

위치와 색상에 따른 분류



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- 002 위치에 따른 분류
- 003 위치와 색상에 따른 분류
- 004 **K-means** 알고리즘의 활용



The background image shows a cozy, rustic interior, likely a cafe or a small restaurant. The walls are made of exposed brick, with a mix of red and grey tones. On the left, there is a wooden shelf with various items, including a glass dome, a small coffee machine, and some boxes. A wooden bar stool with a yellow seat is positioned in front of the shelf. In the center, a long wooden table is set with several yellow chairs. On the right, two wooden surfboards with blue and white designs are leaning against the wall. The lighting is warm and ambient, with a few pendant lights hanging from the ceiling. The text "Part 1" and "K-means algorithm" is overlaid in the center of the image, enclosed in a white, hand-drawn style bracket.

Part 1

K-means algorithm

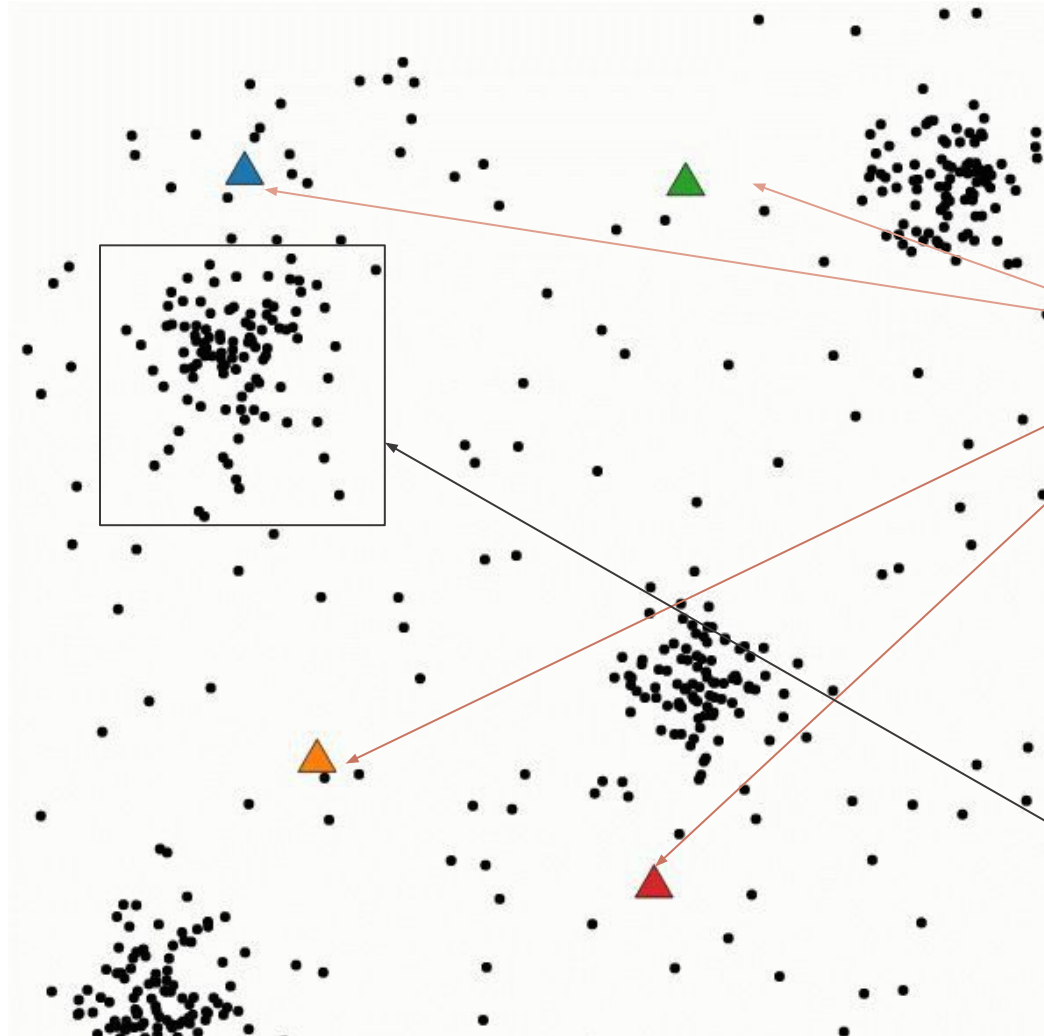
K-means algorithm?

데이터를 무리 짓는 방법

● Centroid

● Distance

● Cluster

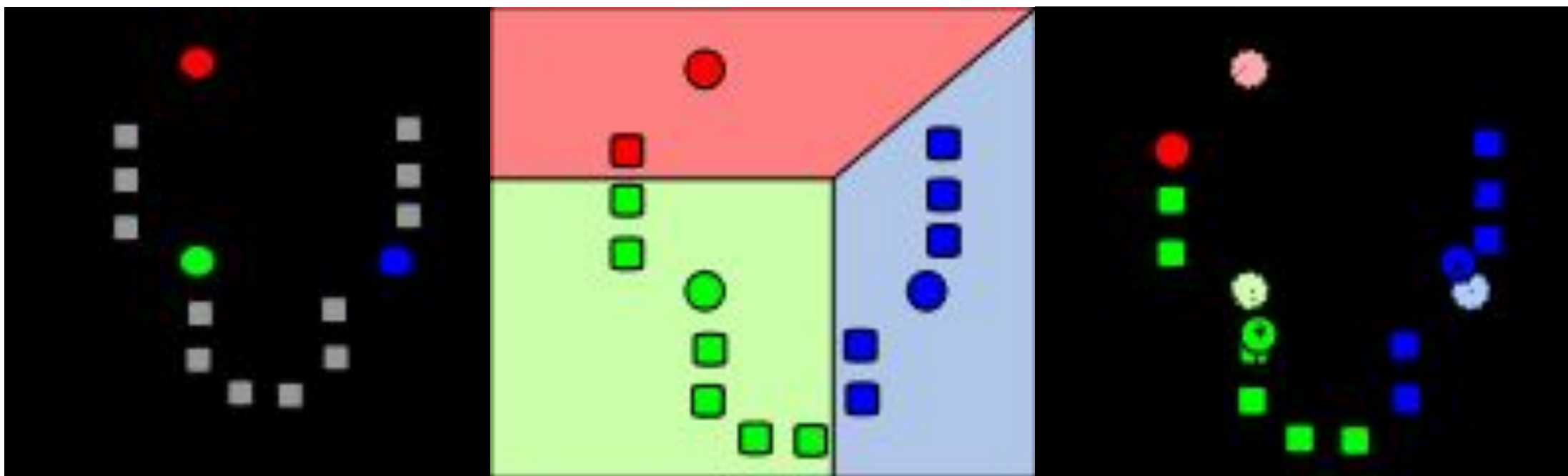


K-means algorithm?

- 중심 설정

- 군집화

- 중심 조정

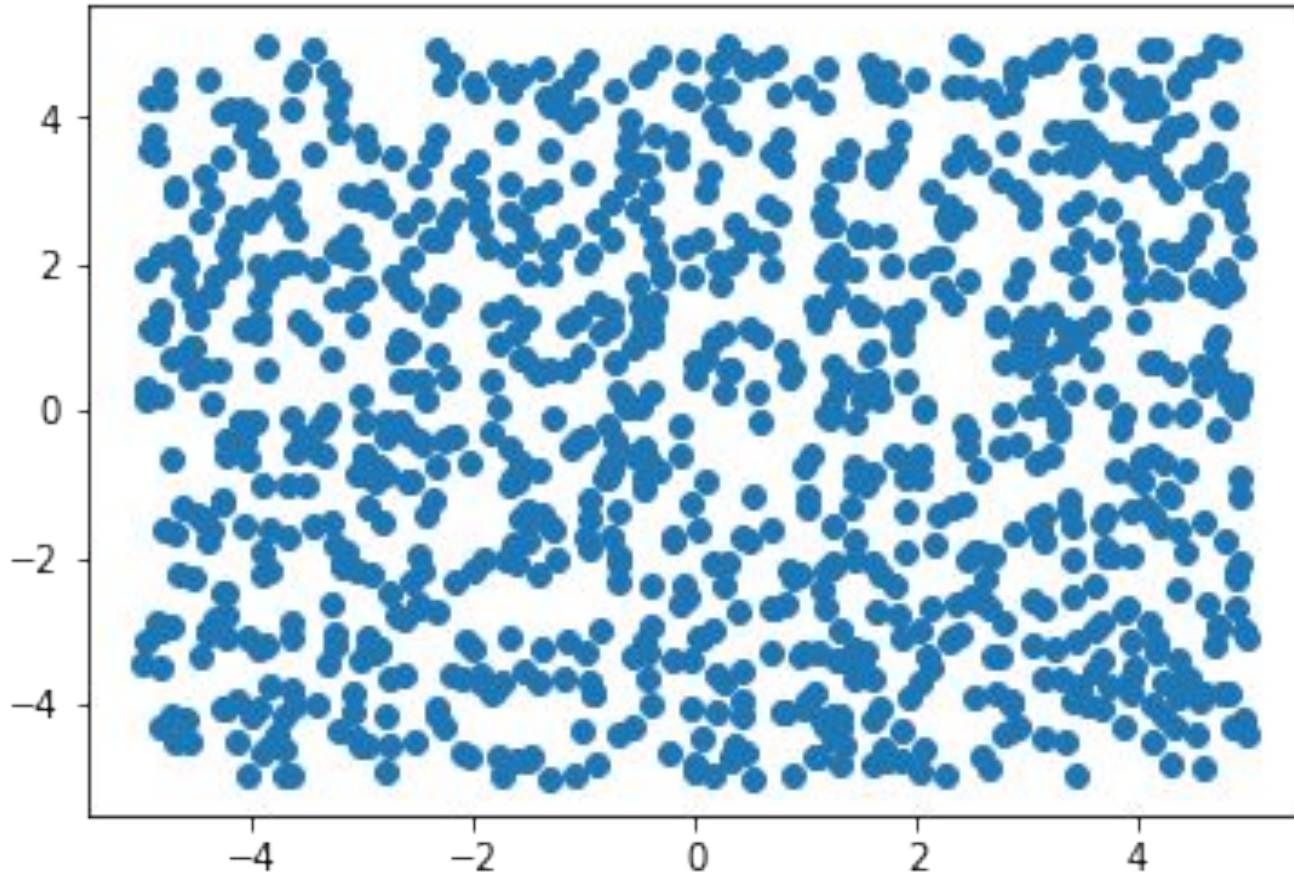


A top-down photograph of three hands holding coffee cups. The top hand holds a white cup with a latte featuring a heart-shaped latte art. The bottom-left hand holds a dark cup with an iced coffee. The bottom-right hand holds a white cup with a latte featuring a leaf-shaped latte art. The background is a blurred wooden table with coffee-making equipment.

Part 2

위치에 따른 분류

Scatter Plot 분류



- 완전히 무작위하게 찍은 1000개의 점

```
def GeneratePointCluster(n_points):
```

```
    x_points = []
```

```
    y_points = []
```

```
    for i in range(n_points):
```

```
        x_points.append(random.uniform(-5.0, 5.0))
```

```
        y_points.append(random.uniform(-5.0, 5.0))
```

#x,y 를 각 점에 리스트 자료형을 이용해서 대입한다.

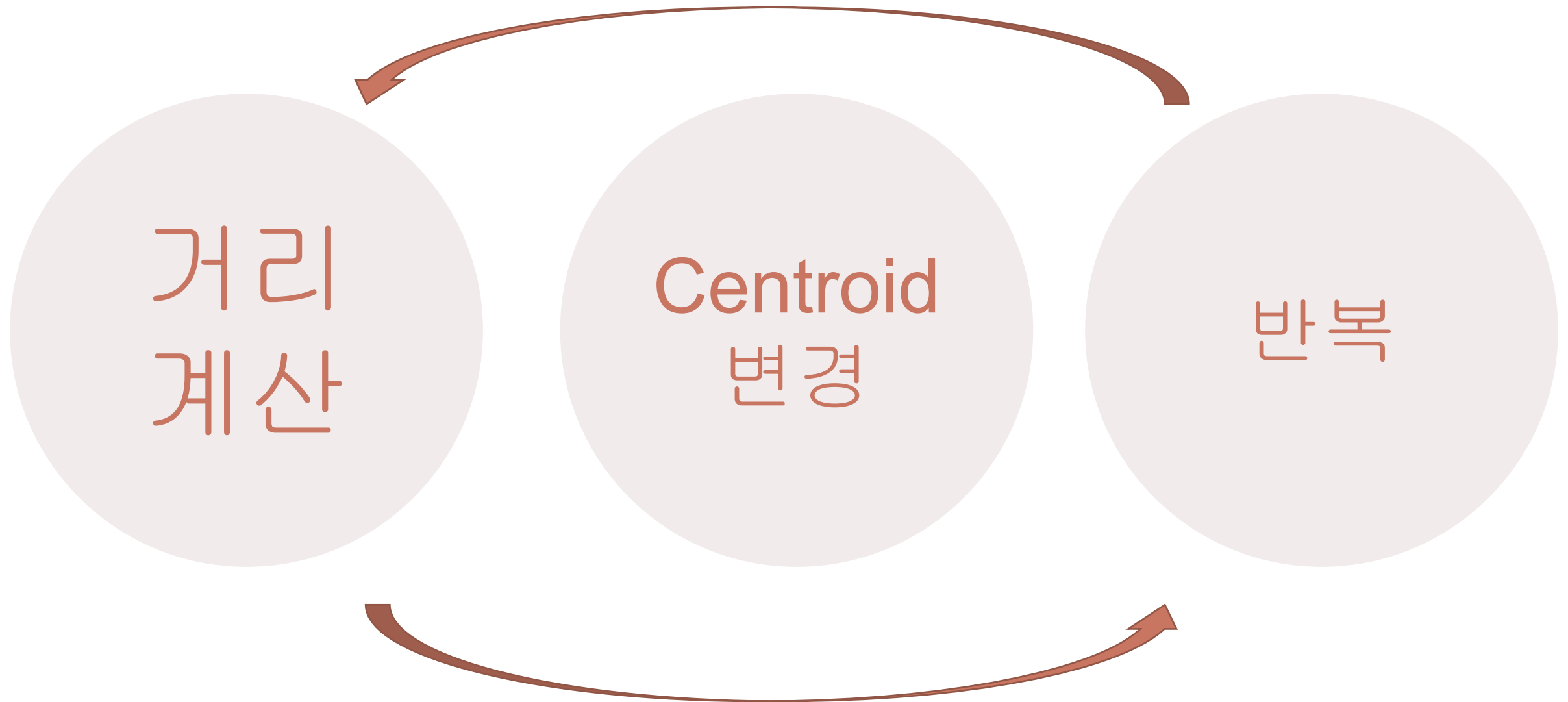
```
    points = [x_points, y_points]
```

```
    return points
```

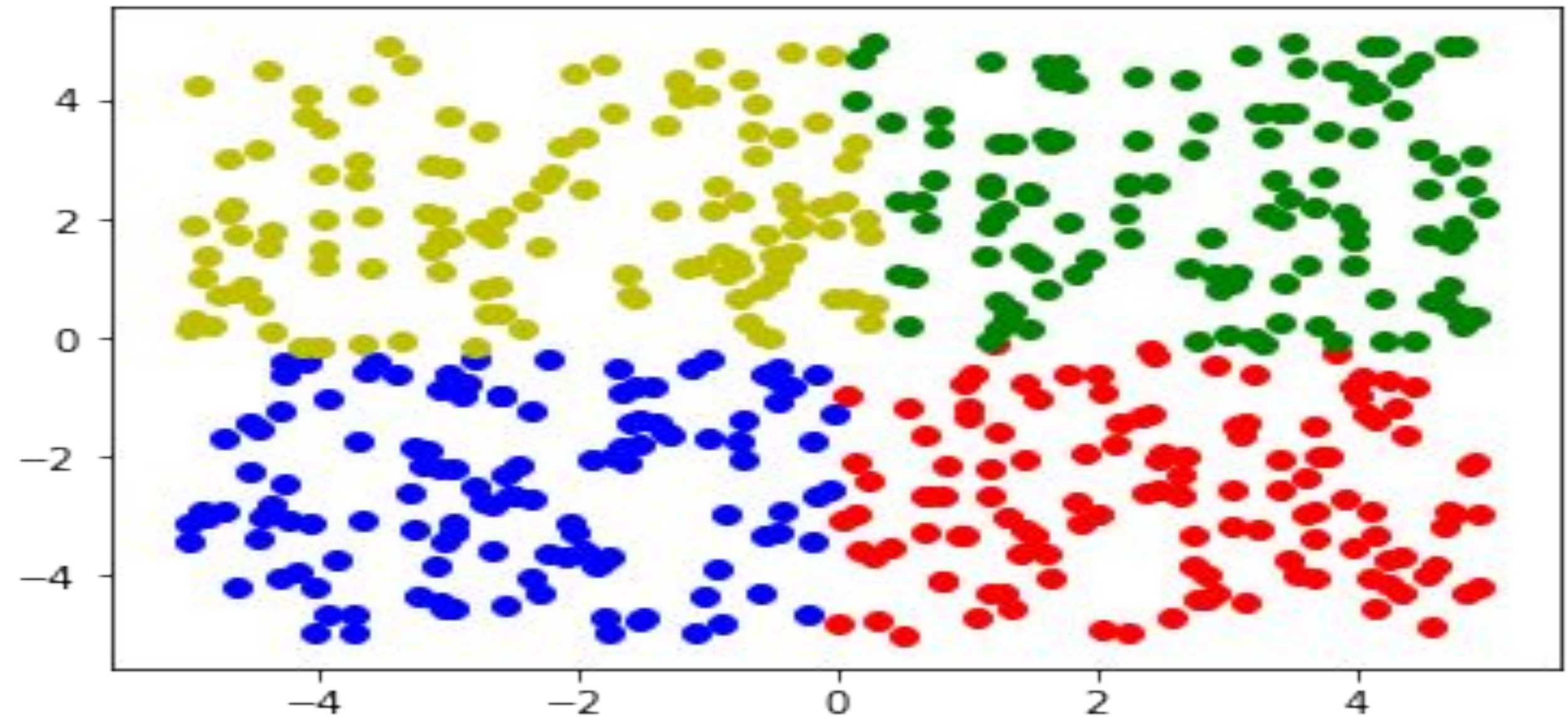
```
data = GeneratePointCluster(1000)
```

```
plt.scatter(data[0],data[1])
```

Scatter Plot 분류 과정



Scatter Plot 분류 완료





Part 3

이미지 분류

순서

- 001 이미지 불러오기 및 처리
- 002 **K-means Algorithm**을 통한 이미지 분류
- 003 분류된 이미지 출력
- 004 **Cost Function**

이미지 불러오기

Shape of the Image

$$\begin{matrix} & & & & \\ & & & & \\ height & \left[\begin{array}{ccc} [r, g, b] & \cdots & [r, g, b] \\ \vdots & \ddots & \vdots \\ [r, g, b] & \cdots & [r, g, b] \end{array} \right] & & \\ & & width & & \end{matrix}$$

```
import numpy as np
import matplotlib.pyplot as plt
import cv2
```

```
# read image using opencv library.
img = cv2.imread('images.jpg', cv2.IMREAD_COLOR)
height = img.shape[0]
width = img.shape[1]
b, g, r = cv2.split(img)
img2 = cv2.merge([r, g, b])
```

```
img2.shape
```

```
(168, 300, 3)
```

Input Image

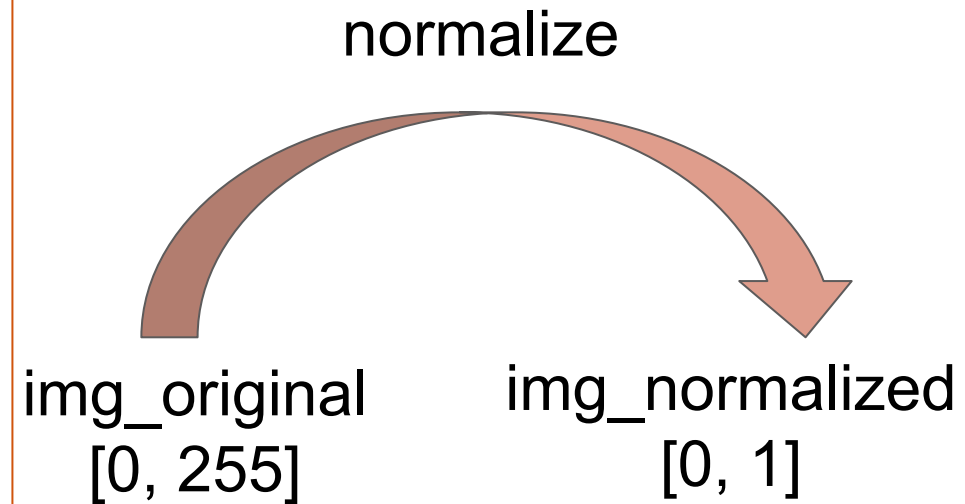


Normalize Image Values

```
# normalize image values.  
img_normalized = np.empty((height, width, 3), dtype=np.float64)  
img_normalized = img_normalize(img2, height, width)
```

Normalize Function

```
def img_normalize(data, height, width):  
  
    normalized_data = np.empty((height, width, 3), dtype=np.float64)  
  
    for y in range(height):  
        for x in range(width):  
            normalized_data[y][x] = data[y][x] / np.array([255,255,255])  
  
    return normalized_data
```

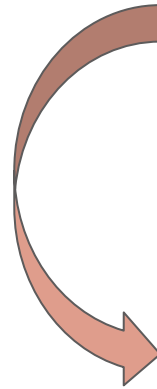


Allocate Initial Centroids Values Randomly

Allocate centroids values.

```
c1_rgb = np.empty(3, dtype=np.float64)
c2_rgb = np.empty(3, dtype=np.float64)
c3_rgb = np.empty(3, dtype=np.float64)
c4_rgb = np.empty(3, dtype=np.float64)
c5_rgb = np.empty(3, dtype=np.float64)
c6_rgb = np.empty(3, dtype=np.float64)
c7_rgb = np.empty(3, dtype=np.float64)
c8_rgb = np.empty(3, dtype=np.float64)
c9_rgb = np.empty(3, dtype=np.float64)
```

```
c1_x = random.randint(0, width)
c1_y = random.randint(0, height)
c1_rgb = img_normalized[c1_y][c1_x]
print(c1_x, c1_y, img2[c1_y][c1_x])
```



```
c1_x = random_x
c1_y = random_y
```

```
c1_rgb = img_normalized[c1_y][c1_x]
```



```
# show the location of initial centroids.
```

```
plt.imshow(img2)
```

```
plt.axis('off')
```

```
plt.title('The location of Initial Centroids')
```

```
plt.plot([c1_x], [c1_y], marker='*', color='red', label='centroid1', markersize=20)
```

```
plt.plot([c2_x], [c2_y], '*', color='orange', label='centroid2', markersize=20)
```

```
plt.plot([c3_x], [c3_y], '*', color='yellow', label='centroid3', markersize=20)
```

```
plt.plot([c4_x], [c4_y], '*', color='salmon', label='centroid4', markersize=20)
```

```
plt.plot([c5_x], [c5_y], '*', color='blue', label='centroid5', markersize=20)
```

```
plt.plot([c6_x], [c6_y], '*', color='purple', label='centroid6', markersize=20)
```

```
plt.plot([c7_x], [c7_y], '*', color='darkcyan', label='centroid7', markersize=20)
```

```
plt.plot([c8_x], [c8_y], '*', color='magenta', label='centroid8', markersize=20)
```

```
plt.plot([c9_x], [c9_y], '*', color='brown', label='centroid9', markersize=20)
```

```
plt.legend()
```

```
plt.show()
```

The location of Initial Centroids



Label Matrix

label each pixels.

```
labelMat = np.empty((height, width), dtype=int)
```

#each entries represent a pixel

(height) x (width) dimension matrix

Label Matrix

$$\begin{bmatrix} 0 & 0 & \dots & 1 & 1 \\ 0 & 0 & & & 1 \\ \vdots & & & 3 & 3 \\ 8 & 8 & \dots & 2 & 3 \end{bmatrix}$$

```
while True:
```

```
    itCount += 1
```

```
    # Initiate/reset cluster values.
```

```
    cluster1_x = np.zeros(0, dtype=np.float64)
```

```
    cluster1_y = np.zeros(0, dtype=np.float64)
```

```
    cluster1_rgb = np.zeros((0, 3), dtype=np.float64)
```

```
    cluster2_x = np.zeros(0, dtype=np.float64)
```

```
    cluster2_y = np.zeros(0, dtype=np.float64)
```

```
    cluster2_rgb = np.zeros((0, 3), dtype=np.float64)
```

```
    cluster3_x = np.zeros(0, dtype=np.float64)
```

```
    cluster3_y = np.zeros(0, dtype=np.float64)
```

```
    cluster3_rgb = np.zeros((0, 3), dtype=np.float64)
```

```
    cluster4_x = np.zeros(0, dtype=np.float64)
```

```
    cluster4_y = np.zeros(0, dtype=np.float64)
```

```
    cluster4_rgb = np.zeros((0, 3), dtype=np.float64)
```

```
    cluster5_x = np.zeros(0, dtype=np.float64)
```

```
    cluster5_y = np.zeros(0, dtype=np.float64)
```

```
    cluster5_rgb = np.zeros((0, 3), dtype=np.float64)
```

```
    cluster6_x = np.zeros(0, dtype=np.float64)
```

```
    cluster6_y = np.zeros(0, dtype=np.float64)
```

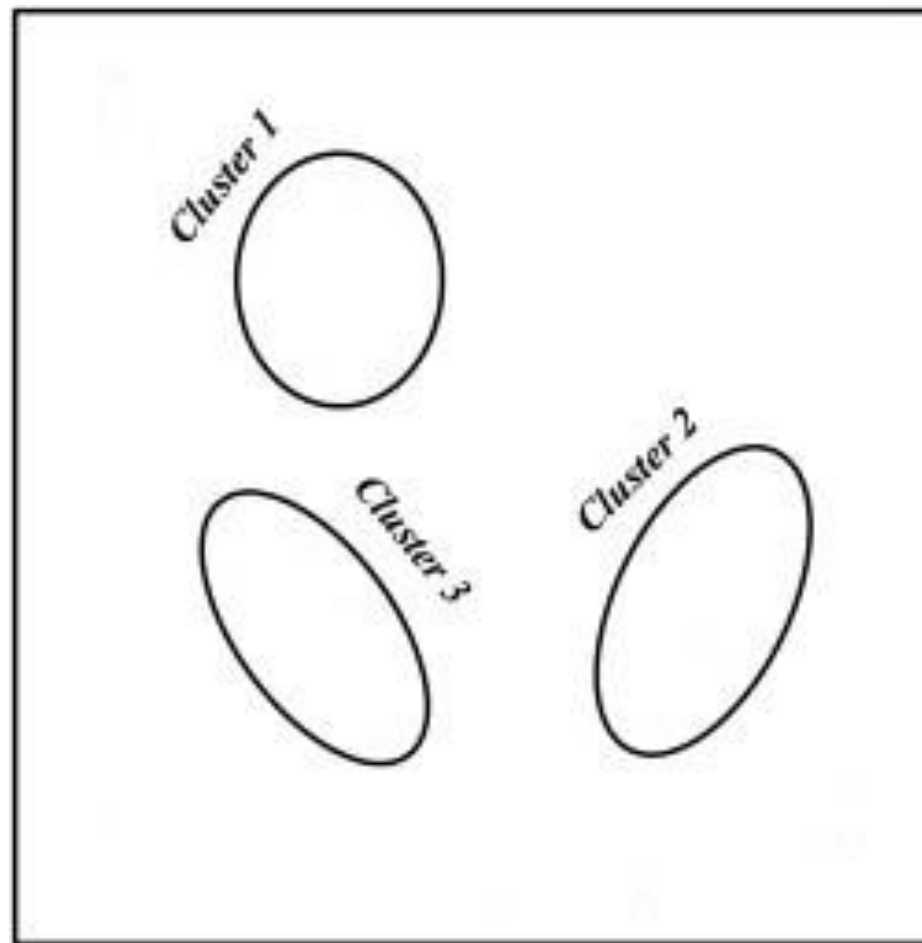
```
    cluster6_rgb = np.zeros((0, 3), dtype=np.float64)
```

```
    cluster7_x = np.zeros(0, dtype=np.float64)
```

```
    cluster7_y = np.zeros(0, dtype=np.float64)
```

```
    cluster7_rgb = np.zeros((0, 3), dtype=np.float64)
```

Empty Cluster 선언




```

for y in range(height):
    for x in range(width):
        # compute distances from each centroids.
        d1 = distance(c1_rgb, img_normalized[y][x], c1_x, x, c1_y, y, lbd)
        d2 = distance(c2_rgb, img_normalized[y][x], c2_x, x, c2_y, y, lbd)
        d3 = distance(c3_rgb, img_normalized[y][x], c3_x, x, c3_y, y, lbd)
        d4 = distance(c4_rgb, img_normalized[y][x], c4_x, x, c4_y, y, lbd)
        d5 = distance(c5_rgb, img_normalized[y][x], c5_x, x, c5_y, y, lbd)
        d6 = distance(c6_rgb, img_normalized[y][x], c6_x, x, c6_y, y, lbd)
        d7 = distance(c7_rgb, img_normalized[y][x], c7_x, x, c7_y, y, lbd)
        d8 = distance(c8_rgb, img_normalized[y][x], c8_x, x, c8_y, y, lbd)
        d9 = distance(c9_rgb, img_normalized[y][x], c9_x, x, c9_y, y, lbd)

        d_list = np.array([d1, d2, d3, d4, d5, d6, d7, d8, d9])

        # allocate pixels to the minimum cluster.
        argMin = d_list.argmin()

        if argMin == 0:
            cluster1_x = np.append(cluster1_x, x)
            cluster1_y = np.append(cluster1_y, y)
            cluster1_rgb = np.append(cluster1_rgb, [img_normalized[y][x]], axis=0)

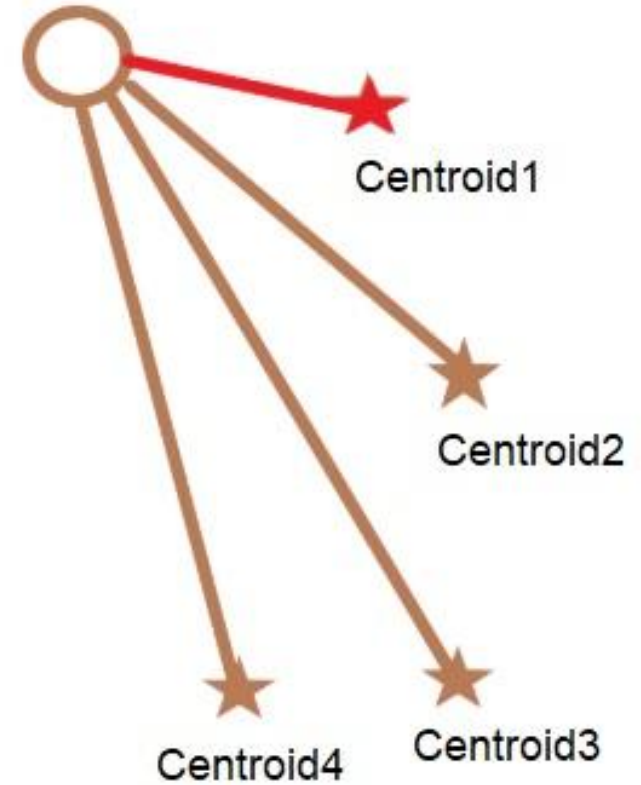
            labelMat[y][x] = 0

        elif argMin == 1:
            cluster2_x = np.append(cluster2_x, x)
            cluster2_y = np.append(cluster2_y, y)
            cluster2_rgb = np.append(cluster2_rgb, [img_normalized[y][x]], axis=0)

            labelMat[y][x] = 1

        elif argMin == 2:
            cluster3_x = np.append(cluster3_x, x)
            cluster3_y = np.append(cluster3_y, y)
            cluster3_rgb = np.append(cluster3_rgb, [img_normalized[y][x]], axis=0)

```



Distance Function

RGB값의 차이

위치의 차이

$$d = \|f(z) - m\|^2 + \lambda * \|z - c\|^2$$

where z denotes the spatial index, $f(z)$ denotes the image value (r, g, b) at the spatial location z , m denotes the centroid of image intensity, c denotes the centroid of spatial location, and λ determines the importance between the image intensity and the spatial relation.

- $z = (x \text{ 좌표}, y \text{ 좌표})$: 해당 픽셀의 위치.
- $f(z) = (r, g, b)$: 해당 위치의 이미지 값.

Lambda \uparrow - 위치의 비중 \uparrow

Lambda \downarrow - 색 (r, g, b) 의 비중 \uparrow

```

# Re-define centroids & print.
print('Iteration Number:', itCount)

new_c1_x = np.mean(cluster1_x)
new_c1_y = np.mean(cluster1_y)
new_c1_rgb = np.mean(cluster1_rgb, axis=0)
print('c1', new_c1_x, new_c1_y, new_c1_rgb)

new_c2_x = np.mean(cluster2_x)
new_c2_y = np.mean(cluster2_y)
new_c2_rgb = np.mean(cluster2_rgb, axis=0)
print('c2', new_c2_x, new_c2_y, new_c2_rgb)

new_c3_x = np.mean(cluster3_x)
new_c3_y = np.mean(cluster3_y)
new_c3_rgb = np.mean(cluster3_rgb, axis=0)
print('c3', new_c3_x, new_c3_y, new_c3_rgb)

new_c4_x = np.mean(cluster4_x)
new_c4_y = np.mean(cluster4_y)
new_c4_rgb = np.mean(cluster4_rgb, axis=0)
print('c4', new_c4_x, new_c4_y, new_c4_rgb)

new_c5_x = np.mean(cluster5_x)
new_c5_y = np.mean(cluster5_y)
new_c5_rgb = np.mean(cluster5_rgb, axis=0)
print('c5', new_c5_x, new_c5_y, new_c5_rgb)

new_c6_x = np.mean(cluster6_x)
new_c6_y = np.mean(cluster6_y)
new_c6_rgb = np.mean(cluster6_rgb, axis=0)
print('c6', new_c6_x, new_c6_y, new_c6_rgb)

```

```

Iteration Number: 38
c1 260.66493916178456 27.064218116268588 [0.11572074 0.38162129 0.48457882]
c2 107.84148727984345 125.49706457925636 [0.32600757 0.34680493 0.33761623]
c3 181.10194805194806 125.75113636363636 [0.27217532 0.30544945 0.25993952]
c4 35.5 125.5 [0.15067694 0.40733803 0.36034405]
c5 255.7118501368133 83.74047568932856 [0.19593563 0.3050982 0.27842394]
c6 182.81551952349437 40.88749172733289 [0.2305628 0.42375391 0.36053386]
c7 110.15813498532768 41.516628627323115 [0.29307492 0.44594002 0.38474079]
c8 259.9481911567664 140.14537740062528 [0.21915071 0.41335855 0.10161749]
c9 36.494127111826224 41.49332260659694 [0.20010096 0.3724468 0.36103229]

```

```

Iteration Number: 39
c1 260.6587784539103 27.057245886860493 [0.11568406 0.38161361 0.48466505]
c2 107.84148727984345 125.49706457925636 [0.32600757 0.34680493 0.33761623]
c3 181.10194805194806 125.75113636363636 [0.27217532 0.30544945 0.25993952]
c4 35.5 125.5 [0.15067694 0.40733803 0.36034405]
c5 255.71837507893076 83.72910966112397 [0.19586135 0.30509573 0.27842394]
c6 182.81551952349437 40.88749172733289 [0.2305628 0.42375391 0.36053386]
c7 110.15813498532768 41.516628627323115 [0.29307492 0.44594002 0.38474079]
c8 259.94753293145794 140.1390935476669 [0.21924274 0.4133617 0.10161757]
c9 36.494127111826224 41.49332260659694 [0.20010096 0.3724468 0.36103229]

```

```

Iteration Number: 40
c1 260.6587784539103 27.057245886860493 [0.11568406 0.38161361 0.48466505]
c2 107.84148727984345 125.49706457925636 [0.32600757 0.34680493 0.33761623]
c3 181.10194805194806 125.75113636363636 [0.27217532 0.30544945 0.25993952]
c4 35.5 125.5 [0.15067694 0.40733803 0.36034405]
c5 255.71837507893076 83.72910966112397 [0.19586135 0.30509573 0.27842394]
c6 182.81551952349437 40.88749172733289 [0.2305628 0.42375391 0.36053386]
c7 110.15813498532768 41.516628627323115 [0.29307492 0.44594002 0.38474079]
c8 259.94753293145794 140.1390935476669 [0.21924274 0.4133617 0.10161757]
c9 36.494127111826224 41.49332260659694 [0.20010096 0.3724468 0.36103229]

```



```
# end the loop if centroids converge, continue clustering if not.
```

```
if centCheck(new_c1_x, new_c1_y, new_c1_rgb, c1_x, c1_y, c1_rgb) and centCheck(new_c2_x, new_c2_y, new_c2_rgb, c2_x, c2_y, c2_rgb) and  
    break  
else:
```

```
    c1_x = new_c1_x  
    c1_y = new_c1_y  
    c1_rgb = copy(new_c1_rgb)
```

```
    c2_x = new_c2_x  
    c2_y = new_c2_y  
    c2_rgb = copy(new_c2_rgb)
```

```
    c3_x = new_c3_x  
    c3_y = new_c3_y  
    c3_rgb = copy(new_c3_rgb)
```

```
    c4_x = new_c4_x  
    c4_y = new_c4_y  
    c4_rgb = copy(new_c4_rgb)
```

```
    c5_x = new_c5_x  
    c5_y = new_c5_y  
    c5_rgb = copy(new_c5_rgb)
```

```
    c6_x = new_c6_x  
    c6_y = new_c6_y  
    c6_rgb = copy(new_c6_rgb)
```

```
    c7_x = new_c7_x  
    c7_y = new_c7_y  
    c7_rgb = copy(new_c7_rgb)
```

```
# To check if values of centroids are same.
```

```
def centCheck(cx, cy, crgb, x, y, rgb):  
    if cx == x and cy == y and (crgb == rgb).all():  
        return True  
    return False
```

Iteration Number: 39

```
c1 260.6587784539103 27.057245886860493 [0.11568406 0.38161361 0.48466505]  
c2 107.84148727984345 125.49706457925636 [0.32600757 0.34680493 0.33761623]  
c3 181.10194805194806 125.75113636363636 [0.27217532 0.30544945 0.25993952]  
c4 35.5 125.5 [0.15067694 0.40733803 0.36034405]  
c5 255.71837507893076 83.72910966112397 [0.19586135 0.30509573 0.27842394]  
c6 182.81551952349437 40.88749172733289 [0.2305628 0.42375391 0.36053386]  
c7 110.15813498532768 41.516628627323115 [0.29307492 0.44594002 0.38474079]  
c8 259.94753293145794 140.1390935476669 [0.21924274 0.4133617 0.10161757]  
c9 36.494127111826224 41.49332260659694 [0.20010096 0.3724468 0.36103229]
```

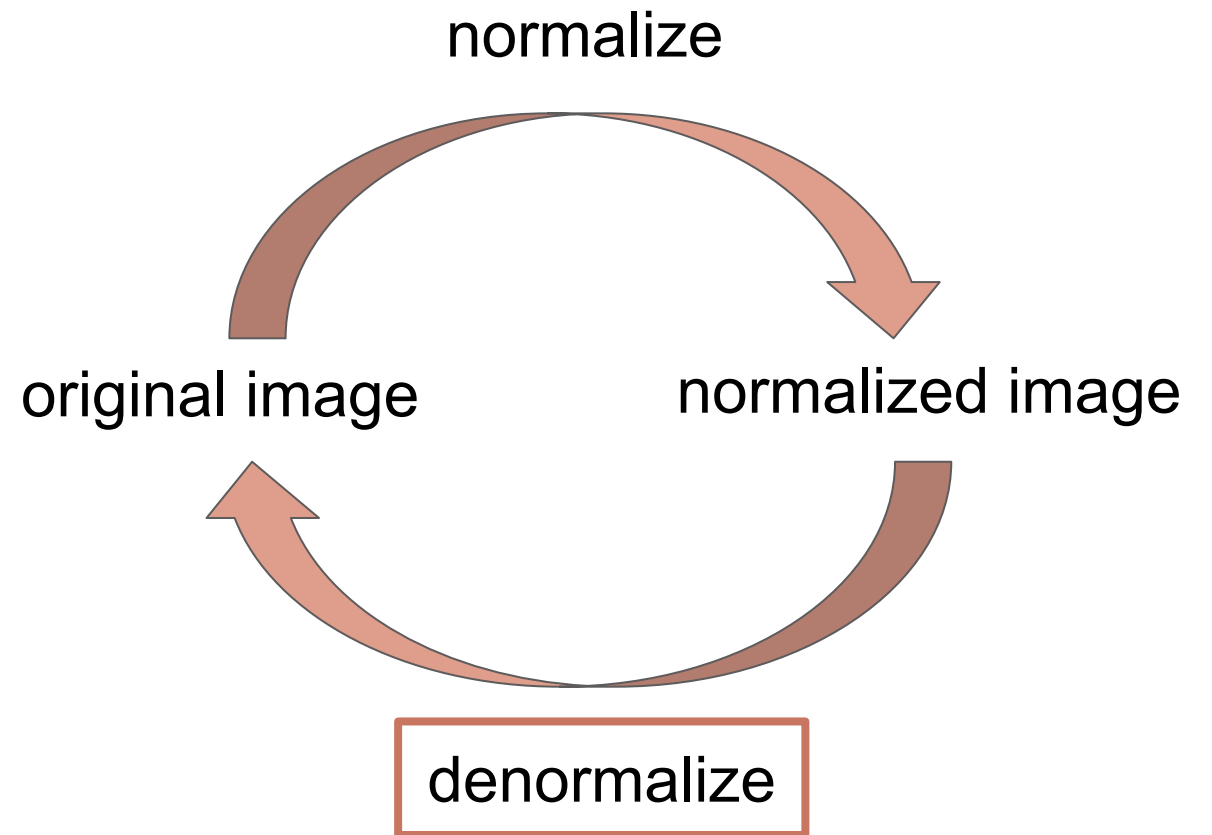
Iteration Number: 40

```
c1 260.6587784539103 27.057245886860493 [0.11568406 0.38161361 0.48466505]  
c2 107.84148727984345 125.49706457925636 [0.32600757 0.34680493 0.33761623]  
c3 181.10194805194806 125.75113636363636 [0.27217532 0.30544945 0.25993952]  
c4 35.5 125.5 [0.15067694 0.40733803 0.36034405]  
c5 255.71837507893076 83.72910966112397 [0.19586135 0.30509573 0.27842394]  
c6 182.81551952349437 40.88749172733289 [0.2305628 0.42375391 0.36053386]  
c7 110.15813498532768 41.516628627323115 [0.29307492 0.44594002 0.38474079]  
c8 259.94753293145794 140.1390935476669 [0.21924274 0.4133617 0.10161757]  
c9 36.494127111826224 41.49332260659694 [0.20010096 0.3724468 0.36103229]
```

Image Denormalize

```
c1_rgb_denorm = np.empty((3), dtype=int)
c2_rgb_denorm = np.empty((3), dtype=int)
c3_rgb_denorm = np.empty((3), dtype=int)
c4_rgb_denorm = np.empty((3), dtype=int)
c5_rgb_denorm = np.empty((3), dtype=int)
c6_rgb_denorm = np.empty((3), dtype=int)
c7_rgb_denorm = np.empty((3), dtype=int)
c8_rgb_denorm = np.empty((3), dtype=int)
c9_rgb_denorm = np.empty((3), dtype=int)

# denormalize image values.
c1_rgb_denorm = img_denormalize(new_c1_rgb)
c2_rgb_denorm = img_denormalize(new_c2_rgb)
c3_rgb_denorm = img_denormalize(new_c3_rgb)
c4_rgb_denorm = img_denormalize(new_c4_rgb)
c5_rgb_denorm = img_denormalize(new_c5_rgb)
c6_rgb_denorm = img_denormalize(new_c6_rgb)
c7_rgb_denorm = img_denormalize(new_c7_rgb)
c8_rgb_denorm = img_denormalize(new_c8_rgb)
c9_rgb_denorm = img_denormalize(new_c9_rgb)
```



하나의 Cluster 출력

```
# plot each clusters.
new_image = np.zeros((height, width, 3), dtype=int)

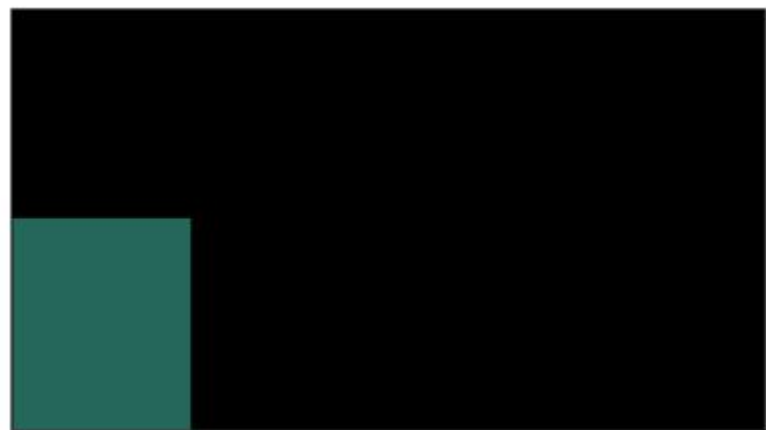
for y in range(height):
    for x in range(width):

        if labelMat[y][x] == 0:
            new_image[y][x] = c1_rgb_denorm
        else:
            new_image[y][x] = [0,0,0]

plt.imshow(new_image)
plt.xticks([])
plt.yticks([])
plt.show()
```



set lambda value.
lbd = 0.1

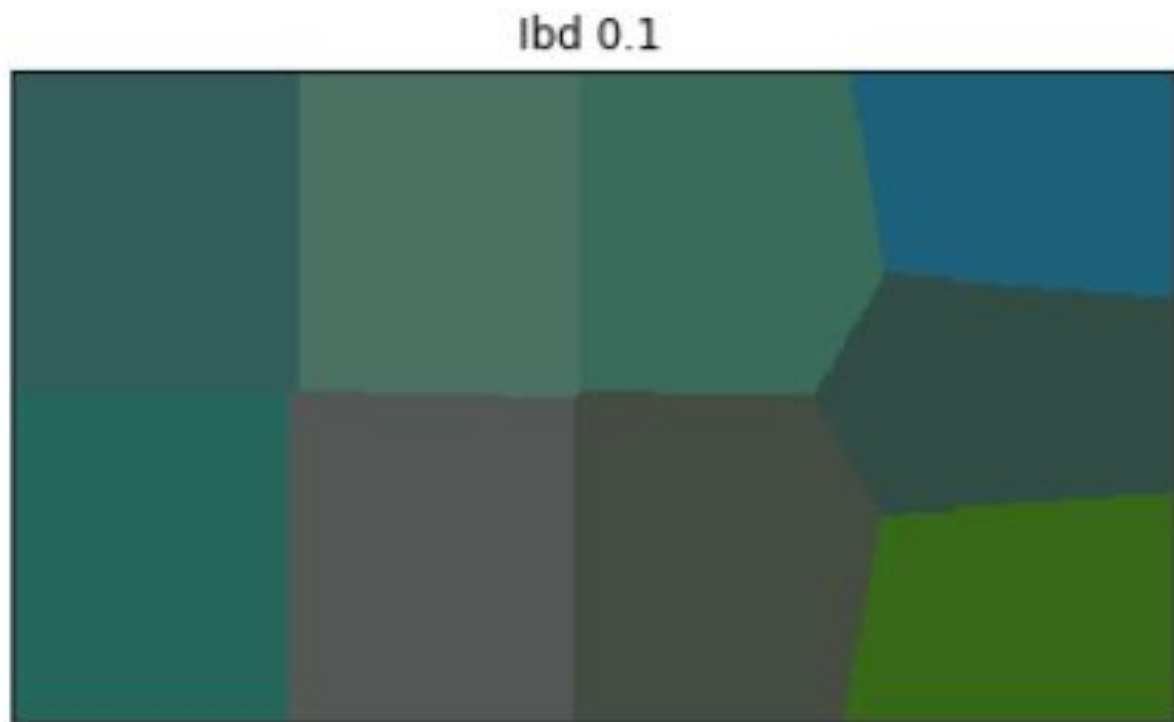


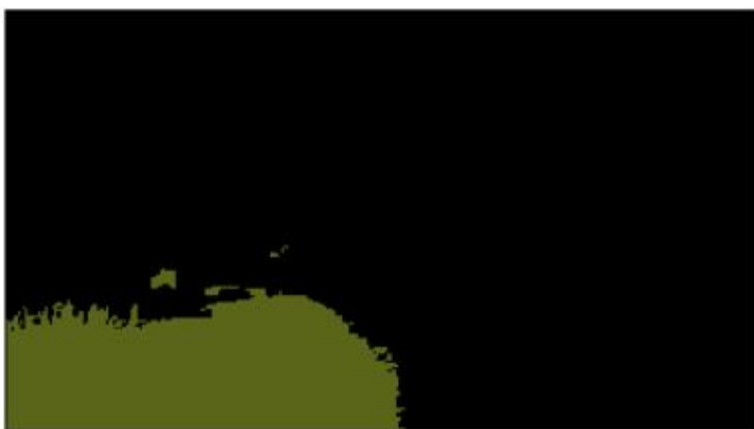
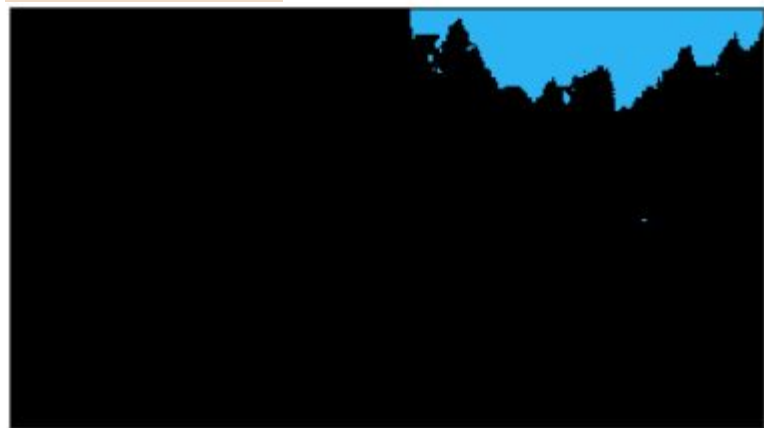
```
new_image = np.empty((height, width, 3), dtype=int)
```

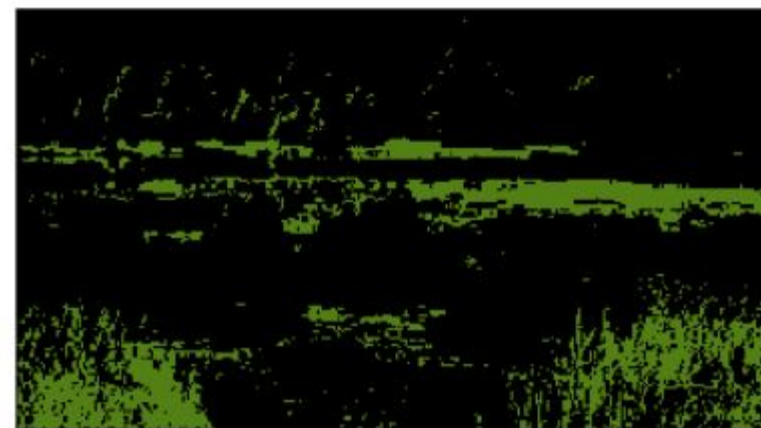
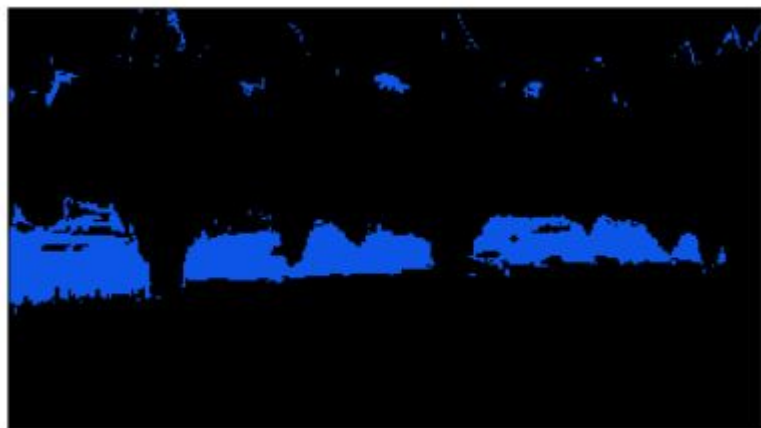
```
for y in range(height):  
    for x in range(width):  
  
        if labelMat[y][x] == 0:  
            new_image[y][x] = c1_rgb_denorm  
        elif labelMat[y][x] == 1:  
            new_image[y][x] = c2_rgb_denorm  
        elif labelMat[y][x] == 2:  
            new_image[y][x] = c3_rgb_denorm  
        elif labelMat[y][x] == 3:  
            new_image[y][x] = c4_rgb_denorm  
        elif labelMat[y][x] == 4:  
            new_image[y][x] = c5_rgb_denorm  
        elif labelMat[y][x] == 5:  
            new_image[y][x] = c6_rgb_denorm  
        elif labelMat[y][x] == 6:  
            new_image[y][x] = c7_rgb_denorm  
        elif labelMat[y][x] == 7:  
            new_image[y][x] = c8_rgb_denorm  
        elif labelMat[y][x] == 8:  
            new_image[y][x] = c9_rgb_denorm
```

```
# Whole Image  
plt.imshow(new_image)  
plt.xticks([])  
plt.yticks([])  
plt.title('lbd {}'.format(lbd))  
plt.show()
```

전체 이미지 출력





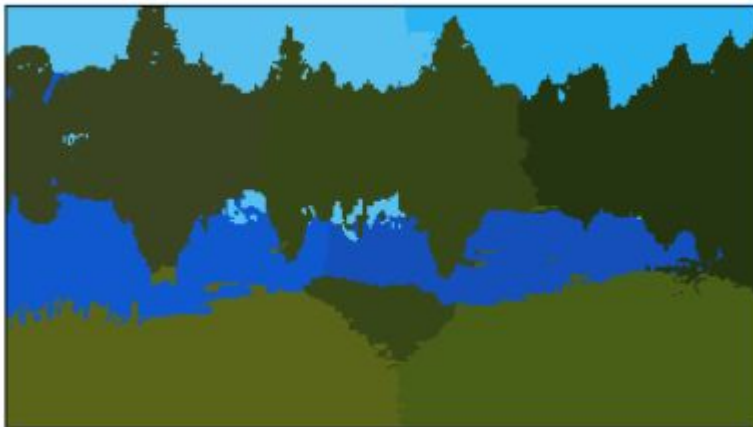


lambda 값에 따른 변화

lbd 0.1



lbd 0.0001



lbd 1e-06

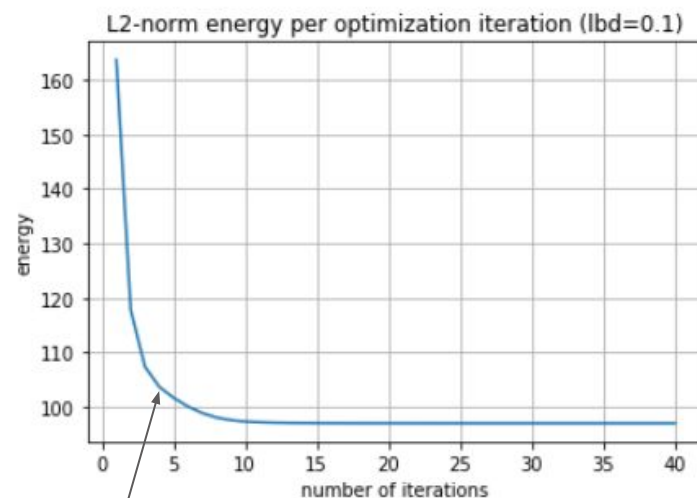


Energy/Cost Function

```
# calculate energy
for y in range(height):
    for x in range(width):
        if labelMat[y][x] == 0:
            energy += distance(new_c1_rgb, img_normalized[y][x], new_c1_x, x, new_c1_y, y, lbd)
        elif labelMat[y][x] == 1:
            energy += distance(new_c2_rgb, img_normalized[y][x], new_c2_x, x, new_c2_y, y, lbd)
        elif labelMat[y][x] == 2:
            energy += distance(new_c3_rgb, img_normalized[y][x], new_c3_x, x, new_c3_y, y, lbd)
        elif labelMat[y][x] == 3:
            energy += distance(new_c4_rgb, img_normalized[y][x], new_c4_x, x, new_c4_y, y, lbd)
        elif labelMat[y][x] == 4:
            energy += distance(new_c5_rgb, img_normalized[y][x], new_c5_x, x, new_c5_y, y, lbd)
        elif labelMat[y][x] == 5:
            energy += distance(new_c6_rgb, img_normalized[y][x], new_c6_x, x, new_c6_y, y, lbd)
        elif labelMat[y][x] == 6:
            energy += distance(new_c7_rgb, img_normalized[y][x], new_c7_x, x, new_c7_y, y, lbd)
        elif labelMat[y][x] == 7:
            energy += distance(new_c8_rgb, img_normalized[y][x], new_c8_x, x, new_c8_y, y, lbd)
        elif labelMat[y][x] == 8:
            energy += distance(new_c9_rgb, img_normalized[y][x], new_c9_x, x, new_c9_y, y, lbd)

energy /= (height*width)

x_num.append(itCount)
y_energy.append(energy)
```



Formula

The energy/cost function is given by:

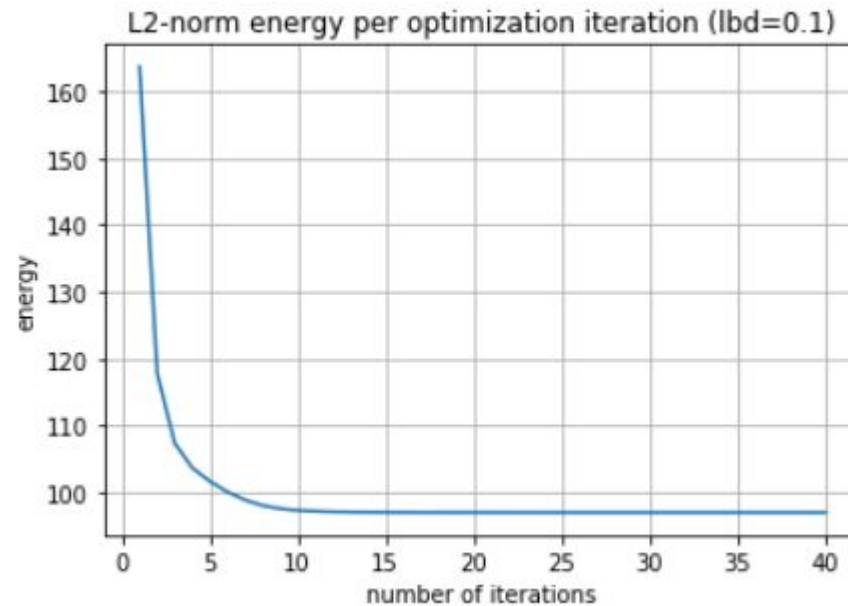
$$\frac{1}{n} \sum_k \sum_{z \in I(k)} \|f(z) - m_k\|^2 + \lambda * \|z - c_k\|^2$$

where $I(k)$ denotes the index set of z that belongs to cluster k , $f(z)$ denotes the image value (r, g, b) at the spatial location z , m_k denotes the centroid of image intensity for cluster k , c_k denotes the centroid of spatial location for cluster k , n denotes total number of pixels, and λ determines the importance between the image intensity and the spatial relation.

- N: 픽셀의 개수/이미지 크기 (height x width)
- M(k): cluster k의 이미지 centroid
- C(k): cluster k의 위치 centroid

Energy/Cost Graph Plot

```
fig, ax = plt.subplots()
ax.plot(x_num, y_energy)
ax.set(xlabel='number of iterations', ylabel='energy',
title='L2-norm energy per optimization iteration (lbd={})'.format(lbd))
ax.grid()
plt.show()
```





Part 4

Applications

SNS 데이터를 활용하여 고객의 마음 읽기

<가정>

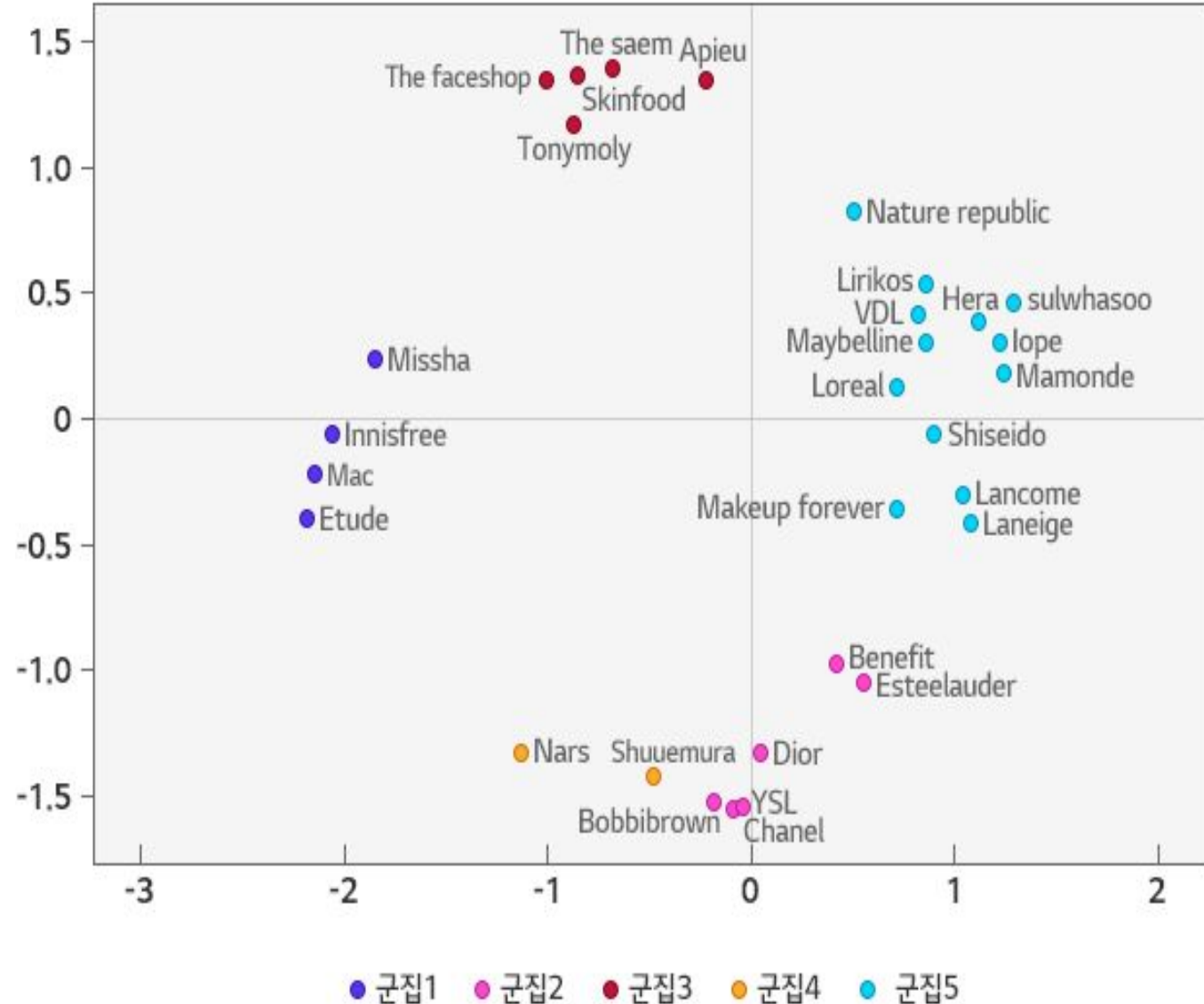
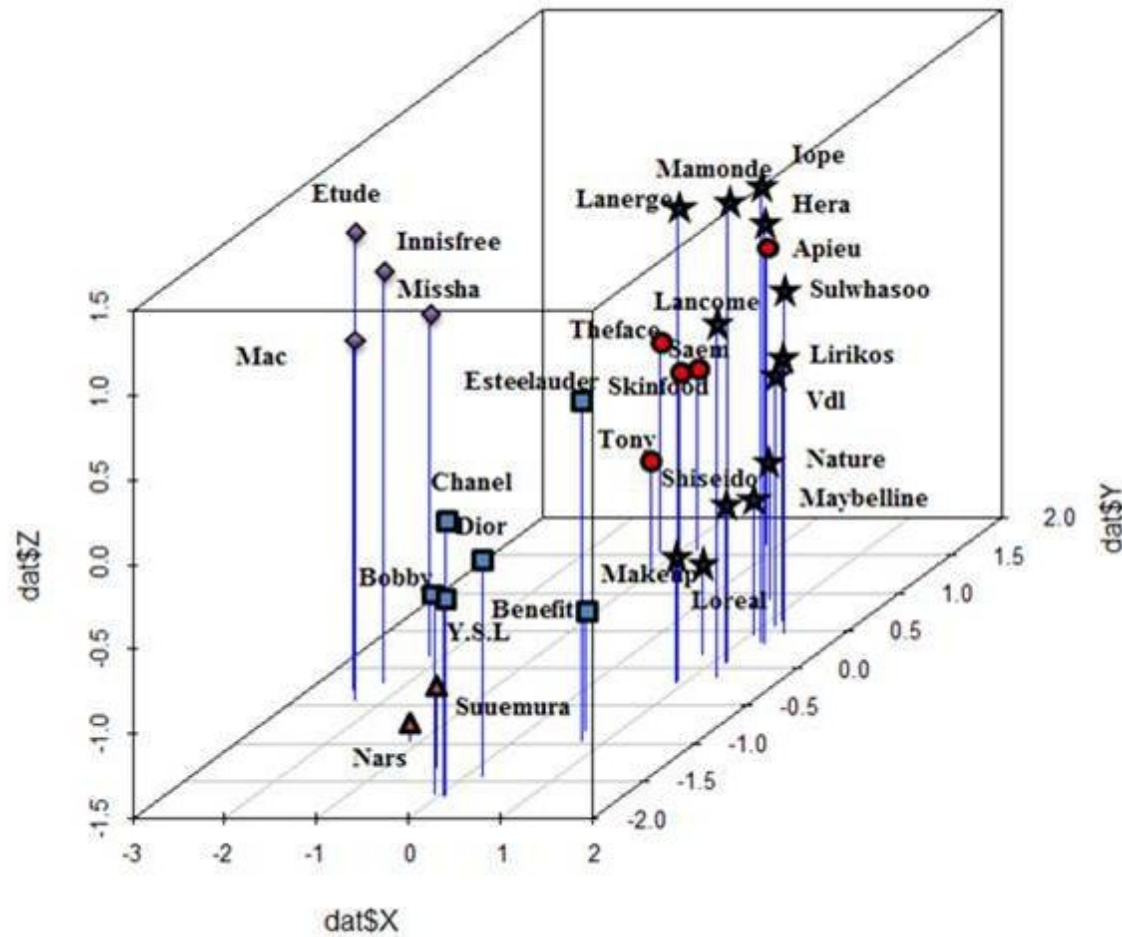
SNS 상에서 두 개의 브랜드가
함께 언급되는 빈도가 많을
수록, 소비자들이 두 브랜드를
더 유사하게 인식할 것이다.




SNS와 화장품 브랜드

Brand Names	Innisfree	Missha	Etude	The faceshop	Mac	...	Nars
Innisfree	-	406	1137	391	195	...	-
Missha	105	-	836	247	185	...	-
Etude	1137	837	-	630	499	...	323
The faceshop	391	246	631	-	116	...	-
Mac	0	0	369	0	-	...	608
...
Nars	89	97	244	-	607	...	-

SNS와 화장품 브랜드



A top-down view of four white ceramic coffee cups arranged in a square on a rustic, circular wooden tray. Each cup contains a latte with intricate brown and white foam art. The cups have dark blue handles. A large, semi-transparent, light beige circle is centered over the image, containing the text 'Thank You' and '감사합니다' in a dark, sans-serif font.

Thank You
감사합니다