

# Unsupervised Learning II

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**BROWN**  
Public Health

# Cluster

- ▶ groups that are similar
- ▶ homogeneous property
- ▶ differences among the groups

# Cluster analysis in two steps

- ▶ Choice of a proximity measure
- ▶ Choice of group-building algorithm

## Proximity between objects

$$D = \begin{pmatrix} d_{11} & d_{12} & \dots & \dots & \dots & d_{1n} \\ \vdots & d_{22} & & & & \vdots \\ \vdots & \vdots & \ddots & & & \vdots \\ \vdots & \vdots & & \ddots & & \vdots \\ \vdots & \vdots & & & \ddots & \vdots \\ d_{n1} & d_{n2} & \dots & \dots & \dots & d_{nn} \end{pmatrix}$$

# Proximity between objects

## 1. Euclidean distance:

$$d_{euc}(x, y) = \sqrt{\sum_{i=1}^n (x_i - y_i)^2}$$

## 2. Manhattan distance:

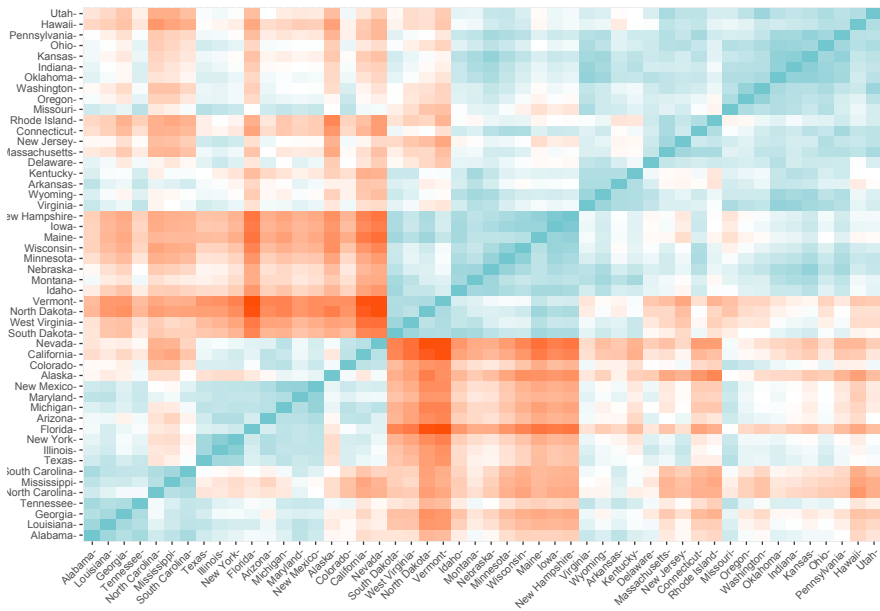
$$d_{man}(x, y) = \sum_{i=1}^n |x_i - y_i|$$

## The arrest data

```
> head(df)
```

	Murder	Assault	UrbanPop	Rape
Alabama	13.2	236	58	21.2
Alaska	10.0	263	48	44.5
Arizona	8.1	294	80	31.0
Arkansas	8.8	190	50	19.5
California	9.0	276	91	40.6
Colorado	7.9	204	78	38.7

# The distance matrix: 0 blue, 200 red: Q1 in prisma



# K-means Clustering Q2

- ▶ High intra-class similarity in the same cluster
- ▶ Each cluster is represented by its center (centroids)
- ▶  $k$  represents the number of groups
- ▶  $C_1 \cup C_2 \cup \dots \cup C_K = 1, \dots, n$
- ▶  $C_k \cap C_{k'} = \emptyset$  for
- ▶ The total within-cluster variation

$$W(C_k) = \sum_{x_i \in C_k} (x_i - \mu_k)^2$$

$$\min \sum_{k=1}^K W(C_k)$$



# K-means Algorithm

1. 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:
  - 2.1 For each of the K clusters, compute the cluster centroid.
  - 2.2 Assign each observation to the cluster whose centroid is closest (Euclidean distance)

## Let's see the output with two clusters

```
> k2 <- kmeans(df, centers = 2, nstart = 25)
> k2
K-means clustering with 2 clusters of sizes 29, 21
```

Cluster means:

	Murder	Assault	UrbanPop	Rape
1	4.841379	109.7586	64.03448	16.24828
2	11.857143	255.0000	67.61905	28.11429

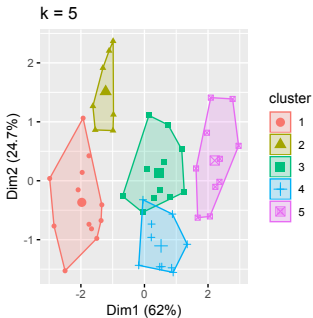
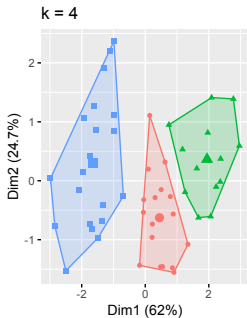
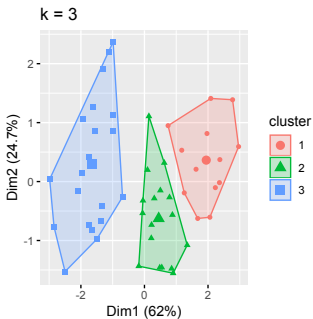
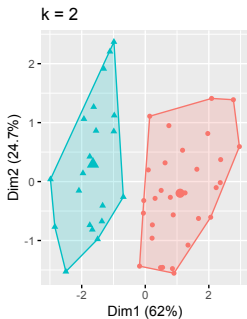
Clustering vector:

Alabama	Alaska	Arizona	Arkansas	California
2	2	2	2	2
Colorado	Connecticut	Delaware	Florida	Georgia
2	1	2	2	2
Hawaii	Idaho	Illinois	Indiana	Iowa
1	1	2	1	1

# The cluster plot: Q3



# How many clusters?



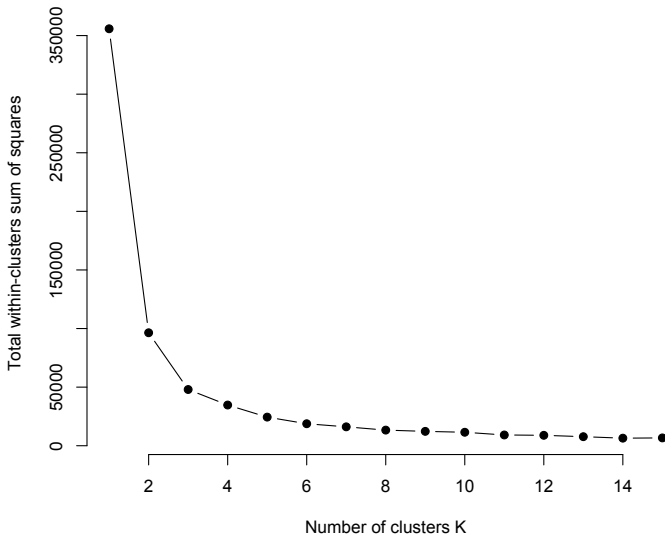
# Elbow Method: number of clusters

Minimize

$$\sum_{k=1}^k W(C_k)$$

1. Compute clustering algorithm for different values of  $k$ .
2. For each  $k$ , calculate the total within-cluster sum of square
3. Plot the curve of wss according to the number of clusters  $k$ .

# How many clusters with the Elbow method?



## Gap Method: number of clusters

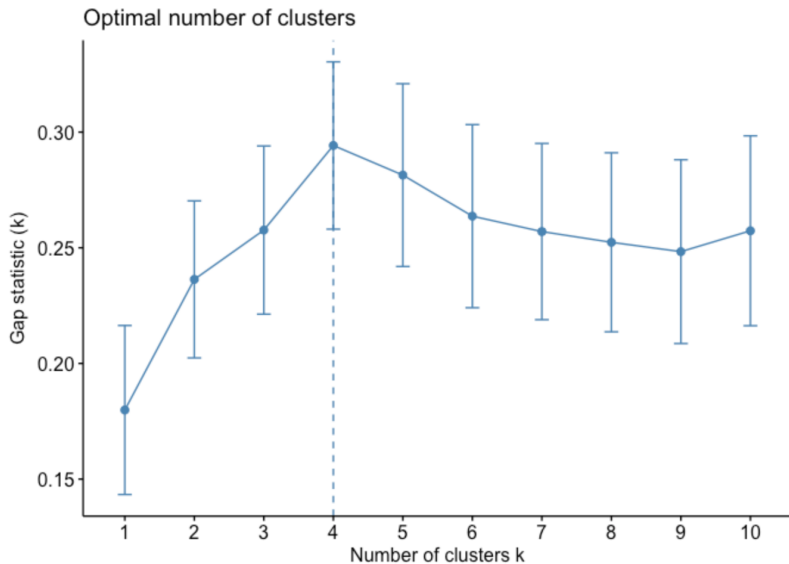
1. Cluster the observed data, varying the number of clusters from  $k = 1, \dots, K$ , and compute the corresponding  $W_k$
2. Generate  $B$  reference data sets and cluster each of them with varying number of clusters  $k = 1, \dots, k_{max}$ . Compute the estimated gap statistics

$$Gap_n(k) = E_n \log(W_k) - \log(W_k)$$

3.  $E_n$  is defined via bootstrapping
4. Aim: maximize  $Gap_n(k)$
5. Compute the standard deviation  $s_k$
6. Choose the number of clusters as the smallest  $k$  such that

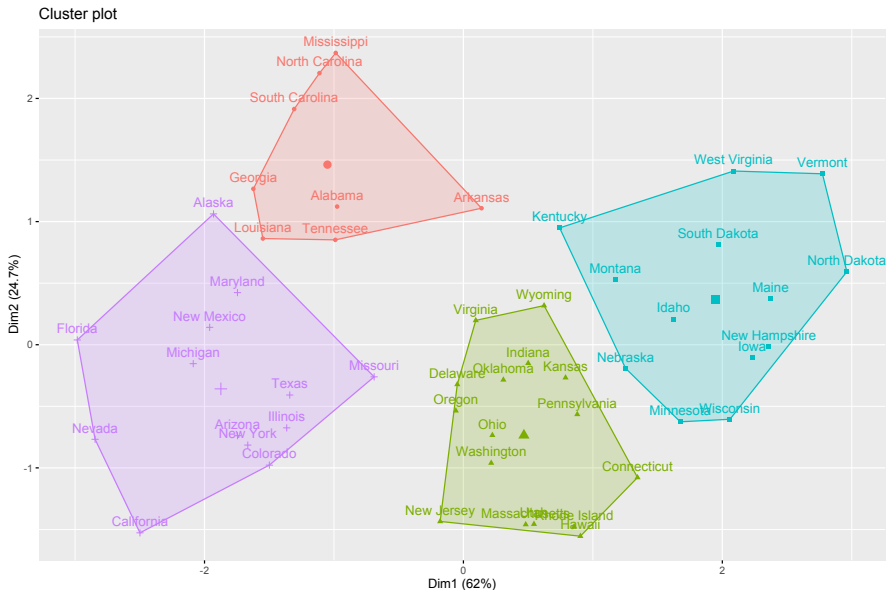
$$Gap_k \geq Gap_{k+1} - s_{k+1}$$

# How many clusters with the Gap method?





# The final output: Q4



# The Hierarchical Clustering

- ▶ Starting out at the bottom of the dendrogram, each of the  $n$  observations is treated as its own cluster
- ▶ The two clusters that are most similar to each other are then fused,  $n-1$  clusters
- ▶ Next  $n-2$  clusters
- ▶ The algorithm proceeds until all of the observations belong to one single cluster, and the dendrogram is complete

# The dendrogram

