


Exam (Solutions)			
	<b>Course:</b>	Numerical Analysis - Sections SIE-GC	
	<b>Lecturer:</b>	Daniel Kressner	
	<b>Date:</b>	29/01/2025	<b>Duration:</b> 3h
<b>Sciper:</b>	<b>Student:</b>		<b>Section:</b>

Evaluation table							
Ex.1	Ex.2	Ex.3	Ex.4	Ex.5	Ex.6	Ex.7	Total

**Do not turn the page before the start of the exam. Read carefully the instructions below.**

### EXAM RULES

- Write everything with a blue or black pen. Do **NOT** use a pencil.
- Please write your surname, name, and Sciper number on **EVERY PAGE** of this document!
- All results (the plots if they are requested, too) and Python code (when requested) **MUST BE TRANSCRIBED ON THESE SHEETS**, which must be submitted at the end of the exam.
- It is **NOT** possible to submit the Python/Jupyter code electronically.
- Scratch paper is provided for your personal notes, but it will not be collected and not be considered for the corrections.
- Numerical results involving floating point numbers need to be reported to at least three significant decimal digits. For example, if the result is 1.234657809E-2, write 1.23E-2 or 0.0123.
- Please note that the exam is **DOUBLE-SIDED**.

### AUTHORIZED MATERIAL

The only authorized material is **1 A4 cheat sheet (front and back) handwritten with pen/pencil**. No additional sheets, notes or books (paper or electronics), or calculator, mobile phone, tablet, laptop or other electronic devices are admitted. The access to the Internet (e-mail, websites) is prohibited.

### VIRTUAL MACHINE LOGIN INSTRUCTIONS

**Before the start of the exam:**

- 1) Sign in with your **GASPAR username and password** (same as for IS-Academia, Moodle, ...);
- 2) Choose the **MATH-251a** virtual machine client;

**After the exam has started:**

- 3) Open the **Jupyter Notebook** application by double clicking the icon on the Desktop;
- 4) In the Jupyter Notebook file browser, go to **Desktop** and then click on **exam2025.ipynb**.

We provide you with a copy of the exam notebook called **exam2025\_copy.ipynb**. If you make some unwanted modifications and do not know how to revert them, you can compare with the copy.



## Exercise 1 (0.7 Points in total)

Given some function  $f : [-1, 1] \rightarrow \mathbb{R}$ , consider the approximation of the integral

$$I(f) = \int_{-1}^1 f(x) \, dx$$

by the quadrature formula

$$Q(f) = \sum_{i=1}^2 \alpha_i f(x_i) \tag{1}$$

for the quadrature weights  $\alpha_1 = 1$  and  $\alpha_2 = 1$ , and quadrature nodes  $x_1 = -\frac{1}{3}$  and  $x_2 = +\frac{1}{3}$ .

**Question 1 (0.3 Points)** Determine the degree of exactness of the quadrature formula (1). *Provide full justification for your answer, including all derivations.*

**Solution:** We check for which monomials  $f(x) = x^s$ ,  $s = 0, 1, \dots$  the quadrature rule gives the exact integral:

$$I(1) = \int_{-1}^1 1 \, dx = 2$$

$$Q(1) = 1 + 1 = 2$$

$$I(x) = \int_{-1}^1 x \, dx = 0$$

$$Q(x) = -\frac{1}{3} + \frac{1}{3} = 0$$

$$I(x^2) = \int_{-1}^1 x^2 \, dx = \frac{2}{3}$$

$$Q(x^2) = \frac{1}{9} + \frac{1}{9} = \frac{2}{9}$$

Since the quadrature formula integrates monomials up to degree 1 exactly, but no longer monomials of degree 2, the degree of exactness is 1.

Point distribution:

- +0.1 for the correct derivation of each monomial;
- +0.05 for the correct degree of exactness;
- -0.05 if all derivations are correct but the degree of exactness is incorrect.

**Question 2 (0.4 Points)** Consider the integrals

$$\int_{-2}^1 f_1(x) \, dx \quad \text{for} \quad f_1(x) = \sin(x),$$

and

$$\int_0^1 f_2(x) \, dx \quad \text{for} \quad f_2(x) = \sqrt{x}.$$

The function `composite_quadrature` in the Jupyter notebook implements the composite quadrature formula  $Q_h(f)$  corresponding to (1) for a given function  $f$  on an arbitrary interval  $[a, b]$  with  $n$  sub-intervals. For both integrals, use this Python function to: (i) compute the error of the composite quadrature formula for  $n = 10$  sub-intervals, and (ii) numerically determine the order of convergence of the composite quadrature formula. Complete the table below with the errors rounded to three significant decimal digits.

*Hint:* The primitives of  $f_1$  and  $f_2$  are  $F_1(x) = -\cos(x)$  and  $F_2 = \frac{2}{3}\sqrt{x^3}$ .

Coefficient	$Q_h(f_1)$	$Q_h(f_2)$
(i) error for $n = 10$	$1.58 \times 10^{-2}$ or 0.0158	$2.83 \times 10^{-3}$ or 0.00283
(ii) order of convergence	1	1

Point distribution:

- +0.1 for each correct answer;
- rounding errors are tolerated.

## Exercise 2 (1.2 Points in total)

This is a multiple choice exercise. **One, and only one, answer is correct for every question.** Clearly mark your answer choice with a cross. Use correction fluid (Tipp-Ex) to remove a cross if you have accidentally crossed an answer. If needed, you can request Tipp-Ex from the proctors. 0.2 points are given if the correct answer is crossed and none of the other three answers is crossed. In all other cases, 0 points are given.

**Question 1 (0.2 Points)** Consider the data

$$\begin{array}{ll} x_1 = -1 & y_1 = 3 \\ x_2 = 1 & y_2 = 0 \\ x_3 = 2 & y_3 = \beta \\ x_4 = 4 & y_4 = \beta. \end{array}$$

Let  $p_3$  be the degree 3 interpolating polynomial for this data, that is,  $p_3(x_i) = y_i$  for  $i = 1, \dots, 4$ . Determine the value of  $\beta$  for which  $p_3(0) = -1$  holds.

- ☐  $-\frac{3}{11}$
- ☐  $\frac{4}{3}$
- ☒ 3
- ☐ 6

**Solution:** The degree 3 interpolating polynomial is given by the Lagrange interpolation formula (lecture notes, Proposition 2.1)

$$\begin{aligned} p_3(x) &= y_1 \frac{(x-x_2)(x-x_3)(x-x_4)}{(x_1-x_2)(x_1-x_3)(x_1-x_4)} + y_2 \frac{(x-x_1)(x-x_3)(x-x_4)}{(x_2-x_1)(x_2-x_3)(x_2-x_4)} \\ &\quad + y_3 \frac{(x-x_1)(x-x_2)(x-x_4)}{(x_3-x_1)(x_3-x_2)(x_3-x_4)} + y_4 \frac{(x-x_1)(x-x_2)(x-x_3)}{(x_4-x_1)(x_4-x_2)(x_4-x_3)} \\ &= 3 \frac{(x-1)(x-2)(x-4)}{(-1-1)(-1-2)(-1-4)} + \beta \frac{(x+1)(x-1)(x-4)}{(2+1)(2-1)(2-4)} + \beta \frac{(x+1)(x-1)(x-2)}{(4+1)(4-1)(4-2)} \\ &= -\frac{1}{10}(x-1)(x-2)(x-4) + \beta \frac{(x+1)(x-1)(x-4)}{6} + \beta \frac{(x+1)(x-1)(x-2)}{30}. \end{aligned}$$

Enforcing the condition  $p_3(0) = -1$  results in the value

$$p_3(0) = \frac{4}{5} + \beta \left( -\frac{2}{3} + \frac{1}{15} \right) = \frac{4}{5} - \frac{9\beta}{15} = -1 \quad \Longleftrightarrow \quad \beta = 3.$$

Point distribution:

- +0.2 for the correct answer;
- 0 points if crosses are ambiguous or multiple boxes are crossed.

**Question 2 (0.2 Points)** The following Python function implements an unknown composite quadrature formula for approximating an integral  $\int_a^b f(x) dx$ .

```
def unknown_composite_quadrature(a, b, n, f):  
    # Unknown composite quadrature formula  
    # - a,b: lower/upper bounds of integration interval  
    # - n: number of sub-intervals  
    # - f: function to integrate  
    h = (b - a) / n  
    xi = np.linspace(a, b, n + 1) # sub-interval boundaries  
    alphas = (h / 3) * np.hstack((0.5, np.ones(n - 1), 0.5)) # weights at xi  
    ci = np.linspace(a + h / 2, b - h / 2, n) # sub-interval mid-points  
    betas = (2 * h / 3) * np.ones(n) # weights at ci  
    Qh = np.dot(alphas, f(xi)) + np.dot(betas, f(ci))  
    return Qh
```

Which composite quadrature formula does this function compute?

- ☐ Composite midpoint formula
- ☐ Composite trapezoidal formula
- ☒ Composite Simpson formula
- ☐ Composite Gaussian formula

**Solution:** *This identical code appears in the course notes (lecture notes, page 64).*

Point distribution:

- +0.2 for the correct answer;
- 0 points if crosses are ambiguous or multiple boxes are crossed.

**Question 3 (0.2 Points)** Suppose that the Newton method is applied to the system of equations  $\mathbf{f}(\mathbf{x}) = \mathbf{0}$  with

$$\mathbf{f}(\mathbf{x}) = \begin{bmatrix} x_1 + \cos(x_2) \\ 5 - x_2 \end{bmatrix}$$

and initial point  $\mathbf{x}^{(0)} = [x_1^{(0)}, x_2^{(0)}]^\top$ . Then the iterates  $\mathbf{x}^{(k)} = [x_1^{(k)}, x_2^{(k)}]^\top$ ,  $k = 1, 2, \dots$ , produced by the Newton method satisfy the recursion:

☒  $\begin{cases} x_1^{(k+1)} = \sin(x_2^{(k)})(5 - x_2^{(k)}) - \cos(x_2^{(k)}) \\ x_2^{(k+1)} = 5 \end{cases}$

☐  $\begin{cases} x_1^{(k+1)} = \cos(x_2^{(k)}) + \sin(x_2^{(k)})(x_2^{(k)} - 5) \\ x_2^{(k+1)} = 5 \end{cases}$

☐  $\begin{cases} x_1^{(k+1)} = x_1^{(k)} - x_1^{(k+1)} - \cos(x_2^{(k+1)}) - \sin(x_2^{(k+1)})(x_2^{(k+1)} - 5) \\ x_2^{(k+1)} = x_2^{(k)} + 5 - x_2^{(k+1)} \end{cases}$

☐  $\begin{cases} x_1^{(k+1)} = \cos(x_2^{(k)}) + \sin(x_2^{(k)})(x_2^{(k)} - 5) - x_1^{(k)} \\ x_2^{(k+1)} = 5 - x_2^{(k)} \end{cases}$

**Solution:** The Jacobian of  $\mathbf{f}$  at  $\mathbf{x}$  satisfies

$$J_{\mathbf{f}}(\mathbf{x}) = \begin{bmatrix} 1 & -\sin(x_2) \\ 0 & -1 \end{bmatrix} \implies J_{\mathbf{f}}(\mathbf{x})^{-1} = \begin{bmatrix} -1 & \sin(x_2) \\ 0 & 1 \end{bmatrix}.$$

Therefore, the Newton method iterates  $\mathbf{x}^{(k+1)} = \mathbf{x}^{(k)} - J_{\mathbf{f}}(\mathbf{x}^{(k)})^{-1}\mathbf{f}(\mathbf{x}^{(k)})$  (lecture notes, page 28) are

$$\begin{bmatrix} x_1^{(k+1)} \\ x_2^{(k+1)} \end{bmatrix} = \begin{bmatrix} x_1^{(k)} \\ x_2^{(k)} \end{bmatrix} + \begin{bmatrix} -1 & \sin(x_2^{(k)}) \\ 0 & 1 \end{bmatrix} \begin{bmatrix} x_1^{(k)} + \cos(x_2^{(k)}) \\ 5 - x_2^{(k)} \end{bmatrix} = \begin{bmatrix} -\cos(x_2^{(k)}) + \sin(x_2^{(k)})(5 - x_2^{(k)}) \\ 5 \end{bmatrix}.$$

Point distribution:

- +0.2 for the correct answer;
- 0 points if crosses are ambiguous or multiple boxes are crossed.

**Question 4 (0.2 Points)** Consider the following linear system of ordinary differential equations:

$$\frac{d\mathbf{u}(t)}{dt} = \begin{bmatrix} -1 & 0 & 0 \\ 0 & -1 & 0 \\ 4 & -2 & -2 \end{bmatrix} \mathbf{u}(t) + \mathbf{b}(t), \text{ with } t > 0, \mathbf{u}(0) = \mathbf{u}_0, \quad (2)$$

and some  $\mathbf{b} : \mathbb{R} \rightarrow \mathbb{R}^3$ ,  $\mathbf{u}_0 \in \mathbb{R}^3$ . The backward (implicit) Euler method applied to (2) with fixed time step size  $\Delta t > 0$  is

- ☐ absolutely stable if and only if  $0 < \Delta t < 1$ .
- ☐ absolutely stable if and only if  $0 < \Delta t < 2$ .
- ☒ absolutely stable for every  $\Delta t > 0$  (unconditionally absolutely stable).
- ☐ not absolutely stable for any  $\Delta t > 0$ .

**Solution:** By Lemma 6.4 (lecture notes), the backward Euler method applied to any linear system is unconditionally absolutely stable.

Point distribution:

- +0.2 for the correct answer;
- 0 points if crosses are ambiguous or multiple boxes are crossed.



**Question 5 (0.2 Points)** Given a smooth function  $f : \mathbb{R} \rightarrow \mathbb{R}$  and  $\bar{x} \in \mathbb{R}$ , consider the finite differences formula

$$\delta_h f(\bar{x}) := \frac{f(\bar{x} - h) - 2f(\bar{x}) + f(\bar{x} + 2h)}{h}.$$

Of which order is this formula for approximating the derivative of the function  $f$  at  $\bar{x} \in \mathbb{R}$ ?

☐ 0

☒ 1

☐ 2

☐ 3

**Solution:** *The Taylor expansions around  $\bar{x}$  are*

$$\begin{aligned} f(\bar{x} - h) &= f(\bar{x}) - hf'(\bar{x}) + \frac{h^2}{2}f''(\bar{x}) + \mathcal{O}(h^3) \\ f(\bar{x} + 2h) &= f(\bar{x}) + 2hf'(\bar{x}) + 2h^2f''(\bar{x}) + \mathcal{O}(h^3). \end{aligned}$$

*Inserting these expansions into the finite differences formula, we get*

$$\delta_h f(\bar{x}) = f'(\bar{x}) + \frac{5h}{2}f''(\bar{x}) + \mathcal{O}(h^2).$$

*Hence, the method is of order 1.*

Point distribution:

- +0.2 for the correct answer;
- 0 points if crosses are ambiguous or multiple boxes are crossed.

**Question 6 (0.2 Points)** Consider a linear system  $A\mathbf{x} = \mathbf{b}$  with

$$A = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 2 & 0 \\ 0 & 0 & 3 \end{bmatrix}$$

and some  $\mathbf{b} \in \mathbb{R}^3$ . For which values of  $\omega > 0$  does the Richardson method defined by

$$P\mathbf{x}^{(k+1)} = (P - A)\mathbf{x}^{(k)} + \mathbf{b}, \quad k = 0, 1, 2, \dots,$$

with  $P = \omega I$  converge to the solution  $\mathbf{x}$  for every starting vector  $\mathbf{x}^{(0)}$  and right-hand side  $\mathbf{b}$ ?

- ☐ For  $\omega > 1$  but not for  $0 < \omega < 1$ .
- ☐ For  $\omega > \frac{1}{2}$  but not for  $0 < \omega < \frac{1}{2}$ .
- ☒ For  $\omega > \frac{3}{2}$  but not for  $0 < \omega < \frac{3}{2}$ .
- ☐ There is no such  $\omega > 0$ .

**Solution:** By Theorem 5.2 (lecture notes), the Richardson method converges if and only if the spectral radius  $\rho(B)$  of  $B = I - P^{-1}A$  is smaller than 1. The eigenvalues of  $B$  are clearly

$$1 - \frac{1}{\omega}, 1 - \frac{2}{\omega}, \text{ and } 1 - \frac{3}{\omega}.$$

Then, for  $\omega > 3/2$ ,  $\rho(B) < 1$  and for  $\omega < 3/2$ ,  $\rho(B) > 1$ .

Point distribution:

- +0.2 for the correct answer;
- 0 points if crosses are ambiguous or multiple boxes are crossed.

## Exercise 3 (0.3 Points in total)

The following Python function implements a fixed-point iteration.

```
def fixed_point(x0, tol, nmax):  
    """  
    Fixed point iteration.  
  
    Parameters  
    -----  
    x0 : float  
        The initial guess for the fixed point.  
    tol : float  
        The desired tolerance for the fixed point.  
    nmax : int  
        The maximum number of iterations.  
  
    Returns  
    -----  
    x_seq : array-like  
        The successive values of the fixed point iterations.  
    res : array-like  
        The value of the residual at each iteration.  
    niter : int  
        The number of iterations performed.  
    """  
  
    niter = 0  
    x_seq = []  
    x_seq.append(x0)  
    xt = 2 * x0 - (x0 - 1) ** 3 - 2 * np.log(x0) - 1  
  
    res = []  
    res.append(x0 - xt) # this measures "how far x0 is from the fixed point"  
    while (abs(res[-1]) > tol) and (niter < nmax):  
        niter = niter + 1  
        x_seq.append(xt)  
        x0 = xt  
        xt = 2 * x0 - (x0 - 1) ** 3 - 2 * np.log(x0) - 1  
        res.append(abs(x0 - xt))  
        if niter ≥ nmax:  
            print("maximum iterations reached without achieving desired tolerance")  
  
    # convert from list to array  
    x_seq = np.array(x_seq)  
    res = np.array(res)  
  
    return x_seq, res, niter
```

**Question 1 (0.2 Points)** Write down the fixed-point iteration. That is, determine the function  $\phi$  that produces the sequence  $x^{(k+1)} = \phi(x^{(k)})$ ,  $k = 0, 1, 2, \dots$ , corresponding to the output `x_seq` of the function `fixed_point`.

**Solution:** We look at the line `xt = 2 * x0 - (x0 - 1) ** 3 - 2 * np.log(x) - 1` to see that the function  $\phi$  is given by

$$\underline{\underline{\phi(x) = 2x - (x - 1)^3 - 2\log(x) - 1.}}$$

Point distribution:

- +0.2 for correct expression  $\phi$ ;
- -0.1 if  $\phi$  isn't defined but the correct recurrence is given;
- Expression in terms of NumPy functions are tolerated.

**Question 2 (0.1 Point)** For the fixed point  $\alpha = 1$  and  $\phi$  from Question 1, determine theoretically the order of the fixed-point iteration  $x^{(k+1)} = \phi(x^{(k)})$ ,  $k = 0, 1, 2, \dots$ . Provide full justification for your answer, including all derivations.

**Solution:** By Theorem 1.2 from the lecture notes, since  $\phi$  is smooth in a neighborhood of  $\alpha = 1$ , we can check the derivatives of the function  $\phi$  evaluated at the fixed point  $\alpha = 1$ :

$$\begin{aligned}\phi'(x) &= 2 - 3(x-1)^2 - \frac{2}{x} \implies \phi'(1) = 0 \\ \phi''(x) &= -6(x-1) + \frac{2}{x^2} \implies \phi''(1) = 2 \neq 0 \\ \phi'''(x) &= -6 - \frac{4}{x^3} \implies \phi'''(1) = -10 \neq 0 \\ \phi^{(s)}(x) &= -\frac{2(s-1)!}{x^s}, s \geq 4 \implies \phi^{(s)}(1) \neq 0, s \geq 4.\end{aligned}$$

Since  $\phi^{(s)}(\alpha) = 0$  for  $s = 1$  but  $\phi^{(s)}(\alpha) \neq 0$  for  $s \geq 2$ , the method is of order 2.

Point distribution:

- +0.05 if the derivatives  $\phi'(1)$  and  $\phi''(1)$  are correctly calculated;
- +0.05 point if based on the calculation the correct order is determined;
- -0.05 if  $\phi''(1) \neq 0$  is not checked;
- 0 points in any other case (missing derivative computations, wrong justification, ...).

## Exercise 4 (0.3 Points in total)

Consider the Hilbert matrix  $A \in \mathbb{R}^{n \times n}$ , which has the entries

$$a_{ij} = \frac{1}{i+j-1}, \quad i, j = 1, 2, \dots, n.$$

The function `hilbert_matrix` in the Jupyter notebook generates this matrix.

**Question 1 (0.1 Point)** Numerically compute the (spectral) condition number  $\kappa(A) = \|A^{-1}\| \|A\|$  of the Hilbert matrix for  $n = 12$ , where  $\|\cdot\|$  denotes the spectral norm of a matrix.

Computed value of  $\kappa(A)$  (rounded to three significant decimal digits):

**Solution:** Using `np.linalg.cond`, we get  $\kappa(A) = \underline{\underline{1.75 \times 10^{16}}}$ .

Point distribution:

- +0.1 for correct values of  $\kappa(A)$ ;
- small deviations from the correct value are tolerated.

**Question 2 (0.1 Point)** Let  $\mathbf{x}$  solve the system  $A\mathbf{x} = \mathbf{b}$  for some nonzero vector  $\mathbf{b} \in \mathbb{R}^{12}$ , where  $A$  is the Hilbert matrix from above for  $n = 12$ . Let  $\hat{\mathbf{x}}$  solve the system  $A\hat{\mathbf{x}} = \hat{\mathbf{b}}$  for a different non-zero vector  $\hat{\mathbf{b}} \in \mathbb{R}^{12}$ . Suppose that the entries of  $\mathbf{b}, \hat{\mathbf{b}}$  satisfy  $|\hat{b}_i - b_i| \leq \epsilon |b_i|$  for  $i = 1, \dots, 12$  and some  $\epsilon > 0$ . Provide a value for  $\alpha$  such that the inequality

$$\frac{\|\hat{\mathbf{x}} - \mathbf{x}\|}{\|\mathbf{x}\|} \leq \alpha \epsilon \tag{3}$$

holds. Briefly justify your choice.

**Solution:** By Lemma 4.3 from the lecture notes,  $\alpha = \underline{\underline{\kappa(A) = 1.75 \times 10^{16}}}$  verifies this inequality. To see this, realize that  $|\hat{b}_i - b_i| \leq \epsilon |b_i| \implies \hat{b}_i - b_i = s_i \epsilon b_i \iff \hat{b}_i = b_i(1 + s_i \epsilon)$  for some  $s_i \in [-1, 1]$ ,  $i = 1, 2, \dots, 12$ . Hence, Lemma 4.3 with  $\epsilon_{\max} = \max_{i=1,2,\dots,12} |s_i \epsilon| \leq \epsilon$  yields the inequality.

Point distribution:

- +0.1 if either  $\alpha = \kappa(A)$  or the value from Question 1 is given.

**Question 3 (0.1 Point)** Validate numerically that the inequality (3) holds for the Hilbert matrix  $A$  for  $n = 12$  and the value of  $\alpha$  you determined in Question 2. For this purpose, choose  $\mathbf{x} = [1, 2, \dots, 12]^\top \in \mathbb{R}^{12}$  and compute  $\mathbf{b} := A\mathbf{x}$ . Further, let  $\hat{\mathbf{x}}$  be the solution produced by the NumPy function `np.linalg.solve(A, b)` and compute  $\hat{\mathbf{b}} := A\hat{\mathbf{x}}$ . Then compute and write down the left- and right-hand side of (3), rounded to three significant decimal digits.

**Solution:** *We get*

$$\frac{\|\hat{\mathbf{x}} - \mathbf{x}\|}{\|\mathbf{x}\|} = \underline{\underline{4.77 \times 10^{-2} \text{ or } 0.0477}},$$

*and*

$$\max_i \frac{|\hat{b}_i - b_i|}{|b_i|} \kappa(A) = \underline{\underline{3.34}}.$$

*Clearly, the inequality holds for this specific example.*

Point distribution:

- +0.05 if left-hand side is correctly computed;
- +0.05 if right-hand side is correctly computed;
- tolerated if correct value for  $\epsilon$  not just  $10^{-16}$  but justified it with something like  $\frac{\|b - \hat{b}\|_2}{\|b\|_2}$ .

## Exercise 5 (0.7 Points in total)

**Question 1 (0.3 Points)** Complete the following Python function such that it implements the Heun method.

```
def heun(f, u_0, T, N):
    """
    Solves an ordinary differential equation
         $u' = f(t, u)$ ,  $t$  in  $(0, T]$ ,
         $u(0) = u_0$ 
    using the Heun method on an equispaced grid of stepsize  $dt = T / N$ .

    Parameters
    -----
    f : function
    u_0 : float
        Starting value.
    T : float > 0
        End point.
    N : int
        Number of time steps

    Returns
    -----
    u : NumPy array
        Approximate solution  $\text{np.array}([u_0, u_1, u_2, \dots, u_N])$ 
    """

    u = np.zeros(N + 1)

    ### BEGIN SOLUTION
    u[0] = u_0
    dt = T / N
    ### END SOLUTION

    for n in range(N):

        ### BEGIN SOLUTION
        u_FE = u[n] + dt * f(n * dt, u[n])
        u[n + 1] = u[n] + dt / 2 * f(n * dt, u[n]) + dt / 2 * f((n + 1) * dt, u_FE)
        ### END SOLUTION

    return u
```

Point distribution:

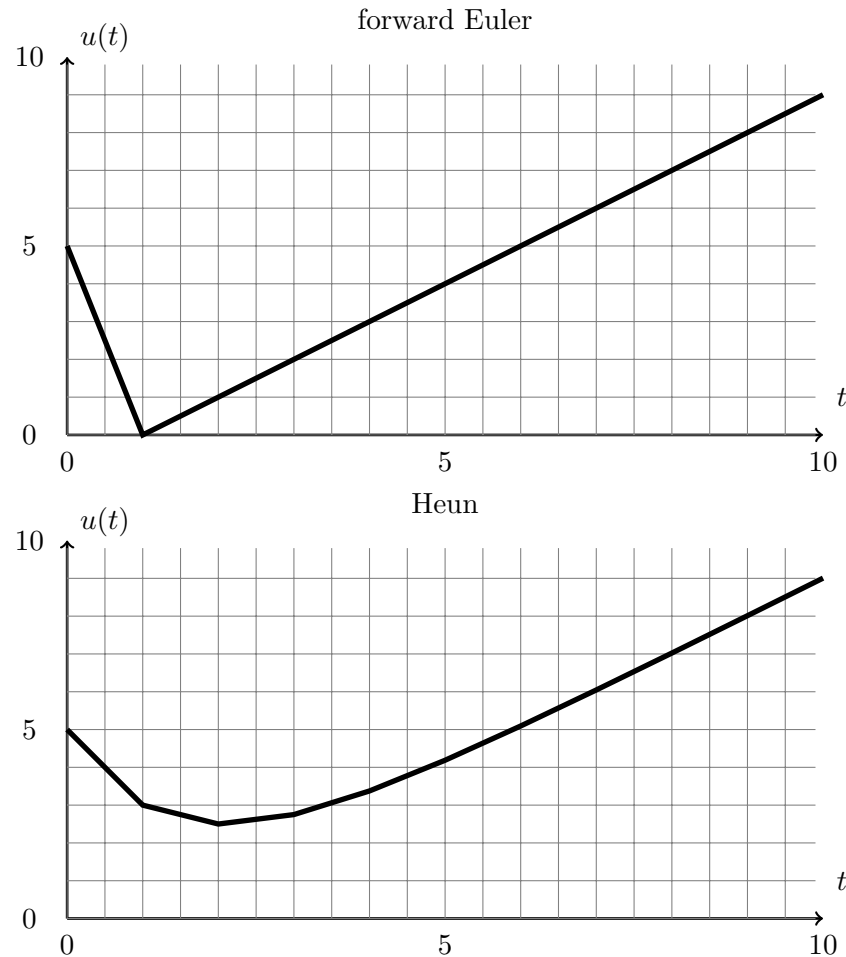
- -0.1 for correct variable initialization;
- +0.1 for correct intermediate step (forward Euler);
- +0.1 for correct next iterate;
- also fine if intermediate is used directly in the next iterate, and the formula as a whole is correct;
- small syntactic errors in the code (wrongly placed parantheses, ...) are tolerated.



**Question 2 (0.2 Points)** Consider the ordinary differential equation

$$\begin{cases} \frac{du(t)}{dt} = t - u(t), & t \in (0, T] \\ u(0) = 5. \end{cases} \quad (4)$$

The Jupyter notebook provides the function `forward_euler`, which implements the forward (explicit) Euler method. Use this implementation of the forward Euler method and your implementation of the Heun method from Question 1 to solve (4) for  $T = 10$  and  $N = 10$  steps. Sketch the two approximations of the solution  $u(t)$  in the plots below. *Do not forget to label the y-axis.*



Point distribution:

- +0.1 per plot if the general shape is correct, the axes are labeled and values approximately correspond to the solution;
- If code from Question 1 was wrong and the graph reflects that mistake, tolerate it as a follow-up mistake;
- −0.1 if graphs are correct, but order is swapped.

**Question 3 (0.2 Points)** Numerically determine the order of convergence of the forward Euler and Heun method applied to problem (4).

*Hint:* The exact solution of (4) is  $u(t) = 6 \exp(-t) + t - 1$ .

	forward Euler	Heun
order of convergence	1	2

Point distribution:

- +0.1 for every correct order.

## Exercise 6 (0.6 Points in total)

Consider the function

$$f(x) = (1 - x) \cos(x), \quad x \in [0, 1]. \quad (5)$$

**Question 1 (0.2 Points)** Use Python to compute the degree 5 interpolating polynomial  $p$  of this function  $f$  at the uniformly spaced nodes  $x_i = \frac{i}{5}$  for  $i = 0, 1, \dots, 5$ . Write down the Python code below and report the value of  $p(0.4)$ .

Python code:

**Solution:**

```
### BEGIN SOLUTION
f = lambda x: (1 - x) * np.cos(x)
x = np.linspace(0, 1, 6)

p = np.polyfit(x, f(x), 5)
p_eval = np.polyval(p, 0.4)
print("Evaluation: p(0.4) = {:.3f}".format(p_eval))
### END SOLUTION
```

Value of  $p(0.4)$  rounded to three decimal digits:

$$\underline{\underline{p(0.4) = 5.53 \times 10^{-1} \text{ or } 0.553}}$$

Point distribution:

- +0.2 if everything is correct;
- -0.1 if there is a small mistake;
- 0 otherwise.

**Question 2 (0.2 Points)** Use Python to compute the derivative  $p'$  of the interpolating polynomial  $p$  from Question 1. Write down the Python code below and report the error  $|p'(0.4) - f'(0.4)|$ .

Python code:

```
### BEGIN SOLUTION
p_der = p[:-1] * np.arange(5, 0, -1)
p_der_eval = np.polyval(p_der, 0.4)
f_der_eval = - np.cos(0.4) - (1 - 0.4) * np.sin(0.4)
error = abs(p_der_eval - f_der_eval)
print("Error: |p'(0.4) - f'(0.4)| = {:.3f}".format(error))
### END SOLUTION
```

Value of  $|p'(0.4) - f'(0.4)|$  rounded to three decimal digits:

$$\underline{\underline{|p'(0.4) - f'(0.4)| = 1.24 \times 10^{-5} \text{ or } 0.0000124}}$$

Point distribution:

- +0.2 if everything is correct (polyder and finite differences accepted);
- -0.1 if there is a small mistake (e.g., order, coefficients);
- 0 otherwise.

**Question 3 (0.2 Points)** Use Python to compute the integral  $I(p) = \int_0^1 p(x) \, dx$  of the interpolating polynomial  $p$  from Question 1. Write down the Python code below and report the error  $|I(p) - I(f)|$ .  
*Hint:*  $I(f) = \int_0^1 f \, dx = 1 - \cos(1)$ .

Python code:

```
### BEGIN SOLUTION
p_int = np.sum(p * 1 / np.arange(6, 0, -1))
f_int = 1 - np.cos(1)
error = abs(p_int - f_int)
print("Error: |I(p) - I(f)| = {:.3f}".format(error))
### END SOLUTION
```

Value of  $|I(f) - I(p)|$  rounded to three decimal digits:

$$\underline{\underline{|I(p) - I(f)| = 7.00 \times 10^{-7} \text{ or } 0.0000007}}$$

Point distribution:

- +0.2 if everything is correct (polyint accepted);
- -0.1 if there is a small mistake (e.g., order, coefficients);
- 0 otherwise.

## Exercise 7 (0.7 Points in total)

Given data  $x_i \in \mathbb{R}$ ,  $y_i \in \mathbb{R}$ , with  $i = 1, 2, \dots, n+1$ , we aim at approximating this data by a function of the form

$$q(x) = a_0 + a_1x + a_2e^x$$

for some real coefficients  $a_0, a_1, a_2 \in \mathbb{R}$ . More precisely, we want to find the least-squares approximation, i.e., the coefficients  $a_0, a_1, a_2 \in \mathbb{R}$  that minimize the least-squares error:

$$\min_{a_0, a_1, a_2 \in \mathbb{R}} \sum_{i=1}^{n+1} (y_i - (a_0 + a_1x_i + a_2e^{x_i}))^2. \quad (6)$$

**Question 1 (0.3 Points)** Rewrite the minimization problem (6) in matrix-vector form. More precisely, determine a matrix  $V \in \mathbb{R}^{(n+1) \times 3}$  such that the vector  $\mathbf{a} = [a_0, a_1, a_2]^\top \in \mathbb{R}^3$  containing the solution  $a_0, a_1, a_2$  of (6) satisfies the minimization problem

$$\min_{\mathbf{a} \in \mathbb{R}^3} \|\mathbf{y} - V\mathbf{a}\|^2, \quad (7)$$

with  $\mathbf{y} = [y_1, y_2, \dots, y_{n+1}]^\top \in \mathbb{R}^{n+1}$ . Write down explicit formulas for the entries of  $V$ :

**Solution:** *The matrix has entries*

$$V = \begin{bmatrix} 1 & x_1 & e^{x_1} \\ 1 & x_2 & e^{x_2} \\ 1 & x_3 & e^{x_3} \\ \vdots & \vdots & \vdots \\ 1 & x_{n+1} & e^{x_{n+1}} \end{bmatrix}$$

or

$$\begin{aligned} V_{i1} &= 1, i = 1, 2, \dots, n+1 \\ V_{i2} &= x_i, i = 1, 2, \dots, n+1 \\ V_{i3} &= e^{x_i}, i = 1, 2, \dots, n+1. \end{aligned}$$

Point distribution:

- +0.3 if matrix or entries of the matrix are correctly written down;
- -0.2 if only case  $n = 2$  is given;
- -0.1 points if  $V$  is starting with  $x_0$  or ending with  $x_n$ ;
- 0 points if only standard Vandermonde matrix (monomial basis) is given.

*Hint:* Note that this is *not* a least-squares polynomial approximation problem. Still, the correct matrix  $V$  can be found in a fashion analogous to the derivation of the Vandermonde matrix for least-squares polynomial approximation problems.

**Question 2 (0.2 Points)** Using your results from Question 1, complete the following Python function such that it computes the least-squares solution  $\mathbf{a} = [a_0, a_1, a_2]^T \in \mathbb{R}^3$  of (7) for given data vectors  $\mathbf{x} = [x_1, x_2, \dots, x_{n+1}]^T \in \mathbb{R}^{n+1}$  and  $\mathbf{y} = [y_1, y_2, \dots, y_{n+1}]^T \in \mathbb{R}^{n+1}$ .

```
def least_squares(x, y):
    """
    Computes the vector of coefficients for the least-squares approximant
     $q(x) = a_0 + a_1 x + a_2 e^x$  given data  $x_i, y_i, i=1, 2, \dots, n+1$ .

    Parameters
    -----
    x : NumPy array of shape (n+1, )
        x-values of the data.
    y : NumPy array of shape (n+1, )
        y-values of the data.

    Returns
    -----
    a : NumPy array of shape (3, )
        Array of coefficients  $a_0, a_1, a_2$ .
    """

    ### BEGIN SOLUTION
    n = len(x) - 1
    V = np.ones((n + 1, 3))
    V[:, 1] = x
    V[:, 2] = np.exp(x)
    a = np.linalg.solve(V.T @ V, V.T @ y)
    ### END SOLUTION

    return a
```

Point distribution:

- +0.1 if matrix  $V$  is correctly assembled;
- +0.1 if normal equations are correctly computed and solved (`np.linalg.lstsq` is also tolerated);
- -0.05 if  $V^T$  instead of  $V$  is assembled and then used as  $V$ ;
- -0.05 if the shape of  $V$  is  $(n+1) \times (n+1)$  instead of  $(n+1) \times 3$ ;
- -0.05 if matrix  $V$  is only assembled for  $n = 2$ ;
- small indexing errors are tolerated;
- 0 points if `np.polyfit` is used, since it computes the least squares approximant in a different basis.

**Question 3 (0.2 Points)** Consider the data points  $x_i = \frac{i}{4}$  and  $y_i = \sin(x_i)\cos(x_i) + x_i^2 - 1$  for  $i = 1, 2, \dots, 10$ . Provide the Python code that utilizes the function from Question 2 to solve the least-squares problem (7) for this data. Report the least-squares error (7).

Python code:

```
### BEGIN SOLUTION
x_data = np.arange(1, 11) / 4
y_data = np.sin(x_data) * np.cos(x_data) + x_data ** 2 - 1

a = least_squares(x_data, y_data)

y_ls = a[0] + a[1] * x_data + a[2] * np.exp(x_data)

ls_error = np.sum((y_data - y_ls) ** 2)
print("Least squares error: Els = {:.2e}".format(ls_error))
### END SOLUTION
```

Value of the least-squares error (7) rounded to three decimal digits.

**Solution:**  $\min_{\mathbf{a} \in \mathbb{R}^3} \|\mathbf{y} - V\mathbf{a}\|^2 = 2.90 \times 10^{-2}$  or 0.0290

Point distribution:

- +0.1 if least-squares coefficients are correctly computed, even if an incorrectly implemented `least_squares` from previous question is referenced;
- +0.1 if the least-squares error (7) is correctly computed and written down;
- −0.05 if the value of the error is not given.