CHAMELEON: Hierarchical Clustering

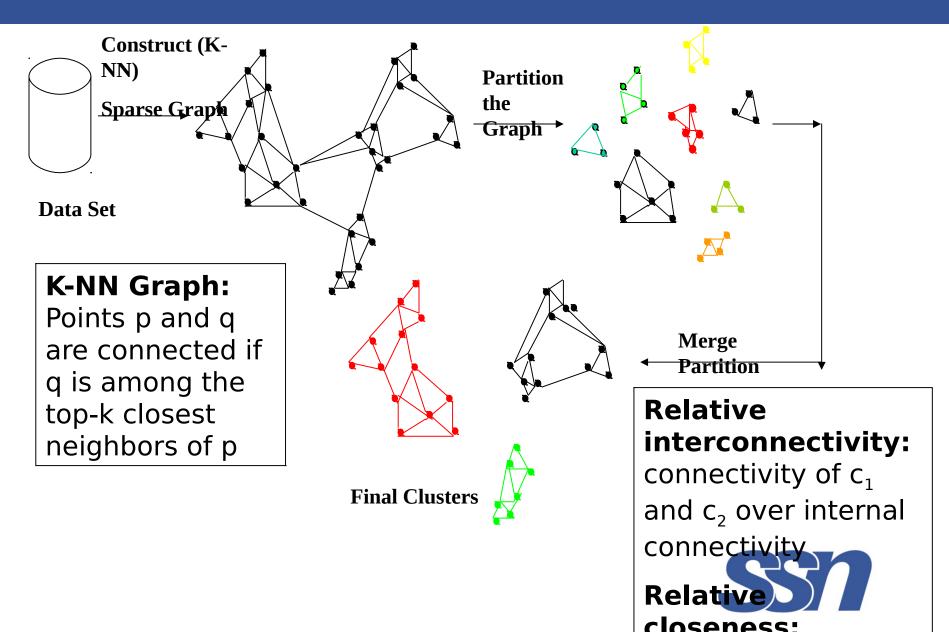


CHAMELEON: Hierarchical Clustering Using Dynamic Modeling

- CHAMELEON: A graph partitioning approach that uses dynamic model to determine the similarity between pair of clusters.
- Cluster similarity is assessed based on
 - How well connected objects within the cluster
 - The proximity of clusters.
- Two clusters are merged only if the interconnectivity and closeness (proximity) between two clusters are high.
- Chameleon adapt to internal characteristics of the clusters being merged

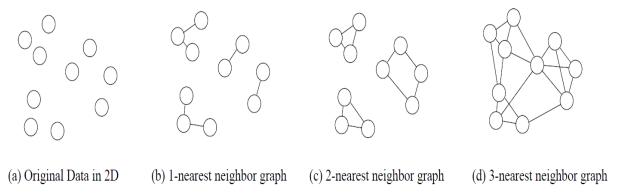


Overall Framework of CHAMELEON



KNN Graphs and Interconnectivity

K-nearest neighbor (KNN) graphs from an original data in 2D:



- Each vertex of the graph represents a data object there exists an edge between vertices if one object is among k-most similar objects to the other.
- The edges are weighted to reflect the similarity between objects.



CHAMELEON: Hierarchical Clustering Using Dynamic Modeling

- A graph-based, two-phase algorithm
 - Use a graph-partitioning algorithm: Cluster objects into
 a large number of relatively small sub-clusters
 - Use an agglomerative hierarchical clustering
 algorithm: Find the genuine clusters by repeatedly
 combining these sub-clusters



CHAMELEON: Partitioning the Graph

- Uses a graph-partitioning algorithm to partition k-nearest neighbor graph into large number of relatively small sub-clusters.
- The cluster C is partitioned into subclusters C_i and Cj so as to minimize the weight of the edges that would be cut hence C be bisected into C_i and Cj.
- It asses the absolute interconnectivity between clusters C_i and Cj.
- + $EC_{\{C_i,C_j\}}$: The absolute interconnectivity between C_i and C_j
 - The sum of the weight of the edges that connect vertices in C_i to vertices in C_i

CHAMELEON: Merging of Sub-Clusters

- Uses Agglomerative hierarchical clustering algorithm that iteratively merges subclusters based on their similarity.
- More similar subclusters are made based on the account of their relative interconnectivity (RI) and their relative closeness of the clusters (RC).
- **Relative Interconnectivity**(RI): $EC_{\{Ci,Cj\}}$: The absolute interconnectivity between C_i and C_j normalized with respect to the internal interconnectivity of two clusters C_i and C_j .
- **Internal Interconnectivity:** The size of the min-cut bisector ECci, the weighted sum of the edges that partition the graph into two roughly equal parts

CHAMELEON: Merging of Sub-Clusters

Relative Interconnectivity (RI): $EC_{\{Ci,Ci\}}$:

$$RI(C_i, C_j) = \frac{|EC_{\{C_i, C_j\}}|}{\frac{|EC_{C_i}| + |EC_{C_j}|}{2}}$$

Absolute interconnectivity defined for cluster C_i and C_j normalized by the average of the respective internal interconnectivities



Relative Closeness & Merge of Sub-Clusters

Relative closeness between a pair of clusters C_i and C_j : The absolute closeness between C_i and C_j normalized w.r.t. the internal closeness of the two clusters C_i and C_j $RC(C_i, C_j) = \frac{\overline{S}_{EC_{\{C_i, C_j\}}}}{\frac{|C_i|}{|C_i| + |C_i|} \overline{S}_{EC_{C_i}} + \frac{|C_j|}{|C_i| + |C_i|} \overline{S}_{EC_{C_i}}}$

where $\overline{S}_{EC_{C_i}}$ and $\overline{S}_{EC_{C_j}}$ are the average weights of the edges that belong to the min-cut bisector of clusters C_i and C_j , respectively, and is the average $\overline{S}_{EC_{\{C_i,C_j\}}}$ weight of the edges that connect vertices in C_i to vertices C_i



Relative Closeness & Merge of Sub-Clusters

Merge Sub-Clusters:

- Merges only those pairs of clusters whose RI and RC are both above some user-specified thresholds
- Discovers arbitrarily shaped clusters of high quality
- The processing cost for high-dimensional data may require $O(n^2)$ time for n objects in worst case.



CHAMELEON: Clustering Complex Objects

