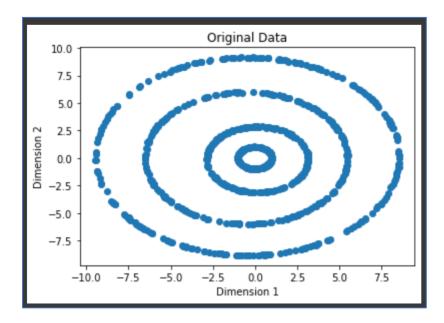
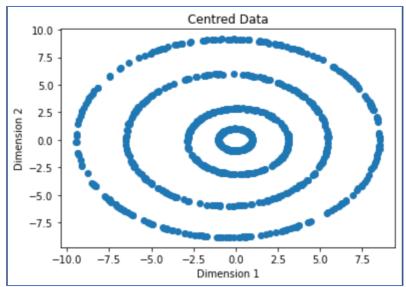
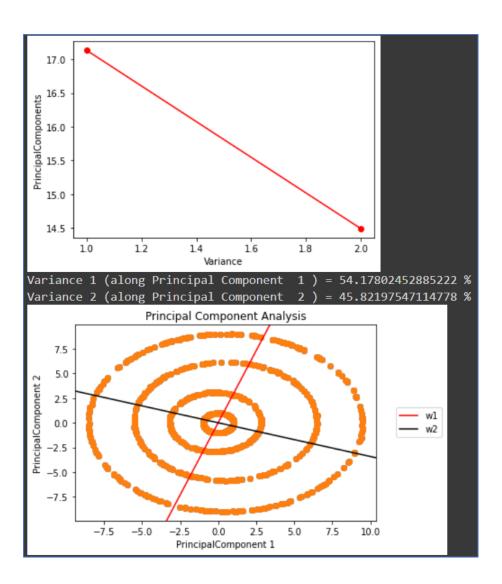
# Question (1)

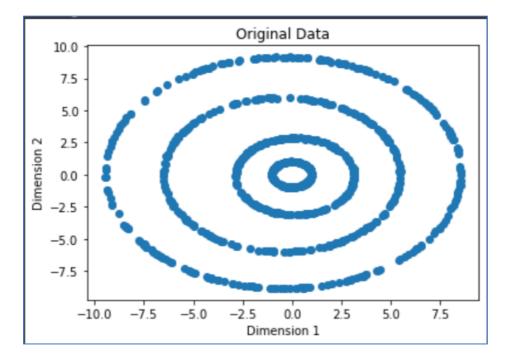
i) PCA after centring on datasetSource code file name: - first\_part\_i.py

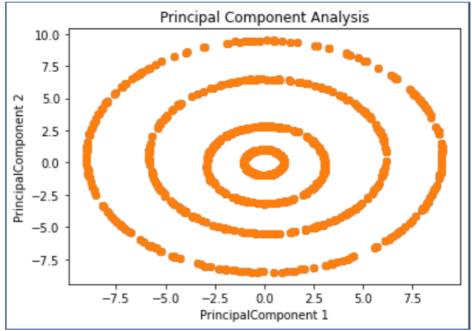






# ii) PCA without centring on dataset Source code file name: - first\_part\_ii.py





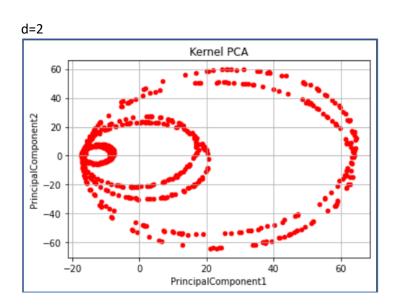
**Observations**: Results obtained are quite same as the part i of this question.

Since the mean of the data set are very small as compared to the dataset hence there is almost no effect of centring the dataset in our case.

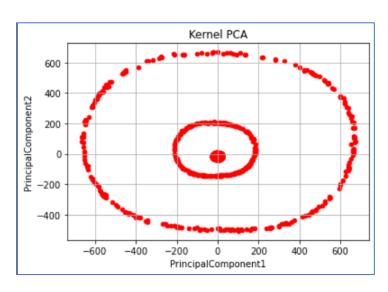
## iii) Kernel PCA on dataset

A. 
$$\kappa(x,y) = (1 + x^T y)^d$$
 for  $d = \{2,3\}$ 

Source code file name: - first\_part\_iii.py



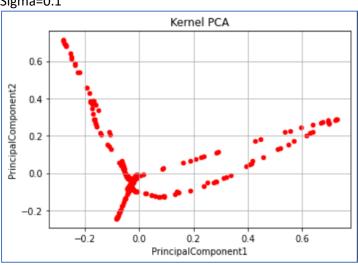
d=3



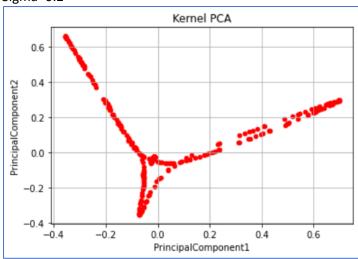
B. 
$$\kappa(x,y) = \exp \frac{-(x-y)^T(x-y)}{2\sigma^2}$$
 for  $\sigma = \{0.1, 0.2, \dots, 1\}$ 

Source code file name: - first\_part\_iii.py

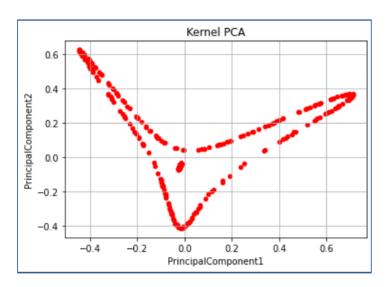
Sigma=0.1



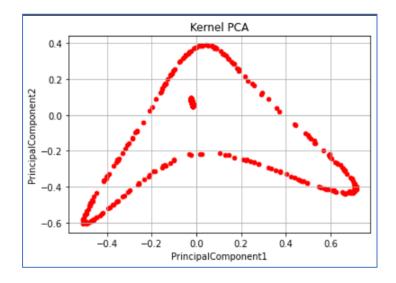
Sigma=0.2



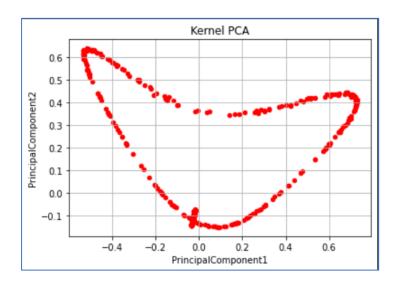
Sigma=0.3



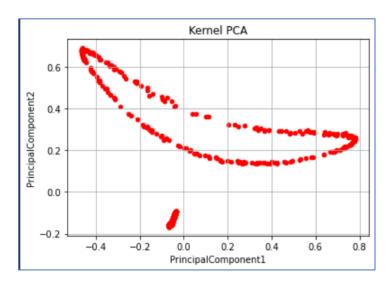
Sigma=0.4



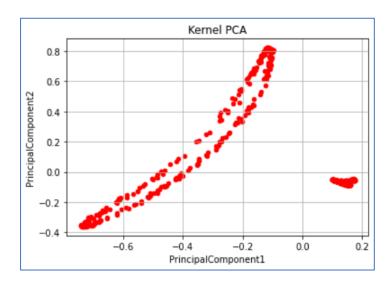
Sigma=0.5



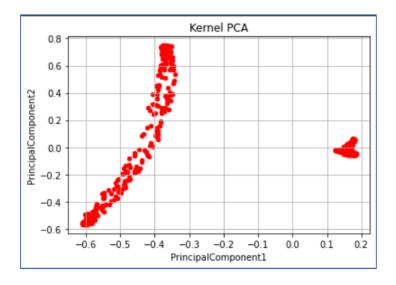
Sigma=0.6



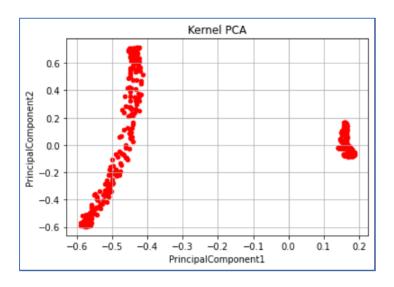
Sigma=0.7



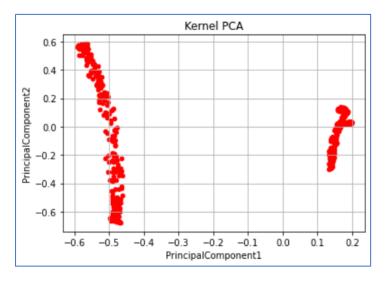
Sigma=0.8



Sigma=0.9



Sigma=1.0

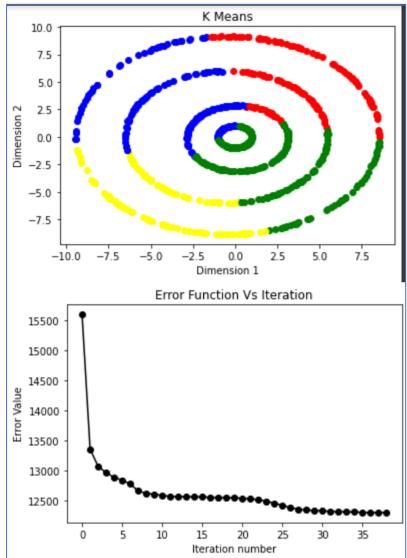


iv) By Observation from the above plots of kernel, degree 3 polynomial kernel is best suited for this dataset. Its variance in the top two components of the kernel is maximum which is approx. 73%. Other variance for degree 2 poly kernel is approx. 68% and the maximum variance for exponential kernel holds for sigma=1.0 and is approx. 15% So, degree 3 polynomial kernel should be chosen for plotting.

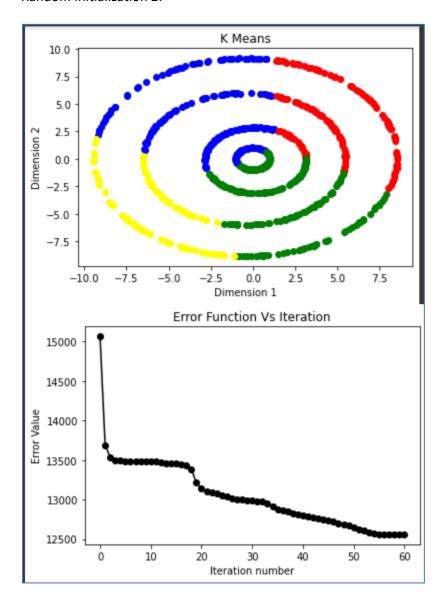
## Question (2)

i) Source code file name: - second\_part\_i.py

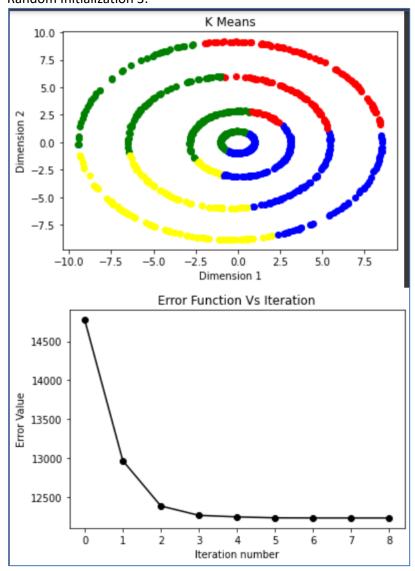
#### Random Initialization 1:



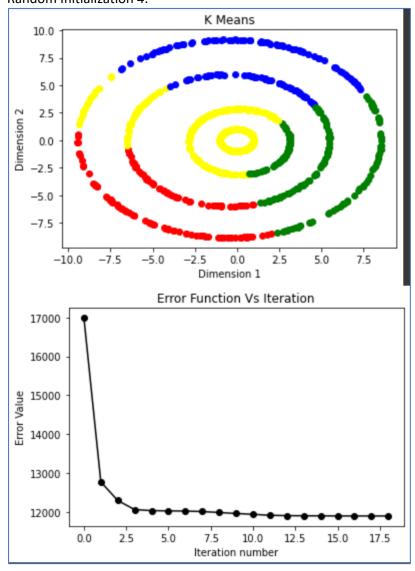
#### Random Initialization 2:



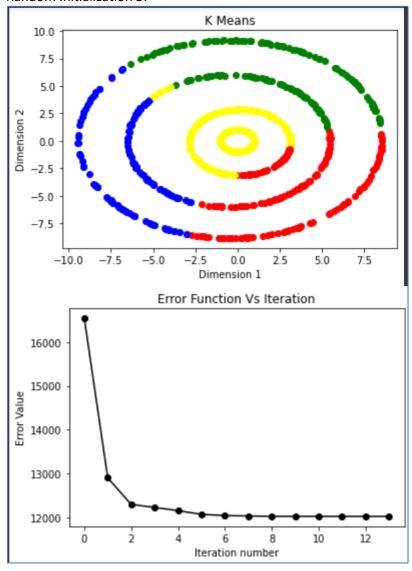
#### Random Initialization 3:



#### Random Initialization 4:

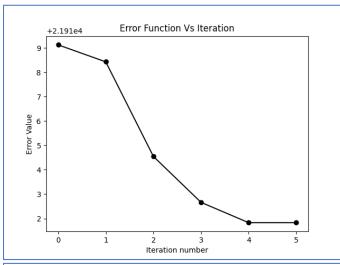


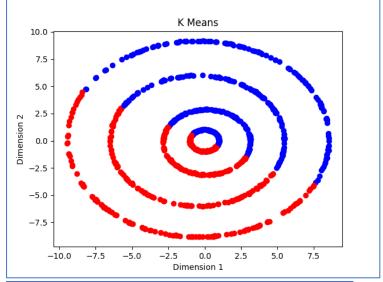
#### Random Initialization 5:

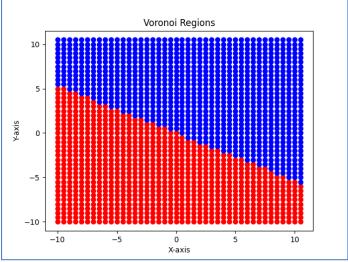


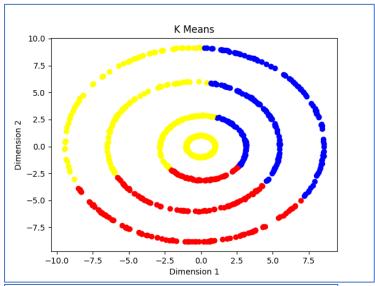
## ii) Source code file name: - second\_part\_ii.py

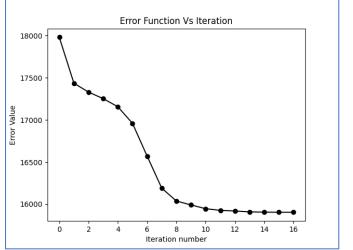


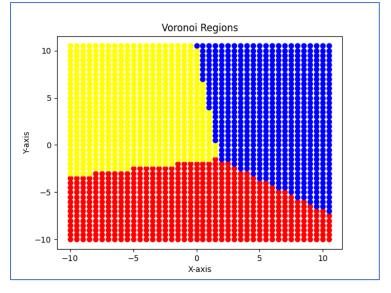


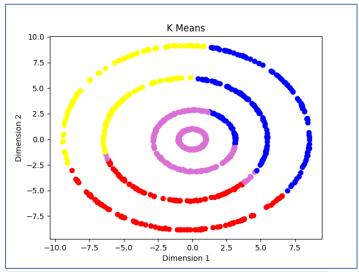


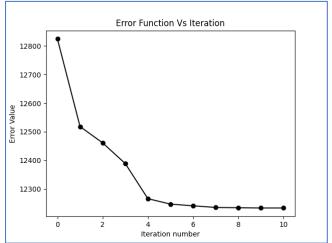


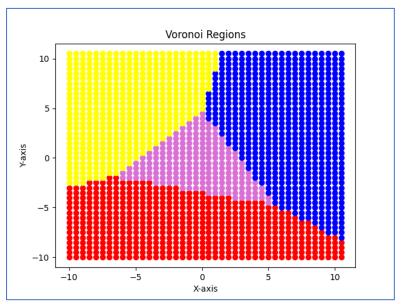




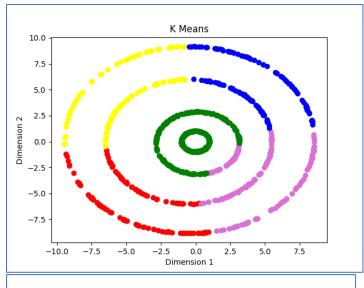


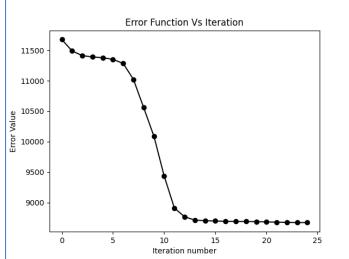


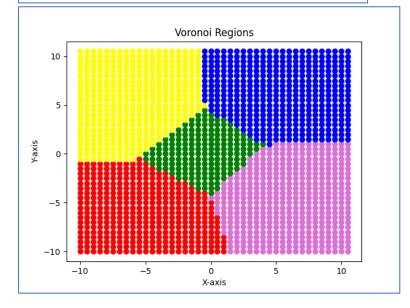




K=5



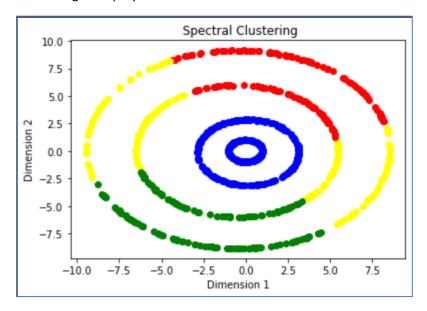




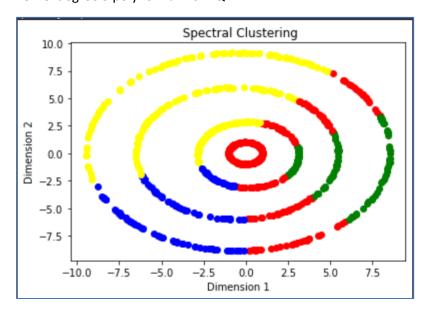
#### iii) Source code file name: - second\_part\_iii.py

Polynomial Kernel with degree 2 is the closest to the expected output which is rings clustered from outwards to inwards.

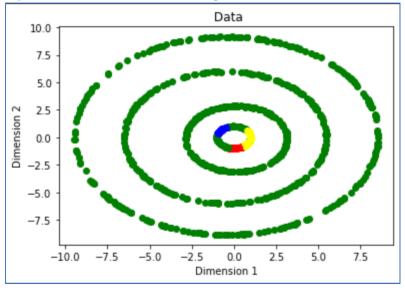
#### Kernel degree 2 polynomial from Q1



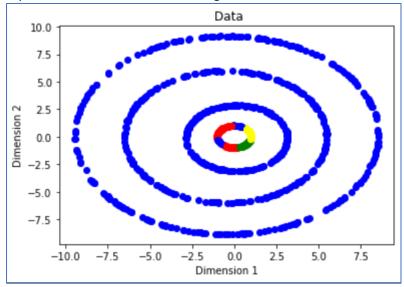
#### Kernel degree 3 polynomial from Q1



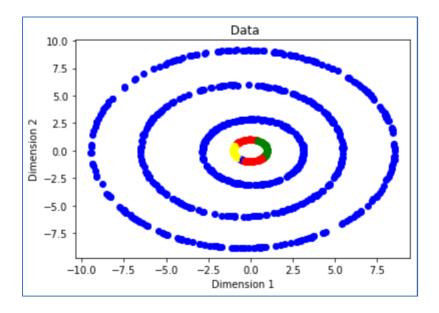
Exponential Kernel function with Sigma=0.1 from Q1



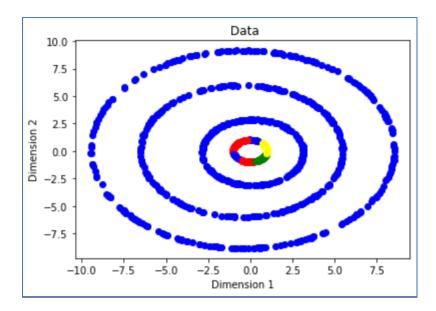
Exponential Kernel function with Sigma=0.2 from Q1



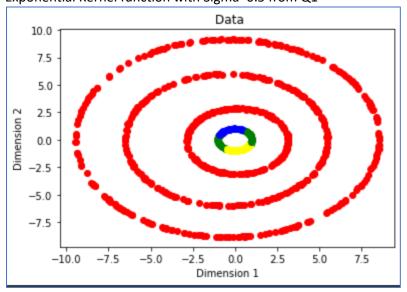
## Exponential Kernel function with Sigma=0.3 from Q1



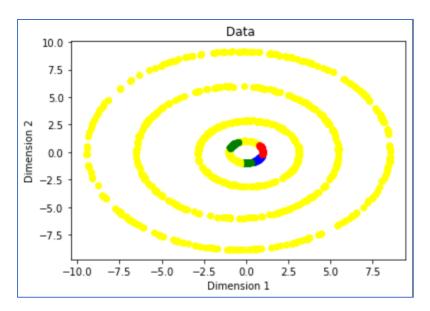
### Exponential Kernel function with Sigma=0.4 from Q1



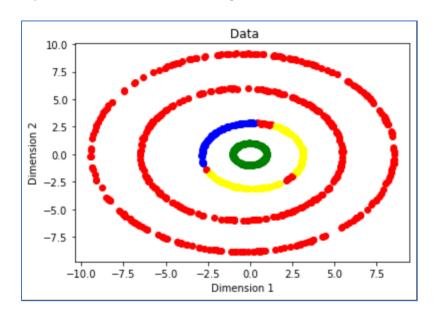
Exponential Kernel function with Sigma=0.5 from Q1



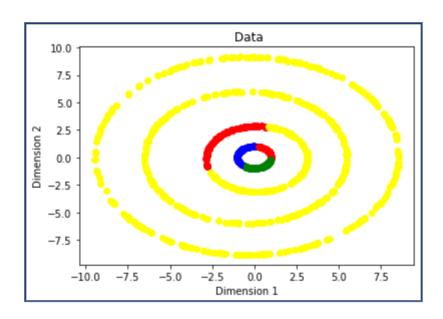
## Exponential Kernel function with Sigma=0.6 from Q1



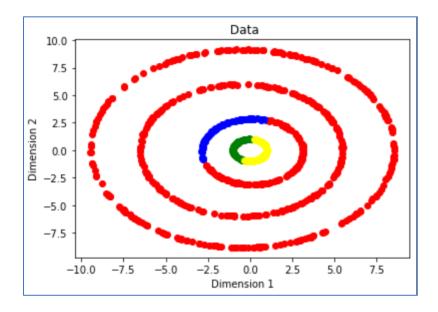
## Exponential Kernel function with Sigma=0.7 from Q1



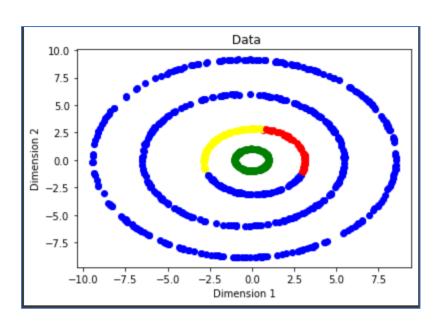
Exponential Kernel function with Sigma=0.8 from Q1



## Exponential Kernel function with Sigma=0.9 from Q1



Exponential Kernel function with Sigma=1.0 from Q1



#### iv) Source code file name: - second\_part\_iii.py

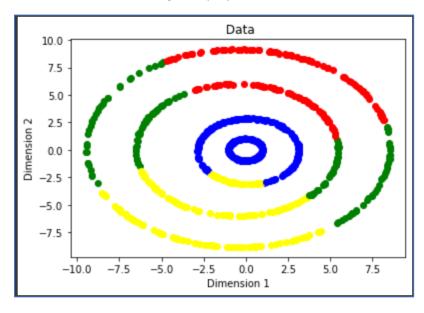
#### Using arg max function to map eigen vectors to clusters

$$\ell = \arg\max_{j=1,\dots,k} v_i^j$$

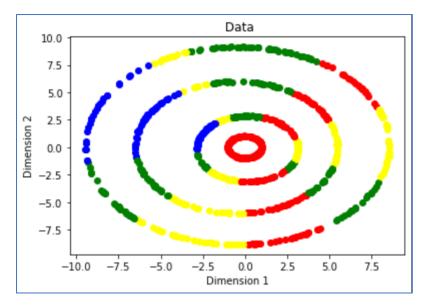
Answer: The results obtained are Better than k-mean clustering which is initialized randomly. As here we are moving to higher dimension. But it is not as good as Normalized mean clustering.

H[n][k] denotes the likelihood of point n to go into the kth cluster So, it performs better as compared to random initialization

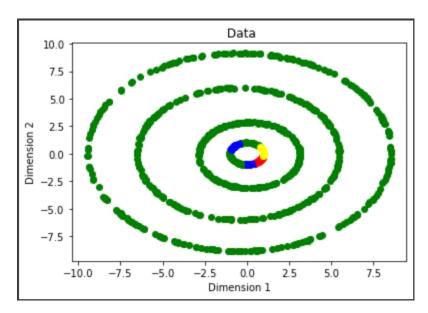
Kernel degree 2 polynomial from Q1



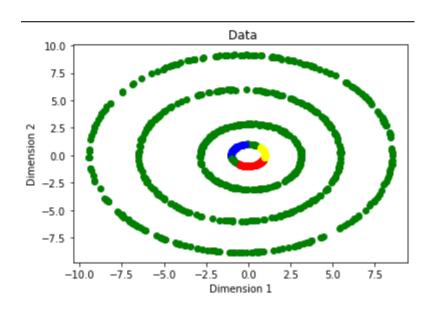
## Kernel degree 3 polynomial from Q1



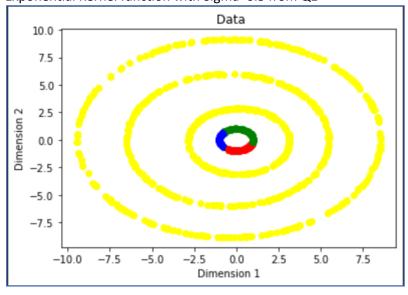
#### Exponential Kernel function with Sigma=0.1 from Q1



Exponential Kernel function with Sigma=0.2 from Q1



Exponential Kernel function with Sigma=0.3 from Q1



Exponential Kernel function with Sigma=0.4 from Q1

