Assignment 1

A superpixel can be defined as a group of pixels that share common characteristics. Simple Linear Iterative Clustering (SLIC) generates superpixels by clustering pixels based on their color similarity and proximity in the image plane. The purpose of this assignment is to understand and implement SLIC Superpixels.

Some pointers before we start:

- Please follow all submission guidlines which are posted on piazza.
- Ensure all outputs are displayed while rendering the PDF.
- Only modify the code blocks which has a "TODO".
- Below you can see some outputs for an image of a cow. These images represent the kind of output that is expected.
- Feel free to reach out to any of the TAs for any doubts/issues.

In [1]:
```
import sys
sys.path
sys.path.remove("/opt/ros/kinetic/lib/python2.7/dist-packages")
```

Let's download the dataset first.

In [2]:
```
!wget http://download.microsoft.com/download/A/1/1/A116CD80-5B79-407E
-B5CE-3D5C6ED8B0D5/msrc_objcategimagedatabase_v1.zip
```

```
--2020-10-28 13:07:51--  http://download.microsoft.com/download/A/1/
1/A116CD80-5B79-407E-B5CE-3D5C6ED8B0D5/msrc_objcategimagedatabase_v1.
zip
Resolving download.microsoft.com (download.microsoft.com)... 23.196.8
0.245, 2600:1408:10:296::e59, 2600:1408:10:283::e59
Connecting to download.microsoft.com (download.microsoft.com)|23.196.
80.245|:80... connected.
HTTP request sent, awaiting response... 200 OK
Length: 44119839 (42M) [application/octet-stream]
Saving to: ‘msrc_objcategimagedatabase_v1.zip’

msrc_objcategimaged 100%[===================>]  42.08M  2.12MB/s    i
n 18s

2020-10-28 13:08:09 (2.31 MB/s) - ‘msrc_objcategimagedatabase_v1.zip’
saved [44119839/44119839]
```

In [3]:
```
!unzip --qq msrc_objcategimagedatabase_v1.zip
```

We only focus on six images in this assignment.

In [4]:
```
im_list = ['MSRC_ObjCategImageDatabase_v1/1_22_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/1_27_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/3_3_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/3_6_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/6_5_s.bmp',
           'MSRC_ObjCategImageDatabase_v1/7_19_s.bmp']
```

In [5]:
```
#All important functions to plot, do not modify this block
%matplotlib inline
import cv2
import matplotlib.pyplot as plt
import numpy as np
import random
import matplotlib.patches as mpatches


def plot_image(im, title, xticks=[], yticks= [], isCv2 = True):
    """
        im: Image to plot
        title: Title of image
        xticks: List of tick values. Defaults to nothing
        yticks: List of tick values. Defaults to nothing
        isCv2: Is the image cv2 image? cv2 images are BGR instead of
 RGB. Default True
    """
    plt.figure()
    if isCv2:
        im = im[:, :, ::-1]
    plt.imshow(im)
    plt.title(title)
    plt.xticks(xticks)
    plt.yticks(yticks)

def superpixel_plot(im, seg, title="Superpixels"):
    """
        Given an image (nXmX3) and pixelwise class mat (nXm),
        1. Consider each class as a superpixel
        2. Calculate mean superpixel value for each class
        3. Replace the RGB value of each pixel in a class with the me
an value

        Inputs:
        im: Input image
        seg: Segmentation map
        title: Title of the plot

        Output: None
        Creates a plot
    """
    clust = np.unique(seg)
    mapper_dict = {i: im[seg == i].mean(axis = 0)/255. for i in clust
}

    seg_img =  np.zeros((seg.shape[0], seg.shape[1], 3))
    for i in clust:
        seg_img[seg == i] = mapper_dict[i]

    plot_image(seg_img, title)
    return

def rgb_segment(seg, n=None, plot=True, title=None, legend=True, colo
r=None):
    """
```

```
    Given a segmentation map, get the plot of the classes
    """
    clust = np.unique(seg)
    if n is None:
        n = len(clust)
    if color is None:
        cm = plt.cm.get_cmap('hsv', n+1)
        mapper_dict = {i:np.random.rand(3,) for i in clust}

    seg_img =  np.zeros((seg.shape[0],seg.shape[1],3))
    for i in clust:
        seg_img[seg == i] = mapper_dict[i][:3]

    if plot:
        plot_image(seg_img,title = title)
    if legend:
        # get the colors of the values, according to the
        # colormap used by imshow
        patches = [ mpatches.Patch(color=mapper_dict[i], label=" :
{l}".format(l=i) ) for i in range(n) ]
        # put those patched as legend-handles into the legend
        plt.legend(handles=patches, bbox_to_anchor=(1.05, 1), loc=2,
borderaxespad=0. )
        plt.grid(True)
        plt.show()

    return seg_img
```

Let's see what the six images are:

In [6]:
```
for i in im_list:
    plot_image(cv2.imread(i),i.split("/")[-1])
```

1_22_s.bmp

1_27_s.bmp

3_3_s.bmp

3_6_s.bmp

6_5_s.bmp

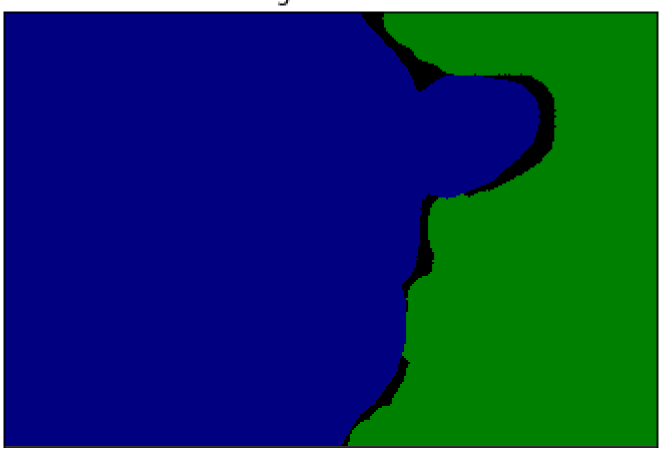
7_19_s.bmp

Get image and visualize it. Its a scenery with 3 elements. You can see the segmentation ground truth in the GT bitmap.

In [7]:
```
im = cv2.imread(im_list[0])
seg = cv2.imread(im_list[0].replace("_s","_s_GT"))

plot_image(im,"Image")
plot_image(seg,"Segmentation")
```

Image

Segmentation



Question 1: K-means on RGB

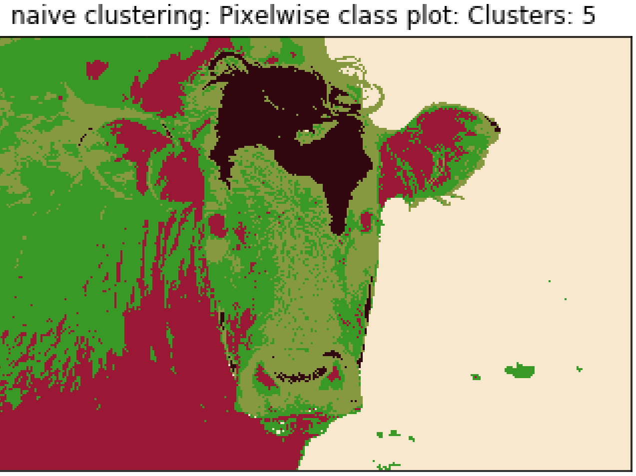
We know k-means clustering algorithm. It is an unsupervised algorithm which minimizes **the within-cluster sum of squares(WCSS).

Complete the pixel clustering function. It should take input an image (dim = (n $\times$ m $\times$ 3)) and number of clusters needed. Does K means clustering work on image pixels? Let the number of clusters be K = 5, 10, 50

In [8]:
```
# KMeans algo
def k_means_algo(k, samples, weight=np.array([])):
    """
        Inputs:
        k: the number of clusters
        samples: the input datapoints

        Output:
        cluster_labels: the cluster number for each sample
    """
    # choose initial clusters according to kmeans++ paper
    if len(weight)>0:
        samples_new = samples*np.sqrt(weight)
    else:
        samples_new = samples
    kcentroids = np.array([random.choice(samples)])
    while len(kcentroids) < k:
        # compute D(x)
        distance = np.ones(len(samples))*10000000000
        for i in range(0, len(kcentroids)):
            if len(weight)>0:
                kcentroids_new = kcentroids[i]*np.sqrt(weight)
            else:
                kcentroids_new = kcentroids[i]
            distance = np.vstack((distance, np.linalg.norm(samples_ne
w-kcentroids_new, axis=1)))
        distance = distance[1:]
        distance = np.min(distance, axis=0)

        # pick next center randomly with weighted probability
        kcentroids = np.vstack((kcentroids, random.choices(samples, d
istance*distance)[0]))


    # run k-means
    iter = 1000
    curr_iter = 1
    hash_clusters = {}
    cluster_labels = np.array([])
    while curr_iter < iter:
        curr_iter += 1

        cluster_labels = np.array([])
        distance = np.ones(len(samples))*1000000000000
        for i in range(0, k):
            if len(weight)>0:
                kcentroids_new = kcentroids[i]*np.sqrt(weight)
            else:
                kcentroids_new = kcentroids[i]
            distance = np.vstack((distance, np.linalg.norm(samples_ne
w-kcentroids_new, axis=1)))
        distance = distance[1:]
        cluster_labels = np.argmin(distance, axis=0)

        kcentroids = np.array([])
        for i in range(0, k):
```

```
            indices_i = np.where(cluster_labels==i)
            new_centroid_i = np.sum(samples[indices_i], axis=0)/len(i
ndices_i[0])

            if(len(kcentroids) == 0):
                kcentroids = np.array([new_centroid_i])
            else:
                kcentroids = np.vstack((kcentroids, new_centroid_i))

    # return cluster number for each sample
    return cluster_labels
```

In [9]:
```
from sklearn.cluster import KMeans
import numpy as  np


def cluster_pixels(im, k):
    """
    Inputs:
        im: the input image of shape (n, m, 3)
        k: the number of clusters

    Output:
        segmap: the output shape of (n, m) where each entry is the cl
uster index it belongs to
    """
    image = []
    for row in range(0, im.shape[0]):
        for col in range(0, im.shape[1]):
            image.append([im[row, col, 0], im[row, col, 1], im[row, c
ol, 2]])
    segmap = k_means_algo(k, np.array(image))
    segmap = np.array(segmap)
    segmap = segmap.reshape(im.shape[0], im.shape[1])
    return segmap

for k in [5, 10, 50]:
    clusters = cluster_pixels(im, k)
    _ = rgb_segment(clusters, n=k, title="naive clustering: Pixelwise
class plot: Clusters: " + str(k),legend = False)
    superpixel_plot(im, clusters, title =  "naive clustering: Superpi
xel plot: Clusters: "+ str(k))
```

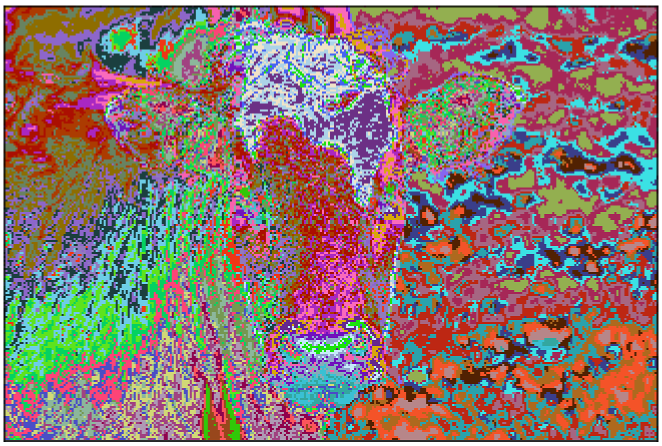

naive clustering: Pixelwise class plot: Clusters: 5


naive clustering: Superpixel plot: Clusters: 5


naive clustering: Pixelwise class plot: Clusters: 10

naive clustering: Superpixel plot: Clusters: 10

naive clustering: Pixelwise class plot: Clusters: 50



naive clustering: Superpixel plot: Clusters: 50

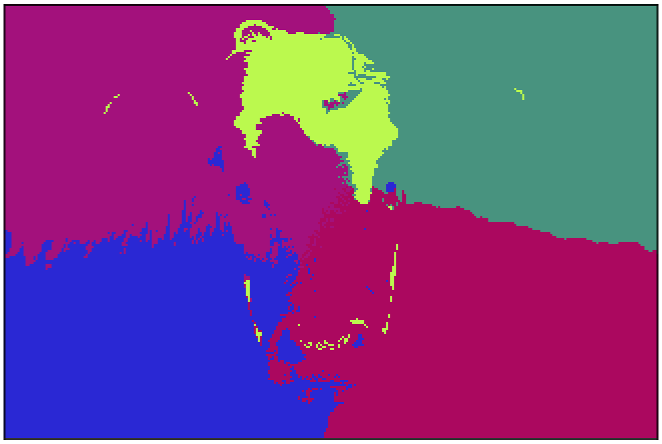
Question 2: Now that you have a function handy, we have a slightly complex task

Instead of making clustering run on RGB space, run the clustering on RGBXY space. What advantages does that give us? (try with clusters = 5, 10, 25, 50, 150)

Answer: The advantages this approach might give is that instead of just considering the color distance, we are also taking into account the pixel proximity, i.e how near the pixels are to each other.

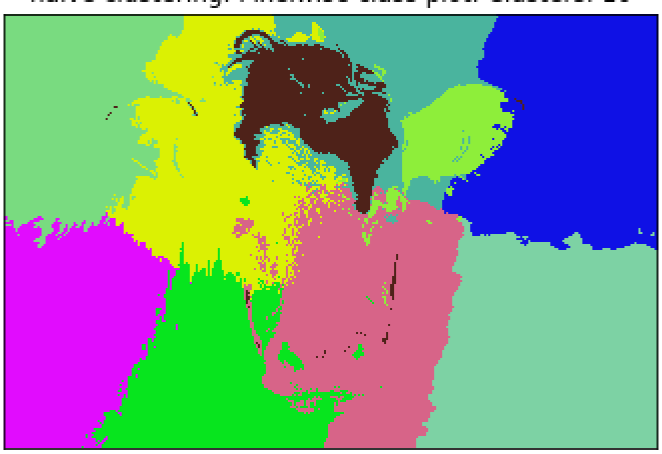
In [12]:
```
#TODO: clustering r,b,g,x,y values
#try k = 20,80,200,400,800

def cluster_rgbxy(im, k):
    """
    Inputs:
        im: the input image of shape (n, m, 3)
        k: the number of clusters

    Output:
        segmap: the output shape of (n, m) where each entry is the cl
uster index it belongs to
    """
    image = []
    for row in range(0, im.shape[0]):
        for col in range(0, im.shape[1]):
            image.append((im[row, col, 0], im[row, col, 1], im[row, c
ol, 2], row, col))
    image = np.array(image)
    segmap = k_means_algo(k, np.array(image))
    segmap = np.array(segmap)
    segmap = segmap.reshape(im.shape[0], im.shape[1])
    return segmap

for k in [5, 10, 20, 50, 80, 150, 200, 400, 800]:
    clusters = cluster_rgbxy(im, k)
    _ = rgb_segment(clusters, n=k, title="naive clustering: Pixelwise
class plot: Clusters: " + str(k), legend=False)
    superpixel_plot(im, clusters, title="naive clustering: Superpixel
plot: Clusters: "+ str(k))
```

naive clustering: Pixelwise class plot: Clusters: 5



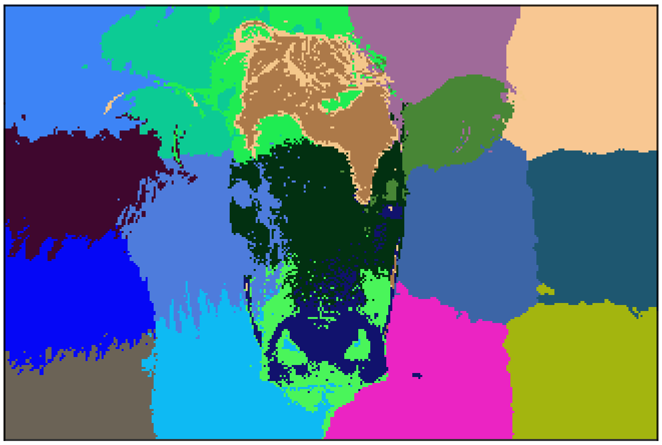
naive clustering: Superpixel plot: Clusters: 5

naive clustering: Pixelwise class plot: Clusters: 10



naive clustering: Superpixel plot: Clusters: 10

naive clustering: Pixelwise class plot: Clusters: 20

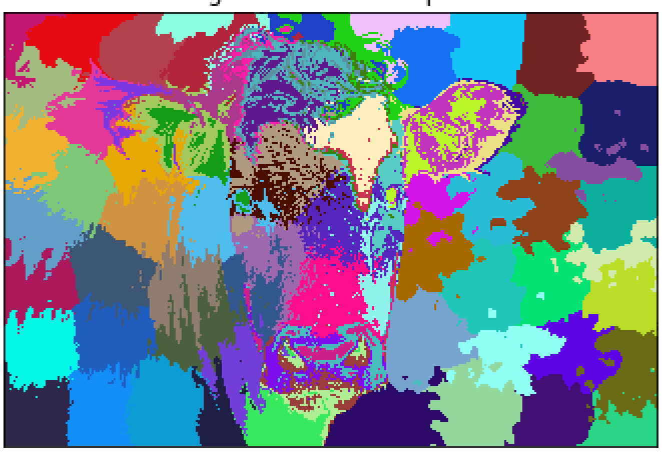


naive clustering: Superpixel plot: Clusters: 20

naive clustering: Pixelwise class plot: Clusters: 50

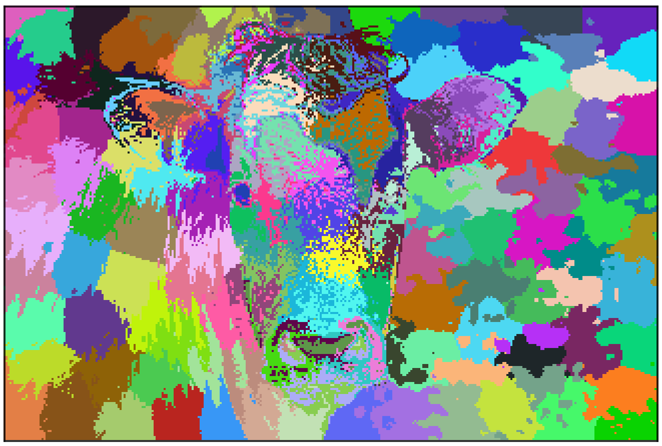
naive clustering: Superpixel plot: Clusters: 50

naive clustering: Pixelwise class plot: Clusters: 80

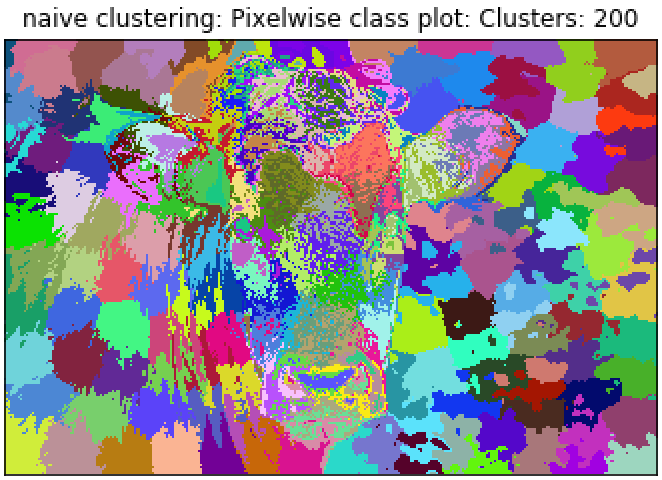


naive clustering: Superpixel plot: Clusters: 80

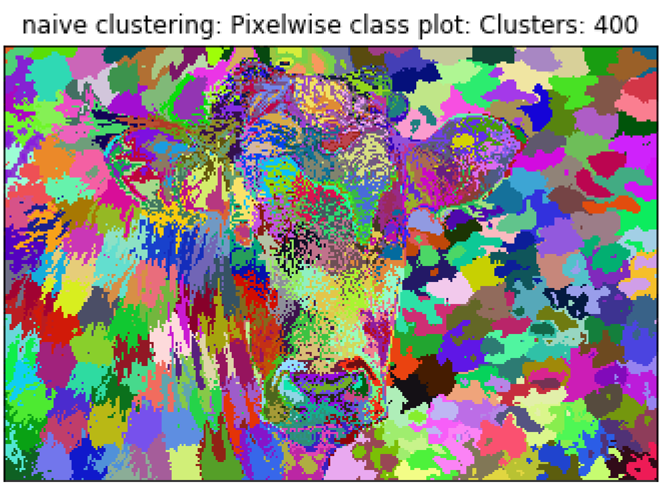
naive clustering: Pixelwise class plot: Clusters: 150



naive clustering: Superpixel plot: Clusters: 150


naive clustering: Pixelwise class plot: Clusters: 200


naive clustering: Superpixel plot: Clusters: 200


naive clustering: Pixelwise class plot: Clusters: 400

naive clustering: Superpixel plot: Clusters: 400

naive clustering: Pixelwise class plot: Clusters: 800

naive clustering: Superpixel plot: Clusters: 800

Modified k-means with weighted distances.

Let $cluster\_center_i$ represent i^{th} cluster center, $cluster\_center_i^{rgb}$ denote the RGB value and $cluster\_center_i^{xy}$ be the corresponding coordinate of the center pixel, respectively.

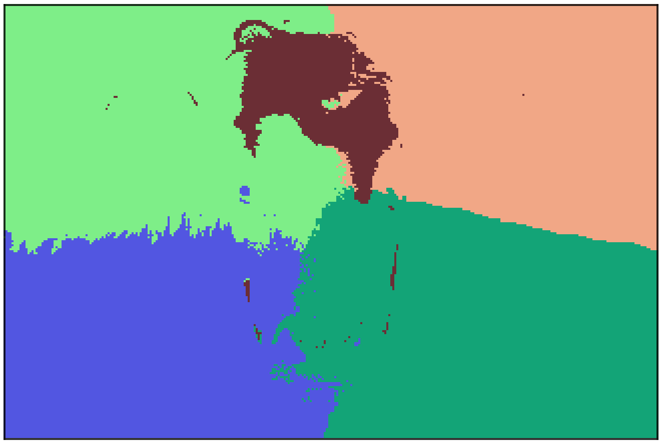
Let x_{rgb} be the the RGB value of a pixel, and let x_{xy} be the corresponding pixel's coordinate.

$$distance(x_{rgb}, x_{xy}) = \lambda_1 * euclidean(x_{rgb}, cluster\_center_i^{rgb}) + \lambda_2 * euclidean(x_{xy}, cluster\_center_i^{xy})$$

Find good values for hyperparmeters λ_1 and λ_2 (try on 250 clusters)

In [14]:
```
#TODO: clustering r,b,g,x,y values with lambdas and display outputs
def cluster_rgbxy(im, k, lambda_1, lambda_2):
    """
    Inputs:
        im: the input image of shape (n, m, 3)
        k: the number of clusters
        lambda_1: the weight value for rgb channels
        lambda_2: the weight value for xy
    Output:
        segmap: the output shape of (n, m) where each entry is the cl
uster index it belongs to
    """
    image = []
    for row in range(0, im.shape[0]):
        for col in range(0, im.shape[1]):
            image.append((im[row, col, 0], im[row, col, 1], im[row, c
ol, 2], row, col))
    segmap = k_means_algo(k, np.array(image), weight=np.array([lambda
_1, lambda_1, lambda_1, lambda_2, lambda_2]))
    segmap = np.array(segmap)
    segmap = segmap.reshape(im.shape[0], im.shape[1])
    return segmap

for k in [5]:
    clusters = cluster_rgbxy(im, k, 9, 16)
    _ = rgb_segment(clusters, n=k, title="naive clustering: Pixelwise
class plot: Clusters: " + str(k), legend=False)
    superpixel_plot(im, clusters, title="naive clustering: Superpixel
plot: Clusters: "+ str(k))
```

naive clustering: Pixelwise class plot: Clusters: 5



naive clustering: Superpixel plot: Clusters: 5

Question 3: SLIC

It doesn't look like we have a very favourable outcome with superpixels simply being implemented as K-means. Can we do better? Have a look at the SLIC paper [here (https://www.iro.umontreal.ca/~mignotte/IFT6150/Articles/SLIC_Superpixels.pdf)](https://www.iro.umontreal.ca/~mignotte/IFT6150/Articles/SLIC_Superpixels.pdf). Incorporate S and m and redefine your distance metric as per the paper.

In [15]:
```
# SLIC algo
def slic_algo(k, image, s, m=10):
    """
        Inputs:
        k: the number of clusters
        image: the input image
        s: parameter for slic algo
        m: hyperparameter for slic algo

        Output:
        cluster_labels: the cluster number for each sample
    """
    # initialize the cluster centers
    kcentroids = np.array([])
    height_image = int(image.shape[0])
    width_image = int(image.shape[1])
    curr_height = int(s // 2)
    curr_width = int(s // 2)
    flag = 0
    while curr_height < height_image:
        while curr_width < width_image:
            if len(kcentroids) == 0:
                kcentroids = np.array([curr_height, curr_width, image
[curr_height, curr_width, 0], image[curr_height, curr_width, 1], imag
e[curr_height, curr_width, 2]])
            else:
                flag = 1
                kcentroids = np.vstack((kcentroids, np.array([curr_he
ight, curr_width, image[curr_height, curr_width, 0], image[curr_heigh
t, curr_width, 1], image[curr_height, curr_width, 2]])))
            curr_width += s
            curr_width = int(curr_width)

            # if k clusters found
            if len(kcentroids) == k and flag == 1:
                break
        curr_width = s // 2
        curr_width = int(curr_width)
        curr_height += s
        curr_height = int(curr_height)

        # if k clusters found
        if len(kcentroids) == k and flag == 1:
            break

    # perturb cluster centers to lowest gradient position
    for i in range(0, len(kcentroids)):
        cluster_x = int(kcentroids[i, 0])
        cluster_y = int(kcentroids[i, 1])
        if (cluster_x+1) >= image.shape[0]:
            cluster_x = int(image.shape[0]-2)
        if (cluster_y+1) >= image.shape[1]:
            cluster_y = int(image.shape[1]-2)
        curr_grad = int(image[cluster_x+1, cluster_y+1, 0]) - int(ima
ge[cluster_x, cluster_y, 0]) + int(image[cluster_x+1, cluster_y+1, 1
]) - int(image[cluster_x, cluster_y, 1]) + int(image[cluster_x+1, clu
```

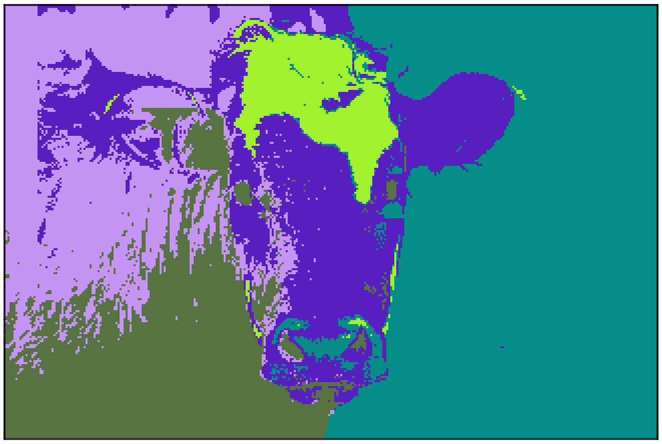
```
ster_y+1, 2]) - int(image[cluster_x, cluster_y, 2])
        for dh in range(-1, 2):
            for dw in range(-1, 2):
                new_cluster_x = int(cluster_x + dh)
                new_cluster_y = int(cluster_y + dw)
                if (new_cluster_x+1) >= image.shape[0]:
                    new_cluster_x = image.shape[0]-2
                if (new_cluster_y+1) >= image.shape[1]:
                    new_cluster_y = image.shape[1]-2
                new_grad = int(image[new_cluster_x+1, new_cluster_y+1
, 0]) - int(image[new_cluster_x, new_cluster_y, 0]) + int(image[new_c
luster_x+1, new_cluster_y+1, 1]) - int(image[new_cluster_x, new_clust
er_y, 1]) + int(image[new_cluster_x+1, new_cluster_y+1, 2]) - int(ima
ge[new_cluster_x, new_cluster_y, 2])

                if new_grad < curr_grad:
                    curr_grad = new_grad
                    kcentroids[i, 0] = int(new_cluster_x)
                    kcentroids[i, 1] = int(new_cluster_y)
                    kcentroids[i, 2] = image[int(kcentroids[i, 0]), i
nt(kcentroids[i, 1]), 0]
                    kcentroids[i, 3] = image[int(kcentroids[i, 0]), i
nt(kcentroids[i, 1]), 1]
                    kcentroids[i, 4] = image[int(kcentroids[i, 0]), i
nt(kcentroids[i, 1]), 2]


    # run slic with initialized cluster centers
    cluster_labels = np.zeros((image.shape[0], image.shape[1]))
    for i in range(0, 100):

        # for each cluster
        pixels_distance = np.ones((image.shape[0], image.shape[1]))*1
000000000000
        cluster_labels = np.ones((image.shape[0], image.shape[1]))*-1
        new_kcentroids = np.zeros((len(kcentroids), 3))
        for j in range(0, len(kcentroids)):

            # scan 2S x 2S region
            for h in range(int(kcentroids[j, 0]-s), int(kcentroids[j,
0]+s)):
                if h<0 or h>=image.shape[0]:
                    continue

                for w in range(int(kcentroids[j, 1]-s), int(kcentroid
s[j, 1]+s)):
                    if w<0 or w>=image.shape[1]:
                        continue

                    distance_lab = np.sqrt((int(image[h, w, 0]) - kce
ntroids[j, 2])*(int(image[h, w, 0]) - kcentroids[j, 2]) + (int(image[
h, w, 1]) - kcentroids[j, 3])*(int(image[h, w, 1]) - kcentroids[j, 3
]) + (int(image[h, w, 2]) - kcentroids[j, 4])*(int(image[h, w, 2]) -
kcentroids[j, 4]))
                    distance_xy = np.sqrt((h-kcentroids[j, 0])*(h-kce
ntroids[j, 0]) + (w-kcentroids[j, 1])*(w-kcentroids[j, 1]))
                    distance = distance_lab + (m/s)*distance_xy
```

```
                    if distance<pixels_distance[h, w]:
                        pixels_distance[h, w] = distance
                        if cluster_labels[h, w] != -1:
                            new_kcentroids[int(cluster_labels[h, w]),
0] -= h
                            new_kcentroids[int(cluster_labels[h, w]),
1] -= w
                            new_kcentroids[int(cluster_labels[h, w]),
2] -= 1
                        cluster_labels[h, w] = j
                        new_kcentroids[j, 0] += h
                        new_kcentroids[j, 1] += w
                        new_kcentroids[j, 2] += 1

        # update cluster centers
        for j in range(0, len(kcentroids)):
            kcentroids[j, 0] = int(new_kcentroids[j, 0] // new_kcentr
oids[j, 2])
            kcentroids[j, 1] = int(new_kcentroids[j, 1] // new_kcentr
oids[j, 2])
            kcentroids[j, 2] = image[int(kcentroids[j, 0]), int(kcent
roids[j, 1]), 0]
            kcentroids[j, 3] = image[int(kcentroids[j, 0]), int(kcent
roids[j, 1]), 1]
            kcentroids[j, 4] = image[int(kcentroids[j, 0]), int(kcent
roids[j, 1]), 2]

    # return cluster number for each pixel of image
    return cluster_labels
```

In [16]:
```
#TODO
###########Algorithm###########
#Compute grid steps: S
#you can explore different values of m
#initialize cluster centers [l,a,b,x,y] using
#Perturb for minimum G
#while not converged
##for every pixel:
####  compare distance D_s with each cluster center within 2S X 2S.
####  Assign to nearest cluster
##calculate new cluster center


def SLIC(im, k):
    """
    Input
        im: image input
        k: number of cluster segments

        Compute
        S: As described in the paper
        m: As described in the paper (use the same value as in the pa
per) follow the algorithm..

    Output
        segmap: 2D matrix where each value corresponds to the image p
ixel's cluster number
    """
    s = np.sqrt((im.shape[0]*im.shape[1]) / k)
    lab_image = cv2.cvtColor(im, cv2.COLOR_BGR2LAB)
    segmap = slic_algo(k, lab_image, s)
    segmap = segmap.reshape(im.shape[0], im.shape[1])
    return segmap
```

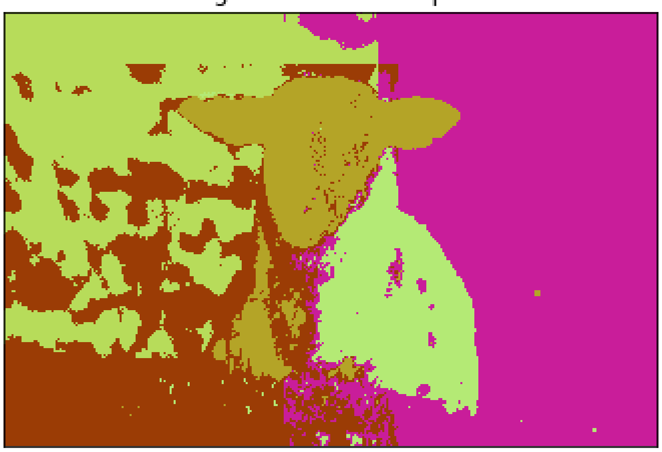
In [17]:
```
#TODO diplay your SLIC results.
for i in im_list:
    im = cv2.imread(i)
    for k in [5]:
        clusters = SLIC(im, k)
        _ = rgb_segment(clusters, n=k, title="naive clustering: Pixel
wise class plot: Clusters: " + str(k), legend=False)
        superpixel_plot(im, clusters, title="naive clustering: Superp
ixel plot: Clusters: " + str(k))
```

naive clustering: Pixelwise class plot: Clusters: 5



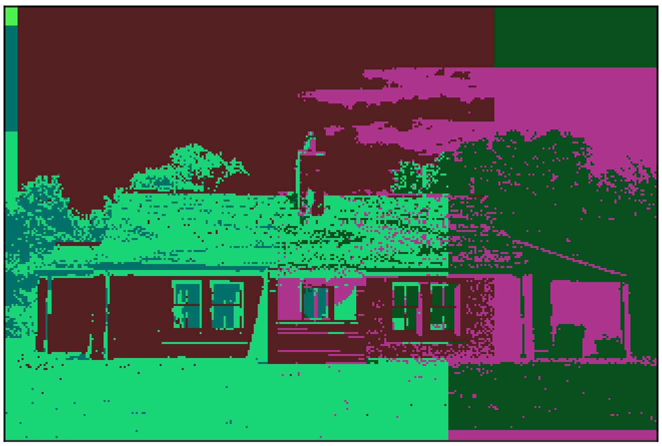
naive clustering: Superpixel plot: Clusters: 5

naive clustering: Pixelwise class plot: Clusters: 5



naive clustering: Superpixel plot: Clusters: 5

naive clustering: Pixelwise class plot: Clusters: 5

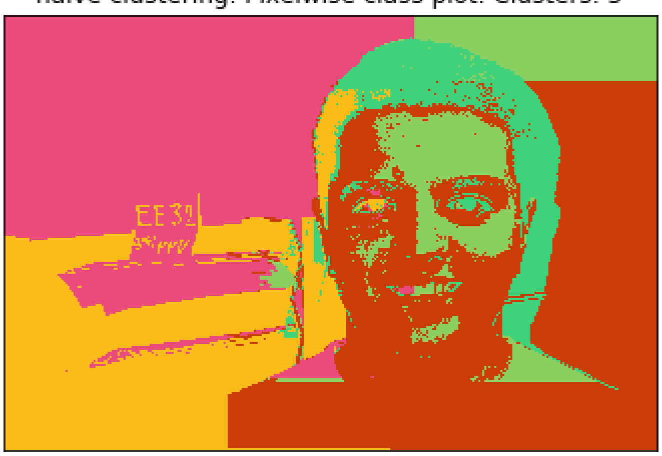


naive clustering: Superpixel plot: Clusters: 5

naive clustering: Pixelwise class plot: Clusters: 5

naive clustering: Superpixel plot: Clusters: 5

naive clustering: Pixelwise class plot: Clusters: 5



naive clustering: Superpixel plot: Clusters: 5

naive clustering: Pixelwise class plot: Clusters: 5

naive clustering: Superpixel plot: Clusters: 5

Bonus Question:

Enforce connectivity: There are many superpixels which are very small and disconnected from each other. Try to merge them with larger superpixels

O(N) algorithm:

1. Set a minimum size of superpixel
2. If the area of a region is smaller than a threshold, we assign it to the nearest cluster

In [ ]:
```
#TODO
```

Your File

Link to your colab/ipynb file: **Insert google drive/colab link here**