

# Root-finding for Nonlinear Equations

Dangxing Chen

Duke Kunshan University

# Many applications

- ▶ Physics, e.g., Navier-Stokes equation
- ▶ Chemistry, e.g., Density functional theory
- ▶ Biology, e.g., Molecular dynamics
- ▶ Finance, e.g., Simulation
- ▶ Data Science, e.g., Machine learning methods
- ▶ ⋮

# N-body simulation

- $N$ -body problem: Predicting the individual motions of a group of celestial objects interacting with each other gravitationally

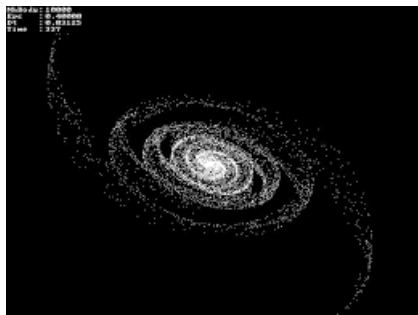


Figure: <https://insidehpc.com/2015/05/direct-n-body-simulation/>

# Diagrams of problem solving

- ▶ E.g.  $N$ -body simulation
- ▶ Identify the problem: Want to predict motions of bodies
- ▶ Formulate the problem: Newtonian mechanics

$$m_i \frac{d^2 \mathbf{x}_i}{dt^2} = - \sum_{j \neq i} \frac{G m_i m_j (\mathbf{x}_i - \mathbf{x}_j)}{\|\mathbf{x}_i - \mathbf{x}_j\|^3}.$$

- ▶ **Question:** How to solve the problem?

# Diagrams of problem solving

- ▶ E.g.  $N$ -body simulation
- ▶ Identify the problem: Want to predict motions of bodies
- ▶ Formulate the problem: Newtonian mechanics

$$m_i \frac{d^2 \mathbf{x}_i}{dt^2} = - \sum_{j \neq i} \frac{G m_i m_j (\mathbf{x}_i - \mathbf{x}_j)}{\|\mathbf{x}_i - \mathbf{x}_j\|^3}.$$

- ▶ **Question:** How to solve the problem? Use computer
- ▶ Discretize the equation (what is the best way?)
- ▶ Efficient method (can we calculate millions or billions of body movements?)
- ▶ **Remark:** Numerical analysis allows us to do this simulation!

Root-finding problem

Bisection method

Newton's method

Secant method

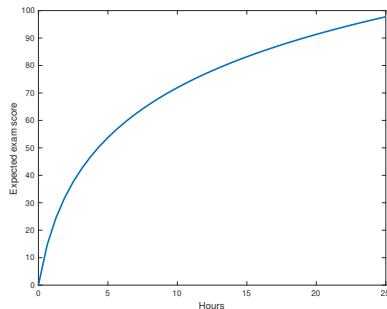
A general theory for one-point iteration methods

System of nonlinear equations

Unconstrained optimization

# Introduction

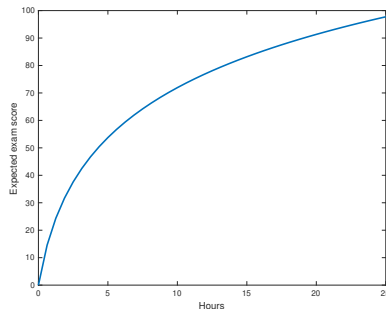
## ► Expected exam score



## ► **Question:** How much should I study in order to get 90?

# Introduction

- ▶ Expected exam score



- ▶ **Question:** How much should I study in order to get 90?
- ▶ Solve  $f(x) = 90$
- ▶ In general, solve  $f(x) = 0$



# Solution method

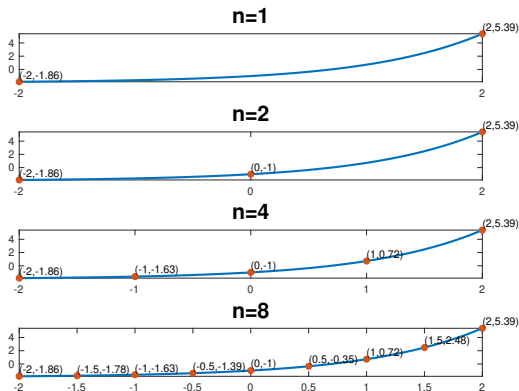
- ▶ **Question:** How to solve for  $f(x) = 0$ ?
- ▶ If  $f(x) = ax + b = 0$ , then  $x = -\frac{b}{a}$
- ▶ If  $f(x) = ax^2 + bx + c$ , then  $x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$
- ▶ **Question:** In general case, how to find  $x$ ?

# Solution method

- ▶ **Question:** How to solve for  $f(x) = 0$ ?
- ▶ If  $f(x) = ax + b = 0$ , then  $x = -\frac{b}{a}$
- ▶ If  $f(x) = ax^2 + bx + c$ , then  $x = \frac{-b \pm \sqrt{b^2 - 4ac}}{2a}$
- ▶ **Question:** In general case, how to find  $x$ ?
- ▶ Suppose the root  $x^*$  is in the interval  $[a, b]$
- ▶ Brute force method: Grid searching
- ▶ Calculate  $f(x_i)$  and find  $\arg \min_{x_i} |f(x_i)|$

# Example

- ▶ E.g.  $f(x) = e^x - 2$  in  $[-2, 2]$ .
- ▶ Root:  $x^* = \log(2) \approx 0.69$



- ▶ **Question:** How to analyze error?

# Analysis

- ▶ **Question:** How to analyze error?
- ▶ **Error:**  $e_n = \arg \min_{x_i} |x_i - x^*| \leq \frac{b-a}{n}$
- ▶ **Question:** How much points we need such that  $e_n < \epsilon$ ?

- ▶ **Question:** How to analyze error?
- ▶ **Error:**  $e_n = \arg \min_{x_i} |x_i - x^*| \leq \frac{b-a}{n}$
- ▶ **Question:** How much points we need such that  $e_n < \epsilon$ ?
- ▶  $\frac{b-a}{n} < \epsilon \Rightarrow n > \frac{b-a}{\epsilon}$
- ▶ **Question:** How to know if there is a root in  $[a, b]$ ?

- ▶ **Question:** How to analyze error?
- ▶ **Error:**  $e_n = \arg \min_{x_i} |x_i - x^*| \leq \frac{b-a}{n}$
- ▶ **Question:** How much points we need such that  $e_n < \epsilon$ ?
- ▶  $\frac{b-a}{n} < \epsilon \Rightarrow n > \frac{b-a}{\epsilon}$
- ▶ **Question:** How to know if there is a root in  $[a, b]$ ?
- ▶ Intermediate value theorem:  $f(a)f(b) < 0 \Rightarrow x^* \in (a, b)$
- ▶ Assumption of the root-finding problems in general:
  - ▶  $f$  is continuous on  $[a, b]$
  - ▶  $f(a)f(b) < 0$
  - ▶  $f$  has exactly one root in  $[a, b]$
- ▶ **Question:** Can we do better than grid searching?

Root-finding problem

Bisection method

Newton's method

Secant method

A general theory for one-point iteration methods

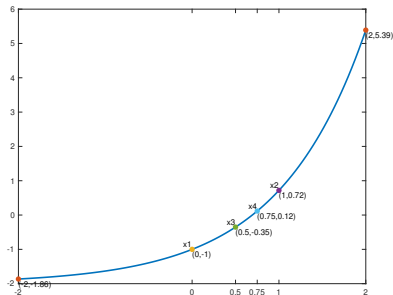
System of nonlinear equations

Unconstrained optimization



# Bisection method

- ▶ **Def: Bisection method**
- ▶ Find the midpoint  $c = \frac{a+b}{2}$ 
  - ▶ If  $f(c) = 0$ , done
  - ▶ If  $f(a)f(c) < 0$ , then  $x^* \in (a, c)$ , let  $b = c$
  - ▶ If  $f(c)f(b) < 0$ , then  $x^* \in (c, b)$ , and  $a = c$
  - ▶ Repeat
- ▶ E.g.  $f(x) = e^x - 2$  in  $[-2, 2]$ .
- ▶ Root:  $x^* = \log(2) \approx 0.69$



- ▶ **Question:** How fast does the error decay?

- ▶ **Question:** How fast does the error decay?
- ▶  $e_n \leq \left(\frac{1}{2}\right)^n (b - a)$
- ▶ **Question:** How many iterations we need such that  $e_n < \epsilon$ ?

- ▶ **Question:** How fast does the error decay?
- ▶  $e_n \leq \left(\frac{1}{2}\right)^n (b - a)$
- ▶ **Question:** How many iterations we need such that  $e_n < \epsilon$ ?
- ▶  $\left(\frac{1}{2}\right)^n (b - a) \leq \epsilon \Rightarrow n > \frac{-\log(\epsilon) + \log(b-a)}{\log(2)}$
- ▶ E.g. For  $a = 0$ ,  $b = 1$ ,  $\epsilon = 10^{-10}$ 
  - ▶ Grid searching:  $n > 10^{10}$
  - ▶ Bisection:  $n > 33$

# Order of convergence

- ▶ **Def: Iterative method**, generate a sequence of improving approximate solutions
- ▶ **Question**: How to measure the interval of convergence and speed of convergence?

# Order of convergence

- ▶ **Def: Iterative method**, generate a sequence of improving approximate solutions
- ▶ **Question:** How to measure the interval of convergence and speed of convergence?
- ▶ **Def:** A sequence of iterates  $\{x_n\}$  is said to converge with **order**  $p \geq 1$  to a point  $x^*$  if

$$|x^* - x_{n+1}| \leq c|x^* - x_n|^p$$

for some  $c > 0$ . If  $p = 1$ , the sequence is said to **converge linearly** to  $x^*$ .

- ▶ **Question:** What is order of Bisection?

# Order of convergence

- ▶ **Def: Iterative method**, generate a sequence of improving approximate solutions
- ▶ **Question:** How to measure the interval of convergence and speed of convergence?
- ▶ **Def:** A sequence of iterates  $\{x_n\}$  is said to converge with **order**  $p \geq 1$  to a point  $x^*$  if

$$|x^* - x_{n+1}| \leq c|x^* - x_n|^p$$

for some  $c > 0$ . If  $p = 1$ , the sequence is said to **converge linearly** to  $x^*$ .

- ▶ **Question:** What is order of Bisection? Linear with  $c = \frac{1}{2}$
- ▶ **Question:** Why this measures the convergence?

# Order of convergence

- ▶ **Def: Iterative method**, generate a sequence of improving approximate solutions
- ▶ **Question:** How to measure the interval of convergence and speed of convergence?
- ▶ **Def:** A sequence of iterates  $\{x_n\}$  is said to converge with **order**  $p \geq 1$  to a point  $x^*$  if

$$|x^* - x_{n+1}| \leq c|x^* - x_n|^p$$

for some  $c > 0$ . If  $p = 1$ , the sequence is said to **converge linearly** to  $x^*$ .

- ▶ **Question:** What is order of Bisection? Linear with  $c = \frac{1}{2}$
- ▶ **Question:** Why this measures the convergence?
- ▶ Suppose  $p = 1$ , if  $c > 1$ , we do not necessarily have convergence
- ▶ **Question:** Why this measures the speed of convergence?



# Speed of convergence

- Suppose  $p = 1$

$$e_1 \leq ce_0,$$

$$e_2 \leq ce_1 \leq c^2e_0,$$

$$e_3 \leq ce_2 \leq c^2e_1 \leq c^3e_0,$$

$$\vdots$$

$$e_n \leq c^n e_0.$$

- Suppose  $p = 2$

$$e_1 \leq ce_0^2,$$

$$e_2 \leq ce_1^2 \leq c^3e_0^4,$$

$$e_3 \leq ce_2^2 \leq c^7e_1^4 \leq c^7e_0^8,$$

$$\vdots$$

$$e_n \leq c^{2^n-1}e_0^{2^n}.$$

# Speed of convergence

- ▶ For  $p = 1$ ,  $e_n \leq c^n e_0$
- ▶ For  $p = 2$ ,  $e_n \leq c^{2^n - 1} e_0^{2^n}$
- ▶ **Question:** For the same  $c$ , how much faster for  $p = 2$ ?

# Speed of convergence

- ▶ For  $p = 1$ ,  $e_n \leq c^n e_0$
- ▶ For  $p = 2$ ,  $e_n \leq c^{2^n-1} e_0^{2^n}$
- ▶ **Question:** For the same  $c$ , how much faster for  $p = 2$ ?
- ▶ For  $p = 1$ , let  $e_m \leq c^m e_0$
- ▶ For  $p = 2$ , let  $e_n \leq c^{2^n-1} e_0^{2^n}$
- ▶ Let  $c^m e_0 = c^{2^n-1} e_0^{2^n}$ , then  $m = \frac{(2^n-1)\log(c) + (2^n-1)\log(e_0)}{\log(c)}$
- ▶ E.g., if  $e_0 = c$ , then  $m = 2^{n+1} - 2$
- ▶ E.g., for  $n = 5$ ,  $m = 62$
- ▶ **Question:** Can we improve the Bisection's method to second order?

Root-finding problem

Bisection method

**Newton's method**

Secant method

A general theory for one-point iteration methods

System of nonlinear equations

Unconstrained optimization

- **Mean Value Theorem (MVT):** Let  $f(x)$  be continuous for  $a \leq x \leq b$ , and let it be differentiable for  $a < x < b$ . Then there is at least one point  $\xi$  in  $(a, b)$  for which

$$f(b) - f(a) = f'(\xi)(b - a).$$

- **Taylor's Theorem:** Let  $f(x)$  be infinitely continuous differentiable on  $[a, b]$ , and let  $x, x_0 \in [a, b]$ . Then

$$f(x) = p_n(x) + R_{n+1}(x),$$

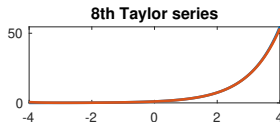
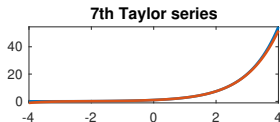
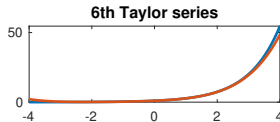
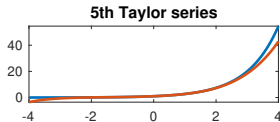
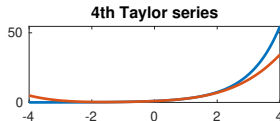
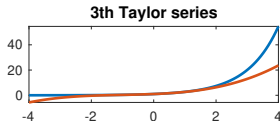
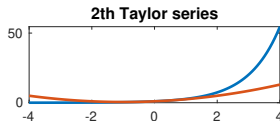
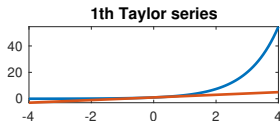
$$p_n(x) = f(x_0) + \frac{(x - x_0)}{1!} f'(x_0) + \cdots + \frac{(x - x_0)^n}{n!} f^{(n)}(x_0),$$

$$R_{n+1}(x) = \frac{(x - x_0)^{n+1}}{(n + 1)!} f^{(n+1)}(\xi),$$

for some  $\xi$  between  $x_0$  and  $x$ .

# Example

► E.g.,  $f(x) = e^x = \sum_{k=0}^{\infty} \frac{x^k}{k!} = 1 + x + \frac{x^2}{2} + \frac{x^3}{6} + \dots$



# Taylor series - Motivation

- ▶ **Question:** Why Taylor series makes sense?
- ▶  $n$ -th order Taylor series at  $x = x_0$

$$f(x) \approx p_n(x) = f(x_0) + \frac{(x - x_0)}{1!} f'(x_0) + \cdots + \frac{(x - x_0)^n}{n!} f^{(n)}(x_0)$$

# Taylor series - Motivation

- ▶ **Question:** Why Taylor series makes sense?
- ▶  $n$ -th order Taylor series at  $x = x_0$

$$f(x) \approx p_n(x) = f(x_0) + \frac{(x - x_0)}{1!} f'(x_0) + \cdots + \frac{(x - x_0)^n}{n!} f^{(n)}(x_0)$$

- ▶ **Goal:** Fit a  $n$ -th degree polynomial to  $f(x)$  around  $x = x_0$
- ▶  $p_n(x) = c_0 + c_1(x - x_0) + c_2(x - x_0)^2 + \cdots + c_n(x - x_0)^n$



# Taylor series - Motivation

- ▶ **Question:** Why Taylor series makes sense?
- ▶  $n$ -th order Taylor series at  $x = x_0$

$$f(x) \approx p_n(x) = f(x_0) + \frac{(x - x_0)}{1!} f'(x_0) + \cdots + \frac{(x - x_0)^n}{n!} f^{(n)}(x_0)$$

- ▶ **Goal:** Fit a  $n$ -th degree polynomial to  $f(x)$  around  $x = x_0$
- ▶  $p_n(x) = c_0 + c_1(x - x_0) + c_2(x - x_0)^2 + \cdots + c_n(x - x_0)^n$
- ▶ Want  $f^{(k)}(x_0) = p_n^{(k)}(x_0)$  for  $k \leq n$
- ▶  $f(x_0) = p_n(x_0) = c_0$
- ▶  $f'(x_0) = p'_n(x_0) = c_1$
- ▶  $f''(x_0) = p''_n(x_0) = 2c_2 \Rightarrow c_2 = \frac{f''(x_0)}{2}$
- ▶  $\vdots$

# Newton's method

- ▶ Suppose we have a good initial guess  $x_0$
- ▶ Motivation: Taylor expansion

$$f(x) = f(x_0) + (x - x_0)f'(x_0) + \frac{(x - x_0)^2}{2}f''(\xi),$$

where  $\xi$  is between  $x$  and  $x_0$

- ▶ **Question:** What happens if  $x^*$  is the true solution?

# Newton's method

- ▶ Suppose we have a good initial guess  $x_0$
- ▶ Motivation: Taylor expansion

$$f(x) = f(x_0) + (x - x_0)f'(x_0) + \frac{(x - x_0)^2}{2}f''(\xi),$$

where  $\xi$  is between  $x$  and  $x_0$

- ▶ **Question:** What happens if  $x^*$  is the true solution?
- ▶  $0 = f(x_0) + (x^* - x_0)f'(x_0) + \frac{(x^* - x_0)^2}{2}f''(\xi)$
- ▶  $x^* = x_0 - \frac{f(x_0)}{f'(x_0)} - \frac{(x^* - x_0)^2}{2} \cdot \frac{f''(\xi)}{f'(x_0)}$
- ▶ **Question:** How to solve this equation?

# Newton's method

- ▶ Suppose we have a good initial guess  $x_0$
- ▶ Motivation: Taylor expansion

$$f(x) = f(x_0) + (x - x_0)f'(x_0) + \frac{(x - x_0)^2}{2}f''(\xi),$$

where  $\xi$  is between  $x$  and  $x_0$

- ▶ **Question:** What happens if  $x^*$  is the true solution?
- ▶  $0 = f(x_0) + (x^* - x_0)f'(x_0) + \frac{(x^* - x_0)^2}{2}f''(\xi)$
- ▶  $x^* = x_0 - \frac{f(x_0)}{f'(x_0)} - \frac{(x^* - x_0)^2}{2} \cdot \frac{f''(\xi)}{f'(x_0)}$
- ▶ **Question:** How to solve this equation?
- ▶  $x^* \approx x_0 - \frac{f(x_0)}{f'(x_0)}$
- ▶ **Question:** Should we just stop here?

# Newton's method

- ▶ Suppose we have a good initial guess  $x_0$
- ▶ Motivation: Taylor expansion

$$f(x) = f(x_0) + (x - x_0)f'(x_0) + \frac{(x - x_0)^2}{2}f''(\xi),$$

where  $\xi$  is between  $x$  and  $x_0$

- ▶ **Question:** What happens if  $x^*$  is the true solution?
- ▶  $0 = f(x_0) + (x^* - x_0)f'(x_0) + \frac{(x^* - x_0)^2}{2}f''(\xi)$
- ▶  $x^* = x_0 - \frac{f(x_0)}{f'(x_0)} - \frac{(x^* - x_0)^2}{2} \cdot \frac{f''(\xi)}{f'(x_0)}$
- ▶ **Question:** How to solve this equation?
- ▶  $x^* \approx x_0 - \frac{f(x_0)}{f'(x_0)}$
- ▶ **Question:** Should we just stop here?
- ▶ Iterate:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Question:** Can this converge?

# Newton's method

- ▶ Suppose we have a good initial guess  $x_0$
- ▶ Motivation: Taylor expansion

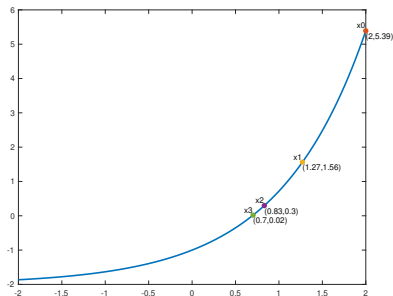
$$f(x) = f(x_0) + (x - x_0)f'(x_0) + \frac{(x - x_0)^2}{2}f''(\xi),$$

where  $\xi$  is between  $x$  and  $x_0$

- ▶ **Question:** What happens if  $x^*$  is the true solution?
- ▶  $0 = f(x_0) + (x^* - x_0)f'(x_0) + \frac{(x^* - x_0)^2}{2}f''(\xi)$
- ▶  $x^* = x_0 - \frac{f(x_0)}{f'(x_0)} - \frac{(x^* - x_0)^2}{2} \cdot \frac{f''(\xi)}{f'(x_0)}$
- ▶ **Question:** How to solve this equation?
- ▶  $x^* \approx x_0 - \frac{f(x_0)}{f'(x_0)}$
- ▶ **Question:** Should we just stop here?
- ▶ Iterate:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Question:** Can this converge?
- ▶ Each time, error  $\frac{(x^* - x_n)^2}{2} \frac{f''(\xi_n)}{f'(x_n)}$  becomes smaller

# Example

- ▶ E.g.  $f(x) = e^x - 2$  in  $[-2, 2]$ .
- ▶ Root:  $x^* = \log(2) \approx 0.69$
- ▶  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} = x_n - \frac{e^{x_n} - 2}{e^{x_n}}$



- ▶ **Question:** How fast does the Newton's method converges?



# Convergence analysis

- ▶ **Question:** How fast does the Newton's method converges?
- ▶  $e_{n+1} = \left| \frac{(x^* - x_n)^2}{2} \frac{f''(\xi_n)}{f'(x_n)} \right|$
- ▶ Suppose  $\left| \frac{1}{2} \frac{f''(\xi_n)}{f'(x_n)} \right| \leq M$
- ▶  $e_{n+1} \leq M e_n^2$
- ▶ **Question:** What is the order of the Newton's method?

# Convergence analysis

- ▶ **Question:** How fast does the Newton's method converges?
- ▶  $e_{n+1} = \left| \frac{(x^* - x_n)^2}{2} \frac{f''(\xi_n)}{f'(x_n)} \right|$
- ▶ Suppose  $\left| \frac{1}{2} \frac{f''(\xi_n)}{f'(x_n)} \right| \leq M$
- ▶  $e_{n+1} \leq M e_n^2$
- ▶ **Question:** What is the order of the Newton's method?
- ▶ Second order
- ▶ **Question:**  $\lim_{n \rightarrow \infty} \frac{e_{n+1}}{e_n^2} = ?$

# Convergence analysis

- ▶ **Question:** How fast does the Newton's method converges?
- ▶  $e_{n+1} = \left| \frac{(x^* - x_n)^2}{2} \frac{f''(\xi_n)}{f'(x_n)} \right|$
- ▶ Suppose  $\left| \frac{1}{2} \frac{f''(\xi_n)}{f'(x_n)} \right| \leq M$
- ▶  $e_{n+1} \leq M e_n^2$
- ▶ **Question:** What is the order of the Newton's method?
- ▶ Second order
- ▶ **Question:**  $\lim_{n \rightarrow \infty} \frac{e_{n+1}}{e_n^2} = ?$
- ▶ **THM:**  $\lim_{n \rightarrow \infty} \frac{e_{n+1}}{e_n^2} = \left| \frac{f''(x^*)}{2f'(x^*)} \right|$

# Convergence analysis - continued

- ▶  $e_{n+1} \leq M e_n^2$
- ▶ **Question:** Does this necessarily always converge?

# Convergence analysis - continued

- ▶  $e_{n+1} \leq M e_n^2$
- ▶ **Question:** Does this necessarily always converge?
- ▶ E.g.,  $f(x) = x^3 - 2x + 2$
- ▶  $f'(x) = 3x^2 - 2$
- ▶  $x_{n+1} = x_n - \frac{x_n^3 - 2x_n + 2}{3x_n^2 - 2}$ .
- ▶ Root:  $x^* \approx -1.77$
- ▶  $x_0 = 0$
- ▶  $1 \rightarrow 0 \rightarrow 1 \rightarrow 0 \rightarrow 1$
- ▶ We need a good initial guess

# Convergence (failure)

▶  $f(x) = \sqrt[3]{x}$  with root  $x^* = 0$

▶ Newton:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} = x_n - \frac{x_n^{\frac{1}{3}}}{\frac{1}{3}x_n^{-\frac{2}{3}}} = x_n - 3x_n = -2x_n.$$

▶ Never converge

▶ **Question:** Why?

# Convergence (failure)

►  $f(x) = \sqrt[3]{x}$  with root  $x^* = 0$

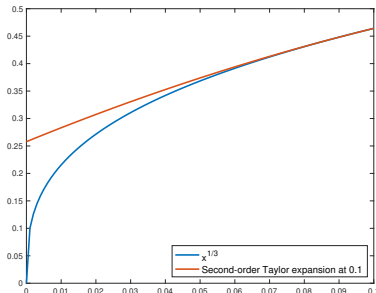
► Newton:

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} = x_n - \frac{x_n^{\frac{1}{3}}}{\frac{1}{3}x_n^{-\frac{2}{3}}} = x_n - 3x_n = -2x_n.$$

► Never converge

► **Question:** Why?

► Taylor series doesn't work well near the origin



Root-finding problem

Bisection method

Newton's method

**Secant method**

A general theory for one-point iteration methods

System of nonlinear equations

Unconstrained optimization



# Secant method

- ▶ Newton's method:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Question:** What if we don't know  $f'(x)$ ?

# Secant method

- ▶ Newton's method:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Question:** What if we don't know  $f'(x)$ ?
- ▶ Numerical differentiation
- ▶  $f'(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$
- ▶  $f'(x) \approx \frac{f(x+h) - f(x)}{h}$
- ▶ **Question:** Is there a way to save some computational efforts?

# Secant method

- ▶ Newton's method:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Question:** What if we don't know  $f'(x)$ ?
- ▶ Numerical differentiation
- ▶  $f'(x) = \lim_{h \rightarrow 0} \frac{f(x+h) - f(x)}{h}$
- ▶  $f'(x) \approx \frac{f(x+h) - f(x)}{h}$
- ▶ **Question:** Is there a way to save some computational efforts?
- ▶ Let  $h = x_{n-1} - x_n$
- ▶  $f'(x_n) \approx \frac{f(x_{n-1}) - f(x_n)}{x_{n-1} - x_n} = \frac{f(x_n) - f(x_{n-1})}{x_n - x_{n-1}}$
- ▶ **Secant method:**

$$x_{n+1} = x_n - f(x_n) \cdot \frac{x_n - x_{n-1}}{f(x_n) - f(x_{n-1})}.$$

- ▶ **Question:** What is the order of the Secant method?

# Convergence analysis

- ▶ Notations:

- ▶  $f[x_{n-1}, x_n] = \frac{f(x_n) - f(x_{n-1})}{x_n - x_{n-1}}$

- ▶  $f[x_{n-1}, x_n, x_{n+1}] = \frac{f[x_n, x_{n+1}] - f[x_{n-1}, x_n]}{x_{n+1} - x_{n-1}}$

- ▶  $\vdots$

- ▶ Error analysis:

$$x^* - x_{n+1} = x^* - x_n + f(x_n) \cdot \frac{x_n - x_{n-1}}{f(x_n) - f(x_{n-1})}.$$

- ▶ By algebraic manipulation (HW)

$$x^* - x_{n+1} = -(x^* - x_{n-1})(x^* - x_n) \frac{f[x_{n-1}, x_n, x^*]}{f[x_{n-1}, x_n]}.$$

- ▶ Use MVT

$$x^* - x_{n+1} = -(x^* - x_{n-1})(x^* - x_n) \cdot \frac{f''(\zeta_n)}{2f'(\xi_n)}.$$

- ▶ **Question:** What is the order?

# Convergence analysis

- ▶ Let  $M = \frac{\max_x |f''(x)|}{2 \min_x |f'(x)|}$
- ▶  $e_2 \leq M e_1 e_0$
- ▶ **Question:** How to get a better recurrence relationship?

# Convergence analysis

- ▶ Let  $M = \frac{\max_x |f''(x)|}{2 \min_x |f'(x)|}$
- ▶  $e_2 \leq M e_1 e_0$
- ▶ **Question:** How to get a better recurrence relationship?
- ▶  $M e_2 \leq M e_1 \cdot M e_0$
- ▶ **Question:** When does this converge (which also simplify the calculation)?

# Convergence analysis

- ▶ Let  $M = \frac{\max_x |f''(x)|}{2 \min_x |f'(x)|}$
- ▶  $e_2 \leq M e_1 e_0$
- ▶ **Question:** How to get a better recurrence relationship?
- ▶  $M e_2 \leq M e_1 \cdot M e_0$
- ▶ **Question:** When does this converge (which also simplify the calculation)?
- ▶  $\delta = \max\{M e_0, M e_1\} < 1$
- ▶  $M e_2 \leq \delta^2$
- ▶  $M e_3 \leq M e_2 \cdot M e_1 \leq \delta^3$
- ▶  $M e_4 \leq M e_3 \cdot M e_2 \leq \delta^5$
- ▶  $M e_n \leq \delta^{q_n}$
- ▶ **Question:**  $q_n = ?$

# Convergence analysis

- ▶ Let  $M = \frac{\max_x |f''(x)|}{2 \min_x |f'(x)|}$
- ▶  $e_2 \leq M e_1 e_0$
- ▶ **Question:** How to get a better recurrence relationship?
- ▶  $M e_2 \leq M e_1 \cdot M e_0$
- ▶ **Question:** When does this converge (which also simplify the calculation)?
- ▶  $\delta = \max\{M e_0, M e_1\} < 1$
- ▶  $M e_2 \leq \delta^2$
- ▶  $M e_3 \leq M e_2 \cdot M e_1 \leq \delta^3$
- ▶  $M e_4 \leq M e_3 \cdot M e_2 \leq \delta^5$
- ▶  $M e_n \leq \delta^{q_n}$
- ▶ **Question:**  $q_n = ?$
- ▶ **Fibonacci sequence:**  $q_{n+1} = q_n + q_{n-1}$  with



# Convergence analysis

- ▶ Let  $M = \frac{\max_x |f''(x)|}{2 \min_x |f'(x)|}$
- ▶  $e_2 \leq M e_1 e_0$
- ▶ **Question:** How to get a better recurrence relationship?
- ▶  $M e_2 \leq M e_1 \cdot M e_0$
- ▶ **Question:** When does this converge (which also simplify the calculation)?
- ▶  $\delta = \max\{M e_0, M e_1\} < 1$
- ▶  $M e_2 \leq \delta^2$
- ▶  $M e_3 \leq M e_2 \cdot M e_1 \leq \delta^3$
- ▶  $M e_4 \leq M e_3 \cdot M e_2 \leq \delta^5$
- ▶  $M e_n \leq \delta^{q_n}$
- ▶ **Question:**  $q_n = ?$
- ▶ **Fibonacci sequence:**  $q_{n+1} = q_n + q_{n-1}$  with  $q_0 = q_1 = 1$
- ▶ **Question:** How to solve this?

# Solution to the sequence

- ▶ Matrix equation:

$$\begin{bmatrix} q_n \\ q_{n+1} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} q_{n-1} \\ q_n \end{bmatrix}$$

- ▶  $\mathbf{q}_{n+1} = \mathbf{A}\mathbf{q}_n$
- ▶ **Question:** What is the relationship between  $\mathbf{q}_{n+1}$  and  $\mathbf{q}_1$ ?

# Solution to the sequence

- ▶ Matrix equation:

$$\begin{bmatrix} q_n \\ q_{n+1} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} q_{n-1} \\ q_n \end{bmatrix}$$

- ▶  $\mathbf{q}_{n+1} = \mathbf{A}\mathbf{q}_n$
- ▶ **Question:** What is the relationship between  $\mathbf{q}_{n+1}$  and  $\mathbf{q}_1$ ?
- ▶  $\mathbf{q}_{n+1} = \mathbf{A}^n \mathbf{q}_1$
- ▶ **Question:** How to calculate  $\mathbf{A}^n$ ?

# Solution to the sequence

- ▶ Matrix equation:

$$\begin{bmatrix} q_n \\ q_{n+1} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} q_{n-1} \\ q_n \end{bmatrix}$$

- ▶  $\mathbf{q}_{n+1} = \mathbf{A}\mathbf{q}_n$
- ▶ **Question:** What is the relationship between  $\mathbf{q}_{n+1}$  and  $\mathbf{q}_1$ ?
- ▶  $\mathbf{q}_{n+1} = \mathbf{A}^n \mathbf{q}_1$
- ▶ **Question:** How to calculate  $\mathbf{A}^n$ ?
- ▶ Use eigen-decomposition  $\mathbf{A} = \mathbf{V}\mathbf{D}\mathbf{V}^{-1}$ , then  $\mathbf{A}^n = \mathbf{V}\mathbf{D}^n\mathbf{V}^{-1}$
- ▶ **Question:** How to calculate the eigen-decomposition?

# Solution to the sequence

- ▶ Matrix equation:

$$\begin{bmatrix} q_n \\ q_{n+1} \end{bmatrix} = \begin{bmatrix} 0 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} q_{n-1} \\ q_n \end{bmatrix}$$

- ▶  $\mathbf{q}_{n+1} = \mathbf{A}\mathbf{q}_n$
- ▶ **Question:** What is the relationship between  $\mathbf{q}_{n+1}$  and  $\mathbf{q}_1$ ?
- ▶  $\mathbf{q}_{n+1} = \mathbf{A}^n \mathbf{q}_1$
- ▶ **Question:** How to calculate  $\mathbf{A}^n$ ?
- ▶ Use eigen-decomposition  $\mathbf{A} = \mathbf{V}\mathbf{D}\mathbf{V}^{-1}$ , then  $\mathbf{A}^n = \mathbf{V}\mathbf{D}^n\mathbf{V}^{-1}$
- ▶ **Question:** How to calculate the eigen-decomposition?
- ▶ Solve for eigenvalues:  $\det(\mathbf{A} - \lambda\mathbf{I}) = 0$
- ▶  $\begin{vmatrix} -\lambda & 1 \\ 1 & 1-\lambda \end{vmatrix} = (-\lambda)(1-\lambda) - 1 = 0 \Rightarrow \lambda = \frac{1 \pm \sqrt{5}}{2}$

# Eigen-decomposition

- ▶ Solve for eigenvectors:  $(\mathbf{A} - \lambda\mathbf{I})\mathbf{v} = \mathbf{0}$
- ▶ 
$$\begin{bmatrix} -\lambda & 1 \\ 1 & 1 - \lambda \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \begin{cases} -\lambda v_1 + v_2 = 0, \\ v_1 + (1 - \lambda)v_2 = 0. \end{cases}$$
- ▶ Reduces to  $-\lambda v_1 + v_2 = 0$
- ▶  $\mathbf{v} = \begin{bmatrix} 1 \\ \lambda \end{bmatrix}$
- ▶  $\mathbf{V} = \begin{bmatrix} 1 & 1 \\ \frac{1+\sqrt{5}}{2} & \frac{1-\sqrt{5}}{2} \end{bmatrix}$  and  $\mathbf{V}^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} \frac{\sqrt{5}-1}{2} & 1 \\ \frac{\sqrt{5}+1}{2} & -1 \end{bmatrix}$
- ▶  $\mathbf{A} = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 1 \\ \frac{1+\sqrt{5}}{2} & \frac{1-\sqrt{5}}{2} \end{bmatrix} \begin{bmatrix} \frac{1+\sqrt{5}}{2} & 0 \\ 0 & \frac{1-\sqrt{5}}{2} \end{bmatrix} \begin{bmatrix} \frac{\sqrt{5}-1}{2} & 1 \\ \frac{\sqrt{5}+1}{2} & -1 \end{bmatrix}$
- ▶ **Question:** Can we simplify the calculation?

# Eigen-decomposition

- ▶ Solve for eigenvectors:  $(\mathbf{A} - \lambda\mathbf{I})\mathbf{v} = \mathbf{0}$
- ▶ 
$$\begin{bmatrix} -\lambda & 1 \\ 1 & 1 - \lambda \end{bmatrix} \begin{bmatrix} v_1 \\ v_2 \end{bmatrix} = \begin{bmatrix} 0 \\ 0 \end{bmatrix} \Rightarrow \begin{cases} -\lambda v_1 + v_2 & = 0, \\ v_1 + (1 - \lambda)v_2 & = 0. \end{cases}$$
- ▶ Reduces to  $-\lambda v_1 + v_2 = 0$
- ▶  $\mathbf{v} = \begin{bmatrix} 1 \\ \lambda \end{bmatrix}$
- ▶  $\mathbf{V} = \begin{bmatrix} 1 & 1 \\ \frac{1+\sqrt{5}}{2} & \frac{1-\sqrt{5}}{2} \end{bmatrix}$  and  $\mathbf{V}^{-1} = \frac{1}{\sqrt{5}} \begin{bmatrix} \frac{\sqrt{5}-1}{2} & 1 \\ \frac{\sqrt{5}+1}{2} & -1 \end{bmatrix}$
- ▶  $\mathbf{A} = \frac{1}{\sqrt{5}} \begin{bmatrix} 1 & 1 \\ \frac{1+\sqrt{5}}{2} & \frac{1-\sqrt{5}}{2} \end{bmatrix} \begin{bmatrix} \frac{1+\sqrt{5}}{2} & 0 \\ 0 & \frac{1-\sqrt{5}}{2} \end{bmatrix} \begin{bmatrix} \frac{\sqrt{5}-1}{2} & 1 \\ \frac{\sqrt{5}+1}{2} & -1 \end{bmatrix}$
- ▶ **Question:** Can we simplify the calculation?

# Calculation

- ▶ Write  $\mathbf{q}_1 = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2$
- ▶  $\mathbf{A}^n \mathbf{q}_1 = c_1 \lambda_1^n \mathbf{v}_1 + c_2 \lambda_2^n \mathbf{v}_2$
- ▶ **Question:** How to solve for  $c_i$ ?



# Calculation

- ▶ Write  $\mathbf{q}_1 = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2$
- ▶  $\mathbf{A}^n \mathbf{q}_1 = c_1 \lambda_1^n \mathbf{v}_1 + c_2 \lambda_2^n \mathbf{v}_2$
- ▶ **Question:** How to solve for  $c_i$ ?
- ▶ Solve  $\mathbf{V} \mathbf{c} = \mathbf{q}_1$
- ▶  $\mathbf{c} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} = \frac{1}{\sqrt{5}} \begin{bmatrix} \lambda_1 \\ -\lambda_2 \end{bmatrix}$
- ▶  $\mathbf{q}_{n+1} = \mathbf{A}^n \mathbf{q}_1 = \frac{1}{\sqrt{5}} \lambda_1^{n+1} \mathbf{v}_1 - \frac{1}{\sqrt{5}} \lambda_2^{n+1} \mathbf{v}_2$
- ▶  $q_{n+1} = \frac{1}{\sqrt{5}} (\lambda_1^{n+2} - \lambda_2^{n+2})$
- ▶ **Question:** What happens for large  $n$ ?

# Calculation

- ▶ Write  $\mathbf{q}_1 = c_1 \mathbf{v}_1 + c_2 \mathbf{v}_2$
- ▶  $\mathbf{A}^n \mathbf{q}_1 = c_1 \lambda_1^n \mathbf{v}_1 + c_2 \lambda_2^n \mathbf{v}_2$
- ▶ **Question:** How to solve for  $c_i$ ?
- ▶ Solve  $\mathbf{V} \mathbf{c} = \mathbf{q}_1$
- ▶  $\mathbf{c} = \begin{bmatrix} c_1 \\ c_2 \end{bmatrix} = \frac{1}{\sqrt{5}} \begin{bmatrix} \lambda_1 \\ -\lambda_2 \end{bmatrix}$
- ▶  $\mathbf{q}_{n+1} = \mathbf{A}^n \mathbf{q}_1 = \frac{1}{\sqrt{5}} \lambda_1^{n+1} \mathbf{v}_1 - \frac{1}{\sqrt{5}} \lambda_2^{n+1} \mathbf{v}_2$
- ▶  $q_{n+1} = \frac{1}{\sqrt{5}} (\lambda_1^{n+2} - \lambda_2^{n+2})$
- ▶ **Question:** What happens for large  $n$ ?
- ▶  $\lambda_2 = \frac{1-\sqrt{5}}{2} \approx -0.62 < 1$
- ▶  $\lim_{n \rightarrow \infty} \lambda_2^n = 0$
- ▶  $q_n \approx \frac{1}{\sqrt{5}} \lambda_1^{n+1}$  for large  $n$
- ▶  $e_n \leq \frac{1}{M} \delta^{q_n}$
- ▶ **Question:** What is the order?

# Order

- ▶ Informal argument
- ▶ Want  $e_{n+1} \leq ce_n^p$  or  $\frac{e_{n+1}}{e_n^p} \leq c$
- ▶  $e_n \leq \frac{1}{M} \delta^{\frac{1}{\sqrt{5}}} \lambda_1^{n+1}$
- ▶  $e_{n+1} \leq \frac{1}{M} \delta^{\frac{1}{\sqrt{5}}} \lambda_1^{n+2}$
- ▶ Calculate  $e_n^{\lambda_1}$  to get ride of  $n$
- ▶ So order is  $p = \lambda_1$
- ▶  $1 < \frac{1+\sqrt{5}}{2} \approx 1.62 < 2$
- ▶ **Remark:** Faster than the Bisection but slower than the Newton
- ▶ **Question:**  $c = ?$

# Order

- ▶ Informal argument
- ▶ Want  $e_{n+1} \leq ce_n^p$  or  $\frac{e_{n+1}}{e_n^p} \leq c$
- ▶  $e_n \leq \frac{1}{M} \delta^{\frac{1}{\sqrt{5}}} \lambda_1^{n+1}$
- ▶  $e_{n+1} \leq \frac{1}{M} \delta^{\frac{1}{\sqrt{5}}} \lambda_1^{n+2}$
- ▶ Calculate  $e_n^{\lambda_1}$  to get ride of  $n$
- ▶ So order is  $p = \lambda_1$
- ▶  $1 < \frac{1+\sqrt{5}}{2} \approx 1.62 < 2$
- ▶ **Remark:** Faster than the Bisection but slower than the Newton
- ▶ **Question:**  $c = ?$
- ▶  $M^{\lambda_1-1} = M^{\frac{\sqrt{5}-1}{2}}$
- ▶ **Question:**  $\lim_{n \rightarrow \infty} \frac{e_{n+1}}{e_n^p} ?$

# Order

- ▶ Informal argument
- ▶ Want  $e_{n+1} \leq ce_n^p$  or  $\frac{e_{n+1}}{e_n^p} \leq c$
- ▶  $e_n \leq \frac{1}{M} \delta^{\frac{1}{\sqrt{5}}} \lambda_1^{n+1}$
- ▶  $e_{n+1} \leq \frac{1}{M} \delta^{\frac{1}{\sqrt{5}}} \lambda_1^{n+2}$
- ▶ Calculate  $e_n^{\lambda_1}$  to get ride of  $n$
- ▶ So order is  $p = \lambda_1$
- ▶  $1 < \frac{1+\sqrt{5}}{2} \approx 1.62 < 2$
- ▶ **Remark:** Faster than the Bisection but slower than the Newton
- ▶ **Question:**  $c = ?$
- ▶  $M^{\lambda_1-1} = M^{\frac{\sqrt{5}-1}{2}}$
- ▶ **Question:**  $\lim_{n \rightarrow \infty} \frac{e_{n+1}}{e_n^p} ?$
- ▶  $\left| \frac{f''(x^*)}{2f'(x^*)} \right|^{\frac{\sqrt{5}-1}{2}}$

- ▶ **Question:** What are pros and cons?

# Comparison

- ▶ **Question:** What are pros and cons?
- ▶ Bisection: Stable, but slow
- ▶ Newton: Fastest, need good initial condition, need to know derivative
- ▶ Secant: Fast, need good initial condition, don't need derivative, computational cost less than the Newton in each step

# Numerical calculation of order

- ▶ Order:  $e_{n+1} \leq ce_n^p$
- ▶ **Question:** How to verify this numerically?



# Numerical calculation of order

- ▶ Order:  $e_{n+1} \leq ce_n^p$
- ▶ **Question:** How to verify this numerically?
- ▶  $\log(e_{n+1}) \approx \log(c) + p \log(e_n)$
- ▶ Fit this by a linear function  $y = ax + b$
- ▶  $a = p, b = \log(c)$
- ▶ **Question:** In practice, lots of fluctuations, how to fit  $y$ ?

# Numerical calculation of order

- ▶ Order:  $e_{n+1} \leq ce_n^p$
- ▶ **Question:** How to verify this numerically?
- ▶  $\log(e_{n+1}) \approx \log(c) + p \log(e_n)$
- ▶ Fit this by a linear function  $y = ax + b$
- ▶  $a = p, b = \log(c)$
- ▶ **Question:** In practice, lots of fluctuations, how to fit  $y$ ?
- ▶ Use the least-squares method to solve this
- ▶  $e_n = \frac{1}{n} \sum_{i=1}^n (y_i - (ax_i + b))^2$
- ▶  $\min_{a,b} e_n$
- ▶ **Question:** How to solve this?

# Numerical calculation of order

- ▶ Order:  $e_{n+1} \leq ce_n^p$
- ▶ **Question:** How to verify this numerically?
- ▶  $\log(e_{n+1}) \approx \log(c) + p \log(e_n)$
- ▶ Fit this by a linear function  $y = ax + b$
- ▶  $a = p, b = \log(c)$
- ▶ **Question:** In practice, lots of fluctuations, how to fit  $y$ ?
- ▶ Use the least-squares method to solve this
- ▶  $e_n = \frac{1}{n} \sum_{i=1}^n (y_i - (ax_i + b))^2$
- ▶  $\min_{a,b} e_n$
- ▶ **Question:** How to solve this? (HW)
- ▶  $\frac{\partial e_n}{\partial a} = 0 = \frac{\partial e_n}{\partial b}$
- ▶  $\hat{a} = \bar{y} - \hat{b}\bar{x}$
- ▶  $\hat{b} = \frac{\sum_{i=1}^n (x_i - \bar{x})(y_i - \bar{y})}{\sum_{i=1}^n (x_i - \bar{x})^2}$

Root-finding problem

Bisection method

Newton's method

Secant method

A general theory for one-point iteration methods

System of nonlinear equations

Unconstrained optimization

# Fixed-point iteration

- ▶ Newton:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Fixed-point iteration:**  $x_{n+1} = g(x_n)$
- ▶ **Question:** What is the theoretical solution here?

# Fixed-point iteration

- ▶ Newton:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Fixed-point iteration:**  $x_{n+1} = g(x_n)$
- ▶ **Question:** What is the theoretical solution here?
- ▶ **Def:**  $x = g(x)$
- ▶ There are many ways to reformulate the root-finding to a fixed-point problem
- ▶ E.g.  $x^2 - a = 0$

# Fixed-point iteration

- ▶ Newton:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Fixed-point iteration:**  $x_{n+1} = g(x_n)$
- ▶ **Question:** What is the theoretical solution here?
- ▶ **Def:**  $x = g(x)$
- ▶ There are many ways to reformulate the root-finding to a fixed-point problem
- ▶ E.g.  $x^2 - a = 0$
- ▶  $x_{n+1} = x_n^2 + x_n - a$
- ▶  $x_{n+1} = \frac{a}{x_n}$
- ▶  $x_{n+1} = \frac{1}{2} \left( x_n + \frac{a}{x_n} \right)$
- ▶ **Question:** When does the fixed-point problem has a solution?

# Fixed-point iteration

- ▶ Newton:  $x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)}$
- ▶ **Fixed-point iteration:**  $x_{n+1} = g(x_n)$
- ▶ **Question:** What is the theoretical solution here?
- ▶ **Def:**  $x = g(x)$
- ▶ There are many ways to reformulate the root-finding to a fixed-point problem
- ▶ E.g.  $x^2 - a = 0$
- ▶  $x_{n+1} = x_n^2 + x_n - a$
- ▶  $x_{n+1} = \frac{a}{x_n}$
- ▶  $x_{n+1} = \frac{1}{2} \left( x_n + \frac{a}{x_n} \right)$
- ▶ **Question:** When does the fixed-point problem has a solution?
- ▶ **THM:** If  $g(x)$  be continuous on  $[a, b]$  and  $a \leq g(x) \leq b$ , then at least one solution.
- ▶ By IVT



# Some analysis

- ▶ Suppose  $g(x)$  continuous on  $[a, b]$  and  $g([a, b]) \subset [a, b]$
- ▶ Suppose we further know  $0 < \lambda < 1$  s.t.  
 $|g(x) - g(y)| \leq \lambda|x - y|, \forall x, y$
- ▶ **Question:** Is the solution unique?

# Some analysis

- ▶ Suppose  $g(x)$  continuous on  $[a, b]$  and  $g([a, b]) \subset [a, b]$
- ▶ Suppose we further know  $0 < \lambda < 1$  s.t.  
 $|g(x) - g(y)| \leq \lambda|x - y|, \forall x, y$
- ▶ **Question:** Is the solution unique?
- ▶ Suppose there are two solutions  $\alpha$  and  $\beta$
- ▶  $|\alpha - \beta| = |g(\alpha) - g(\beta)| \leq \lambda|\alpha - \beta|$
- ▶ **THM:** Unique solution
- ▶ **Question:** What can we say about the convergence?

# Some analysis

- ▶ Suppose  $g(x)$  continuous on  $[a, b]$  and  $g([a, b]) \subset [a, b]$
- ▶ Suppose we further know  $0 < \lambda < 1$  s.t.  
 $|g(x) - g(y)| \leq \lambda|x - y|, \forall x, y$
- ▶ **Question:** Is the solution unique?
- ▶ Suppose there are two solutions  $\alpha$  and  $\beta$
- ▶  $|\alpha - \beta| = |g(\alpha) - g(\beta)| \leq \lambda|\alpha - \beta|$
- ▶ **THM:** Unique solution
- ▶ **Question:** What can we say about the convergence?
- ▶  $e_{n+1} = |x^* - x_{n+1}| = |g(x^*) - g(x_n)| \leq \lambda|x^* - x_n| = \lambda e_n$
- ▶ **THM:**  $e_n \leq \lambda^n e_0$
- ▶  $|x^* - x_0| \leq |x^* - x_1| + |x_1 - x_0| \leq \lambda|x^* - x_0| + |x_1 - x_0|$
- ▶  $|x^* - x_0| \leq \frac{1}{1-\lambda}|x_1 - x_0|$
- ▶ **THM:**  $e_n \leq \frac{\lambda^n}{1-\lambda}|x_1 - x_0|$

## Analysis - continued

- ▶ **Question:** Can we calculate the current error based on  $\lambda$ ?

# Analysis - continued

- ▶ **Question:** Can we calculate the current error based on  $\lambda$ ?
- ▶  $e_n \leq \frac{1}{1-\lambda} |x_{n+1} - x_n|$
- ▶ **Question:** How do we know if such  $\lambda$  exists?

# Analysis - continued

- ▶ **Question:** Can we calculate the current error based on  $\lambda$ ?
- ▶  $e_n \leq \frac{1}{1-\lambda} |x_{n+1} - x_n|$
- ▶ **Question:** How do we know if such  $\lambda$  exists?
- ▶  $g(x) - g(y) = g'(\xi)(x - y)$
- ▶ Let  $\lambda = \max_{a \leq x \leq b} |g'(x)|$
- ▶ **Question:** Checking the whole interval seems require a lot of work. Can we simplify it?

# Analysis - continued

- ▶ **Question:** Can we calculate the current error based on  $\lambda$ ?
- ▶  $e_n \leq \frac{1}{1-\lambda} |x_{n+1} - x_n|$
- ▶ **Question:** How do we know if such  $\lambda$  exists?
- ▶  $g(x) - g(y) = g'(\xi)(x - y)$
- ▶ Let  $\lambda = \max_{a \leq x \leq b} |g'(x)|$
- ▶ **Question:** Checking the whole interval seems require a lot of work. Can we simplify it?
- ▶ **THM:** Suppose that  $g(x)$  is continuously differentiable in some neighboring interval about  $x^*$  with  $|g'(x^*)| < 1$ . Then the result still holds.
- ▶ e.g.  $x^2 - 3 = 0$ , for  $x^* = \sqrt{3}$
- ▶ e.g.  $g(x) = x^2 + x - 3$ ,  $g'(x^*) = 2\sqrt{3} + 1 > 1$ , so diverges
- ▶ e.g.  $g(x) = \frac{1}{2} \left(x + \frac{3}{x}\right)$ ,  $g'(x^*) = \frac{1}{2} \left(1 - \frac{3}{\sqrt{3}^2}\right) = 0$ , so converges
- ▶ **Question:** What is the order of the fixed-point iteration here?

# Analysis - continued

- ▶ **Question:** Can we calculate the current error based on  $\lambda$ ?
- ▶  $e_n \leq \frac{1}{1-\lambda} |x_{n+1} - x_n|$
- ▶ **Question:** How do we know if such  $\lambda$  exists?
- ▶  $g(x) - g(y) = g'(\xi)(x - y)$
- ▶ Let  $\lambda = \max_{a \leq x \leq b} |g'(x)|$
- ▶ **Question:** Checking the whole interval seems require a lot of work. Can we simplify it?
- ▶ **THM:** Suppose that  $g(x)$  is continuously differentiable in some neighboring interval about  $x^*$  with  $|g'(x^*)| < 1$ . Then the result still holds.
- ▶ e.g.  $x^2 - 3 = 0$ , for  $x^* = \sqrt{3}$
- ▶ e.g.  $g(x) = x^2 + x - 3$ ,  $g'(x^*) = 2\sqrt{3} + 1 > 1$ , so diverges
- ▶ e.g.  $g(x) = \frac{1}{2} \left(x + \frac{3}{x}\right)$ ,  $g'(x^*) = \frac{1}{2} \left(1 - \frac{3}{\sqrt{3}^2}\right) = 0$ , so converges
- ▶ **Question:** What is the order of the fixed-point iteration here?  
First



# Higher-order method

- ▶ **Question:** How did Newton get second order?

# Higher-order method

- ▶ **Question:** How did Newton get second order?
- ▶  $g'(x^*) = 0$
- ▶  $g(x) = x - \frac{f(x)}{f'(x)}$
- ▶  $g'(x) = 1 - \frac{(f'(x))^2 - f(x)f''(x)}{(f'(x))^2}$
- ▶  $x_{n+1} = g(x_n) = g(x^*) + (x_n - x^*)g'(x^*) + \frac{(x_n - x^*)^2}{2}g''(\xi_n)$
- ▶  $\left| \frac{e_{n+1}}{e_n^2} \right| = \left| \frac{1}{2}g''(\xi_n) \right|$
- ▶ **THM:** If  $g'(x^*) = g''(x^*) = \dots = g^{(p-1)}(x^*) = 0$ , then  $p$  order convergence with

$$\lim_{n \rightarrow \infty} \left| \frac{e_{n+1}}{e_n^p} \right| = \left| \frac{g^{(p)}(x^*)}{p!} \right|$$

Root-finding problem

Bisection method

Newton's method

Secant method

A general theory for one-point iteration methods

System of nonlinear equations

Unconstrained optimization

# Function with many variables

- ▶ For simplicity, focus on 2-d,  $f(x, y)$
- ▶ Taylor series in 2-d around  $(a, b)$ :

$$\begin{aligned} f(x, y) \approx & f(a, b) + (x - a)f_x(a, b) + (y - b)f_y(a, b) \\ & + \frac{1}{2}(x - a)^2 f_{xx}(a, b) + \frac{1}{2}(y - b)^2 f_{yy}(a, b) \\ & + (x - a)(y - b)f_{xy}(a, b). \end{aligned}$$

- ▶ Gradient:  $\nabla f(x, y) = \begin{bmatrix} \frac{\partial f}{\partial x}(x, y) \\ \frac{\partial f}{\partial y}(x, y) \end{bmatrix}$
- ▶ Hessian:  $\mathbf{H}(x, y) = \begin{bmatrix} \frac{\partial^2 f}{\partial x^2}(x, y) & \frac{\partial^2 f}{\partial x \partial y}(x, y) \\ \frac{\partial^2 f}{\partial x \partial y}(x, y) & \frac{\partial^2 f}{\partial y^2}(x, y) \end{bmatrix}$
- ▶ Taylor series around  $\mathbf{x}_0$  in general:

$$f(\mathbf{x}) \approx f(\mathbf{x}_0) + (\mathbf{x} - \mathbf{x}_0)^T \nabla f(\mathbf{x}_0) + \frac{1}{2}(\mathbf{x} - \mathbf{x}_0)^T \mathbf{H}(\mathbf{x}_0)(\mathbf{x} - \mathbf{x}_0)$$

# Example

- Taylor series in 2-d around  $(a, b)$ :

$$\begin{aligned}f(x, y) \approx & f(a, b) + (x - a)f_x(a, b) + (y - b)f_y(a, b) \\& + \frac{1}{2}(x - a)^2 f_{xx}(a, b) + \frac{1}{2}(y - b)^2 f_{yy}(a, b) \\& + (x - a)(y - b)f_{xy}(a, b).\end{aligned}$$

- $f(x, y) = e^x e^y$  around  $(0, 0)$

# Example

- ▶ Taylor series in 2-d around  $(a, b)$ :

$$\begin{aligned} f(x, y) \approx & f(a, b) + (x - a)f_x(a, b) + (y - b)f_y(a, b) \\ & + \frac{1}{2}(x - a)^2 f_{xx}(a, b) + \frac{1}{2}(y - b)^2 f_{yy}(a, b) \\ & + (x - a)(y - b)f_{xy}(a, b). \end{aligned}$$

- ▶  $f(x, y) = e^x e^y$  around  $(0, 0)$
- ▶  $f_x(0, 0) = f_y(0, 0) = f_{xx}(0, 0) = f_{yy}(0, 0) = f_{xy}(0, 0) = 1$
- ▶  $f(x, y) \approx 1 + x + y + \frac{x^2}{2} + \frac{y^2}{2} + xy$
- ▶  $\nabla f(0, 0) = \begin{bmatrix} 1 \\ 1 \end{bmatrix}, \mathbf{H}(0, 0) = \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix}$
- ▶  $f(x, y) \approx 1 + \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 \\ 1 \end{bmatrix} + \frac{1}{2} \begin{bmatrix} x & y \end{bmatrix} \begin{bmatrix} 1 & 1 \\ 1 & 1 \end{bmatrix} \begin{bmatrix} x \\ y \end{bmatrix}$

# Taylor series in 2-d

► 
$$p_2(x, y) = c_{0,0} + c_{1,0}(x - a) + c_{0,1}(y - b) + c_{2,0}(x - a)^2 + c_{0,2}(y - b)^2 + c_{1,1}(x - a)(y - b)$$

# Taylor series in 2-d

- ▶  $p_2(x, y) = c_{0,0} + c_{1,0}(x - a) + c_{0,1}(y - b) + c_{2,0}(x - a)^2 + c_{0,2}(y - b)^2 + c_{1,1}(x - a)(y - b)$
- ▶ Match  $f(x, y)$  at  $(a, b)$  for derivatives
- ▶  $f(a, b) = p_2(a, b) = c_{0,0}$
- ▶  $f_x(a, b) = \frac{\partial p_2(a, b)}{\partial x} = c_{1,0}$
- ▶  $f_y(a, b) = \frac{\partial p_2(a, b)}{\partial y} = c_{0,1}$
- ▶  $f_{xx}(a, b) = \frac{\partial^2 p_2(a, b)}{\partial x^2} = 2c_{2,0}$
- ▶  $f_{yy}(a, b) = \frac{\partial^2 p_2(a, b)}{\partial y^2} = 2c_{0,2}$
- ▶  $f_{xy}(a, b) = \frac{\partial^2 p_2(a, b)}{\partial x \partial y} = c_{1,1}.$



# Nonlinear systems

- ▶ Linear systems:

$$\begin{aligned}x + y &= 10, \\ 2x + 4y &= 26.\end{aligned}$$

- ▶ Nonlinear systems:

$$\begin{aligned}4x^2 + y^2 - 4 &= 0, \\ x + y - \sin(x - y) &= 0.\end{aligned}$$

- ▶ **Question:** Does grid searching work?

# Nonlinear systems

- ▶ Linear systems:

$$\begin{aligned}x + y &= 10, \\ 2x + 4y &= 26.\end{aligned}$$

- ▶ Nonlinear systems:

$$\begin{aligned}4x^2 + y^2 - 4 &= 0, \\ x + y - \sin(x - y) &= 0.\end{aligned}$$

- ▶ **Question:** Does grid searching work? Yes, with  $n^d$  function evaluation
- ▶ **Question:** Bisection?

# Nonlinear systems

- ▶ Linear systems:

$$\begin{aligned}x + y &= 10, \\ 2x + 4y &= 26.\end{aligned}$$

- ▶ Nonlinear systems:

$$\begin{aligned}4x^2 + y^2 - 4 &= 0, \\ x + y - \sin(x - y) &= 0.\end{aligned}$$

- ▶ **Question:** Does grid searching work? Yes, with  $n^d$  function evaluation
- ▶ **Question:** Bisection? No.
- ▶ **Question:** Newton?

# Newton in 2-d

- Solve

$$f_1(x, y) = 0,$$

$$f_2(x, y) = 0.$$

- With initial guess  $(a, b)$

$$f_1(x, y) \approx f_1(a, b) + (x - a) \frac{\partial f_1}{\partial x}(a, b) + (y - b) \frac{\partial f_1}{\partial y}(a, b),$$

$$f_2(x, y) \approx f_2(a, b) + (x - a) \frac{\partial f_2}{\partial x}(a, b) + (y - b) \frac{\partial f_2}{\partial y}(a, b).$$

- Suppose  $(x^*, y^*)$  is the root

$$0 \approx f_1(a, b) + x^* \frac{\partial f_1}{\partial x}(a, b) + y^* \frac{\partial f_1}{\partial y}(a, b) - a \frac{\partial f_1}{\partial x}(a, b) - b \frac{\partial f_1}{\partial y}(a, b),$$

$$0 \approx f_2(a, b) + x^* \frac{\partial f_2}{\partial x}(a, b) + y^* \frac{\partial f_2}{\partial y}(a, b) - a \frac{\partial f_2}{\partial x}(a, b) - b \frac{\partial f_2}{\partial y}(a, b)$$

# Newton in 2-d - continued

► Solve

$$\begin{bmatrix} 0 \\ 0 \end{bmatrix} = \begin{bmatrix} f_1(a, b) \\ f_2(a, b) \end{bmatrix} + \begin{bmatrix} \frac{\partial f_1}{\partial x}(a, b) & \frac{\partial f_1}{\partial y}(a, b) \\ \frac{\partial f_2}{\partial x}(a, b) & \frac{\partial f_2}{\partial y}(a, b) \end{bmatrix} \begin{bmatrix} x^* - a \\ y^* - b \end{bmatrix}$$

► 
$$\begin{bmatrix} x^* \\ y^* \end{bmatrix} = \begin{bmatrix} a \\ b \end{bmatrix} - \begin{bmatrix} \frac{\partial f_1}{\partial x}(a, b) & \frac{\partial f_1}{\partial y}(a, b) \\ \frac{\partial f_2}{\partial x}(a, b) & \frac{\partial f_2}{\partial y}(a, b) \end{bmatrix}^{-1} \begin{bmatrix} f_1(a, b) \\ f_2(a, b) \end{bmatrix}$$

► Jacobian matrix: 
$$\mathbf{J}(a, b) = \begin{bmatrix} \frac{\partial f_1}{\partial x}(a, b) & \frac{\partial f_1}{\partial y}(a, b) \\ \frac{\partial f_2}{\partial x}(a, b) & \frac{\partial f_2}{\partial y}(a, b) \end{bmatrix}$$

► Newton's iteration:

$$\begin{bmatrix} x_{n+1} \\ y_{n+1} \end{bmatrix} = \begin{bmatrix} x_n \\ y_n \end{bmatrix} - \mathbf{J}^{-1}(x_n, y_n) \begin{bmatrix} f_1(x_n, y_n) \\ f_2(x_n, y_n) \end{bmatrix}.$$

# Example

- ▶ Nonlinear systems:

$$f_1(x, y) = 4x^2 + y^2 - 4 = 0,$$

$$f_2(x, y) = x - \sin(x - y) = 0.$$

- ▶ Jacobian matrix:

# Example

- ▶ Nonlinear systems:

$$\begin{aligned}f_1(x, y) &= 4x^2 + y^2 - 4 = 0, \\f_2(x, y) &= x - \sin(x - y) = 0.\end{aligned}$$

- ▶ Jacobian matrix:

$$\begin{aligned}\mathbf{J}(\mathbf{x}) &= \begin{bmatrix} \frac{\partial f_1}{\partial x}(x, y) & \frac{\partial f_1}{\partial y}(x, y) \\ \frac{\partial f_2}{\partial x}(x, y) & \frac{\partial f_2}{\partial y}(x, y) \end{bmatrix} \\&= \begin{bmatrix} 8x & 2y \\ 1 - \cos(x - y) & \cos(x - y) \end{bmatrix}.\end{aligned}$$

- ▶ Newton's iteration:

$$\begin{bmatrix} x_{n+1} \\ y_{n+1} \end{bmatrix} = \begin{bmatrix} x_n \\ y_n \end{bmatrix} - \begin{bmatrix} 8x_n & 2y_n \\ 1 - \cos(x_n - y_n) & \cos(x_n - y_n) \end{bmatrix}^{-1} \begin{bmatrix} 4x_n^2 + y_n^2 - 4 \\ x_n - \sin(x_n - y_n) \end{bmatrix}$$

# Newton - general cases

- ▶  $f_i(\mathbf{x}) \approx f_i(\mathbf{x}_0) + \nabla f_i^T(\mathbf{x}_0)(\mathbf{x} - \mathbf{x}_0)$
- ▶  $\mathbf{f}(\mathbf{x}) \approx \mathbf{f}(\mathbf{x}_0) + \mathbf{J}(\mathbf{x}_0)(\mathbf{x} - \mathbf{x}_0)$
- ▶  $\mathbf{0} = \mathbf{f}(\mathbf{x}^*) \approx \mathbf{f}(\mathbf{x}_0) + \mathbf{J}(\mathbf{x}_0)(\mathbf{x}^* - \mathbf{x}_0)$
- ▶  $\mathbf{x}^* \approx \mathbf{x}_0 - \mathbf{J}^{-1}(\mathbf{x}_0)\mathbf{f}(\mathbf{x}_0)$
- ▶  $\mathbf{x}_{n+1} = \mathbf{x}_n - \mathbf{J}^{-1}(\mathbf{x}_n)\mathbf{f}(\mathbf{x}_n)$
- ▶ **Question:** Most expensive cost?



# Newton - general cases

- ▶  $f_i(\mathbf{x}) \approx f_i(\mathbf{x}_0) + \nabla f_i^T(\mathbf{x}_0)(\mathbf{x} - \mathbf{x}_0)$
- ▶  $\mathbf{f}(\mathbf{x}) \approx \mathbf{f}(\mathbf{x}_0) + \mathbf{J}(\mathbf{x}_0)(\mathbf{x} - \mathbf{x}_0)$
- ▶  $\mathbf{0} = \mathbf{f}(\mathbf{x}^*) \approx \mathbf{f}(\mathbf{x}_0) + \mathbf{J}(\mathbf{x}_0)(\mathbf{x}^* - \mathbf{x}_0)$
- ▶  $\mathbf{x}^* \approx \mathbf{x}_0 - \mathbf{J}^{-1}(\mathbf{x}_0)\mathbf{f}(\mathbf{x}_0)$
- ▶  $\mathbf{x}_{n+1} = \mathbf{x}_n - \mathbf{J}^{-1}(\mathbf{x}_n)\mathbf{f}(\mathbf{x}_n)$
- ▶ **Question:** Most expensive cost?
- ▶ Solve the linear system
- ▶ E.g.  $N$ -body simulation

$$m_i \frac{d^2 \mathbf{x}_i}{dt^2} = - \sum_{j \neq i} \frac{G m_i m_j (\mathbf{x}_i - \mathbf{x}_j)}{\|\mathbf{x}_i - \mathbf{x}_j\|^3}.$$

- ▶ **Question:** Is it possible to avoid this calculation?

# Fixed-point iteration

- ▶  $\mathbf{x}_{n+1} = \mathbf{g}(\mathbf{x}_n)$
- ▶ For simplicity, let's focus on the linear system only
- ▶  $(\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{b}$ ,  $\mathbf{A} \in \mathbb{R}^n$  with  $n$  large
- ▶ **Question:** Can we avoid  $\mathbf{A}^{-1}$ ?

# Fixed-point iteration

- ▶  $\mathbf{x}_{n+1} = \mathbf{g}(\mathbf{x}_n)$
- ▶ For simplicity, let's focus on the linear system only
- ▶  $(\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{b}$ ,  $\mathbf{A} \in \mathbb{R}^n$  with  $n$  large
- ▶ **Question:** Can we avoid  $\mathbf{A}^{-1}$ ?
- ▶  $\mathbf{x} = \mathbf{b} + \mathbf{A}\mathbf{b} + \mathbf{A}^2\mathbf{b} + \dots$
- ▶ **Question:** How to implement it?

# Fixed-point iteration

- ▶  $\mathbf{x}_{n+1} = \mathbf{g}(\mathbf{x}_n)$
- ▶ For simplicity, let's focus on the linear system only
- ▶  $(\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{b}$ ,  $\mathbf{A} \in \mathbb{R}^n$  with  $n$  large
- ▶ **Question:** Can we avoid  $\mathbf{A}^{-1}$ ?
- ▶  $\mathbf{x} = \mathbf{b} + \mathbf{A}\mathbf{b} + \mathbf{A}^2\mathbf{b} + \dots$
- ▶ **Question:** How to implement it?
- ▶  $\mathbf{x}_{n+1} = \mathbf{A}\mathbf{x}_n + \mathbf{b}$
- ▶ Error:  $\mathbf{e}_{n+1} = \mathbf{A}\mathbf{e}_n$
- ▶ **Question:** How fast does the error decay?

# Fixed-point iteration

- ▶  $\mathbf{x}_{n+1} = \mathbf{g}(\mathbf{x}_n)$
- ▶ For simplicity, let's focus on the linear system only
- ▶  $(\mathbf{I} - \mathbf{A})\mathbf{x} = \mathbf{b}$ ,  $\mathbf{A} \in \mathbb{R}^n$  with  $n$  large
- ▶ **Question:** Can we avoid  $\mathbf{A}^{-1}$ ?
- ▶  $\mathbf{x} = \mathbf{b} + \mathbf{A}\mathbf{b} + \mathbf{A}^2\mathbf{b} + \dots$
- ▶ **Question:** How to implement it?
- ▶  $\mathbf{x}_{n+1} = \mathbf{A}\mathbf{x}_n + \mathbf{b}$
- ▶ Error:  $\mathbf{e}_{n+1} = \mathbf{A}\mathbf{e}_n$
- ▶ **Question:** How fast does the error decay?
- ▶ Suppose  $\mathbf{A} = \mathbf{V}\mathbf{D}\mathbf{V}^{-1}$
- ▶  $\mathbf{e}_n = \mathbf{V}\mathbf{D}^n\mathbf{V}^{-1}$
- ▶ Focus on the eigenvalue with the largest magnitude

# Convergence analysis

- Taylor series in 2d:

$$f(x, y) - f(x_0, y_0) \approx \frac{\partial f}{\partial x}(x_0, y_0)(x - x_0) + \frac{\partial f}{\partial y}(x_0, y_0)(y - y_0).$$

- Matrix equation for vector functions:

$$\begin{bmatrix} f_1(x, y) - f_1(x_0, y_0) \\ f_2(x, y) - f_2(x_0, y_0) \end{bmatrix} \approx \begin{bmatrix} \frac{\partial f_1(x_0, y_0)}{\partial x} & \frac{\partial f_1(x_0, y_0)}{\partial y} \\ \frac{\partial f_2(x_0, y_0)}{\partial x} & \frac{\partial f_2(x_0, y_0)}{\partial y} \end{bmatrix} \begin{bmatrix} x - x_0 \\ y - y_0 \end{bmatrix}.$$

- Inf-norm of a vector  $\|\mathbf{x}\|_\infty = \max_i |x_i|$
- Want:  $\|\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}_0)\|_\infty \leq \lambda \|\mathbf{x} - \mathbf{x}_0\|_\infty$

# Convergence analysis

- ▶  $|f_1(x, y) - f_1(x_0, y_0)| \leq \left| \frac{\partial f_1(x_0, y_0)}{\partial x} \right| |x - x_0| + \left| \frac{\partial f_1(x_0, y_0)}{\partial y} \right| |y - y_0|$
- ▶  $|f_2(x, y) - f_2(x_0, y_0)| \leq \left| \frac{\partial f_2(x_0, y_0)}{\partial x} \right| |x - x_0| + \left| \frac{\partial f_2(x_0, y_0)}{\partial y} \right| |y - y_0|$
- ▶  $|f_i(x, y) - f_i(x_0, y_0)| \leq \left( \left| \frac{\partial f_i(x_0, y_0)}{\partial x} \right| + \left| \frac{\partial f_i(x_0, y_0)}{\partial y} \right| \right) \max(|x - x_0|, |y - y_0|)$
- ▶  $\max_i |f_i(x, y) - f_i(x_0, y_0)| \leq \max_i \left( \left| \frac{\partial f_i(x_0, y_0)}{\partial x} \right| + \left| \frac{\partial f_i(x_0, y_0)}{\partial y} \right| \right) \max(|x - x_0|, |y - y_0|)$
- ▶ Inf-norm of a matrix  $\|\mathbf{A}\|_\infty = \max_i \sum_{j=1}^n |A_{i,j}|$
- ▶  $\|\mathbf{f}(\mathbf{x}) - \mathbf{f}(\mathbf{x}_0)\|_\infty \leq \|\mathbf{J}(\mathbf{x}_0)\|_\infty \|\mathbf{x} - \mathbf{x}_0\|_\infty$
- ▶ Can be easily generalized to high-dimensions

# Convergence analysis

- ▶ Assumptions:
  - ▶ Suppose  $\mathbf{x}^*$  is the solution to  $\mathbf{x} = \mathbf{g}(\mathbf{x})$
  - ▶  $\mathbf{g}(\mathbf{x})$  is continuously differentiable in some neighborhood around  $\mathbf{x}^*$
  - ▶  $\lambda = \|\mathbf{J}(\mathbf{x}^*)\|_\infty \leq 1$
- ▶ **Question:** How to analyze the convergence?



# Convergence analysis

- ▶ Assumptions:
  - ▶ Suppose  $\mathbf{x}^*$  is the solution to  $\mathbf{x} = \mathbf{g}(\mathbf{x})$
  - ▶  $\mathbf{g}(\mathbf{x})$  is continuously differentiable in some neighborhood around  $\mathbf{x}^*$
  - ▶  $\lambda = \|\mathbf{J}(\mathbf{x}^*)\|_\infty \leq 1$
- ▶ **Question:** How to analyze the convergence?
- ▶  $\mathbf{x}^* - \mathbf{x}_{n+1} = \mathbf{g}(\mathbf{x}^*) - \mathbf{g}(\mathbf{x}_n)$
- ▶  $\|\mathbf{g}(\mathbf{x}) - \mathbf{g}(\mathbf{x}_0)\|_\infty \leq \|\mathbf{J}(\mathbf{x}_0)\|_\infty \|\mathbf{x} - \mathbf{x}_0\|_\infty$
- ▶  $\|\mathbf{x}^* - \mathbf{x}_{n+1}\|_\infty \leq \lambda \|\mathbf{x}^* - \mathbf{x}_n\|_\infty \leq \lambda^{n+1} \|\mathbf{x}^* - \mathbf{x}_0\|_\infty$

Root-finding problem

Bisection method

Newton's method

Secant method

A general theory for one-point iteration methods

System of nonlinear equations

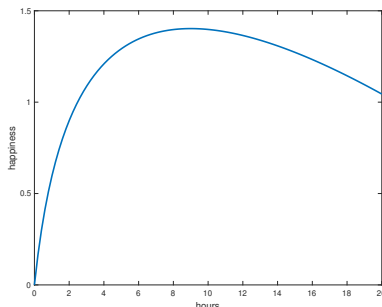
Unconstrained optimization

# Optimization problem

- ▶ In real-life, many problems are formulated to optimization problem

$$\min_x f(x)$$

- ▶ E.g. happiness vs hours



- ▶ **Question:** How to solve this numerically?

# Newton's method for optimization

- ▶ One condition of the minimizer:  $f'(x^*) = 0$
- ▶ Reformulate it to a root-finding problem
- ▶ 
$$x_{n+1} = x_n - \frac{f'(x_n)}{f''(x_n)}$$
- ▶ Newton's method is not the most popular method in optimization
- ▶ Other methods include gradient descent
- ▶ Will cover in optimization courses