# Notebook

January 4, 2020

NBBinder test on a collection of notebooks about some thermodynamic properperties of water

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# 1 Low-Dimensional Fittings

We use the classical least-square method to fit low degree polynomials to the data.

See e.g. Golub and Van Loan (1996) and Trefethen and Bau III (1997) for details on the least-square method.

## 1.1 Importing the libraries

```
[1]: import csv import numpy as np import matplotlib.pyplot as plt
```

## 1.2 Loading the data

This time we use the csv library to read the data from file and use numpy to work with the data.

#### 1.2.1 Loading with csv

We first load the data into a python list with csv.

```
[2]: file = open('water.csv', "r")
water_csv = list(csv.reader(file, delimiter=","))
water_csv
```

```
[2]: [['temp', 'density', 'viscosity'],
        ['Temperature (C)', 'Density (g/cm^3)', 'Viscosity (cm^2/s)'],
        ['0', '0.9999', '0.01787'],
```

```
['5', '1', '1.514'],
['10', '0.9997', '1.304'],
['15', '0.9991', '1.138'],
['20', '0.9982', '1.004'],
['25', '0.9971', '0.894'],
['30', '0.9957', '0.802'],
['35', '0.9941', '0.725'],
['40', '0.9923', '0.659'],
['50', '0.9881', '0.554'],
['60', '0.9832', '0.475'],
['70', '0.9778', '0.414'],
['80', '0.9718', '0.366'],
['90', '0.9653', '0.327'],
['100', '0.9584', '0.295']]
```

#### 1.2.2 Header and datapoints

[9.000e+01 9.653e-01 3.270e-01] [1.000e+02 9.584e-01 2.950e-01]]

We separate the header from the datapoints and have the datapoints put into a numpy array as follows.

```
[3]: header = dict([(water_csv[0][i],water_csv[1][i]) for i in range(3)])
     print(header)
    {'temp': 'Temperature (C)', 'density': 'Density (g/cm^3)', 'viscosity':
    'Viscosity (cm<sup>2</sup>/s)'}
[4]: datapoints = np.array(water_csv[2:]).astype("float")
     print(datapoints)
    [[0.000e+00 9.999e-01 1.787e-02]
     [5.000e+00 1.000e+00 1.514e+00]
     [1.000e+01 9.997e-01 1.304e+00]
     [1.500e+01 9.991e-01 1.138e+00]
     [2.000e+01 9.982e-01 1.004e+00]
     [2.500e+01 9.971e-01 8.940e-01]
     [3.000e+01 9.957e-01 8.020e-01]
     [3.500e+01 9.941e-01 7.250e-01]
     [4.000e+01 9.923e-01 6.590e-01]
     [5.000e+01 9.881e-01 5.540e-01]
     [6.000e+01 9.832e-01 4.750e-01]
     [7.000e+01 9.778e-01 4.140e-01]
     [8.000e+01 9.718e-01 3.660e-01]
```

## 1.3 Linear approximation

Given a set of temperature and density data in the form  $(T_j, \rho_j)$ , we look for a linear relation  $\rho^{(1)}(T) = c + mT$  which is the "best fit" for the data.

One way to approach this problem is to interpret the best fit as minimizing the sum of squares of the residuals. The **residual** for each j measurement is

$$r_j = \rho_j - \rho^{(1)}(T_j),$$

and the sum of squares of the residuals is

$$\min_{c,m\in\mathbb{R}}\sum_{j}(\rho_{j}-\rho^{(1)}(T))^{2}.$$

#### 1.3.1 Matrix form

This can be written in matrix form as

$$\min_{\mathbf{u} \in \mathbb{R}^2} \|A\mathbf{u} - \mathbf{f}\|_2^2,$$

where  $\|\cdot\|_2$  is the Euclidian norm of a vector and

$$A = \begin{bmatrix} T_1 & 1 \\ \vdots & 1 \\ T_n & 1 \end{bmatrix}, \quad \mathbf{u} = \begin{pmatrix} m \\ c \end{pmatrix}, \quad \mathbf{f} = \begin{pmatrix} \rho_1 \\ \vdots \\ \rho_n \end{pmatrix}.$$

The matrix A is a simple **Vandermonde** type matrix obtained from the temperature data,  $\mathbf{u}$  is the unknown vector with the desired coefficients for the approximation, and  $\mathbf{f}$  is the vector with the density measurements.

#### 1.3.2 The Vandermonde matrix

We use the numpy function numpy.vstack() to build the Vandermonde matrix A.

- [[ 0. 1.]
- [ 5. 1.]
- [ 10. 1.]
- [ 15. 1.]
- [ 20. 1.]
- [ 25. 1.]

```
[ 30.
        1.]
[ 35.
        1.]
[ 40.
        1.]
[ 50.
        1.7
Γ 60.
        1.7
Γ 70.
        1.7
[ 80.
        1.]
Γ 90.
        1.7
[100.
        1.]]
```

### 1.3.3 The density measurements

The density data is the second column of the data array.

## 1.3.4 Solution of the least-square problem for the linear approximation

We use the numpy function numpy.linagl.lstsq() to solve the least-square problem.

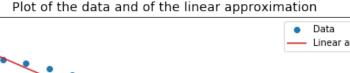
```
[7]: m, d = np.linalg.lstsq(A1, f, rcond=None)[0] print(m,d)
```

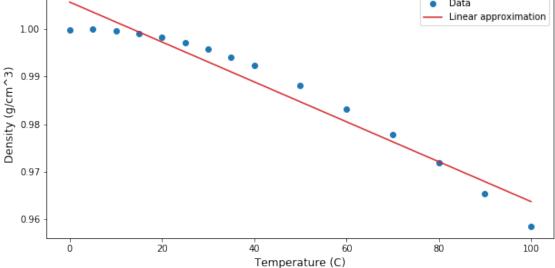
-0.00041965346534652876 1.0056721122112207

## 1.3.5 Visualizing the result

Now we plot the linear approximation along with the data to visualize the quality of the approximation

```
[8]: plt.figure(figsize=(10,5))
   plt.plot(T, f, 'o', label='Data', color='tab:blue')
   plt.plot(T, m*T + d, 'b', label='Linear approximation', color='tab:red')
   plt.title('Plot of the data and of the linear approximation', fontsize=14)
   plt.xlabel(header['temp'], fontsize=12)
   plt.ylabel(header['density'], fontsize=12)
   plt.legend()
   plt.show()
```





# Second-degree approximation

One can see from the plot above that the first-degree approximation doesn't seem to be a very good approximation. We look, now, for a second-degree approximation.

#### The least-square problem 1.4.1

For the second-degree approximation, we look for a second-degree polynomial  $\rho^{(2)}(T) = aT^2 + bT + c$ that best approximates the data in the sense of minimizing the sum of the square of the residuals

$$r_j = \rho_j - \rho^{(2)}(T_j)$$

#### 1.4.2 Matrix form

This can be written in matrix form as

$$\min_{\mathbf{u} \in \mathbb{R}^2} \|A\mathbf{u} - \mathbf{f}\|_2^2,$$

where  $\mathbf{f}$  is as before but the Vandermonde matrix and the vector of unknowns take the form

$$A = \begin{bmatrix} T_1^2 & T_1 & 1 \\ \vdots & 1 \\ T_n^2 & T_n & 1 \end{bmatrix}, \quad \mathbf{u} = \begin{pmatrix} a \\ b \\ c \end{pmatrix}.$$

#### 1.4.3 Vandermonde matrix

In this case, the Vandermonde matrix is

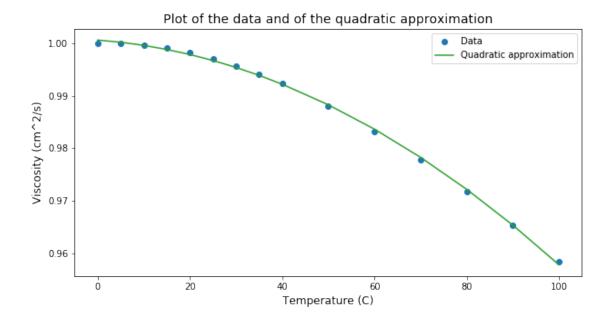
```
[9]: A2 = np.vstack([T**2, T, np.ones(len(T))]).T
     print(A2)
    [[0.000e+00 0.000e+00 1.000e+00]
     [2.500e+01 5.000e+00 1.000e+00]
     [1.000e+02 1.000e+01 1.000e+00]
     [2.250e+02 1.500e+01 1.000e+00]
     [4.000e+02 2.000e+01 1.000e+00]
     [6.250e+02 2.500e+01 1.000e+00]
     [9.000e+02 3.000e+01 1.000e+00]
     [1.225e+03 3.500e+01 1.000e+00]
     [1.600e+03 4.000e+01 1.000e+00]
     [2.500e+03 5.000e+01 1.000e+00]
     [3.600e+03 6.000e+01 1.000e+00]
     [4.900e+03 7.000e+01 1.000e+00]
     [6.400e+03 8.000e+01 1.000e+00]
     [8.100e+03 9.000e+01 1.000e+00]
     [1.000e+04 1.000e+02 1.000e+00]]
```

#### 1.4.4 Solution

```
[10]: a, b, c = np.linalg.lstsq(A2, f, rcond=None)[0]
print(a,b,c)
```

-3.6295100056677867e-06 -6.496768558464583e-05 1.0005991832098982

## 1.4.5 Visualizing the result

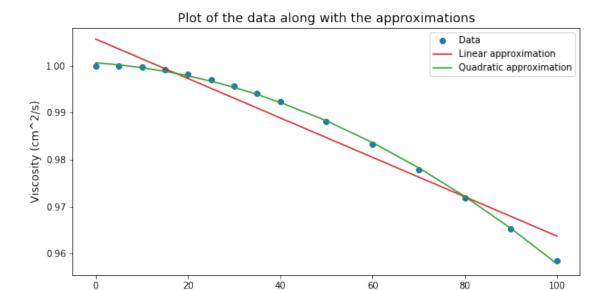


This seems much better

# 1.5 Comparing the two approximations

## 1.5.1 Visual comparison

Visually, the second-degree approximation is way better.



Temperature (C)

## 1.5.2 Comparing the quadratic error

The quadratic error is the sum of the square of the residual errors for each measurement, i.e.

$$\Delta = \sum_{j} r_j^2 = ||A\mathbf{u} - \mathbf{f}||_2^2,$$

for the best approximation obtained. But this error is not normalized by the number of measurements. This is achieved with the **mean quadratic error**:

$$E = \frac{1}{N} \sum_{j} r_j^2.$$

```
[13]: N = len(f)

print(f'Number of measurements: {N}\n')

print(f'Quadratic error for the linear approximation: {np.linalg.lstsq(A1, f, u → rcond=None)[1][0]:.2e}')

print(f'Quadratic error for the quadratic approximation: {np.linalg.lstsq(A2, u → f, rcond=None)[1][0]:.2e}\n')

print(f'Mean quadratic error for the linear approximation: {np.linalg.lstsq(A1, u → f, rcond=None)[1][0]/N:.2e}')

print(f'Mean quadratic error for the quadratic approximation: {np.linalg. u → lstsq(A2, f, rcond=None)[1][0]/N:.2e}')
```

Number of measurements: 15

Quadratic error for the linear approximation: 1.38e-04 Quadratic error for the quadratic approximation: 1.99e-06

Mean quadratic error for the linear approximation: 9.22e-06
Mean quadratic error for the quadratic approximation: 1.33e-07

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