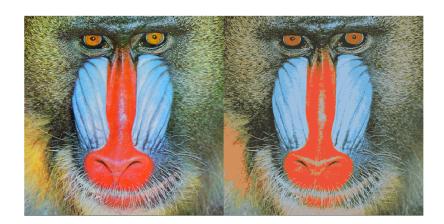
1.

Code is provided.



1d. For each pixel in our uncompressed image, RGB can take any value. Thus, we have 0-255 values for each of R, G, and B. Each of these can be represented with 8 bits, so we have a total of

$$numerator = 512 \times 512 \times 24$$
 bits

to store the uncompressed image.

For the compressed image, RGB can only take one of 16 values. Of course, if we want to store this, we need to create a mapping from each point to its nearest centroid, which will require a constant C bits to store that mapping, in addition to the 4-bits required to store the data for the centroids. Thus, for the compressed image, we have a total of

$$denominator = (512 \times 512 \times 4) + C bits$$

Thus, our compression factor is

$$\frac{numerator}{denominator} = \frac{512 \times 512 \times 24}{(512 \times 512 \times 4) + C} = 6x \ factor \ approximately$$

23. @) From previous hw,

(

$$\frac{\partial P}{\partial x} E(\underline{M}'P) = \sum_{i=1}^{|A|} -CI[f_{(i)}(\underline{M}_i X_{(i)} + P) < I]f_{(i)}$$

$$\Delta^M E(\underline{M}'P) = \sum_{i=1}^{|A|} -CI[f_{(i)}(\underline{M}_i X_{(i)} + P) < I]f_{(i)}$$

end return w\*

-----q2b------q2b------

0.100000 is the optimal value of C

0.500000 is the optimal value of n0

9.000000 is the percent error on testing data

-----q2c------

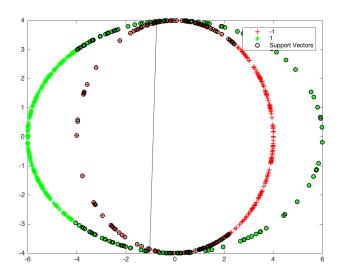
<sup>1.000000</sup> is the optimal value of C

<sup>1.000000</sup> is the optimal value of n0

<sup>8.500000</sup> is the percent error on testing data

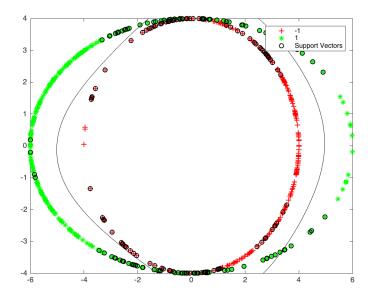
# Q3a.

## 88.0 percent classification accuracy



# Q3b.

## 100.0 percent classification accuracy



# Q3c.

Using a Gaussian kernel function allows us to more richly classify our data from not using a kernel, thus making it easier to classify data using an SVM model.

Q3d.

Optimal value of sigma = 0.2 Accuracy = 100%

	 	a3c	 	
0.200000				