

BRIEF INTRODUCTION TO NUMPY

CS 5010

Quick Overview

- Very useful library used for **manipulating n-dimensional arrays**
- Problem with the native Python list data structure is that it doesn't scale well for more than one dimension
- NumPy is built as an extension of the native Python **list** functionality
- Must remember to import numpy and all modules within:
 - `import numpy` [need to qualify]
 - (often: `import numpy as np`)
 - `from numpy import *` [*no need to qualify*]

Arrays

- An array can hold many types of data, not just numerical data types

```
a = array([0,1,2,3]) # all integers
```

```
a
```

```
Out[12]: array([0, 1, 2, 3])
```

```
mix = array([0,'cat',2.5,7,'hello']) # mixed array
```

```
mix
```

```
Out[14]:
```

```
array(['0', 'cat', '2.5', '7', 'hello'],
```

```
      dtype='<U11') # Unicode character less than 11 characters
```

```
a.dtype # checking the type of array 'a'
```

```
Out[16]: dtype('int32') # integer type
```

Arrays

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

```
charArr =  
array(["hi","hello","goodbye"])
```

```
arr.max()  
Out[19]: 3
```

```
arr.cumsum()  
Out[22]: array([1, 3, 6],  
dtype=int32)
```

```
arr.dtype  
Out[20]: dtype('int32')
```

```
charArr  
Out[21]: array(['hi', 'hello',  
'goodbye'],  
dtype='<U7')
```

```
arr.size  
Out[24]: 3
```

```
arr.sum()  
Out[27]: 6
```

Single-dimension Arrays vs. Lists

- Is there any benefit of 1-D array vs list (which is 1D)
- Yes! Arrays are **memory-efficient** containers that provides fast numerical operations

```
L = range(1000)
```

```
timeit [i**2 for i in L]      # An operation on each element of L
10000 loops, best of 3: 468 µs per loop
```

```
a = arange(1000)    # “a range” not “arrange”
```

```
timeit a**2          # An operation on each ele of array
1000000 loops, best of 3: 1.76 µs per loop
```

NumPy Reference documentation

- Assuming: `from numpy import *`
- `lookfor('create array')`

Search results for 'create array'

`numpy.array`

Create an array.

`numpy.memmap`

Create a memory-map to an array stored in a *binary* file on disk.

... *<more results shown>*

Manual Construction of 1- and 2-D arrays

- ndarrays (n-dimensional arrays) – equivalent to matrices in linear algebra

- **1D:**

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

```
a          Out[4]: array([1, 2, 3])
```

```
a.ndim     Out[5]: 1
```

```
a.shape    Out[6]: (3,)
```

```
len(a)     Out[7]: 3
```

```
type(a)    Out[8]: numpy.ndarray
```

Manual Construction of 1- and 2-D arrays

- **2D:**

```
b = array([(1.5, 2, 3),(4, 5, 6)])
```

```
b
```

```
Out[9]:
```

```
array([[ 1.5,  2. ,  3. ],  
       [ 4. ,  5. ,  6. ]])
```

```
b.ndim      Out[10]: 2
```

```
b.shape     Out[11]: (2, 3)
```

```
len(b)      Out[12]: 2
```

```
type(b)     Out[13]: numpy.ndarray
```


Some Array Operations

```
a = array([(1.5, 2, 3),(4, 5, 6)])
```

a

Out[15]:

```
array([[ 1.5,  2. ,  3. ],  
       [ 4. ,  5. ,  6. ]])
```

sin(a)

Out[16]:

```
array([[ 0.99749499,  0.90929743,  0.14112001],  
       [-0.7568025 , -0.95892427, -0.2794155 ]])
```

Some Array Operations

```
a = b
```

```
b = pow(a,2)
```

```
b
```

```
Out[18]:
```

```
array([[ 2.25,  4.   ,  9.   ],  
       [ 16.   , 25.   , 36.   ]])
```

```
c = pow(a,3)
```

```
c
```

```
Out[20]:
```

```
array([[ 3.375,  8.   , 27.   ],  
       [ 64.   , 125.  , 216.  ]])
```

Data Types Examples

```
d = array([1,2,3], dtype=float) # specify the type
d      Out[22]: array([ 1.,  2.,  3.]
```

```
type(d)    Out[23]: numpy.ndarray
d.dtype    Out[24]: dtype('float64')
```

```
e = array([True, False, False, True])
e      Out[27]: array([ True, False, False,  True], dtype=bool)
e.dtype    Out[28]: dtype('bool')
```

Data Types Examples

```
f = array(['Bonjour', 'Hello', 'Hallo',])
```

```
f
```

```
Out[30]:
```

```
array(['Bonjour', 'Hello', 'Hallo'],  
      dtype='<U7')
```

```
f.dtype
```

```
Out[31]: dtype('<U7')    # Unicode, max. 7 letters
```

Some More Array Operations

```
j = array([[0.0, -1.0], [1.0, 0.0]])
```

```
j
```

```
Out[39]:
```

```
array([[ 0., -1.],  
       [ 1.,  0.]])
```

```
dot(j,j) # matrix product
```

```
Out[40]:
```

```
array([[ -1.,  0.],  
       [ 0., -1.]])
```

Some More Array Operations

- `from numpy import *`
- `from numpy.linalg import *` `# linear algebra`
- `a = array([[1.0, 2.0], [3.0, 4.0]])`

Out[34]:

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

- `u = eye(2)` `# unit 2x2 matrix; "eye" represents "I" (identity)`

u

Out[37]:

```
array([[ 1.,  0.],  
       [ 0.,  1.]])
```

Some More Array Operations

a

Out[41]:

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

```
y = array([[5.0], [7.0]])
```

- **solve(a,y)** # solve a linear matrix equation. solve(a,b) where a is the coefficient matrix and b is the 'dependent variable' values. Returns solution to the system $ax = b$

Out[43]:

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

Indexing ndarrays

- NumPy arrays can be indexed in the same way that native Python lists can
- However, NumPy arrays have additional functionalities
- The function “arange” is a useful NumPy function used to automatically create an ndarray (n-dimensional array) with numbers with certain increments (default 1xn array)

```
p = arange(12)**2
```

```
indices = array([1,2,3,7]) # return values of those indices
```

```
p[indices]          Out[65]: array([ 1,  4,  9, 49])
```

```
p is array([ 0,  1,  4,  9, 16, 25, 36, 49, 64, 81, 100, 121])
```


Indexing ndarrays

```
p2 = arange(10)*2 # 10 numbers, index multiply by 2  
indices = array([1,2,3,7]) # return values of those indices  
p2[indices]          Out[66]: array([ 2, 4, 6, 14])
```

```
p2 is array([ 0,  2,  4,  6,  8, 10, 12, 14, 16, 18])
```

Resizing and Modifying ndarrays

- Another useful feature of NumPy is it's ability to reshape and manipulate the dimensions of the ndarray

```
In [33]: b = arange(12)
```

```
In [34]: b
```

```
Out[34]: array([ 0,  1,  2,  3,  4,  5,  6,  7,  8,  9, 10, 11])
```

```
In [35]: b.shape = 3, 4    # 3 rows, 4 columns
```

```
In [36]: b
```

```
Out[36]:
```

```
array([[ 0,  1,  2,  3],  
       [ 4,  5,  6,  7],  
       [ 8,  9, 10, 11])
```

Resizing and Modifying ndarrays

```
In [37]: b.shape = 3, -1 #use -1, when you aren't sure  
          of dimension for either row or column
```

```
In [38]: b
```

```
Out[38]:
```

```
array([[ 0,  1,  2,  3],  
       [ 4,  5,  6,  7],  
       [ 8,  9, 10, 11]])
```

Note: the total number of datapoints must be **divisible** by the specified dimension, since dimensions are always integers. For example an array of **1x11** *can't* be reshaped with **3** rows or columns.

```
In [39]: b.shape = -1, 3
```

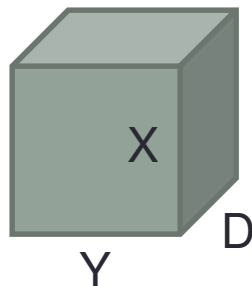
```
In [40]: b
```

```
Out[40]:
```

```
array([[ 0,  1,  2],  
       [ 3,  4,  5],  
       [ 6,  7,  8],  
       [ 9, 10, 11]])
```

Resizing and Modifying ndarrays

- In [8]: `a = arange(30)`
- In [9]: `a.shape = 2,-1,3` # -1 means "whatever is needed"
- In [10]: `a.shape`
- Out[10]: `(2, 5, 3)`
D, X, Y



- In [11]: `a`
- Out[11]:

```
array([[[ 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]]])
```

D=depth; X=row; Y=col

Resizing and Modifying ndarrays

```
# Returning a back to the default 1D (original form):
```

```
In [20]: a = a.flatten()
```

```
In [21]: a
```

```
Out[21]:
```

```
array([ 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])
```

```
In [22]: a = a.ravel()
```

```
In [23]: a
```

```
Out[23]:
```

```
array([ 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])
```

```
In [24]: a.shape = 1, -1
```

```
In [25]: a
```

```
Out[25]:
```

```
array([[ 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]])
```

Stacking Arrays

- We can stack together different arrays. These functionalities allows different arrays to be easily “joined” or “attached” to each other, by specifying the axis
- The “**vstack**” and “**hstack**” are two important functions (stands for vertically/horizontally stack). They both accept **tuple** of the two arrays.
- `p = array([[5,2],[9,6]])`
`p`
 Out[90]:
`array([[5, 2],
 [9, 6]])`
- `q = array([[1,7],[3,0]])`
`q`
 Out[92]:
`array([[1, 7],
 [3, 0]])`

Stacking Arrays

- `p, q`

Out[95]:

```
(array([[5, 2],
        [9, 6]]),
 array([[1, 7],
        [3, 0]]))
```

- `vstack((p,q))`

• Out[96]:

```
array([[5, 2],
        [9, 6],
        [1, 7],
        [3, 0]])
```

- `vstack((q,p))`

• Out[97]:

```
array([[1, 7],
        [3, 0],
        [5, 2],
        [9, 6]])
```

Stacking Arrays

- `hstack((p,q))`

Out[98]:

```
array([[5, 2, 1, 7],
       [9, 6, 3, 0]])
```

- `concatenate((p,q))`
default axis = 0

Out[99]:

```
array([[5, 2],
       [9, 6],
       [1, 7],
       [3, 0]])
```

- `concatenate((p,q), axis=1)`
default axis = 0

Out[100]:

```
array([[5, 2, 1, 7],
       [9, 6, 3, 0]])
```

Note: there is another function called “**dstack**”, which is for “depth” (this is when we have 3 axis).

For arrays with more than two dimensions, **hstack** stacks along their second axes, **vstack** stacks along their first axes, and **concatenate** (a function) allows for an optional argument giving the number of the axis along which the concatenation should happen.

Stacking Higher Dimensions

- Stacking can get complicated for arrays with dimensions greater than 3. Following is a table describing some relevant stacking functions:

<code>column_stack(tup)</code>	Stack 1-D arrays as columns into a 2-D array.
<code>concatenate((a1, a2, ...)[, axis])</code>	Join a sequence of arrays together.
<code>dstack(tup)</code>	Stack arrays in sequence depth wise (along third axis).
<code>hstack(tup)</code>	Stack arrays in sequence horizontally (column wise).
<code>vstack(tup)</code>	Stack arrays in sequence vertically (row wise).

Splitting Arrays

- Similar to stacking, there are splitting functions that split arrays anywhere based on axis and position
- `r = random.randn(4,4)` # generates a random 4x4
- `hsplit(r,4)` # split r into 4 columns
- `hsplit(r, 4)[0]` # get the first (index 0) col
- `hsplit(r, 4)[0].shape` # describe dimensions → (4,1)
- `hsplit(r,(3,4))` # Split a after the 3rd & 4th column
- `hsplit(r,(3,4))[1]` # get the second (index 1) part of split

In a similar fashion to **hsplit**, we can use **vsplit**

The Matrix Object

- `A = matrix('1.0 2.0; 3.0 4.0')` # Matrix: a specialized 2-D array

A

Out[50]:

```
matrix([[ 1.,  2.],  
        [ 3.,  4.]])
```

To get more options:

`A.max()`

Out[52]: 4.0

`A.T` # Transpose

Out[53]:

```
matrix([[ 1.,  3.],  
        [ 2.,  4.]])
```

`A.<tab>` for more options

Matrix Operations

- **X = matrix('5,7')**

- **B = X.T**

B

Out[57]:

```
matrix([[5],
        [7]])
```

- **print A*B** # matrix multiplication

```
[[ 19.]
 [ 43.]]
```

- A

Out[59]:

```
matrix([[ 1.,  2.],
        [ 3.,  4.]])
```

- **A.std()** # standard deviation

Out[60]: 1.1180339887498949

- **B.std()**

Out[61]: 1.0

Can Find Additional Information At...

- SciPy.org NumPy documentation:
- <http://docs.scipy.org/doc/numpy/>
- <http://docs.scipy.org/doc/numpy/reference/>
- <http://docs.scipy.org/doc/numpy/reference/generated/numpy.matrix.html>

Next...

- A very brief introduction to Pandas!

