

Assignment 9 TMA4135 Harvard Hjelmseth

1

We have the following system of equations:

$$(i) \quad x^2 + y^2 = 4 \Rightarrow x^2 + y^2 - 4 = 0$$

$$(ii) \quad xy = 1 \Rightarrow xy - 1 = 0$$

Newton's method on systems is on the form

- Solve the system $J(x_k)\Delta_k = -f(x_k)$

- Let $x_{k+1} = x_k + \Delta_k$

The Jacobian matrix of our system:

$$J(x) = \begin{pmatrix} \frac{\partial}{\partial x}(x^2 + y^2) & \frac{\partial}{\partial y}(x^2 + y^2) \\ \frac{\partial}{\partial x}(xy) & \frac{\partial}{\partial y}(xy) \end{pmatrix} = \begin{pmatrix} 2x & 2y \\ y & x \end{pmatrix}$$

and we have

$$f(x) = \begin{pmatrix} x^2 + y^2 - 4 \\ xy - 1 \end{pmatrix} \quad \text{and} \quad x_0 = \begin{pmatrix} x_0 \\ y_0 \end{pmatrix} = \begin{pmatrix} 2 \\ 0 \end{pmatrix}$$

Giving us

$$f(x_0) = \begin{pmatrix} 2^2 + 0^2 - 4 \\ 2 \cdot 0 - 1 \end{pmatrix} = \begin{pmatrix} 0 \\ -1 \end{pmatrix}$$

and the Jacobian matrix

$$J(x_0) = \begin{pmatrix} 2 \cdot 2 & 2 \cdot 0 \\ 0 & 2 \end{pmatrix} = \begin{pmatrix} 4 & 0 \\ 0 & 2 \end{pmatrix}$$

If we plug these into the expression

$$J(x_k) \Delta k = -f(x_k)$$

We get

$$\begin{pmatrix} 4 & 0 \\ 0 & 2 \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} = -\begin{pmatrix} 0 \\ 1 \end{pmatrix} \Rightarrow \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} = \begin{pmatrix} 0 \\ \frac{1}{2} \end{pmatrix}$$

Giving us

$$\begin{aligned} x_1 &= x_0 + \Delta x = 2 + 0 = 2 \\ y_1 &= y_0 + \Delta y = 0 + \frac{1}{2} = \frac{1}{2} \end{aligned} \Rightarrow \begin{pmatrix} x_1 \\ y_1 \end{pmatrix} = \begin{pmatrix} 2 \\ \frac{1}{2} \end{pmatrix}$$

Now using the same principles again, we get for $k=2$:

$$f(x_1) = \begin{pmatrix} 2^2 + (\frac{1}{2})^2 - 4 \\ 2 \cdot \frac{1}{2} - 1 \end{pmatrix} = \begin{pmatrix} \frac{1}{4} \\ 0 \end{pmatrix}$$

$$J(x_1) = \begin{pmatrix} 2 \cdot 2 & 2 \cdot \frac{1}{2} \\ \frac{1}{2} & 2 \end{pmatrix} = \begin{pmatrix} 4 & 1 \\ \frac{1}{2} & 2 \end{pmatrix}$$

$$\begin{pmatrix} 4 & 1 \\ \frac{1}{2} & 2 \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} = -\begin{pmatrix} \frac{1}{4} \\ 0 \end{pmatrix}$$

$$\begin{aligned} &\stackrel{(I)}{\Rightarrow} 4\Delta x + \Delta y = -\frac{1}{4} \\ &\stackrel{(II)}{\Rightarrow} \frac{1}{2}\Delta x + 2\Delta y = 0 \end{aligned}$$

Solving (II) for Δx :

$$\begin{aligned} (II) \quad \frac{1}{2}\Delta x + 2\Delta y &= 0 \\ \frac{1}{2}\Delta x &= -2\Delta y \\ \Delta x &= -4\Delta y \end{aligned}$$

Putting this back into (I) gives us:

$$\begin{aligned} (I) \quad 4\Delta x + \Delta y &= -\frac{1}{4} \\ 4(-4\Delta y) + \Delta y &= -\frac{1}{4} \\ -16\Delta y + \Delta y &= -\frac{1}{4} \\ \Delta y &= \frac{1}{4 \cdot 15} \\ \Delta y &= \frac{1}{60} \end{aligned}$$

And plugging $\Delta y = \frac{1}{60}$ into (II):

$$\begin{aligned}\Delta x &= -4\Delta y \\ \Delta x &= -4\left(\frac{1}{60}\right) \\ \Delta x &= -\frac{1}{15}\end{aligned}$$

This gives us

$$\begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} = \begin{pmatrix} -\frac{1}{15} \\ \frac{1}{60} \end{pmatrix} \Rightarrow \begin{pmatrix} x_2 \\ y_2 \end{pmatrix} = \begin{pmatrix} x_1 + \Delta x \\ y_1 + \Delta y \end{pmatrix} = \begin{pmatrix} 2 - \frac{1}{15} \\ \frac{1}{2} + \frac{1}{60} \end{pmatrix} = \begin{pmatrix} 1.93 \\ 0.52 \end{pmatrix}$$

Now using the same principles again, we get for $k=2$:

$$f(x_2) = \begin{pmatrix} 1.93^2 + 0.52^2 - 4 \\ 1.93 \cdot 0.52 - 1 \end{pmatrix} \approx \begin{pmatrix} -0.005 \\ 0.004 \end{pmatrix}$$

$$J(x_1) = \begin{pmatrix} 2 \cdot 1.93 & 2 \cdot 0.52 \\ 0.52 & 1.93 \end{pmatrix} \approx \begin{pmatrix} 3.86 & 1.04 \\ 0.52 & 1.93 \end{pmatrix}$$

$$\begin{pmatrix} 3.86 & 1.04 \\ 0.52 & 1.93 \end{pmatrix} \begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} \approx - \begin{pmatrix} -0.005 \\ 0.004 \end{pmatrix}$$

$$\begin{aligned}&\stackrel{(I)}{=} 3.86 \Delta x + 1.04 \Delta y \approx -0.005 \\ &\stackrel{(II)}{=} 0.52 \Delta x + 1.93 \Delta y \approx 0.004\end{aligned}$$

We solve this set of equations, and get:

$$\begin{pmatrix} \Delta x \\ \Delta y \end{pmatrix} \approx \begin{pmatrix} -0.002 \\ 0.003 \end{pmatrix}$$

This gives us

$$\begin{pmatrix} x_3 \\ y_3 \end{pmatrix} = \begin{pmatrix} x_2 + \Delta x \\ y_2 + \Delta y \end{pmatrix} \approx \begin{pmatrix} 1.93 - 0.002 \\ 0.52 + 0.003 \end{pmatrix} = \begin{pmatrix} 1.928 \\ 0.517 \end{pmatrix}$$

This means that since

$$\begin{pmatrix} x_2 \\ y_2 \end{pmatrix} \approx \begin{pmatrix} x_3 \\ y_3 \end{pmatrix}$$

We have started converging towards the actual solution, and have reached a decent approximation of the solution.

(b)

Using the function "newton_sys" in "NonLinearEquations.ipynb"

We find an approximation to the solution:

```
x0 = [2.0, 0.0]

def f(x):
    return array([x[0]**2 + x[1]**2 - 4,
                 x[0]*x[1] - 1])
def jac(x):
    J = array([[x[0]**2, x[1]**2],
               [x[1], x[0]]])
    return J

newton_system(f, jac, x0, max_iter=10)

k = 0, x = [2.0, 0.0]
k = 1, x = [2. 0.5]
k = 2, x = [1.933333333333333 0.5166666666666667]
k = 3, x = [1.931852741096439 0.517637054821929]
k = 4, x = [1.931851652578934 0.517638090204244]
```

This also confirms that our approximation in a) was correct.

c)

Using "newton system" to solve the slightly perturbed system:

$$\begin{aligned}x^2 + y^2 &= 2 \\xy &= 7\end{aligned}$$

with the same initial values:

```
x0 = [2.0, 0.0]

def f(x):
    return array([x[0]**2 + x[1]**2 - 2,
                 x[0]*x[1] - 1])
def jac(x):
    J = array([[x[0]**2, x[1]**2],
               [x[1], x[0]]])
    return J

newton_system(f, jac, x0, max_iter=10)

k = 0, x = [2.0, 0.0]
k = 1, x = [1.5 0.5]
k = 2, x = [1.25 0.75]
k = 3, x = [1.125 0.875]
k = 4, x = [1.0625 0.9375]
k = 5, x = [1.03125 0.96875]
k = 6, x = [1.015625 0.984375]
k = 7, x = [1.0078125 0.9921875]
k = 8, x = [1.00390625 0.99609375]
k = 9, x = [1.001953125 0.998046875]
k = 10, x = [1.0009765625 0.9990234375]
```

We see that the approximation now converges a lot more slowly, and the value it converges towards is also of course different.

Changing the method call a bit after the screenshot was taken, we see that it now takes 18 iterations to reach the chosen convergence tolerance, whilst in b) this only takes 4 iterations.

This is a result of the problem in a having a higher order of convergence.

2 a)

We recall that Simpson's rule is defined as

$$S[f](x_{i-1}, x_i) = \frac{h}{6} (f(x_{i-1}) + 4f(x_{i-\frac{1}{2}}) + f(x_i))$$

$$\text{where } h = x_i - x_{i-1} \quad \text{and} \quad x_{i-\frac{1}{2}} = \frac{x_{i-1} + x_i}{2}$$

We can use that

$$\int_a^b S(x) dx = \sum_{i=1}^m \int_{x_{i-1}}^{x_i} S(x) dx$$

Now if we use equally spaced x_i 's and low degree interpolation we partition the integration interval and obtain

$$\int_{x_{i-1}}^{x_i} f(x) dx = \frac{h}{6} [f(x_{i-1}) + 4f(x_{i-\frac{1}{2}}) + f(x_i)]$$

Now summing over all sub-intervals we obtain,

$$S_M(f) = \frac{h}{6} \sum_{j=1}^m (f(x_{i-1}) + 4f(x_{i-\frac{1}{2}}) + f(x_i))$$

This gives us the composite Simpson's rule:

$$\begin{aligned} \int_a^b f(x) dx &\approx CSR[f]\left([x_{i-1}, x_i]_{j=1}^m\right) = \frac{h}{6} \left[f(x_0) + 4f(x_{\frac{1}{2}}) + 2f(x_1) \right. \\ &\quad + 4f(x_{\frac{3}{2}}) + 2f(x_2) \\ &\quad + \dots + 2f(x_{m-1}) \\ &\quad \left. + 4f(x_{x_{m-\frac{1}{2}}}) + f(x_m) \right] \end{aligned}$$

where:

$$x_j = a + j(b-a)/m, \quad h = (b-a)/m$$



6)

Using the "simpson" function from "Quadrature.ipynb" (Numerical Integration)

```
[1]: %matplotlib inline
from numpy import *
from matplotlib.pyplot import *
from math import factorial
newparams = {'figure.figsize': (8.0, 4.0), 'axes.grid': True,
             'lines.markersize': 8, 'lines.linewidth': 2,
             'font.size': 14}
rcParams.update(newparams)

[2]: def simpson(f, a, b, m=10):
    # Find an approximation to an integral by the composite Simpson's method:
    # Input:
    #   f: integrand
    #   a, b: integration interval
    #   m: number of subintervals
    # Output: The approximation to the integral
    n = 2*m
    x_noder = linspace(a, b, n+1)      # equidistributed nodes from a to b
    h = (b-a)/n                      # stepsize
    S1 = f(x_noder[0]) + f(x_noder[n]) # S1 = f(x_0)+f(x_n)
    S2 = sum(f(x_noder[1:n:2]))       # S2 = f(x_1)+f(x_3)+...+f(x_m)
    S3 = sum(f(x_noder[2::1:2]))       # S3 = f(x_2)+f(x_4)+...+f(x_{m-1})
    S = h*(S1 + 4*S2 + 2*S3)/3
    return S
```

Now using this function with our specific integral:

$$I(0,1) = \int_0^1 \cos(\frac{\pi}{2}x) dx = \frac{2}{\pi} = 0.636619\dots$$

for $m = 4, 8, 16, 32, 64$.

```
[3]: # Assignment 9
def f(x):          # Integrand
    return cos((pi*x)/2)
a, b = 0, 1        # Integration interval
I_exact = 2/pi     # Exact value of the integral (for comparison)
for m in [1, 4, 8, 16, 32, 64]:
    S = simpson(f, a, b, m=m)  # Numerical solution, using m subintervals
    err = I_exact - S          # Error
    if m == 1:
        print('m = {:3d}, I = {:.8f}, S = {:.8f}, error = {:.3e}'.format(m, I_exact, S, err))
    else:
        print('m = {:3d}, I = {:.8f}, S = {:.8f}, error = {:.3e}, reduction factor = {:.3e}'.format(m, I_exact, S, err, err/err_prev))
    err_prev = err
m = 1, I = 0.63661977, S = 0.63807119, error = -1.451e-03
m = 4, I = 0.63661977, S = 0.63662505, error = -5.281e-06, reduction factor = 3.639e-03
m = 8, I = 0.63661977, S = 0.63662010, error = -3.289e-07, reduction factor = 6.228e-02
m = 16, I = 0.63661977, S = 0.63661979, error = -2.054e-08, reduction factor = 6.245e-02
m = 32, I = 0.63661977, S = 0.63661977, error = -1.284e-09, reduction factor = 6.249e-02
m = 64, I = 0.63661977, S = 0.63661977, error = -8.021e-11, reduction factor = 6.250e-02
```

We observe that simpsons comp rule gives us a more accurate approximation than the trapezoid rule. The trapezoid rule is nothing more than the average of the left and right hand Riemann sums. Simpsons rule gives us a weighted average that results in a more accurate approximation.

c)

We recall that the error of Simpson's rule on a single interval is given by

$$|I[f](a, b) - S[f](a, b)| = -\frac{(b-a)^5}{2880} f^{(4)}(\xi)$$

for some $\xi \in [a, b]$

We also know that

$$\begin{aligned} I[f](a, b) &= \int_a^b f(x) dx \\ &= \sum_{k=1}^m \int_{x_{k-1}}^{x_k} f(x) dx \\ &= \sum_{k=1}^m I[f](x_{k-1}, x_k) \end{aligned}$$

Now using the same method as in 2),
by using equally spaced x_i 's and low degree interpolation we
partition the integration interval we get that the error of
Simpson's composite rule can be bounded by :

$$|I[f] - CSR[f]| \leq \frac{M_4}{2880} \frac{(b-a)^5}{m^4} = \frac{M_4}{2880} h^4 (b-a)$$

where $M_4 = \max_{\xi \in [a,b]} |f^{(4)}(\xi)|$