

7-oct-2021

11a

$$\underline{x}_{i+1} = \underline{x}_i - \underbrace{[H_i]^{-1}}_{\uparrow} \underbrace{\nabla f_i}_{\uparrow} \quad \checkmark$$

Quasi-Newton Methods

$$\underline{x}_{i+1} = \underline{x}_i - \lambda_i^* \underbrace{[H_i]^{-1}}_{\uparrow} \nabla f_i$$

$$\Rightarrow \underline{x}_{i+1} = \underline{x}_i + \lambda_i^* \underline{s}_i$$

$$\therefore \underline{s}_i = - \underbrace{[H_i]^{-1}}_{\uparrow} \nabla f_i \quad \checkmark$$

If $[H_i]^{-1}$ is identity matrix \rightarrow steepest descent method.

Either approximate $[H_i]$ with $[A_i]'$ or

" $[H_i]^{-1}$ with $[B_i]'$

$$\therefore \underline{x}_{i+1} = \underline{x}_i - \lambda_i^* [B_i] \nabla f_i$$

$$\underline{s}_i = -[B_i] \nabla f_i$$

How to compute $[B_i]$ $[B_i] \approx [H_i]^{-1}$

Expand $\nabla f(\underline{x})$ about \underline{x}_0 using Taylor series.

$$\nabla f(\underline{x}) \approx \nabla f(\underline{x}_0) + \underbrace{[H_0]}_{\uparrow} (\underline{x} - \underline{x}_0) \quad [A_i] \approx [H_0]$$

$$\nabla f_{i+1} = \nabla f(\underline{x}_0) + [A_i] (\underline{x}_{i+1} - \underline{x}_0) \quad \checkmark$$

$$\nabla f_i = \nabla f(\underline{x}_0) + [A_i] (\underline{x}_i - \underline{x}_0) \quad \checkmark$$

$$\underbrace{\nabla f_{i+1} - \nabla f_i}_{\underline{g}_i} = [A_i] \underbrace{(\underline{x}_{i+1} - \underline{x}_i)}_{\underline{d}_i}$$

(15)

$$\therefore [A_i] \underline{d}_i = \underline{g}_i \quad \left| \begin{array}{l} \underline{d}_i = \underline{x}_{i+1} - \underline{x}_i \\ \underline{g}_i = \nabla f_{i+1} - \nabla f_i \end{array} \right.$$

$$\therefore \underline{d}_i = [B_i] \underline{g}_i \quad [B_i] = [A_i]^{-1}$$

n equations in n^2 unknowns.

the choice for the elements of $[B_i]$ is not unique.

we would like to choose a $[B_i]$ that is close to $(H_0)^{-1}$

- let's say we know $[B_i]$ then how to find $[B_{i+1}]$?

$$[B_{i+1}] = [B_i] + [\Delta B_i] \checkmark$$

Rank 1 updates

$$[B_{i+1}] = [B_i] + [\Delta B_i]$$

$\Delta B_i \leftarrow$ Rank 1 or Rank 2 update.

$$[\Delta B_i] = c \underline{z} \underline{z}^T \quad \underline{z}_{n \times 1}$$

$$[B_{i+1}] = [B_i] + c \underline{z} \underline{z}^T$$

$$\underline{d}_i = [B_{i+1}] \underline{g}_i$$

$$\underline{d}_i = [B_i] \underline{g}_i + c \underline{z} \left(\underline{z}^T \underline{g}_i \right) \quad \text{scalar.}$$

$$c \underline{z} = \frac{\underline{d}_i - [B_i] \underline{g}_i}{\underline{z}^T \underline{g}_i}$$

(116)

$$c = \frac{1}{\underline{z}^T \underline{g}_i} \quad \& \quad \underline{z} = \underline{d}_i - [B_i] \underline{g}_i$$

$$[B_{i+1}] = [B_i] + [\Delta B_i]$$

$$= [B_i] + c \underline{z} \underline{z}^T$$

$$= [B_i] + \frac{1}{\underline{z}^T \underline{g}_i} \left[(\underline{d}_i - [B_i] \underline{g}_i) (\underline{d}_i - [B_i] \underline{g}_i)^T \right]$$

$$[B_{i+1}] = [B_i] + \frac{(\underline{d}_i - [B_i] \underline{g}_i) (\underline{d}_i - [B_i] \underline{g}_i)^T}{(\underline{d}_i - [B_i] \underline{g}_i)^T \underline{g}_i} \quad \text{A}$$

Brodyden's formula

To implement A

we should start with an initial symmetric positive definite matrix $[B_1]$

$$\underline{x}_2 = \underline{x}_1 - \lambda_1^* [B_1] \nabla f_1$$

$$\underline{x}_3 = \underline{x}_2 - \lambda_2^* [B_2] \nabla f_2$$

$$[B_2] = [B_1] + \frac{(\underline{d}_1 - [B_1] \underline{g}_1) (\underline{d}_1 - [B_1] \underline{g}_1)^T}{(\underline{d}_1 - [B_1] \underline{g}_1)^T \underline{g}_1} \quad \checkmark$$

Ex. (A) ensures symmetry of $[B_{i+1}]$ if $[B_i]$ is symmetric.

Rank 2 updates

(19)

$$[B_i] = c_1 \underline{z}_1 \underline{z}_1^T + c_2 \underline{z}_2 \underline{z}_2^T$$

$$[B_{i+1}] = [B_i] + c_1 \underline{z}_1 \underline{z}_1^T + c_2 \underline{z}_2 \underline{z}_2^T$$

$$\underline{d}_i = [B_i] \underline{g}_i + c_1 \underline{z}_1 (\underline{z}_1^T \underline{g}_i) + c_2 \underline{z}_2 (\underline{z}_2^T \underline{g}_i)$$

$$\left(\underline{x}_{i+1} - \underline{x}_i \right) \left. \begin{array}{l} c_1 = \frac{1}{\underline{z}_1^T \underline{g}_i} \quad ; \quad c_2 = - \frac{1}{\underline{z}_2^T \underline{g}_i} \end{array} \right\}$$

$$\underline{z}_1 = \underline{d}_i \quad \& \quad \underline{z}_2 = [B_i] \underline{g}_i$$

$$\underline{d}_i = [B_i] \underline{g}_i + c_1 \underline{z}_1 (\underline{z}_1^T \underline{g}_i) + c_2 \underline{z}_2 (\underline{z}_2^T \underline{g}_i)$$

$$\underline{d}_i - [B_i] \underline{g}_i = \frac{1}{(\underline{z}_1^T \underline{g}_i)} \underline{z}_1 (\underline{z}_1^T \underline{g}_i) - \frac{1}{(\underline{z}_2^T \underline{g}_i)} \underline{z}_2 (\underline{z}_2^T \underline{g}_i)$$

$$\therefore \underline{d}_i - [B_i] \underline{g}_i = \underline{z}_1 - \underline{z}_2$$

$$[B_{i+1}] = [B_i] + \frac{1}{\underline{d}_i^T \underline{g}_i} \underline{d}_i \underline{d}_i^T - \frac{1}{([B_i] \underline{g}_i)^T \underline{g}_i} [B_i] \underline{g}_i ([B_i] \underline{g}_i)^T$$

$$[B_{i+1}] = [B_i] + \frac{\underline{d}_i \underline{d}_i^T}{\underline{d}_i^T \underline{g}_i} - \frac{([B_i] \underline{g}_i) ([B_i] \underline{g}_i)^T}{([B_i] \underline{g}_i)^T \underline{g}_i}$$

Davidon - Fletcher - Powell (DFP) Formula

$$\underline{x}_{i+1} = \underline{x}_i + \lambda_i^* \underline{s}_i$$

$$\underline{d}_i = \underline{x}_{i+1} - \underline{x}_i = \lambda_i^* \underline{s}_i$$

$$\therefore [B_{i+1}] = [B_i] + \frac{(\lambda_i^*)^2 \underline{s}_i \underline{s}_i^T}{\cancel{\lambda_i^*} \underline{s}_i^T \underline{g}_i} - \frac{[B_i] \underline{g}_i \underline{g}_i^T [B_i]}{\underline{g}_i^T [B_i] \underline{g}_i}$$

(B1)

$$\therefore [B_{i+1}] = [B_i] + \frac{\lambda_i^* \underline{s}_i \underline{s}_i^T}{\underline{s}_i^T \underline{g}_i} - \frac{[B_i] \underline{g}_i \underline{g}_i^T [B_i]}{\underline{g}_i^T [B_i] \underline{g}_i}$$

(B2)

(A) & (B) are called inverse update formulas
 they are approximating the inverse of the Hessian.

- It is also possible to develop update formula by approximating the Hessian itself.

$$\underline{g}_i = [A_i] \underline{d}_i$$

$$[A_{i+1}] = [A_i] + [\Delta A_i]$$

$$\therefore [A_{i+1}] = [A_i] + \frac{\underline{g}_i \underline{g}_i^T}{\underline{g}_i^T \underline{d}_i} - \frac{([A_i] \underline{d}_i) ([A_i] \underline{d}_i)^T}{\underline{d}_i^T [A_i] \underline{d}_i}$$

Brodyen - Fletcher - Goldfarb - Shanno (BFGS) formula

- DFP & BFGS formulae are rank2 updates

$$[B_{i+1}] = S_i \left\{ [B_i] - \frac{[B_i] \underline{g}_i \underline{g}_i^T [B_i]}{\underline{g}_i^T [B_i] \underline{g}_i} + \theta_i \underline{y}_i \underline{y}_i^T \right\} + \frac{\underline{d}_i \underline{d}_i^T}{\underline{d}_i^T \underline{g}_i}$$

$$\underline{y}_i = \left(\underline{g}_i^T [B_i] \underline{g}_i \right)^{1/2} \left\{ \frac{\underline{d}_i}{\underline{d}_i^T \underline{g}_i} - \frac{[B_i] \underline{g}_i}{\underline{g}_i^T [B_i] \underline{g}_i} \right\}$$

DFP: $S_i = 1$ & $\theta_i = 0$

BFGS: $S_i = 1$ & $\theta_i = 1$

$$\underline{x}_{i+1} = \underline{x}_i + \lambda_i^* \underline{s}_i$$

one-dimensional minimization

If λ_i^* has some numerical errors \rightarrow DFP method does not ensure positive definiteness of $[B_i]$

DFP is more sensitive to errors in λ_i^* computation

compared to BFGS.

Hence, BFGS is more accurate Quasi-Newton method.

- DFP

- BFGS