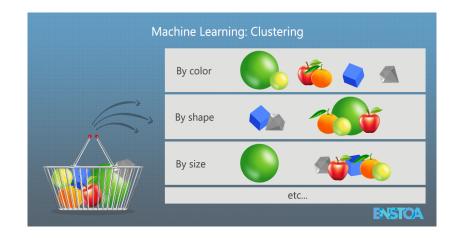
# Clustering



Clustering is grouping data points into groups where data points in one group are similar to each other.

## What is clustering?



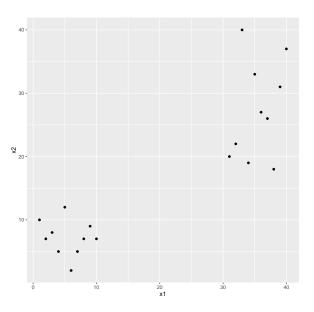
### Methods of Clustering

We will cover two clustering methods:

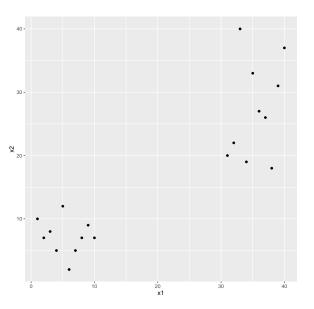
- ► K-means clustering and
- ► Hierarchical clustering

# K-means clustering

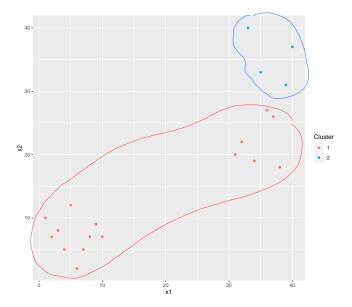
## Example - Data



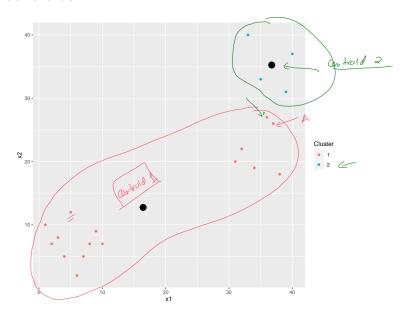
# Step 1: Randomly Assign Points to Clusters



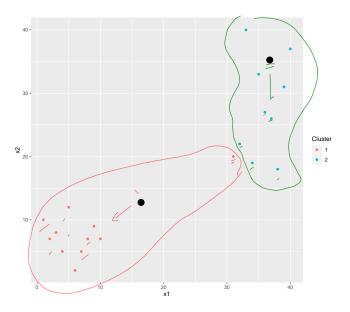
## Step 1: Randomly Assign Points to Clusters



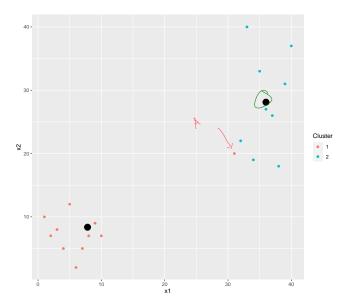
#### Locate centroids



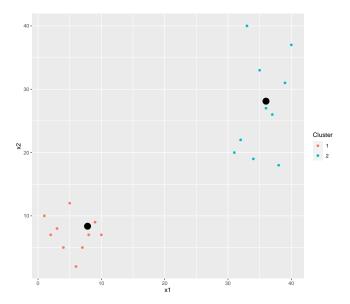
## Reassign Points to clusters



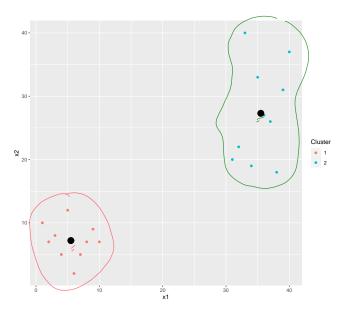
#### Relocate centroids



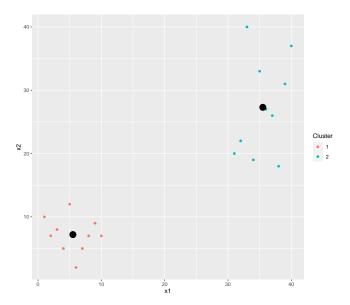
## Reassign Points to clusters



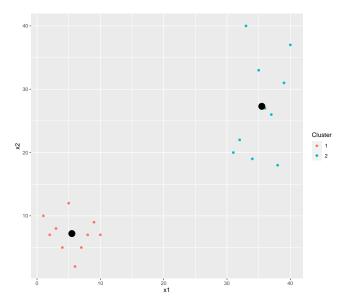
#### Relocate centroids



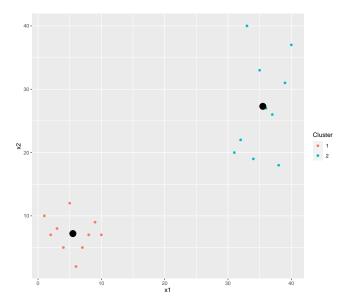
## Reassign Points to clusters



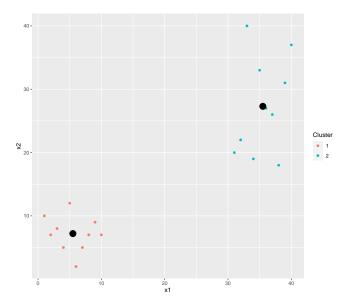
#### Relocate centroids



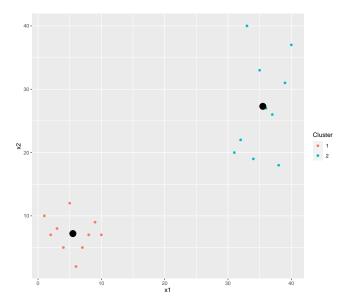
## Step 2: Reassign Points to clusters



## Step 2: Relocate centroids



## Step 2: Reassign Points to clusters



#### Centroids

| Cluster | x1   | x2   |
|---------|------|------|
| 1       | 5.5  | 7.2  |
| 2       | 35.5 | 27.3 |
|         |      |      |

#### K-means Algorithm

- Randomly assign a number, from 1 to K, to each of the observations. These serve as initial cluster assignments for the observations.
- 2. Iterate until the cluster assignments stop changing:
  - (a) For each of the K clusters, compute the cluster centroid. The  $k^{th}$  cluster centroid is the vector of the p feature means for the observations in the kth cluster.
  - (b) Assign each observation to the cluster whose centroid is closest (where closest is defined using Euclidean distance).

#### Dataset

| Point | Х | у |
|-------|---|---|
| A     | 1 | 3 |
| В     | 2 | 2 |
| C     | 3 | 5 |
| D     | 4 | 5 |
| E     | 5 | 6 |
|       |   |   |

## Randomly Assign Cluster to Points

| Cluster Point                   | ху                              | cusks 1: {A, C, P}  |
|---------------------------------|---------------------------------|---|
| 1 A<br>2 B<br>1 C<br>1 D<br>2 E | 1 3<br>2 2<br>3 5<br>4 5<br>5 6 | $Cus k_{1} = \{ k, E \}$ $\frac{1+3+4}{3}, \frac{3+5+5}{3}$ |
|                                 | Ceanod &                        | $= \begin{pmatrix} 8 & 1 \\ \hline 3 & 1 \end{pmatrix}$     |

Control 1 = (2.67, 4.33)

| Cluster | Point | Х | у | (C_1x | C_1y | C_2x | C_2y |
|---------|-------|---|---|-------|------|------|------|
| 1       | Α     | 1 | 3 | 2.67  | 4.33 | 3.5  | 4    |
| 2       | В     | 2 | 2 | 2.67  | 4.33 | 3.5  | 4    |
| 1       | C     | 3 | 5 | 2.67  | 4.33 | 3.5  | 4    |
| 1       | D     | 4 | 5 | 2.67  | 4.33 | 3.5  | 4    |
| 2       | E     | 5 | 6 | 2.67  | 4.33 | 3.5  | 4    |

M: certroid 1 N: certroid 2

MA

|         |       |   |   | (    |      |      |      |      | NA   |
|---------|-------|---|---|------|------|------|------|------|------|
| Cluster | Point | X | у | C_1x | C_1y | C_2x | C_2y | dc1  | dc2  |
| 1       | А     | 1 | 3 | 2.67 | 4.33 | 3.5  | 4    | 2.13 | 2.69 |
| 2       | В     | 2 | 2 | 2.67 | 4.33 | 3.5  | 4 (  | 2.42 | 2.50 |
| 1       | C     | 3 | 5 | 2.67 | 4.33 | 3.5  | 4    | 0.75 | 1.12 |
| 1       | D     | 4 | 5 | 2.67 | 4.33 | 3.5  | 4 (  | 1.49 | 1.12 |
| 2       | Е     | 5 | 6 | 2.67 | 4.33 | 3.5  | 4    | 2.87 | 2.50 |

| Cluster | Point | Χ | У | dc1  | dc2  | min_distance |
|---------|-------|---|---|------|------|--------------|
| 1       | А     | 1 | 3 | 2.13 | 2.69 | 2.13         |
| 2       | В     | 2 | 2 | 2.42 | 2.50 | 2.42         |
| 1       | C     | 3 | 5 | 0.75 | 1.12 | 0.75         |
| 1       | D     | 4 | 5 | 1.49 | 1.12 | 1.12         |
| 2       | Ε     | 5 | 6 | 2.87 | 2.50 | 2.50         |

| Cluster | Point | X | У | dc1  | dc2  | min_distance | New_Cluster |
|---------|-------|---|---|------|------|--------------|-------------|
| 1       | Α     | 1 | 3 | 2.13 | 2.69 | 2.13         | (1)         |
| 2       | В     | 2 | 2 | 2.42 | 2.50 | 2.42         | )1          |
| 1       | C     | 3 | 5 | 0.75 | 1.12 | 0.75         | (1)         |
| 1       | D     | 4 | 5 | 1.49 | 1.12 | 1.12         | 2           |
| 2       | Е     | 5 | 6 | 2.87 | 2.50 | 2.50         | 2           |

#### Total Variance within

- ▶ With the initial Clusters:
- Let M and N are the centroids of cluster 1 and 2 respectively

► Total Variance within

$$=\underbrace{2 \cdot (MA^2 + MC^2 + MD^2 + NB^2 + ND^2)}_{=\underbrace{\frac{1}{3}(AB^2 + AC^2 + AD^2) + \frac{1}{2} \cdot BE^2}_{-}}$$

▶ Total Variance within 19.83

#### Total Variance within

- ▶ With the new Clusters:
- Let H and K are the centroids of cluster 1 and 2, respectively.

Total Variance within

$$= 2 \cdot (HA^2 + HB^2 + HC^2 + KD^2 + KE^2)$$
$$= \frac{1}{3}(AB^2 + AC^2 + BC^2) + \frac{1}{2} \cdot DE^2$$

$$=\frac{1}{3}(D^2+D^2+D^2)+\frac{1}{2}D^2$$

- ▶ Total Variance within 7.67
- ▶ The process of k-means will minimize the total variance within

#### Example

You apply 2-means clustering to a set of five observations with two features. You are given the following initial cluster assignments:

| Observation | $X_1$ | $X_2$ | Initial cluster |
|-------------|-------|-------|-----------------|
| A           | 1     | 1     | 1               |
| В           | 0     | 0     | 1               |
| C           | 0     | 1     | 1               |
| D           | 2     | 1     | 2               |
| E           | 1     | 0     | 2               |

Calculate the total within-cluster variation (Total Variance within) of the initial cluster assignments, based on Euclidean distance measure.

$$\frac{B}{D} = \frac{0}{2} \frac{A}{1} \frac{1}{D} \frac$$

Initial cluster

 $X_2$ 

=)  $V = V_1 + V_2 = \frac{4}{3} + (=7/3)$ (2) uory the carrold:  $M = (\frac{1}{3}, \frac{2}{3}) = V = 2(NA^2 + NA^2)$  $N = (\frac{3}{2}, \frac{1}{2}) = P(3)$