

Predicting a Pitcher's Success with Stuff+

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Introduction

History

- Founded in 1887 as an indoor baseball game
- Officially title softball in 1926
- Defining differences: smaller field, underhand pitch, larger ball, seven-inning games

Trackman

- is a radar-based tracking system used to collect detailed data on each pitch during a game
- Uses two radars and several synchronized optical cameras to collect data
- Collects more than 120 data values per pitch
- In 2026, about 40 collegiate programs are using this system
- The 2026 data set contains information from more than 1,000 games played and over 250,000 pitches

Pitch Types

An effective pitcher is usually armed with a deep pitching arsenal - mixing speeds, grips and movements of the ball to get batters out. There are four pitch types that we focused on: Rise Ball, Drop Ball, Curve Ball, Screw Ball.

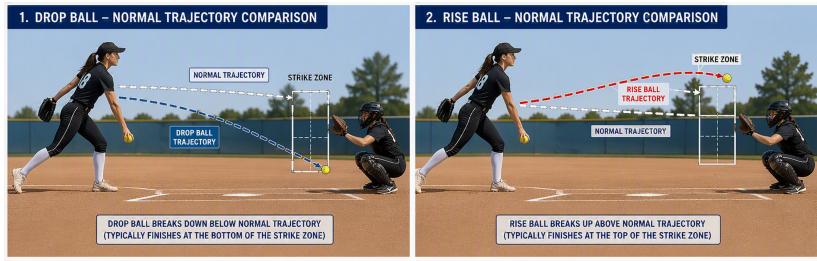
Vertical Break Pitch Types

Drop Ball

- Downward trajectory as it approaches the plate
- Said to have a 6 o'clock rotation (rotates forward)

Rise Ball

- Upward trajectory as it approaches the plate
- Said to have a 12 o'clock rotation (rotates backward)



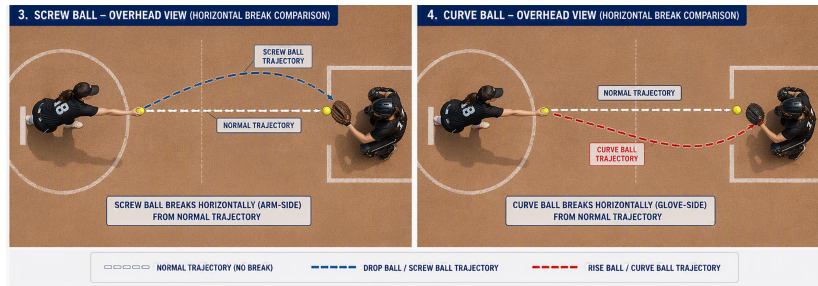
Horizontal Break Pitch Types

Screw Ball

- Moves away from the player
- Said to have a 3 o'clock rotation (for RHP)

Curve Ball

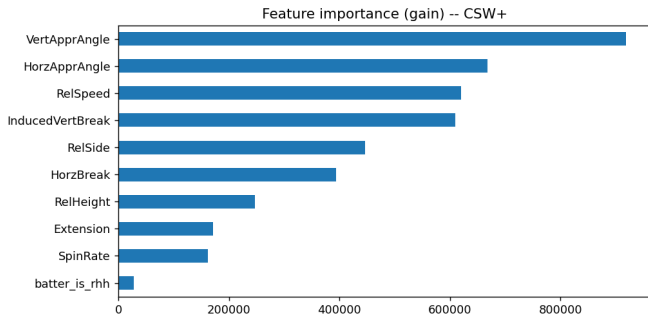
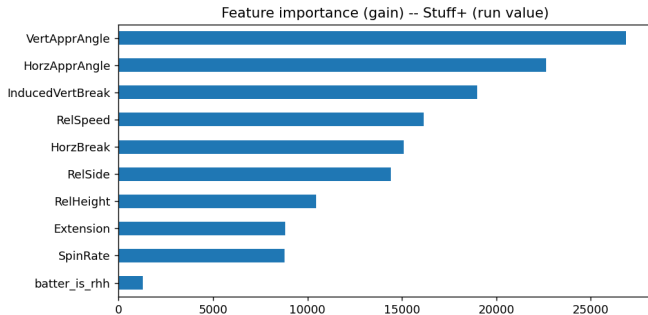
- Moves towards the player
- Said to have a 9 o'clock rotation (for RHP)



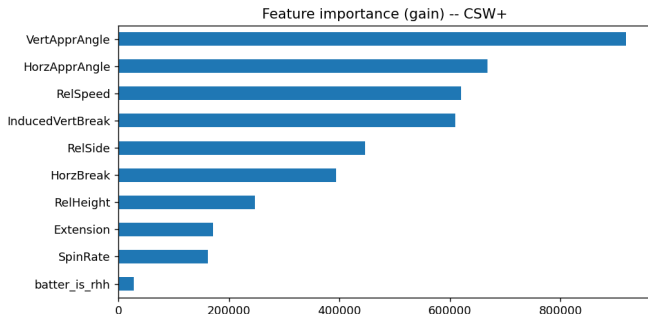
Model Description

Model Development and Training

- Two LightGBM models that grade each pitch from its physical characteristics using the same feature set making their outputs comparable
 - First model: is a regressor fit to per-pitch run value (RV+)
 - Second model: is a binary classifier fit to a called strikes plus whiff (CSW+)
- Feature set consists of Release Speed (RelSpeed), Spin Rate (SpinRate), Release Height (RelHeight), Release Side (RelSide), Extension (Extension), Induce Vertical Break (InducedVertBreak), Horizontal Break (HorzBreak), Vertical Approach Angle (VertApprAngle), and Horizontal Approach Angle (HorzApprAngle)



- Rise balls and fast balls ranked highest in RV+ model, reflecting run prevention
- Changeups and curve balls ranked highest in CSW+ model, reflecting strike-generating ability
- Results suggest RV+ and CSW+ provide complementary measures of pitch quality



Cross-Validation and Model Selection

- 5-fold GroupKFold cross-validation was used, ensuring each pitcher appeared in either set (Training or Validation) but never both, prevents data leakage
- Model settings (hyperparameters) were fixed, and cross-validation was used only to determine the optimal number of boosting iterations (`n_estimators`)
- Early stopping identified the best iteration in each fold using RMSE for RV+ and AUC for CSW+
- The median best iteration count across folds was selected, and each model was then refit on the full dataset using the value.

Aggregation

- Results are reported at three levels
 - Individual pitch
 - Pitcher-pitch-type combination
 - Overall pitcher
- Pitch-type scores averaged and filtered by minimum sample size
- Overall pitcher grades weighted by pitch usage

Model Outputs

- Outputs consist of RV+ score, CSW+ score at both the pitch-type level and total pitcher level
- Models, feature importance plots, and run summaries saved for future use

Model Results

- RV+ and CSW+ leaderboards were led by elite pitchers, supporting model validity
- The two metrics showed strong overall agreement while capturing different aspects of pitch effectiveness.

Top 5 Pitches by RV+ (Min. 100)

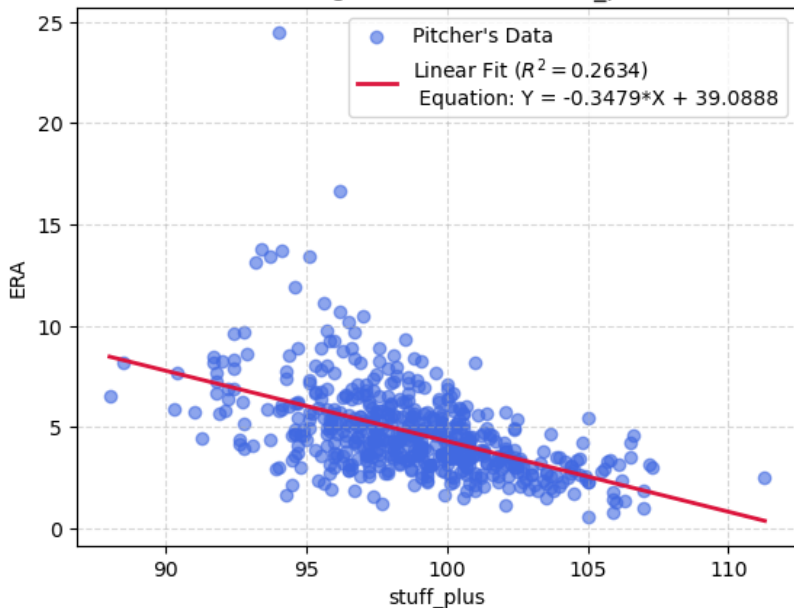
Pitcher	School	Pitch Type	RV+	CSW+
Anneca Anderson	North Texas	Fastball	117.2	101.0
Erin Nuwer	Tennessee	Riseball	110.7	107.6
Sage Mardjetko	Tennessee	Riseball	110.6	107.5
Sidne Peters	Texas A&M	Riseball	110.0	101.8
Tatum Clopton	LSU	Riseball	109.9	99.8

Top 5 Pitches by CSW+ (Min. 100)

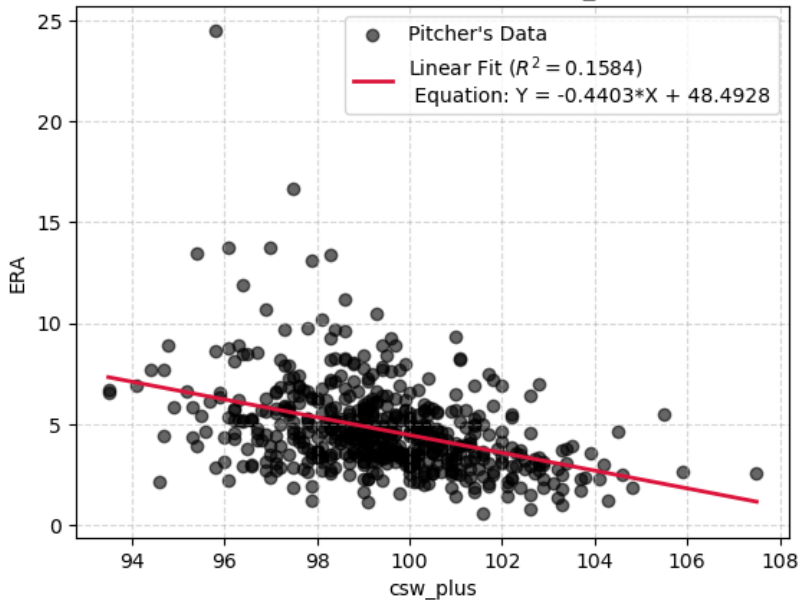
Pitcher	School	Pitch Type	RV+	CSW+
Allyssa Parker	Oklahoma	Changeup	106.4	115.1
Alyssa Faircloth	Miss. State	Changeup	109.0	111.8
Randi Roelling	Georgia	Curveball	103.5	109.6
Alexis Jensen	Nebraska	Curveball	108.7	108.2
Miali Guachino	Oklahoma	Changeup	105.1	108.0

- Rise balls and Fast balls ranked highest in $RV+$, reflecting run prevention value
- Changeups and curve balls ranked highest in $CSW+$, reflecting strike-generating ability
- Results suggest $RV+$ and $CSW+$ provide complementary measures of pitch quality

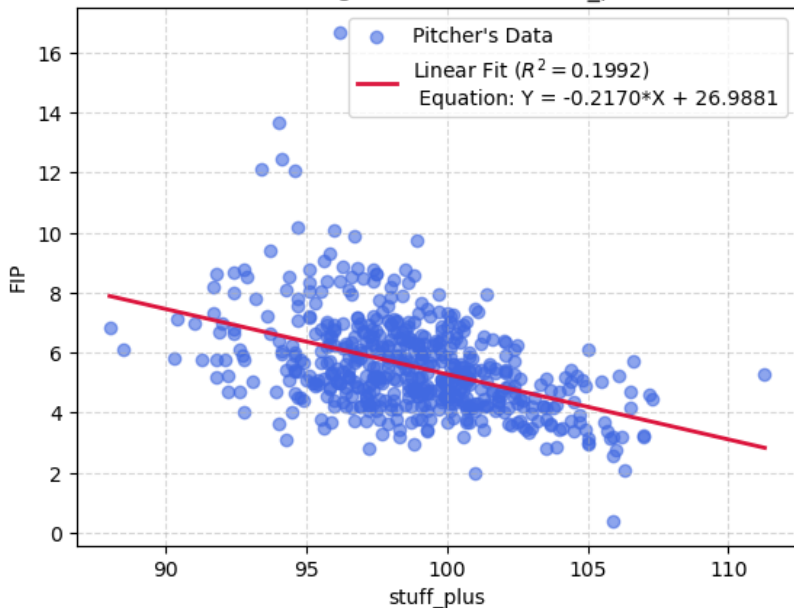
Linear Regression: ERA vs stuff_plus



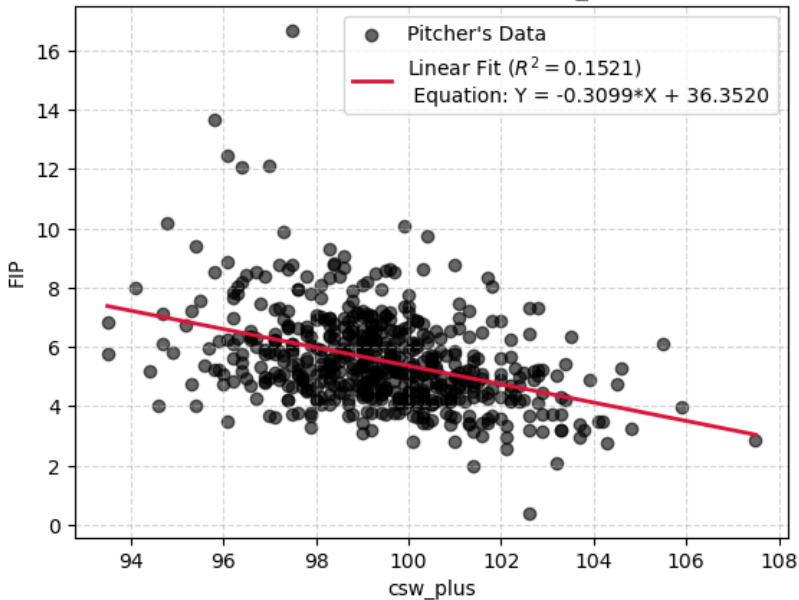
Linear Regression: ERA vs csw_plus



Linear Regression: FIP vs stuff_plus



Linear Regression: FIP vs csw_plus



The Path Forward

Improvements Made in Version 2

- Adding interaction features to the models saw a slight increase in model performance. We are still experimenting with changing out what interaction features we use to find the best set of interaction pairs to use.
- Transitioning to a subset of the data made by Austin Louque that removes noise by only including pitches that are confidently tagged correctly improved the models' performance significantly, indicating that the pitch tags in the original data are likely far from perfect.

- Decreasing learning rate and increasing the max number of estimators greatly improved model performance by allowing the models to more fully converge. This particularly helps the CSW model, but also improved the stuff+ (run-value) model.
- Implementing difference features that measure how much an individual pitch differs from a pitcher's "average" pitch allows for the models to capture a portion of how deceptive a pitcher can be. This allows the model to capture the context of how a pitch might confuse a batter, even if it is not statistically an impressive pitch on its own.

Known Limitations That Need Solving

- Limited data coverage: Current dataset includes pitches from only about 40 collegiate softball programs, limiting model training and league relative normalization to a partial sample of the college softball landscape
- Spin-rate measurement error: Trackman's radar based spin estimates can introduce noise, including occasional double counting that inflates spin rates; correction methods are being evaluated to identify and adjust affected values

- Uneven pitch type sample sizes: Large differences in pitch counts across pitchers and pitch types can reduce the stability of pitch type grades and related aggregate metrics
- Lack of deception reference pitch: Unlike baseball's fastball-centric comparison framework, softball lacks a natural anchor pitch, making it more difficult to quantify deception and tunneling effects.
- Height dependence in vertical approach angle: Vertical approach angle is influenced by release height and pitcher stature, potentially confounding its interpretation; feature normalization is planned to better isolate intrinsic pitch characteristics

References

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Thank You!!
Questions?