Analyzing the Value of Foul Balls in Major League Baseball

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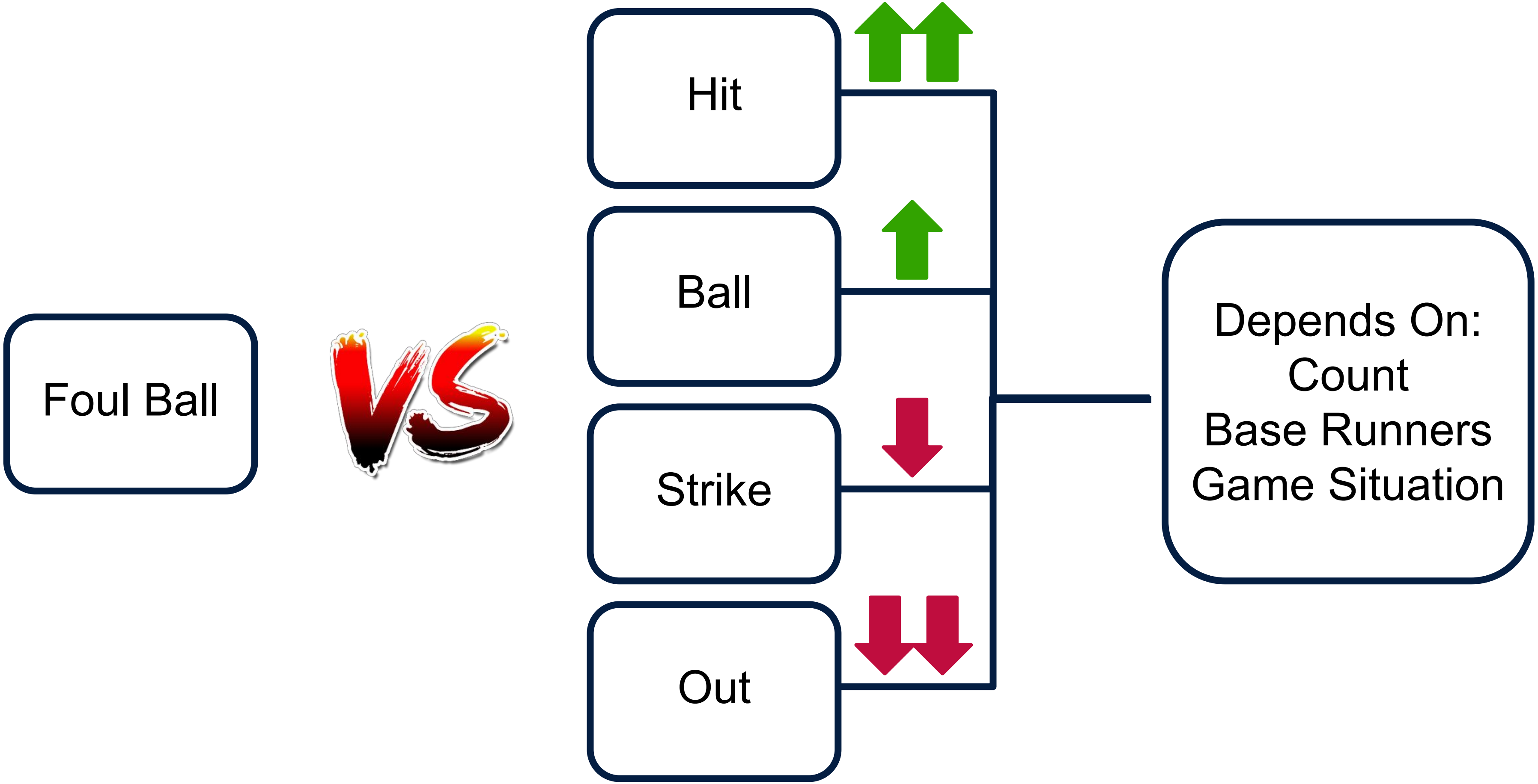
Introduction - Value of Foul Balls

- Count (0/1 strikes vs. 2 strikes)
  - See a different pitch
  - Make the PA longer
- Pitch Quality/Location
  - Good vs. bad pitch
  - Edge vs. heart of plate
- Effect on the batter
  - Time up the pitches
  - Feedback on swing
  - Understanding of pitch arsenal

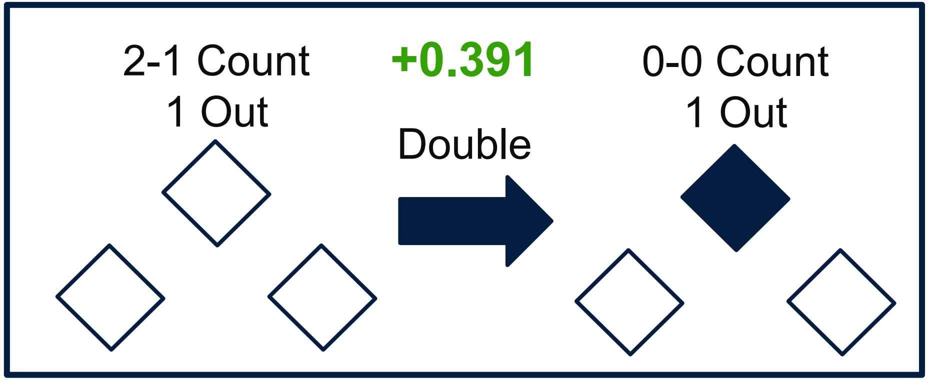
Quantifying the Value of Outcomes

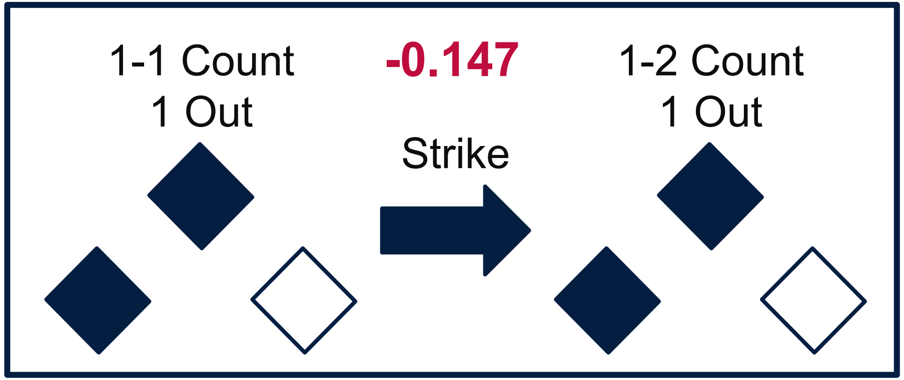


Delta Run Expectancy (ΔRE)

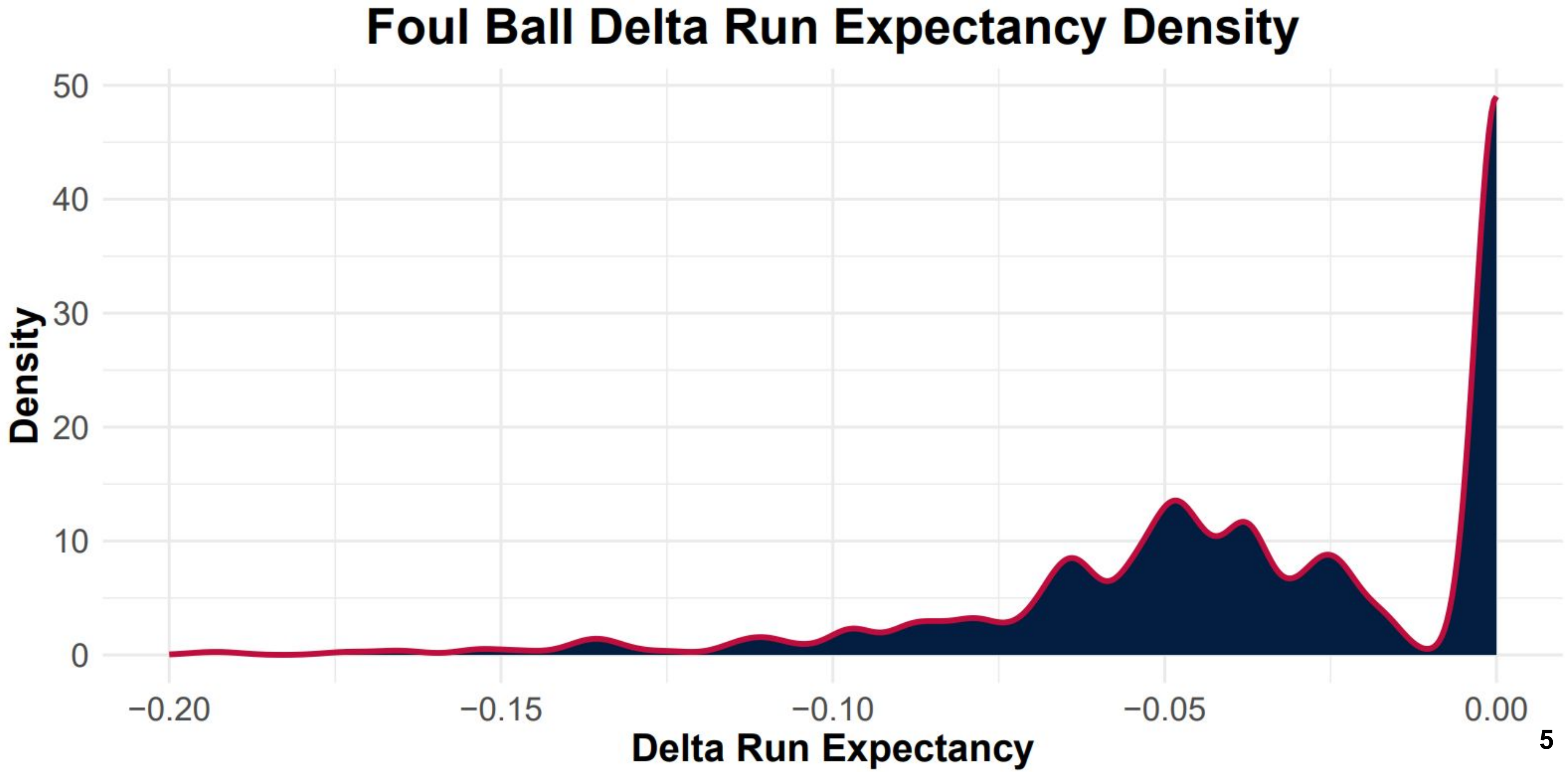
$$\Delta RE = RE_{Post} - RE_{Pre} + RS$$

- Pitch level statistic
- Quantifies difference in run expectancy between pitches





Actual ΔRE of Foul Balls

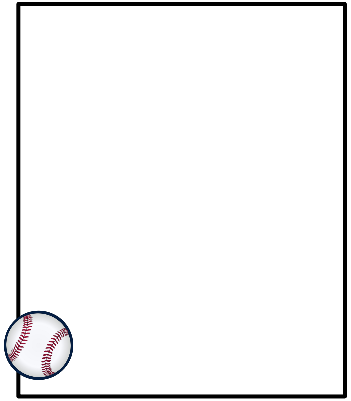


Limitations of Delta Run Expectancy

Kyle Bradish

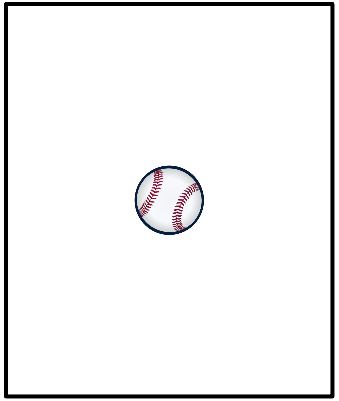
0 ΔRE

Count: 3-2
1st and 2nd
0 Outs



Slider
Stuff+ : 172

Count: 0-2
1st and 2nd
0 Outs



Slider
Stuff+ : 84

Patrick Corbin

0 ΔRE

Both **foul balls** are both valued **equally** by ΔRE.

Foul Ball Runs (FBR)

Value of a foul ball, in terms of runs for the offensive team

$$FBR = \Delta RE - \widehat{\Delta RE} + ME$$

Actual Value	−	**Predicted** Value	+	**Marginal Effect** on Rest of PA

Modeling Methodology

Individual Pitch Stuff Model

Predicted Delta Run Expectancy Model

Marginal Effects of Foul Balls

Foul Ball Runs

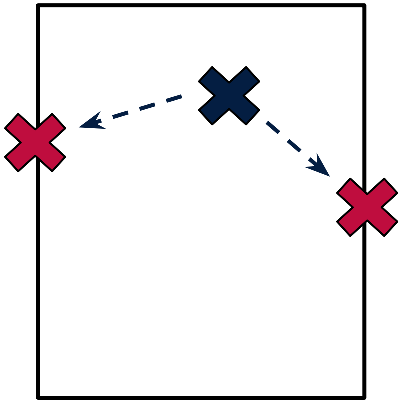
Quantifying Pitch Quality (Stuff)

Pitch Attributes

- Velocity**
- Spin Rate
- Horizontal & Vertical Break**
- Spin Axis**
- Release Point
- Extension
- Batter & Pitcher Handedness

**Used for Comparisons

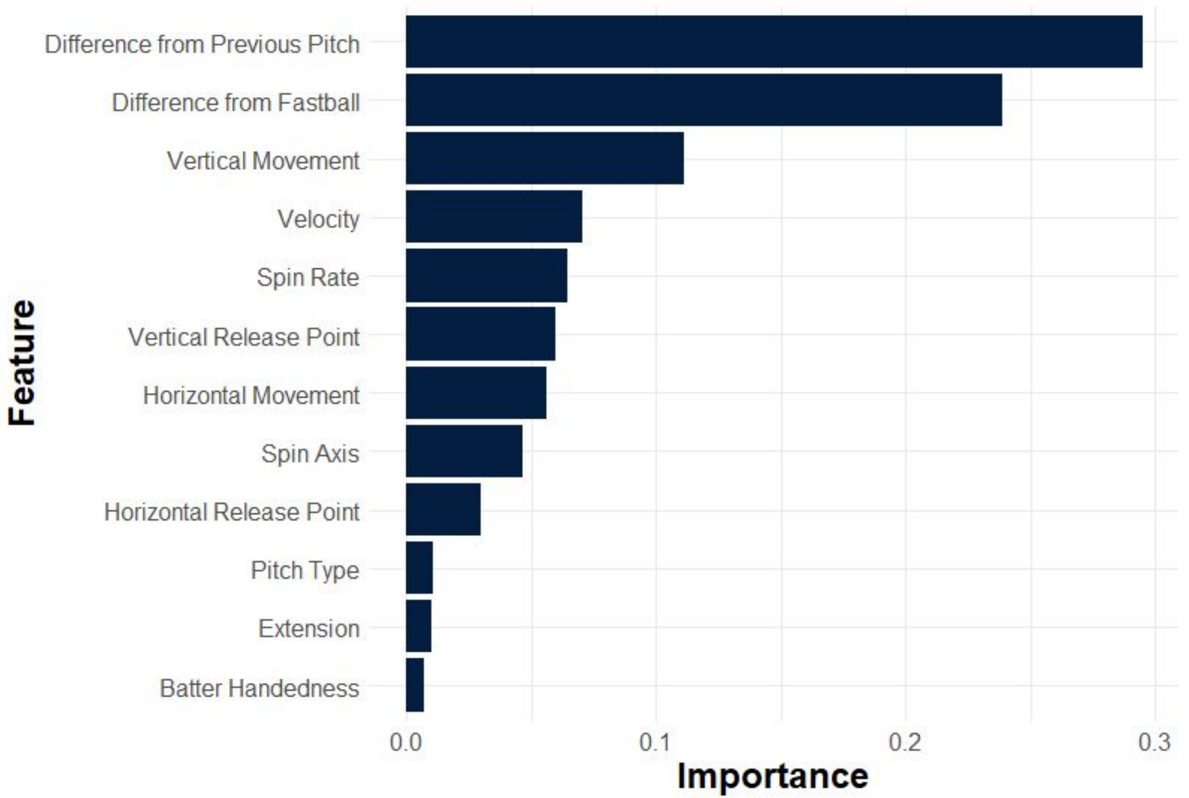
Comparisons (to Previous Pitch and Primary Fastball)



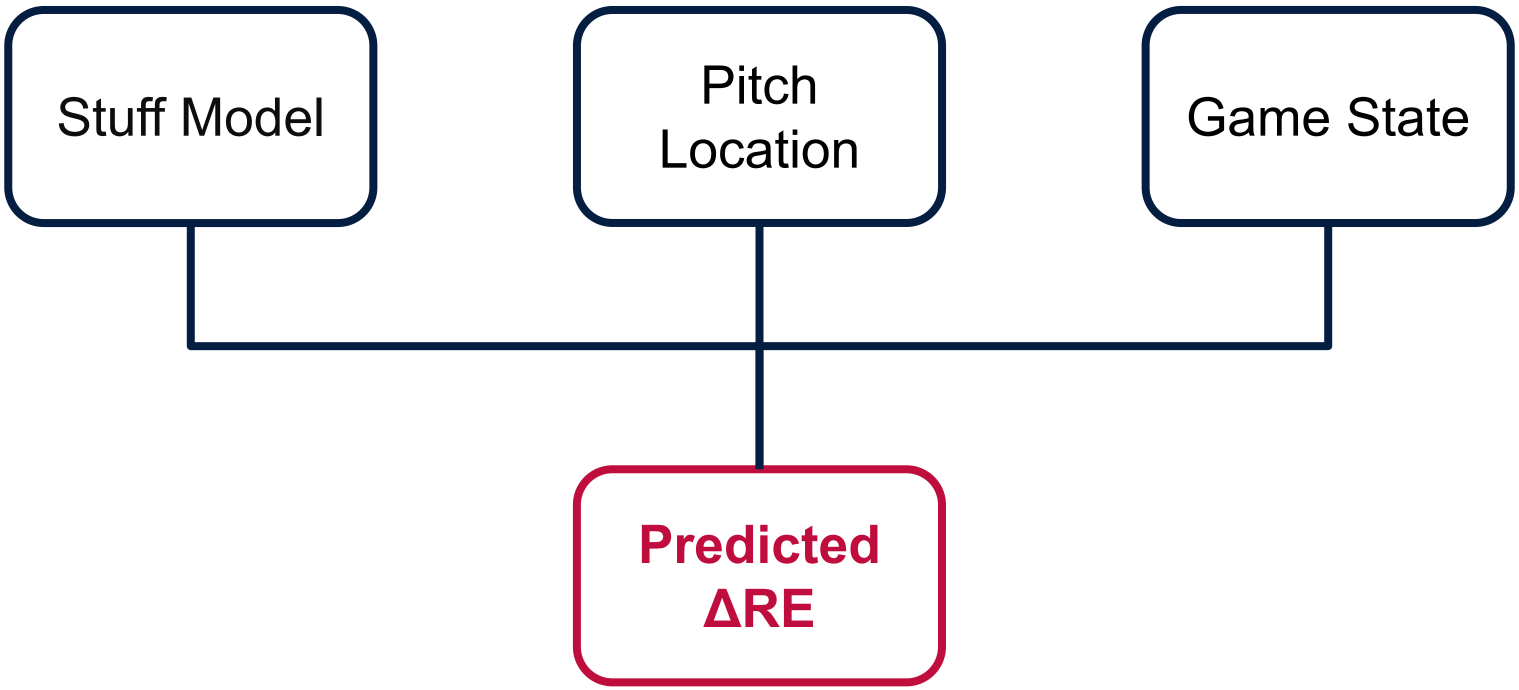
Start Point
End Point

Modeling Pitch Stuff

- Dependent Variable: Mean ΔRE of Pitch Outcome Type
- Trained on 2022 pitches, applied to 2023
- Used extreme gradient boosting (tree algorithm)
- Random search hyperparameter tuning

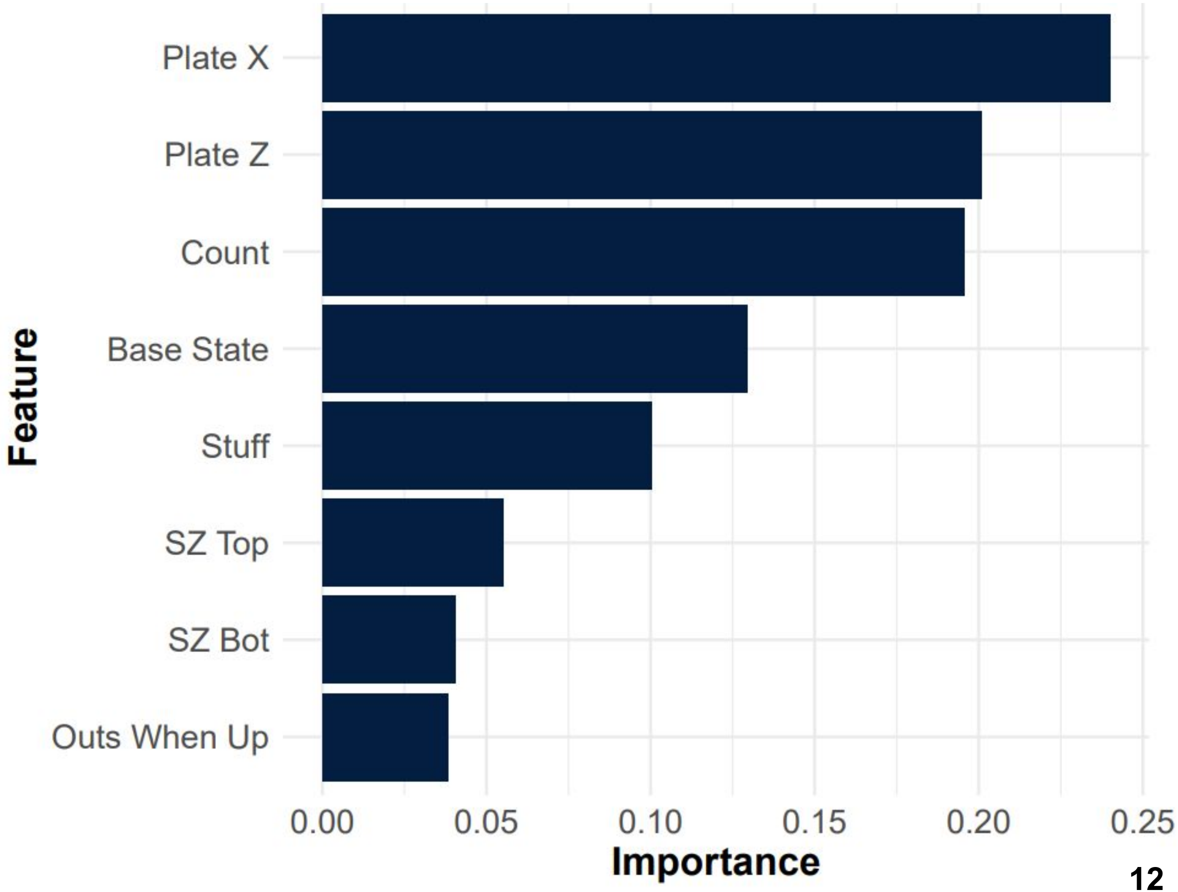


Calculating Predicted Delta Run Expectancy



Predicted ΔRE Model

- Dependent Variable: Pitch ΔRE
- Trained on all 2023 pitches, applied to foul balls
- Used extreme gradient boosting (tree algorithm)
- Random search hyperparameter tuning

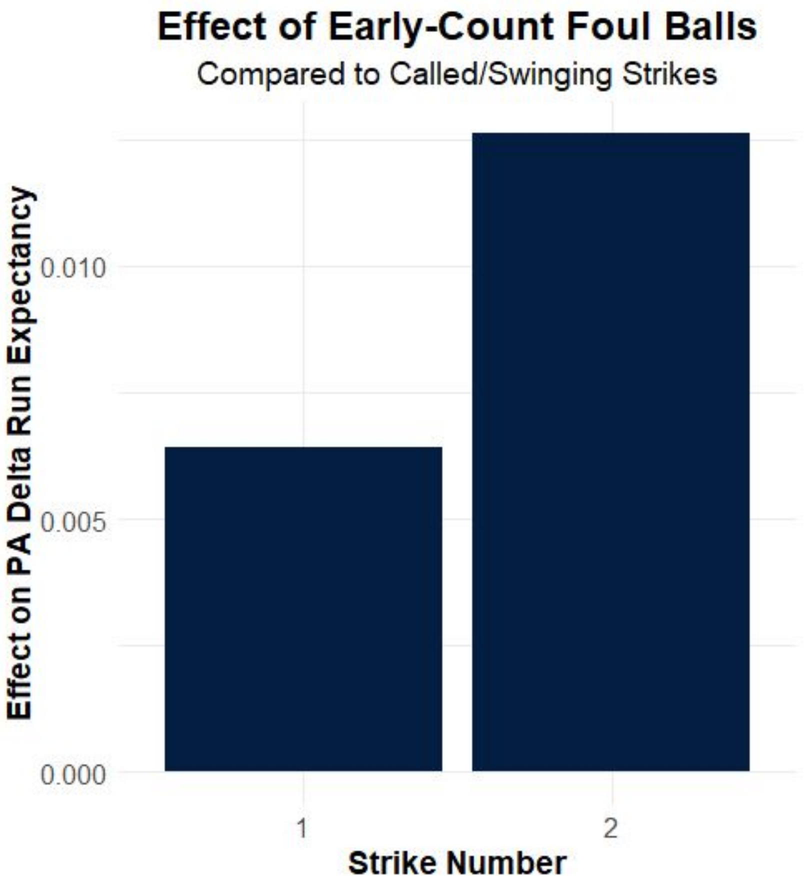


Marginal Effects of Foul Balls

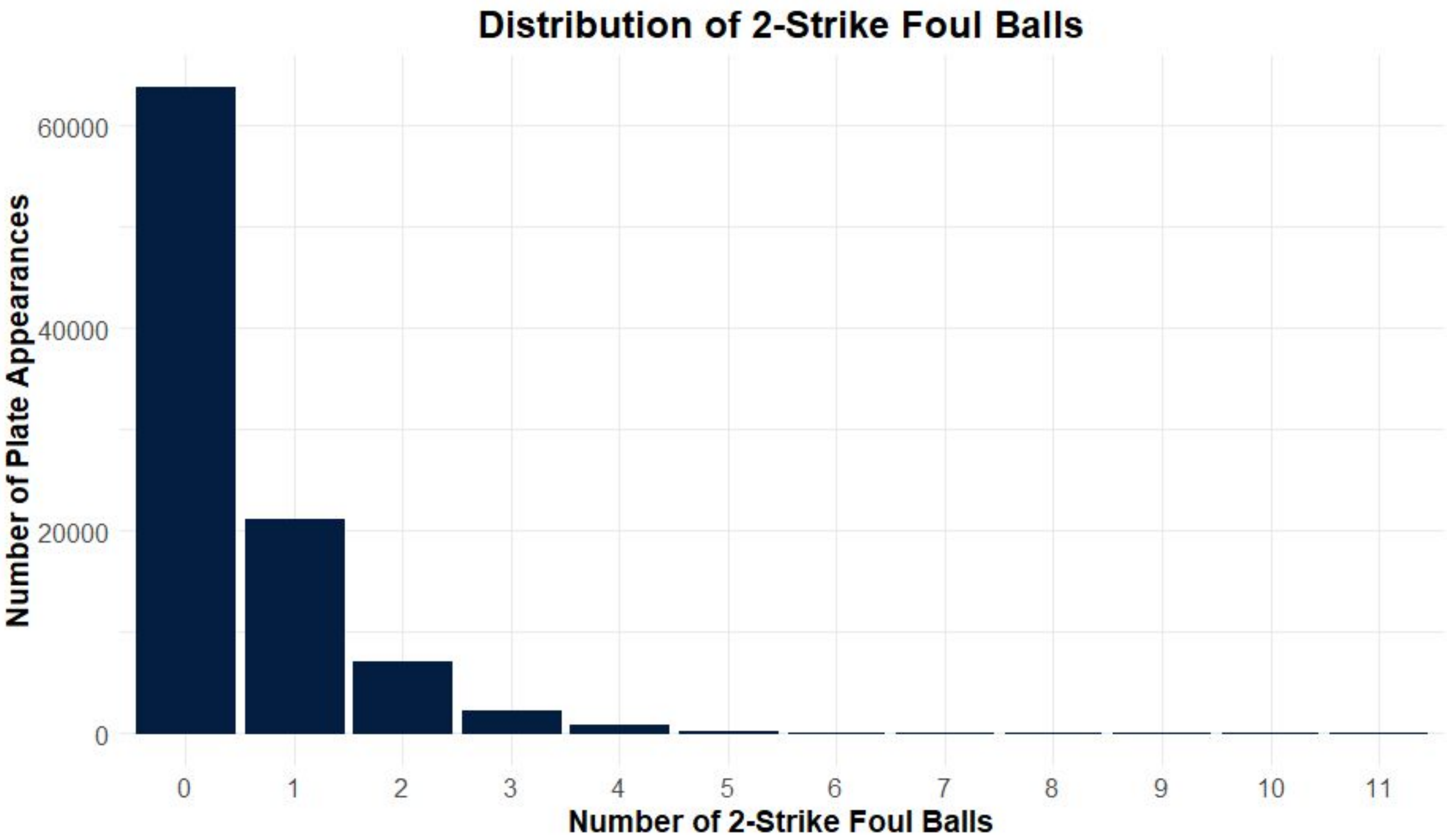
Situation	Actual ΔRE Value	Intuitive Hypothesis
0 & 1 Strike	Negative (Same as CS & SS)	Less Negative (Batter benefits from feedback on swing and timing)
2 Strikes	0	Positive (Batter benefits from seeing another pitch, frustrates pitcher)

Effect of Early-Count Foul Balls

	Dependent Variable: PA Delta Run Expectancy	
	Strike 1	Strike 2
Foul	**0.006 (0.003)****	**0.013 (0.003)****
Batter xwOBA	0.693 (0.033)***	0.553 (0.036)***
Pitcher xwOBA	0.770 (0.038)***	0.725 (0.042)***
Same Hand	-0.016 (0.002)***	-0.017 (0.003)***
Constant	-0.486 (0.016)***	-0.475 (0.018)***
Observations	139,735	94,752
Adjusted R^2	0.007	0.006
Note:	*p<0.1; **p<0.05; ***p<0.01	

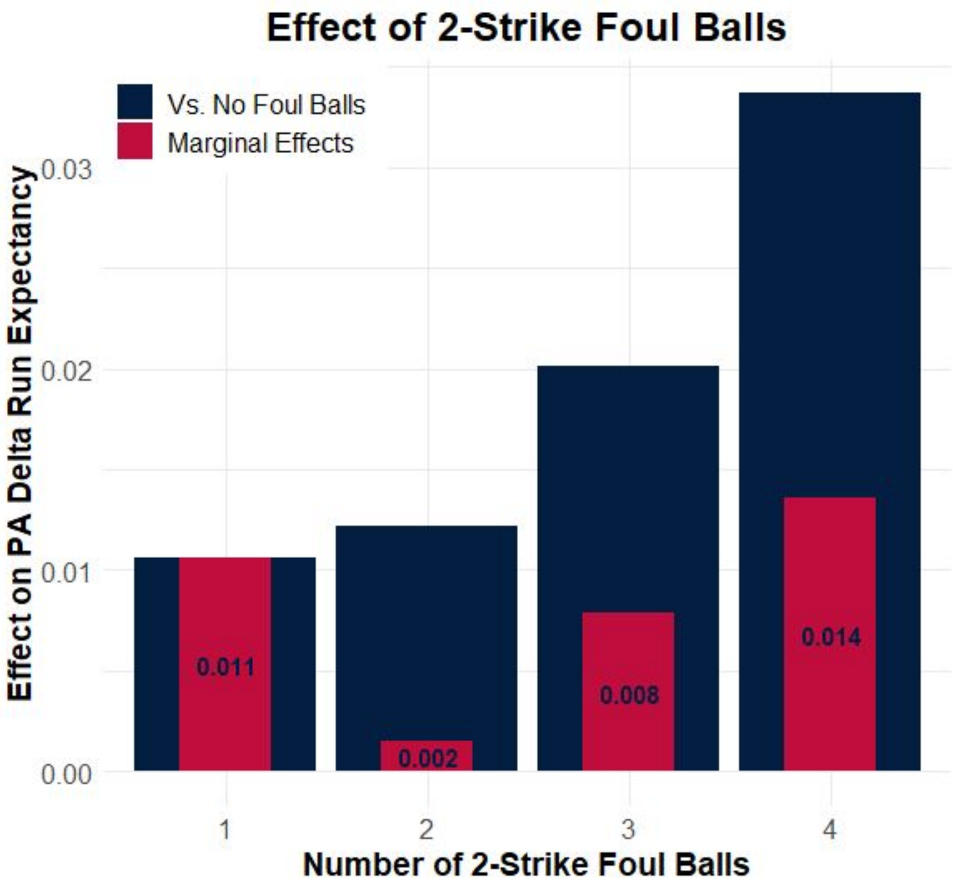


2-Strike Foul Balls



Effect of 2-Strike Foul Balls

	Dependent Variable: PA Delta Run Expectancy
2-Strike Fouls: 1	**0.011 (0.003)*** **
2-Strike Fouls: 2	**0.012 (0.005)** **
2-Strike Fouls: 3	**0.020 (0.009)** **
2-Strike Fouls: 4	**0.034 (0.012)*** **
Batter xwOBA	0.444 (0.036)***
Pitcher xwOBA	0.656 (0.041)***
Same Hand	-0.014 (0.003)***
Number of Balls: 1	0.007 (0.004)*
Number of Balls: 2	0.019 (0.004)***
Number of Balls: 3	0.159 (0.004)***
Constant	-0.468 (0.017)***
Observations	95,554
Adjusted R^2	0.032
Note:	*p<0.1; **p<0.05; ***p<0.01



Calculating FBR

$$FBR = \Delta RE - \widehat{\Delta RE} + ME$$

Actual

Actual ΔRE

—

Predicted

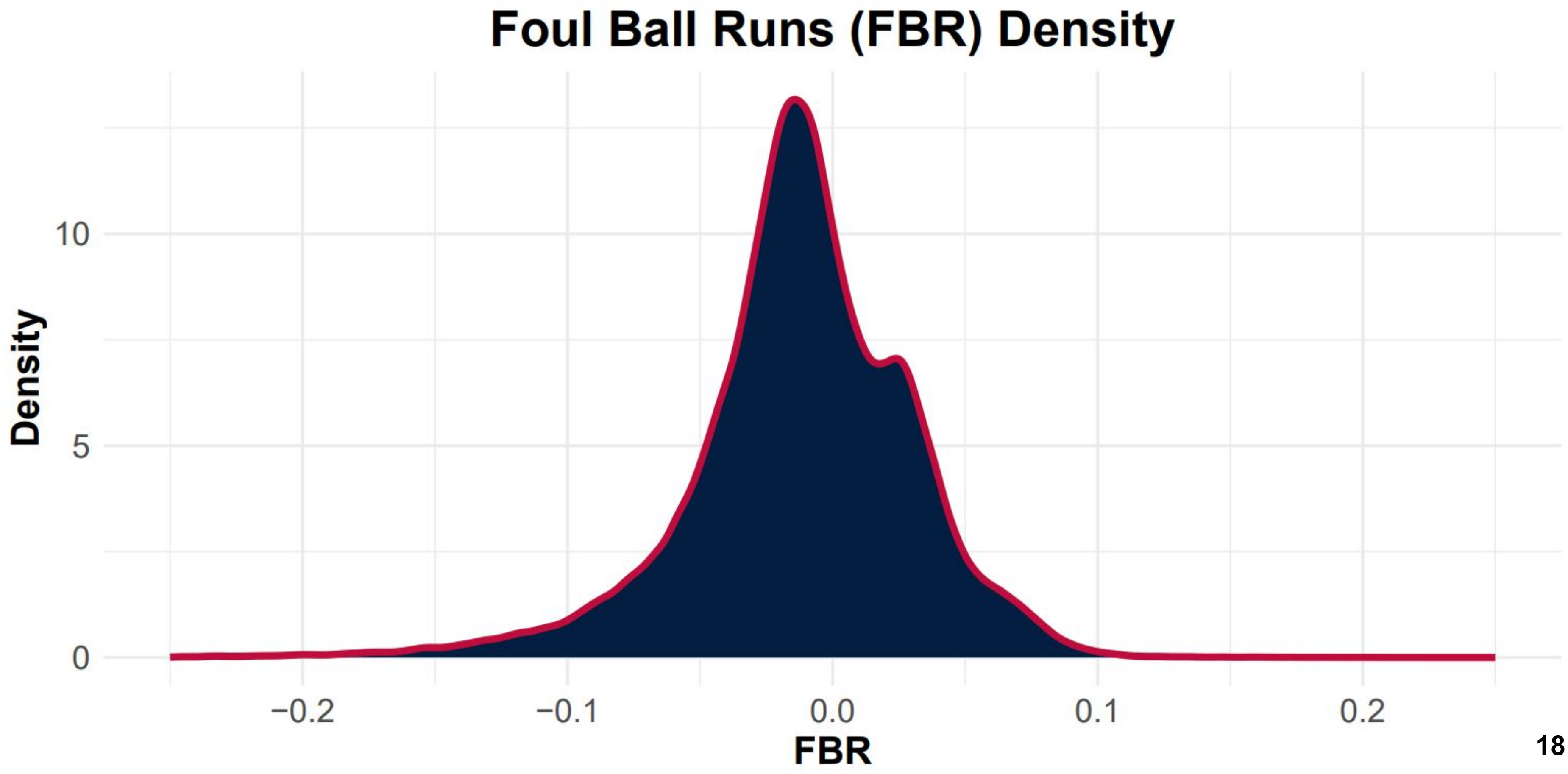
Predicted ΔRE Model:
Stuff Model,
Game State,
Pitch Location

+

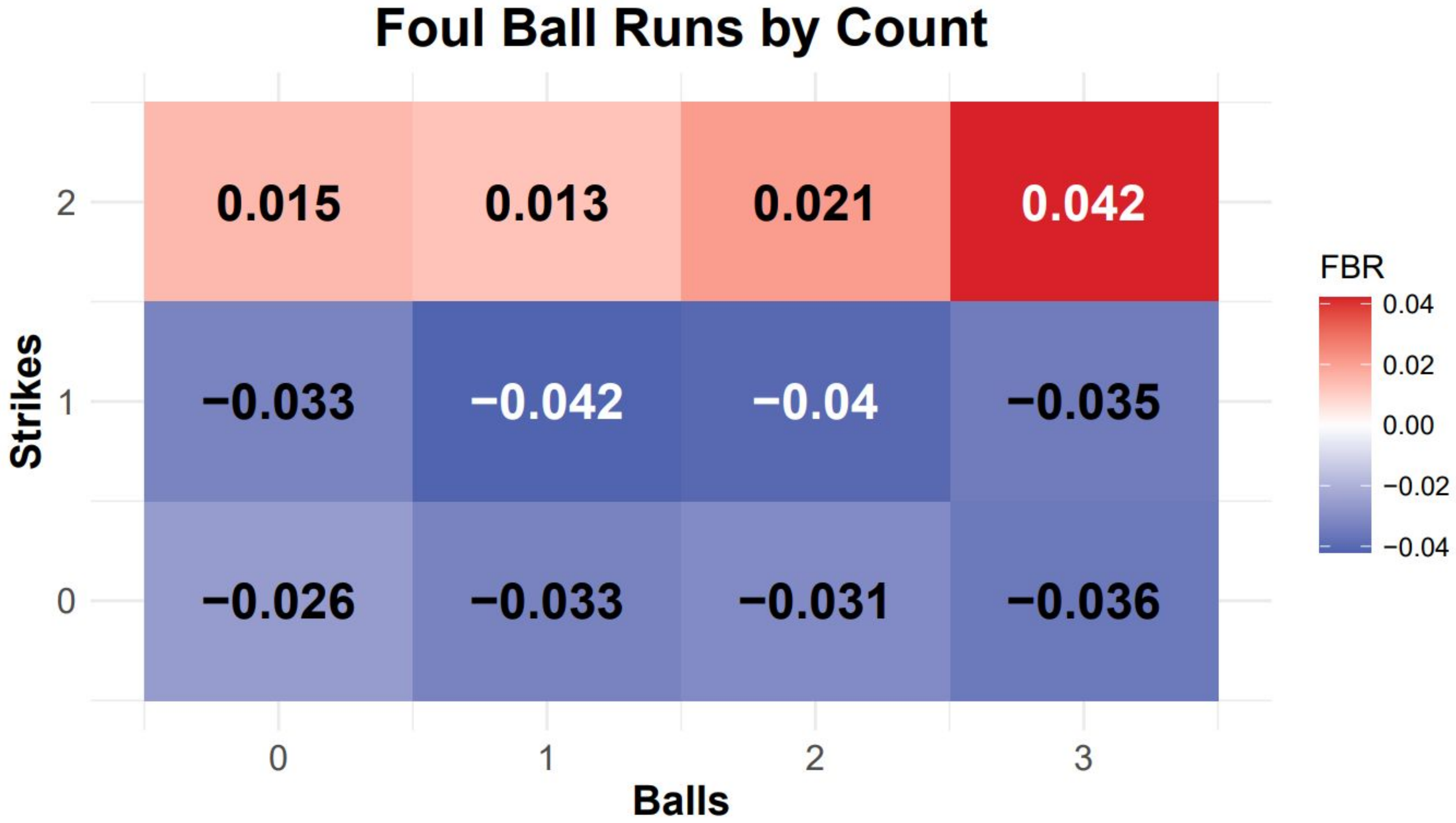
Marginal Effect

0/1 Strike ME,
2 Strike ME

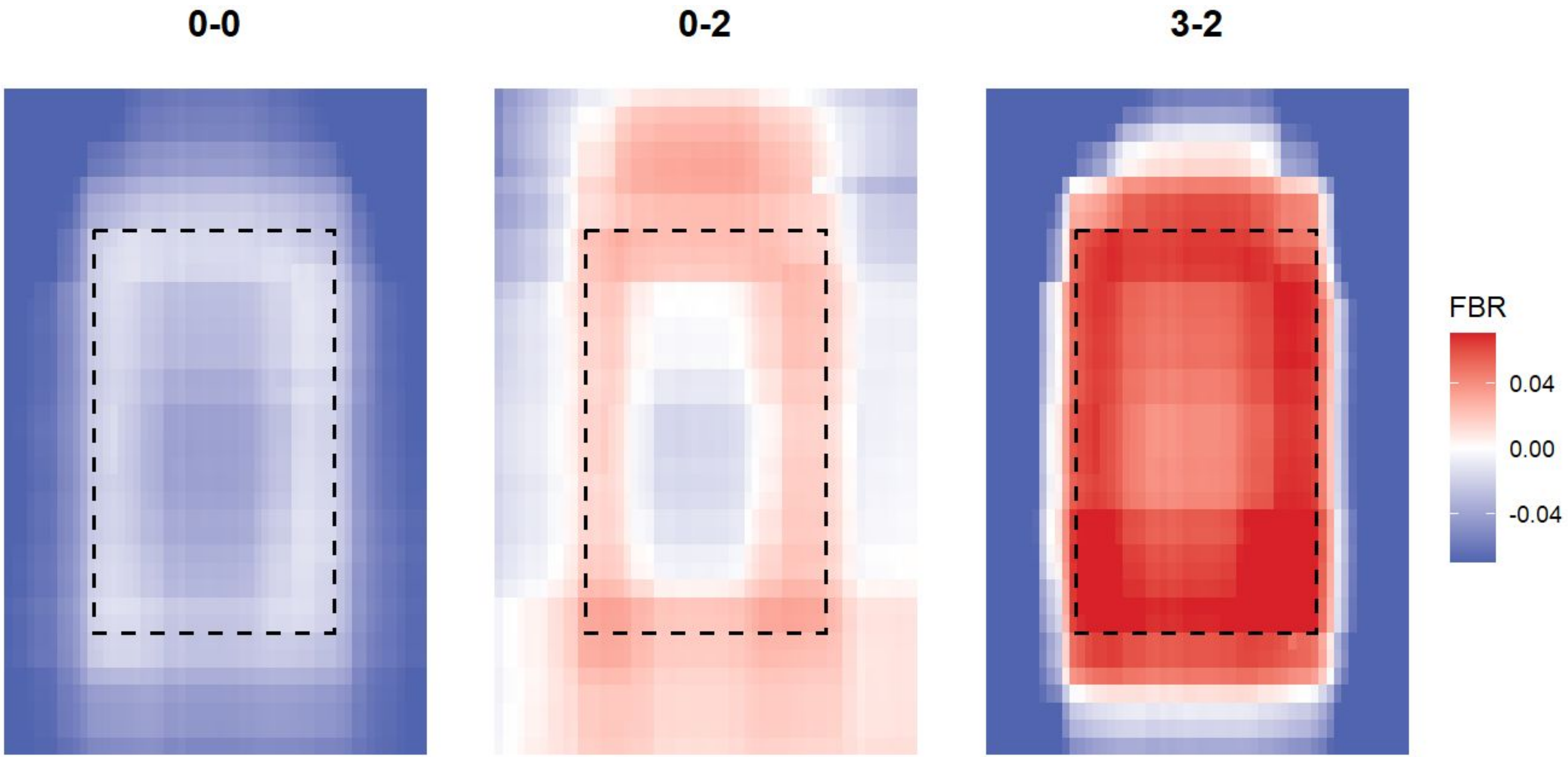
FBR Distribution



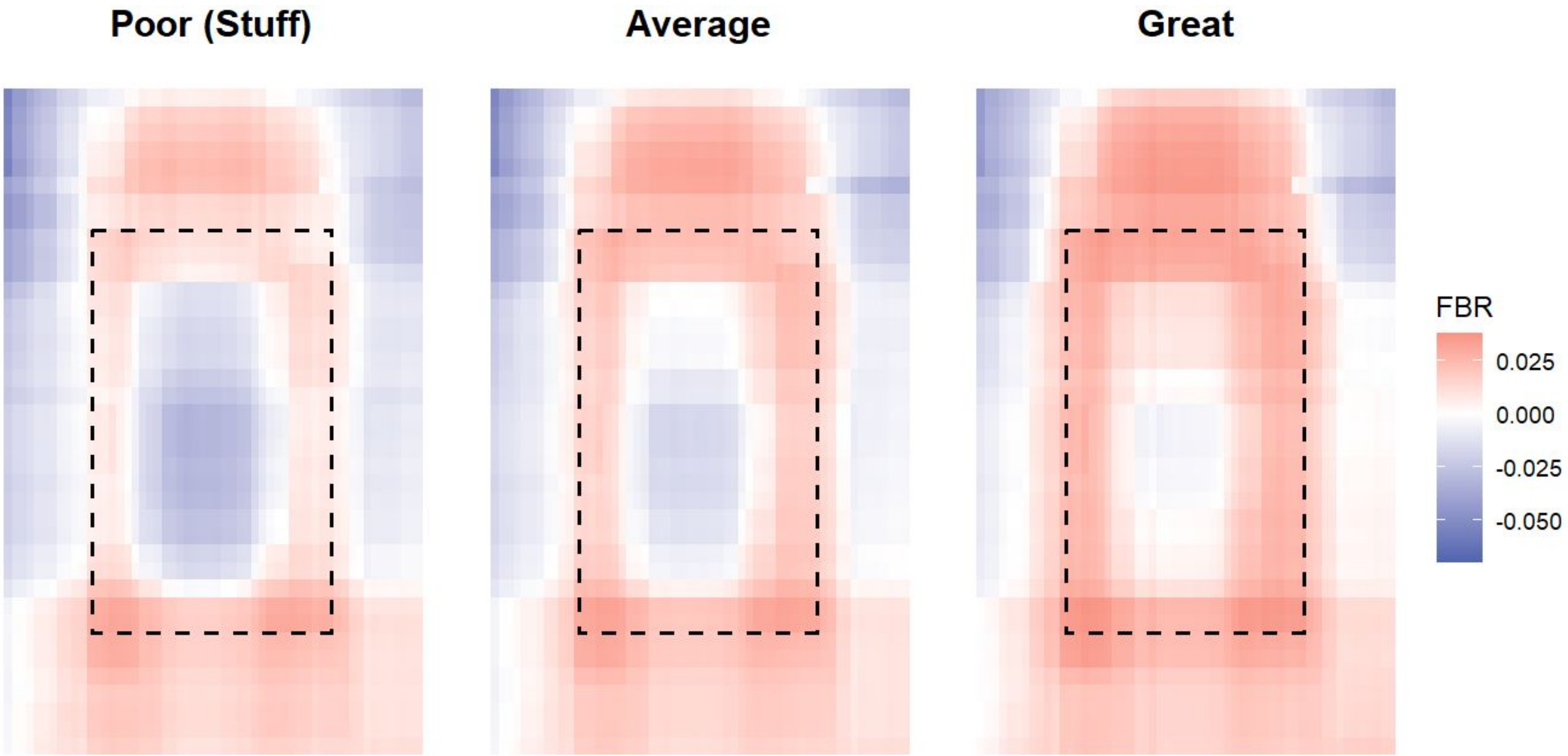
FBR by Count


Foul Ball Runs by Count
Strikes
2
1
0
0.015
0.013
0.021
0.042
−0.033
−0.042
−0.04
−0.035
−0.026
−0.033
−0.031
−0.036
0
1
2
3
Balls
FBR
0.04
0.02
0.00
−0.02
−0.04

FBR by Location and Count

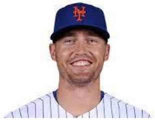


FBR by Location and Stuff (0-2 Count)



Overall FBR Leaders

Top 5

	Batter	Mean FBR
	Ha-Seong Kim	-0.0026
	Jurickson Profar	-0.0027
	Lars Nootbaar	-0.0036
	Brandon Nimmo	-0.0036
	Ji Hwan Bae	-0.0039

Bottom 5

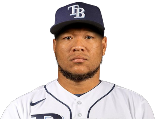
	Batter	Mean FBR
	Aaron Judge	-0.0272
	Eloy Jiménez	-0.0217
	Freddie Freeman	-0.0216
	Brandon Drury	-0.0214
	Christopher Morel	-0.0213

Two strikes FBR Leaders

Top 5

	Batter	Mean FBR
	**Brandon Belt**	0.0302
	**Eugenio Suárez**	0.0295
	**Lars Nootbaar**	0.0292
	**Mookie Betts**	0.0288
	**Brandon Nimmo**	0.0288

Bottom 5

	Batter	Mean FBR
	**Aaron Judge**	-0.0008
	**Freddie Freeman**	0.0108
	**Ryan Mountcastle**	0.0109
	**Jean Segura**	0.0123
	**Harold Ramírez**	0.0132

Analyzing Batter FBR Differences

Ha-Seong Kim

-0.0026 Mean FBR

Aaron Judge

-0.0272 Mean FBR

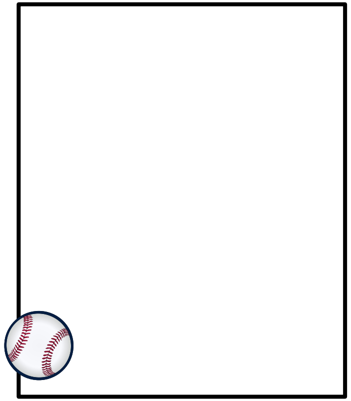
Kim Value	Kim Percentile	Statistic	Judge Value	Judge Percentile
0.0228	57th	2 Strike Mean FBR	-0.0008	**1st**
1.207	**97th**	2SFB : n2SFB Ratio	0.708	71st
17.7	**90th**	Whiff %	36.6	**2nd**
20.4	**91st**	Chase %	19.5	**93rd**
19.8	63rd	Strikeout %	28.4	**16th**

FBR - Revisiting Limitations of ARE

Kyle Bradish

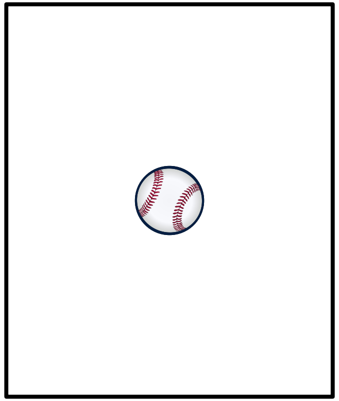
0.09 FBR

Count: 3-2
1st and 2nd
0 Outs



Slider
Stuff+ : 172

Count: 0-2
1st and 2nd
0 Outs



Slider
Stuff+ : 84

Patrick Corbin

-0.01 FBR

Foul ball vs. Bradish is valued **higher** by FBR

Future Enhancements

- Further tune hyperparameters on models
- Compare results with simulation-based methodologies
- Examine effects of foul balls later in the game (look at pitcher fatigue)

Thank You

Questions?