

CP315: Introduction to Scientific Computing

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1 Introduction

CP315 is a set of methods for solving mathematical problems with computers; fair enough - we will be using Maple and MatLab. Fundamental operations that are used: addition and multiplication. These are needed to evaluate a polynomial at a specific value. As we know, polynomials are basic objects in scientific computing \rightsquigarrow efficient evaluation.

1.1 Polynomial Evaluation

Consider a general, fourth-degree polynomial:

$$P(x) = c_0 + c_1x + c_2x^2 + c_3x^3 + c_4x^4$$

- i. Find $P(\frac{1}{2})$ naively requires substituting $\frac{1}{2}$ into $P(x) \rightsquigarrow$ 10 multiplications and 4 additions comes to a total of 14 operations.
- ii. Store powers of $\frac{1}{2}$ progressively \rightsquigarrow 3 multiplications (from the powers) + 4 multiplications (from the coefficients) and 4 additions. The new total is 11 operations.
- iii. *Horner's Method*: Rewrite $P(x)$ "backwards":

$$P(x) = c_0 + x(c_1 + x(c_2 + x(c_3 + x(c_4))))$$

This brings it down to 8 total operations.

Fact: A degree d polynomial can be evaluated in d multiplications and d additions.

Portfolio Part 1: Implement Horner's Method in Maple and/or MatLab.

1.1.1 Variation on the Theme

Evaluate:

$$\begin{aligned} P(x) &= x^5 + x^8 + x^{11} + x^{14} \\ &= x^5(1 + x^3 + x^6 + x^9) \\ &= x^5(1 + x^3(1 + x^3 + x^6)) \\ &= x^5(1 + x^3(1 + x^3(1 + x^3))) \end{aligned}$$

We get a total of 6 multiplications by 3 additions, thus 9 operations.

Overview of Calculus

Theorem 1. *Intermediate Value Theorem*

If $f(x)$ is continuous in $[a, b]$ then $\forall y$, such that, $f(a) \leq y \leq f(b) \exists c$, such that $a \leq c \leq b$ and $f(c) = y$.

Corollary 2. If $f(a), f(b) < 0$, then $\exists c$, such that $f(c) = 0$. Where c is a root of $f(x) = 0$.

Theorem 3. Mean Value Theorem

If $f(x)$ is differentiable in $[a, b]$ then $\exists c$, such that $f'(c) = \frac{f(b) - f(a)}{b - a}$. Thus, there is a point where we will be able to calculate the slope at c .

Corollary 4. Rolle's Theorem

If $f(x)$ is differentiable at $[a, b]$ then $\exists c$, such that $a \leq c \leq b$ and $f'(c) = 0$.

Theorem 5. Taylor's Theorem

If $f(x)$ is $(k+1)$ -differentiable in $[x_0, x]$, $\exists c$, such that:

$$f(x) = f(x_0) + f'(x_0)(x - x_0) + \frac{f''(x_0)}{2!}(x - x_0)^2 + \dots + \frac{f^{(k+1)}(x_0)}{(k+1)!}(x - x_0)^{k+1} + R$$

where $R = \frac{f^{(k+1)}(c)}{(k+1)!}(x - x_0)^{k+1}$, is the remainder. If we know $f(x_0)$, then we can find nearby values $f(x)$ as a polynomial of degree k .

Example 6. $f(x) = \sin(x)$. Find a degree-4 Taylor polynomial (approximation) about $x_0 = 0$.

$$P_4(x) = x - \frac{x^3}{6}$$

with a remainder is $R = \frac{x^5}{120} \cos(c)$. Now, we need to estimate the size of the remainder term:

$$|R| \leq \frac{|x|^5}{120}$$

If $|x| \leq 10^{-4}$ then $|R| \leq \frac{10^{-20}}{120}$. This tells us that for all numbers $\leq 10^{-4}$, R is close to zero and thus the Taylor approximation is accurate.

Theorem 7. Mean Value Theorem for Integrals

If f is continuous in $[a, b]$ and g is integrable in $[a, b]$ and does not change sign in $[a, b]$ then, $\exists c$ such that $a \leq c \leq b$ and

$$\int_a^b f(x)g(x)dx = f(c) \int_a^b g(x)dx$$

Note: This helps because this result gives us a way to evaluate $\int f(x)g(x)$ - as there is no defined way to do this.

2 Floating Point Representation of Real Numbers (\mathbb{R})

IEEE 754 is a standard to model floating point arithmetic on a computer. The problem is that we have finite-precision memory locations to represent infinite-precision numbers, YIKES.

IEEE 754 is a set of **binary** representations of real numbers.

A floating point, or real, number has three parts:

1. Sign (\pm) - s
2. Mantissa (AKA significant digits) - m
3. Exponent - e

These three parts are stored in a word. There are three common precision types:

1. Single: 32 bits, (s: 1, m: 8, e: 23)
2. Double: 64 bits (s: 1, m: 11, e: 52)
3. Long-double: 80 bits, (s: 1, m: 15, e: 64)

Definition 8. A normalized IEEE 754 **floating point number** is the following:

$$\pm 1.b_1b_2\dots b_N \times 2^p$$

where p is an M -bit binary number; where

$$b_i \in \{0, 1\}, i = 1, \dots, N$$

Example 9. 9 decimal and we want to convert to an IEEE FLP number.

$$\begin{aligned} 9 &\rightarrow 1001 \text{ (binary)} \\ +1 &\quad . \quad 001 \times 2^3 \\ N &= 3 \\ P &= 3 \end{aligned}$$

Multiplication by power of 2 \equiv a shift.

Typical double precision parameters in C/MatLab: $M = 11$, $N = 52$.

Example 10. We want to represent 1.

$$\begin{aligned} 1 &\rightsquigarrow 0001 \\ +1 &\quad . \quad 0\dots 0_{52} \times 2^0 \text{ (52 zeroes)} \end{aligned}$$

What is the “next” number we can represent? The answer is: $+1.0\dots 0_{51}1 \times 2^0 \rightsquigarrow 1 + 2^{-52}$, this is 51 zeroes.

Definition 11. Machine epsilon, E_{mach} , is the distance between 1 and the smallest FLP number greater than 1.

Remark 12. For IEEE 754, double precision, we have $E_{\text{mach}} = 2^{-52}$.

2.1 IEEE Nearest Rounding Rule

Example 13. 9.4 in decimal $\rightarrow 1001.\overline{0110}$

The binary representation of $0.4 \approx \frac{1}{2^2} + \frac{1}{2^3} + \frac{1}{2^6} + \frac{1}{2^7} + \dots = \sum_{k=1}^{\infty} \left(\frac{1}{2^{4k+2}} + \frac{1}{2^{4k+3}} \right)$

We need to fit this precision number in 52 bits.

$$1.\underline{001}011001100110\dots0110\underline{0} \times 2^3$$

We have the three bits in the beginning following by 12 sets of 0110:

$$3 \text{ bits} + 12 \times 4 \text{ bits} = 51 \text{ bits}$$

RMR: Look at the 53rd bit to the right of the radix point: $\begin{cases} 1 \rightarrow \text{add 1 to bit 52} \\ 0 \rightarrow \text{do nothing} \end{cases}$

So in our example: 53rd bit is 1, so we add 1 to 52.

Thus, 9.4 is represented as:

$$+1.001\underline{0110} \mathbf{1} \times 2^3$$

which is actually $9.4 + 0.2 \times 2^{-49}$ in decimal.

Remark 14. The IEEE double precision number associated with 9.4 using RNR is:

$$fl(9.4) = 9.4 + 0.2 \times 2^{-49}$$

where 0.2×2^{-49} is the error.

Definition 15.

$$\begin{aligned} x_c &= \text{computed value of } x \\ \text{absolute error} &= |x_c - x| \\ \text{relative error} &= \frac{|x_c - x|}{|x|} \end{aligned}$$

Remark 16. Relative error in IEEE 754 is bounded by:

$$\frac{|fl(x) - x|}{|x|} \leq \frac{1}{2} E_{\text{mach}}$$

2.2 Loss of Significant Digits

Example 17. $E_1 = \frac{1 - \cos(x)}{\sin^2(x)}$ and $E_2 = \frac{1}{1 + \cos(x)}$. $\therefore E_1 = E_2$ in exact arithmetic. Evaluate E_1 and E_2 numerically for $x = 1.000\dots$, $x = 0.100\dots$, $x = 0.010\dots$.

Remark 18. For values of $x < 10^{-5}$, E_1 losses significant digits. For $x < 10^{-8}$, E_1 has no correct significant digits. Well, we are subtracting numbers that are nearly equal.

Example 19. $x^2 + 9^{12}x - 3 = 0$, with $a = 1$, $b = 9^{12}$, $c = -3$.

$$\begin{aligned} \Delta &= \sqrt{b^2 - 4ac} \\ x &= \frac{-b \pm \Delta}{2a} \\ \oplus \rightsquigarrow x &= \frac{-b + b}{2a} = 0 \end{aligned}$$

But how?! We need to restructure the formula, using the conjugate quantity:

$$\begin{aligned} \frac{-b + \sqrt{\Delta}}{2a} &\times \left(\frac{-b + \sqrt{\Delta}}{-b + \sqrt{\Delta}} \right) \\ &= \frac{\Delta - b^2}{2a(b + \sqrt{\Delta})^2} \\ &= \frac{-4ac}{2a(b + \sqrt{\Delta})} \\ &= \frac{-2c}{b + \sqrt{\Delta}} \end{aligned}$$

Note: This formula only applies for degree-2 polynomials.

3 Equation Solving

- We will explore iterative methods to locate solutions of $f(x) = 0$
- Convergence, complexity

We are also going to look at three different methods of solving equations:

1. Bisection
2. Fixed-point
3. Newton's method

3.1 Bisection Method

- We are looking to solve $f(x) = 0$
- Means find r , st $f(r) = 0$
- Existence of r : IVT

Steps:

1. Find $[a, b]$ st $f(a) \times f(b) < 0$
2. Then, $\exists r: a < r < b$ st $f(r) = 0$

Example 20. $f(x) = x^3 + x - 1$, we know $f(0) = -1$, $f(1) = 1$ and thus:

$$\rightsquigarrow \exists r \in [0, 1] \text{ st } f(r) = 0$$

Also:

$$f\left(\frac{1}{2}\right) < 0 \rightsquigarrow f\left(\frac{1}{2}\right) \times f(1) < 0 \rightsquigarrow r \in \left[\frac{1}{2}, 1\right]$$

Next step in the iteration:

$$f\left(\frac{1}{2}\right) > 0 \rightsquigarrow f(0) \times f\left(\frac{1}{2}\right) < 0 \rightsquigarrow r \in \left[0, \frac{1}{2}\right]$$

And thus we know:

$$f\left(\frac{1}{2}\right) < 0$$

We now know that $\frac{1}{2} < f\left(\frac{1}{2}\right) < 1$. We now can check the midpoint of $\left[\frac{1}{2}, 1\right]$ which is $\frac{3}{4}$. Next iteration:

$$f\left(\frac{3}{4}\right) > 0 \rightsquigarrow r \in \left[\frac{1}{2}, \frac{3}{4}\right]$$

Portfolio Part 2: Implement Bisection Method in Maple and/or MatLab.

Algorithm 1

Bisection Method

Input: f , a , b st. $f(a) \times f(b) < 0$; tolerance (ϵ) - e

Output: approximate root r , in $[a, b]$, $f(r) = 0$

```
while (b-a)/2 > e do
    r=(a+b)/2
    if f(r)=0 then return r
    if f(a)*f(r) < 0
        b=r
    else
        a=r
    return (a+b)/2
```

Example 16 cont.

ϵ	#while step	approx r
10^{-4}	13	0.6823
10^{-5}	16	0.6823
10^{-6}	19	0.68232
10^{-7}	23	0.68232780

Definition 21. An approximate solution is correct to p decimal places if the error

$$|x_c - r| < \frac{1}{2}10^{-p}$$

3.1.1 Error Analysis

- Start $[a, b]$
- After n bisection steps $[a_n, b_n]$

$$x_c = \frac{a_n + b_n}{2} \rightsquigarrow |x_c - r| < \frac{b - a}{2^{n+1}}$$

Question 22. How many bisection steps are needed to compute a solution correct to 6 decimal places?

Answer. Error after n bisection steps: $\frac{1}{2^{n+1}}$ and thus

$$\begin{aligned}\frac{1}{2^{n+1}} &< \frac{1}{2}10^{-6} \\ 10^6 &< 2^n \\ \log(10^6) &< \log(2^n) \\ 6 \times \log(10) &< n \times \log(2) \\ 6 &< n \times \log(2) \\ 19.9 &< n\end{aligned}$$

And thus we need 20 steps to compute 0.739085.

3.2 Fixed-Point Iteration

Definition 23. r is a fixed point (fp) of a function $g(x)$, iff $g(r) = r$.

Example 24. $g(x) = x^3$. We have three fixed points: $0, \pm 1$.

Observation. Finding a fp of $g(x) \Leftrightarrow$ solving the equation: $g(x) - x = 0$ where we can define $g(x) - x$ as $f(x)$.

Algorithm 2

FPI

Input: $f(x) = g(x) - x$, initial guess, x_0

Output: approximate solution of $f(x) = 0$, (ie. a fp of $g(x)$)

```
for i = 0..k
    xi+1 = g(xi)
```

If the sequence x_0, x_1, x_2, \dots converges to a value, r , then r is a fp of $g(x)$. For some j : $|x_{j+1} - x_j| < \epsilon$.

Question 25. Can any fct, $f(x)$ be written as $g(x) - x$?

Answer. Yes, and often in more ways than one.

Example 26. $x^2 + x - 1 = 0$

$$x = 1 - x^3 \tag{1}$$

$$x = (1 - x)^{\frac{1}{3}} \tag{2}$$

$$x = \frac{1 + 2x^3}{1 + 3x^2} \tag{3}$$

Use fp iterations with $x_0 = 0.5$.

1. The iterates flip-flop from 0 to 1, **no convergence**
2. The iterates converge to 0.6823 in 25 iterations

Explanation: $|g'(r)| > 1, < 1|$

Example 27.

$$\begin{aligned} g_1(x) &= -\frac{3}{2}x + \frac{5}{2} \quad \text{with } r = 1 \text{ and } |g'_1(1)| = \frac{3}{2} > 1 \\ g_2(x) &= -\frac{1}{2}x + \frac{3}{2} \quad \text{with } r = 1 \text{ and } |g'_2(1)| = \frac{1}{2} < 1 \end{aligned}$$

Thus, we have $x_{i+1} = g_1(x_i)$. Consider $g(x) \rightsquigarrow$

$$x_{i+1} - 1 = -\frac{3}{2}(x_i - 1)$$

denote by $e_i = |1 - x_i|$ then $e_{i+1} = \frac{3}{2}e_i \rightsquigarrow$ error increases, divergent.

Consider $g_2(x)$ with $x_{i+1} = g_2(x_i) \rightsquigarrow$

$$x_{i+1} - 1 = -\frac{1}{2}(x_i - 1)$$

then $e_{i+1} = \frac{1}{2}e_i$. 1

Definition 28. Denote by e_i , the error at step i , of an iterative method.

$$e_i = |r - x_i|$$

The method **converges linearly** with rate, S , if:

$$\lim_{i \rightarrow \infty} \frac{e_{i+1}}{e_i} = S$$

and $S < 1$.

Observation. f -p iteration for $g_2(x)$ converges linearly with rate $S = \frac{1}{2}$.

Theorem 29. Assume g is differentiable.

$$\begin{aligned} g(r) &= r \quad \text{and } r \text{ is an fp of } g \\ |g'(r)| &= S < 1 \end{aligned}$$

Then, the fp iteration for g , converges linearly with rate, S to r . For initial guesses, x_0 , sufficiently close to r .

Example 30. $f(x) = x^3 + x - 1$ in the form of $g(x) = x$.

1. $g_1(x) = 1 - x^3$, now $|g'_1(x)| = 3x^2 \rightarrow x = 0.6823 \rightarrow > 1$
2. $g_2(x) = (1 - x)^{\frac{1}{3}}$, now $|g'_2(x)| = \frac{1}{3}(1 - x)^{-\frac{2}{3}} + 1 \rightarrow x = \dots \rightarrow < 1 \quad \therefore \text{converges}$
3. $g_3(x) = \frac{1 + 2x^3}{1 + 3x^2}$, now $|g'_3(x)| = \frac{(6x^2)(1 + 3x^2) + (6x)(1 + 2x^3)}{(1 + 3x^2)^2} \rightarrow x = \dots \rightarrow 0 < 1$ We have a linear convergence with rate, $S = 0$

3.2.1 Stopping Criteria for FPI

Where do we need to stop the iteration?

1. Bounded absolute error:

$$|x_{i+1} - x_i| < E$$

2. Bounded relative error:

$$\frac{|x_{i+1} - x_i|}{|x_{i+1}|} < \epsilon$$

Example 31. $\begin{cases} g(x) = \frac{x + \frac{2}{x}}{2} \\ x_0 = 1 \end{cases}$. Set up FPI as $g(x) = x$.

$$g(\sqrt{2}) = \frac{\sqrt{2} + \frac{2}{\sqrt{2}}}{2} = \sqrt{2}$$

3.2.2 Forward and Backward Error

Example 32. $f(x) = x^3 - 2x^2 + \frac{4}{3}x - \frac{8}{27}$. Use the bisection method to compute a root with 6 correct significant digits. We have $f(0)f(1) < 0$ and $f(\frac{2}{3}) = 0$.

Observation. 16 steps \rightsquigarrow 0.6666641. We cannot get the 6th digit correct.

IEEE double precision, there are many float point numbers within 10^{-5} of the correct root $r = \frac{2}{3}$.

Definition 33. Suppose a function, f , with root r and $f(r) = 0$. Also, x_a is an approximation to r computed by a root-finding method.

Backwards error (BE): $|f(x_a)|$

Forward error (FE): $|r - x_a|$

BE amount by which we need to change $f(x)$ so that x_a is a solution. FE amount by which we need to change the approximate solution to make it correct.

Remark 34. The problem we encountered with the previous example is that the BE is near $E_{\text{mach}} = 10^{-16}$ and the $FE \approx 10^{-5}$.

Definition 35. Multiple Roots

f , a differentiable function, with root r and $f(r) = 0$ if

$$0 = f(r) = f'(r) = f''(r) = \dots = f^{(m-1)}(r)$$

and $f^{(m)}(r) \neq 0$. Then, f , has a root of multiplicity m , at r ; where r is a multiple root of order m of f .

$$\begin{cases} m = 1; r \text{ single root} \\ m = 2; r \text{ double root} \\ m = 3; r \text{ triple root} \end{cases}$$

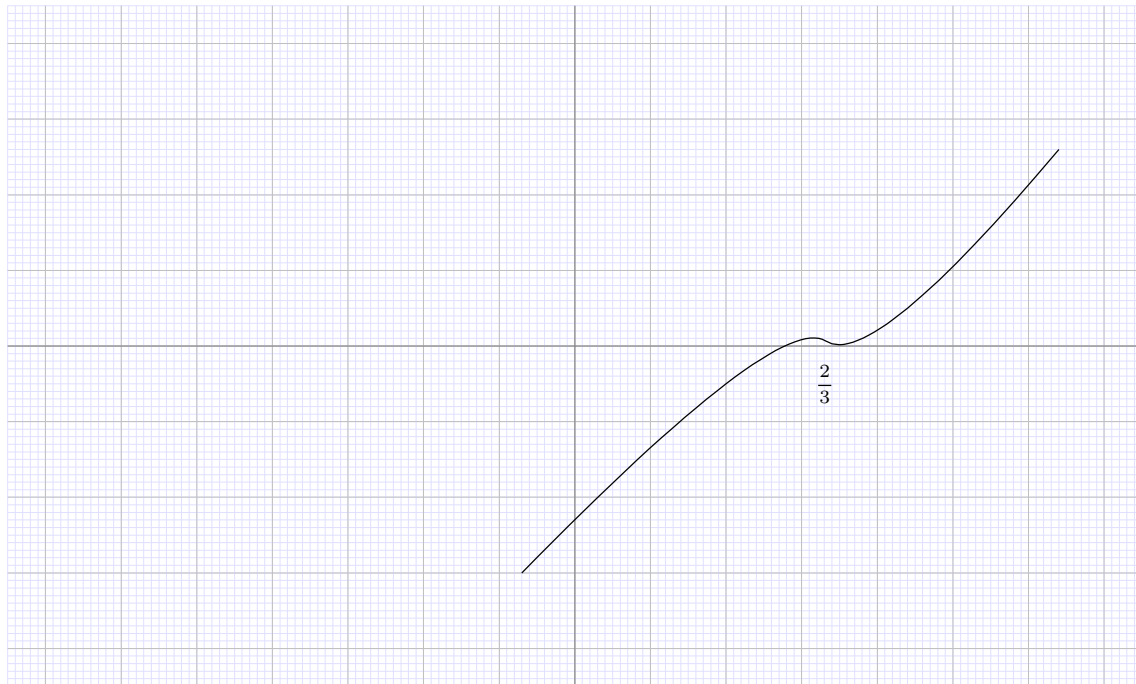
Example 36. $f(x) = x^2$, has a double root at $x = 0$.

$$\begin{array}{rcl} f(0) & = & 0 \\ f'(0) & 2x|_{x=0} & = 0 \\ f''(0) & = & 2 \neq 0 \end{array}$$

Also, $f(x) = x^3$ has a triple root at $x = 0$.

Geometric Intuition.

Graph of $f(x) = \left(x - \frac{2}{3}\right)^3$.



$\frac{2}{3}$ is a triple root. The graph is [supposed to be] flat around the triple root.

Consequence. Large disparity between BE and FE.

$$\text{BE} \ll \text{FE}$$

where BE is the vertical dimension and FE is the horizontal dimension.

Example 37. $f(x) = \sin(x) - x$ has a triple root at $r = 0$ and $x_a = 0.001$ is the approx. root. Compute BE and FE.

$$\begin{aligned} \text{BE: } |r - x_a| &= 10^{-3} \\ \text{FE: } |f(x_a)| &= |\sin(0.001) - 0.001| \\ &\approx 1.6667 \times 10^{-10} \end{aligned}$$

Stopping Criteria. Either make FE small or make BE small.

$$\text{Bisection: } \begin{cases} \text{BE: known} \\ \text{FE: } < \frac{b-a}{2} \end{cases}$$

```
> if abs(f(xa)) < E then ...
> if abs( $\frac{b-a}{2}$ ) < E then ...
```

$$\text{Fixed point: } \begin{cases} \text{BE: known} \\ \text{FE: not known} \end{cases}$$

3.2.3 Wilkinson Polynomial

$$\begin{aligned} W(x) &= (x-1)(x-2)\dots(x-20) \\ &= \prod_{i=1}^{20} (x-i) \end{aligned}$$

It has 20 (simple) roots, $x = 1, \dots, 20$. To compute numerical approximations to the roots of the expanded $W(x)$ is very hard. $W(x) = x^{20} \pm \dots$

3.2.4 Sensitivity of Root Finding

A problem is called sensitive if small errors in the input (the eq. we are solving). This leads to large errors in the output (solution).

We need to measure how far a root is moved when the eq. is changed (perturbed).

Proposition 38. *Supposed, we change $f(x) \rightarrow f(x) + \epsilon g(x)$.*

Let Δ_r be the corresponding change to the root r .

$$f(r + \Delta_r) + \epsilon g(r + \Delta_r) = 0$$

D-d-d-d-drop the Taylor and neglect the higher order terms (H.O.T).

$$\Delta_r \approx -\frac{\epsilon g(r)}{f'(r)}$$

for $\epsilon \ll f'(r)$.

Example 39. Estimate the largest root of

$$P(x) = \left(\prod_{i=1}^6 (x - i) \right) - 10^{-6} x^7$$

Get all emotional and used the sensitivity formula.

$$\begin{aligned} \epsilon &= -10^{-6} \\ g(x) &= x^7 \\ f(x) &= P(x) \end{aligned}$$

Now:

$$\Delta_r \approx \frac{\epsilon 6^7}{5!} = -2332.8 \epsilon$$

and thus:

$$6 + \Delta_r = 6.0023$$

3.3 Newton's Method

Problem. Find a root of a fn, $f(x) = 0$.

The first thing we need to do is start with an initial guess of x_0 . Draw the tangent line to f at x_0 and identify the point where the tangent intersects with the x -axis.

We can get the equation of the tangent line at $(x_0, f(x_0))$.

$$y - f(x_0) = f'(x_0) (x - x_0)$$

where $f'(x_0)$ is the slope. The intersection of the above equation and the x -axis $\rightsquigarrow y = 0$, we obtain:

$$x = x_0 - \frac{f(x_0)}{f'(x_0)}$$

Algorithm 3

Input: $f(x)$, x_0 (initial guess)

Output: approximation to root r st $f(r) = 0$

The way it would iterate:

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

where $i = 0, 1, 2, \dots$

Example 40. $f(x) = x^3 + x - 1$.

First compute $f'(x) = 3x^2 + 1$. Newton iteration is:

$$\begin{aligned} x - \frac{f(x)}{f'(x)} &= x - \frac{x^3 + x - 1}{3x^2 + 1} \\ &= \frac{2x^3 + 1}{3x^2 + 1} \end{aligned}$$

Thus we have a generalized form: $x_{i+1} = \frac{2x_i^3 + 1}{3x_i^2 + 1}$ with $x_0 = 0.1$.

We can perform 6 iterations to give you the root with the correct 8 significant digits: 0.68232780.

Definition 41. Denote e , as the error at step i : $|r - x_i|$.

The iterative method converges quadratically \iff

$$\lim_{i \rightarrow \infty} \frac{e_{i+2}}{e_i^2} = M$$

Remark 42. If $f(r) = 0$, and $f'(r) \neq 0$, then Newton's method converges quadratically to r and thus, $M = \frac{f''(r)}{2f'(r)}$, where M denotes the rate of convergence.

3.3.1 Newton's Method Can Fail

Example 43. $f(x) = 4x^4 - 6x^2 - \frac{11}{4} = 0$ with $x_0 = \frac{1}{2}$ (bi-quadratic equation). We then have the Newton iteration being:

$$x_{i+1} = x_i - \frac{f(x_i)}{16x_i^3 - 12x_i}$$

$$\begin{aligned} x_1 &= -\frac{1}{2} \\ x_2 &= \frac{1}{2} \\ x_3 &= \frac{1}{2} \\ x_4 &= -\frac{1}{2} \\ &\vdots \end{aligned}$$

There is no convergence. Roots are ± 1.3667 . We have an even function st $f(x) = f(-x)$ and thus

$$f\left(\frac{1}{2}\right) = f\left(-\frac{1}{2}\right) = -4$$

The tangent lines at $(\frac{1}{2}, 4)$ and $(-\frac{1}{2}, 4)$ will intersect at the x -axis at $-\frac{1}{2}, \frac{1}{2}$.

Example 44. $f(x) = \sin(2x)$, with $x_0 = 0.75$. Newton's method converges to the root -2π . We converge to and missed the closer root, 0.

Why? This occurs, if $f(x_i)$ is very small, then the tangent line is almost horizontal.

Example 45. $f(x) = x e^x$. Newton iteration with $x_0 = 2$. The Newton iteration is:

$$x_{i+1} = x_i - \frac{x_i e^{-x_i}}{e^{x_i} - x_i e^{-x_i}} = \frac{x_i^2}{x_i - 1}$$

$$\begin{aligned} x_1 &= 4 \\ x_2 &= \frac{16}{3} \\ x_3 &= \dots \\ &\vdots \\ &\rightarrow \infty \end{aligned}$$

This converges to infinity and thus fails.

3.3.2 Multivariate Newton's Method

Example 46. $f_1(x_1, x_2) = x_1^2 + x_2^2 - 8x_1 - 4x_2 + 11 = 0$ and $f_2(x_1, x_2) = x_1^2 + x_2^2 - 20x_1 + 75 = 0$.

These equations give us two circles. We need to solve the system $\begin{cases} f_1(x_1, x_2) = 0 \\ f_2(x_1, x_2) = 0 \end{cases}$. The solution of the system will give us the two points where the circles intersect (twice).

Let's start with the initial condition $(x_1^\circ = 2, x_2^\circ = 4)$. First step: compute 4 partial derivatives.

$$\begin{aligned} \frac{\delta f_1}{\delta x_1} &= 2x_1 - 8 \\ \frac{\delta f_2}{\delta x_1} &= 2x_1 - 20 \end{aligned}$$

And then:

$$\begin{aligned} \frac{\delta f_1}{\delta x_2} &= 2x_2 - 4 \\ \frac{\delta f_2}{\delta x_2} &= 2x_2 \end{aligned}$$

This gives us: $f_1(x_1^\circ, x_2^\circ) = -1$ and $f_2(x_1^\circ, x_2^\circ) = 55$. We can then put these values in a Jacobian matrix: $J(x_1, x_2) = (f_1, f_2) =$

$$\begin{pmatrix} 2x_1 - 8 & 2x_2 - 4 \\ 2x_1 - 20 & 2x_2 \end{pmatrix}$$

We need compute it's value at $(2, 4)$. This gives us:

$$J_{(f_1, f_2)}(2, 4) = \begin{pmatrix} -4 & 4 \\ -16 & 8 \end{pmatrix}$$

To compute the next iterate (x_1^1, x_2^1) . To do this, we compute:

$$\begin{aligned} x_1^1 &= x_1^\circ + \Delta x_1 \\ x_2^1 &= x_2^\circ + \Delta x_2 \end{aligned}$$

Now solve:

$$\begin{pmatrix} -4 & 4 \\ -16 & 8 \end{pmatrix} \begin{pmatrix} \Delta x_1 \\ \Delta x_2 \end{pmatrix} = \begin{pmatrix} 1 \\ -55 \end{pmatrix}$$

Using the values of $\Delta x_1 = 7.125$ and $\Delta x_2 = 7.375$. This gives us:

$$\begin{aligned} x_1^1 &= 2 + 7.125 = 9.125 \\ x_2^1 &= 4 + 7.375 = 11.375 \end{aligned}$$

This converges in 8 iterations.

Algorithm 4

Input: $f_1(x_1, \dots, x_n) = 0$ (square system of non-linear equations)
 \vdots
 $f_n(x_1, \dots, x_n) = 0$
 ϵ , initial point (x_1^0, \dots, x_n^0)
Output: Approx. solution $\vec{r} = (r_1, \dots, r_n)$ st $f_1(\vec{r}) = \dots = f_n(\vec{r}) = 0$

```

i = 1
while (  $\left| f_j(\vec{r}) \right| \geq \text{eps}$ , j = 1) do
    i = i+1
    solve system of linear eqs
     $J_{(f_1, \dots, f_n)}(x_1^i; \dots; x_n^i) \begin{pmatrix} \Delta x_1 \\ \Delta x_2 \end{pmatrix} = \begin{pmatrix} -f_1(\vec{x}^i) \\ \vdots \\ -f_n(\vec{x}^i) \end{pmatrix}$ 
     $x_j^{(i)} = x_j^{(i-1)} + \Delta x_j, j=1 \dots n$ 

```

Let's talk Jacobian dude.

Jacobian $n \times n$ Matrix

$$J_{(f_1, \dots, f_n)}(x_1, \dots, x_n) = \begin{pmatrix} \frac{\delta f_1(\vec{x})}{\delta x_1} & \dots & \frac{\delta f_1(\vec{x})}{\delta x_n} \\ \vdots & \ddots & \vdots \\ \frac{\delta f_n(\vec{x})}{\delta x_1} & \dots & \frac{\delta f_n(\vec{x})}{\delta x_n} \end{pmatrix}$$

3.4 Secant Method (root-finding without derivatives)

We want to replace the tangent with the *secant* line:

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

So we replace the tangent line with a discrete approximation.

Algorithm 5

Input: $f(x)$, x_0 , x_1 , ϵ (two initial guesses)

Output: approximation to the root, r

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

Where $i = 1, 2, 3, \dots$

Error Analysis:

If $f'(r) \neq 0$ (simple root), and the secant method converges, then $e_{i+1} \approx c e_i^\phi$. This is called *superlinear convergence*.

We have the golden ratio, $\phi = \frac{1+\sqrt{5}}{2} \approx 1.6$

4 Systems of Linear Equations

$$\begin{cases} a_{11}x_1 + a_{12}x_2 + \dots + a_{1n}x_n = b_1 \\ a_{21}x_1 + a_{22}x_2 + \dots + a_{2n}x_n = b_2 \\ \vdots \\ a_{n1}x_1 + a_{n2}x_2 + \dots + a_{nn}x_n = b_n \end{cases}$$

In an $n \times n$ system, there are n equations and n variables. The matrix form of a system:

$$\begin{pmatrix} a_{11} & a_{12} & \dots & a_{1n} \\ a_{21} & a_{22} & \dots & a_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ a_{n1} & a_{n2} & \dots & a_{nn} \end{pmatrix} \times \begin{pmatrix} x_1 \\ x_2 \\ \vdots \\ x_n \end{pmatrix} = \begin{pmatrix} b_1 \\ b_2 \\ \vdots \\ b_n \end{pmatrix}$$

Solution methods:

Direct methods:

- Gauss elimination
- Gauss-Jordan
- LU decomposition

Iterative methods:

- Jacobi
- Gauss-Seidel
- Relaxtion

4.1 Vector, Matrix Norms

If we have $\vec{x} = \begin{pmatrix} x_1 \\ \vdots \\ x_n \end{pmatrix}$, we need to measure the size of \vec{x} by the *Euclidean* norm:

$$\|\vec{x}\| = \sqrt{x_1^2 + \dots + x_n^2}$$

Then we have the L_p norm:

$$\|\vec{x}\| = \sqrt[p]{|x_1|^p + \dots + |x_n|^p}$$

The following results occur:

$$\begin{aligned} p=1 & \rightsquigarrow \text{sum of absolute values of the elements of } \vec{x} \\ p=2 & \rightsquigarrow L_p = \text{Euclidean norm} \\ p=\infty & \rightsquigarrow \max |x_i| \end{aligned}$$

We can denote $A = (a_{ij})$, where A is an $m \times n$ matrix (rows \times columns).

We have the *Frobenius* norm:

$$\|A\|_F = \sqrt{\sum_{i=1}^n \sum_{j=1}^m |a_{ij}|^2}$$

where the $\|A\|_F$ has $m \times n$ terms.

p -norms:

$$\|A\|_p = \max \left\| A \vec{x} \right\|_p$$

where $\left\| \vec{x} \right\| = 1$.

Next, we look at 4 square matrices $n \times n$:

$$\|A\|_2 = \max \lambda_i$$

where $i = 1, \dots, n$. λ_i are the eigenvalues of A .

Next, the *spectral* norm:

$$\begin{aligned} \|A\|_1 &= \max_{1 \leq j \leq n} \left(\sum_{i=1}^n |a_{ij}| \right) \\ \|A\|_\infty &= \max_{1 \leq i \leq n} \left(\sum_{j=1}^m |a_{ij}| \right) \end{aligned}$$

4.1.1 Norm Inequalities

1. $\|A\|_2 \leq \|A\|_F \leq \sqrt{n} \|A\|_2$
2. $\frac{1}{\sqrt{n}} \|A\|_\infty \leq \|A\|_2 \leq \sqrt{n} \|A\|_\infty$
3. $\frac{1}{\sqrt{n}} \|A\|_1 \leq \|A\|_2 \leq \sqrt{n} \|A\|_1$

4.1.2 Solution Concepts

Remember: $A \times \vec{x} = \vec{b}$ where the sizes are $n \times n$, $n \times 1$ and $n \times 1$ respectively.

1. If $\vec{b} = \vec{0}$ then it is a homogeneous system
 - Trivial solution of $\vec{x} = \vec{0}$
 - A non-trivial solution exists if $\det(A) = 0$
2. If $\vec{b} \neq \vec{0}$, then it is a non-homogeneous system, denoted as *augmented* matrix

$$A' = \left[A / \vec{b} \right]$$

- System has a solution $\iff \text{rank}(A) = \text{rank}(A')$
- Solution is unique if $\text{rank}(A) = n$; A is considered **full rank**

- If $\text{rank}(A) < n$, then it is denoted as **inconsistent**

Definition 47. *Linearly dependent rows and equations*

$$A = \begin{pmatrix} 1 & -1 & 1 \\ 2 & 1 & -1 \\ 8 & 1 & -1 \end{pmatrix} \rightsquigarrow \begin{cases} r_1 \\ r_2 \\ r_3 \end{cases}$$

And we have: $2r_1 + 3r_2 = r_3$. And r_1 , r_2 and r_3 are linearly dependent.

4.2 Rank and Nullspace of a Matrix ($A: m \times n$)

We can have:

$$\begin{aligned} \text{range}(A) &= \left\{ \vec{y} \in \mathbb{R}^m: \vec{y} = A\vec{x}, \text{for some } \vec{x} \in \mathbb{R}^n \right\} \\ \text{rank}(A) &= \dim(\text{range}(A)) \\ \text{nullspace}(A) &= \left\{ \vec{x} \in \mathbb{R}^n: A\vec{x} = \vec{0} \right\} \end{aligned}$$

Theorem 48. $\dim(\text{nullspace}(A)) + \text{rank}(A) = n$

Where the $\text{rank}(A)$ is the maximum, linearly independent number of rows.

Definition 49. *A is a full rank if*

$$\text{rank}(A) = \min(m, n)$$

A is rank-deficient if

$$\text{rank}(A) < \min(m, n)$$

4.3 Cramer's Method

We have $A\vec{x} = \vec{b}$ where A is an $n \times n$ matrix. We define:

$$A_i = \begin{pmatrix} \vdots & \begin{pmatrix} b_1 \\ \vdots \\ b_n \end{pmatrix} & \vdots \end{pmatrix}$$

with $i = 1, \dots, n$. Then, we can have $x_i = \frac{|A_i|}{|A|}$ with $i = 1, \dots, n$.

Example 50. Given:

$$\begin{aligned} x_1 - x_2 + x_3 &= 3 \\ x_1 + x_2 - x_3 &= 0 \\ 3x_1 + 2x_2 + 2x_3 &= 5 \end{aligned}$$

That looks like:

$$|A| = \begin{vmatrix} 1 & -1 & 1 \\ 2 & 1 & -1 \\ 3 & 2 & 2 \end{vmatrix} = 1 \times \begin{vmatrix} 1 & -1 \\ 2 & 2 \end{vmatrix} - (-1) \times \begin{vmatrix} 2 & -1 \\ 3 & 2 \end{vmatrix} + 1 \times \begin{vmatrix} 2 & 1 \\ 3 & 2 \end{vmatrix}$$

We then have:

$$|A_1| = \begin{pmatrix} 3 & -1 & 1 \\ 0 & 1 & -1 \\ 15 & 2 & 2 \end{pmatrix} = 12, x_1 = \frac{|A_1|}{|A|} = \frac{12}{12} = 1$$

Next:

$$|A_2| = \begin{pmatrix} 1 & 3 & 1 \\ 2 & 0 & -1 \\ 3 & 15 & 2 \end{pmatrix} = 24, x_2 = \frac{24}{12} = 2$$

And:

$$|A_3| = \begin{pmatrix} 1 & -1 & 3 \\ 2 & 1 & 0 \\ 3 & 2 & 15 \end{pmatrix} = 48, x_3 = \frac{48}{12} = 4$$

4.4 Gauss Elimination

The **strategy** is reduce to [upper] triangular form, and then run back substitution. This reduction is carried out by *elementary row operations*:

- Multiply divide by any row or constant value
- Any row can be added/subtracted to/from any row
- Interchange rows

Example 51. Suppose we have the system:

$$\begin{aligned} 2x_1 - x_2 + x_3 &= 4 \\ 4x_1 + 3x_2 - x_3 &= 6 \\ 3x_1 + 2x_2 + 2x_3 &= 15 \end{aligned}$$

Use elementary row operations to obtain:

$$\begin{aligned} x_3 &= 4 \\ x_2 &= 2 \\ x_1 &= 1 \end{aligned}$$

4.4.1 Determinant Computation via GEM

If we have $A \times \vec{x} = \vec{b}$ and by GE we reduce it to $\tilde{A} \times \vec{x} = \vec{b}$. We can then say:

$$\det(A) = \det(\tilde{A})$$

We can then define the property:

$$\det(B) = \prod_{i=1}^n b_{i_i}$$

where B is triangular. From the previous example, we have

$$\det(A) = 2 \times 5 \times \frac{13}{5} = 26$$

where those numbers come from the diagonal of the [upper] triangle matrix.

4.5 Gauss-Jordan

It is an extension of GEM. Use a *pivot* to reduce (to 0). Element below and above the main diagonal - apply back substitution as needed.

$$A \rightsquigarrow^{GJ} I_n$$

4.5.1 Inverse Matrix Computation via GJE

$$(A|I_n) \rightsquigarrow^{GJ} (I_n|A^{-1})$$

Example 52. refer to paper

4.6 LU Decomposition

$$A = L \times U$$

Where L is a lower triangular matrix and U is a lower triangular matrix. We can start by saying A has n^2 elements, L has $\frac{n(n+1)}{2}$ and U has $\frac{n(n+1)}{2}$.