

### III. WEIGHTED LEAST-SQUARES

ERROR:  $e(n) \rightarrow \sum W(n) e^2(n)$

$W(n) \geq 0$

LET:  $\underline{y}^* = \underline{W}^{1/2} \underline{y}$

MORE WEIGHT ON INFORMATIVE DATA !

$\underline{\Phi}^* = \underline{W}^{1/2} \underline{\Phi}$

$\underline{W} = \text{diag}\{W(n)\}$

$\underline{W}^{1/2} = \text{diag}\{\sqrt{W(n)}\}$

$V^* = \|\underline{W}^{1/2}(\underline{y} - \underline{\Phi}\underline{\theta})\|_2^2$

$(\text{diag } \underline{A})^T = \text{diag } \underline{A}$

$= \|\underline{y}^* - \underline{\Phi}^* \underline{\theta}\|_2^2$

$\frac{\partial V^*}{\partial \underline{\theta}} \rightarrow \text{LINE STANDARD}$

$$\left[ \begin{aligned} \hat{\underline{\theta}} &= (\underline{\Phi}^{*T} \underline{\Phi}^*)^{-1} \underline{\Phi}^{*T} \underline{y}^* \\ &= (\underline{\Phi}^T \underline{W} \underline{\Phi})^{-1} \underline{\Phi}^T \underline{W} \underline{y} \end{aligned} \right]$$

IF WEIGHTING:  $\sum \frac{e^2(n)}{W(n)}$

$V^* = \|\underline{W}^{-1/2}(\underline{y} - \underline{\Phi}\underline{\theta})\|_2^2$

$\underline{W} \rightarrow \underline{W}^{-1}$

$$\left[ \hat{\underline{\theta}} = (\underline{\Phi}^T \underline{W}^{-1} \underline{\Phi})^{-1} \underline{\Phi}^T \underline{W}^{-1} \underline{y} \right]$$

### IV. UNDERDETERMINED LEAST-SQUARES

(MANY SOLUTIONS!)

$\underline{\Phi} = \begin{bmatrix} \phantom{\rule{1cm}{0.4pt}} \end{bmatrix}$

# COLUMNS > # ROWS

MINIMAL NORM SOLUTION:

(CONSTRAINT OPTIMIZATION)  $V = \|\underline{\theta}\|_2^2$

UNDER CONDITION

$\underline{y} = \underline{\Phi} \underline{\theta}$

$$\frac{\partial \mathcal{L}}{\partial \underline{\theta}} \left[ \underbrace{\|\underline{\theta}\|_2^2 + \lambda^T (\underline{y} - \underline{\Phi} \underline{\theta})}_{\mathcal{L}} \right]$$

$\frac{\partial \mathcal{L}}{\partial \underline{\theta}} = 2 \underline{\theta} - \underline{\Phi}^T \underline{\lambda}$

$\left. \begin{aligned} \hat{\underline{\theta}} &= \frac{1}{2} \underline{\Phi}^T \underline{\lambda} \\ \underline{y} &= \underline{\Phi} \underline{\theta} \end{aligned} \right\} \underline{y} = \frac{1}{2} \underline{\Phi} \underline{\Phi}^T \underline{\lambda}$

$\frac{\partial \mathcal{L}}{\partial \lambda} = \underline{y} - \underline{\Phi} \underline{\theta}$