

Using Information Underlying Missing Data to Improve Estimation of NFL Field Goal Kicker Accuracy

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Raw statistics

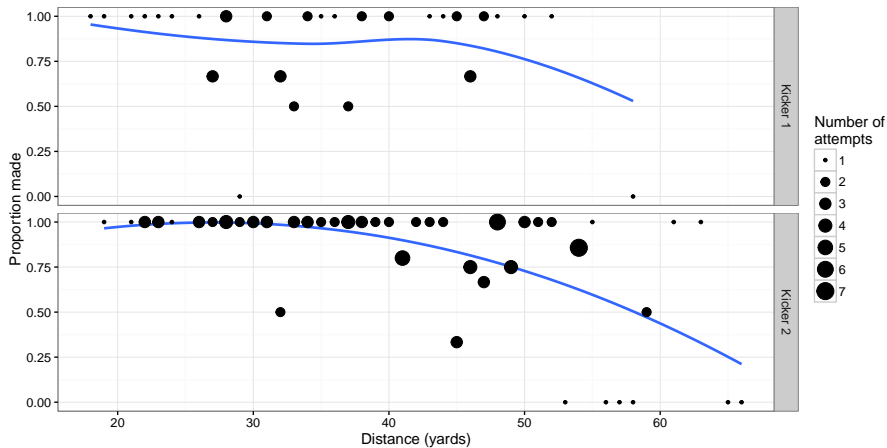
Let's compare two field goal kickers and their proportion of field goals made for the 2009-2011 seasons

Kicker	Proportion made
Kicker 1	0.84
Kicker 2	0.86

If we include the actual counts, we have some sense for uncertainty in these proportions:

Kicker	Number made	Number of attempts
Kicker 1	37	44
Kicker 2	90	105

Taking distance into account



Probit regression to account for explanatory variables

For attempt a for kicker k , let

- Y_{ak} be an indicator of success, i.e. 1 if successful and 0 otherwise, and
- x_{ak} be a vector of explanatory variables, e.g. distance, surface type, etc.

A probit regression model for each kicker k assumes

$$Y_{ak} \stackrel{ind}{\sim} Ber(\theta_{ak})$$

where $Y \sim Ber(\theta)$ indicates a Bernoulli distribution with

$$P(Y = 1) = \theta \quad \text{and} \quad P(Y = 0) = 1 - \theta,$$

and the probability is determined by

$$\theta_{ak} = \Phi(\eta_{ak}) \quad \eta_{ak} = x_{ak}^\top \beta_k$$

where Φ is the cumulative distribution function for a standard normal.

Probit regression analysis

Explanatory variables included in this analysis:

- Distance
- Field surface: indicator for synthetic (as opposed to grass)
- Interaction between distance and field surface

In the model (dropping the k subscript):

$$\eta_a = \beta_0 + \beta_1 \text{Distance}_a + \beta_2 \text{Synthetic}_a$$

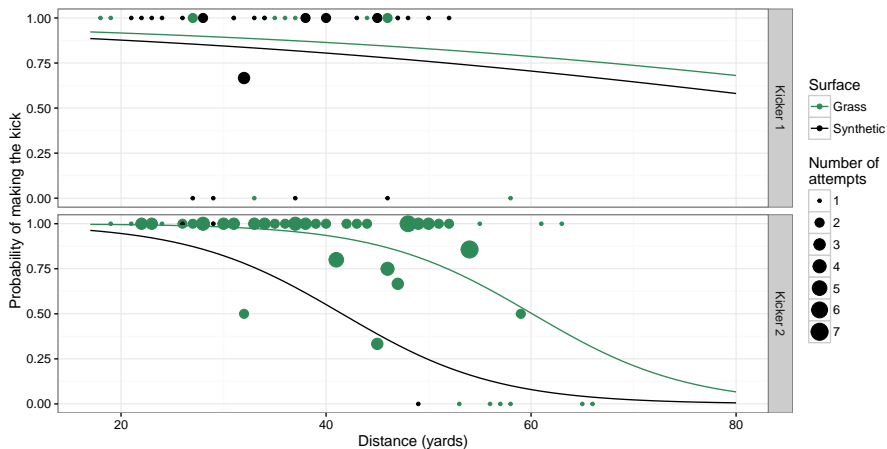
$$\eta_a = \beta_0 + \beta_1 \text{Distance}_a + \beta_2 \text{Synthetic}_a + \beta_3 \text{Distance}_a \cdot \text{Synthetic}_a$$

Number of observations:

Kicker	Grass	Synthetic
Kicker 1	16	28
Kicker 2	102	3

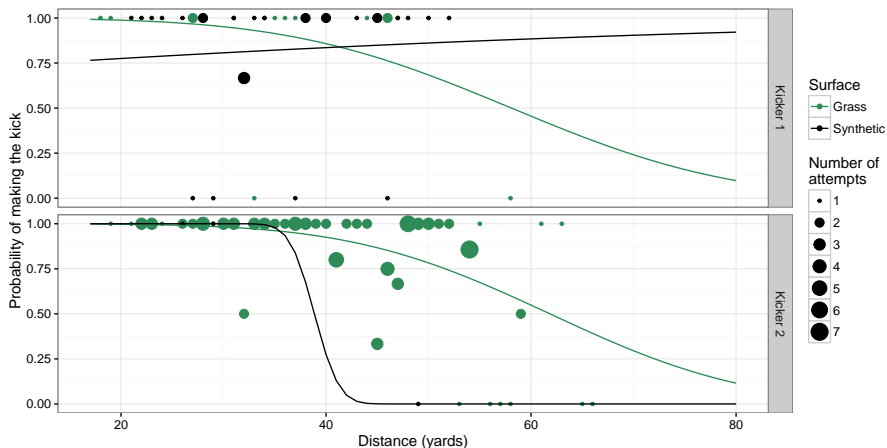
Probit regression analysis

$$\eta_a = \beta_0 + \beta_1 \text{Distance}_a + \beta_2 \text{Synthetic}_a$$



Probit regression analysis with an interaction

$$\eta_a = \beta_0 + \beta_1 \text{Distance}_a + \beta_2 \text{Synthetic}_a + \beta_3 \text{Distance}_a \cdot \text{Synthetic}_a$$



Hierarchical model to borrow information across kickers

A hierarchical probit regression model has the same initial structure:

$$Y_{ak} \stackrel{ind}{\sim} Ber(\theta_{ak}) \quad \theta_{ak} = \Phi(x_{ak}^\top \beta_k).$$

but then we assume a distribution for the β_k , e.g.

$$\beta_k \stackrel{ind}{\sim} N(\mu, \Sigma).$$

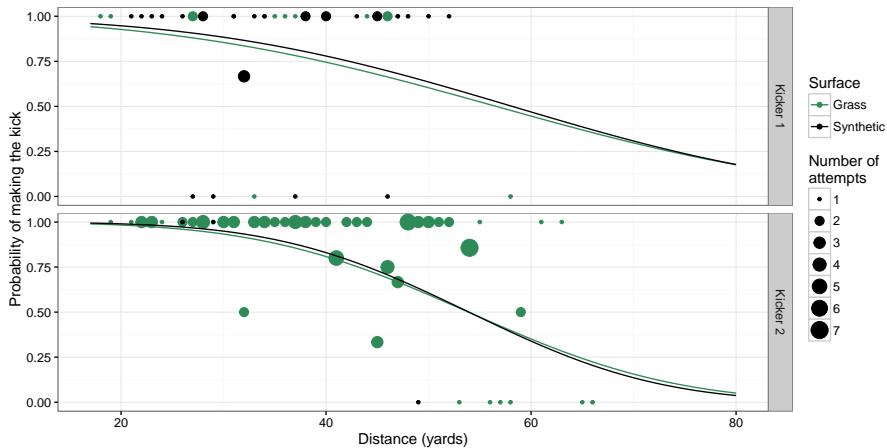
This distribution allows the data to inform us about the

- average effect of the explanatory variables across all kickers (μ) and
- the variability from kicker to kicker around this average (Σ).

If diagonal elements of Σ are estimated to be

- small then kickers are similar and we borrow a lot of information across kickers or
- large then kickers are dissimilar and we do not borrow much information.

Hierarchical probit regression model with interaction



Modeling attempts (or non-attempts)

For **opportunity** i for kicker k , let

- A_{ik} be an indicator of attempt, i.e. 1 if a kick was attempted and 0 otherwise, and
- w_{ik} be a vector of explanatory variables.

A probit regression model for each kicker k assumes

$$A_{ik} \stackrel{ind}{\sim} Ber(\pi_{ik}) \quad \pi_{ik} = \Phi(\zeta_{ik}) \quad \zeta_{ik} = w_{ik}^\top \alpha_k.$$

Two important explanatory variables for determining whether to take a kick are

- the probability of making the kick and
- will making this kick increase my chances of winning.

Explanatory variables for kick attempts

We already “know” the probability of making attempt i for kicker k , its θ_{ik} .

At any instant in the game, we can calculate a team’s win probability using the method of Lock and Nettleton (2014). We use

$$\Delta_{ik} = WP_{ik}(\text{Successful kick}) - WP_{ik}(\text{Current}).$$

Final set of explanatory variables

$$\zeta_{ik} = \alpha_0 + \alpha_1 \Phi^{-1}(\theta_{ik}) + \alpha_2 \Delta_{ik} + \alpha_3 \Phi^{-1}(\theta_{ik}) \Delta_{ik}.$$

Informative missingness model

The full model is

$$\begin{aligned}
 Y_{ak} &\overset{\text{ind}}{\sim} \text{Ber}(\theta_{ak}) & \theta_{ak} &= \Phi\left(x_{ak}^\top \beta_k\right) & \beta_k &\overset{\text{ind}}{\sim} N(\mu, \Sigma) \\
 A_{ik} &\overset{\text{ind}}{\sim} \text{Ber}(\pi_{ik}) & \pi_{ik} &= \Phi\left(\omega_{ik}^\top \alpha\right) \\
 \omega_{ik} &= (w_{ik}, w_{ik} \Phi^{-1}(\theta_{ik})) = (w_{ik}, w_{ik} x_{ak}^\top \beta_k)
 \end{aligned}$$

where

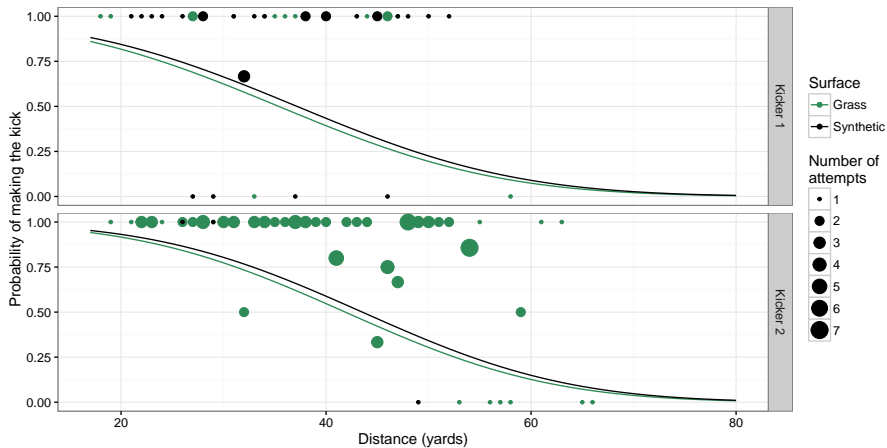
- x_{ak} is a set of explanatory variables that affect the probability of making a kick and
- w_{ik} is a set of explanatory variables that affect the probability of taking a kick.

Data for informative missingness model

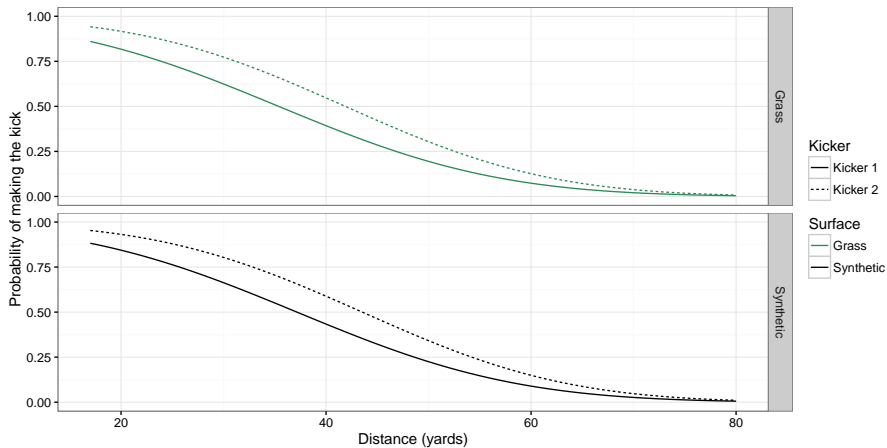
When considering what plays constitute an “opportunity” for a kicker, we considered 4th down plays when an attempted field goal would have been from a distance of no more than 76 yards, and

- a field goal was attempted or
- a field goal was not attempted even though making the field goal would have increased the team's win probability.

Informative missingness analysis



Kicker comparison



Summary

Constructed a hierarchical informative missingness model that

- borrowed information among the kickers
- incorporated information from non-attempts
- to estimate the probability of making a field goal
- as a function of explanatory variables, e.g. distance.

These slides are available at

- https://github.com/jarad/MwSAM2016/raw/master/JaradNiemi_MwSAM2016.pdf
- or on my website <http://www.jarad.me/research/presentations.html>.

Thank you!

Kicker name reveal

