

# Predictive Analytics

## Regression and Classification

Lecture 7 : Part 2

**Sourish Das**

Chennai Mathematical Institute

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# Logistic Regression

- ▶ Logistic Regression with **logit-link**

$$\log\left(\frac{p}{1-p}\right) = x^T \boldsymbol{\beta} = \beta_0 + \beta_1 x_1 + \cdots + x_p \beta_p$$

- ▶ Logistic Regression with **probit-link**

$$\Phi^{-1}(p) = x^T \boldsymbol{\beta} = \beta_0 + \beta_1 x_1 + \cdots + x_p \beta_p$$

- ▶ How to estimate  $\boldsymbol{\beta}$ ?

# Likelihood Function of Probit Model

- ▶ Suppose  $\{y_i, x_i\}_{i=1}^n$  contains  $n$  independent samples
- ▶ For the single observation, the **probit model** is

$$\mathbb{P}(y_i = 1|x_i) = \Phi(x_i^T \beta) = p_i$$

$$\mathbb{P}(y_i = 0|x_i) = 1 - \Phi(x_i^T \beta) = 1 - p_i$$

- ▶ The likelihood of a single observation  $(y_i, x_i)$  is  
 $f(y_i, x_i|\beta) = p_i^{y_i} (1 - p_i)^{(1-y_i)} = \Phi(x_i^T \beta)^{y_i} [1 - \Phi(x_i^T \beta)]^{(1-y_i)}$
- ▶ Since the observations are independent, the joint likelihood of the entire sample is

$$\mathcal{L}(\beta; \mathbf{y}, \mathbf{X}) = \prod_{i=1}^n \left( \Phi(x_i^T \beta)^{y_i} [1 - \Phi(x_i^T \beta)]^{(1-y_i)} \right) \quad \text{cmj}$$

# Log-Likelihood Function of Probit Model

- ▶ The joint likelihood of the probit model is

$$\mathcal{L}(\beta; \mathbf{y}, \mathbf{X}) = \prod_{i=1}^n \left( \Phi(x_i^T \beta)^{y_i} [1 - \Phi(x_i^T \beta)]^{(1-y_i)} \right)$$

- ▶ The log-likelihood function of probit model is

$$\ln \mathcal{L}(\beta; \mathbf{y}, \mathbf{X}) = \sum_{i=1}^n \left( y_i \ln \Phi(x_i^T \beta) + (1 - y_i) \ln(1 - \Phi(x_i^T \beta)) \right)$$

- ▶ The negative log-likelihood function of probit model is

$$-\ln \mathcal{L}(\beta; \mathbf{y}, \mathbf{X}) = - \sum_{i=1}^n \left( y_i \ln \Phi(x_i^T \beta) + (1 - y_i) \ln(1 - \Phi(x_i^T \beta)) \right)$$



# Likelihood Function of Logit Model

- ▶ Suppose  $\{y_i, x_i\}_{i=1}^n$  contains  $n$  independent samples
- ▶ For the single observation, the **logit model** is

$$\mathbb{P}(y_i = 1|x_i) = \frac{\exp(x_i^T \beta)}{1 + \exp(x_i^T \beta)}$$

$$\mathbb{P}(y_i = 0|x_i) = 1 - \frac{\exp(x_i^T \beta)}{1 + \exp(x_i^T \beta)} = \frac{1}{1 + \exp(x_i^T \beta)}$$

- ▶ The likelihood of a single observation  $(y_i, x_i)$  is  $f(y_i, x_i|\beta) = p_i^{y_i}(1 - p_i)^{(1-y_i)} = \left(\frac{\exp(x_i^T \beta)}{1 + \exp(x_i^T \beta)}\right)^{y_i} \left[1 - \frac{\exp(x_i^T \beta)}{1 + \exp(x_i^T \beta)}\right]^{(1-y_i)}$



# Likelihood Function of Logit Model

- ▶ The likelihood of a single observation  $(y_i, x_i)$  is

$$\begin{aligned} f(y_i, x_i | \beta) &= p_i^{y_i} (1 - p_i)^{(1-y_i)} \\ &= \left( \frac{\exp(x_i^T \beta)}{1 + \exp(x_i^T \beta)} \right)^{y_i} \left( \frac{1}{1 + \exp(x_i^T \beta)} \right)^{(1-y_i)} \end{aligned}$$

- ▶ Since the observations are independent, the joint likelihood of the entire sample is

$$\mathcal{L}(\beta; \mathbf{y}, \mathbf{X}) = \prod_{i=1}^n \left( p_i^{y_i} [1 - p_i]^{(1-y_i)} \right),$$

where  $p_i = \frac{\exp(x_i^T \beta)}{1 + \exp(x_i^T \beta)}$



# Maximum Likelihood Estimates of $\beta$

- ▶ The Maximum Likelihood Estimates (MLE) of  $\beta$  is

$$\begin{aligned}\hat{\beta} &= \operatorname{argmax}_{\beta} \mathcal{L}(\beta; \mathbf{y}, \mathbf{X}) \\ &= \operatorname{argmax}_{\beta} \ln \mathcal{L}(\beta; \mathbf{y}, \mathbf{X}) \\ &= \operatorname{argmin}_{\beta} [-\ln \mathcal{L}(\beta; \mathbf{y}, \mathbf{X})]\end{aligned}$$

- ▶ **Gradient Descent Algorithm** can be used to minimise negative log-likelihood function
- ▶ This is general recipe of any statistical model
- ▶ **For simple linear regression one can show that the OLS estimator of  $\beta$  is also MLE**

## In practice...

- ▶ You don't have to implement any optimization
- ▶ There are two Python module which implement logistic regression
  1. statsmodels
  2. sklearn (aka., scikit learn)
- ▶ There is a built-in function called `glm` in R-package named `stats`.
- ▶ You can use whatever you find suitable to you



In the next video...

- ▶ I will discuss the statistical inference with logistic regression...

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