Note that if $Y$ is binary (two-category), the same model could hold, with $K = 2$.

So we have only one threshold $g_1$ separating the two categories.

**Example 2** (54 elderly patients): Let

$$Y_i = \begin{cases} 
1 & \text{if senility is not present in individual } i \\
2 & \text{if senility is present in individual } i 
\end{cases}$$

Explanatory variable $X =$ score on subset of WAIS intelligence test.

See R example on course web page.
The **logistic regression** approach does not assume the unobserved latent variable is normally distributed.

We define $Y$ to be either 1 (success) or 0 (failure) and model $P(Y = 1)$ at a given value $x$ of the explanatory variable $X$ as:

$$
\pi_x = \frac{e^{\beta_0 + \beta_1 x}}{1 + e^{\beta_0 + \beta_1 x}}
$$

where $\pi_x = P(Y = 1|X = x)$.

This is equivalent to modeling the **log-odds** of success with a linear predictor function:

$$
\text{logit}(\pi_x) = \ln \left( \frac{\pi_x}{1 - \pi_x} \right) = \beta_0 + \beta_1 x
$$
A common choice is choosing normal priors on the regression coefficients ($\beta_0$ and $\beta_1$).

Alternately, we could specify beta priors on the success probabilities at selected $x$-values of interest.

We could then express the $\beta$’s deterministically in terms of those success probabilities by back-solving.

See WinBUGS examples on course web page with senility data.