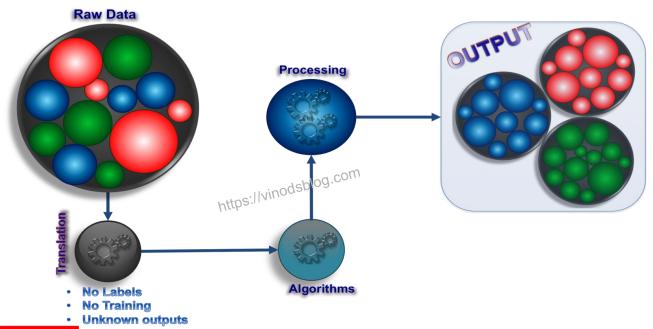
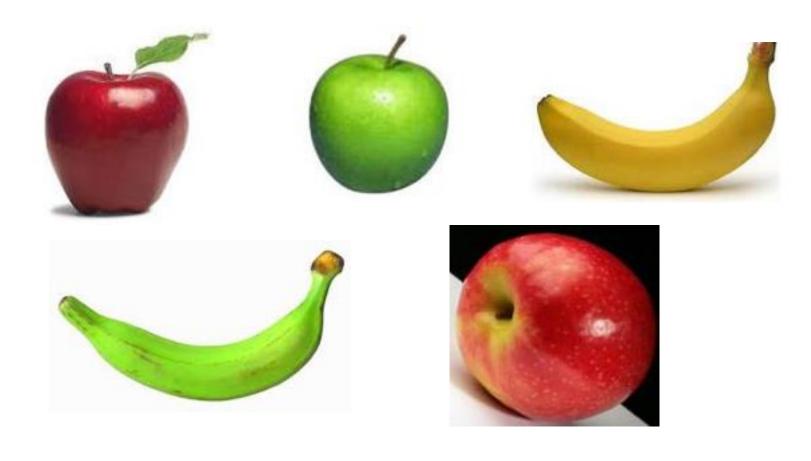
Clustering/Unsupervised Learning

Dr. Ujwala Bharambe

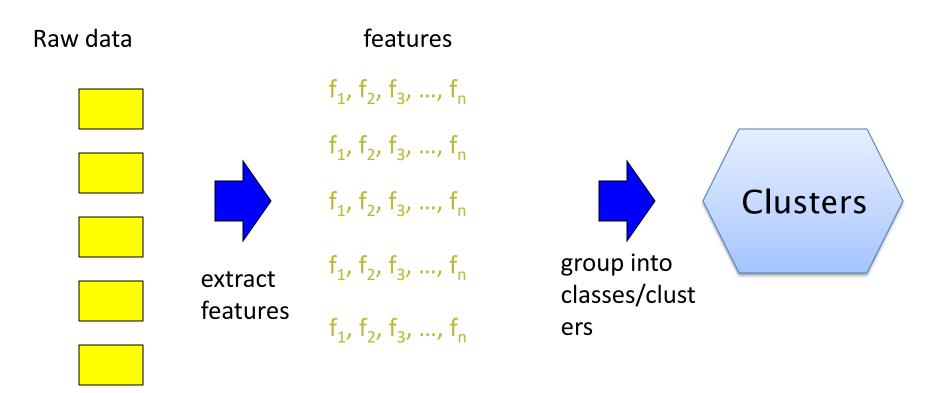
Unsupervised Machine Learning Process Flow





Unsupervised learning: given data, i.e. examples, but no labels

Clustering



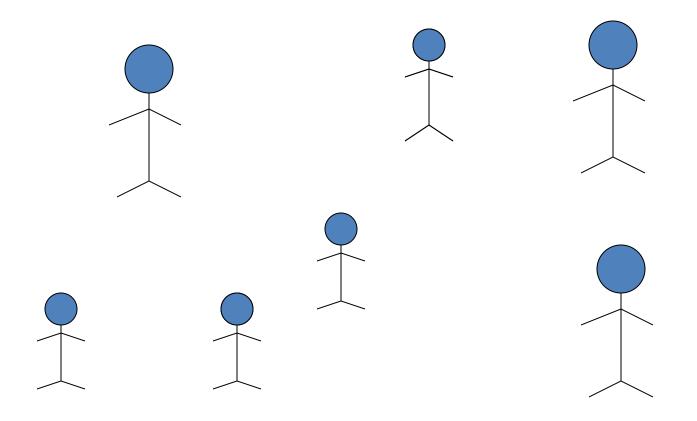
No "supervision", we're only given data and want to find natural groupings

Uncuparticad laarning, ductoring

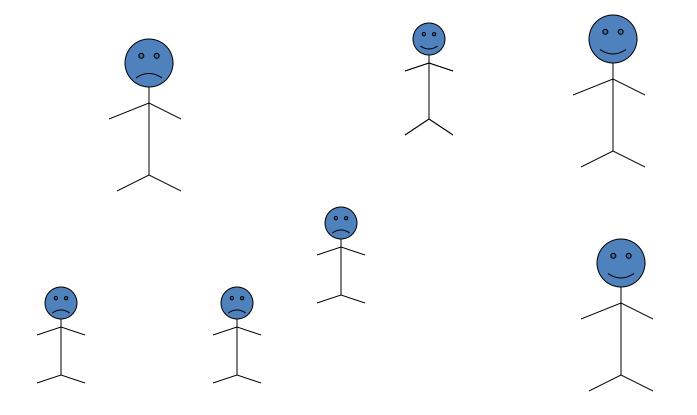
What is Clustering?

- Discovering similarities in a set of objects
- Decrease the amount of information and express it in a concise way
- Clusters structure is not known in advance (classification), however similarity/ measure is usually given a priority.
- The obvious: structure of clusters is highly subjective to object features / criteria considered in an algorithm

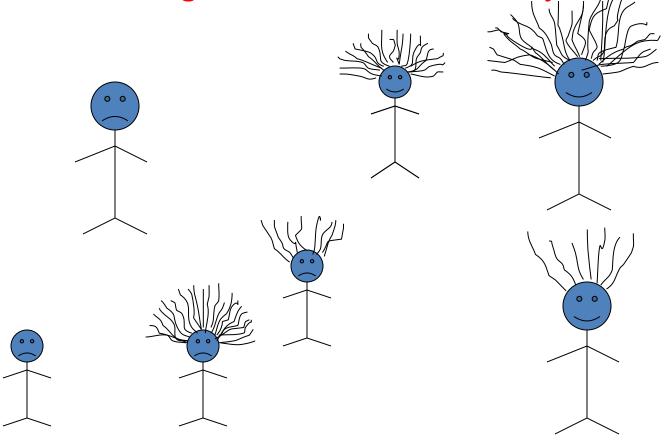
Discovering similarities in a set of objects



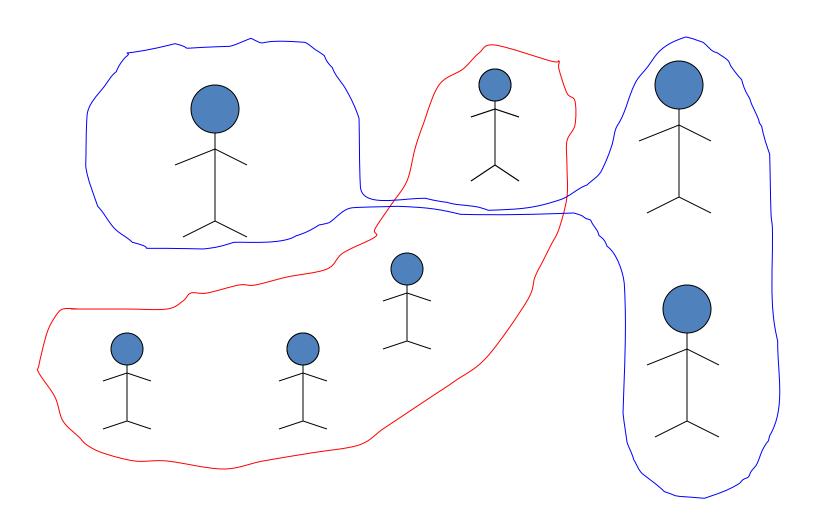
Discovering similarities in a set of objects



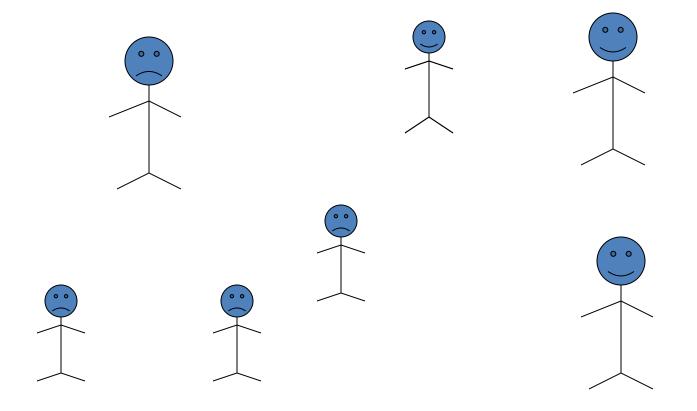
Discovering similarities in a set of objects,



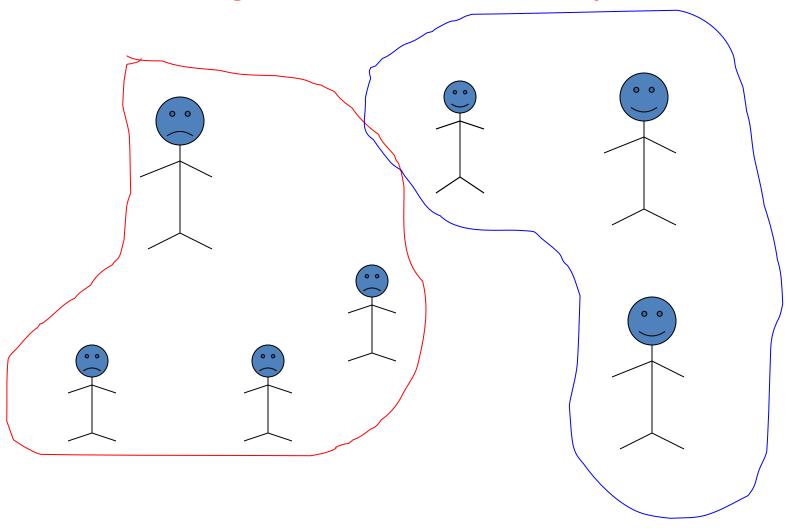
Discovering similarities in a set of objects



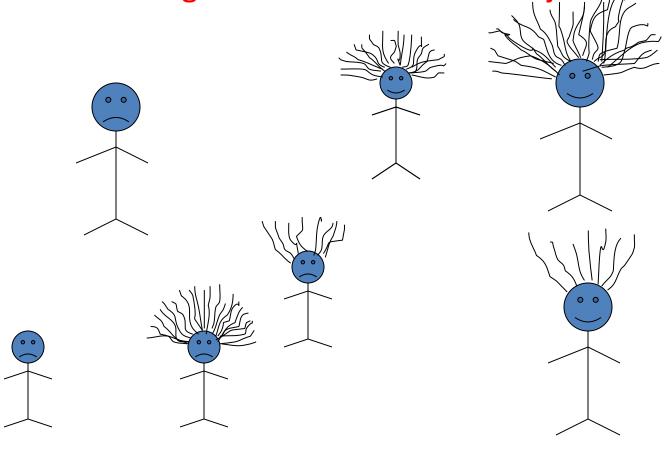
Discovering similarities in a set of objects



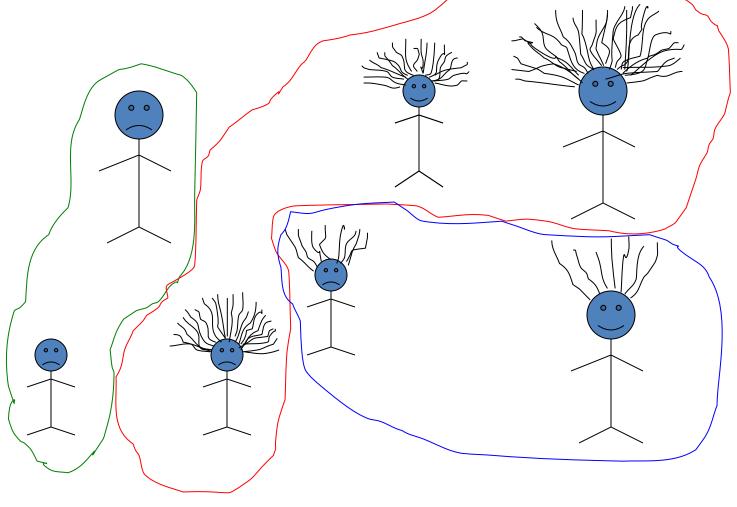
Discovering similarities in a set of objects



Discovering similarities in a set of objects,

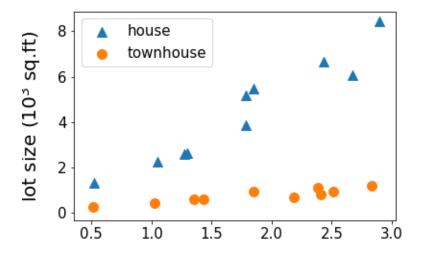


Discovering similarities in a set of objects

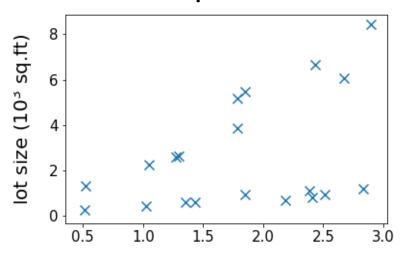


Clustering

- Dataset contains no labels: $x^{(1)}$, ... $x^{(n)}$
- Goal (vaguely-posed): to find interesting structures in the data supervised



unsupervised



Web Search Results Clustering

Search Results for: Jaguar 1 – 6 of 70,000,000

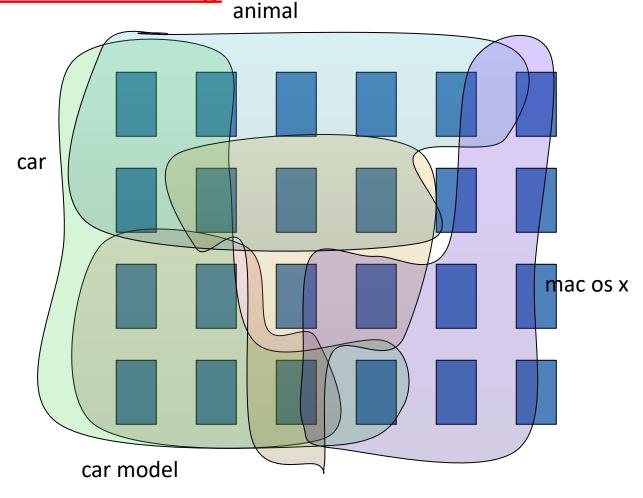
Clusters

- 1. Car
- 2. Animal
- 3. Mac OS
- 4. Other

- 1. Jaguar Official worldwide web site of Jaguar Cars.
- 2. Apple Mac OS X The Apple Mac OS X product page.
- 3. Jaguar UK R is for Racing The essence of the Jaguar breed
- 4. Jaguar General information from Big Cats Online.
- 5. Jaguar AU Jaguar Cars Services and news
- 6. Jaguar -- Defenders of Wildlife Size, appearance, life span and diet.

Web Search Results Clustering

Query "jaguar"

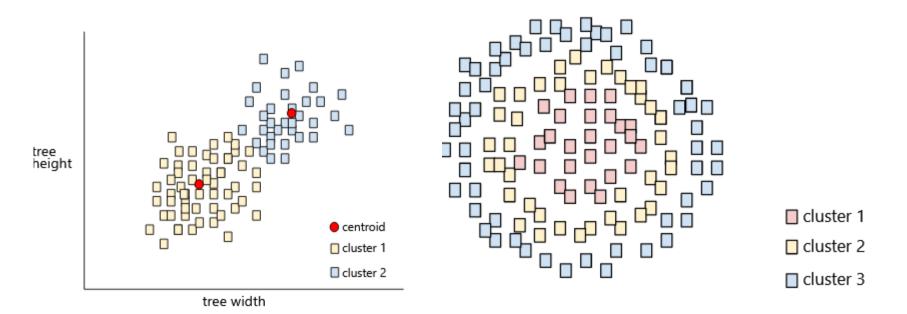


Traditional Clustering Algorithm

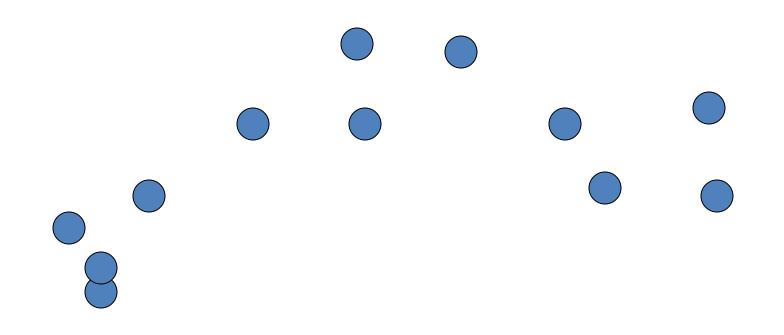
- Distance-based
- Hierarchical
 - Agglomerative Hierarchical Clustering (AHC)
- Flat
 - K-means (can be fuzzy)
 - Single-pass (incremental)

K-Means Clustering

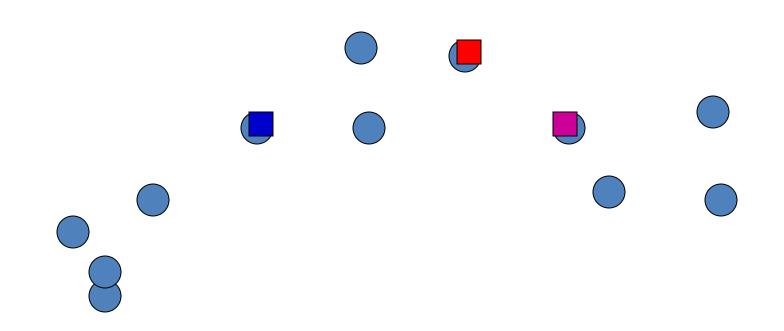
 For example, the <u>k-means</u> algorithm clusters examples based on their proximity to a <u>centroid</u>, as in the following diagram:



K-Means: an example

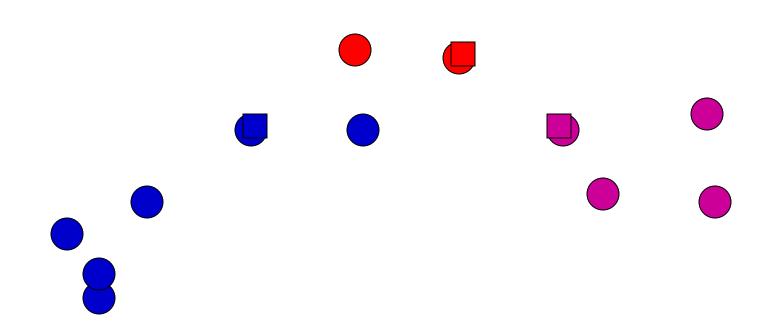


K-Means: an example



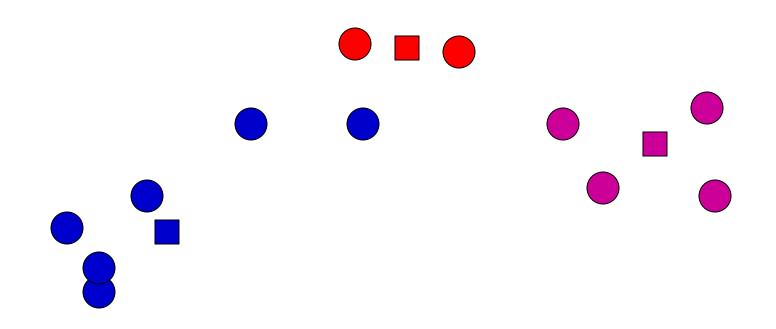
K-means: Initialize centers randomly

K-Means: an example



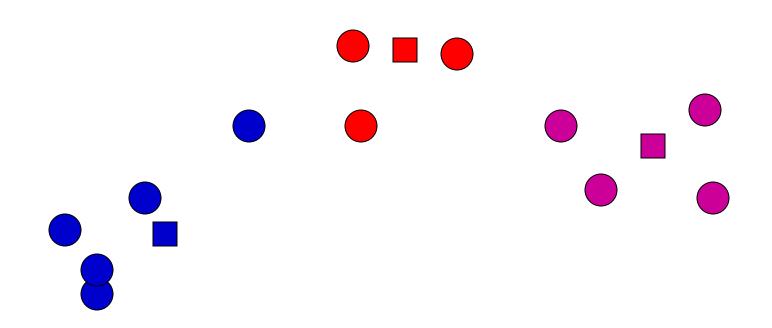
K-means: assign points to nearest center

K-Means: an example



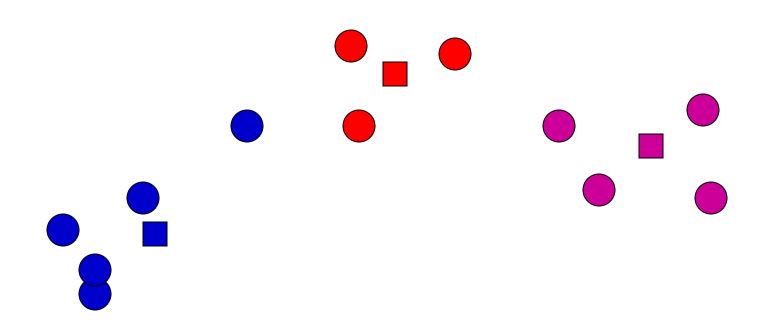
K-means: readjust centers

K-Means: an example



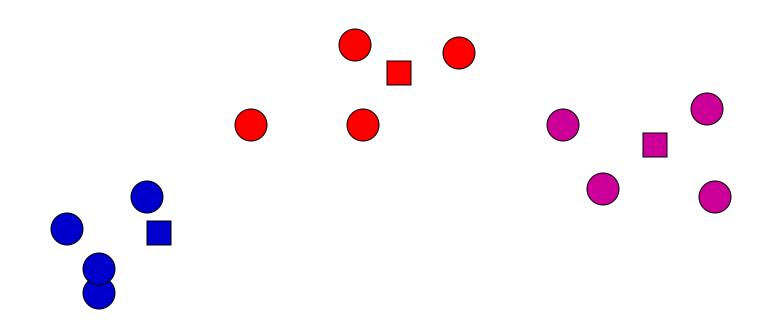
K-means: assign points to nearest center

K-Means: an example



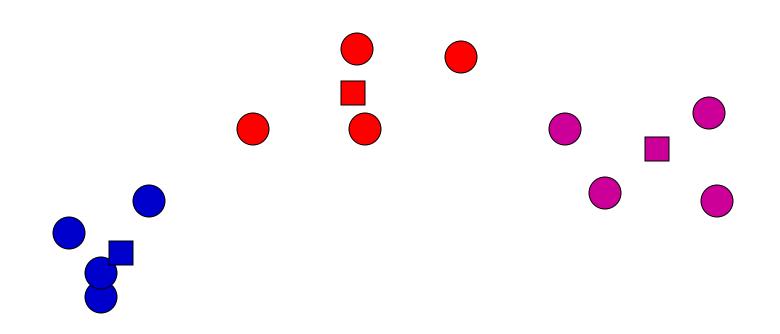
K-means: readjust centers

K-Means: an example



K-means: assign points to nearest center

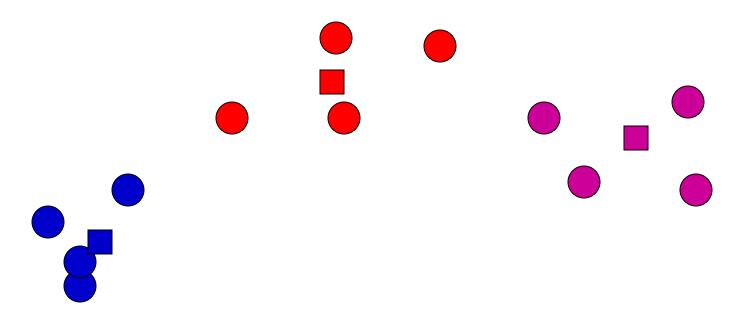
K-Means: an example



K-means: readjust centers

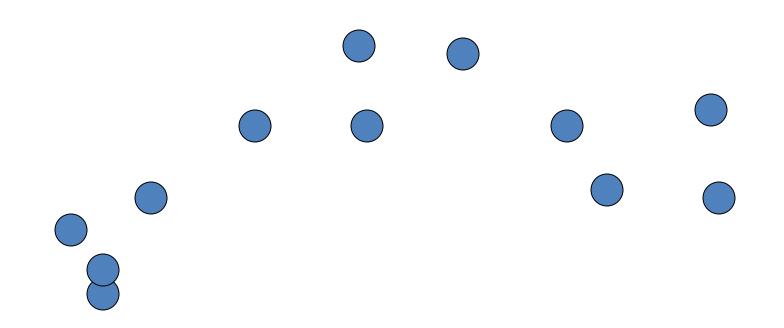
K-Means: an example

K-means: assign points to nearest center



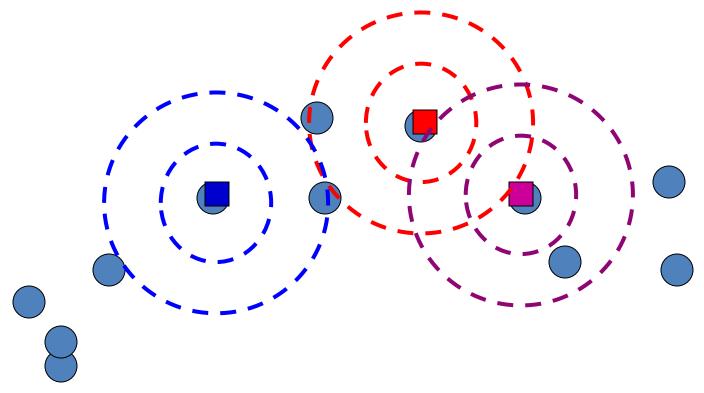
No changes: Done

K-Means: an example



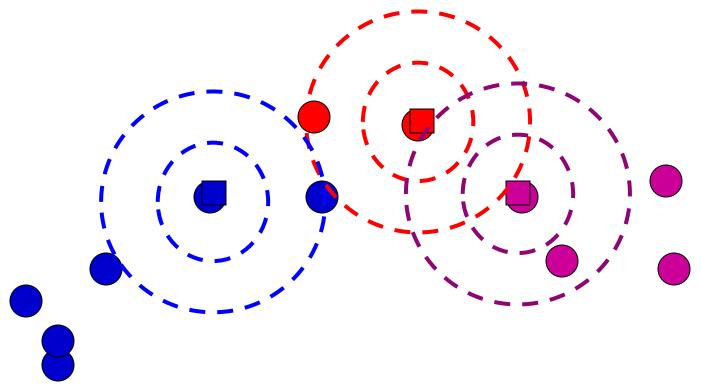
K-means: another view

K-Means: an example



K-means: another view

K-Means: an example



K-means: assign points to nearest center

K-Means

The MacQueen k-means algorithm
 (MacQueen, 1967) aims to separate n objects
 in k non-overlapping groups as to minimize
 the sum of squared errors (i.e. the sum of
 distances between the points and the center
 of their group).

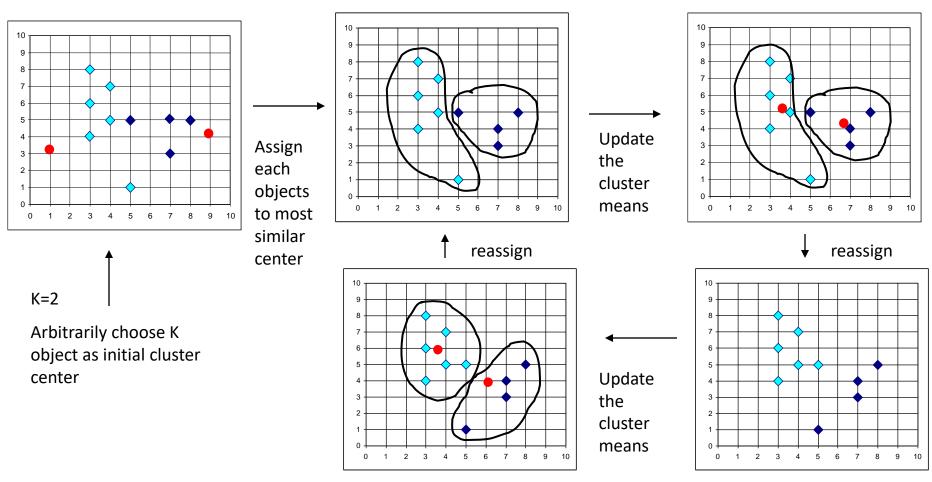
K-Means Clustering

Input: K number of clusters, D: data set containing object
Output: Dataset containing n object

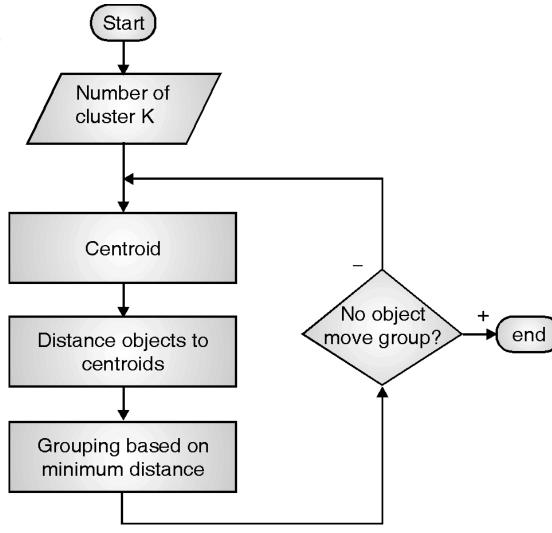
- Given k, the k-means algorithm is implemented in four steps:
 - Partition objects into k nonempty subsets
 - Compute seed points as the centroids of the clusters of the current partition (the centroid is the center, i.e., mean point, of the cluster)
 - Assign each object to the cluster with the nearest seed point
 - Go back to Step 2, stop when no more new assignment

Initial:	1, 5, 2, 4, 5	
Step 1:	1, 5 Mean = 3	2, 4, 5 Mean = 3,67
Step 2:	1, 2 Mean = 1,5	5, 4, 5 Mean = 4,67
Step 3:	1, 2 Mean = 1,5	5, 4, 5 Mean = 4,67

K-Means: an example



K-Means: an example



Variation of the K-Means Method

- A few variants of the *k-means* which differ in
 - Selection of the initial k means
 - Dissimilarity calculations
 - Strategies to calculate cluster means
- Handling categorical data:
 - Replacing means of clusters with <u>modes</u>
 - Using new dissimilarity measures to deal with categorical objects
 - Using a <u>frequency</u>-based method to update modes of clusters
 - A mixture of categorical and numerical data: k-prototype method

mean



The mean is the average or norm.

- · Add up all of the values to find a total.
- Divide the total by the number of values you added together.

32 ÷ 7 = 4.57

The mean is 4.57

median



The median is the middle value.

- ·Put all of the values into order.
- ·The median is the middle value.
- •If there are two values in the middle, find the mean of these two.

The median is 5

mode



The mode is the most frequent value.

- · Count how many of each value appears.
- The mode is the value that appears the most.
- · You can have more than one mode.

2, 2, 3, 5, 5, 7, 8



Given: {2,4,10,12,3,20,30,11,25}

Assume number of cluster i.e. k = 2.

Randomly assign means: $m_1 = 3$, $m_2 = 4$

- $K_1 = \{2,3\}, K_2 = \{4,10,12,20,30,11,25\}, m_1 = 2.5, m_2 = 16$
- $K_1 = \{2,3,4\}, K_2 = \{10,12,20,30,11,25\}, m_1 = 3, m_2 = 18$
- $K_1 = \{2,3,4,10\}, K_2 = \{12,20,30,11,25\}, m_1 = 4.75, m_2 = 19.6$
- $K_1 = \{2,3,4,10,11,12\}, K_2 = \{20,30,25\}, m_1 = 7, m_2 = 25$
- $K_1 = \{2,3,4,10,11,12\}, K_2 = \{20,30,25\}$

Randomly assign alternative values to each cluster

Number of cluster = 2, therefore

$$K1 = \{2,10,3,30,25\}, Mean = 14$$

$$K2 = \{4,12, 20, 11\}, Mean = 11.75$$

Re-assign

$$K1 = \{20, 30, 25\}, Mean = 25$$

$$K2 = \{2,4, 10, 12, 3, 11\}, Mean = 7$$

Re-assign

$$K1 = \{20, 30, 25\}, Mean = 25$$

$$K2 = \{2,4, 10, 12, 3, 11\}, Mean = 7$$

So the final answer is $K_1 = \{2,3,4,10,11,12\}, K_2 = \{20,30,25\}$

K-Means

- Strength: Relatively efficient: O(tkn), where n is # objects, k is # clusters, and t is # iterations. Normally, k, t << n.
- <u>Comment:</u> Often terminates at a local optimum. The global optimum may be found using techniques such as: deterministic annealing and genetic algorithms

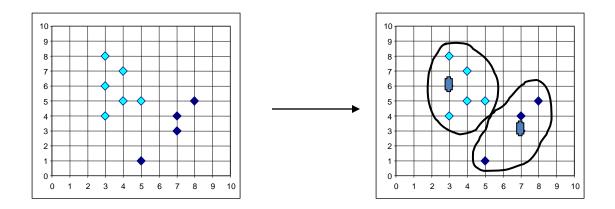
Weakness

- Applicable only when mean is defined, then what about categorical data?
- Need to specify k, the number of clusters, in advance
- Unable to handle noisy data and outliers
- Not suitable to discover clusters with non-convex shapes

Comments on the K-Means Method

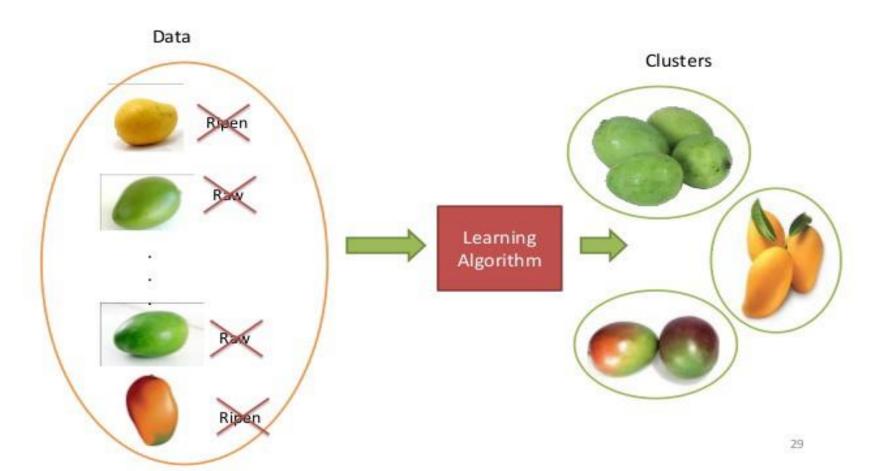
What Is the Problem of the K-Means Method?

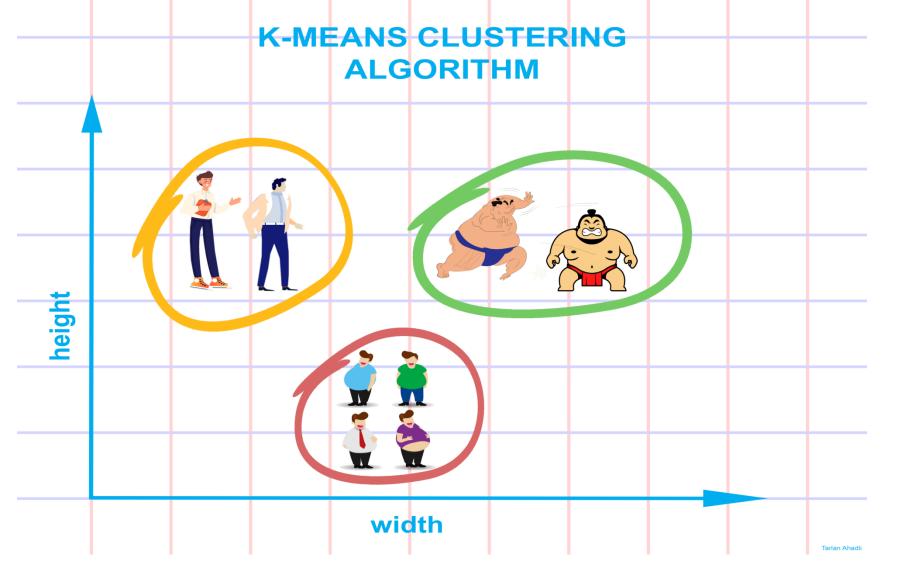
- The k-means algorithm is sensitive to outliers!
 - Since an object with an extremely large value may substantially distort the distribution of the data.
- K-Medoids: Instead of taking the mean value of the object in a cluster as a reference point, medoids can be used, which is the most centrally located object in a cluster.



Clustering

Unsupervised Learning





Clustering

Pros

- It can detect what human eyes can not understand
- The potential of hidden patterns can be very powerful for the business or even detect extremely amazing facts, fraud detection etc.
- Output can determine the un explored territories and new ventures for businesses. Exploratory analytics can be applied to understand the financial, business and operational drivers behind what happened.

Cons

- As seen in above explanation unsupervised learning is harder as compared to supervised learning.
- It can be a costly affair, as we might need external expert look at the results for some time.
- Usefulness of the results; are of any value or not is difficult to confirm since no answer labels are available.