UNIT 4

NUMPY

Contents

NumPy Basics: Arrays and Vectorized Computation:

- Creating ndarrays,
- Data Types for ndarrays,
- Operations between Arrays and Scalars,
- Basic Indexing and Slicing,
- Indexing with slices, Boolean Indexing, Transposing Arrays and Swapping Axes.

What is NumPy?

- NumPy stands for **Numerical Python.**
- NumPy was created in 2005 by Travis Oliphant. It is an open source project and you can use it freely.
- NumPy is a Python library used for working with arrays. It is the fundamental Python package for scientific computing. It adds the capabilities of *N*-dimensional arrays, element-by-element operations (broadcasting), etc.
- It also has functions for working in domain of linear algebra, fourier transform, and matrices.

Why Use NumPy?

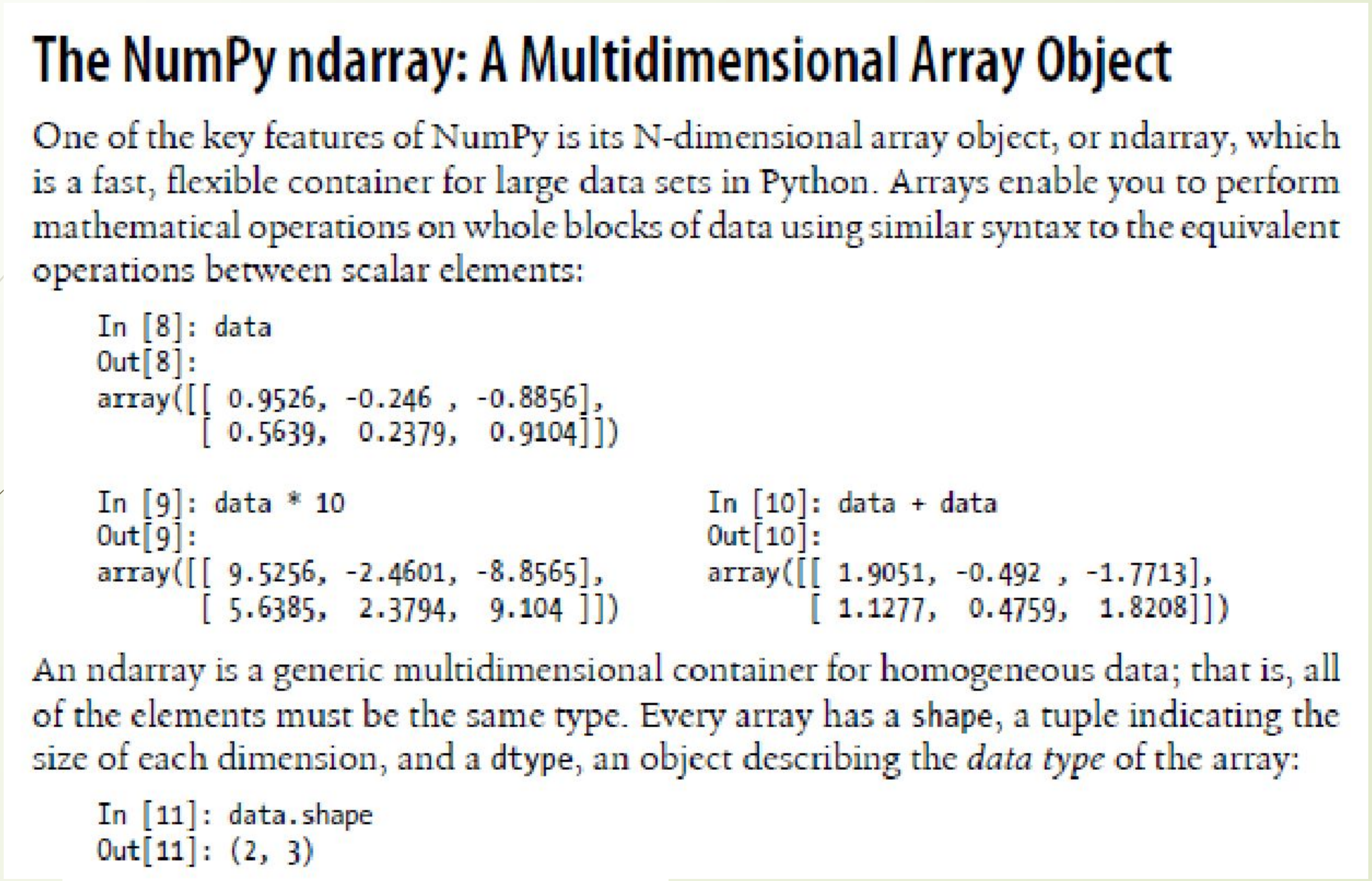
- In Python we have lists that serve the purpose of arrays, but they are slow to process.
- NumPy aims to provide an array object that is up to 50x faster than traditional Python lists.
- The array object in NumPy is called `ndarray`, it provides a lot of supporting functions that make working with `ndarray` very easy.
- Arrays are very frequently used in data science, where speed and resources are very important.

Why is NumPy Faster Than Lists?

- NumPy arrays are stored at one continuous place in memory unlike lists, so processes can access and manipulate them very efficiently.
- This behavior is called locality of reference in computer science.
- This is the main reason why NumPy is faster than lists. Also it is optimized to work with latest CPU architectures.
- Operating on the elements in a list can only be done through iterative

  loops, which is computationally inefficient in Python.
- The NumPy package enables users to overcome the shortcomings of the Python lists by providing the data storage object called ndarray

- The ndarray is similar to lists, but rather than being highly flexible by storing different types of objects in one list, only the same type of element can be stored in each column.
- For example, with a Python list, you could make the first element a list and the second another list or dictionary. With NumPy arrays, you can only store the same type of element, e.g., all elements must be floats, integers, or strings.
- Despite this limitation, ndarray wins hands down when it comes to operation times, as the operations are sped up significantly.



The NumPy ndarray: A Multidimensional Array Object

One of the key features of NumPy is its N-dimensional array object, or ndarray, which is a fast, flexible container for large data sets in Python. Arrays enable you to perform mathematical operations on whole blocks of data using similar syntax to the equivalent operations between scalar elements:

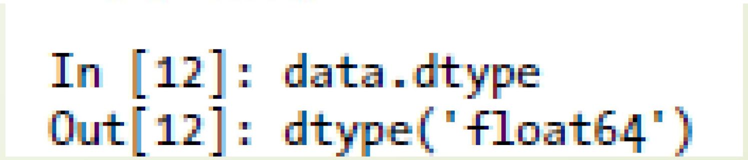
```
In [8]: data
Out[8]:
array([[ 0.9526, -0.246 , -0.8856],
       [ 0.5639,  0.2379,  0.9104]])
```

```
In [9]: data * 10
Out[9]:
array([[ 9.5256, -2.4601, -8.8565],
       [ 5.6385,  2.3794,  9.104 ]])
```

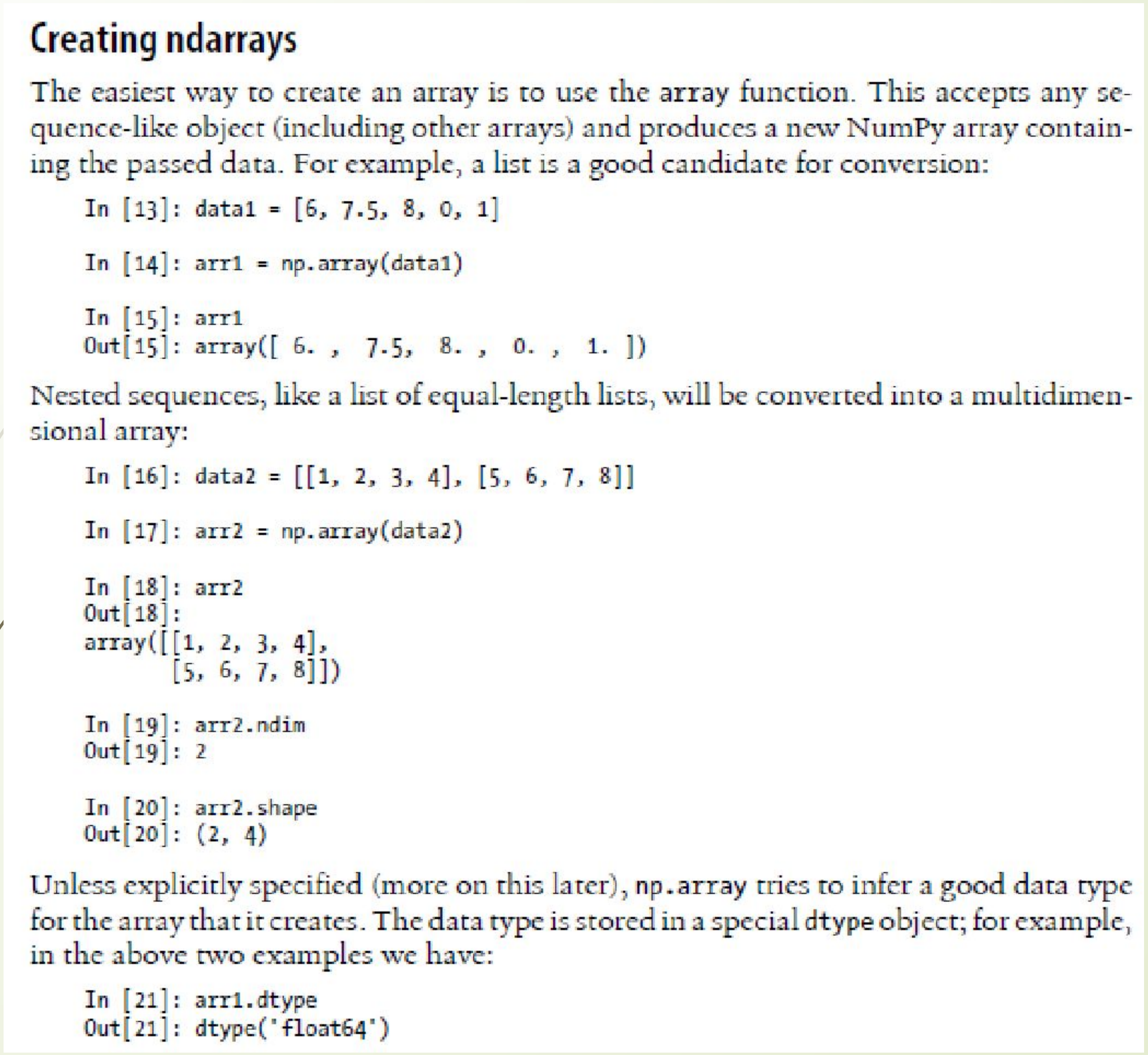
```
In [10]: data + data
Out[10]:
array([[ 1.9051, -0.492 , -1.7713],
       [ 1.1277,  0.4759,  1.8208]])
```

An ndarray is a generic multidimensional container for homogeneous data; that is, all of the elements must be the same type. Every array has a shape, a tuple indicating the size of each dimension, and a dtype, an object describing the *data type* of the array:

```
In [11]: data.shape
Out[11]: (2, 3)
```



```
In [12]: data.dtype
Out[12]: dtype('float64')
```



Creating ndarrays

The easiest way to create an array is to use the array function. This accepts any sequence-like object (including other arrays) and produces a new NumPy array containing the passed data. For example, a list is a good candidate for conversion:

```
In [13]: data1 = [6, 7.5, 8, 0, 1]

In [14]: arr1 = np.array(data1)

In [15]: arr1
Out[15]: array([ 6. ,  7.5,  8. ,  0. ,  1. ])
```

Nested sequences, like a list of equal-length lists, will be converted into a multidimensional array:

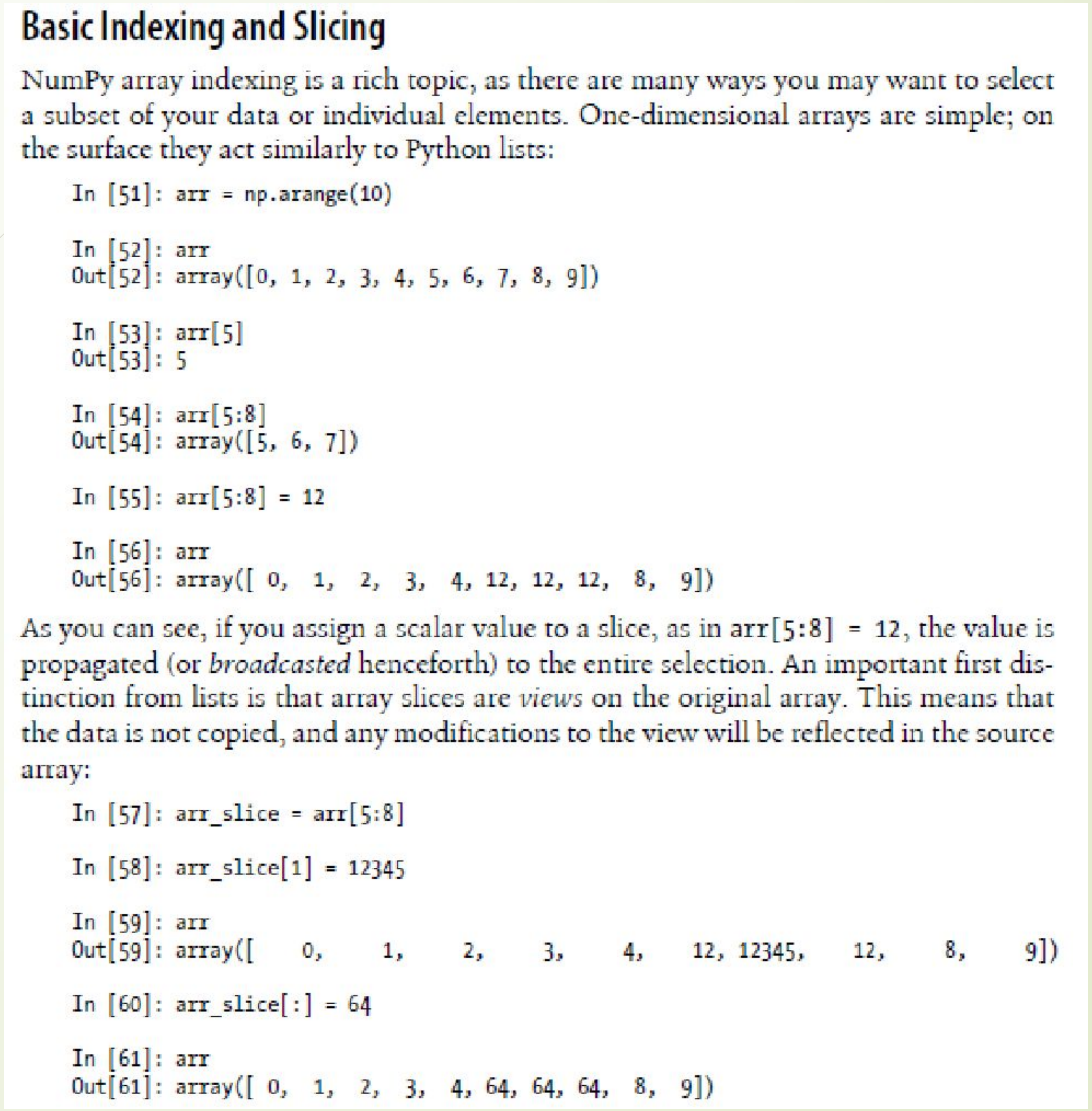
```
In [16]: data2 = [[1, 2, 3, 4], [5, 6, 7, 8]]

In [17]: arr2 = np.array(data2)

In [18]: arr2
Out[18]:
array([[1, 2, 3, 4],
       [5, 6, 7, 8]])

In [19]: arr2.ndim
Out[19]: 2

In [20]: arr2.shape
Out[20]: (2, 4)
```

Unless explicitly specified (more on this later), `np.array` tries to infer a good data type for the array that it creates. The data type is stored in a special `dtype` object; for example, in the above two examples we have:

```
In [21]: arr1.dtype
Out[21]: dtype('float64')
```

Operations between Arrays and Scalars

- Arrays are important because they enable you to express batch operations on data without writing any for loops. This is usually called ***vectorization***.
- Any arithmetic operations between equal-size arrays applies the operation elementwise



Basic Indexing and Slicing

NumPy array indexing is a rich topic, as there are many ways you may want to select a subset of your data or individual elements. One-dimensional arrays are simple; on the surface they act similarly to Python lists:

```
In [51]: arr = np.arange(10)

In [52]: arr
Out[52]: array([0, 1, 2, 3, 4, 5, 6, 7, 8, 9])

In [53]: arr[5]
Out[53]: 5

In [54]: arr[5:8]
Out[54]: array([5, 6, 7])

In [55]: arr[5:8] = 12

In [56]: arr
Out[56]: array([ 0,  1,  2,  3,  4, 12, 12, 12,  8,  9])
```

As you can see, if you assign a scalar value to a slice, as in `arr[5:8] = 12`, the value is propagated (or *broadcasted* henceforth) to the entire selection. An important first distinction from lists is that array slices are *views* on the original array. This means that the data is not copied, and any modifications to the view will be reflected in the source array:

```
In [57]: arr_slice = arr[5:8]

In [58]: arr_slice[1] = 12345

In [59]: arr
Out[59]: array([    0,     1,     2,     3,     4,    12, 12345,    12,     8,     9])

In [60]: arr_slice[:] = 64

In [61]: arr
Out[61]: array([ 0,  1,  2,  3,  4, 64, 64, 64,  8,  9])
```

If you want a copy of a slice of an ndarray instead of a view, you will need to explicitly copy the array; for example `arr[5:8].copy()`.

Higher dimensional arrays 2D and 3D arrays

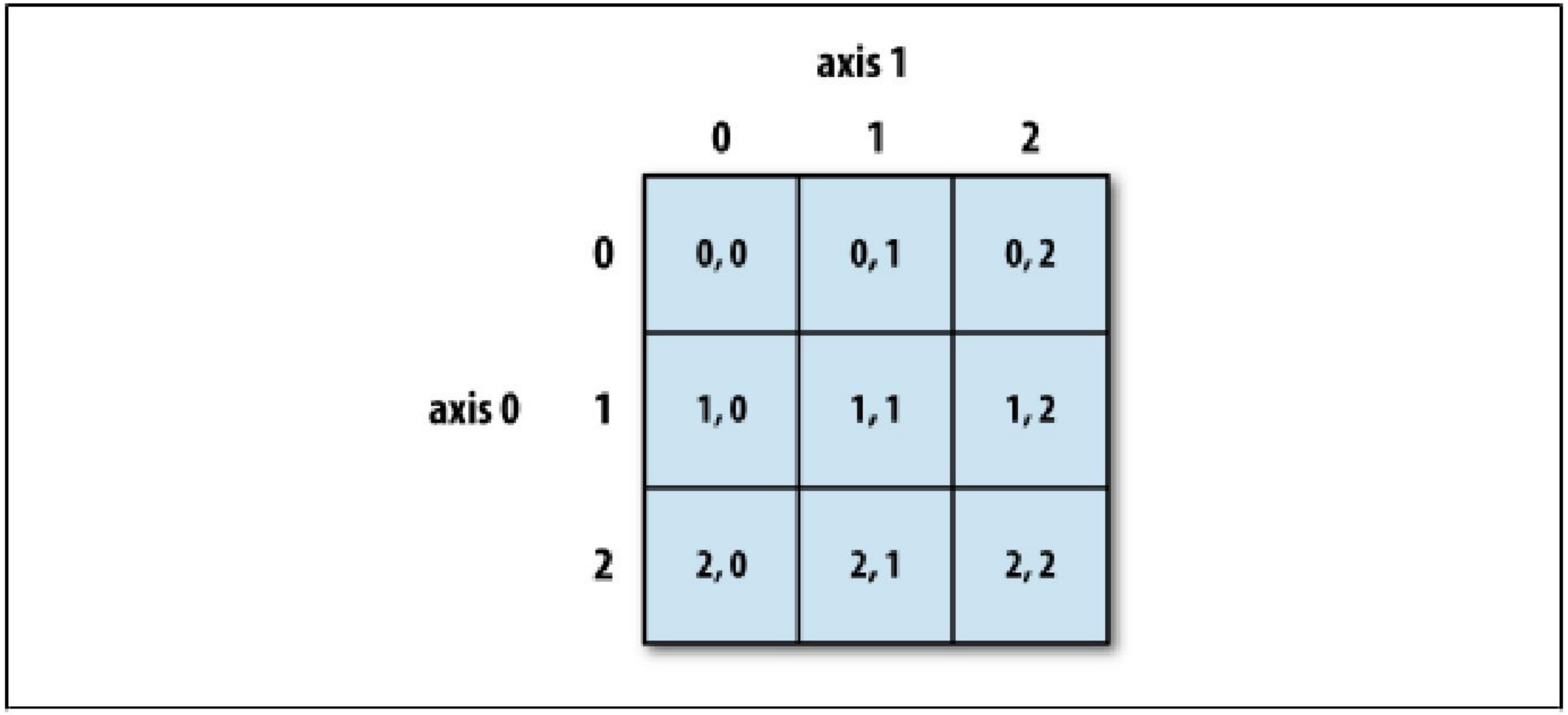
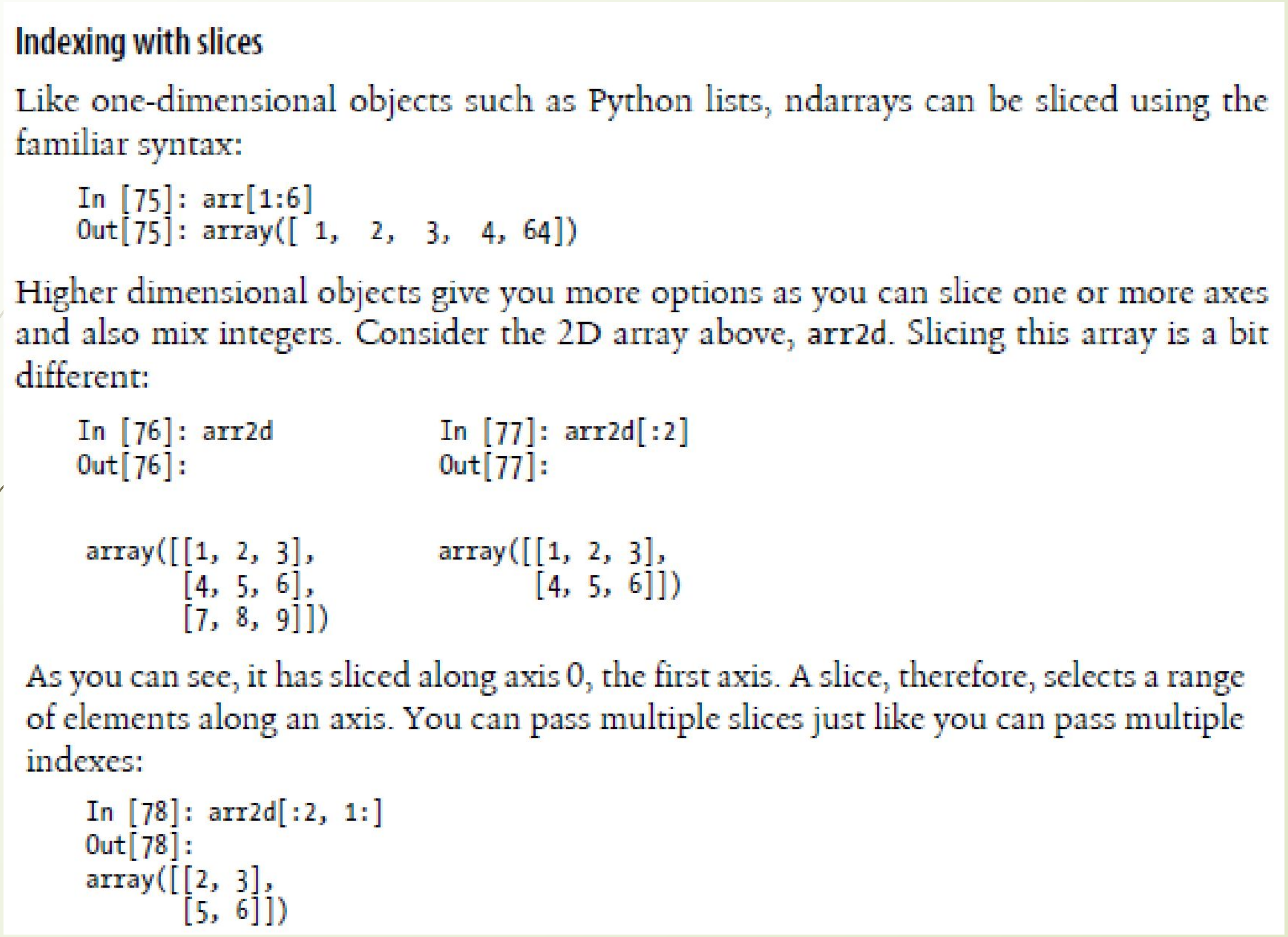


Figure 4-1. Indexing elements in a NumPy array



Indexing with slices

Like one-dimensional objects such as Python lists, ndarrays can be sliced using the familiar syntax:

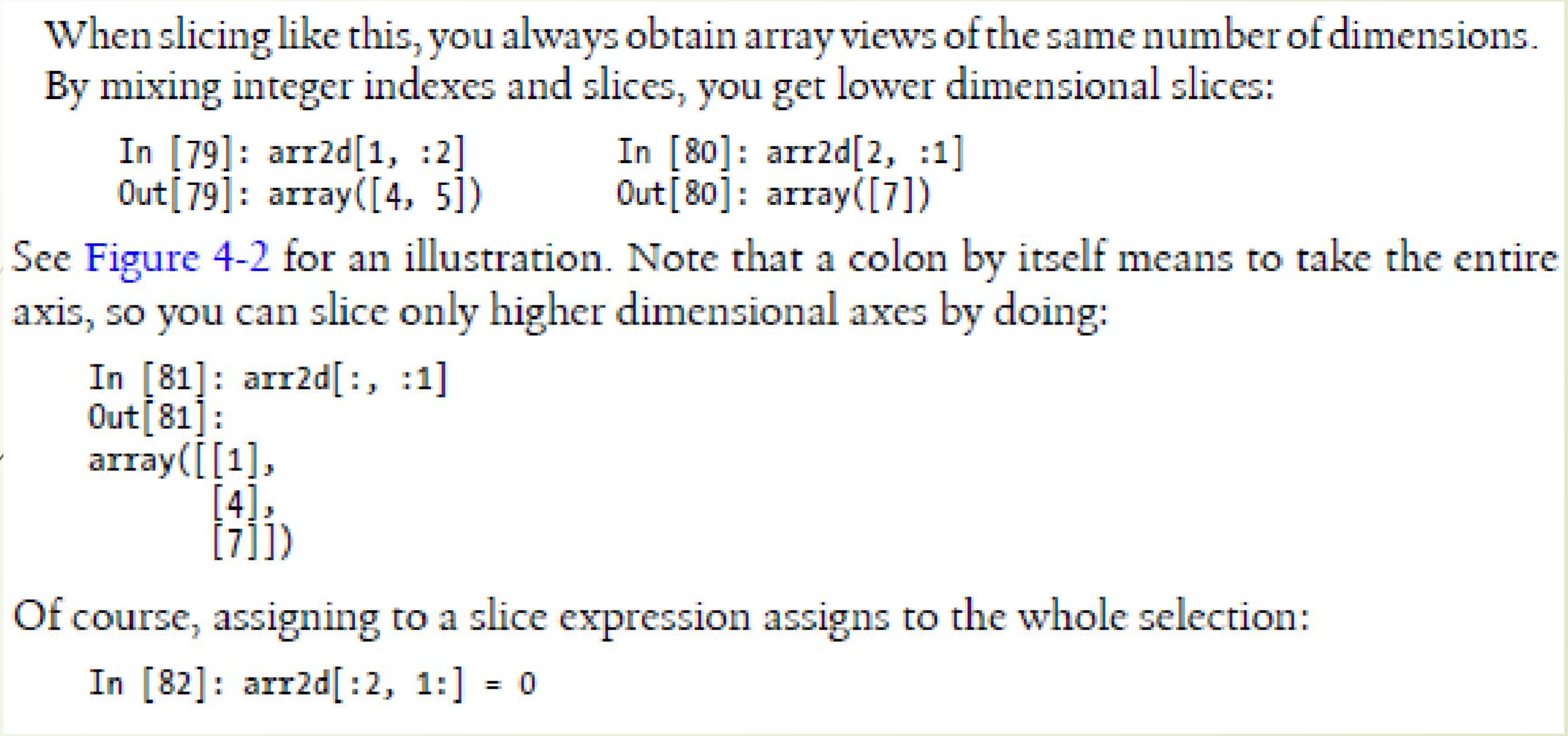
```
In [75]: arr[1:6]
Out[75]: array([ 1,  2,  3,  4, 64])
```

Higher dimensional objects give you more options as you can slice one or more axes and also mix integers. Consider the 2D array above, arr2d. Slicing this array is a bit different:

```
In [76]: arr2d               In [77]: arr2d[:2]
Out[76]:                     Out[77]:


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

As you can see, it has sliced along axis 0, the first axis. A slice, therefore, selects a range of elements along an axis. You can pass multiple slices just like you can pass multiple indexes:

```
In [78]: arr2d[:2, 1:]
Out[78]:
array([[2, 3],
       [5, 6]])
```



When slicing like this, you always obtain array views of the same number of dimensions. By mixing integer indexes and slices, you get lower dimensional slices:

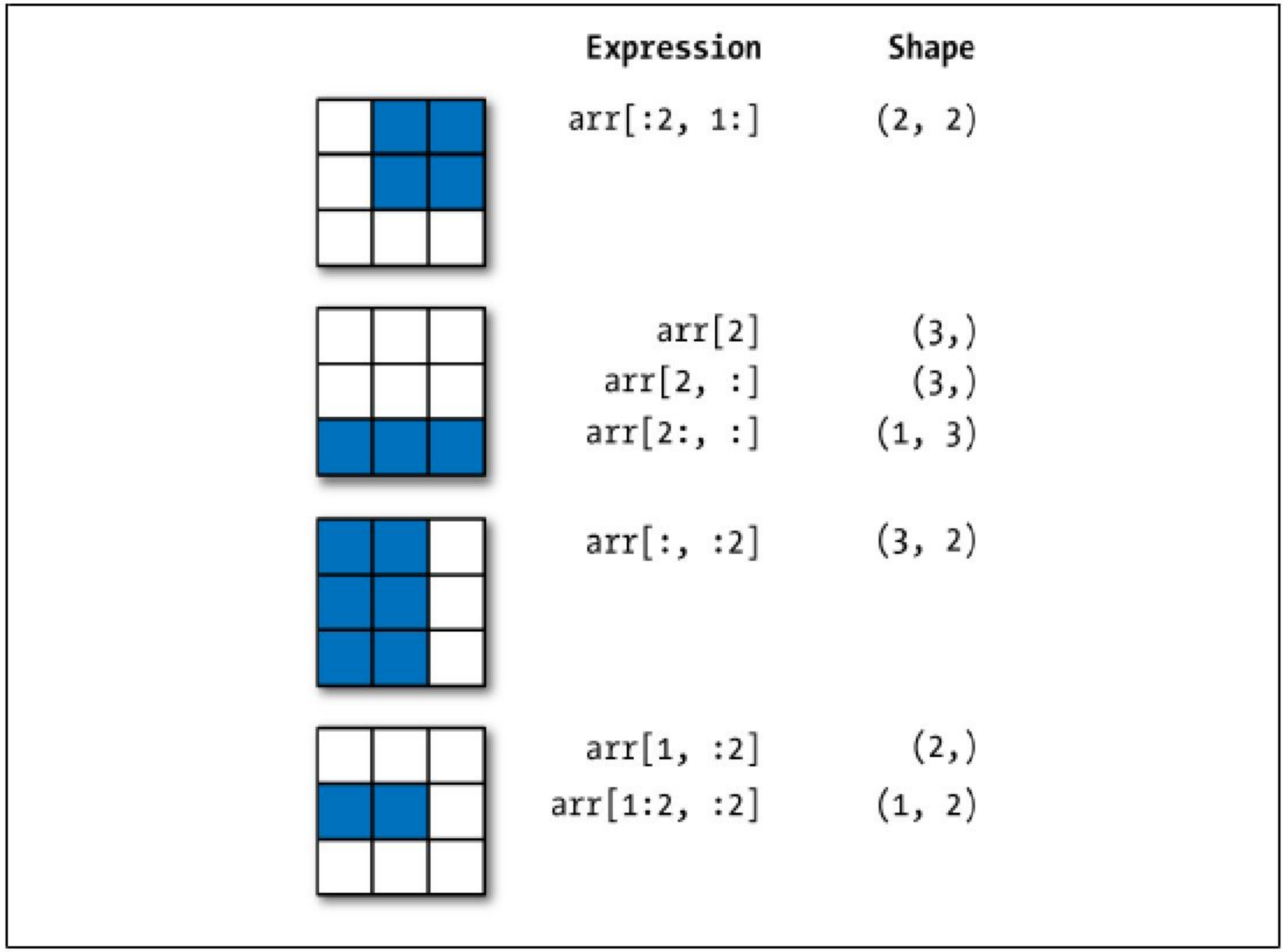
```
In [79]: arr2d[1, :2]             In [80]: arr2d[2, :1]
Out[79]: array([4, 5])            Out[80]: array([7])
```

See Figure 4-2 for an illustration. Note that a colon by itself means to take the entire axis, so you can slice only higher dimensional axes by doing:

```
In [81]: arr2d[:, :1]
Out[81]:
array([[1],
       [4],
       [7]])
```

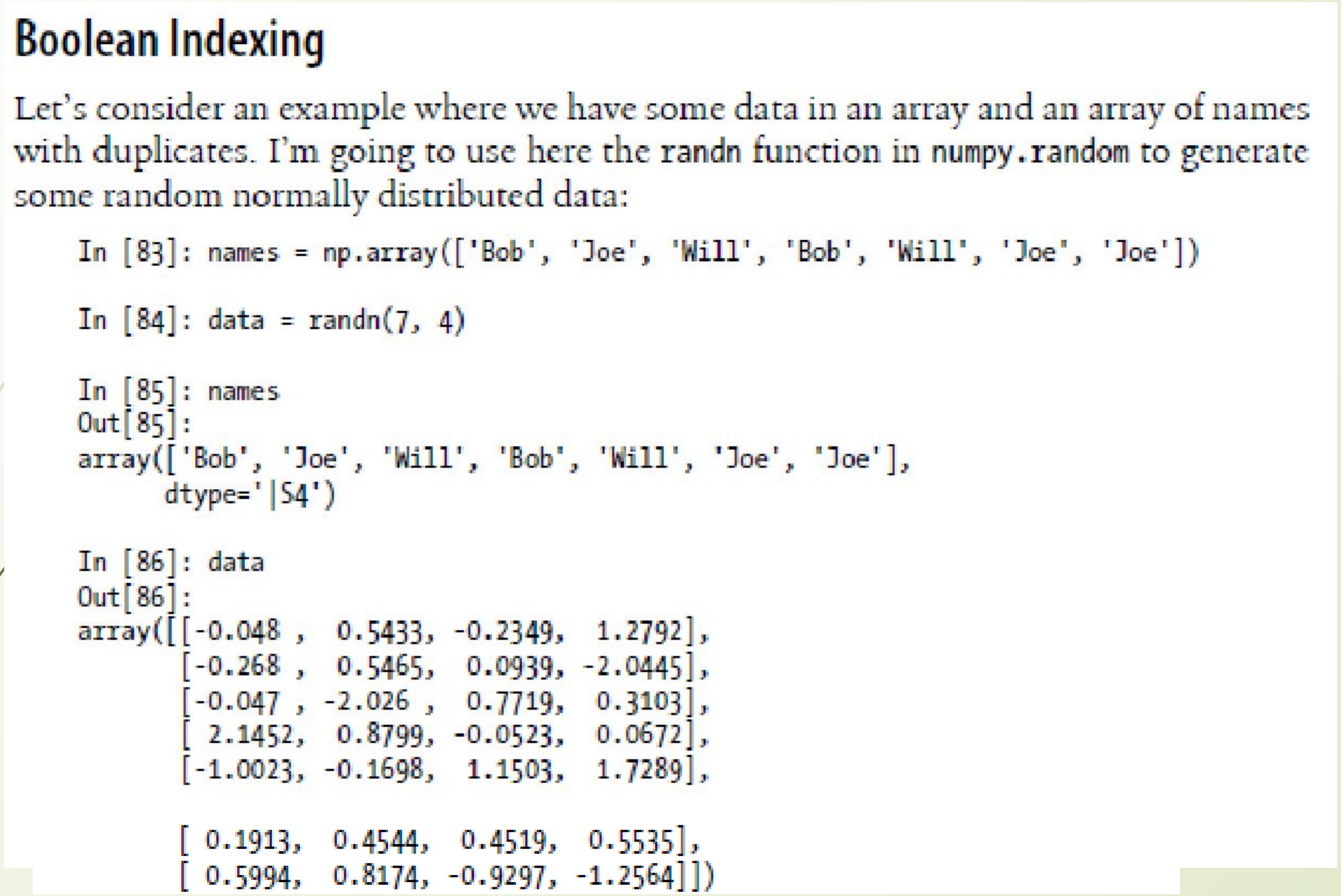
Of course, assigning to a slice expression assigns to the whole selection:

```
In [82]: arr2d[:2, 1:] = 0
```



Expression	Shape
arr[:2, 1:]	(2, 2)
arr[2]	(3,)
arr[2, :]	(3,)
arr[2:, :]	(1, 3)
arr[:, :2]	(3, 2)
arr[1, :2]	(2,)
arr[1:2, :2]	(1, 2)

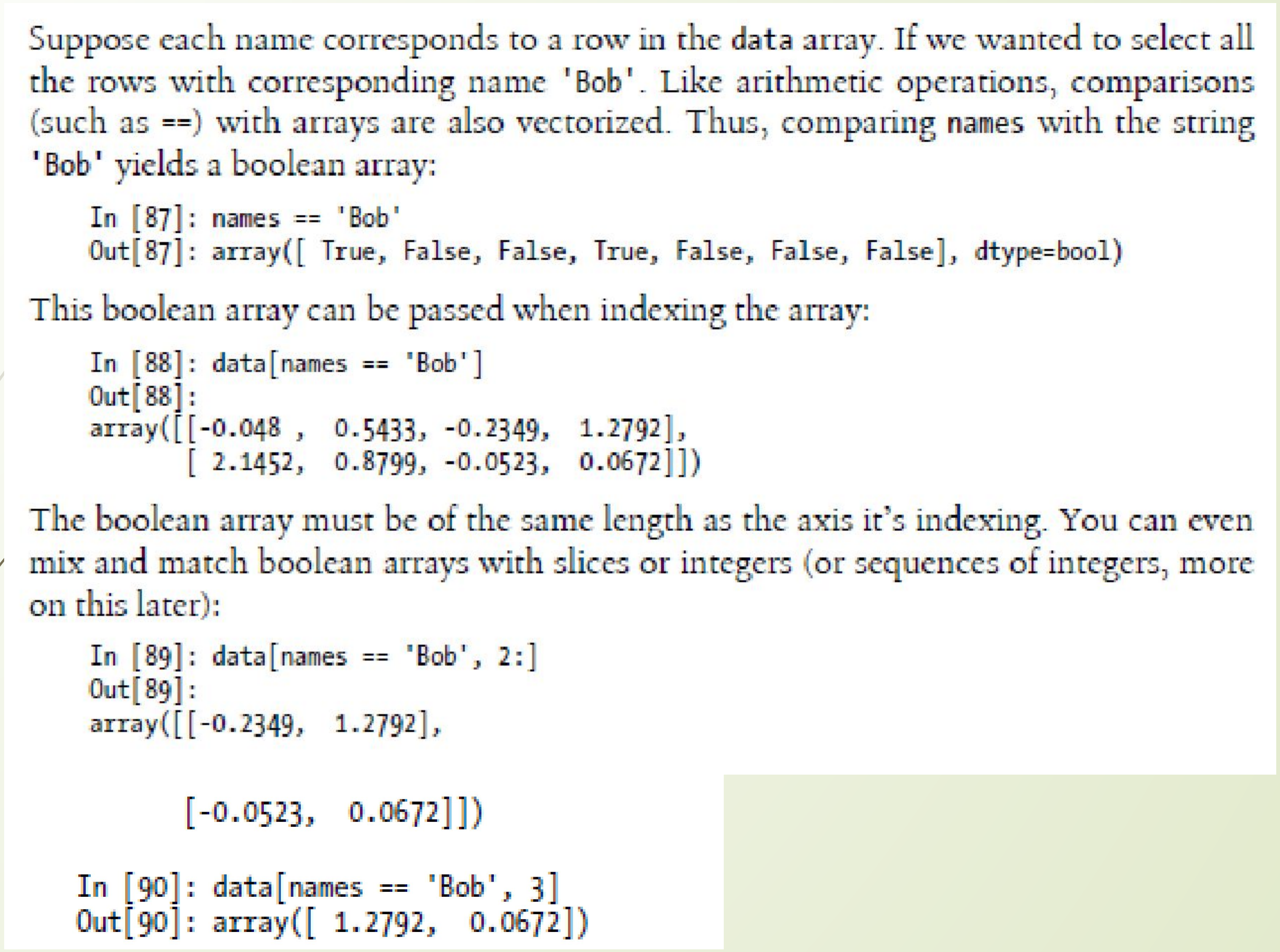
Figure 4-2. Two-dimensional array slicing



Boolean Indexing

Let's consider an example where we have some data in an array and an array of names with duplicates. I'm going to use here the randn function in numpy.random to generate some random normally distributed data:

```
In [83]: names = np.array(['Bob', 'Joe', 'Will', 'Bob', 'Will', 'Joe', 'Joe'])

In [84]: data = randn(7, 4)

In [85]: names
Out[85]:
array(['Bob', 'Joe', 'Will', 'Bob', 'Will', 'Joe', 'Joe'],
      dtype='|S4')

In [86]: data
Out[86]:
array([[-0.048 ,  0.5433, -0.2349,  1.2792],
       [-0.268 ,  0.5465,  0.0939, -2.0445],
       [-0.047 , -2.026 ,  0.7719,  0.3103],
       [ 2.1452,  0.8799, -0.0523,  0.0672],
       [-1.0023, -0.1698,  1.1503,  1.7289],

       [ 0.1913,  0.4544,  0.4519,  0.5535],
       [ 0.5994,  0.8174, -0.9297, -1.2564]])
```


Suppose each name corresponds to a row in the **data** array. If we wanted to select all the rows with corresponding name 'Bob'. Like arithmetic operations, comparisons (such as ==) with arrays are also vectorized. Thus, comparing **names** with the string **'Bob'** yields a boolean array:

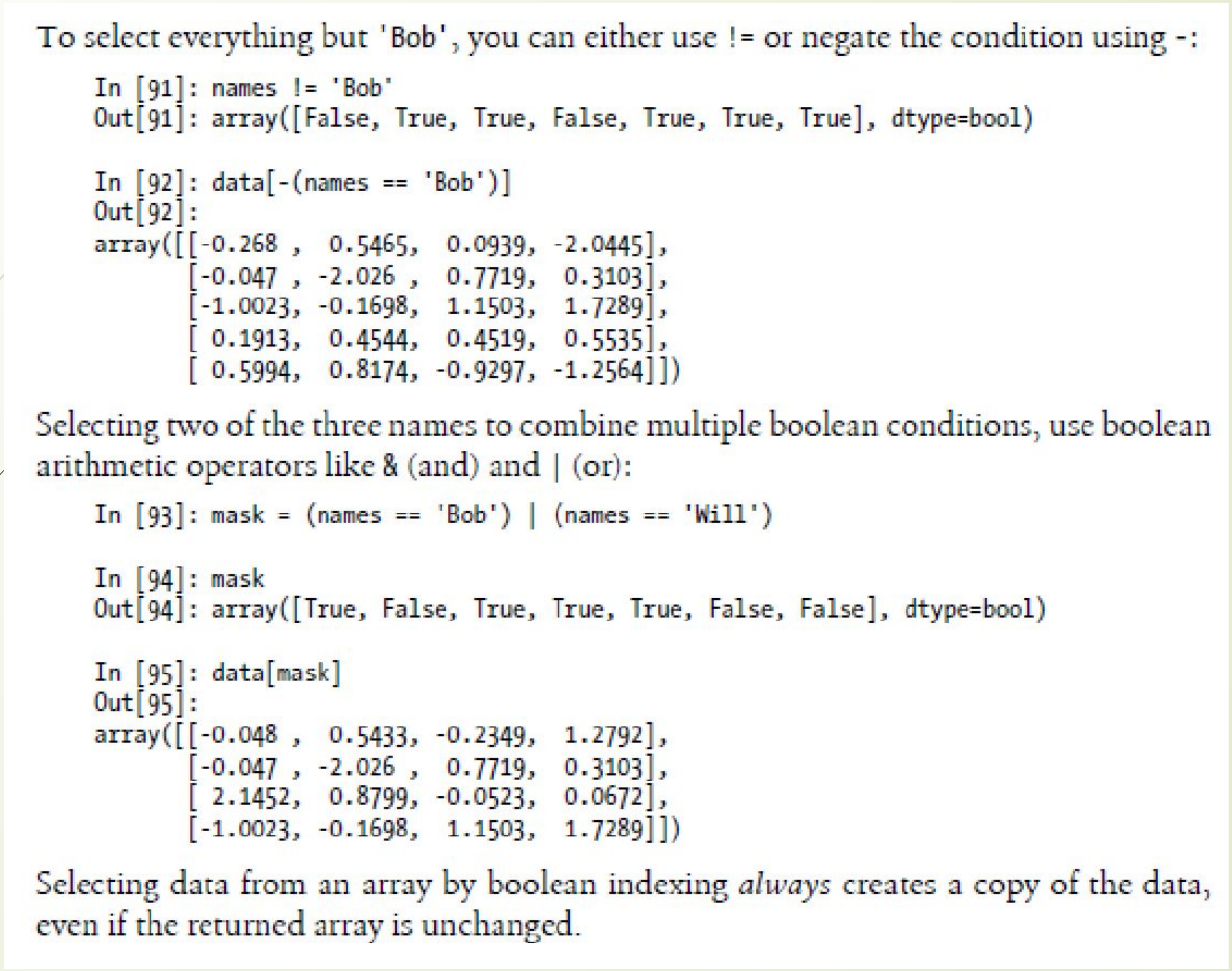
```
In [87]: names == 'Bob'
Out[87]: array([ True, False, False, True, False, False, False], dtype=bool)
```

This boolean array can be passed when indexing the array:

```
In [88]: data[names == 'Bob']
Out[88]:
array([[-0.048 ,  0.5433, -0.2349,  1.2792],
       [ 2.1452,  0.8799, -0.0523,  0.0672]])
```

The boolean array must be of the same length as the axis it's indexing. You can even mix and match boolean arrays with slices or integers (or sequences of integers, more on this later):

```
In [89]: data[names == 'Bob', 2:]
Out[89]:
array([[-0.2349,  1.2792],


       [-0.0523,  0.0672]])

In [90]: data[names == 'Bob', 3]
Out[90]: array([ 1.2792,  0.0672])
```



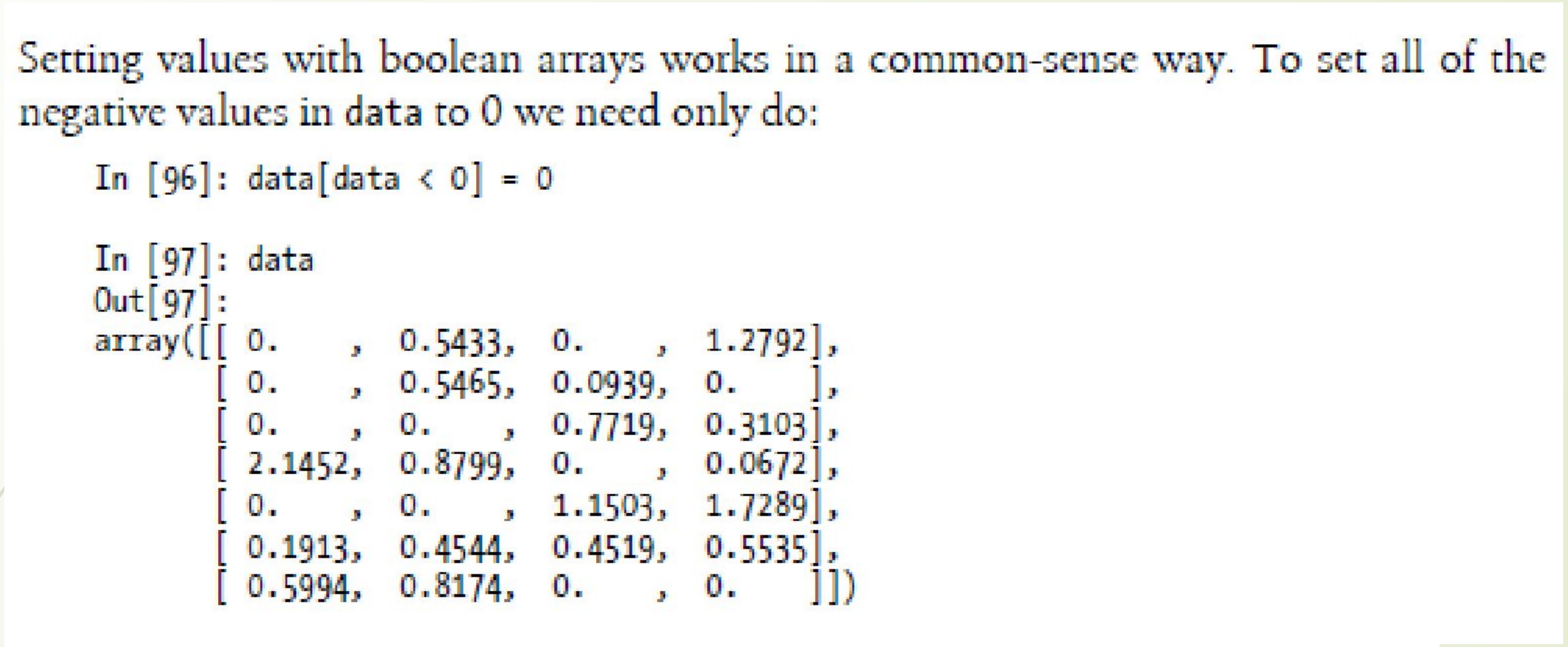
To select everything but 'Bob', you can either use != or negate the condition using -:

```
In [91]: names != 'Bob'
Out[91]: array([False, True, True, False, True, True, True], dtype=bool)

In [92]: data[-(names == 'Bob')]
Out[92]:
array([[-0.268 ,  0.5465,  0.0939, -2.0445],
       [-0.047 , -2.026 ,  0.7719,  0.3103],
       [-1.0023, -0.1698,  1.1503,  1.7289],
       [ 0.1913,  0.4544,  0.4519,  0.5535],
       [ 0.5994,  0.8174, -0.9297, -1.2564]])
```

Selecting two of the three names to combine multiple boolean conditions, use boolean arithmetic operators like & (and) and | (or):

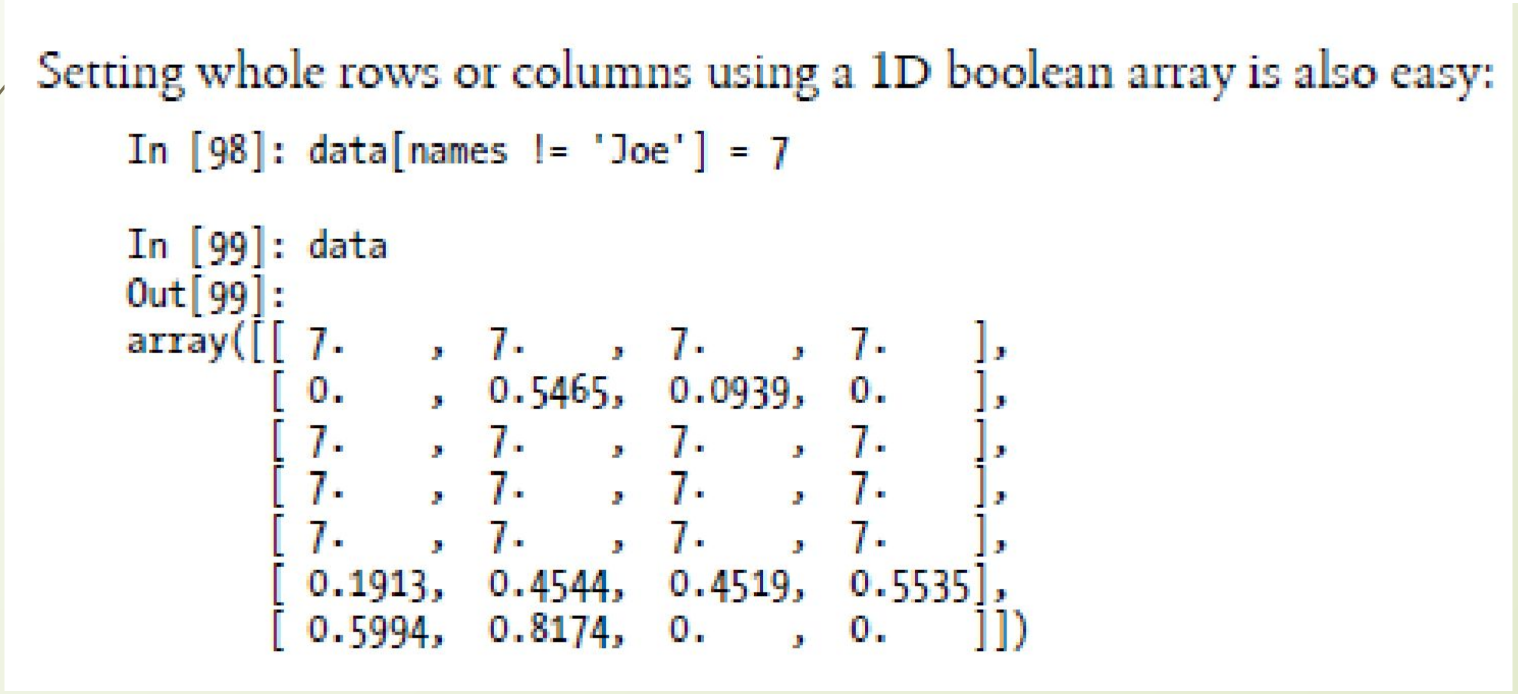
```
In [93]: mask = (names == 'Bob') | (names == 'Will')

In [94]: mask
Out[94]: array([True, False, True, True, True, False, False], dtype=bool)

In [95]: data[mask]
Out[95]:
array([[-0.048 ,  0.5433, -0.2349,  1.2792],
       [-0.047 , -2.026 ,  0.7719,  0.3103],
       [ 2.1452,  0.8799, -0.0523,  0.0672],
       [-1.0023, -0.1698,  1.1503,  1.7289]])
```

Selecting data from an array by boolean indexing *always* creates a copy of the data, even if the returned array is unchanged.



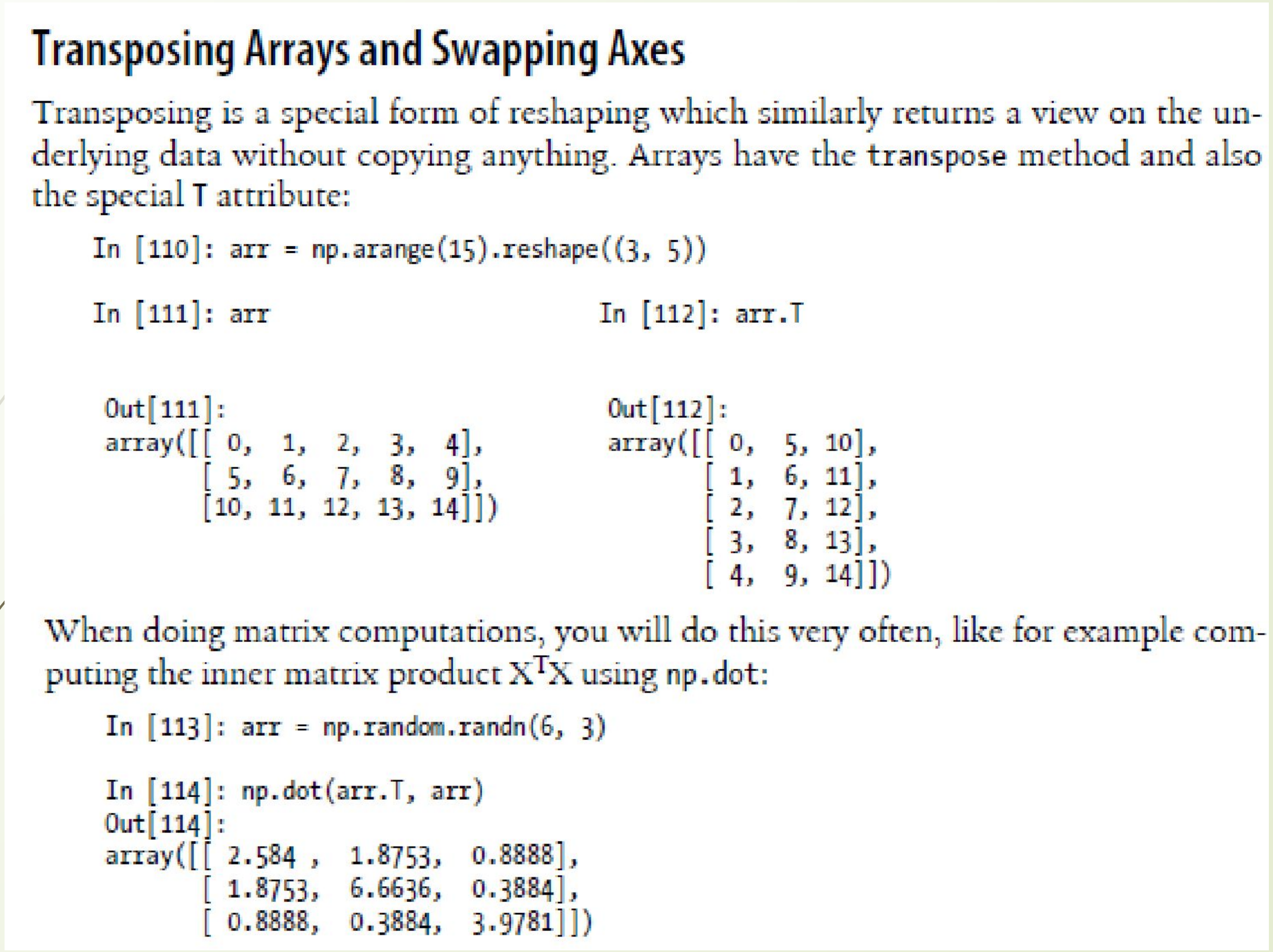
Setting values with boolean arrays works in a common-sense way. To set all of the negative values in data to 0 we need only do:

```
In [96]: data[data < 0] = 0

In [97]: data
Out[97]:
array([[ 0.    ,  0.5433,  0.    ,  1.2792],
       [ 0.    ,  0.5465,  0.0939,  0.    ],
       [ 0.    ,  0.    ,  0.7719,  0.3103],
       [ 2.1452,  0.8799,  0.    ,  0.0672],
       [ 0.    ,  0.    ,  1.1503,  1.7289],
       [ 0.1913,  0.4544,  0.4519,  0.5535],
       [ 0.5994,  0.8174,  0.    ,  0.    ]])
```



Setting whole rows or columns using a 1D boolean array is also easy:

```
In [98]: data[names != 'Joe'] = 7

In [99]: data
Out[99]:
array([[ 7.    ,  7.    ,  7.    ,  7.    ],
       [ 0.    ,  0.5465,  0.0939,  0.    ],
       [ 7.    ,  7.    ,  7.    ,  7.    ],
       [ 7.    ,  7.    ,  7.    ,  7.    ],
       [ 7.    ,  7.    ,  7.    ,  7.    ],
       [ 0.1913,  0.4544,  0.4519,  0.5535],
       [ 0.5994,  0.8174,  0.    ,  0.    ]])
```



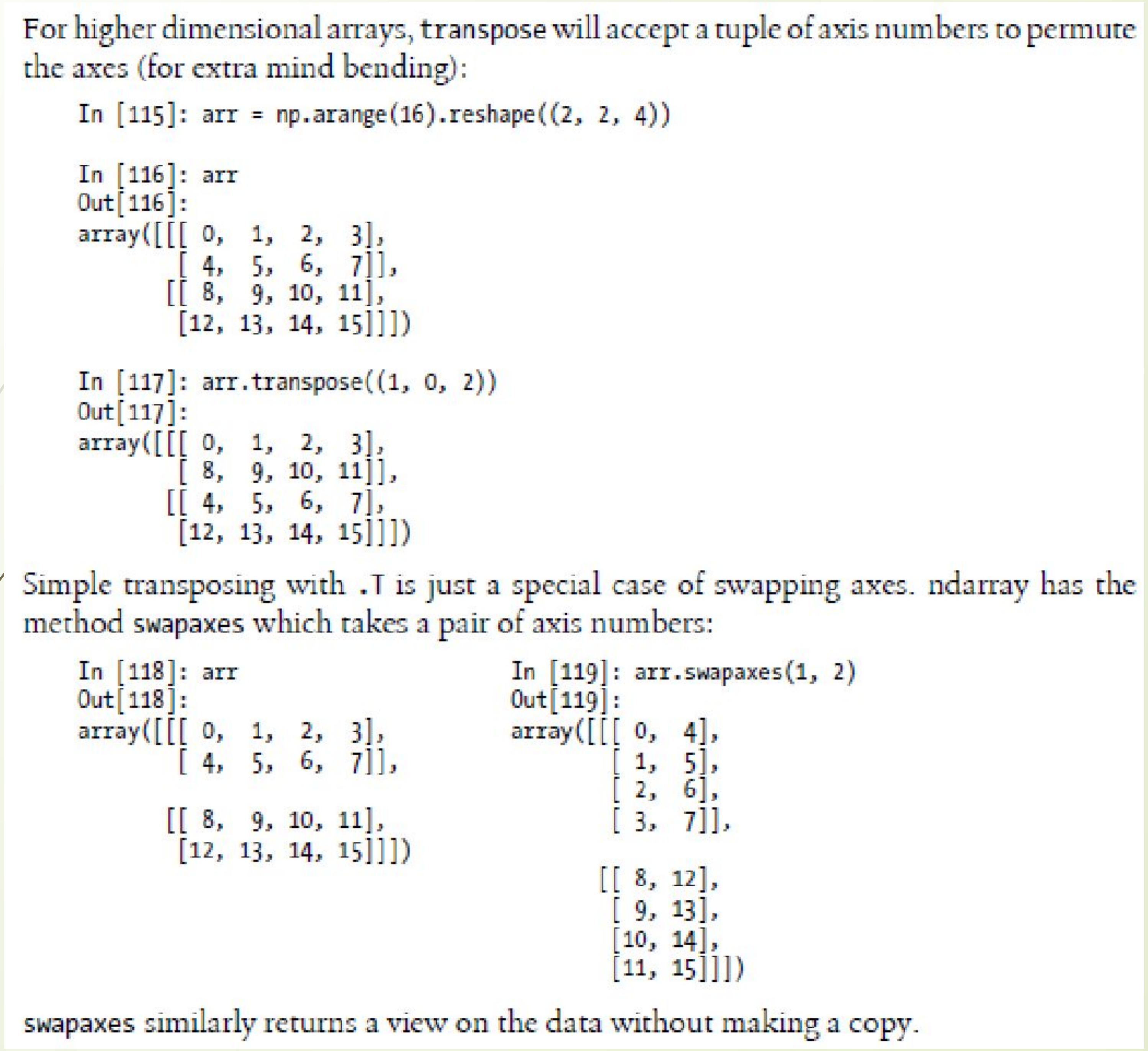
Transposing Arrays and Swapping Axes

Transposing is a special form of reshaping which similarly returns a view on the underlying data without copying anything. Arrays have the `transpose` method and also the special `T` attribute:

```
In [110]: arr = np.arange(15).reshape((3, 5))

In [111]: arr                              In [112]: arr.T


 Out[111]:                                  Out[112]:
 array([[ 0,  1,  2,  3,  4],               array([[ 0,  5, 10],
        [ 5,  6,  7,  8,  9],                      [ 1,  6, 11],
        [10, 11, 12, 13, 14]])                     [ 2,  7, 12],
                                                   [ 3,  8, 13],
                                                   [ 4,  9, 14]])
```

When doing matrix computations, you will do this very often, like for example computing the inner matrix product X^TX using `np.dot`:

```
In [113]: arr = np.random.randn(6, 3)

In [114]: np.dot(arr.T, arr)
Out[114]:
array([[ 2.584 ,  1.8753,  0.8888],
       [ 1.8753,  6.6636,  0.3884],
       [ 0.8888,  0.3884,  3.9781]])
```



For higher dimensional arrays, transpose will accept a tuple of axis numbers to permute the axes (for extra mind bending):

```
In [115]: arr = np.arange(16).reshape((2, 2, 4))

In [116]: arr
Out[116]:
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7]],
       [[ 8,  9, 10, 11],
        [12, 13, 14, 15]]])

In [117]: arr.transpose((1, 0, 2))
Out[117]:
array([[[ 0,  1,  2,  3],
        [ 8,  9, 10, 11]],
       [[ 4,  5,  6,  7],
        [12, 13, 14, 15]]])
```

Simple transposing with .T is just a special case of swapping axes. ndarray has the method swapaxes which takes a pair of axis numbers:

```
In [118]: arr
Out[118]:
array([[[ 0,  1,  2,  3],
        [ 4,  5,  6,  7]],

       [[ 8,  9, 10, 11],
        [12, 13, 14, 15]]])
```

```
In [119]: arr.swapaxes(1, 2)
Out[119]:
array([[[ 0,  4],
        [ 1,  5],
        [ 2,  6],
        [ 3,  7]],

       [[ 8, 12],
        [ 9, 13],
        [10, 14],
        [11, 15]]])
```

swapaxes similarly returns a view on the data without making a copy.