Data Analysis with Python

Intro to NumPy

Aim: learn why **NumPy** is an important library for the data-processing world in Python

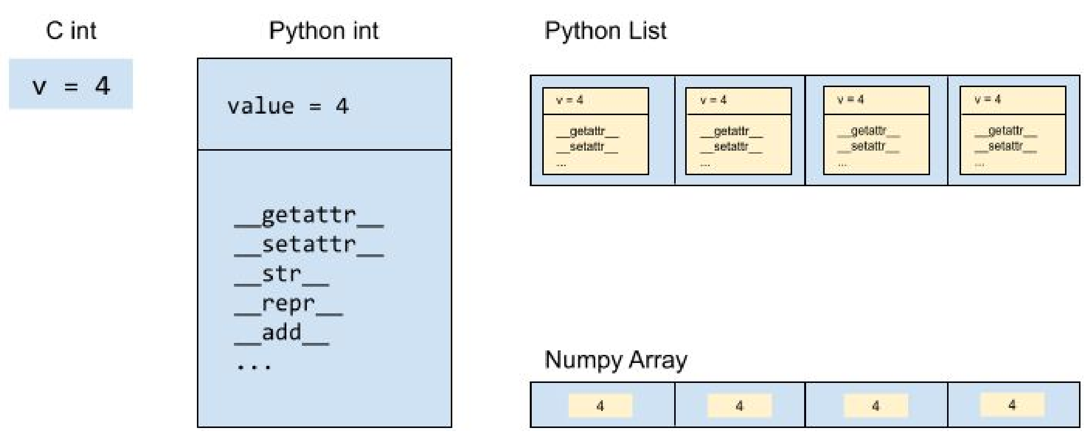
- NumPy provides the following:
    - Computations, memory storage, illustrates how Excel will always be limited when processing large volumes of data and more

Numpy: Numeric computing library

NumPy (Numerical Python): one of the core packages for numerical computing in Python, Pandas, Matplotlib, Statmodels

- many other scientific libraries rely on NumPy
- Major contributions:
    - Efficient numerical computation with C primitives
    - Efficient collections with vectorized operations
    - An integrated and natural Linear Algebra API
    - A C API for connecting NumPy with libraries written in C, C++, or FORTRAN

Let's develop on efficiency. In Python, **everything is an object**, which means that even simple ints are also objects, with all the required machinery to make object work. We call them "Boxed Ints". In contrast, NumPy uses primitive numeric types (floats, ints) which makes storing and computation efficient.



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

import sys
import numpy as np

Basic Numpy Arrays

- Arrays look similar to lists, but NOTE that they are both different

```
In [3]:    # Basic Numpy Arrays
           np.array([1, 2, 3, 4])

           array([1, 2, 3, 4])
```

np.array([1, 2, 3, 4])

```
In [4]:    a = np.array([1, 2, 3, 4])

In [5]:    b = np.array([0, .5, 1, 1.5, 2])
```

a = np.array([1, 2, 3, 4])
b = np.array([0, .5, 1, 1.5, 2])

```
In [6]:    a[0], a[1]

           (1, 2)
```

a[0], a[1]

- Shows how to access **individual elements** within an array
- It's similar to how to access individual elements within a list

```
In [7]:    a[0:]

           array([1, 2, 3, 4])
```

a[0:]

- **Slicing** almost works the same way
- Provides all entries from 0 index up to AND including the max index.
- **Note:** compared to the output above (*In [6]:*), *In[7]:* has a **range (indicates slicing)**
    - Specifically '**:**' results in output containing array([...])

- While *In[6]:*, extracting entries within certain indices provides (1, 2)
    - generally , (...)

```
In [8]:  a[1:3]
         # Indices from 1 up to 3, excluding index 3.

         array([2, 3])
```

a[1:3]

```
In [9]:  a[1:-1]

         array([2, 3])
```

a[1:-1]

```
In [10]:  a[::2]

          array([1, 3])
```

a[::2]

- The index entries right before AND after *2*

a[::int]

- Generally, the entries **right before and after** the specified int

```
In [11]:  b

          array([0. , 0.5, 1. , 1.5, 2. ])

In [12]:  b[0], b[2], b[-1]

          (0.0, 1.0, 2.0)
```

b[0], b[2], b[-1]

- This is an example of **multi-indexing**

```
In [14]:  b[[0, 2, -1]]

          array([0., 1., 2.])
```

b[[0, 2, -1]]

- Compared to the code above (*In[12]*), *In[14]* provides array([...])

- While *In[12]* provides (...)
- Generally, b[index]
  - Provides (...)
- And b[[...]]
  - Provides array([...])
- Provides a numpy array opposed to individual elements (this is much faster)

Array Types

- Numpy library needs to know what is the object being stored

```
In [16]:  a

          array([1, 2, 3, 4])

In [17]:  a.dtype

          dtype('int32')
```

a.dtype

- This is the **default** type

```
In [18]:  b

          array([0. , 0.5, 1. , 1.5, 2. ])

In [19]:  b.dtype

          dtype('float64')
```

b.dtype

- Again, **default** type

```
In [21]:  np.array([1, 2, 3, 4], dtype=float)

          array([1., 2., 3., 4.])
```

np.array([1, 2, 3, 4], dtype=float)

- This changes the data type

```
In [23]:   np.array([1, 2, 3, 4], dtype=np.int8)

           array([1, 2, 3, 4], dtype=int8)
```

np.array([1, 2, 3, 4], dtype=np.int8)

- This change the data type to *int8*
    - IOW smaller integers

```
In [24]:   c = np.array(['a', 'b', 'c'])
```

c = np.array([‘a’, ‘b’, ‘c’])

- Can also store strings

```
In [25]:   c.dtype

           dtype('<U1')
```

c.dtype

```
In [26]:   d = np.array([{'a': 1}, sys])

In [27]:   d.dtype

           dtype('O')
```

d = np.array([{‘a’: 1}, sys])
d.dtype

- Can also store regular objects

However, there is no point in storing strings and regular objects in Numpy

- Numpy is useful for storing numbers, dates, booleans, but not regular objects

Dimensions and shapes

- Above, we created 1 dimensional arrays
- Can also create **matrices** which are 2D arrays

```
In [28]:
# Dimensions and shapes
A = np.array([
    [1, 2, 3],
    [4, 5, 6]
])
```

A = np.array([
    [1, 2, 3],
    [4, 5, 6]
])

- Recall Linear Algebra; This is a 2 x 3 matrix (2 rows 3 cols)

Below, we'll see that Numpy has a ton of attributes & functions that can be used to work with multi-dimensional arrays

```
In [30]:
A.shape
# (2 rows, 3 columns)

(2, 3)
```

A.shape

```
In [40]:
A.ndim
# 2 sets of [[?

2
```

A..ndim

- How many dimensions does it have?
    - 2; 1 vertical, 1 horizontal

```
In [33]:
A.size
# 6 individual numbers within the array

6
```

A.size

- Total number of elements within the array

```
In [34]:    B = np.array([
                [
                    [12, 11, 10],
                    [9, 8, 7]
                ],
                [
                    [6, 5, 4],
                    [3, 2, 1]
                ]
            ])
```

```
B = np.array([
        [
                [12, 11, 10],
                [9, 8, 7]
        ],
        [
                [6, 5, 4],
                [3, 2, 1]
        ]
])
```

- This is a 3 D array

```
In [35]:    B

            array([[[12, 11, 10],
                    [ 9,  8,  7]],

                   [[ 6,  5,  4],
                    [ 3,  2,  1]]])
```

```
In [37]:    B.shape
            # 2 groups, 2 rows in each group, 3 columns in each group

            (2, 2, 3)
```

```
B.shape
```

```
In [39]: B.ndim

3
```

B.ndim

```
In [42]: B.size
         # 12 individual numbers within the array.

12
```

B.size

```
In [44]: C = np.array([
             [
                 [12, 11, 10],
                 [9, 8, 7],
             ],
             [
                 [6, 5, 4]
             ]
         ])
```

- Always be careful when creating multi-dimensional arrays
- As above, if the dimensions do not match i.e. the second list only has one list in it

```
In [45]: C.dtype

dtype('O')
```

C.dtype

- This ends up with the output indicating that the array is of type *object*...

```
In [46]: C.shape

(2,)
```

C.shape

- And the shape shows only 2 elements

```
In [167]:    C

array([list([[12, 11, 10], [9, 8, 7]]), list([[6, 5, 4]])], dtype=object)
```

```
In [47]:    C.size

2
```

C.size

- *2* b/c C consists of 2 lists
- But we basically created it wrong, implying keen attention to detail is needed when creating multi-dimensional arrays

```
In [48]:    type(C[0])

list
```

type(C[0])

- The first object within *C* is of type *list*

Indexing and Slicing of Matrices

Note: Indices START @ 0.

Note: account for multiple dimensions

```
# Square matrix
A = np.array([
#.    0. 1. 2.
    [1, 2, 3], #0
    [4, 5, 6], #1
    [7, 8 ,9]  #2
])
```

A = np.array([
    [1, 2, 3],
    [4, 5, 6],
    [7, 8, 9]
])

```
In [59]:  A[1]

          array([4, 5, 6])
```

A[1]

- The **row** at index 1

```
In [60]:  A[1][0]
          # row first, then column.

          4
```

A[1][0]

```
In [61]:  # A[d1, d2, d3, d4]
          A[1, 0]
          # basically combined the above.

          4
```

A[1, 0]

- **Multi-dimensional selection** of Numpy is recommended over the above *In[60]*

```
In [62]:  A[0:2]
          # All rows from index 0(including 0) up to and excluding index 2.

          array([[1, 2, 3],
                 [4, 5, 6]])
```

A[0:2]

- Notice the difference between *In[59]* above and *In[62]*
    - *In[62]* provides a **range** (slicing involved)
        - And array([[1, 2, 3], …]]) as output
    - While *In[59]* provides a basic index
        - And array([4, 5, 6]) as output

```
In [63]:  A[:, :2]

          array([[1, 2],
                 [4, 5],
                 [7, 8]])
```

A[:, :2]

- I want to select every row (*:*)
- But then I want to select from **column level**
    - Only elements up to 2 (excluding 2)

```
In [64]:  A[:2, 2:]

array([[3],
       [6]])
```

A[:2, 2:]

- Select every row before index 2
- And col level; everything with index 2 and after

```
In [65]:  A

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

In [171]:  A[1] = np.array([10, 10, 10])

In [172]:  A

array([[ 1,  2,  3],
       [10, 10, 10],
       [ 7,  8,  9]])
```

A[1] = np.array([10, 10, 10])

- Can also modify arrays
- Notice that row at index 1 changed to a row filled with 10s

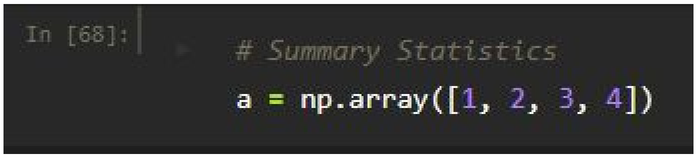
```
In [173]:  A[2] = 99
           # This updates all indices in 2 position as 99.

In [174]:  A

array([[ 1,  2,  3],
       [10, 10, 10],
       [99, 99, 99]])
```

A[2] = 99

- This is an equivalent operation to what is shown above (*In [171]*)

Generally, when dealing with matrices and slicing
Format: Matrix[rowLevel, columnLevel]

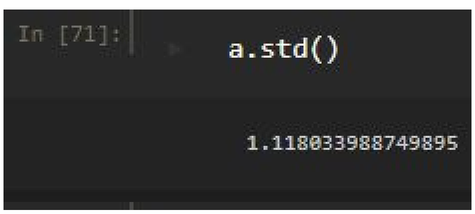
Summary Statistics



a = np.array([1, 2, 3, 4])

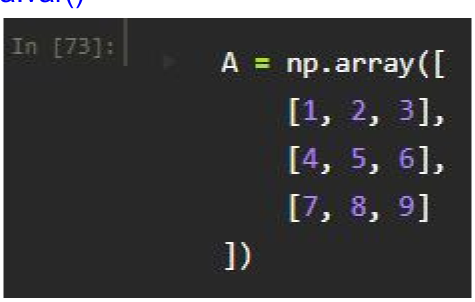
a.sum()

a.mean()



a.std()

a.var()




```
A = np.array([
        [1, 2, 3],
```

[4, 5, 6],
[7, 8, 9]
])

- All of the functions above, shown for basic arrays, can also be applied to matrices

```
In [74]:  A.sum()

          45

In [75]:  A.mean()

          5.0

In [76]:  A.std()

          2.581988897471611

In [77]:  A.var()

          6.666666666666667
```

- We can also use / apply these functions per axis

```
In [78]:  A.sum(axis=0)
          # This provides the sum of numbers within each column index.

          array([12, 15, 18])
```

A.sum(axis=0)

- Note the difference between *In[74]* - *In[77]* and *In[78]*
    - *In[74]* - *In[77]* provides output that takes into consideration the array as a whole
    - *In[78]* provides array([12, 15, 18]) as output

```
In [79]:  A.sum(axis=1)
          # This provides the sum of numbers within each row index.

          array([ 6, 15, 24])
```

A.sum(axis=1)

Generally, Matrix.sum(axis=0)

- Provides the sum of numbers within each **column** index

    array([sumOfcol1, sumOfcol2, sumOfcol3])

- While Matrix.sum(axis=1) provides the sum of numbers within each **row**

    array([sumOfrow1, sumOfrow2, sumOfrow3])

It basically shows the difference between the sum of vertical dimension vs. horizontal dimension

```
In [80]:  A.mean(axis=0)
          # This provides the mean/ avrg. of the numbers within each column index.
          # Ex. For column 1: 1+4+7 = 12 / 3 = 4 <- which is the avrg.

          array([4., 5., 6.])

In [ ]:   A.mean(axis=1)
          # Similar to above.
          # This provides the mean/avg. of the numbers within each row index.
          # Ex. For row 1: 1+2+3 = 6 / 3 = 2
```

A.mean(axis=0)
A.mean(axis=1)

```
In [81]:  A.std(axis=0)

          array([2.44948974, 2.44948974, 2.44948974])

In [82]:  A.std(axis=1)

          array([0.81649658, 0.81649658, 0.81649658])
```

A.std(axis=0)
A.std(axis=1)

Generally,

- Matrix.function(axis=0)
    - Provides the output of the function for each **column i**ndex
- Matrix.function(axis=1)
    - Provides the output of the function for each **row** index

Broadcasting and Vectorized Operations

- Vectorized operations are operations performed between both arrays and scalars

```
In [84]:  # Broadcasting and Vectorized Operations

          a = np.arange(4)
          # Creates an array consisting of 4 entries as the indices.
```

a = np.arange(4)

```
In [85]: a

array([0, 1, 2, 3])

In [86]: a + 10

array([10, 11, 12, 13])

In [87]: a * 10

array([ 0, 10, 20, 30])
```

a + 10

a * 10

- The operation will be applied to each element within the array, resulting in a new array
- This is the concept of ‘**vectorizing**’ the operation
- Note the operations above do not modify the original array

```
In [88]: a

array([0, 1, 2, 3])
```

- Notice when *a* is prompted, *a* is **NOT** modified
- None of *In[86]* and *In[87]* modified *a*

```
In [89]: a += 100

In [90]: a

array([100, 101, 102, 103])
```

a += 100

- This overwrites the behaviour of array modification
- Notice that *In[89]* **MODIFIED** *a*
- The presence of = **MODIFIED** *a*

```
In [91]:  l = [0, 1, 2, 3]

In [92]:  [i * 10 for i in l]

          [0, 10, 20, 30]
```

l = [0, 1, 2, 3]
[i * 10 for i in l]

- Expresses an operation for each of the elements within the collection

```
In [93]:  a = np.arange(4)

In [94]:  a

          array([0, 1, 2, 3])
```

a = np.arange(4)

```
In [95]:  b = np.array([10, 10, 10, 10])

In [96]:  b

          array([10, 10, 10, 10])
```

b = np.array([10, 10, 10, 10])

```
In [97]:  a + b

          array([10, 11, 12, 13])

In [98]:  a * b

          array([ 0, 10, 20, 30])
```

a + b
a * b

- The operations also apply to multiple arrays
- Note: for this to work, arrays must be aligned with same shape

Boolean Arrays

```
In [99]:  # Boolean Arrays

          a = np.arange(4)

In [100]: a

          array([0, 1, 2, 3])
```

a = np.arange(4)

```
In [101]: a[0], a[-1]

          (0, 3)
```

a[0], a[-1]

- The first & last element

```
In [102]: a[[0, -1]]

          array([0, 3])
```

a[[0, -1]]

- Recall multi-index selection
- Notice the difference between *In[101]* and *In[102]*
    - In terms of output as well

```
In [103]: a[[True, False, False, True]]

          array([0, 3])
```

a[[True, False, False, True]]

- Select the elements in this order, indicating (T/F); whether you want to select the element or not
- 4 elements means 4 boolean values will be required
- The above equivalently means a[[select, dont, dont, select]]

In[101] - In[103] basically shows different ways of how to select data

```
In [104]:  a

            array([0, 1, 2, 3])

In [105]:  a >= 2

            array([False, False,  True,  True])
```

a >= 2

```
In [106]:  a[a >= 2]

            array([2, 3])
```

a[a >= 2]

- This **filters** numeric arrays very quickly
- Notice the difference between *In[105]* and *In[106]*
- *In[105]* only consists of boolean operators / predicate (conditions) (>=)
    - This provides an array of booleans as output
        - General output: array([list of booleans...])
- While *In[106]* consists of boolean operators and square brackets (*[ ]*)
    - This provides an array of the entries within certain indices that satisfy the boolean operators as output
        - General output: array([entry 1, entry 2, entry3, entryn...])

```
In [107]:  a.mean()

            1.5
```

a.mean()

```
In [108]:  a[a > a.mean()]

            array([2, 3])
```

a[a > a.mean()]

```
In [109]:  a[~(a > a.mean())]
           # The '~' implies negation of the conditions within the brackets.

            array([0, 1])
```

a[~(a > a.mean())]

```
In [110]: a[(a == 0) | (a == 1)]

array([0, 1])
```

a[(a == 0) | (a == 1)]

```
In [111]: a[(a <= 2) & (a % 2 == 0)]

array([0, 2])
```

a[(a <= 2) & (a % 2 == 0)]

Generally, if the prompt / code consists of ONLY boolean operators (>, <, >=, etc...)

- Then array([boolean1, boolean2, boolean3, boolean,...]) will be the output

If the prompt / code consists of boolean operators within a list / square brackets (*[...]*)

- Then an array of the entries within certain indices that satisfy the boolean operators will be provided as output
- General output: array([entry 1, entry 2, entry3, entryn...])

```
In [112]: A = np.random.randint(100, size=(3, 3))

In [113]: A

array([[11, 46, 67],
       [35, 89, 64],
       [86, 41, 20]])
```

A = np.random.randint(100, size=(3, 3))

- This provides a 3 by 3 array (3 rows, 3 columns) consisting of random numbers within each entry and each number is less than 100

```
In [114]: A[np.array([
              [True, False, True],
              [False, True, False],
              [True, False, True]
          ])]

array([11, 67, 89, 86, 20])
```

A[np.array([

[True, False, True],

[False, True, False],

[True, False, True]

])]

- This provides an array consisting of entries of indices that satisfy *True*

```
In [115]:  A > 30

array([[False,  True,  True],
       [ True,  True,  True],
       [ True,  True, False]])
```

A > 30

```
In [116]:  A[A > 30]

array([46, 67, 35, 89, 64, 86, 41])
```

A[A > 30]

- Notice the difference between *In[115]* and *In[116]*

Generally,

If a prompt / code consists of ONLY a boolean operator

- Then it will provide an array consisting of booleans as output
- ALSO **NOTE** that the output will consist of an extra pair of square brackets (*[ ]*)
- Output:

  array([[boolean1, boolean2, boolean3, booleann,...]
  [..]
  [..]
  ]])

If a prompt / code consists of a condition operator within square brackets (this helps **filter data**)

- Then it will provide a basic array consisting of entries that satisfy the specified conditions
- Output:

  array([entry1, entry2, entry3, entryn, ...])

Linear Algebra

- Important for machine learning

```
In [117]:  # Linear Algebra
           A = np.array([
               [1, 2, 3],
               [4, 5, 6],
               [7, 8, 9]
           ])
```

A = np.array([
[1, 2, 3],
[4, 5, 6],
[7, 8, 9]

])

```
In [118]:   B = np.array([
                [6, 5],
                [4, 3],
                [2, 1]
            ])
```

B = np.array([
    [6, 5],
    [4, 3],
    [2, 1]
])

```
In [119]:   A.dot(B)

            array([[20, 14],
                   [56, 41],
                   [92, 68]])
```

A.dot(B)

- Dot product

```
In [120]:   A @ B

            array([[20, 14],
                   [56, 41],
                   [92, 68]])
```

A @ B

- Cross product

```
In [121]:   B.T

            array([[6, 4, 2],
                   [5, 3, 1]])
```

B.T

- Transpose of matrix B

```
In [122]: A

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

In [123]: B.T @ A

array([[36, 48, 60],
       [24, 33, 42]])
```

B.T @ A

- The B transpose cross product with A

Size of Objects in Memory

- Recall binary explanation
- Differences between objects in Numpy and Python

Int, Floats

```
In [124]: # Size of objects in Memory
          # Int, floats

          sys.getsizeof(1)

14

In [125]: # Longs are even longer
          sys.getsizeof(10**100)

58

In [126]: np.dtype(int).itemsize

4

In [127]: np.dtype(np.int8).itemsize

1

In [128]: np.dtype(float).itemsize

8
```

Lists are even larger

```
In [129]:  # Lists are even larger.

           # A one element list.
           sys.getsizeof([1])

           40

In [131]:  # An array of one element in numpy.
           np.array([1]).nbytes

           4
```

Performance is also important

```
In [132]:  # Performance is also important.

           l = list(range(100000))

In [133]:  a = np.arange(100000)

In [134]:  %time np.sum(a ** 2)

           Wall time: 1 ms

           216474736

In [135]:  %time sum([x ** 2 for x in l])

           Wall time: 54 ms

           333328333350000
```

l = list(range(100000))

a = np.arange(100000)

- Have a list and array consisting of the first 100000 numbers

%time sum([x ** 2 for x in l])

- Create a new list > x squared for x in l > sum everything
    - How long does it take?

Will do the same with Numpy

%time np.sum(a ** 2)

- Notice the difference in time

Generally, performance is a lot faster in the Numpy perspective vs. Python

Useful Numpy Functions

- Explore these in Jupyter Notebook Attached

References

https://en.wikipedia.org/wiki/NumPy

https://numpy.org/

https://www.youtube.com/watch?v=r-uOLxNrNk8

https://github.com/ine-rmotr-curriculum/freecodecamp-intro-to-numpy/blob/master/2.%20NumPy.ipynb

https://docs.scipy.org/doc/numpy-1.13.0/reference/arrays.ndarray.html#array-methods