

intro_Scipy

June 1, 2016

```
In [1]: # Just to know last time this was run:
import time
print time.ctime()
```

Wed Jun 1 17:03:05 2016

1 E Introduction to Scipy

This is part of the Python lecture given by Christophe Morisset at IA-UNAM. More informations at: <http://python-astro.blogspot.mx/>

Scipy is a library with a lot of functionalities, we will not cover everything here, but rather point to some of them with examples. Some useful links about scipy:

- <https://scipy-lectures.github.io/intro/scipy.html>
- <http://docs.scipy.org/doc/scipy/reference/tutorial/>

```
In [2]: %matplotlib inline
import numpy as np
import matplotlib.pyplot as plt
```

```
/Users/christophemorisset/anaconda/lib/python2.7/site-packages/matplotlib/font_manager.py:147:
warnings.warn('Matplotlib is building the font cache using fc-list. This may take some time')
Warning: Matplotlib is building the font cache using fc-list. This may take some time.
```

```
In [3]: import scipy # This imports a lot of numpy stuff, but not the important modules
```

1.0.1 Some usefull methods

```
In [4]: from scipy.stats import nanmean
```

```
In [5]: a = np.array([-2, -1, 1., 2, 3])
b = np.log10(a)
mask = np.isfinite(b)
print a
print b
print mask
print a.mean()
```

```

print b.mean()
print b[mask].mean()
print nanmean(b)

[-2. -1.  1.  2.  3.]
[      nan      nan  0.          0.30103      0.47712125]
[False False  True  True  True]
0.6
nan
0.259383750128
0.259383750128

```

```

/Users/christophemorisset/anaconda/lib/python2.7/site-packages/ipykernel/__main__.py
from ipykernel import kernelapp as app

```

```

In [6]: from scipy.special import gamma
        print gamma(10.3)

```

```

716430.689062

```

```

In [7]: from scipy import constants as cst
        print cst.astronomical_unit # A lot of constants
        from scipy.constants import codata # a lot more, with units. From NIST
        print codata.value('proton mass'), codata.unit('proton mass')

```

```

1.49597870691e+11
1.672621898e-27 kg

```

1.0.2 Integrations

```

In [8]: from scipy.integrate import trapz, cumtrapz, simps
        #help(scipy.integrate) # a big one...
        print '-----'
        help(trapz)
        print '-----'
        help(cumtrapz)
        print '-----'
        help(simps)

```

```

-----
Help on function trapz in module numpy.lib.function_base:

```

```

trapz(y, x=None, dx=1.0, axis=-1)
    Integrate along the given axis using the composite trapezoidal rule.

```

Integrate `y` (`x`) along given axis.

Parameters

`y` : array_like

Input array to integrate.

`x` : array_like, optional

The sample points corresponding to the `y` values. If `x` is None, the sample points are assumed to be evenly spaced `dx` apart. The default is None.

`dx` : scalar, optional

The spacing between sample points when `x` is None. The default is 1.

`axis` : int, optional

The axis along which to integrate.

Returns

`trapz` : float

Definite integral as approximated by trapezoidal rule.

See Also

`sum`, `cumsum`

Notes

Image [2]_ illustrates trapezoidal rule -- y-axis locations of points will be taken from `y` array, by default x-axis distances between points will be 1.0, alternatively they can be provided with `x` array or with `dx` scalar. Return value will be equal to combined area under the red lines.

References

.. [1] Wikipedia page: http://en.wikipedia.org/wiki/Trapezoidal_rule

.. [2] Illustration image:

http://en.wikipedia.org/wiki/File:Composite_trapezoidal_rule_illustration.png

Examples

```
>>> np.trapz([1,2,3])
```

```
4.0
```

```
>>> np.trapz([1,2,3], x=[4,6,8])
```

```
8.0
```

```
>>> np.trapz([1,2,3], dx=2)
```

```
8.0
```

```
>>> a = np.arange(6).reshape(2, 3)
>>> a
array([[0, 1, 2],
       [3, 4, 5]])
>>> np.trapz(a, axis=0)
array([ 1.5,  2.5,  3.5])
>>> np.trapz(a, axis=1)
array([ 2.,  8.])
```

Help on function cumtrapz in module scipy.integrate.quadrature:

```
cumtrapz(y, x=None, dx=1.0, axis=-1, initial=None)
Cumulatively integrate y(x) using the composite trapezoidal rule.
```

Parameters

```
y : array_like
    Values to integrate.
x : array_like, optional
    The coordinate to integrate along. If None (default), use spacing `dx`
    between consecutive elements in `y`.
dx : int, optional
    Spacing between elements of `y`. Only used if `x` is None.
axis : int, optional
    Specifies the axis to cumulate. Default is -1 (last axis).
initial : scalar, optional
    If given, uses this value as the first value in the returned result.
    Typically this value should be 0. Default is None, which means no
    value at ``x[0]`` is returned and `res` has one element less than `y`
    along the axis of integration.
```

Returns

```
res : ndarray
    The result of cumulative integration of `y` along `axis`.
    If `initial` is None, the shape is such that the axis of integration
    has one less value than `y`. If `initial` is given, the shape is equal
    to that of `y`.
```

See Also

```
numpy.cumsum, numpy.cumprod
quad: adaptive quadrature using QUADPACK
romberg: adaptive Romberg quadrature
quadrature: adaptive Gaussian quadrature
fixed_quad: fixed-order Gaussian quadrature
dblquad: double integrals
```

tplquad: triple integrals
romb: integrators for sampled data
ode: ODE integrators
odeint: ODE integrators

Examples

```
-----  
>>> from scipy import integrate  
>>> import matplotlib.pyplot as plt  
  
>>> x = np.linspace(-2, 2, num=20)  
>>> y = x  
>>> y_int = integrate.cumtrapz(y, x, initial=0)  
>>> plt.plot(x, y_int, 'ro', x, y[0] + 0.5 * x**2, 'b-')  
>>> plt.show()
```

Help on function `simps` in module `scipy.integrate.quadrature`:

`simps(y, x=None, dx=1, axis=-1, even='avg')`

Integrate `y(x)` using samples along the given axis and the composite Simpson's rule. If `x` is `None`, spacing of `dx` is assumed.

If there are an even number of samples, `N`, then there are an odd number of intervals (`N-1`), but Simpson's rule requires an even number of intervals. The parameter `'even'` controls how this is handled.

Parameters

```
-----  
y : array_like  
    Array to be integrated.  
x : array_like, optional  
    If given, the points at which `y` is sampled.  
dx : int, optional  
    Spacing of integration points along axis of `y`. Only used when  
    `x` is None. Default is 1.  
axis : int, optional  
    Axis along which to integrate. Default is the last axis.  
even : {'avg', 'first', 'str'}, optional  
    'avg' : Average two results: 1) use the first N-2 intervals with  
           a trapezoidal rule on the last interval and 2) use the last  
           N-2 intervals with a trapezoidal rule on the first interval.  
  
    'first' : Use Simpson's rule for the first N-2 intervals with  
              a trapezoidal rule on the last interval.  
  
    'last' : Use Simpson's rule for the last N-2 intervals with a  
             trapezoidal rule on the first interval.
```

See Also

quad: adaptive quadrature using QUADPACK
romberg: adaptive Romberg quadrature
quadrature: adaptive Gaussian quadrature
fixed_quad: fixed-order Gaussian quadrature
dblquad: double integrals
tplquad: triple integrals
romb: integrators for sampled data
cumtrapz: cumulative integration for sampled data
ode: ODE integrators
odeint: ODE integrators

Notes

For an odd number of samples that are equally spaced the result is exact if the function is a polynomial of order 3 or less. If the samples are not equally spaced, then the result is exact only if the function is a polynomial of order 2 or less.

```
In [9]: dir(scipy.integrate)
```

```
Out[9]: ['IntegrationWarning',  
         'Tester',  
         '__all__',  
         '__builtins__',  
         '__doc__',  
         '__file__',  
         '__name__',  
         '__package__',  
         '__path__',  
         '_dop',  
         '_ode',  
         '_odepack',  
         '_quadpack',  
         'absolute_import',  
         'complex_ode',  
         'cumtrapz',  
         'dblquad',  
         'division',  
         'fixed_quad',  
         'lsoda',  
         'newton_cotes',  
         'nquad',  
         'ode',
```

```

'odeint',
'odepack',
'print_function',
'quad',
'quad_explain',
'quadpack',
'quadrature',
'romb',
'romberg',
's',
'simps',
'test',
'tplquad',
'trapz',
'vode']

```

```

In [10]: # Defining x and y
x = np.linspace(0, 10, 100)
y = np.sin(x)
# Compare the integrales using two methods
print trapz(y, x)
print simps(y, x)

```

```

1.83750758633
1.83909194697

```

```

In [11]: # Cumulative integrale
print cumtrapz(np.abs(y), x)

```

```

[ 5.09284951e-03  2.03194796e-02  4.55246645e-02  8.04514533e-02
 1.24743789e-01  1.77950140e-01  2.39528101e-01  3.08849923e-01
 3.85208914e-01  4.67826642e-01  5.55860873e-01  6.48414152e-01
 7.44542958e-01  8.43267317e-01  9.43580798e-01  1.04446077e+00
 1.14487882e+00  1.24381125e+00  1.34024951e+00  1.43321048e+00
 1.52174647e+00  1.60495491e+00  1.68198755e+00  1.75205909e+00
 1.81445519e+00  1.86853977e+00  1.91376146e+00  1.94965927e+00
 1.97586722e+00  1.99211816e+00  1.99824642e+00  2.00334164e+00
 2.01754235e+00  2.04174210e+00  2.07569419e+00  2.11905248e+00
 2.17137499e+00  2.23212830e+00  2.30069308e+00  2.37637035e+00
 2.45838864e+00  2.54591181e+00  2.63804762e+00  2.73385681e+00
 2.83236266e+00  2.93256097e+00  3.03343028e+00  3.13394229e+00
 3.23307235e+00  3.32980988e+00  3.42316870e+00  3.51219709e+00
 3.59598746e+00  3.67368561e+00  3.74449946e+00  3.80770711e+00
 3.86266420e+00  3.90881048e+00  3.94567550e+00  3.97288346e+00
 3.99015699e+00  3.99732000e+00  4.00241706e+00  4.01559036e+00
 4.03878211e+00  4.07175590e+00  4.11417558e+00  4.16560871e+00
 4.22553095e+00  4.29333144e+00  4.36831900e+00  4.44972917e+00
 4.53673204e+00  4.62844065e+00  4.72392010e+00  4.82219704e+00]

```

```

4.92226959e+00  5.02311758e+00  5.12371293e+00  5.22303013e+00
5.32005670e+00  5.41380353e+00  5.50331491e+00  5.58767835e+00
5.66603380e+00  5.73758248e+00  5.80159500e+00  5.85741879e+00
5.90448477e+00  5.94231312e+00  5.97051821e+00  5.98881251e+00
5.99700951e+00  6.00210788e+00  6.01425236e+00  6.03643367e+00
6.06842568e+00  6.10990226e+00  6.16044057e+00]

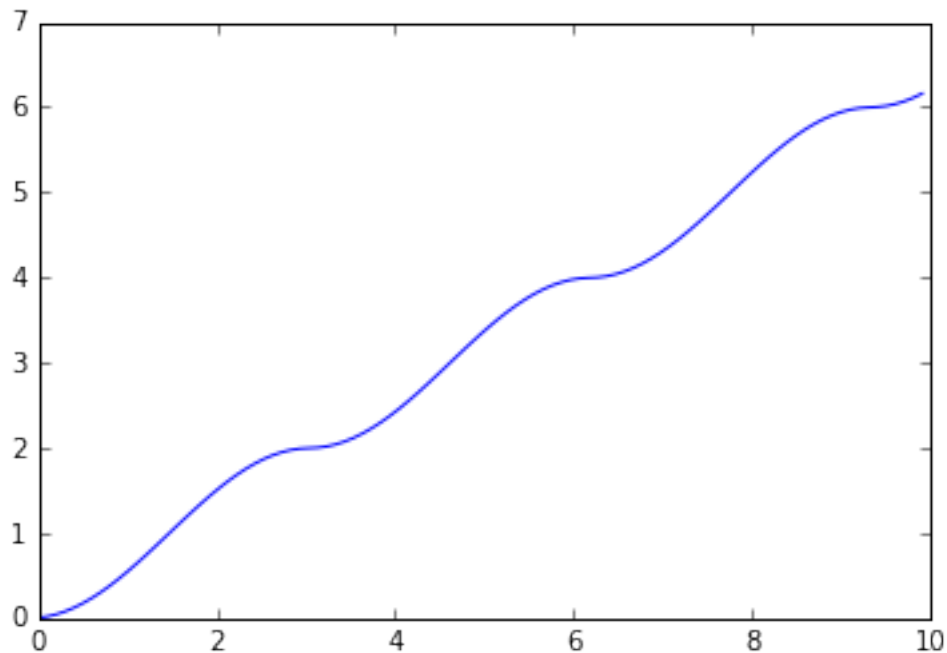
```

```

In [12]: # Cumulative integral
print len(x), len(cumtrapz(np.abs(y), x))
f, ax = plt.subplots()
ax.plot(x[0:-1], cumtrapz(np.abs(y), x));

```

100 99



```

In [13]: from scipy.integrate import quad # To compute a definite integral
from scipy.special import jv # Bessel function
#help(quad)
print quad(lambda x: jv(2.5, x), 0, 10) # Integrate the Bessel function of
(0.8209075326034347, 1.1793289815399173e-08)

```

We now want to evaluate:

$$\int_0^1 1 + 2x + 3x^2 dx$$


```
In [15]: # We want here integrate a user-defined function (here polynome) between 0 and 1
def f(x, a, b, c):
    """ Returning a 2nd order polynome """
    return a + b * x + c * x**2
%timeit I = quad(f, 0, 1, args=(1,2,3)) # args will send 1, 2, 3 to f
I = quad(f, 0, 1, args=(1,2,3)) # args will send 1, 2, 3 to f
print I
Integ = I[0]
print Integ

100000 loops, best of 3: 11.5 µs per loop
(3.0, 3.3306690738754696e-14)
3.0
```

1.0.3 Interpolations

```
In [16]: from scipy.interpolate import interp1d, interp2d, splrep, splev, griddata

In [17]: #help(scipy.interpolate) # a huge one...
help(interp1d)
```

Help on class interp1d in module scipy.interpolate.interpolate:

```
class interp1d(scipy.interpolate.polyint._Interpolator1D)
|   Interpolate a 1-D function.
|
|   `x` and `y` are arrays of values used to approximate some function f:
|   ``y = f(x)``. This class returns a function whose call method uses
|   interpolation to find the value of new points.
|
|   Parameters
|   -----
|   x : (N,) array_like
|       A 1-D array of real values.
|   y : (...N,...) array_like
|       A N-D array of real values. The length of `y` along the interpolation
|       axis must be equal to the length of `x`.
|   kind : str or int, optional
|       Specifies the kind of interpolation as a string
|       ('linear', 'nearest', 'zero', 'slinear', 'quadratic', 'cubic'
|       where 'slinear', 'quadratic' and 'cubic' refer to a spline
|       interpolation of first, second or third order) or as an integer
|       specifying the order of the spline interpolator to use.
|       Default is 'linear'.
|   axis : int, optional
|       Specifies the axis of `y` along which to interpolate.
|       Interpolation defaults to the last axis of `y`.
|   copy : bool, optional
```

```

|     If True, the class makes internal copies of x and y.
|     If False, references to `x` and `y` are used. The default is to copy.
| bounds_error : bool, optional
|     If True, a ValueError is raised any time interpolation is attempted on
|     a value outside of the range of x (where extrapolation is
|     necessary). If False, out of bounds values are assigned `fill_value`.
|     By default, an error is raised unless `fill_value="extrapolate"`.
| fill_value : array-like or (array-like, array_like) or "extrapolate", optional
|     - if a ndarray (or float), this value will be used to fill in for
|     requested points outside of the data range. If not provided, then
|     the default is NaN. The array-like must broadcast properly to the
|     dimensions of the non-interpolation axes.
|     - If a two-element tuple, then the first element is used as a
|     fill value for ``x_new < x[0]`` and the second element is used for
|     ``x_new > x[-1]``. Anything that is not a 2-element tuple (e.g.,
|     list or ndarray, regardless of shape) is taken to be a single
|     array-like argument meant to be used for both bounds as
|     ``below, above = fill_value, fill_value``.
|
|     .. versionadded:: 0.17.0
|     - If "extrapolate", then points outside the data range will be
|     extrapolated. ("nearest" and "linear" kinds only.)
|
|     .. versionadded:: 0.17.0
| assume_sorted : bool, optional
|     If False, values of `x` can be in any order and they are sorted first.
|     If True, `x` has to be an array of monotonically increasing values.
|
| Methods
| -----
| __call__
|
| See Also
| -----
| splrep, splev
|     Spline interpolation/smoothing based on FITPACK.
| UnivariateSpline : An object-oriented wrapper of the FITPACK routines.
| interp2d : 2-D interpolation
|
| Examples
| -----
| >>> import matplotlib.pyplot as plt
| >>> from scipy import interpolate
| >>> x = np.arange(0, 10)
| >>> y = np.exp(-x/3.0)
| >>> f = interpolate.interp1d(x, y)
|
| >>> xnew = np.arange(0, 9, 0.1)

```

```

| >>> ynew = f(xnew)    # use interpolation function returned by `interp1d`
| >>> plt.plot(x, y, 'o', xnew, ynew, '-')
| >>> plt.show()
|
| Method resolution order:
|     interp1d
|     scipy.interpolate.polyint._Interpolator1D
|     __builtin__.object
|
| Methods defined here:
|
| __init__(self, x, y, kind='linear', axis=-1, copy=True, bounds_error=None, fill_value=None)
|     Initialize a 1D linear interpolation class.
|
| -----
| Data descriptors defined here:
|
| __dict__
|     dictionary for instance variables (if defined)
|
| __weakref__
|     list of weak references to the object (if defined)
|
| fill_value
|
| -----
| Methods inherited from scipy.interpolate.polyint._Interpolator1D:
|
| __call__(self, x)
|     Evaluate the interpolant
|
|     Parameters
|     -----
|     x : array_like
|         Points to evaluate the interpolant at.
|
|     Returns
|     -----
|     y : array_like
|         Interpolated values. Shape is determined by replacing
|         the interpolation axis in the original array with the shape of x.
|
| -----
| Data descriptors inherited from scipy.interpolate.polyint._Interpolator1D:
|
| dtype

```

```

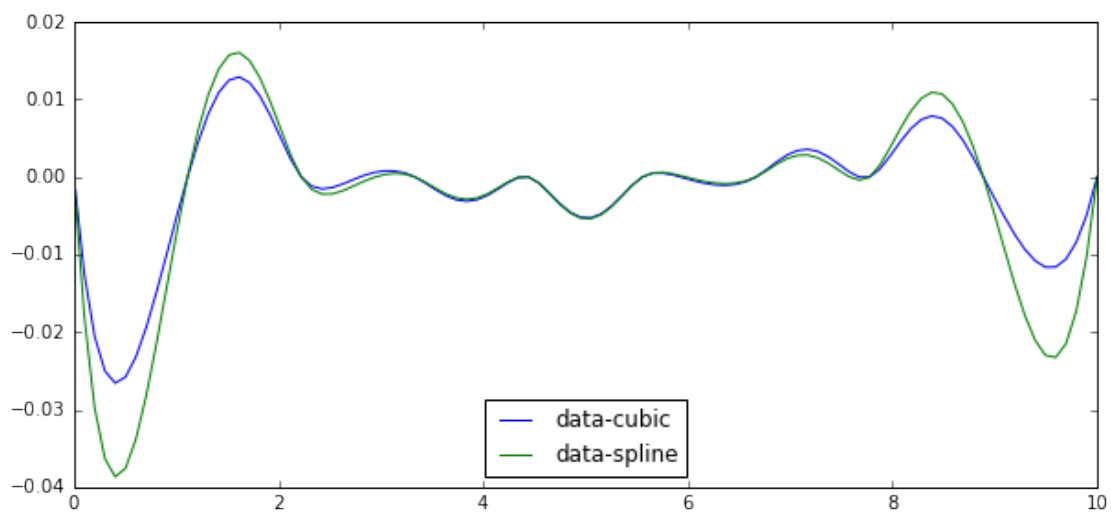
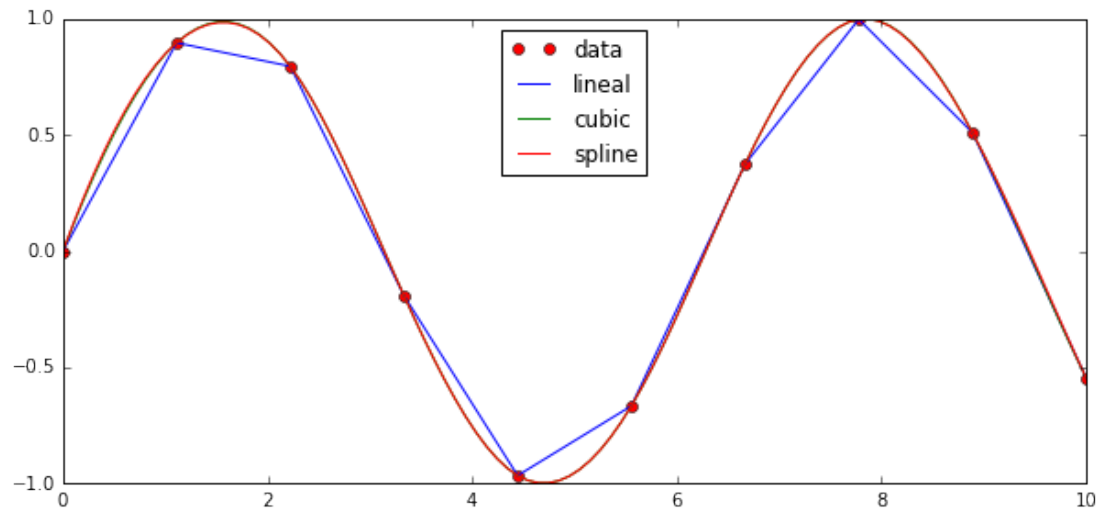
In [18]: x = np.linspace(0, 10, 10)
        y = np.sin(x)
        f = interp1d(x, y) # this creates a function that can be call at any inter
        f2 = interp1d(x, y, kind='cubic') # The same but using cubic interpolation
        tck = splrep(x, y, s=0) # This initiate the spline interpolating function,
        # tck is a sequence of length 3 returned by `splrep` or `splprep` contain
        f3 = lambda x: splev(x, tck) # Evaluate the B-spline or its derivatives.

In [19]: # Defining the high resolution mesh
        xfine = np.linspace(0, 10, 100)
        yfine = np.sin(xfine)
        # Plot to compare the results
        fig, (ax1, ax2) = plt.subplots(2, figsize=(10,10))

        ax1.plot(x, y, 'or', label='data')
        ax1.plot(xfine, f(xfine), label='lineal')
        ax1.plot(xfine, f2(xfine), label='cubic')
        ax1.plot(xfine, f3(xfine), label='spline')
        ax1.legend(loc=9)

        ax2.plot(xfine, (yfine-f2(xfine)), label='data-cubic')
        ax2.plot(xfine, (yfine-f3(xfine)), label='data-spline')
        ax2.legend(loc=8);

```



```
In [20]: x0 = 3.5
          print np.sin(x0), f(x0), f2(x0), f3(x0)

-0.35078322769 -0.306630335983 -0.349437256954 -0.349597252402
```

2D interpolation

```
In [21]: # Defining a 2D-function
          def func(x, y):
              return x * (1+x) * np.cos(4*np.pi*x) * np.sin(4*np.pi*y**2)**2
```

```
In [22]: # Initializing a 2D coordinate grid. Note the use of j to specify that the
          grid_x, grid_y = np.mgrid[0:1:100j, 0:1:200j]
```

```
In [23]: print grid_x
         print grid_y

[[ 0.          0.          0.          ...,  0.          0.          0.          ]
 [ 0.01010101 0.01010101 0.01010101 ..., 0.01010101 0.01010101
   0.01010101]
 [ 0.02020202 0.02020202 0.02020202 ..., 0.02020202 0.02020202
   0.02020202]
 ...,
 [ 0.97979798 0.97979798 0.97979798 ..., 0.97979798 0.97979798
   0.97979798]
 [ 0.98989899 0.98989899 0.98989899 ..., 0.98989899 0.98989899
   0.98989899]
 [ 1.          1.          1.          ...,  1.          1.          1.          ]]
[[ 0.          0.00502513 0.01005025 ..., 0.98994975 0.99497487 1.          ]
 [ 0.          0.00502513 0.01005025 ..., 0.98994975 0.99497487 1.          ]
 [ 0.          0.00502513 0.01005025 ..., 0.98994975 0.99497487 1.          ]
 ...,
 [ 0.          0.00502513 0.01005025 ..., 0.98994975 0.99497487 1.          ]
 [ 0.          0.00502513 0.01005025 ..., 0.98994975 0.99497487 1.          ]
 [ 0.          0.00502513 0.01005025 ..., 0.98994975 0.99497487 1.          ]]
```

```
In [24]: # Generating 1000 x 2 points randomly
         points = np.random.rand(1000, 2)
         values = func(points[:,0], points[:,1])
```

```
In [25]: # griddata is the 2D-interpolating method. We want to obtain values on (g
         # using "points" and "values".
         %timeit grid_z0 = griddata(points, values, (grid_x, grid_y), method='nearest')
         %timeit grid_z1 = griddata(points, values, (grid_x, grid_y), method='linear')
         %timeit grid_z2 = griddata(points, values, (grid_x, grid_y), method='cubic')
```

```
100 loops, best of 3: 14.3 ms per loop
100 loops, best of 3: 9.96 ms per loop
100 loops, best of 3: 16.4 ms per loop
```

```
In [27]: # 4 subplots
         grid_z0 = griddata(points, values, (grid_x, grid_y), method='nearest')
         grid_z1 = griddata(points, values, (grid_x, grid_y), method='linear')
         grid_z2 = griddata(points, values, (grid_x, grid_y), method='cubic')
         fig, ((ax1, ax2), (ax3, ax4)) = plt.subplots(2, 2, figsize=(12, 12))

         ax1.imshow(func(grid_x, grid_y), extent=(0,1,0,1), interpolation='none',
                     origin='upper')
         ax1.plot(points[:,0], points[:,1], 'ko', ms=1)
         ax1.set_title('Original')
```

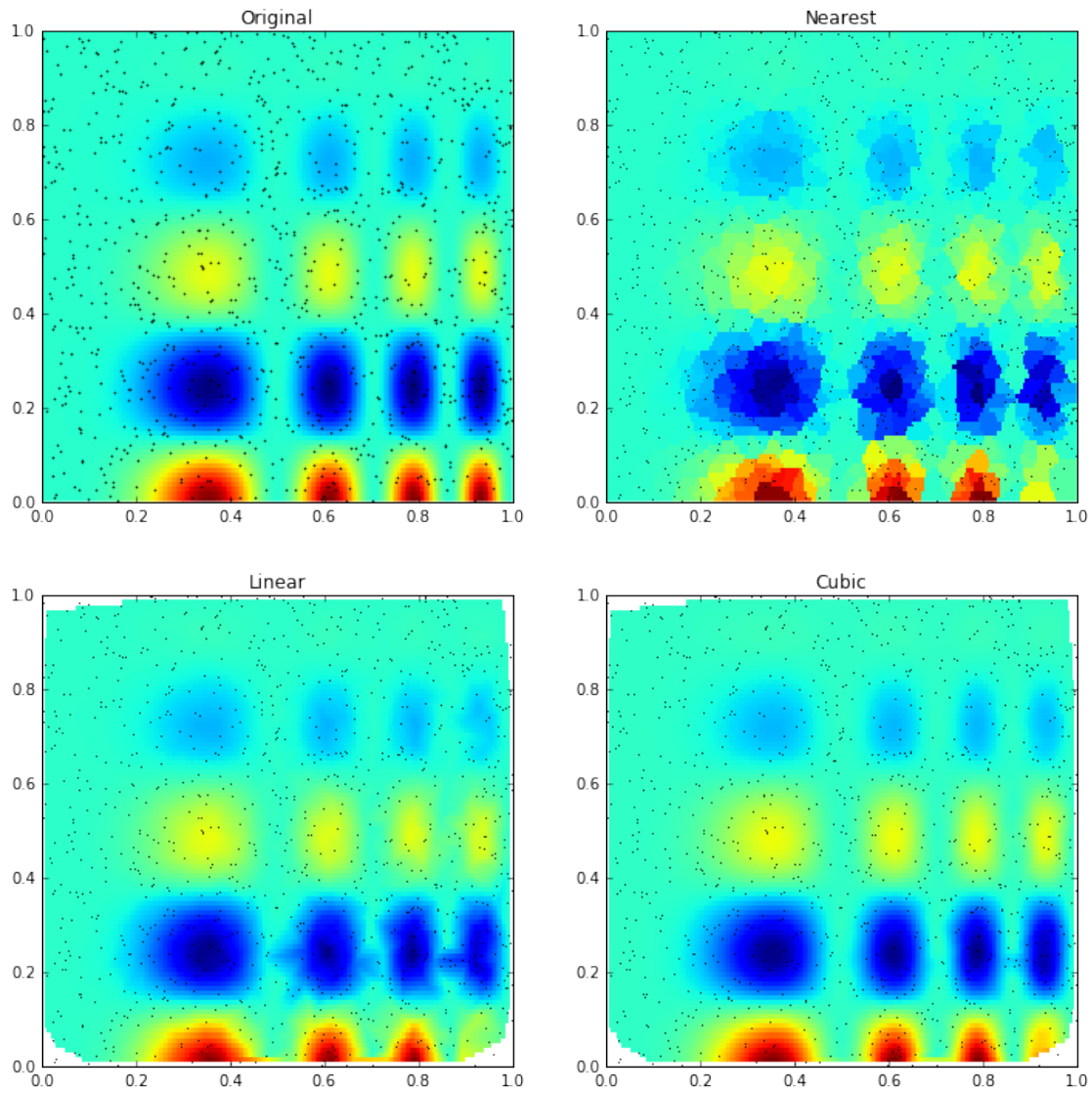
```

ax2.imshow(grid_z0, extent=(0,1,0,1), interpolation='none',
            origin='upper')
ax2.plot(points[:,0], points[:,1], 'k.', ms=1)
ax2.set_title('Nearest')

ax3.imshow(grid_z1, extent=(0,1,0,1), interpolation='none',
            origin='upper')
ax3.plot(points[:,0], points[:,1], 'k.', ms=1)
ax3.set_title('Linear')

ax4.imshow(grid_z2, extent=(0,1,0,1), interpolation='none',
            origin='upper')
ax4.plot(points[:,0], points[:,1], 'k.', ms=1)
ax4.set_title('Cubic');

```



1.0.4 Linear algebra

Scipy is able to deal with matrices, solving linear equations, solving linear least-squares problems and pseudo-inverses, finding eigenvalues and eigenvectors, and more, see here: <http://docs.scipy.org/doc/scipy/reference/tutorial/linalg.html>

1.0.5 Data fit

```
In [28]: from scipy.optimize import curve_fit # this is used to adjust a set of data
```

```
In [29]: help(curve_fit)
```

Help on function curve_fit in module scipy.optimize.minpack:

```
curve_fit(f, xdata, ydata, p0=None, sigma=None, absolute_sigma=False, check_finite=True)
    Use non-linear least squares to fit a function, f, to data.
```

Assumes ``ydata = f(xdata, *params) + eps``

Parameters

f : callable

The model function, f(x, ...). It must take the independent variable as the first argument and the parameters to fit as separate remaining arguments.

xdata : An M-length sequence or an (k,M)-shaped array for functions with k predictors.

The independent variable where the data is measured.

ydata : M-length sequence

The dependent data --- nominally f(xdata, ...)

p0 : None, scalar, or N-length sequence, optional

Initial guess for the parameters. If None, then the initial values will all be 1 (if the number of parameters for the function can be determined using introspection, otherwise a ValueError is raised).

sigma : None or M-length sequence, optional

If not None, the uncertainties in the ydata array. These are used as weights in the least-squares problem

i.e. minimising ``np.sum(((f(xdata, *popt) - ydata) / sigma)**2)``

If None, the uncertainties are assumed to be 1.

absolute_sigma : bool, optional

If False, `sigma` denotes relative weights of the data points. The returned covariance matrix `pcov` is based on *estimated* errors in the data, and is not affected by the overall magnitude of the values in `sigma`. Only the relative magnitudes of the `sigma` values matter.

If True, ``sigma`` describes one standard deviation errors of the input data points. The estimated covariance in ``pcov`` is based on these values.

`check_finite` : bool, optional
 If True, check that the input arrays do not contain nans or infs, and raise a `ValueError` if they do. Setting this parameter to False may silently produce nonsensical results if the input arrays do contain nans. Default is True.

`bounds` : 2-tuple of array_like, optional
 Lower and upper bounds on independent variables. Defaults to no bounds. Each element of the tuple must be either an array with the length equal to the number of parameters, or a scalar (in which case the bound is taken to be the same for all parameters.) Use ``np.inf`` with an appropriate sign to disable bounds on all or some parameters.

.. versionadded:: 0.17

`method` : {'lm', 'trf', 'dogbox'}, optional
 Method to use for optimization. See ``least_squares`` for more details. Default is 'lm' for unconstrained problems and 'trf' if ``bounds`` are provided. The method 'lm' won't work when the number of observations is less than the number of variables, use 'trf' or 'dogbox' in this case.

.. versionadded:: 0.17

`kwargs`
 Keyword arguments passed to ``leastsq`` for ``method='lm'`` or ``least_squares`` otherwise.

Returns

`popt` : array
 Optimal values for the parameters so that the sum of the squared error of ``f(xdata, *popt) - ydata`` is minimized

`pcov` : 2d array
 The estimated covariance of `popt`. The diagonals provide the variance of the parameter estimate. To compute one standard deviation errors on the parameters use ``perr = np.sqrt(np.diag(pcov))``.

How the ``sigma`` parameter affects the estimated covariance depends on ``absolute_sigma`` argument, as described above.

If the Jacobian matrix at the solution doesn't have a full rank, then 'lm' method returns a matrix filled with ``np.inf``, on the other hand 'trf' and 'dogbox' methods use Moore-Penrose pseudoinverse to compute the covariance matrix.

Raises

OptimizeWarning

if covariance of the parameters can not be estimated.

ValueError

if either `ydata` or `xdata` contain NaNs.

See Also

`least_squares` : Minimize the sum of squares of nonlinear functions.

`stats.linregress` : Calculate a linear least squares regression for two sets of measurements.

Notes

With ``method='lm'``, the algorithm uses the Levenberg-Marquardt algorithm through `leastsq`. Note that this algorithm can only deal with unconstrained problems.

Box constraints can be handled by methods 'trf' and 'dogbox'. Refer to the docstring of `least_squares` for more information.

Examples

```
>>> import numpy as np
>>> from scipy.optimize import curve_fit
>>> def func(x, a, b, c):
...     return a * np.exp(-b * x) + c

>>> xdata = np.linspace(0, 4, 50)
>>> y = func(xdata, 2.5, 1.3, 0.5)
>>> ydata = y + 0.2 * np.random.normal(size=len(xdata))

>>> popt, pcov = curve_fit(func, xdata, ydata)
```

Constrain the optimization to the region of ``0 < a < 3``, ``0 < b < 2`` and ``0 < c < 1``:

```
>>> popt, pcov = curve_fit(func, xdata, ydata, bounds=(0, [3., 2., 1.]))
```

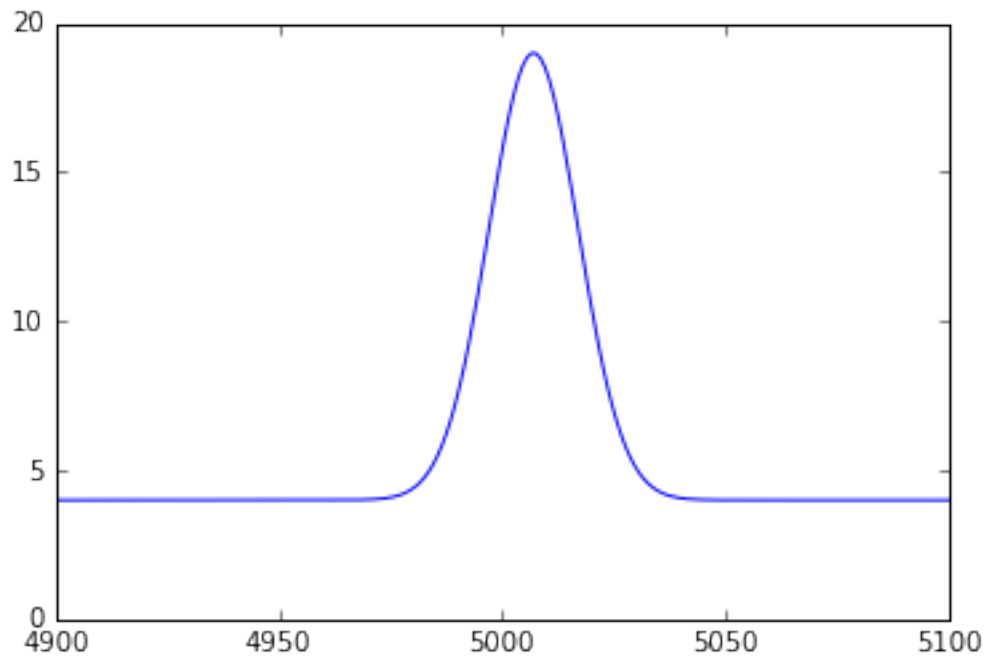
```
In [30]: def gauss(x, A, B, C, S):
...     # This is a gaussian function.
...     return A + B*np.exp(-1 * (x - C)**2 / (2 * S**2))
```

```
In [31]: # We define the parameters used to generate the signal (gaussian at lambda)
...     N_lam = 200
...     A = 4.
```

```

B = 15.
Lam0 = 5007.
Sigma = 10.
# We define a wavelength range
lam = np.linspace(4900, 5100, N_lam)
# Computing the signal
f1 = gauss(lam, A, B, Lam0, Sigma)
f, ax = plt.subplots()
ax.plot(lam, f1)
ax.set_ylim(0,20);

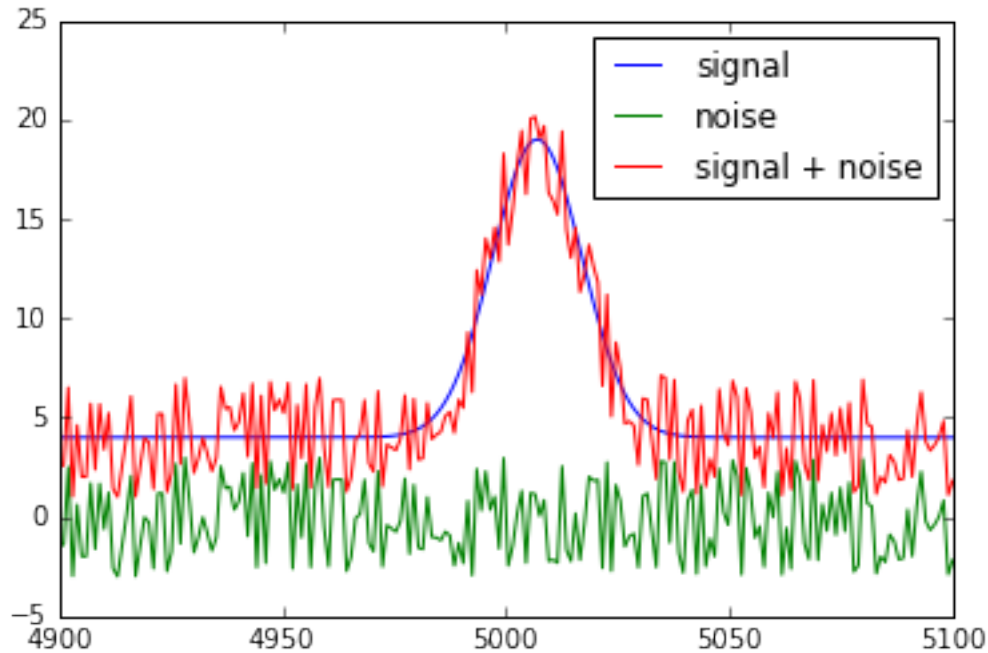
```



```

In [32]: SN = 5. # Signal/Noise
noise = B / SN * (np.random.rand(N_lam)*2 - 1)
f12 = f1 + noise
f, ax = plt.subplots()
ax.plot(lam, f1, label='signal')
ax.plot(lam, noise, label='noise')
ax.plot(lam, f12, label='signal + noise')
ax.legend(loc='best');

```



```
In [33]: # Initial guess:
```

```
A_i = 0.
B_i = 1.
Lam0_i = 5000.
Sigma_i = 1.
fl_init = gauss(lam, A_i, B_i, Lam0_i, Sigma_i)
error = np.ones_like(lam) * np.mean(np.abs(noise)) # We define the error
```

```
In [34]: # fitting the noisy data with the gaussian function, using the initial guess
```

```
fit, covar = curve_fit(gauss, lam, fl2, [A_i, B_i, Lam0_i, Sigma_i], error)
print('  A      B      Lam0      S')
print('{0:.2f} {1:5.2f} {2:.2f} {3:5.2f}'.format(A, B, Lam0, Sigma))
print('{0:.2f} {1:5.2f} {2:.2f} {3:5.2f}'.format(A_i, B_i, Lam0_i, Sigma_i))
print('{0[0]:.2f} {0[1]:5.2f} {0[2]:5.2f} {0[3]:.2f}'.format(fit))
```

```

      A      B      Lam0      S
4.00 15.00 5007.00 10.00
0.00  1.00 5000.00  1.00
3.82 14.95 5006.96  9.96
```

```
In [35]: # Computing the fit on the lambdas
```

```
fl_fit = gauss(lam, fit[0], fit[1], fit[2], fit[3])
```

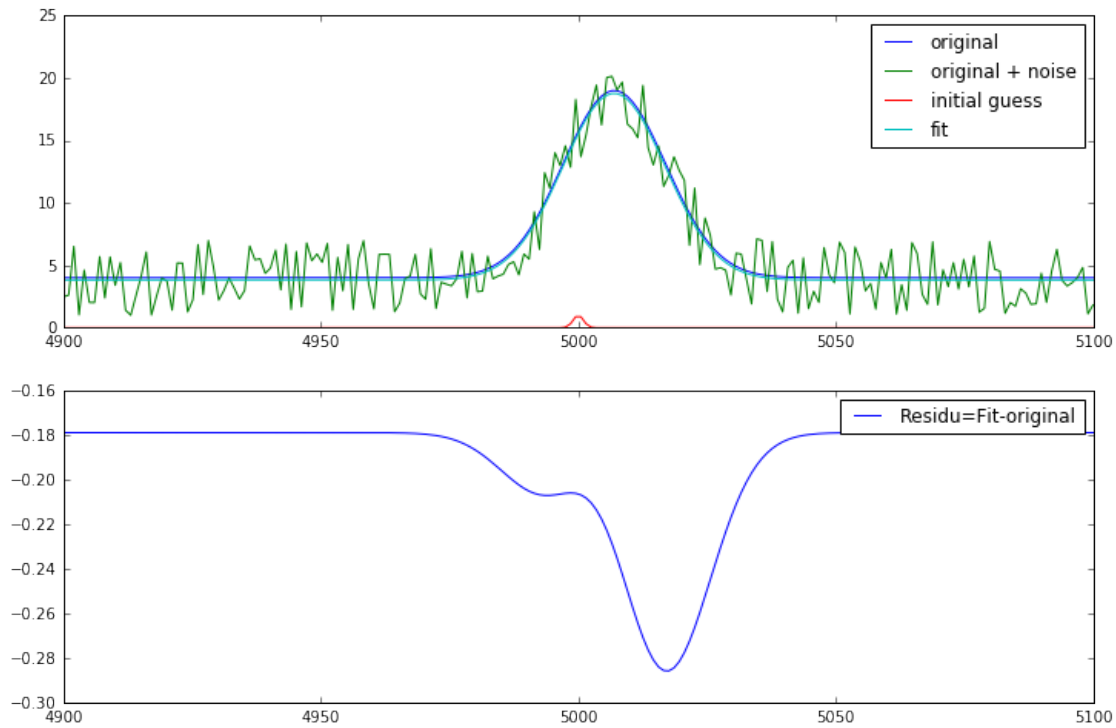
```
In [36]: fig, (ax1, ax2) = plt.subplots(2, 1, figsize=(12, 8))
```

```

ax1.plot(lam, fl, label='original')
ax1.plot(lam, fl2, label='original + noise')
ax1.plot(lam, fl_init, label='initial guess')
ax1.plot(lam, fl_fit, label='fit')
ax1.legend()

ax2.plot(lam, fl_fit - fl, label='Residu=Fit-original')
ax2.legend();

```



```

In [37]: # Integrating using the Simpson method the gaussian (without the continuum)
print simps(fl - A, lam)
print simps(fl2 - fit[0], lam)
print simps(fl_fit - fit[0], lam)

```

```

375.994241195
374.861103061
373.225105596

```

```

In [38]: khi_sq = (((fl2-fl_fit) / error)**2).sum() # The problem here is to determine the error
khi_sq_red = khi_sq / (len(lam) - 4 - 1) # reduced khi_sq = khi_sq / (N - 5)
print khi_sq, khi_sq_red

```

```

252.019224164 1.29240627777

```

1.0.6 Multivariate estimation

```
In [39]: from scipy import stats
```

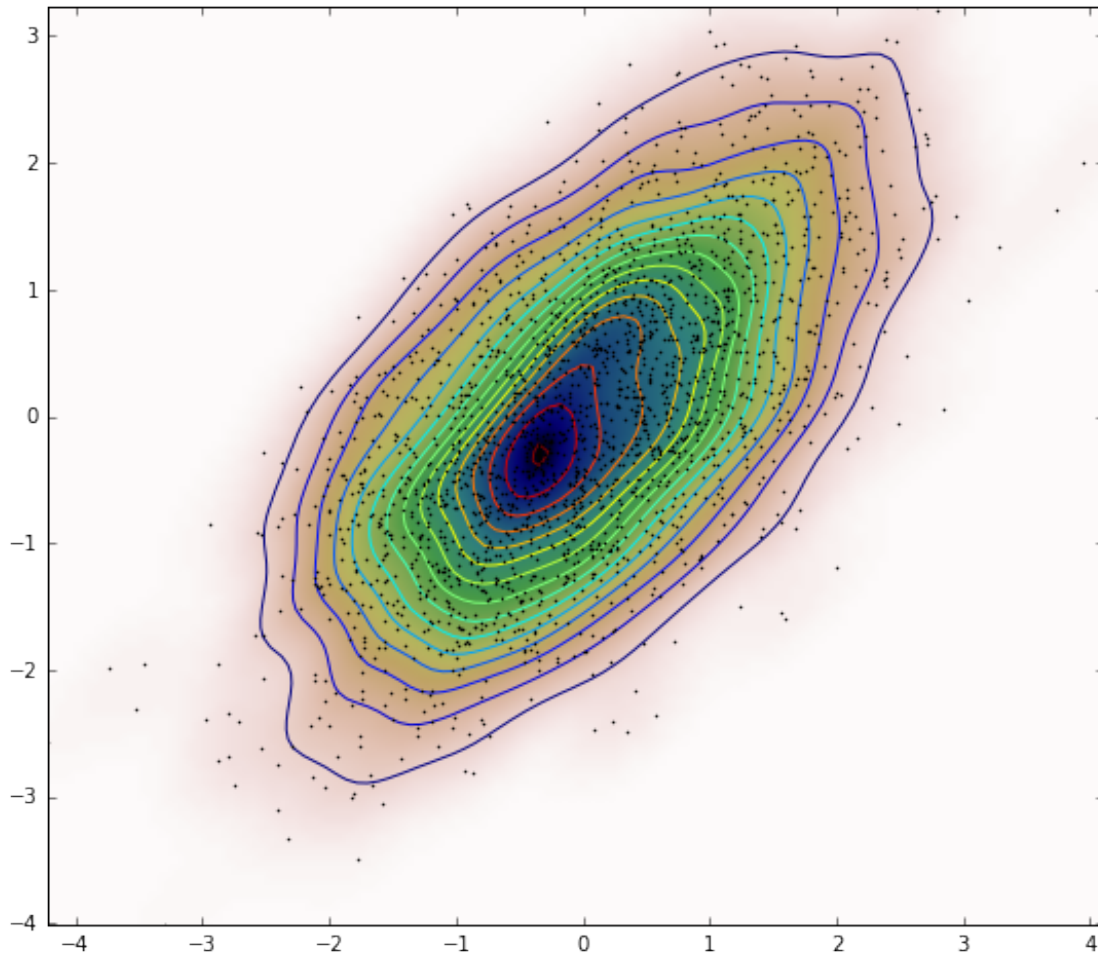
```
In [40]: def measure(n):  
        """Measurement model, return two coupled measurements."""  
        m1 = np.random.normal(size=n)  
        m2 = np.random.normal(scale=0.5, size=n)  
        return m1+m2, m1-m2
```

```
In [41]: # Define the  
        m1, m2 = measure(2000)  
        xmin = m1.min()  
        xmax = m1.max()  
        ymin = m2.min()  
        ymax = m2.max()  
        print xmin, xmax, ymin, ymax
```

```
-4.22246586473 4.11472562257 -4.00698468532 3.22607780801
```

```
In [42]: X, Y = np.mgrid[xmin:xmax:100j, ymin:ymax:100j]  
        positions = np.vstack([X.ravel(), Y.ravel()])  
        values = np.vstack([m1, m2])  
        kernel = stats.gaussian_kde(values)  
        Z = np.reshape(kernel.evaluate(positions).T, X.shape)
```

```
In [44]: fig, ax = plt.subplots(figsize=(12, 8))  
        ax.imshow(np.rot90(Z), cmap=plt.cm.gist_earth_r, extent=[xmin, xmax, ymin,  
        ax.plot(m1, m2, 'k.', markersize=2)  
        ax.set_xlim([xmin, xmax])  
        ax.set_ylim([ymin, ymax])  
        levels = [0.01, 0.02, 0.03, 0.04, 0.05, 0.06, 0.07, 0.08, 0.09, 0.10, 0.11]  
        cs = ax.contour(X, Y, Z, levels=levels); # I dont't know what those levels
```



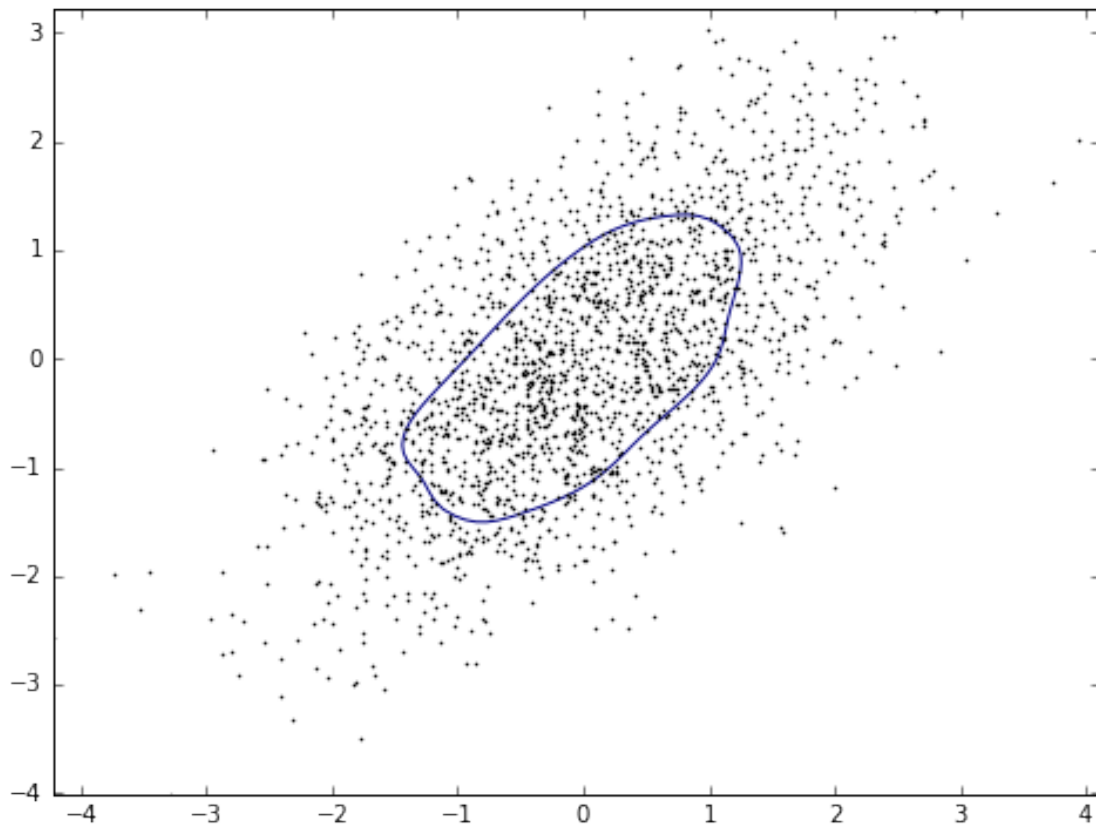
```
In [45]: # We save the contour paths in a list
paths = []
for collec in cs.collections:
    try:
        paths.append(collec.get_paths()[0])
    except:
        pass
```

```
In [46]: # Looking for the number of points inside each contour
print len(m1)
for level, path in zip(levels, paths):
    print('level {0:4.2f} contains {1:2.0f}% of the data'.format(level,
                                                                    path.contain
```

```
2000
level 0.01 contains 96% of the data
level 0.02 contains 90% of the data
```

```
level 0.03 contains 83% of the data
level 0.04 contains 76% of the data
level 0.05 contains 70% of the data
level 0.06 contains 63% of the data
level 0.07 contains 56% of the data
level 0.08 contains 50% of the data
level 0.09 contains 42% of the data
level 0.10 contains 36% of the data
level 0.11 contains 29% of the data
level 0.12 contains 19% of the data
level 0.13 contains 10% of the data
level 0.14 contains 5% of the data
level 0.15 contains 0% of the data
```

```
In [47]: fig, ax = plt.subplots(figsize=(8, 6))
         ax.plot(m1, m2, 'k.', markersize=2)
         ax.set_xlim([xmin, xmax])
         ax.set_ylim([ymin, ymax])
         cs = ax.contour(X, Y, Z, levels=[0.078]); # seems to correspond to 50% of
```

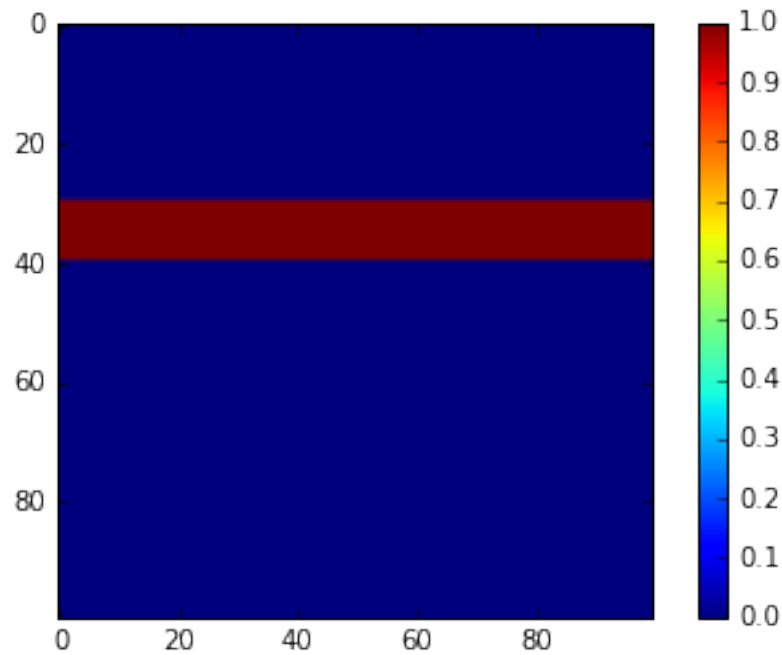


1.0.7 Convolution

More information there: <http://docs.scipy.org/doc/scipy/reference/tutorial/ndimage.html>

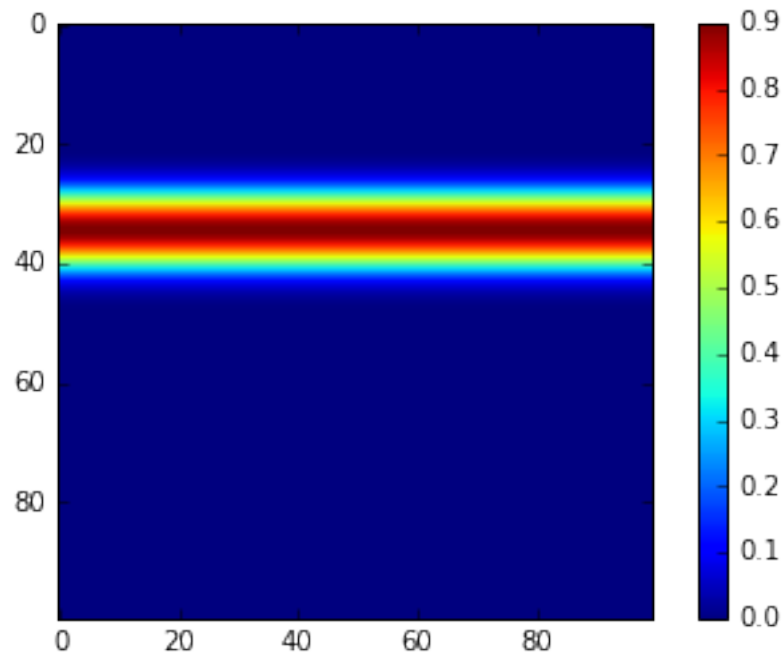
```
In [48]: # Let's define an image representing a long slit of width 10 pixels
        slit = np.zeros((100, 100))
        slit[30:40, :] = 1

In [49]: plt.imshow(slit)
        plt.colorbar();
```

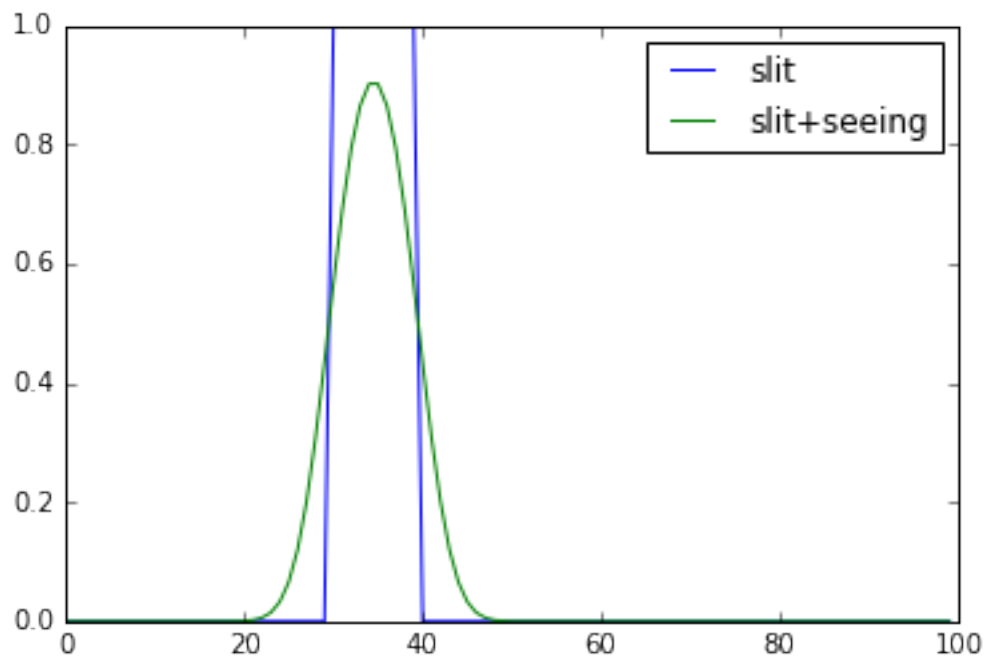


```
In [50]: # This is the routine to apply a gaussian convolution
        from scipy.ndimage.filters import gaussian_filter

In [51]: slit_seeing = gaussian_filter(slit, 3) # Convolve with a gaussian, 3 is th
        plt.imshow(slit_seeing)
        plt.colorbar();
```



```
In [52]: f, ax = plt.subplots()
ax.plot(slit[:,50], label='slit') # original slit
ax.plot(slit_seeing[:,50], label='slit+seeing') # slit with seeing
ax.legend(loc='best');
```



```
In [53]: # Check that the slit transmission is conserved:
        print simp(slit[:,50]), simp(slit_seeing[:,50])

10.0 10.0
```

1.0.8 Quantiles

```
In [54]: from scipy.stats.mstats import mquantiles
```

```
In [55]: #help(mquantiles)
```

```
In [56]: data = np.random.randn(1000)
```

```
In [57]: mquantiles(data, [0.16, 0.84]) # should return something close to -1, 1 (t
```

```
Out[57]: array([-1.0245078 ,  1.04750432])
```

```
In [58]: data = np.array([[ 6.,  7.,  1.],
                          [ 47., 15.,  2.],
                          [ 49., 36.,  3.],
                          [ 15., 39.,  4.],
                          [ 42., 40., -999.],
                          [ 41., 41., -999.],
                          [  7., -999., -999.],
                          [ 39., -999., -999.],
                          [ 43., -999., -999.],
                          [ 40., -999., -999.],
                          [ 36., -999., -999.]])
```

```
In [59]: mq = mquantiles(data, axis=0, limit=(0, 50))
        print mq
        print type(mq)
        mq?
        print mq.mask
```

```
[[ 19.2  14.6  1.45]
 [ 40.   37.5  2.5 ]
 [ 42.8  40.05  3.55]]
<class 'numpy.ma.core.MaskedArray'>
False
```

1.0.9 Input/Output

Scipy has many modules, classes, and functions available to read data from and write data to a variety of file formats.

Including MATLAB and IDL files. See <http://docs.scipy.org/doc/scipy/reference/io.html>