

Python for Data Analysis and Scientific Computing

X433.3 (2 semester units in COMPSCI)

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Course Content Outline

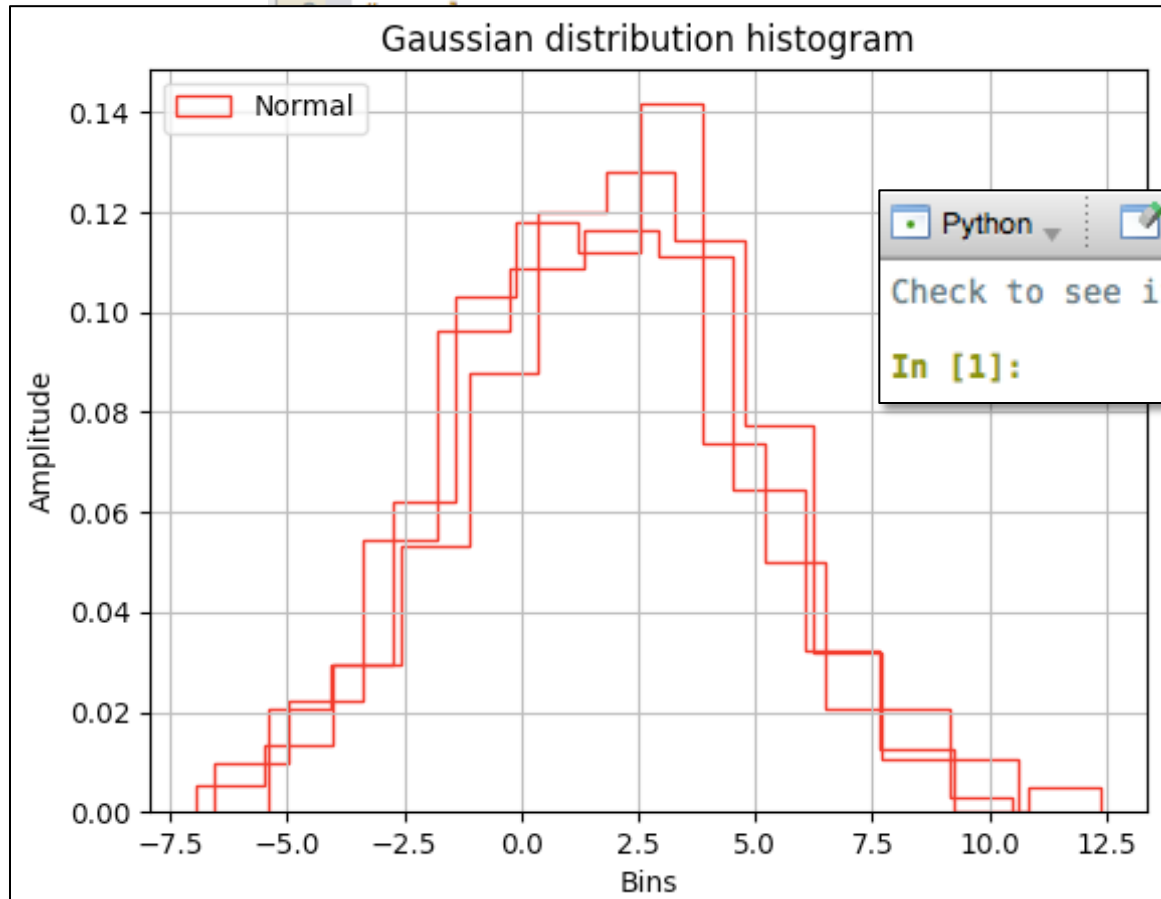
- **NumPy 2/3**
 - Array operations
 - Reductions
 - Broadcasting
 - Array: shaping, reshaping, flattening, resizing, dimension changing
 - Data sorting
 - Good coding practices
 - **NumPy 3/3**
 - Type casting
 - Masking data
 - Organizing arrays
 - Loading data files
 - Dealing with polynomials
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 - Working with files
 - Algebraic operations
 - The Fast Fourier Transform
 - Signal Processing
 - **Scipy 2/2**
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 - Statistics
 - Optimization
 - Multithreading and Multiprocessing
 - **Project**
 - Project Presentation
- Midterm, Project proposal due
- Final Project

Solution

```
1  ## Class exercise in Lecture 5:
2  # 1. Use random from numpy:
3  import pylab as plb
4
5  # 2. Create a dictionary with 5 keys and empty values in A:
6  A = {'home': '', 'office': '', 'bar': '', 'hospital': '', 'library': ''}
7
8  # 3. Using a function, assign random values to each key between [0:10], using a for
9  #     loop ... :
10 def my_function_1(x):
11     for index, key in enumerate(x):
12         x[key] = plb.randint(0,11)
13     return(x)
14 # ... and return the result in B:
15 B = my_function_1(A)
16
17 # 4. Using a function, change the value of any member in B that is less than 5
18 #     with the result from (4.1) (consider using an if statement in a loop):
19 def my_function_2(y):
20     for index, key in enumerate(y):
21         if y[key] < 5:
22             # 4.1 Using normal distrib. with mean=2 and std=3 create a 256pts array:
23             y[key] = plb.normal(2,3,size=256)
24             # 4.2 Using a histogram with 12 bins, plot the result from 4.1:
25             plb.figure('Histogram'), plb.title("Gaussian distribution histogram")
26             plb.hist(y[key], bins=12, histtype='step', normed=True, \
27                     color='red', label='Normal'), plb.legend(loc='upper left')
28             plb.xlabel("Bins"), plb.ylabel("Amplitude"), plb.grid(True), plb.pause(1)
29     return(y)
30 # 5. Assign the result from 4. in C:
31 C = my_function_2(B)
32
33 # 6. Update one of the keys in C with another using the 'pop' feature:
34 A['store'] = A.pop('bar') # The value of the old key is assigned to the new key
35
36 # 7. Update another key in C manually (add the new one and delete the old one):
37 A['shop']=A['library']
38 del A['library']
39
40 # 8. Compare them using a short conditional expression:
41 print('Check to see if A, B and C are equal: ', A is B is C)
```

Solution

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1 ## Class exercise in Lecture 5:
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6 A = {'home': '', 'office': '', 'bar': '', 'hospital': '', 'library': ''}
7
8 # 3. Using a function, assign random values to each key between [0:10], using a for
```



Python

Check to see if A, B and C are equal: True

In [1]:

```
an=2 and std=3 create a 256pts array:
s, plot the result from 4.1:
"Gaussian distribution histogram")
'step', normed=True, \
legend(loc='upper left')
litude"), plb.grid(True), plb.pause(1)
```

using the 'pop' feature:
d key is assigned to the new key

```
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```

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:

```
Python
In [1]: import pylab as plb
In [2]: a = plb.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:

$$e \& f \mid z == (e \& f) \mid z \qquad e \mid f \& z == e \mid (f \& z) , \qquad \text{where } z = e \& f$$

Array operations

- Array operations

- **associativity:**

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

Examples:

```
Python
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 = plb.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 = plb.ones(6)
In [19]: c=(a+b)**2-plb.sqrt(c)
In [20]: c
Out[20]: array([ 1368., 6723., 9408., 15375., 23408., 26243.])

In [21]: d = plb.arange(5)
In [22]: plb.size(a)
Out[22]: 6

In [23]: plb.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:

```
Python
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:

```
Python
In [52]: i = plb.arange(5)-2
In [53]: i
Out[53]: array([-2, -1,  0,  1,  2])

In [54]: plb.sin(i)
Out[54]: array([-0.90929743, -0.84147098,  0.          ,  0.84147098,  0.90929743])

In [55]: plb.cos(i)
Out[55]: array([-0.41614684,  0.54030231,  1.          ,  0.54030231, -0.41614684])

In [56]: plb.tan(i)
Out[56]: array([ 2.18503986, -1.55740772,  0.          ,  1.55740772, -2.18503986])

In [57]: plb.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]: plb.exp(i)
Out[58]: array([ 0.13533528,  0.36787944,  1.          ,  2.71828183,  7.3890561 ])

In [59]: plb.exp2(i)
Out[59]: array([ 0.25,  0.5 ,  1.   ,  2.   ,  4.   ])
```

be aware of your
data to avoid this ->

Array operations

- Array operations
 - **Transpose** an array in NumPy is performed like this:

Examples:

```
Python
In [60]: j = plb.tril(plb.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 = plb.triu(plb.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]: plb.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:

```
Python
In [66]: l = plb.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 = plb.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:

```
Python
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:

```
Python
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:

Examples:

```
Python
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.argmin()   # 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])

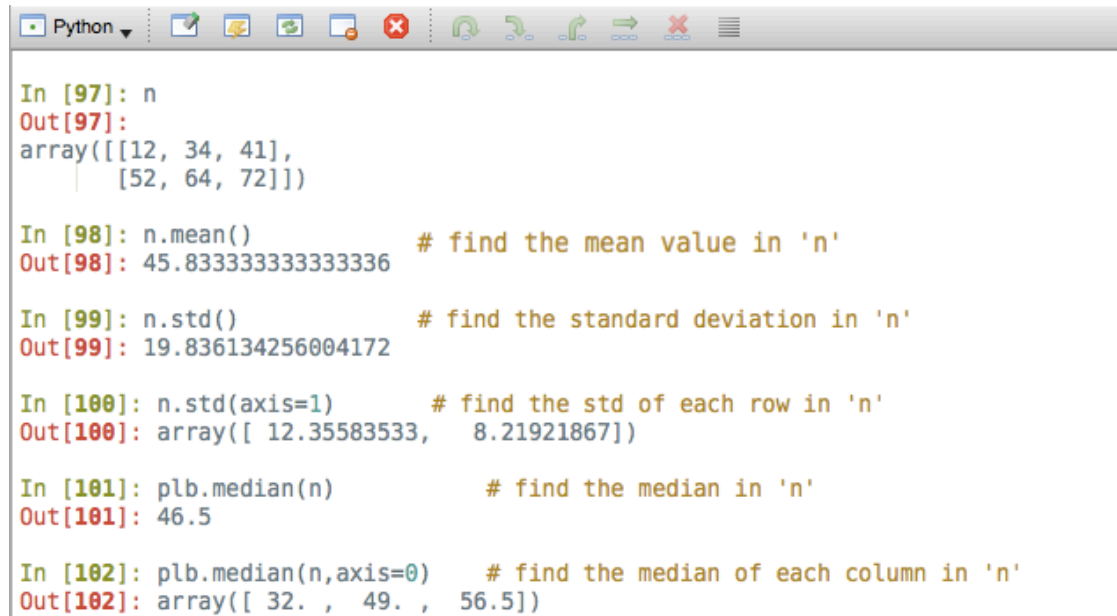
In [95]: n.max(1)     # shows the max value row
Out[95]: array([41, 72])

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

Reductions

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

Examples:



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

In [98]: n.mean()          # find the mean value in 'n'
Out[98]: 45.833333333333336

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])

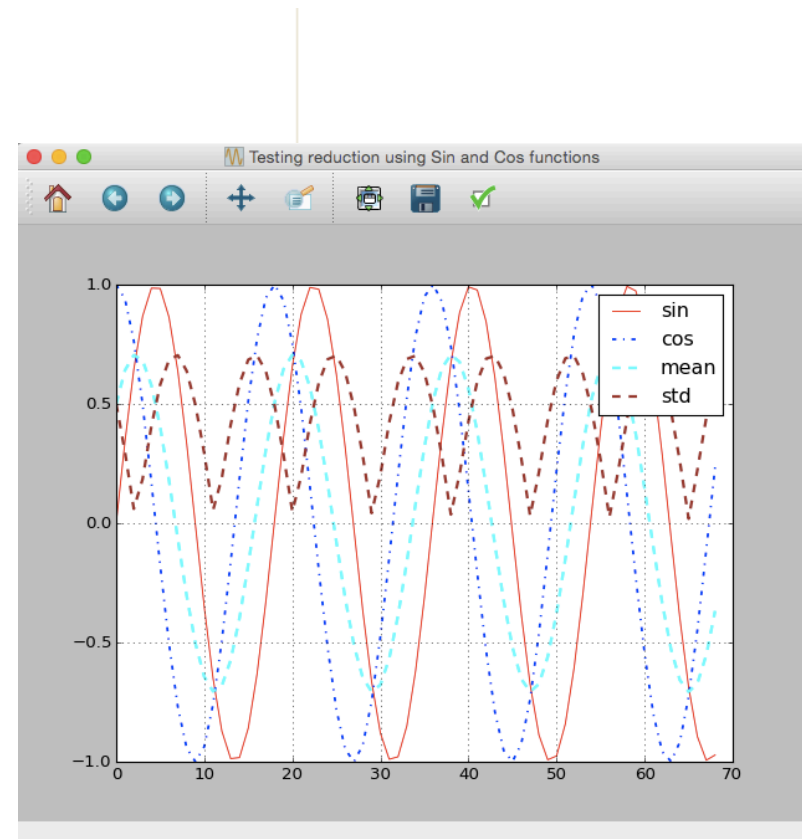
In [101]: plb.median(n)    # find the median in 'n'
Out[101]: 46.5

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

```
Python
In [156]: # Broadcasting - 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	=		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.								t	
20	20			2	3	s			22	23
40	40			2	3	s - repeated			42	43
60	60	+		2	3		=		62	63
80	80			2	3				82	83
100	100			2	3				102	103

Broadcasting

- Broadcasting

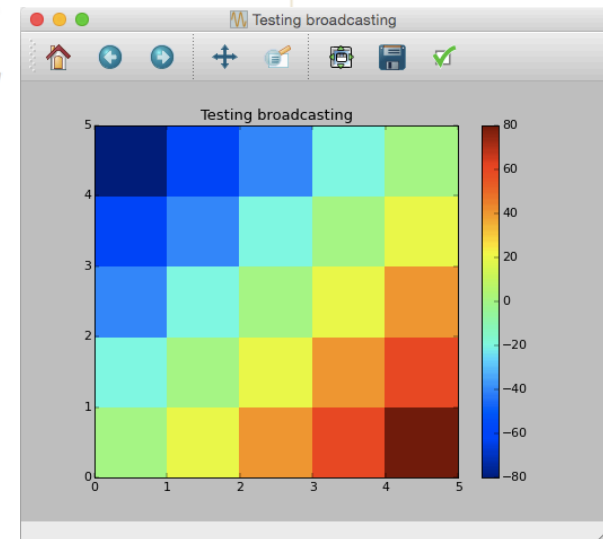
Example:

```
183 ## Broadcasting - example of a 2-D array or square matrix with diagonal = 0:
184 r = plb.array([20,40,60,80,100])
185 print(r)
186 print(r[:,plb.newaxis].shape)    # no change is introduced to 'r'
187 print(r[plb.newaxis,:].shape)    # change the shape of 'r' and add a new axis - 2-D array
188 s = r - r[:,plb.newaxis]         # create a square matrix with diagonal = 0
189 print(s)
190
191 plb.figure('Testing broadcasting', dpi=65)
192 plb.gca(title='Testing broadcasting')
193 plb.pcolormesh(s)    # choosing the printing scheme
194 plb.colorbar()       # adding a colorbar on the side for clarity
195 plb.pause(1)
```

newaxis – expands the dimensions by one unit-length dimension

```
In [1]: print(r[:,plb.newaxis].shape)
(5, 1)

In [2]: print(r[plb.newaxis,:].shape)
(1, 5)
```



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

Example:

```
Python
In [174]: # Broadcasting - 'ogrid' example:

In [175]: plb.ogrid[1:6, 1:6]
Out[175]:
array([[1],
       [2],
       [3],
       [4],
       [5]], array([[1, 2, 3, 4, 5]])

In [176]: u, v = plb.ogrid[1:6, 1:6]    # assign x,y axis to u,v variables

In [177]: u
Out[177]:
array([[1],
       [2],
       [3],
       [4],
       [5]])

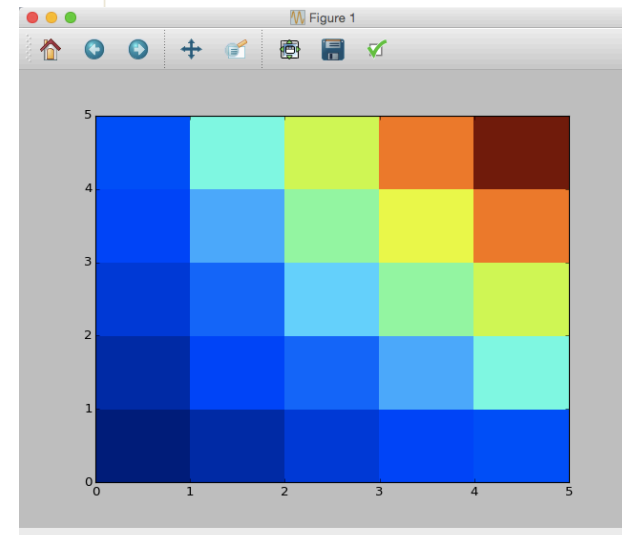
In [178]: v
Out[178]: array([[1, 2, 3, 4, 5]])

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]: plb.pcolormesh(u*v)
Out[180]: <matplotlib.collections.QuadMesh at 0x1059bc208>
```

```
(<module>)>>> u.size
5

(<module>)>>> v.size
5
```



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:

```
Python
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]],

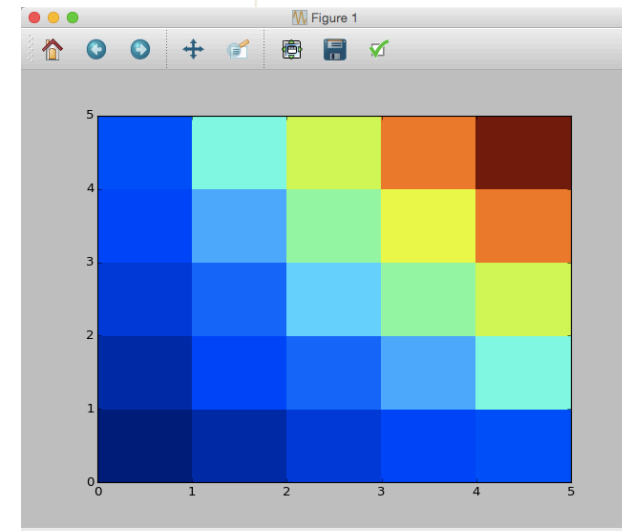
      [[1, 2, 3, 4, 5],
       [1, 2, 3, 4, 5],
       [1, 2, 3, 4, 5],
       [1, 2, 3, 4, 5],
       [1, 2, 3, 4, 5]])

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>
```

```
(<module>)>>> u.size
25
(<module>)>>> v.size
25
```

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)

```
Python
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:

```
Python
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:

```
Python
In [195]: x = plb.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)

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:

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

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

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

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

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

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

In [208]: plb.shape(y[plb.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:

```
Python
In [209]: z = plb.arange(12,15,0.5)

In [210]: z
Out[210]: array([ 12. , 12.5, 13. , 13.5, 14. , 14.5])

In [211]: plb.shape(z)
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

z.resize assigns the change directly to z

In [1]: z
Out[1]: array([[12. , 13.5],
               [12.5, 14. ],
               [13. , 14.5]])

In [2]: z.resize(6,1)

In [3]: z
Out[3]: array([[12. ],
               [12.5],
               [13. ],
               [13.5],
               [14. ],
               [14.5]])
```

Data sorting

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

Example:

```
Python
In [218]: a = plb.rand(12)*10 # create a matrix with 12 random
          # elements bound between 0 and 10
In [219]:
In [220]: a = plb.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]])

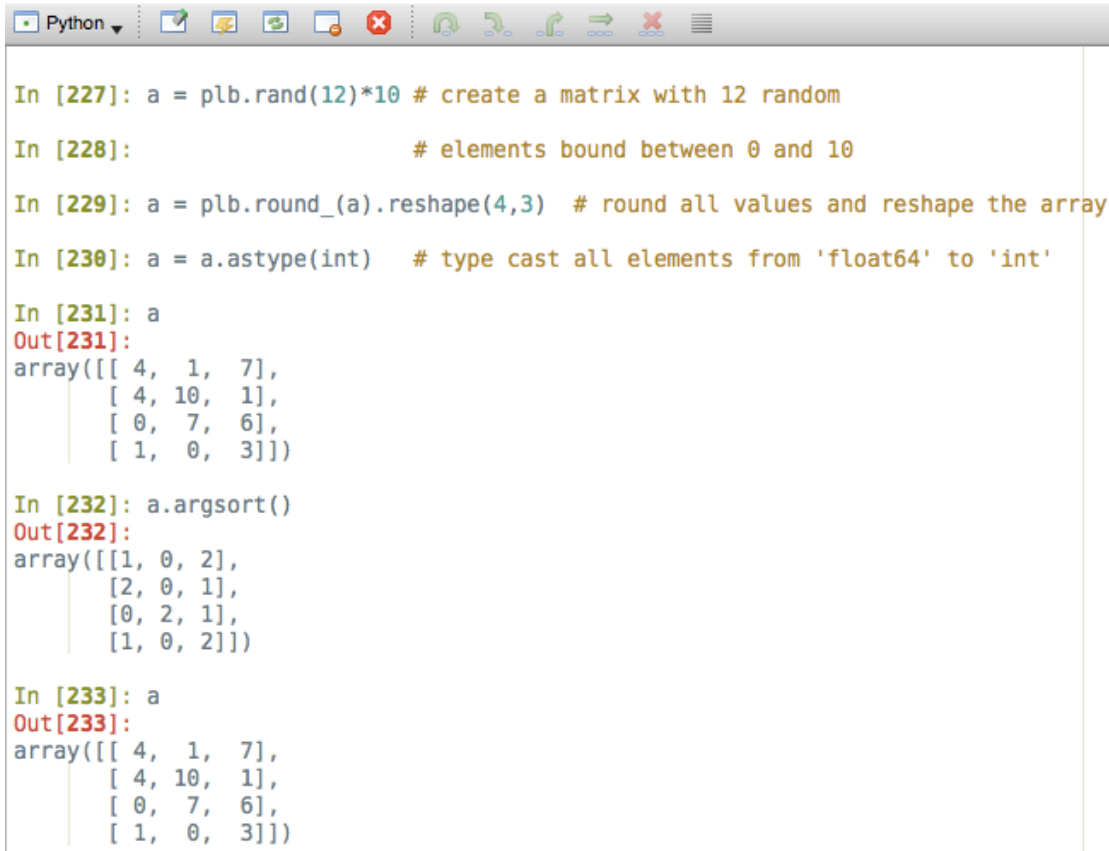
In [223]: a.sort(axis=0) # sort each column (same as 'a.sort(0)')
In [224]: a
Out[224]:
array([[ 1,  0,  4],
       [ 3,  1,  6],
       [ 4,  6,  9],
       [10,  6,  9]])

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]])

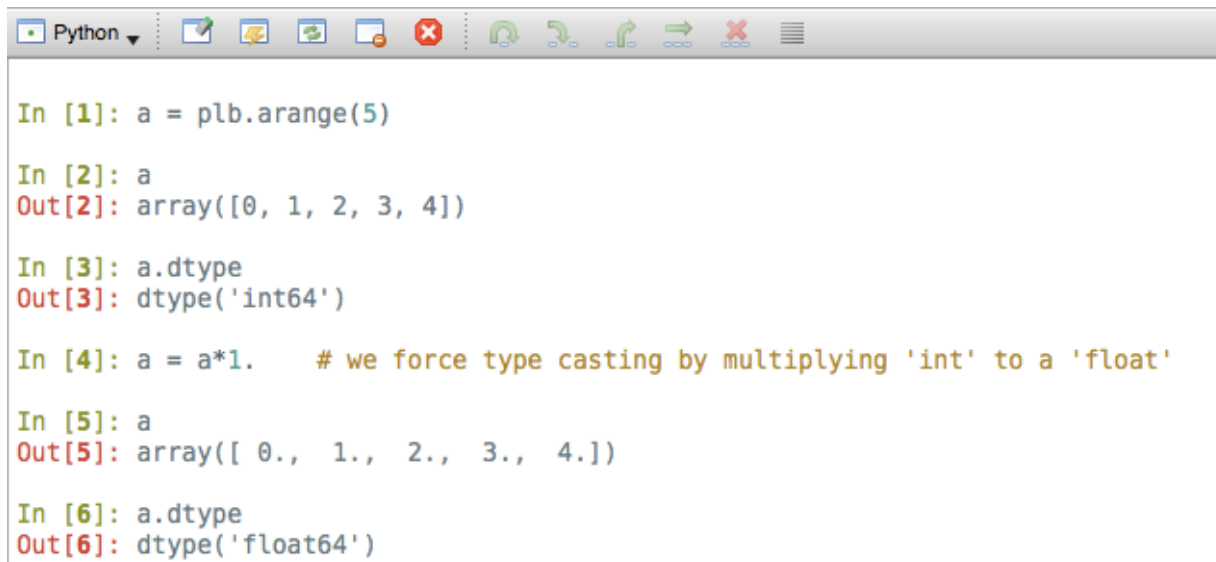
In [233]: a
Out[233]:
array([[ 4,  1,  7],
       [ 4, 10,  1],
       [ 0,  7,  6],
       [ 1,  0,  3]])
```

Type casting

- Type casting – *recap*

Examples:

- `a = 3 + 4` -> creates an **integer**
- `b = 6 + 7.` -> creates a **floating point** number (**higher precision**)



```
In [1]: a = plb.arange(5)

In [2]: a
Out[2]: array([0, 1, 2, 3, 4])

In [3]: a.dtype
Out[3]: dtype('int64')

In [4]: a = a*1.    # we force type casting by multiplying 'int' to a 'float'

In [5]: a
Out[5]: array([ 0.,  1.,  2.,  3.,  4.])

In [6]: a.dtype
Out[6]: dtype('float64')
```

Type casting

- Type casting
 - when forcing to assign a member in an array object with a different type, the assignment is completed, but no type conversion is performed on the array
 - as a result the newly assigned value may be truncated if assigning from a float to an int for ex.

```
Python
In [22]: g
Out[22]: array([ 1.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.])

In [23]: g.dtype
Out[23]: dtype('float64')

In [24]: g[4] = 10    # lets try to asing an 'int' to position 5

In [25]: g          # the type is not changed regardless of the mis-type assignment
Out[25]: array([ 1.,  2.,  2.,  2., 10.,  2.,  2.,  2.,  2.,  2.])

In [26]: g = g.astype(int)  # lets type cast 'g' to 'int'

In [27]: g.dtype
Out[27]: dtype('int64')

In [28]: g
Out[28]: array([ 1,  2,  2,  2, 10,  2,  2,  2,  2,  2])

In [29]: g[4] = 10.5 # lets try to asing a 'float64' to position 5

In [30]: g          # the type is not changed regardless of the mis-type assignment
Out[30]: array([ 1,  2,  2,  2, 10,  2,  2,  2,  2,  2])
```

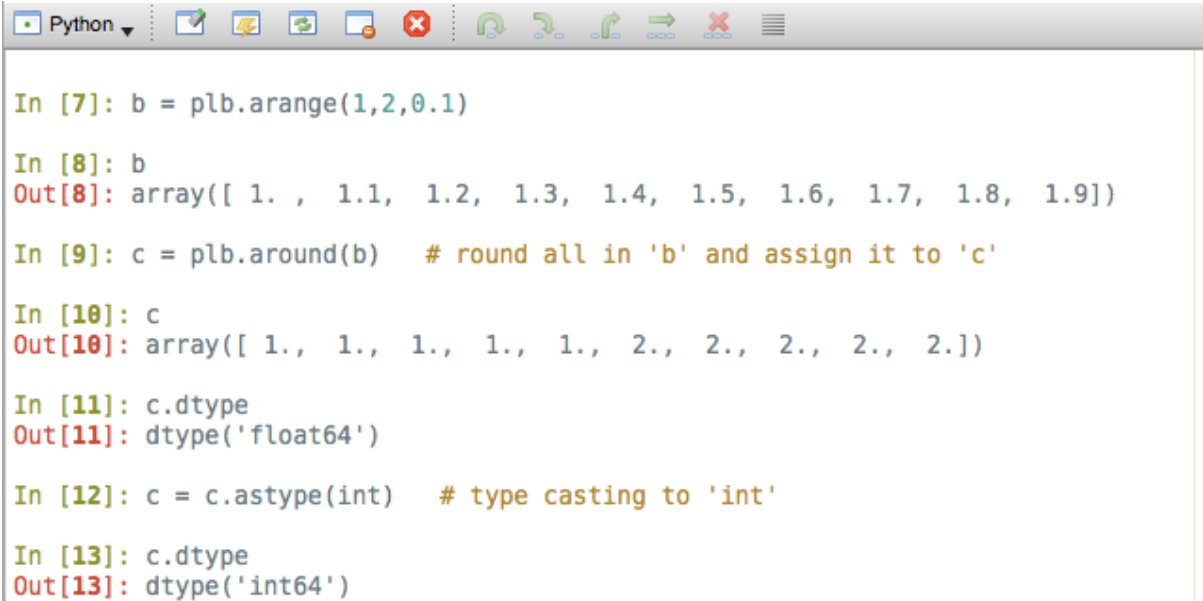
Rounding

- Rounding

- rounding with `round()`:

all numbers having digits after decimal point from **x.0-x.4** are rounded to the **lower** number

all numbers having digits after decimal point from **x.5-x.9** are rounded to the **higher** number



```
In [7]: b = plb.arange(1,2,0.1)

In [8]: b
Out[8]: array([ 1. ,  1.1,  1.2,  1.3,  1.4,  1.5,  1.6,  1.7,  1.8,  1.9])

In [9]: c = plb.around(b)  # round all in 'b' and assign it to 'c'

In [10]: c
Out[10]: array([ 1.,  1.,  1.,  1.,  1.,  2.,  2.,  2.,  2.,  2.])

In [11]: c.dtype
Out[11]: dtype('float64')

In [12]: c = c.astype(int)  # type casting to 'int'

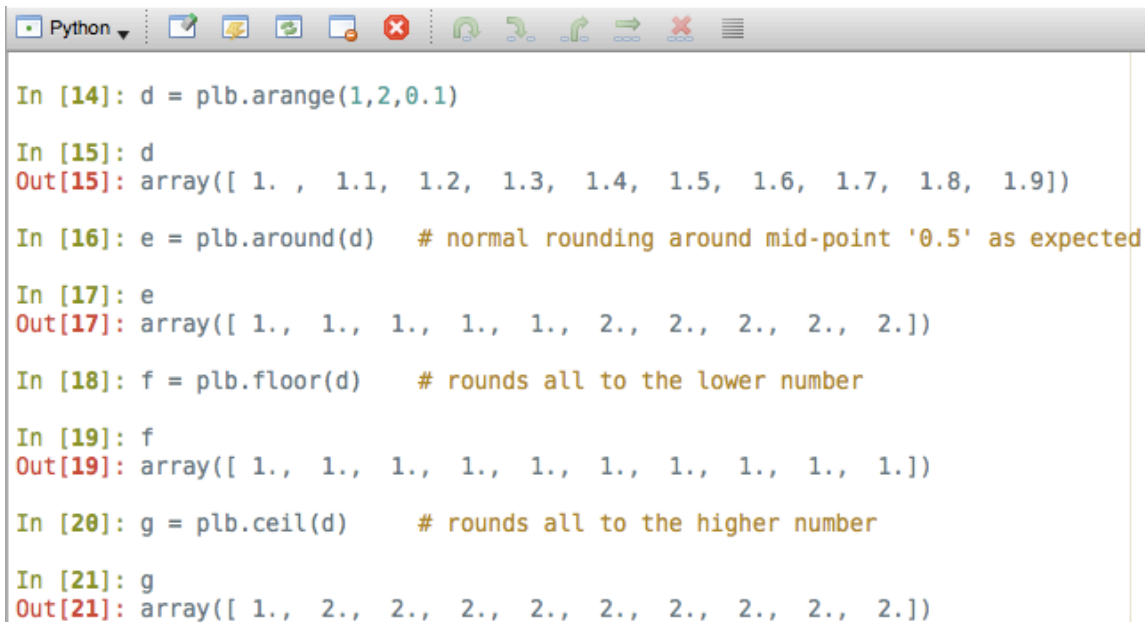
In [13]: c.dtype
Out[13]: dtype('int64')
```

Rounding

- Rounding
 - rounding with `floor()` and `ceil()`:

sometimes there is a need for an alternative way of rounding such as:

- `floor`: rounds to the **lower** number
- `ceil`: rounds to the **higher** number



```
Python
In [14]: d = plb.arange(1,2,0.1)
In [15]: d
Out[15]: array([ 1. ,  1.1,  1.2,  1.3,  1.4,  1.5,  1.6,  1.7,  1.8,  1.9])
In [16]: e = plb.around(d) # normal rounding around mid-point '0.5' as expected
In [17]: e
Out[17]: array([ 1.,  1.,  1.,  1.,  1.,  2.,  2.,  2.,  2.,  2.])
In [18]: f = plb.floor(d) # rounds all to the lower number
In [19]: f
Out[19]: array([ 1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.,  1.])
In [20]: g = plb.ceil(d) # rounds all to the higher number
In [21]: g
Out[21]: array([ 1.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.,  2.])
```

Type info

- Type info – *for NumPy variables only*

- to check the type of a `scalar` or an `array` we use:

`<scalar>.dtype` or `<array>.dtype`

- to check the type of a `scalar` or an `array element` we use:

`plb.dtype(<scalar>)` or `plb.dtype(<array[element]>)`

- to check how many `bytes` a type takes we use:

`plb.<type>().itemsize`

- to check how many `bits` a type takes we use:

`(plb.dtype(plb.<type>).itemsize)*8`

- to check the `minimum`, `maximum values` and the `int type` of a `scalar` variable or `array element` we use:

`plb.iinfo(plb.<type>)`

Type info

- Type info – *for NumPy variables only* – Examples:

- to check the type of a **scalar** or an **array** we use:

```
h = plb.int32(12)          i = plb.arange(4)
h.dtype                    or    i.dtype
dtype('int32')             dtype('int64')
```

- to check the type of a **scalar** or an **array element** we use:

```
plb.dtype(h)              plb.dtype(i[2])
dtype('int32')            dtype('int64')
```

- to check how many **bytes** a type takes we use:

```
plb.int64().itemsize
8
```

- to check how many **bits** a type takes we use:

```
(plb.dtype(plb.int64()).itemsize)*8
64
```

- to check the **minimum**, **maximum values** and the **int type** of a **scalar** variable or **array element** we use:

```
plb.iinfo(plb.int64())
iinfo(min=-9223372036854775808, max=9223372036854775807, dtype=int64)
```

Type info

- Type info – *for NumPy variables only* – Examples:
 - to check the machine limits for **floating point** types namely **resolution**, **minimum**, **maximum values**, **type** we use:

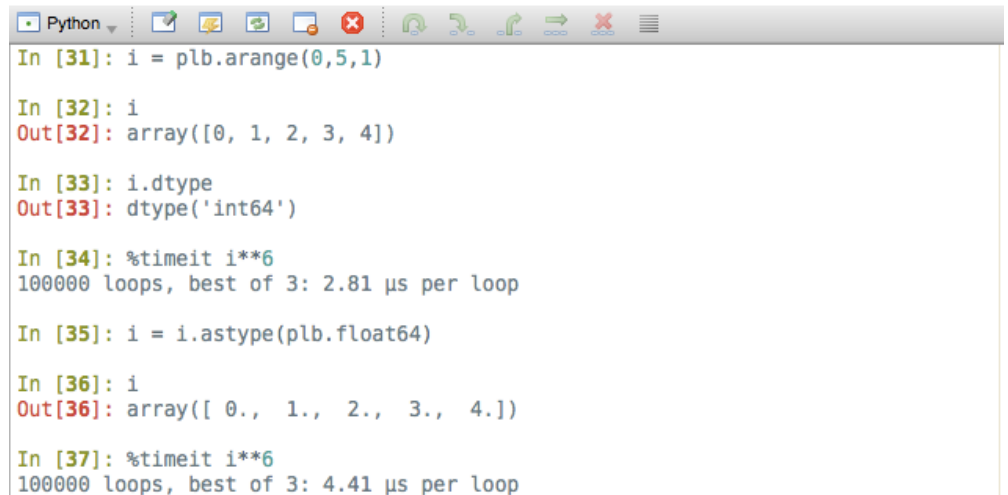
```
plb.finfo(plb.float32())  
finfo(resolution=1e-06, min=-3.4028235e+38, max=3.4028235e+38, dtype=float32)
```

or we can use:

```
plb.finfo(plb.float32()).eps  
1.1920929e-07
```

where, the **eps** attribute shows the smallest representable positive number and is a **float**

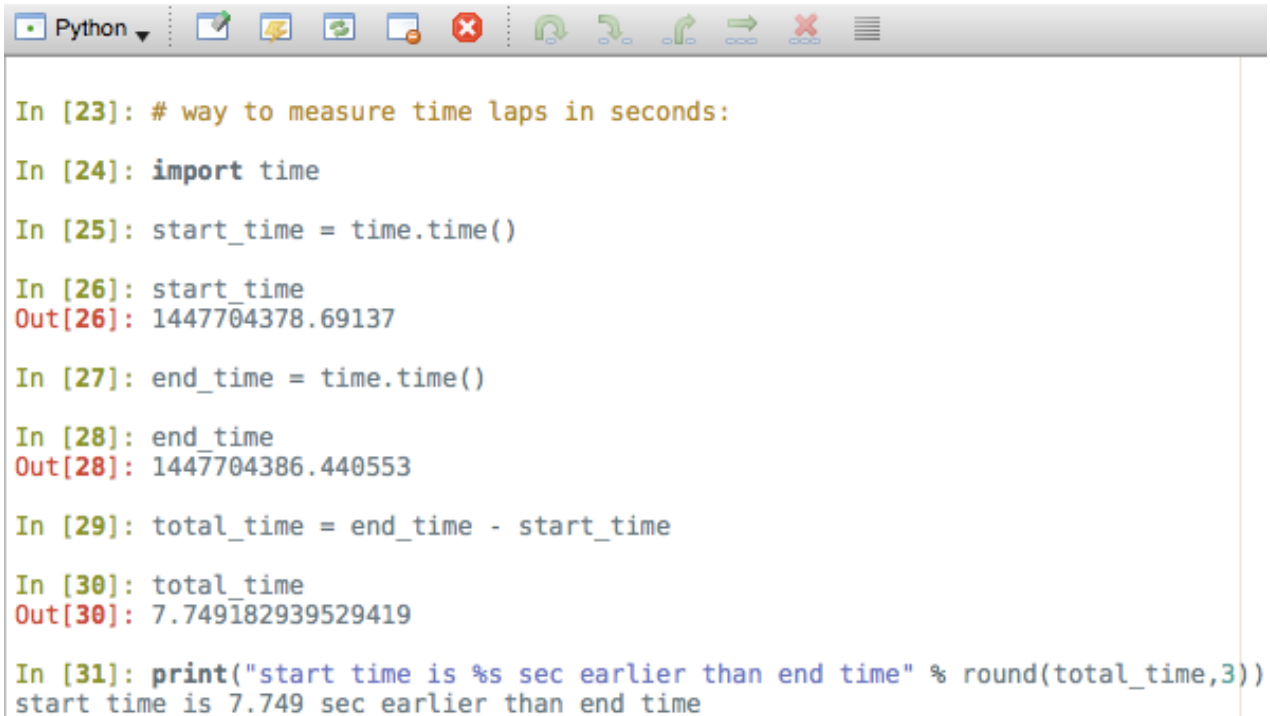
- we can also check for the **speed** of certain computations using different types:



```
Python  
In [31]: i = plb.arange(0,5,1)  
  
In [32]: i  
Out[32]: array([0, 1, 2, 3, 4])  
  
In [33]: i.dtype  
Out[33]: dtype('int64')  
  
In [34]: %timeit i**6  
100000 loops, best of 3: 2.81 µs per loop  
  
In [35]: i = i.astype(plb.float64)  
  
In [36]: i  
Out[36]: array([ 0.,  1.,  2.,  3.,  4.])  
  
In [37]: %timeit i**6  
100000 loops, best of 3: 4.41 µs per loop
```


Type info

- Type info – *for NumPy variables only* – Examples:
 - we can also check for the [speed](#) of execution for larger pieces of code similar to the [tic](#) – [toc](#) functionality in Matlab:



```
In [23]: # way to measure time laps in seconds:
In [24]: import time
In [25]: start_time = time.time()
In [26]: start_time
Out[26]: 1447704378.69137
In [27]: end_time = time.time()
In [28]: end_time
Out[28]: 1447704386.440553
In [29]: total_time = end_time - start_time
In [30]: total_time
Out[30]: 7.749182939529419
In [31]: print("start time is %s sec earlier than end time" % round(total_time,3))
start time is 7.749 sec earlier than end time
```

Masking data

- Masking data
 - it is sometimes necessary to **only observe** certain **part of a large data** set
 - in this way, one can exclude **unwanted** values like **NaN** or **negative numbers**
 - for that reason it is useful to **mask** the **portion of the array**, which is unwanted

```
Python ▾ [Python icon] [Jupyter icon] [File icon] [Edit icon] [Run icon] [Stop icon] [Refresh icon] [Undo icon] [Redo icon] [Help icon] [Menu icon]

In [38]: j = plb.array([12, 34, 41, 52]) # array
In [39]: k = plb.array([1, 0, 0, 1]) # creates a mask
In [40]: l = plb.ma.array(j, mask=k) # creates an array with masked values
In [41]: l[:]
Out[41]:
masked_array(data = [-- 34 41 --],
             mask = [ True False False  True],
             fill_value = 999999)

In [42]: l[0]
Out[42]: masked

In [43]: l[1]
Out[43]: 34

In [44]: l.mask[0]=False # the mask for each array element can be changed
In [45]: l[0]
Out[45]: 12
```

Organizing arrays

- Organizing arrays
 - larger data has to be well organized
 - all fields need to have an appropriate description

```
Python
In [46]: m = plb.zeros((3,), dtype=[('Store:', 'S4'), ('count', int), ('location', float)])
In [47]: m
Out[47]:
array([(b'', 0, 0.0), (b'', 0, 0.0), (b'', 0, 0.0)],
      dtype=[('Store:', 'S4'), ('count', '<i8'), ('location', '<f8')])

In [48]: m.dtype.names # to see only the name fields of each element
Out[48]: ('Store:', 'count', 'location')

In [49]: m['Store:'] = ['East', 'West', 'North'] # assign an array of store names
In [50]: m['count'] = plb.arange(1, 4, 1) # assign a sequence of numbers
In [51]: # individual field indexing will access and assign each individual location:
In [52]: m[0]['location'] = 43.7896; m[1]['location'] = 64.4321; m[2]['location'] = 87.2315
In [53]: m[1]
Out[53]: (b'West', 2, 64.4321)

In [54]: m['location']
Out[54]: array([ 43.7896,  64.4321,  87.2315])

In [55]: m[1]['location'] = 5 # assigning an 'int' to a 'float' it will be recorded
In [56]: m[1]['count'] = 2.345 # assigning a 'float' to an 'int' it will be truncated
In [57]: m
Out[57]:
array([(b'East', 1, 43.7896), (b'West', 2, 5.0), (b'North', 3, 87.2315)],
      dtype=[('Store:', 'S4'), ('count', '<i8'), ('location', '<f8')])
```

Good coding practices

- Good coding practices
- use **short and concise comments** to describe your code when needed
- use **explicit variable names** so that it is easy to understand what they are
- make variable names and comments in **English**
- avoid **changing global variables** in local scope functions
- use **clean style** such as:
 - **spaces** in for loop and if statements
 - **spaces** after commas
 - **spaces** before = and after
- use the **same conventions** as everybody else before you
- **do not hard code** your **variables** to increase **portability**
- make your **code readable** and beautiful to look
- write a **simple** code
- **Import / load** only what you need in your workspace
- **test** your code!

After following these recommendations you will increase the reliability of your code!

You can read more at: <https://www.python.org/dev/peps/pep-0008/#class-names>