

K-PCA

November 3, 2018

In this file we will study the Kernel-PCA

1 Steps:

1.1 We pick a kernel

1.2 We construct the normalized kernel matrix of the data (dimension $m \times m$):

1.2.1

$$K_{zeromean} = K - 2 * \frac{1}{n} K + \frac{1}{n} K \frac{1}{n}$$

1.3 We solve an eigenvalue problem:

1.3.1

$$K \alpha_i = \lambda_i \alpha_i$$

1.4 For any data point (new or old), we can represent it as:

1.4.1

$$y_j = \sum_i (\alpha_{ij} K(x, x_i)), j = 1, \dots, d$$

```
In [2]: import matplotlib.pyplot as plt
        from sklearn.datasets import make_moons
        from numpy import ones, exp, loadtxt, tanh
        from numpy.linalg import eig, norm
        from sklearn.preprocessing import normalize, scale
        import numpy as np

        VERBOSE = False
        def __DEBUG(msg):
            if VERBOSE: print(msg)

        fig = 1
        K2_SIGMA = 0.007

        def liner_kernel(X,Y):
            return np.dot(X,Y)
```

```

def polynomial_kernel(X, Y):
    return (X.T.dot(Y) + 1) ** 2

def gaussian_kernel(X, Y):
    return exp( (-1 * (norm(X - Y) ** 2)) / (2 * (K2_SIGMA ** 2)) )

```

The function that compute the zero mean Garm matrix:

```

In [3]: def k_matrix(A, kernel):

    n = A.shape[0]
    d = A.shape[1]
    K = ones((n, n))
    for i in range(n):
        for j in range(n):
            K[i, j] = kernel(A[i], A[j])

    K_SUM = K.sum() / (n ** 2)
    K_SUMROWS = K.sum(axis=1) / n

    K_ = ones((n, n))
    for i in range(n):
        for j in range(n):
            K_[i, j] = K[i, j] - K_SUMROWS[i] - K_SUMROWS[j] + K_SUM

    return K_

```

In this version of the K-PCA, we will generate only d component where d is the original dimensionality of the dataset

```

In [6]: def kpca(A, kernel):
    n = A.shape[0]
    d = A.shape[1]
    # calculate the kernelized matrix of data
    K = k_matrix(A, kernel)

    # eigendecoposition of kernelized covariance matrix
    eig_values, eig_vectors = eig(K)
    idx = eig_values.argsort()[::-1]
    eig_values = eig_values[idx]
    eig_vectors = eig_vectors[:,idx]

    # project data (only the first d component) d: the number of features in the o
    sub_eig_vectors = eig_vectors[0:d,:]
    #__DEBUG("sub_eig_vectors = \n" + str(sub_eig_vectors))

    A_new = ones((n,d))
    for i in range(n):
        for j in range(d):

```

```

temp = 0
for z in range(n):
    temp += eig_vectors[j,z]*kernel(A[i],A[z])
A_new[i,j] = temp

    __DEBUG("A_new = \n" + str(A_new))
return A_new

```

Read and visualize the data:

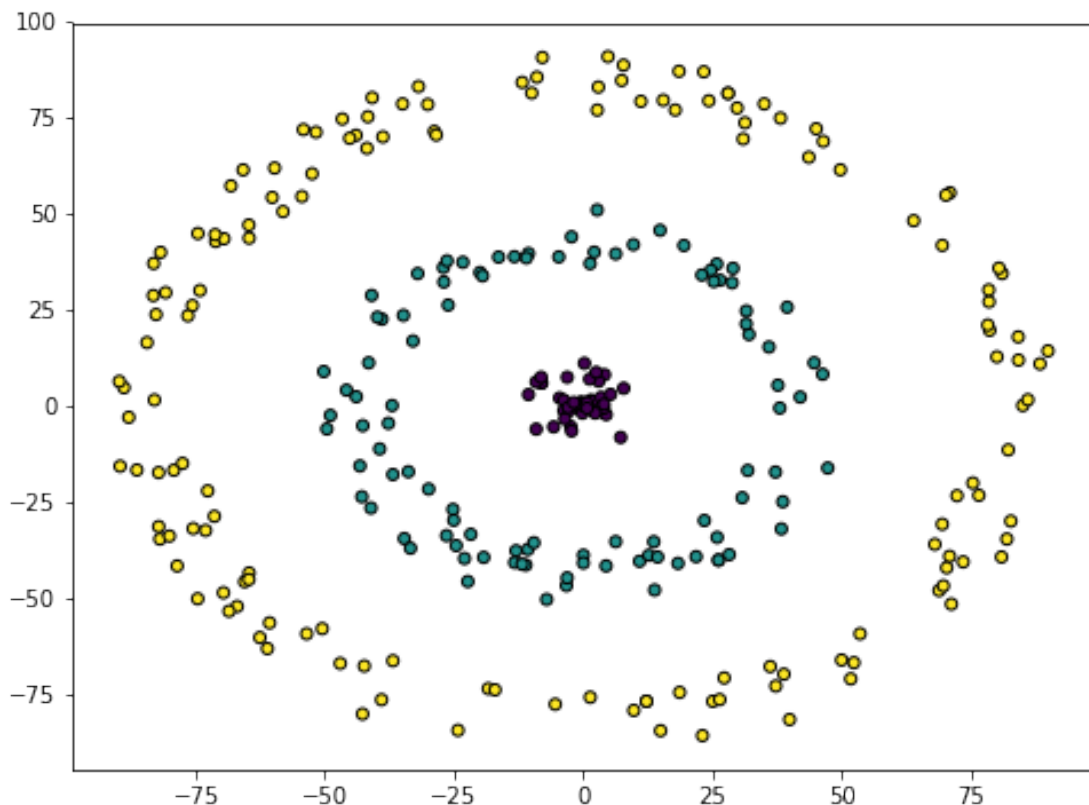
```

In [7]: from numpy import array
        #VERBOSE = True

        data = loadtxt("data.data")
        __DEBUG("data : \n" + str(data))
        d = data.shape[1]
        A = data[:,0:(d-1)]
        Y = data[:,(d-1):d].T[0]

        plt.figure(figsize=(8, 6))
        plt.clf()
        plt.scatter(A[:, 0], A[:, 1], c=Y,s=25, edgecolor='k')
        plt.show()
        fig += 1

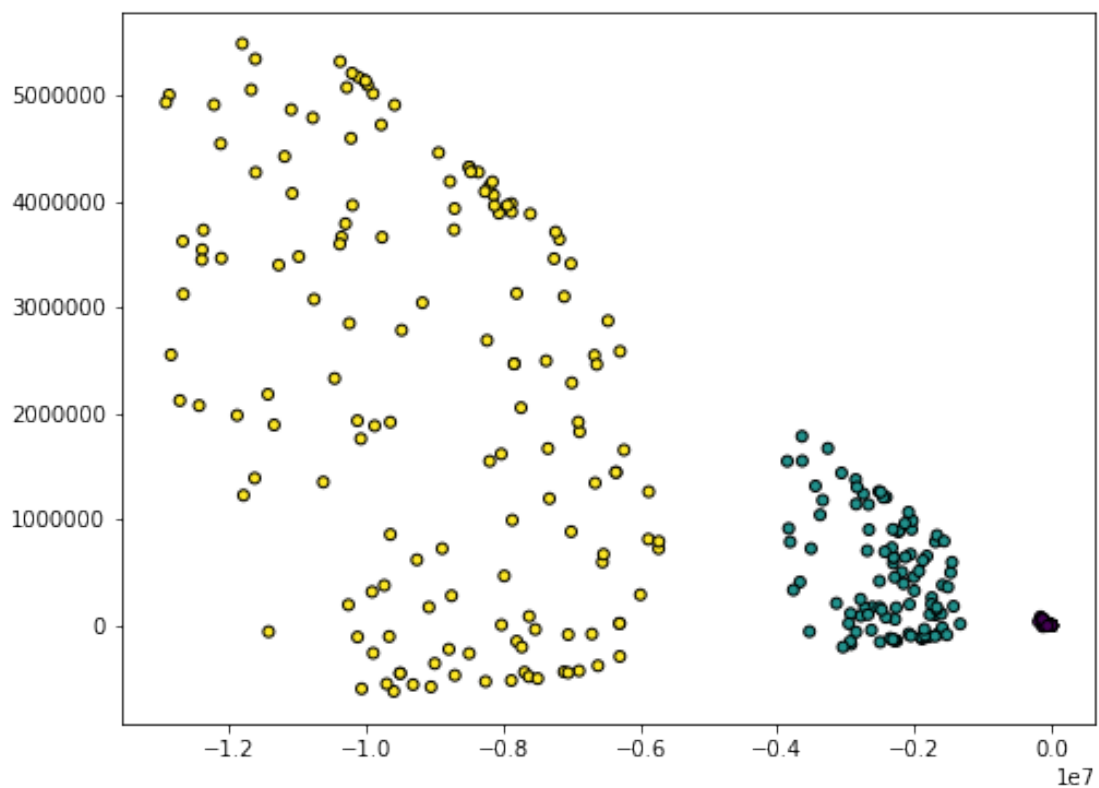
```



Using the polunomial kernel:

```
In [8]: A_new = kpca(A, polynomial_kernel)
plt.figure(fig, figsize=(8, 6))
plt.clf()
plt.scatter(A_new[:, 0], A_new[:, 1], c=Y,s=25, edgecolor='k')
plt.show()
fig += 1
```

C:\Users\Muaz\Anaconda3\lib\site-packages\ipykernel_launcher.py:23: ComplexWarning: Casting complex values to real dtype will discard the imaginary part, leading to inaccuracies



Using rbf kernel:

```
In [9]: sigma_array = [0.09,0.01,0.1,0.3,0.5,1,2]

for sg in sigma_array:
    K2_SIGMA = sg
    A_new = kpca(A, gaussian_kernel)
    plt.figure(fig, figsize=(8, 6))
    plt.clf()
```

```
plt.scatter(A_new[:, 0], A_new[:, 1], c=Y,s=25, edgecolor='k')  
plt.show()  
fig += 1
```

C:\Users\Muaz\Anaconda3\lib\site-packages\ipykernel_launcher.py:23: ComplexWarning: Casting complex values to real discards the imaginary part

