Numerical solutions of nonlinear systems of equations

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October 27, 2014

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 1

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

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

then f is continuous at x_0.

Definition 2 (Fixed Point)

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

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Theorem 3 (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*

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

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

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

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Example 4

Consider the nonlinear system

$$\begin{aligned} 3x_1 - \cos(x_2x_3) - \frac{1}{2} &= 0, \\ x_1^2 - 81(x_2+0.1)^2 + \sin x_3 + 1.06 &= 0, \\ e^{-x_1x_2} + 20x_3 + \frac{10\pi - 3}{3} &= 0. \end{aligned}$$

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

$$\begin{aligned} x_1 &= \frac{1}{3}\cos(x_2x_3) + \frac{1}{6} \equiv g_1(x_1,x_2,x_3), \\ x_2 &= \frac{1}{9}\sqrt{x_1^2 + \sin x_3 + 1.06} - 0.1 \equiv g_2(x_1,x_2,x_3), \\ x_3 &= -\frac{1}{20}e^{-x_1x_2} - \frac{10\pi - 3}{60} \equiv g_3(x_1,x_2,x_3). \end{aligned}$$

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

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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:

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

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

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\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,\\
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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, G has a unique fixed point in D.

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- Approximated solution:
  - Fixed-point iteration (I):
    Choosing $\mathbf{x}^{(0)} = [0.1, 0.1, -0.1]^T$, $\{\mathbf{x}^{(k)}\}$ 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, \\
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  - Result:

k	$x_1^{(k)}$	$x_2^{(k)}$	$x_3^{(k)}$	$\|\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}\|_\infty$
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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as in the Gauss-Seidel method for linear systems.

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    as in the Gauss-Seidel method for linear systems.
  - Result:

k	$x_1^{(k)}$	$x_2^{(k)}$	$x_3^{(k)}$	$\|\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}\|_\infty$
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}

Exercise

Page 636: 5, 7.b, 7.d

Newton's method

First consider solving the following system of nonlinear eqs.:

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

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,

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

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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

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

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

$$J(x_1^{(k)}, x_2^{(k)}) \begin{bmatrix} h_1^{(k)} \\ h_2^{(k)} \end{bmatrix} = - \begin{bmatrix} f_1(x_1^{(k)}, x_2^{(k)}) \\ f_2(x_1^{(k)}, x_2^{(k)}) \end{bmatrix},$$

then

$$\begin{bmatrix} x_1^{(k+1)} \\ x_2^{(k+1)} \end{bmatrix} = \begin{bmatrix} x_1^{(k)} \\ x_2^{(k)} \end{bmatrix} + \begin{bmatrix} h_1^{(k)} \\ h_2^{(k)} \end{bmatrix}$$

is expected to be a better approximation.

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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

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

and

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

The problem can be formulated as solving

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

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

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

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

$$J(\mathbf{x}^{(k)})\mathbf{h}^{(k)} = -F(\mathbf{x}^{(k)}).$$

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Algorithm 1 (Newton's Method for Systems)

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

Theorem 5

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

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

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

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

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

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

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

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

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

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

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

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

Example 6

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

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

where

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f_1(x_1, x_2, x_3) &= 3x_1 - \cos(x_2 x_3) - \frac{1}{2}, \\
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- 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 $\mathbf{x}^{(0)} = [0.1, 0.1, -0.1]^T$:

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

  where

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

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- Result:

k	$x_1^{(k)}$	$x_2^{(k)}$	$x_3^{(k)}$	$\|\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}\|_\infty$
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

Exercise

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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

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

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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

$$M_k(\mathbf{x}) = F(\mathbf{x}^{(k)}) + A_k(\mathbf{x} - \mathbf{x}^{(k)}),$$

where $\mathbf{x}, \mathbf{x}^{(k)} \in \mathbb{R}^n$ and $A_k \in \mathbb{R}^{n \times n}$, and satisfies

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$$A_k(\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}) = F(\mathbf{x}^{(k)}) - F(\mathbf{x}^{(k-1)})$$

and this is the so-called secant equation. Let

$$\mathbf{h}^{(k)} = \mathbf{x}^{(k)} - \mathbf{x}^{(k-1)} \quad \text{and} \quad \mathbf{y}^{(k)} = F(\mathbf{x}^{(k)}) - F(\mathbf{x}^{(k-1)}).$$

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The secant equation becomes

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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

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

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

$$\mathbf{x} - \mathbf{x}^{(k-1)} = \alpha \mathbf{h}^{(k)} + \mathbf{t}^{(k)},$$

for some $\alpha \in \mathbb{R}$, $\mathbf{t}^{(k)} \in \mathbb{R}^n$, and $(\mathbf{h}^{(k)})^T \mathbf{t}^{(k)} = 0$. Then

$$M_k - M_{k-1} = (A_k - A_{k-1})(\alpha \mathbf{h}^{(k)} + \mathbf{t}^{(k)}) = \alpha(A_k - A_{k-1})\mathbf{h}^{(k)} + (A_k - A_{k-1})$$

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

$$\mathbf{h}^{(k+1)} = \mathbf{x}^{(k+1)} - \mathbf{x}^{(k)} \quad \Longrightarrow \quad \mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \mathbf{h}^{(k+1)}$$

and

$$M_k(\mathbf{x}^{(k+1)}) = 0 \Rightarrow A_k \mathbf{h}^{(k+1)} = -F(\mathbf{x}^{(k)})$$

These formulations give the Broyden's method.

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Algorithm 2 (Broyden's Method)

Given $F : \mathbb{R}^n \to \mathbb{R}^n$, an initial vector $\mathbf{x}^{(0)}$ and initial Jacobian matrix $A_0 \in \mathbb{R}^{n\times n}$ (e.g., $A_0 = I$), tolerance TOL, maximum number of iteration M.

Set $k = 1$.

While $k \le M$ and $\|\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}\|_2 \ge TOL$

  Solve $A_k \mathbf{h}^{(k+1)} = -F(\mathbf{x}^{(k)})$ for $\mathbf{h}^{(k+1)}$

  Update $\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} + \mathbf{h}^{(k+1)}$

  Compute $\mathbf{y}^{(k+1)} = F(\mathbf{x}^{(k+1)}) - F(\mathbf{x}^{(k)})$

  Update

$$A_{k+1} = A_k + \frac{(\mathbf{y}^{(k+1)} + F(\mathbf{x}^{(k)}))(\mathbf{h}^{(k+1)})^T}{(\mathbf{h}^{(k+1)})^T \mathbf{h}^{(k+1)}}$$

  Set $k = k + 1$

End While

Solve the linear system $A_k\mathbf{h}^{(k+1)} = -F(\mathbf{x}^{(k)})$ for $\mathbf{h}^{(k+1)}$:

- 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

$$
\begin{aligned}
& A_k^{-1} \\
= & \left[A_{k-1} + \frac{(\mathbf{y}^{(k)} - A_{k-1}\mathbf{h}^{(k)})(\mathbf{h}^{(k)})^T}{(\mathbf{h}^{(k)})^T\mathbf{h}^{(k)}}\right]^{-1} \\
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$$

- 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.
- Steepest Descent method converges only linearly to the sol., 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

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

has the minimal value zero.

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Basic idea of steepest descent method:

- **(i)** Evaluate g at an initial approximation $\mathbf{x}^{(0)}$;
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Definition 7 (Gradient)

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

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Definition 8 (Directional Derivative)

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

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Theorem 9

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

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

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

- Choose $\alpha > 0$ such that $g(\mathbf{x}^{(1)}) < g(\mathbf{x}^{(0)})$: define

$$h(\alpha) = g(\mathbf{x}^{(0)} - \alpha \nabla g(\mathbf{x}^{(0)})),$$

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  - Choose three number $\alpha_1 < \alpha_2 < \alpha_3$, construct quadratic polynomial $P(x)$ that interpolates h at α_1, α_2 and α_3, i.e.,

$$P(\alpha_1) = h(\alpha_1),\ P(\alpha_2) = h(\alpha_2),\ P(\alpha_3) = h(\alpha_3),$$

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Example 10

Use the Steepest Descent method with $\mathbf{x}^{(0)} = (0,0,0)^T$ 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 $g(x_1,x_2,x_3) = [f_1(x_1,x_2,x_3)]^2 + [f_2(x_1,x_2,x_3)]^2 + [f_3(x_1,x_2,x_3)]^2$. Then

$$
\begin{aligned}
\nabla g(x_1,x_2,x_3) &\equiv \nabla g(x) \\
&= \Big(2f_1(x)\frac{\partial f_1}{\partial x_1}(x) + 2f_2(x)\frac{\partial f_2}{\partial x_1}(x) + 2f_3(x)\frac{\partial f_3}{\partial x_1}(x), \\
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Then

$$\begin{aligned} \nabla g(x_1,x_2,x_3) &\equiv \nabla g(x) \\ &= \Bigg(2f_1(x)\frac{\partial f_1}{\partial x_1}(x) + 2f_2(x)\frac{\partial f_2}{\partial x_1}(x) + 2f_3(x)\frac{\partial f_3}{\partial x_1}(x), \\ &\quad 2f_1(x)\frac{\partial f_1}{\partial x_2}(x) + 2f_2(x)\frac{\partial f_2}{\partial x_2}(x) + 2f_3(x)\frac{\partial f_3}{\partial x_2}(x), \\ &\quad 2f_1(x)\frac{\partial f_1}{\partial x_3}(x) + 2f_2(x)\frac{\partial f_2}{\partial x_3}(x) + 2f_3(x)\frac{\partial f_3}{\partial x_3}(x) \Bigg) \end{aligned}$$

For $\mathbf{x}^{(0)} = [0, 0, 0]^T$, we have

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

Let

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

With $\alpha_1 = 0$, we have

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

Let $\alpha_3 = 1$ so that

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

Set $\alpha_2 = \alpha_3/2 = 0.5$. Thus

$$g_2 = g(\mathbf{x}^{(0)} - \alpha_2 z) = 2.53557.$$

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

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

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

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

$$g_3 = P(\alpha_3) = g_1 + h_1\alpha_3 + h_3\alpha_3(\alpha_3 - \alpha_2) \;\Rightarrow\; h_3 = 400.937.$$

Thus

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

so that

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

Since

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

we set

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

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