Using Predictive Models to Assess Future Value of MLB Players

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February 2021

Outline

- Goal
- The data
- The model
- Example analysis

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- Specifically we will be looking at batting average, the proportion of hits to total at bats.

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    - ★ Launch angle, Exit velocity, Hit direction
    - ★ x and y cords
    - ★ events, batter ids, and year

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  - A smooth function is a function that is continuous on a restricted interval.

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- Our data has predictors that have non-linear relationships to our outcome variable, a GAM allows us to have non-linear predictors.
- Lastly, GAMs have the ability to have regularization, which is a method to prevent over fitting model and maintain model accuracy.

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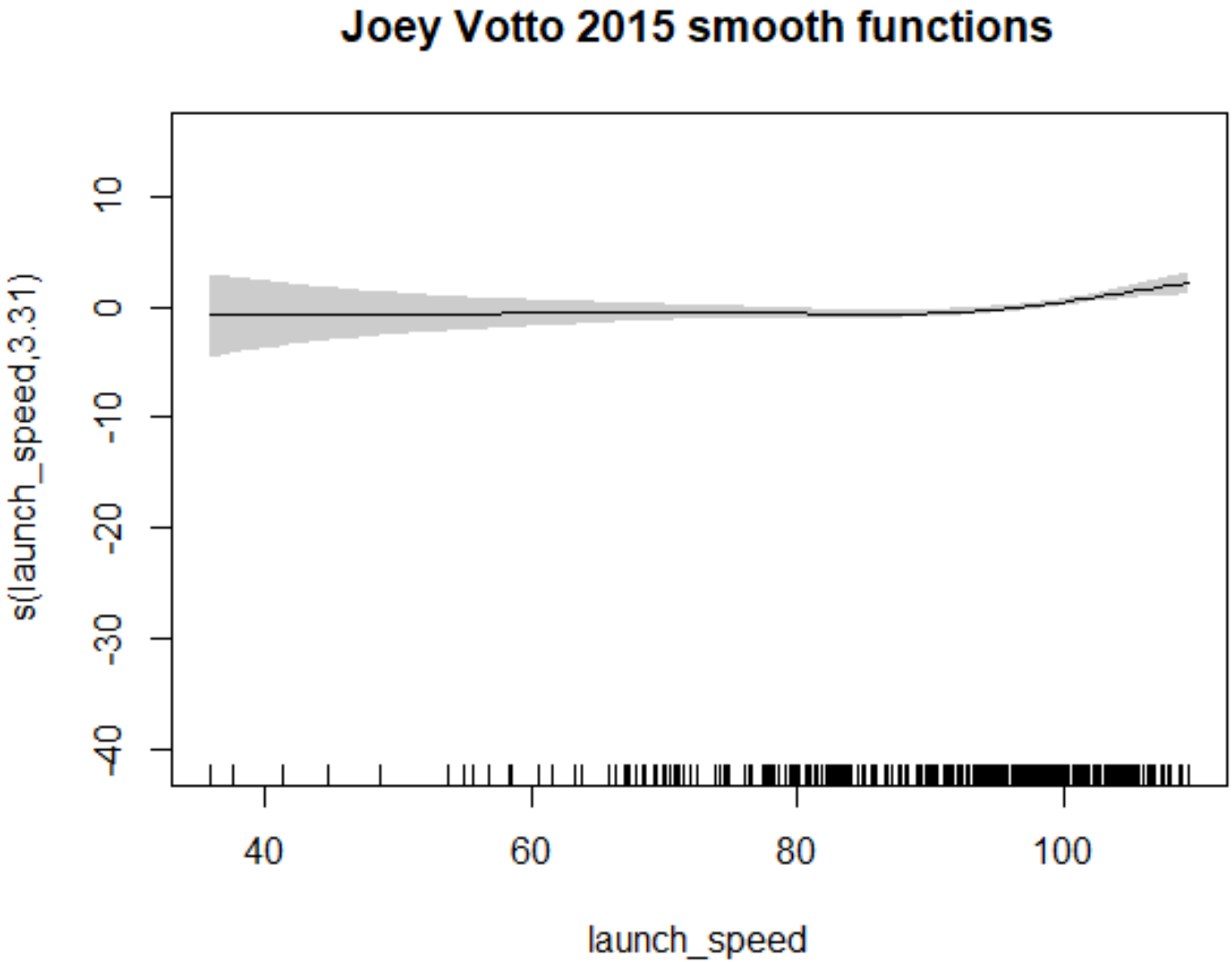
- All other batted balls were predicted with a model that used launch angle, hit direction, and exit velocity.

Creating the model

- We created two models for each player each year, one for ground balls and one for all other ABs.
- We used the models from the previous year to predict the next years values.

Checking the model



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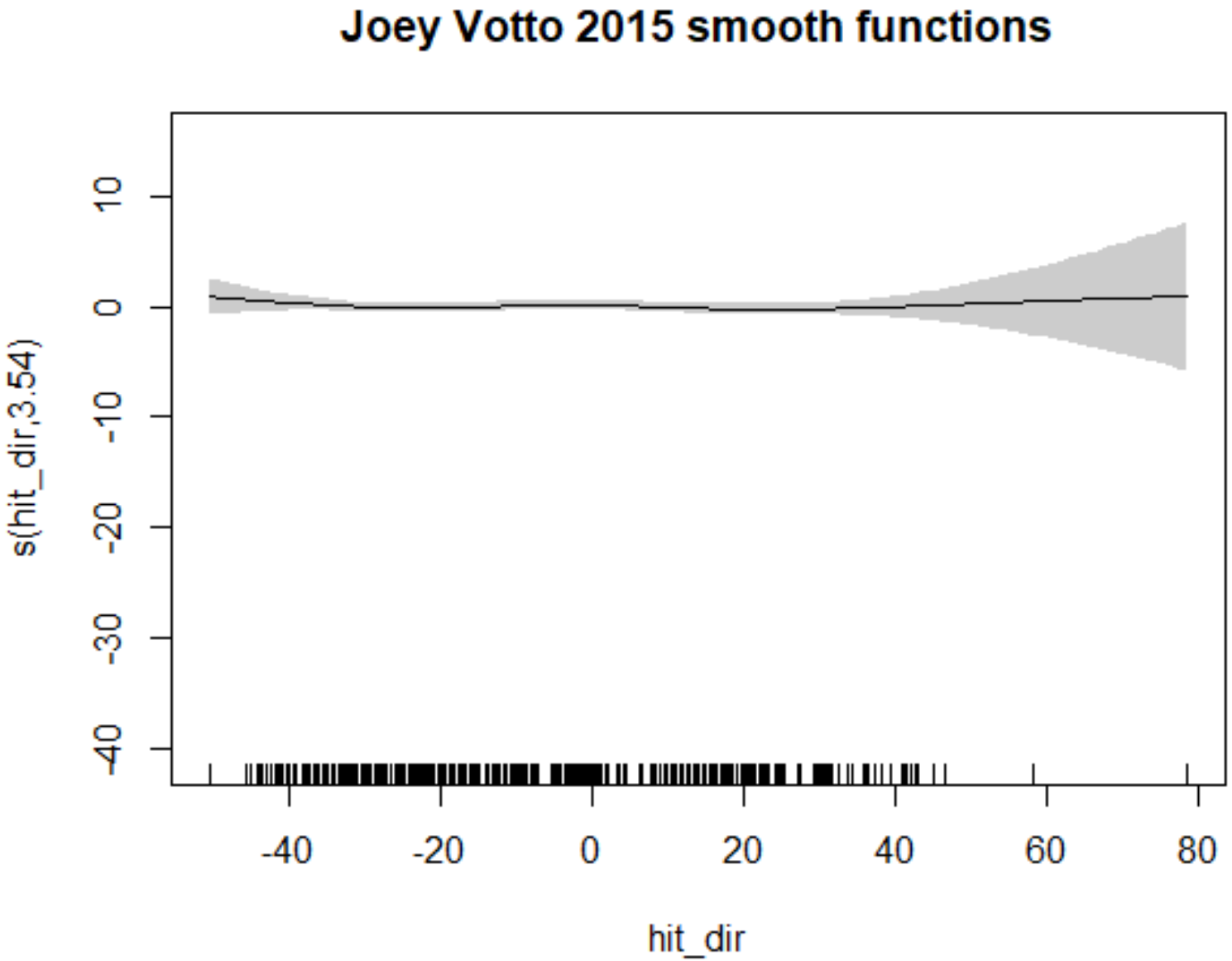

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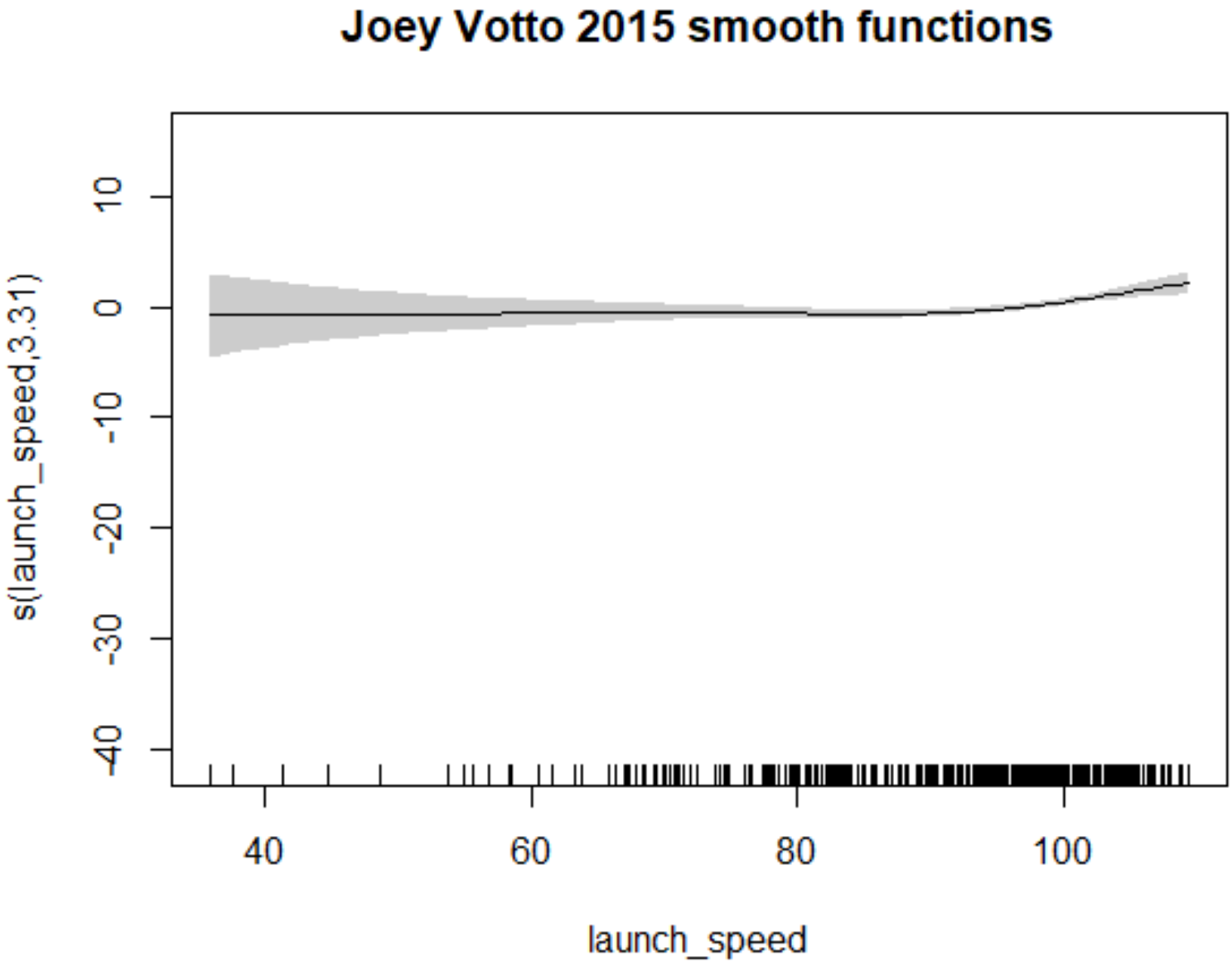

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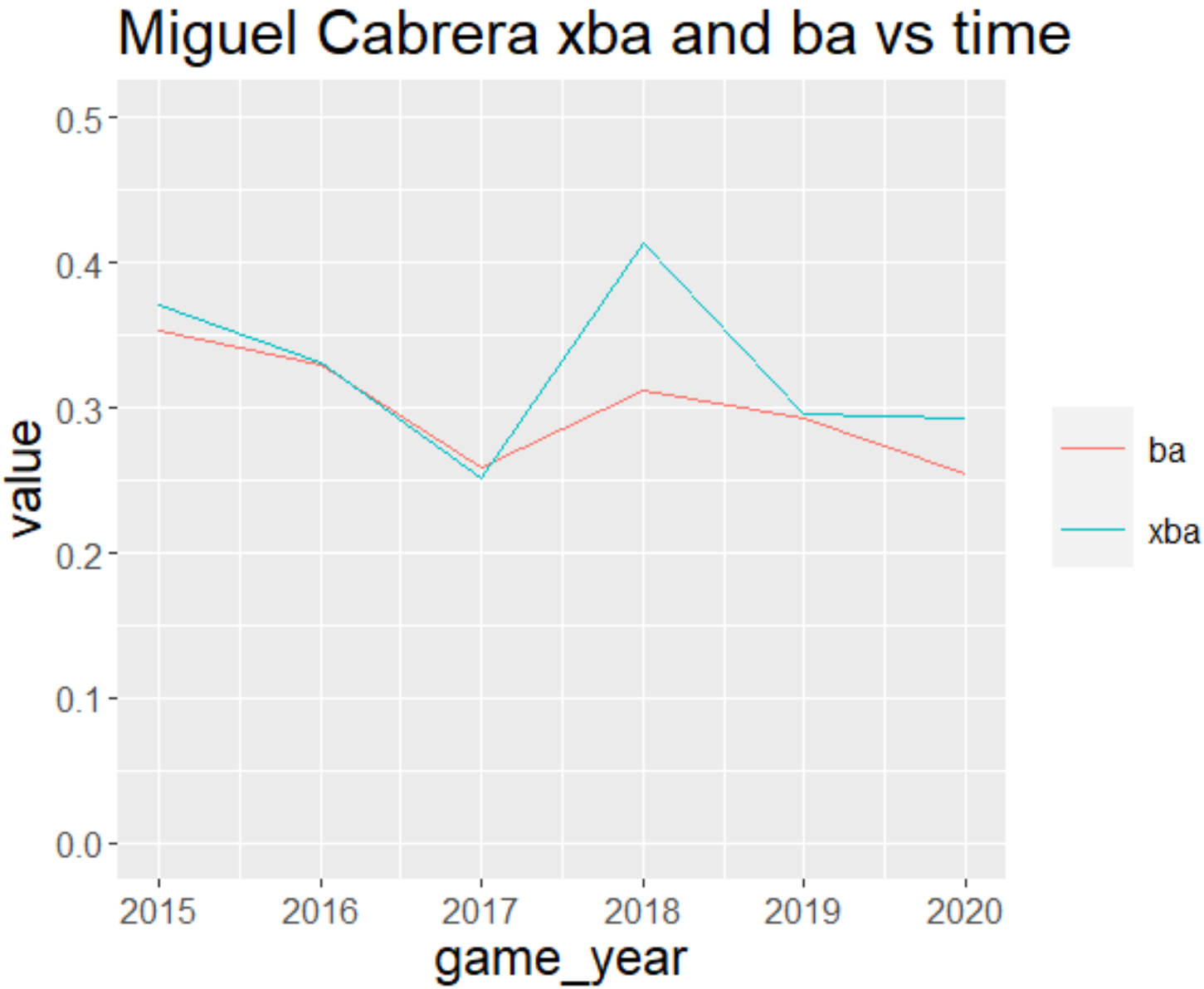
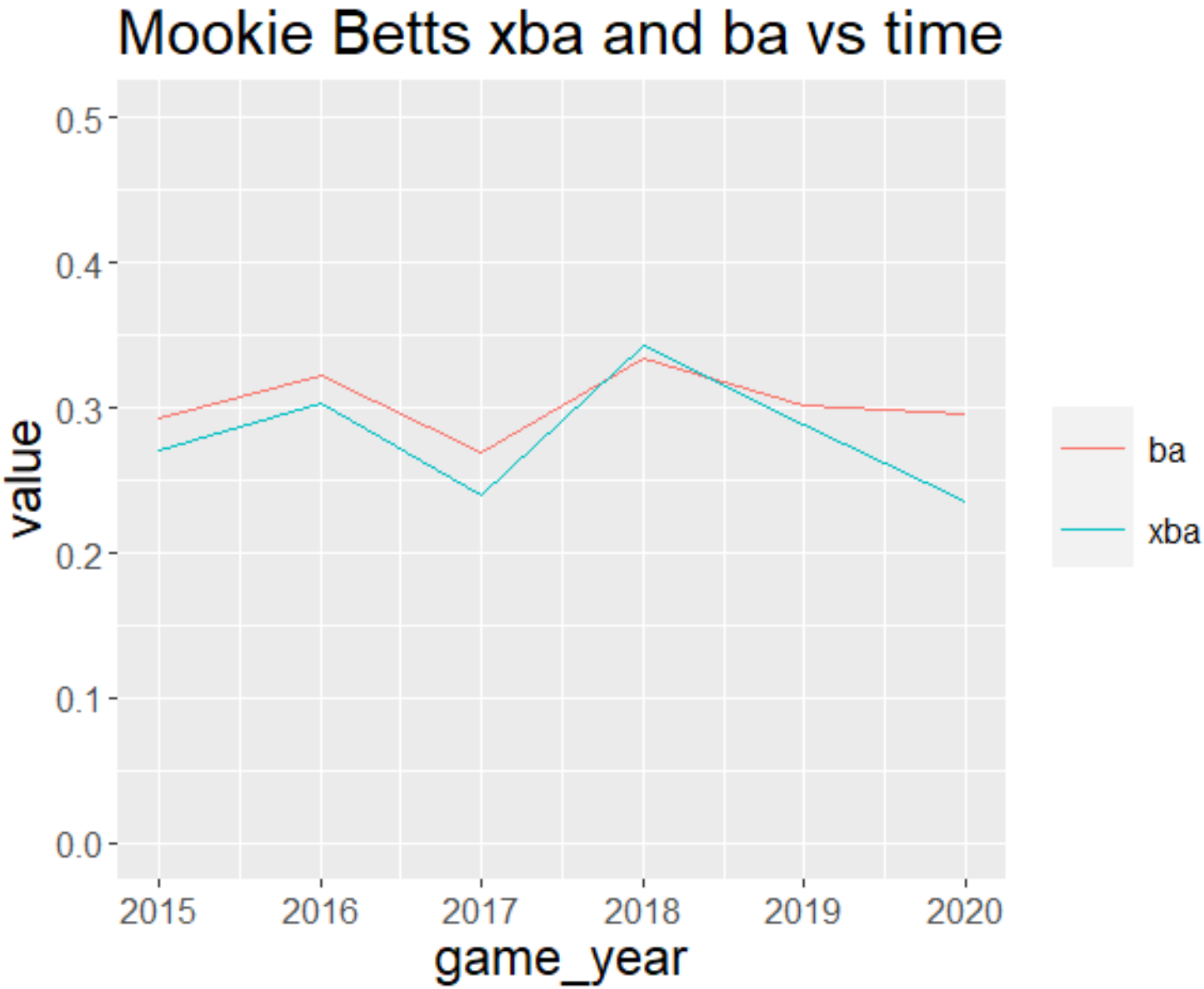
- There are many other reasons for the difference between batting average and expected batting average, like a new training method or new approach, but the model is retrained every year in an attempt to minimize this effect.
- There are also other factors that we didn't include in this model, like speed or age, that could be the cause of difference between observed and predicted batting average.

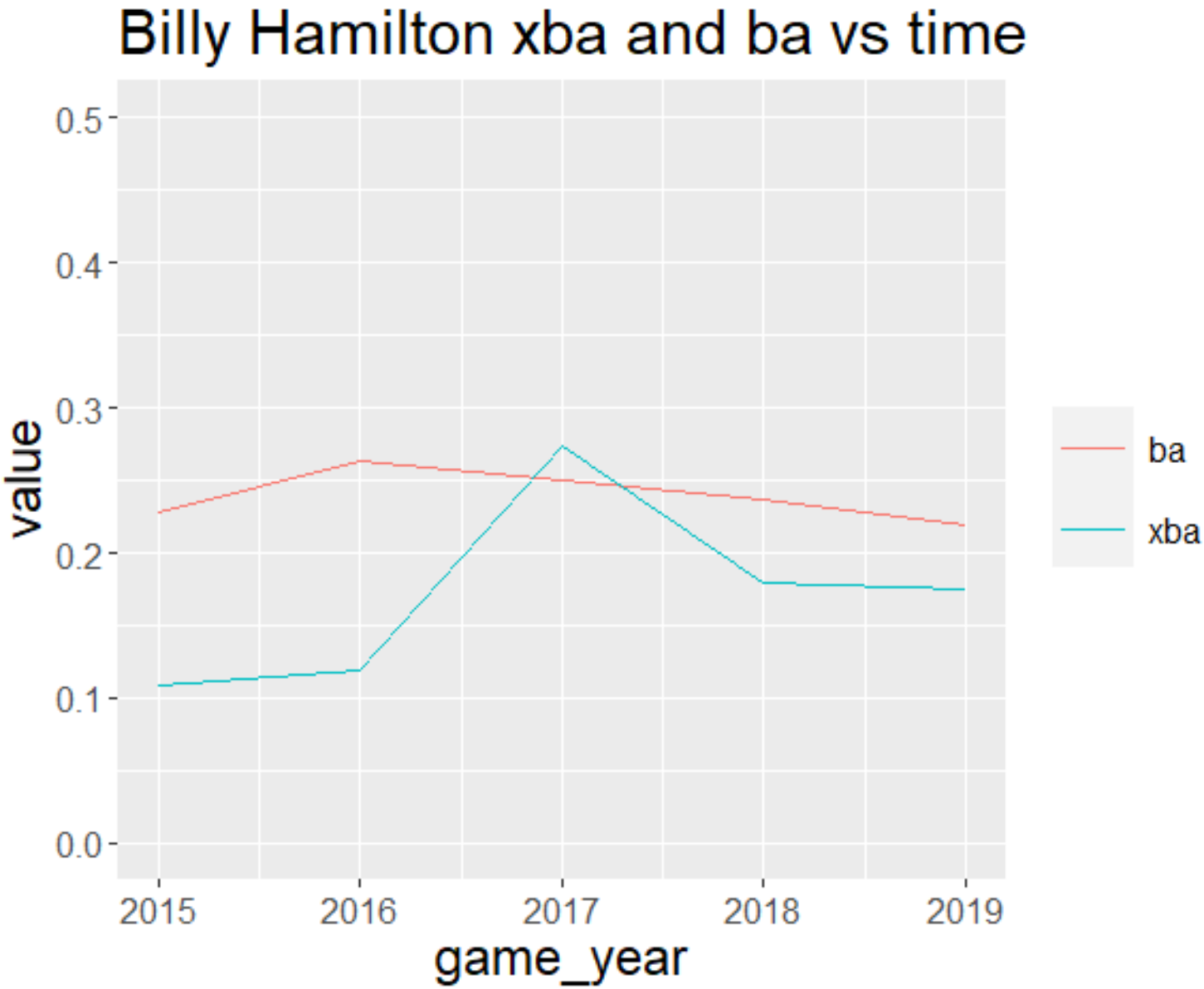
Example analysis - Positive



Example analysis - Negative



Model missteps



Good case for prediction