In this part, I will introduce the mian packages will be used in digitial image process.

Numpy

Numpy is the core library for scientific computing in Python. It provides a high-performance multidimensional array object, and tools for working with these arrays. If you are already familiar with MATLAB, you might find this tutorial useful to get started with Numpy.

To use Numpy, we first need to import the `numpy` package:

In [ ]:
```
import numpy as np
#if u don't have numpy, please use pip/conda install numpy
```

Arrays

A numpy array is a grid of values, all of the same type, and is indexed by a tuple of nonnegative integers. The number of dimensions is the rank of the array; the shape of an array is a tuple of integers giving the size of the array along each dimension.

We can initialize numpy arrays from nested Python lists, and access elements using square brackets:

In [ ]:
```
a = np.array([1, 2, 3])  # Create a rank 1 array
print(type(a), a.shape, a[0], a[1], a[2])
a[0] = 5                 # Change an element of the array
print(a)
```

```
<class 'numpy.ndarray'> (3,) 1 2 3
[5 2 3]
```

In [ ]:
```
b = np.array([[1,2,3],[4,5,6]])   # Create a rank 2 array
print(b)
```

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

In [ ]:
```
print(b.shape)
print(b[0, 0], b[0, 1], b[1, 0])
```

```
(2, 3)
1 2 4
```

Numpy also provides many functions to create arrays:

In [ ]:
```
a = np.zeros((2,2))  # Create an array of all zeros
print(a)
```

```
[[0. 0.]
 [0. 0.]]
```

In [ ]:
```
b = np.ones((1,2))   # Create an array of all ones
print(b)
```

```
[[1. 1.]]
```

In [ ]:
```
c = np.full((2,2), 7) # Create a constant array
```

```
print(c)
```

```
[[7 7]
 [7 7]]
```

In [ ]:
```
d = np.eye(2)         # Create a 2x2 identity matrix
print(d)
```

```
[[1. 0.]
 [0. 1.]]
```

In [ ]:
```
e = np.random.random((2,2)) # Create an array filled with random values
print(e)
```

```
[[0.83956305 0.31308388]
 [0.07434287 0.25186774]]
```

In [ ]:
```
f = np.arange(6).reshape((3, 2))
print(f)
```

```
[[0 1]
 [2 3]
 [4 5]]
```

In [ ]:
```
g=f.reshape((2,-1))
print(g)
```

```
[[0 1 2]
 [3 4 5]]
```

In [ ]:
```
help(np.reshape)
```

```
Help on function reshape in module numpy:

reshape(a, newshape, order='C')
    Gives a new shape to an array without changing its data.

    Parameters
    ----------
    a : array_like
        Array to be reshaped.
    newshape : int or tuple of ints
        The new shape should be compatible with the original shape. If
        an integer, then the result will be a 1-D array of that length.
        One shape dimension can be -1. In this case, the value is
        inferred from the length of the array and remaining dimensions.
    order : {'C', 'F', 'A'}, optional
        Read the elements of `a` using this index order, and place the
        elements into the reshaped array using this index order.  'C'
        means to read / write the elements using C-like index order,
        with the last axis index changing fastest, back to the first
        axis index changing slowest. 'F' means to read / write the
        elements using Fortran-like index order, with the first index
        changing fastest, and the last index changing slowest. Note that
        the 'C' and 'F' options take no account of the memory layout of
        the underlying array, and only refer to the order of indexing.
        'A' means to read / write the elements in Fortran-like index
        order if `a` is Fortran *contiguous* in memory, C-like order
        otherwise.

    Returns
    -------
    reshaped_array : ndarray
        This will be a new view object if possible; otherwise, it will
        be a copy.  Note there is no guarantee of the *memory layout* (C- or
        Fortran- contiguous) of the returned array.

    See Also
    --------
    ndarray.reshape : Equivalent method.

    Notes
    -----
    It is not always possible to change the shape of an array without
    copying the data. If you want an error to be raised when the data is copied,
    you should assign the new shape to the shape attribute of the array::

     >>> a = np.zeros((10, 2))

     # A transpose makes the array non-contiguous
     >>> b = a.T

     # Taking a view makes it possible to modify the shape without modifying
     # the initial object.
     >>> c = b.view()
     >>> c.shape = (20)
     Traceback (most recent call last):
        ...
     AttributeError: Incompatible shape for in-place modification. Use
     `.reshape()` to make a copy with the desired shape.

    The `order` keyword gives the index ordering both for *fetching* the values
    from `a`, and then *placing* the values into the output array.
    For example, let's say you have an array:

    >>> a = np.arange(6).reshape((3, 2))
```

```
>>> a
array([[0, 1],
       [2, 3],
       [4, 5]])

You can think of reshaping as first raveling the array (using the given
index order), then inserting the elements from the raveled array into the
new array using the same kind of index ordering as was used for the
raveling.

>>> np.reshape(a, (2, 3)) # C-like index ordering
array([[0, 1, 2],
       [3, 4, 5]])
>>> np.reshape(np.ravel(a), (2, 3)) # equivalent to C ravel then C reshape
array([[0, 1, 2],
       [3, 4, 5]])
>>> np.reshape(a, (2, 3), order='F') # Fortran-like index ordering
array([[0, 4, 3],
       [2, 1, 5]])
>>> np.reshape(np.ravel(a, order='F'), (2, 3), order='F')
array([[0, 4, 3],
       [2, 1, 5]])

Examples
--------
>>> a = np.array([[1,2,3], [4,5,6]])
>>> np.reshape(a, 6)
array([1, 2, 3, 4, 5, 6])
>>> np.reshape(a, 6, order='F')
array([1, 4, 2, 5, 3, 6])

>>> np.reshape(a, (3,-1))       # the unspecified value is inferred to be 2
array([[1, 2],
       [3, 4],
       [5, 6]])
```

Array indexing

Numpy offers several ways to index into arrays.

Slicing: Similar to Python lists, numpy arrays can be sliced. Since arrays may be multidimensional, you must specify a slice for each dimension of the array:

In [ ]:
```
import numpy as np

# Create the following rank 2 array with shape (3, 4)
# [[ 1  2  3  4]
#  [ 5  6  7  8]
#  [ 9 10 11 12]]
a = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
print('a:\n{}'.format(a))

# Use slicing to pull out the subarray consisting of the first 2 rows
# and columns 1 and 2; b is the following array of shape (2, 2):
# [[2 3]
#  [6 7]]
b = a[:2, 1:3]
print('b:\n{}'.format(b))
```

```
a:
[[ 1  2  3  4]
 [ 5  6  7  8]
 [ 9 10 11 12]]
b:
[[2 3]
 [6 7]]
```

A slice of an array is a view into the same data, so modifying it will modify the original array.

In [ ]:
```
print(a[0, 1])
b[0, 0] = 77    # b[0, 0] is the same piece of data as a[0, 1]
print(a[0, 1])
```

```
2
77
```

You can also mix integer indexing with slice indexing. However, doing so will yield an array of lower rank than the original array. Note that this is quite different from the way that MATLAB handles array slicing:

In [ ]:
```
# Create the following rank 2 array with shape (3, 4)
a = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
print(a)
```

```
[[ 1  2  3  4]
 [ 5  6  7  8]
 [ 9 10 11 12]]
```

Two ways of accessing the data in the middle row of the array. Mixing integer indexing with slices yields an array of lower rank, while using only slices yields an array of the same rank as the original array:

In [ ]:
```
row_r1 = a[1, :]    # Rank 1 view of the second row of a
row_r2 = a[1:2, :]  # Rank 2 view of the second row of a
row_r3 = a[[1], :]  # Rank 2 view of the second row of a
print(row_r1, row_r1.shape)
print(row_r2, row_r2.shape)
print(row_r3, row_r3.shape)
```

```
[5 6 7 8] (4,)
[[5 6 7 8]] (1, 4)
[[5 6 7 8]] (1, 4)
```

In [ ]:
```
# We can make the same distinction when accessing columns of an array:
col_r1 = a[:, 1]
col_r2 = a[:, 1:2]
print(col_r1, col_r1.shape)
print(col_r2, col_r2.shape)
```

```
[ 2  6 10] (3,)
[[ 2]
 [ 6]
 [10]] (3, 1)
```

Integer array indexing: When you index into numpy arrays using slicing, the resulting array view will always be a subarray of the original array. In contrast, integer array indexing allows you to construct arbitrary arrays using the data from another array. Here is an example:

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

```
# An example of integer array indexing.
# The returned array will have shape (3,) and
print(a[[0, 1, 2], [0, 1, 0]])

# The above example of integer array indexing is equivalent to this:
print(np.array([a[0, 0], a[1, 1], a[2, 0]]))
```

```
[1 4 5]
[1 4 5]
```

In [ ]:
```
# When using integer array indexing, you can reuse the same
# element from the source array:
print(a[[0, 0], [1, 1]])

# Equivalent to the previous integer array indexing example
print(np.array([a[0, 1], a[0, 1]]))
```

```
[2 2]
[2 2]
```

One useful trick with integer array indexing is selecting or mutating one element from each row of a matrix:

In [ ]:
```
# Create a new array from which we will select elements
a = np.array([[1,2,3], [4,5,6], [7,8,9], [10, 11, 12]])
print(a)
```

```
[[ 1  2  3]
 [ 4  5  6]
 [ 7  8  9]
 [10 11 12]]
```

In [ ]:
```
# Create an array of indices
b = np.array([0, 2, 0, 1])

# Select one element from each row of a using the indices in b
print(a[np.arange(4), b])  # Prints "[ 1  6  7 11]"
```

```
[ 1  6  7 11]
```

In [ ]:
```
# Mutate one element from each row of a using the indices in b
a[np.arange(4), b] += 10
print(a)
```

```
[[11  2  3]
 [ 4  5 16]
 [17  8  9]
 [10 21 12]]
```

Boolean array indexing: Boolean array indexing lets you pick out arbitrary elements of an array. Frequently this type of indexing is used to select the elements of an array that satisfy some condition. Here is an example:

In [ ]:
```
import numpy as np

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

bool_idx = (a > 2)  # Find the elements of a that are bigger than 2;
                    # this returns a numpy array of Booleans of the same
                    # shape as a, where each slot of bool_idx tells
                    # whether that element of a is > 2.

print(bool_idx)
```

```
[[False False]
 [ True  True]
 [ True  True]]
```

In [ ]:
```
# We use boolean array indexing to construct a rank 1 array
# consisting of the elements of a corresponding to the True values
# of bool_idx
print(a[bool_idx])

# We can do all of the above in a single concise statement:
print(a[a > 2])
```

```
[3 4 5 6]
[3 4 5 6]
```

For brevity we have left out a lot of details about numpy array indexing; if you want to know more you should read the documentation.

Datatypes

Every numpy array is a grid of elements of the same type. Numpy provides a large set of numeric datatypes that you can use to construct arrays. Numpy tries to guess a datatype when you create an array, but functions that construct arrays usually also include an optional argument to explicitly specify the datatype. Here is an example:

In [ ]:
```
x = np.array([1, 2])  # Let numpy choose the datatype
y = np.array([1.0, 2.0])  # Let numpy choose the datatype
z = np.array([1, 2], dtype=np.int64)  # Force a particular datatype

print(x.dtype, y.dtype, z.dtype)
```

```
int64 float64 int64
```

You can read all about numpy datatypes in the documentation.

Array math

Basic mathematical functions operate elementwise on arrays, and are available both as operator overloads and as functions in the numpy module:

In [ ]:
```
x = np.array([[1,2],[3,4]], dtype=np.float64)
y = np.array([[5,6],[7,8]], dtype=np.float64)

# Elementwise sum; both produce the array
print(x + y)
print(np.add(x, y))
```

```
[[ 6.  8.]
 [10. 12.]]
[[ 6.  8.]
 [10. 12.]]
```

In [ ]:
```
# Elementwise difference; both produce the array
print(x - y)
print(np.subtract(x, y))
```

```
[[-4. -4.]
 [-4. -4.]]
[[-4. -4.]
 [-4. -4.]]
```

In [ ]:
```
# Elementwise product; both produce the array
print(x * y)
print(np.multiply(x, y))
```

```
[[ 5. 12.]
 [21. 32.]]
[[ 5. 12.]
 [21. 32.]]
```

In [ ]:
```
# Elementwise division; both produce the array
# [[ 0.2         0.33333333]
#  [ 0.42857143  0.5       ]]
print(x / y)
print(np.divide(x, y))
```

```
[[0.2        0.33333333]
 [0.42857143 0.5       ]]
[[0.2        0.33333333]
 [0.42857143 0.5       ]]
```

In [ ]:
```
# Elementwise square root; produces the array
# [[ 1.          1.41421356]
#  [ 1.73205081  2.        ]]
print(np.sqrt(x))
```

```
[[1.         1.41421356]
 [1.73205081 2.        ]]
```

Note that unlike MATLAB, `*` is elementwise multiplication, not matrix multiplication. We instead use the dot function to compute inner products of vectors, to multiply a vector by a matrix, and to multiply matrices. dot is available both as a function in the numpy module and as an instance method of array objects:

In [ ]:
```
x = np.array([[1,2],[3,4]])
y = np.array([[5,6],[7,8]])

v = np.array([9,10])
w = np.array([11, 12])

# Inner product of vectors; both produce 219
print(v.dot(w))
print(np.dot(v, w))
```

```
219
219
```

You can also use the `@` operator which is equivalent to numpy's `dot` operator.

In [ ]:
```
print(v @ w)
```

```
219
```

In [ ]:
```
# Matrix / vector product; both produce the rank 1 array [29 67]
print(x.dot(v))
print(np.dot(x, v))
print(x @ v)
```

```
[29 67]
[29 67]
[29 67]
```

In [ ]:
```
# Matrix / matrix product; both produce the rank 2 array
# [[19 22]
#  [43 50]]
print(x.dot(y))
print(np.dot(x, y))
print(x @ y)
```

```
[[19 22]
 [43 50]]
[[19 22]
 [43 50]]
[[19 22]
 [43 50]]
```

Numpy provides many useful functions for performing computations on arrays; one of the most useful is `sum`:

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

print(np.sum(x))  # Compute sum of all elements; prints "10"
print(np.sum(x, axis=0))  # Compute sum of each column; prints "[4 6]"
print(np.sum(x, axis=1))  # Compute sum of each row; prints "[3 7]"
```

```
10
[4 6]
[3 7]
```

You can find the full list of mathematical functions provided by numpy in the documentation.

Apart from computing mathematical functions using arrays, we frequently need to reshape or otherwise manipulate data in arrays. The simplest example of this type of operation is transposing a matrix; to transpose a matrix, simply use the T attribute of an array object:

In [ ]:
```
print(x)
print("transpose\n", x.T)
```

```
[[1 2]
 [3 4]]
transpose
 [[1 3]
 [2 4]]
```

In [ ]:
```
v = np.array([[1,2,3]])
print(v )
print("transpose\n", v.T)
```

```
[[1 2 3]]
transpose
 [[1]
 [2]
 [3]]
```

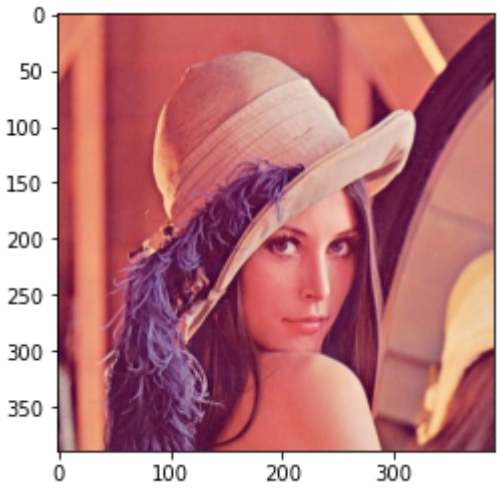
Matplotlib

Matplotlib is a plotting library. In this section give a brief introduction to the `matplotlib.pyplot` module, which provides a plotting system similar to that of MATLAB.

In [ ]:
```
import matplotlib.pyplot as plt
```

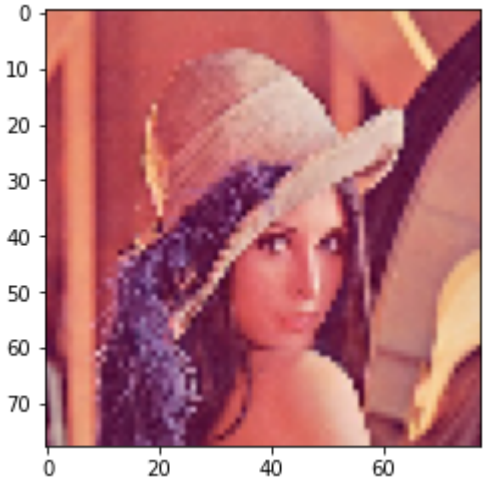
Image operations

In [ ]:
```
image = plt .imread ('demo.jpg')
plt . imshow ( image )
plt.show()
```



The first line reads the image 'demo.jpg' from the hard drive. The second line enqueues an image for display at some point in the future. The final lines blocks the interpreter to show the image. As this image is larger than we need, it is a good idea to make it smaller. This can be done in mu ltiple ways, but a kind of simple first approach is to only keep one of five pixels. This can be done using the fancy indexing in numpy. For example

In [ ]:
```
smaller_image = image [0: -1:5 , 0: -1:5 , :]
plt . imshow ( smaller_image )
plt . show ()
print (" Original image size is: {}". format ( image . shape [0:3]))
print ("New image size is: {}". format ( smaller_image . shape [0:3]))
```




```
 Original image size is: (389, 390, 3)
New image size is: (78, 78, 3)
```

The first line here uses fancy indexing to pick out only every fifth pixel. It starts at the first pixel (index 0), and stops at the last one (index -1), with the step between pixels being 5. This is done for the first two dimensions (the height and width dimensions). For the final

dimension (the color dimension) all information is kept. The final two lines print the sizes of the original image, and of the new smaller image. Now, we will intrduce how to convert matrix to image.

In [ ]:
```
from PIL import Image
smaller_im=Image.fromarray(smaller_image)
print(type(smaller_im))
smaller_im.save('smaller_demo.jpg')
'''
Unlike MATLAB, Python have a lot of image process libary, like PIL, imageio, skimage
'''
```

Out[ ]:
```
<class 'PIL.Image.Image'>
'\nUnlike MATLAB, Python have a lot of image process libary, like PIL, imageio, skim
age, opencv\n'
```

The first line converts np.array type to PIL.Image.Image type. The third line saves the smaller_im in jpg format.

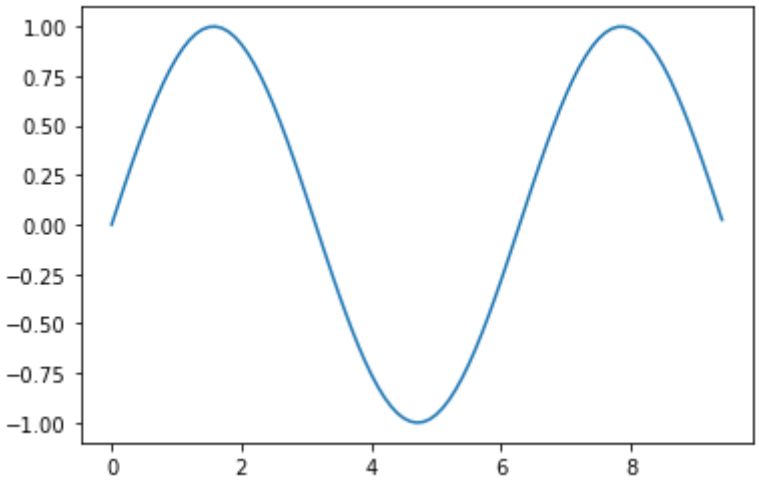
Plotting

The most important function in `matplotlib` is plot, which allows you to plot 2D data. Here is a simple example:

In [ ]:
```
# Compute the x and y coordinates for points on a sine curve
x = np.arange(0, 3 * np.pi, 0.1)
y = np.sin(x)

# Plot the points using matplotlib
plt.plot(x, y)
```

Out[ ]:
```
[<matplotlib.lines.Line2D at 0x7f5531800b50>]
```



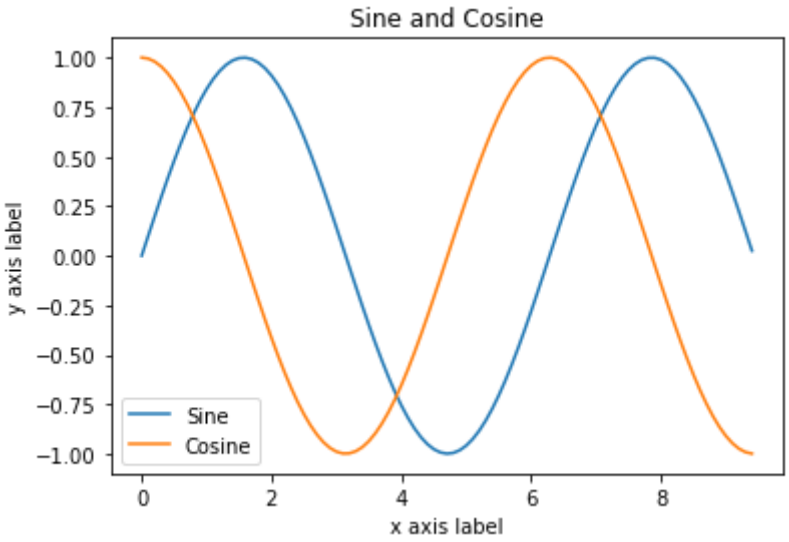
With just a little bit of extra work we can easily plot multiple lines at once, and add a title, legend, and axis labels:

In [ ]:
```
y_sin = np.sin(x)
y_cos = np.cos(x)

# Plot the points using matplotlib
plt.plot(x, y_sin)
plt.plot(x, y_cos)
plt.xlabel('x axis label')
```

```
plt.ylabel('y axis label')
plt.title('Sine and Cosine')
plt.legend(['Sine', 'Cosine'])
```

Out[ ]:
```
<matplotlib.legend.Legend at 0x7f553191eb10>
```



Subplots

You can plot different things in the same figure using the subplot function. Here is an example:

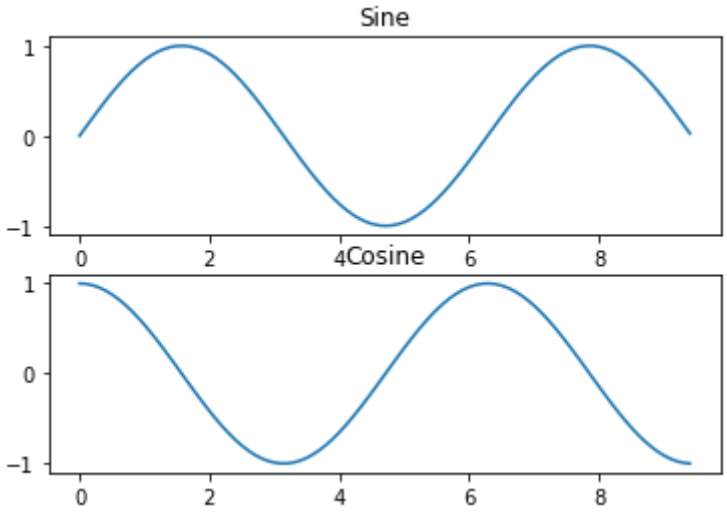
In [ ]:
```
# Compute the x and y coordinates for points on sine and cosine curves
x = np.arange(0, 3 * np.pi, 0.1)
y_sin = np.sin(x)
y_cos = np.cos(x)

# Set up a subplot grid that has height 2 and width 1,
# and set the first such subplot as active.
plt.subplot(2, 1, 1)

# Make the first plot
plt.plot(x, y_sin)
plt.title('Sine')

# Set the second subplot as active, and make the second plot.
plt.subplot(2, 1, 2)
plt.plot(x, y_cos)
plt.title('Cosine')

# Show the figure.
plt.show()
```



You can read much more about the `subplot` function in the documentation.

Python have a lot of libaries and usage, if u encounter difficulties in future class.

Please look for help document->google->(source code)->TA