ECE 595, Section 10 Numerical Simulations Lecture 6: Finding Special Values

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Outline

- Recap from Wednesday
- Root Finding
 - Bisection
 - Newton-Raphson method
 - Brent's method
- Optimization
 - Golden Section Search
 - Brent's Method
 - Downhill Simplex
 - Conjugate gradient methods
 - Multiple level, single linkage (MLSL)

Recap from Wednesday

- Solve linear algebra problems A^{-1} and $A \cdot x = b$
- Gauss-Jordan method $(A' \cdot x = b')$
- Gaussian Elimination $(U \cdot x = b')$
- LU Decomposition ($A = L \cdot U$)
- Singular Value Decomposition $(A = U \cdot W \cdot V^T)$
- Sparse Matrices
- Iterative improvement (subtract $A^{-1}(b'-b)$ from x')
- QR Decomposition ($A = \prod Q_i \cdot R$)



Crout's algorithm



Band diagonal sparse matrix

Finding Zeros

- Relevance in micro & nano research
- Key concept: bracketing
- Bisection continuously halve intervals
- Newton-Raphson method uses tangent
- Laguerre's method for polynomials
- Brent's method adds inverse quadratic interpolation



Importance of Bracketing

- Critically important for both root finding and optimization
- Can always guarantee at least one solution for continuous functions with sign change in 1D
- If more than one solution present, may not be able to guarantee which one is reached – method-dependent

Bisection

- Most stable and reliable approach
- Algorithm:
 - Choose point x_3 in the middle of the bracket with sign change: $[x_1, x_2]$
 - Check sign of $f(x_3)$
 - If non-zero, construct new bracket from midpoint and original point with opposite sign
 - Repeat previous steps



Newton-Raphson Method

- Key assumption: system is nearly linear in region between starting point and root
- When sufficiently close, converge quadratically on correct value (from Taylor expansion)



NR Method Failures

- Getting stuck in a limit cycle is possible
- Can even get worse certain locally flat curves can send you into outer space!



Laguerre's Method

- Specifically for polynomials
- Algorithm
 - Calculate quantities G and H
 - Assume far roots a distance b;
 one root is a distance a away

– Iterate solution as $a \rightarrow 0$

$$P_n(x) = \prod_i (x - x_i)$$
$$G = \frac{d \ln|P_n(x)|}{dx}$$
$$H = -\frac{d^2 \ln|P_n(x)|}{dx^2}$$
$$a = \frac{n}{G \pm \sqrt{(n-1)(nH - G^2)}}$$

Brent's Method: Finding Roots

- Combines bracketing, bisection, and inverse quadratic interpolation
- Guaranteed to converge, but speed can vary with function and quality of initial guess
- Algorithm:
 - Calculate f(a), f(b), f(c)
 - Calculate R, S, T, P, Q
 - Let $b \rightarrow b + P/Q$
 - Repeat as $f(b) \rightarrow 0$





Optimization

- Relevance in micro & nano research
- Convexity
- Search classifications
- Techniques:
 - Brent's Method
 - Golden Section Search
 - Downhill Simplex
 - Conjugate gradient methods
 - Multiple level, single linkage (MLSL)



These and further images from "Numerical Recipes," by WH Press *et al*.



Convexity

- Convex functions have certain properties that aid in finding an optimum:
 - Precisely one optimum in an open set of values
 - Continuous and at least twice differentiable
 - Midpoints always lower than edges i.e., $f[\delta x_1 + (1 - \delta)\delta x_2] < \delta f(x_1) + (1 - \delta)f(x_2)$
- Examples include x², sinh(x)



Search Types

- Local assumes convex/concave problem
- Global uses heuristics to deal with multiple optima
- Non-derivative based no specific assumptions about best search direction
- Derivative based incorporates derivatives to determine search direction

Brent's Method: Finding Optima

- Assumes a concave function
- Algorithm:
 - Evaluate function at bracket endpoints & center
 - Fit parabola
 - Find $x_{min} \& f(x_{min})$
 - Keep two closest points for bracket and repeat until bracket is around $\sqrt{\varepsilon}$
- Infer optimum based



Golden Section Search

- Closely related to bisection approach to finding roots
- Algorithm
 - Taking a downhill step
 - Bracket lowest point with higher values on each side
 - Keep repeating until interval is around $\sqrt{\varepsilon}$

 $f(x_2)$ $f(x_1)$ $f(x_3)$ (x_4) $x_4 \ x_3 \ x_2$ x_1

Downhill Simplex Search

- Simplex is a triangle (2D), tetrahedron (3D), etc.
- Algorithm:
 - Create an N-dimensional simplex: $P_i = P_o + \lambda_i \hat{e}_i$
 - Perform one of 4 steps shown on right
 - Repeat until tolerances reached (e.g., for change in simplex end-points, or function values)



Conjugate Gradient Method

- Assumes convex multidimensional function
- Uses derivative information
- Algorithm:
 - Start with initial g_o=h_o
 - Calculate scalars λ_i , γ_i
 - Construct new vectors g_{i+1} and h_{i+1}, satisfying orthogonality & conjugacy conditions
 - Repeat until tolerance reached
- Note that no *a priori* knowledge of Hessian matrix *A* is required!

$$\begin{split} \lambda_i &= \frac{\mathbf{g}_i \cdot \mathbf{g}_i}{\mathbf{h}_i \cdot \mathbf{A} \cdot \mathbf{h}_i} = \frac{\mathbf{g}_i \cdot \mathbf{h}_i}{\mathbf{h}_i \cdot \mathbf{A} \cdot \mathbf{h}_i} \\ \gamma_i &= \frac{(\mathbf{g}_{i+1} - \mathbf{g}_i) \cdot \mathbf{g}_{i+1}}{\mathbf{g}_i \cdot \mathbf{g}_i} \\ \mathbf{g}_{i+1} &= \mathbf{g}_i - \lambda_i \mathbf{A} \cdot \mathbf{h}_i \\ \mathbf{h}_{i+1} &= \mathbf{g}_{i+1} + \gamma_i \mathbf{h}_i \\ \mathbf{g}_i \cdot \mathbf{g}_j &= 0 \\ \mathbf{h}_i \cdot \mathbf{A} \cdot \mathbf{h}_j &= 0 \end{split}$$

 $\mathbf{g}_i \cdot \mathbf{h}_j = 0$

Multiple Level Single Linkage

- Global search
- Algorithm:
 - Quasi-random
 sequence of starting
 points
 - Local optimization
 (e.g., conjugate
 gradient)
 - Heuristic tracks basins of convergence



M. Ghebrebrhan, P. Bermel, *et al.*, *Opt. Express* **17**, 7505 (2009)

Next Class

- Is on Wednesday, Jan. 23 (because of Martin Luther King, Jr. Day)
- Discussion of eigenproblems
- Please read Chapter 11 of "Numerical Recipes" by W.H. Press *et al*.