

# Newton's Method

## Equation Solving

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Newton's Approach:

Given an approximate solution  $x_0 \in \mathbf{E}$  to  $\mathcal{E}$  and wishes to improve upon it. If  $\bar{x}$  is an actual solution to  $\mathcal{E}$ , then

$$0 = g(\bar{x}) = g(x_0) + g'(x_0)(\bar{x} - x_0) + o\|\bar{x} - x_0\|.$$

Thus, if  $x_0$  is “close” to  $\bar{x}$ , it is reasonable to suppose that the solution to the linearized system

$$0 = g(x_0) + g'(x_0)(x - x_0)$$

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To implement Newton's method we need conditions under which solving this equation is meaningful. In particular, we assume that  $g'(x_0)$  is nonsingular.

# Newton and Newton Like Iterations

The Newton iteration:

$$x_{k+1} := x_k - [g'(x_k)]^{-1}g(x_k).$$

The associated search direction

$$d := -[g'(x_k)]^{-1}g(x_k).$$

is called the Newton direction.

We analyze the convergence behavior of this scheme under the additional assumption that only an approximation to  $g'(x_k)$  is available.

Denote the approximation to  $g'(x_k)$  by  $J_k$ . The Newton-Like iteration scheme:

$$x_{k+1} := x_k - J_k^{-1}g(x_k).$$

# Convergence of Newton's Method

**Theorem:** Let  $g : \mathbf{R}^n \rightarrow \mathbf{R}^n$  be differentiable,  $x_0 \in \mathbf{R}^n$ , and  $J_0 \in \mathbf{R}^{n \times n}$ . Suppose that there exists  $\bar{x}$ ,  $x_0 \in \mathbf{R}^n$ , and  $\epsilon > 0$  with  $\|x_0 - \bar{x}\| < \epsilon$  such that

1.  $g(\bar{x}) = 0$ ,
2.  $g'(x)^{-1}$  exists for  $x \in B(\bar{x}; \epsilon)$  with

$$\sup\{\|g'(x)^{-1}\| : x \in B(\bar{x}; \epsilon)\} \leq M_1$$

3.  $g'$  is Lipschitz continuous on  $clB(\bar{x}; \epsilon)$  with Lipschitz constant  $L$ , and
4.  $\theta_0 := \frac{LM_1}{2}\|x_0 - \bar{x}\| + M_0K < 1$  where  $K \geq \|(g'(x_0)^{-1} - J_0^{-1})y^0\|$ ,  $y^0 := g(x^0)/\|g(x^0)\|$ , and  $M_0 = \max\{\|g'(x)\| : x \in B(\bar{x}; \epsilon)\}$ .

# Convergence of Newton's Method

Further suppose that iteration  $x_{k+1} := x_k - J_k^{-1}g(x_k)$  is initiated at  $x_0$  where the  $J_k$ 's are chosen to satisfy one of the following conditions;

- (i)  $\|(g'(x_k))^{-1} - J_k^{-1})y_k\| \leq K$ ,
- (ii)  $\|(g'(x_k))^{-1} - J_k^{-1})y_k\| \leq \theta_1^k K$  for some  $\theta_1 \in (0, 1)$ ,
- (iii)  $\|(g'(x_k))^{-1} - J_k^{-1})y_k\| \leq \min\{M_2\|x_k - x_{k-1}\|, K\}$ , for some  $M_2 > 0$ , or
- (iv)  $\|(g'(x_k))^{-1} - J_k^{-1})y_k\| \leq \min\{M_2\|g(x_k)\|, K\}$ , for some  $M_3 > 0$ ,

where for each  $k = 1, 2, \dots$ ,  $y_k := g(x_k) / \|g(x_k)\|$ .

# Convergence of Newton's Method

These hypotheses on the accuracy of the approximations  $J_k$  yield the following conclusions about the rate of convergence of the iterates  $x_k$ .

- (a) If (i) holds, then  $x_k \rightarrow \bar{x}$  linearly.
- (b) If (ii) holds, then  $x_k \rightarrow \bar{x}$  superlinearly.
- (c) If (iii) holds, then  $x_k \rightarrow \bar{x}$  two step quadratically.
- (d) If (iv) holds, then  $x_i \rightarrow \bar{x}$  quadratically.

# Convergence of Newton's Method

**Proof:** We begin by establishing the basic inequalities

$$(\star) \quad \|x_{k+1} - \bar{x}\| \leq \frac{LM_1}{2} \|x_k - \bar{x}\|^2 + \|(g'(x_k)^{-1} - J_k^{-1})g(x_k)\|,$$

and

$$(\star\star) \quad \|x_{k+1} - \bar{x}\| \leq \theta_0 \|x_k - \bar{x}\|$$

and the inclusion  $x_{k+1} \in B(\bar{x}; \epsilon)$  by induction on  $k$ . For  $k = 0$  we have

$$\begin{aligned} x_1 - \bar{x} &= x_0 - \bar{x} - g'(x_0)^{-1}g(x_0) + [g'(x_0)^{-1} - J_0^{-1}]g(x_0) \\ &= g'(x_0)^{-1}[g(\bar{x}) - (g(x_0) + g'(x_0)(\bar{x} - x_0))] \\ &\quad + [g'(x_0)^{-1} - J_0^{-1}]g(x_0), \end{aligned}$$

since  $g'(x_0)^{-1}$  exists by the hypotheses. Consequently, the hypotheses (1)–(4) plus the quadratic bound lemma imply that

$$\begin{aligned} \|x_{k+1} - \bar{x}\| &\leq \|g'(x_0)^{-1}\| \|g(\bar{x}) - (g(x_0) + g'(x_0)(\bar{x} - x_0))\| \\ &\quad + \|(g'(x_0)^{-1} - J_0^{-1})g(x_0)\| \end{aligned}$$

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$$\begin{aligned}\|x_{k+1} - \bar{x}\| &\leq \|g'(x_0)^{-1}\| \|g(\bar{x}) - (g(x_0) + g'(x_0)(\bar{x} - x_0))\| \\ &\quad + \|(g'(x_0)^{-1} - J_0^{-1})g(x_0)\| \\ &\leq \frac{M_1 L}{2} \|x_0 - \bar{x}\|^2 + K \|g(x_0) - g(\bar{x})\| \\ &\leq \frac{M_1 L}{2} \|x_0 - \bar{x}\|^2 + M_0 K \|x_0 - \bar{x}\| \\ &\leq \theta_0 \|x_0 - \bar{x}\| < \epsilon,\end{aligned}$$

whereby the induction is established for  $k = 0$ .

# Convergence of Newton's Method

Next suppose that the induction hypothesis holds for  $k = 0, 1, \dots, s - 1$ . We show that it holds at  $k = s$ . Since  $x_s \in B(\bar{x}, \epsilon)$ , hypotheses (2)–(4) hold at  $x_s$ , one can proceed exactly as in the case  $k = 0$  to obtain  $(\star)$ . Now if any one of (i)–(iv) holds, then (i) holds. Thus, by  $(\star)$ , we find that

$$\begin{aligned}\|x_{s+1} - \bar{x}\| &\leq \frac{M_1 L}{2} \|x_s - \bar{x}\|^2 + \|(g'(x_s)^{-1} - J_s^{-1})g(x_s)\| \\ &\leq \left[\frac{M_1 L}{2} \theta_0^s \|x_0 - \bar{x}\| + M_0 K\right] \|x_s - \bar{x}\| \\ &\leq \left[\frac{M_1 L}{2} \|x_0 - \bar{x}\| + M_0 K\right] \|x_s - \bar{x}\| \\ &= \theta_0 \|x_s - \bar{x}\|.\end{aligned}$$

Hence  $\|x_{s+1} - \bar{x}\| \leq \theta_0 \|x_s - \bar{x}\| \leq \theta_0 \epsilon < \epsilon$  and so  $x_{s+1} \in B(\bar{x}, \epsilon)$ .

# Convergence of Newton's Method

(a) If  $\|(g'(x_k)^{-1} - J_k^{-1})y_k\| \leq K$  holds, then  $x_k \rightarrow \bar{x}$  linearly.

(b) If  $\|(g'(x_k)^{-1} - J_k^{-1})y_k\| \leq \theta_1^k K$  for some  $\theta_1 \in (0, 1)$  holds, then  $x_k \rightarrow \bar{x}$  superlinearly.

**Proof:**

$$\begin{aligned}\|x_{k+1} - \bar{x}\| &\leq \frac{LM_1}{2} \|x_k - \bar{x}\|^2 + \|(g'(x_k)^{-1} - J_k^{-1})g(x_k)\| \\ &\leq \frac{LM_1}{2} \|x_k - \bar{x}\|^2 + \theta_1^k K \|g(x_k)\| \\ &\leq \left[ \frac{LM_1}{2} \theta_0^k \|x_0 - \bar{x}\| + \theta_1^k M_0 K \right] \|x_k - \bar{x}\|\end{aligned}$$

Hence  $x_k \rightarrow \bar{x}$  superlinearly.

# Convergence of Newton's Method

(d) If  $\|(g'(x_k)^{-1} - J_k^{-1})y_k\| \leq \min\{M_2\|g(x_k)\|, K\}$ , for some  $M_3 > 0$  holds, then  $x_k \rightarrow \bar{x}$  quadratically.

**Proof:** Again by  $(\star)$  and the fact that  $x_k \rightarrow \bar{x}$ , we eventually have

$$\begin{aligned}\|x_{k+1} - \bar{x}\| &\leq \frac{LM_1}{2} \|x_k - \bar{x}\|^2 + \|(g'(x_k)^{-1} - J_k^{-1})g(x_k)\| \\ &\leq \frac{LM_1}{2} \|x_k - \bar{x}\|^2 + M_2 \|g(x_k)\|^2 \\ &\leq \left[\frac{LM_1}{2} + M_2 M_0^2\right] \|x_k - \bar{x}\|^2 .\end{aligned}$$

# Newton's Method for Minimization

**Theorem:** Let  $f : \mathbf{R}^n \rightarrow \mathbf{R}$  be twice differentiable,  $x_0 \in \mathbf{R}^n$ , and  $H_0 \in \mathbf{R}^{n \times n}$ . Suppose that

1. there exists  $\bar{x} \in \mathbf{R}^n$  and  $\epsilon > \|x_0 - \bar{x}\|$  such that  $f(\bar{x}) \leq f(x)$  whenever  $\|x - \bar{x}\| \leq \epsilon$ ,
2. there is a  $\delta > 0$  such that  $\delta \|z\|_2^2 \leq z^T \nabla^2 f(x) z$  for all  $x \in B(\bar{x}, \epsilon)$ ,
3.  $\nabla^2 f$  is Lipschitz continuous on  $\text{cl } B(\bar{x}, \epsilon)$  with Lipschitz constant  $L$ , and
4.  $\theta_0 := \frac{L}{2\delta} \|x_0 - \bar{x}\| + M_0 K < 1$  where  $M_0 > 0$  satisfies  $z^T \nabla^2 f(x) z \leq M_0 \|z\|_2^2$  for all  $x \in B(\bar{x}, \epsilon)$  and  $K \geq \|(\nabla^2 f(x_0))^{-1} - H_0^{-1}\| y^0$  with  $y^0 = \nabla f(x_0) / \|\nabla f(x_0)\|$ .

# Newton's Method for Minimization

Further, suppose that the iteration

$$x_{k+1} := x_k - H_k^{-1} \nabla f(x_k)$$

is initiated at  $x_0$  where the  $H_k$ 's are chosen to satisfy one of the following conditions:

- (i)  $\|(\nabla^2 f(x_k)^{-1} - H_k^{-1})y_k\| \leq K$ ,
- (ii)  $\|(\nabla^2 f(x_k)^{-1} - H_k^{-1})y_k\| \leq \theta_1^k K$  for some  $\theta_1 \in (0, 1)$ ,
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where for each  $k = 1, 2, \dots$   $y_k := \nabla f(x_k) / \|\nabla f(x_k)\|$ .

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## Newton's Method: Example

Let  $f(x) = x^2 + e^x$ . Then  $f'(x) = 2x + e^x$ ,  $f''(x) = 2 + e^x$ ,  
 $f'''(x) = e^x$ . Given  $x_0 = 1$  we may take  $L = 2$ ,  $M_0 = 4$ , and  $M_1 = \frac{1}{2}$ .  
Hence the pure Newton strategy should converge to  $\bar{x} \approx -0.3517337$   
with

$$\|x_k - \bar{x}\| \leq 2(.676)^{2^k}.$$

The actual iterates are given in the following table.

$x$	$f'(x)$
1	4.7182818
0	1
-1/3	.0498646
-.3516893	.00012
-.3517337	.00000000064

# Convergence of Steepest Descent with Backtracking

$K$	$X$	$f(x)$	$f'(x)$	$s$
0	1	.37182818	4.7182818	0
1	0	1	1	0
2	-.5	.8565307	-0.3934693	1
3	-.25	.8413008	0.2788008	2
4	-.375	.8279143	-.0627107	3
5	-.34075	.8273473	.0297367	5
6	-.356375	.8272131	-.01254	6
7	-.3485625	.8271976	.0085768	7
8	-.3524688	.8271848	-.001987	8
9	-.3514922	.8271841	.0006528	10
10	-.3517364	.827184	-.0000072	12