Optimizing MLB Batting Orders Using a Context-Dependent Monte Carlo Simulation and Metropolis-Hastings Algorithm

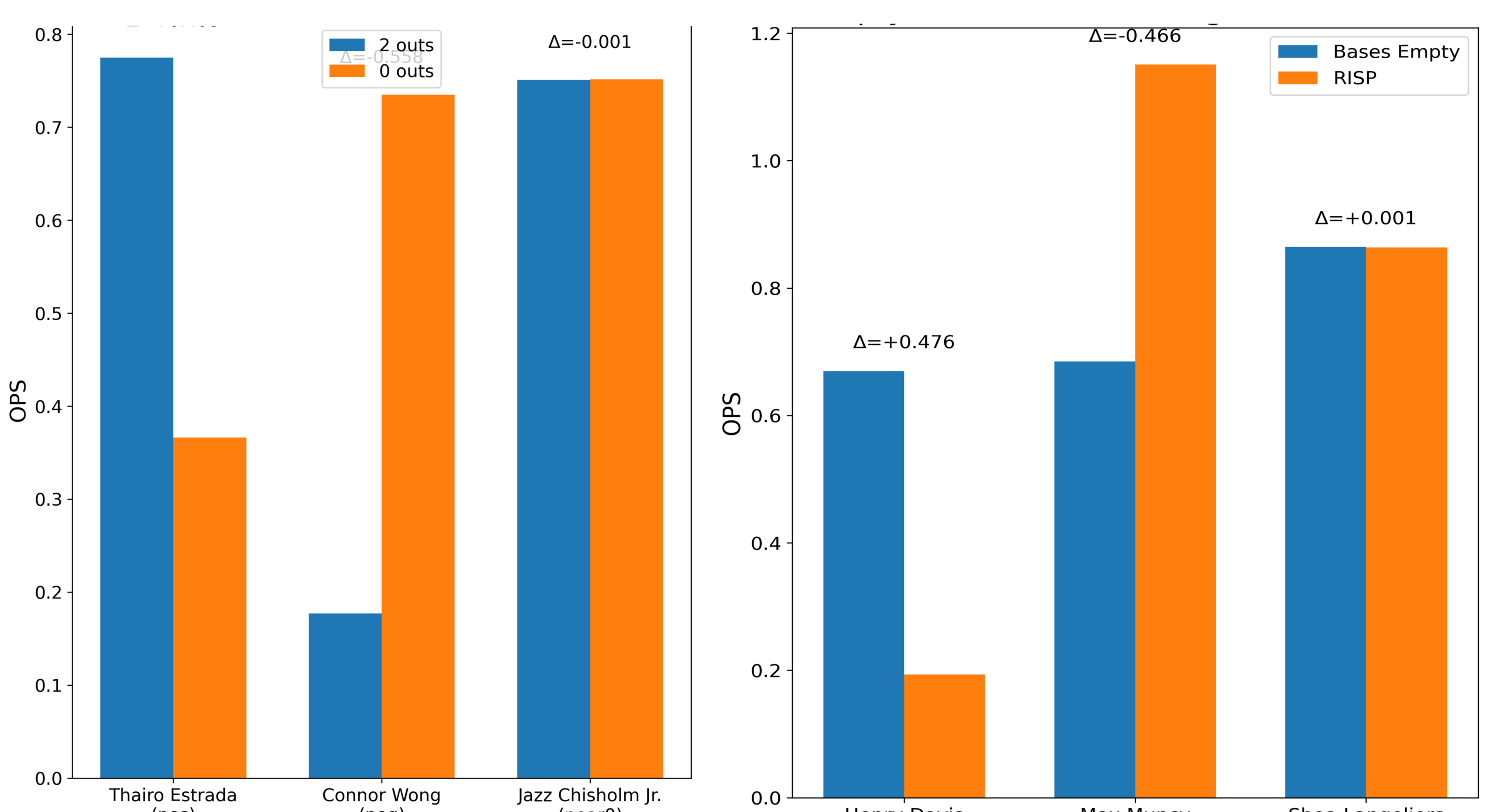
THE COLLEGE OF WOOSTER

Jun Kang | Statistical & Data Sciences | Advised by Dr. Cynthia Lester

Overview

This study develops a simulation-based framework to evaluate and optimize MLB batting orders. Using game-state-dependent event probabilities, the model simulates baseball games one plate appearance at a time while accounting for outs, base-runner situations, and pitcher handedness. It then applies the Metropolis-Hastings algorithm to explore many possible lineup arrangements and identify batting orders that produce higher expected run scoring.

Exploratory Data Analysis



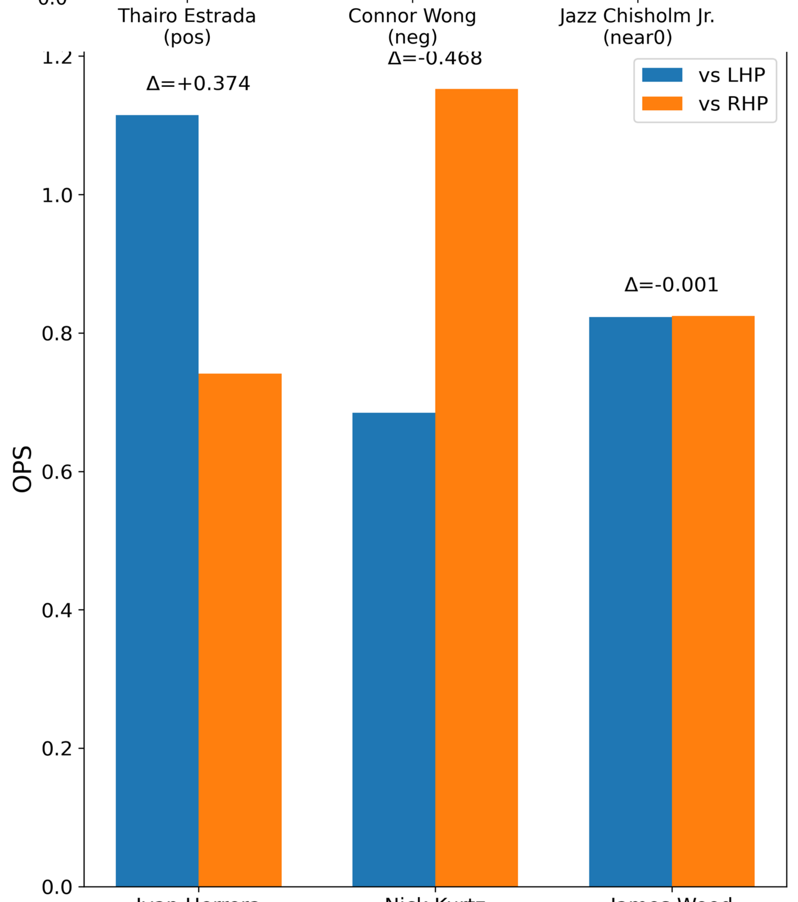


Figure 1. Illustrative examples from the EDA showing that OPS can vary by game context and pitcher handedness.

Exploratory data analysis was used to examine whether offensive performance remains stable across situations. The examples above show that OPS can vary substantially by out count and by pitcher handedness for hitters. In other words, offensive production is not necessarily constant across all plate appearances but may depend on the specific game context. This is important because it suggests that outcome probabilities should not be treated as fixed for every situation. Instead, the model should allow transition probabilities to vary with context.

Markov Chain

A Markov chain is a process in which the next state depends only on the current state. In this study, each state represents the game situation in terms of the number of outs and the base-runner configuration. A plate appearance moves the game from one base-out state to another depending on the outcome, such as a single, double, walk, home run, or out.

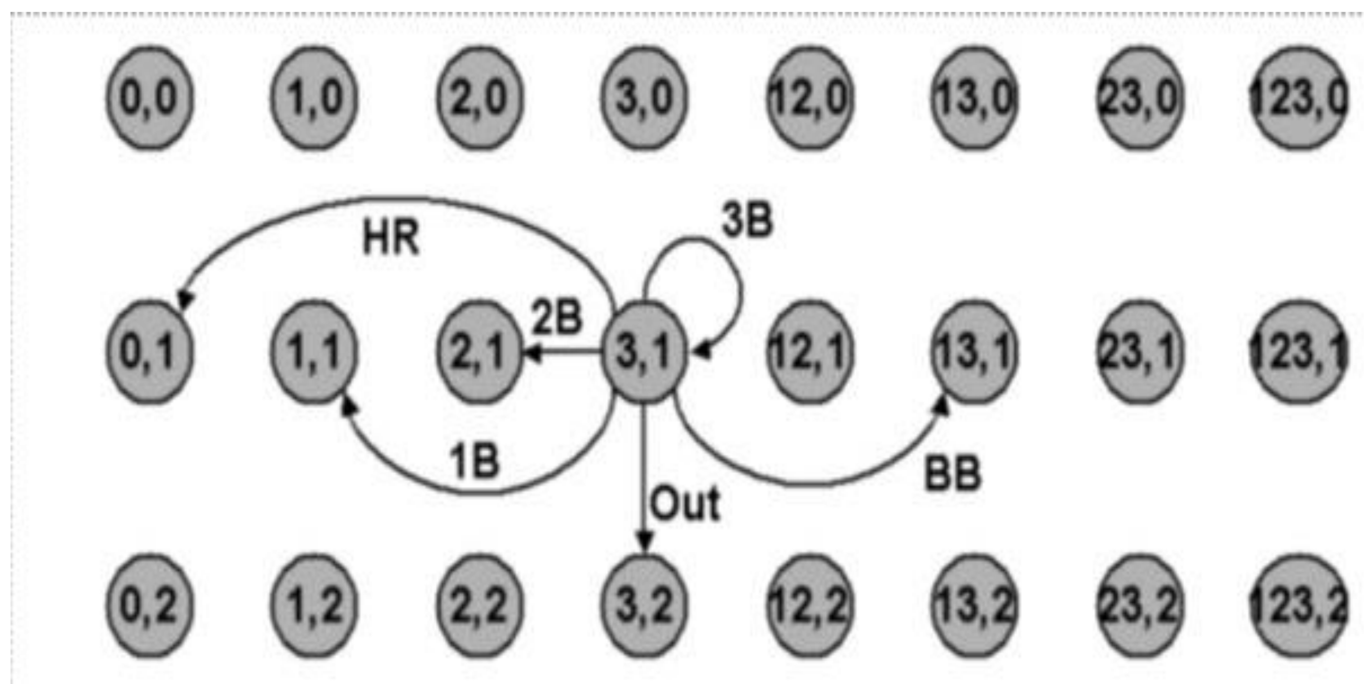


Figure 2. Example of a Markov Chain in baseball

Emanuel Schorsch and AJ Valera. "Baseball Lineup Optimization". In: Swarthmore College Department of Computer Science (2015)

Simulation

Simulation Framework

- Simulate the game one plate appearance at a time.
- Start from the current state: outs, base occupancy, and pitcher handedness.
- Look up the corresponding event probabilities for that state.
- Randomly draw an outcome, such as a single, double, walk, home run, or out.
- Update outs, runner locations, and runs scored based on the outcome.
- Repeat this process across innings, with the batting order carrying over, until a full 9-inning game is completed.

Lineup Search (Metropolis-Hastings algorithm)

- Start from an initial batting order.
- Make a small change to create a new candidate lineup.
- Evaluate the candidate through repeated game simulations.
- Lineups with higher average run production are more likely to be retained.
- Repeat this process many times to identify strong batting orders.

Result

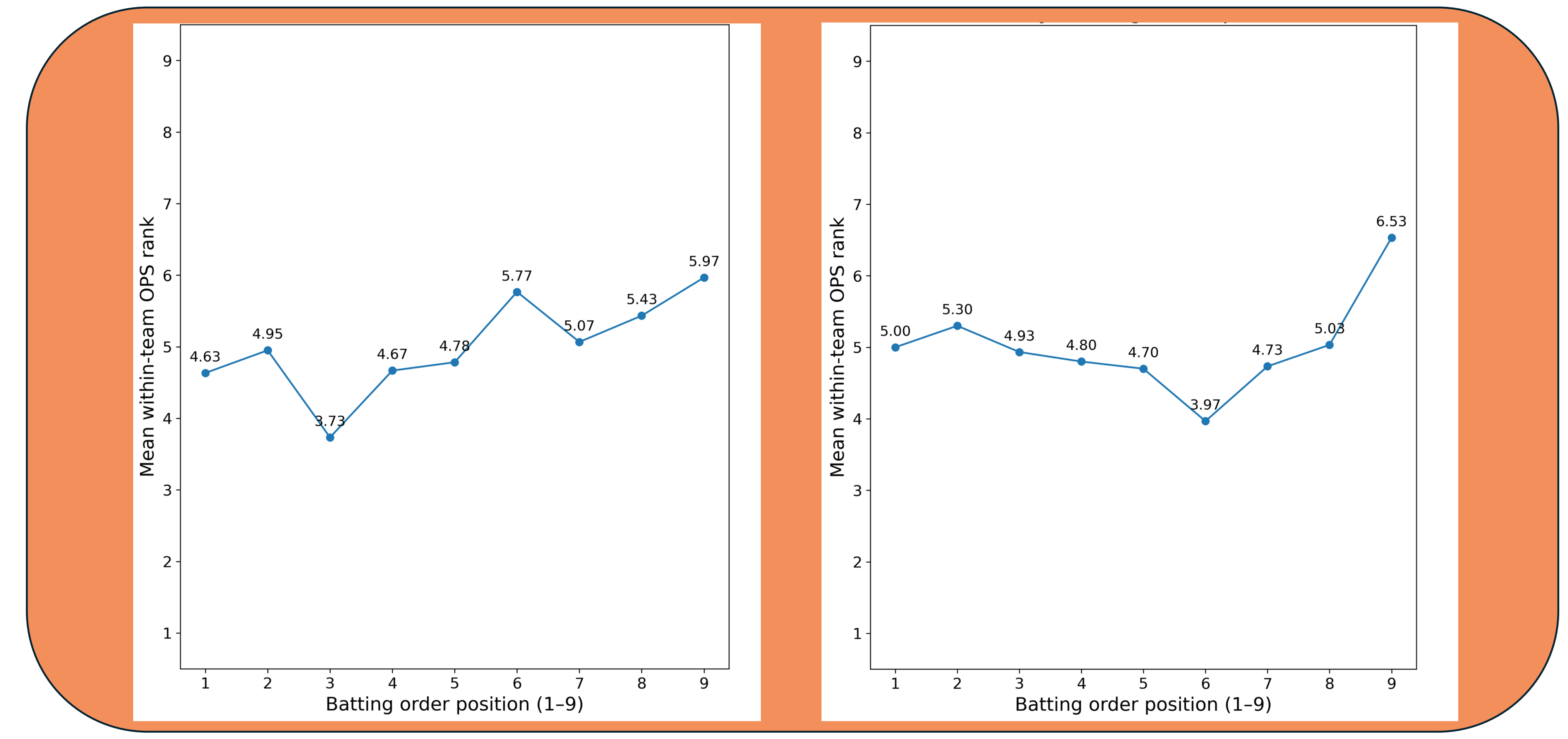


Figure 3. Mean within-team OPS rank by batting-order position for optimized lineups against left-handed pitchers (left) and right-handed pitchers (right). Lower OPS-rank values indicate stronger hitters.

The optimized lineups show clear handedness-specific placement patterns. Because lower OPS rank values correspond to stronger hitters, the results indicate that against left-handed pitchers, better hitters are placed more heavily toward the front of the lineup, with the strongest concentration around the 3rd spot. Against right-handed pitchers, stronger hitters shift more toward the middle of the order, especially around the 6th spot, rather than simply occupying the earliest lineup positions. This suggests that the optimized batting order is not just a descending OPS list, but a handedness-specific arrangement shaped by the run-scoring dynamics of the simulation.

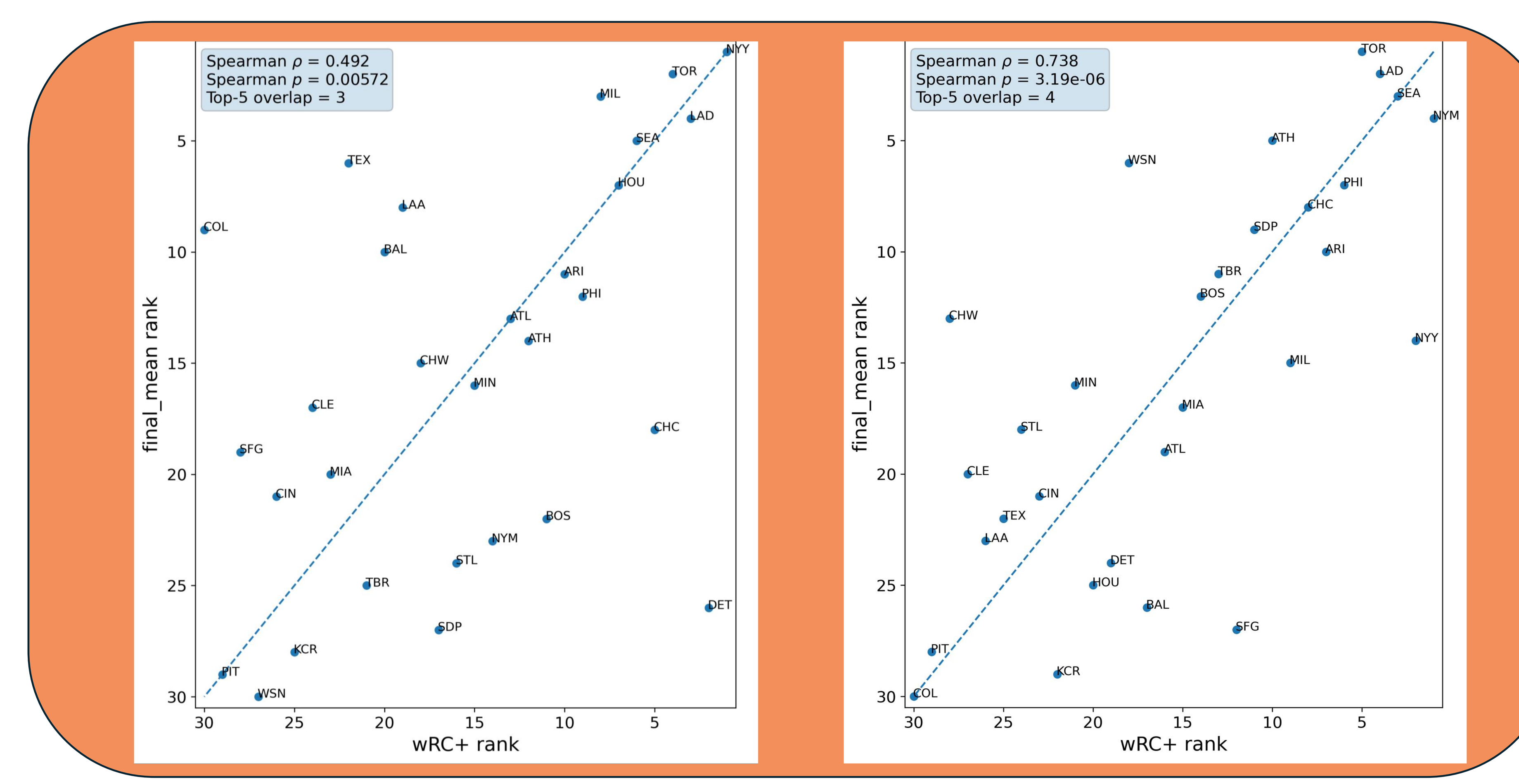


Figure 4. Validation plots comparing team wRC+ rank and simulated mean-run rank against left-handed pitchers (left) and right-handed pitchers (right).

To assess validity, team rankings based on simulated mean runs were compared with team wRC+ rankings. The relationship is positive for both handedness splits, with a moderate correlation against left-handed pitchers (ρ = 0.492) and a stronger correlation against right-handed pitchers (ρ = 0.738). These results suggest that the simulation captures meaningful variation in team offensive quality.