

# HW 7

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ECE M146

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[C]

Step 1,  $r_{ik}$  is assigning  $x_n$  to the closest

cluster for each  $x_n$ . As the equation,  
 $k = \arg \min |x_n - x_i^*|$ . In this equation  $x_i^*$

is a median of  $i$  cluster and  $r_{ik}$  is one  
 when it is belonged to the cluster

Step 2 for  $i \in \{1, 2, \dots, k\}$ , for all  $i$ , update  
 the value of median for  $i$   
 \* median  $\bar{y}_i \cdot x_n: r_{ni} = 1$

$$① f(u_k) = \sum_{n \in k} \|x_n - u_k\|_1 = \sum_{n=1}^N \sum_{i=1}^k |x_{ni} - u_{ki}|$$

[1-a]  $f(\bar{y}) = \sum_{j=1}^m y_j - \bar{y}$  for  $y \in R$ . + subgradient +

$$f(x) \geq f(\bar{x}) + g(\bar{x} - x) \rightarrow f(\bar{x}) - f(x) \geq g(\bar{x} - x)$$

$g$  is a subgradient of  $f$  at  $\bar{x}$  when  $f(x) + g(\bar{x} - x)$  is a  
 global estimator of  $f$

$f$  is subdifferentiable at  $\bar{x}$  when there is at least one  
 subgradient at  $\bar{x}$

$f$  is subdifferentiable at  $\bar{x} =$  subdifferentiable of  $f$  at  $\bar{x}$ .

\*  $f(x) = |x|$

When  $x < 0$  the subgradient is unique.

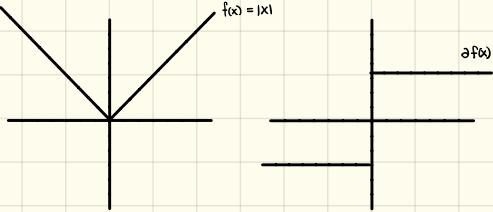
$$\partial f(x) = \{-1\}$$

When  $x > 0$ ,  $\partial f(x) = \{1\}$

When  $x = 0$ , the subdifferential is defined by

$|x| \geq g x$  when  $g$  is 1 or -1,

$$\rightarrow \partial f = \{1, -1\}$$



[1-b]  $\min \sum_{j=1}^m |y_j - \bar{y}|$

To satisfy subdifferentiable, there should be zero at  
 least in one element and  $y_i$  value is getting increasing depends  
 on the increment of index  $i$ . When doing partial  
 derivative of  $f(y_i)$ ,  $\partial f(y_i) = \partial f(y_1) + \partial f(y_2) + \dots + \partial f(y_m)$

the value will be -1 or 1

To minimize it, the median can be zero and the smaller  
 elements can be -1 and the bigger element ( $y_i$ )  
 $(y_i)$  can be +1. So that canceling out each other.

$\bar{y}^*$  we minimize  $\sum_{j=1}^m |y_j - \bar{y}|$  is the median of  $\{y_1, \dots, y_m\}$

(2)

$$2-a) A = \begin{bmatrix} 3 & 2 \\ 2 & 0 \end{bmatrix}, \quad \lambda I = \begin{bmatrix} \lambda & 0 \\ 0 & \lambda \end{bmatrix}, \quad A - \lambda I = \begin{bmatrix} 3-\lambda & 2 \\ 2 & -\lambda \end{bmatrix}$$

$$\det \begin{bmatrix} 3-\lambda & 2 \\ 2 & -\lambda \end{bmatrix} = -(3-\lambda)\lambda - 4 = \lambda^2 - 3\lambda - 4 = 0$$

$$\lambda^2 - 3\lambda - 4 = (\lambda-4)(\lambda+1) = 0 \quad \lambda = 4, -1$$

$$A - \lambda I = \begin{bmatrix} 3-\lambda & 2 \\ 2 & -\lambda \end{bmatrix} = B$$

When  $\lambda = 4$   $B = \begin{bmatrix} -1 & 2 \\ 2 & -4 \end{bmatrix}$   $Bx = 0 \quad -x_1 + 2x_2 = 0$   
 $x_1 = 2x_2$  eigen value : 4  
let  $x_1 = 2, x_2 = 1$  eigen vector :  $\begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{1}{\sqrt{5}} \end{bmatrix} = U_1$

When  $\lambda = -1$   $B = \begin{bmatrix} 4 & 2 \\ 2 & 2 \end{bmatrix}$   $Bx = 0 \quad 2x_1 + x_2 = 0$   
 $2x_1 = -x_2$  eigen value : -1  
let  $x_1 = 1, x_2 = -2$  eigen vector :  $\begin{bmatrix} \frac{1}{\sqrt{5}} & \frac{-2}{\sqrt{5}} \end{bmatrix} = U_2$

$$2-b) U_1^T U_1 = I \quad U_2^T U_2 = I$$

$A = U \Lambda U^{-1}$   
 $U$  : matrix (each column is eigenvalue of A)  
 $\Lambda$  : diagonal matrix

$$U: \begin{bmatrix} 1 & 1 \\ 1 & -2 \end{bmatrix}, \quad U^{-1} = -\frac{1}{5} \begin{bmatrix} -2 & 1 \\ -1 & 2 \end{bmatrix}$$

$$\Lambda: \begin{bmatrix} 4 & 0 \\ 0 & -1 \end{bmatrix}$$

$$A = \begin{bmatrix} 1 & 1 \\ 1 & -2 \end{bmatrix} \begin{bmatrix} 4 & 0 \\ 0 & -1 \end{bmatrix} \begin{bmatrix} -2 & 1 \\ -1 & 2 \end{bmatrix}^{-1}$$

$$= \begin{bmatrix} 8 & 1 \\ 4 & 2 \end{bmatrix} \begin{bmatrix} -2 & 1 \\ -1 & 2 \end{bmatrix} \left( \frac{1}{5} \right)$$

$$= \begin{bmatrix} -16 & -10 \\ -10 & 0 \end{bmatrix} \left( -\frac{1}{5} \right) = \begin{bmatrix} 3 & 2 \\ 2 & 0 \end{bmatrix}$$

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

"""
MU value for b
[[147. 200. 250.]
 [ 0.  0.  0.]
 [137. 141. 57.]
 [31. 70. 125.]]

ITR=10
J = [3.17714549e+09 3.85576888e+09 3.85584076e+09 3.85584076e+09
0.0000000e+00 0.0000000e+00 0.0000000e+00 0.0000000e+00
0.0000000e+00 0.0000000e+00]

ITR=10 K = 16
MU value is
[[204.81911369 223.51605521 229.27264059]
[172.76879134 189.95224768 194.98604428]
[171.33775539 188.33198992 191.81679261]
[169.1043734 186.53001412 190.8369641 ]
[180.1574569 192.45258183 191.58246094]
[177.98176647 190.45088211 190.13512524]
[174.32042506 186.65266953 184.95372542]
[185.28253622 194.40710332 190.35956802]
[188.35814331 194.5698956 187.97761779]
[177.00181633 182.14370675 174.66152041]
[139.04322238 143.81714317 135.72721039]
[143.23318653 147.56318002 139.26170862]
[143.44539854 147.63004615 139.5952234]
[143.05820491 147.00532338 138.40510813]
[143.02923084 147.04781564 138.53027858]
[141.49944227 145.80183048 137.77128362]]

"""

#####
iteration = 10
k = 16 # k value in k-means algorithm
#####
img = cv2.imread("UCLA_Bruin.jpg") # by using imread, read the image
img = cv2.cvtColor(img, cv2.COLOR_BGR2RGB)
#cv2.imshow("UCLA_Bruin.jpg", img)
#cv2.waitKey(0)
#cv2.destroyAllWindows()
INIT_I = 0; INIT_J = 0
for i in range(0,300,1):
    for j in range(0,400,1):
        if img[i][j][0] == 147:
            if img[i][j][1] == 200:
                if img[i][j][2] == 250:
                    INIT_I = j
                    INIT_J = i
MU_ARR = np.zeros((k, 3))
MU_ARR[0] = img[INIT_I][INIT_J]

for K_VAL in range(1,k):
    MAX_X = 0; MAX_Y = 0
    MAX_diff = 0
    for y in range(300):
        for x in range(400):
            MIN_diff_ARR = []
            for index in range(0,K_VAL):
                distance = (MU_ARR[index][0]-img[y][x][0])**2 + \
                           (MU_ARR[index][1]-img[y][x][1])**2 + \
                           (MU_ARR[index][2]-img[y][x][2])**2
                MIN_diff_ARR.append(distance)
            if np.min(MIN_diff_ARR) > MAX_diff:
                MAX_X = x
                MAX_Y = y
                MAX_diff = np.min(MIN_diff_ARR)
            MU_ARR[K_VAL] = img[MAX_Y][MAX_X]

print(MU_ARR)

```

```

J = np.zeros(iteration)
r = np.zeros((300, 400, k))
for itr in range(iteration):
    for i in range(300):
        for j in range(400):
            DISTANCE_ARR = []
            for k_val in range(k):
                DISTANCE_ARR.append(np.sqrt(np.linalg.norm(img[i][j] - MU_ARR[k_val])**2))
            T = np.argmin(DISTANCE_ARR)
            r[i][j][T] = 1
    n = np.zeros(3)
    d = 0
    for k_val in range(k):
        for i in range(300):
            for j in range(400):
                if r[i][j][k_val] == 1:
                    n += img[i][j]
                    d += 1
        MU_ARR[k_val] = n/d
    for k_val in range(k):
        for i in range(300):
            for j in range(400):
                if r[i][j][k_val] == 1:
                    if [itr] += np.linalg.norm(img[i][j] - MU_ARR[k_val])**2
    plt.plot(J)
    plt.show()
img2 = img
for itr in range(iteration):
    for i in range(300):
        for j in range(400):
            Close_diff = (img2[i][j][0] - MU_ARR[0][0])**2 + \
                         (img2[i][j][1] - MU_ARR[0][1])**2 + \
                         (img2[i][j][2] - MU_ARR[0][2])**2
            Close_diff = np.sqrt(Close_diff)
            Close_K = 0
            for k_val in range(1,k):
                data = (img2[i][j][0] - MU_ARR[k_val][0])**2 + \
                       (img2[i][j][1] - MU_ARR[k_val][1])**2 + \
                       (img2[i][j][2] - MU_ARR[k_val][2])**2
                data = np.sqrt(data)
                if data < Close_diff:
                    Close_diff = data
                    Close_K = k_val
            img2[i][j] = MU_ARR[Close_K]
    img2 = cv2.cvtColor(img2, cv2.COLOR_RGB2BGR)

cv2.imshow("NEW_Bruin", img2)
cv2.waitKey(0)
cv2.destroyAllWindows()

```

③

⑥ By the graph, the K means algorithm function is converged to zero for the increasing iteration.

⑦ K is the number of clusters and K made the picture to be more precise and bigger K value in picture is more similar to original picture. because it would have more clusters and could have more various color for consisting image.

⑧ For image,  $24N$  bits which is  $N$ : pixels  
 $24 \cdot 300 \cdot 400$  bits. = 2880000 bits.

For K cluster,  $N \log_2 K + 24K$  (bits)

$$\text{When } K=4, 300 \cdot 400 \log_2 4 + 24 \cdot 4 \\ = 240096 \text{ (bits)}$$

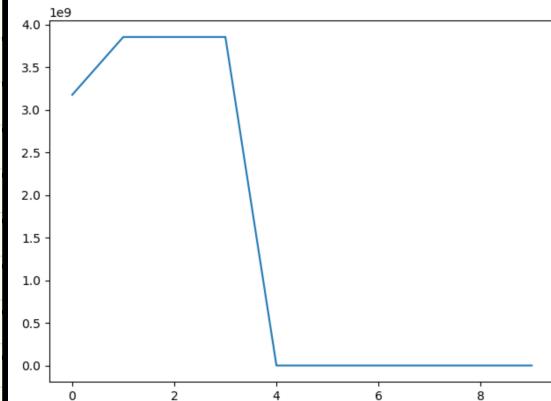
$$\text{When } K=8, 300 \cdot 400 \log_2 8 + 24 \cdot 8 \\ = 360192 \text{ (bits)}$$

$$\text{When } K=16, 300 \cdot 400 \log_2 16 + 24 \cdot 16 \\ = 480384 \text{ (bits)}$$

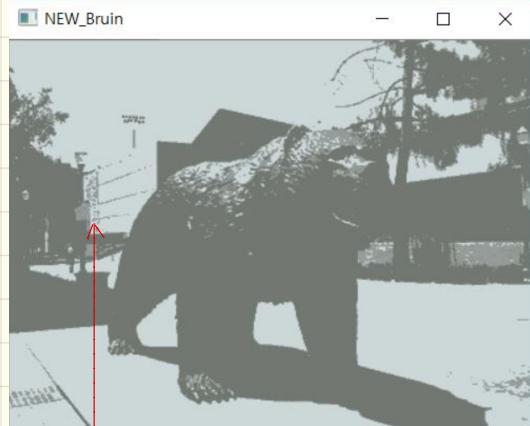
$$\text{original} : K=4 \therefore K=8 \therefore K=16 \\ = 1 : 0.088 \therefore 0.125 \therefore 0.167$$

$$(1.4) \text{Size}(K=4) \approx \text{Size}(K=8)$$

$$(1.4) \text{Size}(K=8) \approx \text{Size}(K=16)$$



When  $K=4$



there is difference.

When  $K=8$



when  $K=16$

NEW\_Bruin

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