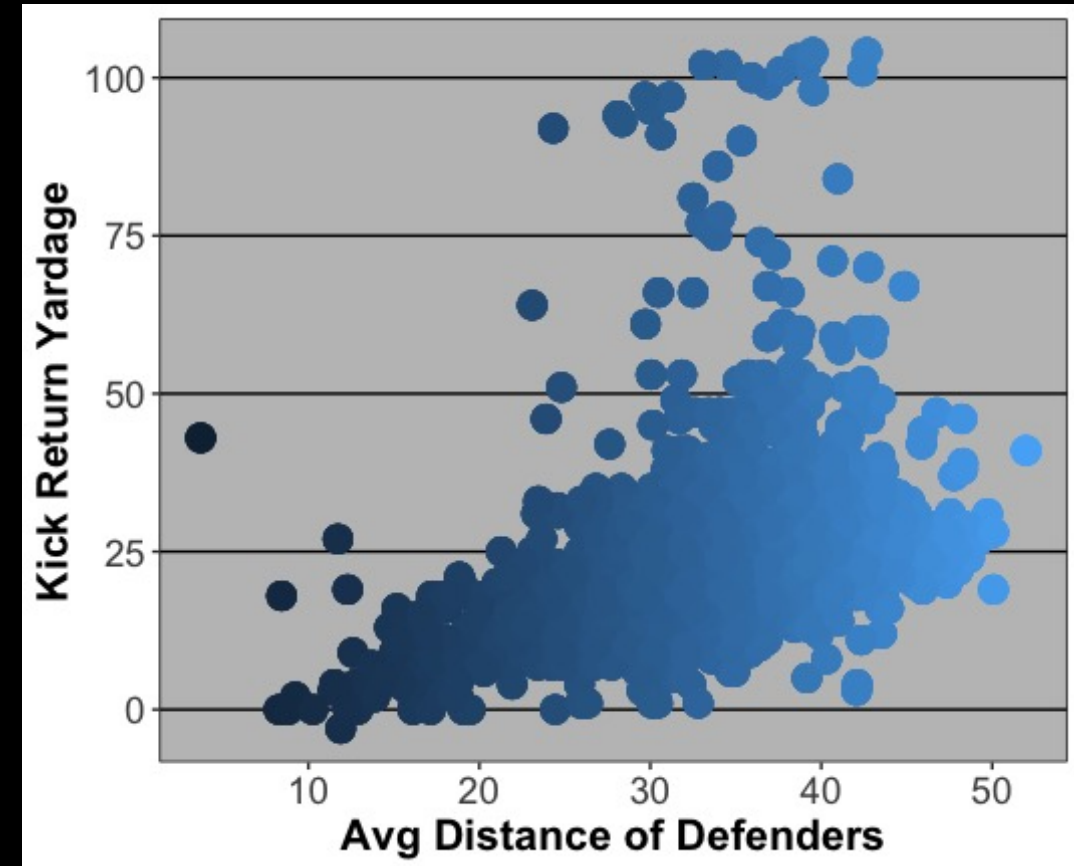
**YARD LINE RECEIVED:** -2 yds  
**AVG DEFENDER DISTANCE:** 33.7 yds  
**Y POSITION:** Right  
**KICK TYPE:** Deep  
**RESULT:** Return

**EXPECTED YARDS:** 26 yds  
**RESULT:** 24 yd line

**LOADING...**

# Why Use Machine Learning for Player Tracking Data?

- Ranking
  - Developing an understanding of successful and unsuccessful attributes
- Payment
  - Creating a tangible metric that can be associated with an increase in pay
- Health
  - Understanding the likelihood of an injury or other statistics that can help make the game safer





# Data Cleaning

- Removing NA values
  - Removed observations when football was tracked
- Filter
  - Kickoff plays only
  - Frame ID of 'Kick Received'
  - No squib or onside kicks
  - Returners only
    - Defenders become a separate feature

```
```{r}
sort(colSums(is.na(tracking2018)))
```
```

|               |          |        |             |
|---------------|----------|--------|-------------|
| time          | x        | y      | s           |
| 0             | 0        | 0      | 0           |
| a             | dis      | event  | displayName |
| 0             | 0        | 0      | 0           |
| team          | frameId  | gameId | playId      |
| 0             | 0        | 0      | 0           |
| playDirection | o        | dir    | nflId       |
| 0             | 555537   | 555537 | 555537      |
| jerseyNumber  | position |        |             |
| 555537        | 555537   |        |             |

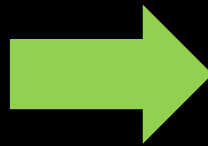
```
```{r}
table(tracking2018[is.na(tracking2018$nflId), "displayName"])
```
```

```
football
555537
```

# Data Cleaning (Continued)

| Display Name | X     | Y     | Team | Returner? |
|--------------|-------|-------|------|-----------|
| Player 1     | 39.08 | 24.57 | Home | No        |
| Player 2     | 41.11 | 32.25 | Home | No        |
| Player 3     | 43.08 | 38.77 | Home | No        |
| Player 4     | 2.5   | 30.5  | Home | Yes       |
| Player 5     | 44.11 | 24.92 | Home | No        |
| Player 6     | 43.9  | 21.75 | Home | No        |
| Player 7     | 39.07 | 41.27 | Home | No        |
| Player 8     | 45.07 | 49.79 | Home | No        |
| Player 9     | 32.17 | 38.71 | Home | No        |
| Player 10    | 50.5  | 46.24 | Home | No        |
| Player 11    | 21.67 | 43.81 | Home | No        |
| Defender 1   | 34.23 | 31.98 | Away | No        |
| Defender 2   | 50.44 | 17.86 | Away | No        |
| Defender 3   | 43.95 | 27.63 | Away | No        |
| Defender 4   | 39.83 | 44.49 | Away | No        |
| Defender 5   | 40.75 | 33.99 | Away | No        |
| Defender 6   | 11.53 | 42.45 | Away | No        |
| Defender 7   | 44.18 | 42.04 | Away | No        |
| Defender 8   | 37.43 | 29.16 | Away | No        |
| Defender 9   | 20.92 | 38.29 | Away | No        |
| Defender 10  | 33.04 | 34.62 | Away | No        |
| Defender 11  | 33.75 | 35.52 | Away | No        |

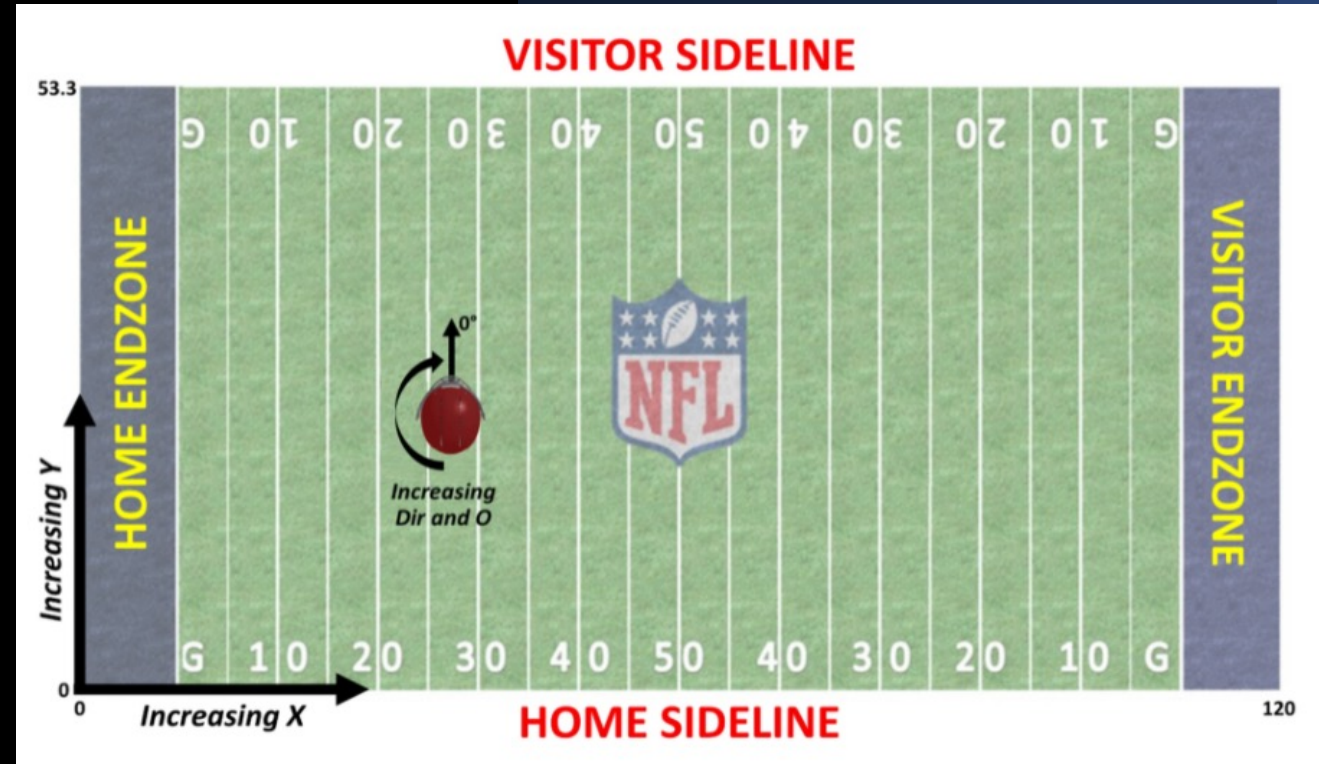
Expanding the data so we go from 1 observation for each player, we have 11 observations for each player to include defenders.



| Display Name | X   | Y    | Team | Returner? | Defender    | X    | Y    |
|--------------|-----|------|------|-----------|-------------|------|------|
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 1  | 41.3 | 10.2 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 2  | 41.5 | 15.3 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 3  | 40.6 | 20.4 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 4  | 41.5 | 22.1 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 5  | 41.5 | 23.4 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 6  | 43.2 | 25.2 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 7  | 40.2 | 35.5 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 8  | 42.5 | 39.3 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 9  | 40.6 | 45.6 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 10 | 41.1 | 50.3 |
| Player 4     | 2.5 | 30.5 | Home | Yes       | Defender 11 | 43.8 | 58.2 |

# Feature Engineering

- Distance (Pythagorean Theorem Used)
- Yard Result
  - YardResult\_Over25 (1 = yes)
- Yard line 'Kicked To'
  - 5 Yard Bin 'Kicked To'
- Y\_Position (Left, Right, or Center)
- Defender Variables
  - Average Distance
  - Average Speed
  - Average Acceleration







# Modeling Stages

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- Linear Regression
- Logistic Regression for 25 Yard line
- ElasticNet
- Random Forest

# Linear Regression

Adjusted  $R^2 = .30$

- As the yard line kicked to decreases by 1 yard, or the further the ball is kicked, the returner typically gains .28 more yards
- As the average distance between the defenders and the returners increases by 1, the returner typically gains an average of .43 more yards.

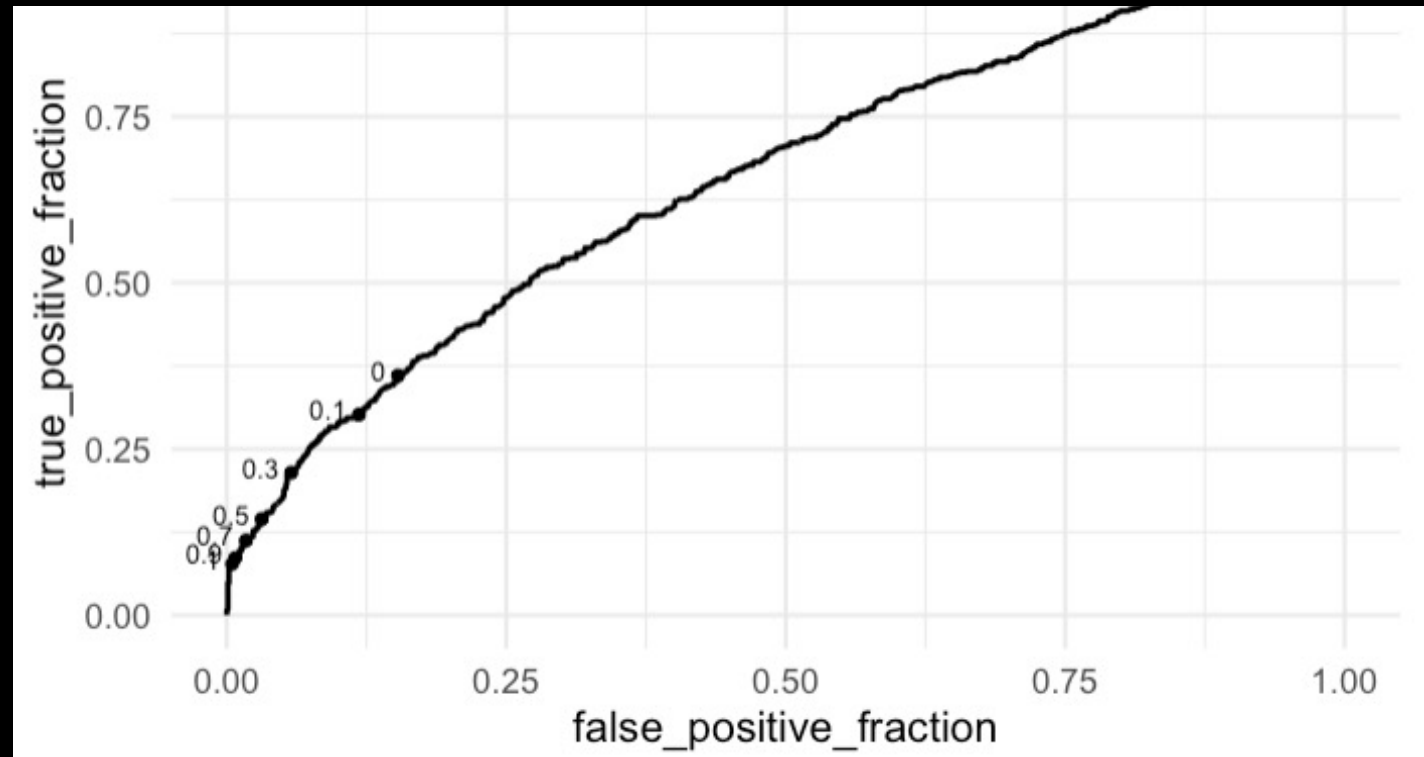
| <i>Predictors</i>           | <b>kick Return Yardage</b> |               |                  |
|-----------------------------|----------------------------|---------------|------------------|
|                             | <i>Estimates</i>           | <i>CI</i>     | <i>p</i>         |
| (Intercept)                 | -4.09                      | -8.53 – 0.35  | 0.071            |
| kickedto yardline           | -0.28                      | -0.36 – -0.19 | <b>&lt;0.001</b> |
| KoTeamAvgDist               | 0.43                       | 0.35 – 0.52   | <b>&lt;0.001</b> |
| KoTeamAvgA                  | 1.09                       | 0.28 – 1.89   | <b>0.008</b>     |
| Y position [left]           | -0.82                      | -1.53 – -0.12 | <b>0.022</b>     |
| Y position [right]          | -0.98                      | -1.69 – -0.27 | <b>0.007</b>     |
| kickType [F]                | 1.00                       | -0.27 – 2.26  | 0.123            |
| kickType [P]                | -2.62                      | -3.76 – -1.49 | <b>&lt;0.001</b> |
| specialTeamsResult [Return] | 10.15                      | 8.22 – 12.07  | <b>&lt;0.001</b> |
| Observations                | 2576                       |               |                  |
| $R^2$ / $R^2$ adjusted      | 0.299 / 0.296              |               |                  |

# Modeling Performance

ROC Plot

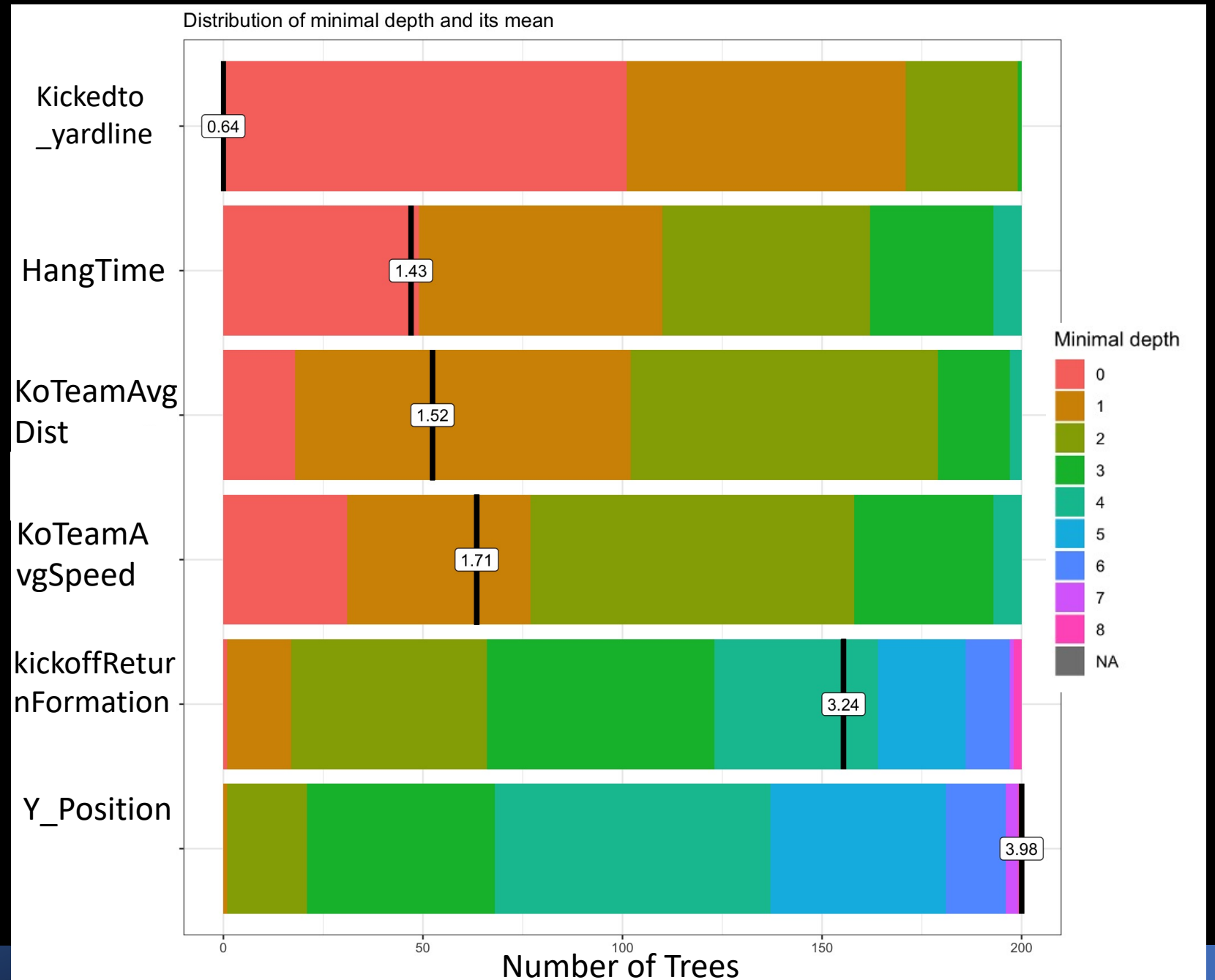
## Logistic Regression

- The AUC for the training and testing sets were .65 and .64 respectively



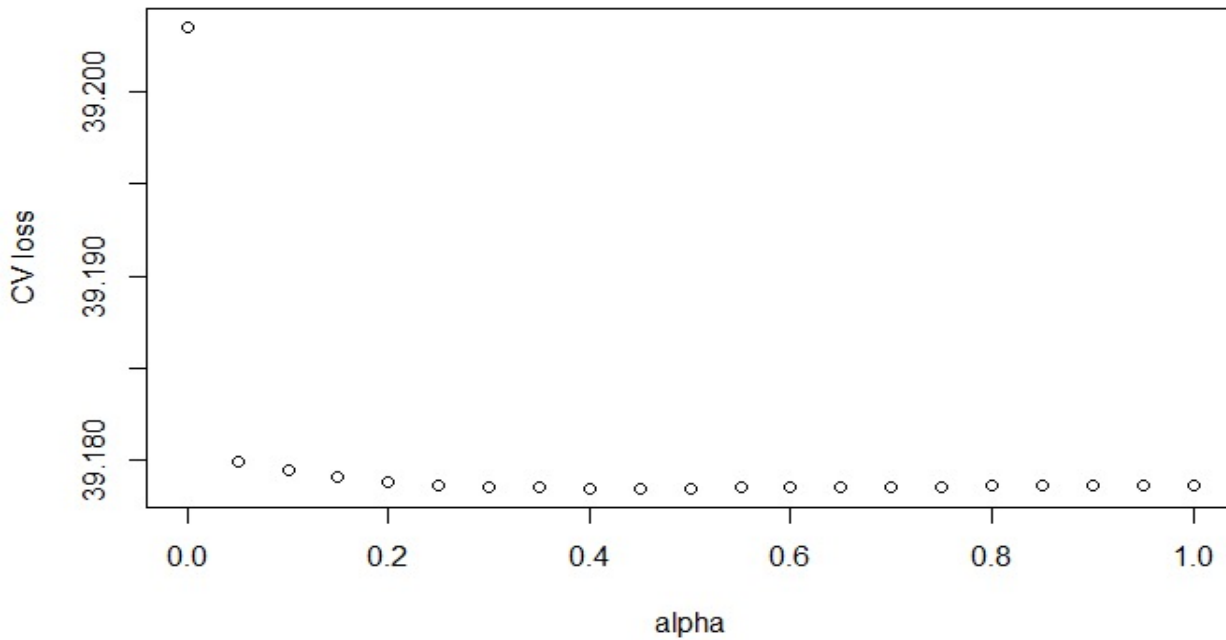
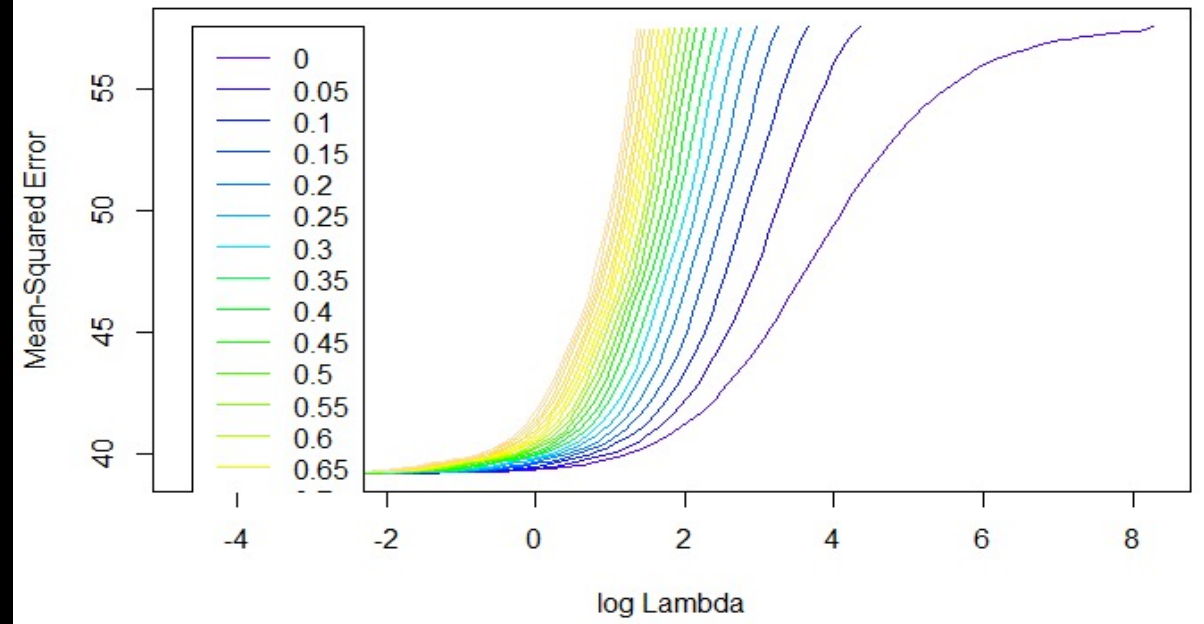


# Random Forest



# ElasticNet

| Best alpha | Lambda.min | Lambda.1se | Error |
|------------|------------|------------|-------|
| 0.45       | 0.039      | 1.10       | 39.18 |



## 1. Metrics from 'Expected Return Yards' Model

**Expected Return Yards:** Yards a returner is expected to gain given X's

**Efficiency:** (Actual Return Yards – Expected Return Yards)

**25 Yard Line Probability:** Likelihood of a returner reaching 25-yard line

## 2. Quantify Special Teams Strategy

- A player can have an idea of when they should or should not return the ball out of the endzone at the moment of catching the ball

## 3. Ranking Players

- Efficiency can be measured and used to rank special teams players

How This Can Be  
Adopted?



# Thank You

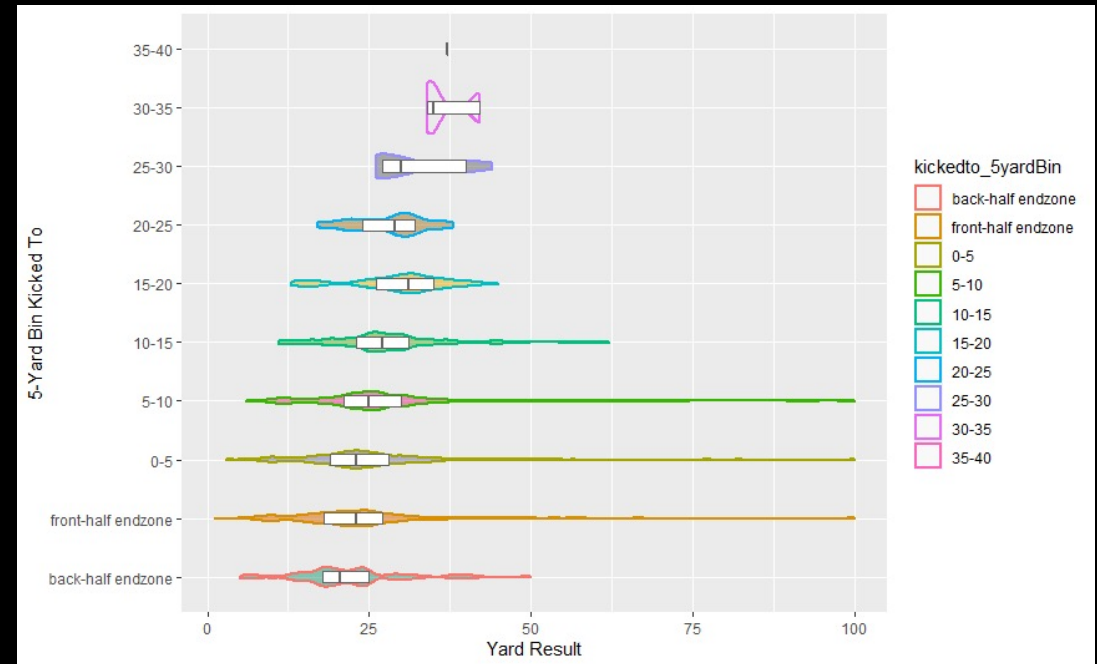
- Any Questions?

# Appendix

# Average Yard Result based on Kick\_to bins

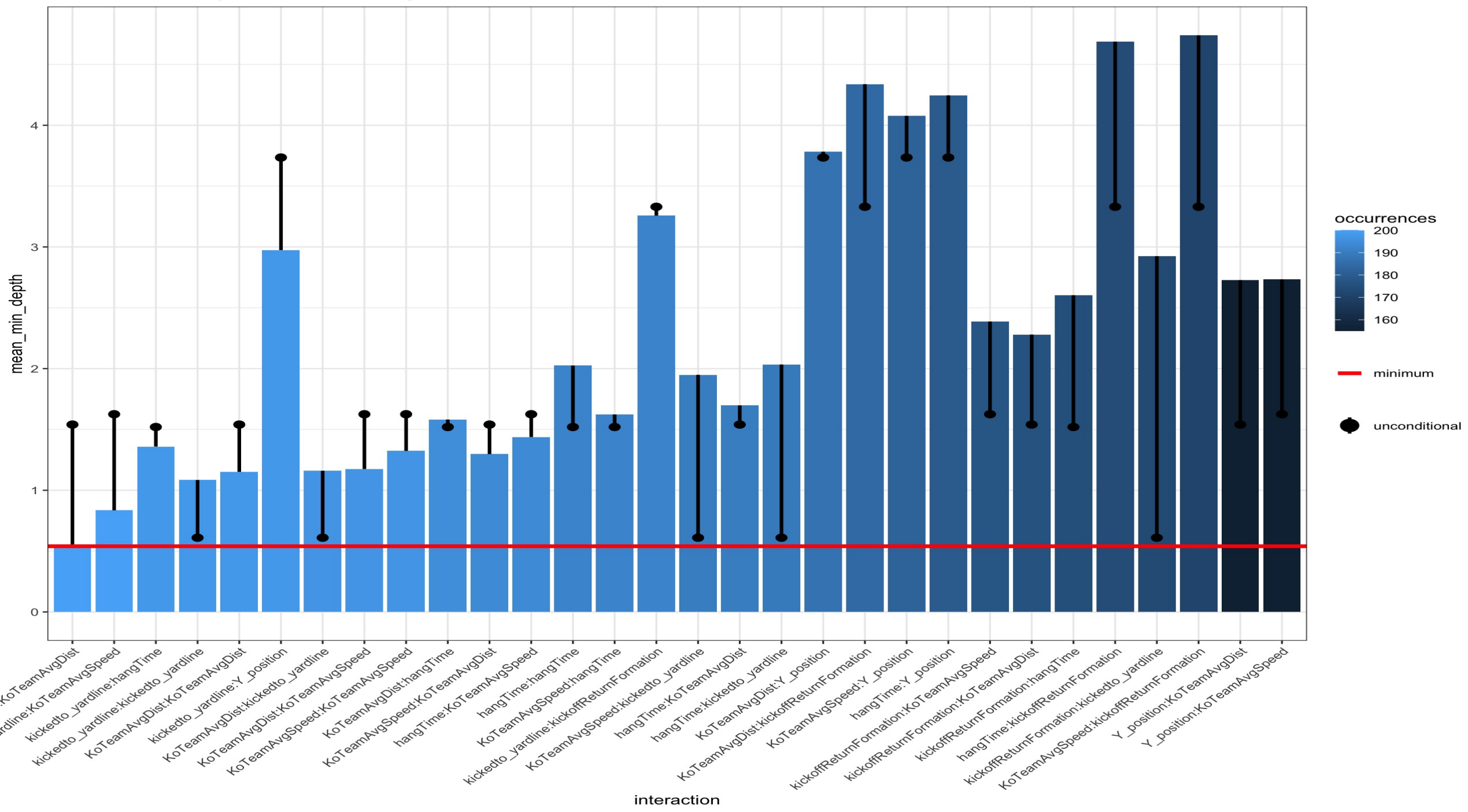
```
```{r}
#Here I am making a shortcut for the ggplot of the returns plot with Bin and yard result
g <- ggplot(returns, aes(x = kickedto_5yardBin, y = yard_result, color = kickedto_5yardBin)) +
  labs(x = '5-Yard Bin Kicked To', y = 'Yard Result')

#Since Boxplots are boring, I made a violin plot instead
g + geom_violin(aes(fill = kickedto_5yardBin), size = 1, alpha = .5) +
  geom_boxplot(outlier.alpha = 0, coef = 0,
    color = "gray40", width = .2) +
  scale_fill_brewer(palette = "Dark2", guide = "none") +
  coord_flip()
```
```

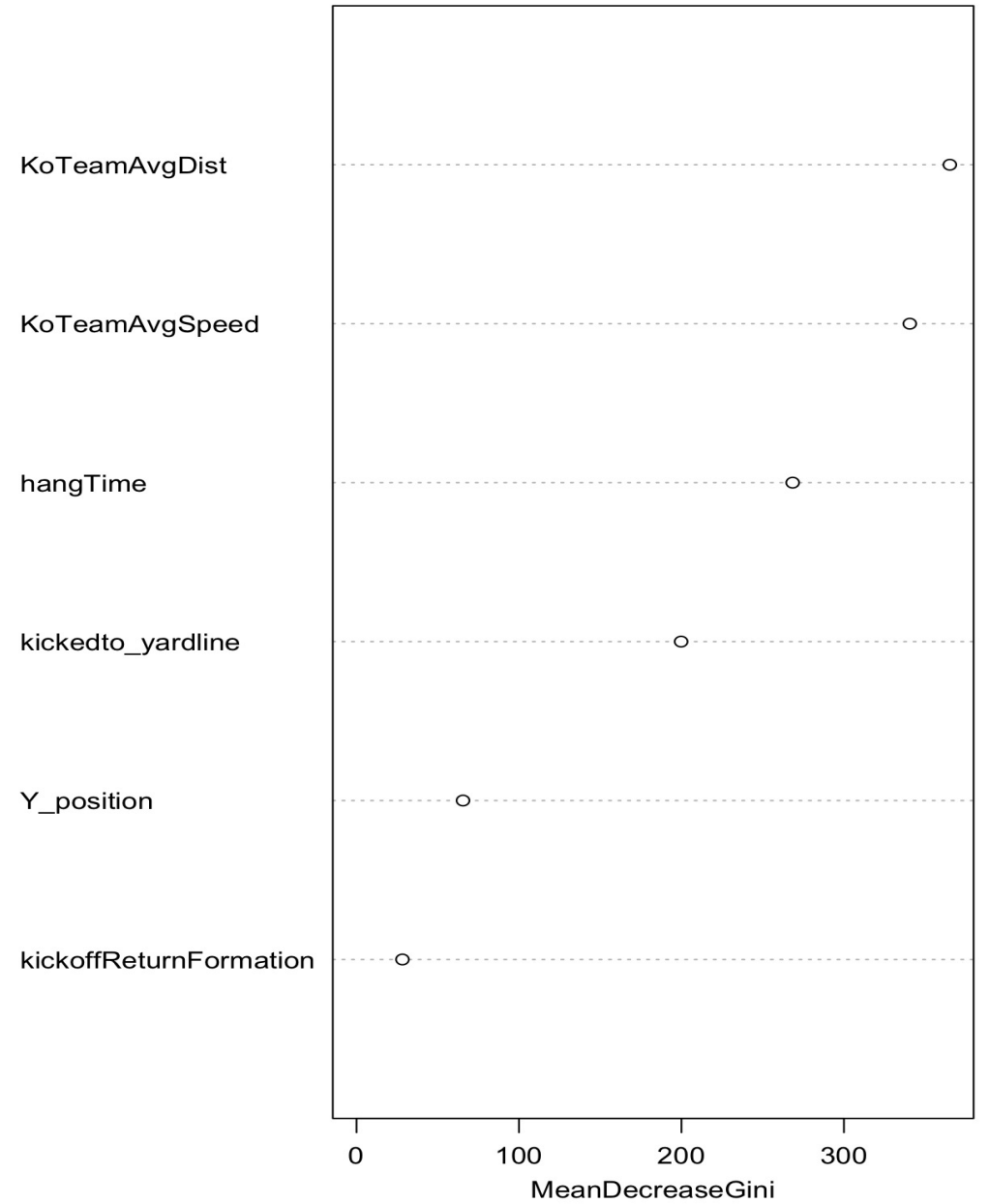
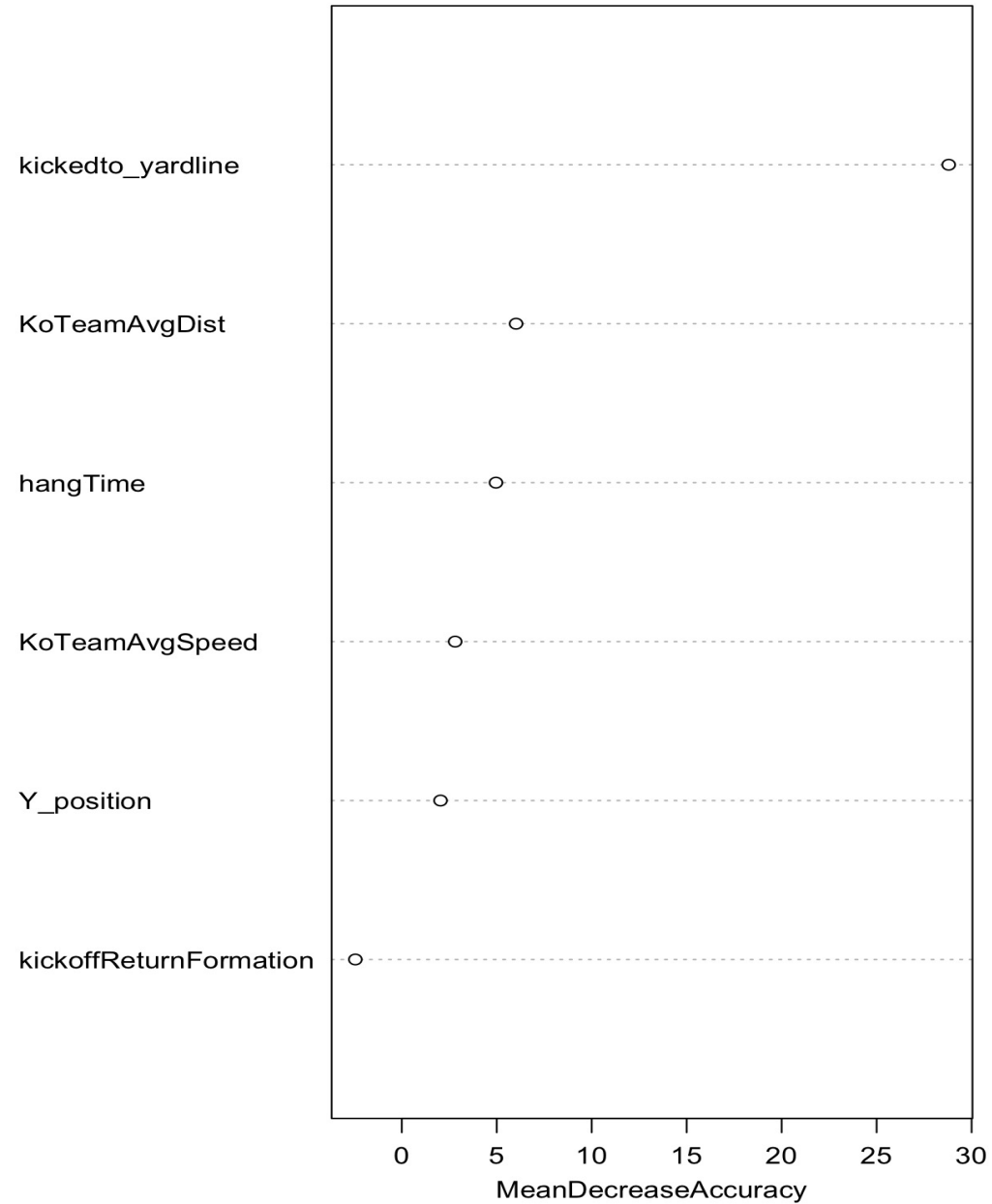




Mean minimal depth for 30 most frequent interactions



NFL\_rf\_fit2

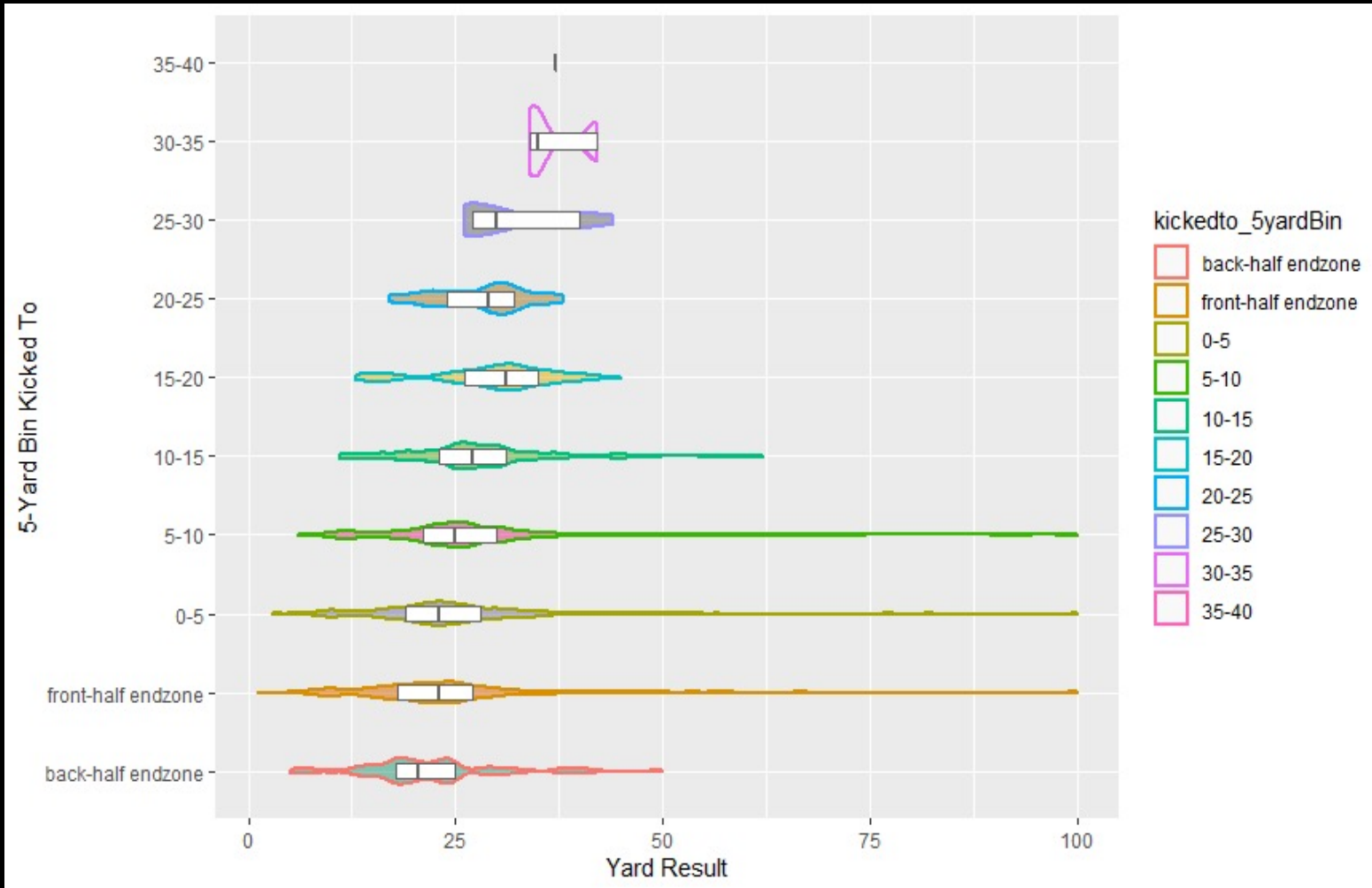


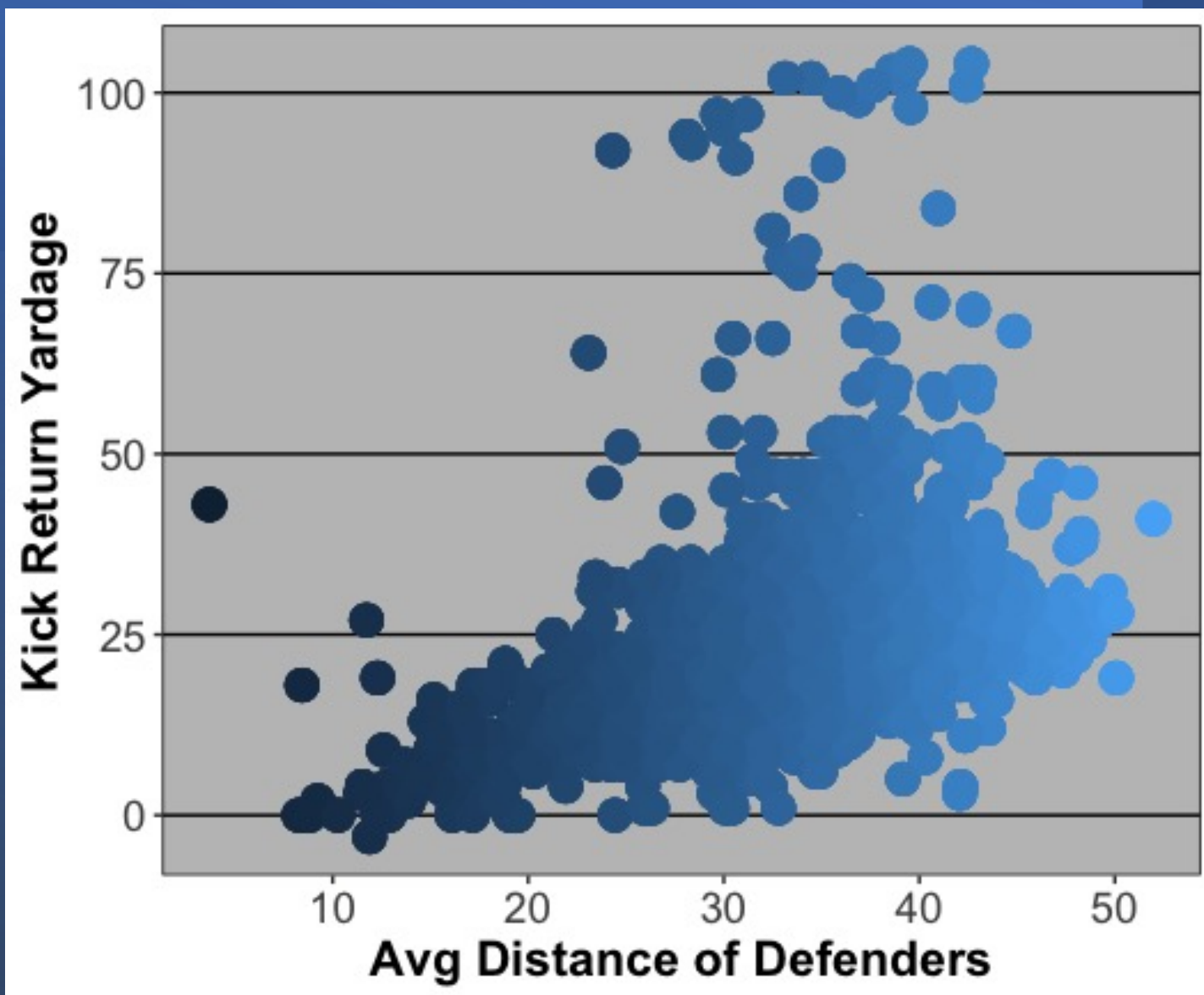
# Average Yard Result based on Yard-line Kick to bins

```
##{r}
#Here I am making a shortcut for the ggplot of the returns plot with Bin and yard result

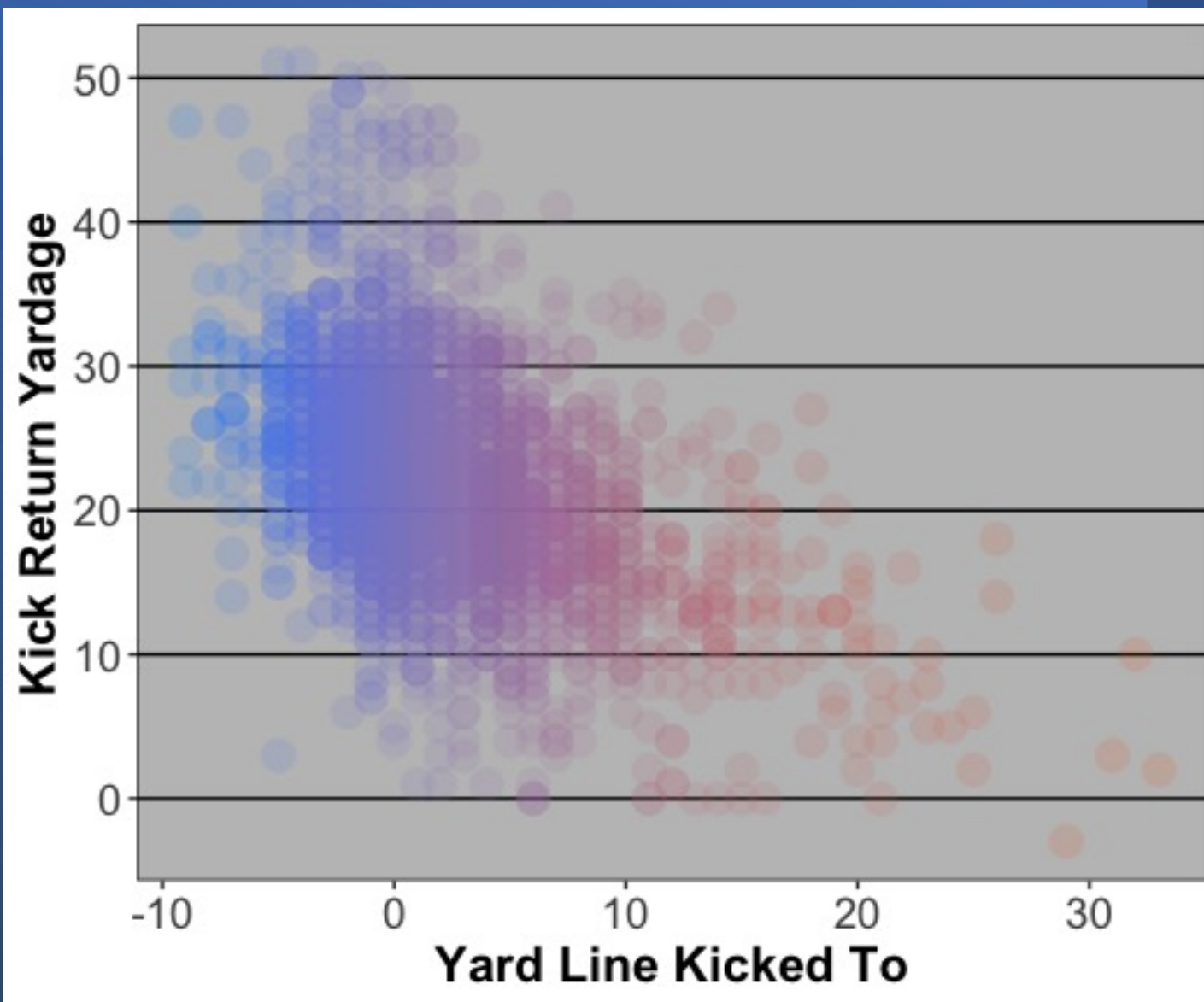
g <- ggplot(returns, aes(x = kickedto_5yardBin, y = yard_result, color = kickedto_5yardBin)) +
  labs(x = '5-Yard Bin Kicked To', y = 'Yard Result')

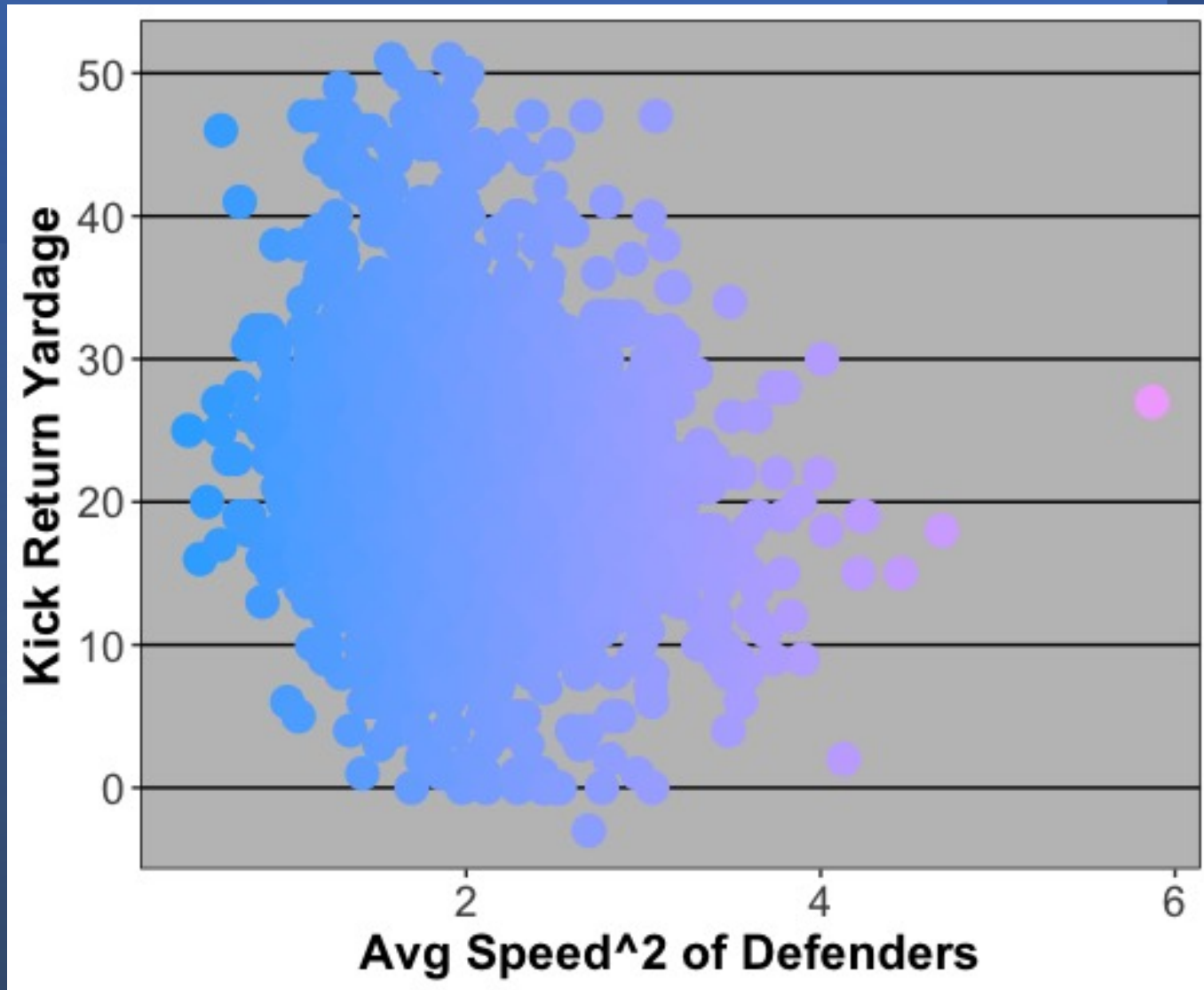
#since boxplots are boring, I made a violin plot instead
b + geom_violin(aes(fill = kickedto_5yardBin), size = 1, alpha = .5) +
  geom_boxplot(outlier.alpha = 0, coef = 0,
    color = "gray40", width = .2) +
  scale_fill_brewer(palette = "Dark2", guide = "none") +
  coord_flip()
```

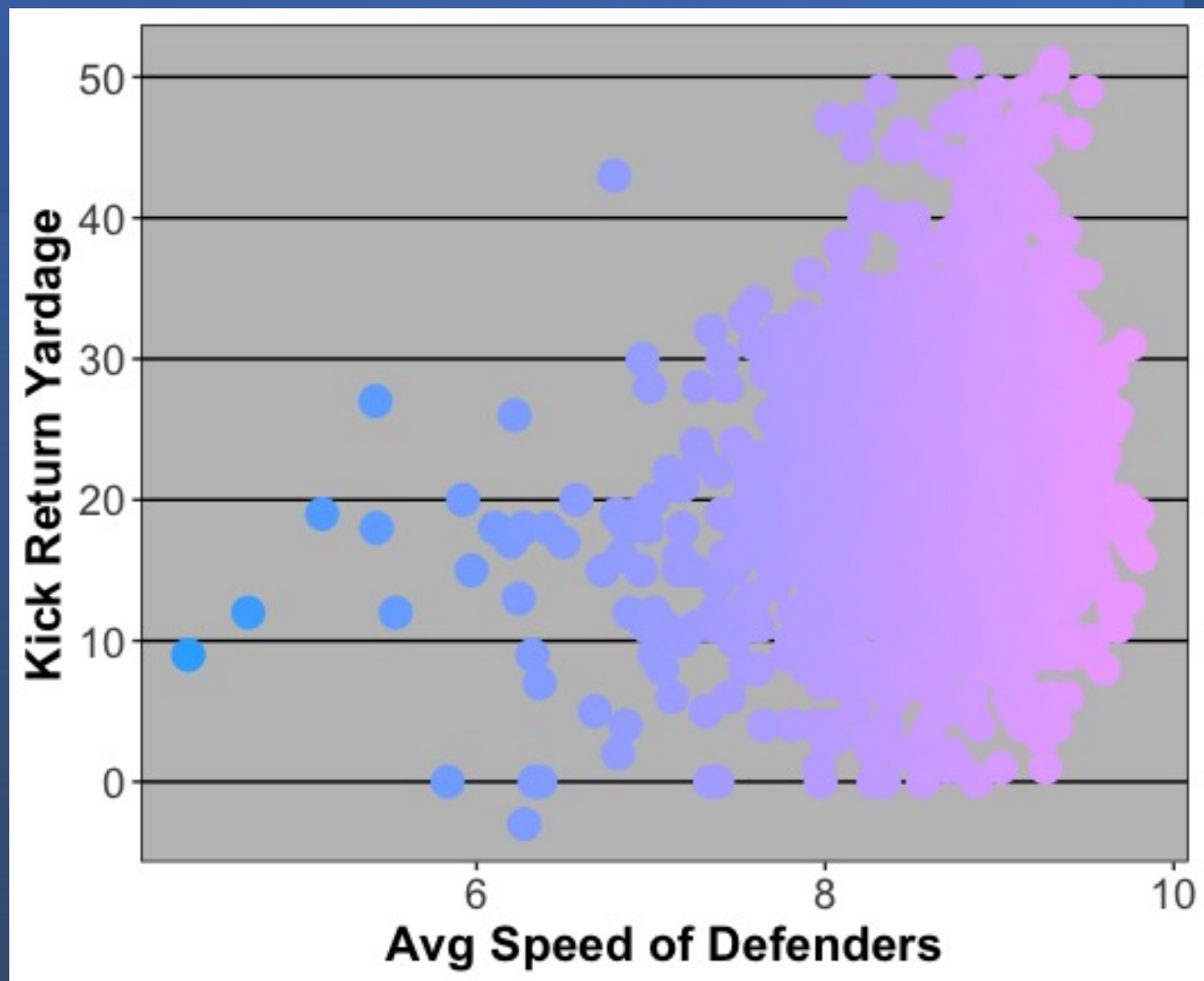












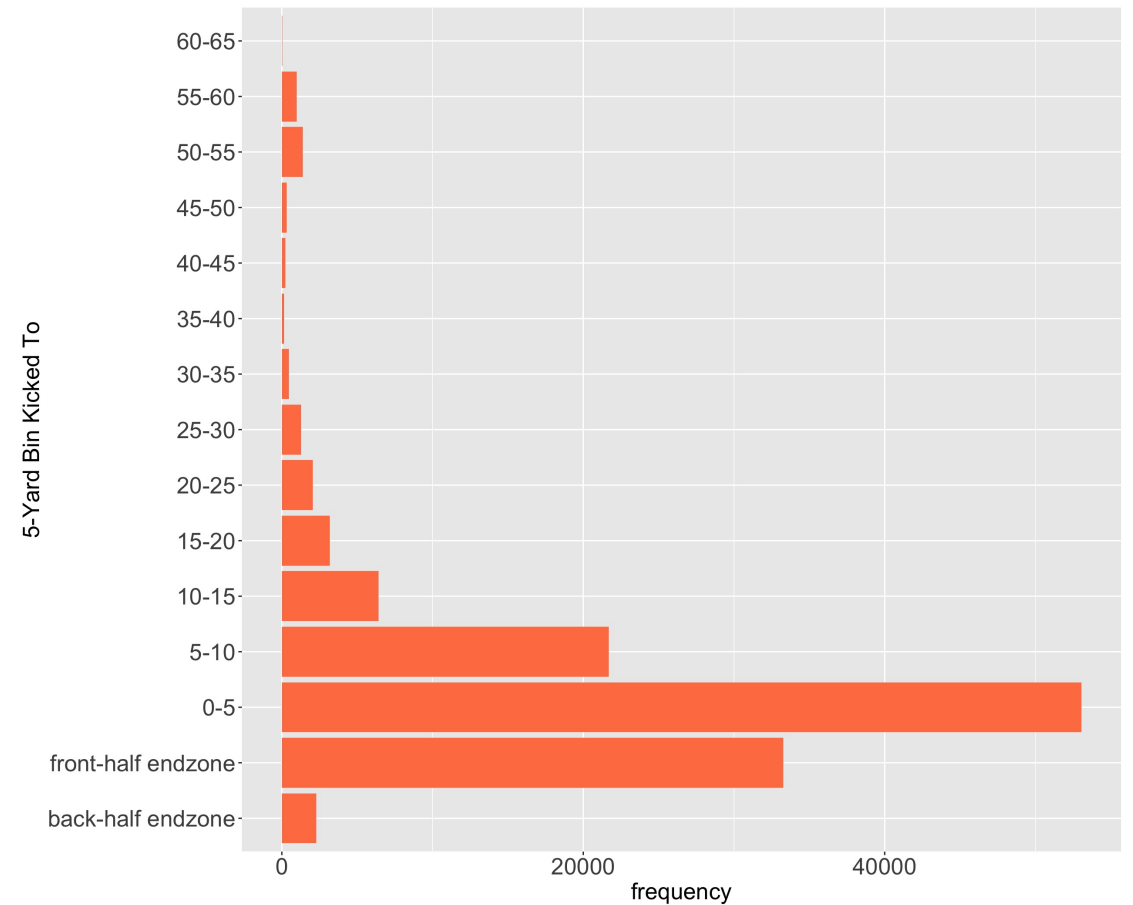
```

```{r}

ggplot(kickoff_returns, aes(x = kickedto_5yardBin)) +
  geom_histogram(stat = "count") +
  coord_flip() +
  xlab('5-Yard Bin Kicked To') +
  ylab('frequency') +
  theme(axis.text=element_text(size=18),
        axis.title = element_text(size=18))

```

```





Multi-way importance plot

