Nonlinear Regression – Part III

Johns Hopkins Engineering

625.461 Statistical Models and Regression

Module 13 – Lecture 13D



Parameter Estimation

Linearization followed by the Gauss-Newton iteration method of parameter estimation

Linearization is accompanied by a Taylor series expansion of $f(\mathbf{x}, \boldsymbol{\theta})$ about the initial point $\boldsymbol{\theta}_0 = [\theta_{10}, \theta_{20}, \dots, \theta_{p0}]'$ with only the linear terms retained.

This yields

$$f(\mathbf{x}_i, \boldsymbol{\theta}) = f(\mathbf{x}_i, \boldsymbol{\theta}_0) + \sum_{j=1}^{p} \left[\frac{\partial f(\mathbf{x}_i, \boldsymbol{\theta})}{\partial \theta_j} \right]_{\boldsymbol{\theta} = \boldsymbol{\theta}_0} (\theta_j - \theta_{j0})$$

Set

$$f_i^0 = f(\mathbf{x}_i, \boldsymbol{\theta}_0)$$

$$\beta_j^0 = \boldsymbol{\theta}_j - \boldsymbol{\theta}_{j0}$$

$$Z_{ij}^0 = \left[\frac{\partial f(\mathbf{x}_i, \boldsymbol{\theta}_0)}{\partial \boldsymbol{\theta}_i}\right]_{\boldsymbol{\theta} = \boldsymbol{\theta}_0}$$

We then have

$$y_i - f_i^0 = \sum_{j=1}^p \beta_j^0 Z_{ij}^0 + \varepsilon_i, \quad i = 1, 2, ..., n$$

$$\mathbf{y}_0 = \mathbf{Z}_0 \boldsymbol{\beta}_0 + \boldsymbol{\varepsilon}$$

Then the LS estimator of β_0 :

$$\hat{\beta}_0 = (\mathbf{Z}_0'\mathbf{Z}_0)^{-1}\mathbf{Z}_0'\mathbf{y}_0 = (\mathbf{Z}_0'\mathbf{Z}_0)^{-1}\mathbf{Z}_0'(\mathbf{y} - \mathbf{f}_0)$$

Since $\beta_0 = \theta - \theta_0$, the revised estimates of θ is

$$\hat{\boldsymbol{\theta}}_1 = \hat{\boldsymbol{\beta}}_0 + \boldsymbol{\theta}_0$$

We may now place $\hat{\theta}_1$ as the initial estimates θ_0 to the above equations on slides 4-5 and then produce another set of revised estimates, say $\hat{\theta}_2$, and so forth.

In general, we have at the kth iteration

$$\hat{\boldsymbol{\theta}}_{k+1} = \hat{\boldsymbol{\theta}}_k + \hat{\boldsymbol{\beta}}_k = \hat{\boldsymbol{\theta}}_k + (\mathbf{Z}_k'\mathbf{Z}_k)^{-1}\mathbf{Z}_k'(\mathbf{y} - \mathbf{f}_k)$$

where

$$\mathbf{Z}_{k} = \begin{bmatrix} Z_{ij}^{k} \end{bmatrix}$$

$$\mathbf{f}_{k} = \begin{bmatrix} f_{1}^{k}, f_{2}^{k}, \dots, f_{n}^{k} \end{bmatrix}'$$

$$\hat{\boldsymbol{\theta}}_{k} = \begin{bmatrix} \theta_{1k}, \theta_{2k}, \dots, \theta_{pk} \end{bmatrix}'$$

This iterative process continues until converges, that is, until

$$\left[\left(\hat{\theta}_{j,k+1}-\hat{\theta}_{jk}\right)/\hat{\theta}_{jk}\right]<\delta, \quad j=1,2,\ldots,p$$

where δ is a small number, say 10⁻⁶.

At each iteration, the residual sum of squares $S(\hat{\theta}_k)$ should be evaluated to ensure that a reduction in its value has been obtained.

