

Solution Hw 6

Problem 8.1

1) Nonlinear LS due to f_0 and r .

Yes, quadratic in A, B .

Analytically, we could find the values of A and B that minimize J for given f_0 and r . Then, plug these into J , which will now be a nonquadratic function of f_0 and r . Next, use a grid search over $0 < r < 1$ and $0 \leq f_0 \leq \frac{1}{2}$.

Problem 8.5

$$5) \quad \underline{y} = \begin{bmatrix} 1 & 1 & \dots & 1 \\ \cos 2\pi f_1 & \cos 2\pi f_2 & \dots & \cos 2\pi f_p \\ \vdots & & & \\ \cos 2\pi f_1(N-1) & \cos 2\pi f_2(N-1) & \dots & \cos 2\pi f_p(N-1) \end{bmatrix} \begin{bmatrix} A_1 \\ A_2 \\ \vdots \\ A_p \end{bmatrix}$$

$\underbrace{\hspace{15em}}_{\underline{H}} \qquad \underbrace{\hspace{2em}}_{\underline{\theta}}$

$$\underline{H}^T \underline{H} \hat{\underline{\theta}} = \underline{H}^T \underline{x} \quad \text{are normal equations}$$

If $f_i = i/N$, the column vectors of \underline{H} are orthogonal (see (4.13)). Thus,

$$\underline{H}^T \underline{H} = \frac{N}{2} \underline{I}$$

$$\Rightarrow \hat{\underline{\theta}} = \frac{2}{N} \underline{H}^T \underline{x} \Rightarrow \hat{A}_i = \frac{2}{N} \sum_{n=0}^{N-1} x(n) \cos 2\pi f_i n$$

$$\begin{aligned}
J_{MIN} &= \underline{x}^T (\underline{I} - \underline{H} (\underline{H}^T \underline{H})^{-1} \underline{H}^T) \underline{x} \\
&= \underline{x}^T (\underline{I} - \frac{2}{N} \underline{H} \underline{H}^T) \underline{x} \\
&= \underline{x}^T \underline{x} - \frac{2}{N} \|\underline{H}^T \underline{x}\|^2 \\
&= \underline{x}^T \underline{x} - \frac{2}{N} \left(\frac{N}{2}\right)^2 \|\hat{\underline{\theta}}\|^2 \\
&= \sum_{n=0}^{N-1} x^2[n] - \frac{N}{2} \sum_{i=1}^p \hat{A}_i^2
\end{aligned}$$

For WLEN, WGN the PDF is

$$\hat{\underline{\theta}} \sim N(\underline{\theta}, \sigma^2 (\underline{H}^T \underline{H})^{-1}) \quad \text{since}$$

$$E(\hat{\underline{\theta}}) = (\underline{H}^T \underline{H})^{-1} \underline{H}^T E(\underline{x}) = (\underline{H}^T \underline{H})^{-1} \underline{H}^T \underline{H} \underline{\theta} = \underline{\theta}$$

$$C_{\hat{\underline{\theta}}} = E[(\hat{\underline{\theta}} - \underline{\theta})(\hat{\underline{\theta}} - \underline{\theta})^T]$$

$$= E[(\underline{H}^T \underline{H})^{-1} \underline{H}^T \underbrace{(\underline{x} - \underline{H} \underline{\theta})}_{\underline{w}} \underbrace{(\underline{x} - \underline{H} \underline{\theta})^T}_{\underline{w}^T} \underline{H} (\underline{H}^T \underline{H})^{-1}]$$

$$= (\underline{H}^T \underline{H})^{-1} \underline{H}^T \sigma^2 \underline{I} \underline{H} (\underline{H}^T \underline{H})^{-1} = \sigma^2 (\underline{H}^T \underline{H})^{-1}$$

$$\text{or } C_{\hat{\underline{\theta}}} = 2\sigma^2/N \underline{I}$$

and since $\hat{\underline{\theta}}$ is a linear function of \underline{x} ,
we have a Gaussian PDF or

$$\hat{\underline{\theta}} \sim N(\underline{\theta}, 2\sigma^2/N \underline{I})$$

Problem 8.27

27) From (8.61)

$$\theta_{k+1} = \theta_k + \left(\underline{H}^T(\theta_k) \underline{H}(\theta_k) - \sum_{n=0}^{N-1} G_n(\theta_k) (\underline{x}_n - \underline{e}^{\theta_k}) \right)^{-1} \cdot \underline{H}^T(\theta_k) (\underline{x} - \underline{e}^{\theta_k})$$

$$[\underline{H}(\theta)]_i = \frac{\partial \underline{f}(\theta)}{\partial \theta} = e^\theta \quad i=0, 1, \dots, N-1$$

$$[G_n(\theta)]_{ii} = \frac{\partial^2 \underline{f}(\theta)}{\partial \theta^2} = e^\theta$$

$$\Rightarrow \underline{H}(\theta) = e^\theta \underline{1} \quad G_n(\theta) = e^\theta$$

$$\theta_{k+1} = \theta_k + \left(N e^{2\theta_k} - \sum_{n=0}^{N-1} e^{\theta_k} (x_{(n)} - e^{\theta_k}) \right)^{-1}$$

$$\cdot e^{\theta_k} \mathbb{1}^T (\underline{x} - e^{\theta_k} \mathbb{1})$$

$$= \theta_k + \frac{e^{\theta_k} (N \bar{x} - N e^{\theta_k})}{N e^{2\theta_k} - N \bar{x} e^{\theta_k} + N e^{2\theta_k}}$$

$$= \theta_k + \frac{\bar{x} - e^{\theta_k}}{2e^{\theta_k} - \bar{x}}$$

To find analytically let $\alpha = e^{\theta} \Rightarrow \hat{\alpha} = \bar{x}$
 and from Prob 8.26 $\hat{\theta} = \ln \bar{x}$.