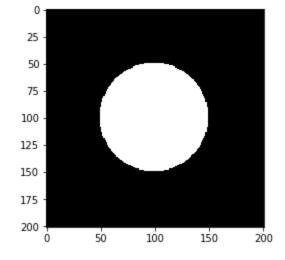
## **AMATH797 PSet1 David Lieberman**

```
In [1]:
        import numpy as np
         import os
         from numpy import linalg
        from numpy.linalg import norm
         import math
        from PIL import Image
        from sklearn.feature_extraction.image import extract_patches_2d
        from sklearn.decomposition import PCA
        import scipy
         import scipy.io as sio
        from scipy.io import loadmat
         import matplotlib.pyplot as plt
        from matplotlib import offsetbox
        from mpl_toolkits.mplot3d import Axes3D
        from mpl_toolkits.mplot3d import proj3d
        %matplotlib inline
        os.chdir(os.path.expanduser(os.sep.join(["~","Desktop","Homework Scans","2020S_AMATH797"
         ])))
        np.random.seed(0)
```

```
In [2]: circle = np.array(Image.open("circle.png"))
#circle = circle.astype('float')/255
plt.imshow(circle, cmap = 'gray', vmin=0, vmax=255)
```

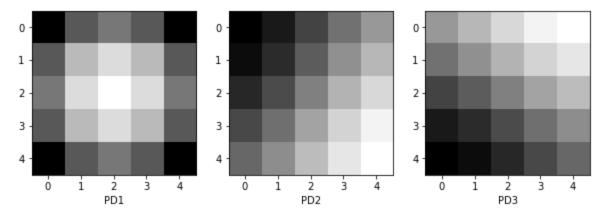
## Out[2]: <matplotlib.image.AxesImage at 0x15cda3ec9c8>



```
In [3]: patches = extract_patches_2d(circle, (5, 5))
    patches = patches.reshape((38809, 25))
    #patches_centered = patches - np.mean(patches[:], axis=0)

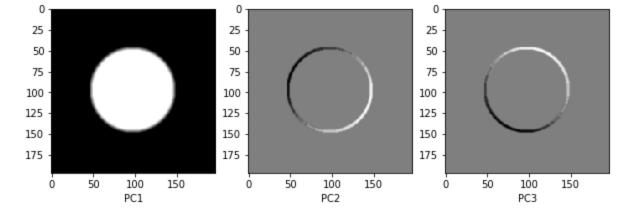
    circle_pca = PCA(n_components = 3)
    circle_pca.fit(patches)
    print(circle_pca.explained_variance_ratio_)
```

```
In [4]: PD = [np.reshape(circle_pca.components_[i], (5,5)) for i in range(3)]
fig = plt.figure(figsize=(10, 10))
for i in range(3):
    fig.add_subplot(1, 3, i + 1)
    plt.xlabel('PD' + str(i + 1))
    plt.imshow(PD[i], cmap = 'gray')
```

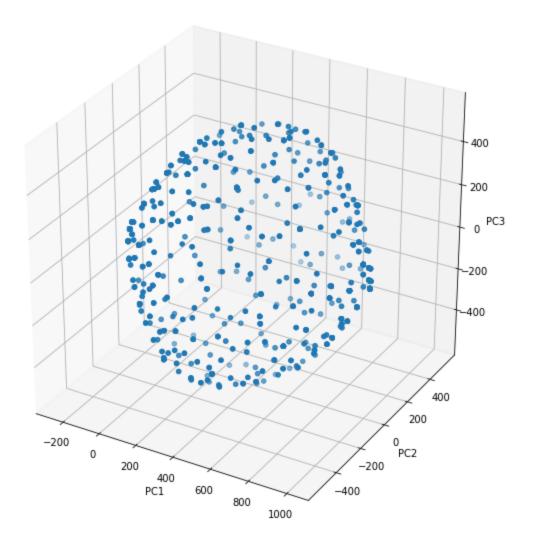


```
In [5]: PC = circle_pca.fit_transform(patches)

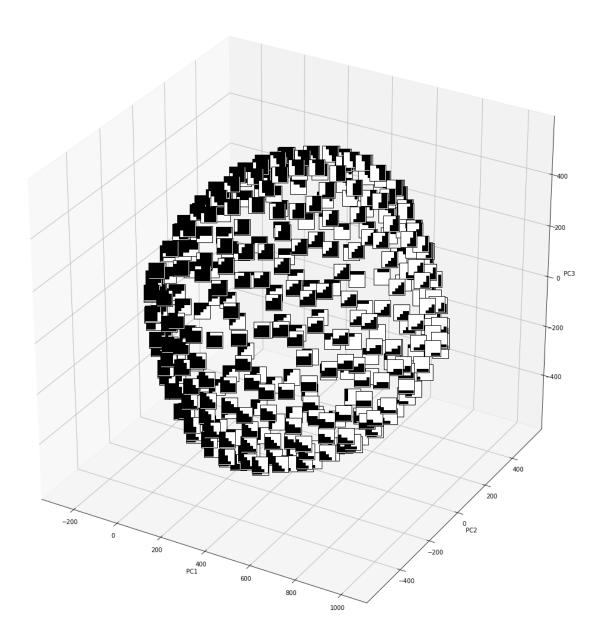
fig = plt.figure(figsize=(10, 10))
for i in range(3):
    fig.add_subplot(1, 3, i + 1)
    plt.xlabel('PC' + str(i + 1))
    plt.imshow(np.reshape(PC[:, i], ((197, 197))), cmap = 'gray')
```



```
In [6]: fig = plt.figure(figsize=(10, 10))
    ax = plt.axes(projection = '3d')
    ax.scatter3D(PC[:, 0], PC[:, 1], PC[:, 2])
    ax.set_xlabel('PC1')
    ax.set_ylabel('PC2')
    ax.set_zlabel('PC3')
    plt.show()
```



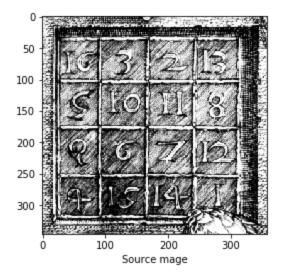
```
In [7]: | xs = PC[:, 0].flatten()
        ys = PC[:, 1].flatten()
        zs = PC[:, 2].flatten()
        fig = plt.figure(figsize=(20, 20))
        ax = fig.add_subplot(111, projection=Axes3D.name)
        ax.scatter(xs, ys, zs)
        ax2 = fig.add_subplot(111, frame_on=False)
        ax2.axis("off")
        ax2.axis([0,1,0,1])
        def proj(X, ax1, ax2):
             """ From a 3D point in axes ax1,
                calculate position in 2D in ax2 """
            x,y,z = X
            x2, y2, _ = proj3d.proj_transform(x,y,z, ax1.get_proj())
            return ax2.transData.inverted().transform(ax1.transData.transform((x2, y2)))
        def image(ax,arr,xy):
             """ Place an image (arr) as annotation at position xy """
            im = offsetbox.OffsetImage(arr, zoom = 5, cmap='gray', norm=plt.Normalize(0,255))
             im.image.axes = ax
            ab = offsetbox.AnnotationBbox(im, xy, xycoords = 'data', frameon = True, pad = 0.1)
            ax.add_artist(ab)
        i = 0
        for s in zip(xs,ys,zs):
            x,y = proj(s, ax, ax2)
             image(ax2, np.reshape(patches[i], ((5, 5))), [x,y])
             i += 1
        ax.set_xlabel('PC1')
        ax.set_ylabel('PC2')
        ax.set_zlabel('PC3')
        plt.show()
```



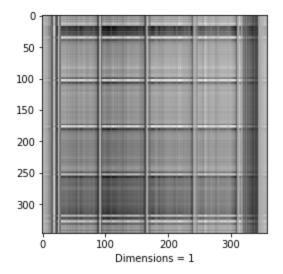
We observe that principal component 1 which captures roughly ~96% of the variance of the data seems to differentiate patches based on their color. Principal components 2 and 3, seem to capture directions for moving vertically and horiztonally (respectively), which are axises of symmetry for the circle. These results are exactly those which we would expect.

```
In [8]: numbers = scipy.io.loadmat('numbers.mat')['mat']
    numbers_mean = np.mean(numbers[:], axis=0)
    plt.imshow(numbers, cmap = 'gray')
    plt.xlabel('Source mage')
    numbers.shape
```

## Out[8]: (346, 358)

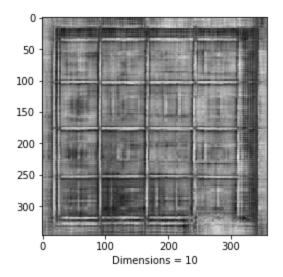


```
In [9]: for i in np.array([1, 10, 20, 100]):
    numbers_pca = PCA(n_components = i)
    numbers_PC = numbers_pca.fit_transform(numbers)
    numbers_reconstruct = numbers_pca.inverse_transform(numbers_PC)
    plt.imshow(numbers_reconstruct, cmap = 'gray')
    plt.xlabel('Dimensions = ' + str(i))
    plt.show()
    print("Component-wise Percentage Total Variance:", numbers_pca.explained_variance_ra
tio_[:10])
    print("Reconstruction Error:", ((numbers - numbers_reconstruct) ** 2).sum())
    print("Compression Rate:", (346 * 358) / (346 * i + i + i * 358))
```



Component-wise Percentage Total Variance: [0.22591042]

Reconstruction Error: 8690.909202650431 Compression Rate: 175.69929078014184

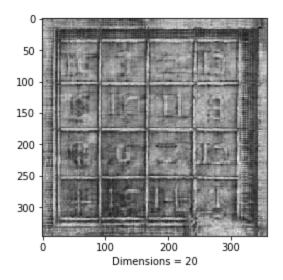


Component-wise Percentage Total Variance: [0.22591042 0.0599177 0.04909906 0.03056869

0.02494228 0.02450543

0.01909028 0.01847125 0.01619839 0.01573313]

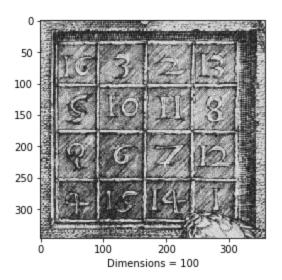
Reconstruction Error: 5788.366782829698 Compression Rate: 17.569929078014184



Component-wise Percentage Total Variance: [0.22591042 0.0599177 0.04909906 0.03056869 0.02494228 0.02450543

0.01909028 0.01847125 0.01619839 0.01573313]

Reconstruction Error: 4501.927216110859 Compression Rate: 8.784964539007092



Component-wise Percentage Total Variance: [0.22591042 0.0599177 0.04909906 0.03056869 0.02494228 0.02450543

0.01909028 0.01847125 0.01619839 0.01573313]

Reconstruction Error: 962.002224382447 Compression Rate: 1.7569929078014184