ProblemSet2-Q2

January 21, 2019

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0.0.1 Problem Set #2
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MACS 30150, Dr. Evans

Due Monday, Jan. 21 at 11:30am

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2. Numerical integration exercises from Evans: Numerical Integration lab

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In [1]: import numpy as np
    import pandas as pd
    from scipy.stats import norm
```

```
Exercise 2.1
In [2]: def g_x(x):
            x = 0.1 * (x ** 4) - 1.5 * x ** 3 + 0.53 * x ** 2 + 2 * x + 1
            return x
        def integr_g_x(g, a , b, N, method):
            if method == "midpoint":
                #Calculate vector of N+1 bar bounds
                bin_cuts = np.linspace(a, b, N + 1)
                #Calculate vector of midpoints
                m = (b - a) / (2*N)
                midpoint = np.linspace(a + m, b - m, N)
                #Evaluate the function at the midpoint
                mid_val = g(midpoint)
                #Add up the area of the bins
                approx_integr = (b-a) / N * sum(mid_val)
            if method == "trapezoid":
                #Calculate vector of N+1 bar bounds
                bin_cuts = np.linspace(a, b, N + 1)
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#Evaluate the function at the bar bounds
                bin_val = g(bin_cuts)
                #Add up the area of the bins
                approx_integr = (b-a) / (2 * N) * (bin_val[0] + 2 * sum(bin_val[1 : N]) + bin_val[1 : N]) + bin_val[1 : N]) + bin_val[1 : N])
            if method == "Simpsons":
                #Calculate vector of N+1 bar bounds
                bin_cuts = np.linspace(a, b, 2*N + 1)
                #Evaluate the function at the bar bounds
                bin_val = g(bin_cuts)
                #Add up the value at bar bounds
                Sum = bin_val[0] + bin_val[2*N]
                for i in range(1, 2*N):
                    if i % 2 == 0:
                         Sum += 2 * bin_val[i]
                    else:
                         Sum += 4* bin_val[i]
                #Add up the area of the bins
                approx_integr = (b-a) / (6 * N) * Sum
            return approx_integr
In [3]: Val = 0.02*(10**5-(-10)**5)+0.53/3*(10**3-(-10)**3)+20
        #Midpoint rule
        M = integr_g_x(g_x, -10, 10, 10000, "midpoint")
        print("The approxiamation value using midpoint rule is: ", M)
        print("The difference with true value is: ", M - Val)
The approxiamation value using midpoint rule is: 4373.333196466634
The difference with true value is: -0.0001368666989947087
In [4]: #Trapezoid rule
        T = integr_g_x(g_x, -10, 10, 10000, "trapezoid")
        print("The approxiamation value using trapezoid rule is: ", T)
        print("The difference with true value is: ", T - Val)
The approximation value using trapezoid rule is: 4373.333607066684
The difference with true value is: 0.00027373335069569293
In [5]: #Simpson's rule
        S = integr_g_x(g_x, -10, 10, 10000, "Simpsons")
        print("The approxiamation value using Simpson's rule is: ", S)
        print("The difference with true value is: ", S - Val)
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The approximation value using Simpson's rule is: 4373.3333333337 The difference with true value is: 3.728928277269006e-11
```

Comparing the values of these integrals to the true analytical value of the integral, we find that Simpson's rule is more accurate.

Exercise 2.2

```
In [6]: def appro_norm(mu, sigma, N, k):
            #Calculate vector of nodes
            z = np.linspace(mu-k*sigma, mu+k*sigma, N)
            #Initialize vector of weights
            weight = np.zeros(N)
            #Calculate vector of weights
            weight[0] = norm.cdf((z[0]+z[1])/2, loc=mu, scale=sigma)
            for i in range(1, N-1):
                weight[i] = integr_g_x(lambda x: norm.pdf(x, loc=mu, scale=sigma), (z[i-1]+z[i]
            weight [N-1] = 1-\text{norm.cdf}((z[N-2]+z[N-1])/2, loc=mu, scale=sigma)
            n = {'nodes' : z, 'weight' : weight}
            df = pd.DataFrame(n)
            return df
        df = appro_norm(0, 1, 11, 3)
        df
Out[6]:
           nodes weight
            -3.0 0.003467
        0
        1
            -2.4 0.014397
        2
            -1.8 0.048943
        3
            -1.2 0.117253
            -0.6 0.198028
        5
             0.0 0.235823
        6
             0.6 0.198028
        7
              1.2 0.117253
        8
              1.8 0.048943
        9
              2.4 0.014397
              3.0 0.003467
        10
Exercise 2.3
In [7]: def appro_log_norm(mu, sigma, N, k):
```

#Calculate vector of nodes

a = np.e**z

z = np.linspace(mu-k*sigma, mu+k*sigma, N)

```
#Initialize vector of weights
            weight = np.zeros(N)
            #Calculate vector of weights
            weight[0] = norm.cdf((z[0]+z[1])/2, loc=mu, scale=sigma)
            for i in range(1, N-1):
                weight[i] = integr_g_x(lambda x: norm.pdf(x, loc=mu, scale=sigma), (z[i-1]+z[i]
            weight [N-1] = 1-\text{norm.cdf}((z[N-2]+z[N-1])/2, loc=mu, scale=sigma)
            n = {'node' : a, 'weight' : weight}
            df = pd.DataFrame(n)
            approxiamation = sum(df["node"]*df["weight"])
            return approxiamation, df
        appro, df = appro_log_norm(0, 1, 11, 3)
        appro
Out[7]: 1.6639409483466545
In [8]: df
Out[8]:
                 node
                       weight
        0
            0.049787 0.003467
        1
            0.090718 0.014397
        2
            0.165299 0.048943
        3
            0.301194 0.117253
        4
            0.548812 0.198028
        5
            1.000000 0.235823
            1.822119 0.198028
        6
        7
            3.320117 0.117253
            6.049647 0.048943
        8
          11.023176 0.014397
        10 20.085537 0.003467
Exercise 2.4
In [10]: appro, df = appro_log_norm(10.5, 0.8, 1000, 8)
        EI = np.e**(10.5+0.5*(0.8**2))
        difference = abs(appro - EI)
        print("approximation of the expected value of income: ", appro)
        print("expected value of income: ", EI)
        print("difference between these two values: ", difference)
approximation of the expected value of income: 50011.429102086586
expected value of income: 50011.08700852173
difference between these two values: 0.34209356485371245
```

Exercise 3.1

```
def gauss(f,a,b,n):
    # Find optimal weights and nodes using p_roots
    [node,weight] = p_roots(n)
    # Compute weight*node and convert the limits of [a, b] to [-1,1]
    G=0.5*(b-a)*sum(weight*f(0.5*(b-a)*node+0.5*(b+a)))
    return G

Gauss = gauss(lambda x: 0.1*x**4-1.5*x**3+0.53*x**2+2*x+1, -10, 10, 3)
    Newton = integr_g_x(lambda x: 0.1*x**4-1.5*x**3+0.53*x**2+2*x+1, -10, 10, 10000, "Simy Val = 0.02*(10**5-(-10)**5)+0.53/3*(10**3-(-10)**3)+20
    print("The result of Gaussian approximation is", Gauss, 'and the absolute error is', print("The result of Newton-Cotes approximation is", Newton, 'and the absolute error is', print("The result of Newton-Cotes approximation is", Newton, 'and the absolute error is', aprint("The result of Newton-Cotes approximation is", Newton, 'and the absolute error is', approximation is to the print of Newton-Cotes approximation is to the pri
```

The result of Gaussian approximation is 4373.333333333333 and the absolute error is 1.81898940. The result of Newton-Cotes approximation is 4373.33333333333 and the absolute error is 3.72892.

Compared with the results in Exercise 2.1, Gaussian approximate is more accurate.

In [13]: from scipy.special.orthogonal import p_roots

Exercise 3.2

The result of Python Gaussian approximate is 4373.33333333334 and the absolute error is 9.094

Exercise 4.1

```
for i in range(N):
               x = xran[i]
                y = yran[i]
                counter += fn(x, y)
            area = (omega[1] - omega[0]) * (omega[3] - omega[2])
            return area*counter/N
        np.random.seed(seed=25)
        while round(MC(circle, [-1, 1, -1, 1], N), 4) != 3.1415:
            N += 1
        print("The smallest number of random draws N is", N)
The smallest number of random draws N is 615
Exercise 4.2
In [16]: def isPrime(n):
            This function returns a boolean indicating whether an integer n is a
            prime number
            INPUTS:
            n = scalar, any scalar value
            OTHER FUNCTIONS AND FILES CALLED BY THIS FUNCTION: None
            OBJECTS CREATED WITHIN FUNCTION:
            i = integer in [2, sqrt(n)]
            FILES CREATED BY THIS FUNCTION: None
            RETURN: boolean
            ______
            for i in range(2, int(np.sqrt(n) + 1)):
                if n % i == 0:
                   return False
            return True
In [17]: def primes_ascend(N, min_val=2):
            This function generates an ordered sequence of N consecutive prime
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numbers, the smallest of which is greater than or equal to 1 using
            the Sieve of Eratosthenes algorithm.
            (https://en.wikipedia.org/wiki/Sieve_of_Eratosthenes)
            INPUTS:
                    = integer, number of elements in sequence of consecutive
                      prime numbers
            min_val = scalar >= 2, the smallest prime number in the consecutive
                      sequence must be greater-than-or-equal-to this value
            OTHER FUNCTIONS AND FILES CALLED BY THIS FUNCTION:
                isPrime()
            OBJECTS CREATED WITHIN FUNCTION:
            primes_vec
                         = (N,) vector, consecutive prime numbers greater than
                            min val
            MinIsEven
                         = boolean, =True if min_val is even, =False otherwise
            MinIsGrtrThn2 = boolean, =True if min_val is
                            greater-than-or-equal-to 2, =False otherwise
            curr_prime_ind = integer >= 0, running count of prime numbers found
            FILES CREATED BY THIS FUNCTION: None
            RETURN: primes_vec
            ______
            primes_vec = np.zeros(N, dtype=int)
            MinIsEven = 1 - min_val % 2
            MinIsGrtrThn2 = min_val > 2
            curr_prime_ind = 0
            if not MinIsGrtrThn2:
                i = 2
                curr_prime_ind += 1
                primes_vec[0] = i
            i = min(3, min val + (MinIsEven * 1))
            while curr_prime_ind < N:</pre>
                if isPrime(i):
                    curr_prime_ind += 1
                    primes_vec[curr_prime_ind - 1] = i
                i += 2
            return primes_vec
In [18]: def equidis(n,d,Type):
            prime = primes_ascend(d)
            if Type == 'Weyl':
                return list((i - i // 1) for i in np.sqrt(prime)*n)
            elif Type == 'Haber':
```

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return list((i - i // 1) for i in np.sqrt(prime)*n*(n+1)/2)
             elif Type == 'Niederreiter':
                 return list((i - i // 1) for i in [n*(2**(j/(n+1)))] for j in range(1, d+1)])
             elif Type == 'Baker':
                 return list((i - i // 1) for i in [n*np.exp(1/j)] for j in range(1, d+1)])
In [19]: equidis(10, 4, 'Weyl')
Out[19]: [0.142135623730951,
          0.32050807568877104,
          0.36067977499789805,
          0.4575131106459054]
In [20]: equidis(10, 4, 'Haber')
Out [20]: [0.7817459305202306,
          0.2627944162882443,
          0.9837387624884428,
          0.5163221085524867]
In [21]: equidis(10, 4, 'Niederreiter')
Out [21]: [0.6504108943996272,
          0.3431252219546259,
          0.08089444404447121,
          0.8666489800943182]
In [22]: equidis(10, 4, 'Baker')
Out [22]: [0.18281828459045002,
          0.4872127070012837,
          0.9561242508608956,
          0.8402541668774148]
Exercise 4.3
In [23]: def g(x,y):
             if x**2+y**2<1:
                 return 1
             else:
                 return 0
         np.random.seed(25)
         def QMC(fn, omega, N, Type):
             x1, x2=omega[0],omega[1]
             y1, y2=omega[2],omega[3]
             if Type=='Weyl':
                 xran=[2*np.array(equidis(i,2,'Weyl'))[0]-1 for i in range(N)]
                 yran=[2*np.array(equidis(i,2,'Weyl'))[1]-1 for i in range(N)]
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```
elif Type=='Haber':
                 xran=[2*np.array(equidis(i,2,'Haber'))[0]-1 for i in range(N)]
                 yran=[2*np.array(equidis(i,2,'Haber'))[1]-1 for i in range(N)]
             elif Type=='Niederreiter':
                 xran=[2*np.array(equidis(i,2,'Niederreiter'))[0]-1 for i in range(N)]
                 yran=[2*np.array(equidis(i,2,'Niederreiter'))[1]-1 for i in range(N)]
             elif Type=='Baker':
                 xran=[2*np.array(equidis(i,2,'Baker'))[0]-1 for i in range(N)]
                 yran=[2*np.array(equidis(i,2,'Baker'))[1]-1 for i in range(N)]
             counter = 0
             for i in range(N):
                 x = xran[i]
                 y = yran[i]
                 counter += fn(x, y)
             area = (omega[1] - omega[0])*(omega[3] - omega[2])
             return area*counter/N
In [24]: def f(x, y):
                 if x ** 2 + y ** 2 <= 1:
                     return 1
                 else:
                     return 0
         while round(QMC(f, [-1, 1, -1, 1], N, "Weyl"),4) != 3.1415:
             N += 1
         print("The smallest number of random draws N with Weyl sequence is", N)
The smallest number of random draws N with Weyl sequence is 1230
In [25]: N = 1
         while round(QMC(f, [-1, 1, -1, 1], N, "Haber"),4) != 3.1415:
             N += 1
         print("The smallest number of random draws N with Haber sequence is", N)
The smallest number of random draws N with Haber sequence is 2064
In [27]: N = 1
         while round(QMC(f, [-1, 1, -1, 1], N, "Niederreiter"),4) != 3.1415:
             N += 1
             if N > 5000:
                 print("The smallest number of random draws N with Niederreiter sequence exceed
                 break
         else:
             print("The smallest number of random draws N with Niederreiter sequence is", N)
```

The smallest number of random draws N with Niederreiter sequence exceeds 5000.

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In [29]: N = 1
     while round(QMC(f, [-1, 1, -1, 1], N, "Baker"),4) != 3.1415:
        N += 1

print("The smallest number of random draws N with Baker sequence is", N)
```

The smallest number of random draws N with Baker sequence is 205

From the above results, we can see that Baker sequence is the fastest one to converge to 3.1415, Weyl sequence is the second one, Haber sequence is the third one and Niederreiter sequence is the slowest one.

In []: