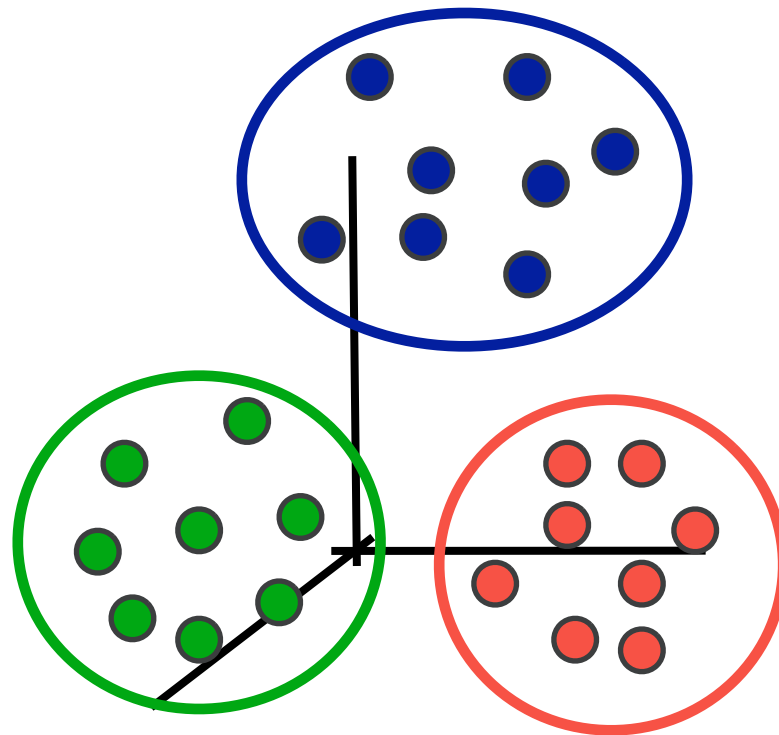


# Clustering, k-means, k-means++ and the advantages of careful seeding

- David Arthur, Sergei Vassilvitskii. *k-means++: The Advantages of Careful Seeding*. In SODA 2007

# What is clustering?

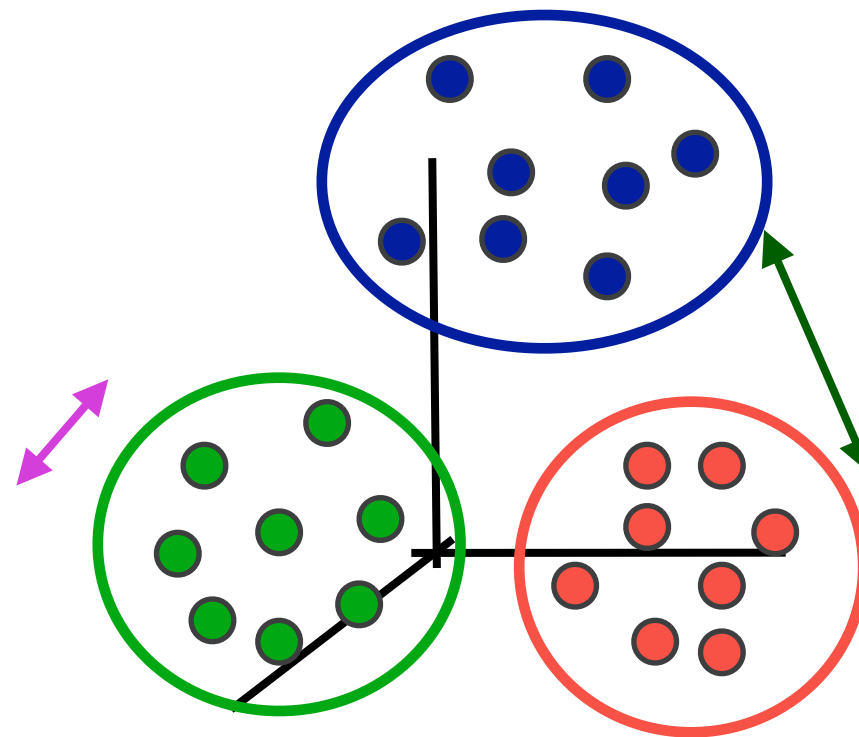
- a **grouping** of data objects such that the **objects within a group** are **similar** (or **near**) to one another and **dissimilar** (or **far**) from the **objects in other groups**



# How to capture this objective?

a **grouping** of data objects such that the **objects within a group** are **similar** (or **near**) to one another and **dissimilar** (or **far**) from the **objects in other groups**

minimize  
intra-cluster  
distances



maximize  
inter-cluster  
distances

# The clustering problem

- **Given** a collection of data objects
- **Find** a grouping so that
  - similar objects are in the same cluster
  - dissimilar objects are in different clusters
- ✦ **Why we care ?**
- ✦ **stand-alone tool** to gain insight into the data
  - ✦ visualization
- ✦ **preprocessing step** for other algorithms
  - ✦ indexing or compression often relies on clustering

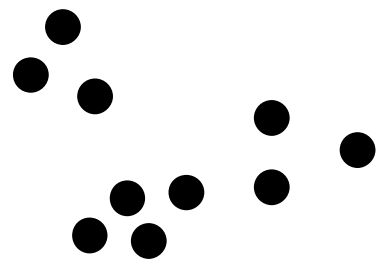
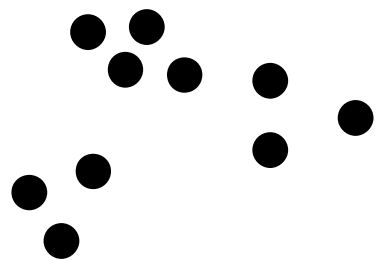
# Applications of clustering

- **image processing**
  - cluster images based on their visual content
- **web mining**
  - cluster groups of users based on their access patterns on webpages
  - cluster webpages based on their content
- **bioinformatics**
  - cluster similar proteins together (similarity wrt chemical structure and/or functionality etc)
- **many more...**

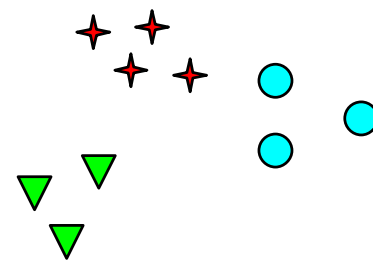
# The clustering problem

- **Given** a collection of data objects
- **Find** a grouping so that
  - similar objects are in the same cluster
  - dissimilar objects are in different clusters
- ✦ **Basic questions:**
  - ✦ what does similar mean?
  - ✦ what is a good partition of the objects?  
i.e., how is the quality of a solution measured?
  - ✦ how to find a good partition?

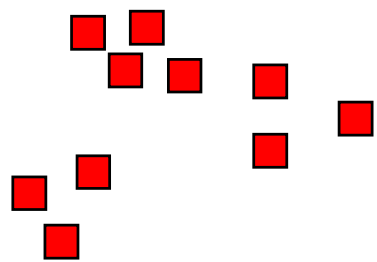
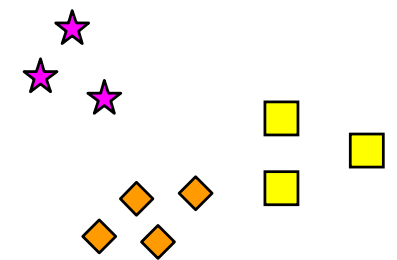
# Notion of a cluster can be ambiguous



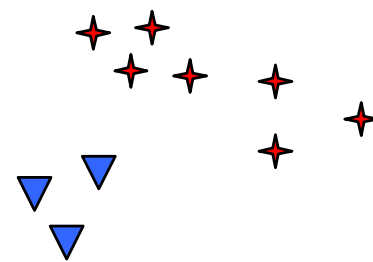
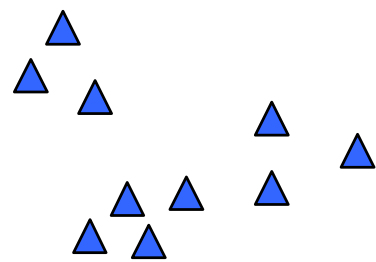
How many clusters?



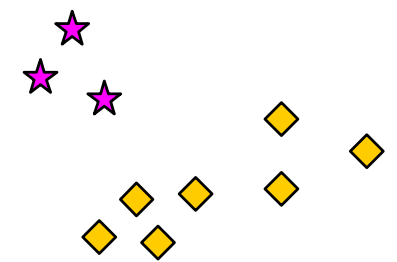
Six Clusters



Two Clusters



Four Clusters

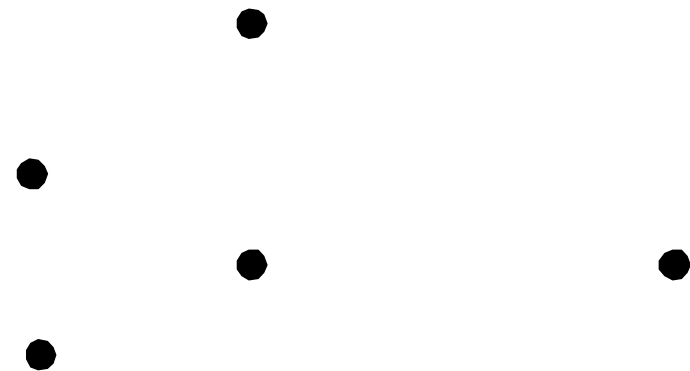
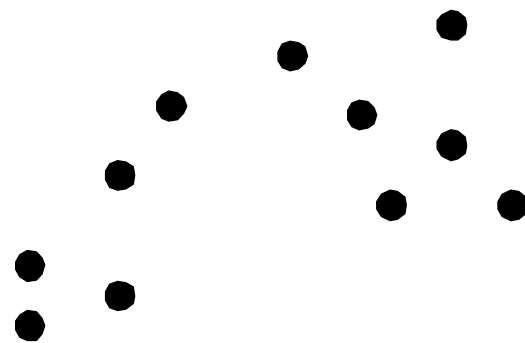


# Types of clusterings

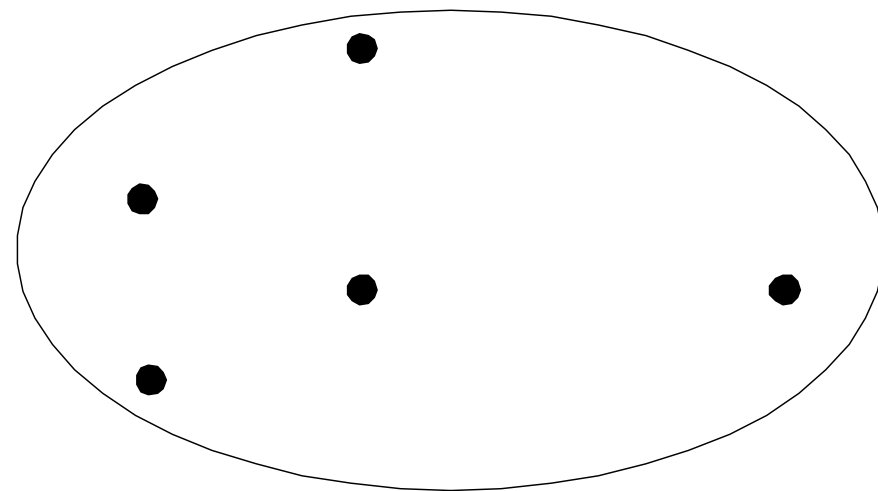
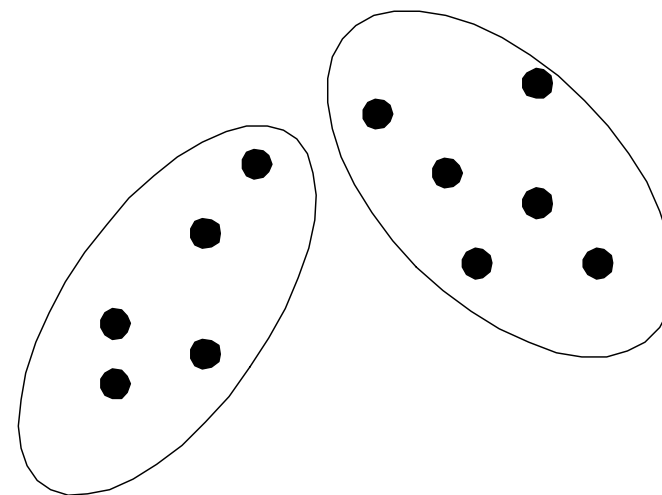
- **Partitional**
  - each object belongs in exactly one cluster
- **Hierarchical**
  - a set of nested clusters organized in a tree



# Partitional clustering



**Original Points**



**A Partitional Clustering**

# Partitional algorithms

- partition the  $n$  objects into  $k$  clusters
  - each object belongs to exactly one cluster
  - the number of clusters  $k$  is given in advance

# The k-means problem

- consider set  $X=\{x_1,\dots,x_n\}$  of  $n$  points in  $\mathbb{R}^d$
- assume that the number  $k$  is given
- **problem:**
  - find  $k$  points  $c_1,\dots,c_k$  (named **centers** or **means**)  
so that the **cost**

$$\sum_{i=1}^n \min_j \{L_2^2(x_i, c_j)\} = \sum_{i=1}^n \min_j ||x_i - c_j||_2^2$$

is minimized

# The k-means problem

- consider set  $X=\{x_1,\dots,x_n\}$  of  $n$  points in  $\mathbb{R}^d$
- assume that the number  $k$  is given
- problem:
  - find  $k$  points  $c_1,\dots,c_k$  (named centers or means)
  - and partition  $X$  into  $\{X_1,\dots,X_k\}$  by assigning each point  $x_i$  in  $X$  to its nearest cluster center,
  - so that the cost

$$\sum_{i=1}^n \min_j ||x_i - c_j||_2^2 = \sum_{j=1}^k \sum_{x \in X_j} ||x - c_j||_2^2$$

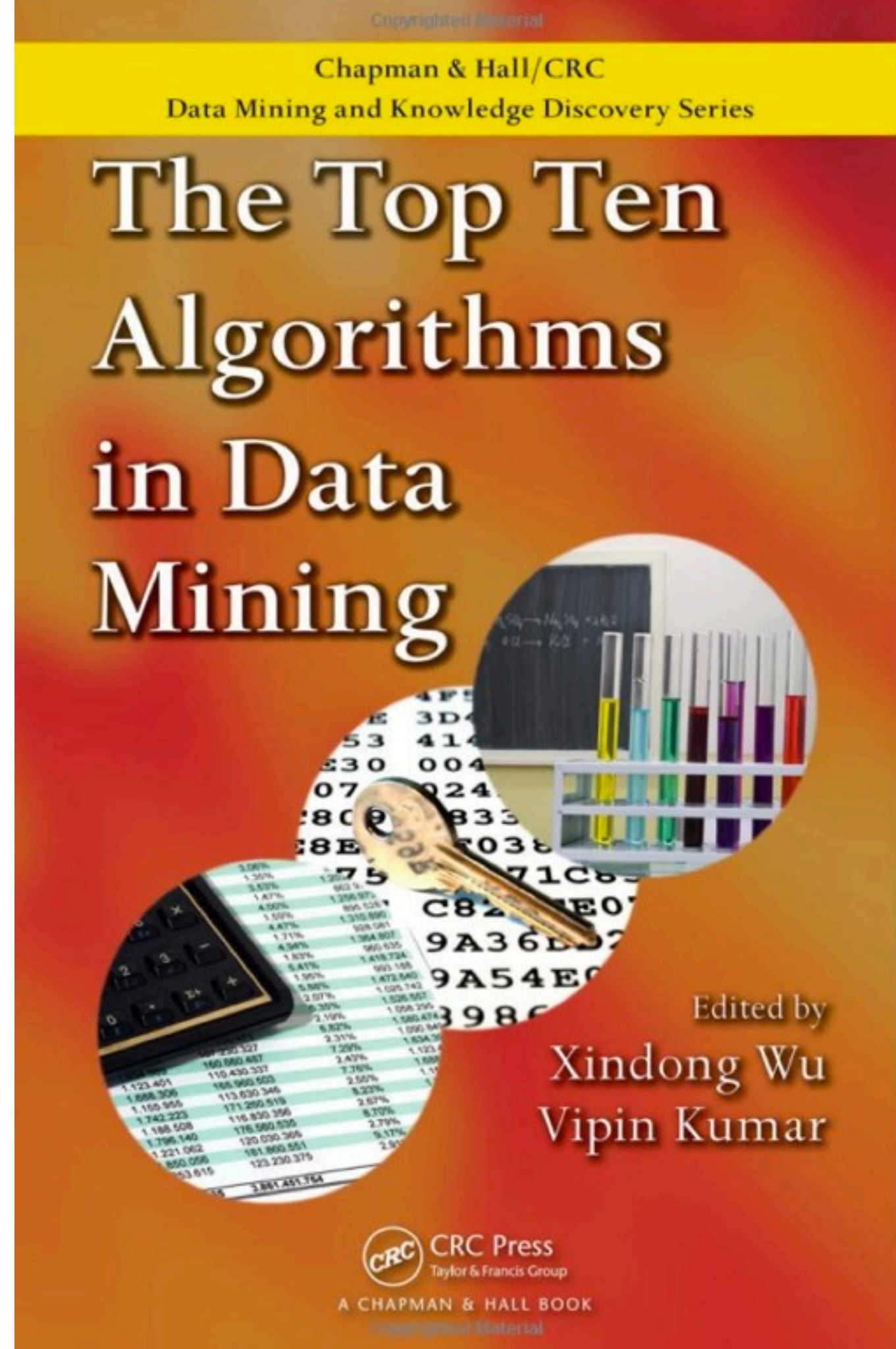
is minimized

# The k-means problem

- $k=1$  and  $k=n$  are **easy** special cases (**why?**)
- an **NP-hard** problem if the **dimension** of the data is at least 2 ( $d \geq 2$ )
- in practice, a **simple iterative algorithm** works quite well

# The k-means algorithm

- voted among the **top-10 algorithms** in data mining
- **one way** of solving the **k-means** problem

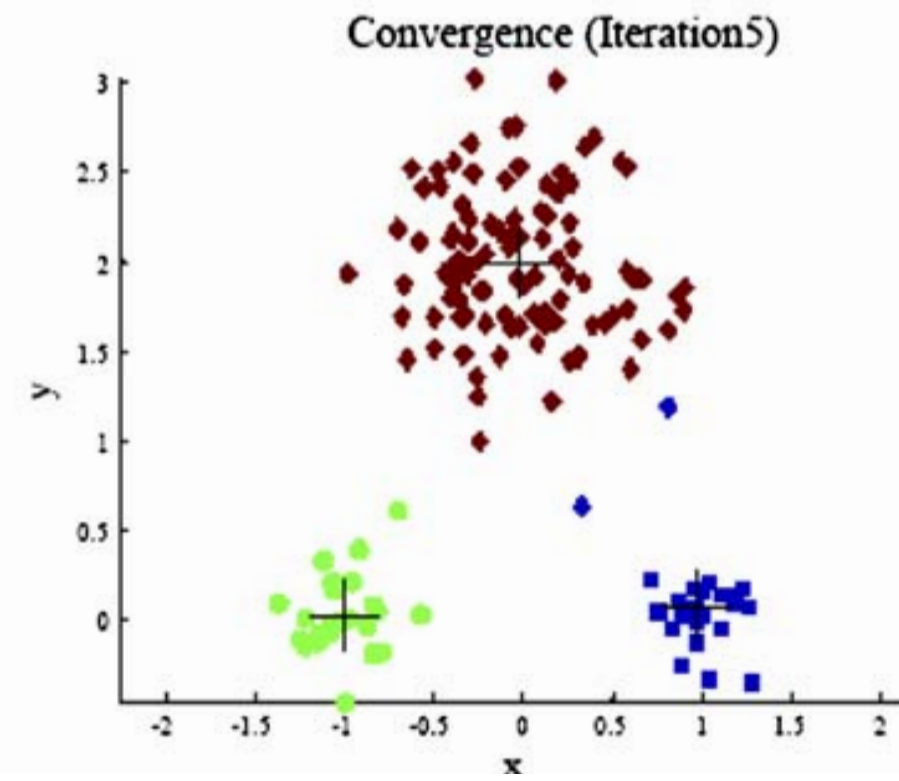
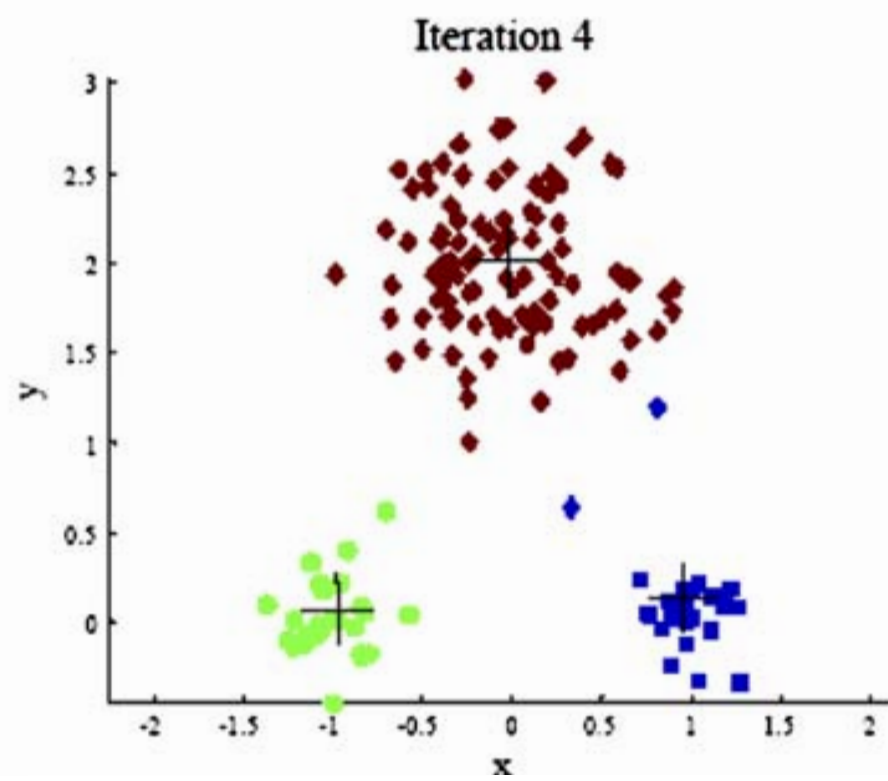
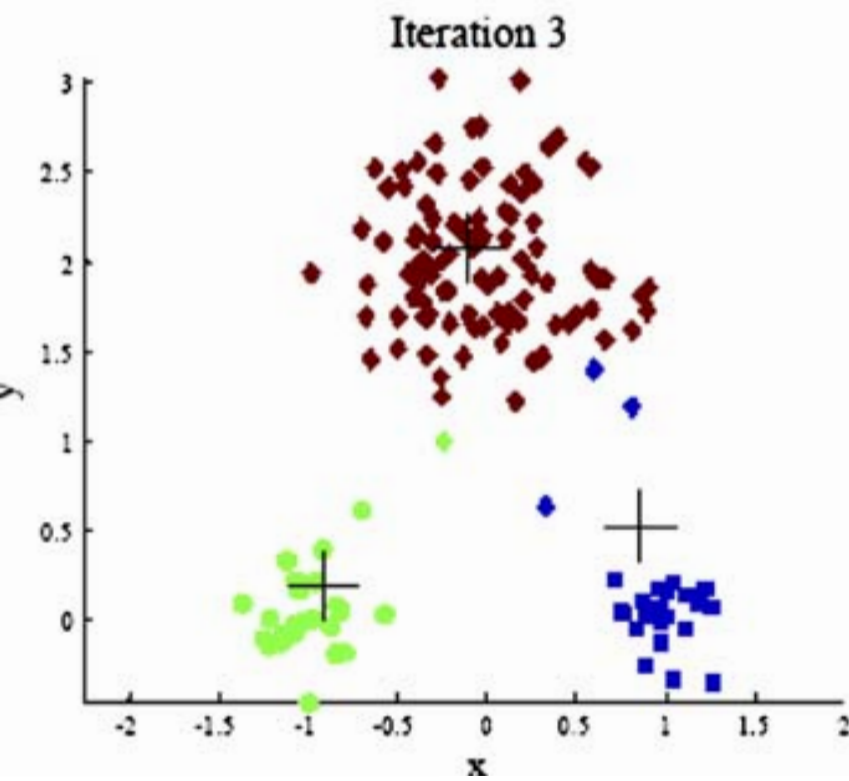
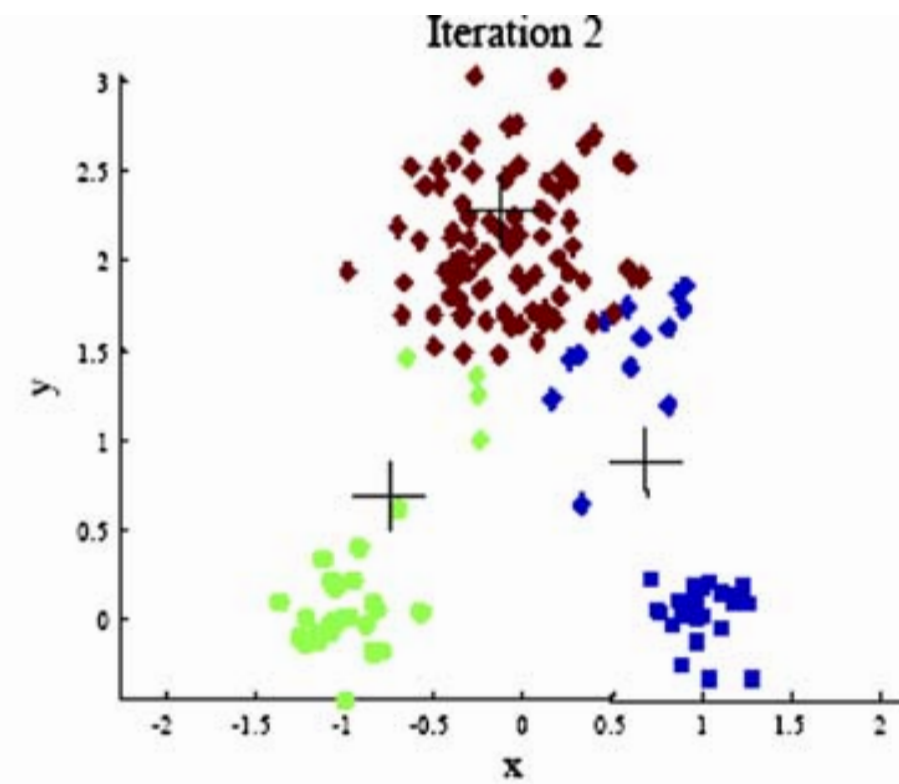
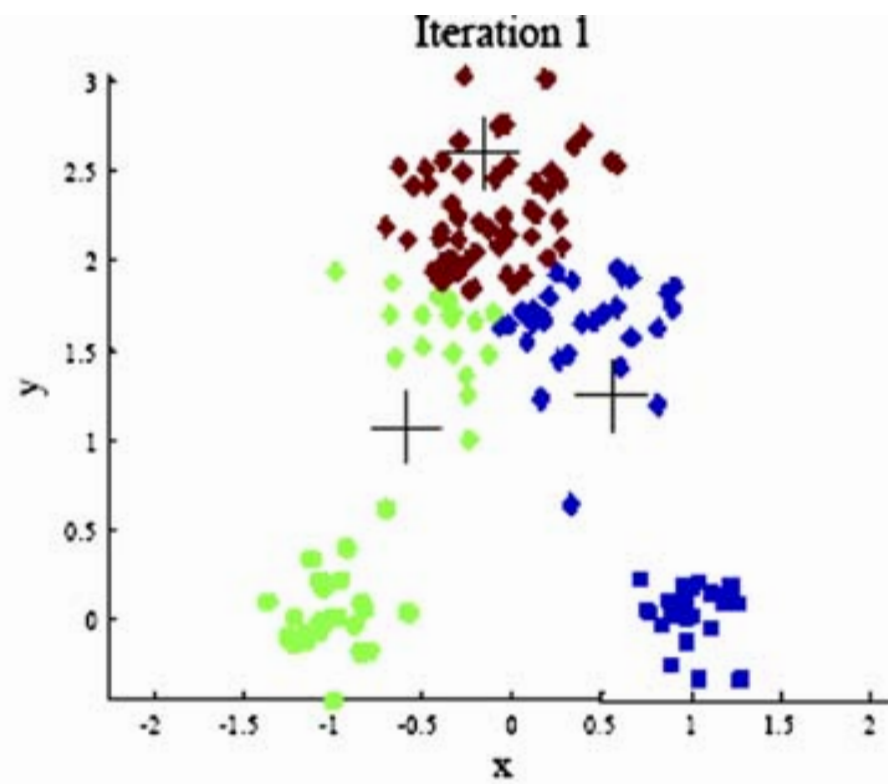
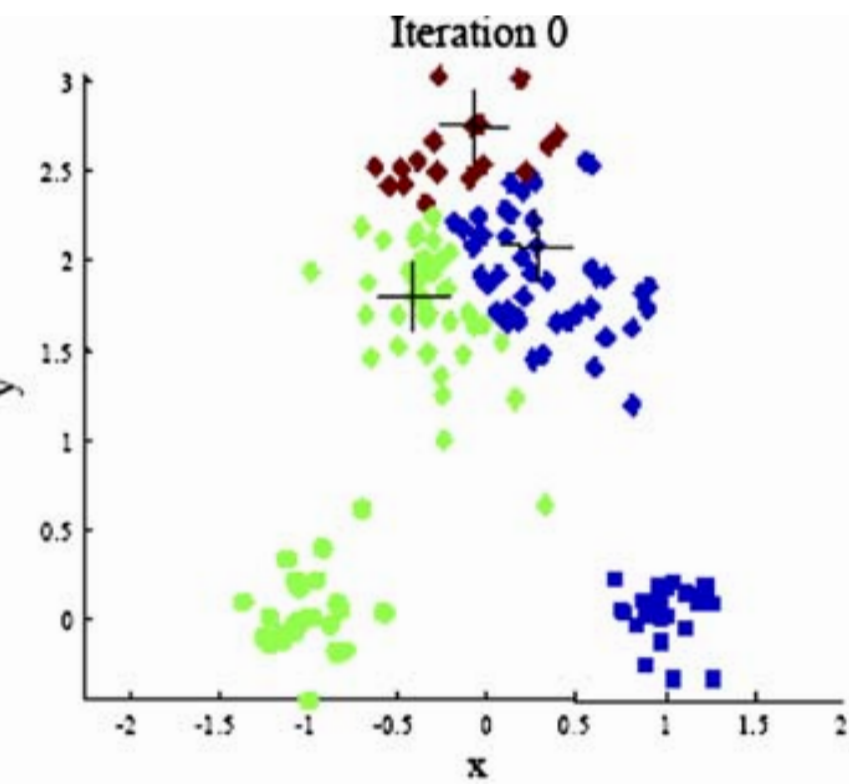


# The k-means algorithm

1. **randomly** (or with another method) pick **k** cluster centers  $\{c_1, \dots, c_k\}$
2. for each **j**, set the cluster  $X_j$  to be the set of points in  $X$  that are **the closest to center  $c_j$**
3. for each **j** let  $c_j$  be **the center of cluster  $X_j$**   
(mean of the vectors in  $X_j$ )
4. repeat (go to step 2) until convergence



# Sample execution

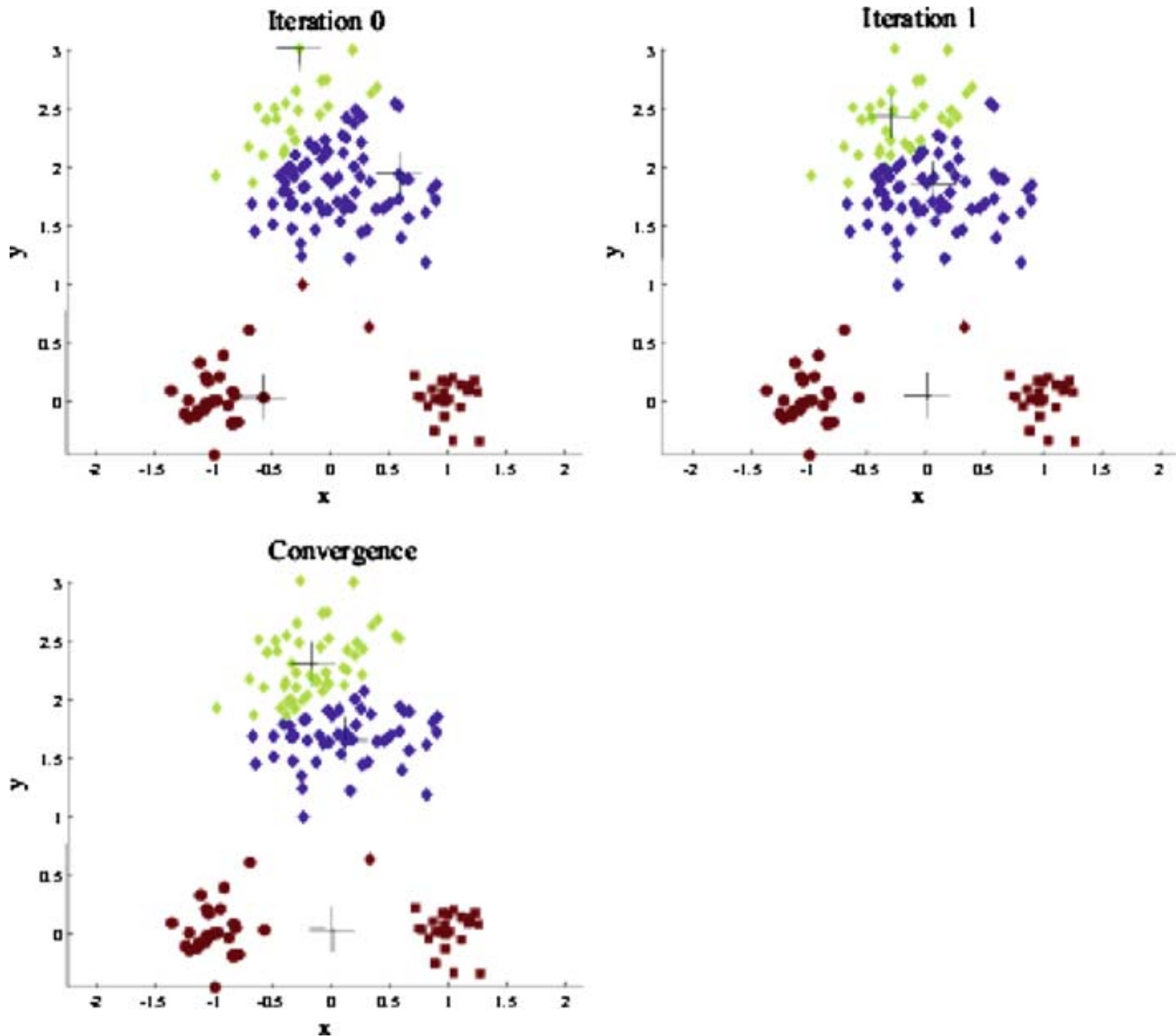




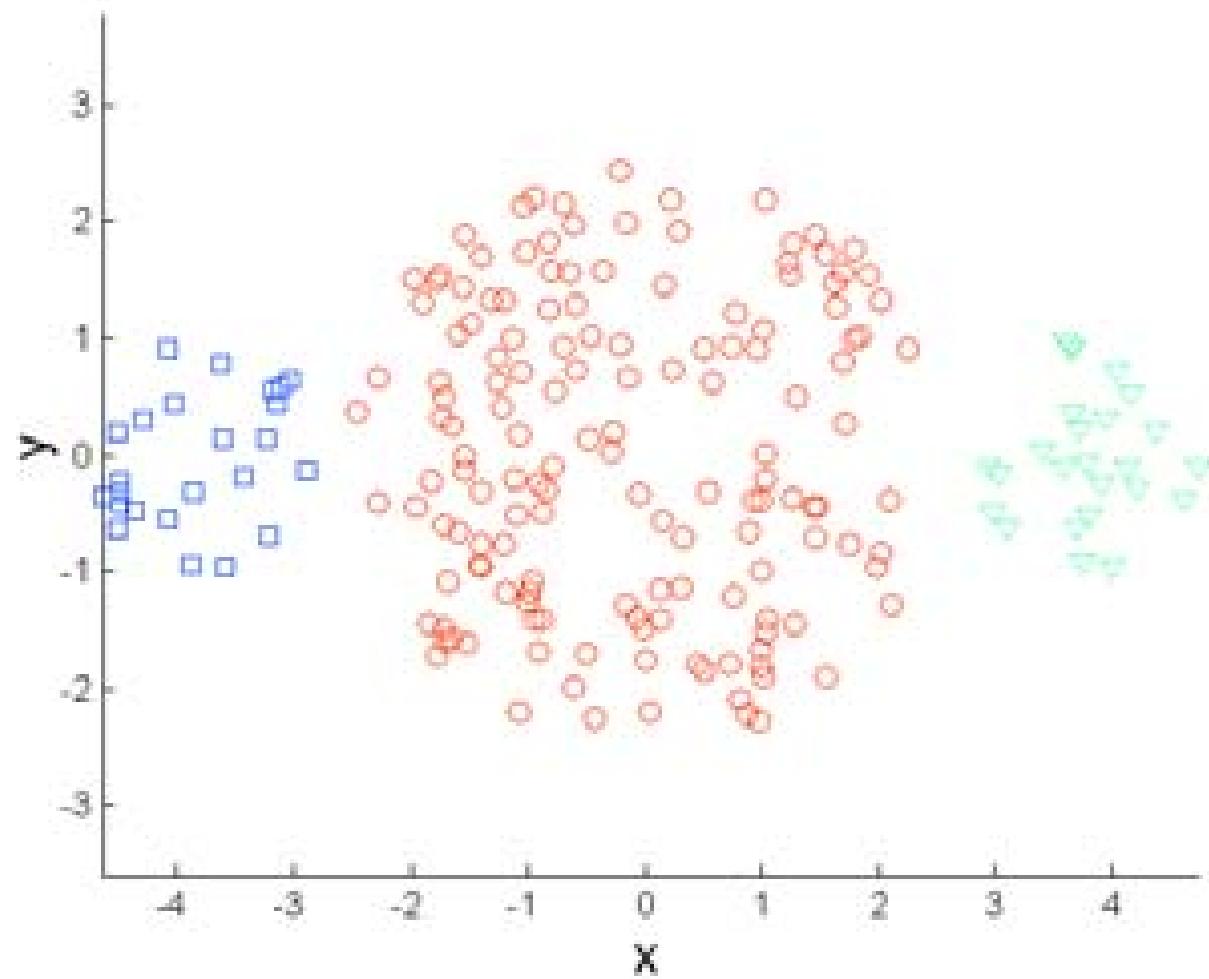
# Properties of the k-means algorithm

- finds a **local optimum**
- often **converges** quickly  
but not always
- the **choice of initial points** can have **large influence** in the result

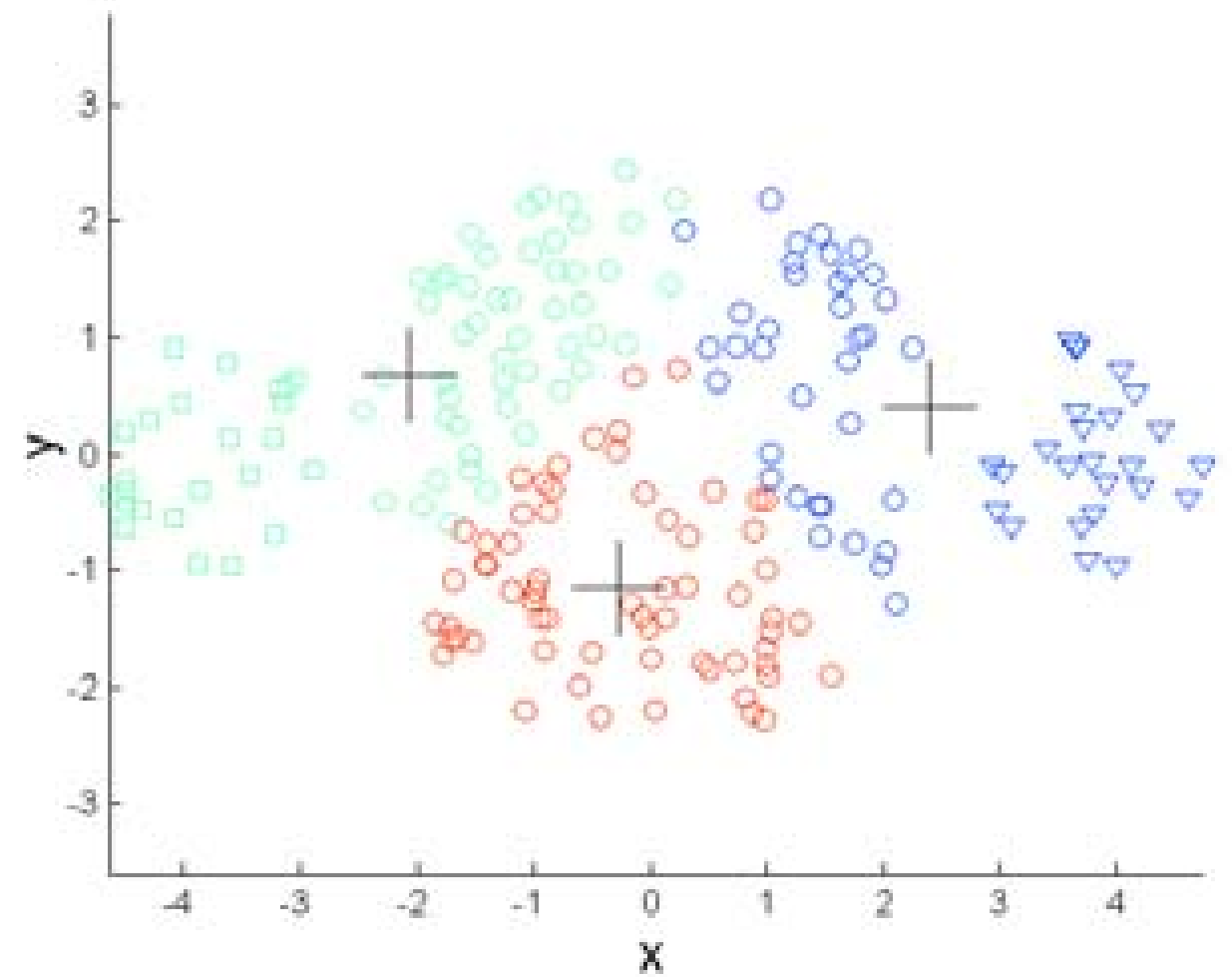
# Effects of bad initialization



# Limitations of k-means: different sizes

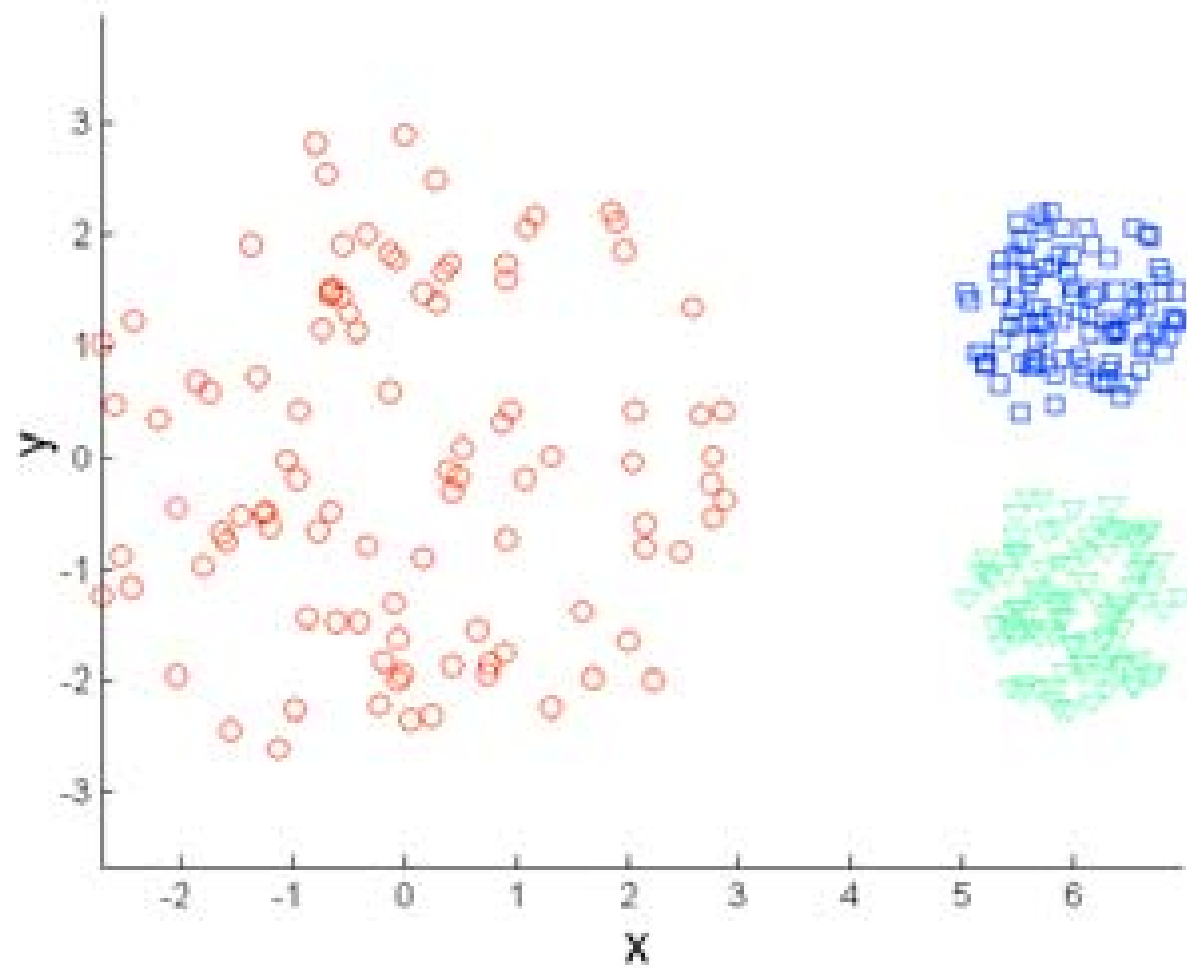


**Original Points**

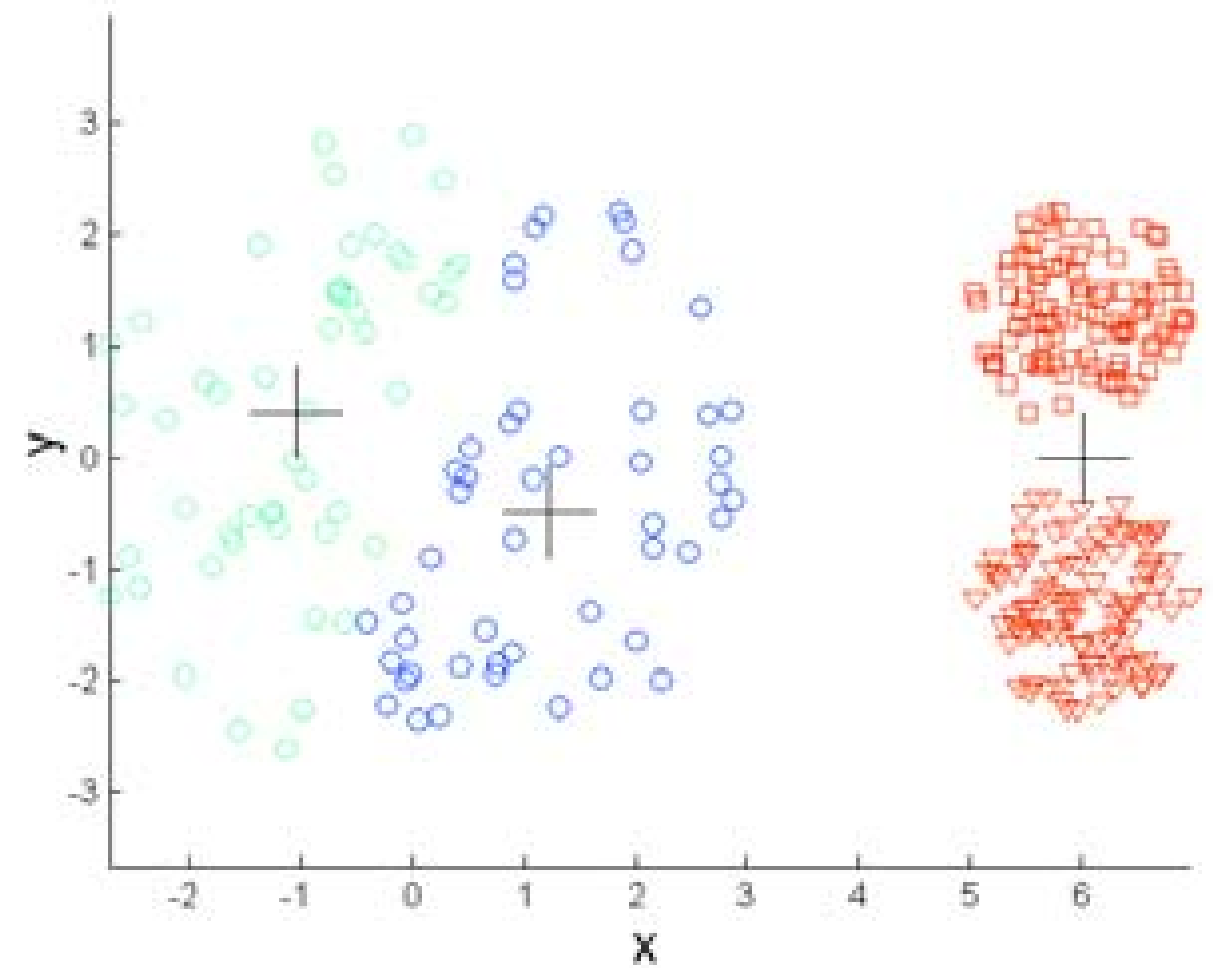


**K-means (3 Clusters)**

# Limitations of k-means: different density

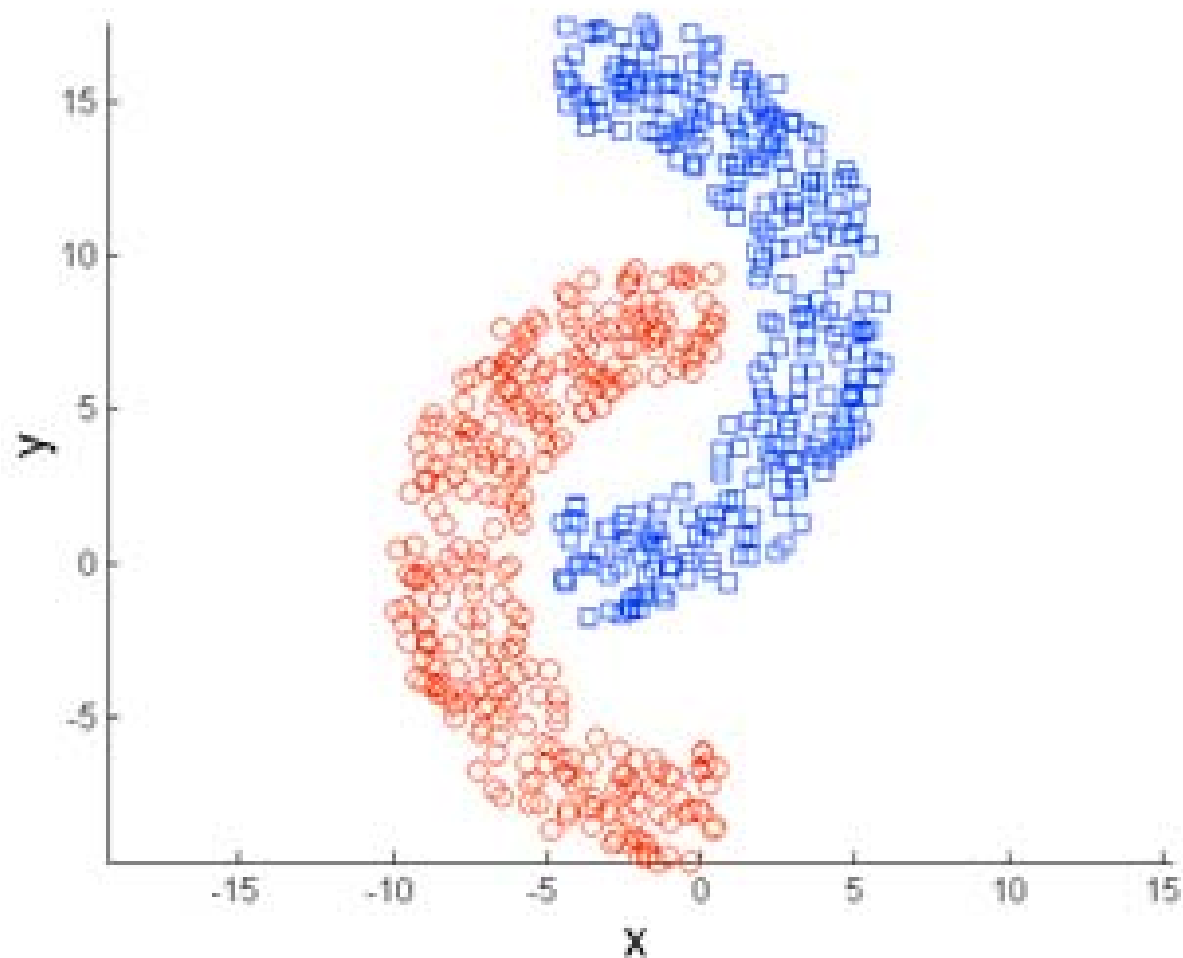


**Original Points**

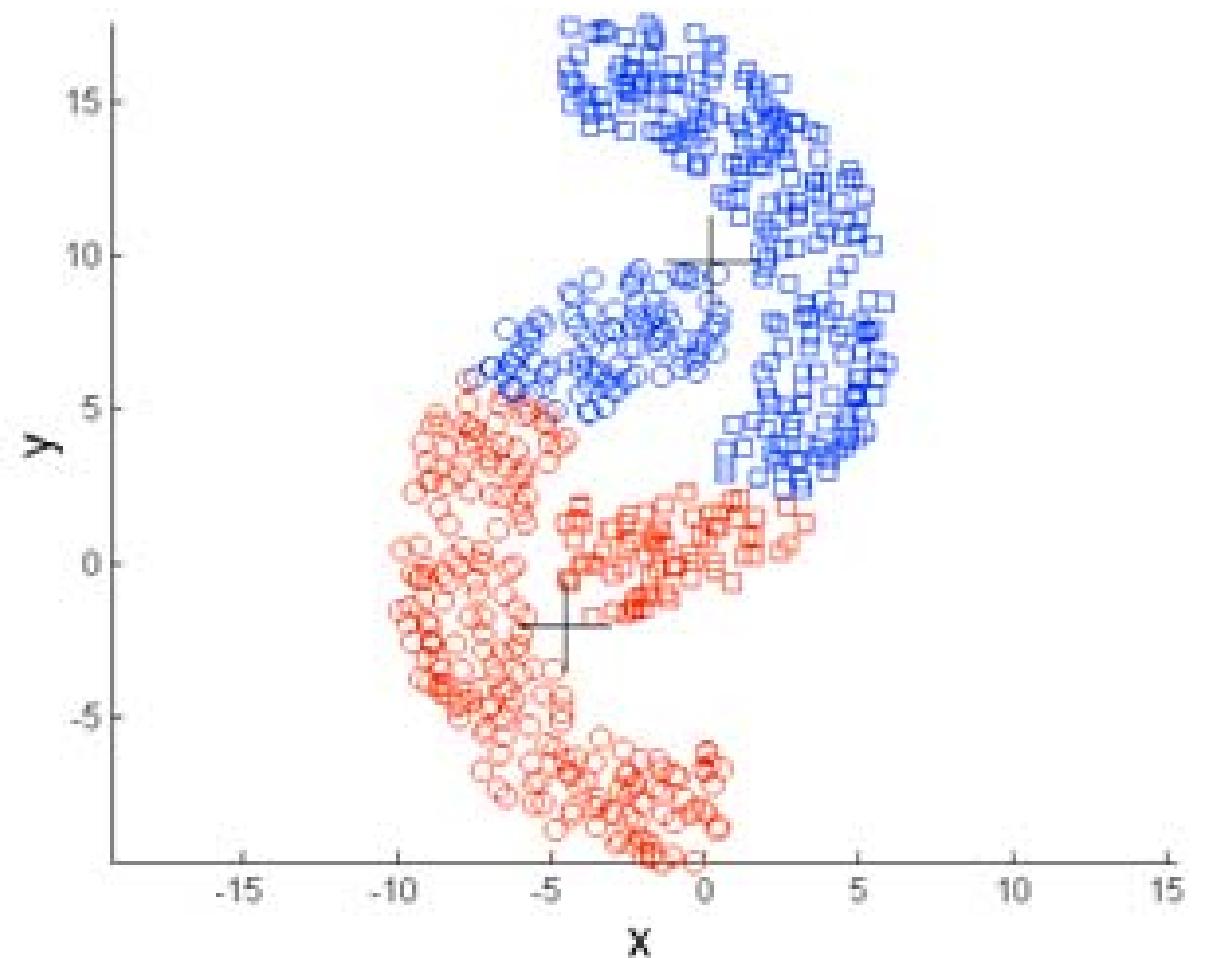


**K-means (3 Clusters)**

# Limitations of k-means: non-spherical shapes



**Original Points**



**K-means (2 Clusters)**

# Discussion on the k-means algorithm

- finds a **local optimum**
- often **converges** quickly  
but not always
- the **choice of initial points** can have **large influence** in the result
- tends to find **spherical clusters**
- **outliers** can cause a problem
- different **densities** may cause a problem

# Initialization

- random initialization
- random, but repeat many times and take the best solution
  - helps, but solution can still be bad
- pick points that are distant to each other
  - k-means++
  - provable guarantees

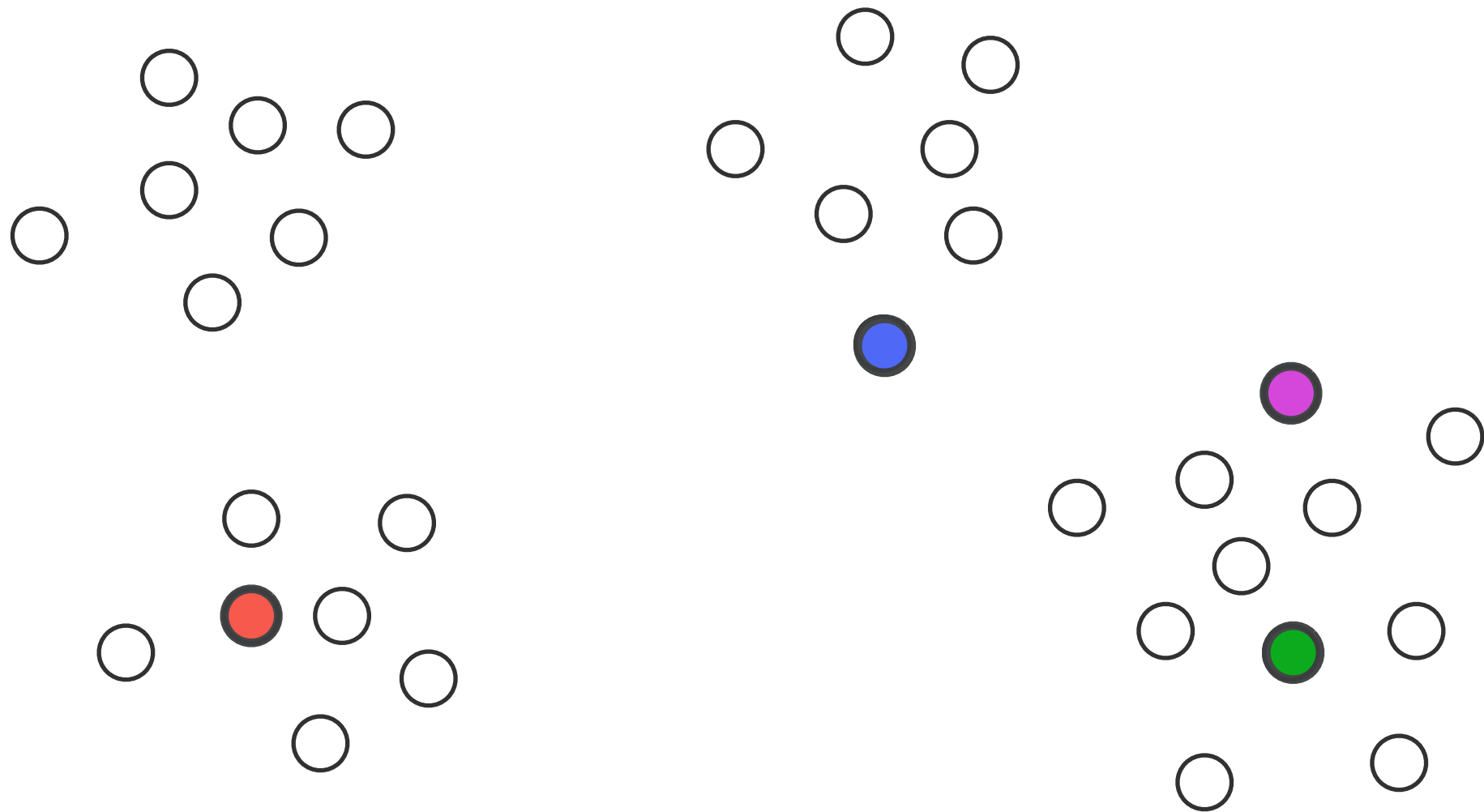
# k-means++

David Arthur and Sergei Vassilvitskii

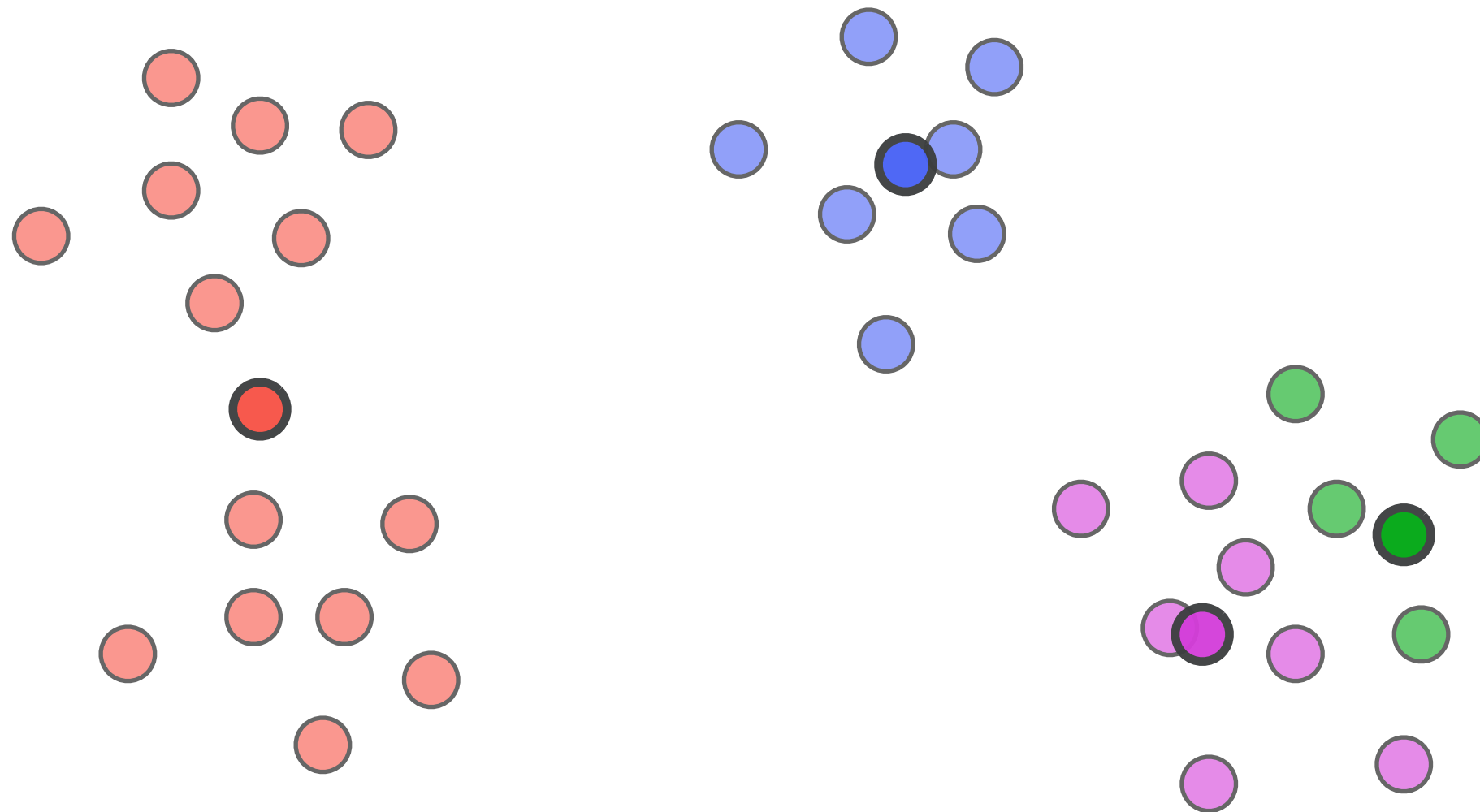
k-means++: The advantages of careful seeding  
SODA 2007



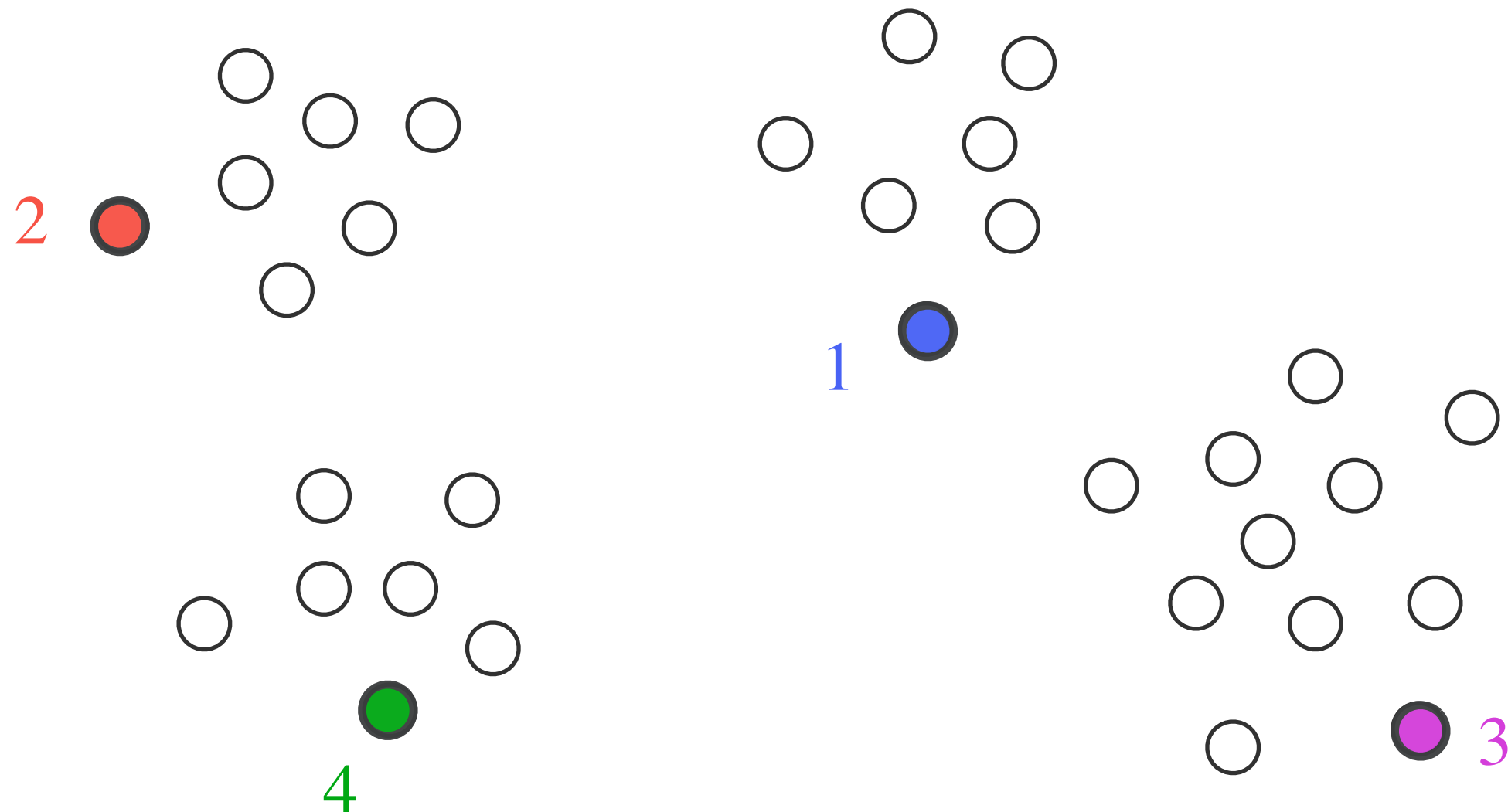
# k-means algorithm: random initialization



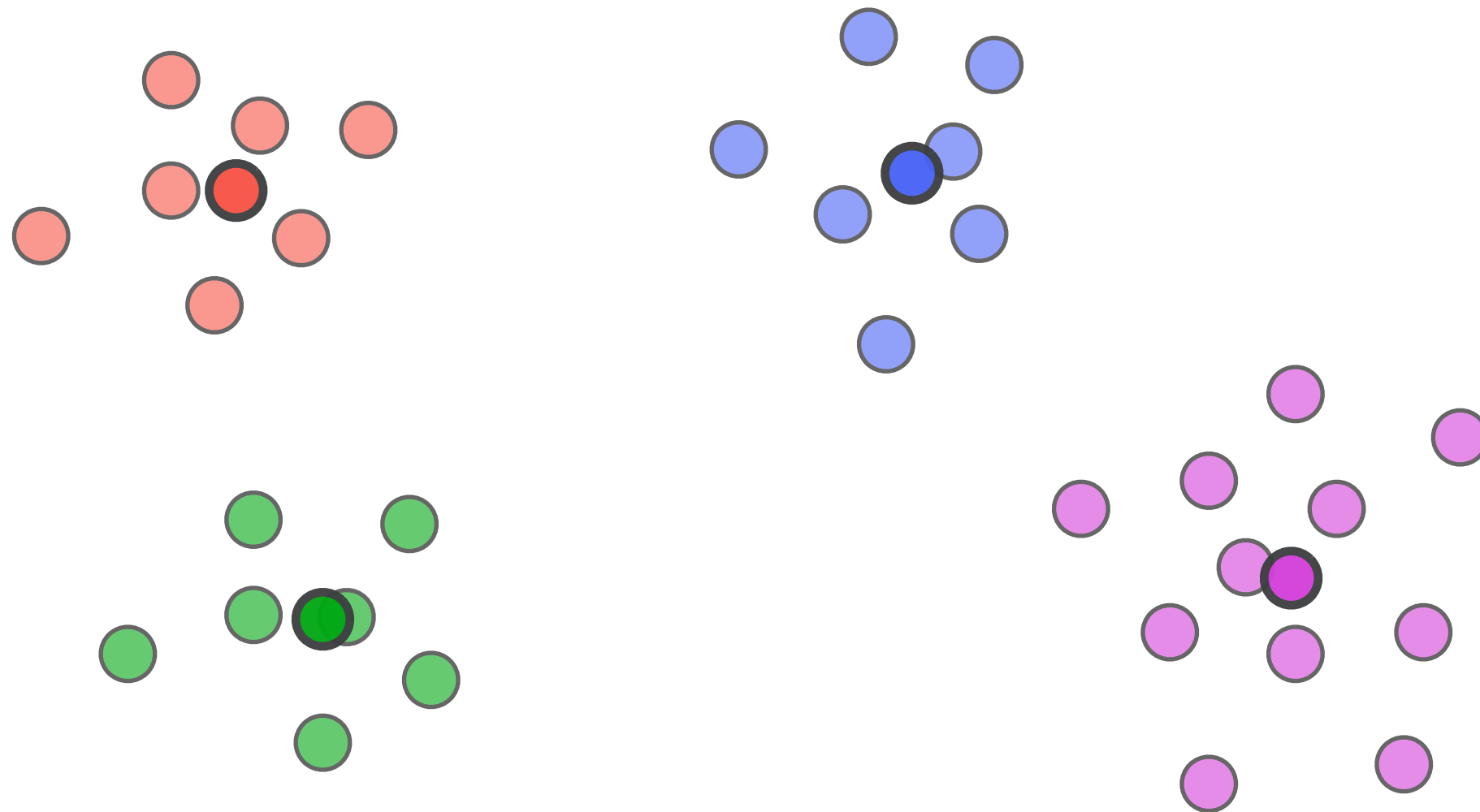
# k-means algorithm: random initialization



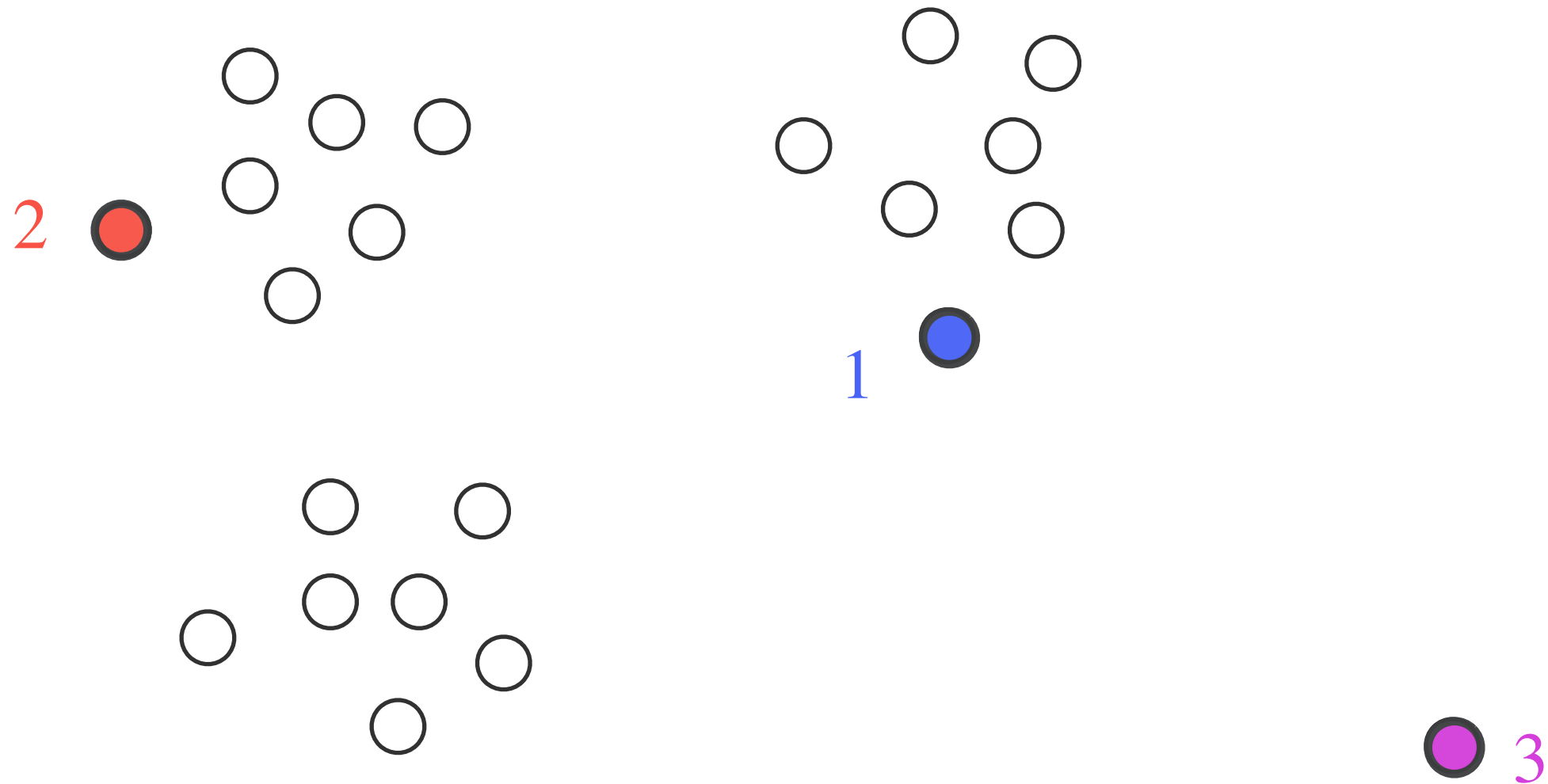
# k-means algorithm: initialization with further-first traversal



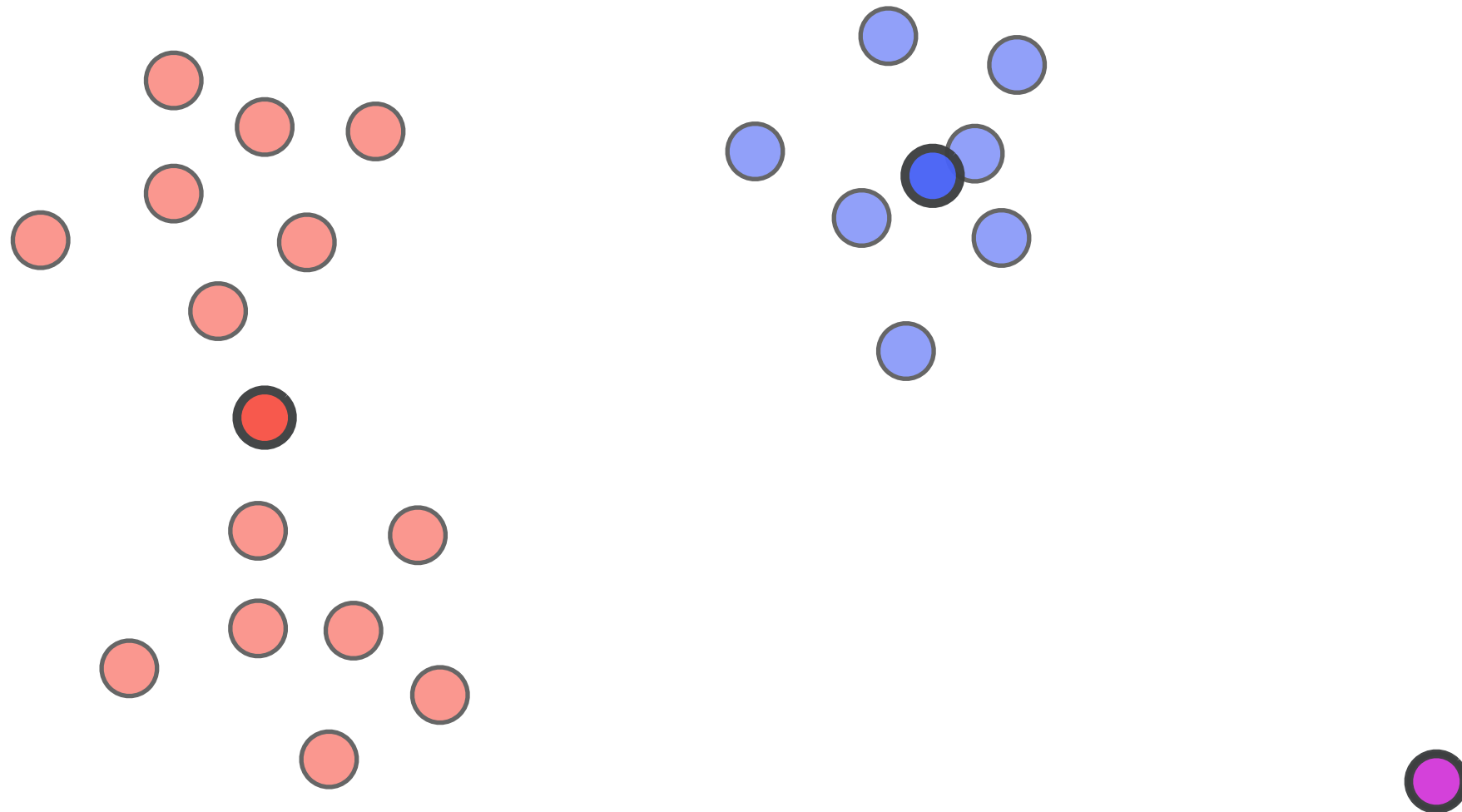
# k-means algorithm: initialization with further-first traversal



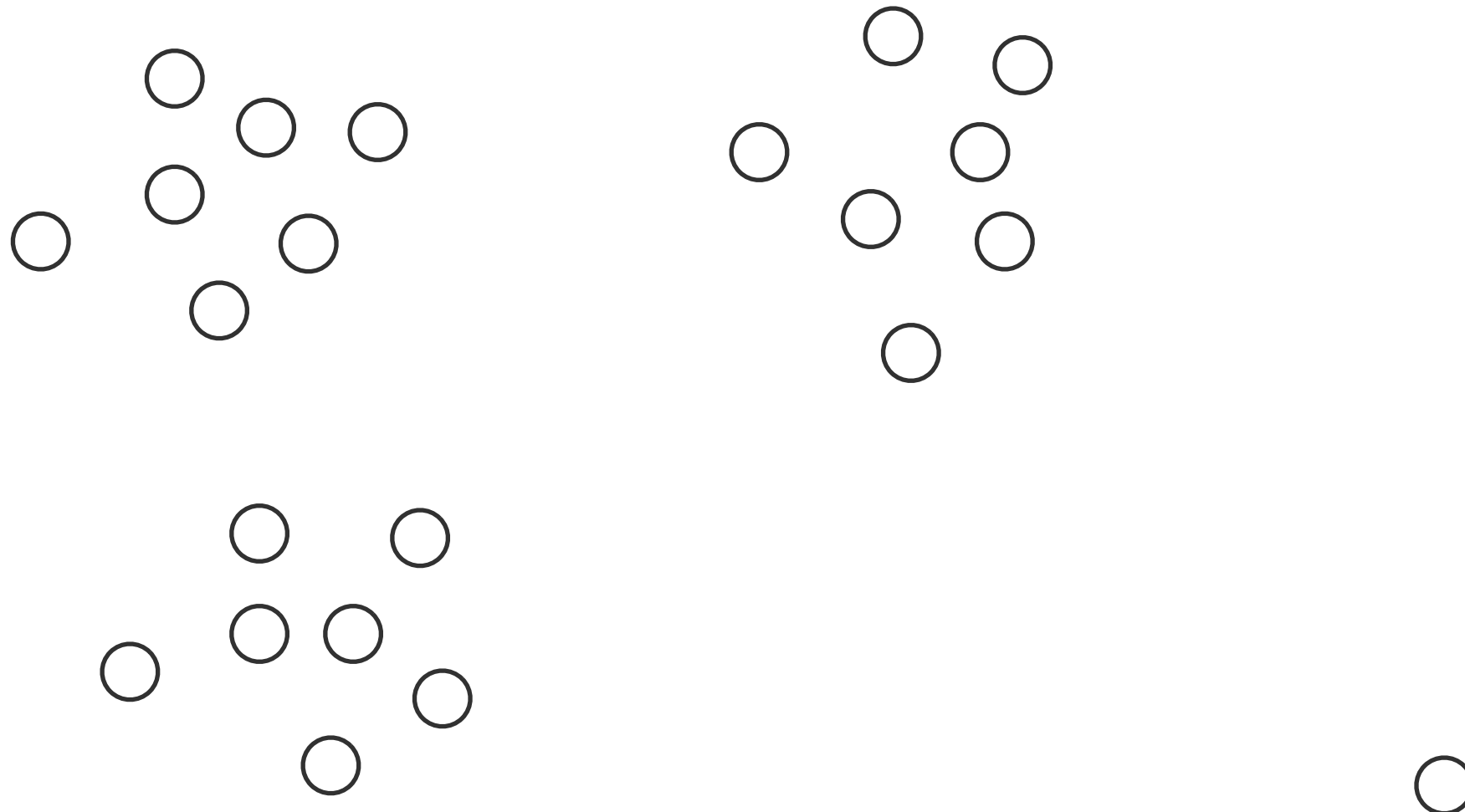
but... sensitive to outliers



but... sensitive to outliers



# Here random may work well



# k-means++ algorithm

- **interpolate** between the two methods
- let  $D(x)$  be the distance between  $x$  and the nearest center selected so far
- choose next center **with probability proportional to**

$$(D(x))^a = D^a(x)$$

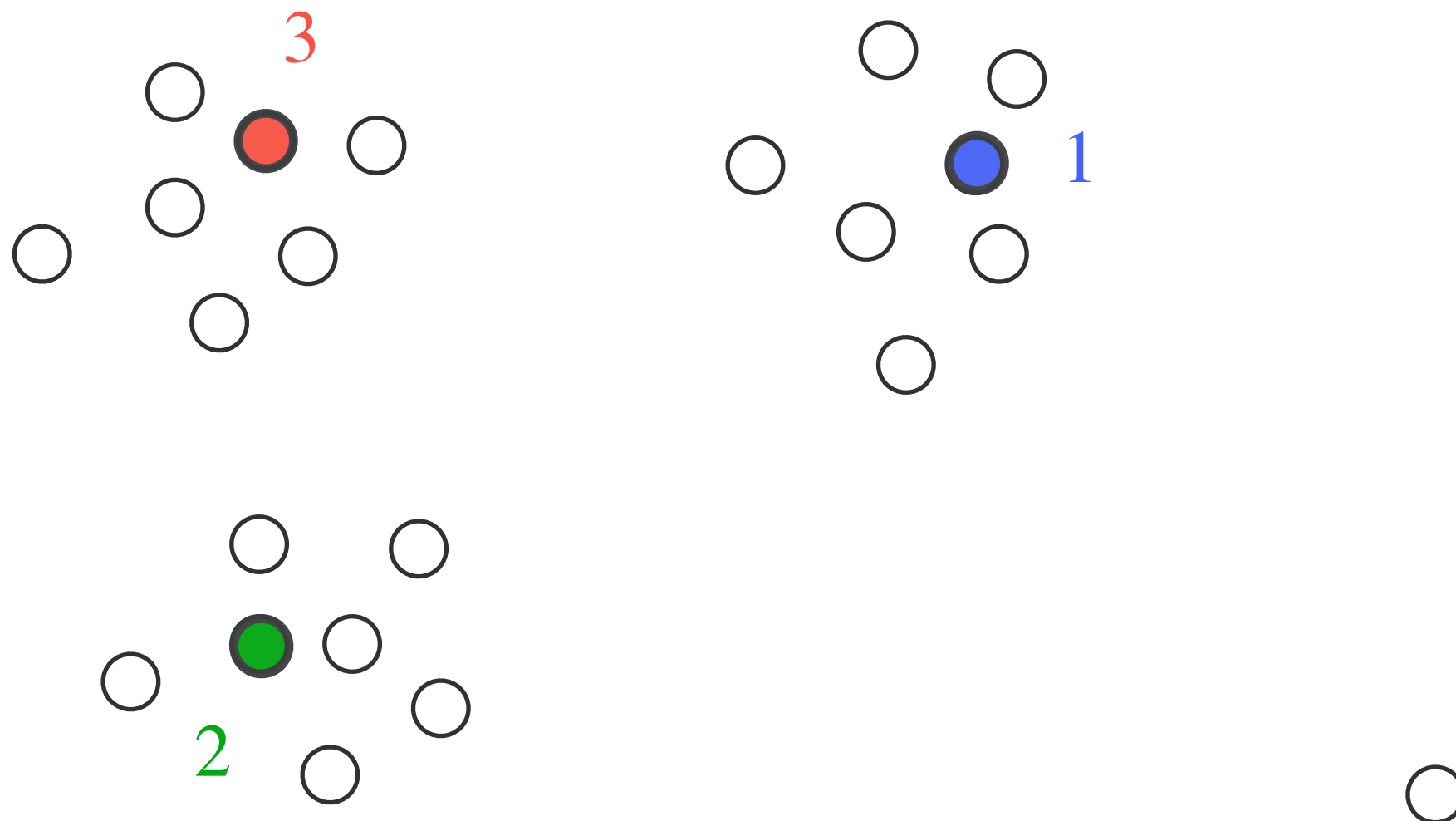
- ✦  $a = 0$       random initialization
- ✦  $a = \infty$     furthest-first traversal
- ✦  $a = 2$       k-means++



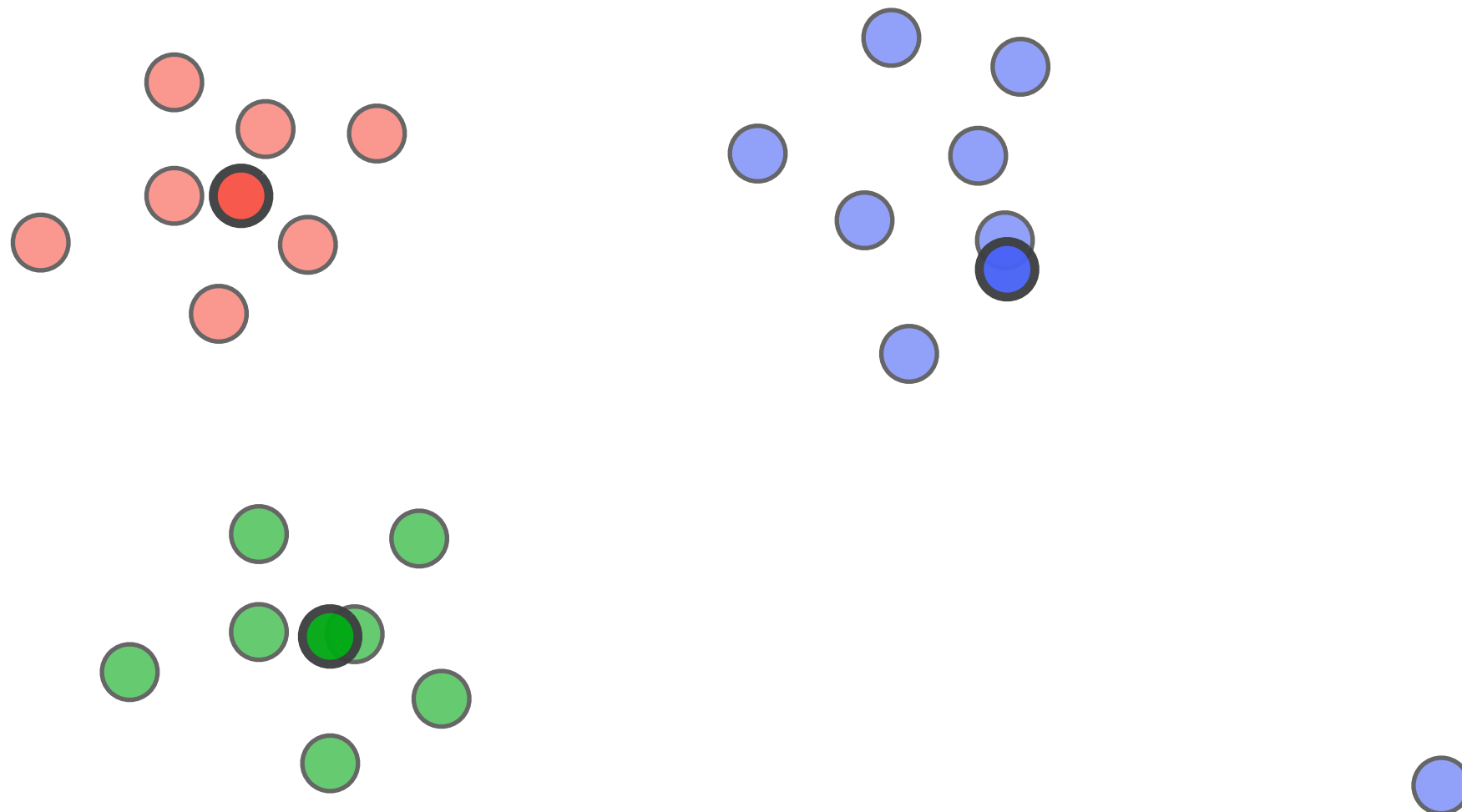
# k-means++ algorithm

- initialization phase:
  - choose the first center uniformly at random
  - choose next center with probability proportional to  $D^2(x)$
- iteration phase:
  - iterate as in the k-means algorithm until convergence

# k-means++ initialization



# k-means++ result



# k-means++ provable guarantee

- approximation guarantee comes just from the first iteration (initialization)
- subsequent iterations can only improve cost

# Lesson learned

- no reason to use **k-means** and not **k-means++**
- **k-means++** :
  - easy to implement
  - provable guarantee
  - works well in practice