

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

## Nonlinear Equations

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<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:
  - ▶  $f(x^*) = 0$
  - ▶  $\mathbf{f}(\mathbf{x}^*) = \mathbf{0}$
- ▶ 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  $\mathbf{f}$ :

# 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:

# Conditions for Existence of Solution

► *Intermediate value theorem* for univariate problems:

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

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

# 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  $x^*$ ,

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

- ▶ Increased multiplicity affects conditioning and convergence:

# Bisection Algorithm

- ▶ Assume we know the desired root exists in a bracket  $[a, b]$  and  $\text{sign}(f(a)) \neq \text{sign}(f(b))$ :
- ▶ Bisection subdivides the interval by a factor of two at each step by considering  $f(c_k)$  at  $c_k = (a_k + b_k)/2$ :

# 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  $C < 1$ :

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



## 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  $|g'(x^*)| < 1$ :
  
  
  
  
  
  
  
  
  
  
- ▶ It is quadratically convergent if  $g'(x^*) = 0$ :

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

# Secant Method

*Demo: Secant Method*

*Demo: Convergence of the Secant Method*

► The *Secant method* approximates  $f'(x_k) \approx \frac{f(x_k) - f(x_{k-1})}{x_k - x_{k-1}}$ .

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

## 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:
- ▶ 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:

# Achieving Global Convergence

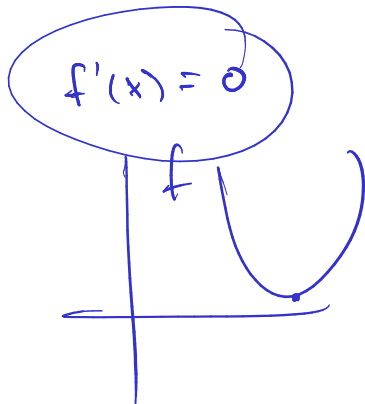
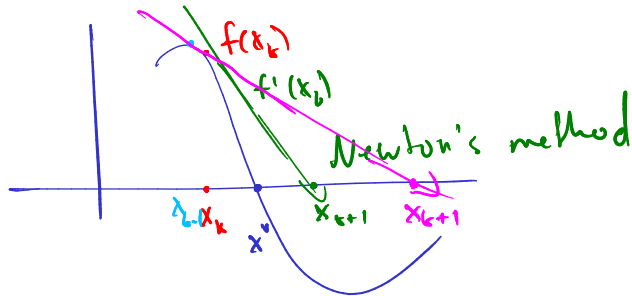
- ▶ Hybrid bisection/Newton methods:

- ▶ Bounded (damped) step-size:

# Nonlinear Solve

$$f(x) = 0$$

$$x_{k+1} = g(x_k)$$



# Systems of Nonlinear Equations

$$f(x) \in \mathbb{R}^n \rightarrow \mathbb{R}, \quad \nabla f(x) \in \mathbb{R}^n \rightarrow \mathbb{R}^n$$

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

$$m=n$$

$$\begin{bmatrix} 0 \\ \vdots \\ 0 \end{bmatrix}$$

- At a particular point  $x$ , the *Jacobian* of  $f$ , describes how  $f$  changes in a given direction of change in  $x$ ,

$$\underline{J_f(x)} = \begin{bmatrix} \frac{df_1}{dx_1}(x) & \cdots & \frac{df_1}{dx_n}(x) \\ \vdots & & \vdots \\ \frac{df_m}{dx_1}(x) & \cdots & \frac{df_m}{dx_n}(x) \end{bmatrix}$$

$$\underline{x_{k+1} = x_k + s_k}$$

$$\underline{J_f(x_k) s_k = -f(x_k)}$$

center



$$\underline{f(x+s) = f(x) + J_f(x) s}$$

$$\Rightarrow 0 = f(x) + J_f(x) s$$

# Multivariate Newton Iteration

*Demo: Newton's method in  $n$  dimensions*

$$|g'(x)| < 1$$

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

$$e_k = x^* - x_k$$

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

$$= J_g(x^*) (x^* - x_{k-1}) + \dots$$

h.o. diff of  $g$   
 $\|x^* - x_{k-1}\|^2$

$$\|e_k\| \leq \|J_g(x^*)\|_2 \|e_{k-1}\| + \dots$$



# Multidimensional Newton's Method

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

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

$$J_g(x) = I - \underbrace{J_f^{-1}(x) J_f(x)}_I - \underbrace{\sum_{i=1}^n H_{f_i}(x) f_i(x)}_0$$

*Handwritten notes: Red double slash // 0 above the second term, and a red circle 0 below the second term.*

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

- To obtain  $\underline{J_f(x_k)}$  at iteration  $k$ , can use finite differences:

$$f: \mathbb{R} \rightarrow \mathbb{R}^n$$

$$J_f(x) \approx \frac{f(x+h) - f(x)}{h}$$

$$J_f(x) = \begin{bmatrix} f'_1(x) \\ \vdots \\ f'_n(x) \end{bmatrix}$$

$$f'_i(x) \approx \frac{f(x+he_i) - f(x)}{h}$$

- $n+1$  function evaluations are needed:  $f(x)$  and  $f(x+he_i), \forall i \in \{1, \dots, n\}$ , which correspond to  $m(n+1)$  scalar function evaluations if  $J_f(x_k) \in \mathbb{R}^{m \times n}$ .

$$f: \mathbb{R}^n \rightarrow \mathbb{R}^n$$

let  $j_i$  be the  $i$ th column of  $J_f(x)$

$$j_i \approx \frac{f(x + e_i h) - f(x)}{h}$$

## Cost of Multivariate Newton Iteration

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

PLU

$O(n^3)$  at each iteration

$$\mathbf{J}_f(\mathbf{x}_k) \neq \mathbf{J}_f(\mathbf{x}_{k+1})$$

- What is the cost of Newton's iteration overall?

$k$  steps

& cost of evaluation of  $f$ :

$$O(kn^3 + kn^2\gamma)$$

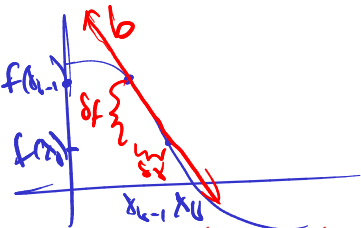
# Quasi-Newton Methods

In solving a nonlinear equation, seek approximate Jacobian  $J_f(x_k)$  for each  $x_k$

- Find  $B_{k+1} = B_k + \delta B_k \approx J_f(x_{k+1})$ , so as to approximate *secant equation*

$$b \delta x = \delta f$$

$$B_{k+1}(\underbrace{x_{k+1} - x_k}_{\delta x}) = \underbrace{f(x_{k+1}) - f(x_k)}_{\delta f}$$



$$\boxed{B_{k+1}} (1 - 1) = 1 - 1$$

- *Broyden's method* solves the secant equation and minimizes  $\|\delta B_k\|_F$ .

$$\delta B_k = \frac{\delta f - B_k \delta x}{\|\delta x\|^2} \delta x^T$$

$$B_{k+1} \delta x = B_k \delta x + \delta B_k \delta x = \cancel{B_k \delta x} + \delta f - \cancel{B_k \delta x}$$

$O(n^2)$  cost / iteration excl. func. eval.

# Safeguarding Methods

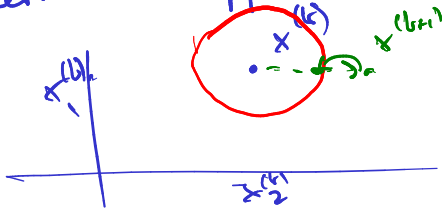
- Can dampen step-size to improve reliability of Newton or Broyden iteration:

$$J_f(x_k) s_k = -f(x_k)$$

$$x_{k+1} = x_k + \alpha_k s_k, \text{ e.g., choose } \alpha_k$$

- *Trust region methods* provide general step-size control:

describes region in which  
our derivative approximation is reliable



converges quadratically  
local

$$\|f(x_{k+1})\| \leq \|f(x_k)\|$$