

### 3.3 BEYOND STEEPEST DESCENT

MAKING "GOOD" ITERATING METHOD

$\min f(x)$ , continuous  $\Rightarrow f(x)$   
START  $x_0$

GENERATE SEQUENCE  $\{x_k\}$  AS

$$x_{k+1} = x_k + t_k \mu_k \quad t_k > 0$$

SUCH THAT

$$\begin{aligned} \text{1)} \quad & f(x_{k+1}) < f(x_k) \quad \text{IF } \nabla f(x_k) \neq 0 \\ & \hookrightarrow \text{DESENT METHOD} \end{aligned}$$

$$\text{2)} \quad \mu_k^T \nabla f(x_k) < 0 \quad \hookrightarrow \text{MOVING IN DES. DIRECTION}$$

$$\varphi_k(t) = f(x_k + t \mu_k) \quad \therefore$$

$$\varphi_k(0) = \nabla f(x_k)^T \mu_k < 0$$

SO FOR  $t$  SMALL

$$f(x_k + t \mu_k) = \varphi_k(t) < \varphi(0) = f(x_k)$$

[ TOO SMALL  $t$  IS BAD - SLOW CONV.  $\Rightarrow 3)$

$$\text{3)} \quad \exists 0 < \beta < 1 \text{ ST. } \mu_k^T \nabla f(x_{k+1}) > \beta \mu_k^T \nabla f(x_k)$$

$t_{k+1}$  NOT TOO SMALL (BY 2+3)

$$\mu_k^T \nabla f(x_k + t_k \mu_k) > \beta \underbrace{\mu_k^T \nabla f(x_k)}_{< 0 \text{ BY 2}} > \mu_k^T \nabla f(x_k)$$

$$\mu_k^T \nabla f(x_k + t_k \mu_k) - \mu_k^T \nabla f(x_k) > (\beta - 1) \mu_k^T \nabla f(x_k) \geq 0$$

IF  $t_k \rightarrow 0$  THEN  $\mu_k = 0$  AND RIGHT HAND SIDE  $< 0$   
 $\Rightarrow$  NO ABDIATION WITH SMALL  $t_k$

BUT WHAT IF  $t_k$  TOO LARGE (MAYBE NOT BEST  
 DECREASE  GOING TOO FAR.

↳  $\exists 0 < \alpha < \beta \in \mathbb{R}$  SUCH THAT

$$f(x_{k+1}) \leq f(x_k) + \alpha t_k \mu_k^T \nabla f(x_k)$$

REWRITE

$$\frac{f(x_k) - f(x_{k+1})}{t_k} \geq \alpha [-\mu_k^T \nabla f(x_k)]$$

↳ RELATIVE DECREASE  $\geq$  FRACTION

OF POSSIBLE DECREASE.

$$\text{DIFFVIEW: } M = \frac{\alpha \mu_k^T \nabla f(x_k)}{\|\mu_k\|}$$

$$\frac{f(x_k) - f(x_{k+1})}{\|x_k - x_{k+1}\|} = \frac{f(x_k) - f(x_{k+1})}{\|\mu_k\| \cdot t_k} \geq M$$

$$f(x_k) - f(x_{k+1}) \geq M \|x_k - x_{k+1}\| \quad \square$$

## THEOREM 3.3.1 WOLFE

LET  $f(x)$  HAVE CONTINUOUS FIRST PARTIAL DERIVATIVES AND BE BOUNDED FROM BELOW. LET  $0 < \alpha < \beta < 1$ ,

IF  $\mu_k, x_k \in \mathbb{R}^n$  ST.

$$\mu_k^T \cdot \nabla f(x_k) < 0$$

THEN  $\exists 0 \leq a_k < b_k$  SUCH THAT

- 4) HOLDS  $\forall t_k \in (0, b_k)$
- 3) HOLDS  $\forall t_{1k} \in (a_k, b_k)$

HOW TO FIND  $t$ ? DIFFICULT

- TRY  $t = 1$

WHEN 4) VIOLATED:

$$f(x_k + t\mu_k) > f(x_k) + \alpha t \mu_k^T \nabla f(x_k)$$

REPLACE  $t$  BY  $t \cdot \beta$  WHERE  $\beta < 1$

[ HOW TO FIND  $\beta$ ? WOLFE METHODS ]

CHOICE OF  $\mu_K$ :

$$-\text{WANT } \mu_K^T \nabla \delta(x_k) < 0 \quad (2)$$

STEEPEST DESCENT:  $\therefore -\mu_K^T Q = \pm$

$$\mu_K = -\nabla \delta(x_k)$$

$\therefore Q$  POSITIVE DEFINITE:

FOR  $\mu_K = -Q \nabla \delta(x_k)$  (4) holds

$$\{-\nabla \delta(x_k)^T Q \nabla \delta(x_k) < 0\}$$

RECALL NEWTON'S METHOD

$$\mu_K = -[H\delta(x)]^{-1} \nabla \delta(x_k)$$

WORKS FOR  $H\delta(x)$  POS DEF.

IF  $H\delta(x)$  NOT POSITIVE DEF. TAKE

$$Q = H\delta(x) + \mu_K I \quad (\text{MV})$$

Find  $\mu_K$ :

$$x^T (H\delta(x) + \mu_K I) x = x^T H\delta(x) x + \|x\|^2 \mu_K$$

$\xrightarrow{\text{want } \geq 0, \text{ however}} \nearrow \nearrow$

$$\bar{\mu}_K = \max_{\|x\|=1} |x^T H\delta(x) x|$$

$$\|x\|=1$$

$\therefore \text{ex } \bar{\mu}_K = 1/\lambda_1$  ~ largest eigen value

$$x^T (H\delta(x) + \mu_K I) x = \|x\|^2 \left[ \frac{x^T H\delta(x) x}{\|x\|^2} + \mu_K \right] \geq \|x\|^2 (-\bar{\mu}_K + \mu_K) > 0$$

$\Rightarrow H\delta(x_k) + \mu_k I$  IS POSITIVE DEFINITE

ALGORITHM:

MIX OF NEWTON &  
STEEPEST DESCENT

INPUT  $x_k$

3) COMPUTE  $\mu_k$  SS.

$H\delta(x_k) + \mu_k I$  IS POSITIVE DEFINITE

3) SOLVE  $A\mu_k$ :

$$(H\delta(x_k) + \mu_k I) \mu_k = -\nabla \delta(x_k)$$

3) COMPUTE  $t_k$  TO SATISFY KARLIE

$$4) x_{k+1} = x_k + t_k A\mu_k$$

↳ APPROXIMATE  $\delta(x)$  BY

NEWTON  
+IAS  $H(x)$



$$Q_k(x) = \delta(x_k) + \nabla \delta(x_k)^T (x - x_k) + \frac{1}{2} (x - x_k)^T A_k (x - x_k)$$

$$\text{WHERE } A_k = H\delta(x_k) + \mu_k I$$

IN PRACTICE:

$$A\mu_k = -A_k^{-1} \nabla \delta(x_k)$$

MAY BE TOO LARGE (NUMERICAL ISSUES)

IDEA:

KEEP THE STEP LENGTH  $\ell_k = \|\mathbf{t}_k\|_p^{(2)}$

AND COMPUTE  $X_{k+1}$  AS:

$$X_{k+1} - X_k = (\mathbf{A}_k + \lambda_k \mathbf{I})^{-1} (\nabla f(X^0))$$

$$\text{WHILE } \|X_{k+1} - X_k\| = \ell_k$$

IS  $\lambda_k$  RUINING THE SOLUTION ??

THEOREM S.S.1

LET  $f$  HAS CONTINUOUS SECOND PARTIAL  
DERIVATIVES,  $X_k \in \mathbb{R}^n$  AND

$$Q_k(\mathbf{x}) = f(X_k) + \nabla f(X_k)^T (\mathbf{x} - X_k) + \frac{1}{2} (\mathbf{x} - X_k)^T \mathbf{A}_k (\mathbf{x} - X_k)$$

THESE EXISTS  $\lambda_k \geq 0$  SUCH THAT

MINIMIZE  $\mathbf{x}_{k+1}$  OF  $Q_k(\mathbf{x})$  SUBJECT TO

$\|\mathbf{x} - X_k\| \leq \ell_k$  IS A SOLUTION TO

$$(\mathbf{A}_k + \lambda_k \mathbf{I})(\mathbf{x} - X_k) = -\nabla f(X_k)$$

IF  $\|\mathbf{A}_k^{-1}(\nabla f(X_k))\| \leq \ell_k$ , PICK  $\lambda_k = 0$ , OTHERWISE

$\lambda_k > 0$  ST  $\|\mathbf{x}_{k+1} - X_k\| = \ell_k$

PROOF APPLY KKT

$$(3) \begin{cases} \min Q_k(x) \\ \text{s.t. } \|x - x_k\|^2 - l_k^2 \leq 0 \end{cases}$$

$$L(x, \mu_k) = f(x_k) + \nabla f(x_k)^T(x - x_k) + \frac{1}{2}(x - x_k)^T A(x - x_k) + \mu_k(\|x - x_k\|^2 - l_k^2)$$

WHERE  $\mu_k$  IS KKT MULTIPLIER ( $\lambda^*$  FROM KKT)

$x^{k+1} \in \arg \min L(x, \mu_k) \leq L(x, \mu_k)$  OR GRADIENT CONDITION

$$0 = \nabla f(x_k) + A_k(x_{k+1} - x_k) + 2\mu_k(x_{k+1} - x_k)$$

so

$$(A_k + 2\mu_k)(x^{k+1} - x^k) = -\nabla f(x_k)$$

$$\text{LET } \lambda_k = 2\mu_k$$

B

$\lambda_k$  CAN BE CHOSEN TO PRESERVE OPT. SOLUTION

$\rightarrow$  GOOD APPROXIMATION TO  $f(x)$

HOPING FULLY

$l_k \dots$  PLUG IN  $\lambda_k$  TO GET THE APPROXIMATION

IS GOOD.