

SCRIPTING AND PROGRAMMING LABORATORY FOR DATA ANALYSIS

Lecture 6 - Introduction to scipy

SCIPY

The Scientific Python (*SciPy*) package contains several tools dedicated to most part of the problems encountered in scientific research, like:

- Interpolation
- Integration
- Optimisation
- Special functions
- Linear algebra
- Fourier transform
- ...

As *Numpy*, also *Scipy* is largely written in Fortran or C, making it very computationally efficient and optimised.

SCIPY

The Scientific Python (SciPy) package contains several tools dedicated to most part of the problems encountered in scientific research, like:

- Interpolation
- Integration
- Optimisation
- Special functions
- Linear algebra
- Fourier transform
- ...

*Before implementing an algorithm
by yourself, check the scipy doc
DO NOT REINVENT THE WHEEL!*

As *Numpy*, also *Scipy* is largely written in Fortran or C, making it very computationally efficient and optimised.

SCIPY-STRUCTURE

SciPy User Guide

- Introduction
- Special functions (`scipy.special`)
- Integration (`scipy.integrate`)
- Optimization (`scipy.optimize`)
- Interpolation (`scipy.interpolate`)
- Fourier Transforms (`scipy.fft`)
- Signal Processing (`scipy.signal`)
- Linear Algebra (`scipy.linalg`)
- Sparse eigenvalue problems with ARPACK
- Compressed Sparse Graph Routines (`scipy.sparse.csgraph`)
- Spatial data structures and algorithms (`scipy.spatial`)
- Statistics (`scipy.stats`)
- Multidimensional image processing (`scipy.ndimage`)
- File IO (`scipy.io`)

(Probably) most useful modules
for scientific computing

Use the help function or
the online documentation to
navigate into the countless
number of modules!

SCIPY-STATS

The module **scipy.stats** contains a large number of probability distributions, summary and frequency statistics, correlation functions and statistical tests, masked statistics, kernel density estimation, quasi-Monte Carlo functionality, and more check the [doc](#)!

In this package you generally invoke an object, then you need various methods to access different available functionalities.

SCIPY-STATS

Probability distributions

Each univariate distribution is an instance of a subclass of **rv_continuous** (**rv_discrete** for discrete distributions):

rv_continuous([momtype, a, b, xtol, ...])

A generic continuous random variable class meant for subclassing.

rv_discrete([a, b, name, badvalue, ...])

A generic discrete random variable class meant for subclassing.

rv_histogram(histogram, *args, **kwargs)

Generates a distribution given by a histogram.

This is a gaussian distribution

SCIPY-STATS

scipy.stats.norm

```
scipy.stats.norm = <scipy.stats._continuous_distns.norm_gen object> [source]
```

A normal continuous random variable.

The location (**loc**) keyword specifies the mean. The scale (**scale**) keyword specifies the standard deviation.

As an instance of the **rv_continuous** class, **norm** object inherits from it a collection of generic methods (see below for the full list), and completes them with details specific for this particular distribution.

functionalities.

SCIPY-STATS

scipy.stats.norm

`scipy.stats.norm = <scipy.stats._continuous_`


A normal continuous random variable.

The location (**loc**) keyword specifies the mean. deviation.

As an instance of the **rv_continuous** class, **norm** methods (see below for the full list), and complete distribution.

functionalities.

Methods

<code>rvs(loc=0, scale=1, size=1, random_state=None)</code>	Random variates.	<i>You can access the functional form</i> 
<code>pdf(x, loc=0, scale=1)</code>	Probability density function.	
<code>logpdf(x, loc=0, scale=1)</code>	Log of the probability density function.	
<code>cdf(x, loc=0, scale=1)</code>	Cumulative distribution function.	
<code>logcdf(x, loc=0, scale=1)</code>	Log of the cumulative distribution function.	
<code>sf(x, loc=0, scale=1)</code>	Survival function (also defined as $1 - \text{cdf}$, but <i>sf</i> is sometimes more accurate).	
<code>logsf(x, loc=0, scale=1)</code>	Log of the survival function.	
<code>ppf(q, loc=0, scale=1)</code>	Percent point function (Inverse of cdf — percentiles).	
<code>isf(q, loc=0, scale=1)</code>	Inverse survival function (Inverse of sf).	
<code>moment(n, loc=0, scale=1)</code>	Non-central moment of order <i>n</i>	
<code>stats(loc=0, scale=1, moments='mv')</code>	Mean('m'), variance('v'), skew('s'), and/or kurtosis('k').	

SCIPY-INTERPOLATION

In the interpolation module (**scipy.interpolate**) you can find (check also [here](#)):

- A class representing an 1D interpolant (**interp1d**), offering several interpolation methods.
- Functions for 1D and 2D (smoothed) **cubic-spline** interpolation, based on the FORTRAN library FITPACK.
- The function **griddata** offering a simple interface to interpolation in N dimensions ($N = 1, 2, 3, 4, \dots$).
- Many others, check [documentation](#)!

SCIPY-INTERPOLATION

- **interp1d** ([doc](#)): create a function based on fixed data points, which can be evaluated anywhere within the domain defined by the given data. An instance of this class is created by passing the 1-D vectors comprising the data.

```
>>> from scipy.interpolate import interp1d
```

```
>>> x = np.linspace(0, 10, num=11, endpoint=True)
```

```
>>> y = np.cos(-x**2/9.0)
```

```
>>> f = interp1d(x, y)
```

```
>>> f2 = interp1d(x, y, kind='cubic')
```

Functions!

*Check the documentation for other
option of interpolation degree*

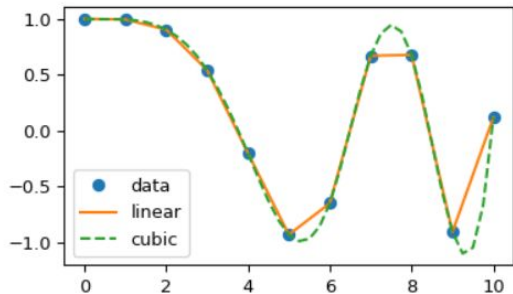
SCIPY-INTERPOLATION

- **interp1d** ([doc](#)): create a function based on fixed data points, which can be evaluated anywhere within the domain defined by the given data. It is created by passing the

```
>>> from scipy.interpolate import
```

```
>>> x = np.linspace(0, 10, num=11)
>>> y = np.cos(-x**2/9.0)
>>> f = interp1d(x, y)
>>> f2 = interp1d(x, y, kind='cubic')
```

```
>>> xnew = np.linspace(0, 10, num=41, endpoint=True)
>>> import matplotlib.pyplot as plt
>>> plt.plot(x, y, 'o', xnew, f(xnew), '-', xnew, f2(xnew), '--')
>>> plt.legend(['data', 'linear', 'cubic'], loc='best')
>>> plt.show()
```



SCIPY-INTERPOLATION

- **Splines** ([doc](#)):

- Procedural usage: two essential steps, first a spline representation of the curve is computed, then the spline is evaluated at the desired points

```
>>> import numpy as np
>>> import matplotlib.pyplot as plt
>>> from scipy import interpolate
```

Cubic-spline

```
>>> x = np.arange(0, 2*np.pi+np.pi/4, 2*np.pi/8)
>>> y = np.sin(x)
>>> tck = interpolate.splrep(x, y, s=0)
>>> xnew = np.arange(0, 2*np.pi, np.pi/50)
>>> ynew = interpolate.splev(xnew, tck, der=0)
```

splrep computes the spline coefficients based on data.

Note the **s** parameter, this represents the smoothing, by setting it to **zero**, you force the spline representation to pass through all data point! Beware: this is not the default.

splev evaluates the spline at new points within the domain of **x**. The function needs the spline object **tck**!

Other functions can evaluate the spline derivative, integral, roots, e.g.:
spalde, splint, sproot

SCIPY-INTERPOLATION

- **Splines** ([doc](#)):

- Object-Oriented usage: the **UnivariateSpline** class does the job. At object creation you pass the data and you directly get a function to be evaluated at different data points

```
>>> import numpy as np
>>> import matplotlib.pyplot as plt
>>> from scipy import interpolate
```

InterpolatedUnivariateSpline

```
>>> x = np.arange(0, 2*np.pi+np.pi/4, 2*np.pi/8)
>>> y = np.sin(x)
>>> s = interpolate.InterpolatedUnivariateSpline(x, y)
>>> xnew = np.arange(0, 2*np.pi, np.pi/50)
>>> ynew = s(xnew)
```

InterpolateUnivariateSpline
computes the spline!
s is now callable

InterpolateUnivariateSpline vs UnivariateSpline:
difference is the smoothing parameter that for the former is set to zero, i.e. the spline passes through all points.

SCIPY-INTERPOLATION

- **griddata** ([doc](#)): Interpolate unstructured D-D data

```
scipy.interpolate.griddata(points, values, xi,  
method='linear', fill_value=nan, rescale=False)
```

Data points:

2-D ndarray of floats with shape (n, D).
n: number of data points
D: number of dimensions

Values at data points:

ndarray of float or complex with shape (n,)

Method could be {'linear', 'nearest',
'cubic'}

Points at which to interpolate data:

2-D ndarray of floats with shape (m, D).
m: number of points
D: number of dimensions

SCIPY-INTERPOLATION

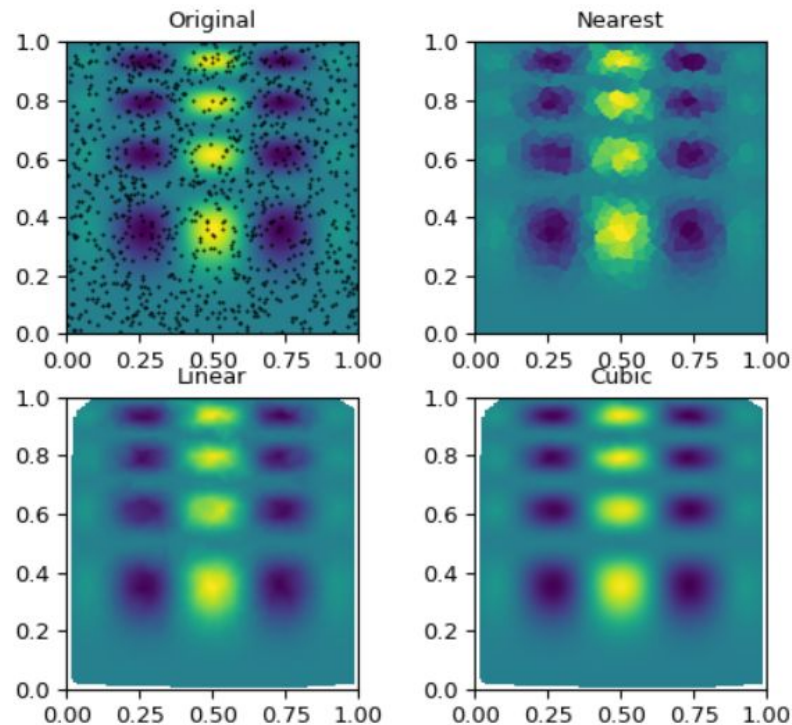
- `griddata` ([doc](#)): Interpolation

```
scipy.interpolate.griddata(p  
method='linear', fill_value=
```

Data points:

2-D ndarray of floats with shape (n, D). ndarray of
n: number of data points
D: number of dimensions

Method could be {'linear', 'nearest',
'cubic'}



SCIPY-INTEGRATION

The **scipy.integrate** sub-package provides several integration techniques to compute integrals (1D or higher). It also includes an ordinary differential equation integrator ([doc](#)).

Methods for integrating functions given the function object:

- **quad**: General purpose integration.
- **dblquad**: General purpose double integration.
- **tplquad**: General purpose triple integration.
- **fixed_quad**: Integrate $\text{func}(x)$ using Gaussian quadrature of order n .
- **quadrature**: Integrate with given tolerance using Gaussian quadrature.
- **romberg**: Integrate function using Romberg integration.

SCIPY-INTEGRATION

The **scipy.integrate** sub-package provides several integration techniques to compute integrals (1D or higher). It also includes an ordinary differential equation integrator ([doc](#)).

Methods for integrating functions given the function object:

```
from scipy import integrate

result = integrate.quad(lambda x: 3*x**2, 0, 5)
print(result)

(125.00000000000001, 1.3877787807814459e-12)
```

- **romberg**: Integrate function using Romberg integration.

*Result contains the computed value
and an estimate of the error*

*We need to provide a function and
integration limits*

SCIPY-INTEGRATION

The **scipy.integrate** sub-package provides several integration techniques to compute integrals (1D or higher). It also includes an ordinary differential equation integrator ([doc](#)).

Methods for Integrating Functions given fixed samples:

- **trapezoid:** Use trapezoidal rule to compute integral.
- **cumulative_trapezoid:** Use trapezoidal rule to cumulatively compute integral.
- **simpson:** Use Simpson's rule to compute integral from samples.
- **romb:** Use Romberg Integration to compute integral from $(2^k + 1)$ evenly-spaced samples.

SCIPY-INTEGRATION

The `scipy.integrate` sub-package

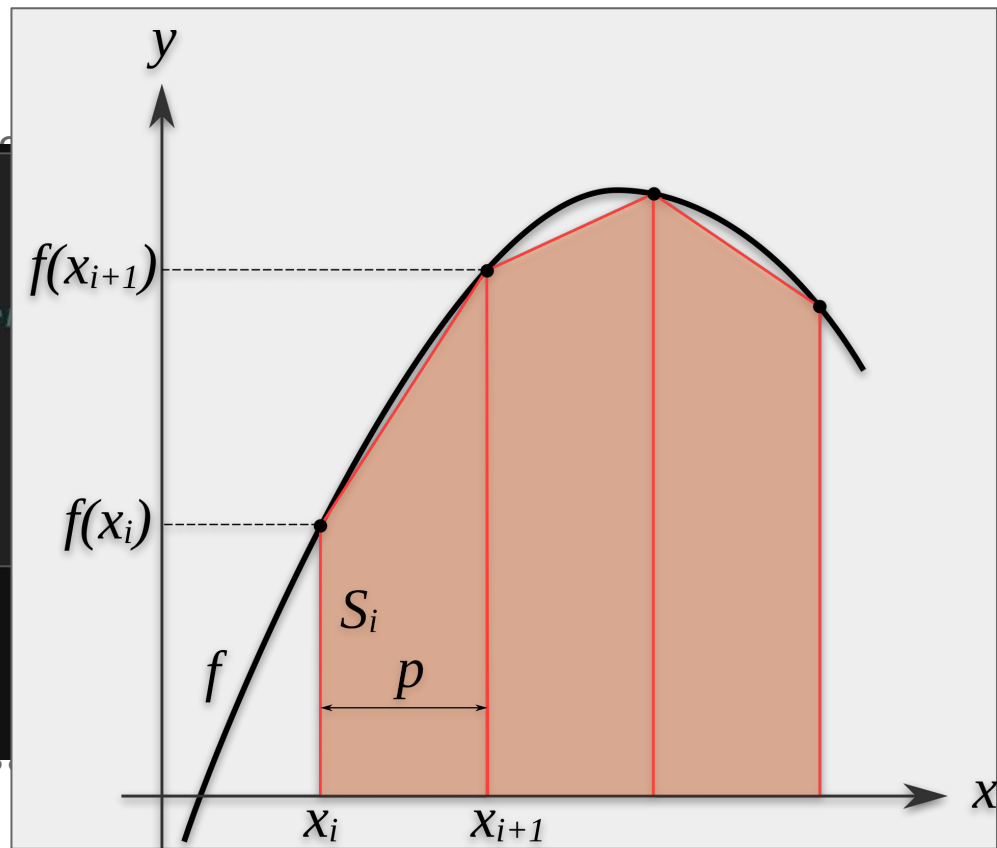
```
def f(x):  
    return 3*x**2  
  
# compute the integral with different number of points  
for i in [100,1000,10000,100000]:  
    x_samp = np.linspace(0,5,i)  
    y_samp = f(x_samp)  
    I = integrate.trapezoid(y_samp,x_samp)  
    print("Result(n =",i,") =", I)
```

```
Result(n = 100 ) = 125.0063769003163  
Result(n = 1000 ) = 125.00006262518775  
Result(n = 10000 ) = 125.00000062512501  
Result(n = 100000 ) = 125.00000000625013
```

x data
points

Function
values

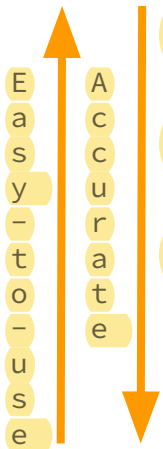
Result from
trapezoidal
rule



SCIPY-INTEGRATION

The **scipy.integrate** sub-package provides several integration techniques to compute integrals (1D or higher). It also includes an ordinary differential equation integrator ([doc](#)).

Methods for integrating differential equations:

- 
- Easy-to-use
- **odeint**: Solve a system of ordinary differential equations using lsoda algorithm only.
 - **ode**: A generic interface class to several numeric integrators.
 - **solve_ivp**: newest scipy integrator pack, allows to employ several integrator techniques and event tracing.
- Accurate

SCIPY-INTEGRATION

`odeint`: Solve a system of ordinary differential equations using lsoda algorithm only.

```
scipy.integrate.odeint(func, y0, t, args=(), Dfun=None,  
col_deriv=0, full_output=0, ml=None, mu=None, rtol=None,  
atol=None, tcrit=None, h0=0.0, hmax=0.0, hmin=0.0, ixpr=0,  
mxstep=0, mxhnil=0, mxordn=12, mxords=5, printmessg=0,  
tfirst=False)
```

func: callable(*y*, *t*, ...) or callable(*t*, *y*, ...) If **tfirst=True** then second signature is assumed

Initial conditions(ICs)
Array with length equal to the number of dependent variables

A sequence of time points for which to solve for *y*

Extra arguments for the function **func**

Let y be the vector $[theta, omega]$. We implement this system in Python as:

```
>>> def pend(y, t, b, c):  
...     theta, omega = y  
...     dydt = [omega, -b*omega - c*np.sin(theta)]  
...     return dydt  
...
```

We assume the constants are $b = 0.25$ and $c = 5.0$:

```
>>> b = 0.25  
>>> c = 5.0
```

For initial conditions, we assume the pendulum is nearly vertical with $theta(0) = \pi - 0.1$, and is initially at rest, so $omega(0) = 0$. Then the vector of initial conditions is

```
>>> y0 = [np.pi - 0.1, 0.0]
```

func: callable(y, t, \dots)
or callable(t, y, \dots)
If **tfirst=True** then
second signature is
assumed

Array with length
to the number of
dependent variables

Ordinary differential equations

```
y0, t, args=(), Dfun=None,
```

We will generate a solution at 101 evenly spaced samples in the interval $0 \leq t \leq 10$.

So our array of times is:

```
>>> t = np.linspace(0, 10, 101)
```

Call **odeint** to generate the solution. To pass the parameters b and c to *pend*, we give them to **odeint** using the *args* argument.

```
>>> from scipy.integrate import odeint  
>>> sol = odeint(pend, y0, t, args=(b, c))
```

The solution is an array with shape (101, 2). The first column is $theta(t)$, and the second is $omega(t)$. The following code plots both components.

SCIPY-INTEGRATION

ode: A generic interface class to several numeric integrators.

```
class scipy.integrate.ode(f, jac=None)
```

f: callable(t, y, ...)



Attributes:

t: (float) Current time.

y: (ndarray) Current variable values.

SCIPY-INTEGRATION

ode: A generic interface class to various integrators.

```
class scipy.integrate.ode(f, jac)
```

f: callable(t, y, ...)

Attributes:

t: (float) Current time.

y: (ndarray) Current variable

Methods

<code>get_return_code()</code>	Extracts the return code for the integration to enable better control if the integration fails.
<code>integrate(t[, step, relax])</code>	Find $y=y(t)$, set y as an initial condition, and return y .
<code>set_f_params(*args)</code>	Set extra parameters for user-supplied function f .
<code>set_initial_value(y[, t])</code>	Set initial conditions $y(t) = y$.
<code>set_integrator(name, **integrator_params)</code>	Set integrator by name.
<code>set_jac_params(*args)</code>	Set extra parameters for user-supplied function jac .
<code>set_solout(solout)</code>	Set callable to be called at every successful integration step.
<code>successful()</code>	Check if integration was successful.

SCIPY-INTEGRATION

```
from scipy.integrate import ode

# system of differential equations
def pend(t, y, b, c):
    theta, omega = y
    dydt = [omega, -b*omega - c*np.sin(theta)]
    return dydt

# function use to save output
def solout(t, y):
    sol.append([t, y[0], y[1]])

# integrator initialisation, here we choose the algorithm dop853
solver = ode(pend).set_integrator("dop853", atol=1e-15, rtol=1e-15, first_step=0.01, nsteps=10000000)
solver.set_solout(solout)
solver.set_initial_value([np.pi - 0.1, 0.0]).set_f_params(0.25, 5.)

sol = []
solver.integrate(10)
sol = np.array(sol)

print(sol)
print(solver.t, solver.y)

[[ 0.00000000e+00  3.04159265e+00  0.00000000e+00]
 [ 1.00000000e-02  3.04156771e+00 -4.98584983e-03]
 [ 5.51377662e-02  3.04083640e+00 -2.74030870e-02]
 ...
 [ 9.95234225e+00 -5.51258405e-02  1.58243397e+00]
 [ 9.98132031e+00 -9.35225827e-03  1.57565811e+00]
 [ 1.00000000e+01  2.00115309e-02  1.56781826e+00]]
10.0 [0.02001153 1.56781826]
```

Methods

<code>get_return_code()</code>	Extracts the return code for the integration to enable better control if the integration fails.
<code>integrate([t, step, relax])</code>	Find $y=y(t)$, set y as an initial condition, and return y .
<code>set_f_params(*args)</code>	Set extra parameters for user-supplied function f .
<code>set_initial_value(y[, t])</code>	Set initial conditions $y(t) = y$.
<code>set_integrator(name, **integrator_params)</code>	Set integrator by name.
<code>set_f_params(*args)</code>	Set extra parameters for user-supplied function jac .
<code>set_solout(solout)</code>	Set callable to be called at every successful integration step.
<code>success()</code>	Check if integration was successful.

SCIPY-INTEGRATION

`solve_ivp`: newest scipy integrator pack, allows to employ several integrator techniques and event tracing.

```
scipy.integrate.solve_ivp(fun, t_span, y0, method='RK45',  
t_eval=None, dense_output=False, events=None,  
vectorized=False, args=None, **options)
```

***fun**: callable(t, y, ...)
The differential equations*

***t_span**: 2-tuple of floats
Interval of integration (t0, tf). The
solver starts with t=t0 and
integrates until it reaches t=tf.*

***y0**: array_like, shape (n,)
Initial conditions*

SCIPY-INTEGRATION

`solve_ivp`: newest scipy integrator pack, allows to employ several integrator techniques and event tracing.

```
scipy.integrate.solve_ivp(fun, t_span, y0, method='RK45',  
t_eval=None, dense_output=False, events=None,  
vectorized=False, args=None, **options)
```

fun: callable(t, y, \dots)
The differential equations

t_eval: Times at which to
store the computed solution,
must be sorted and lie
within t_span .

t_span: 2-tuple of floats
Interval of integration (t_0, t_f). The
solver starts with $t=t_0$ and
integrates until it reaches $t=t_f$.

dense_output: compute a
continuous solution that can
be evaluated at any time
between t_span

y0: array_like, shape $(n,)$
Initial conditions

events: Events to track during integration. The
solver will find an accurate value of t at which
 $event(t, y(t)) = 0$
using a root-finding algorithm

SCIPY-INTEGRATION

`solve_ivp`: newest solver
several integrators

`scipy.integrate.solve_ivp`
`t_eval=None, dense_output=False, vectorized=False, ...`

fun: callable(*t*, *y*, ...)
The differential equations

t_eval: Times at which to
store the computed solution,
must be sorted and lie
within *t_span*.

Returns:

Bunch object with the following fields defined:

t : *ndarray, shape (n_points,)*

Time points.

y : *ndarray, shape (n, n_points)*

Values of the solution at *t*.

sol : *OdeSolution or None*

Found solution as **OdeSolution** instance; None if *dense_output* was set to False.

t_events : *list of ndarray or None*

Contains for each event type a list of arrays at which an event of that type event was detected. None if *events* was None.

y_events : *list of ndarray or None*

For each value of *t_events*, the corresponding value of the solution. None if *events* was None.

SCIPY-INTEGRATION

```
import matplotlib.pyplot as plt
from scipy.integrate import solve_ivp

# system of differential equations
def lotkavolterra(t, z, a, b, c, d):
    x, y = z
    return [a*x - b*x*y, -c*y + d*x*y]

# perform the integration
sol = solve_ivp(lotkavolterra, [0, 15], [10, 5], args=(1.5, 1, 3, 1), dense_output=True)

# densely sample the solution
t = np.linspace(0, 15, 600)
z = sol.sol(t)
```

t_eval: Times at which to store the computed solution, must be sorted and lie within t_span.

dense_output: compute a continuous solution that can be evaluated at any time between t_span

events: Events to track during integration. The solver will find an accurate value of t at which $\text{event}(t, y(t)) = 0$ using a root-finding algorithm

SCIPY-OPTIMISATION

`scipy.optimize` provides functions solvers for several tasks like:

- local and global optimization (e.g. minimization) algorithms;
- constrained and nonlinear least-squares;
- curve fitting;
- root finding.

Check the list of available functions [here](#) and [here](#) for examples.

SCIPY-OPTIMISATION

- **Minimization:** The minimize function provides a common interface to unconstrained and constrained minimization algorithms for multivariate scalar functions.

```
scipy.optimize.minimize(fun, x0, args=(), method=None,  
jac=None, hess=None, hessp=None, bounds=None,  
constraints=(), tol=None, callback=None, options=None)
```

*If your functions is
subjected to constraints,
only few algorithm can
deal with this, check the
doc*

***fun:** callable
the objective function to be minimized.
fun(x, *args) -> float, where x is an
1-D array with shape (n,)*

***x0:** ndarray, shape (n,)
Initial guess. Array of real elements of
size (n,), where n is the number of
independent variables.*

*Check for the best method
for your problem*

SCIPY-OPTIMISATION

- **Minimization:** The interface to unconstrained algorithms for mult

```
scipy.optimize.minimize  
jac=None, hess=None, h  
constraints=(), tol=No
```

If your functions is
subjected to constraints,
only few algorithm can
deal with this, check the
doc

fun: callable
the objective function to
fun(x, *args) -> float, w
1-D array with shape

Global optimization

basinhopping(func, x0[, niter, T, stepsize, ...])

Find the global minimum of
a function using the basin-
hopping algorithm.

brute(func, ranges[, args, Ns, full_output, ...])

Minimize a function over a
given range by brute force.

differential_evolution(func, bounds[, args, ...])

Finds the global minimum of
a multivariate function.

shgo(func, bounds[, args, constraints, n, ...])

Finds the global minimum of
a function using SHG
optimization.

dual_annealing(func, bounds[, args, ...])

Find the global minimum of
a function using Dual
Annealing.

method
m

SCIPY-OPTIMISATION

- Curve fitting: Scipy provides a somewhat generic function (based on the Levenburg-Marquardt algorithm) through `scipy.optimize.curve_fit` to fit a chosen function $f(x_i, \mathbf{p})$ to a given data set (x_i, y_i) , under the assumption $y_i = f(x_i, \mathbf{p})$ with \mathbf{p} the parameters of the “model”.
The algorithm tries to minimize the expression by changing the parameters \mathbf{p}

$$r = \sum_{i=1}^N (y_i - f(x_i, \vec{p}))^2$$

SCIPY-OPTIMISATION

- Root finding: the procedure of finding all x values that solve the equation $f(x) = 0$

Note that problems like $g(x)=h(x)$ fall in this category as you can rewrite them as $f(x)=g(x)-h(x)=0$.

A number of root finding tools are available in scipy's optimize module, e.g.:

- Scalar functions (list not exhaustive see [here](#)):
 - bisect: simple and robust but slow
 - brentq/brentp: robust bracketing method faster than bisect
 - newton: Newton-Raphson (or secant method), needs derivative of f
- Vector functions:

root: most general root finder, the specific algorithm employed has to be chosen problem-wise

REMINDE THAT YOU GENERALLY NEED TO PROVIDE AN INITIAL GUESS!

SCIPY-SPECIAL FUNCTIONS

A **special function** is a function (usually named after an early investigator of its properties) having a particular use in mathematical physics or some other branch of mathematics. Prominent examples include the **gamma function**, **hypergeometric function**, **elliptic functions**, **error function**...

The **scipy.special** module includes the implementation of nearly all special functions that are encountered in scientific research (see [here](#) for the list).

SCIPY-SPECIAL FUNCTIONS

A **special function** is a function (usually named after an early investigator of its properties) having a particular use in mathematical physics or some other branch of mathematics. Prominent examples include the **gamma function**, **hypergeometric function**, **elliptic functions**, **error function**...

Consider the *gamma function* which is a generalization of the factorial to which is related by $\Gamma(n) = (n - 1)!$

```
from scipy.special import gamma

print("The factorial of 3 is ", gamma(4))
print("Gamma can be evaluated for non integers:", gamma(8.7))
print("Gamma gives a complex infinity for negative integer numbers:", gamma(-2))
```

```
The factorial of 3 is  6.0
Gamma can be evaluated for non integers: 21327.693789920282
Gamma gives a complex infinity for negative integer numbers: inf
```