

Exploring Python as Matlab alternative

A scientist view on python

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Aufbau

1 Introduction

2 Basic usage of python (Spyder)

3 3D visualization

4 Numerical mathematics

5 Performance - NumPy-tricks and Cython

6 Parallel Computations

7 Literature

Programming for a Scientist

Usual tasks

- Create or gather data (simulation, experiment)
- postprocessing of data
- visualization and validation
- publish and communicate results

So we want a *high-level* programming language:

- programming is simple
- use elements which are there already
- good prototyping and debugging (interaction)
- hopefully only one tool for all problems

MATLAB

- MATLAB stands for **Matrix laboratory**; initially matrix calculations.
- Interactive system for numerical calculations and visualization (scripting language).

Advantages

- many tools for visualization.
- many additional toolboxes (Symb. Math T., PDE T., Wavelet T.)
- mature and integrated GUI.

Disadvantages

- costly.
- other tasks than matrix calculations can be difficult.

Python: NumPy, SciPy, SymPy

- modular scripting language.

Advantages

- many modules for scientific computations.
- clean code structure.
- much more modules for non-scientific tasks (for example helpful in I/O).
- support different coding paradigm (object-oriented, imperative, functional)
- free and open source.

Disadvantages

- Usage a little bit more complicated (Spyder, ipython).
- not all the special features of other software.
- with flexibility comes complexity.

Aufbau

- 1 Introduction
- 2 Basic usage of python (Spyder)
- 3 3D visualization
- 4 Numerical mathematics
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- 7 Literature

Spyder GUI

The screenshot shows the Spyder GUI interface. The top menu bar includes File, Edit, Search, Source, Run, Interpreters, Tools, View, and Help. The main window has several tabs: Editor (containing the code), Object Inspector, Source, Console, Object, type, Options, and Help. The Editor tab displays Python code for generating a sparse matrix. The Object Inspector pane shows a list of variables with their types. The Console pane shows the Python environment and command-line output.

```
File Edit Search Source Run Interpreters Tools View ?  
Editor : /home/schult/teaching/prog_num/programs/heatsy.py  
douglas.caesarheatsy [d] heatsy [x]  
1 #!/usr/bin/python  
2 ***  
3 Created on Mon Aug 12 17:57:31 2013  
4  
5 Author: jschult  
6  
7  
8 import numpy as np # Multi-dimensional arrays, linear algebra,...  
9 import scipy as sp # SciPy (signal and image processing library)  
10 import scipy.sparse as sparse # user-sparse-matrices  
11 import scipy.sparse.linalg as linalg # Library for sparse  
12  
13 from __future__ import division  
14 from scipy.io import mmread  
15 from scipy import sparse  
16 from matplotlib import pyplot  
17 from matplotlib import cm  
18 from mpl_toolkits.mplot3d import Axes3D  
19 from matplotlib.pylab import*  
20 from scipy import linalg  
21 from pylab import*  
22  
23 from cg import *  
24 from gs import *  
25  
26 def poisson(N):  
27     """ Poisson matrix 2D ***  
28     # Standard deviation Matrix  
29     # data = np.random.normal(0)  
30     # data = np.zeros((N,N))  
31     # diag = [-1,1]  
32     # data += diag * np.eye(data.shape[0])  
33     # locator = sparse.csr_matrix(data, N=N)  
34     # A = (1/(N+2))*sparse.kron(locator, D) + sparse.kron(D, locator)  
35     # print A.todense()  
36     return A  
37  
38 def poisson(N):  
39     """ Poisson matrix 2D. On***  
40     # Standard deviation Matrix  
41     # data = np.random.normal(0)  
42     # data = np.zeros((N,N))  
43     # diag = [-1,0,1]  
44     # data += diag * np.eye(data.shape[0])  
45     # locator = sparse.csr_matrix(data, N=N)  
46     # A = (1/(N+2))*sparse.kron(locator, D)  
47     # print A.todense()  
48     return A  
49  
50 def poisson(N):  
51     """ Poisson matrix 2D. Off***  
52     # Standard deviation Matrix  
53     # data = np.zeros((N,N))  
54     # diag = [-2,4,-2]  
55     # data[1,:] = -2*data[1,:]  
56     # data[-1,:] = -2*data[-1,:]  
57     # diag = [-1,0,1]  
58     # data += diag * np.eye(data.shape[0])  
59     # locator = sparse.csr_matrix(data, N=N)  
60     # A = (1/(N+2))*sparse.kron(locator, D)  
61     # print A.todense()  
62     return A  
63  
64  
Object inspector Variable explorer File explorer  
Console  
Python 2.7.3 (default, Apr 10 2013, 06:20:15)  
(GCC 4.8.3) on linux  
Type "help", "copyright", "credits" or "license" for more information.  
Imported Numpy 1.6.1, Scipy 0.9.0, Matplotlib 1.1.1rc  
Type "Scientific" for more details.  
***  
Internal console Console  
Permissions: Rw End-of-lines: LF Encoding: UTF-8 Line: 24 Columns: 1
```

- **Editor:** data manipulation.
- **Console:** command window and standard output.

- **Object Inspector:** help and list of variables.
- **Grafik:** separate windows.

Lists and tuples

- a **list** is marked with `[...]` (has order, mutable)

```
list = [21, 22, 24, 23]
list.sort(); list
```

`[21, 22, 23, 24]`

- a **tuple** is marked with `(...,)` (has structure, immutable)

```
tuple = (list[0], list[2])
tuple, tuple[0]
```

`((21, 24), 21)`

- Lists of integers ranging from a to b

```
range(a, b+1)
```

list comprehensions

```
[i**2 for i in range(4)]
```

`[0, 1, 4, 9]`

Dictionaries

- index can hold almost arbitrary objects.
- they are good for big data, because indexing is very fast.
- index is unique
- iteration:

```
d = {'a': 1, 'b':1.2, 'c':1j}
for key, val in d.items():
    print key, val
```

```
a 1
c 1j
b 1.2
```

Functions

normal

```
def fun (arg1,arg2=<defaultvalue>,... ,*args,**kwargs)
<code>
    return <returnvalue>
```

anonymous

```
lambda arg: <codeline>
```

- args: Tuple of input-arguments
- kwargs: Dictionary of named input-arguments
- *: unpacks tuple in comma separated list of arguments
- **: unpacks dictionary in list of named arguments
- arguments with defaultvalue are optional
- arguments with names can have arbitrarily order

a bit functional programming

iterators : objects which generates a next element when asked for.

```
import itertools
```

- `imap(function, list)`

generates an iterator which calls `function(x)` for all elements from `list`.

- `ifilter(function, list)`

generates an iterator which returns only elements `x`, for which `function(x)` returns `True`.

```
list(ifilter(lambda x: mod(x,3) == 0,[1,4,6,24]))
```

[6, 24]

non-iterators: map, filter

Vectors and matrixes - NumPy arrays

vectors

```
np.array([1,2,4])
```

matrix

```
np.array([[1,2,4],[2,3,4]])  
np.matrix([[1,2,4],[2,3,4]])
```

- `zeros((n,m))`: $(n \times m)$ - matrix entries all 0.
- `ones((n,m))`: $(n \times m)$ - matrix entries all 1.
- `tile (A,(n,m))`: block matrix with $(n \times m)$ blocks of A

Remark:

- matrix-multiply is achieved with `dot(a,b)` and `*` is elementwise!
- mostly use `array` not `matrix`, because it is the standard-object.

Slicing

```
A = np.array([[1,2,3],[4,5,6],[7,8,9]])
```

A =

| | | |
|---|---|---|
| 1 | 2 | 3 |
| 4 | 5 | 6 |
| 7 | 8 | 9 |

one entry

```
A[1,0]
```

4

lines

```
A[:, :]
```

4 5 6

blocks

```
A[1:3,0:2]
```

| | |
|---|---|
| 4 | 5 |
| 7 | 8 |

individual entries/lines

```
A[(0,-1),:]
```

| | | |
|---|---|---|
| 1 | 2 | 3 |
| 7 | 8 | 9 |

Fancy indexing, copies and views

fancy indexing is indexing an array with integer or boolean arrays.

```
a = [i**2 for i in range(1,10)]
```

```
[1, 4, 9, 16, 25, 36, 49, 64, 81]
```

```
a[a % 3 == 0]
```

```
array([ 9, 36, 81])
```

Remark:

- normal indexing (slicing) creates **views** on the data. It shares the same memory, e.g.

```
b = a[::-3]
```

you can force the copy:

```
b = a[::-3].copy()
```

- fancy indexing creates **copies** from the data.

Advanced arrays

Data types for arrays (dtypes)

- Types: int , uint , float , complex, string ...
- Character Codes : '<typechar><bytes>' : 'i4', 'u4', 'f8', 'c16', 'S25'
- typecast: <object>.astype(<type>)

Example:

```
b = np.array([5, 12345, 'test'], dtype='|S4')
```

```
array(['5', '1234', 'test'], dtype='|S4')
```

Defining types

```
dt = np.dtype('i4',(2,2)) # 2x2 integer array
```

structured arrays

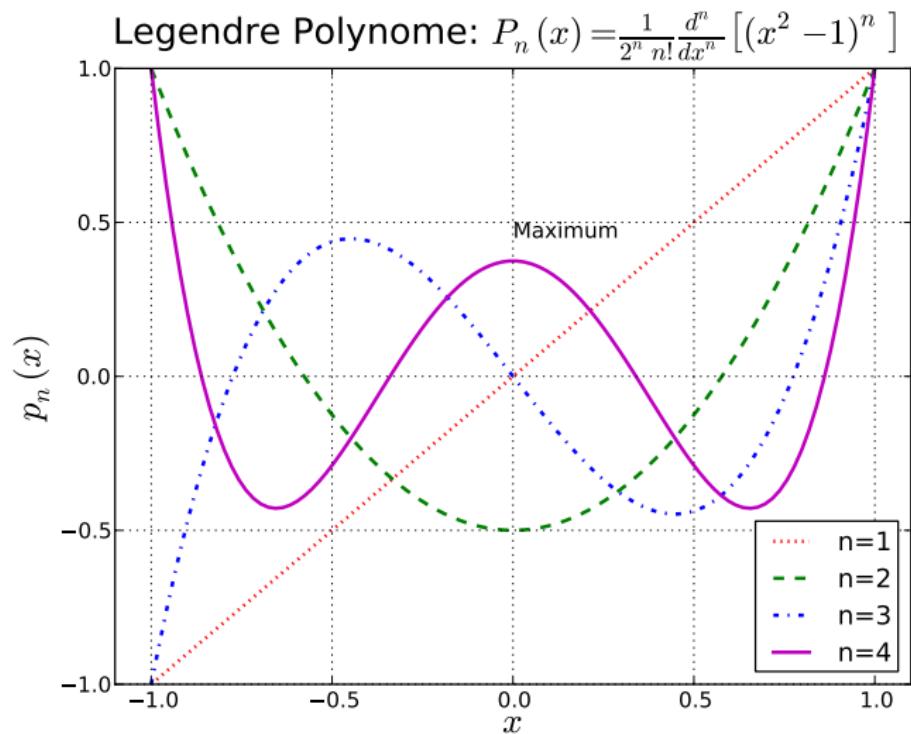
```
ct = zeros(6, dtype=[('name','S40'),('pop','u4')])  
ct[0]['name'] = 'Auckland'  
ct[0]['pop'] = 1418000; ct[0]
```

```
('Auckland', 1418000L)
```

2D visualization via example legendre polynomials

```
import numpy as np    # NumPy
import matplotlib as mpl          # Matplotlib (2D/3D)
import matplotlib.pyplot as plt   # Matplotlibs pyplot
from pylab import *                # Matplotlibs pylab
x = linspace(-1,1,100)
p1 = x; p2 = (3./2)*x**2-1./2
p3 = (5./2)*x**3-(3./2)*x
p4 = (35./8)*x**4 -(15./4)*x**2 + 3./8
plot(x,p1, 'r:', x,p2, 'g--', x,p3, 'b-.', x,p4, 'm-', linewidth=2)
title('Legendre polynomials: $P_n(x) = \frac{1}{2^n n!} \frac{d^n}{dx^n} \left[ (x^2 - 1)^n \right]$', fontsize=15)
xlabel( '$x$' , fontsize= 20)
ylabel ( '$p_n(x)$' , fontsize=20)
text( 0, 0.45 , 'Maximum' )
legend (( 'n=1', 'n=2', 'n=3', 'n=4'), loc='lower right')
grid('on'), box('on'), xlim( (-1.1 , 1.1) )
```

legendre polynomials



together with loadtxt - bye bye gnuplot

```
array = np.loadtxt(fname, delimiter=None, comments='#')
```

- fname: filename.
- delimiter : delimiter. e.g. ',' in comma separated tables. Default is space.
- comments: character for comments. In python e.g. '#'.
- array: return as (multidimensional) array.

more flexible: np.genfromtxt()

Saving figures:

```
plt.savefig('legendre.pdf')
```

Remarks:

- you can use \TeX for rendering all Texts with
`plt.rc('text', usetex=True)`
- You even can save the figures in pgf/TikZ !

Debugging

- pyflakes : syntax-checker (Spyder has it built-in)
- pdb: python debugger (Spyder has it built-in)

In IPython you can use

```
%run -d <script.py>
```

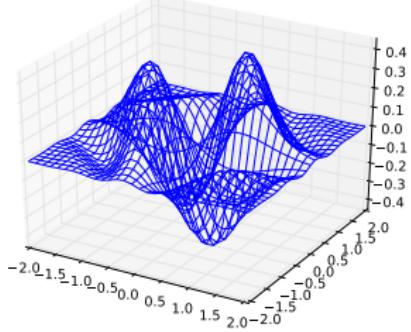
to run the debugger

Aufbau

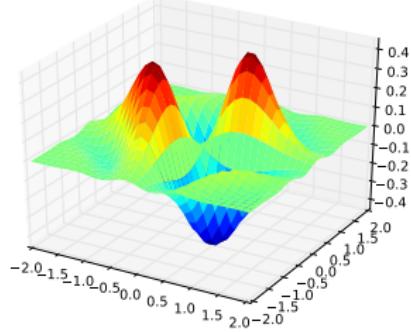
- 1 Introduction
- 2 Basic usage of python (Spyder)
- 3 3D visualization
- 4 Numerical mathematics
- 5 Performance - NumPy-tricks and Cython
- 6 Parallel Computations
- 7 Literature

3D: functionplots (basic)

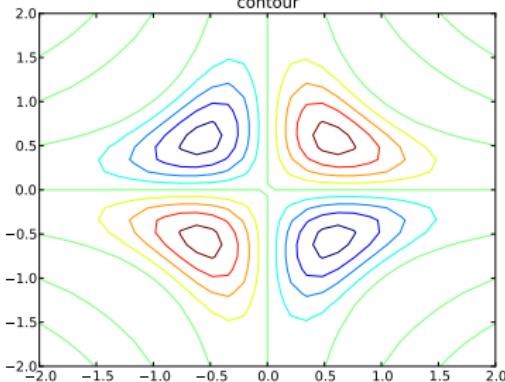
plot_wireframe



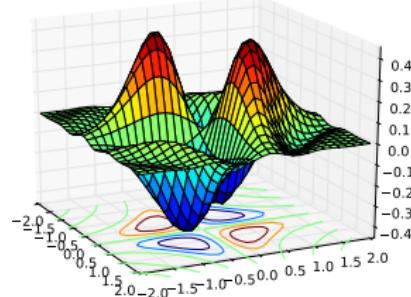
plot_surf



contour



plot_surface+contour



3D: functionsplots - implementation

```
x = linspace(-2,2,30)
y = linspace(-2,2,30)
[X,Y] = meshgrid(x,y)
Z = exp(-X**2-Y**2)*sin(pi*X*Y)
fig=figure()
ax = fig.add_subplot(2, 2, 1, projection='3d')
ax.plot_wireframe(X,Y,Z),title('plot_wireframe')

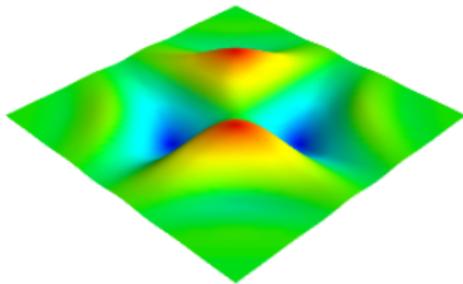
ax = fig.add_subplot(2, 2, 2, projection='3d')
ax.plot_surface(X,Y,Z,rstride=1,cstride=1,cmap=cm.jet,
    linewidth=0),title('plot_surface')

subplot(2, 2, 3)
contour(X,Y,Z,10), title('contour')

ax = fig.add_subplot(2, 2, 4, projection='3d')
ax.plot_surface(X,Y,Z,rstride=1,cstride=1,cmap=cm.jet)
ax.contour(X, Y, Z, zdir='z', offset=-0.5)
ax.view_init(20,-26),title('plot_surface + contour')
```

Mayavi mlab!

```
from mayavi import mlab as ml #majavi mlab  
ml.surf(X.T,Y.T,Z)  
title('plot_surf (mayavi)')
```



4D: Mayavi mlab

Slices

```
ml.pipeline.image_plane_widget(ml.pipeline.scalar_field(V),
    plane_orientation=<'x_axes'|'y_axes'|'z_axes'>,
    slice_index=<idx>)
```

- V : function values $V(i)$ for $(X(i), Y(i), Z(i))$.
- `plane_orientation`: slices through x-/y-/z- axes
- `slice_index`: index in matrices (no direct coordinates)

Volume rendering

```
ml.pipeline.volume(ml.pipeline.scalar_field(V))
```

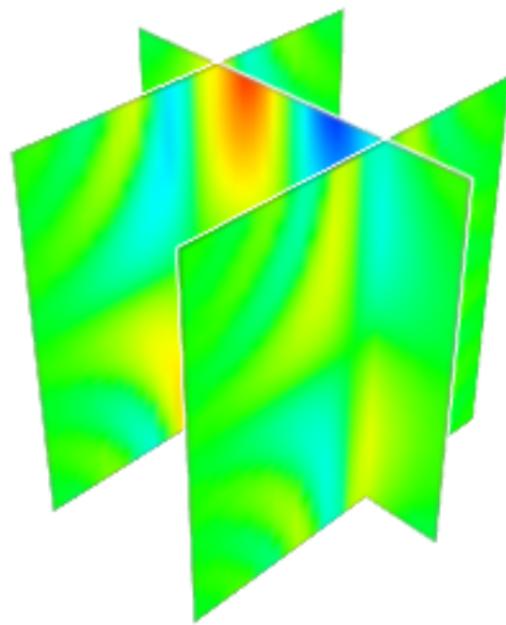
isosurfaces

```
ml.contour3d(V)
```

Example (grid-generating using broadcasting):

```
X, Y, Z = np.ogrid[-2:2:20j,-2:2:20j,-2:2:20j]
V = exp(-X**2-Y**2) * sin(pi*X*Y*Z)
```

4D: Example slice



Aufbau

- 1 Introduction
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- 3 3D visualization
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- 6 Parallel Computations
- 7 Literature

system of linear equations

Let $A \in \mathbb{C}^{n \times n}$ and $b \in \mathbb{C}^n$. the system of linear equations

$$Ax = b$$

is solved (directly) with `solve(A,b)`.

some iterative methods:

- gmres (generalized minimum residual)
- cg (preconditioned conjugate gradient)
- bicgstab (biconjugate gradients stabilized)
- ...

100 Digits-Challenge

Problem

Let A be a 20.000×20.000 matrix, which entries are all zero except of the primes $2, 3, 5, 7, \dots, 224737$ on the diagonal and ones in all entries a_{ij} with $|i - j| = 1, 2, 4, 8, \dots, 16384$.

What is the $(1, 1)$ entry of A^{-1} ?

```
n = 20000
primes = [x for x in range(2,224738) if isPrime(x)]
A = sparse.spdiags(primes,0,n,n) \
+sparse.spdiags(np.ones((15,n)),[2**x for x in range
(0,15)],n,n) \
+sparse.spdiags(np.ones((15,n)),[-2**x for x in range
(0,15)],n,n)
b = np.zeros(n)
b[0] = 1
x0 = sparse.linalg.cg(A,b)
```

Ordinary differential equations

```
r = scipy.integrate.ode(f[, jac])
```

- f: right hand side: $y'(t) = f(t, y)$
- jac: (optional) jacobian matrix
- r.set_integrator(<name>[,<params>]): sets solver <name> with parameters <params>.
- r.set_initial_value(y[, t]): sets initial value.
- r.integrate(t): solves for $y(t)$ and sets new initial value.
- r.successful(): boolean value for success.

Lorenz equations

$$\frac{d}{dt}y_1(t) = 10(y_2(t) - y_1(t))$$

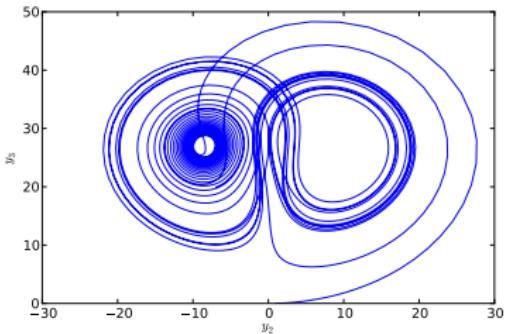
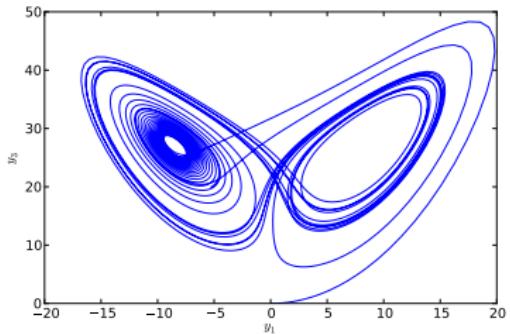
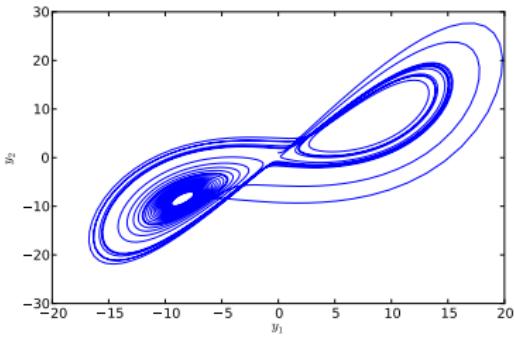
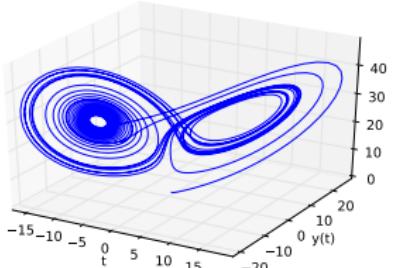
$$\frac{d}{dt}y_2(t) = 28y_1(t) - y_2(t) - y_1(t)y_3(t)$$

$$\frac{d}{dt}y_3(t) = y_1(t)y_2(t) - 8y_3(t)/3$$

Lorenz equations

```
def lorenz_rhs(t,y):
    return array([[10*(y[1]-y[0])], [28*y[0]-y[1]-y[0]*y[2]], [y[0]*y[1]-8*y[2]/3]])
y = array([0,1,0])
r = ode(lorenz_rhs)
r.set_initial_value(y, 0)
r.set_integrator('dopri5',atol=1e-7,rtol=1e-4)
tmax = 30,dt = 0.01,t=[]
while r.successful() and r.t < tmax:
    r.integrate(r.t+dt)
    t.append(r.t)
    y = vstack( (y, r.y) )
fig = figure(figsize=(16,10))
ax = fig.add_subplot(2, 2, 1, projection='3d')
ax.plot(y[:,0],y[:,1],y[:,2]), xlabel('t'), ylabel('y(t)')
subplot(2,2,2),plot(y[:,0],y[:,1]), xlabel('y_1')
subplot(2,2,3),plot(y[:,0],y[:,2]), xlabel('y_1')
subplot(2,2,4),plot(y[:,1],y[:,2]), xlabel('y_2')
```

Lorenz-equations



PDE - Heat equation

Given a rectangular Domain $\Omega \subset \mathbb{R}^2$ and a time dependent function $u(x, t), x \in \Omega, t \in \mathbb{R}^+$ the heat equation is given as:

$$\frac{\partial u}{\partial t} - \alpha \Delta u = 0 \text{ in } \Omega$$

with a constant $\alpha \in \mathbb{R}$. Given are the dirichlet boundary conditions

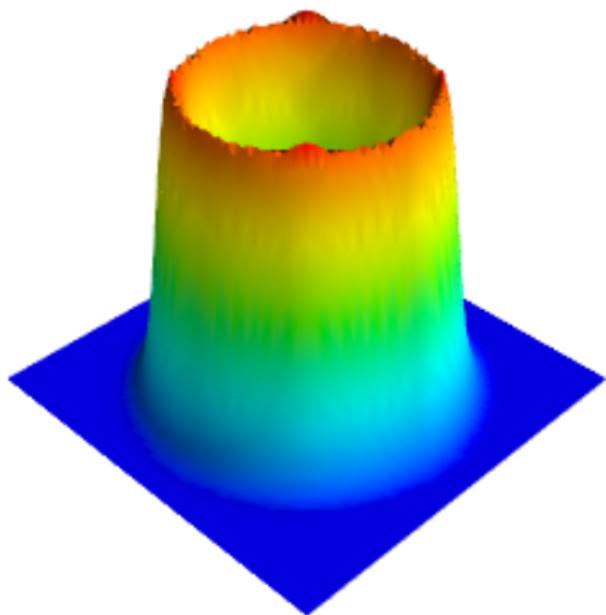
$$u = R, \text{ on } \partial\Omega$$

with a function $R : \partial\Omega \mapsto C(\partial\Omega)$. At $t = 0$ is

$$u(x, 0) = f(x), \forall x \in \Omega.$$

with a arbitrary but fixed initial function $f : \mathbb{R}^2 \mapsto \mathbb{R}$.

heat equation - Exercise!



general non-linear solver

```
fsolve(func, x0, args=(), fprime=None, full_output=0,
       xtol=1.49012e-08, maxfev=0 )
```

Example:

```
from scipy import optimize
x0 = -5 # initial
f = lambda x: abs(2*x - exp(-x))
res,info,i,mesg = optimize.fsolve(f,x0,xtol=1e-5,
    full_output=True)
print ("res: {} \nnfev: {} \nfvec: {}".format(res,info['nfev'],info['fvec']))
```

```
res: [ 0.35173371]
nfev: 13
fvec: [ -1.50035540e-12]
```

gradient-free optimizer w/o constraints

Find minima wo constraints, multidimensional (Nelder-Mead-Simplex):

```
fmin(func, x0, args=(), xtol=0.0001, ftol=0.0001,  
      full_output=0, disp=1)
```

- func: Function handle
- x0: initial vector
- xtol, ftol : tolerance in x and *func*.

Example:

```
optimize.fmin(f,x0)
```

```
Optimization terminated successfully.  
    Current function value: 0.000032  
    Iterations: 21  
    Function evaluations: 42
```

with constraints, multidimensional:

```
fminbound(func, x1, x2, args=(), xtol=1e-05, full_output  
          =0, disp=1)
```

Aufbau

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- 7 Literature

profiler and line profiler

the line_profiler (http://pythonhosted.org/line_profiler/) gives you informationen about how long each individual line took.
use the decorator @profile for the function you want to check.

```
@profile  
def function ():
```

Then call your python-script with the profiler:

```
kernprof.py -l -v <file.py>
```

or use the profiler which gives informationen about how long each function took.

```
python -m cProfile <script.py>
```

NumPy-tricks

Use sliced arrays instead of loops.

Example: 1D-distance:

```
a = randn(1000000)
d = zeros(a.shape[0]-1)
```

Loop:

```
for i in range(0,len(d)):
    d[i] = a[i]-a[i+1]
```

Numpy-slices:

```
d[:] = a[:-1]-a[1:]
```

| | |
|------------------|--------------------|
| pure python loop | 0.993635177612 s |
| numpy slicing | 0.00627207756042 s |
| matlab loop | 0.053599 s |

Cython

Cython is an extension, which allows to...

- call C functions (from libraries).
- use C++ objects.
- give C-types to variables (and gain performance)
- compile Python code (and thus can speedup parts of your code)

Basic usage:

- generate C-code from Python/Cython-code.
- compile the generated C-code (and use the shared lib as module in Python).

Minimal example

File csin.pyx

```
cdef extern from "math.h":  
    double sin(double x)  
def csin(arg):  
    return sin(arg)
```

- cdef: declare C-types or -functions.
- extern: usage of external library functions.

Remark: the normal python-function is only needed to be able to use it as module in python.

Compile

compiling is done with **Distutils**

Create a File '**setup.py**' and put the following in (with replaced
<extensionname> and <filename>.pyx):

```
from distutils.core import setup, Extension
from Cython.Distutils import build_ext

setup(
    cmdclass={'build_ext': build_ext},
    ext_modules=[Extension("(<extensionname>",
        "<filename>.pyx"))]
)
```

Generate c-code and compile

```
python setup.py build_ext --inplace
```

Usage

Load module...

```
import csin
```

...and use it

```
print csin.csin(2)
```

Mandelbrot-set

the Mandelbrot-set is the set of points $c \in \mathbb{C}$ for which the sequence $(z_n)_n$ given by

$$z_0 := c, \quad z_{n+1} = z_n^2 + c, \quad n \in \mathbb{N}$$

is finite.

- Is $|z_n| \geq 2$ then the sequence diverges.
- we use this as stopping criteria.

Mandelbrot: Python

```
def mandel():
    x1 = linspace(-2.1, 0.6, 3001)
    y1 = linspace(-1.1, 1.1, 2001)
    [X,Y] = meshgrid(x1,y1)

    it_max = 50
    Anz = zeros(X.shape)

    C = (X + 1j*Y)
    Z = copy(C) # beware: otherwise it wouldn't be a copy

    for k in range(1,it_max):
        Z = Z**2+C
        Anz += isnan(Z)
    imshow(Anz)
```

Mandelbrot: Cython

Calculation for one point. will be completely optimized.

```
import numpy as np
cimport numpy as np # cython-support of numpy
import scipy as sp
from pylab import *
def cython_mandel(double x,double y):
    cdef double z_real = 0.
    cdef double z_imag = 0.
    cdef int i
    cdef int max_iterations=50
    for i in range(0, max_iterations):
        z_real, z_imag = ( z_real*z_real - z_imag*z_imag
                           + x,2*z_real*z_imag + y )
        if (z_real*z_real + z_imag*z_imag) >= 4:
            return i
    return max_iterations
```

Mandelbrot: Cython II

Python with C-types. This is much faster than standard python.

```
def mandel_cy(int pointsx, int pointsy):
    cdef np.ndarray[double,ndim=1] x = linspace(-2.1,1.2,
        pointsx)
    cdef np.ndarray[double,ndim=1] y = linspace(-1.1,1.1,
        pointsy)
    cdef np.ndarray[double,ndim=2] z = np.zeros([pointsx,
        pointsy])
    for i in range(0,len(x)):
        for j in range(0,len(y)):
            z[i,j] = cython_mandel(x[i],y[j])
    return z
```

| | |
|-------------|-------|
| pure python | 9.4 s |
| python-loop | 6.0 s |
| cython-loop | 1.3 s |
| pure matlab | 6.6 s |

Aufbau

- 1 Introduction
- 2 Basic usage of python (Spyder)
- 3 3D visualization
- 4 Numerical mathematics
- 5 Performance - NumPy-tricks and Cython
- 6 Parallel Computations**
- 7 Literature

Ways of parallelism

ordered by simplicity and/or most effect.

- under the hood (e.g. BLAS-library while using `dot()`)
- multiple processes (`import multiprocessing`)
- MPI (the most powerful) (e.g. `import mpi4py`)
- multiple threads (but this only viable for non-CPU-bound work)

Remark: You can use MPI and multiprocesses in an interactive way in IPython!

multiprocessing

Quick introduction. Starting 2 processes in a pool:

```
from multiprocessing import Pool  
p = Pool(2)
```

use the pool to do a loop in parallel:

```
def f(x):  
    return sin(x) + x + exp(x)  
p.map(f,x)
```

Remark: this example is academic: this is much slower than a normal loop/map (because of overhead). You need much more work in `f` to be more efficient with this.

Use multiprocessing for Mandelbrot

A little less academic. Remember the cython-enhanced calculation of the Mandelbrot-set.

```
def f(xi):
    zrow = zeros(y.shape[0])
    for j,yj in enumerate(y):
        zrow[j] = mandel.cython_mandel(xi,yj)
    return zrow
p = Pool(2) # start Pool of 2 processes
zsum = p.map(f,x) # parallel map
z = vstack(zsum) # create the final matrix
```

We are nearly as fast as the cython-loop in this case.

```
z = mandel.mandel_cy(pointsx,pointsy)
```

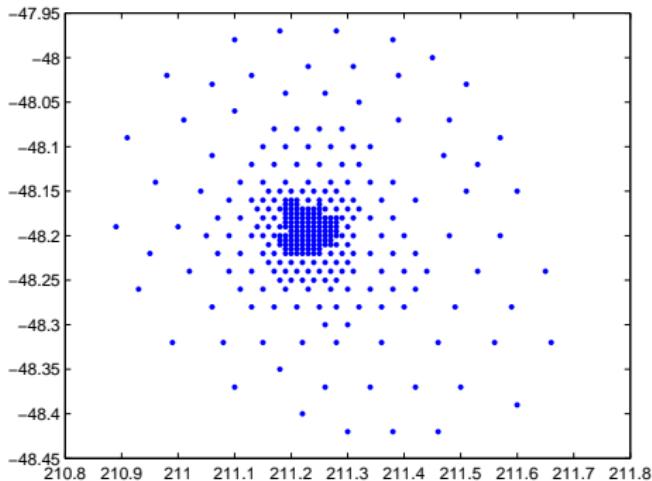
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Literature

-  **NumPy, SciPy** SciPy developers (<http://scipy.org/>),
-  **SciPy-lectures**, F. Perez, E. Gouillart, G. Varoquaux, V. Haenel (<http://scipy-lectures.github.io>),
-  **Matplotlib** (<http://matplotlib.org>)
-  **scitools** (<https://code.google.com/p/scitools/>)
-  **enthought tools** (<http://docs.enthought.com/>)
-  **mayavi** (<http://docs.enthought.com/mayavi/mlab.html>)
-  **Traits user manual** (http://docs.enthought.com/traits/traits_user_manual/index.html)
-  **Cython documentation** Cython developers (<http://docs.cython.org/>),

Interpolate scattered data

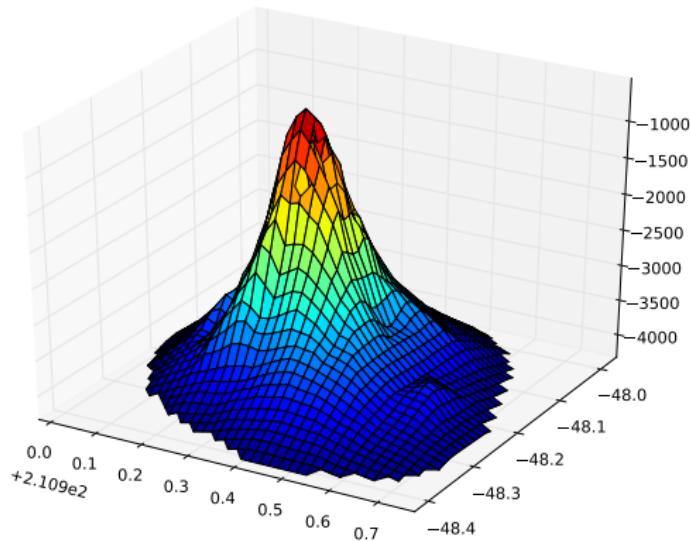


```
ZI = sp.interpolate.griddata ((x,y),z,(XI,YI),  
    method='<method>')
```

- data: vectors x, y, z with $(x(i), y(i), z(i))$.
- matrices XI, YI for interpolated points $(XI(i, j), YI(i, j))$.
- method: '**nearest**': piecewise constant; '**linear**': linear
- interpolates in convex hull of the points $(x(i), y(i))$ otherwise NaN.

Interpolate scattered data

```
XI, YI = mgrid[min(x):max(x):40j,min(y):max(y):40j]
ZI = sp.griddata ((x,y),z,(XI,YI),method='linear')
fig = figure() , ax = Axes3D(fig)
ax.plot_surface(XI ,YI ,ZI,rstride=1,cstride=1)
```

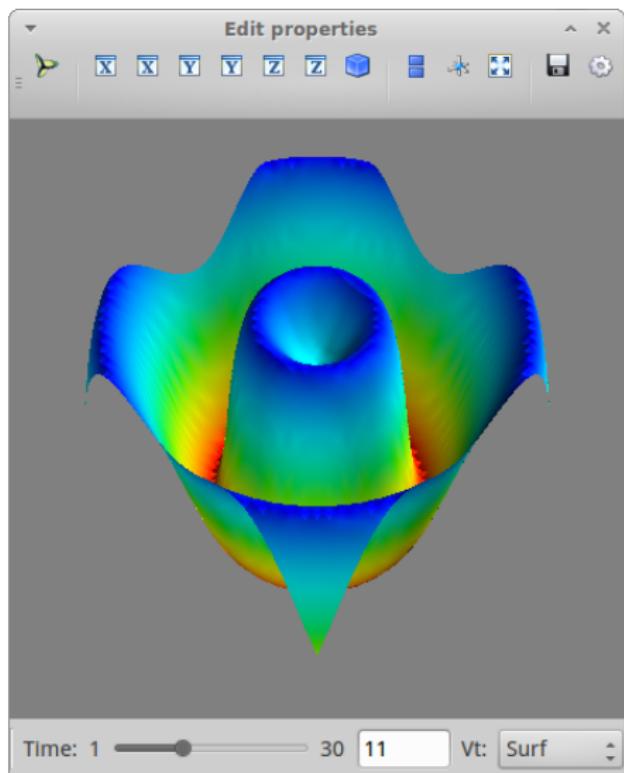


Traits

Extensions to normal
python-objects with the following
properties:

- initialization
- validation
- **visualization**
- notification
- documentation

lets do something like this:



Creation

Imports and classdefinition (cookbook)

```
from traits.api import HasTraits, Range, Enum  
class Visualization(HasTraits):
```

create needed variables with traits:

```
    time = Range(1, 30, 1) # Range-slider  
    vt = Enum ('Surf','Mesh','Contour') #Enumeration
```

Some Types

| Trait | Python Type |
|-------|---|
| Bool | Boolean |
| Float | Floating point number |
| Str | String |
| Array | Array of values |
| Enum | Enum of values |
| Range | Slider with values from/to some constants |

(complete list: http://docs.enthought.com/traits/traits_user_manual/defining.html#other-predefined-traits)

Graphical representation - TraitsUI

use Traits UI and mayavi (cookbook)

```
from traitsui.api import View, Item, Group
from tvtk.pyface.scene_editor import SceneEditor
from mayavi.tools.mlab_scene_model import MlabSceneModel
from mayavi.core.ui.mayavi_scene import MayaviScene
```

create **View**; simple arrangement (item + group)

```
scene = Instance(MlabSceneModel, ()) # cookbook
view = View(Item('scene', editor=SceneEditor(scene_class=
    MayaviScene), height=250, width=300, show_label=False
), #first Item
            Group( #second Item
                  'time', 'vt'
                  orientation='horizontal', layout='normal
                  ''),
            kind='live', title='simple GUI
            )
```

Views

View configuration of a view of given traits. it contains

- **Items**
- **Groups** (groups of Items)

```
View (<itemORgroup>[ , <itemORgroup>, <settings>])
```

settings of window

- height,width, title
- kind: type of window/dialog
 - 'live' : normal window
 - 'wizard': is updated after pressing 'finish'
 - 'panel': embeds inside other windows

View: Items and Groups

an Item is a representation of a Trait:

```
Item (<traitname>[, <settings>])
```

settings of widget

- height, width, padding, tooltip , show_label

a Group is a visual or logical unit. it can hold Items and Groups.

```
Group(<item>[,<item>,<settings>])
```

settings of groups

- orientation
- layout: type of grouping
 - 'normal': one after another.
 - 'flow ': as before but wraps around.
 - 'split ': split-bars between elements.
 - 'tabbed': tabbed elements.

Callbacks

initialization of data and classes.

```
x,y,t = np.mgrid[-1:1:(2.0/50),-1:1:(2.0/50),1:31]
Z = cos(pi*t**0.5*exp(-x**2-y**2))
def __init__(self):
    HasTraits.__init__(self)
    self.plot = self.scene.mlab.surf(self.x[:, :, 0],
                                    self.y[:, :, 0], self.Z[:, :, 0])
```

Change camera viewpoint when first activated

```
@on_trait_change('scene.activated')
def create_plot(self):
    self.scene.mlab.view(45, 210)
```

Decorator: `@on_trait_change('variable')` calls the given function, when the given variable has changed.

Callbacks II

functions for update the plot

```
@on_trait_change('time,vt')
def update_plot(self):
    self.plot.remove() # remove last image
    if self.vt == 'Surf':
        self.plot = self.scene.mlab.surf(self.x
            [:,:,0],self.y[:,:,:0],self.Z[:,:,:self.
            time-1])
    elif self.vt == 'Mesh':
        self.plot = self.scene.mlab.surf(self.x
            [:,:,0],self.y[:,:,:0],self.Z[:,:,:self.
            time-1],representation='wireframe')
    elif self.vt == 'Contour':
        self.plot = self.scene.mlab.contour_surf(self.
            .x[:,:,:0],self.y[:,:,:0],self.Z[:,:,:self.
            time-1],contours=15)
    else:
        print "error in choice of plot-type"
```