



香港城市大學  
City University of Hong Kong

專業 創新 胸懷全球  
Professional · Creative  
For The World

# Cluster Analysis: Different Evaluation Metrics

CS5483 Data Warehousing and Data Mining

# Different aspects for evaluation

- ▶ **Tendency:** Do the objects actually form clusters? Statistical significance?
- ▶ **Quantity:** What is the number of clusters?
- ▶ **Quality:** Are the clusters
  - ▶ Correct if ground truth is provided? **E\_\_\_\_\_ measure.**
  - ▶ “Clear” if ground truth is not provided? **I\_\_\_\_\_ measure.**

# Centroid-based methods

- ▶ The **within cluster s\_\_\_\_\_ of s\_\_\_\_\_ error** (WSS) of the clustering solution as a function of  $k$

$$\text{WSS}(k) := \sum_{j=1}^k \sum_{p \in C_j} \text{dist}(\mathbf{p}, \mathbf{c}_j)^2,$$

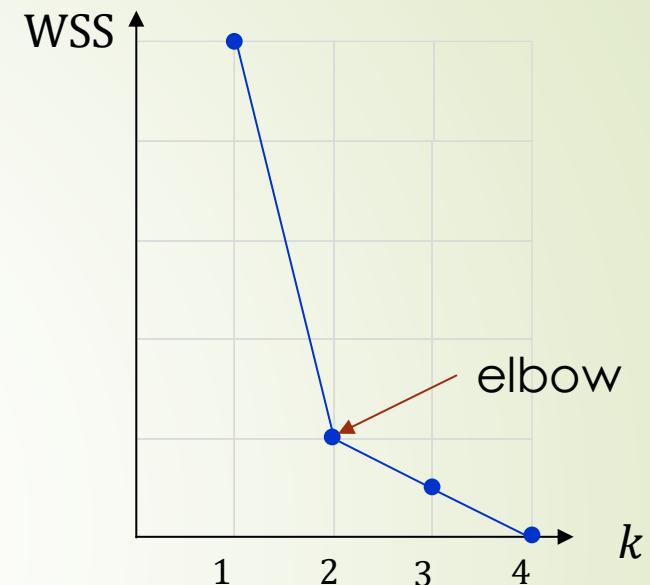
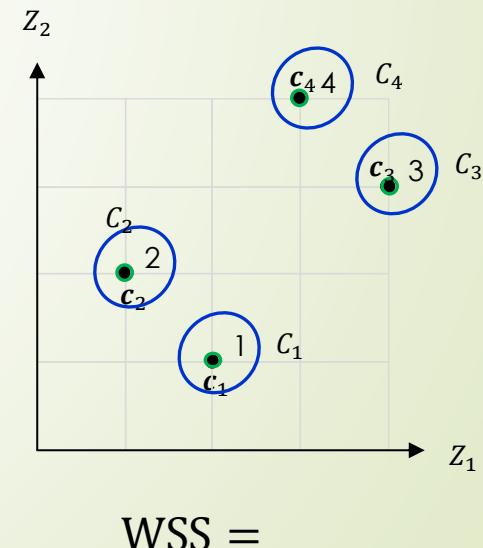
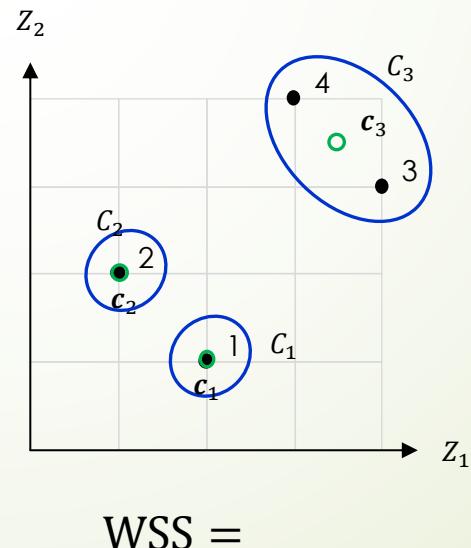
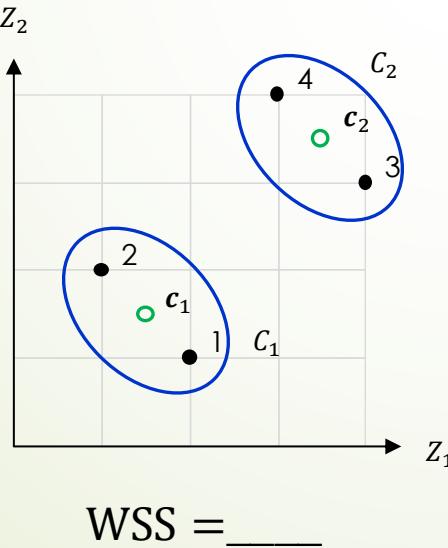
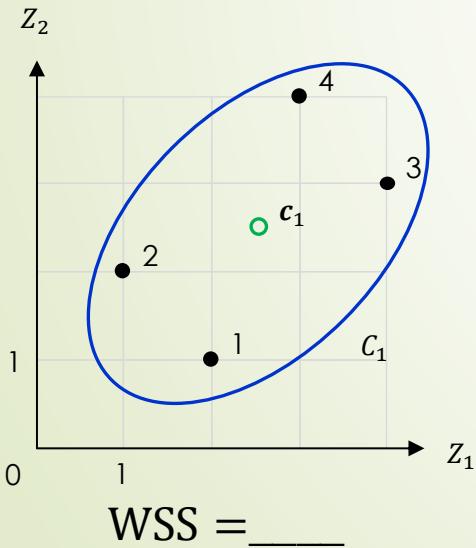
also denoted as  $\text{var}(k)$  in [Han11].

- ▶ WSS is an intrinsic/extrinsic quality measure.
- ▶ WSS is small/large if the clusters are clear, i.e., sample points deviate less from centroids.
- ▶ Should we choose  $k$  by minimizing WSS? Yes/No because

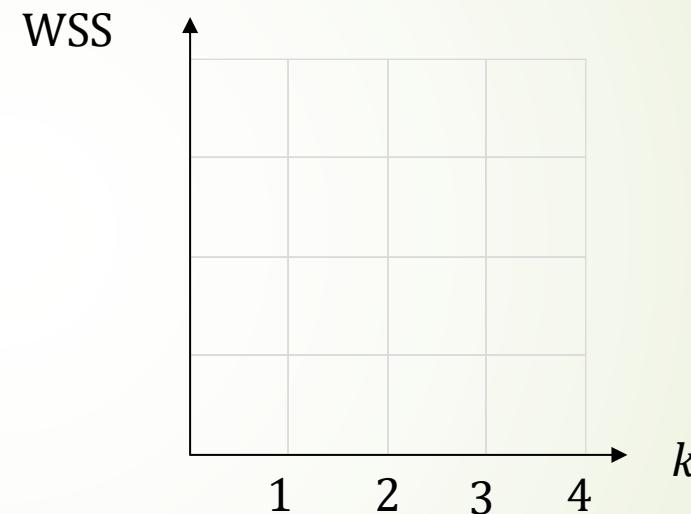
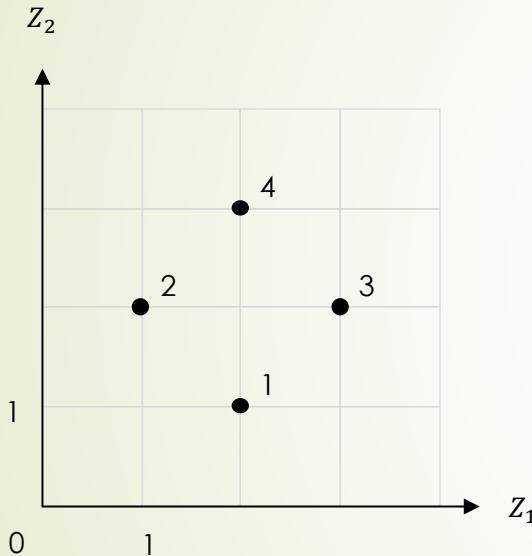
---

# Elbow method

- Choose  $k$  that gives large  $\text{m}$  \_\_\_\_\_ decrease in WSS from  $k - 1$ .
- Any problem of overfitting?



# Limitation of the elbow method



- ▶ The elbow method returns  $k = \underline{\hspace{2cm}}$ .
- ▶ The elbow method can fail. It is only a **h** $\underline{\hspace{5cm}}$ .
- ▶ Other intrinsic measures and analysis?

# Silhouette coefficient

- For any point  $\mathbf{p} \in D$  in the  $i$ -th cluster  $C_i$ :

$$s(\mathbf{p}) := \begin{cases} \text{undefined}, & k = 1 \\ 0, & |C_i| = 1 \\ \frac{b(\mathbf{p}) - a(\mathbf{p})}{\max\{a(\mathbf{p}), b(\mathbf{p})\}}, & |C_i| > 1 \end{cases}$$

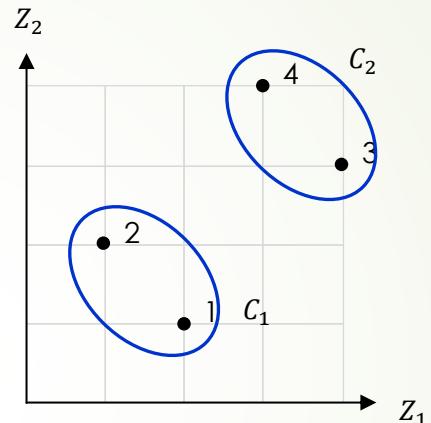
- Mean  $i$ -cluster distance:

$$a(\mathbf{p}) := \frac{1}{|C_i| - 1} \sum_{q \in C_i : q \neq p} \text{dist}(\mathbf{p}, \mathbf{q})$$

- Mean  $n$ -cluster distance:

$$b(\mathbf{p}) := \min_{j : p \notin C_j} \frac{1}{|C_j|} \sum_{q \in C_j} \text{dist}(\mathbf{p}, \mathbf{q})$$

- Quality of  $C_i$ : average  $s(\mathbf{p})$  over  $\mathbf{p} \in C_i$ .
- Overall quality: average  $s(\mathbf{p})$  over  $\mathbf{p} \in D$ .

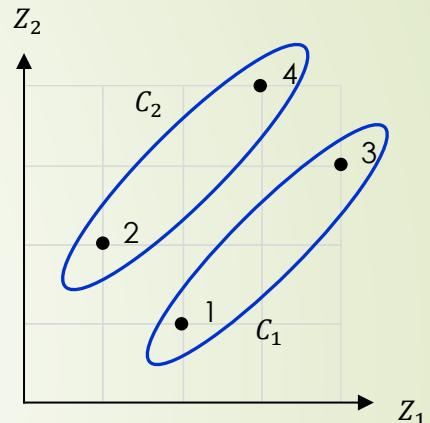


$$a(\mathbf{p}) = \sqrt{2}$$

$$b(\mathbf{p}) = \sqrt{2} + \sqrt{5}/2$$

$$s(\mathbf{p}) = \frac{\sqrt{5}}{2 + \sqrt{5}} \approx 0.53$$

Quality of  $C_1$ : 0.53  
Quality of  $C_2$ : 0.53  
Overall quality: 0.53



$$a(\mathbf{p}) = 2\sqrt{2}$$

$$b(\mathbf{p}) = 1/\sqrt{2} + \sqrt{5}/2$$

$$s(\mathbf{p}) = \frac{\sqrt{5} - 3}{4} \approx -0.19$$

Quality of  $C_1$ : -0.19  
Quality of  $C_2$ : -0.19  
Overall quality: -0.19

# Silhouette coefficient

- For any point  $\mathbf{p} \in D$  in the  $i$ -th cluster  $C_i$ :

$$s(\mathbf{p}) := \begin{cases} \text{undefined,} & k = 1 \\ 0, & |C_i| = 1 \\ \frac{b(\mathbf{p}) - a(\mathbf{p})}{\max\{a(\mathbf{p}), b(\mathbf{p})\}}, & |C_i| > 1 \end{cases} \text{ Why?}$$

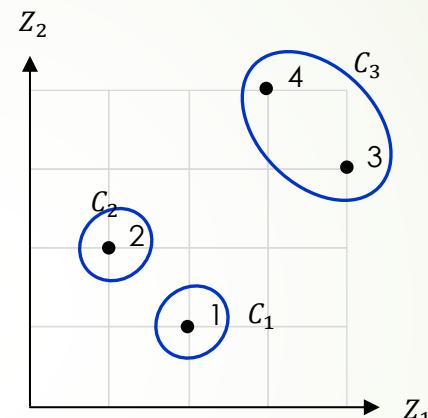
- $s(\mathbf{p}) \in [-1,1]$ : why?

  - $b(\mathbf{p}) > a(\mathbf{p})$ :  $s(\mathbf{p}) = \underline{\hspace{2cm}}$

  - $b(\mathbf{p}) < a(\mathbf{p})$ :  $s(\mathbf{p}) = \underline{\hspace{2cm}}$

- Sometimes we need a more detailed analysis by a silhouette plot.

- The method can fail on non-spherical clusters.



$$s(\mathbf{p}_1) = s(\mathbf{p}_2) = \underline{\hspace{2cm}}$$

$$a(\mathbf{p}_3) = a(\mathbf{p}_4) = \underline{\hspace{2cm}}$$

$$b(\mathbf{p}_3) = b(\mathbf{p}_4) = \underline{\hspace{2cm}}$$

$$s(\mathbf{p}_3) = s(\mathbf{p}_4) = \underline{\hspace{2cm}}$$

Quality of  $C_1$ :  $\underline{\hspace{2cm}}$

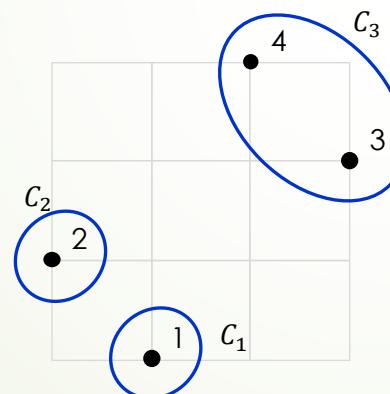
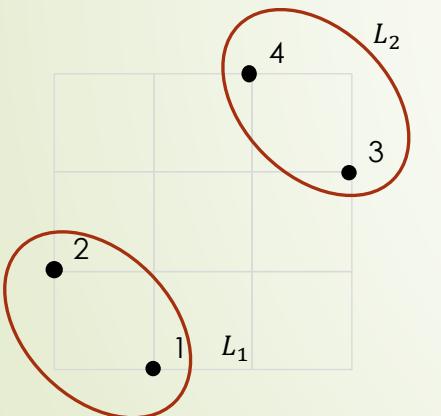
Quality of  $C_2$ :  $\underline{\hspace{2cm}}$

Quality of  $C_3$ :  $\underline{\hspace{2cm}}$

Quality of the clustering:  $\underline{\hspace{2cm}}$

# Extrinsic cluster quality measures

- ▶ Setting: Ground truth is available
  - ▶  $L(\mathbf{p})$ :  $\mathbf{C}_{\text{_____}}$  (class) of  $\mathbf{p}$ . (Ground truth.)
  - ▶  $C(\mathbf{p})$ : Cluster index of  $\mathbf{p}$ .
- ▶ How to compare the clustering solution to the ground truth?

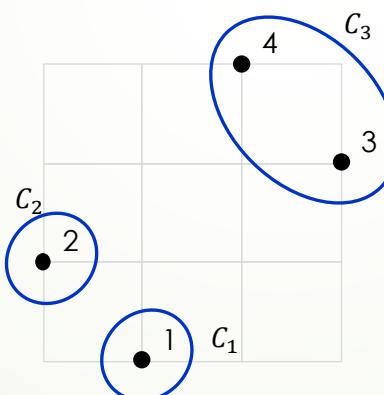
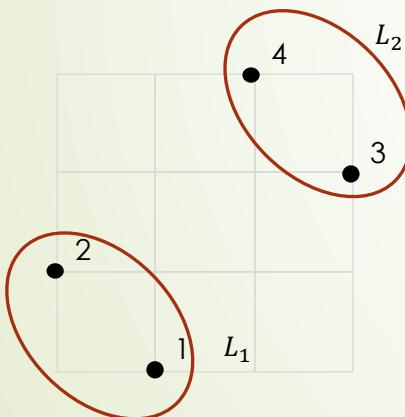


$$\begin{aligned}L(\mathbf{p}_1) &= L(\mathbf{p}_2) = 1 \\L(\mathbf{p}_3) &= L(\mathbf{p}_4) = 2\end{aligned}$$

$$\begin{aligned}C(\mathbf{p}_1) &= 1 \\C(\mathbf{p}_2) &= 2 \\C(\mathbf{p}_3) &= C(\mathbf{p}_4) = 3\end{aligned}$$

# Extrinsic cluster quality measures

- ▶ For two points  $p, q \in D$  to be clustered correctly:
  - ▶  $p, q$  should belong to the same cluster if they are in the same category.
  - ▶  $p, q$  should NOT belong to the same cluster if they are NOT in the same category.
  - ▶ Success indicator:  $\text{correctness}(p, q) = \mathbb{1}(L(p) = L(q) \leftrightarrow C(p) = C(q))$



		correctness( $p_i, p_j$ )			
		1	2	3	4
		1			
		2			
		3			
		4			

Accuracy: \_\_\_\_\_

- ▶ Is accuracy a good performance metric? Yes/No because \_\_\_\_\_

# B-Cubed precision and recall

- For  $p, q \in D$  (allowing  $p = q$ ), compute the confusion matrix

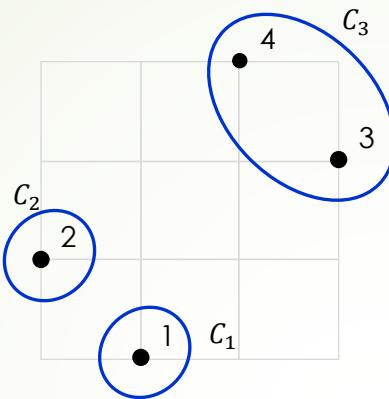
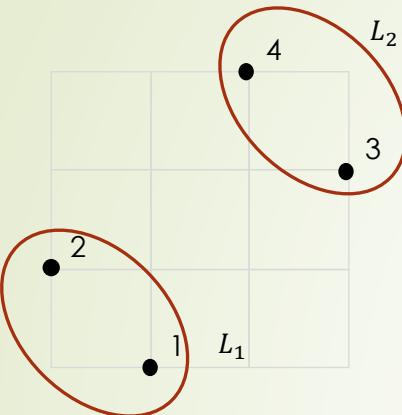
	$C(p) = C(q)$	$C(p) \neq C(q)$
$L(p) = L(q)$	TP	FN
$L(p) \neq L(q)$	FP	TN

- Sample  $p$  and  $q$  from  $D$  with replacement.
  - If  $p, q$  are in the same cluster, what is the chance they are in the same category?

\*recall/precision := —

- If  $p, q$  are in the same category, what is the chance they are in the same cluster?

\*recall/precision := —



precision = \_\_\_\_\_

recall = \_\_\_\_\_

$$\mathcal{C}(\mathbf{p}) = \mathcal{C}(\mathbf{q})$$

$$\mathcal{C}(\mathbf{p}) \neq \mathcal{C}(\mathbf{q})$$

$$L(\mathbf{p}) = L(\mathbf{q})$$

$$\text{TP}=6:$$

$(1,1), (2,2), (3,3), (4,4), (3,4), (4,3)$

$$\text{FN}= \underline{\hspace{2cm}}$$

$$L(\mathbf{p}) \neq L(\mathbf{q})$$

$$\text{FP}= \underline{\hspace{2cm}}$$

$$\text{TN}=8:$$

$(1,3), (3,1), (2,3), (3,2), (1,4), (4,1), (2,4), (4,1)$

Sanity check: total number of counts should be \_\_\_\_\_.

# Alternative formulae

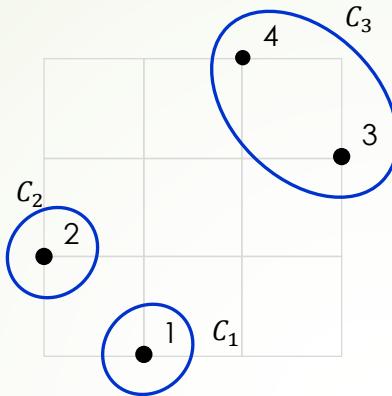
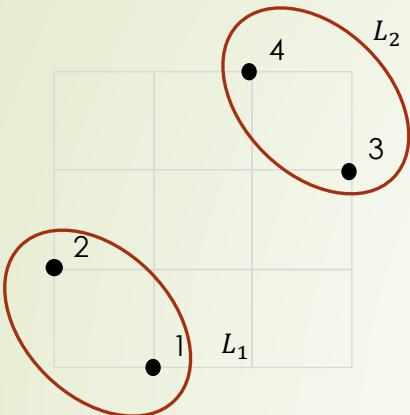
- ▶ B-Cubed precision is the average over  $\mathbf{p} \in D$  of

$$\text{precision}(\mathbf{p}) := \frac{|\{q \in D | C(\mathbf{p}) = C(q), L(\mathbf{p}) = L(q)\}|}{|\{q \in D | C(\mathbf{p}) = C(q)\}|}$$

- ▶ B-Cubed recall is the average over  $\mathbf{p} \in D$  of

$$\text{recall}(\mathbf{p}) := \frac{|\{q \in D | C(\mathbf{p}) = C(q), L(\mathbf{p}) = L(q)\}|}{|\{q \in D | L(\mathbf{p}) = L(q)\}|}$$

- ▶ Advantage: Breaks down the quality measure and its computation to individual point.



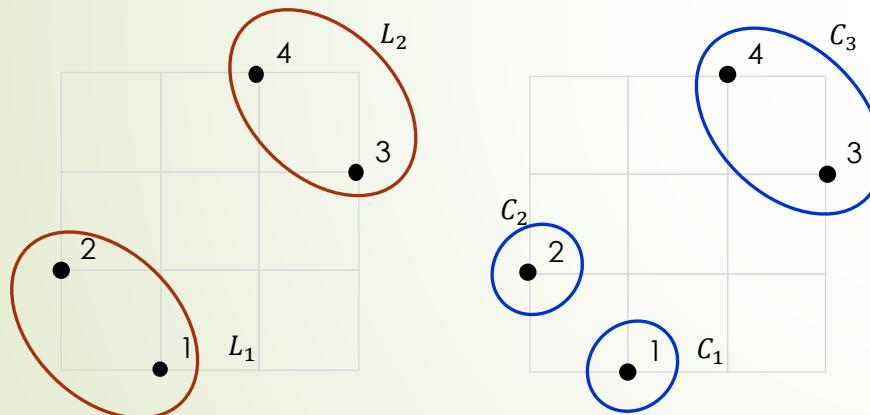
precision = \_\_\_\_\_

recall = \_\_\_\_\_

$i$	1	2	3	4
precision( $p_i$ )			100%	100%
recall( $p_i$ )			100%	100%

# Classes to clusters evaluation (WEKA)

- Match class to cluster labels to maximize correctly classified tuples.
- Use the “classification” error rate as the performance measure.



Number of instances

$L \backslash C$	1	2	3
1	1	1	0
2	0	0	2

Class assignment

Cluster  $\leftarrow$  Class

1  $\leftarrow$  \_\_\_\_\_

2  $\leftarrow$  \_\_\_\_\_

3  $\leftarrow$  \_\_\_\_\_

Accuracy = \_\_\_\_\_ %

- (Optional) There are other extrinsic measures such as the adjusted rand index.

# References

- ▶ 10.4.2 Ordering Points to Identify the Clustering Structure
- ▶ 10.6 Evaluation of Clustering
- ▶ Error in Han11:
  - ▶ Should remove the constraint  $i \neq j$  from (10.29) and (10.30).
- ▶ Supplementary readings:
  - ▶ Amigó, Enrique, et al. "A comparison of extrinsic clustering evaluation metrics based on formal constraints." *Information retrieval* 12.4 (2009): 461-486.
  - ▶ <https://scikit-learn.org/stable/modules/clustering.html#clustering-evaluation>