

Revisão: Inversão linear

$$\bar{d} = \bar{f}(\bar{p}) = \bar{A} \bar{p}$$

\bar{A} = Jacobiana

$$\begin{bmatrix} \partial_{p_1} f_1 & \partial_{p_2} f_1 & \partial_{p_3} f_1 & \dots \\ \partial_{p_1} f_2 & \partial_{p_2} f_2 & \dots & \dots \\ \vdots & \vdots & \ddots & \ddots \end{bmatrix}$$

constante

$$\phi(\bar{p}) = \|\bar{d}^0 - \bar{A} \bar{p}\|^2 = \underbrace{[\bar{d}^0 - \bar{A} \bar{p}]^T [\bar{d}^0 - \bar{A} \bar{p}]}_{\text{forma quadrática}}$$

$$\min_{\bar{p}} \phi \Rightarrow \nabla \phi = \bar{0}$$

$$\nabla \phi = \bar{A}^T \bar{A} \bar{p} - \bar{A}^T \bar{d}^0$$

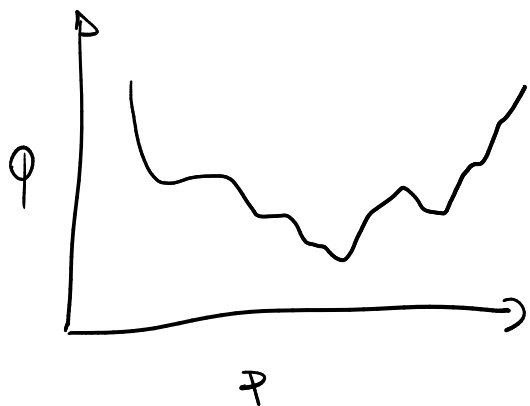


$$\underbrace{\bar{A}^T \bar{A} \bar{p} = \bar{A}^T \bar{d}^0}_{\text{sistema de equações normais}}$$

Inversão não-linear

$$\bar{d} = \bar{f}(\bar{p})$$

$$\phi(\bar{p}) = [\bar{d}^0 - \bar{f}(\bar{p})]^T [\bar{d}^0 - \bar{f}(\bar{p})]$$



Método de Newton

Série de Taylor

$$\phi(\bar{p}) = \underbrace{\phi(\bar{p}_0) + \bar{\nabla}\phi(\bar{p}_0)\bar{\Delta p} + \frac{1}{2}\bar{\Delta p}^T \bar{H}\bar{\Delta p}}_{\psi} + \dots$$

$$\phi(\bar{p}) \approx \psi(\bar{\Delta p}) \quad \bar{H} = \bar{\nabla}\bar{\nabla}^T\phi = \text{Hessiana}$$

$$\min_{\bar{\Delta p}} \psi \Rightarrow \bar{\nabla}_{\bar{\Delta p}} \psi = \bar{0} = \bar{\nabla}_p \phi + \cancel{\frac{1}{2}\bar{H}\bar{\Delta p}}$$

$$\bar{H}\bar{\Delta p} = -\bar{\nabla}_p \phi$$

sistema de equações normais

Processo:

1. \bar{p}_0
2. $\bar{p}_0 \Rightarrow \bar{\Delta p} \Rightarrow \bar{p}_1 = \bar{p}_0 + \bar{\Delta p}$
3. Repete até Niter ou convergência

$$\nabla \phi? \quad \bar{A}?$$

$$\nabla \phi = \nabla [\bar{d}^0 - \bar{F}(\bar{p})]^T [\bar{d}^0 - \bar{F}(\bar{p})] = \nabla [\bar{d}^{0T} \bar{d}^0 + \bar{F}^T \bar{F} - 2 \bar{F}^T \bar{d}^0] = \nabla \bar{F}^T \bar{F} - 2 \nabla \bar{F}^T \bar{d}^0$$

$$\nabla \bar{F}^T = \begin{bmatrix} \partial_{p_1} \\ \vdots \end{bmatrix} [f_1, f_2, \dots] = \begin{bmatrix} \partial_{p_1} f_1, \partial_{p_1} f_2, \dots \\ \partial_{p_2} f_1, \partial_{p_2} f_2, \dots \\ \vdots \end{bmatrix} = \bar{A}^T$$

$$\nabla \bar{F}^T \bar{F} = \begin{bmatrix} \partial_{p_1} \\ \partial_{p_2} \\ \vdots \end{bmatrix} (f_1^2 + f_2^2 + f_3^2 \dots) = \begin{bmatrix} 2f_1 \partial_{p_1} f_1 + 2f_2 \partial_{p_1} f_2 \dots \\ 2f_1 \partial_{p_2} f_1 + 2f_2 \partial_{p_2} f_2 \dots \\ \vdots \end{bmatrix} = 2 \begin{bmatrix} \partial_{p_1} \bar{F}^T \bar{F} \\ \partial_{p_2} \bar{F}^T \bar{F} \\ \vdots \end{bmatrix} = 2 \begin{bmatrix} \partial_{p_1} \bar{F}^T \\ \partial_{p_2} \bar{F}^T \\ \vdots \end{bmatrix} \bar{F} = \bar{A}^T \bar{F}$$

$$\nabla \phi = 2 \bar{A}^T \bar{F} - 2 \bar{A}^T \bar{d}^0 = -2 \bar{A}^T (\bar{d}^0 - \bar{F})$$

$$\bar{H} = \bar{\eta} \bar{\eta}^T \phi = \bar{\eta} \left(-2 \bar{A}^T (\bar{d}^0 - \bar{F}) \right)^T = -2 \begin{bmatrix} \partial_{p_1} \\ \partial_{p_2} \\ \vdots \end{bmatrix} \begin{bmatrix} a_1^T (\bar{d}^0 - \bar{F}) & a_2^T (\bar{d}^0 - \bar{F}) & \dots \end{bmatrix}$$

$$H_{ij} = \partial_{p_i} \bar{a}_j^T (\bar{d}^0 - \bar{F})$$

$$= \partial_{p_i} \left(\partial_{p_j} \bar{F}^T (\bar{d}^0 - \bar{F}) \right)$$

$$= \cancel{\partial_{p_i} \partial_{p_j} \bar{F}^T (\bar{d}^0 - \bar{F})} - \partial_{p_j} \bar{F}^T \partial_{p_i} \bar{F}$$

$$\approx - \partial_{p_j} \bar{F}^T \partial_{p_i} \bar{F} = - \partial_{p_i} \bar{F}^T \partial_{p_j} \bar{F}$$

$$\bar{H} = 2 \begin{bmatrix} \partial_{p_1} \bar{F}^T \partial_{p_1} \bar{F} & \partial_{p_1} \bar{F}^T \partial_{p_2} \bar{F} & \dots \\ \partial_{p_2} \bar{F}^T \partial_{p_1} \bar{F} & \partial_{p_2} \bar{F}^T \partial_{p_2} \bar{F} & \dots \\ \vdots & \vdots & \ddots \end{bmatrix}$$

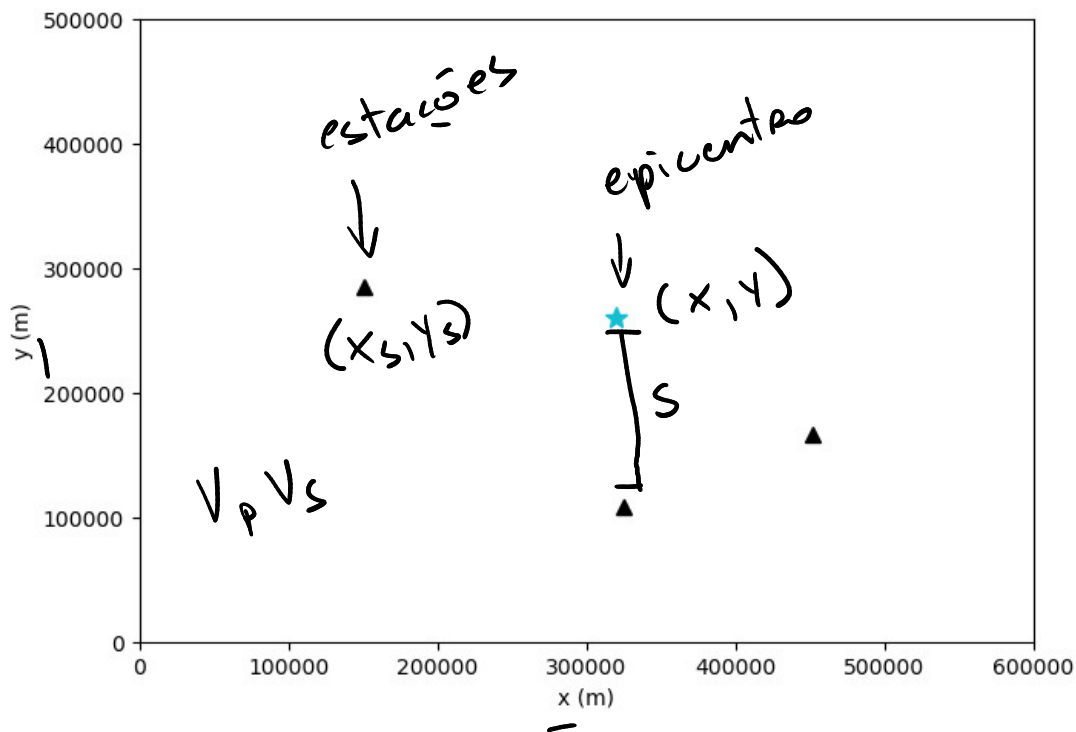
$$= 2 \begin{bmatrix} \partial_{p_1} \bar{F}^T \\ \partial_{p_2} \bar{F}^T \\ \vdots \end{bmatrix} \begin{bmatrix} \partial_{p_1} \bar{F} & \partial_{p_2} \bar{F} & \dots \end{bmatrix}$$

$$= \bar{A}^T \bar{A}$$

$$\bar{H} \bar{\Delta p} = -\bar{\nabla} \phi \Rightarrow \cancel{\bar{A}^T \bar{A}} \bar{\Delta p} = - \left(- \cancel{\bar{A}^T} (\bar{d}^0 - \bar{f}) \right) = \underline{\bar{A}^T \bar{A} \bar{\Delta p} = \bar{A}^T (\bar{d}^0 - \bar{f})}$$

Relação entre linear e não-linear

Exemplo: Localização de epicentros de terremotos



$$t_p = \frac{s}{V_p} \quad t_s = \frac{s}{V_s} \quad s = \sqrt{(x - x_s)^2 + (y - y_s)^2}$$

$$\Delta t = \sqrt{(x - x_s)^2 + (y - y_s)^2} \left(\frac{1}{V_s} - \frac{1}{V_p} \right)$$

$$\bar{P} = \begin{bmatrix} x \\ y \end{bmatrix} \quad \downarrow \quad \text{não-linear} \Rightarrow \bar{\bar{A}}?$$

$$A_{ij} = \frac{\partial \Delta t_i}{\partial p_j} \quad \frac{\partial \Delta t}{\partial x} = \frac{1}{s} \frac{\partial s}{\partial x} \left(\frac{1}{V_s} - \frac{1}{V_p} \right)$$

$$\frac{\partial \Delta t}{\partial x} = \frac{x}{s} \left(\frac{1}{V_s} - \frac{1}{V_p} \right)$$

Para o Python!

Steepest descent

Andar na direção contrária ao gradiente

$$\bar{\Delta}\phi = - \frac{\lambda}{\|\bar{\nabla}\phi\|} \bar{\nabla}\phi$$



passo \Rightarrow determinado
por "line search"



$$\lambda = B^l$$

Levenberg-Marquardt

Controla o tamanho do passo no método de Newton

$$\Gamma(\bar{p}) = \psi(\bar{p}) + \frac{\alpha \Delta \bar{p}^T \Delta \bar{p}}$$

\downarrow
Série de Taylor

$\downarrow \quad \searrow$
linear controle o tamanho de $\Delta \bar{p}$

$$\min_{\Delta \bar{p}} \Gamma \Rightarrow \nabla \Gamma = 0 \quad \nabla \Gamma = \nabla \psi + \bar{H} \Delta \bar{p} + 2\alpha \Delta \bar{p} = 0$$
$$(\cancel{2} \bar{A}^T \bar{A} + \cancel{2} \alpha \bar{I}) \Delta \bar{p} = -(-\cancel{2} \bar{A}^T (\bar{d}^0 - \bar{F}))$$
$$(\bar{A}^T \bar{A} + \alpha \bar{I}) \Delta \bar{p} = \bar{A}^T (\bar{d}^0 - \bar{F})$$

Procedimento prático:

1. começa com α pequeno
2. se ϕ aumenta $\alpha = \alpha \Delta\alpha \Rightarrow$ maior α = menor $\overline{\Delta p}$
3. Calcula novo $\overline{\Delta p}$
4. se ϕ diminui $\overline{p}_k = \overline{p}_{k-1} + \overline{\Delta p}$ e $\alpha = \alpha / \Delta\alpha$

Conclusão

Inversão não-linear \Rightarrow métodos iterativos de buscar o mínimo de $\phi(\bar{p})$

Newton:

1. Aproxima função objetivo por formas quadráticas
2. Resolve vários problemas lineares
3. Problemas de convergência

Steepest descent:

1. Anda na direção oposta ao gradiente
2. Não resolve sistemas lineares
3. Mas precisa de mais passos para convergir

Levenberg-Marquardt:

1. Regularização do tamanho do passo
2. Boa convergência
3. Mas precisa resolver sistema de eq. normais várias vezes