

Python Advance Course via Astronomy street



Sérgio Sousa (IA)

ExoEarths Team (<http://www.astro.up.pt/exoearths/>)

Python Advance Course via Astronomy street

Advance Course Outline:

- Lesson 1: Python basics (T + P)
- Lesson 2: Python with Numpy and Matplotlib (T + P)
- Lesson 3: Science and Astronomy modules (Scipy, Pyfits, Pyraf) (T + P)

Python Advance Course via Astronomy street

Lesson 2: Python with Numpy and Matplotlib

- Object Oriented (OO) – Definition of objects/classes
- Numpy: creating and manipulation numerical data
- Plotting with Matplotlib

Object Oriented Paradigm

Why shall we care about Object Oriented programming???

- Objects are a metaphor that permits a good division of the code and abstraction of the reality
- Allow an easy way to implement changes to existing code or to add new code without changing/destroying much of what was done before.
- Python is based on OO and so are most of the libraries available.
- Almost everything in Python is an object (even functions are in fact Python objects)

Defining Objects/Classes

Simple approach

Class Variables

Instance Variables

Instance Methods (self)

Class Methods (static)

```
class Star:
    """ A simple Star class"""

    grav = 6.67384e-11 # Gravitional constant

    def __init__(self, massin,radiusin):
        self.mass = massin
        self.radius = radiusin

    def get_surface_gravity(self):
        return Star.grav*self.mass/self.radius**2

    @staticmethod
    def get_spectral_types():
        return ['O','B','A','F','G','K','M']

## My functions:

### Main program:
def main():
    print "Hello"
    s1=Star(1.1,0.98)
    print s1.mass
    print s1.radius
    print s1.get_surface_gravity()
    print Star.get_spectral_types()
```

Running this code:

```
Hello
1.1
0.98
7.64392336526e-11
['O', 'B', 'A', 'F', 'G', 'K', 'M']
```

OO things to explore

Object built-in functions and Operators Overloading

1. `__init__ (self [,args...])`

Constructor (with any optional arguments)

Sample Call : `obj = className(args)`

2. `__del__(self)`

Destructor, deletes an object. Sample Call : `del obj`

3. `__repr__(self)`

Evaluatable string representation. Sample Call : `repr(obj)`

4. `__str__(self)`


Printable string representation. Sample Call : `str(obj)`

5. `__cmp__(self, x)`

Object comparison. Sample Call: `cmp(obj, x)`

6. `__add__(self, other)`

Adding objects: Overloading of + operator.
Sample Call: `obj1 + obj2`



```
1#!/usr/bin/python
2
3class Vector:
4    def __init__(self, a, b):
5        self.a = a
6        self.b = b
7
8    def __str__(self):
9        return 'Vector (%d, %d)' % (self.a, self.b)
10
11    def __add__(self, other):
12        return Vector(self.a + other.a, self.b + other.b)
13
14v1 = Vector(2,10)
15v2 = Vector(5,-2)
16print v1 + v2
```

```
$ ./ObjectOverloading.py
Vector (7, 8)
```

OO things to explore

OO Keywords to read about:

- **Abstraction:** The extraction of the key characteristics of a concept or entity from the real world to allow their representation in a computer.
- **Encapsulation:** The values of the variables inside an object are private, unless methods are written to pass that information outside of the object. (Not practicable in Python)
- **Inheritance:** Each subclass inherits all variables and methods of its superclass. (e.g. Animal is a superclass of Dog and Cat)
- **Polymorphism:** Each object can behave as a super class object (e.g. Cat and Dog can behave as Animal)

Other interesting OO keywords to explore for complex applications:

- Abstract Classes
- Interfaces



Good Practices in Python

- Explicit variable names (no need of a comment to explain what is in the variable)
- Style: spaces after commas, around =, etc. A certain number of rules for writing “beautiful” code (and, more importantly, using the same conventions as everybody else!) are given in the Style Guide for Python Code and the Docstring Conventions page (to manage help strings).
- Except some rare cases, variable names and comments in English.
- Good indentation (forced in Python)

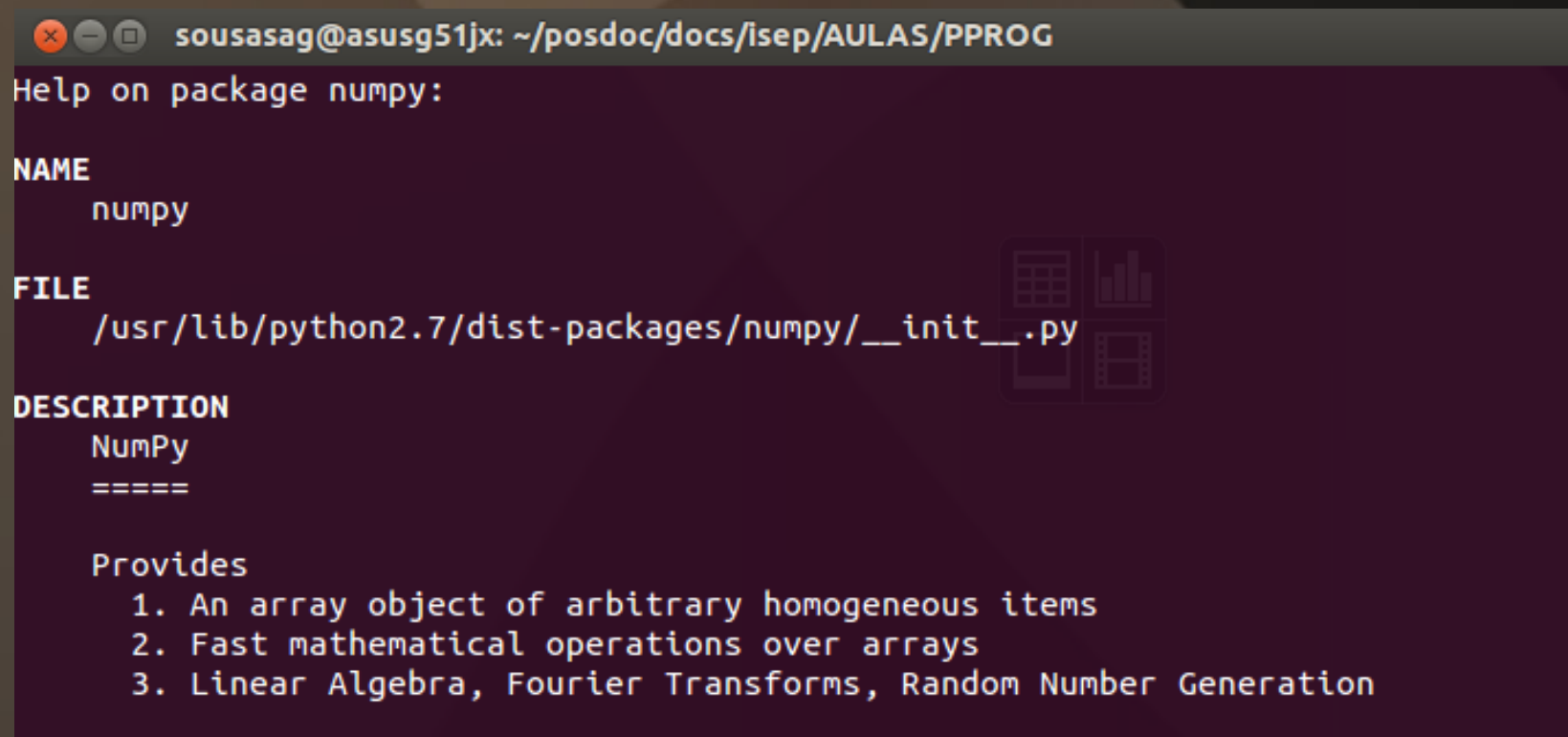
Python Advance Course via Astronomy street

Lesson 2: Python with Numpy and Matplotlib

- Object Oriented (OO) – Definition of objects/classes
- Numpy: creating and manipulation numerical data
- Plotting with Matplotlib

Numpy

```
>>> import numpy
>>> help(numpy)
```



```
sousasag@asusg51jx: ~/posdoc/docs/isep/AULAS/PPROG
Help on package numpy:

NAME
    numpy

FILE
    /usr/lib/python2.7/dist-packages/numpy/__init__.py

DESCRIPTION
    NumPy
    =====

    Provides
    1. An array object of arbitrary homogeneous items
    2. Fast mathematical operations over arrays
    3. Linear Algebra, Fourier Transforms, Random Number Generation
```

Numpy Array vs. Python list

```
example_timeit_numpy.py x
1 #!/usr/bin/python
2 ## My first python code
3
4 ##imports:
5 import numpy as np
6 import timeit
7
8 ## My functions:
9
10 def normal_list():
11     L = range(1000000)
12     L2 = [i**2 for i in L]
13
14
15 def numpy_array():
16     a = np.arange(1000000)
17     a2 = a**2
18
19 ### Main program:
20 def main():
21     print "Normal List:"
22     timer = timeit.Timer("normal_list()", setup="from __main__ import normal_list")
23     print timer.timeit(1)*1000. , 'mili seconds'
24     print "Numpy Array:"
25     timer = timeit.Timer("numpy_array()", setup="from __main__ import numpy_array")
26     print timer.timeit(1)*1000. , 'mili seconds'
27
28
29 if __name__ == "__main__":
30     main()
```

```
$ ./example_timeit_numpy.py
Normal List:
140.730142593 mili seconds
Numpy Array:
7.87591934204 mili seconds
```

Things that you can do with Numpy

- Create Arrays: direct definition

```
>>> import numpy as np
>>> a = np.array([0,1,2,3]) # 1D array
>>> b = np.array([[0, 1, 2], [3, 4, 5]]) # 2D array: 2 x 3 array
>>> c = np.array([[[1], [2]], [[3], [4]]]) # 3D Array
>>> # evenly spaced:
```

```
...
>>> d = np.arange(10) ← Same as range in built in Python
```

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

```
>>> e = np.arange(1,9,2) # start, end (exclusive), step
```

```
>>> e
array([1, 3, 5, 7])
```

```
>>> # by a number of points
```

```
...
>>> f = np.linspace(0, 1, 6) # start, end, num-points
```

```
>>> f
array([ 0. ,  0.2,  0.4,  0.6,  0.8,  1. ]) ← Defining a linear space array
```

```
>>> a
array([0, 1, 2, 3])
```

```
>>> a.ndim
1
```

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

```
>>> b.ndim
2
```

```
>>> len(a)
4
```

```
>>> b.shape
```

```
(2, 3) ← This is a tuple
```

} Some properties of the array object

Things that you can do with Numpy

- Create Arrays: automatic definitions

```
>>> # creation of predefined arrays:
...
>>> a = np.ones((3, 3))
>>> # reminder: (3, 3) is a tuple
... a
array([[ 1.,  1.,  1.],
       [ 1.,  1.,  1.],
       [ 1.,  1.,  1.]])
>>>
>>> b = np.zeros((2,2))
>>> b
array([[ 0.,  0.],
       [ 0.,  0.]])
>>>
>>> c = np.eye(3)
>>> c
array([[ 1.,  0.,  0.],
       [ 0.,  1.,  0.],
       [ 0.,  0.,  1.]])
>>>
>>> d = np.diag([1,2,3,4])
>>> d
array([[1, 0, 0, 0],
       [0, 2, 0, 0],
       [0, 0, 3, 0],
       [0, 0, 0, 4]])
...
```

ones and zeros also work for 1D

Defining an Identity matrix

Defining a diagonal matrix

Things that you can do with Numpy

- Create Arrays: setting different data types

```
>>> #creating with different data types
```

```
...
```

```
>>> a = np.array([1, 2, 3])
```

```
>>> a.dtype
```

```
dtype('int64')
```

```
>>>
```

```
>>> a = np.array([1., 2., 3.])
```

```
>>> a.dtype
```

```
dtype('float64')
```

```
>>>
```

```
>>> a = np.array([1, 2, 3], dtype=float) #bool, complex
```

```
>>> a.dtype
```

```
dtype('float64')
```

```
>>> a = np.array([1, 2, 3], dtype=complex) #bool, complex
```

```
>>> a.dtype
```

```
dtype('complex128')
```

} automatic definition

} Forcing the types

Things that you can do with Numpy

- Indexing in Arrays – getting the values that you need

```
>>> #indexing and Slicing
...
>>> a = np.arange(10)
>>> a
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> a[0], a[2], a[-1]
(0, 2, 9)
>>>
>>> #index in numpy 2D: 2ways:
... a = np.diag(np.arange(3))
>>> a
array([[0, 0, 0],
       [0, 1, 0],
       [0, 0, 2]])
>>> a[1][1]
1
>>> a[1,1]      #using a tuple
1
>>> a[(1,1)]
1
>>> a[1,2] = 26
>>> a
array([[ 0,  0,  0],
       [ 0,  1, 26],
       [ 0,  0,  2]])
>>> a[1]# geting a line
array([ 0,  1, 26])
>>> a[:,2]# getting a row
array([ 0, 26,  2])
```

Indexing arrays is the same as for lists

You can also use tuples for arrays,
simpler notation for n>1 Dimensional arrays

Getting lines and/or rows from a matrix

Things that you can do with Numpy

- Create Arrays: Slicing and Views

```
>>> #slicing:
... a = np.arange(10)
>>> a
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> a[2:9:3] # start;end;step
array([2, 5, 8])
>>> a[:4]
array([0, 1, 2, 3])
>>> a[2:]
array([2, 3, 4, 5, 6, 7, 8, 9])
>>> a[::2]
array([0, 2, 4, 6, 8])
```

Sintaxe for slicing:
array[start:end:step]

Some useful variations

```
>>> #slicing create views, using the same memory... Careful
...
>>> a = np.arange(10)
>>> a
array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> b = a[::2]
>>> b
array([0, 2, 4, 6, 8])
>>> b[0] = 26
>>> b
array([26, 2, 4, 6, 8])
>>> a
array([26, 1, 2, 3, 4, 5, 6, 7, 8, 9])
>>> # to copy use:
... b = a[::2].copy() # this force a copy
>>> b[0] = 12
>>> b
array([12, 2, 4, 6, 8])
>>> a
array([26, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

Important to be aware:

Slicing create views that share the same memory of the original array;

If you want to copy you need to force the copy;

Things that you can do with Numpy

- Create Arrays: Applying masks (can be used as where in IDL)

Next slide for random numbers (wait for it...)

Defining a mask
(which will be an array of booleans)

Applying the mask

Nice for tagging
(check example)

Can also be used to
assign a value to
different places at once

```
>>> #masks (similar to where in IDL)
...
>>> a = np.random.random_integers(0, 20, 15)
>>> a
array([ 6, 18,  6,  3,  5, 14, 15, 16,  8,  1, 20, 20,  5,  7,  8])
>>> mask = (a % 2 == 0)
>>> mask
array([ True,  True,  True, False, False,  True, False,  True,  True,
        False,  True,  True, False, False,  True], dtype=bool)
>>> even_a = a[mask] # this create a copy, not a view
>>> even_a
array([ 6, 18,  6, 14, 16,  8, 20, 20,  8])
>>>
>>> # useful for tagging
... a[a % 2 == 0] = -1
>>> a
array([-1, -1, -1,  3,  5, -1, 15, -1, -1,  1, -1, -1,  5,  7, -1])
>>>
>>> a[[0,1,3]] = 26 # use a list to change n values in one line
>>> a
array([26, 26, -1, 26,  5, -1, 15, -1, -1,  1, -1, -1,  5,  7, -1])
```

Things that you can do with Numpy

- Create Arrays: Applying masks (can be used as where in IDL)

Using np.where()

```
>>> import numpy as np
>>> x = np.arange(15)+12
>>> x
array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26])
>>> ix = np.where(x % 2 == 0)
>>> ix
(array([ 0,  2,  4,  6,  8, 10, 12, 14]),)
>>> x2 = x[ix]
>>> x2
array([12, 14, 16, 18, 20, 22, 24, 26])
>>> np.where(x % 2 == 0, x, -1)
array([12, -1, 14, -1, 16, -1, 18, -1, 20, -1, 22, -1, 24, -1, 26])
>>> x
array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26])
>>> x = np.where(x % 2 == 0, x, -1)
>>> x
array([12, -1, 14, -1, 16, -1, 18, -1, 20, -1, 22, -1, 24, -1, 26])
>>>
```

Define some array with numbers

Using where.
Similar as a mask

You can also tag
with where

Can also be used to
assign a value to
different places at once

Things that you can do with Numpy

- Create Arrays: Random numbers generation

```
>>> # creation of random numbers:
...
>>> a = np.random.rand(4) # uniform in [0, 1]
>>> a
array([ 0.292304 ,  0.66154467,  0.88626098,  0.67117646])
>>>
>>> b = np.random.randn(4) # Gaussian
>>> b
array([-1.07921219, -0.62811542,  0.29934704,  0.12727723])
>>>
>>> np.random.seed(1234) # Setting the random seed
>>>
>>> c = np.random.random_integers(1,50,5) # 5 random integers
>>> c
array([48, 20, 39, 13, 25])
>>>
>>> s = np.random.poisson(5, 10) # see help(np.random) for more distributions
>>> s
array([ 5,  1,  4,  2,  6,  6,  6, 10,  2,  3])
```

← The standard random common to many languages

← A gaussian random number generation. $G(0,1)$

← **Important:** Careful with the seed to generate the random numbers

← To generate the next Euromillions numbers

You can also obtain random numbers following many other statistical distributions. ex. poisson

Things that you can do with Numpy

- Create Arrays: Random numbers generation – The statistical distributions available

```
=====
Univariate distributions
=====
beta          Beta distribution over ``[0, 1]``.
binomial      Binomial distribution.
chisquare     :math:`\chi^2` distribution.
exponential   Exponential distribution.
f            F (Fisher-Snedecor) distribution.
gamma        Gamma distribution.
geometric     Geometric distribution.
gumbel       Gumbel distribution.
hypergeometric Hypergeometric distribution.
laplace      Laplace distribution.
logistic     Logistic distribution.
lognormal    Log-normal distribution.
logseries    Logarithmic series distribution.
negative_binomial Negative binomial distribution.
noncentral_chisquare Non-central chi-square distribution.
noncentral_f Non-central F distribution.
normal       Normal / Gaussian distribution.
pareto       Pareto distribution.
poisson      Poisson distribution.
power        Power distribution.
rayleigh     Rayleigh distribution.
triangular   Triangular distribution.
uniform      Uniform distribution.
vonmises     Von Mises circular distribution.
wald         Wald (inverse Gaussian) distribution.
weibull      Weibull distribution.
zipf         Zipf's distribution over ranked data.
=====
```

>>> help(np.random)

Things that you can do with Numpy

- Arrays: Numerical Operations

```
>>> a = np.array([1,2,3,4])
>>> a + 1
array([2, 3, 4, 5])
>>> 2**a
array([ 2,  4,  8, 16])
>>>
>>> # arrays are objects, operators were overloaded
... b = np.ones(4) + 1
>>> b
array([ 2.,  2.,  2.,  2.])
>>> a - b
array([-1.,  0.,  1.,  2.])
>>> a * b
array([ 2.,  4.,  6.,  8.])
>>>
>>> # warning: NOT matrix multiplication
...
>>> c = np.ones((3,3))
>>> c
array([[ 1.,  1.,  1.],
       [ 1.,  1.,  1.],
       [ 1.,  1.,  1.]])
>>> c * c
array([[ 1.,  1.,  1.],
       [ 1.,  1.,  1.],
       [ 1.,  1.,  1.]])
>>>
>>> # to multiply matrices:
...
>>> c.dot(c)
array([[ 3.,  3.,  3.],
       [ 3.,  3.,  3.],
       [ 3.,  3.,  3.]])
```

Numpy arrays are objects.

Most of the operators were overloaded to represent what we would like.

(One of the advantages of OO programming)

We can do straightforward operations with arrays (similar to IDL)

Careful with the multiplication of arrays:

Use `array.dot(array)` to do a proper algebra multiplication of arrays

Things that you can do with Numpy

- Create Arrays: comparisons and reductions

```
>>> # comparisons
...
>>> a = np.array([1, 2, 3, 4])
>>> b = np.array([4, 2, 2, 4])
>>> a == b
array([False,  True, False,  True], dtype=bool)
>>> a > b
array([False, False,  True, False], dtype=bool)
>>> #logical operations
... np.all([True, True, False])
False
>>> np.any([True, True, False])
True
```

The comparisons operators are also overloaded. You can use it to compare directly arrays.

In addition you also have some useful logical operations in array

There are several reductions that you can do directly from the arrays.

- sum all elements;
- get the mean;
- standard deviation;
- median (is a class method);
- get extremes in array;
- get index of extremes;

Another useful method is the sort(). The default algorithm is the quicksort, but you can choose others. (check with `>>>help(np.sort)`)

```
>>> # some basic reductions:
...
>>> x = np.array([3, 10, 5, 1, 2, 7, 4])
>>> np.sum(x)
32
>>> x.sum()
32
>>> x.mean()
4.5714285714285712
>>> x.std()
2.8713930346059686
>>> np.median(x) # there is no x.median()...
4.0
>>> x.min()
1
>>> x.max()
10
>>> x.argmin() # index of minimum
3
>>> x.argmax() # index of maximum
1
>>> x.sort()
>>> x
array([ 1,  2,  3,  4,  5,  7, 10])
```

Things that you can do with Numpy

- Create Arrays: reductions in 2D

```
>>> #notes on 2D or higher
...
>>> x = np.array([[1, 1], [2, 2]])
>>> x
array([[1, 1],
       [2, 2]])
>>>
>>> x.sum()
6
>>>
>>> x.sum(axis=0)
array([3, 3])
>>>
>>> x.sum(axis=1)
array([2, 4])
>>>
>>> x[:, 0].sum()
3
>>>
>>> x.T # transpose
array([[1, 2],
       [1, 2]])
```

When you have 2D arrays (or with more dimensions) you can also use the methods.

You can also select the axis that you want to reduce using the option inside the method.

Or alternatively you use what you learn on the indexing/slicing

Special note:

How to quickly transpose a matrix

Things that you can do with Numpy

- Create Arrays: data types casting and rounding

```
>>> # data types and Casting
... np.array([1, 2, 3]) + 1.5 # bigger type win
array([ 2.5,  3.5,  4.5])
>>>
>>> # assignment don't change type
... a = np.array([1, 2, 3])
>>> a.dtype
dtype('int64')
>>> a[0] = 1.9 # float will be truncated
>>> a
array([1, 2, 3])
>>>
>>> #forced cast:
... a = np.array([1.7, 1.2, 1.6])
>>> b = a.astype(int) # <-- truncates to integer
>>> b
array([1, 1, 1])
>>>
>>> # Rounding
...
>>> a = np.array([1.2, 1.5, 1.6, 2.5, 3.5, 4.5])
>>> b = np.around(a)
>>> b
array([ 1.,  2.,  2.,  2.,  4.,  4.])
>>> c = np.around(a).astype(int)
>>> c
array([1, 2, 2, 2, 4, 4])
```

Casting: is the transformation of a variable between different data types

When making operations with different data types, the output will be the bigger data type involved.

Careful with Down - casting

Example: Floats will be truncated when passing to integers.

You can also force a cast of an array.

You can use the `around()` to round values.

The result is casted, and you may want to force the cast to a different data-type.

Things that you can do with Numpy

- Polynomials

```
>>> #polynomials
... #3x**2 + 2*x - 1:
... p = np.poly1d([3, 2, -1])
>>> p(0)
-1
>>> p.roots
array([-1.          ,  0.33333333])
>>> p.order
2
>>> p.c
array([ 3,  2, -1])
>>>
>>> q = p * p
>>> q
poly1d([ 9, 12, -2, -4,  1])
>>> q.order
4
```

Polynomials with 1 variable can also be represented by a numpy object (poly1d).

Definition of a polynomial can be done using its coefficients in a list:
Example: $3x^2 + 2x - 1$:
List: $[3, 2, -1] \rightarrow [a_2, a_1, a_0]$

There are some useful methods:

- getting the roots
- getting the order
- getting the coefficients

You can also perform direct operations with polynomials.

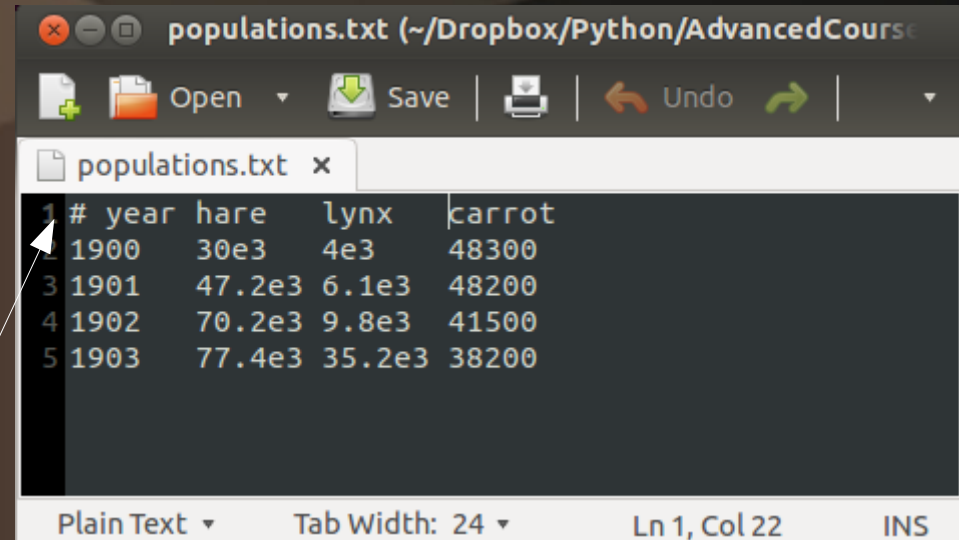
Things that you can do with Numpy

- Reading and writing data to files with Numpy

```
>>> import numpy as np
>>> data = np.loadtxt('populations.txt')
>>> data
array([[ 1900.,  30000.,  4000.,  48300.],
       [ 1901.,  47200.,  6100.,  48200.],
       [ 1902.,  70200.,  9800.,  41500.],
       [ 1903.,  77400.,  35200.,  38200.]])
```

Using `loadtxt()` you can directly obtain the data.

Careful with header in files. They should start with the special character '#'



```
populations.txt (~/.Dropbox/Python/AdvancedCourse)
Open Save | Undo
populations.txt x
1 # year hare lynx carrot
2 1900 30e3 4e3 48300
3 1901 47.2e3 6.1e3 48200
4 1902 70.2e3 9.8e3 41500
5 1903 77.4e3 35.2e3 38200
Plain Text Tab Width: 24 Ln 1, Col 22 INS
```

You can also save the data directly to a file with `savetxt()`.

```
>>> np.savetxt('pop2.txt', data)
>>>
sousasag@asusg51jx:~/Dropbox/Python/AdvancedCourse/examples$ more pop2.txt
1.9000000000000000e+03 3.0000000000000000e+04 4.0000000000000000e+03 4.8300000000000000e+04
1.9010000000000000e+03 4.7200000000000000e+04 6.1000000000000000e+03 4.8200000000000000e+04
1.9020000000000000e+03 7.0200000000000000e+04 9.8000000000000000e+03 4.1500000000000000e+04
1.9030000000000000e+03 7.7400000000000000e+04 3.5200000000000000e+04 3.8200000000000000e+04
```

Python Advance Course via Astronomy street

Lesson 2: Python with Numpy and Matplotlib

- Object Oriented (OO) – Definition of objects/classes
- Numpy: creating and manipulation numerical data
- Plotting with Matplotlib

Matplotlib

```
>>> import matplotlib  
>>> help(matplotlib)
```

```
Help on package matplotlib:
```

NAME

```
matplotlib - This is an object-oriented plotting library.
```

FILE

```
/usr/lib/pymodules/python2.7/matplotlib/__init__.py
```

DESCRIPTION

```
A procedural interface is provided by the companion pyplot module,  
which may be imported directly, e.g.::
```

```
    from matplotlib.pyplot import *
```

```
To include numpy functions too, use::
```

```
    from pylab import *
```

```
or using ipython::
```

```
    ipython -pylab
```

```
For the most part, direct use of the object-oriented library is  
encouraged when programming; pyplot is primarily for working  
interactively. The  
exceptions are the pyplot commands :func:`~matplotlib.pyplot.figure`,  
:func:`~matplotlib.pyplot.subplot`,  
:func:`~matplotlib.pyplot.subplots`,
```

Using Matplotlib

Simple plot – using procedural interface (pyplot)

```
>>> import numpy as np #It will be useful to deal with data
>>> import matplotlib.pyplot as plt #procedural interface
>>>
>>> #simple plot
...
>>> X = np.linspace(-np.pi, np.pi, 256, endpoint=True)
>>> C, S = np.cos(X), np.sin(X)
>>> plt.plot(X, C)
[<matplotlib.lines.Line2D object at 0x2c4f410>]
>>> plt.plot(X, S)
[<matplotlib.lines.Line2D object at 0x350d490>]
>>>
>>> plt.show()
```

numpy useful to deal with data arrays

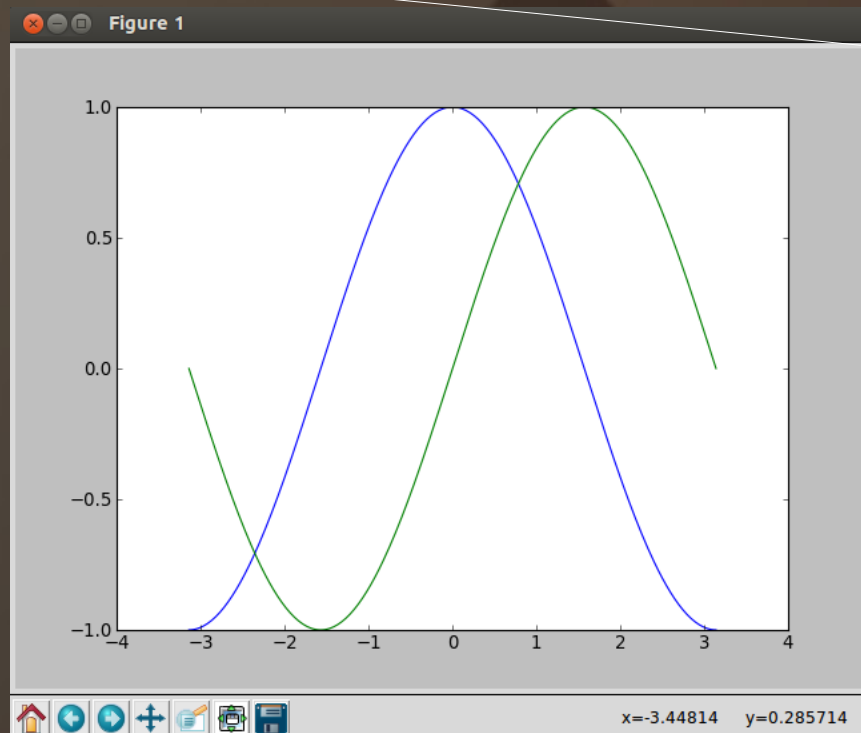
Pyplot – the module to “ignore” objects

Creation of data (x , $\cos(x)$) and (x , $\sin(x)$)

Plot each set of data

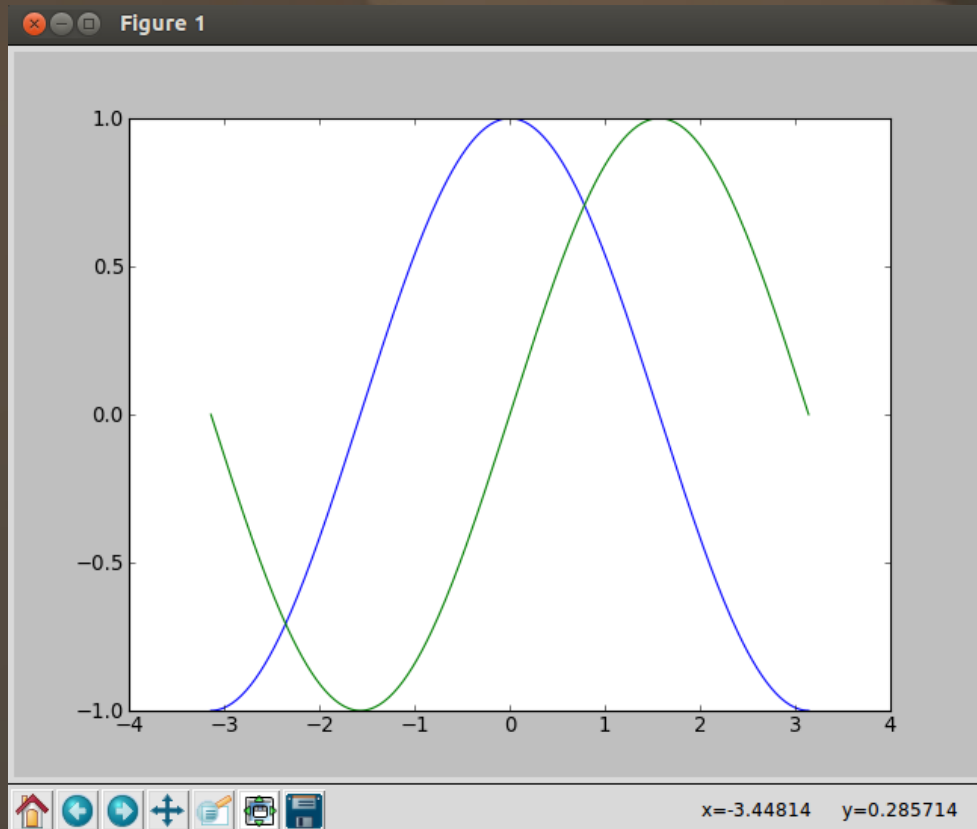
– note that objects are still created and in memory...

Show comand to open the plot window (Freezing the Python interpreter)

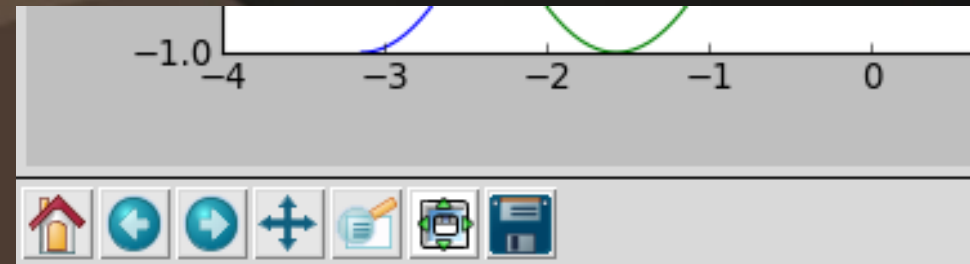


Using Matplotlib

The Plotting window - Figure



The plot window has some nice interactive features that you can easily explore



Show original plot



Undo/Redo visualization



Navigation in the plot



Zoom Rectangle



Customize Subplots



Saving/Exporting Figure

Using Matplotlib

Simple plot – changing default settings – procedural interface

```
# changing some default parameters|
```

```
# Create a figure of size 8x6 points, 80 dots per inch  
pl.figure(figsize=(8, 6), dpi=80)
```

```
# Create a new subplot from a grid of 1x1  
pl.subplot(1, 1, 1)
```

```
X = np.linspace(-np.pi, np.pi, 256, endpoint=True)  
C, S = np.cos(X), np.sin(X)
```

```
# Plot cosine with a blue continuous line of width 1 (pixels)  
pl.plot(X, C, color="blue", linewidth=1.0, linestyle="-")
```

```
# Plot sine with a green continuous line of width 1 (pixels)  
pl.plot(X, S, color="green", linewidth=1.0, linestyle="-")
```

```
# Set x limits  
pl.xlim(-4.0, 4.0)
```

```
# Set x ticks  
pl.xticks(np.linspace(-4, 4, 9, endpoint=True))
```

```
# Set y limits  
pl.ylim(-1.0, 1.0)
```

```
# Set y ticks  
pl.yticks(np.linspace(-1, 1, 5, endpoint=True))
```

```
# Save figure using 72 dots per inch  
# savefig("exercice_2.png", dpi=72)
```

```
# Show result on screen  
pl.show()
```

Defining the figure

Defining a subplot of the figure

Creation of data
(x, cos(x)) and (x, sin(x))

Plot data, setting color, linewidth and
linestyle

Defining x axis limits

Defining x axis ticks

Defining y axis limits

Defining y axis ticks

Possibility to save Figure as .png file

Show command to open the plot window
(Freezing the Python interpreter)

Using Matplotlib

Plotting lines – linestyle and markers :: >>> help(pl.plot)

The following format string characters are accepted to control the line style or marker:

character	description
'_'	solid line style
'--'	dashed line style
'-.'	dash-dot line style
':'	dotted line style
'.'	point marker
','	pixel marker
'o'	circle marker
'v'	triangle_down marker
'^'	triangle_up marker
'<'	triangle_left marker
'>'	triangle_right marker
'1'	tri_down marker
'2'	tri_up marker
'3'	tri_left marker
'4'	tri_right marker
's'	square marker
'p'	pentagon marker
'*'	star marker
'h'	hexagon1 marker
'H'	hexagon2 marker
'+'	plus marker
'x'	x marker
'D'	diamond marker
'd'	thin_diamond marker
' '	vline marker
'-'	hline marker

Using Matplotlib

Plotting lines – colors :: >>> help(pl.plot)

The following color abbreviations are supported:

character	color
'b'	blue
'g'	green
'r'	red
'c'	cyan
'm'	magenta
'y'	yellow
'k'	black
'w'	white

In addition, you can specify colors in many weird and wonderful ways, including full names (`'green'`), hex strings (`'#008000'`), RGB or RGBA tuples (`(0,1,0,1)`) or grayscale intensities as a string (`'0.8'`). Of these, the string specifications can be used in place of a `'fmt'` group, but the tuple forms can be used only as `'kwargs'`.

Example of using RGB to get a blue color:

```
>>> pl.plot(X, C, color="#0000CC", linewidth=3.0, linestyle="-.")  
[<matplotlib.lines.Line2D object at 0x3537350>]  
>>> pl.show()
```

Using Matplotlib

Simple plot with legend – using procedural interface (pyplot)

```
>>> #simple plot with legend
... import numpy as np #It will be useful to deal with data
>>> import matplotlib.pyplot as plt #procedural interface
>>>
>>> X = np.linspace(-np.pi, np.pi, 256, endpoint=True)
>>> C, S = np.cos(X), np.sin(X)
>>> plt.plot(X, C, label=r'$\cos(\theta)$')
[<matplotlib.lines.Line2D object at 0x40e2690>]
>>> plt.plot(X, S, label=r'$\sin(\theta)$')
[<matplotlib.lines.Line2D object at 0x3442550>]
>>> plt.legend(loc='upper left')
<matplotlib.legend.Legend object at 0x40e28d0>
>>>
>>> plt.show()
```

Simply using label in the plot.

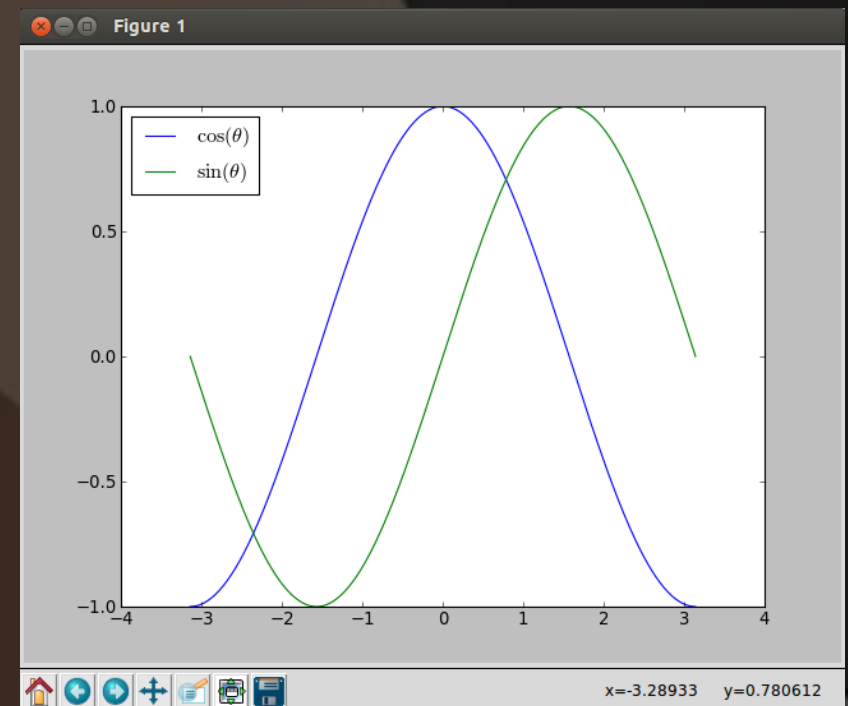
You can use latex with the sintaxe:
r' \$latex_keyword\$'

Then you simple call legend()

You can use the variable loc to set the location of the legend in the plot

The location codes are

Location String	Location Code
'best'	0
'upper right'	1
'upper left'	2
'lower left'	3
'lower right'	4
'right'	5
'center left'	6
'center right'	7
'lower center'	8
'upper center'	9
'center'	10



Using Matplotlib

Objects in Matplotlib

The awareness of the objects will allow a proper control of the plots that you want to create.

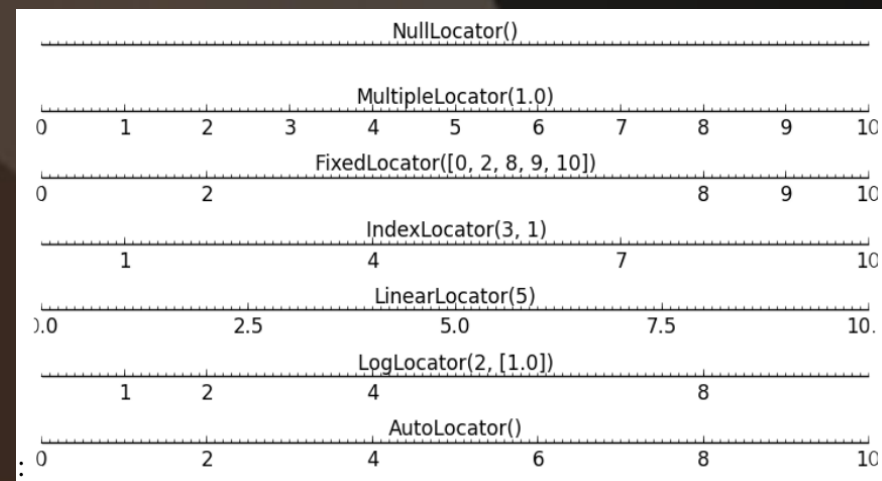
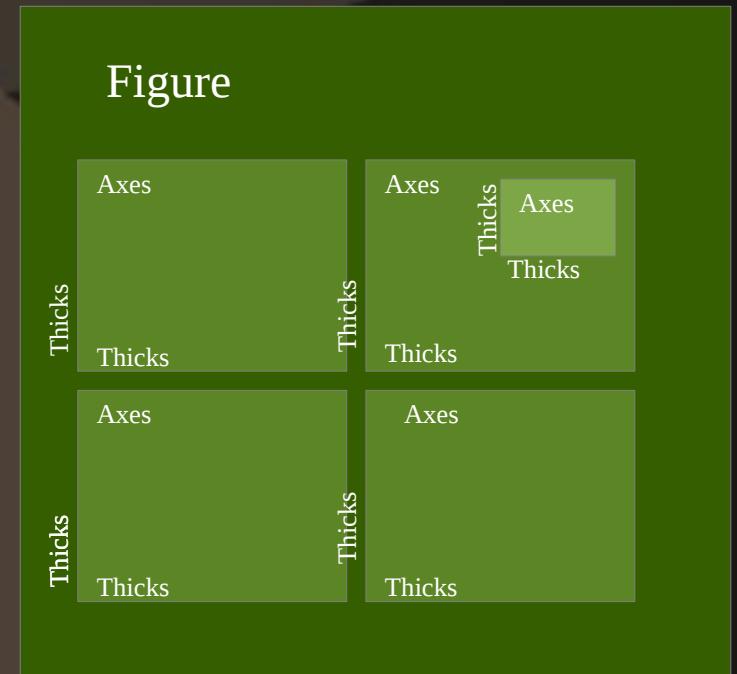
The main objects that you should know:

→ **Figure:** A Figure in matplotlib corresponds to the whole window in the user interface.

→ **Axes:** The axes is the object where you will draw your plot. You can freely control the position of the axes. Within the figure you can create/add axes.

→ **Subplot:** This are actually a specific type of axes, where the positions are fixed on the figure. Within the figure you create subplots. You can create a single subplot, or a grid of subplots within the figure.

→ **Thicks:** Are the objects that control each axe coordinate, uncluding the type of numbers, scale, intervals, etc...



Using Matplotlib

Objects in Matplotlib – An example

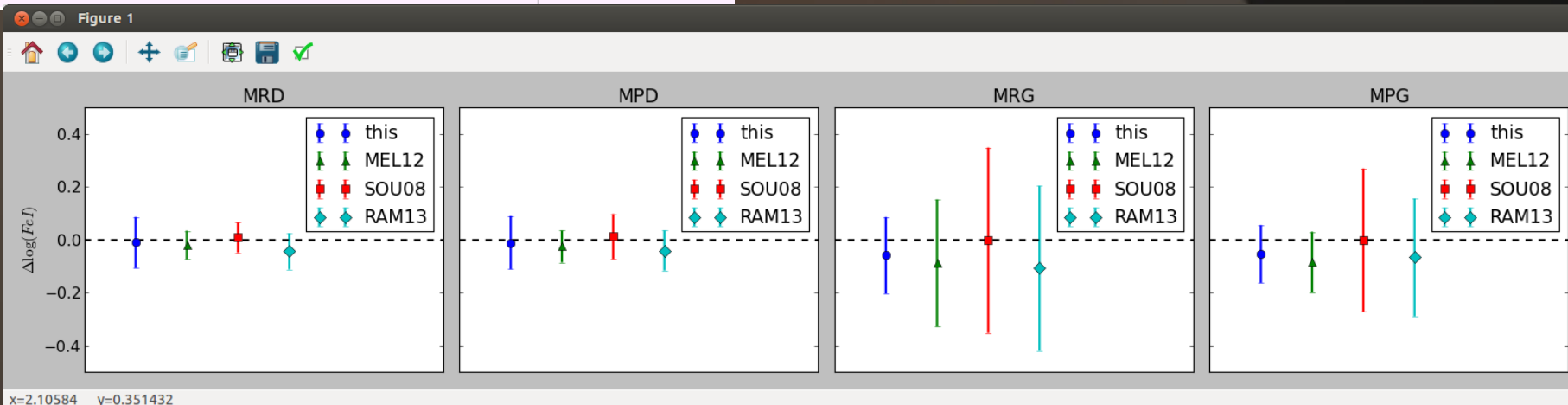
```
114 def plot_ax_star(star,result,axe):
115     linelists = [('_gesEW_mar',1,'this','o'),('_melendez_kur',2,'MEL12','^'),
116                 \('_','_mine_kur',3,'SOU08','s'),('_','_ramirez_mar',4,'RAM13','D')]
117     axe.plot([0,10],[0,0], linestyle='--', color='k', linewidth=2.0)
118     for linelist,i,labelstr,mark in linelists:
119         idstr = star+linelist+'.moog'
120         res = [ (file_r,star_r,nfei_r, dfei_r, sfei_r) \
121                for (file_r,star_r,nfei_r, dfei_r, sfei_r) \
122                  in result if file_r == idstr]
123         (file_r,star_r,nfei_r, dfei_r, sfei_r) = res[0]
124         axe.errorbar([i], [dfei_r], yerr=sfei_r,fmt=mark, label=labelstr, linewidth=2.0, markersize=8)
125     axe.set_xlim(0,7)
126     axe.set_ylim(-0.5,0.5)
127     axe.xaxis.set_visible(False)
128     axe.set_title(star)
129     axe.legend()
130
131
132 def plot_graphs(result):
133     plt.rcParams.update({'font.size': 14})
134
135     fig = plt.figure(figsize=(20, 4))
136     ax1= fig.add_subplot(141)
137     ax1.set_ylabel(r'$\Delta\log(\text{FeI})$')
138     ax2= fig.add_subplot(142,sharey=ax1)
139     plt.setp(ax2.get_yticklabels(), visible=False)
140     ax3= fig.add_subplot(143,sharey=ax1)
141     plt.setp(ax3.get_yticklabels(), visible=False)
142     ax4= fig.add_subplot(144,sharey=ax1)
143     plt.setp(ax4.get_yticklabels(), visible=False)
144
145     plot_ax_star('MRD',result,ax1)
146     plot_ax_star('MPD',result,ax2)
147     plot_ax_star('MRG',result,ax3)
148     plot_ax_star('MPG',result,ax4)
149
150 # fig.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=None, hspace=None)
151 fig.tight_layout()
152
153 plt.show()
```

Main objects:

- 1 Figure
- 4 Axes constructed with subplots
- 8 Thicks automatically constructed

Extra stuff in this example:

- Shared axes
- Changing font size
- Making axes invisible
- Using latex in lables
- Using different symbols and automatic colors
- Automatic legends
- Using error bars



Using Matplotlib

Objects in Matplotlib – An example

```
132 def plot_graphs(result):
133     plt.rcParams.update({'font.size': 14})
134
135     fig = plt.figure(figsize=(20, 4))
136     ax1= fig.add_subplot(141)
137     ax1.set_ylabel(r'$\Delta \log(\text{FeI})$')
138     ax2= fig.add_subplot(142,sharey=ax1)
139     plt.setp(ax2.get_yticklabels(), visible=False)
140     ax3= fig.add_subplot(143,sharey=ax1)
141     plt.setp(ax3.get_yticklabels(), visible=False)
142     ax4= fig.add_subplot(144,sharey=ax1)
143     plt.setp(ax4.get_yticklabels(), visible=False)
144
145     plot_ax_star('MRD',result,ax1)
146     plot_ax_star('MPD',result,ax2)
147     plot_ax_star('MRG',result,ax3)
148     plot_ax_star('MPG',result,ax4)
149
150 # fig.subplots_adjust(left=None, bottom=None, right=None, top=None, wspace=None, hspace=None)
151 fig.tight_layout()
152
153 plt.show()
154
```

Main objects:

- 1 Figure
- 4 Axes constructed with subplots

Extra stuff in this example:

- Changing font size
- Using latex in labels
- Shared axes
- Making axes invisible

Calling a specific function to create each individual plot

Using Matplotlib

Objects in Matplotlib

Only difference is the different data to be plotted

This function does the same plot for each axes.

```
114 def plot_ax_star(star,result,axe):
115     linelists = [('_gesEW_mar',1,'this','o'),('_melendez_kur',2,'MEL12','^'),\
116                 ('_mine_kur',3,'SOU08','s'),('_ramirez_mar',4,'RAM13','D')]
117     axe.plot([0,10],[0,0], linestyle='--', color='k', linewidth=2.0)
118     for linelist,i,labelstr,mark in linelists:
119         idstr = star+linelist+'.moog'
120         res = [ (file_r,star_r,nfei_r, dfei_r, sfei_r) \
121                 for (file_r,star_r,nfei_r, dfei_r, sfei_r) \
122                     in result if file_r == idstr]
123         (file_r,star_r,nfei_r, dfei_r, sfei_r) = res[0]
124         axe.errorbar([i], [dfei_r], yerr=sfei_r,fmt=mark, label=labelstr,\
125                     linewidth=2.0, markersize=8)
126     axe.set_xlim(0,7)
127     axe.set_ylim(-0.5,0.5)
128     axe.xaxis.set_visible(False)
129     axe.set_title(star)
130     axe.legend()
```

Extra stuff in this example:

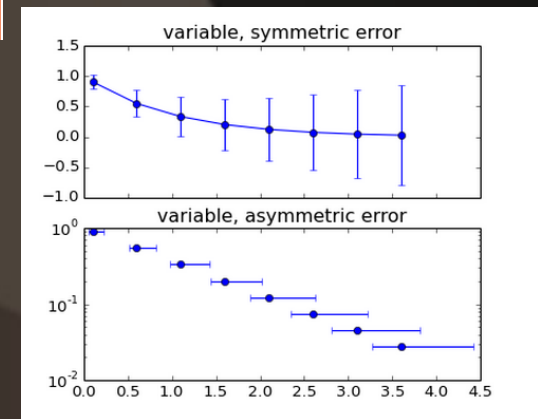
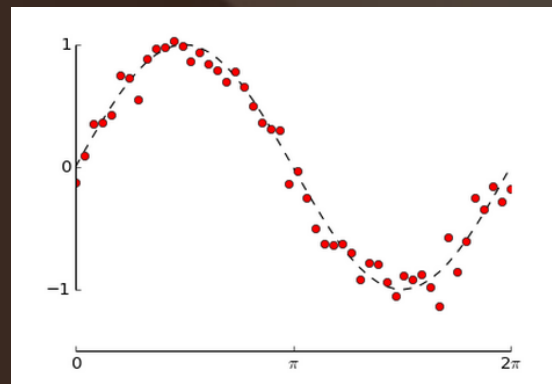
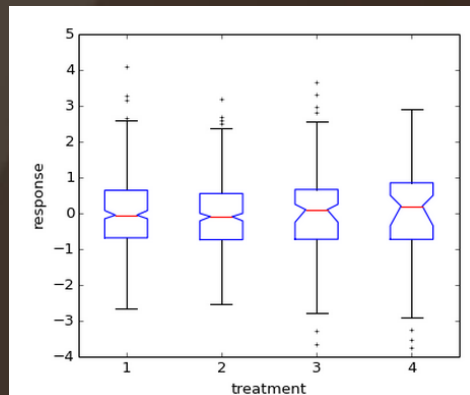
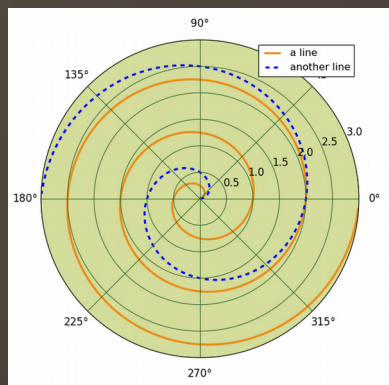
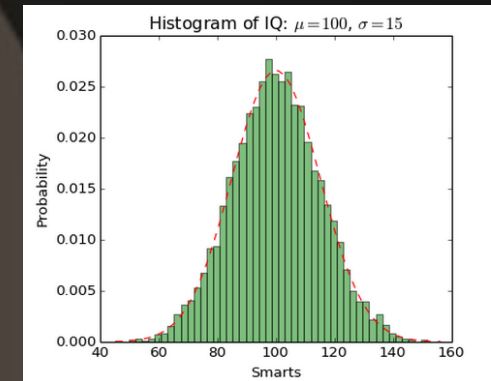
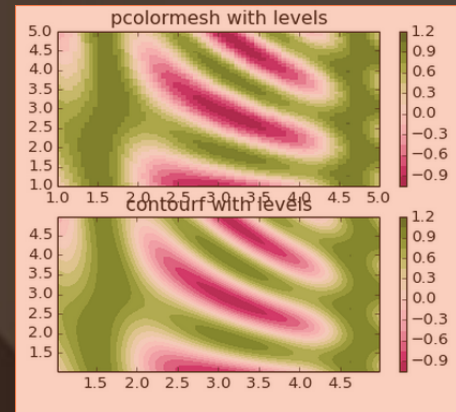
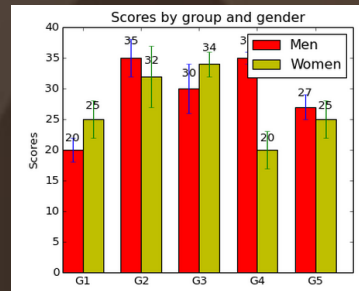
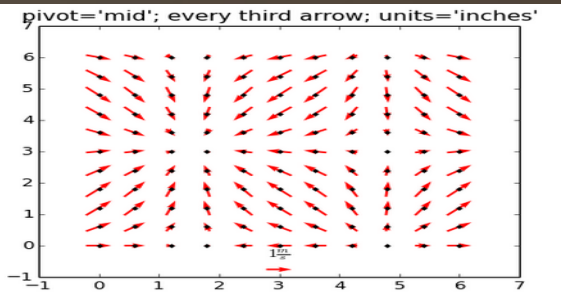
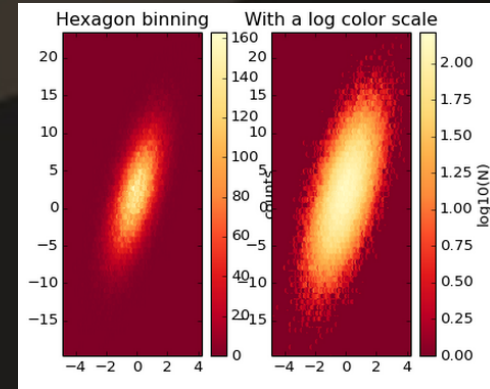
- Horizontal dashed line
- Using different symbols and automatic colors
- Automatic legends
- Using error bars

Matplotlib

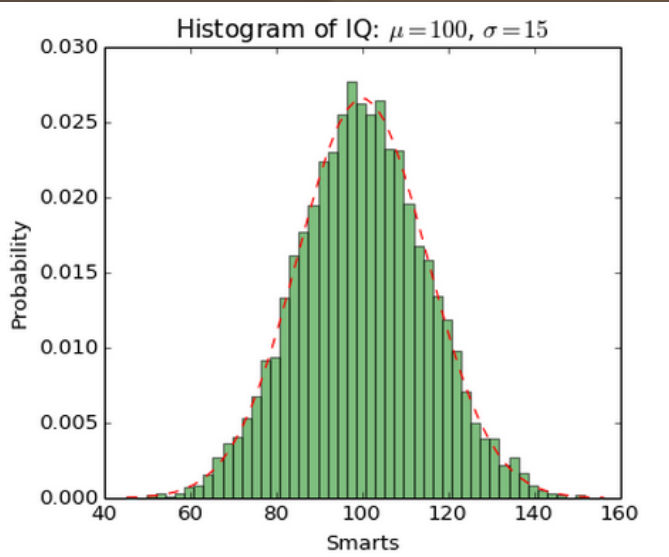
Matplotlib is a huge module which contains many features and many possibilities.

The use of Objects is benefit to control your plot easily. Experience comes with practice

There is a gallery with several examples and source code in Matplotlib: <http://matplotlib.org/gallery.html> (You can use it for your inspiration...)



Matplotlib – Gallery Examples



Random Gaussian Data Generation

Defining number of bins

Plotting histogram

Getting a normal probability density function. `help(mlab)`

(Mlab is a module for Numerical python functions written for compatibility with MATLAB commands with the same names.)

Plotting pdf

Setting titles

Adjusting subplot in Figure

```
"""
Demo of the histogram (hist) function with a few features.

In addition to the basic histogram, this demo shows a few optional features:

* Setting the number of data bins
* The ``normed`` flag, which normalizes bin heights so that the integral of
  the histogram is 1. The resulting histogram is a probability density.
* Setting the face color of the bars
* Setting the opacity (alpha value).

"""
import numpy as np
import matplotlib.mlab as mlab
import matplotlib.pyplot as plt

# example data
mu = 100 # mean of distribution
sigma = 15 # standard deviation of distribution
x = mu + sigma * np.random.randn(10000)

num_bins = 50
# the histogram of the data
n, bins, patches = plt.hist(x, num_bins, normed=1, facecolor='green', alpha=0.5)
# add a 'best fit' line
y = mlab.normpdf(bins, mu, sigma)
plt.plot(bins, y, 'r--')
plt.xlabel('Smarts')
plt.ylabel('Probability')
plt.title(r'Histogram of IQ:  $\mu=100$ ,  $\sigma=15$ ')

# Tweak spacing to prevent clipping of ylabel
plt.subplots_adjust(left=0.15)
plt.show()
```


Matplotlib – Gallery Examples

```
import matplotlib.pyplot as plt
from matplotlib.colors import LogNorm
import numpy as np
from matplotlib.mlab import bivariate_normal
```

```
N = 100
X, Y = np.mgrid[-3:3:complex(0, N), -2:2:complex(0, N)]

# A low hump with a spike coming out of the top right.
# Needs to have z/colour axis on a log scale so we see both hump and spike.
# linear scale only shows the spike.
Z1 = bivariate_normal(X, Y, 0.1, 0.2, 1.0, 1.0) + 0.1 * bivariate_normal(X, Y, 1.0, 1.0, 0.0, 0.0)
```

```
plt.subplot(2,1,1)
plt.pcolor(X, Y, Z1, norm=LogNorm(vmin=Z1.min(), vmax=Z1.max()), cmap='PuBu_r')
plt.colorbar()
```

```
plt.subplot(2,1,2)
plt.pcolor(X, Y, Z1, cmap='PuBu_r')
plt.colorbar()
```

```
plt.show()
```

Normalize a given value to the 0-1 range on a log scale

Create the parameter space grid for the surface plot

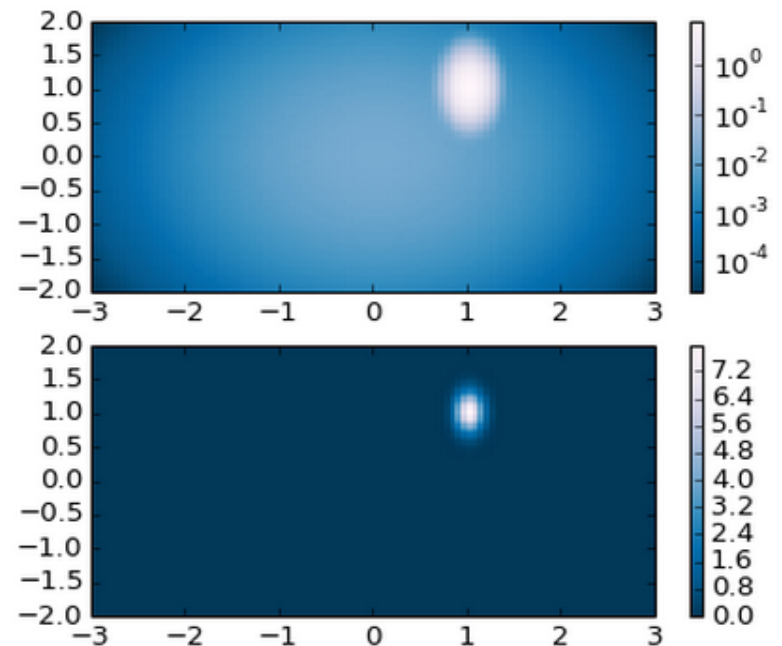
Creating data from bivariate normal distributions

This function does the same plot for each axes.

Creating the subplots – a grid of 2 rows, 1 column

Plotting a color map

Creating a color bar



Matplotlib – Gallery Examples

Necessary Imports

Changing the tick direction at the x and y axes.

Generating the random data

Creating the figure

Plotting the contours

Defining locations manually

Plotting labels on contours

Adding title

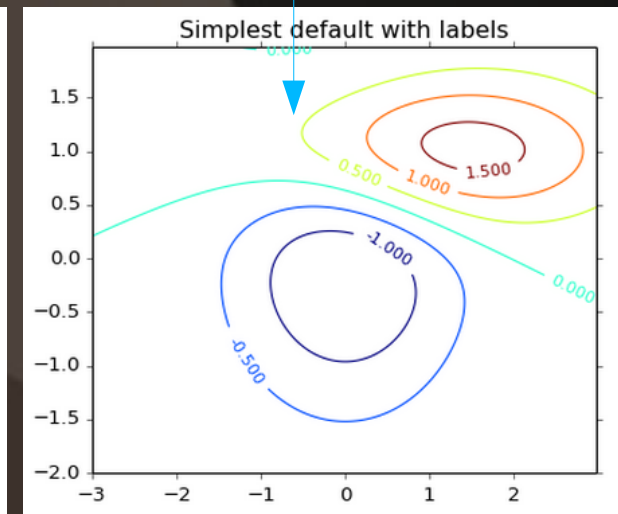
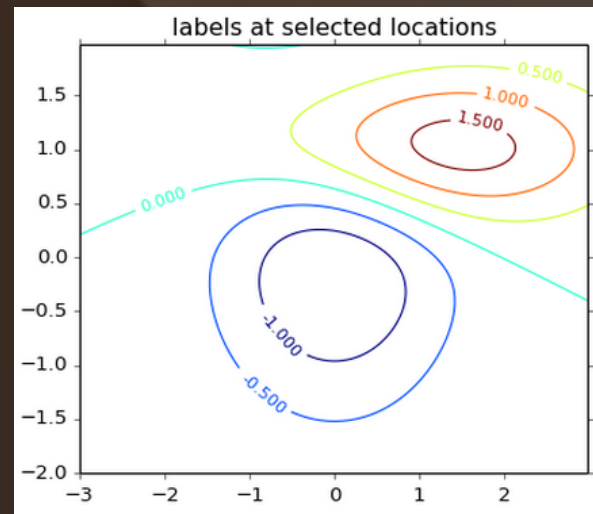
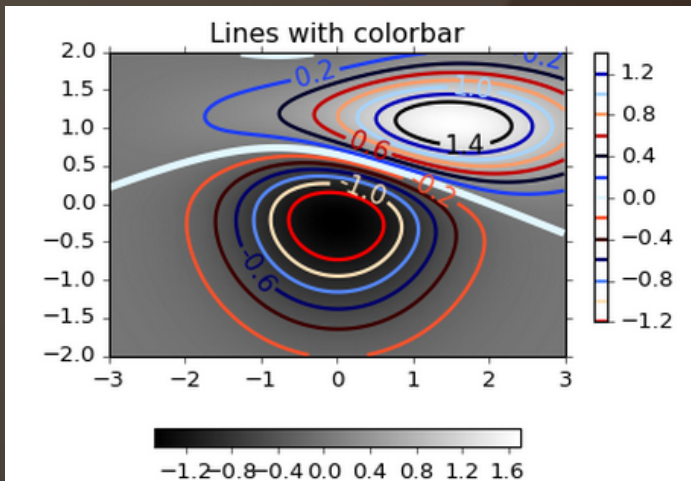
You have more advanced examples:

```
import matplotlib
import numpy as np
import matplotlib.cm as cm
import matplotlib.mlab as mlab
import matplotlib.pyplot as plt

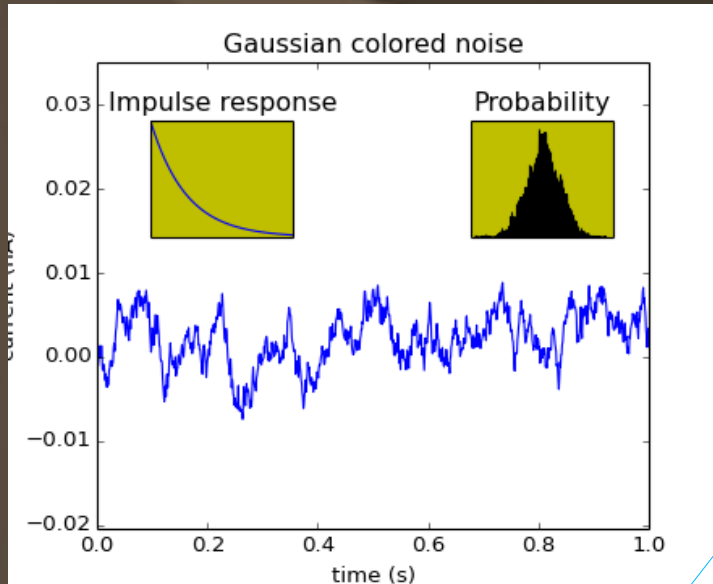
matplotlib.rcParams['xtick.direction'] = 'out'
matplotlib.rcParams['ytick.direction'] = 'out'

delta = 0.025
x = np.arange(-3.0, 3.0, delta)
y = np.arange(-2.0, 2.0, delta)
X, Y = np.meshgrid(x, y)
Z1 = mlab.bivariate_normal(X, Y, 1.0, 1.0, 0.0, 0.0)
Z2 = mlab.bivariate_normal(X, Y, 1.5, 0.5, 1, 1)
# difference of Gaussians
Z = 10.0 * (Z2 - Z1)
# contour labels can be placed manually by providing list of positions
# (in data coordinate). See ginput_manual_clabel.py for interactive
# placement.
plt.figure()
CS = plt.contour(X, Y, Z)
manual_locations = [(-1, -1.4), (-0.62, -0.7), (-2, 0.5), (1.7, 1.2), (2.0, 1.4), (2.4, 1.7)]
plt.clabel(CS, inline=1, fontsize=10, manual=manual_locations)
plt.title('labels at selected locations')
```

Ignoring manual locations you get this plot



Matplotlib – Gallery Examples



Example using pylab directly:

Generating the random data

Plotting main axes.
(Figure is automatically created)

Changing limits for x & y axes(thicks)

Setting titles

Creating 1st axes inside – top right
(yellow background)

Plot Histogram

Empty thicks from axes with setp()

Creating 2nd axes inside – top left

Simple plot

Empty thicks from axes and setting x limit

```
#!/usr/bin/env python

from pylab import *

# create some data to use for the plot
dt = 0.001
t = arange(0.0, 10.0, dt)
r = exp(-t[:1000]/0.05) # impulse response
x = randn(len(t))
s = convolve(x,r)[:len(x)]*dt # colored noise

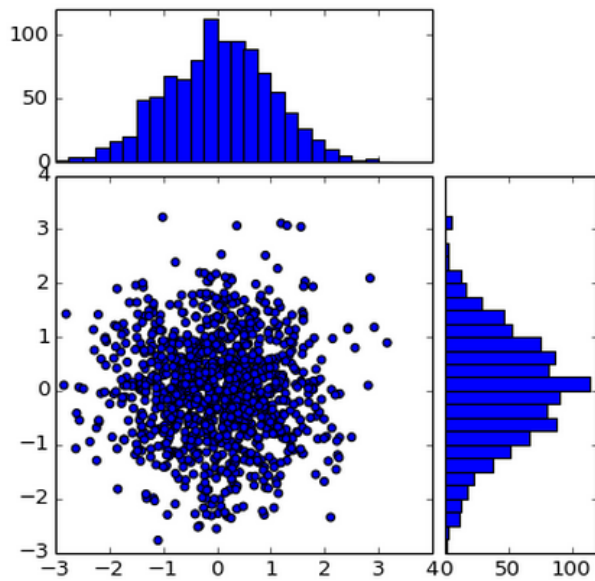
# the main axes is subplot(111) by default
plot(t, s)
axis([0, 1, 1.1*amin(s), 2*amax(s) ])
xlabel('time (s)')
ylabel('current (nA)')
title('Gaussian colored noise')

# this is an inset axes over the main axes
a = axes([.65, .6, .2, .2], axisbg='y')
n, bins, patches = hist(s, 400, normed=1)
title('Probability')
setp(a, xticks=[], yticks=[])

# this is another inset axes over the main axes
a = axes([0.2, 0.6, .2, .2], axisbg='y')
plot(t[:len(r)], r)
title('Impulse response')
setp(a, xlim=(0,.2), xticks=[], yticks=[])

show()
```

Matplotlib – Gallery Examples



Import modules
Need mpl_toolkits.axes

Random data creation

Figure and axes
created with subplot

Create a scatter plot
Set equal scale for xy

Creation of the 2
attached axes for xy

Making x axes invisible in attached axes

Defining limits for the histograms

Defining bins

Plotting histograms in each attached axes

Adjusting thicks manually

Making invisible the default ones
And add thicks manually

```
import numpy as np
import matplotlib.pyplot as plt
from mpl_toolkits.axes_grid1 import make_axes_locatable

# the random data
x = np.random.randn(1000)
y = np.random.randn(1000)

fig, axScatter = plt.subplots(figsize=(5.5,5.5))

# the scatter plot:
axScatter.scatter(x, y)
axScatter.set_aspect(1.)

# create new axes on the right and on the top of the current axes
# The first argument of the new_vertical(new_horizontal) method is
# the height (width) of the axes to be created in inches.
divider = make_axes_locatable(axScatter)
axHistx = divider.append_axes("top", 1.2, pad=0.1, sharex=axScatter)
axHisty = divider.append_axes("right", 1.2, pad=0.1, sharey=axScatter)

# make some labels invisible
plt.setp(axHistx.get_xticklabels() + axHisty.get_yticklabels(),
         visible=False)

# now determine nice limits by hand:
binwidth = 0.25
xymax = np.max( [np.max(np.fabs(x)), np.max(np.fabs(y))] )
lim = ( int(xymax/binwidth) + 1 ) * binwidth

bins = np.arange(-lim, lim + binwidth, binwidth)
axHistx.hist(x, bins=bins)
axHisty.hist(y, bins=bins, orientation='horizontal')

# the xaxis of axHistx and yaxis of axHisty are shared with axScatter,
# thus there is no need to manually adjust the xlim and ylim of these
# axis.

#axHistx.axis["bottom"].major_ticklabels.set_visible(False)
for tl in axHistx.get_xticklabels():
    tl.set_visible(False)
axHistx.set_yticks([0, 50, 100])

#axHisty.axis["left"].major_ticklabels.set_visible(False)
for tl in axHisty.get_yticklabels():
    tl.set_visible(False)
axHisty.set_xticks([0, 50, 100])

plt.draw()
plt.show()
```



Good Practices in Python

- Explicit variable names (no need of a comment to explain what is in the variable)
- Style: spaces after commas, around =, etc. A certain number of rules for writing “beautiful” code (and, more importantly, using the same conventions as everybody else!) are given in the Style Guide for Python Code and the Docstring Conventions page (to manage help strings).
- Except some rare cases, variable names and comments in English.
- Good indentation (forced in Python)

Why Python?

The background of the slide is composed of several overlapping, semi-transparent shapes in various shades of brown and dark grey. These shapes create a layered, organic effect, with some areas appearing lighter due to the overlap of lighter shades and others appearing darker where darker shades overlap. The overall aesthetic is modern and minimalist.