

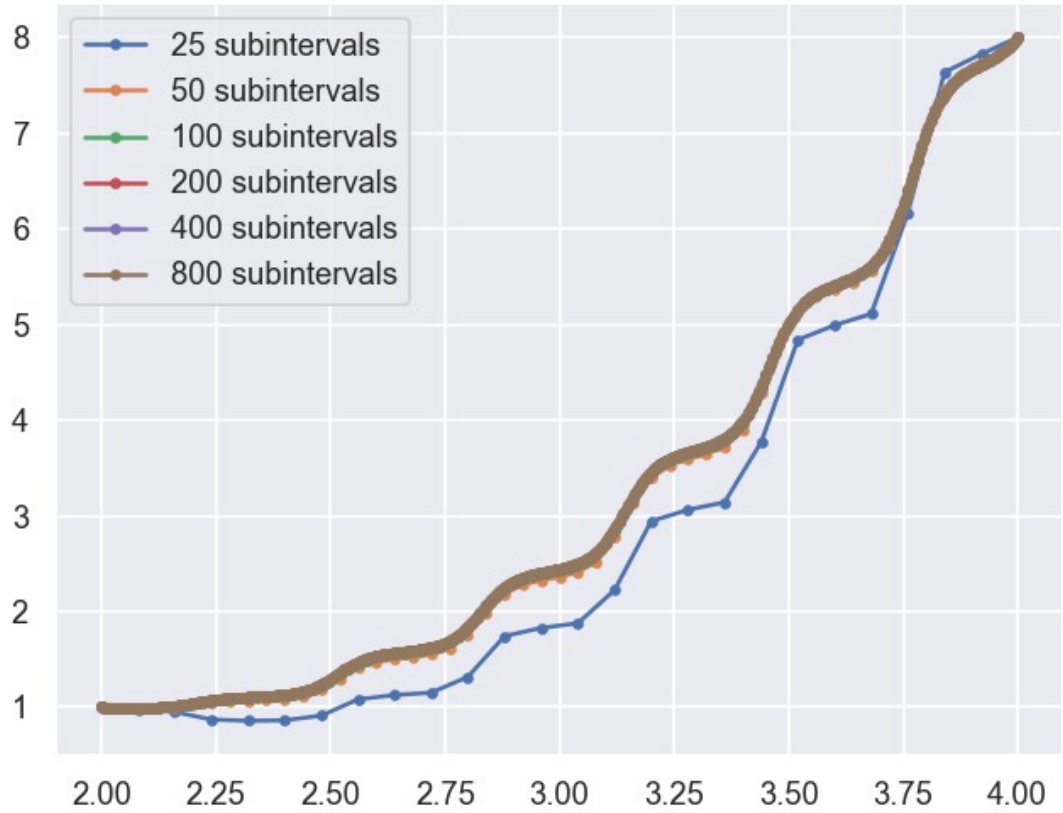
538 Spring 2022 Homework 5 Solutions

1. BVP by finite differences

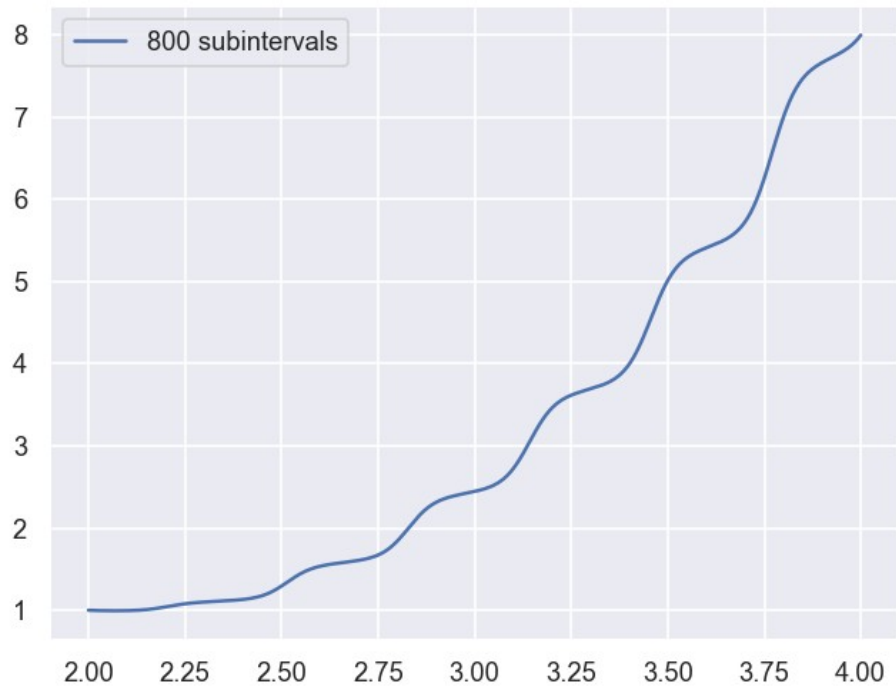
Code:

```
1 from matplotlib import rcdefaults
2 rcdefaults() # restore default matplotlib rc parameters
3 %config InlineBackend.figure_format='retina'
4 import seaborn as sns # wrapper for matplotlib that provides prettier styles and more
5 import matplotlib.pyplot as plt # use matplotlib functionality directly
6 %matplotlib notebook
7 %matplotlib inline
8 sns.set()
9 import numpy as np
10
11 def f(x,Y):
12     global p,q,phi
13     y,yp = Y
14     return np.array([ yp, phi(x) -p(x)*yp - q(x)*y ])
15
16 # coefficients of some random example 2nd order linear ODE
17 def p(x): return 20*np.sin(20*x)
18 def q(x): return -6/x**2
19 def phi(x): return 0*x + 1
20
21 x0 = 2 # a
22 x1 = 4 # b
23 y0 = 1 # alpha, the starting value
24 y1 = 8 # beta, the target ending value
25
26 #plt.figure(figsize=(10,6))
27 plt.plot(x0,y0,'o')
28 plt.plot(x1,y1,'o')
29
30 %matplotlib notebook
31 midpoint_values = []
32
33 for N in [24,49,99,199,399,799]:
34     h = (x1-x0)/(N+1)
35     x = np.linspace(x0,x1,N+2)
36     pv = p(x)
37     qv = q(x)
38     phiv = phi(x)
39
40     # form the matrix A
41     A = np.zeros((N,N))
42     i = np.arange(N+2)
43     A[i[: -2],i[: -2]] = -2 + h**2*qv[1:-1] # main diagonal
44     A[i[1:-2],i[: -3]] = 1 - h/2 *pv[2:-1] # subdiagonal
45     A[i[: -3],i[1:-2]] = 1 + h/2 *pv[1:-2] # superdiagonal
46     A
47
48     # rhs
49     rhs = h**2*phiv[1:-1]
50     rhs
51     rhs[0] -= (1-h/2*pv[1])*y0
52     rhs[-1] -= (1+h/2*pv[N])*y1
53     rhs
54
55     u = np.zeros_like(x)
56     u[0] = y0
57     u[-1] = y1
58     u[1:-1] = np.linalg.solve(A, rhs)
59     u
60     plt.plot(x,u,'.-',label=f'{N+1} subintervals')
61     print(N+1,u[(N+1)//2]) # value at midpoint
62     midpoint_values.append(u[(N+1)//2])
63 plt.legend()
```

Results for various choices of number of gridpoints:



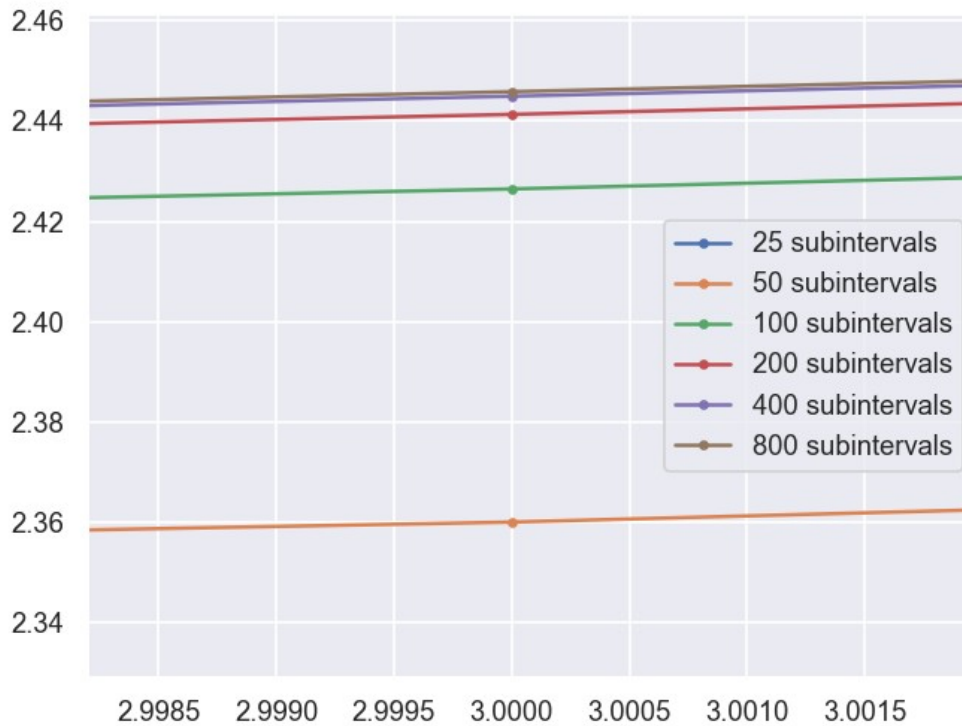
Appears to be converging well.
Best approximation:



Zooming in on $x=3$:

By eyeball, each doubling of the number of subintervals takes care of at least $3/4$ of the error, indicating the error is $O(h^2)$, or even better.

The best estimate of $y(3)$ is approximately 2.446.



```
25 1.8282434586058591
50 2.359954018224484
100 2.426466898570565
200 2.4413598076637095
400 2.444986299125836
800 2.4458870396249535
```

2. Variational equations in Lorenz system¶

```
1 from rk4 import rk4
2
3 def F(t,YV):
4     global ODEF, ODEDF
5     n = int((-1 + np.sqrt(1 + 4*len(YV)) )/2)
6     #print(n)
7     Y = YV[:n]
8     V = YV[n:].reshape((n,n))
9     #print(V)
10    FY = ODEF(t,Y)
11    FV = ODEDF(t,Y)@V
12    return np.append( FY,FV.reshape(n*n) )
13
14 def f(t,Y):
15    x,y,z = Y
16    return np.array([ 10*y - 10*x,
17                    28*x - y - x*z,
18                    -8*z/5 + x*y ])
19
20 def Df(t,Y):
21    x,y,z = Y
22    return np.array([[ -10, 10, 0],
23                    [28-z, -1, -x],
24                    [y, x, -8/5]])
25
26 ODEF = f
27 ODEDF = Df
28
29 Y = [-4, -8, 15]
30 YV = np.append(Y,np.eye(3).reshape(9))
31 F(0,YV)
32 t1 = 10
33 m = 2000
34 h = t1/m
35 ta,yva = rk4(F,0,YV,h,m)
36 yva
37 V1 = yva[3:,-1].reshape(3,3)
38 #display(V1)
39 display('Singular values at t = ' + str(t1) + ': ' + str( np.linalg.svd(V1)[1] ) )
40 plt.figure(figsize=(8,6))
41 plt.subplot(111,aspect=1)
42 plt.plot(yva[1,:],yva[2,:],'-',alpha=0.5)
43 plt.plot(yva[1, 0],yva[2, 0],'go')
44 plt.plot(yva[1,-1],yva[2,-1],'ro')
45 plt.xlabel('y')
46 plt.ylabel('z',rotation='horizontal');
```

```
'Singular values at t =10: [1.66961456e+03 4.23324431e-01 9.43744719e-14]'
```

```
print('Final values:',yva[:3,-1])
```

```
Final values: [ 1.78029292  2.88998527 15.34319187]
```

(b) The singular values are approximately 1700, 0.4, and 10^{-13} .

The large one, 1700, corresponds to rapid exponential separation of nearby trajectories.

The middle one, 0.4, is close to 1, and denotes little or no exponential separation of trajectories along some direction, which is likely to be in the direction along the trajectory. (Consider cars on a one-lane circular track: they can separate and bunch a bit, but cannot separate or converge exponentially.) The very small one indicates there is a direction along which trajectories converge very strongly. This is reflected in the long-term trajectory of the system being confined to a very thin sheet.

3. Dependence on a parameter.

(a)

$$\text{IVP } \frac{\partial y(t,p)}{\partial t} = f(y(t,p), p), \quad y(0,p) = y_0$$

$$\text{Let } v(t,p) \equiv \frac{\partial y(t,p)}{\partial p}.$$

$$\text{Then } \boxed{v(0,p) = 0} \text{ and}$$

$$\frac{\partial v(t,p)}{\partial t} = \frac{\partial}{\partial t} \left(\frac{\partial y(t,p)}{\partial p} \right)$$

$$= \frac{\partial}{\partial p} \left(\frac{\partial y(t,p)}{\partial t} \right) \quad \text{assuming 2nd derivatives are continuous}$$

$$= \frac{\partial}{\partial p} f(y(t,p), p)$$

$$\text{That is, } = \partial_1 f(y(t,p), p) \cdot \frac{\partial y(t,p)}{\partial p} + \partial_2 f(y(t,p), p)$$

$$\boxed{\frac{\partial v(t,p)}{\partial t} = \partial_1 f(y(t,p), p) \cdot v(t,p) + \partial_2 f(y(t,p), p)}$$

which we can co-solve with the IVP for y :

$$(b) \text{ For } f(y,p) = py^3$$

$$\partial_1 f(y,p) = 3py^2, \quad \partial_2 f(y,p) = y^3$$

$$\text{So } \frac{\partial v(t,p)}{\partial t} = 3py(t,p)^2 \cdot v(t,p) + y(t,p)^3$$

$$\text{and } v(0,p) = 0.$$

That is, we solve

$$\boxed{\begin{aligned} y' &= py^3, & y(0) &= y_0 \\ v' &= 3py^2 v + y^3, & v(0) &= 0 \end{aligned}}$$

