

(Adjoint) Sensitivities of a Linear System

Linear System

$$\underline{A} \underline{x} = \underline{b}(\underline{\theta}) \xrightarrow{\text{solve}} \underline{x} \rightarrow \text{loss function } J = \frac{1}{2} (\underline{x} - \underline{x}_r)^T (\underline{x} - \underline{x}_r)$$

reference solution \underline{x}_r
 \downarrow
 loss function

sensitivities
 $\frac{dJ}{d\theta} = ?$

Here:

\underline{A} fixed $\underline{A} = \begin{bmatrix} 10 & 2 & 1 \\ 2 & 5 & 1 \\ 1 & 1 & 3 \end{bmatrix}$

\underline{b} variable (parameter-dependent) $\underline{b} = \begin{bmatrix} \theta_0 \\ \theta_1 \\ \theta_2 \end{bmatrix}$

but we have guess $\hat{\underline{b}} = \begin{bmatrix} 1 \\ 1 \\ 1 \end{bmatrix}$

[A] Solve "classical" problem

[1] Solve $\underline{A} \underline{x} = \underline{b}$ for \underline{x}

[2] Evaluate $J = \frac{1}{2} (\underline{x} - \underline{x}_r)^T (\underline{x} - \underline{x}_r)$

[B] Obtain gradients: $\frac{dJ}{d\theta}$ ← (here: gradient is a row vector)

[1st option] Finite Differences

$$\frac{dJ}{d\theta} = \left[\frac{dJ}{d\theta_0} \quad \frac{dJ}{d\theta_1} \quad \frac{dJ}{d\theta_2} \right]$$

for $\frac{dJ}{d\theta_0}$: $\tilde{\underline{b}} = \underline{b} + \epsilon \underline{e}_0$ usually $1e^{-6}$

Solve $\underline{A} \tilde{\underline{x}} = \tilde{\underline{b}}$ for $\tilde{\underline{x}}$

Evaluate: $\tilde{J} = \frac{1}{2} (\tilde{\underline{x}} - \underline{x}_r)^T (\tilde{\underline{x}} - \underline{x}_r)$

$$\frac{dJ}{d\theta_0} \approx \frac{\tilde{J} - J}{\epsilon}$$

[2nd option] Forward Sensitivities:

Solve $\underline{A} \frac{d\underline{x}}{d\theta} = \frac{d\underline{b}}{d\theta} - \frac{d\underline{A}}{d\theta} \underline{x}$ not correct? wrong shape

here: $\frac{d\underline{b}}{d\theta} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$ for $\frac{d\underline{x}}{d\theta}$

$$\frac{d\underline{A}}{d\theta} = \underline{0}$$

$$\text{solve } \underline{A} \frac{d\underline{x}}{d\theta} = \text{eye}(3) \text{ for } \frac{d\underline{x}}{d\theta}$$

then: $\frac{dJ}{d\theta} = \frac{\partial J}{\partial \theta} + \frac{\partial J}{\partial \underline{x}} \frac{d\underline{x}}{d\theta}$

$$\frac{\partial J}{\partial \theta} = \underline{0}^T$$

$$\frac{\partial \underline{x}}{\partial \underline{x}} = \underline{I}_{3 \times 3} \quad \frac{\partial \underline{x}^T}{\partial \underline{x}} = \underline{I}_{1 \times 3}$$

$$\frac{\partial J}{\partial \underline{x}} = \frac{\partial}{\partial \underline{x}} \left(\frac{1}{2} (\underline{x} - \underline{x}_r)^T (\underline{x} - \underline{x}_r) \right)$$

$$= \frac{1}{2} \left(\underbrace{\frac{\partial (\underline{x} - \underline{x}_r)^T}{\partial \underline{x}}}_{\underline{I}_{1 \times 3 \times 3}} (\underline{x} - \underline{x}_r) + \underbrace{(\underline{x} - \underline{x}_r)^T}_{1 \times 3} \underbrace{\frac{\partial (\underline{x} - \underline{x}_r)}{\partial \underline{x}}}_{\underline{I}_{3 \times 3}} \right)$$

$$= \frac{1}{2} ((\underline{x} - \underline{x}_r)^T + (\underline{x} - \underline{x}_r)^T)$$

$$= \frac{1}{2} \cdot 2 \cdot (\underline{x} - \underline{x}_r)^T = \underline{(\underline{x} - \underline{x}_r)^T}$$

$$\text{then } \frac{dJ}{d\theta} = \underline{0}^T + (\underline{x} - \underline{x}_r)^T \frac{d\underline{x}}{d\theta}$$

[3rd option] Adjoint / Backward Sensitivities

solve $\underline{A}^T \underline{\lambda} = \left(\frac{\partial J}{\partial \underline{x}} \right)^T$ for $\underline{\lambda}$

$$\text{solve } \underline{A}^T \underline{\lambda} = \underline{x} - \underline{x}_r \text{ for } \underline{\lambda}$$

then: $\frac{dJ}{d\theta} = \underbrace{\frac{\partial J}{\partial \theta}}_{\underline{0}^T} + \underline{\lambda}^T \left(\underbrace{\frac{d\underline{b}}{d\theta}}_{\text{eye}(3)} - \underbrace{\frac{d\underline{A}}{d\theta}}_{\underline{0}} \underline{x} \right)$

$$\text{then } \frac{dJ}{d\theta} = \underline{0}^T + \underline{\lambda}^T \text{eye}(3)$$