SoSe 2014: M-TANI: Big Data Analytics

Lecture 4 – 21/05/2014

Sead Izberovic

Dr. Nikolaos Korfiatis

Agenda

- **Recap from the previous session**
- **Clustering**
  - Introduction
  - Distance mesures
  - Hierarchical Clustering
  - Partitional Clustering

Introduction

- Given a set of objects, with a notion of distance between those objects. The task of a clustering algorithm is to group those objects into some number of clusters, so that:
  - Members of a cluster are similar to each other
  - Members of different clusters are dissimilar
- High dimensionality may be hard to interpret

from [2]

Introduction

- **Clustering $\neq$ Classification**
- **Classification**
  - Assigning objects to predifined classes
  - Requires supervised learning
- **Clustering**
  - No predifined classes
  - Assigning objects to clusters (*based on distance*)

Introduction

- **Clustering applications**
  - Clustering DNA sequences
  - Image segmentation
  - Customer segmentation
  - ...

Distance mesures

- **Calculate similarity**
  - Large distance = low similarity
  - Small distance = high similarity

- **Conditions**
  1. $dist(x, y) = d$ with $d: X \times X \rightarrow \boldsymbol{R}$ and $\mathrm{x}, \mathrm{y}, \mathrm{z} \in X$
  2. $dist(x, y) \geq 0$
  3. $dist(x, y) = 0$ if $x = y$
  4. $dist(x, y) = dist(y, x)$
  5. $dist(x, z) \leq dist(x, y) + dist(y, z)$

from [1] and [3]

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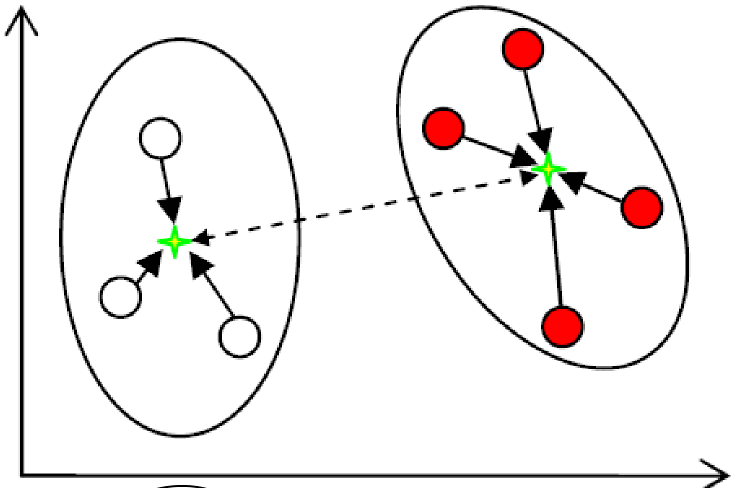
Distance mesures

- Euclidian distance: $dist_{euclid}(X,Y) = \sqrt{\sum_{i=1}^{n}(x_i - y_i)^2}$
- Jaccard distance: $dist_{jaccard}(x,y) = 1 - SIM(x,y)$
- Cosine distance: $dist_{cos}(X,Y) = \frac{\sum_{i=1}^{n} x_i \times y_i}{\sqrt{\sum_{i=1}^{n}(x_i)^2} \times \sqrt{\sum_{i=1}^{n}(x_i)^2}}$
- Edit distance: *smallest number of insertions and deletions of single characters that will convert string **x** to string **y***

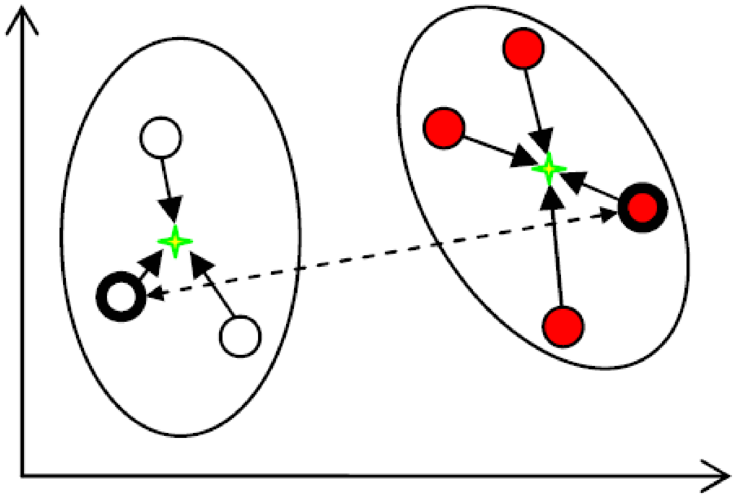
from [2] and [3]

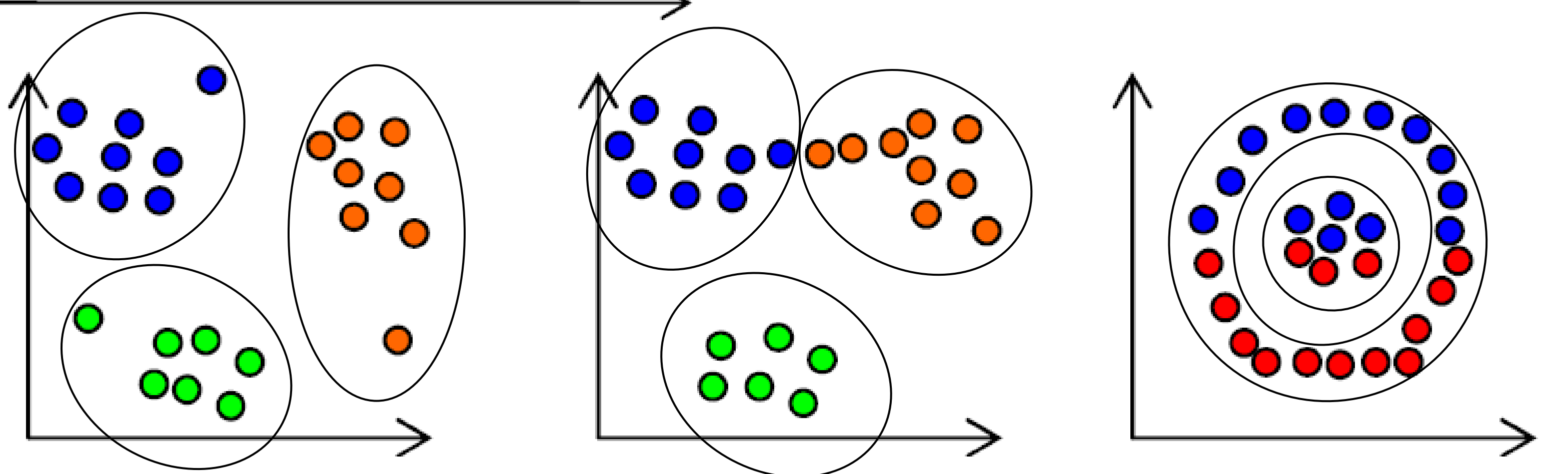
Distance between clusters

Centroid



Medoid/Clustroid

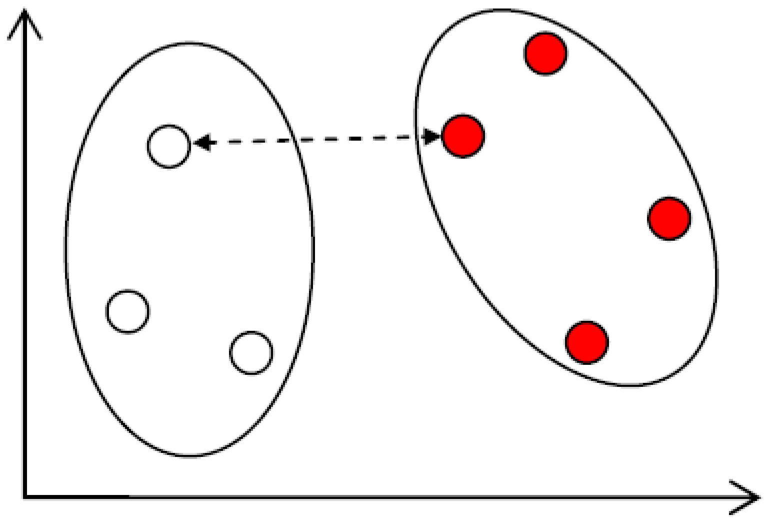




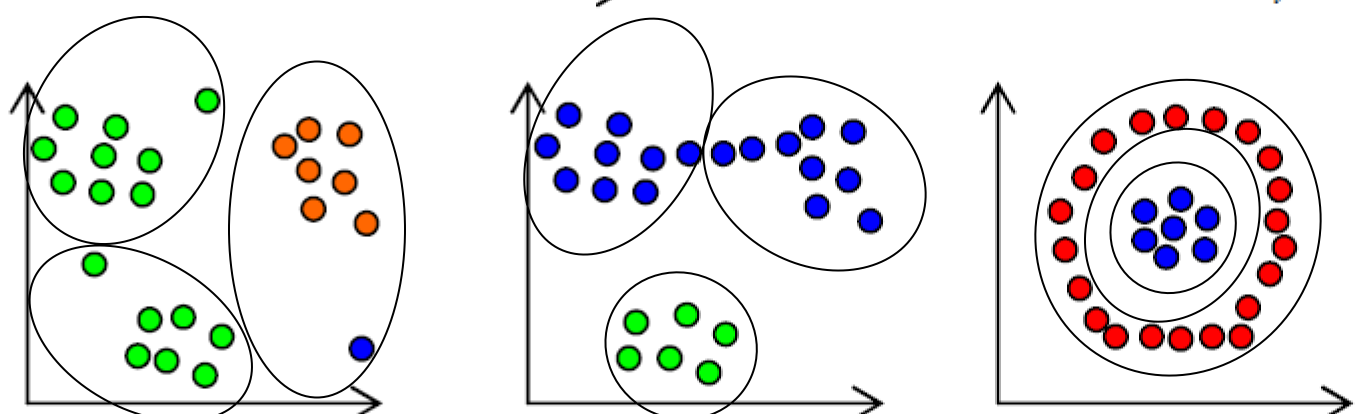
adapted from [3]

Distance between clusters

Single-linkage



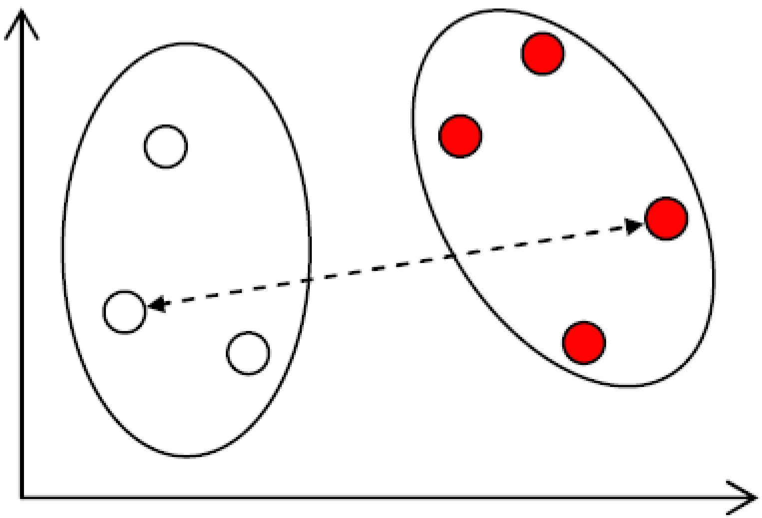
$$dist_{SL}(C_x, C_y) = \min_{x \in C_x, y \in C_y} dist(x, y)$$



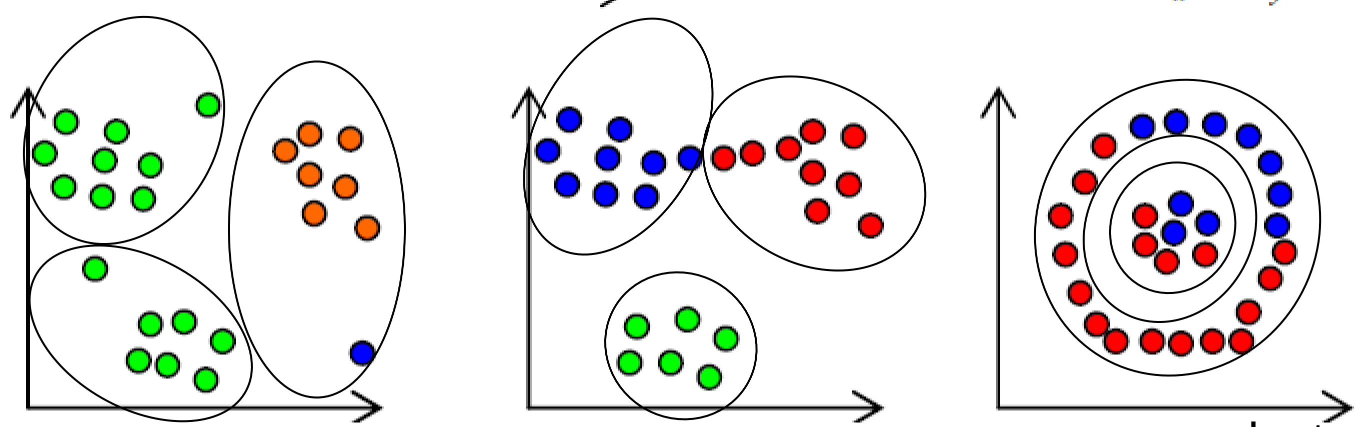
adapted from [3]

Distance between clusters

Complete-linkage



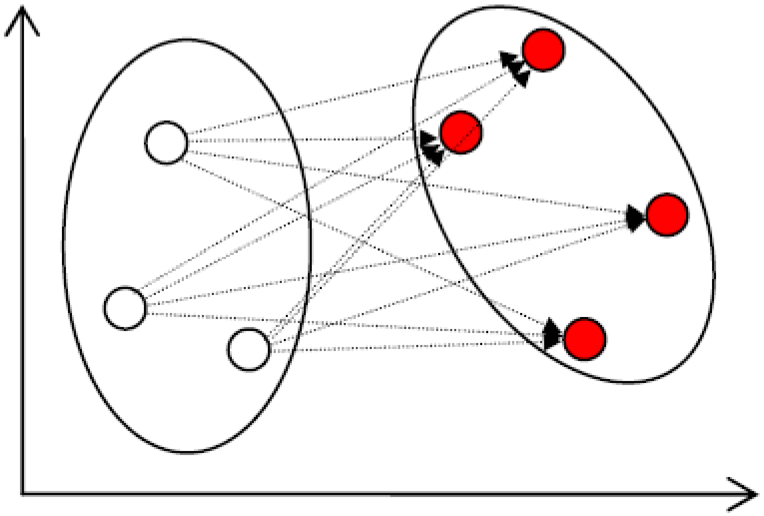
$$dist_{CL}(C_x, C_y) = \max_{x \in C_x, y \in C_y} dist(x, y)$$



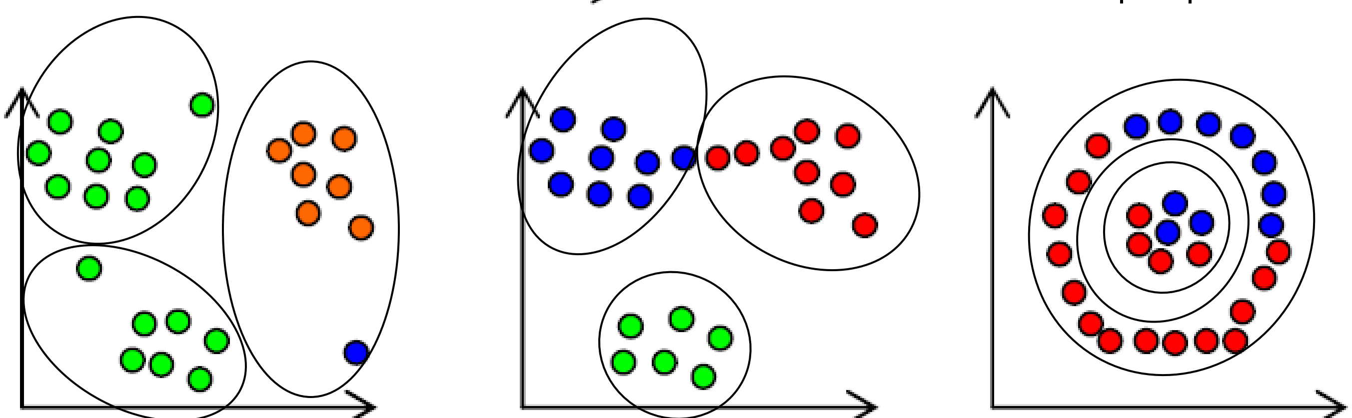
adapted from [3]

Distance between clusters

Average-linkage



$$dist_{AL}(C_x, C_y) = \frac{1}{|C_x| \cdot |C_y|} \cdot \sum_{x \in C_x, y \in C_y} dist(x, y)$$



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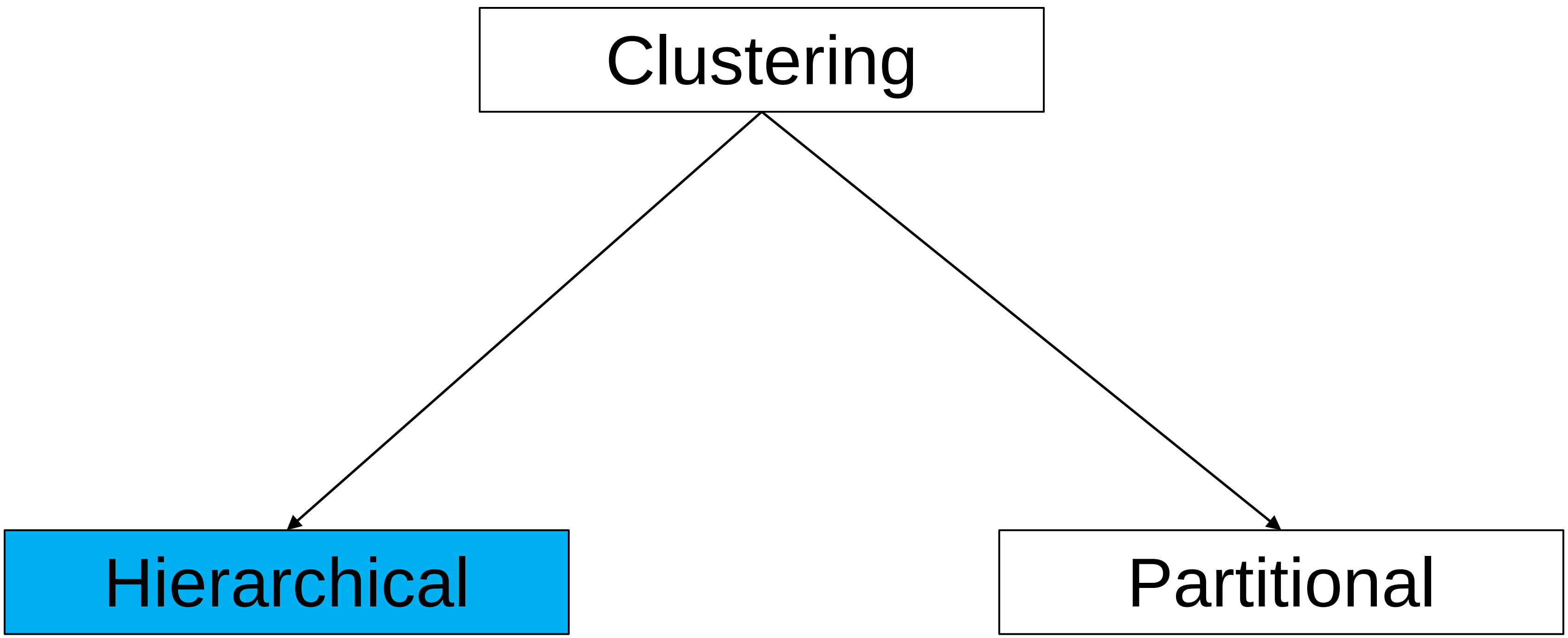
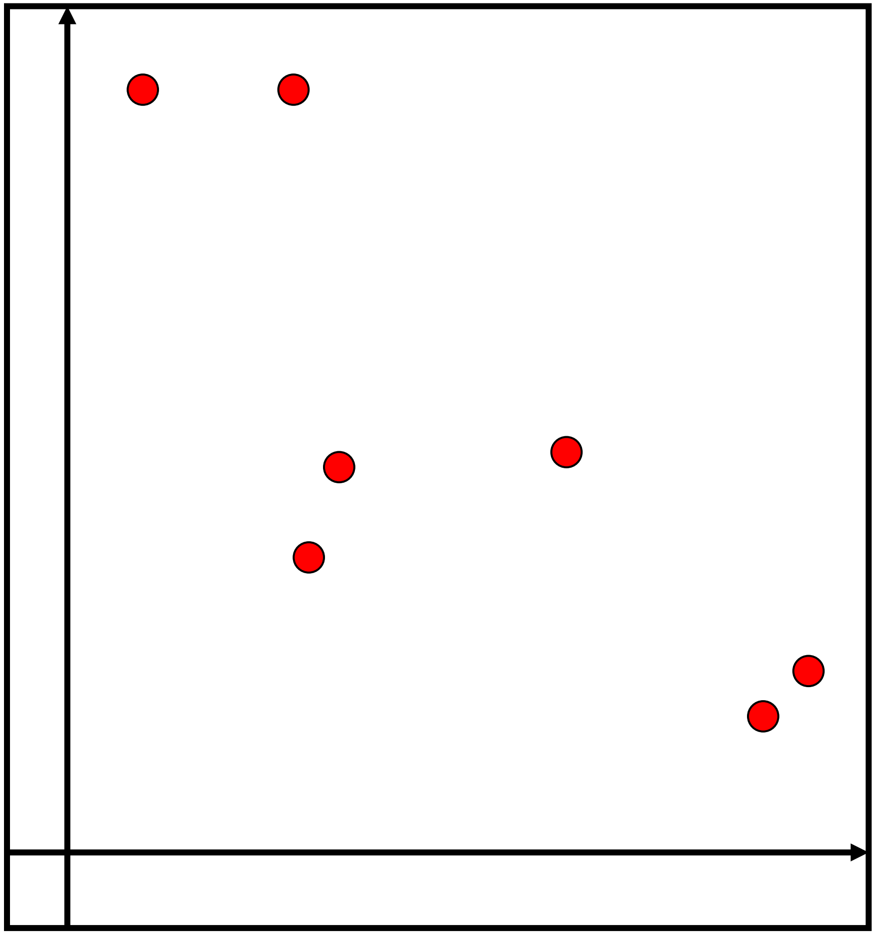
Clustering approches



adapted from [4]

Hierarchical Agglomerative



Single Link

1. Every Object is a cluster
2. Calculate the minimal distance between to clusters
3. Merge clusters with minimal distance
4. Repeat 2. and 3. until we have one big cluster

adapted from [3]

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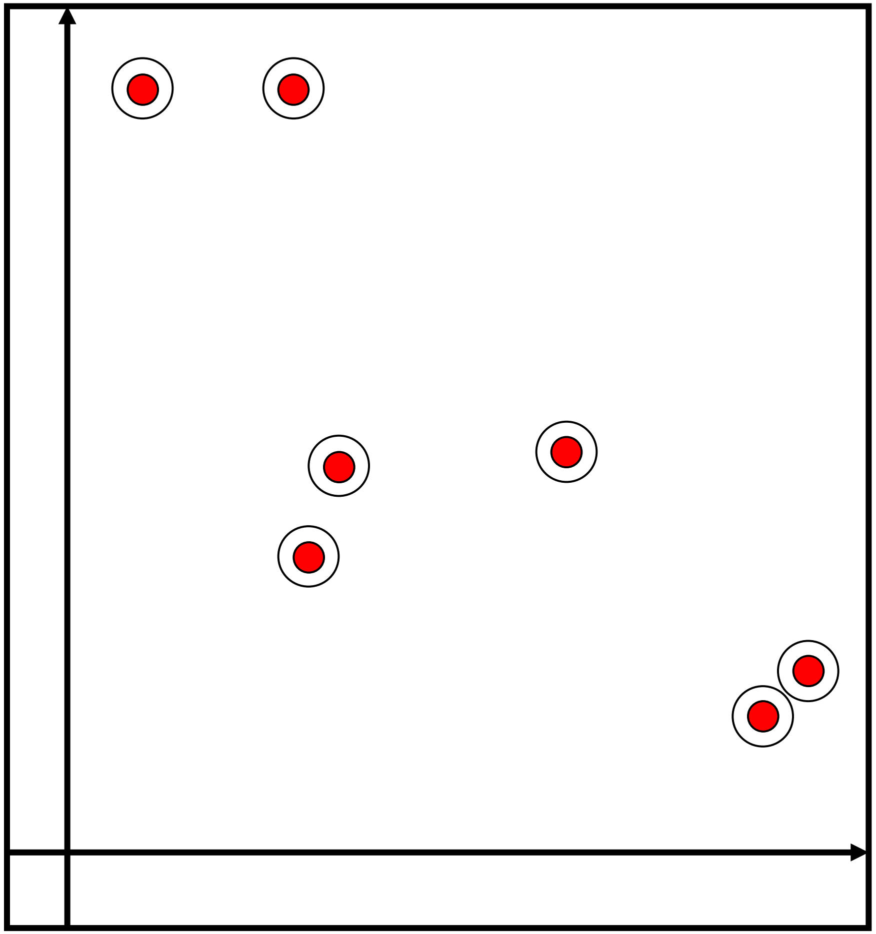

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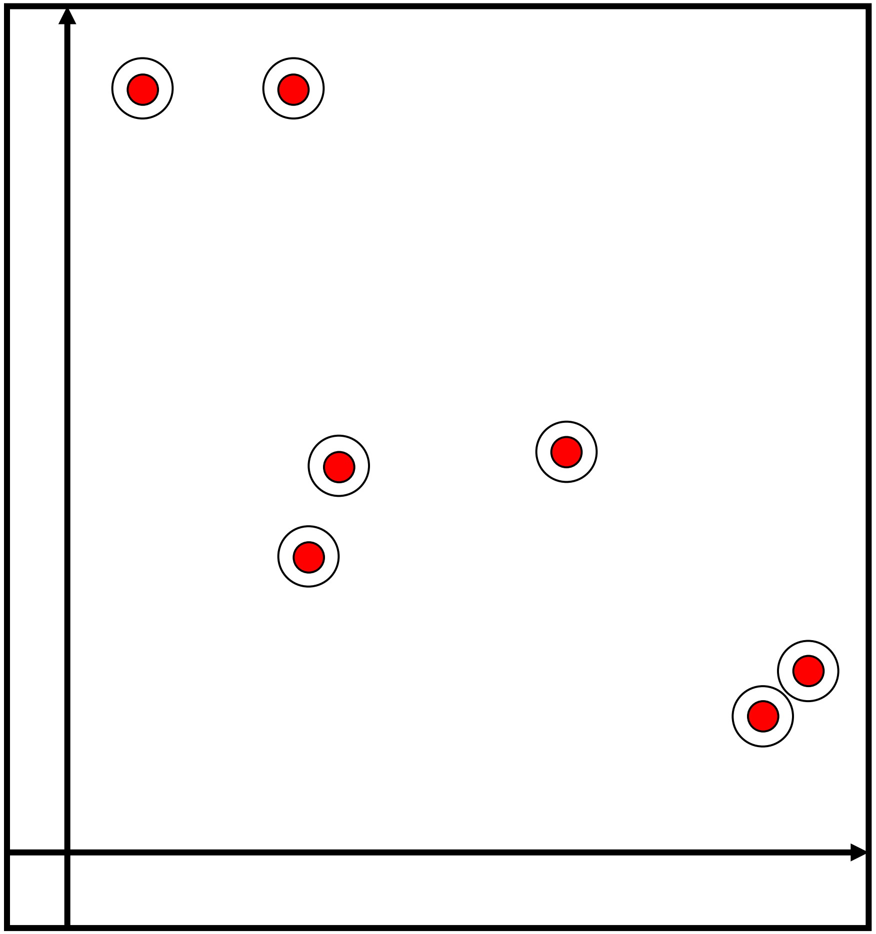

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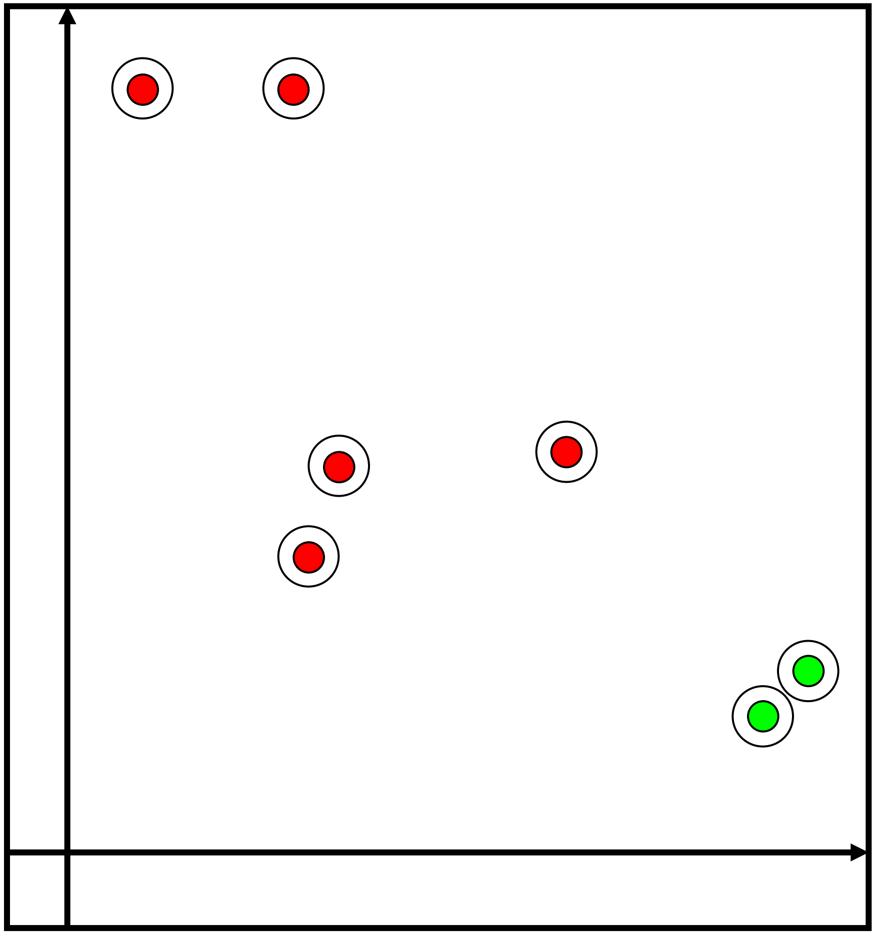

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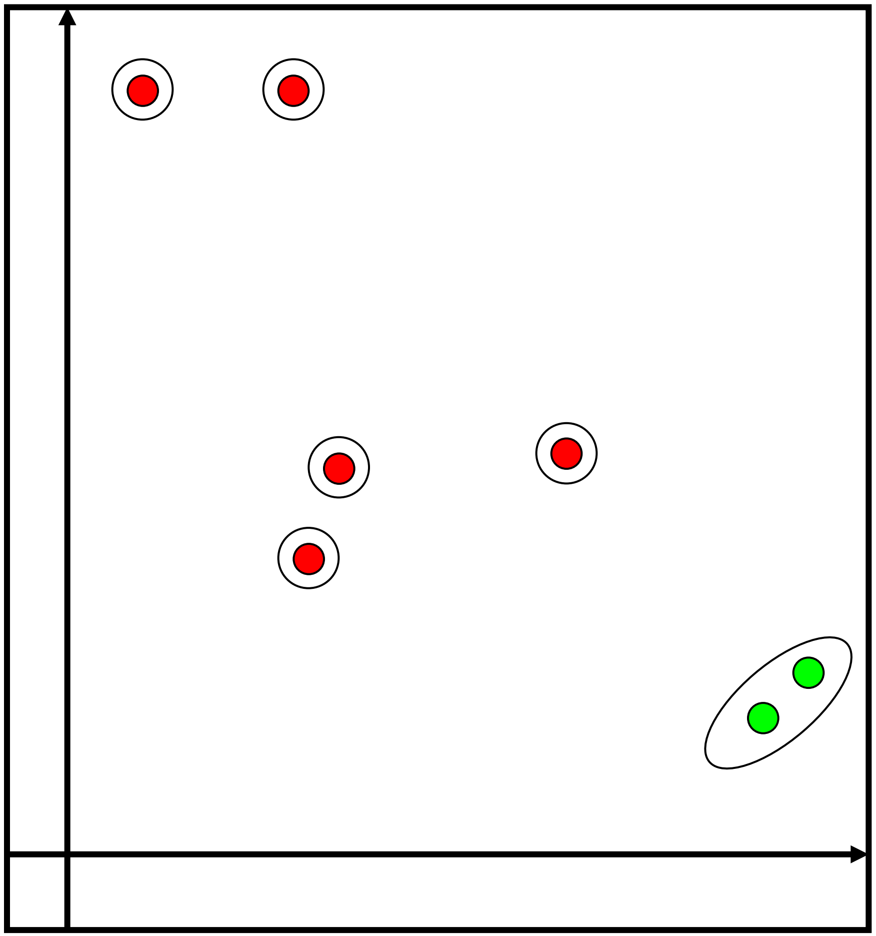
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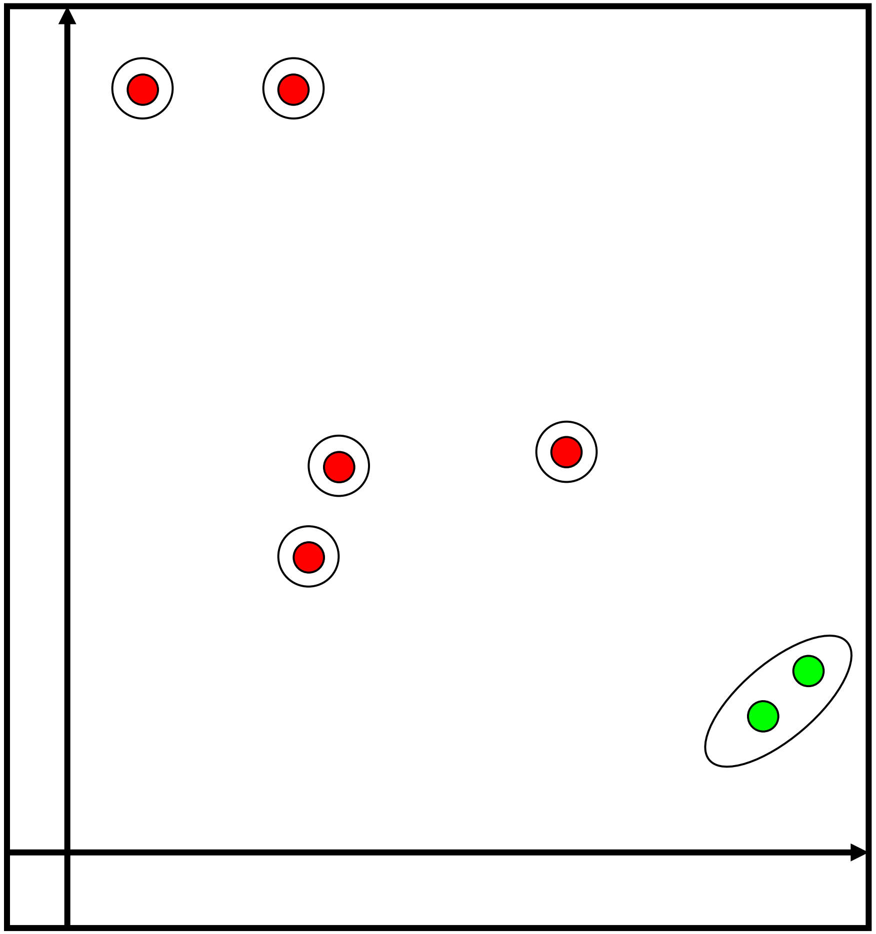

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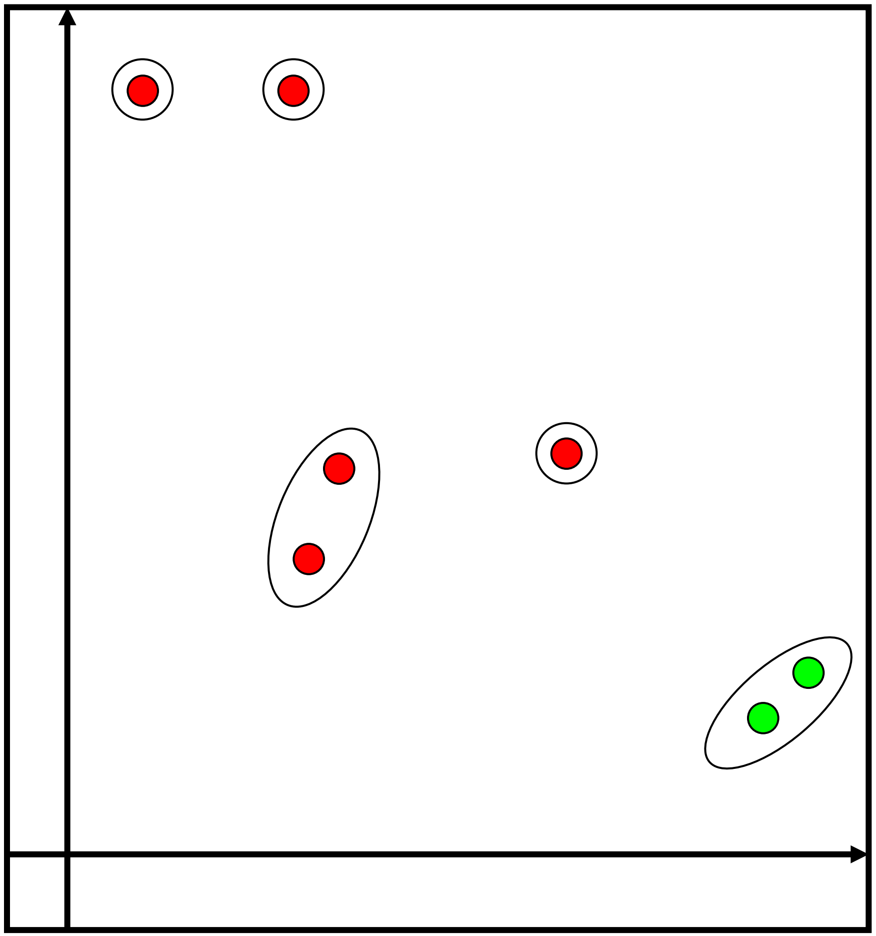

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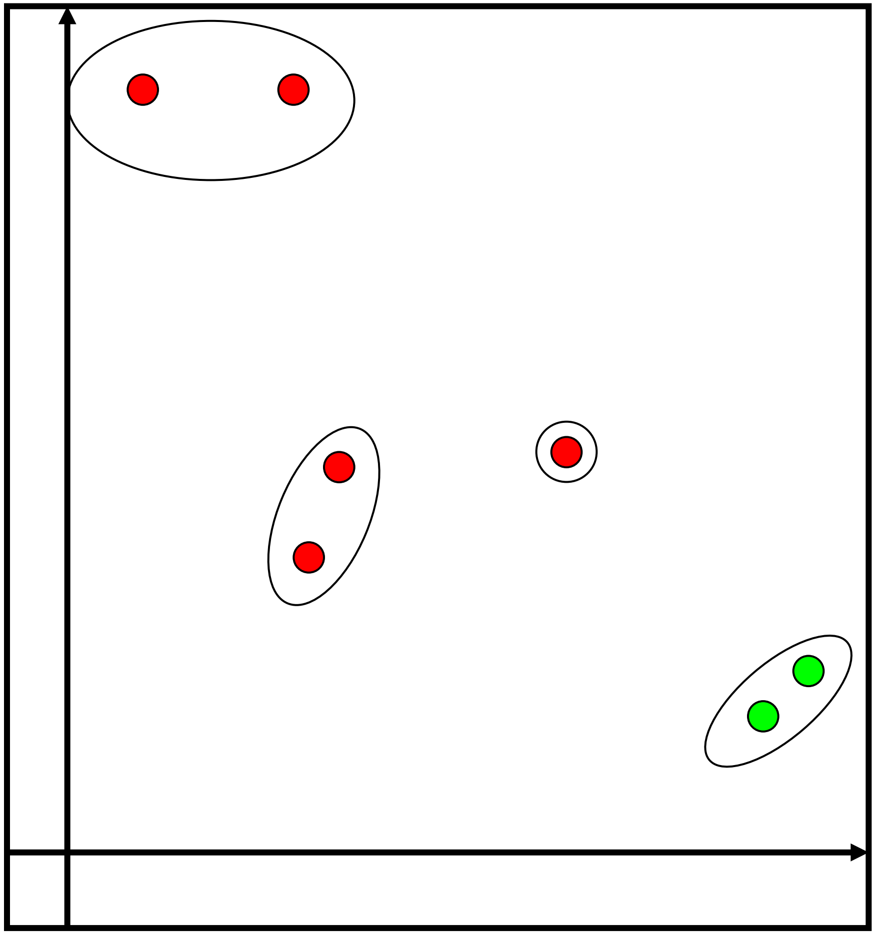

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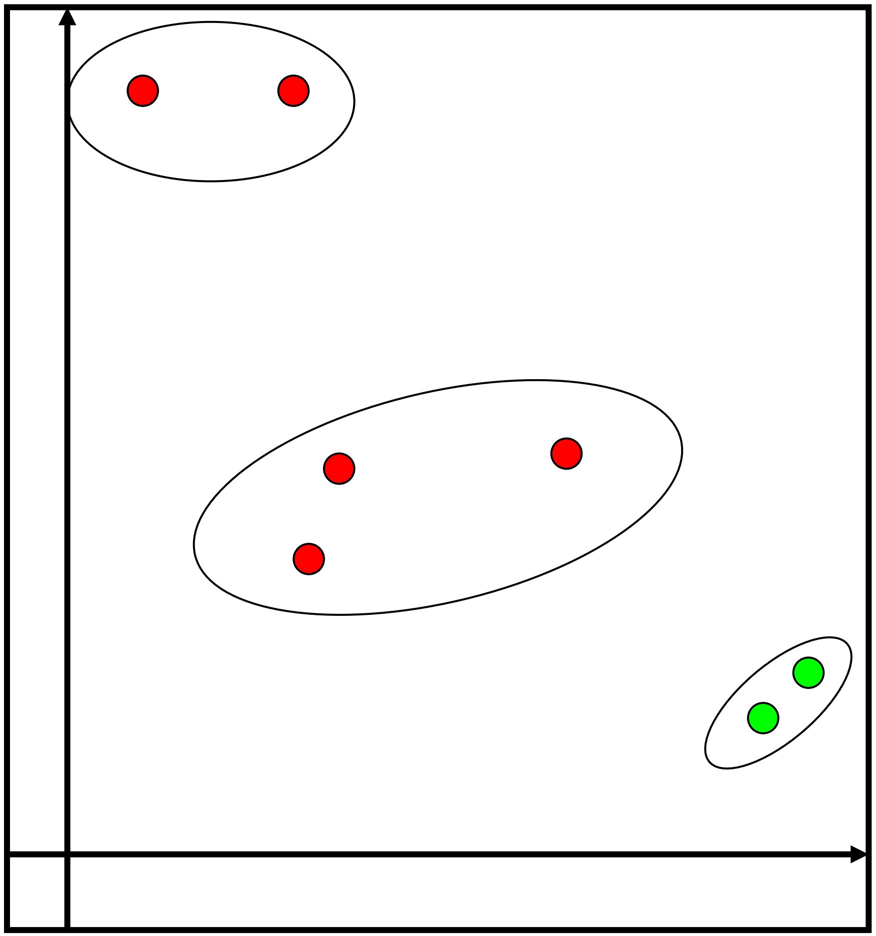

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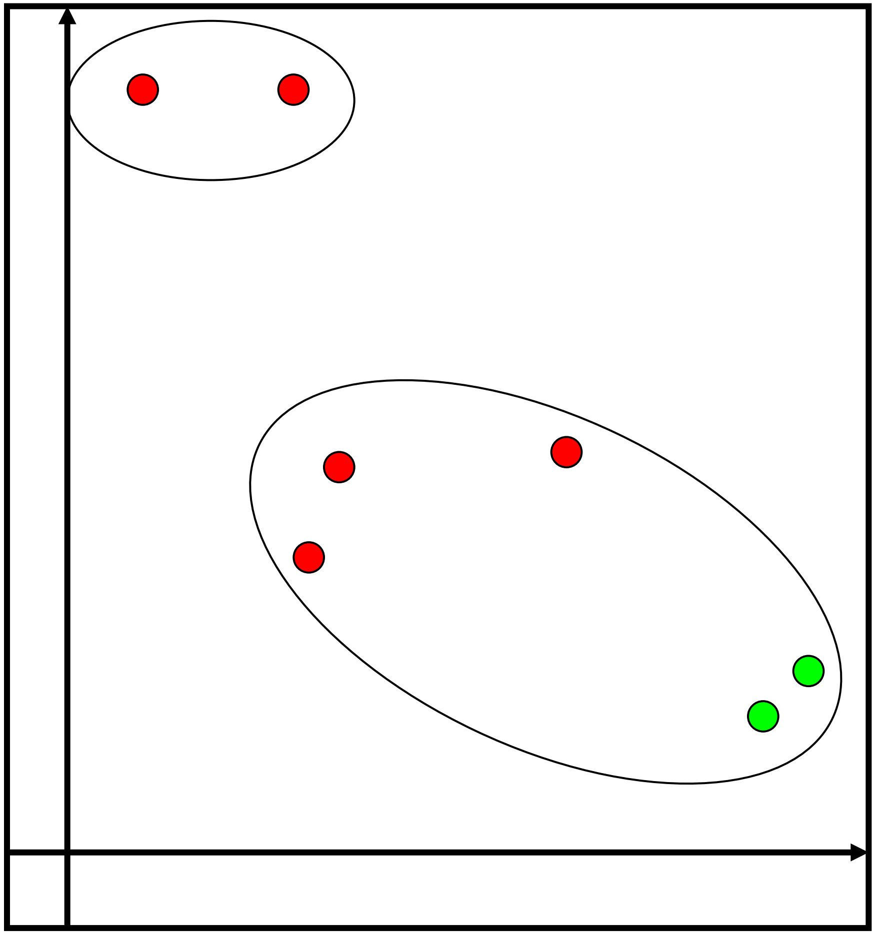

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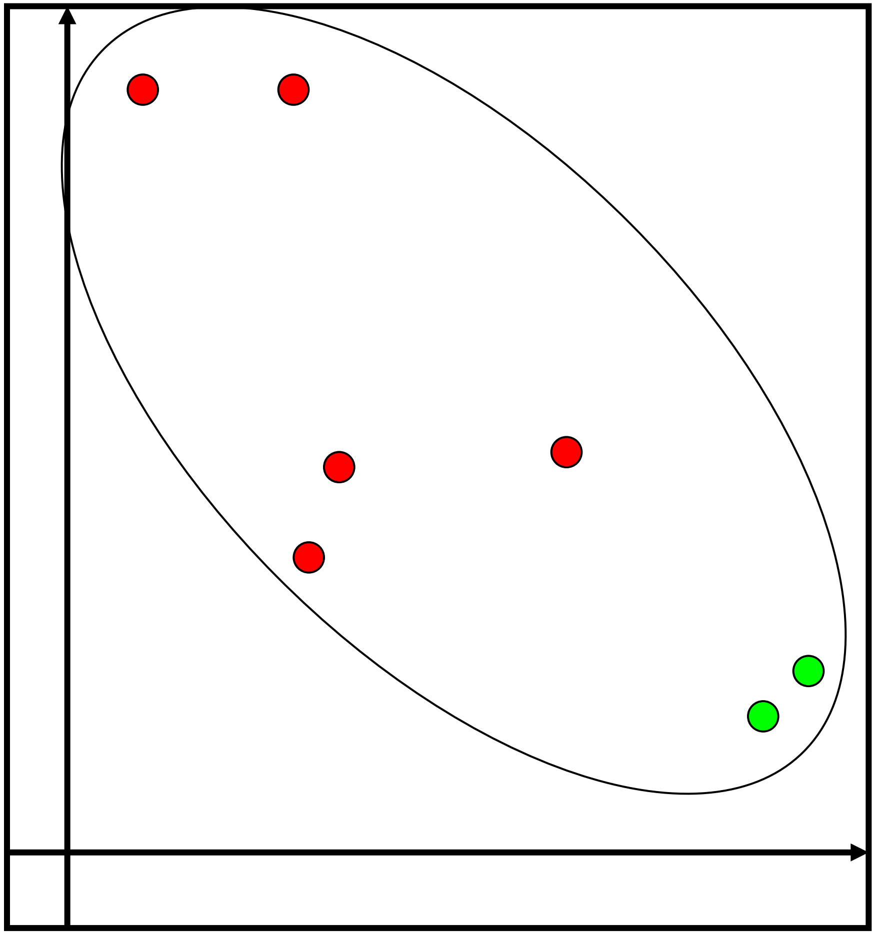

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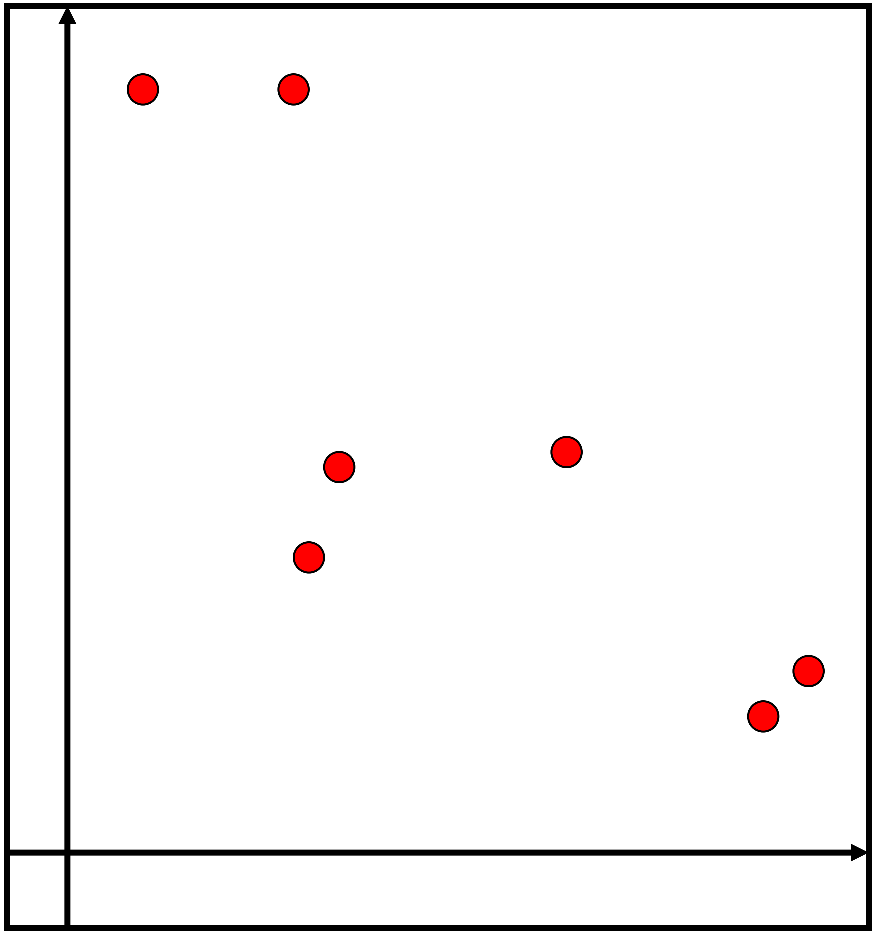

Single Link

1. Find max. distance between objects
2. Split those clusters
3. Repeat 1. and 2. until we have clusters which contain just one object

adapted from [3]

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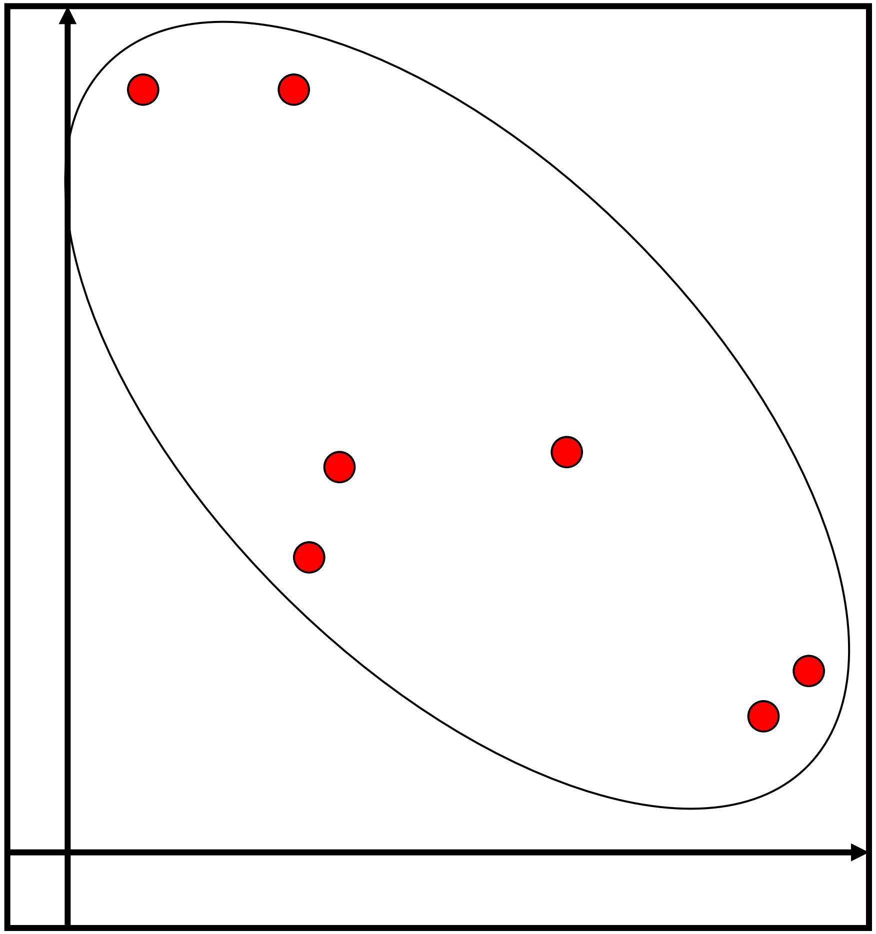

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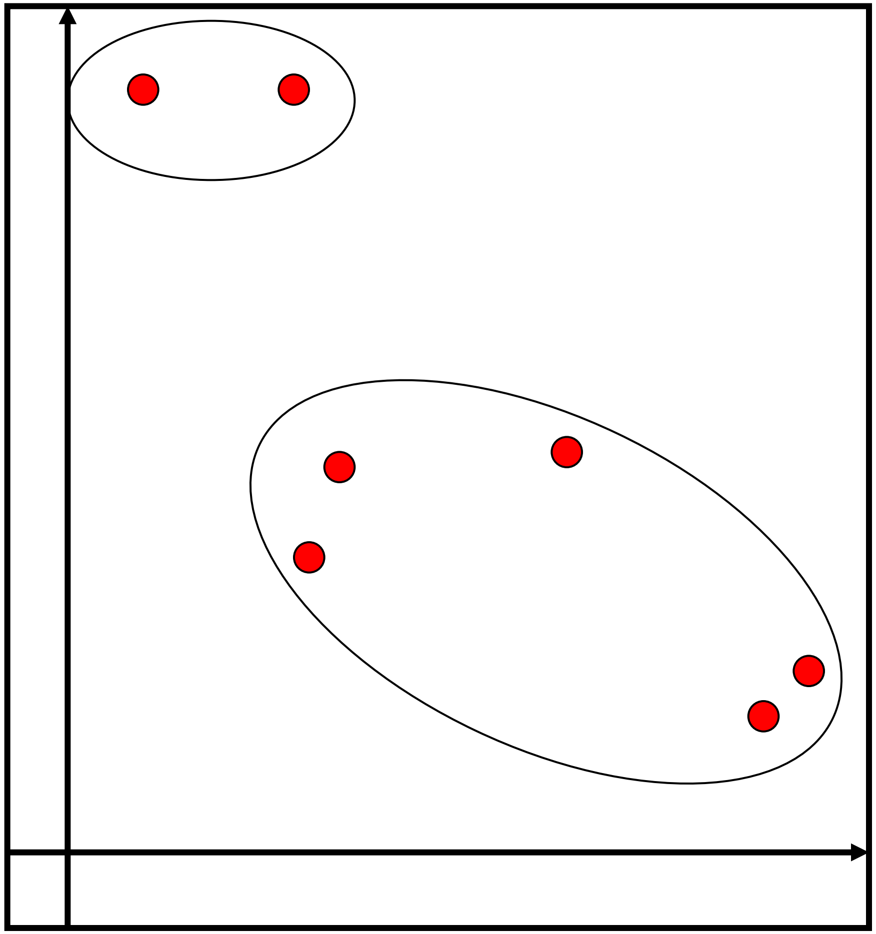

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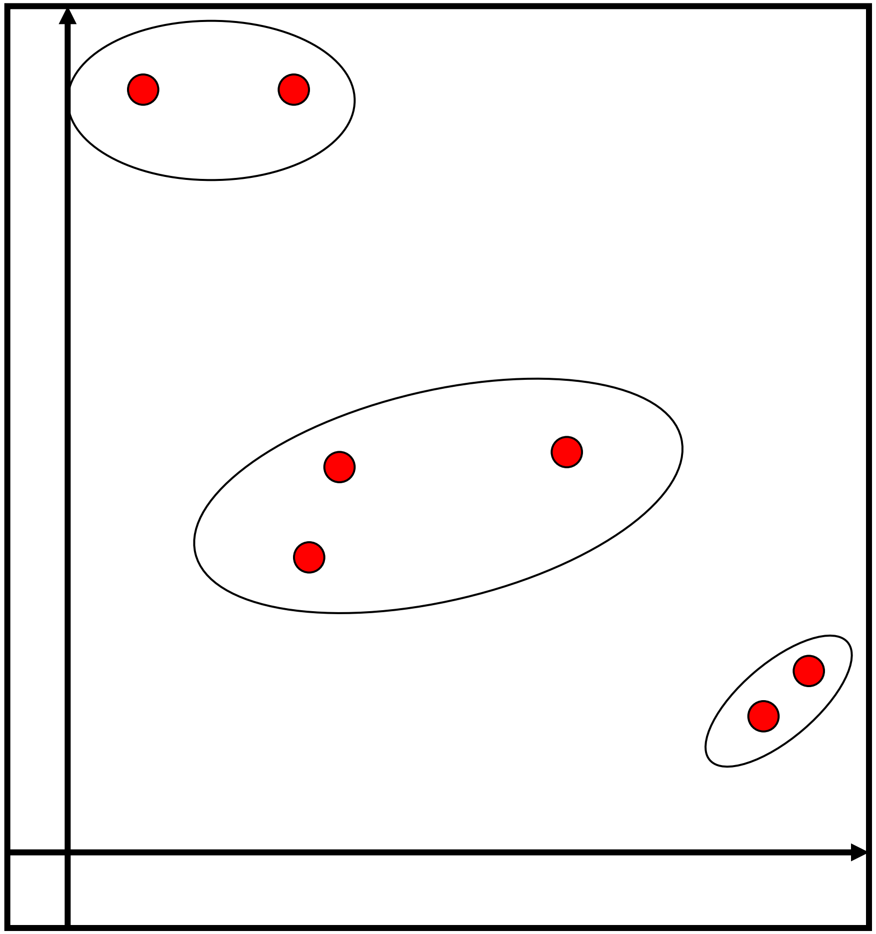

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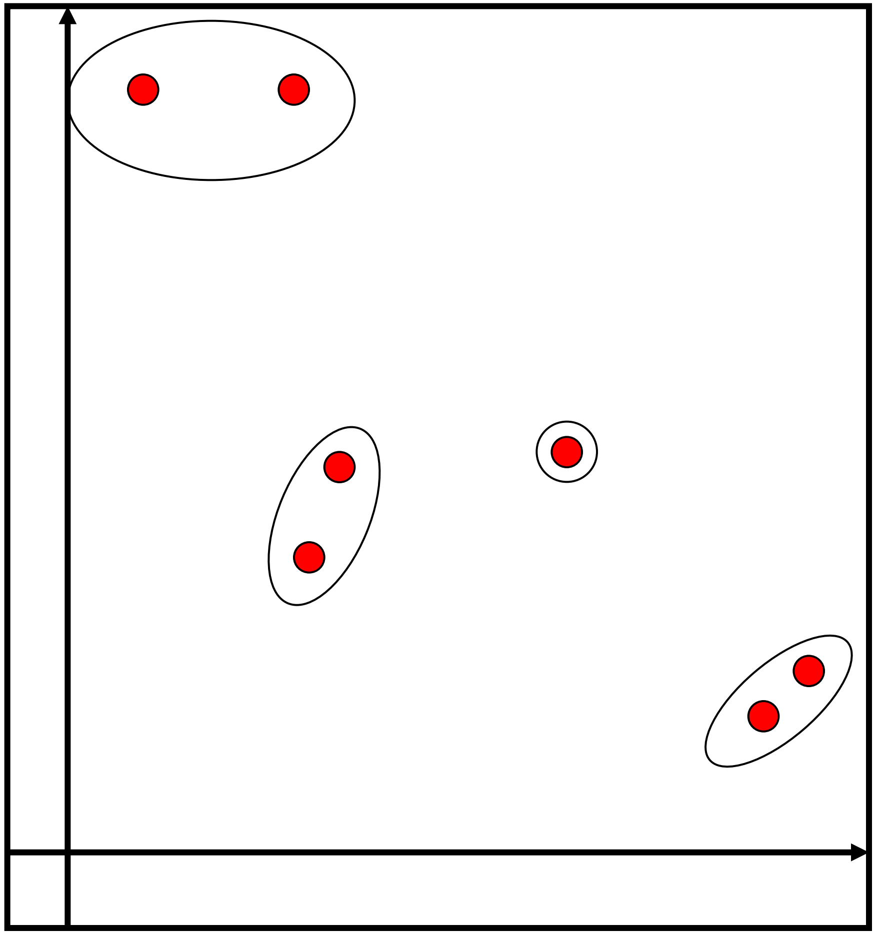

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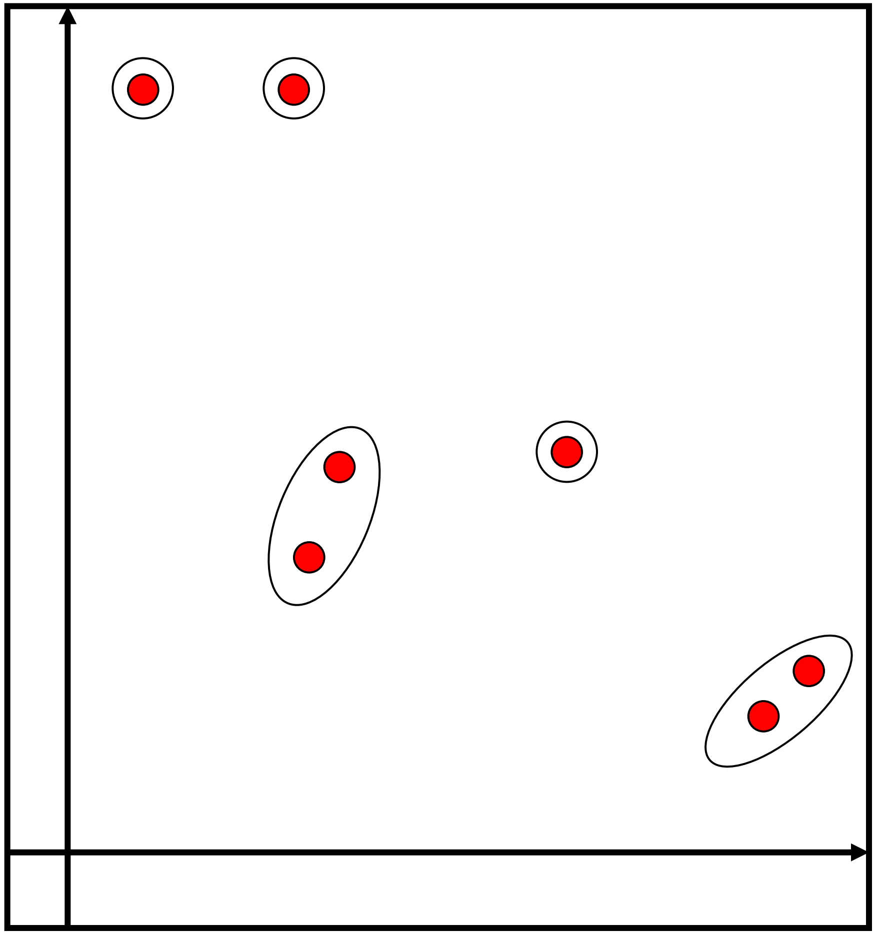

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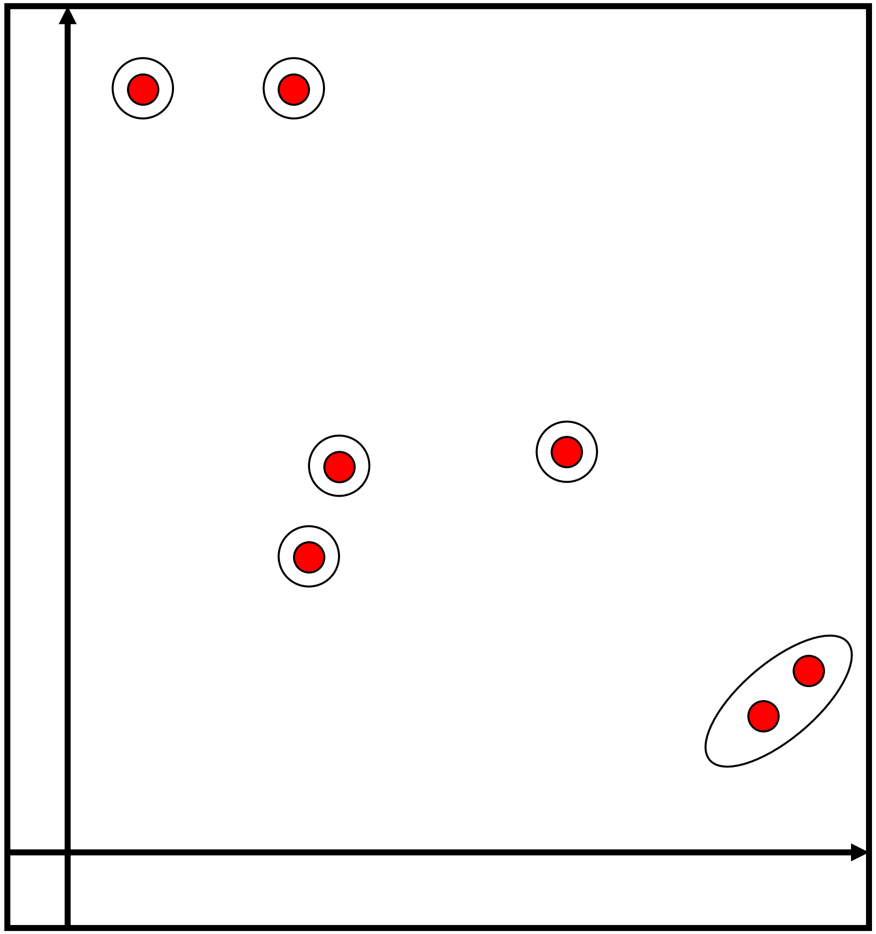

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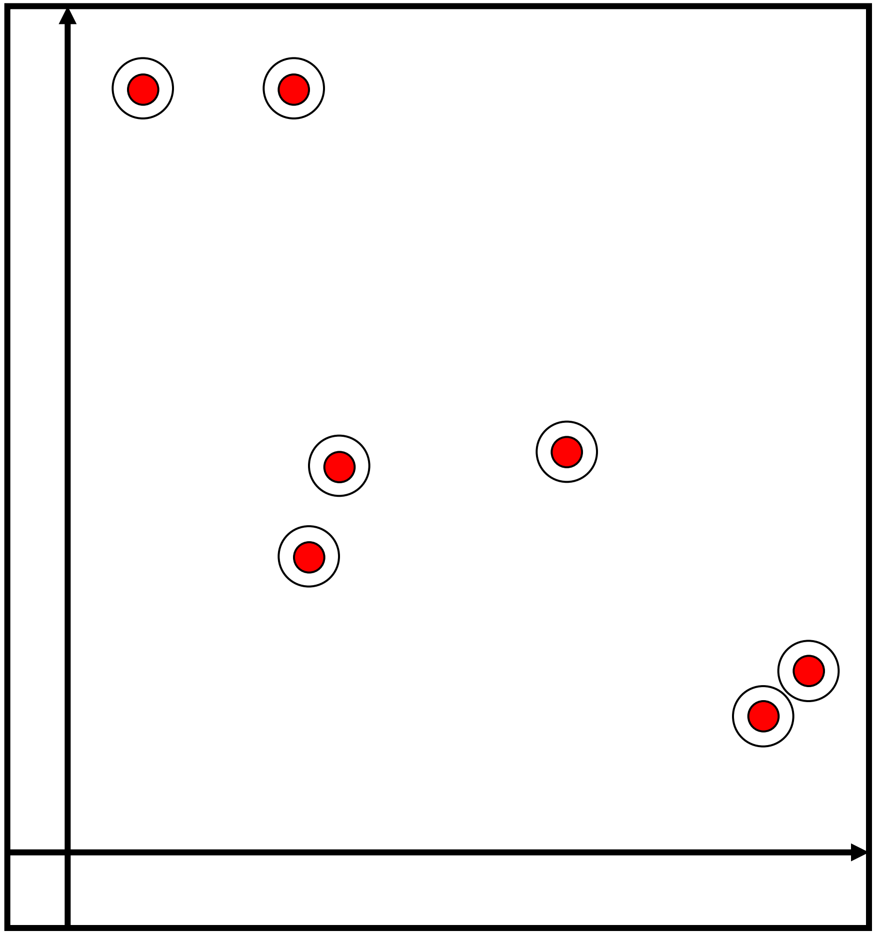

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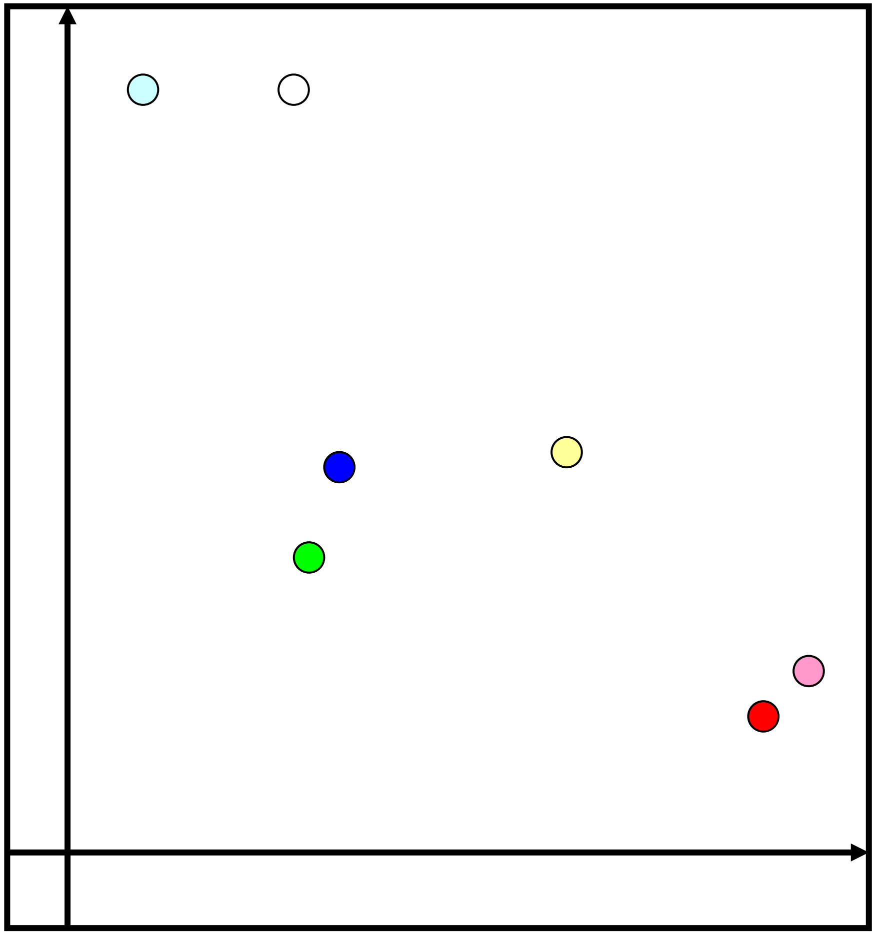
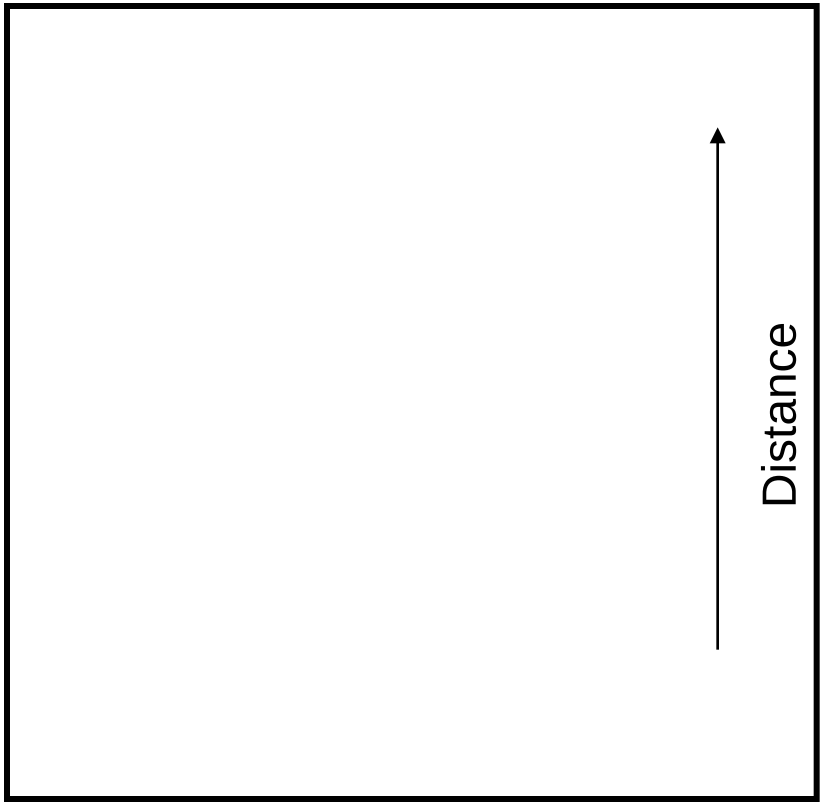
Cluster Visualization



Dendrogram



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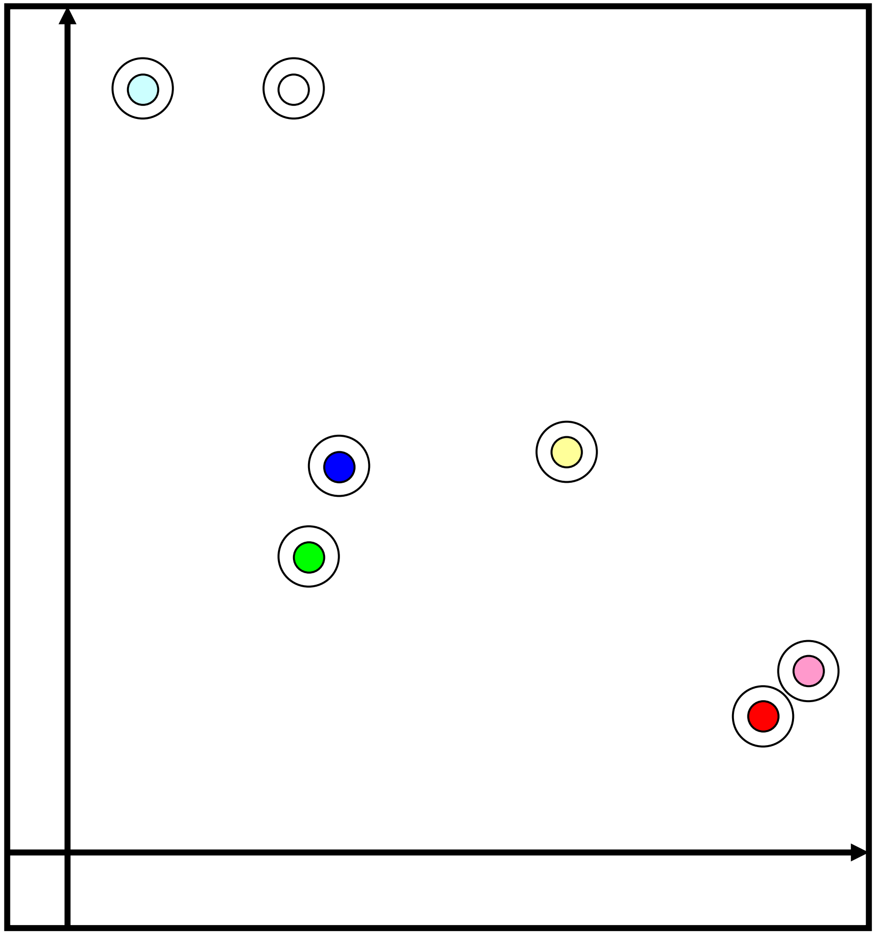

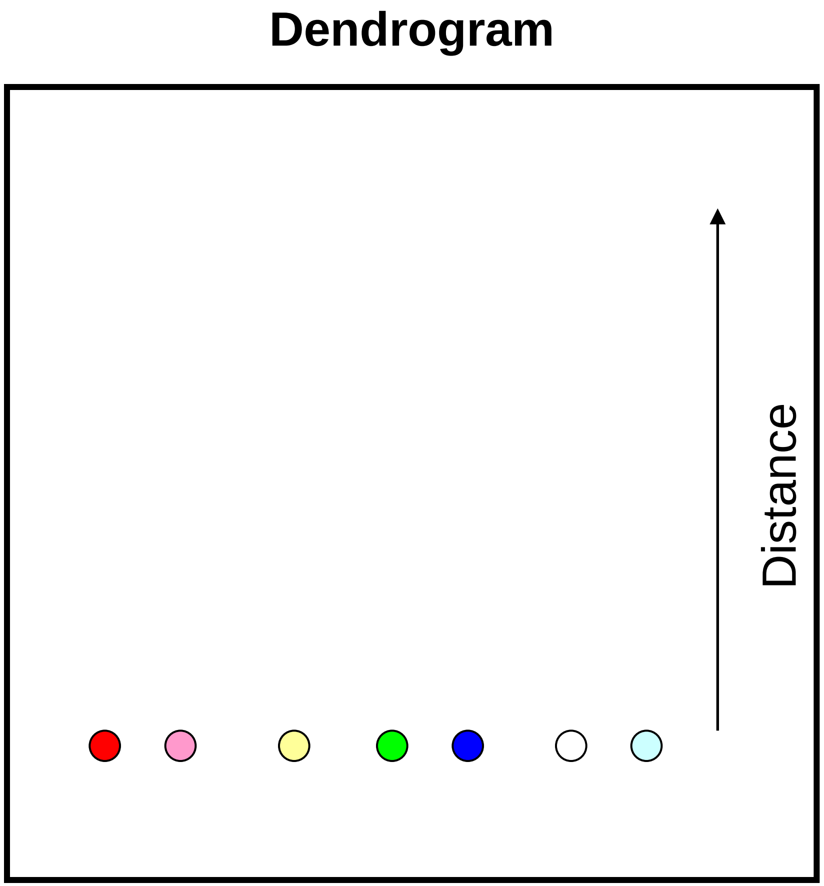

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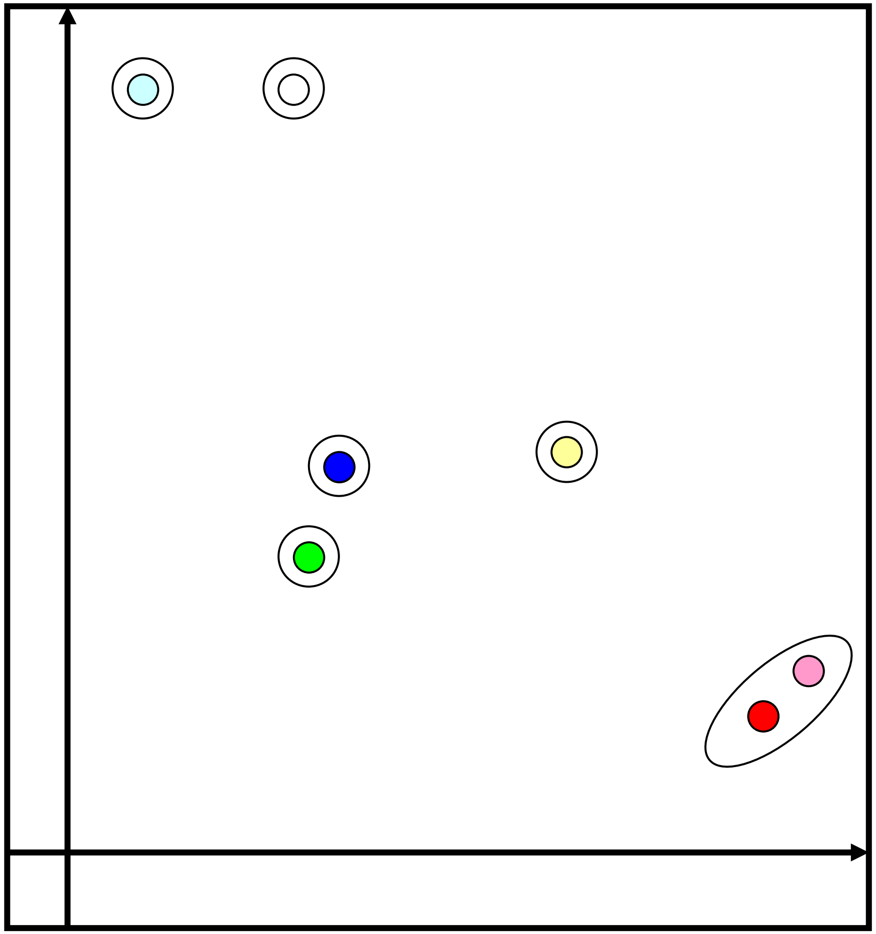
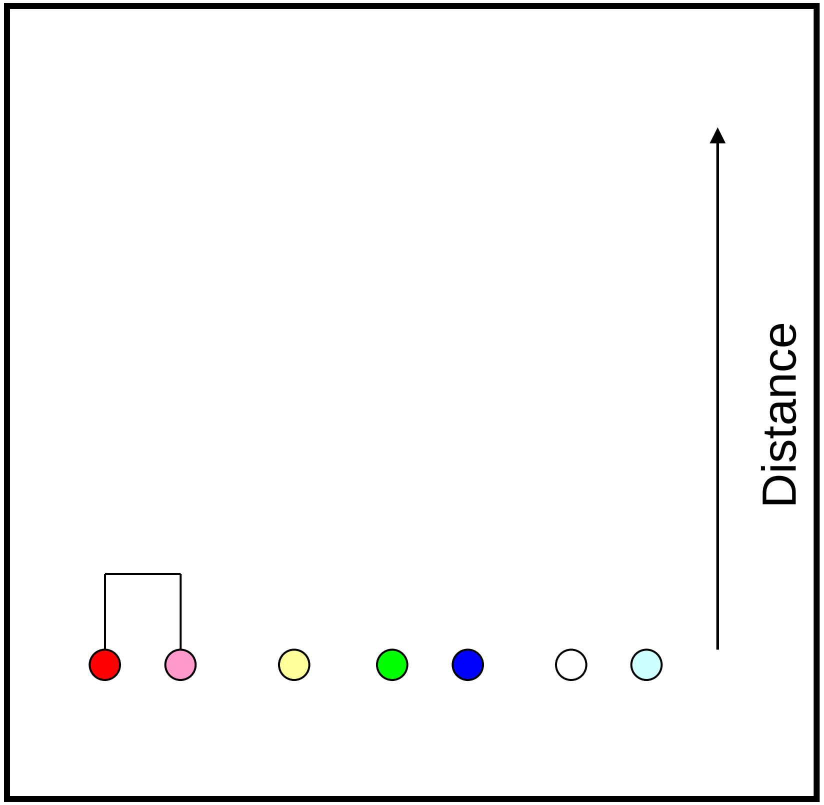


Dendrogram



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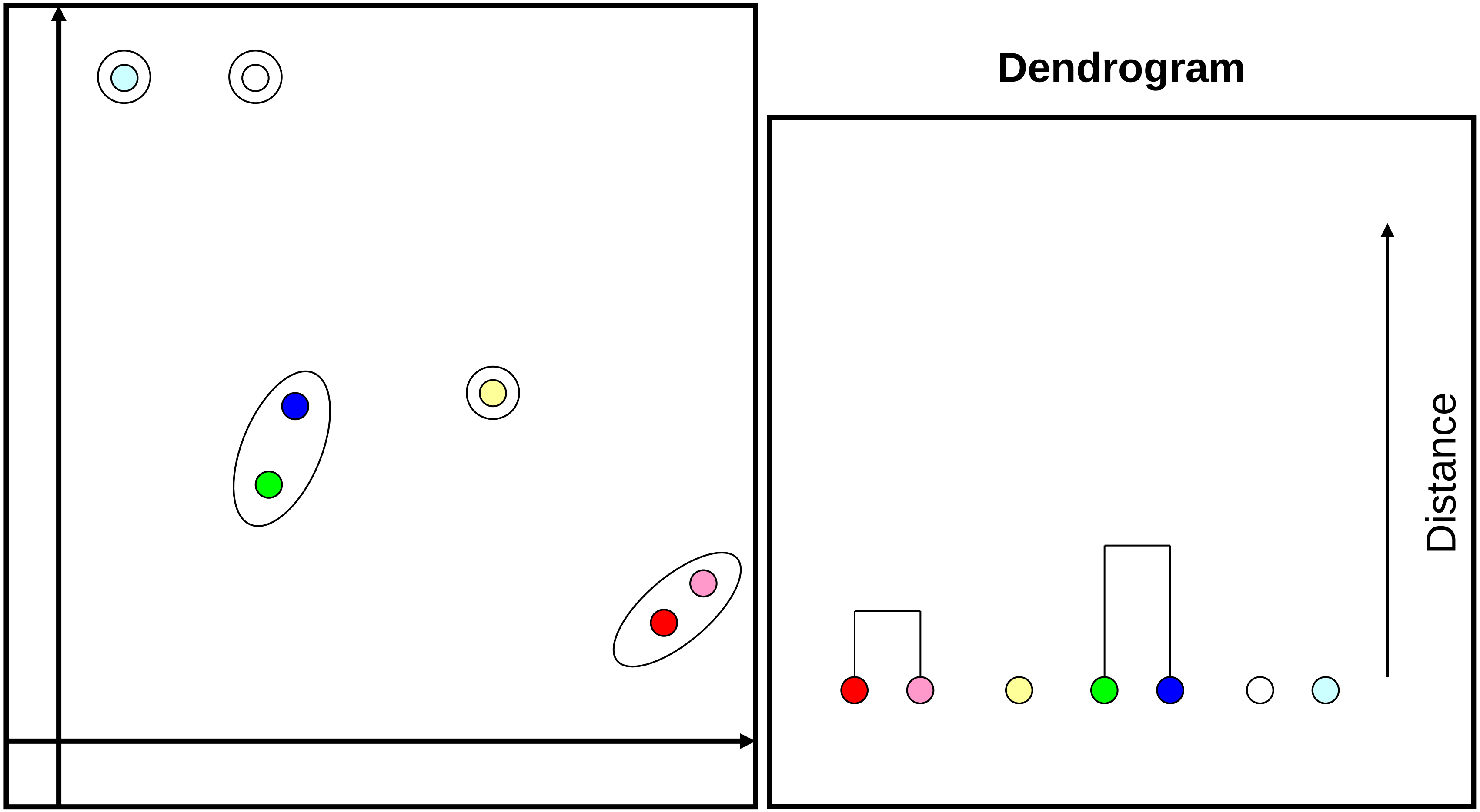

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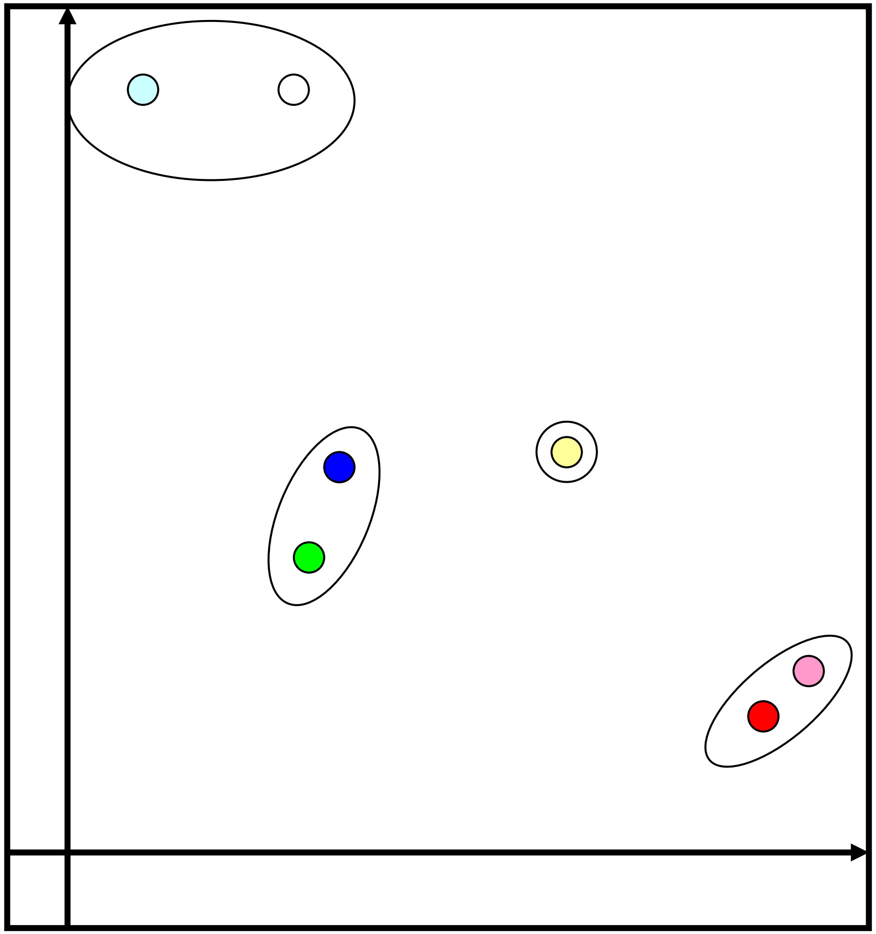

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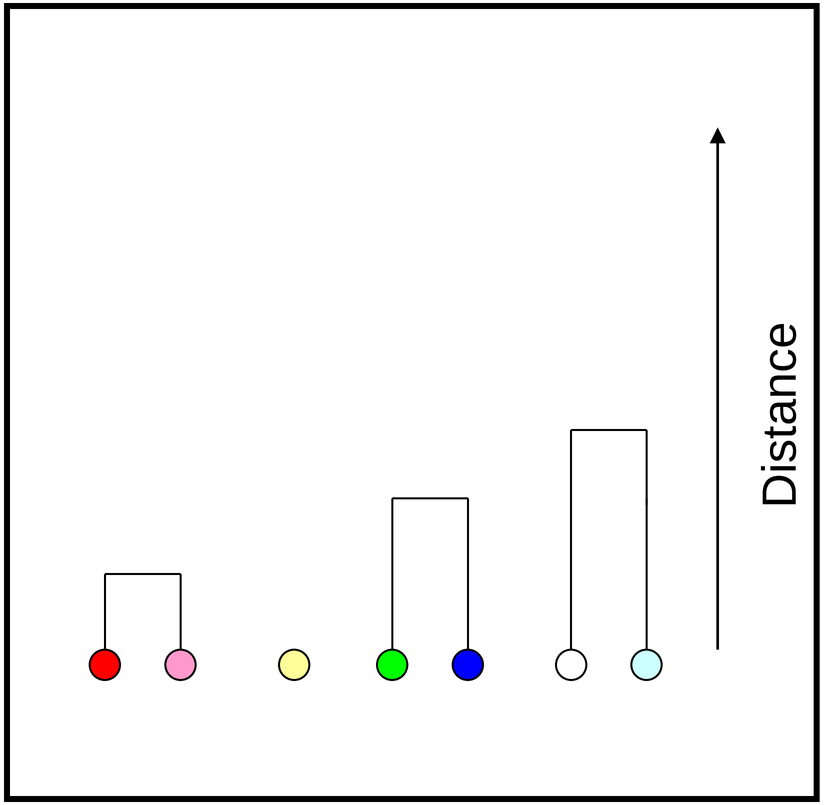

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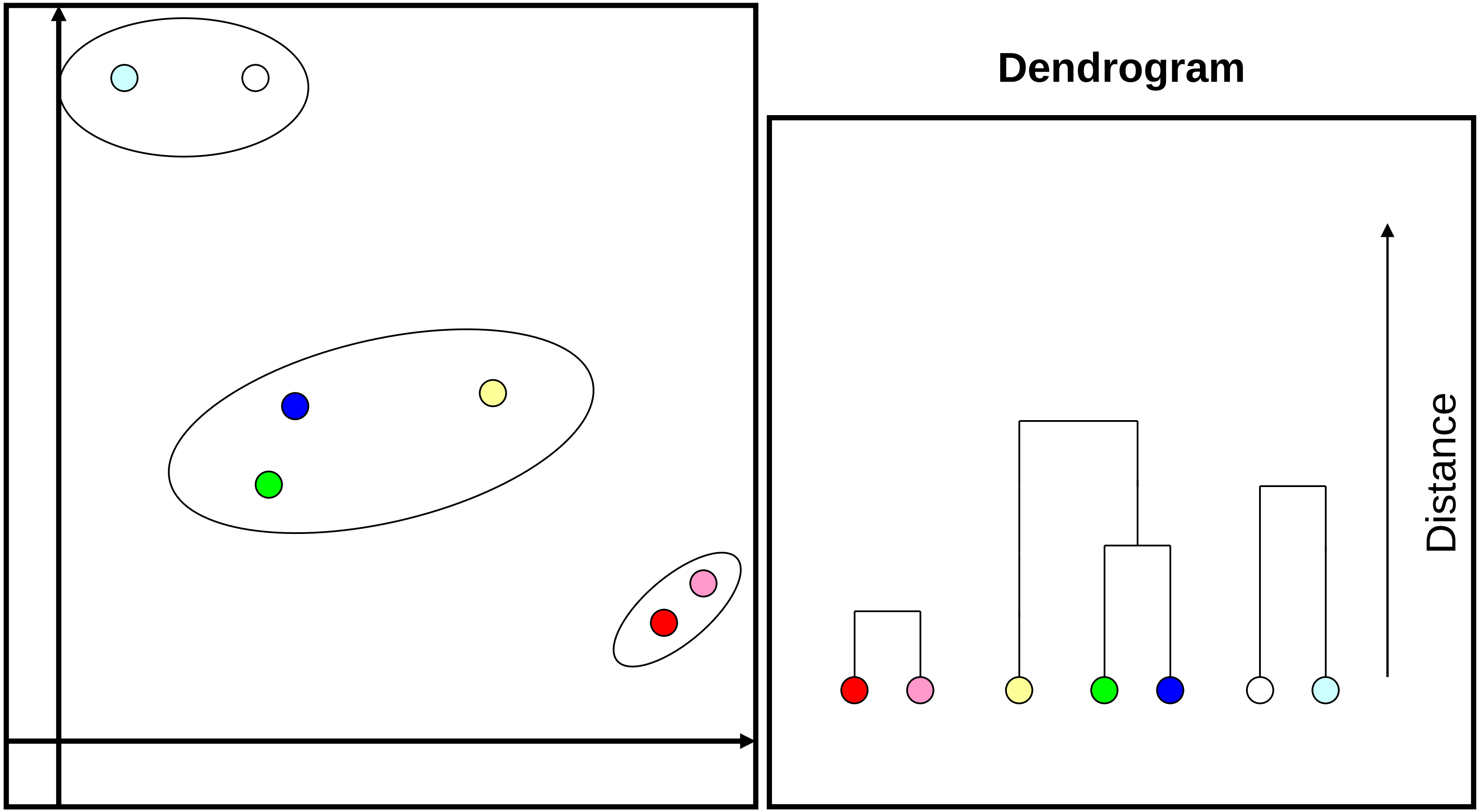

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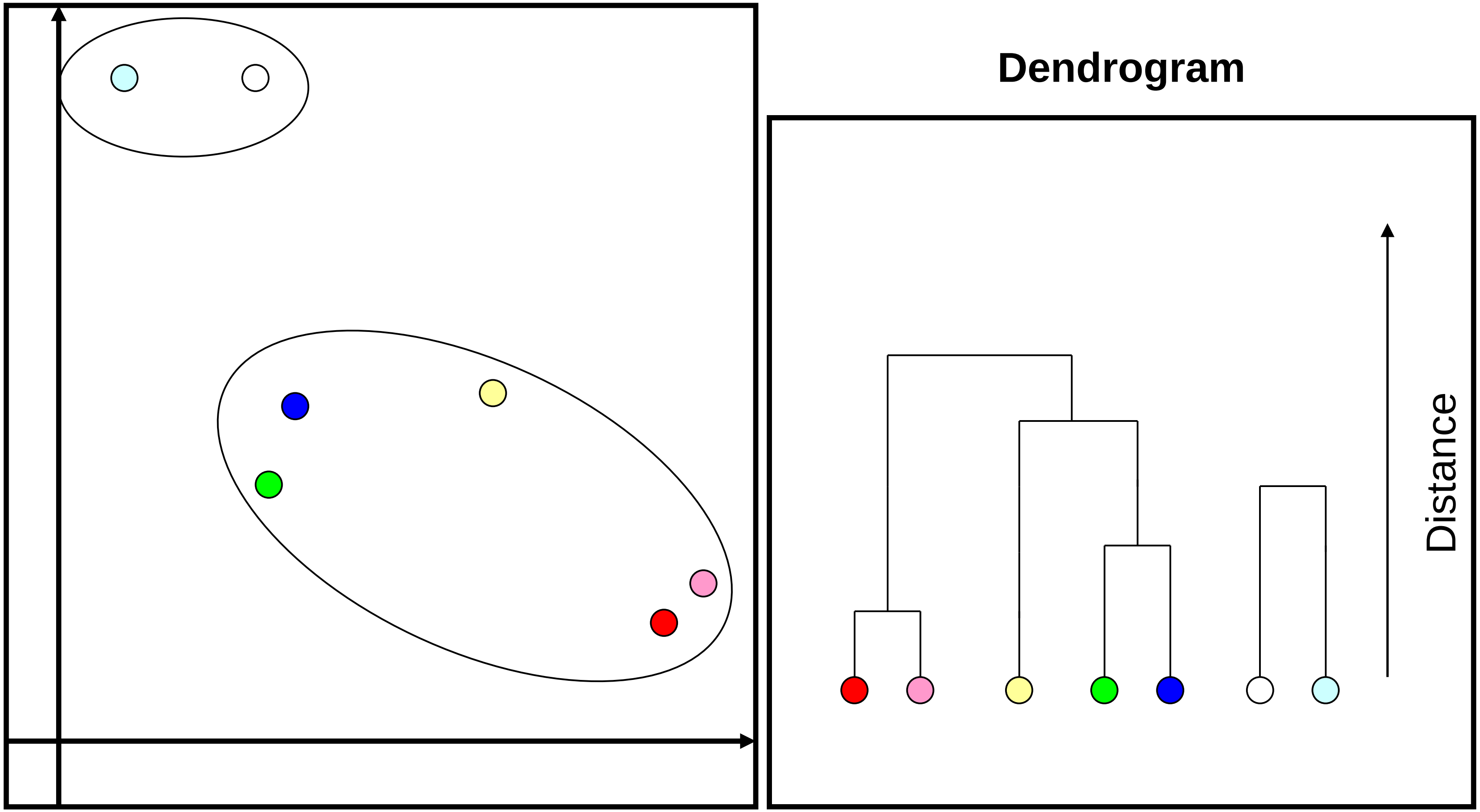

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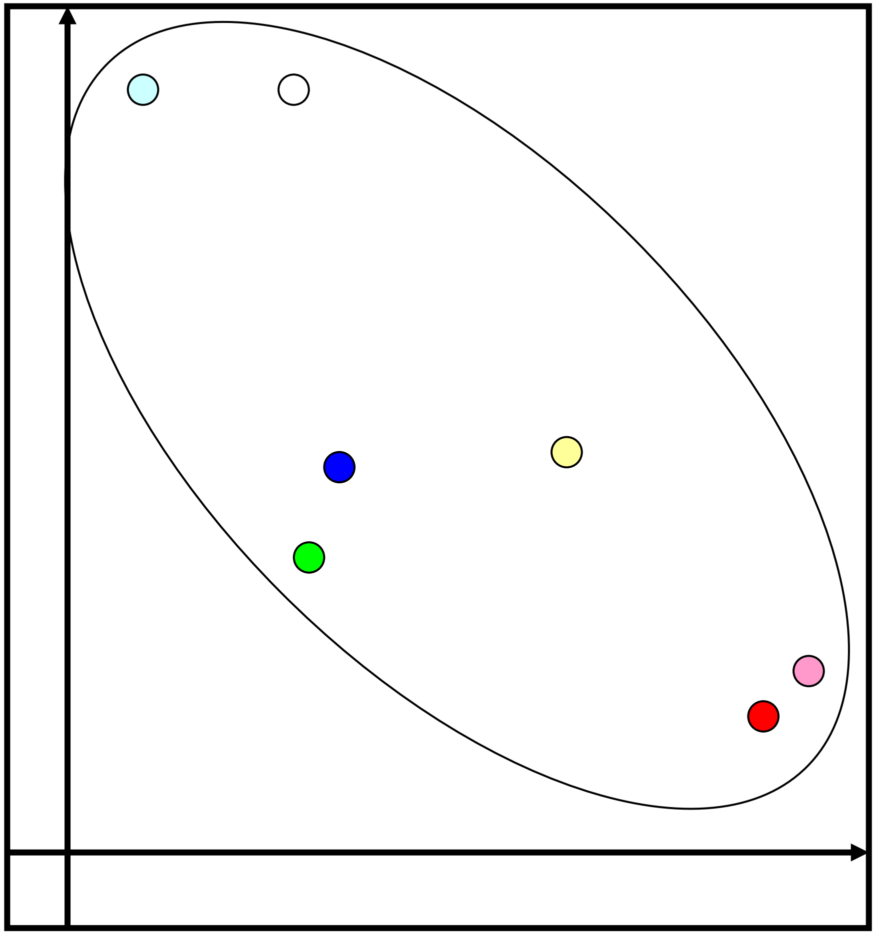

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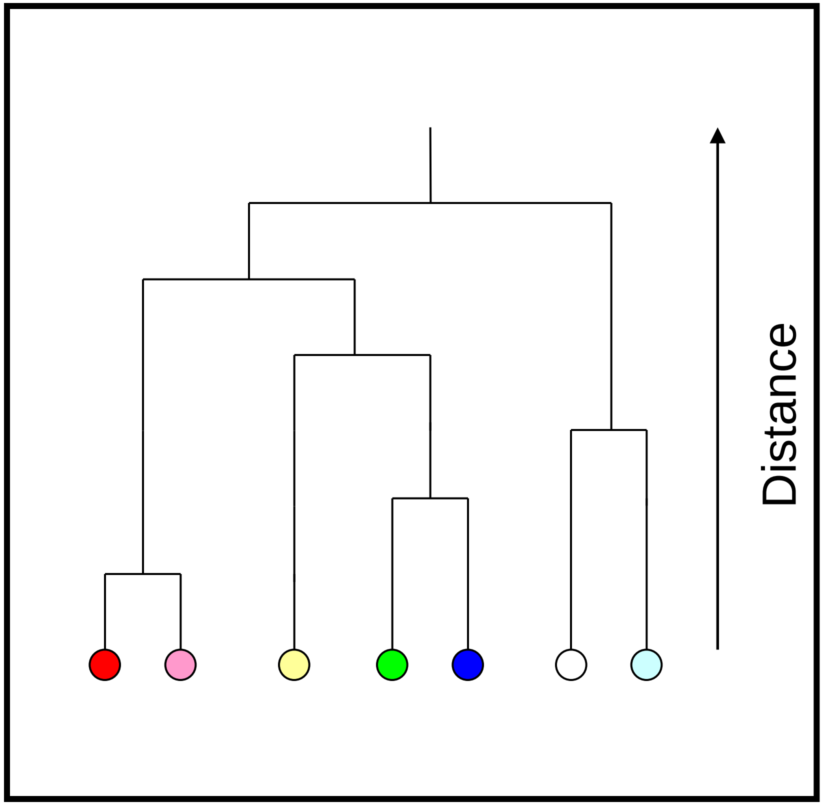

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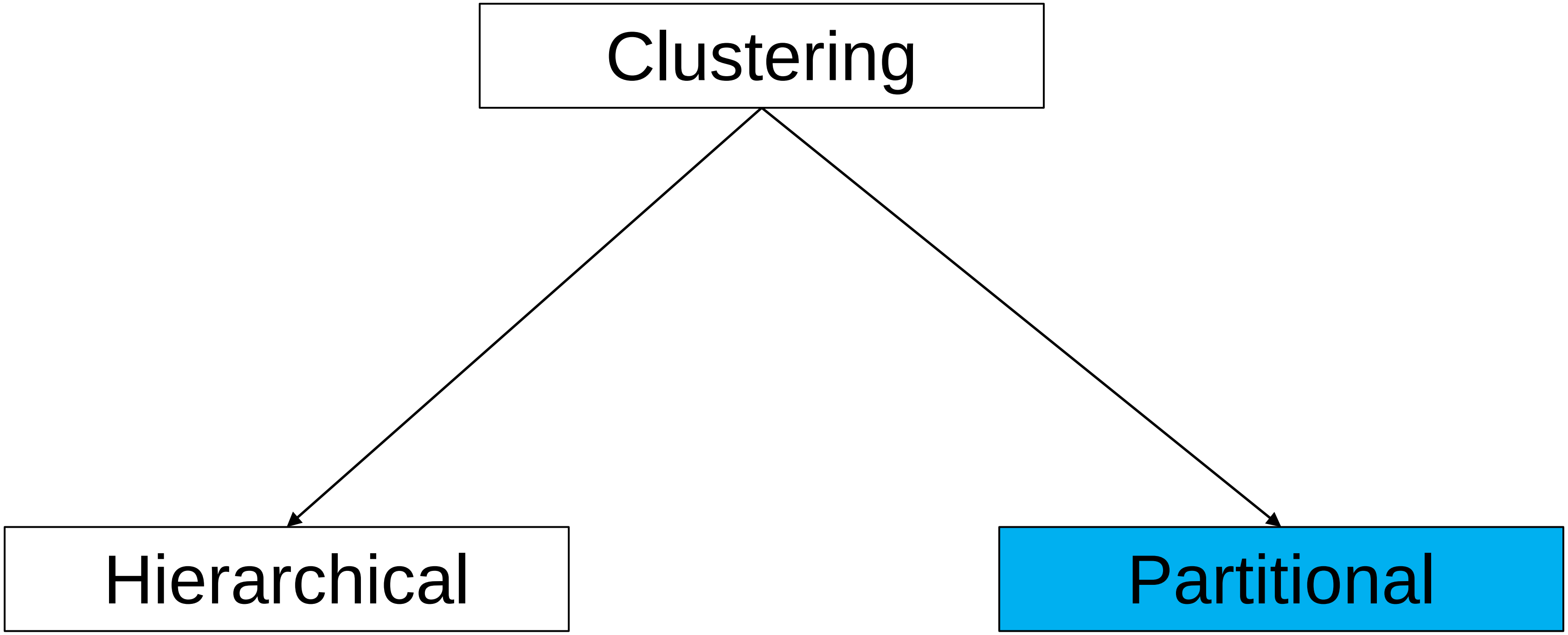
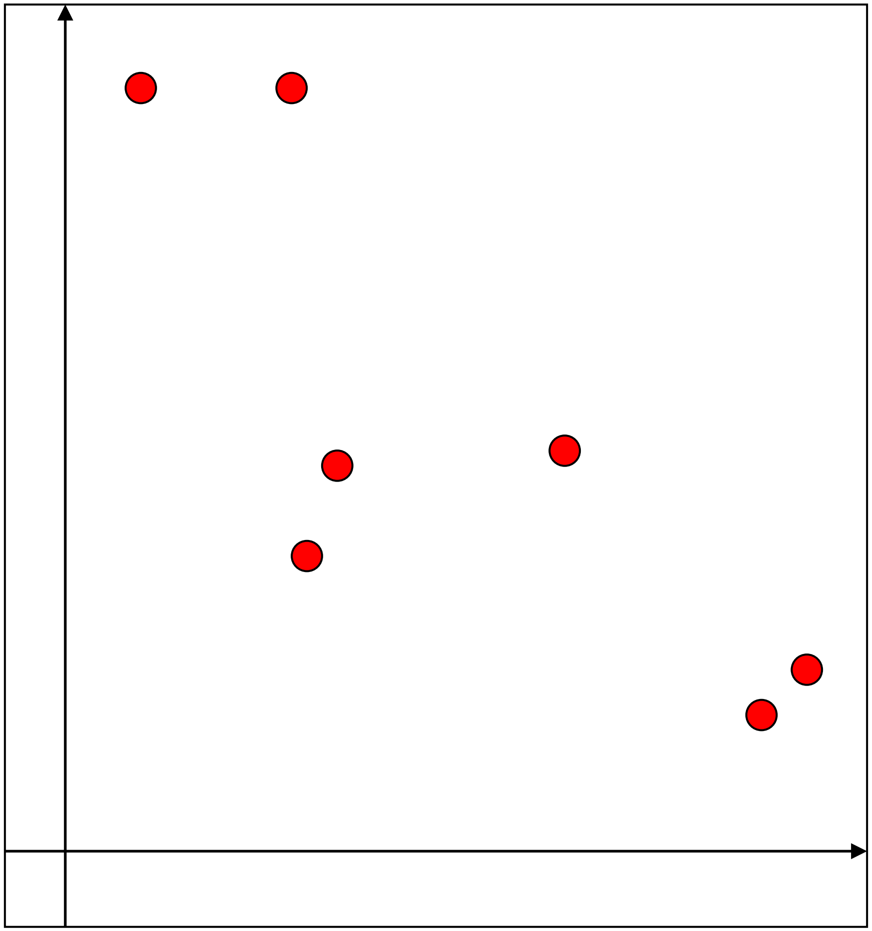
Clustering approches



adapted from [4]

K-Means

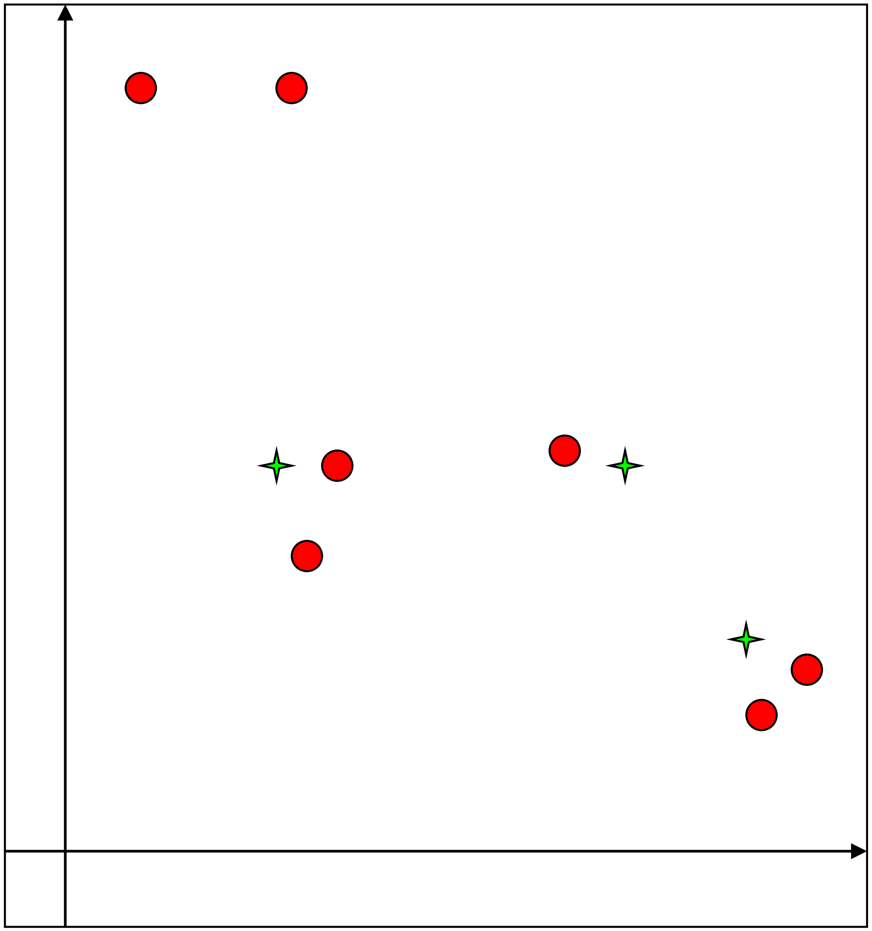


k=3

1. Place k centroids randomly
2. If distance to centroid min. merge to cluster
3. Move the k centroids to the new cluster center
4. Repeat 2. and 3. until we fulfil the stop criteria

adapted from [3]

K-Means



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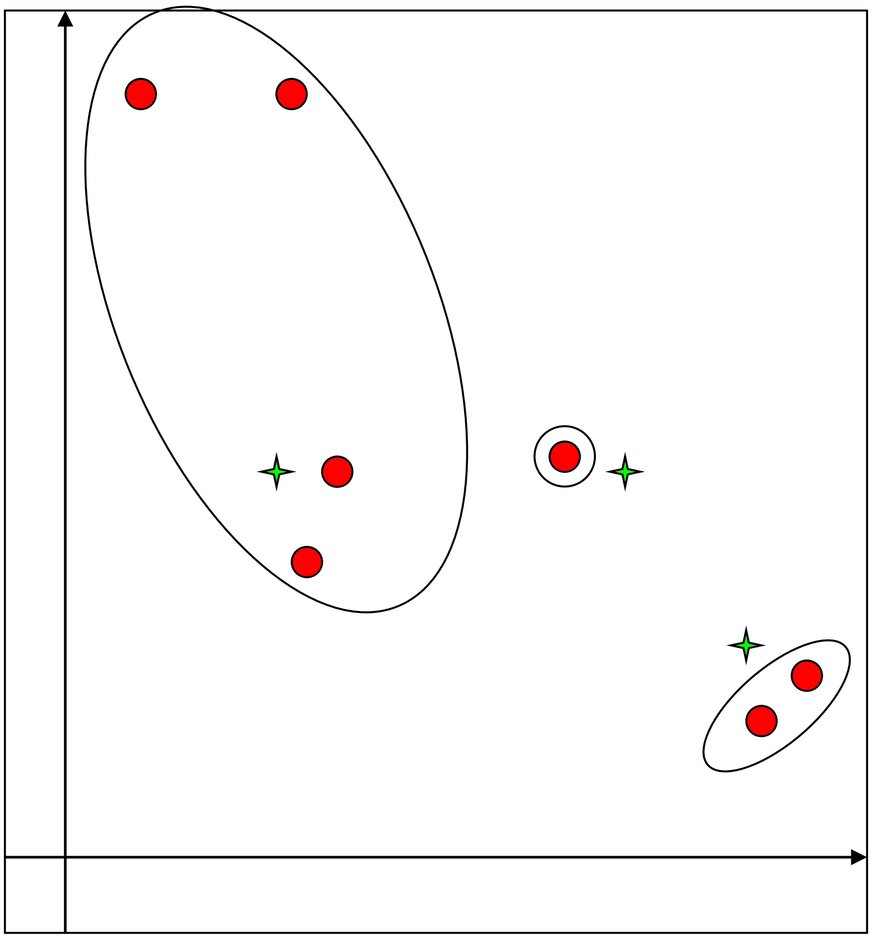

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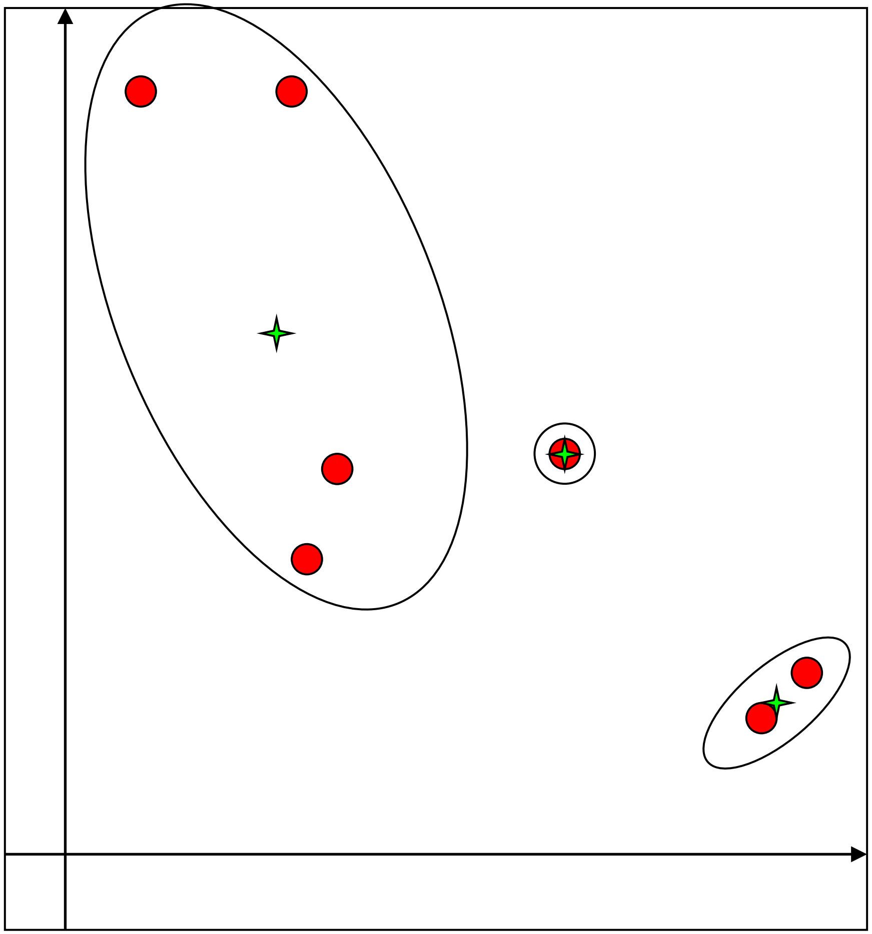

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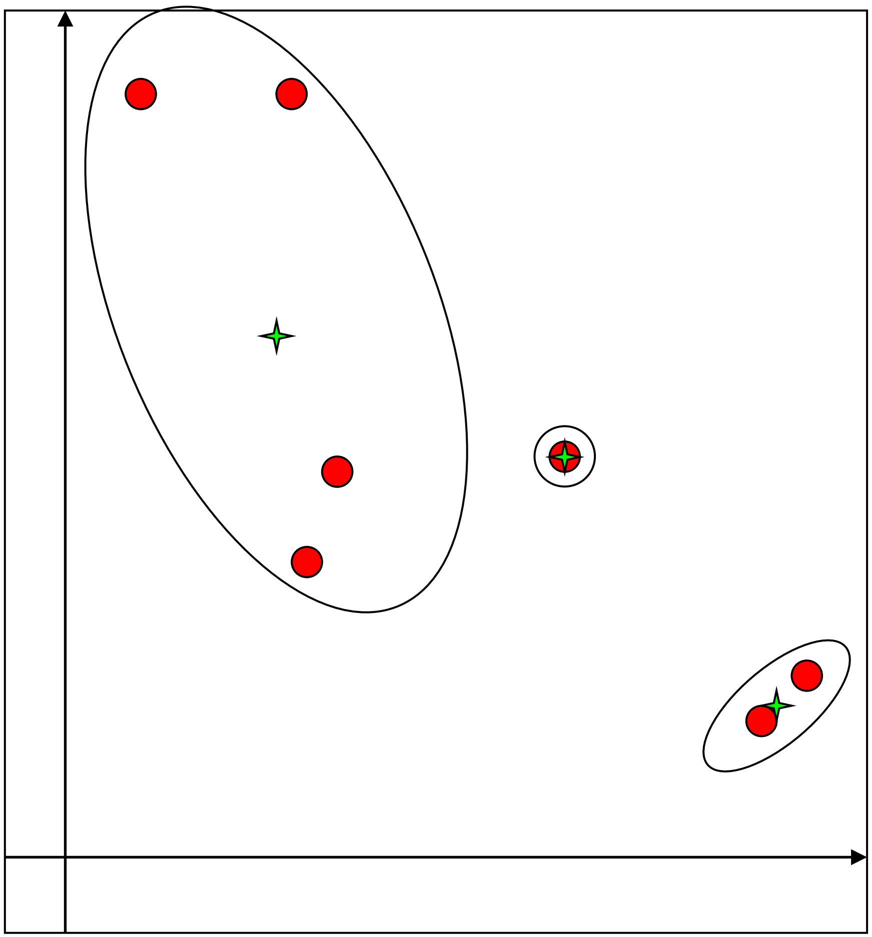

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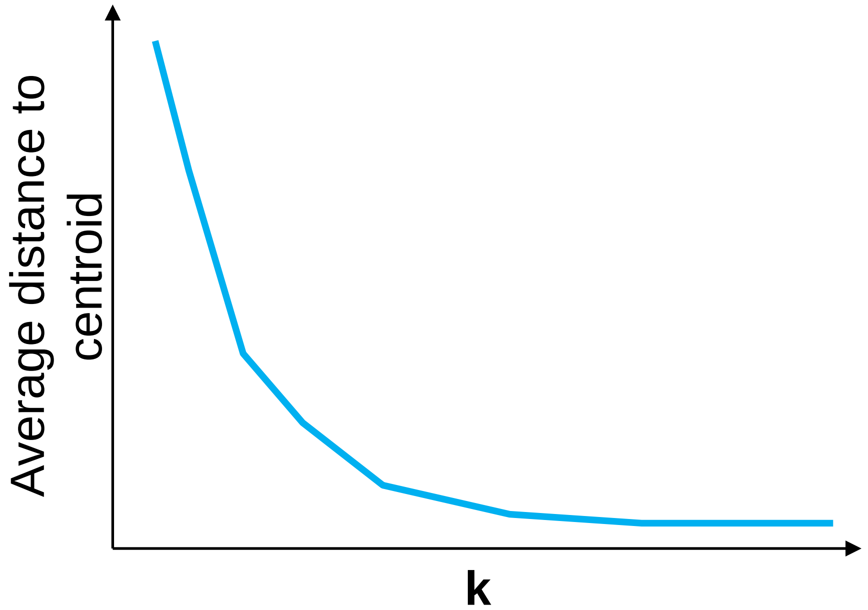
adapted from [3]

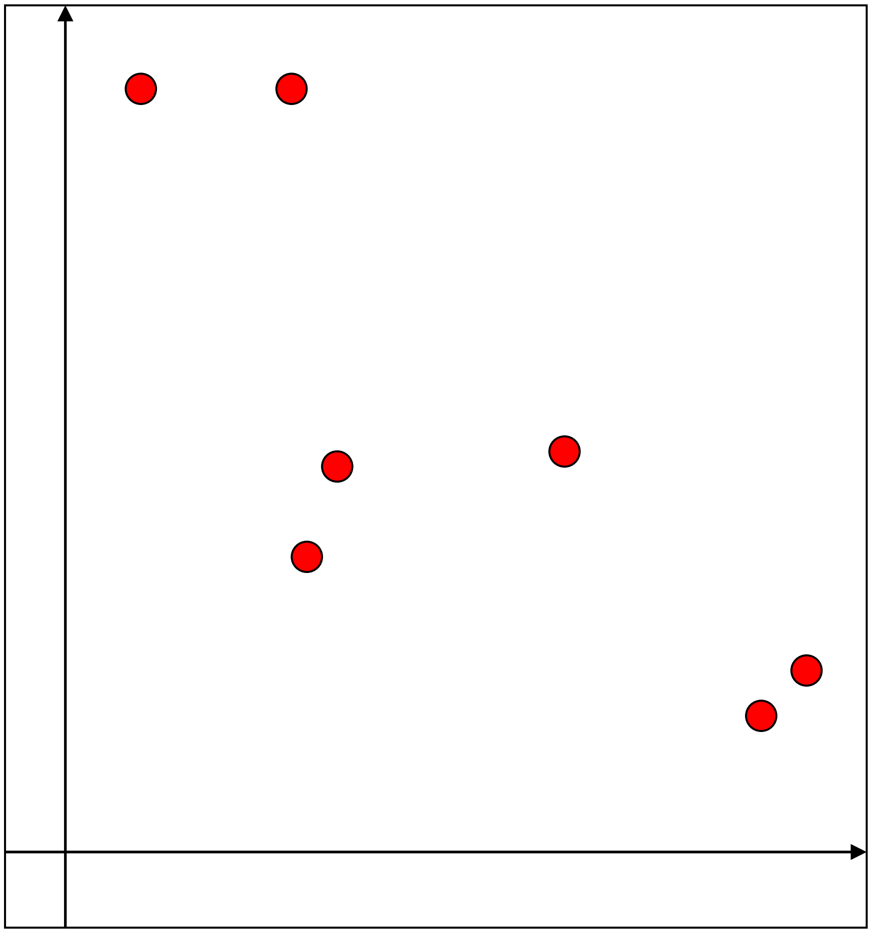
K-Means

- **How to choose the right *k*?**
  - *Try different **k**, looking at the change in the average distance to centroid as **k** increases*
  - *Average falls rapidly until right **k**, then changes little*



from [2]

Clustering on graphs



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- Remove k-1 edges with the highest weights
- Create the clusters

adapted from [3]

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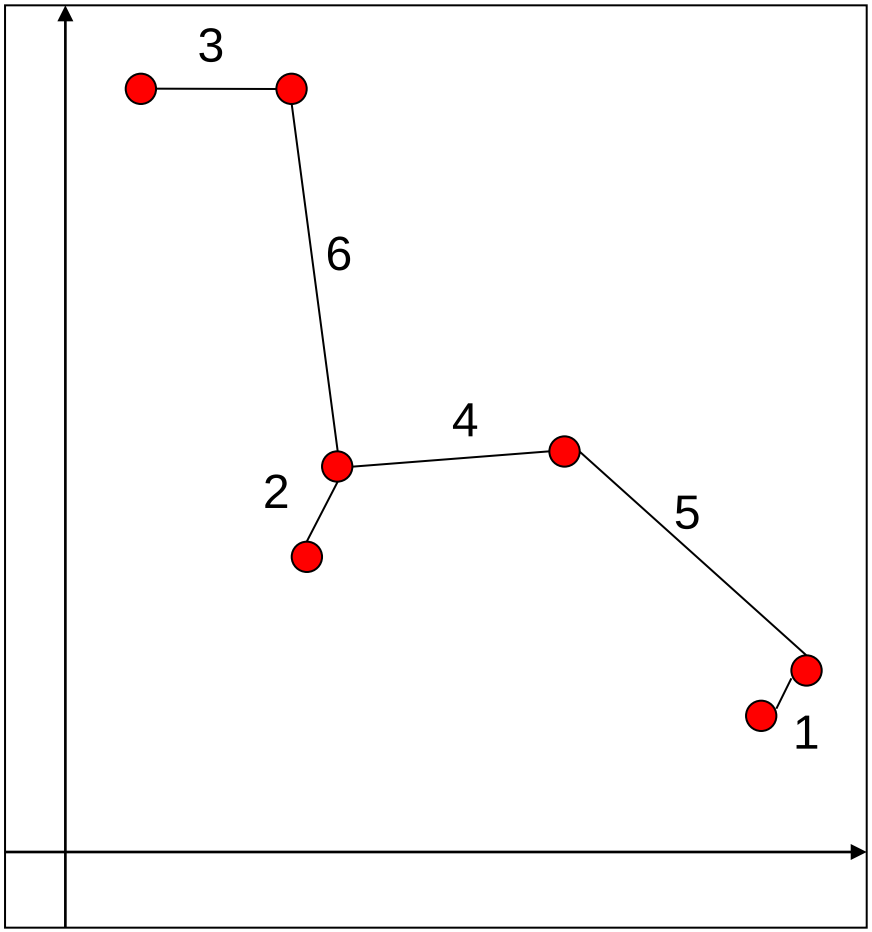

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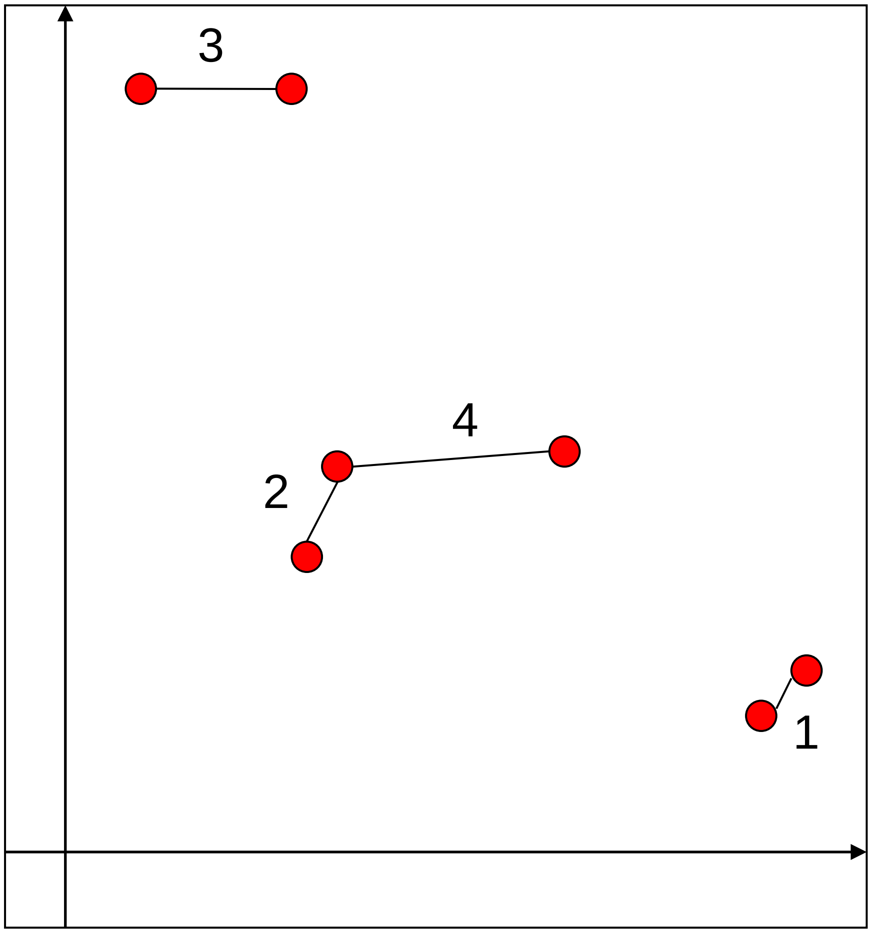
adapted from [3]

Clustering on graphs

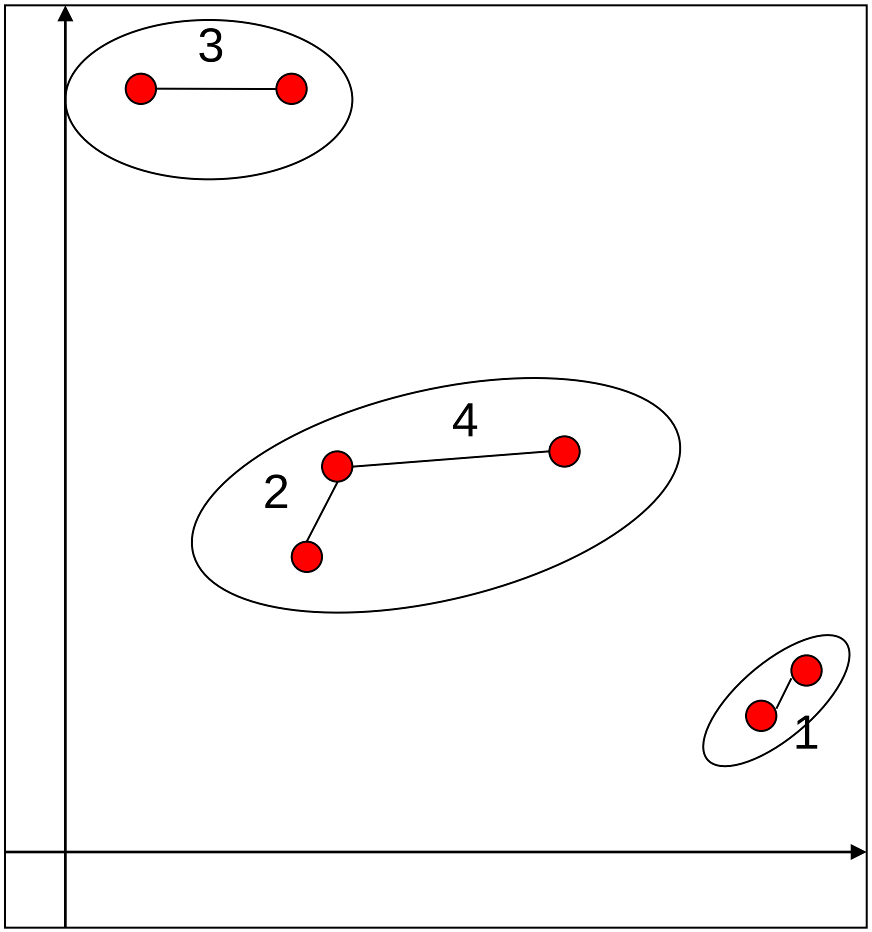


k=3

- Create the MST
- **Remove k-1 edges with the highest weights**
- Create the clusters

adapted from [3]

Clustering on graphs



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- Create the MST
- Remove k-1 edges with the highest weights
- **Create the clusters**

adapted from [3]

Literature

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