

Python for Data Analysis and Scientific Computing

X433.3 (2 semester units in COMPSCI)

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Course Content Outline

- **Introduction to Python[®]**

- Python - pros and cons
- Installing the environment with core packages
- Python modules, packages and scientific blocks
- Working with the shell, IPython and the editor

HW1

- **Basic language specifics 1/2**

- Basic arithmetic operations, assignment operators, data types, containers
- Control flow (if/elif/else)
- Conditional expressions
- Iterative programming (for/continue/while/break)
- Functions: definition, return values, local vs. global variables

- **Basic language specifics 2/2**

- Classes / Functions (cont.): objects, methods, passing by value and reference
- Scripts, modules, packages
- I/O interaction with files
- Standard library
- Exceptions

- **NumPy 1/3**

- Why NumPy?
- Data type objects
- NumPy arrays
- Indexing and slicing of arrays

HW2

- **Matplotlib**

- What is Matplotlib?
- Basic plotting
- Tools: title, labels, legend, axis, points, subplots, etc.
- Advanced plotting: scatter, pie, bar, 3D plots, etc.

HW3

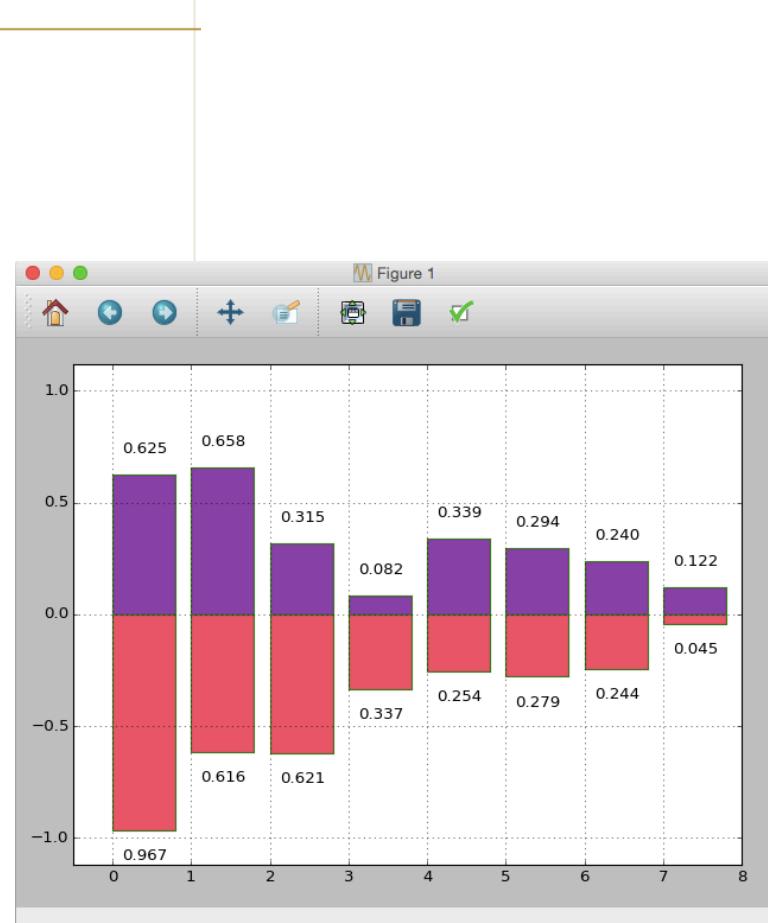
Advanced plotting

- Advanced plotting
 - There are many different types of 2-D and 3-D plotting choices in Matplotlib
 - Matplotlib provides a huge variety of plots aiming at specific visualization of results
 - Some of these types are:
 - Bar plots
 - Scatter plots
 - Imshow
 - Histogram
 - Pie charts
 - Contour plots
 - Polar axis
 - 3-D plots
 - *Text plots*
 - *Grids*
 - *Quiver plots*

Advanced plotting

- Advanced plotting: *bar plot*

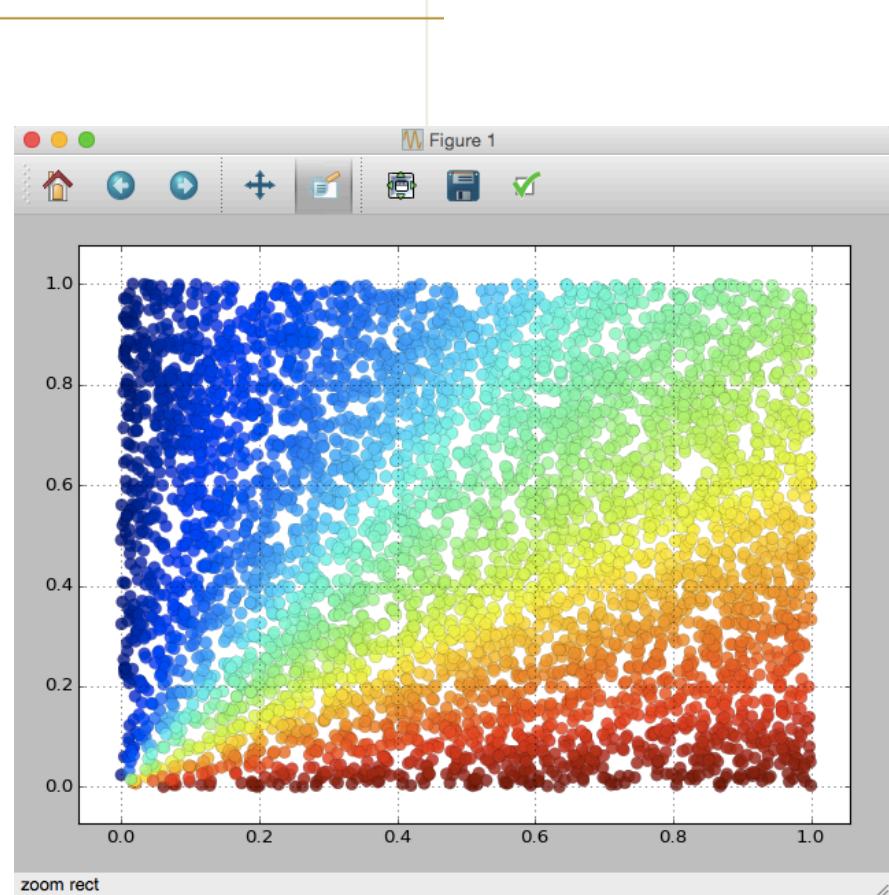
```
244 ## Advanced plotting:  
245 # Bar plot:  
246 import pylab as plt  
247  
248 k = 8  
249 x = plt.arange(k)  
250 y1 = plt.rand(k) * (1 - x / k)  
251 y2 = plt.rand(k) * (1 - x / k)  
252 plt.axes([0.075, 0.075, .88, .88])  
253  
254 plt.bar(x, +y1, facecolor="#9922aa", edgecolor='green')  
255 plt.bar(x, -y2, facecolor="#ff3366", edgecolor='green')  
256  
257 for a, b in zip(x, y1):  
258     plt.text(a+0.41, b+0.08, '%.3f' % b, ha='center', va='bottom')  
259 for a, b in zip(x, y2):  
260     plt.text(a+0.41, -b-0.08, '%.3f' % b, ha='center', va= 'top')  
261  
262 plt.xlim(-.5, k), plt.ylim(-1.12, +1.12)  
263 plt.grid(True)  
264 plt.show()
```



Advanced plotting

- Advanced plotting: *scatter plot*

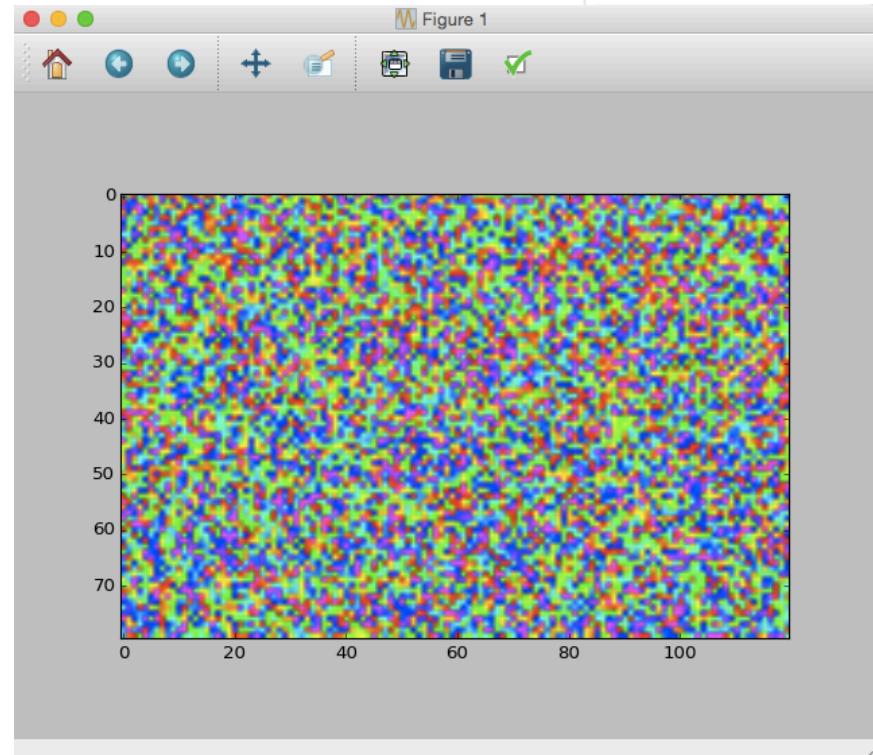
```
312 ## Scatter plot:  
313 import pylab as plt  
314  
315 x = plt.rand(1,2,1500)  
316 y = plt.rand(1,2,1500)  
317 plt.axes([0.075, 0.075 , .88, .88])  
318  
319 plt.clf() # clear the current axis  
320 plt.scatter(x, y, s=65, alpha=.75, linewidth=.125,  
321 c=plt.arctan2(x, y))  
322  
323 plt.grid(True)  
324 plt.xlim(-0.085,1.085), plt.ylim(-0.085,1.085)  
325 plt.pause(1)
```



Advanced plotting

- Advanced plotting: *image plot*

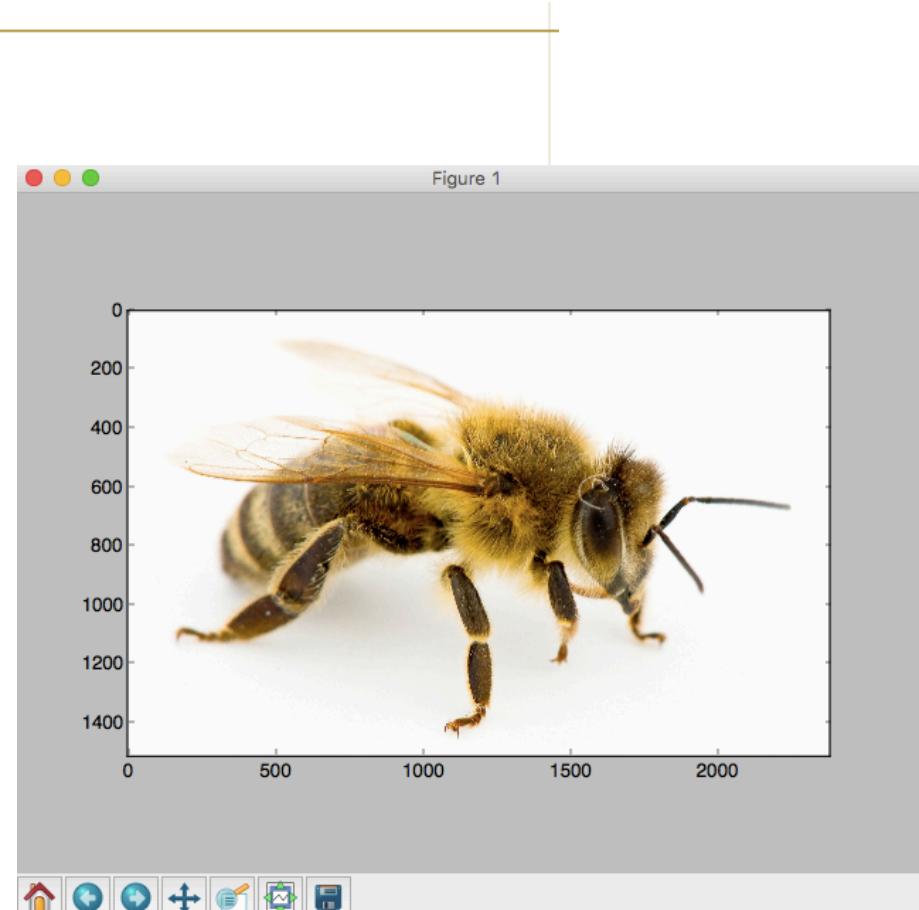
```
358 ## Image 1/2:  
359 plt.cla()  
360 array = plt.random((80, 120))  
361 plt.imshow(array, cmap=plt.cm.gist_rainbow) # with a specific colormap  
362 plt.pause(1)
```



Advanced plotting

- Advanced plotting: *image plot*

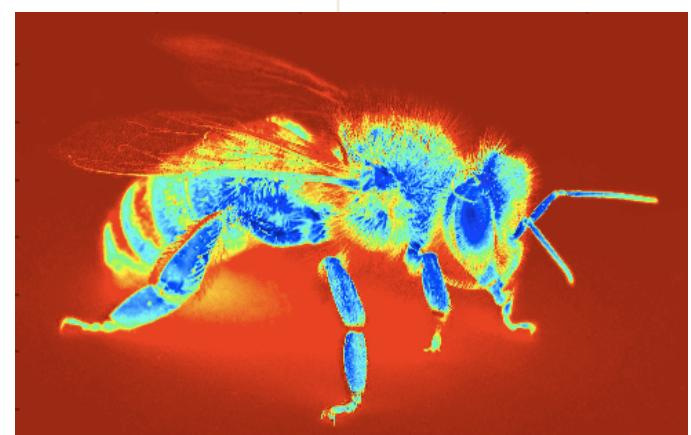
```
364 ## Image 2/2:  
365 import matplotlib.image as img  
366 import matplotlib.pyplot as plt  
367  
368 image = img.imread('files/lecture5/bee.jpg')  
369 plt.imshow(image)  
370 plt.pause(1)
```



Advanced plotting

- Advanced plotting: *image plot 1/3*

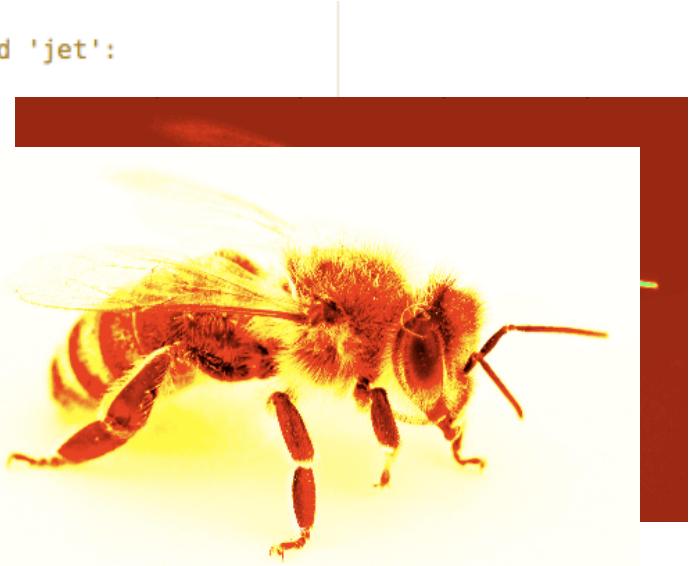
```
372 # luminosity display using 1-channel only (no RGB color).
373 # A default colormap (lookup tabel = LUT) is applied called 'jet':
374 luminosity = image[:, :, 0]
375 plt.imshow(luminosity)
376 plt.pause(5)
377
378 # Other colormaps can be:
379 plt.imshow(luminosity, cmap="hot")
380 plt.pause(5)
381 plt.imshow(luminosity, cmap="spectral")
382 plt.pause(5)
```



Advanced plotting

- Advanced plotting: *image plot 2/3*

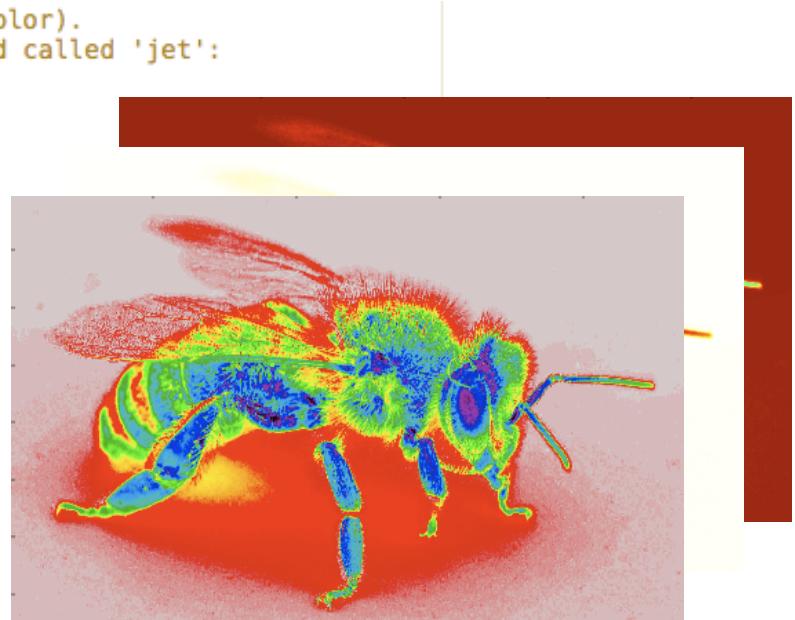
```
372 # luminosity display using 1-channel only (no RGB color).
373 # A default colormap (lookup tabel = LUT) is applied called 'jet':
374 luminosity = image[:, :, 0]
375 plt.imshow(luminosity)
376 plt.pause(5)
377
378 # Other colormaps can be:
379 plt.imshow(luminosity, cmap="hot")
380 plt.pause(5)
381 plt.imshow(luminosity, cmap="spectral")
382 plt.pause(5)
```



Advanced plotting

- Advanced plotting: *image plot 3/3*

```
372 # luminosity display using 1-channel only (no RGB color).
373 # A default colormap (lookup tabel = LUT) is applied called 'jet':
374 luminosity = image[:, :, 0]
375 plt.imshow(luminosity)
376 plt.pause(5)
377
378 # Other colormaps can be:
379 plt.imshow(luminosity, cmap="hot")
380 plt.pause(5)
381 plt.imshow(luminosity, cmap="spectral")
382 plt.pause(5)
```

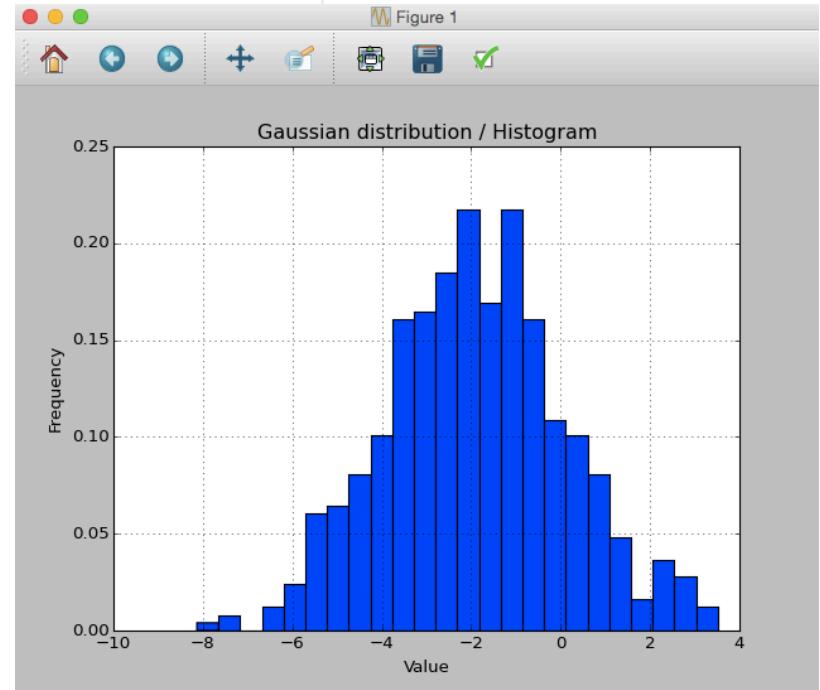


Advanced plotting

- Advanced plotting: *histogram plot 1/2*

```
285 # Histogram 1/2:  
286 import pylab as plt  
287  
288 plt.figure(1)  
289 gaus_dist = plt.normal(-2,2,size=512) # create a random floating point vector  
290  
291 # plot the histogram with specific bin number  
292 plt.hist(gaus_dist, normed=True, bins=24) # default: bins=10, color='blue'  
293  
294 plt.title("Gaussian distribution / Histogram")  
295 plt.xlabel("Value")  
296 plt.ylabel("Frequency")  
297 plt.grid(True)  
298 plt.show()
```

Histogram is great for visualizing statistical distribution of a set of variables in a given pool of samples, divided into classes called bins

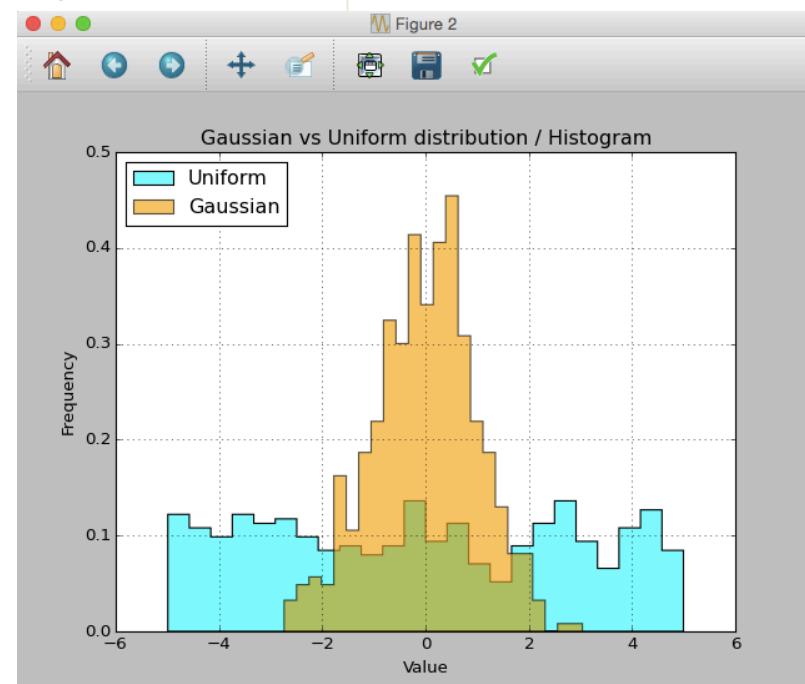


Advanced plotting

- Advanced plotting: *histogram plot 2/2*

```
300 # Histogram 2/2:  
301 plt.figure(2)  
302 gaus_dist = plt.normal(size=512)  
303 unif_dist = plt.uniform(-5,5,size=512) # create uniform distribution vector  
304  
305 # plot the histogram with specific: bin number, color, transparency, label  
306 plt.hist(unif_dist, bins=24, histtype='stepfilled',  
307          normed=True, color='cyan', label='Uniform')  
308 plt.hist(gaus_dist, bins=24, histtype='stepfilled',  
309          normed=True, color='orange', label='Gaussian', alpha=0.65)  
310  
311 plt.legend(loc='upper left')  
312 plt.title("Gaussian vs Uniform distribution / Histogram")  
313 plt.xlabel("Value")  
314 plt.ylabel("Frequency")  
315 plt.grid(True)  
316 plt.show()
```

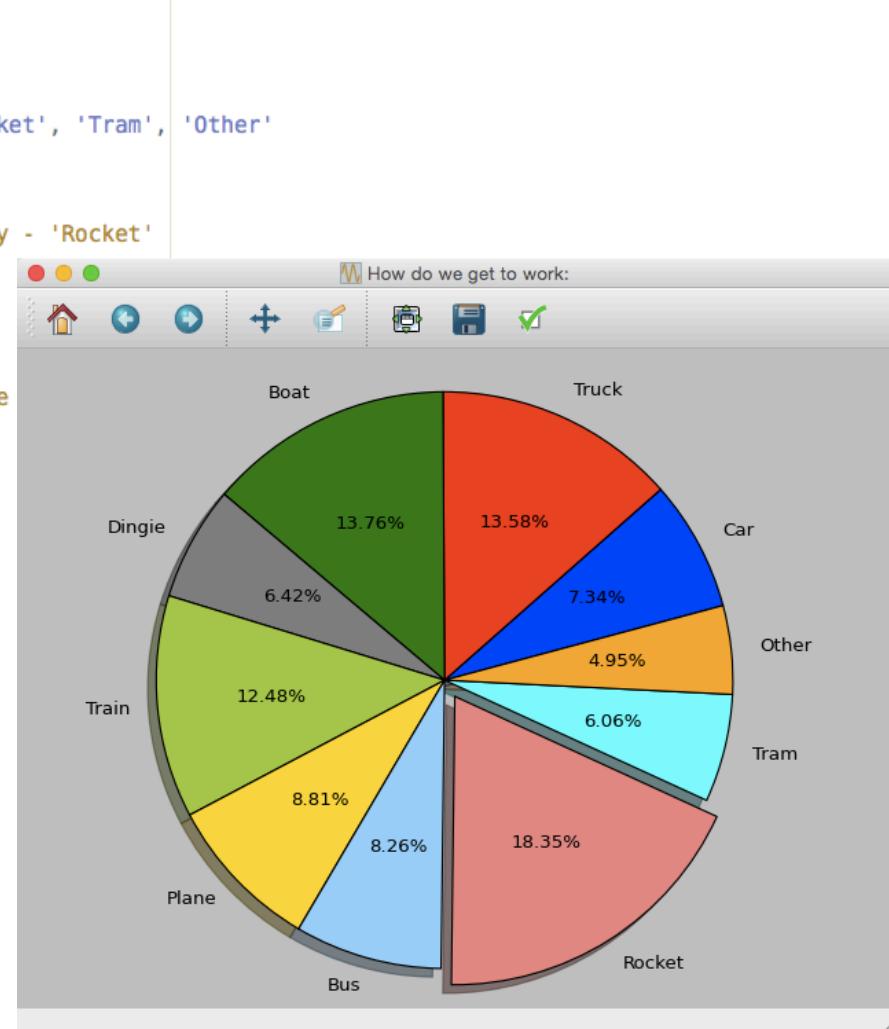
Histogram is **great for** visualizing **statistical distribution** of a set of variables in a given pool of samples, divided into classes called bins



Advanced plotting

- Advanced plotting: *pie chart*

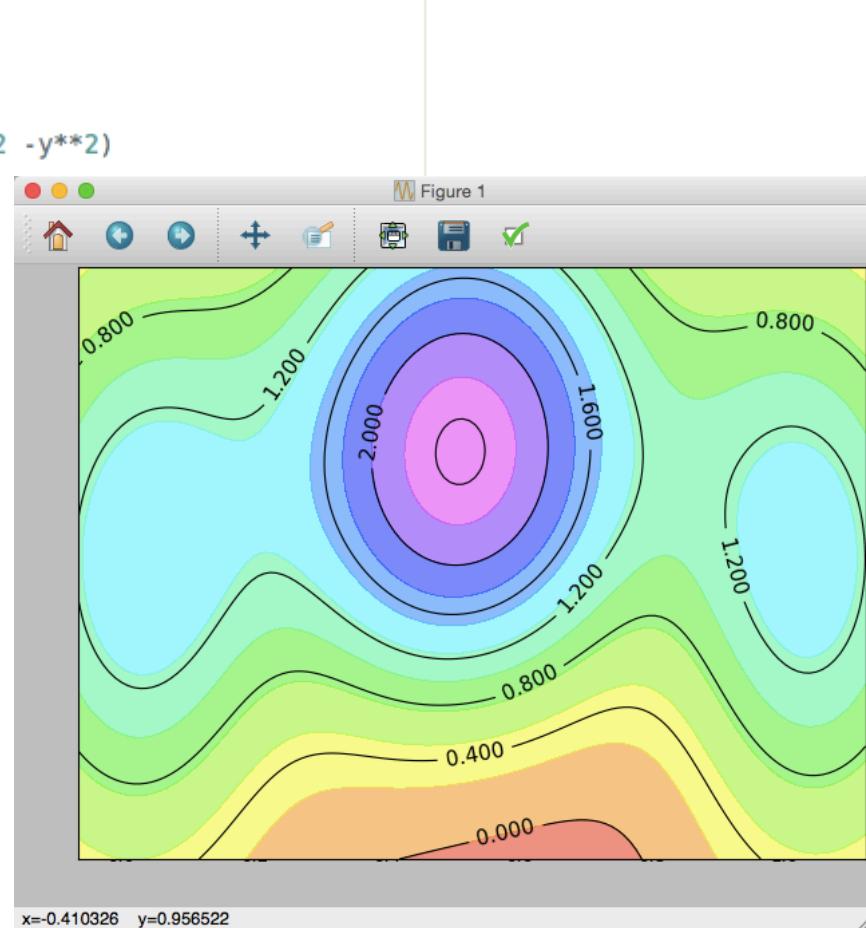
```
318 # Pie chart:
319 plt.figure('How do we get to work:')
320 plt.axes([0.035, 0.035, 0.9, 0.9])
321
322 l = 'Car', 'Truck', 'Boat', 'Dingie', 'Train', 'Plane', 'Bus', 'Rocket', 'Tram', 'Other'
323 b = plt.round_(plt.random(10), decimals=2)
324 c = ['blue', 'red', 'green', 'gray', 'yellowgreen',
325       'gold', 'lightskyblue', 'lightcoral', 'cyan', 'orange']
326 e = (0, 0, 0, 0, 0, 0, 0, 0.05, 0, 0) # 'explode' the 8th slice only - 'Rocket'
327
328 plt.clf()
329 plt.pie(b, explode = e, labels=l, colors=c, radius=.75,
330          autopct='%.2f%%', shadow=True, startangle=15)
331
332 # we set the aspect ratio to 'equal' so the pie is drawn in a circle
333 plt.axis('equal')
334 plt.xticks(()); plt.yticks(())
335 plt.show()
```



Advanced plotting

- Advanced plotting: *contour plot*

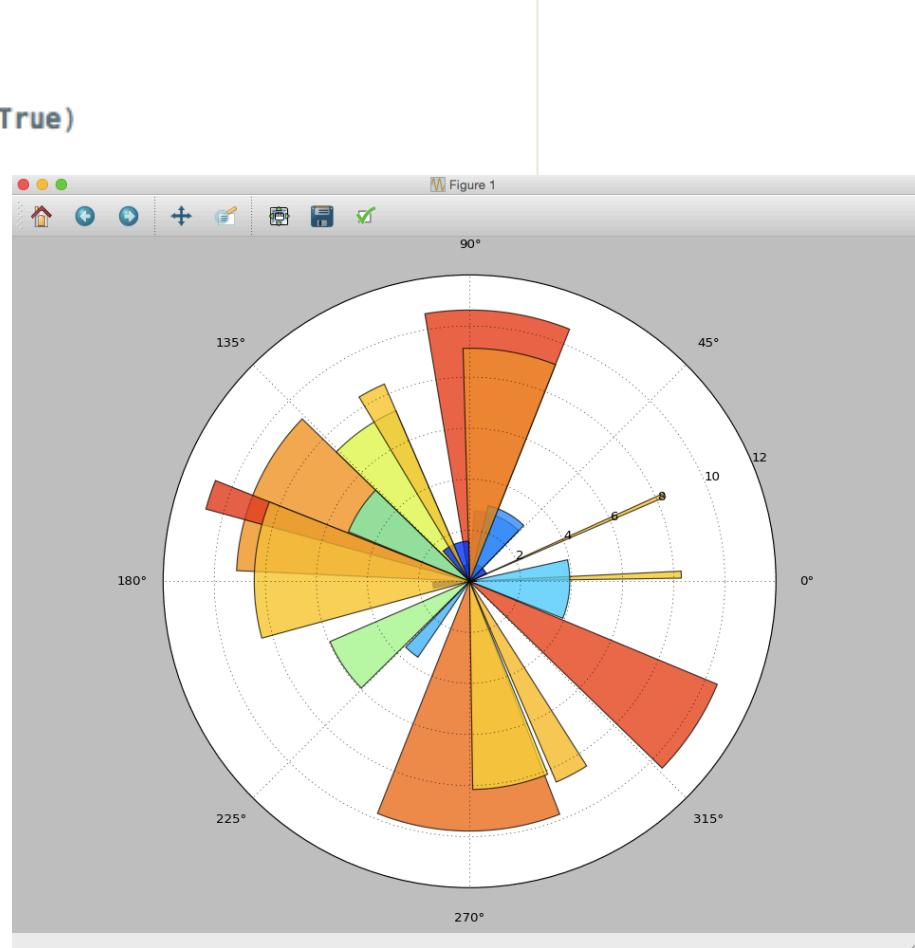
```
337 # Contour plot:  
338 import pylab as plt  
339  
340 def f(x,y):  
341     return (2 - x/3 + x**6 + 2.125*y) * plt.exp(-x**2 -y**2)  
342  
343 n = 128  
344 x = plt.linspace(-2, 2, n)  
345 y = plt.linspace(-1, 1, n)  
346 A,B = plt.meshgrid(x, y)  
347  
348 plt.cla()  
349 plt.axes([0.075, 0.075, 0.92, 0.92])  
350  
351 plt.contourf(A, B, f(A, B), 12, alpha=.50,  
352             cmap=plt.cm.gist_rainbow)  
353 C = plt.contour(A, B, f(A, B), 8, colors='black',  
354                 linewidth=.65)  
355  
356 plt.clabel(C, inline=1, fontsize=14)  
357 plt.xticks(()); plt.yticks()  
358 plt.show()
```



Advanced plotting

- Advanced plotting: *polar plot*

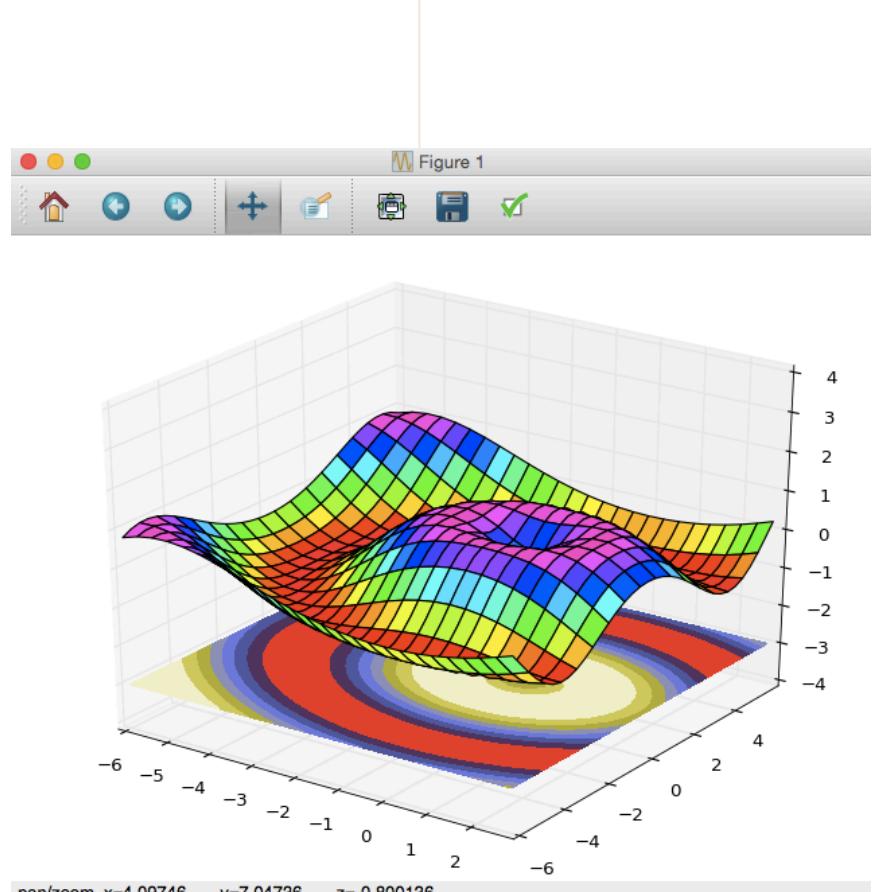
```
360 # Polar plot:  
361 import pylab as plt  
362  
363 a = plt.axes([0.065, 0.065, 0.88, 0.88], polar=True)  
364  
365 q = 24  
366 t = plt.arange(0.015, 3*plt.pi, 3 * plt.pi / q)  
367 rad = 12 * plt.rand(q)  
368 w = plt.pi / 4 * plt.rand(q)  
369 ba = plt.bar(t, rad, width = w)  
370  
371 for r,bar in zip(rad, ba):  
372     bar.set_facecolor(plt.cm.jet(r/12.))  
373     bar.set_alpha(0.75)  
374  
375 plt.show()
```



Advanced plotting

- Advanced plotting: *3-D plot*

```
377 # 3-D plot:  
378 import pylab as plt  
379 from mpl_toolkits.mplot3d import Axes3D  
380  
381 ax = Axes3D(plt.figure())  
382 x = plt.arange(-6, 3, 0.35)  
383 y = plt.arange(-6, 6, 0.35)  
384 x, y = plt.meshgrid(x, y)  
385 k = plt.sqrt(x**2 + y**2)  
386 z = plt.sin(k)  
387  
388 ax.plot_surface(x, y, z, rstride=2, cstride=1,  
389                  cmap=plt.cm.gist_rainbow)  
390 ax.contourf(x, y, z, zdir='z', offset=-3,  
391                  cmap=plt.cm.gist_stern)  
392 ax.set_zlim(-4, 4)  
393  
394 plt.show()
```



pan/zoom, x=4.09746 , y=7.04736 , z=-0.800136

Course Content Outline

- **NumPy 2/3**
 - Array operations
 - Reductions
 - Broadcasting
 - Array: shaping, reshaping, flattening, resizing, dimension changing
 - Data sorting

Midterm

- **NumPy 3/3**
 - Type casting
 - Masking data
 - Organizing arrays
 - Loading data files
 - Dealing with polynomials
 - Good coding practices

Project proposal due

- **Scipy 1/2**
 - What is Scipy?
 - Working with files
 - Algebraic operations
 - The Fast Fourier Transform
 - Signal Processing

HW4

- **Scipy 2/2**
 - Interpolation
 - Statistics
 - Optimization

- **Project**
 - Project Presentation

Final Project

Array operations

- Arrays operations

```
import numpy as np
x = np.array([[1,2],[3,4]], dtype=np.float64)
y = np.array([[5,6],[7,8]], dtype=np.float64)

# Elementwise sum; both produce the array # [[ 6.0 8.0] # [10.0 12.0]]
print(x + y)
print(np.add(x, y))

# Elementwise difference; both produce the array # [[-4.0 -4.0] # [-4.0 -4.0]]
print(x - y)
print(np.subtract(x, y))

# Elementwise product; both produce the array # [[ 5.0 12.0] # [21.0 32.0]]
print(x * y)
print(np.multiply(x, y))

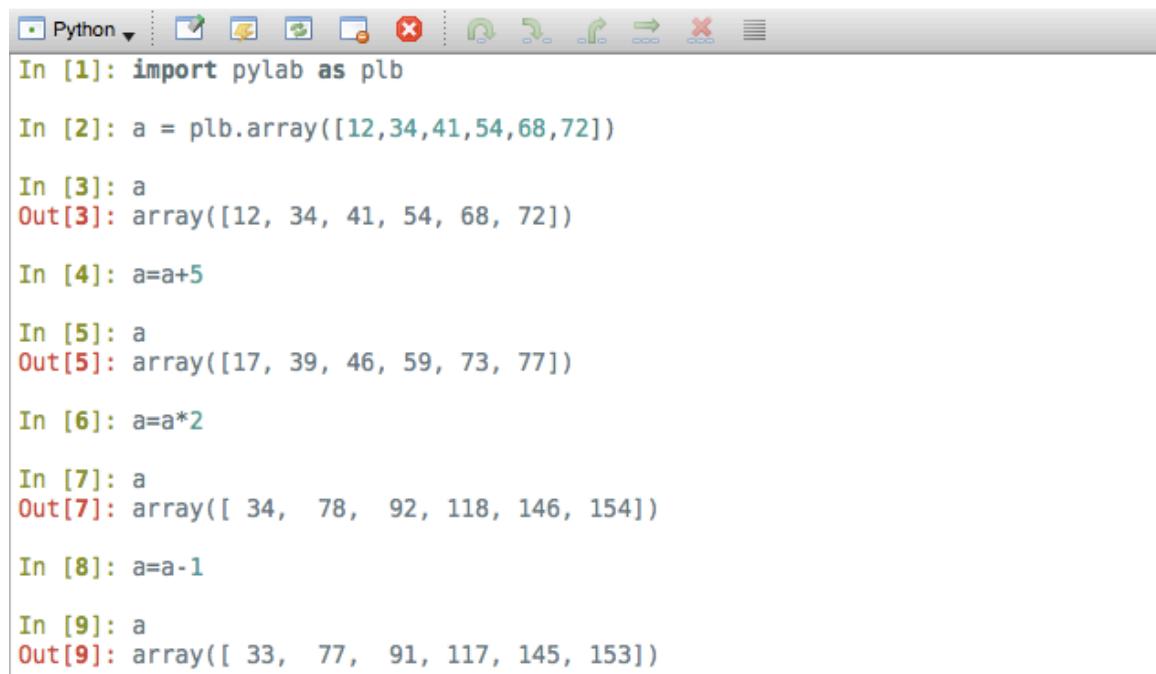
# Elementwise division; both produce the array # [[ 0.2 0.33333333] # [ 0.42857143 0.5 ]]
print(x / y)
print(np.divide(x, y))

# Elementwise square root; produces the array # [[ 1. 1.41421356] # [ 1.73205081 2. ]]
print(np.sqrt(x))
```

Array operations

- Array operations
 - basic **operations of arrays with scalars** are very **simple** and intuitive
 - they performed on **element by element basis**

Examples:



The screenshot shows a Jupyter Notebook interface with a toolbar at the top. Below the toolbar, there are nine code cells labeled In [1] through In [9]. The code consists of importing pylab, creating an array 'a', and performing element-wise operations like addition, multiplication, and subtraction.

```
In [1]: import pylab as plt
In [2]: a = plt.array([12,34,41,54,68,72])
In [3]: a
Out[3]: array([12, 34, 41, 54, 68, 72])
In [4]: a=a+5
In [5]: a
Out[5]: array([17, 39, 46, 59, 73, 77])
In [6]: a=a*2
In [7]: a
Out[7]: array([ 34,  78,  92, 118, 146, 154])
In [8]: a=a-1
In [9]: a
Out[9]: array([ 33,  77,  91, 117, 145, 153])
```

Array operations

- Array operations

- As in any language we need to be aware of NumPy's **precedence**:

- `()` – has the highest precedence order. The inner most bracket expression has the highest precedence
- `F(args...)` – Function calls
- `x[ind:ind]` – Slicing
- `x[index]` – Subscription
- `x.attribute` – Attribute reference
- `**` – power, exponentiation
- `~x` – bitwise not
- `+x, -x` – positive and negative signs
- `*, /, %` – multiplication, division, remainder
- `+, -` – addition, subtraction
- `<<, >>` – bitwise shift
- `&` – bitwise and
- `^` – bitwise xor (exclusive or, meaning both values must be mutually exclusive)
- `|` – bitwise or
- `in, is, not in, is not, <, <=, >, >=, <>, !=, ==` – comparison, membership and identity tests
- `not x` – boolean NOT
- `and` – boolean AND
- `or` – boolean OR

conversions: `bin(x)` – int to bin, `int('0011001', 2)` – bin to int

Examples:

$$e \& f | z == (e \& f) | z \quad e | f \& z == e | (f \& z) , \quad \text{where } z = e \& f$$

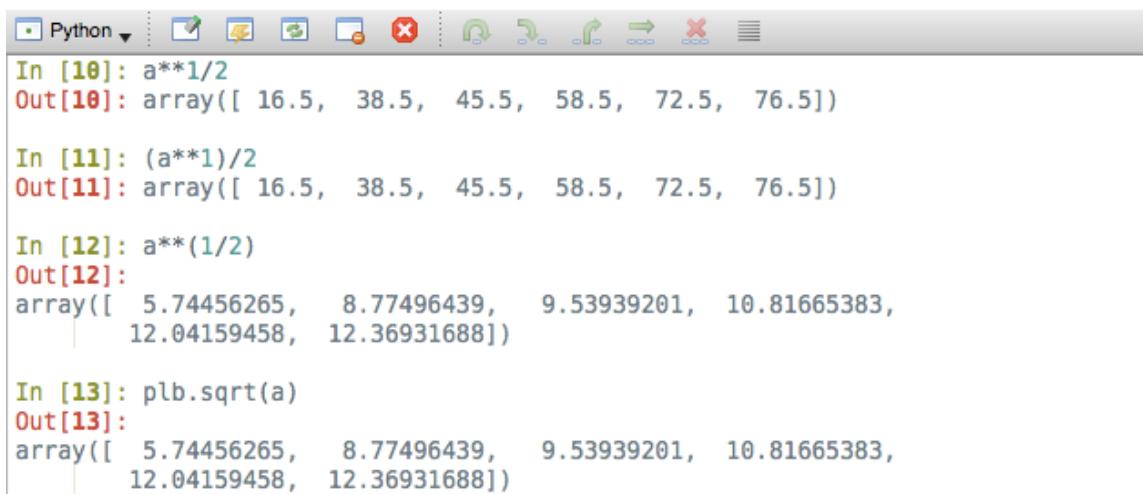
Array operations

- Array operations

- **associativity:**

- $(12 - 32) + 41 = 21 \rightarrow$ left-associative
 - $12 - (32 + 41) = -61 \rightarrow$ right-associative

Examples:



The screenshot shows a Jupyter Notebook interface with a Python kernel. The code cell contains the following Python code and its corresponding output:

```
In [10]: a**1/2
Out[10]: array([ 16.5,  38.5,  45.5,  58.5,  72.5,  76.5])

In [11]: (a**1)/2
Out[11]: array([ 16.5,  38.5,  45.5,  58.5,  72.5,  76.5])

In [12]: a**(1/2)
Out[12]:
array([ 5.74456265,  8.77496439,  9.53939201, 10.81665383,
       12.04159458, 12.36931688])

In [13]: plb.sqrt(a)
Out[13]:
array([ 5.74456265,  8.77496439,  9.53939201, 10.81665383,
       12.04159458, 12.36931688])
```

Array operations

- Array operations
 - arithmetic operations between arrays are also performed element by element
 - NumPy operations are much faster than the ones used by basic math in Python

Examples:

```
Python 
In [14]: b = plt.arange(6)+4
In [15]: b
Out[15]: array([4, 5, 6, 7, 8, 9])

In [16]: a-b
Out[16]: array([-29, -72, -85, -110, -137, -144])

In [17]: a/b
Out[17]:
array([  8.25        ,   15.4        ,  15.16666667,  16.71428571,
       18.125        ,   17.        ])

In [18]: c = plt.ones(6)

In [19]: c=(a+b)**2-plt.sqrt(c)

In [20]: c
Out[20]: array([ 1368.,   6723.,   9408.,  15375.,  23408.,  26243.])

In [21]: d = plt.arange(5)

In [22]: plt.size(a)
Out[22]: 6

In [23]: plt.size(d)
Out[23]: 5

In [24]: a-d
-----
ValueError                                     Traceback (most recent call last)
<ipython-input-24-ba0eb01b3f36> in <module>()
      1 a-d
-----
```

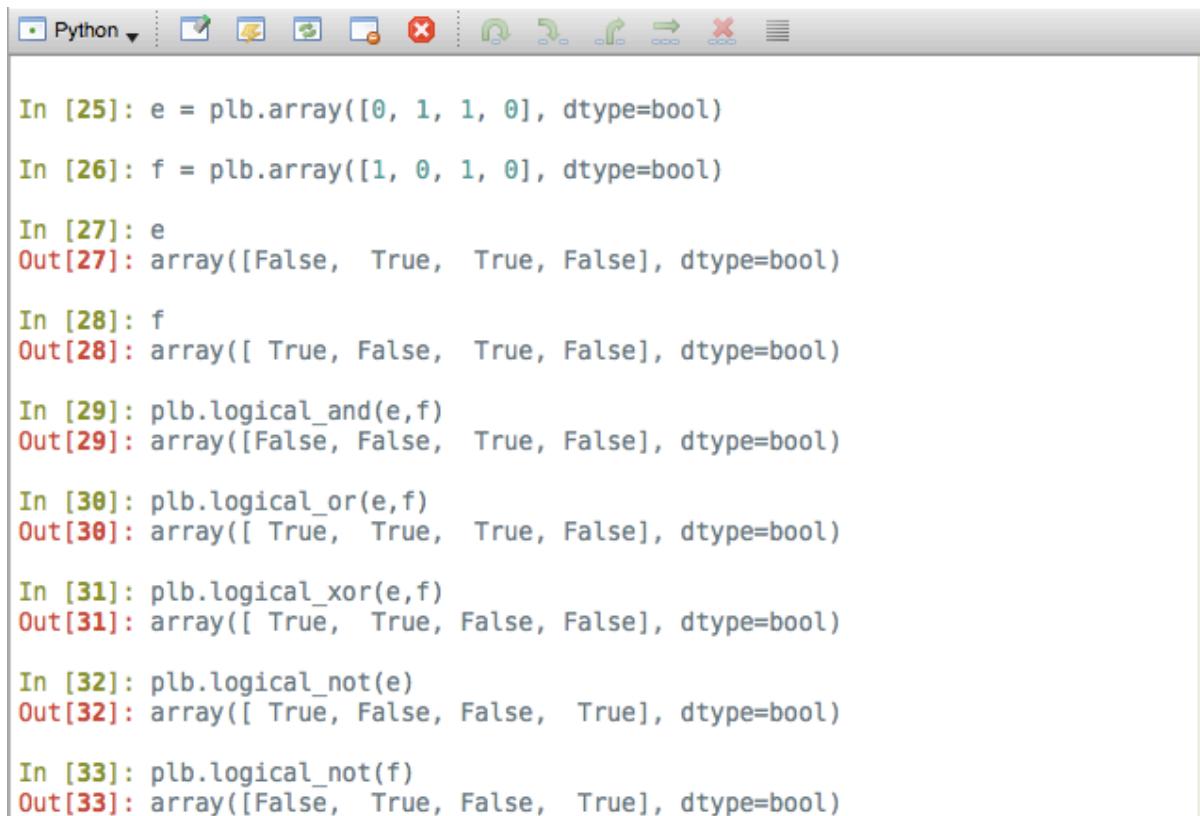
ValueError: operands could not be broadcast together with shapes (6,) (5,)

when performing operations
between arrays they must ->
be of the same shape

Array operations

- Array operations
 - logical operations are built in NumPy

Examples:



The screenshot shows a Jupyter Notebook interface with a Python kernel. The toolbar at the top includes icons for file operations, search, and help. Below the toolbar, the code cells are numbered 25 through 33. Each cell contains an input line starting with 'In [number]:' and an output line starting with 'Out[number]:'. The code demonstrates various logical operations on boolean arrays 'e' and 'f'.

```
In [25]: e = plb.array([0, 1, 1, 0], dtype=bool)
In [26]: f = plb.array([1, 0, 1, 0], dtype=bool)
In [27]: e
Out[27]: array([False,  True,  True, False], dtype=bool)
In [28]: f
Out[28]: array([ True, False,  True, False], dtype=bool)
In [29]: plb.logical_and(e,f)
Out[29]: array([False, False,  True, False], dtype=bool)
In [30]: plb.logical_or(e,f)
Out[30]: array([ True,  True,  True, False], dtype=bool)
In [31]: plb.logical_xor(e,f)
Out[31]: array([ True,  True, False, False], dtype=bool)
In [32]: plb.logical_not(e)
Out[32]: array([ True, False, False,  True], dtype=bool)
In [33]: plb.logical_not(f)
Out[33]: array([False,  True, False,  True], dtype=bool)
```

Array operations

- Array operations
 - arrays in NumPy can be compared in a element by element basis easily:

Examples:

```
In [34]: e
Out[34]: array([False,  True,  True, False], dtype=bool)

In [35]: f
Out[35]: array([ True, False,  True, False], dtype=bool)

In [36]: e == f
Out[36]: array([False, False,  True,  True], dtype=bool)

In [37]: e > f
Out[37]: array([False,  True, False, False], dtype=bool)

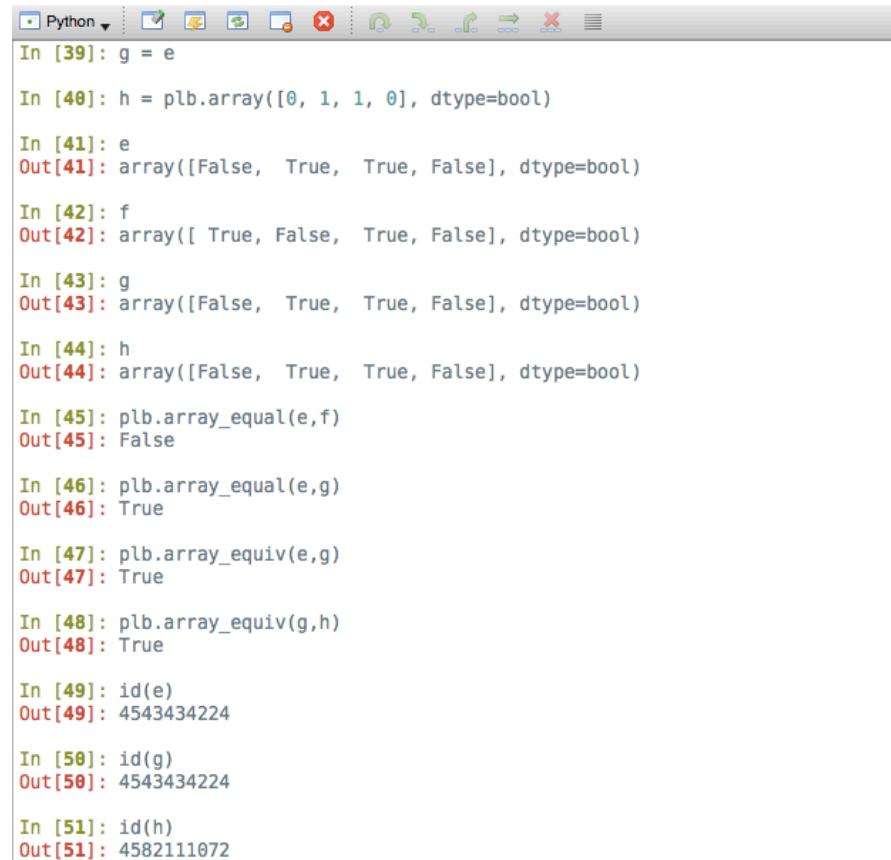
In [38]: e < f
Out[38]: array([ True, False, False, False], dtype=bool)
```

Array operations

- Array operations

- arrays in NumPy can also be compared as whole vectors:

Examples:



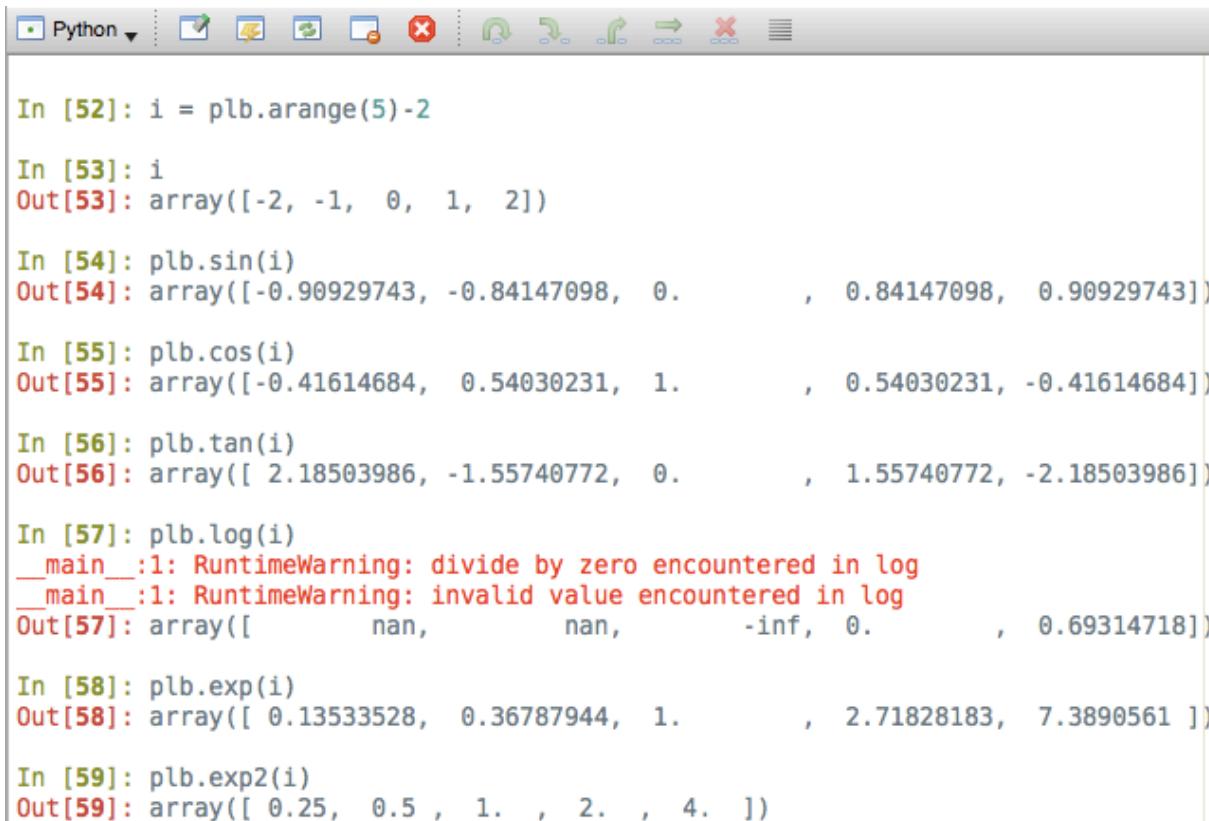
```
Python In [39]: g = e
In [40]: h = plb.array([0, 1, 1, 0], dtype=bool)
In [41]: e
Out[41]: array([False,  True,  True, False], dtype=bool)
In [42]: f
Out[42]: array([ True, False,  True, False], dtype=bool)
In [43]: g
Out[43]: array([False,  True,  True, False], dtype=bool)
In [44]: h
Out[44]: array([False,  True,  True, False], dtype=bool)
In [45]: plb.array_equal(e,f)
Out[45]: False
In [46]: plb.array_equal(e,g)
Out[46]: True
In [47]: plb.array_equiv(e,g)
Out[47]: True
In [48]: plb.array_equiv(g,h)
Out[48]: True
In [49]: id(e)
Out[49]: 4543434224
In [50]: id(g)
Out[50]: 4543434224
In [51]: id(h)
Out[51]: 4582111072
```

Array operations

- Array operations
 - one can take the *sin*, *cos*, *tan*, *log*, *exp* or *exp2* of an array easily in NumPy:

Examples:

be aware of your
data to avoid this ->



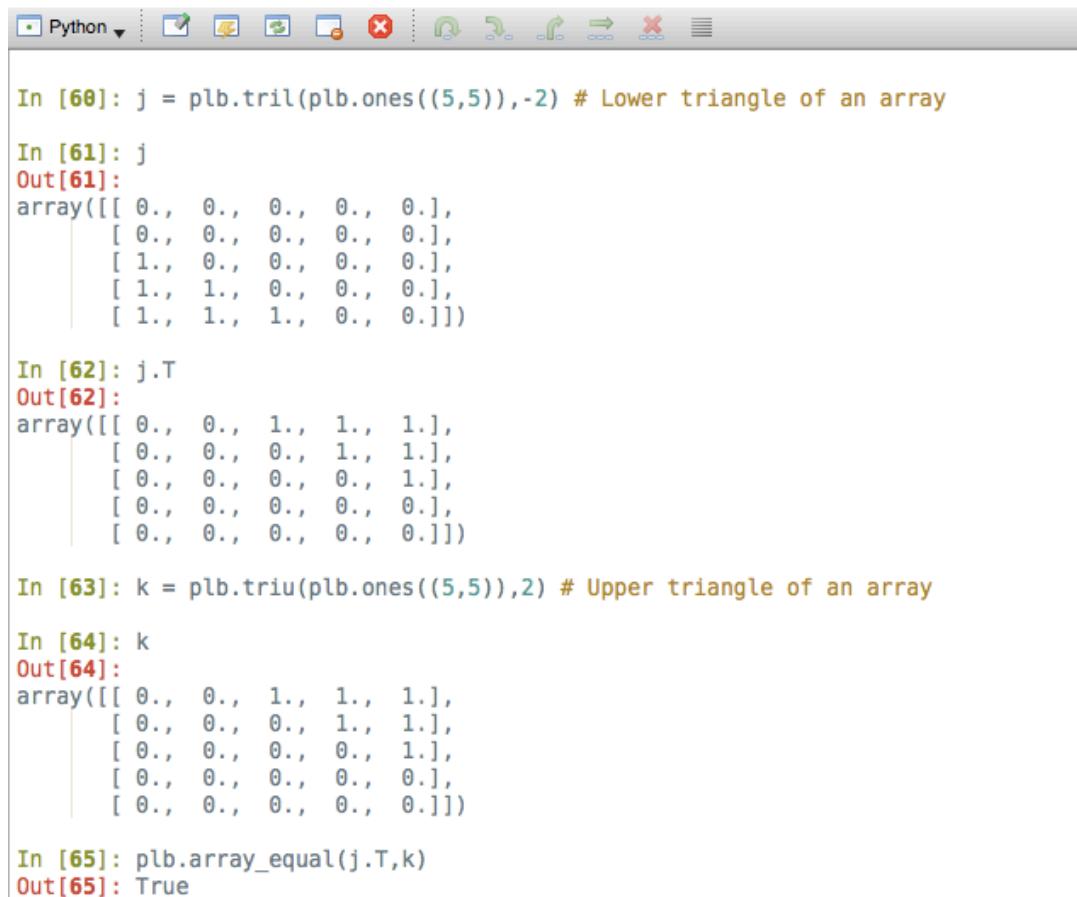
The screenshot shows a Jupyter Notebook interface with a toolbar at the top. Below the toolbar, there are several code cells labeled In [52] through In [59]. The code in each cell uses the `plt` module to perform various mathematical operations on an array `i`. The output for each cell is shown in red. Cells In [52] through In [58] show standard numerical results. Cell In [59] shows a warning about divide by zero and invalid values, followed by the resulting array.

```
In [52]: i = plt.arange(5)-2
In [53]: i
Out[53]: array([-2, -1,  0,  1,  2])
In [54]: plt.sin(i)
Out[54]: array([-0.90929743, -0.84147098,  0.          ,  0.84147098,  0.90929743])
In [55]: plt.cos(i)
Out[55]: array([-0.41614684,  0.54030231,  1.          ,  0.54030231, -0.41614684])
In [56]: plt.tan(i)
Out[56]: array([ 2.18503986, -1.55740772,  0.          ,  1.55740772, -2.18503986])
In [57]: plt.log(i)
__main__:1: RuntimeWarning: divide by zero encountered in log
__main__:1: RuntimeWarning: invalid value encountered in log
Out[57]: array([      nan,       nan,      -inf,   0.          ,  0.69314718])
In [58]: plt.exp(i)
Out[58]: array([ 0.13533528,  0.36787944,  1.          ,  2.71828183,  7.3890561 ])
In [59]: plt.exp2(i)
Out[59]: array([ 0.25,  0.5 ,  1.  ,  2.  ,  4.  ])
```

Array operations

- Array operations

- Transpose an array in NumPy is performed like this:

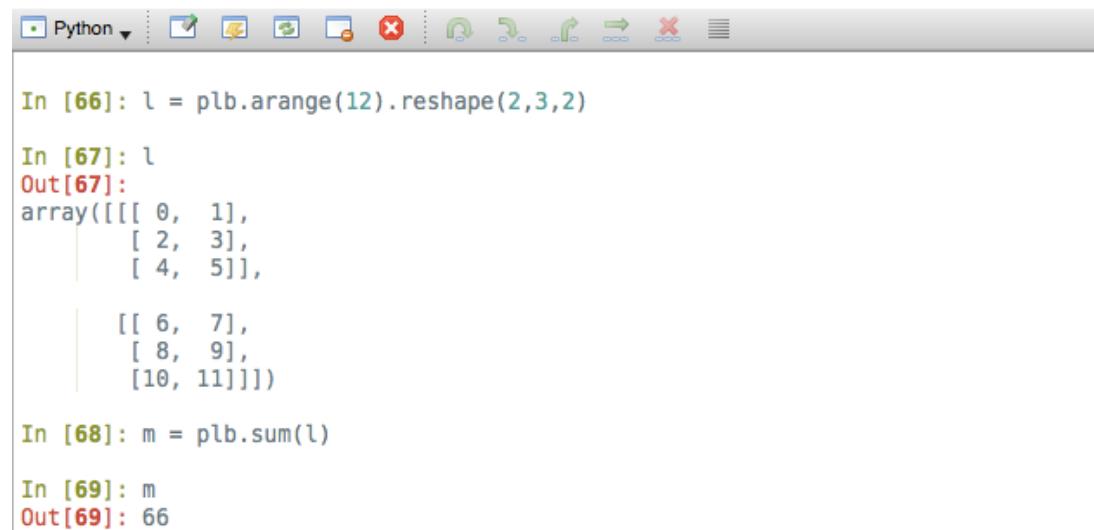


```
In [60]: j = plt.tril(plt.ones((5,5)), -2) # Lower triangle of an array
In [61]: j
Out[61]:
array([[ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.],
       [ 1.,  0.,  0.,  0.,  0.],
       [ 1.,  1.,  0.,  0.,  0.],
       [ 1.,  1.,  1.,  0.,  0.]])
In [62]: j.T
Out[62]:
array([[ 0.,  0.,  1.,  1.,  1.],
       [ 0.,  0.,  0.,  1.,  1.],
       [ 0.,  0.,  0.,  0.,  1.],
       [ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.]])
In [63]: k = plt.triu(plt.ones((5,5)), 2) # Upper triangle of an array
In [64]: k
Out[64]:
array([[ 0.,  0.,  1.,  1.,  1.],
       [ 0.,  0.,  0.,  1.,  1.],
       [ 0.,  0.,  0.,  0.,  1.],
       [ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.]])
In [65]: plt.array_equal(j.T, k)
Out[65]: True
```

Reductions

- Reductions
 - reduction is an **array operation** in which a **special set of array elements** is produced based on a selection or mathematical operation
 - In NumPy there are several methods that process arrays as input and can create a new set of array elements as output based on specific requirements
 - one of the **most basic** methods for **reduction** is *sum*

Examples:



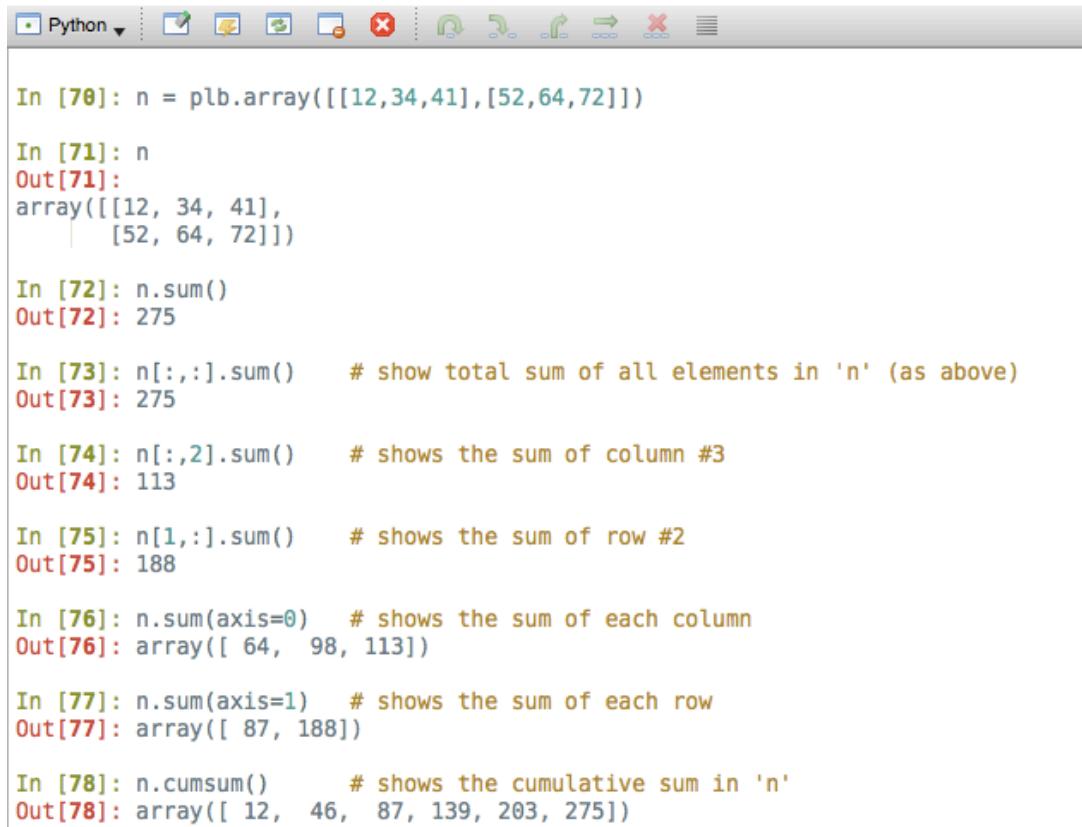
The screenshot shows a Jupyter Notebook interface with a Python kernel. The toolbar at the top includes icons for file operations, cell execution, and help. Below the toolbar, the code cell content is displayed.

```
In [66]: l = plt.arange(12).reshape(2,3,2)
In [67]: l
Out[67]:
array([[[ 0,  1],
       [ 2,  3],
       [ 4,  5]],
      [[ 6,  7],
       [ 8,  9],
       [10, 11]])]
In [68]: m = plt.sum(l)
In [69]: m
Out[69]: 66
```

Reductions

- Reductions
 - *sum* can be performed on specific set of elements from an array such as rows and columns:

Examples:



```
In [70]: n = plb.array([[12,34,41],[52,64,72]])
In [71]: n
Out[71]:
array([[12, 34, 41],
       [52, 64, 72]])

In [72]: n.sum()
Out[72]: 275

In [73]: n[:, :].sum()      # show total sum of all elements in 'n' (as above)
Out[73]: 275

In [74]: n[:, 2].sum()      # shows the sum of column #3
Out[74]: 113

In [75]: n[1, :].sum()      # shows the sum of row #2
Out[75]: 188

In [76]: n.sum(axis=0)      # shows the sum of each column
Out[76]: array([ 64,  98, 113])

In [77]: n.sum(axis=1)      # shows the sum of each row
Out[77]: array([ 87, 188])

In [78]: n.cumsum()         # shows the cumulative sum in 'n'
Out[78]: array([ 12,  46,  87, 139, 203, 275])
```

Reductions

- Reductions
 - logical operations can be performed on rows and columns:

Examples:



```
In [79]: n
Out[79]:
array([[12, 34, 41],
       [52, 64, 72]])

In [80]: p = plb.array([[12,34,41,0],[52,64,0,72]])

In [81]: p
Out[81]:
array([[12, 34, 41,  0],
       [52, 64,  0, 72]])

In [82]: plb.any(p != 0)      # show if there are any elements different than '0'
Out[82]: True

In [83]: plb.all(p != 0)     # show if all elements are different than '0'
Out[83]: False

In [84]: plb.any(p != n)     # show if any elements in 'p' and 'n' are different
Out[84]: True

In [85]: n!=p                  # show if 'n' is different than 'p'
Out[85]: True

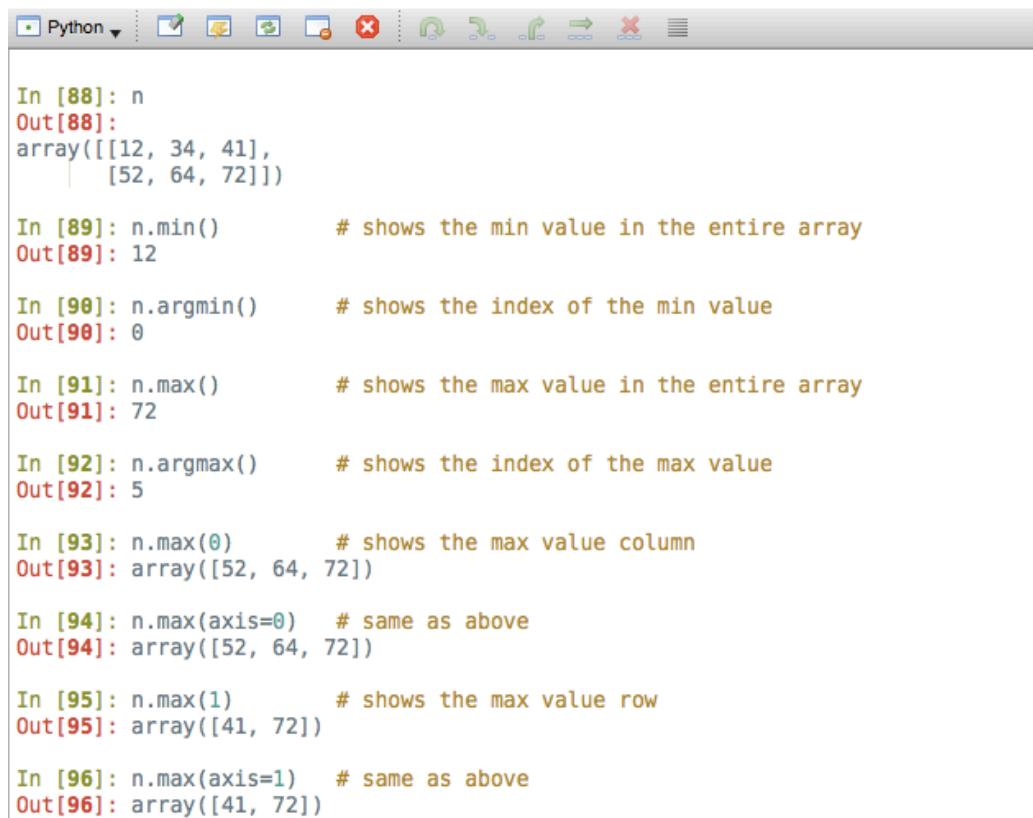
In [86]: n.sum()!=p.sum()      # show if total sum in 'n' is different than the one in 'p'
Out[86]: False

In [87]: n.sum()==p.sum()      # show if total sum in 'n' and 'p' is the same
Out[87]: True
```

Reductions

- Reductions

- *min, max* extremes can be performed on specific set of elements from an array such as rows and columns:



The screenshot shows a Jupyter Notebook interface with a toolbar at the top. Below the toolbar, there are several code cells. The first cell (In [88]) creates a 2D array n. Subsequent cells demonstrate various reduction operations: min, argmin, max, argmax, max along a column (axis=0), max along a row (axis=1), and max with axis specified (axis=1).

```
In [88]: n
Out[88]:
array([[12, 34, 41],
       [52, 64, 72]])

In [89]: n.min()          # shows the min value in the entire array
Out[89]: 12

In [90]: n.argmax()        # shows the index of the min value
Out[90]: 0

In [91]: n.max()          # shows the max value in the entire array
Out[91]: 72

In [92]: n.argmax()        # shows the index of the max value
Out[92]: 5

In [93]: n.max(0)          # shows the max value column
Out[93]: array([52, 64, 72])

In [94]: n.max(axis=0)    # same as above
Out[94]: array([52, 64, 72])

In [95]: n.max(1)          # shows the max value row
Out[95]: array([41, 72])

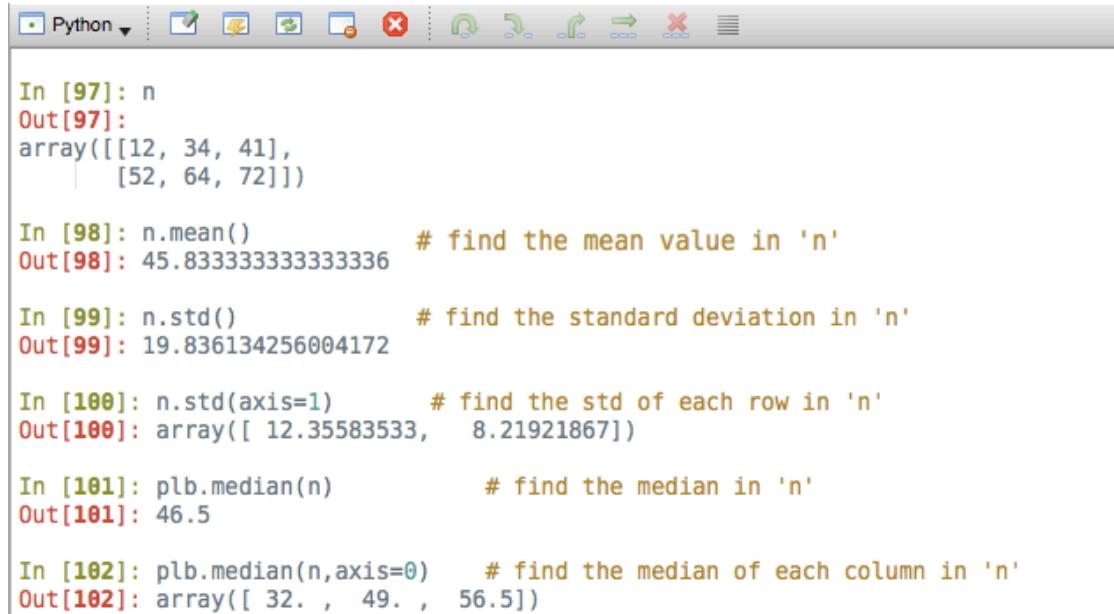
In [96]: n.max(axis=1)    # same as above
Out[96]: array([41, 72])
```

Examples:

Reductions

- Reductions
 - `statistics` can be performed on the arrays as well as on rows and columns:

Examples:



The screenshot shows a Jupyter Notebook interface with a toolbar at the top. Below the toolbar, there are several code cells and their corresponding outputs.

```
In [97]: n
Out[97]:
array([[12, 34, 41],
       [52, 64, 72]])

In [98]: n.mean()          # find the mean value in 'n'
Out[98]: 45.83333333333336

In [99]: n.std()           # find the standard deviation in 'n'
Out[99]: 19.836134256004172

In [100]: n.std(axis=1)    # find the std of each row in 'n'
Out[100]: array([ 12.35583533,   8.21921867])

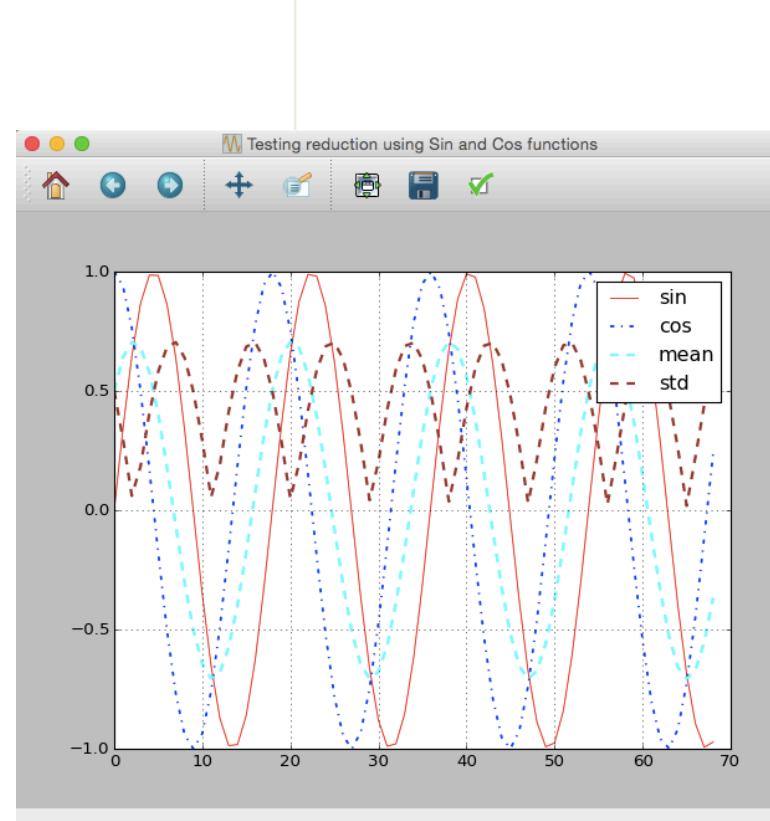
In [101]: plb.median(n)     # find the median in 'n'
Out[101]: 46.5

In [102]: plb.median(n, axis=0)  # find the median of each column in 'n'
Out[102]: array([ 32. ,  49. ,  56.5])
```

Reductions

- Reductions
 - taking the mean and std values of *sin* vs *cos* functions:

```
134 # Example using reduction:  
135 import pylab as plt  
136  
137 x0 = plt.arange(0, 24, 0.35)  
138 x1 = plt.sin(x0)  
139 x2 = plt.cos(x0)  
140 fig = plt.mean([x1,x2],axis=0)  
141 plt.figure('Testing reduction using Sin and Cos functions')  
142 plt.plot(x1,color='r', linewidth=0.8, label='sin')  
143 plt.plot(x2,color='b', linewidth=1.5, linestyle='--',  
144 label='cos')  
145  
146 # plot the mean values of the sin and cos functions:  
147 plt.plot(plt.mean([x1,x2],axis=0), color='cyan', linewidth=2,  
148 linestyle='--', label='mean')  
149  
150 # plot the std values of the sin and cos functions:  
151 plt.plot(plt.std([x1,x2],axis=0), color='brown', linewidth=2,  
152 linestyle='--', label='std')  
153 plt.legend(loc='upper right')  
154 plt.grid(True)  
155 plt.show()
```



Broadcasting

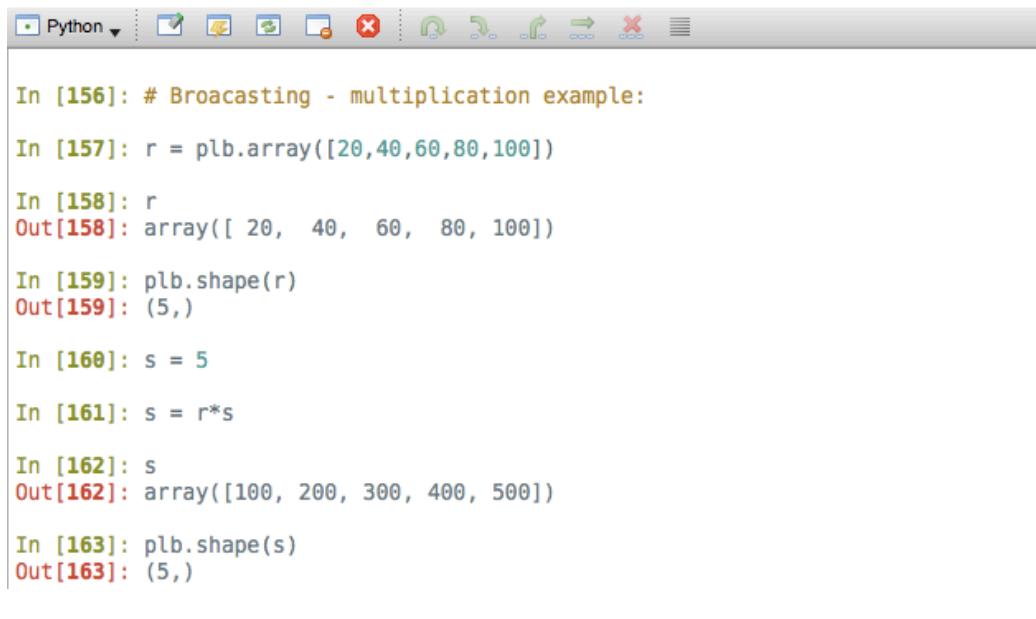
- Broadcasting
 - normally any **operation on arrays** will **require** them to be of the **same size and shape**, like in Matlab
 - in some cases where this rule is not met, **NumPy has a way of overcoming that problem whenever possible**
 - this is called **Broadcasting**
 - in a simple **multiplication of arrays with scalars** (which we have seen so far) this is exactly what NumPy is doing
 - in order to solve the problem **NymPy automatically changes the shape of some arrays or scalars** by repeating some values in order to complete the task

Broadcasting

- Broadcasting

- in this example we **multiply an array with a scalar** and the latter changes its shape by repeating the same scalar to match the shape of the array
- only after this rule is satisfied the multiplication can be performed

Example:



```
In [156]: # Broacasting - multiplication example:  
In [157]: r = plb.array([20,40,60,80,100])  
In [158]: r  
Out[158]: array([ 20,  40,  60,  80, 100])  
In [159]: plb.shape(r)  
Out[159]: (5,)  
In [160]: s = 5  
In [161]: s = r*s  
In [162]: s  
Out[162]: array([100, 200, 300, 400, 500])  
In [163]: plb.shape(s)  
Out[163]: (5,)
```

r	*	s	s - repeated	=	s
20 40 60 80 100	*	5	5 5 5 5 5	=	100 200 300 400 500

Broadcasting

- Broadcasting
 - in this example we **add two arrays of different sizes and shapes**
 - we notice that in order for the addition to be performed both shapes were changed

Example:

```
Python In [164]: # Broadcasting - addition example:  
In [165]: r = plb.array([20,40,60,80,100]).reshape(5,1)  
  
In [166]: r  
Out[166]:  
array([[ 20],  
       [ 40],  
       [ 60],  
       [ 80],  
       [100]])  
  
In [167]: plb.shape(r)  
Out[167]: (5, 1)  
  
In [168]: s = plb.arange(2,4)  
  
In [169]: s  
Out[169]: array([2, 3])  
  
In [170]: plb.shape(s)  
Out[170]: (2,)  
  
In [171]: t = r+s  
  
In [172]: t  
Out[172]:  
array([[ 22,  23],  
       [ 42,  43],  
       [ 62,  63],  
       [ 82,  83],  
       [102, 103]])  
  
In [173]: plb.shape(t)  
Out[173]: (5, 2)
```

r	r - rep.		s		t
20	20		2 3		22 23
40	40		2 3		42 43
60	60	+	2 3	=	62 63
80	80		2 3		82 83
100	100		2 3		102 103

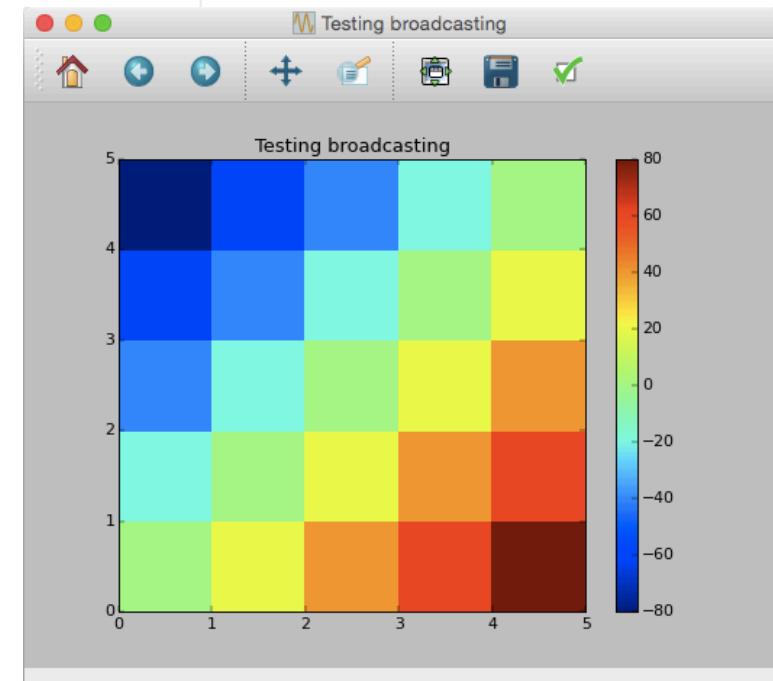
Broadcasting

- Broadcasting

Example:

```
183 ## Broadcasting - example of a 2-D array or square matrix with diagonal = 0:  
184 r = plt.array([20,40,60,80,100])  
185 print(s)  
186 r[:,plt.newaxis] # change the shape of 'r' and add a new axis - 2-D array  
187 s = r - r[:,plt.newaxis] # create a square matrix with diagonal = 0  
188 print(s)  
189  
190 plt.figure('Testing broadcasting', dpi=65)  
191 plt.gca(title='Testing broadcasting')  
192 plt.pcolormesh(s) # choosing the printing scheme  
193 plt.colorbar() # adding a colorbar on the side for clarity  
194 plt.pause(1)
```

newaxis – expands the dimensions by one unit-length dimension

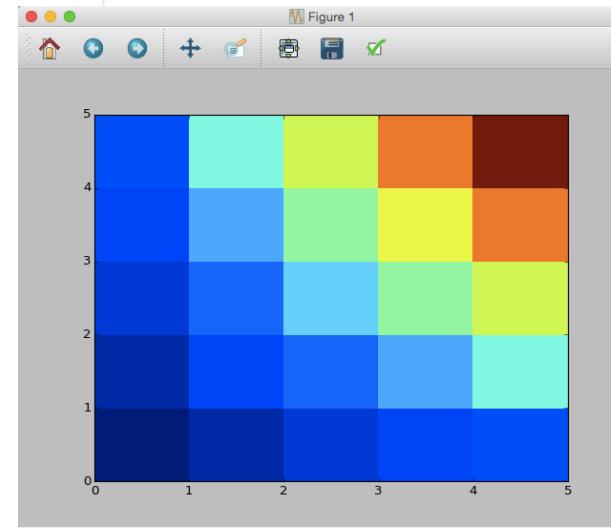


Broadcasting

- Broadcasting

- the Numpy function *ogrid* assists us in making horizontal and vertical shape vector arrays in one line
- we can also assign the **x** and **y** axis to different variables

```
Python In [174]: # Broadcasting - 'ogrid' example:  
In [175]: plt.ogrid[1:6, 1:6]  
Out[175]:  
[array([[1],  
       [2],  
       [3],  
       [4],  
       [5]]), array([[1, 2, 3, 4, 5]])]  
  
In [176]: u, v = plt.ogrid[1:6, 1:6]      # assign x,y axis to u,v variables  
  
In [177]: u  
Out[177]:  
array([[1],  
       [2],  
       [3],  
       [4],  
       [5]])  
  
In [178]: v  
Out[178]: array([[1, 2, 3, 4, 5]])  
  
In [179]: u*v  
Out[179]:  
array([[ 1,  2,  3,  4,  5],  
       [ 2,  4,  6,  8, 10],  
       [ 3,  6,  9, 12, 15],  
       [ 4,  8, 12, 16, 20],  
       [ 5, 10, 15, 20, 25]])  
  
In [180]: plt.pcolormesh(u*v)  
Out[180]: <matplotlib.collections.QuadMesh at 0x1059bc208>
```



Broadcasting

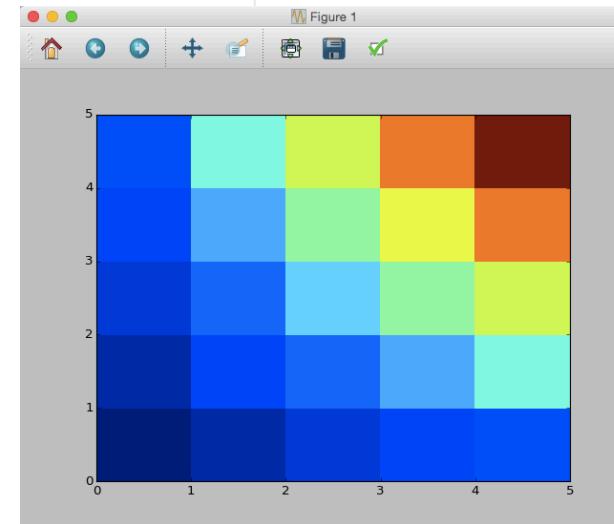
- Broadcasting

- Numpy also provides the function *mgrid*, designed specifically to provide matrices full of indices in case we can't take a full advantage from broadcasting

Example:

```
In [181]: # Broadcasting - 'mgrid' example:  
  
In [182]: plb.mgrid[1:6, 1:6]  
Out[182]:  
array([[[1, 1, 1, 1, 1],  
       [2, 2, 2, 2, 2],  
       [3, 3, 3, 3, 3],  
       [4, 4, 4, 4, 4],  
       [5, 5, 5, 5, 5]],  
  
      [[1, 2, 3, 4, 5],  
       [1, 2, 3, 4, 5],  
       [1, 2, 3, 4, 5],  
       [1, 2, 3, 4, 5],  
       [1, 2, 3, 4, 5]]])  
  
In [183]: u, v = plb.mgrid[1:6, 1:6]  
  
In [184]: u*v  
Out[184]:  
array([[ 1,  2,  3,  4,  5],  
       [ 2,  4,  6,  8, 10],  
       [ 3,  6,  9, 12, 15],  
       [ 4,  8, 12, 16, 20],  
       [ 5, 10, 15, 20, 25]])  
  
In [185]: plb.pcolormesh(u*v)  
Out[185]: <matplotlib.collections.QuadMesh at 0x105944780>
```

we get the same result

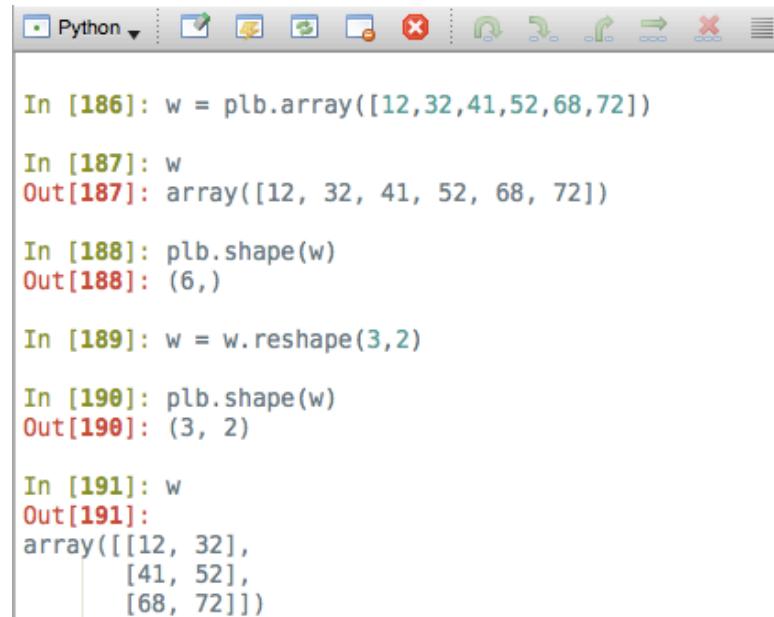


Arrays

- Array: shaping, reshaping, flattening, resizing, dimension changing
 - array manipulation in NumPy is supported by several built in functions such as:
`shape`, `reshape`, `ravel`, `resize`, `newaxis`
 - there are several common techniques we will consider in the next few slides

Using `shape/reshape`:

(we have already used them)



```
In [186]: w = plb.array([12,32,41,52,68,72])
In [187]: w
Out[187]: array([12, 32, 41, 52, 68, 72])

In [188]: plb.shape(w)
Out[188]: (6,)

In [189]: w = w.reshape(3,2)

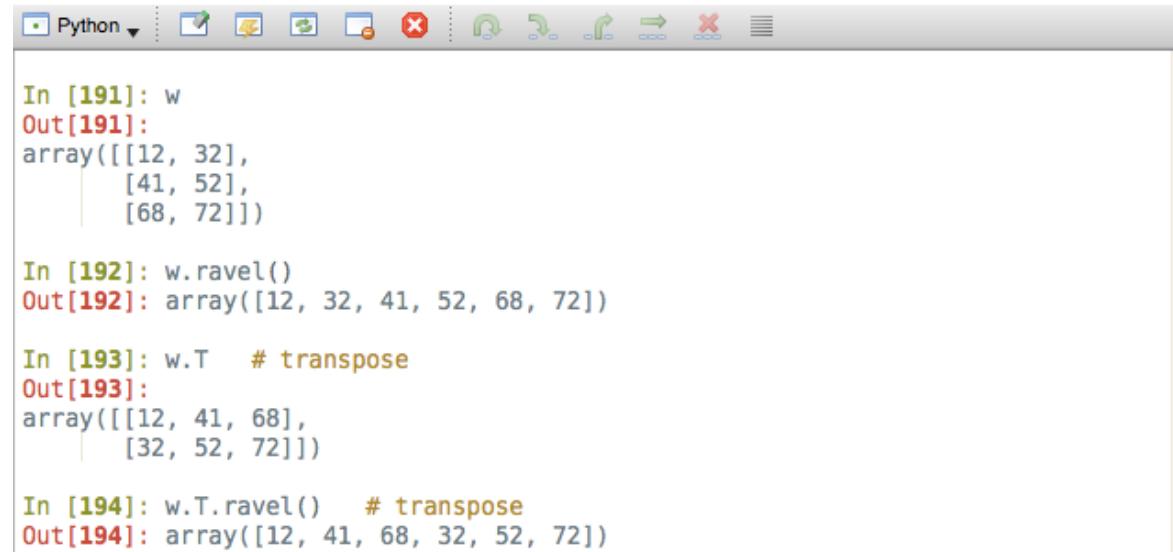
In [190]: plb.shape(w)
Out[190]: (3, 2)

In [191]: w
Out[191]:
array([[12, 32],
       [41, 52],
       [68, 72]])
```

Arrays

- Array: shaping, reshaping, flattening, resizing, dimension changing
 - array manipulation in NumPy is supported by several built in functions such as:
`shape`, `reshape`, `ravel`, `resize`, `newaxis`
 - there are several common techniques we will consider in the next few slides

Using `ravel` for flattening,
hence representing a
multidimensional array
in a flat 1-D vector:



```
In [191]: w
Out[191]:
array([[12, 32],
       [41, 52],
       [68, 72]])

In [192]: w.ravel()
Out[192]: array([12, 32, 41, 52, 68, 72])

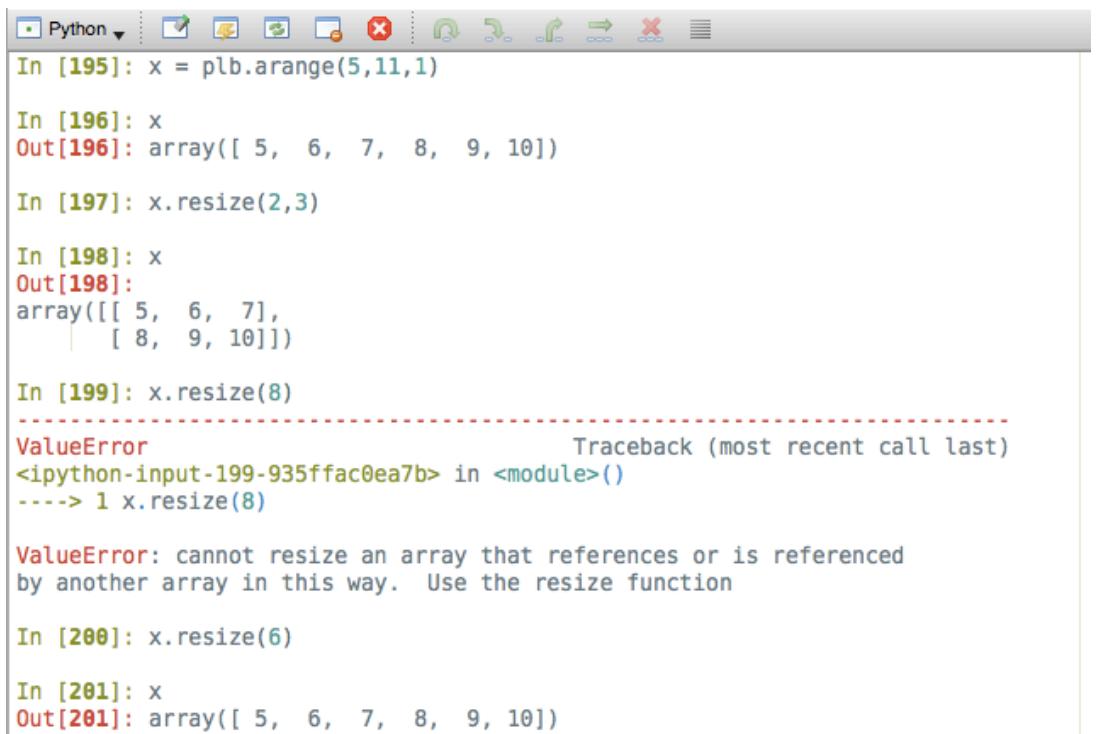
In [193]: w.T    # transpose
Out[193]:
array([[12, 41, 68],
       [32, 52, 72]])

In [194]: w.T.ravel()    # transpose
Out[194]: array([12, 41, 68, 32, 52, 72])
```

Arrays

- Array: shaping, reshaping, flattening, resizing, dimension changing
 - array manipulation in NumPy is supported by several built in functions such as:
shape, reshape, ravel, resize, newaxis
 - there are several common techniques we will consider in the next few slides

Using **resize** for resizing
for existing array:



```
In [195]: x = plt.arange(5,11,1)
In [196]: x
Out[196]: array([ 5,  6,  7,  8,  9, 10])
In [197]: x.resize(2,3)
In [198]: x
Out[198]:
array([[ 5,  6,  7],
       [ 8,  9, 10]])
In [199]: x.resize(8)
-----
ValueError                                Traceback (most recent call last)
<ipython-input-199-935ffac0ea7b> in <module>()
      1 x.resize(8)
----> 1 x.resize(8)

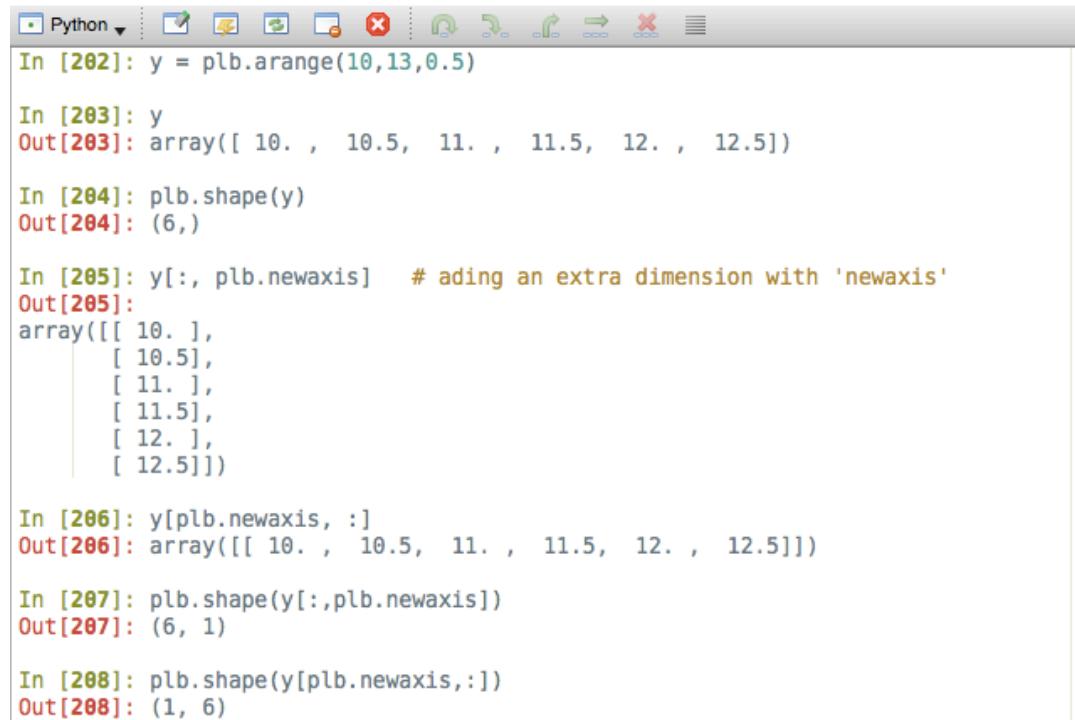
ValueError: cannot resize an array that references or is referenced
by another array in this way.  Use the resize function

In [200]: x.resize(6)
In [201]: x
Out[201]: array([ 5,  6,  7,  8,  9, 10])
```

Arrays

- Array: shaping, reshaping, flattening, resizing, dimension changing
 - array manipulation in NumPy is supported by several built in functions such as:
shape, reshape, ravel, resize, newaxis
 - there are several common techniques we will consider in the next few slides

Using **newaxis** for adding
an extra dimension on an
existing array:



```
In [202]: y = plt.arange(10,13,0.5)

In [203]: y
Out[203]: array([ 10. ,  10.5,  11. ,  11.5,  12. ,  12.5])

In [204]: plt.shape(y)
Out[204]: (6,)

In [205]: y[:, plt.newaxis] # adding an extra dimension with 'newaxis'
Out[205]:
array([[ 10. ],
       [ 10.5],
       [ 11. ],
       [ 11.5],
       [ 12. ],
       [ 12.5]])

In [206]: y[plt.newaxis, :]
Out[206]: array([[ 10. ,  10.5,  11. ,  11.5,  12. ,  12.5]])

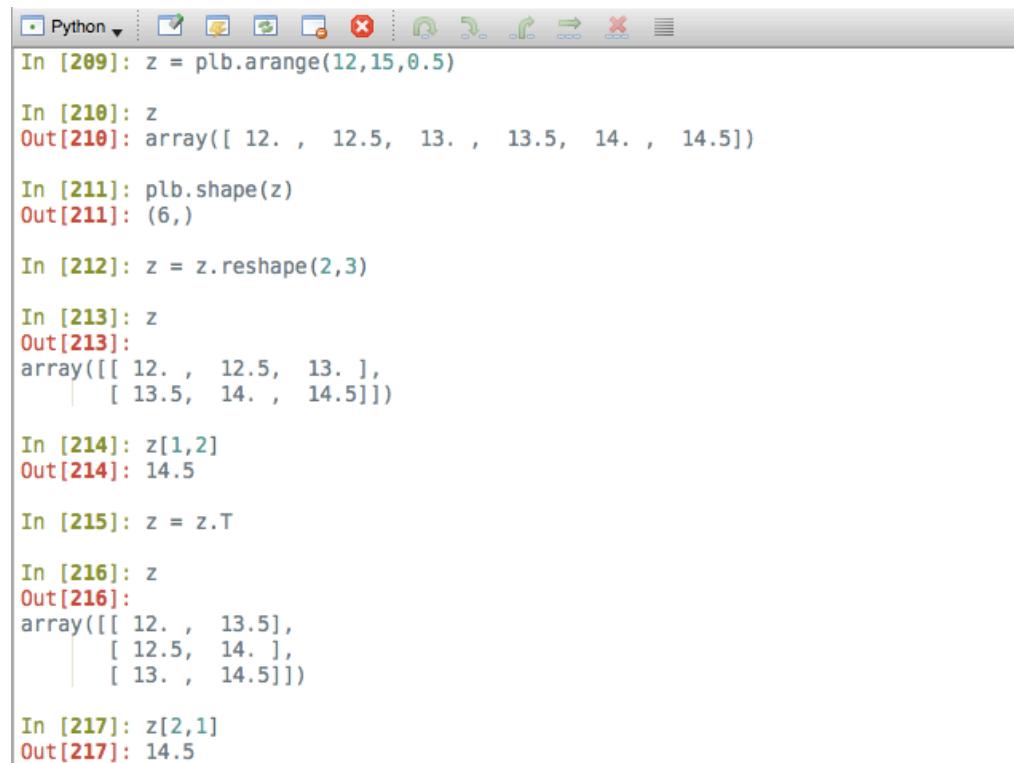
In [207]: plt.shape(y[:,plt.newaxis])
Out[207]: (6, 1)

In [208]: plt.shape(y[plt.newaxis,:,:])
Out[208]: (1, 6)
```

Arrays

- Array: shaping, reshaping, flattening, resizing, dimension changing
 - array manipulation in NumPy is supported by several built in functions such as:
shape, reshape, ravel, resize, newaxis
 - there are several common techniques we will consider in the next few slides

Changing and shifting
dimensions on an
existing array:

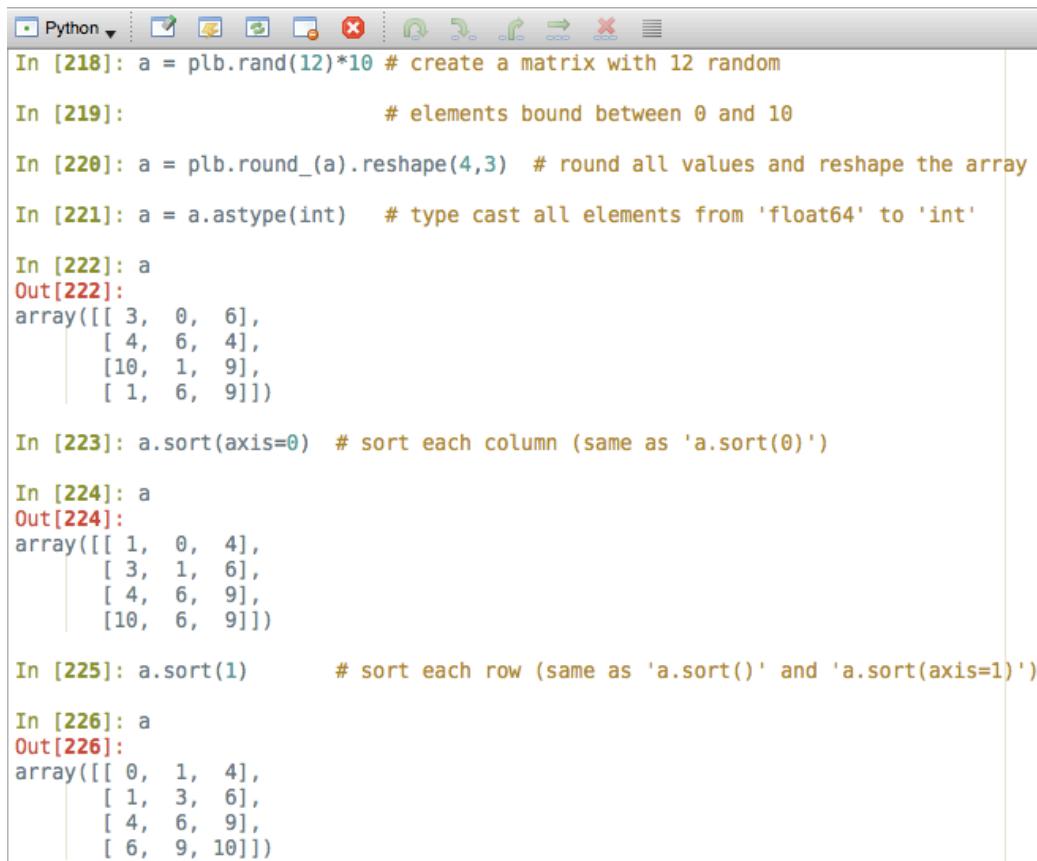


```
In [209]: z = np.arange(12,15,0.5)
In [210]: z
Out[210]: array([ 12. ,  12.5,  13. ,  13.5,  14. ,  14.5])
In [211]: z.shape
Out[211]: (6,)
In [212]: z = z.reshape(2,3)
In [213]: z
Out[213]:
array([[ 12. ,  12.5,  13. ],
       [ 13.5,  14. ,  14.5]])
In [214]: z[1,2]
Out[214]: 14.5
In [215]: z = z.T
In [216]: z
Out[216]:
array([[ 12. ,  13.5],
       [ 12.5,  14. ],
       [ 13. ,  14.5]])
In [217]: z[2,1]
Out[217]: 14.5
```

Data sorting

- Data sorting
 - array data can be sorted on rows and columns basis

Example:



```
In [218]: a = np.random.randint(12)*10 # create a matrix with 12 random
In [219]: # elements bound between 0 and 10
In [220]: a = np.round_(a).reshape(4,3) # round all values and reshape the array
In [221]: a = a.astype(int) # type cast all elements from 'float64' to 'int'
In [222]: a
Out[222]:
array([[ 3,  0,  6],
       [ 4,  6,  4],
       [10,  1,  9],
       [ 1,  6,  9]])

In [223]: a.sort(axis=0) # sort each column (same as 'a.sort(0)')
In [224]: a
Out[224]:
array([[ 1,  0,  4],
       [ 3,  1,  6],
       [ 4,  6,  9],
       [10,  6,  9]])

In [225]: a.sort(1)      # sort each row (same as 'a.sort()' and 'a.sort(axis=1)')
In [226]: a
Out[226]:
array([[ 0,  1,  4],
       [ 1,  3,  6],
       [ 4,  6,  9],
       [ 6,  9, 10]])
```

Data sorting

- Data sorting
 - sorting indices can be returned without sorting the array by calling the `argsort` function

Example:

```
In [227]: a = plb.rand(12)*10 # create a matrix with 12 random
In [228]:                                # elements bound between 0 and 10
In [229]: a = plb.round_(a).reshape(4,3) # round all values and reshape the array
In [230]: a = a.astype(int)      # type cast all elements from 'float64' to 'int'
In [231]: a
Out[231]:
array([[ 4,  1,  7],
       [ 4, 10,  1],
       [ 0,  7,  6],
       [ 1,  0,  3]])

In [232]: a.argsort()
Out[232]:
array([[1, 0, 2],
       [2, 0, 1],
       [0, 2, 1],
       [1, 0, 2]])

In [233]: a
Out[233]:
array([[ 4,  1,  7],
       [ 4, 10,  1],
       [ 0,  7,  6],
       [ 1,  0,  3]])
```