4. Indexing, slicing

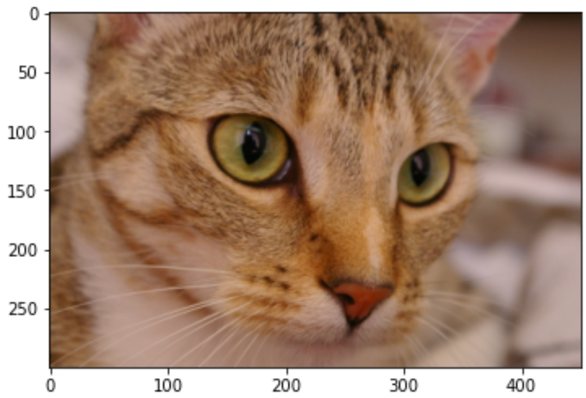
Each element of an array can be located by its position in each dimension. Numpy offers multiple ways to access single elements or groups of elements in very efficient ways. We will illustrate these concepts both with small simple matrices as well as a regular image, in order to illustrate them.

In [1]:
```
import numpy as np
import matplotlib.pyplot as plt
plt.gray();
import skimage
```

```
<Figure size 432x288 with 0 Axes>
```

We first load an image included in the scikit-image package:

In [2]:
```
image = skimage.data.chelsea()
plt.imshow(image);
```



We can check the dimensions of the image and see that it is an RGB image with 3 channels:

In [3]:
```
image.shape
```

Out[3]:
```
(300, 451, 3)
```

4.1 Accessing single values

We create a small 2D array to use as an example:

In [4]:
```
normal_array = np.random.normal(10, 2, (3,4))
normal_array
```

Out[4]:
```
array([[12.99205086,  7.7157832 , 14.66021898,  8.21412356],
       [ 9.19391119,  7.92142871, 13.31222213,  8.19957688],
       [11.08009573,  8.54243953, 12.71096417, 10.09637761]])
```

It is very easy to access an array's values. One can just pass an *index* for each dimensions. For example to recover the value on the last row and second column of the `normal_array` array we just write (remember counting starts at 0):

In [5]:
```
single_value = normal_array[2,1]
single_value
```

Out[5]:
```
8.542439525354693
```

What is returned in that case is a single number that we can re-use:

In [6]:
```
single_value += 10
single_value
```

Out[6]:
```
18.542439525354695
```

And that change doesn't affect the original value in the array:

In [7]:
```
normal_array
```

Out[7]:
```
array([[12.99205086,  7.7157832 , 14.66021898,  8.21412356],
       [ 9.19391119,  7.92142871, 13.31222213,  8.19957688],
       [11.08009573,  8.54243953, 12.71096417, 10.09637761]])
```

However we can also directly change the value in an array:

In [8]:
```
normal_array[2,1] = 23
```

In [9]:
```
normal_array
```

Out[9]:
```
array([[12.99205086,  7.7157832 , 14.66021898,  8.21412356],
       [ 9.19391119,  7.92142871, 13.31222213,  8.19957688],
       [11.08009573, 23.        , 12.71096417, 10.09637761]])
```

4.2 Accessing part of an array with indices: slicing

4.2.1 Selecting a range of elements

One can also select multiple elements in each dimension (e.g. multiple rows and columns in 2D) by using the `start:end:step` syntax. By default, if omitted, `start=0` , `end=last element and step=1` . For example to select the first **and** second rows of the first column, we can write:

In [10]:
```
normal_array[0:2,0]
```

Out[10]:
```
array([12.99205086,  9.19391119])
```

Note that the `end` element is **not** included. One can use the same notation for all dimensions:

In [11]:
```
normal_array[0:2,2:4]
```

Out[11]:
```
array([[14.66021898,  8.21412356],
       [13.31222213,  8.19957688]])
```

In [12]:
```
normal_array[1:,2:4]
```

Out[12]:
```
array([[13.31222213,  8.19957688],
       [12.71096417, 10.09637761]])
```

4.2.2 Selecting all elements

If we only specify `:`, it means we want to recover all elements in that dimension:

In [13]:
```
normal_array[:,2:4]
```

Out[13]:
```
array([[14.66021898,  8.21412356],
       [13.31222213,  8.19957688],
       [12.71096417, 10.09637761]])
```

Also in general, if you only specify the value for a single axis, this will take the first element of the first dimension:

In [14]:
```
normal_array
```

Out[14]:
```
array([[12.99205086,  7.7157832 , 14.66021898,  8.21412356],
       [ 9.19391119,  7.92142871, 13.31222213,  8.19957688],
       [11.08009573, 23.        , 12.71096417, 10.09637761]])
```

In [15]:
```
normal_array[1]
```

Out[15]:
```
array([ 9.19391119,  7.92142871, 13.31222213,  8.19957688])
```

Finally note that if you want to recover only one element along a dimension (single row, column etc), you can do that in two ways:

In [16]:
```
normal_array[0,:]
```

Out[16]:
```
array([12.99205086,  7.7157832 , 14.66021898,  8.21412356])
```

This returns a one-dimensional array containing a single row from the original array:

In [17]:
```
normal_array[0,:].shape
```

Out[17]:
```
(4,)
```

Instead, if you specify actual boundaries that still return only a single row:

In [18]:
```
normal_array[0:1,:]
```

Out[18]:
```
array([[12.99205086,  7.7157832 , 14.66021898,  8.21412356]])
```

In [19]:
```
normal_array[0:1,:].shape
```

Out[19]:
```
(1, 4)
```

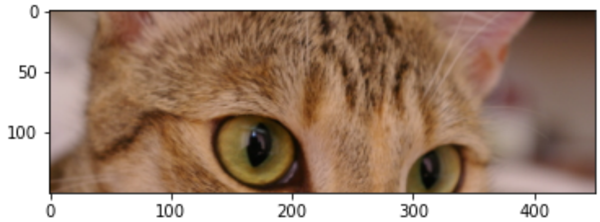
you recover a tow dimensional array where one of the dimensions has a size of 1.

4.2.3 Illustration on an image

We can for example only select half the rows of the image but all columns and channels:

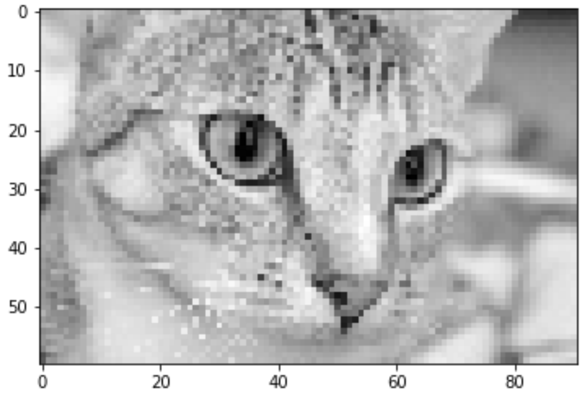
In [20]:
```
image.shape
```
Out[20]:
```
(300, 451, 3)
```

In [21]:
```
sub_image = image[0:150,:,:]
plt.imshow(sub_image);
```



Or we can take every fith column and row from a single channel, which returns a pixelated version of the original image:

In [22]:
```
plt.imshow(image[::5,::5,0]);
```



4.3 Sub-arrays are not copies!

As often with Python when you create a new variable using a sub-array, that variable **is not independent** from the original variable:

In [23]:
```
sub_array = normal_array[:,2:4]
```

In [24]:
```
sub_array
```
Out[24]:
```
array([[14.66021898,  8.21412356],
       [13.31222213,  8.19957688],
       [12.71096417, 10.09637761]])
```

In [25]:
```
normal_array
```
Out[25]:
```
array([[12.99205086,  7.7157832 , 14.66021898,  8.21412356],
       [ 9.19391119,  7.92142871, 13.31222213,  8.19957688],
       [11.08009573, 23.        , 12.71096417, 10.09637761]])
```

If for example we modify `normal_array`, this is going to be reflected in `sub_array` too:

In [26]:
```
normal_array[0,2] = 100
```

In [27]:
```
normal_array
```

Out[27]:
```
array([[ 12.99205086,   7.7157832 , 100.        ,   8.21412356],
       [  9.19391119,   7.92142871,  13.31222213,   8.19957688],
       [ 11.08009573,  23.        ,  12.71096417,  10.09637761]])
```

In [28]:
```
sub_array
```

Out[28]:
```
array([[100.        ,   8.21412356],
       [ 13.31222213,   8.19957688],
       [ 12.71096417,  10.09637761]])
```

The converse is also true:

In [29]:
```
sub_array[0,1] = 50
```

In [30]:
```
sub_array
```

Out[30]:
```
array([[100.        ,  50.        ],
       [ 13.31222213,   8.19957688],
       [ 12.71096417,  10.09637761]])
```

In [31]:
```
normal_array
```

Out[31]:
```
array([[ 12.99205086,   7.7157832 , 100.        ,  50.        ],
       [  9.19391119,   7.92142871,  13.31222213,   8.19957688],
       [ 11.08009573,  23.        ,  12.71096417,  10.09637761]])
```

If you want your sub-array to be an *independent* copy of the original, you have to use the `.copy()` method:

In [32]:
```
sub_array_copy = normal_array[1:3,:].copy()
```

In [33]:
```
sub_array_copy
```

Out[33]:
```
array([[ 9.19391119,  7.92142871, 13.31222213,  8.19957688],
       [11.08009573, 23.        , 12.71096417, 10.09637761]])
```

In [34]:
```
sub_array_copy[0,0] = 500
```

In [35]:
```
sub_array_copy
```

Out[35]:
```
array([[500.        ,   7.92142871,  13.31222213,   8.19957688],
       [ 11.08009573,  23.        ,  12.71096417,  10.09637761]])
```

In [36]:
```
normal_array
```

Out[36]:
```
array([[ 12.99205086,   7.7157832 , 100.        ,  50.        ],
       [  9.19391119,   7.92142871,  13.31222213,   8.19957688],
       [ 11.08009573,  23.        ,  12.71096417,  10.09637761]])
```

4.4. Accessing parts of an array with coordinates

In the above case, we are limited to select rectangular sub-regions of the array. But sometimes we want to recover a series of specific elements for example the elements (row=0, column=3) and (row=2, column=2). To achieve that we can simply index the array with a list containing row indices and another with columns indices:

In [37]:
```
row_indices = [0,2]
col_indices = [3,2]

normal_array[row_indices, col_indices]
```

Out[37]:
```
array([50.        , 12.71096417])
```

In [38]:
```
normal_array
```

Out[38]:
```
array([[ 12.99205086,   7.7157832 , 100.        ,  50.        ],
       [  9.19391119,   7.92142871,  13.31222213,   8.19957688],
       [ 11.08009573,  23.        ,  12.71096417,  10.09637761]])
```

In [39]:
```
selected_elements = normal_array[row_indices, col_indices]
```

In [40]:
```
selected_elements
```

Out[40]:
```
array([50.        , 12.71096417])
```

4.5 Logical indexing

The last way of extracting elements from an array is to use a boolean array of same shape. For example let's create a boolean array by comparing our original matrix to a threshold:

In [41]:
```
bool_array = normal_array > 40
bool_array
```

Out[41]:
```
array([[False, False,  True,  True],
       [False, False, False, False],
       [False, False, False, False]])
```

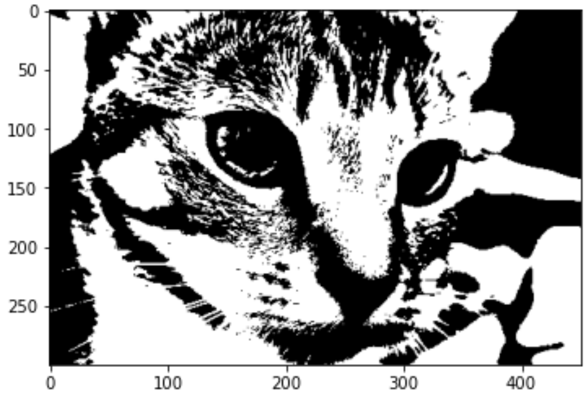
We see that we only have two elements which are above the threshold. Now we can use this logical array to *index* the original array. Imagine that the logical array is a mask with holes only in `True` positions and that we superpose it to the original array. Then we just take all the values visible in the holes:

In [42]:
```
normal_array[bool_array]
```

Out[42]:
```
array([100.,  50.])
```

Coming back to our real image, we can for example first create an image that contains a single channel and then find bright regions in it:

In [43]:
```
single_channel = image[:,:,0]
mask = single_channel > 150
plt.imshow(mask);
```



And now we can recover all the pixels that are "selected" by this mask:

In [44]:
```
single_channel[mask]
```

Out[44]:
```
array([152, 152, 154, ..., 161, 161, 162], dtype=uint8)
```

4.6 Reshaping arrays

Often it is necessary to reshape arrays, i.e. keep elements unchanged but change their position. There are multiple functions that allow one to do this. The main one is of course `reshape` .

4.6.1 `reshape`

Given an array of MxN elements, one can reshape it with a shape OxP as long as $M*N=O*P$.

In [45]:
```
reshaped = np.reshape(normal_array,(2,6))
reshaped
```

Out[45]:
```
array([[ 12.99205086,   7.7157832 , 100.        ,  50.        ,
          9.19391119,   7.92142871],
       [ 13.31222213,   8.19957688,  11.08009573,  23.        ,
         12.71096417,  10.09637761]])
```

In [46]:
```
reshaped.shape
```

Out[46]:
```
(2, 6)
```

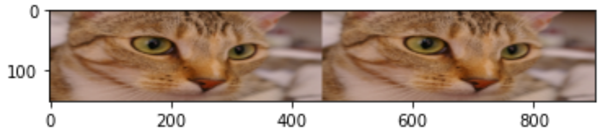
In [47]:
```
300*451/150
```

Out[47]:
```
902.0
```

With the image as example, we can reshape the array from $300x451x3$ to $150x902x3$:

In [48]:
```
plt.imshow(np.reshape(image, (150,902,3)))
```

Out[48]: <matplotlib.image.AxesImage at 0x11a925d60>



4.6.2 Flattening

It's also possible to simply flatten an array i.e. remove all dimensions to create a 1D array. This can be useful for example to create a histogram of a high-dimensional array.

In [49]:
```
flattened = np.ravel(normal_array)
flattened
```

Out[49]:
```
array([ 12.99205086,   7.7157832 , 100.        ,  50.        ,
         9.19391119,   7.92142871,  13.31222213,   8.19957688,
        11.08009573,  23.        ,  12.71096417,  10.09637761])
```

In [50]:
```
flattened.shape
```

Out[50]: (12,)

4.6.3 Dimension collapse

Another common way that leads to reshaping is projection. Let's consider again our `normal_array` :

In [51]:
```
normal_array
```

Out[51]:
```
array([[ 12.99205086,   7.7157832 , 100.        ,  50.        ],
       [  9.19391119,   7.92142871,  13.31222213,   8.19957688],
       [ 11.08009573,  23.        ,  12.71096417,  10.09637761]])
```

We can project all values along the first or second axis, to recover for each row/column the largest value:

In [52]:
```
proj0 = np.max(normal_array, axis = 0)
proj0
```

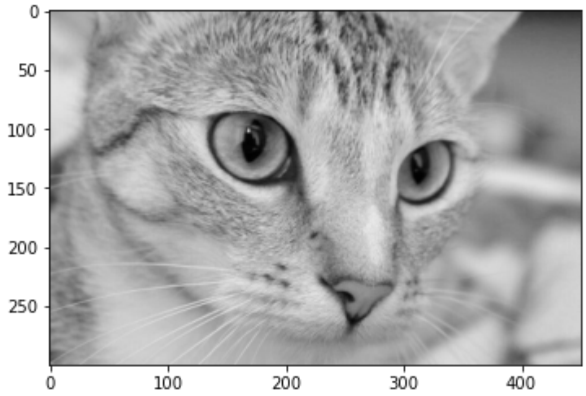
Out[52]:
```
array([ 12.99205086,  23.        , 100.        ,  50.        ])
```

In [53]:
```
proj0.shape
```

Out[53]: (4,)

We see that our projected array has lost a dimension, the one along which we performed the projection. With the image, we could project all channels along the third dimension:

In [54]:
```
plt.imshow(image.max(axis=2));
```



4.6.4 Swaping dimensions

We can also simply exchange the position of dimensions. This can be achieved in different ways. For example we can `np.roll` dimensions, i.e. circularly shift dimensions. This conserves the relative oder of all axes:

In [55]:
```
array3D = np.ones((4, 10, 20))
array3D.shape
```

Out[55]:
```
(4, 10, 20)
```

In [56]:
```
array_rolled = np.rollaxis(array3D, axis=1, start=0)
array_rolled.shape
```

Out[56]:
```
(10, 4, 20)
```

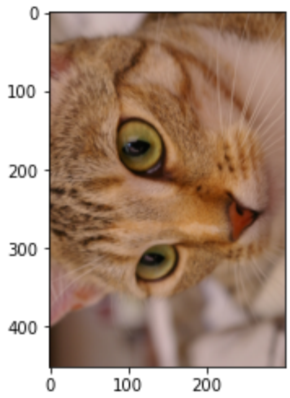
Alternatively you can swap two axes. This doesn't preserver their relative positions:

In [57]:
```
array_swapped = np.swapaxes(array3D, 0,2)
array_swapped.shape
```

Out[57]:
```
(20, 10, 4)
```

With the image, we can for example swap the two first axes:

In [58]:
```
plt.imshow(np.swapaxes(image, 0, 1));
```



4.6.5 Change positions

Finally, we can also change the position of elements without changing the shape of the array. For example if we have an array with two columns, we can swap them:

In [59]:
```
array2D = np.random.normal(0,1,(4,2))
array2D
```

Out[59]:
```
array([[ 1.69380702,  0.45317243],
       [ 0.97985485, -1.10186616],
       [ 2.16001609,  0.29160533],
       [-0.29204481, -0.80523649]])
```

In [60]:
```
np.fliplr(array2D)
```

Out[60]:
```
array([[ 0.45317243,  1.69380702],
       [-1.10186616,  0.97985485],
       [ 0.29160533,  2.16001609],
       [-0.80523649, -0.29204481]])
```

Similarly, if we have two rows:

In [61]:
```
array2D = np.random.normal(0,1,(2,4))
array2D
```

Out[61]:
```
array([[-0.00285876,  0.76241924,  1.18546015, -0.13881594],
       [-1.42554951,  0.36561497,  0.73252833, -1.43307846]])
```

In [62]:
```
np.flipud(array2D)
```

Out[62]:
```
array([[-1.42554951,  0.36561497,  0.73252833, -1.43307846],
       [-0.00285876,  0.76241924,  1.18546015, -0.13881594]])
```

For more complex cases you can also use the more general `np.flip()` function.

With the image, flipping a dimension just mirrors the picture. To do that we select a single channel:

In [63]:
```
plt.imshow(np.flipud(image[:,:,0]));
```