CS 105 Final Project

Team: Thomas Henningson, Josh Pennington, Suhail-Anand Dhilon, Cameron Tsai

Introduction

State a question or set a goal. How can you answer your questions or achieve your goal?

We want to reduce the size of an image database while reducing the amount of information loss in each image.

We will reduce the size of the database by clustering the pixel values of all the images in the database, and replacing them with their cluster mean. We will use K-means clustering to achieve this. We will try many different cluster values in order to find the smallest k that keeps error to a minimum. We will be using mean squared error between the original pixel values and the cluster averages as our error function.

Once we have found a good k-value, we will use huffman encoding to store the cluster values and compress the dataset. We will need to store each images encoding, as well as an encoding of the tree so that it remembers to cluster averages pixel values. We can then compare the total bits used in the compressed images + tree encoding to the entire dataset to find our compression rate.

What data do you need? Can you find it?

We need a basic database of images, preferrably a smaller database with smaller images. This should be relatively easy to find, with databases such as CIFAR-10 and CIFAR-100 existing.

Find a sufficiently large dataset online

After some searching, we were able to find the Linnaeus_5 dataset. This dataset contains 128x128 pixel images belonging to 1 of 5 classes: berry, bird, dog, flower, and other. This dataset is typically used for training image classifiers, but it also suits out purposes. There are a total of 1600 images in each class for a total of 8000 images, giving us plent of data to work with.

Do you need to clean it?

No, we will not need to clean this dataset, since it already suits out purposes very well. However, we will reduce the size of the dataset by selecting a subset of images from each class. This is so that our code runs in a timely manner. We will shoot to have about 100 images total to test our code on, out of the 8000 available.

In [ ]:
```
import random
import matplotlib.pyplot as plt
import pickle
import numpy as np
from sklearn.cluster import KMeans
```

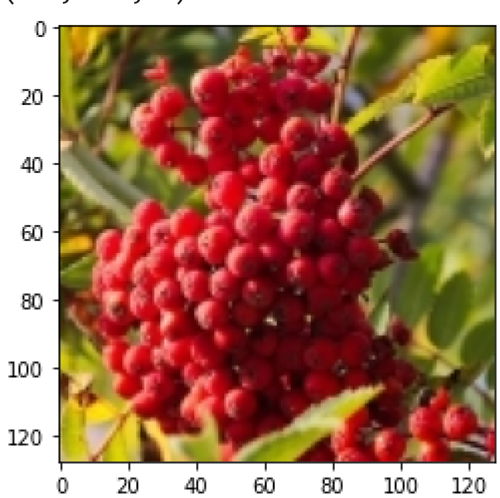
In [ ]:
```
data = []
classes = ["berry", "bird", "dog", "flower", "other"]

for c in classes:
    samp = random.sample(range(1,1201), 20)
    for x in samp:
        image = plt.imread("Linnaeus_5/train/%s/%d_128.jpg"%(c,x))
        pic = image.reshape(128*128*3)
        data.append(pic)

# change to True to get new dataset
if False:
    with open('images.data', 'wb') as f:
        pickle.dump(data, f)
```

Exploratory Data Analysis

Our dataset is pretty straightforward, so we will not need to explore as much. Let us start by visualizing an example image from the dataset.

In [ ]:
```
with open('images.data', 'rb') as f:
    data = pickle.load(f) # retrieve image data

data = np.array(data)
data = np.reshape(data, (100,128,128,3)) # reshape into images

pic = data[random.randint(0, 99)]
print(pic.shape)
plt.imshow(pic) # plot a random image
plt.show()
```

```
(128, 128, 3)
```



As we can see, there is a 128x128 image using RGB color channels. If we print the first pixel of this same image, we can see the range of the RGB channels (whether it is 0-255 or 0-1)

In [ ]:
```
print(pic[0][0])
```

```
[174 178   6]
```

Since these are integer value, we know the range of the RGB channels is 0-255.

Essentially, this is all we need to know about our dataset in order to implement K-means clustering.

Finding a good cluster values

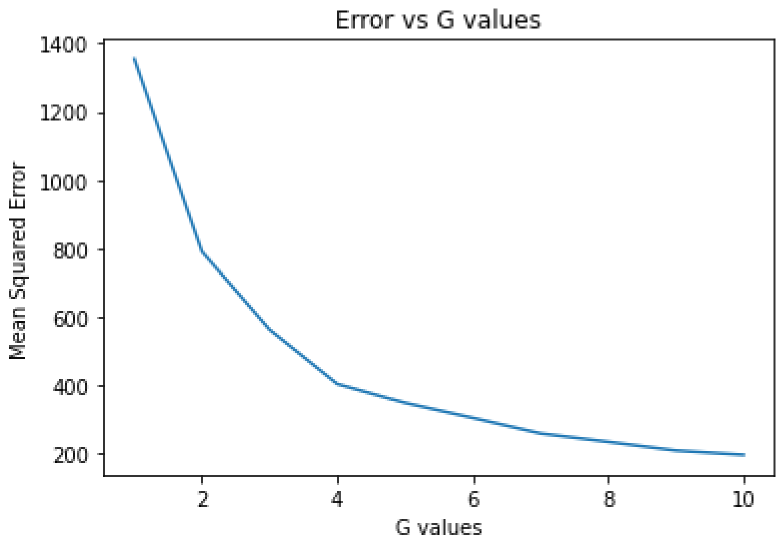
Our algorithm is a two step process, which uses K-means clustering in each step. First, we want to seperate our database of images into different groups which have relatively similar colors. We will do this by clustering the average pixel value of an entire image for all images in the set. We will call this cluster value G, and it is the number of groups the database has been split into, and will therefore be the total number of huffman trees we will have to encode.

The next step will be to cluster all images in each group using all pixel values of every image belonging to said group. This is the meat of the algorithm. We will call this cluster value K. This will be the number of pixel values that will replace the original values in the groups images. K determines the number of leaf nodes in the huffman tree.

Let us start with step one and determine the value of G we should use.

In [ ]:
```
with open('images.data', 'rb') as f:
    data = pickle.load(f)

orig_data = np.array(data) # retrieve image data

imgs = np.reshape(orig_data, (100,128*128,3)) # reshape data to get RGB channels
averages = np.mean(imgs, axis=1) # average along each images RGB

G_vals = [1, 2, 3, 4, 5, 6, 7, 8, 9, 10] # clusters for average pixel values

tot_err = []
for g in G_vals:
    kmeans = KMeans(n_clusters=g, random_state=0).fit(averages) # cluster according to
    labels = kmeans.labels_
    centers = kmeans.cluster_centers_

    # get list of centers for each average pixel
    error = []
    for i in range(labels.shape[0]):
        error.append(centers[labels[i]])

    # measure error between centers and averages in the cluster
    mse = (np.square(averages - error)).mean(axis=None)
    tot_err.append(mse)

plt.plot(G_vals, tot_err)
```

```
plt.title("Error vs G values")
plt.xlabel("G values")
plt.ylabel("Mean Squared Error")
plt.show()
```

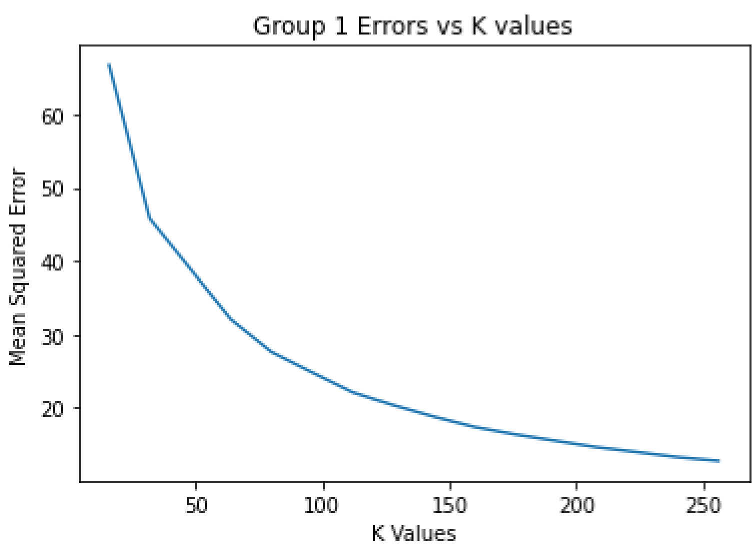


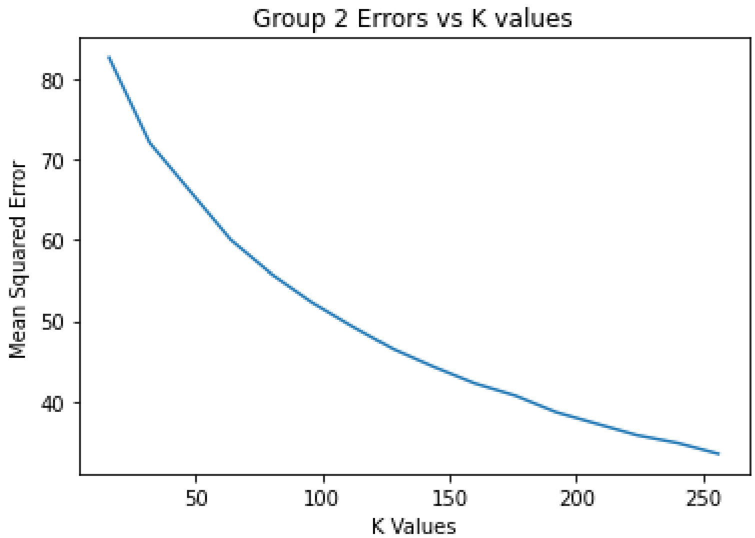
Based on this plot, we want to find the "Elbow" to determine our G value. This is a subjective process, but it seems to us that the elbow of this graph is G=4. We will continue with this G value as our value.

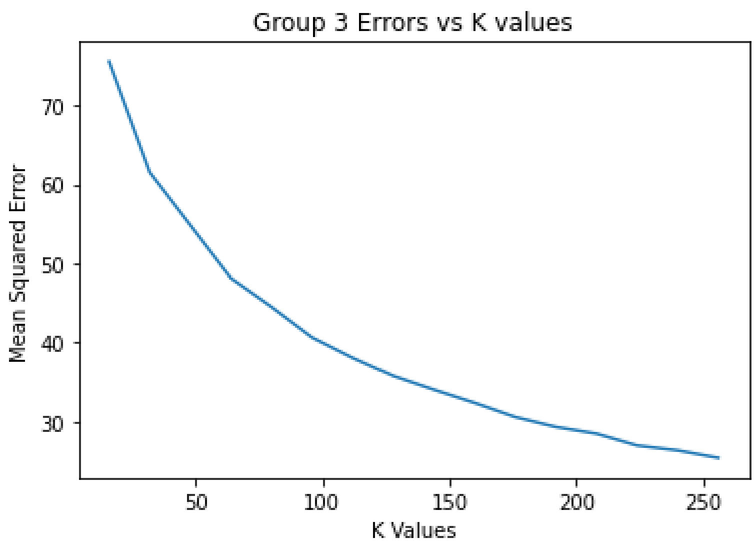
Now we can begin step 2 and find a good K-value. First, we will split the database into the groups we found before, and then we will test many different k-values on each of the groups. We will then plot the same error graphs and find the elbow, just as before.

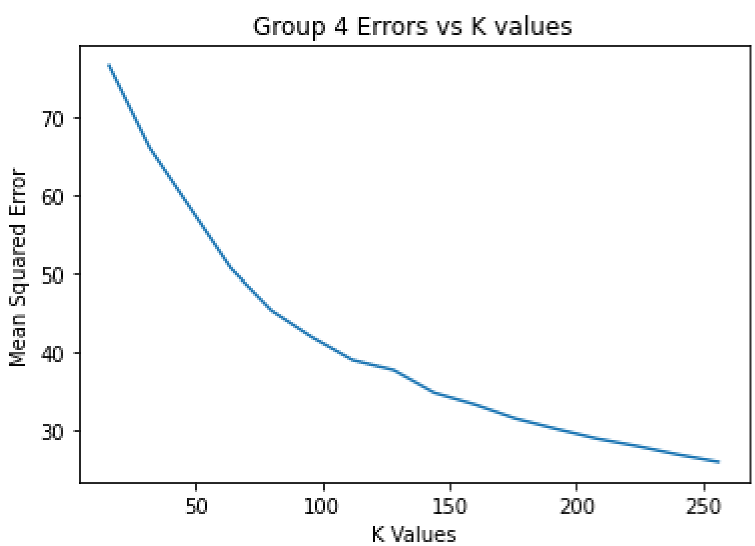
In [ ]:
```
with open('images.data', 'rb') as f:
    data = pickle.load(f)

orig_data = np.array(data) # retrieve image data

imgs = np.reshape(orig_data, (100,128*128,3)) # reshape data to get RGB channels
averages = np.mean(imgs, axis=1) # average along each images RGB

K_vals = [16, 32, 64, 80, 96, 112, 128, 144, 160, 176, 192, 208, 224, 240, 256]
G = 4

kmeans = KMeans(n_clusters=G, random_state=0).fit(averages) # intial group clustering
labels = kmeans.labels_

stratified_data = []
for i in range(G): # stratify images based on intial clustering
    lst = []
    for j,val in enumerate(labels):
        if i == val:
            lst.append(orig_data[j])
    lst = np.array(lst)
    stratified_data.append(lst)

all_error = [] # stores all errors for each cluster value for each batch
for group in stratified_data:
    error = [] # stores error for this specific batch
```

```
    for k in K_vals: # for each cluster value
        comp_data = group.copy() # copy the batch and reshape
        lst = []
        img = np.reshape(comp_data[0], (128*128,3))
        tot = img
        lst.append(img)
        for i in range(1, comp_data.shape[0]): # group all pixels of every image in th
            img = np.reshape(comp_data[i], (128*128,3))
            tot = np.concatenate((tot,img))
            lst.append(img)

        # cluster the pixel values
        kmeans = KMeans(n_clusters=k, random_state=0).fit(tot)
        labels = kmeans.labels_
        centers = np.around(kmeans.cluster_centers_)

        # replace pixel values with averages
        for i in range(len(lst)):
            for j in range(128*128):
                lst[i][j] = centers[labels[(i*(128*128))+j]]

        # Error measurement for pics
        mse = (np.square(group - comp_data)).mean(axis=None)
        error.append(mse)

    all_error.append(error) # append errors to all_error

num = 1
for err in all_error:
    plt.plot(K_vals, err)
    plt.title("Group %d Errors vs K values"%(num))
    num += 1
    plt.xlabel("K Values")
    plt.ylabel("Mean Squared Error")
    plt.show()
```




Group 2 Errors vs K values
Mean Squared Error
80
70
60
50
40
50
100
150
200
250
K Values


Group 3 Errors vs K values
Mean Squared Error
70
60
50
40
30
50
100
150
200
250
K Values


Group 4 Errors vs K values
Mean Squared Error
70
60
50
40
30
50
100
150
200
250
K Values