Numerical Analysis II
Numerical solutions of nonlinear systems of equations

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[1] These slides are based on Prof. Tsung-Ming Huang(NTNU)'s original slides

Outline

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1. Fixed points for functions of several variables
2. Newton's method
3. Quasi-Newton methods
4. Steepest Descent Techniques

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Fixed points for functions of several variables

Theorem

Let $f : D \subset \mathbb{R}^n \to \mathbb{R}$ be a function and $x_0 \in D$. If all the partial derivatives of f exist and $\exists\ \delta > 0$ and $\alpha > 0$ such that $\forall\ \|x - x_0\| < \delta$ and $x \in D$, we have

$$\left| \frac{\partial f(x)}{\partial x_j} \right| \le \alpha,\ \forall\ j = 1, 2, \ldots, n,$$

then f is continuous at x_0.

Definition (Fixed Point)

A function G from $D \subset \mathbb{R}^n$ into $\mathbb{R}^n$ has a fixed point at $p \in D$ if $G(p) = p$.

Fixed points for functions of several variables

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Theorem (Contraction Mapping Theorem)

Let $D = \{(x_1, \cdots, x_n)^T; a_i \le x_i \le b_i, \forall\ i = 1, \ldots, n\} \subset \mathbb{R}^n$. *Suppose* $G : D \to \mathbb{R}^n$ *is a continuous function with* $G(x) \in D$ *whenever* $x \in D$. *Then* G *has a fixed point in* D.

Suppose, in addition, G *has continuous partial derivatives and a constant* $\alpha < 1$ *exists with*

$$\left|\frac{\partial g_i(x)}{\partial x_j}\right| \le \frac{\alpha}{n}, \quad \text{whenever} \;\; x \in D,$$

for $j = 1, \ldots, n$ *and* $i = 1, \ldots, n$. *Then, for any* $x^{(0)} \in D$,

$$x^{(k)} = G(x^{(k-1)}), \quad \text{for each} \;\; k \ge 1$$

converges to the unique fixed point $p \in D$ *and*

$$\| x^{(k)} - p \|_\infty \le \frac{\alpha^k}{1-\alpha} \| x^{(1)} - x^{(0)} \|_\infty .$$

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Example

Consider the nonlinear system

$$\begin{aligned} 3x_1 - \cos(x_2 x_3) - \frac{1}{2} &= 0, \\ x_1^2 - 81(x_2 + 0.1)^2 + \sin x_3 + 1.06 &= 0, \\ e^{-x_1 x_2} + 20x_3 + \frac{10\pi - 3}{3} &= 0. \end{aligned}$$

- Fixed-point problem:
  Change the system into the fixed-point problem:

$$\begin{aligned} x_1 &= \frac{1}{3}\cos(x_2 x_3) + \frac{1}{6} \equiv g_1(x_1, x_2, x_3), \\ x_2 &= \frac{1}{9}\sqrt{x_1^2 + \sin x_3 + 1.06} - 0.1 \equiv g_2(x_1, x_2, x_3), \\ x_3 &= -\frac{1}{20}e^{-x_1 x_2} - \frac{10\pi - 3}{60} \equiv g_3(x_1, x_2, x_3). \end{aligned}$$

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Let $G : \mathbb{R}^3 \to \mathbb{R}^3$ be defined by $G(x) = [g_1(x), g_2(x), g_3(x)]^T$.

- G has a unique point in $D \equiv [-1,1]\times[-1,1]\times[-1,1]$:
  - Existence: $\forall\ x \in D$,

$$|g_1(x)| \le \frac{1}{3}|\cos(x_2x_3)| + \frac{1}{6} \le 0.5,$$
$$|g_2(x)| = \left|\frac{1}{9}\sqrt{x_1^2+\sin x_3+1.06} - 0.1\right| \le \frac{1}{9}\sqrt{1+\sin 1+1.06} - 0.1 < 0.09,$$
$$|g_3(x)| = \frac{1}{20}e^{-x_1x_2} + \frac{10\pi-3}{60} \le \frac{1}{20}e + \frac{10\pi-3}{60} < 0.61,$$

    it implies that $G(x) \in D$ whenever $x \in D$.
  - Uniqueness:

$$\left|\frac{\partial g_1}{\partial x_1}\right| = 0,\ \left|\frac{\partial g_2}{\partial x_2}\right| = 0 \ \text{ and } \ \left|\frac{\partial g_3}{\partial x_3}\right| = 0,$$

    as well as

$$\left|\frac{\partial g_1}{\partial x_2}\right| \le \frac{1}{3}|x_3|\cdot|\sin(x_2x_3)| \le \frac{1}{3}\sin 1 < 0.281,$$

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\begin{aligned}
\left|\frac{\partial g_1}{\partial x_3}\right| &\le \frac{1}{3}|x_2|\cdot|\sin(x_2x_3)| \le \frac{1}{3}\sin 1 < 0.281, \\
\left|\frac{\partial g_2}{\partial x_1}\right| &= \frac{|x_1|}{9\sqrt{x_1^2+\sin x_3+1.06}} < \frac{1}{9\sqrt{0.218}} < 0.238, \\
\left|\frac{\partial g_2}{\partial x_3}\right| &= \frac{|\cos x_3|}{18\sqrt{x_1^2+\sin x_3+1.06}} < \frac{1}{18\sqrt{0.218}} < 0.119, \\
\left|\frac{\partial g_3}{\partial x_1}\right| &= \frac{|x_2|}{20}e^{-x_1x_2} \le \frac{1}{20}e < 0.14, \\
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These imply that g_1, g_2 and g_3 are continuous on D and $\forall\ x \in D$,

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\left|\frac{\partial g_i}{\partial x_j}\right| \le 0.281,\ \forall\ i, j.
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Similarly, $\partial g_i/\partial x_j$ are continuous on D for all i and j. Consequently, has a unique fixed point in D.

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Similarly, $\partial g_i / \partial x_j$ are continuous on D for all i and j. Consequently, G has a unique fixed point in D.

- Approximated solution:
  - Fixed-point iteration (I):
    Choosing $x^{(0)} = [0.1, 0.1, -0.1]^T$, the sequence $\{x^{(k)}\}$ is generated by

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\begin{aligned}
x_1^{(k)} &= \frac{1}{3}\cos x_2^{(k-1)} x_3^{(k-1)} + \frac{1}{6}, \\
x_2^{(k)} &= \frac{1}{9}\sqrt{\left(x_1^{(k-1)}\right)^2 + \sin x_3^{(k-1)} + 1.06} - 0.1, \\
x_3^{(k)} &= -\frac{1}{20} e^{-x_1^{(k-1)} x_2^{(k-1)}} - \frac{10\pi - 3}{60}.
\end{aligned}
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  - Result:

k	$x_1^{(k)}$	$x_2^{(k)}$	$x_3^{(k)}$	$\|x^{(k)} - x^{(k-1)}\|_\infty$
0	0.10000000	0.10000000	-0.10000000	
1	0.49998333	0.00944115	-0.52310127	0.423
2	0.49999593	0.00002557	-0.52336331	9.4×10^{-3}
3	0.50000000	0.00001234	-0.52359814	2.3×10^{-4}
4	0.50000000	0.00000003	-0.52359847	1.2×10^{-5}
5	0.50000000	0.00000002	-0.52359877	3.1×10^{-7}

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- Approximated solution (cont.):
  - Accelerate convergence of the fixed-point iteration:

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as in the Gauss-Seidel method for linear systems.

  - Result:

k	$x_1^{(k)}$	$x_2^{(k)}$	$x_3^{(k)}$	$\lVert x^{(k)} - x^{(k-1)} \rVert_\infty$
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1	0.49998333	0.02222979	-0.52304613	0.423
2	0.49997747	0.00002815	-0.52359807	2.2×10^{-2}
3	0.50000000	0.00000004	-0.52359877	2.8×10^{-5}
4	0.50000000	0.00000000	-0.52359877	3.8×10^{-8}

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0	0.10000000	0.10000000	-0.10000000	
1	0.49998333	0.02222979	-0.52304613	0.423
2	0.49997747	0.00002815	-0.52359807	2.2×10^{-2}
3	0.50000000	0.00000004	-0.52359877	2.8×10^{-5}
4	0.50000000	0.00000000	-0.52359877	3.8×10^{-8}

Newton's method

First consider solving the following system of nonlinear equations:

$$\begin{cases} f_1(x_1, x_2) = 0, \\ f_2(x_1, x_2) = 0. \end{cases}$$

Suppose $(x_1^{(k)}, x_2^{(k)})$ is an approximation to the solution of the system above, and we try to compute $h_1^{(k)}$ and $h_2^{(k)}$ such that $(x_1^{(k)} + h_1^{(k)}, x_2^{(k)} + h_2^{(k)})$ satisfies the system. By the Taylor's theorem for two variables,

$$\begin{aligned}
0 &= f_1(x_1^{(k)} + h_1^{(k)}, x_2^{(k)} + h_2^{(k)}) \\
&\approx f_1(x_1^{(k)}, x_2^{(k)}) + h_1^{(k)} \frac{\partial f_1}{\partial x_1}(x_1^{(k)}, x_2^{(k)}) + h_2^{(k)} \frac{\partial f_1}{\partial x_2}(x_1^{(k)}, x_2^{(k)}) \\
0 &= f_2(x_1^{(k)} + h_1^{(k)}, x_2^{(k)} + h_2^{(k)}) \\
&\approx f_2(x_1^{(k)}, x_2^{(k)}) + h_1^{(k)} \frac{\partial f_2}{\partial x_1}(x_1^{(k)}, x_2^{(k)}) + h_2^{(k)} \frac{\partial f_2}{\partial x_2}(x_1^{(k)}, x_2^{(k)})
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Put this in matrix form

$$\begin{bmatrix} \frac{\partial f_1}{\partial x_1}(x_1^{(k)}, x_2^{(k)}) & \frac{\partial f_1}{\partial x_2}(x_1^{(k)}, x_2^{(k)}) \\ \frac{\partial f_2}{\partial x_1}(x_1^{(k)}, x_2^{(k)}) & \frac{\partial f_2}{\partial x_2}(x_1^{(k)}, x_2^{(k)}) \end{bmatrix} \begin{bmatrix} h_1^{(k)} \\ h_2^{(k)} \end{bmatrix} + \begin{bmatrix} f_1(x_1^{(k)}, x_2^{(k)}) \\ f_2(x_1^{(k)}, x_2^{(k)}) \end{bmatrix} \approx \begin{bmatrix} 0 \\ 0 \end{bmatrix}.$$

The matrix

$$J(x_1^{(k)}, x_2^{(k)}) \equiv \begin{bmatrix} \frac{\partial f_1}{\partial x_1}(x_1^{(k)}, x_2^{(k)}) & \frac{\partial f_1}{\partial x_2}(x_1^{(k)}, x_2^{(k)}) \\ \frac{\partial f_2}{\partial x_1}(x_1^{(k)}, x_2^{(k)}) & \frac{\partial f_2}{\partial x_2}(x_1^{(k)}, x_2^{(k)}) \end{bmatrix}$$

is called the Jacobian matrix. Set $h_1^{(k)}$ and $h_2^{(k)}$ be the solution of the linear system

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then

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In general, we solve the system of n nonlinear equations $f_i(x_1, \cdots, x_n) = 0$, $i = 1, \ldots, n$. Let

$$x = \begin{bmatrix} x_1 & x_2 & \cdots & x_n \end{bmatrix}^T$$

and

$$F(x) = \begin{bmatrix} f_1(x) & f_2(x) & \cdots & f_n(x) \end{bmatrix}^T.$$

The problem can be formulated as solving

$$F(x) = 0, \quad F : \mathbb{R}^n \to \mathbb{R}^n.$$

Let $J(x)$, where the (i,j) entry is $\frac{\partial f_i}{\partial x_j}(x)$, be the $n \times n$ Jacobian matrix. Then the Newton's iteration is defined as

$$x^{(k+1)} = x^{(k)} + h^{(k)},$$

where $h^{(k)} \in \mathbb{R}^n$ is the solution of the linear system

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Algorithm (Newton's Method for Systems)

Given a function $F : \mathbb{R}^n \to \mathbb{R}^n$, an initial guess $x^{(0)}$ to the zero of F, and stop criteria M, δ, and ε, this algorithm performs the Newton's iteration to approximate one root of F.

Set $k = 0$ and $h^{(-1)} = e_1$.
While $(k < M)$ and $(\| h^{(k-1)} \| \geq \delta)$ and $(\| F(x^{(k)}) \| \geq \varepsilon)$
  Calculate $J(x^{(k)}) = [\partial F_i(x^{(k)})/\partial x_j]$.
  Solve the $n \times n$ linear system $J(x^{(k)})h^{(k)} = -F(x^{(k)})$.
  Set $x^{(k+1)} = x^{(k)} + h^{(k)}$ and $k = k + 1$.
End while
Output ("Convergent $x^{(k)}$") or
  ("Maximum number of iterations exceeded")

Theorem

Let x^* be a solution of $G(x) = x$. Suppose $\exists\ \delta > 0$ with

(i) $\partial g_i / \partial x_j$ *is continuous on* $N_\delta = \{x; \|x - x^*\| < \delta\}$ *for all* i *and* j.

(ii) $\partial^2 g_i(x) / (\partial x_j \partial x_k)$ *is continuous and*

$$\left| \frac{\partial^2 g_i(x)}{\partial x_j \partial x_k} \right| \leq M$$

for some M *whenever* $x \in N_\delta$ *for each* i, j *and* k.

(iii) $\partial g_i(x^*) / \partial x_k = 0$ *for each* i *and* k.

Then $\exists\ \hat{\delta} < \delta$ such that the sequence $\{x^{(k)}\}$ generated by

$$x^{(k)} = G(x^{(k-1)})$$

converges quadratically to x^* for any $x^{(0)}$ satisfying $\|x^{(0)} - x^*\|_\infty < \hat{\delta}$. Moreover,

$$\|x^{(k)} - x^*\|_\infty \leq \frac{n^2 M}{2} \|x^{(k-1)} - x^*\|_\infty^2, \forall\ k \geq 1.$$

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Example

Consider the nonlinear system

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\begin{aligned}
3x_1 - \cos(x_2 x_3) - \frac{1}{2} &= 0, \\
x_1^2 - 81(x_2 + 0.1)^2 + \sin x_3 + 1.06 &= 0, \\
e^{-x_1 x_2} + 20x_3 + \frac{10\pi - 3}{3} &= 0.
\end{aligned}
$$

- Nonlinear functions: Let

$$F(x_1, x_2, x_3) = [f_1(x_1, x_2, x_3), f_2(x_1, x_2, x_3), f_3(x_1, x_2, x_3)]^T,$$

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$$\begin{aligned} f_1(x_1, x_2, x_3) &= 3x_1 - \cos(x_2 x_3) - \frac{1}{2}, \\ f_2(x_1, x_2, x_3) &= x_1^2 - 81(x_2 + 0.1)^2 + \sin x_3 + 1.06, \\ f_3(x_1, x_2, x_3) &= e^{-x_1 x_2} + 20x_3 + \frac{10\pi - 3}{3}. \end{aligned}$$

- Nonlinear functions (cont.):
  The Jacobian matrix $J(x)$ for this system is

$$J(x_1, x_2, x_3) = \begin{bmatrix} 3 & x_3 \sin x_2 x_3 & x_2 \sin x_2 x_3 \\ 2x_1 & -162(x_2 + 0.1) & \cos x_3 \\ -x_2 e^{-x_1 x_2} & -x_1 e^{-x_1 x_2} & 20 \end{bmatrix}.$$

- Newton's iteration with initial $x^{(0)} = [0.1, 0.1, -0.1]^T$:

$$\begin{bmatrix} x_1^{(k)} \\ x_2^{(k)} \\ x_3^{(k)} \end{bmatrix} = \begin{bmatrix} x_1^{(k-1)} \\ x_2^{(k-1)} \\ x_3^{(k-1)} \end{bmatrix} - \begin{bmatrix} h_1^{(k-1)} \\ h_2^{(k-1)} \\ h_3^{(k-1)} \end{bmatrix},$$

where

$$\begin{bmatrix} h_1^{(k-1)} \\ h_2^{(k-1)} \\ h_3^{(k-1)} \end{bmatrix} = \left(J(x_1^{(k-1)}, x_2^{(k-1)}, x_3^{(k-1)})\right)^{-1} F(x_1^{(k-1)}, x_2^{(k-1)}, x_3^{(k-1)})$$

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- Result:

k	$x_1^{(k)}$	$x_2^{(k)}$	$x_3^{(k)}$	$\|x^{(k)} - x^{(k-1)}\|_\infty$
0	0.10000000	0.10000000	-0.10000000	
1	0.50003702	0.01946686	-0.52152047	0.422
2	0.50004593	0.00158859	-0.52355711	1.79×10^{-2}
3	0.50000034	0.00001244	-0.52359845	1.58×10^{-3}
4	0.50000000	0.00000000	-0.52359877	1.24×10^{-5}
5	0.50000000	0.00000000	-0.52359877	0

Quasi-Newton methods

- Newton's Methods
  - Advantage: quadratic convergence
  - Disadvantage: For each iteration, it requires $O(n^3) + O(n^2) + O(n)$ arithmetic operations:
    - n^2 partial derivatives for Jacobian matrix – in most situations, the exact evaluation of the partial derivatives is inconvenient.
    - n scalar functional evaluations of F
    - $O(n^3)$ arithmetic operations to solve linear system.
- quasi-Newton methods
  - Advantage: it requires only n scalar functional evaluations per iteration and $O(n^2)$ arithmetic operations
  - Disadvantage: superlinear convergence

Recall that in one dimensional case, one uses the linear model

$$\ell_k(x) = f(x_k) + a_k(x - x_k)$$

to approximate the function $f(x)$ at x_k. That is, $\ell_k(x_k) = f(x_k)$ for any $a_k \in \mathbb{R}$. If we further require that $\ell'(x_k) = f'(x_k)$, then $a_k = f'(x_k)$.

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The zero of $\ell_k(x)$ is used to give a new approximate for the zero of $f(x)$, that is,

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

which yields Newton's method.

If $f'(x_k)$ is not available, one instead asks the linear model to satisfy

$$\ell_k(x_k) = f(x_k) \quad \text{and} \quad \ell_k(x_{k-1}) = f(x_{k-1}).$$

In doing this, the identity

$$f(x_{k-1}) = \ell_k(x_{k-1}) = f(x_k) + a_k(x_{k-1} - x_k)$$

gives

$$a_k = \frac{f(x_k) - f(x_{k-1})}{x_k - x_{k-1}}.$$

Solving $\ell_k(x) = 0$ yields the secant iteration

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In multiple dimension, the analogue affine model becomes

$$M_k(x) = F(x_k) + A_k(x - x_k),$$

where $x, x_k \in \mathbb{R}^n$ and $A_k \in \mathbb{R}^{n\times n}$, and satisfies

$$M_k(x_k) = F(x_k),$$

for any A_k. The zero of $M_k(x)$ is then used to give a new approximate for the zero of $F(x)$, that is,

$$x_{k+1} = x_k - A_k^{-1}F(x_k).$$

The Newton's method chooses

$$A_k = F'(x_k) \equiv J(x_k) = \text{the Jacobian matrix}$$

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However, this secant equation can not uniquely determine A_k. One way of choosing A_k is to minimize $M_k - M_{k-1}$ subject to the secant equation. Note

$$\begin{aligned}
M_k(x) - M_{k-1}(x) &= F(x_k) + A_k(x - x_k) - F(x_{k-1}) - A_{k-1}(x - x_{k-1}) \\
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\end{aligned}$$

For any $x \in \mathbb{R}^n$, we express

$$x - x_{k-1} = \alpha h_k + t_k,$$

for some $\alpha \in \mathbb{R}$, $t_k \in \mathbb{R}^n$, and $h_k^T t_k = 0$. Then

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$$x - x_{k-1} = \alpha h_k + t_k,$$

for some $\alpha \in \mathbb{R}$, $t_k \in \mathbb{R}^n$, and $h_k^T t_k = 0$. Then

$$M_k - M_{k-1} = (A_k - A_{k-1})(\alpha h_k + t_k) = \alpha(A_k - A_{k-1})h_k + (A_k - A_{k-}$$

However, this secant equation can not uniquely determine A_k. One way of choosing A_k is to minimize $M_k - M_{k-1}$ subject to the secant equation. Note

$$\begin{aligned} M_k(x) - M_{k-1}(x) &= F(x_k) + A_k(x - x_k) - F(x_{k-1}) - A_{k-1}(x - x_{k-1}) \\ &= (F(x_k) - F(x_{k-1})) + A_k(x - x_k) - A_{k-1}(x - x_{k-1}) \\ &= A_k(x_k - x_{k-1}) + A_k(x - x_k) - A_{k-1}(x - x_{k-1}) \\ &= A_k(x - x_{k-1}) - A_{k-1}(x - x_{k-1}) \\ &= (A_k - A_{k-1})(x - x_{k-1}). \end{aligned}$$

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$$(A_k - A_{k-1})h_k = A_k h_k - A_{k-1}h_k = y_k - A_{k-1}h_k,$$

both y_k and $A_{k-1}h_k$ are old values, we have no control over the first part $(A_k - A_{k-1})h_k$. In order to minimize $M_k(x) - M_{k-1}(x)$, we try to choose A_k so that

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for all $t_k \in \mathbb{R}^n$, $h_k^T t_k = 0$. This requires that $A_k - A_{k-1}$ to be a rank-one matrix of the form

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$$u_k = \frac{y_k - A_{k-1}h_k}{h_k^T h_k}.$$

Therefore,

$$A_k = A_{k-1} + \frac{(y_k - A_{k-1}h_k)h_k^T}{h_k^T h_k}. \tag{1}$$

After A_k is determined, the new iterate x_{k+1} is derived from solving $M_k(x) = 0$. It can be done by first noting that

$$h_{k+1} = x_{k+1} - x_k \quad \Longrightarrow \quad x_{k+1} = x_k + h_{k+1}$$

and

$$M_k(x_{k+1}) = 0 \;\Rightarrow\; F(x_k) + A_k(x_{k+1} - x_k) = 0 \;\Rightarrow\; A_k h_{k+1} = -F(x_k)$$

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Algorithm (Broyden's Method)

Given a n-variable nonlinear function $F : \mathbb{R}^n \to \mathbb{R}^n$, an initial iterate x_0 and initial Jacobian matrix $A_0 \in \mathbb{R}^{n\times n}$ (e.g., $A_0 = I$), this algorithm finds the solution for $F(x) = 0$.

Given x_0, tolerance TOL, maximum number of iteration M.
Set $k = 1$.
While $k \le M$ and $\|x_k - x_{k-1}\|_2 \ge TOL$
  Solve $A_k h_{k+1} = -F(x_k)$ for h_{k+1}
  Update $x_{k+1} = x_k + h_{k+1}$
  Compute $y_{k+1} = F(x_{k+1}) - F(x_k)$
  Update

$$A_{k+1} = A_k + \frac{(y_{k+1} - A_k h_{k+1})h_{k+1}^T}{h_{k+1}^T h_{k+1}} = A_k + \frac{(y_{k+1} + F(x_k))h_{k+1}^T}{h_{k+1}^T h_{k+1}}$$

  $k = k + 1$
End While

Solve the linear system $A_k h_{k+1} = -F(x_k)$ for h_{k+1}:

- LU-factorization: cost $\frac{2}{3}n^3 + O(n^2)$ floating-point operations.
- Applying the Shermann-Morrison-Woodbury formula

$$\left(B + UV^T\right)^{-1} = B^{-1} - B^{-1}U\left(I + V^T B^{-1} U\right)^{-1} V^T B^{-1}$$

to (1), we have

$$\begin{aligned}
& A_k^{-1} \\
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Steepest Descent Techniques

- Newton-based methods
  - Advantage: high speed of convergence once a sufficiently accurate approximation
  - Weakness: an accurate initial approximation to the solution is needed to ensure convergence.
- The Steepest Descent method converges only linearly to the solution, but it will usually converge even for poor initial approximations.
- "Find sufficiently accurate starting approximate solution by using Steepest Descent method" + "Compute convergent solution by using Newton-based methods"
- The method of Steepest Descent determines a local minimum for a multivariable function of $g : \mathbb{R}^n \to \mathbb{R}$.
- A system of the form $f_i(x_1, \ldots, x_n) = 0, \; i = 1, 2, \ldots, n$ has a solution at x iff the function g defined by

$$g(x_1, \ldots, x_n) = \sum_{i=1}^{n} [f_i(x_1, \ldots, x_n)]^2$$

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Basic idea of steepest descent method:

(i) Evaluate g at an initial approximation $x^{(0)}$;

(ii) Determine a direction from $x^{(0)}$ that results in a decrease in the value of g;

(iii) Move an appropriate distance in this direction and call the new vector $x^{(1)}$;

(iv) Repeat steps (i) through (iii) with $x^{(0)}$ replaced by $x^{(1)}$.

Definition (Gradient)

If $g : \mathbb{R}^n \to \mathbb{R}$, the gradient, $\nabla g(x)$, at x is defined by

$$\nabla g(x) = \left(\frac{\partial g}{\partial x_1}(x), \cdots, \frac{\partial g}{\partial x_n}(x) \right).$$

Definition (Directional Derivative)

The directional derivative of g at x in the direction of v with $\| v \|_2 = 1$ is defined by

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If $g : \mathbb{R}^n \to \mathbb{R}$, the gradient, $\nabla g(x)$, at x is defined by

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Basic idea of steepest descent method:

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The direction of the greatest decrease in the value of g at x is the direction given by $-\nabla g(x)$.

- Object: reduce $g(x)$ to its minimal value zero.
  $\Rightarrow$ for an initial approximation $x^{(0)}$, an appropriate choice for new vector $x^{(1)}$ is

$$x^{(1)} = x^{(0)} - \alpha \nabla g(x^{(0)}), \quad \text{for some constant } \alpha > 0.$$

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  - Solve a root-finding problem $h'(\alpha) = 0 \Rightarrow$ Too costly, in general.
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Example

Use the Steepest Descent method with $x^{(0)} = (0,0,0)^T$ to find a reasonable starting approximation to the solution of the nonlinear system

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\begin{aligned}
f_1(x_1,x_2,x_3) &= 3x_1 - \cos(x_2x_3) - \frac{1}{2} = 0, \\
f_2(x_1,x_2,x_3) &= x_1^2 - 81(x_2+0.1)^2 + \sin x_3 + 1.06 = 0, \\
f_3(x_1,x_2,x_3) &= e^{-x_1x_2} + 20x_3 + \frac{10\pi-3}{3} = 0.
\end{aligned}
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Let $g(x1,x_2,x_3) = [f_1(x_1,x_2,x_3)]^2 + [f_2(x_1,x_2,x_3)]^2 + [f_3(x_1,x_2,x_3)]^2$. Then

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\nabla g(x_1,x_2,x_3) &\equiv \nabla g(x) \\
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For $x^{(0)} = [0, 0, 0]^T$, we have

$$g(x^{(0)}) = 111.975 \quad \text{and} \quad z_0 = \|\nabla g(x^{(0)})\|_2 = 419.554.$$

Let

$$z = \frac{1}{z_0} \nabla g(x^{(0)}) = [-0.0214514, -0.0193062, 0.999583]^T.$$

With $\alpha_1 = 0$, we have

$$g_1 = g(x^{(0)} - \alpha_1 z) = g(x^{(0)}) = 111.975.$$

Let $\alpha_3 = 1$ so that

$$g_3 = g(x^{(0)} - \alpha_3 z) = 93.5649 < g_1.$$

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$$g_2 = P(\alpha_2) = g_1 + h_1\alpha_2 \;\Rightarrow\; h_1 = \frac{g_2 - g_1}{\alpha_2} = -218.878,$$

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Thus

$$P(\alpha) = 111.975 - 218.878\alpha + 400.937\alpha(\alpha - 0.5)$$

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$$0 = P'(\alpha_0) = -419.346 + 801.872\alpha_0 \;\Rightarrow\; \alpha_0 = 0.522959$$

Since

$$g_0 = g(x^{(0)} - \alpha_0 z) = 2.32762 < \min\{g_1, g_3\},$$

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$$0 = P'(\alpha_0) = -419.346 + 801.872\alpha_0 \;\Rightarrow\; \alpha_0 = 0.522959$$

Since

$$g_0 = g(x^{(0)} - \alpha_0 z) = 2.32762 < \min\{g_1, g_3\},$$

we set

$$x^{(1)} = x^{(0)} - \alpha_0 z = [0.0112182, 0.0100964, -0.522741]^T.$$

Form quadratic polynomial $P(\alpha)$ defined as

$$P(\alpha) = g_1 + h_1\alpha + h_3\alpha(\alpha - \alpha_2)$$

that interpolates $g(x^{(0)} - \alpha z)$ at $\alpha_1 = 0, \alpha_2 = 0.5$ and $\alpha_3 = 1$ as follows

$$g_2 = P(\alpha_2) = g_1 + h_1\alpha_2 \;\Rightarrow\; h_1 = \frac{g_2 - g_1}{\alpha_2} = -218.878,$$
$$g_3 = P(\alpha_3) = g_1 + h_1\alpha_3 + h_3\alpha_3(\alpha_3 - \alpha_2) \;\Rightarrow\; h_3 = 400.937.$$

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