

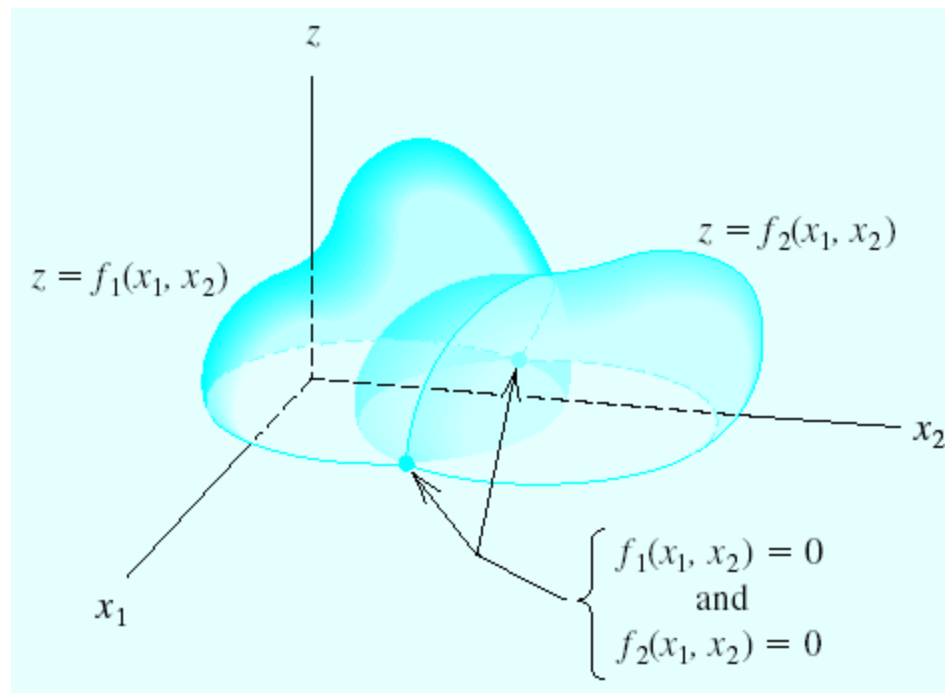
# Numerical Analysis – Solving Nonlinear Equations

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# Nonlinear Equations



Nonlinear functions  $f_1$  and  $f_2$  of  $x_1$  and  $x_2$ .

$$f_1(x_1^*, x_2^*) = 0$$

$$f_2(x_1^*, x_2^*) = 0$$

where  $x_1^*, x_2^*$  are true solution.



# Newton's method(I)

Expanding the equations at  $(x_{1i}, x_{2i})$  by Taylor series,

$$\begin{aligned} f_1(x_1^*, x_2^*) &= f_1(x_{1i}, x_{2i}) + \left. \frac{\partial f_1}{\partial x_1} \right|_i \Delta x_{1i} + \left. \frac{\partial f_1}{\partial x_2} \right|_i \Delta x_{2i} + O(\Delta x_i^2) = 0 \\ f_2(x_1^*, x_2^*) &= f_2(x_{1i}, x_{2i}) + \left. \frac{\partial f_2}{\partial x_1} \right|_i \Delta x_{1i} + \left. \frac{\partial f_2}{\partial x_2} \right|_i \Delta x_{2i} + O(\Delta x_i^2) = 0 \end{aligned}$$

where  $\Delta x_{ki} = x_k^* - x_{ki}$ ,  $k = 1, 2$ .

Ignoring higher order terms,

$$\begin{aligned} \left. \frac{\partial f_1}{\partial x_1} \right|_i \Delta x_{1i} + \left. \frac{\partial f_1}{\partial x_2} \right|_i \Delta x_{2i} &= -f_{1i} \\ \left. \frac{\partial f_2}{\partial x_1} \right|_i \Delta x_{1i} + \left. \frac{\partial f_2}{\partial x_2} \right|_i \Delta x_{2i} &= -f_{2i} \end{aligned}$$



# Newton's method(II)

Rewriting the equations into a matrix form,

$$\nabla F \Delta \mathbf{x} = -f$$

where  $\nabla F$  is the Jacobian.

- Generalization to n-dimension

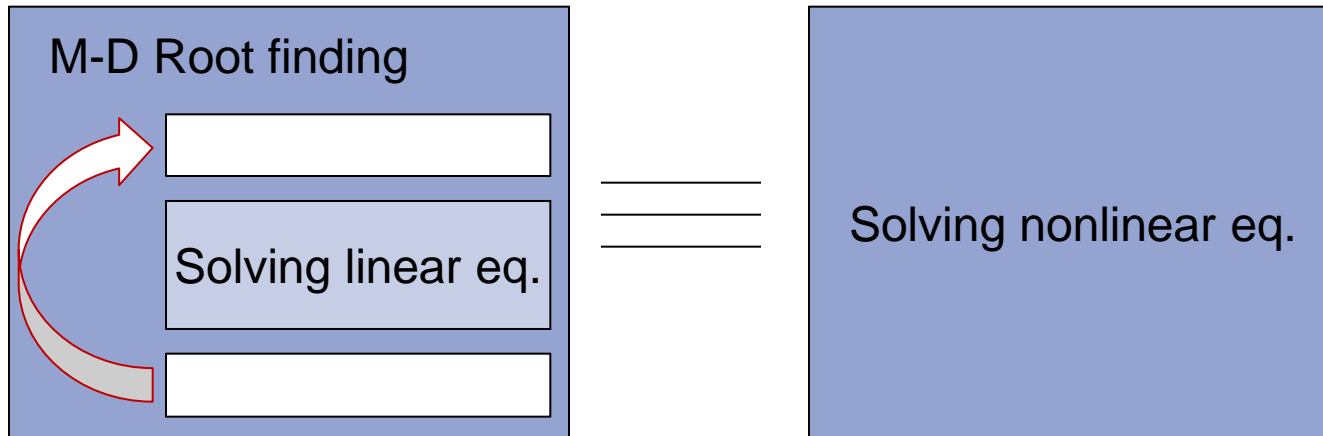
$$J(\mathbf{x}) \Delta \mathbf{x} = -\mathbf{f}$$

$$J(\mathbf{x}) = \begin{bmatrix} \frac{\partial f_1(\mathbf{x})}{\partial x_1} & \frac{\partial f_1(\mathbf{x})}{\partial x_2} & \dots & \frac{\partial f_1(\mathbf{x})}{\partial x_n} \\ \frac{\partial f_2(\mathbf{x})}{\partial x_1} & \frac{\partial f_2(\mathbf{x})}{\partial x_2} & \dots & \frac{\partial f_2(\mathbf{x})}{\partial x_n} \\ \vdots & \vdots & \ddots & \vdots \\ \frac{\partial f_n(\mathbf{x})}{\partial x_1} & \frac{\partial f_n(\mathbf{x})}{\partial x_2} & \dots & \frac{\partial f_n(\mathbf{x})}{\partial x_n} \end{bmatrix}$$



# Solving nonlinear equation

- Multi-dimensional root finding



# Newton's method - Algorithm

- 1) Initial guess  $\mathbf{x}_0 = (x_{10}, x_{20}, \dots, x_{n0})$ , Set  $i=0$ .
- 2) Calculate the Jacobian and  $f$  at  $\mathbf{x}_i$ .
- 3) Solve the linear equation

$$\nabla F \Delta \mathbf{x} = -f$$

to get the update term  $\Delta \mathbf{x}$

- 4) Update the solution

$$\mathbf{x}_{i+1} = \mathbf{x}_i + \Delta \mathbf{x}_i$$

- 5) If(convergence)  $\rightarrow$  stop  
else set  $i=i+1$  and goto 2).



# Eg. Newton's method(I)

$$\mathbf{p}^{(k)} = \mathbf{p}^{(k-1)} - [J(\mathbf{p}^{(k-1)})]^{-1} \mathbf{F}(\mathbf{p}^{(k-1)}), \quad \text{for } k \geq 1,$$

Eg.

$$3x_1 - \cos(x_2x_3) - \frac{1}{2} = 0,$$

$$x_1^2 - 81(x_2 + 0.1)^2 + \sin x_3 + 1.06 = 0,$$

$$e^{-x_1x_2} + 20x_3 + \frac{1}{3}(10\pi - 3) = 0$$

$$\mathbf{p}^{(0)} = (0.1, 0.1, -0.1)^t$$

Sol.

$$J(x_1, x_2, x_3) = \begin{bmatrix} 3 & x_3 \sin x_2x_3 & x_2 \sin x_2x_3 \\ 2x_1 & -162(x_2 + 0.1) & \cos x_3 \\ -x_2e^{-x_1x_2} & -x_1e^{-x_1x_2} & 20 \end{bmatrix}$$



# Eg. Newton's method(II)

$$\begin{bmatrix} p_1^{(k)} \\ p_2^{(k)} \\ p_3^{(k)} \end{bmatrix} = \begin{bmatrix} p_1^{(k-1)} \\ p_2^{(k-1)} \\ p_3^{(k-1)} \end{bmatrix} + \begin{bmatrix} y_1^{(k-1)} \\ y_2^{(k-1)} \\ y_3^{(k-1)} \end{bmatrix},$$

$$\begin{bmatrix} y_1^{(k-1)} \\ y_2^{(k-1)} \\ y_3^{(k-1)} \end{bmatrix} = - \left( J(p_1^{(k-1)}, p_2^{(k-1)}, p_3^{(k-1)}) \right)^{-1} \mathbf{F} \left( p_1^{(k-1)}, p_2^{(k-1)}, p_3^{(k-1)} \right)$$

At each step

the linear system  $J(\mathbf{p}^{(k-1)})\mathbf{y}^{(k-1)} = -\mathbf{F}(\mathbf{p}^{(k-1)})$  must be solved





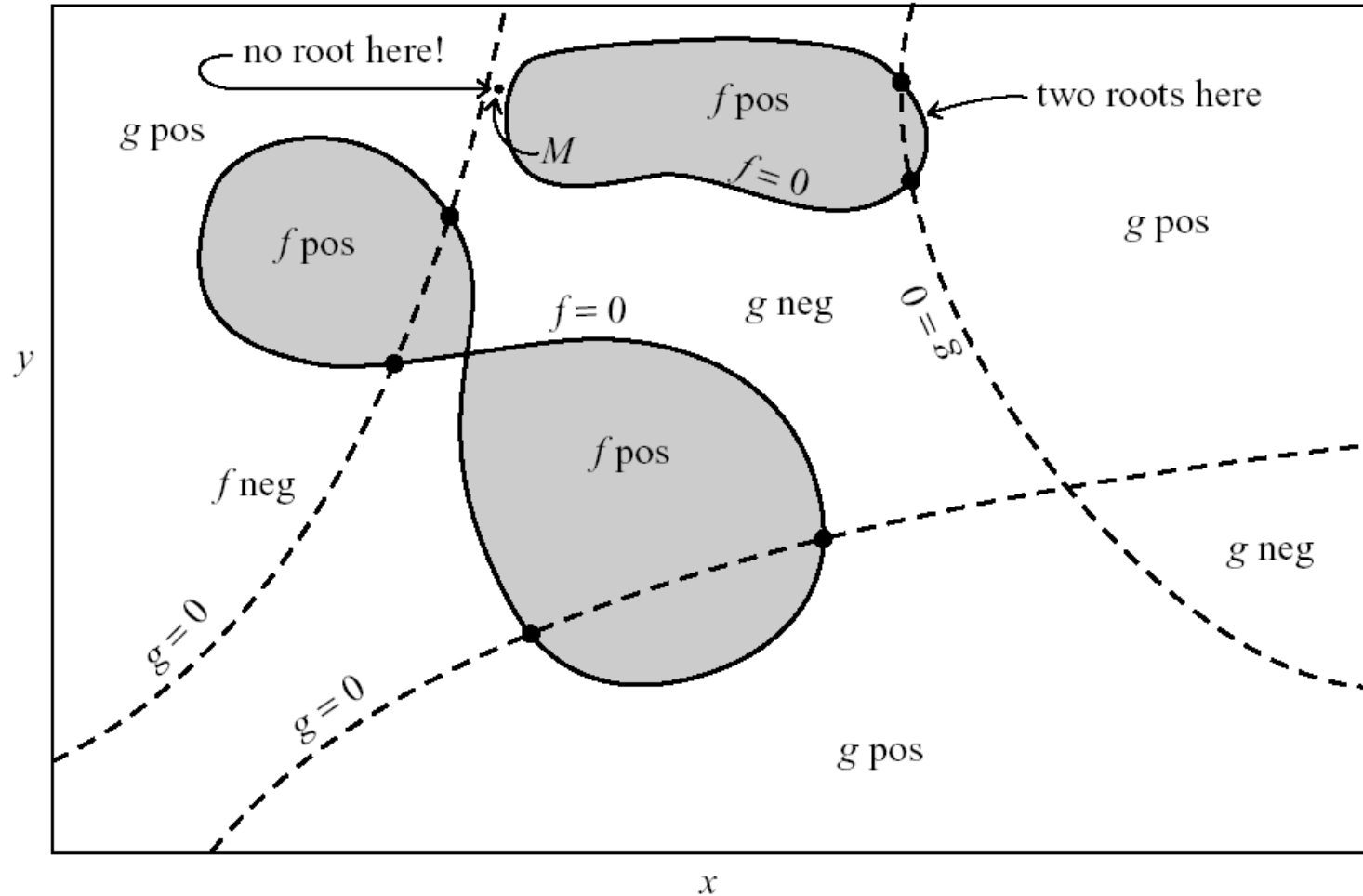
# Eg. Newton's method(II)

## ■ Result:

$k$	$p_1^{(k)}$	$p_2^{(k)}$	$p_3^{(k)}$	$\ p^{(k)} - p^{(k-1)}\ _\infty$
0	0.10000000	0.10000000	-0.10000000	
1	0.49986967	0.01946684	-0.52152047	0.422
2	0.50001424	0.00158859	-0.52355696	$1.79 \times 10^{-2}$
3	0.50000011	0.00001244	-0.52359845	$1.58 \times 10^{-3}$
4	0.50000000	0.00000000	-0.52359877	$1.24 \times 10^{-5}$
5	0.50000000	0.00000000	-0.52359877	$8.04 \times 10^{-10}$



# Discussion



# Quasi-Newton method(I)

## Broyden's method

- Without calculating the Jacobian at each iteration

- Using approximation:

$$f'(p_1) \approx \frac{f(p_1) - f(p_0)}{p_1 - p_0}$$

- Analogy

- ❖ Root finding: Newton vs. Secant
- ❖ Nonlinear eq.: Newton vs. Broyden

➔ Broyden's method is called “**multidimensional secant method**”

\* Read Section 10.3, *Numerical Methods*, 3<sup>rd</sup> ed. by Faires and Burden



# Quasi-Newton method(II)

- Replacing the Jacobian with the matrix A

$$A_i = A_{i-1} + \frac{\mathbf{y}_i - A_{i-1}\mathbf{s}_i}{\|\mathbf{s}_i\|_2^2} \mathbf{s}_i^t$$

$$\mathbf{p}^{(i+1)} = \mathbf{p}^{(i)} - A_i^{-1} \mathbf{F}(\mathbf{p}^{(i)})$$

where the notation  $\mathbf{s}_i = \mathbf{p}^{(i)} - \mathbf{p}^{(i-1)}$  and  $\mathbf{y}_i = \mathbf{F}(\mathbf{p}^{(i)}) - \mathbf{F}(\mathbf{p}^{(i-1)})$

- Important property of calculating  $A_i^{-1}$

$$A_i^{-1} = A_{i-1}^{-1} + \frac{(\mathbf{s}_i - A_{i-1}^{-1}\mathbf{y}_i) \mathbf{s}_i^t A_{i-1}^{-1}}{\mathbf{s}_i^t A_{i-1}^{-1} \mathbf{y}_i}.$$

This update involves only matrix-vector multiplication!



# Eg. Broyden's method

## Results:

$k$	$p_1^{(k)}$	$p_2^{(k)}$	$p_3^{(k)}$	$\ p^{(k)} - p^{(k-1)}\ _2$
0	0.1000000	0.1000000	-0.1000000	
1	0.4998697	$-1.946685 \times 10^{-2}$	-0.5215205	$5.93 \times 10^{-1}$
2	0.4999863	$8.737833 \times 10^{-3}$	-0.5231746	$2.83 \times 10^{-2}$
3	0.5000066	$8.672215 \times 10^{-4}$	-0.5236918	$7.89 \times 10^{-3}$
4	0.5000005	$6.087473 \times 10^{-5}$	-0.5235954	$8.12 \times 10^{-4}$
5	0.5000002	$-1.445223 \times 10^{-6}$	-0.5235989	$6.24 \times 10^{-5}$

Slightly less accurate than Newton's method.

$k$	$p_1^{(k)}$	$p_2^{(k)}$	$p_3^{(k)}$	$\ p^{(k)} - p^{(k-1)}\ _\infty$
0	0.10000000	0.10000000	-0.10000000	
1	0.49986967	0.01946684	-0.52152047	0.422
2	0.50001424	0.00158859	-0.52355696	$1.79 \times 10^{-2}$
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# Steepest Descent Method(I)

- Finding a local minimum for a multivariable function of the form  $g : \mathcal{R}^n \rightarrow \mathcal{R}$

$$g(x_1, x_2, \dots, x_n) = \sum_{i=1}^n [f_i(x_1, x_2, \dots, x_n)]^2$$

- Algorithm

- Evaluate  $g$  at an initial approximation  $\mathbf{p}^{(0)} = (p_1^{(0)}, p_2^{(0)}, \dots, p_n^{(0)})^t$ .
- Determine a direction from  $\mathbf{p}^{(0)}$  that results in a decrease in the value of  $g$ .
- Move an appropriate amount in this direction and call the new value  $\mathbf{p}^{(1)}$ .
- Repeat the steps with  $\mathbf{p}^{(0)}$  replaced by  $\mathbf{p}^{(1)}$ .

$$\mathbf{p}^{(1)} = \mathbf{p}^{(0)} - \hat{\alpha} \nabla g(\mathbf{p}^{(0)})$$

$$\text{where } \nabla g(\mathbf{x}) = \left( \frac{\partial g}{\partial x_1}(\mathbf{x}), \frac{\partial g}{\partial x_2}(\mathbf{x}), \dots, \frac{\partial g}{\partial x_n}(\mathbf{x}) \right)^t$$



# Steepest Descent Method(II)

- Mostly used for finding an appropriate initial value of Newton's methods etc.

