Untitled

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1 Assignment 4

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```
In []: import sys
        import numpy as np
        import cv2 as cv
        import igraph
        from matplotlib import pyplot as plt
        from copy import deepcopy
        import os
        from gaussian import GaussianMixture
In []: BG = 0
     FG = 1
     PR_BG = 2
     PR_FG = 3
```

1.1 Grabcut

- We give a bounding box.
- Assign GMM components to pixels
- Learn GMM parameters from data
- Make graph(n-links between pixels and t-links between source, sink and pixels)
- Estimate segmentation: use min cut to solve
- Repeat the process

1.2 Class GrabCut

- It has function for calculating beta.
- Assigning GMM and calculating component for each pixel.
- Modelling Graph
- Estimate Segmentation

1.3 Implementation Details

- I have used Gaussian Mixture code from github
- For making graph I have used igraph package

- Once we have gaussian trained we make graph.
- Then we calculate mincut.
- the process is repeated

```
In [29]: class GrabCut:
             def __init__(self, img, mask, rect=None, gmm_components=5, neighbours=8):
                 self.img = np.asarray(img, dtype=np.float64)
                 self.out_image = deepcopy(img)
                 self.rows, self.cols, _ = img.shape
                 self.mask = mask
                 self.neighbours = neighbours
                 if rect is not None:
                     self.mask[rect[1]:rect[1] + rect[3], rect[0]:rect[0] +
                               rect[2] = PR_FG
                 self.classify_pixels()
                 self.gmm_components = gmm_components
                 self.gamma = 50
                 self.calculate_beta_smoothness()
                 self.fgd_gmm = GaussianMixture(self.img[self.fgd_indexes])
                 self.bgd_gmm = GaussianMixture(self.img[self.bgd_indexes])
                 self.label_gmm = np.empty((self.rows, self.cols), dtype=np.uint32)
                 self.gc_source = self.cols * self.rows # "object" terminal S
                 self.gc_sink = self.gc_source + 1 # "background" terminal T
             def calculate_beta_smoothness(self):
                 left_diff = self.img[:, 1:] - self.img[:, :-1]
                 up_left_diff = self.img[1:, 1:] - self.img[:-1, :-1]
                 up_diff = self.img[1:, :] - self.img[:-1, :]
                 up_right_diff = self.img[1:, :-1] - self.img[:-1, 1:]
                 self.beta = np.linalg.norm(left_diff)**2 + np.linalg.norm(up_diff)**2
                 if self.neighbours == 8:
                     self.beta += np.linalg.norm(up_left_diff)**2 + np.linalg.norm(
                         up_right_diff)**2
                           self.beta = np.sum(np.square(left\_diff)) + np.sum(np.square(up\_left\_diff))
                 #
                 #
                               np.sum(np.square(up\_diff)) + 
                               np.sum(np.square(up_right_diff))
                 if self.neighbours == 8:
                     self.beta = 2.0 * self.beta / (4 * self.rows * self.cols - 3 *
                                                     (self.rows + self.cols) + 2.0)
                 else:
                     self.beta = 2.0 * self.beta / (2 * self.rows * self.cols - 1 *
                                                     (self.rows + self.cols) + 2.0)
```

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self.beta = 1 / self.beta
             print(self.beta)
    def calculate V(x):
        return self.gamma * np.exp(
            -self.beta * np.sum(np.square(x), axis=2))
    self.left_V = calculate_V(left_diff)
    self.up_left_V = calculate_V(up_left_diff)
    self.up_V = calculate_V(up_diff)
    self.up_right_V = calculate_V(up_right_diff)
def classify_pixels(self):
    self.fgd_indexes = np.where((self.mask == FG) | (self.mask == PR_FG))
    self.bgd_indexes = np.where((self.mask == BG) | (self.mask == PR_BG))
def assign_GMM(self):
    self.label_gmm[self.fgd_indexes] = self.fgd_gmm.which_component(
        self.img[self.fgd_indexes])
    self.label_gmm[self.bgd_indexes] = self.bgd_gmm.which_component(
        self.img[self.bgd_indexes])
def learn_GMM(self):
    self.fgd_gmm.fit(self.img[self.fgd_indexes],
                     self.label_gmm[self.fgd_indexes])
    self.bgd_gmm.fit(self.img[self.bgd_indexes],
                     self.label_gmm[self.bgd_indexes])
def make_n_links(self, mask1, mask2, V):
   mask1 = mask1.reshape(-1)
    mask2 = mask2.reshape(-1)
    self.gc_graph_capacity += V.reshape(-1).tolist()
    return list(zip(mask1, mask2))
def construct_gc_graph(self):
    fgd_indexes = np.where(self.mask.reshape(-1) == FG)
    bgd_indexes = np.where(self.mask.reshape(-1) == BG)
    pr_indexes = np.where((self.mask.reshape(-1) == PR_FG)
                          | (self.mask.reshape(-1) == PR_BG))
    self.gc_graph_capacity = []
    edges = []
    def make_edges(source, sinks):
        return list(zip([source] * sinks[0].size, sinks[0]))
    edges += make_edges(self.gc_source, pr_indexes)
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self.bgd_gmm.calc_prob(self.img.reshape(-1, 3)[pr_indexes])))
    edges += make_edges(self.gc_sink, pr_indexes)
    self.gc_graph_capacity += list(-np.log(
        self.fgd_gmm.calc_prob(self.img.reshape(-1, 3)[pr_indexes])))
    edges += make_edges(self.gc_source, fgd_indexes)
    self.gc_graph_capacity += [9 * self.gamma] * fgd_indexes[0].size
    edges += make_edges(self.gc_sink, fgd_indexes)
    self.gc_graph_capacity += [0] * fgd_indexes[0].size
    edges += make_edges(self.gc_source, bgd_indexes)
    self.gc_graph_capacity += [0] * bgd_indexes[0].size
    edges += make_edges(self.gc_sink, bgd_indexes)
    self.gc_graph_capacity += [9 * self.gamma] * bgd_indexes[0].size
    img_indexes = np.arange(
        self.rows * self.cols, dtype=np.uint32).reshape(
            self.rows, self.cols)
    edges += self.make_n_links(img_indexes[:, 1:], img_indexes[:, :-1],
                               self.left_V)
    edges += self.make_n_links(img_indexes[1:, :], img_indexes[:-1, :],
                               self.up_V)
    if self.neighbours == 8:
        edges += self.make_n_links(img_indexes[1:, 1:],
                                   img_indexes[:-1, :-1], self.up_left_V)
        edges += self.make_n_links(img_indexes[1:, :-1],
                                   img_indexes[:-1, 1:], self.up_right_V)
    assert (len(edges) == len(self.gc_graph_capacity))
    self.gc_graph = igraph.Graph(self.rows * self.cols + 2)
    self.gc_graph.add_edges(edges)
def estimate_segmentation(self):
    mincut = self.gc_graph.st_mincut(self.gc_source, self.gc_sink,
                                     self.gc_graph_capacity)
    print('foreground pixels: %d, background pixels: %d' % (len(
        mincut.partition[0]), len(mincut.partition[1])))
    pr_indexes = np.where((self.mask == PR_FG) | (self.mask == PR_BG))
    img_indexes = np.arange(
        self.rows * self.cols, dtype=np.uint32).reshape(
            self.rows, self.cols)
    condition = np.isin(img_indexes[pr_indexes], mincut.partition[0])
```

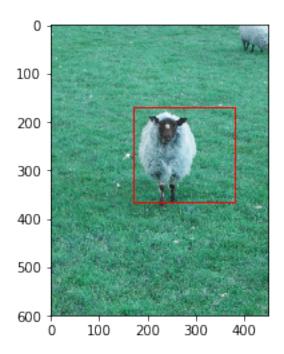
self.gc_graph_capacity += list(-np.log(

```
self.mask[pr_indexes] = np.where(condition, PR_FG, PR_BG)
                 self.classify_pixels()
             def modified_image(self, img2=None):
                 if img2 is None:
                     img2 = deepcopy(self.out_image)
                 mask = self.mask.copy()
                 mask2 = np.where((self.mask == 1) + (self.mask == 3), 255,
                                  0).astype('uint8')
                 return cv.bitwise_and(img2, img2, mask=mask2)
             def run(self, num_iters=2):
                 for _ in range(num_iters):
                     self.assign_GMM()
                     self.learn_GMM()
                     self.construct_gc_graph()
                     self.estimate_segmentation()
                       print("Image after iteration {0}".format(_))
         #
         #
                       plt.imshow(self.modified_image())
                       plt.show()
                       cv.imshow("Image after Iteration {0}".format(_),
         #
                                 self.modified_image())
         #
                       cv.waitKey(0)
                       cv.destroyAllWindows()
In []: def fun(image_path, filename):
            image = cv.imread(image_path)
            f = open(filename, 'r')
            rect = list(f.readline().split())
            rect = [int(i) for i in rect]
            f.close()
            gg = GrabCut(image, np.zeros(image.shape[:2], dtype=np.uint8), rect)
            cv.rectangle(image, (16, 20), (620, 436), (255, 0, 0), 2)
            plt.imshow(image)
            plt.show()
                  cv.waitKey(0)
                  cv. destroyAllWindows()
            gg.run()
            plt.imshow(gg.modified_image())
            plt.show()
In [ ]: image_list = ["images/" + file for file in os.listdir('images')]
        box_list = ["bboxes/" + file for file in os.listdir('bboxes')]
        image_list.sort()
        box_list.sort()
```

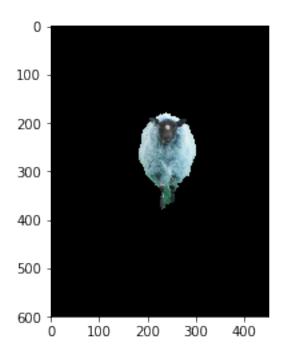
```
for image_path, filename in zip(image_list, box_list):
    fun(image_path, filename)
```

1.4 Various Colour Spaces

```
In [5]: image = cv.imread("images/sheep.jpg")
        rect = (171, 171, 309, 386)
In [6]: def run_on_image(image, rect, image2):
            gg = GrabCut(image, np.zeros(image.shape[:2], dtype=np.uint8), rect)
            plt.imshow(gg.modified_image(image2))
            plt.show()
In [7]: II = deepcopy(image)
        cv.rectangle(II, (171, 171), (380, 366), (255, 0, 0), 2)
        plt.imshow(II)
        plt.show()
        print("RGB")
        run_on_image(image, rect, image)
        print("HSV")
        run_on_image(cv.cvtColor(image, cv.COLOR_BGR2HSV), rect, image)
        print("YUV")
        run_on_image(cv.cvtColor(image, cv.COLOR_BGR2YUV), rect, image)
```

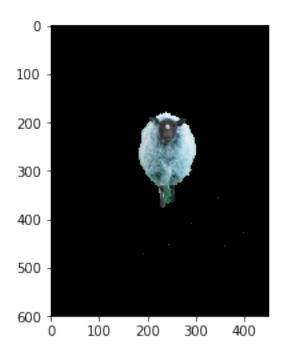


foreground pixels: 15094, background pixels: 254908 foreground pixels: 14954, background pixels: 255048



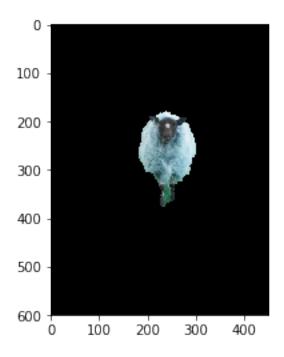
HSV 0.0011274896151577947

foreground pixels: 15119, background pixels: 254883 foreground pixels: 15120, background pixels: 254882



YUV 0.002256453222115342

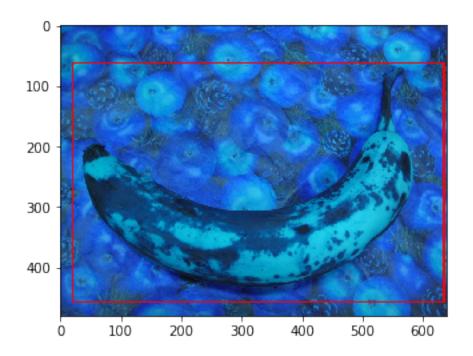
foreground pixels: 15023, background pixels: 254979 foreground pixels: 14626, background pixels: 255376



1.5 Observations:

- There is not much differnce by changing the color space
- Although there can be cases where changing the color space will change the result

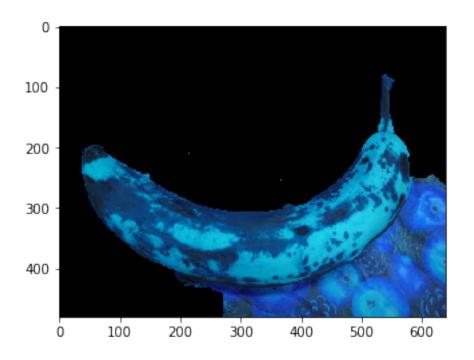
1.6 Number of Iterations



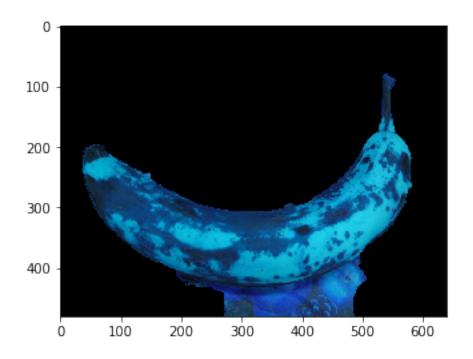
0.0021199558038790126

foreground pixels: 113424, background pixels: 193778

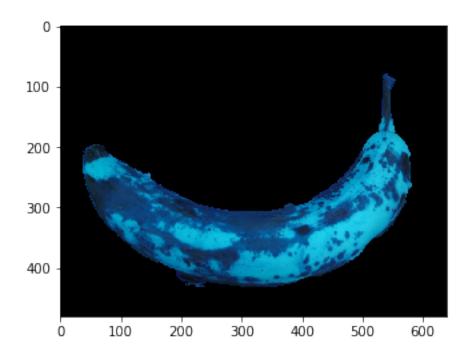
Image after iteration 0



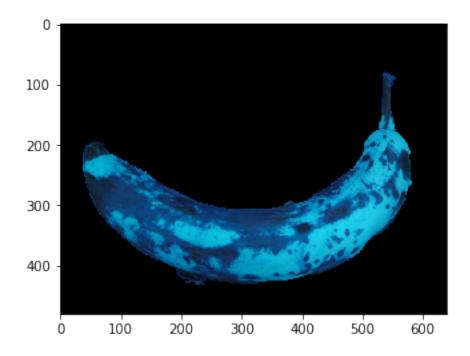
foreground pixels: 87270, background pixels: 219932 Image after iteration 1



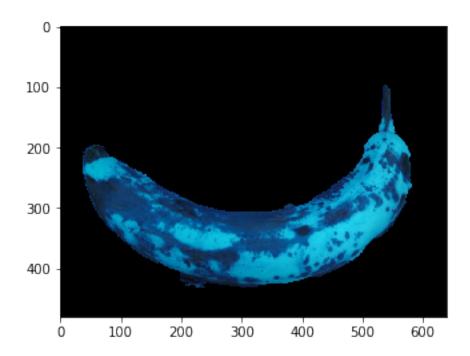
foreground pixels: 73191, background pixels: 234011 Image after iteration 2



foreground pixels: 72505, background pixels: 234697 Image after iteration 3



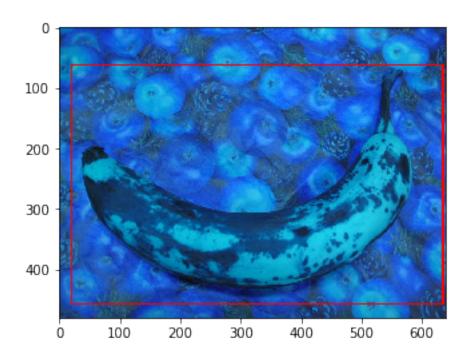
foreground pixels: 72097, background pixels: 235105 Image after iteration 4



1.7 Obseravations:

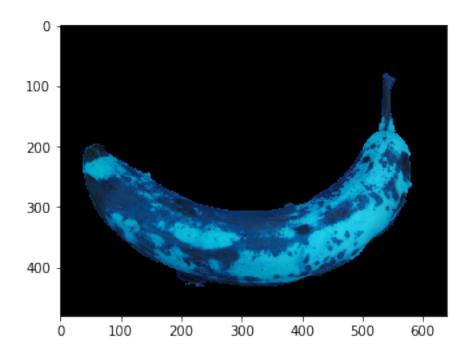
- With increasing the number of iterations the image is getting better.
- however with increasing iteration the improvement is very less.
- After 3rd iteration there is not much visible difference.

1.8 Number of Components in GMM



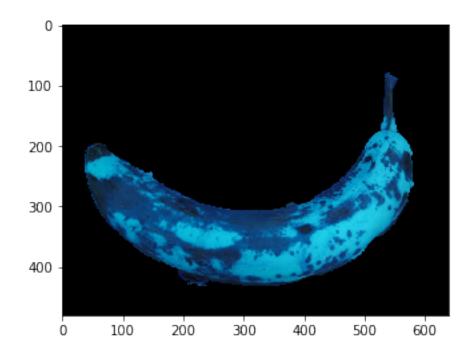
0.0021199558038790126

foreground pixels: 113424, background pixels: 193778 foreground pixels: 87270, background pixels: 219932 foreground pixels: 73191, background pixels: 234011



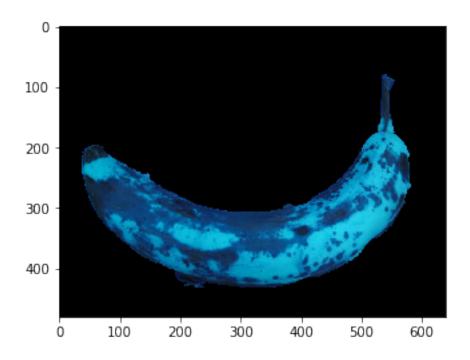
0.0021199558038790126

foreground pixels: 113424, background pixels: 193778 foreground pixels: 87270, background pixels: 219932 foreground pixels: 73191, background pixels: 234011



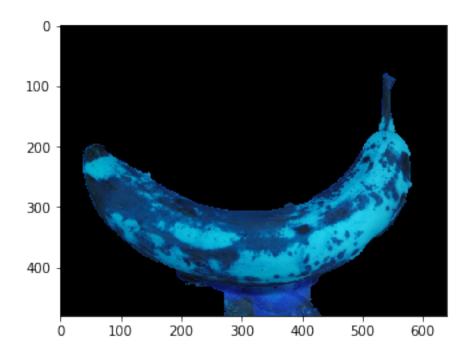
0.0021199558038790126

foreground pixels: 113425, background pixels: 193777 foreground pixels: 87270, background pixels: 219932 foreground pixels: 73191, background pixels: 234011



0.0021199558038790126

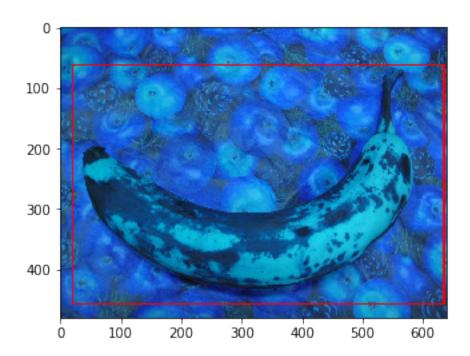
foreground pixels: 116383, background pixels: 190819 foreground pixels: 87277, background pixels: 219925 foreground pixels: 81438, background pixels: 225764



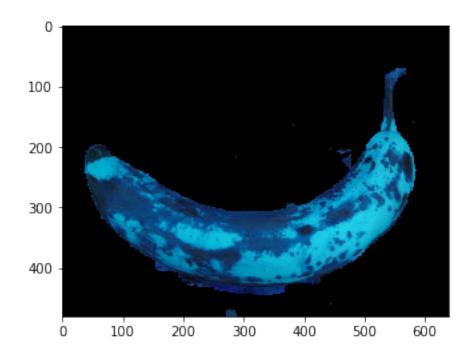
1.9 Observations

- For fewer number of GMM's the grab cut is quite perfect.
- For 8 component the grab cut is comparitevely poorer.
- One reason can be that the distribution is better modelled for less number of components.

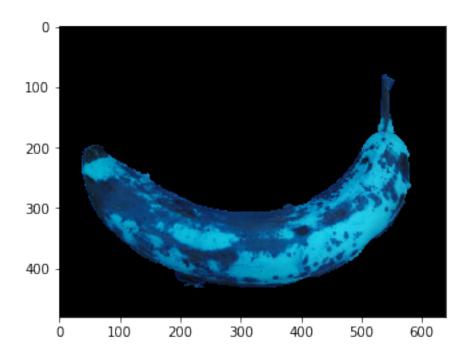
1.10 4 Neighbourhood vs 8 Neighbourhood



foreground pixels: 93906, background pixels: 213296 foreground pixels: 79883, background pixels: 227319 foreground pixels: 76597, background pixels: 230605



foreground pixels: 113423, background pixels: 193779 foreground pixels: 87271, background pixels: 219931 foreground pixels: 73190, background pixels: 234012



1.11 Observations:

- The grab cut is better for 8 neighbour.
- More neighbour is making the graph comapritevely dense thus resulting in better cut.