

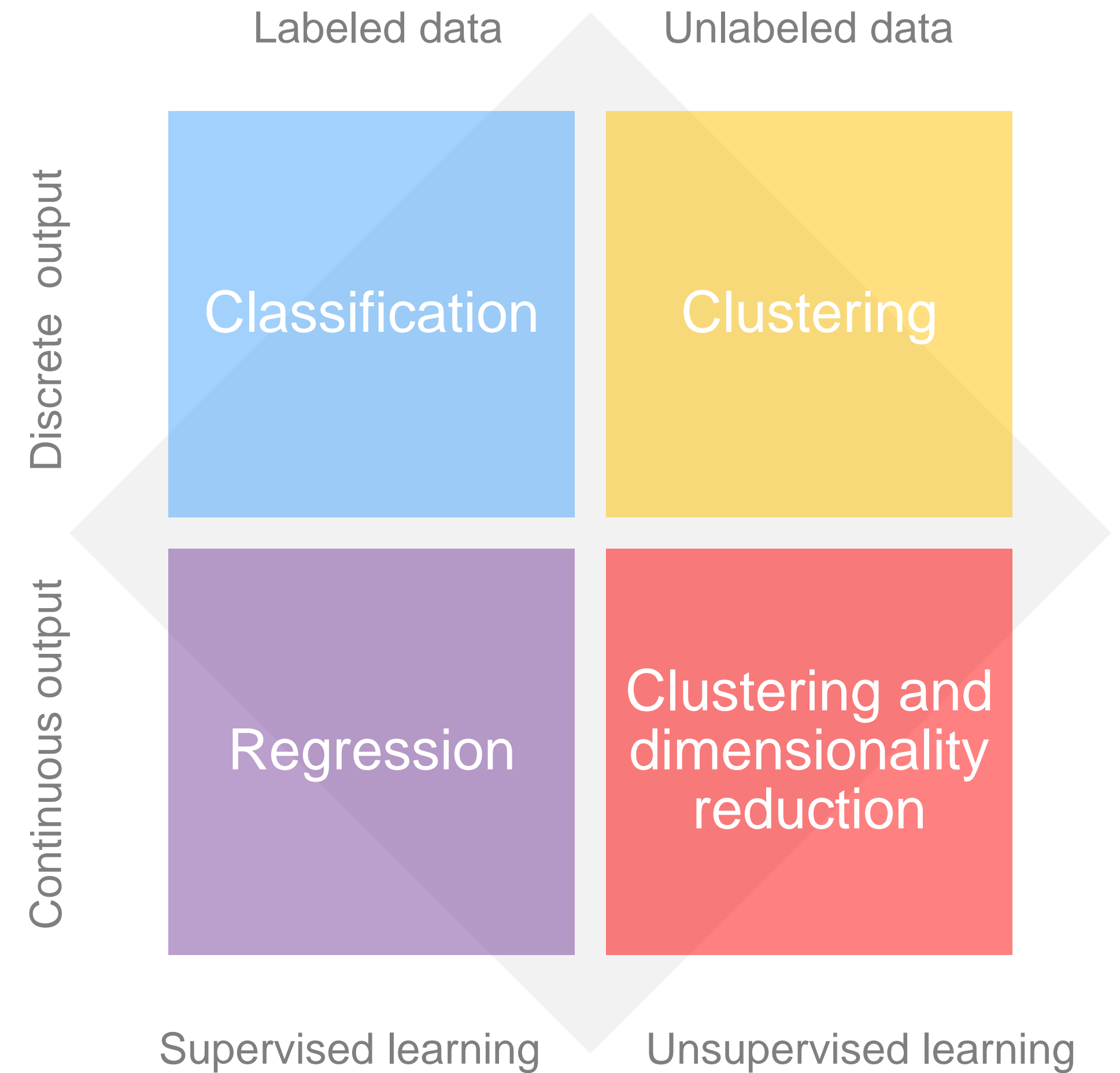
# CREATIVE DATA MINING

Introduction to Unsupervised Machine Learning

06.11.2017

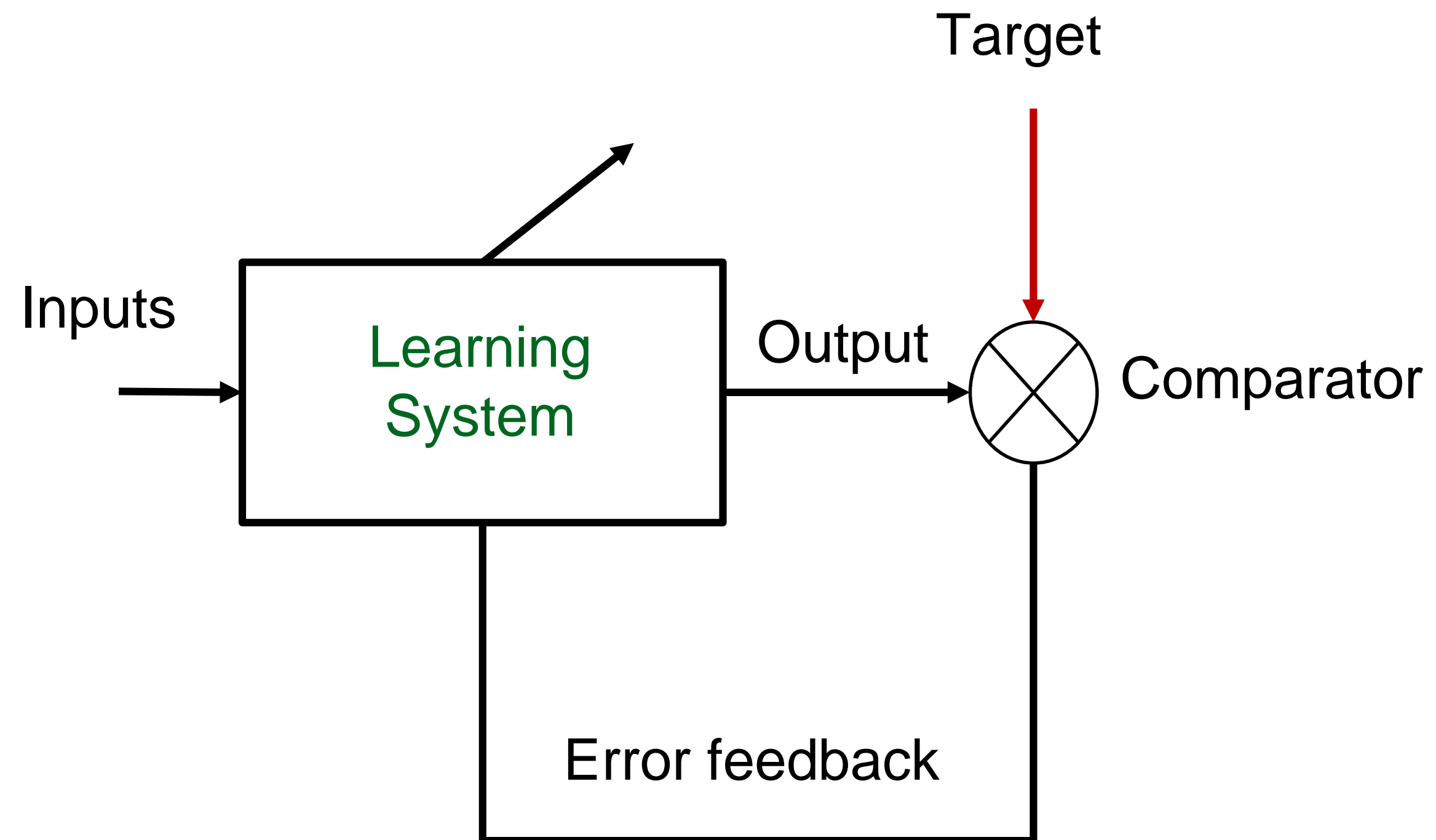
Dr. Varun OJHA

Danielle GRIEGO

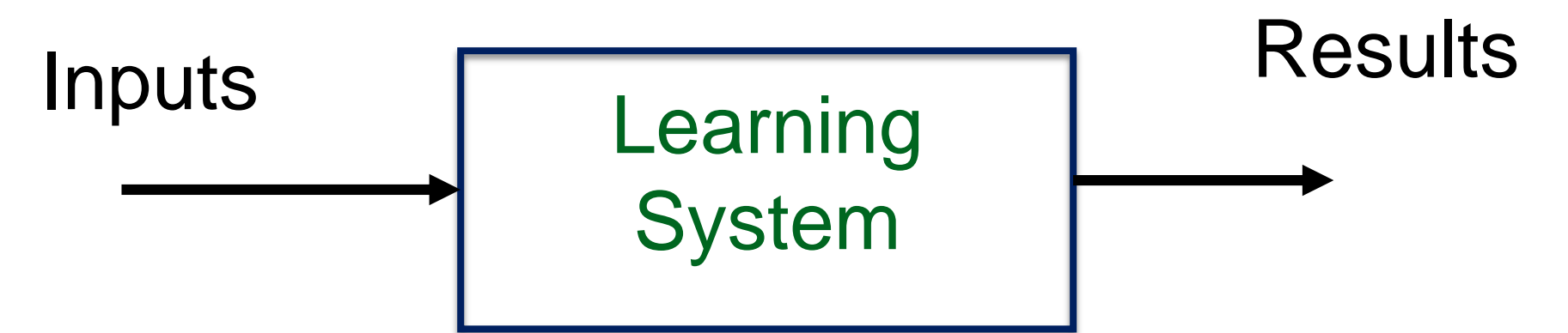


# Learning Systems

## Supervised



## Unsupervised



# Data (unlabeled)

#	Inputs			
	F1	F2	F3	F4
1	76.85	17.27	0.22	34.63
2	76.97	19.54	0.22	34.64
3	77.10	18.51	0.22	34.64
4	85.28	46.09	0.22	34.61
5	85.42	35.83	0.22	34.61
6	88.02	2.59	0.22	34.63
7	77.25	6.34	0.22	34.65
8	77.49	6.98	0.22	34.63
9	85.81	12.18	0.22	34.61

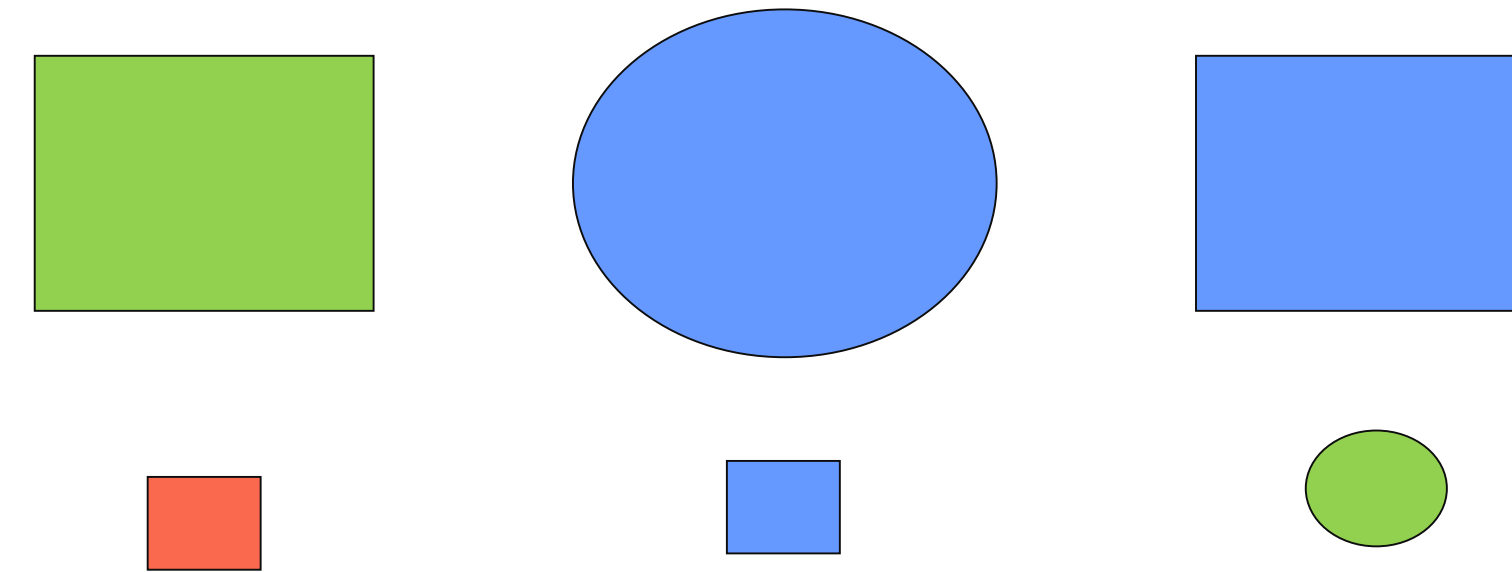
We do not know what is target/output.

We just want to understand some pattern or some sort of grouping of data points.

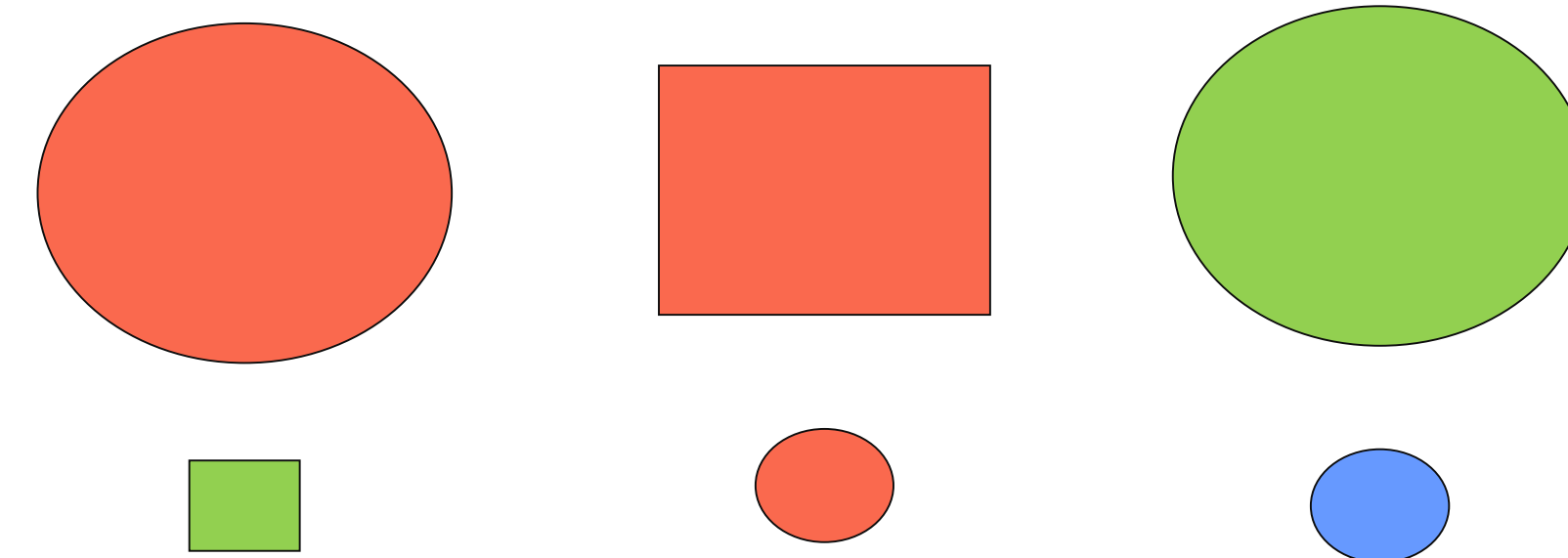
# Data (unlabeled)

## Example: natural concept

Can we form groups of these objects?

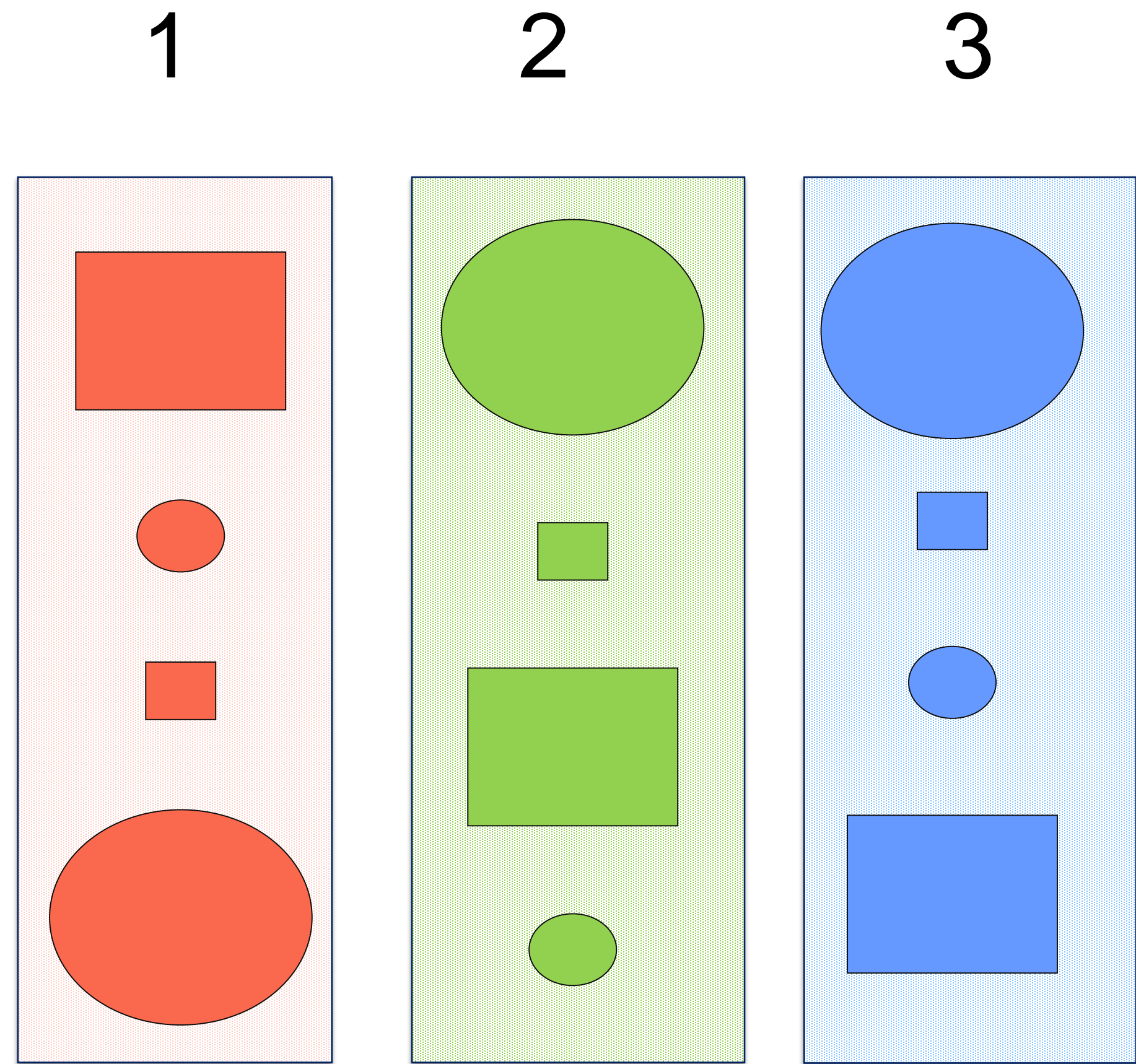


What features these objects has?



# Clustering

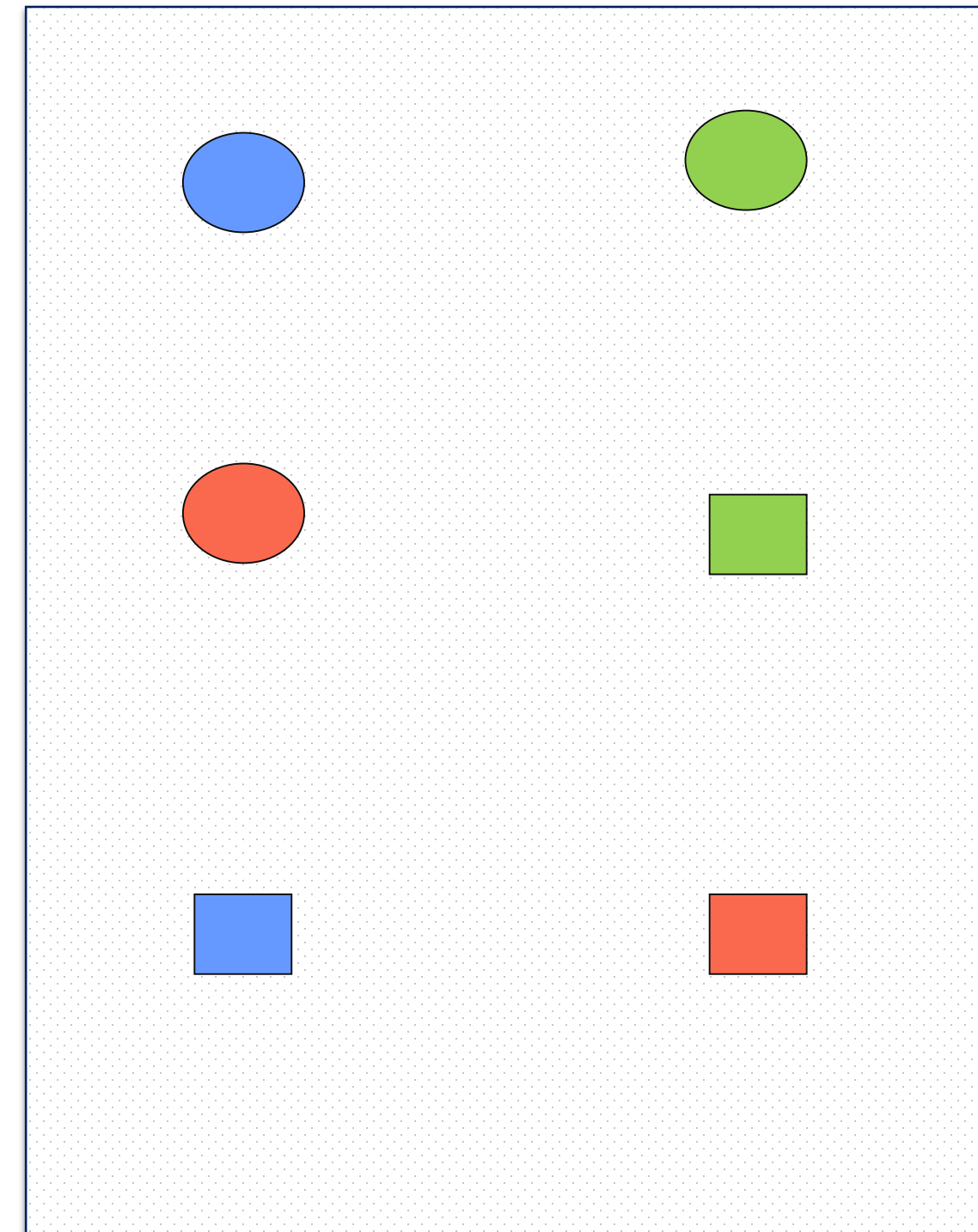
Criteria: Color



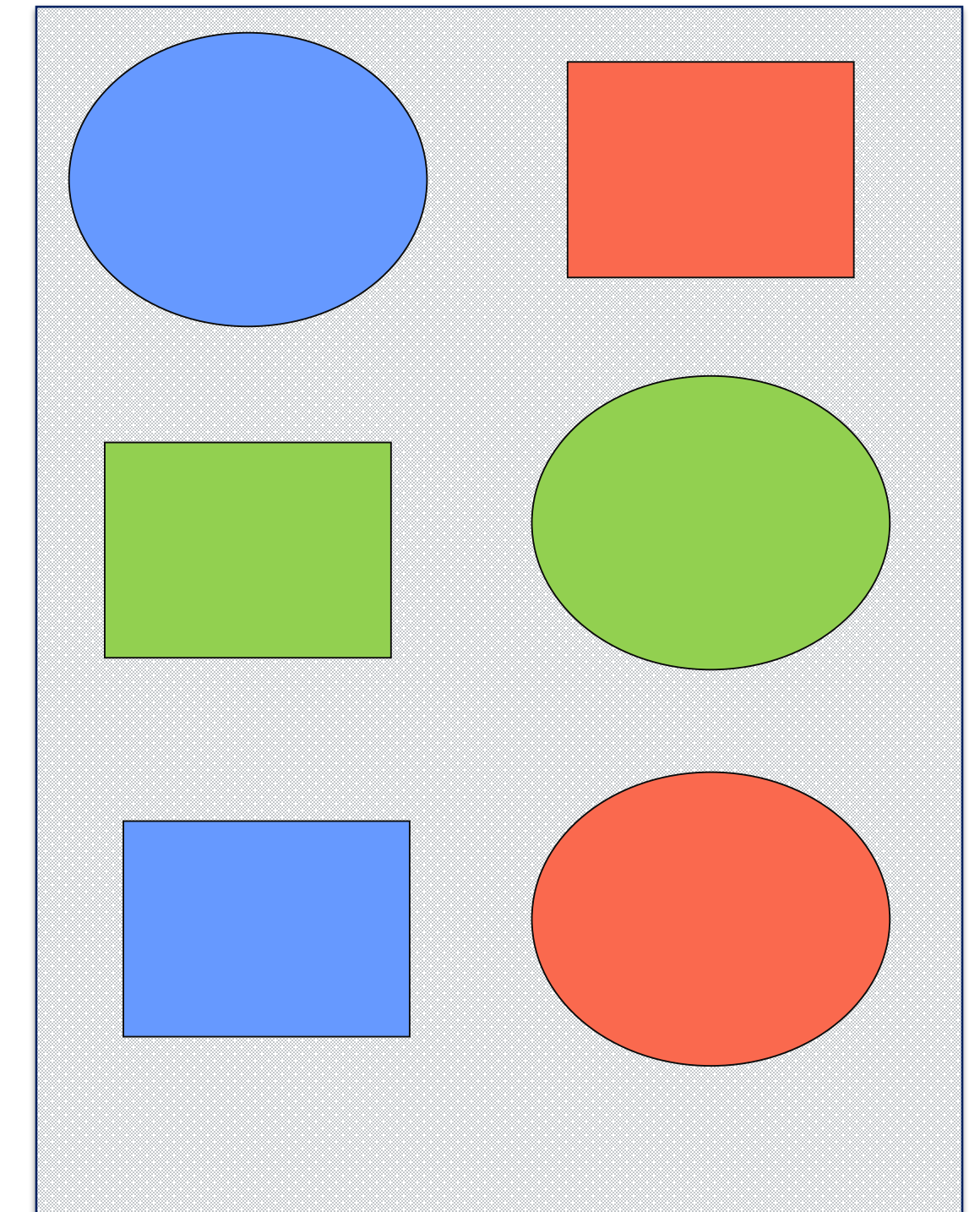
# Clustering

Criteria: Size

1



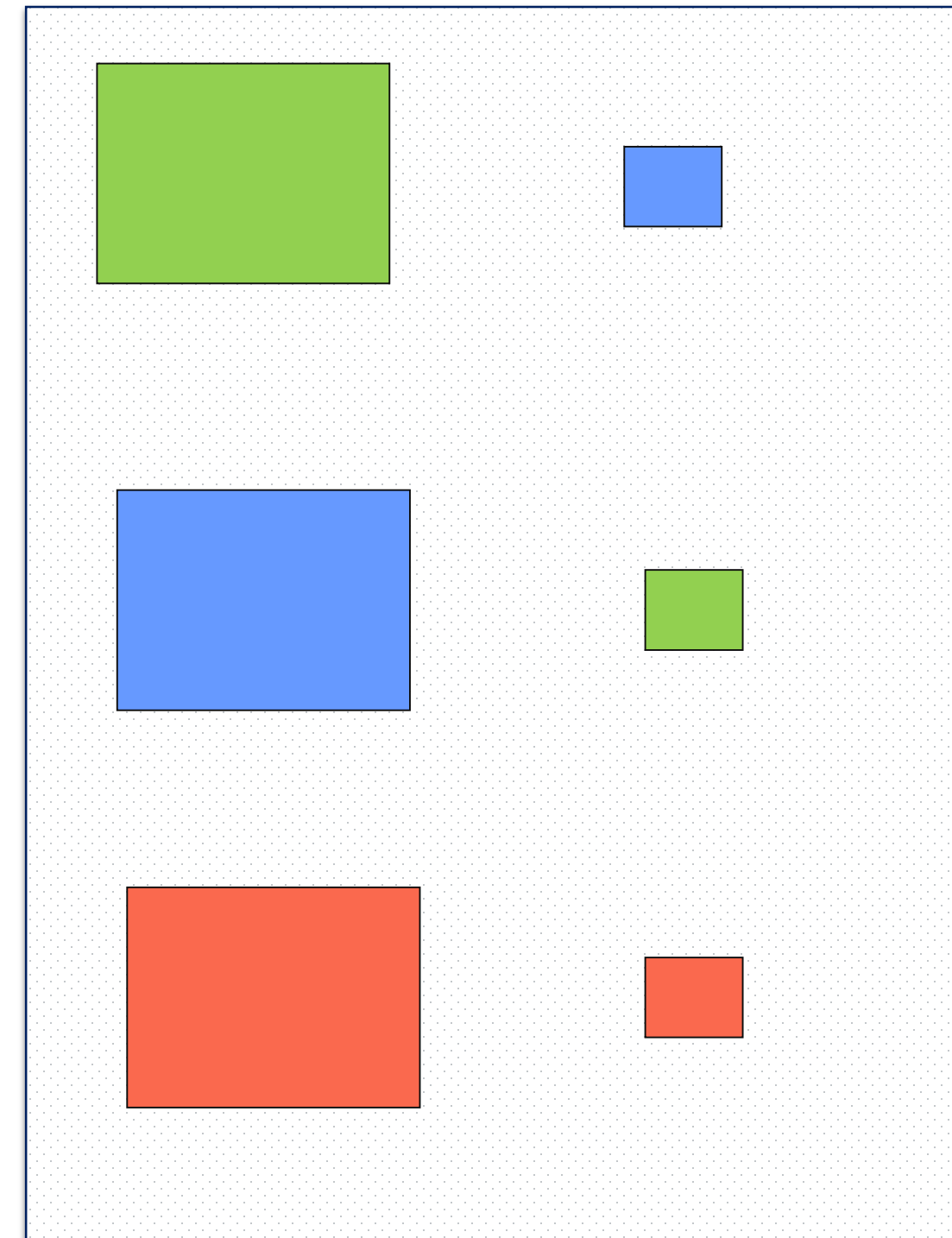
2



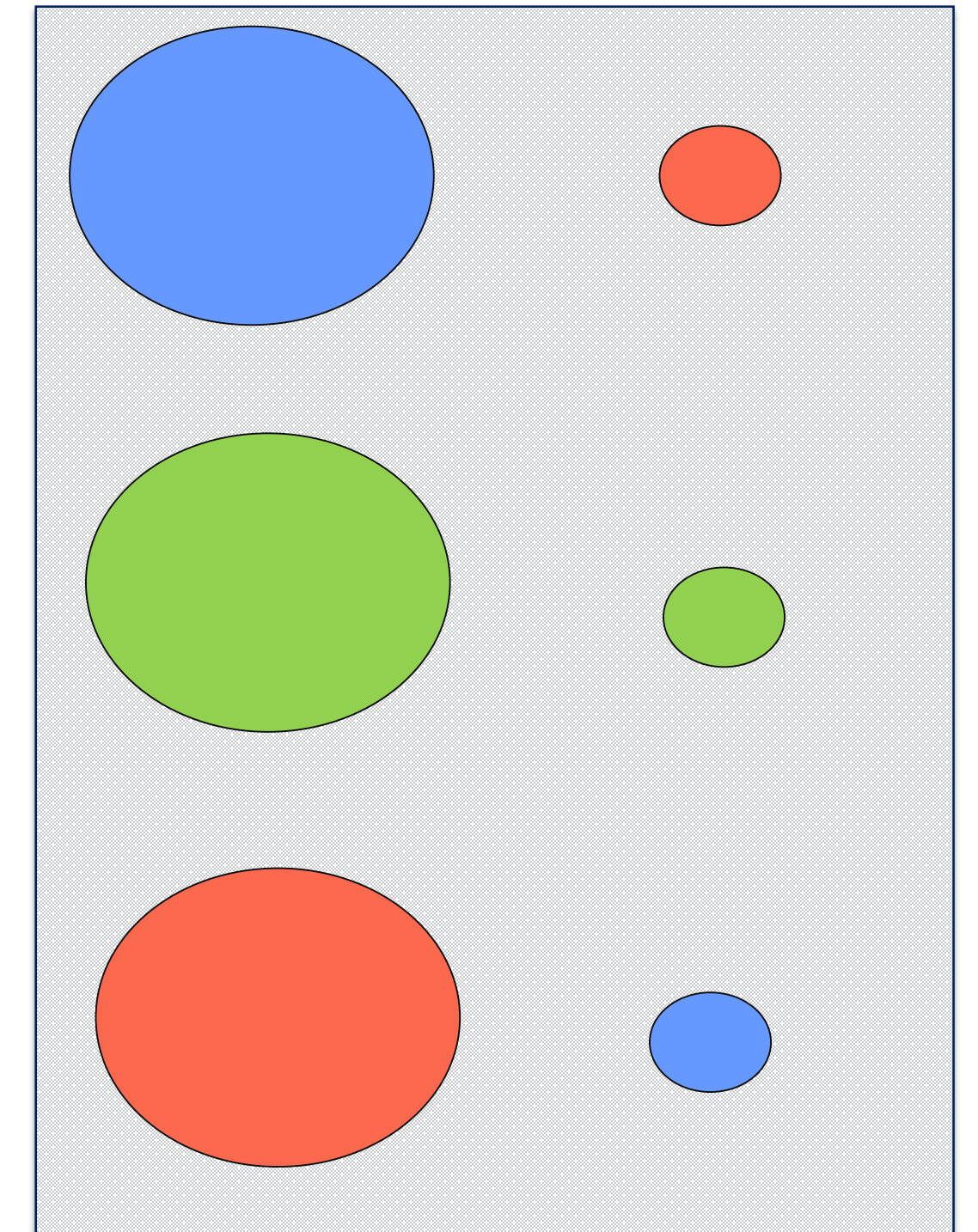
# Clustering

Criteria: Shape

1



2



# Data (unlabeled)

Can we form groups of these samples?

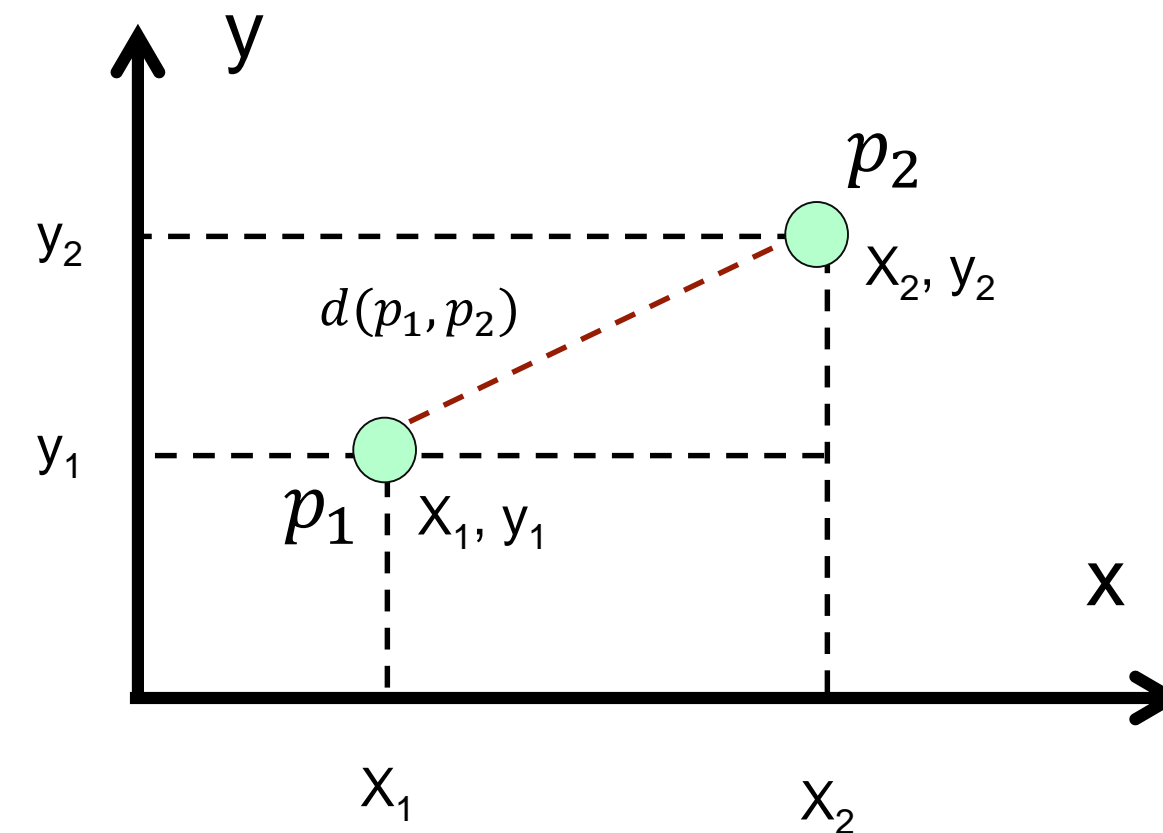
What are the criteria for grouping?

#	Inputs			
	HR	BVP	EDA	TempBF
1	76.85	17.27	0.22	34.63
2	76.97	19.54	0.22	34.64
3	77.10	18.51	0.22	34.64
4	85.28	46.09	0.22	34.61
5	85.42	35.83	0.22	34.61
6	88.02	2.59	0.22	34.63
7	77.25	6.34	0.22	34.65
8	77.49	6.98	0.22	34.63
9	85.81	12.18	0.22	34.61



# Clustering

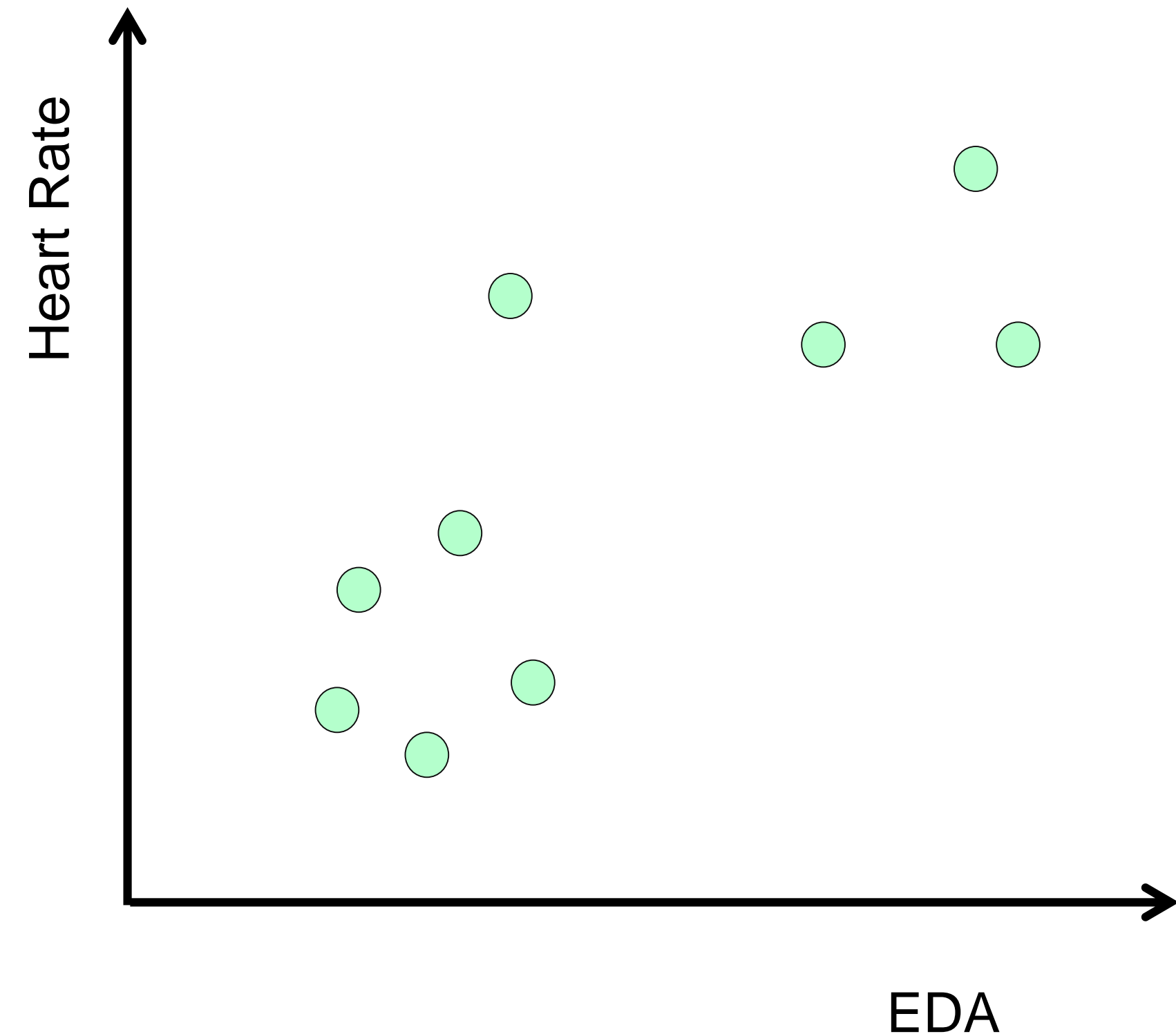
## Distance based: K-Means



Euclidean distance:

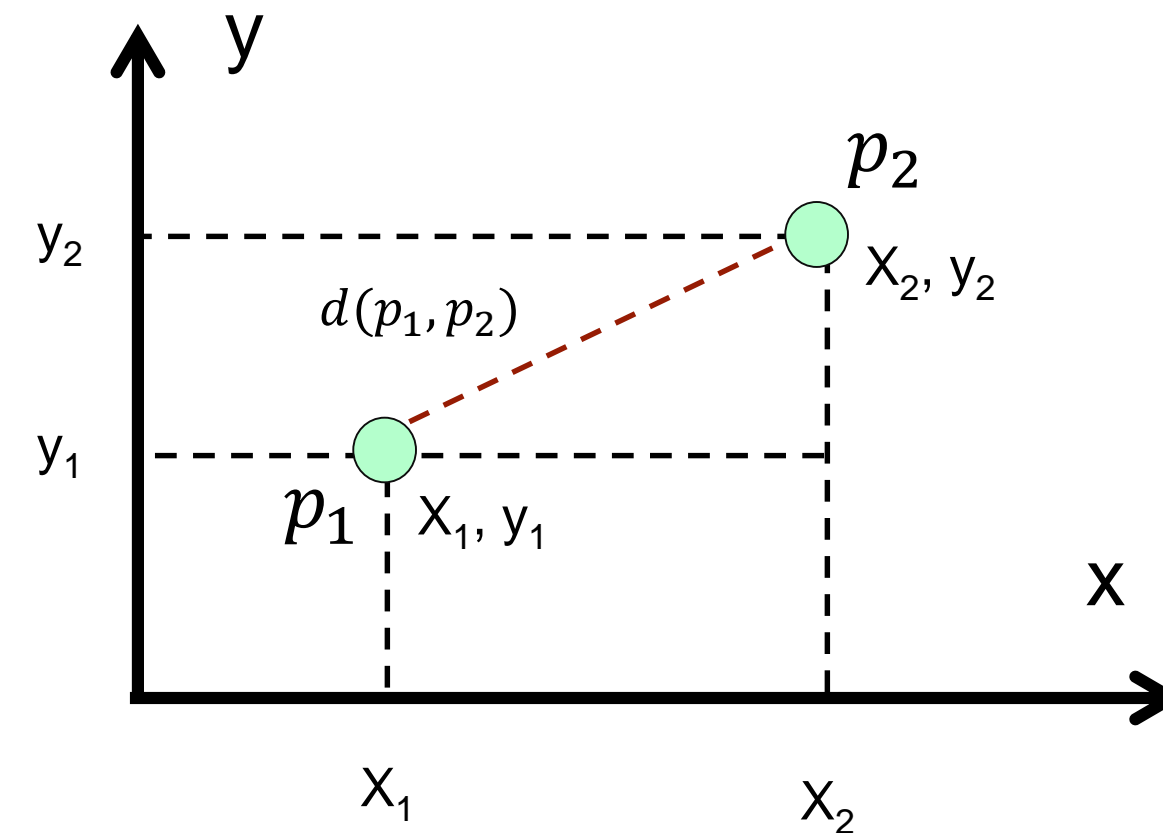
$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

## ESUM data



# Clustering

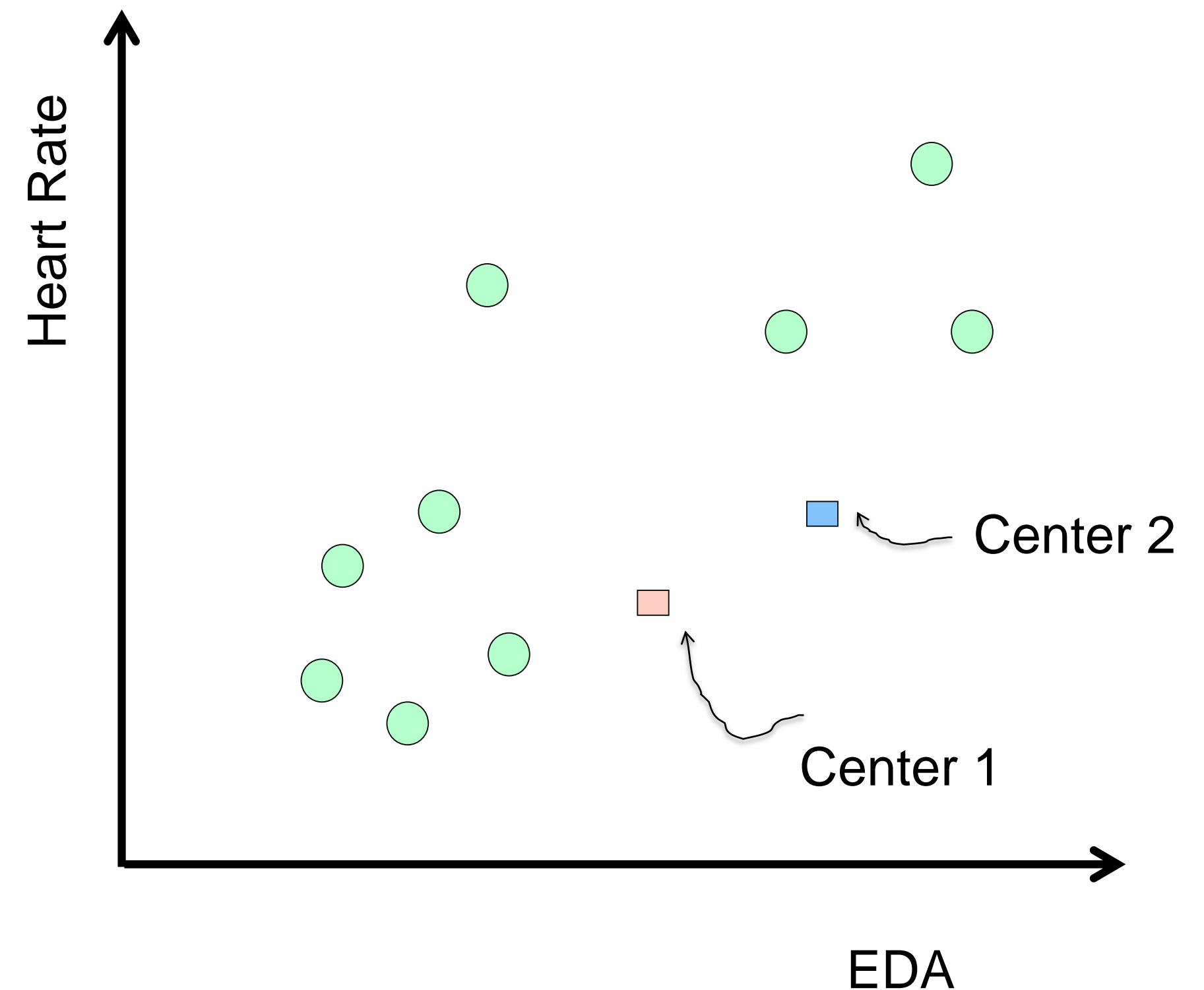
## Distance based: K-Means



Euclidean distance:

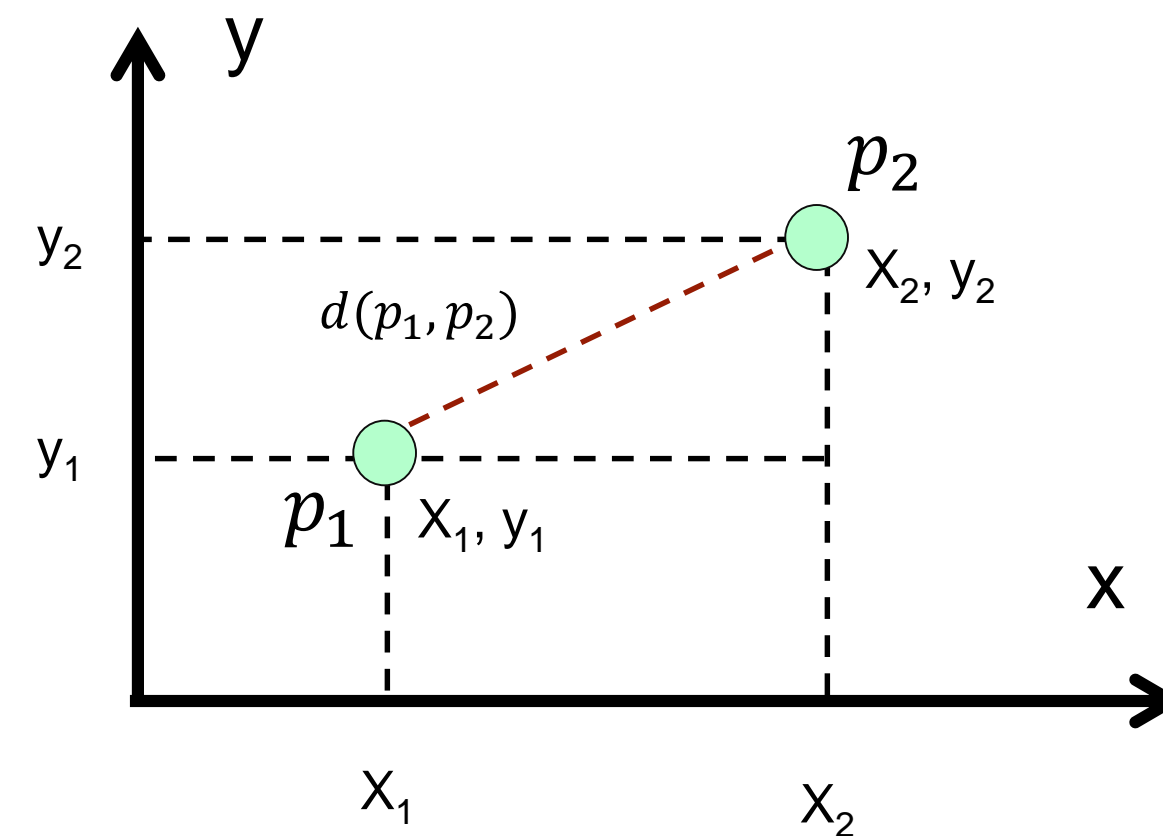
$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

## Defining centers



# Clustering

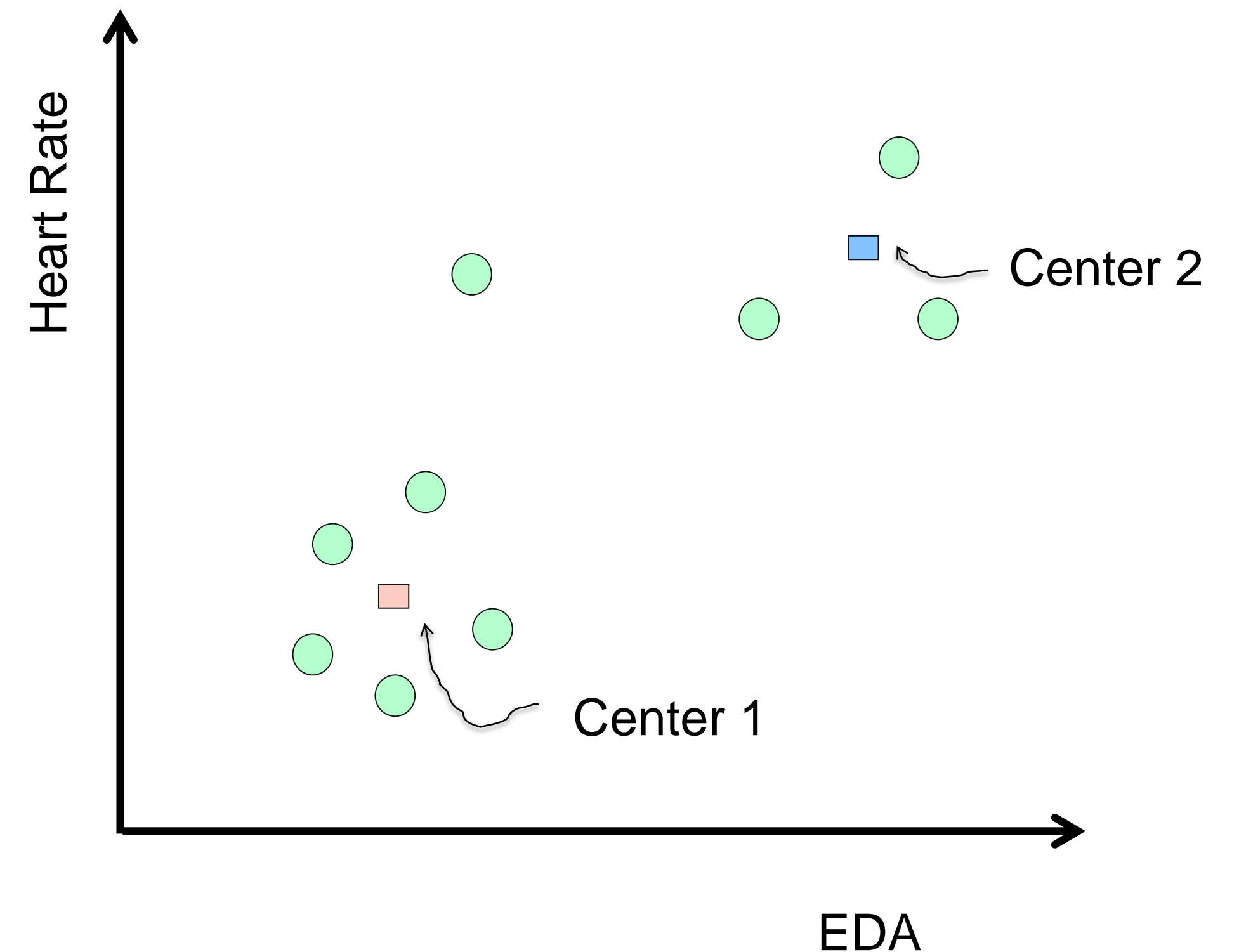
## Distance based: K-Means



Euclidean distance:

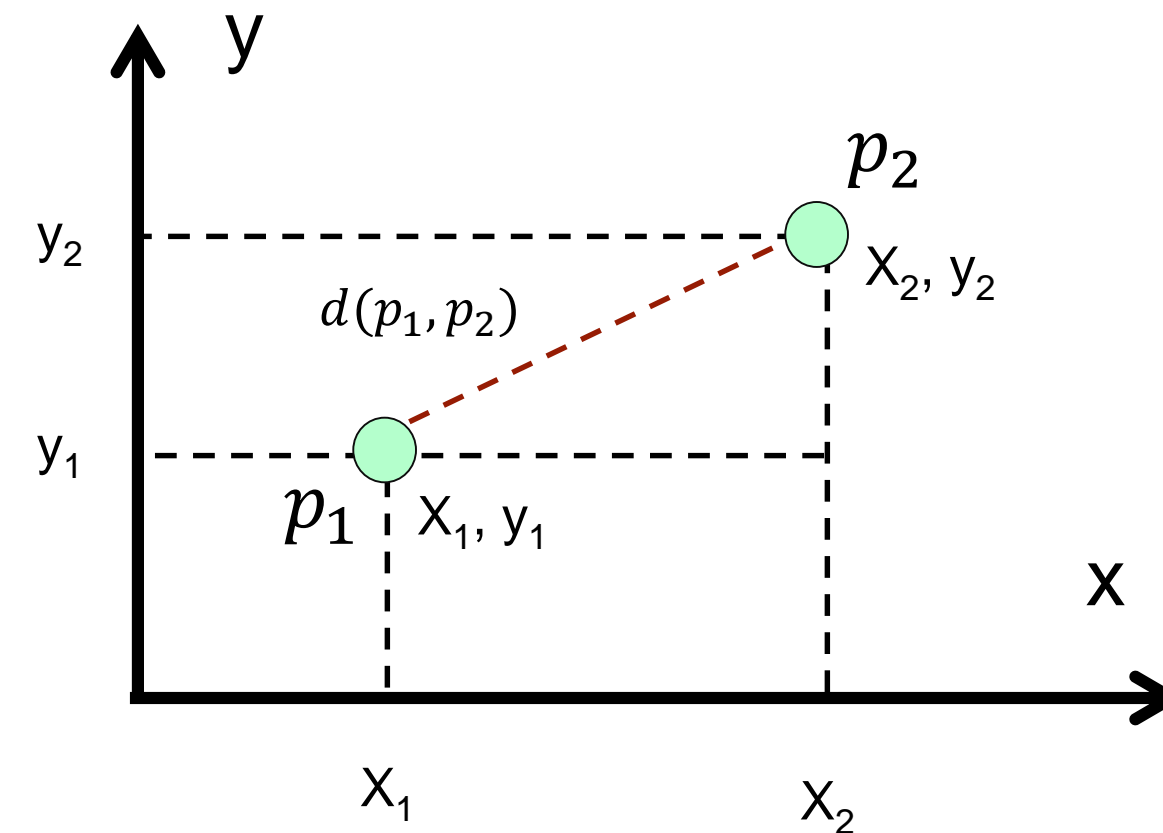
$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

## Results



# Clustering

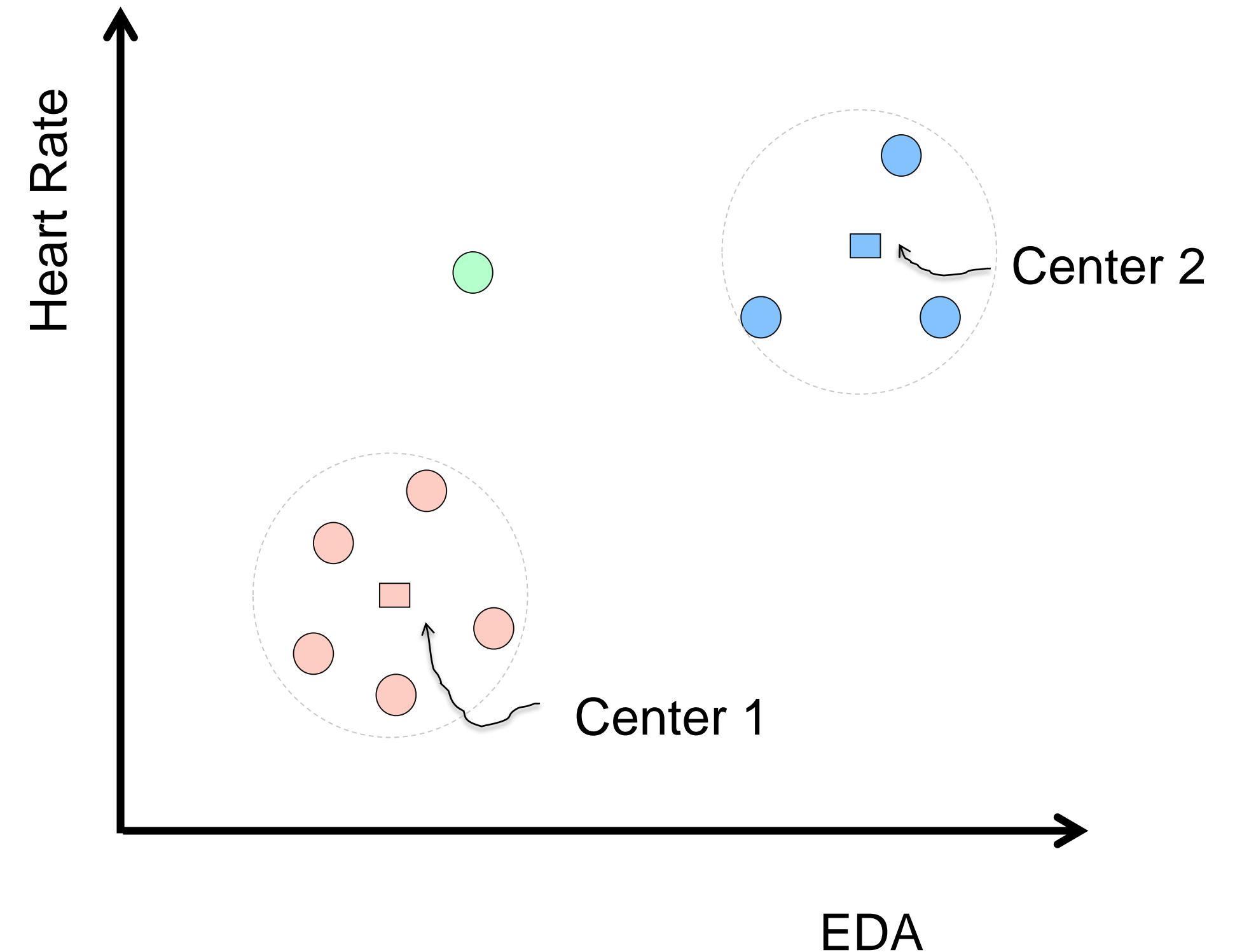
## Distance based: K-Means



Euclidean distance:

$$d(p_1, p_2) = \sqrt{(x_2 - x_1)^2 + (y_2 - y_1)^2}$$

## Results

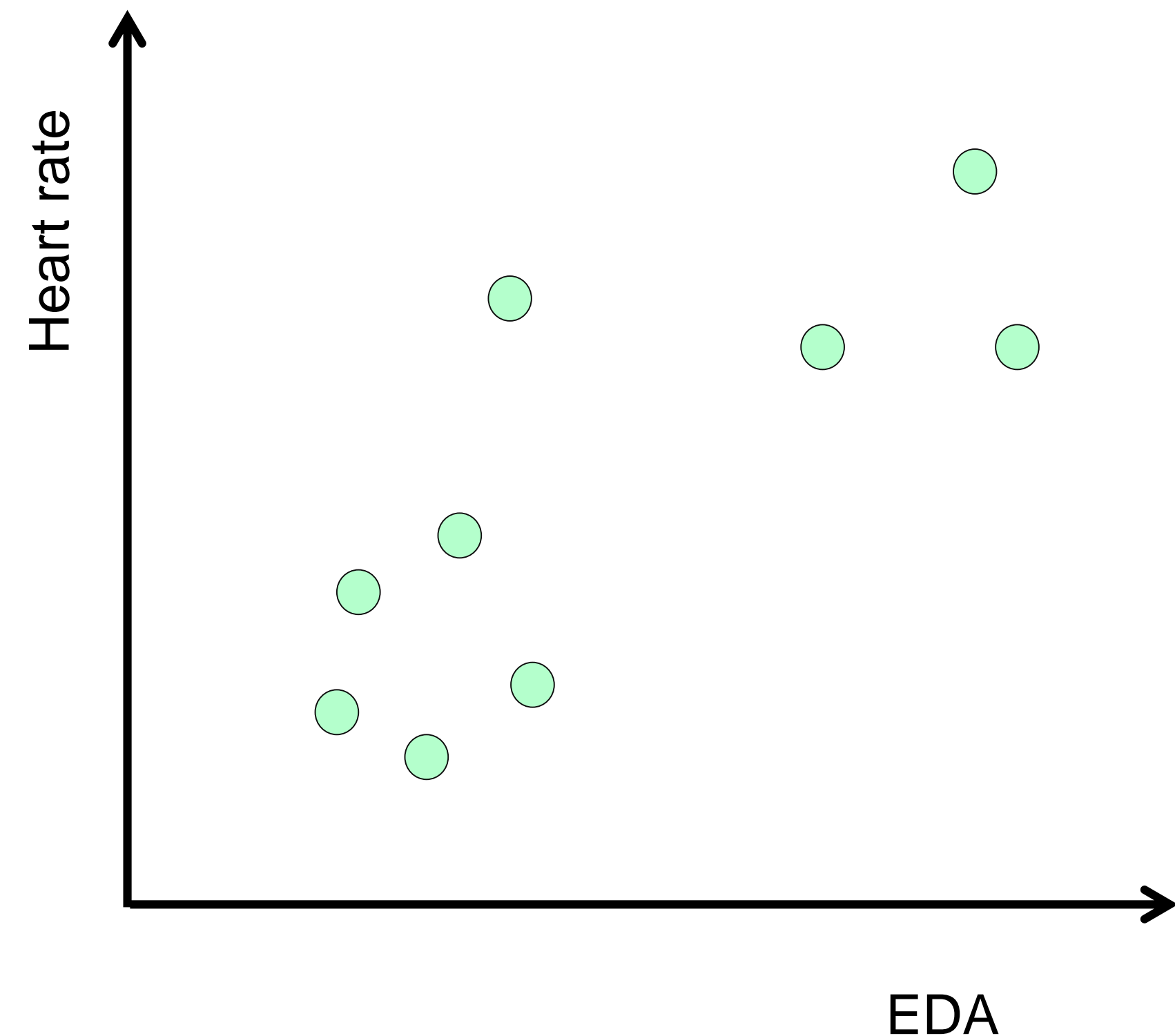


# Clustering

## Density based : DBSCAN

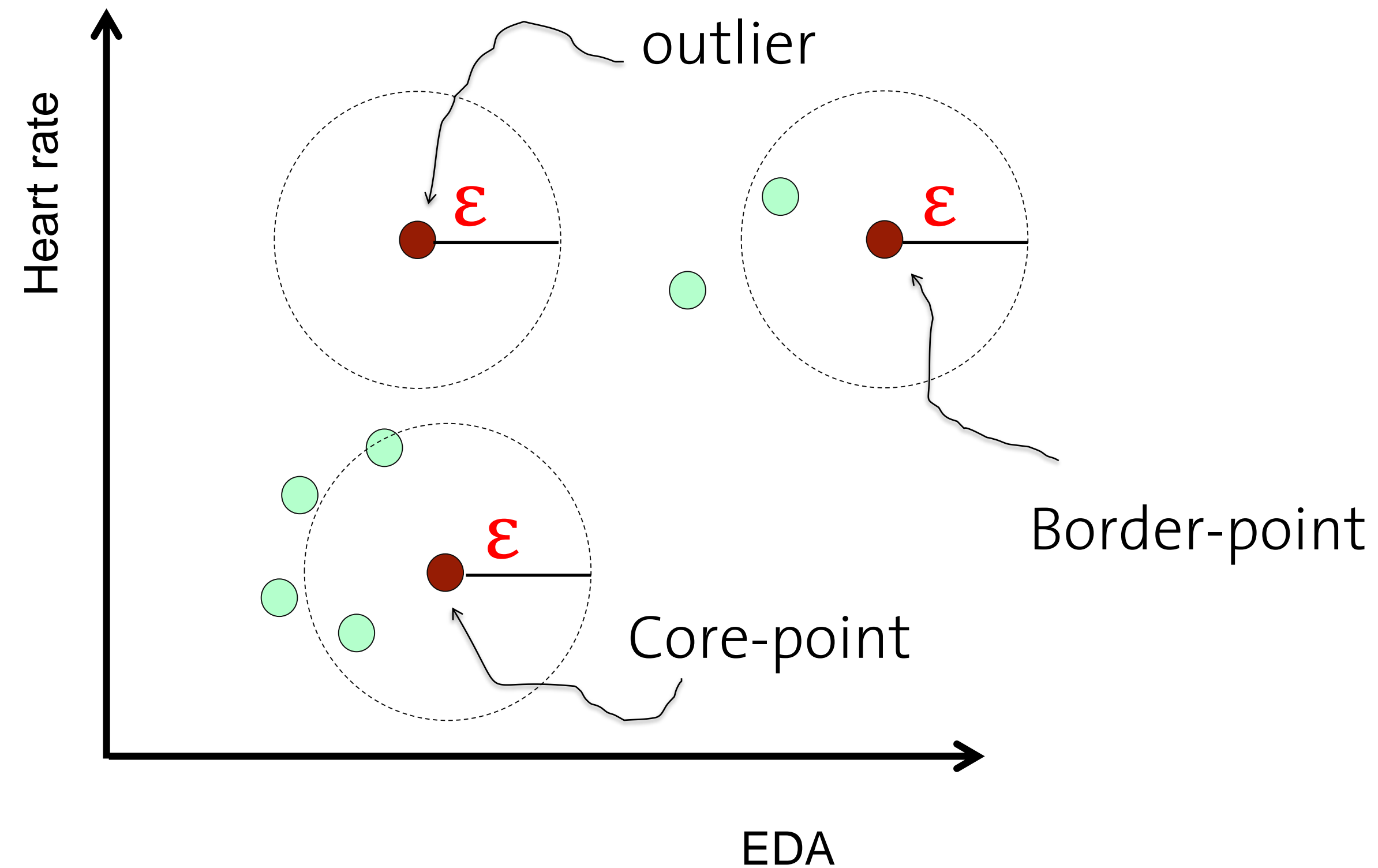
- Select two parameters:
  - $\epsilon$ -Neighborhood
  - $m$ -minimum number of points
- Select a point  $p$  randomly
- Find all points reachable from  $p$  based on  $\epsilon$  and  $m$
- If  $p$  is a *core point*, mark points as a cluster.
- If  $p$  is a *border point*, no points are reachable from  $p$ .
- Select a new point  $p$ .
- Continue until all of the points are visited.

## ESUM data

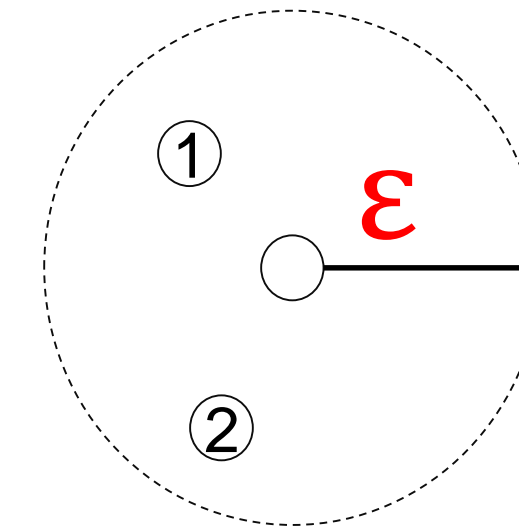


# Clustering

## Density based : DBSCAN



## Define a center

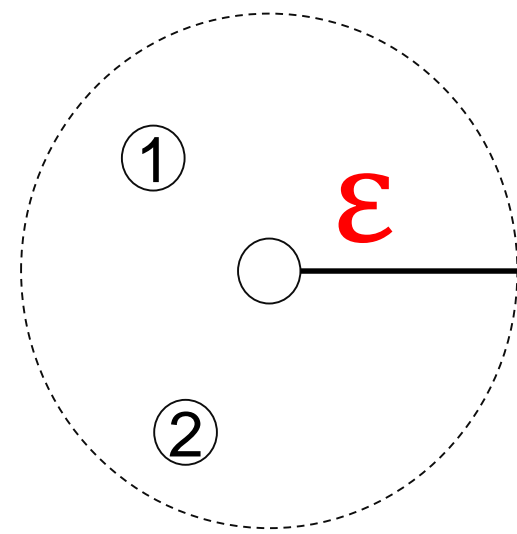


$$\epsilon = 1 \text{ cm}$$

$$m = 2$$

# Clustering (DBSCAN)

For a center



$$\epsilon = 1 \text{ cm}$$

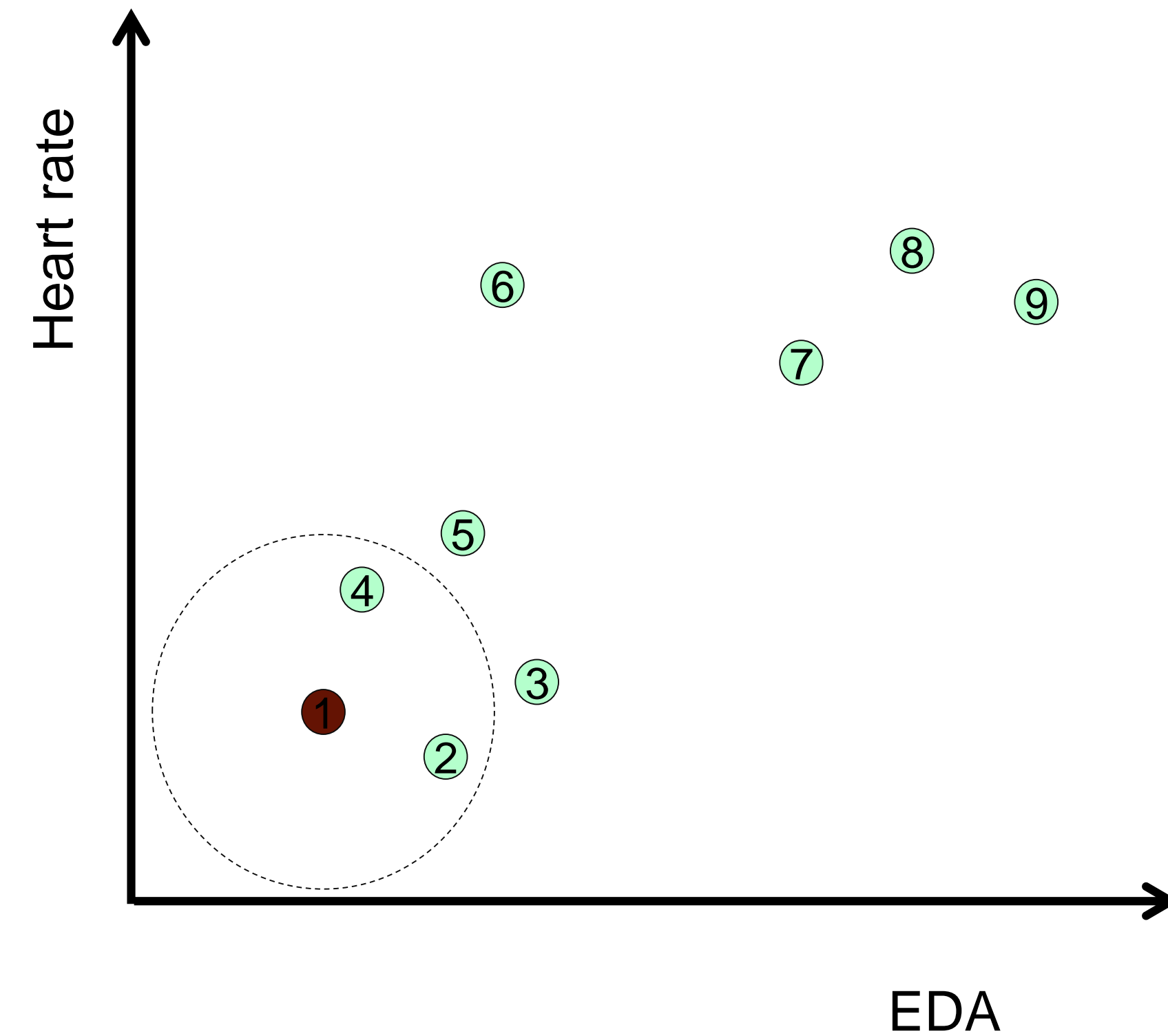
$$m = 2$$

Scanning point

# 1

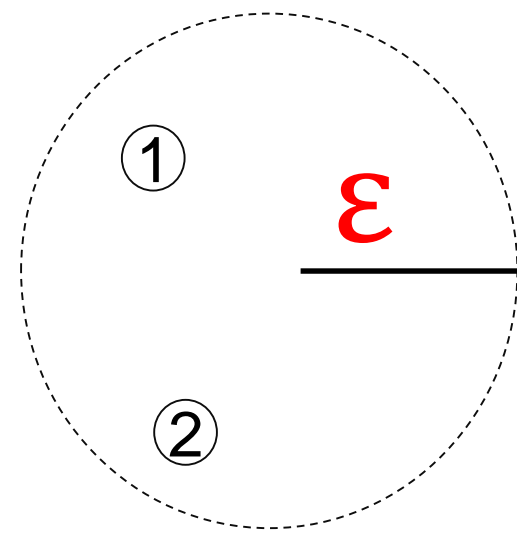
Points in cluster:

1 -> 2,4



# Clustering (DBSCAN)

## For a center



$$\epsilon = 1 \text{ cm}$$

$$m = 2$$

Scanning point

# 2,

#3,

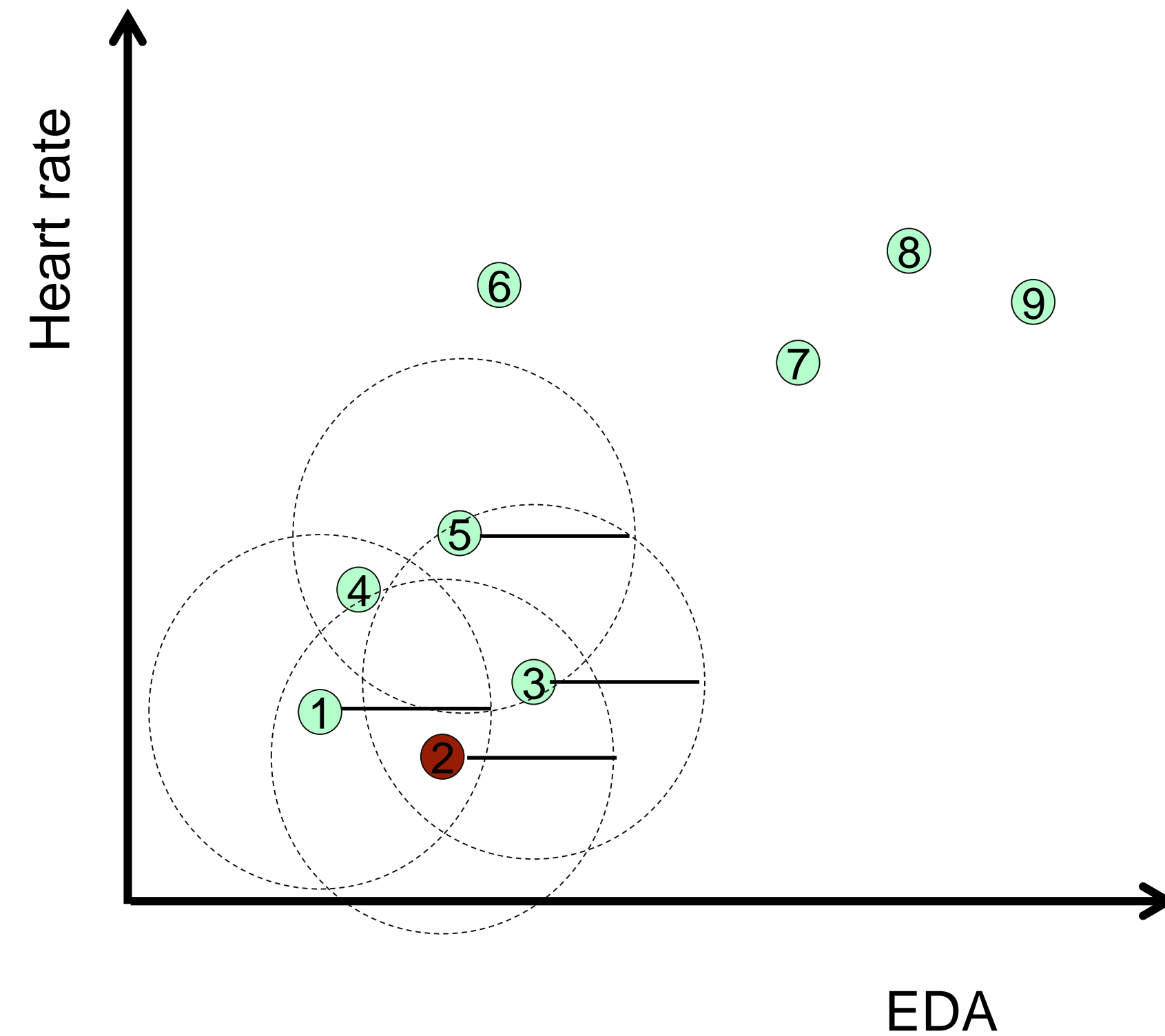
#5

Points in cluster:

2  $\rightarrow$  1, 3,4

3  $\rightarrow$  2, 5

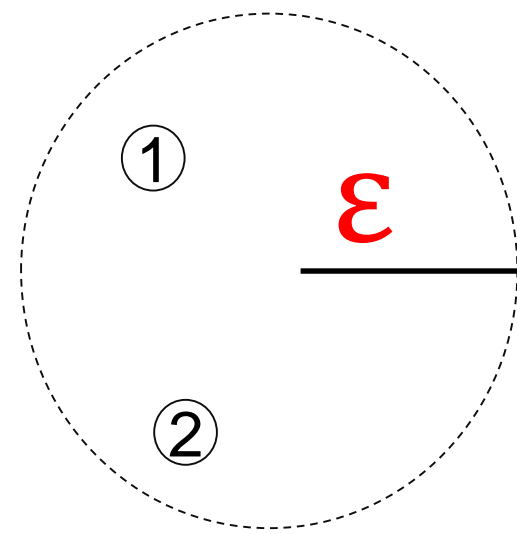
5  $\rightarrow$  4,3





# Clustering (DBSCAN)

For a center



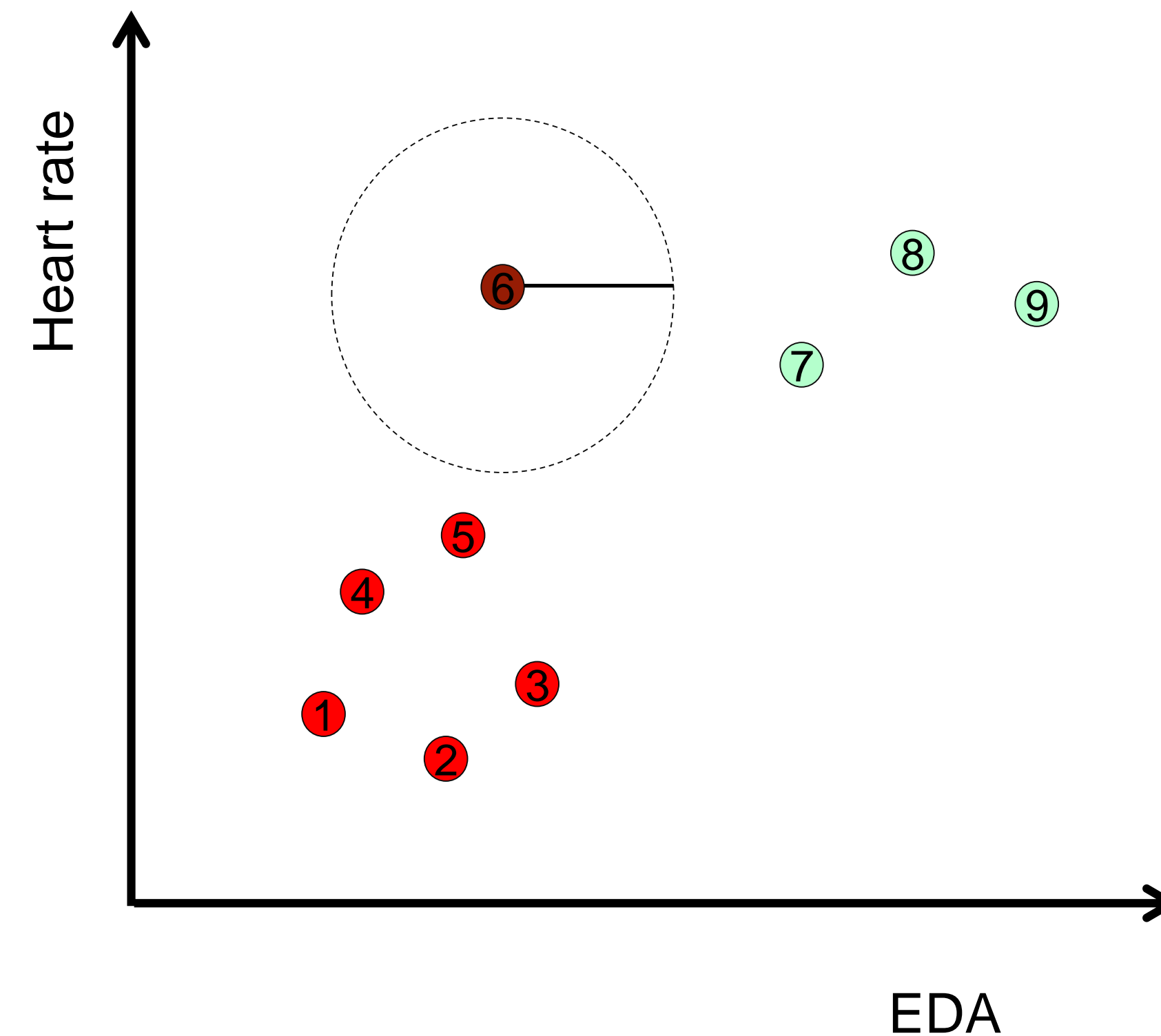
$$\epsilon = 1 \text{ cm}$$

$$m = 2$$

Scanning point  
# 6,

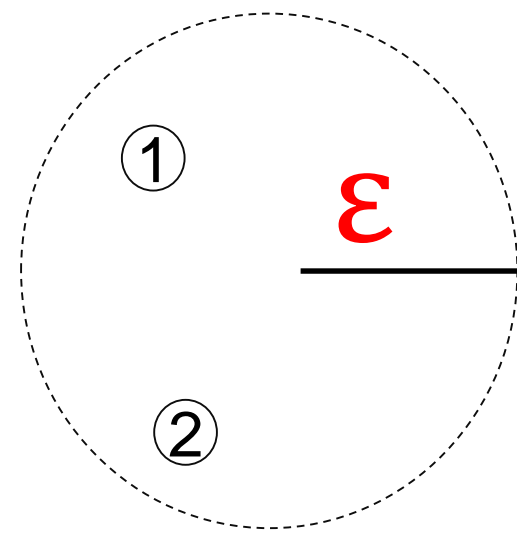
Points in cluster:  
6 ->

Cluster found:  
red



# Clustering

For a center



$$\epsilon = 1 \text{ cm}$$

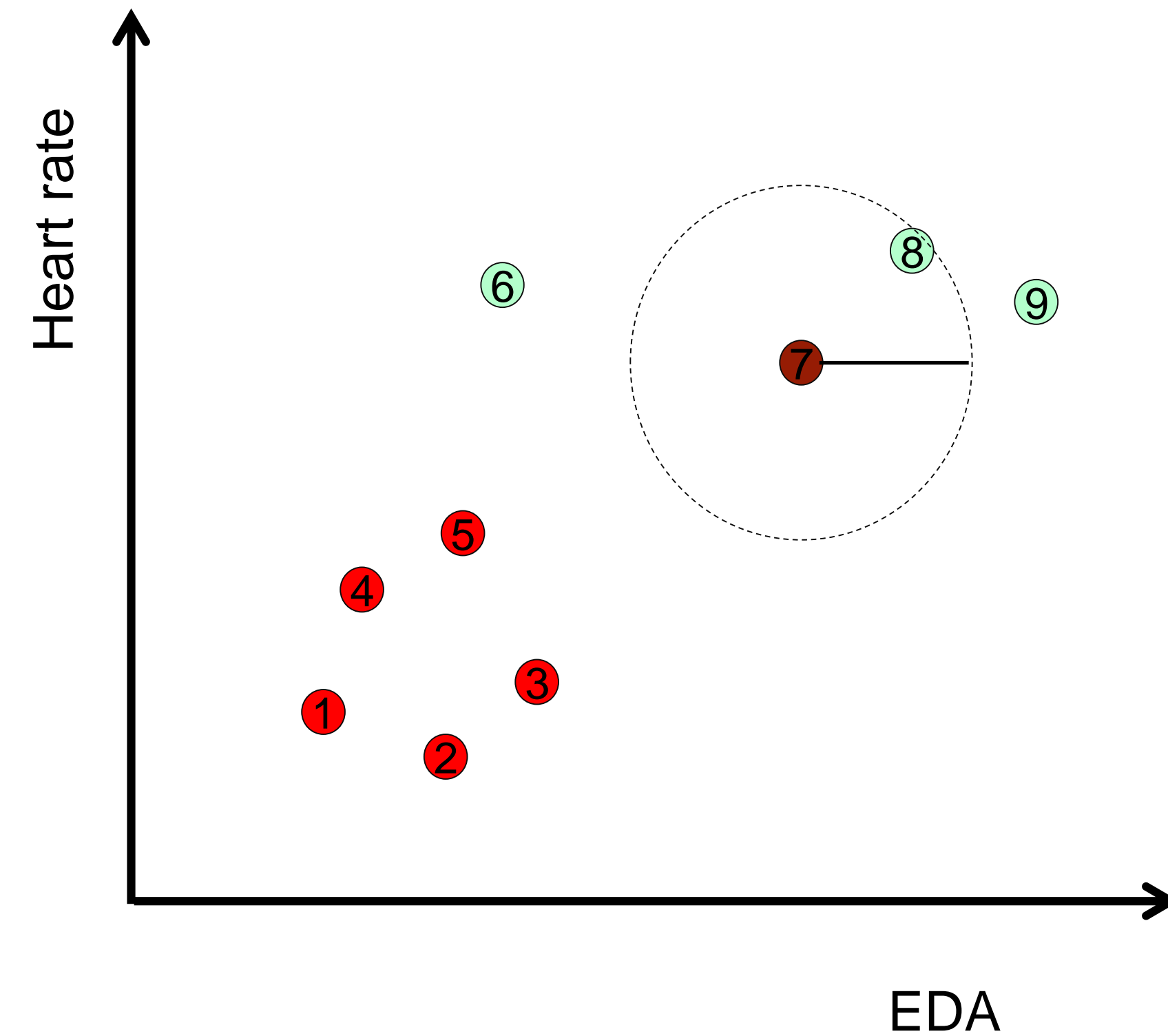
$$m = 2$$

Scanning point

# 7,

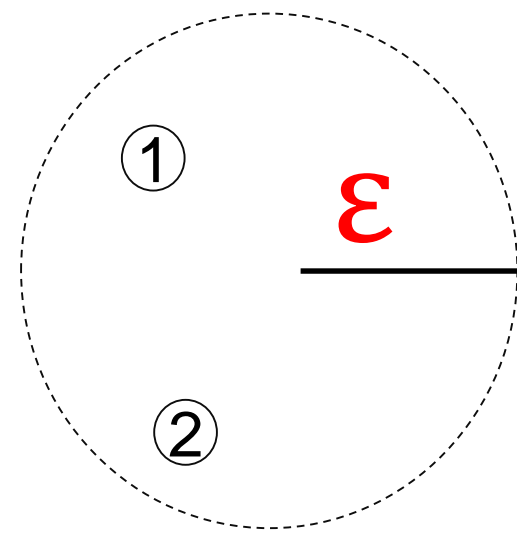
Points in cluster:

7 -> 8



# Clustering (DBSCAN)

For a center



$$\epsilon = 1 \text{ cm}$$

$$m = 2$$

Scanning point

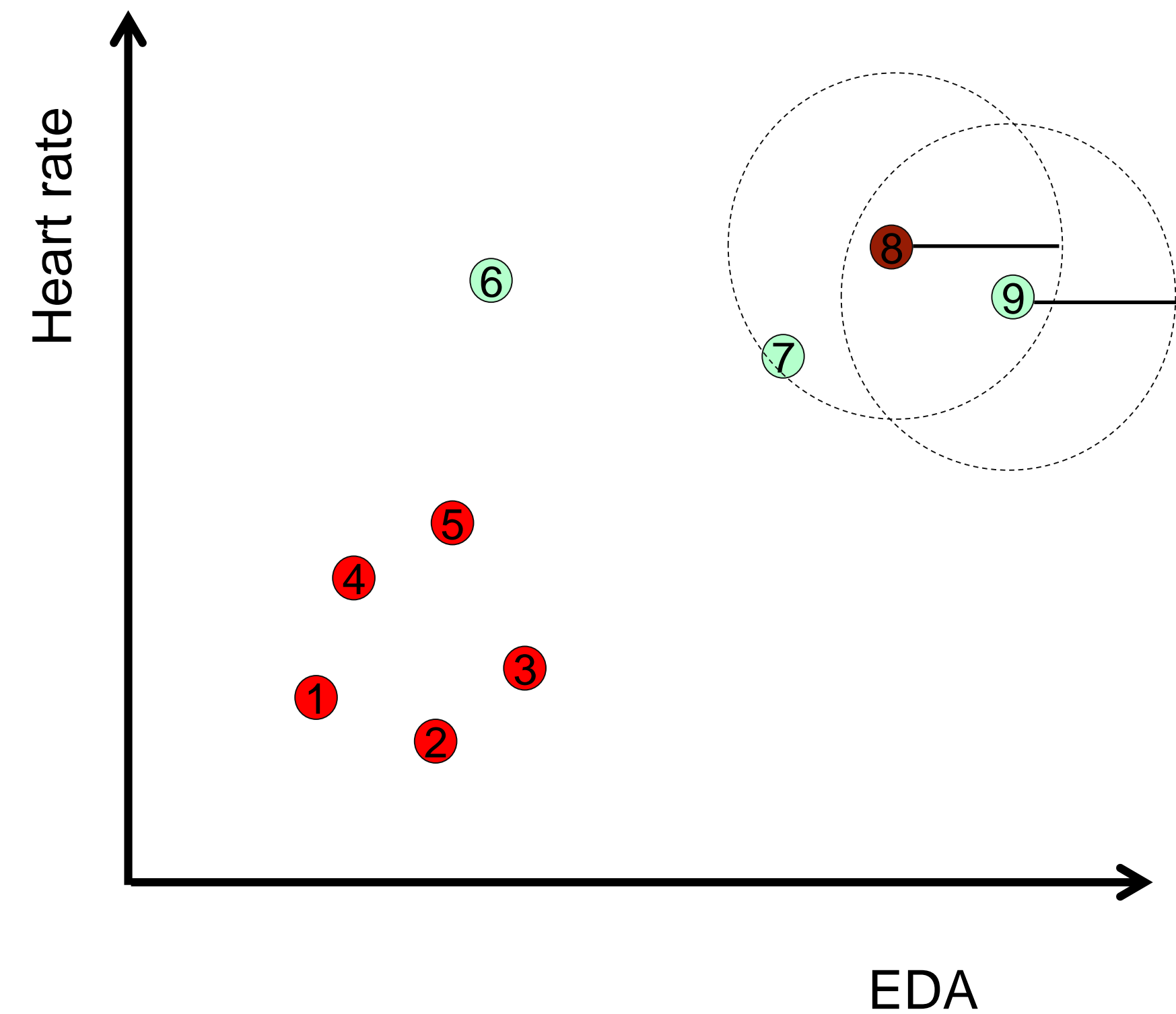
# 8,

#9

Points in cluster:

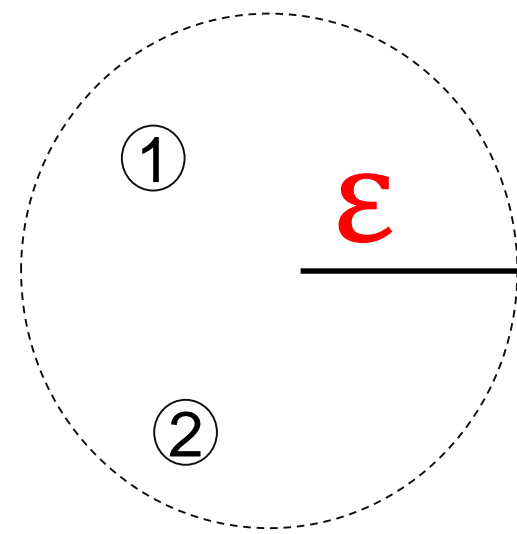
8  $\rightarrow$  7, 9

9  $\rightarrow$  8



# Clustering (DBSCAN)

For a center



$\epsilon = 1 \text{ cm}$

$m = 2$

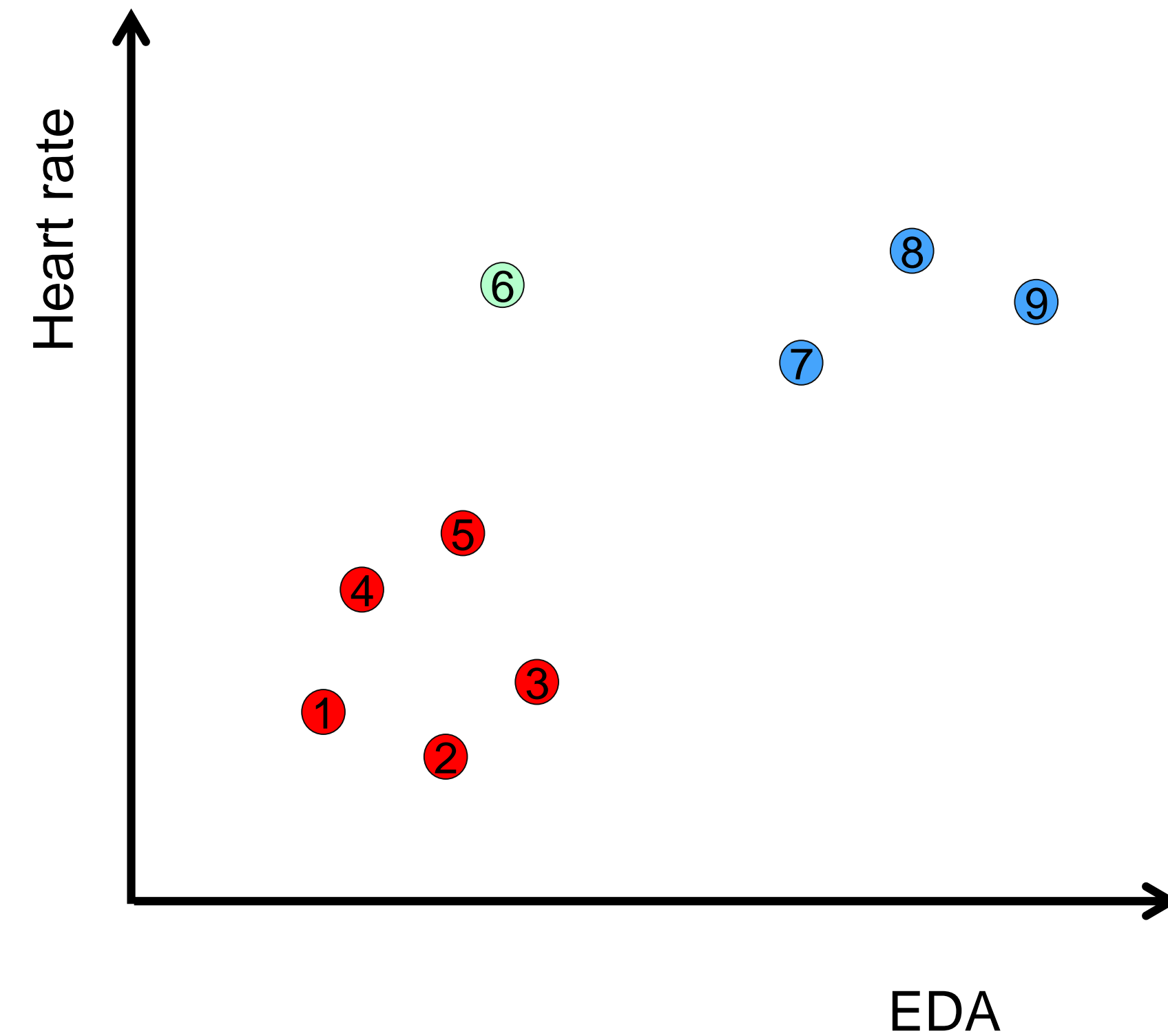
Scanning point

Total cluster 2

Finish

red

blue



Thank you!

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Danielle Griego [griego@arch.ethz.ch](mailto:griego@arch.ethz.ch)