Clustering

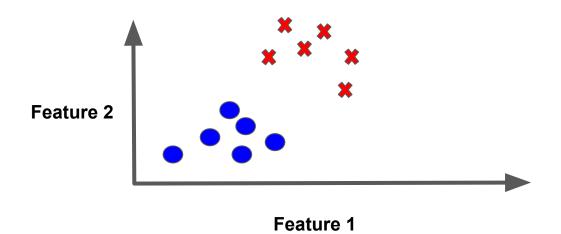
Wajahat Hussain



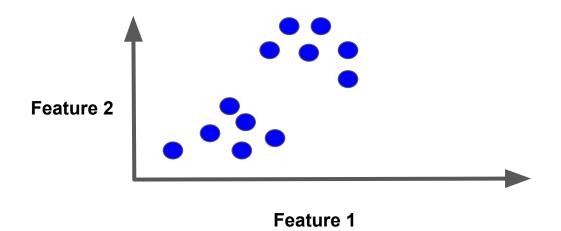
Divide this data into two clusters

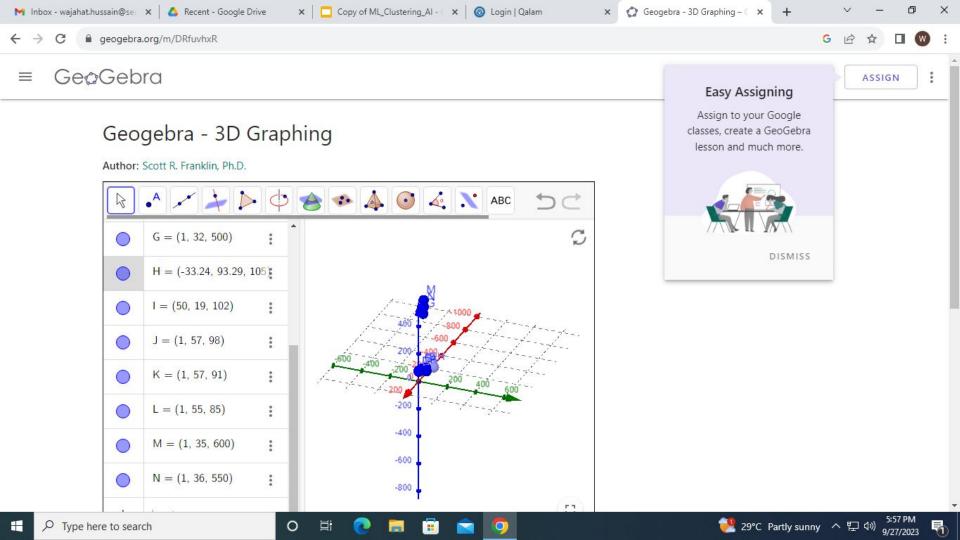
X	Υ
1	2
2	3
3	
4	4 5
1 2 3 4 5 6 7 8 3 4 5	
6	6 7 8 9 2 3
7	8
8	9
3	2
4	3
5	4
6	4 5
6 7	6
8	7
9	8
10	9

Supervised Learning



Unsupervised Learning

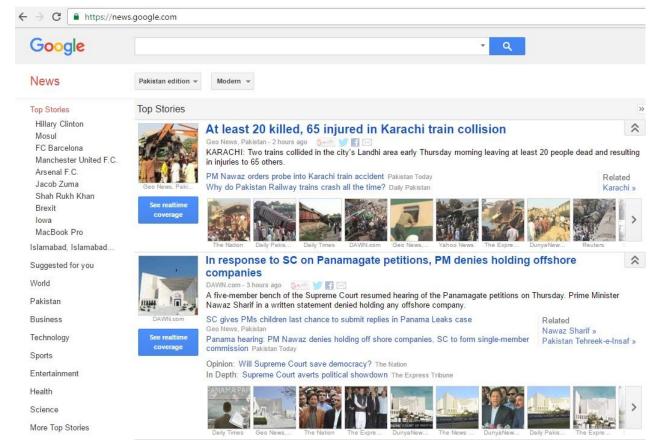




Divide this data into two clusters

X	Υ
1	2
2	3
3	
4	4 5
1 2 3 4 5 6 7 8 3 4 5	
6	6 7 8 9 2 3
7	8
8	9
3	2
4	3
5	4
6	4 5
6 7	6
8	7
9	8
10	9

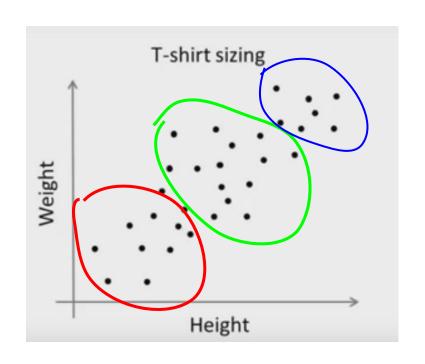
Unsupervised Learning



Unsupervised Learning

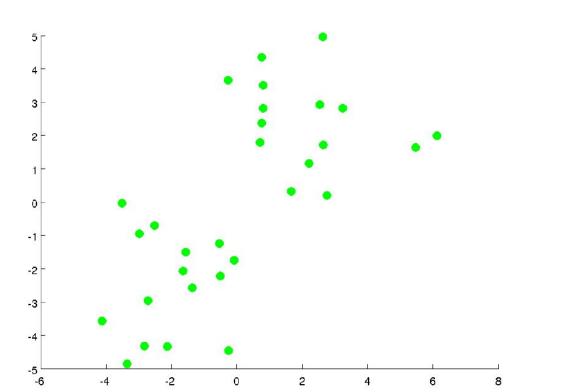


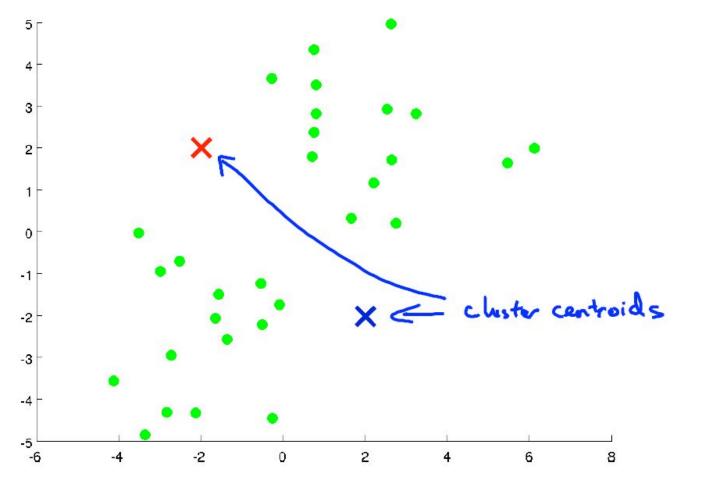
Market segmentation

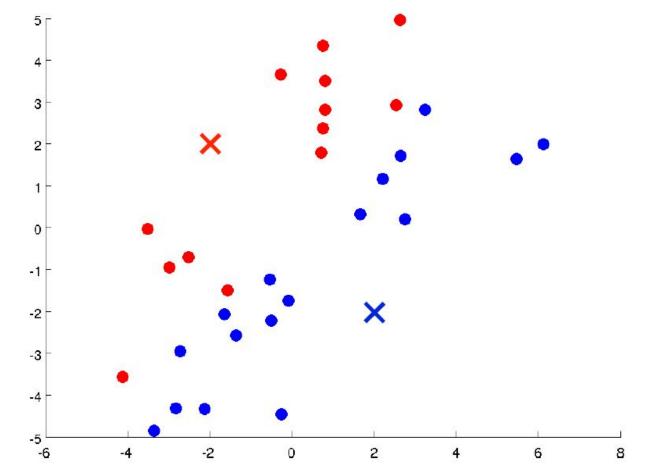


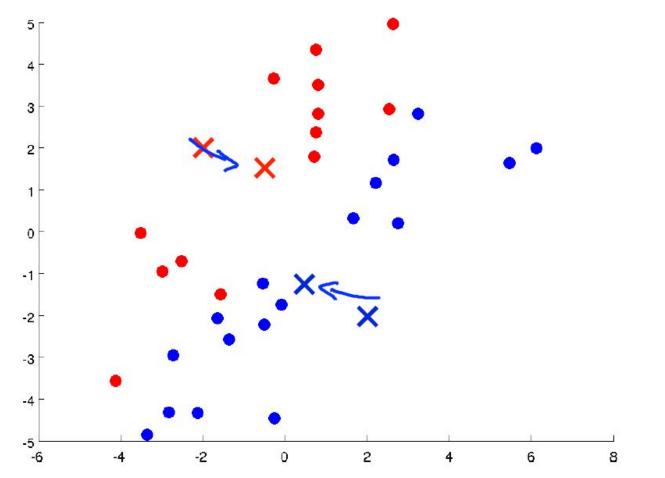
You want to design a shirt. How many sizes should there be?

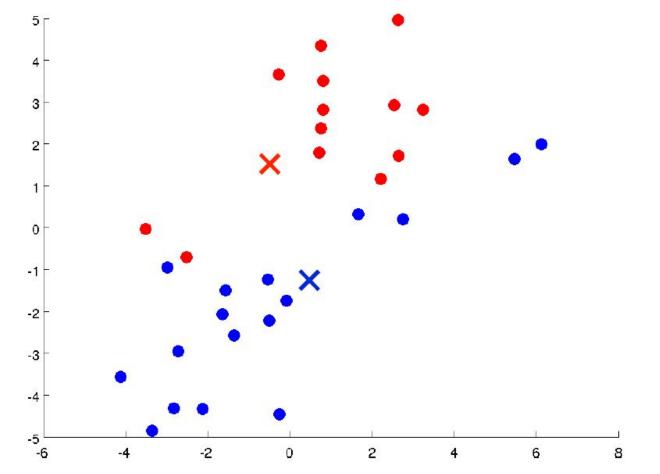
K-means Algorithm

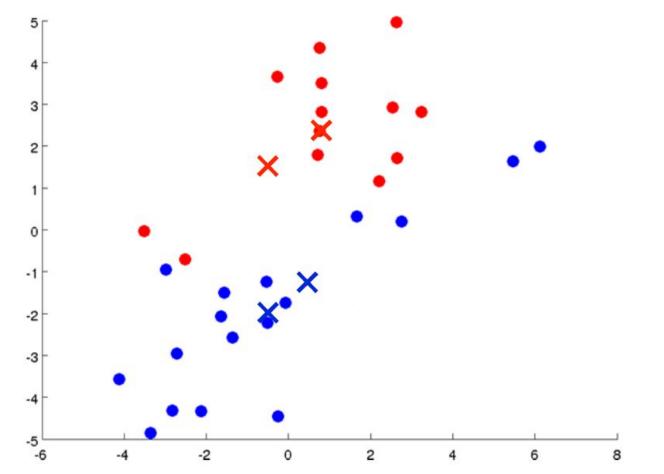


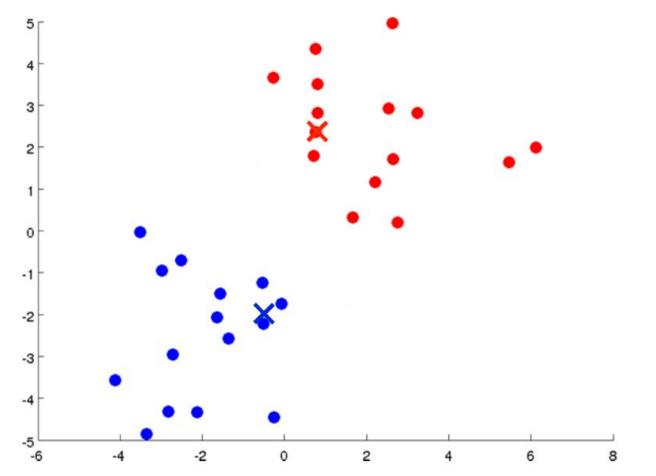


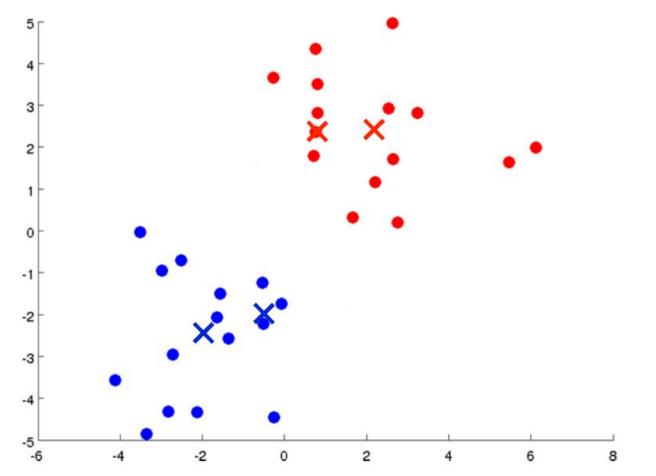


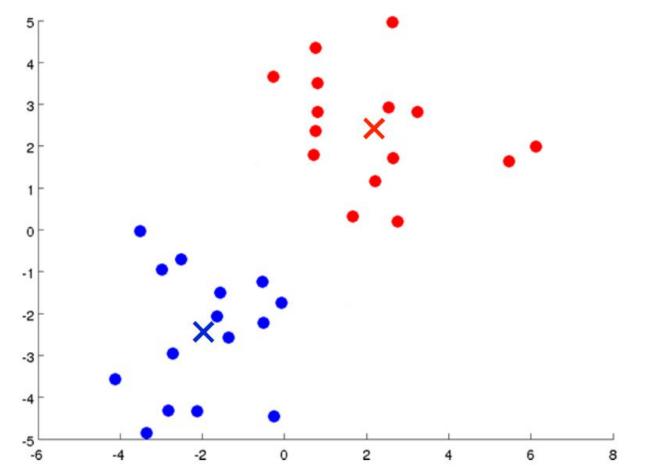


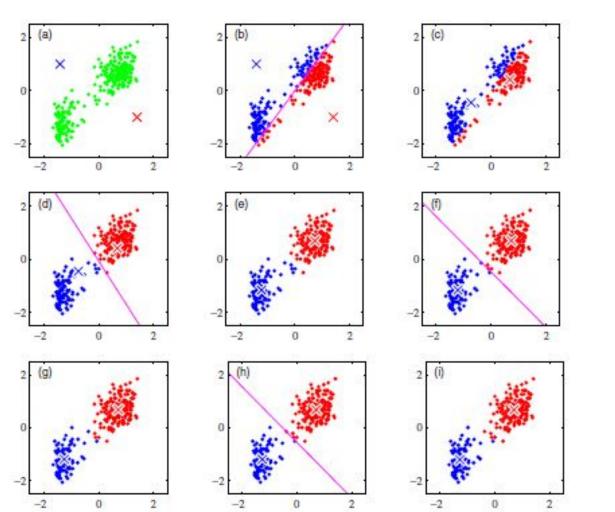






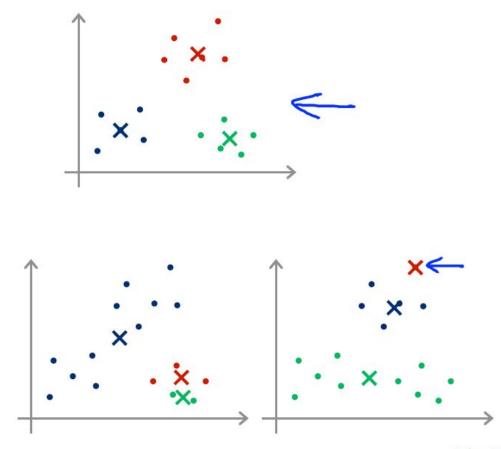






Is there any failure case?

Local optima



K-means algorithm

Input:

- K (number of clusters)
- Training set $\{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$

$$x^{(i)} \in \mathbb{R}^n$$

K-means algorithm

Randomly initialize K cluster centroids $\mu_1, \mu_2, \dots, \mu_K \in \mathbb{R}^n$

```
Repeat {
        for i = 1 to m
           c^{(i)} := \mathsf{index} (from 1 to K ) of cluster centroid
                  closest to x^{(i)}
        for k = 1 to K
           \mu_k := average (mean) of points assigned to cluster k
```

K-means optimization objective

 $c^{(i)}$ = index of cluster (1,2,...,K) to which example $x^{(i)}$ is currently assigned

$$\mu_k = \text{cluster centroid } \underline{k} \ (\mu_k \in \mathbb{R}^n)$$

$$\mu_{c^{(i)}} = \text{cluster centroid of cluster to which example } x^{(i)} \text{ has been assigned}$$
Optimization objective:

Optimization objective:

 μ_1,\ldots,μ_K

$$J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K) = \frac{1}{m} \sum_{i=1}^{m} ||x^{(i)} - \mu_{\underline{c}^{(i)}}||^2$$

$$\min_{c^{(1)}, \dots, c^{(m)}} J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K)$$

One dimensional example. Why average the points?

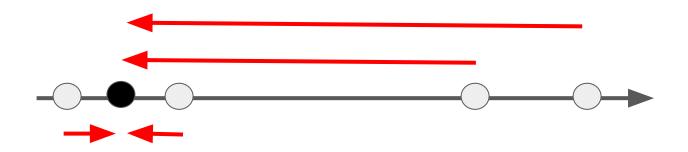
- We assume there is only a single cluster. The cluster center is blue/black circle. Which is a better cluster center? Black or blue?
- Red arrows shows the total error.
- Average of data points represents better cluster representation.



$$J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K) = \frac{1}{m} \sum_{i=1}^{m} ||x^{(i)} - \mu_{c^{(i)}}||^2$$

One dimensional example

- We assume there is only a single cluster. The cluster center is black circle
- Red arrows shows the total error.



$$J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K) = \frac{1}{m} \sum_{i=1}^{m} ||x^{(i)} - \mu_{c^{(i)}}||^2$$

One dimensional example

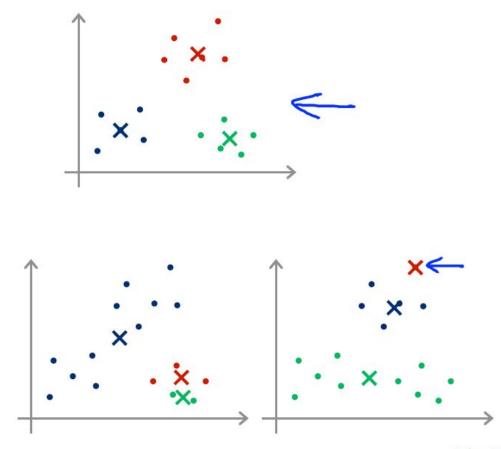
- Now we assume there are two clusters. The cluster centers are black circles.
- Red arrows shows the total error.
- Increasing clusters reduces the error.



$$J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K) = \frac{1}{m} \sum_{i=1}^{m} ||x^{(i)} - \mu_{c^{(i)}}||^2$$

Is there any failure case?

Local optima



How to avoid the local optima?

Random initialization

```
For i = 1 to 100 {  \begin{array}{l} \text{Randomly initialize K-means.} \\ \text{Run K-means. Get } c^{(1)}, \ldots, c^{(m)}, \mu_1, \ldots, \mu_K. \\ \text{Compute cost function (distortion)} \\ J(c^{(1)}, \ldots, c^{(m)}, \mu_1, \ldots, \mu_K) \\ \end{array} \}
```

Pick clustering that gave lowest cost $J(c^{(1)},\ldots,c^{(m)},\mu_1,\ldots,\mu_K)$

One dimensional example



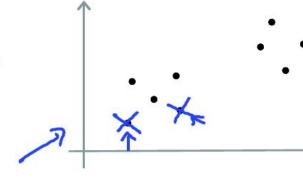
How to randomly initialize the clusters centers?

Random initialization

Should have K < m

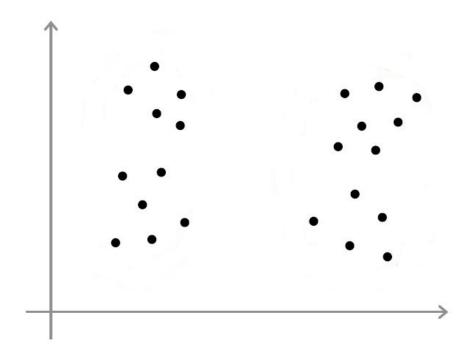
Randomly pick K training examples.

Set μ_1, \dots, μ_K equal to these K examples. $\mu_i = \chi^{(i)}$



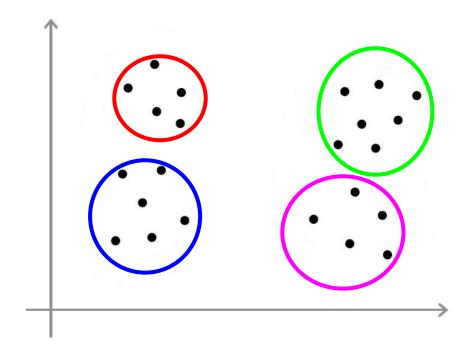
What is the right value of K?

What is the right value of K?



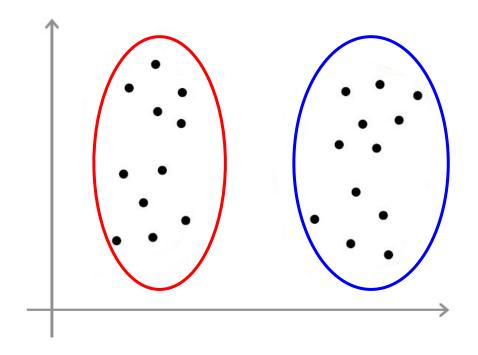
What is the right value of K? 4?

What is the right value of K?



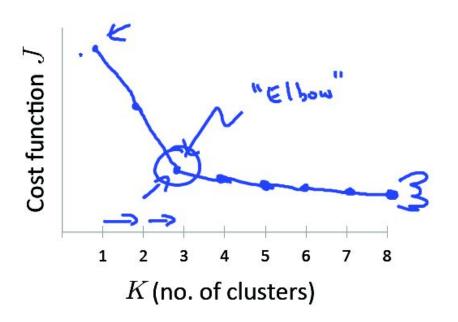
What is the right value of K? 2?

What is the right value of K?



Choosing the value of K

Elbow method:



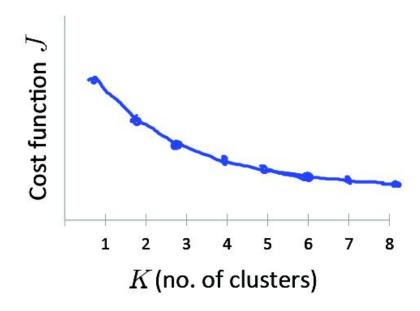


Image Compression Using K-means



Image Compression Using K-means



N pixelsR, G, B Channel8 bits per value

Total bits = 24 N bits

K clusters

Total bits =24 K + N log₂ K bits

http://ieeexplore.ieee.org > document

Love it or leave it? A new look at Signal Fidelity Measures

by Z Wang · 2009 · Cited by 2787 — In this article, we have reviewed the reasons why we (collectively) want to **love** or **leave** the venerable (but perhaps hoary) **MSE**.

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