104A: Homework 3

Daniel Naylor

Question 1

(a)

We know that

$$P_n(x) = \sum_{j=0}^n \left(f_j \prod_{k \neq j} \frac{x - x_k}{x_j - x_k} \right)$$
$$= \sum_{k=1}^n \left(f[x_0, \dots, x_k] \prod_{j=0}^{k-1} (x - x_j) \right) + f[x_0]$$

The coefficient for x^n in Newton's DD is $f[x_0, \ldots, x_n]$, and each Lagrange Polynomial is degree n. Hence, if we differentiate both equations n times we find

$$f[x_0, \dots, x_n] \cdot n! = n! \cdot \sum_{j=0}^n \left(f_j \prod_{k \neq j} \frac{1}{x_j - x_n} \right)$$

$$\implies f[x_0, \dots, x_k] = \sum_{j=0}^n \frac{f_j}{\prod_{k \neq j} x_j - x_k}$$

(b)

Consider any permutation of x_0, \ldots, x_n , and call it $\sigma(x_0, \ldots, x_n)$. We find that the sum of the Lagrangian Polynomials remains unchanged since each data point must reappear at some step in construction. Proceeding in a manner similar to above (differentiating n times) we find

$$f[\sigma(x_0,\ldots,x_n)] = \sum_{j=0}^n \frac{f_j}{\prod_{k\neq j} x_j - x_k}$$

Hence $f[x_0, \ldots, x_n] = f[\sigma(x_0, \ldots, x_n)]$

Question 2

See attached PDF.

Question 3

We know that

$$f[x_0, \dots, x_k] = \frac{f[x_1, \dots, x_k] - f[x_0, \dots, x_{k-1}]}{x_k - x_0}$$

Hence

$$f^{-1}[y_0, y_1] = \frac{f^{-1}[y_1] - f^{-1}[y_0]}{y_1 - y_0}$$

Yet $f^{-1}[y_j] = f^{-1}(y_j) = x_j$, so

$$f^{-1}[y_0, y_1] = \frac{x_1 - x_0}{y_1 - y_0}$$

Forming a P_1 approximation from this we find

$$P_1(0) = f^{-1}[y_0] + f^{-1}[y_0, y_1](0 - y_0)$$

= $x_0 - y_0 \cdot \frac{x_1 - x_0}{y_1 - y_0}$

Given that f(0.5) = -0.106530659712633 and f(0.6) = 0.05118836390597 (for $f(x) = x - e^{-x}$), we find that

$$P_1(0) = 0.5 + 0.106530659712633 \cdot \frac{0.6 - 0.5}{0.05118836390597 + 0.106530659712633}$$
$$= 0.5675445848373328$$

Which gives us an approximation for \bar{x} , a zero of f.

Question 4

We know that

$$f[\underbrace{x_j, \dots, x_j}_{n+2 \text{ nodes}}] = \frac{f^{(n+1)}(x_j)}{(n+1)!}$$

Hence f[0,0] = f'(0) = 0 and f[1,1] = f'(1) = 3. Using this we find

$$f[0] = 0$$

$$f[0,0] = 0$$

$$f[0,0,1] = 2$$

$$f[0,0,1,1] = -1$$

Hence we obtain our 3rd degree polynomial by

$$P_3(x) = 0 + 0(x - 0) + 2(x - 0)^2 - 1(x - 0)^2(x - 1) = 3x^2 - x^3$$

Question 5

See attached PDF.

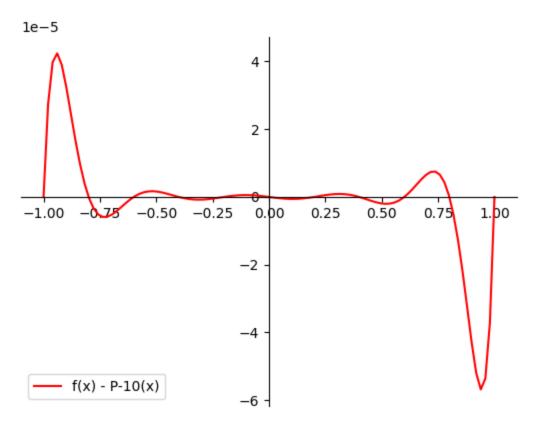
Question 6

See attached PDF.

```
Daniel Naylor
5094024
10/30/2022
r r r
import math
import matplotlib.pyplot as plt
import numpy as np
from typing import List, Tuple
                      Problem 2
def compute divided diff array(data: List[Tuple[float, float]]) -> List[float]:
    IIII
    Given a dataset, return a 1-dimensional array of Divided Difference coefficients.
    The returned array will be of the form:
        f[x_0],
       f[x_0, x_1],
        f[x_0, x_1, ..., x_n]
    J
    ,,,
    n plus 1 = len(data)
    c = [] # the array to return.
    # the name 'c' is used since c[0] corresponds to the first coefficient; easier to read
    for j in range(n plus 1): \# j = 0, \ldots n
        c.append(data[j][1])
    for k in range(1, n_plus_1): \# k = 1, ..., n
        for j in range(n_plus_1-1, k-1, -1): \# j = n, n-1, ..., k
            c[j] = (c[j] - c[j-1]) / (data[j][0] - data[j-k][0])
    return c
test data = [
    (0, 1),
    (1, 2),
    (2, 3),
    (3, 4)
1
print(compute divided diff array(test data))
# output: [1, 1.0, 0.0, 0.0]. correct since this is the polynomial x+1
class poly approx:
    Creates a polynomial approximation given a dataset.
    Acts like a mathematical function.
    ### Attributes
    `data`: The given data
    `coeffs`: The Divided Difference Coefficients, computed with `data`.
    , , ,
        init (self, data: List[Tuple[float, float]]) -> None:
    def
        Creates a polynomial given a dataset. The data should be of the form
        [
```

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(x_0, f_0),
            (x_1, f_1),
            . . .
            (x_n, f_n)
        For example, `[(0, 1), (1, 2), (2, 3)]` for `x+1`
        would be an appropriate dataset.
        self.data = data
        self.coeffs = compute_divided_diff_array(data)
    def call (self, x: float, /) -> float:
        p = self.coeffs[-1]
        for j in range(len(self.data) - 1, -1, -1): \# j = n, n-1, \ldots, 0
            p = self.coeffs[j] + p * (x - self.data[j][0])
        return p
def f(x: float) -> float:
    f(x) = e^{-(-x^2)}
   return math.exp(-x**2)
p 10 data = [
    (j/5 - 1, f(j/5 - 1))
    for j in range(11) \# j = 0, ..., 10
p_10 = poly_approx(p_10_data)
# graphing everything...
domain = np.linspace(-1, 1, 100)
error graph = np.array([
   f(x) - p 10(x)
    for x in domain
])
fig = plt.figure()
ax = fig.add subplot(1, 1, 1)
ax.spines['left'].set position('center')
ax.spines['bottom'].set position('zero')
ax.spines['right'].set_color('none')
ax.spines['top'].set_color('none')
ax.xaxis.set ticks position('bottom')
ax.yaxis.set_ticks_position('left')
plt.plot(domain, error_graph, 'r', label='f(x) - P-10(x)')
plt.legend(loc='lower left')
plt.show()
```



```
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Daniel Naylor
5094024
11/09/2022
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from typing import List, Tuple
                      Problem 5
# natural spline: z = 0 = z = 0
class NaturalSplineInterpolation:
    , , ,
    A natural spline interpolation (piecewise cubic polynomial)
    of a given dataset.
    This class acts like a mathematical function,
    i.e. it can be called with a number as input
    and gives a number as output.
    def init (self, data: List[Tuple[float, float]]) -> None:
        Initializes a spline interpolation based on the given data.
        Data should be of the form:
            (x 0, f 0),
            (x_1, f_1),
            (x n, f n)
        ]
        Each `x` value should be sorted. For example, [(0, 1), (-1, 0)] is an invalid data
input,
        and instead should be [(-1, 0), (0, 1)].
        n = len(data) - 1
        assert n > 0, 'Please provide a valid dataset (at least 2 points)'
        self. data = data
        z = \{ \text{ # natural spline, set } z\_0 \text{ and } z\_n \text{ first }
           0: 0,
            n: 0
        h = [ \# compute values for h_j, length of each sub-interval.
            data[j+1][0] - data[j][0]
            for j in range(n) # 0, ..., n-1
        ]
        # solve for 1, m values
        # use a dictionary for ease of assigning values
        l=\{\} # using 1, ..., n-2
        m = \{1: 2 * (h[0] + h[1])\} # 1, ..., n-1
        for j in range(1, n-1): # 1, ..., n-2
            l[j] = h[j]/m[j]
            m[j+1] = 2 * (h[j] + h[j+1]) - (l[j] * h[j])
        \# compute values of y (what the sums of z add to)
        y= {
            j: -6 * (data[j][1] - data[j-1][1])/(h[j-1]) + 6 * (data[j+1][1] - data[j]
[1])/h[j]
            for j in range(1, n) # 1, ..., n-1
        }
```

```
\# compute the values of k (what the matrix product of right-upper and z's produce)
        k = \{1: y[1]\}
        for j in range(2, n):
            k[j] = y[j] - l[j-1] * k[j-1]
        # finally, compute the remaining z values using k
        # note: this abuses the lower triangular property
        z[n-1] = k[n-1]/m[n-1]
        for j in range(n-2, 0, -1): \# n-2, ..., 1
            z[j] = (k[j] - h[j] * z[j+1])/m[j]
        # FINALLY, compute a, b, c, d coefficients
        a, b, c, d = \{\}, \{\}, \{\}\}
        for j in range(n):
            a[j] = (z[j+1] - z[j]) / (6 * h[j])
            b[j] = z[j]/2
            c[j] = (data[j+1][1] - data[j][1])/h[j] - h[j]/6 * (z[j+1] + 2 * z[j])
            d[j] = data[j][1]
        self. a, self. b, self. c, self. d = a, b, c, d
    def call (self, x: float, /) -> float:
        # determine suitable piecewise spline S j using the following heuristic:
        \# find maximum j such that x \le x (j+1).
        \# if no such j (for whatever reason), then use j=n-1.
        if (x \ge self._data[-2][0]):
            j=len(self._data) - 2
        else:
            \dot{\mathbf{j}} = 0
            while (x > self. data[j+1][0]):
                j=j+1
        shifted x = x - self. data[j][0]
        return self._a[j] * shifted_x**3 + self._b[j] * shifted_x**2 + self._c[j] * shifted_x
+ self. d[j]
# test data
data = [
    (0, 5),
    (1, 3),
    (3, 8),
    (6, -1)
approx = NaturalSplineInterpolation(data=data)
print(
    f'1: {approx(1)}',
    f'2: {approx(2)}',
    f'3: {approx(3)}',
    f'5: {approx(5)}',
    sep='\n'
# Output
# 1: 3.0
# 2: 5.125
# 3: 8.0
# 5: 4.0
```

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```
Daniel Naylor
5094024
11/09/2022
r r r
import numpy as np
import matplotlib.pyplot as plt
from tabulate import tabulate as tab
from typing import List, Tuple
                      Problem 6
class NaturalSplineInterpolation:
    A natural spline interpolation (piecewise cubic polynomial)
    of a given dataset.
    This class acts like a mathematical function,
    i.e. it can be called with a number as input
    and gives a number as output.
    , , ,
    def init (self, data: List[Tuple[float, float]]) -> None:
        Initializes a spline interpolation based on the given data.
        Data should be of the form:
        [
            (x 0, f 0),
            (x_1, f_1),
            (x n, f n)
        J
        Each 'x' value should be sorted. For example, (0, 1), (-1, 0) is an invalid data
input,
        and instead should be [(-1, 0), (0, 1)].
        n = len(data) - 1
        assert n > 0, 'Please provide a valid dataset (at least 2 points)'
        self. data = data
        z = \{ \text{ # natural spline, set } z \text{ 0 and } z \text{ n first} \}
           0: 0,
            n: 0
        h = [ # compute values for h j, length of each sub-interval.
            data[j+1][0] - data[j][0]
            for j in range(n) # 0, ..., n-1
        # solve for 1, m values
        # use a dictionary for ease of assigning values
        l={} # using 1, ..., n-2
        m=\{1: 2 * (h[0] + h[1])\} # 1, ..., n-1
        for j in range(1, n-1): # 1, ..., n-2
            l[j] = h[j]/m[j]
            m[j+1] = 2 * (h[j] + h[j+1]) - (l[j] * h[j])
        # compute values of y (what the sums of z add to)
            j: -6 * (data[j][1] - data[j-1][1])/(h[j-1]) + 6 * (data[j+1][1] - data[j]
[1])/h[j]
            for j in range(1, n) # 1, ..., n-1
        }
```

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```
# compute the values of k (what the matrix product of right-upper and z's produce)
        k = \{1: y[1]\}
        for j in range(2, n):
            k[j] = y[j] - l[j-1] * k[j-1]
        # finally, compute the remaining z values using k
        # note: this abuses the lower triangular property
        z[n-1] = k[n-1]/m[n-1]
        for j in range(n-2, 0, -1): \# n-2, ..., 1
            z[j] = (k[j] - h[j] * z[j+1])/m[j]
        # FINALLY, compute a, b, c, d coefficients
        a, b, c, d = \{\}, \{\}, \{\}\}
        for j in range(n):
            a[j] = (z[j+1] - z[j]) / (6 * h[j])
            b[j] = z[j]/2
            c[j] = (data[j+1][1] - data[j][1])/h[j] - h[j]/6 * (z[j+1] + 2 * z[j])
            d[j] = data[j][1]
        self. a, self. b, self. c, self. d = a, b, c, d
    def call (self, x: float, /) -> float:
        # determine suitable piecewise spline S j using the following heuristic:
        # find maximum j such that x \le x (j+1).
        \# if no such j (for whatever reason), then use j=n-1.
        if (x \ge self. data[-2][0]):
            j=len(self. data) - 2
        else:
            while (x > self._data[j+1][0]):
                j=j+1
        shifted x = x - self._data[j][0]
        return self. a[j] * shifted x**3 + self. b[j] * shifted x**2 + self. c[j] * shifted x
+ self. d[j]
# test data
x data = [
    (0, 1.5),
    (0.618, 0.90),
    (0.935, 0.60),
    (1.255, 0.35),
    (1.636, 0.20),
    (1.905, 0.10),
    (2.317, 0.50),
    (2.827, 1.00),
    (3.330, 1.50)
y data = [
    (0, 0.75),
    (0.618, 0.90),
    (0.935, 1.00),
    (1.255, 0.80),
    (1.636, 0.45),
    (1.905, 0.20),
    (2.317, 0.10),
    (2.827, 0.20),
    (3.330, 0.25)
x approx = NaturalSplineInterpolation(data=x data)
y approx = NaturalSplineInterpolation(data=y data)
```

]

```
'j': [x for x in range(8)],
   'a_j': [*x_approx._a.values()],
   'b j': [*x approx. b.values()],
   'c_j': [*x_approx._c.values()],
   'd_j': [*x_approx._d.values()]
}
print(tab(x coeffs table, headers='keys'))
\# j a_j b_j c_j d_j
  0 0.0105369 0 -0.974898 1.5
# 1 0.102103 0.0195355 -0.962825 0.9
  2 0.987167 0.116635 -0.919659 0.6
3 -1.77355 1.06432 -0.541755 0.35
               -0.962851 -0.503097 0.2
# 4 5.39457
# 5 -3.39333
                3.39057 0.149959 0.1
  6 0.670643 -0.803594
                           1.21579 0.5
  7 -0.147442 0.22249 0.919428 1
y coeffs table = {
   'j': [y for y in range(8)],
   'a_j': [*y_approx._a.values()],
   'b_j': [*y_approx._b.values()],
   'c_j': [*y_approx._c.values()],
   'd_j': [*y_approx._d.values()]
print(tab(y coeffs table, headers='keys'))
  j a_j
                     b_ j
# 0 0.276944 0
                          0.136947 0.75
# 1 -3.00101 0.513454
# 2 2.43045 -2.34051
                          0.454261 0.9
                           -0.124915
                                      1
                                      0.8
  3 -0.273187 -0.00727664 -0.876207
# 4 2.1739 -0.31953 -1.00072
                                      0.45
# 5 -0.784397 1.4348
                          -0.700711
  6 -0.474226 0.465289
                          0.0821273 0.1
  7 0.172483 -0.260277 0.186683 0.2
# graph the parametric function...
t = np.linspace(0, 3.33, 400)
x = np.array([
   x approx(i)
   for i in t
])
y = np.array([
 y approx(i)
  for i in t
])
fig, ax = plt.subplots()
ax.plot(x, y)
plt.show()
```

x coeffs table = {

