

Fisher scoring and iterative reweighted least squares (IRWLS)

Fisher scoring

$$\hat{\beta}^{(t+1)} = \hat{\beta}^{(t)} + F^{-1}(\hat{\beta}^{(t)}) S(\hat{\beta}^{(t)})$$

$$S(\beta) = \sum_{i=1}^n \frac{(y_i - \mu_i) x_i}{\text{Var}(y_i)} \cdot h'(\eta_i) = \mathbf{X}^T \mathbf{D} \Sigma^{-1} (\mathbf{y} - \boldsymbol{\mu})$$

\nearrow $\text{diag}(h'(\eta_i))$ \nwarrow $\text{diag}(\text{Var}(y_i))$

$$F(\beta) = \sum_{i=1}^n \frac{x_i h'(\eta_i) x_i [h'(\eta_i)]^2}{\text{Var}(y_i)} = \mathbf{X}^T \mathbf{W} \mathbf{X}$$

\uparrow $\text{diag}\left[\frac{[h'(\eta_i)]^2}{\text{Var}(y_i)}\right]$

$$\hat{\beta}^{(t+1)} = \hat{\beta}^{(t)} + \left(\mathbf{X}^T \mathbf{W}(\hat{\beta}^{(t)}) \mathbf{X} \right)^{-1} \mathbf{X}^T \mathbf{D}(\hat{\beta}^{(t)}) \Sigma(\hat{\beta}^{(t)})^{-1} (\mathbf{y} - \boldsymbol{\mu}(\hat{\beta}^{(t)}))$$

\swarrow $\mathbf{I} = \left(\mathbf{X}^T \mathbf{W}(\hat{\beta}^{(t)}) \mathbf{X} \right)^{-1} \mathbf{X}^T \mathbf{W}(\hat{\beta}^{(t)}) \mathbf{X}$

$$\text{diag}(h'(\eta_i)) \text{diag}\left(\frac{1}{\text{Var}(y_i)}\right)$$

$$\text{diag}\left[\frac{h_i'(\eta_i)}{\text{Var}(y_i)}\right]$$

$$\text{diag}\left[\frac{h_i'(\eta_i)^2}{\text{Var}(y_i)}\right] \cdot \text{diag}\left[\frac{1}{h_i'(\eta_i)}\right]$$

$$\mathbf{W}(\hat{\beta}^{(t)})$$

$$\mathbf{D}(\hat{\beta}^{(t)})^{-1}$$

$$\hat{\beta}^{(t+1)} = (\mathbf{X}^T \mathbf{W}(\hat{\beta}^{(t)}) \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}(\hat{\beta}^{(t)})$$

$$\left[\underbrace{\mathbf{X} \hat{\beta}^{(t)}}_{\eta(\hat{\beta}^{(t)})} + \mathbf{D}(\hat{\beta}^{(t)})^{-1} (\mathbf{y} - \mu(\hat{\beta}^{(t+1)})) \right]$$

$$= (\mathbf{X}^T \mathbf{W}(\hat{\beta}^{(t+1)}) \mathbf{X})^{-1} \mathbf{X}^T \mathbf{W}(\hat{\beta}^{(t+1)}) \tilde{\mathbf{y}}^{(t)}$$

$\tilde{\mathbf{y}}^{(t)} = (\dots, \tilde{y}_i(\hat{\beta}^{(t)}), \dots)^T$ working response vector

$$\tilde{y}_i(\hat{\beta}^{(t)}) = x_i^T \hat{\beta}^{(t)} + d_i^{-1}(\hat{\beta}^{(t)}) (y_i - \hat{\mu}_i(\hat{\beta}^{(t+1)}))$$

$$\frac{1}{d_i(\eta_i)} = \frac{1}{h_i'(x_i^T \hat{\beta}^{(t)})}$$

$$= x_i^T \hat{\beta}^{(t)} + \frac{y_i - h(x_i^T \hat{\beta}^{(t+1)})}{h'(x_i^T \hat{\beta}^{(t)})}$$

Working weights: $w_i(x_i^T \hat{\beta}^{(t)}) = \frac{h'(x_i^T \hat{\beta}^{(t+1)})}{\text{Var}(Y_i)}$

$W = \text{diag}(w_i)$

\uparrow evaluate at $\hat{\beta}^{(t)}$

\uparrow might involve $\hat{\phi}$

Remark; we need to invert $\sum^T W(\beta^{(k)}) \sum$

\Rightarrow ok if all weights are positive
 $\left\{ \begin{array}{l} w_i \text{ in } W \end{array} \right.$

Usually: convergence established in few steps.

Canonical link: unique maximum

In general: should try several starts to achieve global max