Python Programming for Data Science

Week 41, Monday

External modules:

- Numpy
- Matplotlib

Python external modules

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In addition to the many small modules (like the ones above) - there are some very well developed packages which are extremely useful for Scientific applications.

Python modules for data science

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Pandas

A Python module for data manipulation similar to what you can do in `R` (i.e. arrays with labels).

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A data mining and machine learning toolkit: classification, clustering, regression, etc.

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Scikit-learn

A data mining and machine learning toolkit: classification, clustering, regression, etc.

Tensorflow/Pytorch

A Machine Learning libraries - with particular focus on neural networks and deep learning.

Matlab-like functionality in Python

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numpy, matplotlib and scipy bring a lot of Matlab-like functionality to python:

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Numpy

vector and matrix operations

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Visualization

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Numpy
vector and matrix operations

Matplotlib
Visualization

Scipy
numerical integration, optimization, special functions

Python modules for science: Biology

Biopython

A package containing various tools for bioinformatics and computational biology

- Sequence class for manipulation biological sequences
- Parsing and iterating over various formats: fasta, blast, genbank, pubmed, etc
- Interfaces to external programs: multiple sequence alignment, blast
- Tools for structural biology: PDB
- Phylogenetic tools
- ...

Similar packages exist for many other scientific fields

Python package managers

In the old days, installing Python packages was a bit of a hassle

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- pip
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In this class we'll cover the last two.

pip

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Basic ideas:

- Installing external modules by issuing one command (from the terminal).

  ```
  $ pip install package-name
  ```

  or (if you get permission errors)

  ```
  $ pip install --user package-name
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Basic ideas:

- Installing external modules by issuing one command (from the terminal).

  ```
  $ pip install package-name
  ```

  or (if you get permission errors)

  ```
  $ pip install --user package-name
  ```

- And uninstalling packages is equally easy

  ```
  $ pip uninstall package-name
  ```

Anaconda (miniconda)

Anaconda is a Python distribution for Scientific computing.

You can install packages using the conda command:

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$ conda install some-package-name
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Differences to pip:

- It can install non-Python dependencies if necessary
- Makes it easy to create different environments, containing different versions of modules (and different versions of Python)
- Has a more sophisticated dependency resolution method.

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- Makes it easy to create different environments, containing different versions of modules (and different versions of Python)
- Has a more sophisticated dependency resolution method.

Anaconda also includes pip.

Typical strategy: Try conda first, then pip.

Installing from PyCharm

You can use both pip and conda directly from within PyCharm.

See the Pycharm documentation for details: https://www.jetbrains.com/help/pycharm/installing-uninstalling-and-upgrading-packages.html

Numpy

numpy

Basic ideas:

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- Make it easy to perform operations on a collection of numbers.

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- Make it easy to work with tables (matrices) of numbers

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Basic ideas:

- Make it easy to perform operations on a collection of numbers.
- Make it easy to work with tables (matrices) of numbers
- Much faster than writing loops in Python

In short: whenever you have a list of numbers, consider using numpy.

numpy - importing

```
import numpy
```

numpy - importing

```
import numpy
```

or:

```
import numpy as np
```

numpy - array

The main ingredient in numpy is a new type: the numpy array.

Creating an array from a list or tuple:

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

numpy - array

The main ingredient in numpy is a new type: the numpy array.

Creating an array from a list or tuple:

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

In contrast to lists, numpy arrays are primarily designed to contain elements of the same type.

You can specify a type explicitly:

```
a = np.array([1,2,3,4], np.float)   # np.int, np.bool, ...
```

If not specified, numpy will take a guess.

numpy - array initialization

There are various other ways to initialize numpy arrays

numpy - array initialization

There are various other ways to initialize numpy arrays

Range of numbers:

```
print(np.arange(2.0, 2.4, 0.1))
```

```
[ 2. ,  2.1,  2.2,  2.3]
```

output

numpy - array initialization

There are various other ways to initialize numpy arrays

Range of numbers:

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print(np.arange(2.0, 2.4, 0.1))
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[ 2. ,   2.1,   2.2,   2.3]
```

output

Zeros

```
print(np.zeros(4))
```

```
[ 0.   0.   0.   0.]
```

output

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Range of numbers:

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print(np.arange(2.0, 2.4, 0.1))
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Zeros

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print(np.zeros(4))
```

```
[ 0.  0.  0.  0.]
```

output

Ones:

```
print(np.ones(4))
```

```
[ 1.  1.  1.  1.]
```

output

numpy - operations on arrays

The common mathematical operators are available

```
a = np.arange(1,4)

print(a)
print(3*a)
```

output

```
[1 2 3]
```

numpy - operations on arrays

The common mathematical operators are available

```
a = np.arange(1,4)

print(a)
print(3*a)
```

```
output

[1 2 3]
[3 6 9]
```

numpy - operations on arrays

The common mathematical operators are available

```python
a = np.arange(1,4)

print(a)
print(3*a)
print(a+a)
```

output

```
[1 2 3]
[3 6 9]
[2 4 6]
```

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The common mathematical operators are available

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a = np.arange(1,4)

print(a)
print(3*a)
print(a+a)
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```

output

```
[1 2 3]
[3 6 9]
[2 4 6]
[1 4 9]
```

numpy - operations on arrays

The common mathematical operators are available

```
a = np.arange(1,4)

print(a)
print(3*a)
print(a+a)
print(a*a)
print(a/a)
```

output

```
[1 2 3]
[3 6 9]
[2 4 6]
[1 4 9]
[1. 1. 1.]
```

numpy - operations on arrays

The common mathematical operators are available

```
a = np.arange(1,4)

print(a)
print(3*a)
print(a+a)
print(a*a)
print(a/a)
print(np.cos(a))
```

```
output

[1 2 3]
[3 6 9]
[2 4 6]
[1 4 9]
[1. 1. 1.]
[ 0.54030231 -0.41614684 -0.9899925 ]
```

numpy - operations on arrays

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[1 2 3]
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Note how they automatically apply on all elements.

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[1 2 3]
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```

Note how they automatically apply on all elements.

What would happen if we did the same with normal lists?

numpy - random arrays

You can create arrays with random numbers

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You can create arrays with random numbers

Random floating point numbers between 0 and 1

```
print(np.random.rand(3))
```

```
output
[ 0.53066947  0.03155089  0.39243265]
```

numpy - random arrays

You can create arrays with random numbers

Random floating point numbers between 0 and 1

```
print(np.random.rand(3))
```

```
output
[ 0.53066947  0.03155089  0.39243265]
```

Random integers:

```
# 5 numbers between 1 and 3 (3 not included)
print(np.random.randint(1,3,5))
```

```
output
[2 1 2 2 2]
```

numpy - random arrays

You can create arrays with random numbers

Random floating point numbers between 0 and 1

```
print(np.random.rand(3))
```

```
output
[ 0.53066947  0.03155089  0.39243265]
```

Random integers:

```
# 5 numbers between 1 and 3 (3 not included)
print(np.random.randint(1,3,5))
```

```
output
[2 1 2 2 2]
```

Different distributions:

```
# normal distr: mean=0, stddev=1
print(np.random.standard_normal(2))
```

```
output
[ 1.70067518  0.63932443]
```

numpy - Exercise 1

The previous slide provides us with a very simple way to simulate throwing 2 dice (like we did earlier in the course).

1. Create a one-line python statement that calculates the average of 10,000 throws of the sum of two dice.
   Hint: `np.average()` calculates the average over an array.

numpy - Exercise 1 - solution

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numpy - Exercise 1 - solution

1. *Create a one-line python statement that calculates the average of 10,000 throws of the sum of two dice. Hint: `np.average()` calculates the average over an array.*

```
print(np.average(np.random.randint(1,7,10000) + np.random.randint(1,7,10000)))
```

```
7.041100000000001
```
output

numpy - multidimensional arrays

Common scenario: data set with multiple columns

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Numpy is ideal for handling such data - using 2D arrays.

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Numpy is ideal for handling such data - using 2D arrays.

Initializing from a list of lists:

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

```
output
[[1 2 3 4]
 [5 6 7 8]]
```

numpy - multidimensional arrays: shape

In general arrays can be of any dimension. This is encoded in the *shape* of an array.

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The shape tuple specifies how many values there are in each dimension

```
# 3 values in one dimension
a = np.arange(1,4)

print(a)
print(a.shape)
```

output

```
array([1, 2, 3])
(3,)
```

numpy - multidimensional arrays: shape

In general arrays can be of any dimension. This is encoded in the *shape* of an array.

The shape tuple specifies how many values there are in each dimension

```python
# 3 values in one dimension
a = np.arange(1,4)

print(a)
print(a.shape)

# 2 rows and 4 columns
a = np.array([[1,2,3,4],[5,6,7,8]])

print(a)

print(a.shape)
```

output

```
array([1, 2, 3])
(3,)

array([[1, 2, 3, 4],
       [5, 6, 7, 8]])
(2, 4)
```

numpy - multidimensional arrays: initializing

Many of numpys initializer functions take a shape as argument

```
print(np.zeros(shape=(2,3)))
```

output

```
[[ 0.   0.   0.]
 [ 0.   0.   0.]]
```

```
print(np.random.random((2,3)))
```

output

```
[[ 0.44923652  0.15528157  0.66292896]
 [ 0.5421247   0.44336697  0.27264862]]
```

numpy - arrays: initializing from file

Numpy has very convenient functionality for reading in data from file

numpy - arrays: initializing from file

Numpy has very convenient functionality for reading in data from file

data.txt

```
1 2 3
4 5 6
7 8 9
```

```python
a = np.genfromtxt('data.txt')
print(a)
```

output

```
[[1 2 3]
 [4 5 6]
 [7 8 9]]
```

numpy - array indexing and slicing (1)

You can index into a 1D numpy array just as a list

```
a = np.arange(1,4)
print(a[1])
```

output

```
2
```

numpy - array indexing and slicing (1)

You can index into a 1D numpy array just as a list

```
a = np.arange(1,4)
print(a[1])
```

```
output
2
```

For multidimensional arrays, you just specify an index for each dimension

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

print(a[0,2])
```

```
output
[[1 2 3 4]
 [5 6 7 8]]
3
```

numpy - array indexing and slicing (1)

You can index into a 1D numpy array just as a list

```
a = np.arange(1,4)
print(a[1])
```

output

```
2
```

For multidimensional arrays, you just specify an index for each dimension

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

print(a[0,2])
```

output

```
[[1 2 3 4]
 [5 6 7 8]]
3
```

Note the difference to how you would index into a list of lists

numpy - array indexing and slicing (2)

As for lists, use `:` to indicate that you want a range of values in a given dimension

```
a = np.array([[1,2,3,4],[5,6,7,8],[0,0,0,0]])
print(a)
```

output

```
[[1 2 3 4]
 [5 6 7 8]
 [0 0 0 0]]
```

numpy - array indexing and slicing (2)

As for lists, use `:` to indicate that you want a range of values in a given dimension

```
a = np.array([[1,2,3,4],[5,6,7,8],[0,0,0,0]])
print(a)



print(a[0,1:3])
```

output

```
[[1 2 3 4]
 [5 6 7 8]
 [0 0 0 0]]

[2 3]
```

numpy - array indexing and slicing (2)

As for lists, use `:` to indicate that you want a range of values in a given dimension

```
a = np.array([[1,2,3,4],[5,6,7,8],[0,0,0,0]])
print(a)



print(a[0,1:3])

print(a[0:2,1])
```

```
output

[[1 2 3 4]
 [5 6 7 8]
 [0 0 0 0]]

[2 3]

[2 6]
```

numpy - array indexing and slicing (2)

As for lists, use `:` to indicate that you want a range of values in a given dimension

```
a = np.array([[1,2,3,4],[5,6,7,8],[0,0,0,0]])
print(a)



print(a[0,1:3])

print(a[0:2,1])
```

```
output

[[1 2 3 4]
 [5 6 7 8]
 [0 0 0 0]]

[2 3]

[2 6]
```

If you want all values in a given dimension, just use `:` by itself

```
# Extract second column
print(a[:,1])
```

```
output

[2 6 0]
```

numpy - array indexing and assignment

Just like lists, you can also using indexing to change part of an array, by *assigning* to it:

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

# Setting part of array to zero
a[:,3] = 0
print(a)
```

output

```
[[1 2 3 4]
[5 6 7 8]]

# What is a now?
```

numpy - array indexing and assignment

Just like lists, you can also using indexing to change part of an array, by *assigning* to it:

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

# Setting part of array to zero
a[:,3] = 0
print(a)
```

output

```
[[1 2 3 4]
[5 6 7 8]]

# What is a now?
[[1 2 3 0]
 [5 6 7 0]]
```

numpy - boolean arrays

A condition on an array provides a Boolean array:

```
a = np.array([[1,2,3,4],[5,6,7,8]])
print(a < 4)
```

output

```
[[ True  True  True False]
 [False False False False]]
```

numpy - boolean arrays

A condition on an array provides a Boolean array:

```
a = np.array([[1,2,3,4],[5,6,7,8]])
print(a < 4)
```

```
output
[[ True  True  True False]
 [False False False False]]
```

You use such an array to select values in the original array

```
a = np.array([[1,2,3,4],[5,6,7,8]])
mask = a < 4      # This is a boolean array
print(a[mask])    # Use the mask as index
```

```
output
array([1, 2, 3])
```

numpy - boolean arrays

A condition on an array provides a Boolean array:

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

```
output
[[ True  True  True False]
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```

You use such an array to select values in the original array

```
a = np.array([[1,2,3,4],[5,6,7,8]])
mask = a < 4      # This is a boolean array
print(a[mask])    # Use the mask as index
```

```
output
array([1, 2, 3])
```

Note that we lost the 2D structure of the array, because the relevant values not necessarily line up in rows and columns.

numpy - Exercise 2

Remember the hand-in where we calculated the average of two columns of numbers?

1. If you don't already have it, get experimental_results.txt: https://wouterboomsma.github.io/ppds2021/data/experimental_resu
2. Read this file into a numpy array called `data`.
3. Calculate the average of each of the two columns
4. Create a numpy array called `data_subset`, and set it to contain the first 500 values of the second column of the array.
5. Set all entries in the `data_subset` variable to zero.
6. Now calculate the average of each of the two columns in `data` array again.

numpy - Exercise 2 - solution

1. If you don't already have it, get experimental_results.txt:
   https://wouterboomsma.github.io/ppds2021/data/experimental_results.
2. Read this file into a numpy array called `data`.

```
import numpy as np
data = np.genfromtxt("experimental_results.txt")
```

3. Calculate the average of each of the two columns

```
print(np.average(data[:,0]),
      np.average(data[:,1]))
```

```
outpu
0.495052368 0.498952201
```

numpy - Exercise 2 - solution

1. If you don't already have it, get experimental_results.txt: https://wouterboomsma.github.io/ppds2021/data/experimental_results.
2. Read this file into a numpy array called `data`.

```
import numpy as np
data = np.genfromtxt("experimental_results.txt")
```

3. Calculate the average of each of the two columns

```
print(np.average(data[:,0]),
      np.average(data[:,1]))
```

```
outpu
0.495052368 0.498952201
```

or...

```
print(np.average(data, axis=0))
```

```
outpu
[ 0.49505237  0.4989522 ]
```

numpy - Exercise 2 - solution (2)

4. Create a numpy array called `data_subset`, and set it to contain the first 500 values of the second column of the `data` array.

```
data_subset = data[:500, 1]
```

5. Set all entries in the `data_subset` variable to zero.

```
data_subset[:] = 0
```

6. Now calculate the average of each of the two columns in the `data` array again.

```
print(np.average(data, axis=0))
```

```
[ 0.49505237  0.25336498]
```

output

numpy - Exercise 2 - solution (2)

4. Create a numpy array called `data_subset`, and set it to contain the first 500 values of the second column of the `data` array.

```
data_subset = data[:500, 1]
```

5. Set all entries in the `data_subset` variable to zero.

```
data_subset[:] = 0
```

6. Now calculate the average of each of the two columns in the `data` array again.

```
print(np.average(data, axis=0))
```

```
[ 0.49505237  0.25336498]
```
output

What happened here?

numpy - slices are references!

When you make a slice of an array, numpy doesn't make a new copy of the data

```
a = np.array(((1,2,3), (4,5,6), (7,8,9)))
b = a[0:2, 0:2]
b[0,0] = 8
print(a)
```

output

```
[[8 2 3]
 [4 5 6]
 [7 8 9]]
```

numpy - slices are references!

When you make a slice of an array, numpy doesn't make a new copy of the data

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a = np.array(((1,2,3), (4,5,6), (7,8,9)))
b = a[0:2, 0:2]
b[0,0] = 8
print(a)
```

output

```
[[8 2 3]
 [4 5 6]
 [7 8 9]]
```

This is important when working with large data sets

If you want a copy, use np.copy

```
b = np.copy(a[0:2, 0:2])
```

numpy - conclusions

- Numpy has functionality for handling large amounts of data efficiently
- It handles vectors and matrices in a similar way as Matlab
- It is one of the success-stories of Python: https://www.nature.com/articles/s41586-020-2649-2

Matplotlib

matplotlib

Very powerful, general purpose plotting functionality

matplotlib

Very powerful, general purpose plotting functionality

There are thousands of things you can do with it. We'll just show a few examples here...

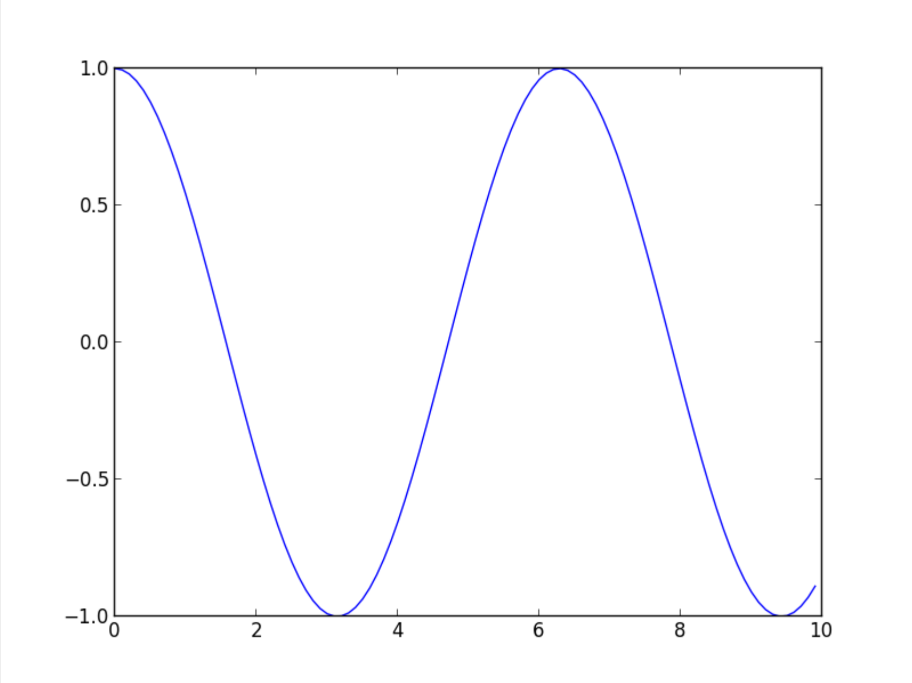
matplotlib - importing

The standard way to import matplotlib:

```
import matplotlib.pyplot as plt
```

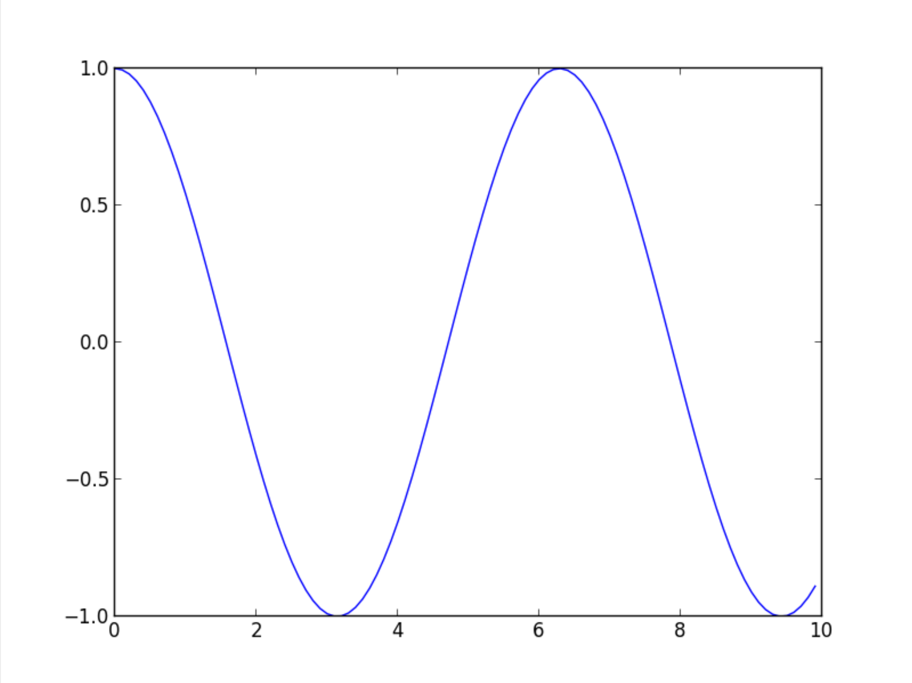
matplotlib - simple plot

```
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 10, 0.1)
y = np.cos(x)
plt.plot(x,y)
plt.show()
```



matplotlib - simple plot

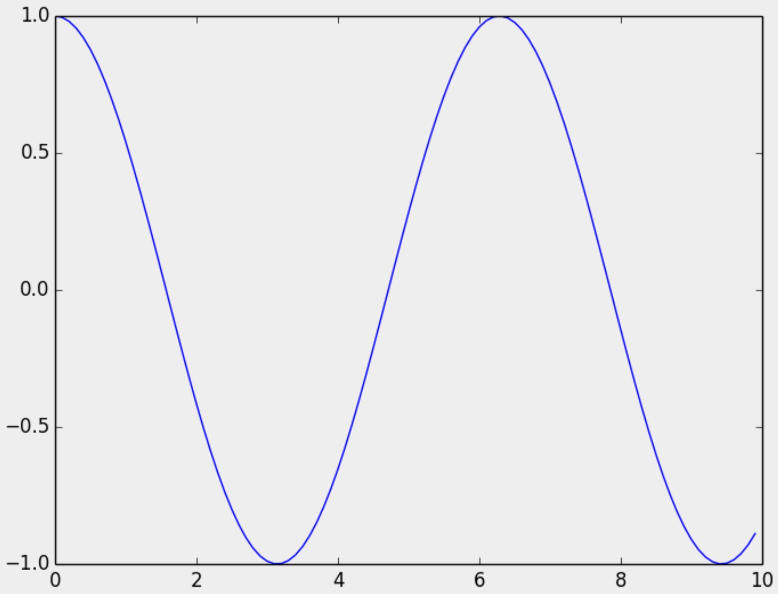
```python
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 10, 0.1)
y = np.cos(x)
plt.plot(x,y)
plt.show()
```



Try it out!

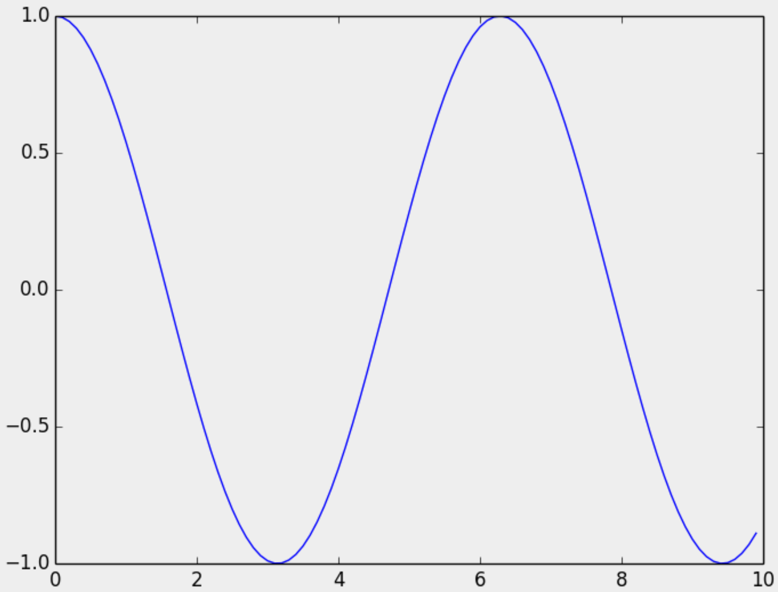
matplotlib - saving to a file

```
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 10, 0.1)
y = np.cos(x)
plt.plot(x,y)
plt.savefig('plot.png',
            transparent=True)
```



matplotlib - saving to a file

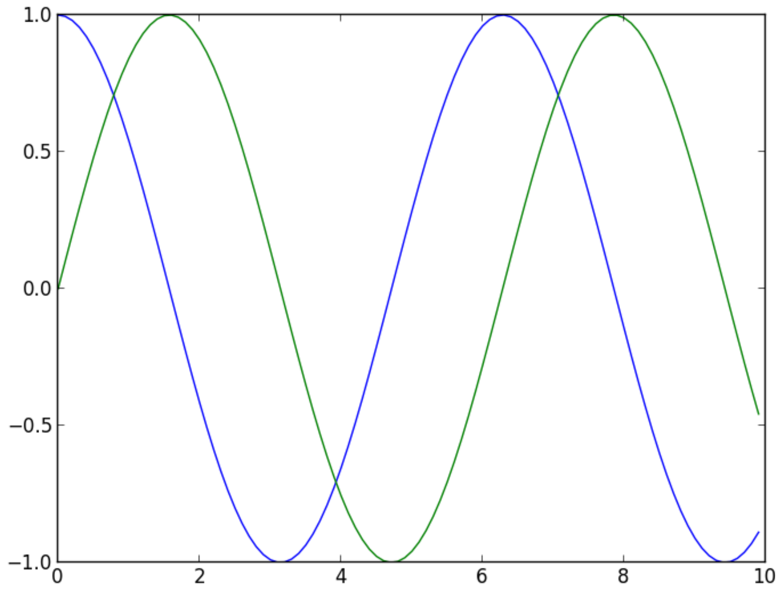
```
import matplotlib.pyplot as plt
import numpy as np
x = np.arange(0, 10, 0.1)
y = np.cos(x)
plt.plot(x,y)
plt.savefig('plot.png',
            transparent=True)
```



Note that you can use `transparent=True` for transparent backgrounds.

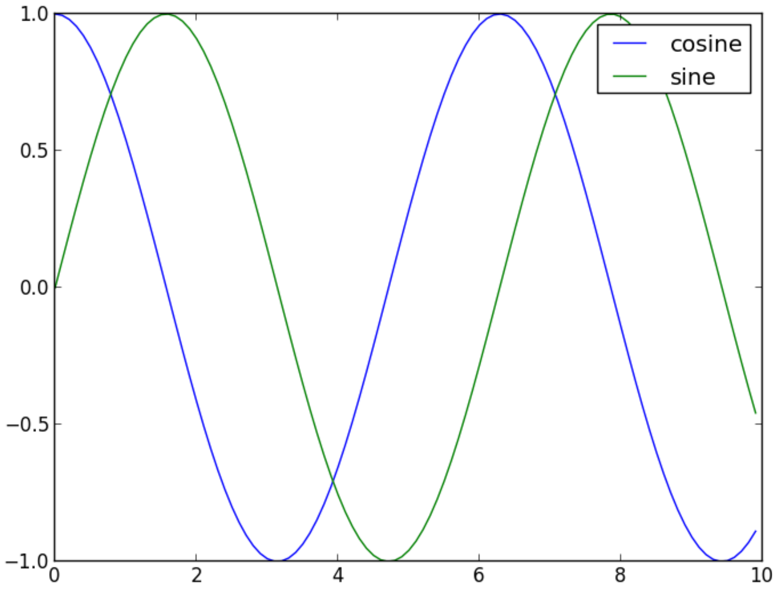
matplotlib - multiple plots

```
import matplotlib.pyplot as plt
import numpy as np

x = np.arange(0, 10, 0.1)

y1 = np.cos(x)
plt.plot(x,y1)

y2 = np.sin(x)
plt.plot(x,y2)

plt.show()
```



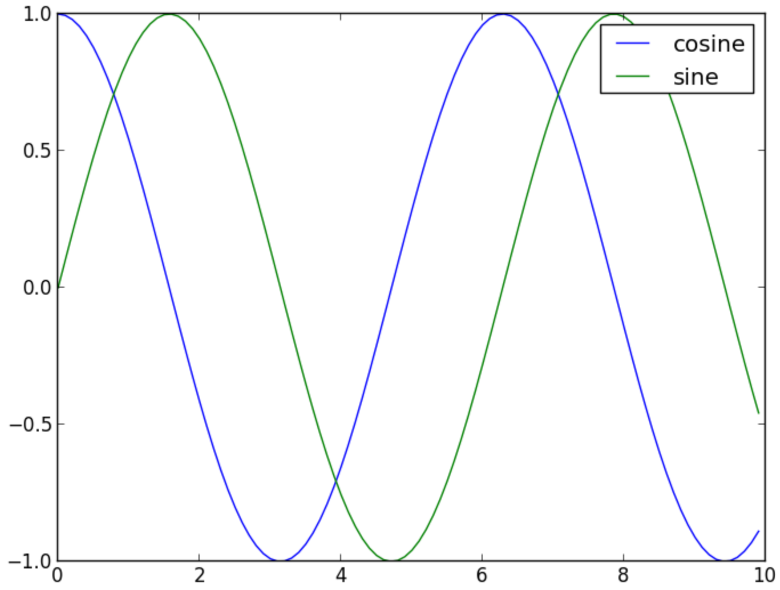
matplotlib - legends

```
import matplotlib.pyplot as plt
import numpy as np

x = np.arange(0, 10, 0.1)

y1 = np.cos(x)
plt.plot(x,y1, label='cosine')

y2 = np.sin(x)
plt.plot(x,y2, label='sine')

plt.legend()

plt.show()
```



matplotlib - legends

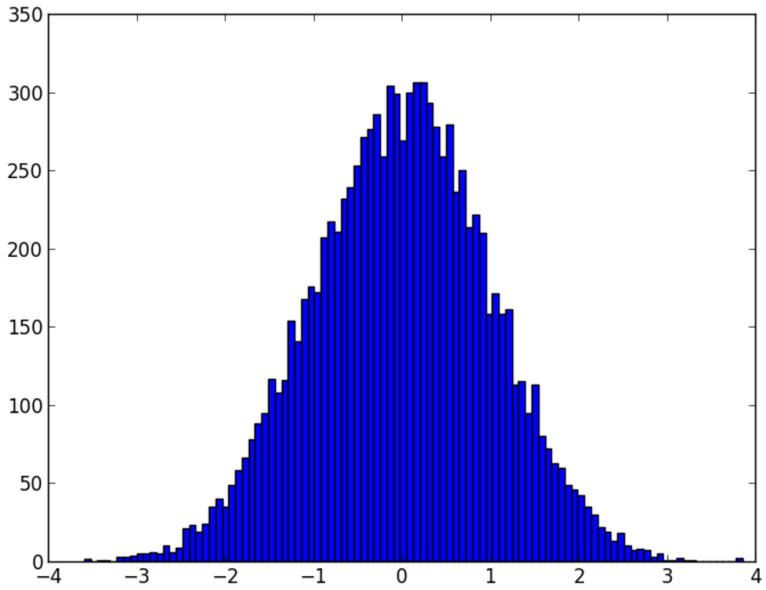
```
import matplotlib.pyplot as plt
import numpy as np

x = np.arange(0, 10, 0.1)

y1 = np.cos(x)
plt.plot(x,y1, label='cosine')

y2 = np.sin(x)
plt.plot(x,y2, label='sine')

plt.legend()

plt.show()
```



Note that the `legend()` automatically reads the labels from the individual plot commands.

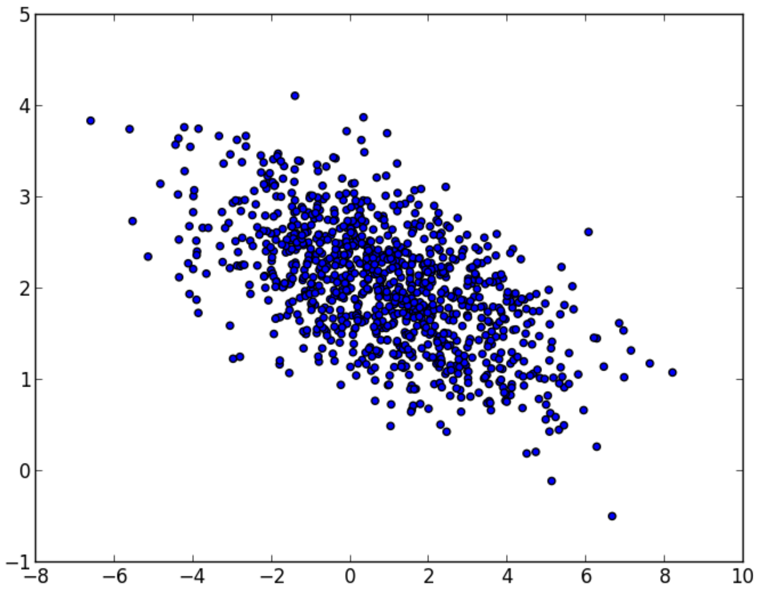
matplotlib - histograms

```
import matplotlib.pyplot as plt
import numpy as np

x = np.random.standard_normal(10000)
plt.hist(x, bins=100)

plt.show()
```



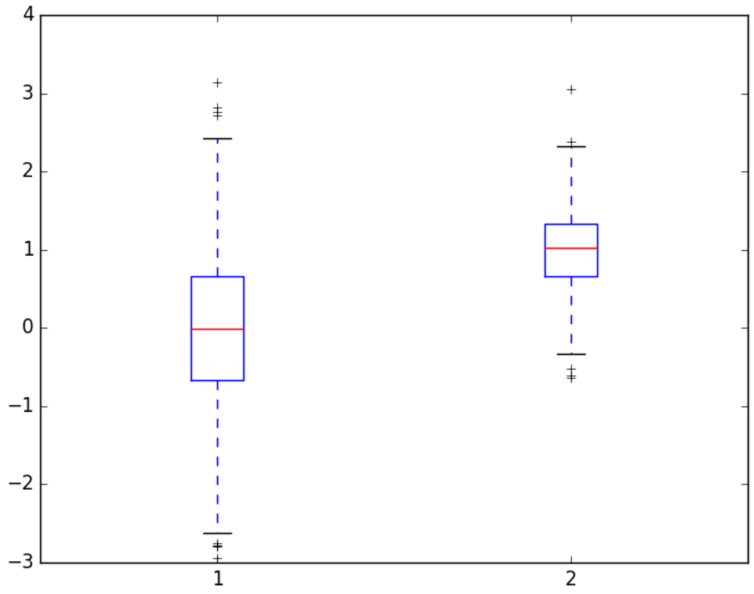
matplotlib - scatter plot

```
import matplotlib.pyplot as plt
import numpy as np

# 2D-Gauss distribution
x = np.random.multivariate_normal(
      mean=(1,2),
      cov=[[1,-0.5],[-0.5,1]],
      size=1000)
plt.scatter(x[:,0],x[:,1])

plt.show()
```



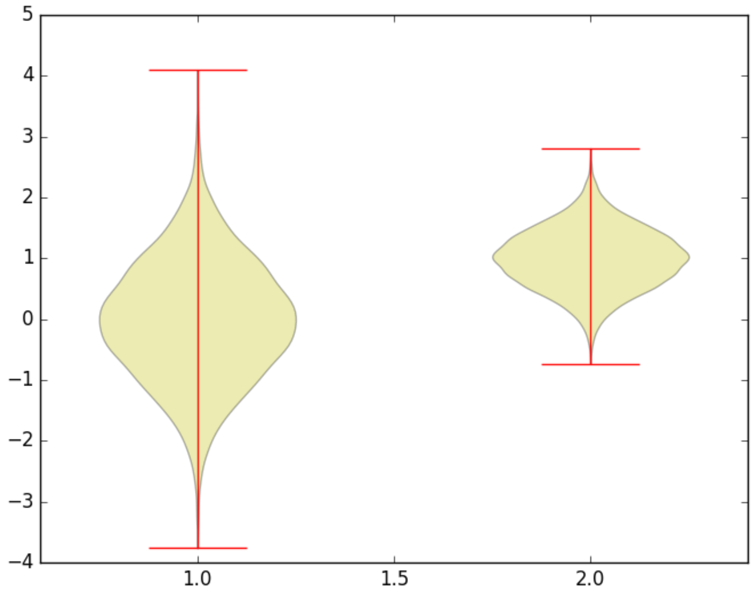
matplotlib - box plot

```
import matplotlib.pyplot as plt
import numpy as np

# Two different distributions
data = [np.random.normal(0, 1,
                         1000),
        np.random.normal(1, 0.5,
                         1000)]
plt.boxplot(data)

plt.show()
```



matplotlib - violin plot

```
import matplotlib.pyplot as plt
import numpy as np

# Two different distributions
data = [np.random.normal(0, 1,
                         10000),
        np.random.normal(1, 0.5,
                         10000)]
plt.violinplot(data)

plt.show()
```



matplotlib - Exercise 1

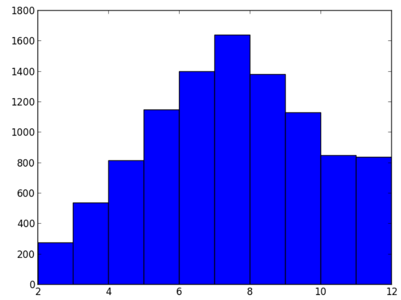
Remember the die example?

```
np.average(np.random.randint(1,7,10000) + np.random.randint(1,7,10000))
```

1. Instead of taking the average, use the `plt.hist` function to plot the distribution of outcomes from the sum of two dice. That is: plot the frequency of observing all the different outcomes.
2. Does the result look like what you would expect?

matplotlib - Exercise 1 - solution

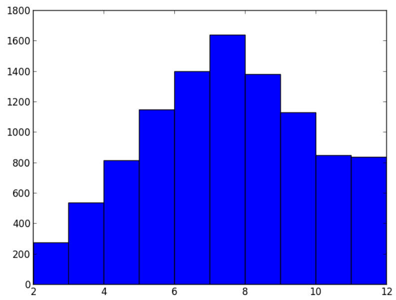
```
import matplotlib.pyplot as plt
import numpy as np

dist = (np.random.randint(1,7,10000) +
        np.random.randint(1,7,10000))
plt.hist(dist)

plt.show()
```



Is this what we expect?

matplotlib - Exercise 1 - solution

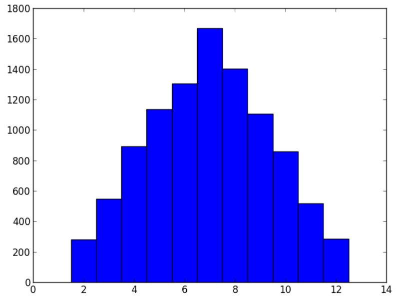
```
import matplotlib.pyplot as plt
import numpy as np

dist = (np.random.randint(1,7,10000) +
        np.random.randint(1,7,10000))
plt.hist(dist)

plt.show()
```



Is this what we expect? No.

Adjust the bin vector to get the right result

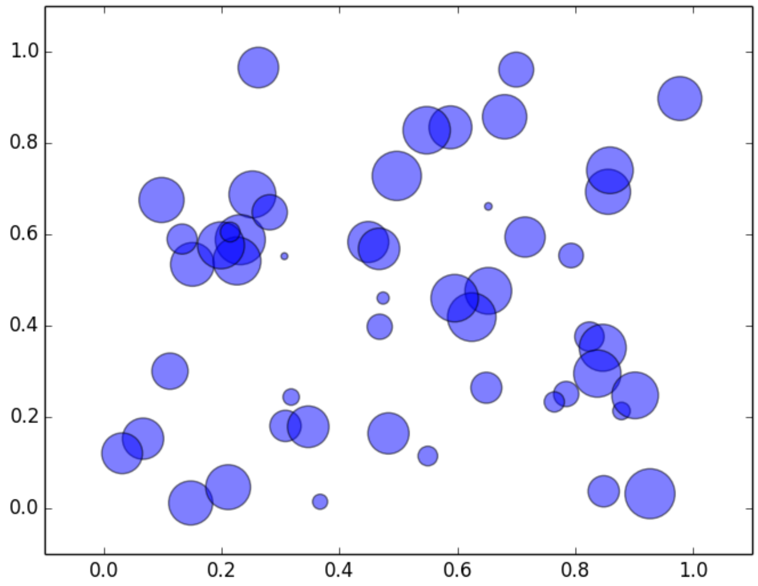
```
plt.hist(dist, bins=np.arange(1.5, 13.5, 1))
```



matplotlib - Opacity

Many of matplotlib functions support an alpha parameter, which sets the opacity

```
import matplotlib.pyplot as plt
import numpy as np

# Create distribution of points
dist = np.random.random((50,2))

# What does this line do?
sizes = np.random.randint(10, 1000,
                          dist.shape[0])


# Create scatter plot
plt.scatter(dist[:,0],dist[:,1],
            s=sizes,
            alpha=0.5) # set opacity

plt.show()
```



matplotlib - Exercise 2

1. Download the data file from:
   https://wouterboomsma.github.io/ppds2021/data/fern_data.t
2. Read the file into a numpy array
3. Create a scatter plot from this data (this might take a while)
4. Check out
   http://matplotlib.org/api/pyplot_api.html#matplotlib.pyplot.sca
   - Figure out how to remove the edges around each poin
     (hint: edgecolor)
   - Figure out how to set the size of each point to 0.5
   - Figure out how to set the color of each point to green
   - Figure out how to remove the axes

matplotlib - Exercise 2 - Solution (1)

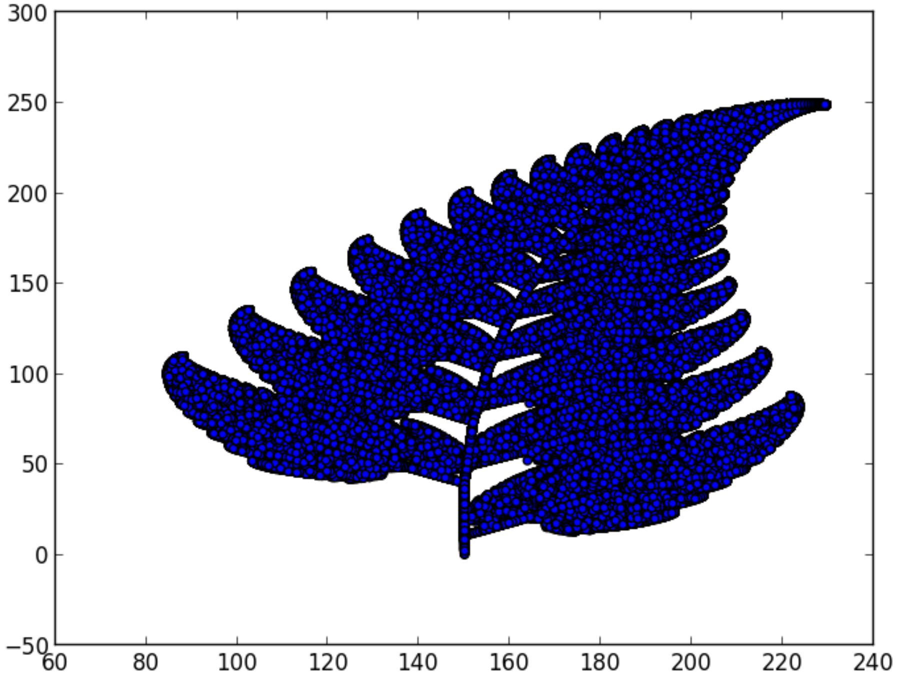
2. Read the file into a numpy array
3. Create a scatter plot from this data (this might take a while)

```
import numpy as np
import matplotlib.pyplot as plt
data = np.genfromtxt('fern_data.txt')

plt.scatter(data[:,0], data[:,1])

plt.savefig('matplotlib_fern1.png')
```

matplotlib - Exercise 2 - Solution (1)

2. Read the file into a numpy array
3. Create a scatter plot from this data (this might take a while)

```
import numpy as np
import matplotlib.pyplot as plt
data = np.genfromtxt('fern_data.txt')

plt.scatter(data[:,0], data[:,1])

plt.savefig('matplotlib_fern1.png')
```



matplotlib - Exercise 2 - Solution(2)

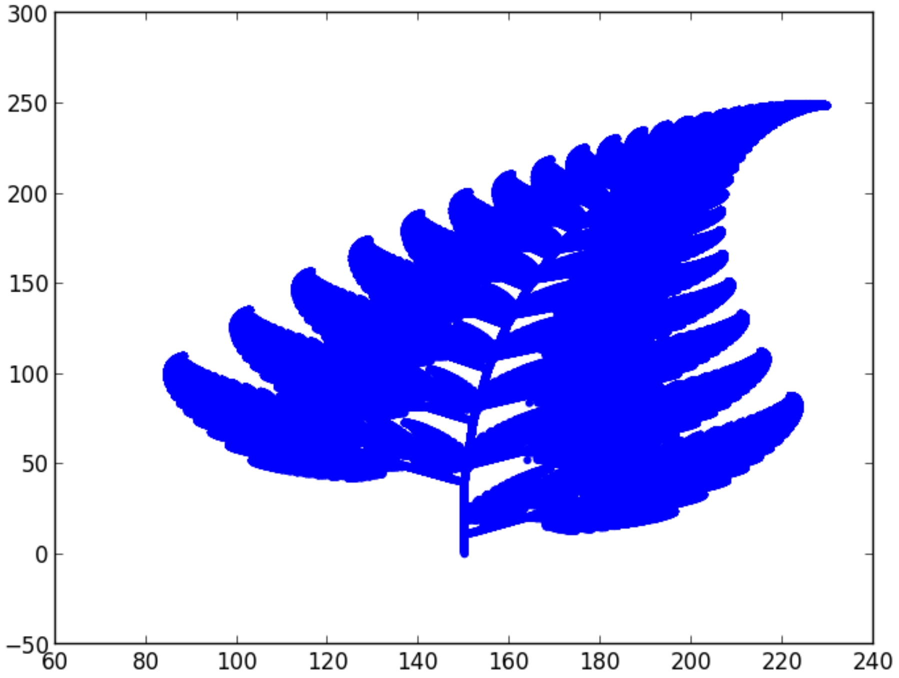
4. Figure out how to remove the edges around each point (hint: edgecolor)

```
plt.scatter(data[:,0], data[:,1],
            edgecolor='none')
```

matplotlib - Exercise 2 - Solution(2)

4. Figure out how to remove the edges around each point (hint: edgecolor)

```
plt.scatter(data[:,0], data[:,1],
            edgecolor='none')
```



matplotlib - Exercise 2 - Solution(3)

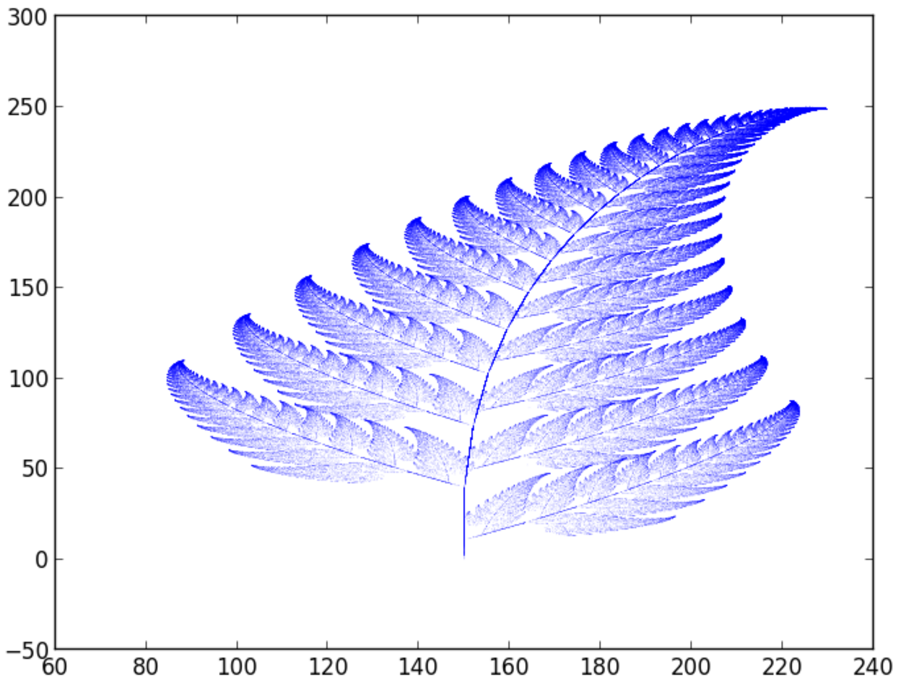
5. Figure out how to set the size of each point to 0.5

```
plt.scatter(data[:,0], data[:,1],
            edgecolor='none',
            s=0.5)
```

matplotlib - Exercise 2 - Solution(3)

5. Figure out how to set the size of each point to 0.5

```
plt.scatter(data[:,0], data[:,1],
            edgecolor='none',
            s=0.5)
```



matplotlib - Exercise 2 - Solution(4)

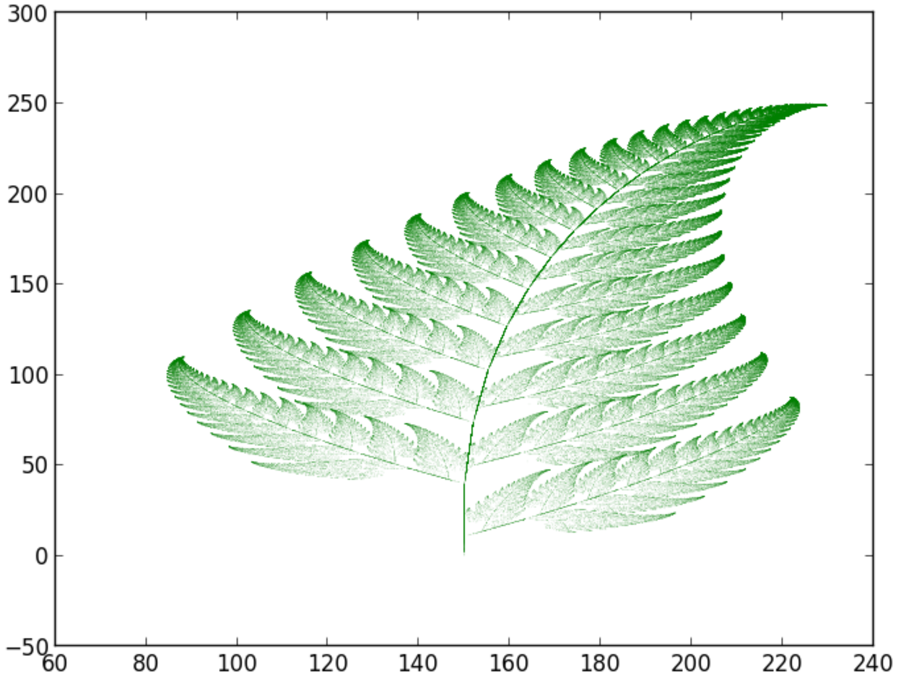
6. Figure out how to set the color of each point to green

```
plt.scatter(data[:,0], data[:,1],
            edgecolor='none',
            s=0.5,
            c='green')
```

matplotlib - Exercise 2 - Solution(4)

6. Figure out how to set the color of each point to green

```
plt.scatter(data[:,0], data[:,1],
            edgecolor='none',
            s=0.5,
            c='green')
```



matplotlib - Exercise 2 - Solution(5)

7. Figure out how to remove the axes

```
plt.axis('off')
```

matplotlib - Exercise 2 - Solution(5)

7. Figure out how to remove the axes

```
plt.axis('off')
```

matplotlib - Exercise 2 - Solution(6)

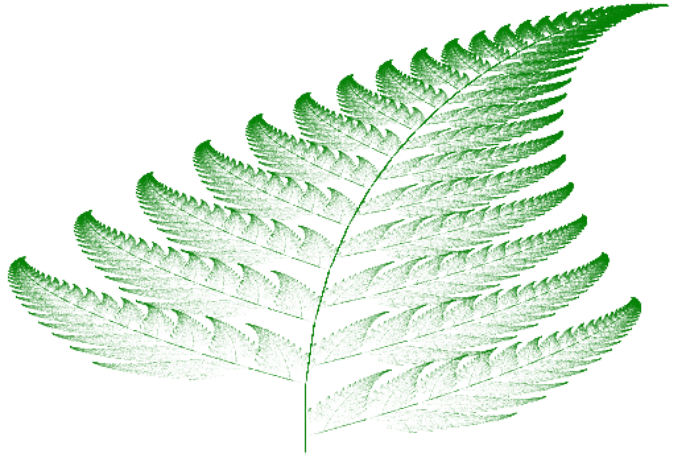
Making background transparent...

```
plt.savefig('matplotlib_fern6.png',
            transparent=True)
```

matplotlib - Exercise 2 - Solution(6)

Making background transparent...

```
plt.savefig('matplotlib_fern6.png',
            transparent=True)
```



For the curious: How the fern was created

```
import random
import matplotlib.pyplot as plt
import numpy as np

# Size of plot
size = (300, 300)

# Start with random coordinates
x, y = random.random(), random.random()

# Start with no points
points = []

# Repeat many times
for i in range(500000):

    # Random number decides action to take
    rand = random.random()

    # This recursion is described in detail
    # on http://en.wikipedia.org/wiki/Barnsley_fern
    if rand < 0.01:
        x, y = 0.0, 0.16 * y
    elif rand < 0.86:
        newx = (0.85 * x) + (0.04 * y)
        newy = (-0.04 * x) + (0.85 * y) + 1.6
        x, y = newx, newy
    elif rand < 0.93:
        newx = (0.2 * x) - (0.26 * y)
        newy = (0.23 * x) + (0.22 * y) + 1.6
        x, y = newx, newy
    else:
        newx = (-0.15 * x) + (0.28 * y)
        newy = (0.26 * x) + (0.24 * y) + 0.44
```