Compressing images with Discrete Cosine Basis

```
In []: %matplotlib inline
    import numpy as np
    import scipy.fftpack
    import scipy.misc
    import matplotlib.pyplot as plt
    plt.gray()

<Figure size 432x288 with 0 Axes>

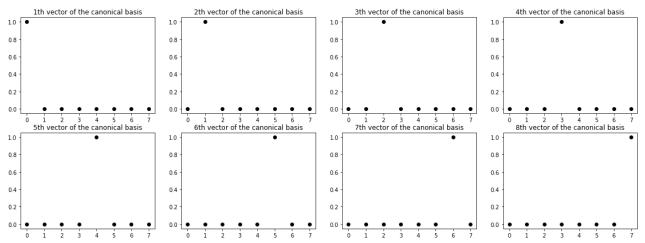
In []: # Two auxiliary functions that we will use. You do not need to read them (but ma
    def dct(n):
        return scipy.fftpack.dct(np.eye(n), norm='ortho')

    def plot_vector(v, color='k'):
        plt.plot(v,linestyle='', marker='o',color=color)
```

5.3.1 The canonical basis

The vectors of the canonical basis are the columns of the identity matrix in dimension n. We plot their coordinates below for n=8.

```
In [ ]:
         identity = np.identity(8)
         print(identity)
         plt.figure(figsize=(20,7))
         for i in range(8):
             plt.subplot(2,4,i+1)
             plt.title(f"{i+1}th vector of the canonical basis")
             plot vector(identity[:,i])
         print('\n Nothing new so far...')
        [[1. 0. 0. 0. 0. 0. 0. 0.]
         [0. 1. 0. 0. 0. 0. 0. 0.]
         [0. 0. 1. 0. 0. 0. 0. 0.]
         [0. 0. 0. 1. 0. 0. 0. 0.]
         [0. 0. 0. 0. 1. 0. 0. 0.]
         [0. 0. 0. 0. 0. 1. 0. 0.]
         [0. 0. 0. 0. 0. 1. 0.]
         [0. 0. 0. 0. 0. 0. 0. 1.]]
         Nothing new so far...
```



5.3.2 Discrete Cosine basis

The discrete Fourier basis is another basis of \mathbb{R}^n . The function dct(n) outputs a square matrix of dimension n whose columns are the vectors of the discrete cosine basis.

```
In [ ]:
            # Discrete Cosine Transform matrix in dimension n = 8
            D8 = dct(8)
            print(np.round(D8,3))
            plt.figure(figsize=(20,7))
            for i in range(8):
                 plt.subplot(2,4,i+1)
                 plt.title(f"{i+1}th discrete cosine vector basis")
                 plot vector(D8[:,i])
           [[ 0.354
                        0.49
                                  0.462
                                           0.416
                                                     0.354
                                                              0.278
                                                                       0.191
                        0.416
                                 0.191 - 0.098 - 0.354 - 0.49
                                                                      -0.462 -0.2781
                        0.278 - 0.191 - 0.49
                                                  -0.354
              0.354
                                                              0.098
                                                                       0.462
                        0.098 - 0.462 - 0.278
              0.354
                                                    0.354
                                                              0.416 - 0.191 - 0.49
               0.354 - 0.098 - 0.462
                                           0.278
                                                    0.354 - 0.416 - 0.191
               0.354 - 0.278 - 0.191
                                           0.49
                                                   -0.354 - 0.098
               0.354 - 0.416
                                  0.191
                                           0.098 - 0.354
                                                              0.49
                                                                      -0.462
                                                                                 0.2781
                                  0.462
               0.354 - 0.49
                                          -0.416
                                                     0.354 - 0.278
                                                                       0.191
                                            2th discrete cosine vector basis
                                                                                                   4th discrete cosine vector basis
          0.370
                                       0.4
                                                                                              0.4
          0.365
          0.360
                                       0.2
                                                                                              0.2
          0.355
                                       0.0
                                                                                              0.0
                                                                   0.0
          0.350
                                       -0.2
                                                                                             -0.2
          0.345
                                                                  -0.2
          0.340
                                       -0.4
                                                                                                   8th discrete cosine vector basis
                5th discrete
                                            6th discrete cosine vector basis
            0.3
                                       0.4
            0.2
                                                                   0.2
                                       0.2
                                                                                              0.2
            0.1
            0.0
                                       0.0
                                                                   0.0
                                                                                              0.0
           -0.1
                                       -0.2
                                                                  -0.2
                                                                                             -0.2
           -0.2
```

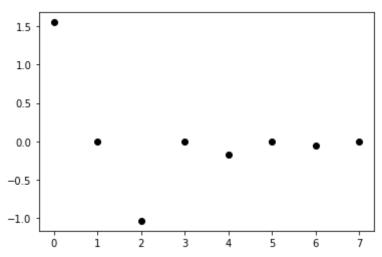
5.3 (a) Check numerically (in one line of code) that the columns of D8 are an orthonormal basis of \mathbb{R}^8 (ie verify that the Haar wavelet basis is an orthonormal basis).

```
In [ ]: | # Your answer here
          print((D8 @ np.transpose(D8)).round(0))
                          0. -0.
                                            0.1
                 0.
                     0.
                                   0.
         [[ 1.
            0.
                              0.
                                            0.]
                 1.
                   -0.
                          0.
                                   0.
            0. -0.
                     1.
                          0.
                              0.
          [ 0.
                 0.
                     0.
                          1.
                              0.
                                   0.
          [-0.
                     0.
                          0.
                              1.
                                   0.
                 0.
                              0.
                                      -0.
                     0.
                          0.
                                   1.
                          0.
                              0. -0.
                                       1.
          [ 0.
                 0.
                     0.
                                            0.1
                     0. -0.
                                       0.
          [ 0.
                              0.
                                   0.
                 0.
                                            1.]]
In [ ]:
          \# Let consider the following vector x
          x = np.sin(np.linspace(0,np.pi,8))
          plt.title('Coordinates of x in the canonical basis')
          plot_vector(x)
```

Coordinates of x in the canonical basis 1.0 0.8 0.4 0.2 0.0 1 2 3 4 5 6 7

5.3 (b) Compute the vector $v \in \mathbb{R}^8$ of DCT coefficients of x. (1 line of code!), and plot them.

How can we obtain back x from v? (1 line of code!).



5.3.3 Image compression

In this section, we will use DCT modes to compress images. Let's use one of the template images of python.

```
image = scipy.misc.face(gray=True)
h,w = image.shape
print(f'Height: {h}, Width: {w}')

plt.imshow(image)

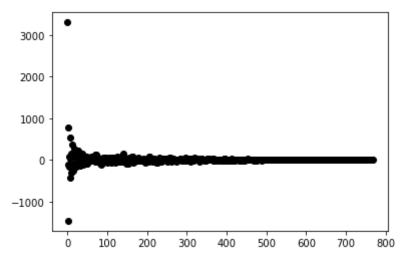
Height: 768, Width: 1024
```

Out[]: <matplotlib.image.AxesImage at 0x7f86984050d0>



5.3 (c) We will see each column of pixels as a vector in \mathbb{R}^{768} , and compute their coordinates in the DCT basis of \mathbb{R}^{768} . Plot the entries of x, the first column of our image.

```
# Your answer here
x = image[:,1] @ np.linalg.inv(dct(768))
plot_vector(x)
```



5.3 (d) Compute the 768 x 1024 matrix dct_coeffs whose columns are the dct coefficients of the columns of image. Plot an histogram of there intensities using plt.hist.

```
In [ ]:
         # Your answer here
         coeffs = (np.linalg.inv(dct(768)) @ image).flatten()
         plt.hist(coeffs)
        (array([6.36000e+02, 1.47189e+05, 6.37024e+05, 5.19000e+02, 4.00000e+01,
                 0.000000e+00, 2.67000e+02, 2.41000e+02, 2.69000e+02, 2.47000e+02]),
         array([-1064.43123878,
                                   -537.21884715,
                                                     -10.00645553,
                                                                      517.20593609,
                  1044.41832772,
                                   1571.63071934,
                                                    2098.84311097, 2626.05550259,
                                   3680.48028584,
                                                    4207.69267746]),
                  3153.26789421,
         <BarContainer object of 10 artists>)
         600000
         500000
         400000
         300000
         200000
         100000
             0
                         ò
               -1000
                               1000
                                        2000
                                               3000
                                                       4000
```

Since a large fraction of the dct coefficients seems to be negligible, we see that the vector x can be well approximated by a linear combination of a small number of discrete cosines vectors.

Hence, we can 'compress' the image by only storing a few dct coefficients of largest magnitude.

Let's say that we want to reduce the size by 98%: Store only the top 2% largest (in absolute value) coefficients of wavelet coeffs .

5.3 (e) Compute a matrix thres_coeffs who is the matrix dct_coeffs where about 97% smallest entries have been put to 0.

```
In [ ]:  # Your answer here
file:///Users/adisrikanth/Documents/NYU_CDS/DS_1014/Homework_5/homework_05_dct.html
```

```
coeffs = np.abs(coeffs)
coeffs.sort()
coeffs = coeffs[::-1]
threshhold = coeffs[23593]

# dct768 = np.linalg.inv(dct(768)) @ image
dct768 = dct(768) @ image
dct768[np.abs(dct768)<threshhold] = 0
dct768 = np.linalg.inv(dct(768)) @ dct768

threes_coeffs = dct768
threes_coeffs</pre>
```

```
Out[]: array([[ 64.99578887, 79.44342592, 80.71002817, ..., 91.2056512, 98.09297156, 104.13929048],
[ 91.06507828, 111.07107303, 110.50154926, ..., 128.7875538, 138.20307674, 146.69260451],
[ 88.81271141, 107.61613455, 100.96029168, ..., 128.19044403, 136.66707391, 144.97402188],
...,
[ 56.70854004, 52.60615976, 56.72224744, ..., 56.44237312, 52.21441327, 53.98436896],
[ 40.01834057, 37.61525326, 41.25723988, ..., 38.70584614, 35.58375021, 36.78324651],
[ 20.74578708, 19.66026933, 21.82342459, ..., 19.68618258, 18.02965993, 18.6353314 ]])
```

5.3 (f) Compute and plot the compressed_image corresponding to thres_coeffs.

```
In [ ]:  # Your answer here
plt.imshow(threes_coeffs)
```

Out[]: <matplotlib.image.AxesImage at 0x7f86b951df40>



```
In [ ]:
```