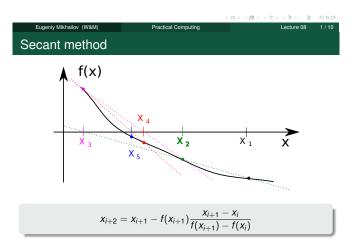
Notes

Root finding continued

Eugeniy E. Mikhailov

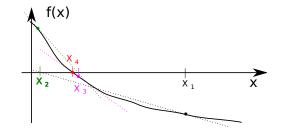


Lecture 08



Need to provide two starting points x_1 and x_2 . Secant method converges with $m = (1 + \sqrt{5})/2 \approx 1.618$ Eugeniy Mikhailov (W&M) Practical Computing

Newton-Raphson method



$$x_{i+1} = x_i - \frac{f(x_i)}{f'(x_i)}$$

Need to provide a starting points x_1 and the derivative of the function. Newton-Raphson method converges quadratically (m = 2), Practical Computing

Numerical derivative of a function

Mathematical definition

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$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

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

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Numerical derivative of a function

Mathematical definition

$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

The initial intent is to calculate it at very small *h*. Remember about roundoff errors (HW01).

Eugenly Mikhailov (W&M) Practical Computing Numerical derivative of a function

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$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

The initial intent is to calculate it at very small *h*. Remember about roundoff errors (HW01). For computers with *h* small enough f(x + h) - f(x) = 0.

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The initial intent is to calculate it at very small *h*. Remember about roundoff errors (HW01). For computers with *h* small enough f(x + h) - f(x) = 0. Let's be smarter. Recall Taylor series expansion

$$f(x + h) = f(x) + \frac{f'(x)}{1!}h + \frac{f''(x)}{2!}h^2 + \cdots$$

Numerical derivative of a function

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$$f'(x) = \lim_{h \to 0} \frac{f(x+h) - f(x)}{h}$$

Practical Computing

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$$f(x + h) = f(x) + \frac{f'(x)}{1!}h + \frac{f''(x)}{2!}h^2 + \cdots$$

So we can see

$$f'_{c}(x) = \frac{f(x+h) - f(x)}{h} = f'(x) + \frac{f''(x)}{2}h + \cdots$$

Here computed approximation and algorithm error.

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Numerical derivative of a function

Mathematical definition

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The initial intent is to calculate it at very small *h*. Remember about roundoff errors (HW01). For computers with *h* small enough f(x + h) - f(x) = 0. Let's be smarter. Recall Taylor series expansion

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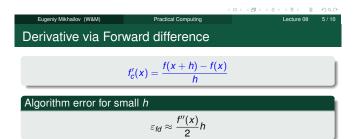
Here computed approximation and algorithm error. There is a range of optimal *h* when both the round off and the algorithm errors are small.

Derivative via Forward difference

 $f_c'(x) = \frac{f(x+h) - f(x)}{h}$

Algorithm error for small h

$$\varepsilon_{\rm fd} \approx \frac{f''(x)}{2}h$$



This is quite bad since error is proportional to *h*.

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Derivative via Forward difference

 $f_c'(x) = \frac{f(x+h) - f(x)}{h}$

Algorithm error for small h

 $\varepsilon_{fd} \approx \frac{f''(x)}{2}h$

This is quite bad since error is proportional to *h*.

Example

$$f(x) = a + bx^{2}$$

$$f(x + h) = a + b(x + h)^{2} = a + bx^{2} + 2bxh + bh^{2}$$

$$f'_c(x) = \frac{f(x+h) - f(x)}{h}$$

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Algorithm error for small h

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Example

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Derivative via Forward difference

$$f'_c(x) = \frac{f(x+h) - f(x)}{h}$$

 $\varepsilon_{\mathit{fd}}$

Algorithm error for small h

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$$\approx \frac{f''(x)}{2}h$$

This is quite bad since error is proportional to *h*.

Example

$$f(x) = a + bx^{2}$$

$$f(x + h) = a + b(x + h)^{2} = a + bx^{2} + 2bxh + bh^{2}$$

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

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So for small *x*, the algorithm error dominates our approximation!

Derivative via Central difference

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$$f_c'(x) = \frac{f(x+h) - f(x-h)}{2h}$$

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$$f_c'(x) = \frac{f(x+h) - f(x-h)}{2h}$$
Algorithm error
$$\varepsilon_{cd} \approx \frac{f'''(x)}{6}h^2$$

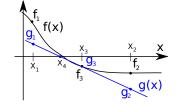
Eugenly Mikhailov (W&M) Practical Computing Lecture 08 Ridders method - smart variation of false position

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Lecture 08

Lecture 08

Solve f(x) = 0 with the following approximation of the function $f(x) = g(x) \exp(-C(x - x_r))$, where g(x) = a + bx i.e. linear. In this case if $g(x_0) = 0$ then $f(x_0) = 0$, but g(x) = 0 is trivial to solve.



One can say that

 $g(x) = f(x) \exp(C(x - x_1)) = a + bx$

Where we choose $x_r = x_1$

Ridders method implementation

- bracket the root between x_1 and x_2 , i.e. function must have different signs at these points: $f(x_1) \times f(x_2) < 0$
- (a) find the mid point $x_3 = (x_1 + x_2)/2$
- Ind new approximation for the root

$$x_4 = x_3 + sign(f_1 - f_2) \frac{f_3}{\sqrt{f_3^2 - f_1 f_2}} (x_3 - x_1)$$

where $f_1 = f(x_1), f_2 = f(x_2), f_3 = f(x_3)$

- Check if x₄ satisfies convergence condition and we should stop
- If rebracket the root, i.e. assign new x_1 and x_2 , using old values
 - one end of the bracket is x_4 and $f_4 = f(x_4)$
 - the other is whichever of (*x*₁, *x*₂, *x*₃) is closer to *x*₄ and provides proper bracket.
- proceed to step 2

Nice features: x_4 is guaranteed to be inside the bracket, convergence of the algorithm is quadratic per cycle (m = 2). But it requires evaluation of the f(x) twice for f_3 and f_4 thus it is actually $m = \sqrt{2}$.

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Root finding algorithm gotchas

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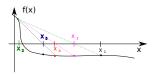
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Root finding algorithm gotchas

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Bracketing algorithms are bulletproof and will always converge, however false position algorithm could be slow.



Root finding algorithm gotchas

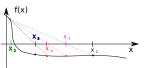
Bracketing algorithms are bulletproof and will always converge, however false position algorithm could be slow.

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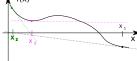
Newton-Raphson and secant algorithms are usually fast but starting points need to be close

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enough to the root. f(x)



Root finding algorithms summary

Root bracketing algorithms

- bisection
- false position

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Ridders

Pro

• robust i.e. always converge.

Contra

- usually slower
- convergence

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• require initial bracketing

See Matlab built in function fzero for equivalent tasks.

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Non bracketing algorithms

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- Newton-Raphson
- secant
- Pro

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

Notes