

Inverse Laplace Transforms Applied to β -NMR

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Let n -vector \mathbf{y} be a set of measurements, corresponding to independent variable \mathbf{x} of equal length. The goal is to find the vector of weights \mathbf{p} , of length m , which satisfies the least squares condition

$$\min \|\mathbf{y} - K\mathbf{p}\|^2, \quad (1)$$

where K is a $n \times m$ kernel matrix composed of function $f(x, z)$ in the following way:

$$K = \begin{pmatrix} f(x_1, z_1) & f(x_1, z_2) & f(x_1, z_3) & \dots \\ f(x_2, z_1) & \ddots & & \\ f(x_3, z_1) & & & \\ \vdots & & & \end{pmatrix}. \quad (2)$$

The final fit function to the data \mathbf{y} is therefore $\sum_i p_i f(\mathbf{x}, z_i)$. Accounting for the errors in \mathbf{y} , the weighted χ_w^2 is given by

$$\chi_w^2 = \|\Sigma(\mathbf{y} - K\mathbf{p})\|^2, \quad (3)$$

where

$$\Sigma = \begin{pmatrix} 1/\sigma_1 & & & \\ & 1/\sigma_2 & & \\ & & \ddots & \\ & & & 1/\sigma_n \end{pmatrix} \quad (4)$$

is the diagonal matrix constructed from the errors in \mathbf{y} . However, due to the noise in \mathbf{y} , the problem is ill-defined: there exist many possible weights \mathbf{p} which produce a function which falls within the scatter and noise of \mathbf{y} . We introduce regularization $m \times m$ matrix Γ in order to minimize

$$\min \|\Sigma(\mathbf{y} - K\mathbf{p})\|^2 + \|\Gamma\mathbf{p}\|^2. \quad (5)$$

This matrix is often chosen to be αI , where the parameter α is a constant, and I is the identity matrix. If α is large, this has the effect of smoothing \mathbf{p} . If α is too small, then \mathbf{p} will appear to be “spiky”. For the sake of generality however, we will preserve the notation of Γ for the most of the following discussion. The solution to Equation (5) also satisfies

$$\mathbf{q} = L\mathbf{p} \quad (6)$$

where \mathbf{q} and L are the block matrices defined by

$$\mathbf{q} = \begin{pmatrix} \Sigma\mathbf{y} \\ \mathbf{0} \end{pmatrix} \quad (7)$$

$$L = \begin{pmatrix} \Sigma K \\ \Gamma \end{pmatrix}. \quad (8)$$

This is proven by showing that $\|\mathbf{q} - L\mathbf{p}\|^2 = \|\mathbf{y} - K\mathbf{p}\|^2 + \|\Gamma\mathbf{p}\|^2$:

$$\|\mathbf{q} - L\mathbf{p}\|^2 = (\mathbf{q} - L\mathbf{p})^T (\mathbf{q} - L\mathbf{p}) \quad (9)$$

$$= (\mathbf{q}^T - \mathbf{p}^T L^T) (\mathbf{q} - L\mathbf{p}) \quad (10)$$

$$= \mathbf{q}^T \mathbf{q} - \mathbf{q}^T L\mathbf{p} - (\mathbf{q}^T L\mathbf{p})^T + \mathbf{p}^T L^T L\mathbf{p} \quad (11)$$

where

$$\mathbf{q}^T \mathbf{q} = \begin{pmatrix} \mathbf{y}^T \Sigma^T & \mathbf{0}^T \end{pmatrix} \begin{pmatrix} \Sigma \mathbf{y} \\ \mathbf{0} \end{pmatrix} = \mathbf{y}^T \Sigma^T \Sigma \mathbf{y} \quad (12a)$$

$$\mathbf{q}^T L \mathbf{p} = \begin{pmatrix} \mathbf{y}^T \Sigma^T & \mathbf{0}^T \end{pmatrix} \begin{pmatrix} \Sigma K \\ \Gamma \end{pmatrix} \mathbf{p} = \mathbf{y}^T \Sigma^T \Sigma K \mathbf{p} \quad (12b)$$

$$\mathbf{p}^T L^T L \mathbf{p} = \mathbf{p}^T \begin{pmatrix} K^T \Sigma^T & \Gamma^T \end{pmatrix} \begin{pmatrix} \Sigma K \\ \Gamma \end{pmatrix} \mathbf{p} = \mathbf{p}^T (K^T \Sigma^T \Sigma K + \Gamma^T \Gamma) \mathbf{p}. \quad (12c)$$

Therefore

$$\|\mathbf{q} - L \mathbf{p}\|^2 = \mathbf{y}^T \Sigma^T \Sigma \mathbf{y} + \mathbf{y}^T \Sigma^T \Sigma K \mathbf{p} + \mathbf{p}^T K^T \Sigma^T \Sigma \mathbf{y} + \mathbf{p}^T (K^T \Sigma^T \Sigma K + \Gamma^T \Gamma) \mathbf{p} \quad (13)$$

$$= (\mathbf{y}^T \Sigma^T - \mathbf{p}^T K^T \Sigma^T)(\Sigma \mathbf{y} - \Sigma K \mathbf{p}) + \mathbf{p}^T \Gamma^T \Gamma \mathbf{p} \quad (14)$$

$$= \|\Sigma(\mathbf{y} - K \mathbf{p})\|^2 + \|\Gamma \mathbf{p}\|^2. \quad (15)$$

We then solve $\mathbf{q} = L \mathbf{p}$ using a non-negative least squares algorithm such that \mathbf{p} may be identified with the vector of weights corresponding to parameters z_i .