

Bennett  
4/17/14

# SOLUTIONS

Math 56 Compu & Expt Math, Spring 2014: Midterm 1

4/17/14, pencil and paper, 2 hrs, 50 points. Good luck!

1. [10 points]

You wish to use a truncated Taylor series about the origin to approximate the smooth function inverse tangent (arctan) of a given real  $x$ , ie,

$$\tan^{-1} x = x - \frac{x^3}{3} + \frac{x^5}{5} - \dots = \sum_{n=1}^{\infty} \left( \sin \frac{n\pi}{2} \right) \frac{x^n}{n}$$

- (a) For a general real  $x$ , find a rigorous bound on the error  $\varepsilon_n$  due to using terms with powers only up to  $n$ . [Hint: you don't need Taylor's theorem.] Write it in big-O notation:

$$\begin{aligned} \varepsilon_n &= \tan^{-1} x - \sum_{k=1}^n \left( \sin \frac{k\pi}{2} \right) \frac{x^k}{k} && \text{just tail of sum survives} \\ &= \sum_{k>n}^{\infty} \left( \sin \frac{k\pi}{2} \right) \frac{x^k}{k} \\ \text{so } |\varepsilon_n| &\leq \sum_{k>n}^{\infty} \left| \sin \frac{k\pi}{2} \right| \frac{|x|^k}{k} && \text{use } |\sin| \leq 1. \\ &\leq \sum_{k>n}^{\infty} |x|^k = |x|^{n+1} \sum_{k=0}^{\infty} |x|^k && k \frac{1}{k} \leq 1 \text{ (quite crude)} \\ &= C |x|^n = O(|x|^n). && \text{geom series} = \frac{1}{1-|x|} \quad [\dots \text{in fact it's } o(|x|^n)] \end{aligned}$$

- (b) What type and rate or order of convergence is this? (Your answer may depend on  $x$ ). Are there any  $x$  where it doesn't converge?

Exponential convergence w/ rate  $r = |x|$

$$\dots \rightarrow e^r$$

$r^n$  diverges for  $r > 1$ , ie  $x < -1$  &  $x > +1$  don't converge.

- (c) Estimate the minimum  $n$  needed to get an absolute error of  $10^{-16}$  at  $x = 0.3$ :

$$r = |x| = 0.3 \quad \text{so want } r^n \approx 10^{-16} \text{ assuming const } C \approx 1$$

$$r^2 = 0.09 \approx 10^{-1} \text{ so need about } n = 32 \quad (16 \text{ nonzero terms}).$$

- 4 (d) What can you deduce about locations of any singularities of  $\tan^{-1}$ ?

Well, it's smooth  $\nearrow x \rightarrow \infty$  so can't be on  $\mathbb{R}$ .

The nearest singularity must be distance  $R=1$  from the origin (in  $\mathbb{C}$ ) since the rate  $r = \frac{|x-x_0|}{R}$  in general

- 1 BONUS: use Euler's relation to find the singularity/singularities

We guess that  $\tan^{-1}z$  blows up at singularities (may not be true).

i.e.  $\tan^{-1}z = \pm\infty$  so  $z = \tan(\pm\infty)$  but we know not real, so try  $\alpha$  in different direction.

$$\text{Euler: } \tan \theta = \frac{1}{i} \frac{e^{i\theta} - e^{-i\theta}}{e^{i\theta} + e^{-i\theta}} = \frac{1}{i} \frac{1 - e^{-2i\theta}}{1 + e^{-2i\theta}} \rightarrow \pm i, \text{ setting } \theta \rightarrow \infty \text{ in any nonreal direction.}$$

2. [8 points] As in homework we wish to find the root of the function  $\sin x$  lying in  $[3, 4]$ .

- 2 (a) Write down the Newton iteration for this function:

$$f(x) = \sin x, f'(x) = \cos x$$

$$x_{n+1} = x_n - \frac{f(x_n)}{f'(x_n)} = x_n - \tan x_n$$

- 4 (b) Sketch the proof that the Newton iteration for a general function  $f(z)$  is quadratically convergent to its root  $f(z) = 0$ : [Hint: evaluate at  $z$  the Taylor expansion about  $x_n$ ]

$\downarrow$  vigorous form of remainder.

$$Q = \underset{\text{since root}}{f(z)} = f(x_n) + (z - x_n)f'(x_n) + \frac{(z - x_n)^2}{2!} f''(q)$$

Divide by  $f'(x_n)$ :

$\uparrow q \text{ btwn. } z \text{ & } x_n$

$$Q = \underbrace{\frac{f(x_n)}{f'(x_n)}}_{x_n - x_{n+1}} + (z - x_n) + (z - x_n)^2 \frac{f''(q)}{2f'(x_n)}$$

$\downarrow$  by the iteration.

$$\text{So } x_{n+1} - z = \underbrace{\frac{f''(q)}{2f'(x_n)} (x_n - z)^2}_{\leq C, \text{ some const, for all } q \text{ near the root } z.}$$

Let  $\varepsilon_n := x_n - z$ , then  $x_{n+1} \leq C \varepsilon_n^2$  Quadratic conv.

$$z \downarrow \nearrow \varepsilon_0 = 10^{-1}$$

- 2 (c) Say for  $f(x) = \sin x$  the iteration starts with  $x_0 = \pi + 0.1$ . Use the above to find the precise number of iterations required to reach the machine relative error of  $10^{-16}$ .

$$C = \frac{f''(q)}{2f'(x_0)} \leftarrow f''(q) = -\sin q \text{ so bounded by 1 in size} \\ \leftarrow x_0 \text{ very close to } z = \pi, \text{ where } f'(\pi) = 1.$$

So, in interval  $[\pi - 0.1, \pi + 0.1]$ , can choose  $C = 1$

$$\text{Thus } \varepsilon_1 \leq 1 \cdot \varepsilon_0^2 = 10^{-2}, \quad \varepsilon_2 \leq 1 \cdot \varepsilon_1^2 = 10^{-4}$$

$$\text{etc. } \varepsilon_3 \leq 10^{-8}, \quad \varepsilon_4 \leq 10^{-16}$$

We are done in 4 iterations.

rigorously,  
we have to know  
 $\cos x > 1/2$  here.

3. [6 points] An engineer gives you the following two facts about a matrix  $A$ :

$$A \begin{bmatrix} 1 \\ 0 \end{bmatrix} = \begin{bmatrix} 0 \\ 10^5 \end{bmatrix}, \quad \text{and} \quad \min_{\|y\|=1} \|Ay\| = 10^{-4}.$$

What can you deduce about the worst-case relative error in the approximate solution to  $Ax = b$ , as solved by a backward stable algorithm with the usual  $\varepsilon_{\text{mach}} \approx 10^{-16}$ ?

an instance of a growth factor, for this  $x = \begin{bmatrix} 1 \\ 0 \end{bmatrix}$ ,  $\|Ax\| = \left\| \begin{bmatrix} 0 \\ 10^5 \end{bmatrix} \right\| = 10^5$

$$\text{So } \|A\| \geq 10^5$$

$\min_{\|y\|=1} \|Ay\|$  says minimum growth of  $10^{-4}$ , & there is a  $\hat{y}$  where achieved,

$$\text{and a } \underbrace{z = A\hat{y}}_{\text{norm } 10^{-4}}, \text{ so } \hat{y} = A^{-1}z \quad \text{so } \|A^{-1}\| = 10^4$$

$$\kappa(A) = \|A\| \|A^{-1}\| \geq 10^{5+4} = 10^9 \quad \text{gives worst-case } \kappa(b) \text{ over all right-hand sides } b$$

Backw Stab. Thm says:

$$\text{relative err } \varepsilon = O(\kappa \varepsilon_{\text{mach}}) \geq 10^9 \cdot 10^{-16} = 10^{-7}$$

→ Worst-case expect at most 7 digits of accuracy.

BONUS: Explain whether it is possible for certain right hand sides (which?) to guarantee relative error close to  $\varepsilon_{\text{mach}}$ ?

$$\text{recall } \kappa(b) = \|A^{-1}\| \cdot \boxed{\frac{\|b\|}{\|A^{-1}b\|}}$$

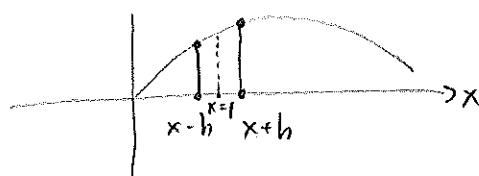
we want best (smallest) here,  
ie  $A^{-1}$  to grow  $b$  the  
most, so  $\kappa(b) = \|A^{-1}\| \cdot \frac{1}{\|A^{-1}\|} = 1$

This is achieved by  $b = z = A\hat{y}$  above.

(or any nonzero multiple)

4. [5 points]

You use a centered-difference approximation to the derivative of  $f(x) = \sin x$ , at  $x = 1$ , i.e. using evaluations at  $1 - h$  and  $1 + h$ . Derive a simple rigorous bound on your absolute error in terms of  $h$ , including the explicit constant.



*(note,  $f'(1) = \cos 1$  not needed to do this.)*

$$\text{formula } \frac{1}{2h}(f(x+h) - f(x-h)) = \frac{1}{2h} \left[ f(x) + h f'(x) + \cancel{\frac{h^2}{2!} f''(x)} + \cancel{\frac{h^3}{3!} f'''(2)} \right. \\ \left. - f(x) - (-h)f'(x) - \cancel{\frac{h^2}{2!} f''(x)} - \cancel{\frac{(-h)^3}{3!} f'''(q)} \right] \\ \text{cancel} \quad \uparrow \quad \text{cancel.} \\ \text{gives } f'(x), \text{ the true derivative.}$$

$$\Rightarrow \text{absolute error} = \underbrace{\frac{1}{2h} \cdot \frac{h^3}{3!} (f'''(q) + f'''(q'))}_{\text{now } f(x) = \sin x \text{ so } f'''(x) = -\cos x, \text{ bounded by } 1 \text{ in size.}} \text{ for some } q, q' \in [x-h, x+h]$$

$$\Rightarrow \text{err} \leq \frac{1}{2h} \frac{h^3}{3!} \cdot 2 = \frac{h^2}{6} \quad \leftarrow \text{this what 'explicit const' means.}$$

*I didn't require you to write to get full score.*

BONUS: Around what  $h$  would have the smallest error in practice and why?

For small  $h$ , roundoff error is of size  $\mathcal{O}\left(\frac{\epsilon_{\text{mach}}}{h}\right)$ , see lecture.

Balancing this against  $\mathcal{O}(h^2)$  gives  $h^2 \approx \frac{\epsilon_{\text{mach}}}{\epsilon_{\text{mach}}}$  i.e.  $h \approx \epsilon_{\text{mach}}^{1/3} \approx 10^{-5}$ .

5. [10 points]

- 3 (a) Is the machine evaluation of  $f(x) = 1/x$  backwards stable? (Assume the usual rules of floating-point, assume 1 is stored exactly, and show work.)

$$\hat{f}(x) = \overset{\downarrow}{1} \oplus f(x) = \frac{1}{x(1+\varepsilon)} (1+\varepsilon_1) \quad \text{for some } |\varepsilon_1|, |\varepsilon_2| \leq \epsilon_{\text{mach}}.$$

$$\stackrel{? \text{ BS}}{=} f(x(1+\varepsilon)) = \frac{1}{x(1+\varepsilon)} \quad \leftarrow \text{for any nonzero } x, \text{ we see} \\ \varepsilon = \varepsilon_1 + \varepsilon_2 + \mathcal{O}(\varepsilon^2) \\ |\varepsilon| \leq 2\epsilon_{\text{mach}}$$

so yes,  $\varepsilon = \mathcal{O}(\epsilon_{\text{mach}})$   
It's B.S.

i.e. forward error. we already did in (a), can reuse.

- 3 (b) Estimate the relative error in the machine computation of  $f(x) = 1 - 1/x$  for general  $x$  (again, assume 1 is stored exactly).

$$\begin{aligned}
 \hat{f}(x) &= 1 \ominus (1 \oplus f_l(x)) \\
 &= \left(1 - \frac{1}{x(1+\varepsilon_1)}(1+\varepsilon_2)\right)(1+\varepsilon_3) \\
 &= \left[1 - \frac{1}{x}(1-\varepsilon_1 + \varepsilon_2 + O(\varepsilon^2))\right](1+\varepsilon_3) \\
 &= \underbrace{1 - \frac{1}{x}}_{\text{true } f(x)} + \underbrace{\frac{\varepsilon_1 - \varepsilon_2}{x}}_{\text{abs. error}} + \left(1 - \frac{1}{x}\right)\varepsilon_3 + O(\varepsilon^2)
 \end{aligned}$$

$$\varepsilon_r = \text{Relative error} = \left| \frac{\text{abs. error}}{f(x)} \right| = \left| \frac{\frac{\varepsilon_1 - \varepsilon_2}{x} + \left(1 - \frac{1}{x}\right)\varepsilon_3}{1 - \frac{1}{x}} \right| = \left| \frac{\varepsilon_1 - \varepsilon_2}{x-1} + \varepsilon_3 \right| \leq \left| \frac{2}{|x-1|} + 1 \right| \varepsilon_{\text{mach}}$$

- 1 (c) For what range of  $x$  is this relative error greater than 1?

$$\left| \frac{2}{|x-1|} + 1 \right| \varepsilon_{\text{mach}} > 1$$

so  $x \in [1 - 2 \times 10^{-16}, 1 + 2 \times 10^{-16}]$  will do.

must exceed  $\approx 10^{16}$

Don't have to be exact here.

- 3 (d) It is easy to show that the machine evaluation of  $f(x) = 1 - 1/x$  is backward stable for all  $x$  not too large (eg  $|x| < 10^3$ ). Explain, citing a relevant theorem, how this is true even though you discovered above that some inputs cause disastrous relative error. [Hint: a picture may help]

If backward stable,

we can apply:

relative (forward) error.

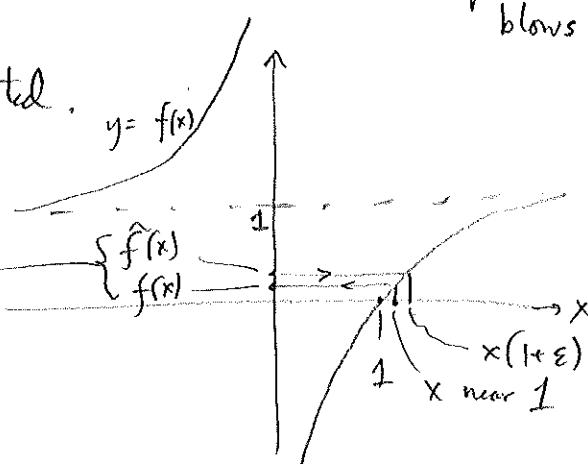
due to catastrophic cancellation, by the way.

$$\text{Bkw. Stab. Thm, says } \varepsilon_r = O(K(x) \varepsilon_{\text{mach}})$$

$$K(x) = \left| \frac{f'(x)x}{f(x)} \right| = \left| \frac{-\frac{1}{x^2}x}{1-\frac{1}{x}} \right| = \frac{1}{|x-1|} \rightarrow \infty \text{ at the same place that } \varepsilon_r \text{ blows up,}$$

so the theorem isn't violated.

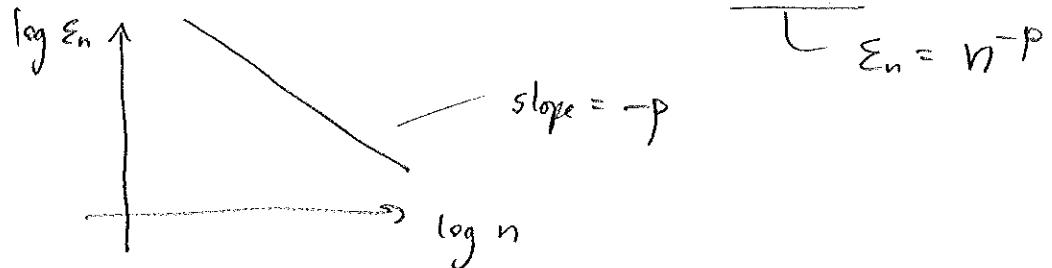
large relative error here.



$\varepsilon = O(\varepsilon_{\text{mach}})$   
backward error small.

6. [11 points] Short-answer questions.

- 2 (a) What axes would you plot to show a linear graph for error  $\varepsilon_n$  converging algebraically with  $n$ ?



- 2 (b) Prove whether  $n = O(\frac{\sqrt{n+n^2}}{\log n})$  as  $n \rightarrow \infty$ .

$$f(n) \uparrow \quad g(n) \uparrow \quad \left| \frac{f(n)}{g(n)} \right| = \frac{n \log n}{\sqrt{n+n^2}} = \frac{\log n}{\sqrt{1+n^{-1}}} \xrightarrow{\text{no upper bound}}$$

since  $\frac{1}{\sqrt{1+n^{-1}}} \geq \frac{1}{\sqrt{2}}$  for all  $n \geq 1$ , say, there's no  $C$  st.  $\left| \frac{f(n)}{g(n)} \right| \leq C \forall n > n_0$

- 2 (c) Prove whether  $e^{-n} = o(n^{-2})$  as  $n \rightarrow \infty$ .

$$\lim_{n \rightarrow \infty} \frac{f(n)}{g(n)} = \lim_{n \rightarrow \infty} \frac{e^{-n}}{n^{-2}} = \lim_{n \rightarrow \infty} \frac{n^2}{e^n} \xrightarrow{\text{L'Hopital's rule}} \lim_{n \rightarrow \infty} \frac{2n}{e^n} \xrightarrow{\text{again L'Hopital's rule}} \lim_{n \rightarrow \infty} \frac{2!}{e^n} \rightarrow 0$$

i.e., "to what"

so, yes.

- 3 (d) How does the machine evaluate  $(1 + 10^{-16}) + 10^{-16}$ ? How could you do this addition of three numbers more accurately on this same machine? [Recall  $\varepsilon_{\text{mach}} \approx 1.1 \times 10^{-16}$ .]

$1 \oplus 10^{-16}$  rounded down to 1, then same happens again  $\Rightarrow$  gives 1.

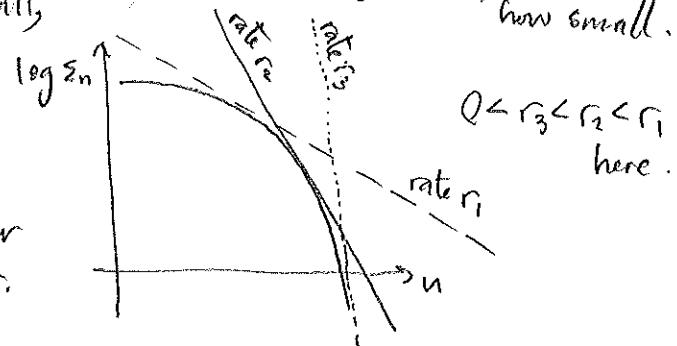
More accurate is to add smallest first, i.e.  $10^{-16} \oplus 10^{-16} \approx 2 \times 10^{-16}$

then  $1 \oplus 2 \times 10^{-16}$  rounds up to  $1 + 2.2 \times 10^{-16}$  to high relative accuracy

- 2 (e) Give a definition of an error  $\varepsilon_n$  having super-exponential convergence as  $n \rightarrow \infty$ .

means, exponential at any rate  $r$ , no matter how small.

$$\varepsilon_n = O(r^n)$$



the graph of  $\varepsilon_n$  curves downwards to ever-steep slopes on log-linear plot.