

Homework #3

① Gaussian Mixture Model & EM Algorithm

dataset: $[-67, -48, 6, 8, 14, 16, 23, 24]$

$k=2$

1.1) Total No of parameters in this GMM $\Rightarrow 4$ And they are: $\begin{Bmatrix} \mu_1, \sigma_1^2 \\ \mu_2, \sigma_2^2 \end{Bmatrix}$ as $k=2$ 1.2) Parameter Initialization \downarrow

$$\begin{array}{l|l} \mu_a = 16 & \mu_b = -56 \\ \sigma_a^2 = 10 & \sigma_b^2 = 12 \end{array}$$

As $k=2$, there are two components i.e. a & b

$P(a) = 0.5$

$P(b) = 0.5$

E-Step \downarrow

$$P(x_i|a) = \frac{1}{\sqrt{2\pi}\sigma_a} \exp\left\{-\frac{(x_i - \mu_a)^2}{2\sigma_a^2}\right\}$$

$$P(x_i|b) = \frac{1}{\sqrt{2\pi}\sigma_b} \exp\left\{-\frac{(x_i - \mu_b)^2}{2\sigma_b^2}\right\}$$

$$a_i = P(a|x_i) = \frac{P(x_i|a)P(a)}{P(x_i|a)P(a) + P(x_i|b)P(b)}$$

$$b_i = 1 - a_i$$

②

Now let's apply the E-step to each of the datapoint given in dataset: $[-67, -48, 6, 8, 14, 16, 23, 24]$

$$X_1^* = -67$$

$$P(X_1|a) = \frac{1}{\sqrt{2\pi \times 10^2}} \exp\left\{-\frac{(-67-16)^2}{2 \times 100}\right\} = \frac{1}{25} \exp\left\{-\frac{(83)^2}{200}\right\}$$

$$= \frac{1}{25} \times 0 = 0$$

$$P(X_1|b) = \frac{1}{\sqrt{2\pi \times 144}} \exp\left\{-\frac{(-67+56)^2}{2 \times 144}\right\} = \frac{1}{30} \times 0.65 = 0.021$$

$$a_1 = P(a|X_1) = \frac{0}{0 + 0.5 \times 0.021} = 0$$

$$b_1 = P(b|X_1) = 1 - a_1 = \underline{\underline{1}}$$

$$X_2 = -48$$

$$P(X_2|a) = \frac{1}{25} \exp\left\{-\frac{(-48-16)^2}{200}\right\} = \frac{1}{25} \times 0 = 0$$

$$P(X_2|b) = \frac{1}{30} \exp\left\{-\frac{(-48+56)^2}{288}\right\} = \frac{1}{25} \times 0.80 = 0.026$$

$$a_2 = P(a|X_2) = \frac{0}{0 + 0.5 \times 0.026} = 0$$

$$b_2 = 1 - a_2 = \underline{\underline{1}}$$

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$$\underline{x_2 = 8}$$

$$P(x_2|a) = \frac{1}{25} \exp\left\{-\frac{(8-16)^2}{200}\right\} = 0.029$$

$$P(x_2|b) = \frac{1}{30} \exp\left\{-\frac{(8+56)^2}{288}\right\} = 0$$

$$a_2 = P(a|x_2) = \frac{0.029 \times 0.5}{0.029 \times 0.5 + 0} = 1$$

$$b_2 = 1 - a_2 = 0$$

$$\underline{x_3 = 6}$$

$$P(x_3|a) = \frac{1}{25} \exp\left\{-\frac{(6-16)^2}{200}\right\} = \frac{1}{25} \times 0.6 = 0.024$$

$$P(x_3|b) = \frac{1}{30} \exp\left\{-\frac{(6+56)^2}{288}\right\} = \frac{1}{30} \times 0 = 0$$

$$a_3 = P(a|x_3) = \frac{0.024 \times 0.5}{0.024 \times 0.5 + 0} = 1$$

$$b_3 = 1 - a_3 = 0$$

$$\underline{x_5 = 14}$$

$$P(x_5|a) = \frac{1}{25} \exp\left\{-\frac{(14-16)^2}{200}\right\} = \frac{1}{25} \times 0.98 = 0.039$$

$$P(x_5|b) = \frac{1}{30} \exp\left\{-\frac{(14+56)^2}{288}\right\} = \frac{1}{30} \times 0 = 0$$

$$a_5 = P(a|x_5) = 1$$

$$b_5 = 1 - 1 = 0$$

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$$\underline{x_6 = 16}$$

$$P(x_6|a) = \frac{1}{25} \exp\left\{-\frac{(16-16)^2}{200}\right\} = \frac{1}{25} \times 1 = 0.04$$

$$P(x_6|b) = \frac{1}{25} \exp\left\{-\frac{(16+56)^2}{288}\right\} = 0$$

$$a_6 = 1$$

$$b_6 = 0$$

$$\underline{x_7 = 23}$$

$$P(x_7|a) = \frac{1}{25} \exp\left\{-\frac{(23-16)^2}{200}\right\} = \frac{1}{25} \times 0.78 = 0.031$$

$$P(x_7|b) = \frac{1}{30} \exp\left\{-\frac{(23+56)^2}{288}\right\} = \frac{1}{30} \times 0 = 0$$

$$a_7 = 1$$

$$b_7 = 0$$

$$\underline{x_8 = 24}$$

$$P(x_8|a) = \frac{1}{25} \exp\left\{-\frac{(24-16)^2}{200}\right\} = \frac{1}{25} \times 0.72 = 0.029$$

$$P(x_8|b) = \frac{1}{25} \exp\left\{-\frac{(24+56)^2}{288}\right\} = \frac{1}{30} \times 0 = 0$$

$$a_8 = 1$$

$$\underline{\underline{b_8 = 0}}$$

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M-Step

After E-Step, we have

$$\begin{array}{l|l} a_1 = a_2 = 0 & b_1 = b_2 = 1 \\ a_3 = a_4 = a_5 = a_6 = a_7 = a_8 = 1 & b_3 = b_4 = b_5 = b_6 = b_7 = b_8 = 0 \end{array}$$

$$\begin{aligned} \mu_a &= \frac{a_1 x_1 + a_2 x_2 + \dots + a_8 x_8}{a_1 + a_2 + \dots + a_8} \\ &= \frac{0 + 0 + 6 + 8 + 14 + 16 + 23 + 24}{6} = \underline{15.166} \end{aligned}$$

$$\begin{aligned} \sigma_a^2 &= \frac{a_1 (\mu_a - x_1)^2 + a_2 (\mu_a - x_2)^2 + \dots + a_8 (\mu_a - x_8)^2}{a_1 + a_2 + \dots + a_8} \\ &= \frac{0 + 0 + 84.02 + 51.35 + 1.35 + 0.69 + 61.37 + 78.03}{6} = \underline{46.136} \end{aligned}$$

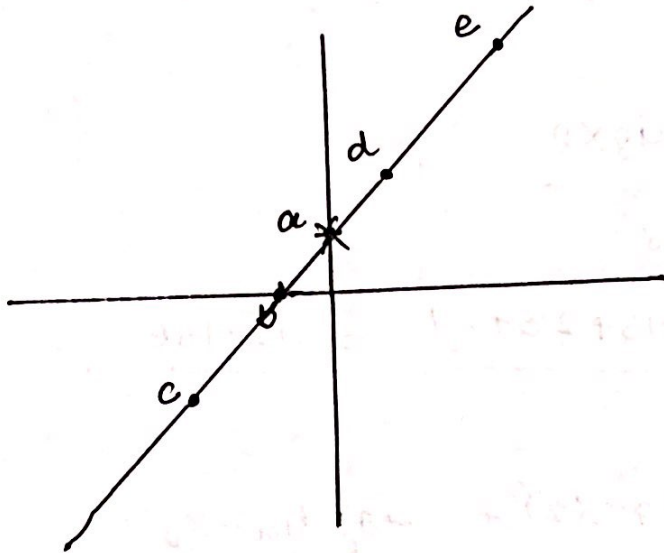
$$\begin{aligned} \mu_b &= \frac{b_1 x_1 + b_2 x_2 + \dots + b_8 x_8}{b_1 + b_2 + \dots + b_8} \\ &= \frac{-67 - 48}{2} = \underline{-57.5} \end{aligned}$$

$$\sigma_b^2 = \frac{90.25 + 90.25}{2} = \underline{90.25}$$

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2) Principle Component Analysis

2.1) dataset: $\{ \overset{a}{(0,1)}, \overset{b}{(-1,0)}, \overset{c}{(-3,-2)}, \overset{d}{(1,2)}, \overset{e}{(3,4)} \}$



$$\text{Mean} = \left(\frac{0+(-1)+(-3)+1+3}{5}, \frac{1+0+(-2)+2+4}{5} \right)$$

$$= (0,1) \equiv \underline{a}$$

Recenter \downarrow

$$X_c \leftarrow X - \bar{X}$$

$$a' = (0,0), b' = (-1,-1), c' = (-3,-3), d' = (1,1), e' = (3,3)$$

Principle Component 1 \downarrow

$$= \frac{1}{\sqrt{1^2+1^2}} (1,1) \Rightarrow \left(\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right)$$

Principle Component 2 \downarrow (orthogonal to PC 1)

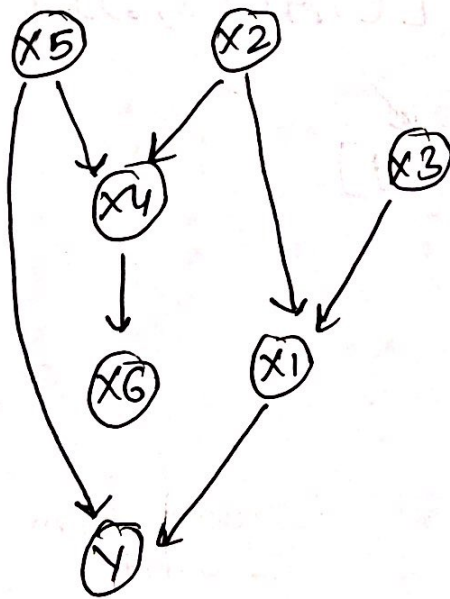
$$= \frac{1}{\sqrt{1^2+1^2}} (-1,1) \Rightarrow \left(-\frac{1}{\sqrt{2}}, \frac{1}{\sqrt{2}} \right) \text{ or } \left(\frac{1}{\sqrt{2}}, -\frac{1}{\sqrt{2}} \right)$$

2.2) Reconstruction Error ↓

$$[]_{m \times n}$$

For an example of a n -dimensional dataset, we can compute n principle components and if we are going to use all n for reconstruction of the data set then, the reconstruction error will be zero as we are selecting all possible n -dimension for the reconstruction.

3) Graphical Model ↓



$$P(Y, X_1, X_2, X_3, X_4, X_5, X_6)$$

$$= P(Y | X_5, X_1) \cdot P(X_1 | X_2, X_3) \cdot P(X_2) \cdot P(X_3) \cdot P(X_4 | X_2, X_5) \cdot$$

$$P(X_5) \cdot P(X_6 | X_4)$$

④ K-Means ↓

4.1

a	b	c	d
3	7	9	5
3	9	7	3

Given ↓

cluster-1 \Rightarrow a, c

cluster-2 \Rightarrow b, d

Iteration-1 ↓

clusters = $\left[\overset{①}{[(3, 3), (9, 7)]}, \overset{②}{[(7, 9), (5, 3)]} \right]$

Recenter-step
centroid = $\left[[(6, 5)], [(6, 6)] \right]$

Iteration-2 ↓

classify step →

	distance from centroid 1	distance from centroid 2
a (3, 3)	$\min(\sqrt{13}) \checkmark$	$\sqrt{18})$
b (9, 7)	$\min(\sqrt{15})$	$\sqrt{10} \checkmark)$
c (7, 9)	$\min(\sqrt{17})$	$\sqrt{10} \checkmark)$
d (5, 3)	$\min(\sqrt{5}) \checkmark$	$\sqrt{10})$

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So, we have new clusters \Rightarrow

$$\text{clusters} = \left[\overset{\textcircled{1}}{[(3,3), (5,3)]}, \overset{\textcircled{2}}{[(9,7), (7,9)]} \right]$$

Recenter step

$$\text{centroids} = \left[[(4,3)], [(8,8)] \right]$$

Iteration 3 \downarrow

classify step \Rightarrow

	distance from centroid 1	distance from centroid 2
a (3,3)	$\min(\sqrt{1}) \checkmark$	$5\sqrt{2}$
b (9,7)	$\min(\sqrt{41})$	$\sqrt{2} \checkmark$
c (7,9)	$\min(\sqrt{45})$	$\sqrt{2} \checkmark$
d (5,3)	$\min(\sqrt{1}) \checkmark$	$\sqrt{34}$

new clusters \downarrow

$$\text{clusters} = \left[\overset{\textcircled{1}}{[(3,3), (5,3)]}, \overset{\textcircled{2}}{[(9,7), (7,9)]} \right]$$

Recenter step

$$\text{centroids} = \left[[(4,3)], [(8,8)] \right]$$

Since new clusters and new centroids iteration 3 are equal to iteration 2, we can say that it has converged and above clusters will be the final clusters.

4.2) Potential function

$$F(\mu, c) = \sum_{j=1}^m ||\mu(c_j) - x_j||^2$$

$$= [(1^2 + 0) + (1^2 + 0) + (1^2 + 1^2) + (1^2 + 1^2)]$$

$$= [1 + 1 + 2 + 2]$$

$$= \underline{\underline{6}}$$

4.3) K-Means ImplementationPseudo code

Step-1 \Rightarrow Process the dataset, ignore the 1st & last column as it is not needed for clustering.

Step-2 \Rightarrow Randomly pick the K-centroids

Step-3 \Rightarrow Now perform the classify & recenter step until it is converged. i.e.

classify step \Rightarrow Assign each of the example / data point to its nearest centroid based on euclidean distance. i.e.

$$c^{(t)}(j) \leftarrow \arg \min_i \|u_i - x_j\|^2$$

Recenter step \rightarrow Now once each data point is assigned to some cluster, find the new centroid for each cluster which is nothing but the average of all points inside that cluster. i.e.

$$u_i^{(t+1)} \leftarrow \arg \min \sum_{j: c(j)=i} \|u_i - x_j\|^2$$

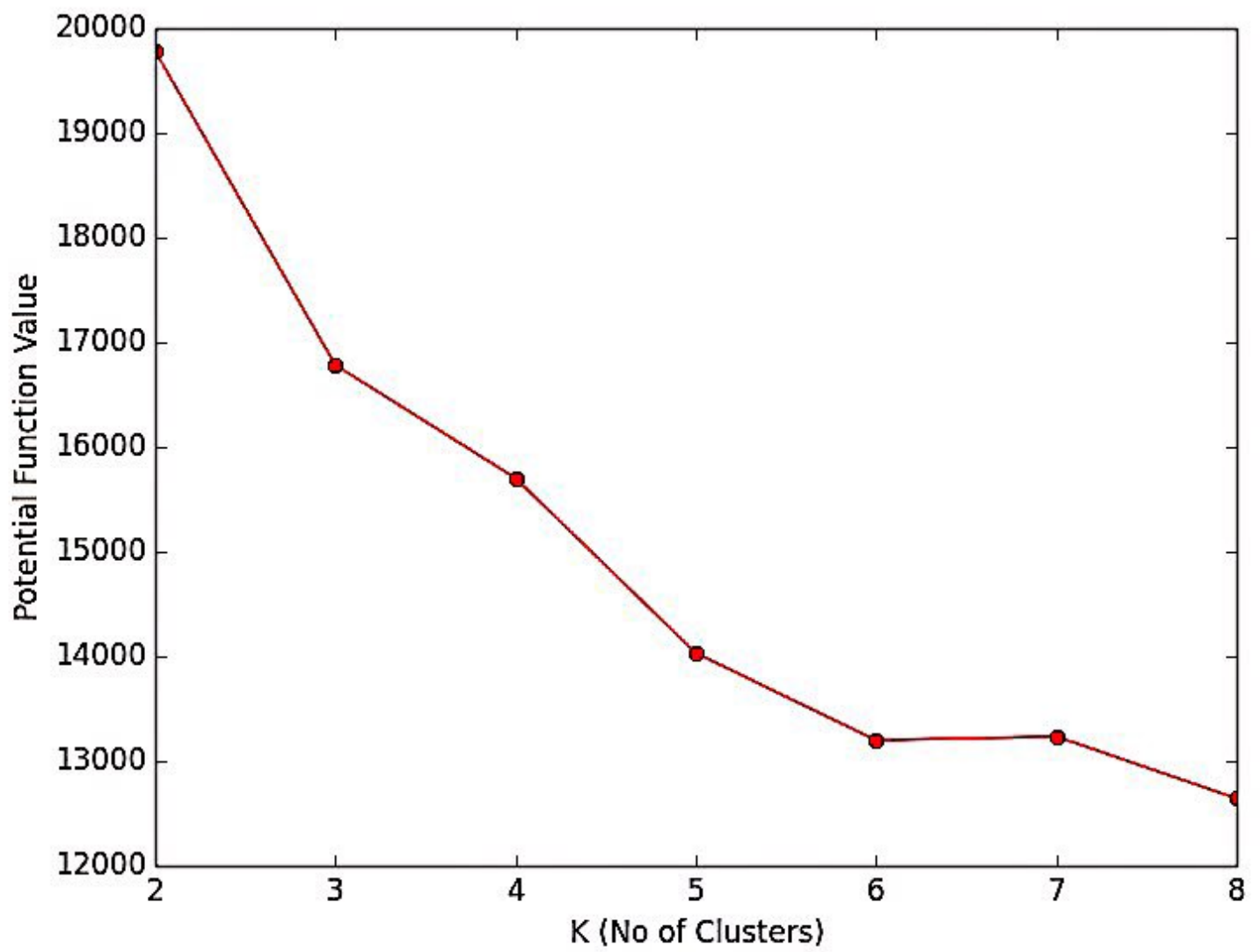
keep performing the classify & recenter step until it is converged.

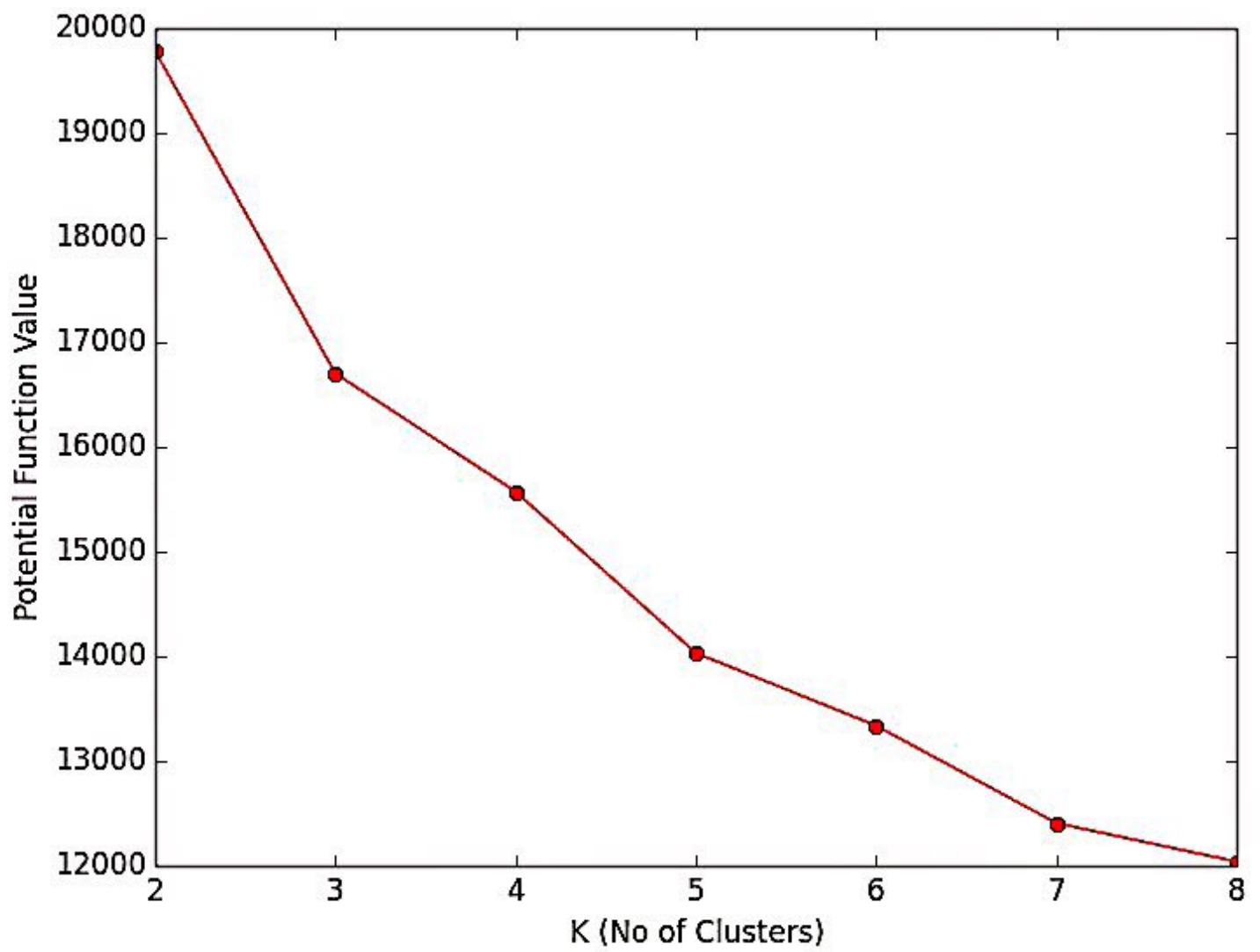
Step-4 find the potential function i.e.

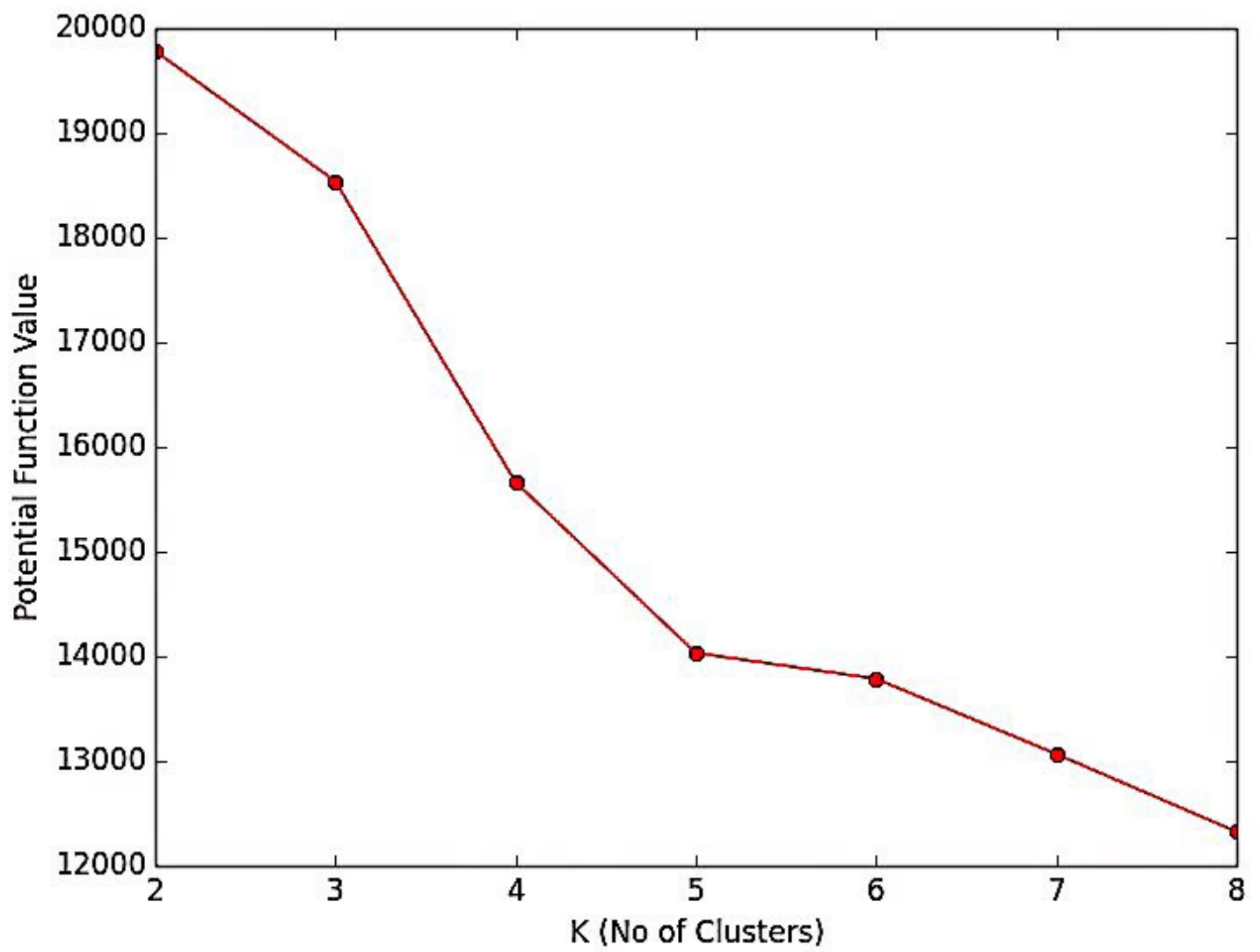
$$F(u, c) = \sum_{j=1}^n \|u_{c(j)} - x_j\|^2$$

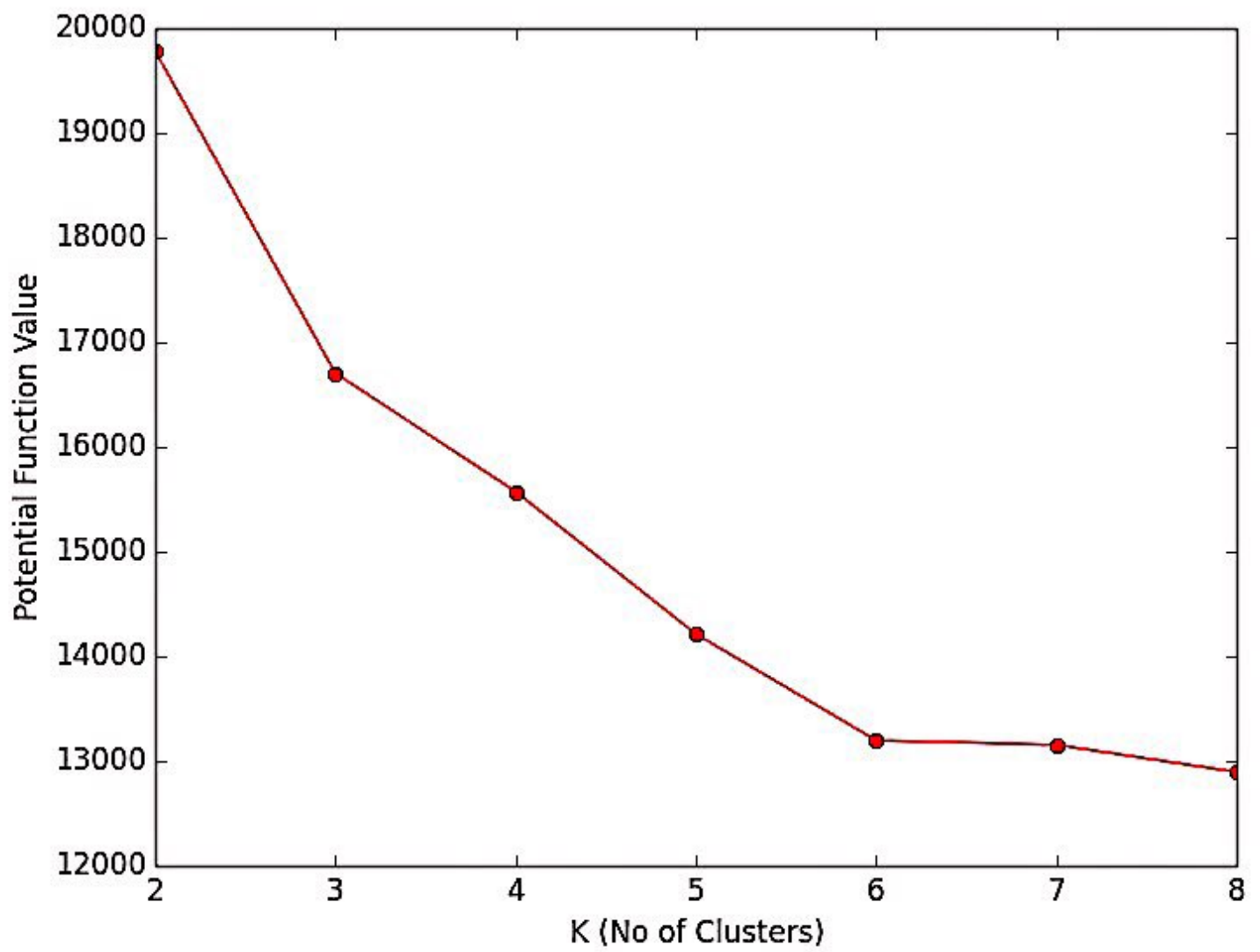
find the $L(k) \vee k$ plot on next page.

We will use the "elbow" method for picking the optimal value of k . And based on the graph plot on next page, we will be choosing $k=6$ as our optimal value as per potential function value decreases abruptly at $k=6$ & stabilizes after that. We won't be choosing the minimum k value with min. potential function. This k can change but we will always follow the elbow rule to determine it.









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[Ashishs-MacBook-Pro:HW3 ashish$ python KMeans.py  
[19782.729804245933, 16713.777153738938, 15575.500891706823, 14032.417674323131,  
13354.78176780874, 13050.624206971424, 13031.282286224101]
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