A Machine Learning Approach to MLB Catcher Framing

Nathan Hemenway and Matthew Boyd

12/10/2021

Introduction

- “Catcher framing is the art of a catcher receiving a pitch in a way that makes it more likely for an umpire to call it a strike – whether that’s turning a borderline ball into a strike, or not losing a strike to a ball due to poor framing.” - MLB.com Glossary

Motivation

- Baseball catchers can influence the call of a ball or strike on how they catch the ball
- Some catchers are better than others at this skill
- Baseball teams are aware of this and are acquiring players good at this skill to win more games
- We want to quantify the best catcher's at framing for the 2021 season
- There are several factors that influence whether a pitch will be a strike or ball
- Catchers getting more strikes translates to more outs, and fewer runs for the opposing team
- https://baseballsavant.mlb.com/sporty-videos?playId=273b22a4-f522-4009-87d1-14176772182d

Data

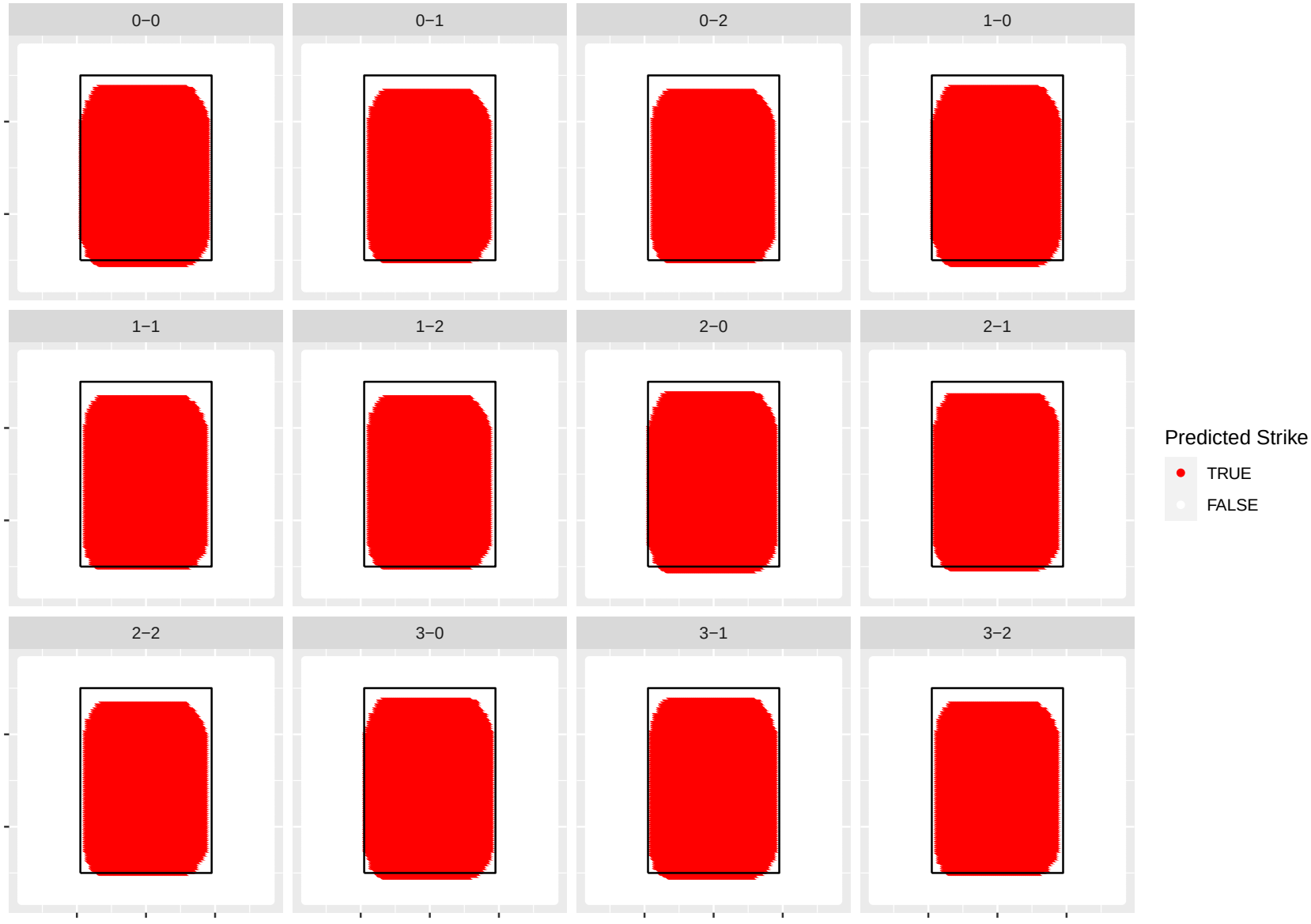
- 2021 pitch data scraped from Baseball Savant through baseballr package
- ~700,000 rows (each for a single pitch)
- Wanted to look at pitches that were not swung at by the batter (called strike or ball)
- ~350,000 rows remain

Variables

- We used:
- Pitch type and pitch release speed, position, and spin rate
- Whether or not the pitcher and batter are right or left handed
- Count, number of outs during the at-bat, and inning number
- Where the pitch landed
- Whether the game was played home or away
- How tall the batter is

Example

- Strike Probability by Location and Count



Logistic Regression Model

```
##           true
## pred           0      1
##   ball    112696  52821
##   strike    5057   5372

## [1] 0.6710468
```

- The variables with significant results were:
- Pitch type, release speed, z release position
- Whether the batter is a lefty/righty
- Count
- Where the pitch landed
- Most of the innings
- Batter height
- Whether it was a home game

Ridge Regression

```
##      true
## pred      0      1
##    0 114268  53642
##    1   3769   4267
```

```
## [1] 0.673701
```

LASSO

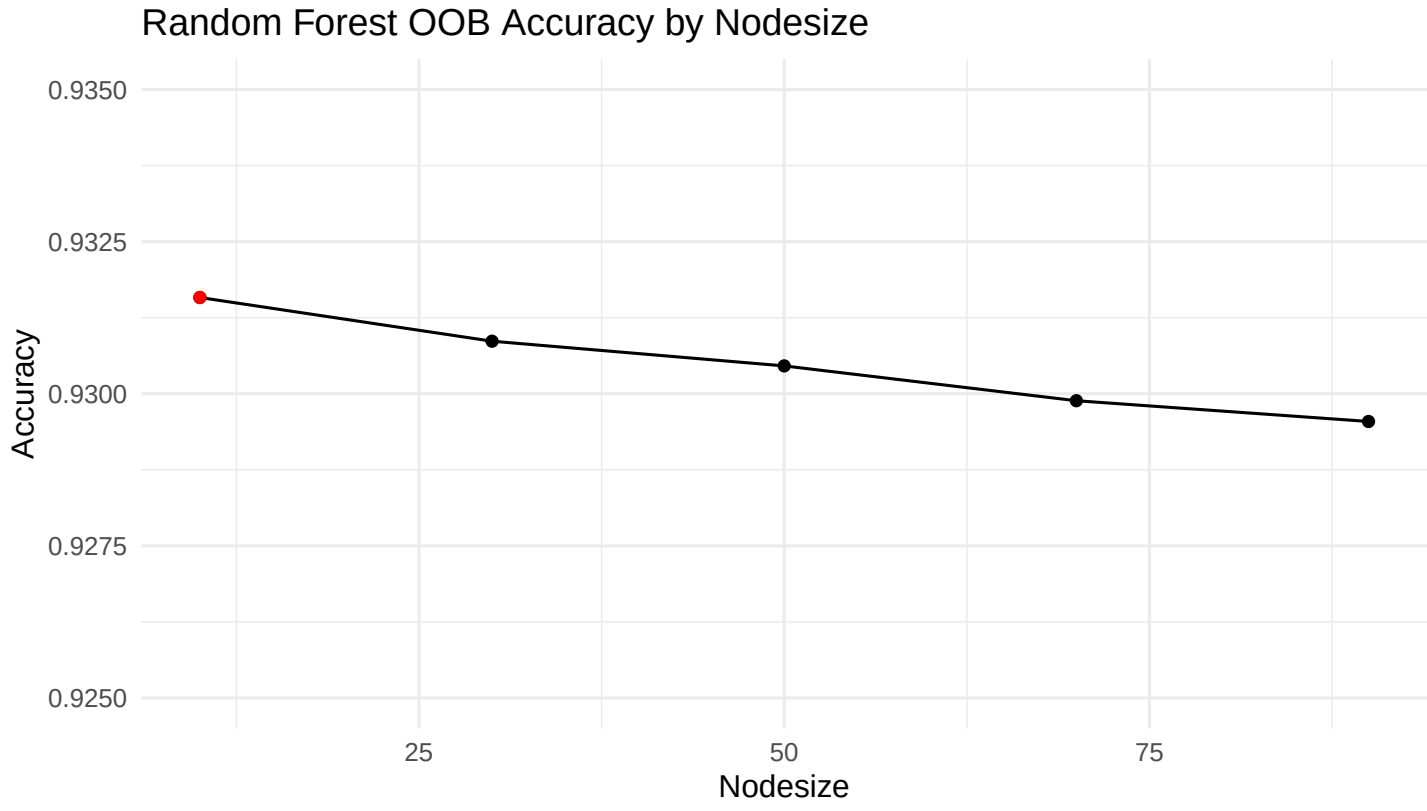
```
##      true
## pred      0      1
##    0 115220  54523
##    1   2817   3386
```

```
## [1] 0.6741046
```

- Some of the non-zero coefficients include:
- Pitch type
- Count
- Outs and Inning
- Batter height
- Whether the game is home or away
- Where the pitch landed

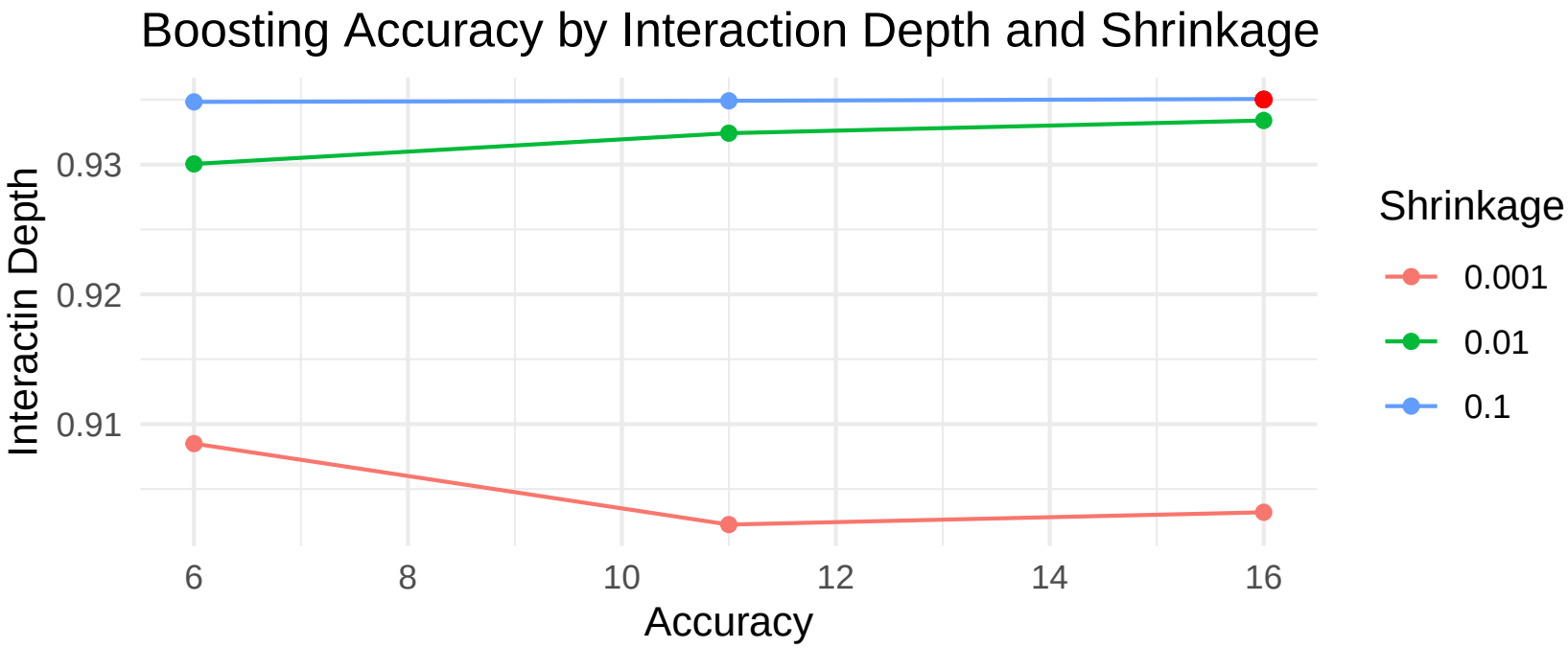
Random Forest

- Tested several Random Forest models
  - Nodesize: 10, 30, 50, 70, 90 | # of Trees: 500
  - Compared Out-Of-Bag Error



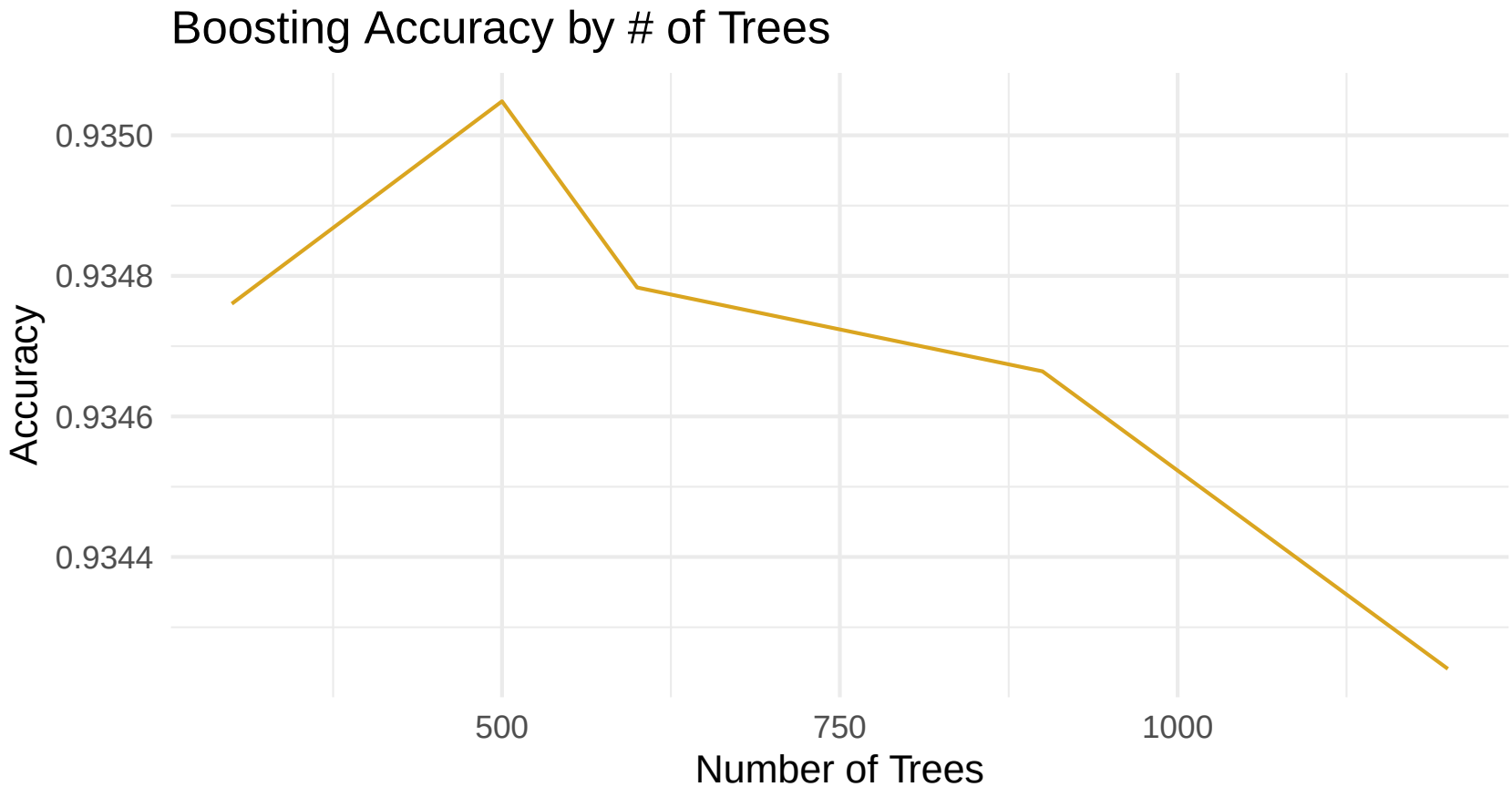
Boosting

- 3 Fold Cross Validation on Boosting
  - Interaction depth: 6, 11, 16
  - Shrinkage: 0.1, 0.01, 0.001
  - Number of Trees: 500
  - Compared CV accuracy
- 27 models took over 5 hours to run



Boosting Part 2

- Only tuned shrinkage and interaction depth
- Now tune trees with interaction depth of 16 and shrinkage of 0.1
- Trees: 300, 500, 600, 900, 1200



Model Comparison

- Boosting with interaction depth of 16, shrinkage of 0.1, and 500 trees has the highest accuracy

```
##       model  accuracy parameter
## 1  boosting 0.9350484       500
## 2  boosting 0.9347835       600
## 3  boosting 0.9347604       300
## 4  boosting 0.9346642       900
## 5  boosting 0.9342408      1200
## 6        rf 0.9315823        10
## 7        rf 0.9308637        30
## 8        rf 0.9304577        50
## 9        rf 0.9298853        70
## 10       rf 0.9295443        90
```

Results

- To give credit to each catcher, we use this equation for every pitch:
  - If strike: 1 - Strike Probability
  - If ball: Strike Probability * -1