Uncertainty analysis in Larch (or IFEFFIT? haven't checked.)

Implementation used in Larch

- Larch uses Imfit package for the Levenberg-Marquardt algorithm.
- Imfit calls Scipy.optimize.leastsq() to call MINPACK's Imdif() and Imder() functions.
- The hessian matrix return by leastsq() is calculated using an approximate hessian matrix calculated by

$$\mathbf{H} = \mathbf{J}(\mathbf{x})^T \mathbf{J}(\mathbf{x})$$

The covariance matrix is calculated by

$$oldsymbol{\Sigma} = \left(\mathbf{J}^T\mathbf{J}
ight)^{-1} = \mathbf{P}ig(\mathbf{R}^T\mathbf{R}ig)^{-1}\mathbf{P}ig)$$

where ${f P}$ is the permutation matrix and ${f R}$ is the upper triangular matrix obtained from the QR decomposition of ${f J}$.

Maximum likelihood estimation

• If we assume that we have a distribution function of y by a model F(x) with parameters θ as f, then the likelihood function is given by

$$L(heta) = \prod_{i=0}^n f_i(\mathbf{y}| heta)$$

the logaritmic likelihood function is given by

$$l(heta) = \sum_{i=0}^n \log f_i(\mathbf{y}| heta)$$

The first derivative is the score function.

$$\mathbf{s}(heta) = egin{pmatrix} rac{\partial l(heta)}{\partial heta_1} \ rac{\partial l(heta)}{\partial heta_2} \ dots \ rac{\partial l(heta)}{\partial heta_n} \end{pmatrix}$$

Uncertainty analysis

maximization of the likelihood function is equivalent to calculating a zero of the score function.

$$\mathbf{s}(\theta) = \mathbf{0}$$

For a nessesary and sufficient condition for a maximum, the Hessian matrix ${\bf H}$ of $l(\theta)$ must be negative definite.

if we take the second derivative of $l(\theta)$ with respect to θ , we get the Hessian matrix ${\bf H}$ of $l(\theta)$.

$$\mathbf{H} = \begin{pmatrix} \frac{\partial^2 l(\theta)}{\partial \theta_1^2} & \frac{\partial^2 l(\theta)}{\partial \theta_1 \partial \theta_2} & \cdots & \frac{\partial^2 l(\theta)}{\partial \theta_1 \partial \theta_n} \\ \frac{\partial^2 l(\theta)}{\partial \theta_2 \partial \theta_1} & \frac{\partial^2 l(\theta)}{\partial \theta_2^2} & \cdots & \frac{\partial^2 l(\theta)}{\partial \theta_2 \partial \theta_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial^2 l(\theta)}{\partial \theta_n \partial \theta_1} & \frac{\partial^2 l(\theta)}{\partial \theta_n \partial \theta_2} & \cdots & \frac{\partial^2 l(\theta)}{\partial \theta_n^2} \end{pmatrix}$$