Nonlinear Equations

1 Introduction

In applications we usually need to find several unknown values x_1, \ldots, x_n . We have *n* equations for x_1, \ldots, x_n

$$f_1(x_1,\ldots,x_n) = 0$$

$$\vdots$$

$$f_n(x_1,\ldots,x_n) = 0$$

and we want to find the solutions.

In many cases the problem can be (approximatively) described by **linear equations**. In this case we have *n* linear equations for *n* unknowns. We will get a unique solution if the matrix is nonsingular. **Example** with n = 2: Find x_1, x_2 such that

zero contours of f, (red) and f, (green)



Here we have one solution $\begin{bmatrix} x_1 \\ x_2 \end{bmatrix} = \begin{bmatrix} \frac{1}{3} \\ \frac{1}{3} \end{bmatrix}$ which is the intersection of the red and the green line.

In other cases the problem is nonlinear, and we obtain *n* nonlinear equations.

Example with n = 2: Find x_1, x_2 such that



[%] Define function f
% Find solution near [0;0]

2 One nonlinear equation

2.1 Introduction

2.2 Bisection Method

Assume that the function f is continuous. If we have two function values f(a), f(b) with opposite signs then the intermediate value theorem guarantees that there must be a point $x_* \in (a,b)$ with $f(x_*) = 0$. This motivates the bisection method:

Algorithm: Bisection method

The algorithm gives a sequence of intervals $[a_k, b_k]$. There exists a solution x_* with

- Initial guesses a_0, b_0 where $f(a_0)$ and $f(b_0)$ have different signs
- For k = 0, 1, 2, ...: $c_k := (a_k + b_k)/2$ If $f(c_k), f(a_k)$ have different sign: $[a_{k+1}, b_{k+1}] := [a_k, c_k]$ If $f(c_k), f(a_k)$ have same sign: $[a_{k+1}, b_{k+1}] := [c_k, b_k]$ If $f(c_k) = 0$: stop

Theorem 2.1. Assume that the function f is continuous on $[a_0, b_0]$. If $f(a_0)$ and $f(b_0)$ have different sign, then the bisection method converges:

$$\lim_{k \to \infty} a_k = \lim_{k \to \infty} b_k = x_* \quad \text{with } f(x_*) = 0.$$

Note that the midpoint c_k satisfies $|c_k - x_*| \le (b_k - a_k)/2$, therefore we have decreasing error bounds E_k

$$|c_k - x_*| \le E_k, \qquad E_{k+1} = \frac{1}{2}E_k$$

If we have error bounds E_k with $E_{k+1} \leq C \cdot E_k$ (where C < 1) we say we have **convergence of order 1**.

2.3 Secant Method

Assume that we have two function values f(a) and f(b). Based on this information we want to find a good guess *c* for the solution x_* : We can approximate f(x) by the linear interpolation

$$p(x) = f(b) + f[a,b](x-b)$$

where $f[a,b] = \frac{f(b)-f(a)}{b-a}$. Then we find c such that p(c) = 0: Solving f(b) + f[a,b](c-b) = 0 for c gives

$$c = b - f(b)/f[a,b].$$

If we have two initial guesses x_0, x_1 we can use this to find an improved guess x_2 . Using x_1, x_2 we find x_3 , etc.

Algorithm: Secant Method

- Initial guesses x_0, x_1
- For k = 1, 2, 3, ...: $x_{k+1} := x_k - f(x_k) / f[x_{k-1}, x_k]$

During the algorithm we have $a = x_{k-1}$ and $b = x_k$. We then compute $c = x_{k+1}$ using the secant. We want to show that the new error $|c - x_*|$ is small:

From the interpolation error we know that

$$f(x_*) - p(x_*) = R(x_*), \qquad R(x_*) = \frac{1}{2}f''(t) \cdot (x_* - a)(x_* - b)$$

(where *t* is somewhere between a, b, x_*). If $|f''(t)| \le C_2$ we have $|R(x_*)| \le \frac{C_2}{2} |x_* - a| \cdot |x_* - b|$. Note that $f(x_*) = 0 = p(c)$. Hence

$$\underbrace{p(c) - p(x_*)}_{f[a,b] \cdot (c-x_*)} = R(x_*)$$

since p(x) is a linear function with slope f[a,b]. Therefore

$$c - x_* = \frac{R(x_*)}{f[a,b]}$$

We have f[a,b] = f'(s) with $s \in [a,b]$. If $|f'(s)| \ge C_1 > 0$ we therefore have with $D := \frac{C_2}{2C_1}$

$$c - x_* | \le D |a - x_*| \cdot |b - x_*|$$
(1)

Since $a = x_{k-1}$, $b = x_k$, $c = x_{k+1}$ we obtain

$$|x_{k+1} - x_*| \le D |x_{k-1} - x_*| \cdot |x_k - x_*|$$

Let $e_k := D |x_k - x_*|$. Multiplying by *D* gives

$$e_{k+1} \leq e_{k-1}e_k.$$

Now assume that

$$e_0 \leq q, \quad e_1 \leq q \qquad ext{with } q < 1$$

Then we obtain

$$e_0 \le q^1, \quad e_1 \le q^2, \quad e_2 \le q^3, \quad e_3 \le q^5, \quad \dots \quad e_k \le q^{F_k}$$

with the **Fibonacci number** F_k (defined by $F_0 = 1$, $F_1 = 1$, $F_{k+1} = F_k + F_{k-1}$). Since q < 1 and $F_k \to \infty$ for $k \to \infty$ we obtain convergence $e_k = D \cdot |x_k - x_*| \to 0$ if our assumptions

$$|f''(t)| \le C_2, \qquad |f'(t)| \ge C_1 > 0$$
 (2)

are satisfied. The order of convergence corresponds to the ratio F_k/F_{k-1} which converges to the golden ratio $\frac{\sqrt{5}+1}{2}$.

Theorem 2.2. Assume that $f(x_*) = 0$ and

- f'(x) and f''(x) exist and are continuous near x_*
- $f'(x_*) \neq 0$.

Then there exists $\delta > 0$, C > 0 such that for $|x_0 - x_*| \le \delta$, $|x_1 - x_*| \le \delta$ we have

- $\lim_{k \to \infty} x_k = x_*$ (convergence)
- $|x_k x_*| \le E_k$ and $E_{k+1} \le CE_k^{\alpha}$ with $\alpha = \frac{\sqrt{5}+1}{2}$ (convergence with order $\alpha > 1$)

Proof. Pick $\varepsilon > 0$ such that on the interval $B_{\varepsilon} = [x_* - \varepsilon, x_* + \varepsilon]$ we have that f'(x) > 0 and f'' is continuous:

For
$$x \in B_{\varepsilon}$$
: $|f'(x)| \ge C_1 > 0, \quad |f''(x)| \le C_2$ (3)

with some constants C_1, C_2 . Let $D = \frac{C_2}{2C_1}$. Pick q < 1 such that $\delta := q/D \le \varepsilon$. Now assume $|x_{k-1} - x_*| \le \delta$, $|x_k - x_*| \le \delta$. Since $\delta \le \varepsilon$ we have $x_{k-1}, x_k, x_* \in B_{\varepsilon}$. We now have

$$|x_{k+1} - x_*| = \frac{|f''(t)|}{2|f'(s)|} |x_k - x_*| \cdot |x_{k-1} - x_*|$$

where the intermediate points *s*,*t* are located between x_0, x_1, x_* . Hence we have $s, t \in B_{\varepsilon}$ and (3) gives

$$|x_{k+1} - x_*| \le D |x_k - x_*| \cdot |x_{k-1} - x_*| \le \underbrace{D\delta}_{q < 1} \cdot \delta < \delta$$

so that we also have $|x_{k+1} - x_*| \leq \delta$.

Therefore we obtain by induction that $|x_k - x_*| \le \delta$ for k = 0, 1, 2, ..., and that

$$|x_{k+1} - x_*| \le D |x_k - x_*| \cdot |x_{k-1} - x_*|$$

As we saw above, this implies that $e_k := D|x_k - x_*|$ satisfies $e_k \le q^{F_k}$ where F_k are the Fibonacci numbers. Since q < 1 and $F_k \to \infty$ we obtain convergence $\lim_{k\to\infty} x_k = x_*$.

It remains to prove convergence of order $\alpha = \frac{\sqrt{5}+1}{2}$: We have shown $e_k \leq \tilde{E}_k := q^{F_k}$. Since the Fibonacci numbers satisfy $F_{k+1} - \alpha F_k = (1-\alpha)^{k+1}$ we have

$$egin{aligned} & F_{k+1} \geq lpha F_k - 1 \ \Rightarrow & q^{F_{k+1}} \leq q^{lpha F_k} \cdot q^{-1} \ \Rightarrow & ilde{E}_{k+1} \leq ilde{E}_k^{lpha} \cdot q^{-1} \end{aligned}$$

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2.4 Newton Method

For the secant method we used the interpolating polynomial with the nodes a, b. Now assume that a = b, and that we know f(a) and f'(a). We can approximate f(x) by the linear interpolation

$$p(x) = f(a) + f[a,a](x-a)$$

where f[a,a] = f'(a). Then we find c such that p(c) = 0: Solving f(a) + f[a,a](c-a) = 0 for c gives

c = b - f(a) / f[a, a].

If we have an initial guesses x_0 we can use this to find an improved guess x_1 , etc.:

Algorithm: Newton Method

- Initial guess x_0
- For k = 1, 2, 3, ...: $x_{k+1} := x_k - f(x_k) / f[x_{k-1}, x_k]$

For the errors we obtain from (1) with $a = b = x_k$, $c = x_{k+1}$ that

$$|x_{k+1} - x_*| \le D |x_k - x_*|^2$$

if the assumptions (2) hold. Multiplying this by D gives with $e_k := D |x_k - x_*|$ that

$$e_{k+1} \leq e_k^2$$

If $e_0 \le q < 1$ we therefore obtain $e_1 \le q^2$, $e_2 \le q^4$, $e_3 \le q^8$,...

$$e_k \leq q^{(2^k)}$$

This means that the error converges to zero as $k \to \infty$, and we obtain the following theorem:

Theorem 2.3. Assume that $f(x_*) = 0$ and

• f'(x) and f''(x) exist and are continuous near x_*

• $f'(x_*) \neq 0$.

Then there exists $\delta > 0$, C > 0 such that for $|x_0 - x_*| \le \delta$ we have

- $\lim_{k \to \infty} x_k = x_*$ (convergence)
- $|x_{k+1}-x_*| \leq C |x_k-x_*|^2$ (convergence of order 2)

Proof. Exactly like the proof of Theorem 2.2.

3 Nonlinear system

We have *n* nonlinear equations $f_1(x_1,...,x_n) = 0,...,f_n(x_1,...,x_n) = 0$. We define the vector-valued function f(x) as

$$f(x) = \begin{bmatrix} f_1(x_1, \dots, x_n) \\ \vdots \\ f_n(x_1, \dots, x_n) \end{bmatrix}$$

The Jacobian f'(x) (often denoted by Df(x)) is the $n \times n$ matrix of first partial derivatives

$$f'(x) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & & \vdots \\ \frac{\partial f_n}{\partial x_1} & \cdots & \frac{\partial f_n}{\partial x_n} \end{bmatrix}$$

Then Taylor's theorem for functions $g(x_1, \ldots, x_n)$ gives that

$$f(x) = \underbrace{f(x^{(0)}) + f'(x^{(0)})(x - x^{(0)})}_{p(x)} + R(x)$$

We assume that the second order partial derivatives $\frac{\partial^2 f_i}{\partial x_j \partial x_k}(x)$ exist and are continuos. Then the remainder term R(x) = f(x) - p(x) satisfies

$$\|R(x)\|_{\infty} \le C \left\|x - x^{(0)}\right\|_{\infty}^{2}$$

If $\left|\frac{\partial^2 f_i}{\partial x_j \partial x_k}(x)\right| \le c_2$ for $i, j, k = 1, \dots, n$ we obtain $C = n^2 c_2$.

We start with an initial guess $x^{(0)}$. Then we approximate the function f(x) by the Taylor approximation $p(x) = b + A(x - x^{(0)})$ with $b := f(x^{(0)})$ and $A := f'(x^{(0)})$. Instead of $f(x) = \vec{0}$ we solve solve $p(x) = \vec{0}$ as follows: Let $d = x - x^{(0)}$, solve the linear system Ad = -b, then let $x^{(1)} := x^{(0)} + d$.

Algorithm: Newton Method

- Initial guess $x^{(0)}$
- For k = 0, 1, 2, ...: $b := f(x^{(k)})$ $A := f'(x^{(k)})$ solve Ad = -b for d (use Gaussian elimination with pivoting) $x^{(k+1)} := x^{(k)} + d$

Let us investigate the errors. For $p(x) = f(x^{(k)}) + f'(x^{(k)})(x - x^{(k)})$ Taylor's theorem gives for $x = x^*$

$$f(x^*) - p(x^*) = R(x^*)$$

Since $f(x^*) = \vec{0} = p(x^{(k+1)})$ we get

$$p(x^{(k+1)}) - p(x^*) = R(x^*)$$

From $p(x) = b + A(x - x^{(0)})$ we get $p(x^{(k+1)}) - p(x^*) = A(x^{(k+1)} - x^*)$ so that

$$\begin{aligned} x^{(k+1)} - x^* &= A^{-1}R(x^*) \\ \left\| x^{(k+1)} - x^* \right\| &\le \left\| A^{-1} \right\| \left\| R(x^*) \right\| \\ \left\| x^{(k+1)} - x^* \right\| &\le \left\| A^{-1} \right\| C \left\| x^{(k)} - x^* \right\|^2 \end{aligned}$$

If we have $||f'(x)^{-1}|| \le c_1$ and $\left|\frac{\partial^2 f_i(x)}{\partial x_j \partial x_k}\right| \le c_2$ we get $C_2 = n^2 c_2$ and $D = c_1 n^2 c_2$ yielding

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

Therefore we obtain the following theorem:

Theorem 3.1. Assume that $f(x^*) = 0$ and

- $\frac{\partial f_i}{\partial x_j}$ and $\frac{\partial^2 f_i}{\partial x_j \partial x_k}$ exist and are continuous near x_* for i, j, k = 1, ..., n
- the matrix $f'(x^*)$ is nonsingular.

Then there exists $\delta > 0$, C > 0 such that for $||x^{(0)} - x_*|| \le \delta$ we have

- $\lim_{k \to \infty} x^{(k)} = x^*$ (convergence)
- $||x^{(k+1)} x^*|| \le C ||x^{(k)} x^*||^2$ (convergence of order 2)

Proof. Since $f'(x^*)$ is nonsingular and f'(x) is continuous, we can find $\varepsilon > 0$ such that on $B_{\varepsilon} := \{x \mid ||x - x^*|| \le \varepsilon\}$ we have

$$||f'(x)^{-1}|| \le c_1.$$

We can then determine c_2 such that $\left|\frac{\partial^2 f_i(x)}{\partial x_j \partial x_k}\right| \le c_2$ on B_{ε} . Then we have for $x^{(k)} \in B_{\varepsilon}$ that $||x^{(k+1)} - x^*|| \le D ||x^{(k)} - x^*||^2$. Now we proceed exactly as in the proof of Theorem 2.3.

4 Nonlinear least squares problem

We have *N* functions $f_1(x_1,...,x_n),...,f_N(x_1,...,x_n)$ for *n* unknowns with N > n. We define the vector-valued function f(x) as

$$f(x) = \begin{bmatrix} f_1(x_1, \dots, x_n) \\ \vdots \\ f_N(x_1, \dots, x_n) \end{bmatrix}$$

We cannot expect to find $x \in \mathbb{R}^n$ such that $f(x) = \vec{0}$ since we have more equations than unknowns. But we can try to find $x \in \mathbb{R}^n$ such that the vector f(x) becomes "as small as possible":

Find $x \in \mathbb{R}^n$ such that $||f(x)||_2$ is minimal

The Jacobian f'(x) (often denoted by Df(x)) is the $N \times n$ matrix (more rows than columns) of first partial derivatives

$$f'(x) = \begin{bmatrix} \frac{\partial f_1}{\partial x_1} & \cdots & \frac{\partial f_1}{\partial x_n} \\ \vdots & & \vdots \\ \frac{\partial f_N}{\partial x_1} & \cdots & \frac{\partial f_N}{\partial x_n} \end{bmatrix}$$

We start with an initial guess $x^{(0)}$. Then we approximate the function f(x) by the Taylor approximation $p(x) = b + A(x - x^{(0)})$ with $b := f(x^{(0)})$ and $A := f'(x^{(0)})$. Instead of $||f(x)|| = \min$ we solve $||p(x)|| = \min$ as follows: Let $d = x - x^{(0)}$, solve the linear least squares problem $||Ad + b|| = \min$, then let $x^{(1)} := x^{(0)} + d$.

Algorithm: Gauss-Newton Method

- Initial guess $x^{(0)}$
- For k = 0, 1, 2, ...: $b := f(x^{(k)})$ $A := f'(x^{(k)})$ find d such that ||Ad + b|| is minimal (use normal equations or QR decomposition) $x^{(k+1)} := x^{(k)} + d$

Convergence of the Gauss-Newton method: We assume that $F(x) := ||f(x)||_2^2 = f_1(x)^2 + \dots + f_N(x)^2$ has a local minimum at $x^* \in \mathbb{R}^n$. Therefore $\frac{\partial F}{\partial x_i}(x^*) = 0$ for $i = 1, \dots, n$, i.e., with $A_* := f'(x^*)$ we have the normal equations

$$\mathbf{A}_*^\top f(x^*) = \vec{0} \tag{4}$$

If our current approximation is $x^{(k)}$ we consider the Taylor approximation $p(x) = b + A(x - x^{(k)})$ with $b = f(x^{(k)})$ and $A = f'(x^{(k)})$. Then we determine $x^{(k+1)}$ such that $||p(x^{(k+1)})||_2$ is minimal, hence we have the normal equations

$$\mathbf{A}^{\top} p(x^{(k+1)}) = \vec{\mathbf{0}}$$
(5)

For the Taylor approximation we know that

$$f(x^*) - p(x^*) = r(x^*), \qquad ||r(x^*)|| \le C_2 \left\| x^* - x^{(k)} \right\|^2$$
 (6)

where C_2 depends on the size of the second order partial derivatives $\frac{\partial^2 f_i}{\partial x_j \partial x_k}$. We also have

$$||A_* - A|| = ||f'(x^*) - f'(x^{(k)})|| \le C_2 ||x^* - x^{(k)}||$$

From (6) we obtain

$$A^{\top}f(x^*) - A^{\top}p(x^*) = A^{\top}r(x^*)$$

Now (4), (5) give for the first term

$$A^{\top}f(x^{*}) = \underbrace{A_{*}^{\top}f(x^{*})}_{0} + (A - A_{*})^{\top}f(x^{*})$$
$$= A^{\top}p(x^{(k+1)}) + (A - A_{*})^{\top}f(x^{*})$$

yielding

$$A^{\top} \underbrace{\left(p(x^{(k+1)}) - p(x^{*}) \right)}_{A \left(x^{(k+1)} - x^{*} \right)} = (A_{*} - A)^{\top} f(x^{*}) + A^{\top} r(x^{*})$$

and

$$\begin{aligned} x^{(k+1)} - x^* &= (A^{\top}A)^{-1}(A_* - A)^{\top}f(x^*) + (A^{\top}A)^{-1}A^{\top}r(x^*) \\ \left\| x^{(k+1)} - x^* \right\| &\leq \left\| (A^{\top}A)^{-1} \right\| \left(C_2 \left\| x^{(k)} - x^* \right\| \left\| f(x^*) \right\| + \left\| A^{\top} \right\| C_2 \left\| x^{(k)} - x^* \right\|^2 \right) \\ \left\| x^{(k+1)} - x^* \right\| &\leq D \left(c \left\| f(x^*) \right\| \cdot \left\| x^{(k)} - x^* \right\| + \left\| x^{(k)} - x^* \right\|^2 \right) \end{aligned}$$

with $D := C_2 \| (A^\top A)^{-1} \| \| A^\top \|$. If the residual $\| f(x^*) \|$ is zero (usually not satisfied) we get quadratic convergence. If $\varepsilon := c \| f(x^*) \|$ is small the error $\| x^{(k)} - x^* \|$ will at first decrease as with quadratic convergence, until $\| x^{(k)} - x^* \| \approx \varepsilon$. From then on we will **only have convergence of order 1** (if the residual $\| f(x^*) \|$ is sufficiently small). If the residual $\| f(x^*) \|$ is too large the **Gauss-Newton method may not be locally convergent**.