EXTRA CHAPTER SLIDES START HERE

Ordinal and Binary Probit Regression

- In Chapter 6(a), we studied a Poisson regression model, a type of model for count data.
- We now examine the **probit regression model**, which we apply to:

1. Binary (2-category) responses, and
2. Multi-category ordinal responses

Example: Ordinal Probit Regression

- **Example 1**: Consider the response variable $Y \in \{1, 2, 3, 4, 5\}$ that indicates the highest educational degree an individual has obtained.
- The categories for Y correspond to: No degree; High school; Asoociate's; Bachelor's; Graduate degree.
- In a regression model, we consider the explanatory variables:

$$X_1 = \text{number of children the individual has}$$

$$X_2 = \begin{cases} 1 & \text{if either parent of individual has obtained college degree} \\ 0 & \text{otherwise} \end{cases}$$

$$X_3 = X_1 X_2 \text{ (interaction variable)}$$

Example: Ordinal Probit Regression

- Using a normal regression model for Y is inappropriate because:
  1. the normal error assumption will be severely violated
  2. the labels $\{1, 2, 3, 4, 5\}$ imply an "equal spacing" between types of degree that may not exist in reality.
- We assume in **probit regression** that the underlying, say, educational achievement of a person is some unobserved continuous variable Z.
- What we observe is the ordinal, categorized version, denoted Y.

Example: Ordinal Probit Regression

- Our model is thus:

$$
\begin{aligned}
Y_i &= g(Z_i), \quad i = 1, \ldots, n \\
Z_i &= \beta_0 + \beta_1 X_{i1} + \beta_2 X_{i2} + \beta_3 X_{i3} + \epsilon_i \\
\epsilon_1, \ldots, \epsilon_n &\overset{\text{iid}}{\sim} N(0,1)
\end{aligned}
$$

- The unknown parameters are: $\boldsymbol{\beta} = (\beta_0, \beta_1, \beta_2, \beta_3)$ and the nondecreasing function $g(\cdot)$, which relates the **latent** variable Z to the **observed** variable Y.
- Note $g(\cdot)$ can capture the location **and** scale of the distribution of the Y_i's, so we may let $var(\epsilon_i) = 1$ and let the intercept $\beta_0 = 0$.

Example: Ordinal Probit Regression

- Since Y takes on $K = 5$ ordered values, define $K - 1$ "thresholds" g_1, g_2, g_3, g_4 that cut the range of Z into 5 categories:

$$y = g(z) = \begin{cases} 1 & \text{if } -\infty < z < g_1 \\ 2 & \text{if } g_1 \leq z < g_2 \\ 3 & \text{if } g_2 \leq z < g_3 \\ 4 & \text{if } g_3 \leq z < g_4 \\ 5 & \text{if } g_4 \leq z < \infty \end{cases}$$

- We will use the Gibbs sampler to approximate the joint posterior of $\{\beta, g_1, g_2, g_3, g_4, \mathbf{Z}\}$.

Full Conditional of $\boldsymbol{\beta}$

- The full conditional of $\boldsymbol{\beta}$ depends only on $\mathbf{Z}$:

$$\pi(\boldsymbol{\beta}|\mathbf{y},\mathbf{z},\mathbf{g}) = \pi(\boldsymbol{\beta}|\mathbf{z})$$

- If we choose a multivariate normal prior

$$\boldsymbol{\beta} \sim MVN(\mathbf{0}, n(\mathbf{X}^{'}\mathbf{X})^{-1})$$

then the full conditional is:

$$\boldsymbol{\beta}|\mathbf{z} \sim MVN\Big[\frac{n}{n+1}(\mathbf{X}^{'}\mathbf{X})^{-1}\mathbf{X}^{'}\mathbf{z}, \frac{n}{n+1}(\mathbf{X}^{'}\mathbf{X})^{-1}\Big].$$

Full Conditional of $\mathbf{Z}$

- We know $Z_i|\boldsymbol{\beta} \sim N(\boldsymbol{\beta}'\mathbf{x}_i, 1)$.
- Given $\mathbf{g}$ and $Y_i = y_i$, then $Z_i \in [g_{y_i-1}, g_{y_i})$. Hence

$$\pi(z_i|\boldsymbol{\beta}, \mathbf{y}, \mathbf{g}) \propto N(\boldsymbol{\beta}'\mathbf{x}_i, 1) \times I_{[a \leq z_i < b]}$$

  (a constrained normal distribution), where $a = g_{y_i-1}, b = g_{y_i}$.
- This can be sampled from fairly easily in `R`.

Full Conditional of $\mathbf{g}$

- Given $\mathbf{y}$ and $\mathbf{z}$, we know g_k must be between $a_k = \max\{z_i : y_i = k\}$ and $b_k = \min\{z_i : y_i = k+1\}$.
- We can choose constrained normal priors on the g_k's so that the full conditional of g_k is $N(\mu_k, \sigma_k^2)$ constrained to the interval $[a_k, b_k)$.

Example: Ordinal Probit Regression

- **Example 1**: Educational achievement data on 959 working males.
- Let's use the priors: $\boldsymbol{\beta} \sim MVN(\mathbf{0}, n(\mathbf{X}'\mathbf{X})^{-1})$ and $p(\mathbf{g}) \propto \prod_{k=1}^{4} \text{dnorm}(g_k, 0, 100)$ constrained so that $g_1 < g_2 < g_3 < g_4$.
- `R` example on course web page: Posterior inference is made on $\beta_1, \beta_2, \beta_3$
- See plot of generated $z_1, \ldots, z_{959}$ against the number of children for individuals $1, \ldots, 959$.
- Different slopes for $X_2 = 0$ and $X_2 = 1$.