

Week 5, lecture 2

Plan:

• Finish Chapter 6

• Exercises # 2 These are:

- Theoretical 1-4

- Coding 5

} examinable.

Convergence Rate for the Newton Method § 6.3

Suppose that f is twice-differentiable and the Hessian $B(x)$ is Lipschitz in a neighbourhood of the minimizer x_* at which the sufficient conditions for optimality hold ($\nabla f(x_*) = 0$, $B(x_*)$ pos. definite).

Suppose that the starting-point x_0 is sufficiently close to x_* and consider the iterates

$$x_{k+1} = x_k + \beta_k^N.$$

Then:

1. The iterates converge: $x_k \rightarrow x_*$ as $k \rightarrow \infty$.

2. The rate of convergence is quadratic:

$$\|x_{k+1} - x_*\|_2 \leq C \|x_k - x_*\|_2^2.$$

No proof!

Remark: By $B(\underline{x})$ Lipschitz in a neighbourhood \mathcal{N} of \underline{x}_* , we mean, that there exists a positive constant K such that

$$\|B(\underline{y}_2) - B(\underline{y}_1)\|_2 \leq K \|\underline{y}_2 - \underline{y}_1\|_2$$

for all \underline{y}_1 and \underline{y}_2 in \mathcal{N} .

Remark: As you go through the different steps in the proof, we get down to:

$$\frac{\|\underline{x}_1 - \underline{x}_0\|_2}{\|\underline{x}_0 - \underline{x}_*\|_2} \leq \underbrace{C}_{\leq 1/2} \|\underline{x}_0 - \underline{x}_*\|_2$$

"Sufficiently close" means the combination on the RHS is $\leq 1/2$.

More about this in Exercises # 2, Question 1.

One more remark: A similar result holds for quasi-Newton methods (e.g. BFGS):

$$\|\underline{x}_{k+1} - \underline{x}_*\|_2 \leq C \|\underline{x}_k - \underline{x}_*\|_2^{1+\epsilon}$$

where $\epsilon > 0$. i.e. better than SD.

For an example of how S.D. ($\epsilon = 0$) can fail, see Exercises # 2, Question 5.

Week 5, Lecture 3

- Question 1
- One other question

Quadratic convergence, Newton Method:

$$\frac{\|x_k - x^*\|_2}{\|x_0 - x^*\|_2} \leq \frac{1}{2^{2^k - 1}}$$

Question 1:
To show this.

Given (from lecture notes):

$$\|x_{k+1} - x^*\|_2 \leq C \|x_k - x^*\|_2^2 \quad (\text{Eq. 6.13})$$

Work through this for different values of k .

$$k=0: \|x_1 - x^*\|_2 \leq C \|x_0 - x^*\|_2^2$$

$$\Rightarrow \frac{\|x_1 - x^*\|_2}{\|x_0 - x^*\|_2} \leq \underbrace{C \|x_0 - x^*\|_2}_{\leq 1/2}$$

The RHS is $\leq 1/2$ for x_0 sufficiently close to x^* . Hence:

$$\frac{\|x_1 - x^*\|_2}{\|x_0 - x^*\|_2} \leq 1/2$$

$k=1$:

$$\|x_2 - x_*\|_2 \leq C \|x_1 - x_*\|_2^2$$

$$\|x_1 - x_*\|_2 \leq \frac{1}{2} \|x_0 - x_*\|_2$$

Sub in:

$$\|x_2 - x_*\|_2 \leq C \left(\frac{1}{2} \|x_0 - x_*\|_2 \right) \left(\frac{1}{2} \|x_0 - x_*\|_2 \right)$$

$$\Rightarrow \|x_2 - x_*\|_2 \leq \frac{1}{2^2} \|x_0 - x_*\|_2 \left(C \|x_0 - x_*\|_2 \right)$$

$$\Rightarrow \boxed{\|x_2 - x_*\|_2 \leq \frac{1}{2^2 \cdot 2} \|x_0 - x_*\|_2}$$

$k=2$:

$$\|x_3 - x_*\|_2 \leq C \|x_2 - x_*\|_2^2$$

$$\leq \left(\frac{1}{2^3} \|x_0 - x_*\|_2 \right) \left(\frac{1}{2^3} \|x_0 - x_*\|_2 \right) \cdot C$$

$$= \frac{1}{2^6} \|x_0 - x_*\|_2 \left(C \|x_0 - x_*\|_2 \right)$$

$$\Rightarrow \boxed{\|x_3 - x_*\|_2 \leq \frac{1}{2^6 \cdot 2} \|x_0 - x_*\|_2}$$

So far: $\|x_k - x_*\|_2 \leq \frac{1}{2^{p_k}} \|x_0 - x_*\|_2$

$k=1$: $p_k = 1$

(2^1)

$k=2$: $p_k = 3$

$k=3$: $p_k = 7$

Guess the pattern:

$$P_k = 2P_{k-1} + 1.$$

PART (B)

This is a first-order inhomogeneous difference equation. Trial solution:

$$P_k = A + B\lambda^k.$$

Sub into the difference equation:

$$A + B\lambda^k = 2(A + B\lambda^{k-1}) + 1.$$

$$\Rightarrow \underline{A} + \underline{B\lambda^k} = \underline{(2A+1)} + \underline{2B\lambda^{k-1}}$$

Equate coefficients of different powers of λ :

$$A = 2A + 1 \Rightarrow A = -1.$$

$$B\lambda^k = 2B\lambda^{k-1}.$$

$$\text{Take } B=1, \lambda=2.$$

Hence:

$$P_k = 2^k - 1 \quad \left(\begin{array}{l} \text{Back-substitution into} \\ P_k = A + B\lambda^k \end{array} \right)$$

This solves PART (C), This is valid for $k=1, k=2, \dots$

In part (d) we put everything together.

Hence:

$$a + b\alpha + c\alpha^2 < a + c_1\alpha b.$$

Hence, $\alpha = 0$ OR :

$$b + c\alpha < c_1\alpha b.$$

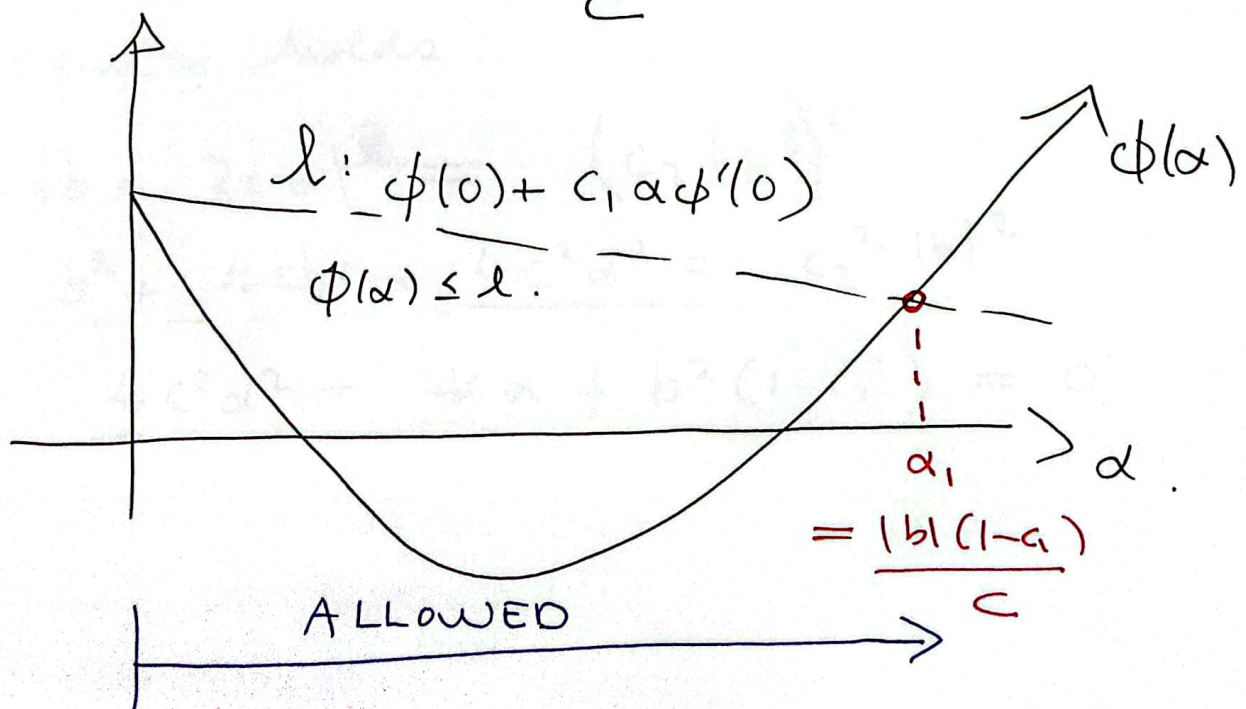
Extreme case with equality:

$$\begin{aligned} b + c\alpha &= c_1\alpha b \\ \Rightarrow b &= \alpha \cdot c_1 b - c \cdot \alpha \\ &= \alpha (c_1 b - c). \end{aligned}$$

$$b + c\alpha = c_1 b.$$

$$\Rightarrow \alpha = \frac{(c_1 - 1)b}{c}$$

OR $\alpha = \frac{|b|(1 - c_1)}{c}$ (positive).



Thus, any $\alpha \in (0, \alpha_1)$ satisfies SWC1.

Here:

$$\alpha_1 = \frac{|b|(1-c_1)}{c}$$

We now look at satisfying SWC2.

SWC2 says:

$$\left. \begin{array}{l} |\phi'(\alpha)| \leq c_2 |\phi'(0)| \\ \text{OR } |\phi'(\alpha)| \leq c_2 |b| \\ \text{OR } |b + 2c\alpha| \end{array} \right\} \begin{array}{l} \phi(\alpha) = a + b\alpha + c\alpha^2 \\ \phi'(\alpha) = b + 2c\alpha \\ \phi'(0) = b \end{array}$$

OR

$$|b + 2c\alpha| \leq c_2 |b|$$

This is a quadratic inequality in α . To solve, we look at the extreme case, where equality holds:

$$|b + 2c\alpha|^2 = (c_2 |b|)^2$$

$$b^2 + 4cb\alpha + 4c^2\alpha^2 = c_2^2 |b|^2$$

$$\Rightarrow 4c^2\alpha^2 + 4bc\alpha + b^2(1-c_2^2) = 0$$

Hence:

~~$$\alpha = -4bc \pm \sqrt{16b^2c^2 - 4}$$~~

$$\alpha = \frac{-4bc \pm \sqrt{16b^2c^2 - 16c^2b^2(1-c_2^2)}}{2 \times 4c^2}$$

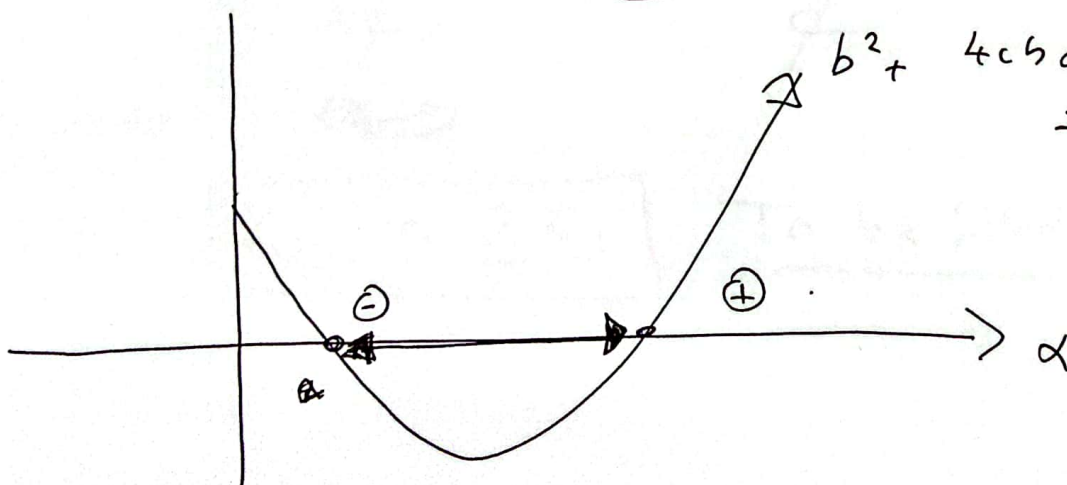
$$\Rightarrow \alpha = \frac{-4bc \pm \sqrt{16b^2c^2 - 16b^2c^2 + 16b^2c^2c_2^2}}{2 \times 4c^2}$$

$$\Rightarrow \alpha = \frac{-4bc \pm 4|b|c c_2^2}{2 \times 4c^2}$$

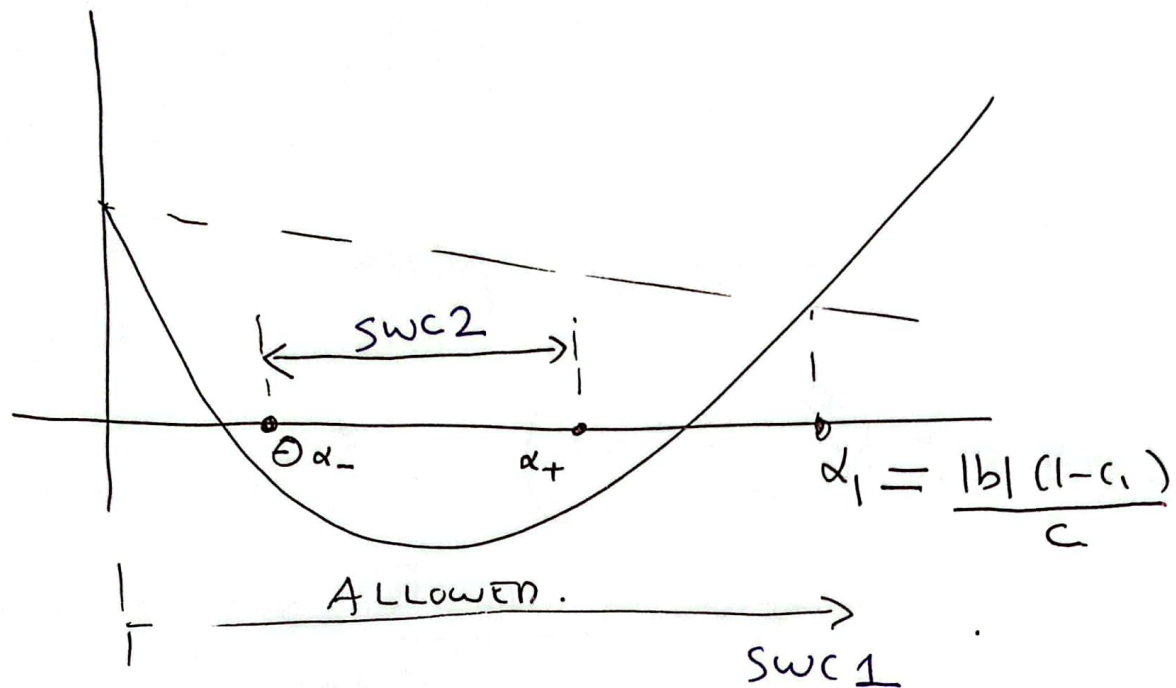
$$= \frac{4|b|c \pm 4|b|c c_2^2}{2 \times 4c^2}$$

$$\Rightarrow \alpha = \frac{|b|c (1 \pm c_2^2)}{2 \cdot c \cdot c}$$

$$\Rightarrow \alpha = \frac{|b|(1 \pm c_2^2)}{2c}$$



Combine the two figures:



We need α_- to be to the left of α_1 .
 for SWC 1 and SWC 2 to be
 satisfied simultaneously. So, to
 produce a contradiction, we would put α_-
 to the right of α_1 :

$$\frac{|b|(1-c_2)}{2\phi} > \frac{|b|(1-c_1)}{\phi}$$

~~\Rightarrow~~ ~~\Rightarrow~~

$$\Rightarrow \boxed{c_2 < \underline{2}c_1}$$

To be filled in later

Question 5.

$$f(x) = \langle a, x \rangle - \frac{1}{2} \langle x, Bx \rangle.$$

B is manifestly symmetric and positive definite.

$$\|x_{k+1} - x^*\|_2 \leq \left(1 - \frac{1}{\kappa(B)}\right)^{\frac{1}{2}} \|x_k - x^*\|_2$$

This is the linear convergence rate for the SD algorithm.

$\kappa(B)$ is the condition number of the matrix.

$$\kappa(B) = \frac{\lambda_{\max}}{\lambda_{\min}} \quad \text{for a P.D. symmetric matrix}$$

For B in Question(5), $\text{cond}(B) > 10^5$.

$$1 - \frac{1}{\kappa(B)} \approx 1.$$

Hence,

$$\|x_{k+1} - x^*\|_2 \lesssim 1 \|x_k - x^*\|_2.$$

No shrinkage of the distance in going from one iteration to the next. SD method fails here.

"SD is to optimization what Euler is to ODEs."