

Data Simulation

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Treatment and Propensity Score

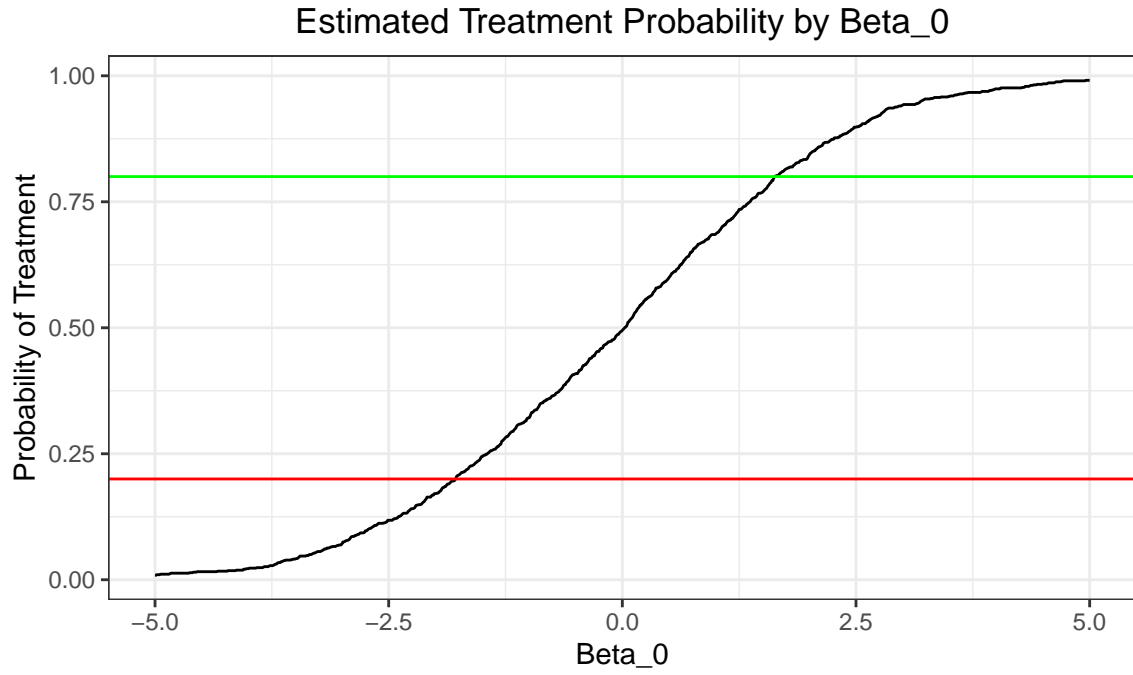
The propensity score is defined as follows:

$$\begin{aligned} e(\mathbf{X}) &= P(Z = 1|\mathbf{X}) = E[Z = 1|X] \\ \beta\mathbf{X}^T &= \text{logit}(E[Z = 1|X]) \\ \implies E[Z = 1|X] &= \frac{\exp(\beta\mathbf{X}^T)}{1 + \exp(\beta\mathbf{X}^T)} \\ E[P(Z = 1)] &= E_X[E_Z(Z = 1|X)] \\ &= E_X\left[\frac{\exp(\beta\mathbf{X}^T)}{1 + \exp(\beta\mathbf{X}^T)}\right] = p \end{aligned}$$

We see that though it is straightforward to create a propensity score model, depending on the distribution of the covariates, it may be very difficult (or impossible) to achieve a closed-form solution to determine the β coefficients needed to explicitly specify the proportion of individuals treated, p .

Then, we will select β coefficients in an empirical fashion after fixing the distributional forms of the covariates we are interested in.

Let $X_1 \sim N(0, 1)$, $X_2 \sim \text{Bernoulli}(0.6)$, representing one continuous and one binary covariate upon which treatment is determined for each subject. Then, we see that we will need to select three β coefficients to satisfy the form $g^{-1}(E[Z = 1|X]) = \beta_0 + \beta_1 X_1 + \beta_2 X_2$, where $g(\mathbf{X}) = \frac{\exp(\beta\mathbf{X}^T)}{1 + \exp(\beta\mathbf{X}^T)} = E[Z = 1|X]$. Fixing β_1 at 2 and β_2 at 3 for simplicity of calculation, we see the following:



Then, we will define our propensity score models as follows:

Low treatment (~20%): $g^{-1}(E[Z = 1|X]) = \beta_{0,20} + \beta_1 X_1 + \beta_2 X_2 = -1.66 + 2X_1 + 3X_2$

High treatment (~80%): $g^{-1}(E[Z = 1|X]) = \beta_{0,80} + \beta_1 X_1 + \beta_2 X_2 = 1.74 + 2X_1 + 3X_2$