LSU Softball: Called Strike Probability Model

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Fall 2025 Final Presentation

Outline

Introduction

Strike Zone Model

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  - Umpires tend to apply their own individualized strike zones, which shift based on pitch location, count, player handedness, and game situation
- We built a **called strike probability model** for LSU Softball that predicts how likely a taken pitch (no swing) is to be called a strike
- The model was originally trained on MLB Statcast data (2020–2024) and later adapted to LSU TrackMan data (2025)

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- Will help improve trainings, player evaluations, scouting, and in-game decision-making for LSU Softball

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- Predict the probability a taken pitch is called a strike using pitch location and handedness
- Visualize LSU-specific strike zone patterns using probability heatmaps
- Use results to help players understand the zone better and make better decisions in games

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- Cleaned by removing rows with missing locations and keeping variables relevant to the model

Exploratory Visualizations

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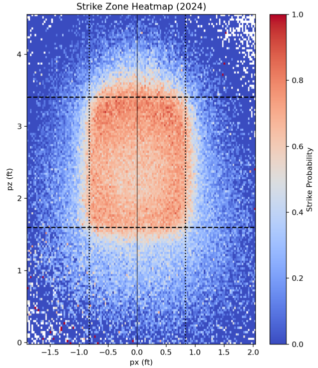
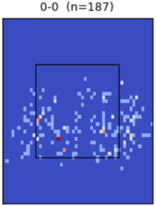
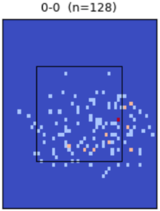
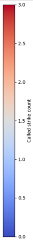
- Heatmaps show the distribution of taken pitches and where umpires most often call strikes





0–0 Count, LHP Curveball





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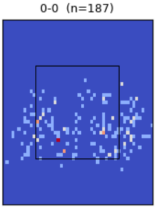

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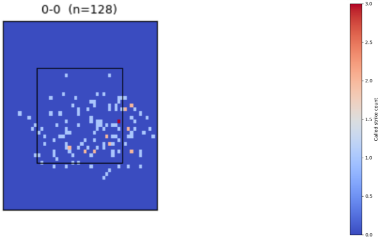

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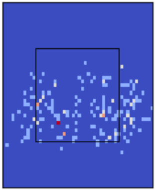
LSU TrackMan Data (2025)

- LSU heatmaps help reveal raw pitch tendencies before modeling. For example, LHP curveballs show wider horizontal variability, and both groups tend to finish low in the zone



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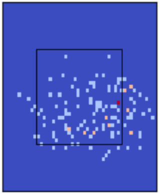

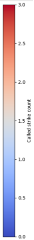

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LSU TrackMan Data (2025)

- LSU heatmaps help reveal raw pitch tendencies before modeling. For example, LHP curveballs show wider horizontal variability, and both groups tend to finish low in the zone
- Patterns differ from MLB due to softball-specific pitch types, release points, and strike-zone geometry, as well as the much smaller size of the LSU dataset

Model Architecture & Methods

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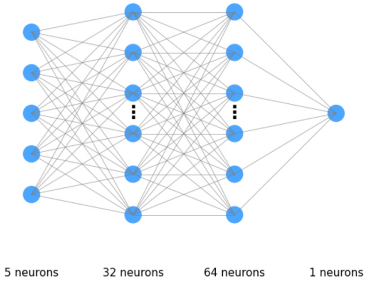
$$W_2 = \begin{bmatrix} w_{1,1} & \cdots & w_{1,32} \\ \vdots & \ddots & \vdots \\ w_{64,1} & \cdots & w_{64,32} \end{bmatrix}$$

$$W_3 = \begin{bmatrix} w_{1,1} & w_{1,2} & \cdots & w_{1,64} \end{bmatrix}$$



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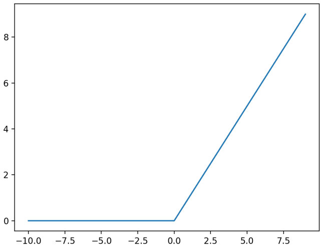
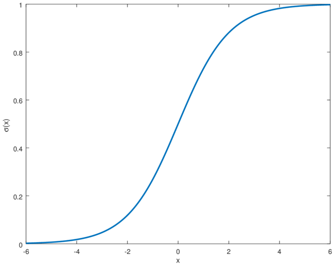
ReLU



Sigmoid



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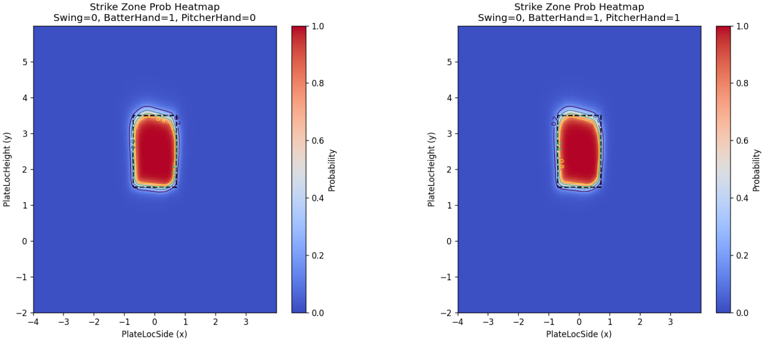
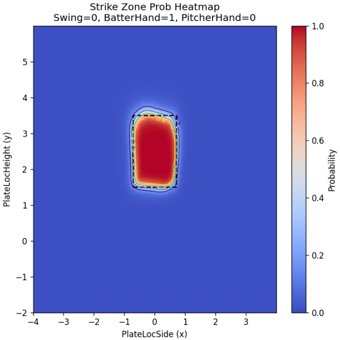
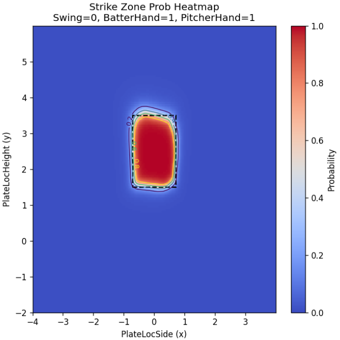
- After surgery, we fine-tuned the expanded model on LSU Softball data to adapt the strike zone to NCAA softball



- The model captures the "true" zone LSU pitchers are actually getting in games, not just the rulebook version.

Model Results & Observations





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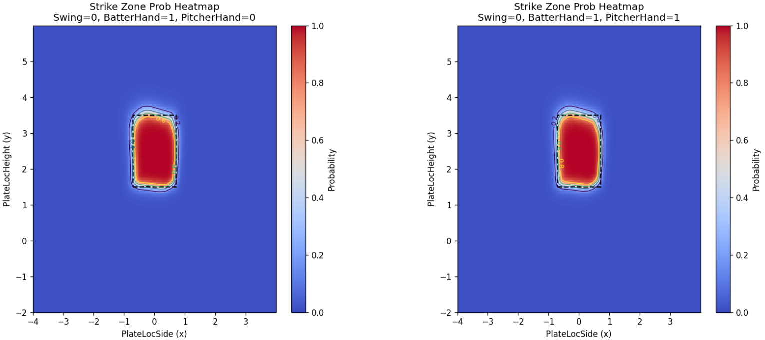

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- Called strike probability is highest in the zone center
- We received 97.5% accuracy

Limitations & Challenges

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- Variations in strike-zone definitions, pitch characteristics, and umpire decision-making prevented MLB patterns from transferring perfectly

Conclusion & Future Work

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- Highlights consistent differences in pitch behavior across pitch types, pitch counts, and pitcher handedness
- Current dataset is relatively small, the patterns are strong and interpretable
- The model offers a practical, data-driven foundation for future training, player development, and decision-making applications

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