

April 19, 2021

## Gauss-Newton

$$h: \mathbb{R}^n \rightarrow \mathbb{R}^m$$

$$f(x) = \frac{1}{2} \|h(x)\|_2^2 \leftarrow \frac{1}{2} \sum h_i(x)^2$$

multi-objective

$h_i(x)$  = error on  $i$ th example

$$\text{Taylor: } h(x+p) \approx \boxed{h(x) + J(x)p}$$

$$J_{i\ell}(x) = \frac{\partial h_i(x)}{\partial x_\ell} \quad J \in \mathbb{R}^{m \times n}$$

$$x_{k+1} = x_k + p_k$$

$$p_k = \arg \min_{p \in \mathbb{R}^n} \|J_k p + h_k\|_2^2$$

( $m > n$ )  $m$   $\begin{bmatrix} \phantom{0} \\ \phantom{0} \\ \phantom{0} \end{bmatrix}$   $\begin{bmatrix} \phantom{0} \\ \phantom{0} \\ \phantom{0} \end{bmatrix}$   $\begin{bmatrix} \phantom{0} \\ \phantom{0} \\ \phantom{0} \end{bmatrix}$

Claim:  $p_k$  is descent dir  
( $J_k$  full rank)

$$\text{Proof: } p_k = - \underbrace{(J_k^T J_k)^{-1}}_{\text{SPD}} \underbrace{J_k^T h_k}_{=\nabla f_k}$$

$$\frac{\partial f(x)}{\partial x_\ell} = \sum_{i=1}^m h_i(x) \frac{\partial h_i(x)}{\partial x_\ell}$$

$J_{i\ell}(x)$

$$= \sum h_i(x) J_{i\ell}(x)$$

$$= [J^T h(x)]_\ell$$

$$f(x_{k+1}) \approx f(x_k)$$

$$- \underbrace{\nabla f(x_k)^T (J_k^T J_k)^{-1} \nabla f(x_k)}_{\text{SPD}}$$

Is this just Newton?

$$p_k = - (J_k^T J_k) \underbrace{J_k^T h_k}_{\text{d/dx}} \quad \text{vs.} \quad p_k = - H_k^{-1} \underbrace{\nabla f_k}_{\text{d/dx}}$$

$$= \sum_{i=1}^m \underbrace{\frac{\partial h_i(x)}{\partial x_t}}_{J_{it}} \underbrace{\frac{\partial h_i(x)}{\partial x_l}}_{J_{il}} + h_i(x) \underbrace{\frac{\partial^2 h_i(x)}{\partial x_t \partial x_l}}_{\text{wavy}}$$
$$(J_k^T J_k)_{tl}$$

•  $f(x) = \frac{1}{2} \|h(x)\|_2^2$  near min  $\Rightarrow h(x) \approx 0$

•  $\Rightarrow J_k^T J_k \approx H_k$





$$s \cdot p_k'(0) + (s-1) (-H_k^{-1} p_k - p_k'(0)) \quad 1 \leq k$$

