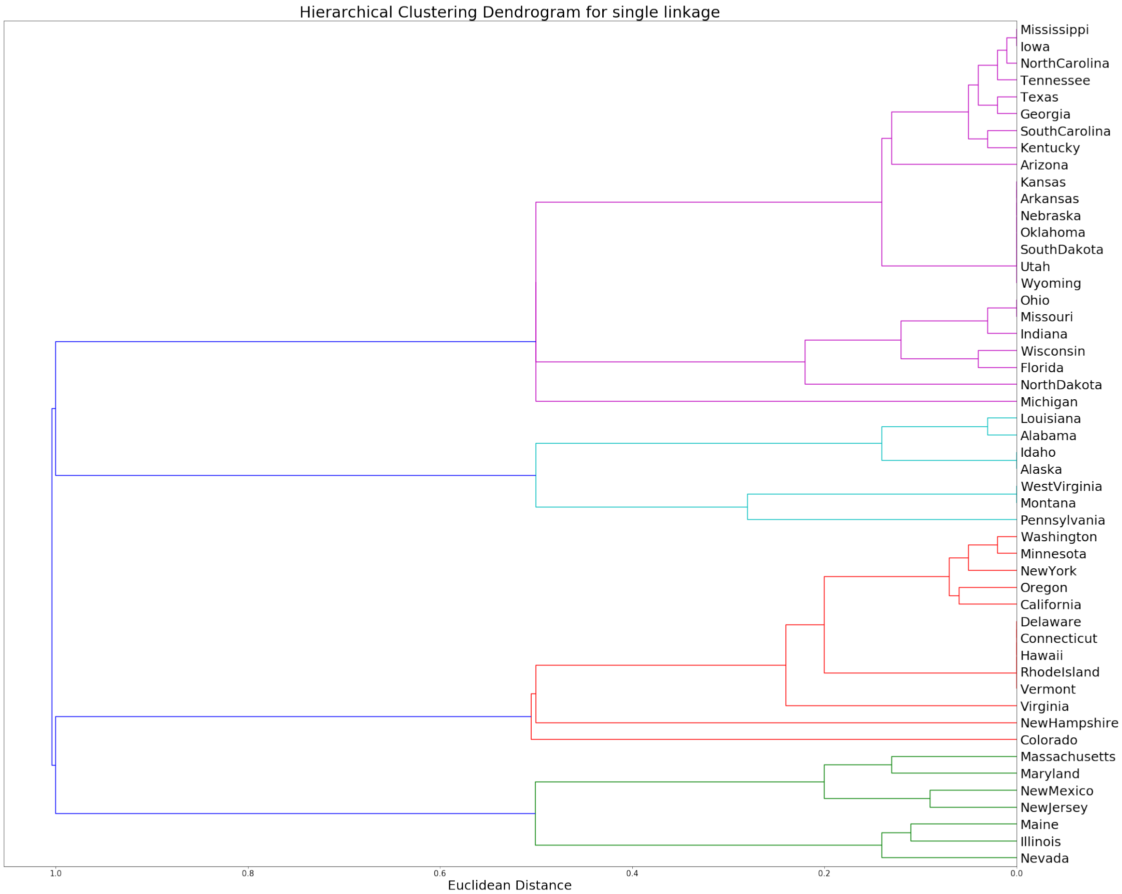
Lab 4 Data Mining

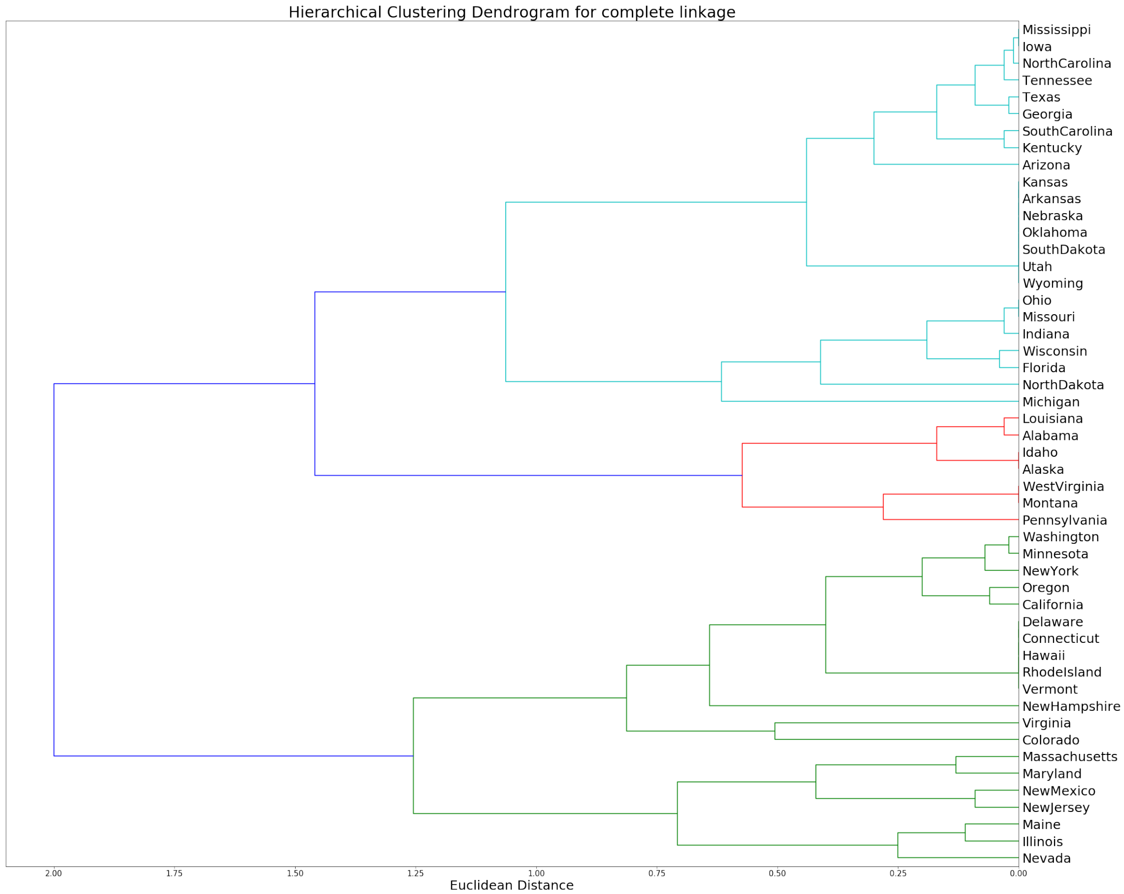
October 31, 2019

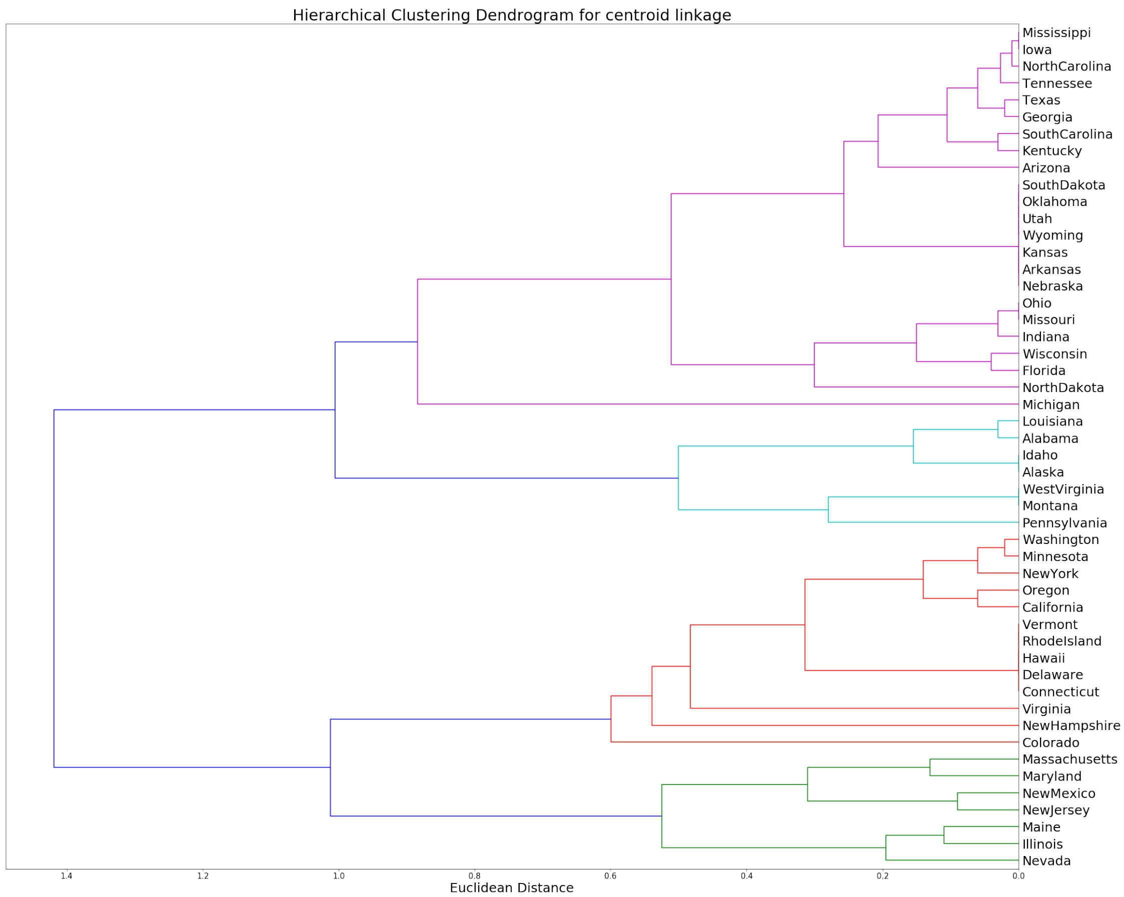
1 Hierarchial Clustering of 2016 Election Data

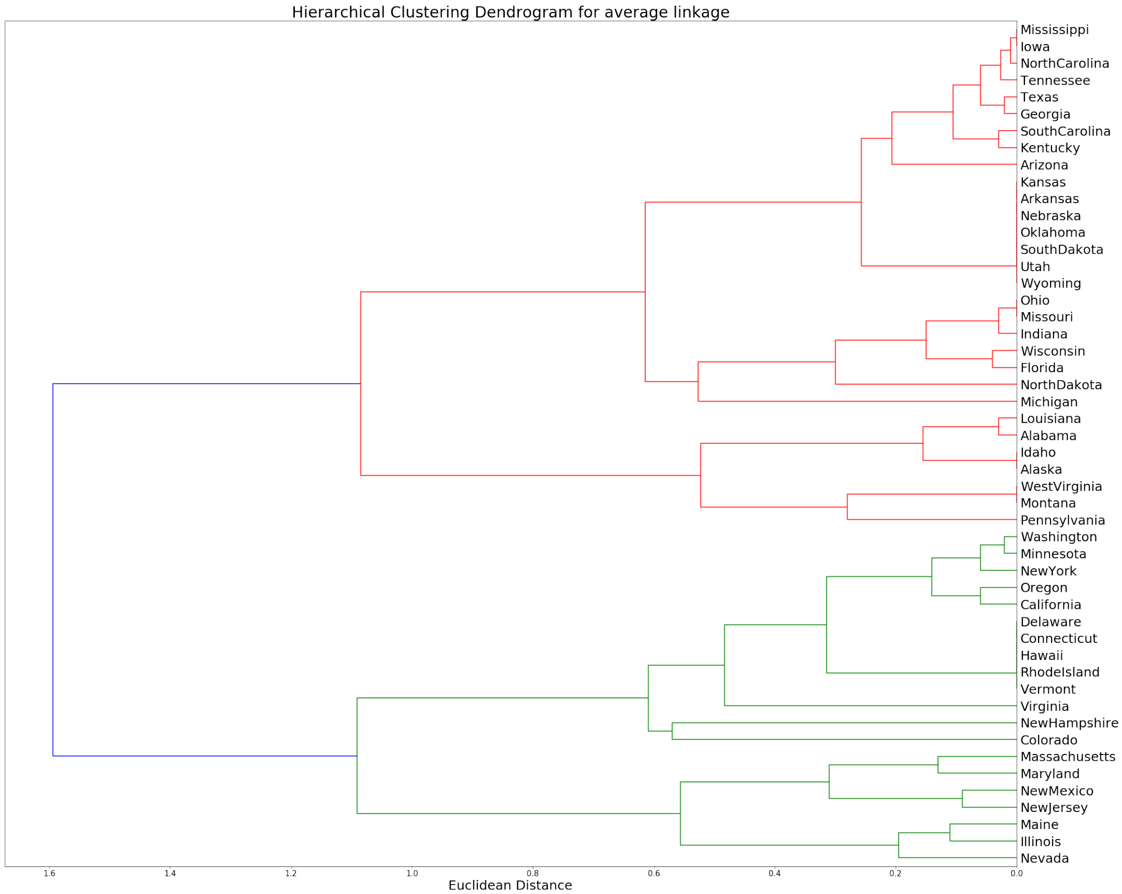
In [1]:
```
#importing external modules
import numpy as np

#import text file and split on the states names and percentages
states = [x.split(' ')[0] for x in open('states.txt').readlines()]
X = np.array([x.split()[1:] for x in open('states.txt').readlines()])
```

In [2]:
```
import scipy.cluster.hierarchy as shc
import matplotlib.pyplot as plt
%matplotlib inline

#create list of linked methods
lst = ['single', 'complete', 'centroid', 'average']

#iterate through each element in linked methods list
for i in lst:
    #create figure canvas
    plt.figure(figsize=(35,30))
    #include title and xlabel
    plt.title('Hierarchical Clustering Dendrogram for '+i+' linkage', fontsize=30)
    plt.xlabel('Euclidean Distance', fontsize=25)
    plt.tick_params(axis='x', labelsize=15)
    #plot dendrogram for each linkage method, statenames on the y axis
    #increasing cluster sizes go from right to left
    dend = shc.dendrogram(shc.linkage(X, method=i, metric='euclidean'),
                          orientation='left',
                          count_sort='descendent',
                          leaf_rotation=360,
                          leaf_font_size=25,
                          labels=states)
```


Hierarchical Clustering Dendrogram for single linkage
Mississippi
Iowa
NorthCarolina
Tennessee
Texas
Georgia
SouthCarolina
Kentucky
Arizona
Kansas
Arkansas
Nebraska
Oklahoma
SouthDakota
Utah
Wyoming
Ohio
Missouri
Indiana
Wisconsin
Florida
NorthDakota
Michigan
Louisiana
Alabama
Idaho
Alaska
WestVirginia
Montana
Pennsylvania
Washington
Minnesota
NewYork
Oregon
California
Delaware
Connecticut
Hawaii
RhodeIsland
Vermont
Virginia
NewHampshire
Colorado
Massachusetts
Maryland
NewMexico
NewJersey
Maine
Illinois
Nevada
1.0
0.8
0.6
0.4
0.2
0.0
Euclidean Distance


Hierarchical Clustering Dendrogram for complete linkage
Mississippi
Iowa
NorthCarolina
Tennessee
Texas
Georgia
SouthCarolina
Kentucky
Arizona
Kansas
Arkansas
Nebraska
Oklahoma
SouthDakota
Utah
Wyoming
Ohio
Missouri
Indiana
Wisconsin
Florida
NorthDakota
Michigan
Louisiana
Alabama
Idaho
Alaska
WestVirginia
Montana
Pennsylvania
Washington
Minnesota
NewYork
Oregon
California
Delaware
Connecticut
Hawaii
RhodeIsland
Vermont
NewHampshire
Virginia
Colorado
Massachusetts
Maryland
NewMexico
NewJersey
Maine
Illinois
Nevada
2.00
1.75
1.50
1.25
1.00
0.75
0.50
0.25
0.00
Euclidean Distance


Hierarchical Clustering Dendrogram for centroid linkage
Mississippi
Iowa
NorthCarolina
Tennessee
Texas
Georgia
SouthCarolina
Kentucky
Arizona
SouthDakota
Oklahoma
Utah
Wyoming
Kansas
Arkansas
Nebraska
Ohio
Missouri
Indiana
Wisconsin
Florida
NorthDakota
Michigan
Louisiana
Alabama
Idaho
Alaska
WestVirginia
Montana
Pennsylvania
Washington
Minnesota
NewYork
Oregon
California
Vermont
RhodeIsland
Hawaii
Delaware
Connecticut
Virginia
NewHampshire
Colorado
Massachusetts
Maryland
NewMexico
NewJersey
Maine
Illinois
Nevada
1.4
1.2
1.0
0.8
0.6
0.4
0.2
0.0
Euclidean Distance



1.1 Conclusions

The dendrograms show that the states are clustered uniformly, thus indicating that the 50 states are split evenly between the two political parties.

2 Image Compression With K-Means

In [3]:
```
#import external image library
from PIL import Image

#function to read in the image and convert it to array
def readImage(filename):

    #convert image to np array
    img = np.array(Image.open(filename))

    #reshape and normalize image to 2d matrix
    reshaped_img = (img / 255.0).reshape(img.shape[0] * img.shape[1], 3)
```

```python
        #return reshaped image
        return reshaped_img
```

In [4]:
```python
#function to calculate the closest centroids
def closestCentroids(img, centroids):

    #initialize empty list to hold minimum generators
    generator = []

    #for loop to dynamically create generator lists
    #for different number of clusters
    for i in range(len(centroids)):
        generator.append([])

    #iterate through length of the original image
    for i in range(len(img)):

        #variable iterates and stores each row of image matrix
        vals = img[i]
        energy = 0

        #using list comprehension to calculate the euclidean distance from image and e
        euclid = [abs(vals[0] - centroids[j][0]) + abs(vals[1] - centroids[j][1])
                  + abs(vals[2] - centroids[j][2]) for j in range(len(centroids))]

        energy = energy + min(euclid)

        #add min euclidian distance
        generator[np.argmin(euclid)].append(vals)

    energies = (min(euclid))

    #return min generators
    return generator, energies
```

In [5]:
```python
#function to update generators for each iteration of k means
def updateGenerators(generator, nclusters):

    #empty array to hold new generators
    new_generators = []

    #loop through the length of number of clusters
    for i in range(nclusters):

        #append the average generator for each dimension
        #return a vector with 3 vals
        new_generators.append(np.average(np.array(generator[i]),axis=0))
```

```
        #return new generators
        return new_generators
```

In [6]:
```
#import external modules
import random

#function to perform k means clustering
def kmeans(img, nclusters):

    energy = []

    #create initial generators from original image matrix
    generator = random.sample(img.tolist(), nclusters)

    #define iterations
    iterations = 10

    #run k means for 10 iterations
    for i in range(iterations):

        #calculate closest generators
        generator, e = closestCentroids(img, generator)
        #update new generators
        generator = updateGenerators(generator, nclusters)
        #append energies to array to access for plots
        energy.append(generator[0][0])

    return generator, energy
```

In [7]:
```
#function to return image to original shape
def replacePixel(img, generator):

    #initialize empty matrix the same size as
    #the original image matrix
    new_img = np.zeros(img.shape)

    #iterate fot the length of the original matrix
    for i in range(len(img)):

        #variable iterates and stores each row of pixels
        vals = img[i]

        #calculate euclidean distance
        euclid = [abs(vals[0] - generator[j][0]) + abs(vals[1] - generator[j][1])
                  + abs(vals[2] - generator[j][2]) for j in range(len(generator))]

        #construct new image matrix
        new_img[i,:]=generator[np.argmin(euclid)]
```

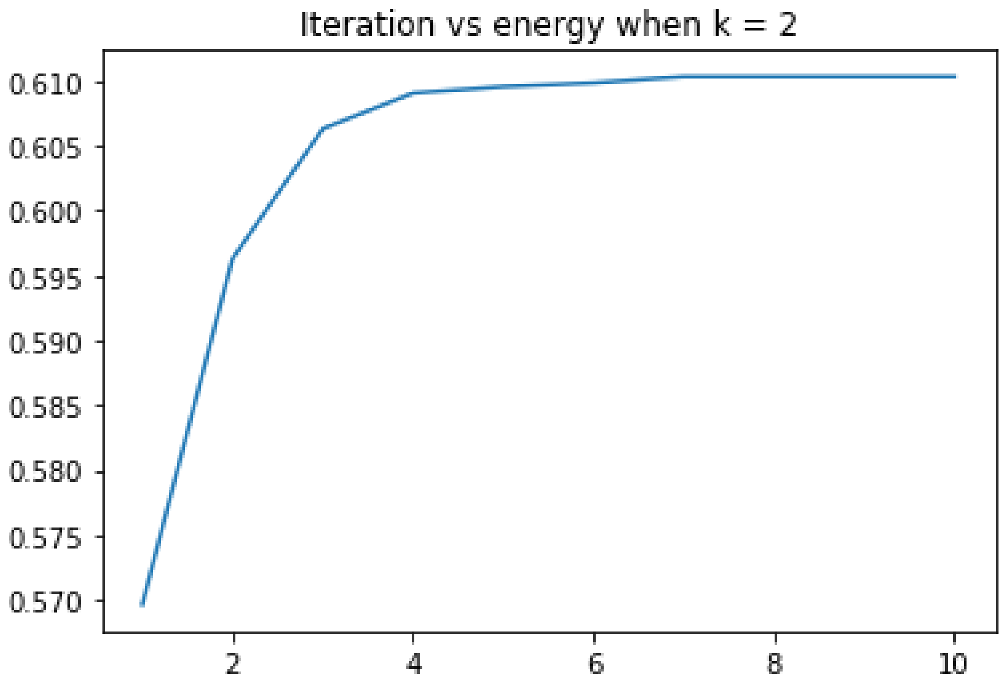
```
    #return new image
    return new_img
```

In [8]:
```
#function to plot new image vs original image for different number of k
def plotImages(new_image, nclusters):

    original_image = np.array(Image.open('mandrill.png'))

    fig, ax = plt.subplots(1, 2, figsize=(20,20))
    ax[0].imshow(new_image)
    ax[0].set_title('Compressed Image when k = ' + str(nclusters), fontsize=18)
    ax[1].imshow(original_image)
    ax[1].set_title('Original Image', fontsize=18)
    plt.show()
```

In [9]:
```
#function to plot the energy vs iteration
def plotEnergy(energy, nclusters):

    iteration = np.arange(0,10)
    plt.plot(np.arange(1,11), energy)
    plt.title('Iteration vs energy when k = {}'.format(nclusters))
    plt.show()
```

2.1 Image Approximation when k = 2

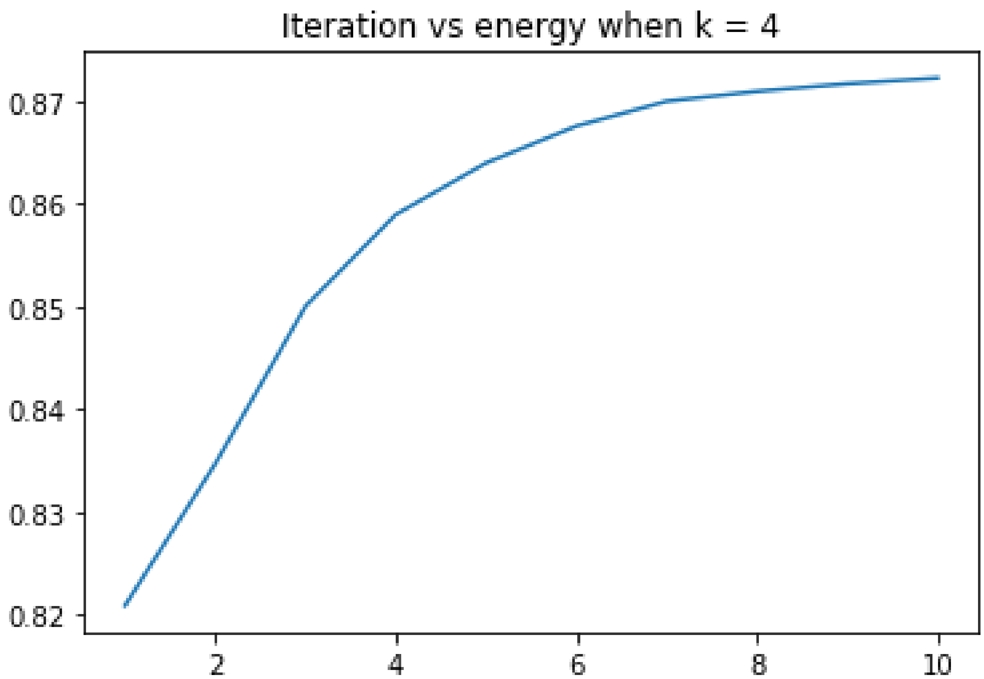
In [10]:
```
#read in original image
img = readImage('mandrill.png')

#kmeans with 2 clusters
nclusters = 2
generator_2, energy_2 = kmeans(img, nclusters)

#plot energy vs iteration
plotEnergy(energy_2, nclusters)

#reconstruct new image
new_img = replacePixel(img, generator_2)
#reshape
new_img=np.reshape(new_img, (512,512,3))
#plot compared images
plotImages(new_img, 2)
```



2.2 Image Approximation when k = 4

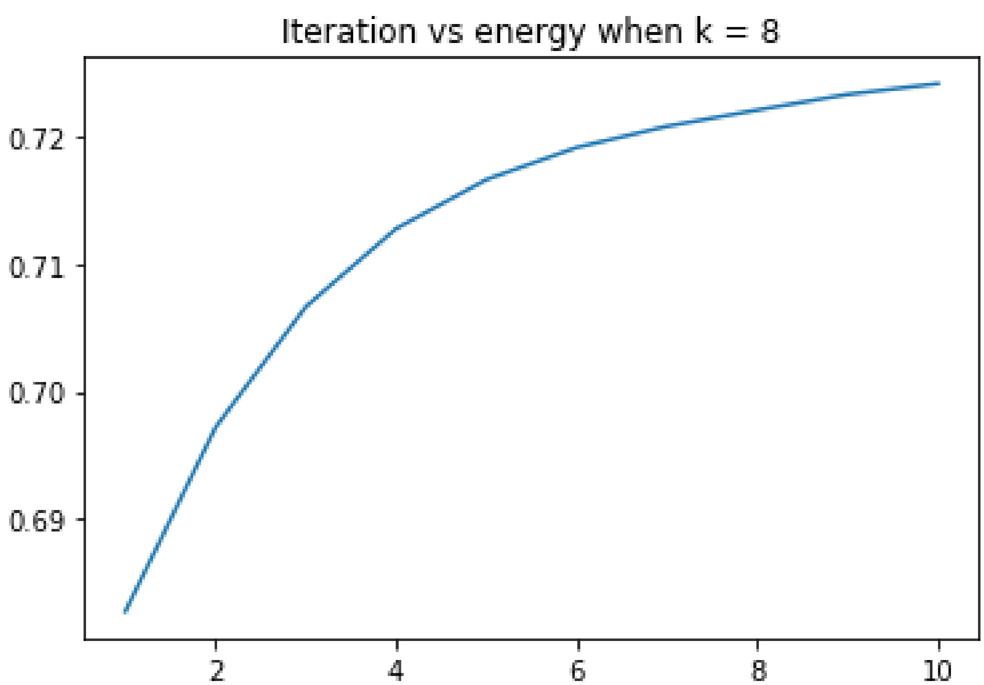
```
In [11]: #kmeans with 4 clusters
         nclusters = 4
         generator_4, energy_4 = kmeans(img, nclusters)
```

```
#plot energy vs iteration
plotEnergy(energy_4, nclusters)

#reconstruct new image
new_img = replacePixel(img, generator_4)
#reshape
new_img=np.reshape(new_img, (512,512,3))
#plot compared images
plotImages(new_img, nclusters)
```



2.3 Image Approximation when k = 8

In [12]:
```
#kmeans for 8 clusteres
nclusters = 8
generator_8, energy_8 = kmeans(img, 8)

#plot energy vs iteration
plotEnergy(energy_8, nclusters)

#reconstruct compressed image
new_img = replacePixel(img, generator_8)
#reshape
new_img=np.reshape(new_img, (512,512,3))
#plot compared image
plotImages(new_img, nclusters)
```



2.4 Conclusions

As the number of clusters increase the more color is indroduced into the compressed image. When k = 2, the compressed image has the least amount of original RGB values represented, while k = 8 has the most color and looks similar to the original image. The energy vs iteration plot shows the direction of clustering. If the graph is increasing, the data is moving in a positive direction towards the generators. If the graph is decreasing, the data is moving in a negative direction towards the generators. Depending if the algorithm converged quickly, the energy will plateau at a certain point.