

# Robust Single Linkage Algorithm and Extract Flat Clustering

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# Introduction

- There are many sources of almost unlimited data:
  - ① Images from the web.
  - ② Speech recorded by a microphone.
  - ③ Records of credit card or other transactions.
- Noise points occasionally draw between two cluster

# Minimum spanning tree

For each  $i$ , set  $r(x_i)$  to the distance from  $x_i$  to its  $k$ th nearest neighbor.

As  $r$  grows from 0 to  $\infty$ :

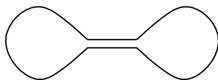
- 1 Construct a graph  $G_r$  with nodes  $\{x_i : r(x_i) \leq r\}$ . Include edge  $(x_i, x_j)$  if  $\|x_i - x_j\| \leq \alpha r$ .
- 2 Let  $\mathbb{C}_n(r)$  be the connected components of  $G_r$ .

## Definition

Set  $r_k(x_i)$  to the distance to  $k$ th nearest neighbor. For any  $r = \max\{r_k(x_i)\}$ , connect points  $x_i$  and  $x_j$ , if  $\|x_i - x_j\| \leq \alpha r$ .

# New distance function

Effect 1: thin bridges



For any set  $Z$ , let  $Z_\sigma$  be all points within distance  $\sigma$  of it.

Figure 1: “Thin bridge” effect.

## Definition

Set  $core_k(x_i)$  to the distance to  $k$ th nearest neighbor.

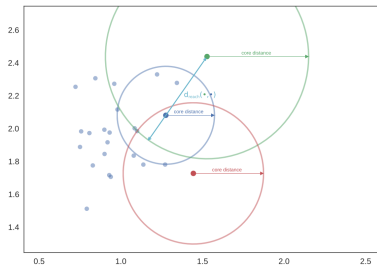
$$d_{\text{mrd}_k}(x_i, x_j) = \max\{core_k(x_i), core_k(x_j), ||x_i - x_j||\}$$

# Mutual reachability distance

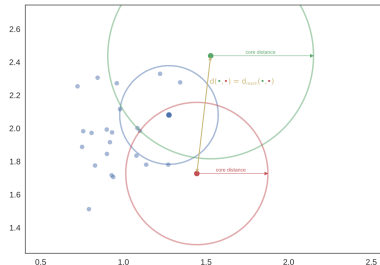
## Definition

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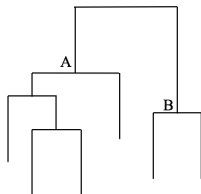
(a)



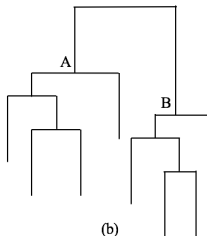
(b)

# Condense tree

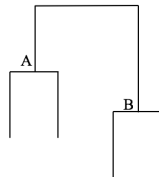
- If left child cluster point number is greater than minimum cluster size, but right side is not, Figure(a), keep the left branch and ignore right cluster;
- If left and right child clusters are both greater than minimum cluster size, Figure(b), we consider that a cluster split and let the split persist the whole tree;
- If left and right child clusters are both fewer than minimum cluster size, Figure(c), we ignore the two cluster.



(a)



(b)



(c)

# Condense tree algorithm

**Input:**  $H[m] \leftarrow$  hierarchy tree

**Output:**  $T[n] \leftarrow$  condense tree

$nodeList \leftarrow BFS(H);$

**for**  $r \leftarrow 0$  **to**  $m$  **do**

**if**  $nodeList[r]$  *is ignored* **then**

        Pass;

**end**

$left \leftarrow nodeList[r].child1;$

$leftCount \leftarrow H[left].childrenSize;$

$right \leftarrow nodeList[r].child2;$

$rightCount \leftarrow H[right].childrenSize;$

**if**  $leftCount \geq minClusterSize$  **and**  $rightCount \geq minClusterSize$  **then**

$T[p++] \leftarrow (nextLabel, ++nextLabel, 1/distance, leftCount);$   
         $T[p++] \leftarrow (nextLabel, ++nextLabel, 1/distance, rightCount);$

**end**

**if**  $leftCount < minClusterSize$  **then**

**for**  $tmpNode$  **in**  $BFS(left)$  **do**

**if**  $tmpNode$  *is leaf* **then**

$T[p++] \leftarrow (nextLabel, tmpNode, 1/distance, 1);$

**end**

            Ignore  $tmpNode$ ;

**end**

**end**

**if**  $rightCount < minClusterSize$  **then**

**for**  $tmpNode$  **in**  $BFS(right)$  **do**

**if**  $tmpNode$  *is leaf* **then**

$T[p++] \leftarrow (nextLabel, tmpNode, 1/distance, 1);$

**end**

            Ignore  $tmpNode$ ;

**end**

**end**

**end**

## Definition

Let  $\lambda = \frac{1}{d_{\text{mrd}_k}}$ . For each cluster we give  $\lambda_{\text{birth}}$  and  $\lambda_p$  to be the lambda value when the cluster split off then became it's own cluster, and the lambda value (if any) when the cluster split into smaller clusters respectively.

$$S(C) = \sum_{p \in C} (\lambda_p - \lambda_{\text{birth}})$$



# Cluster stability algorithm

**Input:**  $T[n] \leftarrow$  condense tree in reverse topological order contains a tuple of (parent,child, $\lambda$ ,childrenSize)

**Output:**  $S[n] \leftarrow$  stability of every node in condense tree

**for**  $r \leftarrow 0$  **to**  $n$  **do**

    currChild  $\leftarrow T[r].\text{child};$

    curr $\lambda \leftarrow T[r].\lambda;$

**if** currChild = prevChild **then**

        min $\lambda \leftarrow \text{Min}(\text{min}\lambda, \text{curr}\lambda);$

**else**

        birth $\lambda[\text{currChild}] \leftarrow \text{min}\lambda;$

        prevChild  $\leftarrow \text{currChild};$

        min $\lambda \leftarrow \text{curr}\lambda;$

**end**

**end**

**for**  $r \leftarrow 0$  **to**  $n$  **do**

$S[r] \leftarrow S[r] + T[r].\lambda - \text{birth}\lambda[T[r].\text{parent}] \times T[r].\text{childrenSize};$

**end**

## Definition

Set  $SC(C)$  is the sum of the stabilities of the child cluster of cluster  $C$ .

$$SC(C) = \sum_{q \in C} S(q)$$

# Flat clustering algorithm

**Input:**  $S[n] \leftarrow$  stability condense tree sorted in reverse topological order

**Output:**  $L[n] \leftarrow$  **True** cluster is selected; **False** otherwise

$L \leftarrow \{\mathbf{True}\};$

**for**  $r \leftarrow 0$  **to**  $n$  **do**

$\text{childList} \leftarrow \{\text{list of node whose parent is } r\};$

$\text{subtreeStabilities} \leftarrow \sum_{c \in \text{childList}} S[c];$

**if**  $\text{subtreeStabilities} > S[r]$  **then**

$L[r] \leftarrow \mathbf{False};$

$S[r] \leftarrow \text{subtreeStabilities};$

**else**

**for**  $\text{tmpNode}$  **in**  $\text{BFS}(r)$  **do**

**if**  $\text{tmpNode} \neq r$  **then**

$L[\text{tmpNode}] \leftarrow \mathbf{False}$

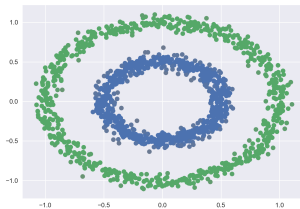
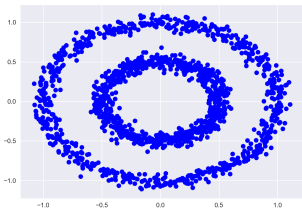
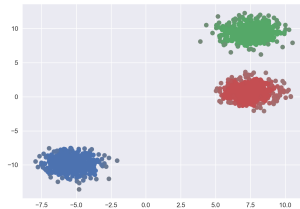
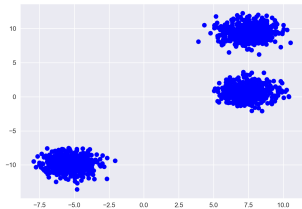
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**end**

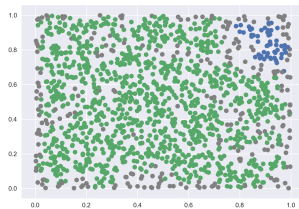
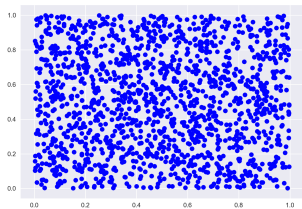
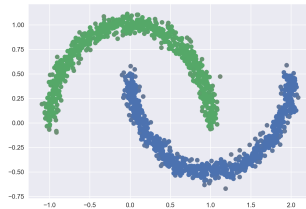
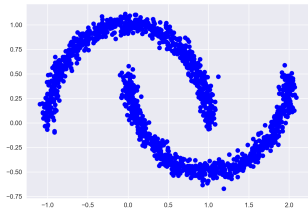
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**end**

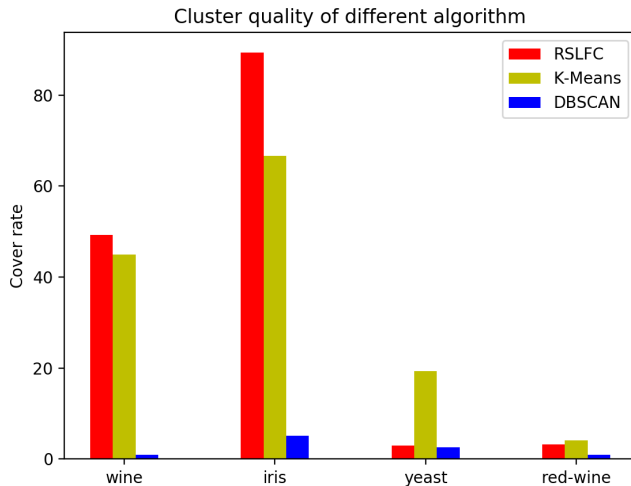
# Experiment



# Experiment (cont.)



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