MATH 578, Assignment 1 Alexandra Tcheng

Problem 1

Part A, using an equidistant grid:

<u>Method</u>: In order to test the numerical order of accuracy of the Lagrange interpolation technique, we must be able to compute the L_{∞} -norm of the error for various h, while keeping the degree of the interpolating polynomial constant. Since the degree of the polynomial (= N) is directly related to the number of points on the grid (= n), via the relation N = n - 1, this means that the only way to change h is to vary the size of the interval [a, b].

For example: Let N = 2, so the grid must have n = 3 points. If we want to get 10 points on the final log-log plot, we can choose $h = \{2^{-0}, 2^{-1}, 2^{-2}, \dots, 2^{-10}\}$, and make the code iterate over the size of the interval, ie:

- When $h = 2^{-0} = 1$, the grid comprises the points: $\{0, 1, 2\}$ (So a = 0 and b = 2).
- When $h = 2^{-1}$, the grid comprises the points: $\{0, \frac{1}{2}, 1\}$ (So a = 0 and b = 1).
- etc.
- 1. When $f(x) = \sin(x)$, the theorem tells us that the theoretical upper bound is:

$$\frac{h^{n}}{4n}||f^{(n)}||_{\infty} \le \frac{h^{n}}{4n} \cdot 1 = O(h^{n})$$
(1)

since $f^{(n)}(x) = \pm \cos(x)$ or $\pm \sin(x)$.

<u>Results:</u> The same behaviour is observed on each graph (see Figures 1, 2 and 3):

- when h is large, the error is $O(10^0)$: the approximation is really poor. However that error cannot exceed 2, since $-1 \le \sin(x) \le +1$.
- as *h* decreases, the approximation becomes better. The measured error lies close to the theoretical error, revealing that using an equidistant grid is not an optimal choice of abscissa points.
- for N = 7, 16, as h becomes very small, the measured error exceeds the theoretical error, and they agree for N = 2. In this range, the results are no longer reliable, since the numbers involved are of $O(\epsilon_{\text{machine}}) \approx 10^{-16}$.

To determine the order of convergence, we refer to Table 1. The third column computes the slope between two consecutive points, ie:

$$slope = \frac{\log(\frac{||E(i-1)||_{\infty}}{||E(i)||_{\infty}})}{\log(\frac{h(i-1)}{h(i)})} = \frac{\log(\frac{||E(i-1)||_{\infty}}{||E(i)||_{\infty}})}{\log(2)}$$
(2)

Based on the graphs, we see that not all points are reliable: In general, one should only consider those values as the error approaches $\epsilon_{\text{machine}}$ (in **boldface** characters in the table).

Overall, those values seem to agree with the theorem, since we expect: $\log(||E||_{\infty}) \leq \log(\frac{h^n}{4n}) = C + n \cdot \log(h)$. And indeed, for

- n = 3, the convergence is $O(h^3)$,

- n = 8, the convergence is roughly of $O(h^8)$,

- n = 17, there are not enough points to assert what the order of convergence is. To make it clear that it is of $O(h^{17})$, one would have to sample the part between $h = 0.791 \dots 0.391$ with more points, and perform a similar analysis.



Figure 1: Log-log plot of $||E||_{\infty}$ and the Theoretical Error vs. h, for $f(x) = \sin(x)$ with N = 2.



Figure 2: Log-log plot of $||E||_{\infty}$ and the Theoretical Error vs. h, for $f(x) = \sin(x)$ with N = 7.



Figure 3: Log-log plot of $||E||_{\infty}$ and the Theoretical Error vs. h, for $f(x) = \sin(x)$ with N = 16.

	N=2			N = 7			N = 16	
h(i)	$ E(i) _{\infty}$	slope	h(i)	$ E(i) _{\infty}$	slope	h(i)	$ E(i) _{\infty}$	slope
1.00E + 02	1.86E + 00	1.0000	1.00E + 02	1.98E + 00	1.0000	1.00E + 02	2.00E + 00	1.0000
5.00E + 01	$1.49E{+}00$	0.3247	$5.00E{+}01$	$1.99E{+}00$	-0.0064	5.00E + 01	$2.00E{+}00$	0.0007
$2.50E{+}01$	1.24E + 00	0.2621	$2.50E{+}01$	$1.79E{+}00$	0.1585	$2.50E{+}01$	$2.00E{+}00$	0.0000
$1.25E{+}01$	1.11E + 00	0.1614	$1.25E{+}01$	$1.43E{+}00$	0.3239	$1.25E{+}01$	1.86E + 00	0.1009
$6.25E{+}00$	1.04E + 00	0.0893	6.25E + 00	1.21E + 00	0.2416	6.25E + 00	$1.49E{+}00$	0.3253
$3.13E{+}00$	1.00E + 00	0.0593	$3.13E{+}00$	1.42E + 00	-0.2356	$3.13E{+}00$	1.34E + 02	-6.4925
1.56E + 00	5.65 E-02	4.1459	1.56E + 00	2.74E-01	2.3755	1.56E + 00	1.74E + 00	6.2691
7.81E-01	2.32E-02	1.2810	7.81E-01	1.18E-03	7.8630	7.81E-01	$5.64 \text{E}{-}05$	14.9090
3.91E-01	3.58E-03	2.6979	3.91E-01	8.23E-06	7.1591	3.91E-01	6.10E-10	16.4961
1.95E-01	4.70E-04	2.9289	1.95E-01	2.28E-08	8.4985	1.95E-01	2.04E-13	11.5447
9.77 E-02	$5.95 \text{E}{-}05$	2.9825	$9.77 \text{E}{-}02$	4.82E-11	8.8836	$9.77 \text{E}{-}02$	1.23E-13	0.7347
4.88E-02	7.46E-06	2.9956	4.88E-02	9.61E-14	8.9698	4.88E-02	8.59E-14	0.5149
2.44E-02	9.33E-07	2.9989	2.44E-02	3.61E-16	8.0570	2.44E-02	4.33E-14	0.9889
1.22E-02	1.17E-07	2.9997	1.22E-02	6.94E-17	2.3785	1.22E-02	2.27E-14	0.9331
6.10E-03	1.46E-08	2.9999	6.10E-03	3.47E-17	1.0000	6.10E-03	8.51E-15	1.4144
3.05E-03	1.82E-09	3.0000	3.05E-03	1.73E-17	1.0000	3.05E-03	4.77E-15	0.8335
1.53E-03	2.28E-10	3.0000	1.53E-03	1.04E-17	0.7370	1.53E-03	2.70E-15	0.8245
7.63E-04	2.85 E-11	3.0000	7.63E-04	5.20E-18	1.0000	7.63E-04	1.49E-15	0.8536
3.81E-04	3.56E-12	3.0000	3.81E-04	2.17E-18	1.2630	3.81E-04	5.53E-16	1.4330
1.91E-04	4.45E-13	3.0000	1.91E-04	1.08E-18	1.0000	1.91E-04	3.36E-16	0.7171
9.54 E-05	5.56E-14	3.0000	9.54 E- 05	7.59E-19	0.5146	9.54 E- 05	1.90E-16	0.8216
4.77E-05	6.96E-15	3.0000	4.77 E-05	3.25E-19	1.2224	4.77 E-05	8.29E-17	1.1971

Table 1: Order of accuracy of the method, for $f(x) = \sin(x)$



Figure 4: Log-log plot of $||E||_{\infty}$ and the Theoretical Error vs. h, for $f(x) = x^6$ with N = 2.

	N=2	
h(i)	$ E(i) _{\infty}$	slope
1.00E + 00	1.47E + 01	1.00
5.00E-01	2.30E-01	6.00
2.50E-01	3.59E-03	6.00
1.25E-01	5.62 E- 05	6.00
6.25 E-02	8.77E-07	6.00
3.13E-02	1.37E-08	6.00
1.56E-02	2.14E-10	6.00
7.81E-03	3.35E-12	6.00
3.91E-03	5.23E-14	6.00
1.95E-03	8.17E-16	6.00
9.77 E-04	1.28E-17	6.00

Table 2: Order of accuracy of the method, for $f(x) = x^6$

2. When $f(x) = x^6$, if (like me) you decreased the size of the interval while maintaining a constant (I chose a = 0), then the theorem tells us that the theoretical upper bound is:

$$\frac{h^n}{4n} ||f^{(n)}||_{\infty} \le \frac{h^n}{4n} \cdot (||\frac{6! \cdot x^{6-n}}{(6-n)!}||_{\infty}) = \frac{h^n}{4n} \cdot (\frac{6! \cdot b^{6-n}}{(6-n)!}) = \frac{h^n}{4n} \cdot (\frac{6! \cdot (a + (n-1) \cdot h)^{6-n}}{(6-n)!}) = O(h^6)$$
(3)

ie: the convergence is expected to be $O(h^6)$ no matter what the degree of the polynomial is!

<u>Results</u>: All 3 graphs display a straight line for the measured error, which has to be interpreted differently depending on N:

- For N = 2, Figure 4 and Table 2 reveal that $||E||_{\infty}$ follows exactly the predictions of the theorem. Data beyond $||E||_{\infty} \approx \epsilon_{\text{machine}}$ should be ignored.
- For N = 7, 16, the estimated error does not appear on the graph. Indeed, it is identically 0, since for N > 6, $f^{(N)} \equiv 0$. Equivalently, since we're trying to approximate x^6 with a polynomial of degree less or equal to 7 or 16, the Lagrange interpolation formula naturally returns x^6 itself. Numerically, the resulting error is thus expected to be very small, so small that it is below machine precision. Yet, for large values of h the computer keeps returning values, which should therefore be discarded.



Figure 5: Log-log plot of $||E||_{\infty}$ and the Theoretical Error vs. h, for $f(x) = x^6$ with N = 7.



Figure 6: Log-log plot of $||E||_{\infty}$ and the Theoretical Error vs. h, for $f(x) = x^6$ with N = 16.



Figure 7: LOG-LOG PLOT OF $||E||_{\infty}$ FOR A CHEBYCHEV GRID (IN GREEN) AND $||E||_{\infty}$ FOR AN EQUIDISTANT GRID (IN BLUE) VS. h, FOR $f(x) = \sin(x)$ WITH N = 16.

Part B, using a Chebyshev grid

<u>Method</u>: Following the same procedure as in the Part A: h is varied by shrinking the interval over which the function is approximated. The code is actually the same as for Part A, except for the building of the grid: the abscissa points are chosen to be the zeros of the appropriate Chebychev polynomial. Note that the h used in the log-log plot is $h = \max_{i=2...n} |x_i - x_{i-1}|$.

<u>Results:</u> Qualitatively, the resulting graphs and tables for $f(x) = \sin(x)$ and $f(x) = x^6$ are extremely similar to those obtained using an equidistant grid, and should be interpreted in the same way.

Quantitatively though, the remarkable difference is that $||E||_{\infty}$ for the Chebychev grid lies lower than the one for the equidistant grid. This becomes more appearant as the degree of the polynomial increases. Figure 7 compares the two errors for N = 16 with $f(x) = \sin(x)$. This agrees with the theory, which states that Chebychev points are an optimal choice of abscissa points for the Lagrange interpolation technique.

Problem 2

•Prove that if $u, v \in L^2$, then (u * v)(x) = (v * u)(x).

SOLUTION:

$$(u * v)(x) = \int_{-\infty}^{+\infty} u(x - y)v(y)dy \stackrel{z = x - y}{\longrightarrow} \int_{+\infty}^{-\infty} u(z)v(x - z)(-dz) = \int_{-\infty}^{+\infty} u(z)v(x - z)dz = (v * u)(x)$$

• Compute $\widehat{u_{(p)}}(\xi) \equiv F(u * u * \dots * u)(\xi)$ for the function $u(x) = \begin{cases} \frac{1}{4} & -2 \le x < 0\\ -\frac{1}{4} & 0 < x \le 2\\ 0 & \text{otherwise} \end{cases}$.

Solution: By induction, p = 1:

$$\begin{aligned} \widehat{u}(\xi) &= \int_{\mathbb{R}} e^{-i\xi x} \ u(x) dx = \frac{1}{4} \left(\int_{-2}^{0} e^{-i\xi x} dx - \int_{0}^{2} e^{-i\xi x} dx \right) = \frac{1}{4} \left(\frac{e^{-i\xi x}}{-i\xi} \Big|_{-2}^{0} - \frac{e^{-i\xi x}}{-i\xi} \Big|_{0}^{2} \right) \\ &= \frac{i}{4\xi} \left(1 - e^{+2i\xi} - e^{-2i\xi} + 1 \right) = \frac{i}{4\xi} \left(1 - e^{+2i\xi} - e^{-2i\xi} + 1 \right) = \frac{i}{\xi} \left(\frac{e^{+2i\xi} - 2 + e^{-2i\xi}}{-4} \right) \\ &= \frac{i}{\xi} \left(\frac{e^{+i\xi} - e^{-i\xi}}{2i} \right)^{2} = \frac{i}{\xi} \sin^{2}(\xi) \end{aligned}$$

<u>p = n</u>: Assume that $\widehat{u_{(n)}}(\xi) = \left(\frac{i}{\xi}\sin^2(\xi)\right)^n$.

p = n + 1:

$$\widehat{u_{(n+1)}}(\xi) \equiv F(\underbrace{u * u * \dots * u}_{n+1 \text{ times}})(\xi)$$

$$= F(\underbrace{u * u * \dots * u}_{n \text{ times}})(\xi) \cdot F(u)(\xi)$$

$$= \left(\frac{i}{\xi} \sin^2(\xi)\right)^n \cdot \frac{i}{\xi} \sin^2(\xi)$$

$$= \left(\frac{i}{\xi} \sin^2(\xi)\right)^{n+1}$$

by the Convolution Theorem

by the previous steps

Therefore, for all $p \in \mathbb{N}$, $\widehat{u_{(p)}}(\xi) = \left(\frac{i}{\xi}\sin^2(\xi)\right)^p$.

• Compute the Fourier transform of the Gaussian function $u(x;s) \equiv \frac{1}{\sqrt{2\pi s^2}} \exp\left(\frac{-x^2}{2s^2}\right)$. SOLUTION:

$$\widehat{u}(\xi) = \int_{-\infty}^{+\infty} \exp(-i\xi x) \cdot \frac{1}{\sqrt{2\pi s^2}} \exp\left(-\frac{x^2}{2s^2}\right) dx = \frac{1}{\sqrt{2\pi s^2}} \int_{-\infty}^{+\infty} \exp\left(-\frac{x^2}{2s^2} - i\xi x\right) dx$$

Rewriting the exponent

$$-\frac{x^2}{2s^2} - i\xi x = -\frac{1}{2} \left(\frac{x^2}{s^2} + 2i\xi x + (i\xi s)^2 - (i\xi s)^2 \right)$$
$$= -\frac{1}{2} \left(\frac{x}{s} + i\xi s \right)^2 - \frac{\xi^2 s^2}{2}$$

$$\implies \widehat{u}(\xi) = \frac{\exp\left(-\frac{\xi^2 s^2}{2}\right)}{\sqrt{2\pi s^2}} \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2}\left(\frac{x}{s}+i\xi s\right)^2\right) \mathrm{d}x \qquad \text{let } y = \frac{x}{s}+i\xi s \quad \Leftrightarrow \quad s\mathrm{d}y = \mathrm{d}x$$
$$= \frac{\exp\left(-\frac{\xi^2 s^2}{2}\right)}{\sqrt{2\pi s^2}} \cdot s \int_{-\infty}^{+\infty} \exp\left(-\frac{1}{2}y^2\right) \mathrm{d}y \qquad \text{using } \int_{-\infty}^{+\infty} \exp\left(-ax^2\right) \mathrm{d}x = \sqrt{\frac{\pi}{a}}$$
$$= \frac{\exp\left(-\frac{\xi^2 s^2}{2}\right)}{\sqrt{2\pi s^2}} \cdot s \cdot \sqrt{2\pi}$$
$$= \exp\left(-\frac{\xi^2 s^2}{2}\right)$$

•Prove that the convolution of p Gaussian functions (with variances $s_1^2, s_2^2, \ldots, s_p^2$) is a Gaussian function with $s = \sqrt{\sum s_i^2}$

Solution: It is proved that the convolution of 2 Gaussian functions with variances s_1^2, s_2^2 is a Gaussian function with variance $s = \sqrt{s_1^2 + s_2^2}$. The claim for *n* Gaussian functions follows by induction.

Using the Convolution Theorem:

$$\begin{aligned} (u_{s_1} * u_{s_2})(x) &= F^{-1} \left(F(u_{s_1} * u_{s_2})(\xi) \right)(x) \\ &= F^{-1} \left(F(u_{s_1})(\xi) \cdot F(u_{s_2})(\xi) \right)(x) \qquad \text{by the Convolution Theorem} \\ &= F^{-1} \left(\exp\left(-\frac{\xi^2 s_1^2}{2} \right) \cdot \exp\left(-\frac{\xi^2 s_2^2}{2} \right) \right)(x) \qquad \text{by the previous question} \\ &= F^{-1} \left(\exp\left(-\frac{\xi^2 \left(\sqrt{s_1^2 + s_2^2} \right)^2 \right)}{2} \right) \right)(x) \\ &= \frac{1}{\sqrt{2\pi (s_1^2 + s_2^2)}} \exp\left(\frac{-x^2}{2 (s_1^2 + s_2^2)} \right) \qquad \text{by the previous question} \\ &=: u(x, \sqrt{s_1^2 + s_2^2}) \end{aligned}$$

Or working only in real space:

$$\begin{aligned} \int_{-\infty}^{+\infty} u(x-y;s_1) \ u(y;s_2) \mathrm{d}y &= \int_{-\infty}^{+\infty} \frac{1}{\sqrt{2\pi s_1^2}} \exp\left(-\frac{(x-y)^2}{2s_1^2}\right) \ \frac{1}{\sqrt{2\pi s_2^2}} \exp\left(-\frac{y^2}{2s_2^2}\right) \mathrm{d}y \\ &= \frac{1}{2\pi s_1 s_2} \int_{-\infty}^{+\infty} \exp\left(-\frac{(x-y)^2}{2s_1^2} - \frac{y^2}{2s_2^2}\right) \mathrm{d}y \end{aligned}$$

Rewriting the exponent:

$$\begin{aligned} -\frac{(x-y)^2}{2s_1^2} - \frac{y^2}{2s_2^2} &= -\frac{(x^2 - 2xy + y^2)s_2^2 + y^2s_1^2}{2s_1^2s_2^2} \\ &= -\frac{x^2s_2^2 - 2xys_2^2 + y^2s_2^2 + y^2s_1^2}{2s_1^2s_2^2} \\ &= -\frac{1}{2s_1^2s_2^2} \cdot \left(y^2(s_1^2 + s_2^2) - 2xys_2^2 + x^2s_2^2\right) \\ &= -\frac{1}{2s_1^2s_2^2} \cdot \left(y^2(s_1^2 + s_2^2) + (2xys_1^2 - 2xys_1^2) - 2xys_2^2 + (x^2s_1^2 - x^2s_1^2) + x^2s_2^2\right) \end{aligned}$$

$$\begin{aligned} &= -\frac{1}{2s_1^2 s_2^2} \cdot \left(y^2 (s_1^2 + s_2^2) - 2xy (s_1^2 + s_2^2) + x^2 (s_1^2 + s_2^2) + 2xy s_1^2 - x^2 s_1^2\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \cdot \left((y - x)^2 (s_1^2 + s_2^2) + 2xy s_1^2 - x^2 s_1^2\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \cdot \left(z^2 (s_1^2 + s_2^2) + 2x (z + x) s_1^2 - x^2 s_1^2\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \cdot \left(z^2 (s_1^2 + s_2^2) + 2x z s_1^2 + x^2 s_1^2\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \cdot \left(z^2 (s_1^2 + s_2^2) + 2 \cdot z \sqrt{s_1^2 + s_2^2} \cdot \frac{xs_1^2}{\sqrt{s_1^2 + s_2^2}} + \left(\frac{x^2 s_1^4}{s_1^2 + s_2^2} - \frac{x^2 s_1^4}{s_1^2 + s_2^2}\right) + x^2 s_1^2\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \cdot \left(\left(z^2 (s_1^2 + s_2^2) + 2 \cdot z \sqrt{s_1^2 + s_2^2} \cdot \frac{xs_1^2}{\sqrt{s_1^2 + s_2^2}} + \frac{x^2 s_1^4}{s_1^2 + s_2^2}\right) + \left(x^2 s_1^2 - \frac{x^2 s_1^4}{s_1^2 + s_2^2}\right)\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \cdot \left(\left(z \sqrt{s_1^2 + s_2^2} + \frac{xs_1^2}{\sqrt{s_1^2 + s_2^2}}\right)^2 + \frac{x^2 s_1^2 s_2^2}{s_1^2 + s_2^2}\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \left(z + \frac{x^2 s_1^2 s_2^2}{s_1^2 + s_2^2}\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \left(z + \frac{x^2 s_1^2 s_2^2}{s_1^2 + s_2^2}\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \left(z + \frac{x^2 s_1^2 s_2^2}{s_1^2 + s_2^2}\right) \\ &= -\frac{1}{2s_1^2 s_2^2} \left(z + \frac{x^2 s_1^2 s_2^2}{s_1^2 + s_2^2}\right) \\ &= -\frac{a^2}{2s_1^2 s_2^2} - \frac{x^2}{2(s_1^2 + s_2^2)}\right) \end{aligned}$$

$$\implies \int_{-\infty}^{+\infty} u(x-y;s_1)u(y;s_2)dy = \frac{1}{2\pi s_1 s_2} \int_{-\infty}^{+\infty} \exp\left(-\frac{a^2}{2s_1^2 s_2^2} - \frac{x^2}{2(s_1^2 + s_2^2)}\right) \frac{da}{\sqrt{s_1^2 + s_2^2}} \\ = \frac{1}{2\pi s_1 s_2 \sqrt{s_1^2 + s_2^2}} \exp\left(-\frac{x^2}{2(s_1^2 + s_2^2)}\right) \int_{-\infty}^{+\infty} \exp\left(-\frac{a^2}{2s_1^2 s_2^2}\right) da \\ = \frac{1}{2\pi s_1 s_2 \sqrt{s_1^2 + s_2^2}} \exp\left(-\frac{x^2}{2(s_1^2 + s_2^2)}\right) \cdot \sqrt{2\pi s_1^2 s_2^2} \\ = \frac{1}{\sqrt{2\pi (s_1^2 + s_2^2)}} \exp\left(-\frac{x^2}{2(s_1^2 + s_2^2)}\right) = u(x, \sqrt{s_1^2 + s_2^2})$$