Lab Instructions - session 1

Introduction to numpy and matplotlib

A review of numpy arrays and matrices + matplotlib

Open an interactive Python environment (python shell, ipython shell, Jupyter notebook, Google Colab), run the following commands, and see the output. Do not close the environment

Creating numpy arrays

```
>>> l = [1,2,3]
>>> l
>>> import numpy
>>> a = numpy.array(l)
>>> a
>>> a[2] = 300
>>> a

>>> type(l)
>>> type(a)

>>> import numpy as np
>>> a = np.array(l)
>>> a

>>> a = np.zeros(10)
>>> a
>>> a.dtype
>>> a[2] = 4
>>> a

>>> a = np.zeros(10, dtype=np.int64)
>>> a
>>> a.dtype
>>> a = np.ones(10)
>>> a
>>> a = np.ones(10) * -20
>>> a
>>> np.full(10, 222)
>>> a = np.arange(10)
>>> a
>>> 2**a
```

Numpy array basic properties

```
>>> a = np.ones(10000)
>>> len(a)
>>> a.shape
>>> type(a)
>>> a.size
>>> a.ndim
>>> a.dtype
>>> a.nbytes
>>> a.itemsize

>>> import sys
>>> sys.getsizeof(a)
```

- Why are the outputs of **`a.nbytes`** and **`sys.getsizeof(a)`** different?

ary, b.nbytes gives you the size of the raw data, while sys.getsizeof(b) gives you the total emory footprint of the entire NumPy array object, including overhead and metadata.

Lists vs. numpy arrays

```
>>> l1 = [1,2,3]
>>> l2 = [4,5,6]
>>> a1 = np.array(l1)
>>> a2 = np.array(l2)
>>> l1+l2
>>> a1+a2
```

Data types

```
>>> a = np.array([1,2,3,4,5,6,7,8,9,10], dtype=np.int64)
>>> b = np.array([1,2,3,4,5,6,7,8,9,10], dtype=np.int32)
>>> c = np.array([1,2,3,4,5,6,7,8,9,10], dtype=np.int16)
>>> d = np.array([1,2,3,4,5,6,7,8,9,10], dtype=np.int8)
>>> e = np.array([1,2,3,4,5,6,7,8,9,10], dtype=np.uint8)
>>> print(a.itemsize, b.itemsize, c.itemsize, d.itemsize, e.itemsize)
>>> print(a.nbytes, b.nbytes, c.nbytes, d.nbytes, e.nbytes)

>>> d-4
>>> e-4

>>> f = np.array([1,2,3,4,5,6,7,8,9,10], dtype=np.float32)
>>> g = np.array([1,2,3,4,5,6,7,8,9,10], dtype=np.float64)
>>> h = np.array([1,2,3,4,5,6,7,8,9,10], dtype=np.float128)
>>> print(f.nbytes, g.nbytes, h.nbytes)

>>> l = np.array([False, True, True])
```

```
>>>  l.dtype
>>>  l = np.array([0, 1, 1], dtype=np.bool)
>>>  l.dtype
>>>  l.nbytes
```

Basic operations

```
>>>  a = np.array([1,2,3])
>>>  b = np.array([4,5,6])
>>>  a+b
>>>  a-b
>>>  a*b
>>>  b**a
>>>  a + 4
>>>  a * 2
>>>  a ** 2
>>>  a.dtype
>>>  a/b        # different in pythons 2.x and 3.x
>>>  a//b

>>>  a = np.array([1.0,2,3])
>>>  a
>>>  a.dtype
>>>  a / b
>>>  a//b    # different in pythons 2.x and 3.x

>>>  a = np.array([1,2,3], dtype=np.float64)
>>>  a
>>>  a.dtype
```

Slicing

```
>>>  a = np.array([0,10,20,30,40, 50, 60, 70, 80, 90, 100])
>>>  a
>>>  a[2]
>>>  a[-2]
>>>  a[2:8]
>>>  a[2:-1]
>>>  a[2:]
>>>  a[:8]
>>>  a[2:8:2]
>>>  a[2:8:-1]
>>>  a[8:2:-1]
>>>  a[::-1]
>>>  a[[1,3,3,4,5]]
```

2D Arrays

```
>>>   A = np.zeros((4,6))
>>>   A
>>>   A = np.zeros((4,6), dtype=np.int32)
>>>   A
>>>   A = np.ones((3,7))
>>>   A
>>>   A = np.ones((3,8), dtype=np.uint8)
>>>   A
>>>   np.full((4,3), 50.0)
>>>
>>>   A = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
>>>   A[1,2]
>>>   A[0,-1]
>>>   A[1,2]
>>>   A.shape
>>>   A.shape[0]
>>>   A.shape[1]
>>>   A.shape[::-1]
>>>   A.size
>>>   A.ndim
>>>
>>>   A[0]
>>>   A[1]
>>>   A[0].shape
>>>   A[0,:]
>>>   A[0,:].shape
>>>   A[[0],:]
>>>   A[[0],:].shape
>>>   A[:,2]
>>>   A[:,[2]]
>>>   A[:,2].shape
>>>   A[:,[2]].shape
>>>
>>>   A[1:3]
>>>   A[1:3, :]
>>>   A[:,:3]
>>>   A[:,::2]
>>>   A[:,::-1]
>>>
>>>   r = np.array([0, 1, 0, 2, 2])
>>>   A
>>>   r
>>>   A[r,:]
>>>
```

```
>>>
>>>  A
>>>  A[:,0] = 1
>>>  A
>>>  A[:,0] = [20,30,40]
>>>  A
>>>
>>>  A
>>>  A.T
>>>
>>>  B = np.array([[1,1,1,1], [2,2,2,2], [3,3,3,3]])
>>>  A
>>>  B
>>>  A + B
>>>  A * B
>>>
>>>  np.dot(A,B)
>>>  A.dot(B)
>>>  A @ B
>>>  A.dot(B.T)
>>>
>>>  I = np.eye(3)
>>>  I
>>>
>>>  np.random.random((2,3))
>>>  np.random.random((2,3))
>>>  np.random.random((2,3))
>>>
>>>  np.random.rand(2,3)
>>>  np.random.rand(2,3)
>>>
>>>  np.random.randn(2,3)
>>>  np.random.randn(2,3)
```

Numpy slices are references (not copies)

```
>>> A = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
>>> b = A[:,1]
>>> b
>>> A
>>> b[1] = 10000
>>> b
>>> A

>>> b = A[:,0].copy()
>>> b
>>> b[1] = -20000
```

```
>>> b
>>> A
```

Masks

```
>>> A = np.array([[1,2,3,4],
                  [5,6,7,8],
                  [9,10,11,12]])
>>> Mask = np.array([[True,  False,  True,  False],
>>>                  [True,  True,   False, False],
>>>                  [False, False,  False,  True]])
>>> Mask.dtype
>>> A
>>> A[Mask]
>>> A[~Mask]
>>> A[Mask] = 222
>>> A
>>> A[~Mask] *= 2
>>> A

>>> A = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])

>>> B = np.zeros_like(A)
>>> B[Mask] = A[Mask]
>>> B

>>> A > 2
>>> Mask = A < 8
>>> Mask
>>> A[Mask]
>>> A[A < 8]
>>> A[A < 8] += 100
>>> A
```

Operations on arrays

```
>>> A = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
>>> A.sum()
>>> A.sum(axis=0)
>>> A.sum(axis=1)
>>> A.min()
>>> A.min(axis=0)
>>> A.max(axis=0,keepdims=True)
>>>
>>> A.max(axis=1)
>>> A.max(axis=1,keepdims=True)
```

```
>>> A.mean(axis=1)
>>>
>>> A.prod(axis=0)
```

Concatenation

```
>>> X = np.array([[1,2],[3,4]])
>>> Y = np.array([[10,20,30],[40,50,60]])
>>> Z = np.array([[7,7],[8,8],[9,9]])
>>> X
>>> Z
>>> np.concatenate((X,Z))
>>> np.concatenate((X,Z), axis=0)
>>> X
>>> Y
>>> np.concatenate((X,Y), axis=1)
>>> np.vstack((X,Z))
>>> np.r_[X,Z]
>>> np.hstack(X,Y)     # error
>>> np.hstack((X,Y))
>>> np.c_[X,Y]
>>> Y
>>> np.tile(Y,(4,3))
```

Reshaping

```
>>> A = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
>>> A.reshape((4,3))
>>> A.reshape((2,6))
>>> A.reshape((2,7))
>>> A.reshape((1,12))
>>> A.reshape((12,1))
>>> A.reshape((12,))

>>> b = A.ravel()
>>> b
>>> b.shape
>>> b.reshape((2,6))

>>> b
>>> b.shape = (2,6)
>>> b
```

```
>>>  f = A.flatten()
>>>  r = A.ravel()
>>>  f
>>>  r

>>>  f[0] = 4444
>>>  f
>>>  A

>>>  r[0] = 4444
>>>  r
>>>  A
```

- What is the difference between **`ravel`** and **`flatten`**? Which one do you think is faster?

Numpy arrays vs numpy matrices

```
>>>  A = np.array([[1,2,3], [1,1,1], [-1,-2,-1]])
>>>  A
>>>  A*A         # element-wise multiplication
>>>  A.dot(A)    # matrix multiplication
>>>  A @ A       # matrix multiplication (same as above)
>>>
>>>  M = np.matrix([[1,2,3], [1,1,1], [-1,-2,-1]])
>>>  M*M
>>>  np.multiply(M,M)

>>>  M=np.mat(A)
>>>  M
>>>  M=np.matrix(A)
>>>  M
>>>  M.T
>>>  M.I
>>>  M.I * M
>>>  M * M.I
>>>  M.A
>>>  type(M)
>>>  type(M.A)

>>>  C = np.matrix("1 2; 3 4; 5 6")
>>>  C
>>>  M*C
```

N-dimensional arrays

```
>>>  A = np.zeros((2,4,3))
>>>  A
>>>  A.shape

>>>  A[:,:,0].shape
>>>  A[:,:,0] = [[1,2,3,4],[5,6,7,8]]
>>>  A[:,:,1] = [[2,2,2,2],[4,4,4,4]]
>>>  A[:,:,2] = [[10,20,30,40],[11,21,31,41]]
>>>  A
>>>
>>>  A[0,:,:]
>>>  A[0]

>>>  A[:,1,:]
>>>  A[:,1]
>>>  A[:,[1]]

>>>  A[:,1].shape
>>>  A[:,[1]].shape

>>>  A[:,:,0]
>>>  A[:,:,2]
>>>  A[:,2:,2]
>>>  A.ravel()
```

Broadcasting

```
>>>  A = np.array([0,1,2,3,4,5,6,7])
>>>  A - 10
>>>  a = np.array([4])
>>>  A * a

>>>  A = np.array([[1,2,3,4], [5,6,7,8], [9,10,11,12]])
>>>  b = np.array([1, 0, 2,-2])
>>>  A
>>>  b
>>>  A-b

>>>  c = np.array([1,2,3])
>>>  c - c
>>>  c - c.reshape((3, 1))
>>>  c - c.reshape((-1, 1))
>>>  c - c[:, np.newaxis]
```

```
>>> c - c[:, None]

>>> A-c
>>> A-c.reshape((3,1))

>>> A = np.arange(24).reshape((2,3,4))
>>> A.shape
>>> A - 2
>>> A - np.array([1,2])
>>> A - np.array([1,2,3,4])
>>> A - np.array([1,2,3])
>>> A - np.array([1,2,3]).reshape((3,1))
>>> A - np.array([1,2])
>>> A - np.array([1,2]).reshape((2,1,1))
>>> A - np.array([[1,2,3,4],[5,6,7,8], [9,10,11,12]])
>>> A - np.array([[1,2,3,4],[5,6,7,8]])
>>> A - np.array([[1,2,3,4],[5,6,7,8]]).reshape((2,1,4))
```

To get a better understanding of broadcasting, read the following (particularly the broadcasting rules) https://numpy.org/doc/stable/user/basics.broadcasting.html

Math functions

```
>>> x = np.arange(0, 2 * np.pi, 0.1)
>>> x
>>> y = np.cos(x)
>>> y
>>> np.sin(x)
>>> np.tan(x)


>>> x = np.linspace(1,8,20)
>>> x
>>> x.shape
>>> np.exp(x)

>>> np.log(x)
>>> np.log10(x)
>>> np.log2(x)
>>> np.floor(x)
>>> np.ceil(x)
>>> np.round(x)

>>> np.sqrt(x)
>>> np.arctan(x)
```

- Here you can find a list of numpy math functions:
    - https://numpy.org/doc/stable/reference/routines.math.html

Plotting with Matplotlib

```
>>>  from matplotlib import pyplot as plt
>>>
>>>  x = np.arange(0, 2 * np.pi, 0.1)
>>>  x
>>>  y = np.cos(x)
>>>  y
>>>  plt.plot(x,y)
>>>  plt.show()

>>>  plt.plot(x,np.sin(x))
>>>  plt.plot(x,np.cos(x))
>>>  plt.show()
```

Reading and displaying images

```
>>>  from matplotlib import pyplot as plt

>>>  I = plt.imread('masoleh_gray.jpg')
>>>  I.shape
>>>  I.dtype
>>>  plt.imshow(I)
>>>  plt.show()
>>>  plt.imshow(I,cmap='gray')
>>>  plt.show()
>>>
>>>  plt.imshow(I[100:200,50:250],cmap='gray')
>>>  plt.show()
```

Task 1 - Practice Vectorization

Consider an arbitrary **A** matrix like

```
A = np.random.rand(200,10)
```

We perform the following operation on **A** to create the matrix **B**.

```
mu = np.zeros(A.shape[1])
for i in range(A.shape[0]):
    mu += A[i]
mu /= A.shape[0]
```

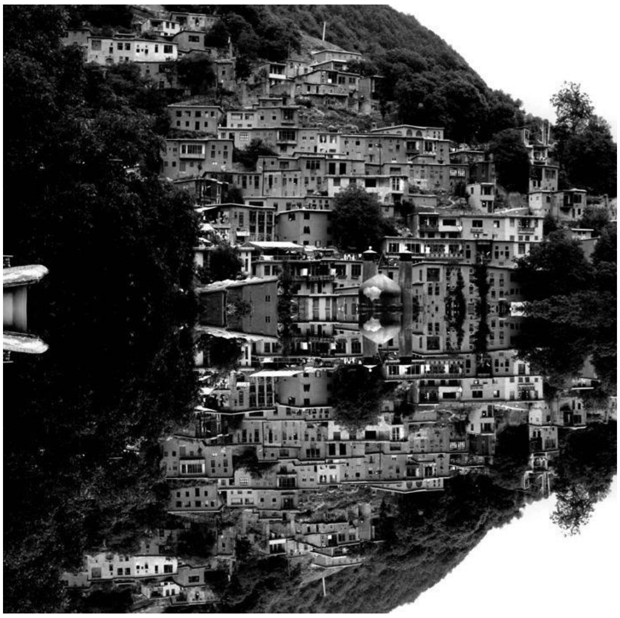
```
B = np.zeros_like(A)
for i in range(A.shape[0]):
    B[i] = A[i] - mu
```

- What does the above piece of code do?
- Write an equivalent program ***without loops***. Do it in just **a single line of code**.

```
B = ...
```

Task 2

Read the image 'masoleh_gray.jpg' and create a new image by vertically concatenating it with its vertically inverted image (like below). Display the new image.



References

1. Numpy Quickstart https://numpy.org/doc/stable/user/quickstart.html
2. https://docs.scipy.org/doc/numpy-dev/user/numpy-for-matlab-users.html
3. https://docs.scipy.org/doc/numpy-dev/user/quickstart.html
4. http://cs231n.github.io/python-numpy-tutorial
5. Broadcasting https://numpy.org/doc/stable/user/basics.broadcasting.html