

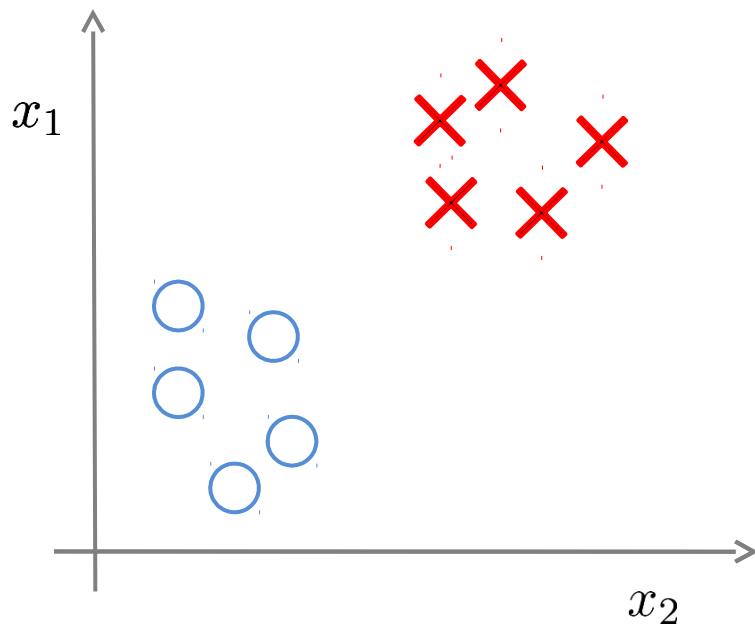


Machine Learning

Clusterin

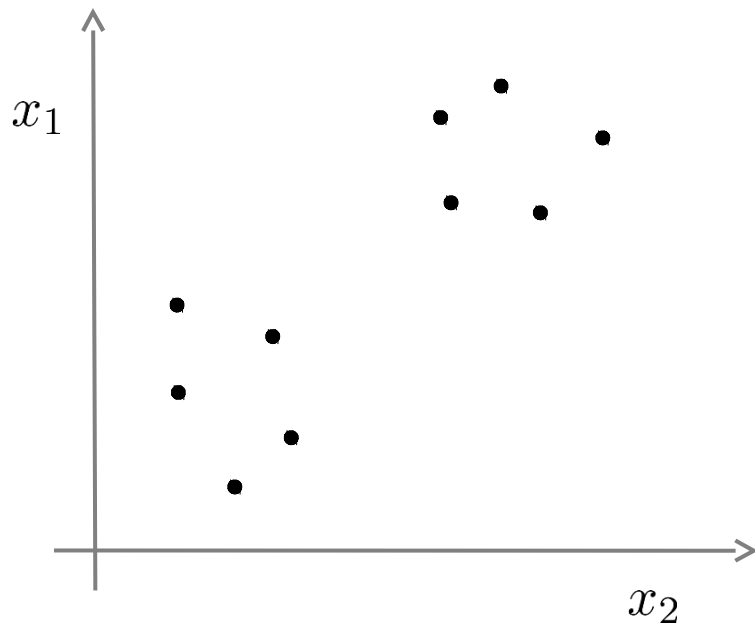
~~Unsupervised~~
learning
introduction

Supervised learning



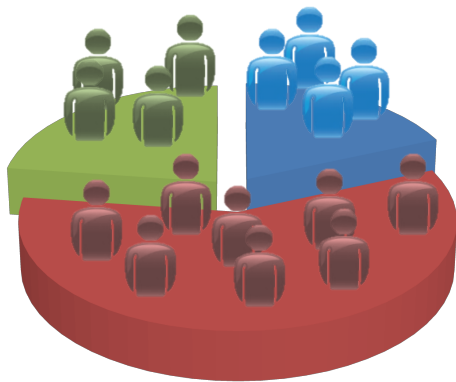
Training set: $\{(x^{(1)}, y^{(1)}), (x^{(2)}, y^{(2)}), (x^{(3)}, y^{(3)}), \dots, (x^{(m)}, y^{(m)})\}$

Unsupervised learning

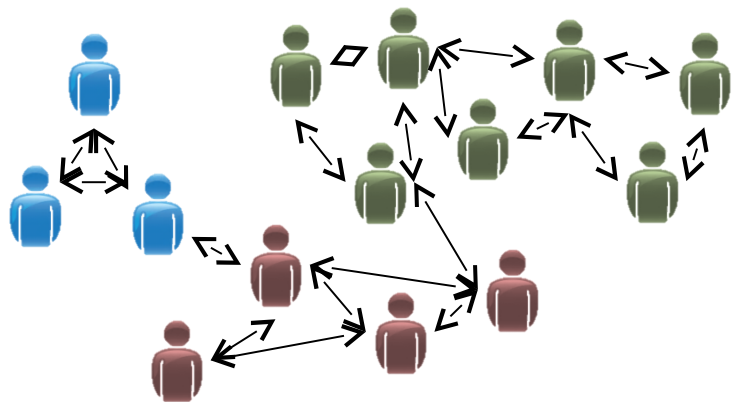


Training set $\{x^{(1)}, x^{(2)}, x^{(3)}, \dots, x^{(m)}\}$

Applications of clustering



Market
segmentation



Social network



Organize computing
clusters

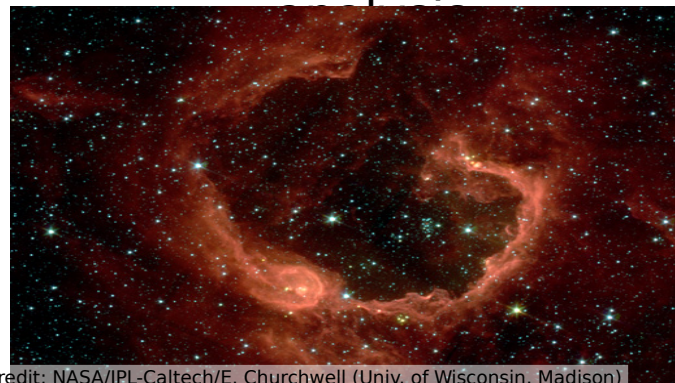


Image credit: NASA/JPL-Caltech/E. Churchwell (Univ. of Wisconsin, Madison)

Astronomical data
analysis

Which of the following statements are true? Check all that apply.

- ☒ In unsupervised learning, the training set is of the form $\{x^{(1)}, x^{(2)}, \dots, x^{(m)}\}$ without labels $y^{(i)}$.

Correct Response

- ☒ Clustering is an example of unsupervised learning.

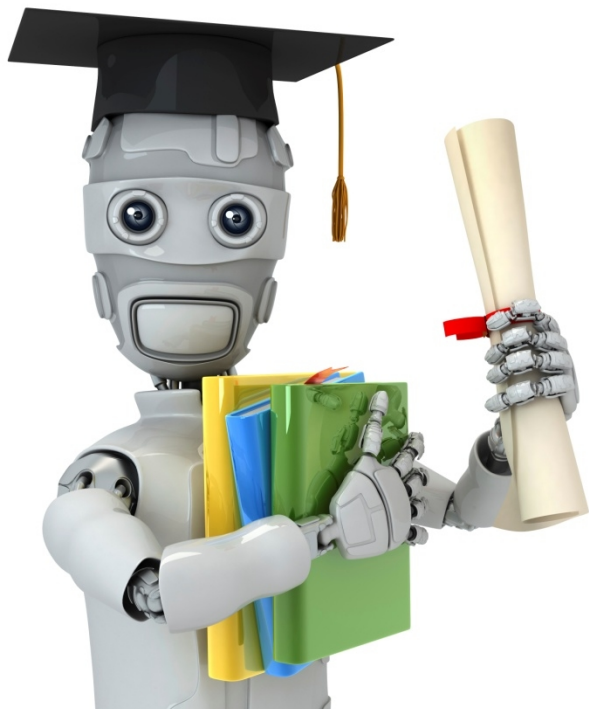
Correct Response

- ☒ In unsupervised learning, you are given an unlabeled dataset and are asked to find "structure" in the data.

Correct Response

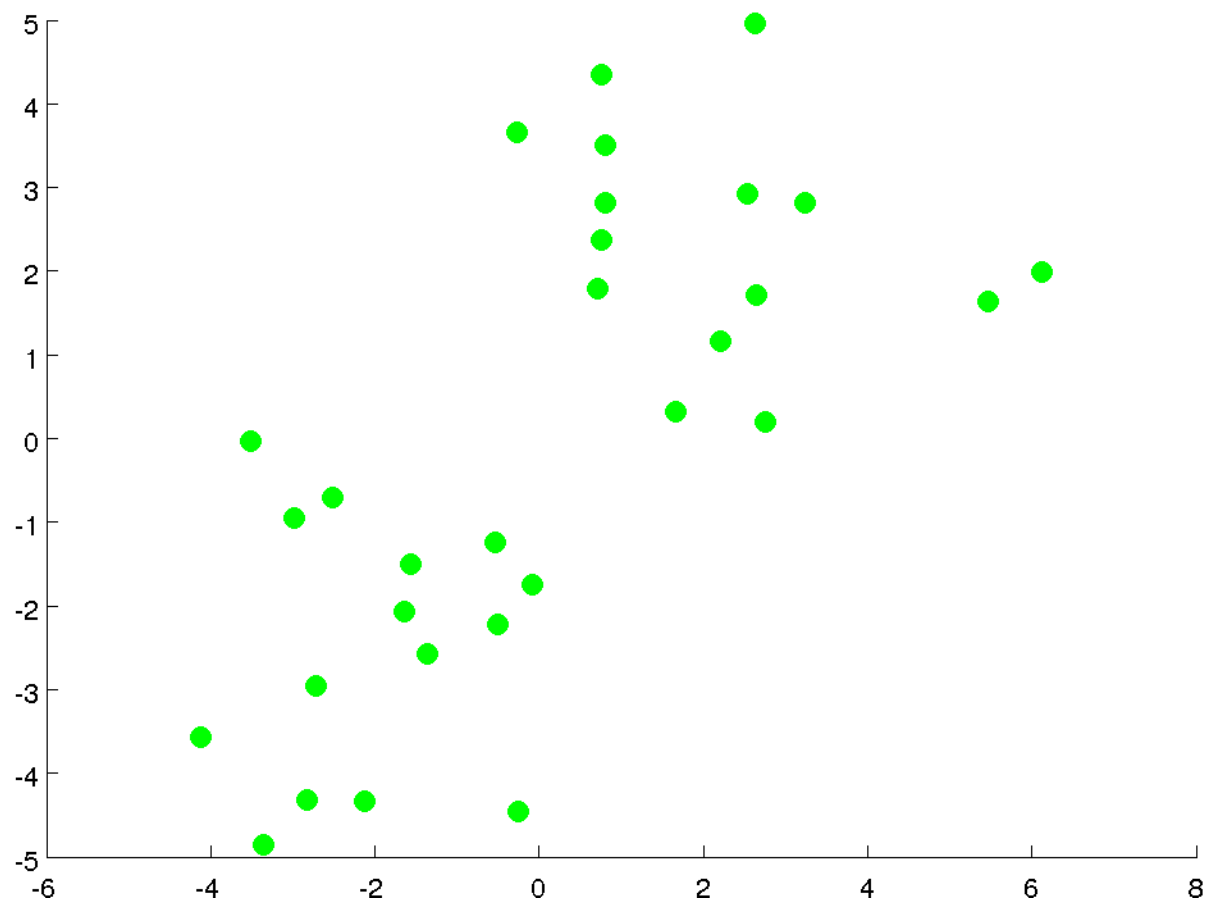
- ☐ Clustering is the only unsupervised learning algorithm.

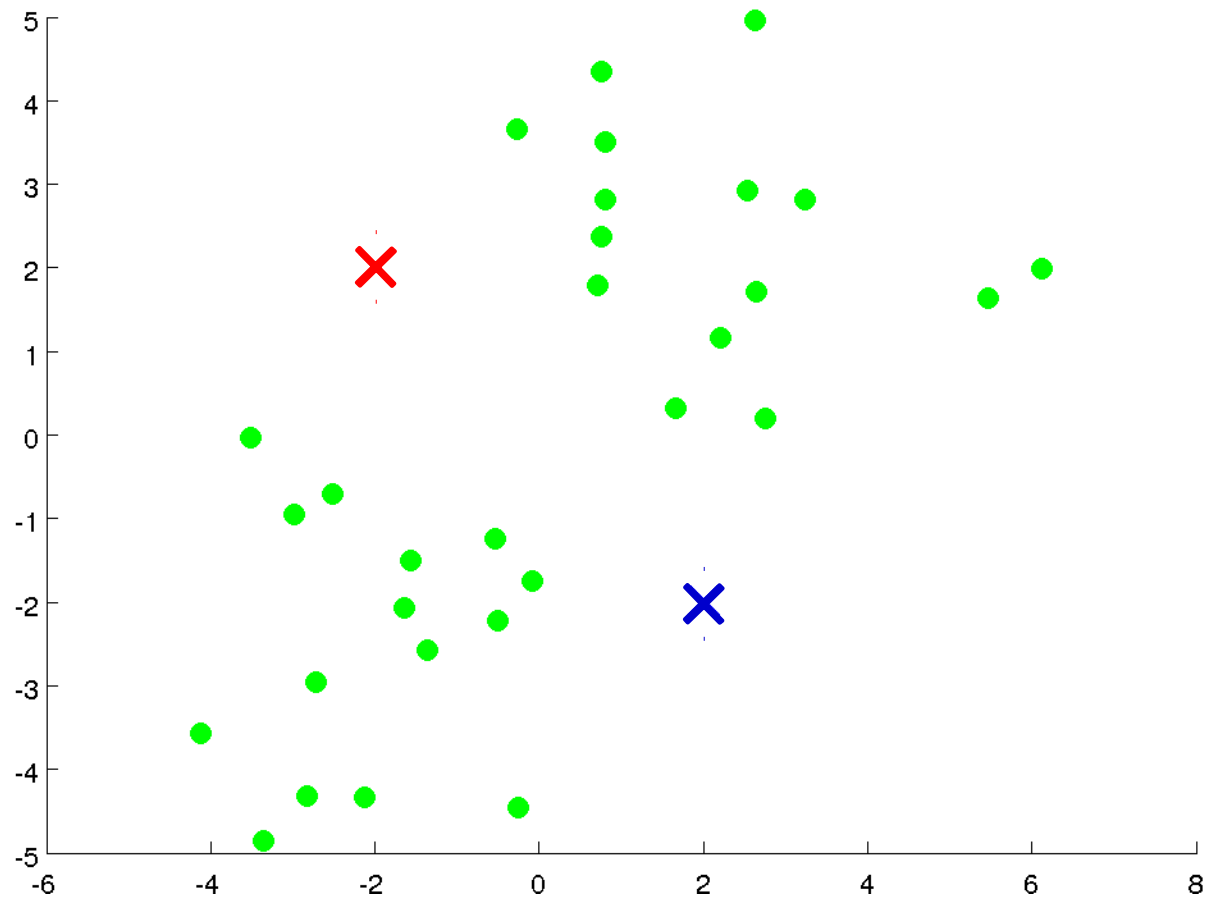
Correct Response

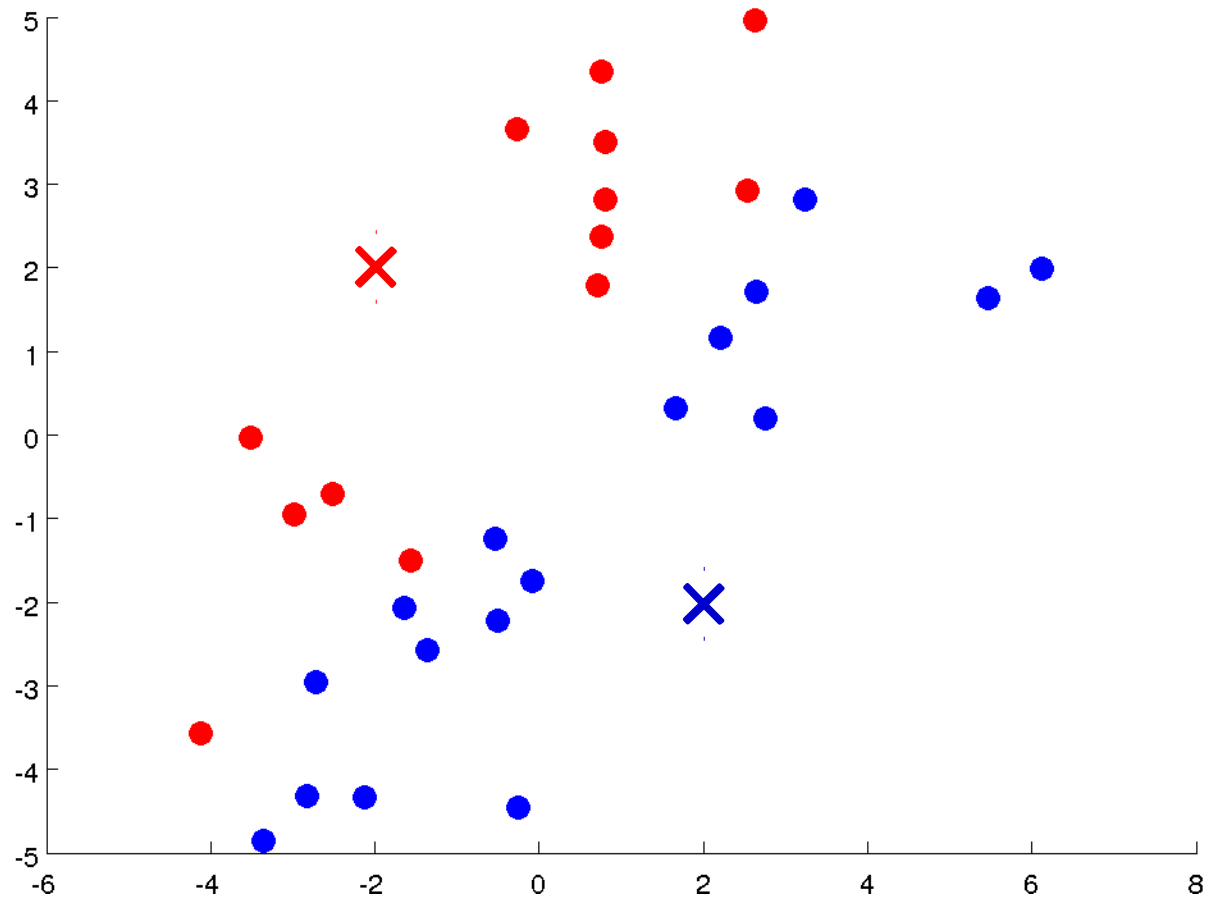


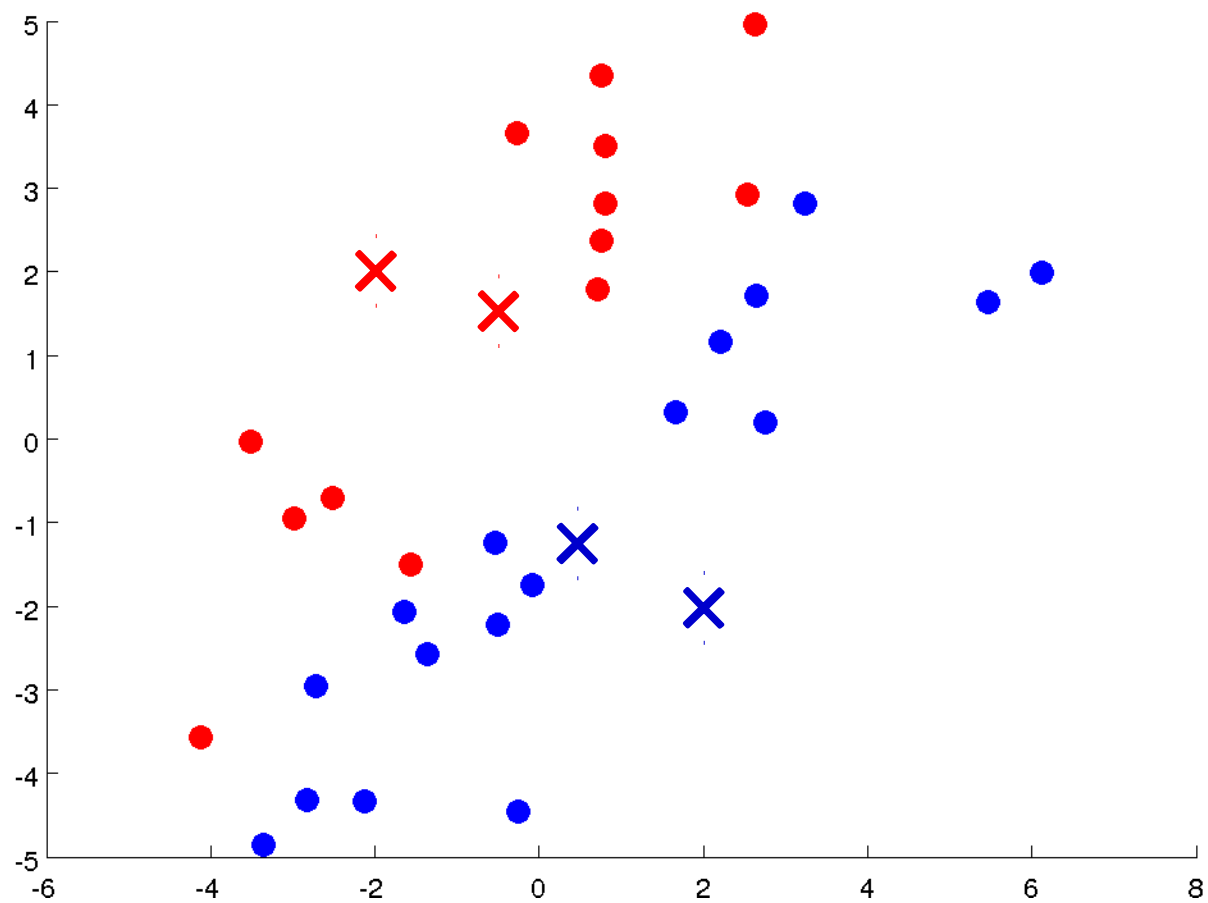
Machine Learning

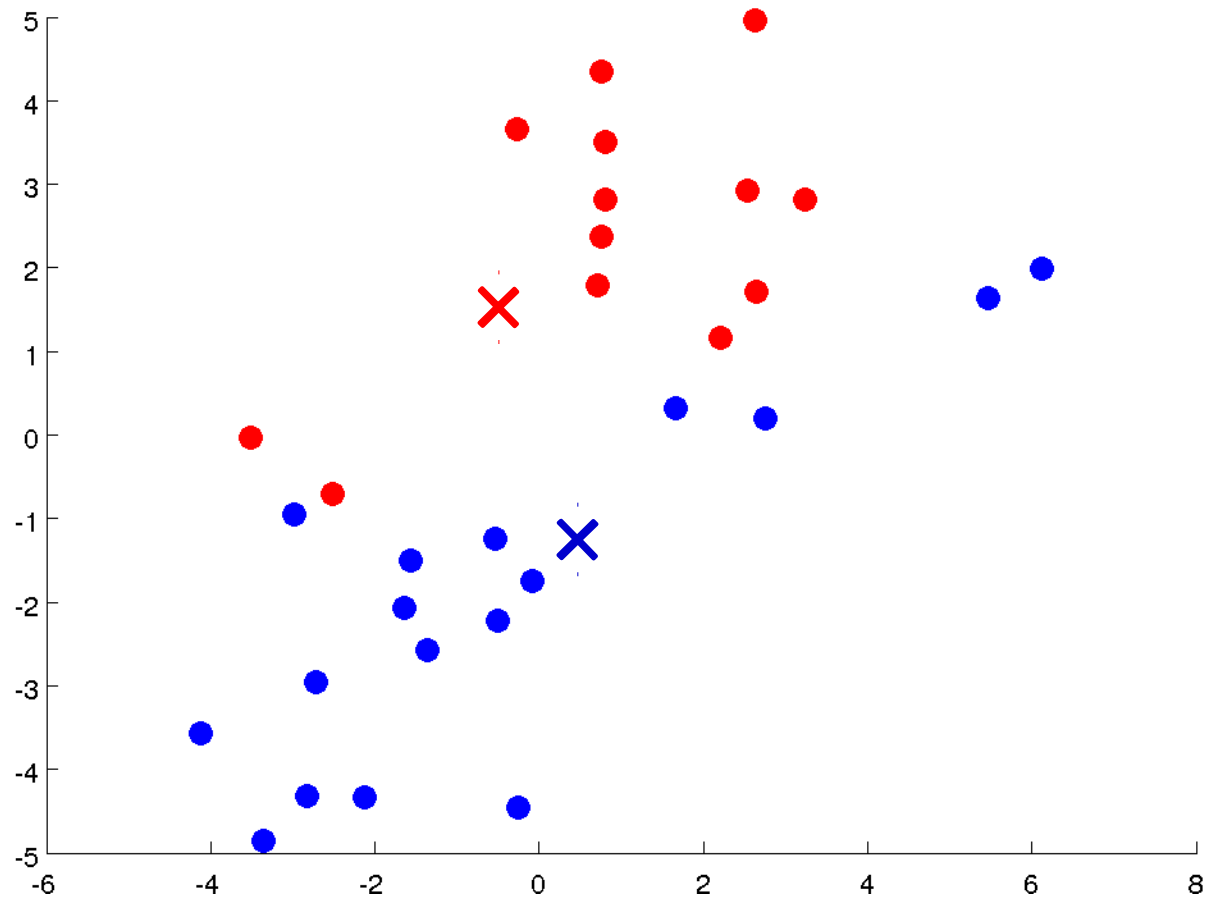
Clusterin g K-means algorithm

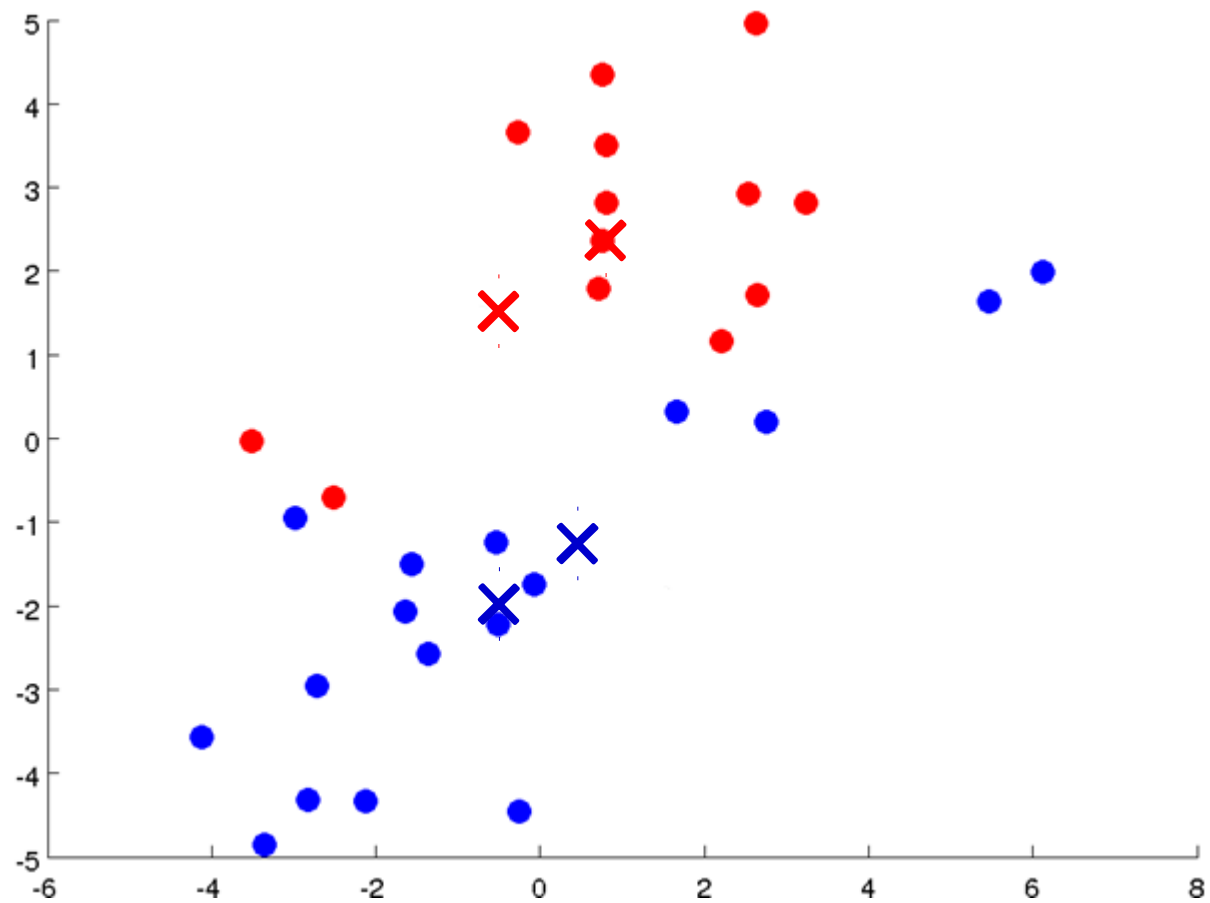


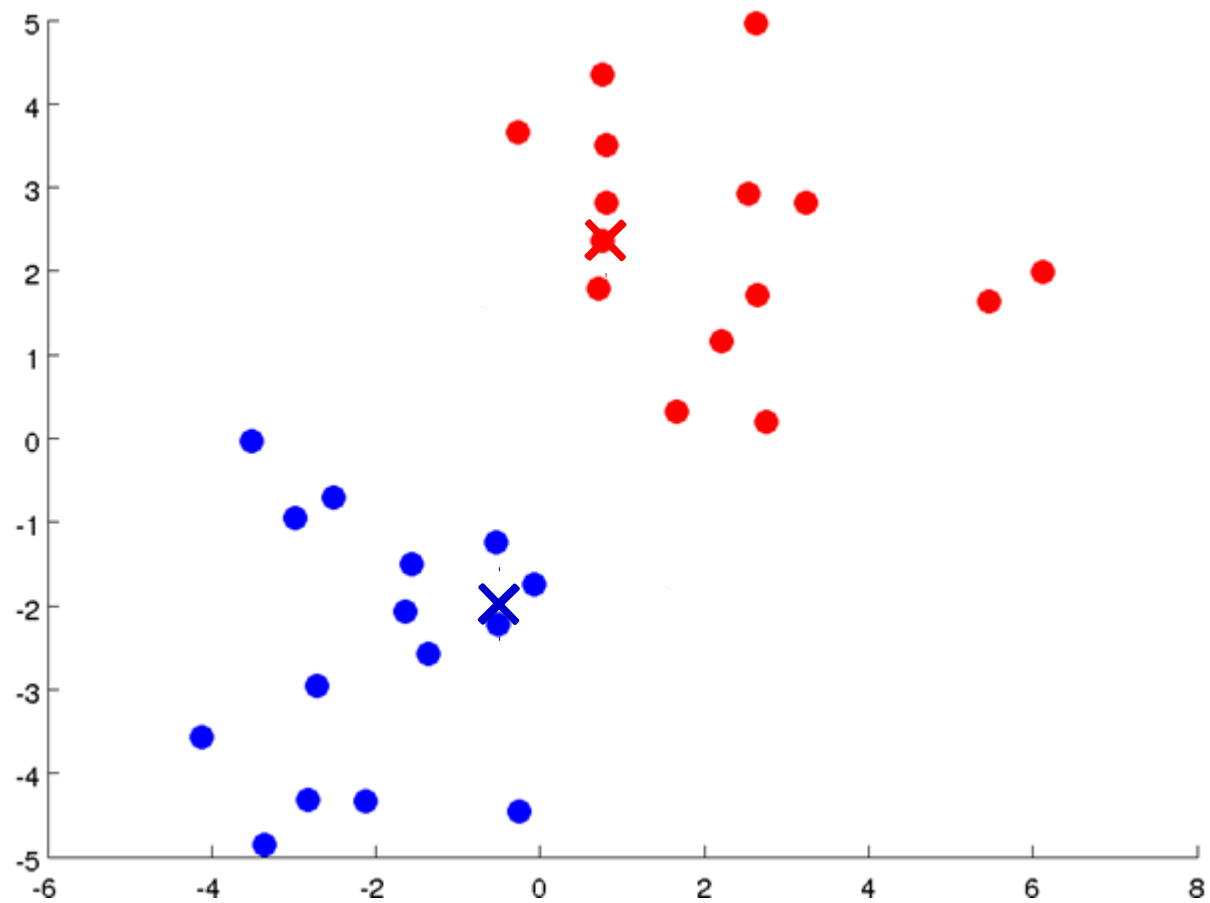


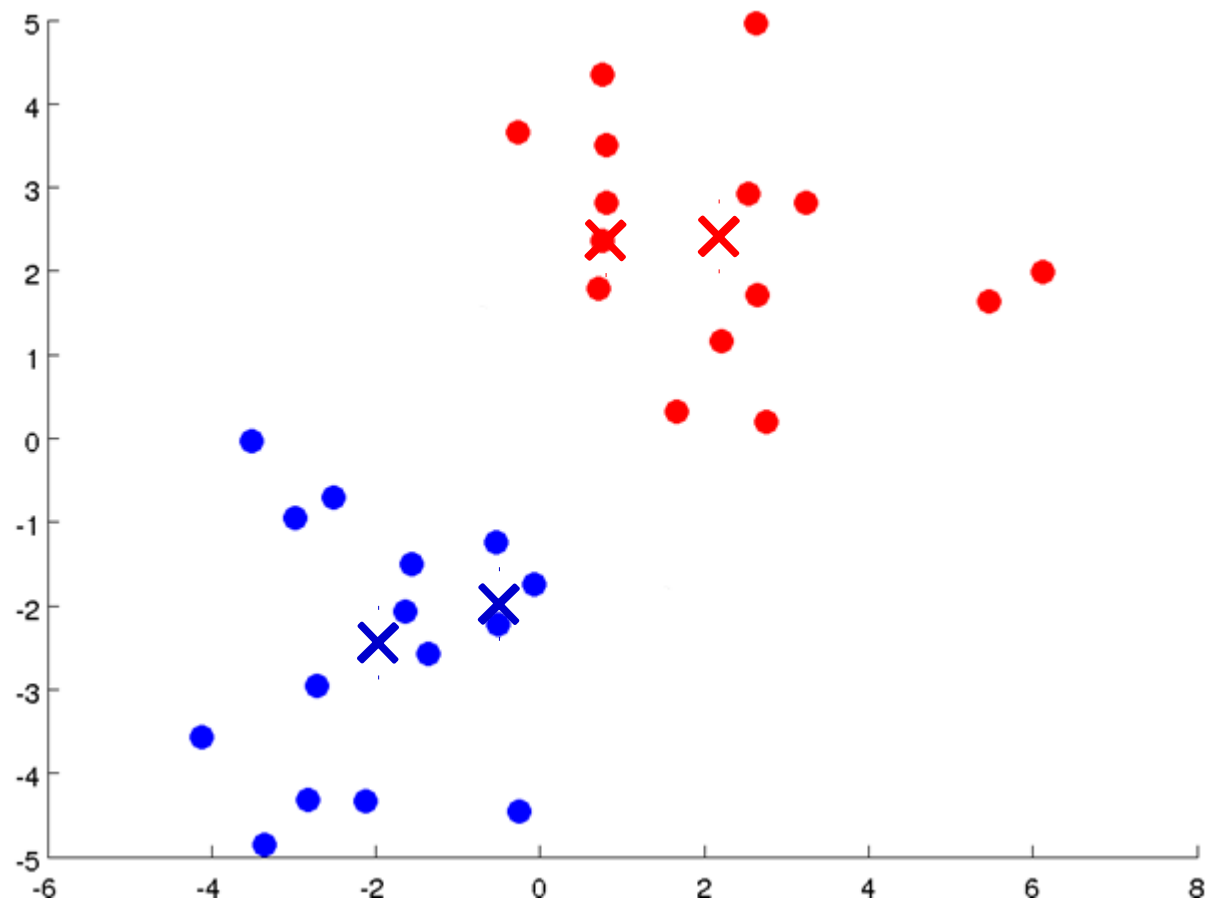


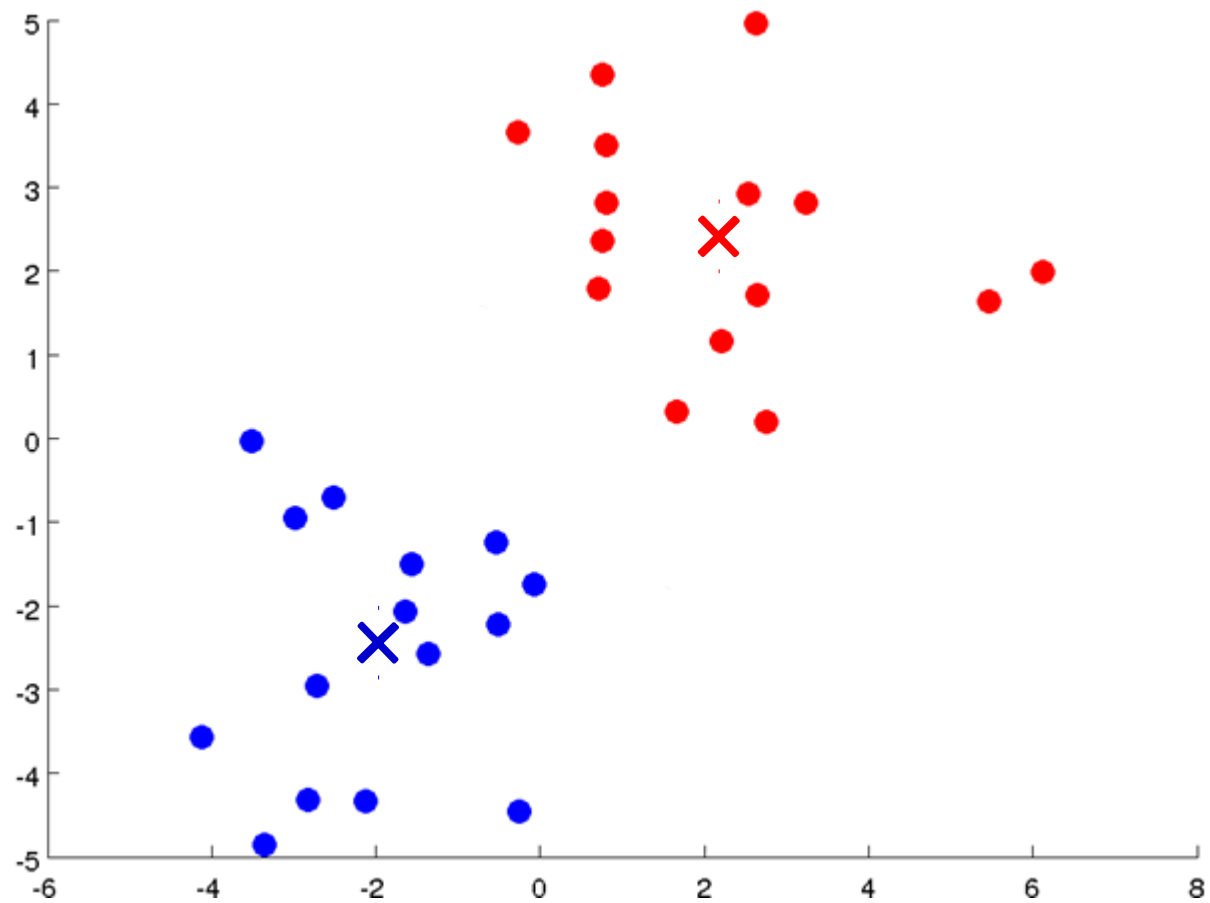












K-means algorithm

assumption



Input:

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

$x^{(i)} \in \mathbb{R}^n$ (drop 1 convention)

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

$c^{(i)} :=$ 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

}

Suppose you run k-means and after the algorithm converges, you have:
 $c^{(1)} = 3, c^{(2)} = 3, c^{(3)} = 5, \dots$

Which of the following statements are true? Check all that apply.

- ☒ The third example $x^{(3)}$ has been assigned to cluster 5.

Correct Response

- ☒ The first and second training examples $x^{(1)}$ and $x^{(2)}$ have been assigned to the same cluster.

Correct Response

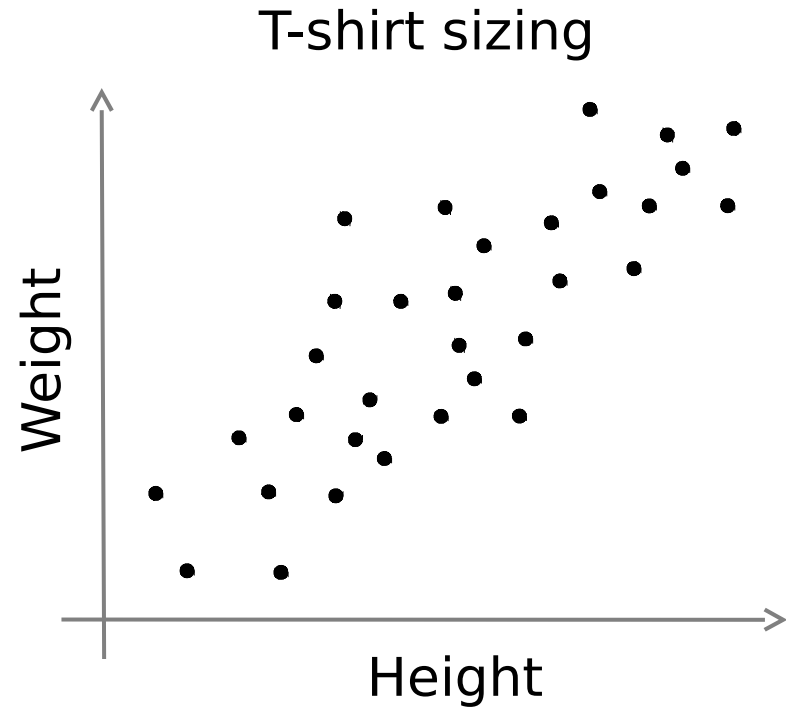
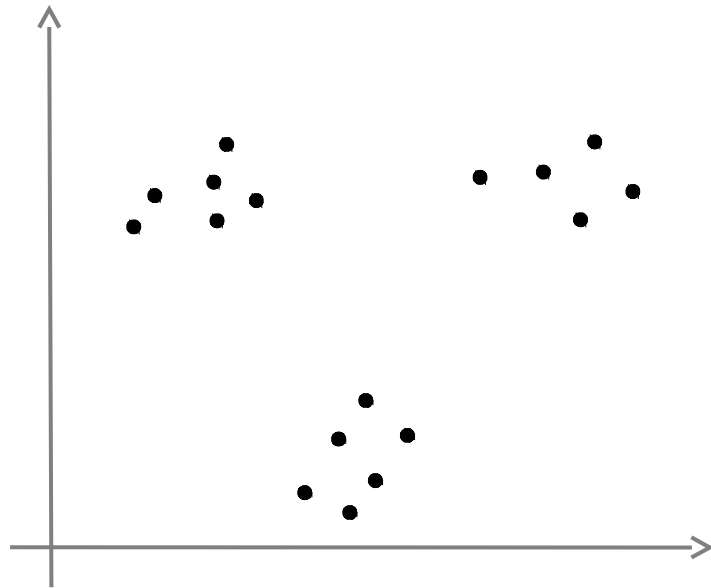
- ☐ The second and third training examples have been assigned to the same cluster.

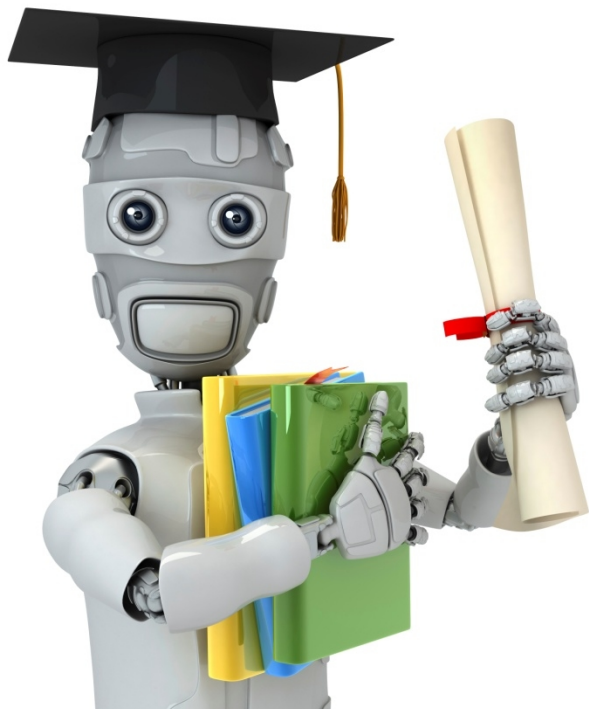
Correct Response

- ☒ Out of all the possible values of $k \in \{1, 2, \dots, K\}$ the value $k = 3$ minimizes $\|x^{(2)} - \mu_k\|^2$.

Correct Response

K-means for non-separated clusters





Machine Learning

Clusterin
~~Optimizati~~
on
objective

K-means optimization objective

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

μ_k = cluster centroid ($\mu_k \in \mathbb{R}^n$)

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

Optimization objective:

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

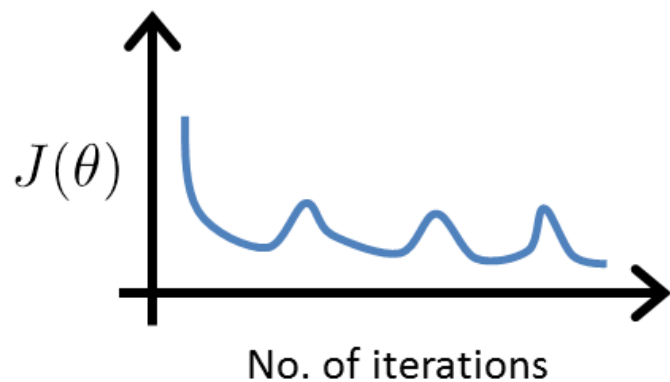
$$\min_{\substack{c^{(1)}, \dots, c^{(m)}, \\ \mu_1, \dots, \mu_K}} J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K)$$

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
 $c^{(i)} :=$ 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
}

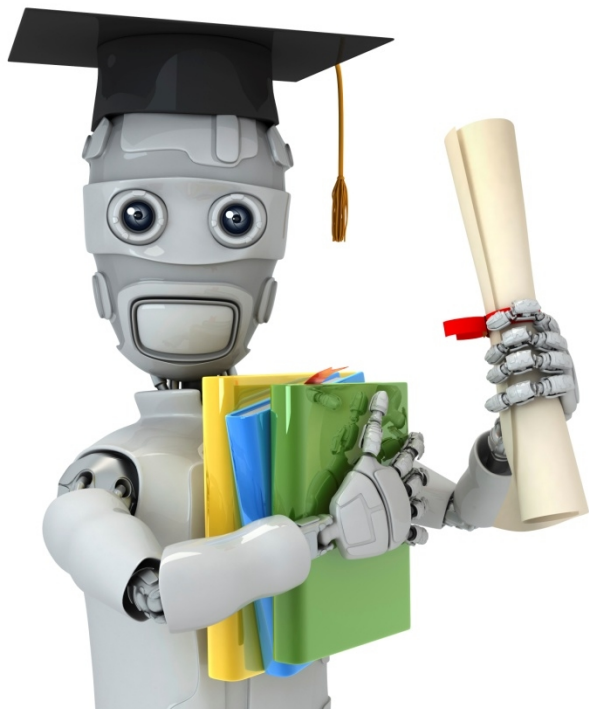
Suppose you have implemented k-means and to check that it is running correctly, you plot the cost function $J(c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_k)$ as a function of the number of iterations. Your plot looks like this:



What does this mean?

- ☐ The learning rate is too large.
- ☐ The algorithm is working correctly.
- ☐ The algorithm is working, but k is too large.
- ☒ It is not possible for the cost function to sometimes increase. There must be a bug in the code.

Correct Response



Machine Learning

Clusterin ~~g~~ Random initialization 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
 $c^{(i)} :=$ 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
}

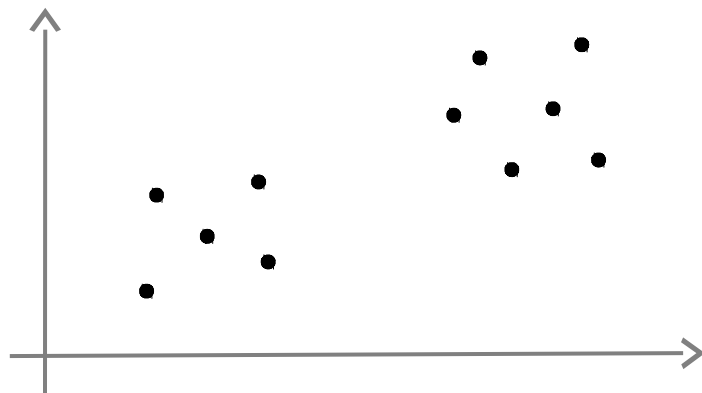
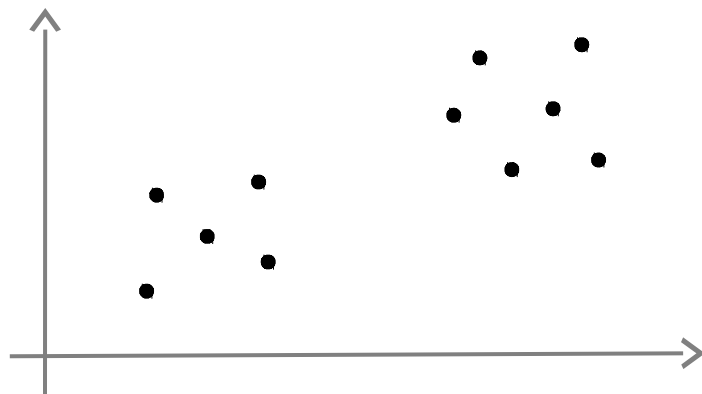
Random initialization

Should have $K < m$

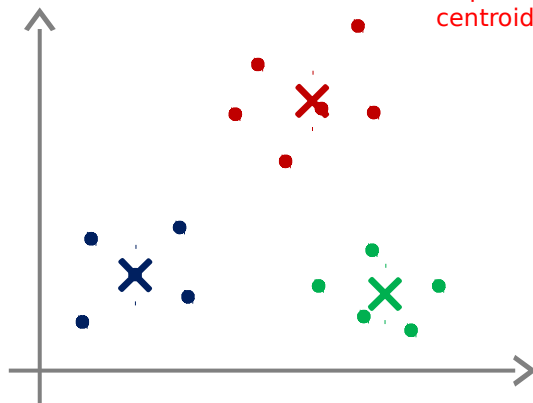
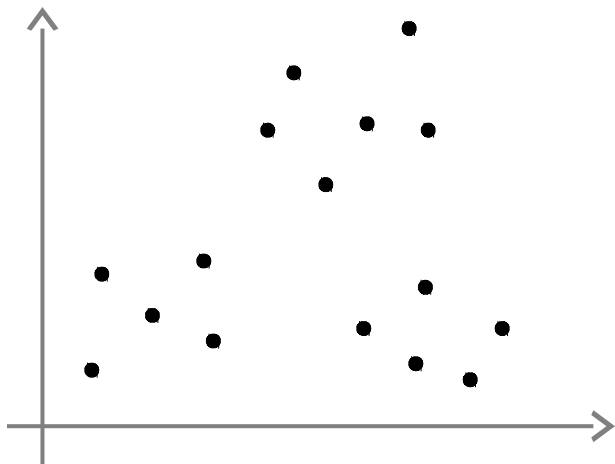
Randomly pick
training
examples.

$$\mu_1, \dots, \mu_K$$

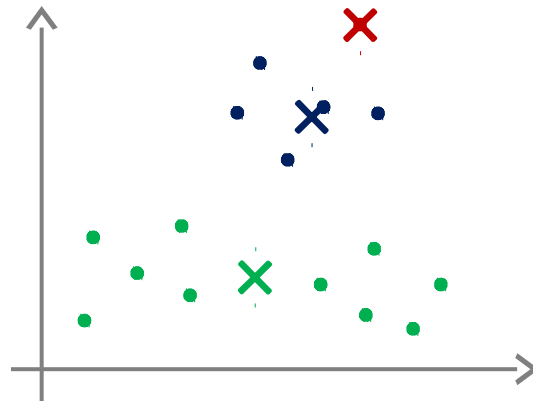
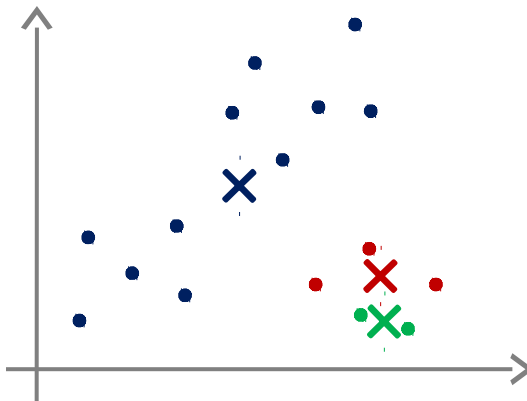
Set μ_1, \dots, μ_K equal
to these
examples.



Local optima



Depending on the initialization of cluster centroids K-means can produce different results



Random initialization

For $i = 1$ to 100 {

Randomly initialize K-means.

Run K-means. Get $c^{(1)}, \dots, c^{(m)}, \mu_1, \dots, \mu_K$.

Compute cost function (distortion)

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

}

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

Which of the following is the recommended way to initialize k-means?

☐ Pick a random integer i from $\{1, \dots, k\}$. Set $\mu_1 = \mu_2 = \dots = \mu_k = x^{(i)}$.

☐ Pick k distinct random integers i_1, \dots, i_k from $\{1, \dots, k\}$.

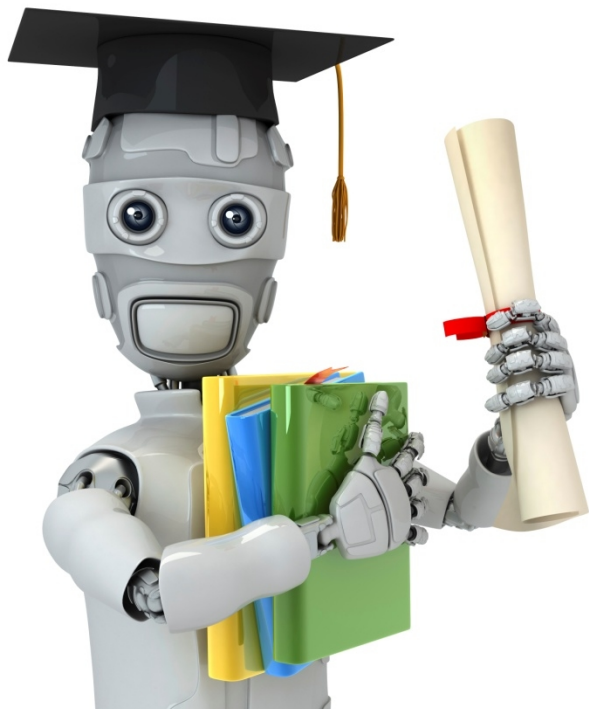
Set $\mu_1 = x^{(i_1)}, \mu_2 = x^{(i_2)}, \dots, \mu_k = x^{(i_k)}$.

☒ Pick k distinct random integers i_1, \dots, i_k from $\{1, \dots, m\}$.

Set $\mu_1 = x^{(i_1)}, \mu_2 = x^{(i_2)}, \dots, \mu_k = x^{(i_k)}$.

Correct Response

☐ Set every element of $\mu_i \in \mathbb{R}^n$ to a random value between $-\epsilon$ and ϵ , for some small ϵ .

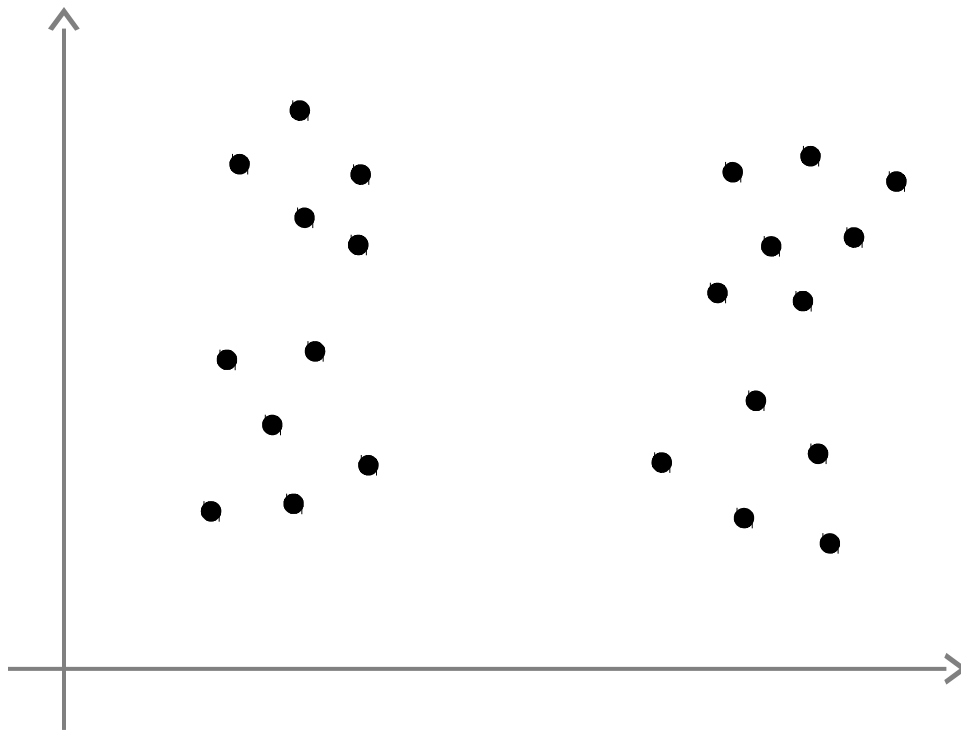


Machine Learning

Clusterin

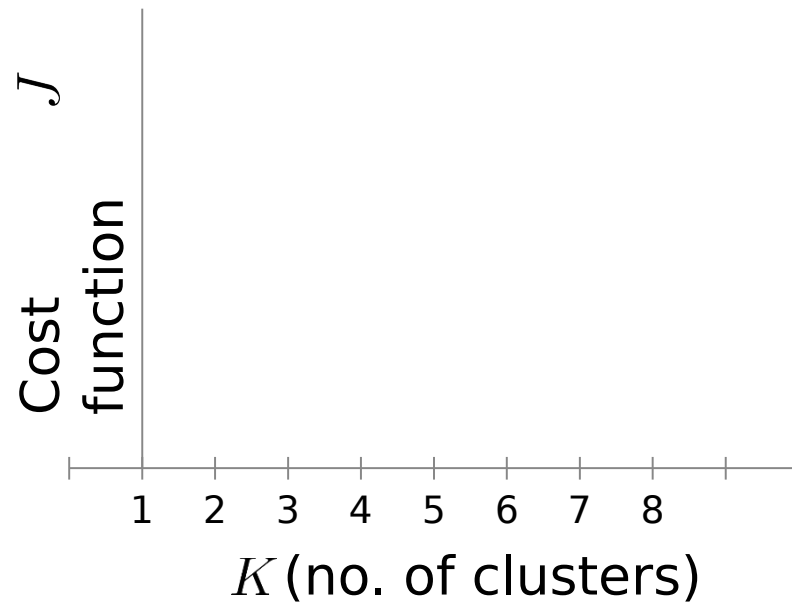
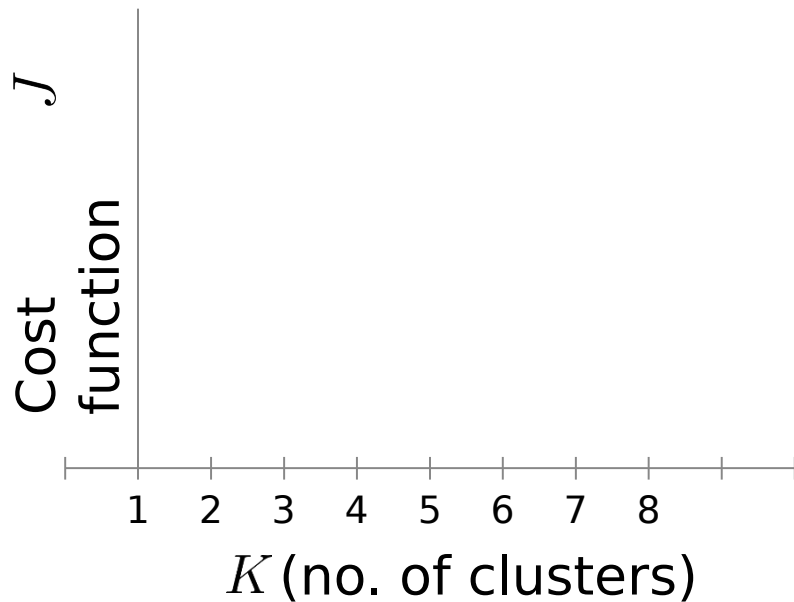
~~Choosing the~~
number of
clusters

What is the right value of K?



Choosing the value of K

Elbow method:



Suppose you run k-means using $k = 3$ and $k = 5$. You find that the cost function J is much higher for $k = 5$ than for $k = 3$. What can you conclude?

- ☐ This is mathematically impossible. There must be a bug in the code.
- ☐ The correct number of clusters is $k = 3$.
- ☒ In the run with $k = 5$, k-means got stuck in a bad local minimum. You should try re-running k-means with multiple random initializations.

Correct Response

- ☐ In the run with $k = 3$, k-means got lucky. You should try re-running k-means with $k = 3$ and different random initializations until it performs no better than with $k = 5$.

Choosing the value of K

Sometimes, you're running K-means to get clusters to use for some later/downstream purpose. Evaluate K-means based on a metric for how well it performs for that later purpose.

