

Group 3: Predicting WAR

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Overview

- ▶ Goal: build a model to predict WAR (Wins Above Replacement)
- ▶ WAR measures a player's total contribution compared to a replacement-level player
 - ▶ It combines multiple aspects of performance: hitting, baserunning, defensive value, positional difficulty, and their playing time, and puts it into a single number.
 - ▶ Interpreted as the number of additional wins a player adds to a team
 - ▶ Since it provides a single encompassing measure of a player's value, WAR is greatly relied on by MLB front offices

Motivation

- ▶ Can a player's current-season performance statistics be used to predict their next season Wins Above Replacement (WAR)?
- ▶ Major League Baseball teams rely heavily on WAR to evaluate a players value, make contract decisions, and project roster needs.
- ▶ It provide a competitive advantage for a team by:
 - ▶ Helps identify declining players
 - ▶ Allows for budgeting and contract planning
 - ▶ Encourages player development and roster optimization
- ▶ Our goal is, by using statistical and machine learning models, we will:
 - ▶ Identify which player statistics best predict future WAR
 - ▶ Compare the performance of three different statistical learning models: OLS, LASSO, and BOOSTING
 - ▶ Build a model that maintains high predictive accuracy

Data used

- ▶ Our data came from baseball-reference.com
- ▶ We used standard batting data from 2020-2025 to build our models (500 obs each year)
 - ▶ 2020-2024 was used for training
 - ▶ 2025 was our test data set
- ▶ Variables:
 - ▶ WAR, age, games played, plate appearances, at bats, runs scored, hits, doubles, triples, home runs, RBIs, stolen bases, caught stealing, walks, strikeouts, batting average, on base percentage, slugging percentage, OPS percentage, OPS+, rOBA, Rbat+, total bases, double plays grounded into, hit by pitch, sacrifice hits, sacrifice flies, intentional walks

Models Used

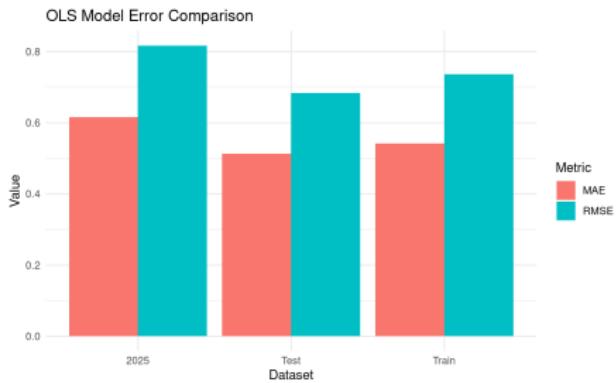
- ▶ OLS
 - ▶ Baseline linear model
 - ▶ Benchmark for comparing models
- ▶ LASSO
 - ▶ Feature selection through L1 regularization
- ▶ Boosting
 - ▶ Tree based method
 - ▶ Good at capturing non-linear patterns

OLS Models

- ▶ OLS identifies and measures the relationship between a response variable and predictor variables.
 - ▶ Finds a best-fitting line through a set of data points
- ▶ Pros: Convenient, accurate regression results for linearly related data
- ▶ Cons: May be too simplistic for real world examples, assumptions of Linear Regression

OLS Metrics Plot

- ▶ Error metrics for both final testing data set (2025) and the training data split into training and testing sets
- ▶ Significant terms:
 - ▶ age, games played, plate appearances, at bats, runs, hits, doubles, triples, home runs, stolen bases, caught stealing, walks, strikeouts, OPS+

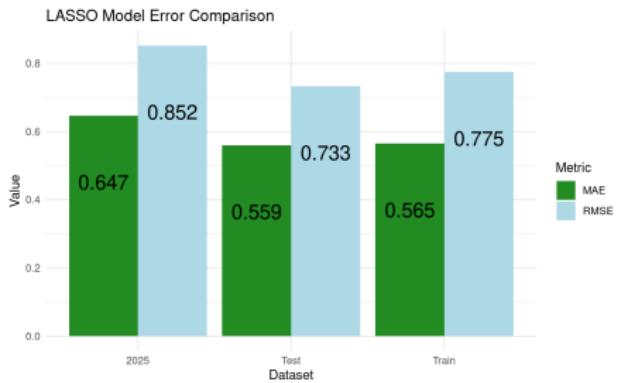


LASSO Models

- ▶ LASSO models perform regularization (L1), which shrinks some coefficients to exactly zero
 - ▶ Essentially feature selection
- ▶ Pros: Produces a more interpretative model, prevents over fitting
- ▶ Cons: LASSO performs poorly when predictors are highly correlated

LASSO Metrics Plot

- ▶ Error metrics for both final testing data set (2025) and the training data split into training and testing sets
- ▶ Shrunk terms:
 - ▶ Plate appearances, home runs, RBIs, batting average, on base percentage, OPS+, rOBA

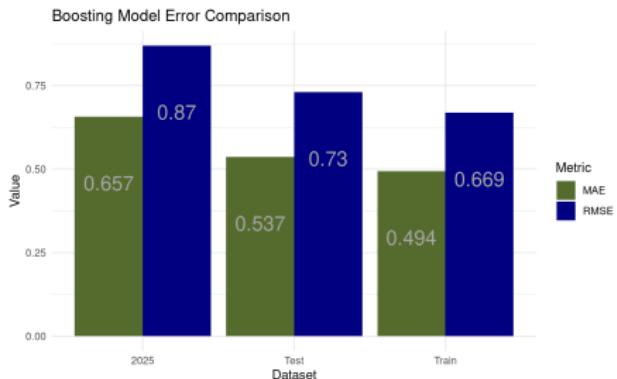


Boosting Models

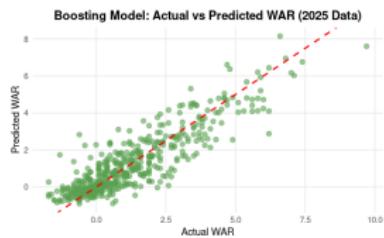
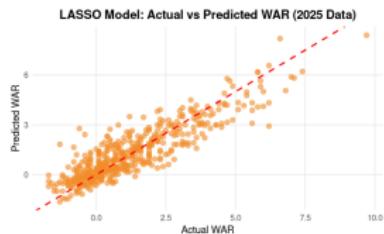
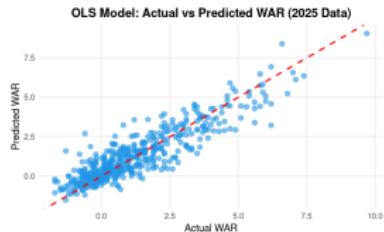
- ▶ Boosting grows trees sequentially using information from previously grown trees
 - ▶ Each tree fit on a modified version of the original data set
- ▶ Pros: High predictive accuracy and captures complex, nonlinear relationships automatically.
- ▶ Cons: Prone to overfitting and requires careful tuning of hyperparameters to perform well.

Boosting Metrics Plot

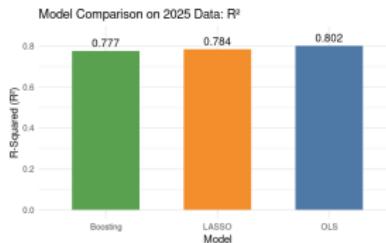
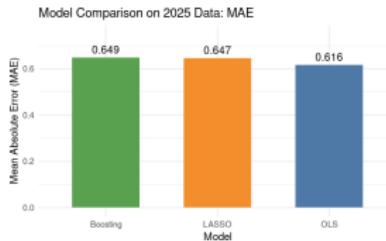
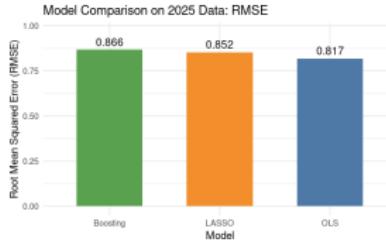
- ▶ Error metrics for both final testing data set (2025) and the training data split into training and testing sets



Model Comparison: OLS, LASSO, and Boosting



Model Comparison: RMSE, MAE, and R²



Player Examples Using OLS model

Player	Prediction	Actual
Aaron Judge	9.051733	9.7
Hunter Goodman	3.174746	3.7
Michael Toglia	-1.032315	-1.7
Bobby Witt Jr.	6.125421	7.1

Key Findings

- ▶ OLS performed the best overall
 - ▶ Lowest prediction error
 - ▶ Highest explained variance
- ▶ LASSO selected a subset of meaningful predictors, making it easier to understand which player stats drive WAR
- ▶ Variables with a strong predictive value: plate appearances, home runs, hits, OPS+, walks, and strikeouts
- ▶ WAR prediction is challenging
 - ▶ some components are hard to obtain from batting-only statistics
 - ▶ player injuries, playing time, or other external factors produce noise

Questions?