UC Berkeley Extension

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, IPyton 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. *project discussion*

Language specifics

- I/O interaction with files
  - when working with data it is generally more convenient to read it from a file containing it
  - in order to store some result the user have to be able to write to a file
  - in order to begin reading from or writing to a file, the user has to specify it

Example:

```
file = open('files/lecture3/test.txt', 'r') # opens file for reading
sentences = file.readlines()
print(sentences)
print(len(sentences))
file.close()

file = open('files/lecture3/test.txt', 'w') # opens file for writing
file.write('We will overwrite the previous text \n and go to a new line as well')
file.close()

file = open('files/lecture3/test.txt', 'r') # opens file for reading
sentences = file.readlines()
print(sentences)
print(len(sentences))
file.close()
```

… the code above will result in:

```
['Hello all, I am a text file :)']
1
['We will overwrite the previous text \n', ' and go to a new line as well']
2
```

Language specifics

- I/O interaction with files
  - below are the possible file mode options for file I/O interaction:
    - r – open file to read-only
      - » Note: you can not write to it, but only to read from it
    - w – open the file to write-only
      - » Note: this option creates a new file or overwrites an existing one
    - a – open file to append to it (use a+ ->to read and append)
      - » Note: it does not delete any previous entries
    - r+ - open file to read and write
      - » Note: it works just like the 'w' option, but you can read the file
    - b – open file in binary mode
      - » Note: used for binary files

Language specifics

- Standard library
    - Some of the top standard library modules in Python are:
    - Os – provides a selected list of operating system level functionality
    - Sys – provides access to some variables used by the interpreter
    - Io – deals with I/O functionality for the three main types of I/O: text, binary and raw
    - Math – it gives access to mathematical functions excluding complex numbers (->cmath)
    - Wave – part of Python core installation, provides interface to the WAV format
    - Audioop – consist of useful tools for operating on digital sound sampled data
    - Html – provides an utility to work with the html language
    - Time – provides functions related to time
    - Calendar – provides various calendar capability
    - Daytime – extended way of manipulating date and time

Language specifics

- Exceptions
  - exceptions in Python are raised when the interpreter finds a problem with executing a code
  - they can be used to notify the user that certain state is reached or a condition is met
  - exceptions can pass messages from one part of the code to another
  - there are different types of errors and some of them are shown below

Example:

```
In [35]: a = [12,34,41,54]

In [36]: a[4]
---------------------------------------------------------------------------
IndexError                                Traceback (most recent call last)
/Users/alex/1.HD/Alex/1.new/Work/3.Berkeley Extension/3. final course material/2.
.py in <module>()
----> 1 a[4]

IndexError: list index out of range

In [37]: a[2]/0
---------------------------------------------------------------------------
ZeroDivisionError                         Traceback (most recent call last)
/Users/alex/1.HD/Alex/1.new/Work/3.Berkeley Extension/3. final course material/2.
.py in <module>()
----> 1 a[2]/0

ZeroDivisionError: division by zero
```

Language specifics

- Exceptions
  - exceptions in Python are raised when the interpreter finds a problem with executing a code
  - they can be used to notify the user that certain state is reached or a condition is met
  - exceptions can pass messages from one part of the code to another
  - there are different types of errors and some of them are shown below

Example:

```
In [38]: a.delete
---------------------------------------------------------------------------
AttributeError                            Traceback (most recent call last)
/Users/alex/1.HD/Alex/1.new/Work/3.Berkeley Extension/3. final course material/2.
.py in <module>()
----> 1 a.delete

AttributeError: 'list' object has no attribute 'delete'

In [39]: a[3] + 'Python'
---------------------------------------------------------------------------
TypeError                                 Traceback (most recent call last)
/Users/alex/1.HD/Alex/1.new/Work/3.Berkeley Extension/3. final course material/2.
.py in <module>()
----> 1 a[3] + 'Python'

TypeError: unsupported operand type(s) for +: 'int' and 'str'
```

Language specifics

- Exceptions

  - in order to handle exceptions, they have to be caught first

Example:

… running the code:

```
while True:
    try:
        a = int(input('Please enter a number: '))
        print('You entered the number ', a)
        print('I will now exit. Good bye!')
        break
    except ValueError:
        print('You entered an invalid number.  Please try again.')
```

… will produce the following result:

```
Please enter a number: q
You entered an invalid number.  Please try again.
Please enter a number: t
You entered an invalid number.  Please try again.
Please enter a number: 5
You entered the number  5
I will now exit. Good bye!
```

Why NumPy?

- Why NumPy?
  - Numpy is the main scientific open-source package for numerical computation in Python
  - Numpy provides:
    - functionality comparable to Matlab,
    - it allows for fast algorithm development and proof-of-concept scientific solutions
    - It provides logic manipulation functionality
    - large set of mathematical functions
    - linear algebra functionality
    - Fast Fourier transform
    - large multidimensional array objects
    - variety of routines for fast operations on arrays
    - different objects, like matrices and masked arrays
    - random simulation
    - sorting
    - statistical operations
    - … and much more

Why NumPy?

- Why NumPy?
  - NumPy's core functionality is the *ndarray*, which stands for *n*-dimensional array
  - NumPy arrays' data structure and standard sequences in Python have some important differences:
    - NumPy array elements must be of the same data type and take the same memory space
    - this gives NumPy the capability to make advanced mathematical calculations possible on large data sets
    - this kind of calculations are executed with higher efficiency and use more concise code as compared to the built-in sequences in Python
    - lists in Python can increase on the fly, while arrays in NumPy are fixed size once created
    - when the size of an ndarray is changed, a new array will be created and the reference (id) to the the original array will be released (lost and deleted)
    - in Python and NumPy, when having arrays of objects, arrays of different sized elements are possible

Why NumPy?

- Why NumPy?
  - The main differences between regular Python objects and NumPy objects are:
    - **Speed** – comparing the results from a simple test on performing addition over a regular Python list and over a NumPy array, reveals that the sum on the latter is faster
    - **Memory efficiency**:
      - NumPy's arrays are more compact than Python lists (example later in slides)
      - a list of lists in Python, would take at 3-5 times more space than a NumPy array using single-precision float type numbers
    - **Functionality** - FFT, convolution, statistics, linear algebra, histograms, etc.
    - **Convenience** – all vector and matrix operations come free with NumPy, while they are efficiently implemented and save unnecessary work

Why NumPy?

- Why NumPy?
  - The main differences between regular Python objects and NumPy objects are:
    - **Speed** – comparing the results from a simple test on performing addition over a regular Python list and over a NumPy array, reveals that the sum on the latter is faster for large calculations

Speed test example:

```python
from numpy import arange
import time

N = int(input('Please enter a number: '))

x = arange(N)
y = range(N)

tic = time.clock()
x.sum()
toc = time.clock()
t_numpy = toc - tic

tic = time.clock()
sum(y)
toc = time.clock()
t_list = toc - tic

print("numpy: %.3e sec" % (t_numpy))
print("list:  %.3e sec" % (t_list))
print("diff:  %.3e sec" % (t_list-t_numpy))
print("ratio: list is %.1i times slower than numpy ndarray" % (t_list/t_numpy))
```

Python

```
In [1]: run speed_test_list_ndarray
Please enter a number: 20000
numpy: 7.300e-05 sec
list:  8.330e-04 sec
diff:  7.600e-04 sec
ratio: list is 11 times slower than numpy ndarray
```

Data type objects

- Data type objects
  - there are five basic numerical types in NumPy:
    - bool – booleans
    - int – integers
    - uint – unsigned integers
    - float – floating point
    - complex – 2 double precision numbers
  - all numerical types in NumPy are instances of the dtype object and you can find them like this:

```
In [1]:  import numpy as np
In [2]:  np.<data type>
             or
In [3]:  dir(np)
```

Data type objects

- Data type objects
  - NumPy supports much larger variety of types than what the standard Python implementation does:

Number type	Data type	Description
Booleans	bool, bool8, bool_	Boolean (True or False) stored as a byte – 8 bits
Integers	byte	compatible: C char – 8 bits
	short	compatible: C short – 16 bits
	int, int0, int_	Default integer type (same as C `long`; normally either `int32` or `int64`) – 64 bits
	longlong	compatible: C long long – 64 bits
	intc	Identical to C `int` – 32 bits
	intp	Integer used for indexing (same as C `size_t`) – 64 bits
	int8	Byte (-128 to 127) – 8 bits
	int16	Integer (-32768 to 32767) – 16 bits
	int32	Integer (-2147483648 to 2147483647) – 32 bits
	int64	Integer (-9223372036854775808 to 9223372036854775807) – 64 bits
Unsigned integers	uint, uint0	Python int compatible, unsigned – 64 bits
	ubyte	compatible: C unsigned char, unsigned – 8 bits
	ushort	compatible: C unsigned short, unsigned – 16 bits
	ulonglong	compatible: C long long, unsigned – 64 bits
	uintp	large enough to fit a pointer – 64 bits
	uintc	compatible: C unsigned int – 32 bits
	uint8	Unsigned integer (0 to 255) – 8 bits
	uint16	Unsigned integer (0 to 65535) – 16 bits
	uint32	Unsigned integer (0 to 4294967295) – 32 bits
	uint64	Unsigned integer (0 to 18446744073709551615) – 64 bits

Data type objects

- Data type objects
  - NumPy supports much larger variety of types than what the standard Python implementation does:

Number type	Data type	Description
Floating-point numbers	half	compatible: C short – 16 bits
	single	compatible: C float – 32 bits
	double	compatible: C double – 64 bits
	longfloat	compatible: C long float – 128 bits
	float_	Shorthand for `float64` – 64 bits
	float16	Half precision float: sign bit, 5 bits exponent, 10 bits mantissa
	float32	Single precision float: sign bit, 8 bits exponent, 23 bits mantissa
	float64	Double precision float: sign bit, 11 bits exponent, 52 bits mantissa
	float128	128 bits
Complex floating-point numbers	csingle	64 bits
	complex, complex_	Shorthand for `complex128` – 128 bits
	complex64	Complex number, represented by two 32-bit floats (real and imaginary components)
	complex128	Complex number, represented by two 64-bit floats (real and imaginary components)
	complex256	two 256 bit floats

  - To check how many bits each type occupies, use one of these notations:
    1) (np.dtype(np.<type>).itemsize)*8
    2) np.<type>().itemsize*8

Data type objects

- Data type objects
  - the difference between signed and unsigned integers and long type variables is:
    - the signed and unsigned types are of the same size
    - the signed can represent equal amount of values around the '0' thus representing equal amount of positive and negative numbers
    - the unsigned can not represent any negative numbers, but can represent double the amount of total positive numbers as compared to the signed type
    - for 32-bit int we have:

      int: –2147483648 to 2147483647

      uint: 0 to 4294967295
    - for 64-bit long we have:

      long: -9223372036854775808 to 9223372036854775807

      ulong: 0 to 18446744073709551615

Data type objects

- Data type objects
  - some of the data types that contain numbers, explicitly specify the bit size of the particular type
  - this is an important thing to know when coding on a 32-bit or 64-bit platforms and a low-level languages are used (C or Fortran)
  - some NumPy data types can be used to:
    - convert python numbers to array scalars (used as functions)
    - convert python sequences of numbers to arrays
    - enter as arguments to the dtype keyword to call various NumPy methods

Data type objects

- Data type objects
  - Examples:
    - convert Python numbers to array scalars (used as functions)

```
In [3]: import numpy as np

In [4]: from sys import getsizeof

In [5]: x=float(2.5)

In [6]: type(x)
Out[6]: float

In [7]: getsizeof(x)
Out[7]: 24

In [8]: x = np.float128(2.5)

In [9]: type(x)
Out[9]: numpy.float128

In [10]: getsizeof(x)
Out[10]: 32
```

… try it in class

Data type objects

- Data type objects
  - Examples:
    - convert Python sequences (lists, tuples, etc.) of numbers to arrays

```
In [11]: a=([12,34,41,52])

In [12]: type(a)
Out[12]: list

In [13]: b=np.int32(a)

In [14]: type(b)
Out[14]: numpy.ndarray

In [15]: getsizeof(a)
Out[15]: 96

In [16]: getsizeof(b)
Out[16]: 80

In [17]: a
Out[17]: [12, 34, 41, 52]

In [18]: b
Out[18]: array([12, 34, 41, 52], dtype=int32)
```

Data type objects

- Data type objects

  – Examples:

    - enter as arguments to the dtype keyword to call various NumPy methods

```
In [19]: c = np.arange(5, dtype=np.float16)

In [20]: type(c)
Out[20]: numpy.ndarray

In [21]: c
Out[21]: array([ 0.,  1.,  2.,  3.,  4.], dtype=float16)

In [22]: getsizeof(c)
Out[22]: 80
```

… try it in class

NumPy arrays

- Difference between a C variable and a Python variable
  - For a C variable, the compiler already knows the type by its declaration:
    - int A = 5;   /* C code */

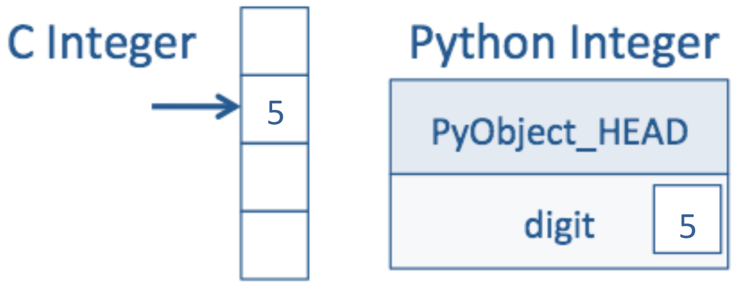
    Steps:

    1. assign <int> to A

  - For a Python variable, is only known that the variable is some sort of Python object at the time of program execution:
    - A = 5   # python code

    Steps:

    1. Set A -> PyObject_HEAD -> typecode to integer
    2. Set A -> val = 5



NumPy arrays

- Difference between a C variable and a Python variable
  - For a C variable, the compiler already knows the type by its declaration:
    - int A = 5; /* C code */
    - int B = A + 10; /* C code */

    Steps:
    1. assign <int> to A
    2. call binary_add<int, int>(A, 10)
    3. assign the result to B
  - For a Python variable, is only known that the variable is some sort of Python object at the time of program execution:
    - A = 5 # python code
    - B = A + 10 # python code

    Steps:
    1. Set A -> PyObject_HEAD -> typecode to integer
    2. Set A -> val = 5
    3. call binary_add(A, 10):

       find typecode in A -> PyObject_HEAD

       A is an integer; The value is A -> val

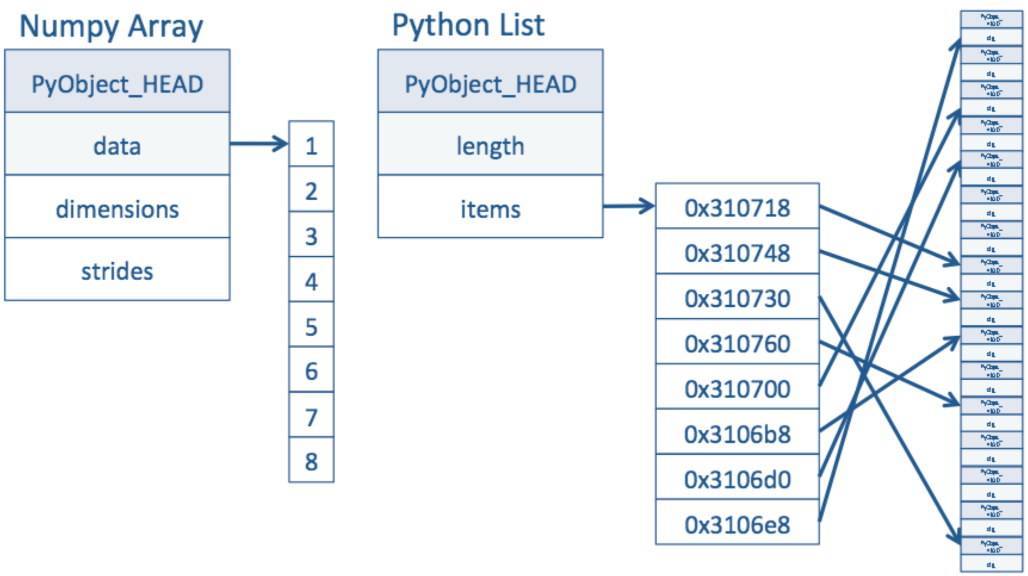
       find that '10' is an integer obj.

       call binary_add<int, int>(A->val, int->val)

       result of this is an integer
    4. set B -> PyObject_HEAD -> typecode to integer
    5. set B -> val to ***result***

NumPy arrays

- Difference between NumPy arrays vs Python Lists
  - NumPy array:
    - A NumPy array is a Python object build around a C array
    - This means that it has a pointer to a contiguous data buffer of values
  - Python Lists:
    - A Python list has a pointer to a contiguous buffer of pointers
    - All of them point to different Python objects, which in turn has references to its data (in this case, integers)
  - Conclusion:
    - NumPy is much more efficient than Python, in the cost of storage and in speed of access



NumPy arrays

- NumPy arrays
  - NumPy provides an N-dimensional array type called – ndarray
  - an ndarray is a multidimensional container
  - it describes a collection of “items” of the same type
  - all items can be indexed using integer type notation
  - each item in an ndarray takes up the same size block of memory, hence they are called homogenous
  - all blocks are interpreted in exactly the same way
  - each item in an array is interpreted by a separate data-type object, one of which is associated with every array and is called dtype
  - besides basic types (booleans, integers, floats, etc.), the data type objects can represent data structures as well
  - each item from an array, is indexed, and is represented by a Python object whose type is one of the array scalar types provided in NumPy
  - these array scalars allow easy manipulation of even more complicated data organization
  - ndarrays can share similar data, so changes in one will reflect in the other
  - this is referred to as *‘view’* and *‘base’* of the ndarray (example later in slides)

NumPy arrays

- NumPy arrays

Example:

```
In [23]: a = np.array([[12, 34, 41], [54, 62, 18], [72, 84, 96]], np.int16)

In [24]: a
Out[24]:
array([[12, 34, 41],
       [54, 62, 18],
       [72, 84, 96]], dtype=int16)

In [25]: a.size
Out[25]: 9

In [26]: a.shape
Out[26]: (3, 3)

In [27]: type(a)
Out[27]: numpy.ndarray

In [28]: a.dtype
Out[28]: dtype('int16')

In [29]: a[2,2]   # this is how we index a particular elemnt in the array (#9)
Out[29]: 96

In [30]: b = a[0,:]

In [31]: b
Out[31]: array([12, 34, 41], dtype=int16)

In [32]: b.shape
Out[32]: (3,)

In [33]: b[2] = 88   # this is how we reassign another value to a member in the array

In [34]: a[2,2] = 99 # the change above also affects the original array

In [35]: a
Out[35]:
array([[12, 34, 88],
       [54, 62, 18],
       [72, 84, 99]], dtype=int16)

In [36]: b
Out[36]: array([12, 34, 88], dtype=int16)
```

… try it in class

NumPy arrays

- NumPy arrays
  - arrays can be constructed using the following reserved words: array, zeros, ones or empty
    - array – will construct an array
    - zeros – will create an array filled with zeroes
    - ones – will create an array filled with ones
    - empty – will construct an empty array to be filled at a later point
  - NumPy array parameters:

    shape: tuple of ints – shape of created array

    dtype: data-type, optional – Any object that can be interpreted as a NumPy data type

    strides: tuple of ints, optional – Strides of data in memory

    buffer: object exposing buffer interface, optional – Used to fill the array with data

    offset: int, optional – Offset of array data in buffer

    order: {'C', 'F'}, optional – Row-major or column-major order

NumPy arrays

- NumPy arrays

Examples:

```
In [37]: c = np.zeros(shape=(4,5))   # the array contains zeroes for all elelements

In [38]: c
Out[38]:
array([[ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.],
       [ 0.,  0.,  0.,  0.,  0.]])

In [39]: d = np.empty(shape=(2,2))   # the array contains meaningless data

In [40]: d
Out[40]:
array([[ 0.,  0.],
       [ 0.,  0.]])

In [41]: e = np.ndarray(shape=(2,3), dtype=complex, offset=np.float_().itemsize, order='C')

In [42]: e
Out[42]:
array([[  0.00000000e+000 +1.72723382e-077j,
          2.12316144e-314 +2.14479474e-314j,
          2.12375379e-314 +2.24090241e-314j],
       [  2.12530167e-314 +2.12303539e-314j,
          2.24504872e-314 +3.27074300e+015j,
          3.28995843e-318 +8.34402697e-309j]])
```

check the 'sizeof' each

... try it in class

Numpy

- Zeros and Empty difference:
  - empty - returns an array of given type and shape, without initializing its entries
  - zeros - return a new array of given shape and type, initialized with zeros
  - empty is therefore be marginally faster, but requires the user to manually set all values in the array. Use with caution
  - Conclusion: there is a small optimization benefit when using empty: it is slightly faster as compared to other initialization of array to zeros or ones

SciPy.org Sponsored By ENTHOUGHT

Scipy.org | Docs | NumPy v1.11 Manual | NumPy Reference | Routines | Array creation routines

numpy.empty

numpy.empty(*shape, dtype=float, order='C'*)

Return a new array of given shape and type, without initializing entries.

Parameters: **shape** : *int or tuple of int*
Shape of the empty array
dtype : *data-type, optional*
Desired output data-type.
order : *{'C', 'F'}, optional*
Whether to store multi-dimensional data in row-major (C-style) or column-major (Fortran-style) order in memory.

Returns: **out** : *ndarray*
Array of uninitialized (arbitrary) data of the given shape, dtype, and order. Object arrays will be initialized to None.

Examples

```
>>> np.empty([2, 2])
array([[ -9.74499359e+001,   6.69583040e-309],
       [  2.13182611e-314,   3.06959433e-309]])         #random
```

```
>>> np.empty([2, 2], dtype=int)
array([[-1073741821, -1067949133],
       [  496041986,    19249760]])                     #random
```

Numpy

Recap:

- \- negative index in Python lists: negative numbers mean that you count from the right instead of the left. So, in a[1,2,3,4], the reference a[3]=4 == a[-1]=4, a[2]=3 == a[-2]=3, etc.

- \- the ‘endpoint’ option: default = True and last element included, False – not included. Observe example:

```
In [10]: plb.linspace(1,5,10)
Out[10]:
array([ 1.        ,  1.44444444,  1.88888889,  2.33333333,  2.77777778,
        3.22222222,  3.66666667,  4.11111111,  4.55555556,  5.        ])

In [11]: plb.linspace(1,5,10, endpoint=False)
Out[11]: array([ 1. ,  1.4,  1.8,  2.2,  2.6,  3. ,  3.4,  3.8,  4.2,  4.6])

In [12]: plb.linspace(1,5,10, endpoint=True)
Out[12]:
array([ 1.        ,  1.44444444,  1.88888889,  2.33333333,  2.77777778,
        3.22222222,  3.66666667,  4.11111111,  4.55555556,  5.        ])
```

NumPy arrays

- NumPy arrays
  - array attributes

T	Same as self.transpose(), except that self is returned if self.ndim < 2.
data	Python buffer object pointing to the start of the array's data.
dtype	Data-type of the array elements.
flags	Information about the memory layout of the array.
flatten	A 1-D iterator over the array.
imag	The imaginary part of the array.
real	The real part of the array.
size	Number of elements in the array.
itemsize	Length of one array element in bytes.
nbytes	Total bytes consumed by the elements of the array.
ndim	Number of array dimensions.
shape	Tuple of array dimensions.
strides	Tuple of bytes to step in each dimension when traversing an array.
ctypes	An object to simplify the interaction of the array with the ctypes module.
base	Base object if memory is from some other object.

*source – NumPy reference

NumPy arrays

- NumPy arrays

Examples:

```
In [43]: f = np.ndarray(shape=(2,3,2), dtype=complex)

In [44]: f
Out[44]:
array([[[  0.00000000e+000 -2.00000013e+000j,
           2.12215769e-314 +9.88131292e-324j],
        [  0.00000000e+000 +0.00000000e+000j,
           0.00000000e+000 -9.84629069e+109j],
        [  0.00000000e+000 +0.00000000e+000j,
           2.25697366e-314 +0.00000000e+000j]],

       [[  0.00000000e+000 +2.25697468e-314j,
           0.00000000e+000 +0.00000000e+000j],
        [ -2.58861351e-056 +0.00000000e+000j,
           0.00000000e+000 -2.05241193e-191j],
        [  2.12381808e-314 +2.25685768e-314j,
          -4.57473710e+035 +2.24500133e-314j]]])

In [45]: f.real
Out[45]:
array([[[  0.00000000e+000,   2.12215769e-314],
        [  0.00000000e+000,   0.00000000e+000],
        [  0.00000000e+000,   2.25697366e-314]],

       [[  0.00000000e+000,   0.00000000e+000],
        [ -2.58861351e-056,   0.00000000e+000],
        [  2.12381808e-314,  -4.57473710e+035]]])

In [46]: f.real.T
Out[46]:
array([[[  0.00000000e+000,   0.00000000e+000],
        [  0.00000000e+000,  -2.58861351e-056],
        [  0.00000000e+000,   2.12381808e-314]],

       [[  2.12215769e-314,   0.00000000e+000],
        [  0.00000000e+000,   0.00000000e+000],
        [  2.25697366e-314,  -4.57473710e+035]]])
```

… try it in class

NumPy arrays

- NumPy arrays

Examples:

```
In [47]: f.imag.flags
Out[47]:
  C_CONTIGUOUS : False
  F_CONTIGUOUS : False
  OWNDATA : False
  WRITEABLE : True
  ALIGNED : True
  UPDATEIFCOPY : False

In [48]: f.imag.data
Out[48]: <memory at 0x110298ce0>

In [49]: f.real.dtype
Out[49]: dtype('float64')

In [50]: f.dtype
Out[50]: dtype('complex128')

In [51]: f.shape
Out[51]: (2, 3, 2)

In [52]: f.T.shape
Out[52]: (2, 3, 2)

In [53]: f.size
Out[53]: 12

In [54]: f.itemsize
Out[54]: 16

In [55]: f.nbytes
Out[55]: 192

In [56]: f.ndim
Out[56]: 3
```

Note - it can be seen that the attributes of ndarray can be used in a nested fashion

… try it in class

NumPy arrays

- NumPy arrays
  - flags – gives information about the memory layout of the array

C_CONTIGUOUS (C)	The data is in a single, C-style contiguous segment.
F_CONTIGUOUS (F)	The data is in a single, Fortran-style contiguous segment.
OWNDATA (O)	The array owns the memory it uses or borrows it from another object.
WRITEABLE (W)	The data area can be written to. Setting this to False locks the data, making it read-only. A view (slice, etc.) inherits WRITEABLE from its base array at creation time, but a view of a writeable array may be subsequently locked while the base array remains writeable. (The opposite is not true, in that a view of a locked array may not be made writeable. However, currently, locking a base object does not lock any views that already reference it, so under that circumstance it is possible to alter the contents of a locked array via a previously created writeable view onto it.) Attempting to change a non-writeable array raises a RuntimeError exception.
ALIGNED (A)	The data and all elements are aligned appropriately for the hardware.
UPDATEIFCOPY (U)	This array is a copy of some other array. When this array is de-allocated, the base array will be updated with the contents of this array.
FNC	F_CONTIGUOUS and not C_CONTIGUOUS.
FORC	F_CONTIGUOUS or C_CONTIGUOUS (one-segment test).
BEHAVED (B)	ALIGNED and WRITEABLE.
CARRAY (CA)	BEHAVED and C_CONTIGUOUS.
FARRAY (FA)	BEHAVED and F_CONTIGUOUS and not C_CONTIGUOUS.

*source – NumPy reference

NumPy arrays

- NumPy arrays
  - flatten – returns a copy of the same flattened array in one dimension

```
In [57]: g = np.arange(12, 24).reshape(3, 4)

In [58]: g
Out[58]:
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])

In [59]: g[:,:]
Out[59]:
array([[12, 13, 14, 15],
       [16, 17, 18, 19],
       [20, 21, 22, 23]])

In [60]: g.flat[6]
Out[60]: 18

In [61]: g.flat[9]
Out[61]: 21

In [62]: g.flat[:]
Out[62]: array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23])

In [63]: g.flatten()
Out[63]: array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23])

In [64]: g.T.flat[6]
Out[64]: 14
```

```
In [33]: g.flatten(order='C')
Out[33]: array([12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23])

In [34]: g.flatten(order='F')
Out[34]: array([12, 16, 20, 13, 17, 21, 14, 18, 22, 15, 19, 23])
```

```
In [18]: g.T
Out[18]:
array([[12, 16, 20],
       [13, 17, 21],
       [14, 18, 22],
       [15, 19, 23]])
```

… try it in class

NumPy arrays

- NumPy arrays

  – shape – besides checking or specifying the shape of an array, by using the shape command we can also re-shape an array so long that we do not change the number of elements in it

Example:

```
In [65]: h = np.array([[12,34,41],[54,67,89],[102,13,45],[78,456,218]])

In [66]: h
Out[66]:
array([[ 12,  34,  41],
       [ 54,  67,  89],
       [102,  13,  45],
       [ 78, 456, 218]])

In [67]: h.shape
Out[67]: (4, 3)

In [68]: h.shape = (2,6)

In [69]: h
Out[69]:
array([[ 12,  34,  41,  54,  67,  89],
       [102,  13,  45,  78, 456, 218]])

In [70]: h.shape = (3,6)
---------------------------------------------------------------------------
ValueError                                Traceback (most recent call last)
<ipython-input-70-76a181f81944> in <module>()
----> 1 h.shape = (3,6)

ValueError: total size of new array must be unchanged
```

NumPy arrays

- NumPy arrays
  - strides – represents the number of bytes (8-bit each) needed to travel in each direction (in memory) in a multidimensional array in order to get to certain element in that array along a given axis

Example:

```
Python
In [71]: i = np.reshape(np.arange(3*4*5), (5,3,4))

In [72]: i
Out[72]:
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11]],

       [[12, 13, 14, 15],
        [16, 17, 18, 19],
        [20, 21, 22, 23]],

       [[24, 25, 26, 27],
        [28, 29, 30, 31],
        [32, 33, 34, 35]],

       [[36, 37, 38, 39],
        [40, 41, 42, 43],
        [44, 45, 46, 47]],

       [[48, 49, 50, 51],
        [52, 53, 54, 55],
        [56, 57, 58, 59]]])

In [73]: np.shape(i)
Out[73]: (5, 3, 4)
```

Note – the given array *i* is stored in a continuous block of memory of:

60 bytes (5*3*4)

NumPy arrays

- NumPy arrays
  - strides

Example:

```
In [74]: i[4][2][1]
Out[74]: 57

In [75]: i[4,2,1]
Out[75]: 57

In [76]: np.dtype(i[4,2,1])
Out[76]: dtype('int64')

In [77]: i
Out[77]:
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11]],

       [[12, 13, 14, 15],
        [16, 17, 18, 19],
        [20, 21, 22, 23]],

       [[24, 25, 26, 27],
        [28, 29, 30, 31],
        [32, 33, 34, 35]],

       [[36, 37, 38, 39],
        [40, 41, 42, 43],
        [44, 45, 46, 47]],

       [[48, 49, 50, 51],
        [52, 53, 54, 55],
        [56, 57, 58, 59]]])

In [78]: i.strides
Out[78]: (96, 32, 8)
```

Note – you can easily refer to an element from the array, knowing its position as shown in lines Out[74]/[75] , or …

… try it in class

NumPy arrays

- NumPy arrays
  - strides

Example:

```
In [79]: np.array([4,2,1])
Out[79]: array([4, 2, 1])

In [80]: np.array([4,2,1]) * i.strides
Out[80]: array([384,  64,   8])

In [81]: sum(np.array([4,2,1]) * i.strides)
Out[81]: 456

In [82]: i.itemsize
Out[82]: 8

In [83]: sum(np.array([4,2,1]) * i.strides)/i.itemsize
Out[83]: 57.0

In [84]: i
Out[84]:
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7],
        [ 8,  9, 10, 11]],

       [[12, 13, 14, 15],
        [16, 17, 18, 19],
        [20, 21, 22, 23]],

       [[24, 25, 26, 27],
        [28, 29, 30, 31],
        [32, 33, 34, 35]],

       [[36, 37, 38, 39],
        [40, 41, 42, 43],
        [44, 45, 46, 47]],

       [[48, 49, 50, 51],
        [52, 53, 54, 55],
        [56, 57, 58, 59]]])
```

Note – … you can calculate it in an iterative way shown in line Out[83]

… try it in class

NumPy arrays

- NumPy arrays
  - transpose – transpose can easily be performed by used a specific attribute (command)

Example:

note:
.T and .transpose()
do the same job!

… try it in class

```
In [85]: i.transpose
Out[85]: <function ndarray.transpose>

In [86]: i.transpose()
Out[86]:
array([[[ 0, 12, 24, 36, 48],
        [ 4, 16, 28, 40, 52],
        [ 8, 20, 32, 44, 56]],

       [[ 1, 13, 25, 37, 49],
        [ 5, 17, 29, 41, 53],
        [ 9, 21, 33, 45, 57]],

       [[ 2, 14, 26, 38, 50],
        [ 6, 18, 30, 42, 54],
        [10, 22, 34, 46, 58]],

       [[ 3, 15, 27, 39, 51],
        [ 7, 19, 31, 43, 55],
        [11, 23, 35, 47, 59]]])

In [87]: np.shape(i.transpose())
Out[87]: (4, 3, 5)
```

NumPy with other languages

- NumPy arrays
  - ctypes:
    - this module is part of the standard Python distribution package
    - it is used for shared C-libraries, in case you have some useful code written in C and would like to put a Python wrapper around it to incorporate a specific routine written in C in your code
    - this possibility opens up a great number of already well written and tested C routines
    - the problem when using this module however is that it can lead to nasty crashes because of poor type checking

Example:

a problem can occur when you pass an array as a pointer to a raw memory location and you forget to check if the subroutine may access memory outside of the array boundaries

NumPy with other languages

- NumPy arrays
  - ctypes:
    - when using *ctypes* remember that this approach uses a raw memory location to a compiled code and it may not be error prone to user mistakes
    - good knowledge of the shared library and this module is a must
    - this approach most times requires extra Python code to handle errors of different kind to:
      - check for the data types
      - array boundaries of the passes objects
    - this however will slow down the interface because of all additional checking and type conversion (C to Python) that is necessary
    - this tool is for people with strong Python skills, but weak C knowledge

NumPy with other languages

- NumPy arrays
  - ctypes:
    - to use *ctypes* you must have the following:
      - have a library to be shared
      - load the library to be shared
      - convert the Python objects to *ctypes* arguments that can be interpreted correctly
      - call the function from the library containing the *ctypes* arguments
    - when using *ctypes* some of the basic attributes that can be used are:
      - data, shape and strides (... for more attributes please refer to the NumPy guide)
    - one should be careful when using temporary arrays or arrays constructed on the fly, because they return a pointer to an invalid memory location since it has been de-allocated as soon as the next Python statement is reached

Examples:

a) (a+b).ctypes – wrong , because the array created as (a+b) is de-allocated before the next statement

b) c = (a+b).ctypes – correct, because *c* will have a reference to the array

NumPy with other languages

- NumPy arrays
  - ctypes:

Examples:

```
In [88]: import numpy as np

In [89]: j = np.array([[12, 34, 99, 32],[41, 52, 45, 16],[64, 88, 67, 58]])

In [90]: j
Out[90]:
array([[12, 34, 99, 32],
       [41, 52, 45, 16],
       [64, 88, 67, 58]])

In [91]: j.ctypes
Out[91]: <numpy.core._internal._ctypes at 0x105999588>

In [92]: j.ctypes.data
Out[92]: 4466631472

In [18]: j.ctypes.shape._length_
Out[18]: 2

In [19]: j.ctypes.strides._length_
Out[19]: 2

In [20]: j.ctypes.shape._type_
Out[20]: ctypes.c_long
```

… try it in class

NumPy with other languages

- NumPy arrays

  – ctypes: Example:

1. begin with writing your C library and save the file 'ctypes_lib.c':

```c
#include <stdio.h>

void myprint(void);
void myprint()
{
    printf("This is ctypes example in Python\n");
}
```

2. install your gcc if you don't have one (skip this step if you do):

   - PC: find a compiler and install using the .exe file. Try using Cygwin - a Unix-like environment on Win
   - Mac OS X in the terminal type: xcode-select –install

3. you need to compile the file as shared library using this notation:

   - PC: $ gcc -shared -Wl,-soname, ctypes_lib -o ctypes_lib.so -fPIC ctypes_lib.c
   - Mac OS X: $ gcc -shared -Wl,-install_name, ctypes_lib.so -o ctypes_lib.so -fPIC ctypes_lib.c

```
Macintosh:lecture4 alex$ gcc -shared -Wl,-install_name,ctypes_lib.so -o ctypes_lib.so -fPIC ctypes_lib.c
[Macintosh:lecture4 alex$
```

NumPy with other languages

- NumPy arrays
  - ctypes: Example:

4. Create your ctypes Python wrapper module ‘ctypes_lib_tester.py’ and execute it:

```python
## Ctypes example of using a C file code:

import ctypes

c_test_lib = ctypes.CDLL('ctypes_lib.so')
c_test_lib.myprint()
```

5. The result should be:

```
Python
This is ctypes example in Python
```

6. If you run:

```
In [1]: c_test_lib.myprint()
Out[1]: 33
```

this only prints the number of characters in the ‘c’ library, so for the text:
“This is ctypes example in Python\n” there are 33, including the end of line character ‘\n’

NumPy with other languages

- NumPy arrays

  – ctypes: Example:

7. If you compile and execute the library in the terminal here is the result:

lecture4 — -bash — 114×16

```
Macintosh:lecture4 alex$ gcc -shared -Wl,-install_name,ctypes_lib.so -o ctypes_lib.so -fPIC ctypes_lib.c
Macintosh:lecture4 alex$ ls -la
total 88
drwxr-xr-x  10 alex  501   340 Oct 24 13:55 .
drwxr-xr-x   9 alex  501   306 Nov 19  2015 ..
-rw-r--r--@  1 alex  501  6148 Oct 24 13:45 .DS_Store
-rw-r--r--   1 alex  501   613 Oct 22 13:52 class excercise.py
-rw-r--r--   1 alex  501   110 Oct 24 13:53 ctypes_lib.c
-rwxr-xr-x   1 alex  501  8376 Oct 24 13:55 ctypes_lib.so
-rw-r--r--   1 alex  501   122 Oct 24 13:55 ctypes_lib_tester.py
-rw-r--r--   1 alex  501  1361 Oct 24 12:55 lecture4 - inverting a non-square matrix using SVD - pseudoinverse.py
-rw-r--r--   1 alex  501    81 Oct 22 13:55 my_array
-rw-r--r--   1 alex  501   439 Oct 19 20:49 speed_test_list_ndarray.py
Macintosh:lecture4 alex$ python ctypes_lib_tester.py
This is ctypes example in Python
Macintosh:lecture4 alex$
```

NumPy with other languages

C/C++

There a various tools which make it easier to bridge the gap between Python and C/C++:

- Pyrex - write your extension module on Python
- Cython -- Cython -- an improved version of Pyrex
- CXX - PyCXX - helper lib for writing Python extensions in C++
- ctypes is a Python module allowing to create and manipulate C data types in Python. These can then be passed to C-functions loaded from dynamic link libraries.
- elmer - compile and run python code from C, as if it was written in C
- PicklingTools is a collection of libraries for exchanging Python Dictionaries between C++ and Python.
- weave - include C code lines in Python program (deprecated in favor of Cython)
- ackward exposes parts of Python's standard library as idiomatic C++
- CFFI - interact with almost any C code from Python, based on C-like declarations that you can often copy-paste from header files or documentation.

Source: https://wiki.python.org/moin/IntegratingPythonWithOtherLanguages#Java

NumPy with other languages

Java

- » Jython - Python implemented in Java
- » JPype - Allows Python to run java commands
- » Jepp - Java embedded Python
- » JCC - a C++ code generator for calling Java from C++/Python
- » Javabridge - a package for running and interacting with the JVM from CPython
- » py4j - Allows Python to run java commands.
- » voc - Part of BeeWare suite. Converts python code to Java bytecode.
- » p2j - Converts Python code to Java. No longer developed.

Source: https://wiki.python.org/moin/IntegratingPythonWithOtherLanguages#Java

NumPy with other languages

Perl

See http://www.faqts.com/knowledge_base/view.phtml/aid/17202/fid/1102

- PyPerl http://search.cpan.org/dist/pyperl/
- Inline::Python
- PyPerlish - Perl idioms in Python

For converting/porting Perl code to Python the tool 'Bridgekeeper' http://www.crazy-compilers.com/bridgekeeper/ may be handy.

PHP

- PiP (Python in PHP) http://www.csh.rit.edu/~jon/projects/pip/
- PHP "Serialize" in Python http://hurring.com/scott/code/python/serialize/ (broken link; see the Web Archive Wayback Machine for the latest working version)

R

- RPy http://rpy.sourceforge.net
- RSPython http://www.omegahat.net/RSPython

Source: https://wiki.python.org/moin/IntegratingPythonWithOtherLanguages#Java