

### Dr. N MEHALA

Department of Computer Science and Engineering



# **Module 4 [Unsupervised Learning]**

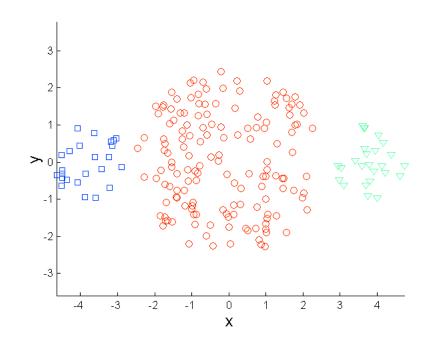
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### **K-Means Clustering: Limitations**

## **Limitations of K-means: Differing Sizes**





3 - 2 - 1 0 1 2 3 4 X

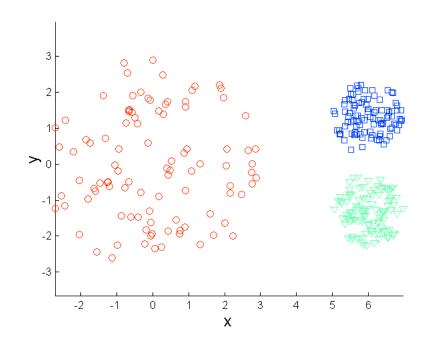
**Original Points** 

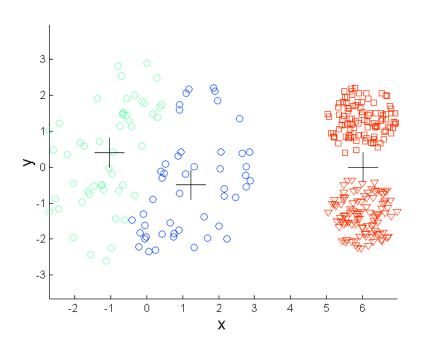
K-means (3 Clusters)

### **K-Means Clustering: Limitations**

## **Limitations of K-means: Differing Density**







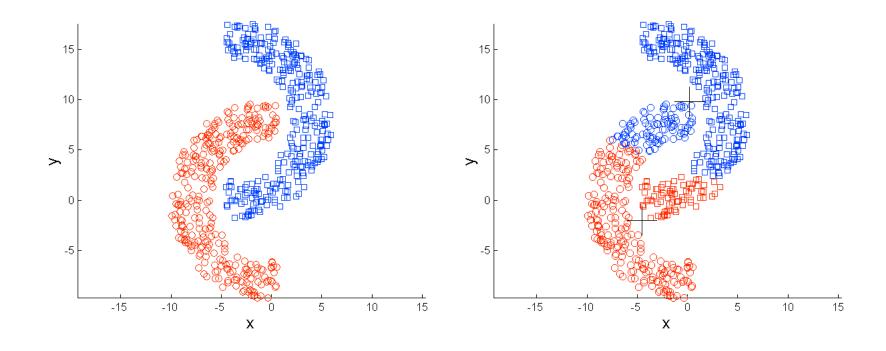
**Original Points** 

K-means (3 Clusters)

### **K-Means Clustering: Limitations**

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



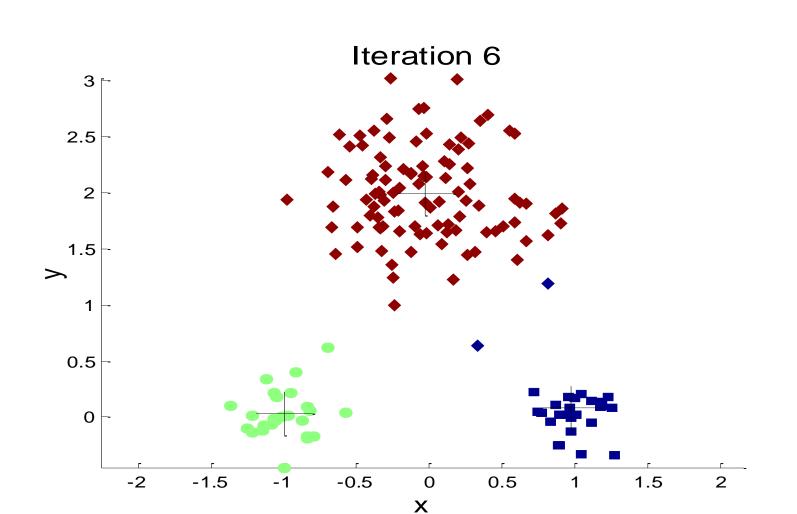


**Original Points** 

K-means (2 Clusters)

### **K-Means Clustering: Limitations**

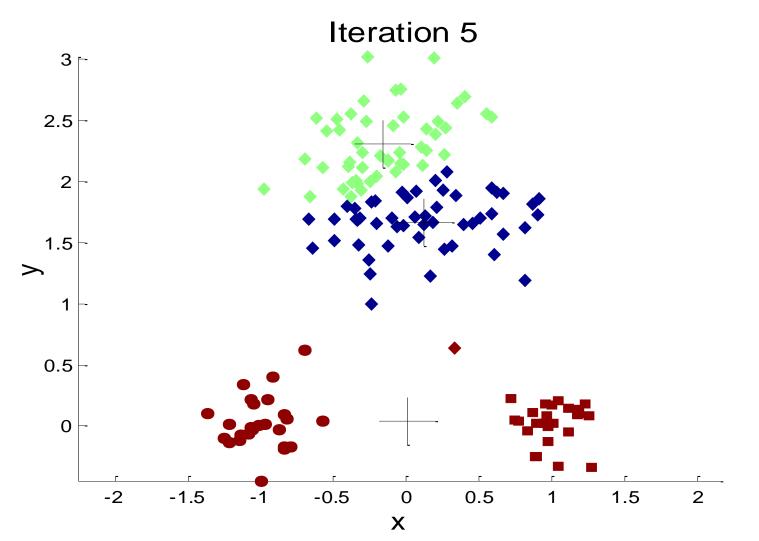
# **Importance of Choosing Initial Centroids**





### **K-Means Clustering: Limitations**

# **Importance of Choosing Initial Centroids**





### **K-Means Clustering: Limitations**

### **Problems with Selecting Initial Points**

- If there are K 'real' clusters then the chance of selecting one centroid from each cluster is small.
  - Chance is relatively small when K is large
  - If clusters are the same size, n, then

$$P = \frac{\text{number of ways to select one centroid from each cluster}}{\text{number of ways to select } K \text{ centroids}} = \frac{K!n^K}{(Kn)^K} = \frac{K!}{K^K}$$

- For example, if K = 10, then probability =  $10!/10^{10} = 0.00036$
- Sometimes the initial centroids will readjust themselves in 'right' way, and sometimes they don't



#### **Solutions to Initial Centroids Problem**

- Multiple runs
  - Helps, but probability is not on our side
- Sample and use hierarchical clustering to determine initial centroids
- Select more than k initial centroids and then select among these initial centroids
  - Select most widely separated
- Postprocessing
- Generate a larger number of clusters and then perform a hierarchical clustering
- Bisecting K-means
  - Not as susceptible to initialization issues



### **Bisecting K-Means Clustering Algorithm**

- To overcome the problem of poor clusters because of kmeans getting caught in a local minimum
- Variant of K-means that can produce a partitional or a hierarchical clustering
- Instead of partitioning the data set into K clusters in each iteration, bisecting k-means algorithm splits one cluster into two sub clusters at each bisecting step (by using kmeans) until k clusters are obtained.
- Hybrid approach between Divisive Hierarchical Clustering (top down clustering) and K-means Clustering.

**Note:** A local minimum means that the result is good but not necessarily the best possible. A global minimum is the best possible



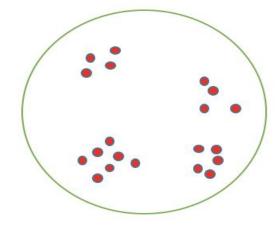
### **Bisecting K-Means Clustering Algorithm**



### **How it Works?**

Step1: Set K to define the number of cluster

Step2: Set all data as a single cluster



### **Bisecting K-Means Clustering Algorithm**

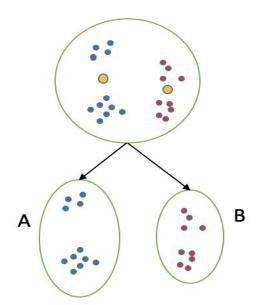


### **How it Works?**

Step1: Set K to define the number of cluster

Step2: Set all data as a single cluster

Step3: Use K-means with K=2 to split the cluster



### **Bisecting K-Means Clustering Algorithm**

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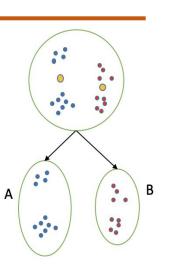
Step3: Use K-means with K=2 to split the cluster

Step4: Measure the distance for each intra cluster

- Sum of square Distance

$$\sum_{i=0}^n \left(X_i - \overline{X}
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Step5: Select the cluster that have the largest distance and split to 2 cluster using K-means





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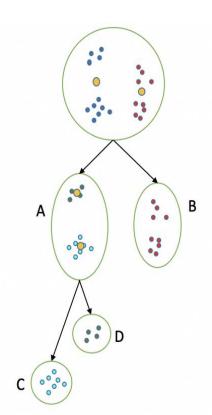
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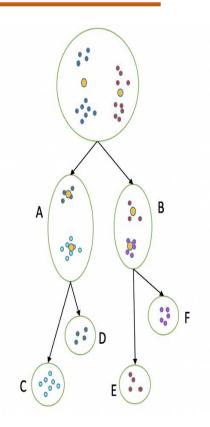
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Step6: Repeat step 3–5 until the number of leaf cluster = K.





### **Advantage of Bisecting K-Means over K-Means**



- Bisecting k-means is more efficient when **K** is large.
- Bisecting k-means produce clusters of similar sizes, while k-means is known to produce clusters of widely different sizes.

### **Summary**

- K-Means Issues
- Bisecting K-Means Clustering



#### Resources

- http://www2.ift.ulaval.ca/~chaib/IFT-4102 7025/public html/Fichiers/Machine Learning in Action.pdf
- http://wwwusers.cs.umn.edu/~kumar/dmbook/.
- ftp://ftp.aw.com/cseng/authors/tan
- http://web.ccsu.edu/datamining/resources.html





# **THANK YOU**

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