Nonlinear Equations
linear $f(x)=y \Rightarrow A x=y$
nonlinear: $f\left(x_{k}\right)=y$ iterative autorob.github.io method


Inverse Kinematics

## How can we solve these equations?

- Spring force:
$F=k x$

What is the displacement when $F=2 \mathrm{~N}$ ?

- Drag force:
$F=0.5 C_{d} \rho A v^{2}=\mu_{d} v^{2}$
What is the velocity when
$F=20 \mathrm{~N}$ ?


- Spring force:

$$
f(x)=k x-F=0
$$

- Drag force: $f(v)=\mu_{d} v^{2}-F=0$


Find the root (zero) of the nonlinear equation $f(v)$


## Nonlinear Equations in 1D

Goal: Solve $f(x)=0$ for $f: \mathcal{R} \rightarrow \mathcal{R}$
Often called Root Finding


Convergence

- The bisection method does not estimate $x_{k}$, the approximation of the desired root $x$. It instead finds an interval smaller than a given tolerance that contains the root.

$$
\Delta t_{k}<\text { to } \Rightarrow \text { stops }
$$

At each iteration: $\Delta t_{k}=\frac{\Delta t_{k-1}}{2}$

$$
\Delta t_{k}=\frac{\Delta t_{0}}{2^{k}}
$$

Convergence rate: $\lim _{k \rightarrow \infty} \frac{\left|e_{k+1}\right|}{\left|e_{k}\right|}=\frac{\Delta t_{0} / 2^{k+1}}{\Delta t_{0} / 2^{k}}=\frac{2^{k}}{2^{k+1}}=\frac{1}{2}$

## Convergence

An iterative method converges with rate $r$ if:
$\lim _{k \rightarrow \infty} \frac{\left\|e_{k+1}\right\|}{\left\|e_{k}\right\|^{r}}=C, \quad 0<C<\infty$
recall power iteration $\lim _{k \rightarrow \infty} \frac{\left\|e_{k+1}\right\|}{\left\|e_{k}\right\|}=\left|\frac{\lambda_{2}}{\lambda_{1}}\right|$
$r=1$ : linear convergence
now Bisection

$$
\|=0.5
$$

$r=2$ : quadratic convergence

Linear convergence gains a constant number of accurate digits each step (and $C<1$ matters!

Quadratic convergence doubles the number of accurate digits in each step (however it only starts making sense once $\left\|e_{k}\right\|$ is small (and $C$ does not matter much)

## Example:

$$
\Delta t_{k}=\frac{|b-a|}{2^{k}}<2^{-4}
$$

Consider the nonlinear equation

$$
2^{k}>\frac{|b-a|}{t o l} \Rightarrow k>\log _{2}\left(\frac{|b-a|}{t o l}\right)
$$

$$
f(x)=0.5 x^{2}-2
$$

and solving $\mathrm{f}(\mathrm{x})=0$ using the Bisection Method. For each of the initial intervals below, how many iterations are required to ensure the root is accurate within $2^{-4}$ ?
A) $[-10,-1.8] \quad k>\log _{2}\left(\frac{8.2}{2^{-4}}\right)=7.03 \rightarrow$ at least 8 ter
B) $[-3,-2.1] \rightarrow$ it can't be used since sign $(f(a))=$ $\operatorname{sign}(f(b))$
C) $[-4,1.9] \quad k>\log _{2}\left(\frac{5.9}{2^{-4}}\right)=6.56 \rightarrow$ at least 7 iter

## Bisection Method - summary

Maxktherincorreet statementabout the Bisection Alethert. -
$\square$ The function must be continuous with a root in the interval $[a, b]$
$\square$ Requires only one function evaluations for each iteration!

- The first iteration requires two function evaluations.
$\square$ Given the initial internal $[a, b]$, the length of the interval after $k$ iterations is $\frac{b-a}{2^{k}}$
$\square$ Has linear convergence

Newton's method

- Recall we want to solve $f(x)=0$ for $f: \mathcal{R} \rightarrow \mathcal{R}$
- The Taylor expansion:
nonlinear function

$$
f(\underbrace{x_{k}+h}_{x_{k+1}}) \approx \underbrace{f\left(x_{k}\right)+f^{\prime}\left(x_{k}\right) h}_{\text {linear approx }}
$$

gives a linear approximation for the nonlinear function $f$ near $x_{k}$.

$$
\begin{aligned}
& f\left(x_{k}+h\right)=0 \rightarrow f\left(x_{k}\right)+f^{\prime}\left(x_{k}\right) h=0 \\
& \quad h=\frac{-f^{\prime}\left(x_{k}\right)}{-f^{\prime}\left(x_{k}\right)} \rightarrow \text { newton step } \\
& x_{0}=\text { initial guess } \\
& x_{k+1}=x_{k}+h
\end{aligned}
$$

Newton's method


## Iclicker question

Consider solving the nonlinear equation

$$
5=2.0 e^{x}+x^{2}
$$

What is the result of applying one iteration of Newton's method for solving nonlinear equations with initial starting guess $x_{0}=0$, i.e. what is $x_{1}$ ?
A) -2
B) 0.75
C) -1.5
D) 1.5
E) 3.0

$$
\begin{aligned}
& f(x)=2 e^{x}+x^{2}-5 \\
& f^{\prime}(x)=2 e^{x}+2 x \\
& x_{1}=x_{0}-\frac{f\left(x_{0}\right)}{f^{\prime}\left(x_{0}\right)}=0-\frac{\left(2 e^{0}+0-5\right)}{2 e^{0}+0}=\frac{-(-3)}{2} \\
& x_{1}=1.5
\end{aligned}
$$

## Newton's Method - summary

Must be started with initial guess close enough to root (convergence is only local). Otherwise it may not converge at all.
$\square$ Requires function and first derivative evaluation at each iteration (think about two function evaluations)
$\square$ What can we do when the derivative evaluation is too costly (or difficult to evaluate)?
$\square$ Typically has quadratic convergence

$$
\lim _{k \rightarrow \infty} \frac{\left\|e_{k+1}\right\|}{\left\|e_{k}\right\|^{2}}=C, \quad 0<C<\infty
$$

## Secant method

Also derived from Taylor expansion, but instead of using $f^{\prime}\left(x_{k}\right)$, it approximates the tangent with the secant line:

$$
x_{k+1}=x_{k}-f\left(x_{k}\right) / f^{\prime}\left(x_{k}\right)
$$

> Secant line:


## Secant Method - summary

Still local convergence
$\square$ Requires only one function evaluation per iteration (only the first iteration requires two function evaluations)
$\square$ Needs two starting guesses
$\square$ Has slower convergence than Newton's Method - superlinear convergence

$$
\lim _{k \rightarrow \infty} \frac{\left\|e_{k+1}\right\|}{\left\|e_{k}\right\|^{r}}=C, \quad 1<r<2
$$

Demo: "Secant Method"
Demo: "Convergence of Secant Method"

## Nonlinear system of equations

Goal: Solve $\boldsymbol{f}(\boldsymbol{x})=\mathbf{0}$ for $\boldsymbol{f}: \mathcal{R}^{n} \rightarrow \mathcal{R}^{n}$

$$
\left\{\begin{array}{l}
x_{1}^{2}+2 x_{1} x_{2}+x_{2}^{3}-4=0 \\
2 x_{1}+3 x_{2}-5=0
\end{array}\right.
$$

In other words, $\boldsymbol{f}(\boldsymbol{x})$ is a vector-valued function

$$
[\square]=\left[\begin{array}{l}
0 \\
0
\end{array}\right]
$$

$$
\boldsymbol{f}(\boldsymbol{x})=\left[\begin{array}{c}
f_{1}(\boldsymbol{x}) \\
\vdots \\
f_{n}(\boldsymbol{x})
\end{array}\right]=\left[\begin{array}{c}
f_{1}\left(x_{1}, x_{2}, x_{3}, \ldots, x_{n}\right) \\
\vdots \\
f_{n}\left(x_{1}, x_{2}, x_{3}, \ldots, x_{n}\right)
\end{array}\right]
$$

If looking for a solution to $\boldsymbol{f}(\boldsymbol{x})=\boldsymbol{y}$, then instead solve

$$
f(x)=f(x)-y=0
$$

Newton's method
Approximate the nonlinear function $\boldsymbol{f}(\boldsymbol{x})$ by a linear function using Taylor expansion:

$$
\overbrace{\boldsymbol{f}(\boldsymbol{x}+\boldsymbol{s})}^{x_{k+1}} \approx \overbrace{\boldsymbol{f f}(\boldsymbol{x})+\boldsymbol{J}(\boldsymbol{x}) \boldsymbol{s}}^{\text {nonlinear approx }} \text { Similar to } \begin{aligned}
& \text { Taylor but } \\
& \text { for ND }
\end{aligned}
$$

$$
\begin{aligned}
& \text { where } \boldsymbol{J}(\boldsymbol{x}) \text { is the Jacobian matrix of the function } \boldsymbol{f} \text { : } \\
& \text { where } \boldsymbol{J}(\boldsymbol{x}) \text { is the Jacobian matrix of the function } \boldsymbol{f} \text { : } \\
& \boldsymbol{J}(\boldsymbol{x})=\left(\begin{array}{ccc}
\frac{\partial f_{1}(x)}{\partial x_{1}} & \ldots & \frac{\partial f_{1}(\boldsymbol{x})}{\partial x_{n}} \\
\vdots & \ddots & \vdots \\
\frac{\partial f_{n}(x)}{\partial x_{1}} & \ldots & \frac{\partial f_{n}(\boldsymbol{x})}{\partial x_{n}}
\end{array}\right) \text { or }[\boldsymbol{J}(\boldsymbol{x})]_{i j}=\frac{\partial f_{i}(\boldsymbol{x})}{\partial x_{j}} \\
& \underset{\sim}{f}(\underset{\sim}{x}+\underset{\sim}{s})=0 \Rightarrow \underset{\sim}{f}(\underset{\sim}{x})+\underset{\sim}{J}(\underset{\sim}{x}) \underset{\sim}{\underset{\sim}{s}}=0 \quad \text { (or } \underset{\sim}{b}+\underset{\sim}{A} \underset{\sim}{s}=0 \rightarrow \underset{\sim}{A} \underset{\sim}{s}=-b \text { for } \underset{\sim}{s} \\
& \underset{\sim}{J} \underset{\sim}{S}=-\underset{\sim}{f} \underset{\sim}{x}(\underset{\sim}{x}) \rightarrow \text { solve for } \underset{\sim}{s}
\end{aligned}
$$

Newton's method

$$
J(x) \underline{S}=-f(x) \text { for le }
$$

Algorithm: start with $x_{0}=$ initial guess for $k=1,2, \ldots$.

$$
\begin{aligned}
& =1,2, \ldots \\
& J=J\left(x_{k}\right) \rightarrow \text { evaluate Jacobian } \rightarrow O\left(n^{2}\right) \\
& b=-f\left(x_{k}\right) \rightarrow \text { evaluate function } \rightarrow O(n) \\
& J s_{k}=b \rightarrow \text { solve for } s_{k} \rightarrow O\left(n^{3}\right) \\
& x_{k+1}=x_{k}+s_{k} \rightarrow \text { upolate }
\end{aligned}
$$

Convergence:

- Typically has quadratic convergence
- Drawback: Still only locally convergent

Cost:

- Main cost associated with computing the Jacobian matrix and solving the Newton step. very expensive method

Example
Consider solving the nonlinear system of equations

$$
\begin{gathered}
2=2 y+x \\
4=x^{2}+4 y^{2}
\end{gathered}
$$

What is the result of applying one iteration of Newton's method with the

$$
\begin{aligned}
& \text { following initial guess? } \quad x_{0}=\left[\begin{array}{l}
1 \\
0
\end{array}\right] \quad f\left(x_{0}\right)=\left[\begin{array}{l}
-1 \\
-3
\end{array}\right] \\
& \underset{\sim}{f(x)}=\left[\begin{array}{l}
2 y+x-2 \\
4 y^{2}+x^{2}-4
\end{array}\right] \quad J=\left[\begin{array}{cc}
1 & 2 \\
2 x & 8 y
\end{array}\right] \quad J_{0}=J\left(x_{0}\right)=\left[\begin{array}{cc}
1 & 2 \\
2 & 0
\end{array}\right] \\
& \left.\left[\begin{array}{ll}
1 & 2 \\
2 & 0
\end{array}\right]\left[\begin{array}{l}
a \\
b
\end{array}\right]=\left[\begin{array}{l}
1 \\
3
\end{array}\right] \Rightarrow \begin{array}{l}
a+2 b=1 \Rightarrow 2 b=1-1.5 \Rightarrow b=-0.25 / / \\
2 a=3 \Rightarrow a=1.5 / 50
\end{array}\right]=\left[\begin{array}{c}
1.5 \\
-0.25
\end{array}\right] \Rightarrow x_{1}=\left[\begin{array}{c}
2.5 \\
-0.25
\end{array}\right] /
\end{aligned}
$$

## Newton's method - summary

$\square$ Typically quadratic convergence (local convergence)
$\square$ Computing the Jacobian matrix requires the equivalent of $n^{2}$ function evaluations for a dense problem (where every function of $\boldsymbol{f}(\boldsymbol{x})$ depends on every component of $\boldsymbol{X}$ ).
$\square$ Computation of the Jacobian may be cheaper if the matrix is sparse.
$\square$ The cost of calculating the step $\boldsymbol{S}$ is $O\left(n^{3}\right)$ for a dense Jacobian matrix (Factorization + Solve)
$\square$ If the same Jacobian matrix $\boldsymbol{J}\left(\boldsymbol{x}_{\boldsymbol{k}}\right)$ is reused for several consecutive iterations, the convergence rate will suffer accordingly (trade-off between cost per iteration and number of iterations needed for convergence)
for $k=1,2$,

$$
\begin{aligned}
& =1,2,\left\{\begin{array}{l}
J\left(x_{k}\right) \rightarrow \text { evaluate Jacobian } \rightarrow O\left(n^{2}\right) \\
\tilde{J}\left(x_{k}\right) \rightarrow \text { some approx. of Jacobian }
\end{array}\right. \\
& b=-f\left(x_{k}\right) \rightarrow \text { evaluate function } \rightarrow O(n) \\
& \text { compute factorization of } J \rightarrow O\left(n^{3}\right) \\
& J s_{k}=b \rightarrow O\left(n^{2}\right) \\
& x_{k+1}=x_{k}+s_{k} \rightarrow \text { updateady factorized } J \rightarrow O
\end{aligned}
$$

$\rightarrow$ perform these two steps only every few iterations
$\rightarrow$ cheaper $\left.\begin{array}{l}\rightarrow \text { slower convex genence }\end{array}\right\}$ trade off!

