

# Maximum likelihood estimation for regression models

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## Warmup

Work on the warmup activity (handout), then we will discuss as a class.

## Warmup

Suppose that we have independent observations  $(\mathbf{x}_1, Y_1), \dots, (\mathbf{x}_n, Y_n)$  from the model

$$Y_i | \mathbf{x}_i \sim N(\mathbf{x}_i^T \boldsymbol{\beta}, \sigma_i^2).$$

Suppose that the variances  $\sigma_1^2, \dots, \sigma_n^2$  are known. Show that the maximum likelihood estimator of  $\boldsymbol{\beta}$  minimizes the weighted sum of squares

$$WSS(\boldsymbol{\beta}) = \sum_{i=1}^n w_i (Y_i - \mathbf{x}_i^T \boldsymbol{\beta})^2 = (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})^T \mathbf{W} (\mathbf{y} - \mathbf{X}\boldsymbol{\beta})$$

## Maximum likelihood estimation and logistic regression

Let  $(\mathbf{x}_1, Y_1), \dots, (\mathbf{x}_n, Y_n)$  be iid samples from the model

$$Y_i | \mathbf{x}_i \sim \text{Bernoulli}(p_i)$$

$$\log \left( \frac{p_i}{1 - p_i} \right) = \mathbf{x}_i^T \boldsymbol{\beta}$$

where the distribution of  $\mathbf{x}_i$  does not depend on  $\boldsymbol{\beta}$ .

$$\ell(\boldsymbol{\beta} | \mathbf{y}, \mathbf{X}) \stackrel{\text{(up to a constant)}}{=} \sum_{i=1}^n \left\{ Y_i \mathbf{x}_i^T \boldsymbol{\beta} - \log(1 + e^{\mathbf{x}_i^T \boldsymbol{\beta}}) \right\}$$

$$U(\boldsymbol{\beta}) = \frac{\partial \ell}{\partial \boldsymbol{\beta}} = \mathbf{X}^T (\mathbf{y} - \mathbf{p})$$

## Newton's method

- ▶ Want  $\beta^*$  such that  $U(\beta^*) = \mathbf{0}$
- ▶ Begin with initial estimate  $\beta^{(0)}$
- ▶ Iterative updates:

$$\beta^{(r+1)} = \beta^{(r)} - (\mathbf{H}(\beta^{(r)}))^{-1} U(\beta^{(r)})$$

## The Hessian

$$U(\beta) = \frac{\partial}{\partial \beta} \ell(\beta | \mathbf{y}, \mathbf{X}) = \mathbf{X}^T (\mathbf{y} - \mathbf{p})$$

$$\begin{aligned}\mathbf{H}(\beta) &= \frac{\partial}{\partial \beta} U(\beta) = \frac{\partial}{\partial \beta} \mathbf{X}^T (\mathbf{y} - \mathbf{p}) = \left( -\frac{\partial \mathbf{p}}{\partial \beta} \right) \mathbf{X} \\ \frac{\partial \mathbf{p}}{\partial \beta} &= \begin{bmatrix} \frac{\partial p_1}{\partial \beta} & \frac{\partial p_2}{\partial \beta} & \dots & \frac{\partial p_n}{\partial \beta} \end{bmatrix} \in \mathbb{R}^{(k+1) \times n}\end{aligned}$$

## Putting everything together

Want to maximize the log likelihood  $\ell(\beta|\mathbf{y}, \mathbf{X})$ .

## Class activity

Work on the class activity:

[https://sta711-s26.github.io/class\\_activities/ca\\_07\\_2.html](https://sta711-s26.github.io/class_activities/ca_07_2.html)

Submit your work on Canvas.