# **Modeling Thought Process**

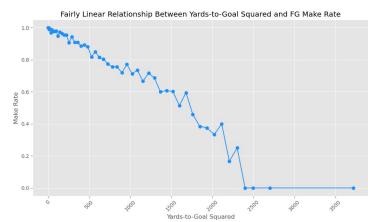
I checked for potential selection bias in the decision to attempt a field goal using a Heckman model. The inverse Mills ratio (IMR) was not statistically significant (p = 0.115) when predicting FG make probability, so I did not include it in the Bayesian model.

I used squared yards-to-goal as the main feature, as it showed a more linear relationship with FG make rate than linear, cubic, or quartic terms, and had the highest R<sup>2</sup> among them. Linear relationships are preferred given the use of hierarchical Bayesian logistic regression.

The model applies Bayesian hierarchical logistic regression with a Gaussian random walk (GRW) for kicker intercepts. This structure allows for partial pooling across kickers and encourages stability in kicker estimates across seasons. The Payesian framework

stability in kicker estimates across seasons. The Bayesian framework also enables more robust estimation of both aleatoric and epistemic uncertainty.

Finally, I added interaction terms between pressure rating (e.g., late game, playoffs, game-tying/winning kicks) and icing, as well as between weather and yards-to-goal, and elevation and yards-to-goal. The intuition being that factors like wind gusts may have a greater effect on long than short kicks.



## **Bayesian Hierarchical Model**

### **Model Definition:**

```
P(Y=1) = \operatorname{sigmoid}(z) = \frac{1}{1 + e^{-z}}
    where Y is FG Result (1: Made, 0: Missed)
   + \alpha_{\mathrm{Kicker}_{i,i}}
    + \gamma_{\text{Kicker}_{i,j}} \cdot \text{Yards to Goal}^2
    + \beta_1 \cdot \text{Is Home Team}
    +\beta_2 · Time of Day
    + \beta_3 \cdot \text{Pressure Rating}
    + \beta_{A} \cdot \text{Iced Kicker}
    + \beta_5 \cdot \text{Pressure Rating} \cdot \text{Iced Kicker}
    +\beta_6 · Season
    + \beta_7 \cdot \text{Wind Gusts} \cdot \mathbb{1}\{\text{Outdoor Stadium}\}\
    +\beta_8 · Wind Gusts · Yards to Goal<sup>2</sup> · \mathbb{I}{Outdoor Stadium}
    +\beta_9 · Temperature · 1{Outdoor Stadium}
    + \beta_{10} \cdot \text{Temperature} \cdot \text{Yards to Goal}^2 \cdot \mathbb{1}\{\text{Outdoor Stadium}\}
    + \beta_{11} \cdot \text{Precipitation Chance} \cdot \mathbb{1}\{\text{Outdoor Stadium}\}\
    + \beta_{12} \cdot \text{Precipitation Chance} \cdot \text{Yards to Goal}^2 \cdot \mathbb{1}\{\text{Outdoor Stadium}\}\
    + \beta_{13} \cdot \text{Snow Severity} \cdot \mathbb{1} \{ \text{Outdoor Stadium} \}
    +\beta_{14} · Snow Severity · Yards to Goal<sup>2</sup> · 1{Outdoor Stadium}
    + \beta_{15} \cdot \text{Elevation}
    + \beta_{16} \cdot \text{Elevation} \cdot \text{Yards to Goal}^2
```

#### **Feature Definitions:**

```
Kicker<sub>i,j</sub>: The i<sup>th</sup> kicker in their j<sup>th</sup> season with:
```

```
- \alpha_{\mathrm{Kicker}_{i,j}} \sim \mathrm{GRW}(\sigma_{\alpha}) : Gaussian Random Walk for kicker intercepts
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- $\gamma_{\mathrm{Kicker}_{i,j}} \sim \mathrm{GRW}(\sigma_{\gamma})$ : Gaussian Random Walk for kicker-YTG slopes
- $-\sigma_{\alpha}, \sigma_{\gamma} \sim \text{Exponential}(1.0)$ : Random walk standard deviations
- Pressure Rating: Contextual weight of the kick, defined as:

```
 \text{Pressure Rating} = \begin{cases} 4 & \text{if (tie/take lead) and (OT or } t \leq 120) \\ 3 & \text{if (tie/take lead and } t \leq 300) \text{ or (stay within one score and } t \leq 120) \\ 2 & \text{if (tie/take lead and } t \leq 600) \text{ or (stay within one score and } t \leq 300) \\ 1 & \text{if (tie/take lead and } t \leq 900) \text{ or (stay within one score and } t \leq 600) \\ 0.5 & \text{if stay within one score and } t \leq 900 \\ 0 & \text{otherwise} \end{cases}
```

- -t = game seconds remaining.
- $Add +1 if season_type = POST.$
- Time of Day: Categorical variable (0: daytime, 1: dusk, 2: nighttime).
- 1{Outdoor Stadium}: Binary indicator (1: outdoor, 0: indoor/dome).
- Iced Kicker: Binary indicator (1: defense called timeout before kick, 0: otherwise).

## **Model Performance**

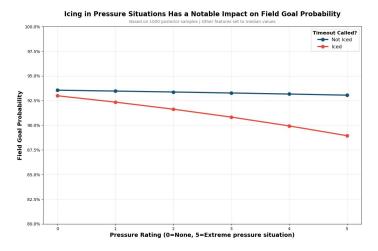
## Comparing Three Models:

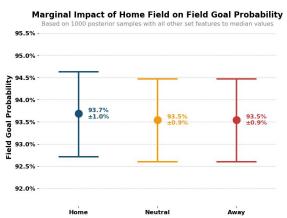
- 1. Simple Model: Bayesian logistic regression with yards-to-goal<sup>2</sup> as the lone slope plus an intercept.
- 2. *Complex Model*: the model referred to in the previous slide.
- 3. Jacob Long Model: a similar Bayesian FG Model (<u>link</u>).

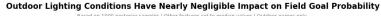
Surprisingly, the simpler model outperforms the complex one in all metrics except AUC. This may be because the complex model treats yards to goal as a kicker-specific Gaussian walk, which could dilute its signal. Both the simple and complex models outperform Jacob Long's model, though this could be because I excluded blocked field goals from training. Blocked FG probability will be modeled separately when deciding between kicking or going for it.

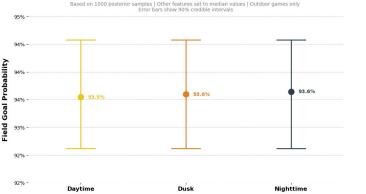
|                  | Brier Score<br>(minimize) | AUC<br>(maximize) | LOOIC<br>(minimize) |
|------------------|---------------------------|-------------------|---------------------|
| Simple Model     | 0.1064                    | 0.7755            | 7249.7              |
| Complex Model    | 0.1063                    | 0.7804            | 7503.9              |
| Jacob Long Model | 0.1160                    | 0.7811            | 8032.7              |

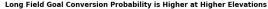
# Effects of Icing, Lighting, and Location on FG Conversion Probability

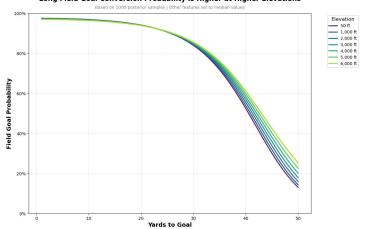












# Effects of Weather on Field Goal Conversion Probability

