



Determining the Value of a Foul Ball

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Pitcher Beneficial



VS

Batter Beneficial





Methodology



Use Out
Probabilities by
Count

Determine Out
Probability Added
on a Foul Ball

Model Probability
on an out Based
on Pitch
Characteristics

Analyze Metric in
Context of Player
and Team
Offensive Output

Create Algorithm
Using These
Components to
Determine the
Probabilities

Model Probability
of Pitch Being
Fouled Off



Data



savant

2020 - 2023
Pitch Level

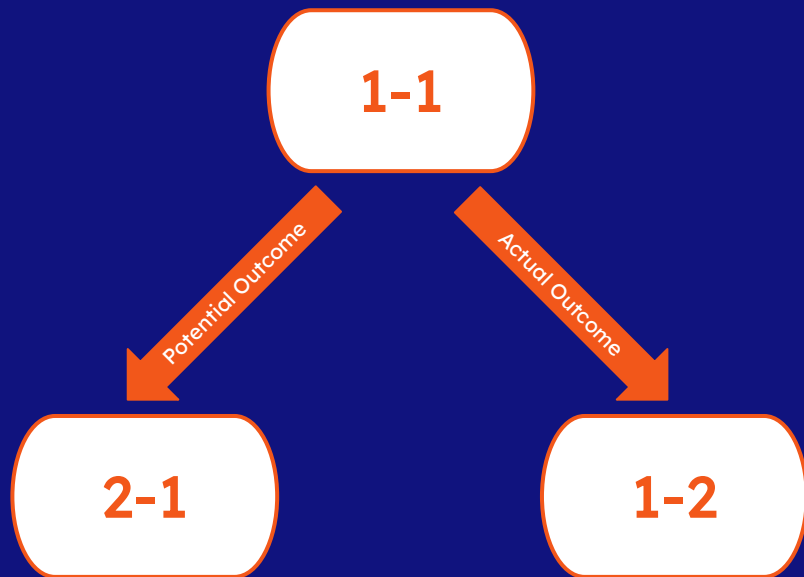


2023 Foul Balls

Creating Out Probabilities



Out Probabilities by Count



		<i>STRIKES</i>		
		0	1	2
<i>BALLS</i>	0	68.47%	73.78%	80.46%
	1	62.69%	69.53%	77.32%
	2	51.30%	61.02%	71.11%
	3	28.46%	41.17%	54.35%

Foul Ball Out Probability Added:
 $77.32\% - 61.02\% = 16.30\%$

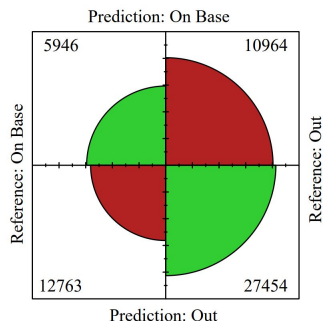


Batted Ball Out Model

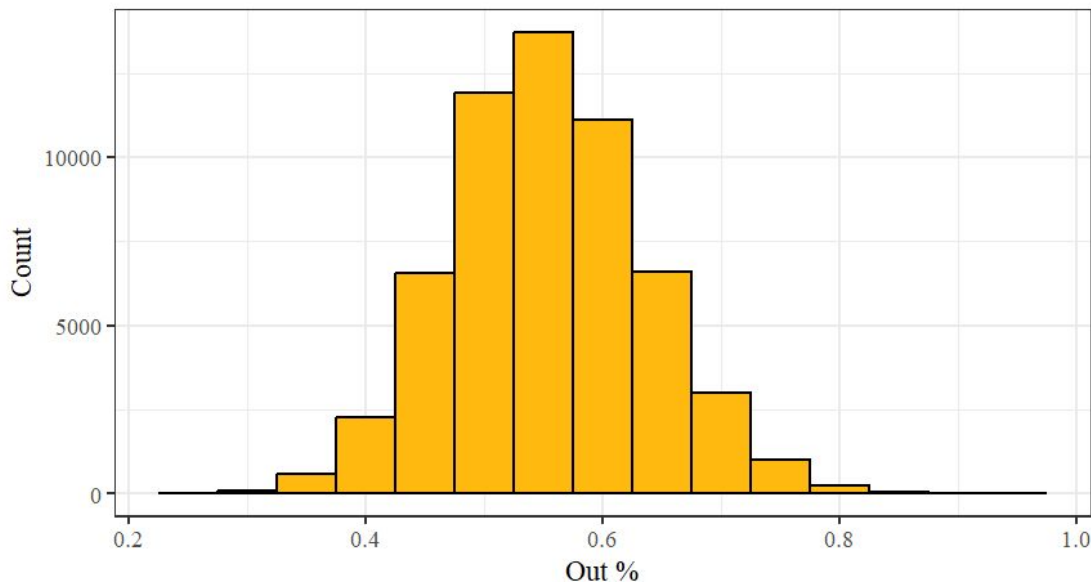


- ❖ Random Forest
- ❖ On Base/Out
- ❖ Predictors Used:
 - Pitch Characteristics*
 - Statcast Zone
 - Batter Handedness

Batted Ball Outcome Confusion Matrix

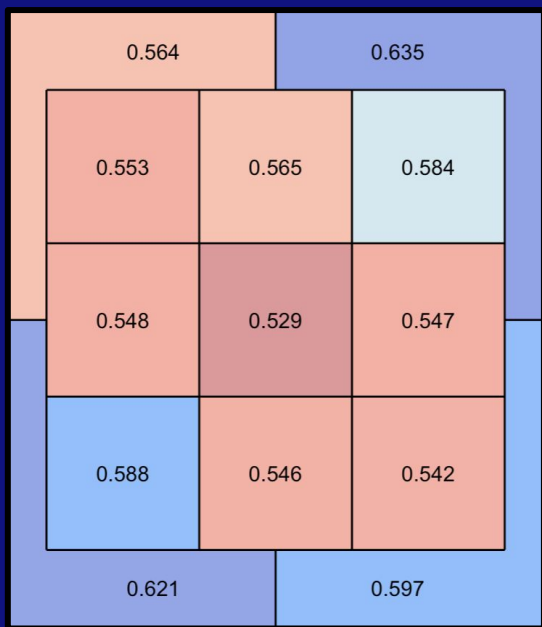


Out % Distribution on Test Set





Out Probability by Zone



Left-Handed Batters

P(Out)

< .521

(.521, .535)

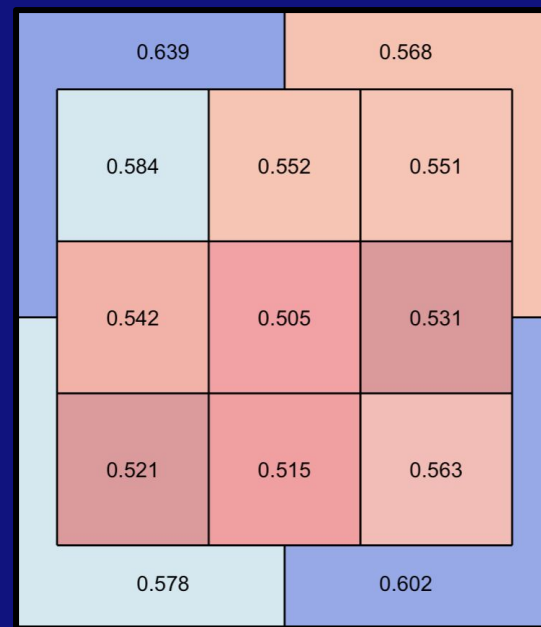
(.536, .550)

(.551, .570)

(.571, .585)

(.586, .600)

> .601



Right-Handed Batters



Foul Ball Model

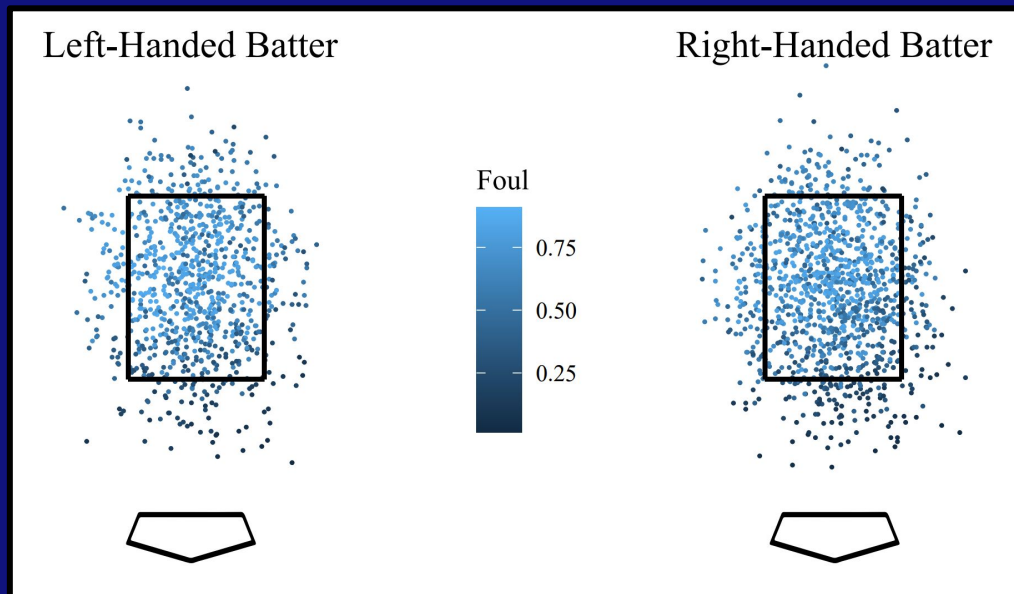
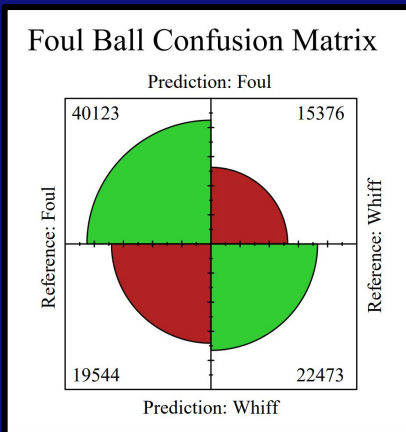


❖ Naive Bayes

$$P(\text{foul or whiff} \mid \text{feature}) = \frac{P(\text{feature} \mid \text{foul or whiff}) \cdot P(\text{foul or whiff})}{P(\text{feature})}$$

❖ Predictors Used:

- Count
- Pitch Characteristics



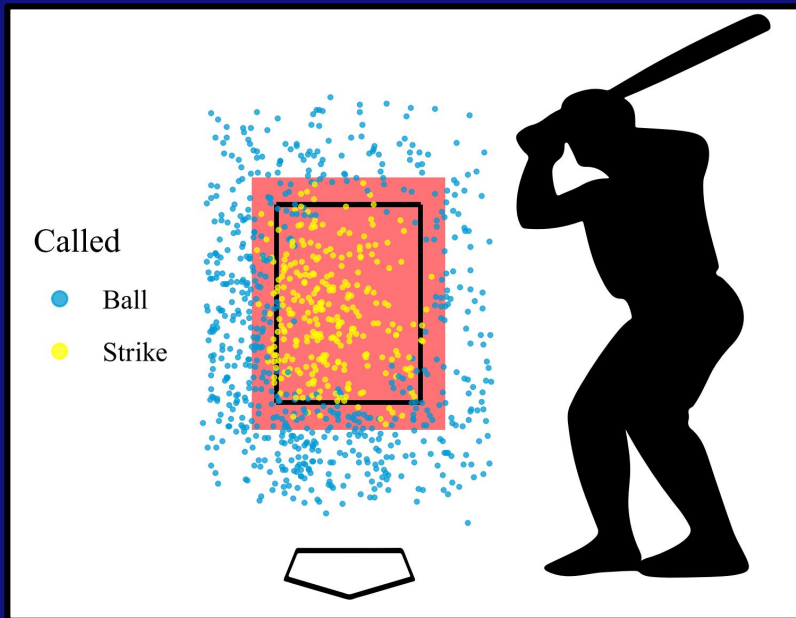


“Hittable” Pitches

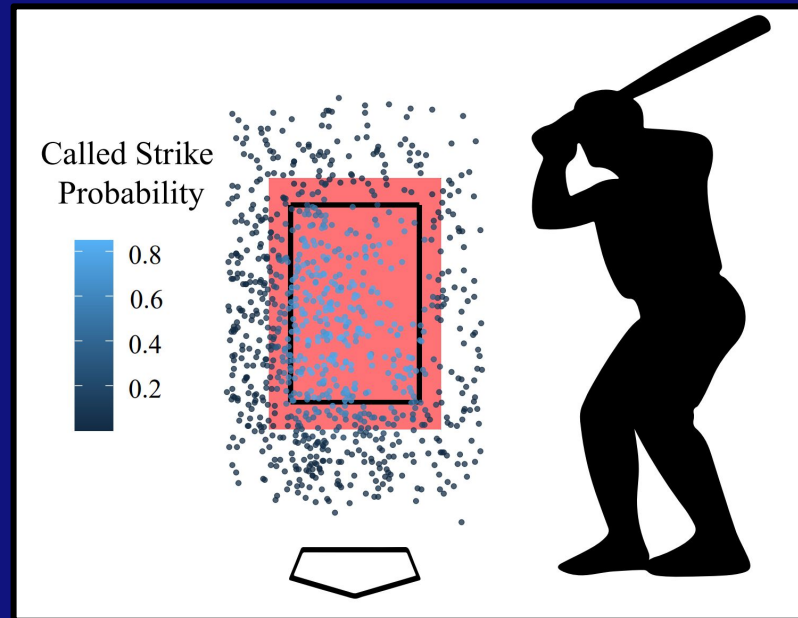


Shohei Ohtani 2023

Called Balls and Strikes



Called Strike Probability



Building an Algorithm



Batter Conditions



Foul Ball **O**ut **P**robability **A**dded

$$\text{Batter FOPA} = \left\{ \begin{array}{ll} P(\text{Count}) - P(\text{Count} \mid \text{No Swing}) , & \text{Not Hittable} \\ P(\text{Count}) - P(\text{Out} \mid \text{Ball in Play}) , & \text{Hittable, } < 2 \text{ Strikes} \\ P(\text{Foul}) - P(K) , & \text{Hittable, } 2 \text{ Strikes} \end{array} \right.$$



Pitcher Conditions



Foul Ball Out Probability Added

$$\text{Pitcher FOPA} = \left\{ \begin{array}{ll} P(\text{Count}) - P(\text{Count} \mid \text{No Swing}), & \text{Not Hittable, } < 2 \text{ Strikes} \\ P(\text{Count}) - P(\text{Count} \mid \text{No Swing}) \\ P(\text{Whiff}) - P(K),^* & \text{Not Hittable, 2 Strikes} \\ P(\text{Count}) - P(\text{Out} \mid \text{Ball in Play}), & \text{Hittable, } < 2 \text{ Strikes} \\ P(\text{Count}) - P(\text{Out} \mid \text{Ball in Play}) \\ P(\text{Whiff}) - P(K),^{**} & \text{Hittable, 2 Strikes} \end{array} \right.$$

* = mean

** = weighted mean

Leaderboards



Shiny App

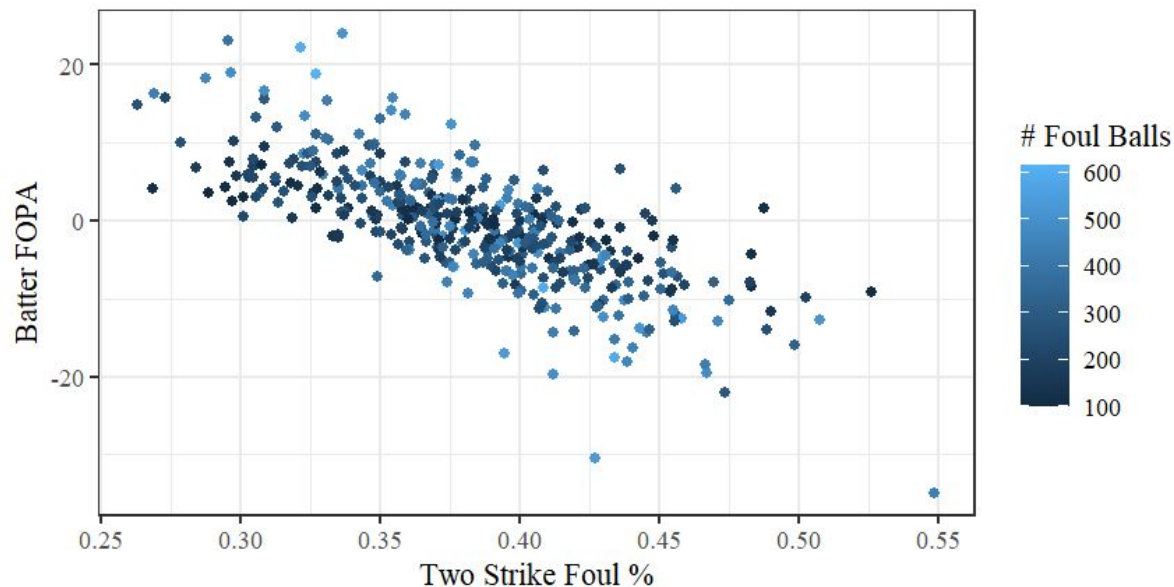




Hitter Metric Analysis



Batter FOPA vs Two Strike Foul %
Minimum 100 Foul Balls



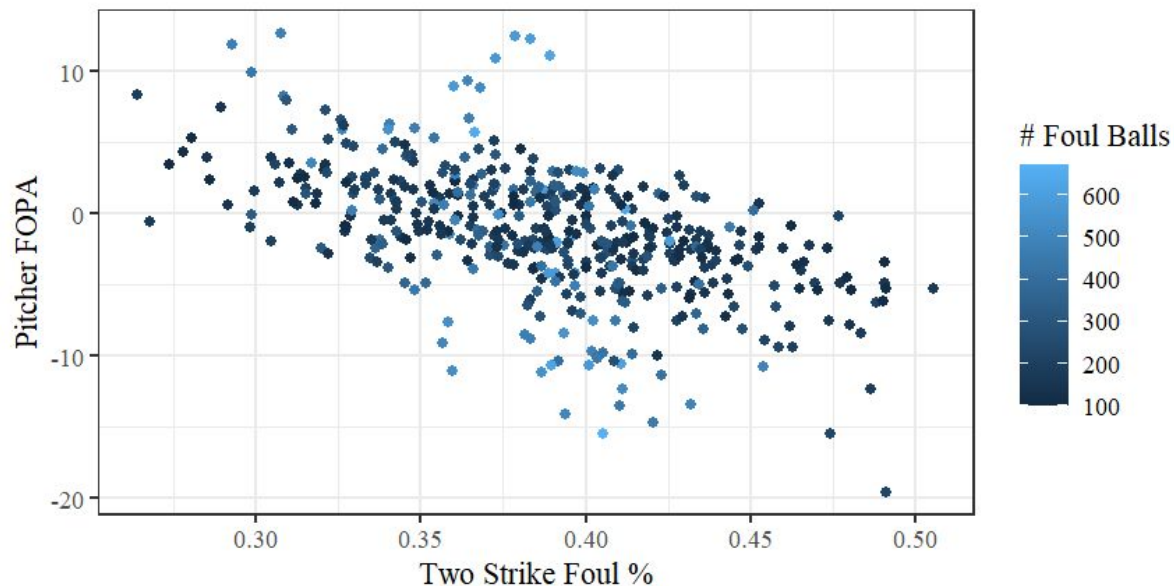
	Player	FOPA
	Ha-Seong Kim	-34.90
	Spencer Torkelson	-30.53
	Alex Call	-22.08
	Willy Adames	-19.74
	Brandon Nimmo	-19.56
	Cody Bellinger	-18.54
	Daulton Varsho	-18.12
	Anthony Santander	-17.57
	Ty France	-17.01
	Spencer Steer	-16.34











Pitcher Metric Analysis



Pitcher FOPA vs Two Strike Foul %
Minimum 100 Foul Balls



Player		FOPA
	Framber Valdez	12.71
	Justin Steele	12.51
	Mitch Keller	12.29
	Kyle Freeland	11.89
	George Kirby	11.07
	Pablo Lopez	10.93
	Kyle Gibson	9.92
	Johan Oviedo	9.37
	Logan Gilbert	8.98
	Yusei Kikuchi	8.90



Shortcomings



- ❖ Interpretation of “good” and “bad” foul balls
- ❖ Model performance
- ❖ Different model types
- ❖ Modeling on a league level
- ❖ Explanatory variables



Questions?