

# Model Explanation Simplification

Dusty Turner

## Building the model

I present below an arbitrary design matrix. It consists of 4 factors,  $x_1$ ,  $x_2$ ,  $y_1$ , and  $y_2$  and all their interactions.

X =

Frame	Intercept	$x_1$	$x_2$	$y_1$	$y_2$	$x_1 \times x_2$	$x_1 \times y_1$	$x_1 \times y_2$	$x_2 \times y_1$	$x_2 \times y_2$	$y_1 \times y_2$
Frame 1	1	$x_{11}$	$x_{21}$	$y_{11}$	$y_{21}$	$x_{11}x_{21}$	$x_{11}y_{11}$	$x_{11}y_{21}$	$x_{21}y_{11}$	$x_{21}y_{21}$	$y_{11}y_{21}$
Frame 2	1	$x_{12}$	$x_{22}$	$y_{12}$	$y_{22}$	$x_{12}x_{22}$	$x_{12}y_{12}$	$x_{12}y_{22}$	$x_{22}y_{12}$	$x_{22}y_{22}$	$y_{12}y_{22}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
Frame N	1	$x_{1N}$	$x_{2N}$	$y_{1N}$	$y_{2N}$	$x_{1N}x_{2N}$	$x_{1N}y_{1N}$	$x_{1N}y_{2N}$	$x_{2N}y_{1N}$	$x_{2N}y_{2N}$	$y_{1N}y_{2N}$

(1)

We use logistic regression to create the model.

$$\log\left(\frac{p}{1-p}\right) = X\beta \quad (2)$$

We can expand this to the following:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 y_1 + \beta_4 y_2 + \beta_5 (x_1 \times x_2) + \beta_6 (x_1 \times y_1) + \beta_7 (x_1 \times y_2) + \beta_8 (x_2 \times y_1) + \beta_9 (x_2 \times y_2) + \beta_{10} (y_1 \times y_2) \quad (3)$$

Where:

- 1)  $\log\left(\frac{p}{1-p}\right)$  is the logit function, the natural logarithm of the odds of the outcome.
- 2)  $\beta_0$  is the intercept of the model.
- 3)  $\beta_1, \beta_2, \beta_3, \beta_4$  are the coefficients for the main effects of the predictors  $x_1, x_2, y_1$ , and  $y_2$  respectively.

- 4)  $\beta_5, \beta_6, \beta_7, \beta_8, \beta_9, \beta_{10}$  are the coefficients for the interaction effects between the predictors.
- 5)  $x_1, x_2, y_1, y_2$  are the independent variables or predictors.
- 6)  $(x_1 \times x_2), (x_1 \times y_1), (x_1 \times y_2), (x_2 \times y_1), (x_2 \times y_2), (y_1 \times y_2)$  are the interaction terms between the predictors.
- 7)  $\epsilon$  is the error term, representing the variation in the outcome not explained by the model.

## Using the model to make predictions

Later we want to use this model to predict something new. Lets use the new data below.

X =

Frame	Intercept	$x_5$	$x_6$	$y_5$	$y_6$	$x_5 \times x_6$	$x_5 \times y_5$	$x_5 \times y_6$	$x_6 \times y_5$	$x_6 \times y_6$	$y_5 \times y_6$
Frame 1	1	$x_{51}$	$x_{61}$	$y_{51}$	$y_{61}$	$x_{51}x_{61}$	$x_{51}y_{51}$	$x_{51}y_{61}$	$x_{61}y_{51}$	$x_{61}y_{61}$	$y_{51}y_{61}$

(4)

$$1) \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_{51} + \beta_2 x_{61} + \beta_3 y_{51} + \beta_4 y_{61} + \beta_5 (x_{51} \times x_{61}) + \beta_6 (x_{51} \times y_{51}) + \beta_7 (x_{51} \times y_{61}) + \beta_8 (x_{61} \times y_{51}) + \beta_9 (x_{61} \times y_{61}) + \beta_{10} (y_{51} \times y_{61})$$

Lets go a step farther an predict another row:

$$2) \log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 x_{51} + \beta_2 x_{71} + \beta_3 y_{51} + \beta_4 y_{71} + \beta_5 (x_{51} \times x_{71}) + \beta_6 (x_{51} \times y_{51}) + \beta_7 (x_{51} \times y_{71}) + \beta_8 (x_{71} \times y_{51}) + \beta_9 (x_{71} \times y_{71}) + \beta_{10} (y_{51} \times y_{71})$$

We know that the results for equation 1 and equation 2 will be different.