

6.7 Nonlinear Least Squares

$$\varphi(x) = \frac{1}{2} r^T(x) r(x) \quad r(x) = y - f(x)$$

Parameters
↓
↑ ↑
Data

$$\varphi(x) = \frac{1}{2} \sum_{j=1}^n r_j^2(x)$$

$$\frac{\partial}{\partial x_i} (\varphi(x)) = \sum_{j=1}^n r_j(x) \frac{\partial}{\partial x_i} r_j(x)$$

$\underbrace{\hspace{10em}}_{[J_r(x)]_{ji}}$

$$= [J_r^T(x) r(x)]_i$$

$$H_\varphi = J(x)^T J(x) + \sum_{i=1}^n r_i(x) H_{r_i}(x)$$

headache
↳ forget about it

$$x_k \quad H_\varphi(x_k) s \approx -\nabla \varphi(x_k)$$

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

"Gauss-Newton"

$$J^T(x) J(x) s = -\nabla \varphi = -J^T(x) r(x)$$

$$\leadsto J(x) s \hat{=} -r(x)$$

\leadsto use QR to solve this least-sq. problem.

WS22p1

Levenberg-Marquardt

$$(J^T(x_k) J(x_k) + \mu_k I) s_k = -J^T(x_k) r(x_k)$$

equivalent LSQ problem:

$$\begin{pmatrix} J(x) \\ \sqrt{\mu} I \end{pmatrix} s \approx \begin{pmatrix} -r(x) \\ 0 \end{pmatrix}$$

$$f(x,y) = x^2 + y^2$$

$$H_f = \begin{pmatrix} 2x & 0 \\ 0 & 2y \end{pmatrix}$$

↳ "Regularization" ↳

6.8 Constrained Optimization

$$\min_x f(x) \quad \text{subject to} \quad g(x) = 0 \\ h(x) \leq 0$$

"equality-constrained optimization"

Necessary cond. for min: $\nabla f(x^*) = 0$

s is a feasible direction at x :

$x + \alpha s$ is feasible for $\alpha \in [0, \epsilon]$
for some $\epsilon > 0$

interior of feasible region: every direction
is feasible

Necessary condition for minimum:

$$\nabla f(x^*) \cdot s \geq 0$$

interior: s is feasible $\nabla f(x) \cdot s \geq 0$
 $-s$ is feasible $\nabla f(x) \cdot (-s) \geq 0$ } $\nabla f(x) = 0$

Necessary at boundary

$$\begin{aligned} & -\nabla f(x^*) \in \text{row-span } Jg(x^*) \\ \Leftrightarrow & -\nabla f(x) = Jg^T \lambda \quad \text{for some } \lambda \end{aligned}$$

"all descent directions at our purported minimum x^* would have to be such that we'd violate the constraint, i.e. change the value of $g(x)$, if we moved in that direction"

Lagrangian function $\mathcal{L}(x, \lambda) = f(x) + \lambda^T g(x)$
 $\nabla \mathcal{L} = 0$