Predictability Score: A Deep Learning Metric for MLB Pitch Sequence Modeling

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Agenda

1. Background
2. Problem
3. Methods
4. Results
5. Practical Applications

Background


NATIONAL
AMERICAN
BATTER

Problem

What’s Going On?

- Limited Pitch Sequencing Statistics
- Most statistics are not pitcher-isolated
    - Hitter strength
    - Team fielding
    - Ballpark factor

Method

Data

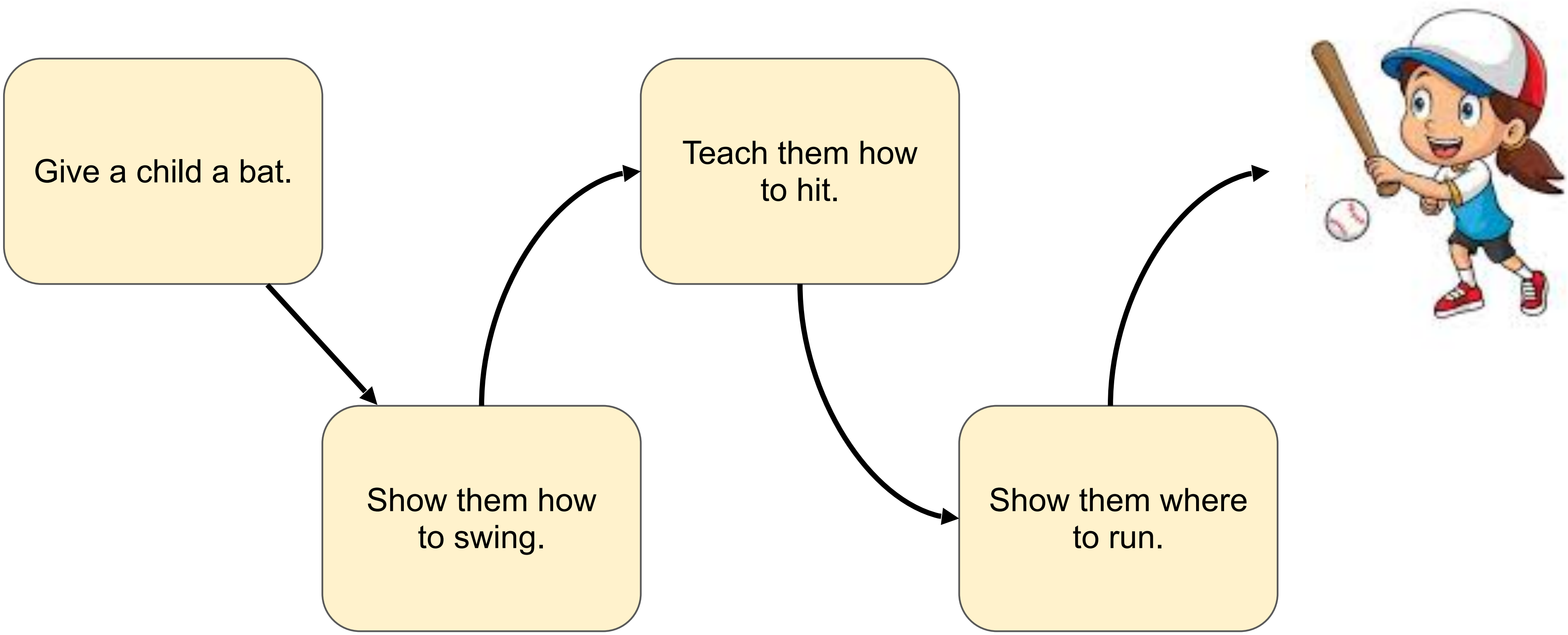
- All 2025 Pitch Sequences from qualifying pitchers (retro 8/10)
- Only sequences ≥ 2 pitches
- Features:
    - Release speed, release position, spin axis, horizontal movement, vertical movement, strike zone location, inning, outs, score, # times through order (pitcher), # times up to bat prior (batter), # runners on, pitcher throws (R/L), batter stands (R/L)

Modeling

1. Run RNN Model
1. Find Test Accuracy per Pitcher
1. Find Normalized Accuracy Gain (NAG)

Normalized Accuracy Gain (NAG) = measures how much better a model performs than random guessing, adjusted for the number of possible outcomes.

Recurrent Neural Networks as T-Ball



Predictability Score Equation

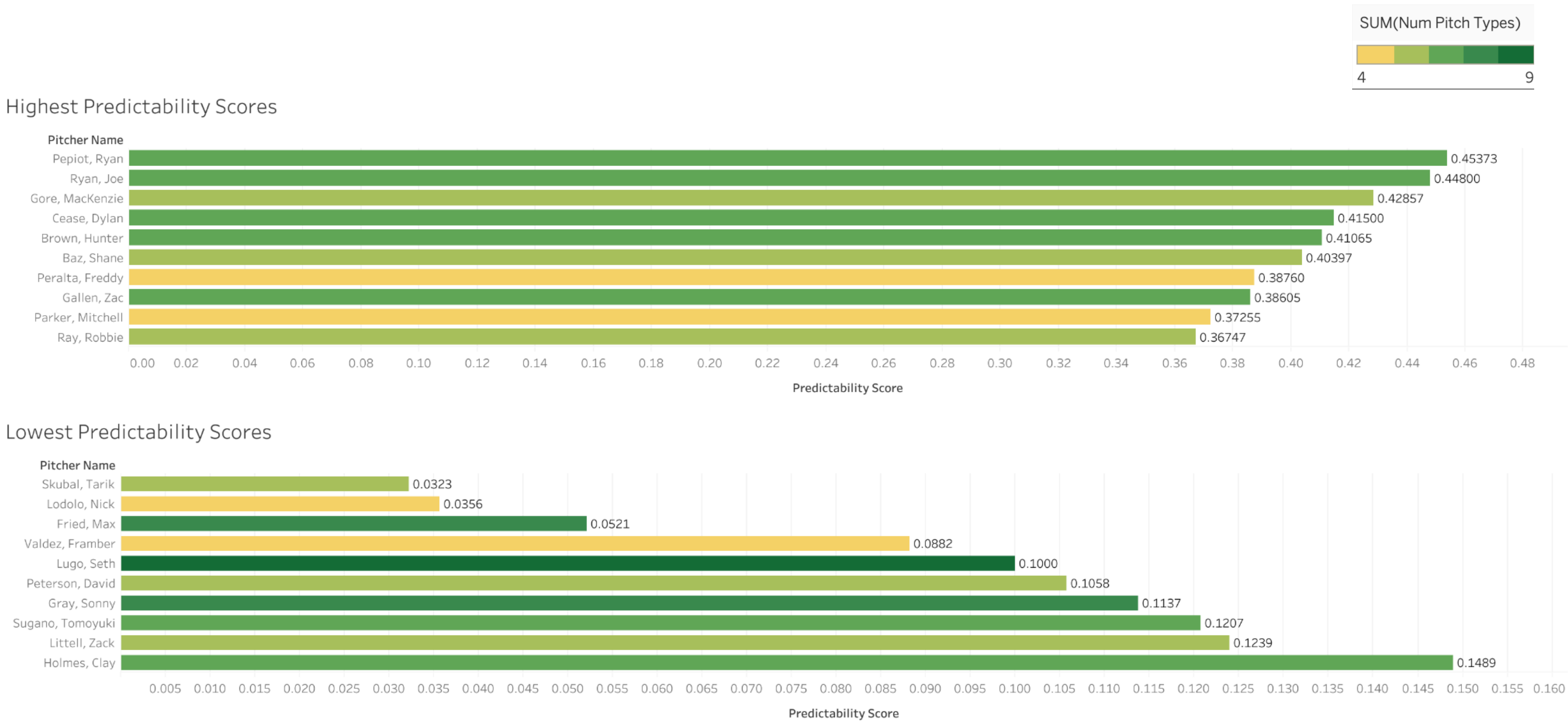
$$NAG = \frac{Accuracy_{model} - \frac{1}{K}}{1 - \frac{1}{K}}$$

Where:

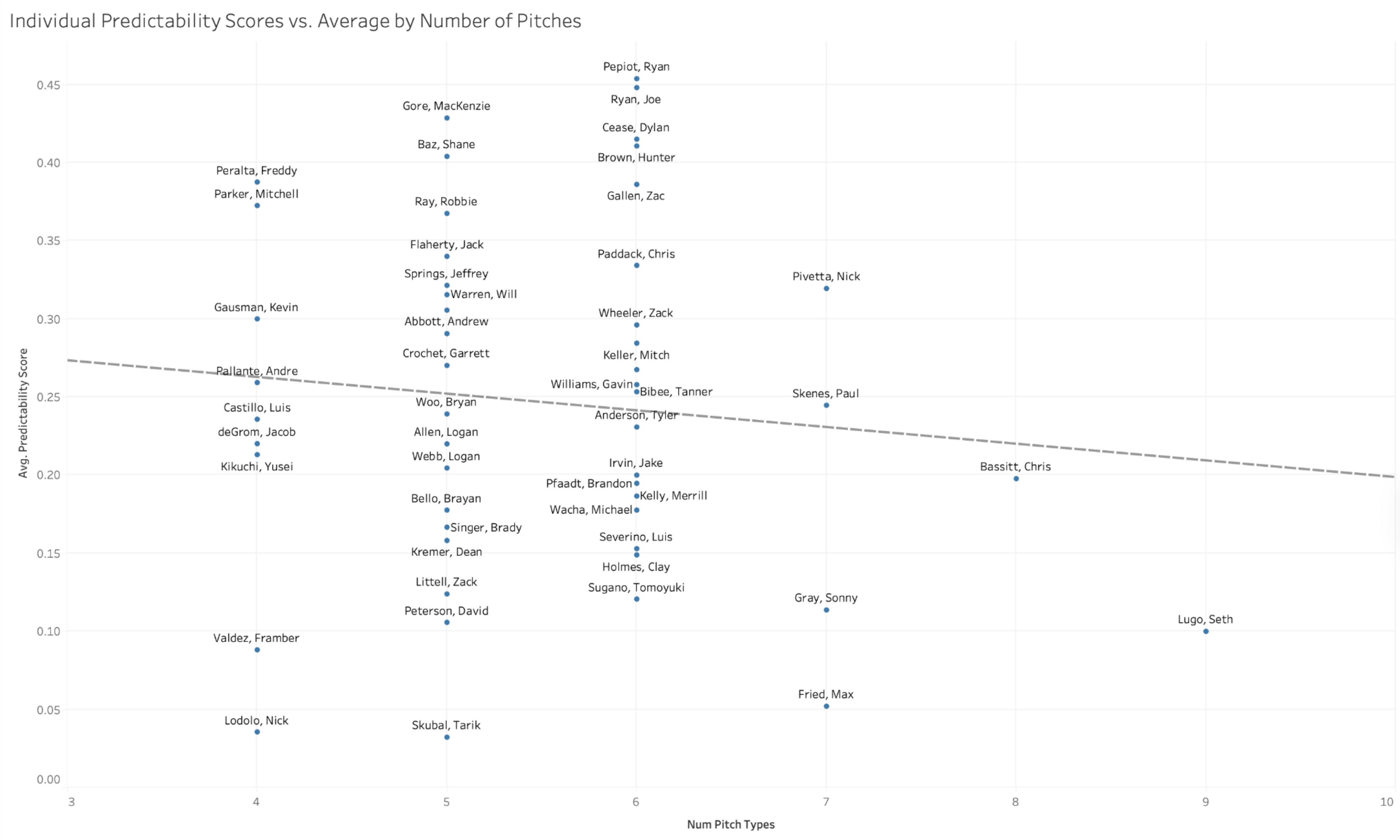
- $Accuracy_{model}$ = Model's prediction accuracy for that pitcher
- K = Number of possible pitches
- $\frac{1}{K}$ = Accuracy from uniform random guessing

Interpretation: 0: No better than random, 1: Perfect prediction

Results



SUM(Num Pitch Types)
4
9
Highest Predictability Scores
Pitcher Name
Pepiot, Ryan
Ryan, Joe
Gore, MacKenzie
Cease, Dylan
Brown, Hunter
Baz, Shane
Peralta, Freddy
Gallen, Zac
Parker, Mitchell
Ray, Robbie
0.45373
0.44800
0.42857
0.41500
0.41065
0.40397
0.38760
0.38605
0.37255
0.36747
0.00 0.02 0.04 0.06 0.08 0.10 0.12 0.14 0.16 0.18 0.20 0.22 0.24 0.26 0.28 0.30 0.32 0.34 0.36 0.38 0.40 0.42 0.44 0.46 0.48
Predictability Score
Lowest Predictability Scores
Pitcher Name
Skubal, Tarik
Lodolo, Nick
Fried, Max
Valdez, Framber
Lugo, Seth
Peterson, David
Gray, Sonny
Sugano, Tomoyuki
Littell, Zack
Holmes, Clay
0.0323
0.0356
0.0521
0.0882
0.1000
0.1058
0.1137
0.1207
0.1239
0.1489
0.005 0.010 0.015 0.020 0.025 0.030 0.035 0.040 0.045 0.050 0.055 0.060 0.065 0.070 0.075 0.080 0.085 0.090 0.095 0.100 0.105 0.110 0.115 0.120 0.125 0.130 0.135 0.140 0.145 0.150 0.155 0.160
Predictability Score


Individual Predictability Scores vs. Average by Number of Pitches
Avg. Predictability Score
Num Pitch Types
0.00
0.05
0.10
0.15
0.20
0.25
0.30
0.35
0.40
0.45
3
4
5
6
7
8
9
10
Pepiot, Ryan
Ryan, Joe
Gore, MacKenzie
Cease, Dylan
Baz, Shane
Brown, Hunter
Peralta, Freddy
Parker, Mitchell
Ray, Robbie
Gallen, Zac
Flaherty, Jack
Paddack, Chris
Springs, Jeffrey
Pivetta, Nick
Warren, Will
Gausman, Kevin
Wheeler, Zack
Abbott, Andrew
Crochet, Garrett
Keller, Mitch
Pallante, Andre
Williams, Gavin
Bibee, Tanner
Skenes, Paul
Woo, Bryan
Castillo, Luis
Anderson, Tyler
deGrom, Jacob
Allen, Logan
Webb, Logan
Irvin, Jake
Kikuchi, Yusei
Bassitt, Chris
Pfaadt, Brandon
Bello, Brayan
Kelly, Merrill
Wacha, Michael
Singer, Brady
Severino, Luis
Kremer, Dean
Holmes, Clay
Littell, Zack
Sugano, Tomoyuki
Gray, Sonny
Peterson, David
Lugo, Seth
Valdez, Framber
Fried, Max
Lodolo, Nick
Skubal, Tarik

Predictability ≠ Hittability

Does not fully capture “damage potential”

High Predictability + High Contact Quality = High Risk

High Predictability + Low Contact Quality = Low Risk

What Can We Do?

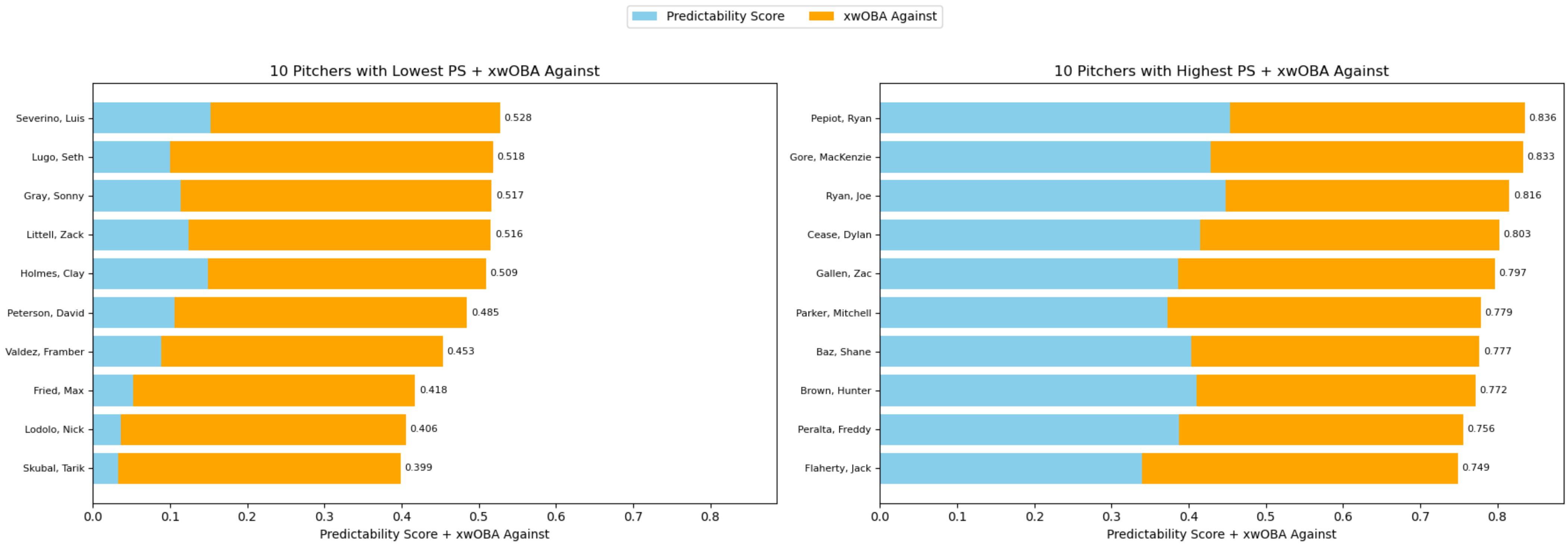
Add Expected Weighted On Base Average Against(xwOBA)

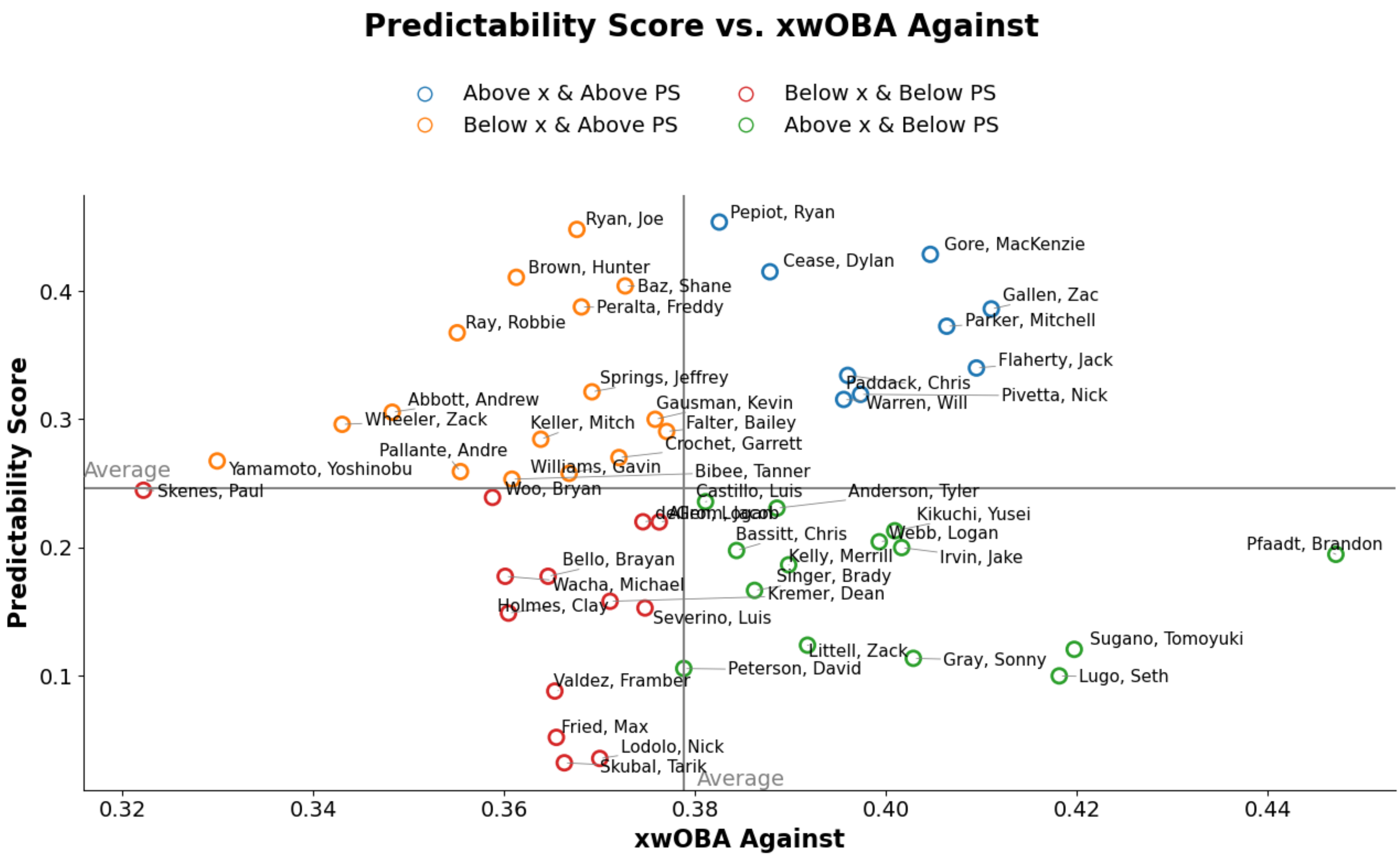
- Measures overall run value allowed
- Links prediction to run prevention
- Captures hidden damage (singles, walks, sustained rallies)

Add Barrel Percent Against

- Measures quality of hard contact
- Reveals cost of predictability
- Differentiates between “safe” and “dangerous” predictability

Predictability Score + xwOBA Against




Predictability Score vs. xwOBA Against
Above x & Above PS
Below x & Above PS
Below x & Below PS
Above x & Below PS
Predictability Score
xwOBA Against
0.1
0.2
0.3
0.4
0.32
0.34
0.36
0.38
0.40
0.42
0.44
Average
Average
Ryan, Joe
Pepiot, Ryan
Gore, MacKenzie
Cease, Dylan
Brown, Hunter
Baz, Shane
Gallen, Zac
Peralta, Freddy
Parker, Mitchell
Ray, Robbie
Flaherty, Jack
Springs, Jeffrey
Paddack, Chris
Pivetta, Nick
Abbott, Andrew
Gausman, Kevin
Warren, Will
Wheeler, Zack
Keller, Mitch
Falter, Bailey
Crochet, Garrett
Pallante, Andre
Williams, Gavin
Yamamoto, Yoshinobu
Bibee, Tanner
Skenes, Paul
Woo, Bryan
Castillo, Luis
Anderson, Tyler
Kikuchi, Yusei
Webb, Logan
Bassitt, Chris
Pfaadt, Brandon
Irvin, Jake
Kelly, Merrill
Bello, Brayan
Singer, Brady
Wacha, Michael
Kremer, Dean
Holmes, Clay
Severino, Luis
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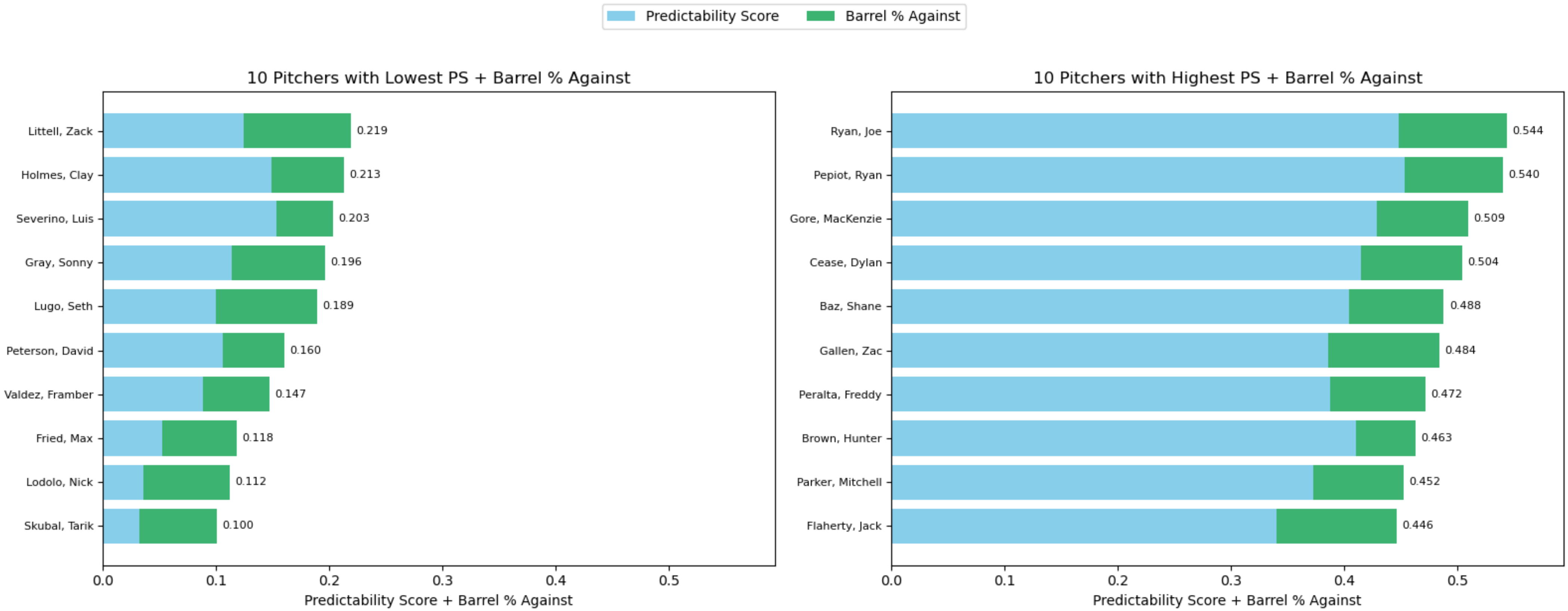
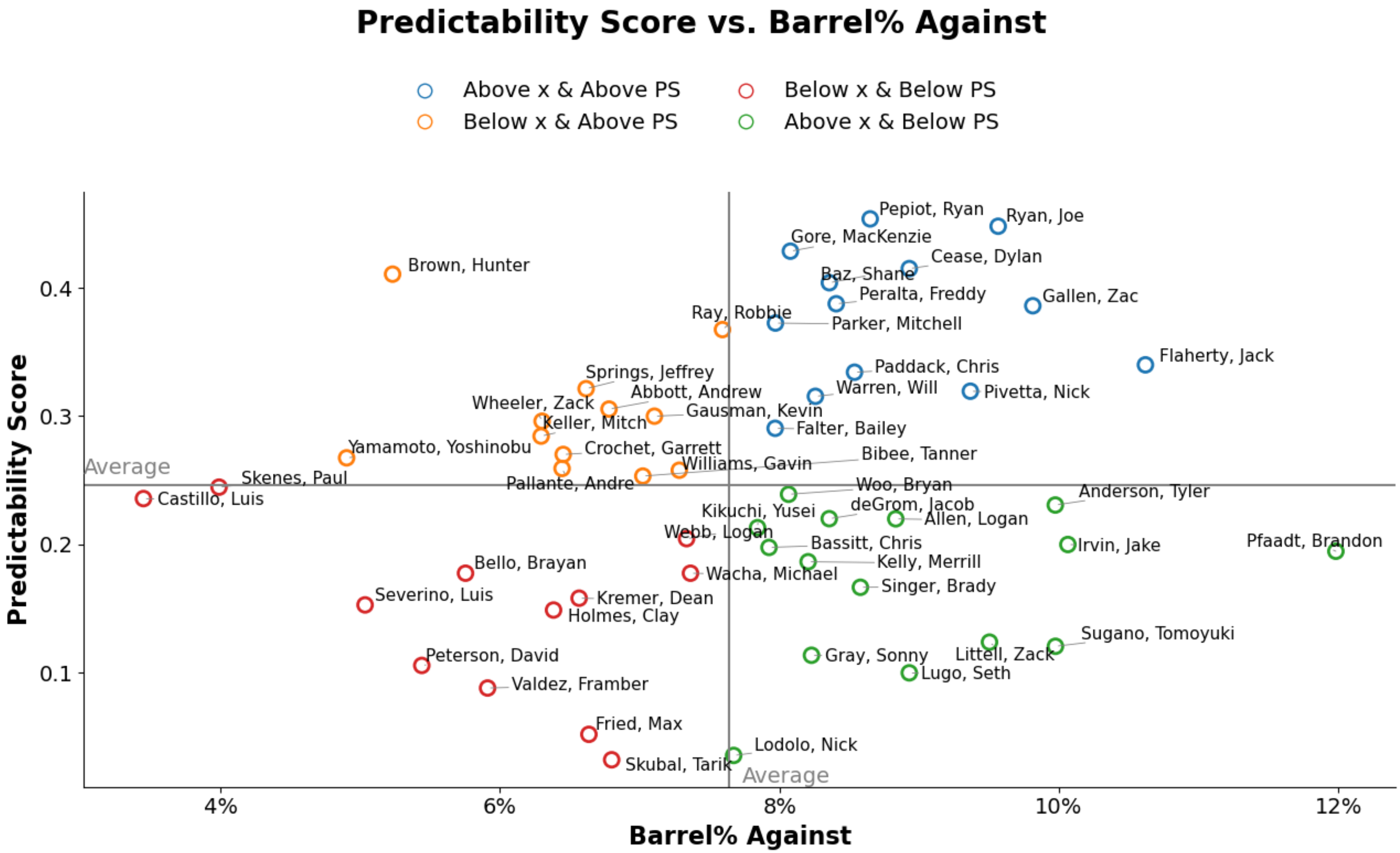
Littell, Zack
Gray, Sonny
Peterson, David
Lugo, Seth
Valdez, Framber
Fried, Max
Lodolo, Nick
Skubal, Tarik

Predictability Score + Barrel % Against





Predictability Score vs. Barrel% Against
Above x & Above PS
Below x & Above PS
Below x & Below PS
Above x & Below PS
Predictability Score
Barrel% Against
Average
Average
0.1
0.2
0.3
0.4
4%
6%
8%
10%
12%
Pepiot, Ryan
Ryan, Joe
Gore, MacKenzie
Cease, Dylan
Baz, Shane
Peralta, Freddy
Gallen, Zac
Parker, Mitchell
Flaherty, Jack
Paddack, Chris
Warren, Will
Pivetta, Nick
Falter, Bailey
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Ray, Robbie
Springs, Jeffrey
Abbott, Andrew
Wheeler, Zack
Gausman, Kevin
Keller, Mitch
Yamamoto, Yoshinobu
Crochet, Garrett
Williams, Gavin
Bibee, Tanner
Pallante, Andre
Skenes, Paul
Castillo, Luis
Woo, Bryan
Anderson, Tyler
Kikuchi, Yusei
deGrom, Jacob
Allen, Logan
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Gray, Sonny
Littell, Zack
Lugo, Seth
Valdez, Framber
Fried, Max
Lodolo, Nick
Skubal, Tarik

Practical Applications

Test Accuracy

Hitting Team

Can be test accuracy percent confident that the model output will be the next pitch.

Pitching Team

If the model is test accuracy percent confident that the next pitch will be pitch x, surprise the hitter and throw pitch y.

Predictability Score

- Identify pitchers with easy to guess patterns
- Target low-PS pitchers in scouting
- Develop young pitchers' unpredictability

PS + xwOBA Against

- Measure overall effectiveness and impact of predictability
- Justify adding pitches to break patterns
- Guide starter vs. bullpen role decisions

PS + Barrel % Against

- Flag "dangerous predictability"
- Avoid power matchups for high-risk pitchers
- Assess risk in hitter-friendly parks

Thank You

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Resources

Major League Baseball. (n.d.). *Baseball Savant*. Retrieved August 10, 2025, from https://baseballsavant.mlb.com/.