

Special Topics in Continuous Optimization and Optimal Control

Local and Global convergence of Newton methods

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Overview

- 1 Introduction
- 2 Background
- 3 Local Conv.
- 4 Failures: NM
- 5 Theorems
- 6 Global Conv.
- 7 Globalization Schemes
- 8 Conclusion

Introduction

Problem:

- ▶ Finding x^* such that $F(x^*) = 0$
- ▶ $F : \mathbb{R}^n \rightarrow \mathbb{R}^n$ (highly) nonlinear
- ▶ Important problem in continuous optimization and optimal control

Newton's method:

- ▶ Iterative method
- ▶ Solve linearized problem
- ▶ Many variants

Globalization strategies:

- ▶ Newton's method only locally convergent
- ▶ Hope to globalize convergence

Lipschitz Condition

- ▶ Given $g: [a,b] \rightarrow \mathbb{R}$ is called Lipschitz continuous with constant $\lambda > 0$ (denoted $g \in Lip_\lambda[a,b]$) if $\exists \lambda > 0$ such that $|g(x) - g(y)| \leq \lambda|x - y|$ for all $x,y \in [a,b]$

Contraction map

- ▶ $g: [a,b] \rightarrow \mathbb{R}$ is called contraction map if $g \in Lip_\lambda[a,b]$ with $\lambda < 1$

Convex set

- ▶ A set C is convex if, for any $x,y \in C$ and $\theta \in \mathbb{R}$ with $0 \leq \theta \leq 1$, $\theta x + (1 - \theta)y \in C$

Convex function

- ▶ A function $f: \mathbb{R} \rightarrow \mathbb{R}$ is convex if its domain (denoted $D(f)$) is a convex set and if, for all $x,y \in D(f)$ and $\theta \in \mathbb{R}$ with $0 \leq \theta \leq 1$,
- ▶ $f(\theta x + (1 - \theta)y) \leq \theta f(x) + (1 - \theta)f(y)$

Summary: Newton Method

- ▶ Fast (i.e. quadratic) local rate of convergence
- ▶ Scale-invariant w.r.t linear transformations of the variables
- ▶ Search direction p^k is not well defined if $\nabla^2 f(x^k)$ is singular, p^k is not a descent if $\nabla^2 f(x^k)$ is not positive definite
- ▶ Minimum points x^k can be attracted to saddle points or local maxima of f
- ▶ Very small neighbourhood of local convergence, Newton's method is not globally convergent
- ▶ Line search, trust region

1. Convergence properties of Newton methods

What is convergence?

- ▶ Convergence means **approaching a limit** as the argument of the function increases or decreases or as the number of terms in the series increases.
- ▶ Types of convergence: local and global
- ▶ **When does it converge locally?** When the initial approximation is already **close enough to the solution**, then the successive approximations of the iterative method guaranteed to converge to a solution locally.
- ▶ Iterative methods for nonlinear equations and their systems, such as Newton's method are usually only locally convergent.

Rate of convergence

- ▶ $\{x^k\} \subset \mathbb{R}^n, x^* \in \mathbb{R}^n, \{x^k\} \rightarrow x^*$ as $k \rightarrow \infty$
- ▶ $\{x^k\} \rightarrow x^*$ with rate r if $\frac{\|x^{k+1} - x^*\|}{\|x^k - x^*\|^r} = c < \infty$, for sufficiently large k
- ▶ $r=1$: linear convergence ($c < 1$)
- ▶ $r=2$: quadratic convergence
- ▶ superlinear convergence: $\frac{\|x^{k+1} - x^*\|}{\|x^k - x^*\|^r} \rightarrow 0$ as $k \rightarrow \infty$

Local Convergence Theorem

- ▶ Single dimension: If
- ▶ $\frac{\partial f}{\partial x}$ bounded away from zero
- ▶ $\frac{\partial^2 f}{\partial x^2}$ bounded
- ▶ Then Newton's method converges given a sufficiently close initial guess (and convergence is quadratic)

Multidimensional

- ▶ If $\|J_F^{-1}(x^k)\| \leq \beta$ (inverse is bounded)
- ▶ $\|J_F(x) - J_F(y)\| \leq l\|x - y\|$ (Derivative is Lipschitz continuous)

Example 1

$$f(x) = x^2 - 1 = 0, \quad \text{find } x \ (x^* = 1)$$

$$\frac{df}{dx}(x^k) = 2x^k$$

$$2x^k(x^{k+1} - x^k) = - \left((x^k)^2 - 1 \right)$$

$$2x^k(x^{k+1} - x^*) + 2x^k(x^* - x^k) = - \left((x^k)^2 - (x^*)^2 \right)$$

$$\text{or } (x^{k+1} - x^*) = \frac{1}{2x^k} (x^k - x^*)^2$$

- We see that the convergence is quadratic

Example 2

$$f(x) = x^2 = 0, \quad x^* = 0$$

$$\frac{df}{dx}(x^k) = 2x^k$$

$$\Rightarrow 2x^k(x^{k+1} - 0) = (x^k - 0)^2$$

$$x^{k+1} - 0 = \frac{1}{2}(x^k - 0) \quad \text{for } x^k \neq x^* = 0$$

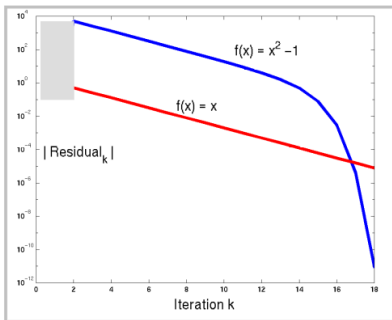
$$\text{or } (x_{k+1} - x^*) = \frac{1}{2}(x_k - x^*)$$

- Note: $\frac{\partial f}{\partial x}^{-1}$ not bounded away from zero
- We see the convergence is linear

Plot

Newton-Raphson Method – Convergence

Example 1,2



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courtesy Alessandra Nardi UCB

Convergence algorithm

Newton-Raphson Method – Convergence

$x^0 =$ Initial Guess, $k = 0$

Repeat {

$$\frac{\partial f(x^k)}{\partial x} (x^{k+1} - x^k) = -f(x^k)$$

$k = k + 1$

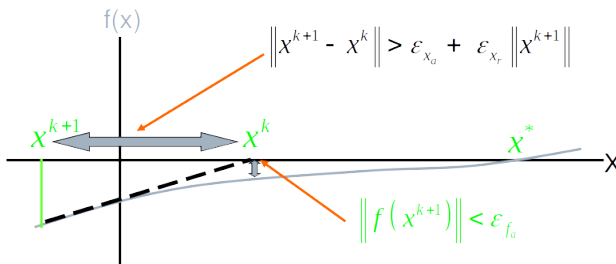
} Until ?

$$\|x^{k+1} - x^k\| < threshold? \quad \|f(x^{k+1})\| < threshold?$$

Newton-Raphson Method – Convergence

Convergence Check

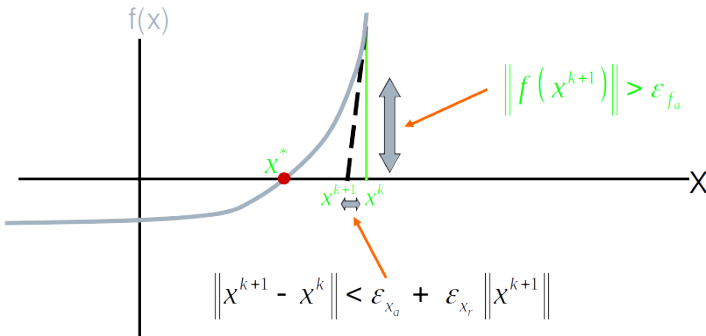
Need a "delta-x" check to avoid false convergence



Newton-Raphson Method – Convergence

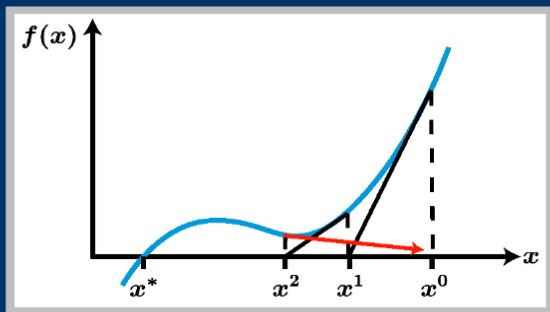
Convergence Check

Also need an " $f(x)$ " check to avoid false convergence



Newton-Raphson Method – Convergence

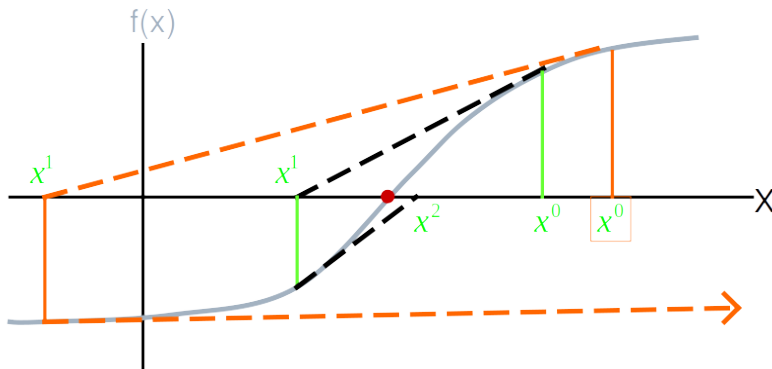
We require that x^0 be “close” to the solution x^*



Newton-Raphson Method – Convergence

Local Convergence

Convergence Depends on a Good Initial Guess

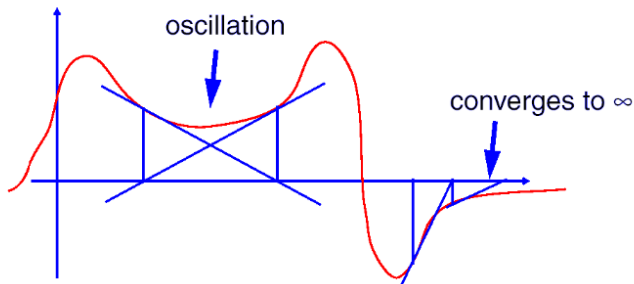


Newton-Raphson Method – Convergence

Local Convergence

Convergence Depends on a Good Initial Guess

Example:



Advantages of Newton Method:

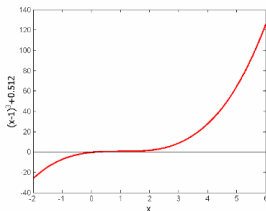
- ▶ Quadratic converges
- ▶ Requires only one guess
- ▶ This is very fast if we are close to a solution
- ▶ Doubles the correct digits in each iteration!

Drawbacks of Newton methods:

- **Divergence at inflection points:** If the initial guess or an iteration value of the root that is close to the inflection point of the function.

Table 1 Divergence near inflection point.

Iteration Number	x_i
0	5.0000
1	3.6560
2	2.7465
3	2.1084
4	1.6000
5	0.92589
6	-30.119
7	-19.746
18	0.2000



Divergence at inflection point for
 $f(x) = (x-1)^3 + 0.512 = 0$

26

Figure: Divergence at inflection points

Drawbacks: Division by zero

► $f(x) = x^3 - 0.03x^2 + 2.4 \times 10^{-6} = 0$

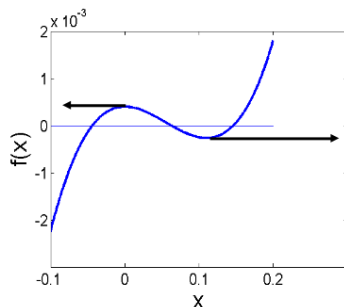


Figure: Pitfall of division by zero or near a zero number

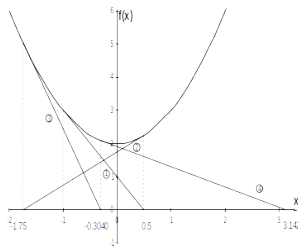
► For $x_0 = 0$ or $x_0 = 0.02$ the denominator will be zero

Drawbacks: Oscillations

- ▶ Oscillations near local maxima and minimum
- ▶ Results may oscillate about the local maximum or minimum without converging on a root but converging on the local maximum or minimum.
- ▶ Leads to division by a number close to zero and may diverge.
- ▶ $f(x) = x^2 + 2 = 0$ has no real roots

Table 2 Oscillations near local maxima and minima

Iteration Number	x_i	$f(x_i)$	$ \epsilon_a \%$
0	-1.0000	3.00	
1	0.5	2.25	300.00
2	-1.75	5.063	128.571
3	-0.30357	2.092	476.47
4	3.1423	11.874	109.66
5	1.2529	3.570	150.80
6	-0.17166	2.029	829.88
7	5.7395	34.942	102.99
8	2.6955	9.266	112.93
9	0.97678	2.954	175.96



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Figure: Oscillations around local minima for $f(x) = x^2 + 2$

Drawbacks: Root jumping

- ▶ In some cases, where the function $f(x)$ is oscillating and has a number of roots, one may choose an initial guess close to a root.
- ▶ However, the guesses may jump and converge to some other root.

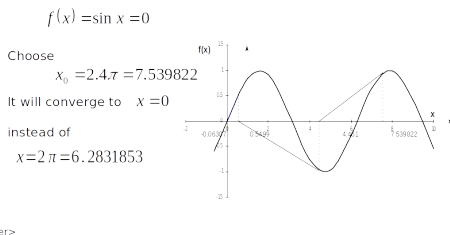


Figure: Root jumping from intended location of root for $f(x) = \sin x$

Theorem

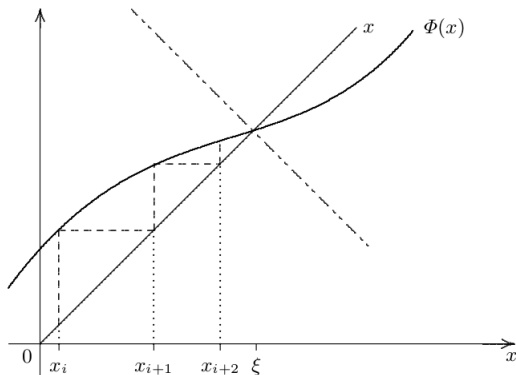
- ▶ Theorem. Let $\Phi : \mathbb{R}^n \rightarrow \mathbb{R}^n$ be an iterative function with fixed point ξ . $U(\xi)$ is a neighbourhood of ξ , a number $p \geq 1$ and a constant $C \geq 0$ (with $C \leq 1$ if $p = 1$) so that for all $x \in U(\xi)$

$$\|\Phi(x) - \xi\| \leq C\|x - \xi\|^p \quad (1)$$

- ▶ Then there is a neighbourhood (subset) $V(\xi) \subset U(\xi)$ of ξ so that for all starting points x_0 the iteration method defined by Φ generates the iteration steps $x_i \in V(\xi) \forall i \geq 0$ that converges to ξ at least with order p

Example

- $E=\mathbb{R}$, Φ is differentiable in a neighbourhood $U(\xi)$ If $0 < \Phi'(\xi) < 1$, then the convergence will be linear (first order), x_i will converge monotonically to ξ



General Convergence Theorem

- ▶ Let the function $\Phi: E \rightarrow E$, $E = \mathbb{R}^n$, have a fixed point ξ : $\Phi(\xi) = \xi$
- ▶ Further let $S_r(\xi) := \{z \mid \|z - \xi\| < r\}$ be a neighbourhood of ξ such that Φ is a contractive mapping in $S_r(\xi)$ that is

$$\|\Phi(x) - \Phi(y)\| \leq K\|x - y\| \quad (2)$$

$0 \leq K < 1$ for all $x, y \in S_r(\xi)$. Then for any $x_0 \in S_r(\xi)$, the generated sequence $x_{i+1} = \Phi(x_i)$, $i = 0, 1, \dots$, has the following properties

- $x_i \in S_r(\xi) \quad \forall i = 0, 1, \dots$,
- $\|x_{i+1} - \xi\| \leq K\|x_i - \xi\| \leq K^{i+1}\|x_0 - \xi\|$ i.e., $\{x_i\}$ converges at least linearly to ξ

Banach Fixed Point Theorem

- Let $\Phi : E \rightarrow E$, $E = \mathbb{R}^n$ be an iterative function, $x_0 \in E$ be a starting point, and $x_{i+1} = \Phi(x_i)$, $i=0,1, \dots$. Further, let a neighbourhood $S_r(x_0) = \{x \mid \|x - x_0\| < r\}$ of x_0 and a constant K where $0 < K < 1$, exist such that

• $\|\Phi(x) - \Phi(y)\| \leq K\|x - y\|$ for all $x, y \in \overline{S_r(x_0)} := \{x \mid \|x - x_0\| \leq r\}$
 • $\|x_1 - x_0\| = \|\Phi(x_0) - x_0\| \leq (1 - K)r < r$

Then it follows that

- $x_i \in S_r(x_0) \forall i = 0, 1, \dots$,
- Φ has exactly one fixed point ξ , $\Phi(\xi) = \xi$, in $\overline{S_r(x_0)}$ and $\lim_{i \rightarrow \infty} x_i = \xi$,
 $\|x_{i+1} - \xi\| \leq K\|x_i - \xi\|$, as well as $\|x_1 - \xi\| \leq \frac{K^i}{1-K}\|x_1 - x_0\|$

Proof of quadratic convergence

Theorem. Assume that f is twice continuously differentiable on an open interval (a, b) and that there exists $x^* \in (a, b)$ with $f'(x^*) \neq 0$. Define Newton's method by the sequence

$$x_{k+1} = x_k - \frac{f(x_k)}{f'(x_k)}, \quad k = 1, 2, \dots$$

Assume also that x_k converges to x^* as $k \rightarrow \infty$. Then, for k sufficiently large,

$$|x_{k+1} - x^*| \leq M|x_k - x^*|^2 \quad \text{if } M > \frac{|f''(x^*)|}{2|f'(x^*)|}.$$

Thus, x_k converges to x^* *quadratically* (A&G, p. 52).

Proof. Let $e_k = x_k - x^*$, so that $x_k - e_k = x^*$. By Taylor's Theorem (A&G, Chap. 1, p. 5), setting $x = x_k$ and $h = -e_k$, we have

$$f(x_k - e_k) = f(x_k) - e_k f'(x_k) + \frac{(e_k)^2}{2} f''(\xi_k)$$

for some ξ_k between x_k and x^* . Since $x_k - e_k = x^*$ and $f(x^*) = 0$, we have

$$0 = f(x_k) - (x_k - x^*)f'(x_k) + \frac{(e_k)^2}{2} f''(\xi_k).$$

Since the derivative of f is continuous with $f'(x^*) \neq 0$, we have $f'(x_k) \neq 0$ as long as x_k is close enough to x^* . So we can divide by $f'(x_k)$ to give

$$0 = \frac{f(x_k)}{f'(x_k)} - (x_k - x^*) + \frac{(e_k)^2 f''(\xi_k)}{2f'(x_k)},$$

which, by the definition of Newton's method, gives

$$x_{k+1} - x^* = \frac{(e_k)^2 f''(\xi_k)}{2f'(x_k)}.$$

So

$$|x_{k+1} - x^*| \leq \frac{|f''(\xi_k)|}{2|f'(x_k)|} |x_k - x^*|^2.$$

By continuity, $f'(x_k)$ converges to $f'(x^*)$ and, since ξ_k is between x_k and x^* , ξ_k converges to x^* and hence $f''(\xi_k)$ converges to $f''(x^*)$, so, for large enough k ,

$$|x_{k+1} - x^*| \leq M|x_k - x^*|^2 \quad \text{if } M > \frac{|f''(x^*)|}{2|f'(x^*)|}.$$

In fact, it can be shown without assuming that x_k converges to x^* , that there exists $\delta > 0$ such that, if $|x_0 - x^*| \leq \delta$, then x_k converges to x^* , and hence from the above argument that the convergence rate is quadratic, but this requires a more complicated argument by induction.

- 1 Minimization Problems
- 2 Global Convergence Definition
- 3 Globalization Schemes
- 4 Conclusions

Minimization Problems

We consider the following minimization problem for a real function $h : \mathbb{R}^n \rightarrow \mathbb{R}$ of n variables

$$\min_x h(x).$$

Definition of Global Convergence

- ▶ The iterative method is called **locally convergent with $V(\bar{x})$** , a neighborhood of \bar{x} , if it generates, for all starting points $x_0 \in V(\bar{x})$, a sequence $\{x_k\}$ that converges to \bar{x} .

[Note that \bar{x} is a minimum point for the function h .]

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- ▶ It is called **globally convergent**, if in addition $V(\bar{x}) = \mathbb{R}^n$.

[Note that \bar{x} is a minimum point for the function h .]

Important Lemma

Let $h : \mathbb{R}^n \rightarrow \mathbb{R}$ be a function which has a continuous derivative $Dh(x)$ for all $x \in V(\bar{x})$.

[Note that $D(\gamma, x) := \{s \in \mathbb{R}^n \mid \|s\| = 1, Dh(x)s \geq \gamma \|Dh(x)\|\}$ and $Dh(x) = \nabla h(x)^T = (\frac{\partial h(x)}{\partial x^1}, \dots, \frac{\partial h(x)}{\partial x^n})$.]

Important Lemma

Let $h : \mathbb{R}^n \rightarrow \mathbb{R}$ be a function which has a continuous derivative $Dh(x)$ for all $x \in V(\bar{x})$.

Suppose further that $Dh(\bar{x}) \neq 0$, and let $1 \geq \gamma > 0$.

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Suppose further that $Dh(\bar{x}) \neq 0$, and let $1 \geq \gamma > 0$.

Then there is a neighborhood $U(\bar{x}) \subseteq V(\bar{x})$ of \bar{x} and a number $\lambda > 0$ such that

$$h(x - \mu s) \leq h(x) - \frac{\mu\gamma}{4} \|Dh(\bar{x})\|$$

for all $x \in U(\bar{x})$, $s \in D(\gamma, x)$ and $0 \leq \mu \leq \lambda$.

[Note that $D(\gamma, x) := \{s \in \mathbb{R}^n \mid \|s\| = 1, Dh(x)s \geq \gamma \|Dh(x)\|\}$ and $Dh(x) = \nabla h(x)^T = (\frac{\partial h(x)}{\partial x^1}, \dots, \frac{\partial h(x)}{\partial x^n})$.]

Globalization Schemes

- ▶ Modified Newton Method with Exact Line Search

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- ▶ Quasi-Newton Method

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- ▶ Modified Newton Method with Exact Line Search
- ▶ Modified Newton Method with Inexact Line Search
- ▶ Quasi-Newton Method
 - BFGS
 - Oren-Luenberger

Modified Newton Method with Exact Line Search

- Choose a starting point $x_0 \in \mathbb{R}^n$.
Choose numbers $\gamma_k \leq 1, \sigma_k, k = 0, 1, \dots$, with
 $\inf_k \gamma_k > 0, \inf_k \sigma_k > 0$.

Modified Newton Method with Exact Line Search

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Choose numbers $\gamma_k \leq 1, \sigma_k, k = 0, 1, \dots$, with $\inf_k \gamma_k > 0, \inf_k \sigma_k > 0$.
- For all $k = 0, 1, \dots$, update

$$x_{k+1} := x_k - \lambda_k s_k$$

where $s_k \in D(\gamma_k, x_k)$, and $\lambda_k \in [0, \sigma_k \|Dh(x_k)\|]$ is such that

$$h(x_{k+1}) = \min_{\mu} \{h(x_k - \mu s_k) : 0 \leq \mu \leq \sigma_k \|Dh(x_k)\|\}.$$

Global Convergence Results for Modified Newton Method with Exact Line Search

- $K := \{x | h(x) \leq h(x_0)\}$ is compact , and
- h is continuously differentiable in some open set containing K .

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Global Convergence Results for Modified Newton Method with Exact Line Search

- ⊖ $K := \{x | h(x) \leq h(x_0)\}$ is compact, and
- ⊖ h is continuously differentiable in some open set containing K .

Then for any sequence $\{x_k\}$ defined by this method:

- ⊖ $x_k \in K$ for all $k = 0, 1, \dots$. The sequence $\{x_k\}$ has at least one accumulation point \bar{x} in K .
- ⊖ Each accumulation point \bar{x} of $\{x_k\}$ is a stationary point of h :

$$Dh(\bar{x}) = 0.$$

Proof for the Method with Exact Line Search: 1

From the definition of the sequence $\{x_k\}$ we have that the sequence $\{h(x_k)\}$ is monotone, i.e., $h(x_0) \geq h(x_1) \geq \dots$. Hence, $x_k \in K$ for all k . K is compact; therefore, the sequence $\{x_k\}$ has at least one accumulation point $\bar{x} \in K$.

Proof for the Method with Exact Line Search: 2-(1)

Assume that \bar{x} is an accumulation point of $\{x_k\}$ but is not a stationary point of h :

$$Dh(\bar{x}) \neq 0. \quad (3)$$

WLOG, let $\lim_{k \rightarrow \infty} x_k = \bar{x}$.

According to the important lemma, there is a neighborhood $U(\bar{x})$ and a number $\lambda \geq 0$ satisfying

$$h(x - \mu s) \leq h(x) - \mu \frac{\gamma}{4} \|Dh(\bar{x})\| \quad (4)$$

for all $x \in U(\bar{x})$, $s \in D(\gamma, x)$, and $0 \leq \mu \leq \lambda$.

Since $\lim_{k \rightarrow \infty} x_k = \bar{x}$, the continuity of $Dh(x)$ together with (3) implies there is k_0 such that for all $k \geq k_0$, $x_k \in U(\bar{x})$ and $\|Dh(x_k)\| \geq \frac{1}{2} \|Dh(\bar{x})\|$.

Proof for the Method with Exact Line Search: 2-(2)

Let $\Lambda := \min\{\lambda, \frac{1}{2}\sigma\|Dh(\bar{x})\|, \epsilon := \Lambda\frac{\gamma}{4}\|Dh(\bar{x})\|\}$.

Since $\Lambda \leq \lambda, x_k \in U(\bar{x}), s_k \in D(\gamma_k, x_k)$, (4) implies that

$$h(x_{k+1}) \leq h(x_k) - \Lambda\frac{\gamma}{4}\|Dh(\bar{x})\| = h(x_k) - \epsilon \text{ for all } k \geq k_0.$$

This means that $\lim_{k \rightarrow \infty} h(x_k) = -\infty$, which contradicts the fact that

$$h(x_k) \geq h(\bar{x}) \text{ for all } k. \text{ Hence, } \bar{x} \text{ is a stationary point of } h.$$

Modified Newton Method with Inexact Line Search

- el= Choose a starting point $x_0 \in \mathbb{R}^n$.
 Choose numbers $\gamma_k \leq 1, \sigma_k, k = 0, 1, \dots$, with
 $\inf_k \gamma_k > 0, \inf_k \sigma_k > 0$.
- el= For all $k = 0, 1, \dots$, obtain x_{k+1} from x_k as follows:
 - el= Select $s_k \in D(\gamma_k, x_k)$.
 Define $\rho_k := \sigma_k \|Dh(x_k)\|$, $h_k(\mu) := h(x_k - \mu s_k)$.
 Then, determine the smallest integer $j \geq 0$ such that

$$h_k(\rho_k 2^{-j}) \leq h_k(0) - \rho_k 2^{-j} \frac{\gamma_k}{4} \|Dh(x_k)\|.$$
 - el= Determine $\bar{i} \in \{0, 1, \dots, j\}$ such that $h_k(\rho_k 2^{-\bar{i}})$ is minimum and let

$$\lambda_k := \rho_k 2^{-\bar{i}}.$$
 - Then, update $x_{k+1} := x_k - \lambda_k s_k$.

[Note that $h(x_{k+1}) = \min_{1 \leq i \leq j} h_k(\rho_k 2^{-i}).$]

Global Convergence Results for Modified Newton Method with Inexact Line Search

- ⊖ $K := \{x | h(x) \leq h(x_0)\}$ is compact, and
- ⊖ h is continuously differentiable in some open set containing K .

Then for any sequence $\{x_k\}$ defined by this method:

- ⊖ $x_k \in K$ for all $k = 0, 1, \dots$. The sequence $\{x_k\}$ has at least one accumulation point \bar{x} in K .
- ⊖ Each accumulation point \bar{x} of $\{x_k\}$ is a stationary point of h :

$$Dh(\bar{x}) = 0.$$

Proof for the Method with Inexact Line Search: 1

From the definition of the sequence $\{x_k\}$ we have that the sequence $\{h(x_k)\}$ is monotone, i.e., $h(x_0) \geq h(x_1) \geq \dots$. Hence, $x_k \in K$ for all k . K is compact; therefore, the sequence $\{x_k\}$ has at least one accumulation point $\bar{x} \in K$.

Proof for the Method with Inexact Line Search: 2

Again, we will prove the second result by **a contradiction**, which is similar to the previous proof in the section of exact line search. Assume that \bar{x} is an accumulation point of a sequence $\{x_k\}$ but not a stationary point of h , i.e.,

$$Dh(\bar{x}) \neq 0.$$

By the important lemma and the hypotheses of the global convergence results, we can show that there is an $\epsilon \geq 0$ for which

$$h(x_{k+1}) \leq h(x_k) - \epsilon$$

for all $k > k_0$. This contradicts the fact that $h(x_k) \geq h(\bar{x})$ for all k .

Therefore, \bar{x} is **a stationary point** of h .

Quasi-Newton Methods

- Choose a starting point $x_0 \in \mathbb{R}^n$ and an $n \times n$ positive definite matrix H_0 . Set $g_0 := g(x_0)$.
- For $k = 0, 1, \dots$ obtain x_{k+1}, H_{k+1} from x_k, H_k as follows:
 - if $g_k = 0$, stop: x_k is a stationary point for h . Otherwise
 - compute $s_k := H_k g_k (\approx H(x_k)^{-1} g_k)$.
 - Update $x_{k+1} = x_k - \lambda_k s_k$ by means of a minimization

$$h(x_{k+1}) \approx \min\{h(x_k - \lambda s_k) \mid \lambda \geq 0\},$$

$$g_{k+1} := g(x_{k+1}), p_k := x_{k+1} - x_k, q_k := g_{k+1} - g_k.$$

- Choose suitable parameters $\gamma_k > 0, \theta_k \geq 0$, and compute $H_{k+1} = \psi(\theta_k, \gamma_k H_k, p_k, q_k)$ where

$$\begin{aligned} \psi(\theta, H, p, q) := & H + (1 + \theta \frac{q^T H q}{p^T q}) \frac{p p^T}{p^T q} \\ & - \frac{(1 - \theta)}{q^T H q} H q \cdot q^T H - \frac{\theta}{p^T q} (p q^T H + H q p^T). \end{aligned}$$

Global Convergence Results for Quasi-Newton Method (BFGS)



$H(\bar{x})$ is positive definite.

[Note that $H(x) := (\frac{\partial^2 h(x)}{\partial x^i \partial x^k})_{i,k=1,\dots,n}$]

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- Given constants $0 < c_1 < c_2 < 1, c_1 \leq \frac{1}{2}$, $x_{k+1} = x_k - \lambda_k s_k$ is chosen so that

$$h(x_{k+1}) \leq h(x_k) - c_1 \lambda_k g_k^T s_k,$$

$$g_{k+1}^T s_k \leq c_2 g_k^T s_k.$$

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Powell (1975) was able to show that $\exists V(\bar{x}) \subseteq U(\bar{x})$ such that the BFGS method is **superlinearly convergent** for all positive definite matrices H_0 and all $x_0 \in V(\bar{x})$. [Note that $H(x) := (\frac{\partial^2 h(x)}{\partial x^i \partial x^k})_{i,k=1,\dots,n}$]

Global Convergence Results for Quasi-Newton Method (A Subclass of Oren-Luenberger)

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It can be shown Stoer (1977) that for all $k \geq 0$

$$\lim_k x_k = \bar{x}$$

$$\|x_{k+n} - \bar{x}\| \leq \gamma \|x_k - \bar{x}\|^2$$

for all positive definite initial matrices H_0 and for $\|x_0 - \bar{x}\|$ small enough

Conclusions for Local- and Global- Properties of Newton Methods

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Conclusions for Local- and Global- Properties of Newton Methods

- ⌚ If a starting point x_0 is chosen sufficiently close to the optimum point \bar{x} , under certain assumptions the sequence $\{x_n\}$ generated by Newton's method is at least locally convergent.
- ⌚ Under certain conditions, the global convergence of Newton's method can be obtained by finding parameters λ_k and search directions s_k for the following update, $x_{k+1} = x_k - \lambda_k s_k$.

Reference

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Thank you very much for your attention.

Do you have any question?