# Root finding continued 

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Lecture 07

## Secant method



$$
x_{i+2}=x_{i+1}-f\left(x_{i+1}\right) \frac{x_{i+1}-x_{i}}{f\left(x_{i+1}\right)-f\left(x_{i}\right)}
$$

Need to provide two starting points $x_{1}$ and $x_{2}$. Secant method converges with $m=(1+\sqrt{5}) / 2 \approx 1.618$

## Newton-Raphson method



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

Need to provide a starting points $x_{1}$ and the derivative of the function. Newton-Raphson method converges quadratically $(m=2)$,

## Numerical derivative of a function

Mathematical definition

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The initial intent is to calculate it at very small $h$.

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Here computed approximation and algorithm error There is a range of optimal $h$ when both the round off and the algorithm errors are small.

## Derivative via Forward difference

$$
f_{c}^{\prime}(x)=\frac{f(x+h)-f(x)}{h}
$$

## Algorithm error

$$
\varepsilon_{f d} \approx \frac{f^{\prime \prime}(x)}{2} h
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## Example

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\begin{aligned}
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f_{c}^{\prime}(x)=b x h+b h
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So for small $x$, the algorithm error dominate our approximation!

## Derivative via Central difference

$$
f_{c}^{\prime}(x)=\frac{f(x+h)-f(x-h)}{2 h}
$$

## Derivative via Central difference

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f_{c}^{\prime}(x)=\frac{f(x+h)-f(x-h)}{2 h}
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## Algorithm error

$$
\varepsilon_{c d} \approx \frac{f^{\prime \prime \prime}(x)}{6} h^{2}
$$

## Bonus problem for the homework 03 ( 5 points)

Plot the $\log _{10}$ of the absolute error of $\sin (x)$ derivative at $x=\pi / 4$
calculated with forward and central difference methods vs the $\log _{10}$ the $h$ value. See $\log \log$ help for ploting with logarithmic axes. The values of $h$ should cover the range $10^{-16}, 10^{-15}, 10^{-14} \cdots 10^{-1}, 1$. At the low end error will be dominated by round offs and at the higher by the algorithm error.
The minimum of the absolute error indicates optimal values of $h$.

## Ridders method - the variation of false position

Solve $f(x)=0$ with linear approximation of the function $g(x)=f(x) \exp (h Q)$
(1) bracket the root between $x_{1}$ and $x_{2}$
(2) evaluate function in the mid point $x_{3}=\left(x_{1}+x_{2}\right) / 2$
(3) find new approximation for the root

$$
x_{4}=x_{3}+\operatorname{sign}\left(f_{1}-f_{2}\right) \frac{f_{3}}{\sqrt{f_{3}^{2}-f_{1} f_{2}}}\left(x_{3}-x_{1}\right)
$$

$$
\text { where } f_{1}=f\left(x_{1}\right), f_{2}=f\left(x_{2}\right), f_{3}=f\left(x_{3}\right)
$$

(9) check if $x_{4}$ satisfies convergence condition
(0) re bracket the root using

- $x_{4}$ and $f_{4}=f\left(x_{4}\right)$
- whichever of $\left(x_{1}, x_{2}, x_{3}\right)$ is closer to $x_{4}$ and provides proper bracket.
(0) proceed to step 1

Nice parts: $x_{4}$ is guaranteed to be inside the bracket, convergence of the algorithm is quadratic $m=2$. But it requires evaluation of the $f(x)$ twice for $f_{2}$ and $f_{1}$ thus actually $m=\sqrt{2}$.

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Bracketing algorithm are bullet proof and will always converge, however false position algorithm could be slow.


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Newton-Raphson and secant algorithm are usually fast but starting points need to be close enough to the root.


## Root finding algorithms summary

Root bracketing algorithms

- bisection
- false position
- Ridders

Pro

- robust i.e. always converge.
Contra
- usually slower convergence
- require initial bracketing

Non bracketing algorithms

- Newton-Raphson
- secant

Pro

- faster
- no need to bracket (just give a reasonable starting point)
Contra
- may not converge

