



(</course/cs450-s19/flow-session/525665/1/)



1

2

(</course/cs450-s19/flow-session/525665/1/)

20 points

Convergence of Steepest Descent

In this problem we will bound the error of the steepest descent iterates for the following function

$$f(\mathbf{x}) = \frac{1}{2} \mathbf{x}^T \mathbf{Q} \mathbf{x} - \mathbf{b}^T \mathbf{x},$$

where $\mathbf{Q} \in \mathbb{R}^{n \times n}$ is symmetric and positive definite. Recall the steepest descent algorithm starts with an initial guess $\mathbf{x}_0 \in \mathbb{R}^n$ and proceeds to compute successive approximations

$$\mathbf{x}_{k+1} = \mathbf{x}_k - \alpha_k \nabla f(\mathbf{x}_k)$$

where α_k is a line search parameter found by solving the following minimization problem

$$\alpha_k = \operatorname{argmin}_{\alpha_k} f(\mathbf{x}_k - \alpha_k \nabla f_k),$$

where $\nabla f_k = \nabla f(\mathbf{x}_k)$. To simplify the notation, we denote $\|\mathbf{x}\|_{\mathbf{Q}}^2 = \mathbf{x}^T \mathbf{Q} \mathbf{x}$ and \mathbf{x}^* minimizes $f(\mathbf{x})$. Please do the following parts.

1. Show that,

$$\alpha_k = \frac{\|\nabla f_k\|_2^2}{\|\nabla f_k\|_{\mathbf{Q}}^2}.$$

2. Show that,

$$f(\mathbf{x}_{k+1}) = f(\mathbf{x}_k) - \frac{\|\nabla f_k\|_2^4}{2\|\nabla f_k\|_{\mathbf{Q}}^2}.$$

(Hint: $\nabla f_k = \mathbf{Q} \mathbf{x}_k - \mathbf{b}$)

3. Show that,

$$\frac{1}{2} \|\mathbf{x} - \mathbf{x}^*\|_{\mathbf{Q}}^2 = f(\mathbf{x}) - f(\mathbf{x}^*).$$

(Hint: \mathbf{x}^* is the solution to $\mathbf{Q} \mathbf{x} = \mathbf{b}$)

4. Show that,

$$f(\mathbf{x}_k) = f(\mathbf{x}^*) + \frac{1}{2} \|\nabla f_k\|_{\mathbf{Q}^{-1}}^2$$

5. Use the expressions in previous parts to show that,

$$\|\mathbf{x}_{k+1} - \mathbf{x}^*\|_{\mathbf{Q}}^2 = \left(1 - \frac{\|\nabla f_k\|_2^4}{\|\nabla f_k\|_{\mathbf{Q}}^2 \|\nabla f_k\|_{\mathbf{Q}^{-1}}^2}\right) \|\mathbf{x}_k - \mathbf{x}^*\|_{\mathbf{Q}}^2.$$

6. Finally, show that,

$$\|\mathbf{x}_{k+1} - \mathbf{x}^*\|_{\mathbf{Q}}^2 \leq \left(\frac{\lambda_n - \lambda_1}{\lambda_n + \lambda_1} \right)^2 \|\mathbf{x}_k - \mathbf{x}^*\|_{\mathbf{Q}}^2,$$

where λ_1 and λ_n are the smallest and largest eigenvalues of \mathbf{Q} respectively.

Hint: Use Kantorovich's Inequality. For positive reals v_1, v_2, \dots, v_n such that $v_1 \leq v_2 \leq \dots \leq v_n$ and for non-negative reals w_1, w_2, \dots, w_n such that $w_1 + w_2 + \dots + w_n = 1$, we have,

$$\left(\sum w_i v_i \right) \left(\sum w_i v_i^{-1} \right) \leq \frac{(v_1 + v_n)^2}{4v_1 v_n}.$$

Be sure to show all your work and provide justifications for every step to receive full credit.

Please submit your response to this written problem as a PDF file below. You may do either of the following:

- write your response out by hand, scan it, and upload it as a PDF.

We will not accept unprocessed pictures taken with your phone.

If you decide to use your phone for scanning, make sure to use an app such as CamScanner (<https://www.camscanner.com/>) to get a readable PDF. Alternatively, there's a fast and convenient scanner in the Engineering IT office in 2302 Siebel that can just email you a PDF. (It's the Fax-machine-looking thing--not the scanner that's attached to one of the computers.)

- create the PDF using software.

If you're looking for an easy-ish way to type math, check out TeXmacs (<http://texmacs.org/>) or LyX (<http://www.lyx.org/>). Both are installed in the virtual machine. (Under "Applications / Accessories / GNU TeXmacs editor" and "Applications / Office / LyX document processor" respectively.)

Submit your response to each problems in this homework as a separate PDF. If you have multiple PDFs that you need to merge into one, try PDF Split and Merge (<http://www.pdfsam.org/download/>).

NOTE: Please make sure your solutions are legible and easy to follow. If they are not, we may deduct up to five points *per problem*.

Review uploaded file (blob:<https://relate.cs.illinois.edu/cf55dd3f-19ae-41f7-9cc3-25c0fc19b2dc>) · Embed viewer

Uploaded file*

未选择任何文件

Your answer is mostly correct. (80.0 %)

- Part 1:

Note that

$$\begin{aligned}
f(\mathbf{x}_k - \alpha_k \nabla f_k) &= \frac{1}{2}(\mathbf{x}_k - \alpha_k \nabla f_k)^T \mathbf{Q}(\mathbf{x}_k - \alpha_k \nabla f_k) - \mathbf{b}^T(\mathbf{x}_k - \alpha_k \nabla f_k) \\
&= \frac{1}{2}(\mathbf{x}_k^T \mathbf{Q} \mathbf{x}_k - \alpha_k \mathbf{x}_k^T \mathbf{Q} \nabla f_k - \alpha_k \nabla f_k^T \mathbf{Q} \mathbf{x}_k + \alpha_k^2 \nabla f_k^T \mathbf{Q} \nabla f_k) - \mathbf{b}^T \mathbf{x}_k + \alpha_k \mathbf{b}^T \nabla f_k \\
&= \frac{1}{2}(\mathbf{x}_k^T \mathbf{Q} \mathbf{x}_k - 2\alpha_k \nabla f_k^T \mathbf{Q} \mathbf{x}_k + \alpha_k^2 \nabla f_k^T \mathbf{Q} \nabla f_k) - \mathbf{b}^T \mathbf{x}_k + \alpha_k \mathbf{b}^T \nabla f_k \\
&= \frac{1}{2}(\alpha_k^2 \nabla f_k^T \mathbf{Q} \nabla f_k - 2\alpha_k(\nabla f_k^T \mathbf{Q} \mathbf{x}_k - \mathbf{b}^T \nabla f_k) + \mathbf{x}_k^T \mathbf{Q} \mathbf{x}_k - 2\mathbf{b}^T \mathbf{x}_k) \\
&= \frac{1}{2}(\alpha_k^2 \nabla f_k^T \mathbf{Q} \nabla f_k - 2\alpha_k(\nabla f_k^T \nabla f_k) + \mathbf{x}_k^T \mathbf{Q} \mathbf{x}_k - 2\mathbf{b}^T \mathbf{x}_k).
\end{aligned}$$

where the third equality follows from the fact that \mathbf{Q} is symmetric and the fifth is from the fact that $\nabla f(\mathbf{x}) = \mathbf{Q}\mathbf{x} - \mathbf{b}$

Note that since \mathbf{Q} is positive definite we have that $\nabla f_k^T \mathbf{Q} \nabla f_k > 0$. Therefore the above expression is a quadratic polynomial with a positive leading coefficient. For a quadratic polynomial $ax^2 + bx + c$ with $a > 0$, minimum is when $x = -b/(2a)$.

This results in the following,

$$\alpha_k = \frac{\nabla f_k^T \nabla f_k}{\nabla f_k^T \mathbf{Q} \nabla f_k}$$

- Part 2:

Reusing our computations from Part 1, we have,

$$\begin{aligned}
f(\mathbf{x}_{k+1}) &= \frac{1}{2}(\alpha_k^2 \nabla f_k^T \mathbf{Q} \nabla f_k - 2\alpha_k(\nabla f_k^T \nabla f_k) + \mathbf{x}_k^T \mathbf{Q} \mathbf{x}_k - 2\mathbf{b}^T \mathbf{x}_k) \\
&= \frac{1}{2}(\alpha_k^2 \nabla f_k^T \mathbf{Q} \nabla f_k - 2\alpha_k(\nabla f_k^T \nabla f_k) + 2f(\mathbf{x}_k)) \\
&= \frac{1}{2} \left(\frac{\|\nabla f_k\|_2^4}{\|\nabla f_k\|_{\mathbf{Q}}^4} \|\nabla f_k\|_{\mathbf{Q}}^2 - 2 \frac{\|\nabla f_k\|_2^2}{\|\nabla f_k\|_{\mathbf{Q}}^2} \|\nabla f_k\|_2^2 + 2f(\mathbf{x}_k) \right) \\
&= f(\mathbf{x}_k) - \frac{\|\nabla f_k\|_2^4}{2\|\nabla f_k\|_{\mathbf{Q}}^2}.
\end{aligned}$$

- Part 3:

We will use the fact that the minimum \mathbf{x}^* of $f(\mathbf{x})$ is the solution to the linear system $\mathbf{Q}\mathbf{x} = \mathbf{b}$. This is easily derived similarly to how we derived α_k in Part 1. Note that

$$\begin{aligned}
\frac{1}{2}\|\mathbf{x} - \mathbf{x}^*\|_{\mathbf{Q}}^2 &= \frac{1}{2}(\mathbf{x} - \mathbf{x}^*)^T \mathbf{Q}(\mathbf{x} - \mathbf{x}^*) \\
&= \frac{1}{2}(\mathbf{x}^T \mathbf{Q} \mathbf{x} - 2\mathbf{x}^T \mathbf{Q} \mathbf{x}^* + \mathbf{x}^{*T} \mathbf{Q} \mathbf{x}^*) \\
&= \frac{1}{2}(\mathbf{x}^T \mathbf{Q} \mathbf{x} - 2\mathbf{x}^T \mathbf{b} + \mathbf{x}^{*T} \mathbf{b}) \\
&= f(\mathbf{x}) - f(\mathbf{x}^*).
\end{aligned}$$

since

$$\begin{aligned}
f(\mathbf{x}^*) &= \frac{1}{2}\mathbf{x}^{*T} \mathbf{Q} \mathbf{x}^* - \mathbf{b}^T \mathbf{x}^* \\
&= \frac{1}{2}\mathbf{x}^{*T} \mathbf{b} - \mathbf{b}^T \mathbf{x}^* \\
&= -\frac{1}{2}\mathbf{x}^{*T} \mathbf{b}.
\end{aligned}$$

- Part 4:

To show this we will use the fact that $\mathbf{x}_k = \mathbf{Q}^{-1}(\nabla f_k + \mathbf{b})$. Plugging this in we have,

$$\begin{aligned}
 f(\mathbf{x}_k) - f(\mathbf{x}^*) &= \frac{1}{2} \langle \mathbf{x}_k, \mathbf{Q} \mathbf{x}_k \rangle - \langle \mathbf{x}_k, \mathbf{b} \rangle + \frac{1}{2} \mathbf{x}^{*T} \mathbf{b} \\
 &= \frac{1}{2} \langle \mathbf{x}_k, \nabla f_k + \mathbf{b} \rangle - \langle \mathbf{x}_k, \mathbf{b} \rangle + \frac{1}{2} \langle \mathbf{x}^*, \mathbf{b} \rangle \\
 &= \frac{1}{2} \langle \mathbf{x}_k, \nabla f_k \rangle - \frac{1}{2} \langle \mathbf{x}_k, \mathbf{b} \rangle + \frac{1}{2} \langle \mathbf{x}^*, \mathbf{b} \rangle \\
 &= \frac{1}{2} \langle \mathbf{Q}^{-1}(\nabla f_k + \mathbf{b}), \nabla f_k \rangle - \frac{1}{2} \langle \mathbf{Q}^{-1}(\nabla f_k + \mathbf{b}), \mathbf{b} \rangle + \frac{1}{2} \langle \mathbf{Q}^{-1} \mathbf{b}, \mathbf{b} \rangle \\
 &= \frac{1}{2} \langle \mathbf{Q}^{-1}(\nabla f_k + \mathbf{b}), \nabla f_k \rangle - \frac{1}{2} \langle \mathbf{Q}^{-1} \nabla f_k, \mathbf{b} \rangle \\
 &= \frac{1}{2} \langle \mathbf{Q}^{-1} \nabla f_k, \nabla f_k \rangle
 \end{aligned}$$

Last equality is because \mathbf{Q} is symmetric $\implies \langle \mathbf{Q}^{-1} \mathbf{b}, \nabla f_k \rangle = \langle \mathbf{Q}^{-1} \nabla f_k, \mathbf{b} \rangle$

- Part 5:

From part 3, the inequality we want to prove becomes

$$f(\mathbf{x}_{k+1}) - f(\mathbf{x}^*) = \left(1 - \frac{(\|\nabla f_k\|_2^4)}{\|\nabla f_k\|_{\mathbf{Q}}^2 \|\nabla f_k\|_{\mathbf{Q}^{-1}}^2} \right) (f(\mathbf{x}_k) - f(\mathbf{x}^*))$$

From part 2, we have,

$$\begin{aligned}
 f(\mathbf{x}_{k+1}) - f(\mathbf{x}^*) &= f(\mathbf{x}_{k+1}) - f(\mathbf{x}_k) + f(\mathbf{x}_k) - f(\mathbf{x}^*) \\
 &= -\frac{\|\nabla f_k\|_2^4}{2\|\nabla f_k\|_{\mathbf{Q}}^2} + f(\mathbf{x}_k) - f(\mathbf{x}^*) \\
 &= \left(1 - \frac{(\|\nabla f_k\|_2^4)}{2\|\nabla f_k\|_{\mathbf{Q}}^2 (f(\mathbf{x}_k) - f(\mathbf{x}^*))} \right) (f(\mathbf{x}_k) - f(\mathbf{x}^*)) \\
 &= \left(1 - \frac{(\|\nabla f_k\|_2^4)}{\|\nabla f_k\|_{\mathbf{Q}}^2 \|\nabla f_k\|_{\mathbf{Q}^{-1}}^2} \right) (f(\mathbf{x}_k) - f(\mathbf{x}^*)).
 \end{aligned}$$

The second equality is from Part 2 and fourth equality is from Part 4.

- Part 6:

Consider the eigenvalue decompositions $\mathbf{Q} = \mathbf{V} \mathbf{\Lambda} \mathbf{V}^T$ and $\mathbf{Q}^{-1} = \mathbf{V} \mathbf{\Lambda}^{-1} \mathbf{V}^T$ and let $\mathbf{u} = \nabla f_k, \mathbf{y} = \mathbf{V}^T \mathbf{u}$

Substituting these values in we have that

$$\frac{(\mathbf{u}^T \mathbf{u})^2}{(\mathbf{u}^T \mathbf{Q} \mathbf{u})(\mathbf{u}^T \mathbf{Q}^{-1} \mathbf{u})} = \frac{(\mathbf{y}^T \mathbf{y})^2}{(\mathbf{y}^T \mathbf{\Lambda} \mathbf{y})(\mathbf{y}^T \mathbf{\Lambda}^{-1} \mathbf{y})} = \frac{1}{\left(\frac{\mathbf{y}^T \mathbf{\Lambda} \mathbf{y}}{\mathbf{y}^T \mathbf{y}}\right) \left(\frac{\mathbf{y}^T \mathbf{\Lambda}^{-1} \mathbf{y}}{\mathbf{y}^T \mathbf{y}}\right)} = \frac{1}{\left(\frac{\sum y_i^2 \lambda_i}{\sum y_i^2}\right) \left(\frac{\sum y_i^2 \lambda_i^{-1}}{\sum y_i^2}\right)}$$

Let $w_i = \frac{y_i^2}{\sum y_i^2}$ and note that $0 \leq w_i \leq 1$ for all $i = 1, \dots, n$ and $\sum_i^n w_i = 1$. And so

$$\frac{1}{\left(\frac{\sum y_i^2 \lambda_i}{\sum y_i^2}\right) \left(\frac{\sum y_i^2 \lambda_i^{-1}}{\sum y_i^2}\right)} = \frac{1}{(\sum w_i \lambda_i)(\sum w_i \lambda_i^{-1})}$$

From Kantorovich Inequality we get,

$$\frac{1}{(\sum w_i \lambda_i)(\sum w_i \lambda_i^{-1})} \geq \frac{4\lambda_1 \lambda_n}{(\lambda_1 + \lambda_n)^2}$$

Using the results of Part 2 we have that

$$\begin{aligned} \|\mathbf{x}_{k+1} - \mathbf{x}^*\|_{\mathbf{Q}}^2 &= \left(1 - \frac{(\nabla f_k^T \nabla f_k)^2}{(\nabla f_k^T \mathbf{Q} \nabla f_k)(\nabla f_k^T \mathbf{Q}^{-1} \nabla f_k)}\right) \|\mathbf{x}_k - \mathbf{x}^*\|_{\mathbf{Q}}^2 \\ &\leq \left(1 - \frac{4\lambda_n \lambda_1}{(\lambda_n + \lambda_1)^2}\right) \|\mathbf{x}_k - \mathbf{x}^*\|_{\mathbf{Q}}^2 \end{aligned}$$

With a bit of algebra, we see that

$$\begin{aligned} 1 - \frac{4\lambda_n \lambda_1}{(\lambda_n + \lambda_1)^2} &= \frac{(\lambda_n + \lambda_1)^2 - 4\lambda_n \lambda_1}{(\lambda_n + \lambda_1)^2} \\ &= \left(\frac{\lambda_n - \lambda_1}{\lambda_n + \lambda_1}\right)^2. \end{aligned}$$

- Proof of Kantorovich's inequality (you don't need to show this)

For each i , define p_i and q_i as the solution to the following equations

$$\begin{cases} v_i = p_i v_n + q_i v_1 \\ v_i^{-1} = p_i v_n^{-1} + q_i v_1^{-1} \end{cases}$$

Solving this system of equations will yield

$$p_i = \frac{v_i/v_1 - v_1/v_i}{v_n/v_1 - v_1/v_n} \geq 0$$

Similarly, we can show $q_i \geq 0$. Then since

$$1 = v_i v_i^{-1} = (p_i v_n + q_i v_1)(p_i v_n^{-1} + q_i v_1^{-1}) = (p_i + q_i)^2 + p_i q_i (v_n - v_1)^2 / (v_n v_1)$$

we know $p_i + q_i \leq 1$.

Setting $p = \sum w_i p_i$ and $q = \sum w_i q_i$, we have

$$p + q = \sum w_i (p_i + q_i) \leq \sum w_i = 1$$

Then,

$$(\sum w_i v_i)(\sum w_i v_i^{-1}) = (p v_n + q v_1)(p v_n^{-1} + q v_1^{-1}) = (p + q)^2 + p q \frac{(v_n - v_1)^2}{v_n v_1}$$

Since $(p - q)^2 \geq 0 \implies 4pq \leq (p + q)^2$,

$$(p + q)^2 + p q \frac{(v_n - v_1)^2}{v_n v_1} \leq (p + q)^2 \left[1 + \frac{(v_n - v_1)^2}{4v_n v_1}\right] = (p + q)^2 \frac{(v_n + v_1)^2}{4v_n v_1} \leq \frac{(v_n + v_1)^2}{4v_n v_1}$$

Reference: <https://www.jstor.org/stable/pdf/2311698.pdf#page=3>