

# Beginner-friendly ML school:

## Clustering and K-Means

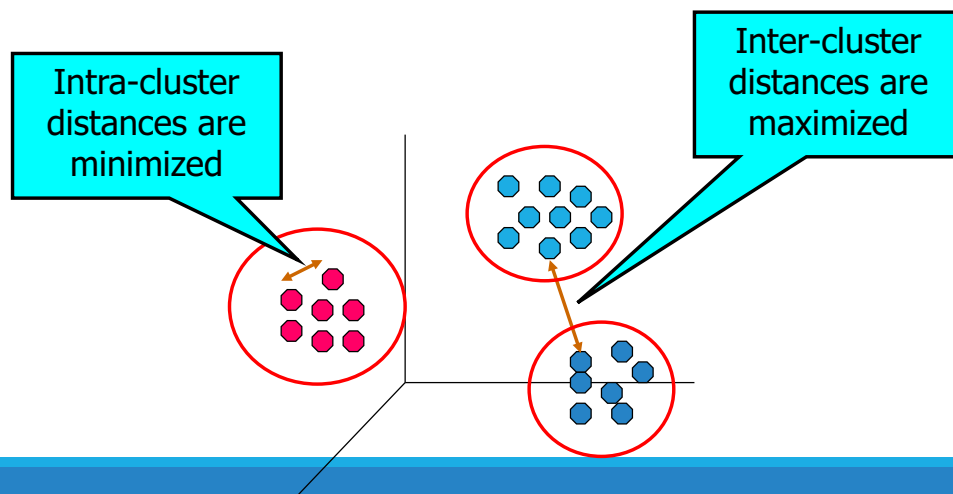
Viviana Acquaviva (CUNY)

w many many thanks to

Ashwin Satyanarayana who has taught clustering in my class many times and put together most of these slides!

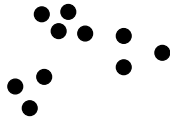
### What is Clustering?

In general a **grouping** of objects such that the objects in a **group** (**cluster**) are similar (or related) to one another and different from (or unrelated to) the objects in other groups

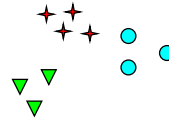
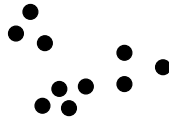


# Notion of a Cluster can be Ambiguous

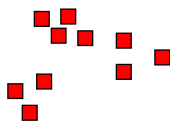
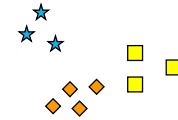
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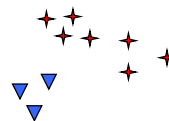
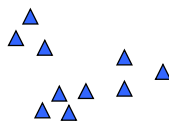
How many clusters?



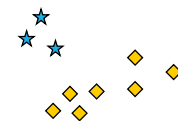
Six Clusters



Two Clusters



Four Clusters



## Types of Clustering

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A **clustering** is a set of **clusters**

Important distinction between **hierarchical** and **partitional** sets of clusters

### Partitional Clustering

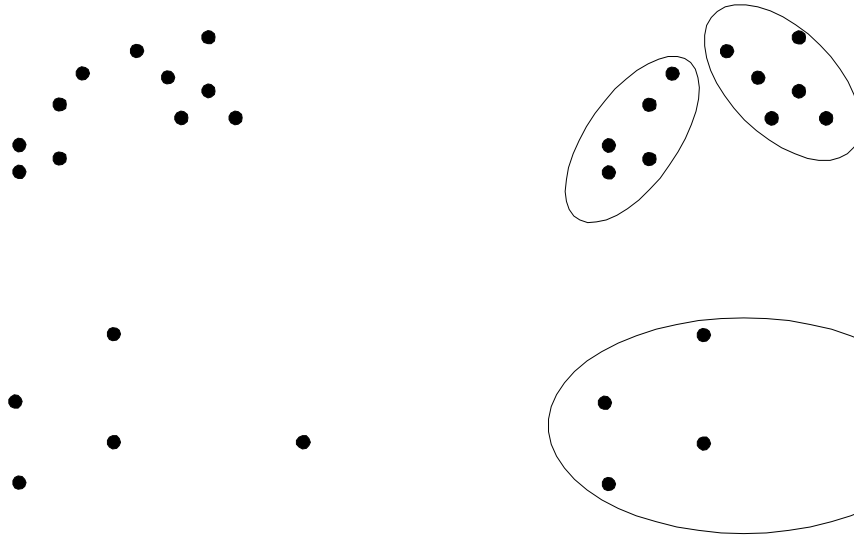
- A division data objects into subsets (**clusters**) such that each data object is in exactly one subset

### Hierarchical clustering

- A set of nested clusters organized as a hierarchical tree

# Partitional Clustering

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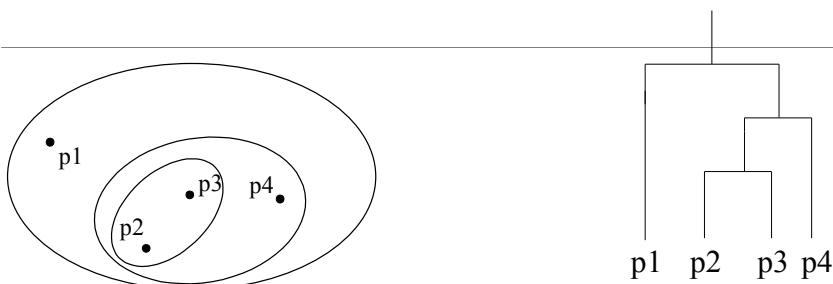


Original Points

A Partitional Clustering

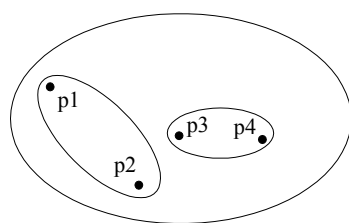
# Hierarchical Clustering

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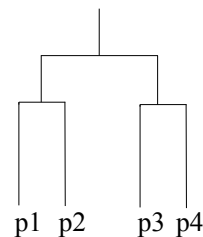


Traditional Hierarchical Clustering

Traditional Dendrogram



Non-traditional Hierarchical Clustering



Non-traditional Dendrogram

# Objective Function

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## Clustering as an optimization problem

- Finds clusters that minimize or maximize an [objective function](#).
- Enumerate all possible ways of dividing the points into clusters and evaluate the 'goodness' of each potential set of clusters by using the given objective function. (NP Hard)
- Can have [global](#) or [local](#) objectives.
  - Hierarchical clustering algorithms typically have local objectives
  - Partitional algorithms typically have global objectives
- A variation of the global objective function approach is to [fit](#) the data to a [parameterized model](#).
  - The [parameters](#) for the model are determined from the data, and they determine the clustering
  - E.g., [Mixture models](#) assume that the data is a 'mixture' of a number of statistical distributions.

## K-means

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# K-means Clustering

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Partitional clustering approach

Number of clusters,  $K$ , must be specified

Each cluster is associated with a **centroid** (center point)

Each point is assigned to the cluster with the **closest** centroid

The objective is to **minimize the sum of distances** of the points to their respective **centroid**




# K-means Clustering

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**Problem:** Given a set  $X$  of  $n$  points in a  $d$ -dimensional space and an integer  $K$ , group the points into  $K$  clusters  $C = \{C_1, C_2, \dots, C_k\}$  such that

$$Cost(C) = \sum_{i=1}^k \sum_{x \in C_i} dist(x, c_i)$$

is **minimized**, where  $c_i$  is the **centroid** of the points in cluster  $C_i$



# K-means Clustering

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- Most common definition is with euclidean distance, minimizing the **Sum of Squares Error (SSE)** function
  - Sometimes K-means is defined like that

**Problem:** Given a set  $X$  of  $n$  points in a  $d$ -dimensional space and an integer  $K$  group the points into  $K$  clusters  $C = \{C_1, C_2, \dots, C_k\}$  such that

$$Cost(C) = \sum_{i=1}^k \sum_{x \in C_i} (x - c_i)^2$$

is minimized, where  $c_i$  is the mean of the points in cluster  $C_i$

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## K-means Algorithm

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### Pseudocode:

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- 1: Select  $K$  points as the initial centroids.
  - 2: **repeat**
  - 3:   Form  $K$  clusters by assigning all points to the closest centroid.
  - 4:   Recompute the centroid of each cluster.
  - 5: **until** The centroids don't change
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# Problem - Initialization

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Initial centroids are often chosen **randomly**, and clusters produced **vary from one run to another**.

Do **multiple runs** and select the clustering with the smallest error

Select original set of points by methods other than random . E.g., pick the most distant (from each other) points as cluster centers (K-means++ algorithm)



## K-means Algorithm – Convergence

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K-means will **converge** for common similarity measures mentioned above.

- Most of the convergence happens in the first few iterations.
- Often the stopping condition is changed to 'Until relatively few points change clusters'

Complexity is  $O(n * K * I * d)$

- $n$  = number of points,  $K$  = number of clusters,  
 $I$  = number of iterations,  $d$  = dimensionality

In general a fast and efficient algorithm



# Limitations of K-means

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You need to specify the number of clusters in advance (although there are ways to find the optimal one).

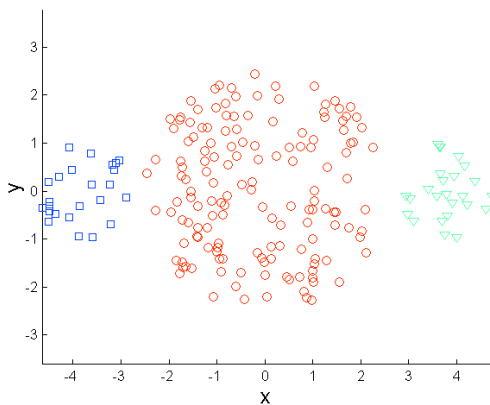
K-means has problems when clusters are of different

- Sizes
- Densities
- Non-globular shapes

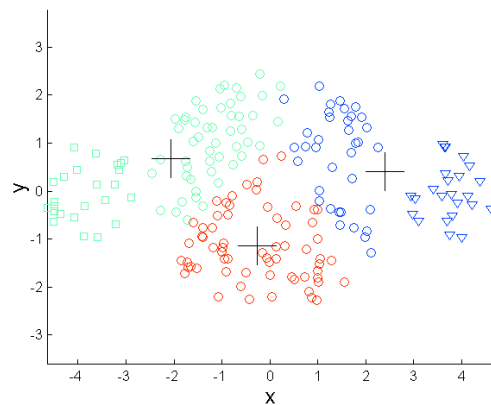
K-means has problems when the data contains outliers.

## Limitations of K-means: Differing Sizes

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Original Points

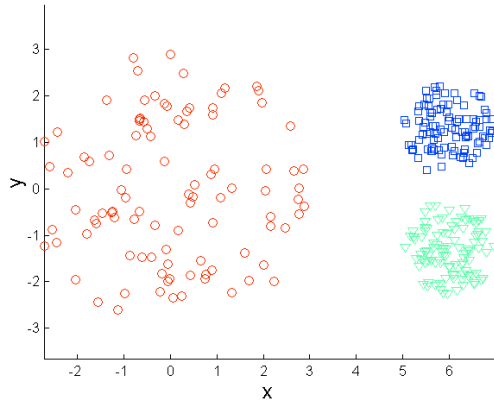


K-means (3 Clusters)

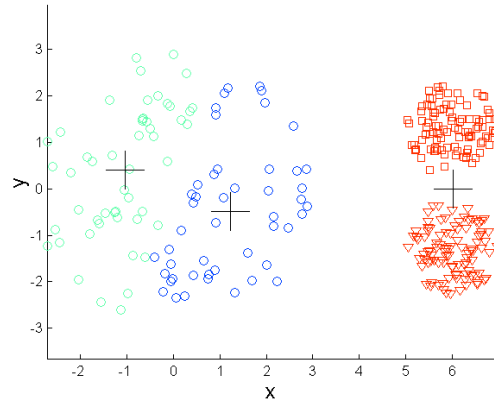


## Limitations of K-means: Differing Density

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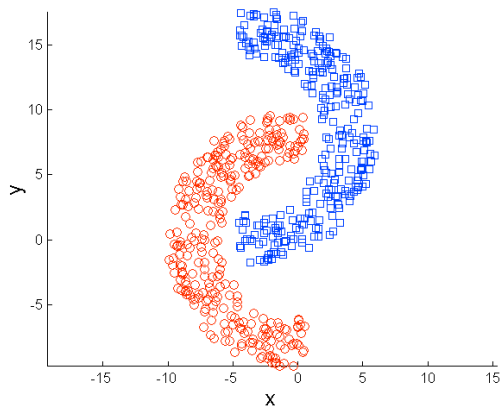
Original Points



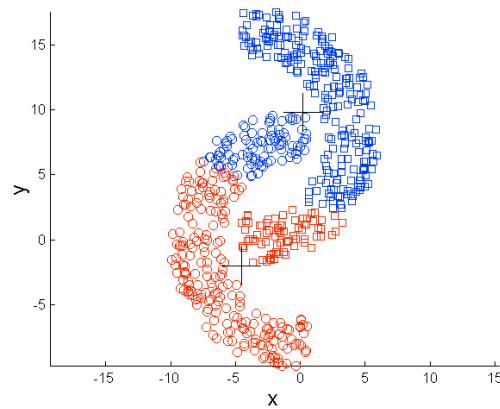
K-means (3 Clusters)

## Limitations of K-means: Non-globular Shapes

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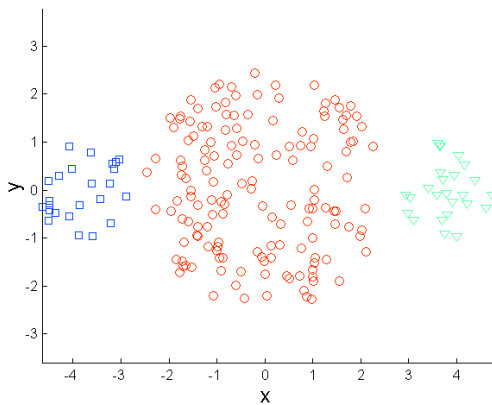


Original Points

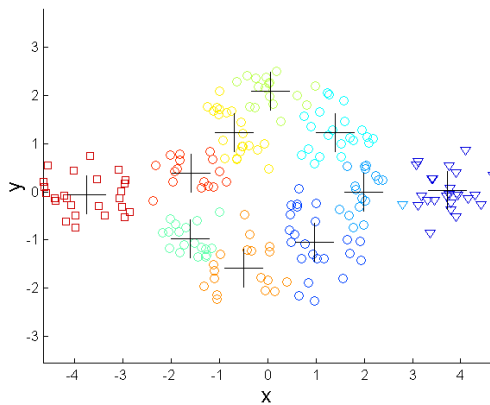


K-means (2 Clusters)

# Overcoming K-means Limitations



Original Points

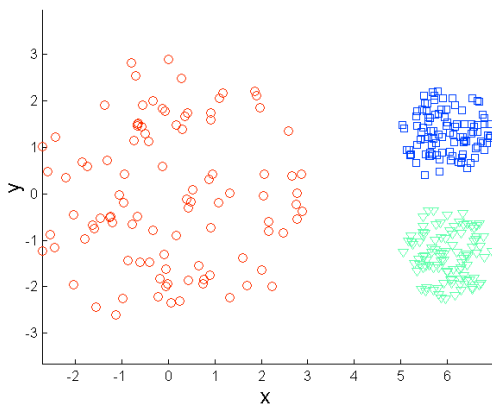


K-means Clusters

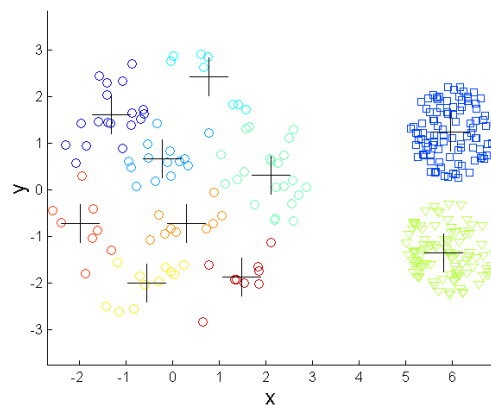
One solution is to use many clusters.

Find parts of clusters, but need to put together.

# Overcoming K-means Limitations



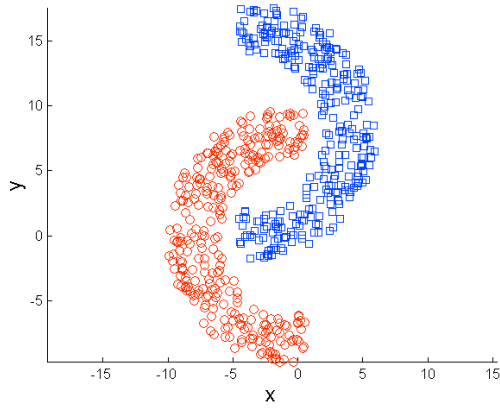
Original Points



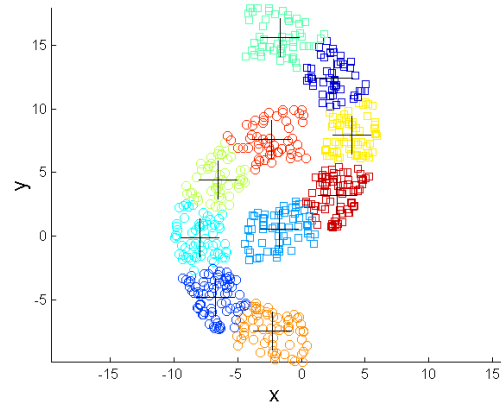
K-means Clusters

# Overcoming K-means Limitations

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Original Points



K-means Clusters

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Let's play:

<https://www.naftaliharris.com/blog/visualizing-k-means-clustering/>