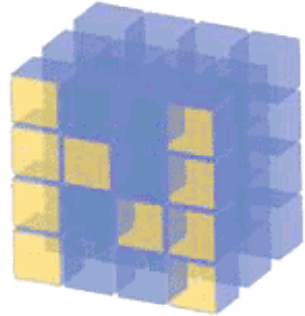




SCIPY,



NUMPY, AND



MATPLOTLIB

..... *Ali Farnudi*



دانشگاه صنعتی شریف



The Abdus Salam
**International Centre
for Theoretical Physics**

- open-source add-on modules
- mathematical and numerical routines
- precompiled, **fast** functions



*provides basic **routines** for manipulating **large arrays** and **matrices** of numeric data.*



*extends the functionality of **NumPy** with a substantial collection of **useful algorithms**.*



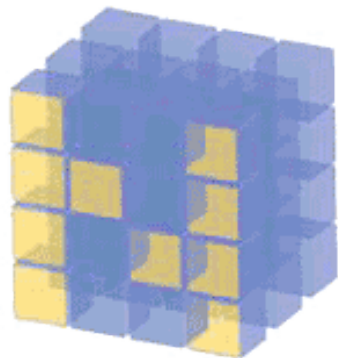
- ◉ **cluster** → Vector Quantisation / Kmeans
- ◉ **fftpack** → Discrete Fourier Transform algorithms
- ◉ **integrate** → Integration routines
- ◉ **interpolate** → Interpolation Tools
- ◉ **io** → Data input and output
- ◉ **lib** → Python wrappers to external libraries
- ◉ **lib.lapack** → Wrappers to LAPACK library
- ◉ **linalg** → Linear algebra routines
- ◉ **misc** → Various utilities that don't have another home.



- ◉ `ndimage` → n-dimensional image package
- ◉ `odr` → Orthogonal Distance Regression
- ◉ `optimize` → Optimisation Tools
- ◉ `signal` → Signal Processing Tools
- ◉ `sparse` → Sparse Matrices
- ◉ `sparse.linalg` → Sparse Linear Algebra
- ◉ `sparse.linalg.dsolve` → Linear Solvers
- ◉ `sparse.linalg.dsolve.umfpack` → Interface to the UMFPACK library:
Conjugate Gradient Method
(LOBPCG)



- ◉ special → Airy Functions [*]
- ◉ lib.blas → Wrappers to BLAS library [*]
- ◉ sparse.linalg.eigen → Sparse Eigenvalue Solvers [*]
- ◉ stats → Statistical Functions [*]
- ◉ spatial → Spatial data structures and algorithms



NumPy

- Polynomial Mathematics
- Statistical computations
- Full suite of pseudo-random number generators and operations
- Discrete Fourier transforms,
- more complex linear algebra operations
- size / shape / type testing of arrays,
- splitting and joining arrays, histograms
- creating arrays of numbers spaced in various ways
- creating and evaluating functions on grid arrays
- treating arrays with special (NaN, Inf) values
- set operations
- creating various kinds of special matrices
- evaluating special mathematical functions (e.g. Bessel functions)
- To learn more, consult the NumPy documentation at <http://docs.scipy.org/doc/>



- You can **import** the modules like most Python packages:

```
25 import numpy  
26  
27 import numpy as np
```

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```
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The **essential** and **basic** unit of NumPy, the array!

- Designed to be accessed just like **Python lists**
- All elements are of the **same type**
- Ideally suited for **storing** and **manipulating large** numbers of elements

- You can **import** the modules like most Python packages:

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27 import numpy as np
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The **essential** and **basic** unit of NumPy, the array!

- Designed to be accessed just like **Python lists**
- All elements are of the **same type**
- Ideally suited for storing and manipulating **large** numbers of elements

```
In [27]: a=np.array([1,2,3,4,5,6,7,8],float)
```

```
In [28]: a
```

```
Out[28]: array([1., 2., 3., 4., 5., 6., 7., 8.])
```

```
In [29]: type(a)
```

```
Out[29]: numpy.ndarray
```

```
In [30]: a[:2]
```

```
Out[30]: array([1., 2.])
```

```
In [31]: a[:6:2]
```

```
Out[31]: array([1., 3., 5.])
```

- Just like lists, **arrays** can be **multidimensional** (Matrix)

```
In [38]: a = np.array([[1, 2, 3], [4, 5, 6]], float)
```

```
In [39]: a
```

```
Out[39]:
```

```
array([[1., 2., 3.],  
       [4., 5., 6.]])
```

```
In [40]: a[0,0]
```

```
Out[40]: 1.0
```

```
In [41]: a[0][1]
```

```
Out[41]: 2.0
```

```
In [42]: a.shape
```

```
Out[42]: (2, 3)
```

➤ Just like lists, **arrays** can be **multidimensional** (Matrix)

➤ Arrays can be **reshaped**

```
In [56]: a = np.array(range(10), dtype=np.uint8)
```

```
In [57]: a
```

```
Out[57]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
```

```
In [58]: a.reshape((5,2))
```

```
Out[58]:
```

```
array([[0, 1],  
       [2, 3],  
       [4, 5],  
       [6, 7],  
       [8, 9]], dtype=uint8)
```

```
In [59]: a
```

```
Out[59]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9], dtype=uint8)
```

► Plain assignment creates a view, **copies** need to be **explicit**

```
In [106]: a = np.array([1, -2, 3], dtype=np.int16)
```

```
In [107]: pointer=a
```

```
In [108]: view=a.view(np.uint16)
```

```
In [109]: copy=a.copy()
```

```
In [110]: a[0]=99
```

```
In [111]: a
```

```
Out[111]: array([99, -2,  3], dtype=int16)
```

```
In [112]: pointer
```

```
Out[112]: array([99, -2,  3], dtype=int16)
```

```
In [113]: view
```

```
Out[113]: array([  99, 65534,    3], dtype=uint16)
```

```
In [114]: copy
```

```
Out[114]: array([ 1, -2,  3], dtype=int16)
```

- You can **fill** an array with a **single value**

```
In [116]: a = np.array([1, 2, 3], float)
```

```
In [117]: a
```

```
Out[117]: array([1., 2., 3.])
```

```
In [118]: a.fill(99)
```

```
In [119]: a
```

```
Out[119]: array([99., 99., 99.])
```

➤ You can **fill** an array with a **single value**

```
In [116]: a = np.array([1, 2, 3],float)
```

```
In [117]: a
```

```
Out[117]: array([1., 2., 3.])
```

```
In [118]: a.fill(99)
```

```
In [119]: a
```

```
Out[119]: array([99., 99., 99.])
```

➤ Arrays can be **transposed** easily

```
In [121]: a = np.array(range(6),float).reshape((2, 3))
```

```
In [122]: a
```

```
Out[122]:
```

```
array([[0., 1., 2.],  
       [3., 4., 5.]])
```

```
In [123]: a.transpose()
```

```
Out[123]:
```

```
array([[0., 3.],  
       [1., 4.],  
       [2., 5.]])
```

➤ You can **fill** an array with a single value

```
In [121]: a = np.array(range(6),float).reshape((2, 3))
```

➤ Arrays can be **transposed** easily

```
In [122]: a
```

```
Out[122]: array([[0., 1., 2.],  
               [3., 4., 5.]])
```

```
In [116]: a = np.array([1, 2, 3],float)
```

```
In [117]: a
```

```
Out[117]: array([1., 2., 3.]])
```

```
In [123]: a.transpose()
```

```
Out[123]: array([[0., 3.],  
               [1., 4.],  
               [2., 5.]])
```

```
In [118]: a.fill(99)
```

```
In [119]: a
```

```
Out[119]: array([99., 99., 99.]])
```

➤ Combining arrays can be done through **concatenation**. Careful, the data is **copied**!

```
In [125]: a = np.array([1,2], float)
```

```
In [126]: b = np.array([3,4,5,6], float)
```

```
In [127]: c = np.array([7,8,9], float)
```

```
In [128]: np.concatenate((a, b, c))
```

```
Out[128]: array([1., 2., 3., 4., 5., 6., 7., 8., 9.]])
```

- You can **fill** an array with a single value
- Arrays can be **transposed** easily
- **Combining** arrays can be done through **concatenation**. Careful, the data is **copied**!

```
In [125]: a = np.array([1,2], float)
In [126]: b = np.array([3,4,5,6], float)
In [127]: c = np.array([7,8,9], float)
In [128]: np.concatenate((a, b, c))
Out[128]: array([1., 2., 3., 4., 5., 6., 7., 8., 9.]
```

- Multidimensional arrays can be **concatenated** along a specific **axis**:

```
In [130]: a = np.array([[1, 2], [3, 4]], float)
```

```
In [131]: b = np.array([[5, 6], [7, 8]], float)
```

```
In [132]: np.concatenate((a,b),axis=0)
```

```
Out[132]:
array([[1., 2.],
       [3., 4.],
       [5., 6.],
       [7., 8.]])
```

```
In [133]: np.concatenate((a,b),axis=1)
```

```
Out[133]:
array([[1., 2., 5., 6.],
       [3., 4., 7., 8.]])
```


➤ Some basic **array** definitions

```
In [142]: np.arange(5, dtype=float)
```

```
Out[142]: array([0., 1., 2., 3., 4.])
```

```
In [143]: np.linspace(30,40,5)
```

```
Out[143]: array([30. , 32.5, 35. , 37.5, 40. ])
```

```
In [144]: np.ones((2,3), dtype=float)
```

```
Out[144]:  
array([[1., 1., 1.],  
       [1., 1., 1.]])
```

```
In [145]: np.zeros(7, dtype=int)
```

```
Out[145]: array([0, 0, 0, 0, 0, 0, 0])
```

```
In [146]: a = np.array([[1, 2, 3], [4, 5, 6]], float)
```

```
In [147]: np.zeros_like(a)
```

```
Out[147]:  
array([[0., 0., 0.],  
       [0., 0., 0.]])
```

➤ Some basic **array** Algebra

```
In [149]: a = np.array([1,2,3], float)
```

```
In [150]: b = np.array([5,2,6], float)
```

```
In [151]: a+b
```

```
Out [151]: array([6., 4., 9.])
```

```
In [152]: a*b
```

```
Out [152]: array([ 5.,  4., 18.])
```

```
In [153]: np.dot(a,b)
```

```
Out [153]: 27.0
```

```
In [154]: b**a
```

```
Out [154]: array([ 5.,  4., 216.])
```

➤ Watch out for automatic shape extension or **broadcasting**

```
In [156]: a = np.array([[1, 2], [3, 4], [5, 6]], float)
```

```
In [157]: b = np.array([-1, 3], float)
```

```
In [158]: a
```

```
Out[158]:
```

```
array([[1., 2.],  
       [3., 4.],  
       [5., 6.]])
```

```
In [159]: b
```

```
Out[159]: array([-1.,  3.])
```

```
In [160]: a+b
```

```
Out[160]:
```

```
array([[0., 5.],  
       [2., 7.],  
       [4., 9.]])
```

- Watch out for automatic shape extension or **broadcasting**

$$a + b = a + b$$

[1., 2.]
[3., 4.]
[5., 6.]

[-1., 3.]
[-1., 3.]
[-1., 3.]

[0., 5.]
[2., 7.]
[4., 9.]

➤ Watch out for automatic shape extension or **broadcasting**

➤ You can control shape extension with **newaxis**

$$a + b = a + b$$

[1., 2.]	[-1., 3.]	[0., 5.]
[3., 4.]	[-1., 3.]	[2., 7.]
[5., 6.]	[-1., 3.]	[4., 9.]

- Watch out for automatic shape extension or **broadcasting**
- You can control shape extension with **newaxis**

```
In [174]: a = np.zeros((2,2), float)
```

```
In [175]: b = np.array([-1., 3.], float)
```

```
In [176]: a + b
```

```
Out[176]:
```

```
array([[ -1.,  3.],  
       [ -1.,  3.]])
```

```
In [177]: a + b[np.newaxis,:]
```

```
Out[177]:
```

```
array([[ -1.,  3.],  
       [ -1.,  3.]])
```

```
In [178]: a + b[:,np.newaxis]
```

```
Out[178]:
```

```
array([[ -1., -1.],  
       [ 3.,  3.]])
```

- NumPy offers a large library of common mathematical functions that can be applied **elementwise** to arrays

```
a = np.array([2, 1, 9], float)
```

```
a.sum() -> 12.0
```

```
a.mean() -> 4.0
```

```
a.prod() -> 18.0
```

```
a.std() -> 3.55902608
```

```
a.var() -> 12.66666666
```

- NumPy offers a large library of common mathematical functions that can be applied **elementwise** to arrays

```
In [183]: a=np.linspace(0.3,0.6,4)
```

```
In [184]: a
```

```
Out[184]: array([0.3, 0.4, 0.5, 0.6])
```

```
In [185]: np.sin(a)
```

```
Out[185]: array([0.29552021, 0.38941834, 0.47942554,  
0.56464247])
```


➤ Axis can be selected for **marginal statistic**:

```
In [187]: a = np.array([[0, 2], [3, -1], [3, 5]], float)
```

```
In [188]: a.mean(axis=0)  
Out[188]: array([2., 2.])
```

```
In [189]: a.mean(axis=1)  
Out[189]: array([1., 1., 4.])
```

```
In [190]: a.max(axis=0)  
Out[190]: array([3., 5.])
```

```
In [191]: a >= 2  
Out[191]:  
array([[False,  True],  
       [ True, False],  
       [ True,  True]])
```

- many built-in routines for linear algebra are in the **linalg** submodule:

```
In [193]: a = np.array([[4, 2, 0], [9, 3, 7], [1, 2, 1]],  
float)
```

```
In [194]: a
```

```
Out[194]:
```

```
array([[4., 2., 0.],  
       [9., 3., 7.],  
       [1., 2., 1.]])
```

```
In [195]: np.linalg.det(a)
```

```
Out[195]: -48.000000000000003
```

```
In [196]: vals, vecs = np.linalg.eig(a)
```

```
In [197]: vals
```

```
Out[197]: array([ 8.85591316,  1.9391628 , -2.79507597])
```

```
In [198]: vecs
```

```
Out[198]:
```

```
array([[ -0.3663565 , -0.54736745,  0.25928158],  
       [-0.88949768,  0.5640176 , -0.88091903],  
       [-0.27308752,  0.61828231,  0.39592263]])
```

➤ many built-in routines for linear algebra are in the **linalg** submodule:

➤ Singular Value Decomposition

```
In [200]: a = np.array([[1, 3, 4], [5, 2, 3]], float)
```

```
In [201]: U, s, Vh = np.linalg.svd(a)
```

```
In [202]: U
```

```
Out[202]:
```

```
array([[ -0.6113829 , -0.79133492],  
       [ -0.79133492,  0.6113829 ]])
```

```
In [203]: s
```

```
Out[203]: array([7.46791327, 2.86884495])
```

```
In [204]: Vh
```

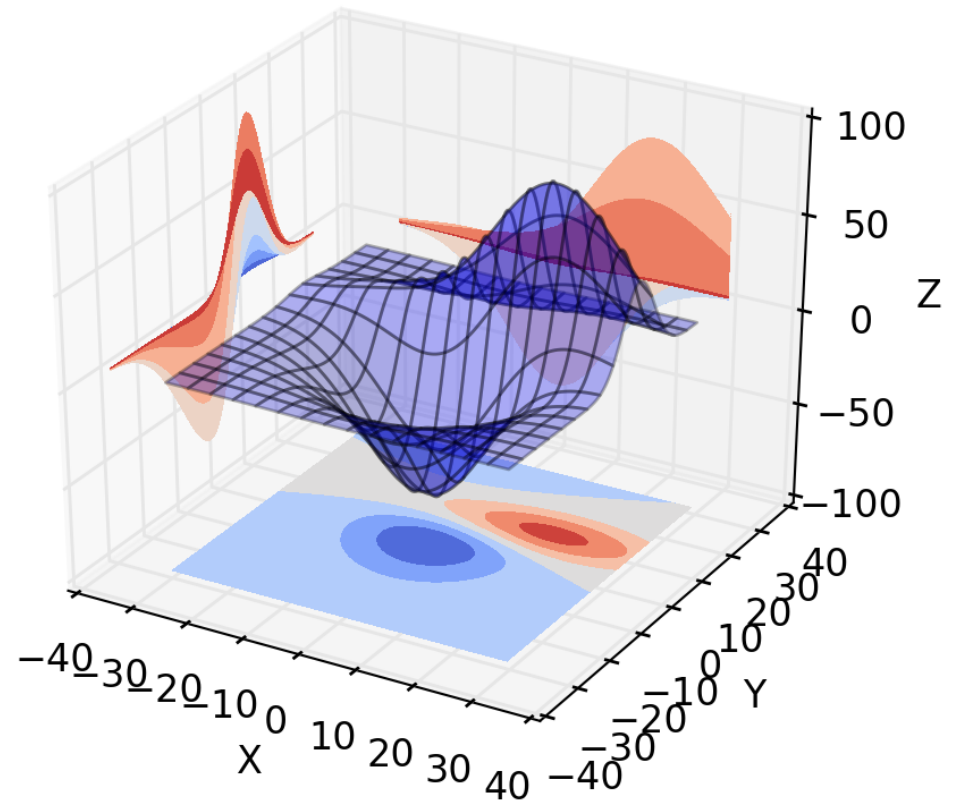
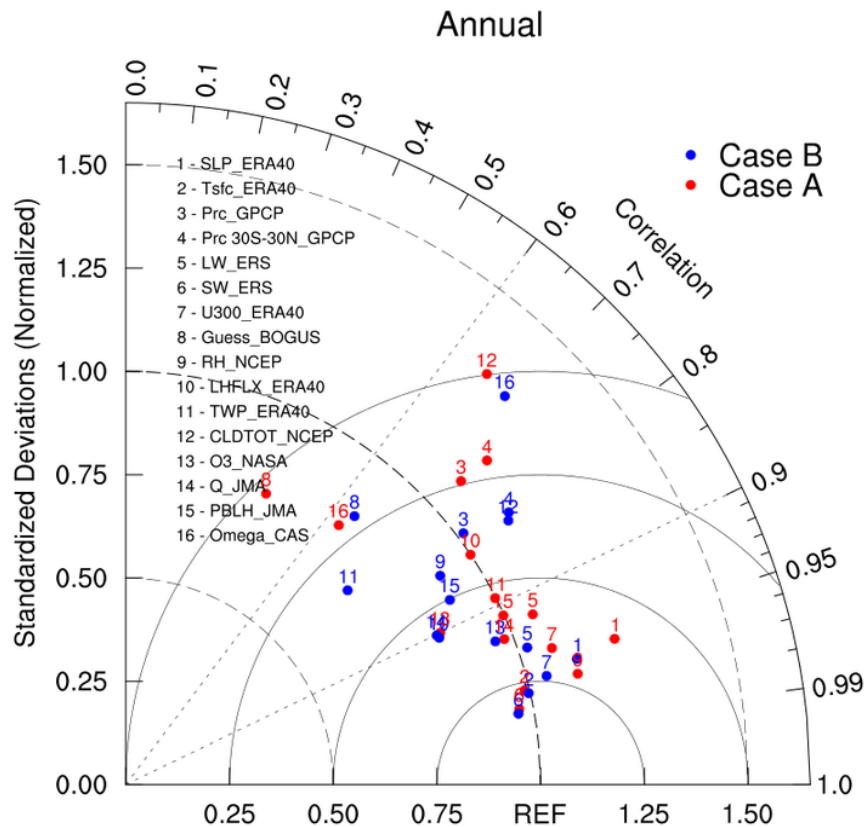
```
Out[204]:
```

```
array([[ -0.61169129, -0.45753324, -0.64536587],  
       [  0.78971838, -0.40129005, -0.46401635],  
       [ -0.046676   , -0.79349205,  0.60678804]])
```



matplotlib

- ▶ Powerful library for **2D data plotting**, some **3D capability** Very well designed (common tasks easy, complex tasks possible).





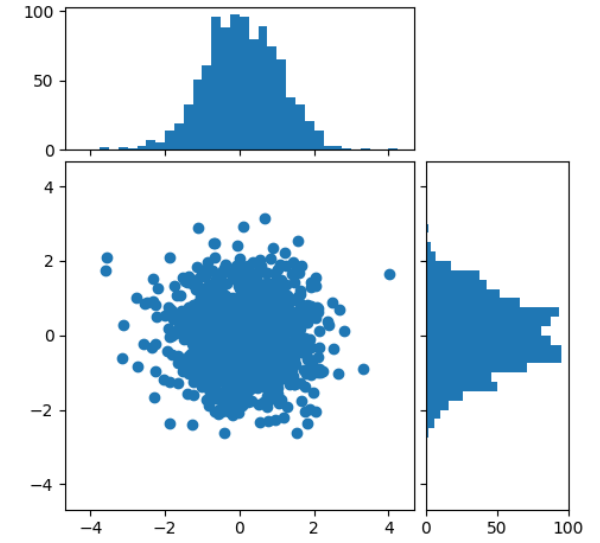
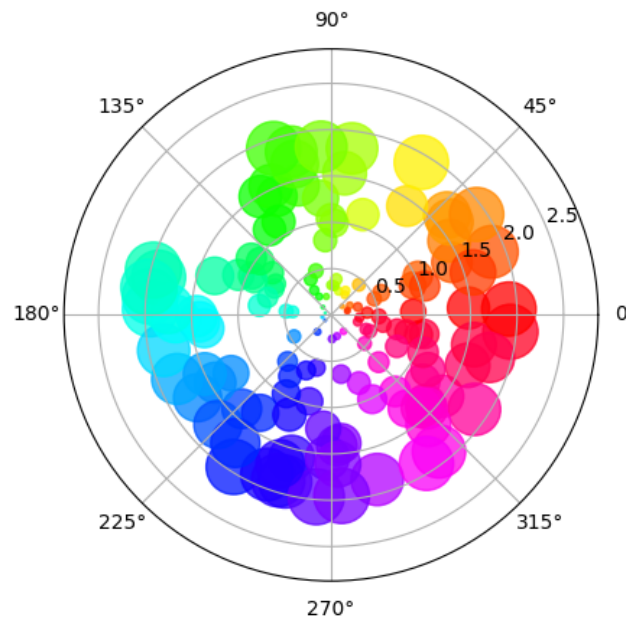
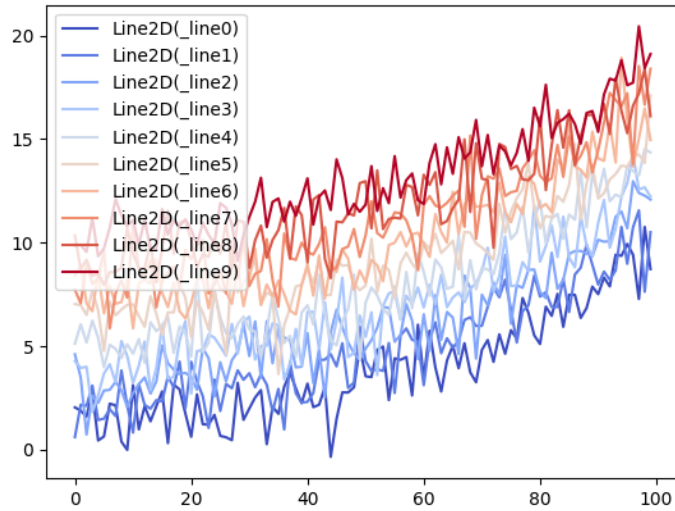
matplotlib

How can I make beautiful plots?

*Take a look at the
Gallery!*

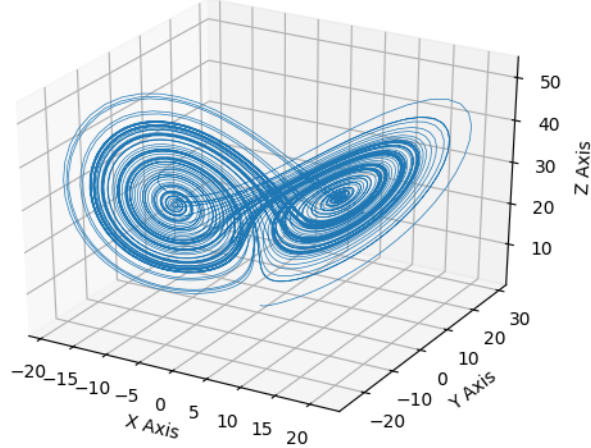


matplotlib

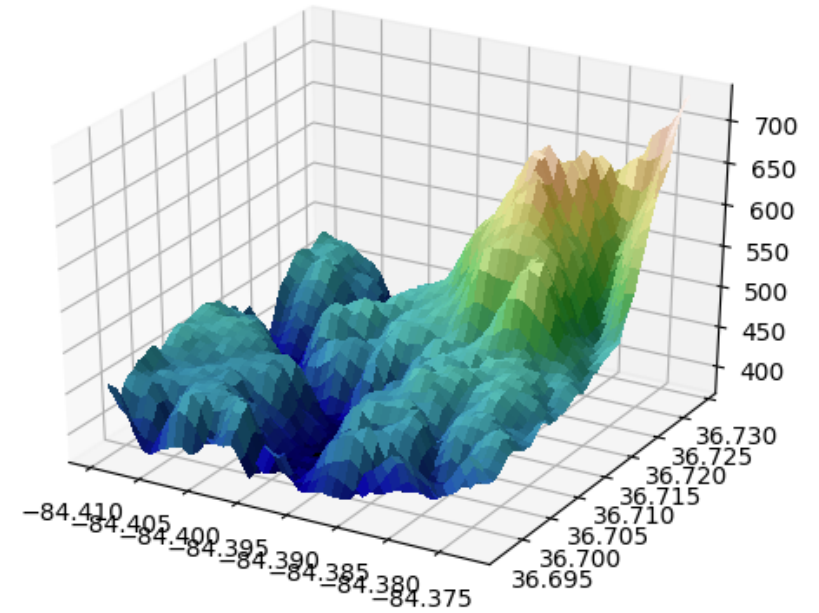
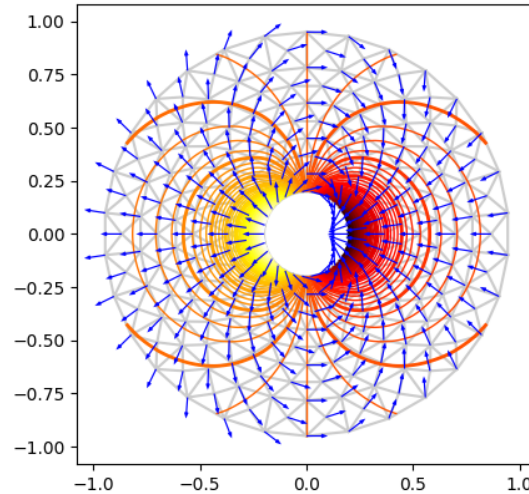


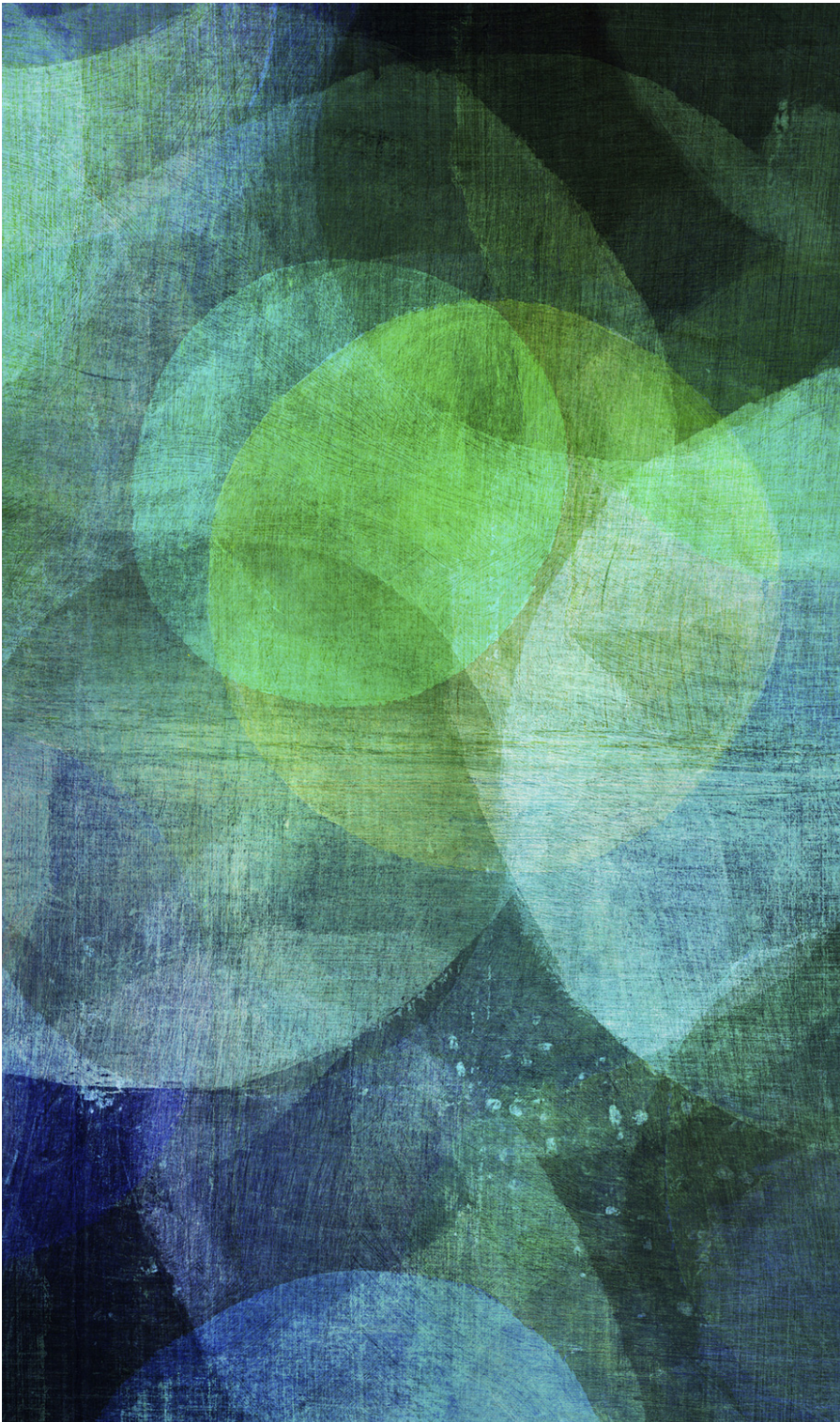
the Gallery!

Lorenz Attractor



Gradient plot: an electrical dipole





EXERCISES

.....

- ▶ particle animation
- ▶ large data memmap