## Solving Nonlinear Equations

Jijian Fan

Department of Economics University of California, Santa Cruz

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#### Overview

■ NUMERICALLY solving nonlinear equation

$$f(x) = 0$$

- Four methods
  - Bisection
  - Function iteration
  - Newton's
  - Quasi-Newton

#### Motivation

Linear equation can be solved analytically

- $Ax = b \qquad \Rightarrow \qquad x = A^{-1}b$
- Methods such as L-U factorization, Gaussian elimination, etc

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Linear equation can be solved analytically

$$Ax = b \Rightarrow x = A^{-1}b$$

 Methods such as L-U factorization, Gaussian elimination, etc

However, nonlinear equation might not be explicitly solved

$$e.g. f(x) = x^{-0.8} + 2x^{0.5} - 3 = 0$$

■ Numerical methods

#### Numerical methods

- "Continuous" means 1, 1.001, ..., 1.999, 2
- "Equality" means 1 = 1.0003

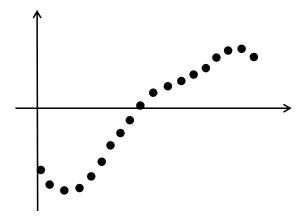


Figure 1: A "continuous" function in computer

#### Bisection Method

- Based on Intermediate Value Theorem
- Start with a bounded interval [a, b] such that f(a)f(b) < 0

```
Sample code
while (b-a)>tol;
if sign(f((a+b)/2)) == sign(f(a))
    a= (a+b)/2;
else
    b= (a+b)/2;
end
x=a:
```

#### Bisection Method

- Advantage
  - Reliable: always finds the root
  - LEAST requirements on functional properties

- Disadvantage
  - Univariate  $f : \mathbb{R} \to \mathbb{R}$
  - Slow log(n)

## <u>Function Iteration</u>

- Solve for fixed point x = g(x) $f(x) = 0 \Leftrightarrow x = g(x) = x - f(x)$
- Start with an initial guess  $\mathbf{x}^{(0)}$  s.t.  $||\mathbf{g}'(\mathbf{x}^{(0)})|| < 1$
- Sample code
  x=x0;
  y=g(x);
  while norm(y-x)>tol;
  x=y;
  y=g(x);
  end

## <u>Function Iteration</u>

- Advantage
  - Could be multivariate  $f : \mathbb{R}^n \to \mathbb{R}^n$
  - Easy-coding
- Disadvantage
  - Not reliable: require differentiability, and
  - Initial x<sup>(0)</sup> should be sufficiently close to a fixed point x\*
  - Only applicable to downward-crossing fixed point  $||g'(x^*)|| < 1$
  - Worth trying even if one or more condition fails

## Function Iteration: Extension

■ Value Function Iteration (VFI)

$$V(k) = \max_{k'} \{u(c) + \beta V(k')\}$$
$$k' = f(k) - c + (1 - \delta)k$$

Rewrite as

$$V(k) = \max_{k'} \{ u(f(k) + (1 - \delta)k - k') + \beta V(k') \}$$

## <u>Function Iteration: Extension</u>

- Make a grid of k
- Make an initial guess V<sup>0</sup>(k) for each k
- Updating: for every k, update

$$V^{i+1}(k) = \max_{k'} \{ u(f(k) + (1 - \delta)k - k') + \beta V^i(k') \}$$

by trying each possible k'

- Repeat updating
- Until V<sup>i+1</sup>(k) is close enough to V<sup>i</sup>(k)



## Newton's Method

■ First-order Taylor approximation

$$f(x) \approx f(x^{(k)}) + f'(x^{(k)})(x - x^{(k)}) = 0$$

■ Solve for the iteration rule

$$x^{(k+1)} \leftarrow x^{(k)} - [f'(x^{(k)})]^{-1} f(x^{(k)})$$

• Start with an initial guess  $x^{(0)}$ 

## Newton's Method

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$$\mathbf{x}^{(k+1)} \leftarrow \mathbf{x}^{(k)} - [\mathbf{f}'(\mathbf{x}^{(k)})]^{-1} \mathbf{f}(\mathbf{x}^{(k)})$$

- Start with an initial guess  $x^{(0)}$
- Pseudo-code

```
for iter=1:maxiter
  [ fval fjac ]=f(x);
  x = x - fjac \ fval;
  if norm(fval) < tol, break, end
end</pre>
```

■ How to calculate the Jacobian Matrix

$$f'(x) = \begin{bmatrix} \partial f_1/\partial x_1 & \partial f_1/\partial x_2 & \dots & \partial f_1/\partial x_n \\ \partial f_2/\partial x_1 & \partial f_2/\partial x_2 & \dots & \partial f_2/\partial x_n \\ \vdots & \vdots & \ddots & \vdots \\ \partial f_n/\partial x_1 & \partial f_n/\partial x_2 & \dots & \partial f_n/\partial x_n \end{bmatrix}$$

- Analytical derivatives
- Numerical derivatives

■ Analytical derivatives example: Cournot duopoly model

$$\begin{split} P(q) &= q^{-1/\eta} \\ C_i(q_i) &= \frac{1}{2} c_i q_i^2 \\ \max_{q_i} \pi_i(q_1, q_2) &= P(q_1 + q_2) q_i - C_i(q_i) \end{split}$$

F.O.C.

$$\frac{\partial \pi_i}{\partial q_i} = P(q_1 + q_2) + P'(q_1 + q_2)q_i - C'_i(q_i) = 0$$

Let

$$\vec{f}(\vec{q}) = \begin{bmatrix} \frac{\partial \pi_1}{\partial q_1}(q_1, q_2) \\ \frac{\partial \pi_2}{\partial q_2}(q_1, q_2) \end{bmatrix}$$

Solve

$$\vec{f}(\vec{q}) = \vec{0}$$



Note that

$$\frac{\partial f_i}{\partial x_j} \equiv \frac{\partial^2 \pi_i}{\partial q_j \partial q_i}$$

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Numerical derivatives

$$f'(x) \approx \frac{f(x+\varepsilon) - f(x)}{(x+\varepsilon) - x} = \frac{f(x+\varepsilon) - f(x)}{\varepsilon}$$

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■ Centered finite difference approximation

$$f'(x) \approx \frac{f(x+\varepsilon) - f(x-\varepsilon)}{(x+\varepsilon) - (x-\varepsilon)} = \frac{f(x+\varepsilon) - f(x-\varepsilon)}{2\varepsilon}$$



■ For multivariate case, let

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

# Quasi-Newton Methods

#### Calculating f'(x) and taking inverse is

- Slow
- Inefficient

#### Goal

- Find a proper approximation of f'(x) or  $(f'(x))^{-1}$
- Update this approximation in a more efficient way

#### Methods

- Secant method
- Broyden's method

## Secant Methods

- Univariate
- Approximate derivatives (tangent) by secant

$$f'(x^{(k)}) \approx \frac{f(x^{(k)}) - f(x^{(k-1)})}{x^{(k)} - x^{(k-1)}}$$

thus

$$[f'(x^{(k)})]^{-1} \approx \frac{x^{(k)} - x^{(k-1)}}{f(x^{(k)}) - f(x^{(k-1)})}$$

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■ Iteration rule

$$\mathbf{x}^{(k+1)} \leftarrow \mathbf{x}^{(k)} - \frac{\mathbf{x}^{(k)} - \mathbf{x}^{(k-1)}}{f(\mathbf{x}^{(k)}) - f(\mathbf{x}^{(k-1)})} f(\mathbf{x}^{(k)})$$

Need two initial value



Generalized secant method for multivariate

- Denote  $A^{(k)}$  as the Jacobian approximant of f at  $x = x^{(k)}$
- Newton iteration

$$x^{(k+1)} \leftarrow x^{(k)} - (A^{(k)})^{-1} f(x^{(k)})$$

■ Secant condition must hold at x<sup>(k+1)</sup>

$$f(x^{(k+1)}) - f(x^{(k)}) = A^{(k+1)}(x^{(k+1)} - x^{(k)})$$



■ Choose A<sup>(k+1)</sup> that minimizes Frobenius norm

$$\begin{split} \min_{A^{(k+1)}} ||A^{(k+1)} - A^{(k)}|| &= \sqrt{\operatorname{trace}((A^{(k+1)} - A^{(k)})^{\top}(A^{(k+1)} - A^{(k)}))} \\ \text{subject to} \end{split}$$

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• Choose  $A^{(k+1)}$  that minimizes Frobenius norm

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subject to

$$f(x^{(k+1)}) - f(x^{(k)}) = A^{(k+1)}(x^{(k+1)} - x^{(k)})$$

■ Solve for A<sup>(k+1)</sup>

$$A^{(k+1)} \leftarrow A^{(k)} + [f(x^{(k+1)}) - f(x^{(k)}) - A^{(k)}d^{(k)}] \frac{d^{(k)^\top}}{d^{(k)^\top}d^{(k)}}$$

where

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

- Improvement: directly update  $B^{(k)} \equiv (A^{(k)})^{-1}$
- Sherman-Morrison formula

$$(A + uv^{\top})^{-1} = A^{-1} + \frac{1}{1 + u^{\top}A^{-1}v}A^{-1}uv^{\top}A^{-1}$$

- Improvement: directly update  $B^{(k)} \equiv (A^{(k)})^{-1}$
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■ Iteration rule

$$B^{(k+1)} \leftarrow B^{(k)} + \frac{(d^{(k)} - u^{(k)})d^{(k)}^{\top}B^{(k)}}{d^{(k)}^{\top}u^{(k)}}$$

where

$$d^{(k)} = x^{(k+1)} - x^{(k)} \qquad u^{(k)} = B^{(k)}[f(x^{(k+1)}) - f(x^{(k)})]$$

#### ■ Pseudo-code

```
Choose initial x
Calculate initial B (usually B = f'^{-1}(x))
loop
update x
if f(x) is close enough to 0 then break
update B
```

# Summary

- Four method to solve nonlinear equations
  - Bisection: robust but relatively slow
  - Function iteration: easy-coding
  - Newton & Quasi-Newton: quick, most popular but not always work
- May not work for the multi-root case