

Logistic Regression

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- Overview

↳ Model: Probability ($Y = c_k | X$)
 \uparrow
 $\{ \text{Yes, No} \}$
 Conditional Distribution
 (Discrimination)

- Decision threshold:

$$P(Y = \text{Yes} | X = ?)$$

\uparrow $> \pi_1$
 \uparrow $> \pi_2$
 \vdots \leftarrow specific value
 $X = x_0$

$$P(Y = \text{Yes} | X = x_0)$$

$>$ Threshold value
 (0.5 \rightarrow 50%)
 or
 (0.1 \rightarrow 10%)
 \vdots

- Linear Framework

- General: $P(X) = \beta_0 + \beta_1 X$

- Logistic Function:

$$\frac{P(X)}{1 - P(X)} = e^{\beta_0 + \beta_1 X}$$

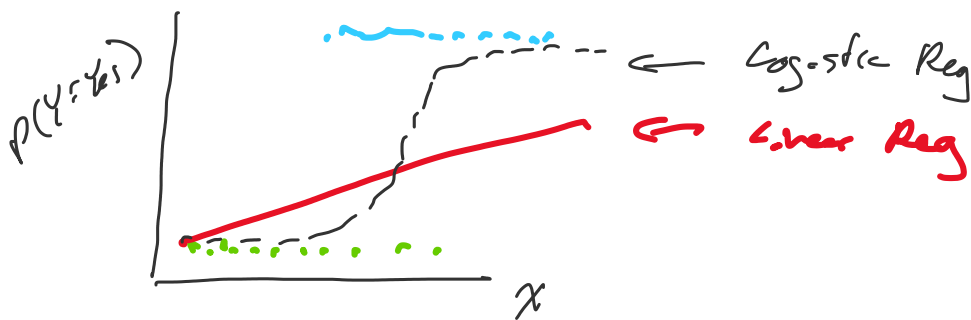
all form

odds. (,)

- Logit function

$$\underbrace{\log \frac{p(x)}{1-p(x)}}_{\text{log odds}} = \beta_0 + \beta_1 x$$

* 250% Prob \rightarrow Class 1 / Yes , < 50% class / No



- Estimation:

- Likelihood function:

$$L(\beta_0, \beta_1) = \left[\prod_{i: y_i=1} p(x_i) \right] \left[\prod_{i: y_i=0} (1-p(x_i)) \right]$$

$\hat{\beta}_0, \hat{\beta}_1$ such that maximize $L(\beta_0, \beta_1)$

\hookrightarrow Maximum Likelihood!

- Prediction

\hookrightarrow Transform:

$$f'(x_0)$$

$$\therefore \hat{P}(x) = \frac{e^{\hat{\beta}_0 + \hat{\beta}_1 x_0}}{1 + e^{\hat{\beta}_0 + \hat{\beta}_1 x_0}} = ?$$

$$\geq 50\% \quad Y=1$$

$$< 50\% \quad Y=0$$

- Multiple Logistic Regression

• Adding terms:

$$\log \frac{P(x)}{1-P(x)} = \beta_0 + \beta_1 x_1 + \dots + \beta_p x_p$$

$$\hat{P}(x) = \frac{e^{\hat{\beta}_0 + \hat{\beta}_1 x_1 + \dots + \hat{\beta}_p x_p}}{1 + e^{\hat{\beta}_0 + \hat{\beta}_1 x_1 + \dots + \hat{\beta}_p x_p}}$$

* As x_j increases, holding all other x_j fixed, log odds of $Y=1$ increases/decreases by β_j factor

↳ confounding variables!