

LECTURE 14CONVERGENCE OF LINE-SEARCH METHODS

A line-search method is called globally convergent if it generates a sequence $\{x_k\}$ s.t.

$$\lim_{k \rightarrow \infty} \nabla_f(x_k) = 0$$

for all $x_0 \in \mathbb{R}^n$.

The global convergence of a line-search method is typically guaranteed as long as the descent directions p_k don't become perpendicular to $\nabla_f(x_k)$ as $k \rightarrow \infty$ and step-lengths α_k are chosen properly.

Angle between $\nabla_f(x_k)$ and p_k θ_k satisfies

$$\cos \theta_k = \frac{\nabla_f(x_k)^T p_k}{\|\nabla_f(x_k)\| \|p_k\|}$$

THM (Zoutendijk)

Let $f: \mathbb{R}^n \rightarrow \mathbb{R}$ be

* Lipschitz continuously differentiable
that is there exists a $\gamma > 0$ s.t.

$$\|\nabla f(x) - \nabla f(y)\| \leq \gamma \|x - y\|$$

for all $x, y \in \mathbb{R}^n$, and

* bounded below.

Suppose also that a line-search method generates

* descent directions p_k , and

* step-lengths α_k satisfying Wolfe conditions.

Then the following holds

$$\sum_{k=0}^{\infty} \|\nabla f(x_k)\|^2 \cos^2 \theta_k < \infty.$$

PROOF

By the sufficient curvature condition

$$\nabla f(x_k + \alpha_k p_k)^T p_k \geq \mu_2 \nabla f(x_k)^T p_k$$

\implies

$$(*) \left(\nabla f(x_k + \alpha_k p_k) - \nabla f(x_k) \right)^T p_k \geq (\mu_2 - 1) \nabla f(x_k)^T p_k$$

Furthermore by Lipschitz continuity of derivatives

$$\left(\nabla f(x_k + \alpha_k p_k) - \nabla f(x_k) \right)^T p_k$$

$$\leq$$

$$\| \nabla f(x_k + \alpha_k p_k) - \nabla f(x_k) \| \| p_k \|$$

$$\leq$$

$$(**) \quad \gamma \| \alpha_k p_k \| \| p_k \| = \gamma \alpha_k \| p_k \|^2$$

Combine (*) and (**) to obtain

$$\alpha_k \geq \frac{(\mu_2 - 1) \nabla f(x_k)^T p_k}{\gamma \| p_k \|^2}$$

Plugging this inequality in sufficient decrease condition

$$f(x_k + \alpha_k p_k) \leq f(x_k) + \alpha_k M_1 \nabla f(x_k)^T p_k$$

$$\leq f(x_k) + \frac{M_1 (\mu_2 - 1)}{\gamma \| p_k \|^2} (\nabla f(x_k)^T p_k)^2$$

$$= f(x_k) + \frac{M_1 (\mu_2 - 1)}{\gamma} \cos^2 \theta_k \| \nabla f(x_k) \|^2$$

That is

$$\frac{\mu_1 (1 - \mu_2)}{\gamma} \cos^2 \theta_k \|\nabla f(x_k)\|^2 \leq f(x_k) - f(x_{k+1})$$

$$\sum_{k=0}^m \cos^2 \theta_k \|\nabla f(x_k)\|^2 \leq \frac{\gamma}{\mu_1 (1 - \mu_2)} \underbrace{(f(x_0) - f(x_{m+1}))}_{\substack{\text{bounded} \\ \text{since } f \text{ is} \\ \text{bounded below}}}$$

Taking the limit as $m \rightarrow \infty$,

$$\sum_{k=0}^{\infty} \cos^2 \theta_k \|\nabla f(x_k)\|^2 \leq \frac{\gamma}{\mu_1 (1 - \mu_2)} \lim_{m \rightarrow \infty} (f(x_0) - f(x_{m+1})) < \infty.$$

□

~~CONVERGENCE OF STEEPEST DESCENT~~

~~For steepest descent~~

~~$\cos \theta_k$~~

Suppose that for a line-search method there exists an $M > 0$ s.t.

$$|\cos \theta_k| \geq M$$

for all large k .

Then by Zoutendijk's theorem

$$M^2 \sum_{k=0}^{\infty} \|\nabla_f(x_k)\|^2 \leq \sum_{k=0}^{\infty} \cos^2 \theta_k \|\nabla_f(x_k)\| < \infty$$

$$\implies \lim_{k \rightarrow \infty} \|\nabla_f(x_k)\| = 0,$$

that is the method is globally convergent

CONVERGENCE OF STEEPEST DESCENT

- For 'steepest descent

$$\begin{aligned} \cos \theta_k &= \frac{\nabla_f(x_k)^T p_k}{\|\nabla_f(x_k)\| \|p_k\|} \\ &= \frac{-\nabla_f(x_k)^T \nabla_f(x_k)}{\|\nabla_f(x_k)\| \|\nabla_f(x_k)\|} = -1 \end{aligned}$$

Therefore the method is globally convergent.

The rate of convergence is linear.

For a quadratic function

$$q(x) = \frac{1}{2} x^T A x + b^T x + c$$

with exact line searches the steepest descent iterates $\{x_k\}$ satisfy

$$\lim_{k \rightarrow \infty} \frac{\|x_{k+1} - x_*\|}{\|x_k - x_*\|} = \frac{\lambda_{\max} - \lambda_{\min}}{\lambda_{\max} + \lambda_{\min}}$$

where

- * x_* is the local minimizer of $q(x)$
- * $\lambda_{\min}, \lambda_{\max}$ are the smallest and largest eigenvalues of A .

~~CONVERGENCE OF NEWTON'S METHOD~~

~~Suppose that $\|\nabla^2 f(x_k)\|$ and~~

~~$\|\nabla^2 f(x_k)^{-1}\|$ remain bounded, that is~~

~~there exists an $M > 0$ s.t.~~

$$\|\nabla^2 f(x_k)\| \|\nabla^2 f(x_k)^{-1}\| \geq M$$

CONVERGENCE OF MODIFIED NEWTON'S METHOD

Let $\widetilde{\nabla}_f^2(x_k)$ denote positive definite modified Hessian matrices.

Suppose $\|\widetilde{\nabla}_f^2(x_k)\|$ and $\|\widetilde{\nabla}_f^2(x_k)^{-1}\|$ remain bounded, that is there exists an $M > 0$ such that

$$(+)\quad \|\widetilde{\nabla}_f^2(x_k)\| \|\widetilde{\nabla}_f^2(x_k)^{-1}\| \leq M.$$

(+) implies

$$\cos \theta_k = \frac{-\nabla_f(x_k)^T \widetilde{\nabla}_f^2(x_k)^{-1} \nabla_f(x_k)}{\|\nabla_f(x_k)\| \|\widetilde{\nabla}_f^2(x_k)^{-1} \nabla_f(x_k)\|}$$

Noting that

$$\begin{aligned} * \nabla_f(x_k)^T \widetilde{\nabla}_f^2(x_k)^{-1} \nabla_f(x_k) &\geq \\ &\lambda_{\min}(\widetilde{\nabla}_f^2(x_k)^{-1}) \nabla_f(x_k)^T \nabla_f(x_k) \\ &= \\ &\lambda_{\min}(\widetilde{\nabla}_f^2(x_k)^{-1}) \|\nabla_f(x_k)\|^2 \end{aligned}$$

and

$$\begin{aligned} * \lambda_{\max}(\widehat{\nabla_f^2(x_k)^{-1}}) &= \|\widehat{\nabla_f^2(x_k)^{-1}}\| \\ &\geq \frac{\|\widehat{\nabla_f^2(x_k)^{-1}} \nabla_f(x_k)\|}{\|\nabla_f(x_k)\|} \end{aligned}$$

we have

$$\begin{aligned} |\cos \theta_k| &\geq \frac{\lambda_{\min}(\widehat{\nabla_f^2(x_k)^{-1}}) \|\nabla_f(x_k)\|^2}{\lambda_{\max}(\widehat{\nabla_f^2(x_k)^{-1}}) \|\nabla_f(x_k)\|^2} \\ &= \frac{1}{\lambda_{\max}(\widehat{\nabla_f^2(x_k)}) \lambda_{\max}(\widehat{\nabla_f^2(x_k)^{-1}})} \\ &= \frac{1}{\|\widehat{\nabla_f^2(x_k)}\| \|\widehat{\nabla_f^2(x_k)^{-1}}\|} \\ &\geq \frac{1}{M} \end{aligned}$$

Therefore ~~the~~_a modified Newton's method ensuring Wolfe conditions is globally convergent.

CONVERGENCE OF QUASI-NEWTON METHODS

Assuming the Hessian approximation

B_k satisfy

$$(+)\ \|B_k\| \|B_k^{-1}\| \leq M$$

it can be similarly shown that

$$|\cos \theta_k| \geq \frac{1}{M}.$$

Quasi-Newton methods with Wolfe conditions and satisfying (+) are globally convergent.

COMPARISON OF METHODS

	<u>Rate of Convergence</u>	<u># FLOPS per iteration</u>
Steepest Descent	Linear	$O(n)$
Modified Newton	Quadratic	$O(n^3)$
Quasi-Newton	Superlinear	$O(n^2)$