

JUAS and MADX in python

For this course a **basic knowledge of Python is assumed**, therefore if you are not familiar with it you can find, in the following sections, few resources to fill the gap. During the course we will use Python3 in a Jupyter notebook and, mostly, the *numpy*, *matplotlib*, *pandas*, *sympy*, *PyNAFF* and *cpymad* packages. We will explain in the following sections how to install this software on your laptops.

After a short introduction where we provided some useful links to get familiar with Python, we will focus on the software setup. Depending on your operating systems (we will consider OSX, Windows and UNIX) you have different procedures to follow.

For **OSX** users, please follow the instructions in the *OSX: Install and run a Docker image* section.

For the **Windows** users, please follow the instructions in the *Windows: Docker Toolbox* section.

For **UNIX** users, please follow the instructions in the instructions in the *UNIX: Anaconda + cpymad* section.

A (very) short introduction to Python

Test Python on a web page

If you are not familiar with Python and you have not it installed on your laptop, you can start playing with simple python snippets on the web: without installing any special software you can connect, e.g., to

<https://www.pythonanywhere.com/try-ipython/> (<https://www.pythonanywhere.com/try-ipython/>)

and test the following commands

```
1 import numpy as np
2 # Matrix definition
3 Omega=np.array([[0, 1],[-1,0]])
4 M=np.array([[1, 0],[1,1]])
5
6 # Sum and multiplication of matrices
7 Omega - M.T @ Omega @ M
8 # M.T means the "traspose of M".
9
10 # Function definition
11 def Q(f=1):
12     return np.array([[1, 0],[-1/f,1]])
13
14 #Eigenvalues and eigenvectors
15 np.linalg.eig(M)
```

You can compare and check your output with the ones here (<https://cernbox.cern.ch/index.php/s/xipyXzX7V9KJbl>).

The *numpy* package

To get familiar with the *numpy* package have a look at the following summary poster

(https://s3.amazonaws.com/assets.datacamp.com/blog_assets/Numpy_Python_Cheat_Sheet.pdf).

Python For Data Science Cheat Sheet
NumPy Basics
Learn Python for Data Science Interactively at www.DataCamp.com

NumPy
The NumPy library is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays.

Use the following import convention:
`>>> import numpy as np`

NumPy Arrays

1D array
axis 0
[1, 2, 3]

2D array
axis 0
axis 1
[[1.5, 2, 3],
 [4, 5, 6]]

3D array
axis 0
axis 1
axis 2

Creating Arrays

```
>>> a = np.array([1,2,3])
>>> b = np.array([[1.5,2,3], (4,5,6)], dtype = float)
>>> c = np.array([[1,5,2,3], (4,5,6)], [(3,2,1), (4,5,6)]], dtype = float)
```

Initial Placeholders

```
>>> np.zeros((3,4))
>>> np.ones((2,3,4),dtype=np.int64)
>>> d = np.arange(10,25,5)
>>> np.linspace(0,2,9)
>>> e = np.full((2,2),7)
>>> f = np.eye(2)
>>> np.random.random((2,2))
>>> np.empty((3,2))
```

I/O

Saving & Loading On Disk

```
>>> np.save('my_array', a)
>>> np.savez('array.npz', a, b)
>>> np.load('my_array.npy')
```

Saving & Loading Text Files

```
>>> np.loadtxt('myfile.txt')
>>> np.genfromtxt('my_file.csv', delimiter=',')
>>> np.savetxt('myarray.txt', a, delimiter=" ")
```

Data Types

<code>>>> np.int64</code>	Signed 64-bit integer types
<code>>>> np.float32</code>	Standard double-precision floating point
<code>>>> np.complex</code>	Complex numbers represented by 128 floats
<code>>>> np.bool</code>	Boolean type storing <code>TRUE</code> and <code>FALSE</code> values
<code>>>> np.object</code>	Python object type
<code>>>> np.string_</code>	Fixed-length string type
<code>>>> np.unicode_</code>	Fixed-length unicode type

Inspecting Your Array

```
>>> a.shape
>>> len(a)
>>> b.ndim
>>> e.size
>>> b.dtype
>>> b.dtype.name
>>> b.astype(int)
```

Array Dimensions
Length of array
Number of array dimensions
Data type of array elements
Name of data type
Convert an array to a different type

Asking For Help
`>>> np.info(np.ndarray.dtype)`

Array Mathematics

Arithmetic Operations

```
>>> g = a - b
array([[ -0.5,  0. ,  0. ],
       [ 1. ,  -3. ,  -3. ]])
>>> np.subtract(a,b)
array([[ -0.5,  0. ,  0. ],
       [ 1. ,  -3. ,  -3. ]])
>>> h = a + a
array([[ 2.5,  4. ,  6. ],
       [ 5. ,  7. ,  9. ]])
>>> np.add(b,a)
array([[ 0.6666667,  1. ,  1. ],
       [ 0.25,  0.4 ,  0.5 ]])
>>> np.divide(a,b)
array([[ 1.5,  4. ,  9. ],
       [ 4. ,  10. ,  18. ]])
>>> np.multiply(a,b)
array([[ 1.5,  8. ,  18. ],
       [ 6. ,  30. ,  54. ]])
>>> np.exp(b)
array([[ 4.4816891,  7.3890561,  20.0855369],
       [ 20.0855369,  49.4025751, 118.8711275]])
>>> np.sqrt(b)
array([[ 1.2247449,  2. ,  3. ],
       [ 2. ,  3.4641016,  5.1961524]])
>>> np.sin(a)
array([[ 0.84147138,  0.90929743,  0.14188496],
       [ 0.41614684,  0.7568025 ,  0.95949297]])
>>> np.cos(b)
array([[ 0.76604444,  0.91354546,  0.14188496],
       [ 0.17364818,  0.93957055,  0.95949297]])
>>> e.dot(f)
array([[ 7. ,  9. ],
       [ 12. ,  3. ]])
```

Comparison

```
>>> a == b
array([[False,  True,  True],
       [False, False, False]], dtype=bool)
>>> a < 2
array([[True,  False, False],
       [True,  False, False]], dtype=bool)
>>> np.array_equal(a,b)
```

Element-wise comparison
Element-wise comparison
Element-wise comparison
Array-wise comparison

Aggregate Functions

```
>>> a.sum()
>>> a.min()
>>> b.max(axis=0)
>>> b.cumsum(axis=1)
>>> a.mean()
>>> b.median()
>>> a.corrcoef()
>>> np.std(b)
```

Array-wise sum
Array-wise minimum value
Maximum value of an array row
Cumulative sum of the elements
Mean
Median
Correlation coefficient
Standard deviation

Copying Arrays

```
>>> h = a.view()
>>> np.copy(a)
>>> h = a.copy()
```

Create a view of the array with the same data
Create a copy of the array
Create a deep copy of the array

Sorting Arrays

```
>>> a.sort()
>>> c.sort(axis=0)
```

Sort an array
Sort the elements of an array's axis

Subsetting, Slicing, Indexing Also see Lists

Subsetting

```
>>> a[2]
>>> b[1,2]
>>> a[0:2]
>>> b[0:2,1]
>>> c[1,...,1]
>>> b[1:]
>>> a[a<2]
>>> a[1:-1]
>>> a[ : -1]
```

Select the element at the 2nd index
Select the element at row 1 column 2 (equivalent to b[1][2])
Select items at index 0 and 1 (equivalent to b[0:2, :])
Select items at rows 0 and 1 in column 1 (equivalent to b[0:2, 1])
Select all items at row 0 (equivalent to b[0:1, :])
Same as [1, :, :]
Reversed array a

Boolean Indexing

```
>>> a[a<2]
array([1])
```

Select elements from a less than 2

Fancy Indexing

```
>>> b[[1, 0, 1, 0], [0, 1, 2, 0]]
>>> b[[1, 0, 1, 0]][:, [0, 1, 2, 0]]
>>> b[[1, 0, 1, 0]][:, [0, 1, 2, 0]]
array([[ 4. ,  2. ,  3. ,  5. ],
       [ 7. ,  9. ,  6. ,  8. ]])
```

Select elements (1,0), (0,1), (1,2) and (0,0)
Select a subset of the matrix's rows and columns

Array Manipulation

Transposing Array

```
>>> l = np.transpose(b)
>>> l.T
```

Permute array dimensions
Permute array dimensions

Changing Array Shape

```
>>> g.reshape(3,-2)
>>> h.resize(2,6)
>>> np.append(h,g)
>>> np.insert(a, 1, 5)
>>> np.delete(a,[1])
```

Flatten the array
Reshape, but don't change data
Return a new array with shape (2,6)
Append items to an array
Insert items into an array
Delete items from an array

Combining Arrays

```
>>> np.concatenate((a,d),axis=0)
array([ 1,  2,  3, 10, 15, 20])
>>> np.vstack((a,b))
array([[ 1. ,  2. ,  3. ],
       [ 1.5,  2. ,  3. ],
       [ 4. ,  5. ,  6. ]])
>>> np.r_[e,f]
array([[ 7. ,  7. ,  0. ,  1. ],
       [ 7. ,  7. ,  0. ,  1. ]])
>>> np.column_stack((a,d))
array([[ 1, 10],
       [ 2, 15],
       [ 3, 20]])
>>> np.c_[a,d]
```

Concatenate arrays
Stack arrays vertically (row-wise)
Stack arrays vertically (row-wise)
Stack arrays horizontally (column-wise)
Create stacked column-wise arrays
Create stacked column-wise arrays

Splitting Arrays

```
>>> np.hsplit(a,3)
(array([1],array([2]),array([3]))
>>> np.vsplit(c,2)
(array([[1.5, 2. , 1. ],
       [ 4. ,  5. ,  6. ]]),
array([[ 3. ,  2. ,  3. ],
       [ 4. ,  5. ,  6. ]]))
```

Split the array horizontally at the 3rd index
Split the array vertically at the 2nd index

DataCamp
Learn Python for Data Science Interactively

You can google many other resources, but the one presented of the poster cover the set of instructions you should familiar with.

The linalg module

To get familiar with the Linear Algebra (*linalg*) module have a look at the following summary poster

(https://s3.amazonaws.com/assets.datacamp.com/blog_assets/Python_SciPy_Cheat_Sheet_Linear_Algebra.pdf).

Python For Data Science Cheat Sheet

SciPy - Linear Algebra

Learn More Python for Data Science [interactively at www.datacamp.com](https://www.datacamp.com)

SciPy

The SciPy library is one of the core packages for scientific computing that provides mathematical algorithms and convenience functions built on the NumPy extension of Python.

Interacting With NumPy

```
>>> import numpy as np
>>> a = np.array([1,2,3])
>>> b = np.array([[1,5], [2,3]], (4,5,6))
>>> c = np.array([[1,5,2,3], (4,5,6)], [(3,2,1), (4,5,6)])
```

Index Tricks

```
>>> np.mgrid[0:5,0:5]
>>> np.ogrid[0:2,0:2]
>>> np.r_[3, [0]*5, -1:1:10]
>>> np.c_[b,c]
```

Shape Manipulation

```
>>> np.transpose(b)
>>> b.flatten()
>>> np.hstack((b,c))
>>> np.vstack((a,b))
>>> np.hsplit(c,2)
>>> np.vsplit(c,2)
```

Polynomials

```
>>> from numpy import polyid
>>> p = polyid([1,4,5])
```

Vectorizing Functions

```
>>> def myfunc(a):
    if a < 0:
        return a*2
    else:
        return a/2
>>> np.vectorize(myfunc)
```

Type Handling

```
>>> np.real(b)
>>> np.imag(b)
>>> np.real_if_close(c, tol=1000)
>>> np.cast['F'](np.pi)
```

Other Useful Functions

```
>>> np.angle(b, deg=True)
>>> g = np.linspace(0, np.pi, num=5)
>>> g[3:] += np.pi
>>> np.unwrap(g)
>>> np.linspace(0, 10, 3)
>>> np.select([c<4], [c*2])
>>> misc.factorial(a)
>>> misc.comb(10, 3, exact=True)
>>> misc.central_diff_weights(3)
>>> misc.derivative(func, 1.0)
```

Linear Algebra

You'll use the `linalg` and `sparse` modules. Note that `scipy.linalg` contains and expands on `numpy.linalg`.

```
>>> from scipy import linalg, sparse
```

Creating Matrices

```
>>> A = np.matrix(np.random.random((2,2)))
>>> B = np.asmatrix(B)
>>> C = np.mat(np.random.random((10,5)))
>>> D = np.mat([[3,4], [5,6]])
```

Basic Matrix Routines

```
Inverse
>>> A.I
>>> linalg.inv(A)
>>> A.T
>>> A.H
Trace
>>> np.trace(A)
Norm
>>> linalg.norm(A)
>>> linalg.norm(A,1)
>>> linalg.norm(A,np.inf)
Rank
>>> np.linalg.matrix_rank(C)
Determinant
>>> linalg.det(A)
Solving linear problems
>>> linalg.solve(A,b)
>>> E = np.mat(a).T
>>> linalg.lstsq(F,E)
Generalized inverse
>>> linalg.pinv(C)
>>> linalg.pinv2(C)
```

Creating Sparse Matrices

```
F = np.eye(3, k=1)
G = np.mat(np.identity(2))
CIC > 0.5) = 0
H = sparse.csr_matrix(C)
I = sparse.csc_matrix(D)
J = sparse.dok_matrix(A)
E.todense()
sparse.linalg.spsolve(csc(A))
Create a 2x2 Identity matrix
Create a 2x2 Identity matrix
Compressed Sparse Row matrix
Compressed Sparse Column matrix
Dictionary Of Keys matrix
Sparse matrix to full matrix
Identify sparse matrix
```

Sparse Matrix Routines

```
Inverse
>>> sparse.linalg.inv(I)
Norm
>>> sparse.linalg.norm(I)
Solving linear problems
>>> sparse.linalg.spsolve(I,1)
```

Sparse Matrix Functions

```
>>> sparse.linalg.expm(I)
>>> help(sparse.linalg.diagsvd)
>>> np.info(sparse.linalg)
```

Also see NumPy

Matrix Functions

```
Addition
>>> np.add(A,D)
Subtraction
>>> np.subtract(A,D)
Division
>>> np.divide(A,D)
>>> A @ D
Multiplication operator
Python's Multiplication
Dot product
Vector dot product
Inner product
Outer product
Tensor dot product
Kronecker product
Exponential Functions
>>> linalg.expm(A)
>>> linalg.expm2(A)
>>> linalg.expm3(D)
Logarithm Function
>>> linalg.logm(A)
Trigonometric Functions
>>> linalg.sinc(D)
>>> linalg.com(D)
>>> linalg.tanh(A)
Hyperbolic Trigonometric Functions
>>> linalg.sinhm(A)
>>> linalg.coshm(D)
>>> linalg.tanhm(A)
Matrix Sign Function
>>> np.signm(A)
Matrix Square Root
>>> linalg.sqrtm(A)
Arbitrary Functions
>>> linalg.funm(A, lambda x: x*x)
Evaluate matrix function
```

Decompositions

```
Eigenvalues and Eigenvectors
>>> la, v = linalg.eig(A)
Solve ordinary or generalized eigenvalue problem for square matrix
Unpack eigenvalues
First eigenvector
Second eigenvector
Unpack eigenvalues
Singular Value Decomposition
>>> U, s, Vh = linalg.svd(B)
Singular Value Decomposition (SVD)
>>> M, N = B.shape
>>> sig = linalg.diagsvd(s,M,N)
Construct sigma matrix in SVD
LU Decomposition
>>> P, L, U = linalg.lu(C)
LU Decomposition
```

Sparse Matrix Decompositions

```
>>> la, v = sparse.linalg.eigs(F,1,2)
>>> sparse.linalg.svds(I,2)
Eigenvalues and eigenvectors
SVD
```

The pandas package

To get familiar with the *pandas* package have a look at the following summary poster

(https://s3.amazonaws.com/assets.datacamp.com/blog_assets/PandasPythonForDataScience.pdf).

Python For Data Science Cheat Sheet

Pandas Basics

Learn Python for Data Science [interactively at www.datacamp.com](https://www.datacamp.com)

Pandas

The Pandas library is built on NumPy and provides easy-to-use data structures and data analysis tools for the Python programming language.



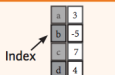
Use the following import convention:

```
>>> import pandas as pd
```

Pandas Data Structures

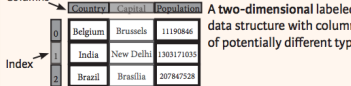
Series

A one-dimensional labeled array capable of holding any data type



DataFrame

A two-dimensional labeled data structure with columns of potentially different types



```
>>> data = {'Country': ['Belgium', 'India', 'Brazil'],
           'Capital': ['Brussels', 'New Delhi', 'Brasilia'],
           'Population': [1190846, 1303171035, 207847528]}
>>> df = pd.DataFrame(data,
                    columns=['Country', 'Capital', 'Population'])
```

I/O

Read and Write to CSV

```
>>> pd.read_csv('file.csv', header=None, nrows=5)
>>> df.to_csv('myDataFrame.csv')
```

Read and Write to Excel

```
>>> pd.read_excel('file.xlsx')
>>> pd.to_excel('dir/myDataFrame.xlsx', sheet_name='Sheet1')
Read multiple sheets from the same file
>>> xls = pd.ExcelFile('file.xls')
>>> df = pd.read_excel(xls, 'Sheet1')
```

Asking For Help

```
>>> help(pd.Series.loc)
```

Selection

Also see NumPy Arrays

```
>>> s['b']
-5
Get one element
>>> df[1:]
Country Capital Population
1 India New Delhi 1303171035
2 Brazil Brasilia 207847528
Get subset of a DataFrame
```

Selecting, Boolean Indexing & Setting

```
By Position
>>> df.iloc[0], [0]
'Belgium'
Select single value by row & column
>>> df.iat[0], [0]
'Belgium'
By Label
>>> df.loc[0], ['Country']
'Belgium'
Select single value by row & column labels
>>> df.at[0], ['Country']
'Belgium'
By Label/Position
>>> df.ix[2]
Country Brazil
Capital Brasilia
Population 207847528
Select single row of subset of rows
>>> df.ix[:, 'Capital']
0 Brasilia
1 New Delhi
2 Brasilia
Select a single column of subset of columns
>>> df.ix[1, 'Capital']
'New Delhi'
Select rows and columns
Boolean Indexing
>>> s[s > 1]
Series s where value is not > 1
>>> s[(s < -1) | (s > 2)]
Series s where value is < -1 or > 2
>>> df[df['Population'] > 120000000]
Use filter to adjust DataFrame
Setting
>>> s['a'] = 6
Set index of Series s to 6
```

Dropping

```
>>> s.drop(['a', 'c'])
Drop values from rows (axis=0)
>>> df.drop('Country', axis=1)
Drop values from columns (axis=1)
```

Sort & Rank

```
>>> df.sort_index()
Sort by labels along an axis
>>> df.sort_values(by='Country')
Sort by the values along an axis
>>> df.rank()
Assign ranks to entries
```

Retrieving Series/DataFrame Information

Basic Information

```
>>> df.shape
(rows, columns)
>>> df.index
Describe index
>>> df.columns
Describe DataFrame columns
>>> df.info()
Info on DataFrame
>>> df.count()
Number of non-NA values
```

Summary

```
>>> df.sum()
Sum of values
>>> df.cumsum()
Cumulative sum of values
>>> df.min()/df.max()
Minimum/maximum values
>>> df.idxmin()/df.idxmax()
Minimum/Maximum index value
>>> df.describe()
Summary statistics
>>> df.mean()
Mean of values
>>> df.median()
Median of values
```

Applying Functions

```
>>> f = lambda x: x*2
>>> df.apply(f)
Apply function
>>> df.applymap(f)
Apply function element-wise
```

Data Alignment

Internal Data Alignment

NA values are introduced in the indices that don't overlap:

```
>>> s3 = pd.Series([7, -2, 3], index=['a', 'c', 'd'])
>>> s + s3
a 10.0
b NaN
c 5.0
d 7.0
```

Arithmetic Operations with Fill Methods

You can also do the internal data alignment yourself with the help of the fill methods:

```
>>> s.add(s3, fill_value=0)
a 10.0
b -5.0
c 5.0
d 7.0
>>> s.sub(s3, fill_value=2)
>>> s.div(s3, fill_value=4)
>>> s.mul(s3, fill_value=3)
```

JupyterLab

JupyterLab is a user-friendly environment to work with Python.

You can find an overview on JupyterLab here (<https://jupyterlab.readthedocs.io/en/stable/>).

In the following section we will explain how to install a Python on your laptop: we propose three different approaches for OSX, Windows and UNIX systems, respectively.

OSX: install and run a Docker image

In order to ease the installation procedure, we prepared a virtual environment that launch a Python3 Jupyter server (the installation on *cpymad* on OSX can be tricky, so we suggest to use the Docker image).

STEP 1: install the Docker Desktop

Please install the Docker Desktop (<https://www.docker.com/products/docker-desktop>).

This is available for MAC and Windows 10 Enterprise and Professional (but not the 'Home Edition'). If you have Windows Home edition please refer to the *Windows: Docker Toolbox* section.

STEP 2: run the Docker image

Once the Docker Desktop is installed and running, open a terminal, move to a folder you want to use for CAS exercises and run the instruction

```
>> docker run -p 8888:8888 -v "$PWD":/cas sterbini/cas_aap_2019
```

This will download the image (~5GB): an internet connection is needed **only for the first time**, afterwards you can work offline.

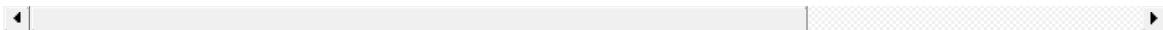
It is very important to have an offline working solution. Our experience with the previous schools showed that the standard WiFi infrastructure does not always meet the needed bandwidth performance. So, even if you have a working online Python environment (e.g. <https://swan.web.cern.ch/> (<https://swan.web.cern.ch/>)) we strongly encourage to use an offline Python distribution.

You should get something as

```
MACBE16107:Tutorials sterbini$ docker run -p 8888:8888 -v "$PWD":/cas sterbini/cas_aap_20
[I 08:37:31.108 LabApp] Writing notebook server cookie secret to /cas/.local/share/jupyter
[I 08:37:31.341 LabApp] JupyterLab extension loaded from /opt/conda/lib/python3.6/site-pa
[I 08:37:31.341 LabApp] JupyterLab application directory is /opt/conda/share/jupyter/lab
[W 08:37:31.343 LabApp] JupyterLab server extension not enabled, manually loading...
[I 08:37:31.353 LabApp] JupyterLab extension loaded from /opt/conda/lib/python3.6/site-pa
[I 08:37:31.353 LabApp] JupyterLab application directory is /opt/conda/share/jupyter/lab
[I 08:37:31.354 LabApp] Serving notebooks from local directory: /cas
[I 08:37:31.354 LabApp] The Jupyter Notebook is running at:
[I 08:37:31.354 LabApp] http://(4bd247dca0ba or 127.0.0.1):8888/?token=ea65f062bfce037fd7
[I 08:37:31.355 LabApp] Use Control-C to stop this server and shut down all kernels (twic
[C 08:37:31.364 LabApp]
```

Copy/paste this URL into your browser when you connect for the first time,
to login with a token:

`http://(4bd247dca0ba or 127.0.0.1):8888/?token=ea65f062bfce037fd7a3b47926393a0d5d`



The last line is the most important one.

STEP 3: open JupyterLab from a browser

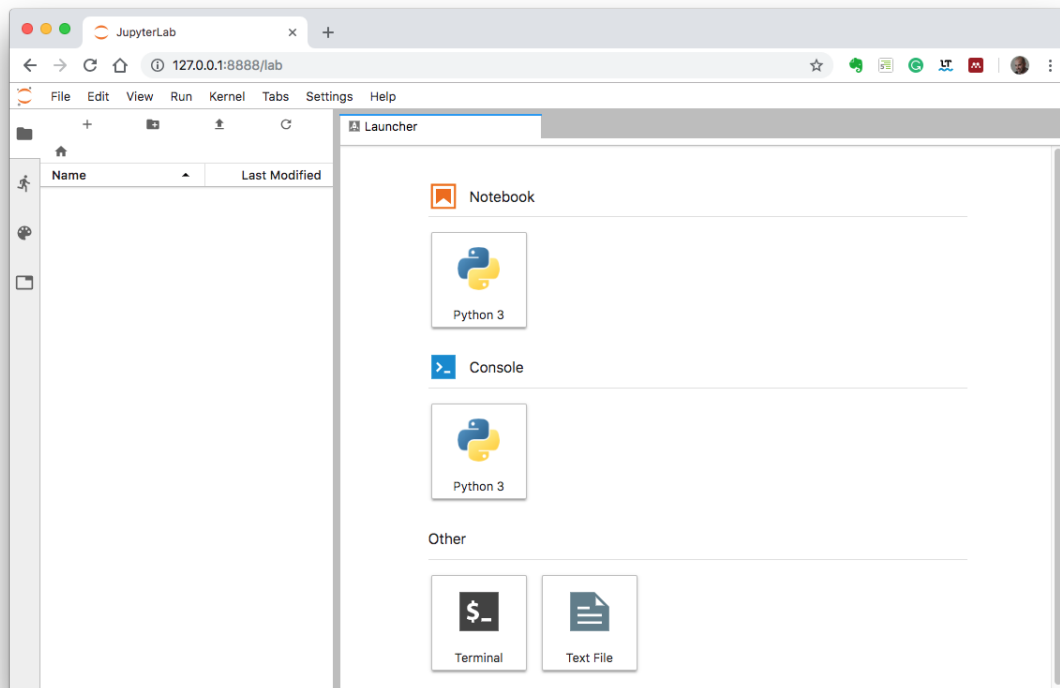
Open a web browser and connect to the python server at (**in this case**, check the last line)

`http://127.0.0.1:8888/?token=ea65f062bfce037fd7a3b47926393a0d5ded381785b0136b`

(`http://127.0.0.1:8888/?token=ea65f062bfce037fd7a3b47926393a0d5ded381785b0136b`)

You have to copy, paste and **edit** the last line on the address field of your browser.

You should see something as



This JupyterLab environment is setup with the software needed for the Optics course.

The *Launcher* tab allows you to open a notebook or console or some basic terminal/editing environment.

You can clic on the *Python 3 Notebook* icon in the *Launcher* tab and test the code example at the end of this document to verify that everything is working as expected.

UNIX: Anaconda distribution

For UNIX system the simplest way to install Python environment on your laptop is to setup manually your environment by installing *anaconda*

(http://docs.continuum.io/_downloads/9ee215ff15fde24bf01791d719084950/Anaconda-Starter-Guide.pdf) from <http://docs.continuum.io/anaconda/> (<http://docs.continuum.io/anaconda/>)

STEP 1: Anaconda installation

We suggest to install the Python 3.7 version (2019.03)

(<https://www.anaconda.com/distribution/>) (<https://www.anaconda.com/distribution/>)

List the packages that are installed with

```
>> conda list
```

and verify that you have *matplotlib*, *numpy*, *scipy*, *pandas*, *sympy*.

If some of them are missing, please install them with, e.g.,

```
>> conda install -c conda-forge matplotlib
```

STEP 2: PyNAFF installation

You can find information on <https://pypi.org/project/PyNAFF/> (<https://pypi.org/project/PyNAFF/>).

In most of the case it is enough to open a terminal and do

```
>> pip install PyNAFF
```

STEP 3: cpymad installation

The standard *anaconda* distribution comes with most of the needed packages but *cpymad*. You can install it following the instructions from <https://github.com/hibtc/cpymad> (<https://github.com/hibtc/cpymad>). In most of the case it is enough to open a terminal and do

```
>> pip install cpymad
```

STEP 4: JupyterLab

Now you can launch from a terminal JupyterLab

```
>> jupyter-lab
```

If JupyterLab is not installed in your system you can install it with

```
>> conda install -c conda-forge jupyterlab
```

The *jupyter-lab* command will open a browser.

The Launcher tab allows you to open a notebook or console or some basic terminal/editing environment.

You can click on the Python 3 Notebook icon in the Launcher tab and test the code example at the end of this document to verify that everything is working as expected.

Windows: Docker Toolbox

If you have Windows 10 Professional or Enterprise you can follow the instructions given for OSX. The other Windows versions are not compatible with **Docker Desktop**.

In alternative to **Docker Desktop**, there is a legacy software called **Docker Toolbox** (we tested it on Windows 10 Home). This comes with an Oracle Virtual Box where you will run the Docker Image.

STEP 1: Docker Toolbox installation

Download **Docker Toolbox** from

<https://github.com/docker/toolbox/releases/download/v18.09.3/DockerToolbox-18.09.3.exe>

(<https://github.com/docker/toolbox/releases/download/v18.09.3/DockerToolbox-18.09.3.exe>)

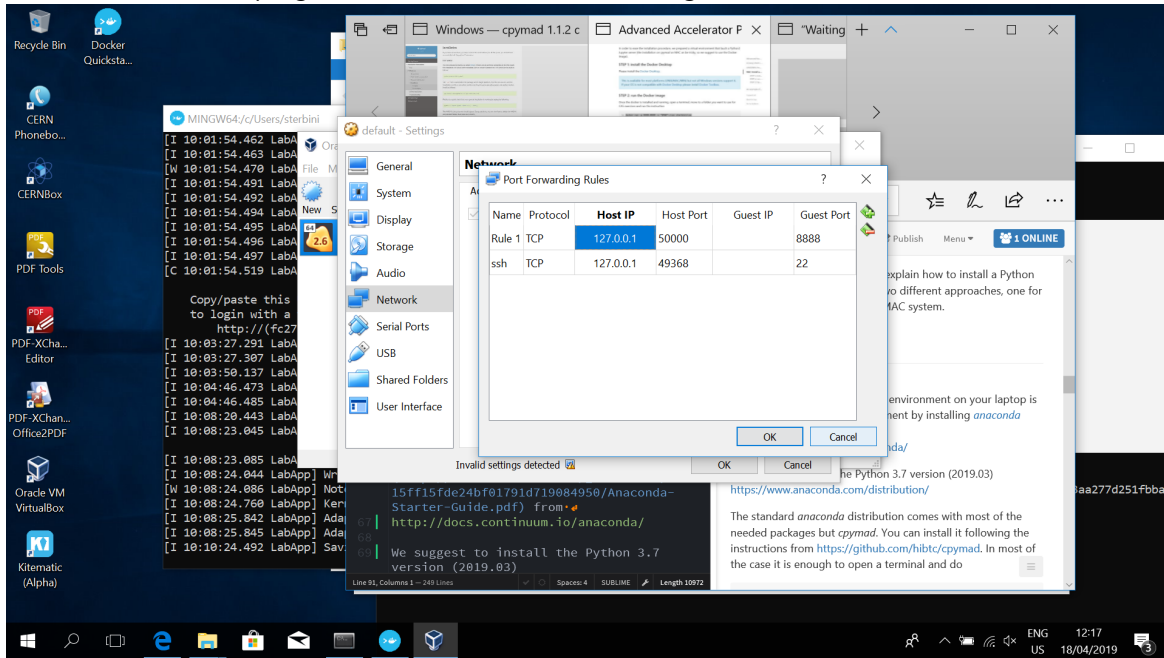
Install it (using custom configuration).

STEP 2: redirect the port 8888

You have to redirect the port 8888 of the virtual machine to the localhost port 50000 (you can use another free port if you like or if port the 50000 is already in use). This can be done from the Oracle VM VirtualBox (icon on your desktop) accessing the menu of the default Virtual machine:

'Settings'->'Network'->'Advanced'->'Port Forwarding'.

Add ('+' icon on the top/right) a rule as shown in the following screenshot



This means that you can access the port 8888 of the virtual machine from the port 50000 of the localhost (127.0.0.1).

STEP 3: install and launch the docker image

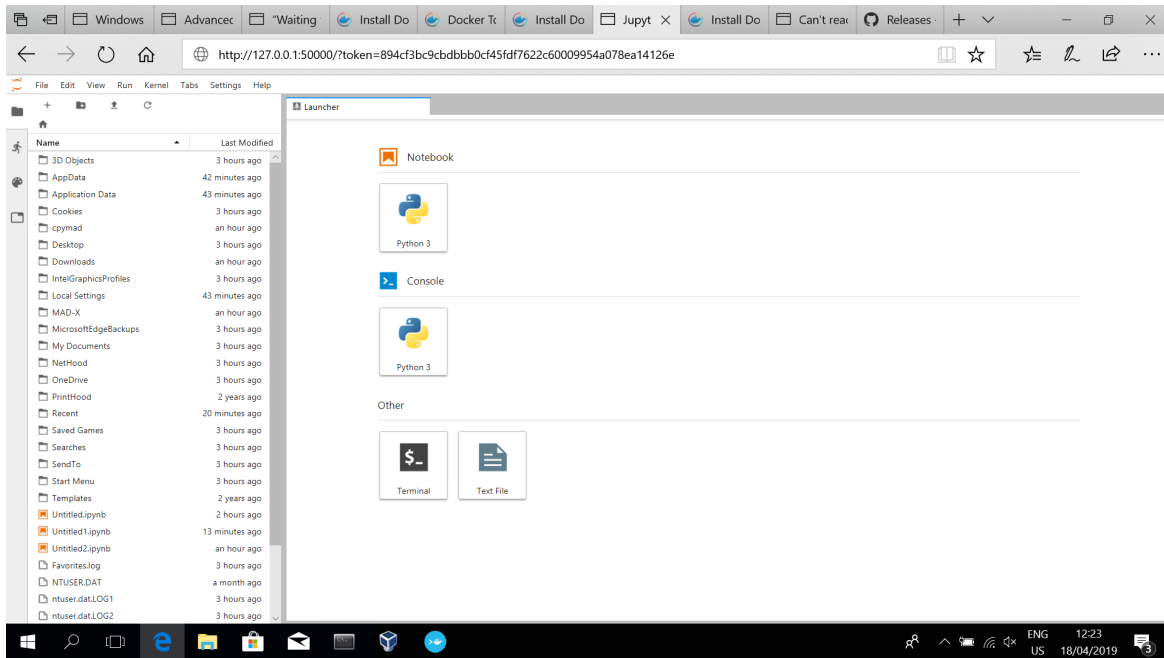
Now open the Docker Quickstart (icon on the Desktop). It will take some time to start the virtual machine. Then move to your home folder typing

```
>> cd
```

Then type

```
>> docker run -p 8888:8888 -v "$PWD":/cas sterbini/cas_aap_2019
```

This download the docker image (only for the first time, ~5 GB) and run it.



The Launcher tab allows you to open a notebook or console or some basic terminal/editing environment.

You can click on the Python 3 Notebook icon in the Launcher tab and test the code example at the end of this document to verify that everything is working as expected.

An example of Python3 notebook in Jupyter Lab.

From the *Launcher* of JupyterLab select the Python 3 Notebook.

You can import the python library of MAD-X (*cpymad*) with the following command.

```
from cpymad.madx import Madx
from matplotlib import pyplot as plt
myMadx = Madx()
```

and now you can twiss a simple FODO cell (more details during the course) with the following code

```

myString=''
! *****
! Second part
! *****

! *****
! Definition of parameters
! *****

l_cell=100;
quadrupoleLenght=5;
f=200;
myK:=1/f/quadrupoleLenght;// m^-2

! *****
! Definition of magnet
! *****
QF: quadrupole, L=quadrupoleLenght, K1:=myK;
QD: quadrupole, L=quadrupoleLenght, K1:=-myK;

! *****
! Definition of sequence
! *****
myCell:sequence, refer=entry, L=L_CELL;
quadrupole1: QF, at=0;
marker1: marker, at=25;
quadrupole2: QD, at=50;
endsequence;

! *****
! Definition of beam
! *****
beam, particle=proton, energy=2;

! *****
! Use of the sequence
! *****
use, sequence=myCell;

! *****
! TWISS
! *****
title, 'My first twiss';
twiss, file=myFirstTwiss.twiss;
...
myMad.input(myString);

```

You can see the *Q1* and *betymax* parameters by executing this cell

```

myString=''
value, table(SUMM,Q1);
value, table(SUMM,betymax);
...
myMad.input(myString);

```

and you can get a pandas dataframe with the information of the lattice by

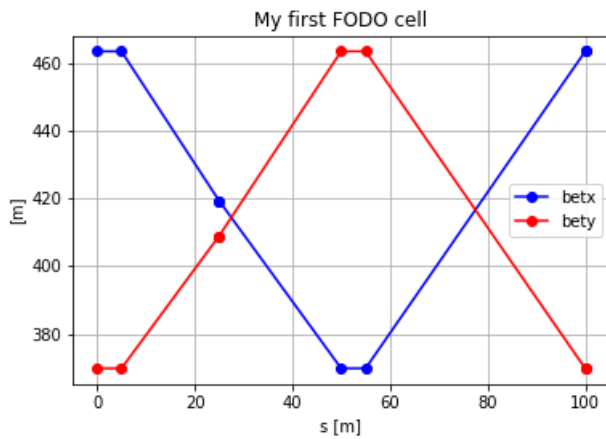
```
myDF=myMad.table.twiss.dframe()
myDF[['name', 's', 'betx', 'bety']].head()
```

You should get something like

	name	s	betx	bety
#s	mycell\$start:1	0.0	463.623288	369.779162
quadrupole1	quadrupole1:1	5.0	463.623288	369.779162
drift_0[0]	drift_0:0	25.0	419.394867	408.967742
marker1	marker1:1	25.0	419.394867	408.967742
drift_1[0]	drift_1:0	50.0	369.779162	463.623288

To plot some data of the *twiss* table you can execute

```
plt.plot(myDF['s'],myDF['betx'],'ob-')
plt.plot(myDF['s'],myDF['bety'],'or-')
plt.legend()
plt.grid()
plt.xlabel('s [m]')
plt.ylabel('β [m]')
plt.title('My first FODO cell')
```



You can do also a bit of symbolic computation with

```

import sympy as sy
import numpy as np
from sympy import init_session
init_session()
la=np.linalg
L_cell=sy.Symbol('L_cell', positive=True);
f_1=sy.Symbol('f_1', positive=True);
f_2=sy.Symbol('f_2', positive=True);
f=sy.Symbol('f', positive=True);

QF=sy.Matrix([[1,0], [-1/f,1]])
DRIFT=sy.Matrix([[1,L_cell/2], [0,1]])
QD=sy.Matrix([[1,0], [1/f,1]])
# This is the OTM
M=DRIFT@QD@DRIFT@QF
M=sy.simplify(M)
M

```

or FTT analysis using PyNAFF, e.g.,

```

import PyNAFF as pnf
import numpy as np

t = np.linspace(1, 3000, num=3000, endpoint=True)
Q = 0.12345
signal = np.sin(2.0*np.pi*Q*t)
pnf.naff(signal, 500, 1, 0, False, window=1)
# outputs an array of arrays for each frequency. Each sub-array includes:
# [order of harmonic, frequency, Amplitude, Re{Amplitude}, Im{Amplitude}]

# My frequency is simply
pnf.naff(signal, 500, 1, 0, False)[0][1]

```

An example of test ipython notebook is shown in

<https://cernbox.cern.ch/index.php/s/JJCu7KRPAjuitVF> (<https://cernbox.cern.ch/index.php/s/JJCu7KRPAjuitVF>)