lasp_reu_python_tutorial_day2

June 11, 2016

1 LASP REU Python Tutorial Day 2

1.1 Imports

Remember the huge stack of science libraries (or the list of built-in libraries)?

So, how to get those?

With imports:

```
In [2]: from math import pi
        tau = 2*pi
        print("The real circular constant is", tau)
        # read tauday.com if you don't believe me. ;)
```

```
The real circular constant is 6.283185307179586
```

How to import other libraries, their functions or their values is very flexible.

One can distinguish mainly 2 kinds: * One imports a function directly into the current `namespace`:

```
from math import sin
```

- import the top module and access via the dot `.`:

  ```
  import math
  print(math.sin(0.5))
  ```

In both cases one can rename the object being imported.

This is a very powerful feature of Python: You can do what you want in terms of how to call things up.

```
In [3]: from math import sin as stupid_sine
        print(stupid_sine(0.5))
```

```
0.479425538604203
```

```
In [4]: import math as i_hate_math
        print(i_hate_math.cos(-1))
```

```
0.5403023058681398
```

1.2 Function returns, packing and unpacking

Functions can return values.
(you saw this in the last exercise already):

```
In [2]: from math import log10

        def mylog(value):
            if value < 0:
                return "Logarithm not defined."
            else:
                return log10(value)

In [4]: result = mylog(-1)
        result

Out[4]: 'Logarithm not defined.'

In [6]: import math
        math.log10(-1)


        ---------------------------------------------------------------------------

        ValueError                                Traceback (most recent call last)

        <ipython-input-6-d12f9764e680> in <module>()
          1 import math
    ----> 2 math.log10(-1)


        ValueError: math domain error
```

Maybe you want to return more than one value?
Python will automatically pack things up:

```
In [7]: from math import log10

        def mylog(value):
            if value < 0:
                return "Logarithm not defined."
            else:
                return value, log10(value)

In [8]: result = mylog(3)
        result

Out[8]: (3, 0.47712125471966244)
```

```
In [9]: print(type(result))
        len(result)
```

```
<class 'tuple'>
```

```
Out[9]: 2
```

Tuples are the immutable version of lists:

```
In [10]: result[0] = 4
```

```
        ---------------------------------------------------------------------------

        TypeError                                 Traceback (most recent call last)

        <ipython-input-10-96551514c210> in <module>()
    ----> 1 result[0] = 4


        TypeError: 'tuple' object does not support item assignment
```

```
In [11]: mylist = list(result)
         mylist
```

```
Out[11]: [3, 0.47712125471966244]
```

```
In [13]: mylist[0] = 5
         mylist
```

```
Out[13]: [5, 0.47712125471966244]
```

and "iterable" as well (meaning I can loop over them):

```
In [16]: for item in result:
             print(item)
```

```
3
0.47712125471966244
```

```
In [17]: waves = [5000, 6000]
```

```
In [18]: for wave in waves:
             print(wave)
```

```
5000
6000
```

```
In [14]: d = {'a':5, 'b':6}
         d

Out[14]: {'a': 5, 'b': 6}

In [15]: for key,val in d.items():
             print(key, val)

b 6
a 5
```

Python will always automatically pack for you (as it did above with result), but will never automatically unpack for you:

```
In [19]: val, res = mylog(3)
         print(val)
         res

3


Out[19]: 0.47712125471966244
```

Because of the automatic packing, you can always have less than required variables, but never more:

```
In [20]: a, b, c = mylog(17)


        ---------------------------------------------------------------------------

        ValueError                                Traceback (most recent call last)

        <ipython-input-20-c3be50ed7773> in <module>()
    ----> 1 a, b, c = mylog(17)


        ValueError: not enough values to unpack (expected 3, got 2)


In [21]: out = mylog(17)

In [22]: type(out)

Out[22]: tuple

In [23]: out[0]

Out[23]: 17

In [24]: out[1]

Out[24]: 1.2304489213782739
```

1.2.1 Interlude: strings

They are also iterables:

```
In [25]: for char in "Han":  # Remember that I decide on the name of my temporary v
             print(char)

H
a
n
```

Strings have a lot of useful support functions (lingo: `methods`) inside them:

```
In [26]: s = "Han shot first!"

In [27]: s.center?

In [28]: s.split()   # by default, spaces are assumed to be the separator

Out[28]: ['Han', 'shot', 'first!']

In [29]: s.split('s')  #  note that the separator can be anything, but it will be r

Out[29]: ['Han ', 'hot fir', 't!']
```

Why are the methods already available when I did not store a string into a variable?

```
In [25]: '{1}, I am your {0}.'.format('father', 'Luke')

Out[25]: 'Luke, I am your father.'
```

Note, I am using the `format` method even so I haven't stored that string anywhere.

Now, even an empty string or a string with only a space has those methods, and one very useful is the 'join' method:

```
In [30]: ' '.join(["It's", 'a','trap!'])

Out[30]: "It's a trap!"
```

1.2.2 Back to functions: Default values

Functions can have optional arguments that hold a default value:

```
In [31]: def sub_reverser(alist, index=0):
             reversed_list = list(reversed(alist))
             return ''.join(reversed_list[index:])

In [33]: ''.join(list(reversed('astring')))

Out[33]: 'gnirtsa'
```

```
In [34]: sub_reverser('astring')

Out[34]: 'gnirtsa'

In [35]: sub_reverser('astring', 3)

Out[35]: 'rtsa'
```

This is a very powerful design feature of Python as well: I only need to write one function, but can use it in very different ways, depending on my default arguments (also known as `keyword argument`).

Ok, let's go to some more meaty science libraries.

1.3 matplotlib gallery

- Can't go into depth of matplotlib library here, very rich and powerful
- Best way to learn: Go to their gallery page http://matplotlib.org/gallery.html

```
In [36]: from IPython.display import IFrame
         IFrame("http://matplotlib.org/gallery.html", width=800, height=350)

Out[36]: <IPython.lib.display.IFrame at 0x1161e5f28>
```

1.4 numpy

For any serious array/vector/matrix based math, you should use the numpy library.

It is faster, because in contrast to lists, it insists on keeping every item the same data-type. This enables under the hood to create C-objects and pass them to the C or Fortran math libraries.

These libraries are decade old standards with very well researched behaviour!

Contrary to the above mentioned freedom for importing, there are some standards that you should just adapt if you don't want to confuse yourself, when searching for tutorials, blogs etc. to help you out.

This standard imports are:

```
In [37]: import matplotlib.pyplot as plt
         import numpy as np
         import pandas as pd
```

Okay, let's do some math:

```
In [39]: mylist = list(range(10))
         mylist

Out[39]: [0, 1, 2, 3, 4, 5, 6, 7, 8, 9]

In [40]: arr = np.array(mylist)
         arr

Out[40]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])
```

Most import feature of numpy arrays is to support vector math, which lists can't do:

```
In [41]: mylist / 3
```

```
---------------------------------------------------------------------------

TypeError                                 Traceback (most recent call last)

<ipython-input-41-ff79ae8890d3> in <module>()
----> 1 mylist / 3


TypeError: unsupported operand type(s) for /: 'list' and 'int'
```

```
In [42]: arr / 3

Out[42]: array([ 0.        ,  0.33333333,  0.66666667,  1.        ,  1.33333333,
                 1.66666667,  2.        ,  2.33333333,  2.66666667,  3.        ])
```

Lingo: `Lists` are Python lists, `arrays` are numpy arrays.
Basic indexing works the same:

```
In [43]: mylist[2:4]

Out[43]: [2, 3]

In [44]: arr[2:4]

Out[44]: array([2, 3])
```

numpy has it's own range function: `arange()` (standing for array-range):

```
In [46]: np.arange(10)

Out[46]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [40]: np.arange?

In [49]: arr = np.arange(1, 11, 2, dtype='float')  # works the same as range, but a

In [50]: arr.dtype

Out[50]: dtype('float64')
```

Handy array creators:

```
In [51]: np.ones(3)

Out[51]: array([ 1.,  1.,  1.])
```

```
In [52]: np.zeros(5)
```

```
Out[52]: array([ 0.,  0.,  0.,  0.,  0.])
```

Multi-dimensional:

```
In [53]: np.ones((2,3))  # rows first, then columns
```

```
Out[53]: array([[ 1.,  1.,  1.],
                [ 1.,  1.,  1.]])
```

Note that the `ones` function wants the dimensions as a tuple if more than 1, to not confuse things with other arguments.

Here's 3D:

```
In [54]: np.zeros((2,4,3))  # the depth dimension (how many 2D arrays) first!
```

```
Out[54]: array([[[ 0.,  0.,  0.],
                 [ 0.,  0.,  0.],
                 [ 0.,  0.,  0.],
                 [ 0.,  0.,  0.]],

                [[ 0.,  0.,  0.],
                 [ 0.,  0.,  0.],
                 [ 0.,  0.,  0.],
                 [ 0.,  0.,  0.]]])
```

Lot's of methods inside the numpy array object:

```
In [55]: arr.
```

```
      File "<ipython-input-55-25a33d75fd04>", line 1
    arr.
        ^
SyntaxError: invalid syntax
```

Most useful:

```
In [56]: arr.mean()
```

```
Out[56]: 5.0
```

```
In [57]: arr.std()
```

```
Out[57]: 2.8284271247461903
```

```
In [58]: arr.dot(arr)
```

```
Out[58]: 165.0

In [59]: np.ones((3,3)).diagonal()

Out[59]: array([ 1.,  1.,  1.])

In [60]: arr.max()

Out[60]: 9.0

In [61]: arr.argmax()  # WHERE is the max?

Out[61]: 4
```

Lazy indexing one of most important functionality:

```
In [63]: arr

Out[63]: array([ 1.,  3.,  5.,  7.,  9.])

In [64]: arr < 3

Out[64]: array([ True, False, False, False, False], dtype=bool)

In [65]: arr[arr<3]

Out[65]: array([ 1.])
```

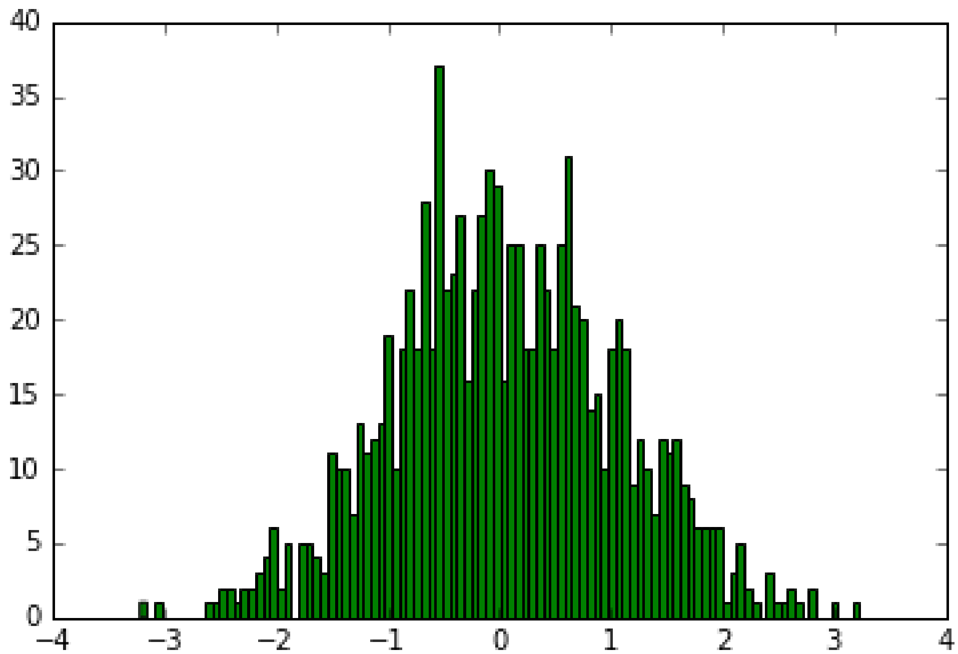
2D numpy (= matrices) have a lot of matrix features:

```
In [66]: arr2d = np.random.randn(2,3)  # randn provides Gaussian-distributed randon
         arr2d

Out[66]: array([[ 0.10057945,  0.06079022,  0.34149928],
                [ 0.46686287, -0.59692558, -0.59996842]])

In [67]: %matplotlib inline

         plt.hist(np.random.randn(1000), bins=100, color='green');
```




```
In [69]: arr2d

Out[69]: array([[ 0.10057945,  0.06079022,  0.34149928],
                [ 0.46686287, -0.59692558, -0.59996842]])

In [70]: arr2d.transpose()

Out[70]: array([[ 0.10057945,  0.46686287],
                [ 0.06079022, -0.59692558],
                [ 0.34149928, -0.59996842]])
```

Absolutely impossible to cover `numpy` even half here, but it's one of the most important tools in Python.

1.5 pandas

Most important high-level data analysis library (in my POV).

It uses `numpy` under the hood.

So, my recommendation: 1. Learn the numpy basics, don't try to get it all in, hardly possible. * For example the scipy quickstart tutorial 2. Learn Pandas first, and whenever they refer to an unknown numpy feature, look that up.

Pandas has a nice 10 minutes intro here: http://pandas.pydata.org/pandas-docs/stable/10min.html

Most important objects in `pandas` are Series and DataFrames

In [72]:
```
import pandas as pd

s = pd.Series(np.arange(10)*24.1)
s
```

Out[72]:
```
0      0.0
1     24.1
2     48.2
3     72.3
4     96.4
5    120.5
6    144.6
7    168.7
8    192.8
9    216.9
dtype: float64
```

Important concept in pandas are the indexes. pandas always keeps the relationship between indices and data intact!

series filtering works the same as for numpy arrays, as it's build on it:

In [73]:
```
s[s<100]
```

Out[73]:
```
0     0.0
1    24.1
2    48.2
3    72.3
4    96.4
dtype: float64
```

DataFrames are the 2D version of Series, complete with column names.

Another very enticing feature of pandas are its datetime abilities:

In [75]:
```
dates = pd.date_range('20130101', periods=10)

print(dates)
df = pd.DataFrame(np.random.randn(10,4), index=dates, columns=list('ABCD')
df
```

```
DatetimeIndex(['2013-01-01', '2013-01-02', '2013-01-03', '2013-01-04',
               '2013-01-05', '2013-01-06', '2013-01-07', '2013-01-08',
               '2013-01-09', '2013-01-10'],
              dtype='datetime64[ns]', freq='D')
```

Out[75]:
```
                   A         B         C         D
2013-01-01 -0.385683 -0.447271 -1.056506 -0.449031
2013-01-02  0.180882 -0.527830  0.495707  0.448709
2013-01-03 -0.691885  1.029479  1.651550  0.669449
```

```
2013-01-04 -0.567650 -0.854710 -0.856430 -0.458681
2013-01-05 -0.423667 -0.812838 -1.590655  1.112229
2013-01-06  0.104276  0.815805 -0.057856 -0.584672
2013-01-07  0.849349 -0.067153 -1.144254 -1.138004
2013-01-08  1.110839  0.349981 -0.982446 -0.533032
2013-01-09  1.145089 -0.058981 -0.019504  0.458360
2013-01-10 -0.848392  1.353922  1.336653 -1.627830
```

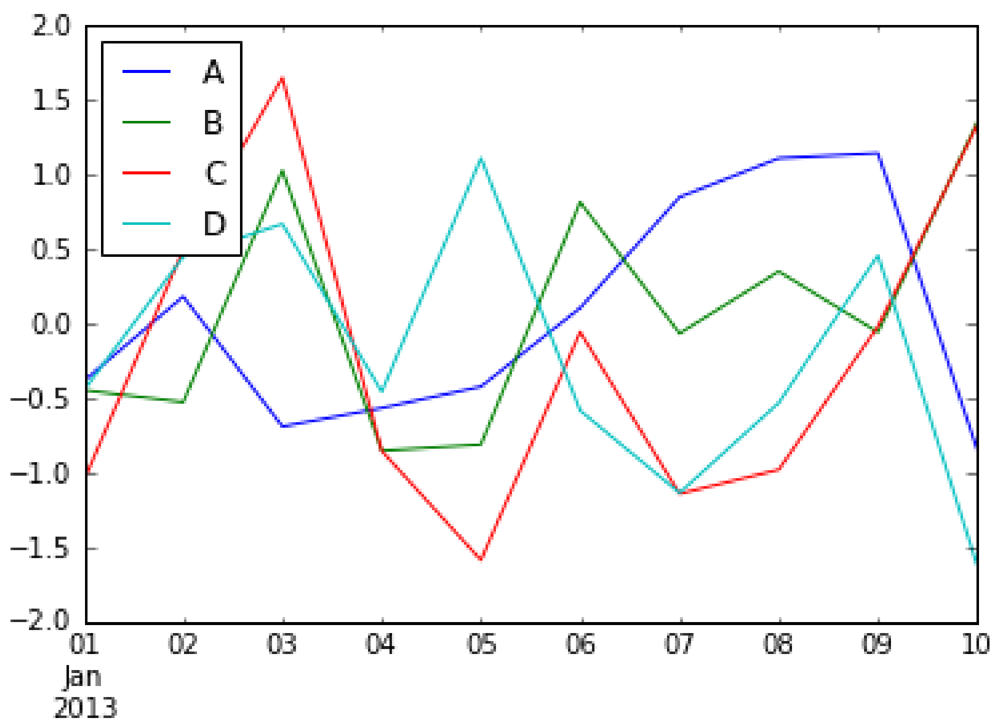
```
In [81]: df.loc['2013-01-01','A':'C']
```

```
Out[81]: A    -0.385683
         B    -0.447271
         C    -1.056506
         Name: 2013-01-01 00:00:00, dtype: float64
```

Coolest part is the automatic datetime and multi-graph plotting of DataFrames:

```
In [82]: df.plot()
```

```
Out[82]: <matplotlib.axes._subplots.AxesSubplot at 0x11875d668>
```



It is using `matplotlib` under the hood, so you could do this yourself, but with much more code.

```
In [85]: df.head()
```

```
Out[85]:                    A         B         C         D
         2013-01-01 -0.385683 -0.447271 -1.056506 -0.449031
         2013-01-02  0.180882 -0.527830  0.495707  0.448709
         2013-01-03 -0.691885  1.029479  1.651550  0.669449
         2013-01-04 -0.567650 -0.854710 -0.856430 -0.458681
         2013-01-05 -0.423667 -0.812838 -1.590655  1.112229

In [86]: df.tail(3)

Out[86]:                    A         B         C         D
         2013-01-08  1.110839  0.349981 -0.982446 -0.533032
         2013-01-09  1.145089 -0.058981 -0.019504  0.458360
         2013-01-10 -0.848392  1.353922  1.336653 -1.627830

In [87]: df.loc['2013-01-4':'2013-01-09', 'B':'C']

Out[87]:                    B         C
         2013-01-04 -0.854710 -0.856430
         2013-01-05 -0.812838 -1.590655
         2013-01-06  0.815805 -0.057856
         2013-01-07 -0.067153 -1.144254
         2013-01-08  0.349981 -0.982446
         2013-01-09 -0.058981 -0.019504
```

Above, using the `.loc` attribute of dataframes, this is the fully official way to select data in a dataframe in all possible ways. The first part will always filter the rows you want, the second part always on the columns.

But if you only want to filter/select on your current index, one can put these conditions directly like an indexing choice into brackets `[]`:

```
In [67]: df['2013-01-4':'2013-01-09']

Out[67]:                    A         B         C         D
         2013-01-04 -0.857795 -0.364065 -0.736198  0.992085
         2013-01-05  0.507128  0.701756 -0.222728  1.348895
         2013-01-06 -0.133285  1.868483  0.013022 -1.437618
         2013-01-07  0.309854 -0.940037 -0.427719  1.073792
         2013-01-08 -1.400886  0.443206 -0.764384  1.315711
         2013-01-09  0.609606 -0.675361  0.042947  0.187821

In [88]: df[df > 0]

Out[88]:                    A         B         C         D
         2013-01-01       NaN       NaN       NaN       NaN
         2013-01-02  0.180882       NaN  0.495707  0.448709
         2013-01-03       NaN  1.029479  1.651550  0.669449
         2013-01-04       NaN       NaN       NaN       NaN
         2013-01-05       NaN       NaN       NaN  1.112229
         2013-01-06  0.104276  0.815805       NaN       NaN
```

```
2013-01-07  0.849349       NaN       NaN       NaN
2013-01-08  1.110839  0.349981       NaN       NaN
2013-01-09  1.145089       NaN       NaN  0.458360
2013-01-10       NaN  1.353922  1.336653       NaN
```

```
In [89]: df.describe()

Out[89]:
                A          B          C          D
       count  10.000000  10.000000  10.000000  10.000000
       mean    0.047316   0.078040  -0.222374  -0.210250
       std     0.755479   0.781589   1.101695   0.858776
       min    -0.848392  -0.854710  -1.590655  -1.627830
       25%    -0.531655  -0.507690  -1.037991  -0.571762
       50%    -0.140703  -0.063067  -0.457143  -0.453856
       75%     0.682233   0.699349   0.366904   0.455947
       max     1.145089   1.353922   1.651550   1.112229
```

In real-life interactive data analysis, one often calculates new sets of values based on measured stuff.

It's a breeze with pd.DataFrames:

```
In [90]: df['E'] = df.A + df.B

In [91]: df['my new column'] = df.C + df.D

In [92]: df['my new column']

Out[92]: 2013-01-01   -1.505537
         2013-01-02    0.944416
         2013-01-03    2.320999
         2013-01-04   -1.315111
         2013-01-05   -0.478425
         2013-01-06   -0.642528
         2013-01-07   -2.282258
         2013-01-08   -1.515478
         2013-01-09    0.438855
         2013-01-10   -0.291178
         Freq: D, Name: my new column, dtype: float64

In [71]: df.head()

Out[71]:
                   A          B          C          D          E
         2013-01-01  0.210685  0.462952  1.447633 -0.656920  0.673637
         2013-01-02  1.395226 -2.062988  0.235129  1.775800 -0.667762
         2013-01-03 -0.233730 -1.109369  0.345990  0.518508 -1.343099
         2013-01-04 -0.857795 -0.364065 -0.736198  0.992085 -1.221860
         2013-01-05  0.507128  0.701756 -0.222728  1.348895  1.208884
```

1.5.1 groupby

Let's have a look at one last powerful feature: Grouping and per-group stats.

First, we need to create something to group by:

```
In [93]: import random

In [94]: group = [random.choice('abc') for _ in range(df.shape[0])]
         group

Out[94]: ['a', 'b', 'b', 'c', 'a', 'b', 'b', 'c', 'a', 'a']

In [95]: df['group'] = group
         df

Out[95]:                    A         B         C         D         E  my new colum
         2013-01-01 -0.385683 -0.447271 -1.056506 -0.449031 -0.832954      -1.50553
         2013-01-02  0.180882 -0.527830  0.495707  0.448709 -0.346947       0.94441
         2013-01-03 -0.691885  1.029479  1.651550  0.669449  0.337594       2.32099
         2013-01-04 -0.567650 -0.854710 -0.856430 -0.458681 -1.422360      -1.31511
         2013-01-05 -0.423667 -0.812838 -1.590655  1.112229 -1.236505      -0.47842
         2013-01-06  0.104276  0.815805 -0.057856 -0.584672  0.920081      -0.64252
         2013-01-07  0.849349 -0.067153 -1.144254 -1.138004  0.782196      -2.28225
         2013-01-08  1.110839  0.349981 -0.982446 -0.533032  1.460820      -1.51547
         2013-01-09  1.145089 -0.058981 -0.019504  0.458360  1.086108       0.43885
         2013-01-10 -0.848392  1.353922  1.336653 -1.627830  0.505529      -0.29117

                    group
         2013-01-01     a
         2013-01-02     b
         2013-01-03     b
         2013-01-04     c
         2013-01-05     a
         2013-01-06     b
         2013-01-07     b
         2013-01-08     c
         2013-01-09     a
         2013-01-10     a

In [96]: g = df.groupby('group')
         g.size()

Out[96]: group
         a    4
         b    4
         c    2
         dtype: int64

In [97]: g.mean()
```

```
Out[97]:                A          B          C          D          E  my new column
         group
         a      -0.128163  0.008708 -0.332503 -0.126568 -0.119455      -0.459071
         b       0.110656  0.312575  0.236287 -0.151129  0.423231       0.085157
         c       0.271594 -0.252364 -0.919438 -0.495857  0.019230      -1.415295
```

Can you imagine how much code you would have to write to do this from scratch?
Ok, exercise time!