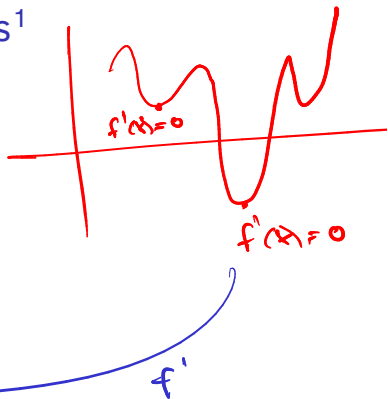
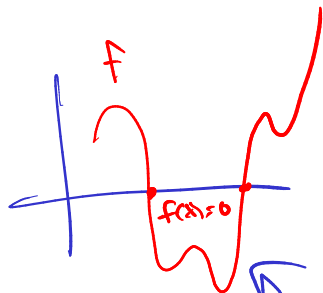


# CS 450: Numerical Analysis<sup>1</sup>

## Nonlinear Equations

University of Illinois at Urbana-Champaign

Optimization



<sup>1</sup>These slides have been drafted by Edgar Solomonik as lecture templates and supplementary material for the book “Scientific Computing: An Introductory Survey” by Michael T. Heath ([slides](#)).

# Solving Nonlinear Equations

- ▶ Solving (systems of) nonlinear equations corresponds to root finding:

- ▶  $f(x^*) = 0$

$\uparrow$   $\nwarrow$   
scalar

- ▶  $f(x^*) = 0$

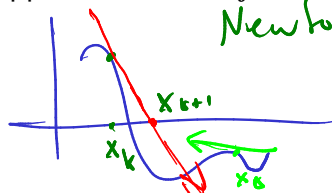
- ▶  $f(x^*) = 0$

$$f\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = 0$$

$$f\left(\begin{bmatrix} x \\ y \end{bmatrix}\right) = \begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix} \leftarrow$$

$$\nabla f(x) = \frac{\partial f}{\partial x}$$

- ▶ Algorithms for root-finding make it possible to solve systems of nonlinear equations and employ a similar methodology to finding minima in optimization.
- ▶ Main algorithmic approach: find successive roots of local linear approximations of  $f$ :



Newton's method

$$f(x_k + \delta x) \approx f(x_k) + \nabla f(x_k) \delta x$$

$$f(x_k + \delta x) \approx f(x_k) + f'(x_k) \delta x$$

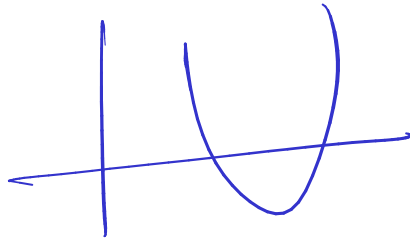
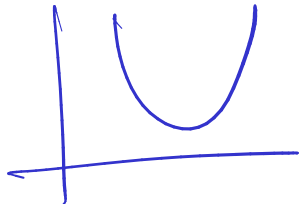
$$0 = f(x_k) + f'(x_k) \delta x$$

$$\delta x = -f(x_k) / f'(x_k)$$

$$\delta x = -f(x_k) / f'(x_k)$$

# Nonexistence and Nonuniqueness of Solutions

- Solutions do not generally exist and are not generally unique, even in the univariate case:



- Solutions in the multivariate case correspond to intersections of hypersurfaces:

$$f\left(\begin{bmatrix} \phantom{x} \\ \phantom{x} \\ \phantom{x} \end{bmatrix}\right) = \begin{bmatrix} \phantom{x} \\ \phantom{x} \\ \phantom{x} \end{bmatrix}$$

$$f_1(x) = 0$$

$\vdots$

$$f_n(x) = 0$$

$$2x_1 = 0$$

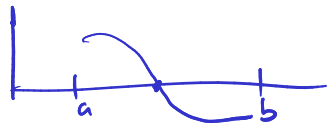
$$3x_2 + x_3 = 0$$

## Conditions for Existence of Solution

- *Intermediate value theorem* for univariate problems:

bracket  $[a, b]$ ,  $\text{sign}(f(a)) \neq \text{sign}(f(b))$

$f$  is continuous



$\Rightarrow \exists x^* \in [a, b], f(x^*) = 0$

- A function has a unique *fixed point*  $g(x^*) = x^*$  in a given closed domain if it is *contractive* and contained in that domain,  $\exists \gamma$

$$\|g(x) - g(z)\| \leq \gamma \|x - z\|$$

Lipschitz continuous

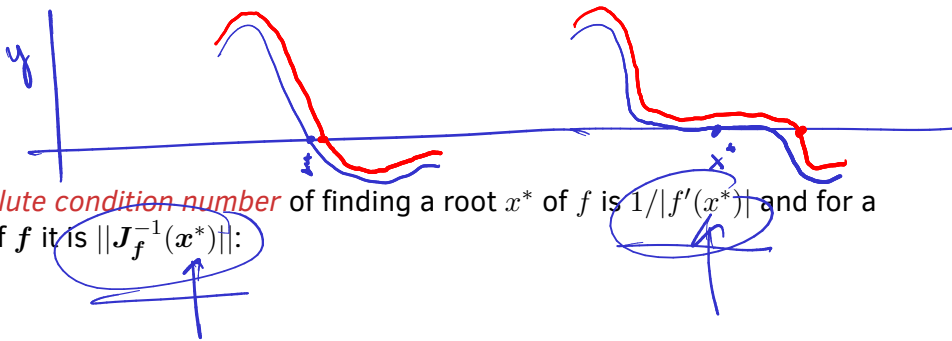
$$g(x^*) = x^*$$

$$\Rightarrow f(x^*) = 0$$

$$\underline{g(x) = f(x) + x}$$

# Conditioning of Nonlinear Equations

- Generally, we take interest in the absolute rather than relative conditioning of solving  $f(x) = 0$ :

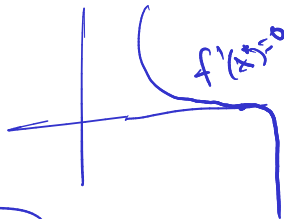
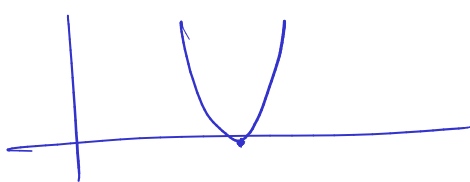


- The *absolute condition number* of finding a root  $x^*$  of  $f$  is  $1/|f'(x^*)|$  and for a root  $x^*$  of  $f$  it is  $\|J_f^{-1}(x^*)\|$ :

## Multiple Roots and Degeneracy

- If  $x^*$  is a root of  $f$  with **multiplicity**  $m$ , its  $m - 1$  derivatives are also zero at  $x^*$ ,

$$f(x^*) = f'(x^*) = f''(x^*) = \dots = f^{(m-1)}(x^*) = 0.$$

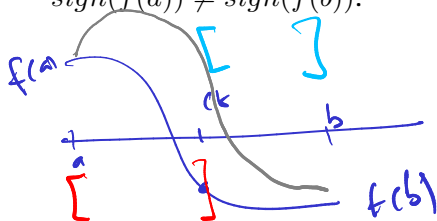


- Increased multiplicity affects conditioning and convergence:

$$\kappa = 1 / f'(x^*) = \infty$$

# Bisection Algorithm

- Assume we know the desired root exists in a bracket  $[a, b]$  and  $\text{sign}(f(a)) \neq \text{sign}(f(b))$ :



$$e_k = c_k - x^* \quad |e_k| \leq \frac{1}{2^k} (b_0 - a_0)$$

- Bisection subdivides the interval by a factor of two at each step by considering  $f(c_k)$  at  $\underline{c_k} = (a_k + b_k)/2$ :

## Rates of Convergence

- Let  $x_k$  be the  $k$ th iterate and  $e_k = x_k - x^*$  be the error, bisection obtains *linear convergence*,  $\lim_{k \rightarrow \infty} \|e_k\| / \|e_{k-1}\| \leq C$  where  $C < 1$ :

for relative accuracy  $\epsilon$

$\sim \log_C(\frac{1}{\epsilon})$  steps

- $r$ th order convergence implies that  $\|e_k\| / \|e_{k-1}\| \leq C$

quadratic  $r = 2$

superlinear  $1 < r < 2$

cubic  $r = 3$

$O(\log \log(\frac{1}{\epsilon}))$

$$\epsilon = 10^{-10}$$

$$\log_C(\frac{1}{\epsilon})$$

$$\sim 10$$

$$\log(\|e_k\|) \geq r \log(\|e_{k-1}\|)$$

increase the digits of accuracy by a factor of  $r$  at each step



# Convergence of Fixed Point Iteration

- Fixed point iteration:  $x_{k+1} = g(x_k)$  is locally linearly convergent if for  $x^* = g(x^*)$ , we have  $|g'(x^*)| < 1$ :

$$e_{k+1} = x_{k+1} - x^* = g(x_k) - g(x^*)$$

$$e_{k+1} = g'(x^*)(x_k - x^*) + O(|x_k - x^*|^2)$$

$$= g'(x^*)e_k + O(|x_k - x^*|^2)$$

- It is quadratically convergent if  $g'(x^*) = 0$ .

$$e_{k+1} = g''(x^*)e_k^2/2 + O(|x_k - x^*|^3)$$

$$g(x^* + \delta x) \approx g(x^*) + g'(x^*)\delta x + O(|\delta x|^2)$$

# Newton's Method

Demo: Newton's Method

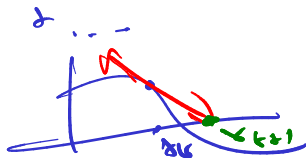
Demo: Convergence of Newton's Method

- ▶ Newton's method is derived from a Taylor series expansion of  $f$  at  $x_k$ :

$$f(x) = f(x_k) + f'(x_k)(x - x_k) + (1/2)f''(x_k)(x - x_k)^2 + \dots$$



secant line  
approximation



- ▶ Newton's method is quadratically convergent if started sufficiently close to  $x^*$  so long as  $f'(x^*) \neq 0$ :

$$g(x) = x - f(x)/f'(x)$$

quad. conv. if  $g'(x^*) = 0$

$$g'(x^*) = 1 - \underbrace{f'(x^*)/f'(x^*)}_1 + \frac{f(x^*)f''(x^*)}{f'(x^*)^2}$$

$\rightarrow 0$

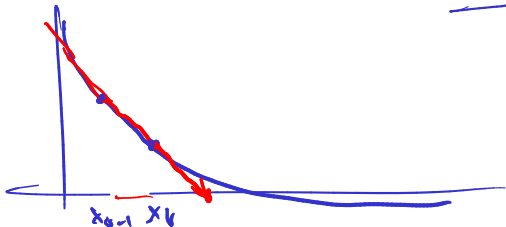
# Secant Method

Demo: Secant Method

- The *Secant method* approximates  $f'(x_k) \approx$

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

Demo: Convergence of the Secant Method



only need to compute  $f(x_k)$  at  $k$ th step  
Newton's method needs  $f(x_k)$  and  $f'(x_k)$

- The convergence of the Secant method is *superlinear* but not quadratic:

$e_{k+1}$   
error depends on  $e_k$  and  $e_{k-1}$

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

$$\log(e_{k+1}) = \log(e_k) + \log(e_{k-1})$$

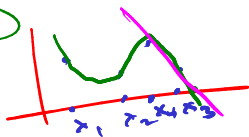
$$r = (1 + \sqrt{5})/2$$

Fibonacci sequence

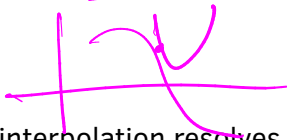
# Nonlinear Tangential Interpolants

- Secant method uses a linear interpolant based on points  $f(x_k), f(x_{k-1})$ , could use more points and higher-order interpolant:

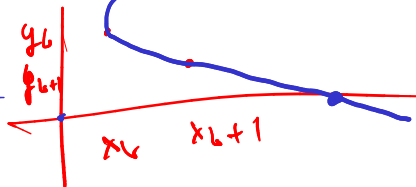
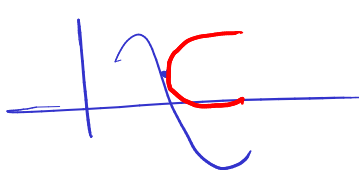
$$(x_0, f(x_0)) \dots (x_k, f(x_k))$$



- Quadratic interpolation (Muller's method) achieves convergence rate  $r \approx 1.84$ :



- Inverse quadratic interpolation resolves the problem of nonexistence/nonuniqueness of roots of polynomial interpolants:



$$(y_k, x_k)$$

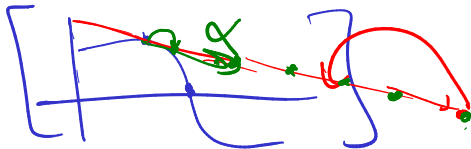
$$(y_{k+1}, x_{k+1})$$

$$\tilde{f}(y) = x \quad x^* \approx \tilde{f}(0)$$

# Achieving Global Convergence

- Hybrid bisection/Newton methods:

Newton with safeguarding using a bracket



- Bounded (damped) step-size:



# Systems of Nonlinear Equations

► Given  $\mathbf{f}(\mathbf{x}) = [f_1(\mathbf{x}) \ \cdots \ f_m(\mathbf{x})]^T$  for  $\mathbf{x} \in \mathbb{R}^n$ , seek  $\mathbf{x}^*$  so that  $\mathbf{f}(\mathbf{x}^*) = \mathbf{0}$

► At a particular point  $\mathbf{x}$ , the *Jacobian* of  $\mathbf{f}$ , describes how  $\mathbf{f}$  changes in a given direction of change in  $\mathbf{x}$ ,

$$\begin{matrix} f_1 \\ \vdots \\ f_m \end{matrix} \quad \underbrace{J_{\mathbf{f}}(\mathbf{x})}_{\text{dependent}} = \begin{bmatrix} \frac{df_1}{dx_1}(\mathbf{x}) & \cdots & \frac{df_1}{dx_n}(\mathbf{x}) \\ \vdots & & \vdots \\ \frac{df_m}{dx_1}(\mathbf{x}) & \cdots & \frac{df_m}{dx_n}(\mathbf{x}) \end{bmatrix} \quad \begin{matrix} x_1 \\ \vdots \\ x_n \end{matrix}$$

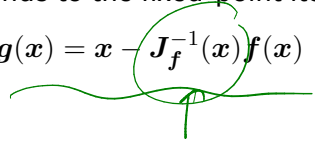
$m=n$

## Multivariate Newton Iteration

- ▶ Fixed-point iteration  $\mathbf{x}_{k+1} = \mathbf{g}(\mathbf{x}_k)$  achieves local convergence so long as  $|\lambda_{\max}(\mathbf{J}_{\mathbf{g}}(\mathbf{x}^*))| < 1$  and quadratic convergence if  $\mathbf{J}_{\mathbf{g}} = \mathbf{O}$ :

# Multidimensional Newton's Method

- ▶ Newton's method corresponds to the fixed-point iteration

$$g(x) = x - J_f^{-1}(x)f(x)$$


- ▶ Quadratic convergence is achieved when the Jacobian of a fixed-point iteration is zero at the solution, which is true for Newton's method:



## Estimating the Jacobian using Finite Differences

- ▶ To obtain  $\mathbf{J}_f(\mathbf{x}_k)$  at iteration  $k$ , can use finite differences:
- ▶  $n + 1$  function evaluations are needed:  $f(\mathbf{x})$  and  $f(\mathbf{x} + h\mathbf{e}_i), \forall i \in \{1, \dots, n\}$ , which correspond to  $m(n + 1)$  scalar function evaluations if  $\mathbf{J}_f(\mathbf{x}_k) \in \mathbb{R}^{m \times n}$ .

## Cost of Multivariate Newton Iteration

- ▶ What is the cost of solving  $\mathbf{J}_f(\mathbf{x}_k)\mathbf{s}_k = \mathbf{f}(\mathbf{x}_k)$ ?
- ▶ What is the cost of Newton's iteration overall?

# Quasi-Newton Methods

In solving a nonlinear equation, seek approximate Jacobian  $\mathbf{J}_f(\mathbf{x}_k)$  for each  $\mathbf{x}_k$

- Find  $\mathbf{B}_{k+1} = \mathbf{B}_k + \delta \mathbf{B}_k \approx \mathbf{J}_f(\mathbf{x}_{k+1})$ , so as to approximate *secant equation*

$$\underbrace{\mathbf{B}_{k+1}}_{\delta \mathbf{B}_k} \underbrace{(\mathbf{x}_{k+1} - \mathbf{x}_k)}_{\delta \mathbf{x}} = \underbrace{\mathbf{f}(\mathbf{x}_{k+1}) - \mathbf{f}(\mathbf{x}_k)}_{\delta \mathbf{f}}$$

- *Broyden's method* solves the secant equation and minimizes  $\|\delta \mathbf{B}_k\|_F$ :

$$\delta \mathbf{B}_k = \frac{\delta \mathbf{f} - \mathbf{B}_k \delta \mathbf{x}}{\|\delta \mathbf{x}\|^2} \delta \mathbf{x}^T$$

## Safeguarding Methods

- ▶ Can dampen step-size to improve reliability of Newton or Broyden iteration:
- ▶ *Trust region methods* provide general step-size control: