
SciPy



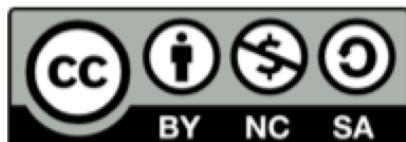
Neelofer Banglawala nbanglaw@epcc.ed.ac.uk
Kevin Stratford kevin@epcc.ed.ac.uk

Original course authors:

Andy Turner
Arno Proeme



Reusing this material



This work is licensed under a Creative Commons Attribution-
NonCommercial-ShareAlike 4.0 International License.

http://creativecommons.org/licenses/by-nc-sa/4.0/deed.en_US

This means you are free to copy and redistribute the material and adapt and build on the material under the following terms: You must give appropriate credit, provide a link to the license and indicate if changes were made. If you adapt or build on the material you must distribute your work under the same license as the original.

Note that this presentation contains images owned by others. Please seek their permission before reusing these images.



www.archer.ac.uk

support@archer.ac.uk



[SciPy] Overview



- NumPy provides arrays, basic linear algebra, random number generation, and Fourier transforms
- SciPy builds on NumPy (e.g. by using arrays) and expands this with (additional) routines for:
 - Numerical Integration (*integrate*)
 - Interpolation (*interpolate*)
 - Optimisation (*optimize*)
 - Special functions (*special*)
 - Linear Algebra and wrappers to LAPACK & BLAS (*linalg*)
 - Signal processing (*signal*)
 - Image Processing (*ndimage*)
 - Fourier transforms (*fftpack*)
 - Statistical functions (*stats*)
 - Spatial data structures and algorithms (*spatial*)
 - File IO e.g. read MATLAB files (*io*)

[SciPy] Useful links



- Note: no PDE solvers (though other packages exist)
- Documentation:
 - <http://docs.scipy.org/doc/scipy/reference/tutorial/>
 - <http://docs.scipy.org/doc/scipy/reference/>
 - <http://scipy-cookbook.readthedocs.org>

[SciPy] Integration



- Routines for numerical integration – single, double and triple integrals
- Can solve Ordinary Differential Equations (ODEs) with initial conditions

[SciPy] Integration : find π I

Calculate π using the double integral for the area of a circle with radius a :

$$\int_{-a}^a \int_{-\sqrt{a^2-x^2}}^{\sqrt{a^2-x^2}} 1 dx dy = \pi a^2$$

```
In [ ]: # numerically solve the integral using dblquad
import numpy as np;
from scipy.integrate import dblquad;

def integrand(y,x): # integrand
    return 1;

# integral for the area of a circle with radius r
def integrate_to_pi(r):
    (area,err) = dblquad(integrand, -1*r,r,
                         lambda x: -1*np.sqrt(r*r-x*x),
                         lambda x: np.sqrt(r*r-x*x));
    return area/(r*r) ;
```

[SciPy] Integration : find π II

Calculate the result and compare with `numpy.pi`

```
In [ ]: # result!
print integrate_to_pi(50.0);

# compare with numpy pi
np.pi - integrate_to_pi(50.0);

# see timing routine from numpy lecture
# %timeit integrate_to_pi(50.0)
```

```
In [ ]: # Ex: calculate the double integral of f(x, y) = y * sin (x)
# for x = [0, pi/2], y = [0, 1]
#
# ANSWER: 1/2
```

[SciPy] Integration : coupled masses I

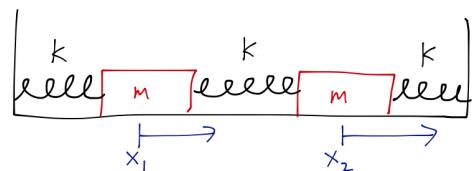


Solve Ordinary Differential Equations (ODEs) with initial conditions, for example normal mode motion of spring-coupled masses.

Two masses, \mathbf{m} , are coupled with springs, each with spring constant \mathbf{k} . Displacement \mathbf{x}_i of each mass is measured from its position of rest.

We can write a system of second-order differential equations to describe the motion of these masses according to Newton's 2nd law of motion, $\mathbf{F} = \mathbf{m a}$:

$$\begin{aligned} m\ddot{x}_1 &= -kx_1 + k(x_2 - x_1) \\ m\ddot{x}_2 &= -k(x_2 - x_1) - kx_2 \end{aligned}$$



To use `odeint`, we rewrite these as 4 first-order differential equations in terms of the masses velocities, \mathbf{v}_i :

$$\begin{aligned} v_1 &= \dot{x}_1 \\ \dot{v}_1 &= -\frac{2k}{m}x_1 + \frac{k}{m}(x_2) \\ v_2 &= \dot{x}_2 \\ \dot{v}_2 &= -\frac{2k}{m}x_2 + \frac{k}{m}(x_1) \end{aligned}$$

[SciPy] Integration : coupled masses II



Exact time-dependent solution for displacement of masses (assuming initial velocities of masses are zero)

```
In [ ]: %matplotlib inline
import numpy as np;
```

```
In [ ]: def x1_t(t,x1,x2,k,m): # exact solution for mass 1 at time t
    w=np.sqrt(k/m);      # initial velocity assumed zero
    a1=(x1+x2)/2.0;
    a2=(x1-x2)/2.0;
    return a1*np.cos(w*t) + a2*np.cos(np.sqrt(3)*w*t);

def x2_t(t,x1,x2,k,m): # exact solution for mass 2 at time t
    w=np.sqrt(k/m);      # initial velocity assumed zero
    a1=(x1+x2)/2.0;
    a2=(x1-x2)/2.0;
    return a1*np.cos(w*t) - a2*np.cos(np.sqrt(3)*w*t);
```

```
In [ ]: # "vectorize" solutions to act on an array of times
x1_sol = np.vectorize(x1_t);
x2_sol = np.vectorize(x2_t);
```

[SciPy] Integration : coupled masses III



Set up a function to give to the ODE solver

```
In [ ]: def vectorfield(w, t, p):
    """Defines the differential equations for the coupled
    spring-mass system. Arguments:
        w : vector of the state variables: w = [x1,y1,x2,y2]
        t : time
        p : vector of the parameters: p = [m,k]
    """
    x1, y1, x2, y2 = w;
    m, k = p;

    # Create f = (x1',y1',x2',y2'):
    f = [y1, (-k * x1 + k * (x2 - x1)) / m,
         y2, (-k * x2 - k * (x2 - x1)) / m];
    return f;
```

[SciPy] Integration : coupled masses IV



Use *odeint* to numerically solve ODEs with initial conditions

```
In [ ]: # Use ODEINT to solve differential equations
from scipy.integrate import odeint;

In [ ]: # Parameters and initial values
m = 1.0; k = 1.0;      # mass m, spring constant k
x01 = 0.5; x02 = 0.0; # Initial displacements
y01 = 0.0; y02 = 0.0; # Initial velocities : LEAVE AS ZERO

In [ ]: # ODE solver parameters
abserr = 1.0e-8; relerr = 1.0e-6;
stoptime = 10.0; numpoints = 250;

In [ ]: # Create time samples for the output of the ODE solver
t = [stoptime * float(i) / (numpoints - 1)
     for i in range(numpoints)];

# contd...
```

[SciPy] Integration : coupled masses V



Use *odeint* to numerically solve ODEs with initial conditions

```
In [ ]: # ... contd

# Pack up the parameters and initial conditions as lists/arrays:
p = [m, k]; w0 = [x01, y01, x02, y02];

# Call the ODE solver
# Note: args is a tuple
wsol = odeint(vectorfield, w0, t, args=(p,), atol=abserr,
               rtol=relerr);
```

```
In [ ]: # Print and save the solution
with open('coupled_masses.dat', 'w') as f:
    for t1, w1 in zip(t, wsol):
        print >> f, t1, w1[0], w1[1], w1[2], w1[3]
```

[SciPy] Integration : coupled masses VI



Plot exact solutions against saved numerical solutions

```
In [ ]: # import modules for plotting
import matplotlib.pyplot as plt;
from matplotlib.font_manager import FontProperties;

# get saved values from saved file
t, x1, y1, x2, y2 = np.loadtxt('coupled_masses.dat', unpack=True);

# contd...
```

[SciPy] Integration : coupled masses VII



Plot exact solutions against saved numerical solutions

```
In [ ]: # figure properties
plt.figure(1, figsize=(10, 3.5)); plt.xlabel('t');
plt.ylabel('x'); plt.grid(True); plt.hold(True);

# plot exact solutions
time=np.linspace(0,stoptime,50);
plt.plot(time, x1_sol(time,x01,x02,k,m), 'r*', linewidth=1);
plt.plot(time, x2_sol(time,x01,x02,k,m), 'mo', linewidth=1);
# plot numerical solutions
plt.plot(t, x1, 'b-', linewidth=1); plt.plot(t, x2, 'g-', linewidth=1);

plt.legend(['$x_{1,sol}$', '$x_{2,sol}$', '$x_{1,num}$',
           '$x_{2,num}$'], prop=FontProperties(size=12));
plt.title('Mass Displacements for the\nCoupled Spring-Mass System');
plt.savefig('coupled_masses.png', dpi=100); # save figure
```

[SciPy] Special functions



- SciPy contains huge set of special functions
 - Bessel functions
 - Legendre functions
 - Gamma functions
 - Bessel functions
 - Airy functions

We will see special functions used in the following sections.

[SciPy] Special functions : drumhead I



- Let's plot the height of a drumhead (Bessel functions)

```
In [ ]: # plot drumhead
from scipy import special;

def drumhead_height(n, k, distance, angle, t):
    kth_zero = special.jn_zeros(n, k)[-1];
    return (np.cos(t) * np.cos(n*angle) *
            special.jn(n, distance*kth_zero));
```

```
In [ ]: theta = np.r_[0:2*np.pi:50j];
radius = np.r_[0:1:50j];
x = np.array([r * np.cos(theta) for r in radius]);
y = np.array([r * np.sin(theta) for r in radius]);
z = np.array([drumhead_height(1, 1, r, theta, 0.5) ;
              for r in radius]);
# contd...
```

[SciPy] Special functions : drumhead II



- Let's plot the height of a drumhead subject to normal modes

```
In [ ]: # ...contd
import matplotlib.pyplot as plt;
from mpl_toolkits.mplot3d import Axes3D;
from matplotlib import cm;

fig = plt.figure(figsize=(10, 6));
ax = Axes3D(fig);
ax.plot_surface(x, y, z, rstride=1, cstride=1, cmap=cm.jet);
ax.set_xlabel('X');
ax.set_ylabel('Y');
ax.set_zlabel('Z');
```

[SciPy] Optimisation



- Several classical optimisation algorithms
 - Quasi-Newton type optimisations
 - Least squares fitting
 - Simulated annealing
 - General purpose root finding

[SciPy] Optimisation : maxima I



Let's locate a few maxima of a Bessel function.

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

```
In [ ]: from scipy import optimize, special;
x = np.arange(0,10,0.01);

for k in np.arange(0.5,5.5):
    y = special.jv(k,x); # Bessel function
    plt.plot(x,y);
    # flip Bessel function about x-axis, turn maxima into minima
    f = lambda x: -1*special.jv(k,x);
    # find minimum between 4 and 10
    x_max = optimize.fminbound(f,0,6);
    plt.plot([x_max], [special.jv(k,x_max)],'ro') ;
plt.title('Different Bessel functions & their local maxima');
```

[SciPy] Optimisation : maxima II



Time for an exercise! Find maxima of the Airy function, $\text{Ai}(x)$

```
In [ ]: # Ex: find ** all ** maxima of Airy function in range x = [-8, 2]
x = np.arange(-8,2,0.01); # x range
ai = special.airy(x)[0]; # Airy function, see online docs
```

```
In [ ]: # What does the Airy function look like?
plt.figure(figsize=(8,4)); plt.plot(x,ai);
```

[SciPy] Optimisation : maxima III



```
In [ ]: # find each maximum (given you can plot the function)
f = lambda x: -special.airy(x)[0]; # use negated of airy function

plt.plot(x,ai);
x_max = optimize.fminbound(f,-8,-6);
plt.plot([x_max], [special.airy(x_max)[0]],'ro');
x_max = optimize.fminbound(f,-6,-3);
plt.plot([x_max], [special.airy(x_max)[0]],'ro');
x_max = optimize.fminbound(f,-3,2);
plt.plot([x_max], [special.airy(x_max)[0]],'ro');
plt.title('Different Airy functions and their local maxima');
```

[SciPy] Optimisation : maxima IV



```
In [ ]: # ... contd
# But what if you don't know what function looks like?
# Could use a fixed 'window' within which to search
# BUT this could pick up a false maximum
minw = -8; maxw = -6; # min, max values for fixed "window"
plt.plot(x,ai);
for w in np.arange(4):
    x_max = optimize.fminbound(f,minw,maxw); # find minima / maxima
    plt.plot([x_max], [special.airy(x_max)[0]],'ro');
    minw+=2; maxw +=2;

plt.title('Different Airy functions and their local maxima');
```

```
In [ ]: # Ex ++: how could you check you have found a genuine
# maximum or minimum?
```

[SciPy] Optimisation : least-squares fit I



Let's use `leastsq` to fit some measured data, $\{x_i, y_i\}$, to a function :

$$y_i = A \sin(2\pi k x_i + \theta)$$

where the parameters A , k , and θ are unknown. The residual vector, that will be squared and summed by `leastsq` to fit the data, is:

$$e_i = \| y_i - A \sin(2\pi k x_i + \theta) \|$$

By defining a function to compute the residuals, e_i , and, selecting appropriate starting values, `'leastsq'` can be used to find the best-fit parameters $\hat{A}, \hat{k}, \hat{\theta}$.

[SciPy] Optimisation : least-squares fit II



Create a sample of the true function and the "measured" (noisy) data. Define the residual function and initial values.

```
In [ ]: # set up true function and "measured" data
x = np.arange(0, 6e-2, 6e-2 / 30);
A, k, theta = 10, 1.0 / 3e-2, np.pi / 6;
y_true = A * np.sin(2 * np.pi * k * x + theta);
y_meas = y_true + 2*np.random.randn(len(x));
```

```
In [ ]: # residual function, e_i
def residuals(p, y, x):
    A, k, theta = p;
    err = y - A * np.sin(2 * np.pi * k * x + theta);
    return err;
```

[SciPy] Optimisation : least-squares fit III



```
In [ ]: # for easy evaluation of model function parameters [A, K, theta]
def peval(x, p):
    return p[0] * np.sin(2 * np.pi * p[1] * x + p[2]);

# starting values of A, k and theta
p0 = [8, 1 / 2.3e-2, np.pi / 3];
print(np.array(p0));
```

[SciPy] Optimisation : least-squares fit IV



Do least squares fitting and plot results

```
In [ ]: # do least squares fitting
from scipy.optimize import leastsq

plsq = leastsq(residuals, p0, args=(y_meas, x));
print(plsq[0]); print(np.array([A, k, theta]));
```

```
In [ ]: # and plot the true function, measured (noisy) data
# and the model function with fitted parameters
plt.plot(x, peval(x, plsq[0]), x, y_meas, 'o', x, y_true);

plt.title('Least-squares fit to noisy data');
plt.legend(['Fit', 'Noisy', 'True']);
```

[SciPy] Convolutions functions I



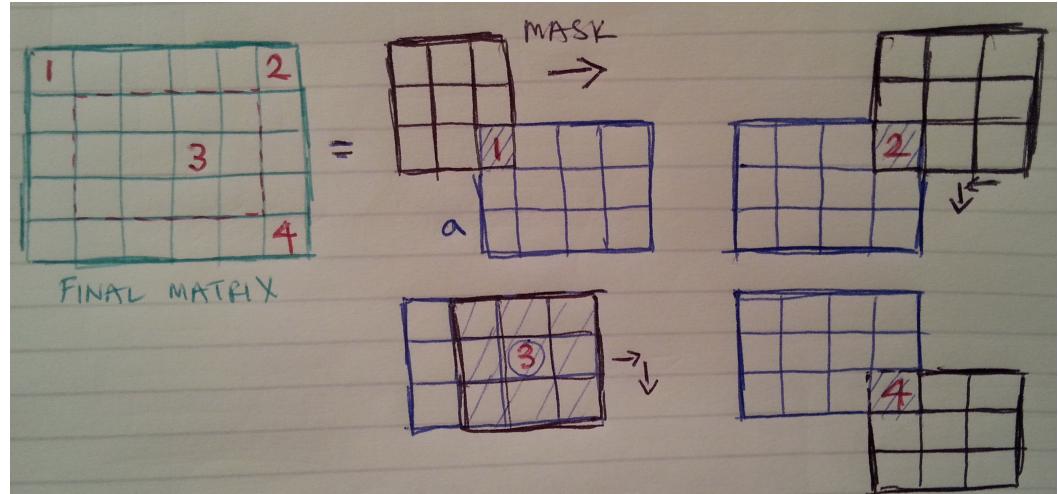
In image and signal processing, the result of applying a filter (or mask) to an image (or signal) can be determined by a convolution between the two.

```
In [ ]: # for example
import numpy as np
from scipy import signal
a = np.array([[1, 2, 3, 4], [5, 6, 7, 8], [9, 10, 11, 12]])
mask = np.array([[1,1,1],[1,0,1],[1,1,1]])
cs = signal.convolve(a, mask)
print a; print; print mask; print; print cs
```

[SciPy] Convolutions functions II



What signal.convolve is doing



[SciPy] Convolutions functions III



SciPy has another convolve function

```
In [ ]: # Ex: Scipy has another convolve function, ndimage.convolve
# What does this produce, when used in 'constant' mode (below)?
from scipy import ndimage
cN = ndimage.convolve(a, mask, mode='constant')

# The default mode for ndimage.convolve is 'reflect'. Investigate.
```

```
In [ ]: # ANSWER
#
# ndimage.convolve only produces the inner dotted matrix as shown
# in the green matrix in the figure i.e. convolution that fits
# the size of array a (not a true (commutative) convolution, like
# signal.convolve. With 'reflect' it replaces 'missing' values
# with adjacent values, e.g.
# cN[0,0]= 23= 5+6+2 (as constant mode)
#         +5+1 (from the left) +1+1+2 (from the top)
# cN[0,3]= 41= 3+7+8 (same as constant mode)
#         +8+4 (from the right) +3+4+4 (from the top)
cN = ndimage.convolve(a, mask, mode='reflect')
print cN
```

[SciPy] Linear algebra



- Wider set of linear algebra operations than in Numpy
 - various decompositions (eigen, singular value)
 - matrix exponentials, trigonometric functions
 - particular matrix equations and special matrices
 - low-level LAPACK and BLAS routines
- Routines also for sparse matrices
 - storage formats
 - iterative algorithms

[SciPy] Linear algebra : inverse matrix I



Let's find inverse of matrix A

$$A = \begin{bmatrix} 1 & 3 & 5 \\ 2 & 5 & 1 \\ 2 & 3 & 8 \end{bmatrix}$$

which is

$$A^{-1} = \frac{1}{25} \begin{bmatrix} -37 & 9 & 22 \\ 14 & 2 & -9 \\ 4 & -3 & 1 \end{bmatrix} = \begin{bmatrix} -1.48 & 0.36 & 0.88 \\ -0.56 & 0.08 & -0.36 \\ 0.16 & -0.12 & 0.04 \end{bmatrix}$$

Note that $I = AA^{-1}$, where I is the identity matrix $I = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix}$

[SciPy] Linear algebra : inverse matrix II



```
In [ ]: # find inverse of matrix
from scipy import linalg
A = np.array([[1,3,5],[2,5,1],[2,3,8]])

invA = linalg.inv(A) # the inveser
print invA; print;

# check inverse gives identity
identity=A.dot(linalg.inv(A))

# This really is the identity if we clean up the errors
np.abs(np.around(identity,0)) # (round up small errors)
```

[SciPy] Other packages



- Pandas
 - Offers R-like statistical analysis of numerical tables and time series
- SymPy
 - Python library for symbolic computing
- scikit-image
 - Advanced image processing
- scikit-learn
 - Package for machine learning
- Sage
 - Open source replacement for Mathematica / Maple / Matlab (built using Python)