

CS522 Advanced Database Systems
Clustering: Cluster Evaluation

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Cluster Evaluation

- ◆ A.K.A. *Cluster Validation*
- ◆ Unsupervised
 - Using no external information other than the data itself
- ◆ Supervised
 - With external information such as given class labels

Reasons Not To Evaluate

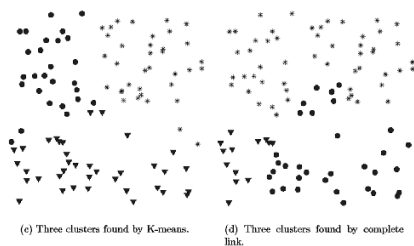
- ◆ Clustering is often used as part of exploratory data analysis
- ◆ Clustering is often used as part of other algorithms
- ◆ Clustering algorithms, in some sense, define their own types of clusters

Reasons To Evaluate ...



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... Reasons To Evaluate



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Questions To Be Answered

- ◆ Do clusters actually exist?
- ◆ How many clusters are there?
- ◆ How good is a cluster/clustering?

Clustering Tendency

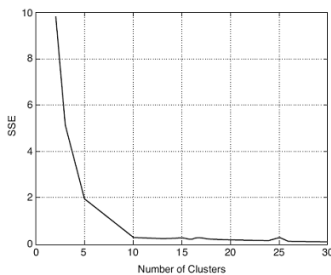
- ◆ Whether clusters exist in the first place
- ◆ Determine clustering tendency
 - Cluster first, then evaluate the quality of the clustering
 - ◆ Need to try several different types of clustering algorithms
 - Statistical tests for spatial randomness

Hopkins Statistic

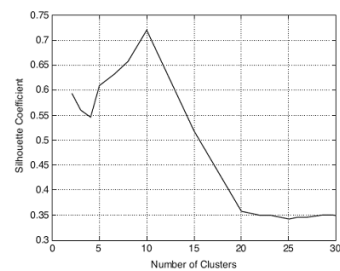
- ◆ Generate p random points in the data space
 - u_i : distance of a randomly generated point to its nearest neighbor in the original dataset
- ◆ Select p random points from the original dataset
 - w_i : distance of a randomly selected point to its nearest neighbor in the original dataset
- ◆ Interpretation of Hopkins Statistic??

$$H = \frac{\sum_{i=1}^p w_i}{\sum_{i=1}^p u_i + \sum_{i=1}^p w_i}$$

Determine The Correct Number of Clusters ...



... Determine The Correct Number of Clusters



Quality (Validity) of Clusters

- ◆ Cohesion
 - Compactness of a cluster
- ◆ Separation

Validity of Prototype-based Clusters

$$cohesion(C_i) = \sum_{\mathbf{x} \in C_i} dist(\mathbf{x}, \mathbf{c}_i)$$

$$separation(C_i, C_j) = dist(\mathbf{c}_i, \mathbf{c}_j)$$

$$separation(C_i) = dist(\mathbf{c}_i, \mathbf{c})$$

Validity of Graph-based Clusters

$$cohesion(C_i) = \sum_{\substack{x \in C_i \\ y \in C_i}} dist(\mathbf{x}, \mathbf{y})$$

$$separation(C_i, C_j) = \sum_{\substack{x \in C_i \\ y \in C_j}} dist(\mathbf{x}, \mathbf{y})$$

Validity of A Clustering

$$validity(C) = \sum_{i=1}^k w_i \times validity(C_i)$$

Cluster Weights

Validity Measures	Weights
$\sum_{\substack{x \in C_i \\ y \in C_i}} dist(\mathbf{x}, \mathbf{y})$	$1/ C_i $
$\sum_{x \in C_i} dist(\mathbf{x}, \mathbf{c}_i)$	1
$dist(\mathbf{c}_i, \mathbf{c})$	$ C_i $

Silhouette Coefficient

- ◆ For the i th object in a cluster
 - a_i : average distance to all other objects in the cluster
 - b_i : minimum of the average distance to the objects in a cluster that does not contain this object

$$s_i = (b_i - a_i) / \max(a_i, b_i)$$

About Silhouette Coefficient

- ◆ Range of s_i ??
- ◆ What is a "good" value of s_i ??
- ◆ Quality of an object: s_i
- ◆ Quality of a cluster/clustering: average s_i

Silhouette Coefficient Example

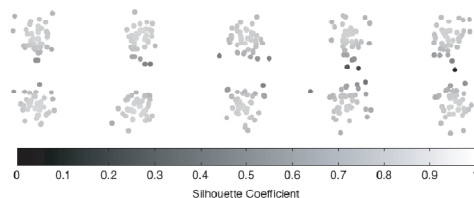
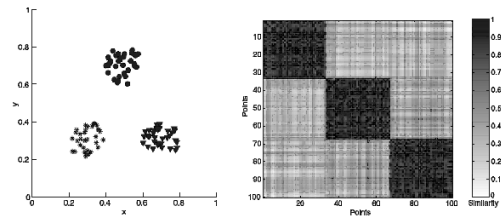


Figure 8.29. Silhouette coefficients for points in ten clusters.

Similarity Matrix

- ◆ Sort the objects by cluster label
- ◆ Similarity Matrix **M**
 - $M(i,j) = \text{similarity}(\mathbf{x}_i, \mathbf{x}_j), 0 \leq M(i,j) \leq 1$

Visualizing Clustering Results Using Similarity Matrix



(a) Well-separated clusters.

(b) Similarity matrix sorted by K-means cluster labels.

Supervised Measures of Cluster Validity

- ◆ Classification-oriented measures
 - Evaluate the extent to which a cluster contains the objects of a single class
- ◆ Similarity-oriented measures
 - Evaluate the extent to which two objects of the same class (or cluster) belong to the same cluster (or class)

Classification-Oriented Measures

- ◆ Entropy
- ◆ Purity
- ◆ Precision, recall, F-measure

Similarity-Oriented Measures – Contingency Table

	Same cluster	Different cluster
Same class	f_{11}	f_{10}
Different class	f_{01}	f_{00}

f – the number of *pairs* of objects

Example

- ◆ Classes: $\{p_1, p_2\}, \{p_3, p_4, p_5\}$
- ◆ Clusters: $\{p_1, p_2, p_3\}, \{p_4, p_5\}$

Similarity Measures

Rand Statistic:
$$R = \frac{f_{00} + f_{11}}{f_{00} + f_{01} + f_{10} + f_{11}}$$

Jaccard Coefficient:
$$J = \frac{f_{11}}{f_{01} + f_{10} + f_{11}}$$