

# Clustering evaluation

# Clustering quality evaluation

## 1. Extrinsic methods (supervised methods)

- ground truth labels are used
- assign a score to a clustering given the ground truth labels

## 2. Intrinsic methods (unsupervised methods)

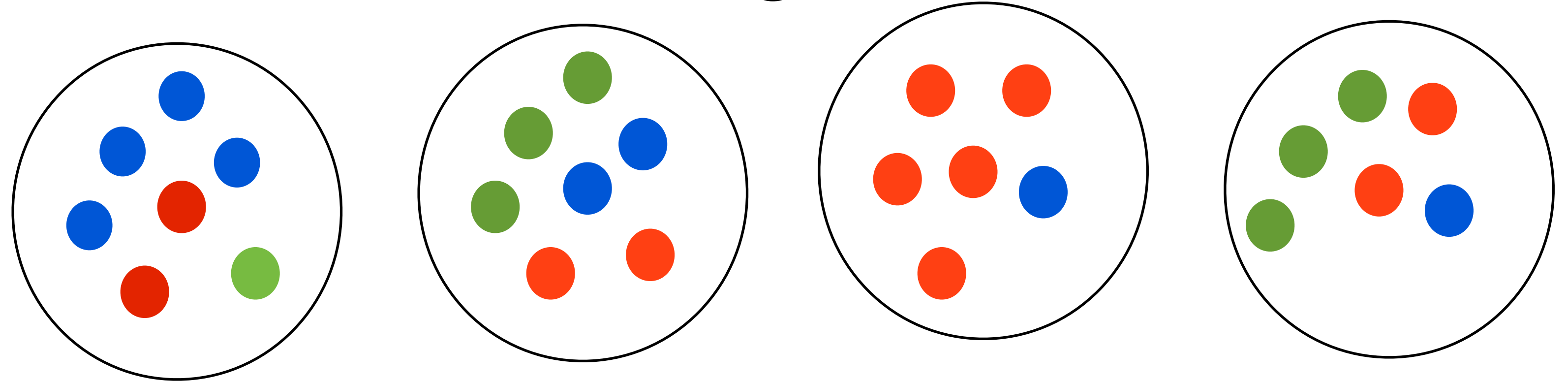
- only the partition of the objects into clusters is used
- examine how well the clusters are separated and how compact the clusters are

# Extrinsic methods: evaluate clustering as classification

1. Assign each cluster the label that appears most in that cluster
2. Merge clusters with the same label
3. Measure Precision, Recall, and F-measure for each label type
4. Compute the macro-average, i.e. the average over all label types (classes), of
  - Precision
  - Recall
  - F-score

# Extrinsic methods: evaluate clustering as classification

Clustering outcome



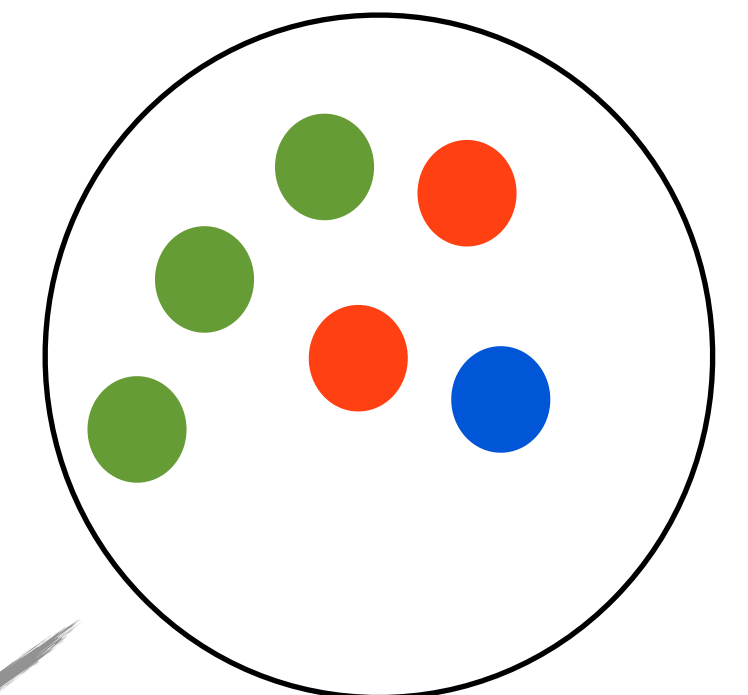
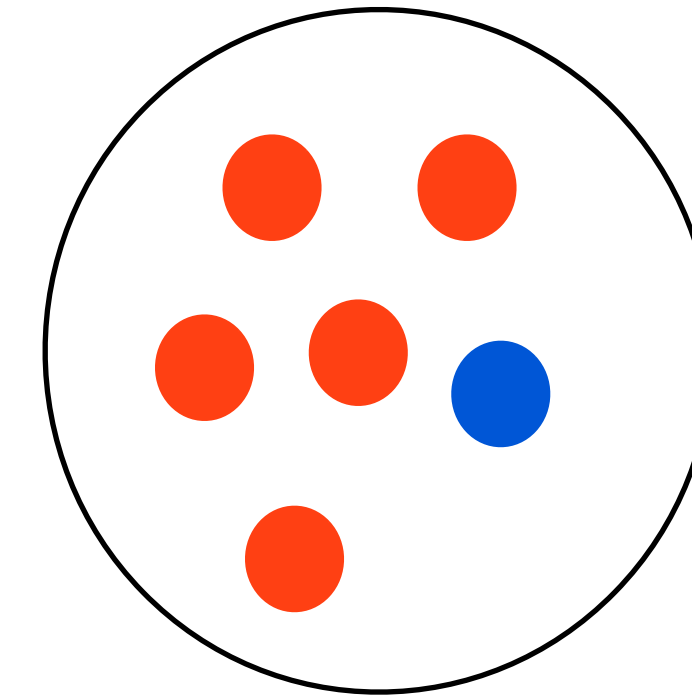
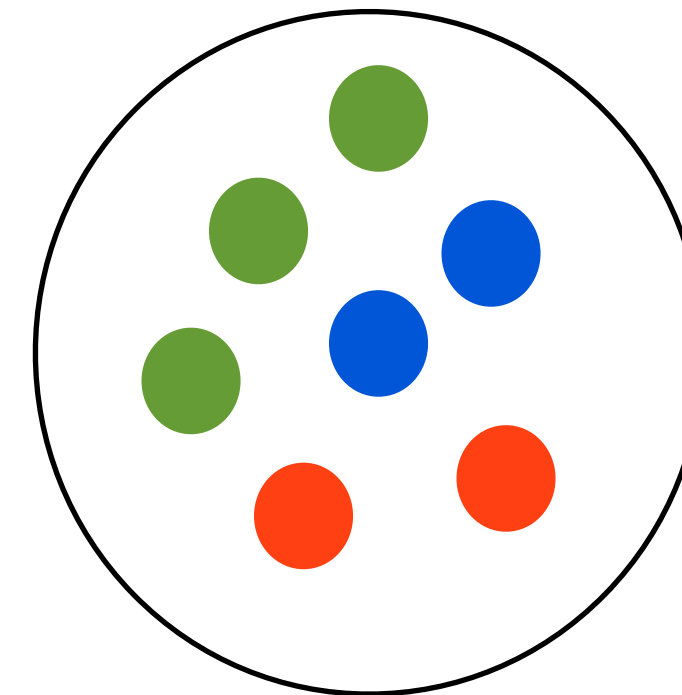
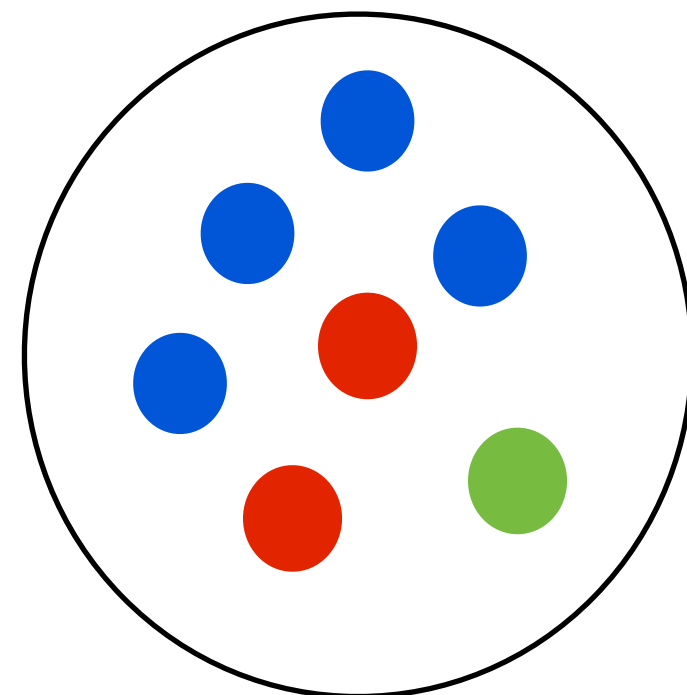
Assign each cluster  
the label that appears  
most in that cluster

Blue

Green

Red

Green

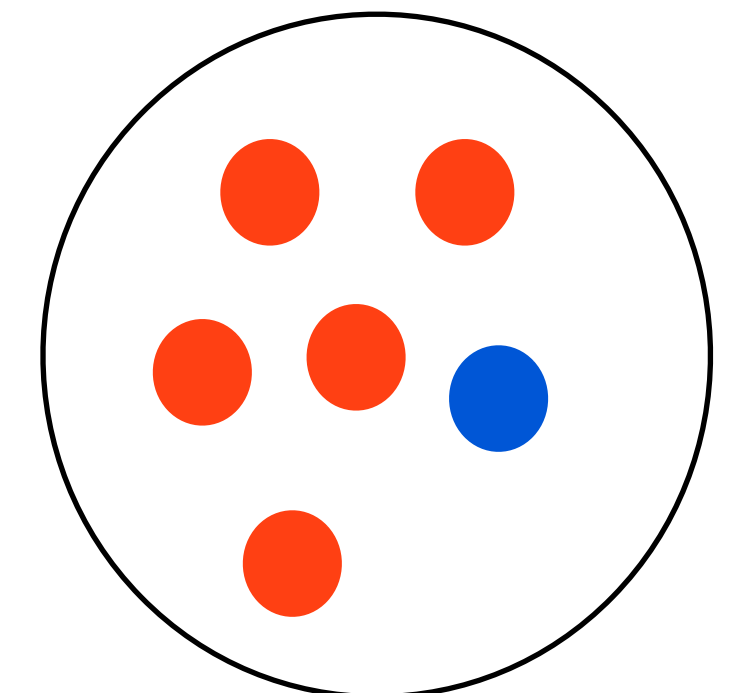
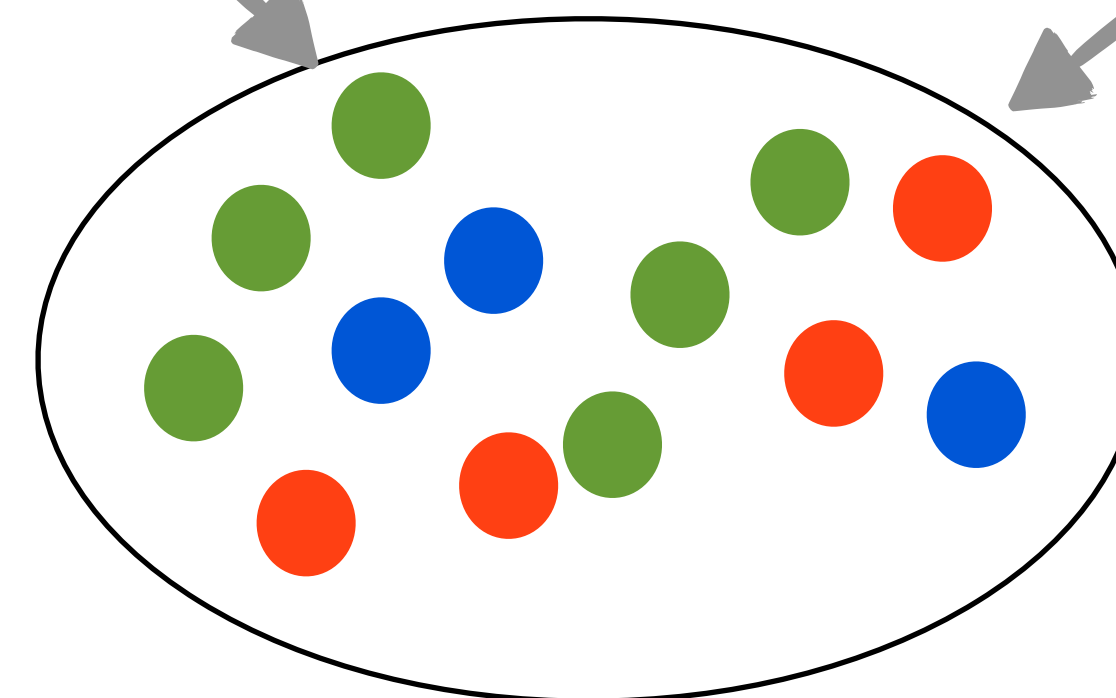
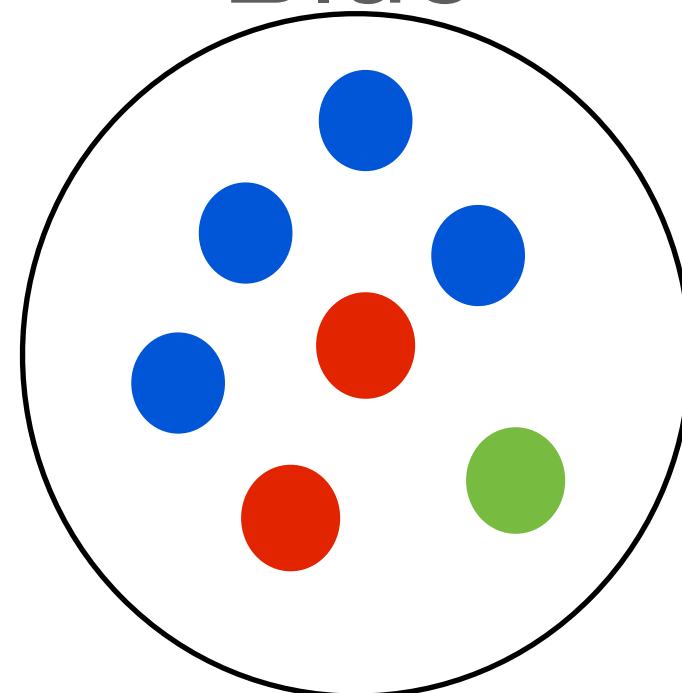


Merge clusters  
with the same label

Blue

Green

Red



# Extrinsic methods: B-CUBED Measure

- Proposed in (Bagga B. Baldwin = B<sup>3</sup>)
  - A. Bagga and B. Baldwin. *Entity-based cross document coreference resolution using the vector space model*, In Proc. of 36th COLING-ACL, pages 79--85, 1998.
- We would like to evaluate clustering without labelling any clusters.

$$\text{precision}(x) = \frac{\text{No. of items in } C(x) \text{ with } A(x)}{\text{No. of items in } C(x)}$$

$$\text{recall}(x) = \frac{\text{No. of items in } C(x) \text{ with } A(x)}{\text{Total no. of items with } A(x)}$$

$A(x)$ : label of  $x$

$C(x)$ : The ID of the cluster that  $x$  belongs to

# Extrinsic methods: B-CUBED Measure

- Compute the average over all the items (instances) that appear in all clusters (N)

$$\text{Precision} = \frac{1}{N} \sum_{p \in DataSet} \text{Precision}(p)$$

$$\text{Recall} = \frac{1}{N} \sum_{p \in DataSet} \text{Recall}(p)$$

$$F\text{--Score} = \frac{1}{N} \sum_{p \in DataSet} F(p)$$

# Intrinsic methods: Silhouette Coefficient

1. Let  $C_1, C_2, \dots, C_k$  be the clusters
2. For object  $x$  (assume  $x \in C_i$ ):
  - $a(x)$ : The mean distance between  $x$  and all other points in the cluster of  $x$ .
  - $b(x)$ : The mean distance between  $x$  and all other points in the *next nearest cluster*.

$$a(x) = \frac{1}{|C_i| - 1} \sum_{y \in C_i, y \neq x} d(x, y) \qquad b(x) = \min_{j=1, \dots, k, j \neq i} \frac{1}{|C_j|} \sum_{y \in C_j} d(x, y)$$

$a(x)$  is a measure of how dissimilar  $x$  is to its own cluster, a small value means it is well matched.

$b(x)$  is a measure of how badly  $x$  is matched to its neighbouring cluster.



# Intrinsic methods: Silhouette Coefficient

## 3. Silhouette Coefficient of $x$

$$s(x) = \frac{b(x) - a(x)}{\max\{a(x), b(x)\}}, \text{ if } |C_i| > 1$$

$$s(x) = 0, \text{ if } |C_i| = 1$$

$s(x)$  close to 1 means that the data is appropriately clustered

$s(x)$  close to -1 means that it would be more appropriate if  $x$  was clustered in its neighbouring cluster

$s(x)$  close to 0 means that  $x$  is on the border of two natural clusters

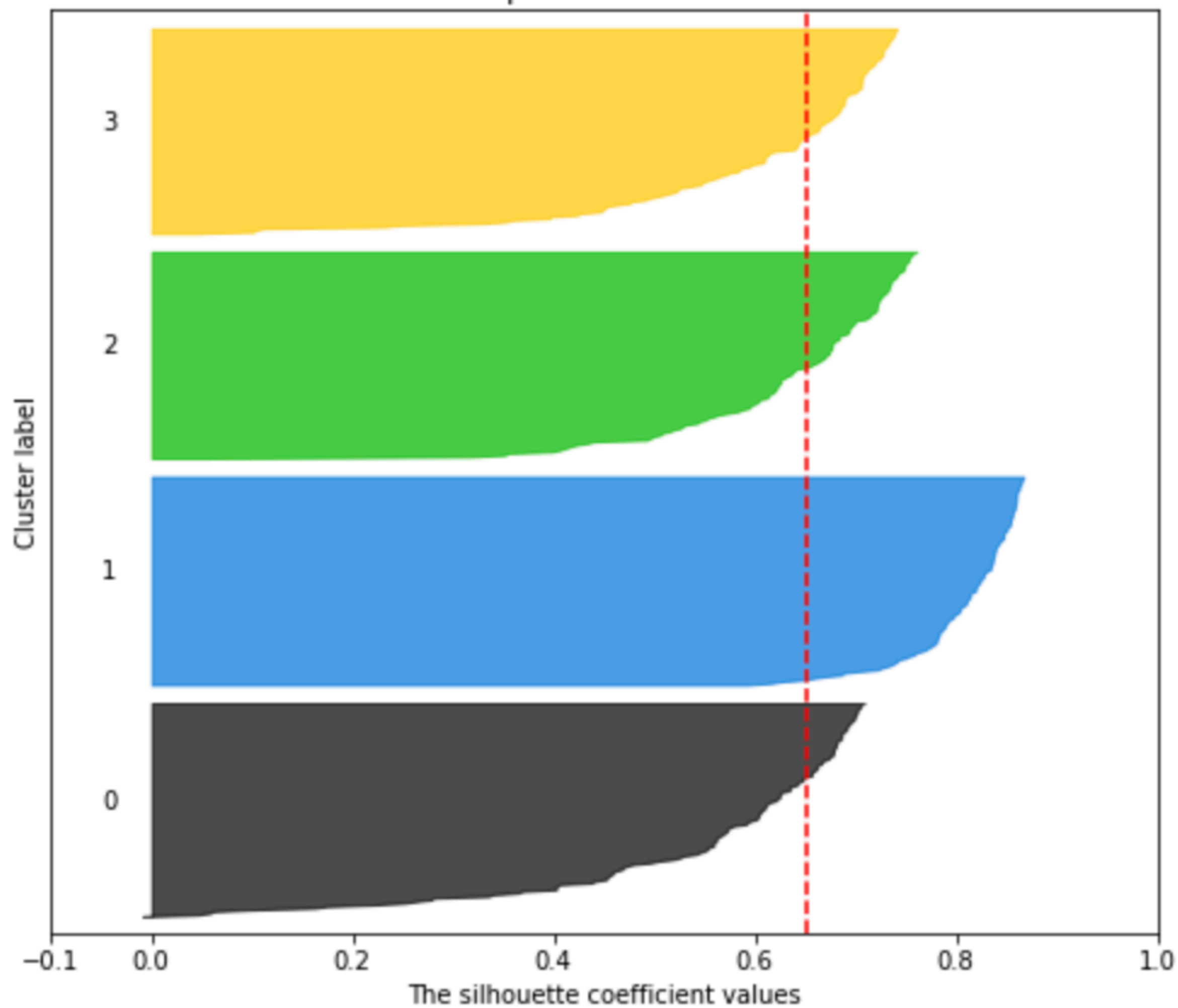
## 4. Silhouette Coefficient of the dataset is the average of Silhouette Coefficients of all objects in the dataset

measure of how appropriately the data have been clustered



# Intrinsic methods: Silhouette Coefficient

The silhouette plot for the various clusters.



The visualization of the clustered data.

