

Project report (4)

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Question 1

Introduction

The purpose of this project is to develop an understanding of numerical integration and differentiation through computation mathematics

Numerical differentiation

In [2]:

```
import numpy as np
import matplotlib.pyplot as plt

def f(x):
    y = np.sin(x)
    return y

def df(x):
    y = np.cos(x)
    return y

def forward_difference(f, x, h):
    x0 = x
    derivative = (f(x0 + h) - f(x0))/h
    return derivative

def backward_difference(f, x, h):
    x0 = x
    derivative = (f(x0+h) - f(x0))/h
    return derivative

def central_difference(f, x, h):
    x0 = x
    derivative = (f(x0+h) - f(x0-h))/(2.0*h)
    return derivative

def print_differences(difference, f, x, values_h, direction):

    if(direction == "forward"):
        for i in range(len(values_h)):
            print("at h =", values_h[i], "forward difference is", difference(f,x,values_h[i]
)], "error = ", abs(df(x) - difference(f,x,values_h[i])))
            forward_error[i] = abs(df(x) - difference(f,x,values_h[i]))
    elif(direction == "backward"):
        for i in range(len(values_h)):
            print("at h =", values_h[i], "backward difference is", difference(f,x,values_h[
i]), "error = ", abs(df(x) - difference(f,x,values_h[i])))
            backward_error[i] = abs(df(x) - difference(f,x,values_h[i]))
    else:
        for i in range(len(values_h)):
            print("at h =", values_h[i], "central difference is", difference(f,x,values_h[i]
)], "error = ", abs(df(x) - difference(f,x,values_h[i])))
            central_error[i] = abs(df(x) - difference(f,x,values_h[i]))

x = np.pi
h = [0.2, 0.1, 0.05, 0.01, 0.005, 0.001, 0.0005]
forward_error = h.copy()
backward_error = h.copy()
central_error = h.copy()
print("\nforward differences")
print_differences(forward_difference, f, x, h, "forward")
print("\nbackward differences")
print_differences(backward_difference, f, x, h, "backward")
print("\ncentral differences")
print_differences(central_difference, f, x, h, "central")
```

```
plt.subplot(3,1,1)
plt.title("forward_error")
plt.plot(h, forward_error)
plt.xlabel("h")
plt.ylabel("error")

plt.subplot(3,1,2)
plt.title("backward_error")
plt.plot(h, backward_error)
plt.xlabel("h")
plt.ylabel("error")

plt.subplot(3,1,3)
plt.title("central_error")
plt.plot(h, central_error)
plt.xlabel("h")
plt.ylabel("error")
```

forward differences

at h = 0.2 forward difference is -0.9933466539753069 error = 0.006653346024693141
at h = 0.1 forward difference is -0.9983341664682823 error = 0.0016658335317176753
at h = 0.05 forward difference is -0.9995833854135631 error = 0.0004166145864369364
at h = 0.01 forward difference is -0.9999833334166452 error = 1.6666583354751907e-05
at h = 0.005 forward difference is -0.9999958333385203 error = 4.166661479731992e-06
at h = 0.001 forward difference is -0.999998333332315 error = 1.6666676849741435e-07
at h = 0.0005 forward difference is -0.99999958333668 error = 4.1666332051271127e-08

backward differences

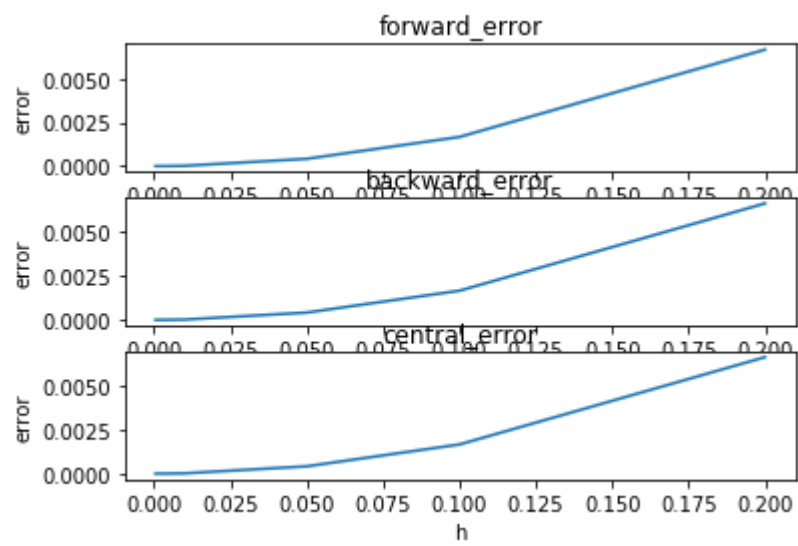
at h = 0.2 backward difference is -0.9933466539753069 error = 0.006653346024693141
at h = 0.1 backward difference is -0.9983341664682823 error = 0.0016658335317176753
at h = 0.05 backward difference is -0.9995833854135631 error = 0.0004166145864369364
at h = 0.01 backward difference is -0.9999833334166452 error = 1.6666583354751907e-05
at h = 0.005 backward difference is -0.9999958333385203 error = 4.166661479731992e-06
at h = 0.001 backward difference is -0.999998333332315 error = 1.6666676849741435e-07
at h = 0.0005 backward difference is -0.99999958333668 error = 4.1666332051271127e-08

central differences

at h = 0.2 central difference is -0.9933466539753069 error = 0.006653346024693141
at h = 0.1 central difference is -0.9983341664682823 error = 0.0016658335317176753
at h = 0.05 central difference is -0.999583385413563 error = 0.0004166145864370474
at h = 0.01 central difference is -0.9999833334166451 error = 1.666658335486293e-05
at h = 0.005 central difference is -0.9999958333385205 error = 4.166661479509948e-06
at h = 0.001 central difference is -0.999998333332315 error = 1.6666676849741435e-07
at h = 0.0005 central difference is -0.999999583336677 error = 4.166633227331573e-08

Out[2]:

Text(0, 0.5, 'error')



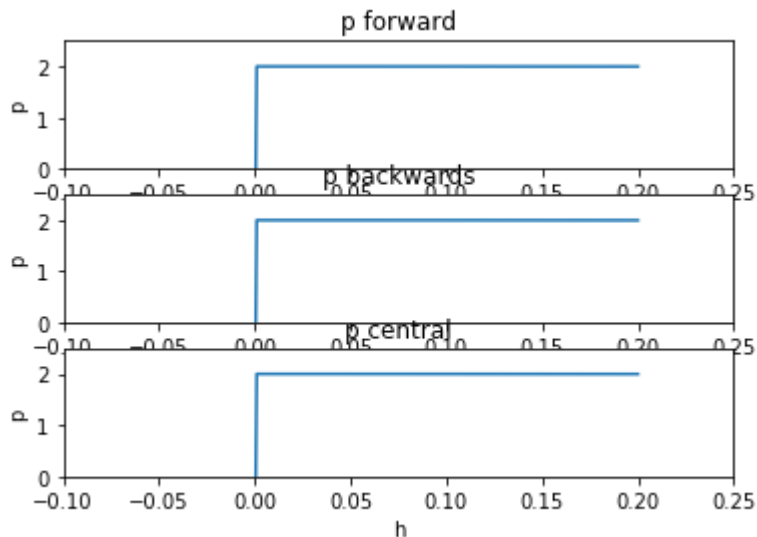
In [3]:

```
def approx(errors, h, p):  
    for i in range(len(h) - 1):  
        p[i] = np.log(errors[i]/errors[i+1])/np.log(h[i]/h[i+1])  
    #print(p)  
  
print("p forward")  
p_forward = h.copy()  
approx(forward_error, h, p_forward)  
  
print("p backward")  
p_backward = h.copy()  
approx(backward_error, h, p_backward)  
  
print("p central")  
p_central = h.copy()  
approx(central_error, h, p_central)  
  
plt.subplot(3,1,1)  
plt.title("p forward")  
plt.plot(h, p_forward)  
plt.xlabel("h")  
plt.ylabel("p")  
plt.xlim([-0.1, 0.25])  
plt.ylim([0, 2.5])  
  
plt.subplot(3,1,2)  
plt.title("p backwards")  
plt.plot(h, p_backward)  
plt.xlabel("h")  
plt.ylabel("p")  
plt.xlim([-0.1, 0.25])  
plt.ylim([0, 2.5])  
  
plt.subplot(3,1,3)  
plt.title("p central")  
plt.plot(h, p_central)  
plt.xlabel("h")  
plt.ylabel("p")  
plt.xlim([-0.1, 0.25])  
plt.ylim([0, 2.5])
```

```
p forward  
p backward  
p central
```

Out[3]:

(0, 2.5)



Observations

I noticed the error between forward, backwards and central are marginal. There little difference in error between all the methods besides central error being slightly better than forwards and backwards difference. However, the varying difference in h values will determine how accurate the approximation is. smaller the h value, smaller the error, vice versa.

Discussion

I believe the reason why there's no difference in error of the forward and backward difference (given that h is the same) is because they're measuring the increment at the same step. As a consequence, the gradient will be the same. So when the differences is removed from an actual derivative it will result in the same. However, since central considers both forward and backward difference it is safe to say that the error difference between the gradient of central difference and the actual derivative is even smaller than forward/backward difference.

The h value determines the actual increment of the steps each difference take, decreasing it will give a more accurate estimate of the derivative at the given point.

Conclusion

in conclusion, h value of 0.0005 and central difference will yield the best estimate in terms of obtaining a gradient at a given point without using a derivative as it has the smallest given error. But forward/backward difference are still pretty accurate on its own.

Numerical integration

In [4]:

```
def midpointquad(func, a, b, N):
    #a = lower limit
    #b = upper limit of integration
    #N = number of points

    x = np.linspace(a,b,N)
    #y = x.copy()
    output = 0.0
    for i in range(N-1):
        output += (x[i+1]-x[i]) * func((x[i] + x[i+1])/2.0)
    return output

def f(x):
    y = 2.0*x
    return y

def runge_func(x):
    y = 1.0/(1.0 + x**2.0)
    return y

print("mid point function of  $\int 2x|_0 \text{ to } 1 \text{ dx} ==$ ", midpointquad(f,0,1,2))
print("mid point function of  $\int 1/(1+x^2)|_{-5} \text{ to } 5 \text{ dx}$ ", midpointquad(runge_func,-5,5,50))
```

```
mid point function of  $\int 2x|_0 \text{ to } 1 \text{ dx} ==$  1.0
mid point function of  $\int 1/(1+x^2)|_{-5} \text{ to } 5 \text{ dx}$  2.7468528501889633
```

the order of accuracy of the mid point method is $O(h^3)$

In [5]:

```

Ns = [11, 101, 1001, 10001]
hs = [1.0, 0.1, 0.01, 0.001]
arctan52 = 2.0*np.arctan(5)
results = Ns.copy()
error = Ns.copy()

for i in range(len(Ns)):
    #print("f(1/(1+x^2))/-5 to 5 =", midpointquad(runge_function, -5, 5, Ns[i]))
    results[i] = midpointquad(runge_func, -5, 5, Ns[i])
    error[i] = abs(arctan52 - midpointquad(runge_func, -5, 5, Ns[i]))
    #print("error for N = ", Ns[i], "is equal to ", error[i])

print("\n\t h\t mid point results \t error")
print("-----")
for i in range(len(Ns)):
    print(Ns[i], "\t", hs[i], "\t", results[i], "\t", error[i])

# since error difference is calculated by 2arctan

```

N	h	mid point results	error
11	1.0	2.736307727635371	0.010493806254660676
101	0.1	2.7468138597748015	1.2325884769737172e-05
1001	0.01	2.7468016571640375	1.2327400567002655e-07
10001	0.001	2.74680153512277	1.2327383558385918e-09

i believe they scale up by 3 orders of magnitude, judging from the difference made by the incrementation of N values. thus the order of accuracy of the mid point method is $O(h^3)$

In [7]:

```

##trap part
def trapezoid(f, a, b, N):
    x = np.linspace(a, b, N+1)
    y = f(x)
    h = (b - a)/N

    sum = 0.0
    for i in range(1,N):
        sum += 2.0*y[i]
    sum = 0.5*h*(f(a) + sum + f(b))
    return sum

def f(x):
    y = 2.0*x
    return y

def runge_function(x):
    y = 1.0/(1.0 + x**2.0)
    return y

print("f(2x)|0 to 1 = ", trapezoid(f, 0, 1, 2))
print("f(1/(1+x^2))|-5 to 5 = ", trapezoid(runge_function, -5, 5, 500))
print("\n")
#####
##
Ns = [11, 101,1001, 10001]
hs = [1.0, 0.1, 0.01, 0.001]
arctan52 = 2.0*np.arctan(5)
results = Ns.copy()
error = Ns.copy()

for i in range(len(Ns)):
    #print("f(1/(1+x^2))|-5 to 5 =", midpointquad(runge_function, -5, 5, Ns[i]))
    results[i] = trapezoid(runge_function, -5, 5, Ns[i])
    error[i] = abs(arctan52 - trapezoid(runge_function, -5, 5, Ns[i]))
    #print("error for N = ", Ns[i], "is equal to ", error[i])

print("N\t h\t trapezoidal results \t error")
print("-----")
for i in range(len(Ns)):
    print(Ns[i], "\t", hs[i], "\t", results[i], "\t", error[i])

# since error difference is calculated by 2arctan
#####

interval = 2
functions = [func1, func2, func3]
solutions = [1.0, 1.0, 1.0]
results2 = solutions.copy()

for i in range(len(functions)):
    results2[i] = trapezoid(functions[i], 0, 1, Ns[i])
    error[i] = abs(solutions[i] - trapezoid(functions[i], 0, 1, Ns[i]))

```

[illegible]
$$\int(2x)|0 \text{ to } 1 = 1.0$$
$$\int(1/(1+x^2))|-5 \text{ to } 5 = 2.7468005476995394$$

N	h	trapezoidal results	error
11	1.0	2.7385222270696588	0.008279306820373034
101	0.1	2.7467773665372195	2.416735281229876e-05
1001	0.01	2.746801287834239	2.460557926298179e-07
10001	0.001	2.7468015314250143	2.4650175234341987e-09

function	results	errors
$\int(2x) _0 \text{ to } 1 =$	1.0	0.0
$\int(3x^2) _0 \text{ to } 1 =$	1.0000490148024705	4.9014802470548346e-05
$\int(4x^3) _0 \text{ to } 1 =$	1.0000009980029956	9.980029955780623e-07

Comparison between trapezoidal rule and mid point rule

As we can see, the order of exactness is the same between the midpoint method and the trapezoidal method in a linear polynomial. However, the order of accuracy is more accurate for the trapezoid method since it gives us a smaller error overall. This intuitively makes more sense as the trapezoidal method should give us a more accurate output. In addition, greater powers of polynomial are more accurate for the trapezoidal method as it means to cover more curvature of the polynomial.

It also seems like trapezoidal rule doesn't work for the integral of 1, this make sense as there is no curivutre for the trapezoidal to take advantage of hence throwing an error. For some reason, there seems to be a greater computational error for larger orders of polynomials inside trapezoidal rule which shouldn't make sense. This is because trapezoidal rule take advantage of the curves.

In [8]:

```
from numpy import polynomial as py

def gauss(f,a,b,N):
    [x,w] = py.legendre.leggauss(N);

    c1 = (b-a) * 0.5
    c2 = (b+a) * 0.5

    sum = 0.0
    for i in range(N):
        sum += w[i]*f(c1*x[i]+c2)
    sum = c1*sum
    return sum

def f1(x):
    y = 3.0*x**2.0
    return y

def f2(x):
    y = 4.0*x**3.0
    return y

def f3(x):
    y = 5.0*x**4.0
    return y

def f4(x):
    y = 6.0*x**5.0
    return y

def f5(x):
    y = 7.0*x**6.0
    return y

def test_function(x):
    y = 2.0*x
    return y

print("f(2x)|0 to 1 =", gauss(test_function, 0,1,2))
funcs = [f1,f2,f3,f4,f5]
funcst = ["3x^2", "4x^3", "5x^4", "6x^5", "7x^6"]
solutions = [1.0,1.0,1.0,1.0,1.0]
N2 = solutions.copy()
N3 = solutions.copy()

for i in range(len(funcs)):
    N2[i] = abs(solutions[i] - gauss(funcs[i],0,1,2))
    N3[i] = abs(solutions[i] - gauss(funcs[i],0,1,3))

#print(N2)
#print(N3)

print("functions      Error for N = 2\t\t Error for N = 3")
```

```
print("-----")
print(funcst[0], "\t", N2[0], "\t", N3[0])
print(funcst[1], "\t", N2[1], "\t", N3[1])
print(funcst[2], "\t", N2[2], "\t", N3[2])
print(funcst[3], "\t", N2[3], "\t", N3[3])
print(funcst[4], "\t", N2[4], "\t", N3[4])
print("Degrees\t 3\t\t\t\t 5")
print()
#####
##
Ns = [3,4,5,6,7,11, 15]
arctan52 = 2.0*np.arctan(5)
results = Ns.copy()
error = Ns.copy()

for i in range(len(Ns)):
    #print("f(1/(1+x^2))/-5 to 5 =", midpointquad(runge_function, -5, 5, Ns[i]))
    results[i] = gauss(runge_function, -5, 5, Ns[i])
    error[i] = abs(arctan52 - gauss(runge_function, -5, 5, Ns[i]))
    #print("error for N = ", Ns[i], "is equal to ", error[i])

print("N\t Gauss-Legendre results Error")
print("-----")
for i in range(len(Ns)):
    print(Ns[i], "\t", results[i], "\t", error[i])
```

$\int(2x) _0 \text{ to } 1 = 1.0$		
functions	Error for N = 2	Error for N = 3

3x^2	0.0	2.220446049250313e-16
4x^3	1.1102230246251565e-16	2.220446049250313e-16
5x^4	0.02777777777777779	2.220446049250313e-16
6x^5	0.08333333333333334	2.220446049250313e-16
7x^6	0.15740740740740744	0.0024999999999997247
Degrees	3	5

N	Gauss-Legendre results	Error
3	4.791666666666666	2.0448651327766343
4	1.8546365914786969	0.8921649424113349
5	3.5347396019544752	0.7879380680644434
6	2.3085027921188503	0.43829874177118144
7	3.0806104010709605	0.3338088671809287
11	2.812290560886776	0.0654890269967443
15	2.760067369009	0.013265835118968283

Observations and Analysis

It seems that the Gauss-Legendre method is really accurate depending on the number of intervals. Ideally errors should be around the order of magnitude of 10^{-16} which has been achieved with low levels of N , given that the interval is small (0 to 1). This is because numbers are infinite and computer memory is finite which means that the smallest possible number would be in order magnitude of -16 . The order of exactness = $2N - 1$. This means that the exactness will increase linearly to the number of interval.

Conclusion

In conclusion, Numerical integration has its limits. However, it is so close to its ideal mathematical expression that it can be overlooked.

In []: