# **ASSIGNMENT 1**

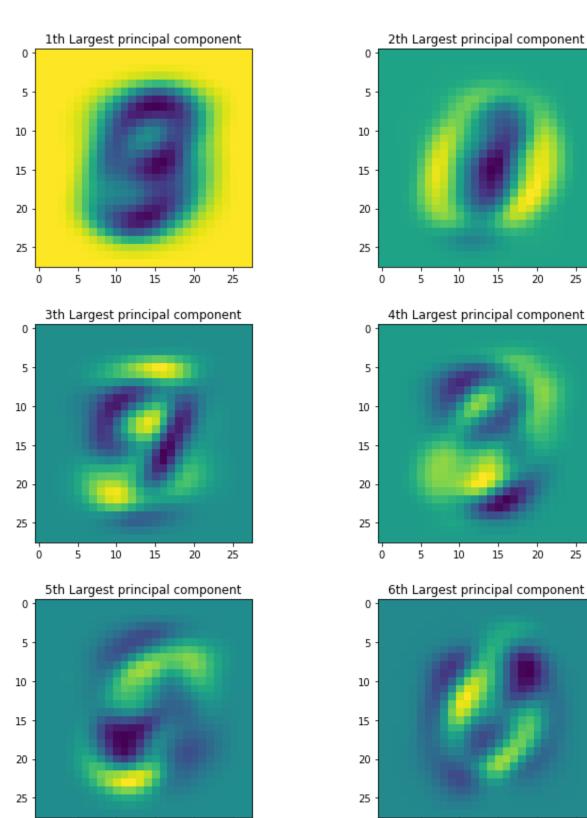
PRML

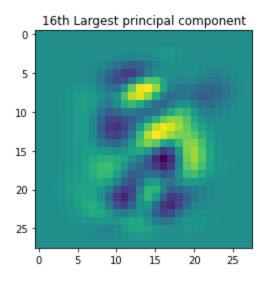
AKRANTH REDDY ME20B100

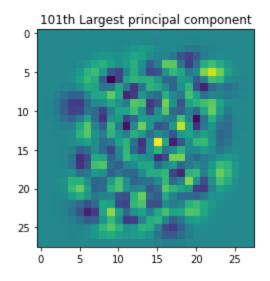
# Question 1

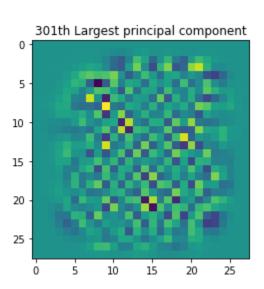
(i)

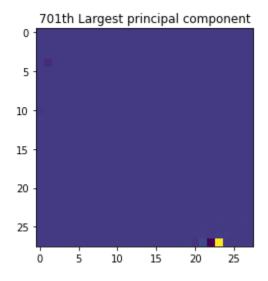
## Images of principal components



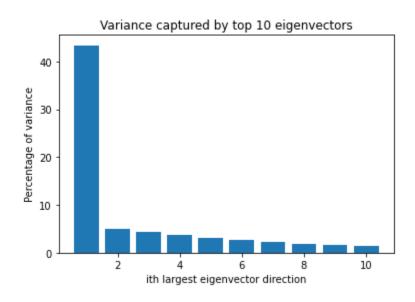


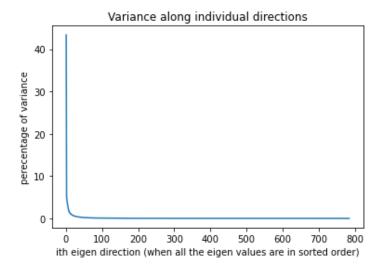


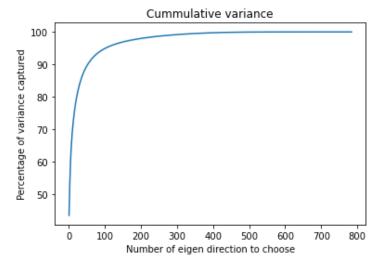




### Variance explained by by principal components





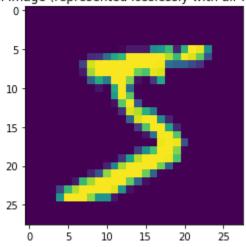


- The largest eigenvector direction (principal component) captures 43% of variance
- Top 10 principal component together captures 69.16% of variance
- Top 100 principal component together captures 94.87% of variance
- Break even point for capturing 95% of variance of 102 principal components.

(ii)

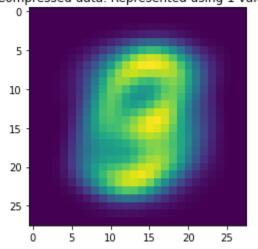
Now we try to represent '5' in compressed form.



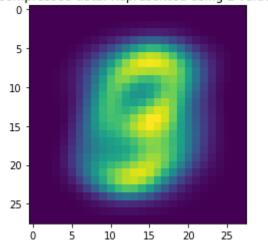


## Compressed data

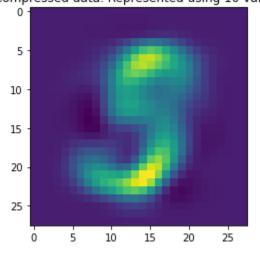
Compressed data. Represented using 1 values



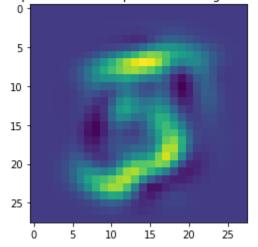
Compressed data. Represented using 2 values



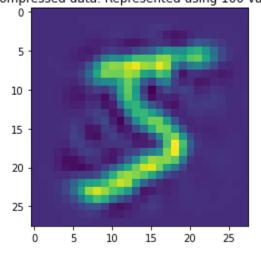
Compressed data. Represented using 10 values



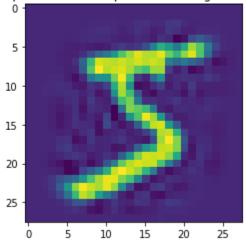
Compressed data. Represented using 25 values



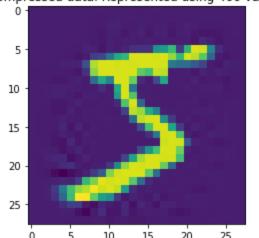
Compressed data. Represented using 100 values



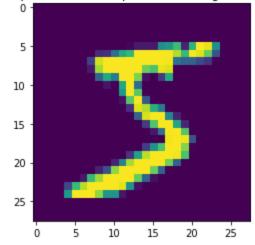
Compressed data. Represented using 200 values



Compressed data. Represented using 400 values



Compressed data. Represented using 700 values

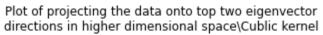


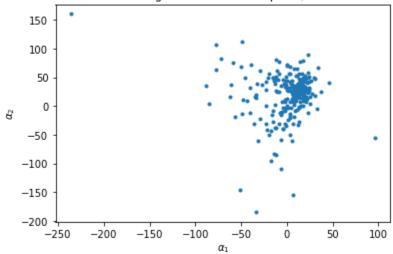
As we can see as more data points are used the better the variance of the original data is captured. But for typical downstream tasks it is enough if we can capture around 95% of variance of data. From graphs and code we can see using 102 principal components capture just close to 95%.

(iii)

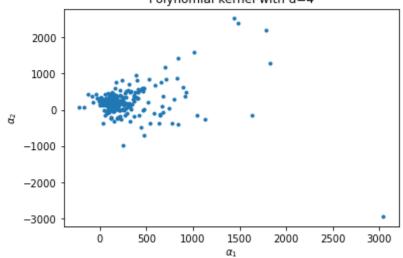
## Polynomial kernel.

Plot of projecting the data onto top two eigenvector directions in higher dimensional space Quadratic kernel 5.0 2.5 0.0 -2.5-5.0-7.5 -10.0-12.510 16 12 14 18



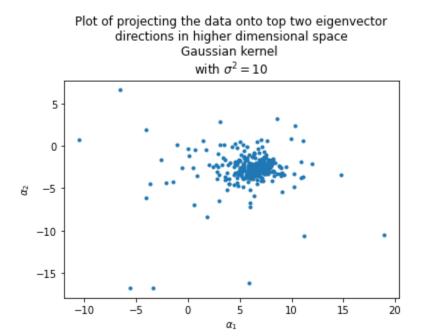


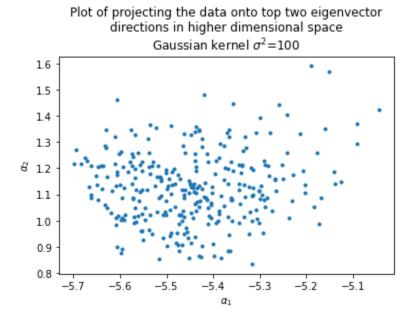
### Plot of projecting the data onto top two eigenvector directions in higher dimensional space Polynomial kernel with d=4

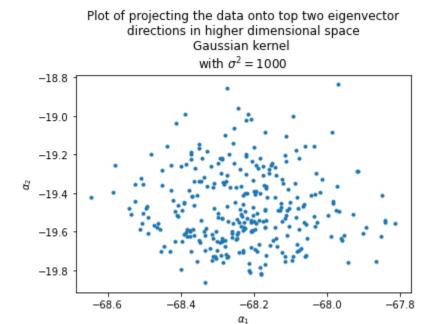


#### Gaussian Kernel

When a gaussian kernel is used with variance between 0.1 and 1 (as given in question) the compiler is not able to handle huge values generated. The values are crossing the limit 111,000 digits so I increased the variance and made plots to compare.







(iv)

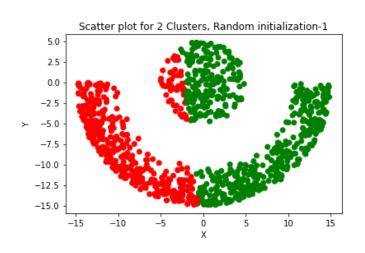
From observing the data we can see that for polynomial kernels all the data points are close, which is not favorable to us because if they are close we can't distinguish different clusters easily, but for gaussian kernels they are spread out.

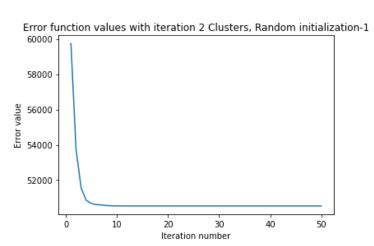
So a gaussian kernel is better in this case.

## Question 2

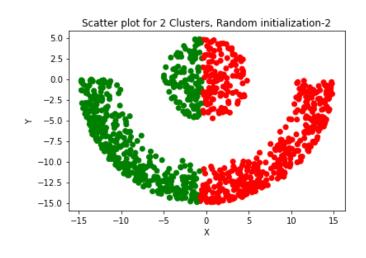
(i)

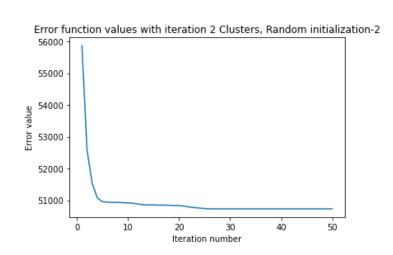
#### Random initialization - 1



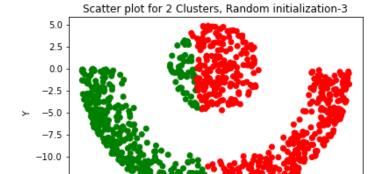


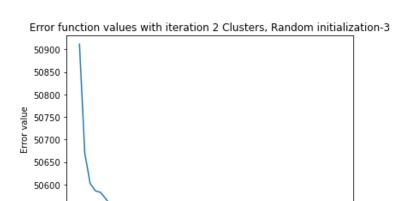
#### Random initialization - 2



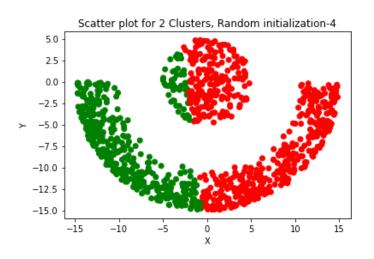


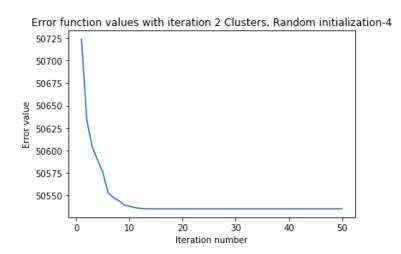
#### Random initialization -3



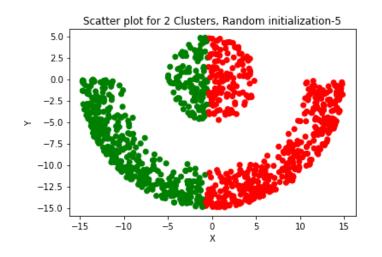


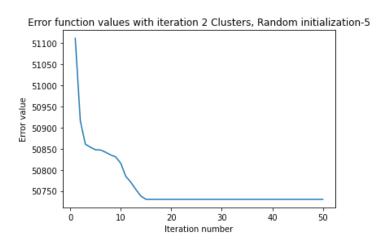
#### Random initialization -4



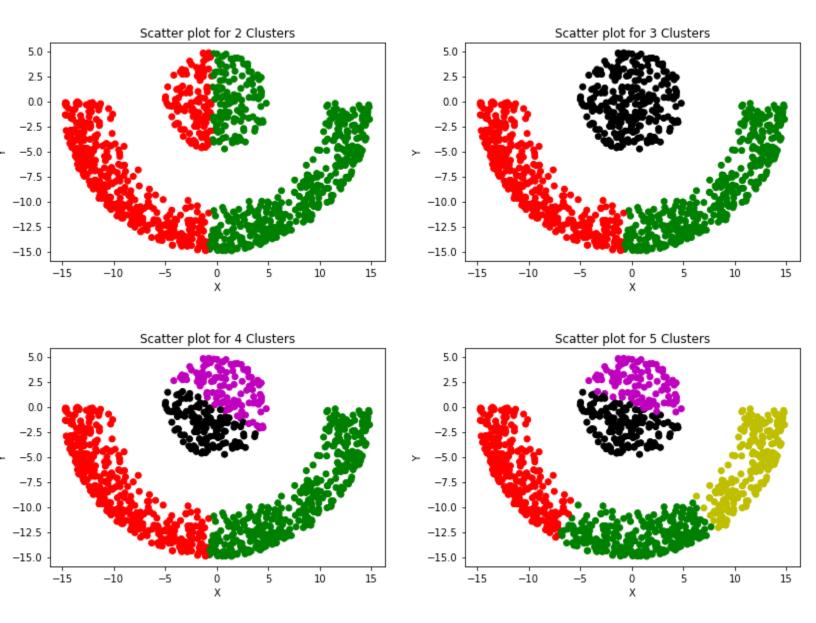


### Random initialization -5

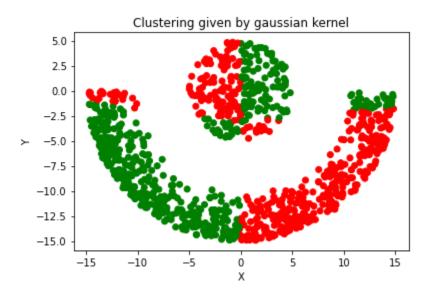




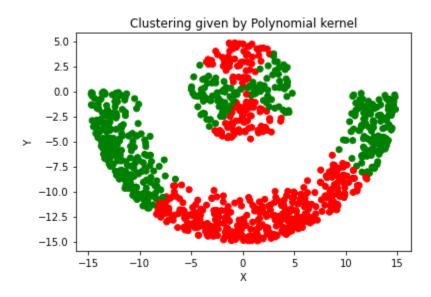
Fix a random initialization and change values of k



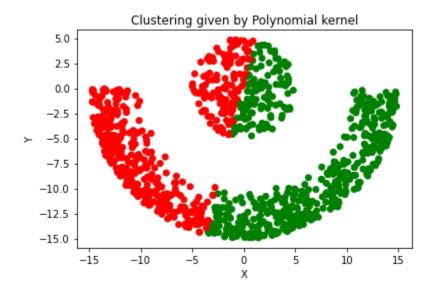
# Gaussian kernel with variance = 10



# Polynomial kernel of degree 2



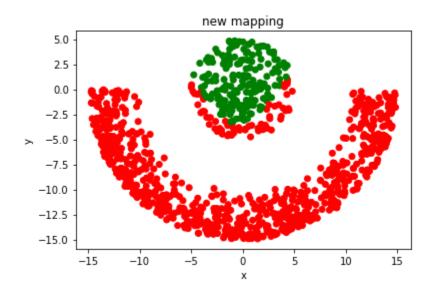
### Polynomial kernel of degree 3



Ideally we want to have two clusters with a center circle in one cluster and remaining in another cluster. But these kernels are performing poorly. They are not doing what we want ideally, but they do capture the nonlinear parameters which otherwise might have missed out.

(iv)

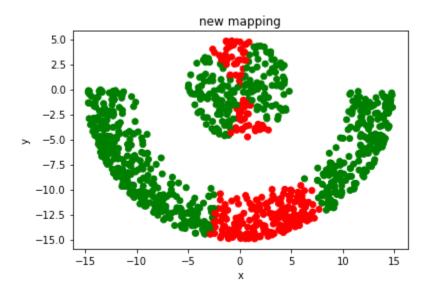
Using other mapping. With gaussian kernel and variance 10.



This mapping is what we want, the center of data belonging to one cluster and the ring belonging to the other cluster.

So the new mapping function worked because We choose H and it so happens that the exact solution that we are looking for is far near to ZL^0.5 that's why we got a near/approx solution.

New mapping with polynomial kernel (quadratic)



This is clearly not helpful.