

Identity of Likelihood Score Statistic to Residual Score Statistic

For logistic regression, let

$\mathbf{X}_A = [\mathbf{1}, \mathbf{X}]$ denote primary model

$\mathbf{X}_E = [\mathbf{1}, \mathbf{X}, \mathbf{W}]$ denote expanded model

Assume both models have full rank

Let $\hat{\boldsymbol{\beta}}_A$ denote mle for \mathbf{X}_A

Let $\tilde{\boldsymbol{\beta}}_E = (\tilde{\boldsymbol{\beta}}_A', \tilde{\boldsymbol{\beta}}_W')'$ denote mle for \mathbf{X}_E

Let $\bar{\boldsymbol{\beta}} = (\bar{\boldsymbol{\beta}}_A', \mathbf{0}')'$ denote restriction of $\tilde{\boldsymbol{\beta}}_E$ to

have $\hat{\boldsymbol{\beta}}_W = \mathbf{0}$ relative to hypothesis $\boldsymbol{\beta}_W = \mathbf{0}$

Let $\mathbf{U}(\boldsymbol{\beta}_E) = \frac{\delta \ln L}{\delta \boldsymbol{\beta}_E} = \mathbf{X}_E' \{ \mathbf{y} - \mathbf{D}_n \boldsymbol{\pi}(\boldsymbol{\beta}_E) \}$

Let $\mathbf{I}(\boldsymbol{\beta}_E) = - \frac{\delta^2 \ln L}{\delta \boldsymbol{\beta}_E \delta \boldsymbol{\beta}_E'} = \mathbf{X}_E' \mathbf{D}_{V(\boldsymbol{\beta}_E)} \mathbf{X}_E$

$\mathbf{V}(\boldsymbol{\beta}_E) = \{ n_i \pi_i(\boldsymbol{\beta}_E) (1 - \pi_i(\boldsymbol{\beta}_E)) \}$ as vector

$\pi_i(\boldsymbol{\beta}_E) = \frac{\exp(\mathbf{X}_{iA}' \boldsymbol{\beta}_A + \mathbf{W}_i' \boldsymbol{\beta}_W)}{1 + \exp(\mathbf{X}_{iA}' \boldsymbol{\beta}_A + \mathbf{W}_i' \boldsymbol{\beta}_W)}$

$Q_S = [\mathbf{U}(\bar{\boldsymbol{\beta}})]' [\mathbf{I}(\bar{\boldsymbol{\beta}})]^{-1} [\mathbf{U}(\bar{\boldsymbol{\beta}})]$

$\pi_i(\bar{\boldsymbol{\beta}}) = \frac{\exp(\mathbf{X}_{iA}' \hat{\boldsymbol{\beta}}_A)}{1 + \exp(\mathbf{X}_{iA}' \hat{\boldsymbol{\beta}}_A)} = \pi_i(\hat{\boldsymbol{\beta}}_A)$

$\mathbf{U}(\bar{\boldsymbol{\beta}}) = \begin{bmatrix} \mathbf{X}_A' \\ \mathbf{W}' \end{bmatrix} [\mathbf{y} - \mathbf{D}_n \boldsymbol{\pi}(\hat{\boldsymbol{\beta}}_A)] = \begin{bmatrix} \mathbf{0} \\ \mathbf{W}' [\mathbf{y} - \mathbf{D}_n \boldsymbol{\pi}(\hat{\boldsymbol{\beta}}_A)] \end{bmatrix}$ since $\mathbf{X}_A' \mathbf{y} = \mathbf{X}_A' \mathbf{D}_n \boldsymbol{\pi}(\hat{\boldsymbol{\beta}}_A)$

$\mathbf{I}(\bar{\boldsymbol{\beta}}) = \begin{bmatrix} \mathbf{X}_A' \\ \mathbf{W}' \end{bmatrix} \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \begin{bmatrix} \mathbf{X}_A & \mathbf{W} \end{bmatrix} = \begin{bmatrix} \mathbf{X}_A' \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{X}_A & \mathbf{X}_A' \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{W} \\ \mathbf{W}' \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{X}_A & \mathbf{W}' \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{W} \end{bmatrix}$

$Q_S = [\mathbf{U}(\bar{\boldsymbol{\beta}})]' [\mathbf{I}(\bar{\boldsymbol{\beta}})]^{-1} [\mathbf{U}(\bar{\boldsymbol{\beta}})]$

$= [\mathbf{0}', *] \begin{bmatrix} * & * \\ * & * \end{bmatrix}^{-1} \begin{bmatrix} \mathbf{0} \\ * \end{bmatrix}$

$= [\mathbf{y} - \mathbf{D}_n \boldsymbol{\pi}(\hat{\boldsymbol{\beta}}_A)]' \mathbf{W} \left\{ \mathbf{W}' \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{W} - \mathbf{W}' \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{X}_A (\mathbf{X}_A' \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{X}_A)^{-1} \mathbf{X}_A \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{W} \right\}^{-1} \mathbf{W}' [\mathbf{y} - \mathbf{D}_n \boldsymbol{\pi}(\hat{\boldsymbol{\beta}}_A)]$
 $= [\mathbf{y} - \mathbf{D}_n \boldsymbol{\pi}(\hat{\boldsymbol{\beta}}_A)]' \mathbf{W} \left\{ \mathbf{W}' [\mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} - \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{X}_A (\mathbf{X}_A' \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)} \mathbf{X}_A)^{-1} \mathbf{X}_A \mathbf{D}_{V(\hat{\boldsymbol{\beta}}_A)}] \mathbf{W} \right\}^{-1} \mathbf{W}' [\mathbf{y} - \mathbf{D}_n \boldsymbol{\pi}(\hat{\boldsymbol{\beta}}_A)]$