

# Chapter 12.3a Bayesian Logistic Modeling

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Chapter 12 Bayesian Multiple Regression and Logistic  
Models

## Example: U.S. women labor participation

- ▶ The University of Michigan Panel Study of Income Dynamics (PSID) is the longest running longitudinal household survey in the world.
- ▶ Information on these individuals includes data covering employment, income, wealth, expenditures, health, marriage, childbearing, and child development.
- ▶ The PSID 1976 survey provides helpful self-reporting data sources for studies of married women's labor supply. A sample includes information on family income exclusive of wife's income (in \$1000) and the wife's labor participation (yes or no).

# The PSID Sample

This PSID sample contains 753 observations and two variables. Table provides the description of each variable in the PSID sample.

Variable	Description
LaborParticipation	Binary; the labor participation status of the wife 1 = yes, 0 = no
FamilyIncome	Continuous; the family income exclusive of wife's income, in \$1000, 1975 U.S. dollars

# A Prediction Problem

- ▶ Suppose one is interested in predicting a wife's labor participation status from the family income exclusive of her income.
- ▶ The response variable (labor participation) is not continuous, but binary – either the wife is working or she is not.
- ▶ One is interested in estimating the probability of a labor participation (yes) as a function of the predictor variable, family income exclusive of her income.
- ▶ Requires a new model that can express the probability of a yes as a function of the predictor variable.

# Graph of the Data

- ▶ Figure displays a scatterplot of the family income against the labor participation status.
- ▶ We see that roughly half of the wives are working and it is difficult to see if the family income is predictive of the participation status.



# Regression Modeling

- ▶ In Chapter 11, when one had a continuous-valued response variable and a single continuous predictor, the mean response  $\mu_i$  was expressed as a linear function:

$$\mu_i = \beta_0 + \beta_1 x_i.$$

- ▶ Moreover we assumed the response  $Y_i$  is Normally distributed with mean  $\mu_i$ .
- ▶ However, such a Normal density setup is not sensible for a binary response  $Y_i$  since the response is not continuous-valued.

# A logistic regression model

- ▶ Recall the definition of odds was introduced – an odds is the ratio of the probability of some event will take place over the probability of the event will not take place.
- ▶ In the PSID example, let  $p_i$  be the probability of labor participation of married woman  $i$ , and the corresponding odds of participation is  $\frac{p_i}{1-p_i}$ .
- ▶ If one applies a logarithm transformation on the odds, one obtains a quantity, called a log odds or logit, that is real-valued.
- ▶ One obtains a model for a binary response by writing the logit in terms of the linear predictor.

# A logistic regression model

- ▶ The response  $Y_i$  is assumed to have a Bernoulli distribution with probability of success  $p_i$ .
- ▶ The logistic regression model writes that the logit of the probability  $p_i$  is a linear function of the predictor variable  $x_i$ :

$$\text{logit}(p_i) = \log\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \beta_1 x_i.$$



# Interpreting the model

- ▶ With the logit function, the regression coefficients  $\beta_0$  and  $\beta_1$  are directly related to the log odds  $\log\left(\frac{p_i}{1-p_i}\right)$  instead of  $p_i$ .
- ▶ The intercept  $\beta_0$  is the log odds when the predictor takes a value of 0. In the PSID example, it refers to the log odds of labor participation of a married woman, whose family has 0 family income exclusive of her income.
- ▶ The slope  $\beta_1$  refers to the change in the log odds of labor participation of a married woman who has an additional \$1000 family income exclusive of her own income.

# Rewriting the Model

- By rearranging the logistic model, one expresses the regression as a nonlinear equation for the probability of success  $p_i$ :

$$\log\left(\frac{p_i}{1 - p_i}\right) = \beta_0 + \beta_1 x_i$$

$$\frac{p_i}{1 - p_i} = \exp(\beta_0 + \beta_1 x_i)$$

$$p_i = \frac{\exp(\beta_0 + \beta_1 x_i)}{1 + \exp(\beta_0 + \beta_1 x_i)}.$$

- This equation shows that the logit function guarantees that the probability  $p_i$  lies in the interval  $(0, 1)$ .