

# STA141C: Big Data & High Performance Statistical Computing

## Lecture 11: Clustering

Cho-Jui Hsieh  
UC Davis

May 24, 2018

# Outline

- Kmeans Clustering
- Graph Clustering

# Supervised versus Unsupervised Learning

## Supervised Learning:

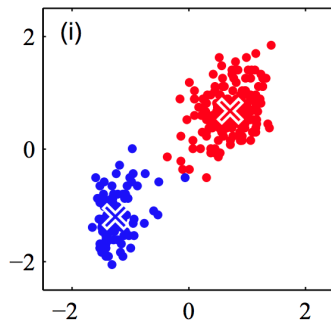
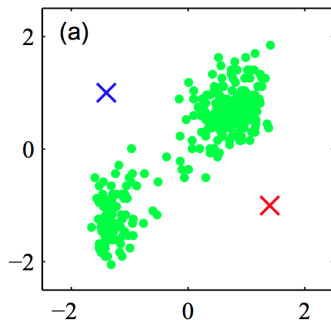
- Learning from **labeled** observations
- Classification, regression, ...

## Unsupervised Learning:

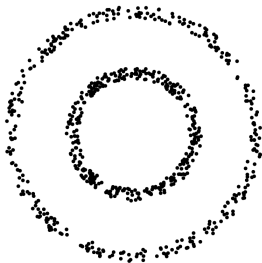
- Learning from **unlabeled** observations
- Discover hidden patterns
- Clustering (today)

# Clustering

- Given  $\{\mathbf{x}_1, \mathbf{x}_2, \dots, \mathbf{x}_n\}$  and  $K$  (number of clusters)
- Output  $A(\mathbf{x}_i) \in \{1, 2, \dots, K\}$  (cluster membership)

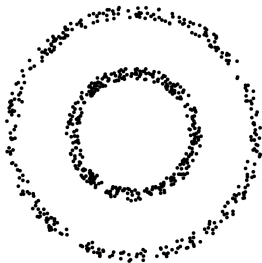


# Two circles

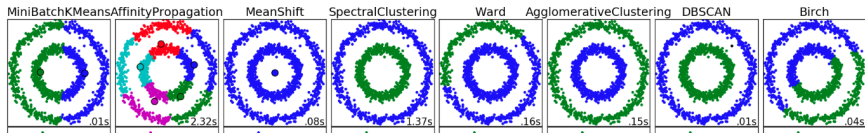


Can we split the data into **two clusters**?

# Two circles

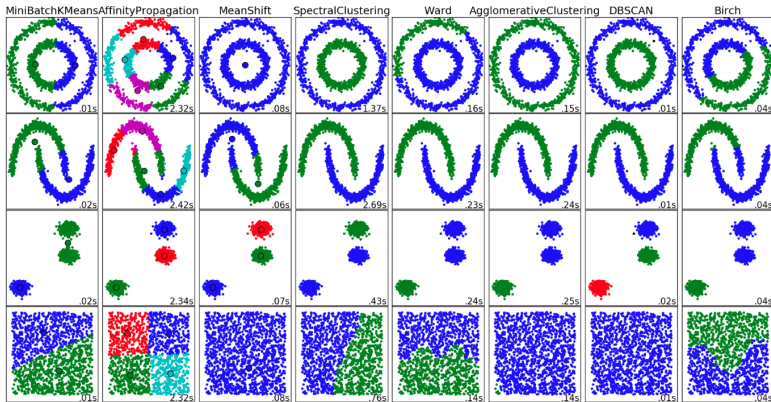


Can we split the data into **two clusters**?



# Clustering is Subjective

- Non-trivial to say one clustering is better than the other
- Each algorithm has two parts:
  - Define the **objective function**
  - Design an algorithm to **minimize this objective function**



# K-means Objective Function

- Partition dataset into  $C_1, C_2, \dots, C_K$  to minimize the following objective:

$$J = \sum_{k=1}^K \sum_{\mathbf{x} \in C_k} \|\mathbf{x} - \mathbf{m}_k\|_2^2,$$

where  $\mathbf{m}_k$  is the mean of  $C_k$ .



# K-means Objective Function

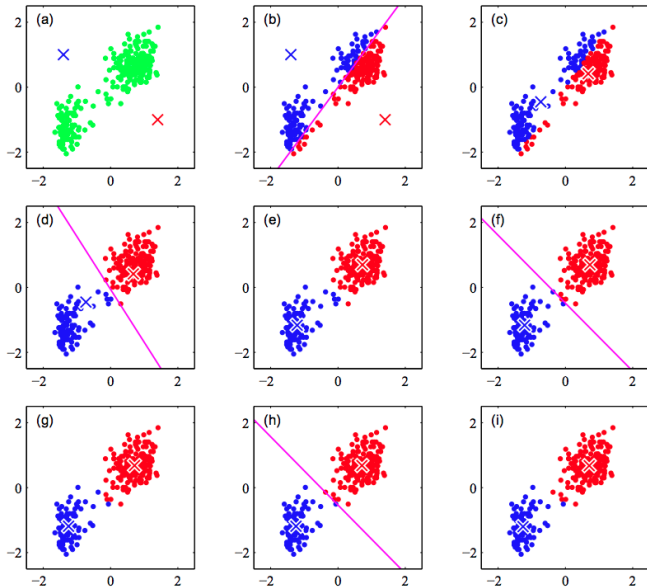
- Partition dataset into  $C_1, C_2, \dots, C_K$  to minimize the following objective:

$$J = \sum_{k=1}^K \sum_{\mathbf{x} \in C_k} \|\mathbf{x} - \mathbf{m}_k\|_2^2,$$

where  $\mathbf{m}_k$  is the mean of  $C_k$ .

- Multiple ways to minimize this objective
  - Hierarchical Agglomerative Clustering
  - Kmeans Algorithm (Today)
  - ...

# K-means Algorithm



# K-means Algorithm

- Re-write objective:

$$J = \sum_{n=1}^N \sum_{k=1}^K r_{nk} \|\mathbf{x}_n - \mathbf{m}_k\|_2^2,$$

where  $r_{nk} \in \{0, 1\}$  is an indicator variable

$$r_{nk} = 1 \text{ if and only if } \mathbf{x}_n \in C_k$$

- Alternative optimization between  $\{r_{nk}\}$  and  $\{\mathbf{m}_k\}$ 
  - Fix  $\{\mathbf{m}_k\}$  and update  $\{r_{nk}\}$
  - Fix  $\{r_{nk}\}$  and update  $\{\mathbf{m}_k\}$

# K-means Algorithm

- Step 0: Initialize  $\{\mathbf{m}_k\}$  to some values

# K-means Algorithm

- Step 0: Initialize  $\{\mathbf{m}_k\}$  to some values
- Step 1: Fix  $\{\mathbf{m}_k\}$  and minimize over  $\{r_{nk}\}$ :

$$r_{nk} = \begin{cases} 1 & \text{if } k = \arg \min_j \|\mathbf{x}_n - \mathbf{m}_j\|_2^2 \\ 0 & \text{otherwise} \end{cases}$$

# K-means Algorithm

- Step 0: Initialize  $\{\mathbf{m}_k\}$  to some values
- Step 1: Fix  $\{\mathbf{m}_k\}$  and minimize over  $\{r_{nk}\}$ :

$$r_{nk} = \begin{cases} 1 & \text{if } k = \arg \min_j \|\mathbf{x}_n - \mathbf{m}_j\|_2^2 \\ 0 & \text{otherwise} \end{cases}$$

- Step 2: Fix  $\{r_{nk}\}$  and minimize over  $\{\mathbf{m}_k\}$ :

$$\mathbf{m}_k = \frac{\sum_n r_{nk} \mathbf{x}_n}{\sum_n r_{nk}}$$

# K-means Algorithm

- Step 0: Initialize  $\{\mathbf{m}_k\}$  to some values
- Step 1: Fix  $\{\mathbf{m}_k\}$  and minimize over  $\{r_{nk}\}$ :

$$r_{nk} = \begin{cases} 1 & \text{if } k = \arg \min_j \|\mathbf{x}_n - \mathbf{m}_j\|_2^2 \\ 0 & \text{otherwise} \end{cases}$$

- Step 2: Fix  $\{r_{nk}\}$  and minimize over  $\{\mathbf{m}_k\}$ :

$$\mathbf{m}_k = \frac{\sum_n r_{nk} \mathbf{x}_n}{\sum_n r_{nk}}$$

- Step 3: Return to step 1 unless stopping criterion is met

# K-means Algorithm

Equivalent to the following procedure:

- Step 0: Initialize centers  $\{\mathbf{m}_k\}$  to some values
- Step 1: Assign each  $\mathbf{x}_n$  to the nearest center:

$$A(\mathbf{x}_n) = \arg \min_j \|\mathbf{x}_n - \mathbf{m}_j\|_2^2$$

Update clusters:

$$C_k = \{\mathbf{x}_n : A(\mathbf{x}_n) = k\} \quad \forall k = 1, \dots, K$$

- Step 2: Calculate mean of each cluster  $C_k$ :

$$\mathbf{m}_k = \frac{1}{|C_k|} \sum_{\mathbf{x}_n \in C_k} \mathbf{x}_n$$

- Step 3: Return to step 1 unless stopping criterion is met



# More on K-means Algorithm

- Always **decrease** the objective function for each update
- Objective function will keep unchanged when step 1 doesn't change cluster assignment  $\Rightarrow$  Converged

# More on K-means Algorithm

- Always **decrease** the objective function for each update
- Objective function will keep unchanged when step 1 doesn't change cluster assignment  $\Rightarrow$  Converged
- May not converge to **global minimum**

Sensitive to initial values

# More on K-means Algorithm

- Always **decrease** the objective function for each update
- Objective function will keep unchanged when step 1 doesn't change cluster assignment  $\Rightarrow$  Converged
- May not converge to **global minimum**
  - Sensitive to initial values
- Kmeans++: A better way to initialize the clusters

# Coming up

- Clustering

Questions?