# AMATH 481/581 - Autumn 2022 Homework #4 Sathvik Chinta

#### 1. Presentation Skills: 2D plotting

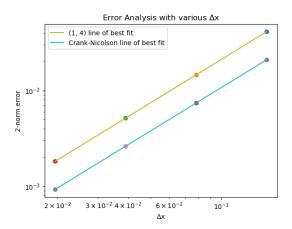


Figure 1: log-log plot of different  $\Delta x$  values against the two norm error for the (1, 4) accurate method against the (2, 2) accurate method (Crank-Nicolson). At every  $\Delta x$  value, the two norm error for the Crank-Nicolson is lower than the two norm error for the (1, 4) accurate method. This shows that the trade off between the temporal (1st order accurate vs 2nd order accurate) and spatial (2nd order accurate vs 4th order accurate) is a fine balance as they both have almost the same slope in the log-log plot (1.5).

#### Appendix: Code:

```
[language=Python]
    import numpy as np
    import scipy.sparse
    import scipy.optimize
    import matplotlib.pyplot as plt
    alpha = 2
    L = 10
    Time = 2
    xspan\,,\ dx\,=\,np.\,linspace\,(-L\,,\ L\,,\ n\,,\ endpoint=False\,,\ retstep=True)
    tspan\;,\;\;dt\;=\;np\;.\;linspace\left(0\;,\;\;Time\;,\;\;501\;,\;\;retstep=True\right)
    lambda\_star = (alpha * dt) / (dx**2)
    e1 = -30 * np.ones(n)
    e2 = 16 * np.ones(n)
    e3 = -1 * np.ones(n)
    A = scipy.sparse.spdiags([e3, e2, e1, e2, e3],
                               [-2, -1, 0, 1, 2], n, n, format='csc')
    A[0, -1] = 16
    A[0, -2] = -1
    A[1, -1] = -1
```

```
A[-1, 0] = 16
A[-1, 1] = -1
A[\,-2\,,\ 0\,]\ =\ -1
A = 1/12 * A
A3 = A. toarray()
sol1 = np.zeros((len(xspan), len(tspan)))
u0 = 10 * np.cos(2 * np.pi * xspan / L) + 30 * np.cos(8 * np.pi * xspan / L)
sol1[:, 0] = u0
for i in range(len(tspan) - 1):
    u1 = u0 + lambda_star * (A@u0)
    sol1[:, i + 1] = u1
    u0 = u1
A5 = sol1[:, -1]
#reshape A5 to a 128x1 matrix
A5 = A5.reshape(128,1)
# %%
# Question 2
e1 = -2 * np.ones(n)
e2 = np.ones(n)
mid \, = \, 1/2 \, * \, lambda\_star \, * \, scipy.sparse.spdiags (\, [\, e2 \, , \, \, e1 \, , \, \, e2 \, ] \, ,
                                             [-1, 0, 1], n, n, format='csc')
mid[0, -1] = 1/2 * lambda_star
mid[-1, 0] = 1/2 * lambda_star
B = scipy.sparse.eye(n) - mid
C = scipy.sparse.eye(n) + mid
A7 = B. toarray()
A8 = C.toarray()
print (A8)
# %%
# Solve suing LU decomposition
sol2 = np.zeros((len(xspan), len(tspan)))
u0 = 10 * np.cos(2 * np.pi * xspan / L) + 30 * np.cos(8 * np.pi * xspan / L)
sol2[:, 0] = u0
PLU = scipy.sparse.linalg.splu(B)
test = PLU.solve(C@u0)
for i in range(len(tspan) - 1):
    u1 = PLU.solve(C@u0)
    sol2[:, i + 1] = u1
    u0 = u1
A9 = sol2[:, -1]
# reshape A9 to a 128x1 matrix
A9 = A9. reshape (128, 1)
print(A9)
A10 = 0
# %%
#Load the exact solution from the file exact_128.csv
exact = np.loadtxt('exact_128.csv', delimiter=',')
#reshape the exact solution to a 128x1 matrix
exact = exact.reshape(128,1)
#find the two norm difference between A5 and exact, save as A11
A11 = np.linalg.norm(A5 - exact)
#find the two norm difference between A9 and exact, save as A12
A12 = np.linalg.norm(A9 - exact)
\# redo both problems with n = 256, load in the exact solution from the file exact_256.csv
n = 256
xspan, dx2 = np.linspace(-L, L, n, endpoint=False, retstep=True)
```

```
tspan, dt = np.linspace(0, Time, (4 * 500) + 1, retstep=True)
e1 = -30 * np.ones(n)
e2 = 16 * np.ones(n)
e3 = -1 * np.ones(n)
A = scipy.sparse.spdiags([e3, e2, e1, e2, e3],
                            [-2, -1, 0, 1, 2], n, n, format='csc')
A[0, -1] = 16
A[0, -2] = -1
A\,[\,1\;,\;\;-1]\;=\;-1
A[-1, 0] = 16
A[-1, 1] = -1
A[-2, 0] = -1
A = 1/12 * A
print (A. toarray ())
sol1 = np.zeros((len(xspan), len(tspan)))
u0 = 10 * np.cos(2 * np.pi * xspan / L) + 30 * np.cos(8 * np.pi * xspan / L)
sol1[:, 0] = u0
for i in range(len(tspan) - 1):
    u1 = u0 + lambda_star * (A@u0)
     sol1[:, i + 1] = u1
    u0 = u1
first = sol1[:, -1]
# %%
e1 = -2 * np.ones(n)
e2 = np.ones(n)
mid \,=\, 1/2 \,\,*\,\, lambda\_star \,\,*\,\, scipy.sparse.spdiags \left(\left[\,e2\,,\,\,e1\,,\,\,e2\,\right]\,,\,\,e2\,\right]
                                                        [-1, 0, 1], n, n, format='csc')
#mid = scipy.sparse.lil_matrix(mid)
mid[0, -1] = 1/2 * lambda_star
\operatorname{mid}[-1, 0] = 1/2 * \operatorname{lambda\_star}
B = scipy.sparse.eye(n) - mid
C = scipy.sparse.eye(n) + mid
# Solve suing LU decomposition
sol2 = np.zeros((len(xspan), len(tspan)))
{\rm u0\, =\, 10\, \, *\, np.\, cos \, (2\, *\, np.\, pi\, *\, xspan\, /\, L)\, +\, 30\, *\, np.\, cos \, (8\, *\, np.\, pi\, *\, xspan\, /\, L)}
sol2[:, 0] = u0
PLU = scipy.sparse.linalg.splu(B)
for i in range(len(tspan) - 1):
     u1 = PLU.solve(C@u0)
     sol2[:, i + 1] = u1
    u0 = u1
second = sol2[:, -1]
#Load the exact solution from the file exact_256.csv
\mathtt{exact} = \mathtt{np.loadtxt} \, (\, \mathtt{`exact\_256.csv'} \, , \ \mathtt{delimiter} = \mathtt{`,'})
#find the two norm difference between A5 and exact, save as A11
A13 = np.linalg.norm(first - exact)
#find the two norm difference between second and exact, save as A12
A14 = np.linalg.norm(second - exact)
\# redo both problems with n = 512, load in the exact solution from the file exact_512.csv
n = 512
\mathtt{xspan}\,,\ \mathtt{dx3}\,=\,\mathtt{np.linspace}(-\mathtt{L}\,,\ \mathtt{L}\,,\ \mathtt{n}\,,\ \mathtt{endpoint=False}\,,\ \mathtt{retstep=True})
tspan, dt = np.linspace(0, Time, (16 * 500) + 1, retstep=True)
e1 = -30 * np.ones(n)
e2 = 16 * np.ones(n)
e3 = -1 * np.ones(n)
A = scipy.sparse.spdiags([e3, e2, e1, e2, e3],
                                 [-2, -1, 0, 1, 2], n, n, format='csc')
A[0, -1] = 16
A[0, -2] = -1
A[1, -1] = -1
A[-1, 0] = 16
```

```
A[-1, 1] = -1
A[-2, 0] = -1
A = 1/12 * A
print (A. toarray())
sol1 = np.zeros((len(xspan), len(tspan)))
u0 \, = \, 10 \, * \, \mathrm{np.cos} \, (2 \, * \, \mathrm{np.pi} \, * \, \mathrm{xspan} \, / \, L) \, + \, 30 \, * \, \mathrm{np.cos} \, (8 \, * \, \mathrm{np.pi} \, * \, \mathrm{xspan} \, / \, L)
sol1[:, 0] = u0
for i in range(len(tspan) -1):
     u1 = u0 + lambda\_star * (A@u0)
     sol1[:, i + 1] = u1
     u0 = u1
\mathtt{first} \ = \ \mathtt{soll} \ [:, \ -1]
# %%
e1 = -2 * np.ones(n)
e2 = np.ones(n)
mid = 1/2 * lambda_star * scipy.sparse.spdiags([e2, e1, e2],
                                                         [-1, 0, 1], n, n, format = 'csc')
#mid = scipy.sparse.lil_matrix(mid)
mid[0, -1] = 1/2 * lambda_star
mid[-1, 0] = 1/2 * lambda_star
B = scipy.sparse.eye(n) - mid
C = scipy.sparse.eye(n) + mid
# Solve suing LU decomposition
sol2 = np.zeros((len(xspan), len(tspan)))
u0 \, = \, 10 \, * \, np.\cos\left(2 \, * \, np.pi \, * \, xspan \, / \, L\right) \, + \, 30 \, * \, np.\cos\left(8 \, * \, np.pi \, * \, xspan \, / \, L\right)
sol2[:, 0] = u0
PLU = scipy.sparse.linalg.splu(B)
for i in range(len(tspan) -1):
    u1 = PLU.solve(C@u0)
    sol2[:, i + 1] = u1
    u0 = u1
\mathtt{second} \ = \ \mathtt{sol2} \ [: \, , \quad -1]
#Load the exact solution from the file exact_512.csv
exact = np.loadtxt('exact_512.csv', delimiter=',')
#find the two norm difference between A5 and exact, save as A11
A15 = np.linalg.norm(first - exact)
#find the two norm difference between second and exact, save as A12
A16 = np.linalg.norm(second - exact)
\# redo both problems with n = 1024, load in the exact solution from the file exact_1024.csv
n = 1024
xspan, dx4 = np.linspace(-L, L, n, endpoint=False, retstep=True)
tspan, dt = np.linspace(0, Time, (64 * 500) + 1, retstep=True)
e1 = -30 * np.ones(n)
e2 = 16 * np.ones(n)
e3 = -1 * np.ones(n)
A = scipy.sparse.spdiags([e3, e2, e1, e2, e3],
                                 [-2, -1, 0, 1, 2], n, n, format='csc')
A[0, -1] = 16
A[0, -2] = -1
A\,[\,1\;,\;\;-1]\;=\;-1
A[-1, 0] = 16
A[-1, 1] = -1
A[-2, 0] = -1
A = 1/12 * A
print (A. toarray ())
sol1 = np.zeros((len(xspan), len(tspan)))
u0 \, = \, 10 \, * \, np.\cos\left(2 \, * \, np.pi \, * \, xspan \, / \, L\right) \, + \, 30 \, * \, np.\cos\left(8 \, * \, np.pi \, * \, xspan \, / \, L\right)
sol1[:, 0] = u0
for i in range(len(tspan) - 1):
     u1 = u0 + lambda_star * (A@u0)
     sol1[:, i + 1] = u1
```

```
u0 = u1
 first = soll [:, -1] 
# %%
e1 = -2 * np.ones(n)
e2 = np.ones(n)
mid \, = \, 1/2 \, * \, lambda\_star \, * \, scipy.sparse.spdiags (\,[\,e2\,,\ e1\,,\ e2\,]\,,
                                                                                                    [-1, 0, 1], n, n, format='csc')
#mid = scipy.sparse.lil_matrix(mid)
mid[0, -1] = 1/2 * lambda_star
mid[-1, 0] = 1/2 * lambda_star
B = scipy.sparse.eye(n) - mid
C = scipy.sparse.eye(n) + mid
# Solve suing LU decomposition
sol2 = np.zeros((len(xspan), len(tspan)))
u0 = 10 * np.cos(2 * np.pi * xspan / L) + 30 * np.cos(8 * np.pi * xspan / L)
sol2[:, 0] = u0
PLU = scipy.sparse.linalg.splu(B)
for i in range(len(tspan) - 1):
        u1 = PLU.solve(C@u0)
         sol2[:, i + 1] = u1
        u0 = u1
\mathtt{second} \ = \ \mathtt{sol2} \ [: \ , \quad -1]
#Load the exact solution from the file exact_1024.csv
\mathtt{exact} \ = \ \mathtt{np.loadtxt} \ ( \ \mathtt{`exact\_1024.csv'} \ , \ \ \mathtt{delimiter} = \mathtt{`,'})
#find the two norm difference between A5 and exact, save as A11
A17 = np.linalg.norm(first - exact)
#find the two norm difference between second and exact, save as A12
A18 = np.linalg.norm(second - exact)
# %%
\#plot the norms of dx, dx2, dx3, and dx4 against A11, A13, A15, A17 on a loglog plot
fig, ax = plt.subplots()
ax.loglog(dx, A11, 'o')
ax.loglog(dx2, A13, 'o')
ax.loglog(dx3, A15, 'o')
ax.loglog(dx4, A17, 'o')
ax.loglog(dx, A12, 'o')
ax.loglog(dx2, A14, 'o')
ax.loglog(dx3, A16, 'o')
ax.loglog(dx4, A18, 'o')
ax.set_xlabel('$\Delta$x')
ax.set_ylabel('2-norm error')
#set the title of the plot to be '(1, 4) method error analysis with various dx'
ax.set_title('Error Analysis with various $\Delta$x')
#make a line of best fit for the data
m, \ b = np.\,polyfit\,(np.\,log\,([\,dx\,,\ dx2\,,\ dx3\,,\ dx4\,]\,)\,\,,\ np.\,log\,([\,A11\,,\ A13\,,\ A15\,,\ A17\,]\,)\,\,,\ 1)
m,\ b=np.\,polyfit\,(np.\log{([dx,\ dx2,\ dx3,\ dx4])}\,,\ np.\log{([A12,\ A14,\ A16,\ A18])}\,,\ 1)
ax. log log ([dx, dx2, dx3, dx4], np. exp (m*np. log ([dx, dx2, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx2, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx2, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx2, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx2, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx2, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx2, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx2, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), label = `Crank-Nicolson ling ([dx, dx3, dx4]) + b), labe
ax.legend()
plt.show()
 plt.savefig('error_analysis.png')
```

### 2. Presentation Skills: 3D plotting

#### Crank-Nicolson method solution

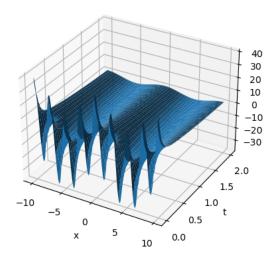


Figure 2: 3d plot of the entire final solution with n = 128 for the most accurate method (Crank-Nicolson). The plot shows that near t = 0, the solution is much more chaotic and fluctuates wildly. In contrast, as time progresses, the solution becomes much more smooth and the heat becomes more normalized. This signifies the heat is spreading out and becoming more uniform through the rod.

## Appendix: Code:

```
[language=Python]
    # %%
    import numpy as np
    import scipy.sparse
    import scipy.optimize
    import matplotlib.pyplot as plt
    # %%
    # Question 1
    alpha = 2
    L = 10
    Time = 2
    n = 128
    xspan\,,\ dx\,=\,np.\,linspace\,(-L\,,\ L\,,\ n\,,\ endpoint=False\,,\ retstep=True)
    \mathtt{tspan}\;,\;\;\mathtt{dt}\;=\;\mathtt{np.linspace}\left(0\;,\;\;\mathtt{Time}\;,\;\;501\;,\;\;\mathtt{retstep=True}\right)
    lambda_star = (alpha * dt) / (dx**2)
    e1 = -30 * np.ones(n)
    e2 = 16 * np.ones(n)
    e3 = -1 * np.ones(n)
    A = scipy.sparse.spdiags([e3, e2, e1, e2, e3],
                                 [-2, -1, 0, 1, 2], n, n, format='csc')
    A[0, -1] = 16
    A[0, -2] = -1
    A[1, -1] = -1
    A[-1, 0] = 16
    A[-1, 1] = -1
    A[-2, 0] = -1
    A = 1/12 * A
```

```
A3 = A. toarray()
# Solve
\mathtt{sol1} \; = \; \mathtt{np.zeros} \, ( \, (\, \mathtt{len} \, (\, \mathtt{xspan} \, ) \, , \; \; \mathtt{len} \, (\, \mathtt{tspan} \, ) \, ) \, )
u0 = 10 * np.cos(2 * np.pi * xspan / L) + 30 * np.cos(8 * np.pi * xspan / L)
sol1[:, 0] = u0
for i in range(len(tspan) -1):
    u1 = u0 + lambda_star * (A@u0)
     sol1[:, i + 1] = u1
    u0\ =\ u1
A5 = sol1[:, -1]
#reshape A5 to a 128x1 matrix
A5 = A5. reshape(128,1)
# %%
# stability analysis
g = lambda z: 1 + 1/12 * lambda_star * (-30 + 32 * np.cos(z) - 2 * np.cos(2 * z))
A1 = abs(g(1))
minimum\_index = scipy.optimize.fminbound(lambda z: -abs(g(z)), -np.pi, np.pi)
A2 = g(minimum_index)
# %%
# Question 2
e1 = -2 * np.ones(n)
e2 = np.ones(n)
\label{eq:mid_star} \mbox{mid} \, = \, 1/2 \, \, * \, \, \mbox{lambda\_star} \, \, * \, \, \mbox{scipy.sparse.spdiags} \, (\, [\, \mbox{e2} \, ] \, , \, \, \mbox{e2} \, ] \, ,
                                                  [-1, 0, 1], n, n, format='csc')
mid[0, -1] = 1/2 * lambda_star
mid[-1, 0] = 1/2 * lambda_star
B = scipy.sparse.eye(n) - mid
C = scipy.sparse.eye(n) + mid
A7 = B.toarray()
A8 = C. toarray()
print (A8)
# %%
# Solve suing LU decomposition
sol2 = np.zeros((len(xspan), len(tspan)))
u0 = 10 * np.cos(2 * np.pi * xspan / L) + 30 * np.cos(8 * np.pi * xspan / L)
sol2[:, 0] = u0
PLU = scipy.sparse.linalg.splu(B)
test = PLU. solve (C@u0)
for i in range(len(tspan) - 1):
    u1 = PLU. solve (C@u0)
    sol2[:, i + 1] = u1
    u0 = u1
A9 = sol2[:, -1]
# reshape A9 to a 128x1 matrix
A9 = A9.reshape(128,1)
print (A9)
A10 = 0
# %%
# make a 3d plot of the solution of sol2
fig = plt.figure()
ax \ = \ fig \ . \ add \_subplot (111 \, , \ projection = '3d \, ')
X, T = np.meshgrid(xspan, tspan)
ax.plot\_surface(X, T, sol2.T)
ax.set_xlabel('x')
ax.set_ylabel('t')
ax.set_zlabel('u')
ax.set_title('Crank-Nicolson method solution')
plt.show()
```