

# Numpy and Matplotlib

[ Background Knowledge for Data Analysis ]

algebra

- relational algebra(SQL)
- linear algebra (Numpy)

Visualization

Crawling

Transformation

Basic Deep learning

# Numpy

- Linear algebra library
- Fundamental package for working with N-dimensional array objects (vector, matrix, tensor, ...)
- Numpy arrays are a fundamental data type for some other packages to use
- Numpy has many specialized modules and functions:

numpy.linalg (Linear algebra)	numpy.random (Random sampling)
numpy.fft (Discrete Fourier transform)	sorting/searching/counting
math functions	numpy.testing (unit test support)

# Practice Together!

## Jun 2019 Data Programming - Numpy & Matplotlib

### Practice: Numpy Library

Basic numpy methods covered in class. All required codes are already written so that you can practice easily.

*You might want these as a reference of solving later image classification problem.*

#### 1. Import Numpy Library

```
import numpy as np
import numpy.random as npr
```

```
# Practice here!
import numpy as np
import numpy.random as npr
```

# Numpy array

- Simple array creation

```
1 import numpy as np
2
3 a = np.array([1,2,3,4])
4 b = np.array([2,3,4,5])
5 print(a)
6 print(b)
```

```
[1 2 3 4]
[2 3 4 5]
```

- Each Numpy array has some attributes:
  - shape(a tuple of the size in each dimension), dtype(data type of entries), size(total # of entries), ndim(# of dimensions), T(transpose)

```
print("shape = ", a.shape, ", dtype = ", a.dtype, ", size = ", a.size, ", ndim = ", a.ndim)

shape = (4,) , dtype = int64 , size = 4 , ndim = 1
```

# Vectors

가 shape !

- Vectors are 1d arrays (or 1<sup>st</sup> order tensors)

```
import numpy as np
import numpy.random as npr
```

```
np.zeros(4) # Return a new array of given shape and type, filled with zeros.
```

```
array([ 0.,  0.,  0.,  0.])
```

```
np.ones(5) # Return a new array of given shape and type, filled with ones.
```

```
array([ 1.,  1.,  1.,  1.,  1.])
```

```
npr.randn(3) # Return samples from the "standard normal" distribution.
```

```
array([ 1.03548977, -0.10369842, -1.6403447 ])
```

```
np.linspace(0, 2, 5) # 5 uniform values in [0, 2]
```

```
array([ 0. ,  0.5,  1. ,  1.5,  2. ])
```

```
np.arange(8) # create array from 0 to 7
```

```
array([0, 1, 2, 3, 4, 5, 6, 7])
```

# Matrices

- Matrices are 2d arrays (or 2<sup>nd</sup> order tensors)

```
np.zeros((2,5))
```

```
array([[ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.]])
```

```
npr.randn(3, 3)
```

```
array([[ 0.84257344,  0.17978292, -0.62112465],
       [ 1.16650643,  0.87555025,  0.05225127],
       [ 1.19749645, -1.38333744,  0.2157709 ]])
```

# Array shape

- Shape returns a tuple listing the length of the array along each dimension

```
1 a = np.array([1,2,3,4])
2 b = npr.randn(3,3)
3 c = npr.randn(3,2,4)
4 print("a = ", a, "\nb = \n", b, "\nc = \n", c)
5 print("a.shape = ", a.shape, "b.shape = ", b.shape, "c.shape = ", c.shape)
```

```
a = [1 2 3 4]
b =
[[-0.6129468 -1.53607928 1.10003604]
 [-0.29755292 0.54630051 -1.8317307 ]
 [ 0.02114839 0.02257444 -0.22226038]]
c =
[[[-1.5262782 -0.26953168 1.10735491 0.14370897]
 [-0.07652912 -0.85846648 0.89918118 -0.44788444]]

 [[-1.29420815 0.25608476 -0.39793983 0.63340769]
 [-0.32379019 1.46029366 -0.07129954 -0.34766979]]

 [[-0.34066753 -0.56823573 1.02060155 -0.15245486]
 [-2.26962498 -1.45004611 -1.13198899 0.58360711]]]
a.shape = (4,) b.shape = (3, 3) c.shape = (3, 2, 4)
```

# Reshaping an array

- Reshape return a new array with a different shape, but it cannot change the number of elements in an array

```
A = np.arange(8)
print(A)
```

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

```
A.reshape(2,4)
```

```
array([[0, 1, 2, 3],
       [4, 5, 6, 7]])
```

```
A.reshape(3,3)
```

```
-----
ValueError                                Traceback (most recent call last)
<ipython-input-57-63445bd75ed1> in <module>()
----> 1 A.reshape(3,3)
```

```
ValueError: cannot reshape array of size 8 into shape (3,3)
```



# Array indexing

- Array Slicing

```
>>> A[0, 3:5]
```

```
array([3, 4])
```

```
>>> A[4:, 4:]
```

```
array([[28, 29], [34, 35]])
```

```
>>> A[:, 2]
```

```
array([2, 8, 14, 20, 26, 32])
```

0	1	2	3	4	5
6	7	8	9	10	11
12	13	14	15	16	17
18	19	20	21	22	23
24	25	26	27	28	29
30	31	32	33	34	35

- Slices are references to memory in the original array

```
1 a = np.array((0,1,2,3,4))
2 b = a[2:4]
3 print(b)
```

가 .

```
[2 3]
```

```
1 b[0] = 10
2 print(a)
```

Changing values in a slice also  
changes the original array!

```
[ 0  1 10  3  4]
```

# Array indexing

- Indexing by position

```
1 a = np.arange(0, 80, 10)
2 print("a = ", a)
3 indices = [1, 2, -3]
4 y = a[indices]
5 print("y = ", y)
```

```
a = [ 0 10 20 30 40 50 60 70]
y = [10 20 50]
```

- Indexing with Booleans

```
1 mask = np.array([0, 1, 1, 0, 0, 1, 0, 0], dtype=bool)
2 y = a[mask]
3 print(y)
4 y = a[a > 20] broadcasting          type casting
5 print(y)
```

```
[10 20 50]
[30 40 50 60 70]
```

가 .

# Indexing with **newaxis**

가

- newaxis is a special index that inserts a new axis in the array at the specified location
- Each newaxis increases the array's dimensionality by 1
- Each newaxis expands the dimensions by adding one unit-length dimension

Use np.newaxis or write "from numpy import newaxis"

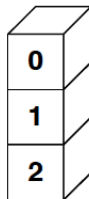
**1 X 3**

```
>>> shape(a)
(3,)
>>> y = a[newaxis,:]
>>> shape(y)
(1, 3)
```



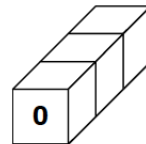
**3 X 1**

```
>>> y = a[:,newaxis]
>>> shape(y)
(3, 1)
```



**1 X 1 X 3**

```
> y = a[newaxis, newaxis, :]
> shape(y)
(1, 1, 3)
```



# Datatype

- Every numpy array is a grid of elements of the same type
- Numpy tries to guess a datatype when you create an array, but you can also explicitly specify the datatype

```
1 a = np.array([1,2])
2 print(a.dtype)
```

int64

```
1 a = np.array([1.0, 2.0])
2 print(a.dtype)
```

float64

```
1 a = np.array([1,2], dtype=np.int64)
2 print(a.dtype)
```

int64

Basic Type	Available NumPy types	Code	Comments
Boolean	<code>bool</code>	<code>b</code>	Elements are 1 byte in size.
Integer	<code>int8, int16, int32, int64, int128, int</code>	<code>i</code>	<code>int</code> defaults to the size of <code>long</code> in C for the platform.
Unsigned Integer	<code>uint8, uint16, uint32, uint64, uint128, uint</code>	<code>u</code>	<code>uint</code> defaults to the size of unsigned <code>long</code> in C for the platform.
Float	<code>float16, float32, float64, float, longfloat</code>	<code>f</code>	<code>float</code> is always a double precision floating point value (64 bits). <code>longfloat</code> represents large precision floats. Its size is platform dependent.
Complex	<code>complex64, complex128, complex, longcomplex</code>	<code>c</code>	The real and imaginary elements of a <code>complex64</code> are each represented by a single precision (32 bit) value for a total size of 64 bits.
Strings	<code>str, unicode</code>	<code>S</code> or <code>a, U</code>	For example, <code>dtype='S4'</code> would be used for an array of 4-character strings.
DateTime	<code>datetime64, timedelta64</code>	See section	Allow operations between dates and/or times. New in 1.7.
Object	<code>object</code>	<code>O</code>	Represent items in array as Python objects.
Records	<code>void</code>	<code>V</code>	Used for arbitrary data structures.

# Mathematical operations

- Basic mathematical functions operate **element-wise** on arrays

```
a = np.array([[1,2],[3,4]], dtype=np.float64)
b = np.array([[5,6],[7,8]], dtype=np.float64)
print("a = \n", a, "\nb = \n", b)
```

```
a =
[[ 1.  2.]
 [ 3.  4.]]
b =
[[ 5.  6.]
 [ 7.  8.]]
```

**a + b**

```
array([[ 6.,  8.],
       [10., 12.]])
```

**a \* b**

```
array([[ 5., 12.],
       [21., 32.]])
```

**a - b**

```
array([[ -4., -4.],
       [ -4., -4.]])
```

**a / b**

```
array([[ 0.2       ,  0.33333333],
       [ 0.42857143,  0.5       ]])
```

**np.sqrt(a)**

```
array([[ 1.       ,  1.41421356],
       [ 1.73205081,  2.       ]])
```

**a \*\* b**

```
array([[ 1.00000000e+00,  6.40000000e+01],
       [ 2.18700000e+03,  6.55360000e+04]])
```

# sum()

- `sum(a, axis=j)` defaults to adding up all the values in an array along the  $j$ th axis
  - if  $a$  is of  $d_0 \times d_1 \times \dots \times d_i$ , the dimension of `sum(a, axis=j)` is  $d_0 \times \dots \times d_{j-1} \times d_{j+1} \times \dots \times d_i$

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

```
1 np.sum(a)
```

```
21
```

```
1 np.sum(a, axis = 0)
```

```
array([5, 7, 9])
```

```
1 np.sum(a, axis = 1)
```

```
array([ 6, 15])
```

# prod()

- `prod(a, axis=j)` defaults to multiply all the values in an array along the  $j$ th axis
  - if  $a$  is of  $d_0 \times d_1 \times \dots \times d_i$ , the dimension of `prod(a, axis=j)` is  $d_0 \times \dots \times d_{j-1} \times d_{j+1} \times \dots \times d_i$

```
1 a = np.array([[1,2,3],[4,5,6]])
2 a.prod(axis = 0)
```

```
array([ 4, 10, 18])
```

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

```
array([ 6, 120, 504])
```



# Dot product

dot !

- `dot()` implements the dot product on vectors

```
1 np.array([1,2,3]).dot(np.array([4,5,6]))
```

32

$1*4 + 2*5 + 3*6$

- For 2D arrays, it is the matrix product

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

```
[[ 6  3]
 [16  7]]
```

$$\begin{bmatrix} 1 & 1 \\ 3 & 2 \end{bmatrix} * \begin{bmatrix} 4 & 1 \\ 2 & 2 \end{bmatrix} = \begin{bmatrix} 1*4 + 2*1 & 1*1 + 1*2 \\ 4*3 + 2*2 & 1*3 + 2*2 \end{bmatrix}$$

# Min/Max

- `min()` and `max()` return minimum value and maximum value, respectively
- `argmin()` and `argmax()` return index of minimum value and index of maximum value, respectively

```
1 a = np.array([2.,3.,0.,1.])
```

```
1 a.min(axis = 0)
```

0.0

```
1 a.argmin(axis = 0)
```

2

```
1 a.max(axis = 0)
```

3.0

```
1 a.argmax(axis = 0)
```

1

# Mean/Std/Var

- `mean()`, `std()`, and `var()` return mean value, standard deviation, and variance along the specified axis

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

```
1 a.mean(axis = 0)
```

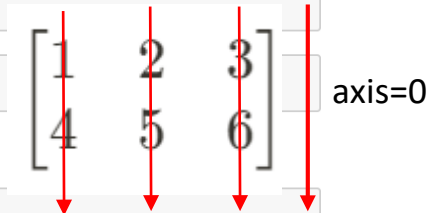
```
array([ 2.5,  3.5,  4.5])
```

```
1 a.std(axis = 0)
```

```
array([ 1.5,  1.5,  1.5])
```

```
1 a.var(axis = 0)
```

```
array([ 2.25,  2.25,  2.25])
```

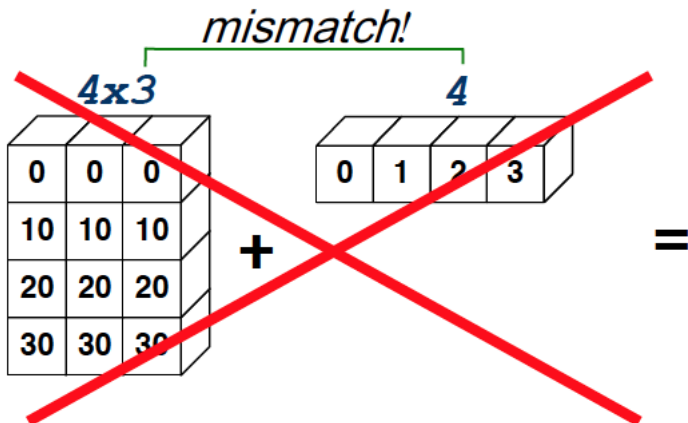


# Broadcasting

- NumPy arrays of different dimensionality can be combined in the same expression
- Arrays with *smaller* dimension are *broadcasted* to match the *larger* arrays, without copying data, so that they have equal size

# Broadcasting Rules

- NumPy *compares* their shapes element-wise in a reverse order
- Two dimensions to *compare* are compatible when they are equal, or one of them is 1
- **ValueError: shape mismatch: objects cannot be broadcast to a single shape" exception**



# Simulating a Cartesian product using broadcasting rather than nested for-loops

```
For each a in A
```

```
    For each b in B
```

```
        y[a.pos][b.pos] = a op b
```



$Y = A \text{ op } B$

(This is much faster!)

$4 \times 3$ 

0	0	0
10	10	10
20	20	20
30	30	30

+

 $4 \times 3$ 

0	1	2
0	1	2
0	1	2
0	1	2

=

0	0	0
10	10	10
20	20	20
30	30	30

+

0	1	2
0	1	2
0	1	2
0	1	2

=

 $4 \times 3$ 

0	0	0
10	10	10
20	20	20
30	30	30

+

 $1 \times 3$ 

0	1	2
---	---	---

=

0	0	0
10	10	10
20	20	20
30	30	30

+

0	1	2
0	1	2
0	1	2
0	1	2

=

*stretch*

0	1	2
10	11	12
20	21	22
30	31	32

 $4 \times 1$ 

0
10
20
30

+

 $1 \times 3$ 

0	1	2
---	---	---

=

0	0	0
10	10	10
20	20	20
30	30	30

+

0	1	2
0	1	2
0	1	2
0	1	2

=

*stretch*

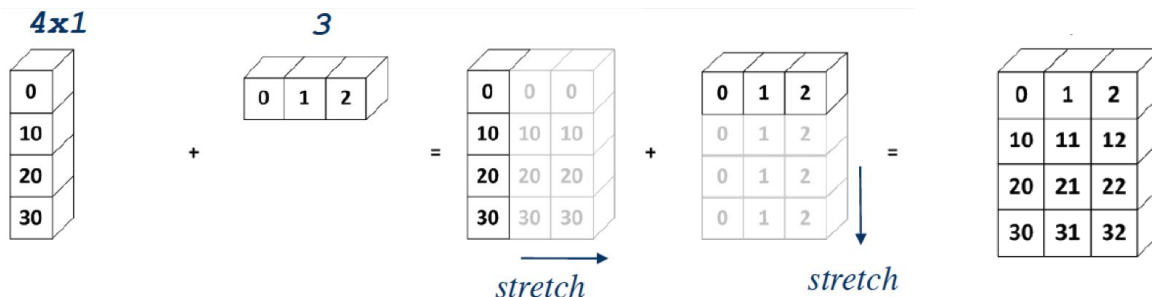
cartesian product

*stretch*

# Broadcasting example

```
1 a = np.array((0,10,20,30))
2 b = np.array((0,1,2))
3 y = a[:, np.newaxis] + b
4 print(a[:, np.newaxis], "+", b, "\n\n", y)
```

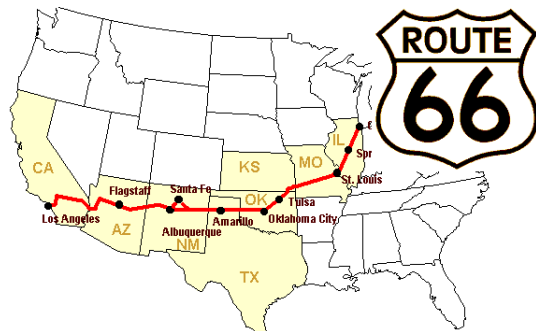
```
[[ 0]          [[ 0  1  2]
 [10]          [10 11 12]
 [20]          [20 21 22]
 [30]] + [0  1  2] = [30 31 32]]
```





# Application: Distances between cities of Route 66

- Given a 1-D array of distances to all cities in Route 66 from Chicago



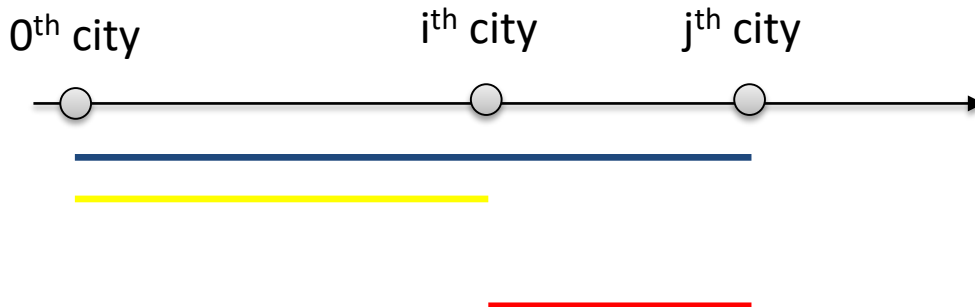
[0, 198, 303, 736, 871, 1175, 1475, 1544, 1913, 2448]

Chicago

Los Angeles

- Construct a 2D array of distances between pairs of cities

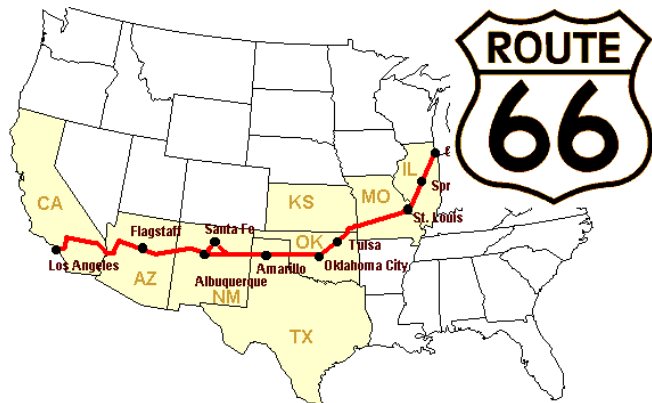
$$\text{dist}'(i, j) = | \text{dist}(0, j) - \text{dist}(0, i) |$$



```
mileposts = np.array([0, 198, 303, 736, 871, 1175, 1475, 1544, 1913, 2448])
distance_array = np.abs(mileposts - mileposts[:, np.newaxis])
print(distance_array)
```

```
[[ 0 198 303 736 871 1175 1475 1544 1913 2448]
 [198 0 105 538 673 977 1277 1346 1715 2250]
 [303 105 0 433 568 872 1172 1241 1610 2145]
 [736 538 433 0 135 439 739 808 1177 1712]
 [871 673 568 135 0 304 604 673 1042 1577]
 [1175 977 872 439 304 0 300 369 738 1273]
 [1475 1277 1172 739 604 300 0 69 438 973]
 [1544 1346 1241 808 673 369 69 0 369 904]
 [1913 1715 1610 1177 1042 738 438 369 0 535]
 [2448 2250 2145 1712 1577 1273 973 904 535 0]]
```

Grid-based or network-based problems can also use broadcasting



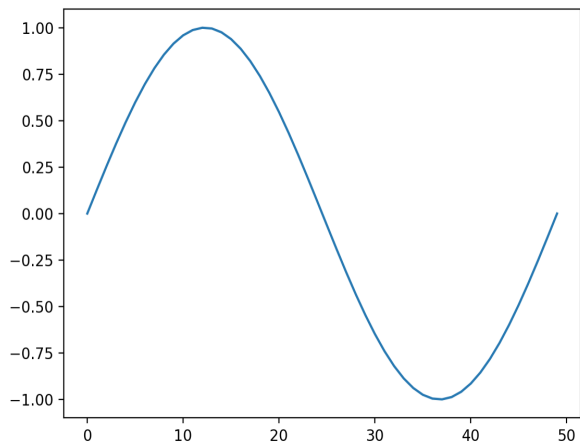
# Matplotlib

- 2D Python plotting library (matplotlib.pyplot mostly used)
- matplotlib.pyplot can do many types of visualizations including:
  - Line plots (using plot)
  - Scatter plots (using scatter)
  - Histograms, bar charts (using hist)
  - Error bars on plots, box plots (using boxplot, errorbar)
  - Images (matrix to image) (using imshow)
  - Pie charts, Polar charts (using pie, polar)
  - Contour maps (using contour or tricontour)
  - Stream plots which show derivatives at many locations (streamplot)

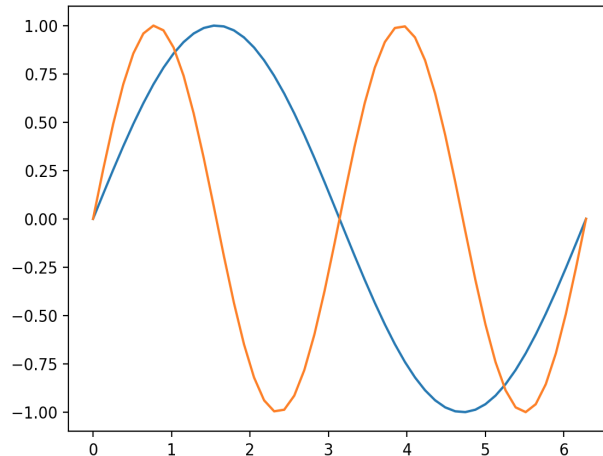
# Line plot

- A line is created connecting each data point together
- Plot against indices
- Multiple datasets

```
%matplotlib notebook
import matplotlib.pyplot as plt
from numpy import *
x = linspace(0, 2*pi, 50)
plt.plot(sin(x))
```



```
plt.plot(x, sin(x), x, sin(2*x))
```



# Line formatting

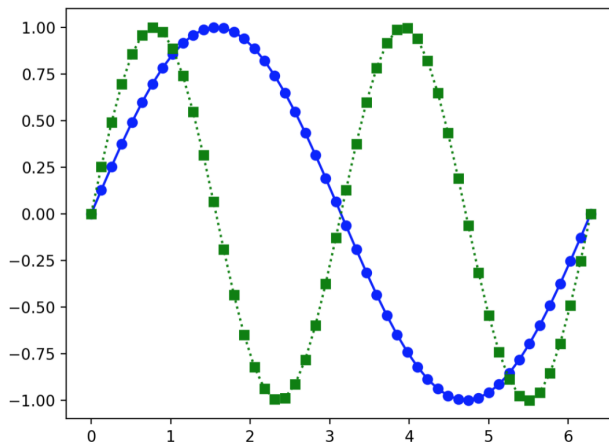
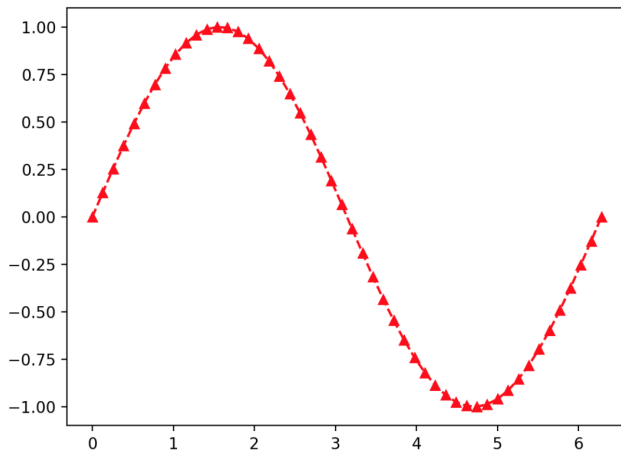
option

!!!

```
plt.plot(x, sin(x), 'b-o') # blue, solid line, circle points
plt.plot(x, sin(x), 'r--^') # red, dashed line, triangle_up points
plt.plot(x, sin(x), 'g:s') # green, dotted line, square points
```

```
plt.plot(x, sin(x), 'r--^')
```

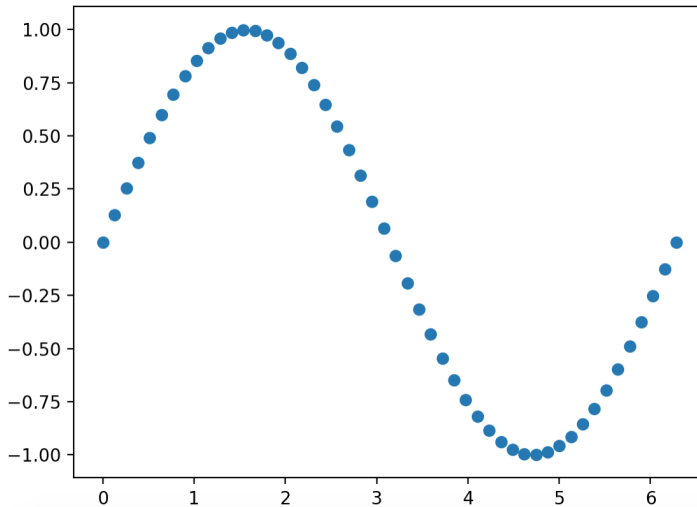
```
plt.plot(x, sin(x), 'b-o',
         x, sin(2*x), 'g:s')
```



# Scatter plot

- display data as a collection of points

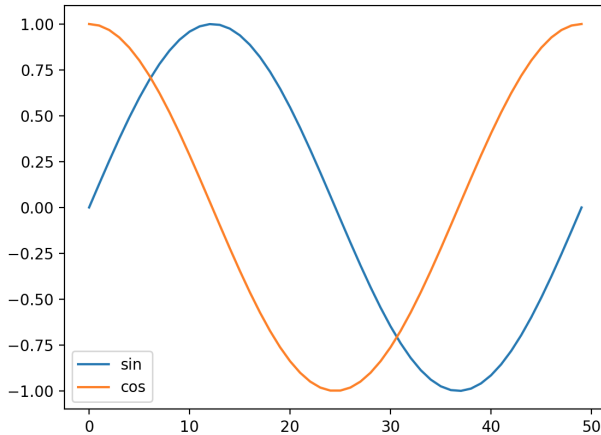
```
x = linspace(0, 2*pi, 50)
y = sin(x)
plt.scatter(x, y)
```



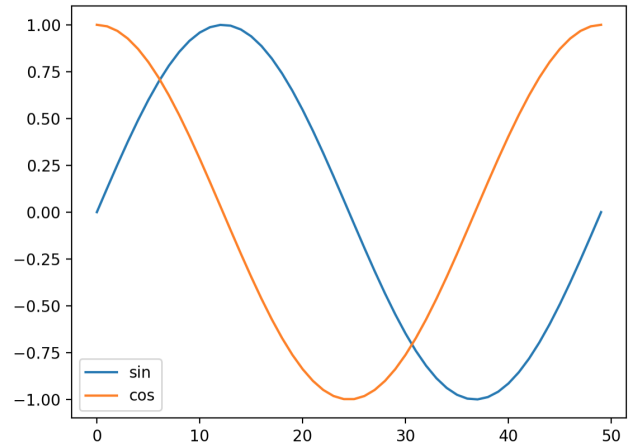
# Legend

- Add labels in plot command
- Or as a list in legend()

```
plt.plot(sin(x), label='sin')
plt.plot(cos(x), label='cos')
plt.legend()
```



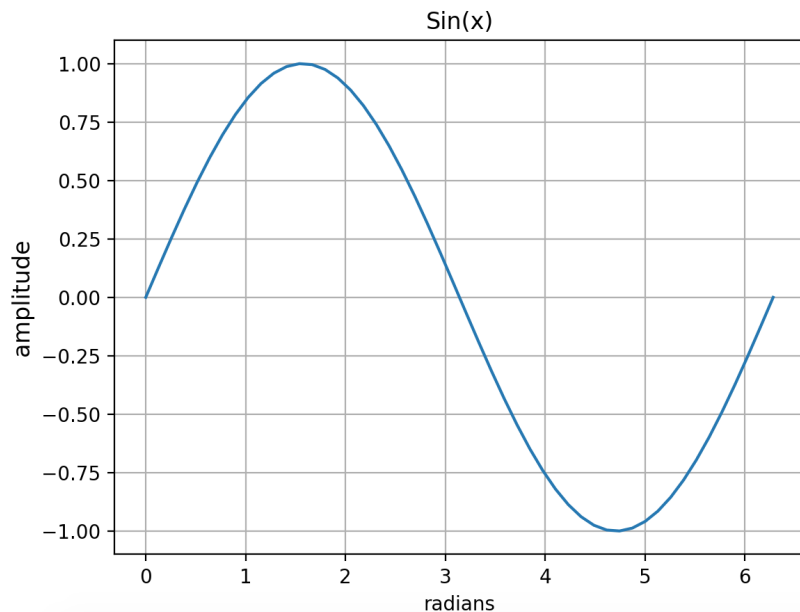
```
plt.plot(sin(x))
plt.plot(cos(x))
plt.legend(['sin', 'cos'])
```





# Titles and Grid

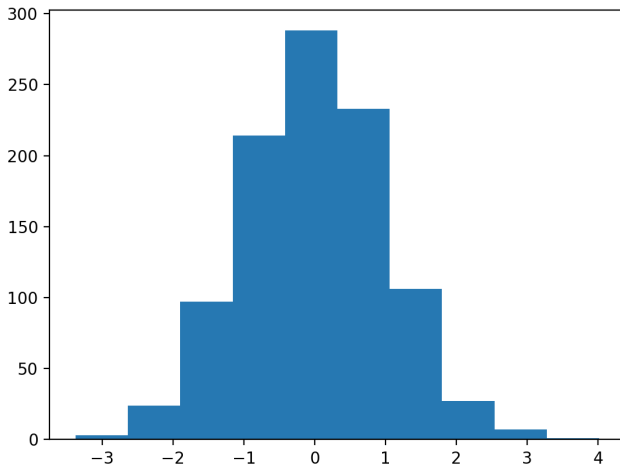
```
plt.plot(x, sin(x))
plt.xlabel('radians')
plt.ylabel('amplitude', fontsize='large')
plt.title('Sin(x)')
plt.grid()
```



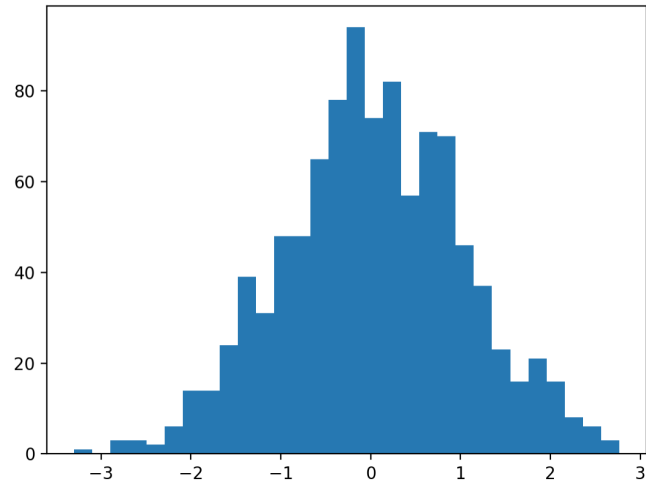
# Histograms

- Plot histogram, defaults to 10 bins
- Change the number of bins

```
plt.hist(npr.randn(1000))
```

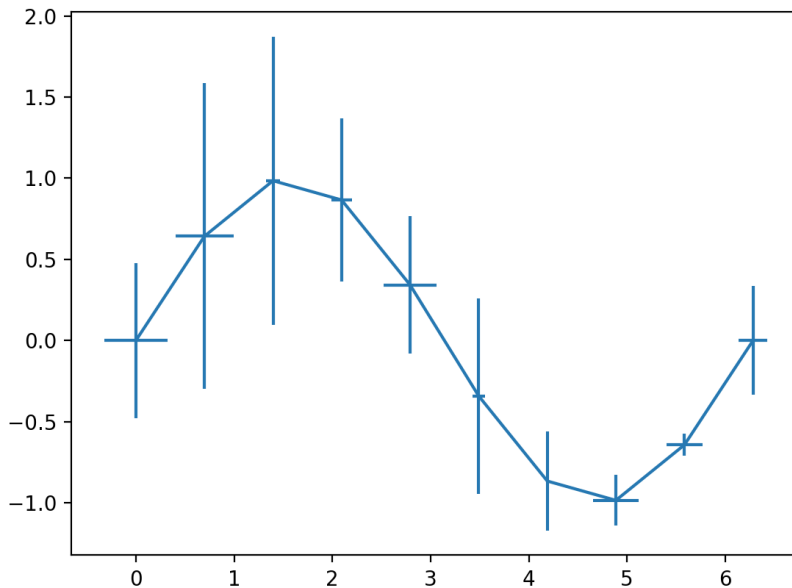


```
plt.hist(npr.randn(1000), 30)
```



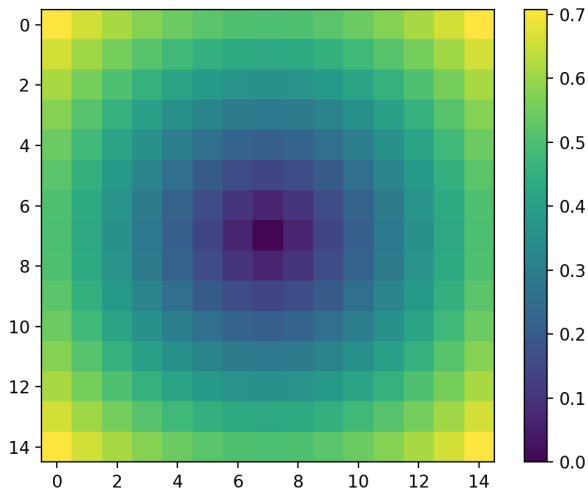
# Plot with error bars

```
x = linspace(0,2*pi,10)
y = sin(x)
yerr = npr.rand(10)
xerr = npr.rand(10)/3
plt.errorbar(x, y, yerr, xerr)
```



# Color Bar

```
a = linspace(0, 1, 15) - 0.5 # a.shape = (1, 15)
b = a[:, newaxis] # b.shape = (15, 1)
dist2 = a**2 + b**2 # broadcasting sum
dist = sqrt(dist2)
plt.imshow(dist); plt.colorbar()
```



Try plotting  
your distance matrix