

# Math 270B HW Answer

6.2 Newton method  $x = \phi(x) = x - \frac{f(x)}{f'(x)}$

Assume  $f(\alpha) = \dots = f^{(m-1)}(\alpha) = 0$  and  $f^{(m)}(\alpha) \neq 0$

$$\phi'(x) = 1 - \frac{f(x) \cdot f'(x) - f(x) f'(x)}{f'(x)^2} = \frac{f(x) f'(x)}{f'(x)^2}$$

Since  $f(\alpha) = 0$  need to do limitation for estimating  $\phi(\alpha)$

$$\begin{aligned} \phi(\alpha) &= \lim_{x \rightarrow \alpha} \frac{f(x) f'(x)}{f'(x)^2} = \lim_{x \rightarrow \alpha} \frac{\left[ \frac{f^{(m)}(\alpha)}{m!} (x-\alpha)^m + O(x-\alpha)^{m+1} \right] \left[ \frac{f^{(m)}(\alpha)}{(m-2)!} (x-\alpha)^{m-2} + O(x-\alpha)^m \right]}{\left[ \frac{f^{(m)}(\alpha)}{(m-1)!} (x-\alpha)^{m-1} + O(x-\alpha)^m \right]^2} \\ &= \lim_{x \rightarrow \alpha} \frac{\frac{f^{(m)}(\alpha)}{m!} (x-\alpha)^m \cdot \frac{f^{(m)}(\alpha)}{(m-2)!} (x-\alpha)^{m-2}}{\left[ \frac{f^{(m)}(\alpha)}{(m-1)!} (x-\alpha)^{m-1} \right]^2} = \frac{[(m-1)!]^2}{m! (m-2)!} = 1 - \frac{1}{m} \end{aligned}$$

Modify Newton's method  $x_{k+1} = x_k - m \cdot \frac{f(x_k)}{f'(x_k)}$

then  $\phi(x) = x - m \cdot \frac{f(x)}{f'(x)}$   $\phi'(x) = 1 - m \cdot \frac{f(x) f'(x) - f(x) f'(x)}{f'(x)^2}$

$\phi'(x) = 1 - m \left( 1 - \frac{f(x) f'(x)}{f'(x)^2} \right)$  then  $\lim_{x \rightarrow \alpha} \phi'(x) = 0$

thus modified Newton method has order 2 convergence.

## 6.5 Steffensen's method

$$X_{k+1} = X_k - \frac{f(X_k)}{\varphi(X_k)} \quad \varphi(X_k) = \frac{f(X_k + f(X_k)) - f(X_k)}{f(X_k)}$$

$$\begin{aligned} \phi(x) &= x - \frac{f(x)}{\varphi(x)} & \phi'(x) &= 1 - \frac{f(x)\varphi'(x) - f'(x)\varphi(x)}{\varphi^2(x)} \\ & & &= 1 - \left[ \frac{f'(x)}{\varphi(x)} - \frac{f(x)\varphi'(x)}{\varphi^2(x)} \right] \end{aligned}$$

$$\lim_{x \rightarrow \alpha} \phi'(x) = 1 - \lim_{x \rightarrow \alpha} \frac{f'(x)}{\varphi(x)} \quad \text{notice} \quad \lim_{x \rightarrow \alpha} \varphi(x) = f'(\alpha)$$

$$\therefore \lim_{x \rightarrow \alpha} \phi'(x) = 0 \quad \text{Steffensen's method is second order}$$

2.1 (a)  $F(x+h) = F(x) + \int_x^{x+h} F(t) dt$

Simply Apply Newton-Leibniz formula

(b)  $F(x+h) = F(x) + h \int_0^1 F(x+\epsilon h) d\epsilon$

$$\int_x^{x+h} F(t) dt \quad \begin{array}{c} \text{change of variable} \\ \hline t = x + h \cdot \epsilon \end{array} \quad \int_0^1 F(x+h\epsilon) \cdot (h d\epsilon) = h \int_0^1 F(x+h\epsilon) d\epsilon$$

(c)  $F(x+h) = F(x) + h \int_0^1 [F(x+h\epsilon) - F(x) + F(x)] d\epsilon$

$$= F(x) + h F'(x) + h \int_0^1 [F(x+h\epsilon) - F(x)] d\epsilon$$

$$(d) \int_0^1 [F(x+\varepsilon h) - F(x)] d\varepsilon$$

$$= \int_0^1 \left( \int_x^{x+\varepsilon h} F'(t) dt \right) d\varepsilon = \int_0^1 \left( \int_x^\infty F''(t) \cdot I_{[x, x+\varepsilon h]}(t) dt \right) d\varepsilon$$

$$I_{[x, x+\varepsilon h]}(t) = \begin{cases} 1 & t \in [x, x+\varepsilon h] \\ 0 & \text{else} \end{cases} \quad \begin{array}{l} \text{indicator function} \\ \text{of Interval } [x, x+\varepsilon h] \end{array}$$

then Apply Fubini's theorem to exchange order of integration

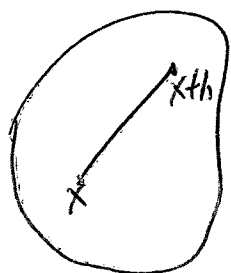
$$= \int_x^\infty \left( \int_0^1 F'(t) \cdot I_{[x, x+\varepsilon h]}(t) d\varepsilon \right) dt = \int_x^\infty F'(t) \cdot \left( \int_0^1 I_{[x, x+\varepsilon h]}(t) d\varepsilon \right) dt$$

$$\int_0^1 I_{[x, x+\varepsilon h]}(t) d\varepsilon = \begin{cases} 0 & t \notin [x, x+h] \\ 1 - \frac{t-x}{h} & t \in [x, x+h] \end{cases}$$

$$= \int_x^{x+h} F'(t) \cdot \left( 1 - \frac{t-x}{h} \right) dt \stackrel{t=x+h\varepsilon}{=} h \int_0^1 F'(x+h\varepsilon) \cdot (1-\varepsilon) d\varepsilon$$

2.2

connect  $x$  and  $x+h$  with segment  $x+ht$  ( $0 \leq t \leq 1$ )



define  $\varphi(t) = F(x+ht)$

$$\varphi'(t) = F'(x+ht)h$$

$$\varphi(1) = F(x+h) = \varphi(0) + \int_0^1 \varphi'(t) dt$$

$$= F(x) + \int_0^1 F'(x+ht)h dt$$

$$= F(x) + F'(x)h + \int_0^1 [F'(x+ht) - F'(x)]h dt$$

$$2.4. \quad (a) \quad f(x) = \frac{1}{2} x^T H x = \frac{1}{2} \sum_{ij} h_{ij} x_i x_j$$

$$\frac{\partial f}{\partial x_s} = \frac{\partial}{\partial x_s} \left( \frac{1}{2} \sum_{ij} h_{ij} x_i x_j \right)$$

$$= \frac{1}{2} \sum_{ij} h_{ij} \frac{\partial}{\partial x_s} (x_i x_j) = \frac{1}{2} \sum_{ij} h_{ij} \left( \frac{\partial x_i}{\partial x_s} x_j + x_i \frac{\partial x_j}{\partial x_s} \right)$$

$$= \frac{1}{2} \sum_{ij} h_{ij} \left( \delta_s^i x_j + x_i \delta_s^j \right)$$

$$= \frac{1}{2} \sum_j (h_{sj} x_j + h_{is} x_i)$$

$$\therefore \nabla f(x) = \begin{pmatrix} \frac{\partial f}{\partial x_1} \\ \frac{\partial f}{\partial x_2} \\ \vdots \\ \frac{\partial f}{\partial x_n} \end{pmatrix} = \frac{1}{2} (H + H^T) x$$

$$f'(x) = \nabla f(x)^T \quad \nabla^2 f(x) = \frac{1}{2} (H + H^T)$$

especially when  $H$  is symmetric  $\nabla f(x) = Hx \quad \nabla^2 f(x) = H$

$$(b) \quad f(x) = b^T A x - \frac{1}{2} x^T A^T A x$$

$A^T A$  is symmetric

$$\nabla f(x) = \nabla (b^T A x) - \nabla \left( \frac{1}{2} x^T A^T A x \right) = A^T b - A^T A x$$

$$\nabla^2 f(x) = -A^T A$$

$$(c) \quad f(x) = \|x\|_2 = \sqrt{x_1^2 + x_2^2 + \dots + x_n^2}$$

$$\frac{\partial f}{\partial x_i} = \frac{1}{2} (x_1^2 + x_2^2 + \dots + x_n^2)^{-\frac{1}{2}} \cdot (2x_i) = \frac{x_i}{\|x\|}$$

$$\nabla f(x) = \frac{x}{\|x\|}$$

$$\frac{\partial^2 f}{\partial x_i \partial x_j} = \frac{\frac{\partial x_i}{\partial x_j} \cdot \|x\| - x_i \cdot \frac{\partial (\|x\|)}{\partial x_j}}{\|x\|^2} = \frac{\delta_j^i}{\|x\|} - \frac{x_i}{\|x\|^2} \cdot \frac{x_j}{\|x\|}$$

$$\therefore \text{Hess}(f) = \frac{1}{\|x\|} \cdot I - \frac{x x^T}{\|x\|^3}$$

2.10

$$L_k(x) = F(x_k) + F'(x_k)(x - x_k)$$

$$F(x) - L_k(x) = F(x) - [F(x_k) + F'(x_k)(x - x_k)]$$

$$= \int_0^1 F'((1-t)x_k + t \cdot x) \cdot (x - x_k) dt - F'(x_k)(x - x_k)$$

$$= \int_0^1 [F'((1-t)x_k + t \cdot x) - F'(x_k)] (x - x_k) dt$$

$$\|F(x) - L_k(x)\| \leq \int_0^1 \|F'((1-t)x_k + t \cdot x) - F'(x_k)\| \cdot \|x - x_k\| dt$$

$$\leq \int_0^1 \underbrace{\gamma \cdot t}_{\text{Lipschitz continuous of } F'} \cdot \|x - x_k\| dt \cdot \|x - x_k\| = \frac{1}{2} \gamma \|x - x_k\|^2$$

2.12

$$x_{k+1} = x_k - [F'(x_k)]^{-1} F(x_k)$$

$$x_{k+1} - x^* = x_k - [F'(x_k)]^{-1} F(x_k) - x^*$$

$$= [F'(x_k)]^{-1} \cdot [F'(x_k)(x_k - x^*) - F(x_k)]$$

$$= [F'(x_k)]^{-1} \cdot [F(x^*) - F(x_k) - F'(x_k)(x^* - x_k)]$$

$$= [F'(x_k)]^{-1} \cdot \int_0^1 [F'((1-\varepsilon)x_k + \varepsilon x^*) - F'(x_k)] d\varepsilon \cdot (x^* - x_k)$$

$$\|x_{k+1} - x^*\| \leq \| [F'(x_k)]^{-1} \| \cdot \int_0^1 \|F'((1-\varepsilon)x_k + \varepsilon x^*) - F'(x_k)\| d\varepsilon \cdot \|x^* - x_k\|$$

when Newton's method start to converge

$$\lim_{k \rightarrow \infty} \| [F'(x_k)]^{-1} \| \cdot \int_0^1 \|F'((1-\varepsilon)x_k + \varepsilon x^*) - F'(x_k)\| d\varepsilon = 0$$

superlinear  
when  $F'$  is Lipschitz,  
(2.10) shows second  
order convergence

2.15. (a)  $q(x) = C^T x + \frac{1}{2} x^T H x$   $H$  is symmetric

$$\nabla q(x) = C + Hx$$

(b) Hessian  $q(x) = H$

$$q(x_0 + p) = q(x_0) + \nabla q(x_0)^T p + \frac{1}{2} p^T \text{Hessian } q(x_0) p = q(x_0) + (C + Hx_0)^T p + \frac{1}{2} p^T H p$$

(c)  $q(x_0 + \alpha p) = q(x_0) + \alpha (C + Hx_0)^T p + \alpha^2 (\frac{1}{2} p^T H p)$

Since  $H$  is positive definite  $\frac{1}{2} p^T H p > 0$

$q(x_0 + \alpha p)$  is a concave up quadratic function

the minimizer  $\alpha^* = \frac{-(C + Hx_0)^T p}{2(\frac{1}{2} p^T H p)} = \frac{-\nabla q(x_0)^T p}{p^T H p} > 0$

2.19.

minimize  $x_1^2 + 2x_2^2$   
s.t.  $x_1 + x_2 - 1 = 0$

$$f(x_1, x_2) = x_1^2 + 2x_2^2$$

$$g(x_1, x_2) = x_1 + x_2 - 1$$

(a) only equality condition. KKT condition is reduced to Lagrange multiplier.

$$L(x_1, x_2, \lambda) = x_1^2 + 2x_2^2 + \lambda(x_1 + x_2 - 1)$$

$$\begin{cases} 2x_1 + \lambda = 0 \\ 4x_2 + \lambda = 0 \\ x_1 + x_2 - 1 = 0 \end{cases}$$

unique solution

$$\begin{cases} x_1 = \frac{2}{3} \\ x_2 = \frac{1}{3} \\ \lambda = -\frac{4}{3} \end{cases}$$

$$\nabla^2 f = \begin{pmatrix} 2 & 0 \\ 0 & 4 \end{pmatrix} > 0$$

$\therefore (\frac{2}{3}, \frac{1}{3})$  is optimal.

(b) minimize  $x_1^3 + x_2^3$   
s.t.  $x_1 + x_2 - 1 = 0$

$$\mathcal{L}(x_1, x_2, \lambda) = x_1^3 + x_2^3 + \lambda(x_1 + x_2 - 1)$$

$$\begin{cases} 3x_1^2 + \lambda = 0 \\ 3x_2^2 + \lambda = 0 \\ x_1 + x_2 - 1 = 0 \end{cases} \quad \begin{cases} x_1 = \frac{1}{2} \\ x_2 = \frac{1}{2} \\ \lambda = -\frac{3}{4} \end{cases}$$

$$f(x_1, x_2) = x_1^3 + x_2^3$$

$$\nabla^2 f = \begin{pmatrix} 6x_1 & 0 \\ 0 & 6x_2 \end{pmatrix} \Big|_{(\frac{1}{2}, \frac{1}{2})} = \begin{pmatrix} 3 & 0 \\ 0 & 3 \end{pmatrix} > 0$$

local minimizer