

# Bayesian Logistic Regression

- ▶ 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:

$$\text{logit}(\pi_x) = \ln\left(\frac{\pi_x}{1 - \pi_x}\right) = \beta_0 + \beta_1 x$$

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- ▶ 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.