

NUR Hand-in 1

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Abstract

In this document, the solutions to the first hand-in exercise are presented.

1 Exercise 1: Poisson distribution

In this section, the solutions to the first exercise are presented.

Our script is given by:

```
1  '''This file implements a function that returns the poisson distribution for an integer
2  k.'''
3  import numpy as np
4  import matplotlib.pyplot as plt
5  from scipy.stats import poisson
6
7  def log_factorial(k):
8      '''Computes the factorial of a number in log space.'''
9      if k == 0:
10         result = 0
11     else:
12         k_values = np.arange(k, 0, -1)
13         result = np.sum(np.log(k_values))
14     return np.float32(result)
15
16  def log_poisson(lamb, k):
17      '''Computes the log of the poisson distribution for a positive mean lambda.'''
18      assert lamb > 0
19      k = np.int32(k)
20
21      result = k * np.log(lamb) - lamb - log_factorial(k)
22      return np.float32(result)
23
24  def poisson(lamb, k):
25      return np.float32(np.exp(log_poisson(lamb, k)))
26
27  lamb_k_values = np.array([np.array([1, 5, 3, 2.6, 100, 101], dtype=np.float32),
28                             np.array([0, 10, 21, 40, 5, 200], dtype=np.int32)])
29
30  np.set_printoptions(precision=8)
31
32  for i in range(len(lamb_k_values[0])):
33      lamb = lamb_k_values[0, i]
34      k = lamb_k_values[1, i]
35      poisson_val = poisson(lamb, k)
36      print(f'for lamb = {lamb:2f} and k = {k:1f}, P_lambda(k) = {poisson_val}'.format())
```

Poisson.py

As apparent from the code above, we have adopted a computation in log space. This avoids possible overflow errors and enables us to compute the Poisson probability for larger (λ, k) pairs. The output for a representative sample of pairs is given below, which demonstrates that the returned Poisson probability is accurate when compared to calculations done in online calculators.

```

1 for lamb = 1.000000 and k = 0.000000, P_lambda(k) = 0.3678794205188751
2 for lamb = 5.000000 and k = 10.000000, P_lambda(k) = 0.018132776021957397
3 for lamb = 3.000000 and k = 21.000000, P_lambda(k) = 1.019340254565515e-11
4 for lamb = 2.600000 and k = 40.000000, P_lambda(k) = 3.61510320423337e-33
5 for lamb = 100.000000 and k = 5.000000, P_lambda(k) = 3.1000581991562844e-36
6 for lamb = 101.000000 and k = 200.000000, P_lambda(k) = 1.2695239237170379e-18

```

poisson_output.txt

2 Exercise 2: Vandermonde Matrix

In this section we look at exercise 2, which is about Vandermonde matrices. The full script is presented below, and the parts of it specific to subquestions will be discussed in appropriate subsections.

Our script is given by:

```

1 # Main code body and plotting code adapted from Marcel van Daalen, at
2 # https://home.strw.leidenuniv.nl/~daalen/Handin_files/vandermonde.py
3
4 import numpy as np
5 import sys
6 import os
7 import matplotlib.pyplot as plt
8 import copy
9 import timeit
10
11 def crout(A):
12     m, n = A.shape
13     for i in range(m):
14         for j in range(n):
15             if i >= j:
16                 A[i, j] = A[i, j] - np.sum(A[i, :j]*A[:j, j])
17             else:
18                 A[i, j] = (A[i, j] - np.sum(A[i, :i]*A[:i, j]))/A[i, i]
19
20     return A
21
22 def forward_sub2(A, b):
23     m, _ = A.shape
24     y = copy.deepcopy(b)
25     for k in range(m):
26         y[k] = (b[k] - np.sum(A[k, :k]*y[:k]))/A[k, k]
27     return y
28
29 def backward_sub2(A, b):
30     _, n = A.shape
31     x = np.zeros_like(b)
32     for i in range(n-1, -1, -1):
33         x[i] = b[i] - np.dot(A[i, i+1:], x[i+1:])
34     return x
35
36 def get_coeffs(y, A):
37     A_decomp = crout(A)
38     fw_sub = forward_sub2(A_decomp, y)
39     coeffs = backward_sub2(A_decomp, fw_sub)
40
41     return coeffs, A_decomp
42
43 def polynomial(x, coeffs):
44     y = np.zeros_like(x)
45     for i in range(len(x)):
46         for j in range(len(coeffs)):
47             y[i] += coeffs[j] * x[i]**j
48     return y
49
50 # Let's get started
51 data=np.genfromtxt(os.path.join(sys.path[0], "Vandermonde.txt"), comments='#', dtype=np.
    float64)

```

```

52 |
53 | x=data[:,0]
54 | y=data[:,1]
55 |
56 | # Construct the matrix.
57 | A = np.zeros([20, 20])
58 | m, n = A.shape
59 | for i in range(m):
60 |     for j in range(n):
61 |         A[i, j] = x[i]**j
62 |
63 | A_orig = copy.deepcopy(A)
64 | # now set up the polynomial function!
65 |
66 | coeffs, crout_LU = get_coeffs(y, A)
67 | xx=np.linspace(x[0],x[-1],1001) #x values to interpolate at
68 | yya = polynomial(xx, coeffs)
69 | ya= polynomial(x, coeffs)
70 |
71 | # Now we'd like to implement neville's algorithm.
72 |
73 | def neville(datax, datay, x_interp):
74 |     y_interp = []
75 |     error_est = []
76 |     for x in x_interp:
77 |         y = datay.copy()
78 |         M = len(datax)
79 |
80 |         for k in range(1, M):
81 |             for i in range(M-k):
82 |                 y[i] = ((x - datax[i+k])*y[i] + (datax[i] - x)*y[i+1]) / (datax[i] -
83 | datax[i+k])
84 |             y_interp.append(y[0])
85 |             error_est.append(np.abs(y[0] - y[1]))
86 |         return y_interp, error_est
87 |
88 | yyb, yyb_err= neville(x, y, xx)
89 | yb, yb_err= neville(x, y, x)
90 |
91 | # Let's implement the error canceling algorithm.
92 |
93 | def error_cancel(A_orig, crout_LU, y, coeffs, iterations):
94 |     for _ in range(iterations):
95 |         v = A_orig @ coeffs - y
96 |         fw_result = forward_sub2(crout_LU, v)
97 |         coeff_corr = backward_sub2(crout_LU, fw_result)
98 |         coeffs = coeffs - coeff_corr
99 |     return coeffs
100 |
101 | c1_coeffs = error_cancel(A_orig, crout_LU, y, coeffs, iterations=1)
102 | yyc1= polynomial(xx, c1_coeffs)
103 | yc1= polynomial(x, c1_coeffs)
104 |
105 | c10_coeffs = error_cancel(A_orig, crout_LU, y, coeffs, iterations=10)
106 | yyc10= polynomial(xx, c10_coeffs)
107 | yc10= polynomial(x, c10_coeffs)
108 |
109 | #Don't forget to output the coefficients you find with your LU routine
110 | print('Coefficients found with LU method (a):\n', coeffs)
111 |
112 | print('Coefficients found with 1 iteration of LU correction (c):\n', c1_coeffs)
113 |
114 | print('Coefficients found with 10 iterations of LU correction (c):\n', c10_coeffs)
115 | #Plot of points with absolute difference shown on a log scale (question 2a)
116 | fig=plt.figure()
117 | gs=fig.add_gridspec(2, hspace=0, height_ratios=[2.0, 1.0])
118 | axs=gs.subplots(sharex=True, sharey=False)
119 | axs[0].plot(x,y, marker='o', linewidth=0)
120 | plt.xlim(-1,101)

```

```

121 axs[0].set_ylim(-400,400)
122 axs[0].set_ylabel('$y$')
123 axs[1].set_ylim(1e-16,1e1)
124 axs[1].set_ylabel('$|y-y_i|$')
125 axs[1].set_xlabel('$x$')
126 axs[1].set_yscale('log')
127 line,=axs[0].plot(xx,yya,color='orange')
128 line.set_label('Via LU decomposition')
129 axs[0].legend(frameon=False,loc="lower left")
130 axs[1].plot(x,abs(y-ya),color='orange')
131 plt.savefig('my_vandermonde_sol.2a.png',dpi=600)
132
133 #For questions 2b and 2c, add this block
134 line,=axs[0].plot(xx,yyb,linestyle='dashed',color='green')
135 line.set_label('Via Neville\'s algorithm')
136 axs[0].legend(frameon=False,loc="lower left")
137 axs[1].plot(x,abs(y-yb),linestyle='dashed',color='green')
138 plt.savefig('my_vandermonde_sol.2b.png',dpi=600)
139
140 #For question 2c, add this block too
141 line,=axs[0].plot(xx,yc1,linestyle='dotted',color='red')
142 line.set_label('LU with 1 iteration')
143 axs[1].plot(x,abs(y-yc1),linestyle='dotted',color='red')
144 line,=axs[0].plot(xx,yc10,linestyle='dashdot',color='purple')
145 line.set_label('LU with 10 iterations')
146 axs[1].plot(x,abs(y-yc10),linestyle='dashdot',color='purple')
147 axs[0].legend(frameon=False,loc="lower left")
148 plt.savefig('my_vandermonde_sol.2c.png',dpi=600)
149
150 #Don't forget to caption your figures to describe them/
151 #mention what conclusions you draw from them!
152
153 # Now, finally, time the different methods.
154
155 def problem_2a():
156     coeffs, crout_LU = get_coeffs(y, A)
157     yya = polynomial(xx, coeffs)
158
159 def problem_2b():
160     yyb, yyb_err= neville(x, y, xx)
161
162 def problem_2c():
163     coeffs, crout_LU = get_coeffs(y, A)
164     c10_coeffs = error_cancel(A_orig, crout_LU, y, coeffs, iterations=10)
165     yyc10= polynomial(xx, c10_coeffs)
166
167 number = 150
168 two_a_time = timeit.timeit(lambda : problem_2a(), number = number)
169
170 two_b_time = timeit.timeit(lambda : problem_2b(), number = number)
171
172 two_c_time = timeit.timeit(lambda : problem_2c(), number = number)
173
174 print(f'Time for {number} iterations of 2a:', two_a_time)
175 print(f'Time for {number} iterations of 2b:', two_b_time)
176 print(f'Time for {number} iterations of 2c:', two_c_time)

```

Vandermonde.py

2.1 2a: fitting by LU decomposition

The relevant code is given by:

```

1 import numpy as np
2 import sys
3 import os
4 import matplotlib.pyplot as plt
5 import copy
6 import timeit

```

```

7
8 def crout(A):
9     m, n = A.shape
10    for i in range(m):
11        for j in range(n):
12            if i >= j:
13                A[i, j] = A[i, j] - np.sum(A[i, :j]*A[:j, j])
14            else:
15                A[i, j] = (A[i, j] - np.sum(A[i, :i]*A[:i, j]))/A[i, i]
16
17    return A
18
19 def forward_sub2(A, b):
20     m, _ = A.shape
21     y = copy.deepcopy(b)
22     for k in range(m):
23         y[k] = (b[k] - np.sum(A[k, :k]*y[:k]))/A[k, k]
24     return y
25
26 def backward_sub2(A, b):
27     _, n = A.shape
28     x = np.zeros_like(b)
29     for i in range(n-1, -1, -1):
30         x[i] = b[i] - np.dot(A[i, i+1:], x[i+1:])
31     return x
32
33 def get_coeffs(y, A):
34     A_decomp = crout(A)
35     fw_sub = forward_sub2(A_decomp, y)
36     coeffs = backward_sub2(A_decomp, fw_sub)
37
38     return coeffs, A_decomp
39
40 def polynomial(x, coeffs):
41     y = np.zeros_like(x)
42     for i in range(len(x)):
43         for j in range(len(coeffs)):
44             y[i] += coeffs[j] * x[i]**j
45     return y
46
47 # Let's get started
48 data=np.genfromtxt(os.path.join(sys.path[0], "Vandermonde.txt"), comments='#', dtype=np.
49                    float64)
50
51 x=data[:,0]
52 y=data[:,1]
53
54 # Construct the matrix.
55 A = np.zeros([20, 20])
56 m, n = A.shape
57 for i in range(m):
58     for j in range(n):
59         A[i, j] = x[i]**j
60
61 A_orig = copy.deepcopy(A)
62 # now set up the polynomial function!
63
64 coeffs, crout_LU = get_coeffs(y, A)
65 xx=np.linspace(x[0], x[-1], 1001) #x values to interpolate at
66 yya = polynomial(xx, coeffs)
67 ya= polynomial(x, coeffs)

```

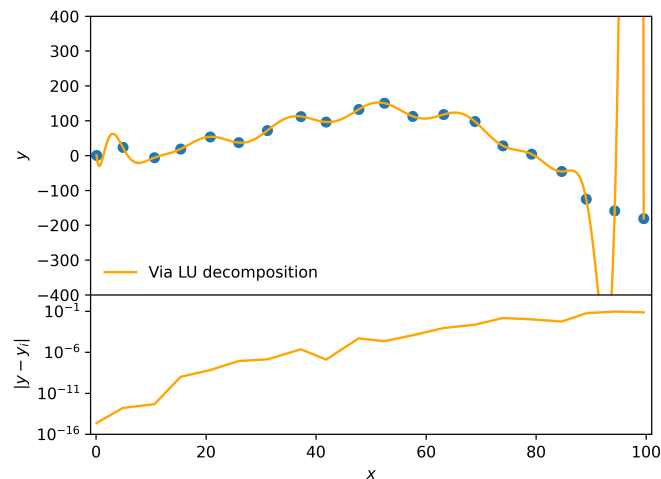
Vandermonde.py

We start by reading in the data points and constructing the $N \times N$ Vandermonde matrix with each entry of the form $V_{ij} = x_i^j$, with i the row index and j the column index (both up to $N - 1$). We then find the coefficients for the unique polynomial that goes through all given points by solving the system $\mathbf{V}\mathbf{c} = \mathbf{y}$ with \mathbf{y} the given y -values for the points.

To do this, we overwrite the Vandermonde matrix by its LU decomposition using Crout's algorithm.

We then solve the system by applying forward substitution, followed by backward substitution.
The result is the unique polynomial given in figure 2.1.

Figure 1: Upper half: the given points in blue, with the polynomial interpolation using LU decomposition in orange. Bottom half: the absolute difference between the interpolation and the given y value at the given points.



```

1 Coefficients found with LU method (a):
2 [ 1.70147517e+01 -1.86599980e+02  2.37038854e+02 -1.09410937e+02
3   2.67337487e+01 -4.05711019e+00  4.16236505e-01 -3.03795406e-02
4   1.63051551e-03 -6.57955383e-05  2.02524984e-06 -4.79493741e-08
5   8.75580154e-10 -1.22942095e-11  1.31443054e-13 -1.05004562e-15
6   6.06574150e-18 -2.39219555e-20  5.76088051e-23 -6.38865757e-26]

```

Vandermonde_output.txt

2.2 2b: fitting by Neville's algorithm

The relevant code is given by:

```

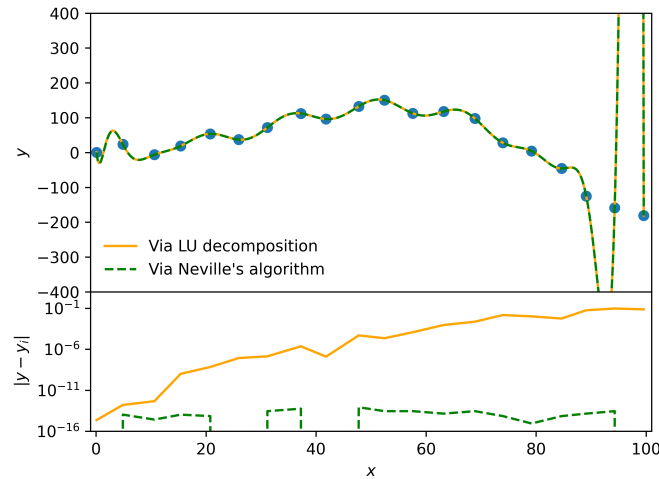
1
2 # Now we'd like to implement neville's algorithm.
3
4 def neville(datax, datay, x_interp):
5     y_interp = []
6     error_est = []
7     for x in x_interp:
8         y = datay.copy()
9         M = len(datax)
10
11         for k in range(1, M):
12             for i in range(M-k):
13                 y[i] = ((x - datax[i+k])*y[i] + (datax[i] - x)*y[i+1]) / (datax[i] -
14 datax[i+k])
15                 y_interp.append(y[0])
16                 error_est.append(np.abs(y[0] - y[1]))
17         return y_interp, error_est
18
19 yyb, yyb_err= neville(x, y, xx)
20 yb, yb_err= neville(x, y, x)

```

Vandermonde.py

Here, we simply pass an array of values to be interpolated into our Neville interpolation function. The resulting polynomial lies on top of the polynomial found in 2a. This is to be expected, as there is a single unique 19th order polynomial that goes through all of these points. See figure 2.2 below:

Figure 2: Upper half: the given points in blue, with the polynomial interpolation using LU decomposition in orange. The polynomial found by Neville's algorithm has been added, and we see that it lies on top of the previous one. Bottom half: the absolute difference between the interpolation and the given y value at the given points. The absolute difference for the second method is orders of magnitude smaller.



```

1 Coefficients found with 1 iteration of LU correction (c):
2 [ 1.73261060e+01 -1.89903192e+02  2.39192506e+02 -1.10031275e+02
3   2.68385894e+01 -4.06885525e+00  4.17169348e-01 -3.04342928e-02
4   1.63295507e-03 -6.58795060e-05  2.02750625e-06 -4.79969536e-08
5   8.76367347e-10 -1.23043727e-11  1.31544235e-13 -1.05080648e-15
6   6.06991727e-18 -2.39377260e-20  5.76454210e-23 -6.39259513e-26]
```

Vandermonde_output.txt

In the next subsection, we shall discuss possible reasons for the difference in absolute error between methods.

2.3 2c: error-cancellation using LU decomposition

The relevant code is given by:

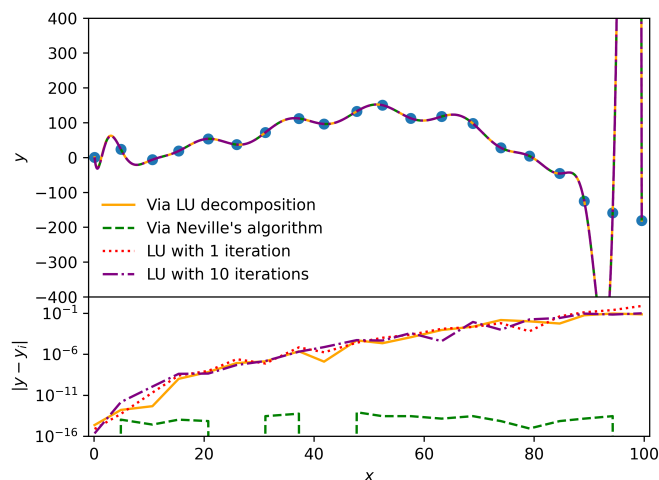
```

1 # Let's implement the error canceling algorithm.
2
3
4 def error_cancel(A_orig, crout_LU, y, coeffs, iterations):
5     for _ in range(iterations):
6         v = A_orig @ coeffs - y
7         fw_result = forward_sub2(crout_LU, v)
8         coeff_corr = backward_sub2(crout_LU, fw_result)
9         coeffs = coeffs - coeff_corr
10    return coeffs
11
12 c1_coeffs = error_cancel(A_orig, crout_LU, y, coeffs, iterations=1)
13 yyc1= polynomial(xx, c1_coeffs)
14 yc1= polynomial(x, c1_coeffs)
15
16 c10_coeffs = error_cancel(A_orig, crout_LU, y, coeffs, iterations=10)
17 yyc10= polynomial(xx, c10_coeffs)
18 yc10= polynomial(x, c10_coeffs)
```

Vandermonde.py

We now iterate on the solution of 2a. We can use the LU matrices calculated previously and solve a new system to find a correction on the coefficients. We do this once with 1 iteration, and then once more with 10 iterations of the error-cancelling algorithm. The results are shown in figure 2.3.

Figure 3: Upper half: the given points in blue, with the polynomial interpolation using LU decomposition in orange, as well as the polynomial found by Neville's algorithm. We have now added 2 additional interpolations, for different iterations of the LU error canceling algorithm. Bottom half: the absolute difference between the interpolation and the given y value at the given points. The absolute difference for the second method is orders of magnitude smaller. The error-canceled LU interpolations are very similar to the initial LU interpolation.



```

1 Coefficients found with 10 iterations of LU correction (c):
2 [ 1.76004367e+01 -1.92813615e+02  2.41090086e+02 -1.10577877e+02
3   2.69309767e+01 -4.07920689e+00  4.17991738e-01 -3.04825810e-02
4   1.63510778e-03 -6.59536551e-05  2.02950069e-06 -4.80390585e-08
5   8.77064968e-10 -1.23133950e-11  1.31634240e-13 -1.05148487e-15
6   6.07365027e-18 -2.39518661e-20  5.76783589e-23 -6.39614985e-26]

```

Vandermonde_output.txt

2.4 2d: Timing the interpolation

Using the timeit module, we execute the code from 2a, 2b and 2c 150 times each. The results are given below:

```

1 Time for 150 iterations of 2a: 1.913271800003713
2 Time for 150 iterations of 2b: 28.733681085999706
3 Time for 150 iterations of 2c: 2.0703072220057948

```

Vandermonde_output.txt

We see that the LU decomposition method is quite quick, and the error cancelling doesn't add that much more time. Neville's algorithm is the clear loser when it comes to efficiency. When we take into account accuracy, though, it becomes apparent that Neville's algorithm does have significantly lower errors in this application. A possible cause for error with the LU decomposition method is roundoff.

We also see that iteration on the LU method