

**Optimization**

**Fourth Class**

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# Chapter Three

## The Steepest Descent and Newton Methods

### Lecture 3

## **Theorem (4): (Convergence Theorem of Newton's Method)**

**1: Let  $f$  is twice continuously differentiable in  $R^n$ .**

**2: Let  $X_k$  be close enough to the solution  $X^*$  of the minimization problem with  $g(X^*) = 0$ .**

**3: If the Hessian  $G(X^*)$  is positive definite matrix.**

**4: If  $G(X)$  satisfies Lipschitz condition**

$$|G_{ij}(X) - G_{ij}(Y)| \leq \beta \|X - Y\|, \text{ for some } \beta, \text{ for all } i, j$$

**where  $G_{ij}(X)$  is the  $(i, j)$  – element of  $G(X)$ .**

**Then**

**1: For all  $k$  Newton's iteration  $X_{k+1} = X_k - G_k^{-1} g_k$  is well defined.**

**2: The generated sequence  $\{X_k\}$  converges to  $X^*$  with a quadratic rate.**

**Algorithm (3): (Newton's Method with Line Search)**

**Step 1:** Given  $X_0 \in R^n, \varepsilon > 0, k = 0$ .

**Step 2:** Compute  $g_k$ . If  $\|g_k\| \leq \varepsilon$  stop.

**Step 3:** Solve  $G_k s_k = -g_k$  for  $s_k$ .

**Step 4:** Find  $\alpha_k$  such that  $f(X_k + \alpha_k s_k) = \min_{\alpha \geq 0} f(X_k + \alpha s_k)$ .

**Step 5:** Set  $X_{k+1} = X_k + \alpha_k s_k$   
,  $k = k + 1$ , and go to step 2.

**Theorem (5):**

- 1: Let  $f: R^n \rightarrow R$  be twice continuously differentiable on an open convex set  $D \subset R^n$ .**
  - 2: Assume that for any  $X_0 \in D$  there exists a constant  $m > 0$  such that  $f(x)$  satisfies  $u^T \nabla^2 f(X) u \geq m \|u\|^2$ , for all  $u \in R^n, X \in L(X_0)$ , where  $L(X_0) = \{X: f(X) \leq f(X_0)\}$  is the corresponding level set.**
- Then the sequence  $\{X_k\}$  generated by Algorithm (3) satisfies:**
- 1: when  $\{X_k\}$  is a finite sequence,  $g_k = 0$  for some  $k$ .**
  - 2: when  $\{X_k\}$  is an infinite sequence,  $\{X_k\}$  converges to the unique minimizer  $X^*$  of  $f$ .**

### Example:

Use the Newton's Method with Line Search to find the minimizer of the objective function  $f(X) = x_1 - x_2 + 2x_1^2 + 2x_1x_2 + x_2^2$ .

Take  $X_0 = [0, 0]^T$  and  $\varepsilon = 0.0001$ .

### Solution:

First, we find the gradient vector  $g(X)$  as:

$$g(X) = \left[ \frac{\partial f}{\partial x_1}, \frac{\partial f}{\partial x_2} \right]^T = [1 + 4x_1 + 2x_2, -1 + 2x_1 + 2x_2]^T.$$

Now, find the Hessian matrix  $G(X)$  as:

$$G = G(X) = \begin{bmatrix} \frac{\partial^2 f}{\partial x_1^2} & \frac{\partial^2 f}{\partial x_1 \partial x_2} \\ \frac{\partial^2 f}{\partial x_2 \partial x_1} & \frac{\partial^2 f}{\partial x_2^2} \end{bmatrix} = \begin{bmatrix} 4 & 2 \\ 2 & 2 \end{bmatrix}.$$

Now, compute  $g_0 = g(X_0) = [1, -1]^T$ .

**Compute**  $G^{-1} = \frac{1}{4} \begin{bmatrix} 2 & -2 \\ -2 & 4 \end{bmatrix} = \begin{bmatrix} \frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & 1 \end{bmatrix}$ .

**Compute**  $s_0 = -G^{-1}g_0 = -\begin{bmatrix} \frac{1}{2} & -\frac{1}{2} \\ -\frac{1}{2} & 1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} =$

$$\begin{bmatrix} -\frac{1}{2} & \frac{1}{2} \\ \frac{1}{2} & -1 \end{bmatrix} \begin{bmatrix} 1 \\ -1 \end{bmatrix} = \begin{bmatrix} -1 \\ \frac{3}{2} \end{bmatrix}.$$

**Compute**  $X_1 = X_0 + \alpha s_0 = \begin{bmatrix} 0 \\ 0 \end{bmatrix} + \alpha \begin{bmatrix} -1 \\ \frac{3}{2} \end{bmatrix} = \begin{bmatrix} -\alpha \\ \frac{3}{2}\alpha \end{bmatrix}$ .

**Evaluate**  $f(X_1) = -\alpha - \frac{3}{2}\alpha + 2\alpha^2 - 3\alpha^2 + \frac{9}{4}\alpha^2 = -\frac{5}{2}\alpha + \frac{5}{4}\alpha^2$ .

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$$\text{Set } \frac{df}{d\alpha} = \mathbf{0} \rightarrow -\frac{5}{2} + \frac{5}{2}\alpha = \mathbf{0} \rightarrow \alpha = \mathbf{1}.$$

$$\therefore \frac{d^2f}{d\alpha^2} = \frac{5}{2} > \mathbf{0} \rightarrow \alpha \text{ is a minimizer of } f(X_1).$$

$$\therefore X_1 = \begin{bmatrix} -\alpha \\ \frac{3}{2}\alpha \end{bmatrix} = \begin{bmatrix} -1 \\ \frac{3}{2} \end{bmatrix}.$$

$$\text{Now, we compute } g_1 = g(X_1) = \begin{bmatrix} \mathbf{0} \\ \mathbf{0} \end{bmatrix}.$$

$$\text{Since } \|g_1\| = \mathbf{0} < \varepsilon.$$

$$\therefore X_1 = \begin{bmatrix} -1 \\ \frac{3}{2} \end{bmatrix} \text{ is the minimizer of } f(X).$$



**H.W.**

Use the **Newton's Method with Line Search** to find the minimizer of the objective *function*  $f(X) = x_1^2 + 2x_2^2$  .

Take  $X_0 = \begin{bmatrix} 1 \\ 1 \end{bmatrix}$  and  $\varepsilon = 0.0001$ .