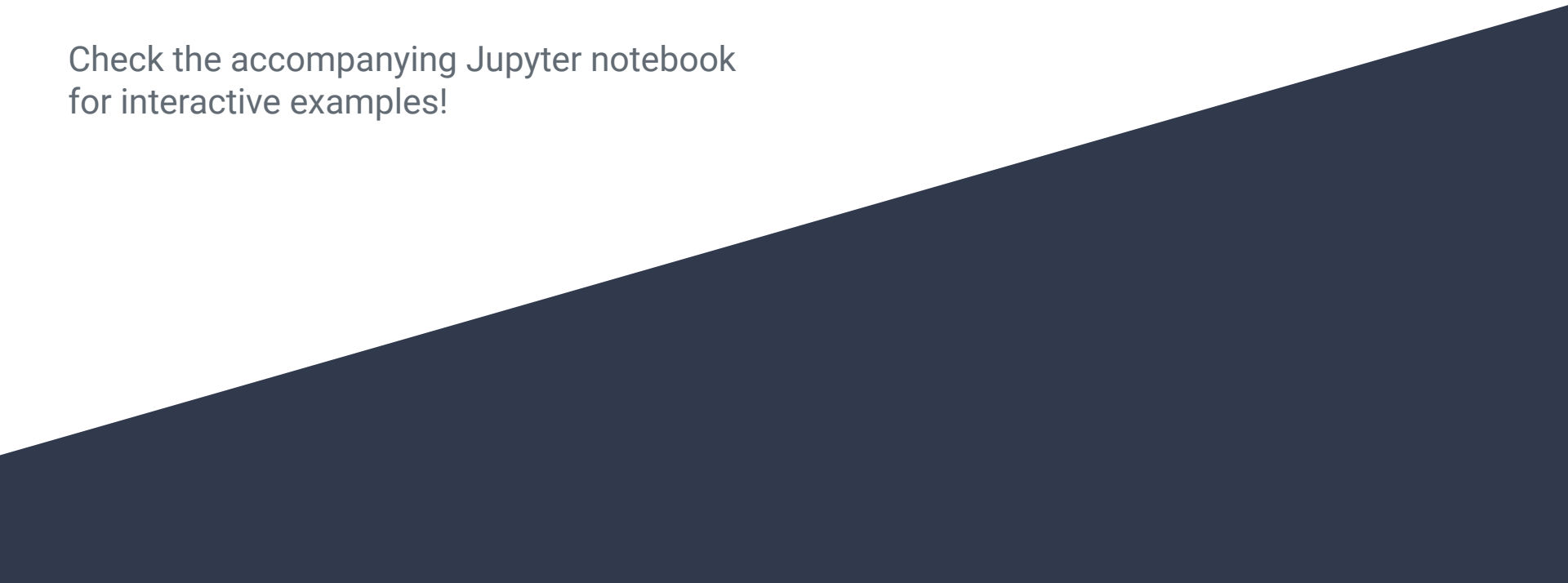


Week 4 - Basic NumPy

Check the accompanying Jupyter notebook
for interactive examples!

A large, dark blue, curved shape that starts from the bottom left and extends diagonally upwards towards the right, filling the lower half of the slide.

Python is Slow

- Interpreted & dynamically typed
- GIL
- Suboptimal data structures (list)

NumPy is ...

... a library for numerical computation

... sometimes faster

- “outsourcing” of slow Python loops to fast C code (*vectorization*)
- static typing
- arrays instead of lists
- in some cases multithreaded*
- used as a building block for other scientific libraries

... sometimes more elegant

- syntax extends even to libraries that don't build on NumPy

* More on multithreading in NumPy:
<https://stackoverflow.com/a/16618280>

Importing Modules

Not all of Python's functionality is available by default.

More specialized tools are organized in **modules** that need to be **imported** before they can be used

You can also import **specific functions** from modules if you don't need the rest

Check the Jupyter notebook for more import syntax!

```
import time

current_time = time.localtime()

print(current_time.tm_year)      # 2021
```

```
from time import localtime

current_time = localtime()

print(current_time.tm_year)      # 2021
```

Reminder: Installing NumPy

NumPy is a third-party module and thus needs to be installed manually!

1. Activate conda environment
2. `pip install numpy`
3. check if it worked by importing numpy in the interactive shell / a Jupyter notebook

The `np.ndarray`

Everything in NumPy is built around the `ndarray`.

Arrays, like lists, store values, but with two limitations:

1. fixed data type
2. fixed number of elements (or *shape*)

NumPy arrays can be created in different ways

```
import numpy as np

# from Python sequences

array1 = np.array([1, 2, 3])
array2 = np.array([1, 2, 3], dtype=float)

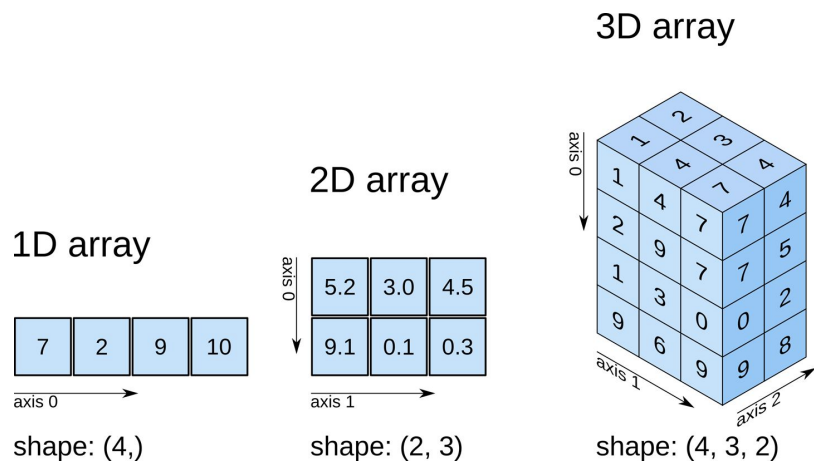
# using NumPy functions

array3 = np.zeros(3)      # [0., 0., 0.]
array4 = np.ones(3)       # [1., 1., 1.]
array5 = np.arange(3)     # [0, 1, 2]
```

...more ways in the Jupyter notebook!

Multidimensional Arrays

NumPy arrays are specifically suited to be **multidimensional** (i.e. nested arrays).



The **shape** is a tuple that specifies the **size of each dimension**

Some ways to create multidimensional arrays:

```
# from Python nested sequences
```

```
arr1 = np.array([[1, 2, 3],  
                 [4, 5, 6],  
                 [7, 8, 9]])
```

```
# many NumPy functions also take a shape  
# argument
```

```
arr2 = np.zeros(shape=(3, 3))
```

Reshaping Arrays

Arrays can be **reshaped** into different shapes.

The number of dimensions may change, but the total number of elements may not.

One of the given dimension sizes may be **-1** and will be inferred automatically.

`array.flatten()` amounts to
`array.reshape(-1)`

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

array = array.reshape(3, 3)
# [[0, 1, 2],
#  [3, 4, 5],
#  [6, 7, 8]]

array = array.reshape(1, 9)
# [[0, 1, 2, 3, 4, 5, 6, 7, 8]]

array = array.reshape(3, -1)
# same as array.reshape(3, 3)

array = array.flatten()      # shape: (9)
```


Basic Indexing

NumPy provides convenient ways to index items in ndarrays:

```
array = np.array([[1, 2, 3],  
                  [4, 5, 6],  
                  [7, 8, 9]])  
  
# sub-array  
sub_array = array[1]      # [4, 5, 6]  
  
# single element  
element = array[0, 2]     # 3  
  
# don't do this:  
element = array[0][2]
```

slices work like they do in Python

```
slice = array[2, 0:2]      # [7, 8]  
slice = array[1:, 2]      # [6, 9]  
slice = array[2, :-1]     # [9, 8, 7]
```

slices are more general sub-arrays

```
slice = array[:, 1]       # [2, 5, 8]
```

you can also get n-dim slices

```
slice = array[:-1, :-1]   # [[1, 2],  
                          # [4, 5]]
```

There are more ways of indexing, which will be covered in the next lecture!

Mathematical Operations

Thanks to the magic of dunder methods, NumPy arrays work with mathematical operators

element-wise operations: +, -, *, /, **

there is also **matrix-multiplication:** @

The work of looping through the array is handled by fast, precompiled C code!

```
# element-wise
```

```
arr1 = np.array([1, 2, 3, 0])  
arr2 = np.array([2, 2, 0, 0])
```

```
result = arr1 + arr2      # [3, 4, 3, 0]  
result = arr1 - arr2      # [-1, 0, 3, 0]  
result = arr1 * arr2      # [2, 4, 0, 0]  
result = arr1 / arr2      # [0.5, 1., inf, nan]
```

```
# matrix multiplication
```

```
mat1 = np.array([[1, 2], [3, 4]])  
mat2 = np.array([[2, 2], [2, 2]])
```

```
result = mat1 @ mat2      # [[ 6,  6],  
                           #  [14, 14]]
```

Broadcasting

What happens if two operand arrays don't have the exact same shape?

1. Step If the arrays have different numbers of dimensions, the smaller shape is padded with ones on its left side.

2. Step If the number of the dimensions matches, but the size of a dimension does not, dimensions with the size of 1 are expanded.

3. Step If the shapes of the arrays still defer after applying the steps 1 and 2, a broadcasting error is raised.

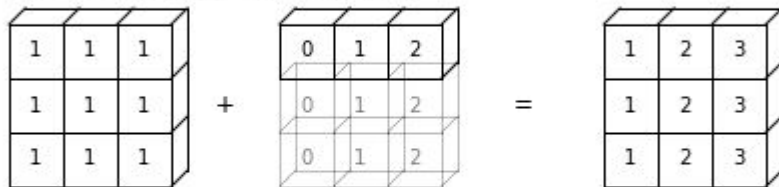
More about broadcasting:

<https://numpy.org/doc/stable/user/basics.broadcasting.html>

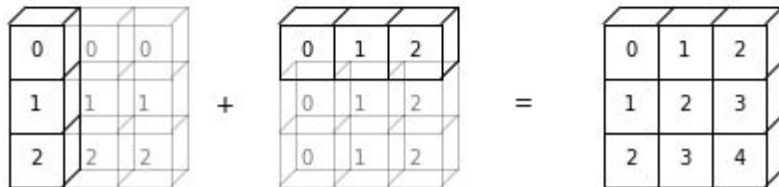
`np.arange(3) + 5`



`np.ones((3, 3)) + np.arange(3)`



`np.arange(3).reshape((3, 1)) + np.arange(3)`



Source:

<https://jakevdp.github.io/PythonDataScienceHandbook/02.05-computation-on-arrays-broadcasting.html>

Element-wise Functions

NumPy provides many functions that take entire arrays as inputs and perform element-wise operations.

A special type of element-wise functions are called **ufuncs** (universal functions). If given multiple arguments, they will perform automatic **broadcasting** where required.

A list of all available ufuncs can be found here:

<https://numpy.org/doc/stable/reference/ufuncs.html#available-ufuncs>

A complete list of all NumPy functions can be found here:

<https://numpy.org/doc/stable/reference/routines.html>

Aggregation Functions

Other functions take one or more arrays as input and reduce it to a single number or an array of lower dimensionality.

- `np.sum`
- `np.min` / `np.max`
- `np.mean`
- `[...]`

They take a special argument which determines along which axis (or axes) to perform the operation.

If left out, it will be performed along all axes.

```
array = np.arange(9).reshape(3, 3)
```

```
# sum of each column
```

```
col_sum = np.sum(array, axis=0)
```

```
# sum of each row
```

```
row_sum = np.sum(array, axis=1)
```

```
# sum of entire array
```

```
arr_sum = np.sum(array, axis=(0, 1))
```

```
# or simply
```

```
arr_sum = np.sum(array)
```

Comparing Arrays

Comparison operators on NumPy arrays work **element-wise** and return a **boolean array**.
Broadcasting is applied.

To check if two arrays are numerically identical, use `np.array_equal(array1, array2)`

`np.allclose(array1, array2)` checks if all values are equal within some error margin

`np.any()` and `np.all()` check if any/all values in an array are True(-ish)

```
arr1 = np.array([1, 2, 3, 4])
arr2 = np.array([0, 2, 3, 0])

equal = arr1 == arr2
# [False, True, True, False]

equal = arr1 == 4
# [False, False, False, True]

equal = np.array_equal(arr1, arr2)
# False
```

Random Numbers

NumPy provides a module for generating arrays of pseudo-random numbers with various distributions.

Check the notebook for examples!

<https://numpy.org/doc/stable/reference/random/generator.html#simple-random-data>