Image Segmentation

Course: Pattern recognition

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INTRODUCTION

Image segmentation is the classification of an image into different groups. Many kinds of research have been done in the area of image segmentation using clustering. In this project, we will explore using the K-Means clustering, NN-cut and spatial k means clustering algorithms to read an image and cluster different regions of the image, K-Means clustering algorithm is an unsupervised algorithm and it is used to segment the interest area from the background. It clusters, or partitions the given data into K-clusters or parts based on the K-centroids, the algorithm is used when you have unlabeled data (i.e., data without defined categories or groups), The goal is to find certain groups based on some kind of similarity in the data with the number of groups represented by K but, it fails sometimes due to the random choice of centroids (Random Initialization) , Meanwhile in spectral clustering The data points should be connected, but may not necessarily have convex boundaries, as opposed to the conventional clustering techniques, where clustering is based on the compactness of data points , K-Means clustering is popular for segmentation but it lacks effective spatial constraint. To address this issue, a general spatial constrained K-Means clustering framework is proposed and shows its effectiveness in image segmentation, Spatial constraints are expressed by points on adjacent positions, which cannot be segmented only by color gaps.

ALGORITHMS OVERVIEW

Approach 1: Regular K-means

k-means clustering is a method of vector quantization, originally from signal processing, that aims to partition n observations into k clusters in which each observation belongs to the cluster with the nearest mean (cluster centers or cluster centroid), serving as a prototype of the cluster.

ALGORITHM 13.1. K-means Algorithm

K-MEANS $(\mathbf{D}, k, \epsilon)$:
$t = 0$
Randomly initialize k centroids: $\boldsymbol{\mu}_1^t, \boldsymbol{\mu}_2^t, \ldots, \boldsymbol{\mu}_k^t \in \mathbb{R}^d$
repeat
  $t \leftarrow t + 1$
  $C_j \leftarrow \emptyset$ for all $j = 1, \cdots, k$
  `// Cluster Assignment Step`
  foreach $\mathbf{x}_j \in \mathbf{D}$ **do**
    $j^* \leftarrow \arg\min_i \left\{ \left\| \mathbf{x}_j - \boldsymbol{\mu}_i^{t-1} \right\|^2 \right\}$ `// Assign` $\mathbf{x}_j$ `to closest centroid`
    $C_{j^*} \leftarrow C_{j^*} \cup \{\mathbf{x}_j\}$
  `// Centroid Update Step`
  foreach $i = 1$ *to* k **do**
    $\boldsymbol{\mu}_i^t \leftarrow \frac{1}{|C_i|} \sum_{\mathbf{x}_j \in C_i} \mathbf{x}_j$
until $\sum_{i=1}^{k} \left\| \boldsymbol{\mu}_i^t - \boldsymbol{\mu}_i^{t-1} \right\|^2 \le \epsilon$

Fig (1)

Approach 2: Normalized Cut (Spectral clustering)

Spectral clustering is flexible and allows us to cluster non-graphical data as well. It makes no assumptions about the form of the clusters. Clustering techniques, like K-Means, assume that the points assigned to a cluster are spherical about the cluster center. This is a strong assumption and may not always be relevant. In such cases, Spectral Clustering helps create more accurate clusters. It can correctly cluster observations that actually belong to the same cluster, but are farther off than observations in other clusters, due to dimension reduction.

ALGORITHM 16.1. Spectral Clustering Algorithm

SPECTRAL CLUSTERING $(\mathbf{D}, k)$:
Compute the similarity matrix $\mathbf{A} \in \mathbb{R}^{n \times n}$
if *ratio cut* **then** $\mathbf{B} \leftarrow \mathbf{L}$
else if *normalized cut* **then** $\mathbf{B} \leftarrow \mathbf{L}^s$ or $\mathbf{L}^a$
Solve $\mathbf{B}\mathbf{u}_i = \lambda_i \mathbf{u}_i$ for $i = n, \ldots, n-k+1$, where $\lambda_n \le \lambda_{n-1} \le \cdots \le \lambda_{n-k+1}$
$\mathbf{U} \leftarrow \begin{pmatrix} \mathbf{u}_n & \mathbf{u}_{n-1} & \cdots & \mathbf{u}_{n-k+1} \end{pmatrix}$
$\mathbf{Y} \leftarrow$ normalize rows of $\mathbf{U}$ using Eq. (16.19)
$\mathcal{C} \leftarrow \{C_1, \ldots, C_k\}$ via K-means on $\mathbf{Y}$

Fig (2)

DISCUSSION

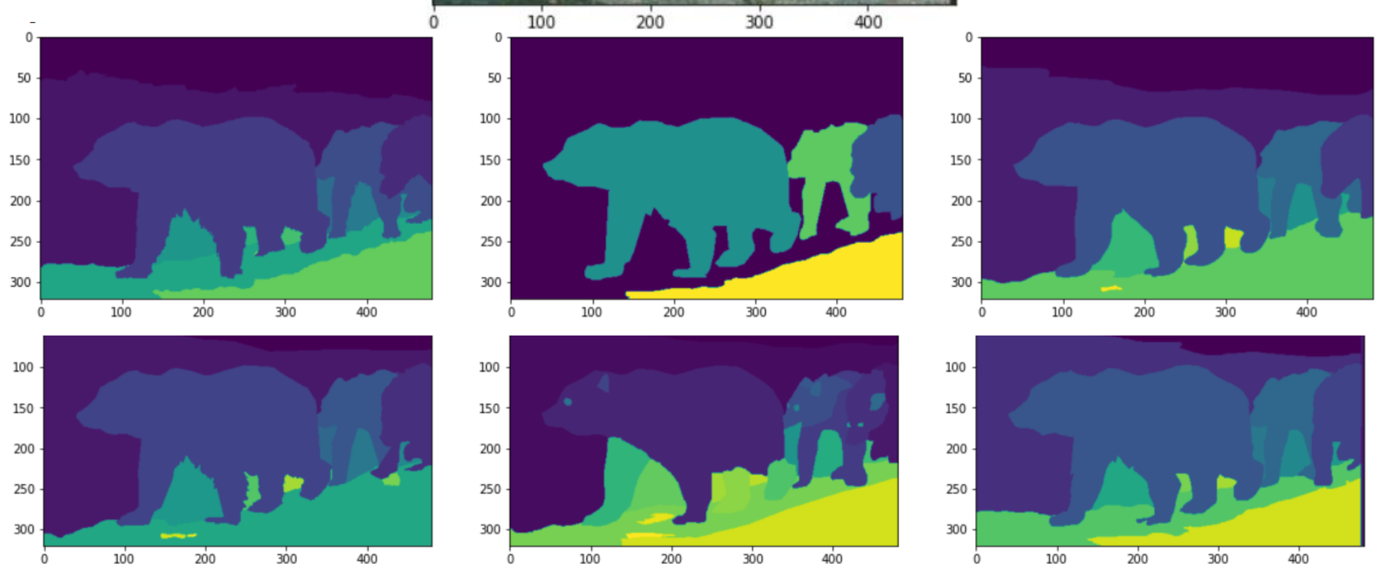
1. Download the Dataset and Understand the Format

The Berkeley Segmentation Benchmark contains 500 images 200 only for testing.

2. Visualize the image and the ground truth segmentation

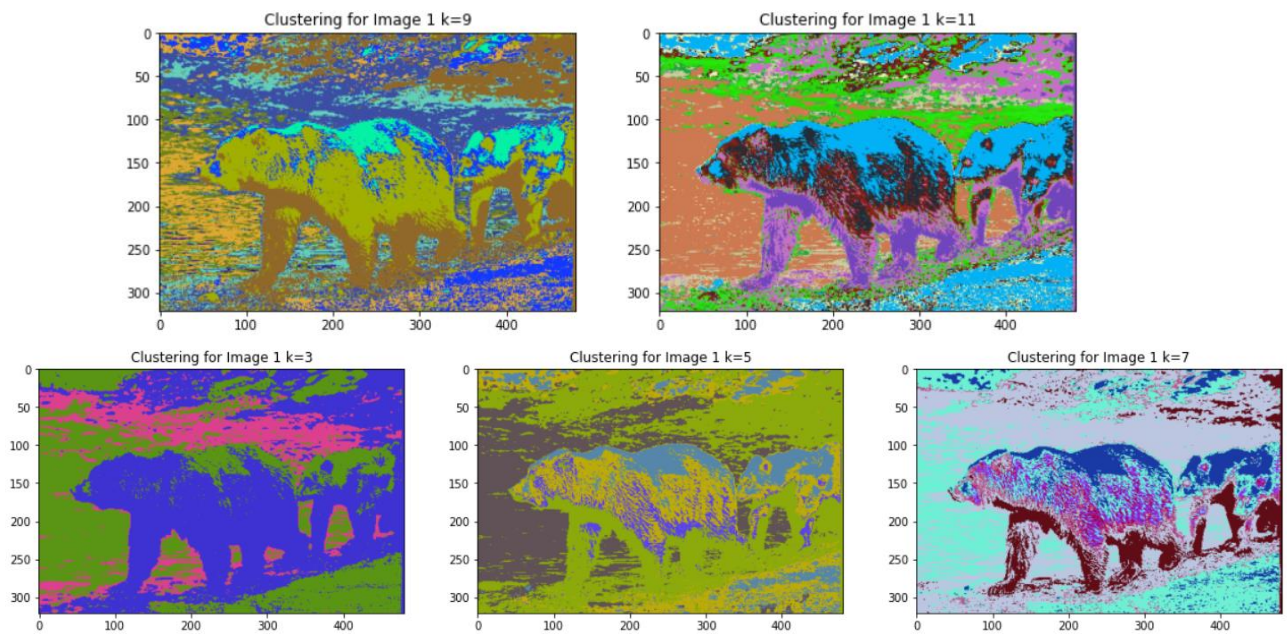
i) A function was developed that takes the path for the folder needed to read and the folder name to select whether it's Ground truth MATLAB files that are needed or the training set images, the function returns a list of the images or a list of ground truth segmentations, this function uses SciPy library to read the MATLAB files.

ii) After loading all training images to a list of images and reading the ground Truth MATLAB files into another list, one sample image was displayed with its corresponding ground truth segmentations giving the results shown in the following figures:



3. **Segmentation using K-means**

i) Two main functions were developed in order to implement K-means clustering for multiple values of K (3,5,7,9,11), **K-means** and **ClusteriseImages**, **K-means** function was developed where it takes number of clusters K as input, Input image(data) to be clustered, the tolerance for error and iterations limit and returns the cluster labels needed to segment the image. K-means function does some preprocessing for the input data (image) where the pixels are scaled to range between [0 1] instead of having values from [0 255] this is done to avoid future errors and in hopes of speeding up the process then the image is reshaped from (MxNx3) image into a Kx3 matrix where K= MxN then the rest of the algorithm explained in the above Fig (1) is applied and it terminates in case the error tolerance is met or the number of iterations exceeded the limit set.
the cluster labels are obtained and forwarded as input for the second function **ClusteriseImages** along with the original data(image) and number of clusters where it then returns the output image after being segmented, this function assigns random color for each cluster and reconstructs the segmented image after the clustering according to the number of k used to for clustering the following figure shows the output for K-means clustering of one image with multiple values of K at (3,5,7,9,11):



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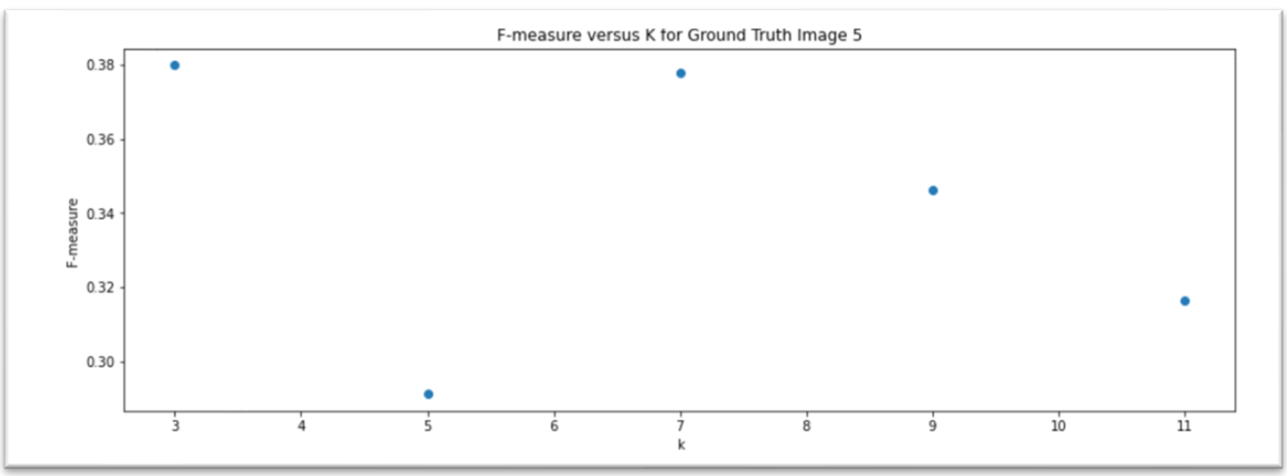
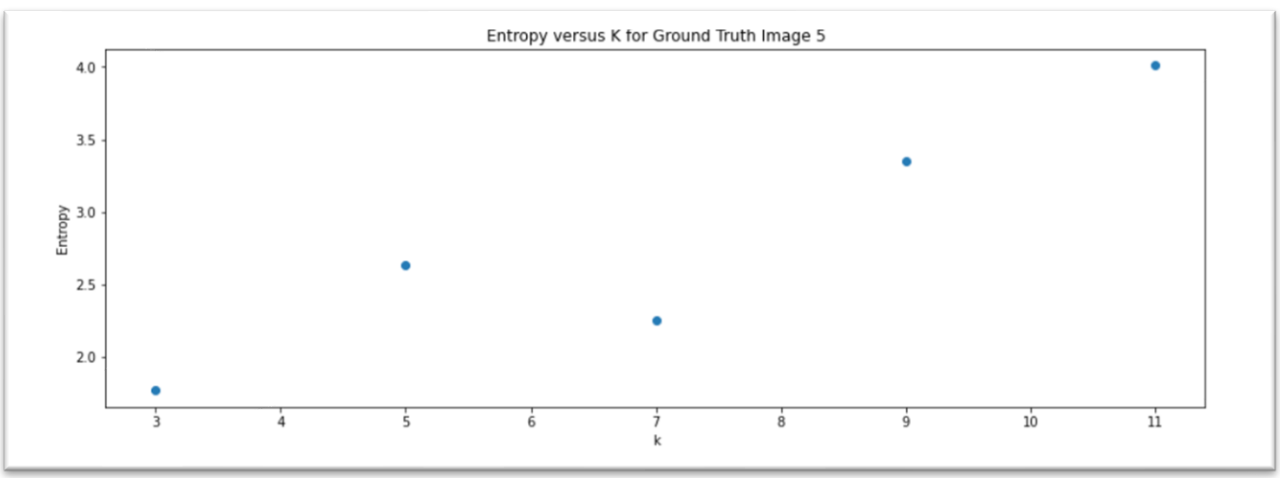
ii) the following results are obtained for the evaluation of the results for segmentation using **F-measure**, **Conditional Entropy** for a sample image with 5 available ground-truth segmentations, for all values of K and the average for the 5 trials:

```
For k =  3  and Ground Truth image number=  1  Fmeasure is  0.3690009688293269
For k =  3  and Ground Truth image number=  2  Fmeasure is  0.43331390255735586
For k =  3  and Ground Truth image number=  3  Fmeasure is  0.357550106899345
For k =  3  and Ground Truth image number=  4  Fmeasure is  0.37974584113606397
For k =  3  and Ground Truth image number=  5  Fmeasure is  0.3799191289960624


For k =  5  and Ground Truth image number=  1  Fmeasure is  0.31716376569652266
For k =  5  and Ground Truth image number=  2  Fmeasure is  0.33403849317441975
For k =  5  and Ground Truth image number=  3  Fmeasure is  0.3071861740925779
For k =  5  and Ground Truth image number=  4  Fmeasure is  0.3294793095331223
For k =  5  and Ground Truth image number=  5  Fmeasure is  0.2910863326310114


For k =  7  and Ground Truth image number=  1  Fmeasure is  0.3816166492919841
For k =  7  and Ground Truth image number=  2  Fmeasure is  0.3704879708506343
For k =  7  and Ground Truth image number=  3  Fmeasure is  0.3579729007839144
For k =  7  and Ground Truth image number=  4  Fmeasure is  0.3756784540036933
For k =  7  and Ground Truth image number=  5  Fmeasure is  0.3779908647839309


For k =  9  and Ground Truth image number=  1  Fmeasure is  0.3529143606891156
For k =  9  and Ground Truth image number=  2  Fmeasure is  0.3101899193660756
For k =  9  and Ground Truth image number=  3  Fmeasure is  0.33788821357813315
For k =  9  and Ground Truth image number=  4  Fmeasure is  0.34582475692313475
For k =  9  and Ground Truth image number=  5  Fmeasure is  0.3462317380101039


For k =  11  and Ground Truth image number=  1  Fmeasure is  0.3200333317342421
For k =  11  and Ground Truth image number=  2  Fmeasure is  0.2872685917312996
For k =  11  and Ground Truth image number=  3  Fmeasure is  0.30426309866850404
For k =  11  and Ground Truth image number=  4  Fmeasure is  0.30944574240698536
For k =  11  and Ground Truth image number=  5  Fmeasure is  0.31648163849550354
Average of the 5 trials =  0.34234194058332246
```

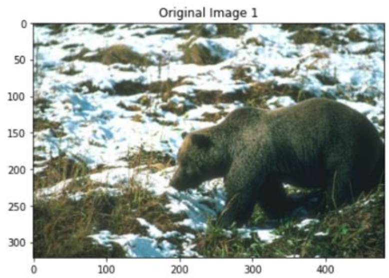


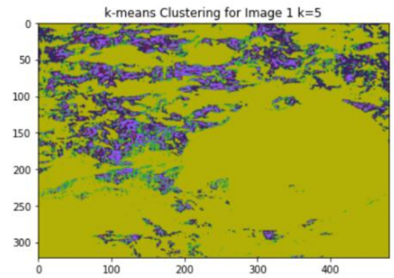
```
For k =  3  and Ground Truth image number=  1  Entropy 1.5808815141550063
For k =  3  and Ground Truth image number=  2  Entropy 1.0394696470776803
For k =  3  and Ground Truth image number=  3  Entropy 1.556118150959105
For k =  3  and Ground Truth image number=  4  Entropy 1.561791436363244
For k =  3  and Ground Truth image number=  5  Entropy 1.769740986194636


For k =  5  and Ground Truth image number=  1  Entropy 2.145571207043817
For k =  5  and Ground Truth image number=  2  Entropy 1.3424116724283541
For k =  5  and Ground Truth image number=  3  Entropy 2.2250573255434
For k =  5  and Ground Truth image number=  4  Entropy 2.2466117770375935
For k =  5  and Ground Truth image number=  5  Entropy 2.639021244380549


For k =  7  and Ground Truth image number=  1  Entropy 1.8832201279978547
For k =  7  and Ground Truth image number=  2  Entropy 1.1956816497290608
For k =  7  and Ground Truth image number=  3  Entropy 1.8735680243604291
For k =  7  and Ground Truth image number=  4  Entropy 1.8538546186456315
For k =  7  and Ground Truth image number=  5  Entropy 2.2561197150441332


For k =  9  and Ground Truth image number=  1  Entropy 2.9364129090228888
For k =  9  and Ground Truth image number=  2  Entropy 1.796244158461129
For k =  9  and Ground Truth image number=  3  Entropy 2.8372653400902497
For k =  9  and Ground Truth image number=  4  Entropy 2.8241671654247873
For k =  9  and Ground Truth image number=  5  Entropy 3.3507365637237463


For k =  11  and Ground Truth image number=  1  Entropy 3.414539374407504
For k =  11  and Ground Truth image number=  2  Entropy 1.647247858239332
For k =  11  and Ground Truth image number=  3  Entropy 3.38945269265993
For k =  11  and Ground Truth image number=  4  Entropy 3.324961744771953
For k =  11  and Ground Truth image number=  5  Entropy 4.009822519324214
Average of the M trials =  2.8050882057334556
```

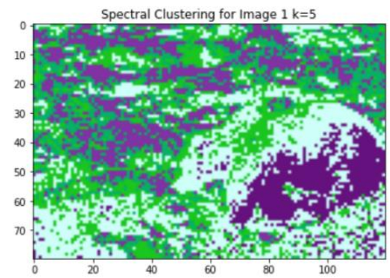


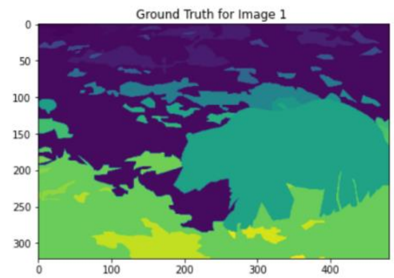
4. **Big Picture**

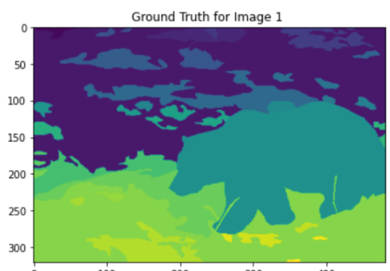
i) Five images were selected to be displayed with their corresponding ground truth the segmentation results using K-means at K=5 contrasted with the segmentation results using NN-cut implemented using the Spectral Clustering function from sklrean library where the affinity is given as 'Nearest neighbor' at K=5 and 5-NN the following results were obtained:

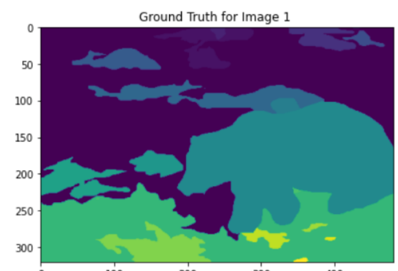


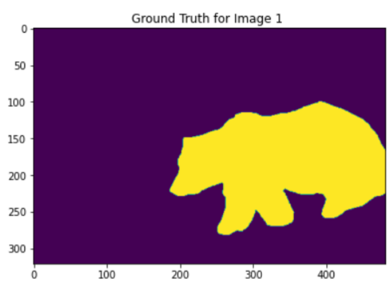


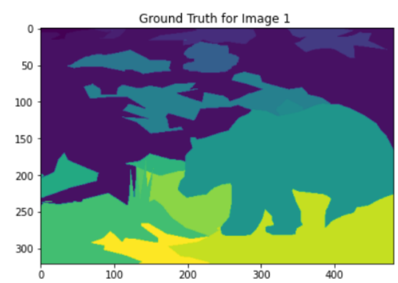


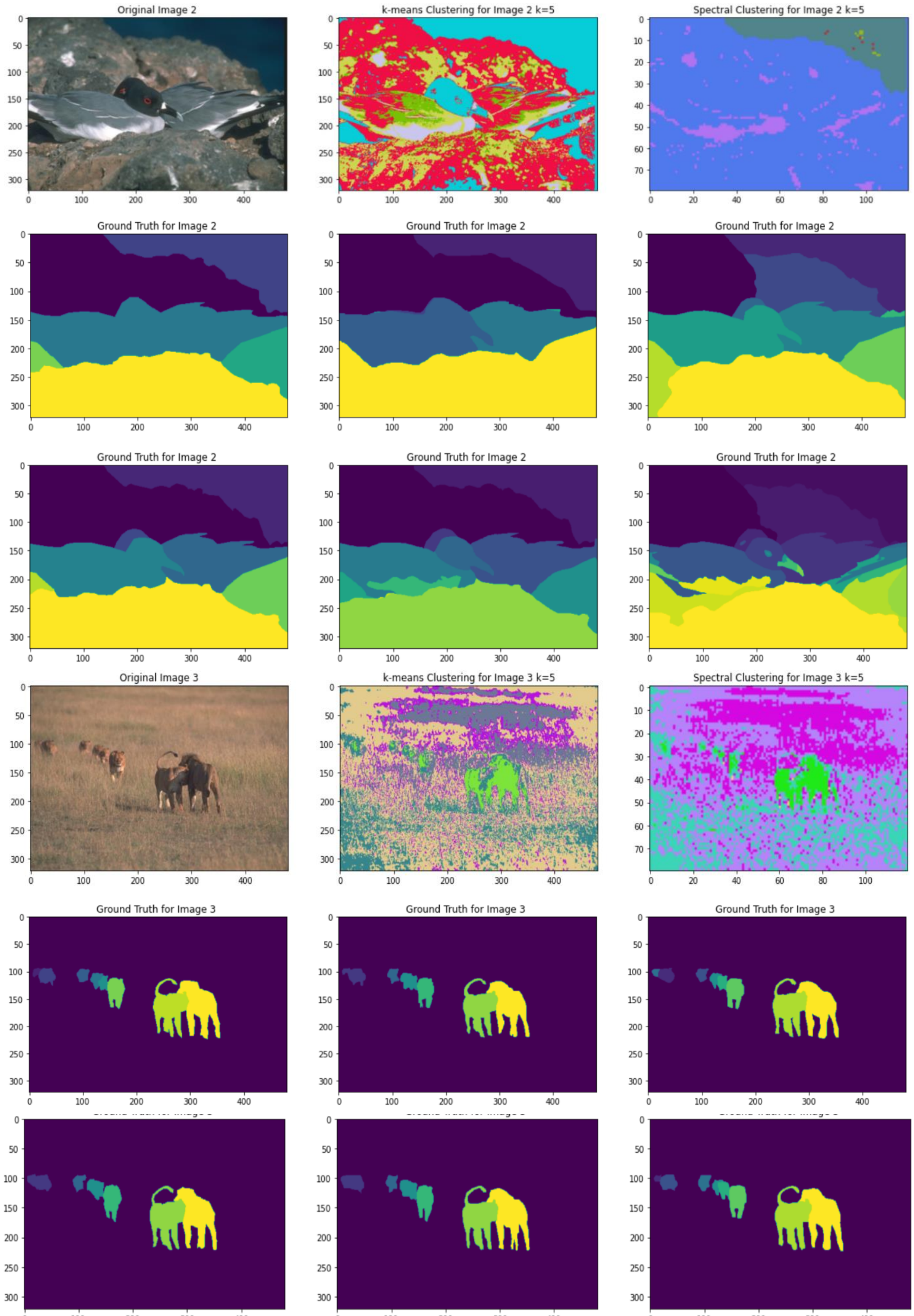


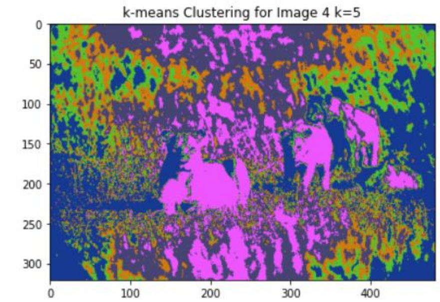
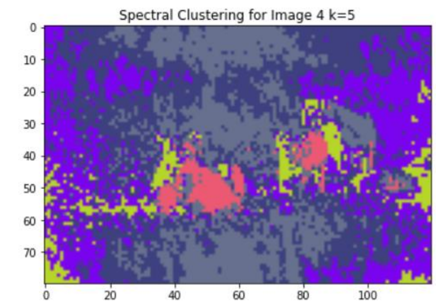
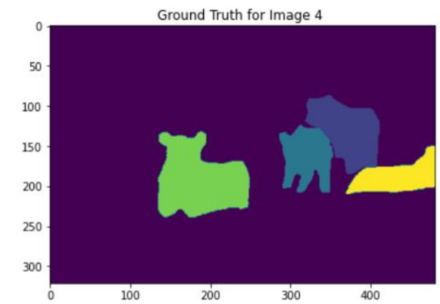
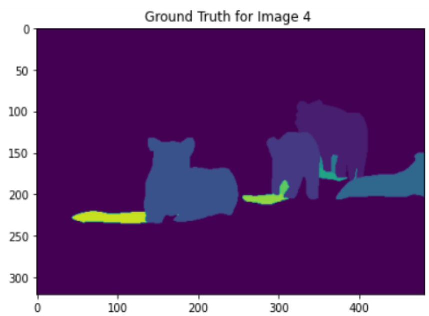









Original Image 2
k-means Clustering for Image 2 k=5
Spectral Clustering for Image 2 k=5
Ground Truth for Image 2
Ground Truth for Image 2
Ground Truth for Image 2
Ground Truth for Image 2
Ground Truth for Image 2
Ground Truth for Image 2
Original Image 3
k-means Clustering for Image 3 k=5
Spectral Clustering for Image 3 k=5
Ground Truth for Image 3
Ground Truth for Image 3
Ground Truth for Image 3


Original Image 4

k-means Clustering for Image 4 k=5

Spectral Clustering for Image 4 k=5

Ground Truth for Image 4

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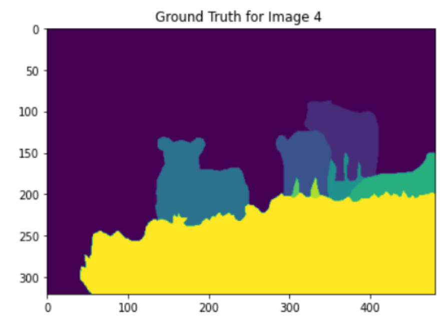
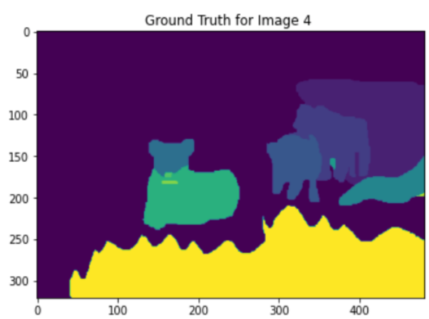

Ground Truth for Image 4

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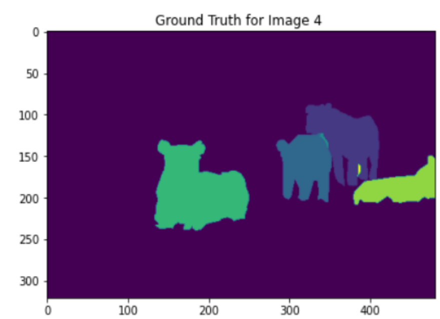
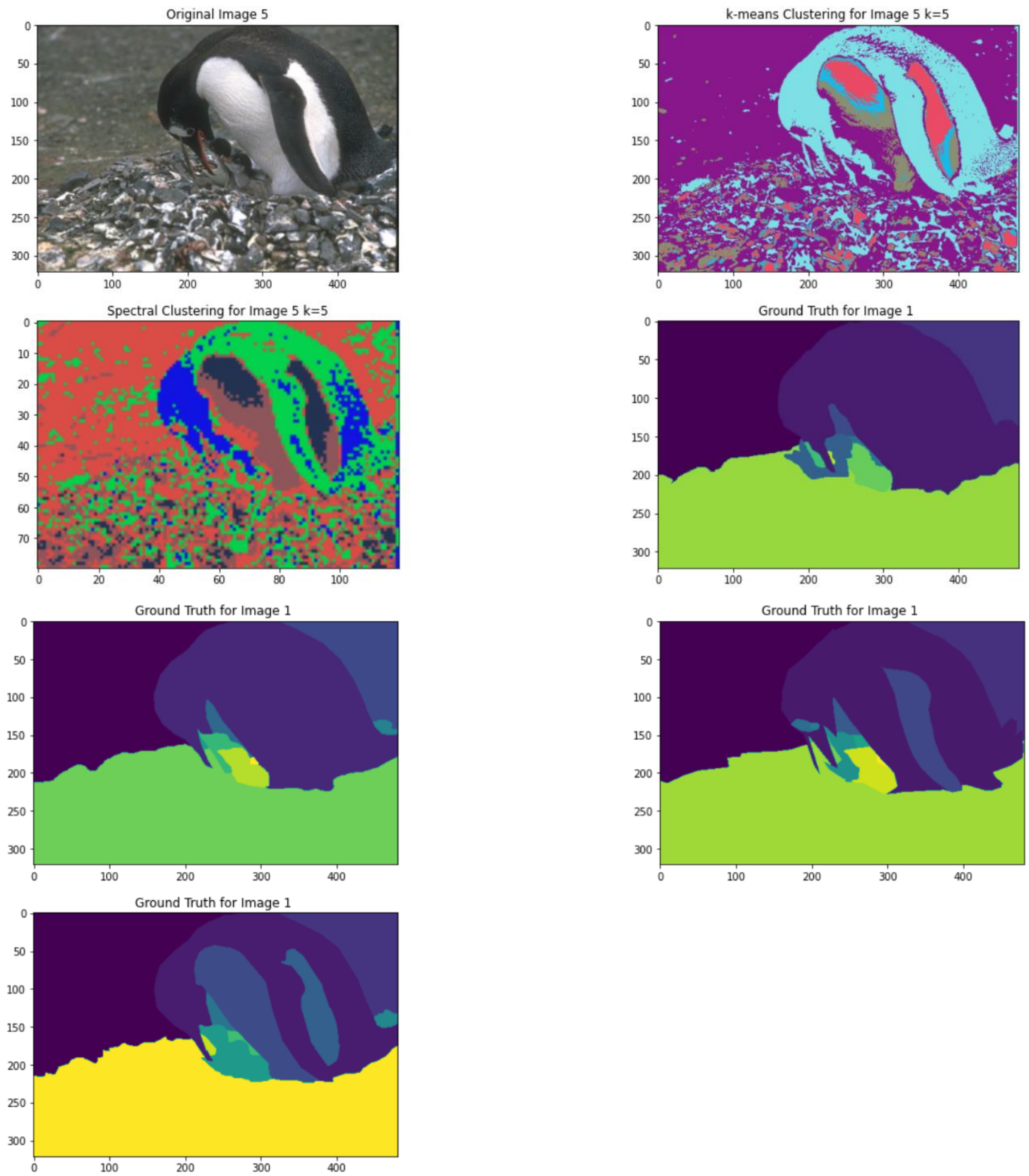
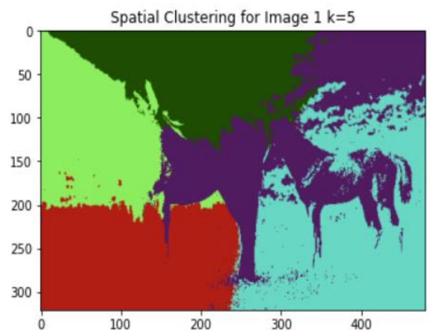
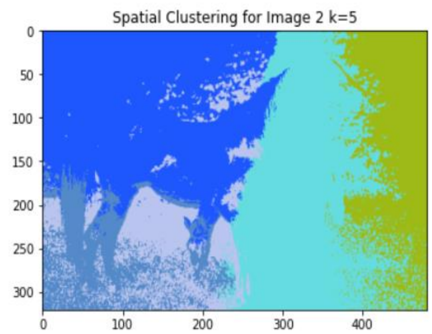

Ground Truth for Image 4

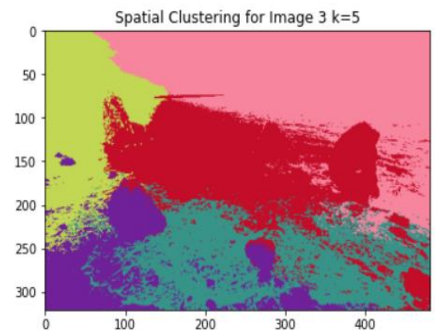

Original Image 5
k-means Clustering for Image 5 k=5
Spectral Clustering for Image 5 k=5
Ground Truth for Image 1
Ground Truth for Image 1
Ground Truth for Image 1
Ground Truth for Image 1

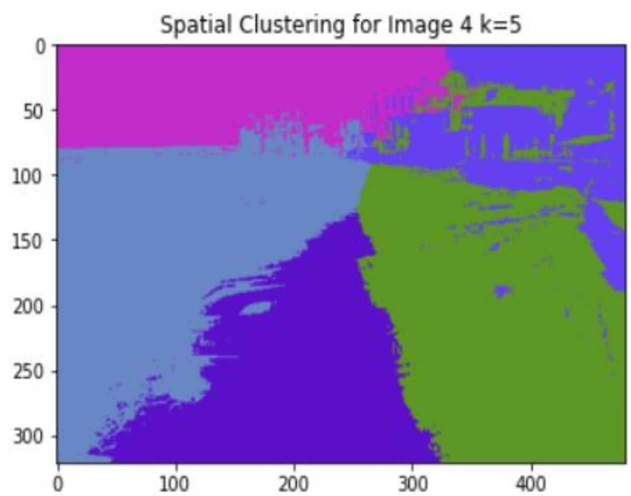
5. **Extra**

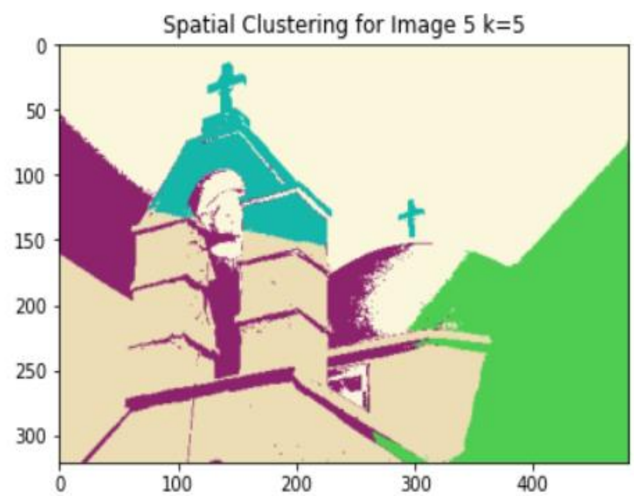
Previously the color features RGB was used but Spatial constraints are expressed by points on adjacent positions, which cannot be segmented only by color gaps so, the layout of the pixels was encoded and the K-means algorithm was modified to consider the spatial constraints by sending to the previously implemented K-means function (M*N,5) matrix , where each pixel location(encoded) is added the following results were obtained when comparing these results with the ones obtained using the regular K-means algorithm in part 2.a :











CONCLUSION

- kernel clustering method such as K-Means and Spectral Clustering have different properties. K-Means is preferable for data that has properties of compactness while Spectral Clustering for data that has properties of connectivity/sparsity (suitable for body pose estimation, foreground extraction, etc.)
- Spectral Clustering is more computationally expensive than K-Means for large datasets because it needs to do the eigen decomposition (low-dimensional space).
- Both results of clustering method may vary, depends on the centroids initialization type.

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