Data Analysis with Python

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NumPy is the fundamental package for scientific computing with Python when it comes to large, multidimensional arrays (vectors) and matrices.

In addition to the fast computation of *NumPy* arrays (way more faster than Python Lists), the main benefit lies in the included mathematical operations like shape manipulation, sorting, selecting, I/O, basic linear algebra, basic statistical operations, random simulation and so on. One should hold in mind that *NumPy* arrays are not as flexible as Python Lists. While the latter one could store different data types in one list, each *NumPy* array only stores values of the same data type!

Examples and more detailed instructions how to use *numpy* can be found here: [http://www.numpy.org/ (http://www.numpy.org/)](http://www.numpy.org/)

Note: If numpy is not yet installed on your system, open the Anaconda prompt (or terminal on Unix systems) and type:

```
conda install numpy
```

In [ ]:
```
# This small Script shows how fast a NumPy Array in comparison to a Python L
ist is.
# Execute this script by pushing Shift+Enter

import time
import numpy as np
import sys

size_of_vec = 1000000

def pure_python_version():
    t1 = time.time()
    X = range(size_of_vec)
    Y = range(size_of_vec)
    Z = [X[i] + Y[i] for i in range(len(X)) ]
    return time.time() - t1, Z

def numpy_version():
    t1 = time.time()
    X = np.arange(size_of_vec)
    Y = np.arange(size_of_vec)
    Z = X + Y
    return time.time() - t1, Z


t1,py_list = pure_python_version()
t2,np_array = numpy_version()

list_mem = sys.getsizeof(py_list)/1000
array_mem = sys.getsizeof(np_array)/1000

print("Computational time for Python List: {} s and the object (memory) size
: {} kB".format(t1,list_mem))
print("Computational time for Numpy Array: {} s and the object (memory) size
: {} kB".format(t2,array_mem))

print("\nTherefore the numpy array is {:.4f} times faster!".format(t1/t2))
```

Array/Matrix indexing

Single element indexing for a 1-D works exactly like indexing for Python-Lists. It is 0-based, and accepts negative indices for indexing from the end of the array.

In [ ]:
```
# Example

# Different routines for the creation of NumPy 1-D arrays:
array_1 = np.array([1.0, 2.0, 3.0]) # Simple 1D array
array_2 = np.zeros(10) # Create an array with 10 elements with value 0
array_3 = np.arange(20.0) # Create an array from 0 to 19
array_4 = np.linspace(0,20,11) # Creates a evenly spaced array from 0 to 20
with 11 elements

print(array_1[-1]) # Print the last element of array_1
print(array_3) # Print all elements of array_3
print(array_4[array_4>10]) # Print all elements of array_4 which are bigger
than 10
```

2-D array indexing works in a similar way.

In [ ]:
```
# Example

array_2D = np.array([[1, 2, 3], [4, 5, 6]]) # create a 2D array (= 2x3 matri
x)

print(array_2D[1,2]) # print element in row 1 column 2
```

It is also possible to slice (accessing more than one element) numpy arrays.

In [ ]:
```
# Example

# Create a more complex Matrix

# First initalize Matrix
x = np.zeros(shape=(10,10)) # create a 10x10 zero-matrix

# Get the shape (number of rows/columns)
rows = x.shape[0]
columns = x.shape[1]

counter = 1

# Loop through each row/column
for i in range(0,rows):
    for j in range(0,columns):
        x[i,j] = counter
        counter = counter + 1

#Array Slicing
print(x[0,:]) # Print the first row of matrix x (using : as symbol for all e
lements in this row)
print(x[0,5:]) # Print the first row starting from column 5
print(x[:,3]) # Print all elements of column 3
```

numpy.loadtxt

The NumPy routine *loadtxt* is a convenient way to load data from a ASCII formatted file into a numpy array. In combination with *matplotlib* and array slicing it is also a fast way to plot data.

In [ ]:
```
# example
# For this example, it is necassary to download the 'simple_data.csv' file f
rom moodle!

data = np.loadtxt("simple_data.csv", delimiter=',')
#print(data)

x_values = data[:,0] # Column 0 contains all x-values
y_values = data[:,1] # Column 1 contains all y-values

import matplotlib.pyplot as plt

plt.plot(x_values, y_values)
plt.show()
```

Task 1: Load and manipulate data from a .csv file

1. Use NumPy's .loadtxt() routine to access the data stored in bitmap_data.csv and store it in a numpy array
2. Get the shape of this array as seen above
3. Loop through each row and column and check if each element is bigger or smaller than 150
   - if the element is bigger or equal 150 set the element value to 1
   - if the element is smaller than 150 set the value to 0

4. Visualize the modified data using the following Code snippet: (Don't forget to import matplotlib!)

```
plt.imshow(<Name of modified NumPy array>, cmap='binary_r')
plt.show()
```

What do you see?

In [ ]:

```
# Solution

# load the bitmap data
data = np.loadtxt("bitmap_data.csv", delimiter=',')

# show raw data
plt.imshow(data, cmap='binary_r')
plt.show()

# classic way
rows = data.shape[0]
columns = data.shape[1]

for i in range(0,rows):
    for j in range(0,columns):
        if data[i,j] >= 150:
            data[i,j] = 1
        else:
            data[i,j] = 0

plt.imshow(data, cmap='binary_r')
plt.show()

# numpy way
# relaod data
data = np.loadtxt("bitmap_data.csv", delimiter=',')

mask = data >= 150

data[~mask] = 0
data[mask] = 1

plt.imshow(data, cmap='binary_r')
plt.show()
```

Data manipulation using NumPy routines

Generate the derivation of a given set of data

The NumPy routine

```
np.gradient(y)
```

generates the derivation of a given function (data).

Smoothing via Moving-Average

Moving average is a simple operation used usually to suppress noise of a signal: we set the value of each point to the average of the values in its neighborhood. With NumPy this is done using the

```
np.convolve(y, np.ones((N,))/N), mode="same")
```

routine.
The derivation and mathematics of this routine is described under the following link:
http://matlabtricks.com/post-11/moving-average-by-convolution (http://matlabtricks.com/post-11/moving-average-by-convolution)

In [ ]:
```
# Example Derivation
import random

x = np.linspace(0,20,100) # Generate an array with 100 elements from 0 to 20
y = np.sin(x) # Calculate f(x) = sin(x)
y2 = np.cos(x) # Calculate f2(x) = cos(x)

dy = np.gradient(y,x) # Generate the derivation

plt.plot(x,y) # f(x)
plt.plot(x,y2) # f2(x)
plt.plot(x,dy,':') # df(x) which should be the same as f2(x)
plt.show()

# Example Smoothing

# Add noise to sin(x) using random numbers between -0.3 and 0.3
y_noise = y
for i in range(0,len(y_noise)):
    y_noise[i] = y_noise[i] + random.uniform(-0.3,0.3)


sm = np.convolve(y_noise, np.ones((5,))/5, mode='same') # Moving Average

plt.plot(x,y_noise)
plt.plot(x,sm)
plt.show()
```

Root finding

Root finding in combination with a derivative is one way to find the turning points of a function. A root exists if the function value assumes the value 0 at any point. Since NumPy arrays do not have continuous values (there is always a step between two elements) it is possible that there is no exact 0 value. Therefore one has to check if there is a sign change between two elements. If a sign change occured the root is between those two elements.

Task 2: RootFinding Alogorithm

1. Develop a function that implements the task described above. Proceed as follows:
   - The function should take two parameters x,y which are both two numpy arrays
   - Create an empty list in which the results will be stored
   - Loop through the y array and check if y[i] > 0 and y[i+1] < 0 or y[i] < 0 and y[i+1] > 0
   - If the condition is true use x[i] and x[i+1] two interpolate the value inbetween
   - Return the result list

In [ ]:

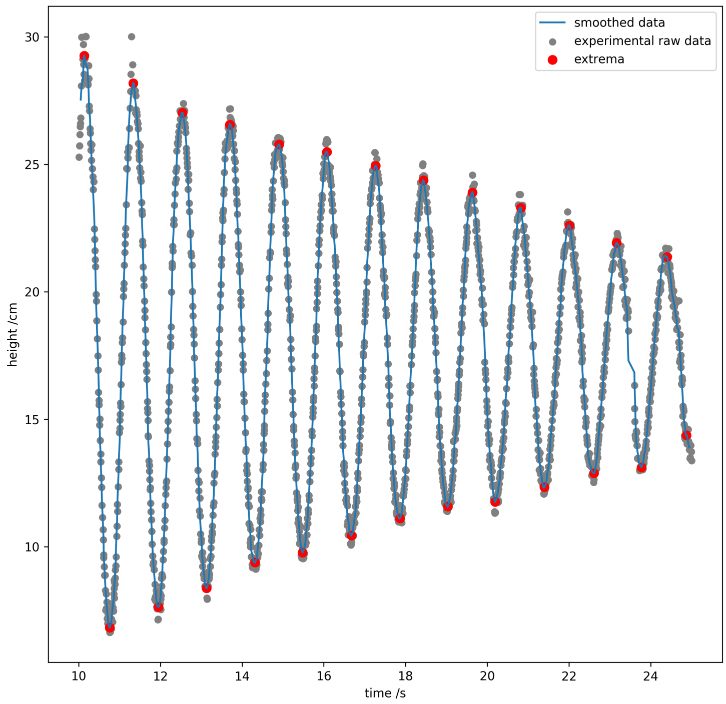
```
# Solution

def root_finding(x,y):
    root_list = []
    for i in range(0,len(y)-1):
        if y[i] == 0:
            root_list.append(x[i])
        elif ((y[i] > 0 and y[i+1] < 0) or (y[i] < 0 and y[i+1] > 0)):
            mid = (x[i] + x[i+1])/2
            root_list.append(mid)
    return root_list
```

In [ ]:

```
# Check if your function works:

x = np.linspace(0,20,1000)
y = np.sin(x)

roots = root_finding(x,y)
roots_y = np.zeros_like(roots)

print(roots)

plt.plot(x, y)
plt.scatter(roots, roots_y, color='red')
```

Task 3: Data Analysis using NumPy

1. Use NumPy's .loadtxt() routine to access the data stored in abstand.dat and store it in a numpy array
2. Plot column 0 against column 1 of the raw data
3. Define a mask to focus the data only on the first oszilations (e.g. t in [10 s, 25 s]) and mask out values larger than 50
4. Use NumPy's *.convolve* routine to smooth the data
5. Find the turning points (minima/maxima) of the masked data. Therefore compute the derivative in combination with the root_finding algorithm.
6. Finally try to create the following plot:



In [ ]:
```
# Solution

raw_data = np.loadtxt("distance_oszilator.dat", delimiter=' ')

# create mask and set filter conditions
mask = np.ones(len(raw_data), dtype=bool)
mask[np.where(raw_data[:,1] > 50)] = False
mask[np.where((raw_data[:,0] > 25) | (raw_data[:,0] < 10))] = False

# for convenience, define a new variable with the masked data
data=raw_data[mask, :]

x = data[:,0]
y = data[:,1]

plt.plot(x,y,':')

# N defines the widht of the smooting window
N = 11
sm = np.convolve(y, np.ones((N,))/N, mode='valid')
# the x values of the smoothed values are reduced by N points
N2 = N//2
sm_x = x[N2:-N2]
plt.plot(sm_x,sm)

plt.show()
```

In [ ]:
```
# compute the derivative
derivative = np.gradient(sm, sm_x)
plt.plot(sm_x, derivative)
# show the y=0 vicinity
plt.ylim(-2, 2)
```

In [ ]:
```
# find and print roots
raw_roots = root_finding(sm_x, derivative)
print(len(raw_roots), raw_roots)
```

In [ ]:
```
# create a list of roots, which are separated by at least dx
dx = 0.2

roots = []
for i in range(len(raw_roots)-1):
    if raw_roots[i+1] - raw_roots[i] > dx:
        roots.append(raw_roots[i])
roots.append(raw_roots[-1])
print(len(roots), roots)
```

In [ ]:
```
# plot the distance of the roots
distance_roots = []
for i in range(len(roots)-1):
    distance_roots.append(roots[i+1]-roots[i])
plt.plot(distance_roots)
```

In [ ]:
```
# interpolate the y-values of the extrema, i.e. roots of the derivative
roots_y = np.interp(roots, sm_x, sm)
plt.plot(x,y)
plt.plot(sm_x, sm)
plt.scatter(roots, roots_y, color='red', s=50)
```

In [ ]:

```
fig = plt.figure(figsize=(10,10))
plt.scatter(x,y, color='gray', s=25, label='experimental raw data')
plt.plot(sm_x, sm, label='smoothed data')
plt.scatter(roots, roots_y, color='red', s=50, label='extrema')
plt.legend()
plt.xlabel('time /s')
plt.ylabel('height /cm')
plt.savefig('final_plot.png', dpi=300, bbox_inches='tight')
plt.show()
```

In [ ]:

```
```