

# Introduction to Artificial Intelligence

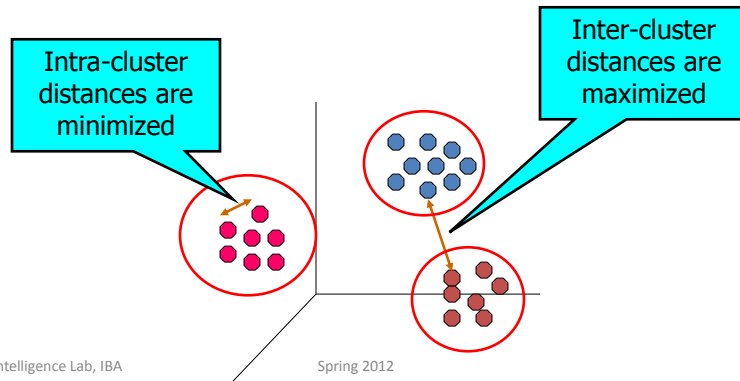
## Unit # 9

## Acknowledgement

- The slides of this lecture have been taken from the lecture slides of CSE652 – “Knowledge Discovery and Data mining” by Dr. Sajjad Haider.

## Cluster Analysis

- Finding groups of objects such that the objects in a group will be similar (or related) to one another and different from (or unrelated to) the objects in other groups



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## Cluster Analysis (Cont'd)

- Cluster: a collection of data objects
  - Similar to one another within the same cluster
  - Dissimilar to the objects in other clusters
- Cluster analysis
  - Finding similarities between data according to the characteristics found in the data and grouping similar data objects into clusters
- **Unsupervised learning:** no predefined classes
- Typical applications
  - As a **stand-alone tool** to get insight into data distribution
  - As a **preprocessing step** for other algorithms

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## Google News

### iPhone activation headaches still trouble users

Computerworld - 1 hour ago

July 02, 2007 (Computerworld) -- It took Iain Gillott 47 hours to activate his iPhone after waiting in the Texas heat Friday afternoon to buy one.

Most iPhone users thrilled but a few are iRate Reuters

Apple iPhone Arrives in the US Techtree.com

Forbes - ZDNet - Ars Technica - Wired News

[all 562 news articles »](#)



- They didn't pick all 3,400,217 related articles by hand...
- Or Amazon.com
- Or Netflix...

### McCain Considers Ways to Reshape Campaign

Washington Post - 35 minutes ago

By Alec MacGillis Sen. John McCain's presidential campaign today announced widespread cutbacks and said it was considering whether to accept public campaign funds after another disappointing fundraising effort that has left the Arizona Republican with ...

McCain's Troubles Mount New York Times

McCain Campaign Struggling, Reduces Staff ABC News

CBS News - Reuters - Angus Reid Global Monitor - Sarasota Herald-Tribune

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## Examples of Clustering Applications

- Marketing: Help marketers discover distinct groups in their customer bases, and then use this knowledge to develop targeted marketing programs
- Land use: Identification of areas of similar land use in an earth observation database
- Insurance: Identifying groups of motor insurance policy holders with a high average claim cost
- City-planning: Identifying groups of houses according to their house type, value, and geographical location
- Earth-quake studies: Observed earth quake epicenters should be clustered along continent faults

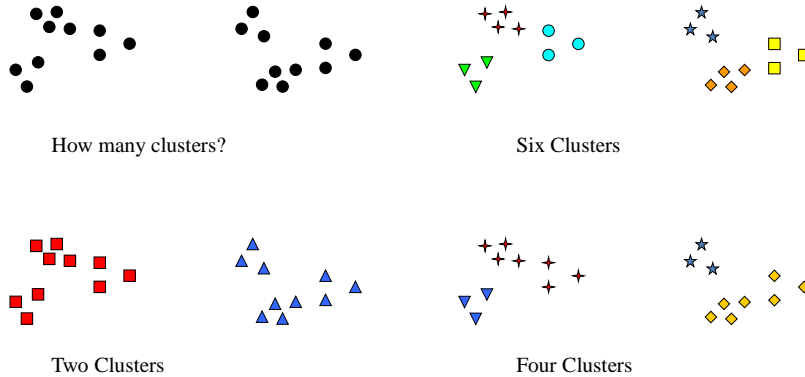
## Other less glamorous things...

- Hospital Records
- Scientific Imaging
  - Related genes, related stars, related sequences
- Market Research
  - Segmenting markets, product positioning
- Social Network Analysis
- Data mining
- Image segmentation...

## What is not Cluster Analysis?

- Supervised classification
  - Have class label information
- Simple segmentation
  - Dividing students into different registration groups alphabetically, by last name
- Results of a query
  - Groupings are a result of an external specification
- Graph partitioning
  - Some mutual relevance and synergy, but areas are not identical

## Notion of a Cluster can be Ambiguous



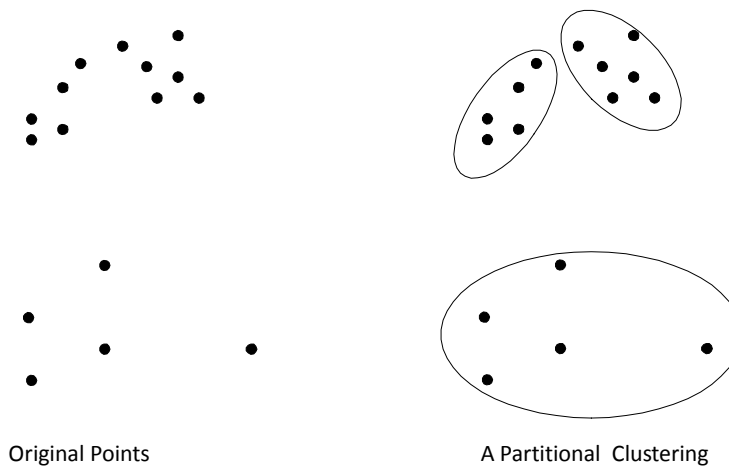
## Quality: What Is Good Clustering?

- A good clustering method will produce high quality clusters with
  - high intra-class similarity
  - low inter-class similarity
- The quality of a clustering result depends on both the similarity measure used by the method and its implementation
- The quality of a clustering method is also measured by its ability to discover some or all of the hidden patterns

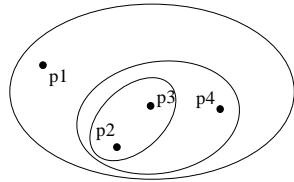
## Types of Clusterings

- A **clustering** is a set of clusters
- Important distinction between **hierarchical** and **partitional** sets of clusters
- **Partitional Clustering**
  - A division data objects into non-overlapping subsets (clusters) such that each data object is in exactly one subset
- **Hierarchical clustering**
  - A set of nested clusters organized as a hierarchical tree

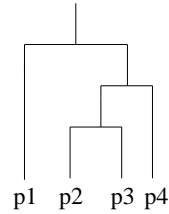
## Partitional Clustering



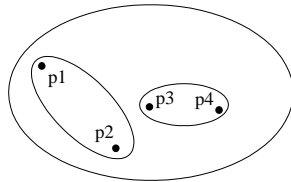
## Hierarchical Clustering



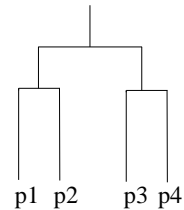
Traditional Hierarchical Clustering



Traditional Dendrogram



Non-traditional Hierarchical Clustering



Non-traditional Dendrogram

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## Measure the Quality of Clustering

- **Dissimilarity/Similarity metric:** Similarity is expressed in terms of a distance function, typically metric:  $d(i, j)$
- There is a separate “quality” function that measures the “goodness” of a cluster.
- The definitions of **distance functions** are usually very different for interval-scaled, boolean, categorical, ordinal ratio, and vector variables.
- Weights should be associated with different variables based on applications and data semantics.
- It is hard to define “similar enough” or “good enough”
  - the answer is typically highly subjective.

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## The *K-Means* Clustering Method

- 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

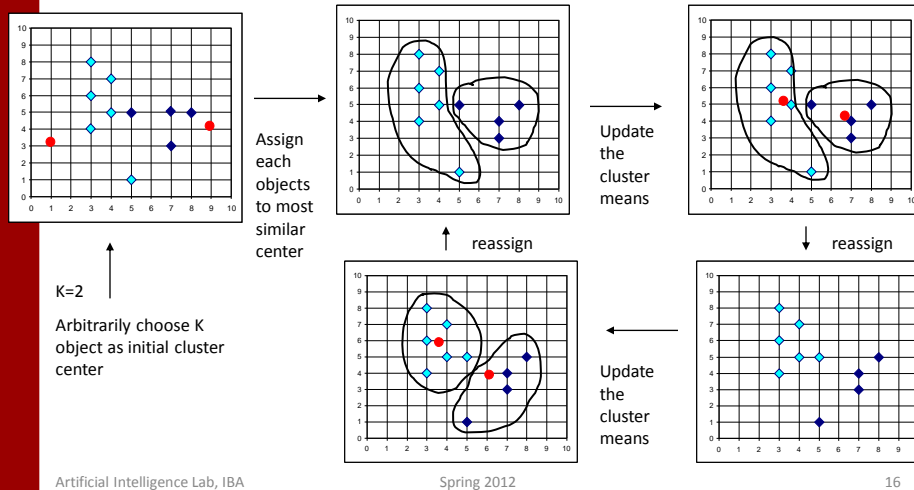
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## The *K-Means* Clustering Method (Cont'd)

- Example





## The K-Means Algorithm

1. Choose a value for K, the total number of clusters to be determined.
2. Choose K instances within the dataset at random. These are the initial cluster centers.
3. Use simple Euclidean distance to assign the remaining instances to their closest cluster center.
4. Use the instance in each cluster to calculate a new mean for each cluster.
5. If the new mean values are identical to the mean values of the previous iteration the process terminates. Otherwise, use the new means as cluster centers and repeat steps 3-5.

## Working of the K-Mean Algorithm

Instance #:	1	2	3	4	5	6
X:	1	1	2	2	3	3
Y:	1.5	4.5	1.5	3.5	2.5	6.0

- Let's pick Instances #1 and #3 as the initial centroids.

	Distance with Centroid1	Distance with Centroid2
• Instance #2	<b>3.00</b>	3.16
• Instance #4	2.24	<b>2.00</b>
• Instance #5	2.24	<b>1.41</b>
• Instance #6	6.02	<b>5.41</b>

- **New centroids are (1, 3) and (2.5, 3.4)**

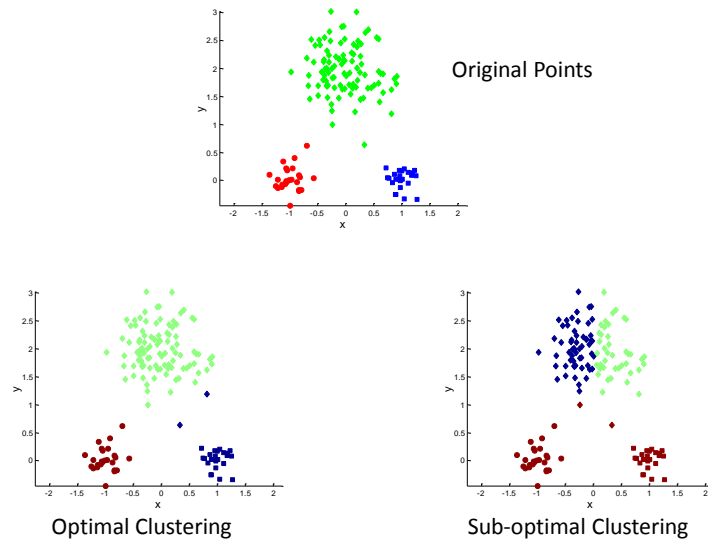
## Comments on the *K-Means* Method

- Strength: *Relatively efficient*:  $O(tkn)$ , where  $n$  is # objects,  $k$  is # clusters, and  $t$  is # iterations. Normally,  $k, t \ll n$ .
- Comment: 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*

## K-Means Clustering – Details

- Initial centroids are often chosen randomly.
  - Clusters produced vary from one run to another.
- The centroid is (typically) the mean of the points in the cluster.
- ‘Closeness’ is measured by Euclidean distance, cosine similarity, correlation, etc.
- 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’

## Two different K-means Clusterings

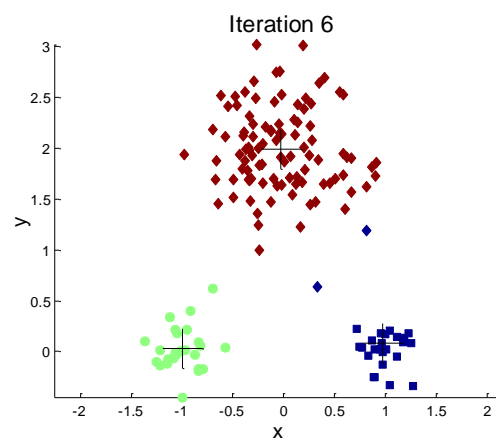


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## Importance of Choosing Initial Centroids

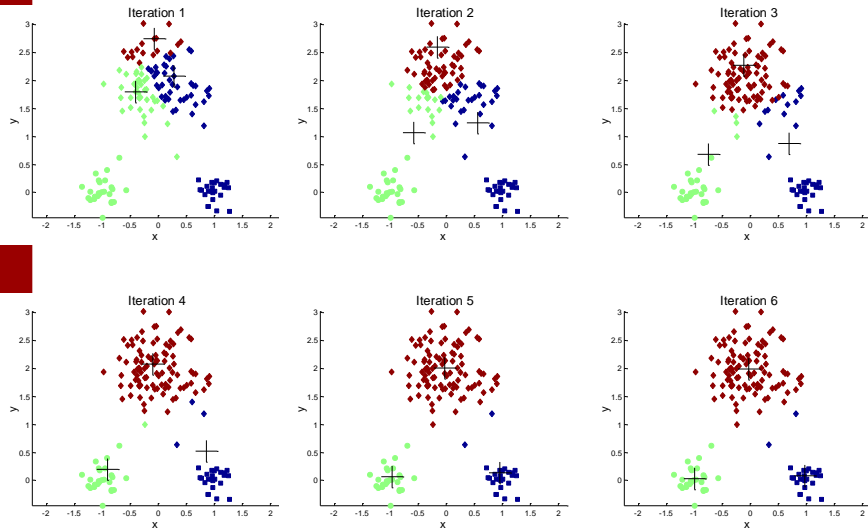


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## Importance of Choosing Initial Centroids

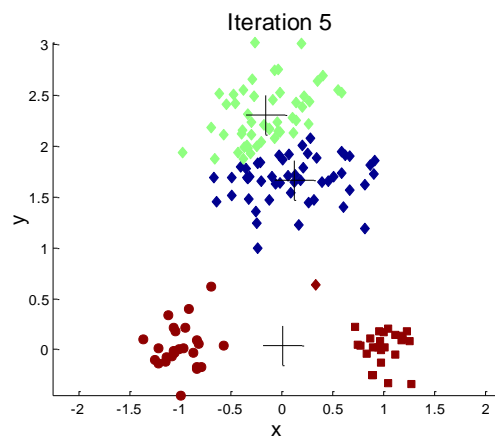


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## Importance of Choosing Initial Centroids ...

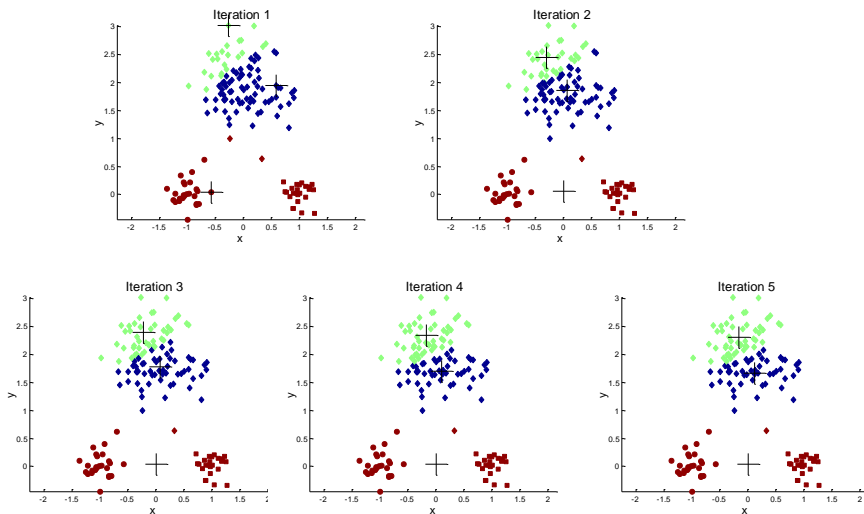


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## Importance of Choosing Initial Centroids ...



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## Evaluating K-means Clusters

- Most common measure is Sum of Squared Error (SSE)
  - For each point, the error is the distance to the nearest cluster
  - To get SSE, we square these errors and sum them.
$$SSE = \sum_{i=1}^K \sum_{x \in C_i} dist^2(m_i, x)$$
  - $x$  is a data point in cluster  $C_i$  and  $m_i$  is the representative point for cluster  $C_i$ 
    - can show that  $m_i$  corresponds to the center (mean) of the cluster
  - Given two clusters, we can choose the one with the smallest error
  - One easy way to reduce SSE is to increase  $K$ , the number of clusters
    - A good clustering with smaller  $K$  can have a lower SSE than a poor clustering with higher  $K$

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## Pre-processing and Post-processing

- Pre-processing
  - Normalize the data
  - Eliminate outliers
- Post-processing
  - Eliminate small clusters that may represent outliers
  - Split 'loose' clusters, i.e., clusters with relatively high SSE
  - Merge clusters that are 'close' and that have relatively low SSE

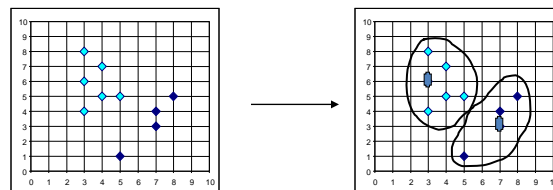
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## What Is the Problem of the K-Means Method?

- 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.



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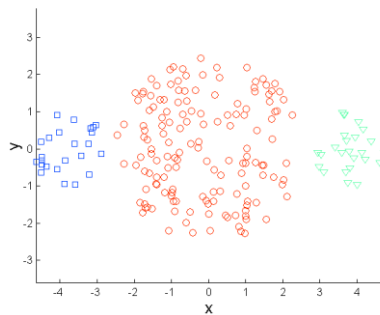
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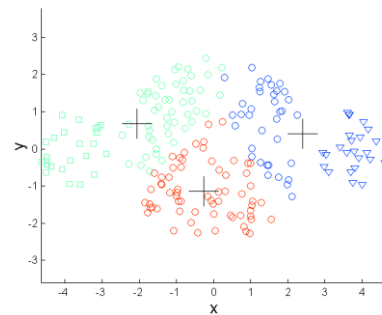
## Limitations of K-means

- K-means has problems when clusters are of differing
  - Sizes
  - Densities
  - Non-globular shapes
- K-means has problems when the data contains outliers.

## Limitations of K-means: Differing Sizes

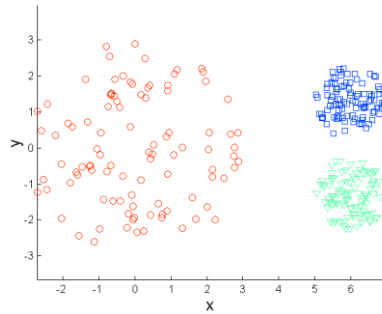


Original Points

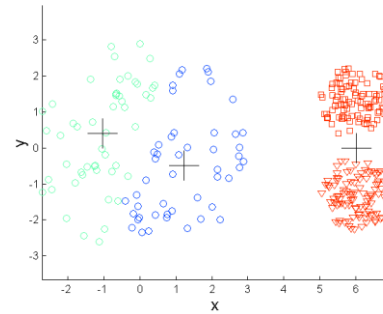


K-means (3 Clusters)

## Limitations of K-means: Differing Density

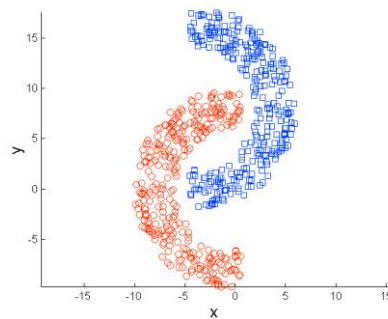


Original Points

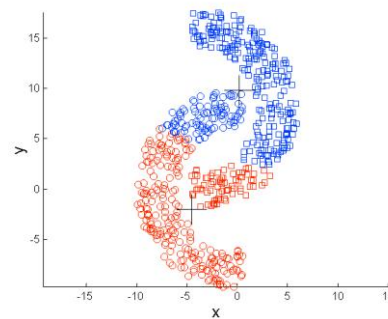


K-means (3 Clusters)

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



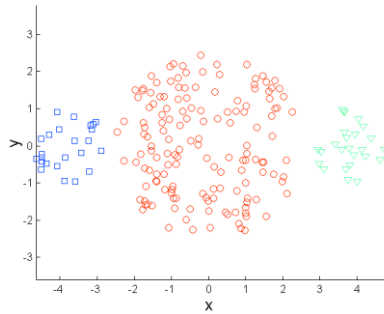
Original Points



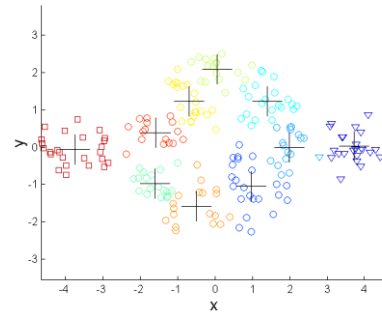
K-means (2 Clusters)



## Overcoming K-means Limitations



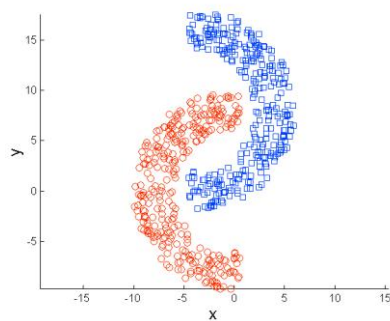
Original Points



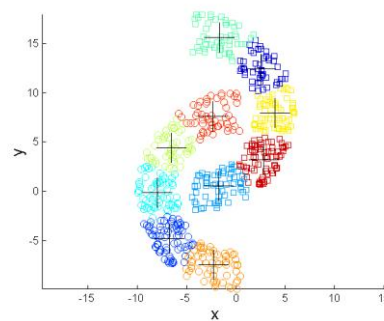
K-means Clusters

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