Data Wrangling

Agenda

- Python Review
- Jupyter / IPython
- Web Scraping
- NumPy
- Pandas

Python Review

Review

Integers
Floating Point

Dynamic Typing – no declarations

```
x = 5
y = 6.3
```

Names start with a letter,   cAsE SeNsiTiVe.
Long names OK.

Review Character Strings

Dynamic typing – no declaration
No memory allocation
Immutable

```
s = "Good Afternoon"

len(s)                # length of string
```

Review String Slicing

```
s = "Good Afternoon"

s[0]  evaluates to "G"

s[5:10] selects "After"      # string slicing

s[:10] selects "Good After"
s[5:]  selects "Afternoon"

s[-4:] selects "noon"     # last 4 characters
```

String Methods

String is a Class with data & subroutines:

```
t = s.upper()
pos = s.find(“A”)

first = “George”
last = “Washington”
name = first + “ “ + last
```

string concatenation

Review Lists

Ordered sequence of items

Can be floats, ints, strings, Lists

a = [16, 25.3, “hello”, 45]

a[0] contains 16

a[-1] contains 45

a[0:2] is a list containing [16, 25.3]

Create a List

```
days = [ ]
days.append(“Monday”)
days.append(“Tuesday”)

years = range(2000, 2014)
```

List Methods

List is a Class with data & subroutines:

d.insert( )
d.remove( )
d.sort( )

Can concatenate lists with +

String split

```
s = “Princeton Plasma Physics Lab”

myList = s.split()          # returns a list of strings

print myList
      [ “Princeton”, “Plasma”, “Physics”, “Lab” ]

help(str.split)             # delimiters, etc.
```

Tuple

Designated by ( ) parenthesis

A List that can not be changed. Immutable.
No append.

Good for returning multiple values from a subroutine function.

Can extract slices.

Review math module

```
import math
dir(math)

math.sqrt(x)
math.sin(x)
math.cos(x)
```

```
from math import *
dir()

sqrt(x)
```

```
from math import pi
dir()

print pi
```

import a module

```
import math            # knows where to find it
```

```
import sys
sys.path.append("/u/efeibush/python")
import  cubic.py       # import your own code
```

```
if task == 3:
    import math        # imports can be anywhere
```

Review Defining a Function

Block of code separate from main.

Define the function before calling it.

```
def myAdd(a, b):          # define before calling
     return a + b

p = 25                    # main section of code
q = 30

r = myAdd(p, q)
```

Keyword Arguments

Provide default values for optional arguments.

```
def setLineAttributes(color=“black”,
    style=“solid”, thickness=1):
    ...

# Call function from main program
setLineAttributes(style=“dotted”)
setLineAttributes(“red”, thickness=2)
```

Looping with the range() function

```
for i in range(10):      # i gets 0 - 9
```

range() is limited to integers

numpy provides a range of floats

Summary

Integer, Float
String
List
Tuple

def function
Keywords: if elif else
while   for in
import   print

Indenting counts   :

Run python as Interpreter

type()
dir()
help()

Jupyter / IPython

lecture02.jupyter.ipynb

Web Scraping

lecture02.web.scraping.ipynb

NumPy

numpy module

Items are all the same type.

Contiguous data storage in memory of items.

Considerably faster than lists.

Class with data and methods (subroutines).

numpy module

```
import numpy

dir()
dir(numpy)
help(numpy)
help(numpy.ndarray)      # class
help(numpy.array)        # built-in function
```

numpy module

```
import numpy
dir(numpy)
help(numpy.zeros)                tuple

a = numpy.zeros( (3,5) )
```

\# create 3 rows, 5 columns

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

\# default type is float64

numpy Array Access

Access order corresponding to printed order:

[row] [column] index starts with 0

a[0][2] = 5

```
[     [ 0.,  0.,  5.,  0.,  0. ],
      [ 0.,  0.,  0.,  0.,  0. ],
      [ 0.,  0.,  0.,  0.,  0. ]  ]
```

NumPy arrays versus Python lists

- Python lists: Very general
  - `a = [1,2]`
  - `b = [[1,2],[3,4]]`
  - `c = [[1,2, ’duh’],[3,[4]]]`
- NumPy arrays:
  - `x = array([1,2])`
  - `y = array([[1,2],[3,4]])`
  - All rows must have same length, etc.
  - All entries must have same data-type, e.g. all real or all complex

Create 1-D Array

```
# 1-D from list
b = np.array( [ 2., 4., 6. ] )
b
```

```
array([ 2.,  4.,  6.])
```

```
# range(start, end, incr) returns a list so
b = np.array( range(10) )
b
```

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

```
# 1-D from tuple
b = np.array( ( 2., 4., 6. ) )
b
```

```
array([ 2.,  4.,  6.])
```

Create 2-D Matrix

```
# 2-D from tuples
m = np.array( [(2.,3.,4.), (5.,6.,7.)])
m
```

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

```
# 2-D from list of lists
m = np.array( [[2.,3.,4.], [5.,6.,7.]])
m
```

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

EXERCISE

Create a (5, 3) 2-d array / matrix with Numpy that looks like the following:

```
array([[ 0,  1,  2],
       [ 3,  4,  5],
       [ 6,  7,  8],
       [ 9, 10, 11],
       [12, 13, 14]])
```

Challenge: do it in 1 line

Pointer vs. Deep Copy

```
a=np.arange(10)
a
```

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

```
b=a
c=a.copy()
```

```
b is a
```

```
True
```

```
c is a
```

```
False
```

Pointer vs. Deep Copy

```
a = numpy.zeros( (3, 3) )
b = a       # b is a pointer to a
c = a.copy()     # c is a new array

b is a     # True
c is a     # False
```

Views

base

Array Arithmetic

```
a = numpy.array( range(10, 20) )
```

a + 5

a – 3

a * 5

a / 3.14

a.sum()

a > 15

    (a > 15).sum()

Array Arithmetic by Index

```
a = numpy.array( range(10) )
b = numpy.array( range(0, 1000, 100) )

a + b            # a[0] + b[0], a[1] + b[1] ...
a – b
a * b            # not row, column matrix product
a / b
```

The 2 arrays must be the same shape.

Row, Column Matrix Product

```
c = numpy.dot(a, b)
```

Dot product of 2 arrays.
Matrix multiplication for 2D arrays.

Cross Product

```
zA = numpy.cross(xA, yA)
```

Note: we have been using *numpy.* functions

Array Shape

```
a = numpy.linspace(2, 32, 16)

a = a.reshape(4, 4)  # ndarray . method

a.shape        # ndarray attribute     tuple (4, 4)

a = numpy.linspace(2,32,16).reshape(8,2)
```

Array Diagonals

```
a = numpy.linspace(1, 64, 64)

a = a.reshape(8, 8)

numpy.triu(a)         # upper triangle
numpy.tril(a)         # lower triangle

numpy.diag(a)         # main diagonal
numpy.diag(a, 1)      # 1 above
numpy.diag(a, -1)     # 1 below
```

Array Data Types

numpy.float64 is the default type

float32
int8, int16, int32, int64, uint8, uint16, uint32, uint64
complex64, complex128
bool   - True or False

a.dtype   shows type of data in array

```
>>> help(numpy.ndarray)
```
Parameters

Attributes

Multi-Dimensional Indexing

```
a = numpy.array( range(12) )
a = a.reshape(2,6)      # 2 rows, 6 columns
```

a[1][5] contains 11

a[1, 5] is equivalent, more efficient

Array Slicing

```
a = numpy.array(range(0, 100, 10))
```

Array([0, 10, 20, 30, 40, 50, 60, 70, 80, 90])

a[2:4] contains 20, 30

a[-4 : -1] contains 60, 70, 80

Slicing returns ndarray

Array Slicing

```
a = numpy.array(range(64)).reshape(8,8)
```

a[3, 4] contains 28

```
asub = a[3:5,  4:6]
```

Very useful for looking at data & debugging.

```
a[:,2]          # all rows, column 2
a[3, 2:5]       # row 3, columns 2 and 3 and 4
```

Array Stuff

a.T
a.min()
a.max()
a.round()
a.var()
a.std()

Organize Arrays

Make a list of arrays named a, b, and c:

```
w = [ a, b, c]

len(w)            # length of list is 3

w[1].max()        # use array method
```

EXERCISE

Conditional Logic with NumPy

Consider these arrays:

```
xarr = np.array([1.1, 1.2, 1.3, 1.4, 1.5])
yarr = np.array([2.1, 2.2, 2.3, 2.4, 2.5])
cond = np.array([True, False, True, True, False])
```

Use native “list comprehension” from Python:

```
result = [(x if c else y)
          for x, y, c in zip(xarr, yarr, cond)]
result
```

```
[1.1000000000000001, 2.2000000000000002, 1.3, 1.3999999999999999, 2.5]
```

Conditional Logic with NumPy

Consider these arrays:

```
xarr = np.array([1.1, 1.2, 1.3, 1.4, 1.5])
yarr = np.array([2.1, 2.2, 2.3, 2.4, 2.5])
cond = np.array([True, False, True, True, False])
```

Use NumPy conditional logic:

```
result = np.where(cond, xarr, yarr)
result
```

```
array([ 1.1,  2.2,  1.3,  1.4,  2.5])
```

Why Conditional Logic with NumPy?

Consider these arrays:

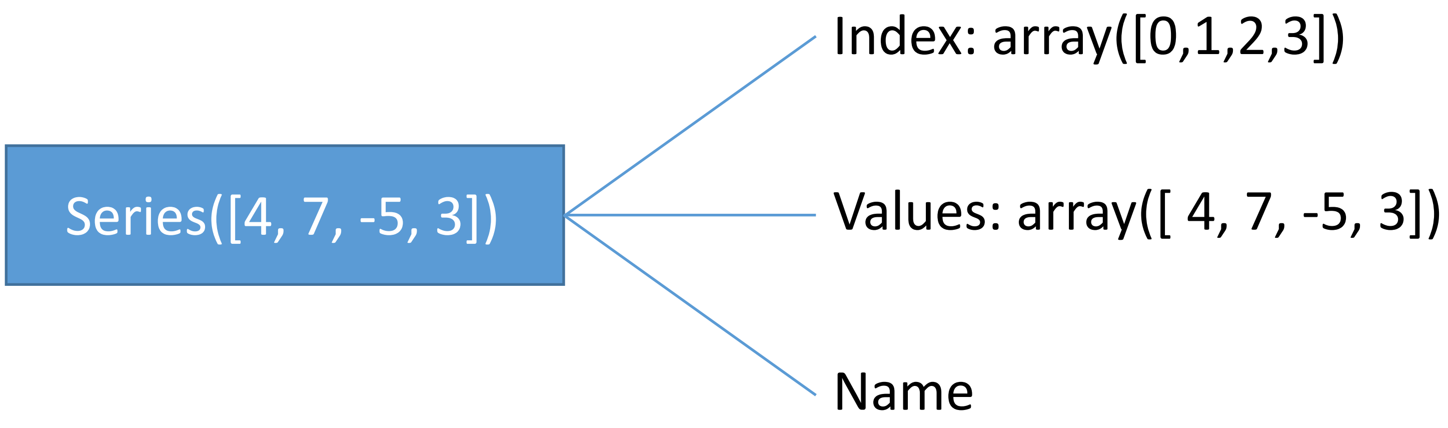
```
arr = randn(4, 4)
arr
np.where(arr > 0, 2, -2)
np.where(arr > 0, 2, arr) # set only positive values to 2
```

```
array([[-1.307 ,  2.    ,  2.    ,  2.    ],
       [-1.0305, -0.2168,  2.    ,  2.    ],
       [ 2.    ,  2.    ,  2.    , -1.3704],
       [-0.544 , -0.7909,  2.    , -0.5366]])
```

(1) Works with vectors / arrays / list by default
(2) Fast

Pandas

Series : pandas 1-D vectors



Series: Index, Values

2 main Series attribues: Index, Values

```
obj2 = Series([4, 7, -5, 3], index=['d', 'b', 'a', 'c'])
obj2
```

```
d    4
b    7
a   -5
c    3
dtype: int64
```

```
obj2.index
```

```
Index([u'd', u'b', u'a', u'c'], dtype='object')
```

```
obj2.values
```

```
array([ 4,  7, -5,  3])
```

Series: element selection

```
obj2['a']
```

```
-5
```

```
obj2['d'] = 6
```

```
obj2[['c', 'a', 'd']]
```

```
c    3
a   -5
d    6
dtype: int64
```

Series: membership

```
'b' in obj2
```

```
True
```

```
'e' in obj2
```

```
False
```

Series: element filtering

```
obj2[obj2 > 0]
```

```
d    6
b    7
c    3
dtype: int64
```

Series: scalar operations

```
obj2 * 2
```

```
d    12
b    14
a   -10
c     6
dtype: int64
```

```
np.exp(obj2)
```

```
d     403.428793
b    1096.633158
a       0.006738
c      20.085537
dtype: float64
```

DataFrame: table in pandas

```
data = {'state': ['Ohio', 'Ohio', 'Ohio', 'Nevada', 'Nevada'],
        'year': [2000, 2001, 2002, 2001, 2002],
        'pop': [1.5, 1.7, 3.6, 2.4, 2.9]}
```

```
DataFrame(data, columns=['year', 'state', 'pop'])
```

	year	state	pop
0	2000	Ohio	1.5
1	2001	Ohio	1.7
2	2002	Ohio	3.6
3	2001	Nevada	2.4
4	2002	Nevada	2.9

DataFrame: table in pandas

```
data = {'state': ['Ohio', 'Ohio', 'Ohio', 'Nevada', 'Nevada'],
        'year': [2000, 2001, 2002, 2001, 2002],
        'pop': [1.5, 1.7, 3.6, 2.4, 2.9]}
frame = DataFrame(data)
```

```
frame
```

	pop	state	year
0	1.5	Ohio	2000
1	1.7	Ohio	2001
2	3.6	Ohio	2002
3	2.4	Nevada	2001
4	2.9	Nevada	2002

DataFrame: columns of lists with indices

```
data = {'state': ['Ohio', 'Ohio', 'Ohio', 'Nevada', 'Nevada'],
        'year': [2000, 2001, 2002, 2001, 2002],
        'pop': [1.5, 1.7, 3.6, 2.4, 2.9]}
```

```
frame2 = DataFrame(data, columns=['year', 'state', 'pop', 'debt'],
                   index=['one', 'two', 'three', 'four', 'five'])
frame2
```

	year	state	pop	debt
one	2000	Ohio	1.5	NaN
two	2001	Ohio	1.7	NaN
three	2002	Ohio	3.6	NaN
four	2001	Nevada	2.4	NaN
five	2002	Nevada	2.9	NaN

DataFrame: columns

```
frame2.columns
```

```
Index([u'year', u'state', u'pop', u'debt'], dtype='object')
```

```
frame2['state']
```

```
one        Ohio
two        Ohio
three      Ohio
four     Nevada
five     Nevada
Name: state, dtype: object
```

```
frame2.year
```

```
one      2000
two      2001
three    2002
four     2001
five     2002
Name: year, dtype: int64
```

DataFrame: inserting data

```
frame2['debt'] = 16.5
frame2
```

	year	state	pop	debt
one	2000	Ohio	1.5	16.5
two	2001	Ohio	1.7	16.5
three	2002	Ohio	3.6	16.5
four	2001	Nevada	2.4	16.5
five	2002	Nevada	2.9	16.5

DataFrame: inserting data

```
frame2['debt'] = np.arange(5.)
frame2
```

	year	state	pop	debt
one	2000	Ohio	1.5	0.0
two	2001	Ohio	1.7	1.0
three	2002	Ohio	3.6	2.0
four	2001	Nevada	2.4	3.0
five	2002	Nevada	2.9	4.0