

# Python for scientific research

## Number crunching with numpy and scipy

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Researcher  
Development



# What we've done so far

- 1 Declare variables using built-in data types and execute operations on them
- 2 Use flow control commands to dictate the order in which commands are run and when
- 3 Encapsulate programs into reusable functions, modules and packages
- 4 **Next:** Number crunching using NumPy/SciPy

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  - Solving differential equations
  - Optimisation
  - ...

# A taste of NumPy

```
1 import numpy as np
2
3 # 1D array/vector
4 x = np.array([1, 2, 3, 4])
5 x.min() # return min of array
6 x.max() # return max of array
7 x.sum() # sum all elements in array
8
9 # 2D array
10 x = np.array([[1, 2, 3], [4, 5, 6], [7, 8, 9]])
11 x*x # element-by-element multiplication
12 x.shape # return dimensions of matrix
13 np.dot(x, x) # matrix multiplication
14 np.mat(x)*np.mat(x) # matrix multiplication (cast as matrix)
```

# A taste of NumPy

```
1 # Generate random numbers
2 np.random.rand() # from a uniform distribution
3 np.random.randn() # from a normal distribution
4 np.random.randn(5, 5) # 5 x 5 matrix of random numbers
5
6 # Create number sequences
7 np.arange(0, 1, 0.1) # 0 to 1 in steps of 0.1
8 np.linspace(0, 1, 100) # 100 values between 0 and 1
9 np.logspace(0, 1, 10) # 10 values between 10^0 and 10^1
```

# A taste of SciPy

```
1 import scipy.stats as sp
2
3 # Create two random arrays
4 x1 = np.random.randn(30)
5 x2 = np.random.randn(30)
6
7 # Correlation coefficientss
8 sp.pearsonr(x1, x2) # pearson correlation
9 sp.spearmanr(x1, x2) # spearman correlation
10 sp.kendalltau(x1, x2) # kendall correlation
11
12 # Statistical tests
13 sp.ttest_ind(x1, x2) # independent t-test
14 sp.mannwhitneyu(x1, x2) # Mann-Whitney rank test
15 sp.wilcoxon(x1, x2) # Wilcoxon signed-rank test
16
17 # Least-squares regression
18 sp.linregress(x1, x2)
```

# Predator prey equations (Lotka Volterra)

$$\frac{du}{dt} = \alpha u - \beta uv$$

$$\frac{dv}{dt} = -\gamma v + \delta uv$$

Where:

- $u$ : is the number of prey (e.g rabbits)
- $v$ : is the number of predators (e.g foxes)
- $\alpha$ : prey growth rate in the absence of predators
- $\beta$ : dying rate of prey due to predation
- $\gamma$ : dying rate of predators in the absence of prey
- $\delta$ : predator growth rate when consuming prey

# Predator prey equations in Python

$$\frac{du}{dt} = \alpha u - \beta uv$$

$$\frac{dv}{dt} = -\gamma v + \delta uv$$

```
1 def predator_prey(x, t):
2     """
3     Predator prey model (Lotka Volterra)
4     """
5     # Constants
6     alpha = 1
7     beta = 0.1
8     gamma = 1.5
9     delta = 0.075
10
11     # x = [u, v] describes prey and predator populations
12     u, v = x
13
14     # Define differential equation (u = x[0], v = x[1])
15     du = alpha*u - beta*u*v
16     dv = -gamma*v + delta*u*v
17
18     return du, dv
```

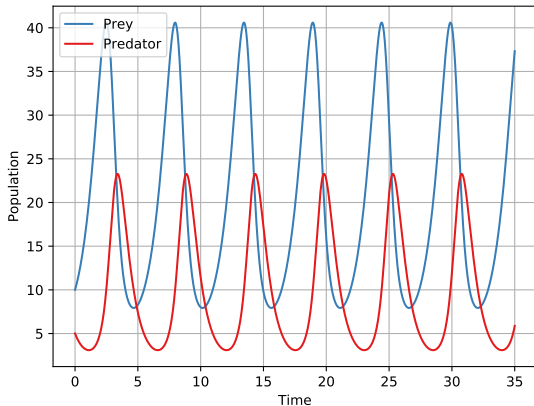
# Solve differential equations

```
1 from scipy.integrate import odeint
2
3 time = np.linspace(0, 35, 1000) # time vector
4 init = [10, 5] # initial condition: 10 prey, 5 predators
5 x = odeint(predator_prey, init, time) # solve
```



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# Fourier transform

```
1 from scipy.fftpack import fftfreq, fft
2
3 # Create frequency vector
4 N = len(time)
5 freq = fftfreq(N, np.mean(np.diff(time)))
6 freq = freq[range(int(N/2))]
7
8 # Compute Fast Fourier Transform
9 y = fft(x[:, 0])/N # compute and normalise fft
10 y = y[range(int(N/2))] # keep only positive frequencies
```

# Fourier transform

