Kickoff Return Success

Curtis M Hope Hill

Presentation Road Map

01 Background

Special Teams & Importance of Kick Returns

02 Data Process

Data Cleaning, EDA & Preprocessing

03 Modeling

Models to predict kick return success.

Problem Statement

NFL Football Team ® has contracted with Hope Hill Data Science to examine special teams plays from the 2018 season to understand factors impacting kickoff return success. A satisfactory project will involve producing a model that is able to predict a successful return at a higher rate than the average from the 2018 season.

"There's three parts to football: offense, defense, and special teams. You'd no more ignore special teams than you would offense or defense."

—Marv Levy

SPECIAL TEAMS

Kicking Game

Kickoffs, Punts, Field Goals, & Point After Att.

Field Position

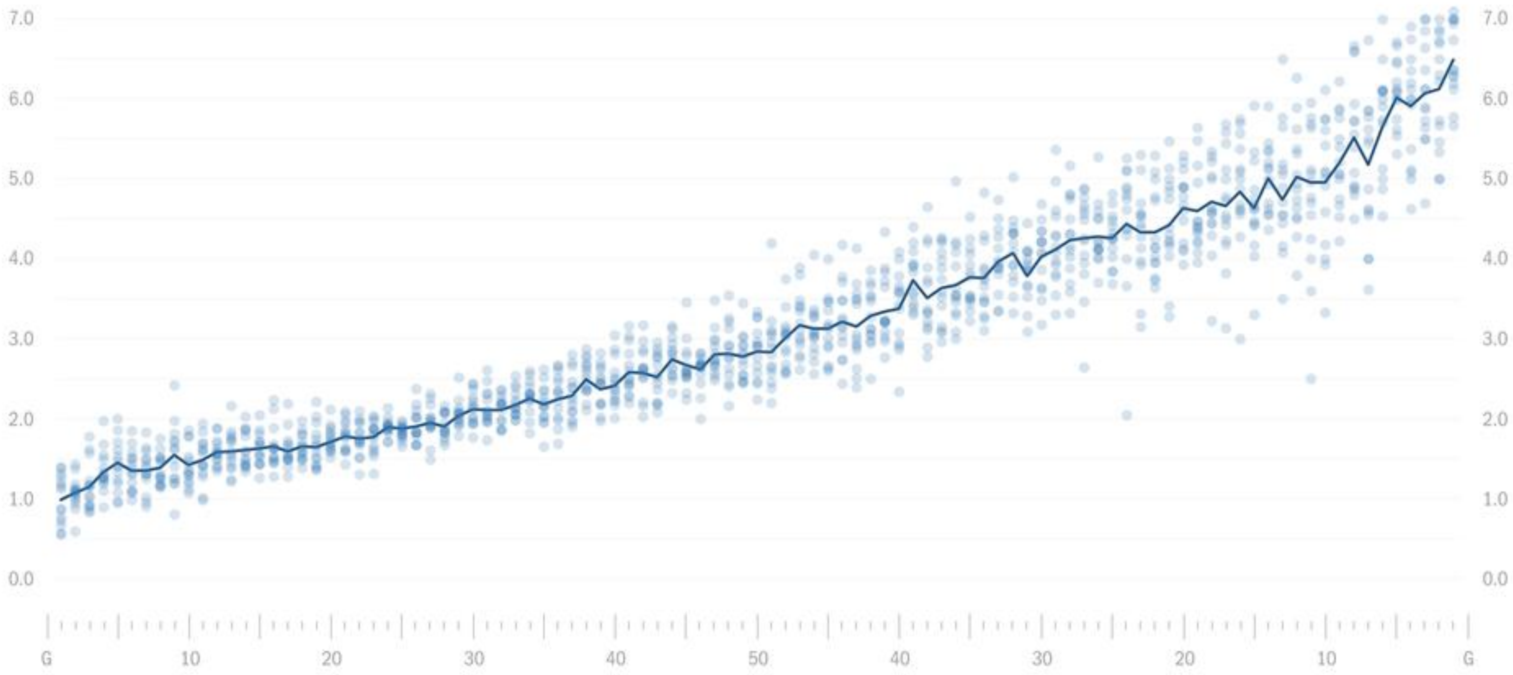
Determine where Offenses start their drives

Points

Account for ~35% of points scored in most seasons

Points Per Drive by Starting Field Position

The results of all non-garbage, regulation offensive drives in FBS vs FBS college football games from 2007 to 2020 are represented in the chart. Average points scored per drive by starting field position over the 14-season span are represented with a blue line. Average points scored per drive by starting field position in each individual season in the 14-season span are represented with blue dots..



Data Process Road Map

01

Data Cleaning

Iterative Cleaning Process and Preprocessing

02

EDA

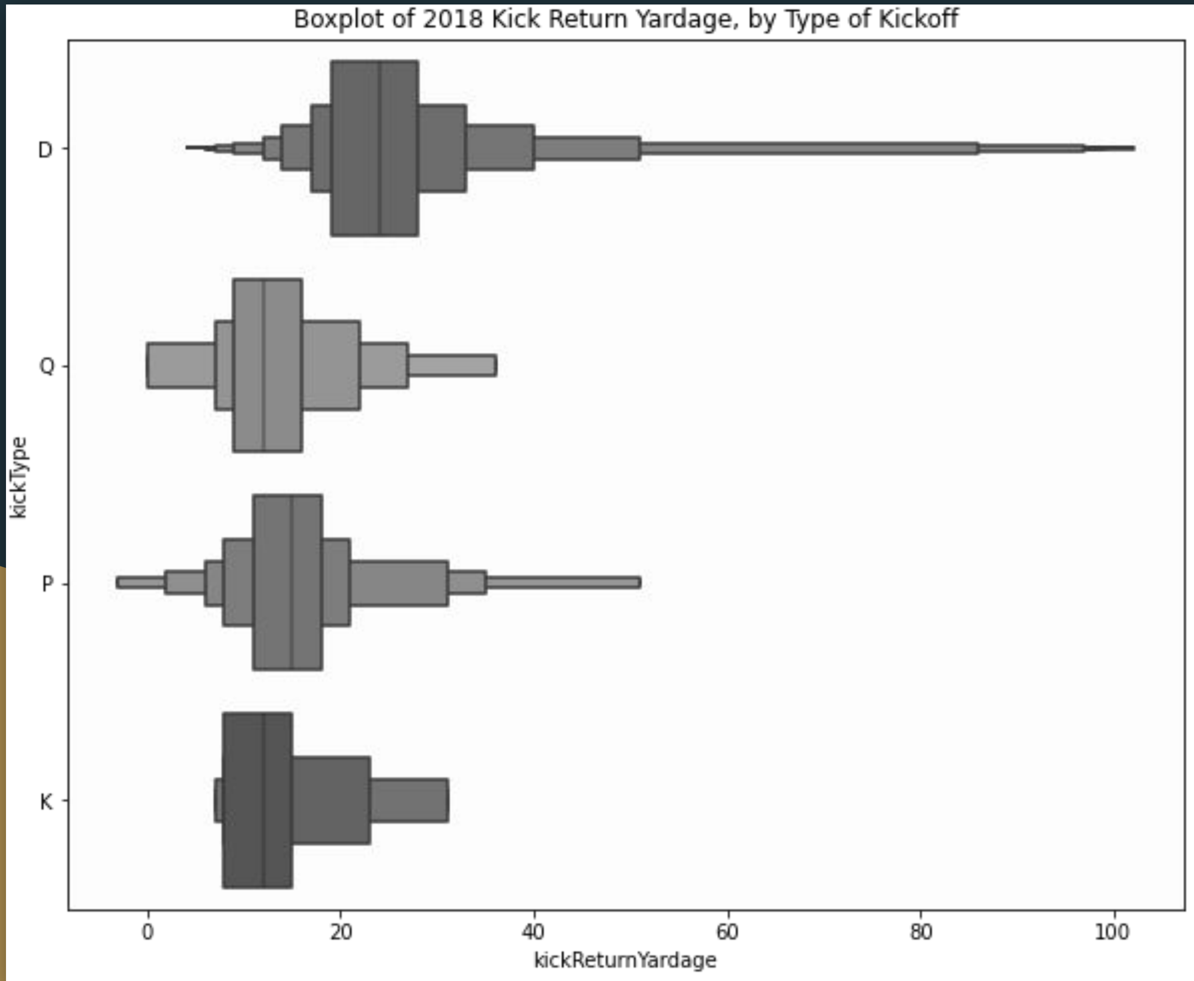
Data Visuals

2018 Special Teams Data

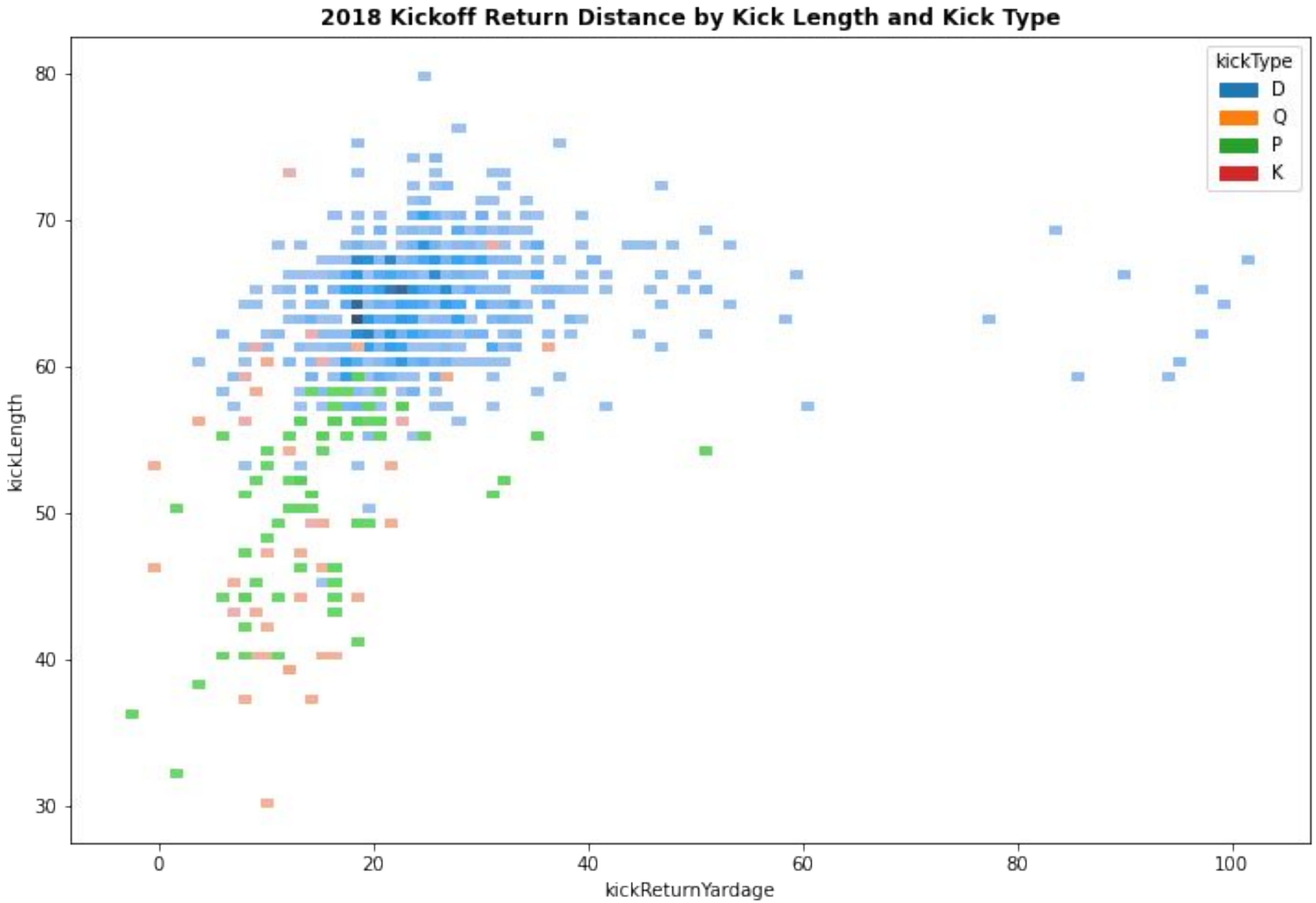
1. **Plays Data**
    a. Each Individual Special Teams play from 2018 Season
    b. Score, Play Type, Yardage Gained, Penalties, Kicker and Returner ID, etc.
2. **Games Data**
    a. Game Information (Date, Time, Week, Home vs. Away Team, etc.)
3. **Player Data**
    a. Individual Player Profiles (Height, Weight, Birth Date, Name, etc.)
4. **Pro Football Focus Scouting Data**
    a. Scouting Information from PFF
    b. Kick Type, Hang Time, Direction of Kick & Return, Formations, etc.
5. **Player Tracking Data**
    a. Frame to frame tracking of players for each special teams play.

Cleaning and Preprocessing

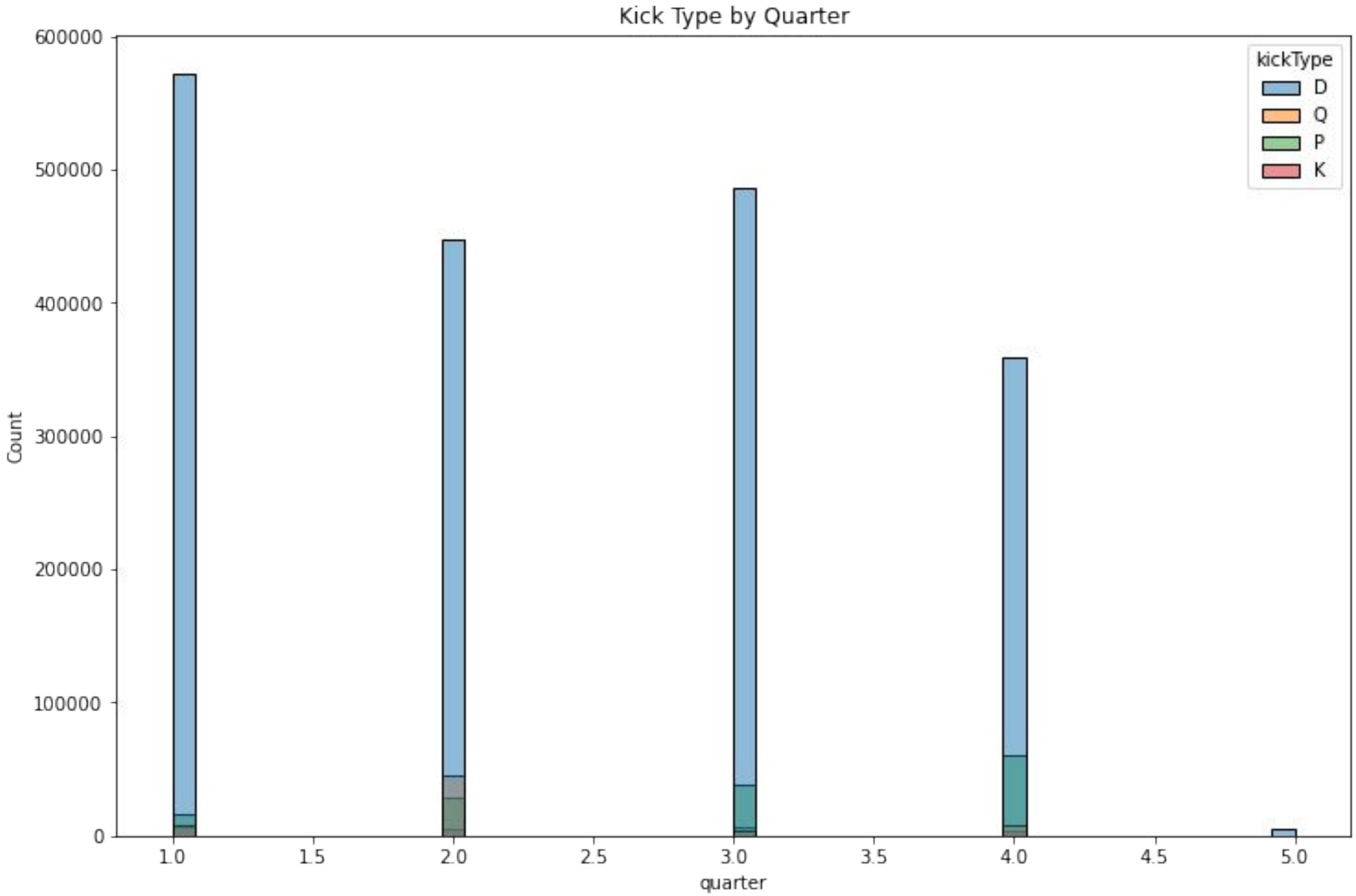
1. Started by subsetting data to Kickoff Returns from the PFF and Plays data
2. Subsetted further to remove:
   a. onside kick attempts
   b. Kickoffs that resulted in a Fumble
   c. Kickoffs with two returners
3. Much of the time was spent addressing null values and converting categoricals to numerical categories
4. Eventually added in Tracking Data and repeated the cleaning further.



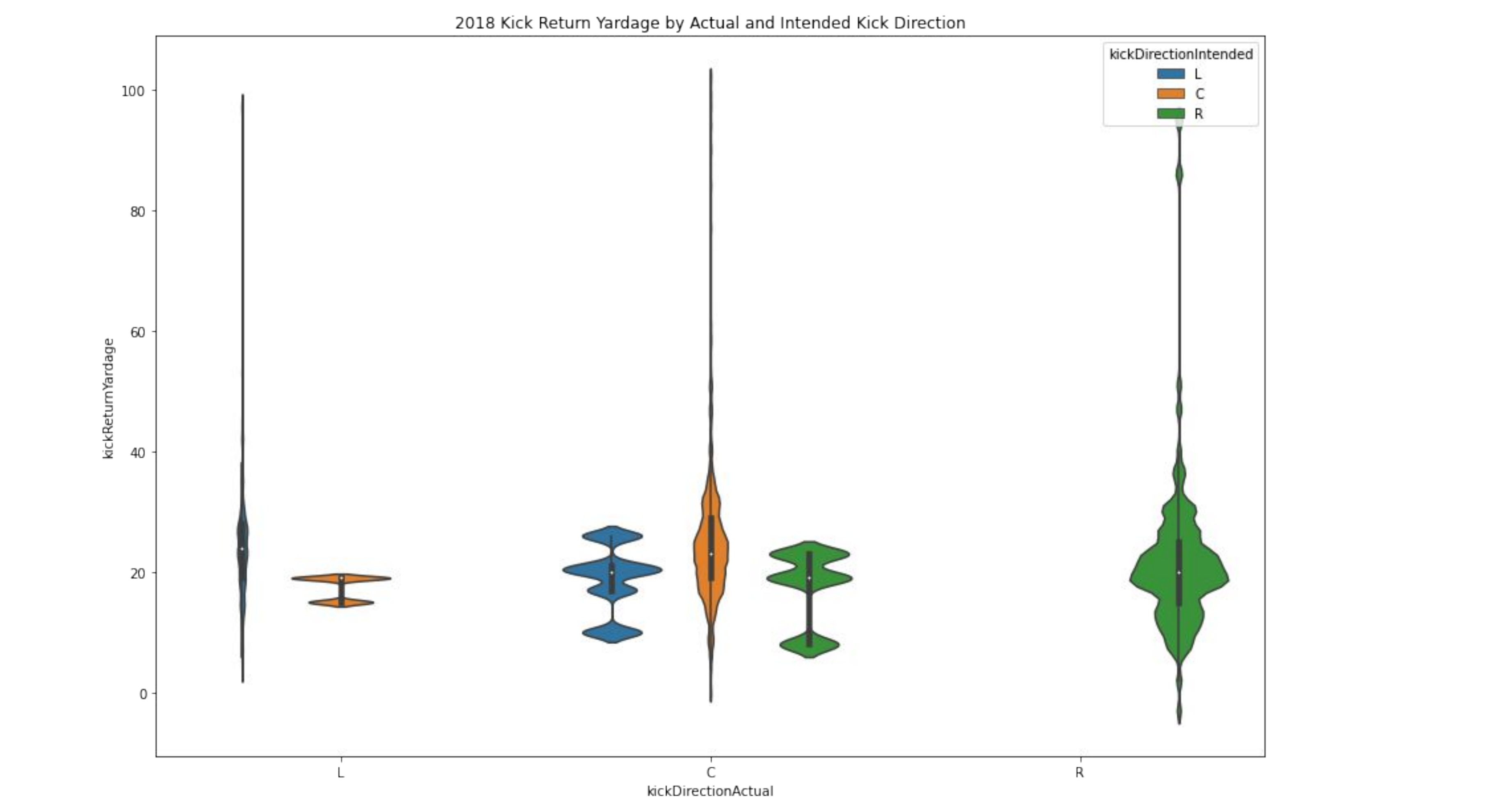
Boxplot of 2018 Kick Return Yardage, by Type of Kickoff
D
Q
P
K
kickType
0
20
40
60
80
100
kickReturnYardage



2018 Kickoff Return Distance by Kick Length and Kick Type
kickType
D
Q
P
K
80
70
60
50
40
30
kickLength
0
20
40
60
80
100
kickReturnYardage



Kick Type by Quarter
kickType
D
Q
P
K
Count
600000
500000
400000
300000
200000
100000
0
1.0
1.5
2.0
2.5
3.0
3.5
4.0
4.5
5.0
quarter


2018 Kick Return Yardage by Actual and Intended Kick Direction
kickDirectionIntended
L
C
R
kickReturnYardage
100
80
60
40
20
0
L
C
R
kickDirectionActual

Modeling Road Map

01 Initial Models

Logistic Regression before Tracking Data

02 Full Models

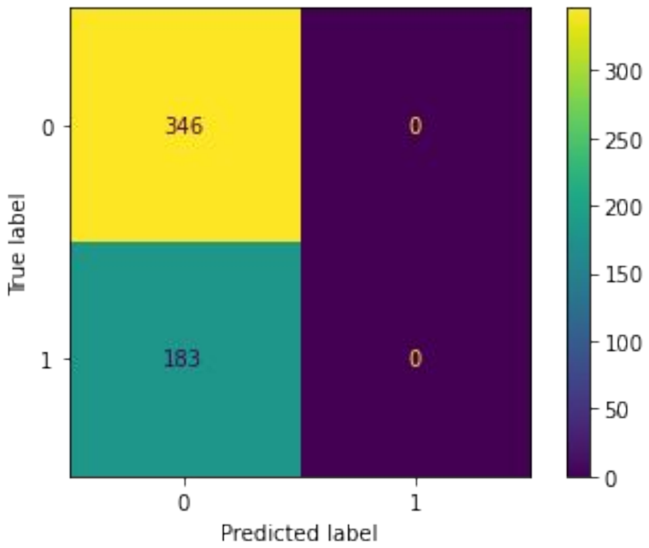
Log Reg, Decision Tree, Bagging Classifier

03 Conclusions

Conclusions, Interpretations, & Future Directions

Initial Modeling

- Successful Return defined as a return of 25 yards or more.
- Baseline:
  - 0 : 65.44 %
  - 1: 34.56 %
- Log Reg Scores
  - Train: 0.6545
  - Test: 0.6541
- **No Class 1 Predicted**



Full Data Models

After seeing that the initial Log Reg model was not predicting above baseline or the positive class, I added in the tracking data to add complexity.

I then attempted the following models:

- KNN
- Logistic Regression
- Decision Tree
- Bagged Decision Tree
- Random Forest

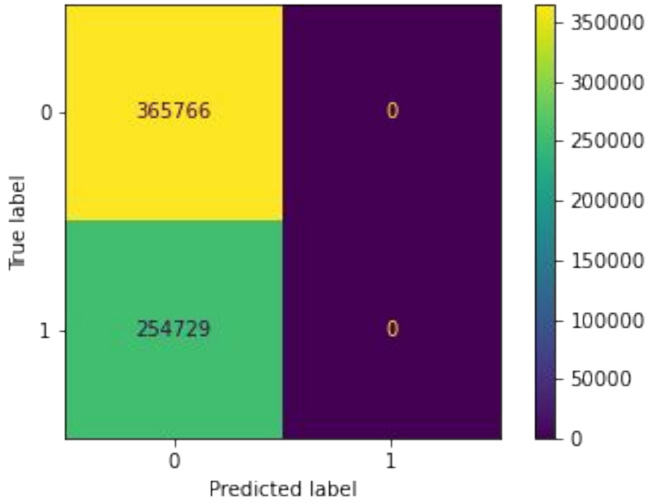
Unfortunately I was only able to fit the Logistic Regression and the Decision Trees due to time and computing constraints.

Baseline Scores for Full Data

Interestingly after further cleaning and adding the tracking data the Baseline scores got slightly closer to a bit above a 60-40 split.

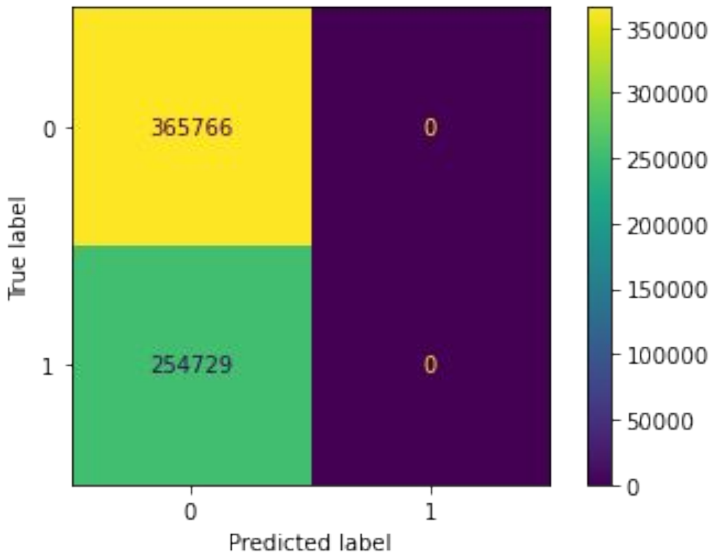
Success Label	Percentage
0	58.95
1	41.05

Logistic Regression Model



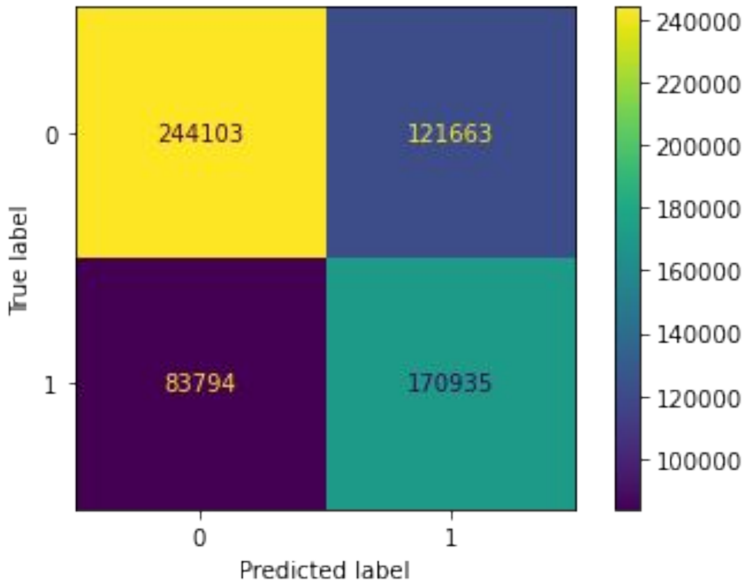
Training Accuracy	.5895
Testing Accuracy	.5895
F1 Score	0

Bagged DT Model

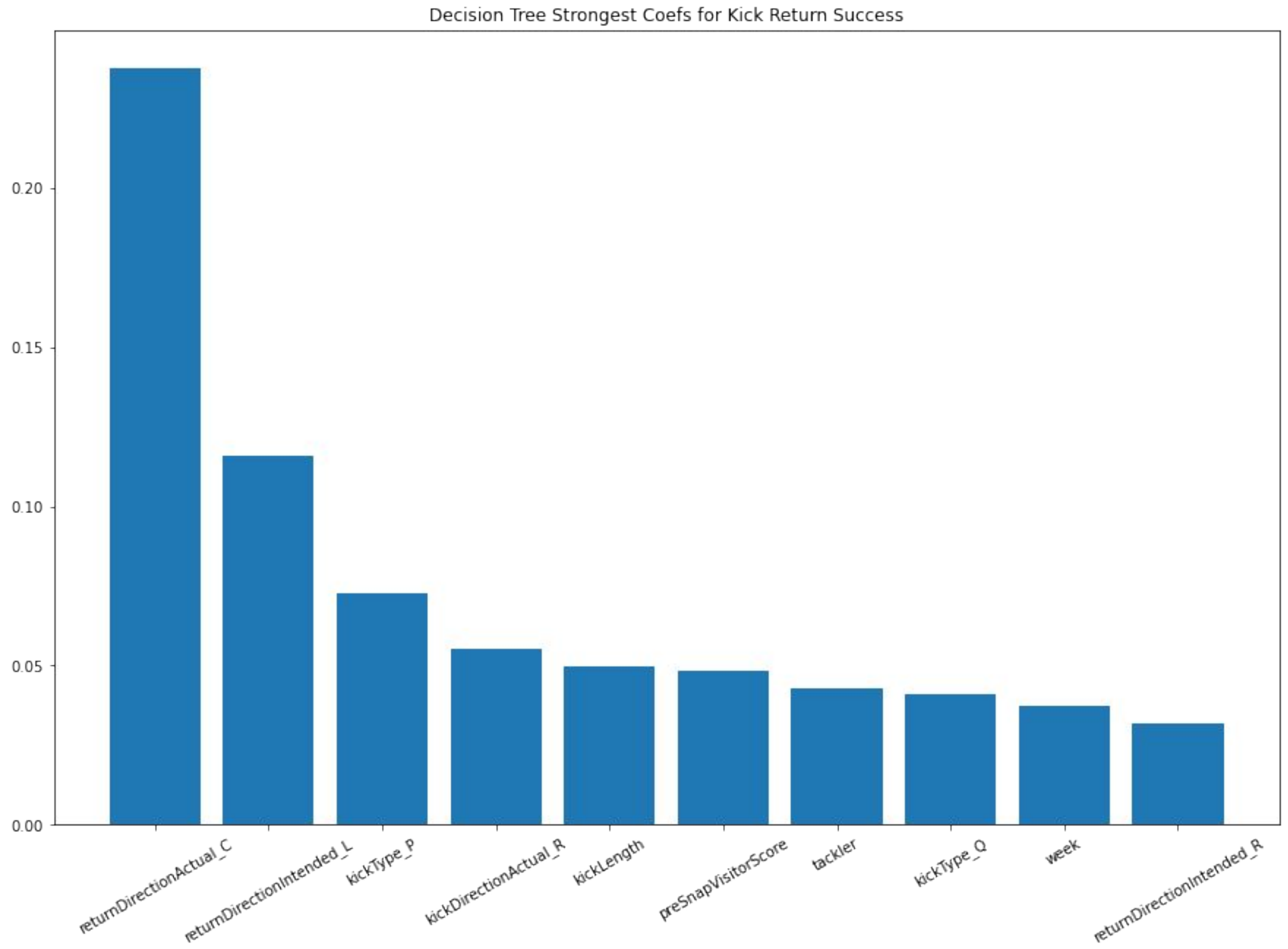


Training Accuracy	.593
Testing Accuracy	.5934
F1 Score	.0734

Decision Tree Model



Training Accuracy	.656
Testing Accuracy	.656
F1 Score	.5302
Recall	.4729
Precision	.6034


Decision Tree Strongest Coefs for Kick Return Success
0.20
0.15
0.10
0.05
0.00
returnDirectionActual_C
returnDirectionIntended_L
kickType_P
kickDirectionActual_R
kickLength
preSnapVisitorScore
tackler
kickType_Q
week
returnDirectionIntended_R

Conclusions and Recommendations

- The Decision Tree Model provided the best model for accurately predicting a successful return, even if it does appear to slightly over predict success.
- For teams receiving a kickoff the DT coefs indicate that returning the kick down the center or intending to return it left are the best bets to try and increase the odds of a successful return.

Limitations

- Computing power and time were the largest constraints.
- Size of the tracking files made them difficult to work with, and I don’t feel that I fully tapped the potential information there.

Future Directions

- Further investigating the tracking data.
- Looking at ways to use data from 2018-2020
- Investigating Punt Returns
- Deploying a working model with Streamlit
- Submitting final findings to NFL’s Big Data Bowl on Kaggle

THANKS!

Does anyone have any questions?

References

- Graph of Points Scored by Starting Position from Brian Fremeau at https://www.bcftoys.com/
- Data from NFL Big Data Bowl 2022 | Kaggle
- Football Slide Theme and images from American Football Day | Google Slides & PowerPoint Template