

Logistic Regression

Part One

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Suggested Reading

- In Ch. 3, skim pages 65-68; we'll come back to generalized linear models later.
- Read pages 68-73 about logistic regression.
- Read Chapter 4.

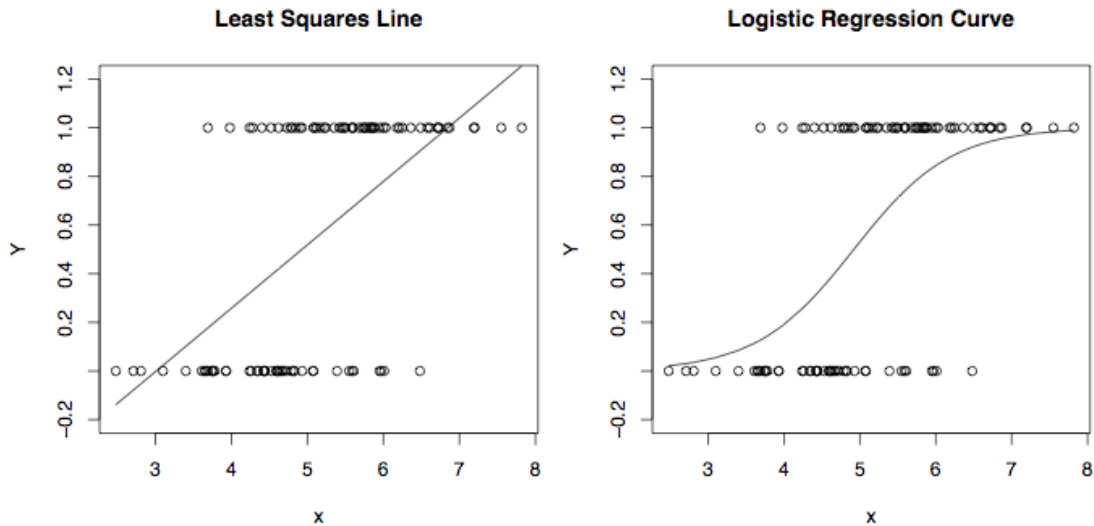
- The discussion of dummy variables in lecture may be clearer than the text's.
- Exactly what do you need to know? See homework problems.

Logistic Regression

For a binary dependent variable:
1=Yes, 0=No

$$Pr\{Y = 1 | \mathbf{X} = \mathbf{x}\} = \pi$$

Least Squares vs. Logistic Regression



Linear regression model for the log odds of the event $Y=1$

$$\log \left(\frac{\pi}{1 - \pi} \right) = \beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}$$

Note π is a *conditional* probability.

Equivalent Statements

$$\log \left(\frac{\pi}{1 - \pi} \right) = \beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}$$

$$\begin{aligned} \frac{\pi}{1 - \pi} &= e^{\beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}} \\ &= e^{\beta_0} e^{\beta_1 x_1} \dots e^{\beta_{p-1} x_{p-1}}, \end{aligned}$$

$$\pi = \frac{e^{\beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}}}{1 + e^{\beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}}}.$$

$$E(Y|\mathbf{x}) = \pi = \frac{e^{\beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}}}{1 + e^{\beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}}}$$

- A distinctly non-linear function
- Non-linear in the betas
- So logistic regression is an example of *non-linear regression*.

$F(x) = \frac{e^x}{1+e^x}$ is called the *logistic distribution*.

- Could use any cumulative distribution function:
$$\pi = F(\beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1})$$
- CDF of the standard normal used to be popular
- Called probit analysis
- Can be closely approximated with a logistic regression.

In terms of log odds, logistic regression is like regular regression

$$\log \left(\frac{\pi}{1 - \pi} \right) = \beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}$$

In terms of plain odds,

- (Exponential function of) the logistic regression coefficients are *odds ratios*
- For example, “Among 50 year old men, the odds of being dead before age 60 are three times as great for smokers.”

$$\frac{\text{Odds of death given smoker}}{\text{Odds of death given nonsmoker}} = 3$$

Logistic regression

- $X=1$ means smoker, $X=0$ means non-smoker
- $Y=1$ means dead, $Y=0$ means alive
- Log odds of death = $\beta_0 + \beta_1 x$
- Odds of death = $e^{\beta_0} e^{\beta_1 x}$

$$\text{Odds of Death} = e^{\beta_0} e^{\beta_1 x}$$

Group	x	Odds of Death
Smokers	1	$e^{\beta_0} e^{\beta_1}$
Non-smokers	0	e^{β_0}

$$\frac{\text{Odds of death given smoker}}{\text{Odds of death given nonsmoker}} = \frac{e^{\beta_0} e^{\beta_1}}{e^{\beta_0}} = e^{\beta_1}$$

Cancer Therapy Example

$$\text{Log Survival Odds} = \beta_0 + \beta_1 d_1 + \beta_2 d_2 + \beta_3 x$$

Treatment	d_1	d_2	Odds of Survival = $e^{\beta_0} e^{\beta_1 d_1} e^{\beta_2 d_2} e^{\beta_3 x}$
Chemotherapy	1	0	$e^{\beta_0} e^{\beta_1} e^{\beta_3 x}$
Radiation	0	1	$e^{\beta_0} e^{\beta_2} e^{\beta_3 x}$
Both	0	0	$e^{\beta_0} e^{\beta_3 x}$

x is severity of disease

For any given disease severity x ,

$$\frac{\text{Survival odds with Chemo}}{\text{Survival odds with Both}} = \frac{e^{\beta_0} e^{\beta_1} e^{\beta_3 x}}{e^{\beta_0} e^{\beta_3 x}} = e^{\beta_1}$$

In general,

- When x_k is increased by one unit and all other independent variables are held constant, the odds of $Y=1$ are multiplied by e^{β_k}
- That is, e^{β_k} is an **odds ratio** --- the ratio of the odds of $Y=1$ when x_k is increased by one unit, to the odds of $Y=1$ when everything is left alone.
- As in ordinary regression, we speak of “controlling” for the other variables.

The conditional probability of $Y=1$

$$\begin{aligned}\pi &= \frac{e^{\beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}}}{1 + e^{\beta_0 + \beta_1 x_1 + \dots + \beta_{p-1} x_{p-1}}} \\ &= \frac{e^{\mathbf{x}'_i \boldsymbol{\beta}}}{1 + e^{\mathbf{x}'_i \boldsymbol{\beta}}}\end{aligned}$$

This formula can be used to calculate a predicted $P(Y=1|\mathbf{x})$. Just replace betas by their estimates

It can also be used to calculate the probability of getting the sample data values we actually did observe, as a function of the betas.

Likelihood Function

$$\begin{aligned}\ell(\boldsymbol{\beta}) &= \prod_{i=1}^n P(Y_i = y_i | \mathbf{x}_i) = \prod_{i=1}^n \pi^{y_i} (1 - \pi)^{1-y_i} \\ &= \prod_{i=1}^n \left(\frac{e^{\mathbf{x}'_i \boldsymbol{\beta}}}{1 + e^{\mathbf{x}'_i \boldsymbol{\beta}}} \right)^{y_i} \left(1 - \frac{e^{\mathbf{x}'_i \boldsymbol{\beta}}}{1 + e^{\mathbf{x}'_i \boldsymbol{\beta}}} \right)^{1-y_i} \\ &= \prod_{i=1}^n \left(\frac{e^{\mathbf{x}'_i \boldsymbol{\beta}}}{1 + e^{\mathbf{x}'_i \boldsymbol{\beta}}} \right)^{y_i} \left(\frac{1}{1 + e^{\mathbf{x}'_i \boldsymbol{\beta}}} \right)^{1-y_i} \\ &= \prod_{i=1}^n \frac{e^{y_i \mathbf{x}'_i \boldsymbol{\beta}}}{1 + e^{\mathbf{x}'_i \boldsymbol{\beta}}} \\ &= \frac{e^{\sum_{i=1}^n y_i \mathbf{x}'_i \boldsymbol{\beta}}}{\prod_{i=1}^n (1 + e^{\mathbf{x}'_i \boldsymbol{\beta}})}\end{aligned}$$

Maximum likelihood estimation

- Likelihood = Conditional probability of getting the data values we did observe,
- As a function of the betas
- Maximize the (log) likelihood with respect to betas.
- Maximize numerically (“iteratively re-weighted least squares”)
- Likelihood ratio tests as usual
- Divide regression coefficients by estimated standard errors to get Z-tests of $H_0: b_j=0$.
- These Z-tests are like the t-tests in ordinary regression.

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