

(1) Suppose for the  $i$ th subject we observe  $x_i$  and  $y_i$ . Let  $p(x_i; \beta) = P(Y = 1 | X = x_i)$ .

Maximum likelihood estimation:

$$\begin{aligned}\ell(\beta) &= \sum_{i=1}^N \left\{ y_i \log p(x_i; \beta) + (1 - y_i) \log(1 - p(x_i; \beta)) \right\} \\ &= \sum_i \left\{ y_i x_i^\top \beta - \log(1 + \exp(x_i^\top \beta)) \right\}\end{aligned}$$

Please derive the blue part.

$$\begin{aligned}[\text{proof}] \quad \ell(\beta) &= \sum_{i=1}^N \left\{ y_i \log p(x_i; \beta) + (1 - y_i) \log(1 - p(x_i; \beta)) \right\} \\ &= \sum_{i=1}^N \left\{ y_i x_i^\top \beta - y_i \log(1 + e^{x_i^\top \beta}) - (1 - y_i) \log(1 + e^{x_i^\top \beta}) \right\} \\ &= \sum_{i=1}^N \left\{ y_i x_i^\top \beta - \log(1 + \exp(x_i^\top \beta)) \right\}\end{aligned}$$

(2) Write Newton-Raphson algorithm to estimate logistic regression.

Reminder: you need to derive the equation

$$\frac{\partial^2 \ell(\beta)}{\partial \beta \partial \beta^\top} = - \sum_i x_i x_i^\top p(x_i; \beta) \{1 - p(x_i; \beta)\}. \quad (0.1)$$

Generate  $X = (1, X_1, X_2)$ , where  $X_j \sim N(0, I_N)$ .

Set true parameter  $\beta = (0.5, 1.2, -1)^\top$ .

Set  $N = 200, 500, 800, 1000$ .

Estimate  $\beta$  using NR algorithm for  $R = 200$  rounds of simulation. For each round of simulation, terminate the iteration when  $\max_j |\hat{\beta}_j^{old} - \hat{\beta}_j^{new}| < 10^{-5}$ . Denote  $\hat{\beta}_j^{(r)}$  as the estimation of  $\beta_j$  in the  $r$ th round of simulation. Then please: for each  $j$ , draw  $(\hat{\beta}_j^{(r)} - \beta_j)$  in boxplot for  $N = 200, 500, 800, 1000$ .

$$\begin{aligned} \text{[proof]: } \frac{\partial \ell(\beta)}{\partial \beta} &= \sum_{i=1}^N y_i x_i - \frac{\exp(x_i^\top \beta)}{1 + \exp(x_i^\top \beta)} \cdot x_i \\ &= \sum_{i=1}^N (y_i - p(x_i; \beta)) x_i \\ \frac{\partial^2 \ell}{\partial \beta \partial \beta^\top} &= - \sum_{i=1}^N \frac{\partial}{\partial \beta} \left( \left( 1 - \frac{1}{1 + \exp(x_i^\top \beta)} \right) \cdot x_i \right) / \partial \beta^\top \\ &= \sum_{i=1}^N - \frac{\exp(x_i^\top \beta)}{(1 + \exp(x_i^\top \beta))^2} x_i x_i^\top \\ &= - \sum_{i=1}^N p(x_i; \beta) (1 - p(x_i; \beta)) x_i x_i^\top = -X^\top W X \end{aligned}$$

Code is in "Problem2.html"

(3) 假设有 $m^+$ 个正例和 $m^-$ 个负例，令 $D^+$ 与 $D^-$ 分别表示正例、反例集合。定义排序“损失”如下：

$$\ell_{rank} = \frac{1}{m^+m^-} \sum_{x^+ \in D^+} \sum_{x^- \in D^-} \left( I(f(x^+) < f(x^-)) + \frac{1}{2} I(f(x^+) = f(x^-)) \right) \quad (0.2)$$

理解：若正例的预测值小于反例，则记一个“罚分”，若相等，则记0.5个罚分。定义AUC：

$$AUC = 1 - \ell_{rank}. \quad (0.3)$$

考虑一种简单的情况，即当数据中不存在 $f(x^+) = f(x^-)$ 时，定义排序“损失”如下：

$$\ell_{rank} = \frac{1}{m^+m^-} \sum_{x^+ \in D^+} \sum_{x^- \in D^-} \left( I(f(x^+) < f(x^-)) \right) \quad (0.4)$$

试证明以上定义的AUC即有限样本下ROC曲线下方的面积。

证明：  $m^+ = TP + FN$ ,  $m^- = TN + FP$

设前 $k$ 个预测值的负例的集合为  $D_k^-$

则  $D_1^- \subseteq D_2^- \subseteq \dots \subseteq D_m^-$  且  $\bigcup_{k=1}^{m^-} D_k^- \setminus D_{k-1}^- = D^-$  令  $D_k^- \setminus D_{k-1}^- = E_k$

对于离散ROC曲线  $\sum_{x^+ \in D^+} \sum_{x^- \in E_k} I(f(x^+) > f(x^-))$  为第 $k$ 个柱体的面积

$$AUC = \frac{1}{m^+m^-} \sum_{k=1}^{m^-} \sum_{x^+ \in D^+} \sum_{x^- \in E_k} I(f(x^+) > f(x^-))$$

$$= \frac{1}{m^+m^-} \sum_{k=1}^{m^-} \sum_{x^- \in E_k} \sum_{x^+ \in D^+} I(f(x^+) > f(x^-))$$

$$= \frac{1}{m^+m^-} \sum_{x^- \in \bigcup_{k=1}^{m^-} E_k} \sum_{x^+ \in D^+} I(f(x^+) > f(x^-))$$

$$= \frac{1}{m^+m^-} \sum_{x^- \in D^-} \sum_{x^+ \in D^+} I(f(x^+) > f(x^-))$$

$$\therefore I(f(x^+) > f(x^-)) + I(f(x^+) < f(x^-)) = 1$$

$$\therefore AUC = \frac{1}{m^+m^-} \sum_{x^+ \in D^+} \sum_{x^- \in D^-} [1 - I(f(x^+) < f(x^-))]$$

$$= 1 - \frac{1}{m^+m^-} \sum_{x^+ \in D^+} \sum_{x^- \in D^-} I(f(x^+) < f(x^-)) = 1 - \ell_{rank}$$

