## BASICS OF NUMPY ARRAYS

NumPy (short for Numerical Python) provides an efficient interface to store and operate on dense data buffers. NumPy arrays are like Python's built-in list type, but NumPy arrays provide much more efficient storage and data operations as the arrays grow larger in size.

We'll cover a few categories of basic array manipulations here:

## Attributes of arrays

Determining the size, shape, memory consumption, and data types of arrays

## Indexing of arrays

Getting and setting the value of individual array elements

## Slicing of arrays

Getting and setting smaller subarrays within a larger array

## Reshaping of arrays

Changing the shape of a given array

## Joining and splitting of arrays

Combining multiple arrays into one, and splitting one array into many

## NumPy Array Attributes

$>$ ndim (the number of dimensions),
$>$ shape (the size of each dimension)
> size (the total size of the array)

```
Example
np.random.seed(0) # seed for reproducibility
x1 = np.random.randint(10, size=6) # One-dimensional array
x2 = np.random.randint(10, size=(3,4)) # Two-dimensional array
x3 = np.random.randint(10, size=(3,4,5)) # Three-dimensional array
print("x3 ndim: ", x3 ndim)
print("x3 shape:", x3.shape)
print("x3 size: ", x3.size)
print("dtype:", x3.dtype)
print("itemsize:", x3.itemsize, "bytes")
print("nbytes:", x3.nbytes, "bytes")
```


## Array Indexing:

$>$ Accessing Single Elements

## Accessing Single Elements

$>$ Indexing in NumPy will feel quite familiar like list indexing,
$>$ In a one-dimensional array, you can access the ith value (counting from zero) by specifying the desired index in square brackets, just as with Python lists
$>$ To index from the end of the array, you can use negative indices
$>$ In a multidimensional array, you access items using a comma-separated tuple of indices
$>$ Unlike Python lists, NumPy arrays have a fixed type. This means, for example, that if you attempt to insert a floating-point value to an integer array, the value will be silently truncated.

## Array Slicing: Accessing Subarrays

Just as we can use square brackets to access individual array elements, we can also use them to access subarrays with the slice notation, marked by the colon (:) character.
The NumPy slicing syntax follows that of the standard Python list; to access a slice of an array $x$, use this:

```
x[start:stop:step]
start - starting array index
stop - array index to stop ( last value will not be considered)
step - terms has to be printed from start to stop
Default to the values start=0, stop=size of dimension, step=1.
```


## Example

$x=$ np.arange $(10)$
$x$
$\operatorname{array}([0,1,2,3,4,5,6,7,8,9])$
$x[: 5]$ \# prints first five elements
$\operatorname{array}([0,1,2,3,4])$
x[5:] \# elements after index 5
$\operatorname{array}([5,6,7,8,9])$
x [4:7] \# middle subarray(from 4th index to 6th index)
$\operatorname{array}([4,5,6])$
While using negative indices the defaults for start and stop are swapped. This becomes a convenient way to reverse an array
$\mathrm{x}[::-1]$ \# all elements, reversed
$\operatorname{array}([9,8,7,6,5,4,3,2,1,0])$
x[5::-2] \# reversed every other from index 5
$\operatorname{array}([5,3,1])$

## Multidimensional sub arrays

Multidimensional slices work in the same way, with multiple slices separated by commas.

For example:
x2
array([[12, 5, 2, 4],
$[7,6,8,8]$,
[ $1,6,7,7]])$
x2[:2,:3] \# two rows, three columns
$\operatorname{array}([[12,5,2]$,
[7,6, 8]])
$x 2[: 3,:: 2]$ \# all rows, every other column(every second column)
$\operatorname{array}([[12,2]$,
[7, 8],
[1, 7]])
Finally, sub array dimensions can even be reversed together
x2[::-1, ::-1]
$\operatorname{array}([[7,7,6,1]$,
[ $8,8,6,7]$,
[4, 2, 5, 12]])

## Reshaping of Arrays

The most flexible way of doing this is with the reshape() method. For example, if you want to put the numbers 1 through 9 in a $3 \times 3$ grid, you can do the following
grid $=n p . \operatorname{arange}(1,10) \cdot$ reshape $((3,3))$
print(grid)
[ $\left.\begin{array}{lll}1 & 2 & 3\end{array}\right]$
[4 5 5 6]
[7 8 9]]

## Array Concatenation and Splitting

## Concatenation of arrays

Concatenation, or joining of two arrays in NumPy, is primarily accomplished through the routines np.concatenate, np.vstack, and np.hstack. np.concatenate takes a tuple or list of arrays as its first argument.
$\mathrm{x}=\mathrm{np} . \operatorname{array}([1,2,3])$
$\mathrm{y}=\mathrm{np} . \operatorname{array}([3,2,1])$
np.concatenate $([\mathrm{x}, \mathrm{y}])$
$\operatorname{array}([1,2,3,3,2,1])$
You can also concatenate more than two arrays at once
$z=[99,99,99]$
print(np.concatenate $([x, y, z])$ )

## [123321999999]

np.concatenate can also be used for two-dimensional arrays
grid $=$ np. $\operatorname{array}([[1,2,3]$,

$$
[4,5,6]])
$$

np.concatenate([grid, grid])
$\operatorname{array}([[1,2,3]$,

$$
\begin{aligned}
& {[4,5,6],} \\
& {[1,2,3],}
\end{aligned}
$$

$[4,5,6]])$

Concatenate along the second axis (zero-indexed)
np.concatenate([grid, grid], axis=1)
$\operatorname{array}([[1, ~ 2, ~ 3, ~ 1, ~ 2, ~ 3], ~$
[4, 5, 6, 4, 5, 6]])

## np.vstack (vertical stack) functions

$x=n p . \operatorname{array}([1,2,3])$
grid = np.array([[9, 8, 7],
np.vstack([x, grid])
$\operatorname{array}([[1,2,3]$,
[9, 8, 7],
[6, 5, 4]])
np.hstack (horizontal stack) functions
$y=n p . \operatorname{array}([[99]$,
np.hstack([grid, y])
$\operatorname{array}([[9,8,7,99]$,
[ 6, 5, 4, 99]])

## Splitting of arrays

The opposite of concatenation is splitting, which is implemented by the functions np.split, np.hsplit, and np.vsplit. For each of these, we can pass a list of indices giving the split points.
$\mathrm{x}=[1,2,3,99,99,3,2,1]$
$x 1, x 2, x 3=n p . \operatorname{split}(x,[3,5])$
$\operatorname{print}(\mathrm{x} 1, \mathrm{x} 2, \mathrm{x} 3)$
[llll 1223$]\left[\begin{array}{ll}99 & 99\end{array}\right]\left[\begin{array}{lll}3 & 2 & 1\end{array}\right]$

Notice that N split points lead to $\mathrm{N}+1$ subarrays. The related functions np.hsplit and np.vsplit are similar

```
grid = np.arange(16).reshape((4, 4))
grid
array([[ 0, 1, 2, 3],
    [4, 5, 6, 7],
    [ 8, 9, 10, 11],
    [12, 13, 14, 15]])
upper, lower = np.vsplit(grid, [2])
print(upper)
print(lower)
```

[ $\left[\begin{array}{llll}0 & 1 & 2 & 3\end{array}\right]$

[ $\left[\begin{array}{llll}8 & 9 & 10 & 11\end{array}\right]$
[12 1314 15] ]
left, right = np.hsplit(grid, [2])
print(léft)
print(right)
[ $\left[\begin{array}{ll}0 & 1\end{array}\right]$
[ 4 5]
[ 8 9]
[12 13]]
[ $\left[\begin{array}{ll}2 & 3\end{array}\right]$
[67]
[10 11]
[14 15]]

## Computation on NumPy Arrays: Universal Functions

## Introducing UFuncs

NumPy provides a convenient interface into just this kind of statically typed, compiled routine. This is known as a vectorized operation.

Vectorized operations in NumPy are implemented via ufuncs, whose main purpose is to quickly execute repeated operations on values in NumPy arrays. Ufuncs are extremely flexible-before we saw an operation between a scalar and an array, but we can also operate between two arrays

## Exploring NumPy's UFuncs

Ufuncs exist in two flavors: unary ufuncs, which operate on a single input, and binary ufuncs, which operate on two inputs. We'll see examples of both these types of functions here.

## Array arithmetic

NumPy's ufuncs make use of Python's native arithmetic operators. The standard addition, subtraction, multiplication, and division can all be used.

```
\(x=n p\).arange \((4)\)
print(" \(\mathrm{x}={ }^{\prime \prime}, \mathrm{x}\) )
print(" \(x+5=", x+5\) )
print("x-5 =", x-5)
print("x*2 =", x*2)
```

Operator Equivalent ufunc Description
+ np.add Addition (e.g., $1+1=2$ )
- np.subtract Subtraction (e.g., 3-2 = 1)
- np.negative Unary negation (e.g., -2)
* np.multiply Multiplication (e.g., 2 * $3=6$ )
$/$ np.divide Division (e.g., $3 / 2=1.5$ )
// np.floor_divide Floor division (e.g., $3 / / 2=1$ )
** np.power Exponentiation (e.g., 2 ** $3=8$ )
$\%$ np.mod Modulus/remainder (e.g., $9 \% 4=1$ )

## Absolute value

Just as NumPy understands Python's built-in arithmetic operators, it also understands Python's built-in absolute value function.
np.abs()
np.absolute()
$\mathrm{x}=\mathrm{np} . \operatorname{array}([-2,-1,0,1,2])$
abs(x)
$\operatorname{array}([2,1,0,1,2])$
The corresponding NumPy ufunc is np.absolute, which is also available under the alias np.abs np.absolute(x)
$\operatorname{array}([2,1,0,1,2])$
np.abs(x)
$\operatorname{array}([2,1,0,1,2])$

## Specialized ufuncs

NumPy has many more ufuncs available like
$>$ Hyperbolic trig functions,
> Bitwise arithmetic,
$>$ Comparison operators,
$>$ Conversions from radians to degrees,
$>$ Rounding and remainders, and much more

## Aggregates

To reduce an array with a particular operation, we can use the reduce method of any ufunc. A reduce repeatedly applies a given operation to the elements of an array until only a single result remains.
$x=n p$.arange $(1,6)$
np.add.reduce(x)
Similarly, calling reduce on the multiply ufunc results in the product of all array elements np.multiply.reduce(x) 120

